

Data Quality Management in the RAVE-Project

Introducing Machine Learning to the Process

RAVE Workshop 2021
28. Januar 2021, Hamburg



Agenda

- Introduction
- Limitations/Challenges of ADQC
- Can this be solved with ML model?
- Feature Selection & Data Compression
- Case Study – First results
- Accuracy and Performance of the model
- Other applications
- Future works



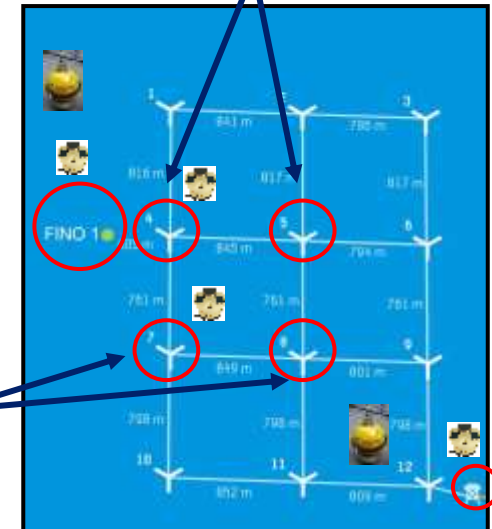
Introduction

- 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 Energy (BMWi) 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 BMWi so far amounted to more than 50 million euros



Wind Farm Outlook

- Commission Date: 2009
- 45 Km North of Borkum
- 30 m water depth
- 12 Wind turbines
 - 6 AREVA WIND M5000
 - 6 Senvion 5M



Introduction



Available Measurements

- Controller signals
- Accelerometers and multiple strain gauges at tower, blades and support structure
- Environmental measurements (Atmosphere, Wind and Sea State)
- Other critical structural measurements
- Other electrical signals

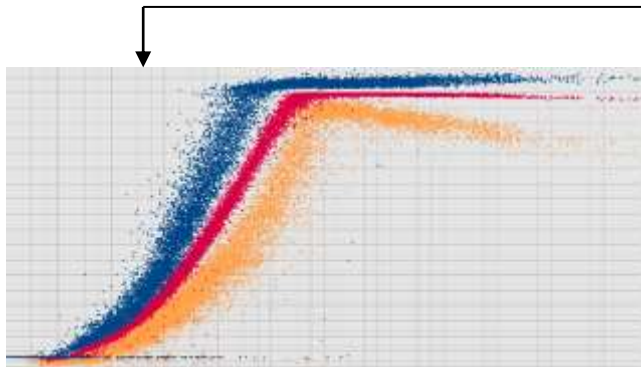
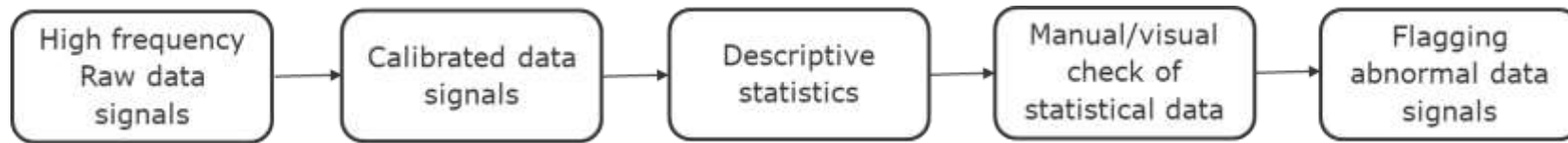
Continuous time series data since 2010

- The data are stored and published via RAVE-Database
- The RAVE-Database is developed, hosted and administrated by BSH,
 - **Most importantly open to the public**
 - ➔ serviceportal.bsh.de

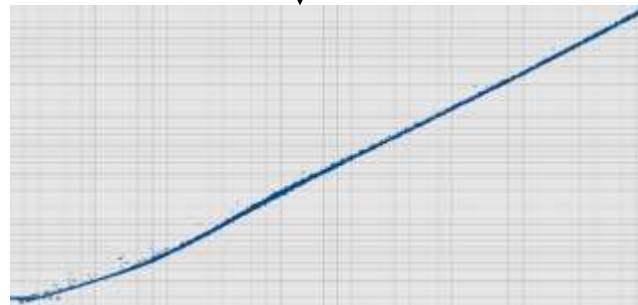


Introduction - Recap

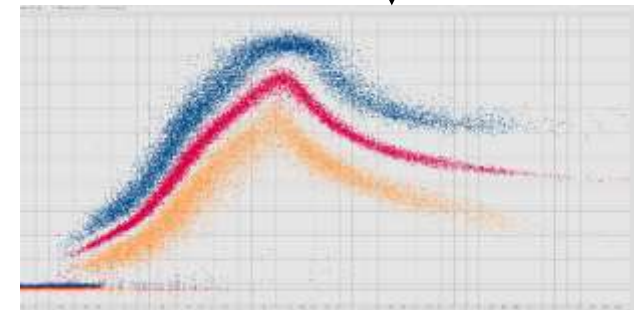
Standard data quality control of measurement data



