DTU

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Wakes – what’s new or what’s important

With Contributions from
Gunnar Larsen, Paul van Laen, Tuhfe Göçmen, Alexander Meyer Forsting, Niels G. Mortensen and many more from DTU Wind

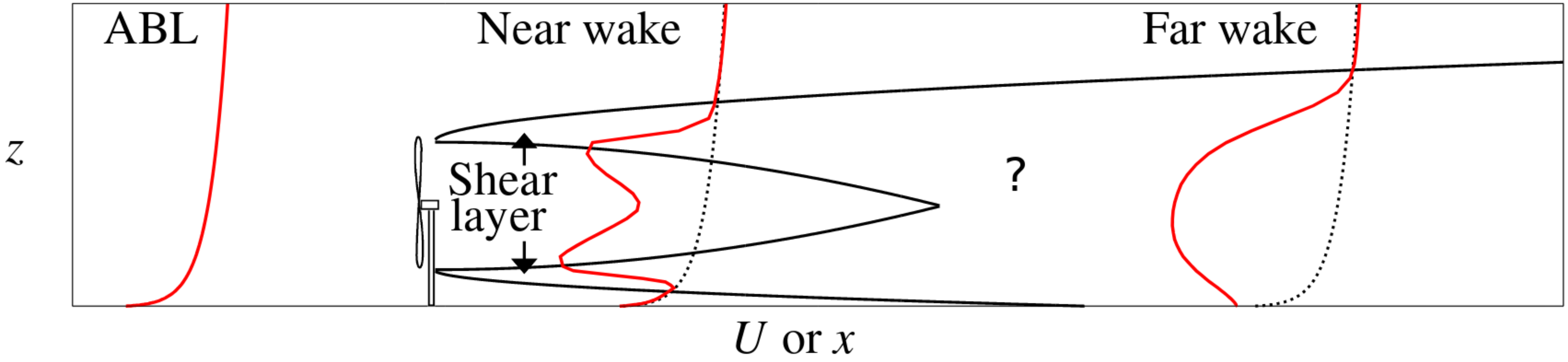
Outline

- Blockage effects & and wakes from windfarms
- AI & wakes – how to predict 1 min average power from a windfarm
- Wakes & Uncertainty
- Cool measurments from a wake
- Control of wind farms

Some words on validation of wake models

Wakes

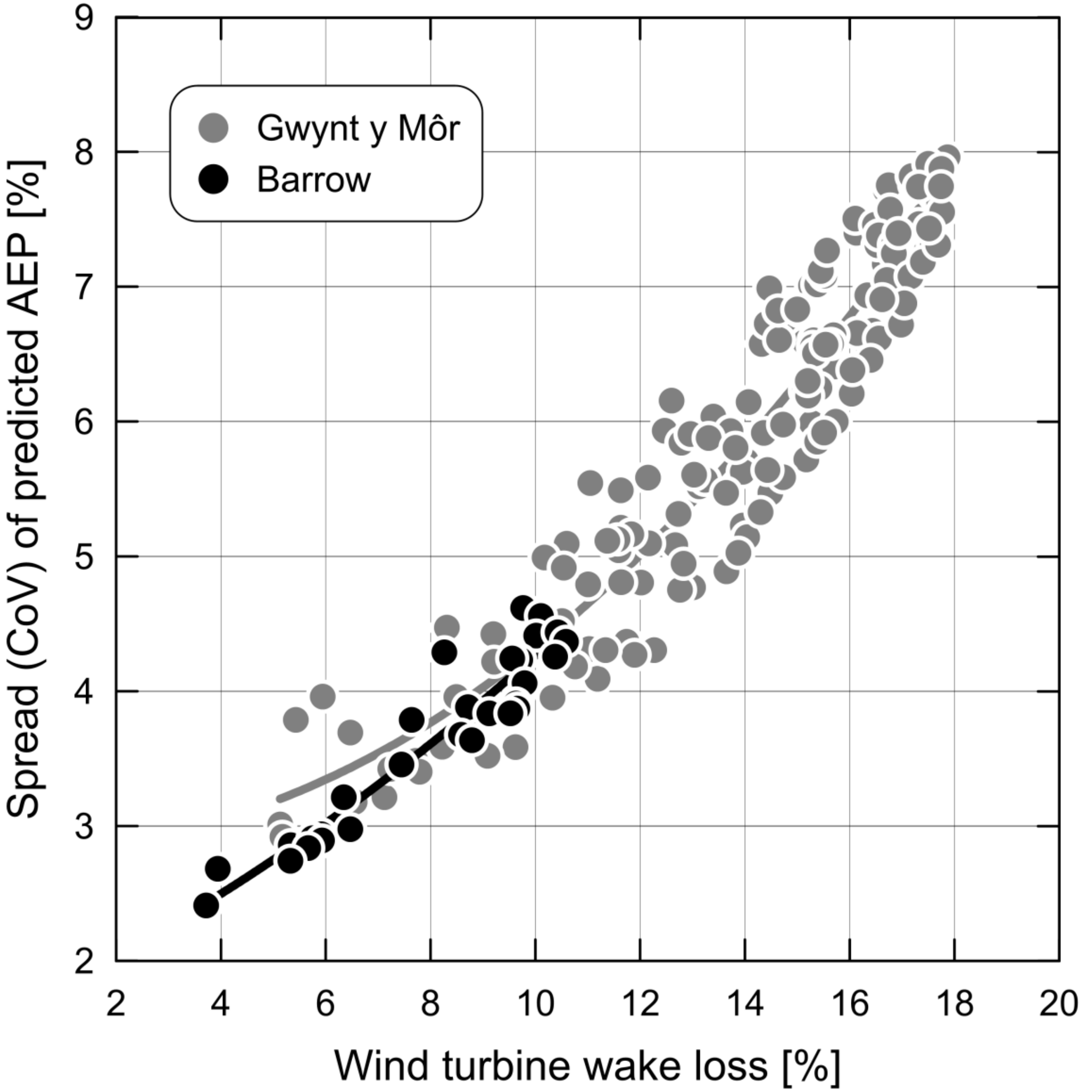
The challenging area



What do we need to validate

- Velocity and turbulence in the wake is important for estimating Wakeloss and loads for the turbine within the wake.
- C_T – the thrust coefficient from the turbin, Inflow conditions U (speed) and Turbulence (and stability)
- Wind farm data in form of power or loads
- All of above needs to be there to validate the wake models

Wake modelling offshore in CREYAP (EWEA, 2015)



- Wake models disagree inside wind farms: uncertainty (CV) $\propto$ WTG wake loss
- Wakes represent a significant wind farm loss
  - Onshore: 6-10%
  - Offshore: 8-14%
- Modelled with separate wake models
  - Model name and specification important
  - Model configuration must be known too!
- WF wake modelling uncertainty (CV)
  - Onshore: 13-18%
  - Offshore: 16-22%
  - Uncertainty $\propto$ WF wake loss
- Classic models seem to provide realistic results for Barrow Offshore Wind Farm

Single Wake – an automate comparison in Pywake in our optimization frame work TOPFARM

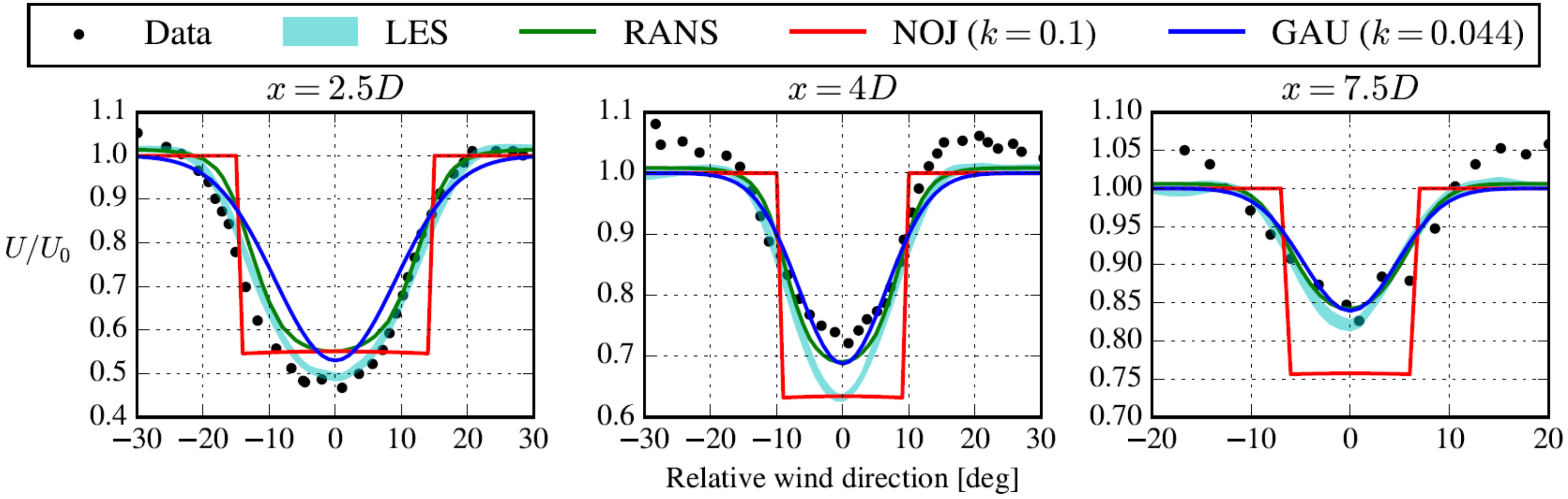


Figure 3: Case 3: Nibe B.

