Condition monitoring of wind turbine drive trains by normal behaviour modelling of temperatures

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Contents

1 Abstract

Condition monitoring and early failure detection are needed to reduce operational costs of wind turbines, particularly for offshore farms where accessibility is restricted. Failure detection technologies should be simple and reliable in order to contribute to the overall aim of cost reduction. Operational data from the Supervisory Control And Data Acquisition (SCADA) system are a potential source of information for condition monitoring and have the advantage of being recorded at each turbine without the costs of additional sensors. Detection of drivetrain failures using these ten-minute data has been successfully demonstrated in the last five years. This paper summarises and evaluates different ways of so-called normal behaviour modelling of temperature using SCADA data, i.e. the prediction of a measured temperature under the assumption that the system is behaving normally. After training, the residual of modelled and measured temperature acts as an indicator for possible wear and failures. Multiple approaches are discussed: linear modelling, artificial neural networks in auto-regressive, feed-forward and layer recurrent configurations, adaptive neuro-fuzzy inference systems and state estimation techniques. A case study with real data reveals differences of approaches, sensitivity to training data and settings of algorithms. Early failure detection of a gearbox failure is demonstrated, although challenges in achieving reliable monitoring without many false alarms become apparent.

2 Introduction

Although wind energy costs have been dramatically decreased in the last decade, maintenance costs still contribute with up to 40 EUR/MWh for offshore farms [MIL14]. Traditional corrective maintenance strategies cannot be used for current projects in remote or offshore locations where limited accessibility would result in extended downtimes. Additionally, the financial losses per downtime are more critical nowadays due to dramatically increased turbine sizes and associated higher energy production. The advanced maintenance strategy of condition-based or predictive maintenance requires health statuses for all critical parts. Temperatures recorded by the Supervisory Control And Data Acquisition (SCADA) system are a cost-effective way to monitor the drive train health as these are commonly available for performance monitoring. In contrast, 'dedicated' condition monitoring systems, which are mainly based on vibration monitoring, are installed as an 'add-on' and may cost 11,000 EUR per turbine [YAN13]. Although SCADA data are usually sampled as low resolution 10 minute averages, slow wear related degradation can be tracked by finding changes in the temperature behaviour – i.e. how the temperature reacts in the transient interaction of turbine loading, cooling systems, heat convection and the environment. In contrast to monitoring of high absolute temperatures which commonly occur only shortly before a fault, the slight changes in the temperature behaviour can develop well in advance. First approaches investigated trends by visually comparing drive train temperatures as a scatter plot against the relative power [WIG08, FEN13] or building clusters of presumed healthy and faulty samples [KIM11, WIL14]. These attempts proved that analysis of SCADA data might help to detect imminent failures, but highly manual interpretation was required. For effective clustering of the condition, training data including faults has to be available, which is not feasible in practice. Recent research has focused on data-driven normal behaviour modelling (NBM), where temperatures are modelled using the history of the signal and / or information from other sensors while assuming normal behaviour, i.e. a healthy turbine [WIL14, SCH13, SUN16]. Further research has e.g. investigated more physical damage modelling or assessment of SCADA alarms. An overview of condition monitoring with SCADA data can be found in a recent review of the authors [TAU16a]. This paper focuses on different approaches of NBM of drive train temperature and ways to detect imminent failures. In a case study, data from a real wind farm are used to briefly demonstrate the functionality and assess the quality of modelling and monitoring.

3 Main section

NBM can be described as modelling a signal with information from the environment and from the process itself as sketched in Figure 1. In the case of the wind turbine considered as a process, the environment might consist of e.g. ambient temperature, wind speed etc. and process variables like turbine power output, rotational speed or temperatures acting as additional inputs. The model uses the information from the inputs to predict the target temperature by learning the relationship during a training phase. Different methodologies for modelling are discussed in chapter 3.1. After training, the residual of measured and modelled signal is expected to be approx. 0 for healthy conditions and different from 0 for faulty conditions. Several techniques to detect anomalies in the residual are discussed in chapter 3.2.

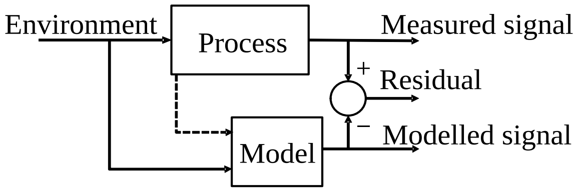

Figure 1: Sketch of NBM principle [TAU16b]

3.1 NBM modelling techniques

The different NBM modelling techniques can be assigned to two main approaches. If historic values of the target are used beside other inputs, the model can be termed auto-regressive with exogenous input (ARX). On the other hand,, full signal reconstruction (FSRC) avoids using the history of the target signal. The most promising FSRC modelling approaches derived from an earlier case study [TAU16b] are compared with three different ARX approaches.

