# Advanced operational analytics with machine learning

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# Turbine Blade Icing Loss

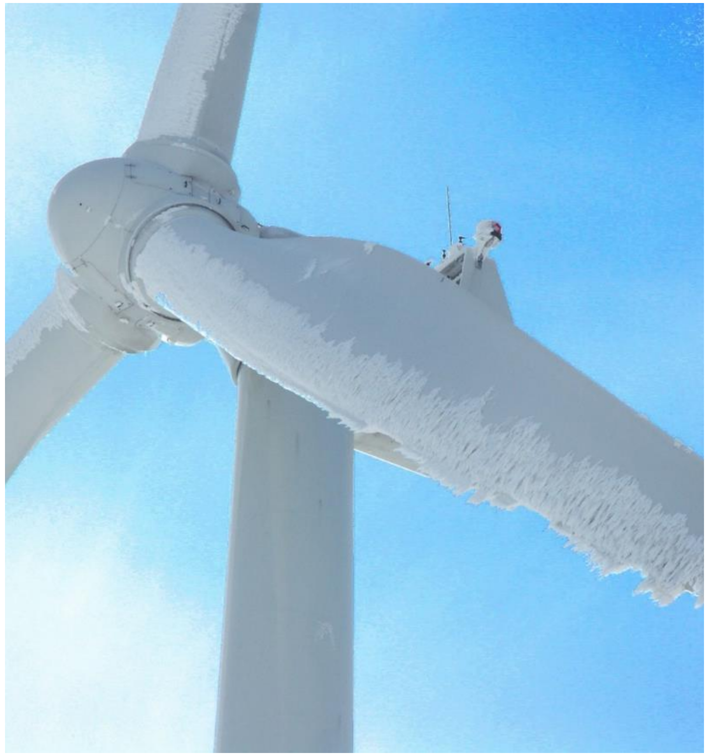
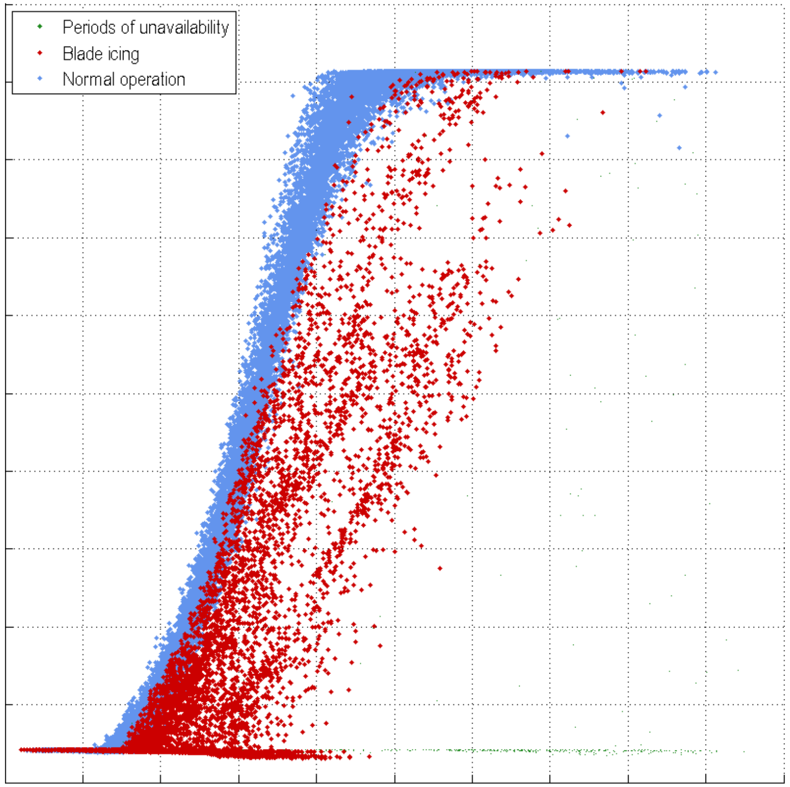