Wind Speed vs Electrical Power

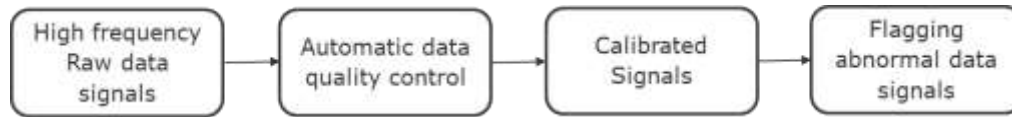


Main shaft torsion vs Electrical Power



Tower tilt moment vs Electrical Power

Introduction – Automatic Data Quality Control



Detailed Flag



Flags : 001000/1 ← Master Flag

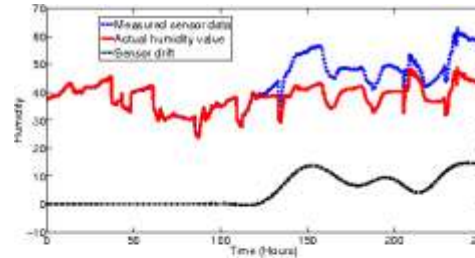
Objective

- 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

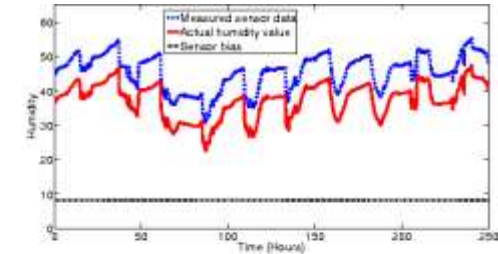
Position	Test Type	Meaning	Thresholds	Description
1	Length	Reduced data length	$N_{crit}\%$	Data of length of some value N_{crit} deviating from N 100%
2	Flat Line	Constant Signal	N/A	All values the same (e.g. bad if sensor is strain gauge, Ok/Check if machine data)
3	Flat Line	Partially Constant	t_{crit}	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.

Limitations/Challenges of ADQC

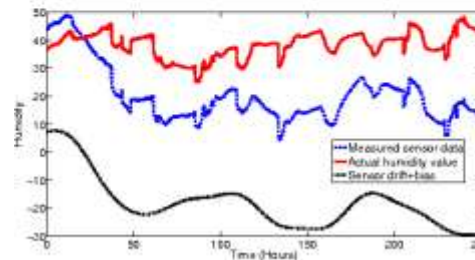
- Detects only 70% of the commonly occurring events
- Time & environmental sensitive events are not detected
- Not using the historically available cleaned data
- No data filling/replacement method available
- No additional advantages



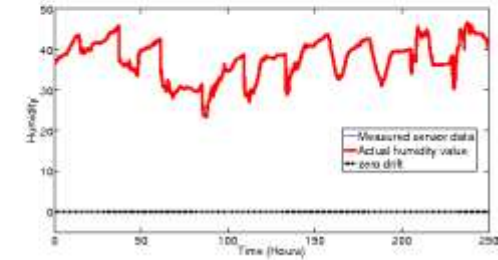
(a) Drifting sensor



(b) Biasing sensor



(c) Drifting & biasing sensor



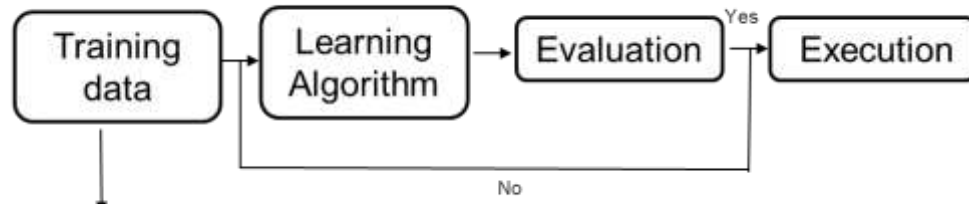
(d) Sensor without drift or bias

ADQC Output – 000000/0

No Events Found

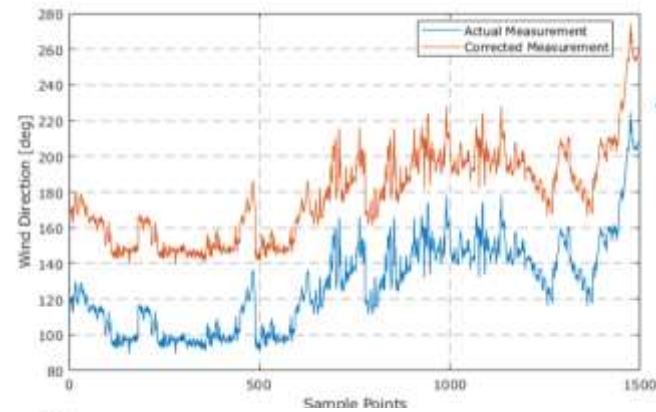
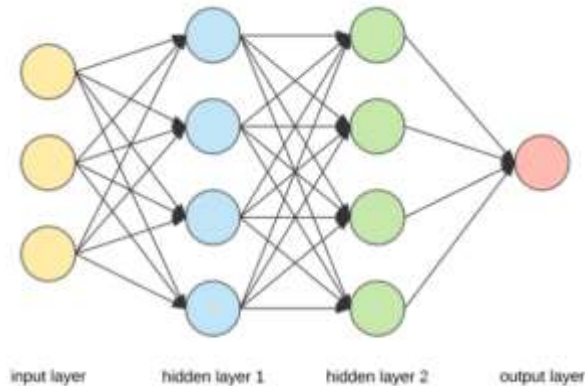


Can this be solved using Machine Learning?



