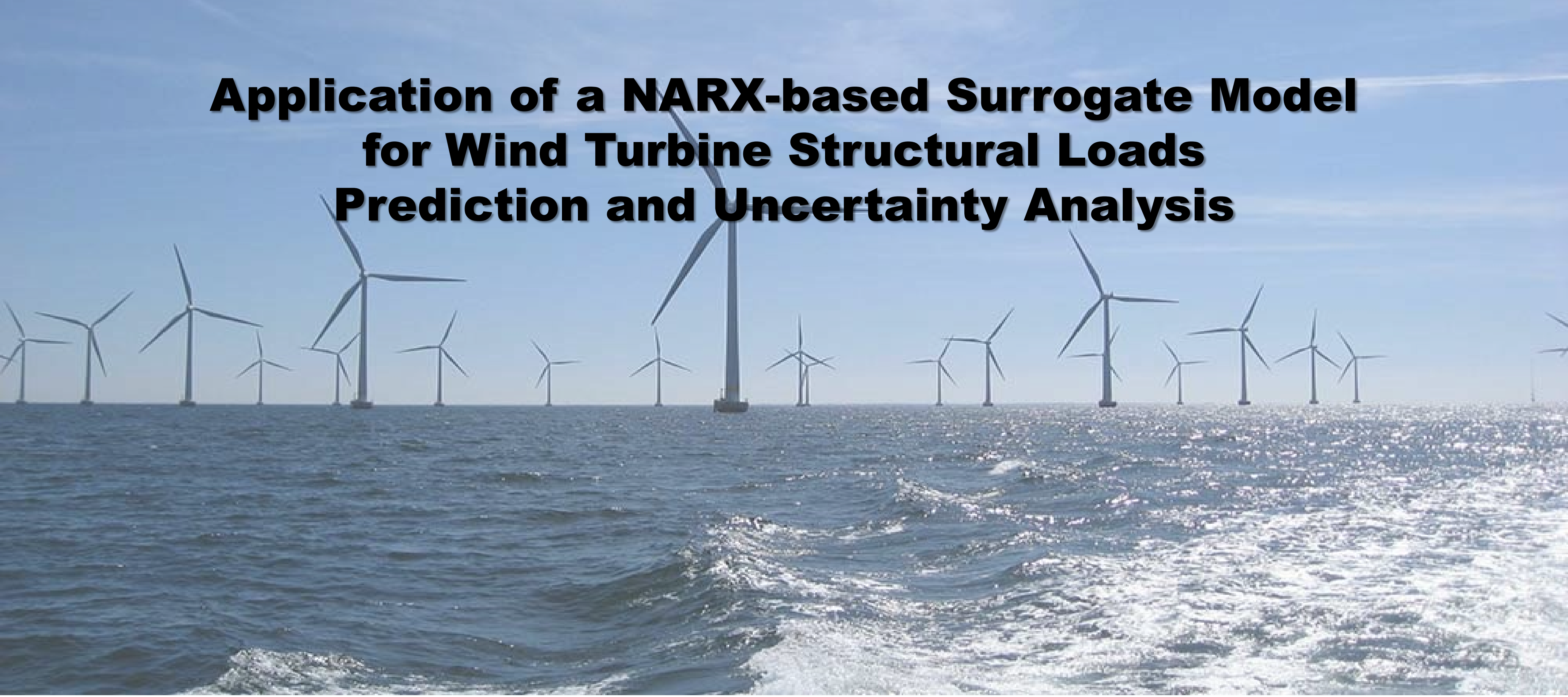
Application of a NARX-based Surrogate Model for Wind Turbine Structural Loads Prediction and Uncertainty Analysis



Presenter: Xu Ning

UNIVERSITY OF BERGEN

RAVE Machine Learning Workshop

10 Oct 2024

Presentation Outline

Ⅰ Introduction

- Motivation
- Problem statement

Ⅱ Surrogate Model

- NARX model
- Training dataset
- Model structure

Ⅲ Evaluation

- Prediction vs Actual
- Uncertainty analysis

Ⅳ Summary

- Summary
- Conclusions
- Limitations
- Outlook

I

Introduction

Introduction

Motivation

- Reduction in computational cost for loads modeling
  - **Nonlinear** and **time-dependent** interaction between wind condition and turbine operation
  - Requires a model faster and cheaper than physical model
- Real-time **monitoring** and **controlling**
  - Blades, tower, main shaft
  - Rotational speed, pitch, yaw
  - Predictive maintenance: reduces risks of excessive loading and structural failures