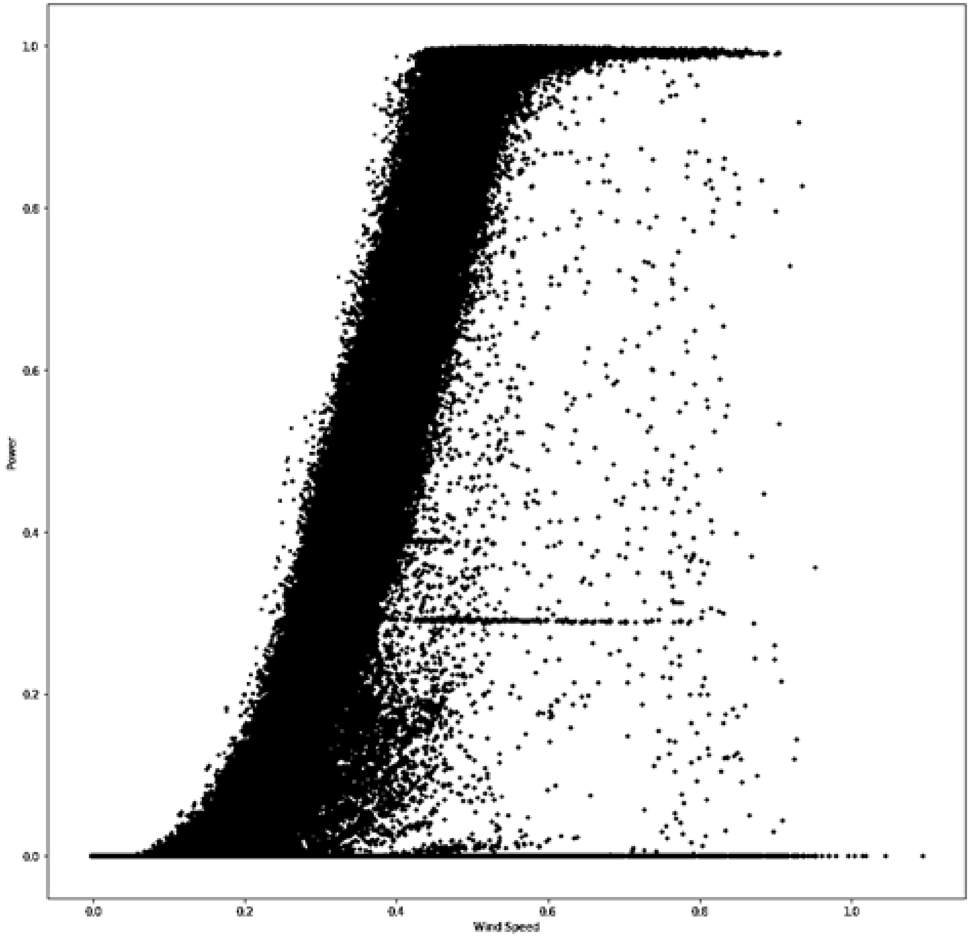
Photo: Kent Larsson, ABVEE

- **Blade icing** is the cause of large production losses through the winter months for many wind farms in the Nordics.
- Identifying and consistently labelling ice affected production is very time consuming to do accurately
- We have received a lot of interest surround **IPS warranty reviews**
- SCADA data enables us to see how effective the systems are at maximizing performance during icing conditions.




- These analyses require a large amount of data from multiple wind farms under varied conditions in order to provide credible results.

# Power Curve Performance Analysis



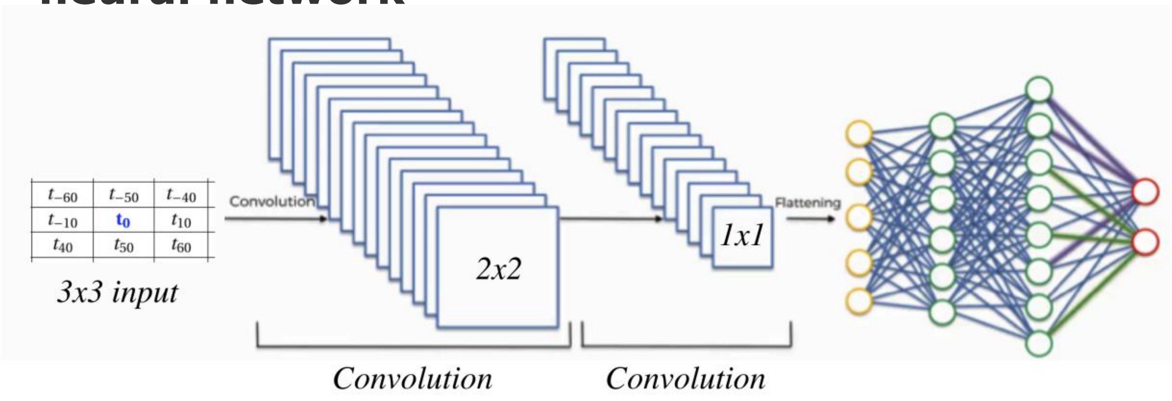

- SCADA analysis is essential for good analysis of turbine performance.
- Labelling performance issues accurately is time consuming and susceptible to human error
- Much of the effort in performance assessments are driven by SCADA analysis section of the work
- Labelling the data using simple logical filters is prone to errors as they miss the nuances in the data and legitimate differences between turbines
- Old automatic labelling models also fail to identify new performance issues

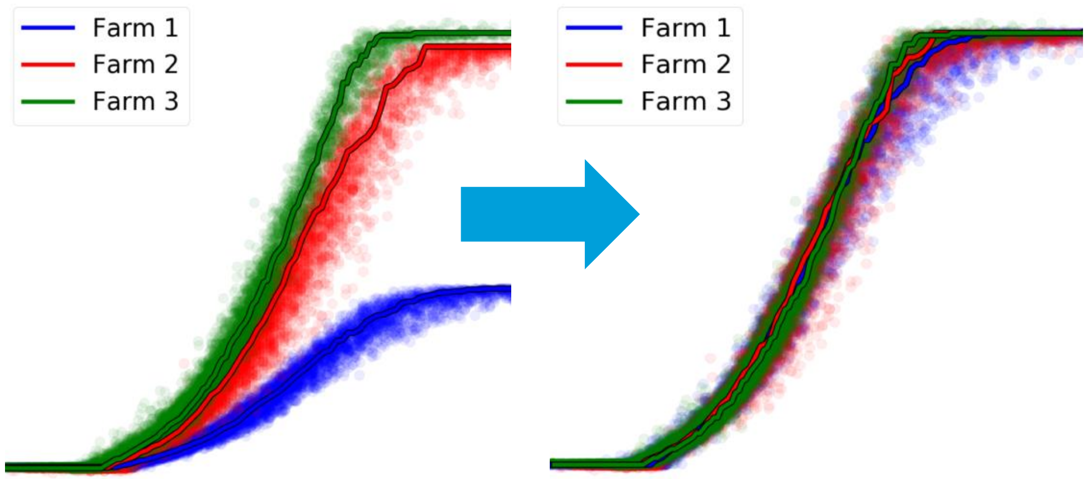
# Machine Learning Labelling Tool

- A training dataset is prepared for each wind farm analysed by manually labelling a subset of the SCADA data from the wind farm

