

Abstract

We propose a computationally simple anomaly detection method that assists operators of wind parks with monitoring the health condition of wind turbines.

We show how SCADA data can be used to automatically learn a large number of simple models that in combination can alert the operator about a variety of potential defects in different components.

The method works without explicit process knowledge and is applicable to each WEC with sufficient number of SCADA sensors.

Offshore Wind Farm Global Tech I



The Global Tech I Offshore wind farm officially started operation in September 2015.

- Area 41km²
- 80 WEC AD 5-116 (ADWEN)
- 5MW rated output
- 400 MW total output
- 313 sensors accessible via SCADA per WEC

Problem

Condition based maintenance requires being aware of the current condition of all components of wind energy converters (WEC). Currently, monitoring relies mainly on explicit models for selected sensor, like warning thresholds for too low/high values or explicitly learned process aware models for common process steps (for example artificial neural networks to monitor the power curve, yaw inertia etc.). Finding common high quality observation models for WECs is difficult, and therefore costly, because of the heterogeneity of their structure, parametrization, location aspects etc.

We needed a way to automatically learn, which value each sensor of each WEC should measure at any given time in respect to other sensors of the same wind power plant. This comparison allows the operator to be aware earlier of changes in the behavior of components than by relying on SCADA alerts only.

“Anomaly” in the context of this project means **“any unexpected qualitative change in the behavior off a WEC in comparison to a past reference time interval”**.