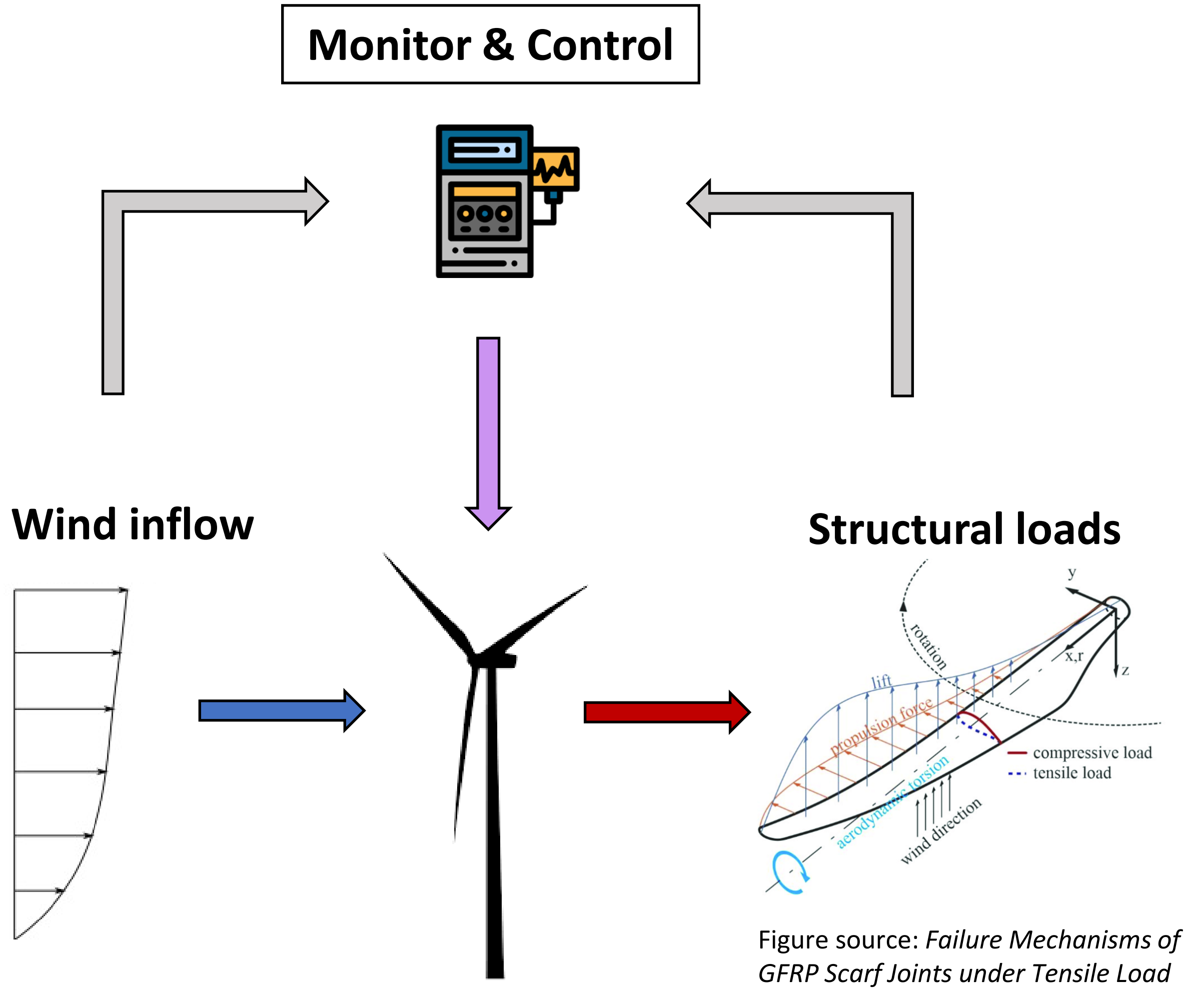


Figure source: *Failure Mechanisms of GFRP Scarf Joints under Tensile Load*

Introduction

Problem Statement

Objectives:

1. To establish an **end-to-end** and **real-time capable** solution for predicting **short-term** wind turbine loads.

INPUT

- Hub height wind speed
- Hub height wind direction
- Wind shear
- Wind veer
- Turbulence intensity
- Yaw angle
- …

TRAINING

NARX-based Surrogate Model

OUTPUT

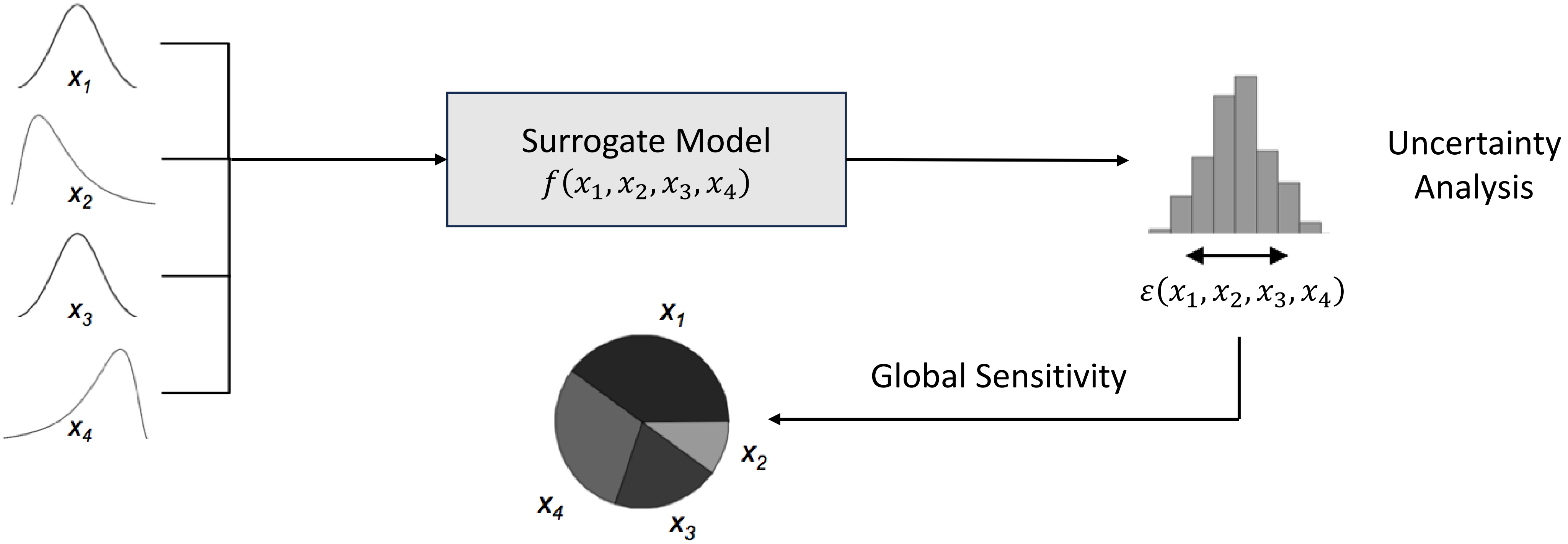
- Blade root moments
- Tower base moments
- Tower yaw moment
- Main shaft torque
- …

Introduction

Problem Statement

Objectives:

2. To evaluate the model performance by **residual analysis** and **uncertainty quantification**.



Ⅱ

Surrogate Model

Surrogate Model

NARX model

- What is a NARX model?
  - Nonlinear AutoRegressive eXogenous model to predict responses of a dynamical system.
  - Past values of the variables of interest.
  - Past (and current) values of driving (exogenous) variables.

$$y(t) = f(y(t-1), y(t-2), \dots, y(t-n_y), u(t-1), u(t-2), \dots, u(t-n_u)) + \varepsilon(t)$$

$y(t)$**:** system output (e.g., blade root moments)

$u(t)$**:** system input (e.g., wind speed, control signals)

n_y **:** number of lagged output terms

n_u **:** number of lagged input terms

f**:** nonlinear function that models the relationship between the past inputs and outputs

$\varepsilon(t)$**:** error term

Surrogate Model

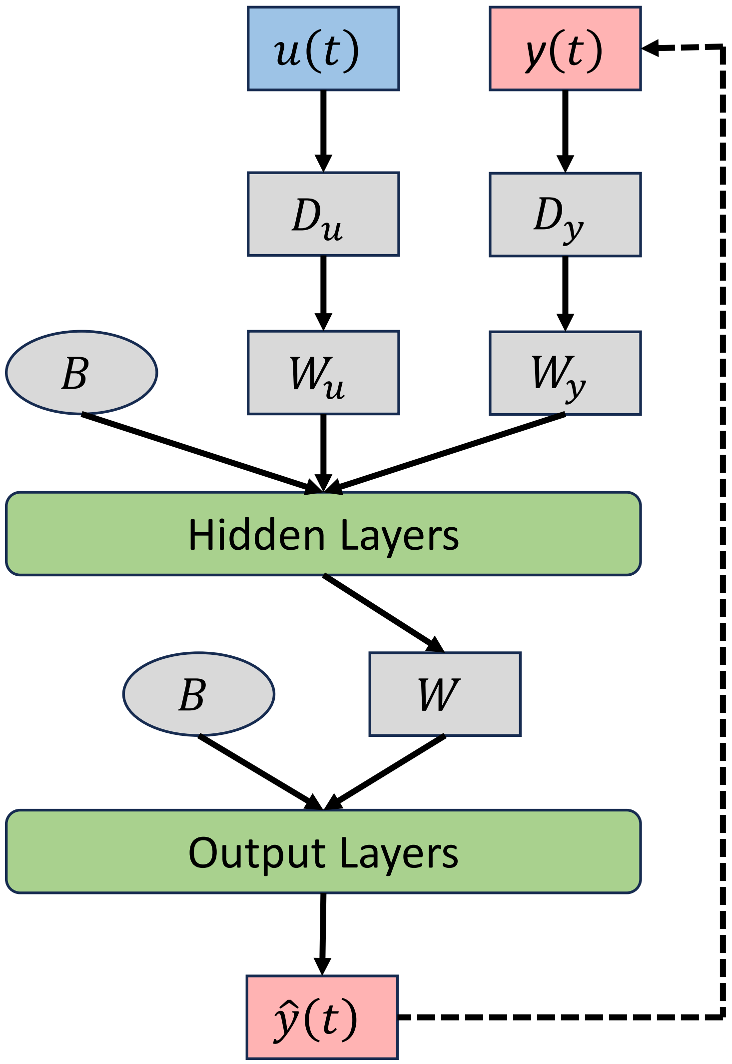
NARX model

- Form of the nonlinear function f?
  - Polynomial, wavelet, Gaussian process (GP), **neural network (NN)**, …

