Evaluation of the Wind Direction Uncertainty And Its Impact on Wake Modelling at the Horns Rev Offshore Wind Farm

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Aero-elastic Section, Wind Energy Department, DTU, Risø

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DTU Wind Energy
Aero-Elastic Design Section - Risø
Outline

1 Why Uncertainty Matters?
   • Introduction
   • Method: Modelling the wind direction uncertainty
   • Results

2 Adding Value to Wind Farm Data
   • Machine Learning and Physical Modelling
   • The FUSED-Wind project
   • A Future Business Concept

3 Conclusion and Future Works
Introduction

Overview of DTU’s Wind Farm Flow Models
Introduction

What Are Those Models used for?

- Estimating Annual Energy Production
- Wind Farm Optimization
Introduction

The Horns Rev test case - Western winds

Reference wind direction
Introduction

Results of the Wake Model Benchmarking: Confusion!

270° ± 2.5°

270° ± 15°

Data
N.O. Jensen
G.C. Larsen
Fuga

Normalized Power \( \left( \frac{P_{Ei}}{P_{E1}} \right) \) [-]

Wind Turbine Number \((i)\) [-]
Introduction

The effect of wind direction uncertainty on wind farm wake measurement
Introduction

The effect of wind direction uncertainty on wind farm wake measurement

[Diagram showing the relationship between wind direction and power ratio, with data points indicating variability due to wind direction uncertainty.]
Introduction

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Sources of wind direction uncertainty

Random/temporal bias from the measurement device
- Yaw misalignment (when yaw sensor is used to measure direction)
- Time drift of the calibration
- Failures
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Atmospheric turbulence
- Small scale turbulence (sub 10-minute)
  - This should be accounted by the models
- Large scale turbulence (i.e. wind directional trends, over 10-minute)
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Wind direction coherence

- Spatial variability of the wind direction
- Different time-control volume averaging
Introduction

Spatial decorrelation of wind direction

The wind direction correlation between M2 and the wind turbines decreases linearly with the distance.
Method: Modelling the wind direction uncertainty

The "traditional" method

- Step 1: Run simulations with fixed and homogeneous wind direction covering the desired wind direction sector
- Step 2: Apply a linear average to reproduce the data post-processing

Final Output (e.g. 270° ± 2.5°)
Method: Modelling the wind direction uncertainty

The proposed method

- Step 1: Run simulations with fixed and homogeneous wind direction
Method: Modelling the wind direction uncertainty

The proposed method

- Step 1: Run simulations with fixed and homogeneous wind direction
- Step 2: Apply a weighted average based on the probability function of a normal distribution on the interval $\pm 3\sigma$
Method: Modelling the wind direction uncertainty

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![Diagram](image)
Results

All the rows, using a row-specific wind direction uncertainty

270° ± 2.5°

270° ± 15°
## Results

Result for the whole wind farm in $\theta = 270^\circ$ 

<table>
<thead>
<tr>
<th></th>
<th>$270 \pm 2.5^\circ$</th>
<th>$270 \pm 15^\circ$</th>
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<tbody>
<tr>
<td>Power Data</td>
<td>64.7%</td>
<td>73.9%</td>
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<tr>
<td>NOJ, Baseline</td>
<td>-20.9%</td>
<td>+0.4%</td>
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3. Conclusion and Future Works
\( \zeta_i(x_i) = \eta(x_i) \)
$$z_i = \zeta_i(x_i) + \varepsilon_i = \eta(x_i, \theta) + \delta(x_i) + \varepsilon_i$$  \hspace{1cm} (2)
The FUSED-Wind project

Connecting All Wind Energy Models in a Workflow

- Collaborative effort between DTU and NREL to create a Framework for Unified System Engineering and Designed of Wind energy plants.
- Based on OpenMDAO, a python based Open source framework for Multi-Disciplinary Analysis and Optimization.
- FUSED-Wind will offer built in capabilities for Uncertainty Quantification, Machine Learning and Optimization.
A Future Business Concept

Concept

WAsP
SmartWake client

Cloud Cluster
SmartWake Server

Wind farm SCADA owners

P.-E. Réthoré
DTU Wind Energy

Uncertainty & Wake
A Future Business Concept

I want to plan a wind farm

Concept

WASp
SmartWake client

Cloud Cluster
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Wind farm SCADA owners

Wake Modelers
A Future Business Concept

I want to plan a wind farm

WAsP
SmartWake client

I want my wake model to be useful

Cluster
Wake Server

Wind farm SCADA owners

Modelers
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Concept

I want to plan a wind farm

WAsP
SmartWake client

I want my wake model to be useful

Wind farm SCADA owners

I want add value to my wind farm SCADA data

P.-E. Réthoré

DTU Wind Energy
A Future Business Concept

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WAsP SmartWake client

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Concept

Uncertainty & Wake

WASP
SmartWake client

Cloud Cluster
SmartWake Server

Wind farm SCADA owners

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A Future Business Concept

Concept

Uncertainty of AEP, fatigue

WAsP
SmartWake client

Cloud Cluster
SmartWake Server

Wind farm SCADA owners

Wake Modelers

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Uncertainty & Wake
Conclusion

- The N.O. Jensen model, the G.C. Larsen model and Fuga are robust engineering models able to provide accurate predictions using wind direction sectors of 30°.

- The discrepancies for narrow wind direction sectors are not caused by a fundamental inaccuracy of the current wake models, but rather by a large wind direction uncertainty included in the dataset.

- We need some models and measurements for wind direction uncertainty to move forwards from this stage.

- Do not "tune" your wake models to match the ±2.5° measurements!!!
Future work

Wind Farm Flow Model Uncertainty

- The method will be applied to other wake models and datasets
- Sample based uncertainty quantification to be investigated
- Work on estimating the wind direction uncertainty using the wind farm dataset

System Engineering

- Opening FUSED-Wind to the public
- Adding Uncertainty Quantification to FUSED-Wind
Thank you for your attention!

- Work funded by EUDP-WakeBench and EERA-DTOC
- Dataset graciously made available by DONG Energy and Vattenfall.
- Article submitted to wind energy and master thesis available on request