# RAVE –ML

The End-to-End cycle of the RAVE model

# AGENDA

- Introduction – how it all started ?
- Automatic data-quality control (ADQC)
- ML-ADQC
- How much data is good data ?
- Can the models be transferred ?
- Sensitivity Analysis
- Future work
- Discussion

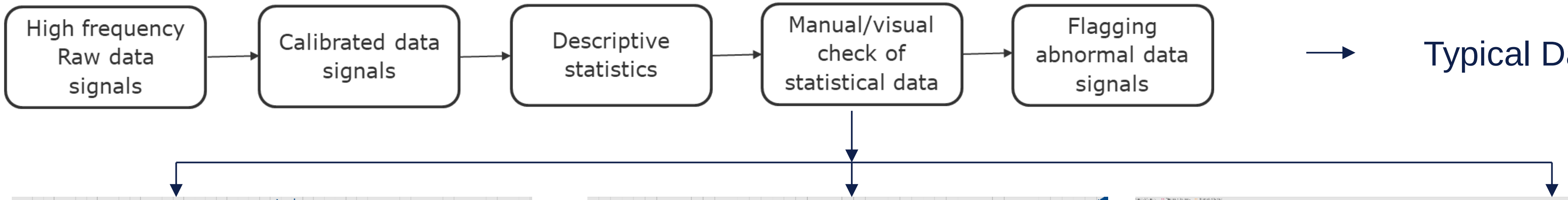
# Project Data – Research at Alpha Ventus (RAVE)

- The research Initiative RAVE carries out research and development work on the offshore test field alpha Ventus.
- RAVE is funded by the Federal Ministry for Economic Affairs and Climatic Actions (BMWK) and coordinated by the Fraunhofer Institute for Wind Energy Systems (IWES).
- In more than 30 research projects, more than 60 partners from science and industry have been working on a wide range of research questions since 2008.
- The financial support from the BMWK so far amounted to more than 50 million euros.

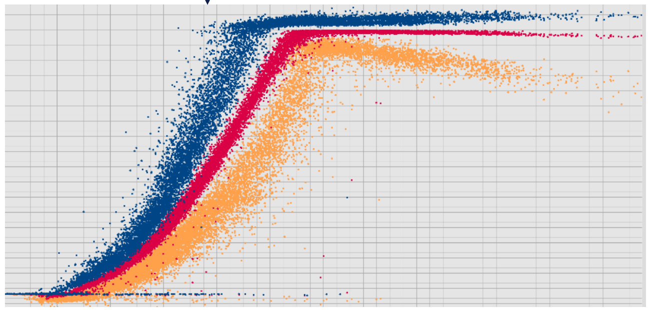
**Wind Farm Outlook**

- 45 Km North von Borkum
- 30 m water depth
- 12 Wind turbines
  - 6 AREVA WIND M5000
  - 6 Senvion 5M
- CAPEX : 250 Million Euros
- More than 10 years of measurement data

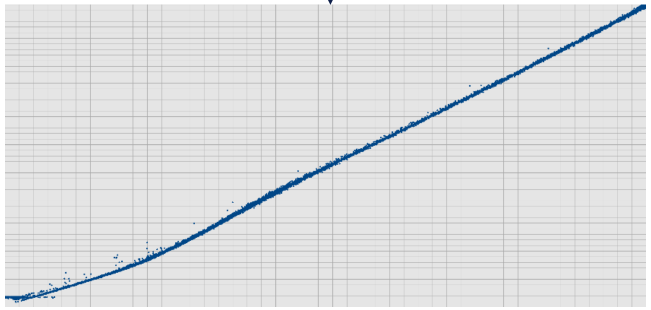
# Introduction – How it all started



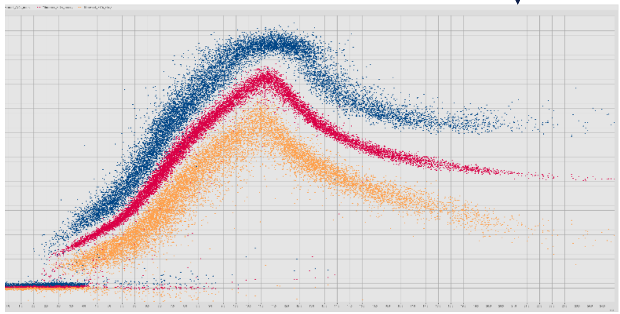

→ Typical Data check process



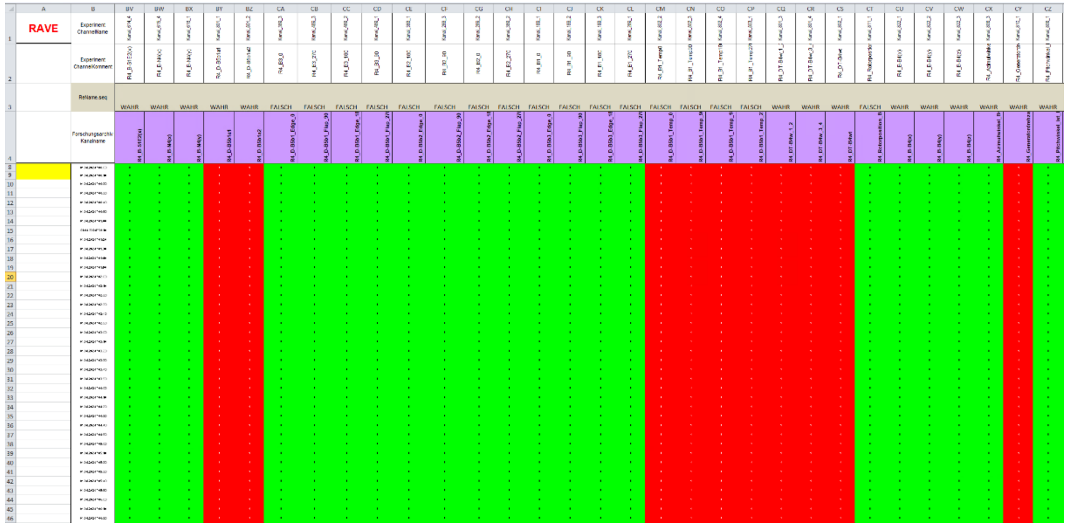
Wind Speed vs Electrical Power



Main shaft torsion vs Electrical Power

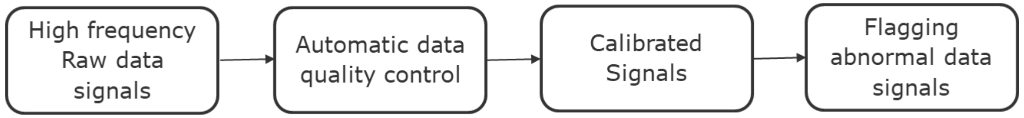


Tower tilt moment vs Electrical Power




→ Typical Visual check output

# Automatic data quality control (ADQC)



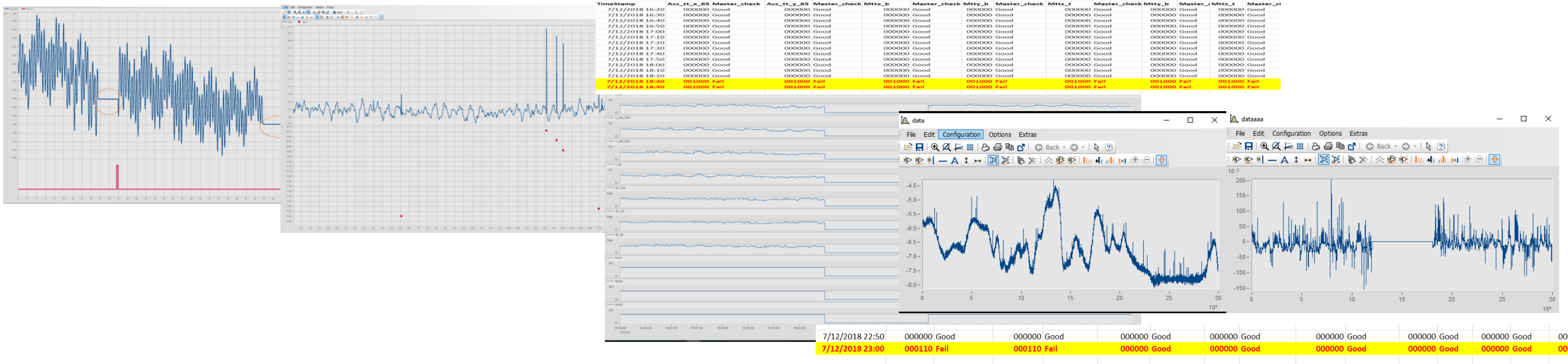


## Objective

- Control the data collected from RAVE wind farm
- Plausibility check on raw signals (0.2 to 50 HZ signals)
- Automating the control and flagging process
- Independent to sensor and measurement system
- Minimal input parameters (Robust model)
- Save time and operational cost
- High quality data for future applications

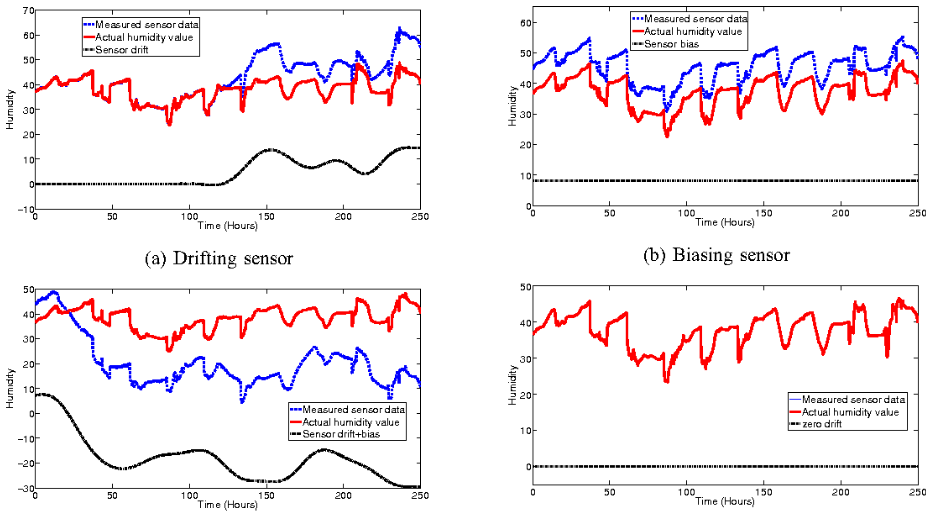
| Position | Test Type | Meaning | Thresholds | Description |
|---|---|---|---|---|
| 1 | Length | Reduced data length | $N_{crit}$% | Data of length of some value $N_{crit}$ deviating from $N$ 100% |
| 2 | Flat Line | Constant Signal | N/A | All values the same (e.g. bad if sensor is strain gauge, Ok/Check if machine data) |
| 3 | Flat Line | Partially Constant | $t_{crit}$ | Constant values for a period of > $t_{crit}$ seconds (e.g. signal dropouts) |
| 4 | Pre-defined Limits | Measurement Range | $\sum ( x_i > x_{crit} ) > 0$ | At least one value outside the measurement range (e.g. ±10 V) |
| 5 | Spike | Spike events exceeded | $n_{crit}$ | Number of spikes found in signal exceeds critical value. |
| 6 | Spike | Low Correlation | $r_{crit}$ | Despiked signal poorly correlated with uncorrected signal. |
| 7 | Visual/ Qualitative | Qualitative assessment | N/A | Data assessed manually (e.g. poor correlation with wind speed). |
| 8–16 | - | *- Spare -* | - | Further tests included here. |

# Automatic data quality control (ADQC)




Limitations/Challenges

- Detects only 70% of the commonly occurring events
- Time & environmental sensitive events are not detected
- Not using the historically available cleaned data
- No data filling/replacement method available
- No additional advantages




(a) Drifting sensor

(b) Biasing sensor

(c) Drifting & biasing sensor

(d) Sensor without drift or bias

→ ADQC Output – **000000/0**

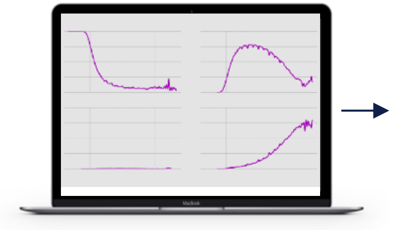
**No Events Found**

# ML-ADQC – General Background

STEP 1
MODEL CREATION

→ MEASUREMENT LOADS DATA

SCADA DATA



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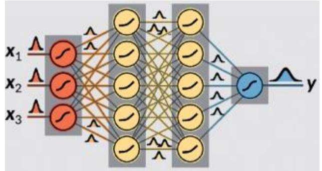
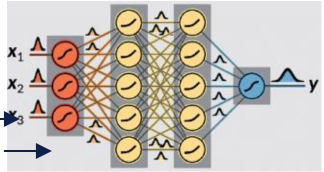