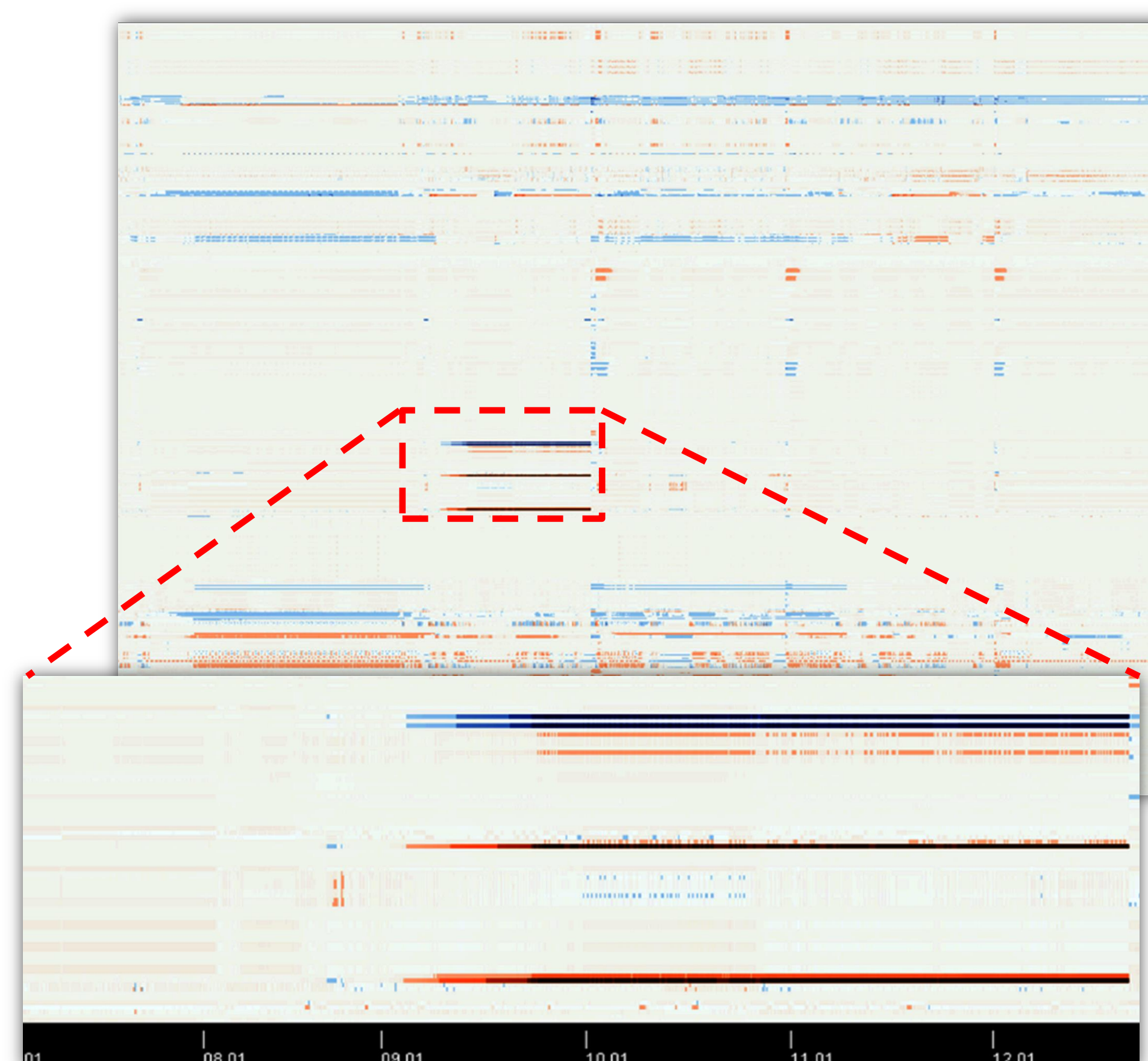
Methods

We use LASSO regression (multiple linear regression with automatic feature selection) to learn predictive models for each sensor. To do this, we use each sensor time series as a feature, as well as time lagged versions of each sensor (the value 10min or 20min ago).

These models can be used to predict which value each sensor should read at any given time. If there is a divergence between the measurement and the prediction, we have an anomaly candidate.

For each sensor we try to learn multiple different models to capture as many distinct data relationships as possible.

