



WHEN TRUST MATTERS

Development and Validation of Automatic Data Quality Control using Probabilistic Bayesian Neural Network

DeepWind 2023

Anish Venu (28)

- Senior Data Science and Domain Expert
- Digitalization & Research
- 4 years with DNV

Agenda

- Introduction
- Project Data – Research at Alpha Ventus (RAVE)
- General Background
- Automatic Data Quality Control using BNN
- Case Study – First Results
- Future Works

Introduction – Standard data quality control of measurement data



Disadvantages

- Time consuming process
- High measurement operational cost
- Impossible to check the high frequency measurements
- Immediate detection of measurement errors are not possible
- Extended measurement campaign
- Added uncertainty



Project Data – Research at Alpha Ventus (RAVE)

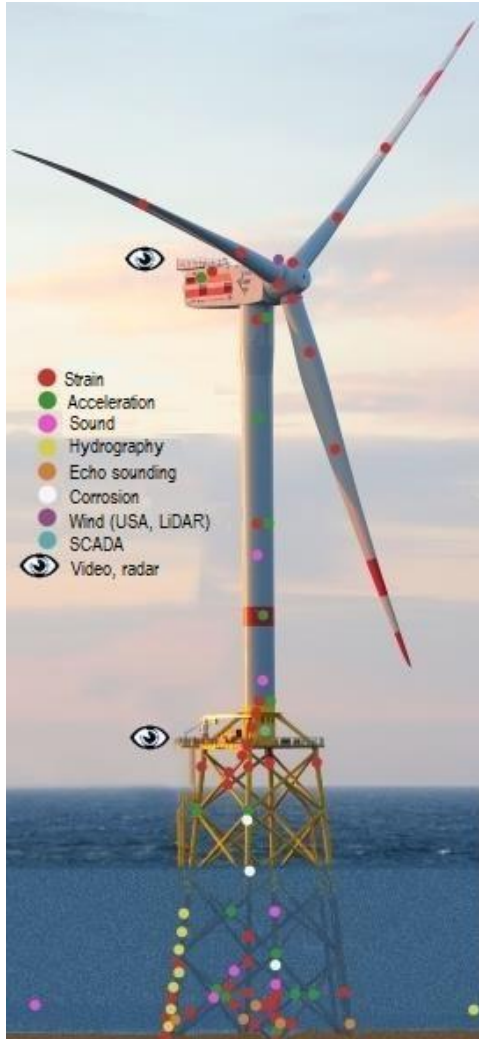
- The research Initiative RAVE carries out research and development work on the offshore test field alpha Ventus.
- RAVE is funded by the Federal Ministry for Economic Affairs and Climatic Actions (BMWK) and coordinated by the Fraunhofer Institute for Wind Energy Systems (IWES).
- In more than 30 research 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



Project Data – Research at Alpha Ventus (RAVE)

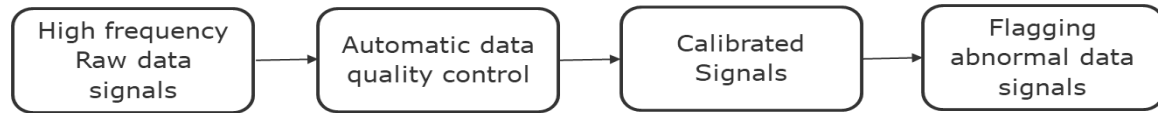


Available Measurements

- Controller Signals
- Acceleration sensors on the tower and blades
- Multiple strain gauges on the tower and blades
- Wind measurements
- Atmospheric measurements
- Sea-State Measurements
- Other critical structural measurements
- Other electrical signals



