University of Stuttgart
Stuttgart Wind Energy (SWE)
@ Institute of Aircraft Design

Bundesministerium
für Wirtschaft
und Klimaschutz

aufgrund eines Beschlusses
des Deutschen Bundestages

Assessment of Deep Learning Models for Turbine Load Prediction Using Alpha Ventus Wind Farm Data

Estimate loads without accurate wind turbine model?

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EERA DeepWind CONFERENCE 2025

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Forschungscluster

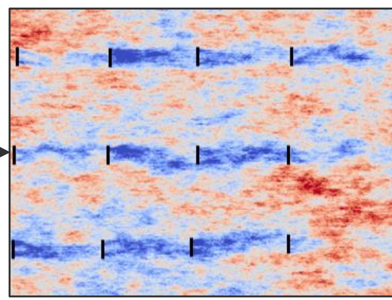
Outline

- **Motivation**
- **Methodology**
  - Transfer Learning
  - Databases
- **Performance of surrogate models (R^2)**
  I. Simulation database only, NREL 5MW
  II. Measurement database only, Senvion 5MW
  III. Transfer Learning: pre-trained model of I. + Senvion 5MW data subset
- **Conclusion**

Motivation

Surrogate model for load prediction

- **Turbine level: lack of the design information**
- **Farm level: limited usable dataset**



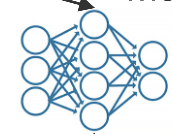
Aeroelastic simulations

Inputs
- Met-ocean characteristics
- Turbine states

- Loads timeseries
- Power

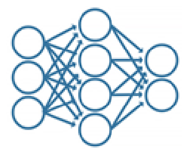
Outputs
- DELs
- Power

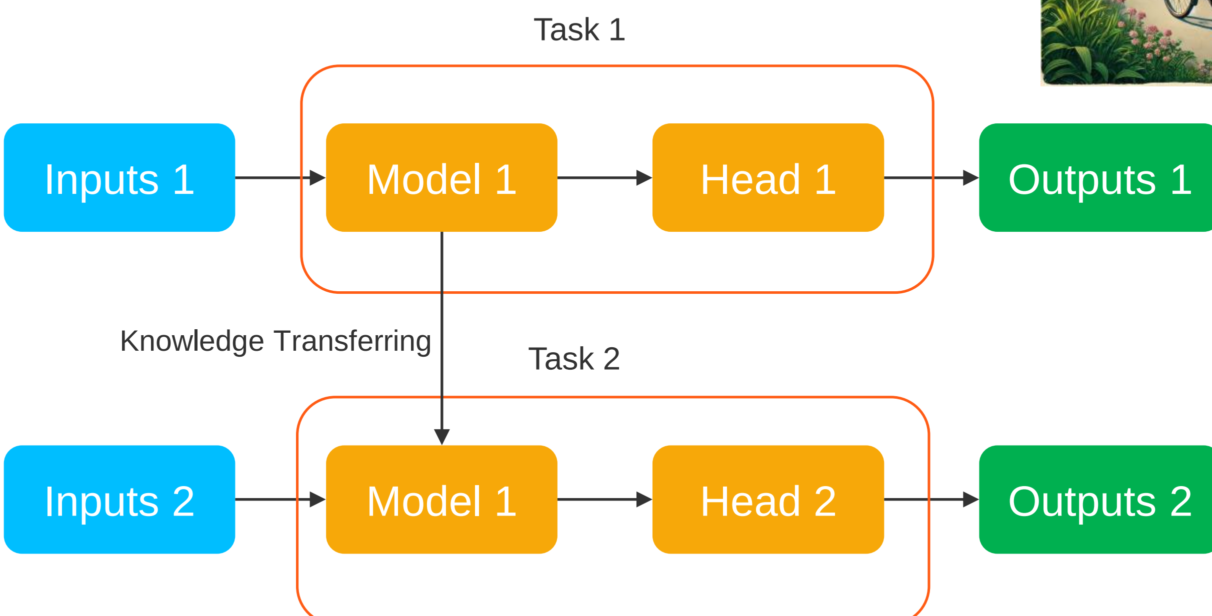
Surrogate model



Methodology

Transfer Learning (TL)





