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Wind Turbine Fault Detection based on Artificial Neural Networks Analysis of SCADA data

Herp, Jürgen, & Nadimi, Esmaeil S.
Mærsk Mc-Kinney Møller Institute, University of Southern Denmark

Abstracts

Slowly developing faults in wind turbine can, when not detected on time, cause severe damage and downtime [1,2]. We propose a fault detection method based on an Artificial Neural Network (ANN) [3] analysis of Supervisory Control and Data Acquisition (SCADA) data. We construct a model for the normal behavior of a wind turbine and evaluate data from two turbines. The fault detection is based on the statistical analysis of the model's residuals.

Concerning turbine vibrations, decomposed in the x and y components, it is shown that the first indications of abnormal behavior is about a month prior to a fault recorded.

Objectives & Data

The aim of this work is threefold: (i) construct a model for the vibration of a healthy wind turbine, (ii) estimate the control threshold necessary for outlier detection, and (iii) evaluate the models effect on the turbines.

The data provided are measurements from two turbines of the same type placed in the vicinity of each other, recorded from Dec-12 2012 to May-31 2013 (referring to as Turbine I) and Dec-12 2012 to Feb-26 2013 (referring to as Turbine II). They comprise environmental, system, and performance parameters.

ANN Model

The ANN is composed of interconnected artificial neurons by weighted links between them. Training the model is done by updating those weights to minimize the residuals $y - \tilde{y}$. The model is trained on data belonging to Turbine I (Dec-12 to Feb-26) randomly divided into training and validation. They include as many variations in ambient and system conditions as possible, under the assumption of normal operation, e.g. cut in and out operations, lubrication, untwisting cables, inspection downtime etc. The model performance is shown in Figure 1.

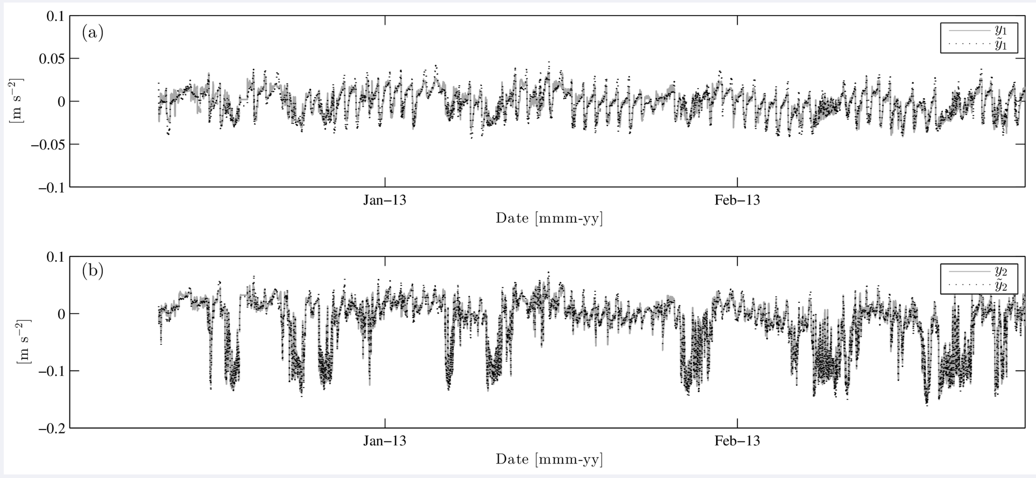

Figure 1: Training & Validation: Model overlay on the data.

Model Evaluation & Fault Detection

In order to address abnormal behavior of the wind turbine, we establish a control bound on the model's residuals, based upon a Generalized Likelihood Test:

$$\begin{cases} \mathcal{H}_o \ if \ \mathcal{L} < h(\eta) \\ \overline{\mathcal{H}_o} \ else \end{cases},$$

with false alarm rate η, control threshold and the maximum likelihood estimation:

$$\mathcal{L} = \frac{\max \mathbb{P}(y|\overline{\mathcal{H}_o})}{\mathbb{P}(y|\mathcal{H}_o)}.$$

In this framework the residuals are supposed to satisfy either a normal distribution with zero mean for fault-free data, $\mathcal{H}_o$, or an alternative hypothesis associated with abnormal behavior, $\overline{\mathcal{H}_o}$. Any measurement exceeding the upper bound of 0.017ms^{-2} or lower bound of -0.016ms^{-2} in the x-direction, or the upper bound of 0.02ms^{-2} or lower bound of -0.02ms^{-2} in the y-direction, is then considered abnormal.

