Technische Universität München
Wind Energy Institute

Overview of Recent Experiments in Wind Farm Control using Scaled Models in a Boundary Layer Wind Tunnel

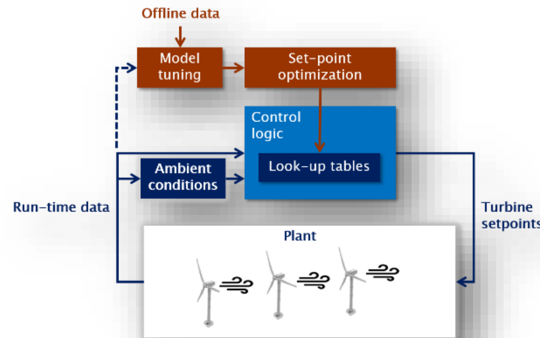
Filippo Campagnolo, Carlo L. Bottasso
Technische Universität München

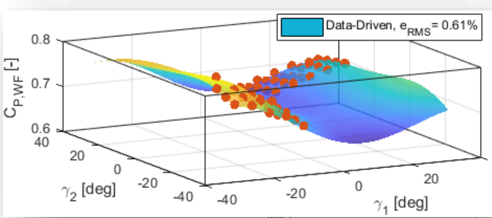
WESE Workshop, Pamplona, Spain, 2-3 October 2019

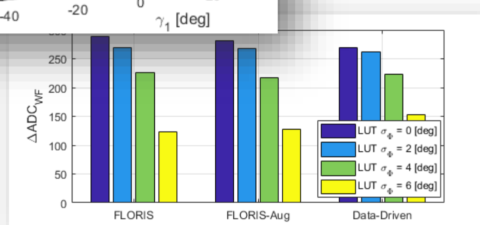
Outline

◀ Scaled wind turbine testing at TUM

Wake deflection control ▶







◀ Experimental results

The Role of Wind Tunnel Testing

Wind tunnel testing:

– Cons:

- Usually impossible to exactly match all relevant physics due to scaling

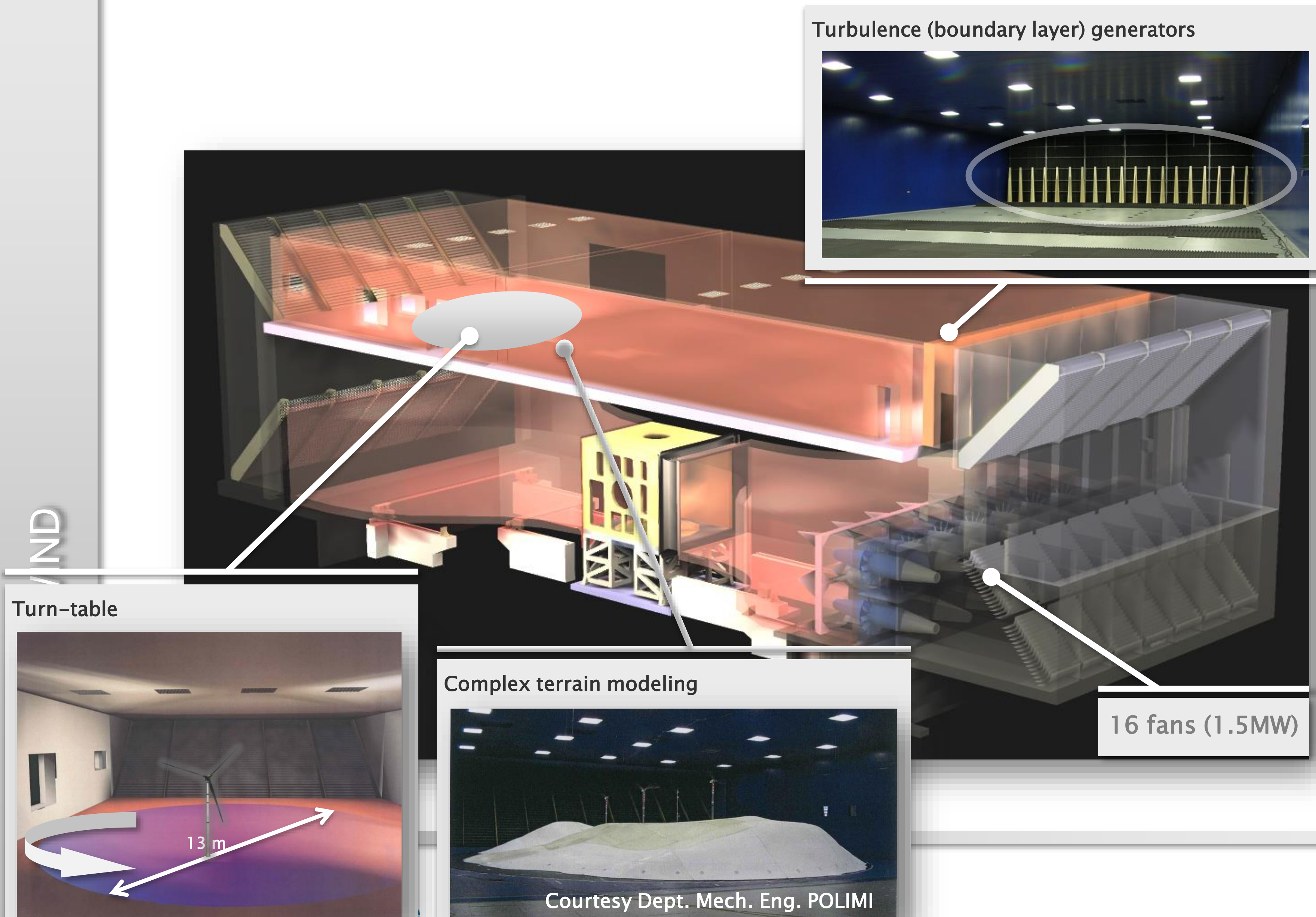
+ Pros:

- Better knowledge/control of conditions/errors/disturbances
- Due to scaling, time runs faster in the wind tunnel
- Relatively low cost compared to full scale testing

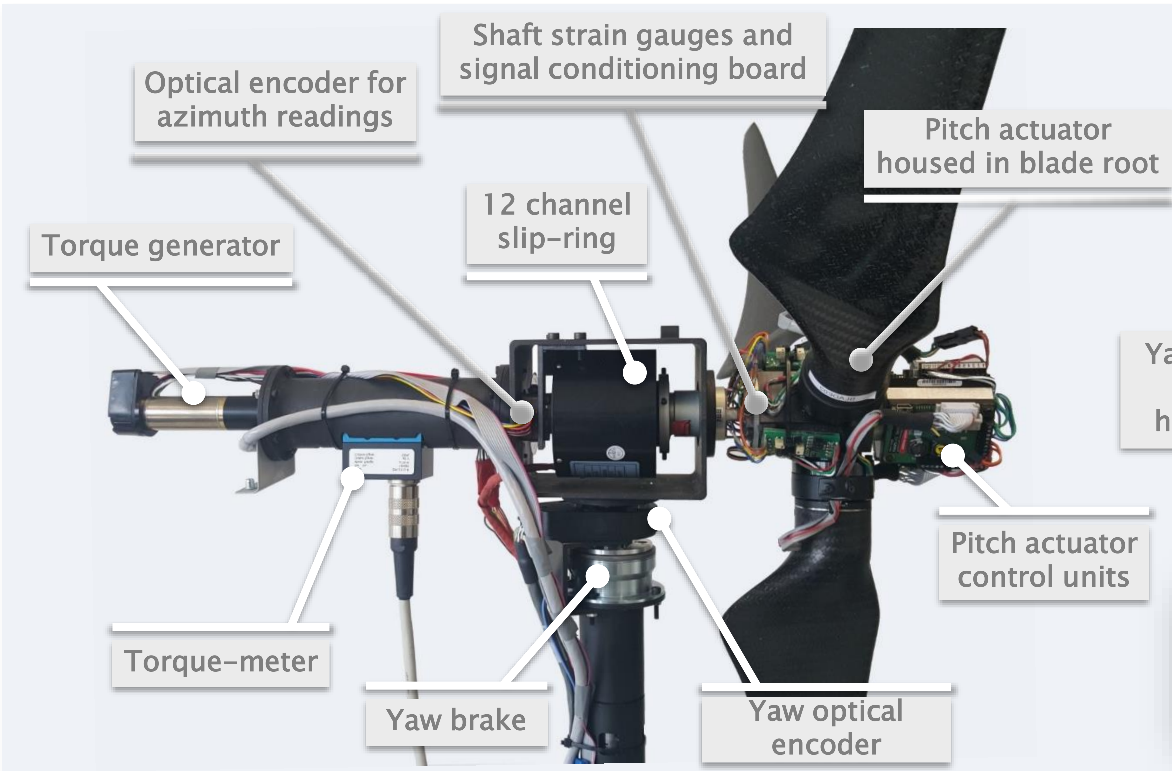
Contributions of this presentation:

- Wind farm control:
  - What is the effect of model accuracy on WFC performance? Do we need highly accurate models or is a rough one good enough?
  - What are the effects of control parameters (e.g. uncertainty level, actuation frequency/filtering)?
- Model adaption/learning from SCADA data: are we learning correctly?

