WHEN TRUST MATTERS

AI for turbine interactions

Testing the intelligence of CFD.ML

Karol Mitraszewski, Tom Levick, Jim Bleeg, Christiane Montavon, Miguel Fernandes

WindEurope Technology Workshop, Lyon, 2nd June 2023

Agenda

- What’s under the hood of CFD.ML
- Validation
- Planned model improvements

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Is CFD.ML an AI black box?

DNV builds trust around it through:

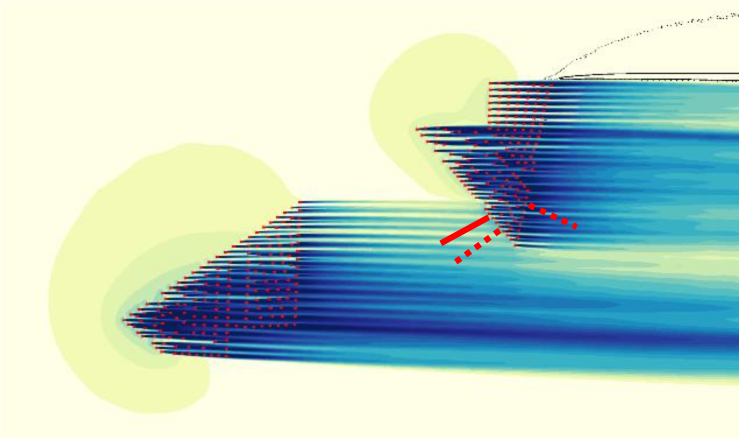
- ✓ Transparent documentation,
- ✓ Carefull validation,
- ✓ And application within the training set envelope.

What is CFD.ML?

CFD

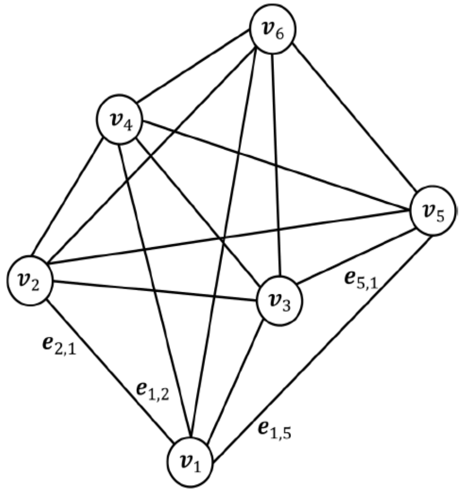
DNV’s CFD RANS modelling of wind farm flows.

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



ML

Machine learning model based on graph neural networks.



CFD.ML

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

What’s a graph neural network?

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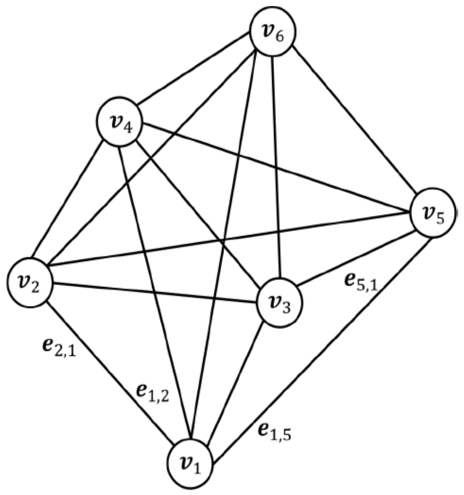
A Graph Neural Network Surrogate Model for the Prediction of Turbine Interaction Loss

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

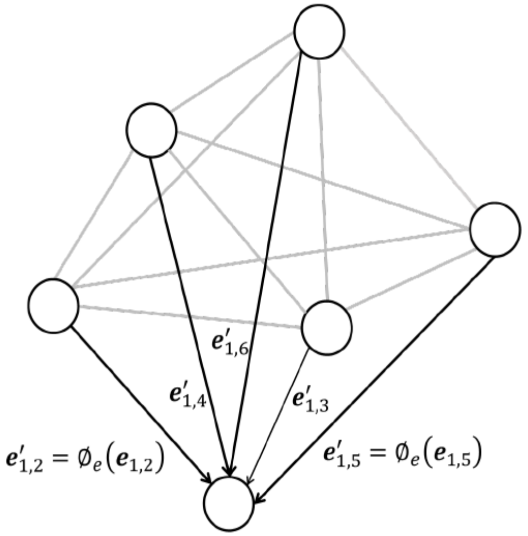
Graph neural network:

- 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.



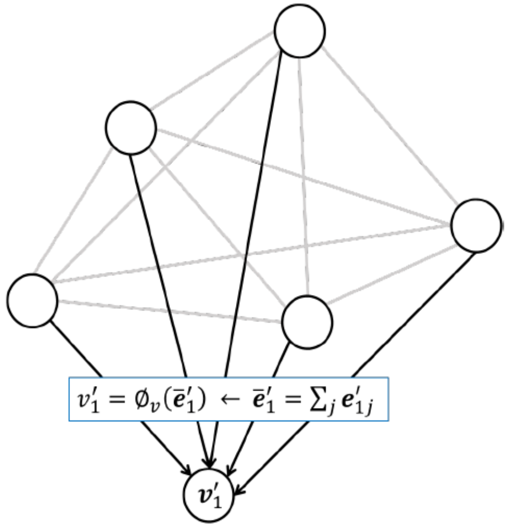
Graph vertices = objects (turbines)



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

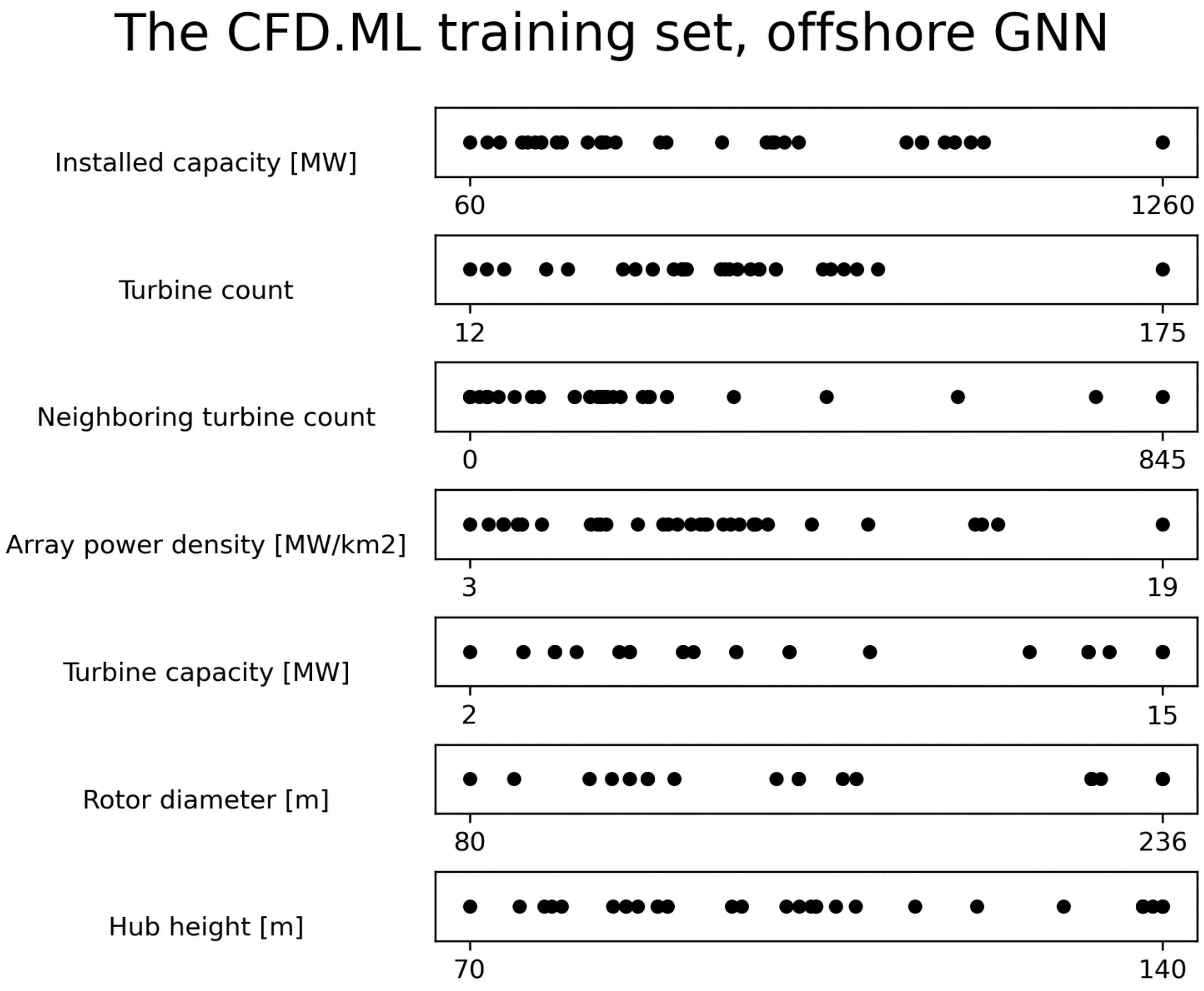
DNV AI assurance experts have evaluated:

- the model
- the training setup

Both seem robust, a scientific paper is pending

What is CFD.ML trained on?

- A healthy mix of turbine technology, farm size, array density etc.
- CFD.ML's offshore training set grows continuously (41 farms currently)
- Currently, the training is based conventional neutral boundary layer capped with an inversion starting at about 600 m and a stably stratified free atmosphere above.
- Soon to be updated with improved CFD modeling method to account better for (varying) stability effects
- There's a separate training set onshore and in the future there might be GNNs dedicated to specific applications (regional/technological/meteorological)



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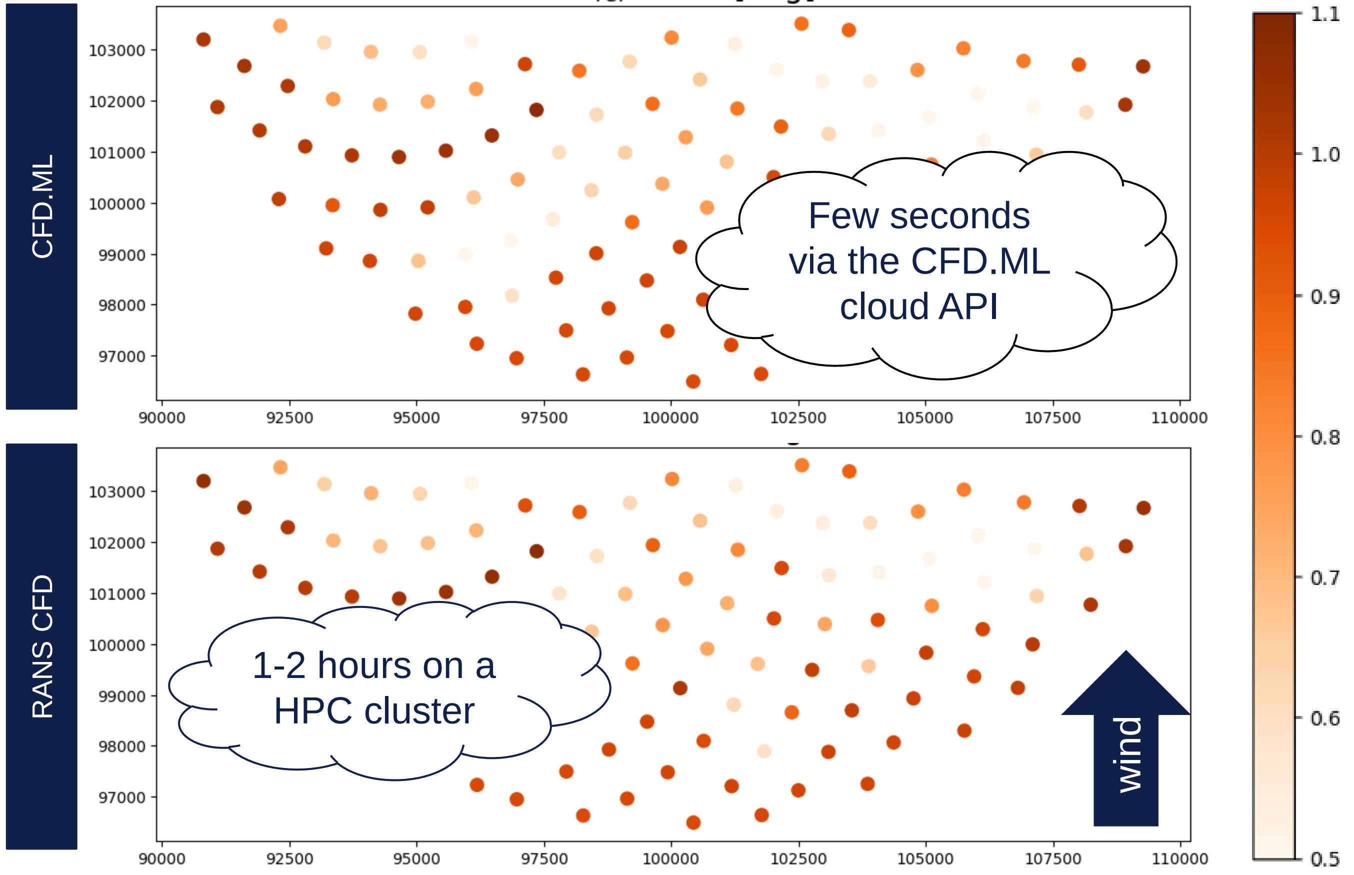
Can CFD.ML replicate CFD?