Windfarm efficiency

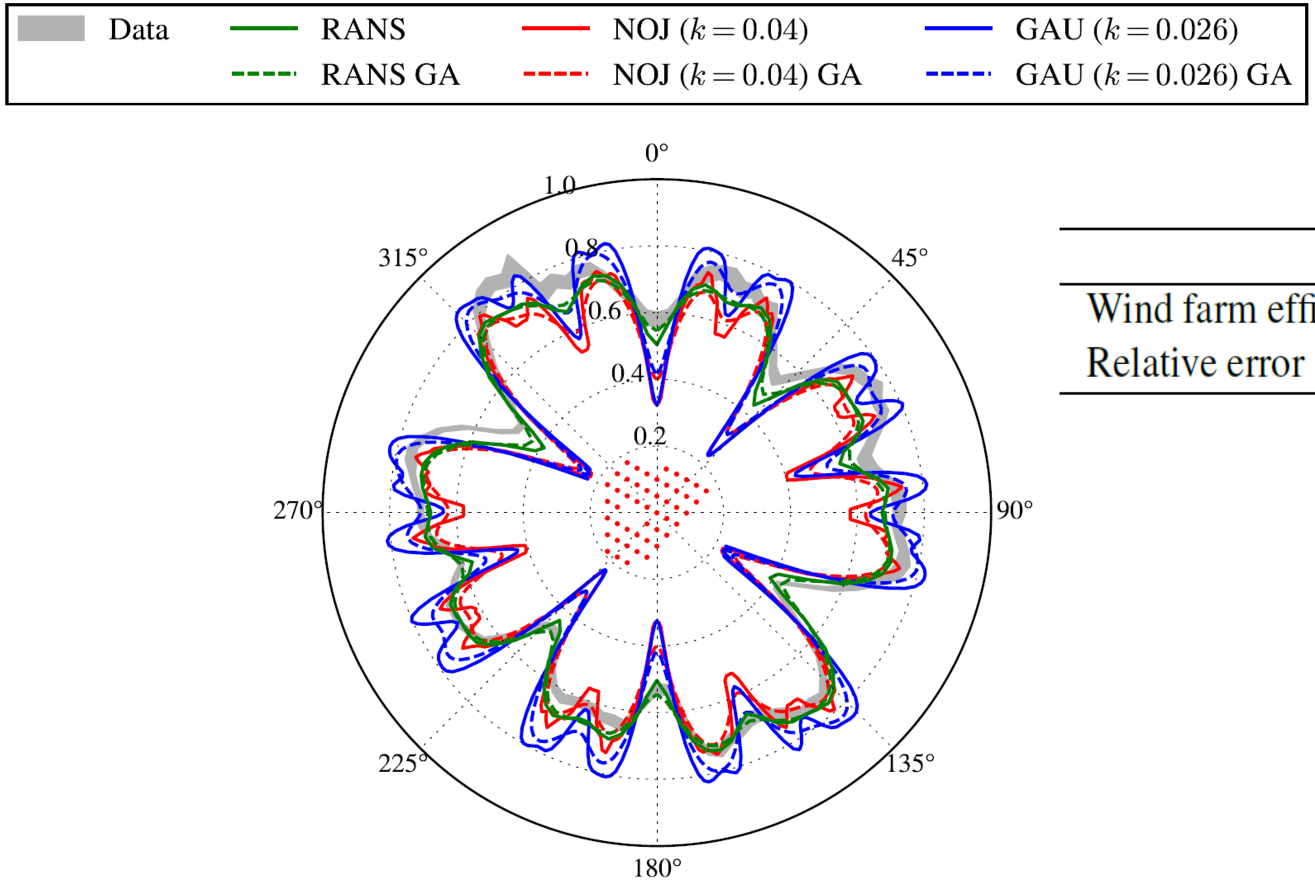
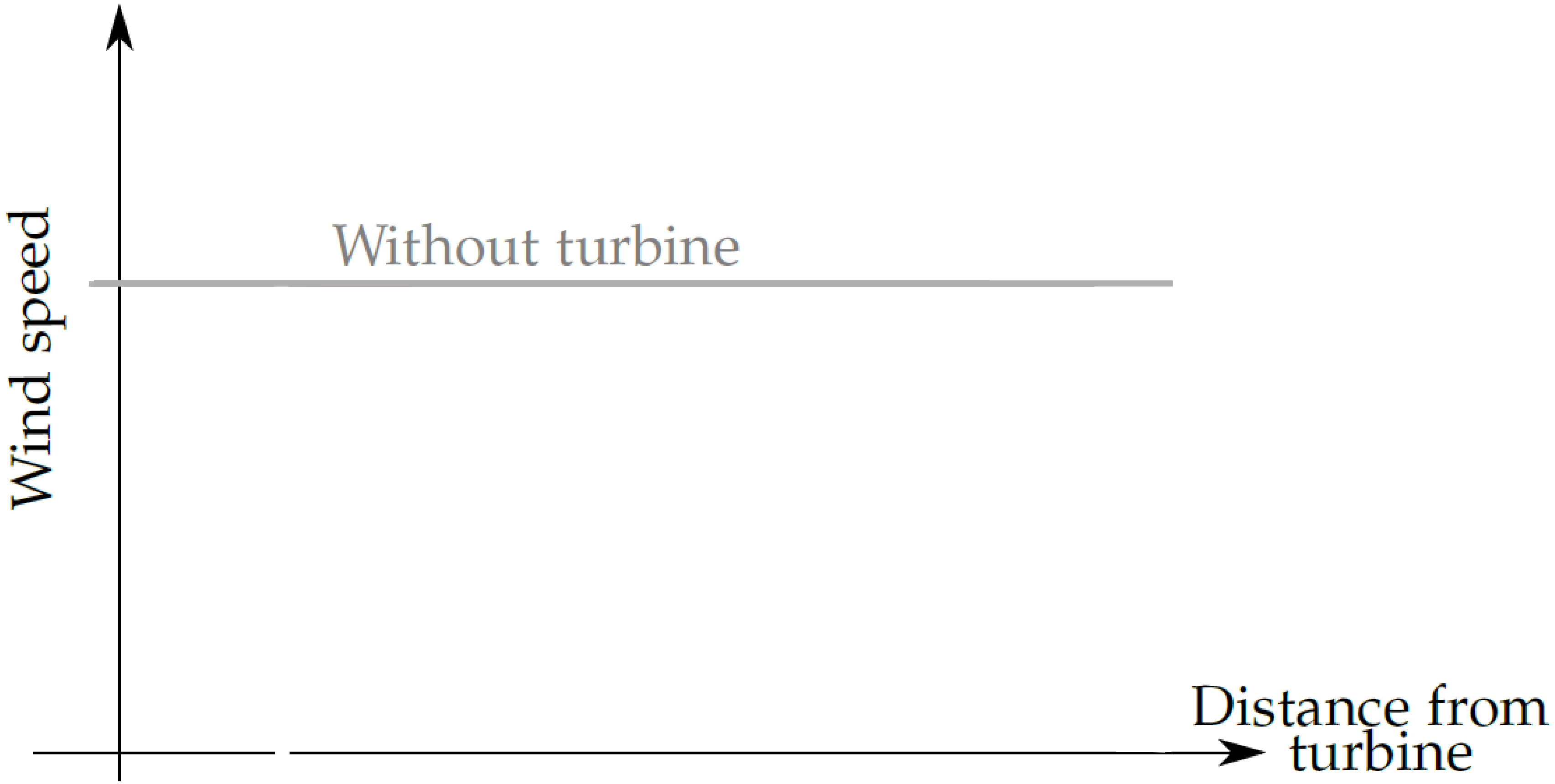


Figure 17: Case 12: Lillgrund wind farm efficiency.

	Measurement data	RANS	NOJ	GAU
Wind farm efficiency	0.66 ± 0.016	0.64	0.58	0.65
Relative error [%]	-	-3	-11	-2