- Normalisation of power curves is necessary to create a consistent training dataset – this greatly improves the predictive performance across the wind farm

- The normalised data is used to train a **convolutional neural network**

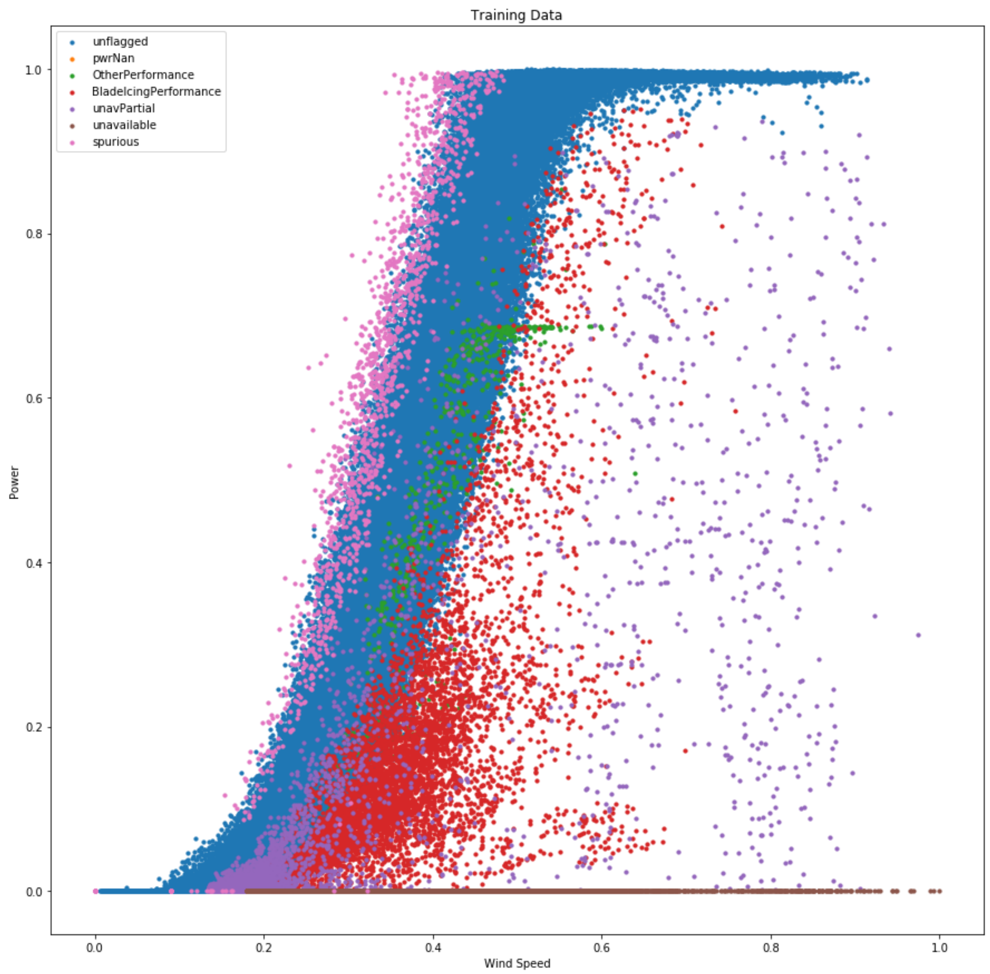


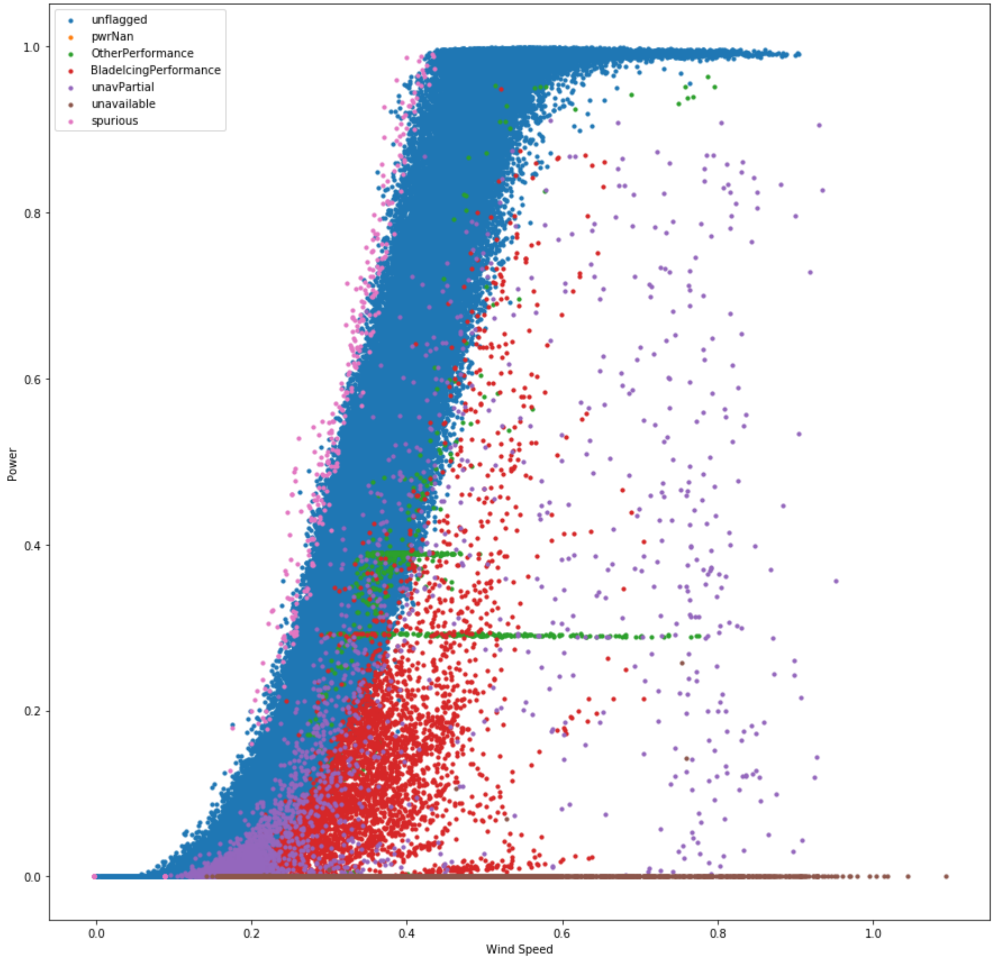




- Time is considered when training the model in order to capture downtime/performance events

- The model is then used to label the remaining data from the wind farm – provided the training data was high quality **the model produces consistent results efficiently**