Turbine I

Applying the ANN model and the fault detection approach results in Figure 2. It is seen that outliers successively following each other increase after Apr-01, and are grouped in longer lasting intervals indicating divergence from a fault-free state prior to a failure on May-16. Statistically, the residuals were interpreted as model errors and as such would be expected to follow a normal distribution. In the absence of any event the residuals indeed follow a normal distribution, as shown in Figure 3 for the shaded region in Figure 2. The corresponding density and quantile plots for the entire training and test subset of Turbine I is seen in Figure 4. Remark that the statistics of the training and validation set differ compared to Figure 3, although it is considered fault-free. The heavy tails are believed to be due to events affecting the turbine not entirely covered by the ANN model.

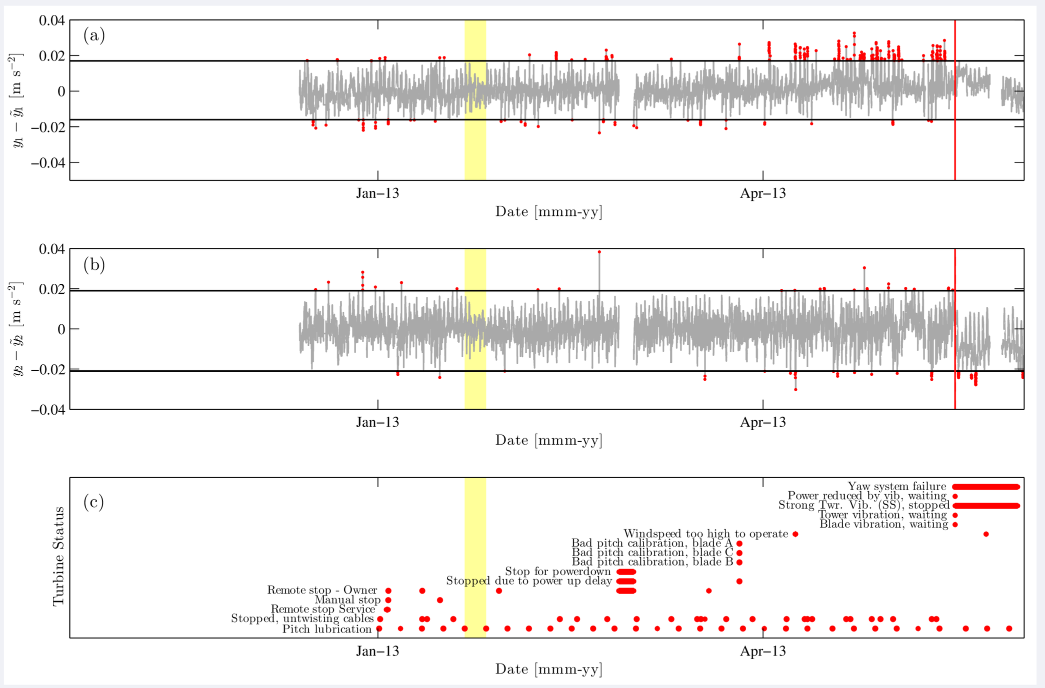

Figure 2: Threshold Detection: (a) & (b): Residuals of the ANN with upper and lower control thresholds. The vertical line indicates an occurrence of a severe fault. (c): Recorded events effecting the turbine performance.

Panel (a), (b) and (d), (e) in Figure 4 still suggest a distribution close to a normal distribution with zero mean. Comparing the training and test statistics implies that the ANN model does not capture all variations; the distribution become more heavy tailed and skewed, thus suggesting that the outliers in panel (a) in Figure 2 are indeed indicating an abnormal behavior prior to a fault.

