WHEN TRUST MATTERS

Boundary layer educated long range wake estimates from WindFarmer CFD.ML

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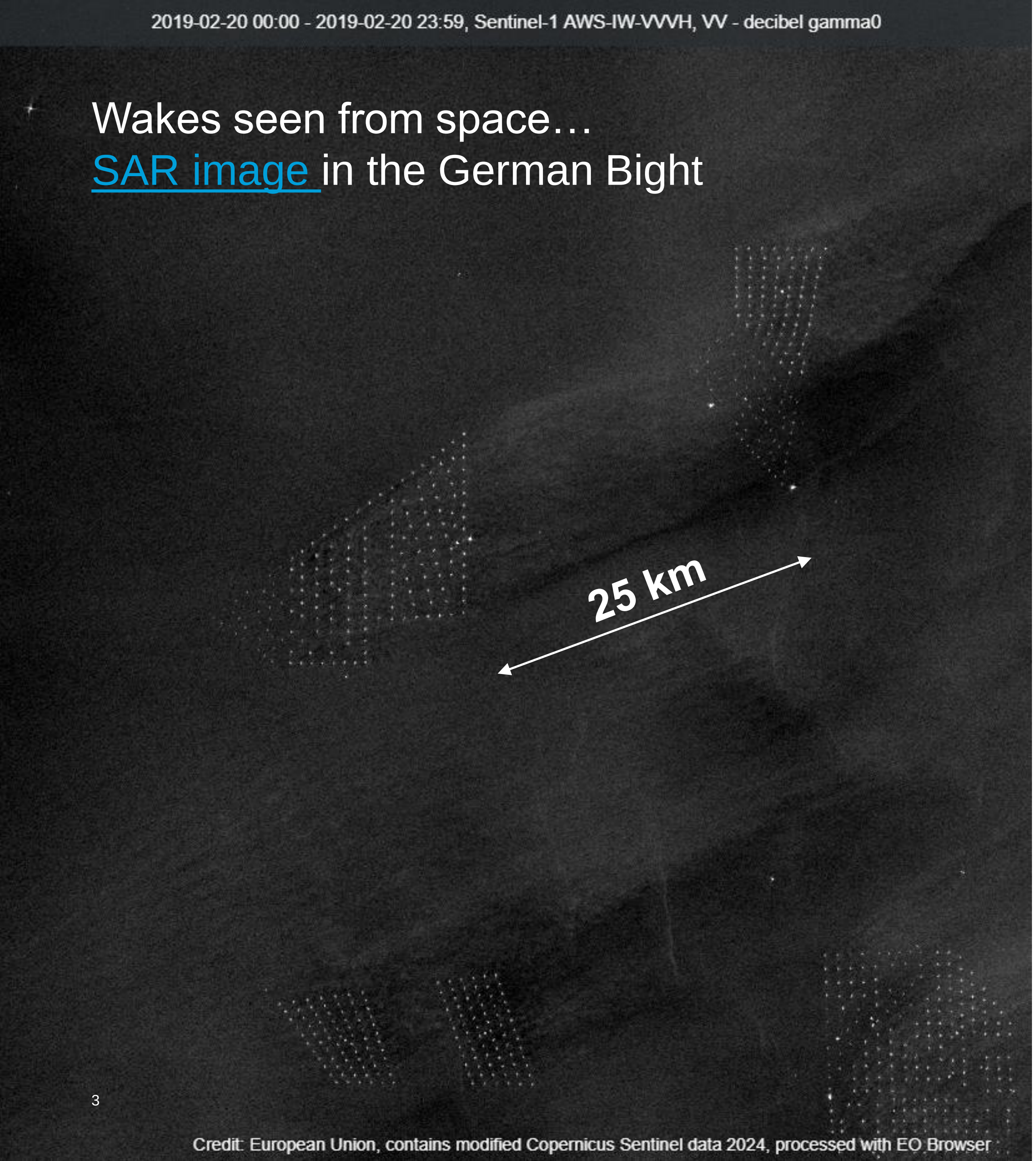
Overview

- The problem of modelling long-range wakes and background
- High fidelity modelling solutions
- Retraining CFD.ML
- Verification against CFD
- Validation against SCADA



Long range wakes

- Wind farm wakes significantly impact AEP, and propagate significant distances.
- We are designing bigger future projects
  - Bigger turbines!
  - More turbines in each farm!
  - Large clusters of wind farms!
- There is significant uncertainty predicting long-range wakes of tomorrow's projects prediction using engineering models validated against older wind farms.

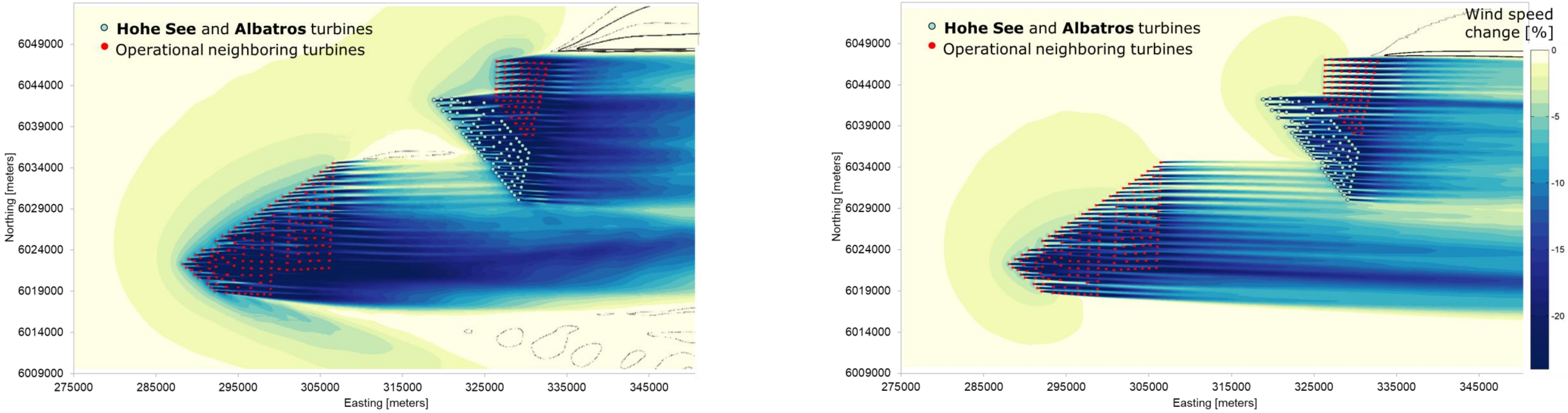
WRF-to-CFD provides a high-fidelity solution

DNV's WRF-to-CFD high fidelity modelling avoids assumptions inherent in engineering models, simulating wind farm wakes across a range of atmospheric conditions.

Wakes in the stable atmosphere generally appear stronger and longer.

Stable atmosphere.

Unstable atmosphere.



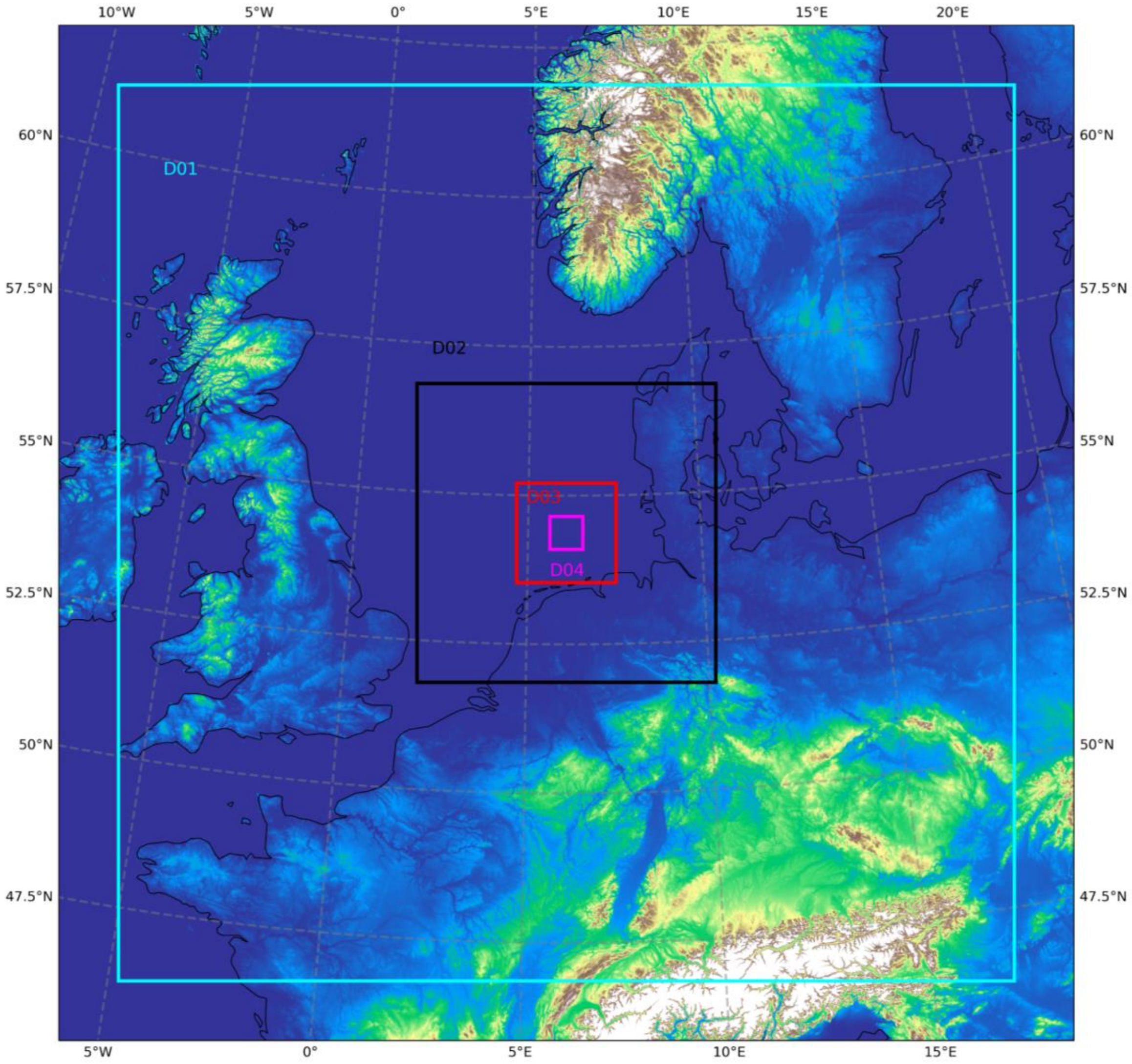
Sources: DNV, EnBW Blockage and cluster-to-cluster interactions from dual scanning lidar measurements

Numerical simulation models setup (WRF-to-CFD)

- Mesoscale WRF model:
  - 4 nested domains: 1600 km to 60 km
  - Vertical levels : 41 overall (up to 19.3 km)
  - Driven by ERA-5 reanalysis
  - Informs boundary conditions for CFD
- Microscale CFD model:
  - 1 domain: 60 km horizontal, 17 km vertical
  - Horizontal cells ranging from 4 m to 200 m
  - Steady state RANS (k-e, modified constants)
  - Transport equation for potential temperature
  - Turbines via actuator disk
  - Discrete set of directions (steps of 10°)

WRF=Weather Research and Forecasting

CFD=Computational fluid dynamics



But RANS CFD is computationally intensive…

It is a good idea to apply high fidelity modelling at some stage in the project to understand impacts of site-specific atmospheric conditions.