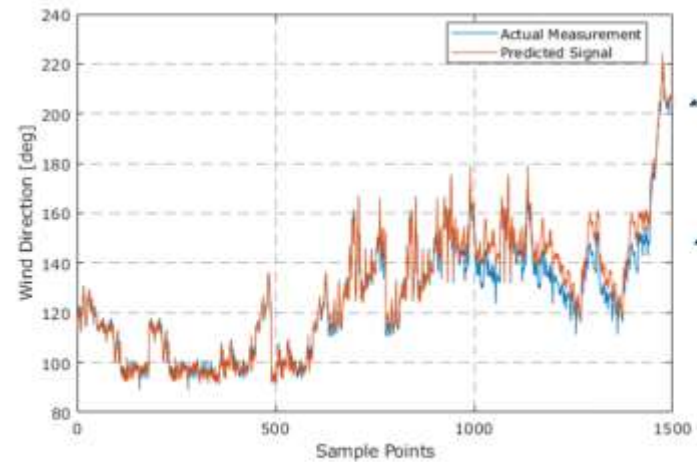
Manually cleaned historical data

Deep Neural Networks



50 degrees offset

ADQC Output
000000 – No events found

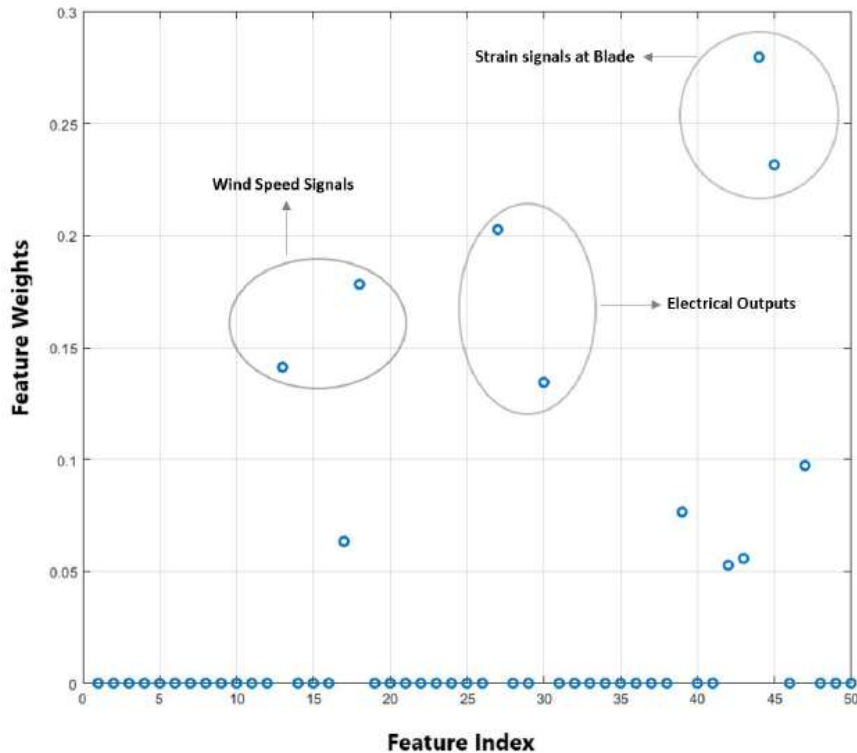


ADQC Output
000000 – No events found

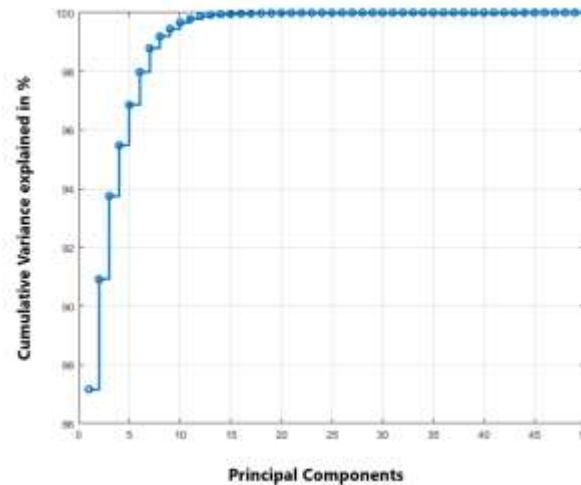
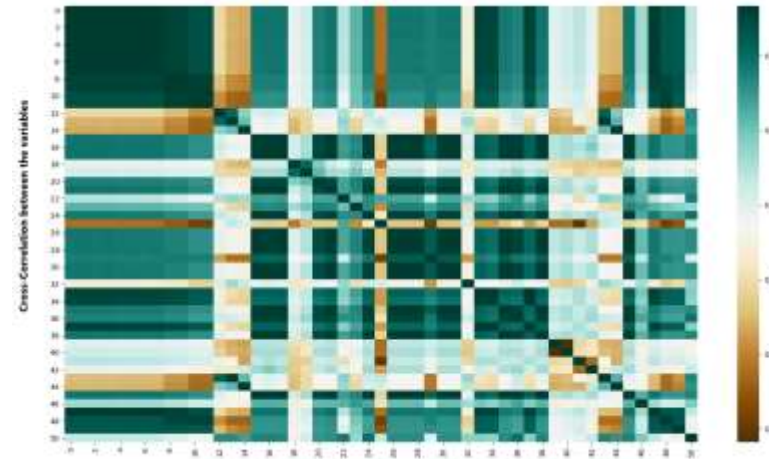
RAVE-ML
0 - Pass