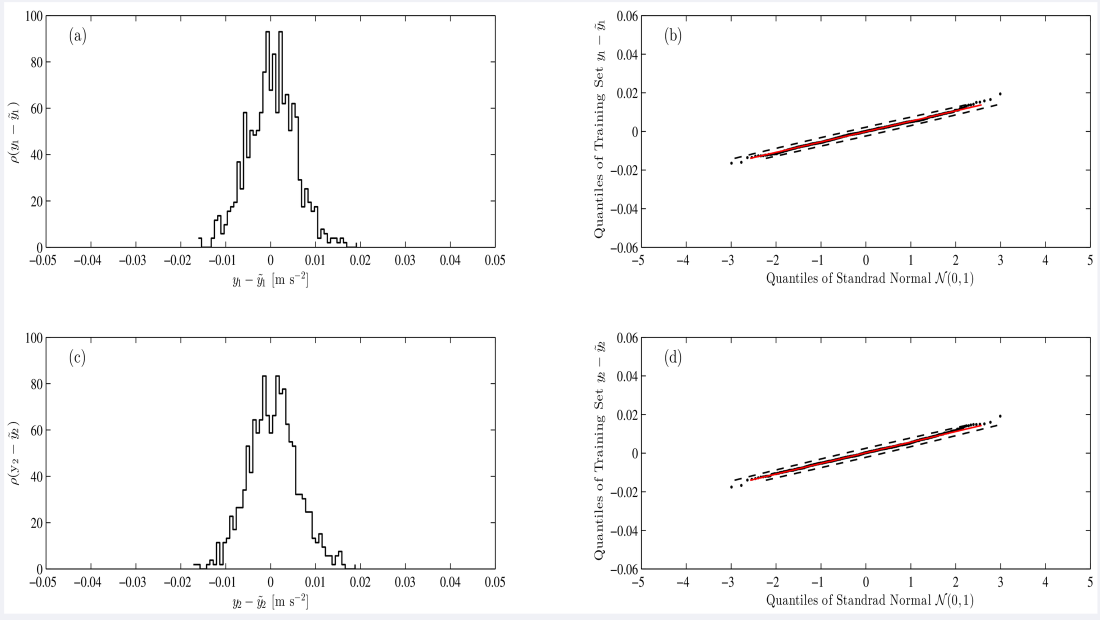

Figure 3: Auto Correlations marked area of Figure 2: From left to right the density distribution of the residuals and the quintiles compared to a normal distribution.

