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DNV

CFD.ML – A NEW HOPE FOR RAPID TURBINE INTERACTION MODELLING?

BACKGROUND

The industry realized that popular engineering wake models, although fast, struggle to accurately predict wake and blockage lossess, especially at contemporary, large-scale wind farm clusters offshore. Sites with frequently occuring stable stratification also present a challenge for today's engineering models.

Model validation exercises are ongoing across the industry and so are activities around new model developments. The latter focus on striking the right balance between model fidelity and computational efficiency.

OBJECTIVE

A next-generation turbine interaction model, capturing flow physics better than today's engineering models:

- Wakes & blockage captured together on a per-turbine, per-flowcase basis, enabling simulation of **complex flow features** occuring especially at large wind farms
- **Accurate predictions** of internal wakes, external wakes (including long-distance cluster wake interactions), and also the global blockage effect.
- **Fast** enough for iterative wind farm design workflows

METHOD

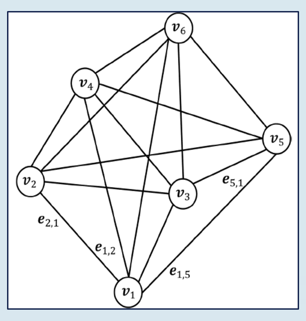
A new, machine learning based approach to turbine interaction modeling:

- **CFD.ML = a RANS CFD surrogate model** approximating high-fidelity wind farm flow simulations with good accuracy, requiring only a fraction of the time needed to run full CFD.
- Graph neural networks (GNNs) succesfully trained to encode the wind speed deficit/speed-up patterns evident in RANS CFD simulations of real life wind farms
- Until recently, used in DNV to increase CFD RANS directional resolution (interpolation between high-fidelity runs)
- Now released as **a stand-alone turbine interaction model**

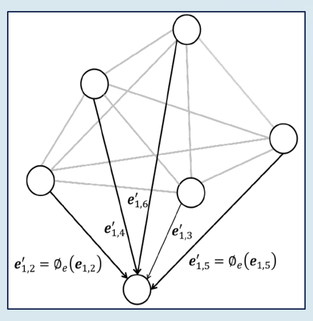
RESULTS

WHAT'S A GRAPH NEURAL NETWORK (GNN)?

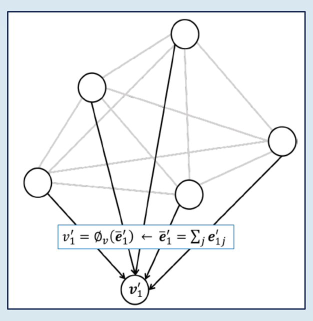
- A type of neural network well suited for learning physical interaction between objects
- allows for a varying number of inputs
- is order invariant



Graph vertices = turbines



Graph edges = relationships between turbines (wakes & blockage)