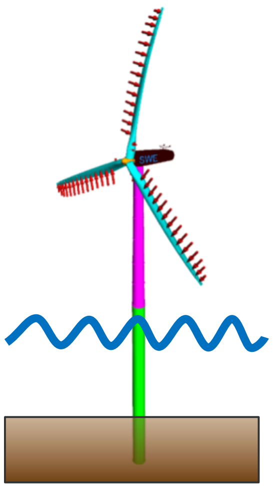
Methodology

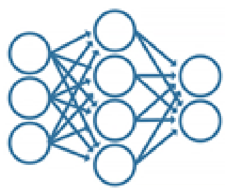
Transfer Learning based on RAVE data

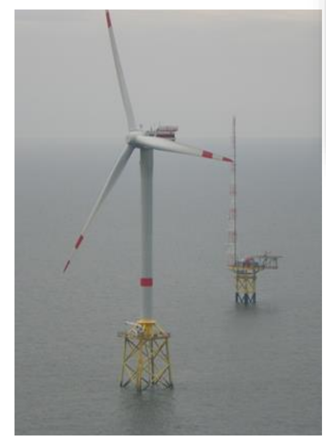
Load surrogate model based on pure aero-elastic simulation of **NREL 5MW**

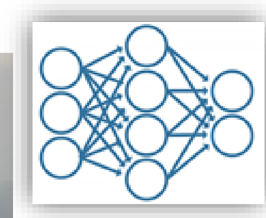
→ Transfer learning with measurement data →

Load surrogate model of **Senvion 5MW**









Methodology

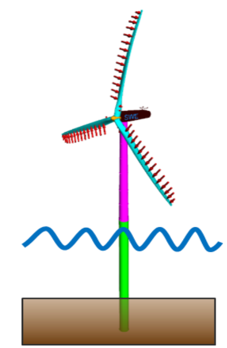
Simulation database with NREL5MW (3240, 9) = 22.5days

Input → OpenFAST simulation → Load time series → Rainflow algorithm → Output

- **Inflow**
  - Wind speed
  - TI
  - Vertical shear
- **Turbine:**
  - Blade Pitch Angle

- Blade root moments: in-plane, out-of-plane
- Tower base moments: fore-aft, side-side

- Damage equivalent loads (DELs)
  - Blade root
  - Tower base
- Power

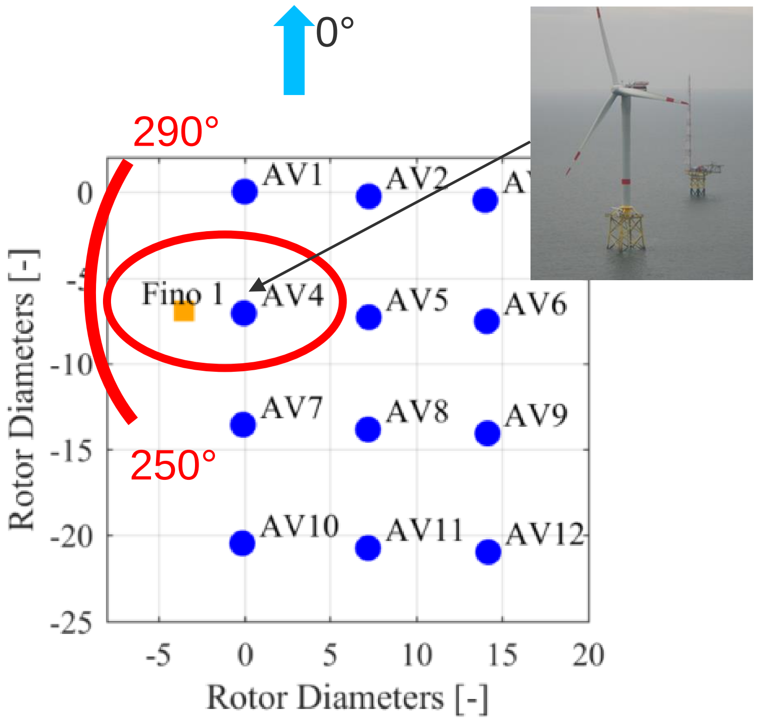


Scheme of a fatigue load database

Sood, I., d’Espierres, C. del F. et, & Meyers, J. (2023). *Quasi-static closed-loop wind-farm control for combined power and fatigue optimization*. 1–24. http://arxiv.org/abs/2305.11710