General Background – Automatic Data Quality Control

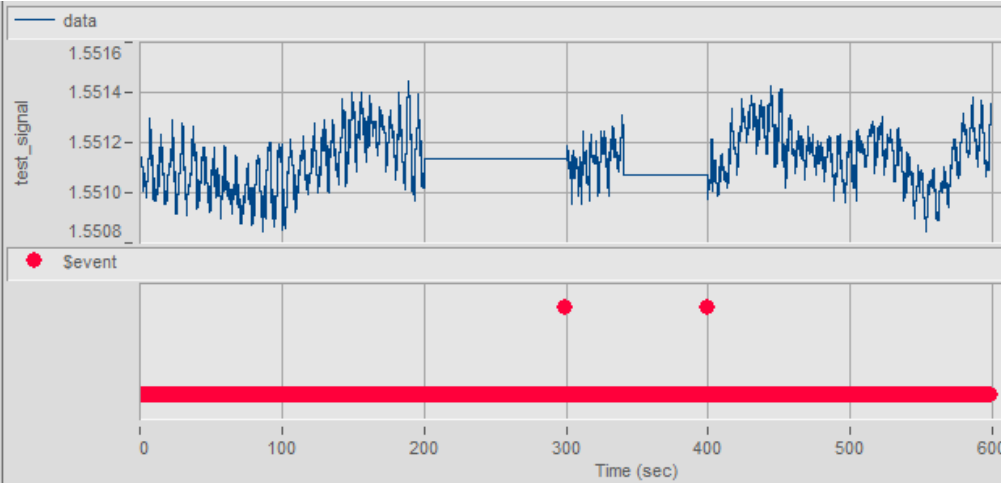


Objective

- 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

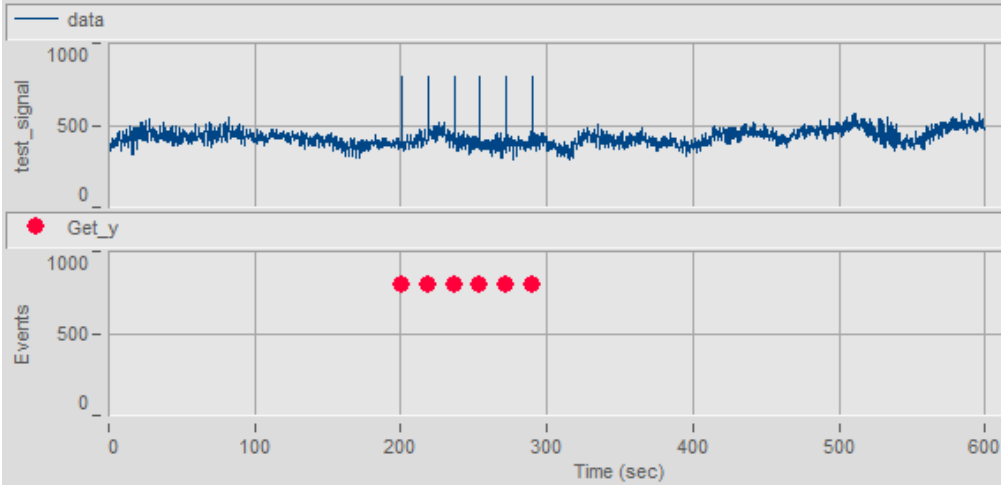
Position	Test Type	Meaning	Thresholds	Description
1	Length	Reduced data length	$N_{crit}\%$	Data of length of some value N_{crit} deviating from N 100%
2	Flat Line	Constant Signal	N/A	All values the same (e.g. bad if sensor is strain gauge, Ok/Check if machine data)
3	Flat Line	Partially Constant	t_{crit}	Constant values for a period of $> t_{crit}$ seconds (e.g. signal dropouts)
4	Pre-defined Limits	Measurement Range	$\sum (x_j > x_{crit}) > 0$	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.

General Background – Automatic Data Quality Control



Flags : 001000/1

Master Flag



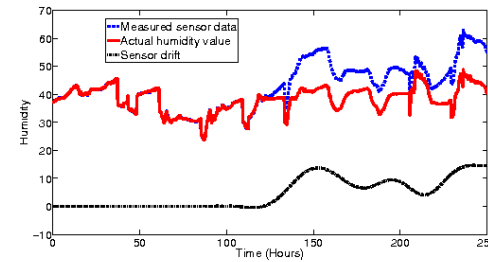
Flags : 000100/1

Master Flag

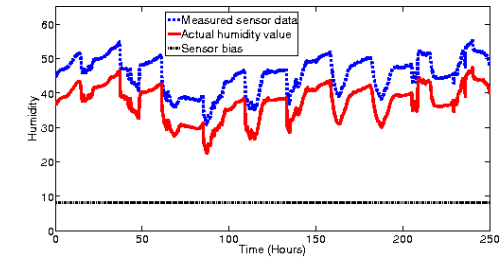
General Background – Automatic Data Quality Control