ML MODEL

STEP 2
PRODUCTION

→ SCADA DATA →

→

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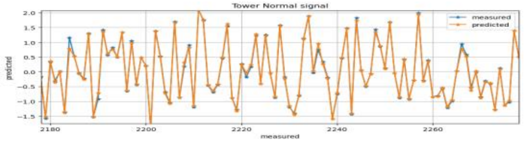
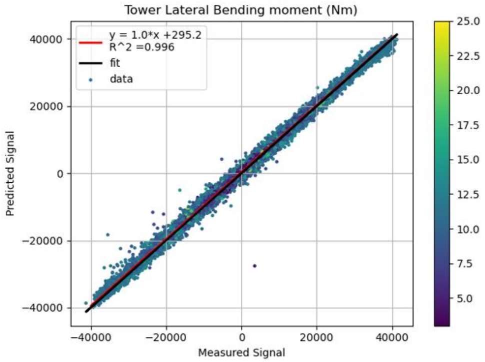


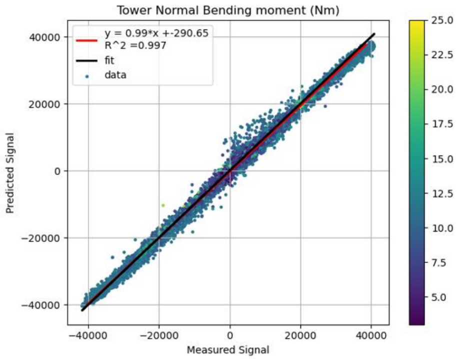

PREDICTED DATA

→ ADQC Output – 000000/0

**No Events Found**

## Performance/Results



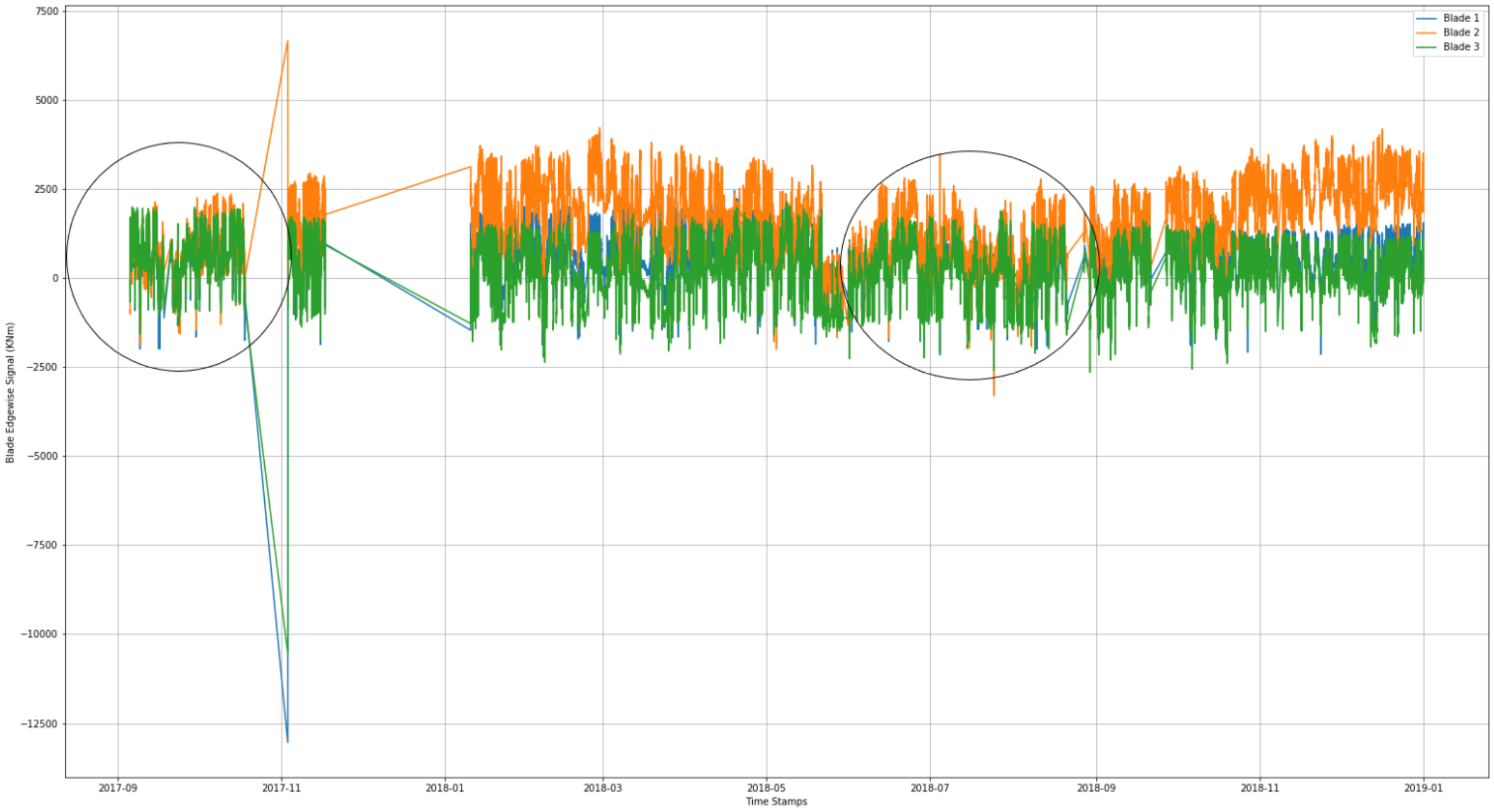




## Questions

- What are the minimum needed inputs & how is the model influenced with additional inputs
- How much data we need ? More data more accuracy ?
- Can the model to be transferred to other turbines?
- How sensitive is the model?
- Can be e used for other applications ?

# Case Study : ML- ADQC

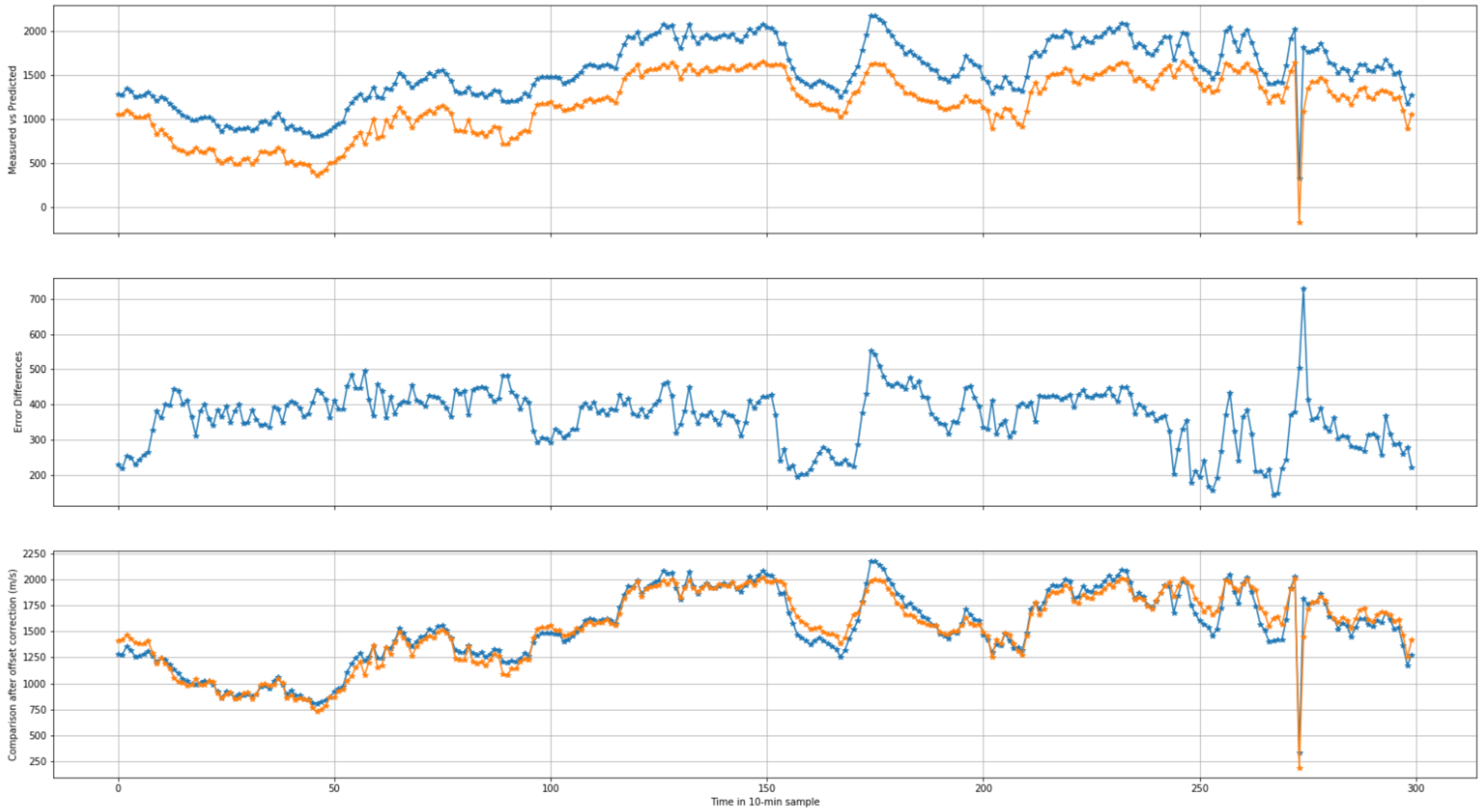
Detection of sensor drift in the blade signals due to temperature change




- Sensor installed and calibrated in Autumn (Black circles)
- Drifting problem in the other seasons

# Case Study : ML- ADQC

Detection of sensor drift in the blade signals due to temperature change




→ Measured vs Estimated

→ Error difference

→ Correcting the measured signal based on Prediction

# How much data is good data ?

What are the minimum needed inputs & how is the model influenced with additional inputs ?

**SCADA**

- Yaw angle
- Generator speed
- Pitch angle
- Electrical power
- Wind speed
- Rotor position

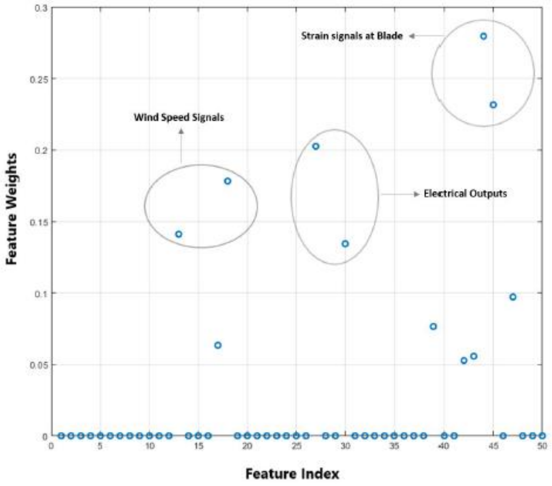
**Tower bottom acceleration**

- Acceleration X direction
- Acceleration Y direction

**Temperature**

- Temp – blade root
- Temp – tower sections
- Temp – nacelle cooling

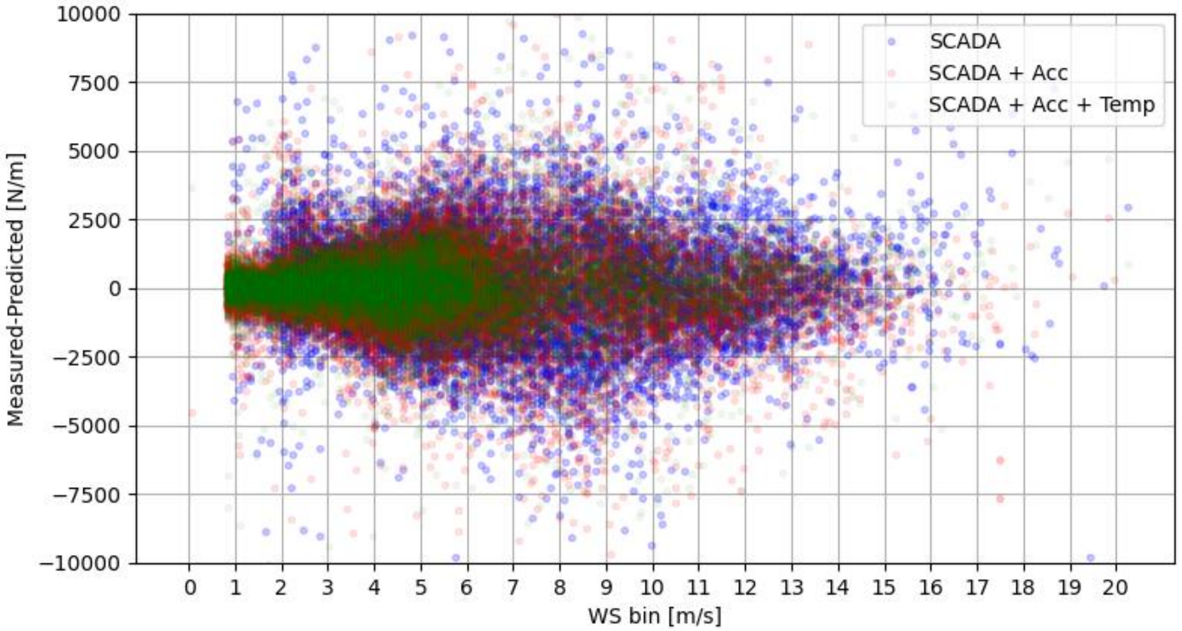
➢ Neighbourhood component analysis was performed to select potential inputs
➢ Approx. 4 years of cleaned database was used
➢ No status filters are applied