3.1.1 FSRC – non-auto-regressive

FSRC is tested by using the two strongest signals from a cross-correlation analysis as inputs to predict a target temperature. Findings from a previous case study indicated that using more or lagged inputs does not necessarily improve the accuracy significantly [TAU16b].

One of the simplest ways of modelling the target temperature is building a weighted sum of the inputs. Although the assumption of linearity may not be true for drive train temperatures, successful failure detection based on linear NBM has been demonstrated [SCH10]. In this work, linear modelling with interactions (LINI) is tested, allowing linear terms, an intercept and products of the input pairs as inputs conducted with a least squares fit solver.

Artificial Neural Networks (ANN) can be applied to various non-linear problems. For NBM of drive train temperatures, feed-forward networks (ANN-FF) have been widely applied, e.g. [SCH10]. A network with one hidden layer of six neurons is trained with Levenberg-Marquard backpropagation. A layer recurrent architecture (ANN-LR) with a delay of two time-steps is investigated to consider the inertia of the system.

Adaptive Neuro-Fuzzy Inference System (ANFIS) as a combination of fuzzy inference and neural network learning has been demonstrated for failure detection [SCH13]. A setup with two Gaussian membership functions per input in combination with a linear output function is trained with a hybrid least squares and backpropagation algorithm.

3.1.2 ARX – auto-regressive

ARX modelling is investigated by using the same two exogenous inputs and historical values of the target temperature. Linear and ANN ARX modelling is supported by the last 20 time-steps of the target temperature.

Non-linear State Estimation Technique (NSET) as proposed by [WAN12] is also investigated with a memory matrix of training states and an estimation of the target via a weight matrix determined by the minimal Euclidean distance of observation and state matrix. NSET can be considered as similar to ARX, because the current observation is used to build the estimate. The number of states in the memory matrix is reduced with a selection algorithm [WAN12]; here an allowed distance to the grid of $\delta = 0.00015$ is used.

3.2 Prediction performance metrics and anomaly detection techniques

The accuracy of predicting a temperature signal can be described by statistical metrics related to the residual, i.e.: the mean absolute error (MAE), standard deviation of absolute error, the root mean squared error, mean absolute percentage error or the coefficient of determination R^2.

Different techniques to detect anomalies in the residual have been proposed for NBM of drive train temperatures. Obviously, a fixed threshold for the residual based on training experience (i.e. the residual distribution) is an easy way of detecting higher temperatures than expected. Averaging the residual for one day has been proven to be beneficial to increase certainty in results [SCH10, SCH13]. An exponentially weighted moving average control chart was proposed to account for cumulating effects [WAN16]. A Mahalanobis distance was suggested considering the training distribution and built for residual and target [BAN15]. A daily 'abnormal level index' was introduced with penalties for residuals based on their assignment to defined zones in the training distribution [SUN16]. Raising an alarm if several alarms in a week occurred has proved to be an efficient way to reduce false alarms [SCH13].

Table 1 gives the details of the investigated anomaly detection techniques in this work.

Technique	Details	Warning	Alarm
Raw residual (RAW)		$>$ X % of a Normal distribution fitted to training residual	$\geq$ 288 ten minute warnings in past 7 days
Daily residual [SCH10] (DAILY)	average of 144 samples		
Mahalanobis distance [BAN15] (MAHAL)	distance is a function of residual and target referencing to training residual and target	$>$ X % of a Weibull distribution fitted to training distance	
Exponentially weighted moving average control chart [WAN16] (EWMA)	past observations weighting with $\lambda = 0.2$	$< \mu - X\sigma$ or $> \mu + X\sigma$ with μ: mean, σ: standard deviation of the training residual	
Abnormal level index [SUN16] (ALI)	penalty= $\begin{cases} 5, \text{if} > 97.5\% \\ 3, \text{if} > 75\% \\ 1, \text{else} \end{cases}$ of Normal distribution fitted to the training residual	fuzzy warning between 0 and 1	moving average of last 7 days' warnings

Table 1: Configuration of anomaly detection techniques (the warning threshold X is calibrated, cp. chapter 3.3.2 and Table 2)

3.3 Case study for gearbox monitoring

Data from a Scottish wind farm with 12 turbines with a rated power of 2-3 MW are analysed. The maintenance records indicate 4 turbines with a gearbox exchange in the investigated 2.5 years of available data. Due to missing maintenance reports, the reasons for the exchanges are unclear. It is assumed that the gearboxes failed and, in general, gearbox bearing failures are the most likely cause. The SCADA data are preprocessed by filtering of non-operational times and checking for valid sensor ranges. NBM with 5 months of training is applied to detect gearbox failures in a drivetrain temperature.