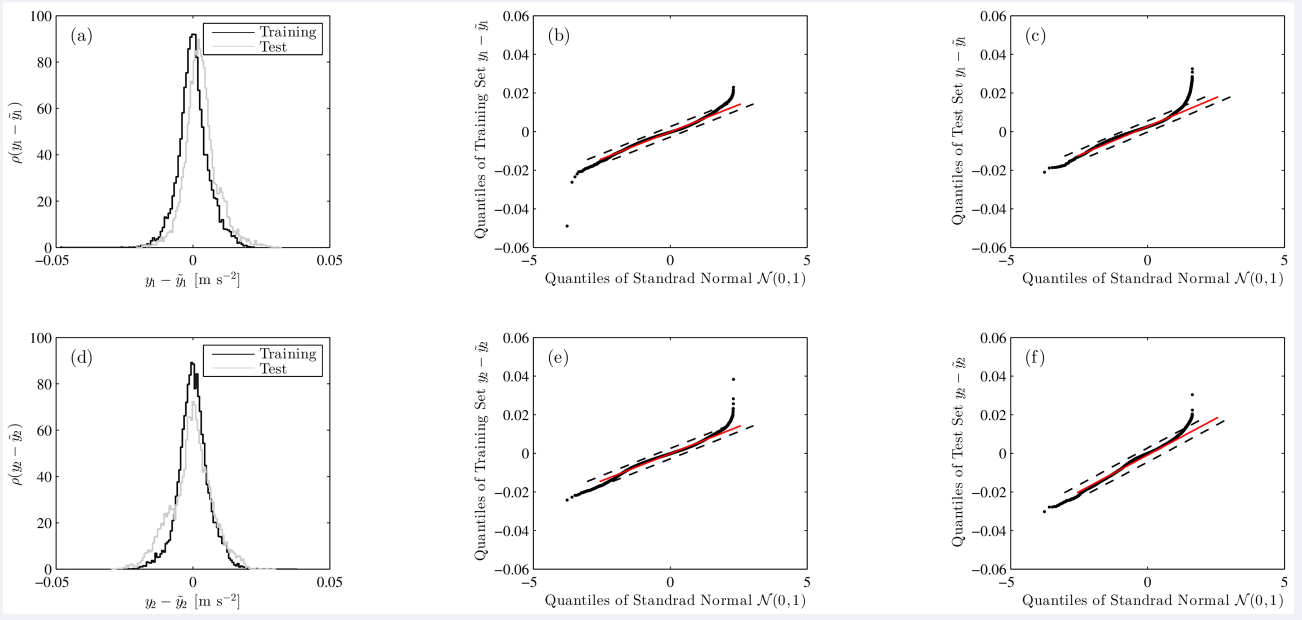

Figure 4: Auto Correlations: From left to right the density distribution of the residuals and the quintiles compared to a normal distribution for both the Training and Test data set.

Turbine II

To test the performance of the model further, we apply it to measurements of Turbine II. The control bounds in Figure 5 indicate that no abnormal behavior can be confirmed for this turbine, which is in agreement with the turbines log. So far this has been preliminary work, and a more in depth investigation is needed as Figure 5 indicates skewed distributions of the residuals with non zero means (Figure 6) , raising the question if the ANN model does not cover all dynamics or infer some of its own. The tendency to negative residuals shows an overestimation of the ANN model and is most likely explained by placing the cause of the fault in Turbine I in the training and validation set, including variations that are not present in the data of Turbine II.

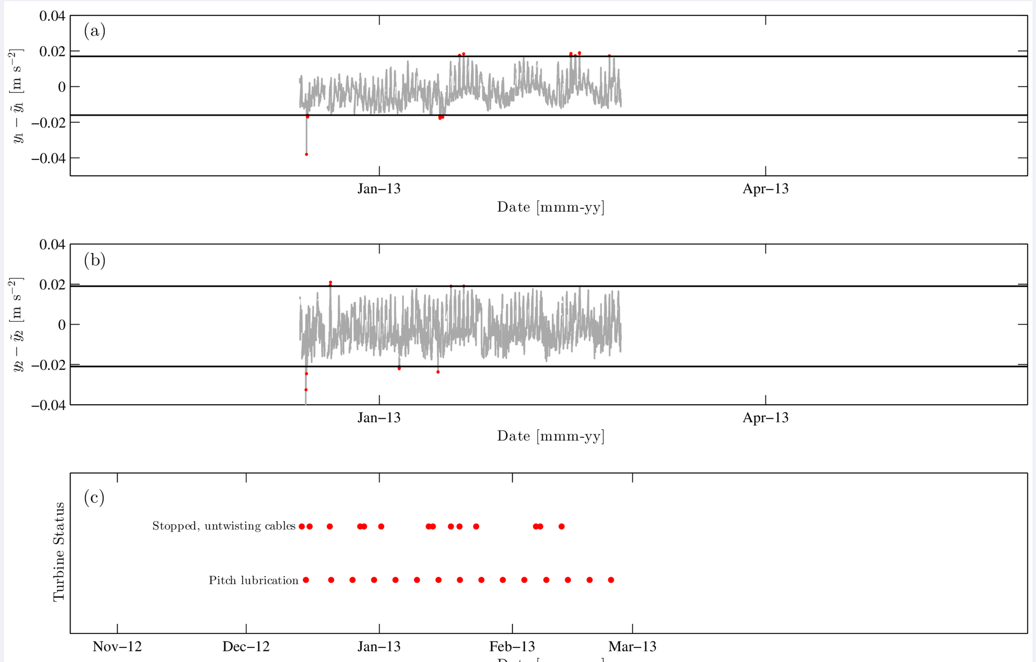

Figure 5: (a) & (b): Residuals of the with upper and lower control thresholds. (c): Recorded event.