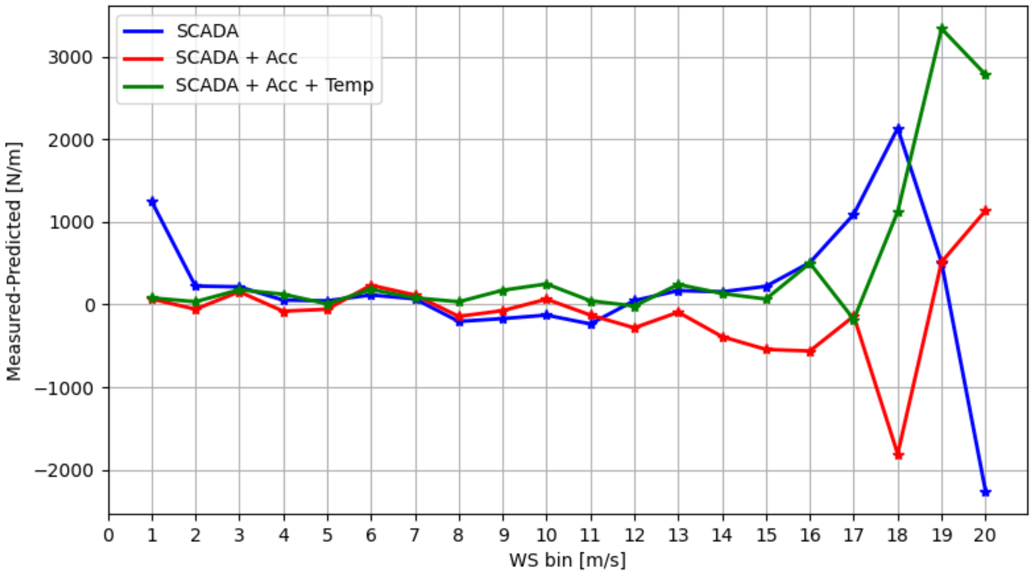


# Experiments/Results

What are the minimum needed inputs & how is the model influenced with additional inputs ?

Tower bottom lateral moment



# Experiments/Results

What are the minimum needed inputs & how is the model influenced with additional inputs ?

| WS bins [m/s] | SCADA | SCADA+ACC | SCADA+ACC+Temp |
|---|---|---|---|
| 1 | 0.228538 | 0.256351 | 0.198047 |
| 2 | 0.036658 | 0.076753 | 0.061565 |
| 3 | 0.152571 | 0.593222 | 0.361466 |
| 4 | 0.020876 | 0.012917 | 0.043916 |
| 5 | 0.027502 | 0.022552 | 0.019618 |
| 6 | 0.025781 | 0.025813 | 0.003829 |
| 7 | 0.020813 | 0.020989 | 0.002504 |
| 8 | 0.010487 | 0.010192 | 0.010859 |
| 9 | 0.011144 | 0.012809 | 0.039385 |
| 10 | 0.001437 | 2.67E-05 | 0.01699 |
| 11 | 0.060068 | 0.05762 | 0.04694 |
| 12 | 0.003884 | 0.005121 | 0.01647 |
| 13 | 0.257998 | 0.276332 | 0.049777 |
| 14 | 0.296748 | 1.12665 | 0.245588 |
| 15 | 0.268693 | 0.721729 | 1.05452 |
| 16 | 0.587111 | 0.057777 | 1.07635 |
| 17 | 0.772031 | 0.155121 | 0.624006 |
| 18 | 0.843967 | 0.8773 | 0.16997 |
| 19 | 0.686175 | 0.298275 | 0.436549 |
| 20 | 0.544554 | 0.385745 | 0.466168 |

**Blade Edgewise**

| WS bins [m/s] | SCADA | SCADA+ACC | SCADA+ACC+Temp |
|---|---|---|---|
| 1 | 0.395507 | 0.331212 | 0.302408 |
| 2 | 1.15613 | 2.58096 | 0.07186 |
| 3 | 0.046797 | 0.026064 | 0.017394 |
| 4 | 0.020248 | 0.01744 | 0.014912 |
| 5 | 0.009194 | 0.003713 | 0.001363 |
| 6 | 0.017614 | 0.010165 | 0.008388 |
| 7 | 0.005165 | 0.001894 | 0.002984 |
| 8 | 0.002694 | 0.00226 | 0.004979 |
| 9 | 0.010226 | 0.004712 | 0.012374 |
| 10 | 0.004082 | 0.004415 | 0.01232 |
| 11 | 0.007904 | 0.005161 | 0.000823 |
| 12 | 0.007558 | 0.004656 | 0.000947 |
| 13 | 0.015135 | 0.004959 | 0.007907 |
| 14 | 0.017338 | 0.015949 | 0.01294 |
| 15 | 0.003546 | 0.019176 | 0.023919 |
| 16 | 0.010162 | 0.003278 | 0.036108 |
| 17 | 0.069055 | 0.038293 | 0.059935 |
| 18 | 0.278864 | 0.265614 | 0.033038 |
| 19 | 0.153538 | 0.139323 | 0.127455 |
| 20 | 0.192408 | 0.20139 | 0.183887 |

**Blade Flatwise**

| WS bins [m/s] | SCADA | SCADA+ACC | SCADA+ACC+Temp |
|---|---|---|---|
| 1 | 0.909236 | 0.187104 | 0.725884 |
| 2 | 0.670418 | 0.859176 | 1.01941 |
| 3 | 27.7187 | 9.05194 | 26.8037 |
| 4 | 5.17227 | 0.440546 | 14.0609 |
| 5 | 0.007918 | 0.143287 | 0.025591 |
| 6 | 0.013794 | 0.058564 | 0.014629 |
| 7 | 0.008105 | 0.000545 | 0.111809 |
| 8 | 0.011382 | 0.027149 | 0.128156 |
| 9 | 0.000916 | 0.015866 | 0.011871 |
| 10 | 0.042295 | 0.026516 | 0.002122 |
| 11 | 0.105571 | 0.032833 | 0.049213 |
| 12 | 0.145776 | 0.01913 | 0.041254 |
| 13 | 0.18451 | 0.009813 | 0.035565 |
| 14 | 0.171966 | 0.005497 | 0.037681 |
| 15 | 0.181599 | 0.062879 | 0.160806 |
| 16 | 0.094837 | 0.189163 | 0.296432 |
| 17 | 0.106726 | 0.522726 | 0.522399 |
| 18 | 0.163479 | 0.412695 | 0.567748 |
| 19 | 0.268413 | 0.712607 | 0.857328 |
| 20 | 0.439551 | 0.960713 | 1.14846 |

**Tower lateral**

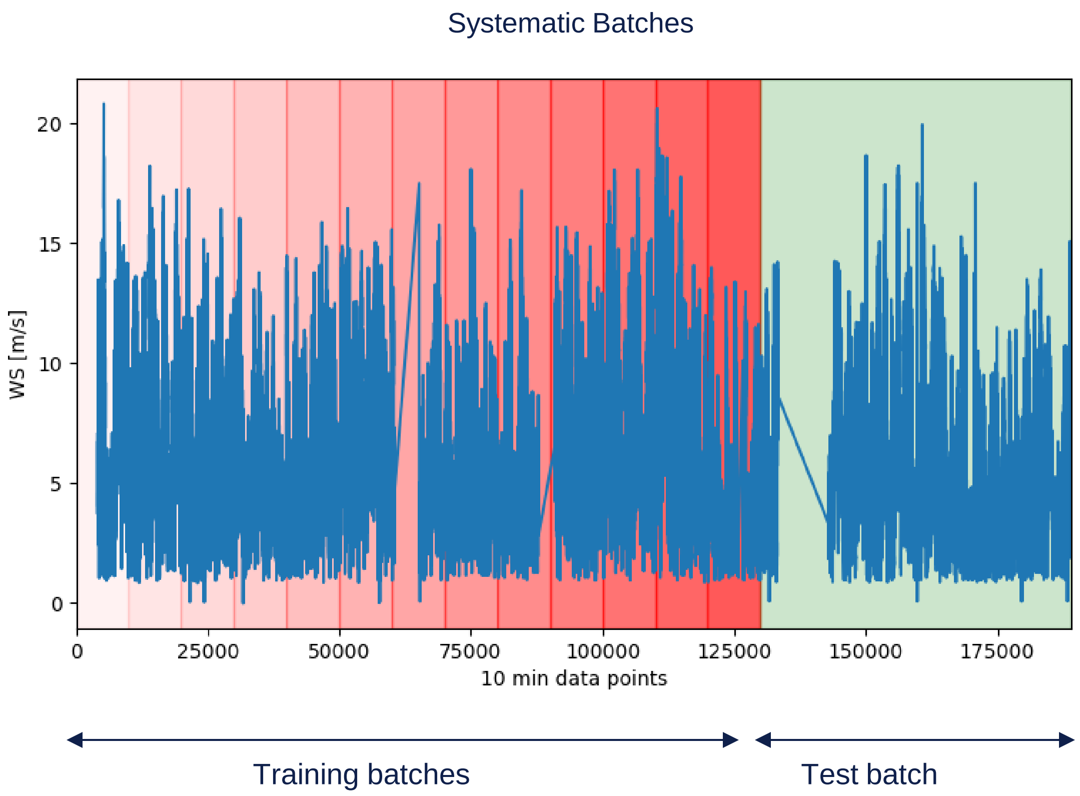
| WS bins [m/s] | SCADA | SCADA+ACC | SCADA+ACC+Temp |
|---|---|---|---|
| 1 | 0.603089 | 0.729556 | 0.274468 |
| 2 | 0.434863 | 0.550394 | 0.1026 |
| 3 | 13.519 | 2.32224 | 5.33617 |
| 4 | 0.126168 | 0.124953 | 0.241274 |
| 5 | 0.052153 | 0.081229 | 0.038149 |
| 6 | 0.014509 | 0.037802 | 0.027586 |
| 7 | 0.043863 | 0.071711 | 0.015598 |
| 8 | 0.060304 | 0.111369 | 0.03091 |
| 9 | 0.09474 | 0.069263 | 0.074753 |
| 10 | 0.062682 | 0.035414 | 0.071117 |
| 11 | 0.046695 | 0.035885 | 0.03777 |
| 12 | 0.053612 | 0.106135 | 0.021085 |
| 13 | 0.055448 | 0.110654 | 0.030419 |
| 14 | 0.020825 | 0.096754 | 0.095957 |
| 15 | 0.008129 | 0.025153 | 0.15125 |
| 16 | 0.151393 | 0.00771 | 0.261153 |
| 17 | 0.339779 | 0.036769 | 0.14487 |
| 18 | 0.425659 | 1.22008 | 0.256193 |
| 19 | 0.403079 | 0.072042 | 0.041557 |
| 20 | 0.442866 | 0.076789 | 0.069633 |

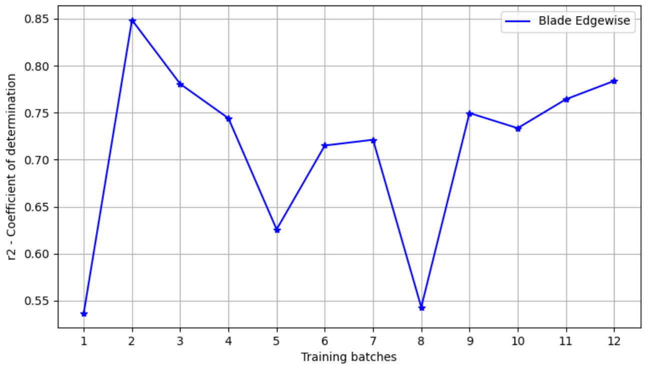
**Tower Longitudinal**

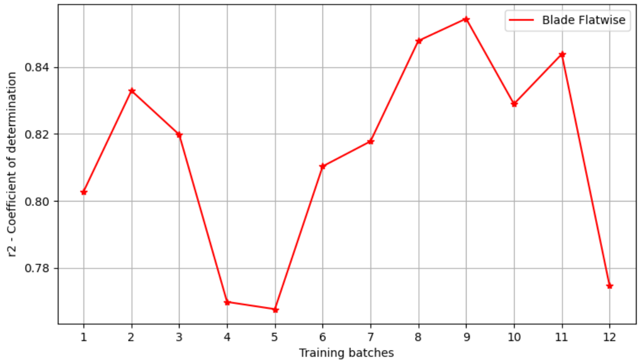
SCADA
SCADA+ACC
SCADA+ACC+Temp

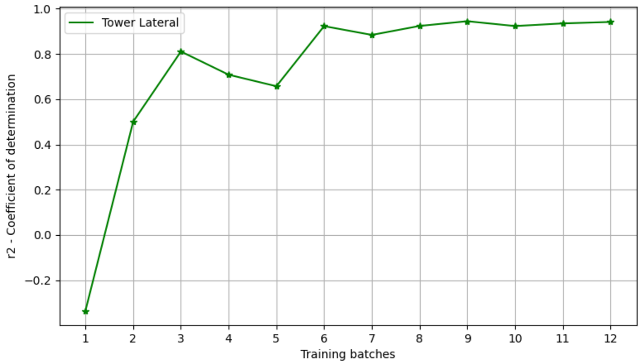
# Experiments/Results

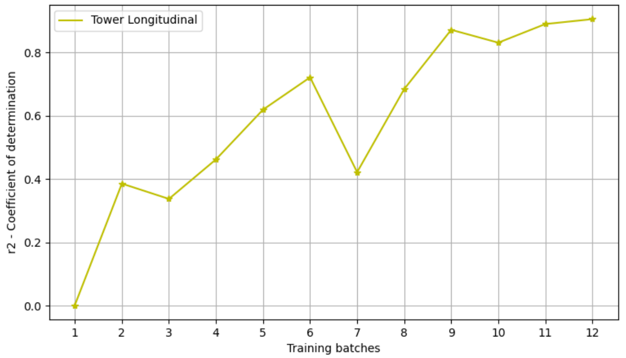
## How much data we need ? More data ? More accuracy ?



