Book of Abstracts

19th EAWE PhD Seminar
6-8 September 2023
Hannover, Germany
19th EAWE PhD Seminar Team

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Our Collaborative Research Centre (CRC) 1463 “Offshore Megastructures” develops new design and operating methodologies for future offshore wind turbines. These turbines need to have increased rotor diameters and rated power outputs compared to the state-of-the-art turbines in order to make offshore wind turbines a cornerstone of the future energy supply. A key point for the achievement of this goal is the development of a digital twin of an offshore wind turbine.

We greatly acknowledge the financial support of the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) - SFB1463 – 434502799.

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## Topics

### TOPIC 1: Wind Farm and wakes
- **Session 1.1** 06.09.2023 - 13:15
- **Session 1.2** 07.09.2023 - 15:30
- **Session 1.3** 08.09.2023 - 09:00
- **Session 1.4** 08.09.2023 - 10:30

### TOPIC 2: Control of wind turbines and wind farms
- **Session 2.1** 06.09.2023 - 10:30
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### TOPIC 3: Aero-elastics and blade technology
- **Session 3.1** 06.09.2023 - 13:15
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### TOPIC 4: Reliability, monitoring, and sensing technology
- **Session 4.1** 06.09.2023 - 10:30
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- **Session 4.4** 08.09.2023 - 10:30

### TOPIC 5: Emerging technologies
- **Session 5.1** 08.09.2023 - 09:00
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### TOPIC 6: Electrical conversion, energy system, and wind power-to-X
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### TOPIC 7: Support structures and geotechnics
- **Session 7.1** 06.09.2023 - 10:30
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### TOPIC 8: Hydrodynamics of offshore wind turbines
- **Session 8.1** 06.09.2023 - 13:15

### TOPIC 9: Floating wind turbines
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### TOPIC 10: Production, O&M, decommissioning and lifetime extension
- **Session 10.1** 06.09.2023 - 10:30

### TOPIC 11: Wind resources, turbulence, and acoustics
- **Session 11.1** 06.09.2023 - 13:15
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### TOPIC 12: General topics of wind energy
- **Session 12.1** 06.09.2023 - 10:30
- **Session 12.2** 07.09.2023 - 15:30
We thank for the support of our sponsors

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<tr>
<th>Time</th>
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<td>Building 3701, Room 265</td>
<td>Registration</td>
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<tr>
<td>9:00</td>
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<td>10:00</td>
<td>Building 3701, Room 267</td>
<td>Control of wind turbines and wind farms</td>
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<td>10:30</td>
<td>Building 3703, Room 335</td>
<td>Production, O&amp;M, decommissioning</td>
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<td>14:45</td>
<td>Building 3702, Room 031</td>
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<td>16:30</td>
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<td>18:00</td>
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<td>Reliability, monitoring and sensing technology</td>
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<td>Aero-elastics and blade technology</td>
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### Tuesday 5 September

#### Opening Session
- Joana Rieck

#### Registration
- Building 3701, Room 268
- Building 3701, Room 267
- Building 3702, Room 031
- Building 3703, Room 023

#### Ice Breaker event
- Building 3701, Room 268

#### Wednesday 6 September

#### Coffee
- Building 3701, Room 268

#### Control of wind turbines and wind farms
- Joana Rieck: Physical design of hybrid power plants
- Oliver Hain: Wind energy management for offshore wind farms
- Ruthie Oetting: Numerical analysis of onshore wind farms

#### Production, O&M, decommissioning and lifetime assessment
- Simon Kamin: Towards a flexible approach to offshore wind farm decommissioning
- Stefan Burmeister: On the recent trend of wind turbine decommissioning
- Norbert Hübner: Hybrid use of LTT welding filler and climate-related impacts in the design of wind turbines and offshore wind farms

#### Wind resource, turbulence and acoustics
- Athanasios Kolios: Opening Session
- Borowski Johanna: Predicting future wind speeds based on climate projections and MCP constrained on wind tunnel measurements
- Bengtslakid: Fatigue crack development in highly loaded groused connections

#### Hydrodynamics of offshore wind turbines
- Timo Löffler: Characterizing wind fields by applying a Langevin Analysis to model wind turbine measurement data
- Marcel Derung: Towards real-time optimal control of wind farms using large-eddy simulations

#### Reliability, monitoring and sensing technology
- Johanna Kuster: Influence of repair measures on the fatigue behaviour of rotor blades
- Friederike Großmann: Investigation of Leading edge erosion and its mitigation on the levelized CO2 price for horizontal axis wind turbines
- Martin Meier: Validation of structural models for wind turbine blades with different levels of fidelity

#### Support structures and geotechnics
- Marcin Miechowki: Advanced methods for oceanic design of offshore jacket substructures
- Erol Can: Analytical integration of CFD’s for oil & gas industries
- Georg Böhm: Biomechanical aspects of the connection between wind turbines and the seabed

#### Wind farm and wakes
- Daniel Estrella: Optimization of offshore wind farm control strategies under consideration of uncertainties
- Marcel Hufner: Offshore wind farm control: From the conceptual design to the final realization

#### Hydrodynamics of offshore wind turbines
- Manuel Dondi: Characterizing wind fields by a superimposed synthetic model on wind farm measurements
- Michaela Schuster: Verification of a new mid-fidelity aerodynamic simulation tool for large wind turbines

#### Aero-elastics and blade technology
- Daniel Schuster: Numerical analysis of onshore wind farms
- Rüdiger Schiller: Fatigue crack development in highly loaded groused connections
- Marco Sottas: Fatigue life predictions for wind turbine blades with different levels of fidelity
Thursday 7 September

10:30 Coffee

Networking Lunch

14:00

Building 3703, Room 023

Aero-elastics and blade technology

Michael Edgar: Aero-structure coupled optimisation of a rotor blade for an up-scaled 25 MW reference wind turbine

Wind resources, turbulence and aerodynamics

Rubert Heissel: Physics informed Machine Learning Approach for Outdoor Sound Propagation Model

Reliability, monitoring and transfer learning

Sieverser Philipp: Towards an aerodynamic wind turbine optimization using CFD with script-based meeting and parametric CAD in the loop

Simulations for wind energy applications

Jorgensen Ole: AI-based refinement of mesoscale induced loads on wind turbines with the Lattice-Boltzmann Method

15:00 Coffee

15:30

Building 3701, Room 268

Control of wind turbines and wind farms

Deepak Kaul: Developing Turbine Control Systems Based on Machine Learning

General topics of wind energy

Daniela Rehfeld: An improved performance of a 5-MW GW turbine model in predicting load characteristics for a large range of wind velocities

Reliability, monitoring and data analysis

Kaelike Stephanie: Methodology for reliability testing in microgrid with wind turbines and electrolyzers using SAVM simulations

Support structures and geotechnics

Prigge Felix: Numerical buckling analysis of rotor blade sandwich panels with spatially distributed material uncertainties

16:00 Dinner

19:00

Building 3701, Room 267

Wind farm and wakes

Saxena Isha: Data Driven Infrastructure Offshore Wind Turbine Behaviour of the tower of an onshore and an offshore wind turbine

Control of wind turbines and wind farms

Edler Amelie: Comparison of the dynamic monitoring and transfer learning of the tower under environmental conditions

Reliability, monitoring and structural health

Oliveira Catarina: Safety control through intelligent population-based structural health monitoring and transfer learning

Support structures and geotechnics

Sanders Immo: Numerical Simulation of Suction Caissons under Axial Loading

19:30

Building 3702, Room 031

Support structures and geotechnics

Goldau Norman: Model testing of a gravity structural steel used in offshore wind turbines

Rolling mode

Eichner Lukas: Design of offshore jacket support foundation in sand

10:00 Keynote Session

Jos Beurskens
Julia Gottschall
Nikhar Abbas

11:00 Meet the Industry

ENERCON GmbH
JÖRSS-BLUNCK-ORDEMANN GmbH
Ramboll GmbH
wpd windmanager GmbH & Co. KG
Wölfel Holding GmbH

12:45 Networking Lunch
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<td>Wind farm and wakes</td>
<td>Building 3703, Room 023</td>
<td>Schaller Jens Peter: RANS based PINN wake surrogate</td>
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<td>Building 3701, Room 268</td>
<td>Abdulrahman Abdullah: High resolution measurements of turbulent structures in atmospheric flows using a wind tunnel test site</td>
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<td></td>
<td>and acoustics</td>
<td>Building 3701, Room 267</td>
<td>Palagonía Emmanuela: Synthetic Design Alternatives for Offshore Wind Turbine Substructures</td>
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<tr>
<td>9:15</td>
<td>Emerging technologies</td>
<td>Building 3702, Room 031</td>
<td>Shear: An investigation of the interaction between floating wind turbines and direct drive generators on grid.</td>
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<td>9:30</td>
<td>Floating wind turbines</td>
<td>Building 3703, Room 335</td>
<td>Abdulrahman Abdullah: Effect of the probe volume on wind speed measured by short-range continuous wave lidars in a wind farm test site.</td>
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TOPIC 1: Wind Farm and wakes

Session 1.1
06.09.2023 - 13:15
Building 3703, Room 027

Daenens Simon  Reinforcement learning for health-aware fleet control of wind farms
Jané-Ippel Christian  Bayesian optimisation of a two-turbine layout around a 2D hill using Large Eddy Simulations
Ruck Nico  Optimisation of flexible wind farm control strategies under consideration of uncertainties
Martins Flavio  3D Unsteady CFD Model for Multi-Rotor Multi-Body Fluid Structure Interaction
Reinforcement learning for health-aware fleet control of wind farms

Simon Daenens\textsuperscript{a}, Timothy Verstraeten\textsuperscript{a}, Jan Helsen\textsuperscript{a}

\textsuperscript{a}Vrije Universiteit Brussel

E-mail: simon.daenens@vub.be

Keywords: Offline reinforcement learning, wind farm control, condition monitoring

1. Introduction

With the increasing demand for renewable energy, wind farms have become a crucial source of sustainable power generation. Offshore wind farms, in particular, hold tremendous potential due to the abundance of wind resources. However, they face unique challenges, including the remote and harsh operating environment. For offshore wind energy to play a mature role in the energy mix, offshore wind farms need to be operated as conventional power plants based on energy demand, while reducing downtime due to maintenance. Current control strategies often focus solely on maximizing power output without considering the impact on the health of individual turbines. This limitation can lead to increased maintenance costs, reduced equipment lifespan, and compromised operational safety. Moreover, in the current state-of-the-art, wind turbines in wind farms are controlled in a greedy way: each turbine maximizes its own performance without considering the wake effect or the farm-wide performance.

Recently, research has been done on collective wind farm control. For example, \cite{1}, \cite{2}, and \cite{3} optimize wind farm performance through wake-steering: a control strategy that uses the yaw angle to deflect the turbine wakes and thus minimize turbine interactions. In \cite{4}, both the yaw and pitch settings are controlled to maximize the power produced while minimizing the overall fatigue. Other papers, such as \cite{5} and \cite{6} optimize the axial induction factor, a measure of the decrease in wind velocity behind a wind turbine, which is mainly controlled by the generator torque and the blade pitch angle. \cite{7} and \cite{8} combine this with the optimization of the turbines’ yaw angles.

While these works have shown great potential in increasing efficiency in wind farms, none of the current methods for wind farm control make use of the large quantities of wind farm data available. Control policies are not learned from data alone (as in supervised learning), but instead require some online interaction with (a simulation of) the environment to be controlled. For a wind farm setting, this can be prohibitively expensive and dangerous due to possible energy losses and damage to the wind turbines, as well as the lack of accurate and computationally efficient simulators.

Efforts have been made to develop high-fidelity wind farm simulators to use in the development of automatic controllers (e.g., FLORIS \cite{11}, OpenFast \cite{12}) but these are simplified versions of reality and do not cover the full dynamic spectrum of farm conditions. Wind farm simulators that could be used to mimic interaction with the environment for reinforcement learning (RL) are not readily available. Large differences between the simulators and the real environment result in uncertainties when transferring learned control policies to reality, increasing the difficulty of implementing these methods in real wind farms.

In the current state-of-the-art, reinforcement learning techniques are often considered for wind farm control. It provides a mathematical framework for learning-based control and has the capacity to deal with challenges such as the nonlinear wake interaction between the turbines in a farm. Research has been done in the past with regards to fleet control of wind turbines, but some challenges remain in transferring the research to practice. While reinforcement learning has proven to be useful in numerous applications, it inherently relies on interaction with
an environment. For some applications, this poses no problems as the environment can be easily simulated (e.g., Atari [9], Go [10]), however, for other domains this can be prohibitively dangerous or expensive.

Since in our case real-time interaction with the environment is impractical and large amounts of pre-collected data are available, a promising solution and the method to be used in this thesis is offline reinforcement learning (also known as batch reinforcement learning), a variation of reinforcement learning where the agent learns from previously recorded experiences instead of learning in real-time through interaction with an environment. This allows us to optimally leverage existing data sets, rather than requiring extensive interactions through the existing real-world controller.

2. Research question and objectives

In this research, we focus on investigating the use of offline reinforcement learning to develop a health-aware wind farm controller that optimizes power output, reduces costs, and ensures safe and reliable operation. We aim to develop a scalable and customizable framework for learning control policies from wind farm data using offline reinforcement learning. This will serve as a proof-of-concept for applying data-driven learning in the context of wind farm control. Then, we will identify meaningful health indicators based on SCADA data and incorporate them into the framework. This will allow us to optimize power production while considering the health status of individual wind turbines. Finally, by analyzing the decisions made by the controller, we can enhance its interpretability and assess the cost-savings generated. This understanding is crucial for stakeholders considering the adoption of a new control system.

3. Research methodology

3.1 Data preprocessing and feature extraction

The wind farm data, including SCADA data and health indicator measurements, will undergo preprocessing to remove noise, normalize the data, and handle missing values. Relevant features, such as wind speed, wind direction, turbine performance parameters, and health indicators derived from condition monitoring techniques, will be extracted from the data.

3.2 Offline reinforcement learning algorithm design

A scalable and customizable offline reinforcement learning algorithm will be designed to learn optimal control policies from the preprocessed wind farm data. This algorithm will consider the complex interactions between wind turbines caused by the wake effect and aim to maximize power generation while incorporating the health indicators as additional constraints.

![Diagram of online and offline reinforcement learning](image)

Figure 1: Pictorial illustration of classic online reinforcement learning (a), and offline reinforcement learning (b). Figure adapted from [13].

In Figure 1, we compare offline RL to the classic online RL. In online RL, the policy $\pi_k$ is updated with streaming data collected by $\pi_k$ itself. The agent continuously interacts with its environment according to its
current policy and uses these interactions to continuously update that policy. In offline RL, all data is collected in advance using some potentially unknown behavior policy $\pi_0$. Then, using this data, a policy is trained without interaction with the environment, and the policy is only deployed after training.

### 3.3 Integration of health indicators into the controller

A comprehensive set of health indicators will be selected based on SCADA data analysis and root-cause analysis. These indicators will be integrated into the offline reinforcement learning framework to develop a health-aware wind farm controller. The integration will enable the controller to make informed decisions that prioritize turbine health while optimizing power generation.

### 4. Expected outcomes

The expected outcomes of this research are as follows:

1. Development of a health-aware wind farm controller: we aim to develop a controller that optimizes power output while considering the health indicators of wind turbines. By leveraging offline reinforcement learning techniques and integrating available wind farm data, this controller will make informed decisions that prioritize turbine health.

2. Improved wind farm performance and reliability: the developed controller is expected to improve overall wind farm performance and reliability. By optimizing power output and considering the health indicators, the controller can contribute to increased energy production, reduced maintenance costs, extended equipment longevity, and enhanced risk mitigation.

3. Insights into the relationship between control actions and turbine health: the analysis of the decisions made by the wind farm controller will provide valuable insights into the relationship between control actions and turbine health. This understanding can contribute to the development of interpretability metrics and further enhance control strategies for improved turbine health and operational efficiency.

### 5. Conclusion

In this research, we will introduce a novel approach to wind farm control by developing a health-aware wind farm controller using offline reinforcement learning. By integrating offline reinforcement learning with available wind farm data and optimizing power generation while considering turbine health, this research aims to improve wind farm performance, reliability, and maintenance efficiency. The expected outcomes have the potential to significantly contribute to the sustainable development of offshore wind farms.

### References


Bayesian optimisation of a two-turbine layout around a 2D hill using Large Eddy Simulations

C. Jané-Ippel\textsuperscript{a}, N. Bempedelis\textsuperscript{a}, R. Palacios\textsuperscript{a}, and S. Laizet\textsuperscript{a}

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E-mail: christian.jane-ippel19@imperial.ac.uk

Keywords: Optimisation, Complex Terrain, Atmospheric Boundary Layer, Large Eddy Simulation

1 Introduction

Many onshore wind farms are likely to be situated on hilly terrain or close to urban centres, influencing the atmospheric boundary layer properties and wind turbine wakes. The complex terrain can induce wind speed-ups, veer, reverse flow and high levels of turbulence intensity affecting the resulting output, loads and wake recovery of the turbines. Thus, accounting for the influence of the topography has proven to be crucial for optimal design and performance of wind farms \cite{1, 2}. Recent work by the authors \cite{3} studied the effects of a 2D hill, a steep hill with a constant section, on the performance of wind turbines with Large Eddy Simulations (LES). It has been found that placing a wind turbine on top of the hill reduces the recirculation zone of the hill wake and accelerates the flow near the wall, improving locally the wind conditions downstream. When placing a second wind turbine at 2.5\textit{D} downstream of the hilltop, it improves its performance by a factor of three when compared to the case with no turbine on the hilltop. If the downstream turbine is located at 5\textit{D} from the top of the hill, there is no noticeable improvement in power production. The different enhancements of power seen for the two different locations suggest that there is an optimal downstream position where the maximum power increment can be obtained. In this study, we exploit further these improved conditions in the hill wake with the aim of improving the power density of wind farms around complex terrain. We perform a Bayesian Optimisation using LES as function evaluation to find the streamwise locations and hub heights that produce the maximum power output in a two-turbine set-up around a 2D hill.

2 Methodology

2.1 Set-up

The complex terrain investigated in this work is a constant section hill studied experimentally by Cao and Tamura \cite{4} defined by a cosine-squared function with a maximum height of \( h = 0.04 \text{ m} \) and half-width of \( L = 0.1 \text{ m} \). The incoming velocity profile of the experiments is defined by a turbulent boundary layer of height \( \delta = 0.25 \text{ m} \), a friction velocity \( u_\tau = 0.1926 \text{ m/s} \) and a roughness length \( y_0 = 0.004 \text{ mm} \). The actuator disc that represents the wind turbines has a diameter of \( D = h \), a thrust coefficient of \( C_T = 0.75 \) and an axial induction factor of \( a = 0.25 \). The design variables of the optimisation are the streamwise locations \((x_1, x_2)\) and hub heights \((h_1, h_2)\) of the two wind turbines and are normalised by the turbine’s diameter. The streamwise locations are within the range of \( x_1 \in [-1.25, 1.25] \) and \( x_2 \in [1.25, 5.00] \), while the hub heights are constrained within \( h_1 \in [0.70, 1.50] \) and \( h_2 \in [0.70, 1.50] \). These variables are subject to spacing constraints to ensure safe operation of the turbines, leaving always more than one diameter of distance between the wind turbine centres \((x_2 - x_1 > 1.05)\). Figure 1 shows a representative sketch of the complex terrain and the wind turbines for \( x_1 = 0.0, h_1 = 1.0, x_2 = 3.75 \) and \( h_2 = 1.0 \).

2.2 Numerical methods

The wind farm simulator WInc3d \cite{5}, part of the high-order finite-difference framework Xcompact3d \cite{6}, is used to perform LES of the flow over complex terrain for high Reynolds numbers. The computational framework offers...
a highly efficient parallelisation strategy with “spectral-like” accurate numerical schemes on a Cartesian mesh. The terrain features are reproduced with an immersed boundary method (IBM), which can be combined with a stress wall model to avoid the prohibitively expensive resolution of the viscous sub-layer. A precursor simulation is run to generate the neutrally stable turbulent boundary layer that is used as inlet boundary condition in the complex terrain simulations. To model the wind turbines, a forcing term is added to the Navier-Stokes equations as the actuator disc method (ADM).

The computational domain has a size of $L_x \times L_y \times L_z = (5 \times 1 \times 1)\delta$. The simulations are performed for a total time of $T_{ct} = 75s$, and the statistics are collected over the last 50s. Results are presented for the mesh $(n_x \times n_y \times n_z = 385 \times 193 \times 128)$, which results in around 9.5M mesh nodes, and the time step used is $dt = 5 \times 10^{-5}$. More details about the numerical methods and validation can be found in Jané-Ippel et al. [3].

2.3 Optimisation

In order to maximise the power of the two-turbine set-up, a Bayesian optimisation (BO) with a Gaussian Process (GP) surrogate model is employed. The optimisation process is implemented using the GPyOpt [7] library in Python. The BO process starts with an initial set of design points, which are generated using Latin Hypercube Sampling (LHS) with 40 samples to cover the design space. From the function evaluation of the initial sample using LES, the GP surrogate model is constructed using the Matérn 5/2 kernel, since it has been proven to be effective for applied problems such as physical experiments [8]. The kernel’s hyperparameters, the variance and lengthscales, are optimised during the BO process. The acquisition function used to determine the next points to evaluate is the Lower Confidence Bound (LCB) criterion. The acquisition weight parameter of the LCB balances the exploration and exploitation by considering both the predicted mean and uncertainty of the surrogate model. A standard value of $w_{LCB} = 2.0$ has been used here.

During the optimisation process, the surrogate model is updated at each iteration with the new evaluations, and the acquisition function selects a batch of design points to evaluate in parallel. The batch size has been selected to be 4 due to the wall-clock time expense of each function evaluation, which is around 12 hours. The BO process has continued until 100 function evaluations, which have been considered to have reached convergence. Figure 2 shows the normalised farm power output as a function of the iteration count.

![Figure 1: Schematic configuration of the complex terrain and design variables representing the actuator disc centre.](image)

![Figure 2: Convergence of the normalised power as a function of the iteration count.](image)
3 Results

To present the results two representative cases will be analysed in detail. The best case from the optimisation will be compared against a reference case which would be a more conventional set-up where one wind turbine is placed on top of the hill and another downstream at a standard distance of 5D. The total power is defined as the sum of each wind turbine normalised by the power generated by a single wind turbine under the influence of the same inlet conditions without the hill presence.

The best case among the function evaluation performed during the BO has achieved a normalised total power of $P_{\text{max}} = 4.45$. This is achieved when the upstream wind turbine produces $P_{\text{max},1} = 2.23$ by being located at $x_1 = 0.2$ and has a hub height of $h_1 = 1.5$ with the downstream wind turbine producing $P_{\text{max},2} = 2.22$ by being located at $x_2 = 1.25$ and $h_2 = 0.97$. Figure 3 shows the time evolution of the power production of each turbine and their cumulative average for the reference $P_{\text{ref}}$ and optimum case $P_{\text{max}}$. For both cases, the power of the wind turbine on top of the hill shows a very similar behaviour with $P_{\text{ref},1}$ being slightly higher than $P_{\text{max},1}$. The chaotic shape of the power series can be explained by the influence of incoming turbulence in the ABL. As seen by the optimum case, there is an obvious increase in power in the downstream turbine when increasing the hub height of the upstream wind turbine and optimising the position of the downstream one compared to the reference case, $P_{\text{max},2} >> P_{\text{ref},2}$. Note that for the optimum case, the downstream wind turbine is able to generate almost as much power as the upstream wind turbine.

The difference between the two cases in the power evolution of the downstream wind turbine can be understood by analysing the time-averaged velocity fields. Figure 4 shows the normalised time-averaged streamwise velocity field in the mid-plane for each case with the streamlines shown with black lines. The white line represents the edge of the recirculation region that has been obtained with the contour of zero velocity to identify the edge of reverse flow. In the reference case, the downstream turbine is affected by both the low velocity shed by the hill and the upstream turbine wake, which explains its low power generation. On the other hand, the optimum case has placed the downstream turbine so that it avoids the turbine and hill wakes and takes advantage of the local acceleration between the hill speed-up and the upstream wind turbine. It can be seen that the optimum case has also reduced drastically the recirculation region compared to the conventional case, something beneficial for hypothetical downstream rows of turbines.

![Figure 3: Power series of the reference (left) and the optimum (right) cases.](image1)

![Figure 4: Normalised time-averaged streamwise velocity field of the reference (left) and the optimum (right) cases. The black lines are the streamlines of the velocity field. The white lines are the contours of zero velocity.](image2)
Further details can be discussed from the second-order statistics. Figure 5 shows the normalised time-averaged streamwise turbulence intensity in the mid-plane for each case. From the reference case, it can be seen that the hill induces high levels of turbulence due to the separation of the flow and that is directly affecting the downstream turbine together with the turbulence generated by the upstream turbine. However, the optimum case is in a cleaner condition affected only partially by the wakes of the hill and upstream turbine. Moreover, it can be seen that the optimum combination of turbines is also suppressing the turbulence shed downstream by the hill if it is compared to the reference case.

Figure 5: Normalised time-averaged streamwise turbulence intensity field of the reference (left) and the optimum (right) cases.

Acknowledgements

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References

Optimisation of flexible wind farm control strategies under consideration of uncertainties

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Keywords: wind farm control, flow modelling

In the future, wind energy will increasingly be in direct competition with both conventional energy sources and other renewable energies. In order to remain competitive, the electricity production costs of wind energy must therefore be further reduced. In addition, wind turbines are increasingly required to actively contribute to grid stability. In order to achieve these goals, greater flexibility is needed with regard to the regulation and grid integration of wind turbines. For this reason, science and industry are currently looking for ways to optimise the operation of wind farms and make them more flexible. A collective control of the turbines of a wind farm makes it possible to flexibly adapt the power to the demand. In addition, the load of individual wind turbines can be better controlled and thus a uniform lifetime consumption for the wind farm can be achieved.

In order to reduce the negative effects of wake interactions within a wind farm, mainly two strategies for wind farm control have been proposed in recent literature, namely wake steering and induction control [1] [2]. Numerical simulations of wind farm effects are an important tool to estimate wake interactions and their influences on turbine performance and structural loads of individual wind turbines. Due to the large number of possible combinations of inflow conditions and turbine operating points, faster engineering models are needed for optimising wind farm control. For power optimisation, there are a number of quasi-static simulation tools that can be used to maximise wind farm performance through wake steering. Due to the lack of fast structural models to determine the influence of control strategies on the structural fatigue loads of the turbines, this has only been considered to a lesser extent [3].

The aim of the work is to develop a method for combined power and load optimisation by coupling a surrogate load model with analytical quasi-static wake models. First, different wake models are compared with each other to find the most suitable model for the respective application. Subsequently, the models are tuned using machine learning methods based on operational data (SCADA, CMS) from the alpha ventus research wind farm. In order to have a broader data base for the development of the models, this data base will be extended with results of the mid-fidelity simulation tool FAST.Farm. In the end, the developed wind farm control strategies will be implemented in FAST.Farm. Finally, in order to better assess the uncertainties, the results will be validated using LES simulations.

This enables the holistic optimisation of flexible wind farm control strategies and should reduce the associated uncertainties in the application.

1 References


3D Unsteady CFD Model for Multi-Rotor Multi-Body Fluid Structure Interaction

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Keywords: Hybrid Methods; Vortex Particle Methods; OpenFOAM; Eulerian-Lagrangian coupling; External Aerodynamics

Abstract

The objective behind this project is to develop a 3D Hybrid solver implemented in OpenFOAM purposed for lift-driven aerodynamics such as wind energy and aircraft aerodynamics. More specifically, this Ph.D. project focuses on the addition of fluid-structure interaction capability by introducing a combination of domain deformation and partitioned fluid-structure coupling methods. In a region close to solid boundaries, the full Navier-Stokes equations (possibly with an arbitrary turbulence model or DNS) are solved on a deforming (meshed) domain and coupled to a structural dynamics model; outside of that region, the flow is solved with a Lagrangian (meshless) vortex particle method. In this hybrid approach, the complexity and size of the deforming mesh problem are substantially reduced as it is only required for a small domain close to the body. Also, the interaction between different bodies moving in each other’s vicinity is facilitated through the Lagrangian (meshless) vortex particle. The project builds upon the work developed during the last eight years by Ph.D. students and PostDocs that resulted in a code currently able to model 2D unsteady viscous problems.

1 Introduction

Real-World wind turbines, rotors, and propellers, among other aerodynamic devices, are often subjected to unsteady aerodynamic loadings due to the three-dimensionality of the near-body flow and the non-linear intricacies caused by the vortical wake behind these bodies. These unsteady, three-dimensional blade air loading conditions can lead to complex aeroelastic phenomena, forming non-linear coupled systems that require high computational resources to model in the customary Computational Fluid Dynamics (CFD) framework. The overall difficulties in predicting the aerodynamic performance and aeroelastic phenomena on wind energy devices have led to higher capital investment and operating costs, making wind energy a costly alternative in comparison with other forms of non-renewable energy sources (e.g., see [1] and [2]). For this reason, a design and analysis tool capable of accurately and efficiently modeling the complex, three-dimensional dynamics of realistic wind energy devices is of great interest. In this work, we present a candidate hybrid Eulerian-Lagrangian CFD framework that enables a designer to accurately assess the high-order, non-linear interactions of the near-body aerodynamic problem (i.e., via the Eulerian framework) mitigating the computational costs by solving only the low-order physics (via the Lagrangian framework) in far-field regions of the flow.

Current research in wind energy is largely based on CFD modeling using Eulerian solvers (e.g., OpenFOAM [3] and OpenFAST [4]), and this scenario is likely a consequence of the high algorithm parallelization and generalization achievable with Eulerian solvers [5]. In the Eulerian framework, fluid fields, such as pressure and velocity, are discretized at specific locations within the computational domain. The fluid flow is then solved by numerically integrating the discretized version of the governing system of equations (e.g., the Navier-Stokes equations) subjected to a given set of boundary conditions. The discretization of the fluid and solid domains can take many different forms, with the Finite Elements [6, 7], Finite Volumes [8, 9] and Finite Differences [10, 11] discretization frameworks being among the most popular in recent research on external flows. The high generalization and parallelization characteristic of modern Eulerian solvers are generally attributable to powerful parallel computing tools.
such as OpenMP, MPI, and CUDA, which extract massive computational power with the use of separate processing units, taking full advantage of multiprocessing architectures [12]. Another advantage of Eulerian solutions is that the discretization of the fluid domain can be done in an anisotropic fashion. Hence, the designer can optimize the use of the computational resources by only seeding gridding points more densely in the directions along which gradients of the flow fields are expected to be higher, such as the normal directions to an immersed wall boundary. Hence, the Eulerian framework renders a wise choice for capturing the viscous phenomena and vorticity generation in the vicinity of solid structures.

However, the numerical discretization of governing equations of dynamic systems, such as done in the Eulerian framework, is intrinsically associated with numeric dissipation and dispersion, which grow in magnitude with the sparsity of the computational grid. Eventually, the need for dense computational grids is a bottleneck of the Eulerian framework that is challenging to overcome, and it often requires the counterproductive densely-seeding of large computational domains. Moreover, the Eulerian framework also imposes a lower cap on the time-step of the dynamical fluid system because of the advective terms (Courant–Friedrichs–Lewy condition [13]). Due to the aforementioned bottlenecks of the Eulerian framework, Lagrangian approaches are now being re-evaluated and are regaining their spotlight in wind energy research. In the Lagrangian framework, the observer follows the fluid parcels as they translate. The flow quantities, such as the velocity and vorticity, are thus given in an inertial frame of reference, as the discretization of fluid quantities takes place in the form of finite fluid parcels. Hence, the need for a computational grid is eliminated in the Lagrangian framework, eliminating the numerical diffusion and dispersion that preside over Eulerian models.

Currently, Vortex Particle Methods (VPMs) are among some of the most popular Lagrangian methods in the literature (e.g., see [14, 15] and, for a detailed review, see [16] and [17]). In VPMs, the flow is discretized into particles that carry vorticity. Such a discretization approach renders an advantage to VPMs: the vortex particles are free to move and thus concentrate on regions of high vorticity, sparing computational resources from being wasted for solving flow regions without any physical importance. Moreover, the onerously small computational time-steppings of the Eulerian framework are also bypassed in VPMs, since the time-step sizing requirements of VPMs are only limited by the desirable scale of phenomena one wants to capture. Successful and computationally-efficient applications of VPMs of external aerodynamics can be found in literature [18, 19, 20]. See also [21] for a detailed review comparing VPMs to other Lagrangian approaches. However, while the Lagrangian framework of the VPMs is arguably a more computationally efficient alternative to traditional CFD for solving the far-flow and wake regions, VPMs can pose issues to modeling viscosity-dominated regimes. For instance, to model wall surfaces using VPMs, one often has to adopt supplementary solvers, such as the Vortex Panel Method [22] or the Immersed Body Technique [23], to be able to model a wall surface reliably. Furthermore, the isotropic nature of the vortex particles of VPMs renders an inefficient solution to the anisotropic character of boundary layer flows. In cases where viscous effects are dominant, the viscous effects must either be ignored, prespecified, or determined by coupling the method to a boundary-layer-type model, making VPM methods inaccurate [24].

Considering the advantages and drawbacks of both Eulerian and Lagrangian frameworks, new research paths that attempt to integrate both frameworks have emerged. The integration of both frameworks can be done in different ways. However, here we focus on the most successful and promising approach originally proposed by Cottet [25]. Cottet proposes the subdivision of the fluid domain into a “near wall” region and a “far-field” region, which are solved in parallel using an Eulerian and Lagrangian description, respectively. Starting from the work of Cotte, recent research focuses on the solution transfer between the Eulerian and Lagrangian domains. For instance, Shi et al. [26] explore the combination of an Eulerian-based Reynolds-averaged Navier-Stokes (RANS) Eulerian solver with a Lagrangian viscous wake method to determine the aerodynamic performance of rotors in several flight conditions. Billuart et al. [27] introduce a weak coupling approach between a body-fitted velocity and pressure solver and a two-dimensional VPM method to simulate incompressible external aerodynamics. In their work, Billuart et al. accommodated different time step sizings across the two solvers, a promising alternative to decreasing the computational times necessary for solving multi-size, multi-body wind energy problems. Palha et al. [28] successfully coupled the finite-element method FEniCS software [29] with a VPM solver to verify two-dimensional benchmark flows relevant to wind energy applications. The work of Palha et al. is part of a collaborative project from the Wind Energy Research Group of TU Delft named pHyFlow, a toolbox for customized numerical solvers for two-dimensional, hybrid CFD of wind energy (see also the contributions of [30]).

The current work extends the two-dimensional hybrid solver pHyFlow to three-dimensional, deformable body problems pertinent to wind energy systems. In its current development stage, the pHyFlow can accurately model multi-body, two-dimensional laminar flow problems via a Finite Elements Methodology. One of the main objectives of the current research project is to replace the Finite Element with a Finite-Volume-Based methodology using OpenFOAM for the solution of the Eulerian flow, thus allowing for the transition from two to three-dimensional
CFD problems. Moreover, this project also concerns the addition of turbulent flow modeling and simulation capabilities to pHyFlow, i.e., by introducing Reynolds-Averaged Navier Stokes (RANS) turbulence modeling, Large-Eddy Simulation (LES), and Direct Numerical Simulation (DNS) capabilities. The driving forces behind the development of this project are twofold. Firstly, using the Eulerian methods allows for accurate solutions of flow quantities near wall boundaries while benefiting from the efficient solution of the Lagrangian framework in the wake and far-field regions. Secondly, in the Lagrangian framework, the dependent variable pressure (Eulerian in nature) is decoupled from the dependent variable velocity. This latter fact will allow us to decompose large, multi-body problems into multiple, decoupled Eulerian models of different degrees of fidelity, different time-stepping, or grid-sizings.

References


Session 1.2
07.09.2023 - 15:30
Building 3703, Room 027

Raby Kaiya  Developing Computationally Efficient Wake Models for Wind Farm Simulation Software
Trigaux Francois  Aeroelastic simulations of the IEA 15-MW turbine in LES using the flexible actuator line method
Mohammadi Mohammad Mehdi  Onward toward the aeroelastic coupling of an actuator sector model
Wellmann Anna  Modeling and simulating wind-induced loads on wind turbines with the Lattice-Boltzmann method
Meijer Jorrit  AI-based refinement of mesoscale simulations for wind energy applications
Developing Computationally Efficient Wake Models for Wind Farm Simulation Software

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Keywords: Wake Modelling, Computational Efficiency, Gaussian Modelling

When assessing and modelling wind farm conditions, the effect of wakes on downwind turbines must be considered to understand resulting power losses due to the associated velocity deficits. Whilst, many simple analytical models such as the 'top-hat' formulation proposed by Jensen (1983) \cite{3}, wind tunnel testing and mathematical modelling has shown that improved efficacy can be achieved by Gaussian ('sombrero') velocity deficit models. However, due to increased model complexity, these incur a greater computational cost \cite{1}.

Strathfarm is a Simulink based simulation tool developed by the University of Strathclyde. This software accurately models and simulates wind farm conditions, allowing fully flexible model creation \cite{2}. Tools such as these wish to achieve a high level of precision, with reasonable computational speed. Specifically, Strathfarm is designed to be run on a standard PC in real-time, with medium fidelity \cite{4}. To achieve the level of accuracy required, two-parameter Gaussian wake-modelling is currently used, however the current methodology fails to meet the desired efficiency.

This project aims to reformulate Strathfarm’s current modelling approach to achieve a more computationally efficient simulation, whilst maintaining a high level of predictive accuracy. This is done via a Fourier series approximation to reformulate the wind velocity deficit as

\[ f(\theta, r_w) \sim a_0 + \sum_{n=1}^{\infty} a_n \cos \left( \frac{2\pi n \theta}{P} \right) + b_n \sin \left( \frac{2\pi n \theta}{P} \right), \]

where

\[ a_n = \int_0^{2\pi} f(\theta, r_w) \cos(n\theta) d\theta, \]

\[ b_n = \int_0^{2\pi} f(\theta, r_w) \sin(n\theta) d\theta, \]

and

\[ f(\theta, r_w) = \frac{(c+1)V_m}{\pi R^{c+1}} \int_0^R \frac{1}{2\pi \sigma} \exp \left\{ -\frac{l^2 - 2l r \sin(\theta) + r^2}{2\sigma^2} \right\} r^d dr, \]

with \( r \) denoting the radial position, \( \theta \) the azimuthal angle and \( R \) the rotor radius.

These may be rewritten as

\[ a_n = \frac{(c+1)V_m}{2\pi^2 \sigma} \int_0^1 \exp \left\{ -\frac{(\frac{\bar{r}}{\sigma} - \frac{1}{2})^2}{2} - \frac{IR}{\sigma^2 \bar{r}} \right\} h(\delta \bar{r}) \bar{r}^d \bar{d} \]

and

\[ b_n = \frac{(c+1)V_m}{2\pi^2 \sigma} \int_0^1 \exp \left\{ -\frac{(\frac{\bar{r}}{\sigma} - \frac{1}{2})^2}{2} - \frac{IR}{\sigma^2 \bar{r}} \right\} v(\delta \bar{r}) \bar{r}^d \bar{d} \]

where

\[ h(\delta \theta) = \int_0^{2\pi} \exp \{ \delta \bar{r} \sin(\theta) \} \sin(n\theta) d\theta, \]
\[ v(\delta \theta) = \int_{0}^{2\pi} \exp \{ \bar{\delta} \sin(\theta) \} \sin(n\theta) d\theta \]

and

\[ \delta = \frac{lR}{\sigma^2}. \]

Due to the high complexity of this integral it cannot be evaluated analytically. Specifically, the terms \( h(\bar{\delta}, \bar{r}) \) and \( v(\delta, \bar{r}) \) must be approximated numerically. A novel exponential model to replace the current polynomial fit has been utilised in order to gain higher fidelity in line with observation. The accuracy of this model is demonstrated in Figure 1.

![Figure 1: Accuracy of Trialled Exponential Model](image)

References


Aeroelastic simulations of the IEA 15-MW turbine in LES using the flexible actuator line method

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Keywords: Aeroelasticity, actuator line model, large eddy simulation, 15-MW wind turbine

1 Introduction

The continuous upscaling and optimization of wind turbine blades has resulted in the development of elongated, highly flexible blades. Consequently, the aeroelastic effects occurring on the rotor are intensified, which can potentially affect the lifetime of the blades. During the turbine design process, engineering tools take into account these aeroelastic effects using simplified models. However, the accuracy of these models is often questioned, especially when sizable rotors are considered. Understanding the amplitude of the aeroelastic effects on large turbine, as well as the limitations of lower order models is therefore critical for further optimization of the blades.

In this study, higher fidelity aeroelastic simulations of the IEA 15-MW reference wind turbine are carried to assess the amplitude of the aeroelastic effects [1]. The results of those simulations are then compared to those obtained with a rigid rotor to exhibit the differences on the loads and wake induced by the flexibility. In a later stage, the results will be compared to lower fidelity models, such as OpenFAST.

2 Methodology

The simulation framework consists in coupling a LES flow solver and a structural solver, using the Actuator Line Method (ALM) as interface. The elements of this simulation framework are quickly reviewed hereunder, but a more extensive description is found in [3].

LES flow solver An in-house developed 4th order difference flow solver is used to solve the Navier-Stokes equations supplemented by a subgrid-scale model. The turbulent inflow consists either in synthetic turbulence generated using the Mann algorithm, or using a co-simulation that simulate an atmospheric boundary layer without the wind turbines. LES allows to simulate the flow unsteadiness, a crucial aspect in aeroelasticity as it is the primary source of the unsteady loads.

Actuator Line Method (ALM) The ALM is used to represent the effect of the blades on the flow as a, equivalent forcing term computed on a line that coincides with the quarter chord of each blade section [2]. This approach drastically reduces the computational cost compared to approaches that solve the flow around the blade. The ALM here deforms according to the structural deformations, which affect the wake behind the turbine.

Structural solver BeamDyn The structural dynamics is solved using the BeamDyn module from OpenFAST [4]. BeamDyn solves the geometrically exact beam theory equations using Legendre spectral finite elements. BeamDyn includes the non-linear effects of large deflections on bending and torsion. Anisotropic composite materials can also be modeled using fully-populated 6x6 mass and stiffness cross-section matrices. Hence, the coupling between different degrees of freedom (in particular, bend-twist coupling) is included. The external aerodynamic loads are transferred to BeamDyn from the ALM, and the root motion of each blade is imposed.
Figure 1: Streamwise velocity $u/U_{hub}$ in a vertical plane intersecting the rotor in its middle.

Figure 2: Tip displacements and torsion averaged over a rotation cycle, expressed in the blade root frame. The envelope around the mean line depicts the standard deviation. $0^\circ$ corresponds to the upwards position.

### 3 Results

In this section, the results obtained for the IEA 15-MW turbine are presented. We consider a linearly sheared inflow with $s = du/dy(y_{hub}/U_{hub}) = 0.14$. Synthetic turbulence generated using the Mann algorithm with a turbulence intensity (TI) of 6% was superposed to the mean sheared velocity profile. Figure 1 shows the streamwise velocity field in the plane of the rotor. The sheared turbulent inflow is clearly visible, as well as the turbulent wake behind the turbine.

The displacement of the blade varies mostly along the rotation due to the sheared inflow and the gravity loads. Figure 2 shows the mean evolution of the displacements and torsion over one rotation, and the standard deviation. In the flapwise (i.e., out-of-plane) direction, the maximal displacement is reached when the blade is oriented upwards, whereas the minimum deflection occurs when the blade is pointing downwards. This is due to the mean shear of the flow that results in higher aerodynamic loads on the upper part of the rotor. The standard deviation is also important, due to the unsteady loads induced by the turbulence. On the contrary, the displacement in the edgewise (i.e., in plane) direction has a very low standard deviation, since it is mostly due to the gravity loads. The mean torsional displacement has the same phase as the gravity displacement, likely due to the coupling between the edgewise loads and the torsion that arise from the large flapwise displacement and, to a smaller extent, the material properties. The asymmetry of the torsional angle between the left and right part of the rotor may cause an additional imbalance in the rotor loads, since this angle importantly affect the angle of attack of the blade.

The blade root moment can also be computed using either the external aerodynamic forces (denoted by $Aero$), or based on the structural response (denoted by $Struct$), i.e., the elastic root moment. Figure 3 shows the power...
spectral density (PSD) of the root moment in the two principal directions. Whereas the largest peaks in magnitude are observed at the rotation frequency and its harmonics, higher frequencies are also present due to the turbulence. The PSD of the external aerodynamic loads is decreased near the bending frequencies in both directions, which arises from the fact the blade is more compliant and hence smooths the variation of the loads at these frequencies. Interestingly, this drop is not visible in the structural response. For the moment in the flapwise direction, a peak is even noticeable at these frequencies. In fact, the aerodynamic damping is less important in this direction, which leads to an increased structural response. However, the amplitude of this peak remains small compared to the one observed at the rotation frequency induced by the gravity.

4 Conclusions and perspectives

This abstract briefly presented results obtained by performing Large Eddy Simulations of a flexible rotor using the actuator line method coupled to a structural solver. The considered wind turbine is the IEA 15-MW, which correspond to the current largest turbines, with very elongated blades that are hence quite flexible. The presented results show that the displacement of the blade tip is important in the flapwise direction (here 11% of the rotor radius) and that it mostly varies along the rotation due to the mean shear of the inflow. In the edgewise direction, the loads and the subsequent displacement is mostly affected by the gravity force. The important difference between the blade root moment spectrum obtained from the structural model and the one obtained from the external aerodynamic and gravity forces and highlights the need of taken into account the structural dynamics in the analysis of the loads.

The full version of this abstract will include a detailed comparison with a rigid rotor to assess how the flexibility of the blades impacts the distribution of the loads and the turbine wake. Comparison with OpenFAST are also envisioned to assess the accuracy of the aerodynamic models for such large rotors.

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References


Onward toward the aeroelastic coupling of an actuator sector model

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Keywords: Large eddy simulation, actuator sector model, aeroelastic coupling, wind energy

In recent years, conducting large eddy simulations has become prevalent for studying the wake flow of wind farms and wind turbines in different conditions as they can speed up the simulations by modeling the turbulence structures below a certain threshold for length and time scales while keeping an acceptable level of fidelity compared to direct numerical simulations. Furthermore, the utilization of turbine models has made it possible to circumvent the modeling of full rotor geometry thereby reducing the computational time further. Together, they have been used to study a wide variety of problems to improve the understanding of physics governing such flows and to investigate different strategies to optimize the operation of wind farms to reduce the energy cost for wind power.

Among different actuator models, the actuator sector model calculates the blade forces on slices of a circle in comparison with the actuator line model where blade forces are calculated on lines and the actuator disk with a circular force calculation. An illustration of an actuator sector is presented in Fig 2. The size of the slice depends on the simulation setup such as time step and mesh resolution, and the properties of the studied turbines such as tip speed ratio [6]. The model offers a speed-up to the overall simulation compared to the actuator line model as larger time steps can be utilized. In comparison to the actuator disk model, although the time steps are similar, the actuator sector results in a near-wake flow similar to one obtained by an actuator line by for instance being able to capture tip vortices as shown in Fig 1. Despite its potential, there was a need to investigate how different choices in the details of the model implementation can affect the results as it was previously shown how they are dependent on each other [5].

Therefore, in a recent work, we performed a parametric study to scrutinize some aspects of the implementation of this model [4]. Several details such as the velocity sampling method, tip/smearing correction, and time-step size were considered to find out which options result in a better agreement with the actuator line model results in terms of the values of power, thrust, and blade forces.

The results showed that sampling velocities at 70% azimuth from the sector beginning provide the best agreement with actuator line results as shown for the power values in. Moreover, it was concluded that although the vortex-based smearing correction in [3] is originally developed for the actuator line model, it is also able to correct
As a continuation of this work, the following questions are to be answered as the main research objectives. The first one is whether the results obtained in [4] for the uniform inflow are valid for a turbulent inflow, especially regarding the velocity sampling method. The second question is to what extent the proposed actuator sector model coupled with an aeroelastic solver resembles the results from an aeroelastically coupled actuator line model in terms of the values of thrust, power, and damage equivalent loads. Moreover, the potential computational gain of using the actuator sector model instead of the actuator line model for this purpose needs to be quantified. As an optional question, it is of interest to investigate the suitability of the choice of smearing correction for an aeroelastically coupled actuator sector model.

To answer these questions, first, similar to the approach used in [4], different velocity sampling methods for the actuator sector model are tested and the error values are calculated compared to the results of the actuator line model for a turbulent inflow. The turbulent inflow will be introduced by using the Mann algorithm [2] or a precursor simulation. For this part, the considered rotor is stiff. Three different mesh resolutions near the rotor plane are used to quantify the mesh sensitivity of the suggested velocity sampling method and to determine whether it performs well in a range of mesh resolutions. Based on the results of this investigation, the previously suggested choice for the velocity sampling method will be re-evaluated.

Moving on to the next question, the aeroelastic coupling will be done using BeamDyn-with 3 choices for degrees of freedom- and ElastoDyn modules of OpenFAST. For each option, the results are compared with its actuator line counterpart, and the potential computational gains are quantified. Moreover, the implications of using different methods in terms of thrust, power, damage equivalent loads, and wake flow are quantified and weighed against the increased computational domain. In this part, the IEA 15 MW reference turbine will be used to intensify the aeroelastic effects [1]. Turning to the suitability of the smearing correction method suggested in [4] for an aeroelastically coupled turbine model, the difference caused by applying the correction on the sampled velocities will be identified. Moreover, an attempt will be made to explore other alternatives that can be used for this purpose.

Based on the results achieved by conducting the proposed study, the preferred implementation of the actuator sector model coupled with the aeroelastic solver of our choice will be used to study the wake flow of wind farms and turbine interactions in forested areas and diurnal cycles at a later stage.
References


Modeling and simulating wind-induced loads on wind turbines with the Lattice-Boltzmann method

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Keywords: Large eddy simulations, Lattice Boltzmann method, Actuator line model, Sliding mesh

Aerodynamic loads strongly affect the lifetime of wind turbines. These loads depend, among other factors, on the different flow situations in the vicinity of the wind turbine. This research project aims to estimate loads on a horizontal axis wind turbine (HAWT) using large eddy simulations (LES). The flow is simulated using the Lattice-Boltzmann method (LBM). Many wind farm simulations use actuator lines (AL) to represent the turbine blades, but this simplified representation may not accurately capture the loads on the HAWT components. Therefore, high-fidelity simulations resolving the blade geometry may be advantageous. The simulation of rotating objects, such as the rotor of a wind turbine, requires the adjustment of the grid during the simulation. A promising approach is the simulation of the rotor by means of a sliding mesh which moves in phase with the rotor. The objective is to compare the accuracy and computational efficiency of the AL and the sliding mesh approach.

1 Introduction

The service life of wind turbines is a decisive factor in the sustainability and economic efficiency of electricity generation. A key factor to the operational lifetime of a wind turbine are the aerodynamic loads acting on its moving parts. These loads vary depending on the flow conditions around the turbine, which are influenced by factors such as wind speed, turbulence, and wake interactions. To better understand and predict wind turbine loads, numerical simulations can be used. This research project two different approaches for simulating the flow around a HAWT using LES are compared. The first approach uses AL to represent the turbine blades as body forces in the flow field. The second approach uses a sliding mesh to resolve the geometry of the blade and its rotation.

2 Wind turbine representation

To estimate the loads acting on a HAWT the wind turbine’s representation is of major importance. A common approach in wind energy research uses so-called actuator lines (AL) to capture the turbine’s effect on the flow field. When AL are used, the aerodynamic forces acting on the rotor blade are estimated along a line that represents the blade. These body forces are subsequently projected to the flow field [12]. AL-based turbine simulations in LBM have been successfully implemented and validated by several authors [9, 4, 1, 10, 13]. The ALM has been shown to be effective in capturing turbine wake structures, but its applicability to highly resolved flow fields near the turbine blades is limited. Due to the reduction of the airfoil section to a point force, the details of the flow field past an airfoil cannot be captured by the AL [11]. Consequently, adaptations to the AL are needed to use it for accurate load estimations. One possible approach is the Actuator surface model [11].

Even refined methods such as the actuator surface model may not be sufficient to estimate the loads on the wind turbine rotors. Thus, a high-fidelity simulation with fully resolved rotor blades is planned. The simulation of rotating objects, such as the rotor of a wind turbine, necessitates an adjustment of the flow field’s grid during the simulation. To avoid the adjustment of the grid at the turbine blade, a rotating grid can be used that moves synchronously with the rotor [6]. A static grid represents the surrounding area. A particular challenge of this approach is the robust and accurate numerical coupling of the moving grid with the static grid.
3 Computational aspects

The high computational cost of LES severely limits their application in wind energy. The LBM is an alternative to conventional Navier-Stokes-based flow solvers. Because of its explicit nature and locality, the LBM is well suited for massively parallel implementations. As a result, implementations using Graphics Processing Units (GPUs) have demonstrated significant performance gains [7]. In this research project, we utilize the GPU version of the VirtualFluids software package with the cumulant LBM [3, 2]. When adding the representation of a wind turbine the specific demands of GPU’s programming model have to be kept in mind. Thus, we also focus on optimizing the turbine’s representation and the coupling between turbine and fluid domain for this computer architecture.

4 Findings

We have determined that the common implementation of the ALM based on [12] is not sufficient for the intended purpose. Sørensen and Shen use a Gaussian regularization kernel to distribute the forces from the actuator line to the fluid domain. In the architecture of VirtualFluids, this force distribution scheme leads to a performance bottleneck and suboptimal scaling properties. An alternative is a force distribution scheme based on an approximation of the Dirac delta function [10, 8]. This scheme has been implemented and tested. The alternative force distributions result in significantly improved performance and scaling. As a result, an important first step toward the feasibility of using the ALM to estimate the loads on the wind turbine rotor has been taken.

5 Conclusions and Outlook

Our work to date shows that the common implementation of the ALM based on [12] is not sufficient for the calculation of wind-induced loads on HAWT. A simulation using the modified actuator-based method and a simulation with geometrically resolved turbine blades will be implemented. The implementations are going to be optimized for efficient computation on GPUs. Individual wind turbines will be simulated with both approaches. A validation against the NREL 5 MW turbine ([5]) is planned. The loads acting on the wind turbine due to the surrounding air flow will be analyzed and compared. The benefits and limitations of both approaches for accurate and reliable load predictions are investigated. A more profound knowledge of the loads acting on the wind turbines can contribute to a better comprehension of the aging processes and facilitate a subsequent optimization of the service life of wind turbines.

Acknowledgements

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References


AI-based refinement of mesoscale simulations for wind energy applications

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Keywords: mesoscale, WRF, LES, analog-ensemble

1 Introduction

Wind energy has emerged as a promising and viable source of renewable energy due to its abundant availability, especially in offshore regions. The estimations of wind resources need to be accurate and is crucial for the development of wind energy projects, such as wind farm (clusters) in the German Bight.

In the pursuit of precision, mesoscale simulation models have become standard tools for estimating wind resources across larger regional landscapes. However, these models have inherent limitations due to their coarse resolution and simplifications of complex atmospheric processes. To counter these limitations, atmospheric Large-Eddy simulation models have emerged as promising alternatives. These models operate at smaller scales, enabling them to capture the intricate turbulence of wind flow and offer improved accuracy, particularly in contexts like wind farm environments.

Nevertheless, a significant challenge arises when considering the feasibility of employing large-eddy simulations for long-term wind resource assessments. The computational demands associated with such simulations present substantial hurdles. Despite their potential for greater accuracy, the computational costs of conducting extensive and prolonged simulations remain a major obstacle. This underscores the need for innovative strategies that can effectively combine the strengths of both mesoscale and large-eddy simulations. This integration into an AI-based model is crucial, offering a quicker and computationally more affordable solution.

2 Method

One method that can be used is called the Analog-Ensemble approach, which has been extensively explored in previous studies [3] [1]. This method is effective because it compares approximated mesoscale results with observations, helping to reduce uncertainty and improve the prediction of the variable of interest. This has been particularly useful for near-surface values, where the use of the Monin-Obukhov similarity theorem (MOST) as a surface boundary condition often leads to either underestimating or overestimating the derived shear stress and scalar flux gradients. The ensemble method, different from neural networks, mainly relies on techniques like bootstrapping, random forest, or stacking. These features make it easy to work with and allow for tracing back the decision-making process.

Looking at other options, we can also delve into deep learning. This involves training an artificial neural network, but it requires a considerable amount of data to work effectively. One strong point of neural networks is their efficiency in managing input/output tasks and parallel processing [2]. This approach adds another dimension to our discussion on refining simulation data, alongside the Analog-Ensemble method.

3 Expected results and outlook

The goal of this research is to devise a method for improving long-term mesoscale simulation data by incorporating short-term large-eddy simulation data. For the mesoscale component, the WRF model [5] will be utilized,
employing grid resolutions spanning kilometers. On the other hand, the PALM model [4] will serve as a reference output for the AI-based model, functioning at significantly finer grid resolutions, often within the order of tens of meters.

This objective will be accomplished through the development of an AI-based model capable of establishing meaningful connections between outcomes from both mesoscale and large-eddy simulations. In Figure 1, the visual representation showcases the comparison. On the left, we have the mesoscale input, characterized by its lower spatial resolution, as generated by the mesoscale model. On the right, the solution offered by the AI-model aligns with LES-compliant information, illustrating the enhanced results.

In the initial phase of the PhD project, an application of the Analog-Ensemble method to a single-point observation could be employed. Subsequently, the project will progress to constructing a multi-point or even full-domain model that departs from reliance on observations and instead integrates LES data. The ultimate outcome will be a model that provides LES-consistent information derived from long-term mesoscale simulation data. To assess the accuracy of the refined data, validation will be carried out using observational data obtained from existing wind farms.

References


Session 1.3
08.09.2023 - 09:00
Building 3703, Room 027

Schøler Jens Peter  RANS based PINN wake surrogate
Korb Henry          How to keep it fast - Upholding Computational Performance While Increasing Complexity in Wind Farm Simulations
Kherlen Jigjid      Data-Driven RANS Closures for Wind Farms Under Neutral Atmospheric Conditions
RANS based PINN wake surrogate

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Keywords: Scientific machine learning, Wake model, Surrogate model, PINN

1 Introduction

Inside wind farms, turbine wake interactions are of critical interest as turbines operating in wakes produce less power and experience higher loads. When modeling wakes there are two main considerations, namely computational speed and accuracy. Engineering models provide speed, but lack accuracy, whereas Computational Fluid Dynamics (CFD) are more accurate, but the computational costs is high. By training a neural network with CFD data, it is possible to approach the speed of the engineering models while maintaining accuracy close to CFD results [1, 2, 3].

The classical data-driven neural network approach has been shown to provide good results but with little explainability and little to no generalization. In recent years, a new approach has been suggested: Physics Informed Neural Networks (PINNs), where PINNs include knowledge of underlying physics in the loss formulation [4]. PINNs have been successfully employed in fluid dynamics and have been shown to improve both explainability and generalization compared to strictly data-driven approaches [5, 6].

In this work, the feasibility of PINNs in the context of wake surrogate models is investigated.

2 Methodology

Data

The training data considered is a Reynolds Averaged Navier Stokes (RANS) simulation of a rotational symmetric wind turbine wake considering a single wind speed. The rotational symmetry is achieved by using a simple Actuator Disc with a constant force distribution, no ground effect, and no rotation. The RANS simulation was conducted with the DTU developed PyWakeEllipSys framework [7], which employs the finite volume code EllipSys3D [8, 9].

Figure 1 shows the RANS training data, with the streamwise flow component $U$ on the left and the cross stream flow component $V$ on the right. The simulations was performed with a 3D representation of the flow, for the training the data was truncated to only consider the $xy$-plane at hub height. Utilizing this simplified flow case allows for rapid iteration and testing of the neural network architecture. In the future, the study will be expanded to include more complex flow cases.
PINN

Two networks are trained: a Physics informed neural network (PINN) and a Data-Driven (DD) without physics information. Both networks use the same feed-forward fully-connected network architecture. The considered architecture is shown in figure 2 and summarized in table 1.

![Image of Neural Network Architecture]

**Figure 2: Illustration showing Neural network architecture.**

What differentiates a Physics Informed neural network from a classical data-driven neural network is the inclusion of physics in the loss function ($\mathcal{L}$), as shown in Equation (1).

$$
\mathcal{L} = \alpha_1 \mathcal{L}_{dd} + \alpha_2 \mathcal{L}_{pi}
$$

Where:

- $\mathcal{L}_{dd}$ is the data-driven loss defined as the mean squared error (MSE) between the predicted output ($g(a_i)$) and the target output ($b_i$), as given in Equation (2).

$$
\mathcal{L}_{dd} = \text{MSE} = \frac{\sum (b_i - g(a_i))^2}{N}
$$

- $\mathcal{L}_{pi}$ is the physics informed loss that incorporates a part of the physics, specifically mass conservation, as represented by the mean squared sum of the partial derivatives of the flow components $U$ and $V$ with respect to $x$ and $y$, as shown in Equation (3). The physics informed loss is evaluated at the same collocation points as the training data.

$$
\mathcal{L}_{pi} = \mu \left[ \left( \frac{\partial U}{\partial x} + \frac{\partial V}{\partial y} \right)^2 \right]
$$

- $\mathcal{L}_{pi,cyl}$ is the physics informed loss evaluated in cylindrical coordinates, as in Equation (4).

$$
\mathcal{L}_{pi,cyl} = \mu \left[ \left( \frac{1}{r} \frac{\partial}{\partial r} (rv_r) + \frac{\partial}{\partial z} (v_z) \right)^2 \right]
$$

The data-driven loss ($\mathcal{L}_{dd}$) is defined as the mean squared error (MSE) between the predicted output ($g(a_i)$) and the target output ($b_i$), as given in Equation (2). The physics informed loss ($\mathcal{L}_{pi}$) incorporates a part of the physics, specifically mass conservation, as represented by the mean squared sum of the partial derivatives of the flow components $U$ and $V$ with respect to $x$ and $y$, as shown in Equation (3). The physics informed loss is evaluated at the same collocation points as the training data.

For the proof-of-concept a truncated version of mass conservation was used considering 2D Cartesian coordinates, this introduces an error as the out of plane velocity is not guaranteed to be zero. In future work this error will be addressed by using a formulation of mass conservation in cylindrical coordinates as in Equation (4). The relative weights of the two losses are denoted by $\alpha_1$ and $\alpha_2$, and is here $\alpha_1 = 0.8$ and $\alpha_2 = 0.2$. Only using mass conservation as the PINN loss is a non-standard approach normally momentum conservation is also included, the efficiency of partial against complete physics will be subject of future work.

Both models were developed using the open-source tool PyTorch [10].

### Table 1: Neural network summary.

<table>
<thead>
<tr>
<th>Hyperparameter</th>
<th>Value</th>
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</thead>
<tbody>
<tr>
<td>No. layers</td>
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<td>Optimizer</td>
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<tr>
<td>Loss ($\mathcal{L}$)</td>
<td>MSE &amp; Mass conservation</td>
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<td>Learning rate</td>
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</tr>
<tr>
<td>Epochs</td>
<td>1000</td>
</tr>
</tbody>
</table>

### 3 Results

In the preliminary results, the performance of the data-driven surrogate model and the PINN surrogate model is evaluated. Figure 3 shows the predictions of the data-driven model, while figure 4 illustrates the predictions of the PINN surrogate model.

It is observed that the PINN model shows promising results, providing more accurate predictions of the $U$ component while producing slightly worse $V$-component predictions.

Furthermore, the mass conservation loss is evaluated for both the data-driven model and the PINN model, see figure 5. The results of the mass conservation shows that adding a physics loss has an impact on the mass conservation evaluation of the network. However, drawing clear conclusions on the effects relating to a better physical interpretation will require further work.
4 Conclusion

In conclusion, this study investigated the feasibility of using Physics Informed Neural Networks (PINNs) as wake surrogate models. The preliminary results showed that the inclusion of a physics informed loss has an impact on the performance of the network, indicating that PINNs could provide a benefit when training neural networks for wind farm applications.

Future work should explore different physics-informed losses such as boundary conditions, momentum conservation, forcing as well as the relative weight between the data-driven and the physics informed losses. These extensions can enhance the accuracy and generalization capabilities of the PINN model. Moreover, additional complex flow cases should be considered to validate the applicability of PINNs in realistic wind farm scenarios.

Overall, PINNs seem promising as a reliable and efficient approach for developing wake surrogate models. Further investigation and refinement of the PINN methodology will contribute to the advancement of wind energy research and development.

References


How to keep it fast - Upholding Computational Performance While Increasing Complexity in Wind Farm Simulations

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Keywords: Lattice Boltzmann Method, GPU, Wind Farm Simulations, Computational Performance

The continued need for the expansion of renewable energy drives a rapid increase in the size of individual wind turbines and whole wind farms. At the same time, the environment in which these turbines are placed becomes more complex. For example, large wind farms exhibit blockage, leading to favorable and unfavorable pressure gradients at different locations in the farms \cite{5}. At the same time, potential to improve wind farm performance with wind farm control increases \cite{6}. The effects on power production but also wind turbine lifetime are crucial to understand. Due to societal constraints onshore turbines are placed in more remote areas such as forests and thus, these effects also must be taken into account \cite[p. 493ff]{7}. These conditions far exceed the assumptions made for common engineering models \cite{3}. Thus, high-fidelity models, namely LES (large eddy simulation), are required to accurately model the physics in such wind farms. However, LES comes with a high computational cost \cite{4}. Furthermore, a growing number of additional models must be incorporated as well. This increases the complexity of the simulation and further degrades the computational performance.

The development of LES based on the lattice Boltzmann method (LBM) in conjunction with the dramatic increase in computing power of massively parallel processors, such as GPUs (graphics processing units), have enabled high-fidelity simulations of wind farms at and above real time. Naturally, the complexity of the simulations showed a progression, from highly idealized case with simple boundary conditions, \cite{2} to more complex inflows, boundaries and wall models \cite{1}. Nevertheless, the simulations lack the model complexity of other solvers. Due to the different numerical scheme and utilized hardware, GPU-resident LBM has unique challenges.

While the bulk scheme is extremely efficient, operations that are straight-forwardly implemented in a CPU-resident Navier-Stokes based solver must be reexamined carefully for implementation in a GPU-resident LBM solver. On the other hand, due to the extremely small timestep required by LBM, other operations become much simpler.

In my contribution I would like to discuss some of our recent advances in the development of the GPU-resident LBM solver VirtualFluids\textsuperscript{1} coupled to our wind farm computation and coupling framework WiFi \textsuperscript{2}. We have improved the representation of the turbines by generalizing our implementation of the actuator line from a single turbine to a farm, including a smearing correction and implementing a coupling to an aeroelastic tool. Each step came with different challenges and had to be examined carefully.

For instance, the results of our efforts to include aeroelastic coupling can be seen in Figure 1. We show that through an adequate choice of parallelization and partitioning of the problem, we incur little to no computational overhead by including aeroelastic coupling. However, if the aeroelastic module is too computationally expensive, we observe a significant increase in computation time.

Furthermore, we have increased the complexity of the inflow by implementing a precursor boundary condition. We have also significantly improved the computational performance of the bulk scheme by partitioning the domain into regions depending on the quantities necessary in the bulk kernel. For example, only a small part of the domain actually needs to compute the velocity, which is not a primary variable in LBM. Only reading and writing the velocity where needed, e.g. in the area of the actuator line, reduces the memory consumption significantly and thus improves computational performance.

\textsuperscript{1}https://www.tu-braunschweig.de/irmb/forschung/virtualfluids
\textsuperscript{2}https://source.coderefinery.org/Hkorb/wifi
Figure 1: Computational performance of aeroelastically coupled simulation. Five different methods for the computation of the turbine response in OpenFAST are compared. AD is a stiff rotor computed only with the AeroDyn module, ED is a simplified representation of a flexible rotor based on the first few modes of the blade and BD3, BD7, BD10 are multibody simulations with the BeamDyn module with polynomials of order 3, 7 and 10, respectively. Ratio of simulated time ($t_{sim}$) to time-to-solution $t_{2s}$ is shown.

I will present a selection of these features and different techniques we used to speed up, parallelize and partition these computations. Within the presentation, I will discuss general aspects of computational performance and techniques available to improve performance. Then I will go through some examples how we used these techniques in our implementations. Finally, I will conclude with an outlook on some of our future developments, such as thermal stratification and complex terrain.

References


Data-Driven RANS Closures for Wind Farms
Under Neutral Atmospheric Conditions

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Keywords: Turbulence modelling, Sparse symbolic regression, Data-driven RANS, Wind farm and Wakes

1 Introduction

The consideration of wind turbine wake effects is essential for estimating wind farm yield and for optimizing wind farm design. The impact of wake effects on wind farms has become more significant than ever, as wind farms are getting larger, and wind turbines are being placed in close proximity to each other to minimize space usage and reduce maintenance costs. For large offshore wind farms, wake losses can lead to 10-20% loss of total power output [1]. Moreover, wake-induced turbulence can result in complex flow patterns that cause structural vibrations in downstream wind turbines, leading to premature fatigue and increased maintenance costs [2].

Therefore, the development of a cost-efficient and accurate wake prediction model is in demand. Although analytical models are cost-efficient, they become less accurate in dense wind farms when the cumulative effect of wakes is present [3]. In such circumstances, numerical models are more suitable. Among numerical models, Large Eddy Simulation (LES) could provide accurate predictions in wind farm simulations, but requires between $10^3$ and $10^4$ CPU hours, rendering it impractical for industrial use [4]. Given these constraints, the Reynolds-averaged Navier-Stokes (RANS) model offers a better balance of accuracy and cost. However, its effectiveness depends on the choice of model and parameters [5], indicating the need for further refinement.

A recent development in improving RANS models is the data-driven framework Sparse Regression of Turbulent Stress Anisotropy (SpaRTA) [6]. This approach introduces two correction terms into standard two-equation models, such as $k-\varepsilon$ or $k-\omega$ models. These terms are derived from high-fidelity data using a sparse regression method, resulting in simplified mathematical expressions, thus avoiding the "black-boxification" issue often linked with neural network-based models. The effectiveness of the framework has been demonstrated in applications such as scaled wind farm [7], as well as with three-dimensional bluff body [8].

Given the above considerations, the current study will utilize the SpaRTA framework on a simulation of a full scale wind farm, exploring its potential for such an application. Moreover, the model obtained will be studied in-depth to understand the physical interpretations of the model, thereby potentially contributing to the further development of turbulence models for wakes in wind farms. In this regard, the main objective of the research is to develop a data-driven RANS model that is both computationally efficient and accurate, capable of predicting wakes, wake interactions, and the power production of a wind farm.

2 Methodology

To implement the SpaRTA framework, the governing equations must be formulated. For this study, the $k-\varepsilon$ model is selected as the baseline model for simplicity. Thus, the governing equations will be based on those of the $k-\varepsilon$ model. In the formulation, two additional terms, the so-called "corrective terms", are introduced. One term is introduced directly into the equations of the Turbulent Kinetic Energy (TKE) $k$ and its dissipation rate $\varepsilon$ to correct for the deficit of the TKE production $R$, while the other, $b_{ij}$, is introduced as a correction for the deviatoric part of the Reynolds Stress Tensor (RST). It is important to note that $b_{ij}$ consists of nine elements but due to its symmetry and zero trace constraints, only five values are independent. Consequently, the following equations are derived.
In the equations, $t$, $U_i$, $P_k$, $v$ and $v_i$ represent time, mean velocity components, production term of $k$, kinematic viscosity, and eddy viscosity, respectively. The parameters $C_{ε1}$ and $C_{ε2}$ are from the $k-ε$ model and are typically determined from existing literature. In equation (3), $δ_{ij}$ denotes the Kronecker delta, and $S_{ij}$ is the strain rate tensor.

The SpaRTA framework consists of three steps. In the first step, the corrective terms are obtained by the “frozen approach”, using high-fidelity data such as LES or high-resolution measurement data. To obtain the two terms, high-fidelity fields of $U_i$, $k$ and RST $τ_{ij}$, are imposed into equations (1) and (2), and the unknowns $R$ and $b^2_{ij}$ are solved for by fixing the known variables. Once the corrective terms are obtained, their validity can be checked by the second step in the framework, incorporating them into the RANS simulation, referred to as "propagation RANS", and comparing the results with the original high-fidelity data. If the results accurately represent the high-fidelity data, the corrective terms can be used to derive an algebraic model through symbolic regression, which serves as the final step in the framework. This process involves preparing a function library in advance, which consists of terms formulated from Pope’s basis tensors and invariants [9], as well as their combinations. Once the library is prepared, a coefficient matrix is optimised to minimize the error between the prediction and the target. The optimization is conducted using sparse-regression with elastic net regularization, which results in many coefficients of the function library being forced to zero. The resulting model is a linear combination of the remained terms from the function library, and can be expressed as: $R = C_{(R)Θ_{(R)}}$ and $b^2_{ij} = C_{(b^2_{ij})Θ_{(b^2_{ij})}}$. Here, $C$ represents the matrix formulation of the function library, and $Θ$ represents the coefficient matrix. The resulting model can be explicitly incorporated into the $k-ε$ model.

For the current study, LES data of a wind farm in a truly neutral Atmospheric Boundary Layer (ABL) is used as a high-fidelity data. The data was obtained from a previous study conducted by Eidi et al. [5]. The data was acquired using an in-house pseudo-spectral code [10]. The domain size of the simulation is 4800 m (480 cells) in the streamwise direction $x$, 400 m (80 cells) in the lateral direction $y$, and 360 m (72 cells) in the vertical direction $z$. The domain is uniformly discretized in each direction, resulting in approximately 5.5 million cells. The simulated wind farm consists of a column of six wind turbines, with the distance between the turbines set at $7D$ in the streamwise direction, where $D$ is the turbine rotor diameter. To model the wind turbines, a non-rotational Actuator Disk (AD) method is implemented.

3 Preliminary results

The current phase of research involves the "propagation RANS" step of the SpaRTA framework, during which the derived corrective terms are being validated. As such, the preliminary results include comparisons of the baseline and propagation RANS outcomes alongside the LES data.

Figure 1 presents a comparison of the $U_i$ and $k$ fields at the mid $x-z$ plane. The topmost image in both (a) and (b) corresponds to the LES field, while the middle and bottom images represent the propagation and baseline RANS fields, respectively. For both $U_i$ and $k$ fields, the propagation RANS shows better accuracy compared to the baseline RANS, particularly in the wake region. The baseline RANS falls short due to its prediction of faster wake recovery, which results from the overprediction of $k$. This is a recognized shortcoming of the $k-ε$ model as reported in [2]. Moreover, the baseline RANS shows a steady increase in $k$ after each turbine, while $k$ remains nearly constant after the second turbine in both the LES and propagation RANS fields. In addition, there is a noticeable drop in the value of $k$ immediately after the turbines in both the LES and propagation RANS, but this
Figure 1: Comparison of (a) $U_x$ and (b) $k$ fields in the $x-z$ plane at $y = 2.5D$. From top to bottom, the figures display LES, propagation RANS and baseline RANS fields, respectively. The ADs are represented by dark rectangles, while the upper and lower edges are by purple solid lines. The dash-dotted line represents the center-line of the AD.

Figure 2: Comparisons of (a) velocity deficits averaged over turbine swept area and (b) power output of each turbine. The velocity deficit is normalized with respect to the inlet of the LES data, while the power output is normalized with respect to the power output of the first turbine in the LES data. The vertical lines represent the locations of the turbines.

The drop is not observed in the baseline RANS. Future studies should investigate these trends. Please note that the region beyond the vertical purple line in the stream-wise direction, as depicted in the figures, corresponds to the non-physical fringe zone in the LES data. Therefore, this area should be excluded from any analysis.

Furthermore, a comparison of velocity deficits averaged over the turbine swept area is presented in Fig. 2(a). The results are normalised with respect to the inlet of the LES data. The black solid line represents the LES, while the dashed red and blue lines correspond to the baseline and propagation RANS results, respectively. The propagation RANS matches well with the LES across the entire domain, demonstrating better performance than the baseline RANS. Similarly, a comparison of the power output for each turbine is depicted in Fig. 2(b). The values are normalised with the power output of the first turbine in the LES data. Again, the propagation RANS performs better than the baseline RANS. The baseline RANS overestimates for all downstream turbines, with this overestimation being particularly significant for the second turbine. The overprediction is thought to be due to the
faster recovery of the wakes, since power output is related to the cube of the incoming velocity.

4 Future work

Future work will involve discovering an explicit algebraic model for the corrective terms. Once a satisfactory model is identified, its performance will be evaluated through accuracy comparisons in predicting power output, $U$ and $k$. It will involve both visual and qualitative evaluations. Additionally, the computational cost of the data-driven model will be assessed in relation to the baseline model. These analyses will help determine the overall value of the data-driven model and assess its potential for practical application. This will lead to the main goal of the current research.

In the long-term research plan, various models will be utilized for wind farm RANS simulations under identical settings, including not only the $k−\varepsilon$ model but also the $k−\omega$ SST and Explicit Algebraic Reynolds Stress Models (EARSM). The results will be analyzed to determine the strengths of each model in different areas of the domain, allowing for a comprehensive evaluation of the data-driven model. Consecutively, model dependency on LES data will be analysed. This will involve the utilization of three additional LES datasets with varying wind turbine positioning. Models will be derived from each LES dataset and cross-validated across the four datasets. This examination will explore the physical interpretation of the models, including the identification of the most common terms present in all models. Furthermore, this assessment could provide insights into the limitations and capabilities of the data-driven approach. In the subsequent research, the study will extend to include non-neutral atmospheric conditions. In reality, stable or unstable conditions are more common for the ABL. Hence, to enhance the applicability of the model, it is essential to investigate the behavior of the model under non-neutral atmospheric conditions.

References


Session 1.4
08.09.2023 - 10:30
Building 3703, Room 027

Bührend Lukas  Numerical Simulations of Boundary Layer Processes relevant for Wind Parks
Centurelli Gabriele  Assessing cluster wake description in engineering models and WRF with Lidar and SCADA
Devesse Koen  Atmospheric Perturbation Model for Modelling Wind-Farm Gravity-Wave Interaction
Paulsen Johannes  Mesoscale effects of the interactions between wind farm clusters with large innovative rotor concepts and the boundary layer
Numerical Simulations of Boundary Layer Processes relevant for Wind Parks

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Keywords: stable boundary layer, large eddy simulation, subgrid-scale model

1 Motivation and Overview

The increasing demand of renewable energy driven by global warming and increasing electricity consumption requires not only the expansion and construction of new wind power plants, but also a massive improvement in their efficiency. The energy profit of wind turbines heavily depends on the wind speed and turbulence in earth's atmospheric boundary layer (ABL), which can be defined as the lowest troposphere part modified by short-term interactions with the surface [10].

The ABL at daytime is dominated by the mixed layer, where convective turbulent processes are induced by the sunlight. However research described here primarily focuses on the stable boundary layer (SBL). As part of the ABL it forms mostly at night as earth's surface becomes cooler than the atmosphere and is characterized by statically stable air with weak intermittent turbulence [10]. These periodically occurring turbulence bursts in the SBL have been observed in boundary layer experiments and replicated by numerical simulations [12] (see Figure 1).

![Figure 1: Kinematic heat flux $F(\theta)$ (horizontally averaged) plotted versus time $t$ and height $z$, obtained from high resolution large-eddy simulations of the antarctic stable boundary layer. The intermittent, periodic turbulence bursts are clearly visible. Plot taken from [12].](image)

For wind parks, the nocturnal situation and the analysis of the SBL is highly relevant since the wake of a turbine at nighttime extends far downstream to other turbines standing behind. In addition, a change of the wind direction over the height of the rotor (Ekman spiral, see [10]) becomes relevant opposed to the convective mixed layer at daytime. Experimentally, researchers study the interaction of wind turbines with the ABL at sites like the DLR Krummendeich research wind farm WiValdi [2] (see Figure 2). There, environmental data like wind speed, temperature, humidity and precipitation are registered by numerous sensors on measurement masts including LiDARs and microwave radiometers. The research site is accompanied by a virtual wind park (digital twin). The simulations enable the investigation of phenomena measured on-site by variation of parameters and boundary conditions.

To numerically analyze the SBL, Large Eddy Simulations (LES) are conducted. They resolve the mean variables (e.g. wind speed and potential temperature). The not resolved turbulence scales are parameterized using a
subgrid-scale (SGS) model (also called closure of the governing equations). In contrast to the daytime convective mixed layer, nighttime turbulences are rather small, which makes the appropriate resolution of the SBL a challenging task and highly dependent on the SGS model chosen. This is illustrated by an inter-comparison of different LES models simulating the SBL as part of the GABLS initiative (Global Energy and Water Cycle Experiment Atmospheric Boundary Layer Study) [4] (see Figure 3a). The initial state and forcings of these simulations are based on the same experimental observations of the Beaufort Sear Arctic Stratus Experiment (BASE).