Limitations

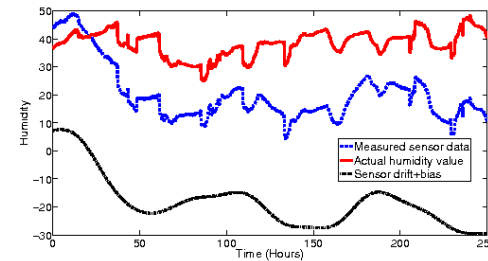
- Detects only 70% of the commonly occurring events
- Time & environmental sensitive events are not detected
- Not using the historically available cleaned database
- No data filling/replacement method available
- No additional advantages



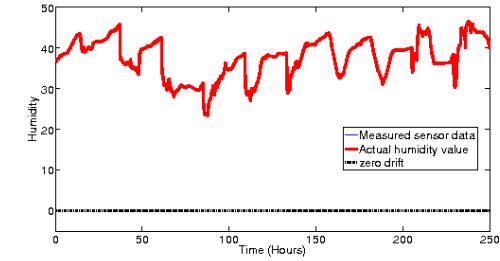
(a) Drifting sensor



(b) Biasing sensor



(c) Drifting & biasing sensor

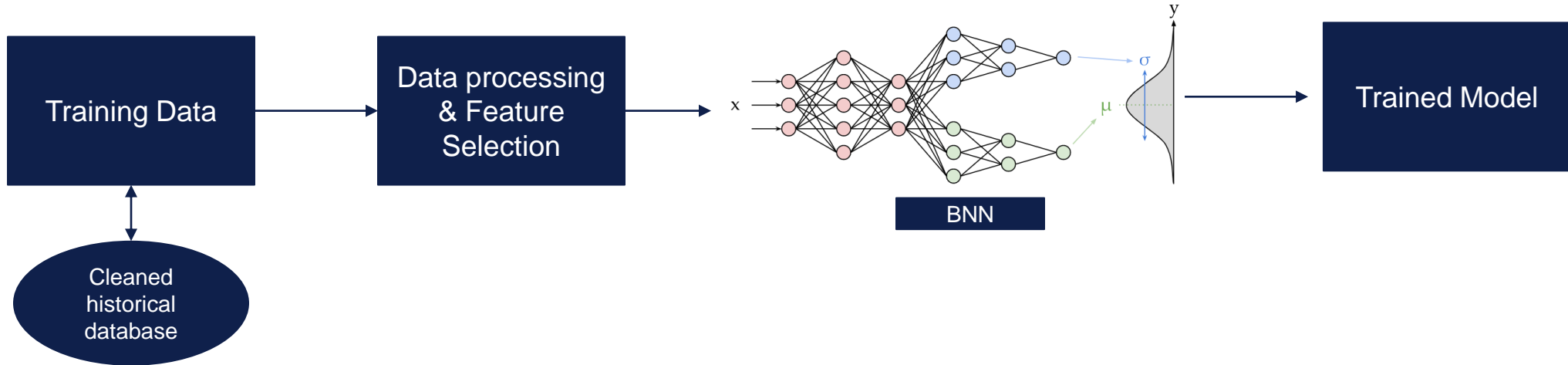


(d) Sensor without drift or bias

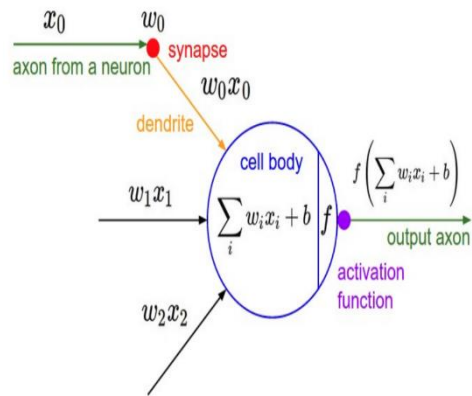