Methodology

RAVE database for Senvion 5MW

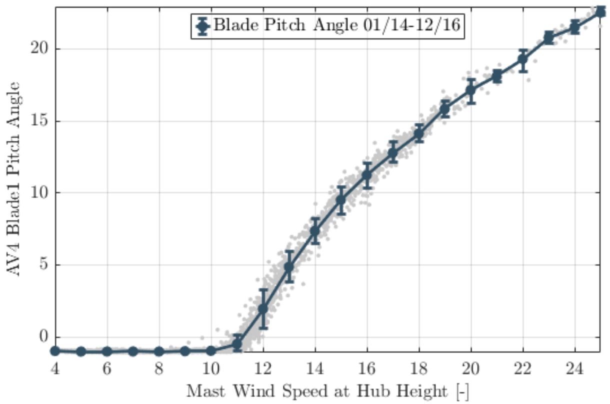


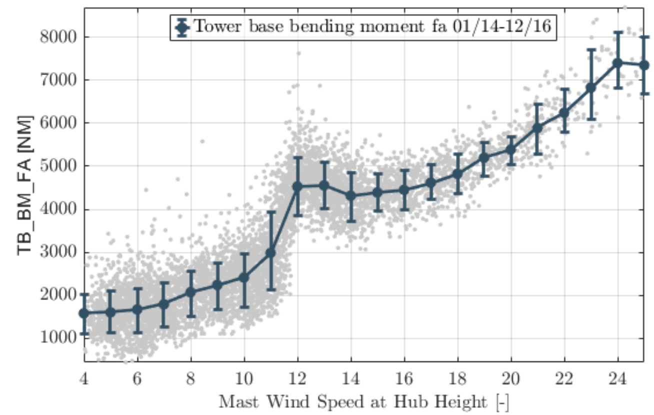
- Meteorological data from FINO1
  - Wind speed
  - TI
  - PLexp (vertical sheer)
- Senvion 5MW (AV4)
  - Blade pitch angle
  - Power
  - Blade1 root moment (edgewise)
  - Blade1 root moment (flapwise)
  - Tower base moment (side-side)
  - Tower base moment (fore-aft)

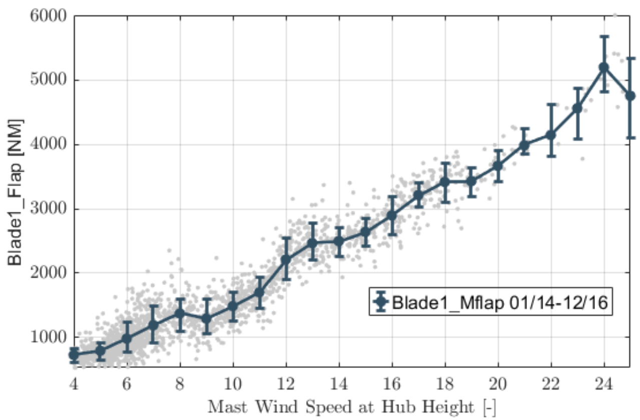
M. Kretschmer, J. Jonkman, V. Pettas, and P. W. Cheng, “FAST.Farm load validation for single wake situations at alpha ventus,” *Wind Energy Sci.*, vol. 6, no. 5, pp. 1247–1262, 2021, doi: 10.5194/wes-6-1247-2021.