Feature Engineering/Data Compression

Neighbourhood Component Analysis

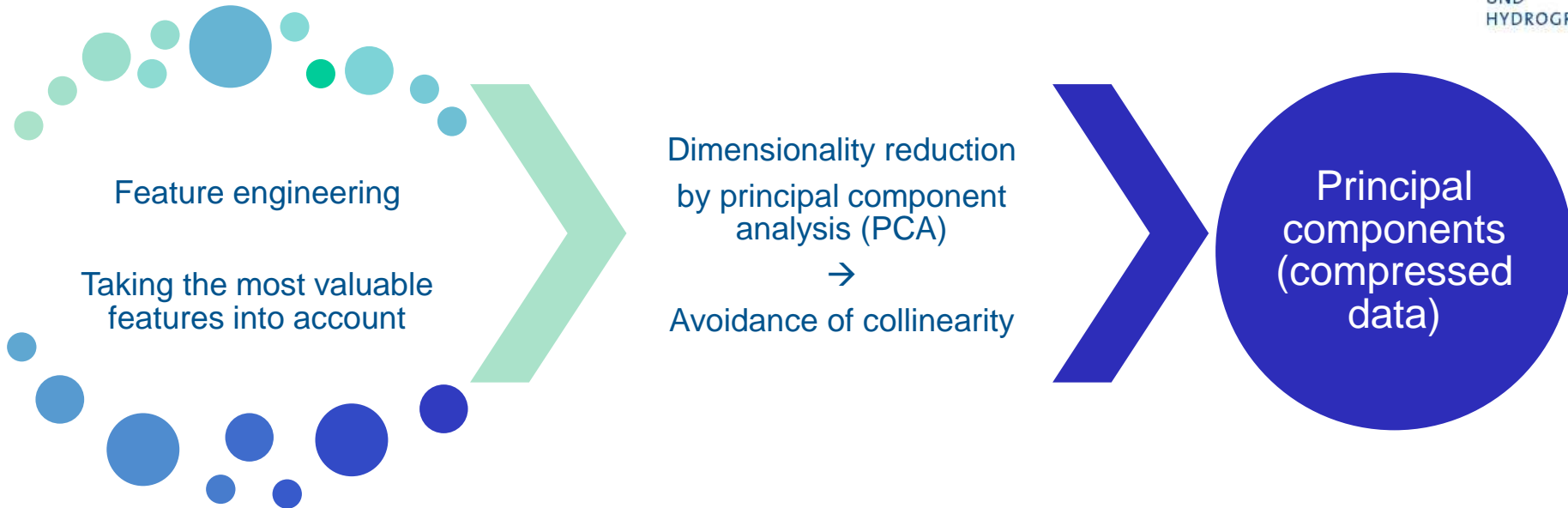


Cross Correlation



Principal Component Analysis

Feature Selection



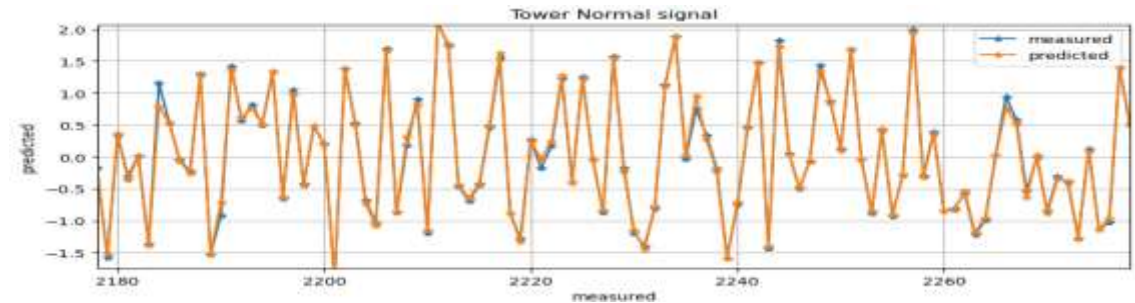
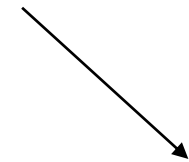
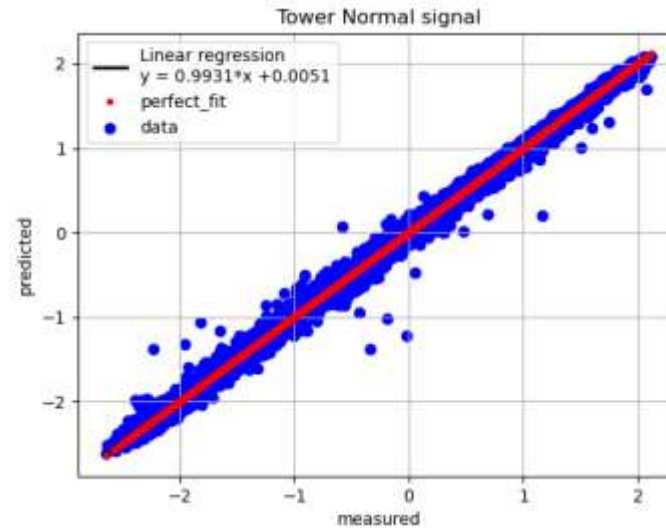
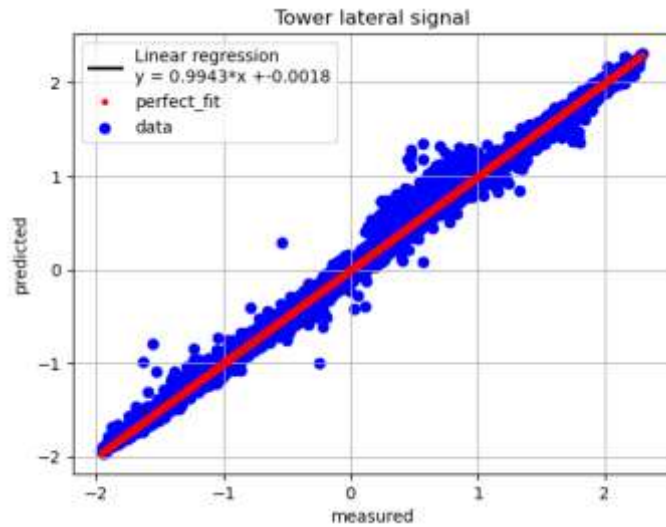
In consideration of the model's robustness the features have been reduced to SCADA data and accelerometers:

- Pitch angle
- Generator speed
- Yaw angle
- Wind speed
- Electrical power
- Accelerometer
 - Support structure
 - Upper tower
- Temperature
- Humidity

Case Study – First Results

Able to estimate all signals (Structural, acceleration, controller , etc..)

Example 1 : Tower signals

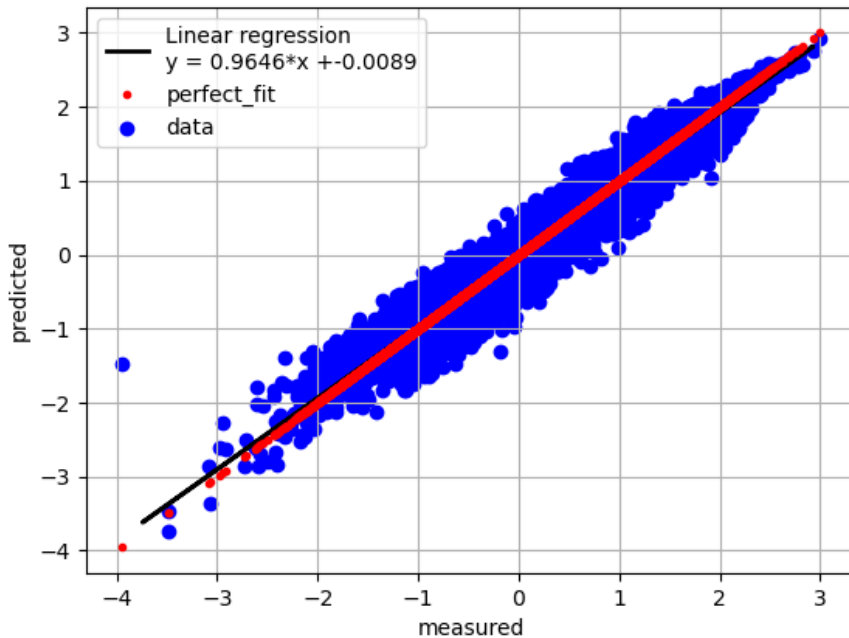


Case Study – First Results

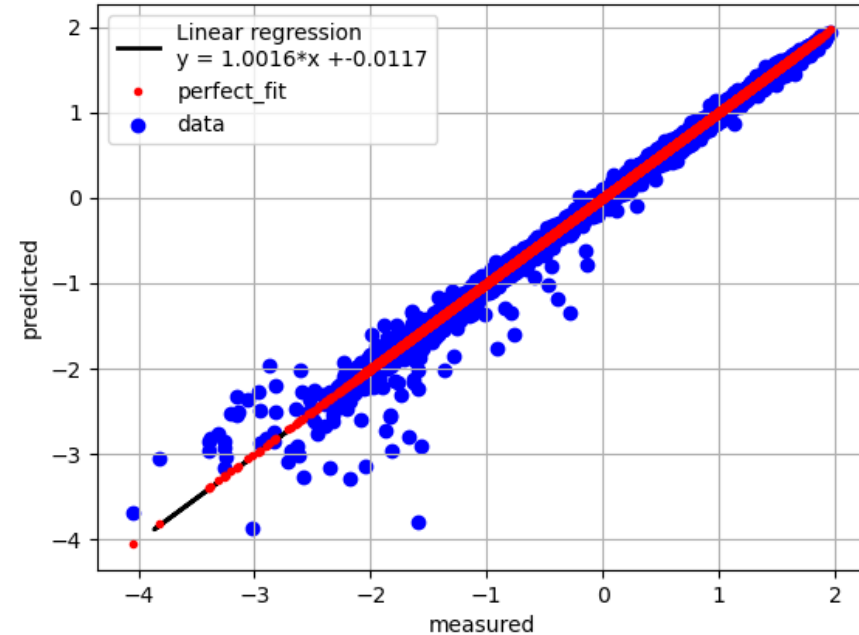
Able to estimate all signals (Structural, acceleration, controller , etc..)