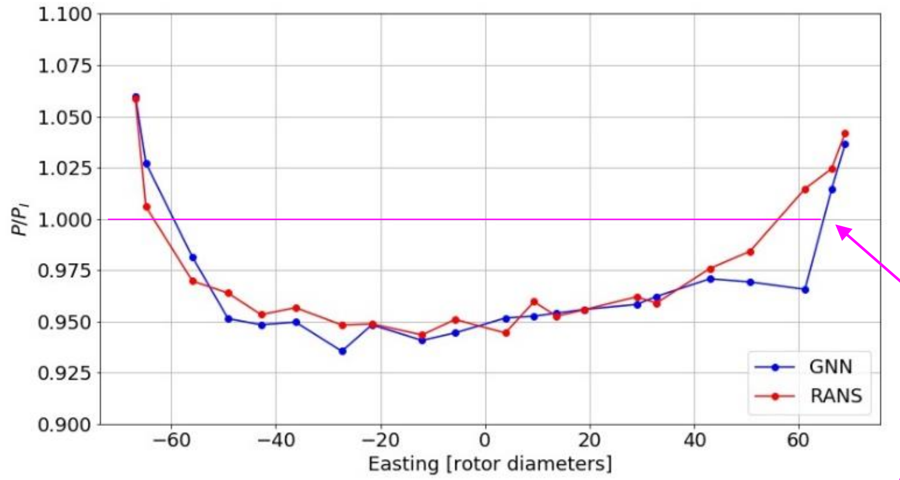
Hypothetical Wind Farm „The Bowl”

110 turbines, 7D spacing

$U_{ref} = 7.1$ [m/s]
$DIR_{ref} = 179$ [deg]

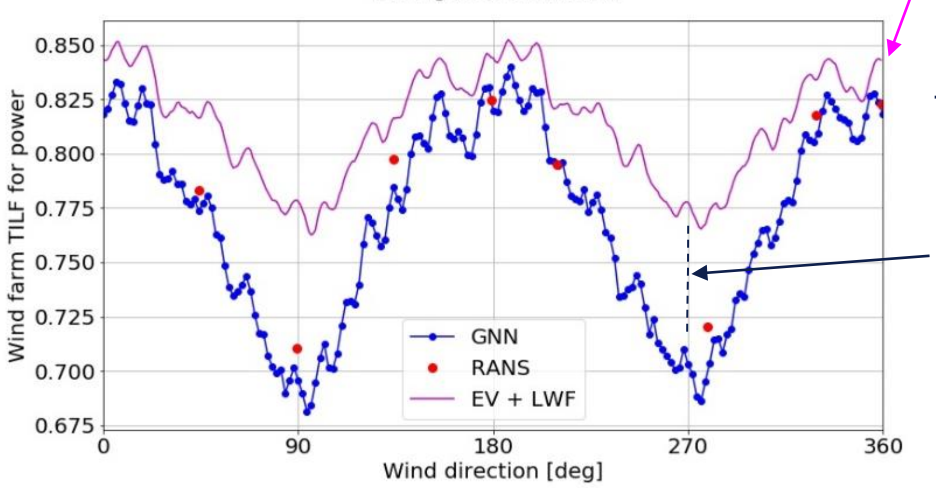


Front row power variations



Wakes-only model

Array efficiency



<u>difference</u> driven partly by CFD.ML's ability to include blockage.

CFD.ML

- **performs well at approximating RANS CFD.**
- **Is fast, may be used in an optimization context.**

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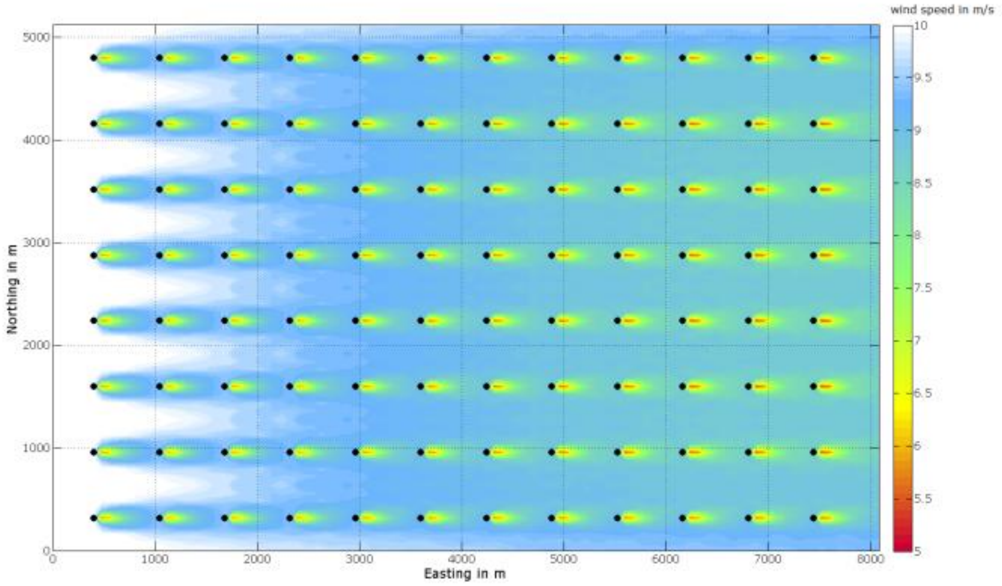
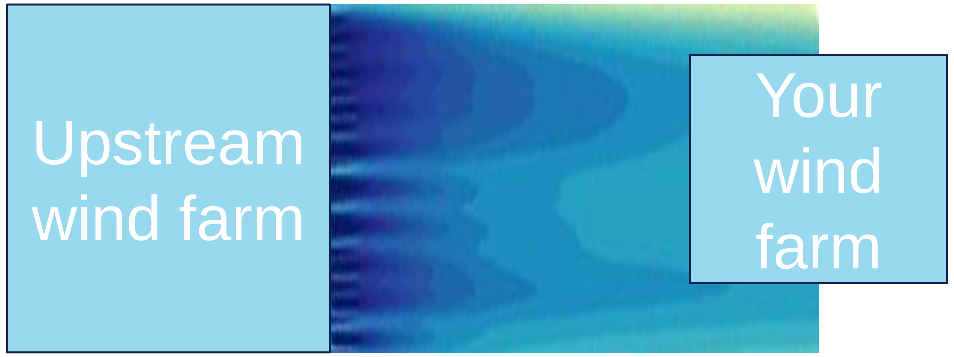
Validation against operational data
- *the three key aspects of a turbine interaction model*

internal wakes

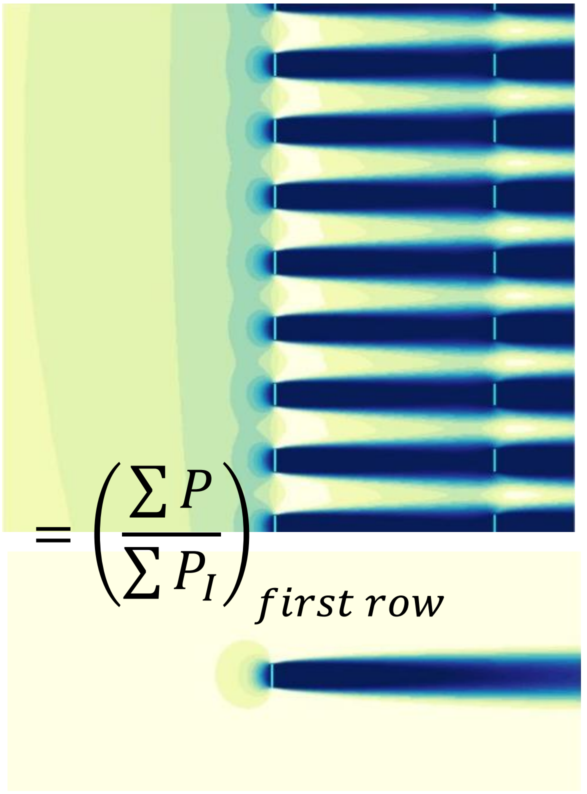


Inflow wind 270° ± 15°

external or cluster wakes



wind farm blockage



$$= \left(\frac{\sum P}{\sum P_I}\right)_{first\ row}$$

Validation against operational data
- *internal wakes*

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Validating the next generation of turbine interaction models

T Levick[1], A Neubert[2], D Friggo[3], P Downes[1], R Ruisi[1] and J Bleeg[1]

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Journal of Physics: Conference Series, Volume 2257, WindEurope Annual Event 2022, 5-7 April 2022, Bilbao, Spain

Citation T Levick *et al* 2022 *J. Phys.: Conf. Ser.* **2257** 012010

- 6 offshore wind farms, validation focussed on internal wakes
- CFD.ML's validation points to a slight overprediction of (internal) wakes

Bias in power output for each time stamp $$\Delta P = P_{\text{modelled}} - P_{\text{measured}}$$

Mean bias over time stamps N $$\text{MBE}_{\text{P}} = \frac{\sum_{i=1}^{n} \Delta P_i}{N}$$

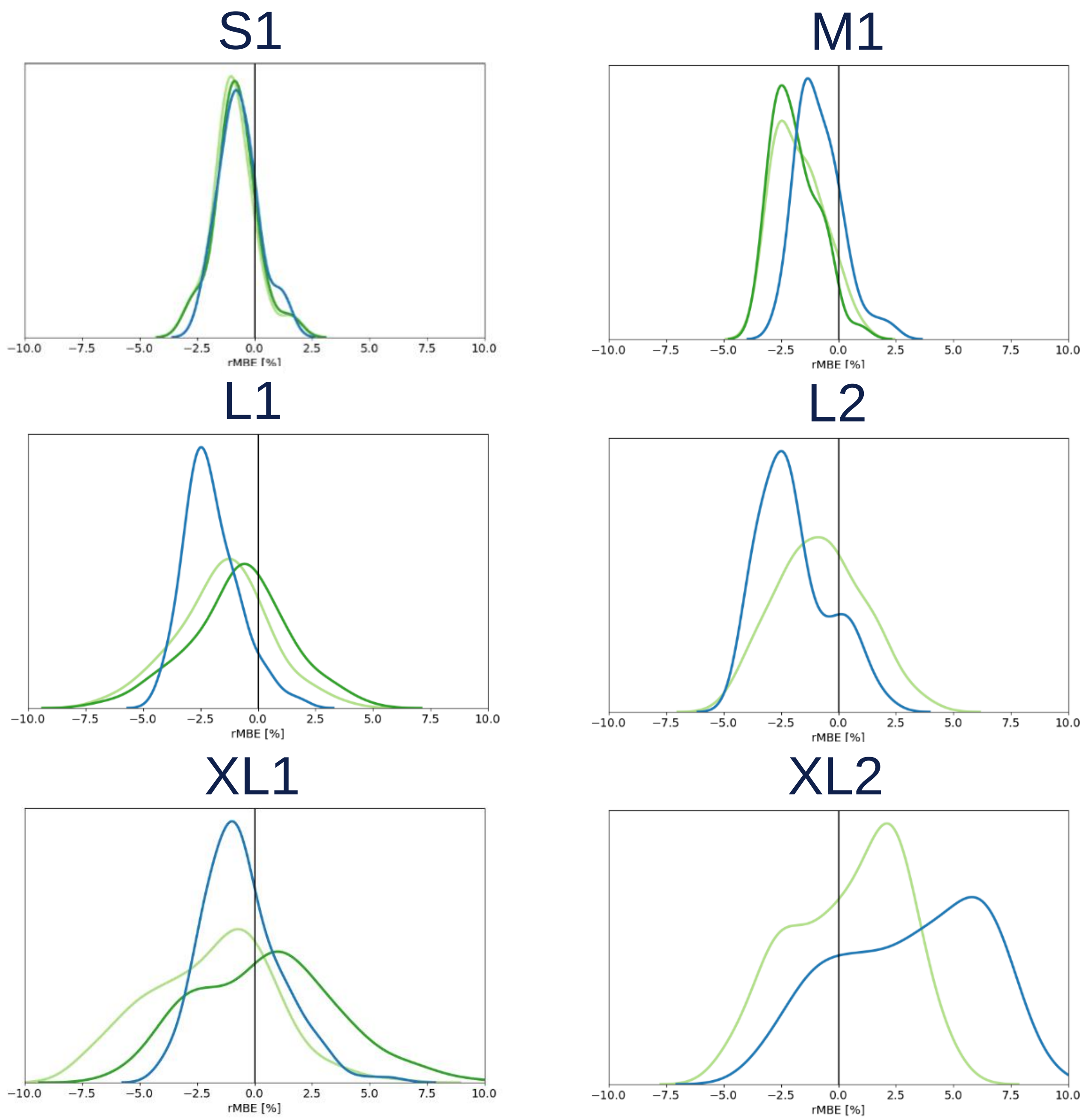
Relative mean bias over time stamps N $$\text{rMBE}_{\text{P}} = \frac{\text{MBE}_{\text{P}}}{\bar{P}}$$

Wind Farm

Model	S1	M1	L1	L2	XL1	XL2
SEVM	0.0	0.0	-1.9	-0.5	0.5	0.8
CFD.ML	-0.7	-0.9	-2.0	-2.0	-0.7	3.0
wfEV 120D (newa)	-0.8	-1.9	-0.9		0.3	
wfEV 120D (wti)	-0.9	-1.8	-1.7	-0.9	-2.0	0.3
wfPARK	-2.5	-5.2	-7.3	-2.9	-8.0	1.2

Validation against operational data - *internal wakes*

Turbine-by-turbine relative mean bias distribution per farm [%]