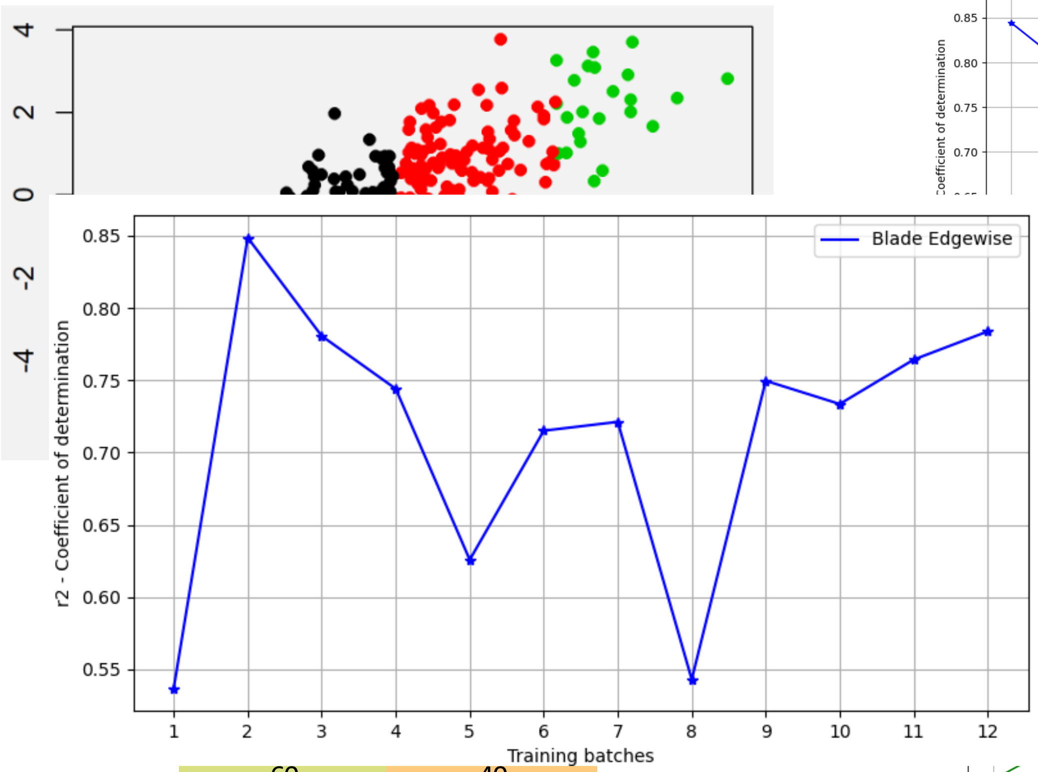



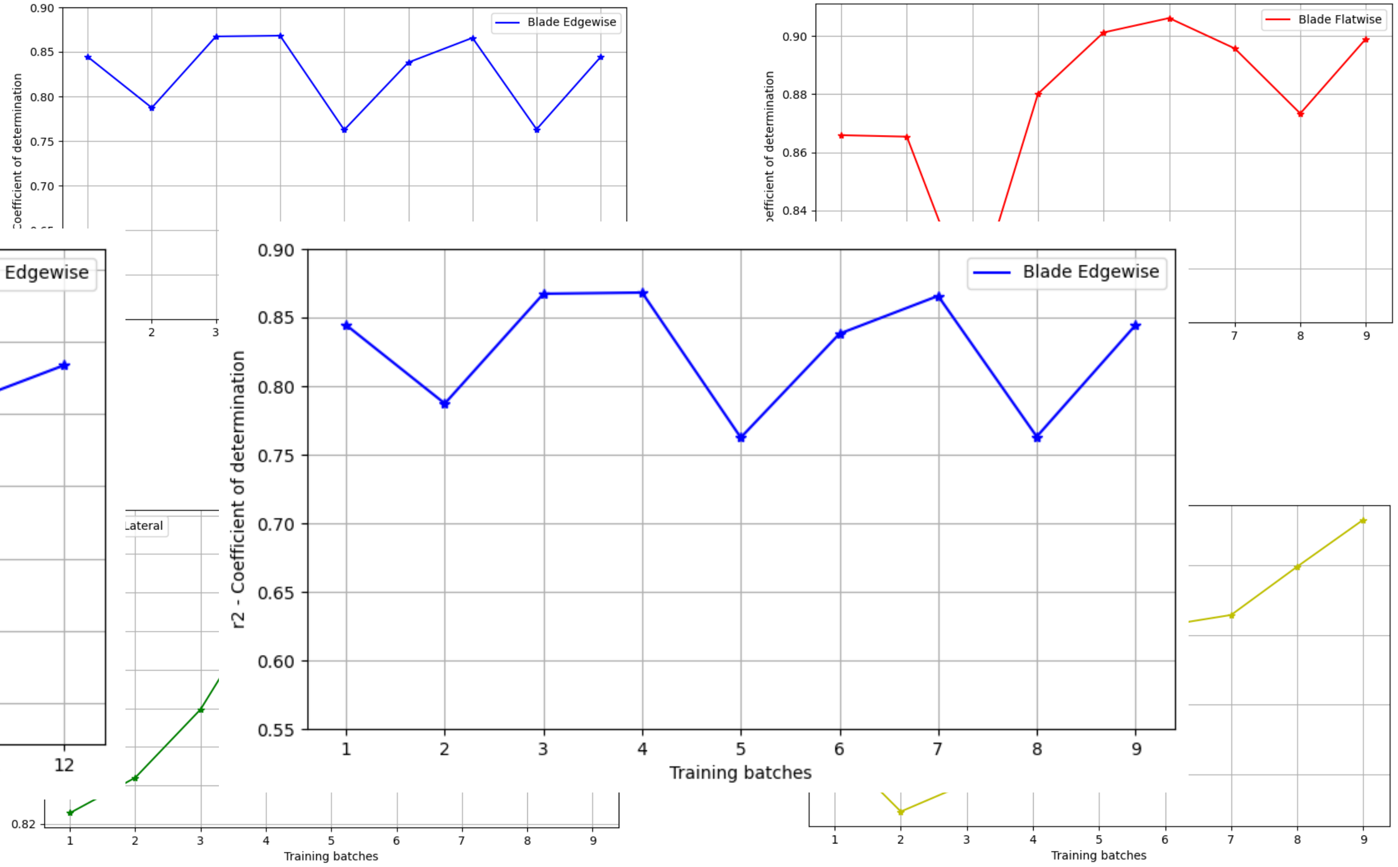

Coefficient of determination ($R^2$) $= \sum(\mu_{cup}.* \mu_{lid})/\sqrt{(\sum(\mu_{cup}.\text{^}2)* \sum(\mu_{lid}.\text{^}2))}$

# Experiments/Results

How much data we need ? More data ? More accuracy ?