Example 1 : Tower signals

Blade Edgewise signal

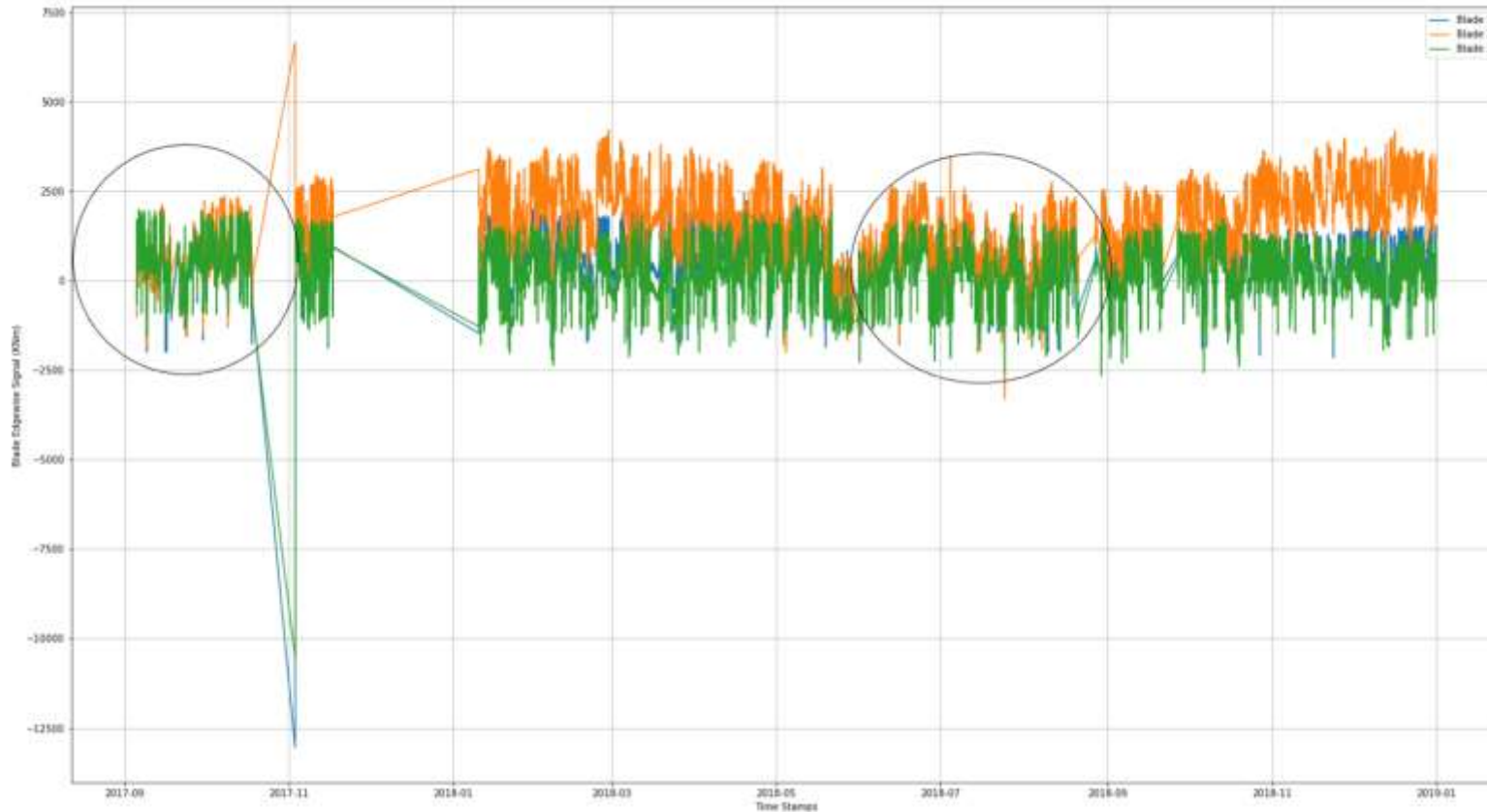


Blade Flapwise signal



Case Study – First Results

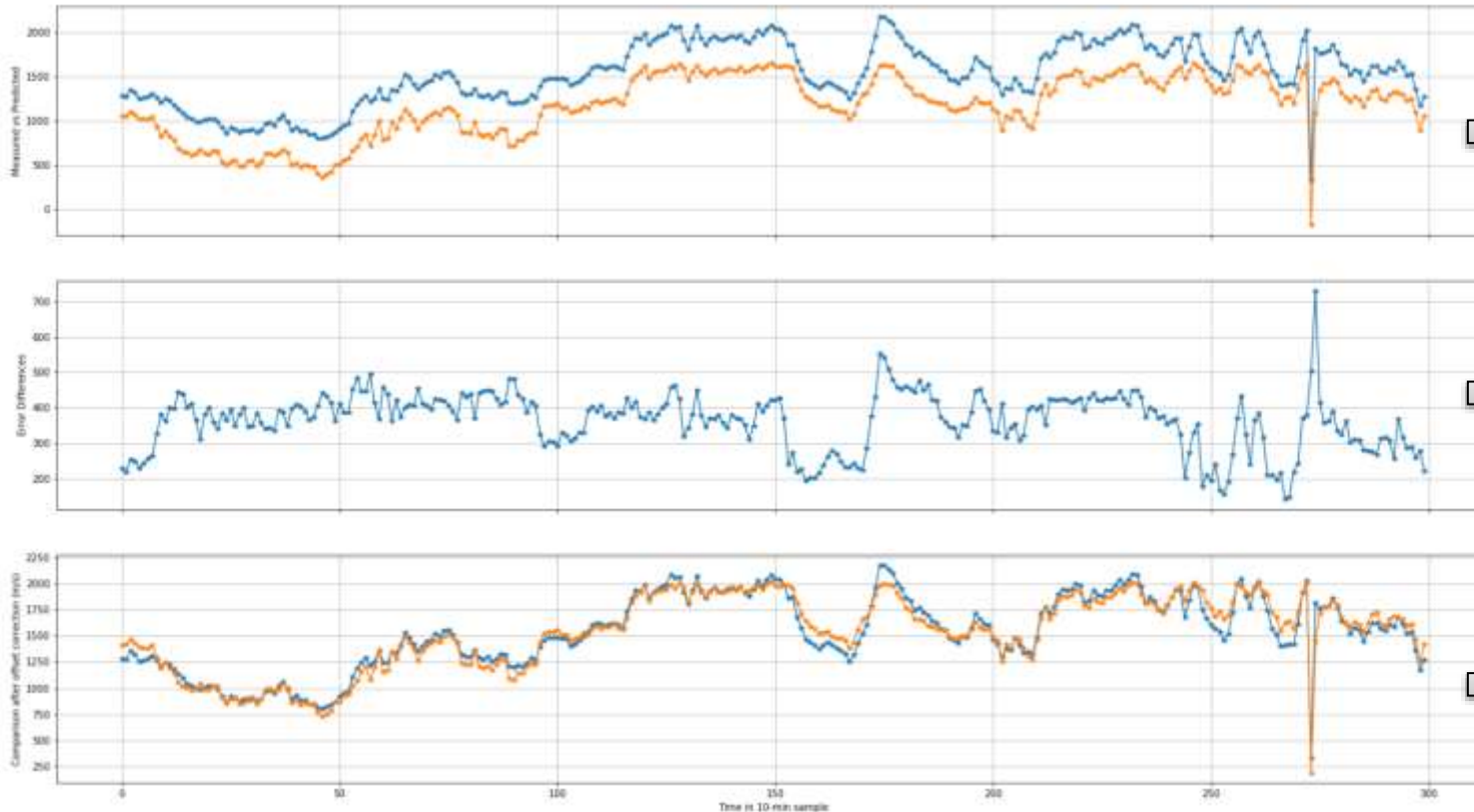
Detection of sensor drift in the blade signals due to temperature change