An unresolved issue in SBL simulations across all SGS models is grid sensitivity [5]. The height of the stable boundary layer in simulations decreases with decreasing grid spacing and the resulting velocity and temperature profiles do not converge even for small grid sizes down to 1m (see Figure 3b).

Furthermore, the sporadic and weak nature of the periodic turbulence bursts in the SBL adds to the complexity of modeling and investigating the nocturnal boundary layer. Although Kelvin-Helmholtz instabilities have been identified as one turbulence trigger [12], exact conditions for the bursts and their periodicity have to be determined and numerical sensitivity studies with varying conditions are necessary to gain new insights in the meteorology of the SBL.

In summary, the primary objective of this research is the numerical analysis of the stable boundary layer using large eddy simulations in different environmental conditions, the analysis of SBL effects on wind power plants and the comparison of the numerical data with experimental results from the DLR wind park in Krummendeich.

### 2 Planned Research Methods and Tools

An established tool for the simulation of atmospheric flows in the ABL is the computational model EULAG [7]. It uses the non oscillatory, robust elliptic solver MPDATA [9] for the governing equations (in a simplified form...
given below in Equations (1.1)-(1.3)). It is planned to apply EULAG for large eddy simulations and the sensitivity analysis of the SBL.

The most promising SGS model to date modeling the SBL with EULAG is an anisotropic variant of the TKE-model proposed by Sullivan et al. [11]. Therefore it is planned to start simulations using this model. An overview and explanation of different SGS is given in the next section.

3 Parameterization of Subgrid-Scale Variables in Large Eddy Simulations

In large eddy simulations, the governing prognostic equations of the mean wind speeds \( \bar{U}, \bar{V} \) and the mean potential temperature \( \bar{\theta} \) assuming no subsidence, dry environment and horizontal homogeneity are [10]

\[
\frac{\partial \bar{U}}{\partial t} = f_c (\bar{V} - \bar{V}_g) - \frac{\partial \bar{u}'w'}{\partial z} \tag{1.1}
\]

\[
\frac{\partial \bar{V}}{\partial t} = -f_c (\bar{U} - \bar{U}_g) - \frac{\partial \bar{v}'w'}{\partial z} \tag{1.2}
\]

\[
\frac{\partial \bar{\theta}}{\partial t} = -\frac{\partial \bar{\theta}'w'}{\partial z}. \tag{1.3}
\]

The first term on the r.h.s. in Equations (1.1) and (1.2) represents the influence of earth’s rotation with \( f_c = 2\omega \sin(\phi) \) the coriolis parameter with earth rotation speed \( \omega \) and latitude \( \phi \). \( \bar{U}_g \) and \( \bar{V}_g \) are the winds speeds at geostrophic equilibrium. The last term in all three equations represents the divergence of turbulent momentum or heat flux. \( w' \) is the deviation from the mean vertical windspeed. \( z \) represents the height.

The number of unknowns exceeds the number of governing equations (1.1)-(1.3). Therefore, a SGS model is necessary to resolve the turbulences and close these equations. A relevant SGS measure is the turbulence kinetic energy (TKE) \( \bar{\varepsilon} = \frac{1}{2}(\bar{u}'^2 + \bar{v}'^2 + \bar{w}'^2) = u'_i u'_j \) (using Einstein summation convention and \( (u', v', w') = (u'_1, u'_2, u'_3) \)). The prognostic equation for \( \varepsilon \) can be written as [11]:

\[
\frac{\partial \bar{\varepsilon}}{\partial t} = -\tau_{ij}S_{ij} + \frac{\varepsilon}{\bar{\theta}} \bar{\theta}'w' + D(\bar{\varepsilon}) - \varepsilon \tag{2}
\]

The first term describes mechanical shear production or loss with the stress tensor \( \tau_{ij} \) and \( S_{ij} = 0.5 \left( \frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right) \). The next term represents buoyant shear production or consumption where \( g = 9.81 \text{ m/s}^2 \) is earth’s gravity. \( D(\bar{\varepsilon}) \) is a TKE diffusion term and \( \varepsilon \) signifies dissipation of TKE. The governing equations can be closed by parameterizing the second moments according to gradient transport theory [10]

\[
\bar{u}'w' = -K_m \frac{\partial \bar{U}}{\partial z} \quad \bar{u}'v' = -K_m \frac{\partial \bar{V}}{\partial z} \quad \bar{\theta}'w' = -K_h \frac{\partial \bar{\theta}}{\partial z}. \tag{3}
\]

The remaining unknowns in the prognostic TKE equation (2) can be parameterized as [11]

\[
\tau_{ij} = -2K_m S_{ij} \quad D = \frac{\partial}{\partial z} \left( K_m \frac{\partial \bar{\varepsilon}}{\partial z} \right) \quad \varepsilon = c_\varepsilon e^{3/2}. \tag{4}
\]

\( K_m \) and \( K_h \) are turbulent diffusivities for momentum and heat. Their modeling depends on the SGS model chosen. Widely used is the Smagorinsky-Lilly model [6] which assumes equilibrium at small scales of energy production and dissipation. There, \( K_m \) is proportional to the square of the average grid spacing \( \Delta \) of the simulation. To avoid the energy equilibrium assumption, a model based on the TKE developed by Deardorff [3] can be applied, which parameterizes the diffusivities as

\[
K_m = c_{m}\varepsilon l^{1/2} \quad K_h = c_{h}\varepsilon l^{1/2}. \tag{5}
\]

\( c_m, c_h \) and \( c_\varepsilon \) are SGS constants obtained empirically by numerical simulations. \( l \) is a mixing length and its value depends on further refinements of the SGS model. For unstable stratification, the mixing length is equal to the average grid spacing, i.e. \( l = \Delta \). Regarding stable stratification, vertical turbulences are reduced and may result in a reduction of the mixing length to [3]
\[ l = \min(\Delta, l_b) \quad l_b = \frac{0.76e^{1/2}}{N} \]  \hspace{1cm} (6)

with the so-called Brunt-Väisälä frequency \( N = \left( \frac{g}{\theta_0} \frac{\partial \theta}{\partial z} \right)^{1/2} \) where \( \theta_0 \) is a reference virtual potential temperature.

Schumann [8] furthermore recommends a refined model for stable stratification. It is derived from second order closure (SOC) models, which solve additional flux budget equations. The mixing length is again \( l = \Delta \) and \( K_m \) is the same as in Equation 5, as well as \( K_h \) for horizontal fluxes. For vertical fluxes, the heat diffusivity is modeled as

\[ K_h = c_h \frac{l e^{1/2}}{1 + 0.3\Delta^2 N^2/e}. \]  \hspace{1cm} (7)

Due to the improved agreement with SOC models and a simple realizability condition, Schumann’s parametrization is implemented in EULAG.

A disadvantage of Schumann’s model is that it does not take into account the anisotropic nature of turbulent flow close to a bounding surface. Sullivan et al. [11] propose a remodeling of Schumann’s parameterization, where the near-boundary flow can be characterized as a shear-driven channel flow and thus becomes anisotropic. Increasing mean shear near the wall (i.e. for \( z \to 0 \)) is taken into account by including a so-called isotropy factor depending solely on the height \( z \) into the expression for \( \tau_{ij} \). The application of Sullivan’s model leads to an improvement of the simulations in the near-wall region, which is especially important when simulating the stable boundary layer.

Acknowledgements

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References

Assessing cluster wake description in engineering models and WRF with Lidar and SCADA

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\textit{Keywords}: Engineering models, Cluster Wakes, Wind farm yield, lidar

1 Introduction

The scale of offshore wind farms has witnessed tremendous growth in recent years, and it is expected to continue expanding significantly in the current and upcoming decades to meet the European carbon neutrality targets. However, simply increasing the installed capacity of offshore wind does not guarantee a seamless transition to a renewable-based grid.

As more and larger wind farms are installed in the limited offshore surface area, there is a real risk of overcrowding the available sites, which could potentially worsen overall efficiency. It is widely recognized that large wind farms and wind farm clusters deplete the lower atmosphere of available energy, creating a phenomenon known as cluster wake, which can extend for tens of kilometers downstream.

To ensure the sustainable development of future wind farms, it is crucial to accurately estimate both the efficiency losses caused by internal wake effects within wind farms and the losses due to wakes from external wind farms reaching the site of interest. Achieving this requires simulating scenarios where hundreds of turbines are considered on a scale of hundreds of kilometers, encompassing both the wind farm of interest and its neighboring counterparts.

This task is beyond the capabilities of high-fidelity models due to the immense computational resources required. Engineering toolboxes, such as windPro, Floris, and Foxes, are the most suitable options for tackling this challenge.

However, these models only account for wake effects by superimposing individual turbine wakes, which typically do not extend beyond a few kilometers. Currently, there is no available superposition model that represents the collective behavior of wakes within a cluster. Therefore, to address this limitation, it is necessary to calibrate wake model coefficients to hinder wake recovery and generate slow-recovering cluster wakes.

Another issue with the simple engineering models concern with the inflow conditions. Homogeneous and stationary inflow conditions are fundamental assumptions taken by the wake models. However, they do not apply to the large scales over which cluster wakes effects need to be computed. This not only diminishes confidence in the models when applied to such scenarios but also unveils the fundamental problem about how to define the inflow conditions. Obtaining actual flow field measurements from real wind farms is rare, leading modelers to rely on SCADA data or modeled wind fields generated by weather research and forecast mesoscale models. Both approaches introduce significant uncertainty.

We try to investigate whether an engineering model (Foxes) with a single calibration for the wake recovery can provide sufficient accuracy in predicting the impact of a single cluster on a target wind farm.
2 Methodology

We focus on the interactions of two already installed clusters of wind farms, the cluster N6 and N8 in the German Bight, 1.

We focus on the period going from August 2018 to June 2019. In this period a lidar measuring campaign was carried on at the Global Tech 1 farm [3, 2] in the N8 cluster. In the time of interest, the two south-westerly farms were still in construction, therefore the lidar could measure the cluster wakes coming from N6.

The performances of clusters N6 and N8 (just Global Tech I) are simulated over the period of interest through the engineering model Foxes. The inflow conditions for any of the turbines are derived from a mesoscale 3D flow field computed through the Weather Research and Forecast (WRF) model. Following a similar procedure to what already done in [4]. The scenarios where the cluster wake of N6 reaches N8 are isolated and compared with Lidar for what concerns the visualization of the flow field 2. Additionally, SCADA data at Global Tech I are introduced to quantify the impact of the cluster wake on the yield of the waked wind farm and verify the prediction of the engineering model. Finally, we compare the engineering models against a WRF simulation considering the presence of the farm via adequate parametrization (Fitch [1]) in order to check whether the time independency of the engineering model compromises the possibility of describing cluster wakes evolution.
Acknowledgements

The work here presented was developed in the framework of the X-Wakes project (FKZ 03EE3008D,A) and C2-Wakes which are funded by the German Federal Ministry for Economic Affairs and Energy (Bundesministerium für Wirtschaft und Energie - BMWi) due to a decision of the German Bundestag. The simulations were performed at the HPC Cluster EDDY, located at the University of Oldenburg (Germany) and funded by BMWi (FKZ 0324005).

References


Atmospheric Perturbation Model for Modelling Wind-Farm Gravity-Wave Interaction

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Keywords: Blockage, Gravity Waves, Atmospheric Boundary Layer

As offshore wind farms continue to grow in size, mesoscale effects such as blockage and gravity waves become increasingly important. To address this, we present a new version of an Atmospheric Perturbation Model (APM), which simulates the interaction of wind farms and the atmospheric boundary layer. This model is coupled to a wake model, enabling two-way feedback between the atmospheric flow and wind-farm power output. Both this coupling and the APM itself have been extensively validated using 27 LES cases, and significantly outperform conventional wake models. Additionally, the APM is relatively fast, and can perform full farm simulations within five minutes on a standard laptop. To promote its use as a research tool, we will release the APM open-source, and give an overview of its capabilities and code structure.

The APM is based on an earlier model by Allaerts and Meyers \cite{Allaerts2019}, which focused on the generation and impact of wind-farm induced gravity waves. The model resolves the meso-scale flows, and couples to a wake model to estimate the turbine inflow velocities. Several improvements have been made to the model, the most important of which is that this coupling now fully captures meso-scale flow variations within the wind farm. Additionally, the impact of this on the wind farm forcing is coupled back to the APM, creating a two-way interaction between the atmospheric flow and the wind farm.

The improved model has been validated using 27 LES simulations of a large wind farm under different atmospheric conditions, ranging from flows without stratification effects to conventionally neutral boundary layers with strong capping inversions. The APM and LES results were compared on both meso- and farm-scale, and on turbine power output. The APM captures the overall effects gravity waves have on wind farm power production, and significantly outperforms uncoupled wake models.

The APM will be made open-source ahead of the PhD seminar. As we believe it is a powerful tool for studying the interaction between wind farms and the atmosphere, we will present its capabilities and code structure. It is designed to be highly modular, allowing for easy implementation of new pressure or turbulence parametrizations, or coupling techniques with engineering wake models.

References

Mesoscale effects of the interactions between wind farm clusters with large innovative rotor concepts and the boundary layer

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Keywords: Innovative rotor concepts, Mesoscale simulation, Wind farm parametrisation, WRF

The accelerated expansion of offshore wind energy is an essential contribution to increasing the share of renewable energy in the power supply and the further decarbonisation of the German energy industry. The German government plans to increase the installed offshore capacity from currently 7.8 GW to 40 GW by 2035 and 70 GW by 2045 [1]. However, in the future, just as important as the installed nominal capacity and the amount of energy provided will be how well the fluctuating feed-in can be planned and matched to the instantaneous demand in the power grid [4]. On-demand electricity delivery is not only necessary when considering the stability of supply, but also has a great impact on the stock price development [5]. Figure 1 shows how the electricity price exemplary decreases with higher wind speed when a high share of wind energy is present.

One concept to possibly mitigate this effect is a low specific rating turbine, e.g. the "hybrid-lambda" rotor [6]. As Figure 2 shows, it features a significantly larger rotor diameter compared to classical turbine concepts despite an equal rated power, resulting in a significantly decreased specific rating and reduced thrust coefficient. Due to its large rotor diameter, it operates outside of the atmospheric boundary layer more frequently than classical turbine concepts do. Also, this low-specific rating rotor is able to produce more electricity during lower wind speeds compared to classical wind turbines, leading to a more stable energy supply and a slight decoupling of the wind speed-electricity price correlation presented in Figure 1.

The objective of the PhD project is to implement new rotor concepts with varying power and thrust curves into mesoscale simulations and to investigate how the interaction between turbines and the atmospheric boundary layer changes for large and innovative rotor concepts with low specific ratings, compared to classical turbine designs and how this impacts the development of large-scale phenomena such as e.g. cluster wakes. Further, we want to improve wind farm parametrisation in mesoscale simulations, such that these new and unconventional rotor concepts can be represented. This is necessary, as the "hybrid-lambda" concept we plan to use features a non-uniform thrust distribution along the radial axis during its light- and strong wind mode respectively [6], which is not captured in current parametrisation schemes.

To investigate the boundary layer interaction of innovative rotor concepts and their impact on wind conditions at a larger scale we plan to use the Weather Research and Forecast model (WRF). Within WRF we use the Fitch parametrisation as a starting point for the representation of wind farms [3]. For the placement of the wind farms and the spacing inside the clusters, we adapt scenarios developed by the Fraunhofer IWES [2]. For our simulations, we will use classical turbine concepts as well as the "hybrid-lambda" rotor.
In a larger context, we plan to investigate how the usage of such new rotor concepts impacts the utilisation of substations and the German electricity grid as a whole. Also, we plan to explore the flow features of innovative rotor concepts inside of a wind farm, to establish an understanding of how large rotor concepts can help mitigate inner farm efficiency reductions. In the later stages of the project, we aim to use climate projections to examine the possible benefits of the large-scale usage of new rotor concepts with changing wind conditions in the future which are possibly triggered by climate change [7].

Figure 1: Simulation of the market value of energy provided by wind turbines as a function of the prevailing mean wind speed at a coastal location in 2030 with current expansion goals considered [5].

Figure 2: Comparison of the altitude of traditionally designed turbines (left) and the “hybrid-lambda” concept (right) and the velocity profile of the atmospheric boundary layer for different boundary layer altitudes of 250 m, 500 m, and 900 m at neutral (N) and stable (S) stratification, respectively (Martin Kühn, ForWind).
Figure 3: Wind speed reduction within the German Bight assuming German expansion targets until 2045 and development with turbines of conventional design [2].

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References


TOPIC 2: Control of wind turbines and wind farms

Session 2.1
06.09.2023 - 10:30
Building 3701, Room 268

Onnen David: Comparison of load- and lidar-based wake estimation in simulations, wind tunnel and field experiments
Bohrer Jan Kai: Wind field reconstruction and prediction for adaptable wind farm control optimisation
Afanasiyeva Nadiia: Improving the Quality of Wind Field Reconstruction Techniques for Lidar-assisted Control of Wind Turbines
Gori Filippo: Wind farm power maximisation via wake steering using Gaussian process-driven yaw-dependent parameter tuning
Janssens Nick: Towards real-time optimal control of wind farms using large-eddy simulations
Flanagan David: Control-Oriented modelling of Wind Farms using Computationally Efficient Methods
Comparison of load- and lidar-based wake estimation
Simulations, wind tunnel & field experiments

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Keywords: Wakes, meandering, wind farm control, state estimation, wind tunnel, field testing

Existing approaches for wind farm flow control are mostly open-loop formulations. To close the loop, suitable feedback signals are required – either for direct feedback or to support model-based control [1]. Especially for wake-steering control, the position of a wind turbine's wake with respect to the next turbine is valuable. It yields information whether the performed wake deflection acts as intended and further allows to update wind farm models in the scope of model based or optimal control [2]. One option to estimate the wake position is to use the rotor of a wake-exposed wind turbine as a sensor for the inflow [3]–[5]. The flapwise blade root bending moments are observed in this case. Another option is to use a lidar for direct wind speed probing, even allowing for feedforward control [6]–[8]. In this work, both lidar- and load-based approaches for the dynamic estimation of the wake centre position are presented, validated, and compared. An Extended Kalman Filter (EKF) formulation is employed to account for the meandering nature of the wake [3], [6]. This allows to compare at time scales of the wake dynamics and tell time-averaged wakes and instantaneous wakes from one another [9].

The validation is conducted at three levels of complexity: Aeroelastic simulations, field experiments, and wind tunnel tests. These methodologies complement each other, which will be highlighted in the presentation. Simulations allow for easy conceptualization of the methodology and provide repeatability as well as insights to all available sensor channels and wake information. Yet, they only represent an idealized scenario thus leave the necessity for experimental validation. This work uses the software HAWC2 [10] and FASTfarm [11].

The field experiments are conducted on two utility scale turbines of 126 m rotor diameter (D), spaced by 2.7 D. The blade bending moments of the downstream turbine (WT2) are used for the load-based wake tracking approach, while a scanning Lidar on the nacelle of the upstream turbine (WT1) is used as a reference, obtaining the flow situation between the turbines (see Figure 1).

The wind tunnel experiments combine the advantages of simulations and field tests: When choosing suitable scaling laws, they represent a realistic experimental environment. Yet, they still offer to manipulate the ambient conditions as desired, thus allow for repeatability of the experiments. This facilitates a comparison among different control and estimation methods under identical conditions. In this work, a 1.8 m model turbine is exposed to wake-like inflow conditions [12]. These are generated in a wind tunnel with an active grid, which imprints both a local wind speed deficit and additional turbulence in a meandering frame of reference. A setup sketch is shown in Figure 2. The experiments focus especially on the involved meandering dynamics. In the atmospheric boundary layer, turbulence patterns of multiple rotor diameters are driving the downstream meandering of the wake. In wind tunnel setups with large model turbines, these scale ratios are hardly reachable until now, thus meandering conditions were difficult to reproduce up to now. This setup allows to make the intrinsically stochastic process of wake meandering repeatable.

The take-away of this work is two-fold: Firstly, the wake-estimation techniques are validated in each environment. Both the load- and lidar-based approaches perform well in simulations and in the wind tunnel, with a root-mean-squared-error (RMSE) of 0.1 - 0.2 D. Note that in these cases a ground truth of the wake position is available for the computation of the RMSE. In the field experiments, the load- and lidar-based estimates can only be compared among each other, here resulting in a RMSE of 0.18 D. This comparison is shown in Figure 3. Secondly, the presentation shows how the different validation methods can mutually be employed, each contributing with its own advantages and covering for the limitations of the other methods.
Figure 1 Lidar-recorded flow situation in field experiment

Figure 2 – Wind tunnel setup: Model turbine exposed to wake-like inflow, which is generated with an active grid

Figure 3 - Wake tracking results from field experiment; blade-load-based EKF formulation is shown in black, Lidar reference is shown in red. Uncertainty intervals are shown for the respective methods
Acknowledgements

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References

Wind field reconstruction and prediction for adaptable wind farm control optimisation

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1 Background

Optimising the control of wind farms according to current and predicted wind conditions shows potential to significantly increase farm power production and extend turbine operational lifetimes by load alleviation [1]. A major challenge in this context is the impact of wakes generated by upstream turbines, leading to reduced wind speeds and enhanced turbulence at downstream turbines. Promising approaches to tackle this problem are wake steering by yaw misalignment and dynamic induction control [2,3].

For model predictive control, it is necessary to reconstruct the wind field from a limited number of measurement points, including turbine sensors and possibly meteorological masts and LIDARs. Based on the estimated state, farm control can be optimised by predicting the influence of control actions on the field evolution and turbine interactions. While promising dynamic flow models have been developed in recent years [4]-[8], there remain challenges in achieving required accuracy, consistency and computational efficiency for real-time control applications. Furthermore, uncertainty treatment and incorporation of measurement sensor data streams need to be improved and dynamic models as well as control algorithms need to be tested in free field applications.

2 PhD project description and methodology

The PhD research projects’ aim is to design a closed-loop wind farm control algorithm to optimize turbine interactions under a given control objective. In this regard, the work will address the utilisation of turbine sensor data and LIDAR measurements for wind field reconstruction and prediction, including uncertainty estimation and propagation. Furthermore, the project will focus on dynamic wind farm flow modelling under unsteady inflow conditions and time variable turbine control actions.

In accordance with the formulated research questions, the methodology covers the control scheme, wind field reconstruction from measurement data and wind farm flow modelling. Figure 1 shows the algorithm for real-time model predictive farm control. Measurement data streams from the available sources are utilised to characterize the wind conditions and reconstruct the flow field. Based on the initial state, farm control is optimised by predicting the short-term, minute scale wind field evolution under variable sets of control actions. The prediction horizon and accuracy should improve, when additional data sources, like LIDAR and upstream positioned met masts are available. After applying the optimised control actions, the algorithm will further monitor the wind field at the measurement points and aim to analyse and extract the control effects on the field evolution and turbine interactions. Hereby, learning algorithms can potentially be adopted to provide feedbacks to predictor and estimator. Comparison of expected outcome and measured effects can be used for continuous model parameter tuning, which incorporates the adaptation to changes in the environmental conditions.
Reconstruction of the wind farm flow field poses a significant challenge due to a limited number of measurement points with corresponding uncertainty and temporal and spatial resolution. In this work, two fields are introduced: The background field, which is constructed exclusively from measurement data and the model field, which includes dynamic turbine-flow interactions and wake evolution. The background field is created from ‘measurement parcels’, which are generated at the turbines’ positions in chosen time intervals and propagated through the field, keeping their respective measured wind speed and direction, as shown in Fig. 2. Shepard interpolation is then used to interpolate the background field at any chosen point in the wind farm, weighting all measurement parcels with their inverse squared point-to-point distance, as can be seen in Fig. 2. Additionally, the parcels’ weighting factors may be set to decline with their age or overall travelled distance.

The background field is used to provide inflow conditions for the flow model at free stream regions. In the current state, a two-dimensional Navier-Stokes solver is used to describe turbine-flow interactions and the behaviour and dissipation of turbine wakes [9]. Combining background and model field provides a full reconstruction of the wind field at a chosen instant in time and the prediction of its evolution, as shown in Fig. 3. In case of forecasting, measurement parcels are not anymore generated at the turbines’ positions, while the remaining parcels propagate further through the field. The interpolation algorithm still allows to estimate the background field at any point in space. Nevertheless, it is expected that the certainty of inflow conditions and the derived fields will decrease dramatically in time. Therefore, the model allows for propagation of a scalar parameter with the flow, which can potentially indicate a measure of uncertainty. Furthermore, it is intended to analyse, how additional data sources, like LIDAR and met masts can improve the inflow description and prediction horizon. Large Eddy Simulations and high frequency SCADA and LIDAR data sets will be used for validation of the flow model and control algorithm.

Previous investigations have found that the description of wake evolution under yaw misalignment depends on three-dimensional physical phenomena, including vortex dynamics and continuity effects [10]. It remains to be analysed, how the present flow model performs in cases of yaw steering in stationary and dynamic cases. Modifications are probably necessary to achieve an acceptable level of accuracy for the intended wind farm control applications.
3 Expected outcomes

The intended outcome of the PhD project is the design and testing of a robust, adaptable, closed-loop wind farm control algorithm. In this regard, intermediate results need to be achieved. First, a measurement-based wind field reconstruction model will be improved to incorporate on-line turbine and potentially LIDAR data streams. The reconstruction scheme will be validated with high frequency SCADA and LIDAR data. Second, the capability of a present wind farm flow model will be assessed and possibly adjusted and extended to capture dynamic effects under varying inflow conditions and control actions. The dynamic model will be validated with SCADA data from measurement campaigns and with Large Eddy Simulations. The improvement of the prediction horizon and accuracy when using LIDAR measurements as additional inflow information will be analysed. Third, the wind field reconstruction and prediction models will be applied to implement the control action optimization scheme. Feedback algorithms will be developed for on-line model parameter tuning based on comparison of expected and monitored turbine measurements. The closed-loop control algorithm will be tested with a Large Eddy Simulation study.

Acknowledgements

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References


Improving the Quality of Wind Field Reconstruction Techniques for Lidar-assisted Control of Wind Turbines

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1 Introduction

The response of a wind turbine to changes in the wind speed is traditionally achieved via a feedback blade pitch and generator torque control. Conventional control system can only react after the wind changes impact the turbine.

Light detection and ranging (lidar) technology measuring the wind in front of the rotor gives the wind turbine the ability to respond to emerging wind dynamics prior to its occurring. However, commercial application remains limited so far, although the potential for improvements in control performance has been shown in literature [5], indicating the need for further research.

Thinking about lidar for control applications, the challenge is to take advantage of the potential of lidar technology taking into account the technological trade-offs. Lidar makes use of the Doppler effect and therefore is restricted by temporal and spatial limitations: By concept, lidar detects the velocity of particles along the beam, the radial or so-called line-of-sight wind speed, and is unaware of the actual wind flow dynamics [1]. By design, current lidar systems are only covering limited points over the rotor disk due to their scan methods (rotating prisms, fixed telescopes) and need to average over a certain time to provide reliable signals. To take advantage of remote sensing for lidar-assisted control of wind turbines, a technique for reconstructing the wind field from the measured data is needed. For that purpose, one needs a closure about the wind field dynamics that can be used to approximate the unavailable data based on the available ones.

The wind field is mostly reconstructed with known parameters (i.e. scan configuration) and assuming static wind models (e.g. homogeneous flow or perfect alignment). Several measurements are usually combined and the wind field is reconstructed using the least-squares method [2]. While these methods already have been successfully applied to real measurements, using dynamic models and advanced methods are promising to improve the quality of the wind field reconstruction (WFR) and by this increasing the benefit of lidar-assisted control.

Addressing the broader question of data-driven approaches versus first-principle approaches in fluid mechanics, [3] note that flows, particularly high Reynolds number atmospheric flows, require consideration of nonlinearities and multiple spatiotemporal scales that are difficult to capture with data-driven approaches, while first-principle approaches are usually computationally too slow for real-time control. Therefore, reducing the complexity of first-principle approaches is important to explore.

Here, a promising approach using a dynamic wind model is developed in [6], reconstructing the 2D wind field between two nacelle-based lidar beams. The authors derive a simplified Large Eddy Simulation (LES) model by applying scale analysis to the incompressible Navier-Stokes equations. Using model-based state estimation techniques, the model incorporates the history of lidar measurements into current and future estimates of the wind field. To reduce the error between actual and estimated wind fields, in a recursive fashion, an unscented Kalman filter [7] is used.

This work is therefore intended to contribute to the development of lidar technology by improving the wind preview quality.
Figure 1: The basic framework to test and evaluate wind field reconstruction methods.

2 Methods

In this work we develop a framework which allows to test and evaluate wind field reconstruction methods for lidar-assisted control.

The basic structure of the framework is presented in Figure 1 and consists of following blocks:

1 Wind Field Generator (providing the reference wind field).
2 Lidar Simulator (simulates a Lidar that provides raw lidar measurements from the reference wind field).
3 Wind Field Reconstruction (reconstructs the wind field from lidar measurement and provides the estimated rotor-effective wind speed)
4 Evaluation (evaluates the quality of the reconstructed wind field comparing it to the reference wind field).

The framework allows to use different representations for each block. We developed following 2D testing strategy:

1 Baseline 2D WFR in nominal environment: Here we used TurbSim [4] for the wind field generator, a simple lidar simulator using a point model, and a baseline WFR assuming perfect alignment, providing the rotor-effective wind speed (REWS). The wind field is evaluated comparing the REWS from the reference wind field to the estimated one. First results are described below.

2 Baseline 2D WFR in LES environment: Here, the above method is applied to a full LES wind field. We expect a lower wind preview quality than in the first step.

3 Advanced 2D WFR based on simplified LES and Kalman filter in nominal environment: Here, we will test the approach of [6] in its nominal environment, generating a wind field with the simplified LES.

4 Advanced 2D WFR based on simplified LES and Kalman filter in LES environment: Here, the above method is applied to a full LES wind field. Here we expect a lower preview quality than in the third step, but a higher one compared to the second step.

3 Results

This section presents the results for the baseline 2D WFR in nominal environment, the first step in our testing strategy. The presented case study employs a IEA Kaimal wind field as a reference and a two-point lidar measurement scheme, and represents an idealized environment.

We first generated a turbulent wind field with a length of 4192 s, a width and height of 128 m, and a mean wind speed of 20 m/s. Then, we calculated the REWS over a rotor disk of 126 m in the center of the wind field as mean over all longitudinal wind components. Further, we simulated a simplified lidar system measuring in two points 128 m in front of the rotor, 20 m to the right and to the left of the hub. From the two line-of-sight wind speeds we then calculated the lidar estimate of the REWS by assuming perfect alignment with the mean wind direction [5].

The first 30 s of the two signals are displayed in Figure 2(a). The REWS has less fluctuations compared to its lidar estimate, since the REWS corresponds to the wind speed spatially averaged over the rotor disk.
Figure 2: (a) Rotor effective wind speed (REWS) and its lidar estimate over time. (b) Coherence between the two signals from (a) over wave number and its theoretical value.

We then calculated the coherence between the reference and estimated REWS and compared it to its theoretical value [5], see Figure 2(b). The coherence from the simulation fits well to the theoretical value, which indicates that the simulation and wind field reconstruction was implemented correctly.

This first results will serve us as a basis for the next steps. For this combination of this IEC Kaimal wind field, scan configuration, the baseline WFR represents the best possible result. However, when replacing the wind field by a more realistic (e.g. generated by LES), we expect that more advanced methods can provide better results.

## 4 Outlook

We will first finish the steps of the 2D testing strategy described above. After these steps, we will extend the method to 3D and develop a similar testing strategy. An extension of the framework will include full aero-elastic simulations to evaluate the methods not only with respect to the wind preview quality, but also for their capability in improving wind turbine control.

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### References


Wind farm power maximisation via wake steering using Gaussian process-driven yaw-dependent parameter tuning

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1 Introduction

Wind energy now plays a central role in meeting world energy requirements, driven by the urgent need to mitigate climate change and a significant recent reduction in its cost. With the deployment of larger farm layouts with closely spaced turbines, it is essential to mitigate the aerodynamic interactions between turbines, which cause annual power losses of 10% to 30% [1, 2, 3]. Wake steering, in which upstream turbines are yawed to deflect their wakes away from downstream machines, is a leading control technique to mitigate the effects of wake-turbine interactions. The current work focuses on model-based wake steering optimisation approaches for wind farm power maximisation.

In optimisation and control applications, low-fidelity wake models are commonly used due to computational constraints. To improve the accuracy of predictions, these models are often calibrated using higher-fidelity data, such as field measurements or LES data, either offline or online. The calibration process accounts for specific operating conditions of the wind farm, including turbine operation, farm layout, wind direction, wind speed, and turbulence intensity. However, in the context of wake steering, these calibration approaches do not account for the parameter dependency on yaw misalignment. Since an optimisation algorithm must explore many different yaw configurations, a wake model where parameters are tuned to a single yaw condition may be inaccurate over successive iterations of an optimisation algorithm, possibly impacting the quality of the resulting wake steering strategy.

To address this limitation, the current research proposes a novel generalisable parameter-tuning approach incorporating meta models, particularly Gaussian Processes (GP), into the optimisation algorithm to constantly adjust the wake model parameters based on the current farm’s yaw configuration. The effectiveness of this approach is evaluated by performing a wake steering optimisation on the Horns Rev wind farm layout [4] using a simple steady analytical wake model, the Jensen model [5], where the wake expansion $k$ parameter is tuned to the power predictions of GCH [6], a more sophisticated steady analytical wake model which captures secondary steering effects. This approach can generally be applied to tune lower-fidelity model parameters given any higher-fidelity data, including field measurements and simulation data. Moreover, although demonstrated in an open-loop wake steering context, this approach can be readily extended to other control strategies and closed-loop frameworks.

2 Methodology

2.1 Wake steering setup

This research conducts open-loop wake steering optimisation to maximise wind farm power production. The Jensen model [5] and the GCH model [6] are used as internal analytical wake models. The investigated farm layout represents the offshore Horns Rev wind farm [4], featuring 80 Vestas V-80 2MW turbines. The farm layout exhibits ten rows and eight columns, with a distance of $7\, \text{rotor diameters} \, D$ between consecutive turbines in streamwise and cross-stream directions. The atmospheric conditions consist of an incoming flow fully aligned with the farm columns with a wind speed of $8 \, \text{m} \, \text{s}^{-1}$ in 5% ambient turbulence intensity. Wind shear and veer are not taken into account.
The optimisation algorithm employed is the gradient-based Sequential Least SQuares Programming (SLSQP) method [7]. The optimisation problem’s objective function is chosen to be the normalised farm power production

\[ G(\gamma) = \frac{P(\gamma)}{P(0)}, \]

where \( \gamma = \{\gamma_i\}_{i=1}^{N} \subseteq \mathbb{R}^N \) are the yaw angles of the \( N \) farm turbines excluding the most downstream row (fixed to \( \gamma = 0 \)), \( P(0) \) is the farm power without wake steering, and \( P(\gamma) \) is the farm power achieved for a particular choice of yaw angles \( \gamma \). In all cases, we solve the constrained maximisation problem

\[ \max_{\gamma} \quad G(\gamma) \]
\[ \text{subject to} \quad -25^\circ \leq \gamma_i \leq 25^\circ, \quad 1 \leq i \leq N. \]

### 2.2 Parameter tuning

The proposed parameter-tuning approach involves generating an initial dataset of optimal wake model parameters based on the farm’s yaw configuration. The dataset is then fitted with a Gaussian Process (see Section 2.3), subsequently used in the wake steering optimisation (2) to predict and set the optimal model parameters at each yaw configuration evaluated by the optimiser. The initial optimal parameter dataset is obtained using a full-factorial experiment approach. For each turbine in the farm (excluding the last row), 11 equally-spaced yaw angles are chosen from the range of \([-25^\circ;25^\circ]\). Subsequently, the wake model parameters are optimised for each permutation of yaw angles for the turbines. Dimensionality reduction techniques are further used to substantially reduce the amount of required data points, as discussed in Section 2.3.

For each yaw configuration, the default expansion coefficient \( k = 0.04 \) of the Jensen model is tuned within the range of \([0,0.15]\) to minimise the root-mean-square error (RMSE) with GCH power predictions. The deflection parameter \( k_d \) is not considered because its impact on farm power prediction is minimal in the investigated conditions. The tuning optimisation problem can be expressed as

\[ \min_k \frac{1}{N} \sum_{i=1}^{N} \left( P_{\text{GCH},i} - P_{\text{GCH},i}^{\text{len}}(k) \right)^2, \]

where \( P_{\text{GCH},i} \) is the power of turbine \( i \), \( N \) is the total number of turbines in the farm, and \( P_{\text{GCH},i}^{\text{len}}(k) \) refers to the power prediction of Jensen with parameter value \( k \). Due to the multimodal and discontinuous nature of the objective function in (3), the global Bayesian optimiser TuRBO [8] is employed.

To integrate the GP tuning of the parameter \( k \) into the wake steering optimisation problem, the objective function \( G(\gamma) \) is modified to incorporate the GP-based estimation of \( k \). By denoting the estimated value of \( k \) as \( \hat{k}(\gamma) \), the modified objective function becomes

\[ G(\gamma) = \frac{P(\gamma,\hat{k}(\gamma))}{P(0,\hat{k}(0))}, \quad \text{with} \quad \gamma \in \mathbb{R}^N, \]

where \( P(\gamma,\hat{k}(\gamma)) \) is the farm power achieved for a particular choice of yaw angles \( \gamma \) and the estimated value \( \hat{k}(\gamma) \) predicted by the trained GP at the given yaw angles \( \gamma \), and \( P(0,\hat{k}(0)) \) is the farm power without wake steering.

### 2.3 Gaussian Processes and dimentionality reduction

A Gaussian Process (GP) is utilised as a surrogate model to estimate the optimal Jensen model parameter \( k \) based on the farm’s yaw configuration. GPs are stochastic processes that can represent any finite set of points through a multivariate normal distribution. This flexible statistical modelling technique enables the estimation of the mean and uncertainty associated with the underlying function. In this study, the covariance function is defined using a radial basis function (RBF) kernel. The GP’s variance and lengthscale hyperparameters are determined by solving the likelihood maximisation problem using the L-BFGS optimisation algorithm [9].

Constructing a high-dimensional GP model for large wind farm layouts, considering all turbine yaw angles involved in wake steering optimisation, poses computational challenges. These challenges arise from the computational complexity of GP hyperparameter tuning, which scales cubically with the number of data points. Additionally, if high-fidelity data is not based on field measurements, numerous higher-fidelity simulations are required to generate the wake model optimal parameter dataset. To address this issue, two approaches are proposed. (i), the
assumption of independent farm columns [10] is made after examining minimal column interference for various turbine spacings and turbulence intensities. Consequently, the GP is constructed based on permutations of yaw angles for a single turbine column, with each column independently adjusting its wake model parameter $k$ according to its specific yaw configuration during wake steering optimisation. (ii), a grouping approach is implemented, forcing turbines within the same group to have equal yaw angles. This enables defining the wake model parameter data points for each permutation of yaw angles for the groups rather than individual turbines.

3 Results

This section outlines the results of wake steering optimisation for wind farm power maximisation using the proposed GP-based yaw-dependent tuning approach. A simplistic two-turbine case is first explored to motivate and demonstrate further the need for such techniques. Considering two aligned Vestas V-80 2MW turbines with a streamwise distance of $7D$ operating in the atmospheric conditions described in Section 2.1, the Jensen parameter $k$ is tuned using (3) to GCH power predictions for a $[-25°; 25°]$ sweep of the upstream turbine yaw angle $\gamma_i$. In Figure 1, the resulting optimal $k$ parameter values are shown. For each turbine yaw angle, the $k$ ranges where the absolute percentage error with GCH farm power predictions is equal to or less than 5 % and 10 % are also included. Results indicate a variation in optimal parameter values depending $\gamma_i$, exhibiting high percentage error values in the observed optimal $k$ parameter range. For instance, when predicting the farm power at $\gamma_i = 25°$ using a $k$ value tuned for $\gamma_i = 0°$, a 20 % percentage error is observed. Generally, a strong sensitivity of optimal wake model parameter $k$ to yaw angle is observed, emphasising the limitations associated with employing a single parameter value in wake steering optimisation, particularly when the yaw configurations to be evaluated by the optimiser are not known in advance.

![Figure 1: Optimal Jensen wake expansion parameter $k$ in a $2 \times 1$ farm layout for a $[-25°; 25°]$ sweep of the upstream turbine yaw angle $\gamma_i$. Dark and light green areas indicate the region where the absolute error to the GCH farm power predictions are equal to or less than 5 % and 10 %, respectively.](image)

The subsequent part of this section presents the results obtained from wake steering optimisation conducted on the Horns Rev wind farm layout, where the Jensen $k$ expansion parameter is tuned with the higher-fidelity GCH power predictions. The tuning of the Jensen $k$ parameter is performed utilising the column-independence (i) and grouping (ii) approaches described in Section 2.3. With the implementation of (i), the optimal $k$ parameter dataset for fitting the GP is required for a single column within the wind farm instead of the entire layout. This assumption effectively reduces the GP dimensions from 72 (representing the number of turbines excluding the last row) to 9 (the count of turbines in a single column excluding the most downstream turbine). By employing the grouping technique (ii), the single column attained from (i) is divided into three equal groups, each comprising three wind turbines. As a result, the GP dimensions are further reduced from 9 to 3, substantially decreasing the necessary optimal $k$ parameter dataset. Figure 2 compares the wake steering optimal yaw angles for the Jensen model using GP-based parameter tuning, the higher-fidelity GCH model, and the Jensen model utilising the default $k$ parameter. While the default Jensen optimal yaw angles primarily saturate the upper bound constraints at 25°, the resulting optimal yaw settings of the GP-tuned Jensen model effectively capture the row-monotonic decrease in yaw angles observed in the GCH optimal decision variables. This behaviour, attributed to the GCH model’s ability to describe secondary steering effects, is not included in the Jensen model formulation, demonstrating that more complex physics can be described by integrating higher-fidelity data. The discrepancies in optimal yaw angles between the GP-tuned Jensen and the GCH are attributed to the grouping simplification (ii), aimed at reducing computational...
complexity. Without the non-essential grouping assumption, the differences in optimal yaw angles are effectively overcome.

Overall, the presented results demonstrate the potential of the GP-based parameter-tuning approach to enhance the capabilities of lower-fidelity wake models. By incorporating any higher-fidelity data, the approach enables a simple model, such as the Jensen model, to capture more complex physics and improve the accuracy of wake steering predictions.

![Comparison of wake steering optimisation results for the Horns rev case. Optimal yaw angles are shown for (a) Jensen with GP-based parameter tuning, (b) GCH, and (c) Jensen with default k parameter.](image)

Figure 2: Comparison of wake steering optimisation results for the Horns rev case. Optimal yaw angles are shown for (a) Jensen with GP-based parameter tuning, (b) GCH, and (c) Jensen with default k parameter.

### References


Towards real-time optimal control of wind farms using large-eddy simulations

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1 Introduction

In the last decade, much research has been done into receding-horizon control strategies to maximize energy extraction in wind farms by mitigating effects of turbine wake interactions. More recently, Refs. [3, 4, 5] have introduced an optimal control framework for wind farm power maximization based on high-fidelity large-eddy simulations (LES) of the wind farm boundary layer, combining both induction and yaw control. In their latest study [5], an overall power gain of 34 % was observed for an aligned $4 \times 4$ wind farm. However, these LES-based studies were intended as benchmarks to demonstrate the potential of LES-based wind farm control, since LES is commonly considered too slow for practical, real-time applications. A real-time LES plant model would result in significant gains that are realizable in practice.

2 Objectives

The present work investigates the feasibility of using LES as a real-time control model for power maximization in wind farms. In order to speed up the computations, we aim to leverage insights from Ref. [2] (in the context of turbulent flow forecasting in the atmospheric boundary layer) by resorting to coarser grid formulations both in space and time. Here, the coarsening approach is projected onto the LES-based receding-horizon optimal wind farm control framework from Ref. [5].

The objectives of the present study are twofold. On the one hand, by varying the spatial and temporal resolution of the LES control model, we explore the trade-off between computational speed and performance of the controllers in terms of power gains and farm efficiencies. On the other hand, we perform a parameter study on the receding-horizon control framework. For the latter, we investigate the influence of the optimization horizon and the control update time, again in the context of the aforementioned trade-off between speed and power gain.

3 Methodology and results

The proposed methodology is investigated on the TotalControl reference power plant, consisting of 32 DTU 10MW turbines that are aligned in an $8 \times 4$ pattern (see Ref. [1]). To investigate the effect of the grid resolution, three different coarseness levels are defined for the LES-based controllers. For each of these (coarse) grid levels, ten optimization cases with varying optimization horizon and control update times are run for a total control time of 1800 s (encompassing just under three flow-through times for the given wind farm). All controllers are evaluated on the same fine-grid LES reference simulation. Figure 1 and Table 1 show, for example, snapshots of the flow field through the wind farm on the different (spatial) grid resolutions considered throughout this work, as well as the reference grid that is used to evaluate the control actions. For the forward and adjoint simulations, we employ the in-house code SP-Wind, which uses a pseudo-spectral discretization in the streamwise and spanwise direction, and a fourth-order energy-conservative finite difference discretization in the vertical direction.
Table 1: Grid resolutions for the different coarseness levels.

<table>
<thead>
<tr>
<th>Grid level $i$</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resolution $x$ [m]</td>
<td>$\Delta x^i$</td>
<td>80</td>
<td>60</td>
<td>40</td>
</tr>
<tr>
<td>Resolution $y$ [m]</td>
<td>$\Delta y^i$</td>
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<td>25</td>
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<td>Resolution $t$ [s]</td>
<td>$\Delta t^i$</td>
<td>2.5</td>
<td>2.5</td>
<td>2.0</td>
</tr>
</tbody>
</table>

Our simulations show that the control update time and the optimization horizon are the predominant factors determining the overall power gain. For optimal performance, the optimization horizon should be long enough to account for turbine-wake interaction within the optimization window, and the control update time should be short enough to mitigate end-of-time effects originating from the finiteness of the optimization window. Interestingly, it is found that coarsening the LES grid of the control model does not necessarily deteriorates the results in terms of power gain, whereas the associated computational speed-up can be substantial.

In the end, using the coarse grid formulations and a good choice of the receding-horizon control parameters, we achieve near-parity between the LES-based control algorithm and real-time speed while maintaining competitive power gains. As such, we demonstrate the potential of coarse-grid LES for practical wind farm control.

4 Planned research

For the moment, in our control loop, we still assume the entire flow field from the reference simulation is available. In practice, the flow field should be reconstructed based on measurements of the flow, e.g. LiDAR measurements, using a state estimator (e.g. a Kalman filter or using 4D variational data assimilation). As a next step towards practical wind farm control, future work will therefore focus on the design of an efficient state estimator tailored to wind farm control, which can then be incorporated into the LES-based wind farm controller proposed here. The state estimation, however, also introduces additional reconstruction errors. In that case, the question still remains whether combined LES-based state estimation and control can be fast enough for real-time applications, and how the additional reconstructions errors originating from the state estimation will affect the performance of the controllers.
Figure 1: Snapshot of the flow field at different LES grid resolutions used for receding-horizon optimal control. Colors represent the velocity magnitude [ms$^{-1}$]. Black dots represent wind turbine locations.
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Control-Oriented modelling of Wind Farms using Computationally Efficient Methods

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1 Motivation

Based on site conditions and economics, offshore wind turbines are often clustered in farms to best utilise limited site sizes. As a result of this limited spacing of turbines, downstream wind turbines are exposed to wake effects. These wake effects have been shown to reduce performance and increase structural loads on the turbines in the affected regions. [1] It is clear that effective wind farm flow controls are needed to minimise the wake effects and improve overall wind farm performance.

Conventional control methods are heavily focused on maximising the performance of individual wind turbines. Studies have estimated that wind farms lose between 10-23% of their potential power due to wake interaction effects between individual wind turbines within the wind farm. [2] Therefore a more holistic approach to wind farm flow control is needed to ensure that these losses are minimised.

In recent years, a number of wake and wind farm models have been established and widely-used within the research community. Various pieces of literature and review papers have tested their performance in modelling the wake effects within a wind farm and quantified the increase in performance yielded by implementing aerodynamic control decisions to a wind farm. However, the majority of these tests have focused on steady-state wind conditions that do not reflect the real conditions endured on a wind farm. [3]

In the same trail of thought, the speed at which controls are implemented are a critical feature in wind farm control as conditions often change at wind farm sites. In the current state of the art, effective wind farm control has been demonstrated for specific sample permutations of conditions. However, there is limited knowledge and implementation of wind farm flow control techniques that can react rapidly (near real-time) to changing conditions.

Therefore, there is a clear knowledge gap and motivation to further understand the area of control-oriented modelling and its deployment to near real-time control of wind farms.

2 Proposed Methodology

In work currently in progress, the model FAST.FARM is being used to simulate a wind farm. The potential from here is to investigate whether machine learning methods can be combined with existing model reduction methods in order to create a wind farm wake estimator that is computationally efficient yet provides acceptable levels of fidelity to implement wind farm control decisions. Recent developments in machine learning have yielded incredible results in a multitude of areas. Therefore, in
a wind farm flow control context there is a scientific argument to explore its potential use in creating computationally efficient wind farm wake estimators.

In developing a wake estimator of this form, one can forecast what the flow conditions will be in a wind farm a number of timesteps in advance. This forecasting provides the time to implement control decisions into a wind farm, thus optimising its performance. In order for this to be achievable in a real world context some form of control loop is needed. In this research a closed-loop control mechanism is proposed.

Closed-loop control mechanisms are a major part of many real-time application of controllers to a system. Therefore, once the aforementioned reduced order wake estimator is functional, the proposed methodology is to create a closed-loop control framework of a wind farm. A diagram of the proposed (simplified) framework of this system is displayed in figure 1. As this is only at the proposition stage it is subject to change where with greater understanding of the estimator and control of wind farm flows, a more substantive control architecture shall be produced.

Explaining the figure, the framework commences with initial conditions being inputted into a wind farm model (or when fully developed, a real wind farm). Based on the flows within the wind farm, the proposed wake estimator will forecast what the flow conditions of the wind farm will be a number of timesteps into the future. These forecasted conditions shall be inputted into an control decision optimiser. This optimiser shall run numerous control decision permutations and select the most optimal one. The decision is implemented and the process continues.

This framework is proposed as from current review of literature, closed-loop control of wind farms hold great promise to improve wind farm performance and it provides an opportunity to compare the performance of the estimator built in the earlier stages of this research with more established ones. [4] [5]

![Figure 1: Proposed Initial Framework](image)

### 3 Acknowledgements

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4 References


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- Zengler Clemens: RANS simulation of a wind turbine in complex terrain - impact of flow deceleration and acceleration in combination with turbine modeling on power, thrust and induction
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Wind Turbine Lifetime Extension-Oriented Control System
Based on Machine Learning

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Keywords: wind turbine lifetime extension, wind turbine control, machine learning

1 Introduction

The lifespan of wind farms is limited compared to conventional power plants. Wind turbines typically require replacement or major refurbishment after 20-25 years of operation [10]. For instance, coal-fired power plants operate for 46 years on average on the global scale while often reaching the age of 60 [4]. As the global demand for energy continues to grow, there is an increasing interest in finding ways to extend the lifetime of wind farms and improve their overall performance. Another challenge is the process of wind farm decommissioning, which is not fully environmentally friendly yet, mostly due to the complications with the recycling of disposed wind turbine blades. While this issue is receiving abundant attention from the academic community [6], the stage of wind farm decommissioning still requires significant amounts of finances and time. Thus, prolonging the operational life of wind turbines is an important area of research and development that has significant implications for the future of renewables and the global fight against climate change.

During the first two months of this project, a preliminary literature review was conducted. Various strategies and research directions related to wind farm lifetime extension were observed, including condition or health monitoring, predictive maintenance, improved inspection methods, advanced control systems, and digital twins, among others [9]. The optimisation of control algorithms has emerged as a particularly promising area of research, as it has the potential to directly extend the service life of wind turbine components and reduce the frequency of repairs, unlike the approaches relying on timely maintenance, which can be costly and time-consuming [8].

Based on the preliminary literature review, this abstract further summarises how models based on machine learning can be used to solve the problem raised in the current project, describes initial research goals and expected results, as well as the methodology that will be used throughout the process.

2 Concept overview

In recent years, numerous machine learning techniques have been studied and successfully implemented in different areas, including wind energy [1]. The principle of rewarding and penalising a neural network was initially designed to train the model to perform well in certain settings, including video games. This approach is called reinforcement learning (RL), which received a rapidly rising interest in various fields, including wind engineering, with particularly promising potential for implementing it in advanced control systems [2], [7]. Nevertheless, such type of deep learning does not always perform well under certain scenarios, for example, when there are no clear rules for designing the rewarding and penalising algorithms. This problem led to the development of similar networks using curiosity-driven reinforcement learning (CDRL), which is a type of machine learning that focuses on encouraging an agent to explore its environment and learn new patterns by providing rewards for novel or unexpected experiences rather than simply maximising a predefined reward function [3]. This can lead to more robust and adaptable learning, as the agent is constantly exploring new possibilities and refining its understanding of the environment. The applications of CDRL in wind energy still require extensive research, and it is suggested that CDRL can be used to train a control system to operate the wind turbine or wind farm in a manner that optimises the system’s resilience, such as by reducing loads and extending service life.
3 Research goals and expected results

The orientation of control on lifetime extension, as the main research question in this study, implies focusing on the reduction of wind turbine loads and fatigue by adjusting the control system algorithms based on output from novel machine learning models. The model itself will be fed with integrated data from such sources as wind turbine characteristics, weather and wind properties, maintenance logs, condition or health monitoring systems, supervisory control and data acquisition (SCADA), or prognostic models either predicting a failure or the remaining lifetime of components in a wind turbine, depending on the data availability. Considering the principles of how neural networks are trained, the fusion of data from multiple sources has the potential to improve the accuracy of the model. It is also important to note, that attention is likely to remain on specifically adjusting the control system parameters rather than introducing a new system due to the warranty obligations wind farm operators normally have to follow.

It is planned to study and test multiple types of control strategies and other machine learning techniques in addition to CDRL and RL when conducting the literature review and pilot trials. Moreover, such relevant areas as implementations of the digital twin concept will be actively observed throughout the project. A more precise concept will be developed based on the observed performance of various machine learning models.

By the end of the project, the developed system is expected to deliver a new method for optimisation of existing wind turbine control systems with a balance between performance and longevity.

4 Research methodology

1 Extended literature review. Further study will include discovering and analysing more relevant academic resources in order to better identify the existing knowledge, respective gaps, and a clearer research question together with a more precise idea for solving it.

2 Project-specific academic training. Additional courses will be required for developing a better understanding of available machine learning models and their successful implementation for attaining the project objectives.

3 Collaboration with an industrial partner. Although using open-source data brings numerous benefits, including replicability and transparency that allow further comparative analysis, the necessary quality and quantity of data might not be available. Due to this reason, it has been decided to establish cooperation with a private company which can provide the required data.

4 Data collection and pre-processing: A simplified pilot study under idealised conditions is planned at this stage. For adequate results, it is vital to ensure that the collected data is in the correct format, clean, and free of errors. This may involve removing duplicates, handling missing values, converting categorical variables to numerical variables, etc. The data will include wind turbine characteristics with respective data from SCADA and/or condition monitoring systems provided by an industrial partner. Additional model improvement could be achieved by accessing such data as maintenance logs or output from prognostic models predicting a component failure, its remaining lifetime, or wind properties.

5 Data processing. As per common practice, this process will involve such sub-stages as feature extraction, model selection, training, and trials consisting of testing and validation procedures.

6 Deployment of the suggested control system. For accurate adjustments in further stages, it will be essential to observe the performance of the developed model in a control system for a wind turbine and its influence on other subsystems by modelling and conducting simulations or testing it with a digital twin.

7 Adjustment of the model. Based on how the system performs under initial settings, the system might require modifications to provide optimal performance.

8 Project management. Agile methodologies were chosen for the project due to their suitability to the specifics of this study and potential benefits highlighted by both industry and academia [5].

Acknowledgements

The author would like to gratefully acknowledge the School of Engineering at the University of Edinburgh for the provided studentship and research funding used in this project.
References


1 Introduction and context

The power curve of a wind turbine relates a wind speed with a specific energy production of the turbine. The wind speed is the one measured at hub height at the position of the turbine, if the turbine was absent. The underlying assumption is that the only relevant flow parameter dictating the power of the turbine is the wind speed at the position of the turbine. Uncertainty is mainly associated with wind shear, atmospheric stability, air density, and turbulence intensity. Apart from this also yaw misalignment can play a role. However, flow inhomogeneity in the streamwise direction is usually not considered as a parameter. Studies based on large-eddy simulation (LES) and measurement data suggest that flow deceleration or acceleration behind the turbine can have a significant impact on the aerodynamic performance of a turbine, consequently altering the power performance with respect to a reference power curve obtained in a homogeneous flow field [1, 2]. An example of this phenomenon is presented in figure 1, which shows Reynolds-averaged Navier Stokes (RANS) simulation results of the DTU 10 MW reference wind turbine [3] on a two-dimensional Gaussian hill for different roughness lengths $z_0$ on the surface, altering flow separation and eventually the downstream flow development. In case of a high deceleration ($z_0 = 0.005m$), the aerodynamic power is reduced by over 15 percent compared to operation in a homogeneous flow field. Similar results were obtained by Troldborg et al. [1].

The influence of the flow field on the power performance is especially important if a turbine is to be erected in complex terrain. Flow acceleration, deceleration, variation in shear, turbulence intensity and stability lead to the situation, that the performance of a wind turbine needs to be reassessed on basis of a site calibration [4, 5, 6]. In this procedure, a met mast is erected at the position of the turbine and at a reference site and the respective measured wind speeds correlated [4]. Based on this data, the power performance of the turbine can be evaluated afterward. However, the fact that only information of the flow at the position of the turbine is used, introduces uncertainties. It is desirable to know the effect of the terrain on the turbine performance before installation to reduce energy production uncertainties and identify optimal installation sites.

Although the effect of terrain can be modeled in high-fidelity computational fluid dynamics (CFD) simulations, it is desirable to incorporate it into low-fidelity engineering models, promoting the fundamental understanding of the flow physics involved and the usage in preliminary site assessment.

2 Research question

The PhD project is developed around the question of what exactly needs to be known about the flow in complex terrain or more generally speaking about an inhomogeneous flow field to achieve accurate aerodynamic performance predictions and how this information can be included in engineering models. Apart from that, it needs to be asked if our current understanding and modelling of aerodynamic turbine performance is sufficient to explain its variation in different terrains.
At the PhD seminar, insights into the question of how certain modeling aspects of the wind turbine affect the aerodynamic performance in complex terrain are to be given. Special emphasis is put on the influence of the controller and the loading model of the actuator disc, which is used to model the turbine in the CFD simulations.

3 Methodology

With respect to the overall PhD project, CFD is used to investigate the aerodynamic performance of a turbine in complex terrain. The results from this are intended to be used in a second step to promote understanding of the inherent physics and eventually derive an engineering model.

At the present stage, CFD simulations are performed based on the RANS equations. As RANS-closure the $k-e-fp$ model developed for wind turbine wake flows is used [7]. The investigated case is a wind turbine positioned on a two-dimensional Gaussian hill as shown in figure 1. The wind turbine is modeled as an actuator disc. As inflow, a neutral atmospheric boundary layer is imposed. As flow solver, the inhouse-code EllipSys3D [8, 9] is used. Previously, the impact of domain size, mesh size and RANS model formulation on the aerodynamic performance was investigated to avoid systematic errors.

4 Expected outcome

The PhD project is intended to deliver insights into the aerodynamics involved in the operation of a wind turbine in complex terrain. Furthermore, engineering models shall be derived to account for the effect of complex terrain on the performance already in the development phase of wind energy projects.

For the PhD seminar, it is expected to present preliminary results of the impact of deceleration and acceleration of the flow field behind a turbine on thrust, power and induction. Consequences of different modelling decisions regarding control strategies and rotor loading of the turbine will be shown. The differences to the results from classical streamtube theory will be discussed.
Acknowledgements

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References


Development of an open-source controller for small stall-regulated horizontal-axis wind turbines

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1 Introduction

Small wind turbines, characterized by a power of less than 50-60 kw have been the object of rising interest over the last years [1]. In particular, these machines can aid the spreading of renewable energy to off-grid systems and remote areas. One of the crucial issues that need to be addressed when designing small wind turbines concerns the reduction of the levelized cost of energy [2]. For this reason, these turbines are generally stall-controlled allowing a reduction of costs in comparison to pitch-controlled machines. However, designing stall-control turbines represents a complex problem.

First of all, the design of the turbine blades requires a trade-off between maximising energy production and guaranteeing stall at high wind speeds. Uncertainty in the aerodynamic response of the rotor under stall conditions introduces further complexity. Additionally, the control system must be properly designed in order to guarantee adequate performance and minimize loads.

In this work, the open-source research controller currently under development at the University of Florence is presented (UNIversity of Florence COntroller, UNICO). The controller was developed using MATLAB Simulink and is characterized by innovative control strategies for both below and above rated conditions. Hence, the objective is to show the advantages of the proposed controller in comparison to state of the art approaches under multiple test conditions.

![Diagram](image)

Figure 1: (a) Definition of main wind turbine operating regions (b) typical performance curve of stall-regulated turbine.
2 Control of stall-regulated turbines

The majority of small wind turbines use passive regulation systems rather than pitch control as this allows to reduce costs and to avoid installing blade pitching systems within small nacelles, which poses a significant challenge. Hence, the controller acts solely on the generator torque in order to govern the turbine behaviour.

Standard design of a controller for stall-regulated wind turbines divides the turbine behaviour into three regions. In Region 1 the turbine follows the minimum rotational speed when the wind speed is below the cut-in value. In this region, the turbine does not produce any power. In region 2, the turbine operates in below rated wind speed, i.e. the wind speed at which the turbine produces nominal power. Here, the turbine needs to extract the maximum available power, operating at the optimal tip speed ratio. Finally, in region 3, the turbine rotates at the rated rotational speed and the power should be maintained at the rated value. For stall-controlled wind turbines, the power is limited by the onset of stall of the blades, which reduces aerodynamic loading and hence limits the rotational speed. Generally, the performance of the turbine in this region is the result of a compromise between guarantying reliable operation and maximising power. An additional region is generally defined as 2.5 which controls the switch between regions 2 and 3. Here, a linear variation of the rotor speed from the value at the end of region 2 to the rated value is generally imposed. Finally, for the cut-off wind speed the turbine is stopped to avoid any structural damage.

The proposed controller UNICO presents novel strategies in both below and above rated conditions. In region 2 the most common approach is the \( k - \omega^2 \) control [3], where the generator torque, \( T_g \), is controlled using a squared law of the rotational speed, \( \omega \),

\[
T_g = k \omega^2
\]

This approach guarantees high reliability, however it does not allow the maximisation of energy production. In the UNICO controller both the \( k - \omega^2 \) law or the tracking of the optimal tip speed ratio can be employed. In the latter case, a Proportional-Integral (PI) controller is implemented, which tracks the optimal rotational speed of the turbine, obtained from the CP-TSR curve (see Figure 2 (a)). The characteristic equation of the PI controller is:

\[
u(t) = k_p e(t) + \frac{k_p}{T_i} \int e(\tau) d\tau,
\]

where \( e(t) \) is the error between the reference signal that needs to be tracked by the controller and the current value of the variable. The first element on the right hand side of Eq. (1) is the proportional term which provides a proportional control action to the error value. The second term is a function of the integral of the error and reduces steady-state discrepancies from the reference value. The controller was tuned by defining the parameters \( k_p \) and \( k_i \) of the proportional and integral terms respectively.

![Figure 2: (a) Example of CP-TSR curve (b) Inversion of CP-TSR curve for control in region 3](image)

In the above-rated region, most controllers use a linear law to calculate the generator torque as a function of the wind speed. In this way, when the wind speed increases the generator torque also rises, causing the blades to stall and slowing down the rotor. Therefore, the loads are limited, achieving better reliability. In the UNICO controller an innovative control strategy is proposed that tracks the optimal power coefficient even in region 3.
this way, power production is maximised, achieving near rated power over a larger range of wind speeds. A PI controller is used to track the reference rotor speed which guarantees the maximum power for a given wind speed. The reference wind speed is calculated from the CP-TSR curve of the turbine. The wind speed is assumed known and the turbine is controlled in order to achieve nominal power. In detail, the target power coefficient is calculated as,

$$C_p = \frac{P_N}{\frac{1}{2} \rho \pi R^2 V^3}$$

(3)

the power coefficient is used to estimate the reference tip speed ratio, which in turn is used to calculate the reference rotational speed that is tracked by the controller. This is done by inverting the CP-TSR function (Figure 2 (b)). Since this function cannot be directly inverted, only the part of the curve at small tip speed ratios is considered, as in region 3 the turbine will work in this part of the curve (see stall mode in Figure 2(a)).

3 Methodology

The UNICO controller is tested for multiple cases by performing Blade Element Momentum (BEM) simulations in OpenFAST. Tests are performed considering the Small Reference Wind Turbine (SRWT) designed by the University of Florence. This machine is a three-bladed horizontal axis wind turbine. The diameter of the rotor is 16m and the rated power is 50 kw.

The performance of the controller is compared with ROSCO controller [4] developed by NREL which was tuned with standard control strategies (i.e. \( k - \omega^4 \) law and a linear law for generator torque in regions 2 and 3 respectively). The performance of the two controllers is tested performing step-tests of 100 seconds, where the wind speed is increased from 1 m/s to 20 m/s with 1 m/s increments. Two different tests are performed with varying air density: one at standard air density (1.24 \( \text{kg/m}^3 \)), and one at a density of 1 \( \text{kg/m}^3 \). In this way, the effect of different installation altitudes on the controller is shown. Additionally, results obtained with the two controllers are compared by using different sets of polars at varying \( N_{crit} \) in order to compare the effect of uncertainty in the aerodynamic design of the turbine on the tuning of the controller.

4 Results

Figure 3 shows the behaviour of the UNICO controller against the OpenFast ROSCO controller. Results show how the rotor is capable of correctly following the rated power for wind speed larger than the rated value. No excessive acceleration of the rotor or oscillations in generator power are observed. Instead, the ROSCO controller is not capable of maintaining constant power as it applies a linearly increasing generator torque in region 3.

Additionally, the UNICO controller is more stable when uncertainty in the aerodynamic performance of the turbine is introduced. Indeed, the discrepancy between the power curve calculated for the two \( N_{crit} \) values is reduced significantly.

Figure 3 (b) shows the variation of the rotor torque as a function of the rotational speed. The UNICO controller is capable of following the minimum speed and the rated speed correctly, as represented by the constant rotational speed trends at 25 and 56 rpm, respectively. In above rated condition, the rotor speed decreases as the generator torque is kept constant and the turbine stalls.
An additional comparison is carried out considering a smaller value of air density, \( \rho = \frac{1}{2} \text{kg/m}^3 \). Indeed, constant torque controllers need to be tuned depending on the elevation, and consequently the air density, of the installation site. Additionally, changes in air density due to temperature may affect the behaviour of the turbine. In this case, if the ROSCO controller, which employs a linear law to control the generator torque in region 3, is not properly tuned, the turbine does not achieve rated power and a significant decrease in power output is observed. In contrast, the novel control strategy proposed for region 3 achieves an almost constant power in above rated conditions, independently of the air density.

Finally, Figure 4 (b) shows the generator torque response. Due to the reduced air density the UNICO controller shows an increase in rotational speed in Region 3, rather than a reduction as observed in Figure 3(b). Indeed, by using the power curve to define the reference wind speed, the controller accelerates in order to compensate for the reduced density.

References


Operational Network Planning for Different Multi-Terminal High Voltage Direct Current Offshore System Interfaced Wind Integration

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Keywords: wind power integration, static security assessment, contingency ranking index, RAS FUBM

Accurate short-term forecasting of wind energy power outputs is crucial in power grids since wind power efficiency is significantly affected by daily variations in air density, wind speed, wind speed distribution, and wind turbine performance [1]. A broader range of worst-case wind energy (i.e., High wind (HW) and Low wind (LW)) scenarios will result in an accurate model, which will assist the Transmission System Operator (TSO) in making better decisions, particularly when considering analysis of the grid security (i.e., the ability of balancing generation and demand even after occurrence of faults). Security analysis is crucial for optimum operational planning of power networks, particularly when integrating grids with high levels of variable wind resource. To this end, static security assessment is a decision support tool available to the System Operator (SO) for analysing the feasibility of the operation of the network, by considering a wide range of operating conditions, which includes instances of faults or contingencies [2]. In this context, the contingencies are focussed on multiple worst-case scenarios with or without the N-1 security criterion (which states that the operation of the system should continue following faults in any one component). During the evaluation, the decision will be made whether or not to take any necessary remedial actions, to alleviate congestion in the system following any contingencies [2] [3].

This paper presents the Remedial Action Scheme Flexible Universal Branch Model (RAS FUBM) framework for purposes of static security analysis in networks with high levels of variable wind power integration. Meanwhile, the Contingency Ranking Index (CRI) is used to measure the impact and severity of each contingency on the system. The RAS FUBM framework essentially produces an optimum operating schedule including the list of any remedial actions for a test system with a mixed generation profile (i.e., both conventional and wind resource) and under both pre- and post-contingency conditions. The RAS FUBM framework will therefore play a critical role in reducing the security risk posed by the variability of wind resource and mitigating the impact of the worst-case wind output disruption in the systems with high penetration of wind resource.

The FUBM is a general-purpose mathematical model, which can be used to model several power system components such as Voltage Source Converters (VSC), Phase Shifter Transformers (PST), and Control Tap Changing Transformers (CTT). It is a powerful universal model that adds more freedom and flexibility to mathematically model different types of components for operational planning problems using a mixture of state variables and constraints [4]. The researcher can then utilise this model to replicate the operation of the standard Alternating Current (AC) branches or the AC/Direct Current (DC) interfaces in a single frame of reference.

The CRI is crucial for identifying the most critical lines or generators in the system, but the focus of this research was on identifying the most severe multiple scenarios. The Severity (S) of each scenario was determined, based on the active power flow via each transmission line [5] and the formula given by:

\[ S = \sum_{j,k=1}^{l} \left( \frac{P_{jk}}{P_{jk}^{\text{max}}} \right)^n, \quad (j,k) = 1, \ldots, l \]

Where \( P_{jk} \) is the power flow from bus \( j \) to \( k \), \( P_{jk}^{\text{max}} \) is the upper thermal limit and \( l \) is the number of branches. The ranking list was then determined by calculating the severity of each scenario (i.e., HW Low Demand (HWLD),...
HW High Demand (HWHD), LW Low Demand (LWLD), and LW High Demand (LWLD)). The sum of the severity of each scenario gives the CRI values, through ranking the following formulation:

$$CRI = \sum_{i=1}^{ns} S_i , \quad i = 1, \ldots, ns (i.e. number of scenario)$$

Using the ‘VSC in-model’ within the FUBM [4][6], several VSC control strategies can be mathematically incorporated within the RAS FUBM framework as shown in Figure 1. Researcher [7] provides through analysis of meshed MT-HVDC topology with three wind farms connected to the Substation Ring Topology (SRT). In this way, the RAS FUBM is an advanced optimisation and decision support tool, which can be used by system operators to schedule remedial actions from VSCs that are present in a MT-HVDC link. Such remedial actions in effect can be used to alleviate impact of stresses on the system following contingencies for example by reducing the thermal stress in the transmission lines and to render the system embedded with the Multi-Terminal HVDC (MT-HVDC) system more secure, by incorporating several control mechanisms.

![Figure 1: RAS FUBM framework](image)

A modified IEEE30 bus system (refer to Figure 2) linked to wind resources and embedded with MT-HVDC has been tested to evaluate the RAS FUBM application. Multiple scenarios both with and without contingency (i.e., outages at branch 38) have been considered as a critical case that requires RAS control actions to restore a secure operational state. The simulation for the contingency did not create any islands.

Figure 3 shows the ranking of multiple scenarios in terms of the Severity Index calculated based on the thermal limit formulation. This figure shows that during the case without contingency the CRI has the lowest thermal stress, however when branch 38 disconnected, the thermal stress in the system escalated. The greatest CRI values occurred when demands were the highest for both situations, but when demands were reduced the CRI values dropped dramatically. In order to alleviate the congestions during a contingency at high demands, conventional control and droop control were adopted. The most severe conditions occurred when the control methods were set at a high DC voltage at slack VSC (VSC1). Meanwhile, when the DC voltage was set near to the minimum limit the CRI values declined marginally. The ranking of the CRI can be increased and decreased depending on the DC voltage set at the reference VSC. This ranking provides a better idea to be aware of any anomalous conditions, when numerous scenarios happen in the system and ensure that the required remedial measures can be performed, particularly when a contingency case strikes. Necessary control action is important to ensure that the power system can restored to a secure state after the contingency, whether N-1 contingency or multiple scenarios. On the other hand, this control can prevent a chronological chain of tripping events that will ultimately end in the system collapsing (i.e., black out).

Figure 4 reveals that when the wind penetration was higher, generators 1 and 2 dropped tremendously for the HWHD case and generators 3,4,5 and 6 for the HWLD case. Despite this, these generators rose rapidly when the wind penetration was at the lowest level. The impact of the controls, both conventional and droop, utilising high voltage and lower voltage settings, can be seen not only at the CRI values but also in the generation optimal active power schedule (refer to Figure 4). Table 1 summarise the highest and the lowest production of the generation optimal active power schedule for numerous scenarios utilising multiple control strategies. This indicates that the buses connected to the DC system via VSC could minimize the electricity generated by the conventional generator while obtaining the greatest power from the wind.

The outcomes of this study will be valuable to the Electricity System Operator in selecting appropriate sorts of control methods to relieve the occurring congestion in systems with embedded MT-HVDC links, which can improve network security in such systems. The results also clearly show that MT-HVDC links
are a viable candidate for large-scale variable offshore wind integration in a more secure and stable manner to existing power systems.

Figure 2: MT-HVDC network model.

Figure 3: Contingency ranking index for all scenarios.

Table 1: Power generation from generators in all scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>HWHD</th>
<th>LWLD</th>
<th>HWLD</th>
<th>LWHD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generator with the highest production</td>
<td>4,5</td>
<td>1,2</td>
<td>3</td>
<td>3,6</td>
</tr>
<tr>
<td>Generator with the lowest production</td>
<td>1,2</td>
<td>3,4</td>
<td>5,6</td>
<td>3</td>
</tr>
</tbody>
</table>
Figure 4: Generation optimal active power flow profile for the contingency scenarios with control strategies.

References


Mitigating leading edge erosion in wind farms through optimal erosion-safe mode control

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Keywords: leading edge erosion, wind farm control, wakes, optimization

1 Introduction

Leading edge erosion (LEE) on wind turbine blades is a common problem that is heavily affected by the local wind and rain climate. Without preventive initiatives, LEE can occur after just a few years of operation and may require expensive unplanned repairs [4]. In addition, LEE negatively affects the aerodynamic properties of the blade as it degrades over time [2].

This study investigates the effects of implementing a simple LEE control strategy in a wind farm optimization framework. The LEE control strategy will utilize an operational mode called erosion safe mode (ESM) in which the rotor speed is reduced during heavy rainfall to limit the impact velocity of the droplets. This operational mode causes a negative impact on energy production but can potentially reduce repair costs during the operational phase [1].

The implementation of the ESM will be simulated on different sites using mesoscale weather data provided by the Danish Meteorological Institute (DMI) to characterize the joint wind and rain climate. The optimal control settings of the ESM will be determined using numerical optimization and the sensitivity to different input parameters will be tested. To capture the effects on both energy production and operational costs, the optimization problem is formulated such that it seeks to minimize the levelized cost of energy (LCoE).

2 Methodology

The optimization problem can be classified as a non-linear, continuous optimization where variables and models are continuous. In addition, the optimization is constrained by a single, deterministic objective. Finally, the optimization involves multiple different disciplines such as wind turbine control, meteorology, and cost modeling.

The mathematical formulation of the optimization problem can be written as:

\[
\min_{\omega_{ESM}, I_{thres} \in \mathbb{R}} \quad LCoE(\omega_{ESM}, I_{thres})
\]

subject to

\[
AEP_{loss} \leq AEP_{loss,upper}
\]

\[
0 \leq \omega_{ESM} \leq \omega_{rated}
\]

\[
0 \leq I_{thres}
\]

where \(LCoE(\omega_{ESM}, I_{thres})\) is the objective function which in this case is the levelized cost of energy. Two design variables are considered, namely the maximum allowed rotor speed during ESM operation \(\omega_{ESM}\) and the rain rate threshold which activates the ESM operation \(I_{thres}\). The optimization problem is subjected to a single inequality constraint which limits the AEP loss when running in ESM operation. In addition, there are bounds on the two design variables.
The optimization and design problem will be implemented through TOPFARM, a wind farm optimization tool under development by DTU Wind Energy, based on FUSED-Wind and OpenMDAO [5]. The overall flow of the ESM implementation is visualized in Figure 1. Initially, the mesoscale weather data will be used to generate a 3D look-up table (LUT) which will have dimensions (wind speed bins, wind direction bins, and rain rate threshold). The value of each element will correspond to the normalized number of rain events above the threshold in each wind speed and wind direction bin, e.g. for a slice with a rain rate threshold of 0 mm/hr, we would simply consider all events and thereby get the original joint distribution of wind speed and direction. This look-up table will be used during optimization to calculate the fraction where ESM operation is activated.

Next, we will need to instantiate the wind farm by specifying turbine type, site conditions, and layout. Given the wind farm layout, we can compute the reference AEP which represents the energy production we would obtain without any ESM operation.

We then get to the actual optimization loop, which starts with initializing the design variables, i.e. the maximum tip speed during ESM operation and the rain threshold at which the ESM operation is activated. Using the maximum tip speed during ESM operation, we can compute a new rotor speed curve assuming that the ratio between power or thrust and rotor speed does not change when switching between normal and ESM operation. These new curves should be recalculated every time the maximum tip speed is updated.

Based on the new ESM power and thrust curves, we then calculate the AEP we would get from operating entirely in ESM. Next, we extract the slice from our 3D look-up table corresponding to the chosen rain threshold. This slice allows us to estimate the ratio between normal and ESM operation. This value indicates how big of a fraction we should take from the reference AEP and ESM AEP. We use this to calculate the actual AEP (and AEP loss compared to the reference AEP). This AEP value is fed directly into our objective function.

Finally, we will need to define the cost components that go into calculating the LCoE. For simplicity, we assume a fixed cost for the initial investment. We will use an erosion prediction model to determine the damage state of the blade, which can directly be linked to repair costs [6].

### 3 Preliminary results and future works

As a motivating example, we run an optimization for the offshore wind farm Princess Amalia located on the Dutch Continental Shelf in the Netherlands. The wind farm consists of 60 Vestas V80-2MW wind turbines. For simplicity, we will assume that the liquid impingement can be used as a proxy for erosion. The liquid impingement is defined as the amount of rain that hits the tip of the blade and can therefore be calculated based on the wind speed, rain rate, and rotor speed curve of the turbine [3]. We can then simply account for the added erosion costs by assuming a fixed price for every meter of impingement. This way we penalize the objective function when operating at high rotor speeds during rain. The added erosion cost was assumed to be fixed at 250 EUR/(MW-m). The optimization was performed using random search which is a heuristic method that is already implemented in TOPFARM. The optimization was found to be feasible with a global minimum corresponding to a unique set of design variables. We find the optimal design variables as $\omega_{ESM} = 14.1$ m/s and $I_{thres} = 3.0$ mm/hr. It was found that these settings activated ESM operation 0.46 % of the time which resulted in an AEP loss of 0.30 %. The improvement in LCoE when using ESM with the optimal settings was found to be 0.13 %. Though this improvement appears to be very small, the actual cost savings from using optimal ESM operation will amount to several thousand euros.
In addition, we have performed a small parametric study to evaluate the sensitivity of the erosion cost parameter. We evaluate the surface response of the objective function for three different erosion costs, i.e. 0, 250, and 1000 EUR/(MW·m). The results can be found in Figure 2 which shows that the optimal ESM settings are very sensitive to the added erosion cost parameter.

Figure 2: Surface response of the objective function with added erosion costs of a) 0, b) 250 and c) 1000 EUR/(MW·m)

This preliminary study was used as a proof of concept to show the potential of implementing a leading edge erosion control strategy in a wind farm optimization framework. Numerical optimization was used to determine the optimal ESM control settings for a simplified case study of the offshore wind farm Princess Amalia. The optimization was feasible with an optimal LCOE of 22.92 EUR/MWh corresponding to a reduction of 0.13% from the reference design. The optimization problem was found to be very sensitive to erosion cost parameters representing the added expense from operating during rainfall.