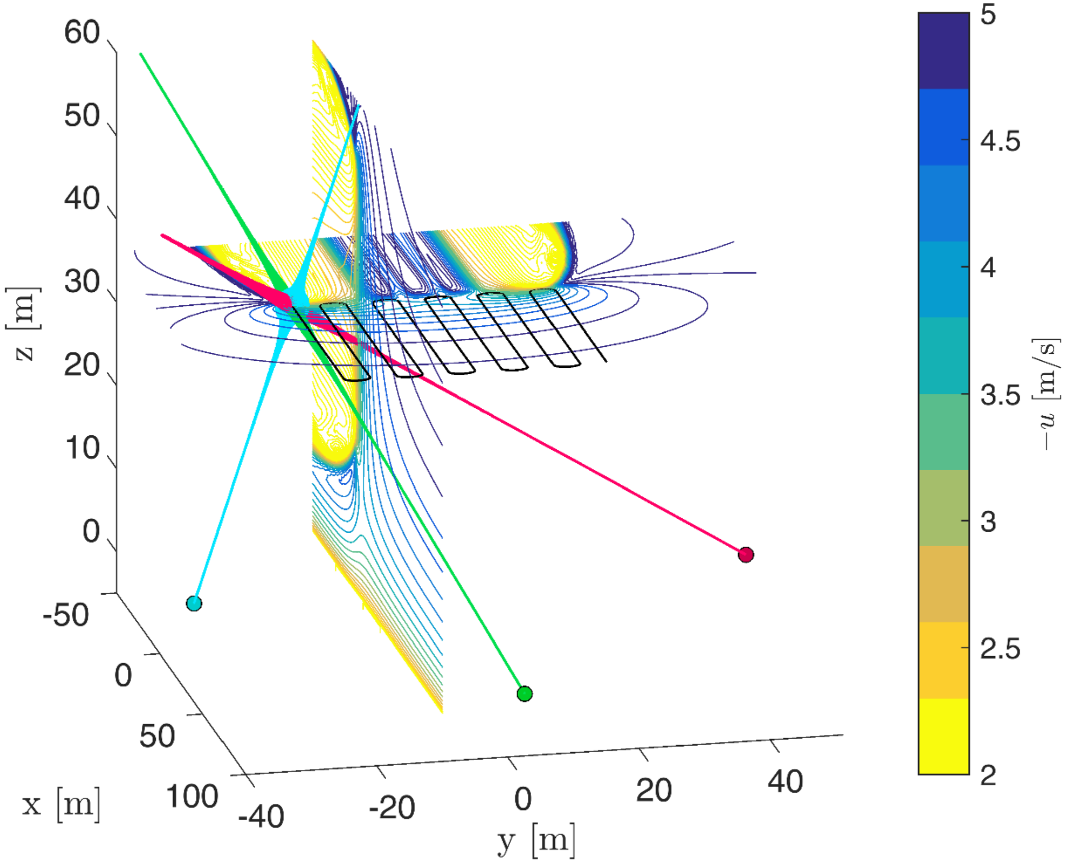
Blockage effects

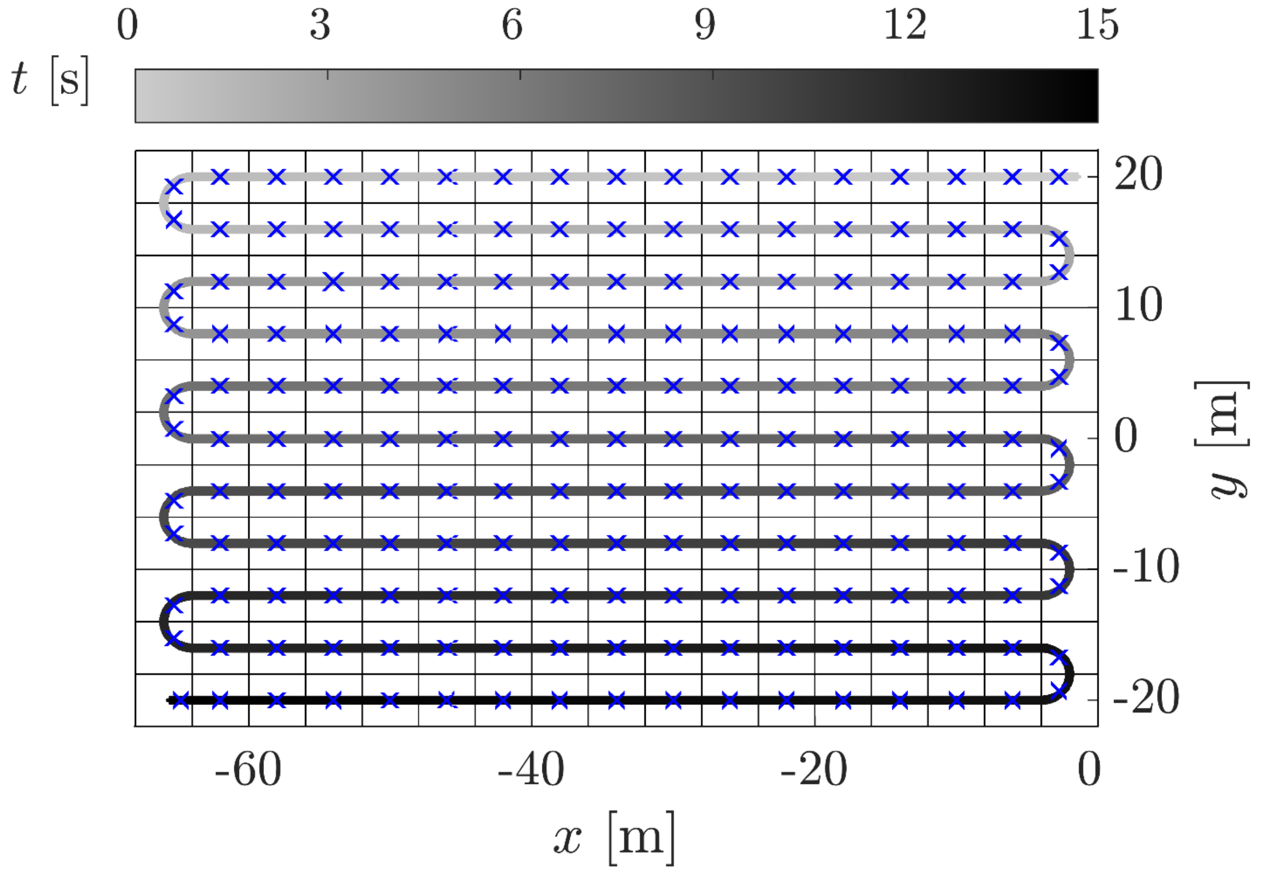
Induction zone

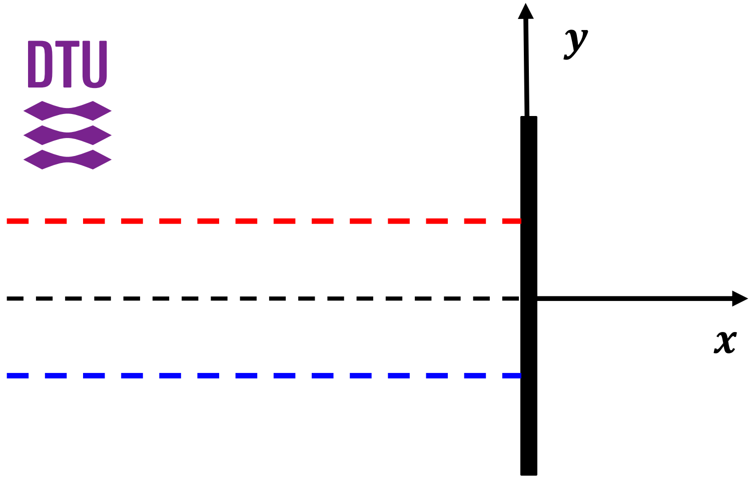


CFD validation with wind scanner

The lidar measurements

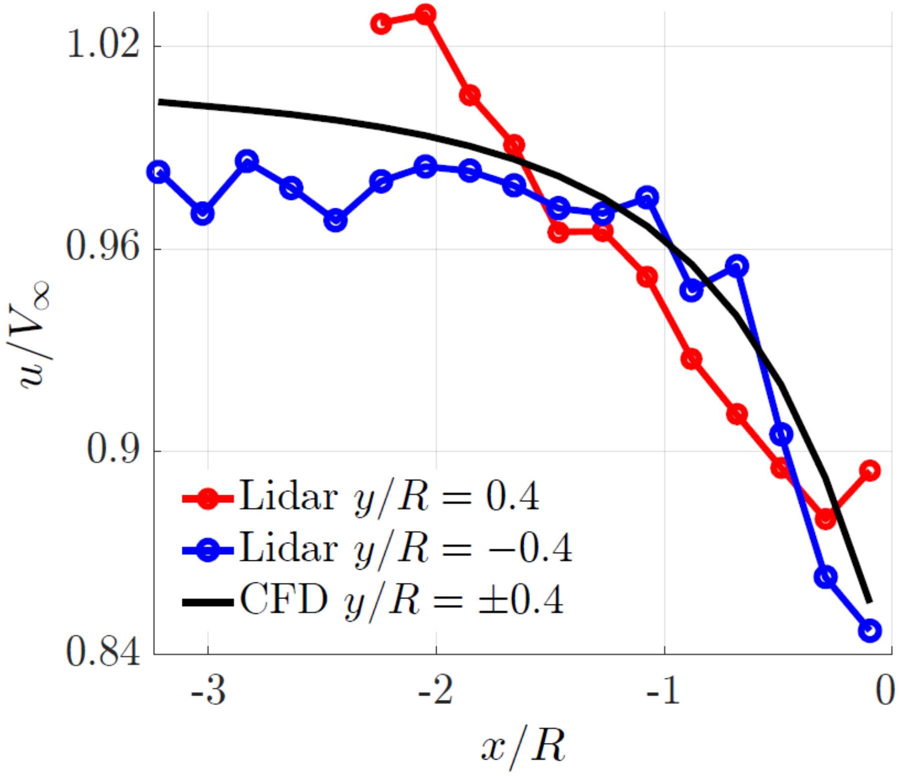




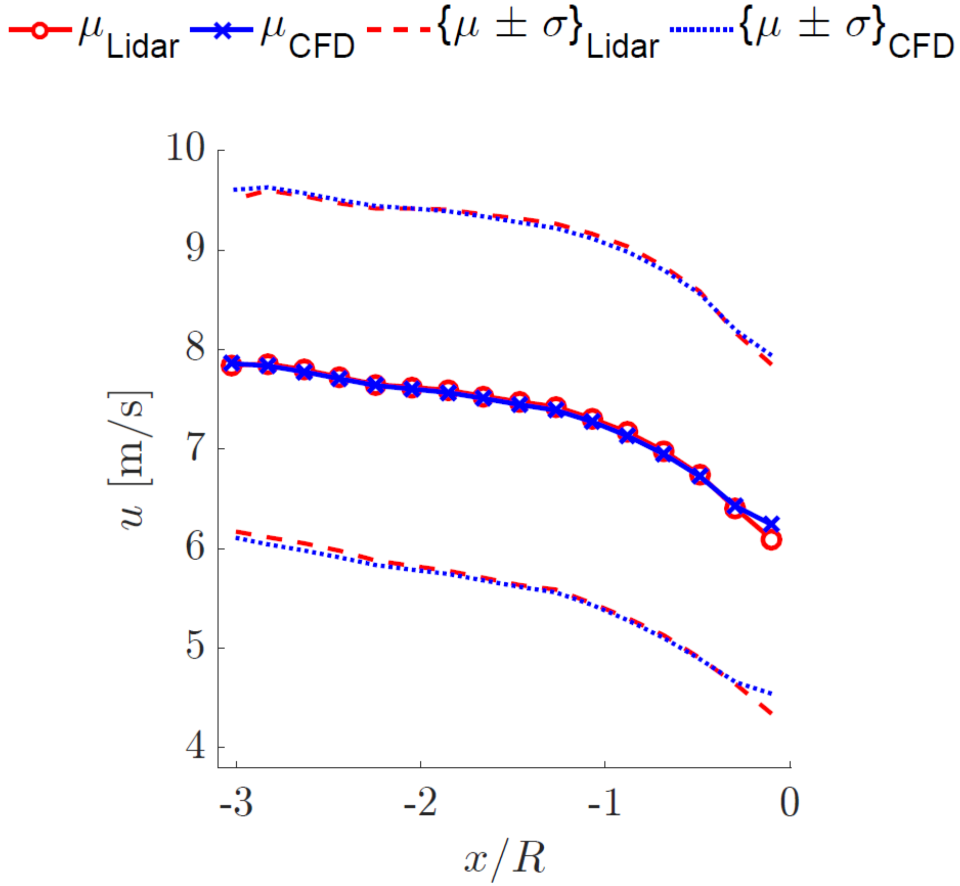


New stochastic CFD validation method

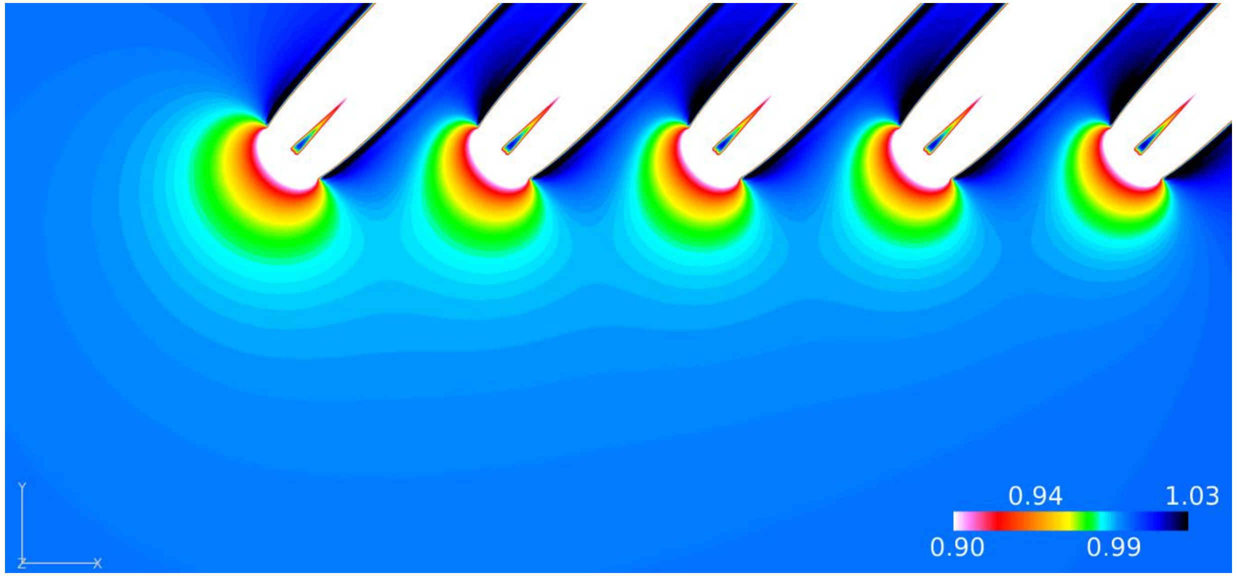
Typical deterministic approach

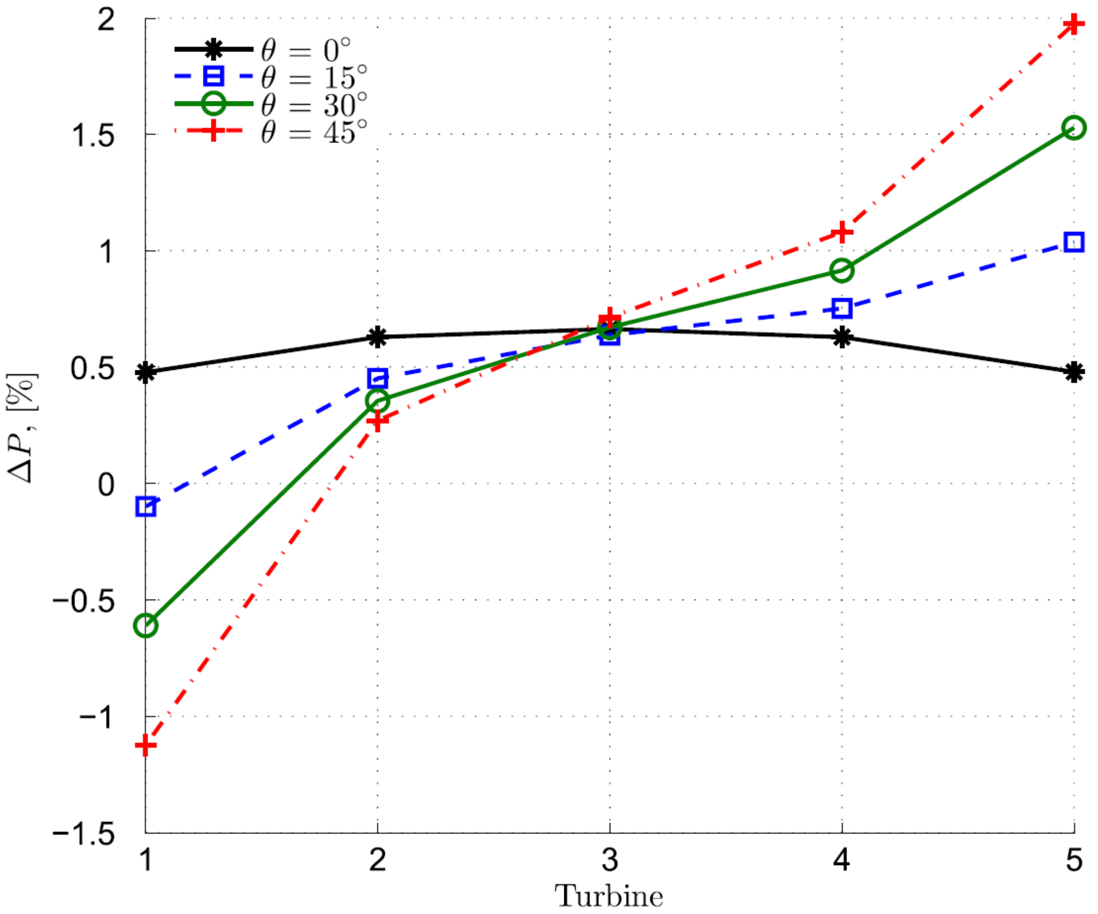


New stochastic approach



Wind farm power change free from wakes





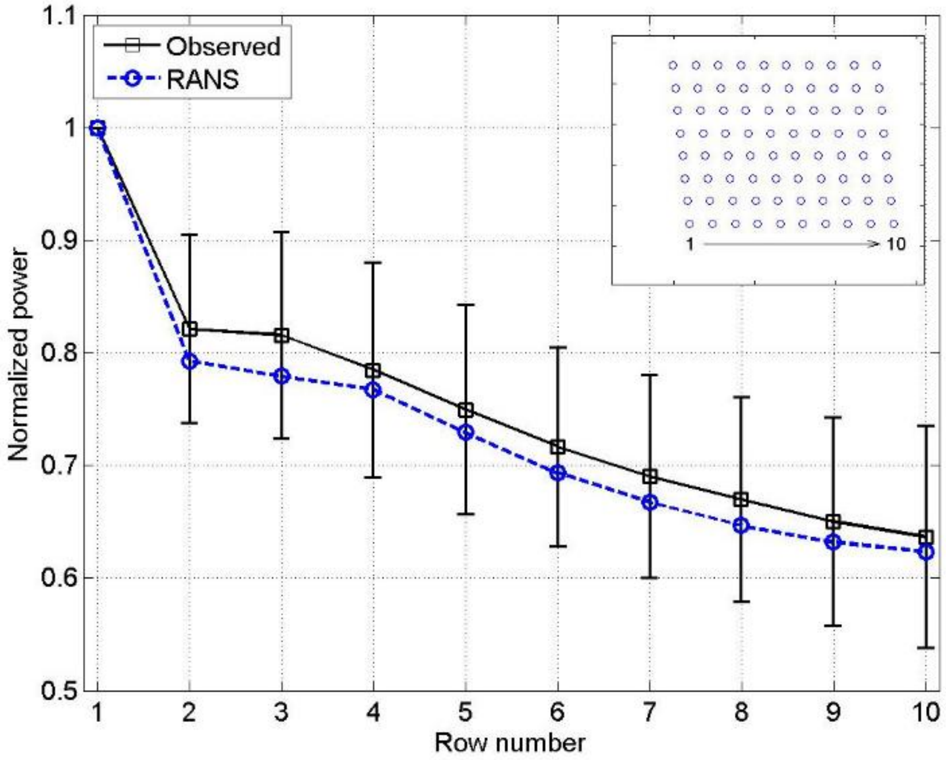
Global blockage effect (GBE)

- Primary: Induction zones of turbines in wind farms add up
- Secondary: Turbines act together as obstruction and divert flow around wind farms
- Estimated loss in AEP due to GBE: 1-3%

DTU model solutions:

- EllipSys3D, RAND-CFD with actuator disks
- Coupled FUGA
- Simple wake model + simple induction zone model

James Bleeg et al. (2018)