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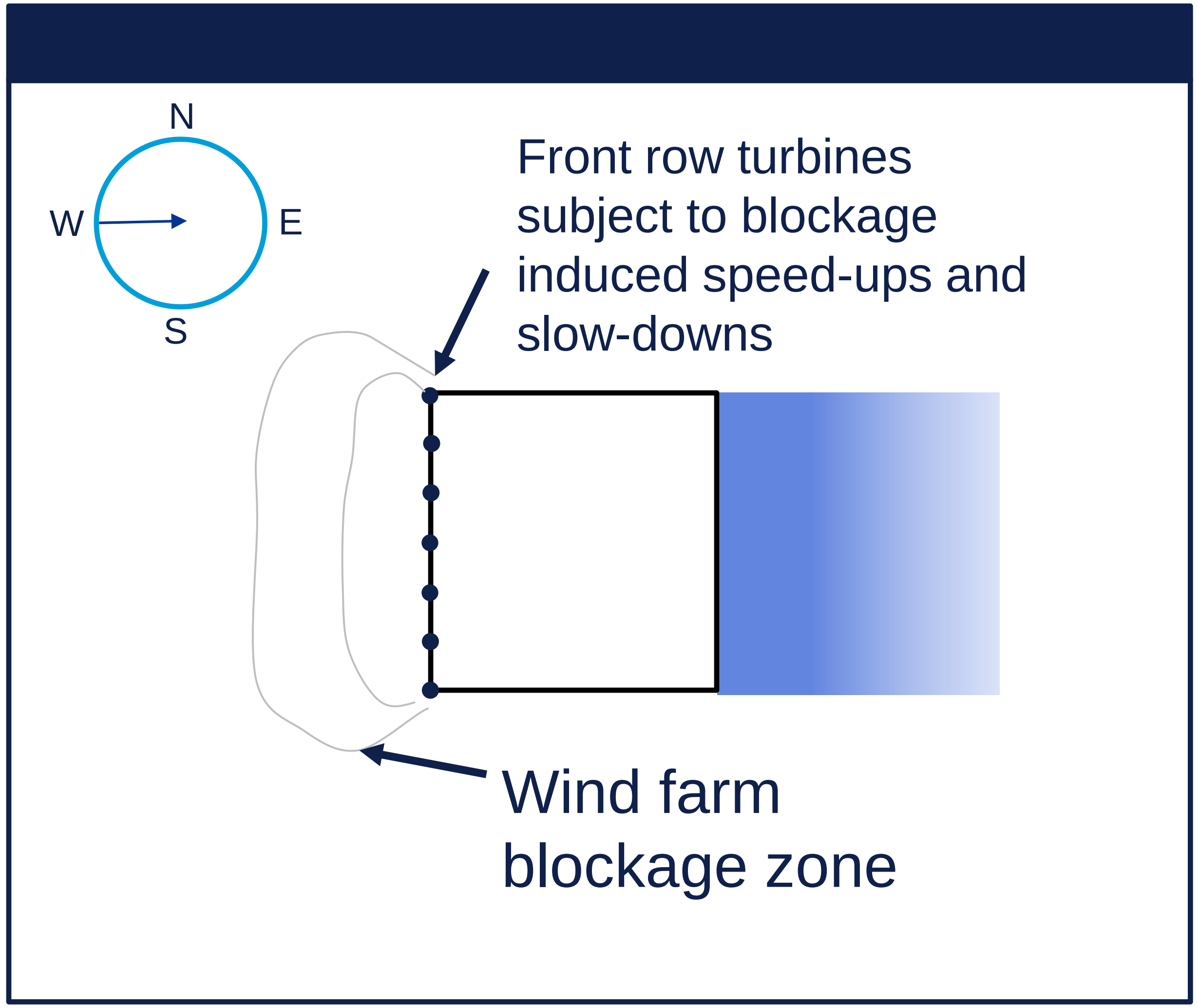
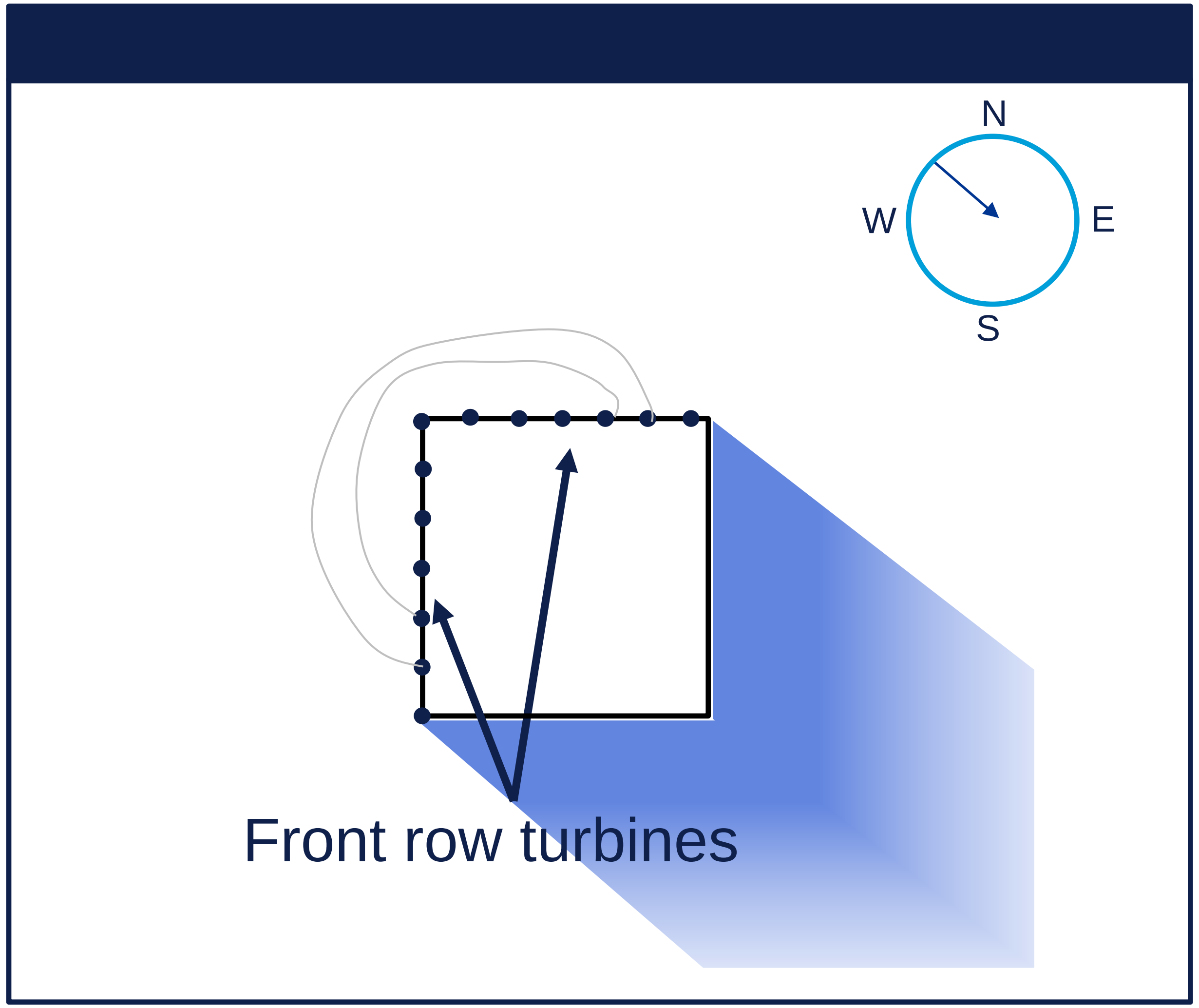
- 6 offshore wind farms, validation focussed on internal wakes
- CFD.ML's validation points to a slight overprediction of (internal) wakes
- CFD.ML's error spread is smaller than in the case of engineering models in 5/6 wind farms – better predictions of production patterns

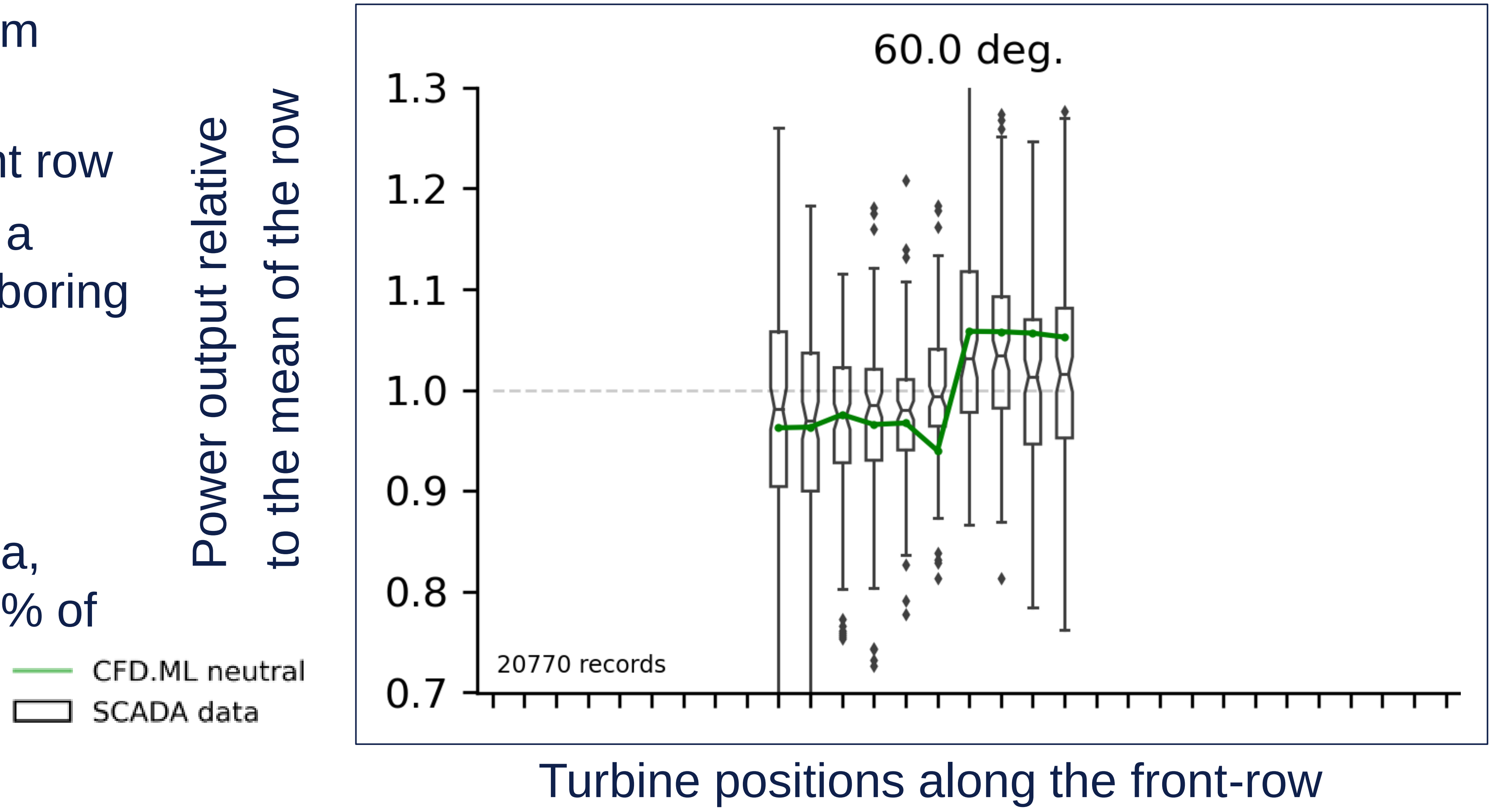
Validation against operational data
- *blockage-induced front-row power variations*





Validation against operational data
- *blockage-induced front-row power variations*

- A large offshore windfarm
- Relative power output variations along the front row
- Flowcases shown have a long fetch and no neighboring wakes.
- 20deg bins, no filter on stability in data
- Boxes entail 50% of data, outer whiskers entail 90% of data, centerline is the **median**



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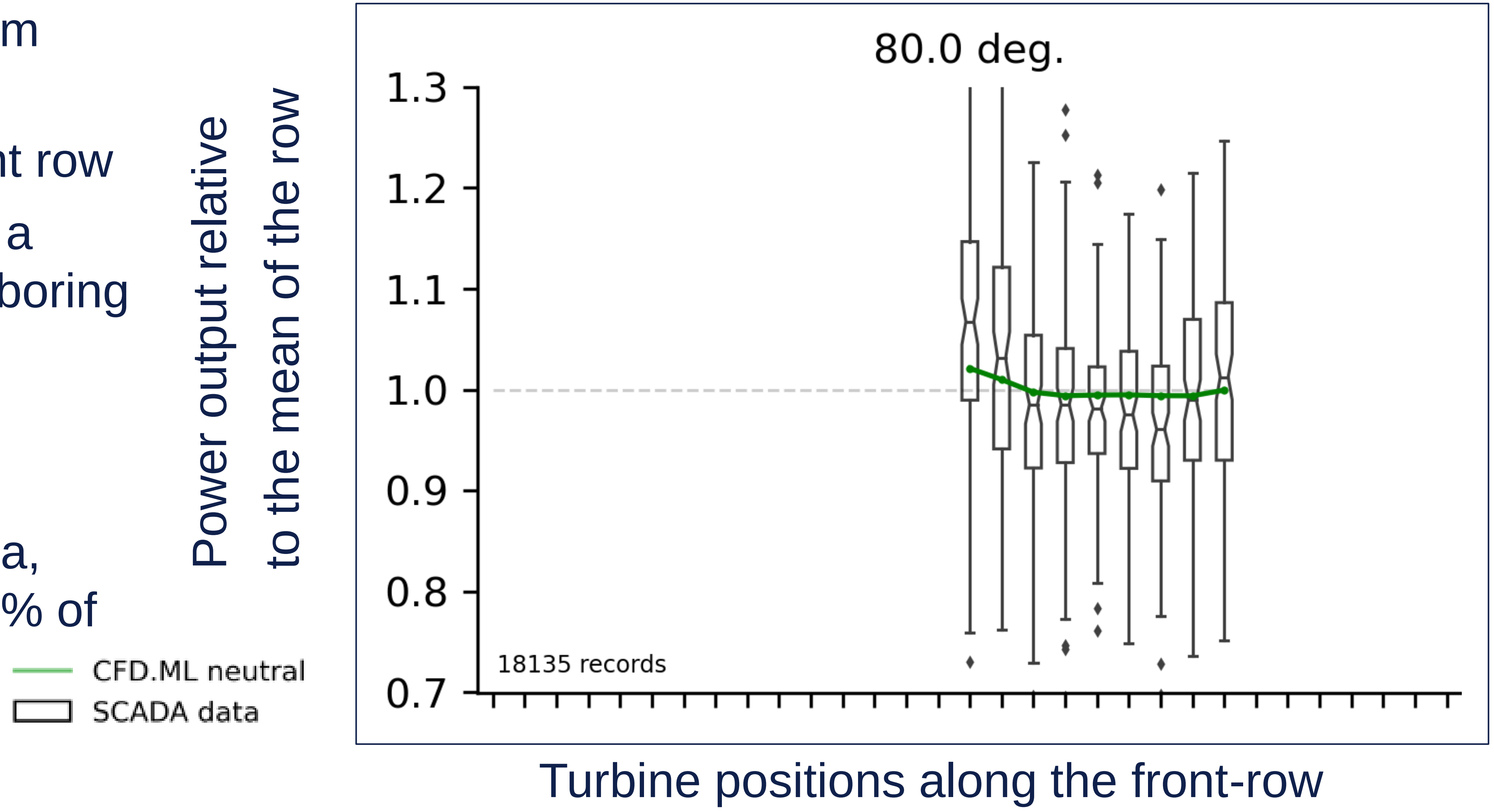