The simplistic implementation will be further improved by:

- Implement the erosion prediction model to get more realistic erosion cost estimates
- Extend the ESM control settings from a global wind farm level to individual turbines.
- Implement the effects of aerodynamic degradation on energy production.
- Perform a sensitivity analysis of the wind and rain climate to assess how the optimal control settings would vary for other sites

References


TOPIC 3:
Aero-elastics and blade technology

Session 3.1
06.09.2023 - 13:15
Building 3703, Room 335

Schuster Daniel
Verification of a new mid-fidelity aeroelastic simulation tool for large wind turbines

Antunes Ana
Validation of structural models for wind turbine blades with different levels of fidelity

Cespedes Moreno Juan Felipe
Quantification of performance difference between two and three-dimensional flows around blade root sections
Verification of a new mid-fidelity aeroelastic simulation tool for large wind turbines

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Keywords: mid-fidelity methods, fluid-structure interaction, aeroelasticity, vortex methods

Wind Energy is expected to play a major role in the future energy supply given the recognized need to reduce the carbon emissions [6]. To be able to fulfil this potential, wind turbines have steadily grown in size over the past years and will continue to do so: future wind turbines will likely have diameters of up to 400 m and a rated power of more than 20 MW [1]. These new wind turbines will consist of large, slender structures which are more prone to large deformations than current generations of wind turbines [10]. Additionally, they will be subject to yet unknown loads, as they will reach further into the atmospheric boundary layer [2]. Nonlinear dynamic phenomena become more dominant and the interactions between the different components of the wind turbine as well as with their environment have to be considered in more detail.

Due to these factors, currently used simulation methods relying on low-fidelity methods such as Blade Element Momentum Theory and linear beam theories might not be sufficient to realistically approximate the behaviour of such large wind turbines [2]. High-fidelity methods like computational fluid dynamics or full three-dimensional finite element analysis are however too computationally expensive to be employed during the design process [10]. Instead, mid-fidelity methods seem to present an attractive compromise between computational effort and accuracy.

Therefore, we are developing a mid-fidelity nonlinear aeroelastic approach, which combines the unsteady vortex lattice method (UVLM) and a flexible multi-body system/finite elements approach. The structural model consists of rigid bodies, geometrically exact beams and holonomic and non-holonomic constraints [4], [5]. The aerodynamic forces are computed using the UVLM, which is a well-established tool to compute the three-dimensional vortex dominated flow of an ideal fluid around lifting as well as non-lifting surfaces [9]. The nonlinear structural and aerodynamic equations are coupled strongly using an approach based on the principle of virtual work.

In this work, we verify our tool by comparing the results of aeroelastic simulations using our tool with results obtained by OpenFAST [8], one of the current standard tools. By investigating the NREL 5 MW reference wind turbine [7] with rotor blades of length 61.5 m as well as the NREL 15 MW turbine [3] with large slender blades of length 117 m, it can be shown that for the latter geometrical nonlinearities are relevant for the aeroelastic behaviour and thus a nonlinear structural model is required.
Acknowledgements

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References

Validation of structural models for wind turbine blades with different levels of fidelity

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Keywords: wind turbine blades, structural modelling, numerical validation

1 Introduction

In recent years, a steep increase in rotor size and capacity of wind turbines has been observed. This increase in blade length comes with a consequent higher flexibility of these structures, thus bringing new challenges in terms of aeroelastic modelling, which is of great importance for the correct prediction of the wind turbine’s power production, stability and loading conditions [1].

For this reason, having realistic structural models for wind turbine blades is crucial. This can prove to be a challenge, due to the complex nature of these structures, both in terms of the composite materials used in their manufacture and their geometry (curved, twisted and tapered structures with a complex cross-sectional shape).

Composite laminates can introduce anisotropy through, for example, the stacking sequence of the laminates. This can be a design choice, as is the case with bend-twist coupled blades, which have a potential load alleviation effect [2], or simply due to local discontinues (spar caps, shear webs endings).

The coupling between bending and torsion in wind turbine blades is, however, always present inherently, as a result of their geometry. This was not an important effect in earlier blade designs, but as blades become longer and more slender, larger deflections take place and it becomes significant [3]. Other effects such as warping, which is usually neglected in structural models found in common aeroelastic codes, may also become an important factor in the mechanical behaviour of the blades [4].

The main goal of this study is to assess the accuracy of different structural models in the prediction of static deflections of complex beam structures, as wind turbine blades. Based on the results, one can better quantify the gaps of 1D beam lower-fidelity models (such as those used in aeroelastic codes, e.g. HAWC2), by comparing them with higher-fidelity ones (such as full 3D finite element models), understanding fundamental differences and identifying possible areas of improvement.

2 Methodology

A comprehensive test matrix has been defined, covering a broad range of linear and nonlinear static analyses of increasingly complex beam structures, outlined in Table 1. The baseline case consists on a cantilever beam loaded uniformly or at the tip.

The different analyses include prismatic and non-prismatic (tapered, curved and twisted) beam structures, with different cross-sections (solid / thin-walled, rectangular / elliptical) and materials (isotropic and anisotropic). These are performed in an incremental fashion, gradually adding layers of complexity, to be able to assess which characteristics of wind turbine blades are most problematic for the accurate prediction of static deflections. A final comparison using reference wind turbine blade models will also be performed, to verify the conclusions drawn from these standard analyses.

In terms of numerical models, it is intended to compare one-dimensional (1D) beam models, shell models (2D) and full three-dimensional (3D) finite element models. The 1D beam model analysed, here corresponding to the lower-fidelity level, is the one implemented in HAWC2, an aeroelastic multibody based code which uses the floating frame of reference formulation, with each body modelled by Timoshenko beam elements [5, 6]. The shell
and 3D finite element models analysed, corresponding to the higher-fidelity levels, are generated in the commercial 
software ABAQUS [7], using both shell and solid elements. All formulations considered allow for the inclusion of 
geometrically-nonlinear effects.

The static deflections computed with the different level of fidelity models, for each test case analysed, are 
compared with analytical solutions (when available) or reference cases found in the literature. In addition, since 
high-fidelity tools are employed in the analysis, there is also the prospect of evaluating the stress and strain fields 
and assess the reliability of different stress recovery processes used in the design of wind turbine blades.

<table>
<thead>
<tr>
<th>Beam type</th>
<th>Material</th>
<th>Cross-section</th>
<th>Loading conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prismatic</td>
<td>Isotropic</td>
<td>Rectangular solid and box section</td>
<td>Concentrated force at beam tip</td>
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<td>Concentrated moment at beam tip</td>
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<td></td>
<td>Uniformly distributed load</td>
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<tr>
<td></td>
<td></td>
<td>Elliptical (solid and hollow)</td>
<td>Concentrated moment at beam tip</td>
</tr>
<tr>
<td>Tapered</td>
<td>Isotropic</td>
<td>Rectangular solid and box section</td>
<td>Concentrated force at beam tip</td>
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<td></td>
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<td>Elliptical (hollow)</td>
<td>Concentrated force at beam tip</td>
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<td>Twisted</td>
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<td>Elliptical (hollow)</td>
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<td>Curved</td>
<td>Isotropic</td>
<td>Rectangular solid and box section</td>
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<td>Concentrated force at beam tip</td>
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<td>Elliptical (hollow)</td>
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<tr>
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<td>Box section</td>
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<td>Airfoil</td>
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<td>Wind turbine blade</td>
<td>Anisotropic</td>
<td>Airfoil</td>
<td>Concentrated force at beam tip ¹</td>
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<td>Uniformly distributed load</td>
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Table 1: Preliminary test matrix.

3 Preliminary results and expected outcomes

The initial verification cases from Table 1, concerning the prismatic isotropic beam of rectangular cross-section 
loaded at its tip by a concentrated force or moment (illustrated in Figure 1), have been finalized and show a good 
agreement between the different level of fidelity models compared.

¹Also applied at an offset from the shear centre (to assess the torsional behaviour).
²Also including coupling due to the composite laminates (bend-twist and extension-shear coupling).
The same beam is used in both analyses, whose properties are based on those from [8]. It has a length of \( L = 50 \) m, a square cross-section of \( 1 \times 1 \) m\(^2\), a Young’s modulus of \( E = 30 \) MPa and a Poisson’s ratio of \( \nu = 0 \).

The main difference between the two cases lies in the linearity of the solution – case 1 (concentrated force) is characterized by small, linear deflections, whereas large, nonlinear deflections take place in case 2 (concentrated moment). A single force of \( F = 50 \) N is considered in case 1. In case 2, four increments in the applied moment are simulated – the moment magnitude is defined as \( M = \lambda m \), where \( m = \pi EI L^2 \) and \( \lambda = [0.5, 1, 1.5, 2] \), with \( m = 2 \) corresponding to a full revolution of the beam on itself.

There are known analytical solutions for both cases analysed. Respectively, for case 1, the transverse beam displacement can be calculated as [9]

\[
u_3(x_1) = \frac{F}{6EI_2} \left( x_1^3 - 3Lx_1^2 \right)
\]  

(1)

and, for case 2, the beam displacement components in the \( x_1 \) and \( x_3 \) directions are given by [10]

\[
u_1(x_1) = \rho \sin \left( \frac{x_1}{\rho} \right) - x_1, \quad \nu_3(x_1) = \rho \left( 1 - \cos \left( \frac{x_1}{\rho} \right) \right)
\]  

(2)

where \( \rho = EI_2/M \).

The results obtained from the 1D beam models (both HAWC2 and ABAQUS formulations) and a 3D solid elements model built in ABAQUS are presented against the respective analytical solutions in Figures 2 (case 1) and 3 (case 2). A very good agreement is observed between the different models and formulations compared, which is expected, since a very simple model is here considered.

A similar analysis is to be carried out for the remaining cases outlined in Table 1. As the complexity of both the structure and the analysis increases, discrepancies are expected to be detected between the different level of fidelity models compared. This is particularly relevant in the cases concerning anisotropic or non-prismatic beams undergoing large deflections, where, for example, three-dimensional effects become significant. It is from the analysis of these more complex cases, using high-fidelity tools, that important differences between the numerical models formulations, relevant for the accurate prediction of wind turbine blades’ behaviour, can be identified and addressed.
Figure 3: Case 2 – Comparison of beam deflection computed by different models, $\lambda = [0.5, 1, 1.5, 2]$ (right to left).

References


Quantification of performance difference between two and three-dimensional flows around blade root sections

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Keywords: Thick airfoils, aerodynamic design, three-dimensional effects, RANS simulations.

Introduction

The root section of a wind turbine blade is made up of thick airfoils that smoothly transition from a cylindrical cross-section, where the blade is attached, to thinner airfoils in the outer part of the blade, where most of the energy is captured [1]. The aerodynamic design of the thick airfoils in the root section is challenging for two main reasons, firstly, their large thickness (typically above 36\%) commonly causes detachment of the boundary layer in the upper and lower parts of the airfoil, which makes the flow difficult to model [4, 6, 10]. Secondly, this section is more prone to three-dimensional effects caused by centrifugal forces and Coriolis, which scale with the chord over the local radius ($c/r$), and make the 2D flow of this airfoil differ significantly from their 3D behavior in the blade [3, 5]. This discrepancy between two-dimensional and three-dimensional results affects BEM\textsuperscript{1} implementations that rely on tables with 2D data from the airfoils to model the forces [4, 10].

Consequently, this PhD thesis aims to bridge the gap between the 2D and 3D CFD results in the blade root section by incorporating terms that model the 3D forces in the 2D simulation. For this, the first step of the project is quantifying the difference between these flows, which is what is presented in this document.

To compare the flows, it is required to extract the two-dimensional conditions, local angle of attack ($\alpha$), and Reynolds number, from a three-dimensional simulation to compute the two-dimensional case. This is not trivial as natural concepts in 2D, such as the angle of attack, cannot simply be measured directly from the 3D flow and have to be modeled, in this case with an average azimuthal method [11]. Furthermore, the comparison could be complex given that varying parameters in 3D (pitch, inflow wind speed, and rotational speed) affect simultaneously and disproportionately the two-dimensional parameters of different sections of the blade.

Methodology

The study has been conducted using the DTU 10 MW reference turbine [2]. And the simulations were carried out using Ellipsys3D [8, 9, 12], the pressure-based incompressible Reynolds averaged Navier-Stokes flow solver developed at DTU. The study case assumes, in both 2D and 3D simulations, a fully developed turbulent boundary layer on the blade surface using the $\kappa - \omega$ SST model by Menter et al. [7]. Furthermore, all simulations are considered in steady state.

The three-dimensional simulations consider only the three blades which constitute the rotor. The surface mesh of the blades contains 256 cells in the chord-wise direction and 128 cells in the span-wise direction. The volume mesh was of the O-O type and was generated using HypGrid, a hyperbolic mesh generator written by Sørensen [13]. It is generated by growing the rotor surface using 128 cells until it generates an approximate sphere with a radius 20 times the rotor’s radius. In total, the surface mesh contains approximately $14.1 \times 10^6$ cells.

Each two-dimensional simulation considers a cross-section of the blade and uses the same distribution of 256 cells in the chord-wise direction as the 3D case of the corresponding section. The two-dimensional mesh is grown

\textsuperscript{1}Blade Element Momentum Theory
from the airfoil mesh distribution using 128 cells. It forms an O-mesh with approximately $32.7 \times 10^3$ cells and a radius of approximately 40 times the airfoil’s chord.

The angle of attack of each 2D simulation is determined with the azimuthal average method [11, 14]. This is done by extracting the flow in several planes parallel to the rotor plane before and after the rotor itself. In each plane, the azimuthal average of the axial and tangential velocity is calculated. By taking the results of several planes before and after the rotor, each velocity component is interpolated at the rotor position in each radial location. This results in the axial and tangential velocities as a function of the radius, which are used to reconstruct the velocity triangle and determine the angle of attack as a function of the radius. This technique is more accurate to determine average values, which is appropriate for this case because steady state is considered.

In order to determine the behavior of each radial section in a range of angles of attack, the combination of three-dimensional parameters, inflow wind speed, angular velocity, and pitch, must be varied. For simplicity, so far only the pitch angle has been varied from $+3^\circ$ to $-10^\circ$, where a negative pitch refers to feathering and a decrease in the thrust coefficient. However, the range of this variation is to be expanded and other parameters will also be varied.

**Results**

Figure 1 shows the flow direction according to the wall shear in the blade from the 3D simulation at pitch=0, wind speed of 8 m/s, and angular velocity of 0.67 rad/s. The flow in the radial direction indicated in the image implies the existence of the three-dimensional effects previously mentioned.

![Figure 1: Flow direction in both sides of the blade surface calculated from the wall shear.](image)

With the results of the three-dimensional simulation, at several radial positions, the Reynolds number is extracted and the angle of attack is calculated with the average azimuthal method. With this input, the two-dimensional simulation is calculated. At each radial section, the lift and drag coefficients are compared in Figure 2. The differences between the 2D and 3D results are most notorious at the root, below $r/R = 0.3$, where the relative thickness is the highest, above 36%. At the beginning of the blade, as the relative thickness approaches 100% the airfoils in the 2D simulation behave similar to a cylinder, with decreasing lift and increasing drag. However, in the 3D case, the radial flow in these sections prevents the lift from falling and the increase in drag is not as pronounced. Furthermore, there is also some discrepancy between 2D and 3D at the tip of the blade, for the last 10% of the radius. These are due to the tip vortex but are not the primordial importance of this project.

In the three-dimensional simulations, the wind speed and angular velocity are kept constant and the pitch is varied in an effort to change the angle of attack of each radial section without largely affecting the Reynolds number. As a result, the Reynolds number remains almost constant, with changes only to its third significant digit in every case. The changes in the angle of attack are shown in Figure 3. It shows that as the pitch varies, the angle of attack of the root sections is almost unaffected, and most of the variation is seen in the outer part of the blade. This suggests that other parameters other than the pitch should be varied to explore the behavior of the blade root sections in a wide range of angles of attack.

Although the changes in the angle of attack at the root are limited, it is still possible to plot the gap between lift and drag coefficients for 3D and 2D computations as a function of the angle of attack:

$$
\Delta C_l(\alpha) = C_{l,3D}(\alpha) - C_{l,2D}(\alpha) \\
\Delta C_d(\alpha) = C_{d,3D}(\alpha) - C_{d,2D}(\alpha)
$$
Figure 2: Lift and drag coefficients along the blade calculated as 2D and 3D at zero pitch angle.

Figure 3: Angle of attack of different radial sections as a function of the pitch angle.

This is shown in Figure 4. Here it is seen that for most radial sections above $r/R = 0.2$ the difference between 2D and 3D cases tends to decrease with a lower angle of attack. However, a much larger range in angles of attack is required to produce meaningful conclusions, especially at the blade root ($r/R < 0.2$).

**Conclusion and future work**

In the case of average or steady flows, the azimuthal average technique is appropriate to determine the two-dimensional conditions from a three-dimensional simulation. This allows a one-to-one comparison between the simulations which isolates the three-dimensional effects in the flow.

The discrepancy between two and three-dimensional results is highly significant for sections of the blade below $r/R = 0.3$, where the relative thickness of the airfoils is typically above 36%. The two-dimensional simulations predict a behavior with low lift and high drag, reminiscing of a cylinder. In contrast, in the three-dimensional simulation, the 3D effects boost the behavior at the root sections increasing the lift without drastically increasing the drag.

The discrepancy between the 2D and 3D cases varies with the angle of attack, but a wide range in this parameter is required to provide further insights. It was found that only changing the blade’s pitch angle is insufficient to cover a significant range of angles of attack in the blade root section. Therefore, a wider range of pitch angles and other parameters such as wind speed and rotor angular velocity must be considered.

Subsequent steps in this project aim to include terms in the 2D simulation that account for the three-dimensional effects in order to close the gap between the results. This is meant to provide more accurate two-dimensional results that can be used for better blade design in optimization algorithms.
Figure 4: Difference in lift and drag coefficients between 3D and 2D simulations as a function of AoA.

References


Session 3.2
07.09.2023 - 14:00
Building 3703, Room 023

Werthen Edgar  Aero-structural coupled optimization of a rotor blade for an upscaled 25 MW reference wind turbine
Ribnitzky Daniel The “Hybrid-Lambda” rotor: A concept overview and wind tunnel validations
Seelemeyer Philipp Toolchain for an aerodynamic wind turbine optimization using CFD with script-based meshing and parametric CAD in-the-loop
Pamfil Bogdan Wind turbine stability analysis with rotating modes
Aero-structural coupled optimization of a rotor blade for an upscaled 25 MW reference wind turbine

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**Keywords:** Wind turbine blade, Structural optimization, Composite structures

One major challenge of the wind turbine industry is the reduction of the levelized cost of energy (LCoE) while following the strong demand for a higher annual energy production (AEP). To meet these goals, larger wind turbine sizes are required. The common method of upscaling existing wind turbine designs comes along with the problem of faster growing blade masses and costs compared to the AEP [1]. Investigations in new technologies to improve the structural efficiency of larger blades can be supported by aero-structural coupled optimizations [2]. The present work introduces a two-step aero-structural coupled design process to capture the multi-disciplinary trade-offs between costs and AEP, aiming at minimizing LCoE for a 25 MW wind turbine. In a first step, a preliminary aero-structural optimisation is carried out using simplified and fast methods. The output is then refined with respect to additional design criteria with an advanced optimization process, including an aero-servo-elastic coupled loads analysis. The process is applied to a 25 MW blade, upscaled from the IEA 15 MW reference wind turbine [3]. Based on the results of an utilization analysis, the structural design is adapted, and a stiffness optimization is performed. The optimum airfoil positions are identified to reduce the amount of material while limiting losses in the aerodynamic performance. The obtained blade designs are shown in figure 1 and facilitate a consistent AEP compared to the upscaled reference design. A mass reduction of 35% could be achieved, which results in a reduced LCoE of 1.7% compared to the purely upscaled blade design.

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![Figure 1: Rel. airfoil- (left) and spar cap thickness (right) of the aero.-struct. opt. design](image-url)
References


The “Hybrid-Lambda” rotor: A concept overview and wind tunnel validations

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Keywords: Low-wind-turbine, rotor design, rotor aerodynamics, system engineering, scaling of wind turbines, wind tunnel tests

1. Introduction
In the last decades, wind turbines have been designed in order to reduce the levelized cost of energy of wind power. With the rise of installed capacity, the exchange price already tends to zero on windy days (1). Future wind turbine design should focus more on improving the value of wind power in the entire energy supply system. Therefore, an increased and more steady power feed-in at low wind speeds would be desirable, while the power feed-in at strong wind speeds could be partially reduced, as sufficient power will be available from the increasing number of conventional wind energy converters (2). This power characteristic contradicts physical and technical principles as a large swept area would be needed to capture more energy on light wind days, while the swept area should be reduced in strong winds to limit the design driving loads. But rotor blades with mechanically adjustable length do not seem to be economically and technically feasible in the near future. Therefore, we want to introduce an innovative aerodynamic rotor concept which allows the above-mentioned power curve characteristics without the use of additional mechanical actuators.

2. Aerodynamic concept: The Hybrid-Lambda Rotor
The main idea of the concept, as described by Ribnitzky in (3), is to dramatically increase the rotor swept area, while maintaining the design driving loads on a similar level. This is accompanied by designing the outer part of the blade (e.g. outer 30% of the rotor) for a higher TSR (compared to the inner part) and to reduce the design axial induction factor in the outer region, resulting in a much slender outer section. The design methodology can be applied to any given wind turbine rotor by adjusting the main design variables, namely the specific rating, the TSRs for the inner and outer part of the blade, the spanwise position of the transition between the two design regions, and the desired axial induction factors for the two blade regions. In this study we applied the methodology to a 15 MW offshore wind turbine to simplify the understanding of the concept and to discuss a use case. The IEA 15 MW reference turbine serves as a basis for the design (4).

The rotor is designed to operate in a light wind and a strong wind mode. Figure 1 visualizes the desired axial induction in the two operating modes.
In light wind conditions, the rotor will be operated at the high TSR of 11 and the slender outer part fully contributes to the increased power capture. The outer part is now operating in its design point, defined as the high TSR, an axial induction factor of 0.21 and the optimal angle of attack (the latter is here derived from the optimal lift to drag ratio). The inner part of the rotor operates like a conventional rotor with an axial induction factor close to 0.33 but the reader should bear in mind that this part is not operating in its design point, as it is designed for a lower TSR of 9. In stronger winds (but still below rated wind speed) the design value of the stationary RBM is reached. Then, the TSR will be reduced, the torque generation will be shifted to the inner section of the rotor and the outer region can be greatly relieved, as it is not operating in its aerodynamic optimum anymore. In this way the outer part of the rotor disc gets more permeable, the lever arm of the resulting bending force is reduced and additional peak shaving ensures the limitation of the loads.

3. Objectives:
In this study we provide an overview of the design concept of the “Hybrid-Lambda” rotor and the investigations using quasi-static BEM simulations. The concept was scaled to a wind tunnel turbine model with a diameter of 1.8 m. We explain the scaling approach and evaluate the resulting blade design of the model turbine with BEM simulations. The results from the simulations are further compared to the experimental investigations regarding rotor averaged quantities such as power, thrust and flapwise blade root bending moments (RBM), as well as spanwise resolved variables such as axial induction and angle of attack. This leads us to two research questions: First, whether it is possible to scale the “Hybrid-Lambda” concept to wind tunnel size. Second, the concept may violate the assumptions of independent blade elements in the BEM theory as strong gradients along the blade span are present. We investigate if these three dimensional effects are present in the experimental investigations.

4. Methodology:
The blade designs of the full scale wind turbine as well as the model turbine are investigated with quasi-static BEM simulations. The blades and the tower are modelled as rigid structures, as aeroelasticity is not in the scope of this study. The BEM code is implemented as described in (5), including Prandtl tip-loss and root-loss corrections as well as the Glauert high thrust correction with the approximation by Buhl). The inflow is modelled as steady and uniform. In the wind tunnel experiments, thrust and RBMs are measured with strain gauges. The power is measured with a torque meter on the main shaft and an encoder that measures the rotational
speed. The spanwise resolved axial induction and the angle of attack is measured with a 2D Laser-Doppler-Anemometer (LDA) with the bisectrix method by Herráez (6).

5. Results:

The objectives of the scaling approach are twofold. First, we want to replicate the axial induction distribution over the blade span for the light wind and strong wind mode. Second, the model turbine should show a similar change in the angle of attack distribution when switching between the operating modes. The blade design of the model turbine is mainly constrained by the need for a minimum Reynolds number and manufacturing constraints like minimum thickness, leading edge radius and trailing edge thickness. To allow for a sufficiently high Reynolds number we reduced the design TSRs from 11 and 9 for the full scale turbine to 7.5 and 6 for the model turbine. Lower design TSRs lead to larger chord lengths and therefore increase the Reynolds number. Further, low Reynolds number airfoils are used to reduce the losses in aerodynamic efficiency due to the much lower Reynolds numbers of the model turbine. Figure 2 shows the good agreement of the axial induction distribution for the full scale and the model turbine in quasi-steady BEM simulations. As low Reynolds number airfoils operate at much lower angle of attack, the exact same distribution can not be replicated for the model turbine. However, the characteristic change in the distribution is transferred within the scaling approach, as seen in Figure 3. When changing from the light wind mode to the strong wind mode the angle of attack is lowered in the outer section of the blade and increased in the inner section. In this way, the lever arm of the resulting bending forces is reduced and peak shaving can be applied with lower losses of the power coefficient.

By the time of submitting this abstract, the experimental investigations are still due. The BEM theory relies on the assumption that the blade elements are independent of each other and radial flow is neglected. The measurement data will reveal to what extent these assumptions are violated since the model turbine will reproduce all three dimensional effects.

Figure 2: Axial induction over blade span for the full scale turbine (dashed lines) and model turbine (solid lines) for the light wind mode (dark blue, purple), transition (red, green) and strong wind mode (yellow, light blue)
Figure 3: Angle of attack distribution for the full scale turbine (dashed lines) and model turbine (solid lines) for the light wind mode (dark blue, purple), transition (red, green) and strong wind mode (yellow, light blue)

References


Toolchain for an aerodynamic wind turbine optimization using CFD with script-based meshing and parametric CAD in-the-loop

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Keywords: CFD, mesh generation, wind turbine optimization, parametric CAD

This abstract presents first preliminary results, the current status and a short outlook around creating an automated optimization toolchain for aerodynamic wind turbine development using CFD. The outline of the toolchain follows the approach of geometry creation followed by an automated mesh generation and evaluation of the flow field with CFD. In contrast to different approaches, using for example mesh deformation [1], the parametric CAD model of the turbine remains an active component of the toolchain and is updated using a construction table. Furthermore, the automated mesh generation is explicitly linked to the geometry and thus repeated in each optimization step.

The benefits of this approach are the available high-quality CAD geometry in each optimization step and a very robust fully structured mesh generation approach which is quicker than comparable automated unstructured approaches and shows good convergence of the CFD solution due to high mesh quality. The toolchain allows design changes without extensive manual input [4].

1 Parametric CAD model

The CATIA CAD rotor model includes parametrized airfoil shapes with the B-Spline method [2] shown in Figure 1 a). This guarantees airfoils that are smooth in shape and curvature especially around the nose section to avoid negative effects of badly discretized airfoil geometries and allows for airfoil optimization. To ensure a correct representation of the airfoil, the limits for satisfactory agreement by Kulfan [3] were used. To fit the B-Spline to the given airfoil shape, the CATIA build-in optimizer is used.

The wind turbine blade is constructed following a fully parametrized construction technique allowing for changes of twist, radius, prebend, sweep or chord length. Changes in the geometry are done through the linked construction table to ensure direct access to all relevant parameters for external toolchain components. The blade shown in b) is furthermore surrounded by a mesh-support structure which follows the blade design changes correspondingly. Since the following mesh generation will be fully automated using structured mesh elements only, reference lines between the internal mesh blocks are given. Each line in b) serves as an outline for structured mesh segments. Including these supports directly into the CAD model improves the meshing stability while containing a high mesh orthogonality, especially at the tip section.

Figure 1: a) Airfoil parametrization with B-splines. b) Parametric blade with mesh-support structure
Figure 2 shows three different designs created from the same CAD file by updating the construction table. The CAD model is stable over different test cases, including a slim, small and high aspect ratio 20m blade as well as more blunt designs like the shown 120m blade. The main benefit in keeping the CAD model persistent in the optimization loop during design changes is maintaining a high mesh quality due to frequent remeshing as well as the accessibility of the blade geometry without subsequent processing in each optimization step.

![Figure 2: Generalized blade designs created with the same CAD-file based on different construction tables](image)

### 2 Automated mesh generation and CFD setup

The mesh generation is performed in Pointwise by using its glyph interface and the corresponding glyph client for scripting in python. For the fully structured mesh generation, each boundary from the blade surface elements as well as the mesh-support structure have been labelled in the CAD model. The python-based tool RoMeO (Rotor Mesh Optimization) is then used to create grid points on the referenced geometries and connect all support structures into a structured blade mesh. RoMeO includes the blade mesh generation, creation of boundary conditions for the CFD calculation and export of the grid in the correct file format.

For CFD, the chimera technique for overset grids in the DLR TAU code is used. The blade mesh is embedded in a multi-component farfield mesh with refinements downstream of the rotor. Additionally, the blade mesh can be combined with either simplified hub designs or the fully modelled generator and tower models of the turbine. The outer mesh-support structure can be kept constant during design changes of the blade to simplify the interpolation between multiple grid components. Furthermore, the discretization of the rotor can easily be adapted by implementing an automatically generated new blade mesh into the existing CFD setup to e.g. match flow requirements or conduct a grid convergence study of varying grid resolution.

### 3 Conclusion and outlook

To improve the speed of setting up a CFD simulation and allow for design changes, the toolchain RoMeO has been set up. It is based on a highly parametrized CAD model of a wind turbine rotor blade that can adapt to various design changes by updating the existing shape through a design table. The fully structured mesh generation is automated using a python script that follows support geometry from the CAD model for quickly generated, robust and high quality grids. The toolchain has been used for mesh generation of rotors between 20m and 120m radius with varying planforms, tip shapes and twist distributions. The CFD calculations show good convergence while the CAD model and meshing are robust.

The current work focuses on closing the optimization loop by integrating the toolchain into an optimization framework to iteratively improve rotor designs. Furthermore, the automated scripting will be generalized to extend its use to other CFD applications like for example aircraft or helicopter industry.

### 4 References


Wind turbine stability analysis with rotating modes

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Keywords: Floating offshore wind turbine, Eigenvalue, Periodicity, Rotational, Non-rotational, Time domain, Frequency domain, Campbell diagram, Waterfall plot, Coleman, Floquet, Fourier, Hill, State-space model

1 Introduction

Wind turbines (WTs) are usually modelled as dynamical systems that can be simulated in the time domain. Due to blade geometry and azimuthal blade motion, the system matrices would contain time varying periodic terms that are necessary to be taken into account for the main objectives of this study, which are to perform a frequency analysis and solve the eigenvalue problem (or stability analysis). To carry out a stability analysis, it is known in literature that performing a computationally demanding eigenvalue analysis for sampled time steps at varying blade azimuthal angles [4] does not provide a thorough representation of the overall periodic behavior. It would neither be accurate to average system matrices over a period for a given rotational speed [4]. The Coleman transform is a well known alternative method used for eigenvalue and frequency domain analyses in the case that it leads to a time invariant system. However, in the presence of periodicity in the system, the Coleman transform alone is not always applicable without having to rely additionally on a more advanced method, like Floquet’s or Hill’s. The Coleman transform is also only usable for a rotor with a number of blades being equal to or greater than three. Floquet’s method addresses these limitations by requiring initially to perform a time integration simulation for as many number of different initial conditions as number of states, to get the response after one period of rotation [1]. Moreover, Hill’s method of infinite determinants is based directly on the Fourier series of the system matrix, and it avoids the time integration procedure by generating an expanded eigenvalue problem [5]. That being said, in this present study, Hill’s method is tested for a simplistic floating offshore wind turbine (FOWT).

Due to tower pitch motion, there is a blade azimuthal periodicity that occurs after application of the Coleman transform. An eigenvalue analysis is computed through Hill’s method to plot natural frequencies with respect to rotational speed on a Campbell diagram [3]. Afterwards, a comparison is made to the time domain simulations of initial disturbances in the non-transformed model. To achieve that, frequency domain responses are calculated with a time dependant model for varying rotational speeds and displayed on a waterfall plot. The waterfall plot is generated by carrying out time domain simulations for each rotational speed, and relying afterwards on the Fast Fourier transform algorithm applied to time response signals to obtain frequency response ones [3]. A good match is obtained both for time histories of disturbed responses and natural frequencies as functions of rotational speed.

2 Methodology

In this case study, a FOWT is modelled with four degrees of freedom (DOFs), as schematized in Figure 1. This simplified model has three blades each having a lumped mass \( m \) concentrated at a distance \( L \) (center of inertia) from the hub, and a nacelle mass identified as \( M \). Also, the tower height from the floater platform is labelled \( H \). The model includes a pivoting tower motion that corresponds to the floater’s pitch motion, as well as blades deflection only in flap-wise direction. Solely the contribution of the first flap mode (1\(f\)), with eigenshape \( \phi_{1f} \) and eigenfrequency \( \omega_{1f} \), is taken into account in the modal superposition approximation of the total deflection without considering further blade modes. The system’s first DOF represents the tower pitch (\( \xi_5 \)) angle and the other three are associated to the blade deflections modal amplitudes, which can be expressed either in the fixed non-rotational (NR: \( a_0, a_c, a_s \)) or rotational (R: \( a_1, a_2, a_3 \)) coordinate system. Figure 1 shows the blade deflection
modal amplitudes for each blade (as \( a_l \) with index \( l = 1, 2, 3 \)) in the primitive \( R \) coordinate system, whereas Figure 2 shows them in the transformed NR framework, also called multi-blade coordinates. In the multi-blade coordinate system, the DOF \( a_0 \) refers to the collective flap-wise motion amplitude of the blades, \( a_c \) is the fore-aft tilting motion amplitude of the rotor, and \( a_s \) is a yawing motion amplitude of the rotor.

\[
\begin{bmatrix}
\dot{\xi}_1(t) \\
\dot{\xi}_2(t) \\
\dot{\xi}_3(t) \\
\dot{\xi}_4(t)
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
\phi(t) \\
\theta(t) \\
\beta(t) \\
\Omega(t)
\end{bmatrix}
\]

\[
\dot{\theta}(t) = \frac{1}{I_{zr}} \left[ M_{zz} + m \left( I_{xx} \phi \right)^2 \right]
\]

\[
K_{zz} = K_{\text{Tor}}
\]

\[
M_{\text{NR}} = T^{-1} M_{\text{NR}} T + T^{-1} C_{\text{NR}} T
\]

\[
K_{\text{NR}} = T^{-1} K_{\text{NR}} T + T^{-1} C_{\text{NR}} T + T^{-1} K_{\text{NR}} T
\]

\[
(1)
\]

In Equation 2, the state-space matrix \( A \) multiplies the vector \( q \) that contains the states as DOFs, and an input forcing term \( Bu \) is added. For an eigenvalue analysis, the free-vibration condition load-case is considered, meaning that no input forces are externally applied (\( F = 0 \)) to the system.

\[
\begin{bmatrix}
\dot{q} \\
\dot{q}
\end{bmatrix} =
\begin{bmatrix}
0 & M^{-1} K \\
I & M^{-1} C
\end{bmatrix}
\begin{bmatrix}
q \\
\dot{q}
\end{bmatrix} +
\begin{bmatrix}
0 \\
0
\end{bmatrix}
\]

\[
(2)
\]

2.1 State-space model

The time \( t \) dependent blade azimuthal angular position \( \Psi_l(t) \) is expressed as \( \Psi_l(t) = 2\pi/3 (l-1) + \Omega t \) for each blade of index \( l = 1, 2, 3 \). Using the azimuthal angular position, one can transform the DOFs \( \phi \) from the \( R \) to the NR framework using the Coleman multi-blade transformation matrix \( (T^{-1}) \), as indicated in Equation 1. In other words, the purpose of applying a Coleman transform is to describe the blades instantaneous deflections in the NR framework in relation with the collective blades motion, and the rotor yaw and tilt motions in the NR framework. Once the DOFs are defined in either one of the two coordinate systems, a state-space matrix \( A \) is formed through a system of equations for the velocity \( \dot{\phi} \) and acceleration \( \ddot{\phi} \) components \([2]\), with the acceleration equations representing the equations of motion (EOMs). The state-space matrix or system matrix \( A \) is composed of the Mass \( (M) \), Stiffness \( (K) \) and Damping \( (C) \) symmetric matrices that are expressed differently depending of the coordinate system \([5]\). Mass and Stiffness matrices are defined in Equation 1. Here \( I \) refers to inertia, \( K \) to stiffness, and \( \phi_{f,L} \) to the first flap mode eigenshape value at position \( L \) from the rotor hub where each blade’s mass is lumped.

Furthermore, we add a Rayleigh damping modelled with a Stiffness matrix proportionality by a factor \( \beta \).

Figure 1: Sketch of the 4 DOFs simplified FOWT model.

Figure 2: Multi-blade fixed (NR) coordinates for flap-wise motion of a three-bladed WT \([5]\).
2.2 Hill’s method of infinite determinants

Periodicity in a system can often be eliminated by relying on the Coleman transformation and changing the framework of the EOMs from a R to NR framework [5]. When periodic terms are present in the state-space system matrix $A$, such as inertia terms within the Mass matrix or sheared inflow velocity related terms, these can be rendered time invariant through an additional method, such as Hill’s method. In this particular case, the pitching motion inertia components $I_{5,5}, I_{6,6}, I_{7,7}, I_{8,8}$ and $I_{9,9}$ from Equation 1 are azimuthally periodic. Therefore, applying a Coleman transform alone is not sufficient to render the system to become time invariant. Because of the azimuthal periodicity of the system, the system matrix $A$, the state DOFs $q$ and their time derivative $\dot{q}$ can be expressed as truncated Fourier series (from -N till N), and so can be the state-space Equation 2, as detailed in Equation 3. This results in $2N+1$ subsystems of state-space equations associated to index $l$. These subsystems equations can be linked to an overall eigenvalue problem expressed for all equations in the form of an expanded hyper-eigenvalue problem for a hypermatrix $\tilde{A}$. There are theoretically an infinite amount of eigenvalues $\hat{\lambda}_{r,s}$. However, due to the truncation of the Fourier series, only a limited number of eigenvalues are considered and those are equal to a principal eigenvalue $\hat{\lambda}_{s,0}$ with a variation by integer multiples of $\Omega$ [2, 5]. The expanded hyper-eigenvalue problem equations are associated to modes of indices $r,s$, where $s$ relates to a specific subset of state-space equations and $r$ to a DOF from that subset. According to Equation 3, when index $l = j = 1$ and $j = 0$, then the term $-i\Omega$ can be grouped with $A_{0,0}$ as $\tilde{A}_{0,0} = -i\Omega$ and applied as a factor to a corresponding eigenvector component $q_{r,0}$. Equation 3 shows how the hyper-matrix $\tilde{A}$ is composed of system matrices $A_{i,j}$ containing $j^{th}$ harmonic coefficients of the Fourier series for a given rotational speed $\Omega$ [5, 2]. The natural frequencies of the system defined in the NR framework can be obtained by solving the eigenvalue problem shown in Equation 3.

$$\sum_{l=-N}^{N} (i\Omega) e^{i\Omega l} \phi(i) \sum_{j=0}^{N} A_{i,j} e^{i\Omega j} q(j) = \sum_{l=-N}^{N} \sum_{j=0}^{N} A_{i,j} e^{i\Omega j} e^{i\Omega l} q(j) = \sum_{l=-N}^{N} \sum_{j=0}^{N} A_{i,j} e^{i\Omega j} e^{i\Omega l} q(j) = \sum_{l=-N}^{N} \sum_{j=0}^{N} A_{i,j} e^{i\Omega j} q(j) = \sum_{l=-N}^{N} \sum_{j=0}^{N} A_{i,j} q(j)$$

$$\hat{\lambda}_{r,s} = \lambda_{r} + is\Omega$$

3 Results

In Figures 3 and 4, time responses obtained via the time dependant model in Equation 1 are compared to Hill’s method results.

Figure 3: Time responses for initial state $q_0 = [1; 0; 0; 1; 0; 0; 0; 0]$ in the NR framework.

Figure 4: Time responses for initial state $q_0 = [1; 0; 0; 1; 0; 0; 0; 0]$ in the R framework.
Irrespective of the coordinate system, Hill’s method is reliable to predict the same time responses as when using the linear time dependent model. For the dynamical system at hand, a truncation using $N=2$ elements as coefficients within the Fourier expansion from Equation 3, is sufficient to have a perfect expansion for an exact representation of the system equations. As for the Campbell diagram results from Figure 5, they are generated by performing an eigenvalue analysis in the NR framework via Hill’s method. Figure 5 also displays a waterfall plot for frequency domain responses from the linear time dependent model. This confirms the fitting with natural frequencies obtained through Hill’s method, and finally four principal rotating modes are recognizable: 1st platform pitch mode, and 1st backward (BW), symmetric, and forward (FW) flap-wise modes [3].

![Campbell diagram natural frequencies and waterfall plot](image)

**Figure 5**: Campbell diagram natural frequencies (hollow circles) and waterfall plot of frequency response with respect to rotational speed. Light orange colour indicates peak amplitude values on a logarithmic scale.

## 4 Conclusion

Hill’s method was implemented and its time responses were seen to be identical to those obtained with the linear time variant model. Additionally, we show that the eigenvalue analysis calculated through Hill’s method provided fitting values with those derived from the frequency domain analysis computed with the linear time-variant model. This also implied that Hill’s hyper-matrix $\hat{A}$ was assembled properly and that the right eigenvalues were selected as principal ones. In terms of future work, it would be relevant to use Floquet’s method to compare time and frequency domain responses with current results, and do a more extensive stability analysis of damping too.

## References


TOPIC 4:
Reliability, monitoring, and sensing technology

Session 4.1
06.09.2023 - 10:30
Building 3702, Room 031

Dierksen Niklas  Uncertainty quantification in model updating with Monte Carlo sampling and global optimisation
Ragnitz Jasper  Model Updating for damage localisation and quantification using a multi-objective extension of the Global Pattern search
Galhardo António  Safety control and lifetime prediction of wind turbines based on digital twins and structural health monitoring
Yıldırım Busra  Uncertainty quantification of the floating wind turbine modelling chain
Shadmani Alireza  Probabilistic peridynamics model for damage calculation of wind turbine blades
Uncertainty quantification in model updating with Monte Carlo sampling and global optimisation

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- **Keywords**: model update, structural health monitoring, damage localization, optimisation, reliability, monitoring and sensing technology

## 1 Introduction

To reduce the maintenance costs of offshore wind turbines, precise and reliable structural health monitoring (SHM) methods are needed. Model updating has proven to be a very suitable way of detecting, localising and quantifying damages. Due to the prevailing uncertainty in FE modelling and in the measurements, robust model updating methods are needed. Here, an approach is presented, which is based on Monte Carlo sampling and global optimisation and, therefore, presents an alternative to the widely used Bayesian model updating methods [1-3].

## 2 Method

**Modal based model updating:**

The basic idea behind modal-based model updating is that a structural change, e.g., a damage, is to be detected by a change in the modal quantities [4]. Model updating in structural application often uses a parameterised FE model. This model is used to determine a combination of updating parameters that minimises the difference between the simulation model and the measurement data. Based on the resulted parameter settings, conclusions about the structural change can be drawn.

A structural change (e.g., a damage) can be expressed by a reduction of stiffness of individual elements of the FE model. To avoid having to adjust each element individually, damage distribution functions can be used [5]. These need only a few parameters to describe the stiffness reduction over the whole structure. One schematic drawing of a damage distribution function with three parameters can be seen in Figure 1a. \(\mu\) defines the position of the damage, \(\sigma\) the width of the damage and \(D\) the intensity of the damage. Global optimisation methods like the Global Pattern Search algorithm (GPS) [6] can be used to solve these minimisation problems and to find the corresponding updating parameters (\(\mu\), \(\sigma\) and \(D\)).

**Robust model updating:**

The result of non-robust model updating is one set of optimal updating parameters that minimises the difference between the measurement data and the simulation model. This offers a good solution if the used measurement data is accurate. If uncertainty is present in the measurement data, this also affects the results of the model updating. Scattering measurements also lead to scattering updating parameters.
Therefore, the goal of robust model updating is to take into account the uncertainty of the measurements to determine the influence on the updating variables. If there is sufficient information about the variance of the measured values it is possible to create artificial measurement combinations. These can cover all possible combinations resulting from the measured variance. To create these samples Monte Carlo sampling or pseudorandom sequences like Sobols’ or Halton sequences can be used. These artificial measurements can be used to perform independent non-robust model updating runs, collecting only the end results of the independent calculations. This collection of optimal updating parameters provides information about the variance of the updating parameters.

Validation example
The proposed method is validated on a laboratory steel beam, which was presented in Wolniak et al [5] and is shown in Figures 1b and 1c. The experiment is a cantilever beam with fishplates attached to the top and bottom sides with several screw connections. The beam is equipped with 15 accelerometers and excited with a contact-free electromagnetic shaker. The fishplates can be exchanged with damaged ones, where saw cuts have been introduced to reduce stiffness (see Figure 1d). Fishplates with three different damages type are available and they can be attached to nine different locations, resulting in 27 different damage scenarios. The first four natural frequencies related to pure vertical bending mode shapes are identified using the Bayesian operational model analysis (BAYOMA) [7]. BAYOMA is able to quantify the standard deviation to the associated mean value for the corresponding metrics.

Figure 1: a) damage distribution function – visualisation; b) experimental setup – illustration [5]; c) experiment setup – photo [5]; d) damaged fishplate [5]
3 Results

The proposed method is demonstrated on the experimental setup with a representative damage scenario. Here, the large damage (see Figure 1d) is applied to the centre of the beam, at position 555mm. The results of the robust model updating and the non-robust model updating are demonstrated using the cumulative distribution function in Figure 2. The three subplots show the individual updating parameters of the damage distribution function $\mu$, $\sigma$ and $D$. The results of the robust approach are shown in blue, the ones of the non-robust in red. In this experimental setup, only the position and the width of the damage can be quantified with measurements. Accordingly, the true values of the experiments are only shown in the first and second plot, displayed with black dashed lines.

It can be seen in all plots that the solution of the non-robust method is a part of the solution of the robust method. Also, in the first and second subplot, the non-robust solutions are close the measured values. The true position and width of the damage is part of the solution of the robust method, but the position of the highest probability is not at the measured value.

Even though the result of the non-robust method is very accurate, it is not able to find the correct values exactly. Also, the results of the non-robust method rely on a single set of data and are therefore more prone to measurement outliers. Taking into account the measurement uncertainty provides a more reliable result, which is able to determine the variance of updating parameters.

4 Future work

Although the importance of robust model updating and the capability of the new approach could be shown, the new method needs more investigations. Mainly because the computational time is too high at the moment if applied to complex FE models. Also, the experimental setup needs to be varied to validate the intensity of the damage.

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References


Model Updating for damage localisation and quantification using a multi-objective extension of the Global Pattern search

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1 Introduction

Wind energy is one of the key drivers to reduce the environmental impact of fossil energy production. In order to increase the attractiveness of wind energy, it is necessary to reduce its costs. Specifically, the maintenance cost of offshore wind energy systems makes up a crucial part of the emerging costs [6]. Thus reliable and precise structural health monitoring (SHM) methods could be used to reduce these costs. To tackle this issue, this work presents a model updating method that uses a robust multi-objective extension of the global pattern search [3] to locate and quantify damage in mechanical structures.

2 Method

The basic principle of model updating is based on the assumption that structural damage, i.e., changes in material properties, geometric properties or both [7], can be detected by a shift of the modal quantities. Model updating methods compare these modal quantities resulting from the measurement analysis with simulation results via objective functions and adjust the model based on selected parameters using mathematical optimisation. The choice of parametrisation greatly impacts the quality of the results and the number of iterations needed by the chosen optimisation algorithm. In this work, a damage distribution function which models damage via a reduction of the local stiffness based on three parameters for the location $\mu$, width $\sigma$ and the intensity of the damage $D$, is used [8].

Another critical aspect, aside from the parameter selection, is the optimisation algorithm employed. While deterministic or heuristic algorithms provide one solution based on the evaluation of a objective function, probabilistic algorithms also take the uncertainty of the input variables into account and can estimate the posterior distribution of the model parameters, thus providing a better understanding of the results obtained. The approaches can further be divided into single- and multi-objective optimisations, depending on the number of objective functions used. Single-objective approaches evaluate the obtained result using one objective function, resulting in a single optimal sample. Multi-objective approaches evaluate the outcome based on several objective functions which results in multiple Pareto-optimal solutions. While several heuristic and deterministic multi-objective algorithms, such as NSGA-II [2], have been developed and studied, there has been limited research focus on robust multi-objective algorithms that effectively incorporate uncertainty into the optimisation process.

This research adapts the deterministic Global Pattern search approach, to solve uncertain multi-objective Problems. The main idea is based on the work of Ide et al. [4], where an uncertain multi-objective optimisation problem can be viewed as a deterministic multi-objective problem, for every realisation of the uncertain input. The generation of uncertain input data can be achieved by means of Monte Carlo sampling. If a generated set of model parameters is Pareto-efficient for at least one of the generated Monte Carlo samples, it is referred to as flimsily robust efficient.
An empirical cumulative distribution function (CDF) for the robust model updating problem can be estimated by considering only the flimsily robust efficient solutions. The described optimisation algorithm is used to locate and quantify damage of a modular laboratory experiment with reversible damage mechanism presented in Wolniak et al. [8]. A figure depicting the beam is provided in Fig 1. Two objective functions are used to evaluate the discrepancy between the modal quantities of the measurement and the simulation. The first objective function compares the eigenfrequencies derived from the damaged state of the model \( f_{S1,k} \) in dependence of the model parameters \( x \) with the corresponding eigenvalues of the measurement \( f_{M1,k} \). This comparison considers not only the damaged states but also incorporates the undamaged states, represented by \( f_{S0,k} \) and \( f_{M0,k} \), respectively.

\[
\varepsilon_1^2(x) = \sum_{k=1}^{N_{\text{modes}}} \left( \frac{f_{S1,k}(x) - f_{S0,k}}{f_{S0,k}} - \frac{f_{M1,k} - f_{M0,k}}{f_{M0,k}} \right)^2,
\]

The second objective function employs a similar metric to assess the similarity between the associated mode shapes.

\[
\varepsilon_2^2(x) = \sum_{k=1}^{N_{\text{modes}}} \left( \frac{\Phi_{S1,k}(x)}{\Phi_{S1,k}(x)} - \frac{\Phi_{S0,k}}{\Phi_{S0,k}} \right) - \left( \frac{\Phi_{M1,k}}{\Phi_{M1,k}} - \frac{\Phi_{M0,k}}{\Phi_{M0,k}} \right)^2,
\]

Both modal quantities, i.e., the eigenfrequencies and mode shapes, are obtained from measurement data using the Bayesian operational modal analysis (BAYOMA) [5], which estimates the standard deviation of the modal quantities in addition to the mean value. The statistical quantities are used for the required Monte Carlo sampling of the input variables.

### 3 Result

The algorithm used in this study is applied to update the damage distribution function for nine separate damage positions. Fig. 2 illustrates the cumulative distribution functions of the model parameters for the resulting nine updating procedures. The beam, subject to the optimisation process, possesses a length of 1.205 m and is clamped at the coordinate position of 1.205 m. In the initial plot of Fig. 2, the estimated location of the damage position \( \mu \) is shown using a CDF for all nine damage positions. The dashed lines in the plot depict the centre of the real damage position. While all of the calculated distributions are in the correct order and estimate the damage position close to the actual damage positions, there is still an offset observed in all positions, pointing towards the free end of the beam. As only uncertainties introduced by the measurement setup were considered, this is likely due to a model error.

The second and third plots of Fig. 2 depict the width \( \sigma \) and Intensity \( D \) of the damage distribution functions. It is noticeable that besides some small deviations, all of the different damage positions exhibit similar behaviour. As all of the damage scenarios were generated using the same uniform distributed damage type, this result is consistent with the experimental setup.
Figure 2: Cumulative distribution functions for all three damage parameters on nine different damage positions
4 Future Work

Further research is needed to assess the impact of the difference in damage sensitivity between the simulation model and the real system on the estimation of the damage location, as all of the damage positions had a slight offset. As more concepts of multi-objective robust efficiency are available [1], the next steps will include the investigation of the influence of the chosen concepts. Potential areas for future exploration are also to apply the presented algorithm to the damage localisation of more complex structures.

Acknowledgements

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References


Safety control and lifetime prediction of wind turbines based on digital twins and structural health monitoring

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1 Introduction

Some of the most significant challenges in the wind energy industry are due to a large number of wind turbines currently reaching the end of their design life. The inability to operate turbines safely beyond the design life can hinder investment in this type of energy and compromise ecological sustainability goals. Wear, caused by fatigue phenomena, is a key factor in the structural health of wind turbines.

This work aims to address this challenge by developing methodologies that allow for the safe operation of wind turbines beyond the design life through the combination of structural monitoring, numerical modelling, and machine learning models. This will enable early identification of damage and continuous estimation of remaining life, to ensure optimized and intelligent generation of wind energy.

2 State of the art

Approximately one fourth of Europe's wind energy production capacity is provided by wind turbines that will reach the end of their design life in the next 5 years [1], making it essential to have tools that allow for the assessment of a possible life extension.

Modelling wind turbines can be done using software such as OpenFAST [2,3]. The main challenges associated with numerical modelling of wind turbines stem from the difficulty of accessing measurements to calibrate model parameters, primarily due to confidentiality issues. Thus, it is crucial to develop in-situ tests to collect mechanical and geometric parameters for adjusting numerical models, as well as conducting monitoring programs to validate the models' ability to relate actions to structural responses.

Procedures for sensor calibration and fatigue damage estimation in instrumented sections are well established using classical methodologies (cycle counting using the Rainflow algorithm and application of the Miner's rule based on S-N curves) [4,5]. An important challenge is extrapolating these results to non-instrumented sections of a wind turbine. Existing methodologies [6,7,8] rely on estimates of modal properties that are difficult to obtain under operating conditions, thus requiring new scientific developments to achieve reliable results. Machine learning methods, which have been widely reported in the literature for predicting and extracting meaningful information from structural responses [9], are a promising tool to address this problem. Among the techniques currently reported in the literature and applied in practice, neural networks have shown superior capability for response prediction and fatigue life consumption [9,10], with different types proving effective, including recurrent networks [11], autoencoders [12], and deep knowledge networks [13].
3 Monitoring and testing in wind turbines

The methodologies for safety control and estimation of the useful life of wind turbines defined in this work will be based not only on the definition of models but also on the analysis of measurements. This includes SCADA data, as well as data from structural health monitoring (SHM) systems, which provide structural responses such as stress to characterize fatigue phenomena, and vibrations to characterize stiffness distributions.

A geometric survey of the turbines has been conducted. Obtaining blade geometry from original equipment manufacturers is typically impossible, due to industrial property restrictions. Therefore, measurements were performed for two different wind turbine models, using laser scanning techniques [14]. This enables the possibility of working with 3D CAD files of the blade surface (see Figure 3.1), which will be crucial in adjusting parameters that relate to turbine geometry, such as its structural and aerodynamic properties.

![Figure 3.1- Results of blade laser scanning](image1)

![Figure 3.2 - Completed sensor setup in one turbine](image2)

Furthermore, the installation of detailed SHM systems in wind turbines operated by Ventient Energy is ongoing. The systems consist of accelerometers and strain gauges, located at the three blades and on the tower, and are designed for continuous monitoring of vibration and strain at a frequency of 50 Hz. The turbines to be instrumented are all nearing the end of their design life. The installation of this type of sensors in turbine blades is not common and will yield a valuable database of measurements, which can be used in the development of innovative modelling strategies. The completed setup in one wind turbine is illustrated in Figure 3.2.

![Figure 3.3 - Acceleration module prototype](image3)

![Figure 3.4 - Strain module prototype](image4)

Since the installation of traditional instrumentation systems requires costly equipment and complex procedures, an alternative set of sensing equipment is being developed in parallel with the use of state-of-practice systems. This innovative approach has cost effectiveness and simplicity as its main goals, and consists on developing sensor modules using low-cost electronics such as MEMS accelerometers and Arduino microprocessor boards. A module has been developed for measuring triaxial acceleration (Figure 3.3) and another for 4 strain gauges (Figure 3.4).
4 Future Work

4.1 Modelling of wind turbines and dynamic wind action

The practical and economic impossibility of monitoring all sections that are crucial in terms of damage occurrence motivates the development of aeroelastic numerical models based on the obtained geometric data. Modelling wind turbines is a complex multidisciplinary task that involves knowledge of structural dynamics, aerodynamics, and control. The first step in the development of wind turbine models will be the estimation of mass and stiffness distribution of components. The effects of wind action on the structure will then be estimated through CFD analyses on blade sections and the tower. Finally, control algorithms for the nacelle and blade angles, as well as the rotor torque, will be included in these models. This will define the aeroelastic models capable of reproducing the behaviour and estimating the structural response of the turbines to wind action.

4.2 Model updating using intelligent optimization techniques

The structural and operational complexity of wind turbines, combined with the sophistication requirements of aeroelastic models, justifies the need for a detailed adjustment of the intervening variables for safe operation and optimization of the useful life [15,16]. This is a highly indeterminate and challenging inverse problem, which will be addressed by defining automated adjustment methodologies [17] applicable to any turbine model. Three distinct criteria are considered: firstly, the adjustment of control algorithms for operational variables; secondly, the adjustment of stiffness distributions using operational modal analysis; thirdly, the calibration of structural responses to estimate fatigue phenomena and the corresponding life expectancy.

The adjustment procedures will be performed by generating populations of candidate models and selecting the ones that exhibit the best correlation, measured with suitable objective functions, with the real responses. Optimization procedures based on Bayesian approaches [18] or other statistical or artificial intelligence methods [15,16] will be developed.

4.3 Damage identification and life prediction methodologies

This work will also focus on the development of methodologies for automatic damage identification and estimation of the useful life of turbine components, considering fatigue limit states. In instrumented sections, damage identification will be directly obtained by modelling the relationships between actions (SCADA) and responses (SHM) using machine learning models such as neural networks [19] or ensemble models [20] (random forests, gradient boosting, etc.). The estimation of fatigue-related life expectancy will be obtained by acquiring S/N spectra and comparing them with reference curves. For non-monitored sections, aeroelastic models will be added to this procedure to obtain transfer functions between the responses of non-instrumented sections and the data acquired from the monitored sections. For stress-acceleration relationships, Bayesian methodologies [18] will be employed.

Finally, machine learning models will be developed, with the goal of relating SCADA data to fatigue wear indicators. This will enable accurate estimations of life expectancy through analysis of historical SCADA data and real-time visibility of a turbine’s current fatigue wear.

5 Acknowledgements

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6 References


Uncertainty quantification of the floating wind turbine modelling chain

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1 Introduction

Wind energy industry has accelerated in the last decades with the increasing energy demand and green transition efforts. The turbine size has increased to harness greater energy from the wind up to a point where it is impractical to install larger turbines on land. This limitation combined with the greater wind resources offshore and the limited social acceptance of large onshore wind turbines accelerated a transition to offshore installations. This transition has started with bottom fixed foundations that are structurally and economically feasible up to a water depth of 50-60 m. According to [7], 70\% of the global offshore wind potential is located in water depths greater than 60 m which requires the introduction of floating wind turbines (FWTs).

From the first FWT installation of a Hywind Spar in Norway in 2008 [9], floater designs have improved but still the best design and modeling practices are not established yet. To promote FWT installations there is a need for a better understanding of FWT design and its cost driving mechanisms. There are several design constraints/considerations which can be investigated to increase the cost competitiveness of FWTs including operational strategies to maximize energy production while minimizing the loading and floater motion, mass optimization, scalability, design standardization, installation/decommission activities, corrosion protection, and finally compliance to the standards [2].

High fidelity tools including computational fluid dynamics and finite element models have greater precision compared to fast engineering tools. On the other hand, considering the design matrix, high-fidelity tools have high computational cost to include in the design iteration process [1]. Currently, design applications of FWTs are dependent on the engineering tools where the digital models and their input data contain uncertainty due to the related assumptions and modeling choices which can affect the final design. Compared to bottom-fixed wind turbines, FWTs have more complex physics involved considering the low frequency motion of floating platform and rotor which causes a direct aero-hydro coupling [3].

Due to the multi-physics interaction inherent for FWTs, further understanding of the floater design and operation can be achieved by taking into consideration the effects of uncertainties on the design performance with a systems engineering approach.

For this purpose, OpenMDAO is chosen as a primary framework for integrating the FWT design assessment modelling chain. MDAO is an open-source software for multidisciplinary design, analysis, and optimization [5]. In OpenMDAO, the model can be constructed as a set of components, and solvers required for different physics applications can be coupled which provides an efficient modeling solution for a multiphysics optimization problem. Initial steps of this approach include selection of the methods and tools, application/learning phase of the tools, combination with OpenMDAO and finally creating the optimization framework with the selected constraints to see how can existing FWT design frameworks be expanded and optimized, to consider reliability based and probabilistic design approaches for floater and moorings. The flowchart of the proposed framework can be seen below in Figure 2.

The main intended application of this work is the systematic uncertainty quantification and design sensitivity assessment of a wind turbine floater on a system level. The project is using OpenMDAO and a specifically tailored modeling chain to promote more efficient FWT and farm designs. The primary objective of this work is to create a fast preliminary design framework based on MDAO and capable of taking uncertainties into account considering...
the serviceability limit states, and utilize the framework to create insights on the primary dependencies and cost drivers of floating wind turbine design.

An important feature of the proposed design framework is that it aims to complete the entire modelling chain only with open-access tools and scripts that can be accessed through a single programming environment in Python.

2 Methodology

2.1 Design Framework

2.1.1 Model Details

After selecting the platform/turbine concepts, the initial step towards completing the design framework is to implement and integrate the tools required for the coupled analysis. For this purpose, a parameterized component geometry and a quadrilateral surface mesh of the geometry should be generated. The mesh is required in order to run a potential flow solver to obtain the hydrodynamic properties of the floater. The first challenge encountered here was to combine several meshing tools and converting all information in a format suitable for running potential flow solutions.

![Quadrilateral mesh for the submerged part of the selected platform concept.](image)

PyHAMS, a python wrapper for an open-source potential flow solver HAMS [8], is selected to obtain hydrodynamic coefficients. Being a well validated open-source code with parallel computing abilities, lower computational time is expected for this part. Moorings are implemented using MoorPy which is a python based mooring system modeling tool using a quasi-static modeling approach [6].

The current framework does not intend to optimize the wind turbine rotor features such as aerodynamics. Hence, the rotor is considered with fixed design. This allows for a simplification of the way the aerodynamic properties are represented. A Machine Learning model will be trained to estimate rotor dynamic forces as function of the wind input and floater motion. This model is trained independently from the floater and is later included in the design loop to feed rotor thrust time series to the design assessment process. Previously, a similar approach is adopted in QuLAF [4] where pre-computed fixed rotor thrust, moment and aerodynamic damping are used in the design loop in frequency domain. In this stage of the project, the controller is not tuned for the new design.

The initial implementation of the optimization framework is planned to be without the use OpenMDAO, in order to focus on the top-priority challenge; this is considered to be the coupling of the different modelling steps needed to obtain a design evaluation. After the tools are combined without any further problems, the optimization framework will be implemented in OpenMDAO including the reliability based design constraints, with additional focus on improving computational efficiency.
Figure 2: Numerical modeling steps to be followed in this work.

References


Probabilistic peridynamics model for damage calculation of wind turbine blades

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Abstract

Composite laminates are widely used in various industries, particularly in wind turbine blades, owing to their high strength and lightweight properties. The tip section of the blades, namely the leading edge, is prone to severe damage due to erosion, where predicting and analyzing the damage behavior of the leading edge is a complex task. To this end, meshless methods such as peridynamics have gained significant attention in computational mechanics and engineering owing to their ability to overcome the limitations of traditional mesh-based methods. These methods offer advantages, such as flexibility in point distribution, adaptability to complex geometries, and the ability to model large deformations. This study focuses on probabilistic approaches for calculating the damage to composite laminates combined with peridynamics.

Keywords: Probabilistic approaches, Peridynamics, Leading-edge erosion, Composite laminates

1. Introduction

Wind turbine blades (WTBs), particularly in their tip sections, are often subjected to impacts from high-velocity objects, such as rain, atmospheric particles, hail, and sand, over their service life. These effects may cause erosion damage at the blade leading edge, thus decreasing the aerodynamic performance and power output of wind turbines. Furthermore, these issues necessitate frequent maintenance and repair, thus increasing the energy expenditure.

Leading-edge erosion (LEE) of WTBs is a major problem that affects the performance and longevity of offshore wind energy systems. Repetitive impacts eventually cause the surface coating to erode. The development and progression of LEE involve different stages. Initially, an incubation period occurs during which little or no damage is visible on the surface. After the incubation period, the erosion rate accelerated until it reached its maximum. Eventually, the erosion rate decelerates to a steady-state erosion state. The duration of each stage is primarily affected by the strength properties of the coating material and the weather conditions to which it is exposed [1]. The damage calculation of WTBs is crucial for optimizing maintenance planning, assessing energy production losses, and ensuring the structural integrity of blades.

The finite element method (FEM) is widely used for the damage assessment of WTBs, but requires a mesh, which can be challenging to generate for complex geometries and may lead to computational inefficiencies. Additionally, the FEM may struggle to accurately capture crack initiation and propagation in materials with complex failure mechanisms. Because of this, meshless methods have recently been developed to more accurately model the fracture and damage processes.

This study reviews the state-of-the-art probabilistic models used to calculate the damage caused by leading-edge erosion. Probabilistic models that incorporated environmental parameters, rainfall intensity, and raindrop size distribution were explored to quantify the probability of composite laminate damage. Furthermore, this study discusses the integration of probabilistic models with peridynamics approaches.
2. Related works

Peridynamics is a nonlocal continuum mechanics theory that is capable of accounting for long-range interactions between material points. This approach has been successfully utilized to simulate the fracture and damage processes of various materials, including composite laminates [1]. The fracture mechanisms of the laminated composites exposed to low-velocity impact and static indentation were simulated using this approach. It has also been used to examine the development of fatigue cracks in multi-layered heterogeneous material structures [1]. For the purpose of analyzing damage in composite laminates, a number of peridynamics models have been developed. To study the effects of impact on composite materials, for instance, a bond-based peridynamic model including matrix plasticity has been created [2]. This model replicates the dynamic fracture behavior and cracking velocity of laminated composites by taking into account the continuous bond parameter. Composite laminates' failure and damage under different loads have also been studied using peridynamics models. To examine the dynamic impact damage and quasi-static tensile failure of laminated composites, another study created a peridynamic model based on finite element analysis. To capture the complicated failure behaviors, this model takes into account the anisotropy of the laminate and presents an empirical damage model [4].

Erosion damage has often been evaluated using deterministic methods. However, the adoption of probabilistic techniques is required due to the uncertainty in environmental conditions and material characteristics. These methods consider the uncertain nature of the erosion damage to provide a more precise estimate of the blade's remaining service life. Probabilistic methods have also been proposed for predicting erosion deterioration [5], [6]. These studies combined likelihood distributions of rainfall characteristics (intensity and droplet size) and wind velocity as inputs for a fatigue analysis model that calculates the expected lifespan of a blade coating. Probability-based models were formulated to forecast the remaining strength and fatigue endurance of the composite laminates. A model grounded in micro-macro damage mechanics was developed to delineate the impact of various types of damage on the mechanical performance of composite laminates. This model predicts how damage types and stiffness deterioration progress over time, and provides a correlation between the remaining stiffness and residual strength [3].

3. Methodology

This research involves the utilization of probabilistic approaches to calculate the probability of failure of WTBs subjected to erosion damage. This study also intends to explore the integration of probabilistic approaches with peridynamics by developing an appropriate limit state function.

First, probabilistic approaches are utilized to assess the uncertainties associated with load and material properties. Probabilistic models will be developed to capture the variability in factors, such as rainfall intensity, raindrop size distribution, and blade material properties. Probabilistic methods such as the first-order reliability method (FORM) and second-order reliability method (SORM) will be employed to generate representative scenarios of erosion-induced damage.

To validate the proposed method, a Monte Carlo simulation (MCS) will be implemented to calibrate and validate probabilistic models and computational simulations. This research will also involve collaboration with industry partners to access real-world operational data and incorporate them into the analysis.

These research methods involve a combination of numerical simulations, statistical analyses, experimental investigations, and data-driven modeling. The integration of probabilistic approaches, Peridynamics, and data-driven techniques will provide a comprehensive framework for assessing and predicting the damage caused by leading-edge erosion in offshore WTBs.

A flowchart illustrating the general procedure of this study is presented below:
3.1. Research questions

This study aims to address two key questions associated with the probabilistic approach for damage calculation combined with peridynamics with respect to leading-edge erosion in WTBs.

- How can probabilistic approaches effectively capture uncertainties in material properties for incorporating the erosion damage evolution?
- How can peridynamics be integrated with probabilistic approaches to accurately predict the progressive damage and failure behavior of composite materials in wind turbine blades?

Addressing these research questions will provide valuable insights into the probabilistic damage process of leading-edge erosion in offshore WTBs, enabling more accurate prediction of damage evolution, improved maintenance strategies, and enhanced reliability of wind energy systems. In addition, addressing these questions involves developing and implementing probabilistic approaches that can effectively capture uncertainties in material properties and integrating them with peridynamic models. This can involve using several probabilistic techniques to reduce the computational cost while still providing accurate estimates of structural failure statistics. It may also involve the development of innovative methods for estimating discretization and sampling errors to improve confidence in numerical predictions.

3.2. Expected outcomes

This research is expected to yield several important outcomes in the field of probabilistic damage processes of leading-edge erosion in offshore WTBs.

- Quantification of uncertainties: This research provides methods for quantifying the uncertainties associated with environmental conditions, loads, and material properties that influence LEE. This will enable a more accurate probabilistic analysis and prediction of damage progression.
- Enhanced modeling and simulation techniques: This study advances the application of probabilistic approaches in modeling and simulating erosion-induced damage in WTBs. This includes the development of innovative algorithms and methodologies to capture the random nature of the erosion process and its impact on structural integrity.
- Integration of peridynamics with probabilistic approaches: This study explores the integration of peridynamics, a non-local continuum mechanics theory, with probabilistic approaches to predict the progressive damage and failure behavior of composite materials in WTBs. This hybrid modeling approach provides more accurate and realistic predictions of damage evolution.

The expected outcomes of this research, as shown in Figures 2 and 3, will contribute to the advancement of knowledge in the field of LEE of offshore WTBs, leading to improved design practices, maintenance strategies, and operational decision making for wind energy systems.
Figure 2: (a) Computational model of coating with randomly distributed bubbles subject to droplet impact (b) stress evolution in presence of bubbles within the coating [7]

Figure 3: Damage on the surface based on (a) absolute principal stress, (b) signed von Mises, and (c) critical plane model [8]

References

Session 4.2
06.09.2023 - 13:15
Building 3702, Room 031

Christoffers Marcel  Influence of repair measures on the fatigue behaviour of rotor blades
Jüchter Julian    Characterizing wind fields by applying a Langevin Analysis to model wind turbine measurement data
De Pascali Marco  Design of a 1m-rotor wind turbine model for wind tunnel testing
Reinhardt Tim     Influence of the rotor nacelle assembly modelling on the eigenfrequencies of offshore wind turbines with monopile foundations
Influence of repair measures on the fatigue behaviour of rotor blades

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Keywords: Fatigue Damage Modelling, fatigue life, composite repair

1 Introduction

Due to their excellent mechanical properties, corrosion resistance and suitability for lightweight designs, fibre reinforced composites are the material of choice for rotor blades of wind energy converters. However, the blades in particular are subject to the cyclic loading conditions experienced during wind turbine operation. Therefore, accurate modelling of fatigue damage plays an important role in predicting the lifetime and planning maintenance of wind turbines and repair.

2 Project MMRB-RC

The performance and reliability of the rotor blade is crucial for the efficiency of a wind turbine. The blades account for a large part of the turbine costs - their repair and maintenance costs are comparatively high. The MMRB-RC research project will investigate rotor blade repairs using vibration and sound-based methods for damage localization and structural health monitoring. In addition, the fatigue damage behavior of rotor blades will be analyzed in detail to develop and improve numerical fatigue prediction methods for wind turbine rotor blade monitoring.

3 Fatigue Damage Modeling

The Institute of Structural Analysis has a longterm experience in modeling the nonlinear response of composites under static and cyclic loading. This includes an inhouse developed fatigue damage model (FDM) which is continuously extended \cite{1} \cite{2} \cite{3}. This model will also be used in the project outlined here and will be further extended to include repair processes and their effects on fatigue behaviour.

The central element of the FDM is an energy-based hypothesis from civil engineering, originally developed for reinforced concrete structures. This hypothesis states that the damage state of a quasistatically loaded material is comparable to that of a cyclically loaded material if the magnitude of the energy dissipated during the damage is the same. In this context, it is irrelevant how the damage occurred, instead only the amount of dissipated energy is decisive. In order to apply the energy hypothesis, parametric pre- and post-critical stress-strain relationships must be specified for each loading direction, obtained from experimental tests for characterisation. It is noted that orthotropic or transversely isotropic material behaviour is assumed, as is typical for FRP. In order to save computation time, the quasi-static energy is divided into load blocks. It is now described how the fatigue analysis of a single load block works for a given load direction. The input variables required are the number of load cycles of the load block under investigation and the stress components from the FE analysis for each element and integration point. The analysis can be described in six sub-steps shown in Figure 1. In the first step, the amount of dissipated energy up to failure is determined with the help of the calculated maximum stresses for the current load block and the corresponding quasi-static stress-strain curves. The energy balance hypothesis is then applied and the energy is transferred from the static to the fatigue consideration. Then the value of the fatigue failure
stresses, which is very important for the damage calculation, is determined by means of virtual fatigue-related stress-strain curves. The number of load cycles until failure is also a decisive calculation parameter in damage prediction. For this purpose, experimentally obtained S-N curves are used to determine the number of load cycles to failure for a given stress ratio. Then, based on the initial strains of the original material, the previously calculated fatigue failure strains and the number of load cycles to failure, so-called strain evolution curves are determined. The shape of these curves is based on experimental observations and shows typical non-linear behaviour. With the help of the strain development curves, the fatigue-related increase in strain is determined on the basis of the normalised service life for the current calculation step. Thus, as the number of load cycles increases, the fatigue strains increase. The updated reduction factors for strength and stiffness are then determined iteratively using the underlying stress-strain relationships and the energy hypothesis.

![Figure 1: Schematic representation of the Fatigue Damage Model [1]](image)

4 Future Work

In the MMRB-RC project, the influence of repair measures on fatigue damage behaviour is to be investigated in detail. A core part of the project are experiments on a 30 m laboratory rotor blade, a repaired 60 m offshore rotor blade and on small-scale rotor blades. The project involves the construction of finite element models of test specimens and rotor blades as well as the simulation of the fatigue damage behaviour taking into account the effects of repair sites. The influence of repair sites on the various methods for structural monitoring is analysed and the algorithms are further developed on the basis of the measurement results of the tests on FKV test specimens, a large-scale rotor blade test and the offshore measurement campaign. The fatigue damage model to be developed for repair sites requires material parameters for the representation of the fatigue behaviour of the materials, as well as for the characterisation of the repair sites. These parameters - if not yet available - are determined in coupon tests. Accompanying FE-models of these are later used for test verification and parameter identification of the FDM. On the basis of the characterisation tests carried out on the coupon level a suitable material theory is to be developed that can describe the influence of repair sites on the fatigue damage behaviour. Particular consideration should be given to the stiffness jumps that occur at the edges of repair points, which can cause local stress ratios that deviate significantly from the global load ratio. The developed material theory for the description of the fatigue influence of repair locations is to be implemented into the existing FDM. For this purpose, the programming of an interface
an interface is necessary, which transfers the FDM parameters of the pre-damaged structure after a fatigue simulation to the model provided with repair points as initial values. The implementation of Haigh diagrams is also conceivable, which describe the influence of different stress ratios on the fatigue damage behaviour.

Acknowledgements

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Applying a Langevin Analysis to model wind turbine data
to distinguish different inflow conditions

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1. General idea and motivation

The control of wind farms, particularly in the context of wake steering, is a current area of research. In order to implement these control strategies, it is crucial to have accurate information about the wind field [1]. This study aims to distinguish between various wind fields by utilizing a Langevin Analysis [2] of the measurement data obtained from wind turbines. Unlike other methods such as LiDAR measurements [3] or blade bending moment measurements [4] that require additional measurement equipment, our proposed approach solely relies on standard wind speed and power data collected by the wind turbine itself. This eliminates the need for any extra instrumentation.

2. Experimental investigations

To explore the potential application of the Langevin Analysis in distinguishing different wind fields, a series of experiments were conducted in the Oldenburg wind tunnel. Four distinct inflow cases were generated using an active grid and measured using an array of 21 hot wires. These cases include two horizontal gradient fields denoted as "Increasing" and "Decreasing," where the wind speeds progressively increase or decrease from left to right. Additionally, a reference case without any gradient (labeled as "Reference") and a wake case with two model turbines (referred to as "Wake") were generated, as depicted in Figure 1.

During the experiments, mean wind speeds ranging from 3 m/s to 7.5 m/s were generated to cover the entire partial load range of the model turbines. The MoWiTO 0.6 (Model Wind Turbine Oldenburg), with an approximate diameter of 0.6 m, was exposed to these varied inflow conditions.

3. The Langevin Analysis

The measured power output of the MoWiTO 0.6 turbine, along with the measured wind speed, serves as input for calculating drift and diffusion coefficients within the framework of the Langevin Analysis. These coefficients are computed for fixed intervals of wind speed and power, providing insights into the turbine's behavior under specific flow conditions. The drift coefficient, derived from the underlying Langevin equation, describes the average power development in the subsequent time step. On the other hand, the diffusion coefficient quantifies the magnitude of random deviations from this mean drift within the corresponding power and wind speed interval.

Figure 2 demonstrates the distinguishable nature of these coefficients across the investigated inflow cases, enabling the characterization of various flow scenarios using the Langevin Analysis. Notably, in comparison to the reference case, all other cases exhibit a greater number of drift coefficients within a given power interval. Furthermore, the
Drift coefficients differ between individual cases even for identical power and wind speed intervals. Figure 3 further illustrates discernible differences among the diffusion coefficients, as well.

To quantitatively assess the disparities between the cases, Figure 4 showcases the drift and diffusion values for a fixed wind speed interval \( u \in [6.75 \text{ m/s}; 7.00 \text{ m/s}] \). It is evident that the reference case stands apart from the other cases in terms of drift behavior. However, the increasing and decreasing case are very similar. Considering the diffusion coefficients as well, a distinction between the increasing and decreasing cases becomes feasible. Therefore, the findings suggest that the Langevin Analysis holds promise for effectively differentiating between various inflow conditions and could potentially be utilized for wind farm control purposes.

Figure 1: Shown are all four configurations of the active grid and the setup for the wake case. On the right-hand side of each frame, the corresponding wind speed distribution measured by the hot-wire array is shown. These are one-minute mean values of the wind speed at the same point in time during the experiment. The red circle indicates the area that is covered by the rotor blades of the MoWiTO 0.6 during the subsequent measurements.
Figure 2: Here the drift coefficients for all the wind speed and power intervals of all four cases are shown. The wind speed intervals have a width of 0.25 m/s and the power intervals have a width of 1 W each.

Figure 3: Here the diffusion coefficients for all the wind speed and power intervals of all four cases are shown. The wind speed intervals have a width of 0.25 m/s and the power intervals have a width of 1 W each.
Figure 4: The left-hand side of the figure shows the drift in dependence of the power for a fixed wind speed interval of $u \in [6.75 \text{ m/s}, 7.00 \text{ m/s}]$ for each inflow condition. The right-hand side of the figure shows the diffusion in dependence of the power for a fixed wind speed interval of $u \in [6.75 \text{ m/s}, 7.00 \text{ m/s}]$ for each inflow condition.

Acknowledgments

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Design of a 1m-rotor wind turbine model for wind tunnel testing

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Keywords: Scaled model wind turbine, sizing procedure, target geometry, mechatronic system

1. Introduction

Nowadays, wind energy is by far the most promising and the fastest-growing renewable energy resource. An extremely resourceful tool in supporting research in wind technology is wind tunnel testing of scaled wind turbine models, enabling the development of mathematical models and validating simulation tools.