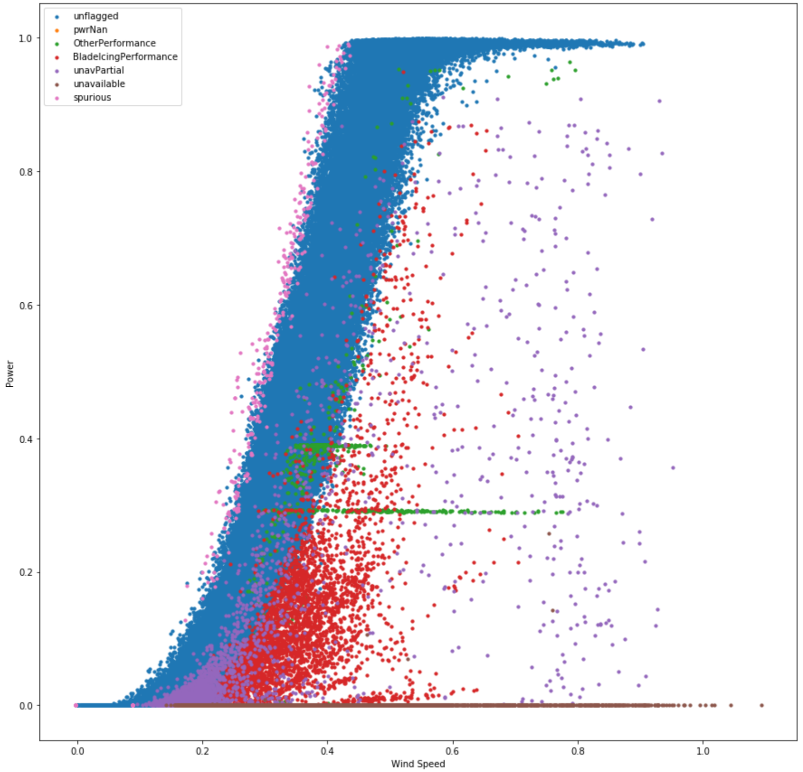
# Example: Turbine Blade Icing Loss



# Example: Turbine Blade Icing Loss

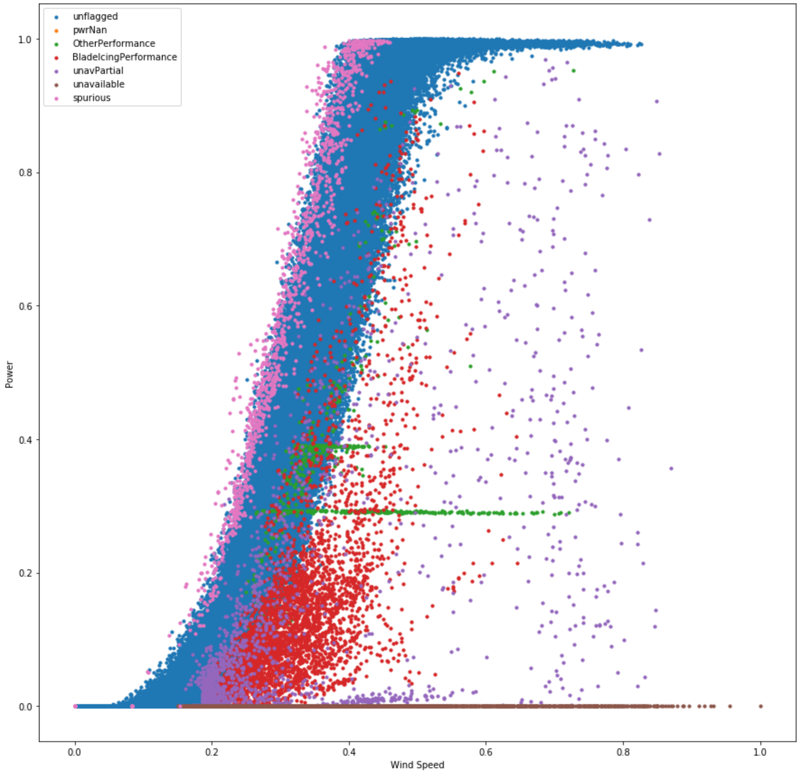
Machine learning labels




| | | Predicted | |
|---|---|---|---|
| | | Blade icing | No icing |
| Actual | Blade icing | 86.0% | 14.0% |
| | No icing | 0.3% | 99.7% |

- The model applies the learned flags with **high precision**
- Minimal manual flagging is required which can be carried out when checking the results

