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

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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

Cluster

PC

FUGA Light
InfiniPARK
Larsen’s
stationary

DWM-HAWC2

FUGA

Infinite WF

Rapid-DWM

NO Jensen

Instationary

Stationary
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

Rotor diameters [-]

270°
Introduction

Results of the Wake Model Benchmarking: Confusion!

270° ± 2.5°

270° ± 15°
Introduction

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

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The effect of wind direction uncertainty on wind farm wake measurement

[Graph showing the power ratio P2/P1 as a function of wind direction]
Introduction

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

**Sources of wind direction uncertainty**

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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)
## Sources of wind direction uncertainty

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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.
Introduction

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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

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

**The proposed method**

- **Step 1:** Run simulations with fixed and homogeneous wind direction
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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 ±3σ
- Step 3: Apply a linear average to reproduce the data post-processing
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 ± 2.5°</th>
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<tbody>
<tr>
<td>Power Data</td>
<td>64.7%</td>
<td>73.9%</td>
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<td>NOJ, Baseline</td>
<td>-20.9%</td>
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\[ \zeta_i(x_i) = \eta(x_i) \] (1)
$z_i = \zeta_i(x_i) + \varepsilon_i = \eta(x_i, \theta) + \delta(x_i) + \epsilon_i$
Machine Learning and Physical Modelling

System Engineering - Augmented Intelligence
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

P-E. Réthoré
Wake Modelers

Wind farm SCADA
owners
A Future Business Concept

I want to plan a wind farm

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I want my wake model to be useful

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I want add value my wind farm SCADA data

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Uncertainty of AEP, fatigue

? t0 result

? t1 result

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P.-E. Réthoré
DTU Wind Energy

t0 result

t1 result
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