In this scenario, the project goal is the design of a 1m-rotor scaled model of the DTU 10MW Reference Wind Turbine (RWT) that represents an evolution of PoliMi D2.4m [1]. The model (Polimi D1m) has to be as close as possible to the target geometry, defined by the scaling of the reference turbine. The turbine main requirements are a compact and robust nacelle, a stiff tower (to keep high first natural frequency) and a model capable of showing a realistic energy conversion process in terms of dimensionless power coefficient and especially dimensionless thrust coefficient. Moreover, the model should be featured by closed-loop controls (IPC) and complete sensorization, enabling testing of the major and newest control techniques and evaluating the main parameters of interest.

2. Analysis of matched and unmatched quantities

The first step for the scaling process has been defining the length scaling factor ($\lambda_L$) and the velocity scaling factor ($\lambda_V$). Due to wind tunnel constraints they have been set to $\lambda_L = 180$ and $\lambda_V = 2$. The major non-dimensional parameters governing the system dynamics are derived and analyzed. In particular the properties remaining constant between the full scaled model and the miniaturized one are described.

• The Tip Speed Ratio: $\text{TSR} = \frac{\omega R}{V}$. It is always verified that $\text{TSR}_{\text{scaled model}} = \text{TSR}_{\text{full model}}$ for any $\lambda_V$ and $\lambda_L$. This matching guarantees the exact kinematic flow similarity between scaled and reference turbine rotors [4].

• Chord based Reynolds number: $Re = \frac{\rho c V_{rel}}{\mu}$. It represents the ratio between inertial and viscous forces and, as it influences the lift and drag coefficients, it has a great impact on performance and loading of the rotor. By adopting the correct scaling law, yields the Reynolds numbers ratio $\frac{Re_{\text{scaled}}}{Re_{\text{full}}} = \lambda_V \lambda_L = 360$. This condition, known as Reynolds’s discrepancy, means that the two systems do not satisfy the dynamic flow similarity [3]. Since in these conditions, it is hard to replicate the aerodynamic performance of the full-scale machine by using a geometrically scaled copy of its rotor, a performance matched rotor is adopted.
• The $i$-th non-dimensional natural frequency: $\hat{\Omega}_i = \frac{\Omega_i}{\omega}$. If the lowest $N$ non-dimensional frequencies of the scaled and full-scale system are equal, the eigenvalues of the two systems have the same relative placement among themselves [2]. However, since the model is not designed for aeroelastic tests, this similarity is neglected.

• The thrust coefficient: $C_T = \frac{F_T}{0.5 \rho A V^2}$. The thrust has a great impact on the wake speed deficit. Being the wake reproduction crucial for the aim of this work, a targeted aerodynamic design is adopted in order to match the $C_T$.

3. Description of the turbine model sub-assemblies

The designed model is shown in Figure 1, with a particular focus on the main 3 sub-assemblies, Nacelle, Rotor and Tower. Following a brief description of the 3 sub-assemblies is given.

3.1 Rotor

This subgroup, shown in Figure 2, is supported by the nacelle and it is composed of blades, pitch assemblies and hub. The latter is made by a single structural component in aluminum as it satisfies the requirement of a simple and rigid layout. The pitch assembly design is aimed at creating a compact layout which gives structural support for the blades roots and guarantees the pitch actuation mechanism implementation. The pitch actuator has been sized according to the IPC technique, to alleviate the 3P fatigue loads. The sizing process led to the selection of Harmonic Drive RSF Mini 5B, providing zero backlash and advanced positioning accuracy. Moreover, it is compact and lightweight, crucial characteristics for this application.

In the assembly, the shaft actuator is kept still, letting the case rotate. The unusual choice to keep the shaft fixed has been driven by encumbrance optimization. The assembly is composed of a primary flange, attached to the hub, and connected to the actuator Harmonic Drive one. On the primary flange a THK crossed roller bearing is fit as it resists bending moment, avoiding the use of 2 ball bearings. The bearing allows the Harmonic Drive actuator motion transmission, but above all it supports the loads involved.
The blade design is carried out thought a dedicated optimization algorithm. The aerodynamic design aimed at:

- matching the reference $C_T$ (dimensionless thrust coefficient)
- generating a blade geometry able to host the actuator case, used for IPC.

The $C_T$ has been taken as target, since for floating offshore wind turbines as well as wind farm studies, matching the correct scaled thrust force is of greater interest for its contribution in the overall dynamics.

### 3.2 Nacelle

The nacelle unit is shown in Figure 3. The nacelle frame constitutes the structural component of the unit made by two aluminum parts, connected by two supports. The vertical frame face hosts a THK crossed roller bearing supporting the rotor shaft and a proximity sensor to detect the rotor angular rotation.

The shaft, carrying the slip ring, transmits the motion from the rotor, moved by the aerodynamic forces, to the main actuator. In particular, being hollow, it allows the electrical cables coming from the slip ring to reach the proximity sensors and the Harmonic drive controllers bypassing the nacelle bearing.

The through bore slip ring is connected to the shaft by means of locking screws, and it provides power to the actuator controllers and proximity sensor present in the rotor. The through bore configuration of the collector allowed to overcome a limitation of the former wind turbine model; by aligning the main actuator with the rotor, belt transmission and further components are avoided.

The torque actuator has been sized on the basis of requirements for rotational speed, torque, and limited weight of the component.

### 3.3 Tower

The main issues related to the tower design lied in the yaw mechanism implementation, and the dynamic analysis performed to ensure that the first flexural eigenfrequency is placed far from
the excitation frequencies, in particular between 1P (rotational speed) and 3P (rotor blade passing frequency). About the tower unit design the layout proposed is equipped with a 6-axis load cell and for it a modal analysis has been carried out to check the previous frequency constraint. The load cell is placed at the tower unit top, and it acts as connection with the rotor-nacelle assembly. This transducer measures forces up to 145N along the radial direction and 290N in the axial one and detects moments up to 5 Nm around the x, y, and z axes.

This layout is equipped with yaw actuation mechanism placed at the top of the tower unit, under the balance. Being inside the tower, the actuation mechanism is not subject to wind perturbations.

4 Conclusions

The 1m-rotor scaled wind turbine model design has been completed delivering a solid model, consistent with its target geometry. The PoliMi D1m is sensorized by means of a 6-axis load cell, measuring the loads acting on the rotor-nacelle assembly and the actuator encoders.

Pitch, yaw and torque control is performed through their respective actuators. Despite the Reynolds number discrepancy, the matching of the $C_T$ has been achieved thanks to the use of suitable airfoils and an optimization algorithm.

The nacelle unit configuration results to be improved compared with the former model, in terms of compactness, robustness and level of complexity. Furthermore the modal analysis ensured a correct dynamic behavior of the tower.

The result of this work, is an advanced and robust mechatronic system. Clearly, only the actual construction and the testing session in wind tunnel can assess its quality.

5 References


Influence of the rotor nacelle assembly modelling on the eigenfrequencies of offshore wind turbines with monopole foundations

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1 Introduction

Despite the advances in the modelling of offshore wind turbines, most recently with the improvement of the soil-structure interaction [1], discrepancies between the identified (as built) and computed eigenfrequencies of the structure still exist [2], [3]. These discrepancies are especially severe for the second order eigenfrequencies, where the measured frequencies deviate between 25\% and 50\% from the finite element computations, see Figure 1.

![Figure 1: Comparison of measured and as-designed eigenfrequencies in relation to eigenfrequencies computed with the integrated OWI-lab FE model, adapted from [3]. Upper half: first order fore-aft and side-side frequencies. Lower half: second order fore-aft and side-side frequencies.](image-url)
Current state of the art models commonly model the rotor nacelle assembly as a point mass [2], [3]. However, this approach fails to accurately take the influence of the modal properties of the blades into account and might lead to the observed discrepancies for the second order eigenfrequencies [4].

The objective of this contribution is to investigate the influence of the rotor nacelle assembly modelling approach on the computed eigenfrequencies of offshore wind turbines. A more detailed modelling approach of the rotor nacelle assembly will be proposed to reduce the discrepancy between the measured and computed eigenfrequencies.

2 Methodology

The integrated model of the offshore wind turbine will be developed in Openseespy [5]. Timoshenko beams will be used for the support structure in conjunction with a lumped mass formulation. The hub and nacelle will be modelled as point masses connected to the tower top by rigid links. Based on the geometric and material parameters of the NREL 5 MW reference turbine [6], the blades will be modelled using beam elements and will be connected to the hub mass node. The modelling approach of the blades will be validated by comparing the resulting modal properties of a clamped blade with results obtained from OpenFast.

3 Outlook

The proposed modelling approach of the rotor nacelle assembly promises to be an improvement over the current point mass approach in the estimation of the second eigenfrequency of offshore wind turbines with monopile foundations. Moreover, the proposed approach allows for the inclusion of parameters such as the pitch angle of the blades and the yaw angle of the entire assembly.

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References


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Data Driven Infrastructure Planning For Offshore Wind Farms
Investigations towards data normalisation using Gaussian processes for the estimation of modal parameters of a lattice tower under environmental conditions

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Keywords: Gaussian process regression, Environmental conditions, Data normalisation, Damage detection

1 Introduction

Structural health monitoring (SHM) damage identification adopts a comprehensive five-tier hierarchical approach [12]. The first two levels involve making reliable statements about the occurrence and precise location of damage. In contrast, the subsequent tiers deal with the identification of the specific categorisation of the damage and the prediction of the remaining life time. In the pursuit of damage detection, the classification of selected damage-sensitive features into ‘healthy’ and ‘defect’ categories proves adequate. This approach has the distinct advantage of requiring only data from the undamaged system. To effectively monitor a structure, the key damage-sensitive features are continuously extracted from the measurement data and compared with the healthy state of the structure. Any significant deviation can then be interpreted as a potential failure. Nevertheless, changes in environmental conditions (ECs) have the ability to influence the behaviour of the structure [4]. As a result, changes in the monitored damage-sensitive characteristics induced by such changes may lead to false positive damage identifications. Distinguishing between structural changes due to actual damage and those due to displacement of ECs is therefore a major challenge. Consequently, to ensure the reliability of the SHM system, an additional imperative is to make the selected features insensitive to EC variations. This aspect is referred to as data normalisation in the context of SHM. A common methodology involves modelling the relevant damage-sensitive features based on the ECs hypothesised to underlie their variability [5]. This involves the use of a regression model that captures the interplay between the ECs and the damage-sensitive features, using an assorted set of EC values. The present study introduces an innovative approach using heteroscedastic Gaussian processes (GPs) to encapsulate the influence of ECs on the designated damage-sensitive features. GPs have been shown to be effective in a variety of regression tasks [10] and have yielded successful results in the area of data normalisation for SHM [2]. A salient feature of this technique is its ability to generate a predictive probability distribution as opposed to a single prediction point. This facet allows the calculation of confidence intervals and the seamless incorporation of uncertainty into all subsequent analyses [10]. In the next phase of the study, these results will be used to investigate the feasibility of detecting structural damage using the normalised features. The data normalisation framework presented in this paper takes the modelling of damage sensitive features of the Leibniz University Test Structure for Monitoring (LUMO) around temperature and wind speed into account. Jonscher et al. [6] as well as Möller et al. [9] have already investigated data normalisation for the natural frequencies of LUMO. Furthermore, in [6] also the the subspace with a second order modal assurance criterion (S2MAC) [3] was investigated. In this study, the less strong assumption regarding homoscedasticity shall be replaced by the more feasible assumption of heteroscedasticity. And, as highlighted in [7], the angular representation of the S2MAC serves as a damage-sensitive feature in this study. In this paper, the proposed data normalisation scheme is first rigorously evaluated in terms of its performance on a dedicated test set. Subsequently, its effectiveness in detecting damage within the LUMO structure is investigated.
2 Application

For the application, measurement data from the Leibniz University Test Structure for Monitoring (LUMO) are used. LUMO is a nine metre high lattice tower equipped with 9 acceleration measurement levels and various metrological data. It is possible to use different damage mechanisms by removing threaded rods at certain points of the tower. A detailed description of the experimental setup and the measurement campaign can be found in [11]. During the study period, the damage mechanism is investigated at the lowest possible damage position (approximately 70 cm height). In this work, the S2MAC values of the first two bending modes in both directions (B1x, B1y, B2x, B2y) are investigated as damage sensitive features. To extract the modal parameters, Bayesian operational modal analysis (BAYOMA) is used in this study. BAYOMA is a frequency domain method based on the statistics of the discrete Fourier transformation of a Gaussian distributed signal [1]. Based on the observations in [7], the S2MAC in the smallest angle between the mode shape and the mode subspace can be described by

\[ \alpha_{S2MAC} = \arccos(\sqrt{S2MAC}). \]  

(1)

This form is a more meaningful form of representation of the S2MAC as a damage-sensitive feature. As defined by Rasmussen et al. [10], a Gaussian process (GP) model describes a distribution over functions and the regression problem is to recover the functional dependence \( y_i = f(x_i) + \varepsilon_i \). Assuming independent, normally distributed noise terms \( \varepsilon_i \sim N(0, \sigma_i) \), where the noise variances \( \sigma_i \) are modelled by \( \sigma_i = r(x_i) \), the regression problem becomes a heteroscedastic one [8]. For the evaluation of the GP accuracy the \( R^2 \)-Score,

\[ R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - f_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}, \]

(2)

where \( y_i \) and \( f_i \) are the measurements and predictions respectively, and \( \bar{y} \) is the mean of the measurement data, is used. The result of the investigation is shown in Fig. 1.

![Figure 1: R²-Score of the predicted S2MAC values of the GP for a training set.](image)

It can be seen that the individual S2MAC values can be mapped by the GPs in terms of variability due to wind and temperature. However, it is noticeable that the \( R^2 \) values of the second bending mode pair are significantly lower than those of the first bending mode pair. Possible reasons for this are that not all ECs can be represented sufficiently well by the GP, or that the amount of test data is too small, allowing outliers to have a significantly greater influence on the result. Nevertheless, the \( R^2 \) values show that, in principle, a trend in the data can be
reproduced by the GP. But in order to ensure that the coverage of the ECs in the training data is sufficient for the subsequent damage identification, the respective statistical measures for both quantities were compared in Fig. 2.

Here it can be seen that there is a corresponding EC coverage of the training and test set. For damage detection, the probability distributions from the identification of BAYOMA were compared with those of the GPs. The Hellinger distance is a suitable measure for this and serves as novelty metric in this study. This metric is defined for two normal distributions $P \sim \mathcal{N}(\mu_1, \sigma_1^2)$ and $Q \sim \mathcal{N}(\mu_2, \sigma_2^2)$ as

$$H^2(P, Q) = 1 - \frac{2 \sigma_1 \sigma_2}{\sigma_1^2 + \sigma_2^2} \exp \left(\frac{-(\mu_1 - \mu_2)^2}{4 (\sigma_1^2 + \sigma_2^2)}\right).$$ (3)

The maximum distance is 1 and the minimum distance is 0. For the investigated damage scenario the results of the proposed novelty detection method are shown in Fig. 3.

The results in Fig. 3 show that the damage is particularly well detected by the second bending mode and only to a small extent by the first pair of bending modes. The reason for this may be the shape of the second bending mode which, as seen in Fig. 4, has a larger deflection at the location of the damage.
3 Results

It was shown that data normalisation of the S2MAC by means of heteroskedastic GPs works and that damage detection based on this is possible. However, there is still room for improvement in terms of training performance, especially for higher modes. This is relevant because these seem to be more sensitive for damages near the ground.

Acknowledgements

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References

Domain Generalization Potential of Data-Driven Methods for Predictive Maintenance in Wind Energy Systems

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Keywords: Predictive maintenance, Wind turbines, Machine learning, Domain generalization, Transfer learning, Continuous learning

1. Context

With the rapid growth of the offshore wind installations, the costs for operation and maintenance (O&M) of wind turbines must be reduced. 25% to 40% of the levelized costs of energy (LCoE) can be attributed to their O&M [1, 2]. To reduce these LCoE, it is necessary to monitor the health conditions of wind turbines in order to avoid unplanned failures of critical components, and to enable wind farm operators to perform predictive maintenance [3, 4]. Therefore, nowadays companies already monitor several parameters like vibrations, oil quality, and temperatures, i.e., valuable information used to determine if maintenance is required based on irregularities [5]. Such systems are typically referred to as condition monitoring systems [6]. Furthermore, the turbines are equipped with a supervisory control and data acquisition (SCADA) system gathering valuable information that is mainly used to monitor the operation and performance but might also be used for deriving the turbine’s condition [5]. Besides processing those data in model-based solutions, data-driven approaches in the form of machine learning are being explored [7]. Although these data-driven methods have shown great potential in predictive maintenance applications, their ability to generalize on unseen data from new machines or new environmental conditions are limited [8]. Furthermore, due of the tendency of overfitting to data used to train the data-driven models, the applicability of the models is limited. These properties often restrict the use in industrial applications. For a commercial use of machine learning methods in predictive maintenance of wind turbine components, data-driven models must be transferable to different wind turbines in various wind farms.

2. Research Questions

For a successful scientific investigation, research questions are defined in this chapter. In the following, different wind turbines and wind farms will be referred to as domains. The transferability of data-driven models to different domains is understood as domain generalization [9]. The research questions are composed of three different parts. First, it should be investigated how a data-driven model can be transferred to a different domain without changing the model. This research can also serve to define the limitations of a data-driven model, which is also a scientifically relevant topic.

- How can the generalization capability of data-driven models for predictive maintenance in wind turbines be improved through transfer learning?

Furthermore, the concept of data drift detection is investigated to assess when the accuracy of a data-driven model drops due to a domain shift and how to initiate countermeasures.
How can data drift detection be usefully applied in data-driven predictive maintenance for wind turbines to assess whether the data-driven model needs to be updated?

Finally, a possible reaction to the drop in accuracy of a data-driven model in the context of continuous learning is investigated to increase the robustness of a predictive maintenance tool in use.

How should a framework be designed and implemented to increase the robustness of predictive maintenance for wind turbines using continuous learning?

With the help of these defined research questions, methods can be conceptualised in the upcoming sections.

3. Planned Research Methods

To ensure an adequate depth for the research project, it is helpful to select a specific component of a wind turbine as the object to be studied for predictive maintenance. By means of this restriction, specific physical principles of this component can be utilized to ensure the interpretability of data-driven models. To obtain an overview which components are interesting for an investigation, Carroll et al. carried out a study in which different components of wind turbines were tested for their failure rate, repair time and the resulting costs for the replacement [10]. Regarding this, the pitch system, the generator, or the gearbox are interesting components as they represent a combination of high failure rate and high downtime.

Applying a data-driven predictive maintenance model to different wind turbines can lead to a domain shift. This can be manifested through different sensor technologies, degradation states of the components, environmental conditions and designs of wind turbines. Transfer learning methods can be used to counteract the decrease in model performance due to the domain shift. In this research, methods of transfer learning will be used to generate a weighting of the individual data points of the domains for a training process, with the help of which a higher domain generalization capability can be achieved.

If predictive maintenance tools are considered in usage, a change in the current data distribution may occur even after model training has been completed. The aim of the future research is the development of a data drift detection to register a domain shift that takes place during operation. In addition, it would be beneficial to see if a data drift detection can also be used to determine the type of the data drift. For example, whether the change in the data distribution can be differentiated into internal and external parameters of the wind turbine. That’s important, because not all changes in the data distributions necessarily result in an update of the model.

Due to a natural change in the data distribution during the operation of a wind turbine, the accuracy of the data-driven predictive maintenance model can decrease. In this case, continuous learning can be used to update the model and thus increase the accuracy again. The extent to which this methodology is suitable for the wind application is investigated in future research with the help of different datasets. The creation of a framework for automated model updating is also conceivable.

Different datasets can be used for future research. On the one hand, operating data for several wind turbines from different wind farms are available. Furthermore, test bench trials of various wind turbine components are accessible. Moreover, an investigation of the performance behaviour of the model informing a domain shift from test bench to real operation is promising. With enhanced expertise in this field, the test bench operation could be improved.

4. Expected Outcomes

Several points can be mentioned as expected outcomes of future research.

A methodology how data-driven predictive maintenance models can be transferred between different wind turbines or wind farms

A data drift detection that allows to detect the decrease of a data-driven model performance due to changes in the internal or external parameters of wind turbines

A framework for continuous learning of data-driven wind turbine predictive maintenance tools with the purpose of providing consistent models of high predictive accuracy
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Safety control through intelligent population-based structural health monitoring and transfer learning

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Keywords: Structural health monitoring, populations of structures, artificial intelligence, transfer learning, deep learning, wind turbines

1 Introduction

Structural Health Monitoring (SHM) is currently used in safety management and control of a wide range of structures, during and after their design lifespan, as an essential component of surveillance plans implemented by the managers of these structures. This is increasingly implemented in the wind generator industry, addressing one of the industry's main challenges: the lifetime of these types of structures and the need to extend it. The analysis of SHM data for structural condition characterization has been implemented based on sequences of computational learning techniques and artificial intelligence capable of learning and reproducing the behaviour and response to structural actions. However, unlike other application domains, the combination of actions, unique geometry, and physics of each structure has motivated the development of specific methodologies for structural condition characterization for each structure. Therefore, this PhD work aims to develop and implement standardized SHM techniques and procedures using deep artificial neural networks and transfer learning between wind turbines or between wind farms.

2 State of the art

A large set of structures, with a highly valuable social, economic, and environmental, are operated during and after their design lifespan with maintenance, preservation, and surveillance plans, thus ensuring safety and resource optimization \cite{1}. In the wind energy industry, which is rapidly growing and facing one of its biggest challenges, the lifetime assessment and extension of wind turbines \cite{2} is crucial and SHM is revealing itself increasingly necessary for its appropriate characterization \cite{1}. SHM has been narrowly defined as the set of disciplines addressing the development of damage identification techniques, but its scope is broader and encompasses safety control, rapid post-event assessment, and decision support in management and maintenance \cite{3,4}.

SHM methodologies are classified as \cite{1} inverse when they rely on fitting physical models to acquired data from real structures \cite{1,5}, or as direct when they are based on training data models (statistical or artificial intelligence) to extract information about the structural condition \cite{1,5,6}. Inverse methodologies allow for a more precise characterization of the structural condition but have the significant disadvantage of requiring specific (typically digital) physical models for each structure, which can be time-consuming, costly, and sometimes imprecise due to being an indeterminate problem \cite{1,5,6}. The direct methodologies provide a less precise characterization of the structural condition but work in real-time and rely on generic data models that are trained in an identical and automatic manner for any structure \cite{1,6}. Neither approach allows for the extraction of information from one structure, such as limit values or damage-response relationships, to be used for safety control of another structure \cite{7,8}. Direct methodologies are more widely used than inverse methodologies and are conceptually composed of three operations \cite{1} (feature extraction, structural response modelling, and condition classification), traditionally implemented separately using signal processing, data transformation, regression, and classification techniques \cite{1,6,9,10}.
The development and application of deep artificial neural networks have allowed for the standardization of SHM approaches by combining the three operations into unified models capable of learning and reproducing relationships within the data [8], [11]. Notable examples include convolutional networks [12], recurrent networks [13], autoencoders [14], [15], and deep knowledge networks [16].

Recently, direct SHM methodologies based on transfer learning have been developed, which not only standardize methods but also allow for the relationship of information extracted from different structures [8]. Initially implemented in machine condition monitoring, these methods are now being applied to infrastructure as well, serving as tools for implementing population-based SHM, aimed at leveraging the learning and reproduction of relationships observed among groups of structures [7], [17] – [21]. In this domain, feature-based methodologies [8], [22], are more commonly used, with adversarial generative networks [8], instance-based methods [23], and parameter adjustment-based approaches [8], [18] also being reported.

### 3 Installation of the SHM system in wind turbines

SHM systems are being installed and tested on wind turbines nearing the end of their lifespan at Ventient Energy portfolio. The continuous acquisition of vibrations, strains, and temperatures on the towers and wind turbine blades will provide a substantial dataset for the intended analyses and the development of methodologies proposed in this study. This instrumentation is expected to cover wind turbines with the same operational characteristics, allowing the application of the concept of population-based structural health monitoring.

### 4 Population-based prediction of operation and power

In this section of the work, the prediction of operations parameters based on actions, the prediction of actions based on actions and the prediction of operations parameters from actions and operation parameters will be made. In the end, a benchmark of actions, operation parameters and response predictions (single WT Vs. multi WT) will be made.

Power predictions based on deep neural networks, particularly Multi-Layer Perceptron, have already been performed, considering a set of input variable combinations and a few neurons in each hidden layer that results from multiplying a multiplicative index by the number of input variables in the corresponding case under analysis.

![Figure 4.1. Results of normalised MAE for each case of combination of input variables with a MLP neural network and for each one of the multiplicative indexes is showed using: (a) ReLu activation function and (b) tanh activation function.](image)
5 Future work

In the next steps, Population-based prediction of structural and mechanical responses will be made, with the prediction of the structural/mechanical responses based on actions and operation parameters and actions, the prediction of the structural/mechanical responses from structural/mechanical responses, and the prediction of the structural/mechanical responses from structural/mechanical responses and actions/operation parameters, with the benchmark of actions, operation parameters and response predictions (single WT Vs. multi WT). Also, will be development innovative and new methodologies to damage identification and lifetime assessment using population-based methods, considering identify real-time for single turbine and identify real-time for multi turbine.

The last step of this PhD’s work consists of its ultimate aim, which is the definition of an optimal wind-farm sensor layout, which, given the ability to correlate responses and operation between neighbouring turbines, and considering cost and accuracy / robustness, will allow for a widespread application of SHM, for lifetime assessment and damage identification purposes.

6 Acknowledgements

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7 References


Comparison of the dynamic behaviour of the tower of an onshore and an offshore wind turbine

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Keywords: dynamic behaviour, structural health monitoring, data normalization, influence of environmental and operating conditions

1 Introduction

Structural health monitoring is a method that monitors the state of a structure, like wind turbines based on damage sensitive features. In vibration-based monitoring, natural frequencies are often used as a damage-sensitive feature. The modal parameters are influenced by environmental and operating conditions (EOCs). For this reason, it currently takes about a year to learn the monitoring system. To shorten this time, it would be desirable to be able to transfer knowledge about the dynamic behaviour of one wind turbine (WT) to another. In cooperation with the Institute of Structural Analysis (Leibniz University Hanover), the environmental and operational influences, as well as the dynamic behaviour of an onshore WT were compared with an offshore WT as part of a student project. The aim of the comparison was to work out the possibilities and problems of transferring knowledge of the dynamic behaviour. The data was normalised using linear regression. In this abstract, only the changes in the natural frequencies (EF) due to the EOCs are considered.

The onshore WT has a capacity of 3.4 megawatts (MW). The turbine has a hybrid tower (hub height 122 m), with the lower 57 m being constructed with prestressed segmental concrete rings. The rest of the tower is made of steel tubes. The rated speed of the turbine is 14 rotations per minute (rpm) at a wind speed of 10 m/s. The offshore WT is part of the "Alpha Ventus" wind farm. The turbine is founded on a tripod and has a capacity of 5 MW. The hub height is 90 m (steel tower). The maximum rotor speed is 14.8 rpm at a nominal wind speed of 12.5 m/s.

2 Comparison of the dynamic behaviour

The EOCs onshore include wind direction, wind speed, outside temperature, power, pitch angle, rotor speed and nacelle position. Offshore, wave height, wave period, tide level and water temperature are added, so the influence of the EOCs offshore is more complex. The calculation of correlation coefficients for the operation of the WTs showed that wind speed, pitch angle and power had a large influence on the modal parameters for both WTs (Figure 1). The rotor speed had a relevant influence only for the onshore one. The outdoor/water temperature both had a minor influence. The wind direction and nacelle position are neglected in the data normalisation. The wave period showed a relevant influence on the EF. However, this effect could not be considered in the data normalisation because the data basis was too poor. Wave height and tide level could also be neglected. The subsequent data normalisation did not allow a general statement about the change in EF of the respective modes. In part, the EFs decreased due to the elimination of the EOCs and other EFs increased (Table 1). It was striking that the EF of the second pair of modes were most strongly affected (-1.47% onshore; 5.10% offshore). Furthermore, for almost all modes, the change in EF was greater in the FA direction than in the SS direction.
# 19th EAWE PhD Seminar on Wind Energy

6-8 September 2023
Hanover, Germany

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**Figure 1:** correlation coefficients EOCs and EF

**Table 1:** Change of EF through data normalisation

<table>
<thead>
<tr>
<th>Mode</th>
<th>before normalization</th>
<th>windspeed</th>
<th>+ power</th>
<th>+ rotor speed</th>
<th>+ Pitch angle</th>
<th>percentual change [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>onshore</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>f1</td>
<td>0.3073</td>
<td>0.308</td>
<td>0.3091</td>
<td>0.3098</td>
<td>0.309</td>
</tr>
<tr>
<td></td>
<td>f2</td>
<td>0.2969</td>
<td>0.2969</td>
<td>0.297</td>
<td>0.2971</td>
<td>0.2971</td>
</tr>
<tr>
<td>2</td>
<td>f3</td>
<td>1.4616</td>
<td>1.4516</td>
<td>1.4431</td>
<td>1.44</td>
<td>1.4404</td>
</tr>
<tr>
<td></td>
<td>f4</td>
<td>1.4731</td>
<td>1.4666</td>
<td>1.4595</td>
<td>1.4563</td>
<td>1.4559</td>
</tr>
<tr>
<td>3</td>
<td>f5</td>
<td>3.1468</td>
<td>3.1467</td>
<td>3.1496</td>
<td>3.1502</td>
<td>3.1498</td>
</tr>
<tr>
<td></td>
<td>f6</td>
<td>3.035</td>
<td>3.0348</td>
<td>3.0363</td>
<td>3.0368</td>
<td>3.0361</td>
</tr>
</tbody>
</table>

| **offshore** |                        |           |         |              |               |                       |
| 1             | f1                   | 0.3356    | 0.3355  | 0.3367       | 0.3367        | 0.3305                | **-1.5431**           |
|               | f2                   | 0.3306    | 0.3307  | 0.3314       | 0.3314        | 0.3304                | **-0.0605**           |
| 2             | f3                   | 1.4026    | 1.406   | 1.4067       | 1.4311        | 1.4378                | **2.4482**            |
|               | f4                   | 1.3576    | 1.3596  | 1.3877       | 1.4093        | 1.4305                | **5.0961**            |
| 3             | f5                   | 2.2669    | 2.2612  | 2.2501       | 2.2463        | 2.1891                | **-3.2936**           |
|               | f6                   | 2.3641    | 2.3637  | 2.3644       | 2.3644        | 2.3546                | **-0.4035**           |
3 Discussion

The comparison of the EOCs and the dynamic behaviour make it possible to determine similarities and differences between the WTs and to derive possibilities and problems for the transfer of knowledge. The wind speed had a decisive influence. However, it is not the mean wind speed of a location that is decisive here, but probably the turbulence intensity. The mean wind speed offshore was 1.5 m/s greater than onshore. Nevertheless, the influence of wind speed on EF was lower offshore than onshore. No information was available on turbulence at the sites. In general, however, turbulence is greater onshore [1]. Turbulence causes steady fluctuations in wind speed, which excite the wind turbines [2]. The turbulence of the wind speed cannot be measured, which is why a quantitative assessment of the influence of this parameter is not possible. Possibly, the influence of wind speed can be related to the classification of WTs into classes according to IEC 61400-1, which also considers the turbulence intensity of a site.

An influence of the power as a function of the rated power could not be proven. Since the power of a WT depends on the pitch angle, the wind speed and the high-speed number, it is not clarified whether the normalisation of the power e.g. takes the influence of the pitch angle into account twice when its influence is also eliminated individually. On the other hand, the power can also be seen as a superordinate parameter. The pitch angle showed correlation values of up to 0.6 for both WTs. The comparison of the EOCs showed that both turbines pitched up to an angle of 25° for power limitation. The pitch activity, which causes momentary disturbances of the thrust that excite the tower [3], was greater offshore. The offshore WT was operated at full load more often than the onshore WT due to the higher wind speed. The influence of pitch activity was greater for the dampers than for the EF. To quantify the influence, a finer subdivision of the operating classes must be made for data normalisation.

The influence of the rotor speed also depends on the operating range. Offshore, the turbine was often operated in the nominal rotor speed. Here, the distance to the 3P frequency is large. The onshore WT was often operated at lower rotor speeds in the partial load range. The distance to the 3P frequency is smaller here, which means that the tower excitation will be greater. The offshore WT showed an intersection of the 3P frequency with the EF of the first mode pair. This does not seem to have any influence on the correlation between rotor speed and modal parameters, as the WT is mainly operated at higher rotor speeds.

Wave height and wave period have different influences depending on the foundation of the WT. In the literature it was stated that the wave height has a significant influence on a monopile [4]. In the tripod structure studied here, the influence of wave height was small. The wave period can play a role in the reflection of the waves, e.g. within a jacket structure [5]. The tidal level should only have an influence from an average tidal range of more than 1m [6]. Furthermore, a different influence depending on the type of foundation can also be assumed here.

4 Conclusion

The results did not allow for precise specifications that a given EF will change by exactly one value related to one parameter. The formulation of trends and relevant parameters was possible as explained above. These findings can already shorten the learning process. The transfer of findings from one onshore WT to another onshore WT might be easier than to an offshore WT due to the similar EOCs. The fluctuating influences of the EOCs on the EF prove to be problematic when transferring knowledge. In addition, the influence of different foundation types must be investigated more closely, as further problems may arise here. The influences of soil conditions and surface relief have also not yet been clarified. However, it is also possible that no transfer of knowledge can take place here. Based on the results, there is a need for further research in the influence of turbulence intensity on the modal parameters. In addition, onshore and offshore WT should be compared with each other to further support the theses presented here. A finer subdivision of the data in the data normalisation as well as other methods for normalisation should be investigated. The influence/error of the linear regression method used here can be identified.

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References


Data Driven Infrastructure Planning for Offshore Wind Farms

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¹Keywords: LCoE, NPV, Bayesian Parameter Estimation, Maximum Likelihood Estimation, Posterior Expectation

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1 Introduction

With UK’s target of increasing offshore wind production to 50GW by 2030, it is becoming even more pressing to bring down the costs of large-scale offshore wind energy [1]. However, there are still several challenges that pertain in the field of operation and maintenance of offshore wind turbines. One such issue is the impact of the failures and repairs of the wind turbines on the overall cost estimation (e.g., in terms of Levelised Cost of Energy) at the beginning. The LCoE of energy systems is an important indicator of the cost-effectiveness of different energy sources.

Mathematically,

\[
\text{LCoE} = \frac{\text{NPV}_{\text{cost}}}{\text{NPV}_{\text{energy production}}} \tag{1}
\]

Net Present Value (NPV) here takes a discounted cash flow approach for evaluating the time value of money. NPV can be calculated as:

\[
\text{NPV}_{\text{cost}} = \sum_{t=0}^{T} \frac{\text{OPEX}_t + \text{CAPEX}_t}{(1 + r)^t} \tag{2}
\]

where OPEXt and CAPEXt are the operational and capital expenditure costs incurred at time t and T is the total lifetime of the project and r is the discount rate. OPEX itself can be majorly broken down to variable OPEX (VarOPEX) and fixed OPEX (FixOPEX) [2]. The VarOPEX component is a function of failure/repair instances of the turbine (and the farm as a whole). Contractual income, loan repayment and operational expenditure are the main contributing factors in the VarOPEX. Contractual income relies on the availability of the offshore wind farm apart from the base revenue [3]. Expected Energy Not Served (EENS) is an important metric for grid operators as well because it helps them to identify and prioritize investments in reliability improvements. EENS is the expected amount of energy that is not supplied to the consumers by the energy systems during the considered time due to failures and system shortages [4]. It depends on the reliability standards and availability of the wind turbines. Unexpected failures can cause great losses as it becomes difficult to arrange for the alternative source of electricity.
The ability to predict the failures and repairs will help determine the impact of the power outages on the consumers as well as providers [5].

There are currently various tools available for the determination of the unavailability for offshore wind farms in the initial stages. The models utilised in these tools are tailored towards the simplifying assumptions. They consider that all the turbine components are repairable and the time to these failures and repairs are exponentially distributed. This may lead to sub-optimal results. Bains et al. [6] discusses the difference between the NPV evaluated theoretically and practically of a 1.2 GW project. The net present value of the project was 64.2 % lower when using operational experience to estimate cable failure rates, compared to using literature inputs. This paper also points to severe uncertainties that are faced during the evaluation of NPV and the need for advanced statistical techniques to help in economic evaluation.

This research aims to improve these uncertainty calculations. In the long term, this research can lead to more reliable maintenance schedules, resulting in cost reduction and better decision-making for investors. In the short term, it can aid in the planning and execution of maintenance activities. Consequently, this project aims to improve the estimation and uncertainty quantification of the costs at the beginning of construction of the wind farm. To this end, this paper aims to analyse the SCADA data pertaining to a fleet of wind turbines taken over several years, and to frame a statistical model that more accurately models failures and repair times of wind turbines.

2 Research Question

This research aims to answer the following questions:

- How can failure and repair processes be modeled more accurately using a statistical model taking into consideration any uncertainties?
- Is there any correlation between the failure instances and the environmental factors of a wind turbine? If yes, how can it be modelled?
- How can the data be used to optimize the installation and operation and maintenance procedure?

3 Methodology

This project involves preparing a statistical model to make predictive maintenance more accurate by generalising models for failure and repair processes in repairable components of an offshore wind energy system. The methodology used in this paper is as follows:

- DATA: SCADA data, metmast data and turbine logs are used for this project. The SCADA data consists of the SCADA signals like generator RPM, generator bearing temperature, rotor rpm in latest average period, total active power, etc. Metmast data consists of wind speed, wind direction, ambient temperature etc.

- PROCESSING: This data is processed according to the wind turbine logs to determine the periods of availability and unavailability. The values of interest are time to repair and time to failure that are calculated once we know the duration of availability of the wind turbine.

- MODEL: A new statistical model characterising the times to failure for each turbine is prepared to understand the impact of the environment on the the wind turbines’ failures. The parameter evaluation for this model (e.g., failure rate, mean time to failure) is carried out by using maximum likelihood estimation and bayesian inference.

Let $T_1, T_2, \ldots, T_n$ be random variables representing the times to failure of a wind turbine, each distributed according to a density $P(t \mid \theta)$, where $\theta$ is an unknown model parameter. The
prior density function of the model parameter $\theta$ is denoted by $P(\theta)$ and the posterior density as $P(\theta \mid t_1 \ldots t_n)$. To estimate the parameter $\theta$, Maximum Likelihood Estimation (MLE) and Posterior expectation method for Bayesian Parameter Estimation are used.

In MLE, the log likelihood function $\ell(\theta)$ is maximized to obtain a value of $\theta$, where

$$
\ell(\theta) = \log L(\theta) = \sum_{i=1}^{n} \log P(t_i \mid \theta)
$$

(3)

$$
\hat{\theta} = \arg \max_{\theta} \ell(\theta)
$$

(4)

i.e. finding the value of $\theta$ that maximises the log function.

In Bayesian analysis, we may use the posterior expectation of $\theta$ as an estimate:

$$
\hat{\theta} = \int \theta P(\theta \mid t_1 \ldots t_n) d\theta
$$

(5)

where the posterior density is determined through Bayes’s theorem [7]:

$$
P(\theta \mid t_1 \ldots t_n) \propto P(\theta) \prod_{i=1}^{n} P(t_i \mid \theta)
$$

(6)

The data used initially was obtained from the EDP Renewables [8], which opened the SCADA and log data from one of the wind farm containing 16 wind turbines each of 2MW. The data comprises 5 wind turbines. The available data is processed to obtain the relationship between the environmental conditions and the conditions of the wind turbine such as rotor speed, rotor temperature, and net power production. The power curve of the wind turbines is also provided on the website. The wind speed vs. power curve is plotted using the SCADA data.

4 Results

As seen in figure 1, the initial results indicate a direct proportionality between the rotor temperature and power production. Different colours represent different phases of the generator. The power curve obtained by plotting the wind speed vs power is shown in figure 2. The failure instances are represented in red whereas low wind speed areas are shown in blue. These low wind speed instances will be further used for extracting a time series data of availability and unavailability of the wind turbines. This data will then be used to calculate times to failure and times to repair of the wind turbine. These times to failure and times to repair will be used as an input for the parameter estimation of a probability density function as stated above in the methodology.
5 Conclusion

This research focuses on determining a more generalised statistical model pertaining to times to failure (and repair) in offshore wind turbines, which in turn could lead to better estimations of impacts of failure/repairs on measures such as Expected Energy Not Served or LCoE in offshore wind farms. Moreover, these models are used to simulate the failures and repairs of the wind turbine components and to determine any correlations between the failures and repairs and their wider environmental conditions. This newly developed model will then be used to simulate an exemplar wind farm with variety of options for transmission.

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[1] S. Bourne. Can the UK achieve its 50 GW offshore wind target by 2030?
Session 4.4
08.09.2023 - 10:30
Building 3702, Room 031

- Fernandes De Oliveira Junior Adelmo: Improving Acoustic Emission Measurement Reliability in Remote Sites by Using a Mobile Verification Setup
- Rodrigues Faria Bruno: Lifetime counting of a wind turbine tower based on fatigue accumulation
- Xu Ronghua: Energy spectral analysis of wire breaks in post-tensioned tendons for wind turbines
Improving Acoustic Emission Measurement Reliability in Remote Sites by Using a Mobile Verification Setup

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\textit{Keywords}: Acoustic Emission, Verification, Sensor, Reliability

1. Introduction

Acoustic emission testing is a non-destructive technique that is gaining more and more relevance in the wind industry over the past few years. Acoustic emission testing can for example be used to detect transient events like cracks on monopiles and tower [5], while the analysis of continuous signals exemplary can help to assess ice formation on blades [1] and the severity of the wear state of gearboxes [3]. To perform reliable measurements, the sensors must be calibrated, and any mistrust should rely on the sensor functionality. One of the objectives of our current research is to construct a mobile verification set-up for acoustic emission sensors that can be used in the field. This work will present a preliminary verification setup that works on a workbench with the purpose to demonstrate the concept and enter standardization.

2. Experimental Setup

Figure 1 presents a preliminary verification setup composed of a propagation medium made of an aluminium plate, two acoustic emission conical sensors (transmitter and receiver), one acoustic emission sensor to be verified, a function generator and an acoustic emission DAQ system. The propagation medium carries the acoustic emission waves. Since the properties of the propagation medium (geometry, material, and shape) and the acoustic coupling between the sensor and propagation medium have an influence on the measurement with an acoustic emission sensor [2][6], a comparable setup for verification and application setup is generally beneficial.

The applied acoustic emission conical sensor is described in [6] and [7] in detail. It is composed of a brass back mass and a conical PZT-5A ceramic as sensitive element. The transmitter receives 10 trigger sine signals from the function generator model 32210A supplied by Agilent, with frequency of 150kHz, amplitude 10V, and converts the electric signal into an elastic wave in the propagation medium. The receiver and the acoustic emission sensor to be verified detect the acoustic wave and the acoustic emission DAQ system, model board PCI-2, supplied by Mistras, is responsible for the acquisition of the AE sensor signal.

3. Verification Protocol

The verification protocol consists of two steps. The first step is to perform a setup auto-check. In this step the transmitter generates a pulse. This pulse is measured by the receiver only. Figure 2(a) (line in blue) presents a typical signal time-series of that kind.

Then, the signals are converted to the frequency domain and an averaged frequency spectrum is obtained. Figure 2(b) (line in blue) presents a typical signal of the receiver in the frequency domain. This averaged frequency is compared with a previous reference measurement by the means of equations 1, 2 and 3, and the procedure found in [4]. If the significance value stays within acceptable limits, the setup auto-check is approved, and the actual sensor verification step follows.
Figure 1: Preliminary verification setup composed of an aluminium plate as propagation medium, two acoustic emission conical sensors (transmitter and receiver) and one acoustic emission sensor to be verified.

For this task, another 10 pulses are generated and measured by the acoustic emission sensor to be verified in a similar way as in the previous step. The acoustic emission sensor to be verified is approved, if the significance value stays below a certain limit. Figure 2(a) (line in orange) presents a typical signal time-series of wide-band differential acoustic emission sensor model WD 100-900 kHz supplied by Mistras. Figure 2(b) (line in orange) presents the same signal in the frequency domain.

\[
\frac{\int_f ^{f_2} \tilde{U}^2(f)df}{\int_f ^{f_{\text{end}}} \tilde{U}^2(f)df} \quad (1)
\]

\[
\langle f_{\text{peak}} \rangle = \sqrt{\int_f ^{f_{\text{peak}}} \frac{f \cdot \tilde{U}(f)df}{\int_f ^{f_{\text{end}}} \tilde{U}(f)df}} \quad (2)
\]

\[
\text{dB} = 20 \log \left( \frac{U_{\text{max}}}{1 \mu \text{V}} \right) - dB_{\text{preamplifier}} \quad (3)
\]

4. Discussions

It is important to emphasise that this setup is a first step with the objective to prove the concept, and to investigate the possibility to use a small aluminium plate as propagation medium. The final setup must be adequate to be used...
Considering the propagation medium, low lateral dimensions of the propagation medium can cause several problems caused by the fact that the reflect waves from the edges can interfere with the primary wave front. This can lead to problems, especially if the edges of the propagation medium are damaged. In this case the reflected wave pattern can change considerably in a way that the previous reference signals can not be used to auto-check the setup. Figures 2(a) presents the signal time-series of the receiver and the sensor to be verified, respectively. After approximately 60µs the sensors detect the reflected waves from the edges of the aluminium plate. Tables 1 and 2 present the signal parameters evaluations of the setup auto check and the acoustic emission sensor, respectively. As can be noticed, the significance values stay below the limits for both cases, therefore, the setup and acoustic emission sensor were approved.

Finally, another aspect to be mentioned is that the setup must be also able to receive a broad variety of acoustic emission sensors which needs to be considered in the concepts for the coupling of the sensors to be verified to the propagation medium.
5. Future Works

As mentioned in the previous section, the setup needs further investigations to confirm whether such a small aluminium plate is adequate to capture all the features to proper evaluate the various acoustic emission sensors. The setup itself must be modified to be capable of verifying a broad range of acoustic emission sensor types and to be robust enough to operate in the field. This is aimed to be investigated in environmental tests in a climate chamber to simulated temperature changes and humidity. Additionally, vibration and shock resistance tests are required. Another aspect to be investigated is the repeatability of the verification setup and its tolerance to human operation.

6. Conclusion

This paper has shown a concept of wave-based verification setup for acoustic emission sensors that works on a workbench. The criteria to approve a sensor are based on significance values of the signal in the frequency domain. More investigations are required to prove that such small aluminium plate can be used as propagation medium. In addition, the design must be improved in order to be capable to operate in the field. In that sense, a robust version of the receiver and transmitter was discussed. This new design has shown a reduced sensitivity both in the frequency and time domain, however it is more adequate to operate in the field.

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References


Introduction

The use of continuous structural health monitoring (SHM) systems has become increasingly important in recent years for assessing the condition of infrastructures such as offshore wind turbines (OWTs) [1]. The method provides a continuous assessment and is a valuable complement to conventional on-site inspections and as-built data analysis [2–5]. In particular, strain-based measurement using strain gauges (SGs) is important because changes in the condition of a structure are primarily indicated by relative displacements of its components [6–8]. These sensors can be used, for example, to monitor the local damage-sensitive areas of the structure, such as, e.g., tower structure joints. At the same time, in view of the increasing digitalisation, the digital twin is being researched in the construction industry [9]. The digital twin is essentially based on linking real subcomponents of the building with digital representatives and must represent the real building as accurately as possible [10]. The information required for this must be obtained through monitoring systems that ensure a lifelong link between the real and virtual systems. The problem is that for large structures the changes in state due to ageing are very small [11]. However, the measurement system is also subject to initial measurement uncertainties, so that it is often not possible to distinguish between measurement errors and changes in the condition of the structure [12]. In addition, the behaviour of the measurement system changes with time because it is not the structure that ages, but the measurement system itself. Therefore, the aim of this work is to determine how to distinguish between sensor degradation and building degradation. A correlation analysis should make it possible to distinguish between both.

2 Test setup and simulated aging effects

To detect sensor degradation, this paper uses the sensor type Strain Gauge (SG), which is often used in structural monitoring. The advantage of using SGs is that the individual components of the measurement chain can be assembled according to individual needs. In this context, this means applying partial SGs to the specimen unprotected from external influences. This makes it possible to visualize ageing phenomena in sensors more quickly. We decided to do this because it is not the ideal configuration of the measuring points that is important, but the description of the method of sensor degradation. Otherwise, months or even years would be required to detect potential ageing phenomena in measurement systems. The test setup used is shown in Figure 1.

![Figure 1: Test setup for the investigation of sensor degradation in strain gauges (SGs) with the use of a displacement-controlled load using laser triangulation sensor (LTS); left: realized test setup, right: idealized static system.](image-url)
The left figure shows the realized test setup, the right figure visualizes the idealized static system. The test setup consists of a base plate with an upstand made of the material Alloy 36 fixed by screws. Alloy 36 is a nickel-iron alloy with low thermal expansion. The coefficient of thermal expansion is calculated to be approx. 
\[ \alpha_{T, \text{Alloy 36}} = 0.50 \cdot 10^{-6} \text{ /K} \] for the used temperature range of \( T = -10^\circ \text{C} \ldots + 50^\circ \text{C} \) and is therefore almost smaller by a factor of 10 than for steel (\( \alpha_{T, \text{Steel}} = 13.0 \cdot 10^{-6} \text{ /K} \)).

The sample with the SG's applied is installed in the test setup to create the static system shown in Figure 1 on the right. At each quarter position, 3 SGs are applied to the specimen to measure the strain as the specimen deforms. Using the general stress equation, this 4-point bend test can be used to compare the theoretical strain to be measured with the actual strain, and the magnitude of the measured quantity can be made plausible. For example, if we look at the left side specimen (left quarter position), we see that two of the three SGs are unprotected, while one SG is protected. In this way, we ensure an unaged measurement point that serves as a reference for detecting sensor degradation. In the next step of the experiment, the sample is loaded in a displacement-controlled manner by applying a deflection at the center of the sample field via wing nuts. The deflection is measured using high-precision laser triangulation sensors (LTS), which have a higher accuracy than the SGs and are therefore suitable for monitoring the test performance. A reference measurement is made at the beginning of the test period. Comparison measurements are then performed after each aging phase. Both measurements are performed identically by applying a deflection \( w = [0.0; 0.5; 1.0; 1.5; 2.0; 2.5; 3.0] \text{ mm} \) at 20 \( ^\circ \text{C} \) and 50 % RH and measuring the strain of the SGs. Thus, we have defined all controllable boundary conditions so that changes in the measured signal indicate aging.

The aging phenomena for the measurement system are simulated by varying the temperature and humidity in a climate chamber. The temperature and humidity cycles are shown in Figure 2.

Temperatures and humidity can be divided into four phases. The actual aging process of the measurement system does not occur as a result of changes in temperature, but as a result of changes in humidity. After passing through the four aging phases, a mechanical stress measurement is performed to detect changes in the behavior of the measurement system.

### 3 Correlation Analysis for Sensor Degradation Detection

In this section, we analyze the acquired measurement data. For this purpose, we have plotted the raw data over time in the left sub-figure of Figure 3. In this diagram, we can see the measured values of SG 1 and SG 5 and recognize that at the beginning of the measurement (Day 0), the measured value difference is relatively small, while it increases over time. The unprotected SG 5 shows a drift in the measured values and a clear time-variant behavior, while the protected SG 1 provides reproducible measurements, i.e. does not show any drift in the measured values. In addition, the red box shows an example of how both SGs react to changing environmental conditions (temperature and humidity). Again, SG 5 shows more significant changes in the measurement signal than SG 1 due to the measurement point protection. The red dashed lines show the mechanically induced strains during the test. At these time points, the sample was deflected as described in section 2. Day 0, Day 6 and Day 23 are used for evaluation.
The right subfigure of Figure 3 shows the result of the correlation analysis between SG 1 and SG 5. While the blue line represents the reference of the test to day 0, the orange and green lines show a clear shift on the y-axis. With this correlation analysis it is possible to detect sensor degradation in the SHM system. Thus, it can be reliably said that there is no damage to the structure, but there is damage to the SHM system.

In order to determine which of these sensors (SG 1 or SG 5) is subject to aging in the next step, the raw data signal (Figure 3, left subfigure) can be used for qualitative evaluation. For the quantitative evaluation, the autocorrelation analysis should be performed according to the scheme in Figure 3, right subfigure. In this case, the autocorrelation between SG 1 at day 0 and SG 1 at day 6 or 23 is evaluated.

<table>
<thead>
<tr>
<th>Day 0</th>
<th>Day 6</th>
<th>Day 23</th>
</tr>
</thead>
<tbody>
<tr>
<td>SG 1</td>
<td>SG 5</td>
<td>SG 1</td>
</tr>
<tr>
<td>( \gamma_0 ) in ( \mu m/m )</td>
<td>-738.79</td>
<td>-440.30</td>
</tr>
<tr>
<td>( m )</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>( \sigma ) in ( \mu m/m )</td>
<td>2.43</td>
<td>2.43</td>
</tr>
</tbody>
</table>

We see that SG 1 deviates only -0.2% and -0.4% from the reference value after day 6 and day 23, respectively, while SG 5 deviates significantly from the reference value with +144% and +142%. This shows that the unprotected SG 5 is subject to sensor degradation and should be replaced in practice. The slope of the autocorrelation regression and the standard deviation hardly changed during the measurements, so they will not be discussed further in this work.

4 Conclusion and Outlook

In this paper, we have presented a redundancy approach for robust SHM systems. This approach considers hardware redundancy, i.e., a redundant number of sensors measuring the same physical quantity in close vicinity to the component to be monitored. For this purpose, we used SGs and subjected them to ageing through temperature and relative humidity cycles. At different times, we analysed the correlation between two SGs and the autocorrelation of each SG. With this study, we were able to show that the presented hardware redundancy approach provides a robust method for detecting sensor degradation. In future studies, we will perform this investigation over a longer period of time and analyse whether not only a measurement drift, but also a change in...
the slope of the regression coefficients or a change in the standard deviation occurs. Both are also indicators of sensor degradation.

Acknowledgements

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References

Lifetime counting of a wind turbine tower based on fatigue accumulation

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Keywords: Fatigue counting, Damage accumulation, Strain gauges, Yaw sweeps, Rainflow counting

1 Abstract

The study focuses on developing a local fatigue counting approach for wind turbines to calculate consumed lifetime of the tower. The study aims to address challenges associated with current steel structures fatigue assessment techniques. First, addressing the reliability of strain gauges for long-term operation by applying repetitive calibration verifications at idling operations where the turbine linearly yaw while perceiving low wind speeds, so called yaw sweeps routines. Secondly, calculating the counted fatigue lifetime by summing 10-minutes tower damages and their linear accumulation, based on Palmgren-Miner rule, from the V52 research turbine at the DTU Risø Campus using 5 years of measurement data.

2 Introduction

Whether life extension strategies will be a common goal in the near future by the wind energy industry, consumed lifetime estimations of wind turbines’ main structures should be pursued in a reliable and deterministic way. The IEC 61400-1 standard proposes a design lifetime of 20 years for onshore wind turbines.

In this matter, the focus of the given research on the tower is justified by the fact that lifetime of the tower might represent a limiting feature in wind farms life extension strategies, as the first are not easily replaceable structures and are often site-specific, differently from general rotor-nacelle designs for reference operation classes. Damage estimations of the tower are valuable to maximize the life operation of the wind turbine [1]. A next step would be not only to estimate but to extrapolate damage [2].

However, taking one step backwards, the deterministic fatigue assessment of the tower relies on long-term high frequency strain measuring devices. Strain gauges are widely used for this propose in SHM (Structural Health Monitoring) campaigns, with the drawback of showing degradation over time, generating zero drifted signals and being temperature sensitive [3, 4]. Efforts needs to be taken to validate the reliability of strain gauges for long time-series measurements before fatigue damage estimations can be done.

In this study, results from the investigation of a 850 kW V52 Research wind turbine located at DTU Risø Campus in Denmark and with a 44 m hub height will be presented. A database of approximately 5 years (from January 2018 to May 2023) was available, including 50 Hz tower bottom full-bridge strain gauge signals denoted MxB and MyTB with 90° angular shift on the inside of the tower bottom.

3 Methodology

In order to validate the reliability of the V52 tower bottom strain gauges, a yaw sweep re-calibration procedure recommended by IEC 61400-13 [5] was followed. A Python routine was developed to identify such specific idling operations, where the controller linearly yaw the wind turbine so to detwist its power cable. During a yaw sweep, low wind speeds are perceived and the most significant contribution for the bending moment is the rotor overhang misalignment, which should be constant over time for different yaw sweeps. Conclusively, two relevant parameters,
the offset ($M_{\text{offset}}$) and the amplitude ($M_{\text{ampl}}$) of the bending time-series during a yaw sweep (e.g. $M_{\text{TB yaw sweep}}$ see Figure 1) can be evaluated as shown in Equation 1. It is worth mentioning that each sensor output ($M_{\text{TB}}$ and $M_{\text{MyTB}}$) is a composition of 4 strain gauges connected in a full-bridge layout (diametrically opposed pairs), in which temperature effects should be compensated. The final measurement is only based on bending contributions, static compression from the turbine weight is not included.

$$M_{\text{TB yaw sweep}}(\gamma) = M_{\text{ampl}} \cdot \sin(\gamma(t) + \phi) + M_{\text{offset}}$$

where the $M_{\text{ampl}}$ represent the rotor overhang moment and the $M_{\text{offset}}$ represent the necessary shift to the curve to achieve zero bending moment when the rotor is perpendicular to the sensor. The yaw angle $\gamma(t)$ will be linearly dependent of time ($t$) as the yaw speed ($\frac{2\pi}{T}$) is constant during the yaw sweep. In addition, $T$ is the yaw sweep period (which was known to be around 14 minutes) and the phase $\phi$ should allow the comparison between the $M_{\text{TB}}$ and $M_{\text{MyTB}}$ radial sensors’ position ($6^\circ$ difference).

Once the strain recordings are verified, consumed fatigue lifetime of the wind turbine tower could be evaluated through linear fatigue damage accumulation. The translation between tower bottom bending moment ($M_b$) to stress ($\sigma_b$) was based on the cross section and its correspondent second moment of area ($W$).

$$\sigma_b(\theta) = \frac{\pm M_b(\theta) \cdot d}{W}$$

where $M_b(\theta)$ is the bending moment of a given radial position $\theta$ (North = $0^\circ$) retrieved from contributions from $M_{\text{TB}}$ and $M_{\text{MyTB}}$, as shown in Equation 3, $\sigma_b(\theta)$ the stress resultant from the bending moment, $W$ is the second moment of area, $D$ is the outer and $d$ the inner diameter.

The high frequency stresses have been rainflow counted, according to ASTM E1049-85, and 10-minutes damages have been generated for the 5 years time period of the measurements. The mean stresses were not included in the rainflow counting routine, only the stress ranges, which neglect possible $M_{\text{offset}}$ variability. The correspondent two-slope stress-cycles (SN) curve for the V52 tower material was selected from the DNVGL-RP-C203 [6], category "D" (S355 - butt weld) in air, as shown in Figure 3. Based on Palmgren-Miner rule (see Equation 4), the 10-minutes damages have been summed to estimate the fatigue damage on points of the tower bottom and at along and crosswind directions, so called fore-aft and side-side, to identify general damage trends.

$$D = \sum_{i} \sum_{j} \frac{n_{ij}}{N_{\max ij}}$$

where $D$ is accumulated damage, $n_{ij}$ and $N_{\max ij}$ are counted cycles and cycles to failure. Last two are dependent on $i$ as the bin stress range (a number of 100 bins is recommended by [5]) and $j$ as the 10-minutes binned damage.

### 4 Results

#### 4.1 Strain gauges verification

For the 5 year measurement period, 66 yaw sweeps were identified. Figure 1 exemplifies the yaw angle down-sampled to 1-minute period during a typical yaw sweep and the bottom tower bending moment.

![Figure 1: Yaw sweep operation identified on May 5, 2018 at 8h40. The figure show the 50 Hz raw bending moment (black), the fitted sinusoidal function $M_{\text{TB yaw sweep}}$ (blue) and the 1-minute yaw angle (red) for around one and a half yaw sweep.](image-url)
The calibration factors proposed for MxTB and MyTB are presented in Figure 2. The rotor overhang moment $M_{ampl}$, or only overhang moment, over time had a standard deviation of 3.59 kNm for MxTB (c) and 5.43 kNm for MyTB (d), normalizing based on their means, resulting in 1.43% and 2.12% error respectively, which is relatively small, but correction schemes could be considered.

![Figure 2: Strain gauge offset and overhang moment (amplitude) for different yaw sweeps. Out of the 66 operations, 40 for MxTB and 46 for MyTB are included in the plot as those matched R-Squared > 0.95 for the fitting routine.](image)

### 4.2 Bottom tower damage

Figure 3 shows a 10-minutes damage from the fore-aft bending rainflow histogram counted cycles and bin damages depending on the stress amplitude range representing a high damage case. The bottom tower consumed fatigue lifetime is presented in Figure 4 for 6 different $\theta$ values. It is possible to identify almost a linear trend for all $\theta$ and fore-aft and side-side motions. However, steeper damage increments are observed locally.

![Figure 3: Rainflow histogram of a fore-aft 10-minutes damage on April 12, 2018, 11h20 (blue bars). In addition, the damage accumulated to each bin (red markers), which is related to the SN curve inserted chart.](image)

![Figure 4: Tower bottom consumed fatigue life based on 10min-damage. Besides 6 equally spaced angular positions ($\theta$), along-wind (fore-aft) and cross-wind (side-side) artificial damages are included. An availability of 97.6% was obtained.](image)
5 Discussion

The calibration factors over around 5 years of data have shown a low zero drift compromise of the strain gauges recordings. The variability of both offset and amplitude for both sensors might be explained by a positive correlation of those parameters to the mean wind speed. Higher mean wind speed also led to poorer fitting performances due to wind induced harmonics. Interestingly, the $M_{ampl}$ for MyTB results had quite significant correlation with the measured temperature.

The Risø low mean wind speed of 5.4m/s might justify the very low damage accumulation of the most critical tower position over the 5 years (0.12% leading to an expected lifetime of around 4000 years), knowing that the V52 is a class IA wind turbine. For the sake of comparison, using the 10-minutes seed presented in Figure 3, that had a mean wind speed of 13.5m/s, the simplest damage extrapolation would lead to a 30 years fatigue lifetime. The disregard of the second slope of the SN curve, also led to a 4 times reduction in the initial expected lifetime (comparing only 2018 results). Finally, the average daily damage in a mean wind speed bin of 10m/s was of $0.35 \times 10^{-5}$ throughout the 5 years, which is close to the order of magnitude of the $2.08 \times 10^{-5}$ daily average fatigue damage found for a V90 [1].

The 5 years consumed fatigue lifetime of the tower bottom showed a great difference between fore-aft and side-side damage accumulations. And higher damage’s trends can be observed at each years’ beginnings, due to higher wind speeds at winter season.

6 Conclusion

Counting fatigue can be a challenging task as it is mainly based on measurements, but it can lead to valuable deterministic damage estimations of wind turbine towers. The strain gauges were found to be fairly reliable for the 5 years of operations, as no significant zero drift was observed. However, a methodology on how to re-calibrate the devices in a “worst case” scenario should be developed. The reliability and uncertainty of capture matrices for damage extrapolation should be studied based on fine references [1, 2] together with understanding the reliability of different rainflow counting methods and their tuning (bin size, time range, etc) for damage accumulation [7].

7 Acknowledgements

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References


Energy spectral analysis of wire breaks in post-tensioned tendons for wind turbines

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Keywords: Wind turbine; Post-tensioning; Wire break; Acoustic emission; Spectral analysis

1 Introduction

In 2021, onshore wind turbines in Germany contributed over 15\% to the country’s total gross electricity generation, making them one of the most essential components of Germany’s clean energy transition [1]. The efficiency of power generation in wind turbines is greatly influenced by the hub height, as it affects the wind speed at the rotor blades. Generally, a higher hub height results in increased economic efficiency, with a rule of thumb suggesting a yield increase of up to 1\% per meter of hub height [2]. To achieve greater hub heights, the use of prefabricated hybrid towers has gained popularity in recent years [3]. These towers combine a prestressed concrete tower with an attached steel tube tower, offering modularity and cost-efficiency in transportation and assembly. The concrete tower is constructed using precast segments and is externally post-tensioned to ensure structural stability. Maintaining the proper condition of the tendons is crucial for tower safety and performance. Conventional methods like visual inspection and magnetic stray field measurement [4] are often time-consuming and limited due to restricted access. To address these limitations, alternative non-destructive testing (NDT) techniques based on structure-borne sound are being explored. Acoustic emission (AE) testing as a promising NDT technique involves investigating acoustic signals emitted by the structure when subjected to stress or deformation. It serves as a valuable tool for the detection of structural changes such as crack formation and wire breaks. Extensive research has been dedicated to AE analysis of tendon wire breaks. [5] presents a comprehensive AE feature analysis of wire breaks in several prestressed bridge girders. In [6], the acoustic wave propagation due to tendon wire breaks is investigated through laboratory experiments as well as long-term AE monitoring of concrete structures in situ. Also, wire break-like signals generated using a rebound hammer are detected and analyzed in [7]. This study focuses on the spectral analysis of wire breaks in externally post-tensioned tendons, commonly employed in hybrid wind turbine towers. The wire breaks are conducted under controlled boundary conditions of a laboratory setting. All wire break events were recorded with conventional AE sensors with a main sensitivity between 25 and 80 kHz.

2 Methodology

Acoustic emission (AE) refers to the release of elastic waves resulting from structural alterations within a material subjected to stress. Figure 1 illustrates the principle of AE measurements, which involves the propagation of emitted waves through the material and their detection using appropriate measuring instruments. Piezoelectric sensors are commonly employed to acquire AE signals by converting the detected mechanical values (e.g. velocity or acceleration) into electrical voltages. Subsequently, through processes such as amplification, filtering, and digitization the analog signals are transformed into digital format and stored for further analysis. AE analysis can be classified into two categories: parameter-based and signal-based approaches, depending on the storage format, as depicted in figure 1. In parameter-based analysis, AE parameters such as peak amplitude or signal energy are utilized to evaluate the characteristics associated with the observed structural changes. In contrast, signal-based analysis involves the use of the entire waveform to interpret and classify fracture mechanics. Several investigation
methods, originally developed in seismology, have been successfully applied in material research \[8\] and condition monitoring \[9\], including techniques such as magnitude squared coherence (MSC) for quantifying signal similarity and moment tensor inversion (MTI) for determining fracture types.

![Figure 1: Principle of measurement and analysis of acoustic signals](image)

This study presents a methodology for signal-based energy spectral analysis of tendon wire breaks. The discrete Fourier transform (DFT) is employed to extract the energy spectrum from the recorded signals \(\text{Rec}(t)\). The DFT operates by converting a discrete-time sequence of signal samples into its frequency representation. The transformed signal in the frequency domain \(\text{Rec}(f)\) can be expressed as follows:

\[
\text{Rec}(f) = \mathcal{F}\{\text{Rec}(t)\} = \sum_{n=0}^{N-1} \text{Rec}(n \cdot \Delta t) \cdot e^{-2\pi jmf} \Delta t
\]

where \(N\) represents the sum of the samples and \(\Delta t\) denotes the sampling interval. In signal processing, the energy of a discrete-time signal is defined as the sum of the squared magnitude of the signal’s samples in the time domain. Notably, Parseval’s theorem establishes a fundamental relationship between the energy of a signal and its spectral energy density. According to this theorem, the signal’s total energy is equivalent to the sum of the energy contributions across all frequency components present in its spectrum. Consequently, the energy \(E(f)\) of a discrete signal at a specific point can be quantified as the squared magnitude of the corresponding frequency component in the signal’s spectrum, multiplied by the sampling interval and scaled by the factor \(1/N\):

\[
E(f) = \frac{1}{N} |\text{Rec}(f)|^2 \cdot \Delta t = \frac{1}{N} \sum_{n=0}^{N-1} \text{Rec}(n \cdot \Delta t) \cdot e^{-2\pi jmf} \Delta t^2 \cdot \Delta t
\]

where \(f = \frac{m}{N \cdot \Delta t}\) (\(m = 0, 1, 2, \ldots, N - 1\))

3 Experiments

To conduct the experiments on tendon wire breaks, a specially designed test rig measuring 12 m x 4 m was constructed. The test frame consisted of two longitudinal and two transverse reinforced concrete (RC) beams, providing a robust structural frame. Four SUSPA EX30 type tendons, each comprising 30 parallel wires, were individually post-tensioned to 700 kN. A steel plate measuring 4 m x 0.85 m x 0.05 m was affixed to one of the transverse RC beams, with stressing anchors located on it, replicating the transition section of a real hybrid tower (figure 2a). At the opposite end, each tendon was mounted to a specific anchor set supplied by Max Bögl, creating fixed anchors on this side (figure 2b). These fixed anchors were integrated into the RC beam, emulating the configuration commonly observed in the concrete foundation of a real hybrid tower, where fixed tendon anchors are typically embedded. The experiment setup thus reproduces key aspects of a hybrid tower system, enabling the investigation and analysis of tendon wire breaks under controlled laboratory conditions that closely resemble real-world scenarios.

The experiments involve severing 30 wires in each of four post-tensioned tendons, resulting in 120 wire breaks in total. To capture the AE signals produced by each wire break, 24 piezoelectric sensors were installed on the test
Figure 2: (a) Stressing anchors of the tendons; (b) Fixed anchors of the tendons mounted with the specific anchor set supplied by Max Bögl.

Eight sensors were placed directly on the tendon, another eight on the RC beam connected with fixed anchors, and the remaining eight sensors on the steel plate on the other RC beam. For the purpose of data collection, three measuring systems were employed, each comprising eight measuring channels. Figure 3 illustrates the arrangement of sensors employed during the experiments conducted on tendon four.

Figure 3: Layout of piezoelectric sensors for wire break experiments on tendon four.

4 Some results and future work

This study presents an energy spectral analysis based on a case study involving 30 wire breaks conducted on tendon four. Figure 4a illustrates the energy distribution across frequencies for a single wire break detected at sensor position 9, with the normalized cumulative energy distribution represented by a red line. Additionally, figure 4b provides an overview of the normalized cumulative energy distribution across frequencies for all 30 wire breaks in tendon 4, measured at the same sensor position 9. The sensor position for the analysis is arbitrarily chosen to serve as an illustrative example of the results. The findings indicate that the wire break energy concentrates within a low-frequency range, with frequencies between 5 and 20 kHz contributing to over 90% of the total energy. Future work will encompass a statistical analysis of the energy distribution, considering all 120 wire breaks recorded across all 24 sensor positions.
Figure 4: (a) Energy spectrum of a single wire break in tendon 4; (b) Normalized cumulative energy distribution of all 30 wire breaks in tendon 4

Acknowledgements

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References


TOPIC 5:
Emerging technologies

Session 5.1
08.09.2023 - 09:00
Building 3701, Room 267

Panagiotou Emmanouil  Synthetic Design Alternatives for Offshore Wind Turbine Substructures
Yahaya Taiwo         Computational study of vortex induced wind turbine for electricity generation in low latitude tropical regions
Edirisinghe Dylan S  Droplet impact modelling to predict the rain-induced Erosion of wind turbine blades
Synthetic Design Alternatives for Offshore Wind Turbine Substructures

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Keywords: Artificial Intelligence, Mixed Data, Offshore Substructures, Gaussian Mixture Models, Data Augmentation

Abstract

Substructures are of major importance to the initial design process of offshore wind turbines. However, obtaining real-world data for these substructures can be challenging due to limited availability. We present an approach for generating synthetic data of offshore wind turbine substructures using a small dataset of existing structures. We formulate the substructures as mixed tabular data, incorporating attributes such as dimensions and different connection types. To capture the complex mixed distribution inherent in the limited data available, we use Mixed Deep Gaussian Mixture Models (MDGMM) \cite{1, 2}. By utilizing MDGMM, we can perform augmentation, clustering, and visualization, enabling a deeper understanding of the underlying patterns in the data.

1 Introduction

In the context of offshore wind turbine design, acquiring real-world data for substructures is challenging due to data scarcity. This is problematic for AI applications since training such models requires a large amount of data. To address this issue, different augmentation methods can be used to generate synthetic instances, that enlarge the training data. Nonetheless, most data augmentation approaches assume a single data type (discrete or continuous), which is not true in most real-world scenarios. Indeed, in our study, the features of a jacket substructure are of mixed nature, e.g. number of legs (discrete) and top radius (continuous). Therefore, we employ an approach based on a Mixed Deep Gaussian Mixture Model (MDGMM) \cite{1, 2} to capture the intricate mixed distribution present in the limited data. We demonstrate the proximity between the synthetic structures and the real data by comparing their distributions, and assess their utility by evaluating a predictive model trained on the augmented dataset.

2 Offshore Substructure Designs

We formulate offshore substructure designs as tabular data with both continuous and discrete features as seen in Figure 1 and specified hereafter: L is the number of layers, H is the total height, N is the number of legs (or the number of nodes for each layer), R_b is the base (bottom) radius, R_t is the top radius, \( E = \{E_0, E_1, \ldots\} \) are the different layer heights and \( C = \{C_0, C_1, \ldots\} \) are the different connection types (or brace types) between layers. From this formulation, it is evident that our design space is characterized by mixed attributes of nominal (C), ordinal (L, N), and continuous (H, R_b, R_t, E) data types.

As stated previously, such data containing specific information about the geometric properties of substructures are generally not available. We gather data from the 4C Offshore database \cite{3}, to create our dataset of 100 real jacket structures. Furthermore, insights into the assessment of the structures are acquired by performing five simulation tests for each structure, namely, compression, pushover, and torsion to simulate loads from the tower, a wave-induced load case, as well as, a combination of the above. A visual example of the resulting deformations on the simulated structures is presented in Figure 2. The cost of a structure is estimated by its total mass, resulting in six output values for each structure, which serve as the predictive target values for the AI model.
However, for the purposes of prediction-making using AI, a dataset as limited as merely 100 samples is of minimal utility. Therefore we focus on augmentation techniques tailored for mixed data, to further populate our dataset with synthetic substructures.

3 Synthetic data generation

Since our definition of a substructure contains both discrete and continuous features, we use an approach based on a Mixed Deep Gaussian Mixture Model (MDGMM) [1, 2]. This approach maps the mixed features into a continuous latent space, by considering the inter-dependencies of all features. MDGMMs are a series of Mixtures of Factor Analyzers (MFA). At each layer, clustering is performed and the dimensionality of the latent space is reduced. The final multi-layer architecture, inspired by Neural Networks, enables complex mixed patterns to be captured by composing simple functions of the intermediate layers. To generate synthetic data, samples are drawn in the final latent representation, and layers are inverted sequentially using the Bayes rule. Further post-processing of the synthetic samples can be performed to ignore structures that violate some domain-specific constraints (e.g. inconsistent layer heights).

4 Results & Discussion

Using the 100 instances of real structures, we fit the MDGMM to map the mixed input space into a two-dimensional continuous mixture of Gaussians. Using this mixture, we then sample latent representations and, by inverting the model, we map them back to the original mixed feature space. To assess the quality of the generated samples, we first inspect the distribution of the data qualitatively. As seen in Figure 3 the feature distributions are similar...

Figure 1: Graphical representation of every feature of our substructure formulation.

Figure 2: Visualizations of the four structural simulations.
for real and synthetic data, for both the continuous feature (total height of the structures, top left plot), as well as the count distribution of the discrete feature (number of layers, bottom left plot). Additionally, upon observing the latent space (right), it becomes apparent that structural patterns are recognized, since similar structures have spatial proximity in the latent space. For example, taller structures are on the left part of the latent space, while structures of different numbers of layers are clustered together.

Finally, we demonstrate that our synthetic data can be used for predictive AI by training a Multi-layer Perceptron (MLP) model to predict the six output target values (Section 2). We conduct nine experiments, each time using either Real, Synthetic, or Augmented (Real & Synthetic) data to train, and evaluate, the model. The synthetic data in this case are 1000 samples from the MDGMM, while the augmented data are a mixture of real and synthetic samples. All evaluations are performed on previously unseen data, using 5-fold cross-validation.

We observe that using the augmented data for training maintains a low Mean Squared Error (MSE) when testing on real data, while also performing well in predictions for synthetic and augmented data. This suggests that the augmentation method assists the MLP in making accurate predictions for the real data, while simultaneously enhancing generalizability since the sampled synthetic data cover a larger area of the design space. Thereby, more diverse structures are added to the training data, that still are in-distribution with regard to the real structures.

### Acknowledgements

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References


Computational study of vortex induced wind turbine for electricity generation in low latitude tropical regions

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Keywords: Vortex, axial velocity, circumferential velocity, outlet velocity, radial velocity, vorticity

Abstract

Harnessing the enormous energy in natural vortices is seemingly impossible due to its transient and stochastic nature. This research investigated the possibility of synthesized vortex for electricity generation. The designed turbine triggered wind vortex by harvesting free stream wind through a component which translates the wind flow patterns to swirling format. The swirling wind movement is coupled with solar thermal energy to create a buoyancy effect. The detailed design of the turbine chamber and its aerodynamics were studied. The governing equations were examined. Average axial, circumferential, radial, outlet velocities and vorticity in the turbine chamber were also analysed at 2.5, 5.0 and 7.5 m/s inlet wind speeds respectively and the wall temperature was 10°C. The simulation results show that all the considered parameters increase in accordance with the increment in the inlet wind speed. In conclusion, the preliminary study shows that vortex inducement is feasible and confirmed the potential for electricity generation.

Introduction

This research is on a novel vortex-induced wind turbine which aims to develop a sustainable technology to generate electricity by hybridizing solar and wind resources. The plant will be powered by ambient wind speed and vortex. This plant incorporates solar energy as the heat source to induce wind vortex and buoyancy effect for rotation of a vertical axis wind turbine. The plant operation contrasts with the traditional open air wind turbines that harness wind speed only, concentrated solar plant that uses heat transfer fluid and solar panel that works on photo-electric effect.

The application of wind power generation system is also associated with novel inventions such as bladeless turbine, Omni-directional vane guided wind turbine and others [1]. However, the spread of conventional wind turbine globally is not even. America, Asia, and Europe have been the major players in the field of wind turbine for electricity production. The bane of this skewness are either due to environmental factors, lack of appropriate information or insufficient technical known-how. Considering the environmental conditions, not all regions of the world are exposed to viable wind resources for power generation. Some regions are susceptible to low wind resource but have more than enough solar energy resource to explore [2].

This new system will harness free stream wind speed like conventional wind turbine, heat the wind by solar thermal energy for stack effect and induced vortex to increase the speed of the wind within the compartment of the turbine. The vortex then interacts with a vertical axis rotor installed at the centre of the turbine to trickle electric energy. Two factors are majorly responsible for artificial vortex creation. These are interactive surface and relative wind speed. The addition of heat only gives buoyancy to the vortex. Capturing mechanical energy from twisting wind required the exploration of these factors for the creation of artificial vortex [3].
Methods

The computational scope covered in this research involved the prototype design and simulation of the wind flow pattern in the turbine chamber with SolidWorks. The schematic diagram of the turbine chamber is as shown in Figure 1.

![Figure 1: Turbine chamber](image)

The glass receivers are important parts of the structure which harvest solar energy. The receivers were designed to collect solar radiation at two tilt angles namely: optimum tilt angle for maximum solar radiation and optimum tilt angle for maximum air flow. The base and top receivers collect solar radiation at optimum tilt angle for maximum solar radiation and the mid receiver allows sun rays at optimum tilt angle for maximum air flow. The equations for the two factors are as follow:

\[ T_{\text{max.rad.}} = \theta + 25^\circ \]
\[ T_{\text{max.airflow}} = 90^\circ - \omega \]

A look into the flow turbine chamber shows that it is possible to extract energy from wind in three conditions. The free wind stream influx into the turbine excites the turbine rotor. This wind flow interacted with inner surface of the turbine envelope to generate vortex. It then takes a smear of heat to create buoyancy effect. The possible power from these conditions are power due to ambient wind speed, swirling wind speed and buoyancy effect.

\[ P_{\text{ambient wind speed}} = \frac{1}{2} \rho_a v^3 \text{Area}_{\text{swept}} \]
\[ P_{\text{swirling wind speed}} = \frac{1}{2} \rho_a \omega^3 \text{Area}_{\text{circumferential}} \]
\[ P_{\text{buoyancy}} = \rho_a g \nu_b \beta \Delta T \text{volume}_{\text{swept}} \]
\[ \text{Area}_{\text{swept}} \text{(blade swept area)} = DH \]
\[ \text{Area}_{\text{circumferential}} \text{(blade circumferential area)} = \pi DH \]
\[ \text{volume}_{\text{swept}} \text{(blade swept volume)} = \frac{1}{4} \pi D^2 H \]

where:

- \( \rho_a \) = ambient air density (kg/m\(^3\))
- \( v \) = ambient wind speed (m)
- \( \omega \) = angular wind speed (rad)
- \( \nu_b \) = vertical wind speed due to buoyancy (m)
- \( g \) = gravitational acceleration (m/s\(^2\))
- \( \beta \) = coefficient of volume expansion (1/k)
The total extractable power \( P_T \) from the turbine is summation of equation 1, 2, and 3.

\[
P_T = P_{ambient\ wind\ speed} + P_{swirling\ wind\ speed} + P_{buoyancy}
\]

Sequel to the model design is study of the flow outlines in the turbine chamber at 2.5, 5 and 7.5 m/s inlet wind speeds and 10°C wall temperature. The chamber aerodynamics is studied using flow simulation solver in SolidWorks version 2023. Error! Reference source not found. presents an illustration of the flow’s morphology.