Manual labels



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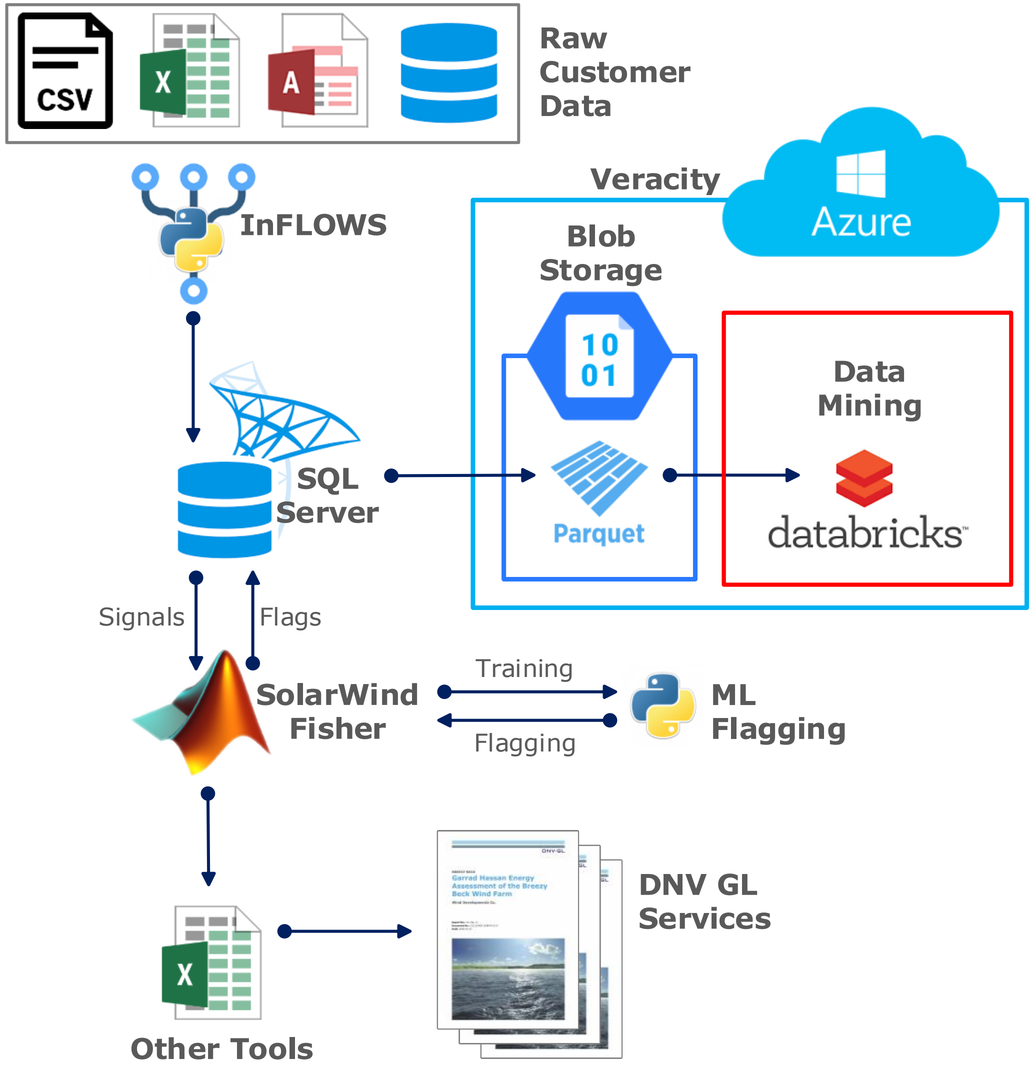
# Data Mining Overview

600+ Windfarms,
6,000+ turbines and
20,000+ turbine years

- **50 GW** of operating wind and solar plant data
- A suite of data mining tools can be used for analysis of the entire portfolio.
- ‘Big questions’ can now be tackled efficiently using analytical methods
- **What questions would you ask 50 GW-worth of data?**