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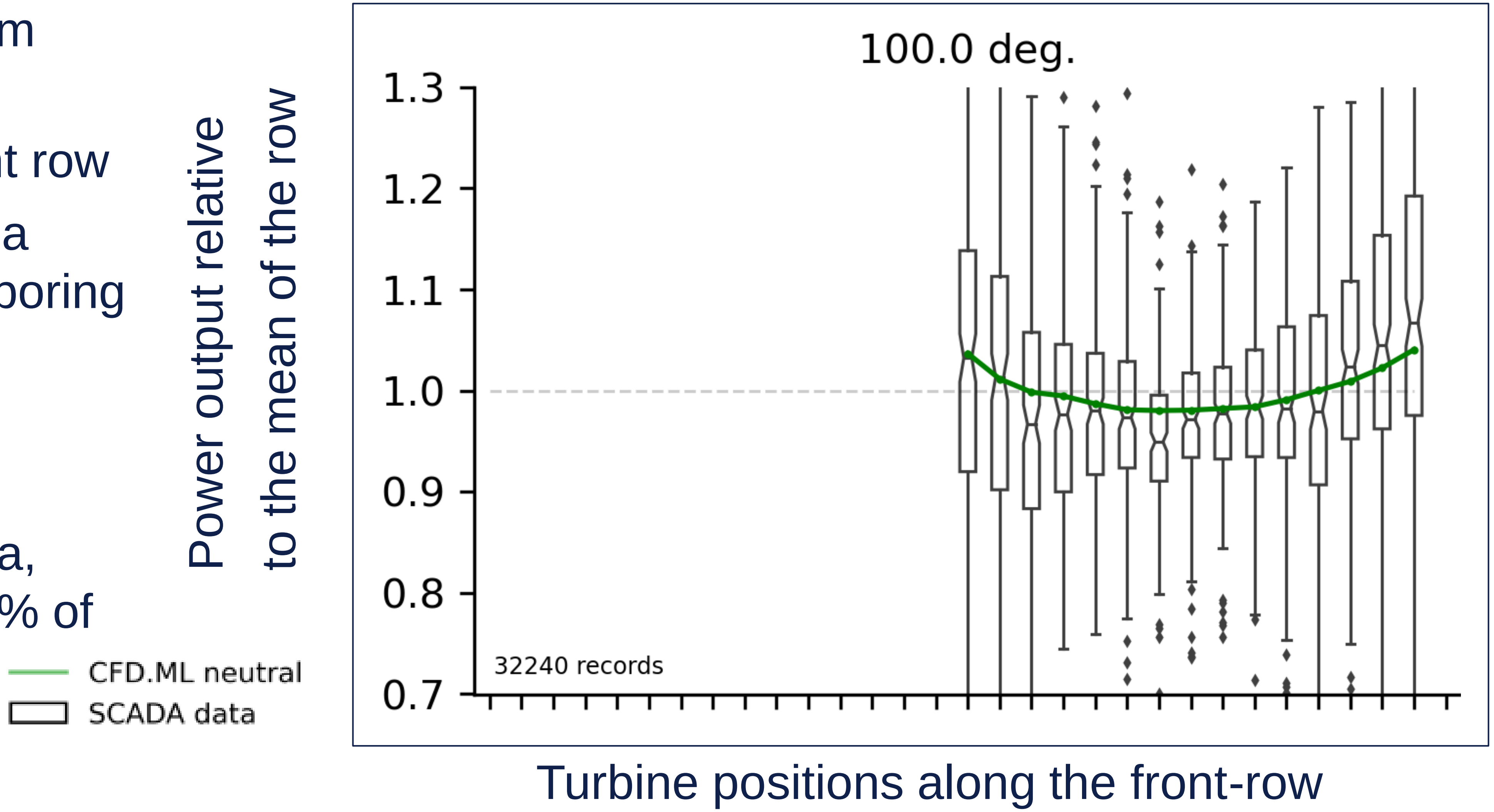

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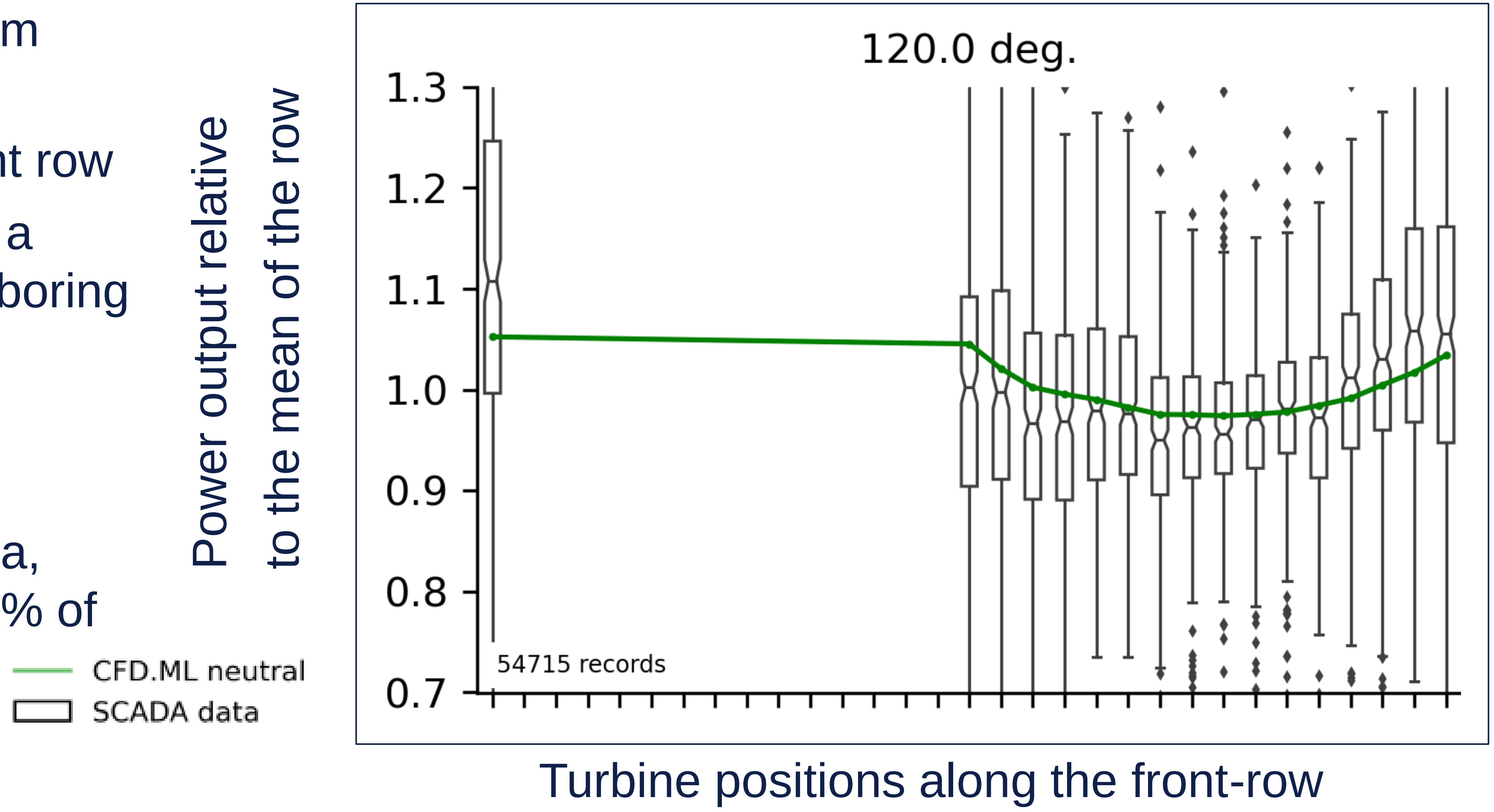

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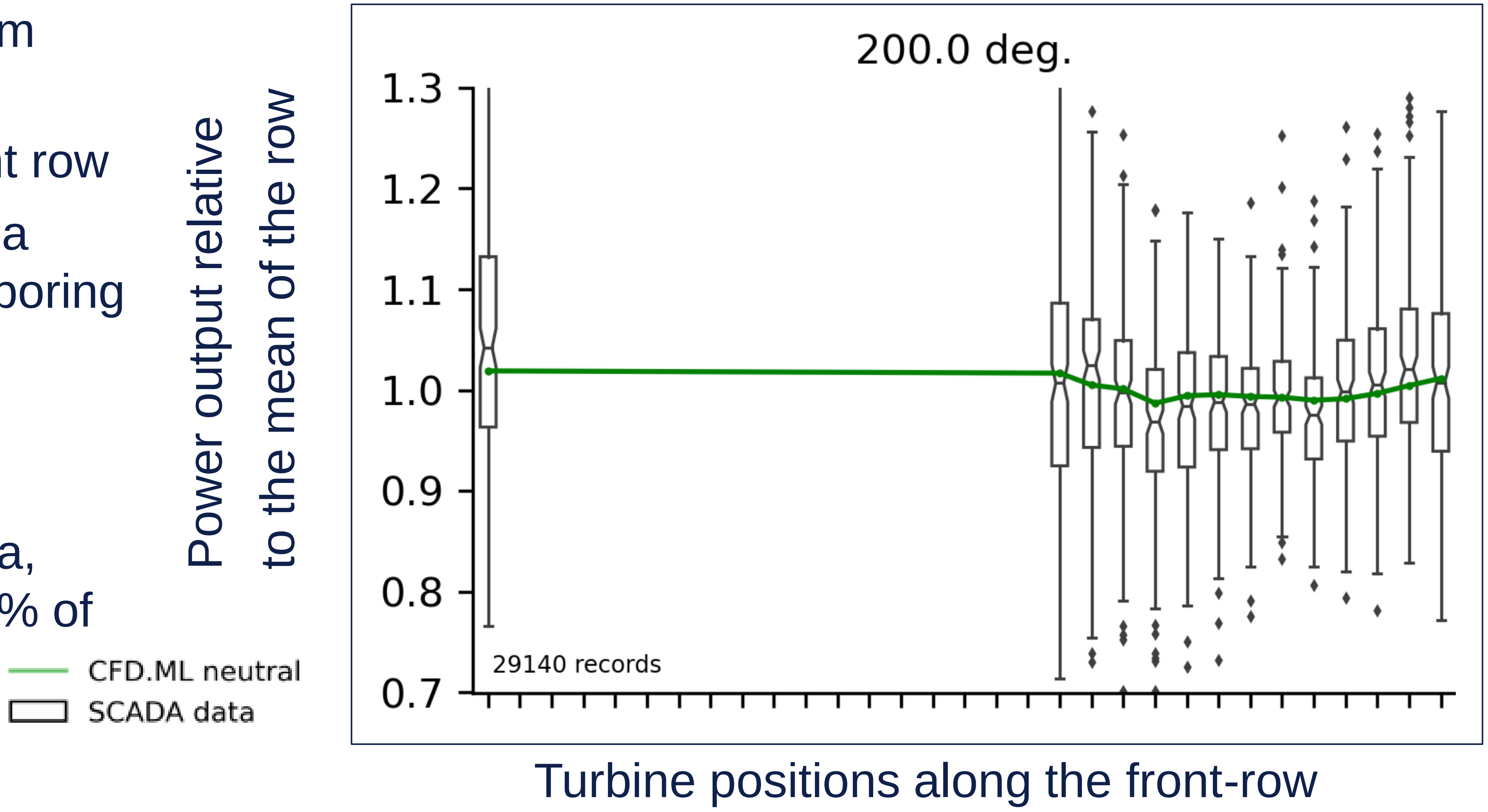