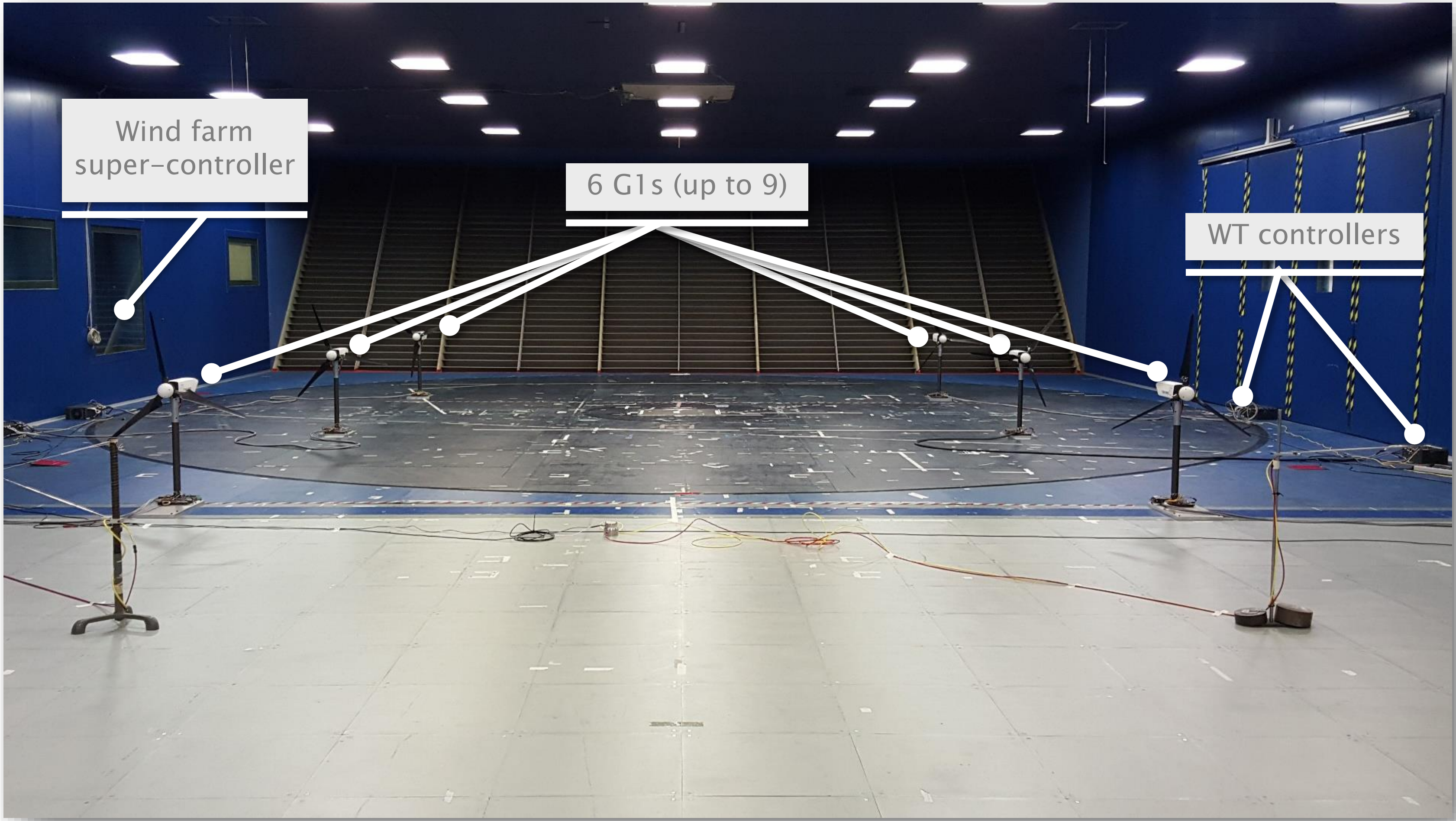
The Politecnico di Milano Wind Tunnel



G1 – Generic Scaled Wind Turbine for Wind Farm Control Applications



TUM Scaled Wind Farm Facility

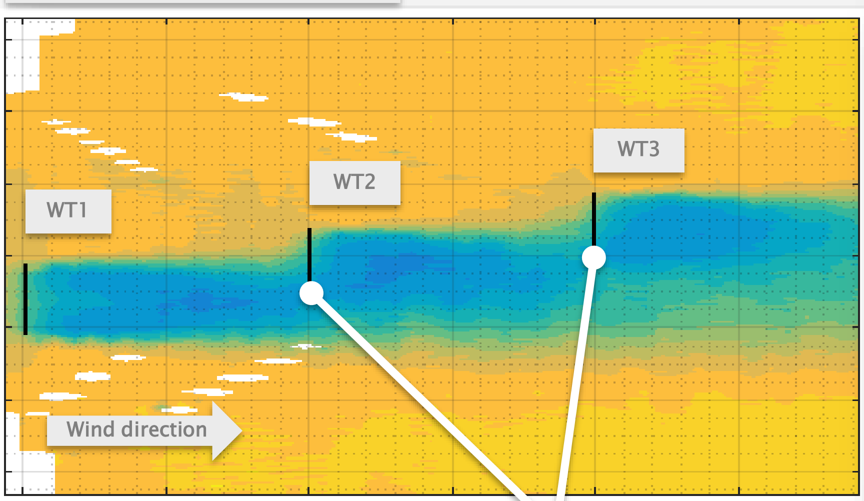


Earlier Experiences in Wake Deflection Wind Farm Control

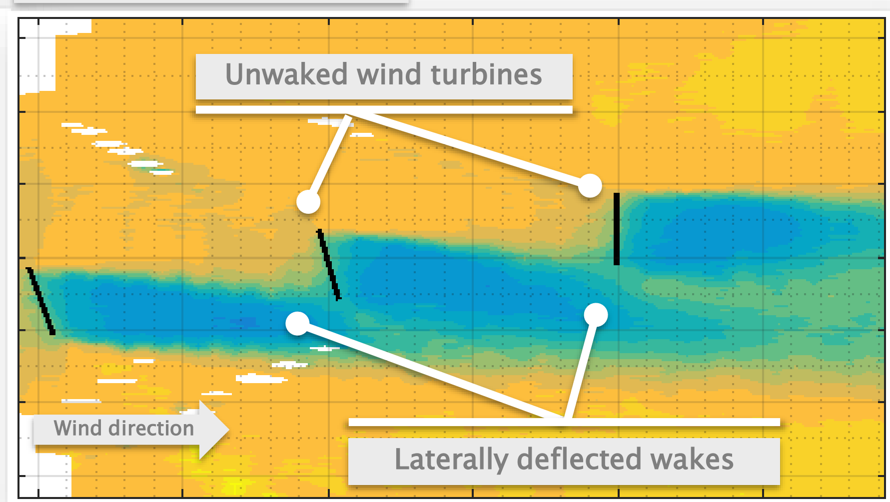
From 2016: constant mean wind direction, turbulent & sheared flow

Wake visualization with DTU scanning LiDARs:

Without wind farm control



With wind farm control

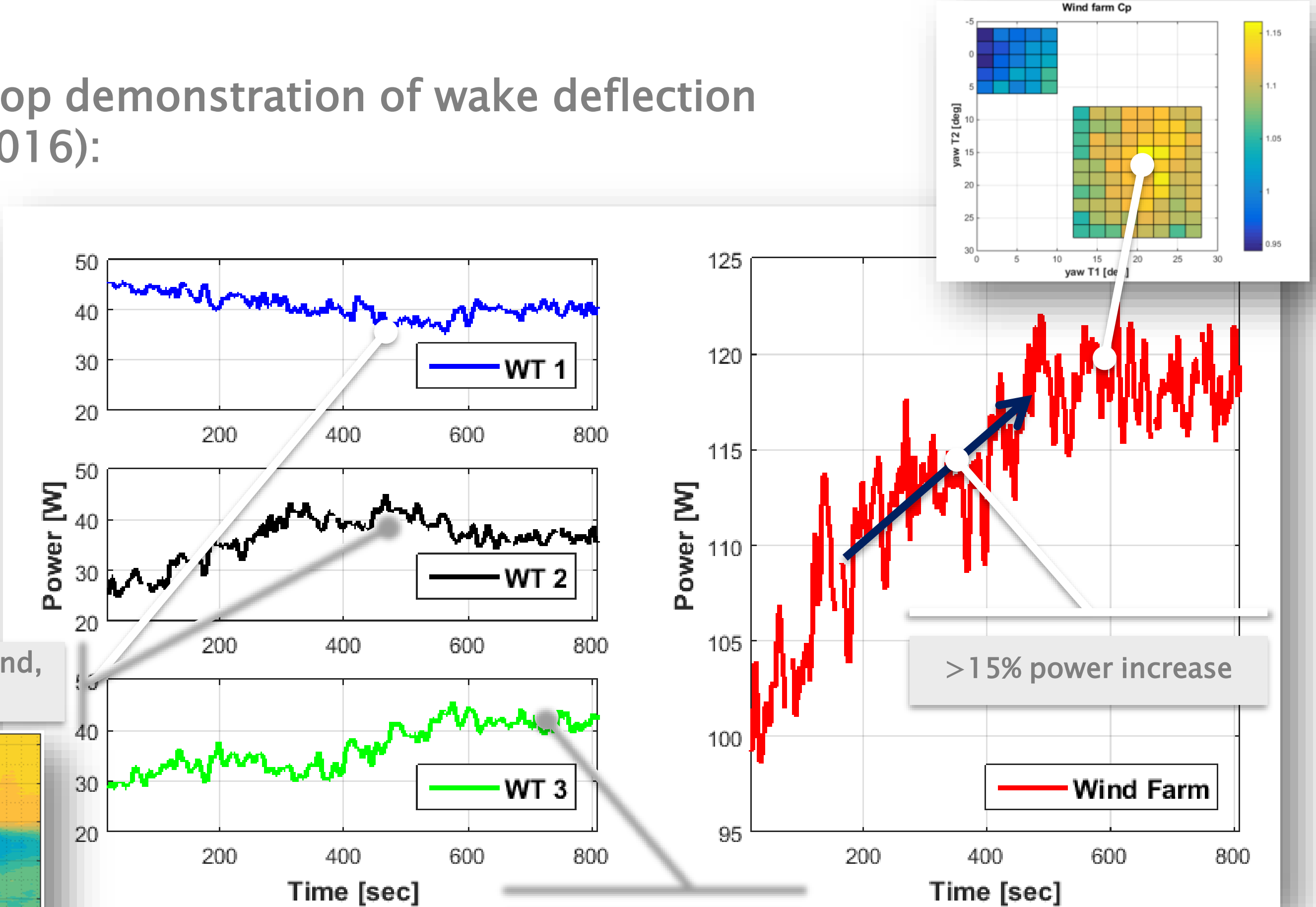


TUM.ScaledWIND

Wind Energy Institute

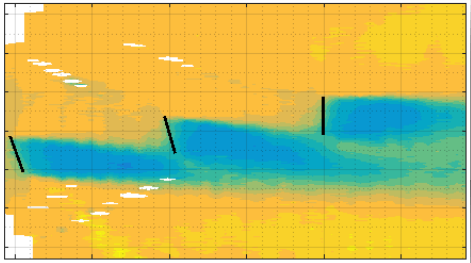
Wake Deflection Wind Farm Control

First ever closed-loop demonstration of wake deflection control (February 2016):



>15% power increase

WT1 & WT2 yaw out of the wind, loosing power



Significant power gain for WT3

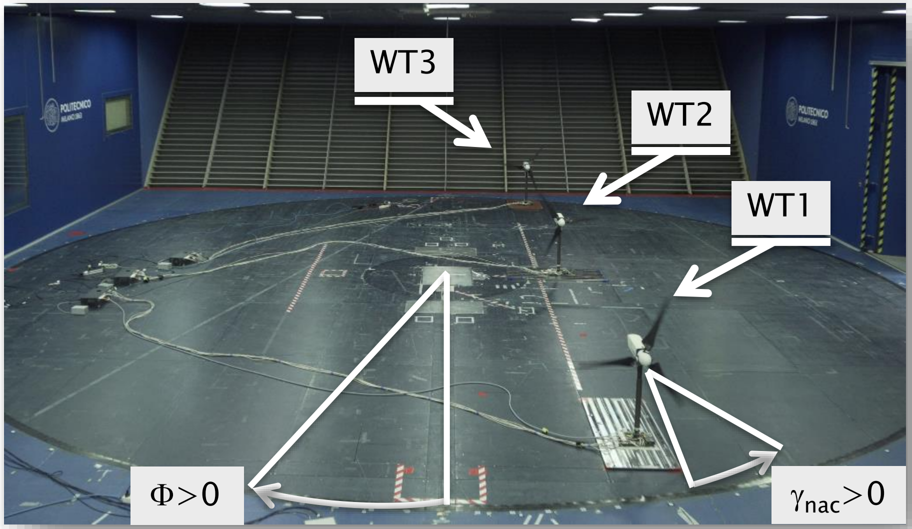
Control algorithm: closed-loop extremum seeking formulation