ADQC Output – 000000/0

No Events Found

Automatic Data Quality Control Using Bayesian Neural Network



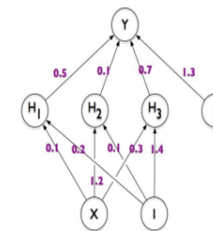
Neutral network state of Art



Conditional Probability : Bayes Theorem

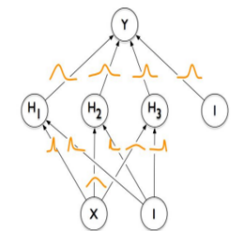
$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

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)

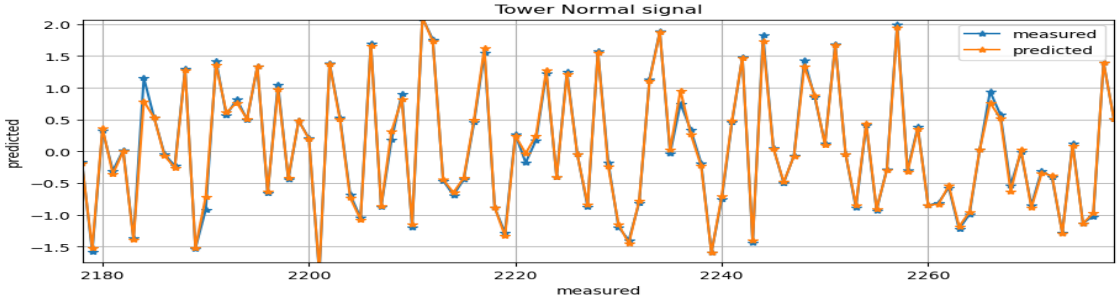
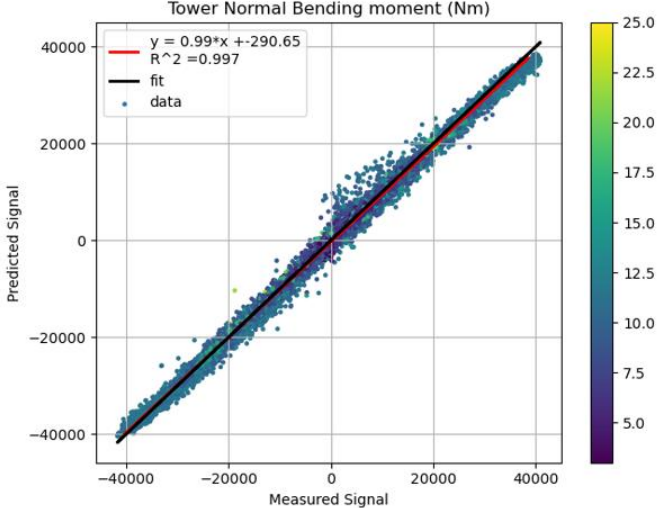
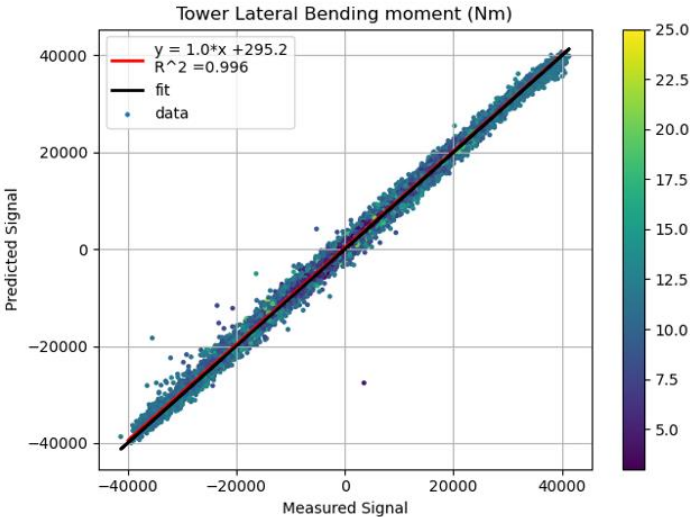
Bayesian Neural Net



