Machine Learning – the latest news

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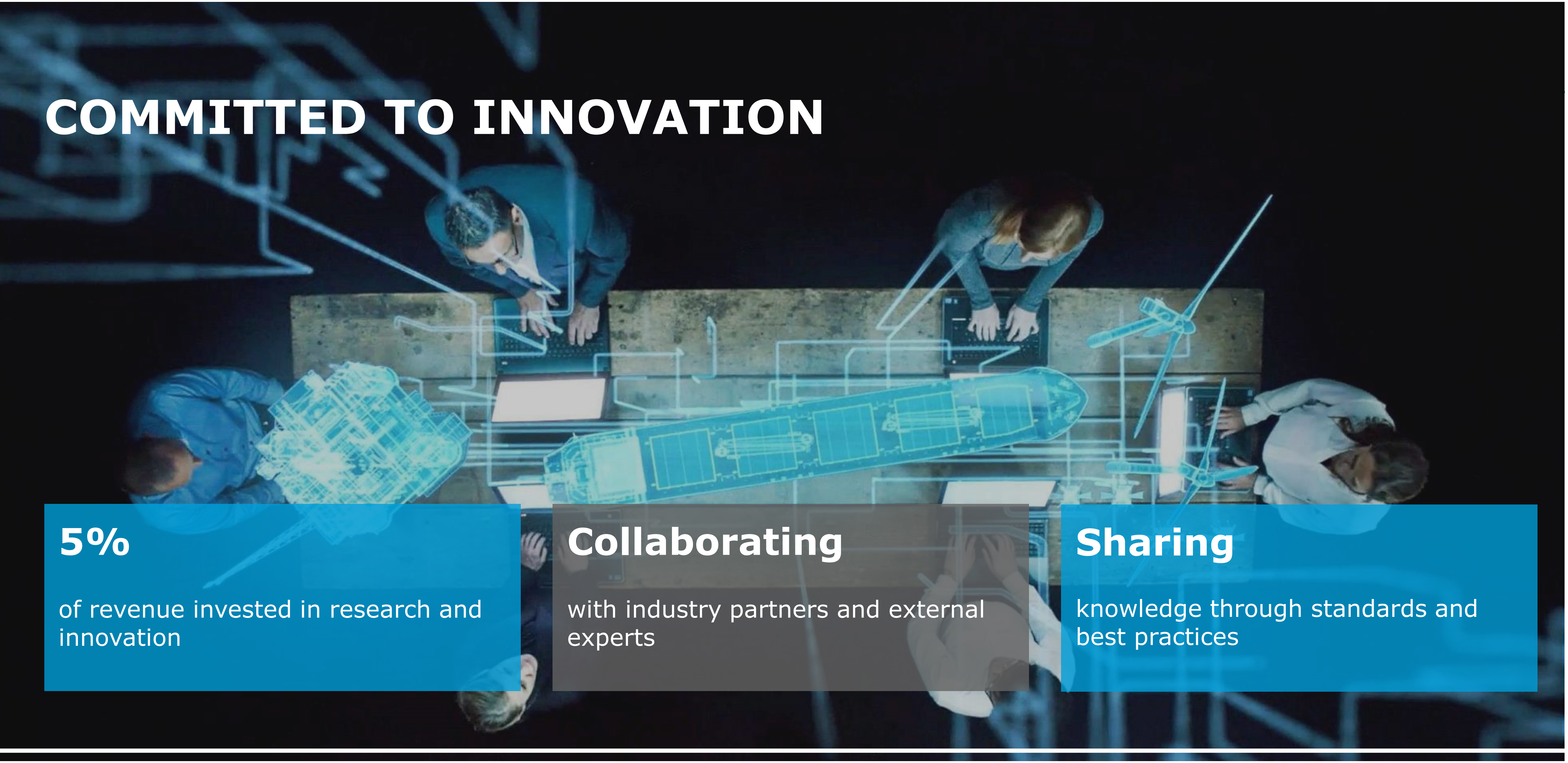