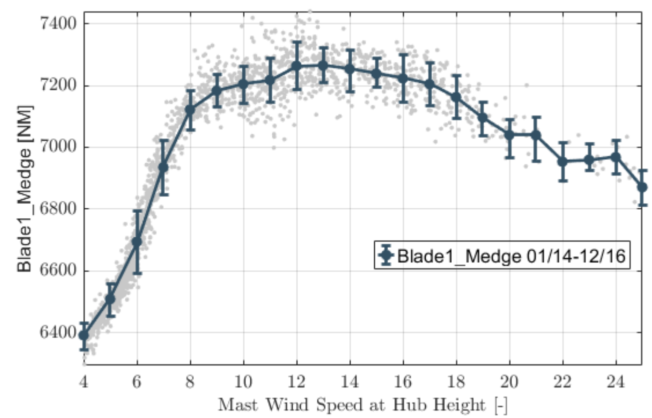
Results

Filtered database of AV4 (Senvion 5MW) (1728, 9) = 12 days



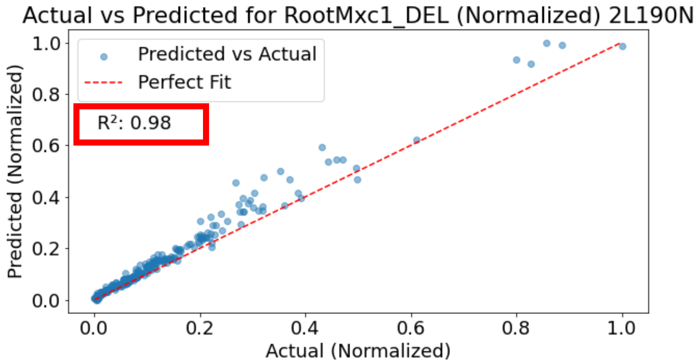


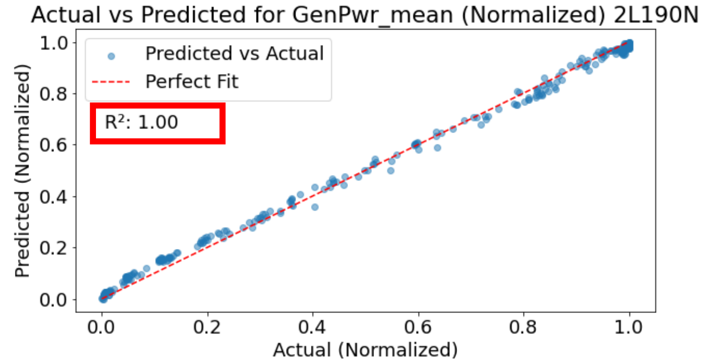


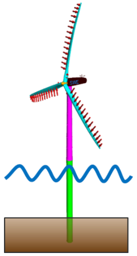


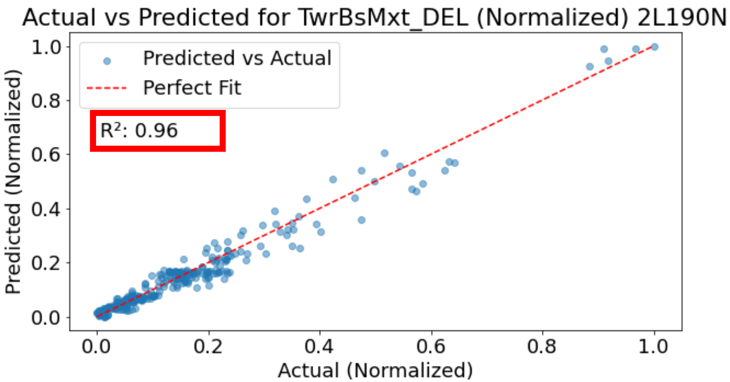
Results

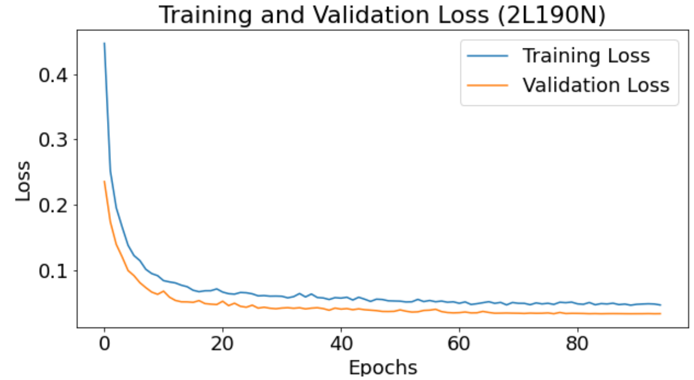
Surrogate model of NREL 5MW, **pure simulation database**