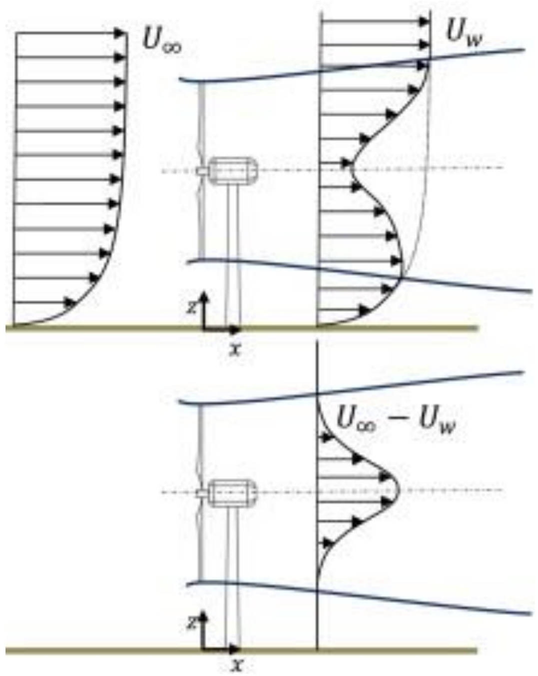


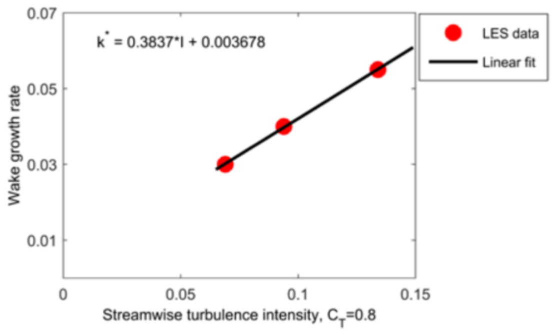
AI & wakes

Short-term Wake Modelling

Gaussian Deficit Model

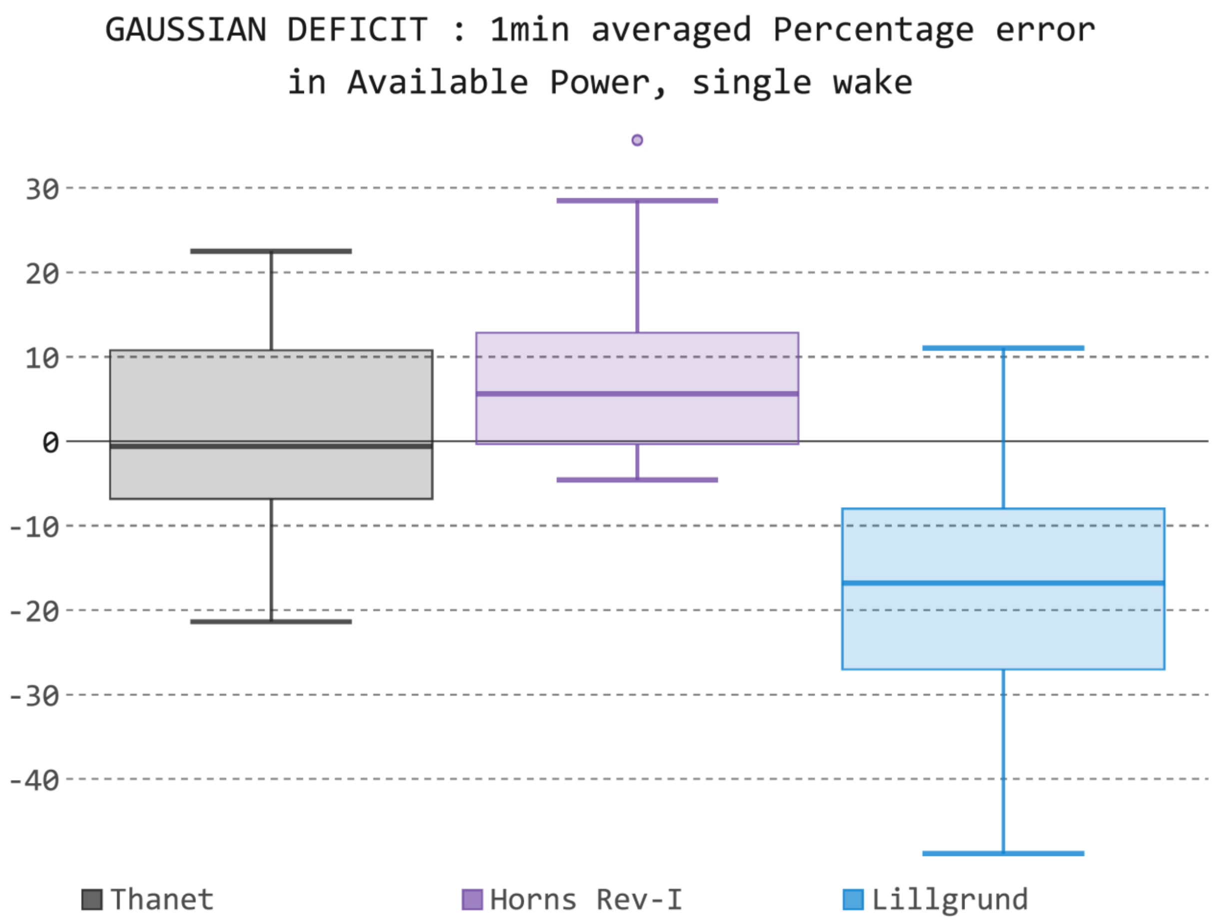
- Gaussian Deficit →First Time in 1Hz SCADA





$$k^* = a\,TI + b$$

$$a = 0.3837$$
$$b = 0.003678$$



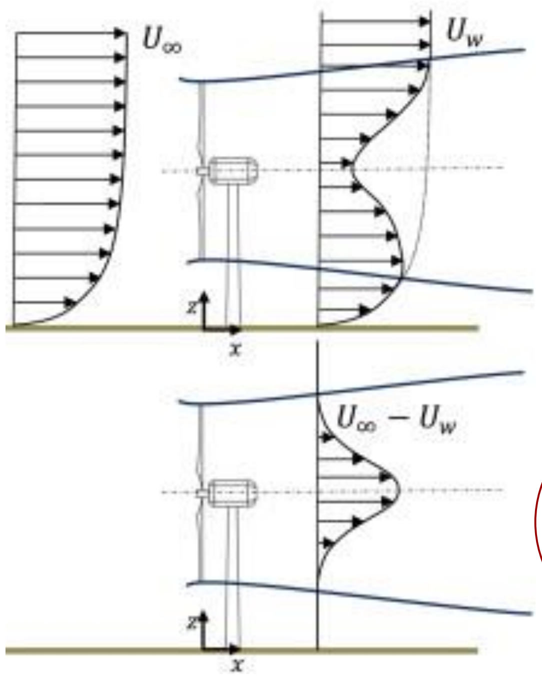
Majid Bastankhah and Fernando Porté-Agel. A new analytical model for wind-turbine wakes. *Renewable Energy*, 70:116–123, 2014

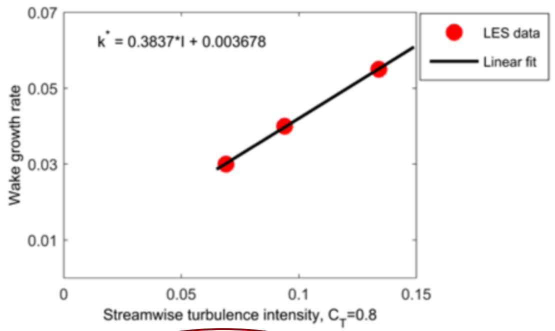
Mahdi Abkar and Fernando Porte-Agel. Influence of atmospheric stability on wind-turbine wakes: A large-eddy simulation study. *Physics of Fluids*, 27(3):1–20, 2015

Short-term Wake Modelling

Re-calibration of Gaussian Deficit Model

- Gaussian Deficit →Bayesian Re-calibration

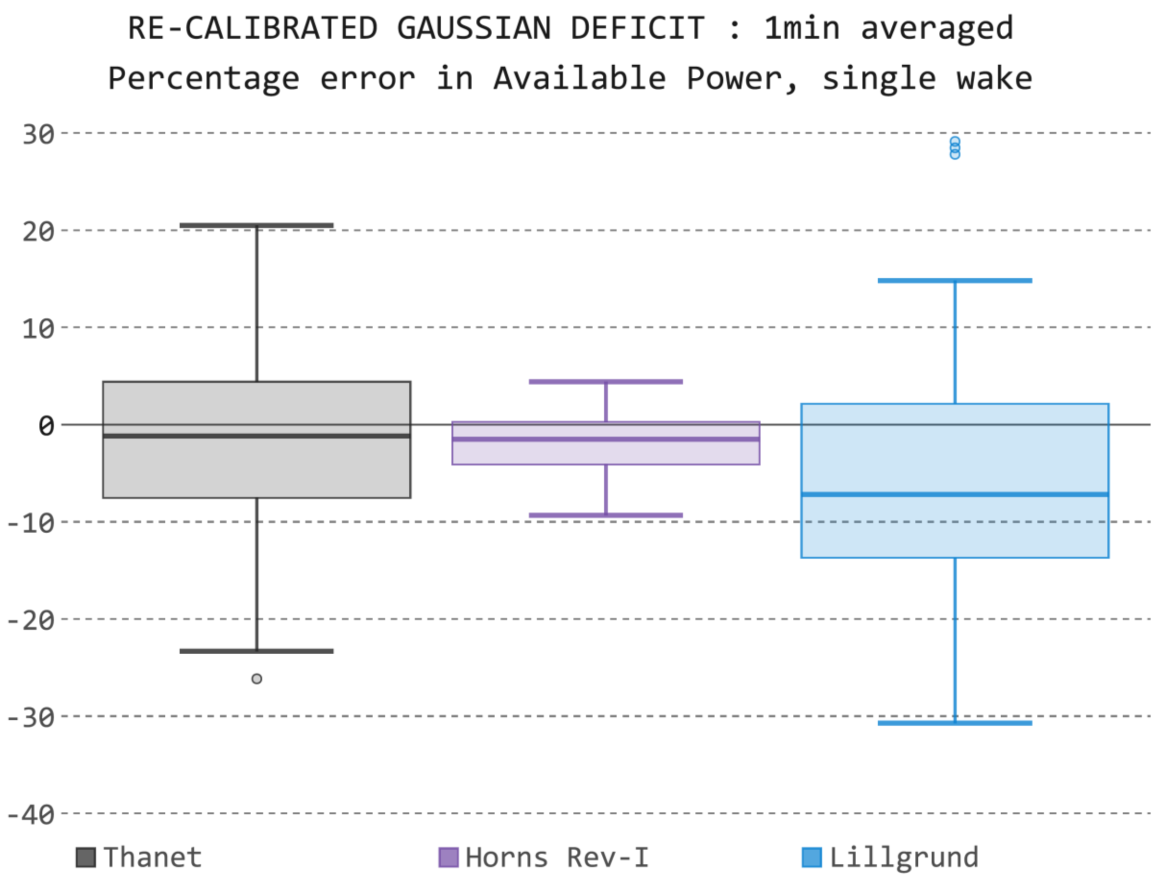




$$k^* = a\,TI + b$$

$$a = 0.3837$$
$$b = 0.003678$$

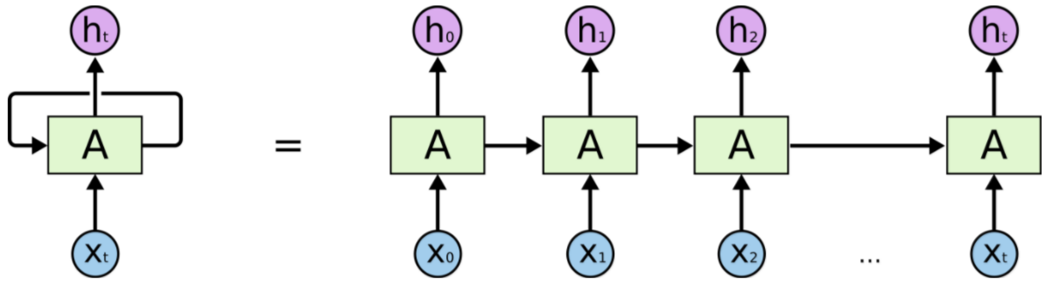
	a	b
Thanet	0.421	0.0025
Horns Rev	0.223	0.0039
Lillgrund	2.42	0.0042