COMMITTED TO INNOVATION

5%

of revenue invested in research and innovation

Collaborating

with industry partners and external experts

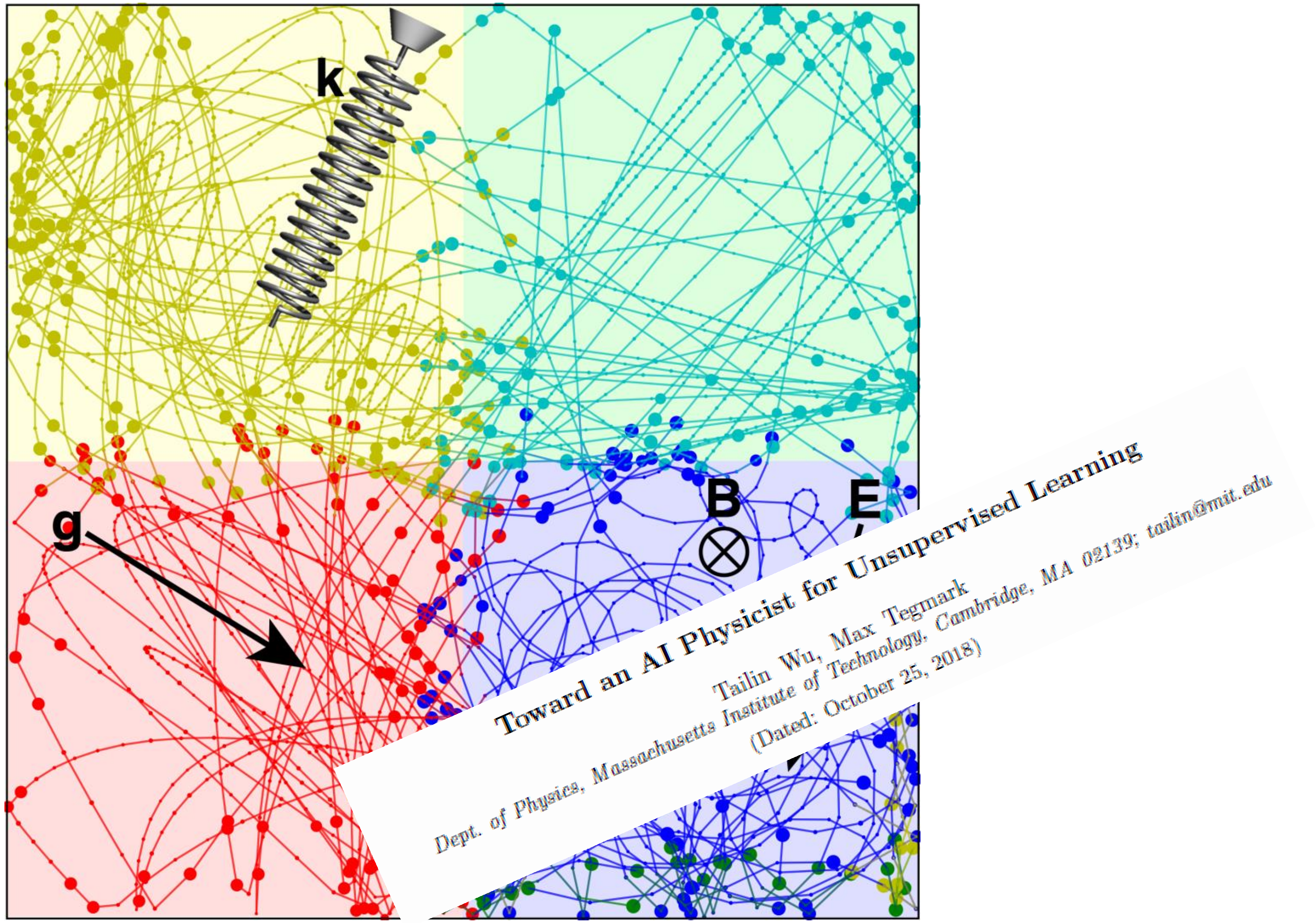
Sharing

knowledge through standards and best practices

- $a = F/m$

$$
\begin{aligned}
\frac{\partial \overline{u}}{\partial t} + \overline{u}\frac{\partial \overline{u}}{\partial x} + \overline{v}\frac{\partial \overline{u}}{\partial y} + \overline{w}\frac{\partial \overline{u}}{\partial z} =& f\overline{v} - \frac{1}{\rho_0}\frac{\partial \overline{p}_1}{\partial x} + \nu\nabla^2\overline{u} \\
& - \left(\frac{\partial \overline{u'^2}}{\partial x} + \frac{\partial \overline{u'v'}}{\partial y} + \frac{\partial \overline{u'w'}}{\partial z}\right), \\
\frac{\partial \overline{v}}{\partial t} + \overline{u}\frac{\partial \overline{v}}{\partial x} + \overline{v}\frac{\partial \overline{v}}{\partial y} + \overline{w}\frac{\partial \overline{v}}{\partial z} =& - f\overline{u} - \frac{1}{\rho_0}\frac{\partial \overline{p}_1}{\partial y} + \nu\nabla^2\overline{v} \\
& - \left(\frac{\partial \overline{u'v'}}{\partial x} + \frac{\partial \overline{v'^2}}{\partial y} + \frac{\partial \overline{v'w'}}{\partial z}\right), \\
\frac{\partial \overline{w}}{\partial t} + \overline{u}\frac{\partial \overline{w}}{\partial x} + \overline{v}\frac{\partial \overline{w}}{\partial y} + \overline{w}\frac{\partial \overline{w}}{\partial z} =& g\frac{\overline{\theta}_1}{\theta_0} - \frac{1}{\rho_0}\frac{\partial \overline{p}_1}{\partial z} + \nu\nabla^2\overline{w} \\
& - \left(\frac{\partial \overline{w'u'}}{\partial x} + \frac{\partial \overline{w'v'}}{\partial y} + \frac{\partial \overline{w'^2}}{\partial z}\right), \\
\frac{\partial \overline{\theta}}{\partial t} + \overline{u}\frac{\partial \overline{\theta}}{\partial x} + \overline{v}\frac{\partial \overline{\theta}}{\partial y} + \overline{w}\frac{\partial \overline{\theta}}{\partial z} =& \alpha_h\nabla^2\overline{\theta} \\
& - \left(\frac{\partial \overline{u'\theta'}}{\partial x} + \frac{\partial \overline{v'\theta'}}{\partial y} + \frac{\partial \overline{w'\theta'}}{\partial z}\right), \\
\frac{\partial \overline{u}}{\partial x} + \frac{\partial \overline{v}}{\partial y} + \frac{\partial \overline{w}}{\partial z} =& 0,
\end{aligned}
$$