TUM.ScaledWIND

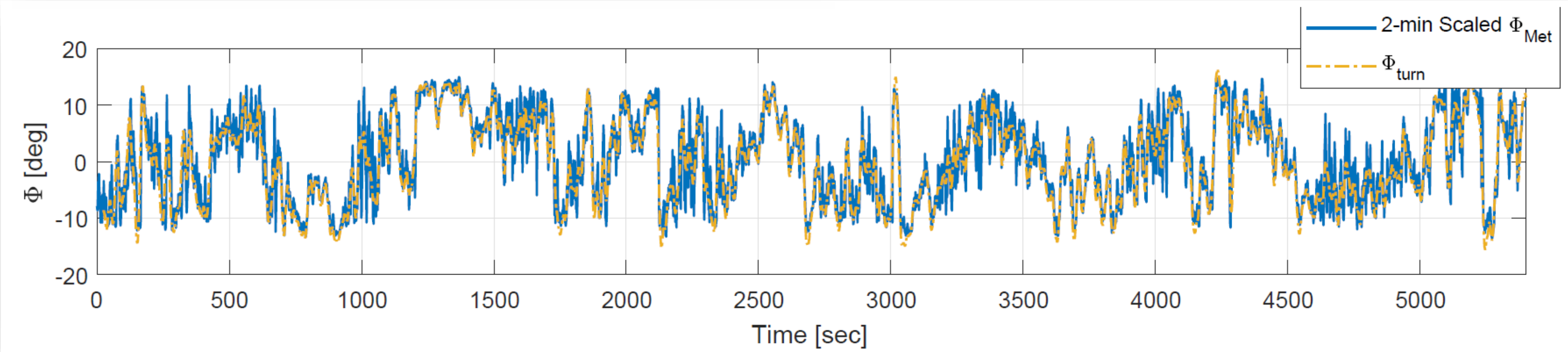
Wind Energy Institute

2016 Bayerischer Energiepreis

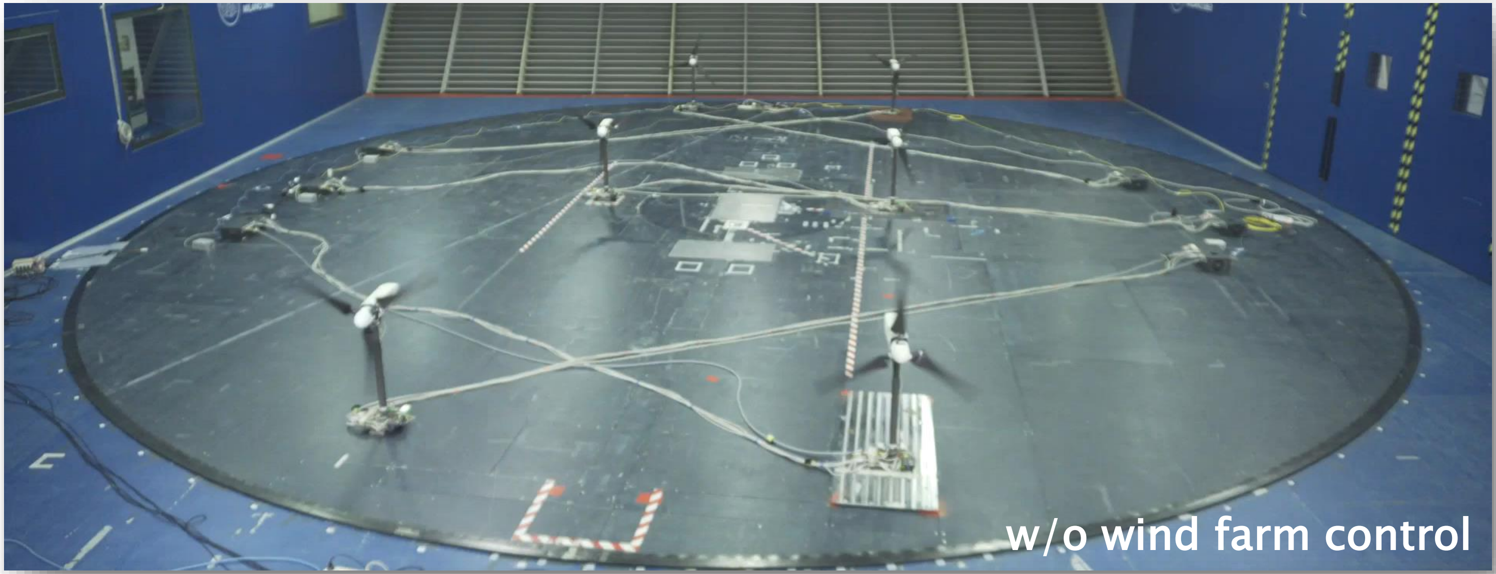
Variable Wind Direction Experiment



- Reproduced with the **turntable**
- Mimic **full-scale** variability of wind direction, accounting for **scaling** and hardware limitations



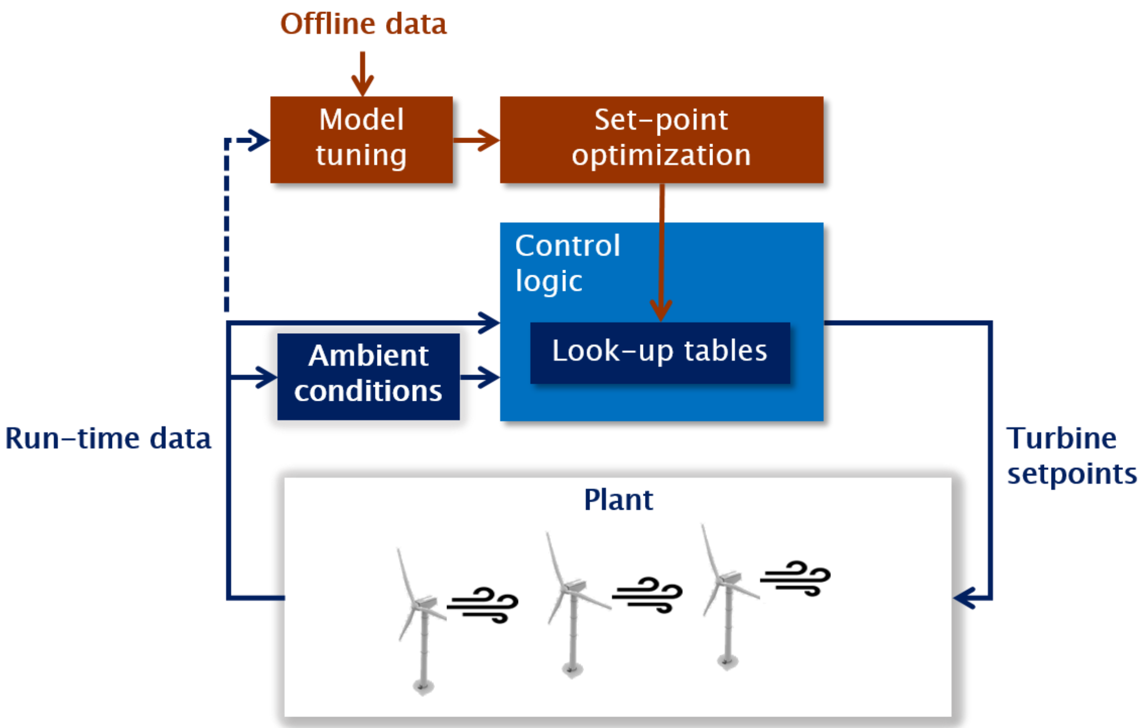
Variable Wind Direction Experiment



TUM.ScaledWIND

Wind Energy Institute

Open-Loop Wake Deflection



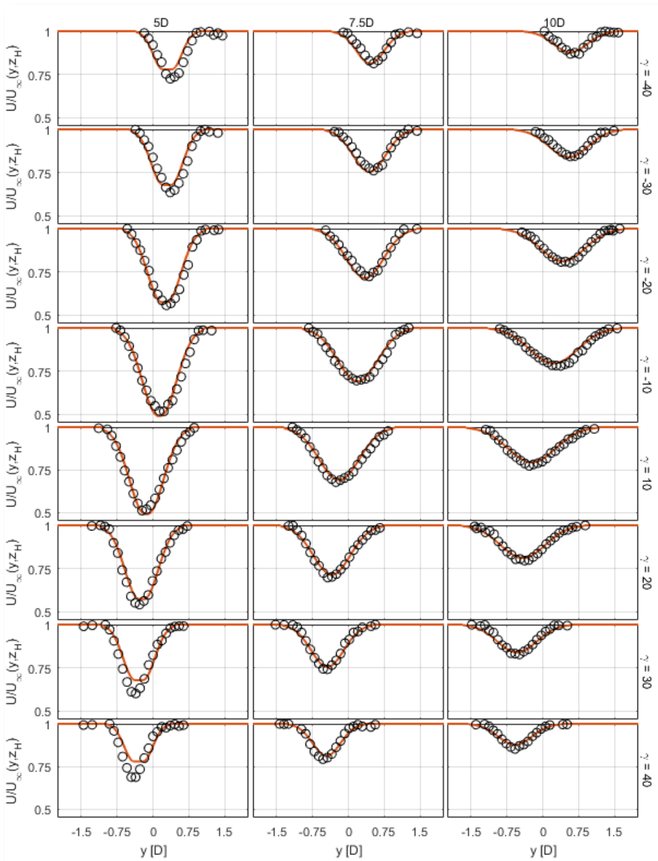
Based on LUTs obtained with **three different** static wind farm models:

- **Lower accuracy**: baseline "FLORIS", tuned with wind tunnel wake data
- **Intermediate accuracy**: "FLORIS-Aug", with extra error terms for unmodelled effects
- **Higher accuracy**: "Data-Driven" response surface (no modelling)

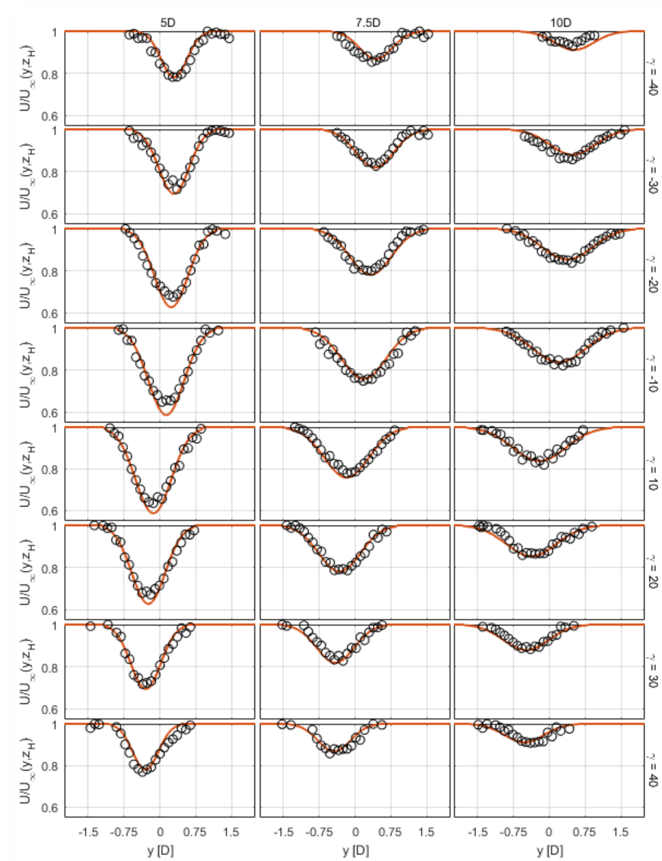
Baseline FLORIS Model

Gaussian wake model, tuned with single G1 **wake** measurements

Offshore Inflow Conditions (mod-TI)