Short-term Wake Modelling

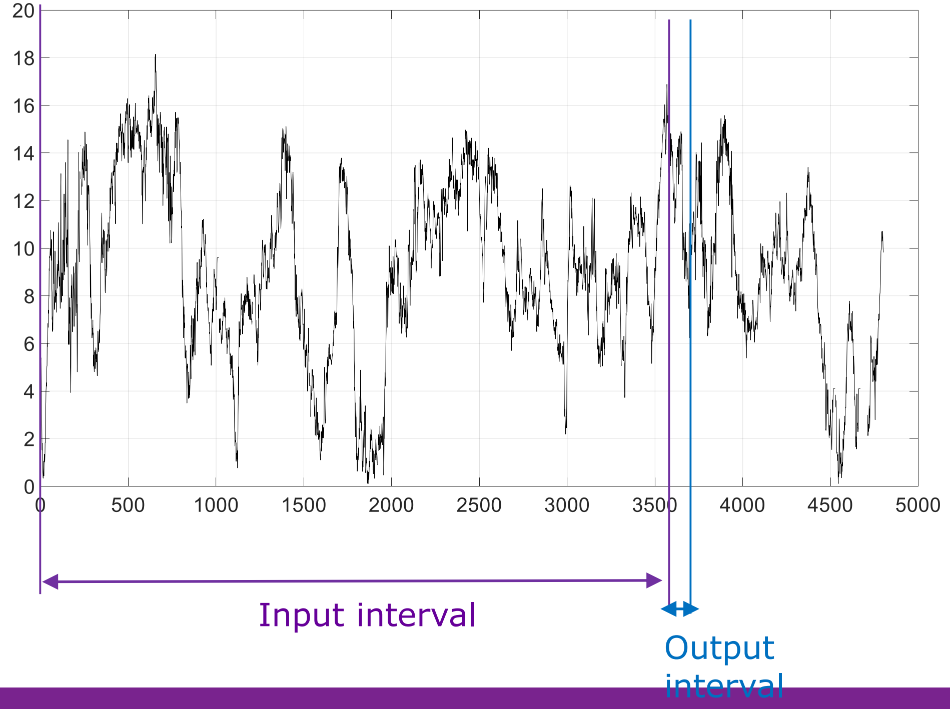
Machine Learning for short-term wakes

- Machine Learning Platform – TensorFlow
  - With Keras wrapper in Python
  - Fast & easy to apply
- The deep learning algorithm – LSTM
  - Long Short-term Memory
  - Special building unit for RNN
  - Shown to perform faster & better for highly fluctuating time series



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

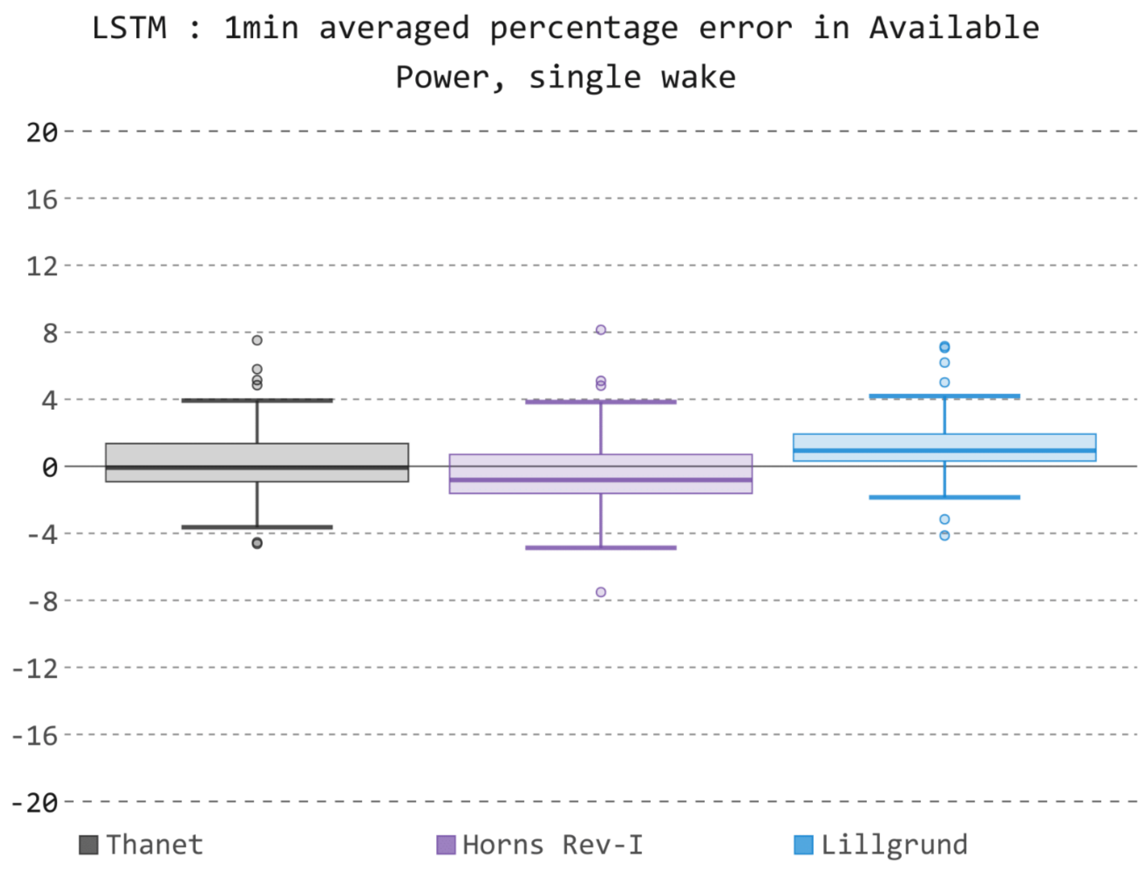
- The inputs from the upstream turbines
  - Defined at every minute (WD dependent)
  - WD, Ueff, std(Ueff), ct + uncertainties
  - Data fed for the previous 1-hour
    - Time window of 1-hour shifted forward at every minute



Short-term Wake Modelling

Machine Learning for short-term wakes

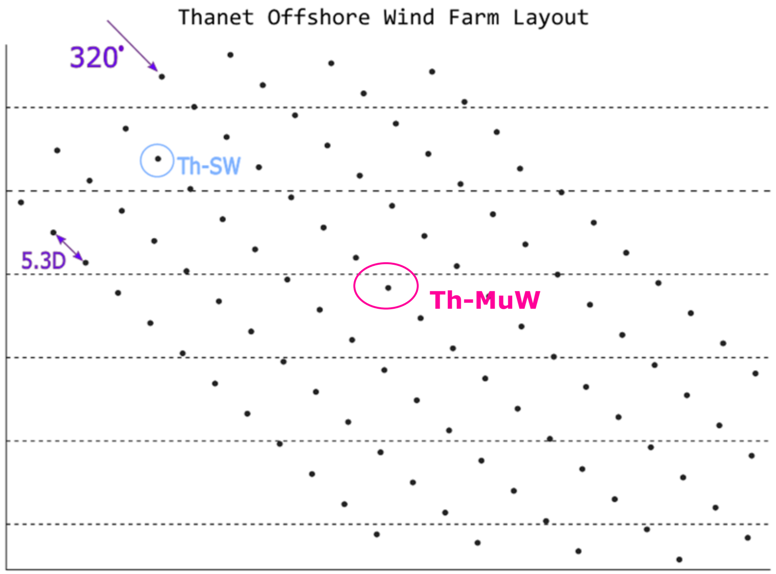
- Machine Learning Platform – TensorFlow
- The inputs from the upstream turbines
  - Defined at every minute (WD dependent)
  - WD, Ueff, std(Ueff), ct + uncertainties
  - Data fed for the previous 1-hour
    - Time window of 1-hour shifted forward at every minute
- The output
  - Ueff at the downstream turbine
- New network (or model) per WF per turbine per minute
  - Still feasible real time!
    - 20 epochs
    - Batch size = 64
    - Single hidden layer with 18 neurons

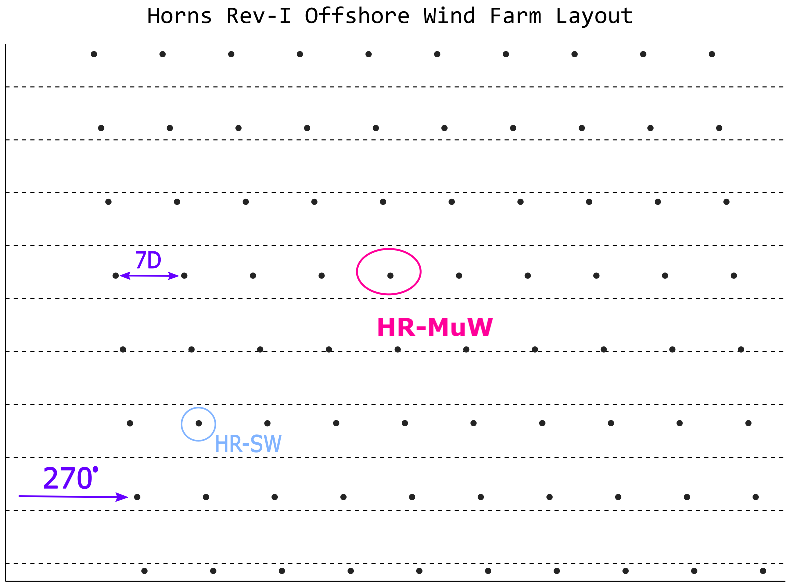


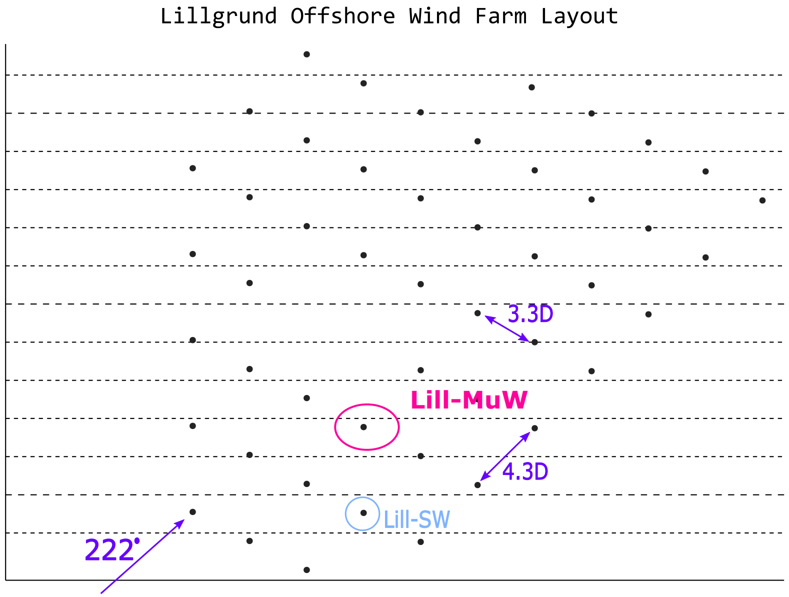
Short-term Wake Modelling

Machine Learning for short-term wakes

- Multiple Wake (MuW) & overall Wind Farm (WF) output investigation
  - Same inflow for all three wind farms → 2-hours data with fairly perpendicular wind
    - For Lillgrund, only the lower left corner of the WF is available → 12 turbines
  - Same architecture for the neural network → same hyper-parameters for the LSTM