Aggregating all impacts on the i-th turbine

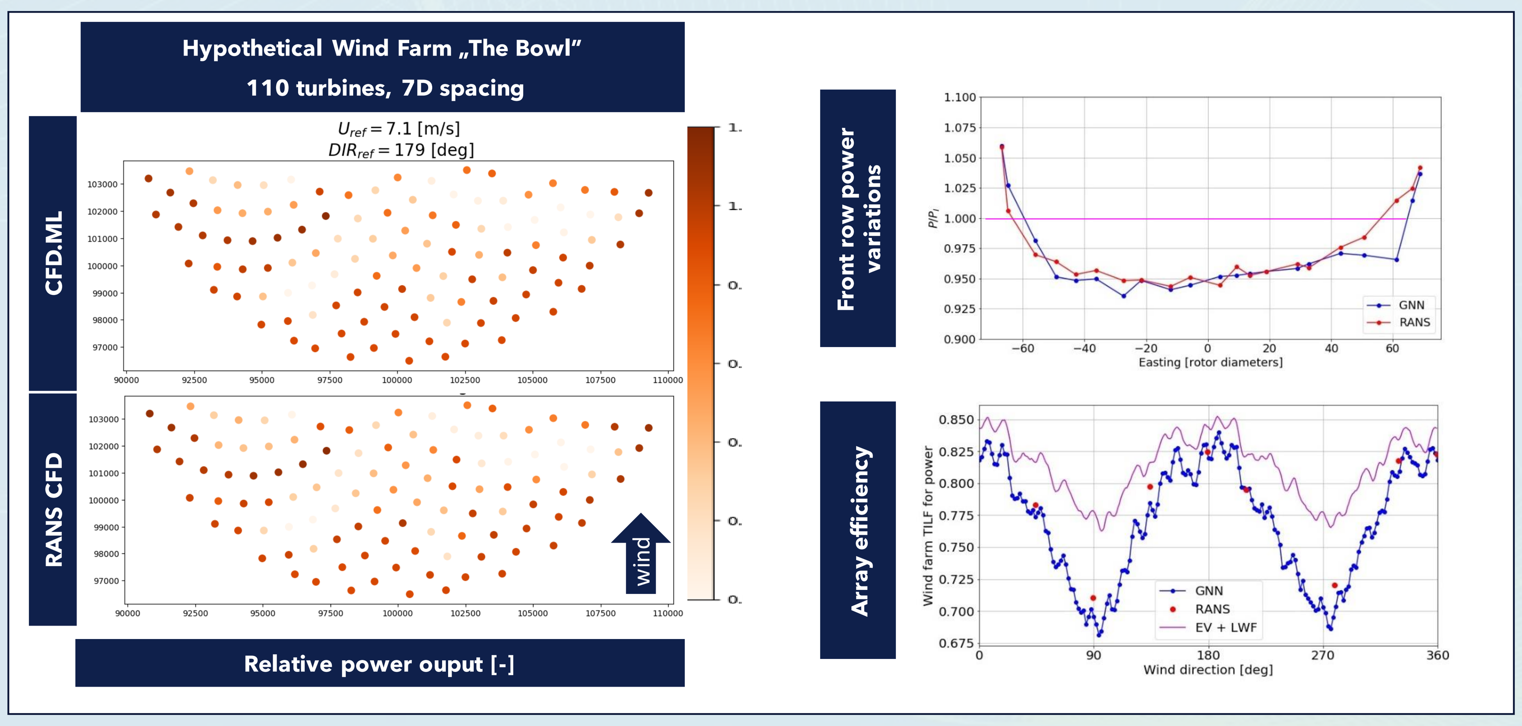
The GNN predicts wind speed deficits and/or speed-ups at the every turbine caused by wakes & blockage impacts of its neighbors as function of:

- downwind and crosswind distance to the (wake&block.) sending turbine
- Ct, rotor and hub-height of the sender
- Relative position in the array
- [Future] ABL properties, stability, turbulence, etc.

Read more:

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

HOW WELL CAN CFD.ML REPLICATE RANS CFD?



VALIDATION – INTERNAL WAKES & BLOCKAGE PATTERNS

$$\Delta P = P_{\text{modelled}} - P_{\text{measured}}$$

$$\text{MBE}_{\text{P}} = \frac{\sum_{i=1}^{n} \Delta P_i}{N}$$

$$\text{rMBE}_{\text{P}} = \frac{\text{MBE}_{\text{P}}}{\bar{P}}$$

6 Offshore Wind Farms

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	-0.9	-1.8	-1.7	-0.9	-2.0	0.3

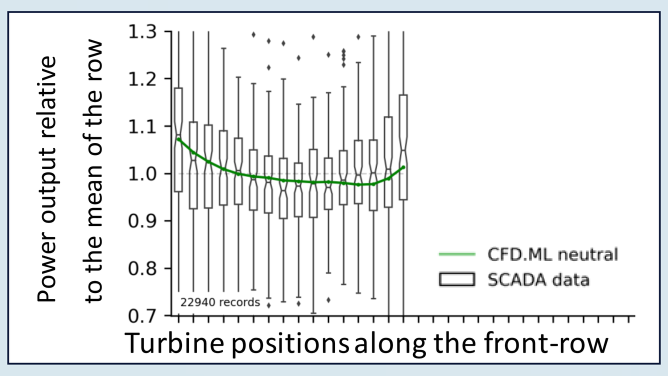
(Neutral) CFD.ML validation summary:

- slight overprediction of internal wakes, but
- **visibly smaller spread** of the error (not shown)
- **good predictive skill of blockage** induced variations on a per-turbine basis
- underprediction of cluster wakes (not shown)

Read more:

PAPER • OPEN ACCESS
Validating the next generation of turbine interaction models
To cite this article: T Levick et al 2022 J. Phys.: Conf. Ser. 2257 012010

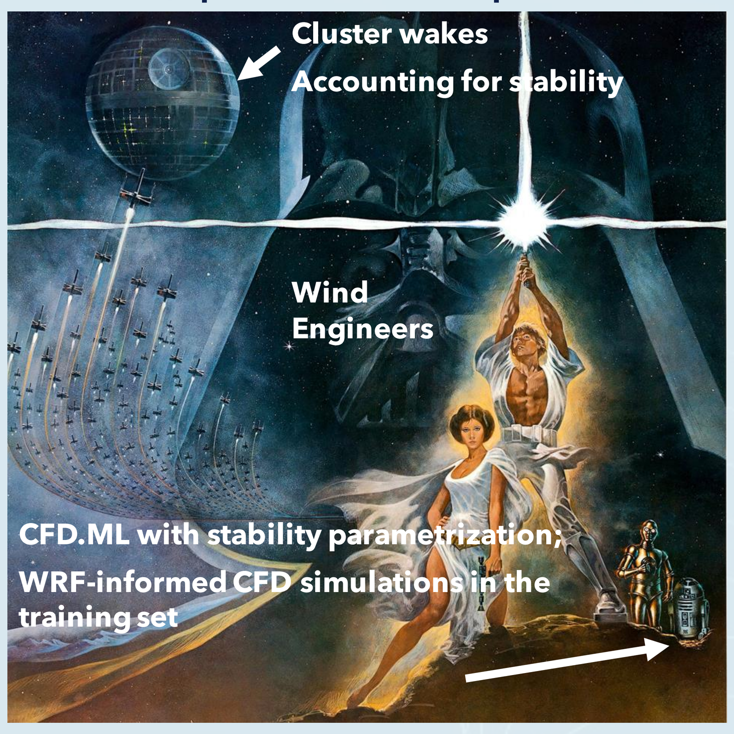
Undisturbed inflow to a large offshore wind farm



OUTLOOK

- To address the issues revealed in validation, we are working on **parametrizing different atmospheric stability conditions and boundary layers in the GNN.**
- And we will extend the training set with **stable CFD simulations having WRF-informed boundary conditions.**
- Our hopes are high that this will improve model accuracy significantly and deliver a future-ready solution for turbine interaction modeling!

Wake Wars, Episode IV: A New Hope



CONCLUSIONS

- CFD.ML as a stand-alone turbine interaction model is a **promising approach.**
  - **accurate and fast** enough
  - trained on a high-fidelity model derived from first principles, hence no tuning to historic 10-min SCADA dataset involved (**future-ready**)
  - while we are still working on major enhancements to CFD.ML, it already is available for testing in beta – and free of charge!
  - we seek collaboration partners willing to participate in validation efforts onshore and offshore
- CFD.ML may also be „anchored locally" to CFD simulations of one particular wind farm site, effectively enabling layout design iterations based on high-fidelity flow&wake modeling.

REFERENCES

- James Bleeg 2020 J.Phys.: Conf. Ser. 1618 062054
- T Levick et al 2020 J. Phys.: Conf. Ser. 2257 012010
- Mitraszewski K et al, AI for turbine interactions, WindEurope Technology workshop 2023, Lyon
- DNV webinar recording (Aug 2023): Addressing offshore wake prediction biases [LINK]

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