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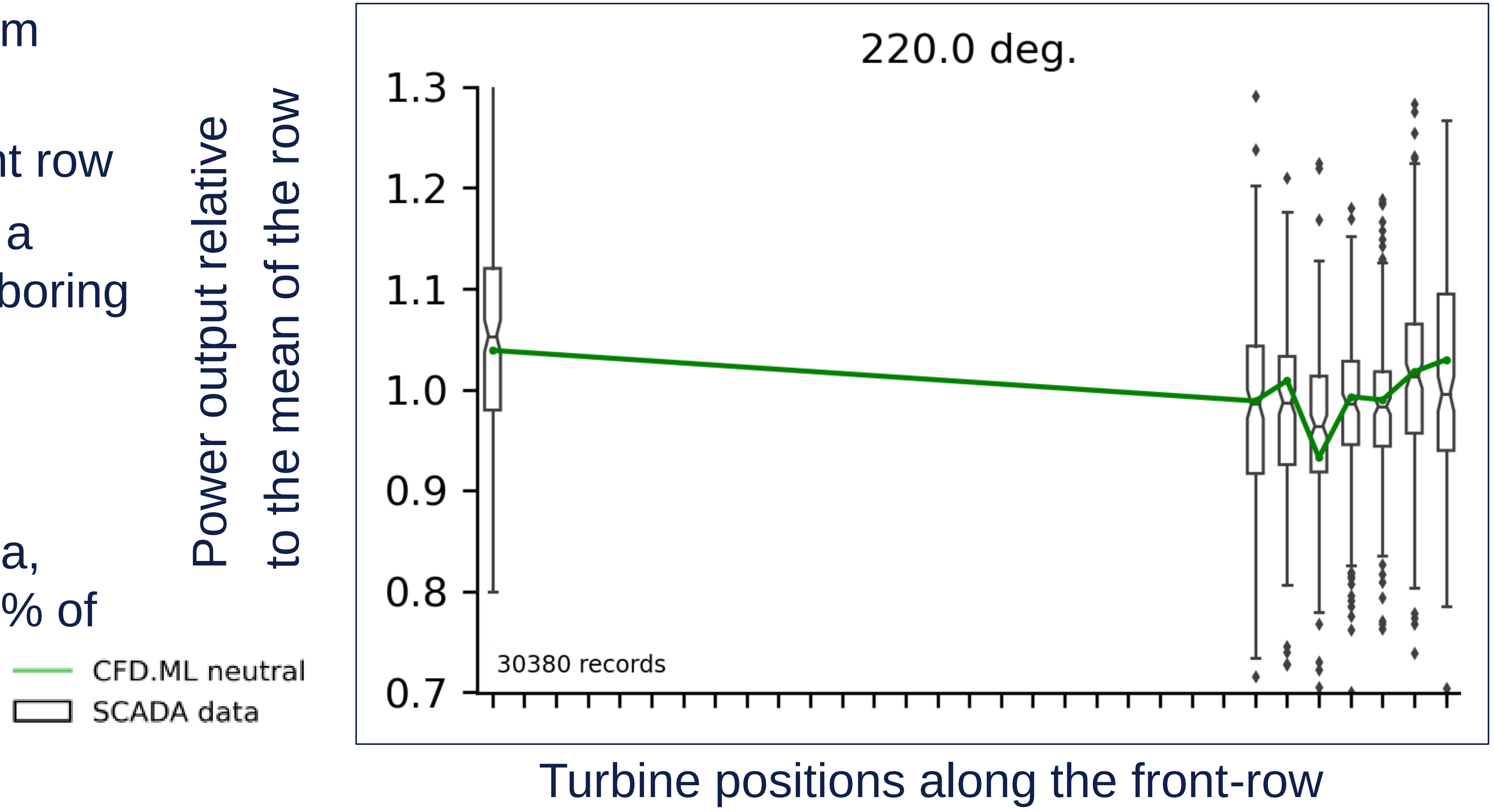

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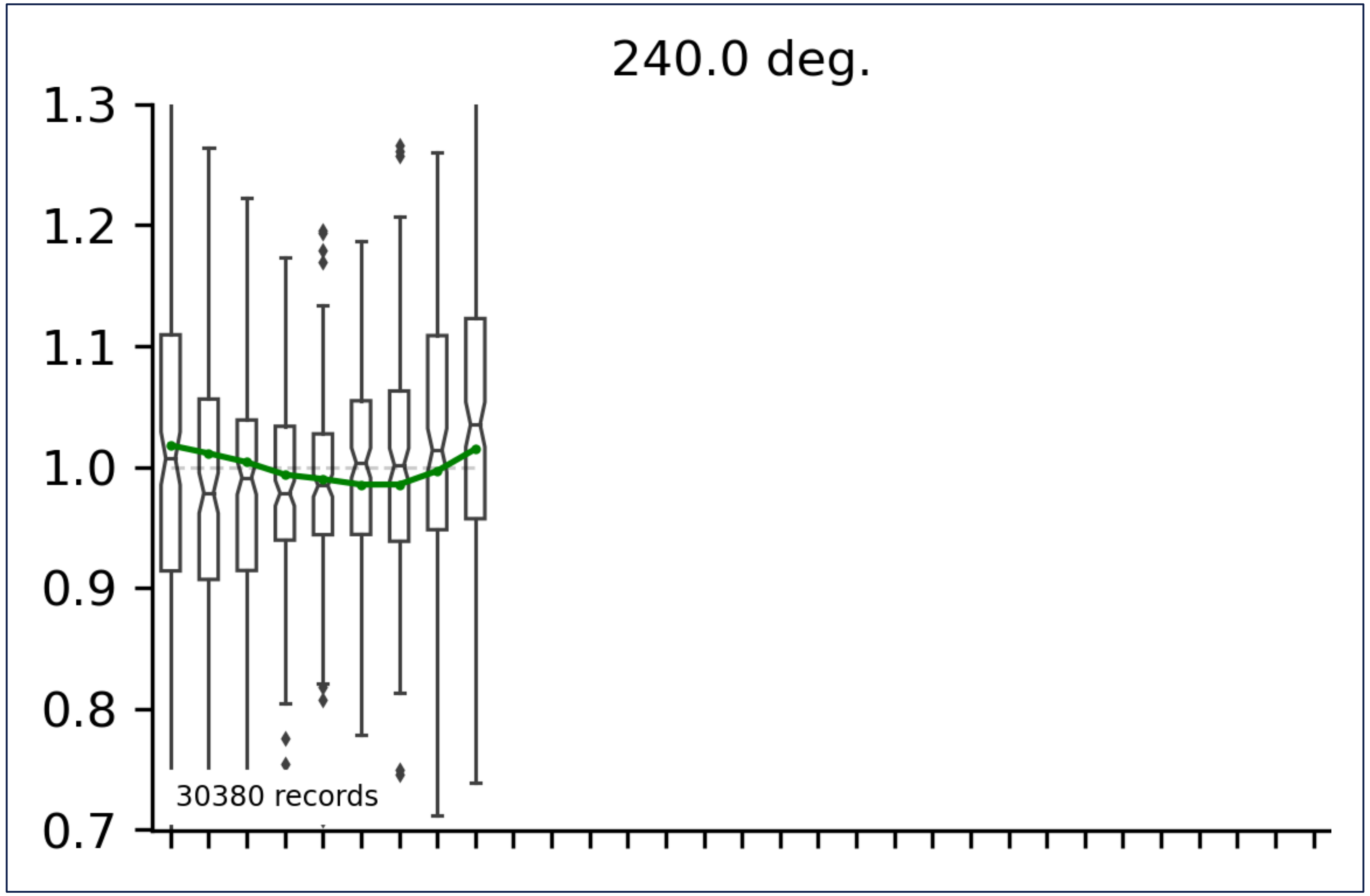

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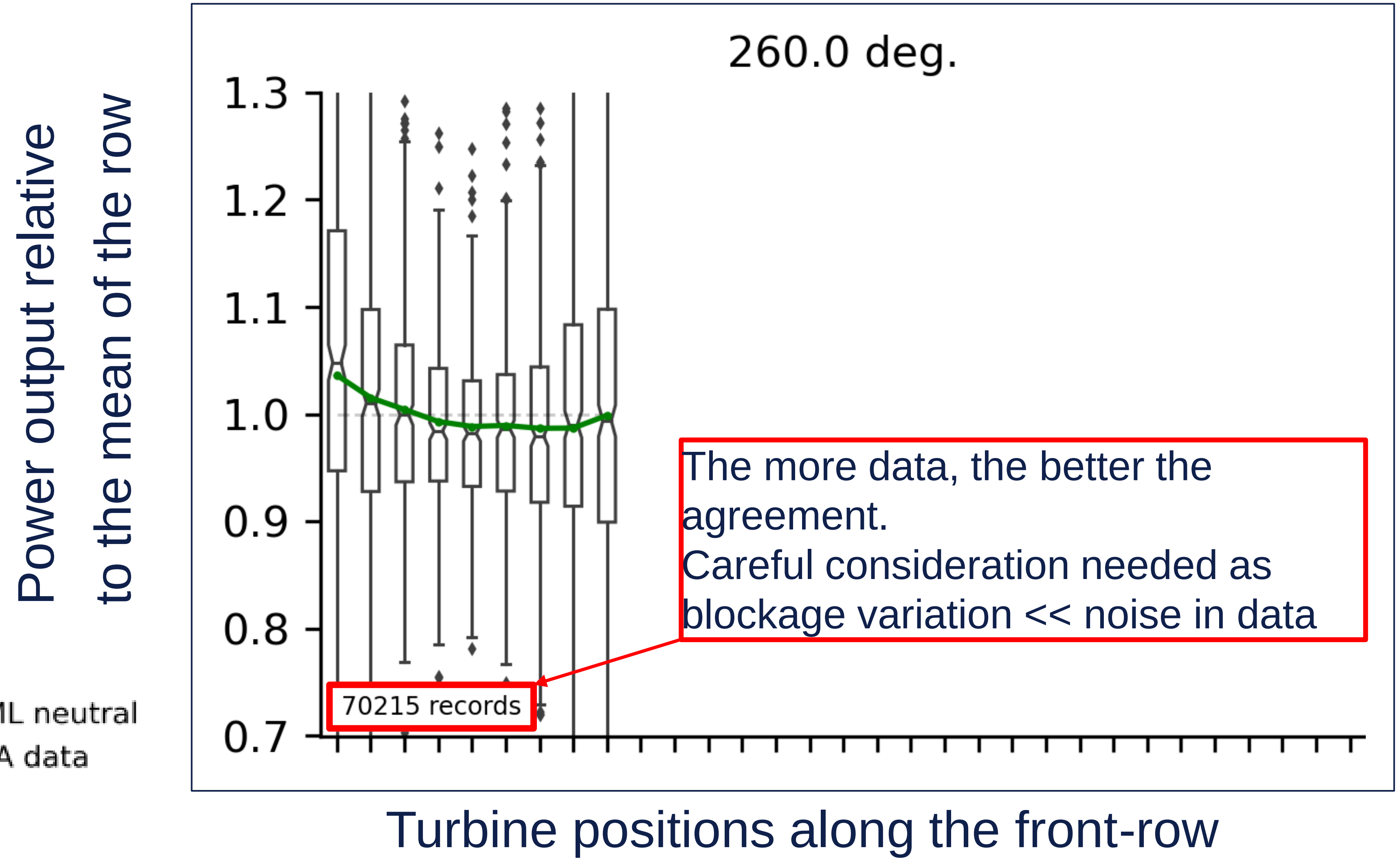