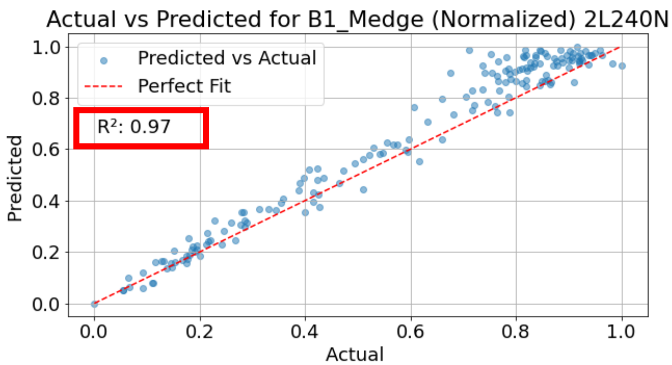


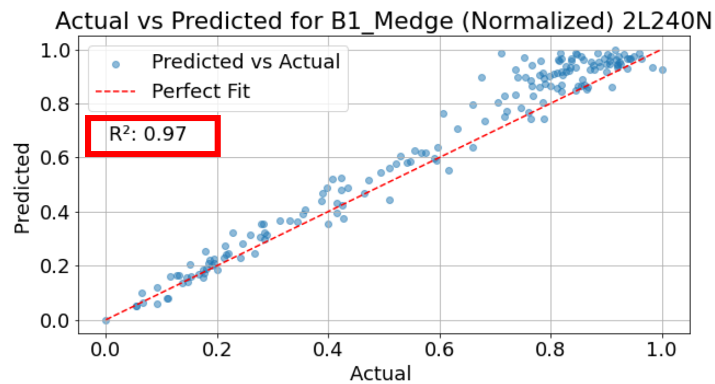


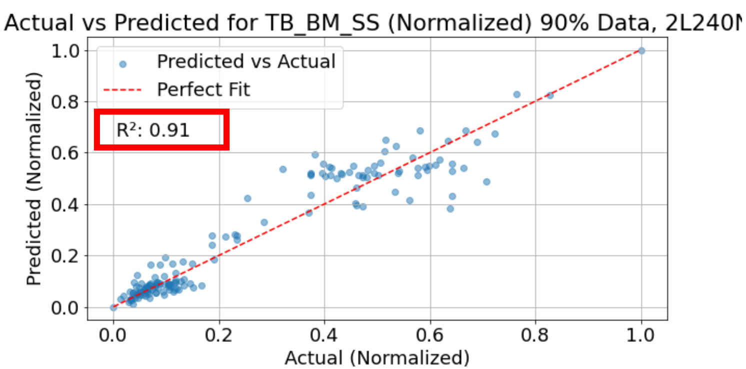


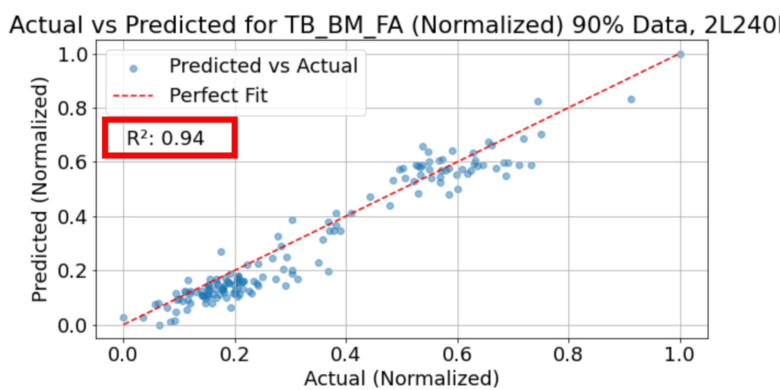
Results