    1. High-dimensional spaces (multiple inputs and outputs)
    2. Capture intricate nonlinearity
    3. Fully data-driven (minimal manual tuning)

- Why NARX model?
  - Nonlinear, time-dependent dynamical system
  - Historical data and Exogenous input
  - Integration with control system

NARX Neural Network



Surrogate Model

Training dataset

To train an **end-to-end** model: directly from wind condition and operation to loads.

INPUT

- Hub height wind speed mean: U_{90m}
- Hub height wind speed standard deviation: σ_U
- Wind shear: $\Delta U = U_{90m} - U_{30m}$
- Wind veer: $\Delta\theta = \theta_{90m} - \theta_{30m}$

- Yaw misalignment: $\gamma = \theta_{yaw} - \theta_{90m}$
- Pitch angle: β

OUTPUT

- Flapwise blade root moment: M_b
- North-south tower base moment: M_t
- Tower top yaw moment: M_y
- Main shaft torque: T_m

Surrogate Model

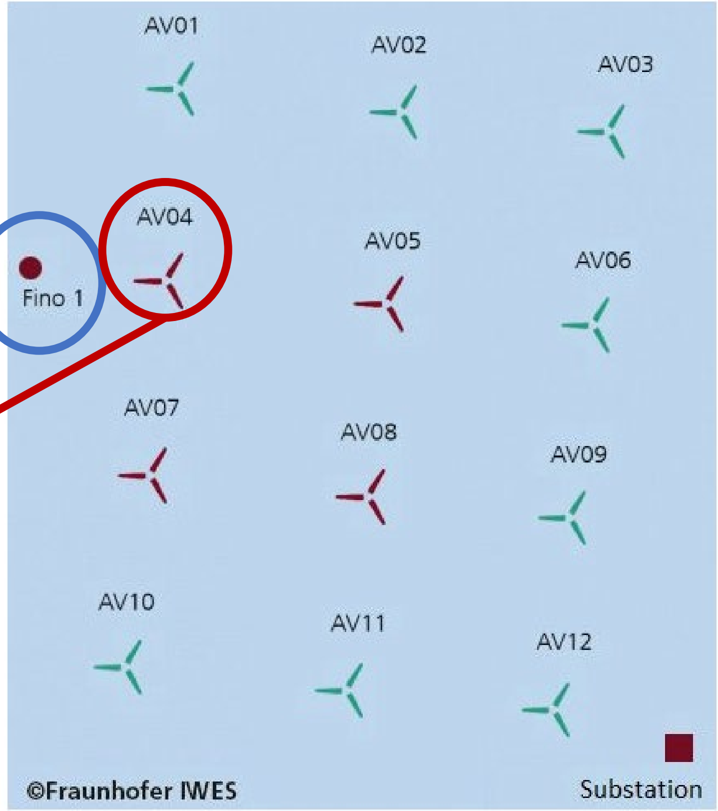
Training dataset

To train an **end-to-end** model: directly from wind condition and operation to loads.

RAVE DATA

- F1_v(30) [m/s]
- F1_v(90) [m/s]
- F1_dir(30) [°]
- F1_dir(90) [°]

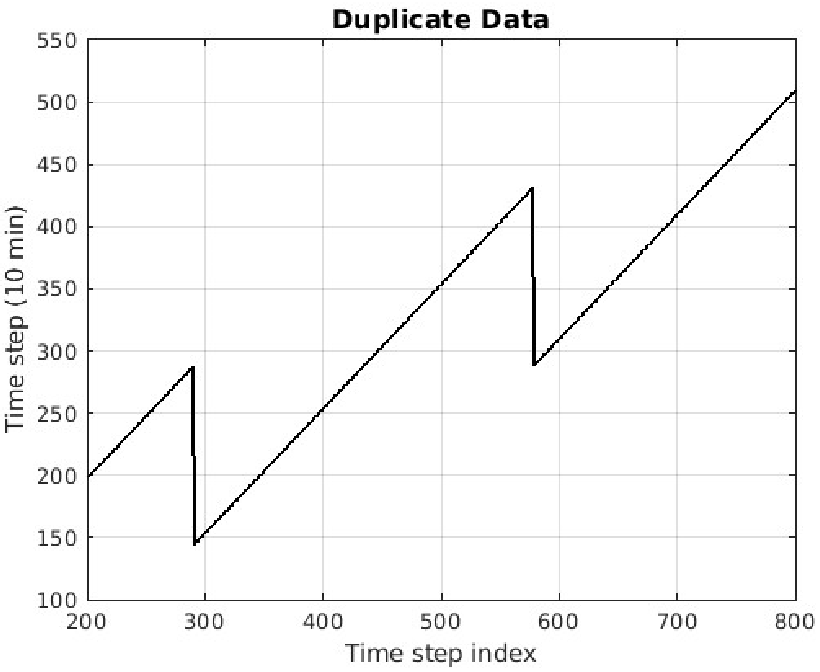
- R4_Pitchwinkel_Ist_B4_50Hz [°] AV-04
- R4_WYaw [deg°] AV-04
- R4_DT-A23ot [kNm] AV-04
- R4_DT-B4wt [kNm] AV-04
- R4_DT-A12u_1_2 [kNm] AV-04
- R4_D-B5b1a2 [kNm] AV-04