Onshore Inflow Conditions (high-TI)

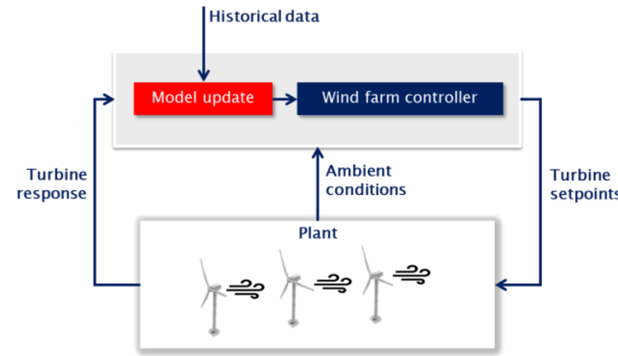


FLORIS-Aug Model

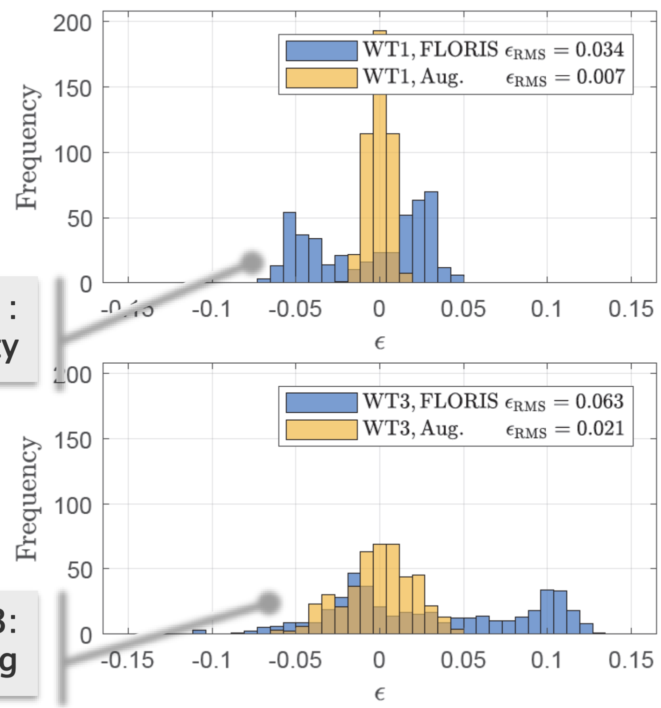
Question: can we learn from SCADA data, and do we learn the right things?

Approach:

1. Augment FLORIS with unmodelled effects:
   - Secondary Steering (SS)
   - Non-uniform speed and direction (orography)
   - Flow acceleration outside of wake
2. Machine learning: ML SVD using SCADA data



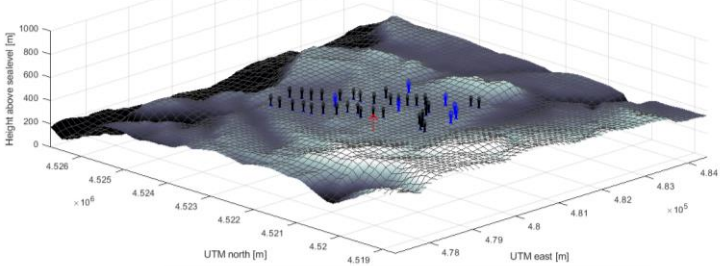
Wind tunnel: power error improvement by machine learning

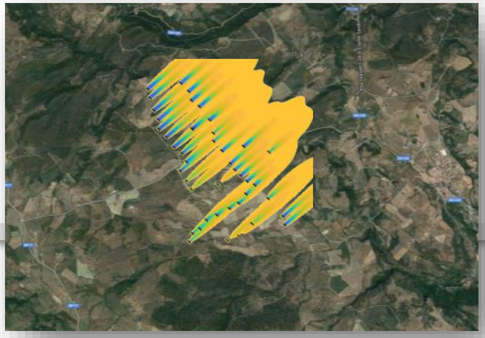


Driving effect on WT1: inflow non-uniformity

Driving effect on WT3: secondary steering

Field testing: learning of orographic effects (ongoing)