Surrogate model of Senvion 5MW, **pure measurement database**



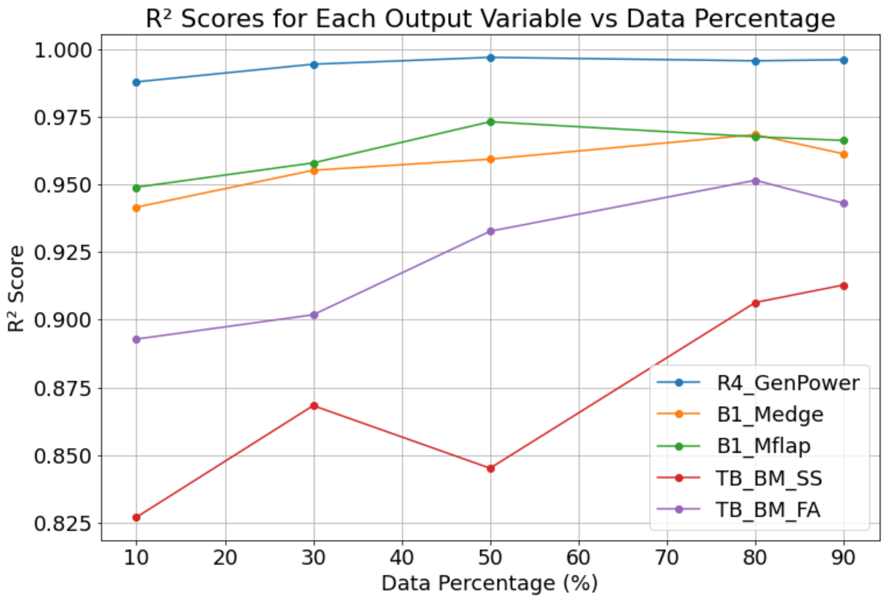






Results

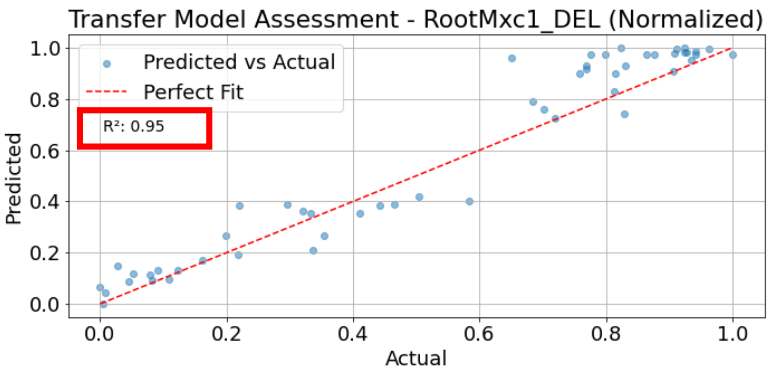
Model performance with difference subset of data