3.3.1 Normal behaviour prediction performance

The prediction performance of the different modelling approaches is visualised in Figure 2 for all turbines in the farm which are not affected by gearbox exchanges. The results indicate that NSET outperforms all other approaches. ANNFF, ANNLR and ANFIS perform with similar accuracy. Using historic values in an ARX setup does not prove to be truly beneficial for ANN modelling. Linear ARX modelling results in poor performance and is excluded subsequently.

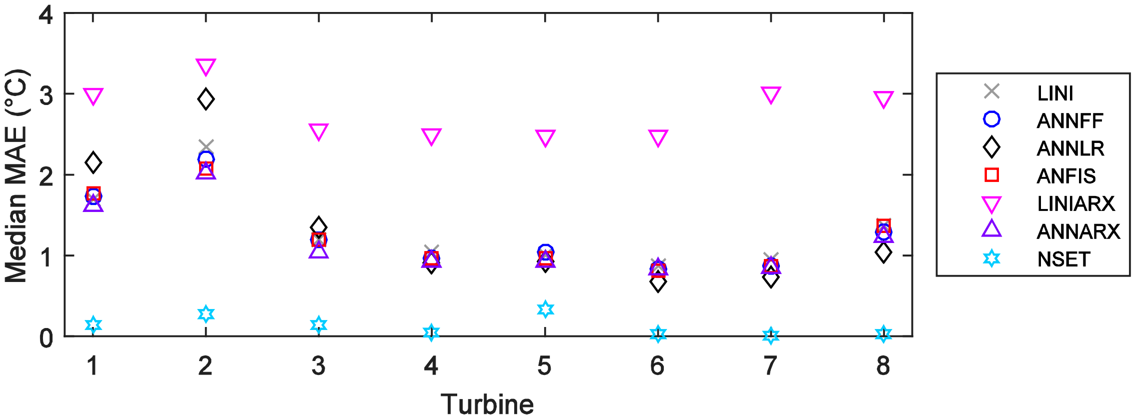

Figure 2: Median of monthly performance for turbines without gearbox exchange

3.3.2 Calibration of anomaly detection thresholds

The warning thresholds for the anomaly detection techniques are calibrated with modelling results of one turbine without gearbox exchange. In a simple optimisation the thresholds are decreased in steps of 0.05 as long as no alarms are issued. The resulting thresholds are summarised in Table 2. The parameters for the ALI calculation are not calibrated due to the higher complexity of this technique.

	LINI	ANNFF	ANNLR	ANFIS	ANNARX	NSET
RAW (%)	95.25	98.45	97.50	98.10	99.45	65.95
DAILY (%)	93.75	97.55	98.50	97.20	98.90	72.20
MAHAL(%)	87.85	93.35	95.40	92.15	97.35	85.90
EWMA (-)	3.00	3.70	3.75	3.55	4.35	0.70

Table 2: Calibrated warning threshold X for different techniques (cp. Table 1)

3.3.3 Gearbox failure

Evaluation of the maintenance records indicate a gearbox failure and finally exchange in turbine A. From the daily residuals shown in Figure 3 it is difficult to visually identify the change in the behaviour before the failure. The sinusoidal variation of the residual indicates that the training has not learned this effect probably caused by seasonal temperature changes.

Application of the calibrated anomaly detection techniques resulted in the alarm patterns given in Figure 4. All alarms which are close to the end of the time axis can be considered as valid alarms for the gearbox degradation. Using LINI modelling, the earliest alarms which are not interrupted for more than two weeks until the end are raised approx. 25 days before failure for RAW, DAILY, MAHAL and EWMA anomaly detection. ANNFF modelling results in an early alarm 30 days before failure for RAW, MAHAL and EWMA and even 35 days in advance for DAILY. Similar results are obtained for ANNLR with 34, 23, 29 and 30 days for RAW, DAILY, MAHAL and EWMA, respectively. ANFIS modelling gives an early alarm (24 days) only for RAW anomaly detection (DAILY: no, MAHAL: 4, EWMA: 7 days). Failure detection with ANNARX and NSET and the discussed anomaly detection techniques does not work at all. LINI modelling and MAHAL anomaly detection are affected by alarms long before the fault, which could also indicate the gearbox degradation, but might be false alarms. The fuzzy alarm generated by the ALI technique shows an upward trend for all modelling techniques except NSET. However, it has to be noted that ALI levels of a similar magnitude occurred in the turbine used for calibration.