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

Case Study – First Results

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

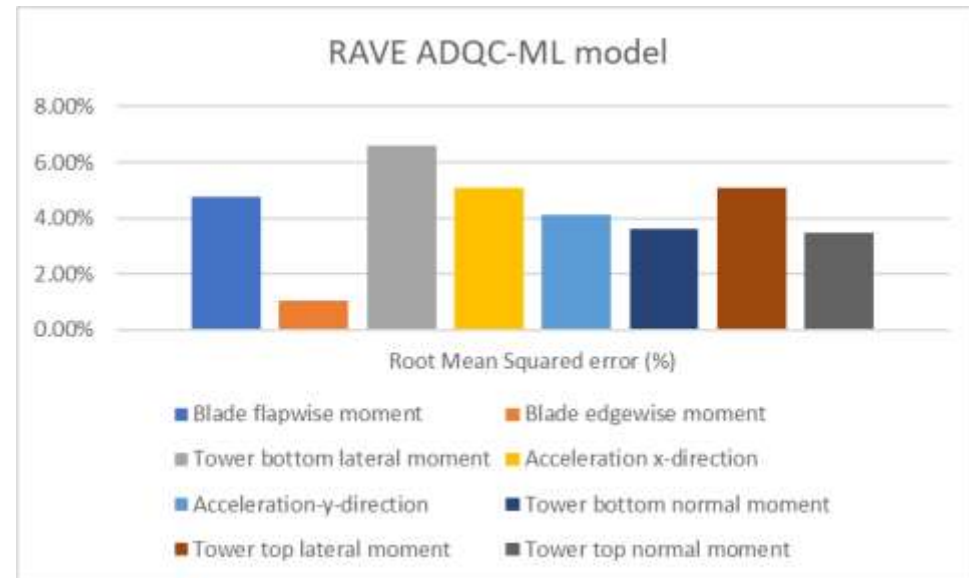
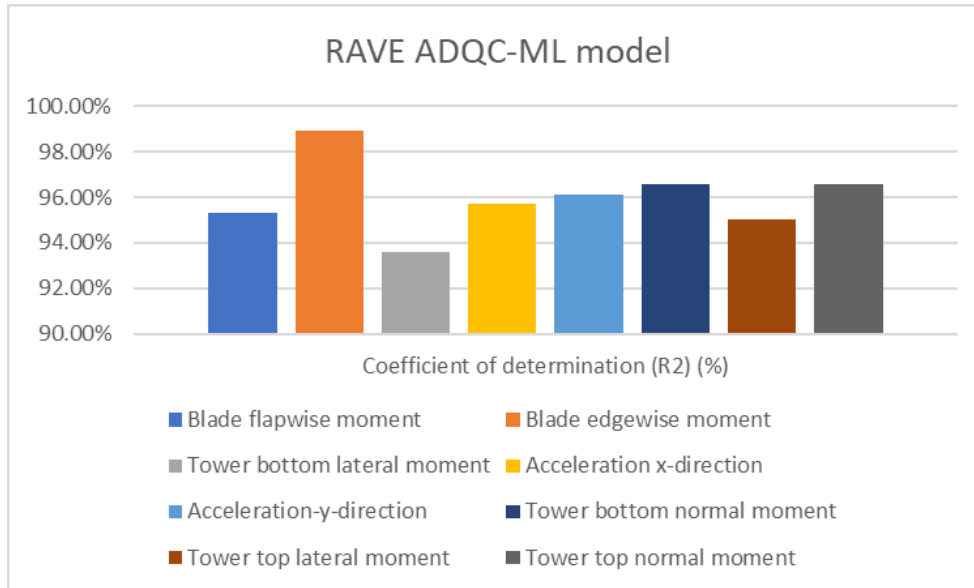