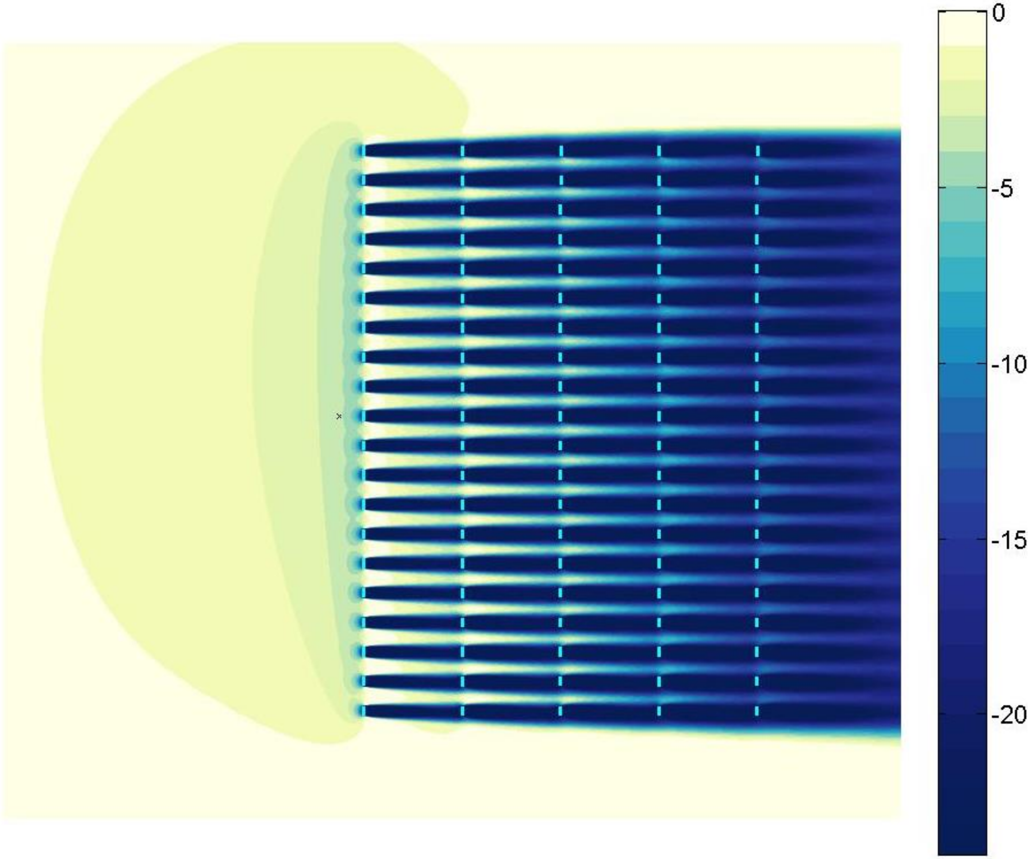
AI Physicist!



Turbine interaction loss predictions with high-fidelity flow modelling

Advantages

- Directly simulate the two-way coupling between wind farm and atmosphere
- Includes oft-neglected first-order influences such as atmospheric stability (e.g. gravity waves)
- Captures both wake *and* blockage effects