The challenge is how to consider these impacts when:

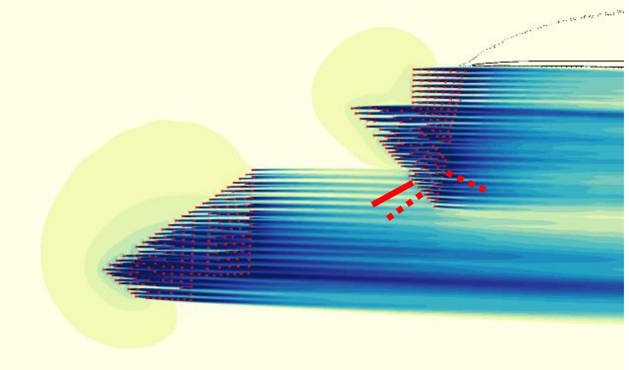
- Performing wind farm design optimisation, assessing 1000s of layouts
- Where this is little budget at early stages of project development
- To assess the impact of small changes to the project

Introducing CFD.ML

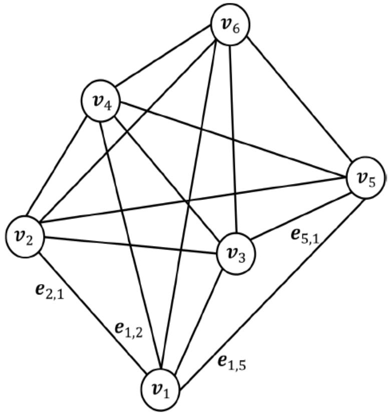
WRF-to-CFD + A.I. = CFD.ML

DNV's WRF-to-CFD RANS modelling of wind farm flows.

The highest fidelity modeling applied at scale in wind farm energy production assessments.



Machine learning model based on graph neural networks.



PAPER • OPEN ACCESS

A Graph Neural Network Surrogate Model for the Prediction of Turbine Interaction Loss

To cite this article: James Bleeg 2020 *J. Phys.: Conf. Ser.* **1618** 062054

A surrogate model for RANS CFD applied to turbine interaction modeling.

Fast enough to use in wind farm optimization context.

Captures flow physics better than engineering wake models

no up-front tuning to SCADA

PAPER • OPEN ACCESS

A Graph Neural Network Surrogate Model for the Prediction of Turbine Interaction Loss

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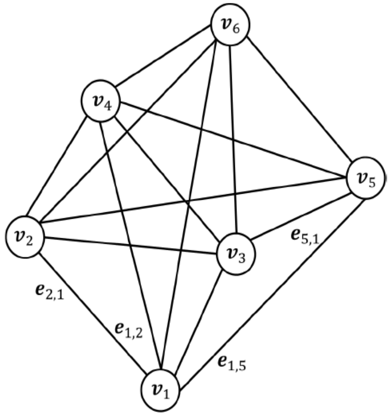
What's a graph neural network?

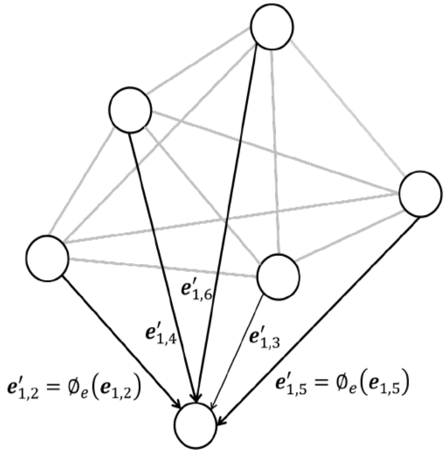
Graph neural network:

- is well suited to learning physical interaction between objects
- allows for varying number of inputs (turbines)
- is order invariant

The GNN predicts **wind speed deficits** at the i-th turbine caused by wake & blockage.



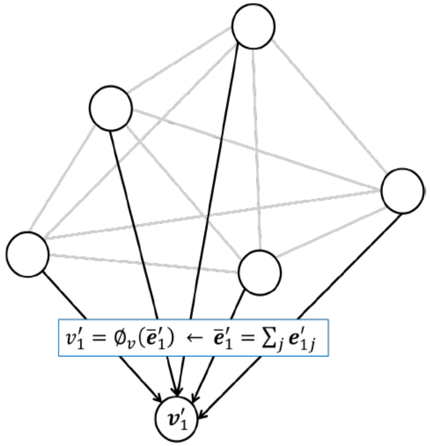
Graph vertices = objects (turbines)



Graph edges = relationships between objects (wakes)

calculation of wake impacts coming from all neighbors as function of:

- downwind and crosswind distance to the sender
- Ct, rotor and hub-height of the sender



Aggregate all impacts on the i-th turbine

DNV AI assurance experts have evaluated:

- the model
- the training setup

Both seem robust, a scientific paper is pending

DNV

AI model development process

Train & Test

- We train the GNN “brain” of CFD.ML to replicate the Turbine Interaction Loss Factors predicted by CFD

Verify

- We verify the new model against CFD data held completely outside the training and test data

Validate

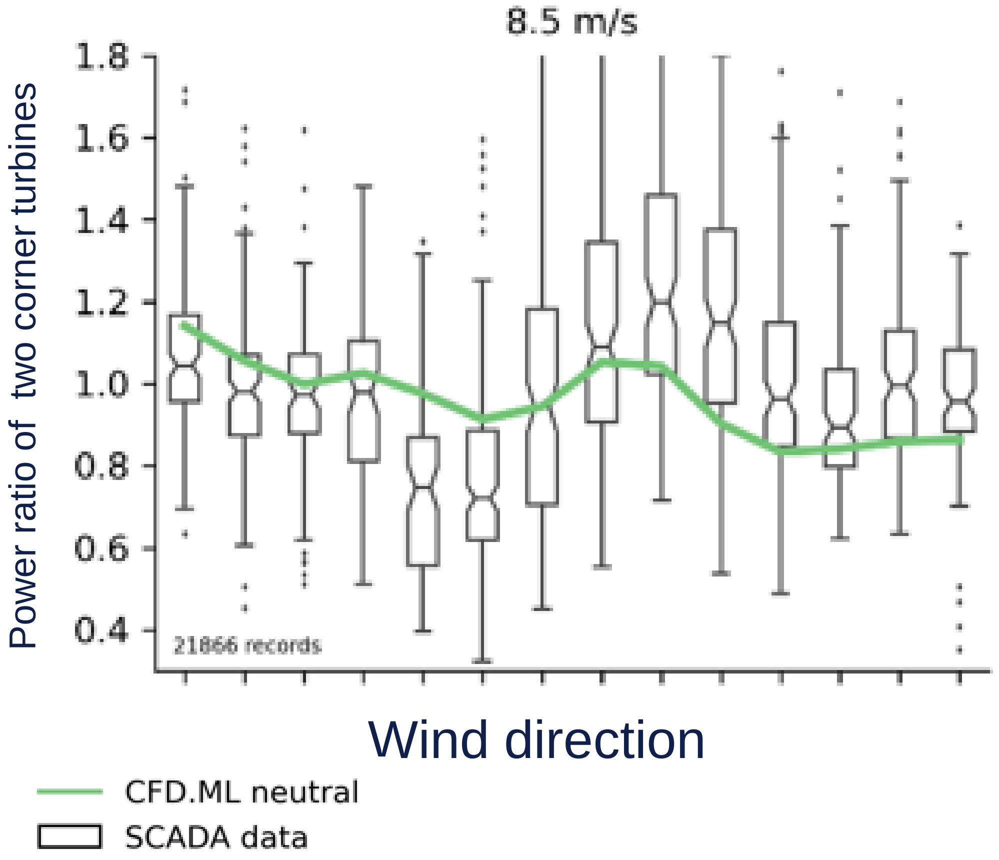
- Against real world measurements (e.g. SCADA power)

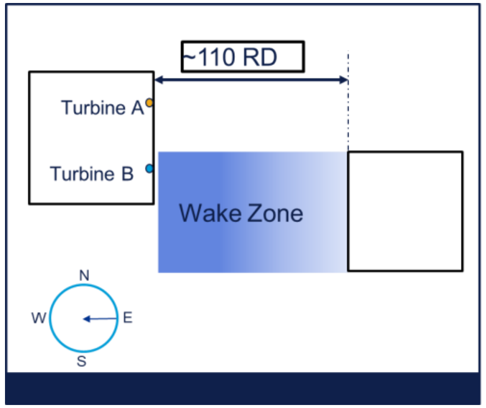
2023 CFD.ML Validation
- underprediction of *cluster wakes*

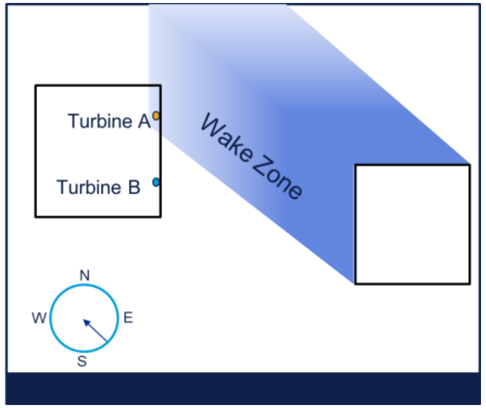
V1 CFD.ML, trained on only offshore neutral atmospheric conditions

- predicted blockage and internal wake impacts quite well
- fails to capture the cluster wake impact (right)

…but CFD.ML has learnt a lot since last year!