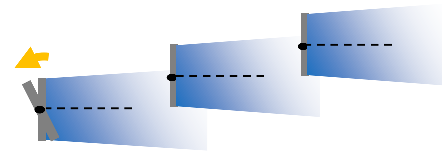


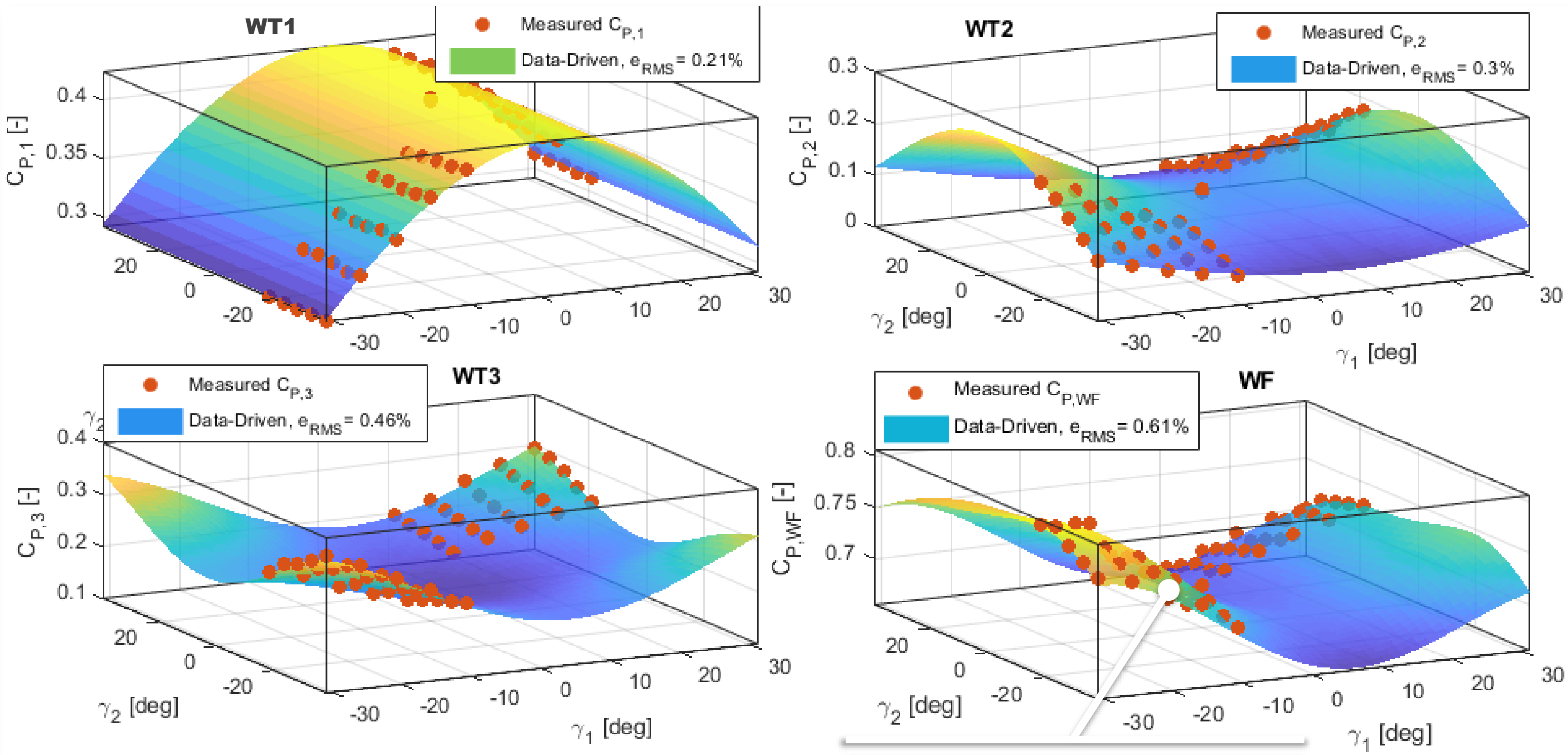


Data-Driven Response Surface Model

Best-fitting of measured C_P

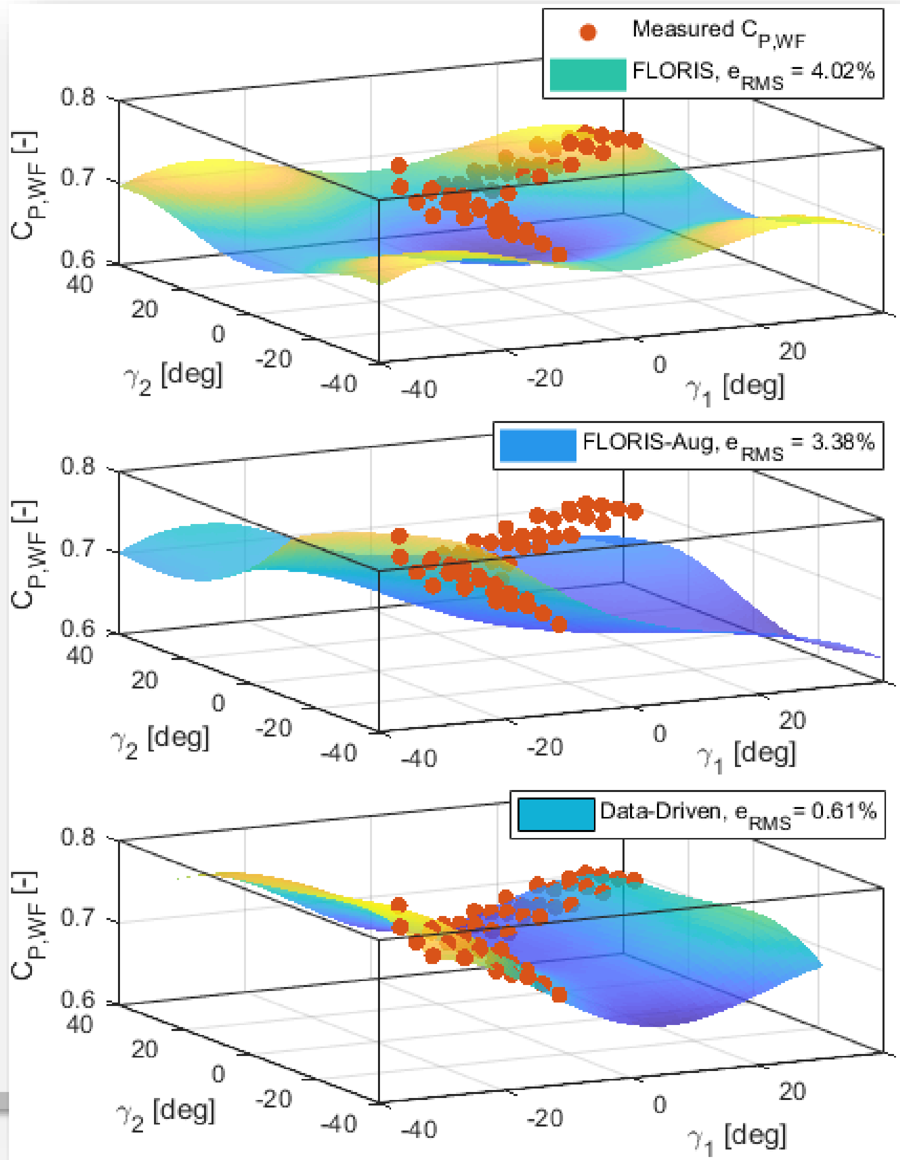
$\gamma > 0$

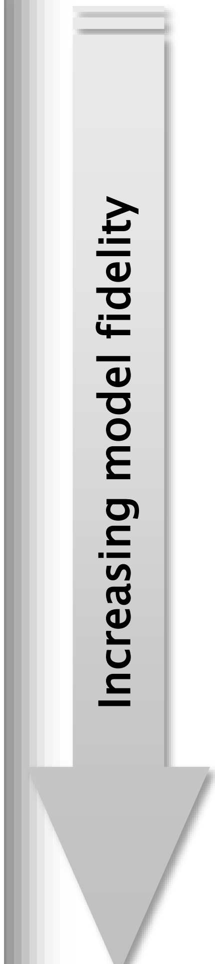




Very precise representation of wind farm power output
Assumed as **ground truth**

Model Accuracy Comparison



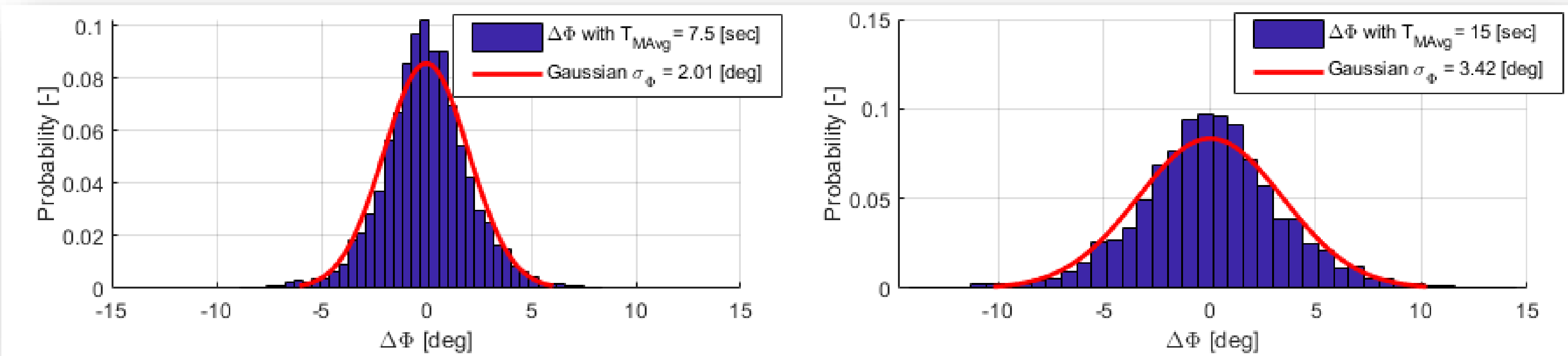


What are the Effects of Control Parameters?

Effects of filtering

Wind tunnel experiment:

- Negligible yaw sensor error
- Negligible wind vane error
- Only uncertainty: **effect of wind direction filtering**

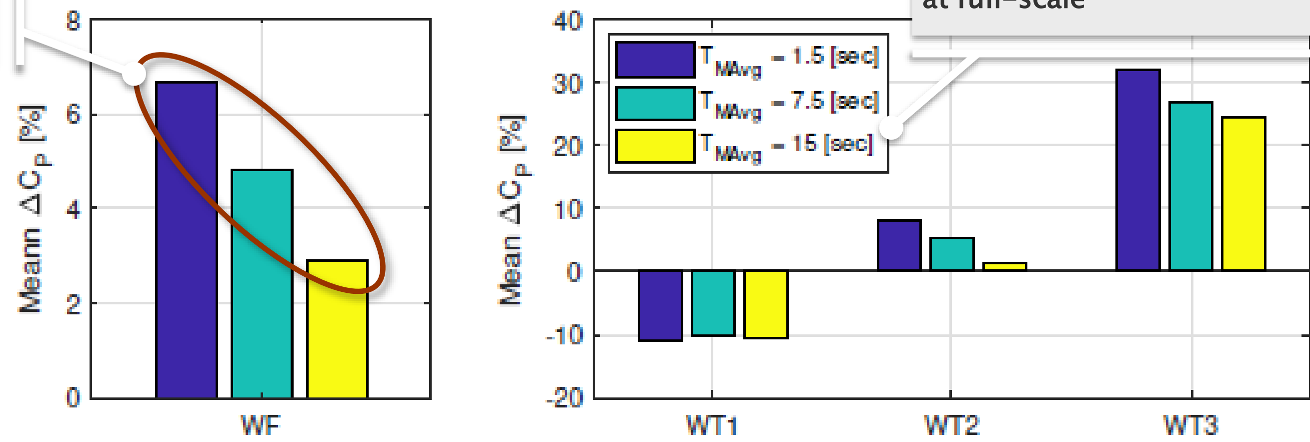


Robust LUTs computed according to Rott et al. 2018

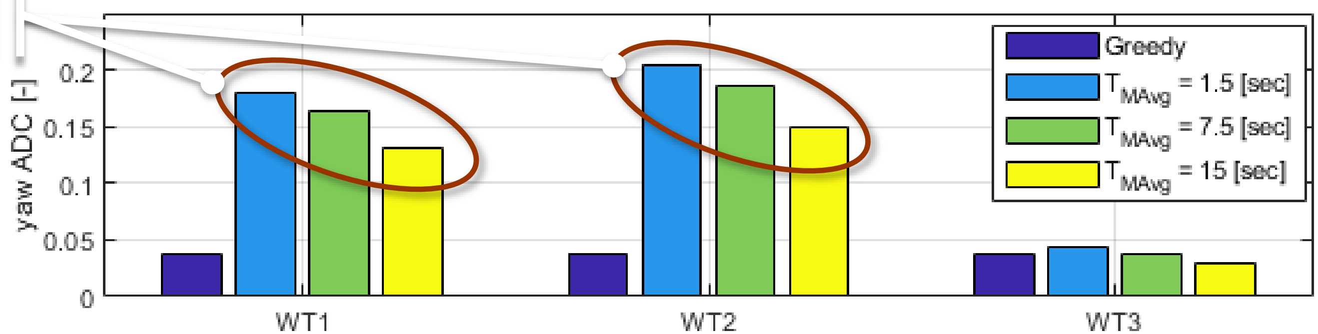
Effects of Time Filtering FLORIS LUTs with $\sigma_\Phi = 0$