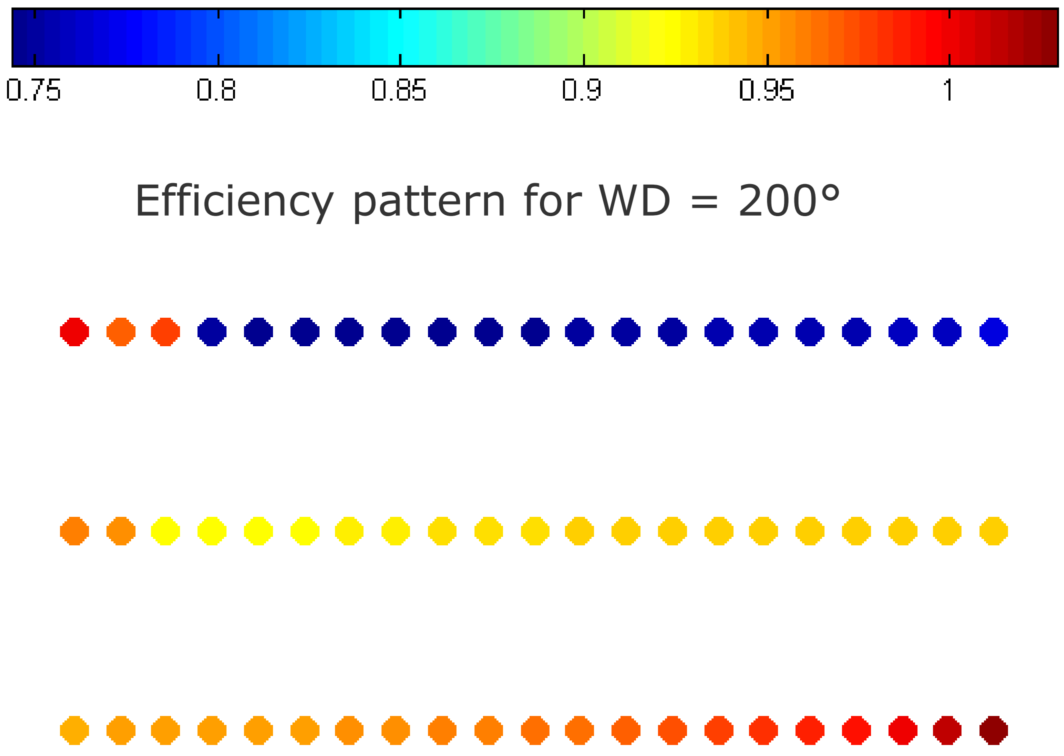
Disadvantages

- Slow
- Expensive
- Cannot realistically optimize a turbine layout

Another option for predicting turbine interaction loss

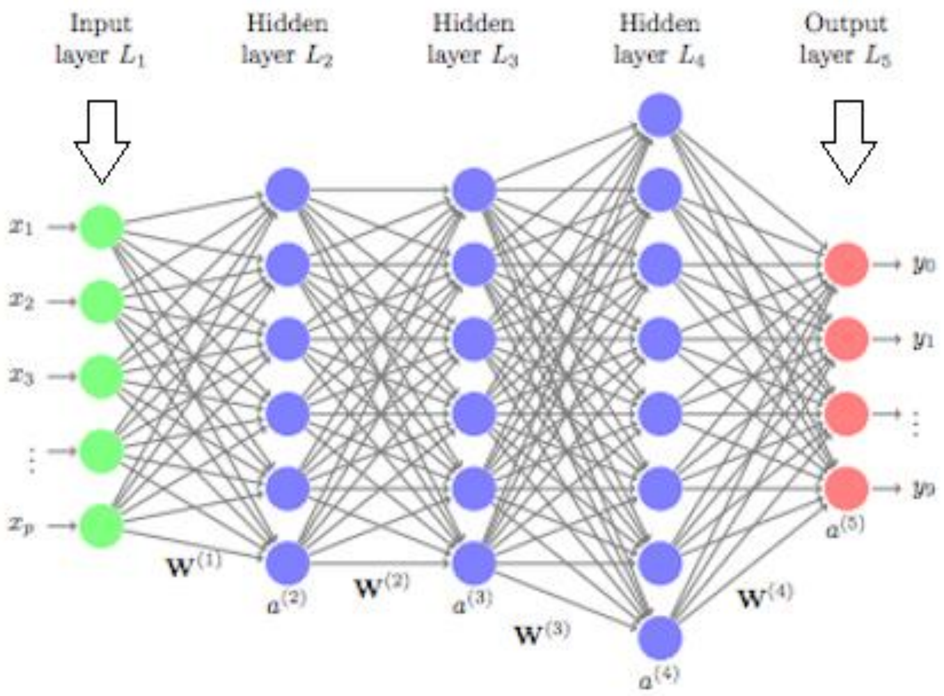
Objective: *Combine the accuracy benefits of a high-fidelity flow model with the speed of a reduced-order model*

Idea: *Train a machine learning model to estimate what the high-fidelity flow model would predict at each turbine location*

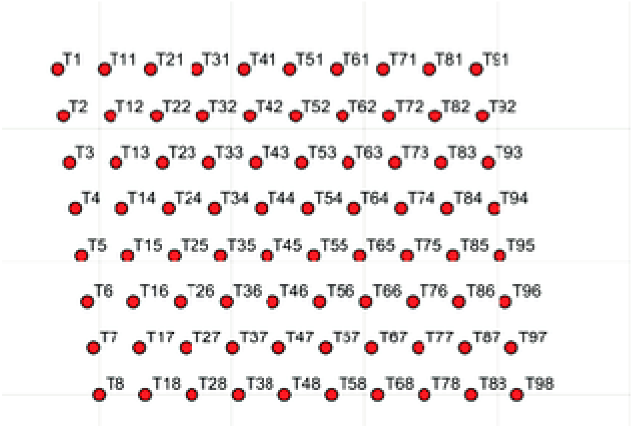


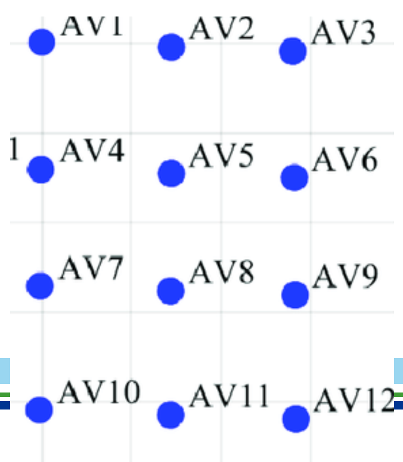
Challenge

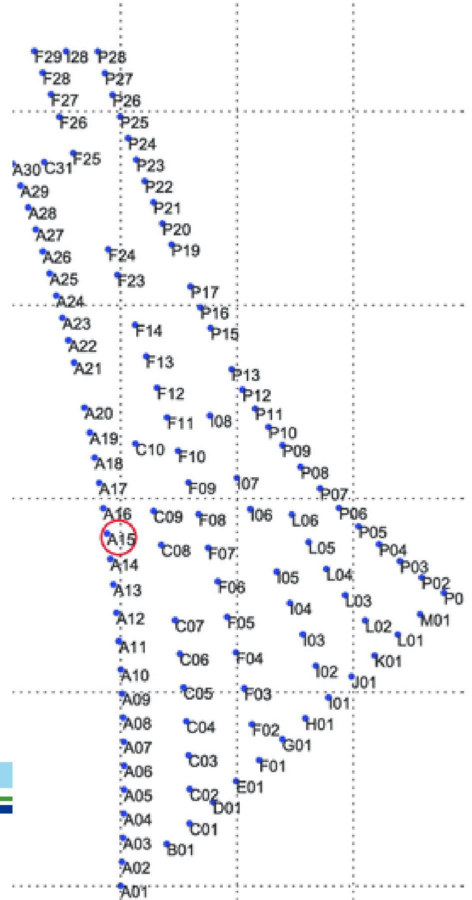
Neutral network: Fixed number of inputs in a fixed order