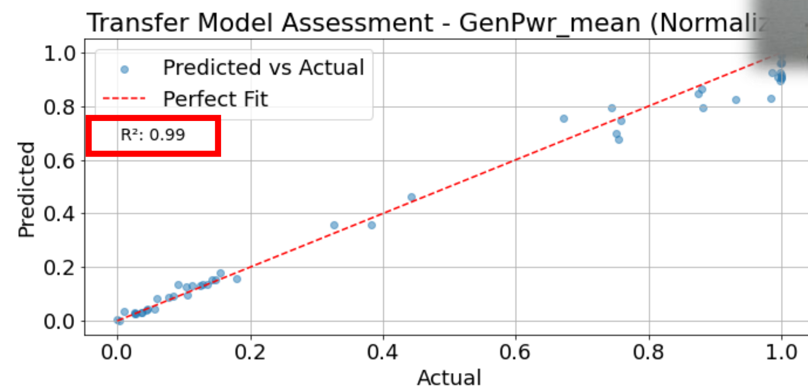


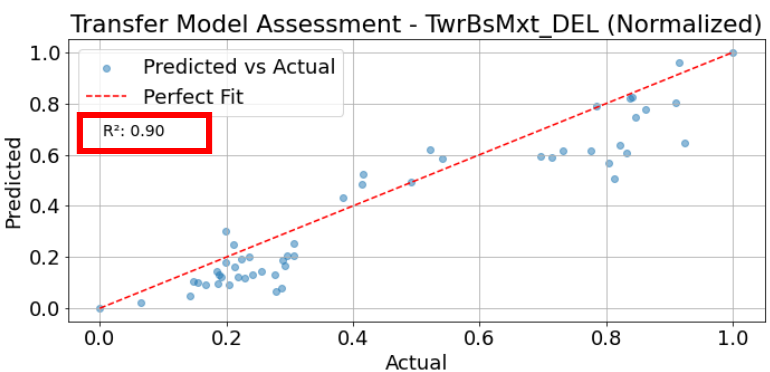
Data amount (%)	Days of data used
10	1.2
30	3.6
50	6
80	9.6
90	10.8

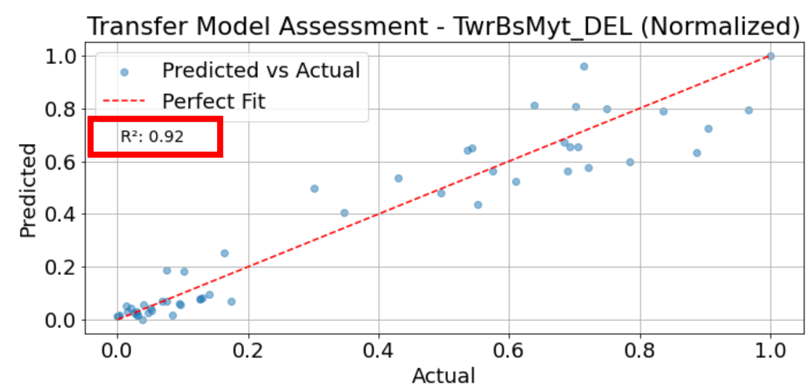
Results

TL model, 30% of RAVE database

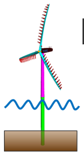








Conclusion



I. ANN model trained on simulation data

- effectively predict turbine loads

II. Surrogate load model trained on measurement data

- much data available, e.g., more than a week of filtered clean data (1 ~ 2 year of raw data)
- worse prediction on tower base DEL: large deviations on tower based moments, Hydro conditions

III. Transfer learning model

- only a few data available, days of clean data (several months of raw data)

Further steps

- Include hydro conditions
- Wake-induced loads (AV5)

Lessons learned

- Tuning of deep learning models

Reference

FlexiWind Project

https://www.ifb.uni-stuttgart.de/en/research/windenergy/projects/FlexiWind/

i. Sood, I., d'Espierres, C. del F. et, & Meyers, J. (2023). *Quasi-static closed-loop wind-farm control for combined power and fatigue optimization*. 1–24. http://arxiv.org/abs/2305.11710

ii. M. Kretschmer, J. Jonkman, V. Pettas, and P. W. Cheng, "FAST.Farm load validation for single wake situations at alpha ventus," *Wind Energy Sci.*, vol. 6, no. 5, pp. 1247–1262, 2021, doi: 10.5194/wes-6-1247-2021.

iii. G. Xu, W. Yu, and T. Kim, "Wind turbine load estimation using machine learning and transfer learning," *J. Phys. Conf. Ser.*, vol. 2265, no. 3, 2022, doi: 10.1088/1742-6596/2265/3/032108.

iv. J. Liew and G. C. Larsen, "How does the quantity, resolution, and scaling of turbulence boxes affect aeroelastic simulation convergence?," J. Phys. Conf. Ser., vol. 2265, no. 3, pp. 1–10, 2022, doi: 10.1088/1742-6596/2265/3/032049.

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Thank you!