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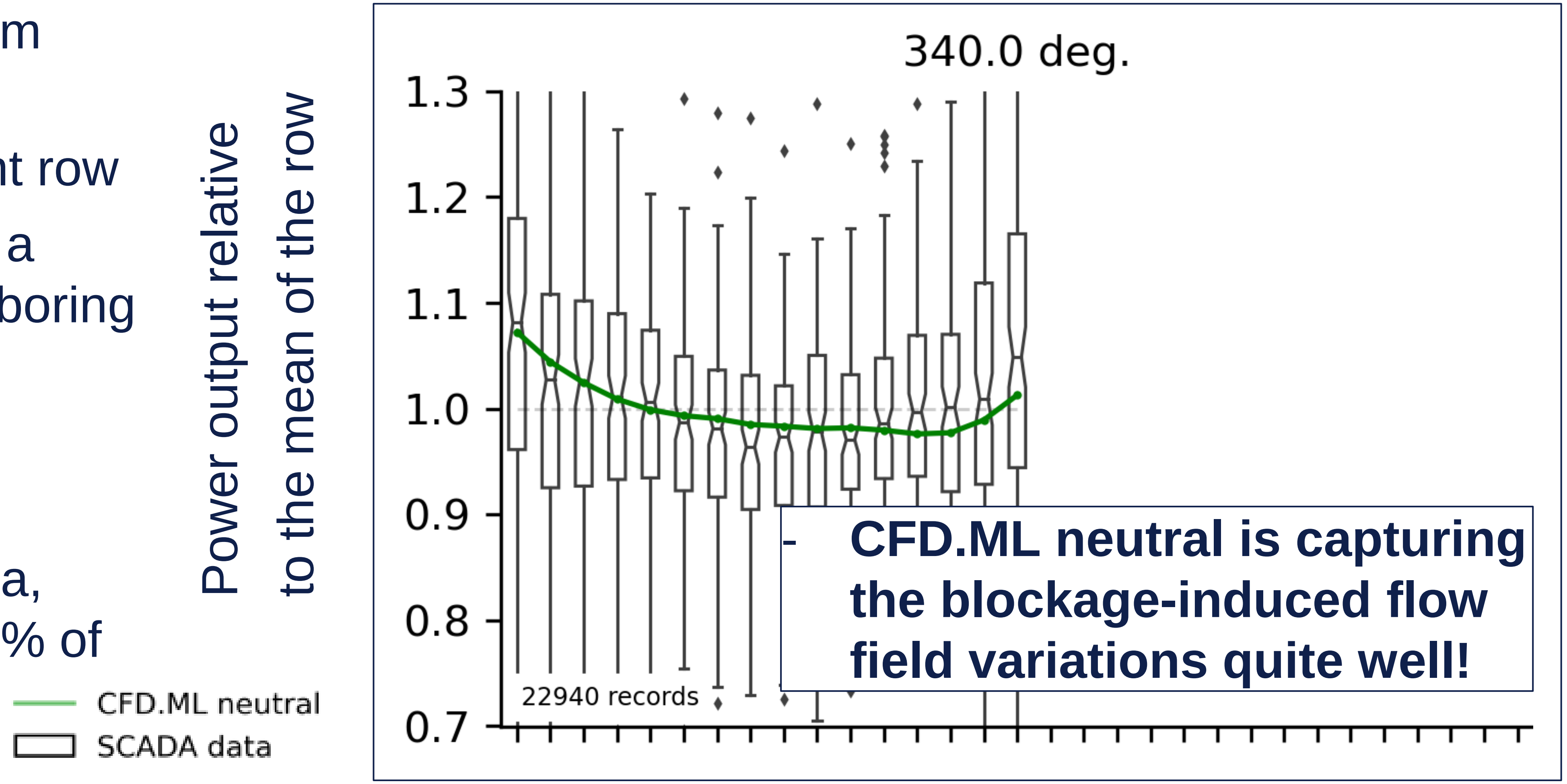
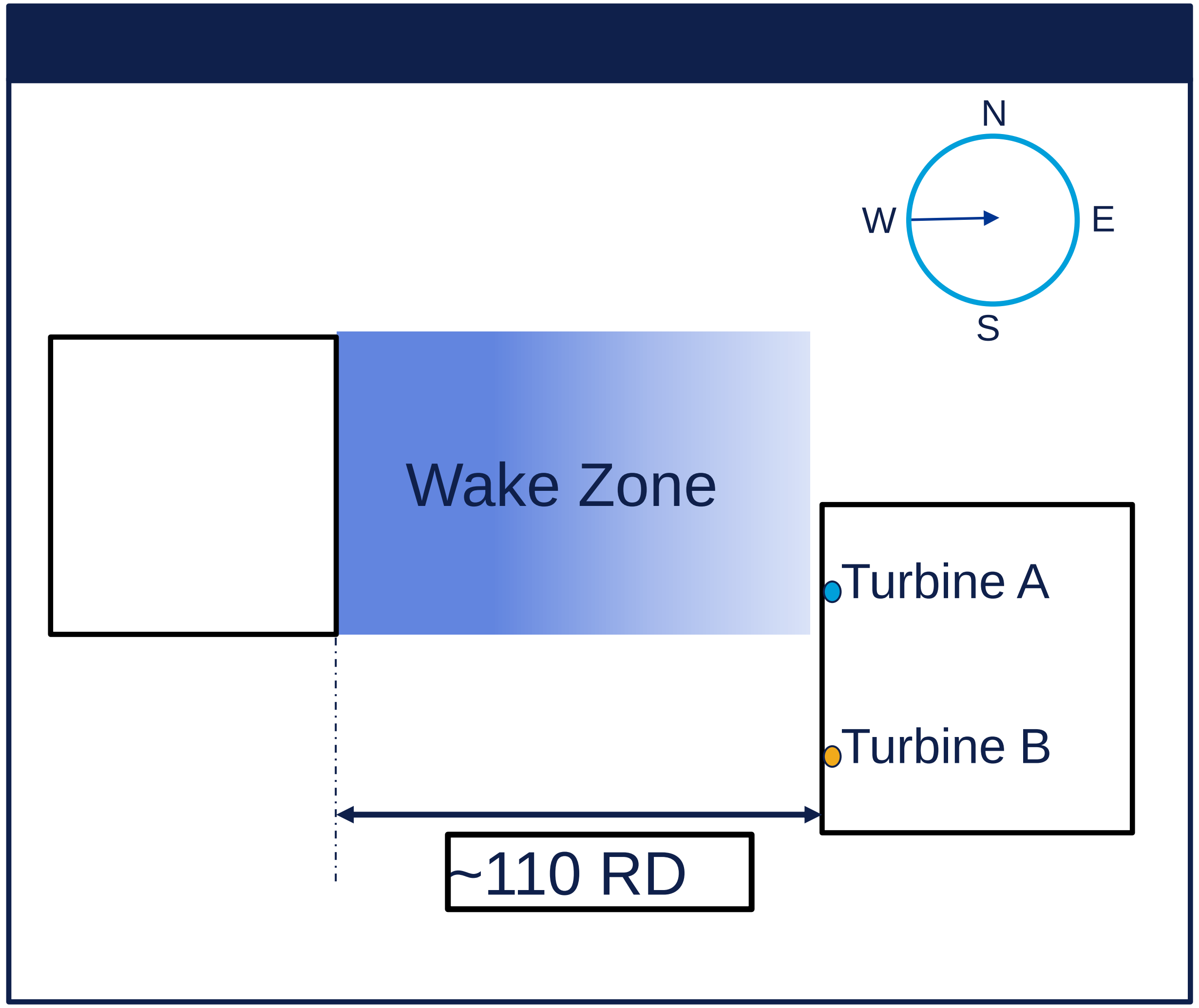
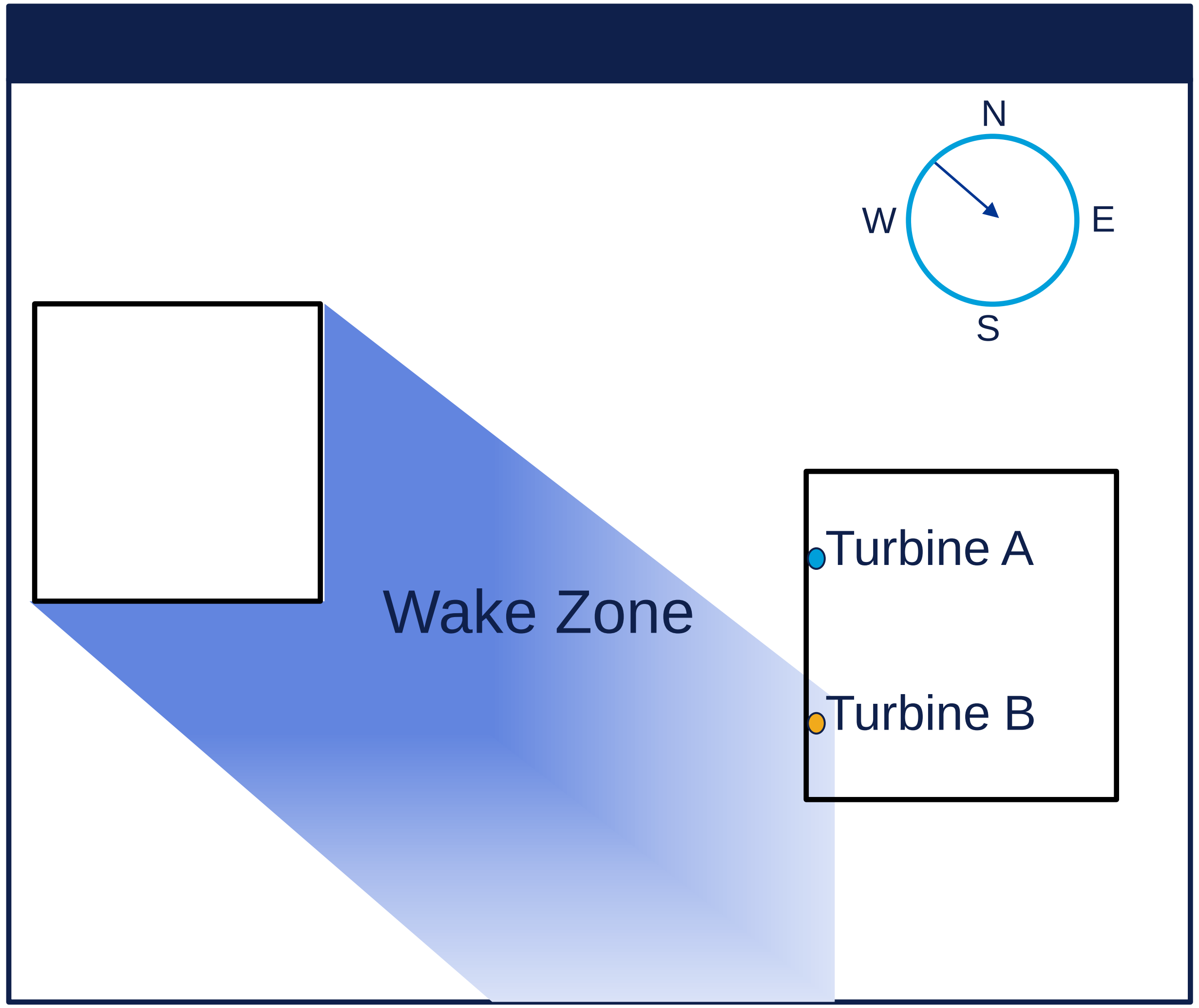


- **CFD.ML neutral is capturing the blockage-induced flow field variations quite well!**

Turbine positions along the front-row

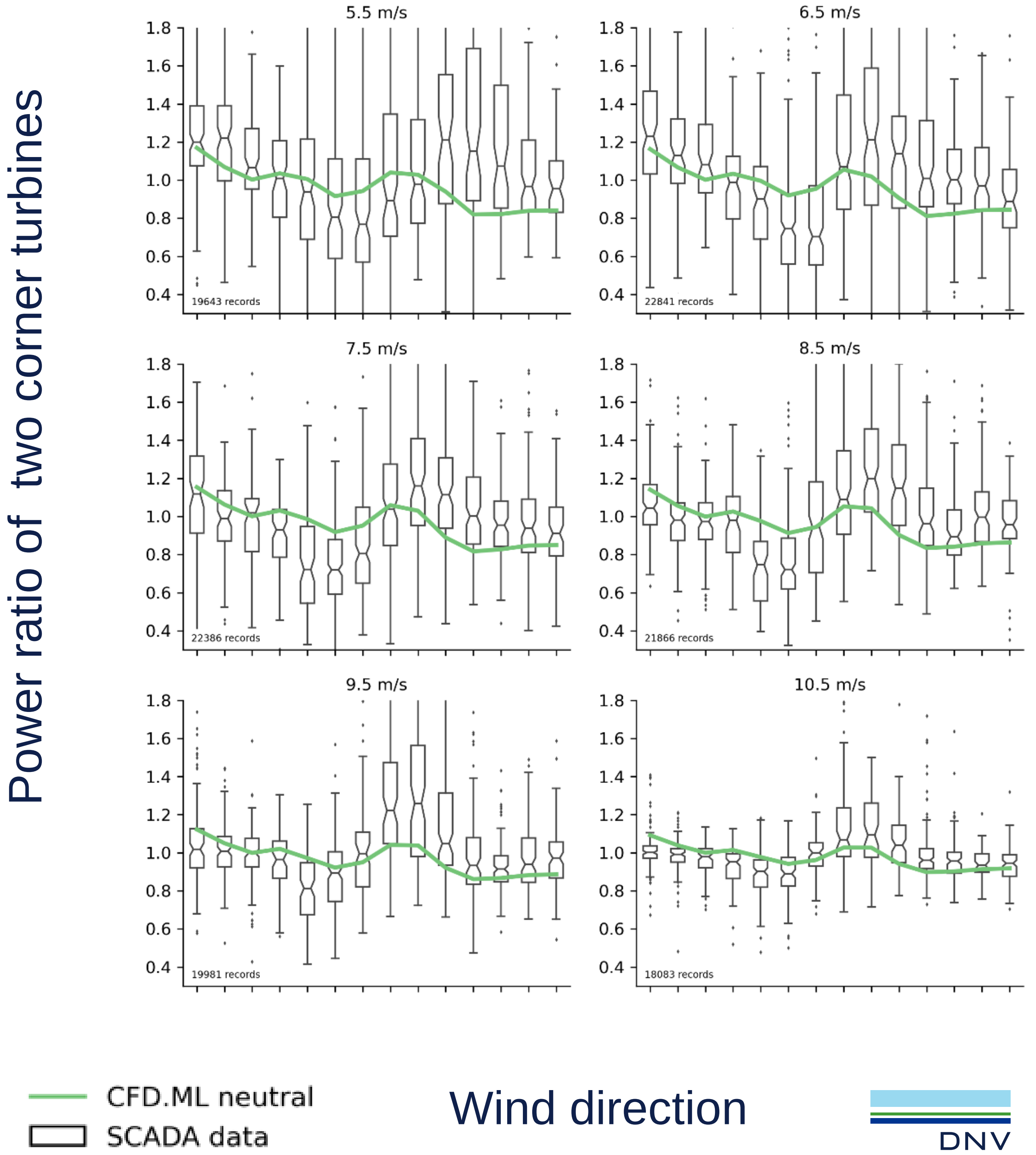
Validation against operational data
- *cluster wakes*





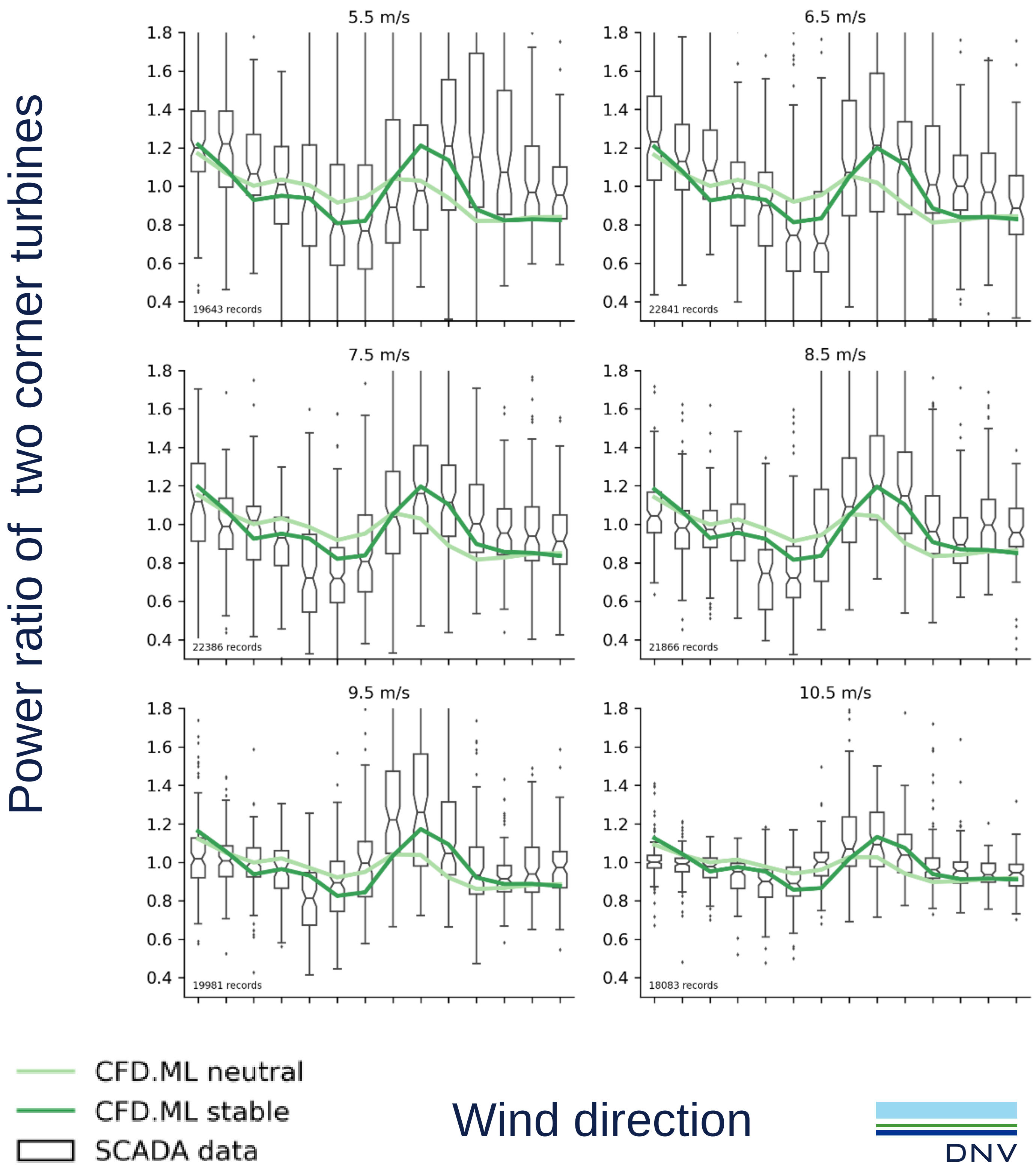
Validation against operational data - *cluster wakes*

- 5 deg directional bins, 1 m/s wind speed bin, no data filtering on stability
- Boxes entail 50% of data, outer whiskers entail 90% of data, centerline is the **median**
- **CFD.ML neutral fails to capture the amplitude of the signal** (underprediction of cluster wakes).