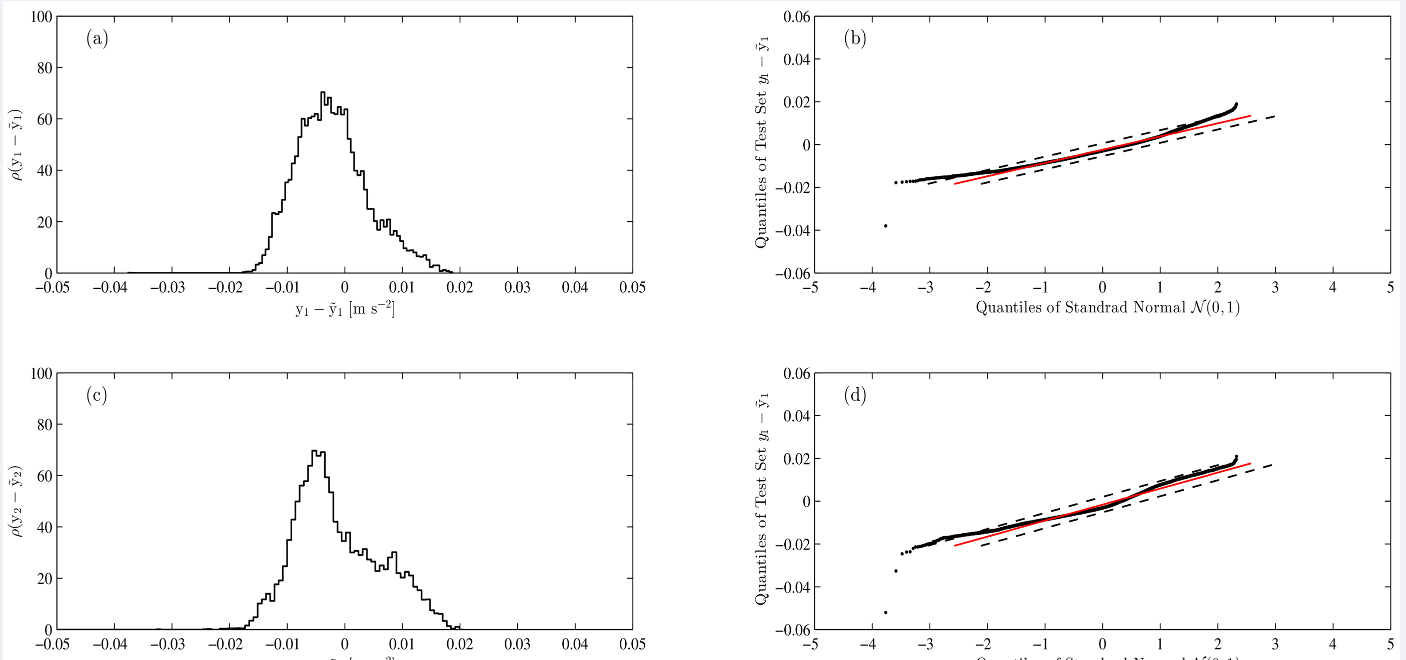

Figure 6: Auto Correlations: From left to right the density distribution of the residuals and the quintiles compared to a normal distribution.

Conclusion

This work shows that ANN besides over-temperature detection [4, 5, and others] is applicable for monitoring wind turbines. However, the dilemma of Turbine II places the challenge of building robust ANN models on selection the "proper" training and validation set in order to account for most of the variations a turbine experiences while still satisfying the assumption of being fault-free.

Future research will focus on the real-time inference of ANN in order to avoid presented dilemmas and include fault identification.

References

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