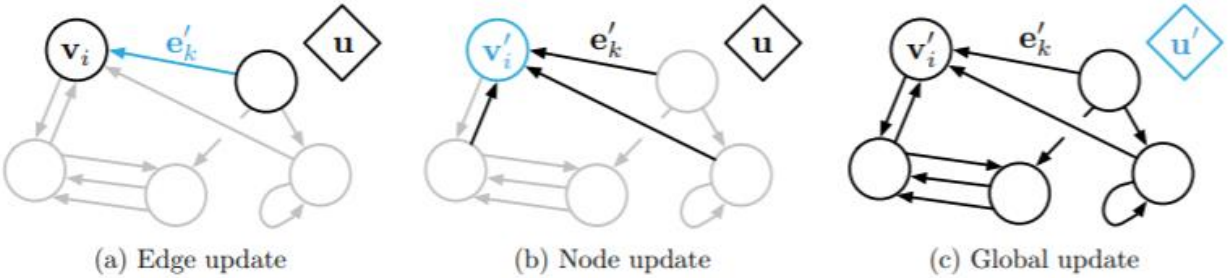
Wind farms: Variable number of turbines with no clear order

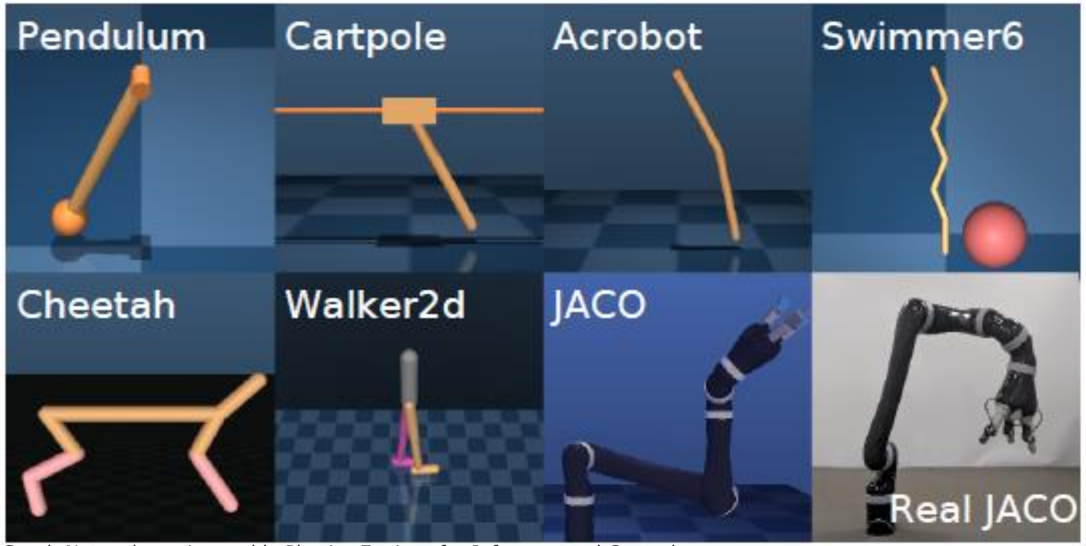






Solution: Graph Networks





Graph Networks as Learnable Physics Engines for Inference and Control.
Alvaro Sanchez-Gonzalez, Nicolas Heess, Jost Tobias Springenberg, Josh Merel, Martin Riedmiller, Raia Hadsell, Peter Ba

Allows for different numbers of inputs

Order invariant

Well-suited to learning physical interactions between objects

Battaglia PW, et al. "Relational inductive biases, deep learning, and graph networks"
https://arxiv.org/pdf/1806.01261.pdf

Current implementation – We are starting simple

- Graph networks comprising MLPs constructed using PyTorch

- Inputs
  – Turbine coordinates
  – Rotor diameter
  – C_t at plateau of the C_t curve
  – Wind direction

- Output / Prediction
  – U / U_I for each turbine

U = Effective wind speed (i.e. the wind speed used to look up power in the power curve).

The "I" subscript denotes the situation where the turbine is operating in isolation