Results and Discussion

The result from the simulation is as shown below.

**Turbine chamber Aerodynamics results**
The results clearly show that as the inlet windspeed increases the output parameters also increase except for the circumferential velocity which remain constant. This is because the curved surface area of the structure is a fixed entity. The vorticity also increases in proportion to the inlet windspeed.

**Acknowledgements**

Unreserved appreciation goes to German Academic Exchange Service (DAAD) and Petroleum Technology Development Fund (PTDF), Nigeria for the scholarships offered to the author.

**References**

Droplet impact modelling to predict the rain-induced Erosion of wind turbine blades

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Keywords: droplet impact; blade erosion; CFD; impact pressure; lateral jet

1. Introduction

The wind turbine industry has grown rapidly since the last decade progressing towards manufacturing giant offshore turbines with larger blades. Lengthy wind blades result in high tip speed whereas the impact of rain droplets is significant in blade erosion, especially at the leading edge (Leading Edge Erosion-LEE) [1]. Eroded blades degrade the turbine performance, reducing the Annual Energy Production (AEP) by up to 5% [2,3]. Periodic repairing and new coating solutions for the leading edge of wind blades are the main precautions against rain erosion [4].

To achieve the precautions strategies, the most fundamental stage of erosion, the liquid droplet impact should be studied and analysed having reliable accuracy. Experimental observation on droplet impact is limited due to capturing the nano-second scale impact. Analytically, the approximation value for the peak impact pressure of a single droplet was developed by modifying the water-hammer pressure.

On the other hand, numerical studies are significantly useful to study the liquid droplet impact phenomenon by not only calculating the peak pressure but also the pressure distribution on the surface throughout the impact time. Therefore, the current research trend is led by CFD (Computational Fluid Dynamic) and FSI (Fluid Structure Interaction) studies on droplet impact observing the detailed picture of this nano-scale incident. Following the trend this research was conducted to understand the droplet impact using the CFD analysis, as a preliminary step for estimating the repair frequencies and exploring the new coating systems.

Typical rain generally consists of 1-5 mm droplets, whereas this study focused on the single impact of a 2 mm drop. The droplet impact speed was approximately determined as 100 m/s considering the average terminal velocity of rain and the general tip speed of the blade. The next section of this extended abstract explains the modelling and the simulation procedure of the single droplet impact followed by the mesh and time-step convergence tests. The result and discussion section compares the peak pressure of the current study with analytical and previous CFD studies while discussing the impact pressure variation on the surface and the water velocity behaviour inside the droplet during the impact.

2. Single Droplet Impact

Three-dimensional fluid domain for single droplet impact is modelled in SOLIDWORKS, discretized the domain using ANSYS ICEM and CFD simulations were carried out using ANSYS CFX. The droplet shape is considered a full sphere to simplify the basic model. Thus, the domain size is determined by doing an initial simulation for a whole droplet having a larger spread area. Figure 1(a) illustrated the finalized domain area with dimensions which is an axisymmetric quarter domain where the water droplet is placed inside a cylindrical air domain. This approach is used to reduce the computational power.

Hexagonal O-grid mesh elements were used to discretise the fluid domain. Mesh was refined especially along the axial (minimum discretization is 0.0008 mm) and radial direction (minimum discretization is 0.015 mm) from the impact point, where the instant peak pressure implies. A mesh convergence test was conducted to determine the optimum mesh configuration consisting of $2.7 \times 10^5$ elements. Figure 1(b) illustrates the finalized mesh configuration.
Multiphase (Air/Water - Eulerian) CFD simulations were carried out with the VOF (Volume of fluid) free-surface model. The droplet was initialized by giving 100 m/s. The transient simulations were carried out for 50 µs for an optimized time step size of 10 ns. The impact surface is denoted as the no-slip wall where the top and circumferential surfaces of the cylinder are open to atmospheric pressure. Symmetry planes are defined with rotational periodicity along the axial direction.

2.1 Mesh Convergence test
Four mesh configurations were studied under the mesh convergence test named coarse, medium, fine, and finest solving for the same 100 nano-second time-step. Mainly the mesh refinement is done along the radial direction from the impact location and the peak impact pressure difference is used as convergence criteria. Table 1 summarized the results of the mesh convergence test. Fine mesh with $2.7 \times 10^5$ elements is chosen as reliable enough to predict the peak pressure with bearable computational power.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Number of elements</th>
<th>Peak pressure difference with respect to the finest mesh</th>
<th>Solving time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coarse</td>
<td>$0.6 \times 10^3$</td>
<td>8.0%</td>
<td>~2 hr</td>
</tr>
<tr>
<td>Medium</td>
<td>$1.4 \times 10^3$</td>
<td>4.2%</td>
<td>~4 hr</td>
</tr>
<tr>
<td>Fine</td>
<td>$2.7 \times 10^5$</td>
<td>2.1%</td>
<td>~9 hr</td>
</tr>
<tr>
<td>Finest</td>
<td>$5.2 \times 10^5$</td>
<td>-</td>
<td>~20 hr</td>
</tr>
</tbody>
</table>

2.2 Time-step independent test
The fine mesh was further simulated for three different time-step sizes to capture the more reliable impact pressure behaviour. Time-step sizes were determined as 100, 10 and 1 nano-second. Table 2 summarized the peak pressure difference and behaviours for different time steps. Since the difference between the 10 ns and 1ns is less than 1%, a time step size of 10 ns was selected as the optimum time step.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Size of time-step (ns)</th>
<th>Peak pressure difference with respect to small-time step</th>
<th>Solving time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Large</td>
<td>100</td>
<td>7.3%</td>
<td>~9 hrs</td>
</tr>
<tr>
<td>Medium</td>
<td>10</td>
<td>0.3%</td>
<td>~4 days</td>
</tr>
<tr>
<td>Small</td>
<td>1</td>
<td>-</td>
<td>~10 days</td>
</tr>
</tbody>
</table>

3. Results and Discussion
The droplet impact can be discussed with several stages based on the pressure variation on the surface during the impact time. Just before the droplet impact (Figure 2(a)), the pressure at the impact centre rises rapidly since
the droplet compresses the air layer near the impact surface. At the stage of the exact impact (Figure 2(b)), this pressure reaches its peak value. This CFD study resulted in 58 MPa peak impact pressure. Then immediately after the impact (Figure 2(c)), the pressure is starting to decrease shifting the peak surface pressure outward to the impact centre. This peak pressure location can be identified as the circumference of the contact circle between the droplet and the surface. In other words, the location is very close to the droplet spread circumference after the impact. At this stage, the water droplet starts to collapse against the surface tension and spread while releasing the water at the contact circle indicating a lateral jet velocity of around 450 m/s. However, there is no such peak pressure at a particular location in the next stage (Figure 2(d)). Instead, approximate constant pressure was maintained up to a certain radius and decreased gradually towards the spread radius. At the very last stage (Figure 2(e)), pressure continuously decreases with the spread radius having negligible pressure compared with the peak impact pressure.

The value for the peak pressure can be compared with the modified water hammer shown in Equation 1 [5].

$$ p = \frac{\beta}{2} \rho C v $$

In that equation $\beta/2$ is the correction coefficient for the spherical shape of the droplet and $\beta$ approaches unity as the impact velocity is increased. Considering the 1000 kg/m3 water density ($\rho$) and 1400 m/s acoustic velocity ($C$), peak pressure ($p$) should not exceed 70 MPa for 100 m/s impact speed ($v$), when $\beta$ is unit. 58 MPa peak pressure recorded in this study matches the range of the modified water hammer pressure and the value is reliable since the speed of the droplet is not as high as other applications. Furthermore, the trend of the pressure variation is compared with the B. Amirzadeh et al. results [5] and the pressure behaviour of the current study quite matches with the reference CFD study having less than 2% differences.

4. Conclusion

Modelling and understanding of single droplet impact at a micro level are necessary to address the very complex rain erosion precaution strategies in wind turbine blades. This extended abstract discussed the modelling and CFD analysis of a 2 mm spherical water droplet impact at 100 m/s velocity into a rigid surface. Impact pressure behaviour was discussed based on several stages: just before the impact, exactly at the impact, immediately after impact and later. 58MPa peak pressure was observed at the impact location and compared the value with the modified water hammer pressure. Thus, the trend of the pressure variation is validated with previous studies.

The research is supposed to extend by simulating fluid-structure interaction and multiple impact behaviour to predict the wind turbine blade erosion rates.

Acknowledgements

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References


Figure 2 (a) Just before the impact (b) Exactly at the impact (c) immediately after impact (d) Later stage (e) Fading stage
Session 5.2  
08.09.2023 - 10:30  
Building 3701, Room 268  

Lochhead Robert  
Thermoplastic Blades for Multi-Rotor Wind Turbine Application  

Pynaert Niels  
Unsteady aerodynamic simulations of an airborne wind energy system in realistic flight and environmental conditions using computational fluid dynamics  

Crismer Jean-Baptiste  
Large Eddy Simulation of Airborne Wind Energy Systems flying optimal trajectories in turbulent wind
Thermoplastic Blades for Multi-Rotor Wind Turbine Application

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Keywords: Multi Rotor Wind Turbine (MRWT), Thermoplastics, Finite Element Analysis, Blade Element Momentum Theory, Recycling, Manufacturing, Sustainability

Wind energy is expected to play a major role in the future energy supply, in particular offshore wind which is expected to increase 15-fold in the next two decades [1]. The current trend to fulfil this potential is to increase the size of the turbine, with some turbines on the market reaching 15MW – this is expected increase to 20MW in the near future [2]. However, with the increase of turbine size comes new challenges, particularly with structural loading and the non-linear control of these large, slender structures. Furthermore as the current generation wind turbines is further upscaled into the multi-megawatt scale, the energy capture from upscaling is being mitigated by the rising costs of manufacture [3]. Therefore, a structural and economic limit may exist in regards to the size of the conventional single rotor turbine, beyond which point they become unfeasible. One concept that can address these issues is the Multi Rotor Wind Turbine (MRWT). This is where multiple small rotors are utilised, equivalent to one large rotor producing the same rated power:

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure1.png}
\caption{Concept of Multi Rotor Wind Turbine [4]}
\end{figure}

MRWT systems can retain the economic advantage of smaller sized systems, whilst potentially achieving a larger overall capacity for a similar rated single rotor turbine. Further advantages of this concept include [3]:
- Reduced aerodynamic loading
- O&M cost savings due to smaller component size
- Improved energy capture due to the blockage effect on incoming flow and increased availability[5]

By utilising smaller rotors, reduced loading can be seen on the individual turbines. This suggests there is a possibility for turbine blades to be made of different materials than are typically used for single rotor turbine applications. One promising group of materials is thermoplastics, which is a set of polymers that becomes pliable or mouldable at certain temperatures. Whilst thermoplastics have been shown to have similar mechanical properties when compared to thermsets typically used in single-rotor turbine applications [6], the key advantage is that they are readily recyclable, meaning at end of life the blades can be properly disposed of and the raw materials used to create the blade can be retained.
The aim of this work is to conduct a feasibility study for using thermoplastic-based blades in a MRWT application. The work will determine the aerodynamic blade loading requirements seen in MRWT applications by using DNV’s Bladed software, which is a simulation tool that can be used to determine the loads and performance of a wind turbine blade [7]. A model will then be created that is representative of the blade being used in this particular MRWT application using CAD packages. Potential thermoplastic materials will be identified, reviewed and applied to the blade model for analysis. Finite element analysis will then be utilised to assess the mechanical performance of the blade under the blade loading cases previously determined, and will be repeated for a number of suitable thermoplastics. Finally, appropriate manufacturing and recycling processes will be reviewed for the thermoplastic selected for the MRWT blade, and a lifetime cost analysis will be performed.

Acknowledgements

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References


Unsteady aerodynamic simulations of an airborne wind energy system in realistic flight and environmental conditions using computational fluid dynamics

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Keywords: Airborne wind energy, Computational fluid dynamics, Chimera

Airborne wind energy (AWE) is an emerging technology for the conversion of wind energy into electricity by flying crosswind patterns with a tethered aircraft connected to a generator, either on board or on the ground. Having a proper understanding of the unsteady interaction of the wind with this highly dynamic system during operation is key to developing viable AWE systems [1]. High-fidelity simulation tools are needed to correctly predict these interactions, which will provide insights into the design and operation of advanced and efficient AWE systems. The goal of this contribution is to simulate the time-varying aerodynamic forces acting on an AWE system in a realistic crosswind flight maneuver using computational fluid dynamics (CFD). The realistic crosswind flight maneuver includes the effects of reel-in/reel-out, variations of flight speeds and a logarithmic wind profile.

Methodology

Previous work [2] demonstrated the feasibility of using the Chimera/overset technique to simulate aerodynamic behavior over a prescribed circular flight trajectory of the reference multi-megawatt AWE system [3]. In [2] only the wing is considered. For this contribution, the work presented in [2] is extended by including the horizontal and vertical tail in the CFD simulations to predict the aerodynamic forces and moments acting on the whole aircraft. This is done by developing different C-structured meshes for the horizontal and vertical tail which are connected to the wing component mesh using the Chimera/overset technique as indicated in Figure 1.

Figure 1: (left) CFD model, purple; overset boundaries, (right) Overset cell types: green; solved, red; donor, blue; receptor.
Furthermore, the flight path of the AWE system is optimized with the AWE system dynamics and optimal control toolbox AWEbox [4] and is prescribed to the CFD model. The motion of the AWE system is included by overlaying the moving body-fitted C-structured mesh attached to the AWE aircraft over the cartesian background mesh as indicated in Figure 2. A logarithmic wind profile is simulated in the background mesh by imposing the logarithmic profile as velocity inlet and inlet profiles for the turbulent kinetic energy $k$ and dissipation rate $\omega$, to satisfy the turbulence model equations [5]. The Chimera/overset technique connects the background and aircraft mesh, interpolating the solution at the overset boundary.

The flow physics are solved using incompressible unsteady RANS in Fluent, using a timestep of 0.01 seconds to simulate a trajectory of 75 seconds. Turbulence is modeled using the k-omega SST model using wall functions. The convective terms in the momentum equations are discretized in space using a first-order upwind scheme. Time integration is performed using a first-order implicit scheme.

**Results**

The model mismatch between the CFD model and aircraft aerodynamic model in the controller of AWEbox is assessed. Some initial results are shown here for a uniform wind velocity of 10 m/s. The lift coefficient is plotted in Figure 3 (left). The dashed black line is the lift coefficient calculated by the aerodynamic model in AWEbox without control surfaces, the dashed blue line is a CFD prediction with wing only in and solid blue the full aircraft. The CFD model predicts less lift than predicted by AWEbox, which could be explained by the negligence of viscous effects in the aerodynamic model in AWEbox. This can be analyzed in more detail in future studies.

**Figure 2:** Implementation of the flight trajectory

**Figure 3:** (left) Lift coefficient over 1 loop for the AWEBox model and CFD model. (right) Wake visualization using $q$-criterion.
In Figure 3 (right), the wake is visualized using the q-criterion at 64 seconds of simulation time. The wingtip vortices follow the shape of the flight path but are convected downstream.

Conclusions and outlook

In this work, a proof of concept for the simulation of airborne wind energy trajectories in a CFD environment for a complete aircraft is described. The overset technique has been proven to be a robust approach to simulating rigid body motion and aircraft aerodynamics. The framework gives some promising initial results for future detailed studies. In the next step, the aerodynamic model presented here will be coupled to a structural model, to perform fluid-structure interaction simulations. Secondly, also the control surface deflections will be taken into account in the CFD model and the moments around the center of gravity will be tracked to assess if the trajectory is flyable. Thirdly, model-based feedback control using the aerodynamic forces and moments from the CFD model is foreseen. Finally, a study on the dependence on grid, timestep and turbulence model is recommended for further work.

References

Large Eddy Simulation of Airborne Wind Energy Systems
flying optimal trajectories in turbulent wind

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Keywords: Airborne Wind Energy, Large Eddy Simulations, Actuator Line, Lifting Line

1 Introduction

Airborne Wind Energy Systems (AWES) consist of rigid-wing aircraft or soft kites connected to the ground by a tether and harvesting power from the wind. Pumping-mode AWES are considered here: they generate power during the reel-out phase and consume a fraction of this power during the reel-in phase. Those devices fly complex trajectories which require advanced control strategies. In Haas et al. [5], a LES framework was used to study AWES farms in realistic turbulent winds. The AWES were solely represented by their main wings, each being modelled as a single actuator line (AL) in the LES. The system dynamics were computed using a 3DOF point-mass model coupled to a closed-loop path tracking controller from the optimal control toolbox awebox [4].

In the present work, we aim at developing a LES framework to study more realistic models of AWES in realistic turbulent winds. The reference rigid wing AWES of [3] is considered and is modeled using multiple ALs; one for each lifting surface. The toolbox awebox is also used to generate reference trajectories and control the 6DOF rigid-body motion of the aircraft.

As a first step, the device is flown on a prescribed trajectory, using the kinematics and the control inputs (deflection of control surfaces) obtained using the trajectory optimization tool of awebox. The aerodynamic loads are measured and are then compared to those obtained by the optimizer. In a second step, preliminary results of a closed-loop controlled flight (using a MPC controller) will be presented.

A simplified model is also developed in order to provide a faster platform for the investigations of AWES in turbulent winds and development of the controller: the aircraft is represented using multiple lifting lines (LL), and it flies in a frozen turbulent flow field; one from the LES solver taken at some time. The output of the AL and LL models are also compared.

2 Methodology

2.1 Flow solver

Large-eddy simulation (LES) is performed using an in-house fourth-order finite difference solver [2, 9]. The code solves the incompressible Navier-Stokes equations. The subgrid-scale model used here for LES is a regularized variational multiscale (RVM) [6, 1]. The mesh is a cartesian staggered grid and the time integration is performed using a second order Adams-Bashforth scheme. The turbulence in the inflow is taken into account using Mann boxes [8], where the velocity fluctuations are pre-calculated using the Mann algorithm and injected at the inlet.
2.2 Wing models

Within the flow solver, the wings are modelled using actuator lines [10]. This method has three main steps. Firstly, the effective flow velocity is interpolated from the grid to the actuator curve control points. Secondly, the aerodynamic forces are computed using the obtained velocities and the airfoil polar data. Finally, the forces are distributed on the flow grid and taken into account via a volumic force term added to the flow equations.

A second model is used. It consists of a lifting line. The lifting line is built using horseshoe vortices and vortex rings assemblies [7], where the shed vortex sheet accounts for the influence of the wake. The induced velocity is evaluated for each vortex segment using the Biot-Savart law and allows to have an accurate representation of the effective velocity at each airfoil section.

2.3 Numerical setup

The modelled wing is the rigid wing reference AWES described in [3]. This AWES has a wing span of 42.5 m and an aspect ratio of \( AR = \frac{b^2}{S} = 12 \).

In the different cases studied, the wing fly a trajectory having a radius \( R = 2.5b \). The flow is driven by imposing a mean flow velocity \( U_\infty = 10 \text{ m/s} \) at the inflow, and with added turbulence. In the LES flow solver, the size of the domain is \( 9D \times 3D \times 3D \), where \( D = 2R \) is the diameter of the trajectory, with 768 \( \times 256 \times 256 \) grid points. It thus correspond to approximately 85 points per \( D \) or 17 points per \( b \). The domain is sketched in Figure 1. The turbulence is injected in the domain through a 12\( D \) long Mann box with a turbulence intensity of 6\%, using the Kaimal spectrum. The wake flow is measured, downstream of the centre of rotation, in vertical planes from 1\( D \) to 5\( D \). The flow statistics are accumulated over two Mann box flow through times (thus 24\( t^* \) where \( t^* = \frac{U_\infty t}{D} \)) and after it has developed for 12\( t^* \).

![Figure 1: Computational domain with its relative dimensions, where \( x \) is the streamwise, \( y \) is the vertical and \( z \) the transverse direction.](image)

The lifting line is used to develop a computationally cheap simulation environment. For this kind of simulations, the wing is simply flown in a frozen turbulent wind field following the prescribed trajectory.

3 Results

A first trajectory consisting of one loop have been generated with [4]. It consist of a single loop containing a reel-out and reel-in phase. It is depicted in Figure 2.

The forces projected by the trajectory generator and those recorded from the LES are compared in Figure 3. Some differences are noted. First, we observe a phase shift between the forces from awebox and those from the LES. Also, awebox tends to overestimate the force in the \( y \)-direction while it underestimates the force in the \( x \)-direction. Despite those differences the agreement is fair.

4 Conclusion and perspectives

In this work, a LES framework combined with an actuator line (AL) approach is developed. A simplified lifting line model is also developed. The LES-AL framework aims to provide a high fidelity environment to study kites in turbulent and realistic atmospheric conditions while the simplified lifting line model aims at providing a faster tool to investigate control strategies. The trajectories are generated using awebox. The forces measured in the LES
Figure 3: Force in the body frame in the y-direction (a) and in the x-direction (b).

are compared to those predicted by the trajectory generator. An overall good agreement is obtained.

As following work, we project to use the forces measured in LES-ALM to tune the kite controller and perform controlled flight rather than flight using a prescribed trajectory. Even though the present work focuses on rigid-wing AWES, the simulation framework is being developed so as to also handle soft kites in the future. Flying in other environments, such as crossing strong wakes from wind turbines, will also be considered. The methodology will then allow to study the behavior of AWES in many conditions, and asses the efficiency of various control strategies.

Acknowledgements

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funded by the Fonds de la Recherche Scientifique de Belgique (F.R.S.-FNRS) under Grant No. 2.5020.11 and by the Walloon Region.

References


TOPIC 6:
Electrical conversion, energy system, and wind power-to-X

Session 6.1
07.09.2023 - 14:00
Building 3701, Room 267

Buckhold Sarah  Feasibility Analysis of Using Stranded Wyoming Wind Resource for Green Hydrogen Production
Oudich Younes  Methodology for battery sizing in microgrids with wind turbines and electrolyzers using EMT simulations
Nguyen Thuy-Hai  Adequacy Computations for Power Systems with a High Share of Offshore Wind Generation: Application to Belgium

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Keywords: Electrolyser, Hybrid energy system (HES), Green hydrogen (GH\textsubscript{2}), Optimal sizing, Power-to-X (PtX)

1 Introduction

A hybrid energy system (HES) refers to multiple energy conversion devices operating together to satisfy a specific energy demand, procuring using as many renewable energy resources (RES) as possible in its topology and operating isolated from centralized energy systems. At the moment, wind and solar are the predominant RESs applied in HESs because of the development of both technologies. However, new configurations of HESs started using more energy storage devices (ESD) due to their fast growth in recent years. Some of these technologies can be categorized within Power-to-X (PtX), which main purpose is converting surplus electricity from RESs into carbon-neutral synthetic fuels \cite{1}. Green hydrogen (GH\textsubscript{2}), produced from electrolysis plants, is the most promising of these fuels to enable sectors such as energy, transportation, industry, and buildings a transition from fossil fuels to carbon-free energy carriers. Nevertheless, cost competitiveness and infrastructure are still challenges for GH\textsubscript{2}.

Under this context, accurate design and sizing of HESs are crucial for motivating different stakeholders to invest in the adoption of electrolysis plants as ESDs in the new topologies of HESs. This paper presents some insightful information regarding the influence of market structure and the principal sizing techniques applied to HESs in the available literature procuring points such as RESs generation mix, transmission assets, demand profiles, and GH\textsubscript{2} production.

2 Market Structures for Designing and Sizing HESs

The structure of energy markets tends to evolve according to the main resources in the share of the generation mix, so higher participation of RES forces to establish different rules to keep competitiveness in this stage, but above all ensure the security of the system. Here, three approaches for market payments are widely considered in international power systems such as capacity, energy, and ancillary services \cite{2}.

From the perspective of HESs, a correct decision for participating interchangeably in these markets can represent a good opportunity for ensuring revenues in the lifetime of the plant. Additionally, endowing GH\textsubscript{2} purchase agreements can improve the profitability of HESs based on the generation of multiple energy carriers, but it should correspond to individual compromises since a market exclusively dedicated to hydrogen has not been set up until now. Some references as \cite{2, 3} suggest defining some market archetypes to ensure a proper analysis regarding the return on investments in HESs, which must include features for current and future markets. Table 1 summarizes some of the recommended market aspects in the designing stage of HESs from the perspective of RES participation and GH\textsubscript{2} production taking into account different market payments.

1 Fixed-energy payment: It refers to set payments for the energy provided to the system or demands, normally in hour steps (kilowatt-hour), and it can be used as the baseline for analyzing the revenue of HESs. Under this scheme, the share of RES tends to be low, and they receive a fixed rate for every unit of energy produced. Also, the main goal is to minimize the generation cost of each plant, usually using the levelized cost of energy (LCOE) as the main indicator \cite{3}. From the perspective of GH\textsubscript{2} production, this scenario limits its production because of the spare capacity in the HES.
Table 1: Proposed Market Archetypes for Designing of Hybrid Energy Systems Focused on GH\textsubscript{2} Production

<table>
<thead>
<tr>
<th>Defined Market Archetypes</th>
<th>Share of RES Energy Market Revenue</th>
<th>Capacity Market Revenue</th>
<th>Services Market Revenue</th>
<th>GH\textsubscript{2} Production</th>
<th>Objective Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed-energy payment</td>
<td>Low (&lt;10%)</td>
<td>Fixed per unit</td>
<td>Negligible</td>
<td>Negligible</td>
<td>LCOE</td>
</tr>
<tr>
<td>Energy-market dominant</td>
<td>Moderate (10% -25%)</td>
<td>Time-varying</td>
<td>Low to negligible</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>Capacity-and service-</td>
<td>High (25% or higher)</td>
<td>Low and time-varying</td>
<td>Moderate</td>
<td>Moderate</td>
<td>NPV or capacity value</td>
</tr>
<tr>
<td>dominant</td>
<td></td>
<td></td>
<td>to high</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2 Energy-market payment: This archetype considers moderate participation of RES generators, and it is based on PJM markets, highly applied in Europe, in which RES plants are allowed to participate in time-varying energy markets as well as balancing markets [4, 5]. These features could endorse the production of GH\textsubscript{2} in this scenario, however, more strict requirements in the controllability and energy forecast of the HES are demanded to avoid penalties on the delivered energy as well a correct determination of the energy mix. Additionally, the production of GH\textsubscript{2} will be time-varying, and it could slightly improve the revenue in service markets compared with the archetypes presented in [2]. Therefore, a more complex objective function should be satisfied in this scenario procuring to maximize the profit of the HES while its total cost is minimized through the lifetime. The net present value (NPV) appears as a widely used metric for this purpose in previous studies under stochastic and deterministic perspectives.

3 Capacity-and-service payment: The archetype is based on payments for the effective available capacity altogether with payments for keeping the stability of the system against short-term disturbances in a scenario ruled by the high participation of RES generators [6]. Here, maximizing the capacity of each HES and providing ancillary services on the demand side would ensure the main profits for investors. For this reason, NPV can be applied as an indicator metric in formulating the optimization problem, but simpler versions applied capacity values focusing only on the revenues from them. However, in the HES case, extra income for the ancillary market and GH\textsubscript{2} can be added to the mentioned metrics.

In this classification, the consulted references consider the owners or operators of HPPs as price takers, which means they accept the prices imposed by the stated markets because the scope of the analysis is to determine the economic viability of building an HPP. On the other hand, the stated archetypes are not considering policy aspects like incentives related to the massive penetration of GH\textsubscript{2} in energy systems, especially promoted in the EU under the endorsement of PtX projects.

3 Optimal Sizing for HESs

Defining the proper size for HESs is not a widely spreading topic in research as a set due to the high development of methods and techniques for sizing each of the individual elements (RES generators wind or PV, ESDs, coupling architecture, among others) inside the HES layout. Nevertheless, some aspects are crucial for the optimal sizing of these systems such as shared infrastructure, projected shadowing, physical location of assets (applicable for virtual HESs), interconnection to larger power or energy systems, and isolated operation [7]. Thus, different mathematical formulations and optimization techniques are employed in previous research, which follows the general overview illustrated in Fig. 1 consisting of three stages: Input data, integrated HES model, and optimization problem formulation [2].

1 Input data: Refers to accurately representing the energy resources, GH\textsubscript{2} or storage requirements, and market features. At the moment, wind and solar resources have been widely characterized in multiple sources of statistical or tailored time-series data for almost all zones worldwide in different resolutions. However, some statistical pre-treatment should be needed for specific locations or to represent physical phenomena in wind turbines or PV panels (e.g., wind flow within turbines’ layout or shadowing among generators). In addition, for the storage capacity and GH\textsubscript{2} required capacity, some deterministic formulations have been stated in the literature, for example, references [1, 8].

2 Integrated HES model: This stage defines the topology of the HES based on the coupling technology chosen for the plant, which can be in the AC or DC sides, as well as its physical location which can be land-based...
or offshore. Considering the different technologies for RES, storage systems, and GH\textsubscript{2} production, different potential architectures, and layouts can be suitable for the optimal sizing of HESs. In fact, some topologies can include a common AC or DC coupling for all the technologies, a DC coupling for PV and storage systems combined with either a common coupling point or AC coupling with wind generators, and no point of common coupling [9]. In addition, the extra components and auxiliary systems should be included in this stage to ensure the continuous operation of the HESS and GH\textsubscript{2} production, which is also referred to as the balance of plant (BoP).

3 Optimization problem formulation:Corresponds to the most complex stage in the sizing process because of the uncertainty in some of the parameters defined in the previous stages and the grade of variability in the revenue from markets, especially for GH\textsubscript{2} because of the lack of an intended market and a generalized approach for controlling HESs destined to hydrogen production [1]. However, in the formulation of the problem is recommended to include the relevant design variables, non-design input parameters, and objective and constraint functions within the structure of the chosen algorithm for solving the problem In the case of HESs, some of the variables can have multiple objectives depending on the control approach, so the literature suggests applying a highest-level aggregation of system performance and cost into a single profitability metric, typically LCOE, NPV, or similar [3, 8]. In addition, Table 2 is intended to summarize the most common approaches for sizing HESs based on multiple RESs and GH\textsubscript{2} production.

4 Conclusions

The literature review suggests that many researchers are still trying to adapt statistical solutions applied to the individual technologies used within HESs because of the well-developed energy market and incentives defined for each. However, in multi-energy carrier systems, the need for establishing dedicated markets, e.g. for GH\textsubscript{2}, appears as a mandatory step in successfully integrating this type of new sustainable energy carriers. It helps to improve the financial viability of HESs as well as reduce the uncertainty regarding the designing and sizing stages in the short and medium term.

On the other hand, controllers applied in HESs should be also improved to ensure profitability and grid compliance under the presence of variable generation and uncertainty. In this sense, some future works regarding the update of these controllers against the emergence of new markets and advancement in electrolyzers are suggested in this paper.
Table 2: Common Approaches for Designing and Sizing of HESs Based on Multiple Energy Carriers [2]

<table>
<thead>
<tr>
<th>Design Elements</th>
<th>Approaches for Designing and Sizing of HESs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Availability RES</strong></td>
<td>- Time series data with variable bin resolution (typically a representative year)</td>
</tr>
<tr>
<td></td>
<td>- Statistical models (Probability density function - PDF)</td>
</tr>
<tr>
<td></td>
<td>- Bulk statistics collection</td>
</tr>
<tr>
<td><strong>Market Features</strong></td>
<td>- Time series data with variable bin resolution (typically a representative year)</td>
</tr>
<tr>
<td></td>
<td>- Single power purchase price</td>
</tr>
<tr>
<td></td>
<td>- Individual purchase agreements for GH</td>
</tr>
<tr>
<td></td>
<td>- Bulk statistics collection</td>
</tr>
<tr>
<td><strong>Topology of HESs (RES generators, ESD, and GH₂ systems)</strong></td>
<td>- Simplified parametric representation (infrastructure and operational costs)</td>
</tr>
<tr>
<td></td>
<td>- Deterministic models</td>
</tr>
<tr>
<td></td>
<td>- Detailed physical models (technical performance and costs)</td>
</tr>
<tr>
<td></td>
<td>- High-detail physical models (technical interaction among technologies)</td>
</tr>
<tr>
<td><strong>BoP and Operation</strong></td>
<td>- Simplified parametric representation (infrastructure and operational costs)</td>
</tr>
<tr>
<td></td>
<td>- Medium and high-fidelity modeling (infrastructure and plant operation)</td>
</tr>
<tr>
<td></td>
<td>- Adopting existing single models within multiple topologies systems of HESs</td>
</tr>
<tr>
<td></td>
<td>- High-detail physical models (technical interaction among technologies)</td>
</tr>
<tr>
<td><strong>Design Variables – Optimization Problem (*)</strong></td>
<td>- Technology type</td>
</tr>
<tr>
<td></td>
<td>- Emplacement</td>
</tr>
<tr>
<td></td>
<td>- Capacity</td>
</tr>
<tr>
<td></td>
<td>- Interconnection topology</td>
</tr>
<tr>
<td></td>
<td>- Control strategies</td>
</tr>
<tr>
<td><strong>Design Constraints and Objective Function – Optimization Problem</strong></td>
<td>- Objective(s): Profitability, cost of a specific energy carrier, or similar</td>
</tr>
<tr>
<td></td>
<td>- Constraints: Size of components, operation, location, markets, policy, or similar</td>
</tr>
<tr>
<td><strong>Algorithms – Optimization Problem</strong></td>
<td>- Monolithic nonlinear programming - NLP</td>
</tr>
<tr>
<td></td>
<td>- Monolithic mixed-integer linear programming - MILP (gradient-based and gradient-free)</td>
</tr>
<tr>
<td></td>
<td>- Decomposition of monolithic MILP in NLP suboptimizations</td>
</tr>
</tbody>
</table>

* Applicable for every technology in HESs

References


Feasibility Analysis of Using Stranded Wyoming Wind Resource for Green Hydrogen Production

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June 2, 2023

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Keywords: Wind Energy, Hydrogen, Wind Hydrogen Hybrid

1 Introduction

Hydrogen has become a front-runner in the international clean energy transition as a medium with great potential in the energy storage and transportation industries. Fang (2019) [1] and Glenk and Reichelstein (2019) [2] have investigated the feasibility of producing hydrogen via electrolysis directly from renewable wind energy, however the most expensive part of these projects remain the cost of the electricity. Due to the limitations of existing electrical infrastructure in the United States there are many locations that feature great wind resource, but are not able to be developed due to their distance from electrical grid connection. This distance leaves this wind a stranded resource, or a resource that is not currently able to be developed. Hydrogen may provide the transportable energy medium necessary to take advantage of this stranded wind resource. To analyze this possibility, the Wind Integration National Dataset Toolkit Long-term Ensemble Dataset (WTK-LED) Weather Research and Forecasting (WRF) model is used to identify these areas of high wind resource that are then cross-referenced with current infrastructure and resources, shown in Figure 1, to recognize potential development regions of stranded wind resource for hydrogen production. The portion of the WTK-LED model used for the current study models the wind and atmospheric conditions of the continuous United States from 2001 to 2020, has a grid resolution of 4-km, and outputs at hourly intervals. This study focuses on using this dataset to analyze the state of Wyoming for potential locations of stranded wind resource. A basic financial analysis of a sample project is then performed to calculate effective cost per kilogram of produced hydrogen at these potential development sites.

2 Methods

To quantify the available wind power throughout the state of Wyoming, WIND TKE-LED hourly wind speed output at 100-m height is converted to available power using the 2020 NREL Annual Technology Baseline (ATB) 4 MW Reference Power Curve [3] for all years between 2001 and 2020. The power output is totaled for each year and then all years are averaged together to give an average yearly power output for all areas across the state. This available power is then plotted on the same 4-km grid as the modeled wind speed to visualize areas of higher potential wind power. Current electric transmission lines are plotted along with potential hydrogen transport conduits such as highways, railways, and pipeline. Potential water resources are also identified and mapped as water will be an important factor in hydrogen production through electrolysis. Locations with high wind power potential that are close in proximity to existing pipelines, highway, or rail, close to potential water resource, but far from existing electrical transmission lines will highlighted as potential sites.

Once wind power resource is estimated, financial costs of sample wind power and hydrogen electrolysis projects are estimated using NREL’s 2021 Electricity ATB [4] and NREL’s 2020 Transportation ATB [5] datasets respectively. Both high temperature and low temperature electrolysis systems will be analyzed for a sample 30-year lifespan project. The effective cost per kilogram of hydrogen is then approximated for the sample project at
Figure 1: Estimated average yearly wind power output for the state of Wyoming using NREL ATB 4 MW reference power curve overlayed with electric transmission lines, highway, rail, and currently installed wind turbines.

the wind conditions of the potential sites identified earlier. From there, feasibility of off-grid wind-hydrogen hybrid generation stations can be analyzed by comparing estimated cost per kilogram of hydrogen projected at these sites with values given in the DOE National Clean Hydrogen Strategy and Roadmap [6].

3 Results and Conclusions

Results show that the state of Wyoming has many sites featuring large wind resource that are too far from from existing electrical infrastructure to be developed. As seen in Figure 1, currently installed wind farms are located very near large electrical transport lines. Figure 1 also shows that there are many locations of good but stranded wind resource that are also close to existing highway and rail. This could both help with ease of the development of the site and with potential transportation methods for the produced hydrogen. Pipeline and water resources will be shown in a manner similar to Figure 1 by mapping over wind resource and comparing locations with those of the electric grid, highway, and rail. Locations estimated to be near means of transportation and water, but far from means of electrical connection will be highlighted as potential sites for the project.

NREL’s 2021 Electricity ATB and 2020 Fuel ATB datasets are used to estimate costs for installing both wind and hydrogen portions of the production plant respectively. Wind conditions analyzed earlier in the analysis will be used as inputs to the financial analysis to calculate the effective cost per kilogram of hydrogen that is then mapped to show how hydrogen costs from a hybrid project vary depending on the input conditions of location, and electrolyser type. An analysis will be performed to connect predicted wind speeds with their corresponding cost per kilogram hydrogen output. Locations highlighted previously as potential locations for the project will then be analyzed for resultant cost per kilogram to conclude if producing hydrogen using Wyoming’s stranded wind resource is financially feasible.
4 References


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Methodology for battery sizing in microgrids with wind turbines and electrolyzers using EMT simulations

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Keywords: Wind farm, Hydrogen electrolyzer, Grid following, Grid forming, Battery energy storage system.

Introduction

Due to global warming concerns, the drive to significantly participate in the electricity market and compete with the traditional power plant is one of the present wind farms (WFs) challenges, because of the wind intermittence. To tackle the latter issue, water electrolysis (EZ) technologies are seen as a resilient solution to produce long-term green energy storage in power-to-gas plants, as depicted in Figure 1. However, conversion of the full wind power into hydrogen in an isolated microgrid is still demanding, due to the actual control structure of the WFs. Indeed, the latter are controlled in grid following mode (GFL) \cite{5}, which tries to follow the frequency of an existing grid. In the considered microgrid, no grid is present. Therefore, a new component achieving grid forming (GFM), namely setting the microgrid voltage and frequency, is needed. In the present work, a battery energy storage system (BESS) will play the role of a grid, including the GFM structure. Consequently, the considered microgrid in this work includes a WF, an EZ, and a BESS.

![Figure 1: Cumulative installed water electrolysis worldwide by technology [2]](image)

The focus here is brought on optimizing the BESS size to stabilize the microgrid, having the full produced power of the WF converted into hydrogen. The work is performed via electromagnetic transients (EMT) simulations, done with PSCAD simulator. First, the modeling of the WF components including its control structure is assessed. Next, a detailed BESS electrical model and its performance having GFL and GFM as control strategies in a simple microgrid case is addressed. Besides, a simplified EZ electrical model will be discussed at the grid point of view. Finally, the BESS optimization for microgrid stability via EMT simulations is performed, and the results are discussed.
Application and results

The isolated microgrid assessed in this work is presented in Figure 2, where the WF power is fully converted to hydrogen, and the BESS presence is only to smooth the latter power transfer. All the components are connected at the point of connection (POC). The considered offshore WF contains wind turbines (WTs) modeled by a doubly-fed induction generator (DFIG) of 2 MW rated active power each. More WT characteristics are given in Table 1 [4]. Regarding the BESS, since only a few seconds of EMT simulations are performed, it is modeled as a voltage source connected to an AC-DC converter, neglecting the state of charge. Finally, from the grid point of view, the EZ is modeled simply by a ZIP load model[3].

![Figure 2: The isolated microgrid considered](image)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated Apparent power [MVA]</td>
<td>2.5</td>
</tr>
<tr>
<td>Rated Active power [MW]</td>
<td>2.0</td>
</tr>
<tr>
<td>Rated wind speed [m/s]</td>
<td>11</td>
</tr>
<tr>
<td>Rated rotor speed [rpm]</td>
<td>12</td>
</tr>
<tr>
<td>Voltage (Base) [kV]</td>
<td>33</td>
</tr>
</tbody>
</table>

Table 1: Some characteristics of the considered wind turbine [4]

The optimization of the BESS size methodology is done straightforwardly by decreasing its size in each EMT simulation, until the stability of the microgrid is lost. Figure 3 displays the impact of taking a BESS size equal to 5%$S_B$ on the stability of the microgrid system, where $S_B$ is the considered base apparent power of the system, equal to the WF maximum active power output. The signals $P$, $Q$, $V_{rms}$, and $I_{rms}$ are the active power, reactive power, RMS voltage, and RMS current respectively in per unit. As it can be noticed from the figure, the full power produced by the WF is transferred to the EZ, without any stability issues. However, for a BESS size lower than 5%$S_B$, the stability is lost, as shown in the example of 4%$S_B$ Figure 4. Consequently, the minimum required BESS size found for the considered microgrid is 5%$S_B$.

Conclusion

Based on this isolated microgrid case, it has been shown via EMT simulations that a BESS capacity size of at least 5% the WF power capacity is needed to keep the system stable. Nevertheless, several additional factors should be accounted for, such as the dynamics of the wind, the wake effect, and the start-up process of the wind turbine. Besides, the used methodology for BESS sizing in the present work focuses on small signal stability, which provides a clearer picture of the BESS requirements for small microgrids (e.g. 10–40 MW). For larger systems, other factors could further impose constraints on the sizing/number of the BESS units, such as the impact of inter-array cables, the topology of the WF, and the total harmonic distortion.
Figure 3: 5% $S_B$ BESS size performance on the microgrid’s stability.

Figure 4: 4% $S_B$ BESS size performance on the microgrid’s stability.

Acknowledgements

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References


Adequacy Computations for Power Systems with a High Share of Offshore Wind Generation: Application to Belgium

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Keywords: Adequacy, Offshore energy, Optimal Power Flow, Power Systems

1 Introduction

Offshore wind has the potential to deliver large amounts of low-carbon, renewable energy to fulfill the electrical needs, and it has become cost-competitive with fossil-powered alternatives. Therefore, large-scale offshore wind will be an important part of the future carbon-neutral electricity system. In 2022, 8 GW of offshore wind was installed around the world, which brings the global cumulative offshore wind power capacity to 64 GW [1]. The proportion of offshore wind generation is likely to sharply increase in future power systems. In Belgium, there is now 2.2 GW of offshore wind farms installed in the North Sea, which produce 10% of the total electrical demand, and it is planned to reach 6 GW by 2030. However, offshore wind is inherently intermittent, weather-dependent and hard to predict. Future power systems may therefore face new challenges to ensure a reliable electrical supply, which can be evaluated through power systems reliability studies. One important aspect of reliability is the adequacy, defined as the long-term ability of the power system to cover its load in steady-state conditions. It is an indicator of having sufficient generation capacity to satisfy current and future consumer demand or system operational constraints. The adequacy studies are carried out by the transmission system operator (TSO) and the policy-makers notably on a long-term perspective (5 - 10 years) in order to define future energy policies.

Hence, the objective of this paper is to consider the evolution of the adequacy of power systems with a high share of offshore wind generation. The potential evolutions of the power system for allowing the integration of offshore wind farm power into the grid will also be studied (through grid expansion and/or storage). The novel contributions of this work are the consideration of aerodynamic power losses of offshore wind farms within the adequacy tool, as well as the impacts on adequacy of using hydrogen to accommodate the fluctuations of offshore wind energy.

2 Methodology

Currently, adequacy calculations rely on sequential Monte-Carlo simulations. In practice, Monte Carlo simulations can be used to estimate reliability indices by simulating the actual operation and random behavior of the considered electrical system [5]. Sequential simulations allow the use of detailed hourly generation and load models, which makes them ideally suited to the analysis of time-dependent generating sources such as offshore wind generation. The idea is to sample successive system states while maintaining the time correlation between consecutive steps. The Monte-Carlo sampling process is sequential, i.e., it accounts for all contingencies and operating characteristics inherent to the power system in a chronological time-consistent way (thus keeping seasonal, weekly and diurnal patterns). The models used to generate times series for offshore generation, load and conventional production are explained in sections 2.1, 2.2 and 2.3. These times series are then fed to an optimization tool described in section 2.4. The whole methodology is then summarized in section 2.5.
2.1 Offshore wind generation

The offshore generation model is composed of two main parts, i.e., the wind model and the wind turbine generator model. These two parts are described as follows.

2.1.1 Wind model

Usually, only a wind speed model is needed for adequacy assessment. However, when taking the wake effects into account, the wind direction also has an important influence on the power output of wind turbines. Moreover, when generating wind data, it is important to maintain the correlation between wind speeds and wind directions at different locations. To that end, we use a Vector Auto-Regressive Moving Average (VARMA) model, which augments the ability of ARMA models (that accurately represent time dependencies) with a representation of cross-variable correlations.

2.1.2 Wind turbine generator output

With the wind model, offshore wind time series (hourly power profiles for a year) are generated using a Machine Learning model developed in [3]. This surrogate model is trained on wind farm simulations and yields fast and accurate predictions of the farm output. Complex aerodynamic phenomena such as wake effects and turbulence are thus taken into account. Indeed, wake effects can cause average power losses up to 20% [4] of the installed wind farm power, which is significant when considering the high amount of future offshore wind.

2.2 Load

An hourly load profile describing the evolution of load throughout an entire year is needed, as the simulations are sequential. This profile incorporates diurnal cycle, weekday/weekend patterns, as well as seasonal trends. Based on historical data, an Auto-Regressive Moving Average (ARMA) model is built, which generates load factor times series that are then multiplied by a yearly peak load.

2.3 Conventional units

Conventional generation units (nuclear, gas, coal,...) are represented using a two-state model (up or down state). The up-down-up cycle for a yearly sequence can be generated using a random sampling technique from the corresponding state residence time probability distributions. Here, the time to failure ($TTF$) and time to repair ($TTR$) are known and are exponentially distributed:

\[ TTF = -MTTF \times \ln U \]  
\[ TTR = -MTTR \times \ln U' \]

where $MTTF$ is the mean time to failure, $MTTR$ is the mean time to repair, $U$ and $U'$ are two uniformly distributed random number sequences between 0 and 1.

2.4 DC Optimal Power Flow

The objective of the DC Optimal Power Flow (DC-OPF) is to find the optimal dispatch of power generation that minimizes the cost related to the operation of the power system, while respecting all physical constraints. The various constraints include:

- Electrical balance: The total produced power (by conventional units and renewable sources) should meet the electrical load demand. In case of imbalances, production is curtailed (production exceeds load) or energy is not served (load exceeds production).
- The power of each generator should not exceed maximum power capacity.
- A DC load flow is used to compute the power flows within the electrical network. The flows are limited by the maximum capacity of the lines.

The DC-OPF tool used in this work was developed in [2].
2.5 Sequential Monte-Carlo

For each Monte-Carlo year, the simulation procedure for adequacy assessment is briefly described as follows (see Fig. 1):

1. Create a model for the availability of conventional generation units using chronological simulations.
2. Generate time series of the output of each wind farm using the time-series VARMA model and the Machine Learning proxies.
3. Generate load time series.
4. Run a DC Optimal Power Flow.
5. Compute the reliability indices, which are averaged over all generated scenarios (until convergence is achieved).

This process is carried out on a yearly basis (8760 hours), and repeated until a specified degree of confidence has been reached. Once the convergence is achieved, the simulation can be terminated. The stopping criterion used in this work is:

$$\frac{\sigma(X)}{\sqrt{N} \cdot E(X)} < \varepsilon$$  \hspace{1cm} (3)

where $X$ is the reliability index, $N$ is the number of sampling years, $E(X)$ is the mean value, $\sigma(X)$ is the standard deviation and $\varepsilon$ is a convergence threshold. The reliability indices used in this work are the Loss Of Load Expectation (LOLE) [h/year] and the Loss Of Energy Expectation (LOEE) [MWh/year]. The LOLE is defined as the expected number of hours in the year during which the electricity consumption exceeds the production, whereas the LOEE computes the expected energy not served.

3 Test case

Our test case is a simplified representation of the Belgian high voltage network (380 kV and 200 kV). The adequacy of the Belgian power system will be assessed for the years 2025 and 2030, taking into account potential evolutions of the system under different scenarios. Indeed, a nuclear phase out has been planned for 2025, which might have a significant impact on the reliable supply of electricity. In 2030, the new offshore zone is expected to be finished (increasing the offshore capacity from 2.2 GW to 6 GW). Grid expansion is planned in order to accommodate the higher share of offshore wind power, located in the North Sea (North of the country). This would allow the electricity to flow though the rest of the country. Additional interconnections with neighboring countries are also
envisioned for 2030. Moreover, a storage solution (via batteries or hydrogen, centralized or distributed) will also be studied, in order to alleviate the need for grid investments. Thus, the considered scenarios for the evolution of the Belgian power system will be:

- No grid expansion to accommodate the increased offshore generation
- 2 new lines of 6 GW each, to flow the power coming from the offshore farms in the North through the rest of the country
- A reduced grid expansion (to reduce grid investments and allow for other technologies to be used for the new lines), combined with storage
- No grid expansion but a centralized storage solution (to absorb the excess of renewable energy when production is too high or load is low)
- No grid expansion but a distributed storage solution

The different scenarios will be compared in terms of reliability of supply, investments costs, ecological impact and operational costs. Considered storage solutions involve batteries, but also the use of hydrogen through electrolyzers, $H_2$ storage and hydrogen-to-power units.

Acknowledgements

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References


Session 6.2
08.09.2023 - 10:30
Building 3701, Room 267

Keslake Rachael
Feasibility of production of synthetic fuel in an offshore environment

Isbister Callum
Evaluation of Acoustic Noise Emitted by Power Electronic Equipment
in a Variable-Speed Wind Turbine

Wagner Martin
Langevin analysis of control parameters in wind turbines

Souza De Alencar Mauricio
Graph-based diffusion solvers for wind farm collection system layout
optimization
Feasibility of production of synthetic fuel in an offshore environment

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Keywords: Offshore wind, Hydrogen, Methane, Methanol, Ammonia, Power-to-X

1 Introduction

The need to find alternative solutions for our energy supply is becoming an ever more concerning problem, when considering the effects of both the current political issues with a major natural gas supplier like Russia, as well as the climate emergency at hand. The route solution to these problems lies both in renewables and the ability to create substitutes for our current energy supplies (oil, natural gas) locally. The concept explored here combines these two solutions. That is through the production of synthetic fuels in the form of hydrogen, methane, methanol, or ammonia.

Currently the global energy sector currently makes up 73% of greenhouse gas emissions [1], this energy sector includes electricity, heat and transport, all currently fuelled predominantly by fossil fuels. Renewables seem, on the surface, to only solve the electricity portion of this problem, and this is currently the focus, however there is potential for renewables, like offshore wind, to fuel almost the entire energy sector of the world, branching into the harder reach areas of heating and transport.

Currently discussions of hydrogen tend to focus on its use as an energy storage solution, smoothing out the intermittency of renewable energy supplies like solar and wind. In this it is key due to its ability to store over long term thus smoothing out seasonal variations in these energy supplies. But the characteristic that makes hydrogen unique amongst energy storage solutions is the diversification of end uses. Hydrogen can be used in its own form without being converted back to electricity, a highly inefficient process. Through using hydrogen this way harder to decarbonise sectors, such as the chemical sector can be reached.

One issue with hydrogen is it is difficult to store and transport due to its low density(11 m\textsuperscript{3} at standard temperature and pressure [2]), and its tendency to cause embrittlement in metals, meaning transporting high purity hydrogen through existing gas pipelines is possible only with certain steel alloys or with added, costly, safety measures.

This is not the case for hydrogen derivatives such as ammonia, methanol, or methane. All already high demand commodities. Currently 38% of all globally produced hydrogen is used to make ammonia, producing 175 Mt annually [3], ammonia is a key chemical used in fertilisers and has potential to be used as a transport fuel. Hydrogen is also used to produce methanol, of which currently 98 Mt are produced per year, methanol is the largest chemical feedstock to the plastic industry[4], methanol is also a basic fuel feedstock due to its suitability as a fuel with high efficiencies and low emissions in pure form or mixed with gasoline and ethanol [5], being used currently in Iceland to fuel Vulcanol cars [6], and M100 fuels (100% methanol composition) being tested in China [7]. Methane is what makes up natural gas, with demand in 2020 reaching 2,670 million tonnes [8]. Natural gas is a key part of the UK energy supply, making up one third of the UK’s electricity and 85% of homes using natural gas central heating [9].
The solution is therefore using offshore wind farms to produce hydrogen which is stored and consumed as a synthetic fuel which is transported to land either through liquid pipelines or using ship tankers. The push for hydrogen carriers, such as ammonia and methanol, leads to the opening of energy trade from regional to global, the decarbonising of key sectors of the transport industry, the decarbonising of chemical industries and a potential green alternative to aid in the transition of the world from fossil fuels to a world of electricity and hydrogen. The key area of work to facilitate the future production of these fuels is assessing the suitability of existing infrastructure to their production.

The question as to which is most suitable to produce is dependent on many factors with the most important considerations including the available resources in the area for production as well as the demand for the product.

The overall research question posed in this work is to determine the feasibility of production of synthetic fuels at current and future wind farm locations, then, through analysis of existing and planned infrastructure, determine, for different locations in UK waters, the best location of such a plant.

2 Chosen processes

The chosen processes explored in this work are summarised in Figure 1 below. With two versions for hydrogen, two versions for methane, four versions for methanol and 2 versions for ammonia. The methods were chosen

<table>
<thead>
<tr>
<th>Hydrogen</th>
<th>Methane</th>
<th>Methanol</th>
<th>Ammonia</th>
</tr>
</thead>
<tbody>
<tr>
<td>V1 → PEM electrolysis</td>
<td>V1 → DAC CO₂ capture</td>
<td>V1 → PEM electrolysis and DAC CO₂ capture</td>
<td>V1 → PEM electrolysis</td>
</tr>
<tr>
<td>V2 → AEL electrolysis</td>
<td>V2 → Seawater CO₂ capture</td>
<td>V2 → PEM electrolysis and Seawater CO₂ capture</td>
<td>V2 → AEL electrolysis</td>
</tr>
</tbody>
</table>

![Diagram showing chosen processes](image)

Figure 1: Showing the chosen processes analysed in this work, boxes in green show the processes which are varied within the production of each synthetic fuel, and blue boxes show the processes which are kept the same. DAC stands for Direct Air Capture; PEM stands for Proton Exchange Membrane; AEL stands for Alkaline electrolysis unit.

3 Methodology

The methodology of this work involves the below general steps.

1. Modelling the chosen process units based on energy input from offshore wind farms (both currently operational and planned) using power data developed from previous own work
2. Determining from this model the expected levels of synthetic fuel production for the 10 routes (the multiple versions of the production of the four synthetic fuels)
3. Size these units and determine the suitability of placement in UK waters considering existing infrastructure available
4. Analysis of multiple datasets on existing and future planned infrastructure to highlight the areas with greatest potential for offshore synthetic fuel production

4 Results

So far only step one has been completed. With results for synthetic fuel production levels for all 46 offshore wind farms currently operational in UK waters. A snapshot of the results for PEM (version 1) hydrogen production for Barrow offshore wind farm for December 2006, are shown below in Figure 2.

![Graph of hydrogen production levels for Barrow offshore wind farm in December 2006](image)

*Figure 2: Graph of hydrogen production levels for Barrow offshore wind farm in December 2006, compared to the wind farm power output in the same period.*

The above results are the preliminary mass and energy balances completed on the ten different versions of synthetic fuel production. It must be noted no sizing has yet been done, meaning there may be instances where these levels cannot be reached due to limitations in sizes of units higher up in the production steps. However, to determine this these results will be used as a basis, and the necessary alterations made to the expected output of the synthetic fuel plant.

5 Conclusion

Next steps include perfecting the visualisation of the above data, due to its large size, followed by continued work on the next steps outlined above in the Methodology section.

6 Acknowledgements

Thanks to my supervisors for their ongoing support, OREC for their support and help with data acquisition, as well as AURA and EPSRC for funding this PhD.

7 References


Evaluation of Acoustic Noise Emitted by Power Electronic Equipment in a Variable-Speed Wind Turbine

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Keywords: Power Converters, Acoustics

The global capacity of installed offshore wind is expanding to meet the ever-increasing power demands of the world’s population. The increased reliance on wind technology is helping to achieve climate targets around Europe and aiding in the transition towards energy independence and therefore a decreased reliance on volatile foreign imports of fossil fuels. There is a particular interest in the expansion of offshore wind which presents the benefits of a higher wind resource and less disruption to communities and other industries onshore. There are current plans in place for a potential eight-fold expansion of offshore wind in Europe by the year 2050 [1]. However, with wind turbines being placed offshore, this has the potential to present problems to marine habitats and eco-systems which are present near wind farm sites. Modern day variable speed wind turbines utilise power converters to allow for maximum power capture, voltage control and to ensure a constant frequency output for grid connection. They can also be used offshore to provide reactive power compensation and for AC-DC conversion for long distance transmission. Semiconductor devices allow for fast switching with minimal power losses and so are used within power converters to control power flow.

Switched mode operation of semiconductors causes the emission of acoustics, the existence of which has been proven via experimentation by various papers [2][3][4]. The experiments prove that there is the emission of noise from both the switching action of the transistor and also due to the ageing of the device, caused by power cycling. These emissions have the potential to exist in a range of frequencies and intensities which could pose a risk to marine life present on wind farm sites [5]. Despite this, minimal research has been conducted exploring the characteristics of the acoustic emissions from semiconductor technology and the effects it may have on marine habitats. The current literature which exists in the area focuses on proving the existence of emissions as a result of switched mode operation and degradation of the transistors and is explored purely in the context of condition monitoring and failure detection. The emission of acoustics during the full lifetime of a wind farm is shown in Figure 1.

\textbf{Figure 1 - Acoustic Emissions of a Wind Farm [6]}
This project reviews the literature and analyses it in terms of the potential impacts of the acoustics on the behaviour and health of marine wildlife. There are currently widely available models which exist to describe both the electrical and thermal behaviour of semiconductor devices [7], but there is no widely accepted model for the acoustic emissions of such devices. This project investigates the available literature related to the acoustic emissions from semiconductor devices present offshore in generator and transmission systems. Through the use of Simulink software, a basic IGBT behavioural model was created and analysed to allow for a methodology to be derived into the potential routes to modelling the acoustic emissions. Through examination of both the model and the existing literature, various methods were outlined which could be used in the future to derive the acoustic emission noise spectrum using either electrical or thermal quantities of the basic IGBT model. With this knowledge, this will allow for any future attempts at acoustic emission modelling which are coupled with experimental data, to easily identify the values to measure alongside the intensities and frequencies of the noise spectrum to allow for any potential correlations to be easily identified. This paper suggests methods to creating an acoustic model of a singular IGBT, which could potentially pave the way to creating a full power converter model. The model can then be used in parallel with an environmental impact assessment which analyses the hearing characteristics of fish and marine mammals near wind turbines to understand the full effects of the power converters acoustic emissions.

References


Langevin analysis of control parameters in wind turbines

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Keywords: Langevin analysis, Stochastic differential equations, Power conversion, Control dynamics

1 Introduction

The fluctuating nature of the wind resource is one of the main challenges in wind energy. Especially in future scenarios with a predominant share of renewable energy producers, the resulting power fluctuations of wind turbines can have severe consequences for the power grid. One idea is to mitigate these influences by the attenuation of the generated power peaks at the level of turbine control. Since problems in the power grid usually occur at time scales of seconds, it is important to consider the control dynamics at these time scales as well. This is equivalent to considering the impact of the turbulent inflow conditions, which typically show strong dynamical changes at these time scales. Our main research question is therefore: How can we describe the dynamics of the control parameters of a wind turbine at this time scale of seconds?

Our approach to address this question is a Langevin model \cite{1}. This model describes the temporal evolution of a control parameter as composed of both a deterministic and a random contribution. The coefficients describing both contributions can be estimated from a temporally highly resolved data set, using a binning of the state space \cite{2}. An example of the resulting drift field, obtained from a 2 day interval of 1 Hz SCADA data of a wind turbine, is shown in Fig. 1. A clear separation line between positive and negative drift values can be identified. This line is composed of stable fixed points of the system and is also known as the Langevin power curve \cite{3}. Due to dynamical changes of the turbulent inflow, the point of operation in the drift field will fluctuate around this line, but the control system of the turbine will always drive it back towards the stable fixed points. Consequently, the presented model is capable of describing the dynamics of power conversion at a time scale of seconds, in contrast to the commonly used 10-min averaged values according to the standard IEC 61400-12-1.

2 Model

In the context of wind turbines, the Langevin model was first applied to the dynamics of the power output $P$ in dependency of the wind speed $u$ \cite{1}. The temporal evolution of $P$ is then described by a Langevin equation:

\[
\frac{d}{dt} P(t) = D_P^{(1)}(P,u) + \sqrt{D_P^{(2)}(P,u)} \cdot \Gamma(t). \tag{1}
\]

In eq. 1, a drift coefficient $D_P^{(1)}$ describes the deterministic part of the dynamics. In contrast, the second term of the sum accounts for the noisy part of the dynamics, containing the so-called diffusion coefficient $D_P^{(2)}$ and Gaussian white noise $\Gamma(t)$. Both $D_P^{(1)}$ and $D_P^{(2)}$ can be estimated from a temporally highly resolved data set, using a binning of the state space \cite{2}. An example of the resulting drift field, obtained from a 2 day interval of 1 Hz SCADA data of a wind turbine, is shown in Fig. 1. A clear separation line between positive and negative drift values can be identified. This line is composed of stable fixed points of the system and is also known as the Langevin power curve \cite{3}. Due to dynamical changes of the turbulent inflow, the point of operation in the drift field will fluctuate around this line, but the control system of the turbine will always drive it back towards the stable fixed points. Consequently, the presented model is capable of describing the dynamics of power conversion at a time scale of seconds, in contrast to the commonly used 10-min averaged values according to the standard IEC 61400-12-1.

3 Results

We now extend the Langevin model to the dynamics of the generator torque $T_{gen}$. Data of $T_{gen}$ can be obtained directly from SCADA data via $T_{gen} = P/(2\pi f_{gen})$, with the electrical power output $P$ and the rotational frequency
Figure 1: Power drift field and Langevin power curve obtained from a 2 day interval of 1 Hz SCADA data of a wind turbine. The black points mark stable fixed points of the dynamics. The colour scale was cut at a certain value in order to visualize the differences in sign of $D_p^{(1)}$. Power is normalized to rated power.

$f_{\text{gen}}$ of the generator. Since the generator torque control normally uses $f_{\text{gen}}$ as an input signal, it turns out that a 3D Langevin analysis in the $u$-$f_{\text{gen}}$-$T_{\text{gen}}$ space is required to capture the short time dynamics of the generator torque control. Furthermore, turbulent fluctuations of the wind will change both $T_{\text{gen}}$ and $f_{\text{gen}}$, so that one needs to consider two coupled Langevin equations

$$\frac{d}{dt} T_{\text{gen}}(t) = D_{T_{\text{gen}}}^{(1)}(T_{\text{gen}}, u, f_{\text{gen}}) + \sqrt{D_{T_{\text{gen}}}^{(2)}(T_{\text{gen}}, u, f_{\text{gen}}) \cdot \Gamma_{T_{\text{gen}}}(t)}$$

$$\frac{d}{dt} f_{\text{gen}}(t) = D_{f_{\text{gen}}}^{(1)}(f_{\text{gen}}, u, T_{\text{gen}}) + \sqrt{D_{f_{\text{gen}}}^{(2)}(f_{\text{gen}}, u, T_{\text{gen}}) \cdot \Gamma_{f_{\text{gen}}}(t)}.$$  

(2)
(3)

We then use a Nadaraya-Watson estimator to obtain the drift and diffusion coefficients. We find that the resulting drift fields of both $T_{\text{gen}}$ and $f_{\text{gen}}$ are physically reasonable and capture the dynamics of the control system responding to fluctuations of the turbulent inflow.

Additionally, we apply a Langevin analysis in the dimensionless $c_p$-$\lambda$-space, using the two equations

$$\frac{d}{dt} c_p(t) = D_{c_p}^{(1)}(c_p, \lambda) + \sqrt{D_{c_p}^{(2)}(c_p, \lambda) \cdot \Gamma_{c_p}(t)}$$

$$\frac{d}{dt} \lambda(t) = D_{\lambda}^{(1)}(\lambda, c_p) + \sqrt{D_{\lambda}^{(2)}(\lambda, c_p) \cdot \Gamma_{\lambda}(t)}.$$  

(4)
(5)

This reduces the description of the control dynamics to two dimensions. The resulting two-dimensional drift field for the same data set as in Fig. 1 is shown in Fig. 2. Notably, the stable fixed points in the drift field resemble the typical concave shape of the $c_p(\lambda)$-curve.
Figure 2: Drift field of $c_p$ and $\lambda$ from a 2 day interval of 1 Hz SCADA data of a wind turbine. The black points mark stable fixed points of the dynamics. The colour scale labels drift values of $c_p$ and was cut at a certain value in order to visualize the differences in sign of $D_{c_p}^{(1)}$.

Acknowledgements

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References


Machine Learning surrogate models for wind farm collection system layout optimization

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Keywords: machine learning, combinatorial optimization, offshore wind power

Introduction

Within a wind power plant (WPP), the collection system comprises the electrical connection of the wind turbine (WT) generators to power substations through electrical cables (also called inter-array cables). These circuits enable the energy produced by the WTs to flow to the substations that aggregate their power and export it to the point of connection to the grid. This subsystem can represent around 10% of the total investment cost of a new offshore plant.

The design of such system is constrained by the limited cable capacity and the avoidance of cable crossings, which confers the optimization of the cable layout a computational complexity that scales exponentially with the number of wind turbines. One formulation of the problem that takes into account only the capacity limit of the cables is known as the capacitaded minimum spanning tree (CMST) problem and it has been proven to be NP-hard [5] (i.e. there are no known algorithms with polynomial complexity that can find the global optimum).

The collection system optimization problem fall into the general family of constrained combinatorial optimization (CO), which are often found within the field of Operations Research. Exact optimal solutions for this problem can be obtained by solving mixed integer linear programming (MILP) formulations, while sub-optimal solutions can be reached with lower computational cost by heuristic or meta-heuristic methods [6]. Since the problem belongs to the NP-hard class, solving the MILP model becomes already costly as the number of turbines exceed about a hundred.

A common approach to overall WPP optimization is to optimize AEP first (exploring turbine quantity, characteristics and positions) and other systems subsequently, in a sequential manner. However, increasing AEP usually implies moving turbines away from each other to reduce wake losses, which increases the distances to be covered by the collection system, effectively requiring a compromise between the optimization of the two systems. The interplay of models from different disciplines and frequent occurrence of discrete-valued design variables make the optimization problem typically non-convex. Iterative techniques for searching the global optimum are necessary and the computational cost of each iteration will limit how thorough this search can be. This lays the case for the use of surrogate models, which comprise alternative models that produce a similar (low-fidelity) result as the original model (high-fidelity), but take less computations to run.

Among the methods to create surrogate models, artificial intelligence (AI) has been gaining momentum in the past decades. Within AI is the field of machine learning (ML), which studies algorithms that rely on experience (e.g. data) to improve their performance on solving some task. Within ML, two techniques that show promise in performing the surrogate model task for our problem are regression using supervised learning (SL) and combinatorial optimization with reinforcement learning (RL). Both may use artificial neural networks (ANN) as part of their implementation.

Objectives

The overall objective of the PhD study is to advance the state-of-the-art of surrogate models for integrated optimization of WPPs. More specifically, the following research question will be investigated:
• Is it possible to generate representative training datasets for supervised learning surrogate models?
• Can ML techniques provide fast and accurate surrogate models adequate for integrated WPP optimization?
• How well do ML models generalize across WPP sites and cable sets?

The expected outcomes that will support the answers to the above questions are:

• Database of optimal or near-optimal solutions to the collection system layout for a variety of arrangements of WPP elements, properties and cable sets (i.e. the training dataset);
• Obtain implementations of state-of-the-art heuristics and meta-heuristics for solving the collection system layout (i.e. the benchmarks);
• Implement a RL framework for training optimal collection system layout builders with different architectures;
• Implement a SL framework for experimenting with different ANN architectures for estimating the optimal collection system cost;
• Compare ML models against each other and against the benchmark techniques;
• Application of the most useful ML models for integrated optimization and discussion on the compromises between solution quality and computational complexity;

Methods

The collection system cable layout optimization problem is typically modeled using graphs. Wind generators and electrical substations are nodes in the graph and the possible or desired electrical connection between them are the graph’s edges. Both nodes and edges can have a collection of attributes relevant to the problem. An example of a graph that encodes a layout solution is shown in Figure 1.

Classic graph algorithms are helpful in measuring solution quality, assessing and enforcing constraints and obtaining sensible bounds or starting points for the optimization, even if some constraints need to be relaxed. For example, simple heuristics that minimize total cable length (instead of cost) can provide an upper bound that helps branch-and-cut MILP solvers to converge faster. Similarly, the minimum spanning tree (likely violating cable capacity) can provide a starting point for ML layout builders. The solutions from state-of-the-art heuristics and meta-heuristics and exact numerical algorithms (such as branch-and-cut) will be used as training/validation data.

The development of ML models offer many degrees of freedom (hyperparameters) in terms of both their internal architecture as well as their training strategy. Literature that describes related ML models will inform the exploration of this design space. RL approaches seen to be chosen more frequently when dealing with CO problems [4]. Some combined ML + classic CO algorithms are also described [1].

One common difficulty with applying ANN to graphs is the structural rigidity of the input layer of the ANN (usually of fixed size), which can’t be directly mapped to varying size graphs. Some approaches to circumvent this problem have been proposed, such as Graph Convolutional Networks [3], Graph Attention Networks [8, 2] and diffusion over graphs [7].

High solution quality (i.e. small optimality gap) and low computational cost are conflicting goals; discussing the compromise between the two is part of the work proposed here. Ideally, the surrogate models should be able to improve upon the best available heuristics and meta-heuristics in at least one of those goals, while keeping the other goal within the useful range for integrated optimization. The most important assessment is the computational complexity, which describes how the computational cost grows as a function of the problem size. Another important discussion is how the cost of training should be taken into account in the assessment of the application’s computational cost.
Figure 1: Example of an optimized layout for a constrained collection system design problem.

References


TOPIC 7:
Support structures and geotechnics

Session 7.1
06.09.2023 - 10:30
Building 3703, Room 335

Qian Han  Data-driven assistant for conceptual design of offshore jacket substructures
Drexler Sebastian  Analytical integration of Dirlik’s distribution for bilinear S-N curves
Mclaughlin Emmet  A review of the existing methods of phase field modelling for fatigue life predictions
Raúl Beltrán  Hysteretic Nonlinear Model for Describing Fatigue Behavior of Concrete in Hybrid Towers
Borgelt Jakob  Fatigue crack development in axially loaded grouted connections
Data-driven assistant for conceptual design of offshore jacket substructures

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Keywords: offshore jackets, conceptual design, feature engineering, machine learning

1 Introduction

The offshore wind energy sector has witnessed significant advancements in recent decades, leading to the standardization of design methods for offshore substructures in industry standards like DNVGL and IEC. The design process typically comprises three phases: conceptual design, iterative design, and detailed design, incorporating structural assessments for ultimate limit states (ULS), fatigue limit states (FLS), and accidental limit states (ALS) in specific design load cases [1]. Among these phases, the conceptual design plays a crucial role in enhancing efficiency, reducing costs, and assessing financial feasibility by determining key features of the initial structural model, such as the substructure topology, which significantly impacts the number of iterations required in subsequent design phases [2]. As offshore wind turbines continue to increase in power capacity, the development of offshore megastructures is underway, necessitating the consideration of a wide range of influential factors across various life phases during the conceptual design of substructures. However, estimating geometric dimensions during the conceptual design phase heavily relies on engineers' experience and intuition, potentially leading to biases due to limited information. Consequently, there is a pressing need to propose a more efficient and accurate approach to performing conceptual design. Machine learning (ML) techniques, which have rapidly evolved and demonstrated their efficacy across diverse applications, hold immense potential in assisting structural designs within the field of civil engineering, such as the researches in [3] [4]. By utilizing ML algorithms, it is possible to develop intelligent systems that can assist engineers in generating optimized conceptual designs. These systems can learn from existing data, capture complex relationships between design parameters, and provide more accurate estimations of geometric dimensions. The integration of ML techniques has the potential to significantly improve overall design outcomes and ensure the overall structural integrity of offshore substructures.

This work proposes a preliminary investigation on developing a ML-based assistant for conceptual design of offshore jackets that are one of typical offshore substructures usually constructed in the deep-water windfarms. To develop it, the research basis and corresponding methods in terms of feature engineering and ML model are introduced in Chapter 2. Furthermore, a demonstration application is performed in Chapter 3, which presents the results of feature engineering and a ML model predicting a vital structural feature, jacket weight. In the end, the conclusion and outlook based on the current research are discussed in the final chapter.

2 Research basis and methods

2.1 Self-developed dataset of offshore jackets

In order to analyze correlations among various features associated with offshore jackets, train ML models, and predict the structural features of jackets, we have developed a comprehensive dataset consisting of hundreds of existing offshore jacket substructures mainly from the East Asia, Europe and the US. Each instance in the dataset encompasses two distinct groups of features, capturing both the structural information of jackets and the essential external influence factors that impact their design. The first group comprises crucial structural features such as jacket weight, jacket height, top and bottom radius, layer number and leg number. These features play a fundamental role in defining the regular topologies of the collected jackets, enabling researchers to classify and categorize different designs based on their structural attributes. The second group of features summarizes the
essential external factors that influence the design of jackets. It includes information related to the rotor-nacelle-assembly (RNA), tower specifications, and site conditions. By incorporating these external influence factors into the dataset, researchers gain a comprehensive understanding of how these parameters affect the design and performance of offshore jacket substructures.

2.2 Factor Analysis of Mixed Data (FAMD)

To analyze the correlations among features in our dataset of offshore jacket substructures and support our predictive modeling efforts, factor analysis should be implemented. However, our dataset consists of categorical variables (like construction region) and numerical variables (like the dimension features of jackets). To address this issue, FAMD was applied in the factor analysis, which is a multivariate analysis technique designed for datasets that contain a combination of categorical and numerical variables. It overcomes this limitation by effectively handling mixed data types, providing a comprehensive analysis of the relationships within the dataset [5]. On the one hand, it enabled dimensionality reduction, extracting essential information while minimizing irrelevant features. This reduction allowed us to work with a more manageable dataset for subsequent analysis. On the other hand, FAMD identified external features that exhibited higher correlations with the specific structural feature of interest, aiding in predicting jacket characteristics.

2.3 Sequential Neural Network (SNN)

To perform estimations of jacket structural features based on the feature correlations identified through FAMD on the jacket dataset, Sequential Neural Network (SNN) models were employed to leverage its capabilities in capturing complex patterns within the dataset and enabling accurate predictions. The SNN operates based on the concept of sequential data processing, where information flows through interconnected layers of neurons. The building process of the SNN involves defining the model structure including input and output layers, hidden layers with activation functions, and establishing appropriate loss functions and optimization algorithms. By training the SNN on the FAMD-derived dataset, it is aimed to showcase the predictive power of the model in estimating jacket structural features based on the highly correlated external features identified through FAMD.

3 Demo estimation of jacket weight based on the results of FAMD

3.1 Results of FAMD on the jacket dataset

After performing FAMD on the jacket dataset, the first four principal components with cumulative variance larger than 50% were selected for further analyses. Table 1 lists the FL of features in these four components, in which the features are ordered according to the magnitudes of FL in the first component. The corresponding scatter plot of the features in the space of the first and second component is shown in Figure 1.

Table 1: FL of features in the first four principal components

<table>
<thead>
<tr>
<th>Features</th>
<th>Component 0</th>
<th>Component 1</th>
<th>Component 2</th>
<th>Component 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated power</td>
<td>0.72</td>
<td>0.02</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Jacket weight</td>
<td>0.65</td>
<td>0.03</td>
<td>0.00</td>
<td>0.02</td>
</tr>
<tr>
<td>RNA weight</td>
<td>0.64</td>
<td>0.00</td>
<td>0.00</td>
<td>0.04</td>
</tr>
<tr>
<td>Tower weight</td>
<td>0.50</td>
<td>0.08</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>Rotor diameter</td>
<td>0.48</td>
<td>0.15</td>
<td>0.13</td>
<td>0.01</td>
</tr>
<tr>
<td>Jacket height</td>
<td>0.47</td>
<td>0.10</td>
<td>0.21</td>
<td>0.00</td>
</tr>
<tr>
<td>Water depth</td>
<td>0.45</td>
<td>0.07</td>
<td>0.11</td>
<td>0.03</td>
</tr>
<tr>
<td>Bottom radius</td>
<td>0.42</td>
<td>0.01</td>
<td>0.16</td>
<td>0.00</td>
</tr>
<tr>
<td>Wind speed at hub height</td>
<td>0.16</td>
<td>0.23</td>
<td>0.32</td>
<td>0.00</td>
</tr>
<tr>
<td>Top radius</td>
<td>0.15</td>
<td>0.24</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>Wave period</td>
<td>0.11</td>
<td>0.07</td>
<td>0.00</td>
<td>0.58</td>
</tr>
<tr>
<td>Leg number</td>
<td>0.08</td>
<td>0.41</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Layer number</td>
<td>0.06</td>
<td>0.19</td>
<td>0.64</td>
<td>0.17</td>
</tr>
<tr>
<td>Leg diameter</td>
<td>0.04</td>
<td>0.27</td>
<td>0.15</td>
<td>0.02</td>
</tr>
<tr>
<td>Brace diameter</td>
<td>0.03</td>
<td>0.32</td>
<td>0.19</td>
<td>0.02</td>
</tr>
<tr>
<td>Wave height</td>
<td>0.02</td>
<td>0.04</td>
<td>0.06</td>
<td>0.51</td>
</tr>
</tbody>
</table>
The values of FL reveal valuable insights into the correlations among external and structural features. The FL list and scatter plot provide a comprehensive understanding of the relationships among these features. According to Table 1, the first eight features including three structural features (jacket weight, jacket height, bottom width) and five external features (rated power, RNA weight, tower weight, rotor diameter, water depth) have larger FL in the first component. This indicates, on the one hand, a strong correlation between these features and the overall variability captured by the first component. Meanwhile, the scatter plot illustrates that these features are located close to each other, reinforcing their interrelationship, as shown in the red box. On the other hand, the jacket weight, being among the structural features with larger FL in the first component, plays a crucial role in determining the overall variability captured by the first component. The presence of external features with significant FL in the first component suggests their considerable influence on the variation in the jacket weight. This finding highlights the relevance of considering these external factors in predicting and understanding the jacket weight.

3.2 SNN model for estimating jacket weight and prediction results

The observed correlations among the external and structural features provide meaningful perspectives for potential predictive modeling. The larger values of FL of five external features and jacket weight in the first component and their close proximity in the scatter plot suggests a strong association among these factors. This revelation guides the development of a SNN model to predict jacket weight (output) based on the highly correlated external features (inputs). The SNN architecture consists of three hidden layers with 64, 32, and 16 elements, respectively. ReLU is used as the activation function, while the mean squared error (MSE) serves as the loss function. The Adam optimization algorithm is employed to train the model. The dataset is divided into training sets (75% of the data), validation sets (15% of the data), and testing sets (10%).