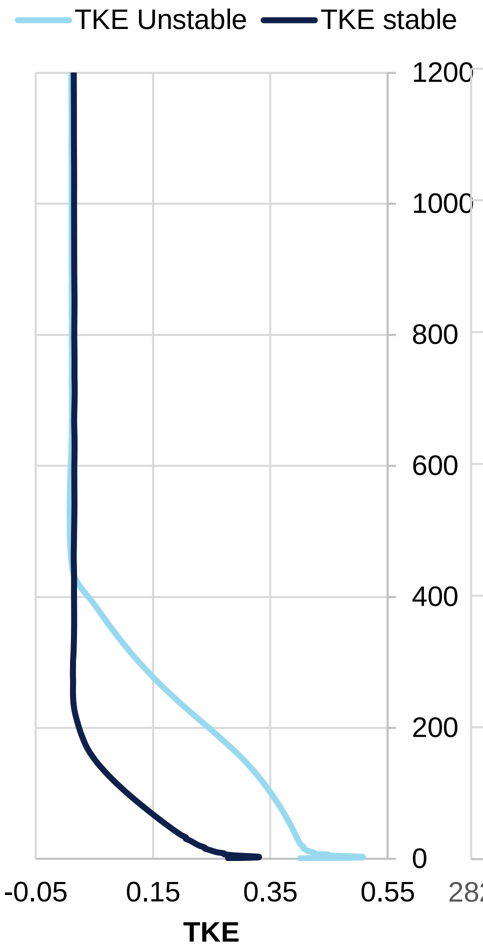


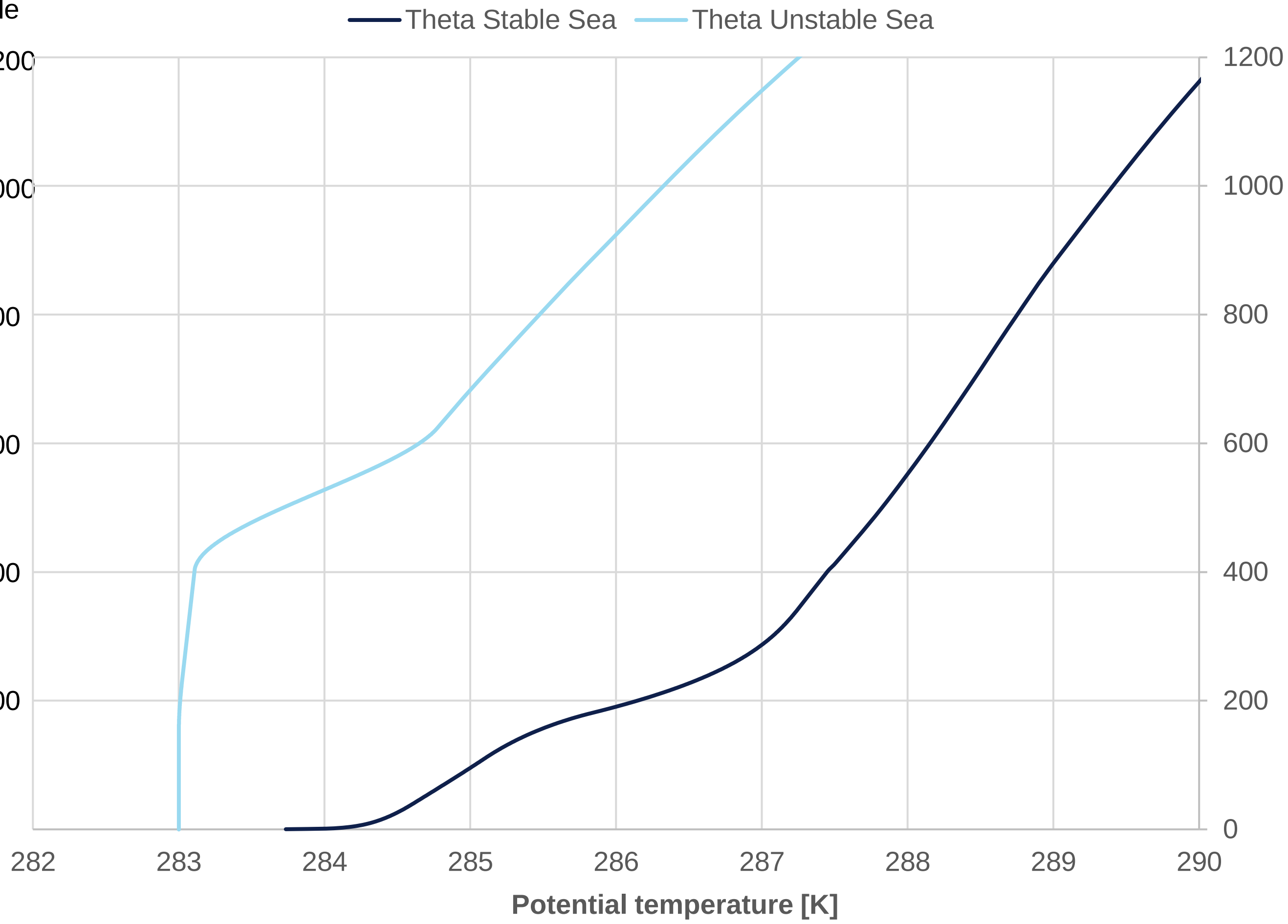


Atmospheric conditions
- stable and unstable offshore boundary layers

Vertical profiles of potential temperature and turbulent kinetic energy differ greatly in stable and unstable atmospheric conditions.

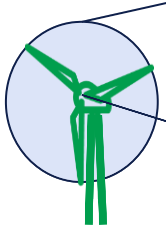
These profiles drive mixing in the atmosphere, how momentum is transferred from above, hence how fast wakes recover.



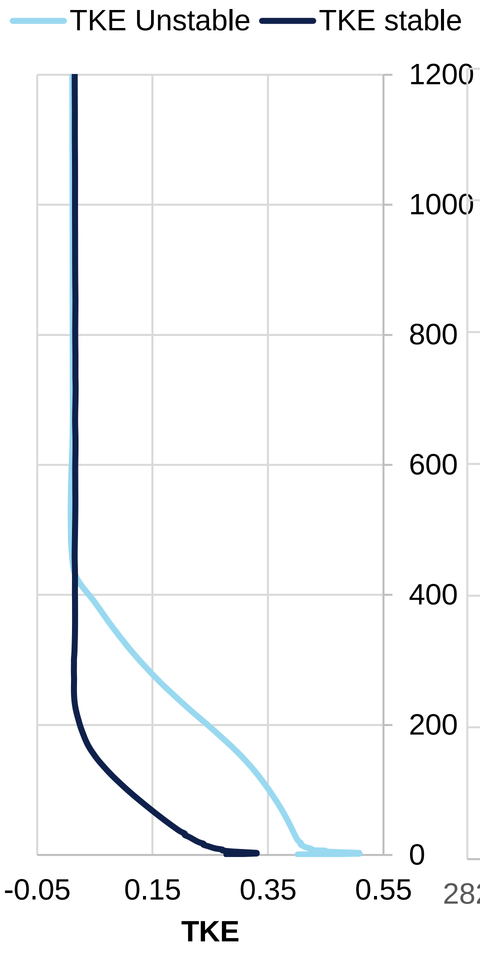


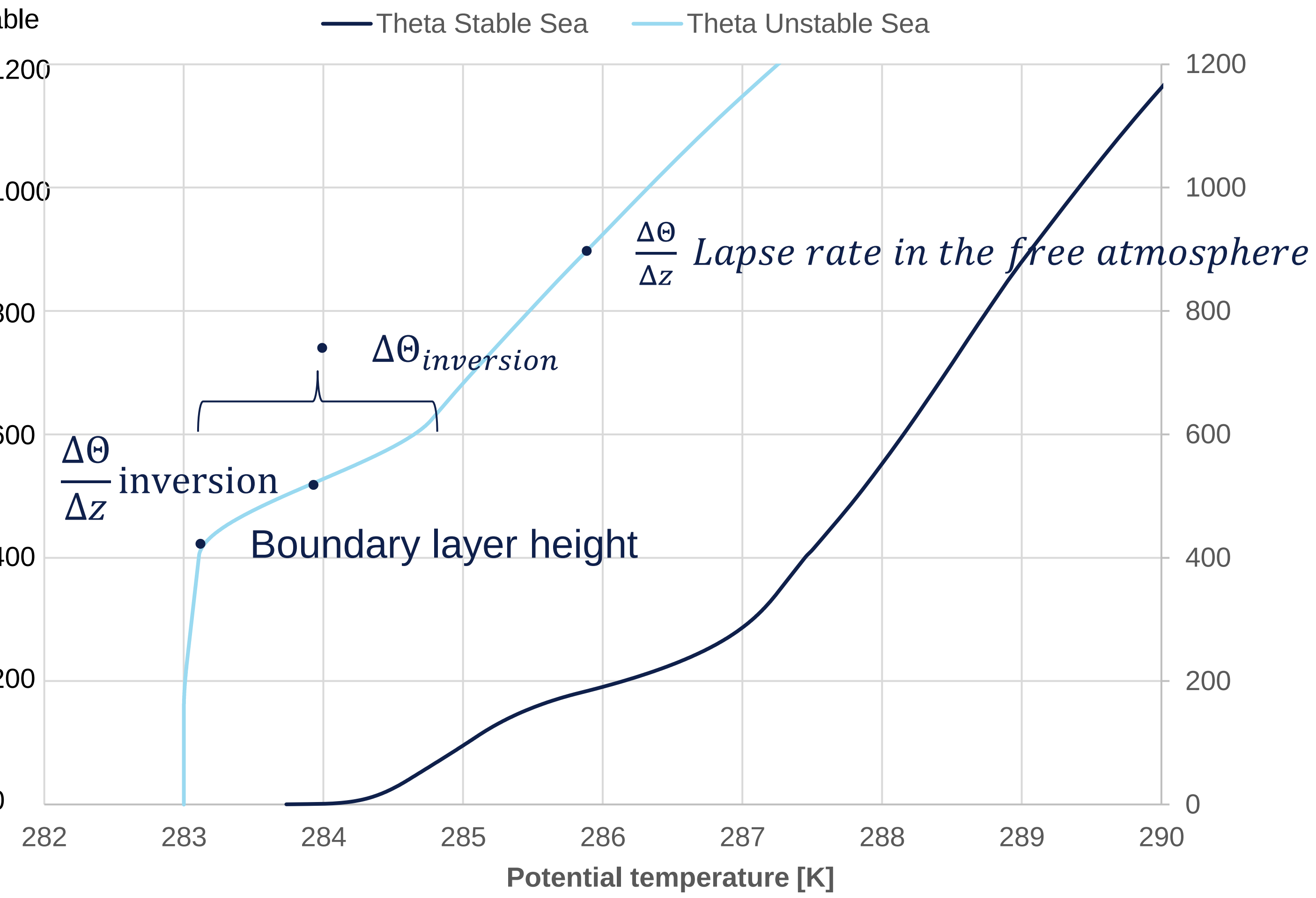
Atmospheric conditions
- inputs into CFD.ML