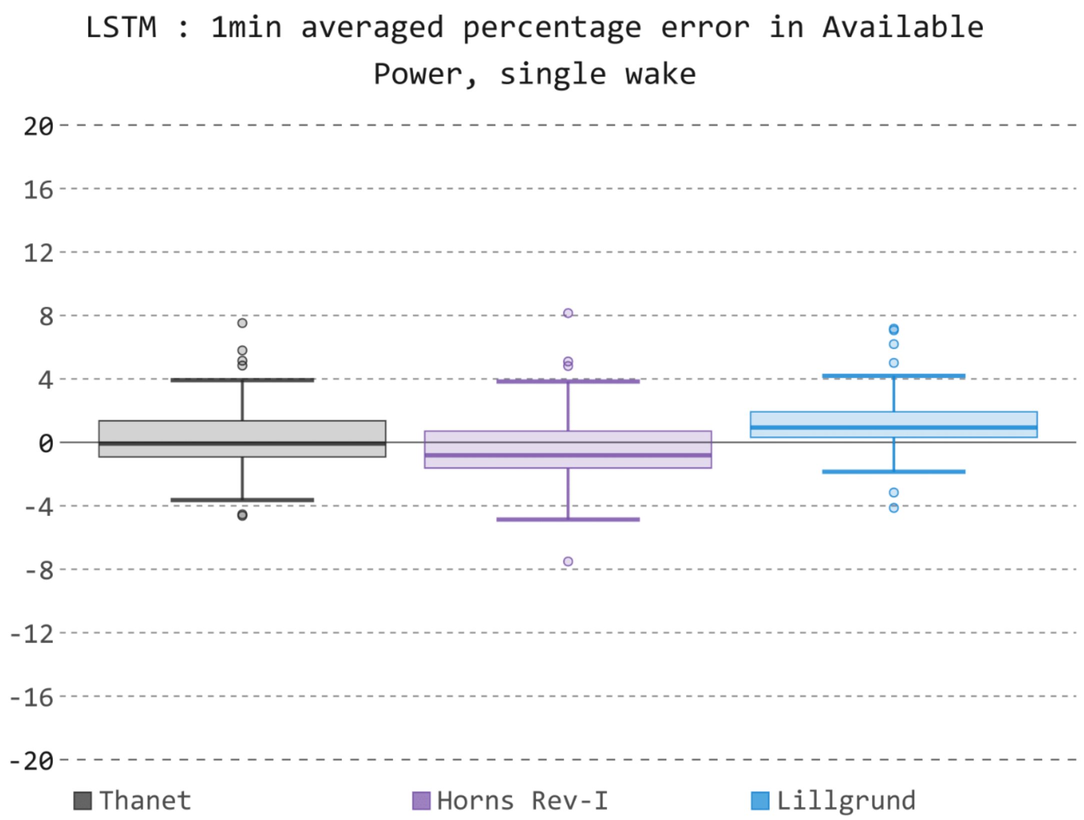


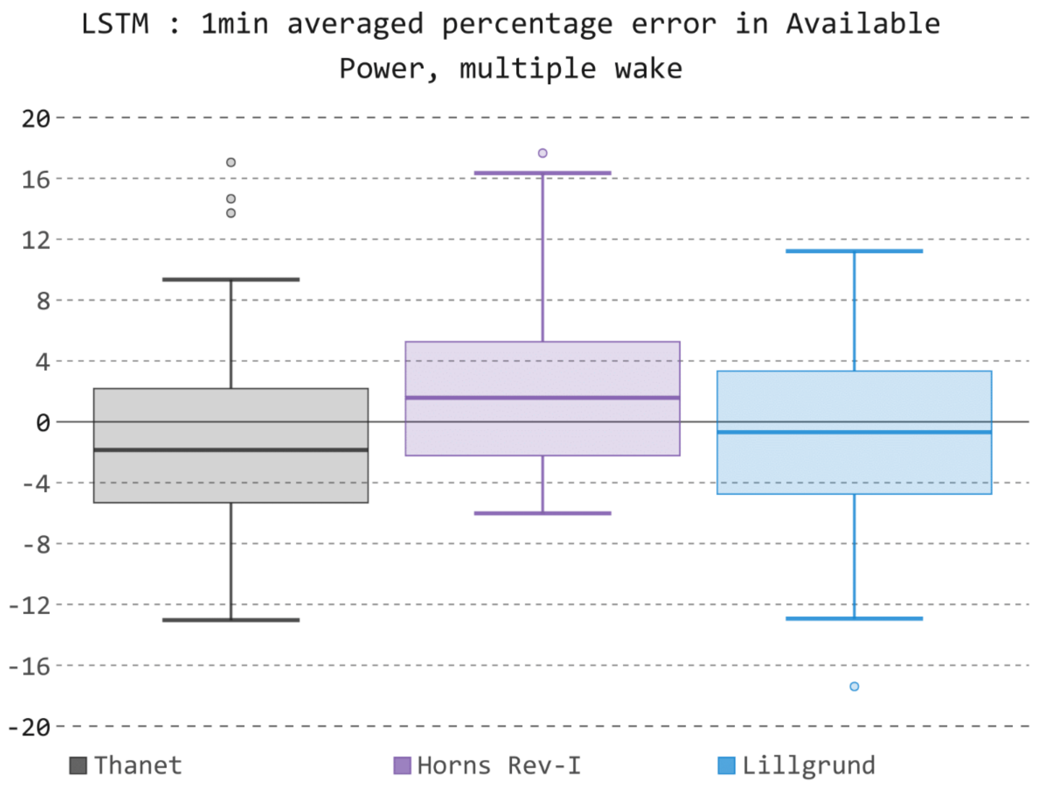




Short-term Wake Modelling Single vs Multiple wake

Machine Learning for short-term wakes

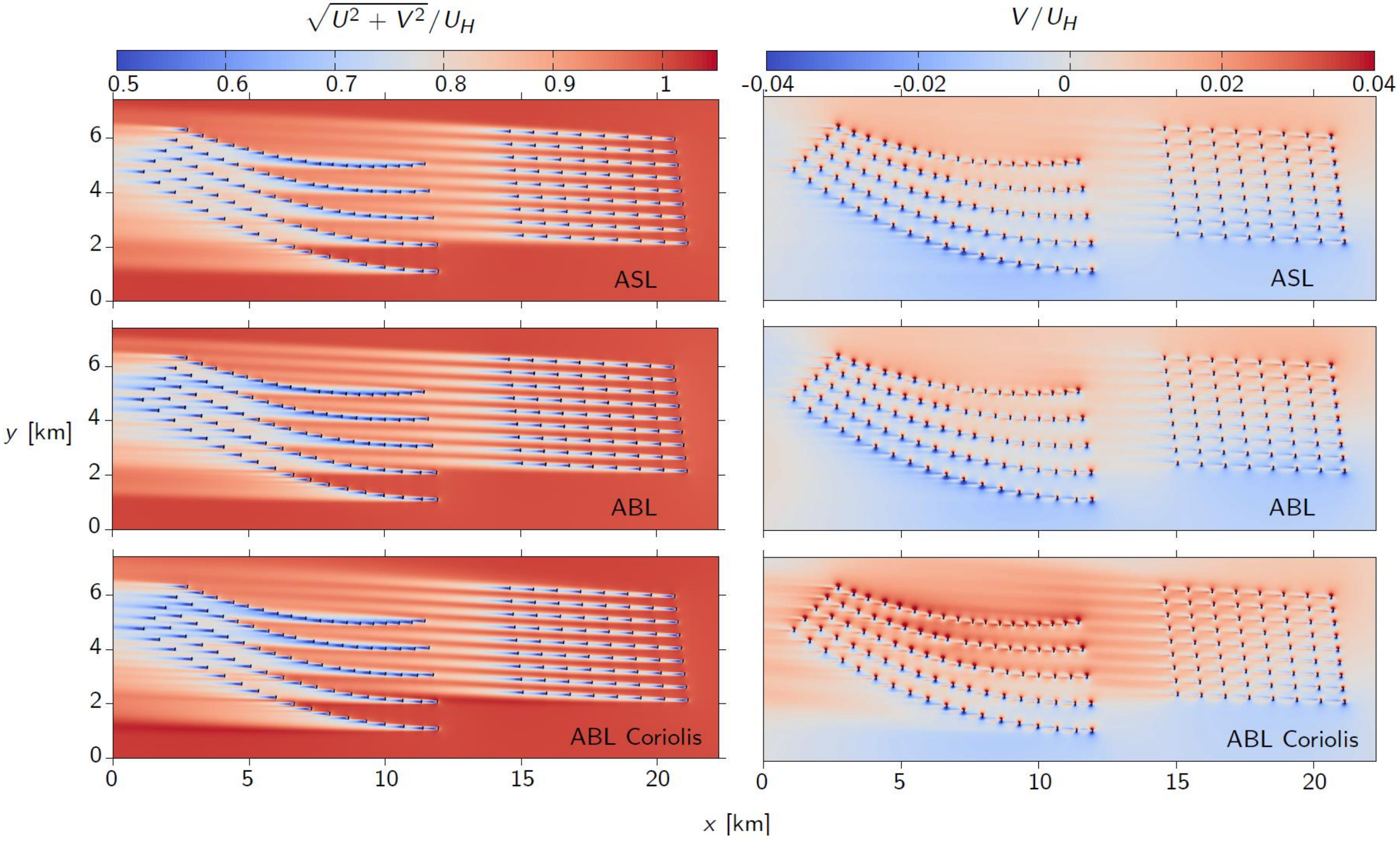




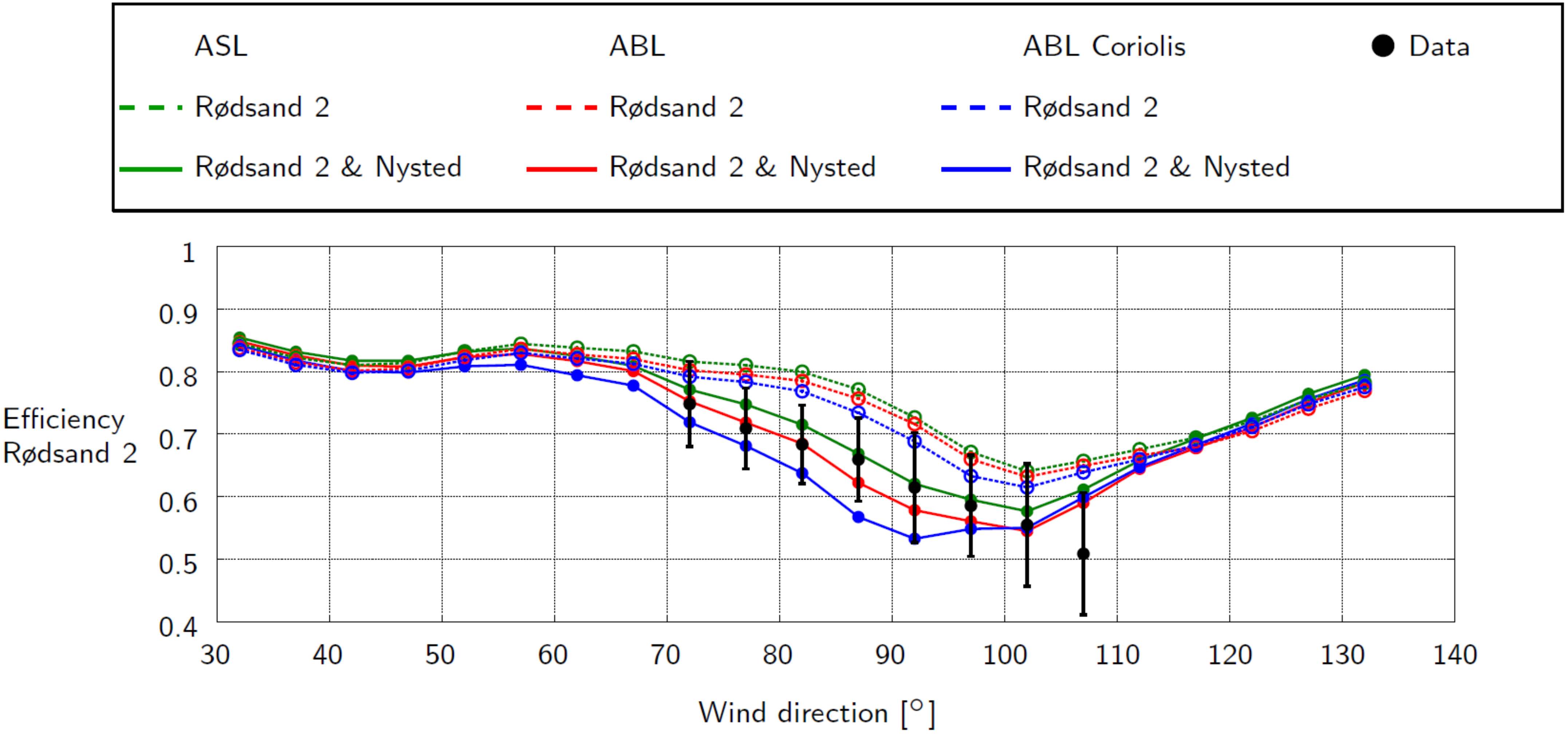
- Still robust, but growing uncertainties with increasing complexity → case based model update is required
- Generalizability of machine learning wake modelling (perhaps in synthesis with physical modelling) is the hot research topic for us now!

Effect of Coriolis force

Modelling wakes at Rødsand & Nysted - Rans (ASL, ABL, ABL+ Coriolis force)