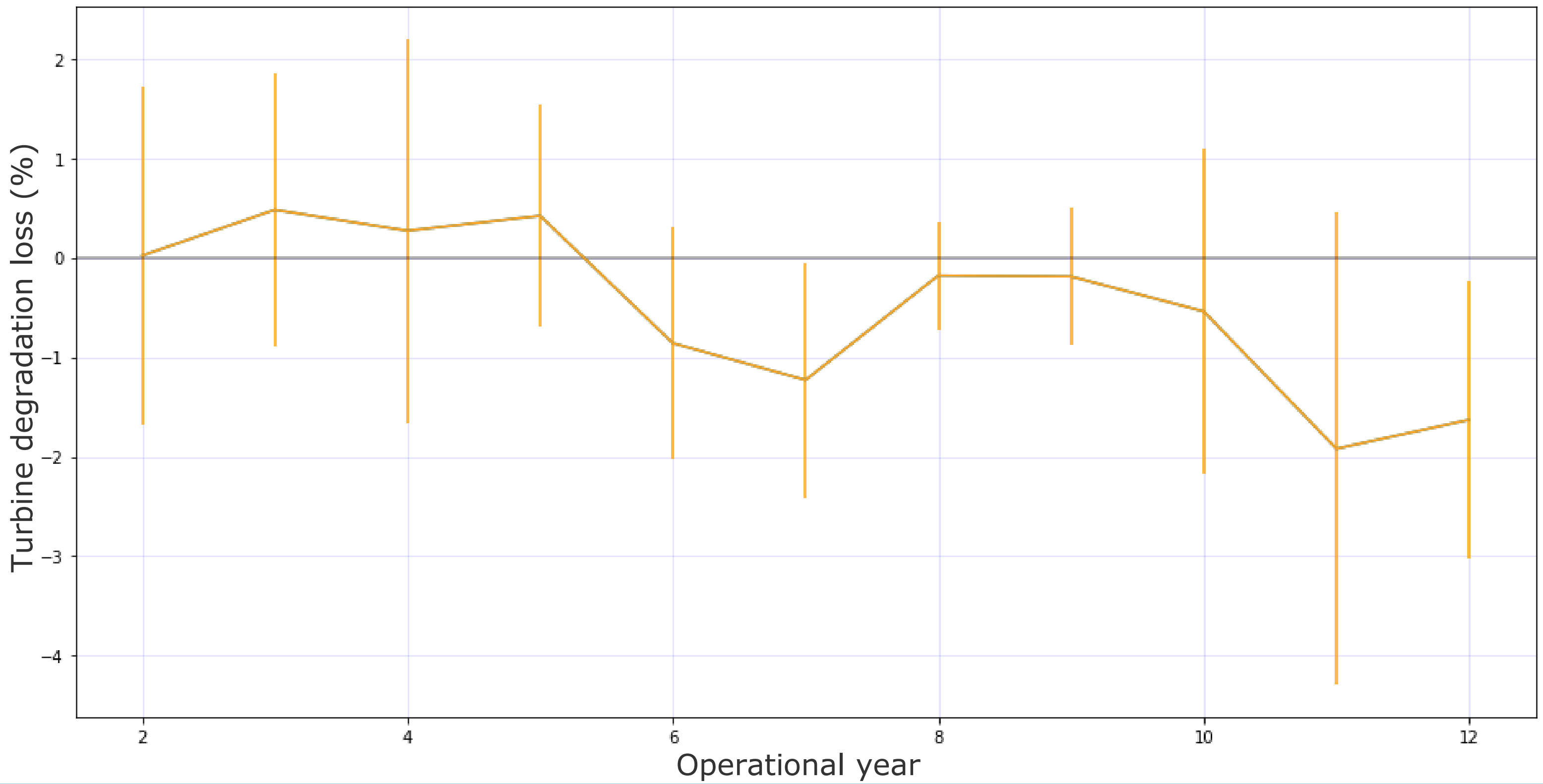
# Data Mining Methodology




- ‘InFLOWS’ universal SCADA data ingest tool improving efficiency and standardising data.
- ML Flagging tool to speed up data labelling.
- Storage of standardised, cleaned and labelled datasets in Veracity data container.
- Data mining of Veracity data using Azure Databricks.

# Example: Turbine Degradation Study

- Assumed turbine degradation rate is an important input to an energy assessment of a wind farm – with a **loss ranging from 1.0% to 1.3% over 20 years.**




- **This study confirmed our assumptions**
- More work is being done to investigate how projects located in the Nordic region align with our turbine degradation assumptions

| Year | Loss | WF_count | Turb_count | Std |
|---|---|---|---|---|
| 2 | 0.02 | 241 | 6516 | 1.7 |
| 3 | 0.48 | 167 | 5362 | 1.37 |
| 4 | 0.27 | 98 | 3422 | 1.93 |
| 5 | 0.42 | 68 | 2996 | 1.12 |
| 6 | -0.86 | 51 | 2484 | 1.17 |
| 7 | -1.23 | 35 | 2333 | 1.18 |
| 8 | -0.18 | 12 | 262 | 0.54 |
| 9 | -0.19 | 7 | 74 | 0.69 |
| 10 | -0.54 | 4 | 26 | 1.63 |
| 11 | -1.92 | 3 | 17 | 2.37 |
| 12 | -1.63 | 2 | 6 | 1.4 |