- X, Y
- Wind direction
- Rotor diameter
- Ct
- Coriolis parameter (Latitude)



- TI^{top}
- $\frac{dV}{dz}$ top
- U^{hub}
- Hub height
- TI^{hub}
- $\frac{dV}{dz} hub$





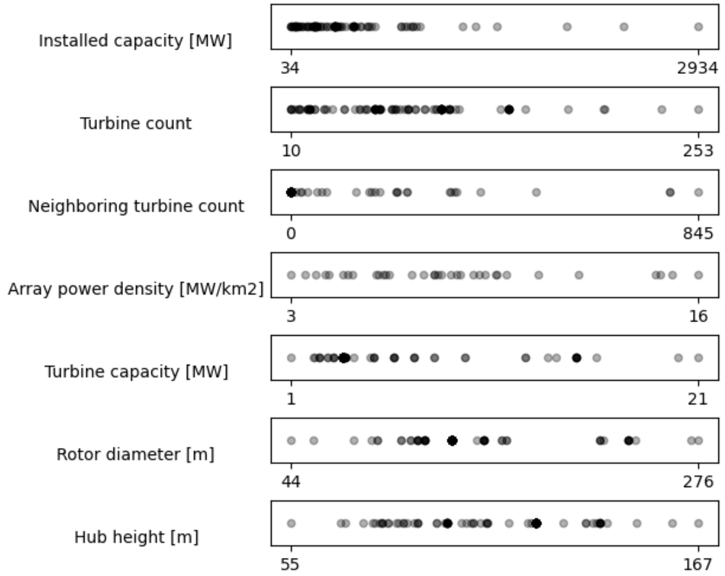
- Inputs included in the 2023 model
- Expanded inputs in the latest model

Training data

The CFD.ML V2 includes onshore and offshore wind farms across the full range of project sizes. A significant increase above the V1 training data.

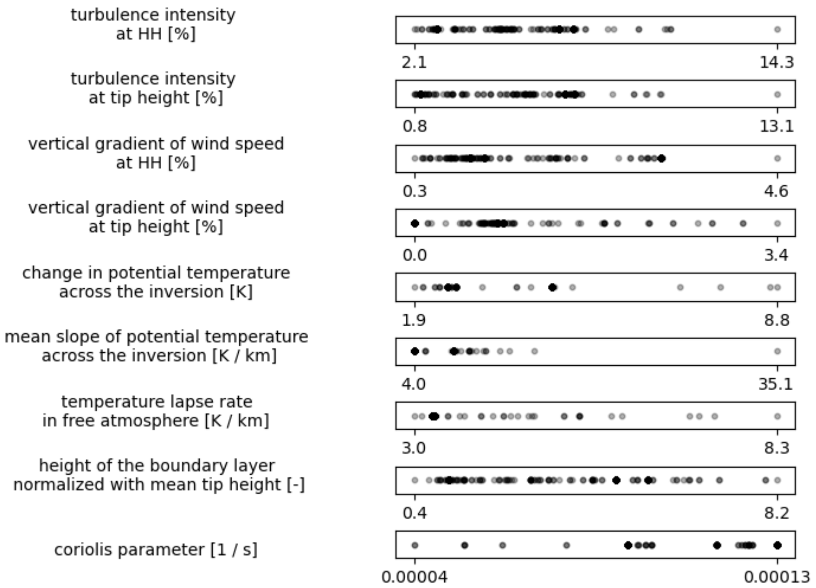
Windfarms	**119**
of which onshore	*79*
of which offshore	*40*
Turbines in wind farms	16,414
Simulation cases	2,620
Turbines simulated	71,579
Pairwise interactions	252,679,536

Wind farms



1 distinct case in training set

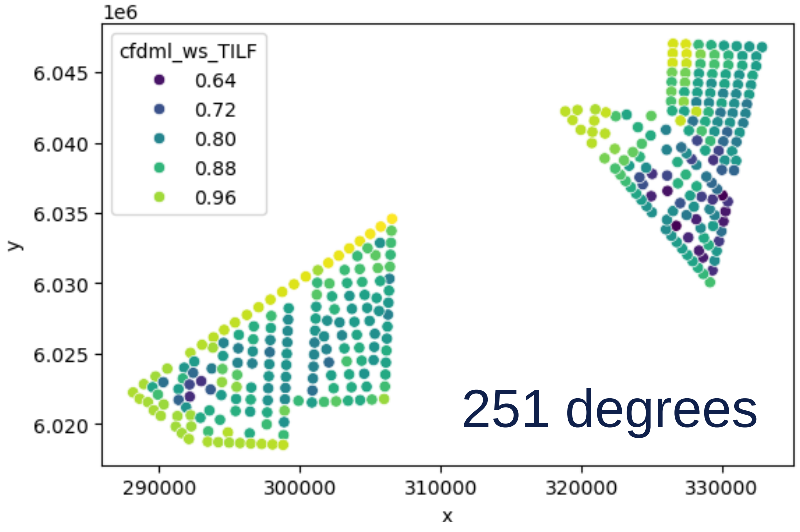
Atmospheric conditions

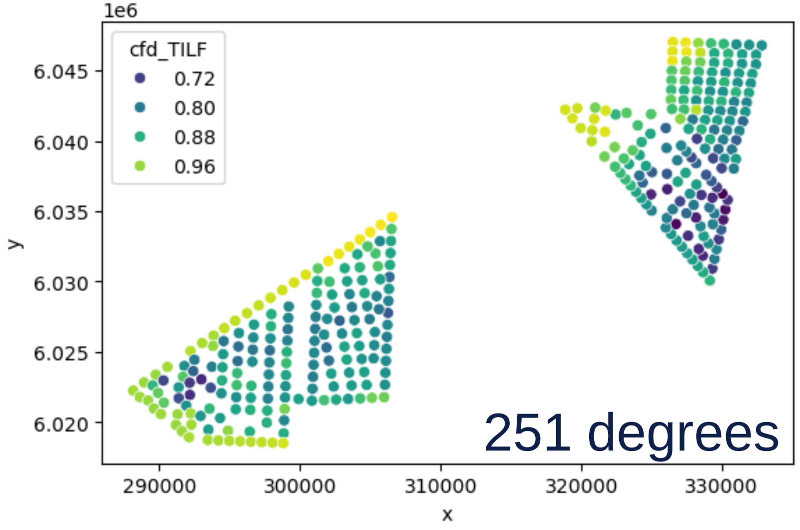


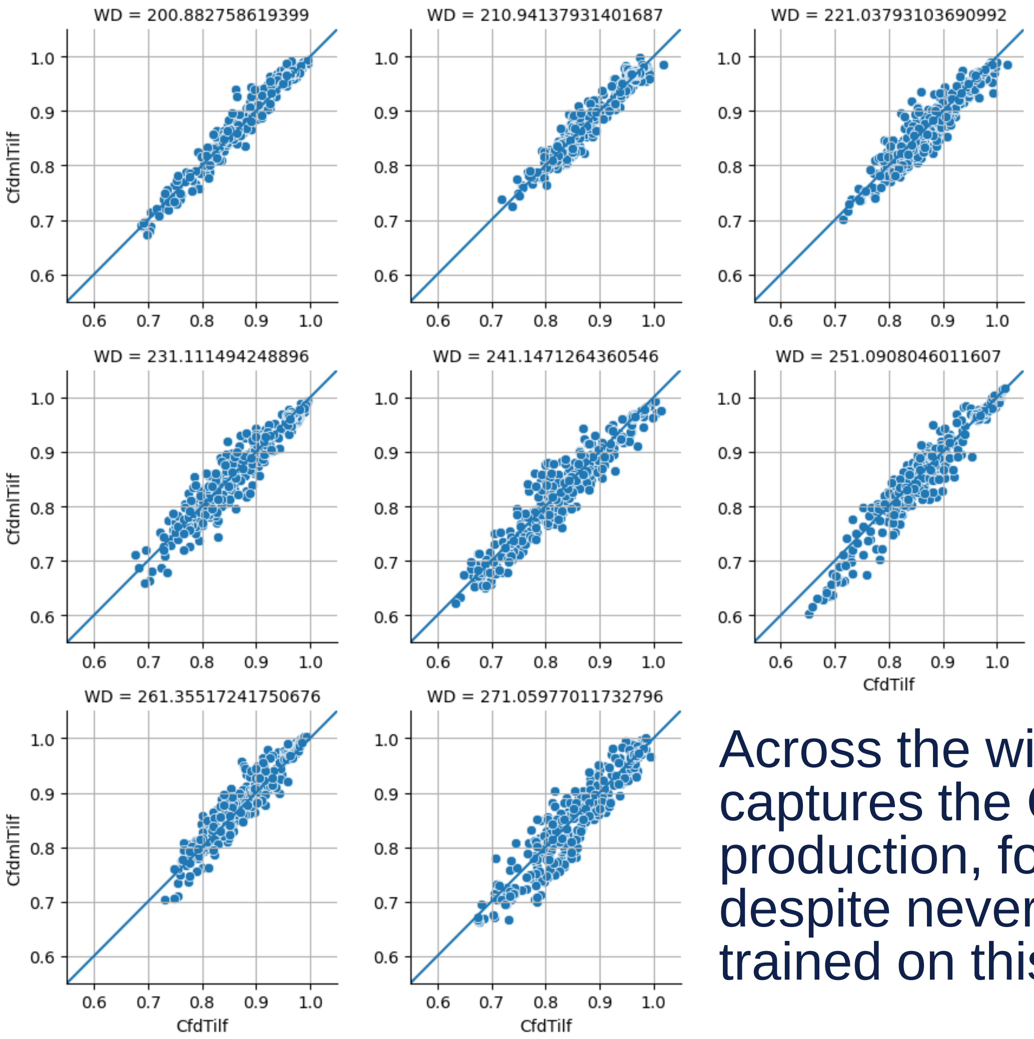
Multi-stability CFD.ML is trained against a full spectrum of atmospheric conditions