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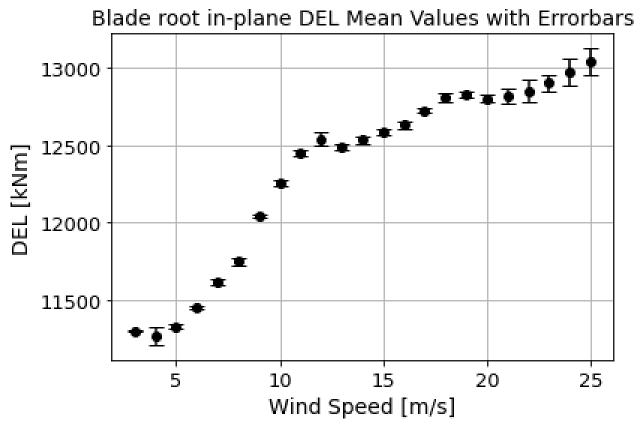
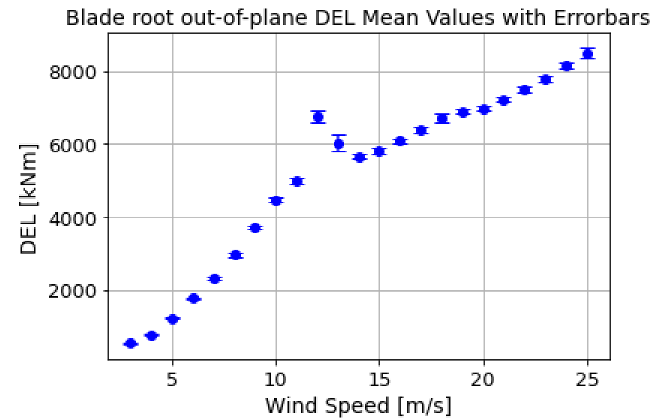
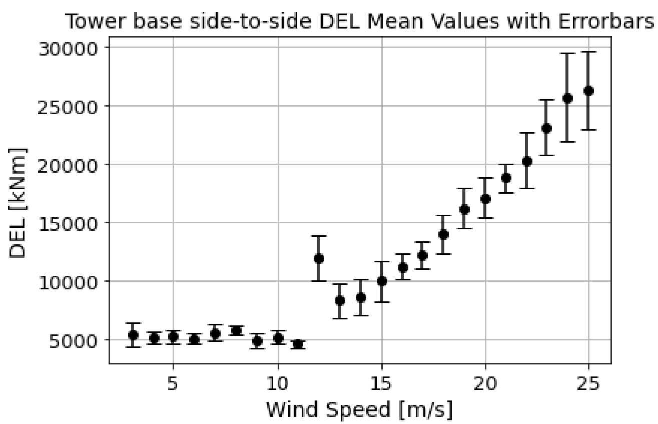
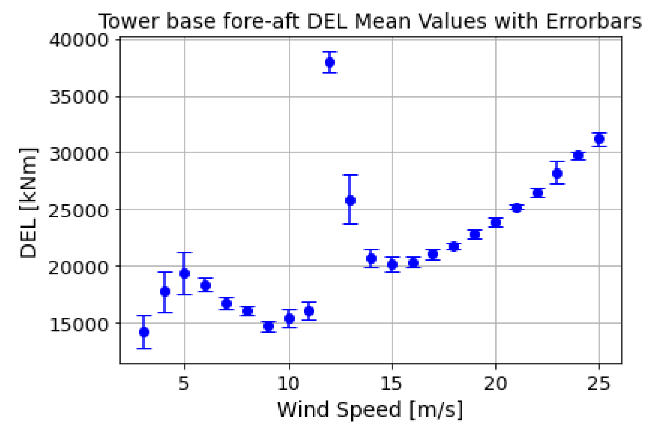
D1.2 Method of creating a database for the future wind farm

Problem simplification









Parameter space for OpenFAST simulations

- NREL 5MW RWT, **24** seeds, <u>600s</u>

Input parameter	Values	Units	**Nr.**
Wind speed	[4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 19, 25]	m/s	15
TI	[3, 10, 20]	%	3
Vertical shear	[0.05, 0.12, 0.16]	\	3
Pitch angle	Default (by WT controller)	deg	

- 24*15*3*3=3240 (*<u>10mins</u>)

Sood, I., d'Espierres, C. del F. et, & Meyers, J. (2023). Quasi-static closed-loop wind-farm control for combined power and fatigue optimization. 1–24. http://arxiv.org/abs/2305.11710

Determine layers and neurons