The results of the SNN model are evaluated using various visualizations and metrics. Five scatter plots are shown in Figure 2, which depict the 2D relationships between each input feature and the corresponding jacket weight. The scatter plots display the real datapoints in blue and the prediction datapoints in red, showcasing a good match between the two sets. This observation indicates that the SNN model effectively captures the underlying patterns and relationships in the dataset. To further assess the performance of the model, a diagram illustrating the variation trend of loss values for the training and validation sets across different iteration steps is also presented in Figure 2. The curves display a converging trend, validating the plausibility of the SNN model and suggesting that it successfully learns and generalizes from the dataset.

Additionally, the R2 value, a commonly used metric to assess prediction accuracy, was computed for the SNN model. The obtained R2 value of 0.66 indicates the adequate prediction accuracy of the SNN model. This metric highlights the effectiveness of the SNN in capturing the complex relationships between the external features and jacket weight. Overall, the described SNN model demonstrates its efficacy in estimating jacket weight based on the highly correlated external features.
4 Conclusion and outlook

This preliminary demo estimation substantiates that the application of FAMD in feature engineering can effectively reduce the dimensionality of the dataset, select correlated features, and thus save the training time. Based on the results of FAMD, the good performance of SNN model for predicting jacket weight provides valuable insights and new directions for conceptual design of offshore jacket substructures in the wind energy industry. In further works, enhanced correlation analyses for feature selection will be performed to explore more factors providing a more comprehensive understanding of their influences on jacket topologies. Meanwhile, the Integration of additional ML techniques is also crucial, as comparing and combining multiple models may further enhance the accuracy and robustness of the predictions.

Acknowledgements

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References


Figure 2 Five scatter plots between each input feature and the corresponding jacket weight, and a diagram showing the variation trend of loss values for training and validation sets
Analytical integration of Dirlik’s distribution for bilinear S-N curves

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2023-06-02
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Keywords: fatigue, spectral methods, frequency domain analysis, Dirlik

Abstract

The application of spectral methods within the early design of offshore wind turbine (OWT) support structures is a popular approach to reduce computing times and to make large-scale optimizations with multi-location focus feasible. The speed-increase associated with frequency domain analyses (FDA) in comparison to the state-of-the-art time-domain simulations comes typically with a reduction in accuracy, which can be quite significant dependent on the load case and boundary conditions. For one, non-linear effects cannot be modeled and need to be linearized. For another, simplifications and assumptions are often in place to make FDA applicable which do not fully reflect the real world’s behavior. One common approach while using FDA is the assumption that the response of an OWT support structure is narrow-banded, meaning it vibrates only at a single natural frequency and solely within the corresponding mode shape. The peaks of this vibration are assumed to be Rayleigh distributed which allows for an analytical description of the expected fatigue damage and makes the FDA approach very fast.

Real response spectra of OWT support structures can be rather broad-banded and irregular. The Rayleigh approach cannot be used. To get accurate fatigue estimates the response spectra can be transformed into time series which then need to be evaluated through rainflow counting. This proceeding is the most accurate, but eliminates the FDA speed advantage. To avoid this, approximations of the rainflow stress ranges can be applied. A widely used approach is the empirical Dirlik distribution determined by a fit of results obtained in various numerical simulations with different broad-banded spectra\cite{2}.

Analytical descriptions of the expected fatigue damage with applied Dirlik distribution exist, but solely for single slope S-N curves\cite{1}. An application of this approach on OWT support structures can be too conservative since their fatigue behaviors are mainly driven through wave loading. Depending on the location, up to 60\% of their lifetimes, only slight to moderate sea states occur. As a consequence, the stress ranges within the support structures are rather low and the fatigue evaluation is done exactly within the S-N curve region where a second slope would provide more fatigue strength. Therefore, this study derives the analytical description of the expected fatigue damage under consideration of the Dirlik’s rainflow stress range distribution in combination with a two slope S-N curve.

References


A review of the existing methods of phase field modelling for fatigue life predictions

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Keywords: Phase field, S-N Curve, Fatigue, Cyclic loading

Development of fatigue design curves, which are often referred to as S-N curves, can be a costly and time-consuming endeavour, requiring numerous samples to be tested to failure under differing cyclic loading stress amplitudes, stress concentration factors (K), and stress ratio (R). Fatigue testing produces highly scattered data due to material variability. Current standards, such as BS 7608 \cite{1}, state that the design curve should be considered in favour of the base fatigue curve, due to the fact the design curve uses the arithmetic mean of the cycles to failure at a given stress amplitude, minus two standard deviations, resulting in a probability of survival of 97.7\% \cite{2}. The purpose of this study is to review existing methodology for the prediction of S-N curves via the use of phase field modelling techniques, and discuss the possibility to increase the scope beyond S-N curves, via introducing material variability, to produce a variety of data points allowing the fatigue design curve to be estimated.

Phase field modelling is an innovative approach to fracture mechanics, that has grown in popularity over the past two decades, and has been used to model crack propagation \cite{3}, hydrogen embrittlement \cite{4}, composites delamination \cite{5}, and the focus of this study S-N curves \cite{6}\cite{7}. Phase field modelling stems from Griffith’s theory of crack propagation \cite{8}, based of thermodynamic principals and energy balance, Griffith (1920) stated that cracks will propagate if the potential energy in the solid is equal to or exceeding the energy requirements to increase the surface area of the crack, known as the critical energy release rate ($G_c$). Although the theory forms the basis of fracture mechanics, it’s not without its limitations, as explained by Franfort and Marigo (1998) \cite{9}, such as predicting crack initiation, crack path and crack jumps along the crack path, the paper went on to write Griffith’s functional in the variational form, and proposed that viewing the problem as a matter of energy minimization, would allow the limitations to be overcome. However, the minimization of the total energy is hindered by the unknown nature of the crack tip parameter. In order to solve for this, a phase field parameter ($\phi$) was introduced, to show the crack tip not as a sharp interface, but a smooth function between the fully cracked material, and fully intact material \cite{3}. Alessi et al (2018) \cite{6} proposed that phase field modelling can be used to predict fatigue damage by the introduction of a fatigue degradation function $f(\alpha)$, which effectively degrades the material toughness as a function of the accumulated strain during the loading stage. Schreiber et al \cite{7} went a different route suggesting that crack growth can be simulated via increasing the driving force of fracture, through a linear Miner’s law rule. The focus of this study is to thoroughly review the existing methods of phase field modelling for fatigue life predictions and compared their advantages and disadvantages for fatigue analysis.

References

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Crack initiation and growth. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 379(2203).


Hysteretic Nonlinear Model for Describing Fatigue Behavior of Concrete in Hybrid Towers

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Keywords: Fatigue, Concrete, Hysteresis Models

Wind towers are subjected to cyclic loading during their service life. As the load cycles are repeated and damage occurs, the elastic response of the concrete changes. Both increased strains (Figure 1) and a change in the shape of hysteresis cycles (Figure 2) are evidence of this change in elastic behavior. This phenomenon is often mistaken for a simple increase in the nonlinear behavior of concrete [1]. In addition to the simple change in nonlinear behavior, structures continuously subjected to cyclic loads such as those mentioned above are induced to a state of nonequilibrium caused by so-called conditioning. This conditioning state is responsible for the transition of the material to a new elastic state, which occurs when the specimen is under continuous cyclic loading. This conditioning state depends on the frequency and lower and upper stress levels of the cyclic loading [2]. While conditioning at strains of order $10^{-6}$ can be considered a reversible process, conditioning at higher stress levels with strains of order $10^{-3}$ (See Figure 1) introduces irreversible changes in the concrete structure, which causes additional changes in the nonlinear elastic response of the concrete. In the present investigation we will address the change in hysteresis behavior and the evolution of the nonlinear ultrasonic characteristics of concrete under high strain conditioning. For this purpose, fatigue tests were carried out at three different stress levels in prismatic concrete samples a/h = 100/300 mm and ultrasonic measurements were taken. In the same way, the change in deformations is analysed with a similar measurement frequency. We analyse the data using a Preisach-Mayergoyz space picture for the elastic behavior of the concrete [3,4], which reproduces the hysteresis and discrete memory seen in the data. On the basis of these results, we propose a model to evaluate different cyclic loading regimes. The analysis of the evolution of nonlinear parameters for conditioning strains in the order of $10^{-3}$ is relevant for practical applications, as wind energy towers are subjected to cyclic deformations in precisely this range of values.
Acknowledgements

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References

Fatigue crack development in axially loaded grouted connections

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Keywords: Grouted Connections, Crack Detection, Structural Health Monitoring

Abstract

Offshore structures are considerably subjected to dynamic loading. Hence, the fatigue behaviour of grouted connections typically used to connect foundation and support structure are of particular interest. This study presents a new test concept for cyclic axially loaded grouted connections using fibre optical sensory integrated into the grout annulus. It aims to provide insight into the mechanisms of damage initiation and propagation through real-time crack detection. Specimens have been designed such that they can be opened after test conduction and provide a submerged condition during testing. Test results show three phases of fatigue degradation, declared as stable, incremental, and progressive degradation. Furthermore, phase changes are not directly characterised by the appearance of cracks, but by their propagation. Visual analysis of the opened specimen and laser data confirmed failure between grout and inner tube. The overall test concept, including the openable test specimen and the novel measurement set-up, is found to be functional. They significantly improve the possibilities for crack and degradation development analysis for grouted connections under cyclic loading.

1 Introduction

Grouted connections are used for various offshore support structures in the wind energy sector. In monopile and jacket structures, grouted connections link the transition piece and jacket legs, respectively, to the foundation piles. These connections are formed by joining two overlapping steel tubes of varying diameters, utilising high-strength mortar as filling material of the annulus. In addition, shear keys are placed on the facing steel surfaces to enhance the load capacity and reduce the risk of slippage [1–3]. As offshore structures are considerably subjected to cyclic loading, the fatigue behaviour of grouted connections is of particular interest. This abstract is limited to axially loaded grouted connections as used in jacket structures.

Previous investigations have found two main damage mechanisms of axially loaded grouted connections under cyclic loading. Besides grout crushing in front of the shear keys, diagonal cracks appear due to failure of the compression struts between corresponding shear keys [4–8]. Experimental investigations on cyclic axially loaded grouted connections under submerged conditions by Raba [9] have shown that the fatigue degradation behaviour exhibits different phases of displacement development. Initially, there is only a small increase in displacement, followed by a constant increase. Finally, the failure of the specimen occurred due to a disproportionate increase in displacement. The shape of the displacement development is driven by the damage mechanisms grout crushing and crack development, but the interaction between them is still under investigation. In particular, information on crack initiation, location, and development is of interest. Therefore, this abstract provides an experimental approach using a novel Fibre-Bragg-grating (FBG) sensory for the crack detection within the grout material during cyclic loading. This may provide a basis for the disaggregation of the fatigue degradation of cyclic axially loaded grouted connections.
2 Testing concept

A novel testing concept has been developed to improve the understanding of the fatigue degradation of cyclic axially loaded grouted connections based on crack detection within the grout material. This concept involves fatigue testing on a scaled openable specimen. The specimen is shown in Figure 1(a), (b) and consists of an inner tube, grout material, and a separable outer tube. The outer half-shells are connected by bolts. There are five levels of circumferential shear keys spaced 50 mm apart on the facing surfaces of the inner and outer tubes. The openable specimen allows inspection of crack pattern after fatigue testing. An additional sealing allows the specimen to be flooded to provide realistic submerged conditions during testing.

In addition, a novel FBG measurement set-up is implemented within the grout annulus to allow crack detection during testing, thus providing more insight into the crack evolution during cyclic loading of grouted connections. The FBG sensors are placed in the centre of the grout annulus between the different levels of the shear keys, as shown in Figure 1(c); they are equal in length than the shear key spacing (50 mm) and are distributed over 80° in circumferential direction. Functionality of the FBG sensors is based on the change in periodic refractive index to measure a reflected wavelength with a spectrum of 48 nm. The sensors measure compressive and tensile strains that are integrated over the measurement length, limited by two anchor plates at the end of each sensor. Based on the wavelength spectrum and sensor length, each sensor can measure displacements up to 1.3 mm.

![Figure 1: Novel test specimen: (a) Assembled; (b) Exploded view; (c) FBG sensor set-up](image)

The specimen is tested using a hydraulic pulsator with a pure axial force controlled load and a load frequency of 2 Hz. The upper and lower load limits are constant for the test and in compression-compression condition. The termination criterion is set at a maximum displacement between the inner and outer tube of 15 mm.

3 Results

In this section the measured machine displacement and FBG data is evaluated. The crack pattern exposed by the opening of the specimen at the end of the test is used for comparison.

Figure 2(a) shows the displacement development over the endured cycles with a grey dashed line. The specimen reached the failure criterion of 15 mm displacement after 238 000 cycles. The displacement curve can be roughly divided into 3 phases. Up to 138 000 cycles, there is almost no increase in displacement (stable phase). This phase is followed by a constant increase in displacement for a further 58 000 cycles (incremental phase). At the end of the test, an enormous increase in displacement is observed, as 42 000 cycles result in an additional displacement of more than 10 mm; this phase is referred to as progressive phase. The displacement development corresponds to the observations made in the previous research mentioned in section 1. Note that the transition between the phases is smooth and that the classification presented here represents one way of describing the displacement development during cyclic loading. In the future, a more comprehensive analysis of the test series may yield an objective criterion for identifying these phase changes.
To explain the aforementioned phase changes in the displacement development, the FBG data during testing is evaluated; the measured wavelength for each sensor is shown in Figure 2(a) with coloured lines. The location of the FBG sensor is shown in the thumbnail of the specimen. Increasing wavelengths correlate with positive strains and therefore sensor elongation. For the first 50 000 cycles there is no significant change in wavelength for any of the sensors. At 50 000 cycles FBG 1 shows a clear kink and detects the first crack (A). This crack opens up with further cycles until a second crack is detected by FBG 2 at approximately 88 000 cycles. Compared to the displacement curve, the initiation of these cracks does not affect the displacement development. A change in the displacement curve occurs with the excessive opening of cracks 1 and 2 at 138 000 cycles (C). The crack opening stops at 155 000 cycles and is accompanied by the appearance of 3 additional cracks in the lower part of the connection, detected by sensors FBG 3, FBG 4, and FBG 5 (D). It can be excluded that only one additional crack is detected, as the measurement of the three lowest FBG sensors is completely different for further cycles. The crack detected by FBG 4 opens up at 175 000 cycles and leaves the measurement range shortly afterwards. The opening of the crack detected by FBG 5 correlates with the change from incremental to progressive displacement growth.

Figure 2(b) shows a section of the grout annulus after opening the specimen. It can be seen cracks appeared all along the circumferential direction. Therefore, a virtual FBG sensor axis is used to show the height at which the sensors are located in the grout material. The inner tube with shear keys is shown on the left hand side in Figure 2(b). The outer tube has been removed. During the test conduction, the inner tube moves through the grout material until the maximum displacement of 15 mm is reached; this can be confirmed by the gaps above the shear keys of the inner tube. The imprints of the shear keys of the outer tube are seen on the right edge of the grout body, confirming that there is no movement between the grout material and the outer tube. Diagonal cracks develop from the shear keys of the inner tube to the shear keys of the outer tube, except at the highest level. At this level a horizontal crack can be observed (FBG 1). However, there is at least one crack within the measurement range of each FBG sensor, confirming the measurement data. Note that the crack width after opening the specimen cannot be directly compared to the FBG measurements as the measurement range ends at...
approximately 1.3 mm elongation. In addition, it cannot be ruled out that careful opening of the specimen influences the crack width. In general, the crack pattern of the opened specimen shows additional conspicuous compared to the measurement data, such as multiple cracks in the area of the FBG 4 sensor. However, the FBG measurements are able to visualise the sequence of crack appearance and the effect of each crack on the development of the connections displacement. It can be seen that it is not the crack initiation but the crack opening that is responsible for the changes in displacement. In combination with the crack pattern, additional information about the critical damage interface can be obtained.

4 Conclusion

This abstract presents a novel measurement set-up for the crack detection in cyclic axially loaded grouted connections. The measurement system includes FBG sensory within the grout annulus. Insight into the crack development during testing is obtained. Crack initiation and opening are detected by the sensors and can be located as they occur. As the specimen is designed to be openable, it is possible to correlate the crack pattern with the FBG measurement after the test has been completed. The critical area of damage can be identified as the interface between the inner tube and the grout material. The FBG data matches the crack pattern of the opened specimen and confirms the suspected crack direction. However, further evaluation is required to fully understand the fatigue degradation of cyclic axially loaded grouted connections.

Acknowledgements

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References

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Zinas Orestis  
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Sanders Immo  
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Elahi Seyed Ahmad  
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Study on Scour Around Monopiles Under Coupling Effects of Periodic Tides and Monopile Vibration

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\textbf{Keywords:} monopile; scour; periodic tides; monopile vibration

\section*{ABSTRACT}

Foundation scour poses a threat to the operation of offshore wind turbines (OWTs) as it can gradually reduce the embedded depth of the footing piles of the foundation. Despite some studies and investigations having been carried out, the understanding of scour around OWT foundations in marine environment is not very clear to date. The main reason is that the vibration of OWTs and periodic ebb and flow of tides have rarely been considered in previous studies. How these two factors impact the scour progress respectively and together is the research question this study will address. The study considered four scour scenarios, including scour in unidirectional current, scour in periodic tides, scour around vibrating monopile in unidirectional currents, as well as scour around vibrating monopiles in periodic tides. The results show that both monopile vibration and periodic tides have remarkable impact on scour development.

\section*{1 INTRODUCTION}

The offshore wind energy has become an effective and powerful method of addressing the increasingly climate crisis, and the offshore wind turbines (OWTs) are blooming around the world [1]. Despite the invention and application of many foundation types for OWTs in both nearshore and offshore wind farms, bottom fixed foundation remains the dominant option in the global offshore wind industry. Among these foundation types, monopile foundation is the most popular [2]. Over 75% constructed OWTs are deployed in nearshore sites and supported by monopiles, the safety of which is threatened by tide and current induced scour around the foundation, as it can dramatically reduce the embedded depth of the foundation [3] [4].

Many efforts have been made in the past decades to improve the understanding on scour [5] [6], most of which are focused on scour mechanism and prediction method for equilibrium depth of scour pit around stationary structures in unidirectional current. While these findings have provided valuable insights into scour problems in bridge engineering, they may not fully capture the complexity of scour scenarios faced by OWT foundations in marine environments. In addition to unidirectional currents, OWTs are also exposed to wave action, ebb and flow, and vibrations induced by environmental loads and OWT operations, which pose further uncertainties in scour problems around OWT foundations. Some laboratory model tests have been conducted to investigate the scour in waves [7] and tides [8] [9]. The impact of monopile vibration has also been investigated in laboratory tests [10] [11]. All these studies are valuable to further understand the scour in marine environments, but there are still some limitations. For example, these studies reported some results, but further mechanisms explanation were lacked. Moreover, these studies focused on the impact of one specific factor, how they work together to impact the scour progress is not clear to date.

With concern to the limitations discussed above, the aim of this study is to investigate how periodic tide and monopile vibration work together impact scour. In this study, a numerical model consists of a water tank, sediment, and monopile will be established and used to investigate how monopile vibration and reciprocal current individually and work together to influence the scour development.
2 NUMERICAL MODEL

The numerical model was constructed using FLOW3D-HYDRO software. As shown in Figure 1, it consisted of a water tank, a scaled pile, a sediment area, and a fluid region. The pile’s diameter \((D)\) of in the numerical model was 0.05 m with a length of 0.3 m, 0.08 m of which was embedded in the sediment. The sediment is composed of sand with characteristics outlined in Table 1. The sediment region had a length of 1 m, width of 0.32 m (6.4D), and a depth of 0.08 m. The numerical model of water tank is 1.2 m (24D) long and 0.32 m (6.4D) wide, with a pair of blocks placed at the inlet and outlet of water tank to smooth the current and prevent scour of sediment at the inlet and outlet. To smooth the current and prevent sediment scouring at the inlet and outlet, a pair of baffles were placed at each end of the water tank. The fluid region's water depth was 0.15 m, and the current velocity was 0.25 m/s, with its direction reversing periodically in reciprocal current scenarios.

![Figure 1. Numerical model established in FLOW3D-HYDRO](image)

Table 1 displays the four scenarios considered in the study. The first scenario involves a stationary monopile installed in unidirectional current, representing a classic static scour scenario. The resulting data will be used as a reference to compare with other scenarios. The second scenario involves a vibrating monopile in unidirectional current, to analyse the effect of monopile vibration on scour development. In the third scenario, the current direction reverses every 30 minutes while the monopile remains stationary during numerical calculation. The fourth scenario considers both monopile vibration and periodic reversal of current direction to examine the combined effect of monopile vibration and reciprocal current on the scour development process.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Monopile Vibration</th>
<th>Current condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>×</td>
<td>Unidirectional Current</td>
</tr>
<tr>
<td>2</td>
<td>×</td>
<td>Reciprocal Current ((T=60\text{min}))</td>
</tr>
<tr>
<td>3</td>
<td>Amplitude: 1cm</td>
<td>Unidirectional Current</td>
</tr>
<tr>
<td></td>
<td>Frequency: 0.5Hz</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Amplitude: 1cm</td>
<td>Reciprocal Current ((T=60\text{min}))</td>
</tr>
<tr>
<td></td>
<td>Frequency: 0.5Hz</td>
<td></td>
</tr>
</tbody>
</table>

3 RESULTS

Figure 2 depicts the time evolution of maximum scour depth around the monopile in all considered scenarios. To facilitate generalization and comparison, all scour depth results have been normalized using the pile diameter. It should be noted that the location of maximum scour depth around the monopile may vary with time. Therefore, the data at different time points in Figure 2 are measured at different positions around the monopile. It can be observed that the maximum scour depth decreases every 30 minutes in the reciprocal current scenario with a period of 60 minutes. This can be attributed to the refilling of the scour pit at the backside and lateral side of the monopile. When the flow direction is reversed, the wake vortex induced deposition at the backside (fore side in the previous half cycle) of the monopile will backfill the scour pit at the position where it was usually the...
deepest in the previous half cycle. As the half cycle is long enough, after the short-term backfilling at the flow reverse point, the scour pit will develop faster. Consequently, a deeper scour depth will gradually develop at the fore and lateral sides of the monopile. Finally, the maximum scour depth around the monopile in reciprocal current is deeper than that in unidirectional current.

![Figure 2](image)

**Figure 2.** Time development of normalized maximum scour depth around the monopile

In scenario 3, the monopile continuously vibrates in the unidirectional current during the simulation. The results shown in Figure 2 demonstrate that the maximum scour depth in this scenario continues to develop rapidly despite some fluctuations. This is understandable since the fore-back direction vibration of the monopile can significantly alter the turbulence around the pile, leading to instability in the development of the scour depth. Figure 3 shows a comparison of flow patterns around a static pile and a vibrating pile, indicating that the vibration of the pile exacerbates the vortex around it. In addition, the downward flow at the upstream side of the pile in the vibrating scenario is stronger than that in the stationary pile scenario. As a result of the influence of pile vibration, Figure 2 illustrates that the final maximum scour depth in the vibration scenario is significantly deeper than that in both the unidirectional current scenario and the reciprocal current scenario.

![Figure 3](image)

**Figure 3.** Flow patterns around (a) static pile and (b) vibrating pile.

Scenario 4 investigated the combined effects of vibration and reciprocal current. The results demonstrate a significant backfilling at the end of each half cycle, followed by a faster scour pit development rate. Figure 2 illustrates that the backfilling at the second current direction reversal point is not as remarkable as the first one. It can be attributed to two reasons: firstly, the scour pit has reached a quasi-equilibrium state when the variation of scour pit is relatively moderate, secondly, the vibration of the pile decreased the backfilling process. It is shown in Figure 2 that, under the impact of pile vibration, the scour depth development speeds in the last two half cycles of scenario 4 are notably faster than in all other scenarios considered in this study. Consequently, the maximum scour depth at the end of the simulation in scenario 4 is the deepest among all the scenarios.

As shown in Figure 2, the normalized scour depth at the end of the simulation of scenario 1 is about 0.76D, while for the other three scenarios, it is 0.83D, 0.86D, and 0.89D respectively. This indicates that both monopile
vibration and reciprocal current can increase the scour depth in a long term. It shows that the coupling effect of monopile vibration and reciprocal current can increase the final scour depth by 17.11%. As shown in Figure 2 that only scenario 1 has reach an equilibrium scour depth at the end of the simulation, it implies that the impact of pile vibration and reciprocal current may be higher than illustrated in Figure 6. It should be noted that these factors, although important, are not the primary factors, such as current velocity, determining the scour development. Consequently, the influence of these factors on scour is limited.

4 Conclusions and Future Work

To further understand the scour around the monopile, a numerical model was established and used to investigate how monopile vibration and reciprocal current individually and work together to affect scour around a monopile. Based on the findings presented above, the main conclusions of this study can be summarized as follows:

- Reciprocal current can cause noticeable backfilling of scour pit when current direction is reversed. However, it can cause a faster scour speed and deeper scour depth after the backfilling.
- The scour depth development speed around vibrating monopile is faster than that around stationary monopile.
- Both monopile vibration and reciprocal current can increase the final scour depth around a monopile. The coupling effect of monopile vibration and reciprocal current can result in the deepest scour depth.

The study of scour progress at a vibrating monopile around periodic tides is a relatively new topic in the field of offshore engineering. This study represents a preliminary investigation into the coupling effect of vibration and periodic tides on scour. The flow patterns around a vibrating monopile in periodic tides are complex and can be influenced by any variation in the characteristics of these factors. For instance, changes in ebb and flow patterns, as well as in monopile vibration periods, amplitudes, and directions, can significantly alter the fluid-structure interaction around a monopile and affect the scour process. More extensive research is needed to investigate the impact of these factors on scour in greater detail.

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3D Probabilistic Site Characterization

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Keywords: Probabilistic site characterization - Bayesian methods - Spatial variability - Conditional Random Fields

Reliability methods in geotechnical design are gradually gaining more attention among the geotechnical community over the recent years. Site investigation is located on the basis of geotechnical RBD. A sound geotechnical analysis necessitates the systematic uncertainty quantification in the inputs of geotechnical models, which can only be achieved through the application of more rigorous probabilistic methods for analyzing efficiently site investigation products and uncertainties associated with the inherent variability of the soil material [6], and the limited and sparse - compared to the size of the site at hand - data, collected in site investigation programs.

Offshore foundations in the context of wind farms are subject to uncertainties during their design and assessment [7]. Traditionally, these uncertainties have been addressed using semi-probabilistic approaches that combine expert knowledge, engineering experience, and geophysical/geotechnical field test data to derive deterministic subgrade models. By utilizing sparse site-specific CPT soundings and by adopting a fully probabilistic - Bayesian framework, this ongoing study aims to construct a three-dimensional (3D) Random Field model of the cone-tip resistance parameter \( q_c \), to explicitly characterize its spatial correlation structure and the statistical uncertainty in the Random Field parameters (hyperparameters), i.e. standard deviation \( \sigma \) and scales of fluctuation in each direction \( (\theta_v, \theta_h) \) [2]. For this scope, the current study proposes a hierarchical Bayesian methodology [4] and leverages advanced sampling methods, such as Markov Chain Monte Carlo (MCMC) algorithms [1], [3], [5], to derive a predictive 3D interpolation map for the cone tip resistance \( q_c \), accompanied by Bayesian credible intervals that capture the uncertainty in the predictions.

The outcomes of this ongoing research aim to contribute to the advancement of data-driven site-characterization practices to offshore wind farms and to serve as an efficient tool for complementing and supporting sound engineering judgement and expert knowledge in design decisions for pile foundations.
1 Example results of the ongoing study

Figure 1: Example MCMC trace plots and histograms for the (3D) Random Field (hyper-)parameters, based on 250 simulated values (after burn in period of 250 samples); \( \sigma \): standard deviation, \( \theta_v \): vertical scale of fluctuation, \( \theta_h \): horizontal scale of fluctuation; dimensions of the site: 100x200 (xy plane) x 24m (depth); assumption of isotropy in xy plane (single \( \theta_h \))
Figure 2: Top: Example of a 2D Random field (along a line of the site); Bottom: Conditional random field at a specific x coordinate; dimensions of the site: 25m x 3.5m (depth); CI: Credible intervals, trend: polynomial function for the mean
Acknowledgements

Acknowledgements, if any.

References


Numerical Simulation of Suction Caissons under Axial Loading

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Keywords: Suction Bucket, Suction Caisson, SAniSand, Numerical Modelling, Soil Structure Interaction, Scaling

In recent years, suction caissons (also known as suction buckets) have emerged as an optional foundation type for offshore wind energy generators (OWEG). Not much experience exists in design and lifetime performance of this type of foundation and simple, precise and reliable models and approaches need to be developed. In offshore geotechnics, prototype testing is associated with great expenses, thus testing onshore and at smaller scales is favourable.

Since the consolidation stresses in small-scale model tests are decreased due to smaller overburden, aspects such as the stiffness change when structures are simply scaled down geometrically. Also, distance and volume change with different exponents to length. This leads to complex interaction when transient (e.g. flow and pressure change) effects are regarded.

One approach to scaling can be numerical simulation; the laws of physics that govern the behaviour of soil material apply at both the small and the prototype scale. A finite element (FE) model which incorporated these constitutive relations can be scaled to an arbitrary size as long as the underlying qualitative behaviour of the considered elements such as soil, steel and water do not change. In the presented project, a finite element (FE) model was developed and calibrated at the small scale to answer two main questions:

- Is it worthwhile to use a rather complex constitutive model?
- Which aspects of the small-scale model test need to be incorporated into the numerical model?

To achieve this, two constitutive models were used; once a simple linear-elastic elasto-plastic model and once the advanced SAniSand model \cite{2}. Different setups of model test were then simulated to find the influence of the geometric boundary conditions.

The small-scale model tests the numerical model is based on were carried out in a circular test tank with a diameter $D_t = 2.5m$. A model suction caisson with Diameter $D_o = 0.61m$ and Skirt Length of $L = 0.61m$ was used. In Figure 1 the testing facility and caisson are depicted with their respective instrumentation.

The FE-Software ABAQUS \cite{1} was used to model the caisson under loads and displacements in compressive and tensile direction. To investigate their respective influence in the calculations, the testing container, gap at the caissons lid invert, and the incomplete penetration of the caisson into the soil were studied independently. Figure 2 (a) shows the model setup.

The calibration of the linear-elastic elasto-plastic (Mohr-Coulomb, MC) constitutive model is described in \cite{3}. Calibration of the 15 parameters of the SAniSand constitutive model was done by a multi-step approach. First, the parameter ranges were narrowed down using triaxial test results, where possible. Next, about 10 drained triaxial tests were back-calculated and the results were fitted by changing parameter sets with particle swarm optimization (PSO) \cite{4, 5}. Last, the parameter sets gained from PSO were compared and parameters for the final set were selected.

Back-calculations of the tests yielding the drained tensile capacity $F_{dr,t}$ in model tests enabled to adapt the interface friction and earth-pressure coefficient (i.e. $k \cdot \tan(\delta)$) to each model test (cf. Figure 3). For generic simulations, a representative value was chosen. The drained tensile capacity could be very well met as can be seen in Figure 3. As the correlation of $k \cdot \tan(\delta)$ and $F_{dr,t}$ is still ongoing, $F_{dr,t}$ was not well met in calculations using SAniSand. When considering the stiffness, only the value at the very onset of the tests was met well. The force-displacement relation in the FE-modelling was changed abruptly from stiff to soft behaviour, while the transition in model tests was more gradual.
Displacement of the caisson in tensile and compressive direction was simulated at different velocities to gain insights into the fundamental bearing behaviour of the foundation with and without pore-water pressures developing. A clear quantitative difference in the stiffness of the response was observed when the caisson penetration was reduced, which was attributed to the reduced frictional interface. In simulations in which the gap was modelled, the stiffness was clearly reduced in compressive direction until the lid came in contact with the modelled soil surface. Interestingly, almost no difference in stiffness of the response was observed after contact was established compared to tests without initial gap opening. In all monotonic (i.e. drained and undrained) tests, the influence of the testing container was investigated and found to be significant.

The cyclic loading of the caisson was modelled for $N = 15$ cycles in order to limit computation time and accumulated error as well as the likelihood of completion of the analysis. From the results depicted in Figure 4, it is evident that the pore-water pressure could be modelled a lot better than the resulting displacements. Even though the absolute displacements are very small compared to the model test, they are captured with higher accuracy when the SAniSand model is employed. Also, the SAniSand model does show an increasing accumulation of displacements under compressive loads where the MC model does not.

The influence of gap height, caisson penetration and testing container were studied. When modelling loading in compressive direction, these factors need to be considered for both constitutive models. Under tensile loading, caisson penetration is the most important of the investigated parameters. Even though the MC constitutive model can, in combination with hydraulic-mechanical coupling, represent transient effects, the cyclic effects of soil behaviour are not incorporated. The SAniSand constitutive model can fill this gap with its ability to simulate such effects. Yet there are some caveats when it comes to calibration and performance of the advanced constitutive model. This raises the question how these results might be simplified to be accessible by a broad clientele.
Figure 2: Setup of the numerical model.

Figure 3: Back-calculation of the $F_{dr,x}$-tests in three model tests.

Figure 4: Back-calculation of three model tests with cyclic load.
Acknowledgements

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References


Thermometric investigation of fatigue crack initiation from corrosion pits in structural steel used in offshore wind turbines

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Keywords: Corrosion fatigue; Corrosion Pit; Fatigue; Crack initiation; Thermography

In offshore wind support structures, corrosion fatigue is one of the most important damage processes. The steel foundation is exposed to fatigue loading from varying wind and wave induced loads, while its surface deteriorates and its strength degrades when exposed to the corrosive sea environment. Besides mass loss due to uniform corrosion, pitting corrosion primarily aids in the initiation of fatigue cracks since pits are the source of geometrical stress concentrations. To investigate the fatigue crack initiation from corrosion pits, constant load amplitude uniaxial fatigue tests were performed on specimens that were extracted from corroded plates that had been exposed to the marine environment of the Belgian North Sea.

1. Test set-up and method

Dog-bone shaped specimens were cut from coupons that had been in the seawater for almost 22 months at several locations in a monopile structure. Surface scans of the fatigue specimens were performed with a Keyence VR-5000 wide-area 3D measurement system to assess the corroded surfaces. Subsequently, the specimens were subjected to a uniaxial fatigue test with constant load amplitude. The surface temperature of the specimens was continuously monitored with an infrared thermal camera to assess the onset of damage. To avoid reflection and obtain high emissivity, the specimens are coated matt black.

A schematic sketch of the set-up is shown in Figure 1, and in Figure 2 photograph of a specimen before testing and also the experimental set-up is shown. Two gold-coated mirrors with 98% reflection in the desired wavelength range of 2-5 μm have been positioned next to the specimen as shown in Figures 1. As such, the infrared camera can record images containing both the front and back sides of the specimen. In addition to this, the specimen can be seen from 360° around. This allows recording crack initiation from corrosion pits near the edge of the specimen. To allow compensation of the effect of environmental temperature changes, a reference specimen is installed near the mirrors and also observed by the camera. Also, to reduce interference, the camera, specimens and mirrors were covered.
Figure 1: Schematic top view of the set-up for fatigue testing of corroded specimens showing the test and reference specimens, and the infrared camera and mirrors

Distance IR-camera - mirrors ca. 115 cm

Figure 2: Photograph of a specimen before testing and the set-up with infrared camera and mirrors for fatigue testing of corroded specimens

Testing was done at a frequency of 10 Hz with a camera sampling frequency of 100 Hz. Three stress ranges have been selected, i.e. 350, 315 and 285 MPa, and the load ratio has been set equal to 0.1. These stress ranges were chosen as a trade-off between having to deal with high cycle fatigue (HCF) and reducing the quantity of data. An initial test series of five specimens is presented in this work.

The thermal images were post-processed offline which allowed adjusting the region of interest (ROI) during post-processing. The fast Fourier transformation (FFT) method was selected to filter the thermoelastic temperature amplitude from the thermal images. The first harmonic of the recorded temperature has been shown to allow identification of the fatigue crack initiation and propagation [1] as it is directly related to the principal stress and change in compliance of the specimen.

2. Results

In Table 1, the applied cyclic stress values and number of cycles to failure for the tested specimens are listed.
Table 1: Results of fatigue testing of corroded specimens

<table>
<thead>
<tr>
<th>Specimen</th>
<th>Stress range (MPa)</th>
<th>Max. stress (MPa)</th>
<th>Cycles to complete failure</th>
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<tr>
<td>SPF 9-2</td>
<td>350</td>
<td>389</td>
<td>134,361</td>
</tr>
<tr>
<td>SPF 9-1</td>
<td>315</td>
<td>350</td>
<td>189,177</td>
</tr>
<tr>
<td>SPF 9-3</td>
<td>285</td>
<td>311</td>
<td>251,768</td>
</tr>
<tr>
<td>SPF 70-1</td>
<td>350</td>
<td>389</td>
<td>124,975</td>
</tr>
<tr>
<td>SPF 70-2</td>
<td>315</td>
<td>350</td>
<td>132,865</td>
</tr>
</tbody>
</table>

For both specimen series SPF 9-X and SPF 70-X there is an inverse relation between the number of cycles to failure and the applied stress range. The number of cycles to failure at the same applied stress range are lower for the test specimens extracted from coupon 70 which can be attributed to a more severe presence of corrosion pits.

The surface scan height maps of the corroded sides of specimen SPF 9-1 are shown in Figure 3. The rectangular red box indicates the region where the fatigue crack initiated (based on the fractography performed after the test).

Figure 3: Surface height scan of test specimen SPF 9-1

Figure 4 shows the top view of the fracture surface of the same specimen. The fatigue crack is situated at the right top side and is indicated by the yellow dashed contour. The fatigue crack region has a smoother appearance than the remainder of the fracture surface and clearly has some pits at its right edge. The right-hand side of this fracture surface corresponds with the back side of the specimen. That part of the surface height scan which includes those pits is also indicated in this figure. As it can be seen on the fracture surface, multiple fatigue cracks were initiated from the corrosion pits and then combined to one large crack.

Figure 4: Top view of fracture surface
Figure 4: Fracture surface of specimen SPF 9-1; The dashed yellow contour indicates the fatigue fracture and red arrows indicate the corrosion pits; The height map (right) shows the pits from which the fatigue crack has initiated and grown.

From the thermal measurements, the average temperature of the reference specimen was subtracted to omit the environmental temperature changes. Subsequently, a FFT was performed on the thermometric images for load cycles 140,000 to 150,000. The amplitude and phase of the first harmonic are plotted in Figure 5. Mainly on the phase plot, distinct regions with an aberrant appearance compared to the remainder of the specimen can be observed. Besides the phase and amplitude plots, the height map of the corresponding part of specimen’s surface was added. The red arrows link the corrosion pits with the regions with a distinct amplitude and phase difference.

![FFT Amplitude and Phase Plots](image)

Figure 5: The amplitude (left) and phase (center) plots of the temperature’s first harmonic for load cycles 140,000 to 150,000; and the height map (right) of the specimen SPF 9-1.

In order to determine the moment of fatigue crack initiation based on these phase and amplitude plots, a threshold value for the amplitude or phase difference has to be defined. This threshold depends on the noise level of the signal and will be determined with statistical techniques. A preliminary analysis is illustrated in Figure 6. The first harmonic temperature amplitude is plotted for pixel (20,40), which is centrally located in the ROI and is located in the vicinity of relatively large corrosion pits. The point (20,40) is indicated by the black circles in Figure 5. A very steep increase can be observed from image 1,750,000 (cycle 175,000) onwards. This is the moment where the fatigue crack has started to propagate. Comparing this number of cycles to the total number of cycles for this test, it can be concluded that the complete rupture has happened rapidly after the crack initiation (the crack propagation stage accounted for a mere 7.5% of the total fatigue life). Also, around image 600,000, a slight peak is visible which might be caused by an arrested fatigue crack.

![Threshold Analysis](image)

Figure 6: First harmonic temperature amplitude of a specific pixel in the vicinity of relatively large corrosion pits on the specimen SPF 9-1.

**References**

Model testing of a gravity foundation in sand

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Keywords: accumulation, cyclic loading, drained conditions, gravity-based foundation, model testing, offshore

1 Introduction
Offshore wind farms are essentially designed to help in Germany's eventual transition away from fossil fuels like coal, gas, and oil toward renewable energies. The expansion of offshore wind energy therefore represents an important component in climate policy for the conversion of the energy supply. [1]

To achieve this ambitious goal, wind turbines with a total height of over 300 meters are to be built in the future. These offshore megastructures are thus subject to hardly known impacts and conditions, making it impossible to scale up existing structures and thus requiring fundamentally new concepts. Within the framework of the Collaborative Research Center 1463, the special design and operating conditions of offshore megastructures are to be described by specific model approaches and combined in an overall model to form a digital twin. [2]

The entire wind turbine as well as the foundation structure are particularly exposed to cyclic effects from wind and waves, so that the design of the foundation must focus strongly on the effects of cyclic loads. However, neither validated calculation methods nor a uniform design procedure exist for this purpose. In order to be able to investigate and describe the behavior of the soil under cyclic loads, a new small scale model was set up for experimental investigation.

2 Methodology
The experimental model stand consists of a round stainless steel container (D = 1.5 m, H = 1.3 m) open at the top. This is fixed on a vibration table (1.6 m x 1.6 m x 0.4 m) (Figure 1).

Figure 1: Test tank for physical experiments with pore water pressure transducers inside the model foundation and the sandbed.

The vibration table is driven by four unbalanced motors, which are mounted in opposite directions to produce a linear, vertically directed sinusoidal vibration when the motors are running synchronously.
The stainless steel tank is filled with approximately 2.2 t of quartz sand. The fine sand used has similar mechanical properties to North Sea sand and is poor-graded. During the initial installation, the sand was pluviated in order to install the sand free of air. Underneath the sand is a layer of gravel about 0.15 m thick and a water reservoir which can be fed from the outside via three inlets by means of a pump. The offshore foundation tested is a gravity model foundation with two model foundations sizes \(D_1 = 25\) cm and \(D_2 = 15\) cm) and masses \(m_1 = 55\) kg and \(m_2 = 15\) kg. The load on the model foundations is applied with the aid of a horizontally positioned electro-mechanical test cylinder. Test control and monitoring is performed with the associated electronic measurement and control unit. The test cylinder is located outside the container on a frame.

Before each test series, the soil must be put to a defined relative density using a preparation method in order to achieve reproducible results. This is achieved by first loosening the sand by means of flow and then compacting it with the vibration table at a defined vibration intensity. Segregation effects are not to be expected due to the poorly graded sand. The gravel and the water reservoir are intended as a water distribution plane in order to obtain a largely homogeneous flow when applying an upward hydraulic gradient.

For the drained tests, a frequency of approx. 0.5 Hz and 1000 cycles is planned. For the partially drained tests, the frequency will be increased to 3 Hz and the dissipation of the excess pore water pressure will be reduced by increasing the viscosity of the water by adding Hydroxypropylmethylcellulose (HPMC). [3] The resulting rotation of the foundation or the differential settlement is measured without contact by two height-adjustable optical laser displacement sensors. These are located above the foundation and are mounted on a crosshead. In addition, the excess pore water pressure is measured under each foundation as well as at different levels in the sand.

### 3 Results

Both foundation \((D_1 \text{ und } D_2)\) were used for the monotonic as well as for the cyclic tests. The influence of preshearing on the initial bearing capacity was also investigated. The tests were run with 15 cycles and a displacement-controlled control load of 0.1 mm, which corresponds to about 5% of \(H_{ult}\) for medium dense sand. (Figure 2) However, the influence of this preconditioning is marginal. The soil thus exhibits a loose to medium-dense relative density.

![Figure 2: Precycling with 15 cycles, displacement controlled maximum value 10 mm (a) for different relative densities (b)](image)

The objective is to investigate and describe the cyclic deformation accumulation at the same relative density. Important variables are the size of the foundation, the relative density of the soil, the cyclic load \(H_{max}/H_{ult}\) as well as the load type (one way/ two way loading). These variables are later used for validation of computational models. Accumulation of excess pore water pressure in the tests with low loading frequency and water as pore fluid is not expected due to the relatively permeable sand and could not be measured. In the first step, the eccentricity of the resulting horizontal load was selected so that no gaping joint was created. Figure 3 shows the rotation over the number of cycles in the drained test series. [4]
4 Validating numerical approaches

One objective of the project is the development of calculation methods for the prediction of foundation behavior under cyclic loading with large numbers of load cycles. The aim is to develop a methodology that is as simple and transparent as possible, using the results of cyclic element tests as input. The starting point is the Excess-Pore Pressure Estimation (EPPE) method, which uses the results of cyclic DSS tests to predict the reduction in bearing capacity of the foundation system due to accumulated excess pore water pressures [5]. The model tests presented will be used both to understand system behavior under cyclic loading and to validate the methods to be developed. This work is still in progress.

In possible, later funding periods, it is planned to extend the model tests to other foundation designs (e.g. monopiles).

Acknowledgements

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Design of offshore jacket support structure for experimental fatigue life evaluation

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Keywords: Offshore jacket support structure; fatigue life; experimental design; inspection and maintenance planning; structural health monitoring

Operators of offshore wind farms are increasingly faced with the question of whether and for how long wind turbines can continue to operate. Various options are available to assess the condition of a turbine, including inspections of the entire structure and/or critical components. The resulting information can be integrated into the reliability analysis of the structure, enabling an updated assessment of the current and projected condition of the turbine. Due to flawed design, manufacturing errors, or construction mistakes, it is possible that the targeted fatigue life (typically 20-25 years) may not be achieved. In such cases, operators have several options to ensure the safe operation of the turbine until the intended service life is reached. One option is to carry out repair measures to address any potential damage. Additionally, the monitoring and inspection planning can be adjusted to facilitate earlier and more reliable detection of damages and to initiate timely repair actions.

Using a real experimental structure, the accelerated fatigue life of an offshore jacket structure is intended to be simulated. In this experiment, the fatigue design as well as maintenance and monitoring aspects should be incorporated as realistically as possible. This abstract aims to explain the objective and concept of the experiment. At this stage of the process, the focus is primarily on the development of the experimental structure that enables the implementation of the experimental concept. As a foundation structure for wind turbines, a three-dimensional jacket serves as a template for the experimental structure. Jackets are systems composed of steel tubular legs and braces that are connected through welded joints. These points of imperfection are referred to as hotspots, where fatigue cracks can develop\cite{1}. Jacket structures are designed to reliably function throughout their intended service life. Welded joints can be imperfect, leading to a reduction in the fatigue life of individual components. The question arises as to how this flaw influences the fatigue life of the entire structural system. Various methods can be employed to analyze this situation. Numerical models can be used to investigate stress states and potential load redistributions resulting from redundancies in the system. Inspections can verify the occurrence and propagation of cracks. Various structural health monitoring (SHM) methods are suitable for monitoring the overall structure globally and examining the structural behavior at critical locations. At the end, the question remains: How much remaining useful life does the structure have before reaching its fatigue life, and what measures need to be taken to achieve the targeted fatigue life? Behind the answer to this question lies a decision problem that must handle uncertainties in the processed information\cite{2}.

Figure 1 (left) illustrates the stepwise concept for the development of the experimental structure. The first step is a basic design for a structure, which is iteratively updated based on the requirements stemming from the subsequent fatigue calculations. For the interim final design, a monitoring and inspection plan is established, defining the maintenance measures during the experiment. Subsequently, the experimental structure is fabricated. After updating the models through a system identification of the manufactured structure, the experiment can be conducted. The following sections provide a more detailed description of the individual components of the concept.
Figure 1: Concept for the development of the experimental structure (left) / Initial design (right).

The initial design of the structure is subject to requirements that arise from the defined objective of the experiment. When designing the structure, the subsequent steps in the concept must be considered. The complexity of the structure, driven by the desires of the experiment, must be balanced with the feasibility of the experiment. Since the aim is to investigate the influence of damage on the overall structure, the load-bearing system must exhibit redundancy. Therefore, the structure should be three-dimensional to be capable of redistributing loads from damaged components without experiencing system failure and possess damage tolerance.

The structure consists of the components of a jacket, which are tubular steel braces and legs connected by welds, enabling the analysis of known damage mechanisms (fatigue cracks) in combination with the behavior of the overall system. Considering the background regarding erroneous designs or manufacturing, intentional flaws can be introduced into the welds. Besides overlapping weld connections between two braces at a node, weld irregularities provide the best means to deliberately provoke damage at a specific location. Such irregularities (e.g., weld reinforcement, weld undercut, and inclusions) are listed in [3]. Another option to provoke damage is the omission of post-weld treatment or altering the cross-section to reduce load-bearing capacity. To align with the problem statement, the weak spot should significantly impact the fatigue life calculation.

The structure needs to be downscaled from real jackets to enable conducting the experiments at the BAM facilities. For the height and width of the system, a scale factor of 1:10 appears to be reasonable. At the same time, the cross-sectional dimensions must be adjusted accordingly. However, it may not be feasible to use the same scaling factor for the cross-sections, as it could lead to an excessively small thickness that would result in unrealistically low load-bearing capacity of the structure. Therefore, the scaling of the cross-sections (and other dimensions) must be coupled with the scaling of the applied load. The type, direction, magnitude and frequency of the load need to be defined under consideration of the BAM facilities.

Based on these requirements for the structure and the constraints of complexity and feasibility, an initial numerical design has already been created, which is depicted in Figure 1 (right). This demonstrator, with a maximum height of 2.30 meters and a distance between the base points of 1.92 meters, has a reduced number of braces and thus fewer nodes to investigate and monitor. This is achieved by restricting the structure to a single level and three legs. The legs need to be connected to ground via connection plates. The upper end point of the legs is a steel plate designed in such a way that a horizontal load can be applied laterally, generating torsional stress within the structure, among other effects. From the initial studies conducted using an FE model, the base points and connections of the plate and legs were identified as the locations with the highest stresses. It is important to ensure that rather the welded joints of the legs and braces are most prone to fatigue. A more detailed model is required to examine the relevant areas and the influence of the introduced flaws more precisely.

With the initial design in place, a fatigue calculation needs to be performed. A model is required to calculate the fatigue loading on each detail of the structure based on the S-N relationship. Regarding the loading, the stresses generated by a specified single-stage load at the hotspots are considered. Regarding the resistance, the permissible stress range over a certain number of load cycles is determined from the Wöhler curve for the corresponding details. The fatigue calculation also incorporates partial safety factors defined in the relevant
guidelines. In [4], for example, these values depend, among other factors, on the inspection concept, which thus influences the fatigue calculation. If the fatigue calculation yields insufficient fatigue life, the design needs to be modified. Various parameters can be adjusted for this purpose, including topology, geometry, dimensions, materials, and structural loading. By iteratively changing the corresponding parameters, a design can be found that reaches the targeted scaled service life in the unweakened state but exhibits insufficient fatigue life in the weakened state.

For the preliminary final design, a monitoring and inspection plan can be developed. This plan depends on the type and extent of damage mechanisms to be investigated. Additionally, methods for monitoring, inspection, and repair as well as their integration into the models must be considered. An analogy between these methods and the real-world applications needs to be established since laboratory conditions differ from real-world conditions. The models used here include a fracture mechanics model, which is necessary for inspection planning, and a model for calculating the dynamic response of the system. The latter represents the link between monitoring data and damage. Furthermore, a model for capacity calculation is required, which determines the system reliability through pushover analysis. This reliability needs to be taken into account in the inspection planning.

Ideas and approaches have already been developed and tested in numerical studies on how to perform risk-based maintenance planning [5, 6, 7, 8]. This study aims to apply these concepts to a real structure. The monitoring and inspection plan follows a decision tree that leads to actions based on gathered information and model updates. The optimal strategy, which defines thresholds and other parameters for the actions, needs to be determined using the Value of Information (VoI) before conducting the experiment [9]. Additionally, for the monitoring concept, the Optimal Sensor Placement (OSP) can be determined [10]. By parameterizing the strategies, the monitoring and maintenance plan can be adaptively adjusted during the lifetime simulation after incorporating new information.

In addition to inspection and monitoring data, SCADA (Supervisory Control and Data Acquisition) data should also be incorporated for the application of a complete concept. However, in the planned experimental setup, SCADA data is not available as only the foundation structure is considered. SCADA data generally provides information about the loadings experienced by the structure, inferred from operational and environmental data. In the absence of SCADA data, the controlled experiment can directly provide data on the loading conditions. In principle, all possible information should be gathered to ensure the safe execution of the experiment. However, only the information that would realistically be available based on the maintenance plan should be utilized.

By using different inspection and monitoring methods, the effectiveness of each method can be assessed. The focus can be placed on vibration-based monitoring, which provides information about the modal properties of the system and can thus reveal global damage [11]. The extent to which this helps in the framework for making timely decisions regarding interventions should be investigated in the experiment.

To summarize, the experiment concept requires three models:

1. Model for fatigue analysis (S-N, fracture mechanics)
2. Model for strength analysis (pushover, reliability)
3. Model for dynamic analysis (integration of monitoring and damage)

All models should be probabilistic, meaning that the model parameters are assigned with random variables to account for uncertainties and allow for model adjustment after fabrication.

In the next step, the designed test structure is manufactured. Special attention must be paid to the quality of the welds and the creation of the weak points. Following the manufacturing of the structure, system identification is performed. In preliminary tests, the system responses of the real structure are compared with the values from the numerical models. Based on this comparison, the model assumptions can be adjusted to match the real structure. Bayesian updating is used for this purpose [12, 13]. After updating the models, the monitoring and inspection plan needs to be updated accordingly.

The experiment is initiated with the newly established plan for implementation. At specific time points, information is gathered from monitoring and inspection. For vibration-based monitoring, the fatigue loading is paused and replaced by dynamic excitation of the structure. Once the modal properties are captured, the fatigue loading is resumed. In the event of damage, actions to be taken, such as repair, must be predetermined through the maintenance planning. This also applies to unexpected damages that occur at non-designated locations. If no damages occur within the planned timeframe, adjustments to the loading can be made. The end of the experiment...
is reached when the scaled number of load cycles has been applied to the structure. The concept can then be used to assess the potential for extending the service life.

The experiment involves the intentional and potentially unintended damage to the structure. In the design of the structure, if possible, the requirement should include the provision that the structure is not a one-time product but rather that damaged elements can be replaced or repaired, allowing for the repetition of this or other experiments on the structure. For the preferred type of weakness (weld irregularity), repair of the damage is a viable option.

Acknowledgements

The author thanks Professor Yuri Petryna from Technische Universität Berlin for supervision and Ronald Schneider and Matthias Baßler from BAM for their help during the doctoral studies.

References

TOPIC 8:
Hydrodynamics of offshore wind turbines

Session 8.1
06.09.2023 - 13:15
Building 3701, Room 267

Meyer Jannik  The simulation of nonlinear crane load motion during offshore operations using Heavy Lift Vessels
Satari Ramish  Temporal scour evolution around a monopile and a jacket structure: An experimental study
Herdayanditya Ivandito  Preliminary Experimental Study of Wave Field Around Monopile
The simulation of nonlinear crane load motion during offshore operations using Heavy Lift Vessels

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Keywords: OWT installation, Crane operation, offshore operation, non-linear motion, frequency domain modelling, time domain modelling

Offshore operations need to require specific safety standards, e.g. with regard to technician safety at sea. In this overview of several experimental and numerical studies, these safety standards are investigated regarding heavy lift vessels and the coupling of their motion with the crane load motion. Due to these coupling effects, nonlinear crane load motions occur in regular waves. These nonlinearities have been observed in physical model tests in the wave flume of Ludwig-Franzius-Institute (cf. Figure 1), which have been presented at last year’s eawe PhD seminar in Bruges. The main reason for the nonlinearities is the coupling between excitation frequency (wave frequency) and the natural frequency of the crane pendulum.

![Figure 1: Nonlinear crane load motion during regular wave tests [1]](image-url)
Using a nonlinear time domain model like OrcaFlex, these nonlinearities could be resembled in numerical models. Nonetheless, the aim of the overall project, which is related to the CRC 1463 – Offshore megastructures, is the development of a real-time capable model, based on frequency domain results. Hence, a frequency domain model was developed. This model showed a very good agreement regarding amplitudes of vessel motion and crane load motion but could not resemble the influence of the natural frequency of the crane pendulum on the crane load motion (see Figure 2). Nonetheless, the origin of the nonlinearity is clear, since the motion response spectrum of the crane load has two distinct peaks: One at the wave frequency, and the other at the natural period of the pendulum. This is clearly visible in the numerical time domain results in Figure 2 (d).

Figure 2: Comparison between time domain and frequency domain model [1]

Based on these clear findings, the present study will aim at the incorporation of the nonlinearities in the frequency domain model, leading to a weakly nonlinear model in frequency domain. Therefore, the influence of the nonlinearities in realistic, irregular seastates will be investigated in physical model tests as well as time domain simulations. Afterwards, a clear formulation of the relationship between wave frequency, crane natural frequency and the motion amplitudes at the respective frequencies will be derived. This clear relationship will then be used to adapt the frequency domain model to a weakly nonlinear model.

Acknowledgements

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References

Temporal scour evolution around a monopile and a jacket structure: An experimental study

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**Keywords:** Offshore wind energy, Scour, Monopile, Jacket, Sediment transport, Laboratory test

1 Introduction and motivation

Reliable prediction of scour on foundation structures is becoming increasingly important as offshore wind energy development progresses. As part of the lifecycle management of offshore foundation structures, reliable prediction of scour rate is critical for safe design and economic operation. The importance of scour development is reflected in the considerable number of available publications dealing with scour development under a wide range of hydraulic boundary conditions [Sumer & Fredsoe, 2002]. However, the vast majority of these studies focus on scour development on simple monopiles. Less attention has been paid to more complex structures such as jackets. Jacket structures are considered to be of great importance for the development of offshore wind energy, as they can provide a stable and economic foundation, especially at great water depths. However, compared to monopiles, the scour of jacket structures is more complex and is characterised by being divided into a local and a global scour development. While local scour development is critical to the stability of the foundation structure, global scour development can have a significant and large-scale impact on the marine environment. Initial studies (Welzel et al., 2019) suggest that global scour development does not follow local scour development in time, so existing predictive approaches for local scour development are unlikely to be applicable to global scour development.

In this context, laboratory experiments were carried out in order to improve the understanding of scour development around monopile and jacket type offshore wind foundations. The study focuses on the comparison of the local and global scour development around a jacket structure in reference to a monopile. The main objectives are:

a) High-resolution measurement of scour evolution over time around a jacket and a monopile in combined current-wave conditions.

b) Description of differences in the temporal evolution of local and global scour depths at the jacket structure.

c) Comparison of temporal evolution of maximum scour depth between jacket structure and monopile by calculating scour rates and time scales.
2 Experimental setup

The physical model tests were conducted at a scale of 1:45 for the jacket structure and 1:75 for the monopile structure in a 3D wave and current basin at the Ludwig-Franzius Institute for Hydraulic, Estuarine, and Coastal Engineering at Leibniz University Hannover. The wave and current basin has a total length of 40 m, a width of 25 m and provides a modular sediment pit in its centre with dimensions of 9.15 m x 6.65 m. For more details about the test facility, readers are referred to [Welzel et al., 2019]. The monopile structure was simulated by a transparent pile made of acrylic glass with a diameter of 0.12 m. The jacket structure is similar to the one previously studied by Welzel et al. (2019) and is shown in Figure 1. Both structures were installed parallel to each other with a sufficient distance in the sediment pit. Scour development over time was measured using echo sounder devices at four different locations around the monopile and at two local measurement points and two global measurement points around the jacket structure. A total of 12 tests were conducted in which irregular waves (Jonswap spectra) with significant wave heights between $H_{m0} = 0.10 - 0.18$ m and peak wave periods between $T_p = 1.86 - 4.10$ s were superimposed with currents ranging from $U_c = 0.117$ to $0.397$ m/s. Water depth was also varied and ranged between 0.6 m and 1 m.

![Figure 1: Schematic view of the jacket model with dimensions and angles.](image)

3 Results and discussion

Preliminary results are provided as time series of the scour development around both structures in Figures 2 and 3.

Figure 2 illustrates the scour progression over time around a monopile, which is characterized by a steady increase of scour depth around the hole circumference of the pile. As expected, the largest scour depth occurred at the upstream side of the pile (echosounder position 7), driven by the horseshoe vortex, whereas the smallest scour developed at the downstream side (echosounder 5). The difference in scour depth between the upstream and downstream side of the pile develops early during the scouring process but remains quite constant over the further course of the test. A difference in scour depth between the lateral sides can also be found, which slightly larger scour depths on the side where the waves are coming from (echosounder 8).

For the same test conditions, the scour around the jacket structure is illustrated in Figure 3.

While a continuous increase in scour depth over time is also observed at the main piles of the jacket (echosounder E1 and E2), a clear structure-related difference between the local scour at the main piles and the global scour below the structure is evident here. The global scour process (echosounder E3 and E4), which does
not result from the direct interaction of individual structural elements with the flow, but from the large-scale change in the flow field caused by the overall structure, is significantly less intense at the beginning of the test and proceeds more slowly. However, from about 4 hours of the experiment, a clear intensification of the global scour process can be observed, so that the difference in scour depth between the local scour (E1 and E2) and the global scour (E3 and E4) decreases over time. One reason for this could be that with the increase of the local scour, the flow is additionally influenced in such a way that an intensified global scouring occurs.

Figure 2: Scour progression around monopile under combined wave-current conditions with $H_{m0} = 0.178\,\text{m}$, $T_p = 4.1\,\text{s}$, $U_c = 0.232\,\text{m/s}$. Current is coming from the left, waves from the top side.

Figure 3: Scour progression around jacket under combined wave-current conditions with $H_{m0} = 0.178\,\text{m}$, $T_p = 4.1\,\text{s}$, $U_c = 0.232\,\text{m/s}$. Current is coming from the left, waves from the top side.

4 Conclusions

The study highlights the importance of distinguishing between global and local scour processes around complex offshore structures such as jacket foundations. The results can lead to improved scour predictions and scour maintenance approaches for complex offshore structures.
Acknowledgements

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References

Preliminary Experimental Study of Wave Field Around Monopile

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Keywords: Experiment, wave field, monopile

1 Background

Renewable energy is seen as one way to address the global climate change problem. One form of renewable energies is offshore wind energy which has grown 36% annually in the last ten years \cite{10}. There are various kinds of offshore wind energy structures, ranging from fixed to floating structures where monopiles have become the most installed structures in the offshore wind industry \cite{8}. It is further expected that the diameter of the monopile will increase and can reach 10 m diameter as for 15 MW wind turbine \cite{2}.

Wave field around monopile is an important aspect to estimate the safety of marine operations. The most practical approach is to assume that the wave field around monopile is the same as the incoming waves (e.g. crew transfer operability analysis \cite{11} ). Nevertheless, the monopile can disturb the incoming wave field. The short waves regime can suffer from the diffracted waves \cite{6} while the long waves regime, which is expected to not diffract so much, can suffer the nonlinear diffracted waves \cite{4}. Many studies have been delivered to understand the disturbance of monopile to the waves by means of wave runup. It is concluded that nonlinear interaction of the incoming waves and the monopiles is an important aspect that cannot be neglected, otherwise the runup will be underestimated \cite{5,1}.

The wave runup nonlinearity can be captured with nonlinear simulations \cite{3}. However, the simulations requires high computation cost which is too costly for marine operations analysis. Linear Transfer Function of runup has been employed with linear potential flow solution, though the results differ in low frequency spectral and high wave steepness cases \cite{7}. Research of nonlinear transfer function is currently conducted to have a fast estimation of wave field around monopile. This method will be verified against experimental study where preliminary of the experimental study is given in this extended abstract.

2 Experimental Setup

The experiment is performed in the Coastal & Ocean Basin (COB) in Oostende, Belgium. The wave basin is a square of 30m x 30m. The water depth of the simulations is maintained at 1.4 m. Piston wave makers are installed at the two sides of the basin while the other two sides are with wave beach absorbers as shown in Figure 1a. A monopile model, made of plexiglass, is placed at slightly after the middle of the basin to assure that the waves have developed. The monopile diameter ($D$) is 0.40 m. In the first campaign, 20 wave gauges are placed around the monopile at the downwave side which the configuration is shown in Figure 1b and Figure 1c. The probes are distributed in angular location of $\theta = 0, \frac{1}{8} \pi, \frac{1}{4} \pi, \frac{1}{2} \pi$. In this study, only the two lines of probes are investigated, line 1 and line 5, where the radial positions, $r$ are 0.25 m and 1 m respectively.

In the beginning, the incident waves are checked to assure if the incident waves are as the theoretical waves. Further, employing the group velocity of the waves, the data window that is analysed is the time window without reflection waves from the beach. Three wave scenarios: regular waves, bichromatic waves and irregular waves are performed in the basin. In this extended abstract, two regular wave cases with period of one second ($T = 1$ s) with different steepness $kA = 0.075$ and $kA = 0.15$ are provided as study case where $k$ is the wave number and $A$ is wave amplitude.
3 Results and Discussion

Time series and the FFT analysis of the wave cases are provided in Figure 2. Beside the analysis from the experimental study, estimation from the linear potential flow solution [6] is also provided. Generally, it is seen that the wave crest of the experimental study is higher than the estimation from the linear potential flow solutions. Further, it is noticeably seen that the higher steepness of incoming waves gives higher difference between the experimental wave field and the linear potential flow. The angular position of C is also noticed to show good agreement to the crest of the linear potential flow solution.

The FFT estimation also shows that in higher steepness case, the higher harmonic amplitude becomes significant. This can be seen as well in the skewness of the time series. For instance, Probe 1B and Probe 1C shows significant skewness when the wave steepness increases. Furthermore, the nonlinearity influence seems to become less when the location of the probes is far from the monopile as seen between line 1 and line 5.

Observation on the downwave location (1D) also shows interesting crest collision that travels around the monopile. The collision is shown in Figure 3. This is the wave Type 2 [9] which is noticed in the surface piercing cylinder and is the cause of significant increase at the downwave side.

4 Conclusion and Future Work

Experimental study of wave and monopile in this preliminary study shows promising results. The methodology that is implemented gives results that are in agreement with findings in the literature that: 1. the wave crest from linear potential flow tends to underestimate the actual wave elevation. 2. increasing steepness will give more nonlinearity. Wave Type 2 phenomena is also captured in the experiments.

Future study will include analysis of the other wave sets. Visual observation from the camera inside the monopile will also be explored to obtain the wave runup at the upwave side of the monopile.
The experimental study is also performed with the help of the Coastal & Ocean Basin Team. This research is conducted with Energy Transition Fund (ETF) under PhairywinD project. The results are compared with linear potential flow solution (Lin).

Figure 2: Analysis Results for wave cases with $T = 1$. The results are compared with linear potential flow solution (Lin).

Figure 3: Wave Type 2 that travels around the monopile

Acknowledgements

This research is conducted with Energy Transition Fund (ETF) under PhairywinD project. The experimental study is also performed with the help of the Coastal & Ocean Basin Team.
References


TOPIC 9:
Floating wind turbines

Session 9.1
07.09.2023 - 14:00
Building 3702, Room 031

Messmer Thomas  Wind tunnel investigation of the wake dynamics of a floating offshore wind turbine
Hubert Antonin  Wake dynamics study of a floating wind turbine model through phase-averaging
Sripathy Kiran  Experimental study of the dynamic induction of a surging actuator disc
Wind tunnel investigation of the wake dynamics of a floating offshore wind turbine

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Keywords: FOWT, wake, aerodynamics, wind tunnel experiment, model wind turbine

1 Introduction

A floating offshore wind turbine (FOWT) interacts with the incoming wind field and ocean waves resulting in additional complex motions of the turbine compared to a bottom-fixed machine. These added movements affect the turbine itself as well as the generated wake and its development with increasing distance to the turbine [1, 2].

In a wind farm, the wake of a wind turbine is likely to be the inflow for turbines located downstream inside the farm and result again in additional dynamics which might lead to higher extreme loads, fatigue loads and power losses. Due to the lack of full scale data, either wind tunnel experiments or numerical investigations might help to better understand the wake of floating wind turbines.

In this study, the wake dynamics of a model wind turbine submitted to imposed motions are investigated experimentally in the large wind tunnel of the University of Oldenburg (UOL). This research aims to understand the impact of the different motions of a floating wind turbine on the wake generated (recovery, turbulence, dynamics, etc).

2 Methodology

2.1 Experimental set-up

For this research, wind tunnel measurements were carried out using the Model Wind Turbine Oldenburg (MoWiTO 0.6) mounted on a Stewart platform to mimic motions of a floating wind turbine [3]. The system is shown in the figure 1 (a). This set-up was installed in the closed-loop wind tunnel (3 × 3 m\textsuperscript{2} inlet section) of the university of Oldenburg. The tests were done with different turbulent conditions, including laminar inflow (TI \approx 0.3 \%) and cases with higher turbulence intensity (TI \in [1.5, 10] \%). The turbine was moved by the platform following harmonic motions in fore-aft and side-to-side degrees-of-freedom (DoFs).

A total of 19 hot wire anemometers, arranged horizontally, were installed on an array to measure the wind speed in the wake of the turbine at different downstream positions ranging from 2D to 10D downstream, with D, the rotor diameter equal to 0.58 m. This set-up enabled to measure horizontal wind profiles of velocity in the wake of the turbine with a high sampling frequency of 6 kHz.

2.2 Cases investigated

Complex platform motions were idealised with sinusoidal motions, characterised by a frequency of motion, \( f_p \) and an amplitude, \( A_p \). A graphical visualisation of such a motion can be seen in the figure 1 (b). Frequencies of motion up to 5 Hz and amplitude up to 70 mm were tested. To allow a direct comparison with a real scale floating wind turbine, two dimensionless parameters are used [2, 4, 5]:

\[
\begin{align*}
St &= f_p D/U_0 \\
A^* &= A_p/D
\end{align*}
\]
In equation (1), $S_t$ is a Strouhal number, also called wake reduced frequency. It can be seen as a ratio of two characteristic times: period of one rotor oscillation to the time for an air particle to travel 1D. The higher the $S_t$, the more the unsteadiness. $A^*$ is the reduced amplitude with respect to the rotor diameter. $S_t$ from 0 to 1.0 and $A^*$ from 0.7 % to 15 % were tested. These are typical values observed at full scale. The turbine was operated at various thrust coefficient by pitching its blades, $C_T$ in [0.6, 1.0] were tested.

![Figure 1: (a) MoWiTO 0.6 mounted on the Stewart platform of the UOL (b) Scheme of a floating wind turbine undergoing surge movement following harmonic motion](image)

3 Results

At the conference, the impact of different motions on the development of the wake of a floating turbine will be presented. The following quantity will be discussed:

- Profiles of wind speed in the wake
- Profiles of turbulence intensity in the wake
- Recovery
- Wake dynamics: spectra and coherent structures

Acknowledgements

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References


Wake dynamics study of a floating wind turbine model through phase-averaging

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Keywords: Floating wind turbine, wake dynamics, phase-averaging

Floating wind energy is a resource with a great potential: the absence of obstacle and stronger winds set its efficiency higher than the onshore one (new wind turbine models have capacity factor of 30-35\% for onshore while offshore reach 42-55\% [4]). This leads to an increase of the number of floating wind farm projects in Europe, while knowledge on the subject is still lacking. Indeed, in a wind farm it is important to understand the wake generated by an upstream wind turbine. It affects the wind of the downstream wind turbine by dropping its velocity and increasing the turbulence intensity, leading to wind farm energy losses and acceleration of the downstream wind turbine blades fatigue. Different studies have demonstrated that floater motions only slightly affect the wake in global-average [1, 10, 2]. However, the frequency domain shows their impact on wake parameters such as wake center, wake surface, potential downwind energy, etc. The objective here is to provide informations on the wake dynamics of a wind turbine model subjects to harmonic motions thanks to phase-averaging.

The experiments are carried out in the Atmospheric Boundary Layer (ABL) wind tunnel at LHEEA - Research Laboratory in Hydrodynamics, Energetics and Atmospheric Environment - in Centrale Nantes, France. It is a $2\text{m} \times 2\text{m}$ cross-section and $24\text{m}$ long facility, with a motor of $45\text{kW}$ allowing a maximum speed of $10\text{m/s}$. Spires are installed at the entrance of the test section and performed metal plates are placed on the ground along $26\text{m}$. This configuration allows a 1:500 marine neutral ABL with a roughness length of $z_0 = 5.5 \times 10^{-6}\text{m}$, a power-law exponent of $\alpha = 0.11$ and an integral length scale of $L_u = 240\text{m}$ at hub at full scale [5, 11]. The model used is a porous disk of diameter $D = 160\text{mm}$ and hub height $z_{hub} = 120\text{mm}$ reproducing a 1:500 reduced-scale of FLOATGEN, the floating wind turbine installed on a barge at the SEM-REV test site. The porous disk motions are imposed by a 3DoF system, the studied cases are presented in Table 1 and are computed according to real FLOATGEN second order movements related to the interaction floater/mooring lines/wind - not interaction wave/wave. Finally, a Stereo PIV (S-PIV) system is placed at $8.125\text{D}$ downstream the turbine model to measure the three-components of velocity of the plan normal to the flow.

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</tbody>
</table>

A phase-averaging algorithm is processed based on the sinusoidal motion signal. Each S-PIV snapshots are associated with a time phase and a kernel smoothing - using Epanechnikov function - is performed all along the motion signal [12]. Because of the presence of meandering, the wake can artificially be widen and its velocity deficit be reduced. Two frames of reference can be defined: the Fixed Frame of Reference (FFoR) and the Meandering Frame of Reference (MFFoR) - a modified Weighted Geometric-Center (WGC) algorithm is computed in order to obtain the MFFoR [9, 6]. The former gives the influence of the disk on the downstream flow and therefore on a potential downstream wind turbine, while the latter follows the wake and its physics [3, 8, 7].
FFoR results are shown in Figure 1 and MFoR in Figure 2. Two main physics can be extracted from these figures: the pitch/heave one and the surge one. For the first one, Figure 1 shows that the wake surface increases and decreases at the same time as the y-coordinate of the wake center. The decrease is accompanied by a widening of the wake bottom, particularly visible at phase and . The hypothesis is that these motions do not impact the wake surface but rather translate it vertically, the widening of the wake bottom related to a flattening of the wake on the ground. In the other hand, surge case seems to have less impact, its wake center and surface is only slightly modified along the phases. Nevertheless, Figure 2 its wake radii along y and z - i.e. the distance between the wake center and the right and top edge of the wake - are correlated with each other, and are accompanied by an increase and decrease of the potential wake energy (not shown here). The hypothesis is that surge motion compresses and expances the wake without impacting the wake center, related to a wake ‘pumping’.

Figure 1: FFoR velocity deficit fields for different phases for: (a) pitch , (b) pitch , (c) heave and (d) surge . The dashed line circle and the black plus represent the porous disk emplacement, the full line and the cross are respectively the wake (0.1 velocity deficit contour) and its center.
Figure 2: MFoR wake shape for different phases $[0, \frac{2\pi}{3}, \frac{2\pi}{3}, \frac{4\pi}{3}, \frac{5\pi}{3}]$ for: (a) pitch $f_{red} = 0.14$, (b) pitch $f_{red} = 0.28$, (c) heave $f_{red} = 0.09$ and (d) surge $f_{red} = 0.11$.

References


1 Introduction

Due to active efforts by governments all over the world to electrify ground transport, significant increase in demand for green energy is anticipated. To keep up with this rising demand, large scale wind turbines are being widely manufactured and deployed. For instance, the Haliade-X rotor from General Electric has a rotor tip height of 260 m. At such a large scale, unsteady inflow effects such as wind speed shear, direction veer, gusts, atmospheric instability cease to be trivial [8].

Rotors subjected to the above mentioned unsteady inflow events will momentarily undergo unsteady loading, in an otherwise quasi steady operation state. This causes the induced flow-field to fluctuate as well. Due to inertial effects of the fluid, there is a phase lag between the loading and induced flow-field variation of the rotor, which is referred to as dynamic inflow/induction/wake in the literature [17].

BEM1 model, the current industrial workhorse for wind turbine design has dynamic inflow models to treat the phase lag [9,10,18]. However, these dynamic inflow models were tailored for unsteady load variation arising from blade pitching. Such models need to be enhanced for modelling dynamic induction due to unsteady inflow events. To this end, the author’s research will involve experimental studies of various unsteady inflow events on a rotor to characterise their effects on dynamic induction and verify the validity of existing dynamic inflow models for such events.

An interesting case of dynamic induction is the unsteady inflow experienced by the rotor due to the six DOF2 platform motion of an offshore floating wind turbine. Various studies have been performed at airfoil, blade, rotor and wake scales to characterise the effect of floating platform motion on the unsteady aerodynamics of wind turbine [1,3,4,6,7,11–16]. Among the six DOF platform motions, surge and pitch motions were found to significantly influence the rotor aerodynamics [13]. Therefore, for the first experimental campaign scheduled for the last week of June, 2023, this served as the motivation for investigating dynamic induction arising from imposed surge motion on a rotor.

Specifically, the following research questions from previous numerical studies will be explored in this campaign:

- Is the amplitude of rotor loading variation proportional to maximum surge velocity?

- How much does surge velocity influence the phase difference between loading and induced flow-field variation?

- Does negative thrust coefficient during surge correspond to propeller/vortex ring state?

2 Methodology

The experiment will be performed at the W-tunnel of the TU Delft aerospace faculty. It is an open jet tunnel with a test section area of $60 \times 60\,\text{cm}$. Circular porous plate of 20 cm diameter, as shown in Figure 1, will be used as

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1Blade Element Momentum
2Degrees of freedom
surrogates for the rotor. For obtaining mean flow quantities, porous plate can be a satisfactory substitute for a lab scale rotor, as long as their thrust coefficients are matched[2]. By adjusting the porosity ratio, the loading exerted by the porous plate can be controlled.

![Circular porous plates with different porosity](image)

**Figure 1:** Circular porous plates with different porosity

Surge motion will be realised by imposing a sinusoidal motion on the disc with the aid of an in-house reciprocating mechanism, that can reach amplitudes and frequencies as high as 7.5 cm and 10 Hz respectively. Both the disc and connecting tower will be constructed using lightweight composite material. Porous plate loads and flow-field upstream/downstream of the plate will be measured using load cell and planar PIV setups. Refer to Figure 2 for the schematic of the test setup.

The load cell will be located between the plate and tower. Although it is possible to obtain loads on the plate from PIV, load cell will be used in order to obtain data with very high temporal resolution. As far as the PIV setup is concerned, two cameras will be employed to obtain planar PIV measurements at locations upstream (domain 1) and downstream (domain 2) of the plate. These measurement planes are oriented along the xy-plane. Owing to axisymmetric nature of the wake with respect to x-axis, it is sufficient to obtain flow-field data from one plane orientation. Phase locked PIV will be employed to obtain averaged data at 12 different phases of a surge cycle. For every porosity ratio of the disc, five different combinations of surge amplitudes and frequencies, shortlisted based on the review of previous studies in [5], will be investigated.

### 3 Expected Outcomes

The findings from the surging porous plate campaign will be used to validate the induced flow-field results from BEM and vortex model simulations as well as rotor load variations from CFD simulations performed in the past. The unsteady load variation due to surge motion might create favourable conditions for the trailing vortices to leapfrog over one another, whose destabilization can promote flow mixing between wake and outer wake, resulting

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3 Particle Image Velocimetry
4 Computational Fluid Dynamics
in swifter wake deficit recovery. This can be inferred from the induced flow-field distribution obtained from PIV measurements at different downstream locations for static and surge cases.

And, using load cell data, the influence of surge on the aeroelastic behaviour of the rotor can be determined more accurately. Therefore, with these outcomes, this experiment intends to explore the benefits and drawbacks of floating platform motion with respect to rotor aerodynamics of a wind turbine.

References


Session 9.2
08.09.2023 - 09:00
Building 3702, Room 031

Lee Kai
An investigation of the interaction between floating wind turbines and direct drive generators air gaps.

Philipp Christian
Floativin - Langevin analysis of floating wind turbines

Minne Leon Jan
Implementation and Evaluation of a Simplified Mooring Line Model for Offshore Wind Turbines
An investigation of the interaction between floating wind turbines and direct drive generators air gaps

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Keywords: Floating wind turbine, Air gap, Direct Drive generators

1 Introduction

The utilisation of Floating offshore wind turbines (FOWTs) has been suggested as a viable strategy to improve the cost-effectiveness of offshore wind energy generation. This technology can harness wind power in regions where water depths surpass the capacity of fixed-bottom structures, reaching depths of over 60 meters and extending up to 350 meters. Future iterations of this technology are expected to expand its capabilities to depths of up to 700 meters \cite{1}. Notwithstanding its potential, the technology still remains in its nascent stages, as the floating structure necessitates sufficient buoyancy to support the turbine’s mass and constrain pitch, roll, and heave motions within acceptable thresholds \cite{4}.