Verification of CFD.ML against CFD - Hose-Albatros

Wind speed turbine interaction loss factors in Unstable conditions





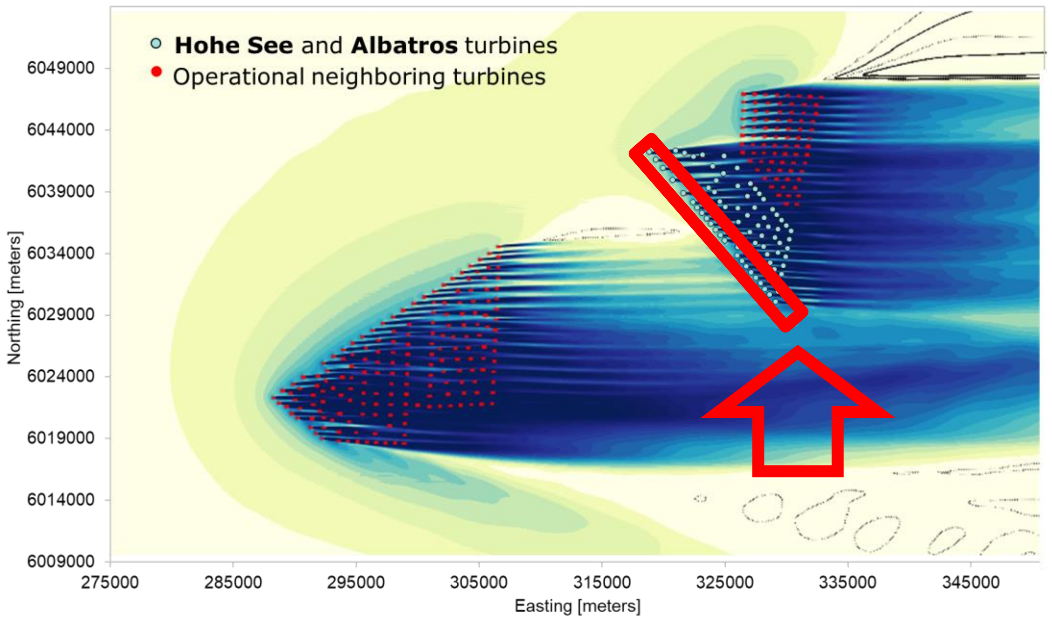


Across the wider cluster CFD.ML captures the CFD pattern of production, for all wind directions despite never having been trained on this cluster.

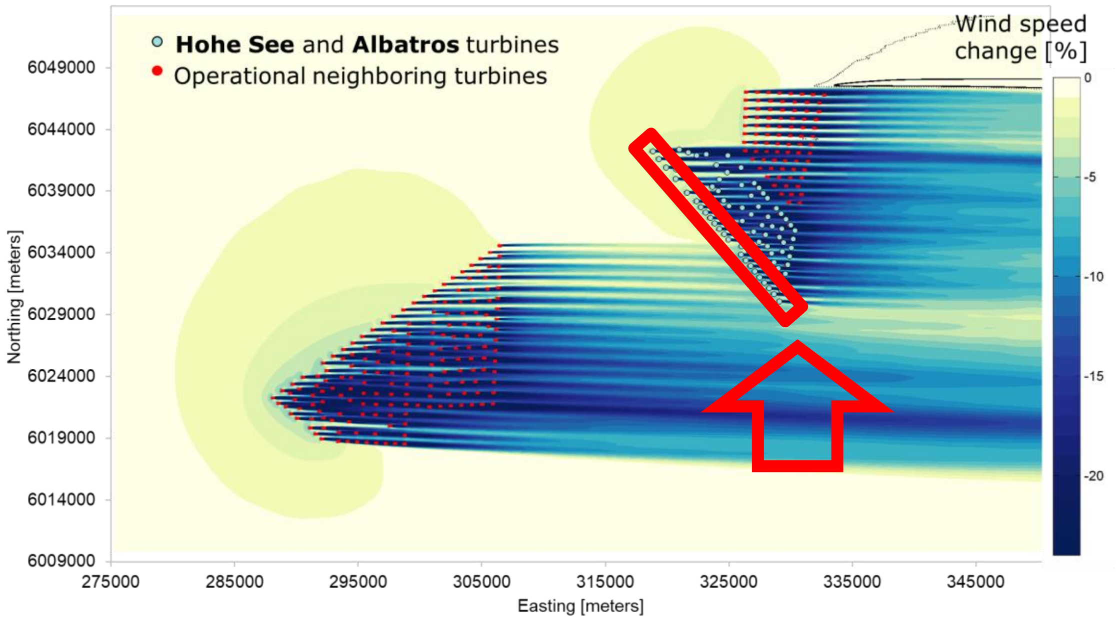
Sources: DNV, EnBW

Stable and unstable CFD at Hohe-See+Albatros

Stable atmosphere.



Unstable atmosphere.



Looking at the front row turbines, that are half waked…

Sources: DNV, EnBW Blockage and cluster-to-cluster interactions from dual scanning lidar measurements

Stable and unstable CFD at Hohe-See+Albatros

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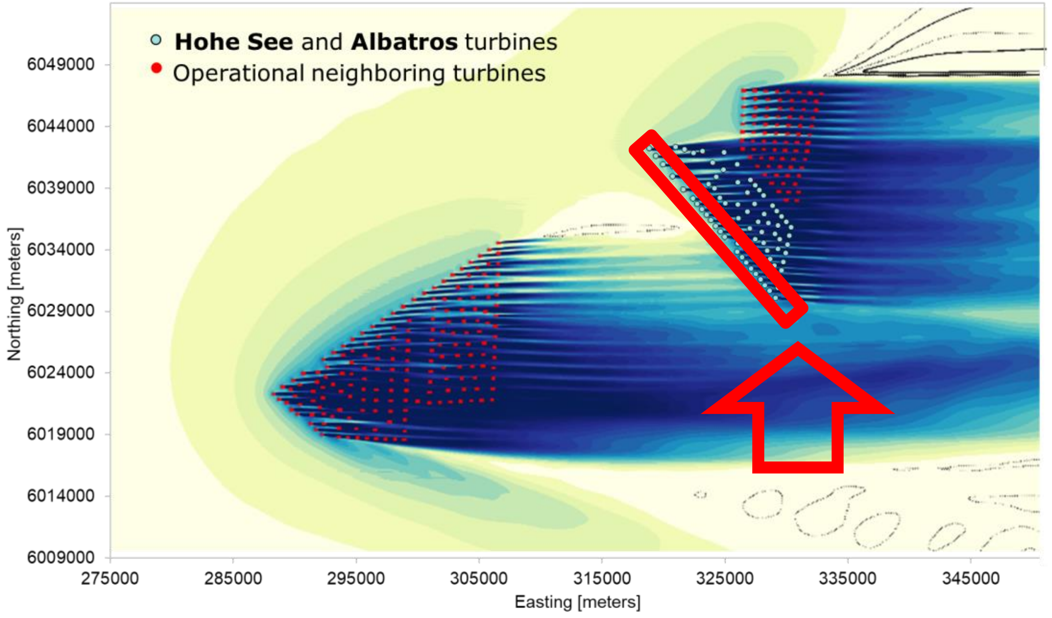

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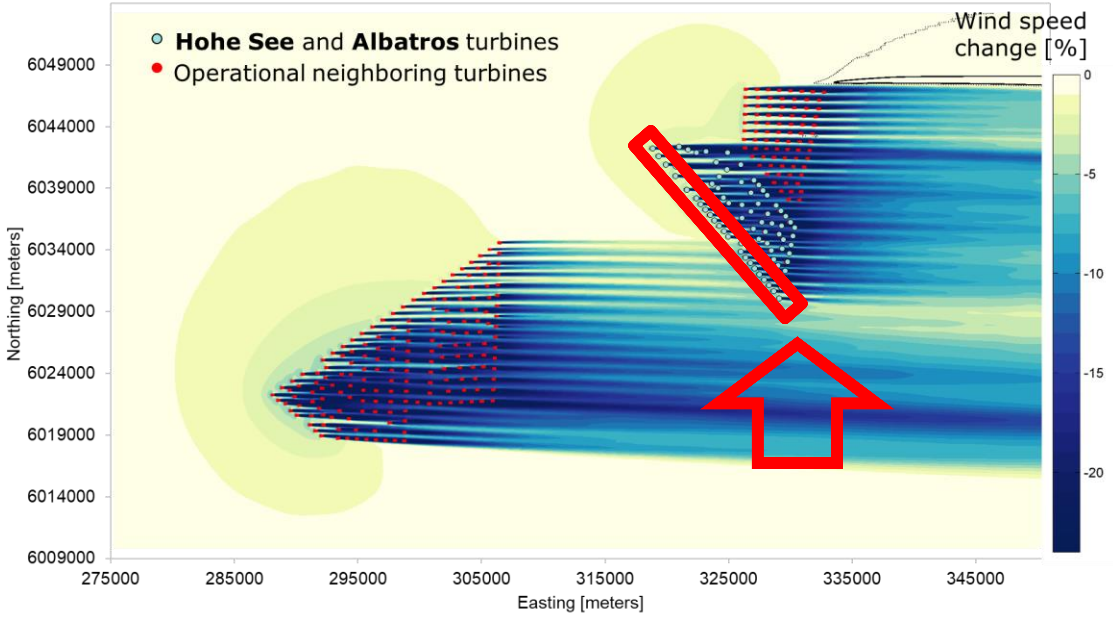