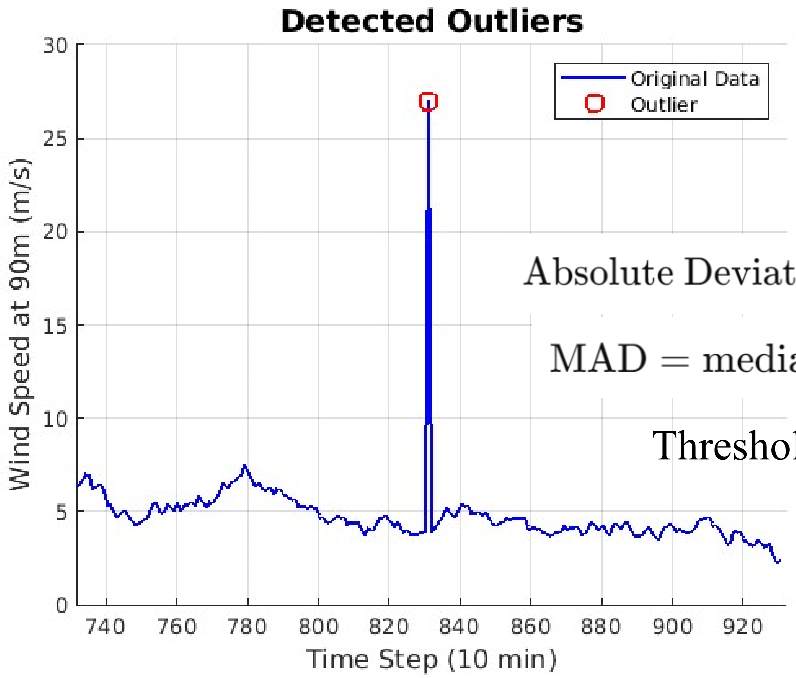


Surrogate Model

Training dataset

- Preprocessing
  - remove duplicate data
  - remove outliers





$$\text{Absolute Deviation} = |x_i - \text{median}(x)|$$

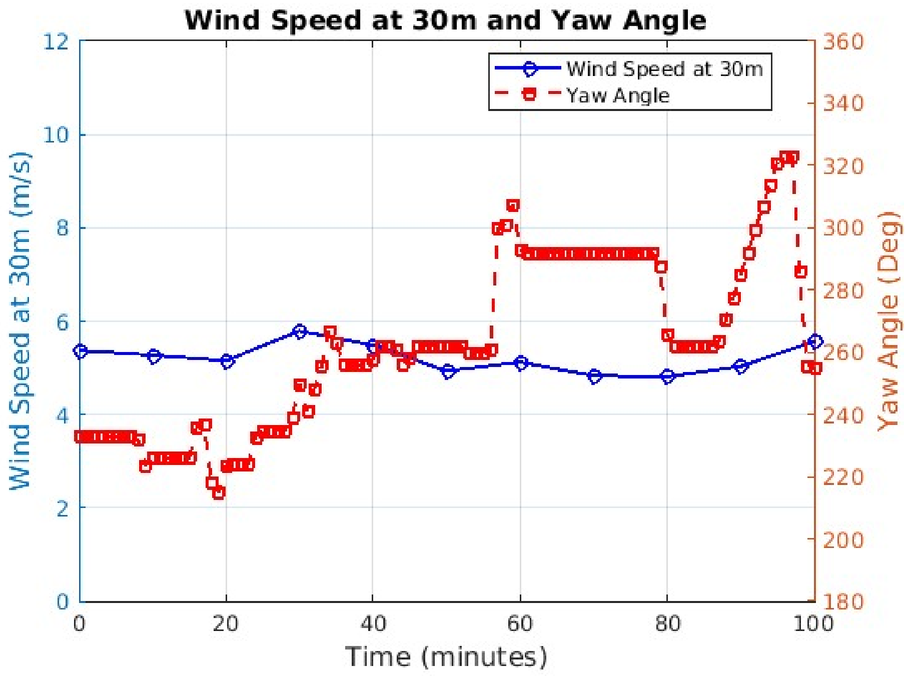
$$\text{MAD} = \text{median}(|x_i - \text{median}(x)|)$$

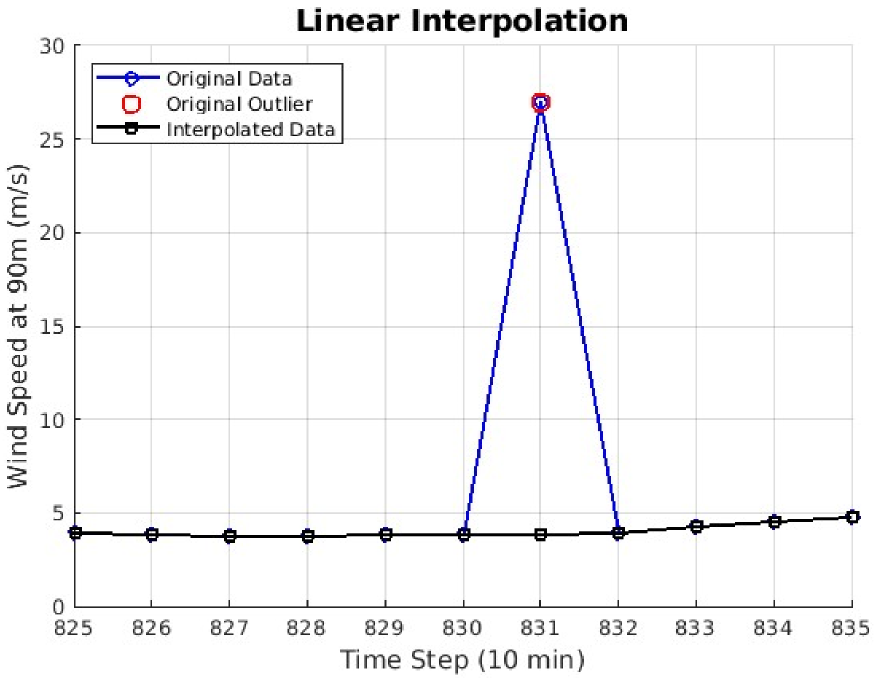
Threshold: $3 \times \text{MAD}$

Surrogate Model

Training dataset

- Preprocessing
  - unify time steps
  - linear interpolation





Surrogate Model

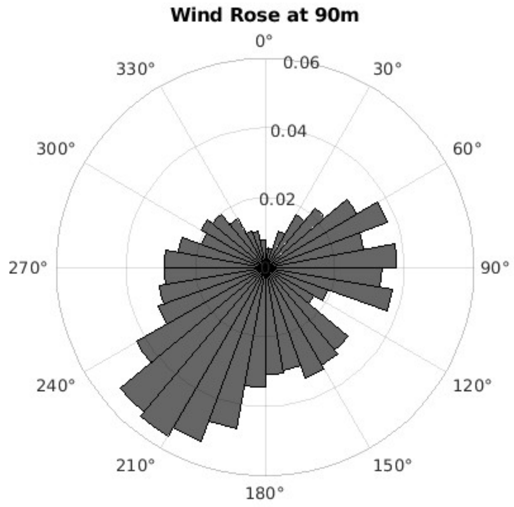
Training dataset

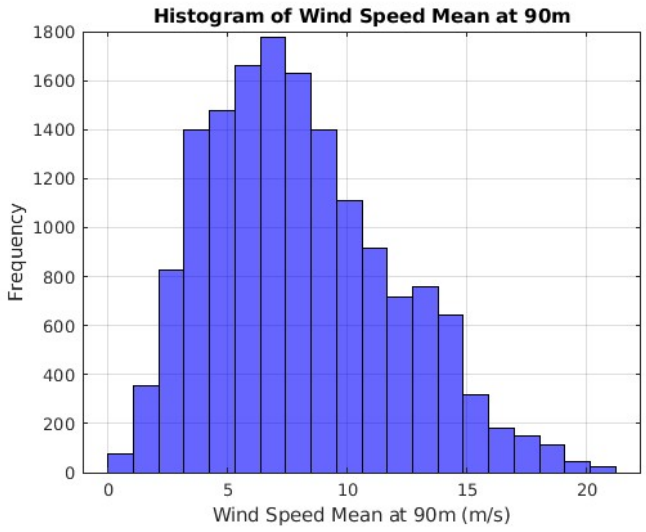
Training dataset period:

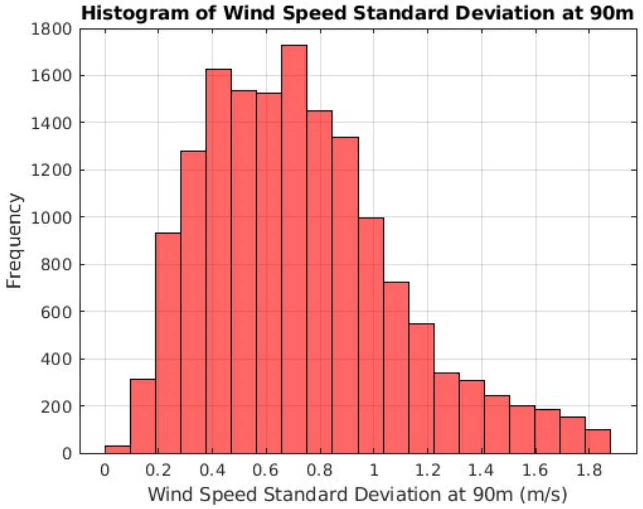
2016.09.01 – 2017.02.28

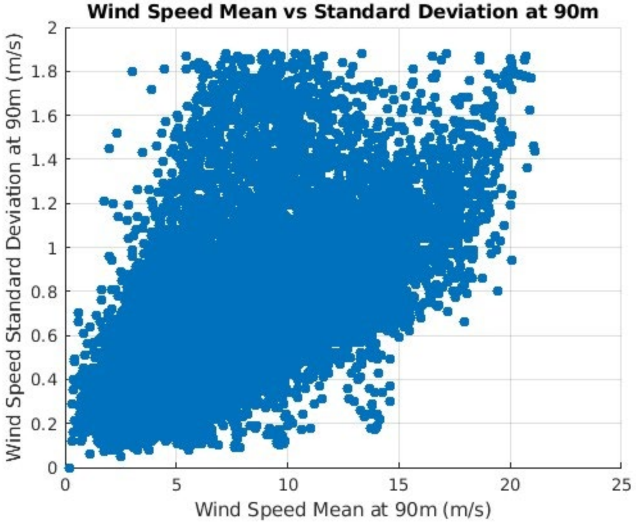
Training dataset

sample number: **15553**









Surrogate Model

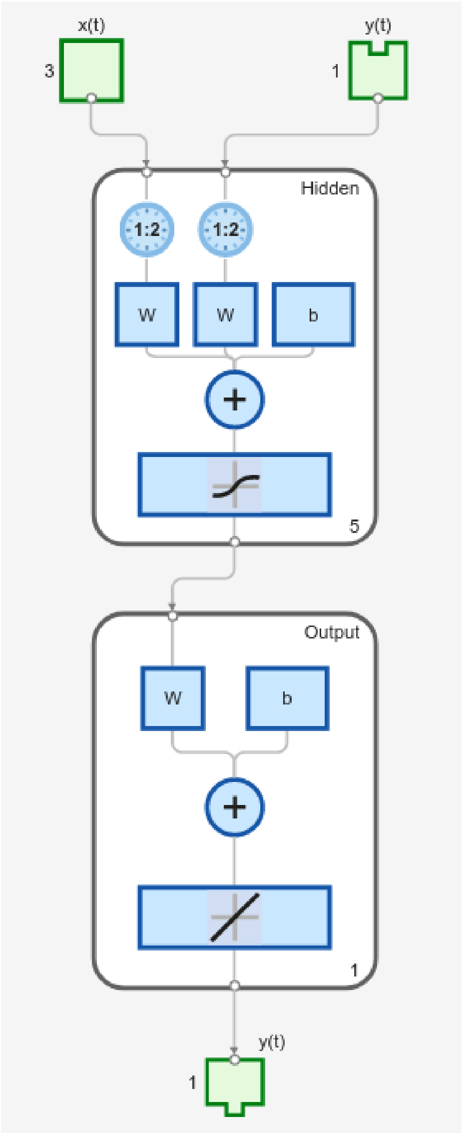
Model structure

- Model parameters:
  - **Lag for exogeneous input: 6**
  - **Lag for output: 6**

  1 hour

  - **Sizes of hidden layer: 10**

- Stationary assumptions:
  1. **Stable mean**
  2. **Stable variance**



Multiple Exogenous Inputs $x_1, x_2, x_3, \ldots$

\+

Past Output y_d

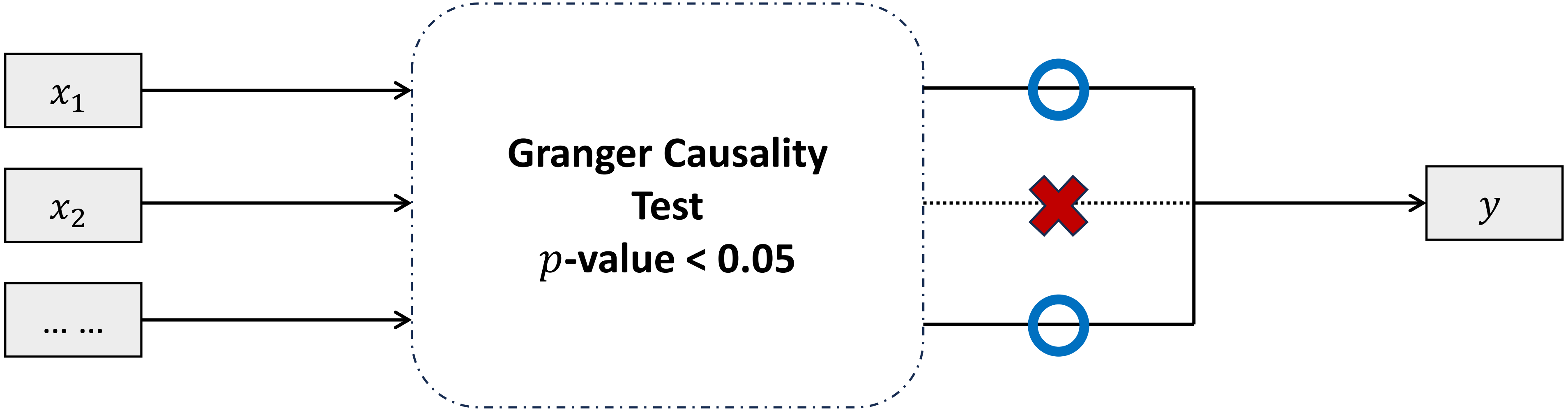
Single Output $\hat{y}$

Surrogate Model

Model structure

➢ Determination of input variables

- **Granger-cause test:** a statistical hypothesis test for determining whether one time series is useful in forecasting another.
- If knowing the past values of one variable improves the prediction of another, it is said to **Granger-cause** the second variable.