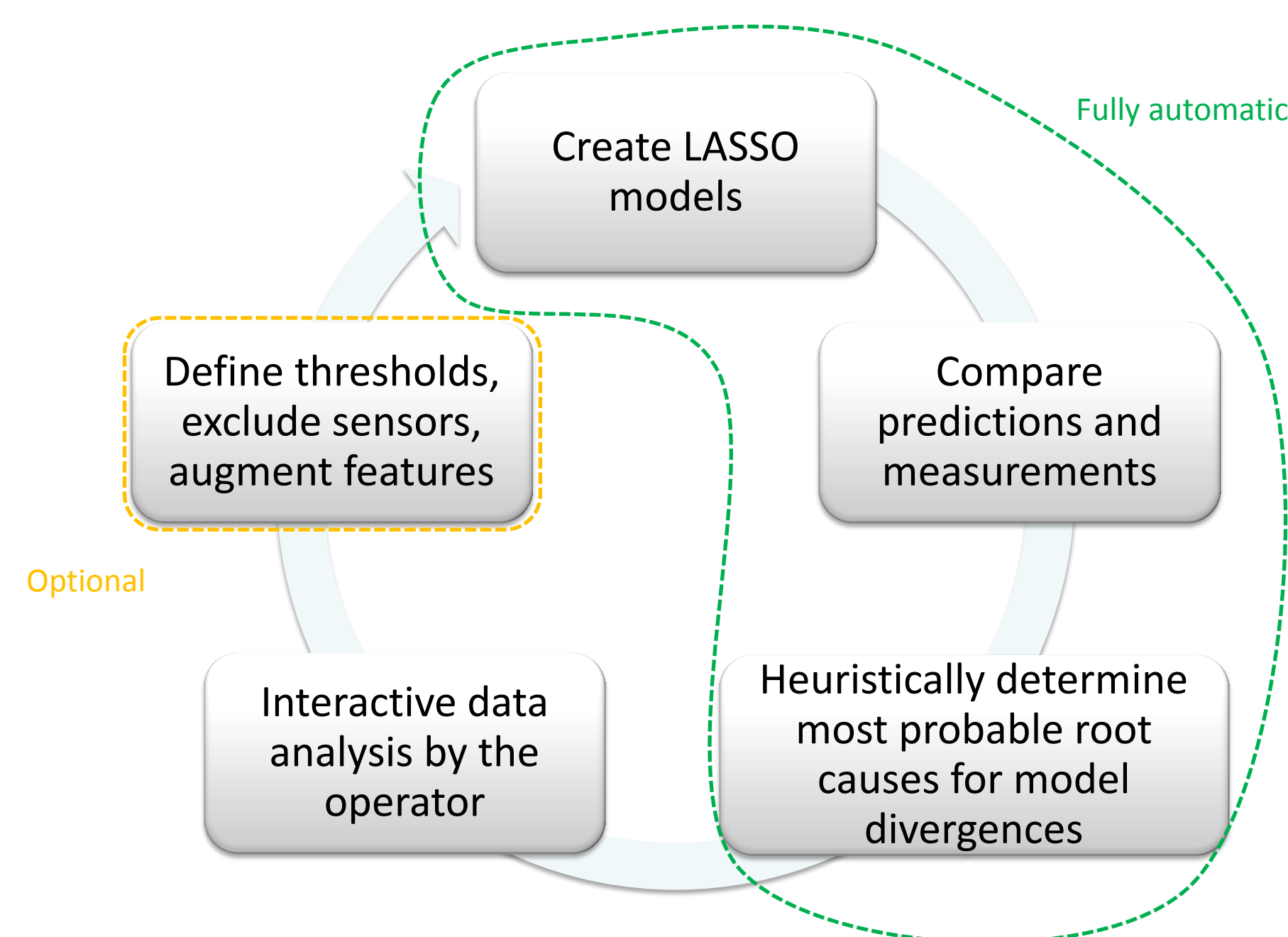
Outputs of one model per row



One pixel column per 10min interval

The chart above shows the divergences of each model from the real sensor measurement per time step. Blue represents values lower than expected, orange stands for too high values. We can see a simultaneous qualitative change in several models, indicating a change. We can't simply assume, that the target sensor of the respective model has changed, because the main reason for the divergence might be a change in a model predictor. We employ a heuristic to determine the most probable root causes for all observed changes.

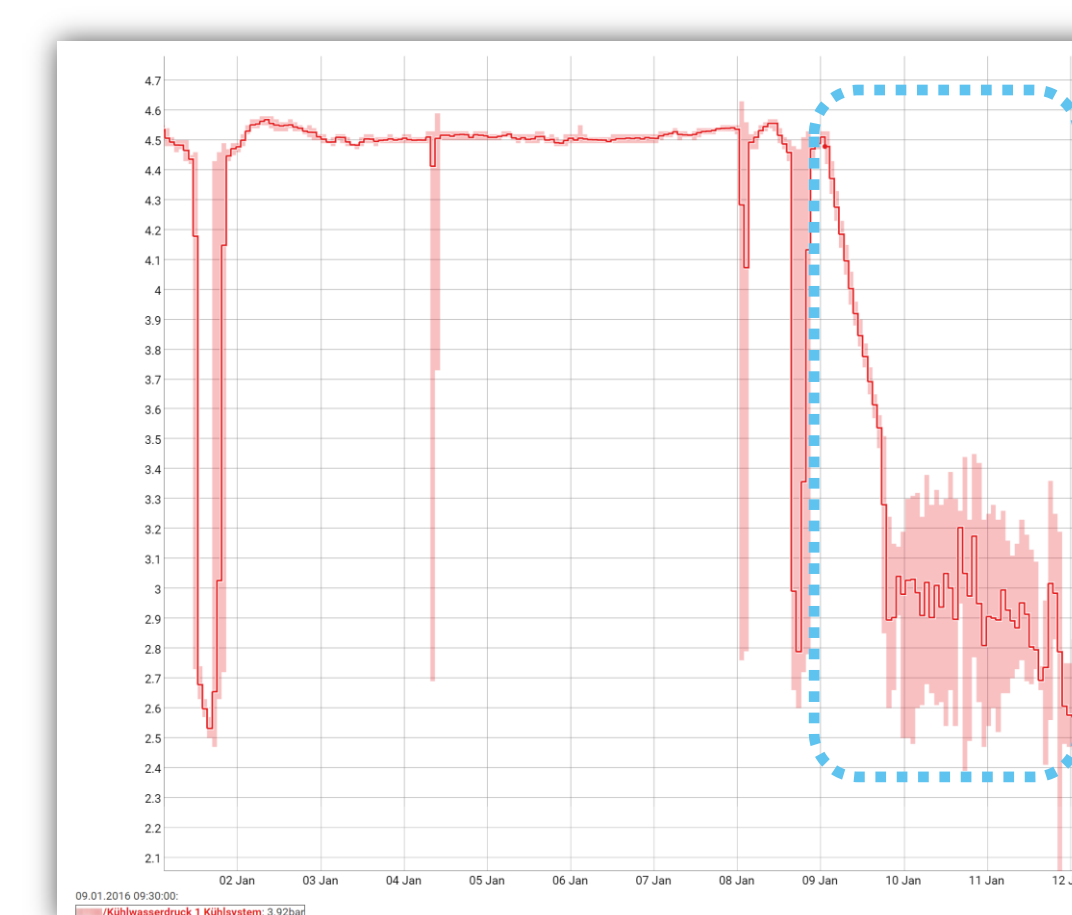
Fully automatic learning



The learning, application and evaluation of models is fully automatic. Learning 700 models per WEC for a four month data interval takes less than a minute. The operator is still responsible for interpreting the found anomalies and suggesting adequate actions.