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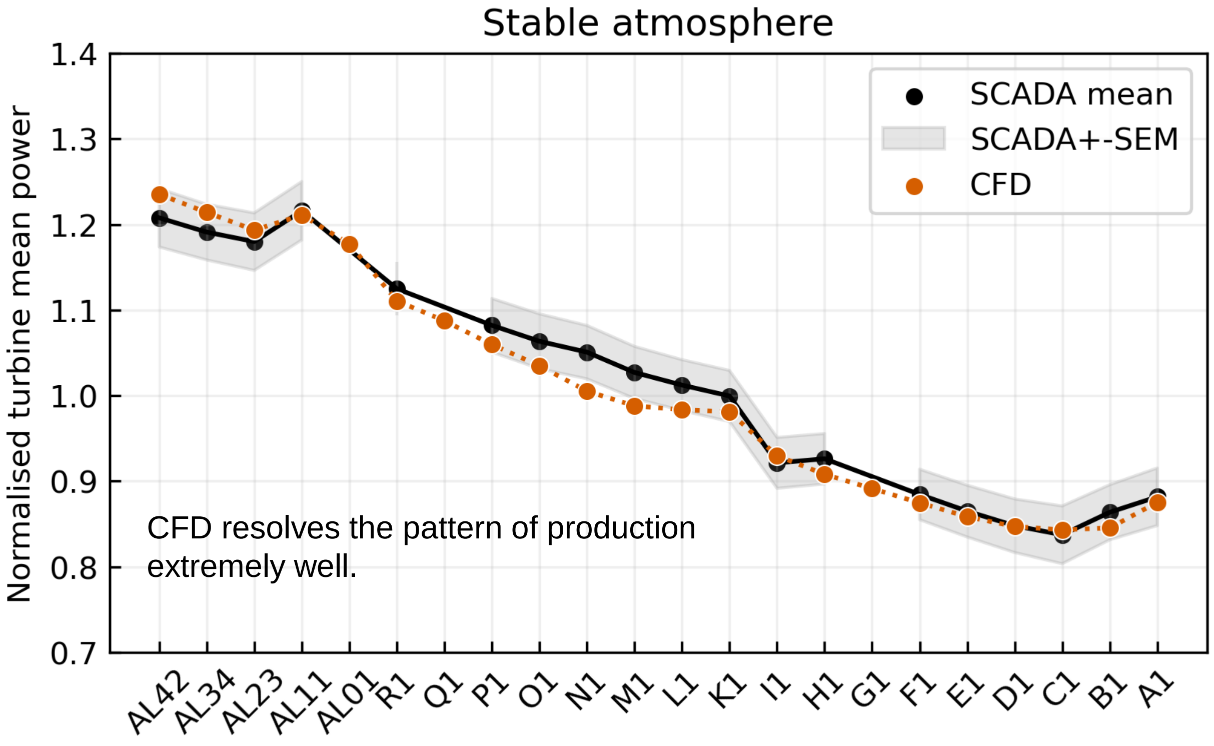
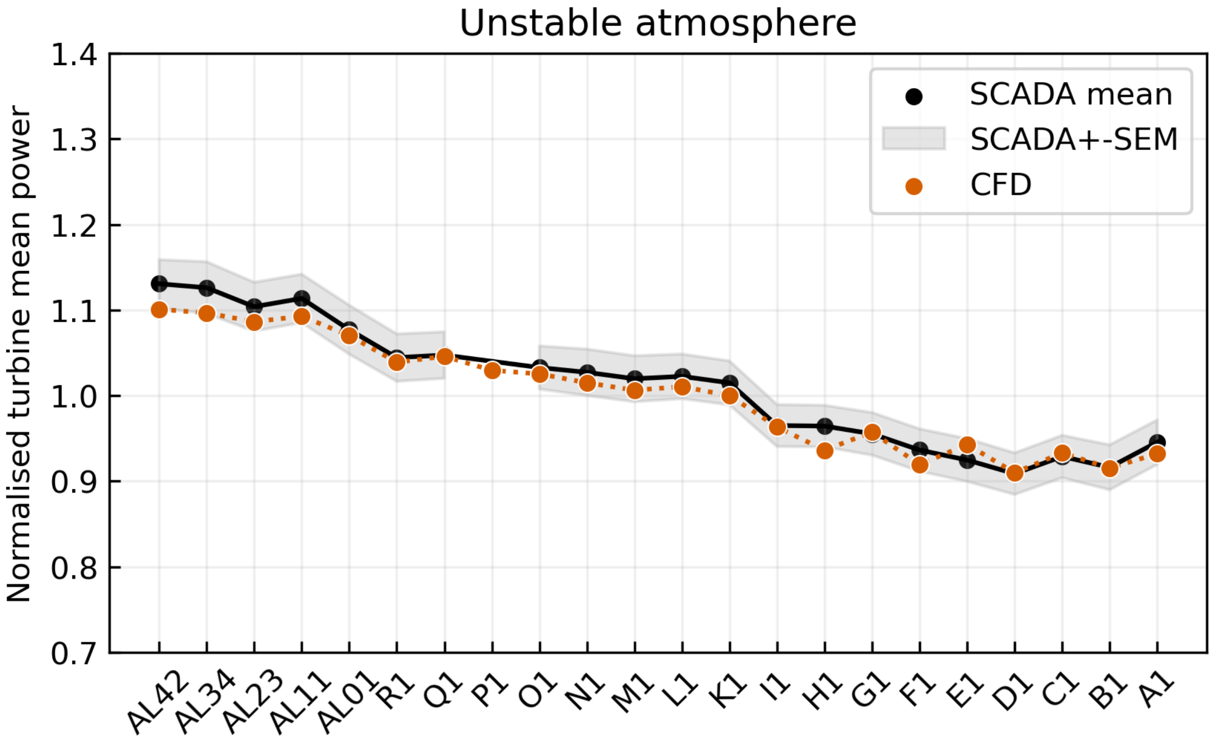
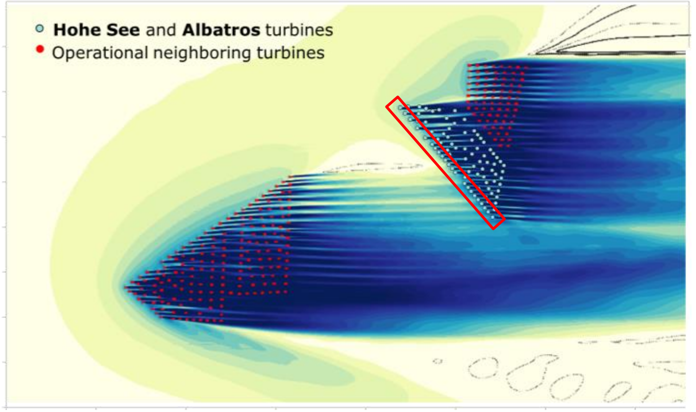
Front row PoP at Hohe-See+Albatros: CFD vs SCADA

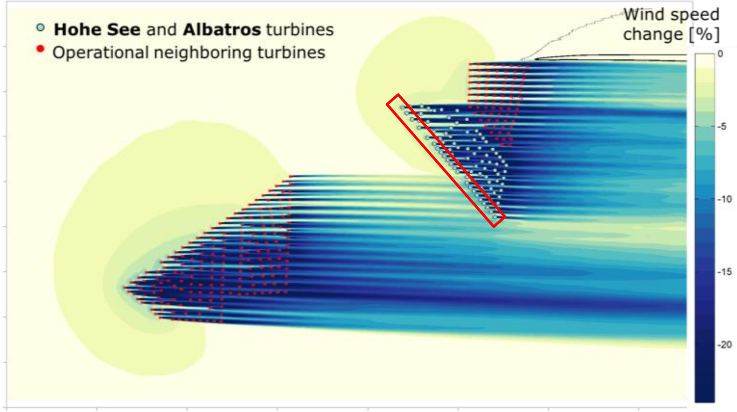






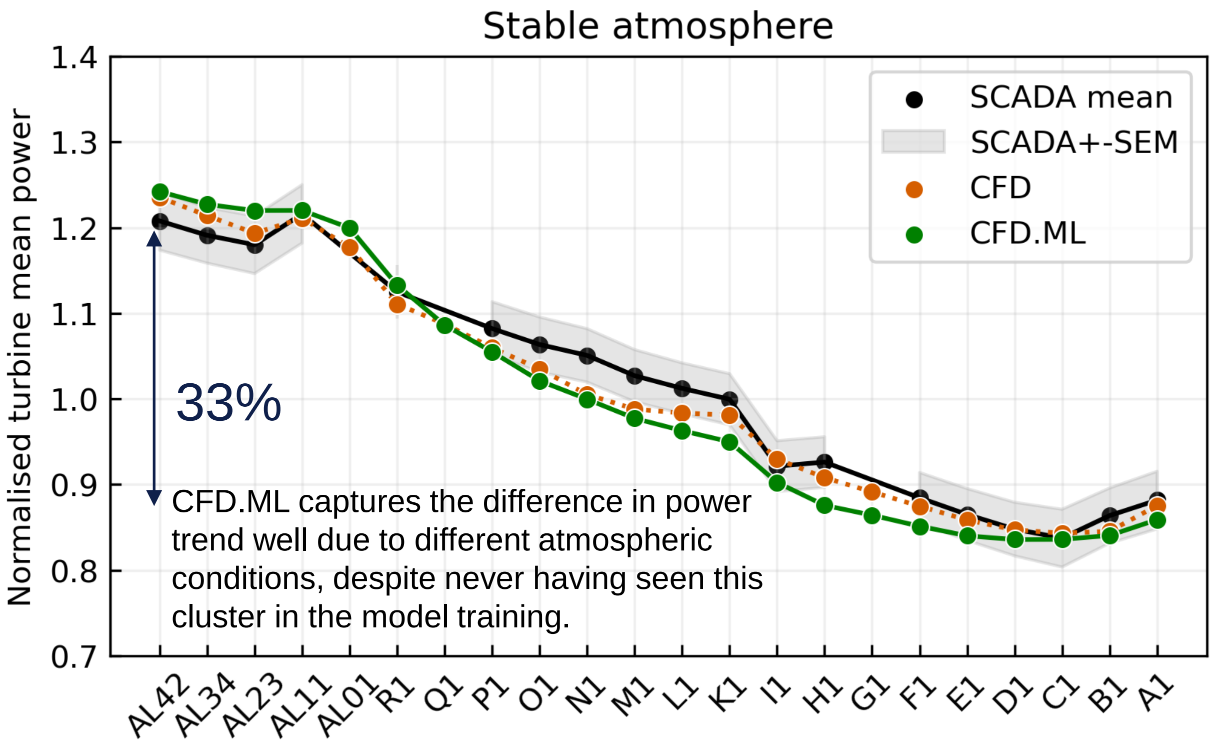
Plots show 253° to 283° bin average of front row turbines.