Wake efficiency



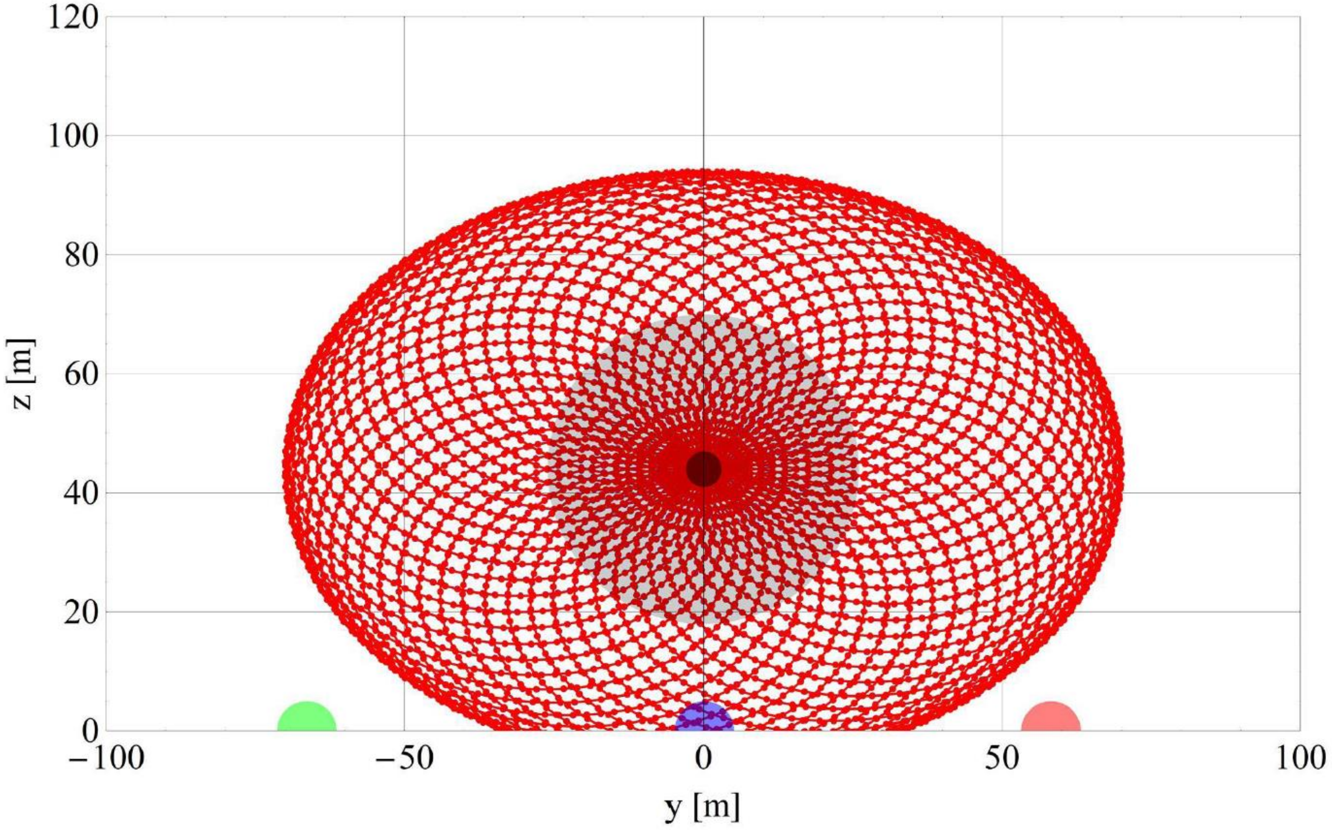
Conclusion of wakes & coriolis

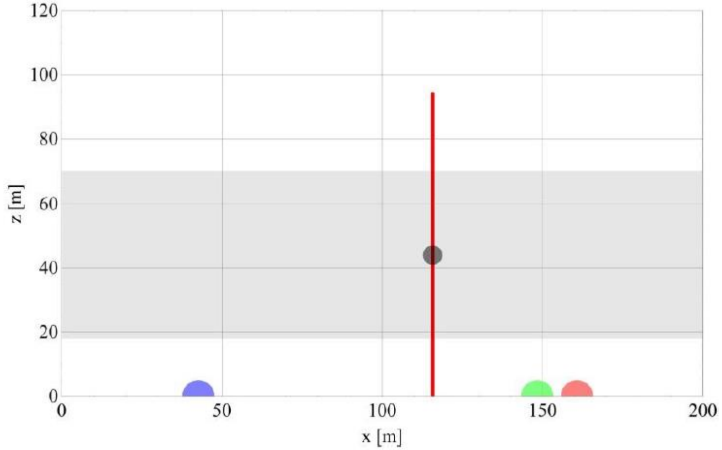
Do we need to model the Coriolis force in RANS?

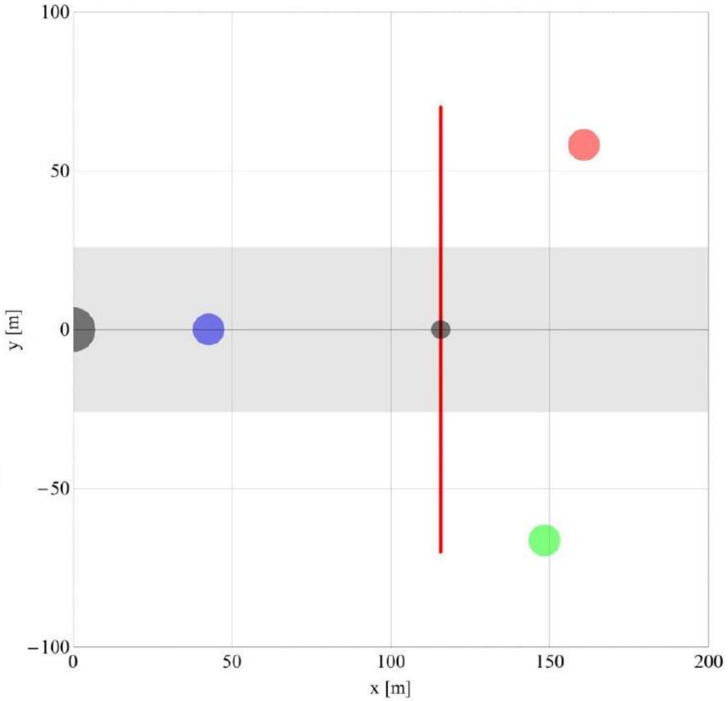
- Single wind farm ⇒ not really.
- Wind farm wake interaction ⇒ YES!