Results

The anomaly detection used four months of data to learn on average 700 different regression models per WEC (about 2-3 distinct models per sensor) from a four month reference time interval. The anomaly evaluation heuristics subsequently flagged a number of interesting behavioral changes in the data, many of which were either not signaled by the SCADA system or with longer delay than our method. Some types of failures detected:

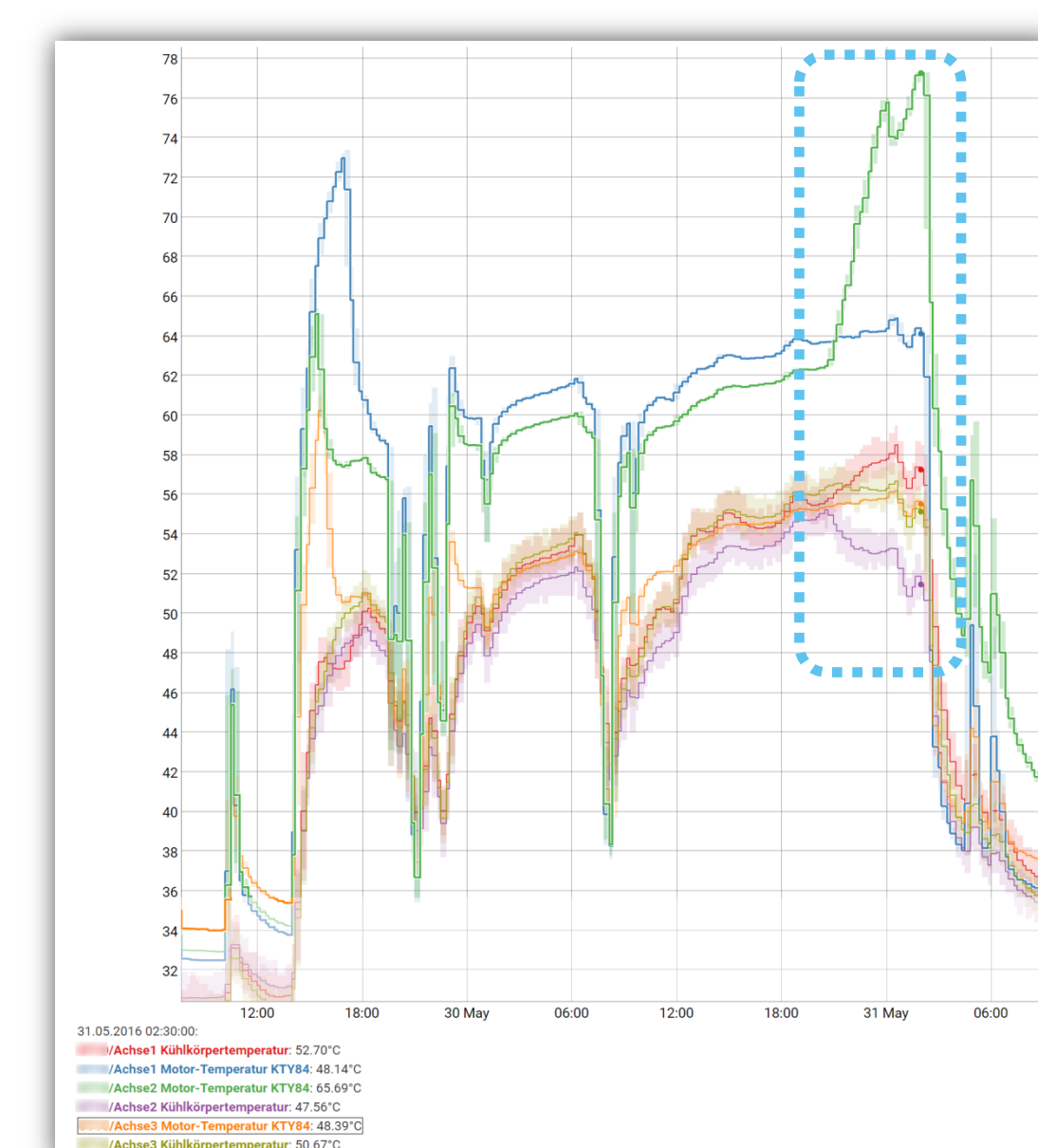


Coolant leak

SCADA signaled an error only as soon as the water pressure dropped below 1.5bar, two days later than our method