Data

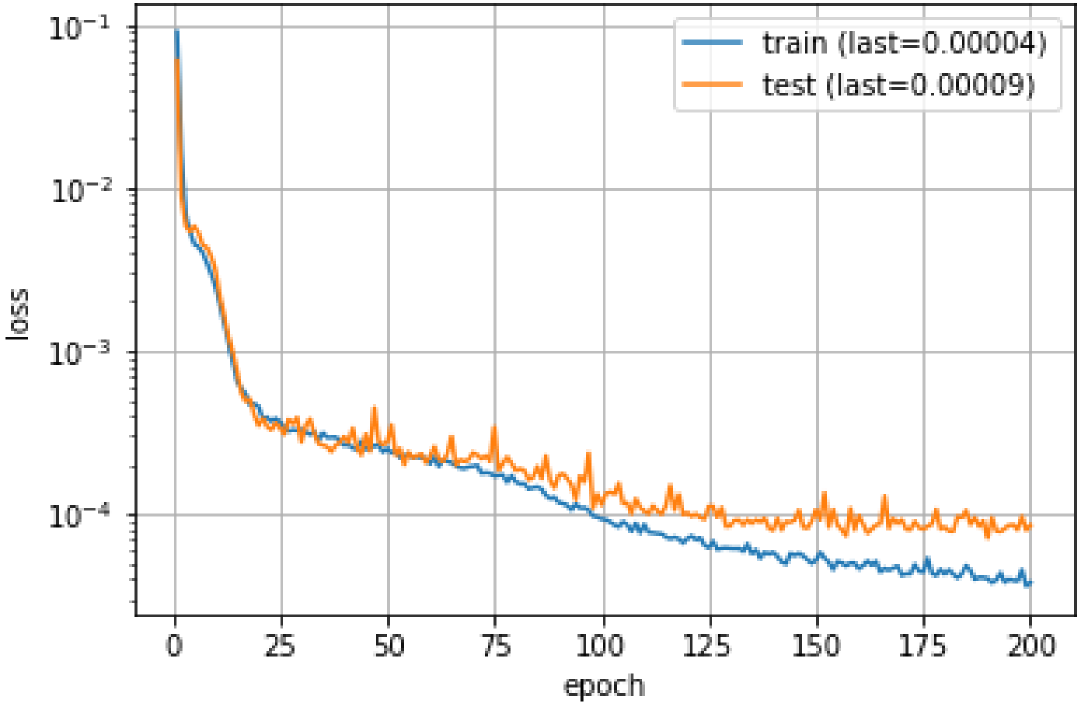
10^6

- 41 different wind farms

- Simulated with steady-state RANS CFD
  - Neutral boundary layer with capping inversion and stably stratified free atmosphere
  - Below-rated wind speeds
  - Varying wind directions
  - 182 simulation in total ($\longrightarrow 10^6$)