# Drivetrain Integrity Monitor

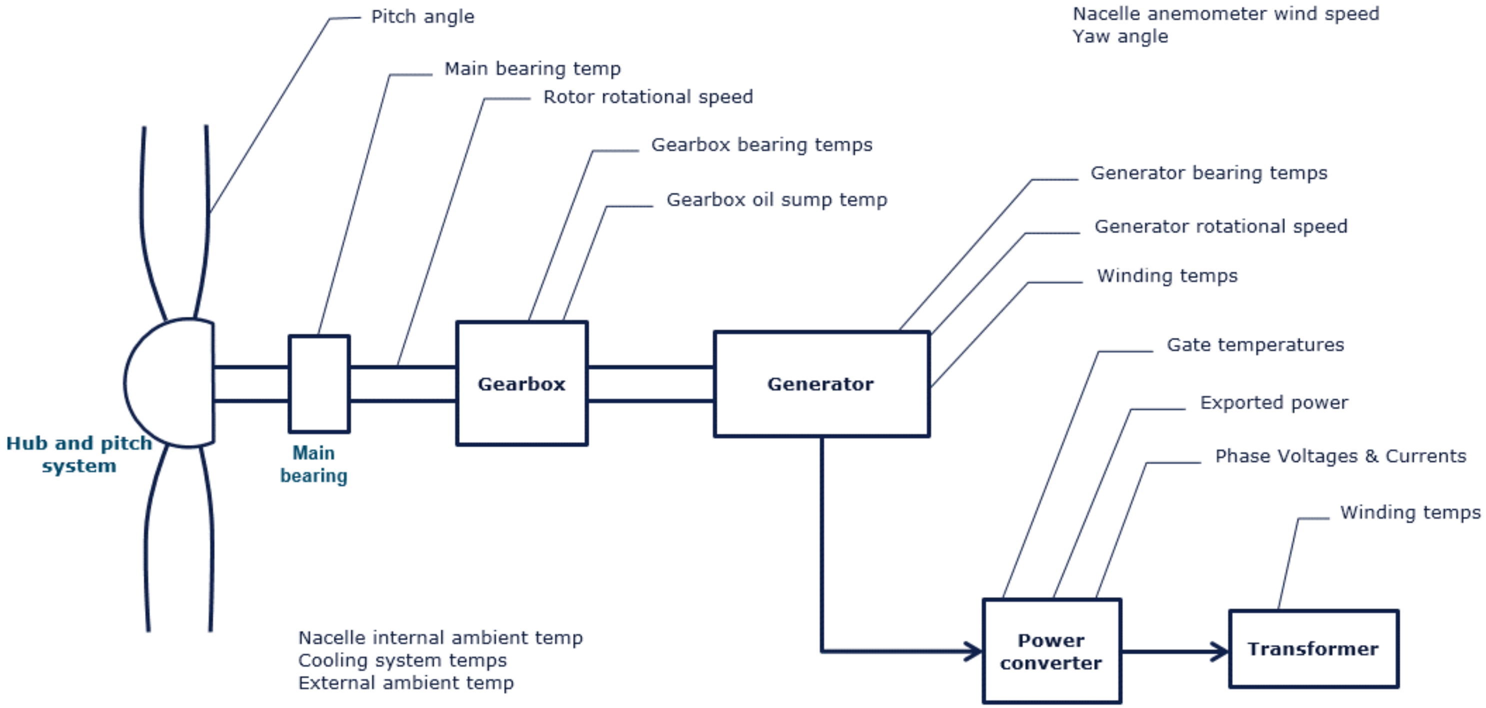
- One of the six modules contained within WindGEMINI

- Failure detection algorithm that uses existing 10-minute SCADA data

- Based on trending of the temperature signals from the wind turbine drivetrain

- The assumption is that an increase in temperature is indicative of dissipation caused by an anomaly

- No additional sensors are required





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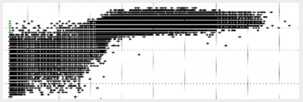
# Machine Learning Approach