Strong impact on cluster power gain

Correspond to 2, 10, 20 min at full-scale



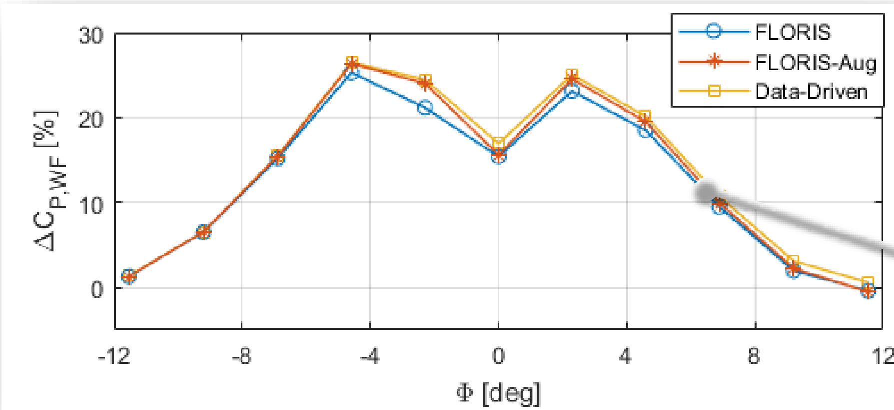
Modest effect of filtering on yaw actuator duty cycle

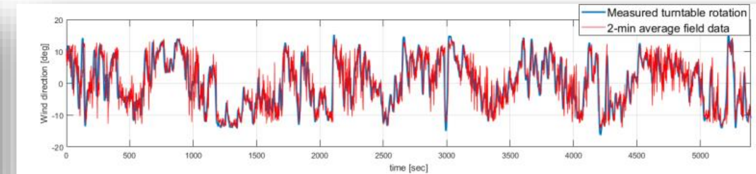


$$\mathrm{ADC} = \frac{1}{T}\int_0^T \frac{|\dot{\gamma}|}{\dot{\gamma}_{max}}\,dt$$

Is Model Accuracy Important for WFC?

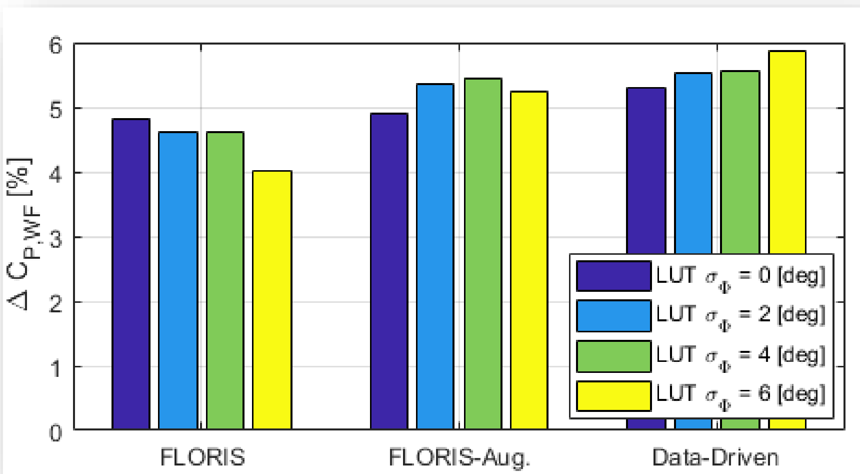
Constant wind direction experiments: apparently not much





Power gains:
FLORIS: +10.7%
FLORIS-Aug: +11.5%
Data-Driven: +11.8%

Variable wind direction experiments: yes, model accuracy is important!



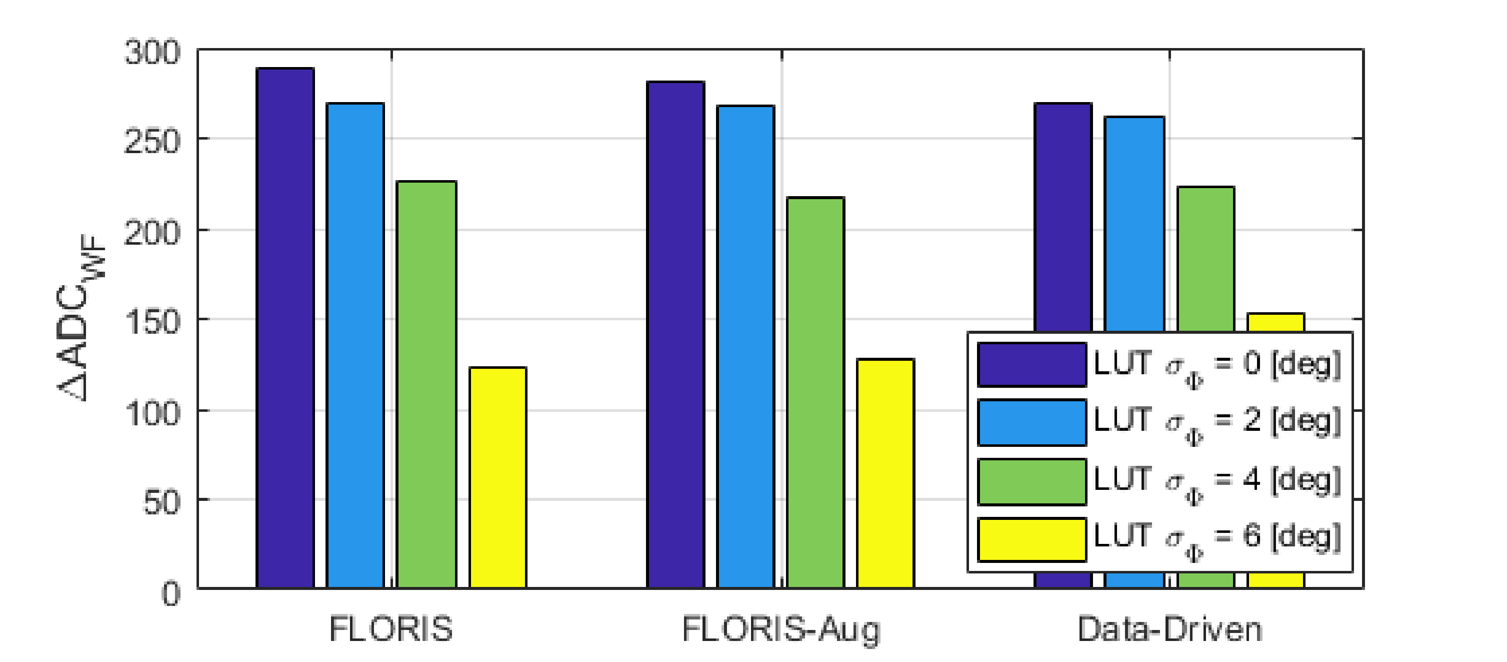
Possible reasons:

- Direction uncertainties
- Limited yaw rate
- Wake dynamics

TUM.ScaledWIND

Effect of Robust LUTs on ADC

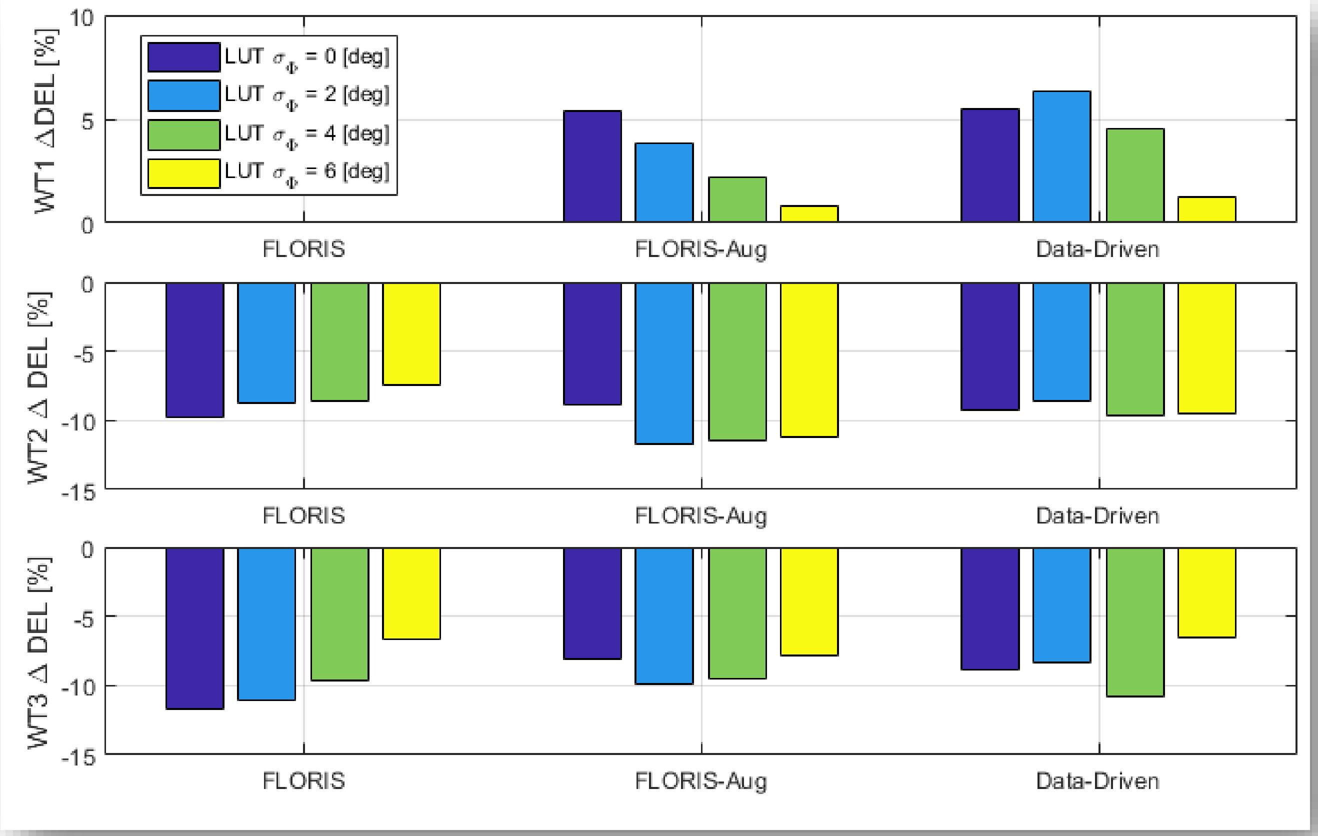
- Robust LUTs mitigate $\mathrm{ADC_{WF}}$ increase
- Modest effect of model used for LUT computation



$$\mathrm{ADC_{WF}} = \frac{1}{3}\sum_{i=1}^{3}\frac{1}{T}\int_{0}^{T}\frac{|\dot{\gamma}_i|}{\dot{\gamma}_{max}}\,dt$$

Effects of Model and Robustness on DEL

- Only marginal DELs increase of **WT1** for robust LUTs
- Strong **reduction** of DELs for WT2 and WT3
- **A better model implies lower DELs**



Note: shaft rotating DELs

Open-Access Database

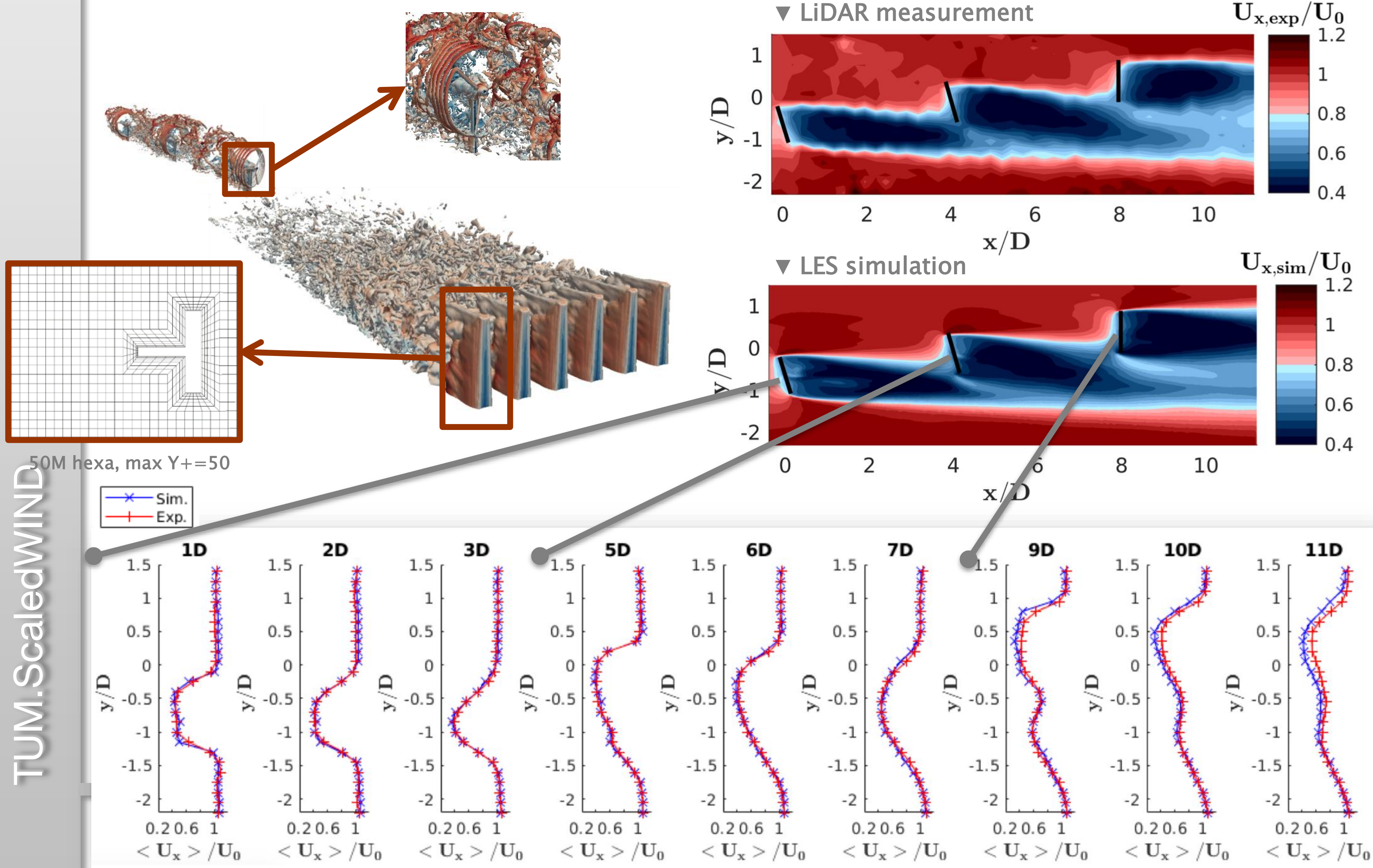
Publicly available datasets:

- Single & multiple wake measurements (triple hot wire)
- Broad range of environmental (TI & shear) and wind turbine operating conditions (yaw misalignment & derating)
- Steady and time-varying wind direction

Applications: validation and tuning of CFD, medium-fidelity and engineering wake models

Data available upon request to the CL-Windcon consortium

Validation of LES Digital Copy of Experiments



TUM.ScaledWIND

Concluding Remarks

Wind tunnel testing:

- Not a perfect match of reality, but very useful for better understanding
- Fast and relatively inexpensive

Main conclusions from latest experiments:

- Better models pay off: improved power capture, reduced loading
- Excessive filtering strongly affects performance
- Recommended recipe: robust LUTs + better models + rapid filtering

Outlook:

- Better models by learning from operational data
- Beyond WFC: similar models applicable to lifetime estimation, predictive maintenance, feed-in to digital twins, …

Acknowledgements

Work in collaboration with:
J. Schreiber, E. Nanos, J. Wang, R. Weber

CL-Windcon

Work supported in part by European Union's Horizon 2020 R&I Program under grant agreement No. 727477 (**"CL-WINDCON"**)