Surrogate Model

Model structure

Granger-cause test results

	Flapwise Blade Root Moment	North-south Tower Base Moment	Tower Top Yaw Moment	Main Shaft Torque
Hub height Wind Speed (Mean)	O	O	O	O
Hub height Wind Speed (SD)	O	O	O	O
Wind Shear	O	✖	O	O
Wind Veer	✖	✖	✖	✖
Yaw Misalignment	✖	✖	✖	✖
Pitch Angle	O	✖	✖	✖

Ⅲ

Evaluation

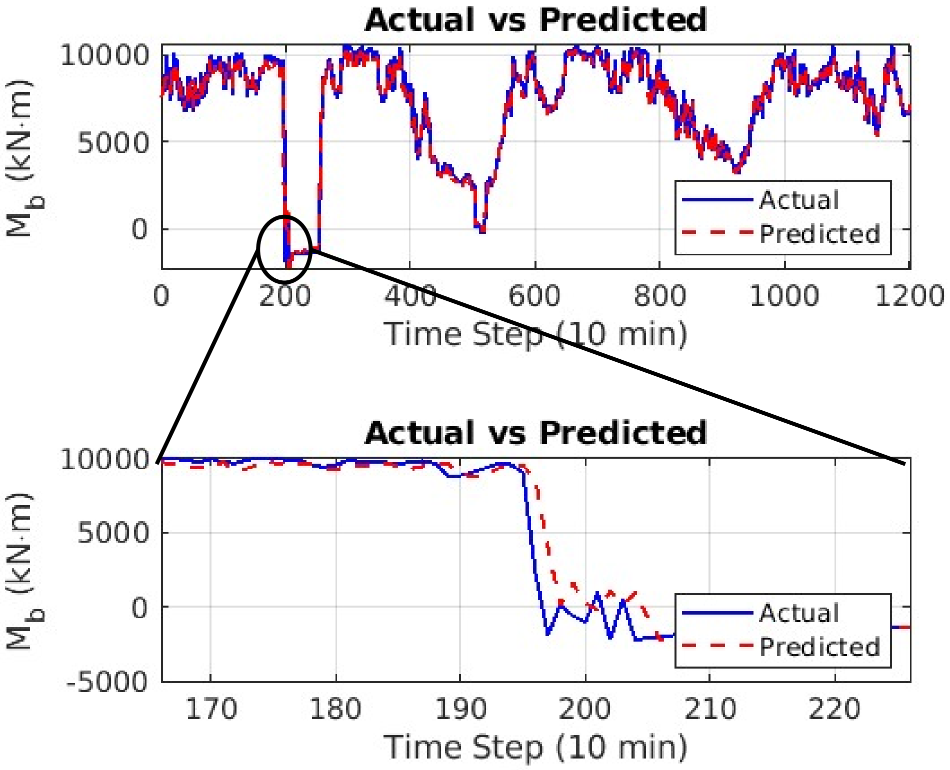
Evaluation

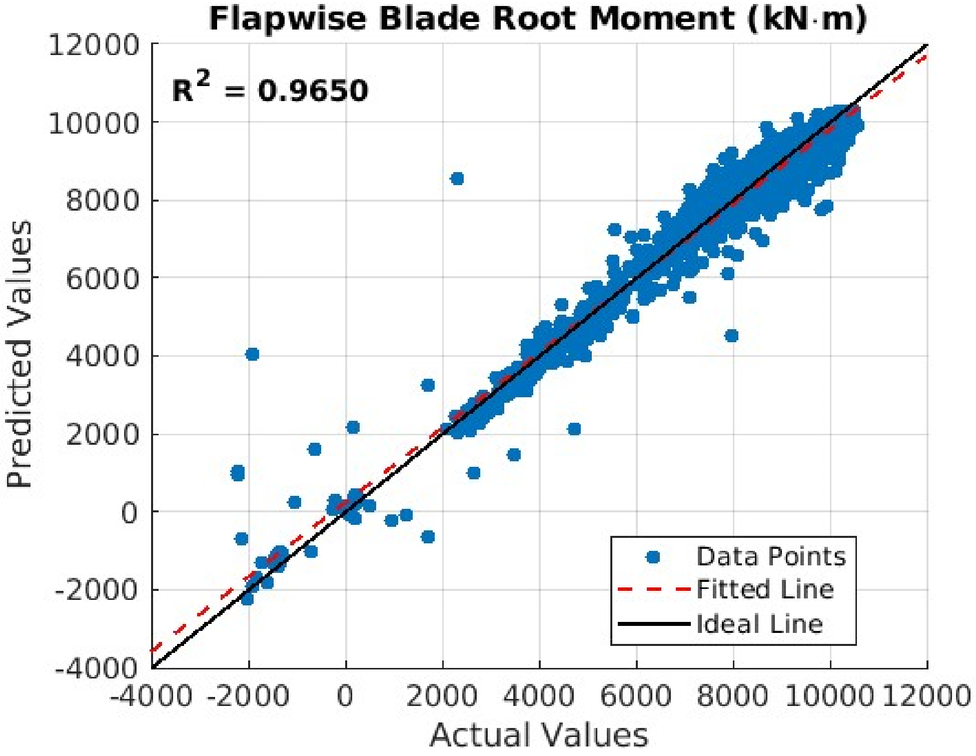
Prediction vs Actual

Flapwise Blade Root Moment

MAE: 350.2 (4.8%)

RMSE: 536.0 (7.3%)





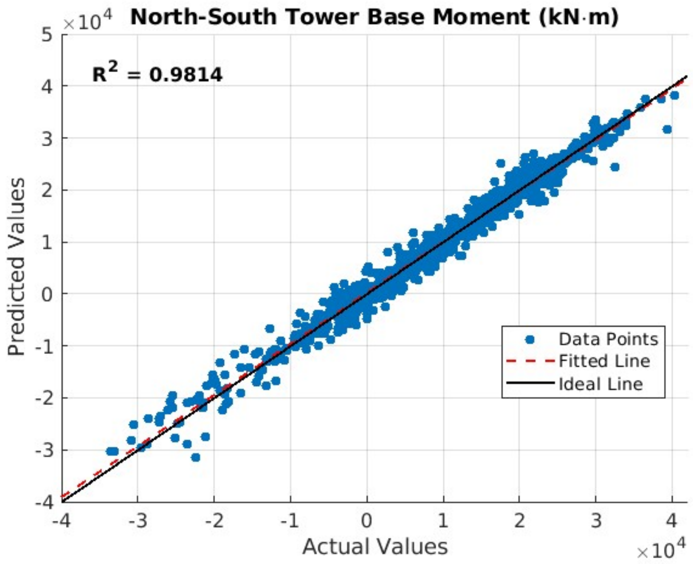
Evaluation

Prediction vs Actual

North-south Tower Base Root Moment

MAE: 1149.8 (10.0%)

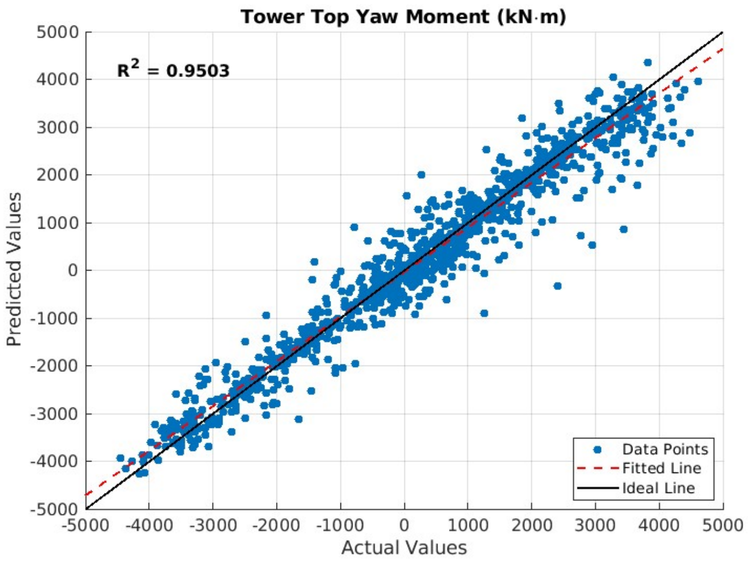
RMSE: 1695.6 (14.7%)