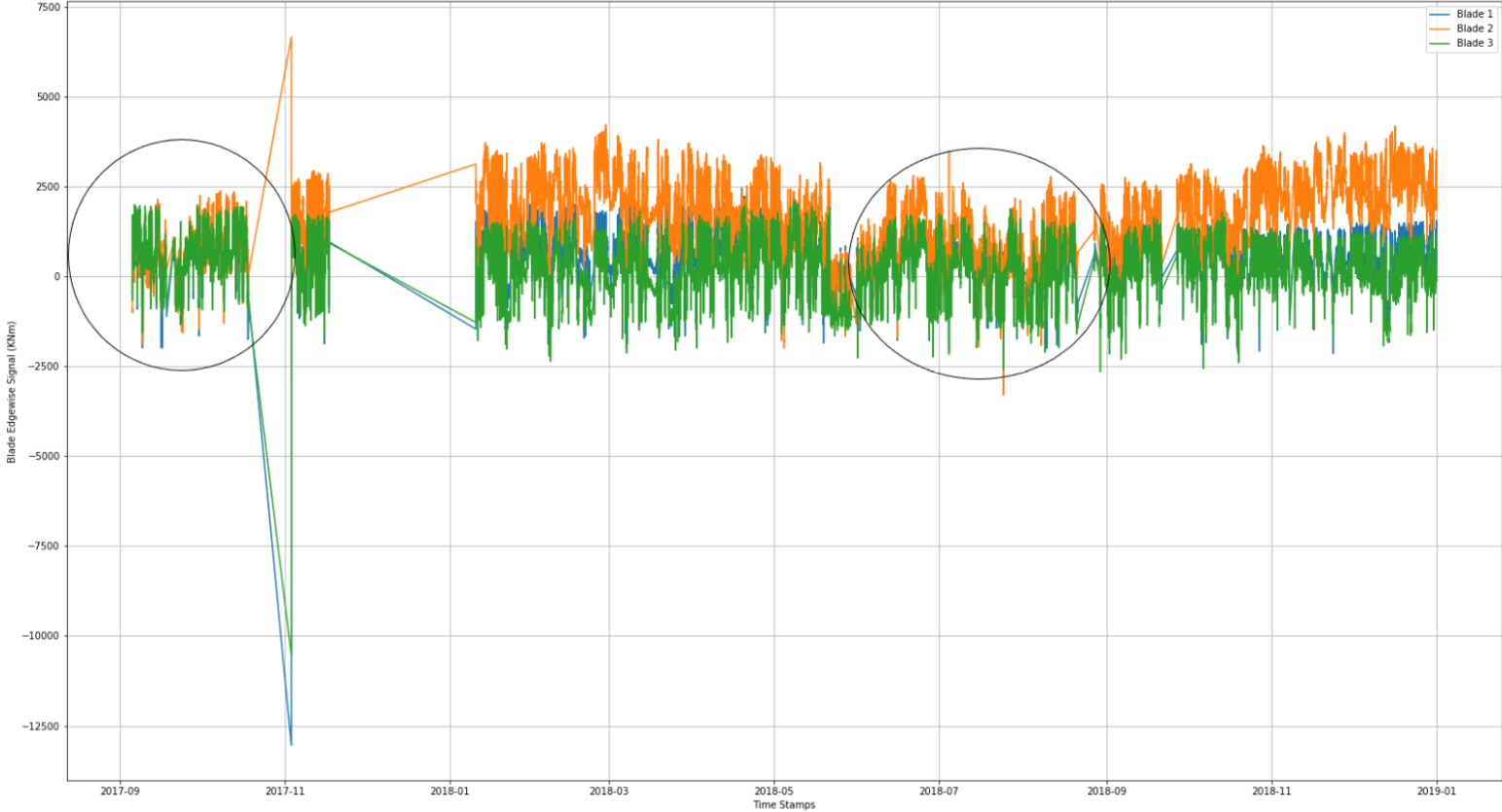
- Parameters represented by *distributions*
- Introduce a *prior distribution* on the weights $P(\mathbf{w})$ and obtain the *posterior* $P(\mathbf{w} | \mathcal{D})$ through *Bayesian learning*
- Regularization* arises naturally through the prior $P(\mathbf{w})$
- Enables principled *model comparison*