Validation against operational data - *cluster wakes*

- 5 deg directional bins, no data filtering on stability
- Boxes entail 50% of data, outer whiskers entail 90% of data, centerline is the **median**
- CFD.ML neutral **fails to capture the amplitude of the signal** (underprediction of cluster wakes).
- CFD.ML stable **does a better job.**
  It is a 50/50 blend of predictions from a neutral-only gnn and a gnn trained on neutral&stable CFD sims. It's an experimental approach.
- This prompted refinements in the underlying CFD model...



Agenda

- What's under the hood of CFD.ML
- Validation
- Planned model improvements

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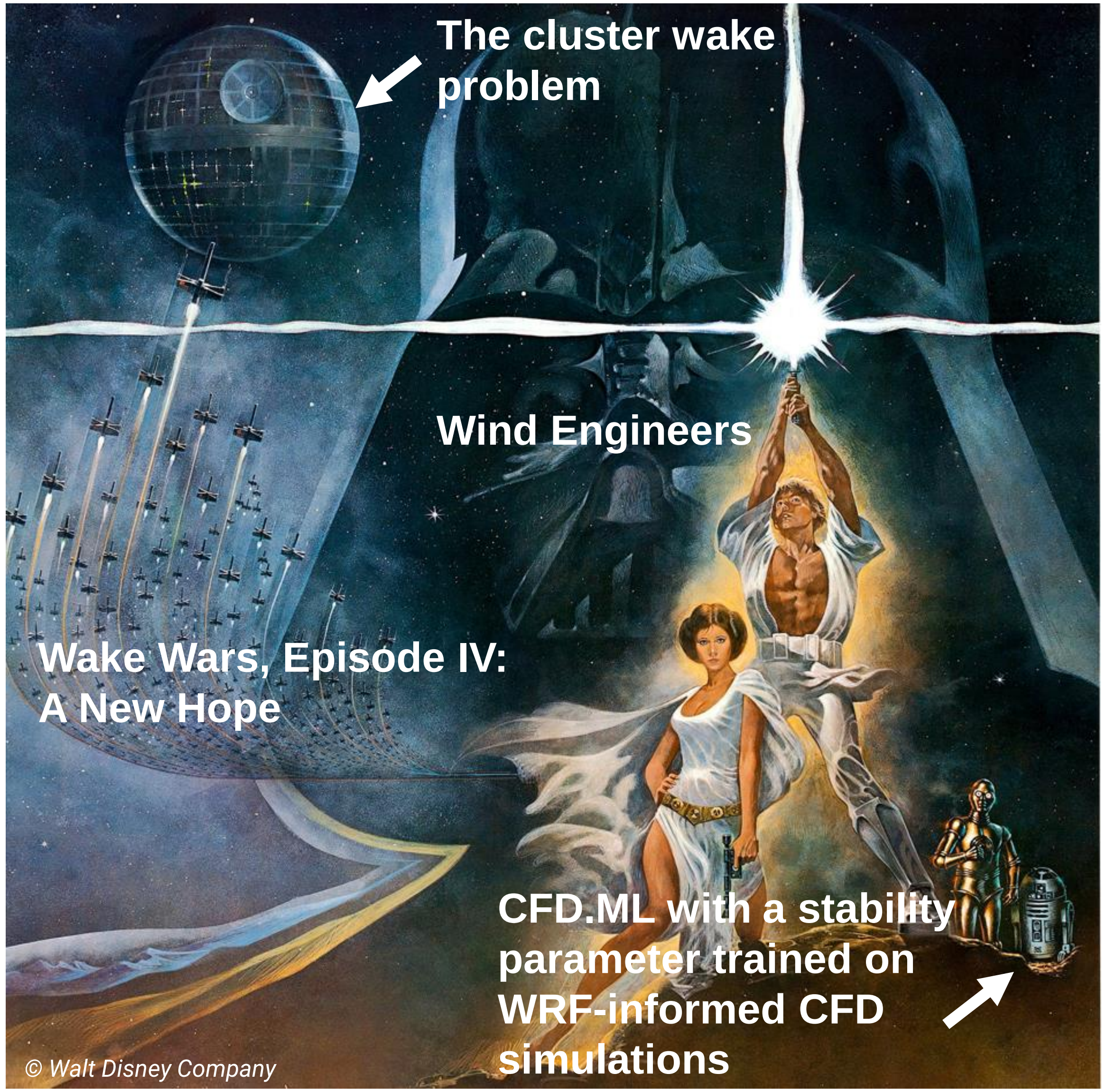
Work in progress:
Validation of the improved CFD model

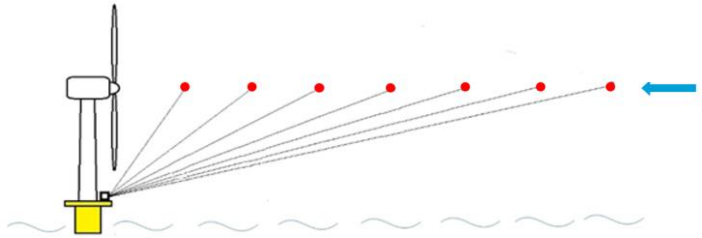
- Efforts at DNV to further improve the predictive skill of our CFD model.
- Promising research direction: WRF-informed boundary conditions in the CFD simulations.
- Good outcome of a validation against SCADA data and LiDAR measurements at a a large German offshore cluster, measurements.

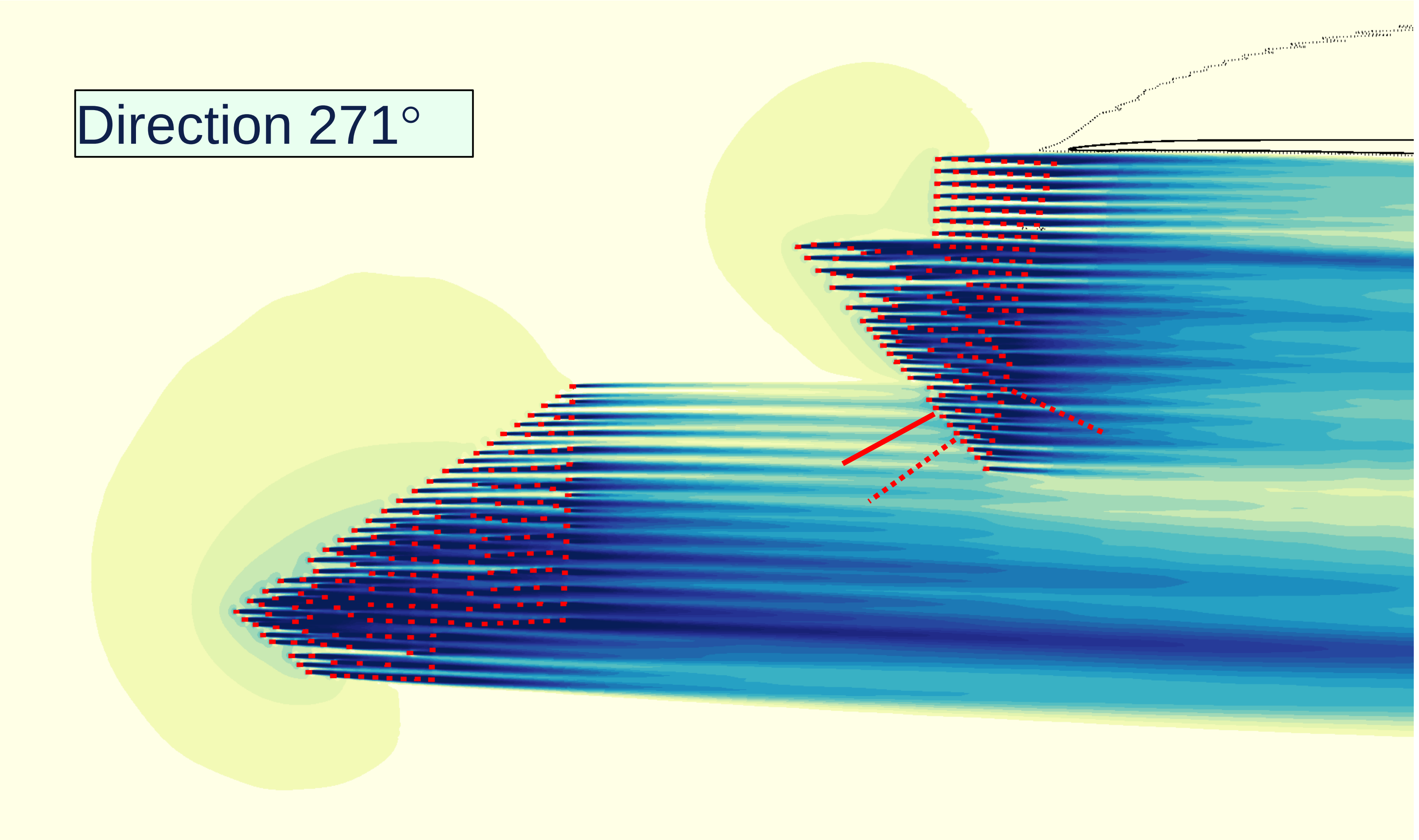
C. Montavon et al „Blockage and cluster-to-cluster interactions from dual scanning lidar measurements", WESC 2023, Glasgow



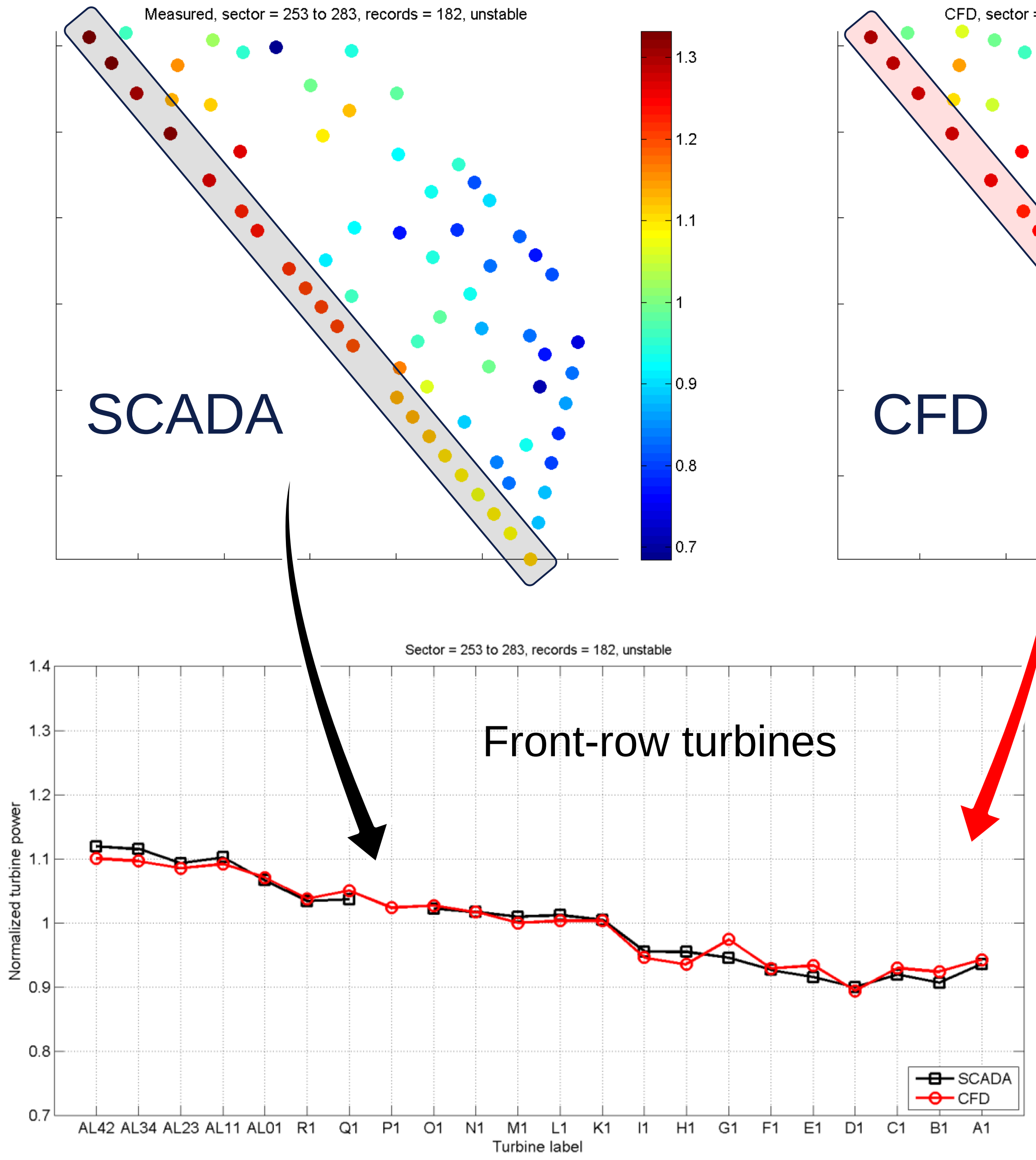
Work in progress:
Validation of the improved CFD model