Tower Top Yaw Moment

MAE: 314.6 (18.5%)

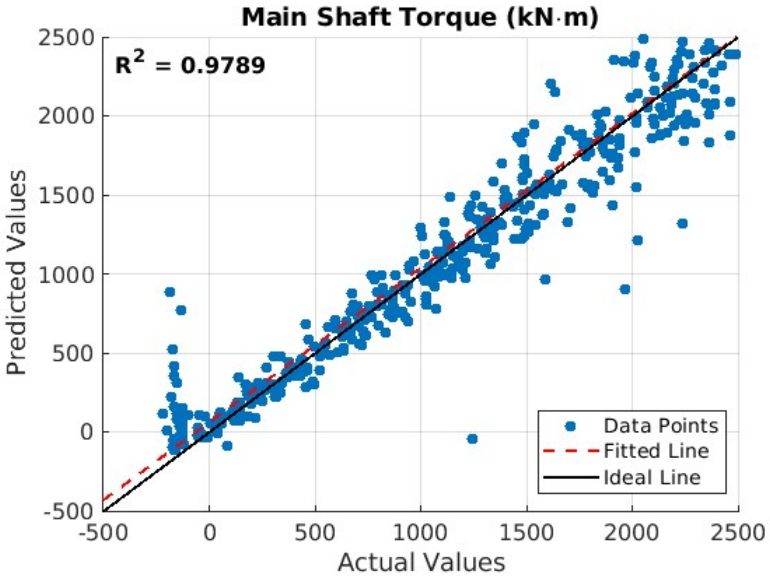
RMSE: 479.8 (28.3%)



Main Shaft Torque

MAE: 120.4 (4.4%)

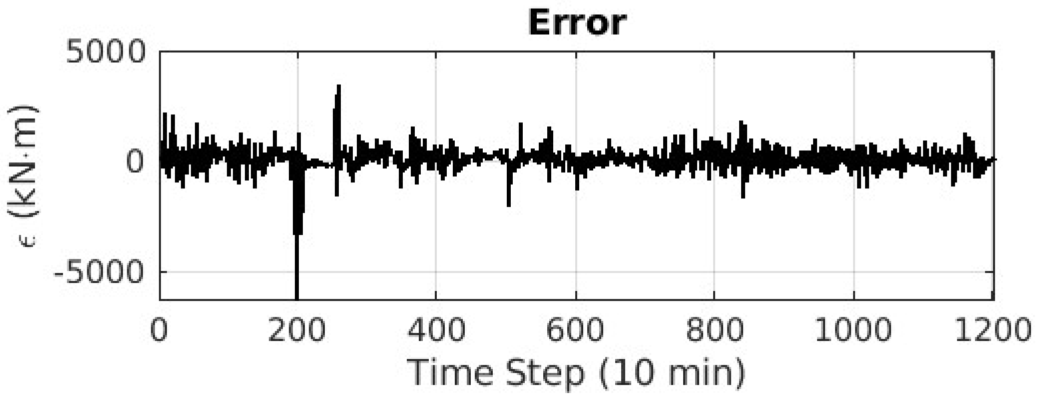
RMSE: 237.1 (8.6%)

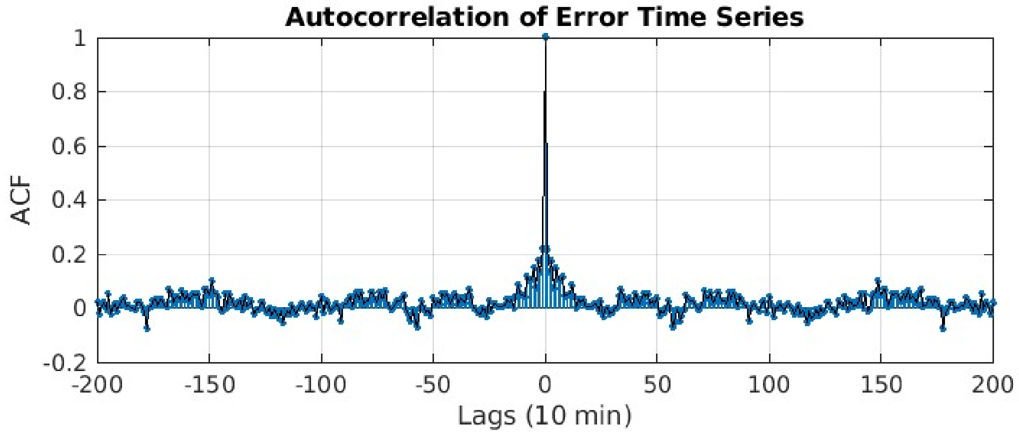


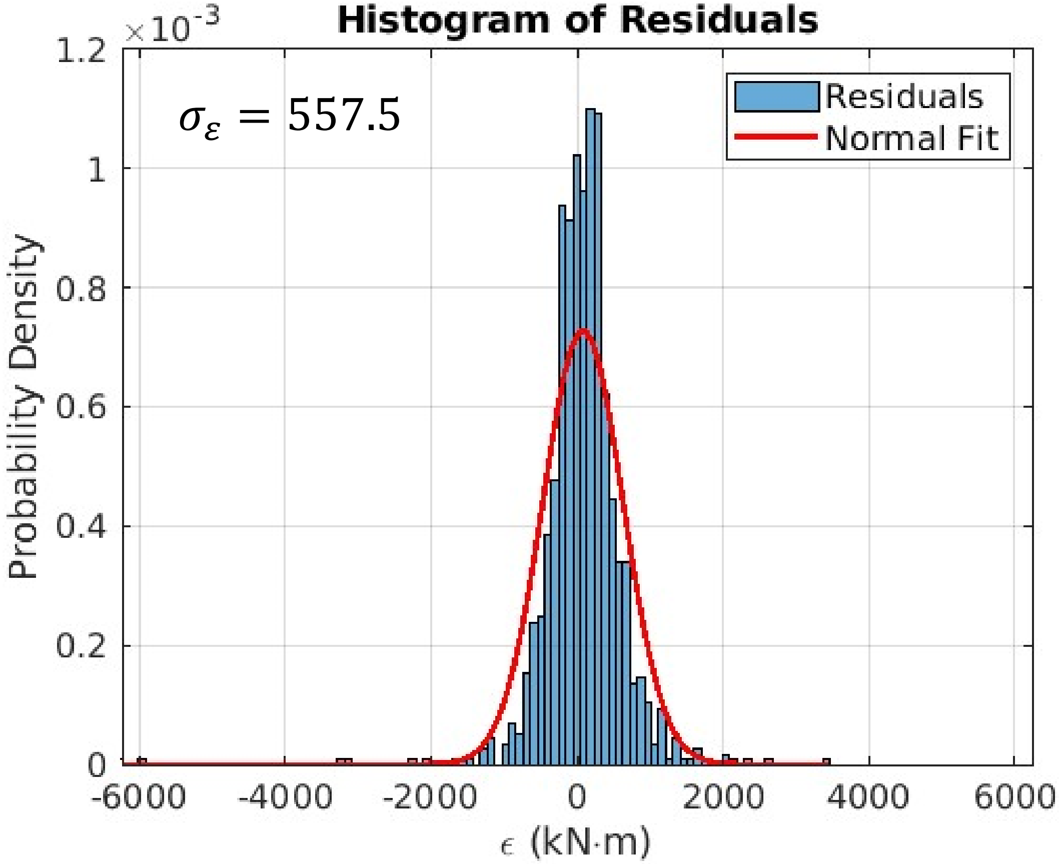
Evaluation

Uncertainty analysis

95% Confidence Interval: ± 1092.6 ($\pm$ 14.9%)