Historical data



Model training

$y = f(x_1,x_2)$

Measured input

$x_1,x_2$

Output estimate

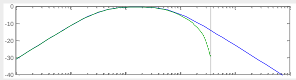
$\hat{y} = f(x_1,x_2)$

Measured output

$y$

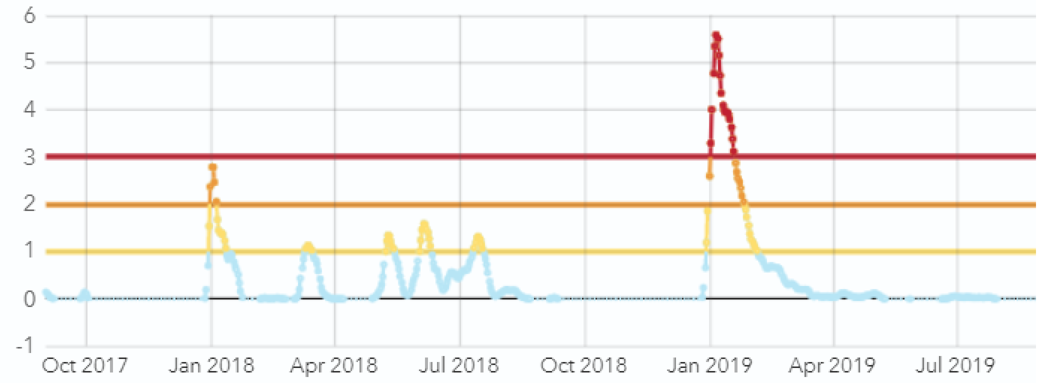
-

Filtering



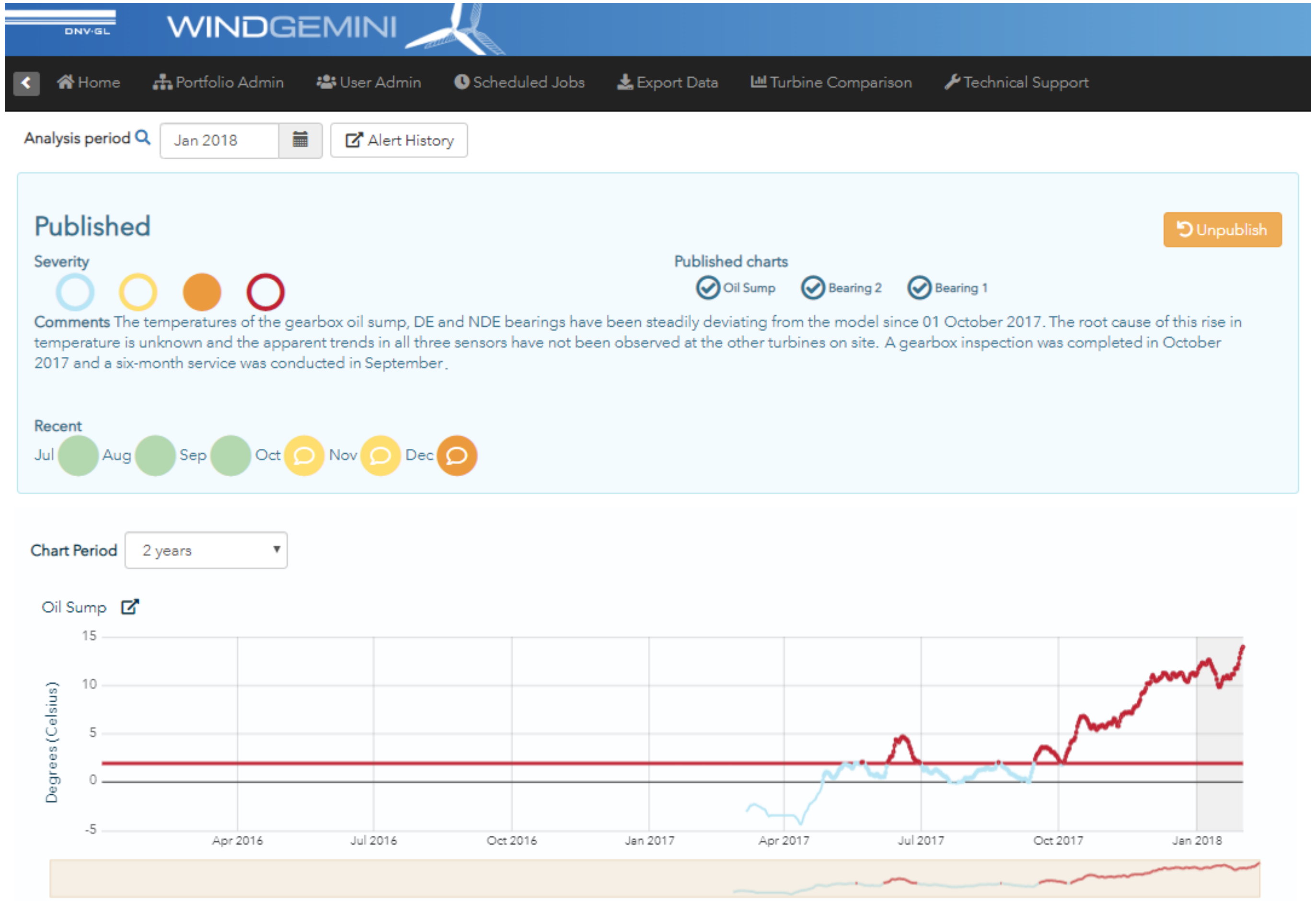
Nonlinear weighting function

- A period of normal operation is used to establish an expected relationship between input signals (power, ambient temperature, rotor speed) and the drivetrain temperatures being monitored
- The model is used for ongoing monitoring of the real temperatures
- Frequency domain filtering reduces noise and the impact of step changes (e.g. following sensor replacements), reducing the number of false positives
- A weighting function automatically assigns a gravity to the alerts



# Case study – October 2017

- In March 2017 a 2MW turbine experiences a gearbox failure
- WindGEMINI identifies an anomaly following the return to service
- Investigation showed one of the replaced components was defective
- Further analysis showed this was also having an effect on power curve efficiency (~94%)
- Issue was raised with the OEM and rectified, with an increase in performance and avoiding the risk of another failure and claim



# Thank you

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