Automatic Data Quality Control Using Bayesian Neural Network

Example : Tower Signals



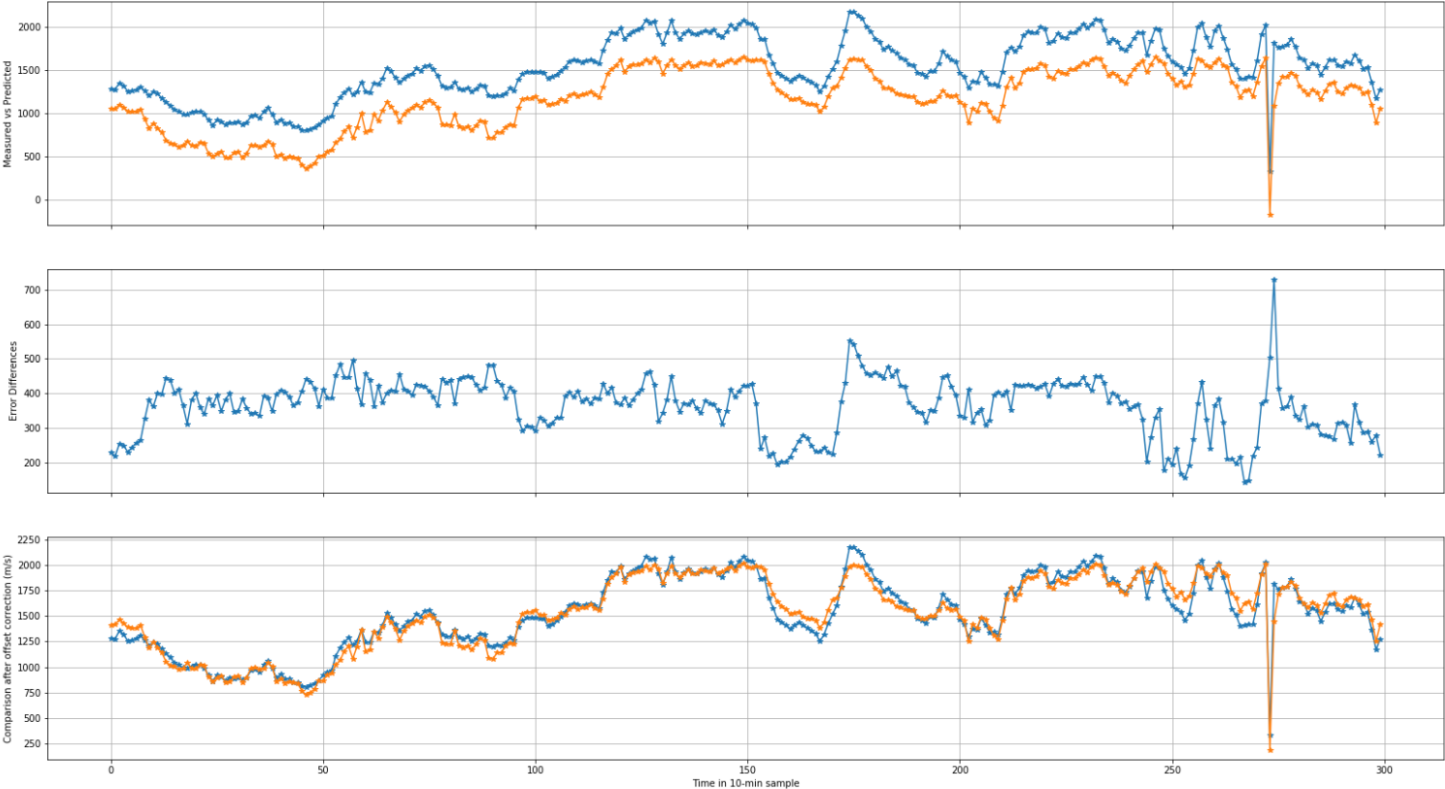
Case Study – First Results



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

Case Study – First Results

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



Measured vs Estimated



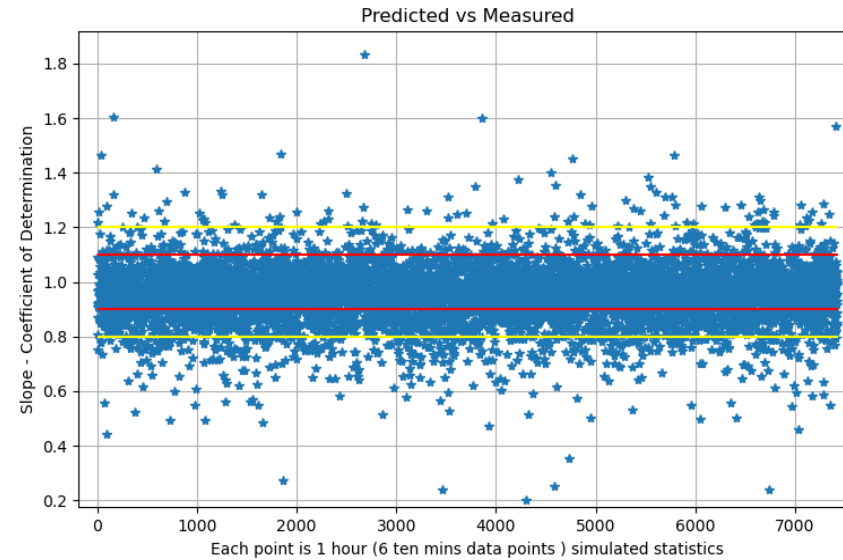
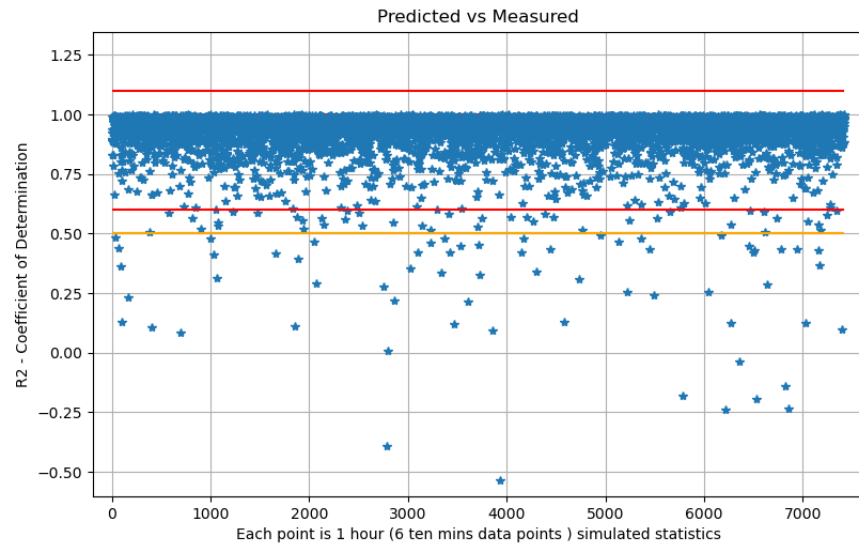
Error difference



Correcting the measured signal based on prediction

Future Work

➤ Past performance based data flagging strategy



- Calculating the metrics (Predicted vs Measured) for 1 day window
- Comparing the calculated metrics with the historical performance
- Flagging the data falling outside the threshold range

Thank You

Anish Venu
E-Mail: anish.venu@dnv.com

Hans-Peter Link
E-Mail: Hans-Peter.Link@dnv.com



BUNDESAMT FÜR
SEESCHIFFFAHRT
UND
HYDROGRAPHIE



Projektträger Jülich
Forschungszentrum Jülich



Bundesministerium
für Wirtschaft
und Energie