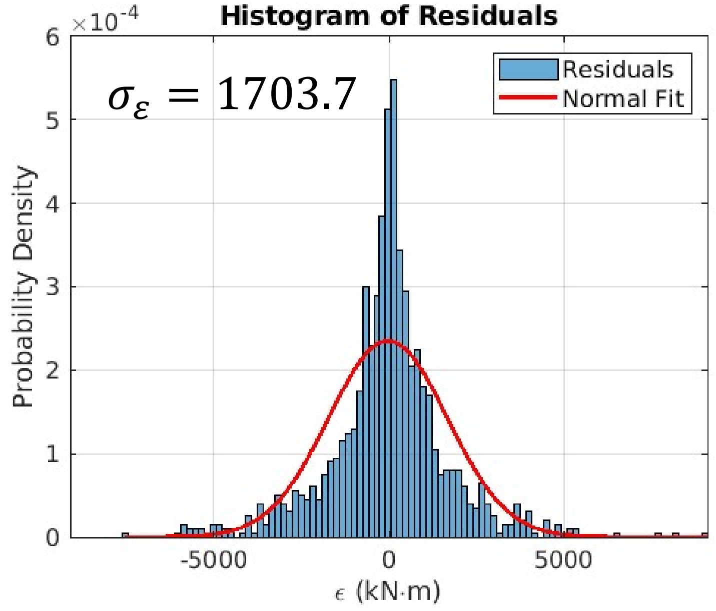


Evaluation

Uncertainty analysis

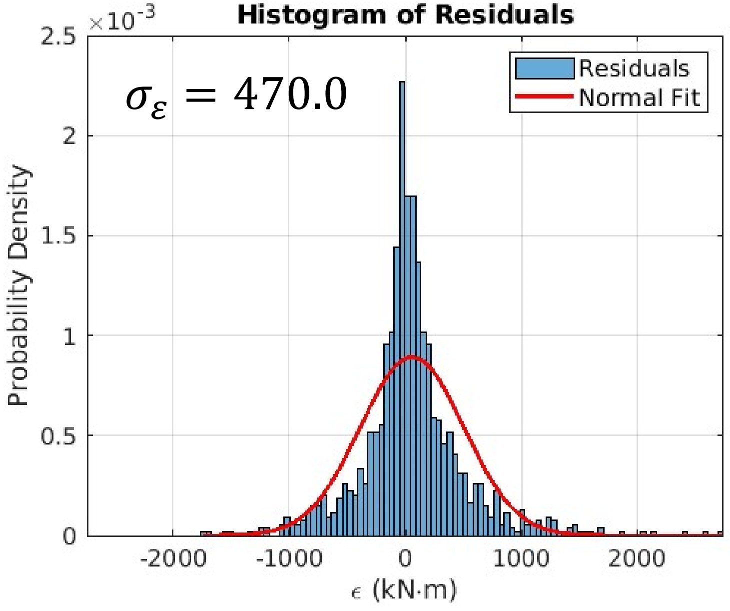
North-south Tower Base Root Moment

95% CI: ± 3339.3 ($\pm 29.0\%$)



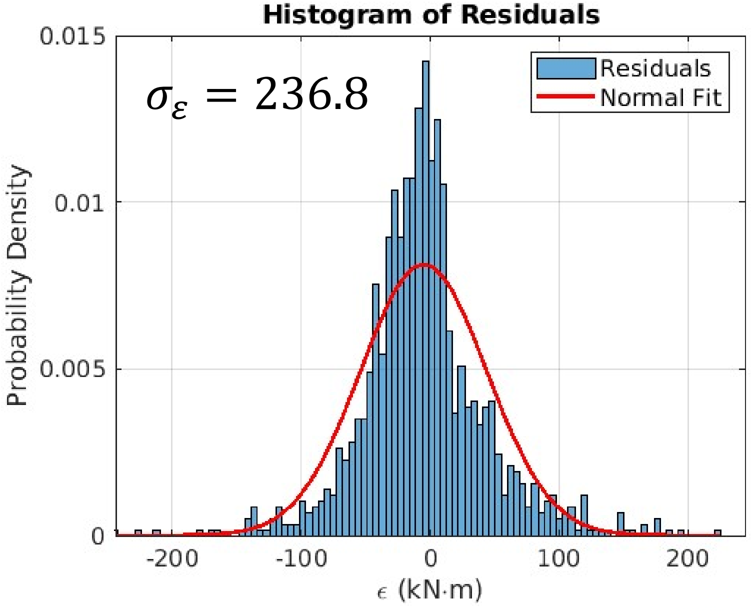
Tower Top Yaw Moment

95% CI: ± 921.1 ($\pm 54.2\%$)



Main Shaft Torque

95% CI: ± 464.1 ($\pm 16.9\%$)



Ⅳ

Summary

Summary

Summary & conclusions

- Methodology
  - NARX-based surrogate model trained with 10-min measurement data from FINO1 and AV04 of Alpha Ventus.
  - Inputs: wind condition and operational state; Output: wind turbine structural load.
  - Granger-causality test to select multiple input variables for each output quantity.
  - Accuracy and uncertainty of the surrogate model are quantified by MAE, RMSE, R^2 and confidence interval.

- Conclusions
  - NARX-based surrogate model captures the temporal variation well (with high R^2).
  - Good prediction accuracy in flapwise blade root moment, much worse in tower top yaw moment (miss information in input).

Conclusions

Limitations & outlook

➢ Limitations & potential improvements

- Better methods than linear interpolation in preprocessing data.
- Scenario classification.
- Higher sampling frequency.
- Determination of model structure parameters.
- Sensitivity analysis for each input variable and uncertainty propagation.

➢ Outlook

- Prediction of maximum loads and DELs.
- Close-loop surrogate model for multiple time step prediction.
- Incorporate with high-fidelity simulation data (e.g. LES) for model training.

Xu Ning, Ph.D. student under LESWIND project

- Marine atmospheric boundary layer meteorology, wind-wave interaction
- Multiscale modelling of offshore wind farms under varying wind-sea conditions
- Application and improvement of reduce-order models in offshore wind energy

Bergen Offshore Wind Centre (BOW)

Geophysical Institute

University of Bergen, Norway

Email: xu.ning@uib.no

Linkedin: *www.linkedin.com/in/xu-ning-a88877234*

Thank you for your attention!

UNIVERSITY OF BERGEN