Cool wake measurements

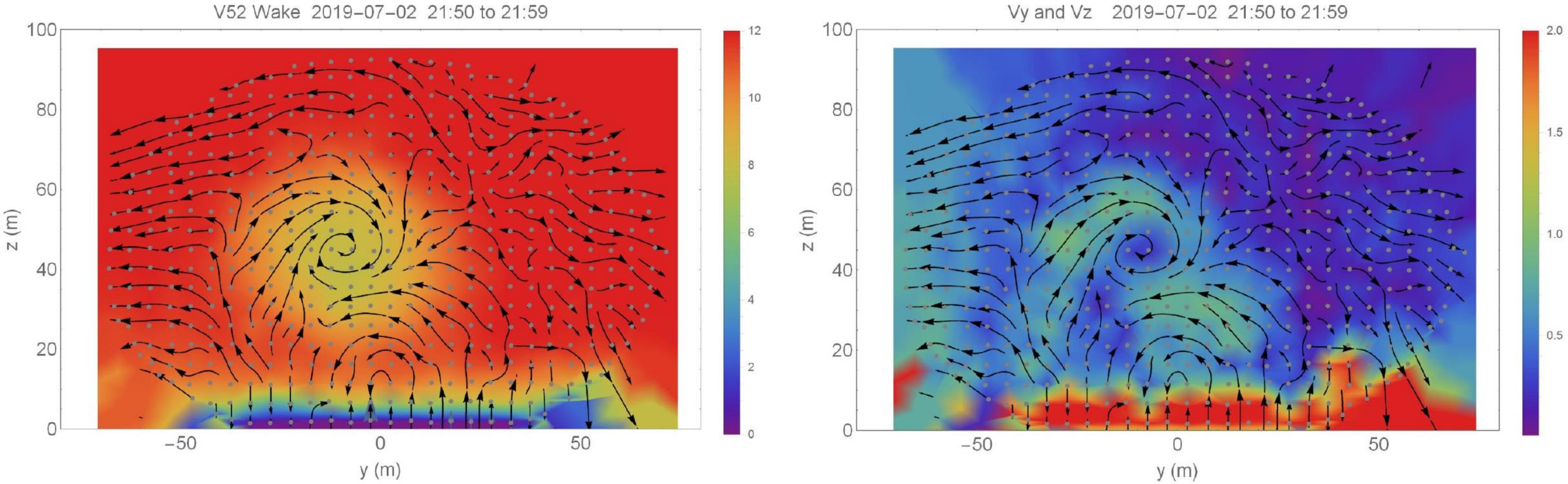
WindScanner trajectory



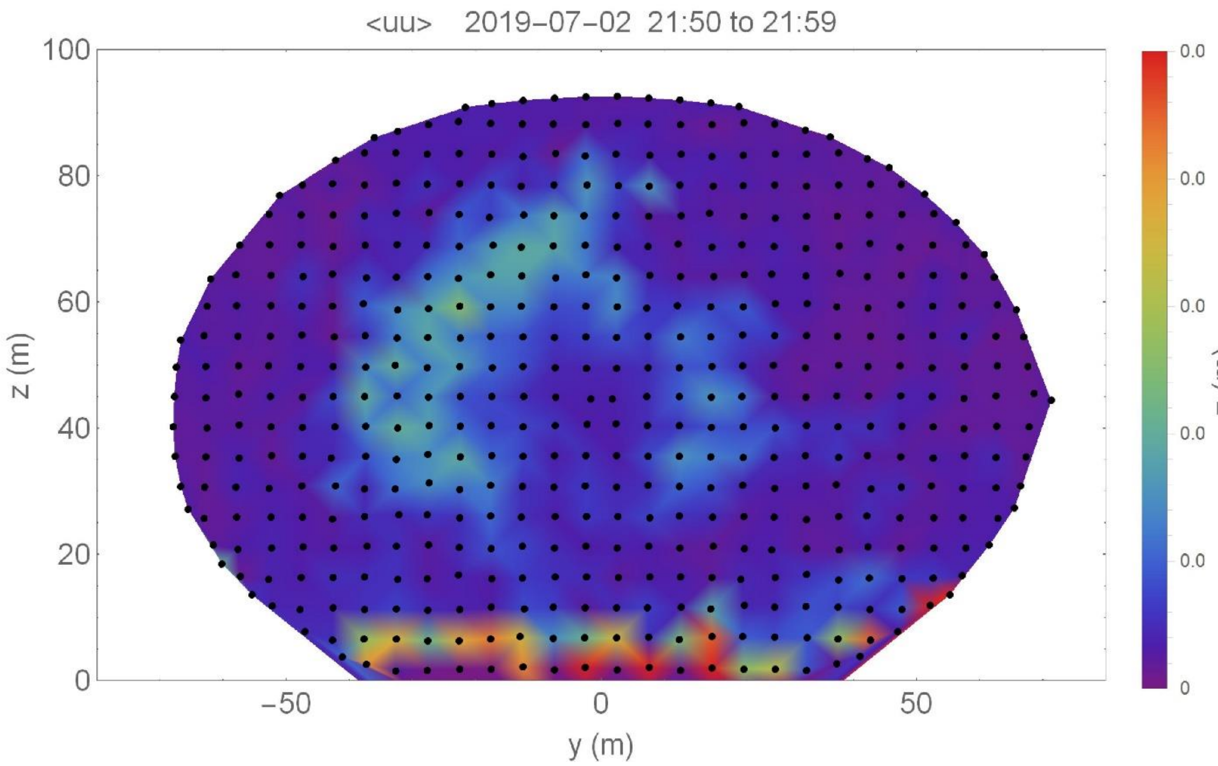


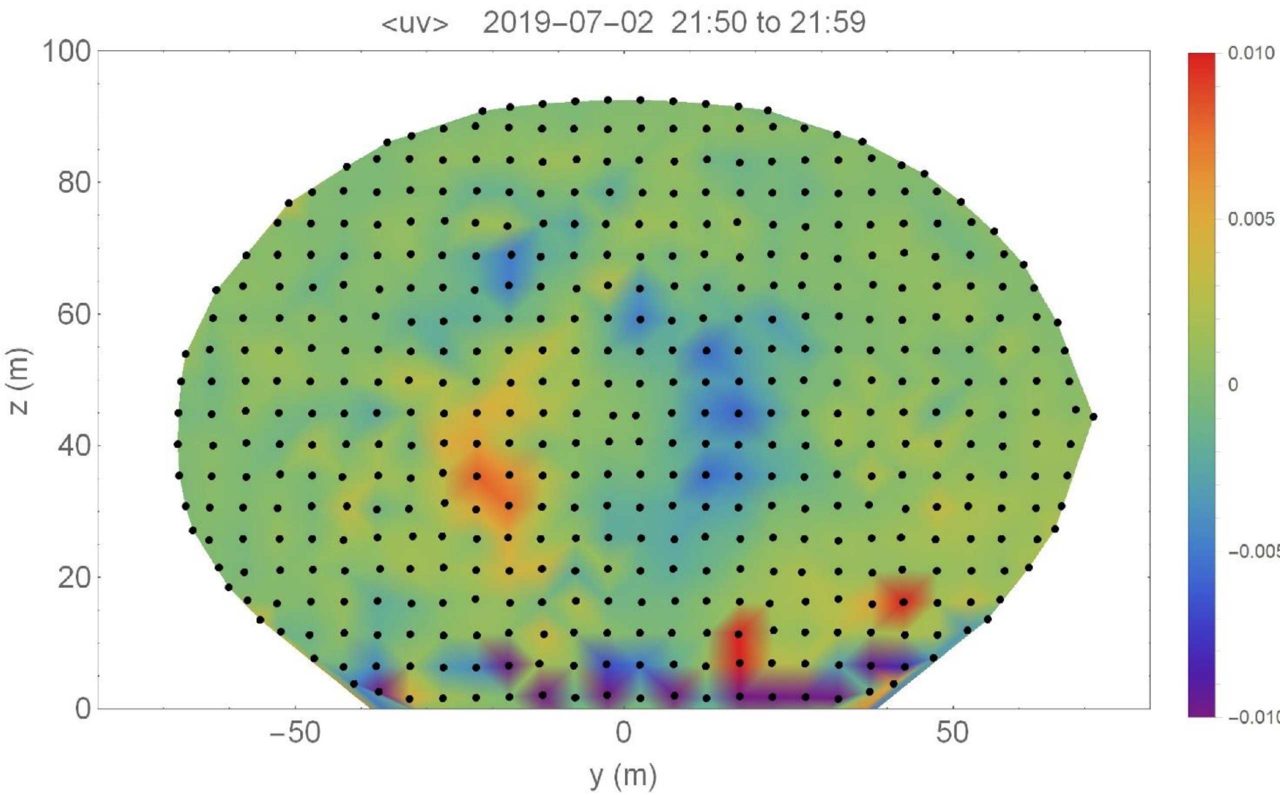


3D WindScanner wake measurements



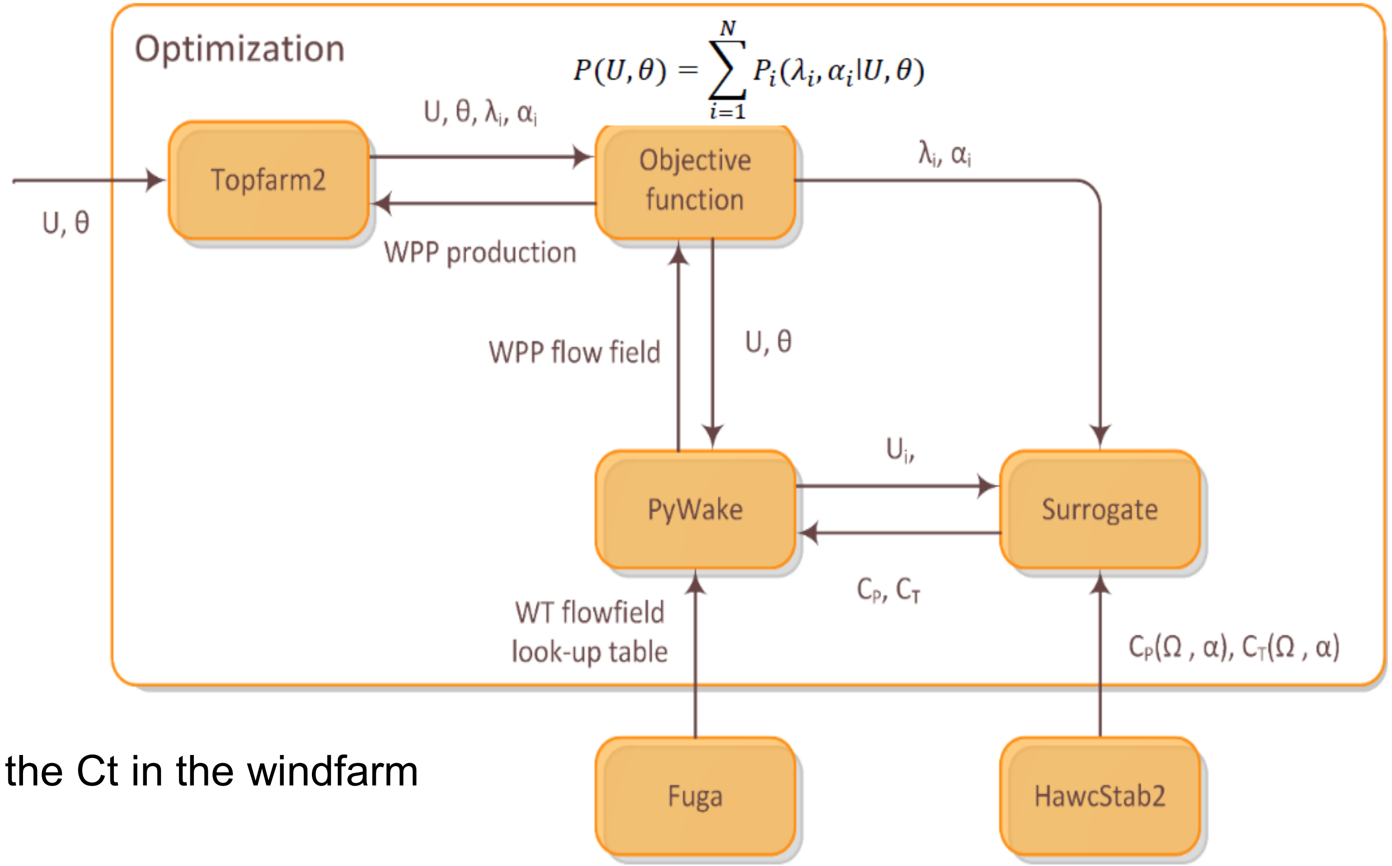
Second order statistics





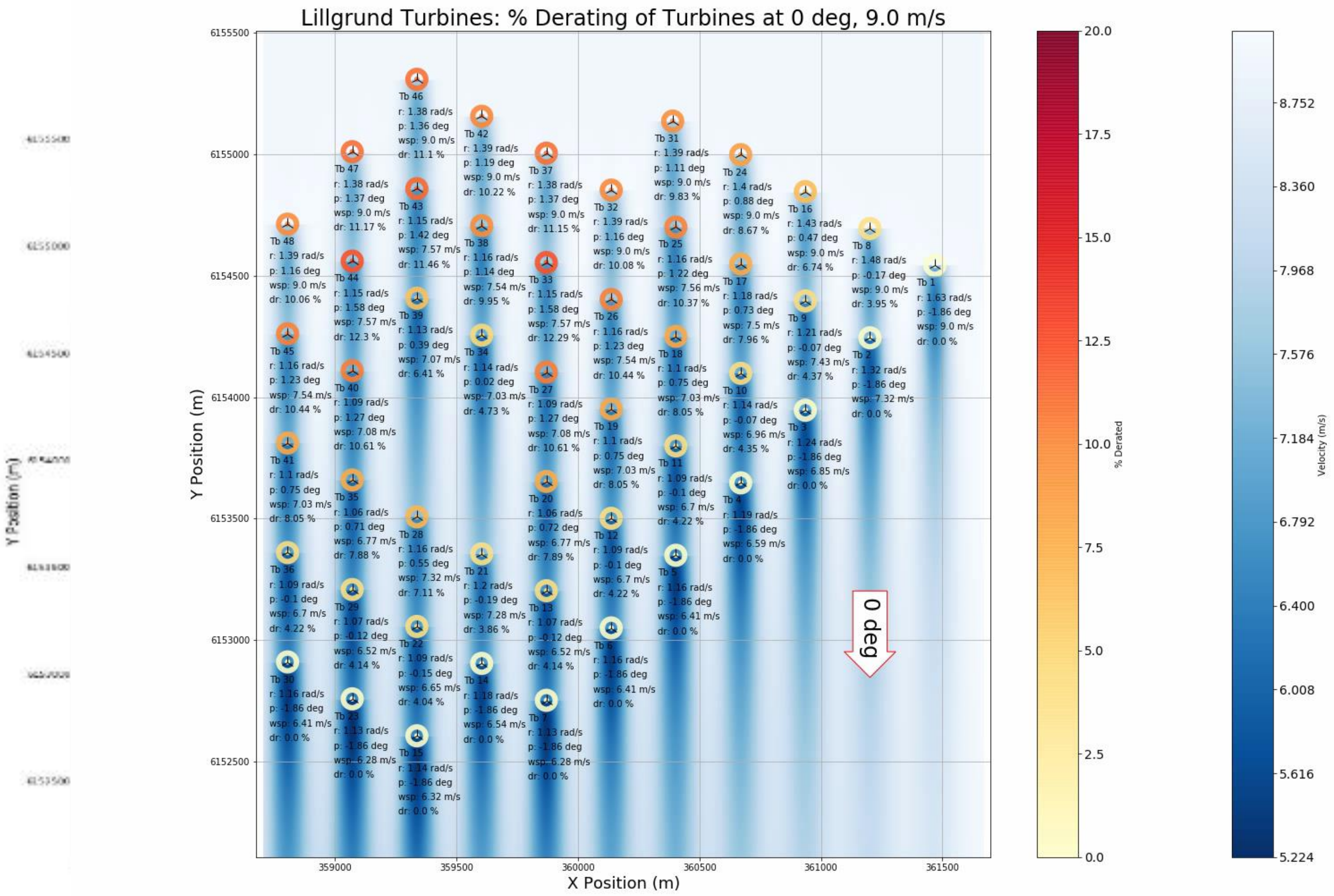
Windfarm control

Work flow and optimizer



Here we optimize on the Ct in the windfarm

Lillgrund case study



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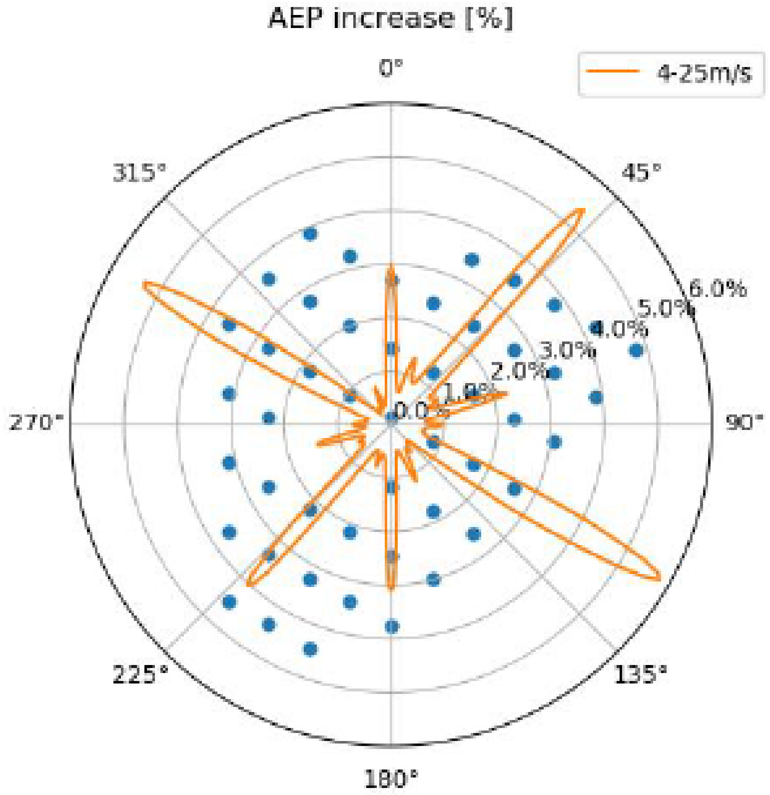
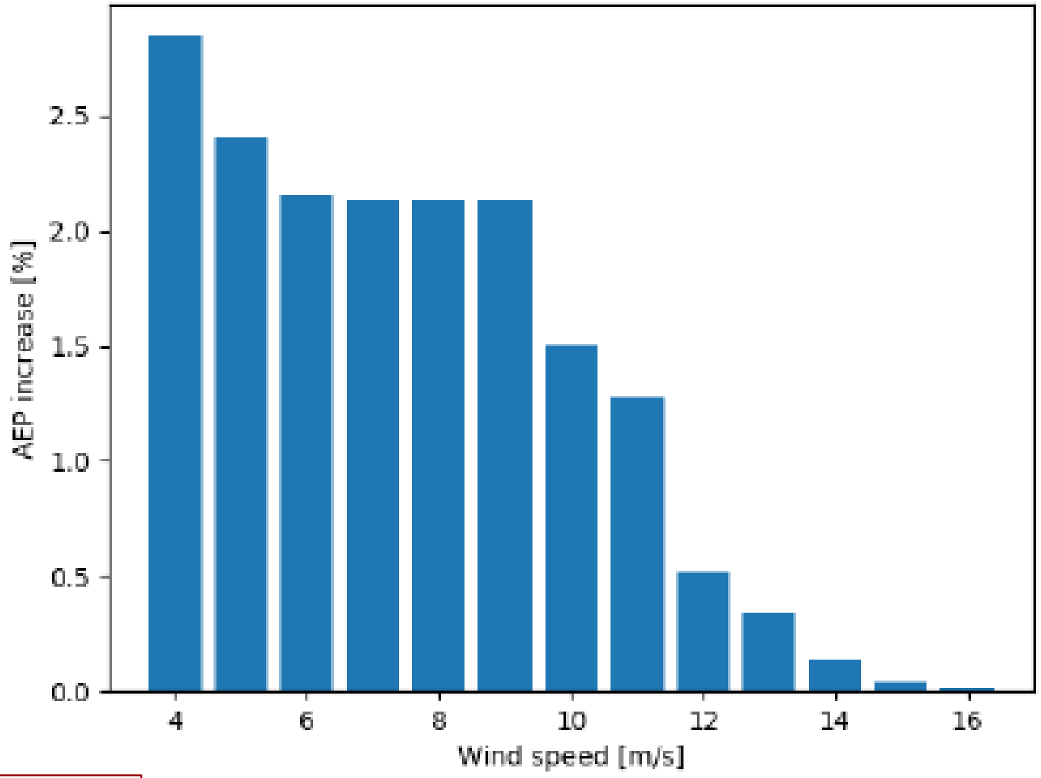
Lillgrund case study ,AEP gain





A two-parameter optimization tool showsthat production gains are in fact possible through de-rating

Lillgrund … 1 degree wind direction resolution and 1m/s wind speed resolution Overall AEP gain of 1 %

Summary

- How to improve the wake modelling
  - Use better physical models together with data to delvelop models engineering models that answer things like blockage, more precis wake losses
  - Combine scada with physical models and AI in short term prediction of power output from windfarms
  - Detailed atmospheric wake campaign to understand the transition from near wake to far field wakes (using windscanners etc)