Randomizing Batches



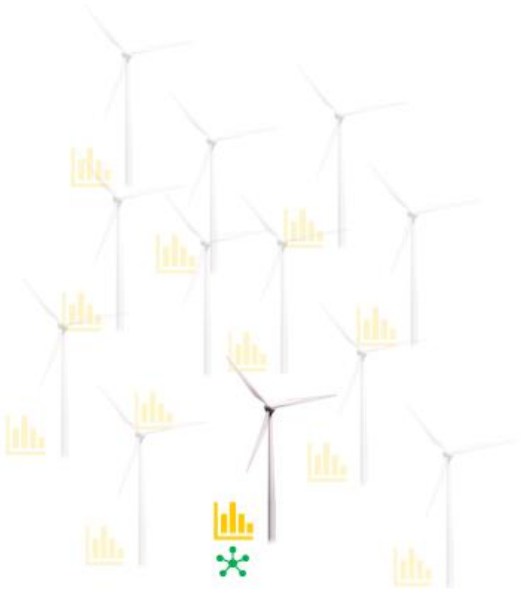

| | |
|---|---|
| 60 | 40 |
| 70 | 30 |
| 80 | 20 |
| 90 | 10 |



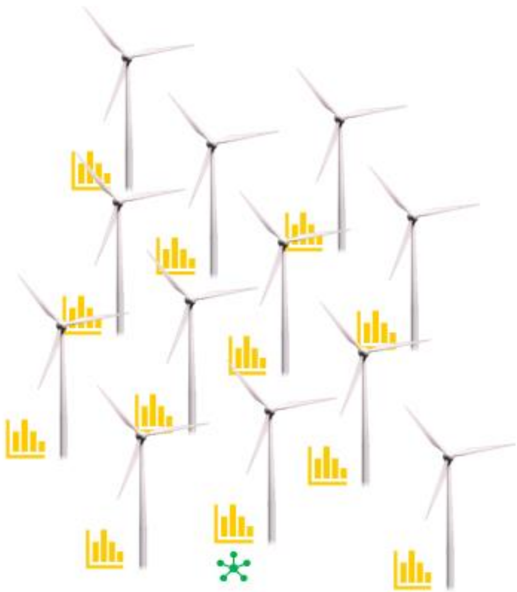
DNV

# Can the model be transferred ?

## Transferring ML Models

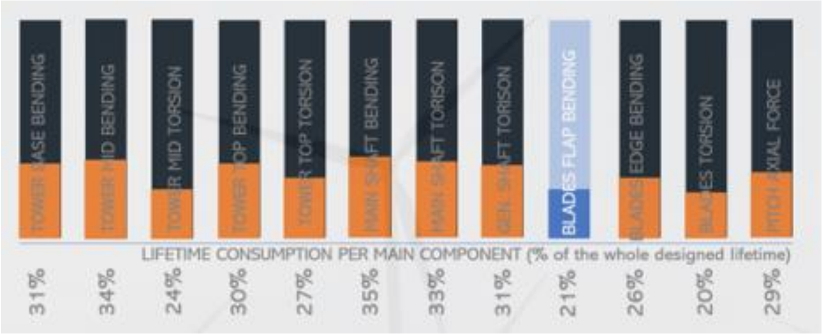


Model built based on one turbine



Transferred to other turbines

## Reliable Lifetime Estimation



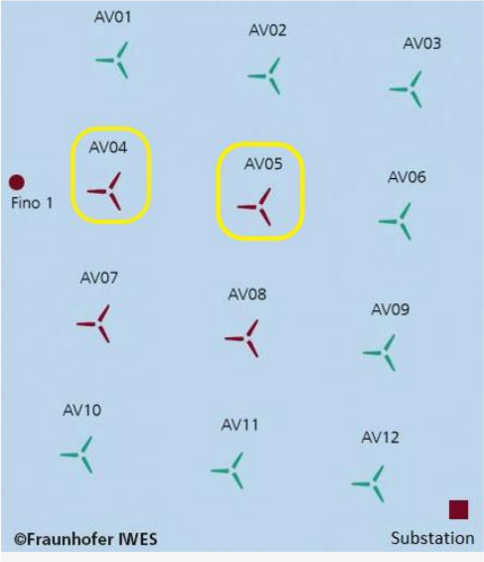

## Measurement Data fulfilment/extrapolation

Turbine 1

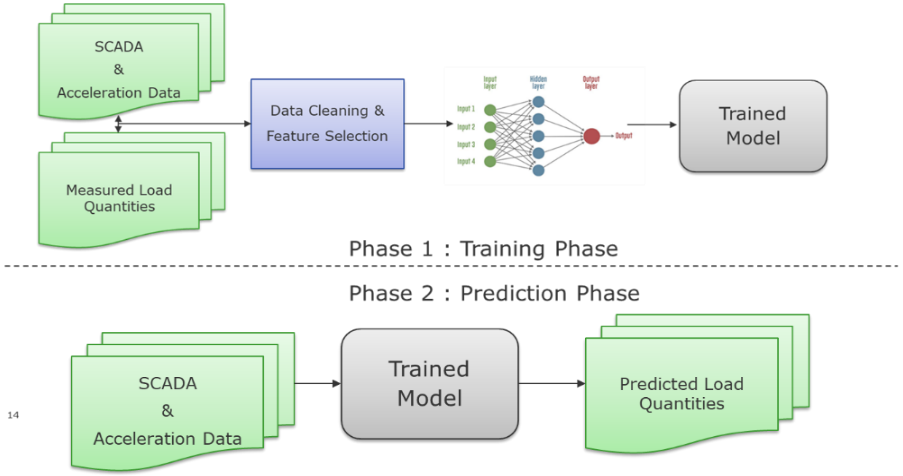
Turbine 2

# Can the model be transferred ?

## RAVE Wind farm layout

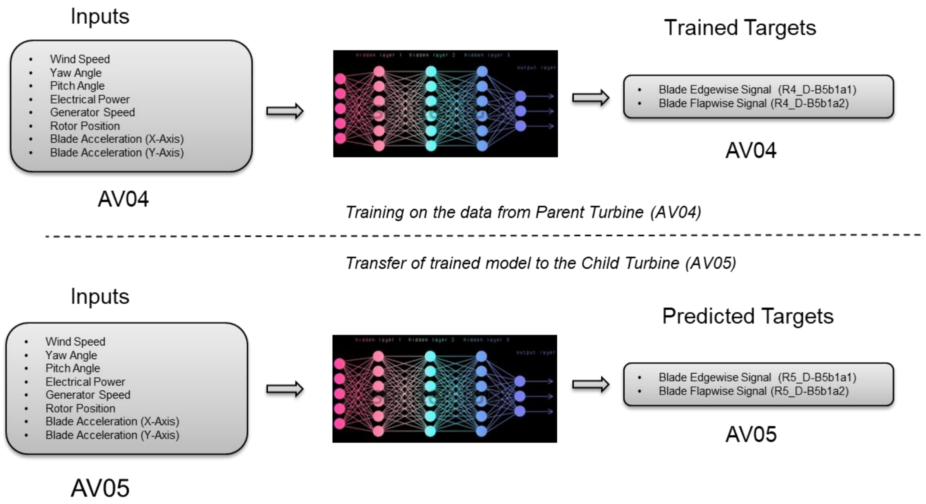


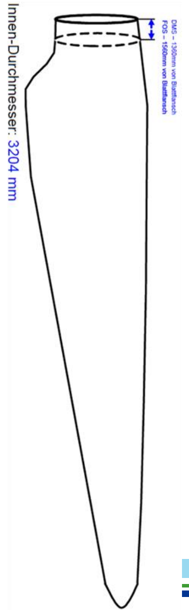

## Model Outlook




*Data from **AV04** (Parent) was used to train the model. Inputs from **AV05** (Child) was given to the trained model to estimate the load signals from **AV05.***