**Measured
vs
Estimated**

Error difference

**Correcting the
measured signal
based on prediction**

Accuracy/Performance of the model



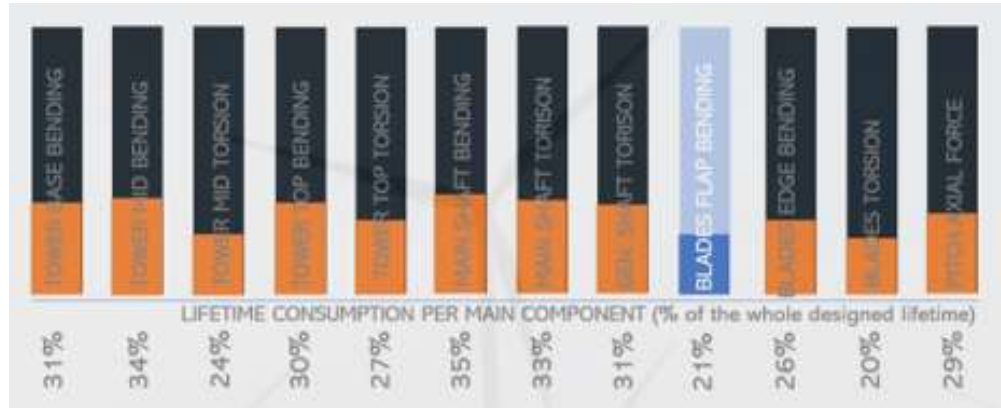
$$R^2 = 1 - \frac{\text{Variance}(DEL_{Estimated} - DEL_{Real})}{\text{Variance}(DEL_{Real})}$$

$$RMSE = \sqrt{\sum(DEL_{Estimated} - DEL_{Real})^2}$$

- Quantification of important signals are shown here
- Accuracy/performance range applicable to most of the signals available in RAVE project

Other applications

Reliable Lifetime Estimation



Wind farm optimization



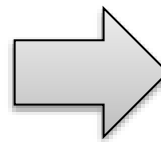
Model built based on one turbine

Transferred to other turbines

Measurement Data fulfilment/extrapolation



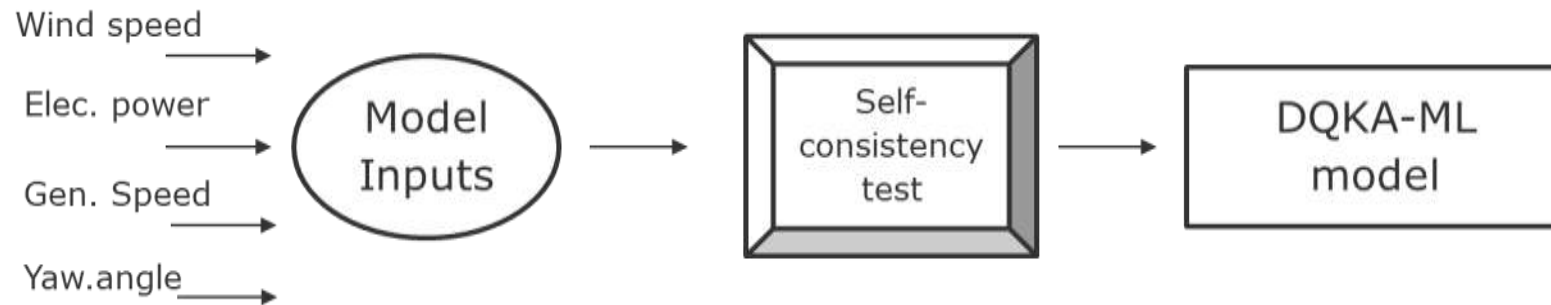
Turbine 1



Turbine 2

Future Work

➤ Self consistency test for model's input variables



- **Flagging strategies... how can we compare estimated and measured data to flag ?**
- **How can we quantify the uncertainties ?**
- **Providing calibration factors along with the flags**

Thank you for your attention !!!!

Questions ??

Anish Venu
Data Scientist - DNVGL
Anish.Venu@dnvgl.com

Nick Hansen
Project Engineer – UL Intern.
Nick.Hansen@ul.com

Marten Schmager
Scientist - BSH
Marten.Schmager@bsh.de

Contact Details

Kai Herklotz

Tel.: +49 (0)40 3190-3230

E-Mail: Kai.Herklotz@bsh.de

Hans-Peter Link

Tel.: +49 (0)4856 901-46

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

Tom Neumann

Tel.: +49 (0)4421 4808-814

E-Mail: Thomas.Neumann@ul.com