- Trained on 145 simulations

- Tested against 39 simulations



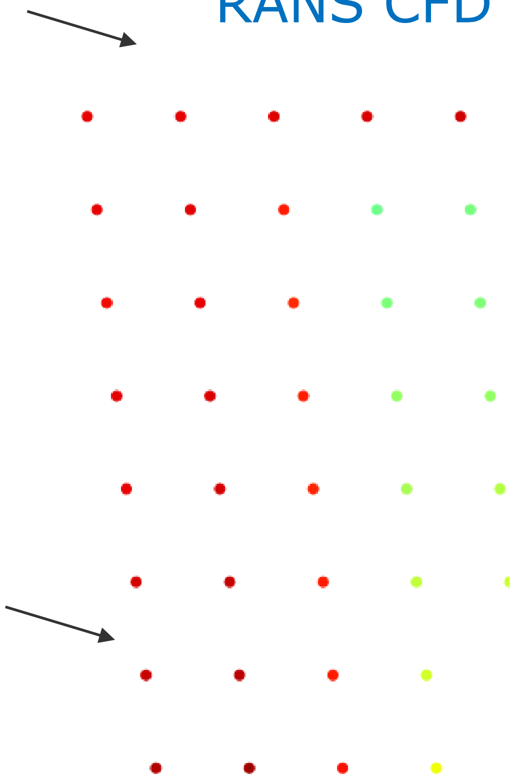
DNV·GL

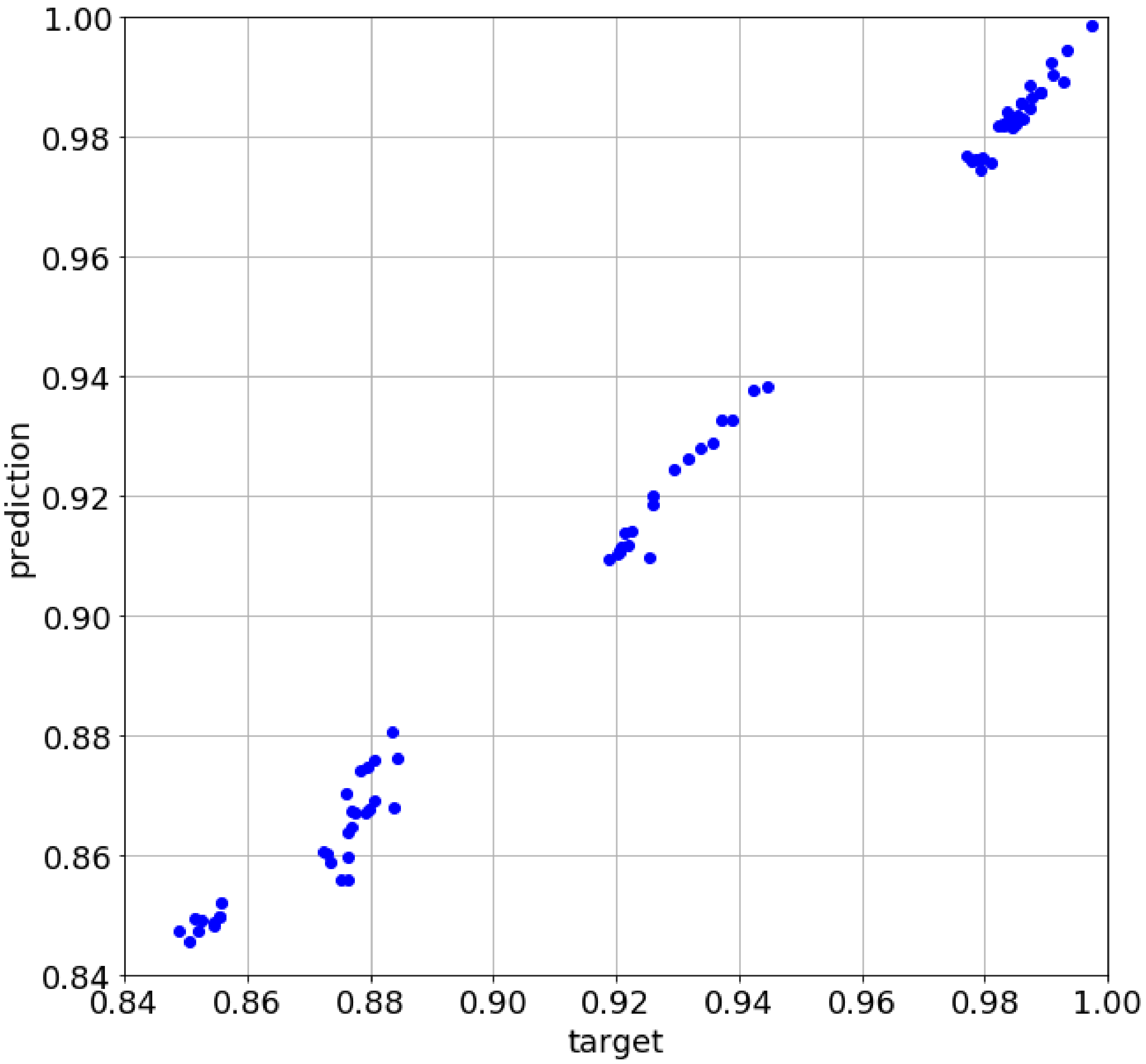
Compare ML pre… direction = 289°

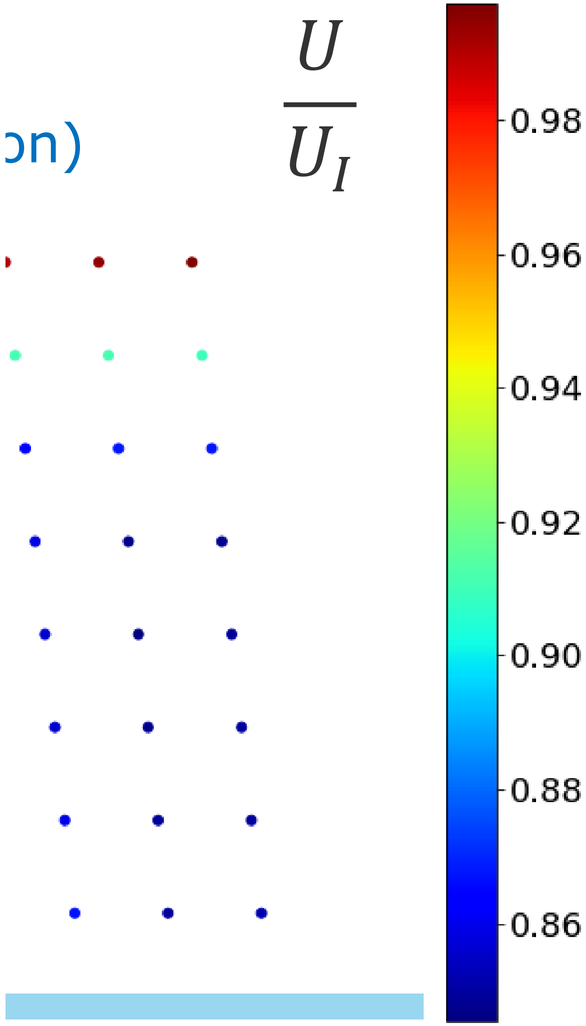
Horns Rev 1 CFD … this wind direction

Pattern is well-ca…

RANS CFD … on)