Model Details →

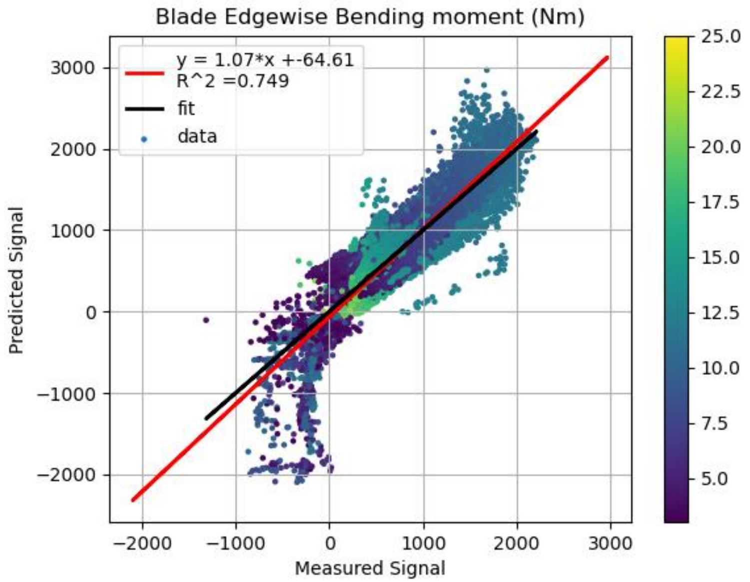


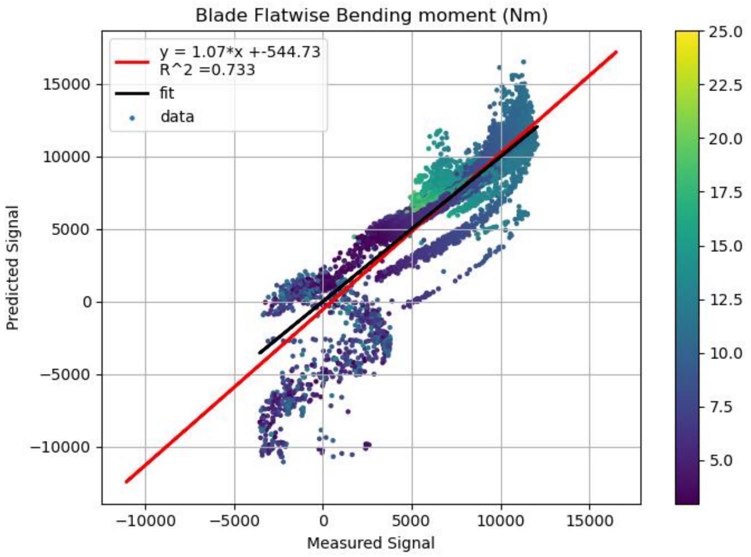



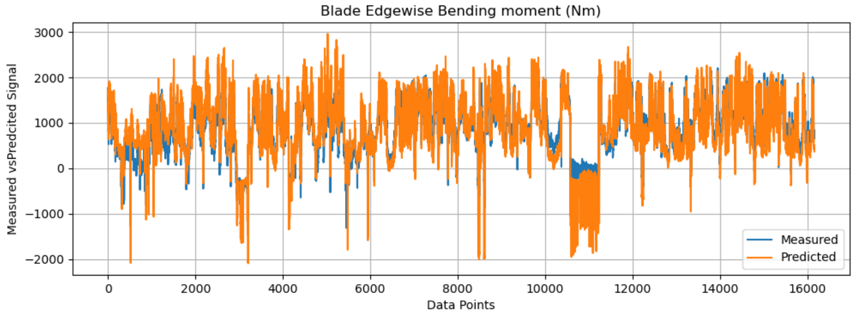


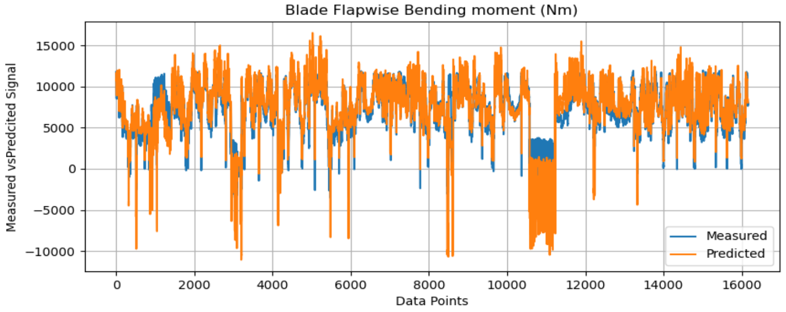

DNV

# Can the model be transferred ?

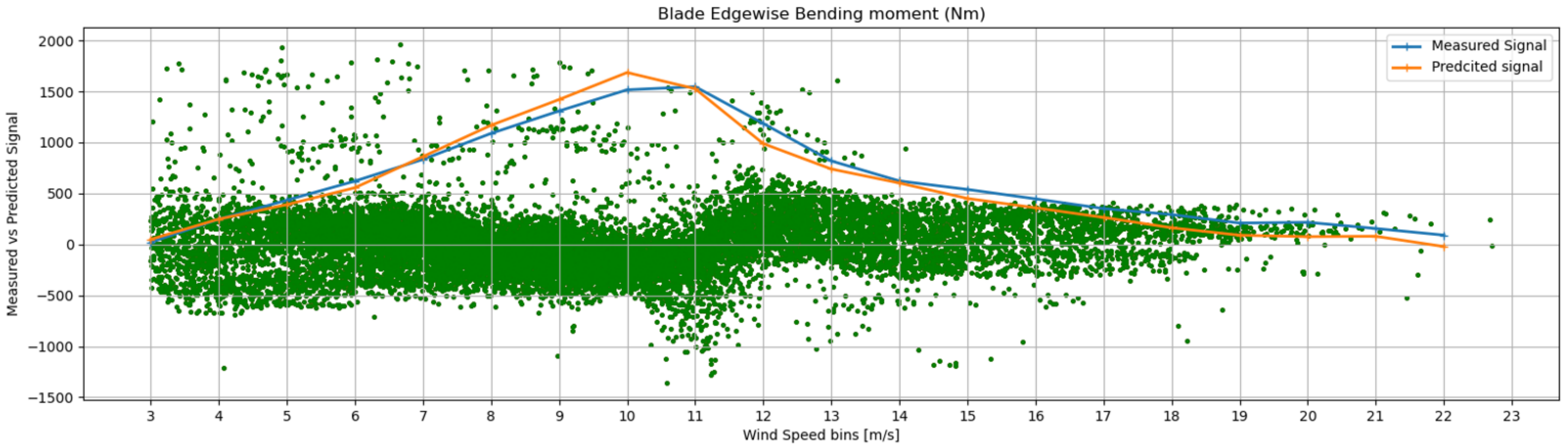


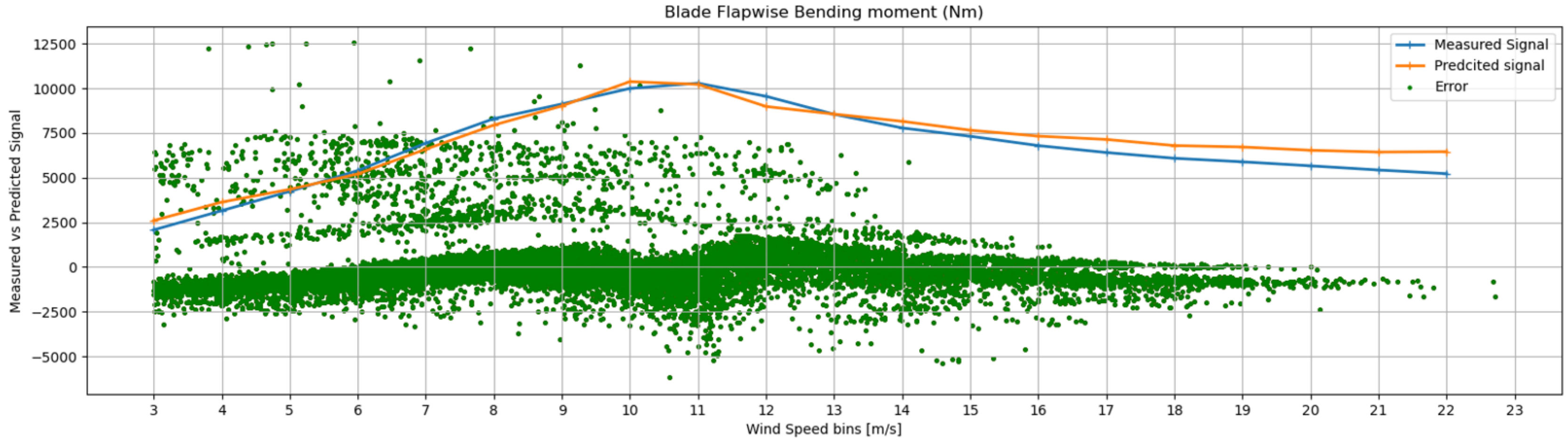



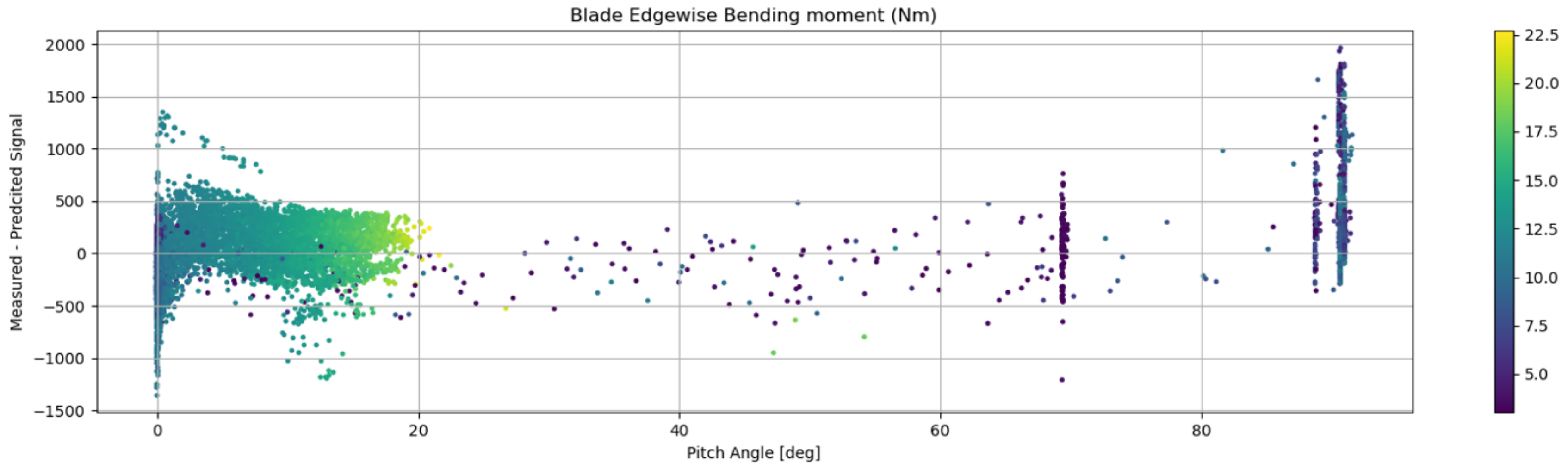



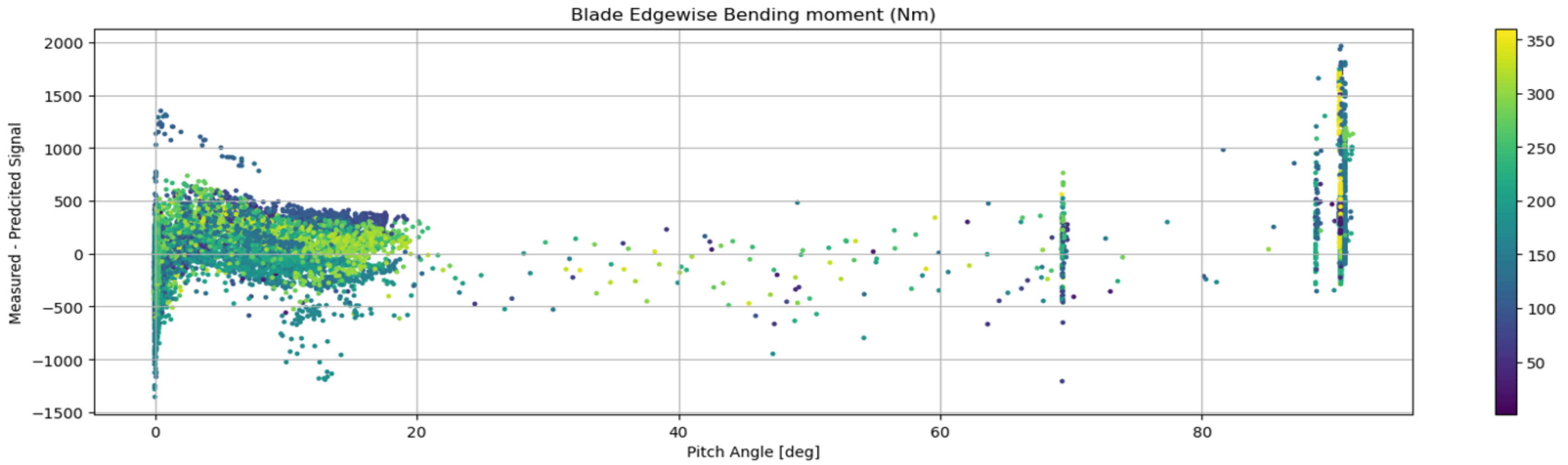
# Can the model be transferred ? First Results ….



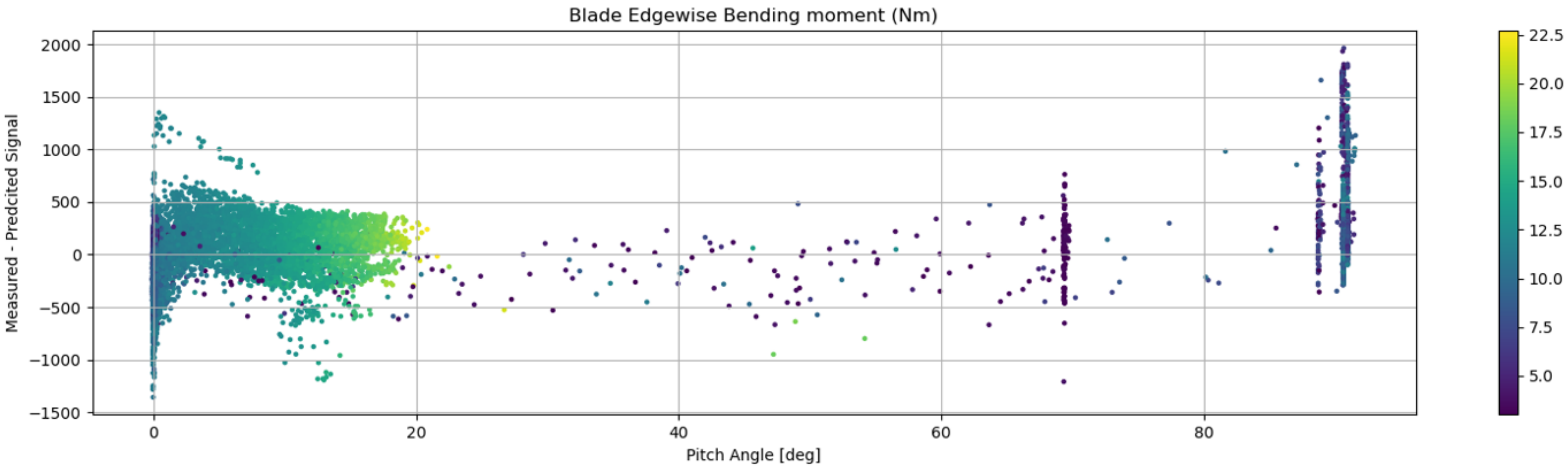



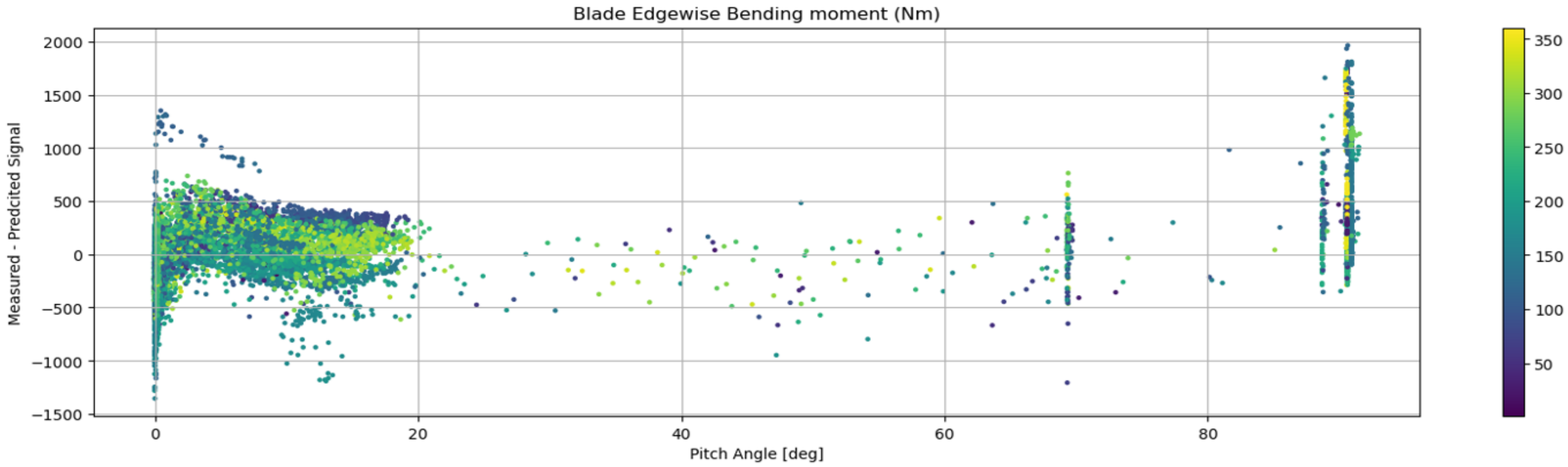
# Sensitivity Analysis – Error vs Pitch vs WS/WD