Failure of heatsink

Drop of heatsink temperature of the pitch motor 3 with simultaneous increase of the respective motor temperature

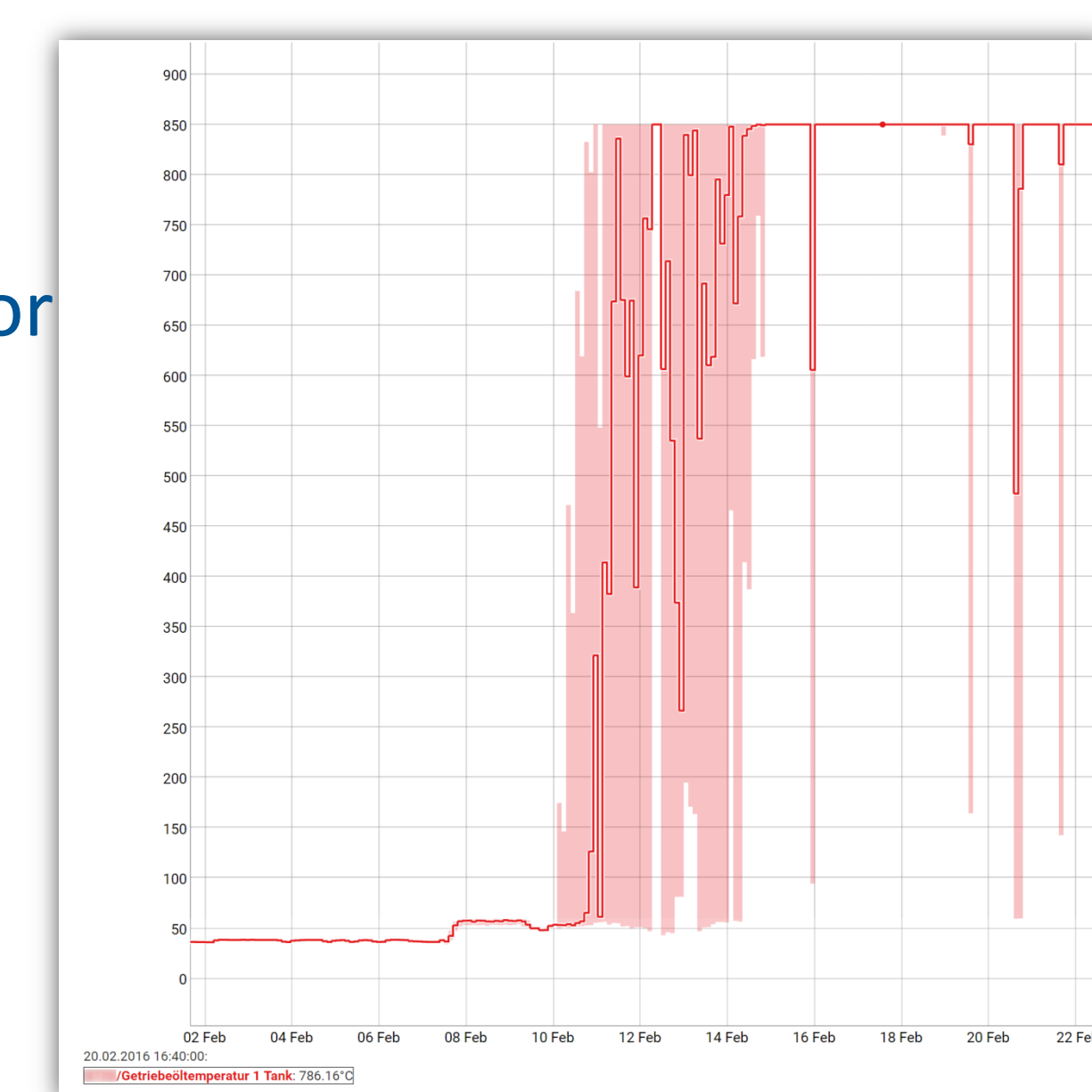


Nacelle misalignment

A wind direction sensor is drifting, leading to a misalignment of nacelle orientation and wind direction

Sensor defects

Most common error reason: Hardware related defects on sensor, cable insulation, conductivity etc. Values are implausible



Conclusions

The anomaly detection method can be used with any SCADA sensor data and was used in this use case to great effect. The operator was able to detect many defects, sensors and components, he would not be aware of by relying on SCADA alerts only. Due to the space restrictions of this poster we recommend our accompanied paper for further details.