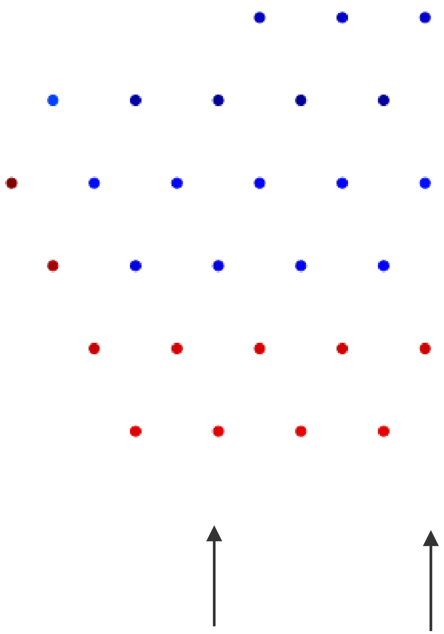


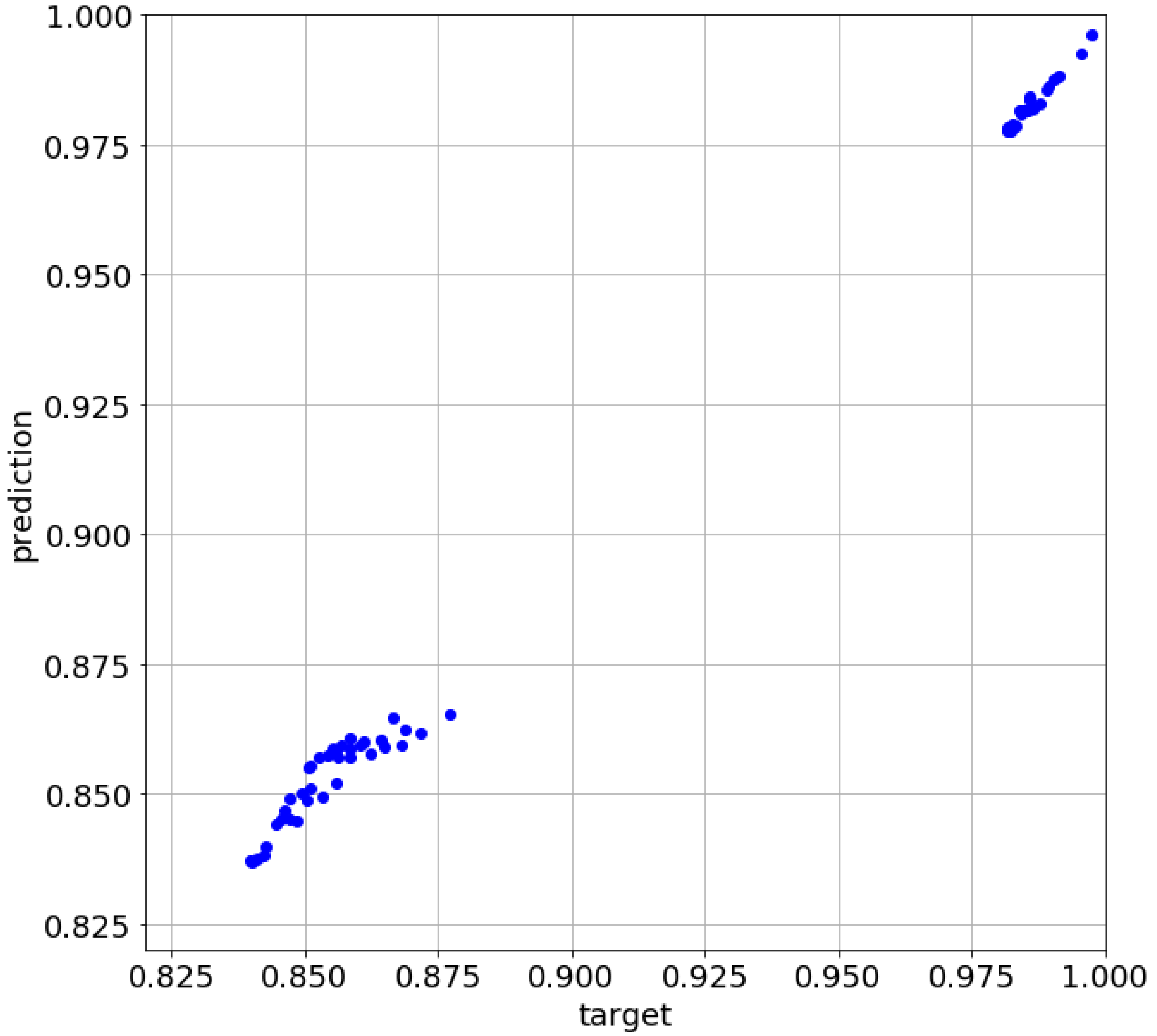
Compare ML pr n with 60 turbines, 6D spacing, an

This wind farm is

Pattern is well-c

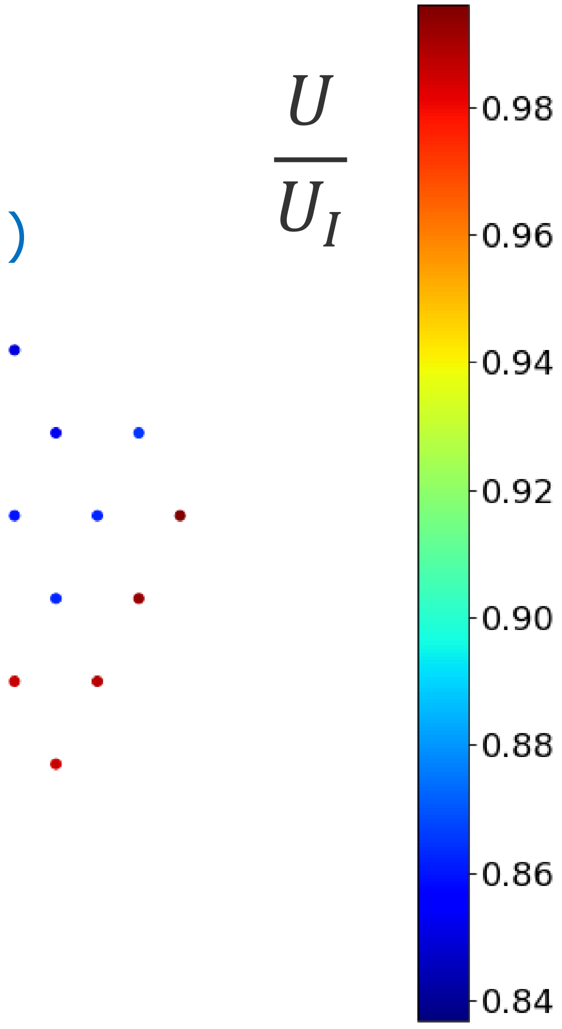
RANS CFD





n)

$$\frac{U}{U_I}$$



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Still a ways to go

- Can we predict the variation with wind speed?
- Can we predict the sensitivity to atmospheric stability?
- Can we handle mixed turbine types?
- TBD

Goals

- *Low end*: A tool that can interpolate between CFD results at a given wind farm (e.g. translate simulation results for 6 wind directions into results for 180 directions)
  - Benefit: Reduces the number of high-fidelity simulations needed to conduct a complete turbine interaction analysis of a wind farm.

- *High end*: A machine learning model reliable enough that it can be used on wind farms that are not part of the training set
  - Benefits: Turbine interaction loss predictions high-fidelity models accuracy and engineering model speed. Wind farm layouts could then be optimized considering both wakes *and* blockage

Summary

- High-fidelity CFD takes a long time
- Trend in AI to “learn physics”
- New model developed that “learns” CFD
- Some very promising first results
- Much more to follow!

Thank you

DISCLAIMER

This presentation shows models and results that are the product of professional research only.

Techniques and methods demonstrated here are not in commercial use by DNV GL.

The work presented within this presentsion represents research in progress. As such, any findings are preliminary and subject to change.

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SAFER, SMARTER, GREENER

Backup

A little more insight into the statistical accuracy

- The red line indicates that the mean absolute bias (i.e. mean error over a wind farm) across all the test predictions is a little over 0.1%

- The worst wind farm bias was 1.5%