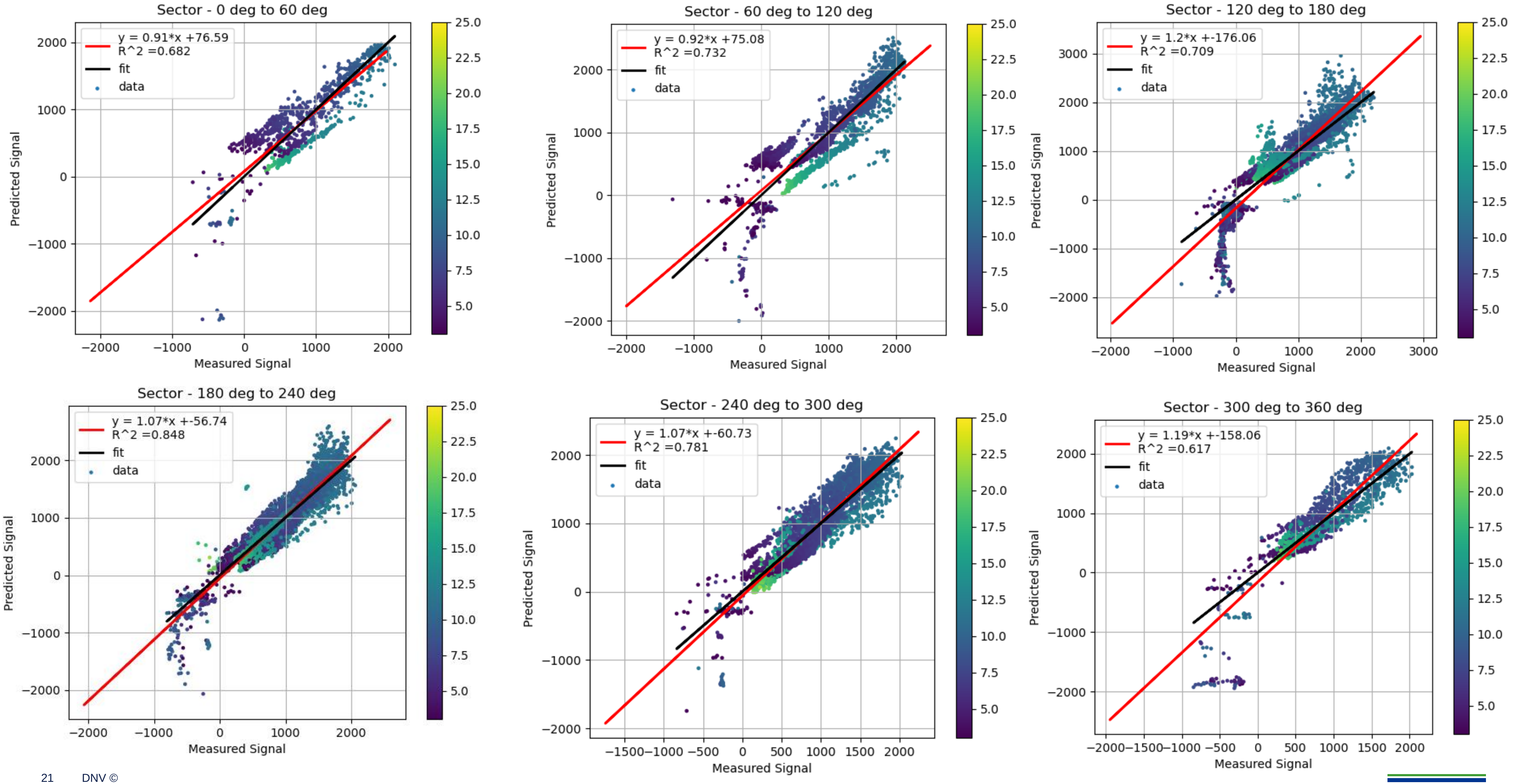



# Sensitivity analysis – Error vs pitch vs WS/WD

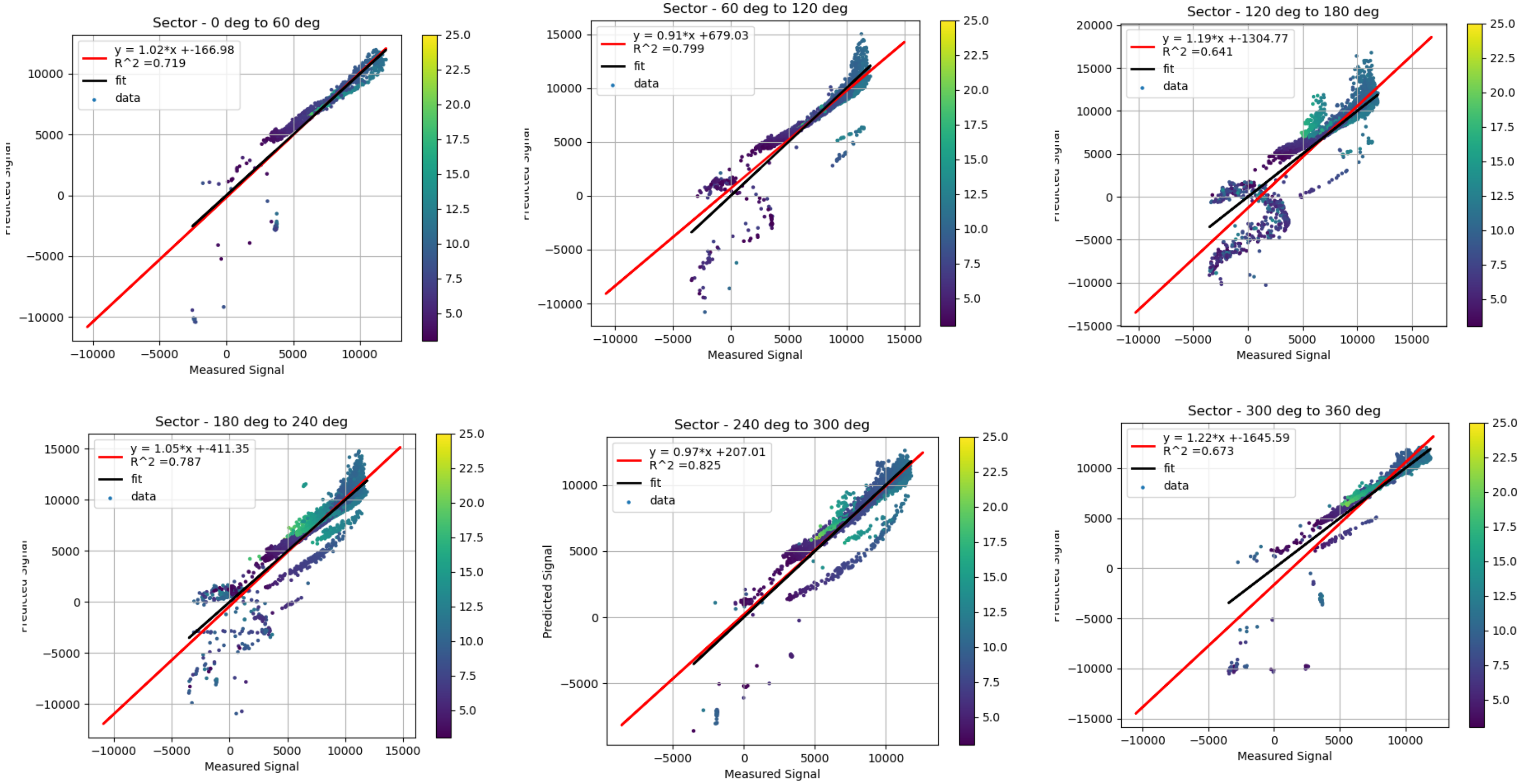


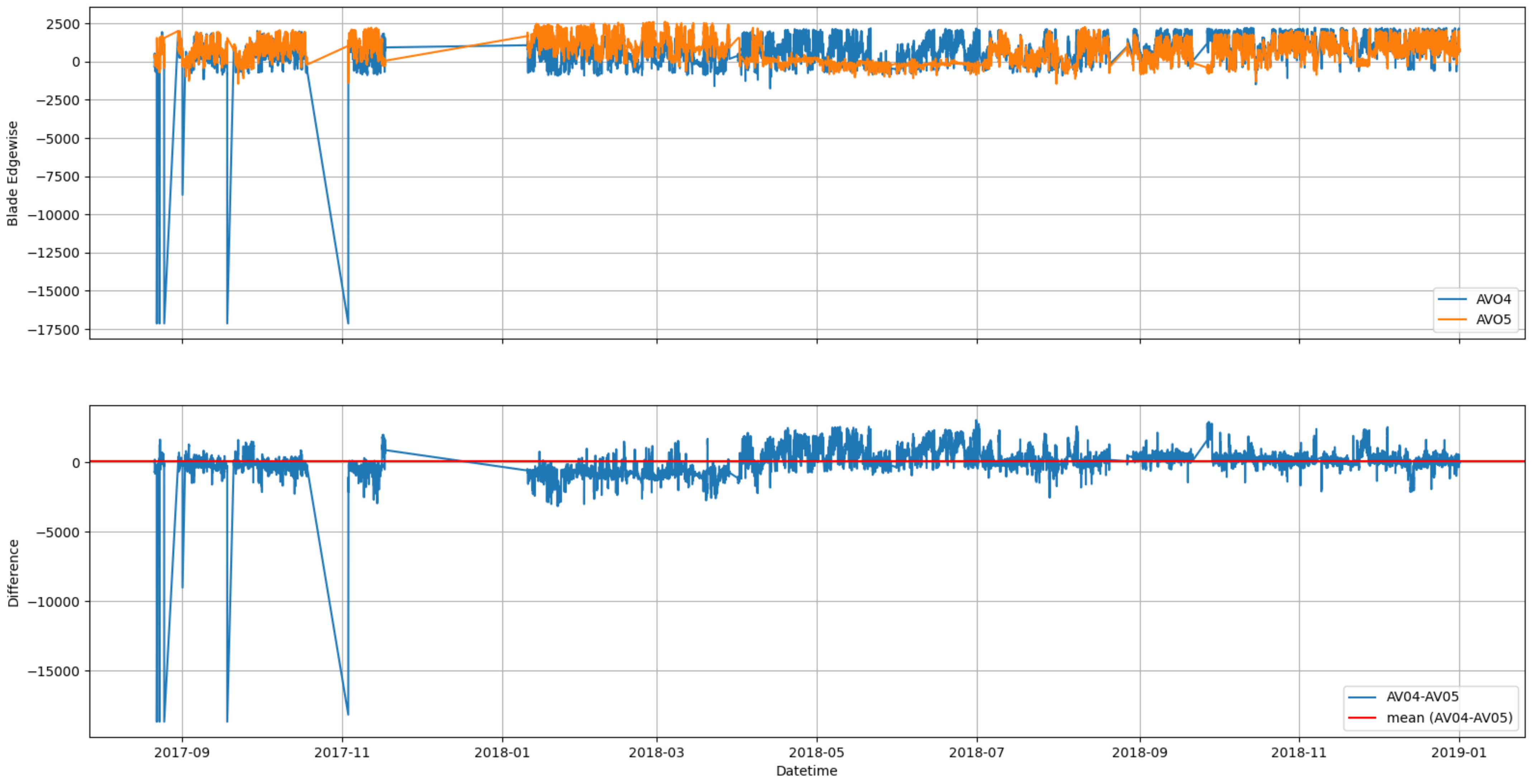
# Sector evaluation – Blade Edgewise



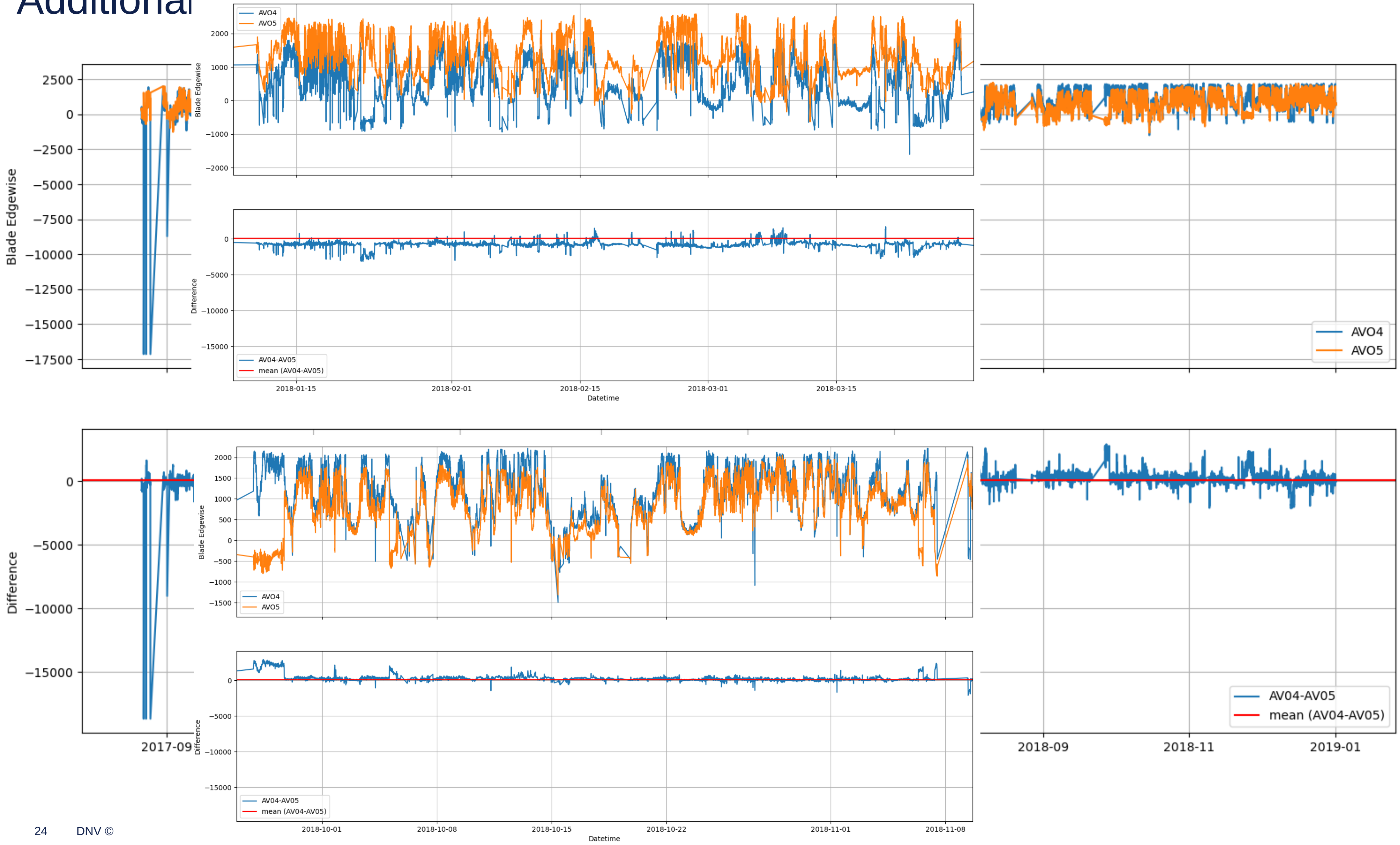
# Sector evaluation – Blade Flapwise



# Additional findings

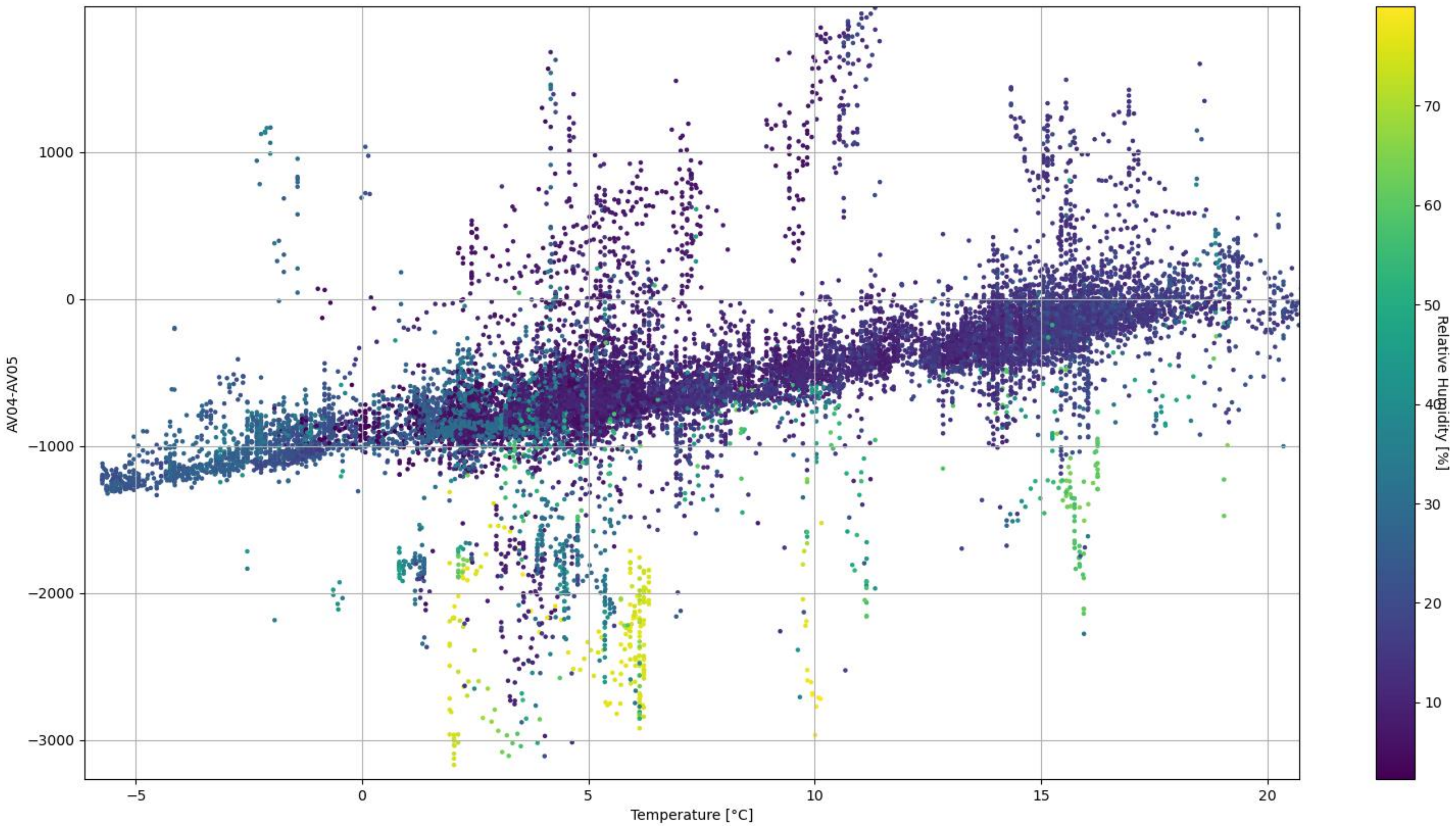


# Additional

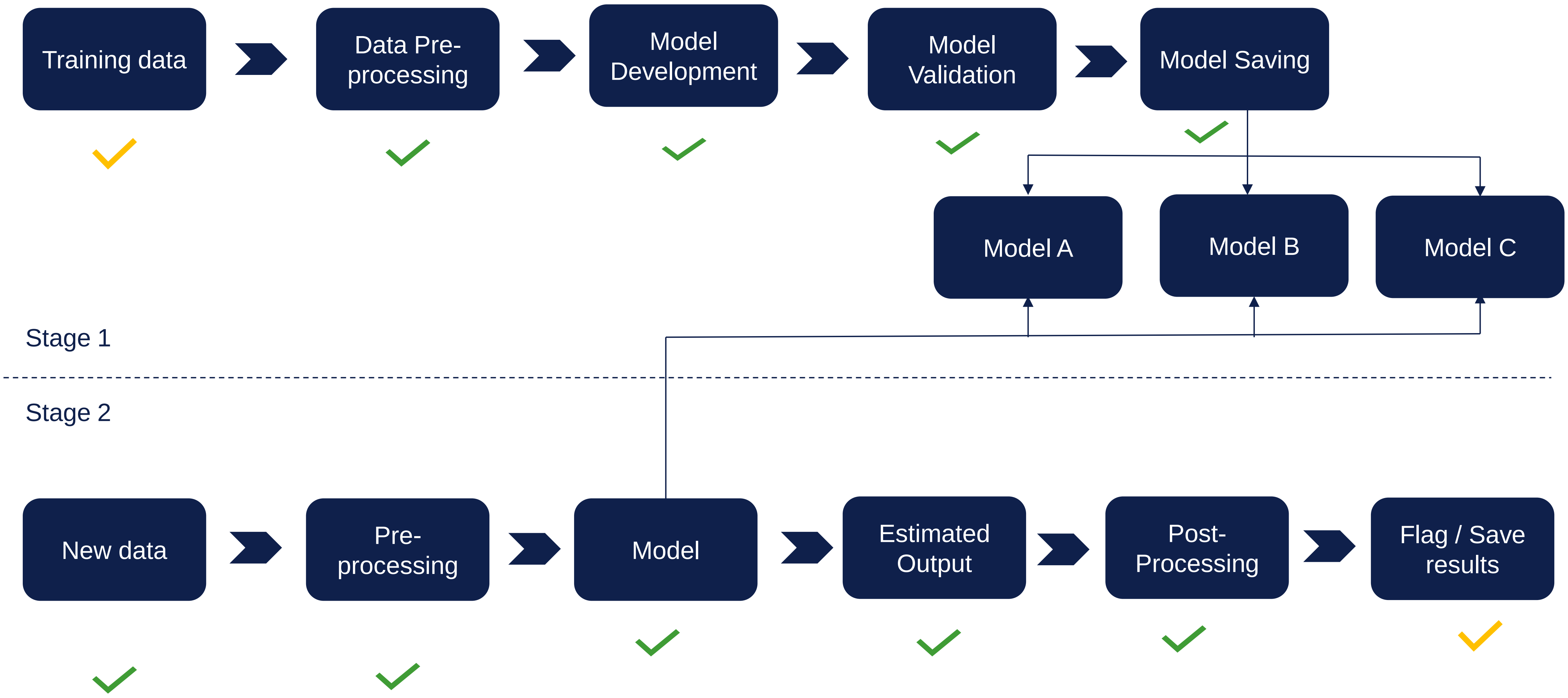


Blade Edgewise
AVO4
AVO5
Difference
AV04-AV05
mean (AV04-AV05)
Datetime
2017-09
2018-09
2018-11
2019-01
2018-01-15
2018-02-01
2018-02-15
2018-03-01
2018-03-15
2018-10-01
2018-10-08
2018-10-15
2018-10-22
2018-11-01
2018-11-08

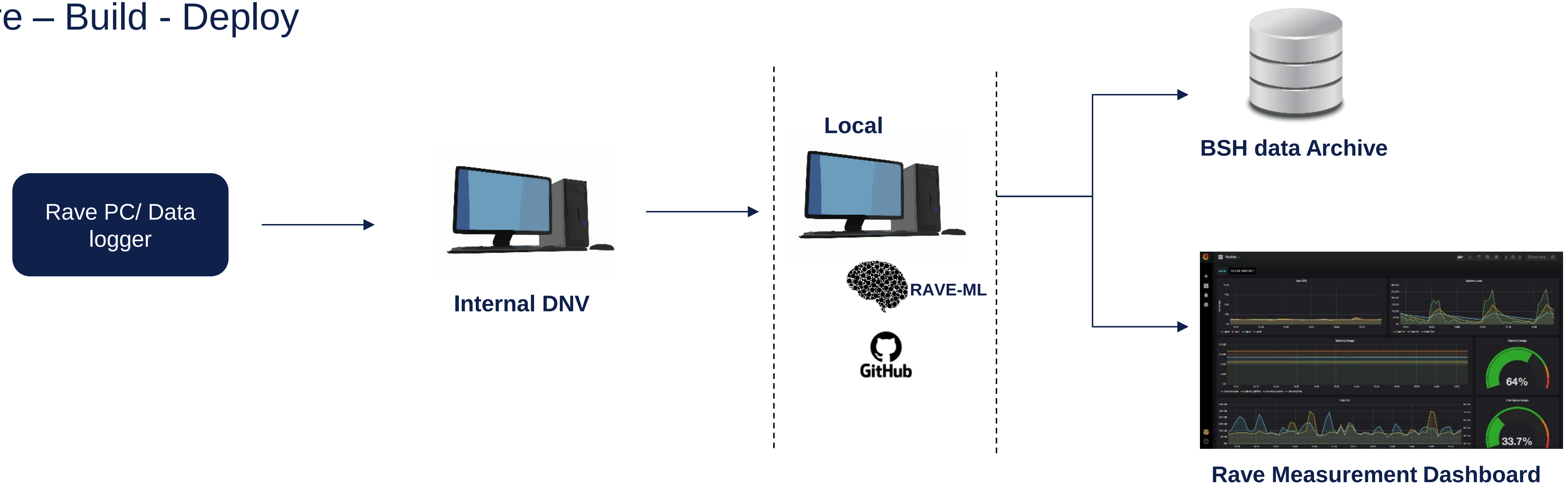
# Additional findings



# Prepare – Build - Deploy



# Prepare – Build - Deploy




**Quick demo of the dashboard …**

# References

- https://rave-offshore.de/en/events.html - All details regarding the ML model, data preparation, network etc. can be found here
- https://github.com/RAVE-DNV/RAVE-Data-Quality-Control - Github repository
- https://iopscience.iop.org/article/10.1088/1742-6596/1618/2/022006/pdf