As the investigation of deeper water environments advances, it is crucial to consider the significant impact of aerodynamic and hydrodynamic forces on FOWT \cite{7}. Additionally the presence of external loads from wind or waves, in conjunction with the internal magnetic attraction within the air gap, complicates the issue where the rotor may be drawn closer to the stator leading to a detrimental impact on the efficiency of the system and an increase in the loads experienced by the bearings. In addition, the deviation of the air gap may lead to significant operational downtime as a precautionary measure against generator malfunction. \cite{2, 3, 10}

The presence of an air gap in rotating machinery is typically an undesired but inevitable consequence of the physical motion required between the stator and rotor components. A rise of 1mm in airgap typically requires an extra 3-5mm of magnet substance to maintain the expected magnetic flux. In the case of larger rotating machines, a significant quantity of magnetic material is utilised to minimize flux leakage. This is due to the fact that the gap is proportionally sized to the rotor diameter, approximately 0.1\% of the generator diameter. Although minimizing air gaps can be beneficial in terms of efficiency and magnet cost, they necessitate the use of more rigid and heavier structures. \cite{5, 6, 9}

A comprehensive investigation on the structural integrity of air gap design for a direct-drive permanent magnet floating wind turbine (DD PM FWT) generator at a 15MW scale is currently lacking. Thus far, the only documented information regarding this subject pertains to a spar buoy infrastructure that has the capacity to support wind turbines with a maximum power output of 5MW \cite{10} or pertaining to fixed bottom platforms at 15MW \cite{5}. It would be of academic interest to extend certain research discoveries to include the innovative 15MW NREL/IEA prototype turbine on a Semi-Submersible floater and beyond. This study intends to provide a preliminary review on the correlation between different nacelle masses and heightened motion in particular degrees of freedom (DOF), on the closure of the air gap in the generator. The objective is to determine the minimum air gap size and the requisite generator rigidity for the purpose of minimizing the eccentricity existing between the rotor and stator. Additionally, the research will in investigate the corresponding escalation in foundation and mooring expenses required to counteract such motions.
2 Methodology

The entirety of the Ph.D. program consists of two distinct phases. The initial element of the analysis examines the influence of incremented nacelle mass on the buoyant structure’s motion and the corresponding air gap dimensions. The second aspect being examined pertains to the evaluation of the impact of external aerodynamic and hydrodynamic forces on the air gap’s dimensions. Presently, the research emphasis is exclusively directed toward the former phase.

Regardless of the investigated phase, it is imperative to identify the primary factors that affect the air gap of the generator. Only by including these parameters in models is it possible to precisely evaluate the generator air gap condition for floating turbines. variety of factors that may impact the structural integrity of a generator system air gap, include, but are not limited to, gravitational forces, wave and wind loads, magnetic attraction, elongation resulting from centrifugal force, elongation resulting from thermal expansion, and possible manufacturing or assembly inconsistencies.

The following subsections give a comprehensive overview of the research objective and the procedures employed. It will be followed by two additional sections that discuss the software tools utilised for the mechanical design of the floating platform and turbine, as well as the electrical design of the nacelle generator.

2.1 Model Overview

The FWT model will incorporate a nacelle that houses the generator. The examination of the fluctuations in nacelle mass and the effects of various external forces encountered at different water depths on the air gap deflection over time are topics that hold significant research interest. To clarify, the objective of the study is to investigate the impact of transitioning from a fixed bottom to a floating environment on the deflection of the air gap within the generator, and to accomplish this objective, it is necessary to conduct both static and dynamic analyses on the aforementioned model. For the static analysis, the primary focus lies on the internal magnetic force of attraction and its impact on the deflection of the air gap. The observed deflection is hypothesized to exhibit similarities to the response observed in a scenario where the bottom is fixed to the seabed. Subsequently, examine the transient response of the deflection of the air gap, by superimposing the combined influences of aerodynamic, hydrodynamic forces, and nacelle mass into the analysis. This allows for the determination of the nacelle’s acceleration across multiple degrees of freedom over real-time, providing a clearer understanding of which DOF is predominantly influenced under those environmental conditions and ultimately determining the behavior of air gap deflection over time at each DOF.

The disparity in air gap deflection between static and dynamic analysis provides insight into the magnitude of risk offshore environments pose to turbine operation in comparison to onshore environments. This knowledge is crucial for implementing appropriate design measures to ensure the safe functioning of direct drive generators, specifically in mitigating the occurrence of air gap closure.

The computer-aided design illustrations of direct-drive generators will bear resemblance to the one emphasised in [9], and the electromagnetic and structural design parameters of NREL 15-MW reference Direct-Drive Generators are documented in [5].

2.2 Floating Turbine Motions

Following the completion of the model via Ansys workbench, it is crucial to employ high-fidelity simulation tools that can accurately estimate wave load input and aerodynamic load at specific water depths. Ashes, OrcaFlex, and OF2 (OpenFAST & OpenFOAM) are tools that are capable of modeling the interactions between external wave and wind loading on structures. Ashes primarily utilise a graphical user interface (GUI) rather than a command line interface (CLI), in contrast to openfast. Therefore, during the preliminary phase, ahses will be employed to facilitate the process.

2.3 Generator Force Model

Following the identification of aero and hydro-dynamically induced nacelle motions, further examination will be carried out to determine the magnetic attraction forces within the direct-drive generator that impact the behavior of the air gap. Note here, the focus of the study revolved around the internal rotor configuration of a radial flux N40 grade Neodymium permanent magnet generator.
To understand the calculation of Maxwell radial stress, it is important to consider the Magnetic circuits as it can be conceptualized as a means of depicting the interplay between magnetomotive force, flux, and reluctance in a manner analogous to how electrical circuits elucidate the relationship between voltage, current, and resistance. The stator and rotor iron is assumed to possess infinite permeability, thereby there exists no flux leakage. Consequently, the only remaining factors contributing to reluctance are the air gap and magnet, as illustrated in the magnetic circuit depicted in Figure 1 (Left).

Equation 1 presents the calculation that entails dividing the flux by the area it traverses, which is commonly referred to as the magnetic flux density. In general, it is necessary to expand the equation in order to determine the total flux. This quantity is equivalent to the magnetomotive force (MMF) $F_m$ divided by the total reluctance $R_T$.

$$B_g = \frac{\phi_g}{A_m} = \frac{F_m}{(R_g + R_m) \cdot A_m}$$  \hspace{1cm} (1)

The magnet reluctance $R_m$ and magnetomotive force $F_m$ remain constant, while the only variable parameter is the air gap reluctance $R_g$. The equation presented below can be utilised to compute this factor:

$$R_g = \frac{h_g}{A_m \cdot \mu_o \cdot \mu_{air}} = \frac{h_g}{W_m \cdot L_s \cdot \mu_o \cdot \mu_{air}}$$ \hspace{1cm} (2)

Where $w_m$ is the width of the magnet, $L_s$ is the axial length of the machine, $h_g$ is the air gap height, $\mu_o$ is the permeability of free space and $\mu_r$ is the relative permeability, where it is 1 for air and 1.05 for neodymium magnets. It should be noted the magnetic flux traverses the same quantity of area for both scenarios, so when finding the reluctance of neodymium magnet it would similar. It should be noted that this value $R_g$ is subject to change, as it is contingent upon $h_g$, a pivotal variable that is sensitive to alterations stemming from external motion and variation in nacelle mass.

The radial stress can be estimated as follow:

$$\sigma_r = \frac{B_g^2}{2\mu_o}$$ \hspace{1cm} (3)

Hence, it is theoretically possible to forecast the pattern of behaviors in relation to the air gap clearance as shown below.

Figure 1: (Left) Magnetic circuit diagram for a pole pair (Right) a simple correlation between Maxwell radial stress and air gap deflection for the NREL 15 MW reference turbine.

3 Expected Outcomes and Future Work

The expected output depends on the scale of the turbine model. In certain designs, the root mean square (RMS) acceleration of the wind turbine nacelle can reach as low as 0.03 gravity (g) in a sea state characterized by a sig-
nificant wave height of ten meters and water depths of up to 200 meters [8]. According to the findings of the study, it is indicated that a value below 0.3g (equivalent to 2.94 m s$^{-2}$) can ensure a satisfactory level of performance for a floating turbine with a power output of 5MW. Nevertheless, when considering a 15 MW direct drive generator wind turbine, several factors will experience an increase, such as the system’s mass and the tower’s height. Hence, even minor pitch or roll rotations can lead to significant movements at the nacelle. Furthermore, the operational efficiency of Direct-drive generators is dependent on the level of tolerance for air gap clearance. There is a suggestion that in order to achieve optimal functionality, it is advisable to restrict the eccentricity, which represents the deviation of the air gap, to a maximum range of +/- 10%. Despite this, in order to account for the higher level of compliance in larger generators, it is necessary to establish a higher nominal limit of at least 15 to 20% unless stronger grade magnets are utilized or more rigorous mooring layouts are deployed.

The major outcome of this study is to enhance the comprehension regarding the impact of increased nacelle mass and external loading in deeper sea state environment on the integrity of the air gap in comparison to the sole influence of static attraction force resulting from a magnetic field in a fixed bottom scenario. After conducting an evaluation of wind and wave loading in conjunction with the augmented and reduced nacelle mass on air gap displacement through static and dynamic analysis, future research endeavors will strive to expand the study’s purview by integrating thermal expansion characteristics and investigate how the propagation in an air gap is affected by various other floating platforms. Furthermore, in a static model, it is customary to initially assign a nominal value for the air gap clearance and flux density, 1.06T for the 15MW reference model. However, when considering the impact of external load, the new air gap clearance will become known. The radial stress can be determined per time step and subsequently incorporated into the model to observe the temporal evolution of flux density.

References


Floativin - Langevin analysis of floating wind turbines

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Keywords: Stochastic differential equation, Langevin equation, floating wind turbines

1 Introduction

Floating wind turbines have gained significant importance in the renewable energy sector, enabling the exploitation of wind resources in deep offshore locations. The movement of these turbines is highly influenced by wind and wave conditions, making it essential to understand and analyze their dynamic behavior \cite{1} \cite{4}. The inherent dependence of turbine movement on wind and wave conditions necessitates a comprehensive understanding of the complex interactions between these environmental factors and the floating structure. By employing the Langevin analysis method, which considers random fluctuations, a more accurate representation of the turbine’s movement characteristics can be obtained \cite{3}. This approach enhances our ability to model and predict the behavior of floating wind turbines under varying conditions. This analysis can be further utilized to develop new models for simulations, enabling more accurate predictions of turbine behavior and aiding in the optimization of design and operational strategies \cite{2} \cite{5}. Moreover, the Langevin analysis serves as a powerful tool for failure detection. By comparing the observed movement patterns with the intended behavior, deviations can be identified, indicating potential issues or malfunctions. Therefore, the results of the analysis may contribute to the development of effective monitoring and maintenance strategies, ensuring the optimal performance and longevity of floating wind turbines in real-world conditions.

2 Langevin equation

In the context of a one-dimensional system, the Langevin equation can be expressed using the Kramers-Moyal coefficients \cite{3}. This formulation captures the dynamics of the system as:

\begin{equation}
    x(t) = D^{(1)}(x(t),t) + \sqrt{D^{(2)}(x(t),t) \cdot \Gamma(t)}
\end{equation}

In this equation, $D^{(1)}$ represents the first Kramers-Moyal coefficient, which characterizes the deterministic behavior of the system. It accounts for the drift term that governs the systematic evolution of the system over time. The $D^{(2)}$ term, on the other hand, corresponds to the second Kramers-Moyal coefficient, which captures the diffusion or stochastic component of the system. It quantifies the random fluctuations that impact the system’s trajectory. Lastly, $\Gamma(t)$ denotes delta correlated white noise with a variance of 2, representing the random nature of the system’s fluctuations. By considering the interplay between these coefficients, the Langevin equation provides a framework for modeling and understanding the behavior of the system in a stochastic setting.

In our particular case, we are considering a two-dimensional coupled Langevin equation to describe the system dynamics. The equations are given by:
\( \dot{x}(t) = D_1(x(t), y(t), t) + \sum_{i=1}^{3} \sqrt{D_{1i}^2(x(t), y(t), t)} \cdot \Gamma_i(t) \)  
(2)

\( \dot{y}(t) = D_2(x(t), y(t), t) + \sum_{i=1}^{3} \sqrt{D_{2i}^2(x(t), y(t), t)} \cdot \Gamma_i(t) \)  
(3)

Here, the variable \( x(t) \) represents a state variable in the x dimension, while \( y(t) \) represents a state variable in the y dimension. The terms \( D_1(x(t), y(t), t) \) and \( D_2(x(t), y(t), t) \) capture the drift terms specific to each dimension, describing the deterministic behavior of the system in the x and y directions, respectively.

The terms \( D_{1i}^2(x(t), y(t), t) \) and \( D_{2i}^2(x(t), y(t), t) \) correspond to the diffusion coefficients associated with each dimension. These coefficients govern the stochastic or random fluctuations in the system and can depend on the state variables \( x(t) \) and \( y(t) \), as well as time \( t \).

Furthermore, the summation \( \sum_{i=1}^{3} \) accounts for the presence of multiple noise sources indexed by \( i \), with \( \Gamma_i(t) \) representing delta correlated white noise processes for each dimension. The square root of the diffusion coefficients multiplied by the noise terms represents the stochastic contribution to the dynamics in each dimension.

This can also be expressed with a shorter notation, with a drift vector and a diffusion matrix:

\[
\dot{\bar{x}}(t) = \bar{D}_1(\bar{x}(t), t) + \sqrt{\bar{D}_2(\bar{x}(t), t)} \cdot \bar{\Gamma}(t)
\]

(4)

By considering this coupled Langevin equation, we can model the interactions and correlations between the x and y dimensions, allowing for a more comprehensive understanding of the system’s behavior and its response to both deterministic and stochastic influences.

### 3 Models

In the analysis of the movements of floating wind turbines, two distinct sets of movement parameters are considered: surge and sway, and pitch and roll

\[
\bar{x}_1 = \begin{pmatrix} \text{surge} \\ \text{sway} \end{pmatrix}, \quad \bar{x}_2 = \begin{pmatrix} \text{pitch} \\ \text{roll} \end{pmatrix}.
\]

(5)

These movements are typically modeled independently due to their unique characteristics and impacts on the turbine’s performance and stability.

The first model we use is a simple Langevin model

\[
\dot{\bar{x}}(t) = \bar{D}_1(\bar{x}(t), t) + \sqrt{\bar{D}_2(\bar{x}(t), t)} \cdot \bar{\Gamma}(t)
\]

(6)

that focuses solely on the displacement of the turbine variables \( \bar{x} \). This model captures the overall movement of the turbine in terms of its displacement. It provides a fundamental understanding of the turbine’s position changes in response to the given conditions. However, the simplicity of this model limits its ability to capture the finer details of the turbine’s motion and the associated effects on its performance.

In contrast, the second Langevin model, the periodic Langevin model

\[
\dot{\bar{x}}(t) = \bar{v}(t) \quad \dot{\bar{v}}(t) = \bar{D}_1(\bar{x}(t), \bar{v}(t)) + \sqrt{\bar{D}_2(\bar{x}(t), \bar{v}(t))} \cdot \bar{\Gamma}_v(t),
\]

(7)

we consider is a more comprehensive periodic model that takes into account not only the displacement \( \bar{x} \) but also the velocity of the displacement \( \bar{v} \). This model recognizes the dynamic nature of the turbine’s movements, capturing the oscillatory behavior. It offers insights into the cyclic patterns and periodic forces acting on the turbine, which can be crucial for assessing structural integrity, fatigue life, and power generation capabilities.

Comparing the two models allows us to evaluate their respective strengths and limitations in capturing the turbine’s movements. The simple model provides a basic understanding of the turbine’s overall position changes, whereas the periodic model adds a more detailed and dynamic perspective. The choice between these models depends on the specific objectives of the analysis and the level of accuracy required in capturing the turbine’s behavior.
4 Results

The data used in our study is sourced from Hywind Scotland, a floating wind farm situated off the east coast of Scotland. The data is collected at intervals of half an hour with a sampling frequency of 10 Hz.

We present one of our current findings, which focuses on the simple model’s representation of the pitch-roll movement. This particular result is visually illustrated in Figure 1.

Upon analyzing the drift map, a distinct pattern emerges, revealing the existence of a single stable fixed point within the system. This fixed point is centered around \( \text{Pitch} \approx -0.07 \) and \( \text{Roll} \approx -0.0075 \). In all other regions of the drift map, a regular pattern becomes evident, suggesting a predictable behavior characterized by consistent variations in pitch and roll.

Using the trained model, we have the capability to simulate data that resembles the observed behavior of the system. Figure 2 provides an illustrative example of this synthetic data. However, it is worth noting that the simple model falls short in capturing the periodic nature of the system’s behavior. Despite its limitations in this regard, the simple model still serves as a valuable tool for approximating the overall dynamics of the system.

Figure 1: Drift maps of the simple Langevin model of the Pitch-Roll movement of a floating wind turbine.

Figure 2: Comparison of real world data to simulated data with the simple model.
5 Next steps

In the next steps of our project, we plan to undertake several important tasks. Firstly, we will compare the results obtained from the simple model to those of the periodic model in order to identify any significant differences or improvements, particularly in capturing the periodic nature of the time signalss. Additionally, we intend to utilize both models to generate synthetic time series data, enabling us to explore their respective capabilities and potential applications further. Furthermore, we will compare these synthetic time series with real-world time series data to assess the models’ effectiveness in capturing the underlying patterns and dynamics accurately. Another crucial aspect of our analysis will involve examining the effects of different weather conditions on the drift maps derived from the models, helping us gain insights into the influence of various factors on the overall behavior. Lastly, we will focus on identifying nonstationarities within the dataset, seeking any trends or irregularities that may exist over time. These nonstationarities could cause a deviations from the regular pattern in the drift map and they could potentially indicate a malfunction in the wind turbine.

References

Implementation and Evaluation of a Simplified Mooring Line Model for Offshore Wind Turbines

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1. Introduction

The generation of clean and renewable energy in large quantities is crucial for effectively addressing the current global energy and environmental challenges, such as the ever-growing demand for energy and the progressing climate change and pollution levels. For renewable energy generation, wind turbines may be used transforming the kinetic energy stored within the moving wind into electricity. Although the space available to place those structures on land is limited, the amount of unused space in sea areas is significantly larger. These sea areas additionally provide stronger and more consistent wind speeds compared to onshore locations. Around Europe, roughly 80\% of the sea surface is associated with deep water areas with water depths of over 50 m. In such areas, fixed foundations are deemed to be uneconomical or technically unfeasible. Here, offshore wind turbines may be installed in such a way that their foundations float within the sea, whereby one of several concepts is used to make the turbine float.

In any floating offshore wind turbine concept, the wind turbine is held in place by connecting it to the seabed using mooring lines. These mooring lines may either be tightened at all times, as for so-called tension-leg platforms (TLP), or loaded extremely dynamically while undergoing significantly large movements, when other types of floating concepts are used and/or a rough sea state is present.

At the Institute of Structural Analysis (ISD) at Leibniz Universität Hannover, a Fortran-based mid-fidelity aero-hydro-servo-elastic simulation framework for large offshore wind turbines called DeSiO (Design and Simulation Framework for Offshore Support Structures) is currently in development. The mechanical framework of DeSiO uses director based kinematics and a total Lagrangian description. It ensures objectivity and path independence. Moreover, an energy conserving/dissipation time integration method is implemented. The goal of this work is to find and incorporate within DeSiO a suitable and sufficiently accurate mooring line model depicting real physical behavior, such as loads acting on the mooring line, deformations, movements and stresses, which is not easily done due to the various forces acting on mooring lines and their possibly distinctive flexibility. The incorporation opens up the possibility of carrying out coupled multibody simulations, wherein the floating wind turbine and the mooring lines interact with each other, ultimately leading to a sufficiently accurate depiction of the real structure behavior and stresses. Such coupled systems may then be used to investigate whether the system components will fail or deform excessively or not due to the loads acting on them. Moreover, the model shall fit into the underlying mid-fidelity concept, whereby the balance of accuracy and computational cost is optimized. Also, all decisive characteristics of DeSiO, such as the conservation of objectivity and path independence, must be contained within the model.

As a first step towards the incorporation of the model, a two-dimensional numerical mooring line model is implemented within MATLAB. Here, the current state of the model and the possible future additions are presented.

2. Current State of the Model

From sea surface to seabed, a mooring line may generally consist of a metallic wire rope being connected to the floating structure, a long fibre rope, e. g., made out of polyester, and a mooring chain ensuring that the end of the
mooring line connected to the anchor lays down on the seabed in the general case, which then results in purely horizontal loading of the anchor. This leads to the need for a model which is able to include several mooring line segments with different properties. Here, a finite element formulation introduced by Aamo and Fossen [1], wherein linear shape functions and lumped masses are used for all elements, is chosen for the spatial discretization.

Furthermore, the long fibre ropes are able to stretch in the range of 20% of their initial length, so that large deformations take place. Moreover, the mooring line undergoes large displacements and rotations, e.g., due to unsteady currents and the movement of the floating structure. This leads to the necessity for the model to accurately take into account geometric nonlinearities. In accordance with this requirement, all formulations are based on a system of non-linear wave equations in the Lagrangian frame of reference, which may be physically interpreted as the equations of motion of the mooring line. Here, large strains are taken into account by using the Biot strain definition.

Mooring lines may be affected by several types of loads. Here, static and hydrostatic forces like self-weight and buoyancy are taken into account. Moreover, hydrodynamic forces like inertia and drag forces are incorporated within the Morison equation, whereby forces resulting from the velocities and accelerations of water currents and waves in the two-dimensional space are taken into account. Additionally, seabed interaction is taken into account by using Hooke springs and Newton viscous dampers for ground normal forces and friction forces as ground tangential forces. Here, the ground is modeled as horizontal. The according model modifications to include arbitrary seabed shapes were shown and tested by Desiré et al. [2].

Further characteristics of the model are the neglection of compressional, bending and torsional stiffnesses, the incorporation of linear elasticity in the form of Hooke springs and internal viscous damping in the form of Newton dampers within the mooring line, and a finite difference formulation for time discretization. Herein, the central difference is used for approximating the acceleration and the backward difference is used for the velocity.

The qualitative result when using the MATLAB-based model for the calculation of an example configuration of a mooring line coming to rest in still water is shown in Figure 1. Here, the spacial variables $x$ [m] and $z$ [m] are used as the abscissa and ordinate within the diagram. The direction of $z$ generally differs within the literature and is chosen to increase downwards herein. The mooring line is separated into segments shown as lines, which are connected by nodes shown as dots. At both ends, the line is held in both the $x$ and $z$ direction by supports shown as squares. The forces drawn as arrows are the sum of self-weight, buoyancy and ground normal forces. Finally, the horizontal seabed is shown as a dashed line. Since no dynamic external forces due to currents or waves are present, a static solution is reached after a sufficiently large amount of time due to the velocity of the mooring line itself being damped out by internal viscous damping, the damping forces within the Morison equation and the ground normal damping forces. As can be seen, perfect equilibrium is reached at the seabed, which is represented by the sum of forces being equal to zero. Due to the ground normal spring stiffness being set to be very high, the mooring line does not sink into the seabed. For verification purposes, the result may be compared to the analytical solution for a static catenary line in future work.
3. Outlook on Future Work

To improve the scope of physical influences incorporated within the model and the predictability of the behavior of the mooring line when reacting to these influences, the model is planned to be extended by the following elements.

A quasi-static initial calculation step, possibly in combination with a subsequent dynamic relaxation step, is planned to get implemented. This strategy is explained in the MoorDyn User’s Guide [3], whereby MoorDyn is an extension for FAST v8/OpenFAST, an open-source wind turbine simulation tool.

Stationary concentrated forces induced by buoys or weights, as shown by Rodríguez Luis et al. [7], and non-stationary concentrated forces induced by the moving fairlead, which is the connection point to the floating structure, shall be incorporated. Here, aerodynamic forces resulting from steady wind currents and random wind fluctuations, which act on the floating structure connected to the mooring line, and loads induced by ship and ice collision may be implemented. All of these loads may be taken into account either − as planned for the simulation within DeSiO − by using a multibody model of a floating wind turbine being coupled to mooring lines, or by adding the loads onto the fairlead node of the mooring line, whereby the wind turbine model is calculated externally and the loads are interchanged by both models sequentially.

Then, alternative shape functions for the finite element model, an hp-adaptive scheme to change the element size and the degree of the polynomial shape functions automatically, and a formulation using the discontinuous Galerkin method shall be implemented. For mooring line modeling, these strategies where used by Palm et al. [6]. When mooring lines, e. g., relax and are then re-tensioned, snap loads appear, which may damage the mooring line and influence its fatigue life. The discontinuous Galerkin method has been proven to depict such snap-loads during an investigation by Palm et al. [5].

Moreover, a three-dimensional model which also includes multiple mooring lines shall be implemented. Due to this approach, more realistic three-dimensional wave states can be taken into account, whereby the distribution of waves may be determined using stochastic approaches.

To take into account the influence of the bending stiffness on the behavior of the mooring line, angular stiffness and damping can be added to the nodes of the finite element model, whereby the line segments are looked upon as infinitely stiff with regard to bending. Then, compression can also be taken into account more realistically than by setting the respective compression stiffness of the mooring line to zero. This is done by limiting the compression load to Euler’s critical load with an effective length $L_e$ of the line segment of $L_e \equiv L$, where $L$ is the current line segment length. These concepts are also planned to get implemented into the framework and are explained in the documentation for OrcaFlex [4], a program system for the dynamic analysis of offshore marine systems.

For the validation and verification of the model, results may be compared to the results of different numerical model simulations and scale model testings, as can be found extensively in the literature.

Finally, the model shall be incorporated within DeSiO, whereby the preservation of important characteristics of the framework such as a director-based formulation, objectivity, path independence and the underlying mid-fidelity concept must be secured.

Acknowledgements

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References


TOPIC 10: Production, O&M, decommissioning and lifetime extension

Session 10.1
06.09.2023 - 10:30
Building 3703, Room 027

Kainz Samuel: Tradeoffs between economics and climate-related impacts in the design of offshore wind farms
Guilloré Adrien: Tradeoffs between economics and climate-related impacts in the design of wind turbines and airborne kites
Hübner Martin: Hybrid use of LTT welding filler metals for fatigue strength improvement of high-strength steel components
Großmann Friederike: Investigation of Leading edge erosion and its mitigation on the levelized cost of energy for horizontal axis wind turbines
Tradeoffs between economics and climate-related impacts in the design of offshore wind farms

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Keywords: Offshore wind farms, eco-design, value-based design, environmental impact, LCA

Wind energy has become one of the cheapest sources for generating electricity, achieved through drastic reduction of the technology’s levelized cost of energy over the last two decades. Now that cost-parity in main markets is achieved, how can wind energy systems be designed such that their economic and environmental value is maximized for all relevant stakeholders, from developers and equipment manufactures up to societies as a whole? This question is addressed by development and application of an eco-conscious design toolchain for offshore wind farms considering both environmental and economic cost and value. The underlying work is based on research carried out at the Technical University of Munich over the last few years [1–4].

The global architecture of the toolchain is illustrated in Figure 1. The automated holistic evaluation tool consists of mass, cost, layout, cabling, O&M, and installation models covering all wind energy system components, an energy harvest model taking wakes, load-specific electrical losses and down-times into account, a cradle-to-grave LCA model, and a simple electricity grid model. These models are partly adapted from open-source state-of-the-art models and partly originally developed at TUM. The evaluation tool computes economic and environmental cost.

![Figure 1: Global architecture of the toolchain](image-url)
Table 1: Classification of the design metrics [1] and computed values for the case study Horns Rev 3

<table>
<thead>
<tr>
<th>Economic perspective [€/MWh]</th>
<th>Environmental perspective [kgCO₂eq/MWh]</th>
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of energy (COE), value of energy (VOE), and net value of energy (NVOE) of most common European offshore wind farms, approximated through more than 200 model parameters. The economic metrics correspond to the levelized cost of energy (COE), revenue (VOE), and profit (NVOE). On the other hand, environmental metrics reflect the farm’s lifetime impact on climate change: carbon footprint of the generated electricity (COE CO₂), displaced-from-grid greenhouse gases (VOE CO₂), and grid-avoided grid greenhouse gases (NVOE CO₂).

A constrained multi-objective optimization module calls the evaluation tool at each design instantiation, until it converges to a pareto front of non-dominating optimal solutions. This automated design tool delivers optimized design parameters that trade economic and environmental metrics. Various constraints such as specific power, plant capacity, land use, or turbine types can be applied to account for realistic conditions.

The toolchain is applied to evaluate and redesign the case study Horns Rev 3, located at the Danish shore in the North Sea. The farm consists of 49 geared turbines with rated power of 8.3 MW, rotor diameter of 164 m, and hub height of 105 m placed on monopiles in shallow water with approximately 15.5 m water depth. After voltage transformation from 33 to 220 kV, the generated electricity is transferred about 43 km to shore through submarine export cables.

Table 1 lists the results for the six metrics of interest. The low expected revenue hence negative profit results from the assumption that electricity is solely sold on the Danish spot market, modelled with 2015-2018 data mainly featuring low average prices. Power purchase agreements and subsidies such as feed-in tariffs are not considered yet. On the environmental side, results indicate that the farm’s environmental cost is more than one order of magnitude lower than the displaced grid greenhouse gases, resulting in a high NVOE CO₂.

One main feature of the toolchain is its high level-of-detail with respect to COE CO₂ evaluation. Figure 2 illustrates the COE CO₂ breakdown by life phase for the case study Horns Rev 3. The main contributors are the production stage of the components (materials extraction and manufacturing) and the operation & maintenance phase mainly due to component replacement and associated vessel traffic. At end-of-life, a significant share of COE CO₂ can be shifted to subsequent life cycles due to materials’ recyclability.

In Figure 3 the COE CO₂ breakdown by components and materials is illustrated. Steel in nacelle, support structure, tower, and hub drives the emissions. The impact of nacelle is that great since it contains the farm’s most sensitive parts for failures resulting in relatively high demand for components replacement & reparation and associated vessel traffic.

![Figure 2: Breakdown of COE CO₂ by life phase for Horns Rev 3](image)

Finally, the wind farm is re-designed considering the introduced economic and environmental metrics. Design variables and associated ranges are rated power (3-20 MW), rotor diameter (40-250 m), hub height (30-250 m), number of turbines (3-200), and average turbine spacing (3-18 rotor diameters). Constraints are only set to specific
In a nutshell, this work highlights the potential of integrating environmental and economic value into the design of offshore wind farms. Small deviations from economic optima allow for significant improvement of environmental cost and value. Thereby, the study demonstrates that inclusion of value beyond purely economic metrics allows to maximize the positive impact of wind energy for all relevant stakeholders and can thereby further accelerate the energy transition. Ongoing and future work aims at extension of the toolchain scope to integrate analysis of onshore wind farms and airborne wind energy systems, and to include further value metrics into the design framework.
References


Tradeoffs between economics and climate-related impacts in the design of wind turbines and airborne kites

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Keywords: Beyond LCoE, value, design of wind energy systems, LCA, environmental impact

Over the years, wind energy systems have been designed to minimize the cost of energy aiming at making them competitive with other technologies. However, now that wind is competitive, how can we increase its value for society? And how much would a societal gain cost other stakeholders? This work tries to preliminarily answer these questions from the perspective of the design of wind energy systems\textsuperscript{[1, 2]}.

First of all, new design metrics are defined considering the life-cycle greenhouse gases emissions of an energy asset, mirroring existing economic concepts of costs, value (i.e. revenue for monetary terms) and net value (i.e. profit), as explicited in table 1. Then, a multidisciplinary design toolchain is developed to estimate the desired metrics for any given onshore turbine configuration. Here the rotor diameter and hub height are selected as main design variables, for preliminary sizing. It is used for multi-objective optimizations, as schematized on figure 1.

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<tr>
<td>Net value</td>
<td>NVOE\textsubscript{\textit{CO2}}</td>
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Table 1: Classification of the design metrics used in this present work\textsuperscript{[1]}.

Figure 1: Schematic illustration of the workflow for the eco-conscious multi-objective design optimization of wind energy systems. Rounded squares represent variables, squares are models and trapezoids are merit functions\textsuperscript{[1]}.
On a first step, cost-based design can be expanded to include not only monetary costs, but also environmental costs. Although wind turbines produce green renewable energy, they also generate various impacts on the environment, as all human endeavors. Among all impacts, the present work focuses on greenhouse gases (GHG) emissions produced by a turbine over its entire life cycle. An automated model is developed to assess GHG emissions for various turbine configurations (parameterized in terms of rated power, rotor diameter, and hub height) using a Life-Cycle Assessment (LCA) methodology. A multi-objective optimization is formulated that finds trade-offs between the monetary and the environmental costs of energy. When applied to resizing an onshore turbine, it is found that 1% increase in monetary cost can buy about 5% decrease in environmental cost, as can be seen on figure 2.

Figure 2: Pareto front of COE\(_{CO2}\) vs. COE\(_{\epsilon}\) (left) for the case of resizing an onshore wind turbine. Rotor diameter and hub height of the Pareto optimal designs (right) [1].

On a second step, a system-level approach is taken where not only the turbine costs are considered, but also the value (benefits) of the generated energy. On the monetary side, market spot prices are correlated with the wind resource, leading to the definition of economic value (revenue) and net value (profit). The same logic is applied to define environmental value metrics, where the electrical grid GHG emissions are correlated with the wind resource to estimate displaced emissions. A location in north of Germany (LN, with high wind resource) and a location in south of Germany are considered (LS, with lower wind resource). When the multi-objective design problem is formulated in terms of value -instead of cost-, it is found that optimal solutions are characterized by a very low specific power, because producing in low winds generates the highest environmental value. More importantly, here again there is a large multiplier between economic losses and environmental benefits (i.e. being altruistic pays off), see figure 3.
Figure 3: Pareto front on the system-level between a net economic value point of view (NVOE$_e$) and a net environmental value point of view (NVOE$_{CO2}$) (top). LN denotes the north-german location, and LS the south-german location. Optimal diameters (D) and hub heights (H) for the solutions of the Pareto front (bottom) [1].

Figure 4: Comparison of the carbon footprint (lifecycle greenhouse gases emissions) broken down by main components for two sizes of conventional horizontal-axis wind turbines (HAWT) and three sizes of airborne wind energy system (AWES, here a drag power kite) as estimated by the developed automated LCA model.
Finally, the LCA model is also applied to Airborne Wind Energy Systems (AWES) using the case of rigid drag power kites, in cooperation with the company Kitekraft GmbH. It is found that this technology has the potential to have a reduced environmental impact, mostly because of the absence of material-intensive towers, figure 4.

The whole approach, method and results will be presented. This on-going work suggests the existence of new opportunities for the future development of wind energy where, by shifting the focus slightly away from a purely cost-driven short-term perspective, longer-term benefits for the environment (and, in turn, for society) may be obtained.

References


Hybrid use of LTT welding filler metals for fatigue strength improvement of high-strength steel components

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Keywords: welding, LTT (Low Transformation Temperature) fatigue, high-strength steels, residual stress,

Motivation

Wind turbines are a key element of the energy transition. The height of wind turbines can significantly increase the energy output [1]. For this purpose, high-strength steels (R e ≥ 690 MPa) offer a possibility to increase the output. E.g., a same cross section of a tower segment at higher stability. A limiting factor for welding high-strength steels is the fatigue strength in welds due to unavoidable residual stress [2, 3]. There are several conventional methods to reduce residual stress, such as high frequency impact treatment (HFMI), however these are often time-consuming and costly [4]. An alternative is the use of LTT (Low Transformation Temperature) welding fillers, which reduce tensile residual stress during cooling of the weld metal. This is achieved due to the martensitic phase transformation near ambient temperature, which generates a volume expansion [5]. A hybrid application of LTT and conventional welding filler is promising to have less impact of the integrity of welds. For that LTT filler is only added selectively to points which are particularly critical for fatigue fracture like areas with high residual stress [6]. In order to make LTT fillers suitable for industrial use, safe application and design rules are required.

Research question

The research question in this project is how to evaluate the integrity and stability of hybrid LTT welds. Therefore, the main goal is to develop an evaluation concept for LTT hybrid welds. Mainly it is necessary to find an optimum between high compressive residual stress (high LTT-content) and sufficiently high toughness (low LTT-content). Welded longitudinal stiffeners serve as specimen, since high residual stresses are to be expected and an additional LTT-layer can be implemented easily [7]. This will be carried out by means of both experimental tests and simulation (Figure 1). Base Material will be the high-strength steel S700M.

Figure 1 - a) Implementation of an LTT-hybrid layer and b) weld simulation of a longitudinal stiffener
Procedure

The project procedure can be divided into two steps. First step is an experimental-numerical approach. On the one hand, welding tests of the LTT filler in longitudinal stiffeners with varying weld position and parameters are carried out to get different residual stress results. The determination of weldability and residual stress are in focus. On the other hand, the numerical analysis of the LTT addition with different parameters is carried out [8]. Both approaches, experiments and simulations, should result in an optimization loop to find an optimal weld geometry to reduce residual stress (Figure 2).

![Figure 2 - Flow chart for optimizing the weld geometry of the LTT-layer by means of experiments and simulation](image)

Second step is the lifetime evaluation of the longitudinal stiffeners with the optimized weld geometry. Fatigue tests will be carried out and compared with conventional and HFMI treated welds. The evaluation concept is based on the local concept with FKM-guideline nonlinear and fracture mechanical properties [9]. The confirmation of the evaluation concept on component scale is secured by experimental validation on a demonstrator.

Conclusion

The expectation of this project is to develop an evaluation concept for LTT hybrid welds in high-strength steels. The reduction of residual stress by using LTT weld filler is sufficiently demonstrated in the literature [5] [6], however the industrial use is not common. In fact, that several variants of LTT weld geometries are implemented during the experiments and simulations, an idea is given which weld geometry have the strongest influence in the residual stress reduction. Fatigue strength of weld should be improved to increase the service life expectancy of welded components, by using LTT filler [7]. Through the hybrid use of LTT filler, the integrity of weld should be less affected, in particular the toughness. Using the established calculation procedure of the FKM guideline nonlinear, verification can be achieved.

Outlook

Through this project, an increasing acceptance of LTT fillers in high-strength steels should be achieved. Besides the working packages of this project, publications, guidelines and information sheets will be also generated. The gained project knowledge can be helpful, especially for small and medium-sized enterprises (SMEs) with welding activities, without research capacities. The advantage of LTT filler for SMEs in welding activity is the easy handling with existing welding equipment, without extensive rework like HFMI. Since steel construction and therefore welding is essential for wind turbines, welding companies can also benefit in this segment. Especially, to build higher wind turbines with high-strength steels within safe parameters with regards to fatigue strength.
Acknowledgements

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This project is carried out by the Bundesanstalt für Materialforschung und -prüfung (BAM) and the Fraunhofer Institute for Mechanics of Materials IWM.

References

Investigation of Leading edge erosion and its mitigation on the levelized cost of energy for horizontal axis wind turbines

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Keywords: dynamic stall, leading edge erosion, passive flow control, vortex generator, gurney flap

The damage to wind turbines caused by erosion due to weather and atmospheric conditions leads to significant performance losses in the generation of renewable wind energy. In addition, the flow around the rotor blades, which is altered by erosion, is superimposed by transient flow effects during operation, which leads to increased misalignment of the rotor blades and consequently to dynamic stall. It is investigated whether and how the occurrence of this flow phenomenon and the associated power degradation can be counteracted by installing passive flow control devices, in this case vortex generators (VGs) and Gurney flaps (GFs). When properly applied, they reduce flow separation and thus provide both an increase in lift force and a reduction in drag. With their help, dynamic stall should be delayed or even prevented. On a pitching airfoil, time-resolved surface pressure is recorded and the flow field quantities are measured using a laser-based optical method (particle image velocimetry (PIV)) to record the highly unsteady effects. Finally, an estimation of the gain collapse due to erosion will be performed using the program QBlade.

1. Introduction

Wind turbines are constantly exposed to all kinds of weather conditions. These depend on geographical location the turbine is stationed, but are subject to strong fluctuations in the most common cases. Especially on the German coast, where large offshore wind turbines with rotor diameters of more than 200m are increasingly installed, harsh conditions prevail. Rain, snow and hail enriched with salty aerosols, which are stirred up by breaking waves, hit the rotor blades of the wind turbines at high speeds. This results in erosion phenomena, especially at the leading edge of the rotor blade. Figure 1 shows examples of eroded blade profiles. While Figure 1(a) shows an early stage of erosion, in (b) the rotor blade coating suffers severe degradation over a large area.

![Figure 1: Eroded rotor blades of a wind turbine. (a) pits and gauges. (b) leading edge delamination [11]](image)

In this work, special attention is paid to the influence of rain. It is one of the most important problems due to its frequency and its impact on the turbine from the moment it is put up [1].
Figure 2 shows the effect of leading edge erosion (LER) on the power curve of a wind turbine. The graph illustrates that the power output decreases with increasing severity of erosion, see the blue (LER1) and green (LER05) curves versus the red curve of an undamaged blade (clean). This results in significant losses of about 20% at a wind speed of 11 m/s for wind turbine operators.

Various measures can be taken to minimize erosion on wind turbines, such as using more resistant materials, installing protective coatings on the blades, or adjusting the rotor blade geometry to reduce particle impact [1]. However, these are primarily related to new turbine design and it is equally important to address already existing turbines. Erosion changes the geometry of the blade profiles with significant effects on the flow around the rotor blade. In certain cases, flow detachment and so-called dynamic stall occurs. However, attachment of the airflow is essential to generate lift and to convert the energy of the wind into usable energy in the form of electricity. Dynamic flow separation which often occurs on horizontal wind turbines, is caused by temporal changes of the effective angle of attack. Its origin is manifold such as the occurrence of turbulence, changing flow velocities, change of wind direction or wake flow from other wind turbines in wind farms and results in flow misalignment along the rotor blades. In general, this leads to the fact that at a critical value of the angle of attack (AOA), the flow can no longer follow the geometry of the rotor blade. [2]

This effect cannot yet be integrated as a design parameter in the construction of wind turbines due to the unpredictability of misaligned flow. If the leading edge of a rotor blade is additionally eroded, the effect of flow separation is intensified. Additional forces and moments now act on the turbine, not only reducing the energy production but also the lifetime of the turbine.

Passive flow control devices like Gurney Flaps (GFs) can effectively enhance wind turbine performance. By attaching L-profiles to the trailing edge of rotor blades, GFs modify the Kutta condition and increase lift, resulting in improved efficiency [3, 4, 5]. The height of GFs plays a crucial role in their effectiveness, as demonstrated in various studies [4, 5, 6]. Moreover, GFs allow for a reduction in blade chord by more than 10%, enabling lighter and more cost-effective designs [7]. GFs can be incorporated in both new and existing wind turbines to boost power output and extend service life. However, GFs can lead to abrupt stall behaviour and increased fatigue loads [8]. To address this issue, additional passive control devices like vortex generators (VGs) can be installed [9]. VGs, attached to the upper surface of the airfoil, create vortices that delay or suppress flow separation, thereby counteracting the undesirable effects of GFs [4, 6].

Up to now, VGs are primarily attached at the root of the rotor blades. At this location the blades are particularly thick for stability reasons and the effective angle of attack is production-related suboptimal, which may cause flow separation. Some numerical and very isolated experimental studies could show the potential of passive control devices such as VGs or GFs on horizontal wind turbines. For example, it can be seen in Figure 2 that VGs have the potential to vastly improve the performance of eroded rotor blades. However, the amount of data is very limited and studies that intensively address the interaction of the four elements described (dynamic stall, leading edge erosion, vortex generators, and Gurney flaps) are lacking. This gap will be explored and filled in this work.

2. Research methods

The aim of the dissertation is to understand the influence of leading edge erosion on the physics of dynamic stall. Proposals for the equipment of wind turbines with VGs and GFs shall be developed such that the performance of
wind turbines is enhanced and the power output of wind farms is increased. Furthermore, a data basis for the validation of numerical models with respect to effects of LER, VGs, and GFs shall be established.

Firstly, LER will be quantified. This will include a listing of the types of erosion and their influence on rotor blade polars. The polars altered by erosion will be compared and validated against existing data from actual wind turbines. Secondly, techniques for modelling LER will be investigated. Possibilities for modelling may include turbulators such as ZigZag tape or foils with cut-outs that can be placed on a model rotor blade. Other methods may include 3D printing or milling leading edges from a wing airfoil with erosion-like holes and grooves. The most suitable method of modelling has to be determined. Results will be obtained on a 2D airfoil. The findings will then be transferred to a 3D model with rotor diameter of three meters. Figure 3 shows a possible configuration of turbulators and passive flow control devices on a wing profile.

In the following, the influence of LER on dynamic stall is investigated. Based on this, as well as on the findings of the current DFG project, the combinations of LER with VGs, LER with GFs, and LER with VGs and GFs in interaction with dynamic stall will be investigated. These investigations are all initially performed in an open test section of the former laminar wind tunnel of the Institute of Fluid Mechanics and Technical Acoustics (ISTA) on an oscillating 2D airfoil, see the 3D CAD model in Figure 4. The large splitter plates between which the profile is mounted are made of acrylic glass. They are utilized to simulate a 2D flow and to allow optical access for the PIV.

Figure 5 (left) schematically shows the measurement locations. Pressure measurements are performed to determine surface pressure coefficients that are integrated to obtain lift, drag, and moment coefficients. Simultaneously, PIV is used to obtain flow field quantities on the upper surface of the airfoil, thus providing information about the dynamic stall mechanism. By using stereo PIV and multiple PIV plane locations, phase-averaged three-dimensional flow field quantities are obtained, as indicated by the different green planes in Figure 5. Additionally, time-resolved PIV, allows each PIV image to be associated with a pressure distribution, which allows direct comparison between the detected separation and the measured pressure values. By using different configurations with VGs and GFs, a configuration which best counteracts the effects of LER can thus be determined.

Figure 3: Possible configuration of a generic 2D airfoil with VGs, GFs and ZigZag tape as a modelling option for LER. [10]

Figure 4: 3D CAD model of test stand for 2D oscillating airfoils.
With the knowledge gained from the 2D studies, the configuration with the best results is finally transferred to a rotating 3D test rig, the Berlin Research Turbine (BeRT). BeRT serves as a unique wind turbine demonstrator and allows the study of specific fluid dynamic phenomena using a fully equipped rotating system. As part of the Hermann Föttinger Institute's closed wind tunnel at the Technical University of Berlin, BeRT is a crucial component of the research work. At this test rig, stereo PIV measurements will then be combined with load, power, pressure, and quantitative flow visualization data to investigate the effect and flow mechanisms of VGs and GFs on a wind turbine with LER. The test setup is shown in Figure 5 (right).

References


TOPIC 11: Wind resources, turbulence, and acoustics

Session 11.1
06.09.2023 - 13:15
Building 3701, Room 268

Bock Marcel  Investigation of intermittency in LES with synthetic turbulent inflow
Moreno Daniela  Center of Wind Pressure: A comparison between atmospheric and standard synthetic wind fields
Pinilla Sebastian  Reconstruction of wind fields by a superstatistical synthetic model constrained on wind tunnel measurements
Borowski Johanna  Predicting future wind speeds based on climate projections and MCP-methods
Investigation of intermittency in LES with synthetic turbulent inflow

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The turbulence of the atmospheric boundary layer is one of the most important factors influencing the loads and power output of a wind turbine. One characteristic of turbulent flow are velocity increment statistics. Wind measurements have shown that these exhibit non-Gaussian behaviour and have a higher probability for extreme events [1, 2]. This phenomenon is called intermittency and can be illustrated by the refined similarity hypothesis (K62) [3, 4]. According to this, the deviation from Gaussianity for the velocity increment statistics follows a log normal distribution, which can be described by a phenomenological intermittency parameter.

To represent the turbulent fluctuations near the surface, various models were introduced to be used as inflow for simulations. One of these models is the Mann model [5, 6] which displays Gaussian velocity statistics including Gaussian velocity increment statistics. In the present work, the behaviour of a Mann wind field and a recently developed non-Gaussian wind field which is closely related to the Mann model [7] are compared in high resolution computational fluid dynamics simulations with OpenFOAM. For this purpose, these two wind fields are used as inflow into Large eddy simulations (LES) in the form of a volume force and are transported through the flow in an empty domain (fig. 1). There is good agreement between the velocity spectra of the originally injected wind fields and the resolved velocity spectra in LES at potential wind turbine positions. Furthermore, the well known decrease in turbulent intensity due to dissipation occurs downstream. By analysing the velocity increments, we find that the intermittency decreases with a non-Gaussian wind field while the flow develops intermittency downstream in the LES with a Gaussian wind field. Independently of the applied inflow model, a state is established in which turbulence characteristics can be described by the above, mentioned intermittency parameter from the refined similarity hypothesis (K62) [3, 4] (fig. 2). The determined intermittency parameter of the LES is in the order of magnitude of wind measurements and ideal turbulence [2].

Acknowledgements

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References


Center of wind pressure: A comparison between atmospheric and standard synthetic wind fields

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Keywords: Wind modelling, Atmospheric turbulence, Load estimation, Wind turbine

1 Introduction and Motivation

The loads induced on an operating wind turbine (WT) are estimated by numerical simulations of the interaction between the incoming wind and the components of the WT. Within the generation of synthetic wind fields for the simulations, wind models such as the standard Kaimal or Mann are recommended by standard guidelines \cite{1} for reproducing the turbulent structures on the atmospheric wind. These standard models consider assumptions and simplifications of the atmospheric flow. Such reductions in the complexity of the atmospheric wind allow the analysis, at an acceptable time and computational cost, of a very broad range of environmental conditions and operating scenarios.

Consequently, in seeking its simplification, the proposed standard models neglect some structures of the atmospheric wind. Under certain conditions, such events might add highly significant loads on the WT. Particularly, little attention has been devoted to describing large-scale turbulent structures taking place on the plane perpendicular to the main direction of the flow, the so-called rotor plane. An example of those particular structures of the atmospheric turbulent wind would be a body of high wind speed affecting only the top half of the rotor plane; as a result, a tilt moment on the main bearing might be enhanced. Or, if the high-speed structure acts only on the right half of the rotor plane, then a moment might be experienced at the main bearing in the yaw direction.

Such turbulent events on the rotor plane and their effect on loads of a WT have been investigated in \cite{7}. The authors defined the pressure induced tilt ($T_{\text{tilt}}$) and yaw ($T_{\text{yaw}}$) moments of the WT as the product of a point force and a lever. For a wind field $u(y_i,z_i,t)$ defined at $n$ grid points with individual locations $(y_i,z_i)$, inside the area $A$ covered by the rotor, the normal point force $F(t)$ is defined as,

$$ F(t) = \sum_{i=1}^{n} \rho \frac{CT}{2} \cdot u^2(y_i,z_i,t) \cdot dA $$

where $\rho$ is the density of the air and $CT$ the thrust coefficient of the WT. Following, the authors introduced the center of wind pressure ($\text{CoWP}$) as the lever for calculating $T_{\text{tilt}}$ and $T_{\text{yaw}}$. The $\text{CoWP}(t)$ is calculated from the mean of the normal forces weighted by their position as,

$$ \text{CoWP}_z(t) = \frac{\sum_{i=1}^{n} z_i \cdot \rho \frac{CT}{2} \cdot u^2(y_i,z_i,t) \cdot dA}{\sum_{i=1}^{n} \rho \frac{CT}{2} \cdot u^2(y_i,z_i,t) \cdot dA}. $$

Note that in Eq. (2), $\text{CoWP}_z(t)$ is calculated for the vertical direction $z$. The equivalent calculation is performed for $\text{CoWP}_y(t)$ by considering the horizontal component $y_i$ in the numerator. Hence,

$$ T_{\text{tilt}} = F(t) \cdot \text{CoWP}_z(t) $$

$$ T_{\text{yaw}} = F(t) \cdot \text{CoWP}_y(t). $$
Next, the authors in [7] set the same wind fields \( u(y, z, t) \), used for the calculation of \( T_{\text{tilt}} \) and \( T_{\text{yaw}} \), as incoming flow for running Blade Element Momentum (BEM) simulations. The simulated moments \( \hat{T}_{\text{tilt}} \) and \( \hat{T}_{\text{yaw}} \) were then estimated. Interestingly, the authors reported that the calculated pressure induced \( T_{\text{tilt}} \) and \( T_{\text{yaw}} \) showed a high correlation to the corresponding \( \hat{T}_{\text{tilt}} \) and \( \hat{T}_{\text{yaw}} \) from the simulations. Therefore, it was shown that certain events on loads of a WT can be estimated directly from the CoWP \( P(t) \). Accordingly, either measured or synthetic fields \( u(y, z, t) \) might be enough information for predicting certain load events through the estimation of CoWP \( P(t) \). Furthermore, an accurate characterization of the CoWP \( P(t) \) from the atmospheric wind and its correct modelling into synthetic fields for numerical simulations, might result in more realistic estimation of the loads by numerical simulations. Particular events might not be properly captured under the assumptions currently considered by the standard wind modeling.

In this work, we aim to measure, characterize and compare the statistics of the CoWP \( P(t) \) for different wind fields. First, we consider atmospheric wind fields measured on a spatial grid. Then, we evaluate two standard (by the IEC norm [1]) synthetic wind fields: Kaimal[3] and Mann[5, 6]. Differences between the atmospheric wind and the standard models might be relevant for estimations of the resulting dynamic interactions not only between the incoming flow and the WT, but also between different elements of the WT.

2 Results and Discussion

One-point and two-point statistics of the resulting CoWP \( P(t) \) are investigated. As an example, Fig. 1 shows an excerpt of the time series of the fluctuations of CoWP \( P_z(t) \) in the vertical direction \( z \), resulting from a Kaimal, a Mann, and an atmospheric wind field. The fluctuations CoWP \( P_z(t) \) are assumed around the mean value \( \langle CoWP_z(t) \rangle \) where \( \langle \cdot \rangle \) denotes the time average.

![Figure 1: Excerpt of time series of CoWP \( P_z(t) \) for Kaimal, Mann and Atmospheric wind fields.](image)

Fig. 2 shows the power spectrum over frequency of CoWP \( P(t) \), in (a) for the horizontal direction \( y \) and in (b) for the vertical direction \( z \). In this case, the spectra are calculated not for single wind fields as in Fig. 1, but from ensembles of 7 random realizations of the Kaimal, Mann, and atmospheric wind fields. The solid black line depicts as reference, a decay \( E(f) \propto f^{-5/3} \). As can be observed in Fig. 2(a), the fluctuations of the atmospheric wind contain a lower energy content at lower frequencies. This is correspondingly confirmed by lower values of the variance \( \langle (CoWP_y(t))^2 \rangle \). At frequencies higher than 2Hz, Mann wind fields depict lower energy content compared to Kaimal wind fields.

In contrast, the spectra in the vertical direction shown in Fig. 2(b) reflect higher energy content in the atmospheric wind fields at frequencies higher than 0.1Hz. Here, special attention has to be given to the effect of the wind profile assumed by the standard wind models in the resulting CoWP \( P_z(t) \). As in Fig. 2(a), Mann wind fields show lower energy content in the fluctuations of CoWP \( P_z(t) \) at higher frequencies, compared to the Kaimal fields.

Up to this point, the recently introduced Center of Wind Pressure was calculated for measured atmospheric wind fields, as well as for the Kaimal and Mann synthetic standard wind fields. The comparison between them...
has shown significant differences. Particularly, the energy content of the fluctuations in the frequency domain reveals discrepancies not only between the different wind fields but also when contrasting the calculations in the horizontal and vertical directions. This holds specially for the atmospheric fields. A complete statistical description of the statistics of the Center of Wind Pressure is intended to be presented within the scope of this investigation. Furthermore, we aim to include in our comparison results from non-standard wind field models such as the Continuous Time Random Walk (CTRW) model [4, 8] or the Superstatistical model [2].

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References


Reconstruction of wind fields by a superstatistical synthetic model constrained on wind tunnel measurements

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Keywords: turbulence, intermittency, wind field model, multifractional Brownian motion

The modelling of atmospheric turbulence has gained more significance for the forecasting of wind turbine loads. Several wind field models have been proposed like the spectral algorithm by Mann [1], which is able to simulate three-dimensional fields assuming the velocity field as Gaussian and using Taylor’s frozen turbulence hypothesis to interpret time series. Nevertheless, Gaussian models are not able to reproduce strong events whose probability density functions are characterized by heavy tails. Looking into this problem Friedrich et al. [2] proposed a superstatistical wind field which can be understood as an extension of [1] based on the joint $n$-point PDF and the superposition of Gaussian distributions, following the K62 model, that is able to be coupled by real wind measurements through multipoint fractional Brownian bridges [3]. In that previous work, the generated wind field was coupled with measurements by the GROWIAN campaign, which was achieved with propeller anemometers mounted on two met masts in front of a 3MW turbine. In this project, we aim to reconstruct wind fields from wind tunnel measurements downstream. Using an active grid, we thus deploy the statistical methods from above in order to reproduce atmospheric extreme fluctuations, e.g., gusts, in the wind tunnel.

Figure 1 shows preliminary results of the application of the approach, being Figure 1(a) a sample of the superstatistical wind field while Figure 1(b) shows the probability density functions of the velocity increments for different scales with respect to the integral length. This demonstrates that the approach is able to reproduce non-Gaussian properties that are common in turbulence measurements.

![Superstatistical wind field](image1)

(a) Superstatistical wind field

![Velocity increment PDFs](image2)

(b) Velocity increment PDFs

Figure 1: Superstatistical wind field model
Furthermore, an example of the reconstruction through a fractional Brownian bridge of a time series from a set of prescribed points, that could belong to a group of measurements, is presented in Figure 2. Here, the Hurst exponent $H$ not only plays a role to define the randomness of the resulted time series but also relates this to the K62 model. The comparison of $H$ as well as the intermittency coefficient $\mu$ between the reconstructed series and the entire turbulence signal, will be used in a posterior step to determine the accuracy of the approach.

Figure 2: Fractional Brownian bridge considering different Hurst exponents $H$.

References


Predicting future wind speeds based on climate projections and MCP-methods

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Keywords: wind energy site assessment, wind climate, climate change, CMIP6, uncertainty, long-term referencing, Measure-Correlate-Predict (MCP)

Precise knowledge of the wind climate at a target site is crucial for estimating the wind potential not only in the planning phase of wind farms, but also during their lifetime of 20 years and more. For this purpose, measurement campaigns are carried out in the planning phase of a wind energy project, typically covering a full yearly cycle.

These on-site measurements (short–term data) are extended with a wind time series based on numerical data (long-term data) covering at least 10 years. The link between the short-term and long-term data is typically established by statistical methods based on the overlapping time period of both data sets, commonly known as Measure-Correlate-Predict (MCP) methods [1]. In current site assessment industry standards (e.g., the German Technical Guideline (TR6) for Wind Turbines) it is assumed that the wind climate of the past corresponds to that of the future.

In view of climate change, however, it is questionable whether projecting past wind speed into the future is still a reliable assumption. Therefore, this presentation focuses on analyzing the applicability of using climate projections and advanced MCP-methods for predicting future wind speeds. A consistent methodology from the short-term to the long-term to the future climate projection is presented (Figure 1).

The analysis is applied to sites with long-term measurements in varying terrain complexity – simple (Cabauw (NL) [2]), heterogeneous (Lindenberg (GER) [3] and Hamburg (GER) [4]) and complex terrain (Karlsruhe (GER) [5]). The historical wind climate was predicted based on measurement and ERA5– reanalysis [6] data. To predict the future wind climate, an ensemble of two CMIP6 model data is used as long-term data in the MCP-method. Based on the ensemble of future predictions an uncertainty estimation for the future wind climate is obtained.

First results using the global climate models MPI-ESM-1-2-HR [7] and IPSL-CM6A-LR [8] indicate that implementing climate model data into the process of determining the future wind resource is promising. In the historical overlap period, the predicted wind speeds based on climate model data reasonably agree with measurement data and the historical prediction. This emphasizes that using the MCP method to correct climate model data to a target site is a great benefit in wind energy site assessment. Analyzing the near future (2041 – 2070) and far future (2071 – 2100) wind speed predictions reveal seasonal changes. In the summer months July to September a decrease in wind speed is detected while in winter the models show no clear tendency. A more detailed analysis of the summer months shows a less frequent occurrence of higher wind speeds while the occurrence frequency rises in the range of 3 – 5 m/s. However, an increase of the climate model ensemble is necessary to increase the robustness of the conclusion. Further a first approach to obtain an uncertainty estimation based on the climate model ensemble is shown.
Acknowledgements

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References


Session 11.2  
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Building 3701, Room 268

Juliust Hessel  
Physics-informed Machine Learning Approach for Outdoor Sound Propagation Model

Adeel-Ur-Rehman Arslan  
Improved performance of k- Omega SST turbulence model in predicting airfoil characteristics for a large range of airfoil thicknesses

Hegab Mohamed  
The Spatial Development of Turbulence and its Effect on Aerodynamics
Physics-informed Machine Learning Approach for Outdoor Sound Propagation Model

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Keywords: acoustics, atmospheric-influence, physics-informed machine learning, numerical model

1 Introduction and State of the Art

With the increasing number of wind power plants and the transition to larger and more powerful turbines, the noise generated by wind turbines has become a significant concern and accurate noise predictions are crucial in addressing this issue [6]. Sound waves are produced through the interaction between the wind and the rotating blades (aerodynamic noise) or by other sources within the turbine, and they propagate through the atmospheric boundary layer which is heavily influenced by atmospheric and ground characteristics [4].

Outdoor sound propagation simulation encompasses a wide range of state-of-the-art approaches, including numerically solving physics-based models (such as the wave equation, Helmholtz equation’s or linearized Euler equation), as well as Lagrangian models, heuristic models, and statistical models. Numerical physics-based models employed in outdoor sound propagation simulations include the parabolic equation method (PE) [21], boundary element method (BEM) [17], and finite-difference time-domain method (FDTD) [2]. Heuristic models or engineering noise models, encompass methods such as the ISO 9613-2 method [8] and Harmonoise model [19, 18]. Example of Lagrangian model is a particle based model [7]. Moreover, statistical models applied to outdoor sound propagation analysis comprise of machine learning analysis [14] and geostatistical models [1]. Comparisons between these methods has been compared by Hart [5].

In the past two decades, the linearized Euler finite-difference time-domain method has become widely accepted as a prominent model for simulating outdoor sound propagation. This method offers several advantages inherent in time-domain approaches. Firstly, it enables the generation of comprehensive frequency responses through a single simulation. Secondly, it allows for the incorporation of non-linear effects and the consideration of moving and realistic sources. When dealing with a moving medium, it is crucial to employ finite-difference time-domain implementations that accurately capture both the medium velocity and the acoustic sound pressure [20]. A model developed at DLR namely AKU3D is a FDTD sound propagation model which describes the motion of sound waves in the presence of moving medium. Describing the presence of moving medium is important for outdoor sound propagation since the condition of the atmosphere heavily determine the propagation of the sound waves [2]. The linearized Euler equation (LEE) which is used for this model, is described as follows:

\begin{equation}
\frac{\partial \mathbf{u}''}{\partial t} + (\mathbf{u} \cdot \nabla) \mathbf{u}'' + (\mathbf{u}'' \cdot \nabla) \mathbf{u} = -\alpha \nabla p'' - \alpha'' \nabla \bar{p} + \nu \nabla^2 \mathbf{u}'',
\end{equation}

with \( \alpha = \frac{1}{\bar{\rho}} \) and \( \alpha'' = -\frac{1}{\kappa} \frac{p''}{\bar{\rho}} \frac{1}{\bar{\rho}} \)

\begin{equation}
\frac{\partial p''}{\partial t} + \mathbf{u} \cdot \nabla p'' + \mathbf{u}'' \cdot \nabla \bar{p} = -\kappa \bar{\rho} \nabla \cdot \mathbf{u}'' - \kappa p'' \nabla \cdot \mathbf{u}
\end{equation}

with \( \kappa = \frac{c_p}{c_v} = \frac{c^2 \bar{\rho}}{\bar{\rho}} \)

The numerical solver will then solve for \( \mathbf{u}'' \) (the velocity of the particle) and \( p'' \) (the pressure of the acoustic wave), with other variables such as \( \bar{\rho} \) (the pressure of the flow field), \( \bar{\mu} \) (the velocity of the flow field), \( \bar{\rho} \) (the air density) and \( \kappa \) (the coefficient of the ratio of the specific heats of air at constant pressure (\( c_p \)) and constant volume (\( c_v \)) are given. Note that \( \kappa \) can also be obtained from the speed of sound wave (\( c \)), \( \bar{\rho} \) and \( \bar{\mu} \).
2 Challenges of PDE-based Simulation and the Emergence of Machine Learning Methods

Despite the advantages, physics-based simulations like AKU3D (or other PDE-based techniques in general) suffer from high computational costs when simulating high frequency sound waves. This can be attributed to various factors. Firstly, the higher frequency waves simulation necessitate a finer grid resolution, which significantly increases computational requirements and data storage. Moreover, the interactions between high frequency waves and the atmospheric fields introduce complexities that are challenging to accurately model, thus demanding additional computational power. [16]

We propose an approach that is a data-driven solution utilizing machine learning techniques for simulating outdoor sound propagation. In recent times, there are two prominent methods for integrating data and machine learning into numerical simulations which are Physics-informed neural networks (PINNs) and Neural Operators. Machine learning approach has the capability to capture intricate non-linear phenomena and effectively incorporate physical constraints and knowledge, hence combining it with physical equation could enhances the accuracy and reliability of the resulting models, making them more robust and suitable for accurately simulating outdoor sound propagation [9].

The main idea of the PINN approach in this case is to incorporate the LEE during the training of the neural network. By minimizing the loss function, the PINN aims to minimize both the data-driven and LEE which is the physics-driven terms. The equation can be expressed as follows: [9]:

$$\mathcal{L}_{\text{PINN}} = \mathcal{L}_{\text{DD}}(u(t,x), \hat{u}(t,x)) + \mathcal{L}_{\text{Physics}}(\hat{u}(t,x))$$

Here, $\mathcal{L}_{\text{DD}}$ is a data-driven loss function, e.g. L1, which takes as input the target values $u(t,x)$ and the output from the model $\hat{u}(t,x)$ like a normal machine learning problem. $\mathcal{L}_{\text{Physics}}$ is the residual function modeling, requiring the residual of the PDEs of the physics system to be satisfied by the output of the neural network. The process of choosing the physics-based loss term would be an integral part of the research since it depends on the problem and the specific case for acoustical-meteorological coupled simulation needs to be investigated [10] since also similar research using PINN for acoustical-meteorological coupled simulation has been done but the respective PINN models failed to produce accurate estimates for the physics-informed loss function at a certain spatial complexity [15].

Different with PINN, Neural Operators, on the other hand, focus on learning and approximating mathematical operators or transformations using neural networks. The inspiration of Neural operators came from the approximation of Operators by Chen and Chen [3]. The known and popular Neural operators nowadays are DeepOnet [13] and Fourier or Graph Neural Operators (GNO and FNO) [12, 11]. Note that the cited papers are the methods which then the operator $L$ will be learnt from our data which are obtained via numerical simulation or from real observation.

3 Key Steps

As our research is still in its early stages, having commenced just one month ago, we have not yet obtained any results. However, the key steps involved in achieving the desired results are as follows:

1. Implementation of the physics equation of acoustics in moving media as an additional loss term for neural networks, PINN approach.

2. Learning the operator that maps the input function (consisting of time and space) into the PDE problem, specifically addressing pressure and particle velocity, employing the neural operator methodology.
3. Assessing the accuracy of our models, ensuring that they are capable of providing reliable and precise results.
4. Evaluating the computational efficiency of the implemented techniques to optimize the performance and reduce computational costs.
5. Quantifying the uncertainty associated with our findings, allowing us to understand the limitations and potential variability in the results.

4 Future Goals

The main questions for the research are:

**Research question 1**: Which machine learning approaches is the best for the simulation?

**Research question 2**: How does the performance of machine learning approaches compare to traditional numerical simulation in terms of knowledge acquisition and computational efficiency?

**Research question 3**: How well can the machine learning approaches generalize to a more complex input?

References


Improved performance of k- Omega SST turbulence model in predicting airfoil characteristics for a large range of airfoil thicknesses

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Keywords: aerodynamics, turbulence, thick and thin airfoils

A large number of airfoils intended for wind turbine rotor blade applications were tested against the standard k-omega shear stress transport (SST) turbulence model, k-omega SST turbulence model modified for the $a_1$ constant (a.k.a $a_1$ method), Spalart-Allmaras turbulence model, and panel method using X-Foil. The results of airfoil lift, drag polar and coefficient of pressure were compared against experimental wind tunnel data, where available. The standard k-Omega SST turbulence model overpredicts the Reynolds shear stresses on the airfoil suction side of the airfoil, delays the flow separation, and underpredicts the flow separation region. The thickness of airfoils under consideration ranges from 11% to 36% of the chord length (c). The error in the prediction of lift and drag coefficient was quantified in linear, stall, and post-stall range of angle of attack (AoA), and up to 20% improvement in the prediction of lift and drag coefficient can be observed in the stall range of AoA for some airfoils. Based on the results, a linear function of the $a_1$ value against the airfoil thickness is formulated that can be used for the tuning of the standard k-Omega SST turbulence model for other airfoil thickness values. The $a_1$ method and its applicability is only tested for airfoils and is highly dependent on airfoil geometry.

1. Introduction

The prediction of airfoil characteristics i.e. lift and drag coefficient and the angle at which the maximum lift coefficient is observed is still difficult. This is attributed to the unsteady nature of the flow, the separation of flow on the airfoil suction side, and the flow hysteresis, especially at AoA of maximum lift coefficient and AoA’s of the post-stall region. Two of the most commonly known methods for computing airfoil coefficients are panel methods (X-Foil) and Reynolds averaged Navier Stokes (RANS) simulations. RANS simulations using standard k-Omega SST turbulence model for turbulence closure fails to accurately calculate the airfoil coefficients. The standard K-Omega SST turbulence model overestimates turbulent eddy viscosity ($\mu_t$) in the region of the flow separation. Thus, a straightforward approach is to tune the standard k-Omega SST model for the production of turbulent eddy viscosity. A similar approach has been studied by Matyushenko et al. [1], which shows a value of $a_1$ equal to 0.28 provides the best agreement in the prediction of aerodynamic coefficients. However, Matyushenko et al. only studied a limited airfoil thickness from 15% to 21% of the airfoil chord length and the data for the drag coefficient has not been presented. As wind turbines are getting bigger than ever before, the thick airfoils are more commonly used in wind turbine rotor blade designs. The present study aims to study a wide range of airfoil thicknesses. The airfoils under consideration are shown in Fig:1, ranges from 11% to 36% of the airfoil chord length.
2. Methodology

Open-source computation fluid dynamics (CFD) code OpenFOAM v2006 is used to solve incompressible RANS equations using SIMPLE algorithm. The O grid computation grid is used for each airfoil that extends from the leading edge of the airfoil to a radius of 300c. The grid has 512 points on the airfoil surface and a y-plus of less than 1 in order the resolve the boundary layer fully. That resulted in a grid of $130 \times 10^3$ cells. The inletOutlet boundary condition at the farfield and noSlip boundary condition at the airfoil surface is used.

The RANS approach to close incompressible Navier stokes equations for turbulence assumes that Reynold’s shear stresses are proportional to the local strain rate, which for a 2D incompressible flow takes the form of the Eq: 1.

$$-\rho u'v' = \mu_t (\frac{\partial u}{\partial y} + \frac{\partial v}{\partial x})$$

(1)

where $\mu_t$ is a constant of proportionality, called eddy viscosity, also known as turbulent viscosity and $\rho$ is the density of the fluid. The k-Omega SST is a two-equation eddy viscosity model which solves for the transport equations of the turbulent kinetic energy ($k$) and the specific rate of dissipation ($\omega$). These two variables are then used to compute eddy viscosity $\mu_t$ through the expression given in Eq: 2.

$$\mu_t = \frac{\rho a_1 k}{\max (a_1 \omega; |S| F_2 F_3)}$$

(2)

$|S|$ represents the scaler measure of strain rate. $F_2$ and $F_3$ are the blending functions to control the production of $\mu_t$.

$a_1$ is the ratio between the turbulent kinetic energy ($k$) and the Reynolds shear stresses $u'v'$, which tends to a constant value of 0.31 at the outer region of the boundary layer. In CFD a higher value of $a_1$ will result in higher turbulent eddy viscosity that in turn would increase the capacity of the boundary layer to withstand higher pressure gradient thus the onset and location of flow separation will not be accurately predicted by CFD. However, a lower value of $a_1$ will increase the contribution of SST viscosity limiter, which results in a lower value of $\mu_t$, consequently lower turbulent friction near the wall. This would promote the flow separation on the suction side of the airfoil. This approach of adjusting $a_1$ is also known as $a_1$ method. In the present study, the above-mentioned airfoils are tested against different values of $a_1$ to achieve a better agreement with the wind tunnel results.

3. Results
To keep this abstract short only the results of Clark-Y airfoil having a thickness of 11% w.r.t. the chord length of the airfoil thickness are presented here. Fig. 3 shows the velocity field over the airfoil for AoA 11° to AoA 15° and for \( \alpha \) values from 0.31 to 0.27. It can be seen that, the standard k-Omega SST turbulence model with \( \alpha \) value of 0.31 underestimates the flow separation region and the onset of flow separation is also delayed. Similarly, as the \( \alpha \) value is decreased the flow separation region becomes larger and larger because lower results in lower eddy viscosity. The best agreement for Clark-Y airfoil is obtained with \( \alpha \) values of 0.27.

The lift and drag coefficients for Clark-Y airfoil at Reynold’s number of 393k are shown in Fig. 3. The results are in good agreement with the experiment when the k-Omega SST turbulence model uses a value of 0.27 for \( \alpha \). Spalart-Allmaras model and X-Foil both over-predict the lift coefficient, especially in the stall and post-stall range and the results of both these models are closely matched with the standard k-Omega model. The drag coefficient results are also in good agreement with \( \alpha \) equal to 0.27, especially in post-stall range of AoA.
Figure 3: Lift and Drag Coefficient for Clark-Y airfoil

Acknowledgments

Special acknowledgments to Tom Wester, Post Doc. at For-Wind, University of Oldenburg, Germany for providing experimental data for the Clark-Y airfoil.

References

The Spatial Development of Turbulence and its Effect on Aerodynamics

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Keywords: wind energy, computational fluid dynamics, openFOAM, active grid, wind tunnel

Abstract

Our today's world is facing many environmental challenges, perhaps the most serious one is the climate change crisis. Therefore, the utilization of green energy is strongly encouraged to reduce greenhouse gas emissions. Many renewable energy resources have been studied, among which wind is one of the most significant resources that offer reliable, sustainable, and eco-friendly alternatives. Although wind turbine technologies have been studied extensively, there is still a lack of information about some of the physical fundamentals such as the air turbulent flow, and the parameters that control its behavior. So far, most of the wind tunnels used for airflow simulation can only work under laminar flow conditions. Simulating the natural turbulent airflow through a normal wind tunnel is quite challenging. Recently, a promising research line has emerged, that can potentially generate simulated forms of the naturally turbulent airflow, which is the active grid wind tunnel. However, there is still a lack of information about the turbulent flow generated by the active grid and the pathways used to fully control it. Therefore, this research aims not only to construct a model of the turbulent flow generated by the active grid but also to study the influencing physical parameters and accordingly predict and control its behavior.

Introduction

The characteristics of turbulence are still a fundamental field in physical research. Most of the research is based on simulation experiments in wind tunnels, especially in wind tunnels with active grids to control turbulence. However, turbulence is characterized by structures in time and space.

The thesis will investigate turbulent structures in all dimensions by computational fluid dynamic methods. To do so, time-resolved simulations of wind tunnel experiments, including active grid turbulence are to be done. The resulting turbulent structures and their development in space are to be analyzed and compared to the local measurement data available in the wind tunnel experiments. This will lead to a deeper understanding of the characteristics of flow.
turbulence. Especially the bridge between intermittency and spatial structures will be the focus of the investigation.

The results will enable further research to be done on the effect of turbulence in aerodynamic wind tunnel experiments. Although a few measurements on aerodynamic structures such as airfoils or wind turbines exist, there is a lack of understanding of the actual process of turbulent interaction with the structures. This investigation, again validated by existing measurement data from the wind tunnel, shall lead to a physical approach to the interaction of turbulence with wall-based structures.

Improving the turbulence modeling will pave the way to model and control the inducted turbulence inside the wind tunnel, apply and approve the modeling technique practically in the wind tunnel and test the model practically, and compare the practical results with the results from the computing model.

Motivation of the work

- The modeling results for the turbulence inside the wind tunnel don’t fit with the experimental results with 100% accuracy.
- There is no complete control for the turbulence parameters in the far part of the wind tunnel.
- We can’t expect the full behavior of the turbulence before conducting the experiment.
- Needs to optimize the variables of the active grid of the wind tunnel, and so the turbulence variables.

Aim of work

- Model the wind tunnel with the optimum conditions.
- To fit the results from the modeling with the experimental results from the wind tunnel test.
- To control the produced turbulent from the active grid:
  - By controlling the active grid wind tunnel parameters.
  - By controlling the CFD conditions.

Methodology

The model for closed section wind tunnel (without active grid) is made by OpenFOAM 10, pimplefoam approach, 1000000 of mesh cells built by blockMesh [1].

The inlet velocity of the air stream was adjusted to be 25 m/s at a pressure condition at the inlet of zero gradients. The outlet condition for the pressure difference was 0 bar, with a zero-gradient velocity to the outlet. At this point, according to Reynold’s number equation, it equals 3276000, which means there should be turbulent flow existing in the boundary layer. The time step was set to be 0.01 seconds at y+ of 1. Subsequently, the results were analyzed by paraFoam [2][3].
Results

As shown in Figure 1, the flow inside the wind tunnel is fully laminar flow, unlike the flow around the walls. The flow velocity near the boundary layer increases gradually from zero to 25 m/s, and then remains constant at 25 m/s. A section of the wind tunnel was sliced in the middle of the inlet by 1 m, as shown in Figure 2(a,b).

![Figure 1(a): Velocity distribution in the cross-section of the wind tunnel.](image1)

![Figure 1(b): Sliced cross section in the wind tunnel.](image2)

Figure 2 shows the velocity distribution, in which the velocity of the air increases gradually from 0.0 on the wall to over 25 m/s. Eventually, it declines to 25 m/s, and remains constant at this velocity. Theoretically, 25 m/s is the maximum velocity that is supposed to be achieved, however, exceeding the velocity limit slightly is attributed to the unbalanced distribution of velocity near the walls which, according to mass balance laws, will push the velocity further to cover the small mass rate near to the wall.

![Figure 2: Velocity distribution of the airflow across the line from the bottom to the top of the wind tunnel in the sliced cross-section.](image3)
Figure 3 shows that the mesh selected was fine enough to introduce turbulent flow inside the boundary layer, but the velocity distribution shows otherwise. The boundary layer shows that the flow is completely laminar, which seems to contradict.

Two possible explanations might account for the occurred contradiction, which are: (1) the model needs more time to capture the turbulence generated by the flow, while the model is flat, (2) the LES model can’t sense the turbulent flow in the very small boundary layer. Accordingly, the same model will be remodelled by DES (LES with Kw sst). The boundary layer height is increasing from zero to more than 5 cm at the end of the tunnel, which is consistent with the boundary layer theory.

![Figure 3: velocity distribution near wall and corner (a) with grid lines. (b) without grid lines.](image)

References

Session 11.3
08.09.2023 - 09:00
Building 3701, Room 268

Abdulrazek Abdulkarim  High resolution measurements of turbulent structures in atmospheric flows using a met mast array
Uluocak Sinem  Effect of the probe volume on wind speed measured by short-range continuous wave lidars in a free-field test site
Meyer Paul  Tackling turbulence intensity from a lidar perspective
Unraveling Turbulent Flows Structures: High-Resolution Measurements with the Met Mast Array

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Keywords: Turbulence, Length scale, Spatial structures, Met mast Array

The nature of wind fields is turbulent, which comes with frequent changes in speed and direction, often creating strong gusts. Such turbulent flows can affect, for example, wind turbine loads and performance causing damages resulting in expensive downtimes and failures \cite{1}. Hence, it is essential to measure and analyse the characteristics of turbulent structures and thus comes the importance and benefit of utilizing a measurement system which capable to tackle such wind fields. To better understand the connection between these effects and the incoming turbulent flow, a met mast array consisting of three masts has been installed near the coast of the northern sea in Germany and is now in operation since April 2023. The array is installed between two 4.2 MW class wind turbines and has 2 100m in height masts and 1 150m in height mast tower. In total this meteorological mast array is equipped with 51 3D ultrasonic and 32 cup anemometers that are distributed at different heights and positions, as seen in Figure 1, while simultaneously covering the swept area of the turbines at the site.