- Directions where the measurements along the (dual-scanning) lidar lines are affected by both blockage AND wakes from neighbouring clusters
  - Example from direction 271°
  - Unstable conditions
  - Wind speed on the plateau of the thrust curve
  - Upstream farm 5km

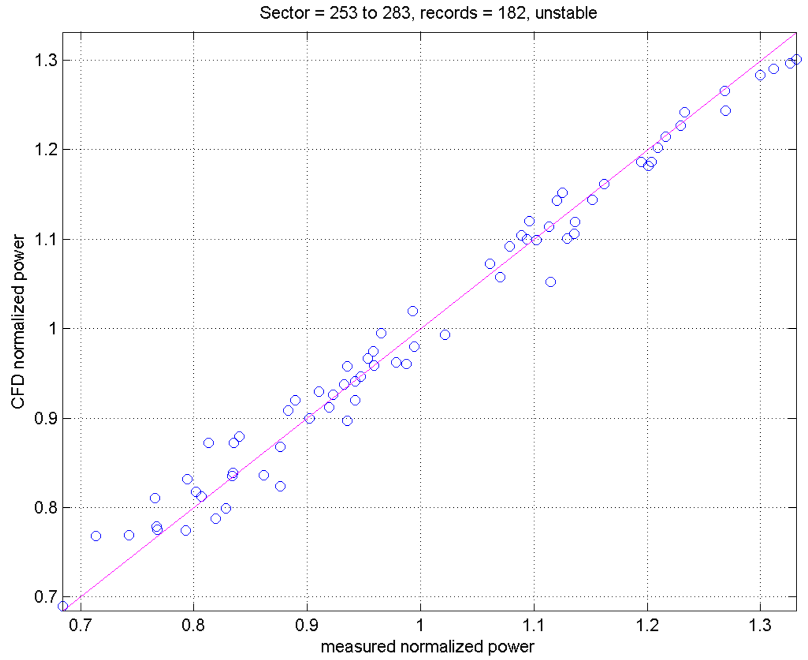




Pattern of production (253° -283°), unstable



CFD vs SCADA, array



- Interfering cluster wake and blockage
- Whole array normalised power well captured by CFD
- Less variation across the line of leading turbines than in stable conditions
  - lowest producing produces 20% less than highest producing turbine *

* Note: only applicable on plateau of thrust curve, will be less at higher wind speeds!

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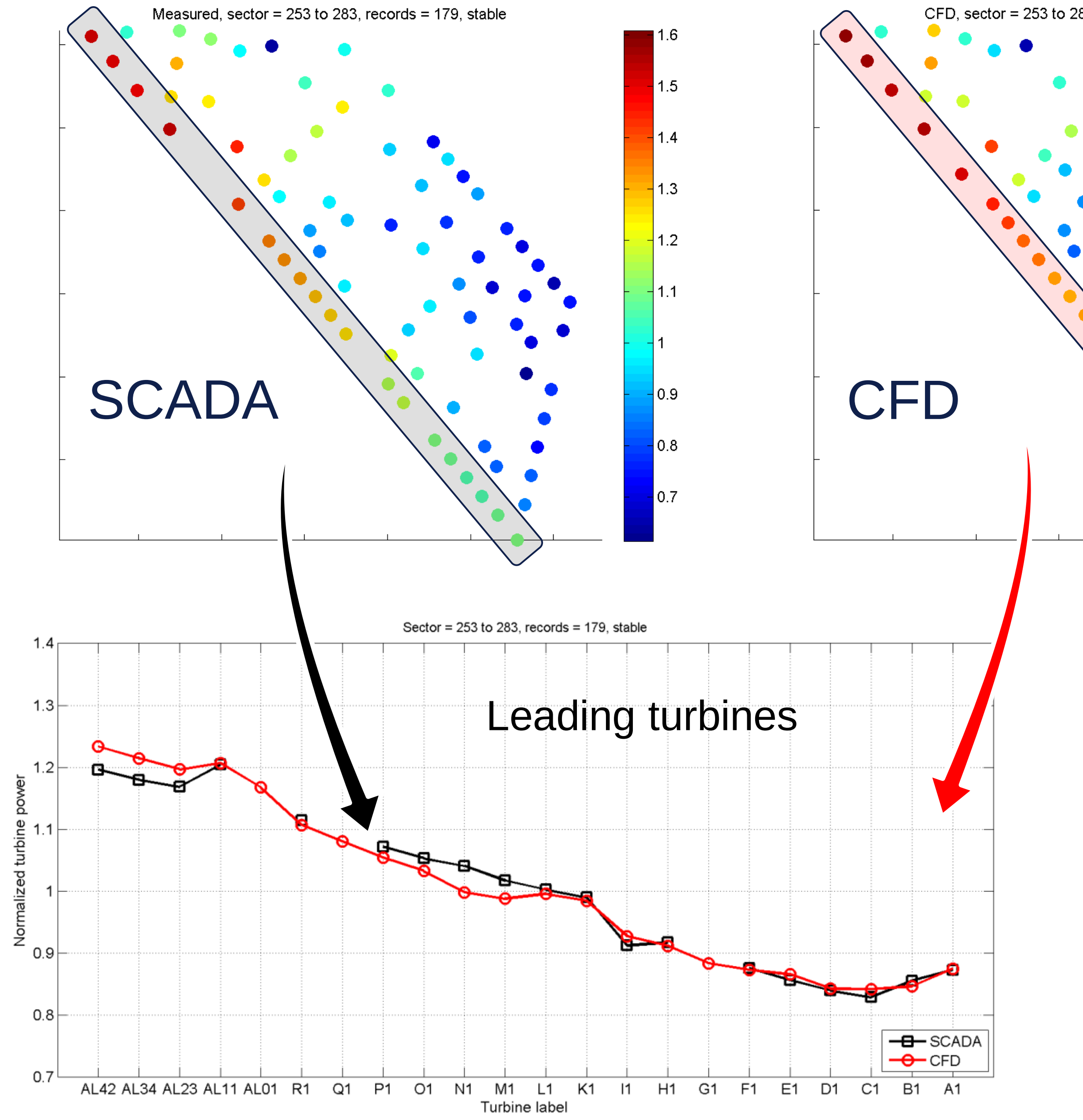
Pattern of production (253° -283°), stable



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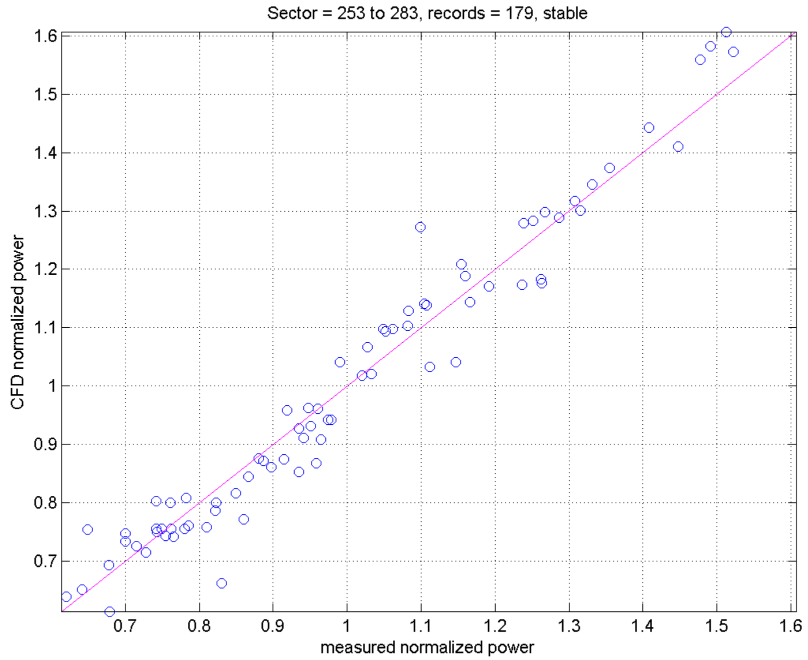


- Interfering cluster wake and blockage
- Whole array normalised power well captured by CFD
- Large variation across the line of leading turbines
  - lowest producing produces 33% less than highest producing turbine *

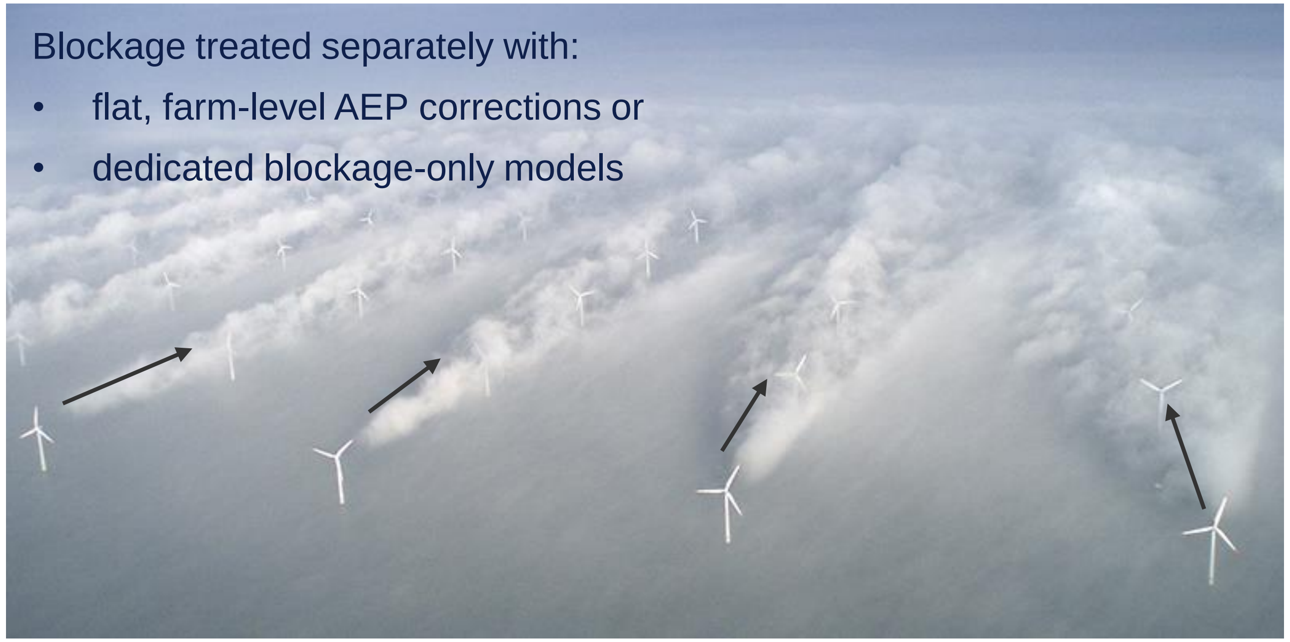
* Note: only applicable on plateau of thrust curve, will be less at higher wind speeds!

EnBW DNV

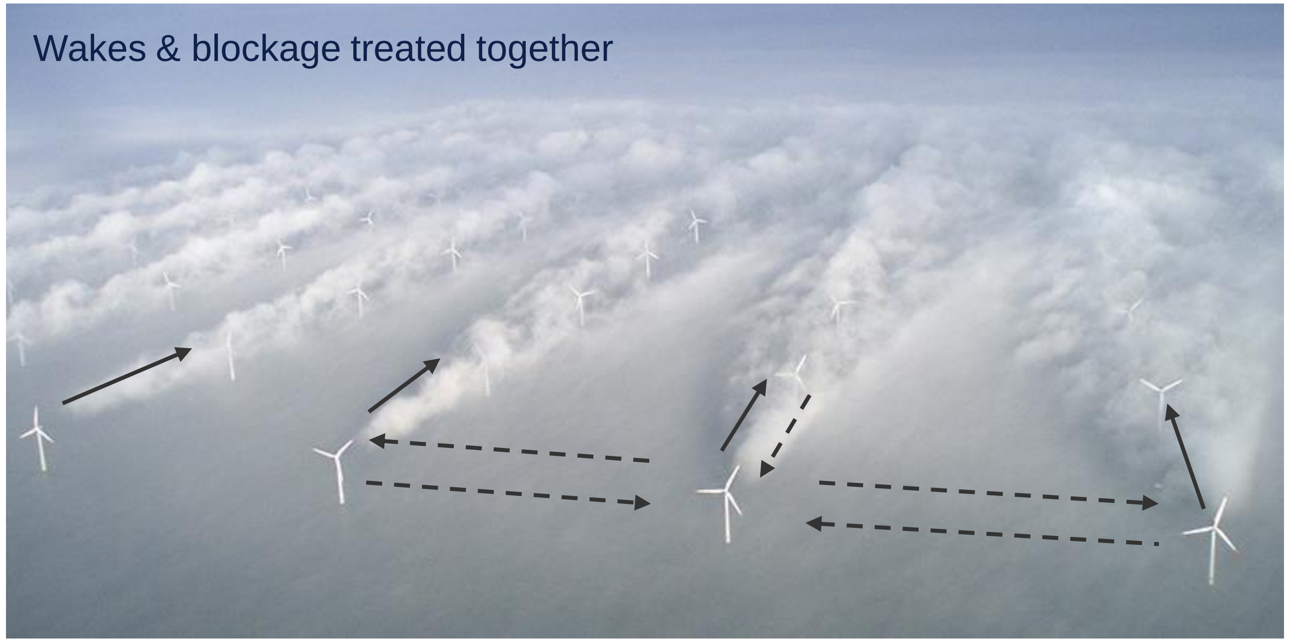
Summary

- CFD.ML has the potential to become the **next generation, fast-turnaround turbine interaction model** when applied stand-alone in energy production assessments of wind farms.
- DNV is working towards that goal through model improvements and validation
- **CFD.ML cloud API is available** to selected partners in private preview mode and will be soon available through DNV's WindFarmer:Analyst.
- Already now CFD.ML can be used to:
  - (cautiously) predict blockage & wakes
  - identify cases lying outside the operational envelope of traditional models
  - interpolate between discrete CFD simulations

Classic wake models



Next generation turbine interaction models (CFD.ML)



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Thank you

karol.mitraszewski@dnv.com, tom.levick@dnv.com

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