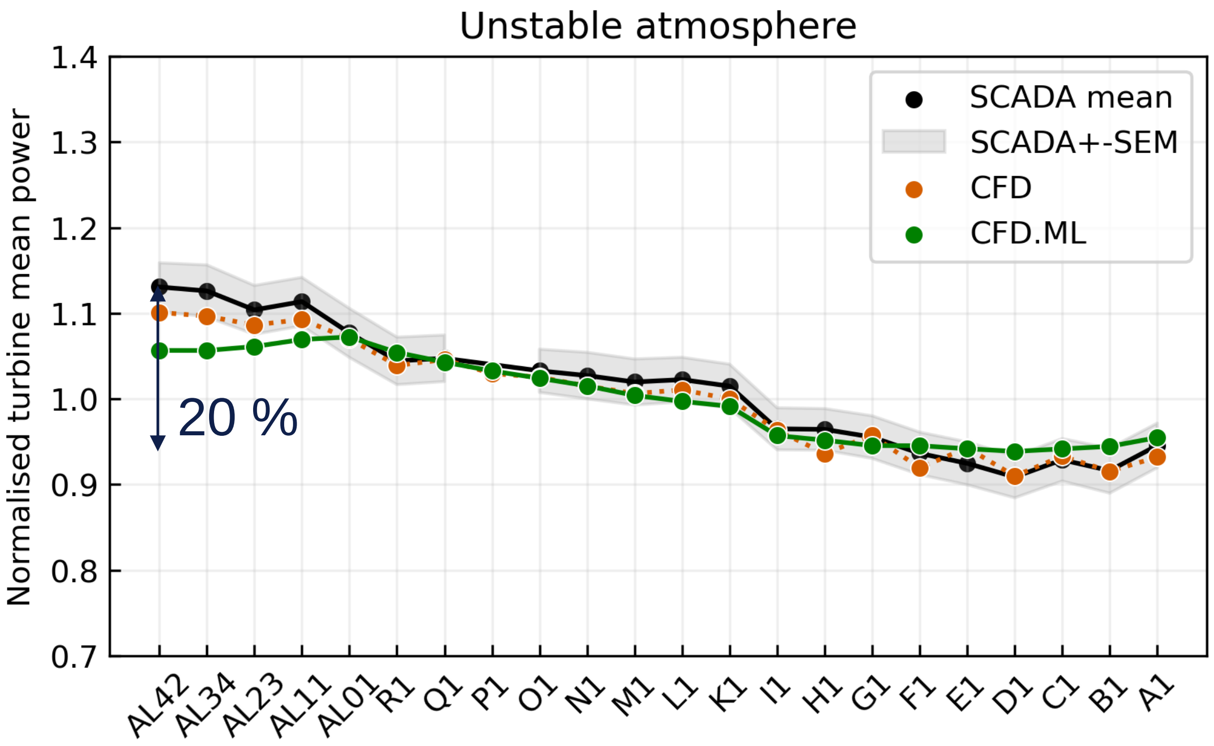
- Removed turbines with <0.95% availability
- Normalised to front row average power

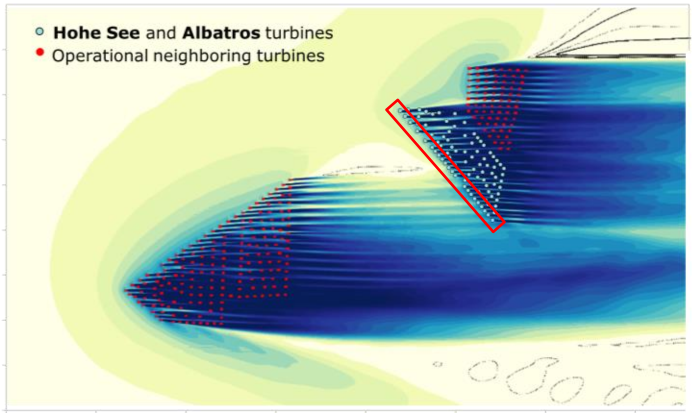


Sources: DNV, EnBW

Front row PoP at Hohe-See+Albatros: CFD.ML vs.CFD vs.SCADA







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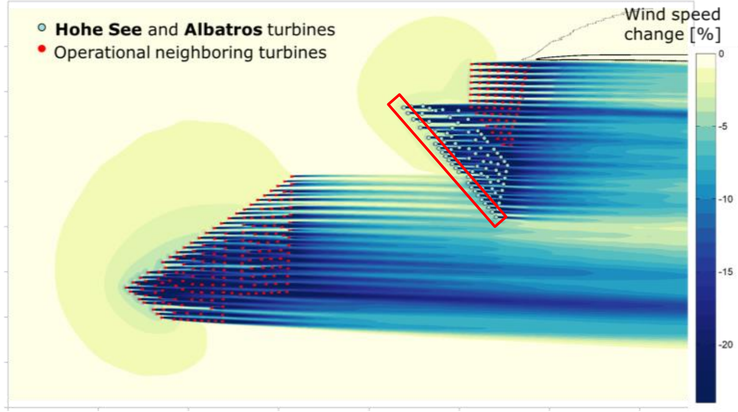
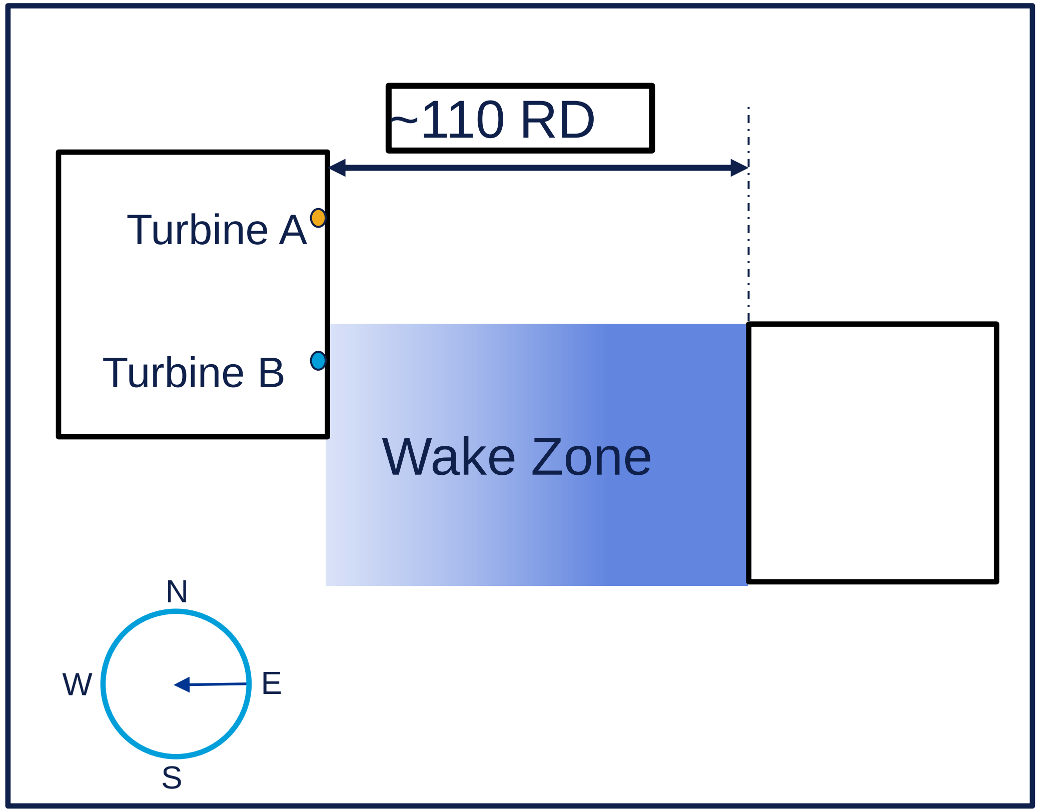