The met mast array is a state of the art designed specifically for high temporal and spatial resolution measurements of atmospheric turbulence at many different scales. The array is also used to measure the incoming flow under varying atmospheric conditions and covering the span of the rotor diameter as well as the wake of the front wind turbine. Furthermore, study the effect of the wake on the back turbine such as the cause of increase in the turbulence of wind which will cause increase of mechanical loads on the back turbine \cite{2}. Moreover, we are interested in different size of turbulent structures which has different statistics on large scales compared to smaller ones. Therefore, the positioning of the sensors plays an important role.

In contrast to existing measurement masts, e.g., the GROWIAN measurement masts, that spans an extensive measurement area in a spatial grid of 76 x 100m$^2$ with minimum of 25m in distance between two anemometers \cite{3}, this met mast array has sensors distributed horizontally and vertically in a logarithmic fashion. This unevenly distributed arrangement of the anemometers allows to capture a large variety of scales ranging from 1m up to 115m in distance and each one more than once and study the spatial and temporal structures presented in wind field on site. By this setup we can study the small-scale structures in the atmospheric flow which causes fluctuations in the power production as an instant example as well as fluctuation in mechanic loads and causes additional torque \cite{4}.

The analysis of the turbulence intensity and mean wind speed is not sufficient to characterize wind fields rather we are going to describe the turbulent flow on site using the velocity increment statistics. Moreover, turbulence properties such as the integral length scale or Taylor length scale will be identified to investigate the correlation of measurement points and up to which scale correlated turbulent structures can be expected in the field. The shape factor $l_2$ will be investigated as well to quantify the extent of intermittency \cite{1}.

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Keywords: Turbulence, Length scale, Spatial structures, Met mast Array

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Acknowledgements

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References


Effect of the probe volume on wind speed measured by short-range continuous wave lidars in a free-field test site

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Keywords: short-range continuous lidar, WindScanner, lidar probe volume, free-field, wind field reconstruction

1 Introduction

One of the key parameters on the power curve validation, estimation of wind turbine loads [1] and control of the wind turbines [2] is the information of the flow around the wind turbine, especially the inflow. Wind speed is usually obtained from cup anemometers mounted on a fixed met mast in front of a turbine. However, as the turbine height increases, met mast height and the cost increases accordingly. Moreover, installing met masts in offshore is not easy and not always possible. A feasible alternative to met masts is using remote sensing measurement techniques such as lidar. Although there are different types of lidars, their working principle is the same and based on Doppler shift. The main drawback of lidar measurements is spatially averaged wind speed over a cylindrical volume of air since a laser beam cannot be focused perfectly on an infinitesimal point in space. The probe volume increases with the increasing measurement distance [1] and thus it can be assumed that also the spatial averaging effect does.

Although many comparisons of lidar measurements with met masts give good correlation on the 10-minute averaged rotor equivalent wind speed and the wind direction at hub height [3], there is no studies investigating the effect of the probe volume in detail. However, it is important to assess the uncertainties related to the measurements, in particular considering the growing turbine sizes.

This study aims to analyse the probe volume effect on wind speed measured by short-range continuous wave lidars in a free-field test site. To do so, lidar line-of-sight velocities will be compared with the reference measurements obtained from met mast array. This will be followed by an uncertainty analysis on reconstructed 2D wind velocities.

2 The measurement campaign

2.1 WiValdi test site

WiValdi (Wind Validation) is a full-scale test site in Krummendeich, Germany including three fully-equipped turbines (WT1-3) and a total of five meteorological measuring masts (M1-5) as shown in Figure 1. Two multi-MW wind turbines, which are positioned exactly behind each other towards the main wind direction also allow for experiments on the wake flow. The short-range continuous lidar measurements are planned to be performed around the second wind turbine having the triple mast array placed upstream of it. The met mast array consists of three masts with 100 m (M2, M4) and 150 m height (center mast, M3), positioned upstream of wind turbine 2 (WT2) and oriented towards the main wind direction. In this way, the array makes it possible to measure the turbulent wind field across the whole rotor area of WT2 before it actually reaches WT2. They are highly equipped with 32 cup anemometers and 51 3D ultrasonic anemometers in total in order to be able to measure wind velocity and direction. WT1 and WT2 are Enercon E-115 EP3 wind turbines, with a capacity of 4.2 MW, a total height of 150 m and a rotor diameter of 115 m. About 690 sensors measuring acceleration, strain, temperature and torque are installed onto wind turbine generator that enable comprehensive knowledge of its overall behaviour, especially in relation to the rotor blades.
2.2 WindScanner measurements

The lidars are two identical continuous wave short-range WindScanners developed and manufactured by the Technical University of Denmark [4]. The measurement range is up to 300 m by design and the sampling rate is 450 Hz. They are able to scan different trajectories synchronously with their steerable laser beam having a full opening angle of 120° through the use of two prisms and two prism motors.

We decided to place the WindScanners on the wind turbine road (Figure 1) where they are downstream of WT2 in order to have a good coverage of the met mast array from approximately 1D (115m) distance within the limitation of lidar focus distance. The range of the focus distance, probe length, elevation and opening angle is estimated for both scanners to get measurements at the mast array using the hub height (92 m) and the lowest probe height (20 m) and in Table 1.

<table>
<thead>
<tr>
<th></th>
<th>M2</th>
<th>M3</th>
<th>M4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focus distance of WS1 [m]</td>
<td>132.9 - 98.0</td>
<td>144.3 - 112.9</td>
<td>169.0 - 143.2</td>
</tr>
<tr>
<td>Focus distance of WS2 [m]</td>
<td>210.7 - 190.7</td>
<td>173.8 - 148.9</td>
<td>143.9 - 112.4</td>
</tr>
<tr>
<td>Probe length of WS1 [m]</td>
<td>5.6 - 3.1</td>
<td>6.6 - 4.1</td>
<td>9.1 - 6.5</td>
</tr>
<tr>
<td>Probe length of WS2 [m]</td>
<td>14.1 - 11.5</td>
<td>9.6 - 7.0</td>
<td>6.6 - 4.0</td>
</tr>
<tr>
<td>Elevation angle of WS1 [°]</td>
<td>43.8 - 11.8</td>
<td>39.6 - 10.2</td>
<td>33.0 - 8.0</td>
</tr>
<tr>
<td>Elevation angle of WS1 [°]</td>
<td>25.9 - 6.0</td>
<td>31.9 - 7.7</td>
<td>39.7 - 10.2</td>
</tr>
<tr>
<td>Opening angle [°]</td>
<td>65.4</td>
<td>82.2</td>
<td>85.8</td>
</tr>
</tbody>
</table>

Table 1: Estimated focus distance, probe length and elevation angle range for both WindScanners at hub height (92 m) and at 20 m height and for the three met mast arrays.

3 Methodology

3.1 Probe volume effect on line-of-sight velocity

The probe volume size increases proportionally with the square of the focal distance, \( f \), (Eqn. 2) which means that the effect of spatial averaging significantly increases for the measurement points at larger focus lengths [5].

\[
\Gamma = \frac{\lambda f^2}{\pi a^2}
\]  

where \( a \) is the effective radius of the lidar’s telescope, \( \lambda \) is the wavelength of lidar laser and \( \Gamma \) is the half width half maximum.

Probe length is commonly defined as \( 2\Gamma \) and the relation between the focus distance and the probe volume can be seen in Figure 2. However, there is no detailed study and presented relation about the effect of probe volume on the measured velocity. Therefore, line-of-sight velocities of lidars will be compared with the reference.
velocities i.e. mast sensor measurements in this case. These measurements will be performed at each anemometer position along each mast. The velocity measured by anemometers will be projected into line-of-sight direction using azimuth and elevation angles of the lidar. The pointing error for both the elevation and azimuth angles can be assumed to be 0.5 mrad ($\approx 0.03^\circ$) [6].

![Figure 2: Probe length (2L) dependence on focus distance [7] function for a continuous wave lidar](image)

Besides correlation plots of mast and lidar data for each measurement point, the difference between reference line-of-sight velocities ($v_{LOS,ref}$) and lidar line-of-sight velocities ($v_{LOS,WS}$) will be calculated using Eqn. 2 for every probe volume.

$$\Delta v_{LOS} = \frac{v_{LOS,ref} - v_{LOS,WS}}{v_{LOS,ref}}$$  \hspace{1cm} (2)

The line-of-sight velocities will be compared for different wind speeds and directions and also at different atmospheric stability conditions.

### 3.2 Uncertainty analysis on reconstructed wind velocities

The 2D wind field i.e. horizontal ($u$) and vertical ($v$) wind velocity components can be calculated using the Eqn. 3 and with the assumptions of no vertical component ($w = 0$) and homogeneous flow.

$$v_{LOS} = \begin{bmatrix} \cos(\chi) \cos(\delta) \\ \sin(\chi) \cos(\delta) \\ \sin(\delta) \end{bmatrix} \cdot \begin{bmatrix} u \\ v \\ w \end{bmatrix}$$  \hspace{1cm} (3)

where $\chi$ and $\delta$ are the azimuth and elevation angles of the laser beam line-of-sight.

Using the error propagation formula, the total uncertainty on the reconstructed wind velocity components at each probe volume can be estimated by inserting the obtained errors of line-of-sight measurements and the pointing accuracy of the lidar leading to uncertainty in azimuth and elevation angle. Moreover, since the met mast array allows to analyse different combinations of azimuth, elevation and probe length (see Table 1), data can be classified in a way that two parameters can be kept almost constant to examine the effect of the third parameter. For example, the effect of zero vertical velocity assumption can be investigated using different azimuth and elevation angles having the same probe volumes.

### 4 Conclusion

We have designed a free-field measurement campaign in order to investigate the probe volume effects of short-range continuous wave lidars on wind speed measurements. The line-of-sight velocities of lidars will be compared with the reference line-of-sight velocities measured by met mast anemometers at different locations and at different atmospheric conditions. Then, the detailed uncertainty analysis on 2D reconstructed wind velocity will be conducted.
Acknowledgements

This work was funded by the German Federal Ministry for Economic Affairs and Climate Action (grant no. 0325936H) on the basis of a decision by the German Bundestag.

References


1 Introduction

The Light detection and ranging (lidar) technology has been established as reliable technology within the wind energy industry for wind resource measurements. Low costs, easy handling and reusability of the wind lidar devices are among other advantages of this technology that more and more cause the replacement of traditional met masts. Multiple studies have proven the usability of lidar measurements for wind resource parameters, such as the 10 minute mean wind speeds [3].

However, for the design of wind turbines, also the turbulence within these periods is of interest. The IEC guideline 61400-1 specifies the turbulence intensity (TI) as the standard deviation divided by the mean wind speed [4]:

\[ T_R = \frac{\sigma_u}{\langle u \rangle}. \] (1)

Whereas the lidar technology is able to cover the general climatology and distribution of the TI, the correlation between the TI measured by an IEC conform met mast with cup anemometry and a vertical profiling lidar is significantly lower than for mean wind speeds [9]. Additionally, the full three-dimensional Reynolds stress tensor

\[ R = \begin{bmatrix} \langle u'^2 \rangle & \langle u'v' \rangle & \langle u'w' \rangle \\ \langle v'u' \rangle & \langle v'^2 \rangle & \langle v'w' \rangle \\ \langle w'u' \rangle & \langle w'v' \rangle & \langle w'^2 \rangle \end{bmatrix} \] (2)

cannot be accurately recovered by standardized vertical profiling lidar measurements [9]. Causes are far-reaching and include among the others, the significantly larger probe volume and the measurement configurations. In the literature adopted measurement configurations and methodologies can be found, to increase the accuracy of the results, both for ground and nacelle based lidars [2, 10, 8].

Apart from the aforementioned fact, that TI values and in more detail the Reynolds stress tensor \( R \) retrieved from lidar and from cup anemometry cannot be compared directly against each other, the TI parameter is not exclusively describing the turbulent structures. Other parameters, such as e.g. length scales can have a significant impact on turbulence-induced loads on a wind turbine. E.g. [1] showed the impact of varying spectral parameters for the Mann turbulence generator [5] on wind turbine loads. But also higher-order statistics and increment statistics can have an impact on turbine structures [7].

Thus, with this study, we want to find out, which wind parameters need to be measured and estimated in order to provide a useful dataset for the design of wind turbines. We want to deepen into the question whether the capabilities of lidar measurements can cover this demand.

2 Methods

In this study we use the comprehensive wind measurement dataset from the Testfeld BHV. Ground and nacelle based lidars as well as high frequent measurements from an IEC conform met mast are used for the analysis [6]. Additionally, extensive load measurements have been performed on a 8 MW wind turbine located within the Testfeld. A visualization of the Testfeld can be seen in Fig. 1.
We will analyze the comprehensive dataset of wind measurements in terms of turbulent structures and statistics measured by the varying sensors. Doing so, we will take a more detailed look at the velocity spectra and co-spectra retrieved from lidar, sonic and cup anemometry in order to derive more representative parameters for the design of wind turbines. This analysis will be accompanied with aeroelastic simulations to evaluate the impact of these parameters on wind turbine loads.

### 3 Expected Outcome

As it was mentioned before, a vertical profiling lidar can accurately measure the first moments, whereas it lacks some accuracy in the second order moments. This can also be seen for the measurements at the Testfeld BHV, displayed in Fig. 2.

![Figure 2: Correlations for mean (left) and standard deviation (right) of the horizontal wind speed measured from cup (x-axes) and vertically profiling lidar (y-axes) at a height of 115 m from one year of measurements at the Testfeld BHV.](image)

With this study, we want to tackle the simplification of the turbulent structures into turbulence intensity as defined by the IEC guideline. As lidars cannot measure this parameter in the same way, a cup anemometer does,
new parameters to characterize the turbulent structures are needed. Here, we analyze wind and corresponding
turbine load measurements to enable more site dependent wind turbine design.

In more detail, we want to:

• find parameters describing the turbulent structures more deterministic than the IEC parameter turbulence
  intensity,
• specify the accuracy of these parameters measured by lidar,
• determine, if lidar measurements lead to equivalent aeroelastic loads.

Concluding, this study is supposed to provide a baseline for turbulent wind siting measurements, using lidars,
that can be used for the more realistic design of turbine.

References


TOPIC 12:
General topics of wind energy

Session 12.1
06.09.2023 - 10:30
Building 3701, Room 267

Obradovic Katarina  Physical design of hybrid power plants
Schubert Jenny  Numerical Accuracy of Principal Geodesic Analysis on the Sphere
Märtings David  Derivation of a nonlinear coupling element for the modelling of the soil structure interaction of large offshore wind turbines
Wenske Anne-Kathrin  On the way to high(er) fidelity FSI simulations
Khan Mehtab  Guidelines on Accurate Numerical Simulation of Atmospheric Gravity Waves in Wind Farm Applications
Physical design of hybrid power plants

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Keywords: hybrid power plants, physical design, layout optimization, cable network optimization

1 Introduction

Up until now, single-technology renewable power plants (RPPs) have been the most widespread way of renewable energy sources deployment. Up to recently, the main focus is mostly on the development of wind power plants (WPPs) and solar photovoltaic power plants (SPPs). WPP and SPP developers want to achieve the best possible plant performance at the lowest possible cost. Thus, significant research has been undertaken to understand how to optimize the design power plants for objectives of performance, cost, and overall profitability. In particular, physical design optimization focuses on a set of problems around the selection of technologies (wind turbines and solar placement), and the siting of those technologies (their layout) within given site boundaries and also often optimizing the layout and topology of the electrical collection system, as well as other plant physical features of the plant [1] [17].

With the global tendency of moving forward from incentives [9] [18], the participation in merchant markets will likely become necessary [12]. Thus, design objectives are shifting from producing energy at the lowest levelized cost (LCOE) to maximizing overall profitability from possibly multiple revenue streams [13]. This change in approach will become important in future power systems where a large share of renewables is present [24].

Recently, in order to ensure better profitability of a single facility connected at a single point of connection (POC) to the power grid, interested parties (developers, owners and operators) have started to consider so-called hybrid power plants (HPPs). The main characteristics of HPPs, as defined in this work, are that they combine at least two power-generating units (with or without energy storage) that are co-located with a common POC. Regarding the first property, research has shown that HPPs of wind and solar technologies together can benefit from negative correlation of wind and solar resources in various locations around the world [19]. That indicates the possibility of complementing them and achieving a smoother power production over different time scales, thus leading to higher plant-level capacity factors and reduced output power variability compared to RPP [23] [20]. As for the other two properties of HPP, using the same area for the installment of PV panels and wind turbines (WTs) can reduce development costs such as permitting, land acquisition, resource assessment, labor, but also costs related to operation and maintenance. Furthermore, grid congestion has become major challenge for most of the power systems. Thus, shared POC emerges as one of the prominent characteristics. Considering HPP’s physical design and feasibility, all three properties play a major role and differentiate HPP design from the design of a RPP.

2 Research state of the art

Prior to focusing on HPP design, it is worth reviewing the literature connected to the optimization of RPPs having in mind a similar nature of the problem. For WPPs, mostly addressed challenge is wind farm layout optimization (WFLO). In WFLO, the objective is usually defined as the maximization of annual energy production (AEP) or minimization of LCOE [17]. Used methods that support such goals are various - Donovan worked on the improvement of mixed integer programming [10], in [29] novel pseudo-gradient concept is developed, while Bai et al. [5] worked on improvements using genetic algorithm (GA). Apart from them, the literature is filled with research that uses these and similar methods. Thus, Kunakote et al. (2022) [21] did a comparison of twelve
different mostly used metaheuristic methods while Azlan et al. (2021) [4] systematically compared the most popular basic algorithms. The latter also presented key details in modelling and designing the wind farm layout configuration. Directly affected by WFLO, the design of an electrical network is a special optimization problem that requires careful attention since it can affect the economic side of the project by large. Paper [25] presents a comprehensive review of the optimization areas for electrical sub-problem, common methods, and objectives for offshore WPPs along with a discussion on the advantages and disadvantages of each. For example, in [26] simultaneous optimization of cable network layout and WT layout design is done using internal rate of return (IRR) as an objective. The problem of optimal cable layout design with different constraints, goals and approaches is targeted in [28] [27] [14] [22], in [8] the model for calculations of optimal cross sections of the cables is proposed, while paper [32] addressed solving economical layout and economical cross-section problems simultaneously taking account power losses as well.

Nevertheless, as far as optimization is considered, up until now predominately addressed challenges in the area of HPP research are sizing and operational strategies of such plants [15] [7] [2]. That being said, until now very few research work has been published that addresses the peculiarities in physical design of HPPs such as the influence of WTs on the production and performance of solar PV panels, the layout design of collocated WTs and PV elements and benefits of shared electrical infrastructure and how to optimize one [11]. Interestingly, these are the issues that are often very important to developers of utility scale HPPs.

Bi and Law (2023) [6] did a study on how the waves and wind can influence the power production of floating SPP that is co-located with offshore WPP focusing on issues related to floating solar PV, with no consideration of the possible mutual influence of two co-located technologies. Silva et al. (2022) [23] and Kumar et al. (2016) [20] analysed the idea of upgrading the existing utility-scale WPP to an HPP by adding solar PV. The former compared the different strategies applied when planning the extension of WPP’s lifetime, while the latter focused on the savings in PV installations. Golroodbari et al. (2021) [16] discussed the idea of adding floating solar PV to existing offshore WPP and assessed the techno-economic feasibility of such an approach from the cable network perspective concluding the need for subsidies. However, no optimization of the electrical infrastructure has been done. Ara et al. (2021) [3] provided a simplified mathematical model of the shadow effect of WTs on PV panels and argued the feasibility of developing offshore HPP from scratch compared to adding solar PV to existing WPP. For both scenarios, they used LCOE as an objective. Tripp et al. [31] modelled the shadow effect WT has on PV panels and introduced a simplified approach in the optimization process of HPP layout. Stanley and King [30] addressed the shadow effect and provided a methodology to perform physical design accounting for plant resilience. Furthermore, they portrayed the sensitivity of the solution on objectives, resources, assumptions, costs and power purchase agreements. Nonetheless, to the authors’ best knowledge, no paper has addressed the holistic optimization of the electrical network of HPPs combined with siting of elements taking into account the mutual influence of the units. In addition to that, very few papers have approached the problem of physical design having profitability as the objective (IRR, NPV) rather than reduced costs (LCOE).

3 Objectives

The objective of this PhD is to develop the specific methodology for the physical design of large-scale HPPs through multidisciplinary optimization while addressing multiple objectives of interest to developers, operators and investors. The focus will be directed to unique optimization problems for these applications - one of which is electrical network design and layout design. The project will address physical couplings (such as shading of solar panels, electrical performance, etc) as well as the shared costs (logistics, infrastructure) to look at holistic optimization of the system design for overall profitability rather than LCOE.

This PhD will investigate and develop optimization approaches for the physical design of HPPs that account for their operational strategy and overall profitability. This involves taking into consideration a variety of technologies including, but not limited to, wind, solar PV, battery storage, Power-to-X, etc. The outcome will be applied to a series of real-world case studies for existing and planned hybrid facilities.

4 Research questions

Targeted research questions for this PhD are visually presented in the Figure 1.
19th EAWE PhD Seminar on Wind Energy
6-8 September 2023
Hannover, Germany

Figure 1: Visual representation of addressed challenges within this PhD

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[25] J.-A. Pérez-Rúa and N. Cutululis. Electrical Cable Optimization in Offshore Wind Farms - A review. IEEE Access, 7:85796–85811, 2019. This work is licensed under a Creative Commons Attribution 3.0 License. For more information, see http://creativecommons.org/licenses/by/3.0/.


Numerical Accuracy of Principal Geodesic Analysis on the Sphere

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Keywords: principal geodesic analysis, model order reduction, singularities, hybrid mechanical systems, director-based dynamics

Abstract. We investigate Principal Geodesic Analysis (PGA) in director based dynamics of mechanical systems with potential applications to motion analysis and model order reduction (MOR). MOR requires highly accurate and efficient implementations of the logarithm maps and the resulting lifts across multiple branches. The talk addresses an optimized implementation of the logarithm map and resulting lift for the manifold $S^2$. We conduct detailed numerical experiments on mechanical systems to achieve maximal accuracy in spite of the singularities.

1 DIRECTOR-BASED DYNAMICS

We look at mechanical systems modeled with beam or shell elements. For that we will briefly introduce the two formulations used in the simulation software DeSiO. [2]

1.1 Geometrically Exact Shell

The geometrically exact shell has a configuration manifold $Q^h = \mathbb{R}^3 \times S^2$ of dimension five in $Q = \mathbb{R}^3 \times \mathbb{R}^3$ of dimension six, with configuration map $q : S_0 \times [0,T] \rightarrow Q$. Any point across the geometrically exact shell is represented by the position on the cross-section $\theta^3 \in [-\frac{1}{2}H_0,\frac{1}{2}H_0]$ ($H_0$ standing for the initial thickness of the shell) and the surface coordinates $(\theta^1, \theta^2) \in S_0$ and is described by

\begin{equation}
q(\theta^1, \theta^2, t) = (x_0(\theta^1, \theta^2, t), d_3(\theta^1, \theta^2, t)) \in Q \cong \mathbb{R}^6, \nonumber
\end{equation}

\begin{equation}
h(x_0, d_3) = ||d_3||^2 - 1 \in \mathbb{R}^1, \nonumber
\end{equation}

$h$ being the constraint map.

1.2 Geometrically Exact Beam

The geometrically exact beam, or Simo-Reissner beam, has a configuration manifold $Q^h = \mathbb{R}^3 \times SO(3)$ of dimension six in $Q = \mathbb{R}^3 \times \mathbb{R}^{3 \times 3}$ of dimension twelve, with the configuration map $q : [0,L_0] \times [0,T] \rightarrow Q$. Any point belonging to the geometrically exact beam is represented by the cross-sectional coordinates $(\theta^1, \theta^2) \in A_0$ and the length coordinate $\theta^3 \in [0,L_0]$ ($L_0$ standing for the initial length of the beam) as

\begin{equation}
q(\theta^3, t) = (x_0(\theta^3, t), d_1(\theta^3, t), d_2(\theta^3, t), d_3(\theta^3, t)) \in Q \cong \mathbb{R}^{12}, \nonumber
\end{equation}

\begin{equation}
h(x_0, d_1, d_2, d_3) = (||d_i||^2 - 1)_{i=1}^3, d_1, d_2, d_3, d_3 \in \mathbb{R}^6, \nonumber
\end{equation}

$h$ again being the constraint map.

2 BASICS OF PGA ON THE SPHERE

Principal geodesic analysis (PGA) is the generalizes version of Principal Component Analysis (PCA) to the non-Euclidean setting of Riemannian manifolds. [1] With our set of data points (snapshots) on a manifold or a product
of manifolds, we first need to lift our data to a tangent space to then be able to perform PCA in said tangent space; see Fig. 1.

Since we look at the motion analysis of mechanical systems, we want to smoothly lift trajectories. For that we have to look at logarithms over multiple branches and the handling of the occurring singularities.

2.1 Exponential map, logarithm map and lift

The unit 2-sphere \( S^2 = \{ d \in \mathbb{R}^3 \mid ||d|| = 1 \} \), with \( d \) being called a director. Its tangent space and exponential map are defined as

\[
T_d S^2 = \{ \vec{v} \in \mathbb{R}^3 \mid \langle \vec{d}, \vec{v} \rangle = 0 \} \cong \{ \vec{d} \}^\perp,
\]

\[
\exp_d (\vec{v}) = \begin{cases} 
\vec{d}, & ||\vec{v}|| = 0, \\
\cos(||\vec{v}||) \vec{d} + \sin(||\vec{v}||) \frac{\vec{v}}{||\vec{v}||}, & ||\vec{v}|| > 0.
\end{cases}
\]

It is globally defined and surjective. Clearly we have \( \exp_d (\vec{v}) = -\vec{d} \) for every tangent vector of length \( ||\vec{v}|| = \pi \), and the open disk \( D_\pi := \{ \vec{v} \in T_d S^2 \mid ||\vec{v}|| < \pi \} \) is a maximal domain of injectivity of \( \exp_d \). Now the logarithm map \( \log_d : S^2 \setminus \{-d\} \to D_\pi \) has the explicit representation

\[
\log_d (\vec{e}) = (d, \vec{v}), \quad \vec{v} := \begin{cases}
0, & ||\vec{e} - \langle \vec{d}, \vec{e} \rangle d|| = 0, \\
\arccos\langle d, \vec{e} \rangle \frac{\vec{e} - \langle \vec{d}, \vec{e} \rangle d}{||\vec{e} - \langle \vec{d}, \vec{e} \rangle d||}, & ||\vec{e} - \langle \vec{d}, \vec{e} \rangle d|| > 0,
\end{cases}
\]

where \( \vec{e} - \langle \vec{d}, \vec{e} \rangle d \) is the projection of \( \vec{e} \) on \( \{d\}^\perp \) and \( ||\vec{v}|| = \arccos\langle d, \vec{e} \rangle \in (0, \pi) \) is the angle between \( d \) and \( \vec{e} \).

We now want to construct a smooth lift across multiple branches of the logarithm. The open annuli \( A_k := D_{k\pi} \setminus D_{k\pi} \) for \( k > 1 \) are also maximal domains of injectivity, with \( D_r := \{ \vec{v} \in T_{\vec{d}} S^2 \mid ||\vec{v}|| < r \} \) the open disk with radius \( r \). This leads to a sequence of branches \( \log_d^{\kappa} \) of the logarithm map as local inverses of \( \exp_d : A_k \to S^2 \setminus \pm d \). Setting \( A_0 := D_\pi \setminus 0 \), we recover the principal branch \( \log_d \) as the smooth extension of \( \log_d^{0} \) to \( D_\pi = A_0 \cup \{0\} \).

For every tangent vector \( \vec{v} \in A_k \), we then have a unique axis-angle representation \( \vec{v} = \theta \vec{u} \) with \( ||\vec{u}|| = 1 \) and angle \( \theta = ||\vec{v}|| \in (k\pi, (k+1)\pi) \). We can now define smooth bijections \( \Phi^{k} : A_k \to A_k \) such that \( \exp_d (\Phi_k^{\kappa}(\vec{v})) = \exp_d (\vec{v}) \):

\[
\Phi_k^{\kappa}(\vec{v}) = \Phi_k^{\kappa}(\theta \vec{u}) := \begin{cases} 
([\ell - k] \pi + \theta) \vec{u}, & \ell - k \text{ even}, \\
([\ell + k + 1] \pi - \theta)(-\vec{u}), & \ell - k \text{ odd}.
\end{cases}
\]

Since \( \exp_d \) maps every annulus \( A_k \) bijectively to \( S^2 \setminus \pm d \), every “even” boundary \( \partial D_{2k\pi} \) to \( d \) and every “odd” boundary \( \partial D_{(2k+1)\pi} \) to \( -d \), all branches of the logarithm map are thus naturally expressed in terms of the principal branch:

\[
\log_d^{\kappa} : S^2 \setminus \pm d \to A_k, \quad \log_d^{\kappa} (\vec{e}) := \Phi_k(\log_d (\vec{e})), \quad k \in \mathbb{N}.
\]

To be able to lift smooth curves on \( S^2 \) we need to consider the singularities of \( \log_d^{\kappa} \) in \( \pm d \). For a unique smooth lift a curve has to pass through \( \pm d \) with nonzero speed. Then we can construct a lifted curve by switching between appropriate branches of the logarithm map. This is possible since the closures \( \bar{A}_k \) cover the entire tangent space, \( T_{\vec{d}} S^2 = \bigcup_{k \in \mathbb{N}} \bar{A}_k \).
3 Accurate Implementation

Logarithm, lift and projection have been implemented in C++. [3] The goal is to achieve the maximal possible accuracy for computations in double precision floating point arithmetic (64 bit IEEE 754 format). Ideally we would like to achieve machine precision or to get close to it; however, this seems impossible due to the singularities.

To test our implementation, we looked at the simulation data of 9 different mechanical systems (both beam and shell models), including two 5 MW wind-turbine beam models. The turbines consist of 160 nodes and are simulated over 4001 time steps. Throughout the simulation the turbine starts slowly turning from standstill. To get data for the $S^2$-lift, we take apart each rotation matrix into its three directors and treat all first, second, and third directors as one set of snapshots respectively.

![Figure 2: Angular distributions of errors for most accurate logarithm (left) and least accurate logarithm (right).](image)

![Figure 3: Angular distributions of lift errors by branch; left/blue = $\log_{d,0}$ (13 558 281 directors), middle/red = $\log_{d,1}$ (156 483 directors), right/green = $\log_{d,2}$ (12 533 directors). The middle distribution actually corresponds to angles $\theta \in [\pi, 2\pi]$, the right one to $\theta \in [2\pi, 3\pi]$.](image)

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Derivation of a nonlinear coupling element for the modelling of the soil-structure interaction of large offshore wind turbines

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Keywords: multibody system, director-based finite element method, nonlinear coupling element, soil-structure interaction, offshore wind turbine

ABSTRACT

The increasing demand for clean energy has led to the development of very large wind turbines, Consequently, the dimensions of the whole structure increase and thus its sensitivity to large structural deformations becomes more relevant. The demand for a simulation tool analysing and designing those wind turbines requires a robust nonlinear structural model which allows to consider large deformations and large rotations in long-time simulations without suffering from numerical errors due to an inaccurate representation of physical quantities like objectivity and path independence as well as conservation of invariants.

Existing simulation tools, e.g., FAST [1]. Bladed [2] or HAWC2 [3] use multi-body approaches with finite elements and rigid bodies based on geometrically linear or slightly nonlinear theories. However, these theories are not suitable for analysing the higher-order geometrically nonlinear effects that occur in large and slender wind turbines. Maintaining objectivity, path independence and preserving invariants is crucial to avoid cumulative errors in nonlinear dynamic calculations, especially simulating long-term periods, as it is necessary for offshore wind turbine design.

The newly developed aero-hydro-servo-elastic simulation framework, DeSiO, consists of a robust nonlinear multibody system finite element scheme in the total Lagrangian description, considering director-based kinematics [4] to present geometrically exact kinematics. In order to ensure the conservation of energy and to preserve linear and angular momentum, we apply a conservative and dissipative time integration scheme developed by Gebhardt et al. [5]. The geometrically exact beam elements are used to model the tower and the slender blades. Rigid components, like hub and nacelle, are idealized by rigid bodies.

In the present work, the soil-structure interaction is presented, which is modelled by means of consistent objective spring-, mass- and damping elements. Considering two finite element nodes, a relative displacement generates elastic forces. Accordingly, relative velocity causes damping forces and relative accelerations cause inertia forces. To match realistic damping properties, we parameterise the dissipation function given in [6]. The main innovation is consistently maintaining objectivity, following the philosophy of our structural model. On the example of the NREL 15 MW reference offshore wind turbine with a monopile foundation, we show a significant impact on the dynamic behaviour caused by the soil-stiffness, -mass and –damping properties.
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On the way to high(er) fidelity FSI simulations

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Keywords: fluid-structure interaction, arbitrary Lagrangian-Eulerian, fully Eulerian, finite element method

1 Motivation

When developing methods to simulate the behavior of physical entities, a trade-off must be made between cost and accuracy. Real world processes are reduced into abstract models which can then be treated with appropriate numerical algorithms. Depending on the computational resources available and the type of insight one wishes to gain from a simulation, some methods are more attractive than others. Fluid-structure interaction (FSI) simulation, specifically for (offshore) wind turbines, is no exception to this.

Several methods exist to model e.g. the aeroelasticity of rotor blades [3, 6] with varying degrees of accuracy and efficiency, some of which – like the blade element momentum model – rely on additional aeroelastic airfoil data and corrections to produce accurate results. To better understand the shortcomings of these efficient methods and to improve them further we aim to derive an FSI model based on the finite element method (FEM) by using techniques described in e.g. [5, 7].

2 Methods

The interaction in FSI is a bidirectional one – the fluid applies forces on the structure, which deforms accordingly. This deformation in turn influences the fluid motion. Thus both physical systems have to be considered in an accurate FSI model. In general, the methods for performing FSI simulations can be divided into two groups. The two subsystems can be solved separately and their respective solutions fed into the other system. Depending on the amount of subiterations per timestep between the two systems one derives either a weakly or a strongly coupled method. This partitioned approach allows for the combination of sophisticated state of the art software for each subproblem by outer means. However, depending on the amount of subiterations, the coupling conditions at the interface may only be fulfilled approximately. To get around this, decreasing timestep sizes become necessary.

Alternatively, one can solve the fully coupled system in one go. This is the so called monolithic approach, which by design is always strongly coupled. From a mathematical viewpoint, the monolithic approach is the more attractive one, as it comes with a complete variational formulation of the entire system. This enables the derivation of error estimates, as well as the employment of implicit time-stepping schemes or optimisation techniques [4].

Since fluid and solid equations are usually described in Eulerian and Lagrangian terms, respectively, these two different coordinate systems must be combined to formulate a monolithic scheme. In Eulerian coordinates, we do not track individual particles, but observe the quantities of interest, e.g. flow velocity, at fixed spatial points. In the Lagrangian view, on the other hand, the fate of individual particles is of interest, and therefore the computational domain is deformed accordingly. Each viewpoint can be seen as the natural choice in their respective application, i.e. flows and structural deformation.

A well established method to combine these two systems into a common frame is the Arbitrary Lagrangian-Eulerian (ALE) method. Here, the fluid domain is moved with regards to the solid deformation. With implicit
mesh moving, the fluid equations are transformed from the (moved) current state onto an artificial fixed reference configuration without physical meaning. This approach offers high resolution at the interface between the fluid and the solid domain, since the interface aligns with the edges of the computational mesh at all times. The ALE method can also be used to enforce the coupling conditions in partitioned approaches. However, the transformation introduces further nonlinearities and the overall success of the simulation depends on its regularity, which may break down in cases of extreme deformations like topological changes. Expensive remeshing also becomes a necessity when the structural deformation is large. However, more efficient remeshing techniques as the extended ALE method [1] are being developed. We illustrate some of these considerations with a simplified FSI simulation that is largely based on [8].

Instead of transforming the fluid domain, the solid equations can be formulated in Eulerian coordinates. This is the basic idea behind the rather new fully Eulerian approach, introduced in [2], where the transformation maps between domains that both have physical meaning. However, due to the Eulerian description of the coupled system, the computations take place on moving domains with moving interfaces. This approach also allows the interface to cut through cells of the computational mesh, thus requiring methods for interface tracking and treatment of cut cells. However, since now both domains in the mapping are of physical nature, the transformation of the solid onto Eulerian coordinates is always well posed. This approach allows us to handle large deformations. Furthermore, this viewpoint comes more natural in cases with small or presumably negligible influence from solid to fluid (e.g. monopiles in water).

3 Outlook

Although the fully Eulerian approach comes with plenty of difficulties, we see its advantages when it comes to the simulation of FSI in wind turbines. Namely, large deformations that become more apparent with the more slender rotor blades, the interaction of water and tower and the simulation of one or more rotating blades give reason to further explore this method. For these reasons, we wish to investigate fully Eulerian FSI modelling techniques, where the initial focus is on the conceptual design process rather than the specific application (e.g. hydro- or aeroelasticity). For this, the coupling conditions, time stepping schemes, convergence analysis and solving techniques are some areas that will need special attention. Instead of complex turbulence modelling, we will work with laminar flows governed by the Navier Stokes equations interacting with elastic solids. Both fluid and solid shall be described in the same spatial dimension, that is, we aim to couple two dimensional fluids with two dimensional structures. Later, we plan to expand to the three dimensional case.

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References


Guidelines on Accurate Numerical Simulation of Atmospheric Gravity Waves in Wind Farm Applications

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Keywords: Gravity waves, Froude number, Inversion layer, Large eddy simulation, Wind farm

Introductory Summary
There is growing interest in atmospheric gravity wave impacts on wind farms. Therefore, accurately numerically simulating atmospheric/wind-energy flow fields, including wind-farm-induced gravity waves, is important. Two main considerations in such simulations are the overall domain size to fully capture the long wavelength of atmospheric gravity waves and using Rayleigh damping near domain boundaries to mitigate spurious gravity wave reflections. Often both of those considerations are treated ad hoc rather than systematically. This work aims to systematically assess the proper overall domain size and Rayleigh damping strategy as a function of background atmospheric parameters that control atmospheric gravity wave characteristics.

Introduction
Atmospheric Gravity Waves (AGWs) are buoyancy-driven waves and can be triggered by any vertical perturbations under stable atmospheric conditions. Wind farm-induced AGWs have been known in the wind energy sector for a decade. For the first time, Smith (2010) suggested that large wind farms displace the inversion layer causing AGWs in the free atmosphere aloft [5]. Later, several numerical studies of large wind farms confirmed this phenomenon and found it critical to wind farm performance. For instance, the pressure feedback of the AGWs can slow down the free-stream velocity ahead of a wind farm, which contributes to the global blockage effect. Some researchers suggest that the global blockage effect is caused entirely by gravity waves [5, 1, 3]. Any maybe some just to the cumulative turbine induction [7]. Allaerts and Meyers (2018a) introduced the term ‘regional efficiency’ of wind farms by stressing that it is on the same order of magnitude as the localized efficiency of a wind farm [2]. The regional efficiency accounts for global blockage caused by the gravity waves, whereas the localized efficiency may include the wake and wind turbine induction effects. They later estimated a 4 to 6% reduction in the annual energy production of the Belgian-Dutch offshore wind-farm cluster due to blockage caused by the gravity waves [1]. Besides blockage, flow speed up caused by gravity waves at the far end of a wind farm, which can assist the wake recovery, is also noticed in an LES study [4].

Numerical modelling is the most viable option for studying AGWs and their impacts on wind farms. Experimental campaigns to detect the gravity wave signature of a wind farm would require measurements at heights beyond the Atmospheric Boundary Layer(ABL), something that, to the authors knowledge, has never been measured. Moreover, the wavelengths of wind farm-induced AGWs range from a few hundred meters to several tens of kilometers, possibly requiring measurement fields far wider than the wind farm area. Therefore, all the work done on wind farm-induced gravity waves is numerical. Generally, ad-hoc approaches decide the domain size and damping layer parameters required to dampen the AGWs to avoid reflections from the boundaries. To surmount these ad-hoc processes, we have been working to propose a baseline for simulating wind farm-induced AGWs. So far, we have investigated the dependency of numerical setup on physical parameters under conditions like the free atmosphere and found the Froude number ($Fr = U/\sqrt{\mathcal{L}}$) to be the most critical. Thus, optimal domain size and Rayleigh damping layer parameters for large eddy simulation (LES) of flow over a 2D hill and through wind farm canopies were investigated for a range of $Fr$ practical to wind farms. A wind farm canopy imposes the total wind-farm drag force on the flow in a region covering the wind farm size.

Our ultimate aim is to propose simulation guidelines that include wind farm-induced AGWs. Incorporating the actual temperature structure of the atmosphere is essential. Therefore, the impacts of inversion temperature gradient and height on the numerical setup while simulating wind farm-induced gravity waves are under investigation.

Methods
With SOWFA, incompressible Navier-Stokes equations, including the Boussinesq approximation, are solved for LES of flow over a 2D hill and through wind farm canopies. The bell-shaped hill, Witch of Agnesi, is included
Table 1: Non-dimensional parameters with their practical values tested in this study.

<table>
<thead>
<tr>
<th>Non-dimensional parameters</th>
<th>Definition</th>
<th>Practical values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Fr$</td>
<td>$U/L/N$</td>
<td>0.1-0.5</td>
</tr>
<tr>
<td>$Si$</td>
<td>$H/L$</td>
<td>0.016-0.4</td>
</tr>
<tr>
<td>$\bar{X}$</td>
<td>$X/\lambda_{hor}$</td>
<td>0.5-6.0</td>
</tr>
<tr>
<td>$\bar{L}_c$</td>
<td>$L_c/\lambda_{ver}$</td>
<td>0.3-2.0</td>
</tr>
<tr>
<td>$L_d$</td>
<td>$L_d/\lambda_{ver}$</td>
<td>0.5-2.0</td>
</tr>
<tr>
<td>$1/\tau$</td>
<td>$(\tau N)^{-1}$</td>
<td>0.1-50</td>
</tr>
</tbody>
</table>

in the setup as terrain-conforming mesh. The primary reasons to simulate flow over the hill include simplicity, computational affordability, and the availability of an analytical solution to compare with. Moreover, our focus is to handle the AGWs in simulations; thus, the source of AGWs is less critical. A wind farm canopy is a surrogate to model a wind farm quickly, where wind farm drag is uniformly distributed in a control volume covering the annulus area of rotors and wind farm length. A wind farm thrust coefficient ($C_{ft}$), given in Eq. 1, is used to calculate the total drag force, which is equivalent to the sum of the drag force of individual wind turbines in a wind farm.

\[
C_{ft} = \frac{\pi C_t}{4 s_x s_y}
\]  

(1)

Where $C_t$ is the individual turbine thrust coefficient, and $s_x$ and $s_y$ are non-dimensional distancing among the turbines, accounting for the density of wind turbines in a wind farm.

Spurious interaction of the AGWs with the boundaries leads to reflections mitigated by Rayleigh damping layers (RDL) in our work. In an RDL, the computed velocity vector at a point is relaxed toward a reference velocity at that point using a body force. The damping coefficient ($1/\tau$) and damping layer thickness ($L_d$), collectively termed damping characteristics, are the most critical RDL features. Often, tedious tuning is required to acquire damping characteristics applicable to a specific case. However, our investigation gives us good insights into the choice of optimal damping characteristics, RDL configuration, and domain size. These findings are discussed in the Results section below. A setup is considered optimal if it limits the reflection coefficient ($Cr$) to less than 10%, where $Cr$ is quantified by the ratio of downwards to upward propagating wave energy in the flow field [6].

In our work so far, we simulated a linearly stratified free atmosphere; the ABL and the inversion layer were not considered. Uniform inflow velocity at the inlet and slip conditions were used at the bottom and top in a rectangular domain containing either a hill or a wind farm canopy. The flow was periodic in the lateral direction. Moreover, all simulations use RDLs at the inlet, outlet, and top boundary. In the next step, we simulate the same scenarios but with conventionally neutral ABL capped by an inversion layer and the free atmosphere aloft. We take optimal setups for various $Fr$ from our previous study and vary the temperature stratification inside the inversion layer and its height to inspect the impacts of $Fr = U/\sqrt{gH}$ on the adopted setup. We tune the setup if needed to minimize the AGW reflections off the boundaries. At this point, the primary focus is the inversion layer effects on the setup; therefore, surface stability, turbulence due to the surface, and Coriolis force will not be included yet.

Results and Conclusions

Figure 1 gives the vertical velocity for flow over the Witch of Agnesi hill with $Fr$ 0.1. This figure illustrates the physical problem of handling AGW reflections in numerical modelling. As seen in the top plot, the reflections completely contaminate the flow because the damping coefficient is very low to dampen the waves effectively. However, as the mid plot shows, the waves are properly dampened at the boundaries when appropriate damping characteristics are used. Using strong damping coefficients causes reflections from the interface of the non-damped domain and the damping layer as if it is a wall.

The non-dimensional parameters in Table 1 are critical in simulating linearly stratified uniform flow over terrain and through wind farm canopies. These non-dimensional parameters can be acquired by normalizing the flow equations. Froude Number ($Fr$) and shape parameter ($Si$) are the only physical parameters among this set, whereas the other four are numerical, mainly non-dimensional lengths ($X$, $L_c$, $L_d$). We investigated the dependency of optimal numerical setups on $Fr$ and domain size, and the findings are discussed below.

Figure 2a, shows the reflection coefficient against $1/\tau$, which is the damping coefficient ($1/\tau$) normalized with the Brunt-Vaisala frequency ($N$). For practical values of uniform inflow velocity ($U$), $N$, and wind farm length ($L$) in wind farm applications, $Fr$ is 0.1 – 0.5. Thus, $Cr$ for a range of $Fr$ is plotted against $1/(\tau N)$ to determine the
Figure 1: Vertical velocity field of flow over the Witch of Agnesi hill for $Fr = 0.1$ with (top) weak damping coefficient, (middle) with tuned damping characteristics, and (bottom) with strong damping coefficient. The regions outside and at the left, top, and right of the red-dashed box are Rayleigh damping layers at the inlet, top, and outlet, respectively.

Figure 2: Reflection coefficient against: (a) damping coefficient for a range of $Fr$, (b) damping characteristics for $Fr = 0.5$, (c) domain length for $Fr = 0.1$ and 0.5, and (d) domain height for $Fr = 0.1$ and 0.5.
optimal damping coefficient. We observe that the optimal damping coefficient for Fr 0.1 corresponds to 1/τ = 10, whereas, for other Fr, it is around 1/τ = 2.5. The impact of damping layer thickness normalized with effective vertical wavelength(λver) on the reflections is shown in Figure 2b, where in general, the reflections reduce for increasing Ld. For optimal 1/τ, the range of optimal Ld is 1 – 1.5 times the effective vertical wavelength, and increasing beyond 1.5λver is redundant. Also, very low or high 1/τ leads to higher reflections; thus, the optimal 1/τ range is 1 to 10.

The location of boundaries is also critical in simulating AGWs. The physical AGWs propagate upwards as the only source is at the bottom of the domain. The commonly used boundary conditions at the top cannot absorb or radiate the wave energy out of the domain. Thus, the waves reflect and contaminate the physical solution upon interacting with the physical state of the flow. Likewise, the wave energy accumulates as the simulations advance in time and appears as reflected waves from other boundaries, mainly from the inlet. One way to avoid these reflections is to put the boundaries far away from the zone of interest, e.g., the wind farms, which would cost enormous computational resources for LES setups. Therefore, the optimal location of the boundaries, in combination with the optimal RDL layers, is essential to explore. Figure 2c, gives the reflection coefficient against the domain length normalized by the effective horizontal wavelength(λhor) for Fr 0.1 and 0.5 with two lengths of the Witch of Agnesi hill each. We can see that the domain length should accommodate at least one effective horizontal wavelength to limit the reflections below 10%. Domain lengths over one λhor may be redundant. Likewise, the effect of the non-damped domain height(Lz%) on reflections is given in Figure 2d. Both for Fr 0.1 and 0.5, Cr is low when Lz is around one. However, the damping layer thickness required with Fr 0.1 is 1.5λver, and that of Fr 0.5 is just one vertical wavelength.

In conclusion, the optimal damping characteristics depend on the Froude number when linear temperature profiles are used for the free atmosphere, and the ABL and inversion layers are not included. The optimal damping coefficient for Fr <0.1 is around 10 on the non-dimensional scale, and for Fr >0.1, it is about 2.5. The damping layer thickness should be 1 to 1.5 times the effective vertical wavelength for all Fr. The domain length scales with the effective horizontal wavelength, not the hill or canopy length. Thus, the optimal domain length should be greater than one λhor, again applicable to all Fr. Similarly, the non-damped height of the domain should be greater than one vertical wavelength for the damping layer thickness being 1.5λver for Fr 0.1, and λver for Fr 0.5. Thus, we can infer that relatively thicker damping layers are required for Fr <0.1.

Besides Fr, Fr1 is an essential physical parameter in this study, which may impact the setup. Currently, we are investigating if the optimal setups acquired thus far are valid for various inversion strengths, i.e., Fr1. Shortly we will also include the stable and convective ABL.

References


### Session 12.2
**07.09.2023 - 15:30**
**Building 3701, Room 267**

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Innovative combination approach for environmental parameters of offshore wind turbines

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Keywords: directional depending contour plot, probabilistic models, wind and wave combination method

Offshore wind energy is rapidly gaining momentum as a key component of sustainable power generation. With the aim of increasing offshore wind capacity to 120 gigawatts over the next seven years, nine European countries recently joined forces to promote this renewable energy source [1]. As wind turbines become larger, the need to optimise their design becomes paramount. One promising component is the use of stochastic methods to analyse uncertain factors such as wind and wave conditions. CRC 1463 plays an important role in this endeavour, focusing on the development of innovative methods for the design of large offshore wind turbines. By using the knowledge gained from CRC 1463, the industry can improve efficiency, reduce costs and accelerate the deployment of offshore wind energy turbines. This contribution discusses an innovative wind and wave combination method, and the results obtained by applying the method. The current industry practice for wind turbine design is to use the design load cases provided by guidelines like Det Norske Veritas and Germanischer Lloyd (DNV GL). Specifically, this study focuses on the wind and wave conditions using a table extracted from the DNV GL as an example. The selected wind and wave conditions have a return period of 50 years and include scenarios with wind-wave misalignment and multi-directionality, where the mean wind direction may differ from the wave direction. Currently, the time dependency of the environmental parameters is mainly taken into account in the design of an OWT [3]. The challenge is to find a combination method that accounts for both temporal and directional dependencies in extreme events.

To address this challenge, a novel method is presented to show the directional dependence between the significant wave height and the concurrent wind speed at the reference site. A wave rose is used to illustrate the maximum significant wave height for each month and its corresponding direction. The 3h mean values of the significant wave height are assigned a 10min maximum value for the wind speed occurring in the same period. The combination method uses a sector size of 30°. The data basis is provided by hindcast data from the CoastDat2 database, which was evaluated for the reference location of the digital twin for CRC 1463 [2]. The simulated data cover 66 years from 1949 to 2015. The data points are analysed using the Weibull distribution, which was proofed by goodness of fit tests. The events with a 50 year return period are calculated for this sector and the procedure is repeated for adjacent sectors with a 1° step to achieve a smooth transition.

Although high significant wave heights and wind speeds are observed in this example, it is important to note that not all waves and their corresponding wind speeds necessarily fall within the same sector. The contour plot in Figure 1 shows the combination of significant wave height and wind speed for a 50 year return period. This combination approach produces a contour plot that considers the direction and impact of waves together with the expected simultaneous wind speeds for a 50 year return period, as required for the OWT-design according to current guidelines. For future research, this method opens up several avenues of analysis. It offers flexibility in terms of investigating different observation and return periods, as well as varying the sector size for the combination method. Furthermore, the evaluation of this method at different sites is a crucial next step to assess its applicability and performance in different environmental conditions. By considering these factors, researchers can gain a deeper understanding of the robustness and effectiveness of the method.

In conclusion, the integration of a directional contour plot method presented in this study is very promising for optimising the design of offshore wind turbines. By considering both the temporal and directional dependence of wind and wave conditions, this innovative approach allows for a more comprehensive understanding of extreme events.

As offshore wind continues to grow as one of the most important sustainable energy sources, the use of innovative methods such as directional contour analysis will play a crucial role in achieving ambitious capacity targets.
Figure 1: Contour of significant wave high with a return period of 50 years at the reference site and contour of simultaneous wind speed with a return period of 50 years.

References


Assessing the performance of the ALM in close-proximity Darrieus turbines: a critical analysis

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Keywords: Actuator Line Model (ALM), VAWT, Darrieus, Hydrokinetic Turbines, Computational Fluid Dynamics (CFD), Proper Orthogonal Decomposition (POD)

1. Background and motivation

Recent research suggests that vertical-axis turbines possess promising features that make them suitable for closely spaced installations, opening up new opportunities for wind and hydrokinetic applications [1]. In Vertical axis wind turbines (VAWTs), they demonstrate potential for offshore floating applications due to their lower center of gravity. Similarly, vertical-axis hydrokinetic turbines (VAHTs) offer a cost-effective solution for utilizing “hidden hydropower” from channels and small rivers. However, as applications become more sophisticated, reliable and low-cost simulation tools are required to incorporate other complex effects.

In this context, the scientific community is currently focused on the development of low- or medium-order approaches that can effectively capture the main effects on performance and wake recovery while maintaining low computational costs. Analytical models and theoretical estimates have been proposed, but they are unable to fully capture the intricate three-dimensional flow structures in the wake or the interaction region between rotors. Consequently, the reintroduction of Computational Fluid Dynamics (CFD) methods is necessary to gain valuable insights into these aspects. The use of “hybrid” methods, which combine CFD with a lumped-parameter aerodynamic model like Actuator Line Method (ALM), has shown promising results in terms of both accuracy and computational cost [2]. Nevertheless, further research is required to determine if ALM can adequately capture the efficiency increase that arises from closely deployed rotors in a VAWT farm.

2. Research scope and objectives

Moving from this background, the present study aims at understanding if the ALM is able to cope with the complex array effects occurring when multiple rotors are deployed in close proximity, together with the associated performance augmentation [3]. ALM simulations were performed for both a wind and an hydrokinetic rotor, and validated against the blade-resolved CFD data from Zanforlin et al. [4] (3B-VAWT) and from a recent work of the authors [3] (3B-VAHT), respectively. The comparison of the two datasets was carried out in terms of:

a. turbine performance, in terms of overall performance and torque profiles over a revolution;

b. flow kinematics, with particular reference to the local AoA, sampled from both ALM and blade-resolved simulations via the LineAverage method, recently validated by the authors on vertical-axis turbines [5];

c. wake development. The wake has been analysed in this work using Proper Orthogonal Decomposition (POD) to analyze the capability of the ALM to reproduce the wake modes of closely-spaced Darrieus turbines.

3. Research methods

3.1 Actuator Line Method

The Actuator Line Method (ALM) is a computational tool that is being extensively used for simulating wind turbines. The corresponding workflow is the following. First, the position of the actuator line corresponding to the turbine blade is located on the computational grid. Then, the blade Reynolds number and angle of attack are sampled from the local flow field and are combined with the available polar data and sub-models to compute the corresponding aerodynamic forces. The latter are eventually projected into the computational domain as momentum source terms in the Reynolds-Averaged Navier-Stokes (RANS) solver. Additional information about the code formulation employed in this study can be found in [2].
A different ALM formulation was also used, referred to as Frozen ALM. This approach allows the differentiation of errors stemming from the forces data or their associated ad-hoc models, and those resulting from other factors such as the projection function or the angle of attack (AoA) sampling. In Frozen ALM, the aerodynamic coefficients are not derived from tabulated airfoil polar data; instead, they are directly obtained from a blade-resolved CFD simulation.

3.2 Proper Orthogonal Decomposition (POD)

In the present work, POD was applied, in order to compare the wakes produced by the blade-resolved CFD and the ALM. More in detail, the flow field data at each spatial point on the two-dimensional domain was stored into a unit vector, $\chi^n_m$, where $n$ is the number of spatial points, and $m$ is the number of timesteps. In this way, an $n \times m$ matrix $U$ could be formed. This matrix is then decomposed via Singular Value Decomposition (SVD) into three other matrices, two of which contain the coherent structures in the spatial and temporal domains, in addition to the matrix of eigenvalues:

$$U = \begin{bmatrix} \chi^1_n & \cdots & \chi^m_n \\ \vdots & \ddots & \vdots \\ \chi^n_1 & \cdots & \chi^n_m \end{bmatrix}, \quad U = \phi \Sigma \phi^T$$

\hspace{1cm} (1)

In this study, the POD analysis was conducted within a selected area spanning 6D in the crosswind direction and 5D in the streamwise direction, located 1D downwind the centre of the rotors. It should be noted that the POD analysis was only carried out on the 2B-VAHT rotor due to the availability of the blade-resolved CFD data.

4. Results

4.1 Turbine loads

Fig. 1 shows the profile of blade torque coefficient ($C_T$) along one revolution, averaged over the two rotors for both the wind and hydrokinetic turbines pairs (3B-VAWT and 2B-VAHT) compared with the corresponding blade-resolved RANS results of Zanforlin et al. [4] and Mohamed et al. [3].

Regarding the 3B-VAWT pair, the ALM was able to reconstruct the trend of the torque coefficient profile in the upwind region ($0^\circ \leq \theta \leq 180^\circ$), capturing the azimuthal position of the peak torque with a slight overestimation in its magnitude compared to the reference data. In the downwind section ($180^\circ \leq \theta \leq 360^\circ$), nonetheless, the ALM achieved a fair prediction of the torque coefficient trend, although overestimating energy extraction along the whole blade path within the downwind region. For the 2B-VAHT on the other hand, the ALM was able to reproduce the torque profile in the whole pitch-up phase ($0^\circ < \theta < 90^\circ$), up to its peak value for both single and twin rotors. In the pitch-down phase ($90^\circ < \theta < 180^\circ$) instead, the ALM tends to underpredict torque production in both stand-alone and twin configurations. The opposite trend is observed in the downwind region, where the ALM overpredicts the blade loads with respect to reference data along the whole blade path.

Fig. 1 instantaneous torque variation for 3B-VAWT and 2B-VAHT resulted from the ALM compared to that of the BR-CFD.
4.2 Local blade kinematics

To assess the ability of the ALM to replicate the flow characteristics around the 3B-VAWT pair, the velocity profiles in the streamwise (X) and crosswise (Y) directions were compared between the ALM and blade-resolved CFD data. This comparison is depicted in Fig. 2-(a). At TSR = 2.7, the ALM demonstrates favorable agreement with the blade-resolved CFD data. However, there are some discrepancies observed, including: (i) Upwind blockage effect: Particularly noticeable is the X-velocity deficit at the center of the rotor (Y/D = 0); (ii) Slope of Y-velocity variation: This refers to the degree of expansion of the flow at the sides of the twin rotor and within the gap.

In the case of the 2B-VAHT, the local AoA was measured and compared to the AoA obtained from the blade-resolved CFD data in Ref. [3], as illustrated in Fig. 2-(b). For both TSRs, the predicted trend of AoA variation by the ALM demonstrates strong agreement with the blade-resolved CFD. Moreover, the ALM successfully captures the increase in AoA induced in the gap region (90° < θ < 225°) due to the mutual interaction of the rotors.

4.3 Wake flow field

Fig. 3 shows a comparison of the percentage of the POD modal energy captured by each spatial mode, as well as the cumulative total energy captured up to each mode, at TSR = 3. Notably, the Frozen ALM and blade-resolved CFD exhibited a close match, with the first two modes capturing 96% and 94% of the total modal energy, respectively. In contrast, for the ALM, the first two modes accounted for only 67% of the total energy. These differences in the distribution of flow modal energy among the various modes between the ALM and blade-resolved CFD can be better understood by examining the corresponding modal spatial patterns.

Fig. 3 also displays the mean and spatial modes obtained at TSR = 3 for blade-resolved CFD, Frozen ALM, and ALM. The mean flow in the ALM simulation shows greater acceleration than that in the blade-resolved CFD and Frozen ALM on both the leeward and windward sides. The Frozen ALM, on the other hand, exhibits higher acceleration within the area of mutual interaction between the wakes of the two turbines at 2 < X/D < 4.

Regarding the spatial modes, the first two modes of both the blade-resolved CFD and the Frozen ALM show pairs of similar coherent structures with a streamwise phase shift, representing the velocity fluctuation pattern due to the shedding streets in both leeward and windward directions. The size and position of the coherent structures in the first two modes match notably between the blade-resolved CFD and the Frozen ALM. For the ALM, the first two modes represent a pair of coherent structures that are produced near the rotors due to the windward streets. The 3rd and 4th modes depict a breakdown of these windward structures in addition to those formed due to the leeward streets. Interestingly, the 3rd and 4th modes of the ALM show good agreement with the 1st and 2nd modes of the blade-resolved CFD and the Frozen ALM.
The results of the validation campaign have demonstrated that the ALM is capable of accurately reproducing the local flow kinematics, which is essential for closely-spaced Darrieus turbine applications. The load analysis showed that the ALM can capture the instantaneous load with good to fair accuracy, although this may be case-dependent due to the sensitivity of the geometrical and operating conditions. The wake analysis conducted through performing POD analyses revealed that the main flow fluctuating patterns from the blade-resolved simulation are well captured by the ALM. In short, the ALM requires much less computational resources compared to blade-resolved CFD for simulating a twin-rotor configuration, with a computational time difference of almost two orders of magnitude. This makes the ALM an attractive alternative for complicated and interdisciplinary applications.

References


Numerical buckling analysis of rotor blade sandwich panels with spatially distributed material uncertainties

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1 Introduction

Sandwich-structured composites are used as the trailing edge panels in rotor blades. These panels are designed to be both lightweight and stiff at the same time. Reducing the blades relative mass is one key element of the development of larger rotor blades and more powerful wind turbines. The high stiffness of the panel is required to keep the structural integrity at axial compression loads from large flapwise bending moments. If designed insufficient, one possible failure mechanism is panel buckling at which large out of plane deformations and high strains and stresses occur. The overall stiffness of the structure is abruptly decreased at the beginning of buckling, which can lead to structural failure of the panel and in other parts of the rotor blade subsequently. The load at which buckling occurs is generally highest for a perfect flat panel. Any kind of imperfections, such as curvature or small irregular geometric out of plane deformations result in a reduced buckling load. Spatial distributed material properties can be seen as another kind of imperfection to the perfect panel. It is known that the material properties in rotor blades such as elastic moduli are subject to deviations and that the assumed material properties in the design process are just the mean value of a statistical distribution [1]. Although the positive effect of an optimization of the spatial distribution of material properties on the buckling load is well investigated [2][3], it is unclear how random distributions effect the buckling load. These random deviations of material properties can originate from locally different fiber-matrix ratios, curing parameters of the epoxy resin, fiber undulations or damages. Depending on the reason of the material property deviation, the spatial distribution is considered to be more local or global. Because the investigation of the spatial distribution of material properties in a rotor blade is a destructive and therefore a very expensive procedure, the actual distribution is unknown to the authors yet. Therefore, different kinds of spatial material property distributions and their effect on the buckling load are investigated using stochastical finite element simulations.

2 Methodology

In this study, a finite element model of a 1 m long and 0.42 m wide perfectly flat sandwich panel is used. The sandwich panel consists of two face sheets made of bi-axial glass fiber reinforced epoxy and a pvc foam core in between. The spatial material distributions are applied to the top and bottom face sheets as randomly generated two-dimensional noise patterns. This pattern generation is done by an inverse fast Fourier transformation of an amplitude spectrum with a random phase shift. It results in a superposition of harmonic sinusoidal functions with different amplitudes. By varying the amplitude spectrum, the appearance of the pattern is altered. This variation is done by applying a low pass filter to the amplitude spectrum. Varying the cut-off wavelength of this lowpass filter results in a local or global variation of the spatial distribution between. The variance of the pattern is calculated by a sum over the power spectral density of the resulting amplitude spectrum. Ten materials with equally spaced elastic properties ($E_{11}$, $E_{22}$, $G_{12}$) are then mapped to the randomly generated patterns. Examples for these patterns can be seen in Figure 1a) for three different amplitude spectrums. The material property distribution of each face sheet of each panel is a subset of a normal distribution with the nominal material properties as mean value and 4% standard deviation as discovered in [1]. Thus, for an infinite number of generated panels of each cut-off wavelength the material distribution of the numerical model coincides with the test results. Figure 1b) shows the normal distribution of the elastic properties for an infinite number of numeric panels.
3 Results

Linear buckling simulations were performed with 100 randomly generated distribution patterns for 12 different amplitude spectrums with different cut-off wavelengths of the low pass filter. The mean value of the buckling force as well as the standard deviation were calculated from the simulation results. These results were normalized by the buckling force of a perfect panel with homogeneous material properties of the nominal values. The normalized mean values and the standard deviations are shown in Figure 2. While the standard deviation increases with increasing cut-off wavelength, the mean value has a minimum at a cut-off wavelength of 0.5 m. It can be considered that certain wavelength components in the amplitude spectrum of the spatial distribution act as critical local imperfections. These imperfections induce buckling and reduce the buckling load, which results in an overall reduced mean value. Very short and very long wavelength components seem to have a less negative effect on the buckling behavior and the mean value of the buckling load is almost identical to the load of the panel with homogeneous nominal material properties.

![Figure 1: Examples of different spatial material property distributions of the finite element model obtained from different amplitude spectrums with short, medium and long cut-off wavelengths. (b) Resulting probability function of the 10 elastic material properties for an infinite number of randomly generated patterns.](image)

![Figure 2: Mean value and standard deviation of normalized buckling force for different cut-off wavelengths.](image)
Acknowledgements

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References


Transition Predictions of DU 00-W-212 and Investigation of Linear Solver Methods for High Reynolds Numbers

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**Keywords**: High Reynolds numbers, 2-D RANS, 3-D DES, Transition models, Iterative methods

1. Introduction

In high Reynolds number flows, dominated by inertial forces, complex phenomena such as separation, turbulence, and transition occur. Transition denotes the shift from a laminar state to a turbulent state, significantly impacting the aerodynamic behaviour of airfoils. The design of modern wind-turbine airfoils necessitates reliable predictions for various thicknesses, shapes, and Reynolds numbers. Airfoils in large offshore wind turbines typically operate within chord-based Reynolds numbers ranging from 3 to 15 million. Notably, turbulence transition within the airfoil boundary layer greatly influences the aerodynamics near the design operating point. In multi-megawatt horizontal-axis wind turbines, thick profiles (≥25%) are employed in the inboard and midspan regions to enhance blade stiffness, reduce weight, and minimize costs and fatigue loads. At midspan, desirable aerodynamic characteristics include low sensitivity to roughness, moderate to high lift, and a high lift-to-drag ratio. Numerical simulations, particularly Computational Fluid Dynamics (CFD), have proven invaluable in investigating high Reynolds number flows over airfoils. CFD facilitates detailed analysis of the flow field, providing insights into phenomena like flow separation and vortex shedding. However, accurately modelling the transition process and capturing its impact on airfoil aerodynamics poses ongoing challenges. To address these challenges, researchers have developed various solution approaches for high Reynolds number flows over airfoils. These models aim to accurately predict the transition process and capture flow characteristics at different angles of attack and Reynolds numbers. Selecting an appropriate turbulence model is critical to ensure reliable and accurate results in these simulations. Key features of CFD analyses of wind turbine airfoils are discussed, and the solution strategies, turbulence models, transition models, and grid generation procedures, are previously summarized in [1]. Direct Numerical Simulation (DNS) [2,3] and Large Eddy Simulation (LES) [4] have been employed to capture the laminar to turbulent transition with high accuracy. The computational cost of DNS and LES increases rapidly with increasing Reynolds number (Re). DNS is currently feasible only for low Reynolds numbers, while LES can handle problems with Re approximately one magnitude higher. To solve massively separated flows, Detached Eddy Simulation (DES) has emerged as an alternative. DES is a modification that allows one- and two-equation turbulence models to behave like LES in regions with sufficient grid refinement. Strelets [5] performed DES using two different turbulence models, focusing on airfoil flow cases at moderate Re and angles in the post-stall region. For transitional simulations, DES has been combined with transition models used in RANS solvers, as demonstrated by Sorensen et al. [6] employing the γ–Reθ transition model. Michna et al. [7] conducted an extensive analysis of the aerodynamic characteristics of the DU91-W2-250 airfoil at varying Reynolds numbers (3-6 million) using Unsteady Reynolds-Averaged Navier-Stokes (RANS) simulations with the transition Shear Stress Transport (SST) turbulence model. The study aimed to understand the impact of turbulence and transition on the airfoil's performance. Similarly, Rogowski et al. [8] compared the aerodynamic properties of the same airfoil using 2D RANS and 3D DES analyses at a Reynolds number of 3 million, employing the transition SST turbulence model to account for transitional flow effects. Their goal was to assess the accuracy and applicability of each method under high Reynolds flow conditions. Calafell [9] utilized the VMS-WALE Large Eddy Simulation (LES) approach to investigate high Reynolds number flows around the DU91-W2-250 airfoil geometry, studying two different airfoil geometries as well. The focus was on understanding the complex flow structures and turbulence characteristics using LES, which can capture large-scale turbulent motions. Bangga et al. [10] examined the flow field around the DU97-W-300 airfoil at a Reynolds number of 3.2 million. They employed a hybrid RANS/LES turbulence model known as Delayed Detached Eddy Simulation (DDES) to accurately capture both the Reynolds-averaged and large-scale turbulent flow features. Diakakis et al. [11] investigated the flow field
around various airfoil geometries at high Reynolds numbers up to 40 million. They employed the RANS equations with transition models to simulate the flow behaviour, aiming to understand the aerodynamic characteristics and performance of different airfoil geometries under extreme Reynolds flow conditions. Jung [12] conducted a study to evaluate the capabilities of transition models in accurately capturing the aerodynamic characteristics of high Reynolds flows. The research focused on assessing the effectiveness of transition models in predicting transitional flow phenomena and their impact on the overall aerodynamic behaviour of airfoils in high Reynolds flow regimes. The transition from laminar to turbulent flow on the suction side of the DU 00-W-212 airfoil occurs rapidly near the leading edge at angles of attack (α) around 6° and 10° for a Reynolds number (Re) of 3 × 10^6, and at angles of attack of approximately 4° and 8° for a Reynolds number of 9 × 10^6. However, accurately predicting these transition points through simulations can be challenging. Simulating high Reynolds flows requires a careful balance between accuracy and computational costs. Advances in computational power and optimization techniques enable more efficient simulations while maintaining improved accuracy. The choice of linear solver method is crucial for accurate and efficient simulations; as linear solvers play a vital role in solving the linear systems of equations that arise during numerical solution. Traditional linear solver methods, such as direct methods (e.g., Gaussian elimination) and iterative methods (e.g., Jacobi, Gauss-Seidel), are commonly used in aerodynamic simulations. Direct methods guarantee accuracy but can be computationally expensive, especially for large-scale problems. Iterative methods offer improved computational efficiency but may suffer from slow convergence for certain linear systems, affecting both accuracy and speed. Krylov subspace methods, including Conjugate Gradient (CG), Generalized Minimal Residual (GMRES), and Bi-Conjugate Gradient Stabilized (BiCGSTAB), are powerful iterative solvers for large-scale problems in high Reynolds flow simulations. These methods construct a subspace of vectors iteratively and exhibit faster convergence rates compared to traditional iterative methods, particularly for ill-conditioned and sparse linear systems commonly encountered in computational fluid dynamics (CFD) simulations. The choice of linear solver method depends on factors such as problem size, matrix properties, and computational resources. Direct solvers are advantageous for smaller problems where accuracy is critical and computational resources are sufficient. Krylov subspace methods are particularly effective for large-scale problems, striking a balance between accuracy and computational efficiency. They are well-suited for sparse linear systems commonly encountered in high Reynolds flow simulations.

This study focuses on analyzing the aerodynamic characteristics such as flow separation and the transition from laminar to turbulent flow on the airfoil surfaces of the DU 00-W-212 wind turbine airfoil at high Reynolds numbers (Re = 3, 9, 15 × 10^6). To accomplish this, various turbulence and transition models are examined using the SU2 CFD solver. The simulations involve both 2-D and 3-D flow simulations utilizing RANS and DES methods. Additionally, the study investigates the effect of selection of iterative methods employed as linear solvers in the SU2 framework. As future works, 3-D DES results and investigation of iterative methods (Krylov subspace methods) will be also presented with speed-up analysis.

2. Simulation details

2-D computational domains are generated using Pointwise software. A structured O-grid with 837 x 183 cells is utilized, with clustering near the surface. Normal extrusion is applied while ensuring that the y+ value is maintained below 1. To enable grid-independent simulations, five computational grids were generated by systematically increasing and decreasing the grid cell size by a factor of \sqrt{2}. The present study employs the steady-state Reynolds-Averaged Navier-Stokes (RANS) equations to investigate the aerodynamic behavior of the airfoil. Two turbulence models, namely the Spalart-Allmaras (S-A) and the k-ω SST (SST) models, are utilized in conjunction with two different transition models. The numerical solution employs the Euler implicit method, employing a Low Mach Roe scheme with second-order spatial integration and the Venkatakrishnan slope limiter. A scalar upwind solver is employed for turbulence modeling, utilizing a first-order spatial integration scheme. To ensure accurate convergence, the simulations are performed with a maximum of 40,000 iterations, considering a residual value of 1e-12 as the convergence criterion. The linear solver employed in the transition simulations is the FGMRES method, utilizing LU-SGS preconditioning. Furthermore, for 3-D simulations at a Reynolds number of 3 million, transient simulations using the Detached Eddy Simulation (DES) method are performed. The time step employed in these simulations is 2e-5 seconds. The implicit Euler time integration scheme, in conjunction with the dual-time stepping method, is employed. The linear solver utilized for the DES simulations is the FGMRES method with LU-SGS preconditioning. In order to investigate the selection of linear solver, FGMRES and BiCGSTAB methods which are available methods in SU2 are used with ILU and LU-SGS preconditioners [13]. The level of fill-in in the ILU preconditioner is also examined. The analyses are performed by using 3-D
RANS simulations for $Re = 3 \times 10^6$ and a.o.a. = 15 deg. Simulations are run for 10000 iteration steps. The current results are obtained by using 28 CPUs in TRUBA HPC clusters. Speed-up analysis will be also considered.

3. Preliminary Results

The results of 2-D RANS simulations were also presented previously in WESC2023 [14]. In Figure 1, the change of transition point on the upper surface of airfoil with respect angle of attack for $Re = 3 \times 10^6$ is presented. The results are compared with experimental results [15] conducted in RUZGEM, METU and literature. In Figure 2, lift curves are given for different Reynolds numbers. For $Re = 9 \times 10^6$ and $Re = 15 \times 10^6$, the numerical results are compared with experimental results in the literature [16]. In Figure 3, the comparison of BiCGSTAB and FGMRES linear solvers with different preconditioners; ILU(2) and LU-SGS.

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References

Figure 1: Comparison of turbulence models and transition model with experimental results and literature in terms of transition location change with respect to angle of attack for $Re = 3 \times 10^6$ and $Re = 9 \times 10^6$.

Figure 2: The change of lift coefficient curve with respect to turbulence models and transition models for 3 different Re numbers in comparison to experimental results.

Figure 3: Residual history for 3-D RANS simulations of DU00-W-212 for $Re = 3 \times 10^6$, $\alpha = 15$ deg.
A Story of a PhD – Expectations vs. Reality

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1 Motivation

Reading the thesis of other PhDs often gives the impression that a PhD is a coherent path to follow. New PhD students at the beginning can feel overwhelmed as they struggle to see this coherent path for their research topic. On the other hand, when talking to PhDs who completed their thesis, reality often shows that none of the coherent stories happened the way they are told. Therefore, this presentation aims to compare the expectations of the author as a young PhD student to the outcome of the thesis. The presentation, given at the EAWE PhD seminar in Nantes 2019 is compared to the results of the thesis and some insights into the challenges that were faced are given. This way, the presentation aims to encourage young PhDs to be confident about their work and “just get started and find their story on the way”.

2 Retrospectives of a PhD

Throughout my PhD studies, I faced a couple of questions which probably occur for most PhD students at some point on their way. This presentation will address these questions and gives insights into the approaches that were chosen to answer these questions. As a PhD student starting a new topic at the institute only little knowledge was available to build on. Many of my colleagues used the method of “just try to use what former colleagues have developed and find out where to continue”. However, this approach did not work for me since there was no former colleague. Therefore, the first big challenge was the question “How do I find my research questions?”

In consequence, I ended up with a huge research scope as formulated in my abstract for the PhD seminar 2019: The aim of this research is to be able to simulate vibrational interactions between the generator magnetic field and the wind turbine combining the analysis of service life time, design dependency and modelling depth. As a result, the minimum model depth required to calculate the service life of the wind turbine under consideration of the generator will be identified. What this meant throughout the PhD will be discussed in this presentation.

As outlined in the quote, one aim of the thesis was to develop a software coupling for electro-mechanical interactions in wind turbines. This was based on literature: The inverse impact from the generator to the wind turbine has not yet been investigated, though two-way coupling effects in wind turbines are of significant importance for the calculated load levels [1]. The coupling was developed successfully and also validated with a little test bench [2]. However, it turned out that the software coupling of a multi-body model wind turbine and a FEM generator model was computationally too expensive to perform an analysis of service lifetime with it. This brought me to the question “How do I cope with “negative results or dead ends?” And how can I continue towards the analysis of service lifetime?

While I was trying to figure out how electro-mechanical interactions in wind turbines can be analysed with a two-way coupling of solvers, other researchers were also working on the field and new
publications appeared, e.g. [3]. Some of the methods were close to my approaches and I had to clearly differentiate my work from these publications. “What do I do, if others publish similar work?” is a question, which is commonly faced by PhD students and will be discussed in the presentation. The presentation will give insights into the personal approaches to address the outlined questions and offer a forum for discussion. It is important to mention that every PhD is different and very individual so the presented approach can only be claimed as some possible way out of many.

3 Takeaways

In summary, if I would do my PhD again, I would:

• Look for fellow students earlier and try to establish closer collaboration with them more actively. The possibility to test new ideas in a discussion with people working on a similar topic helps to identify the strengths and weaknesses of concepts early on.
• Worry less about dead ends. To find out that something does not work is also a result. This is common knowledge but we still often do not feel good when it happens to us.
• Start writing the thesis earlier. Trying to write ideas and results down, missing aspects in the causality chain get obvious faster than in oral discussions and vague notes.
• Keep the scope wide, as it gives you more freedom to explore multiple questions and change direction when you face a dead end. However, it is important to not lose yourself in the field. Therefore, specific short-term goals are also needed.
• Choose a topic that is new to the institute just because I find it most interesting. Interest in the topic itself helps to keep motivation high when things do not work out.

References

Impact of geometrically non-linear cross-sectional deformations of rotor blades on aerodynamic properties

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Abstract

The rotor blade is a key component in generating power for wind turbines. The outer geometry is essential for the aerodynamic performance. This can be influenced by the selection of aerodynamic airfoils. In the rotor blade design process, the lift-to-drag ratio plays a crucial role in choosing airfoil and twist angle. As rotor blades increase considerably in size \cite{1}, they are also expected to become more flexible. This means that deformations can occur in a cross-section of the rotor blade during operation. If the external geometry changes, the lift-to-drag ratio can alter as well.

The aim of this work is to analyze and quantify the in-operation cross-sectional deformations and its impact on the aerodynamic characteristics for an exemplary wind turbine. For the analysis the IEA 15 MW RWT rotor blade \cite{2} is used in a finite element simulation. For normal operation, different load scenarios are examined for the rated windspeed of 10 m/s and different partial safety factors. The simulation focuses on bending loads. Flapwise and edgewise bending moments are applied individually.

Multiple cross-sections along the blade span are evaluated and the lift-to-drag ratios are determined using Xfoil \cite{3}. Figure 1 shows an example for a cross-sectional deformation caused by edgewise bending of the rotor blade with different amplification factors (left-hand side). On the right side the corresponding lift-to-drag ratios can be seen. As the amplification factor $s$ increases, the deformation in the trailing edge panel (section between spar cap and trailing edge) on the pressure side deforms visibly. Regarding the lift-to-drag ratio, this leads to an increase at the same angle of attack. It has to be noted that this can only be seen by increasing the deformation by a factor $s = 10$. The results for several positions along the rotor blade and different load cases will be shown and discussed in the presentation.

Keywords: Cross-Sectional Warping, Simulation, Wind Turbine, Xfoil, Aerodynamics

Figure 1: Deformation of an exemplary cross-section for the maximum edgewise bending moment (left) and change of lift-to-drag ratio (right). The parameter $s$ is a magnification factor for the deformation.
References