- https://zenodo.org/record/4923193/files/BAYESIAN%20NEURAL%20NETWORK%20FOR%20ESTIMATING%20%20FATIGUE%20LOADS%20ON%20WIND%20TURBINES.pdf

# Thank You

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# THANK YOU

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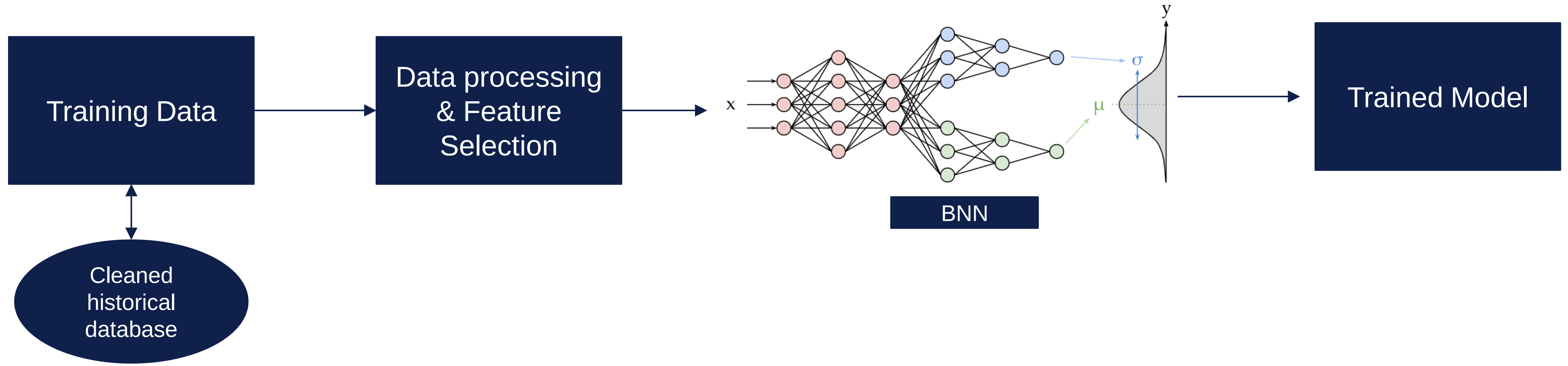
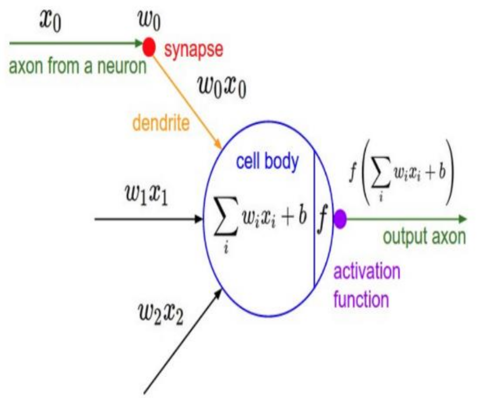
# Experiments/Results - Bayesian Neural Network

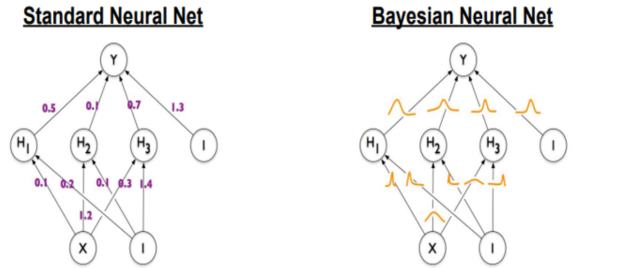



### Neutral network state of Art




### Conditional Probability : Bayes Theorem

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$$




**Standard Neural Net**

- Parameters represented by *single, fixed values (point estimates)*
- Conventional approaches to training NNs can be interpreted as *approximations* to the full Bayesian method (equivalent to MLE or MAP estimation)

**Bayesian Neural Net**

- Parameters represented by *distributions*
- Introduce a prior distribution on the weights $P(\mathbf{w})$ and obtain the posterior $P(\mathbf{w} \mid \mathcal{D})$ through Bayesian learning
- Regularization arises naturally through the prior $P(\mathbf{w})$
- Enables principled model comparison