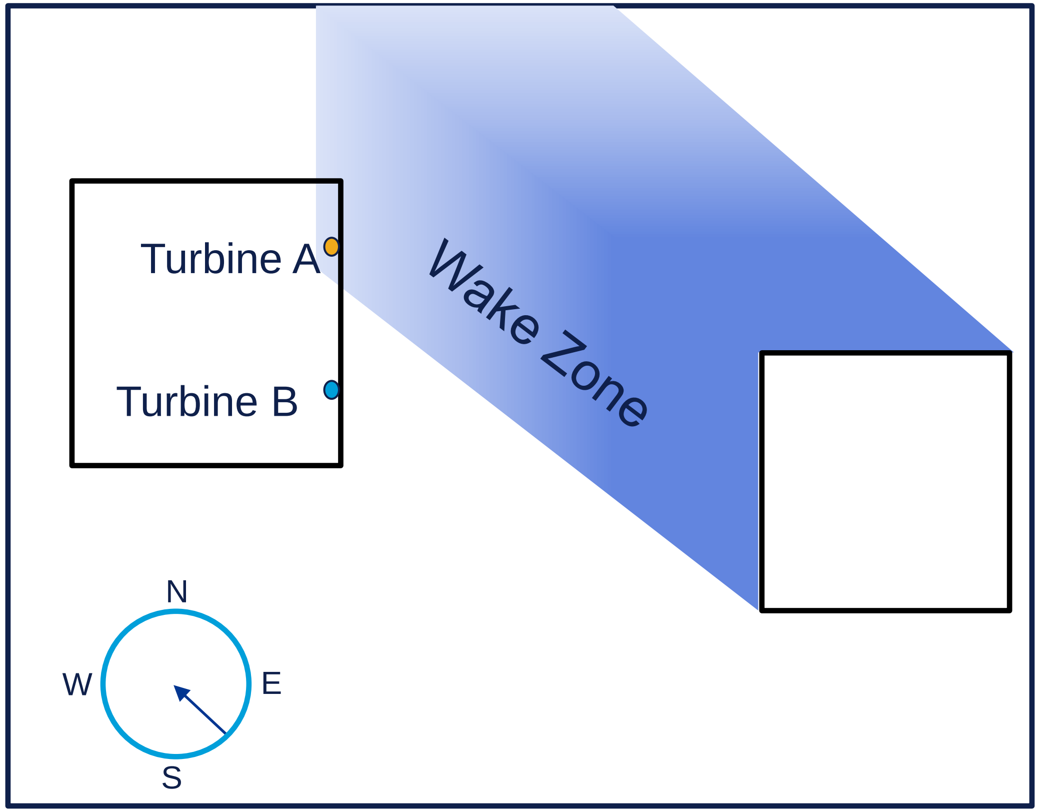
Sources: DNV, EnBW

DNV

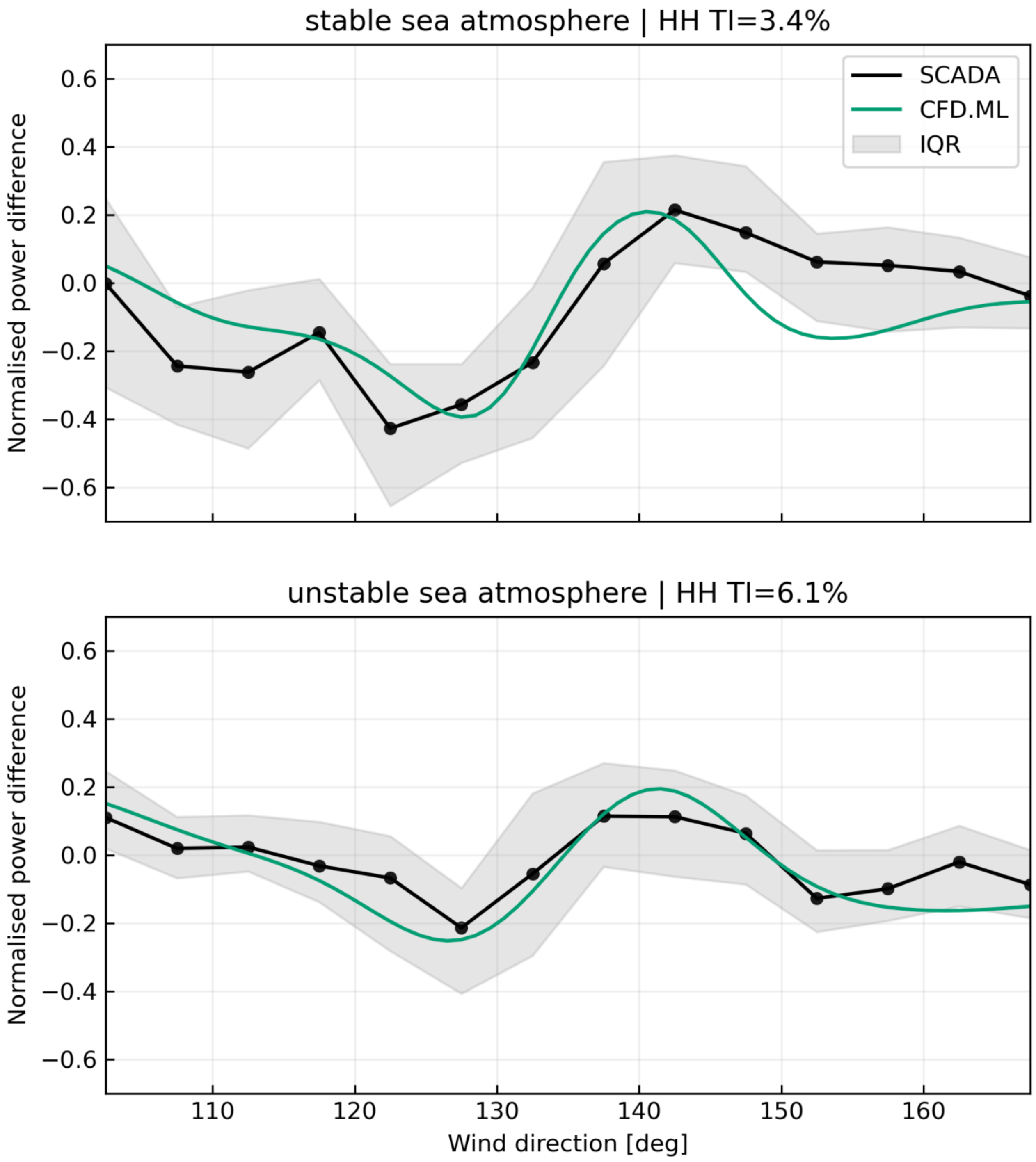
Validation against operational data

- cluster wakes measured via corner turbine power differences
- revisiting 2023 case





Normalised power difference =[P (TA) – P (TB)] / 0.5 [P (TA) + P (TB)]



Corner turbines normalised power difference by direction

Modelled data

- Gaumond averaging applied to by-direction modelled results
  - $\sigma = 3$ for stable CFD.ML
  - $\sigma = 5$ for unstable CFD.ML
  - *Note, some uncertainty in the choice of σ*
- Direction offset +13
- Reference wind speed on thrust curve plateau: 8 m/s

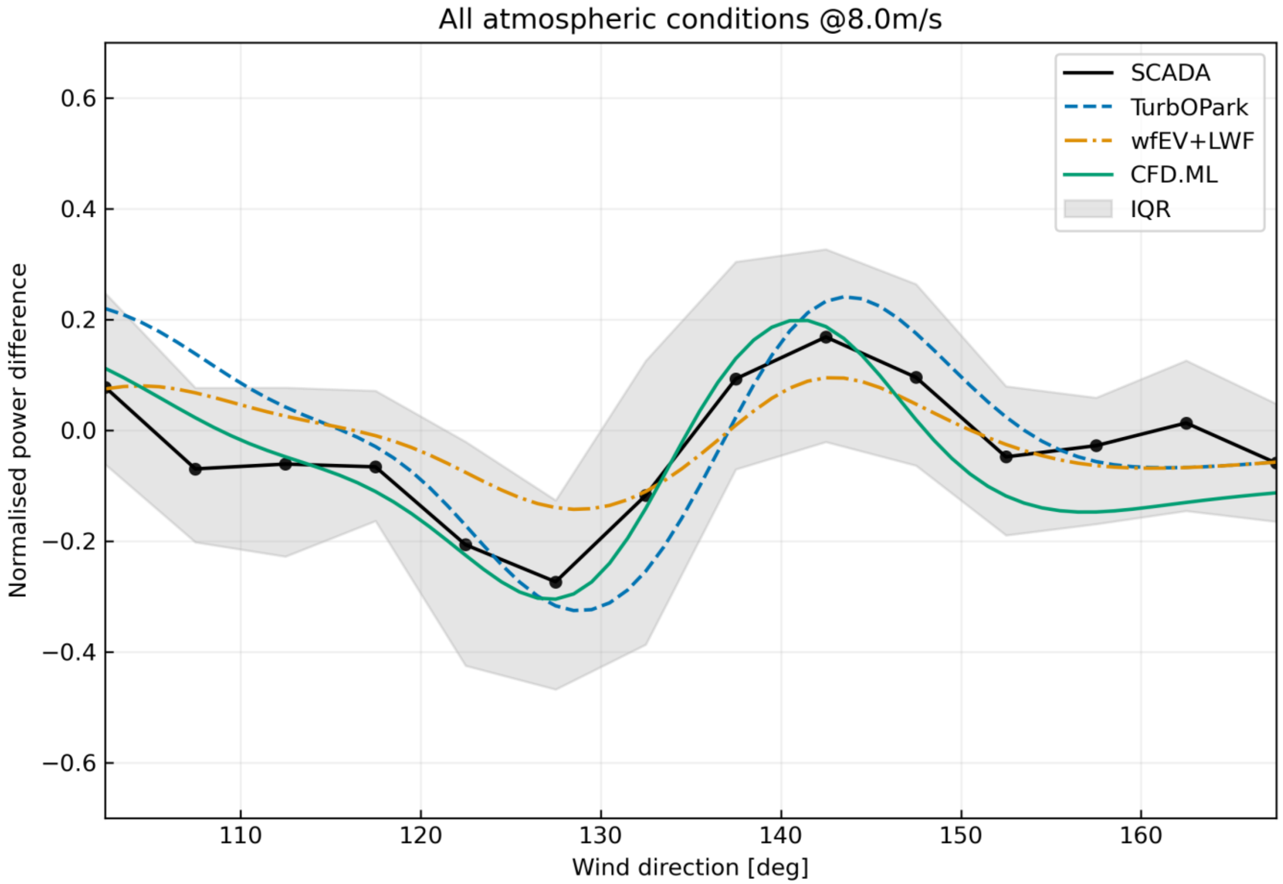
SCADA:

- Wind speed: 7.5 to 8.5 m/s
- 5-degree direction bins
- Stability split by Monin-Obukhov Length (MOL) from Vortex series
  - Unstable + Neutral = $\mathrm{MOL} < -50$ or $|\mathrm{MOL}| > 500$
  - Stable = $10 < \mathrm{MOL} \leq 500$

Normalised power difference =

[P (TA) – P (TB)] / 0.5 [P (TA) + P (TB)]

Corner turbines normalised power difference by direction – all data



- CFD.ML overall from weighted average of predicted stable / unstable Gaumond averaged powers: 41% stable
- For wfEV+LWF and TurbOPark
  - TI = 5.3 %
  - $\sigma = 4$ for Gaumond average
- All models
  - Reference speed ~8 m/s
  - Direction offset +13

Summary

- Continued and expanded training has improved the WindFarmer CFD.ML model's ability to model offshore long-range wakes, across a range of atmospheric conditions
- CFD.ML v2 predicted stronger long-range wakes than WindFarmer's eddy viscosity + LWF model at our test site.
  - Note this is one wind speed, integration over all speeds for AEP may show less discrepancy.

Next steps

- Defining the process for creating the atmospheric conditions inputs
  - Regional input pre-sets will allow a straightforward analysis, but more accuracy likely when using inputs customised for your project.
- Repeat previous validations for internal wakes and blockage using WindFarmer CFD.ML v2

You can get access to WindFarmer's CFD.ML via the WindFarmer web API

- v1 available now
- v2 release planned during summer 2024
- Contact us at windfarmer@dnv.com

Thanks To

- **James Bleeg** for the persistent R&D efforts that underpin this work,
- **Miguel Fernandes** and **Karol Mitraszewski** for model refinement, deployment and verification
- **Christiane Montavon** for valuable insights and feedback
- **Olly Maunder** and **Rick Edwards** for building the scalable cloud compute architecture to enable simulations of larger wind farms with WindFarmer CFD.ML
- **EnBW** and **Enbridge** for granting permission to make the validations conducted at the Hohe See and Albatros offshore wind farms public.

Find out more

https://www.dnv.com/software/services/windfarmer/

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