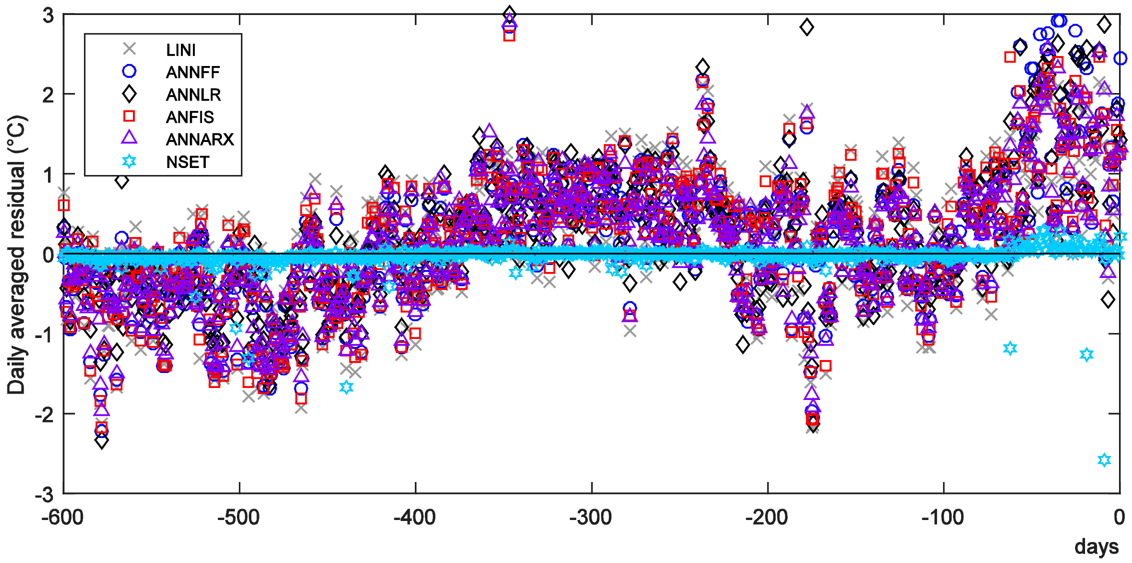

Figure 3: Residual of modelled and measured temperature before a gearbox failure

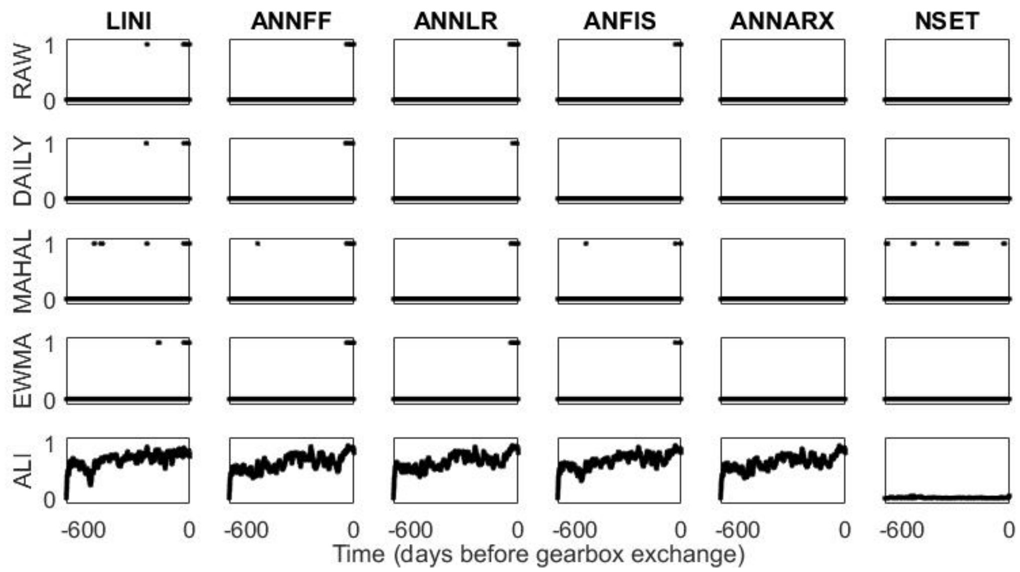

Figure 4: Alarms of different NBM modelling techniques and ways of anomaly detection

3.3.4 Validation with remaining turbines in farm

Application of the modelling and anomaly detection techniques on the other three turbines undergoing a gearbox exchange resulted in less clear and probably many false alarms. However, ANNFF and ANNLR modelling generated the best compromise of possible early alarms and minimal possible false alarms in two of three cases.

Testing the algorithms on the remaining turbines without noted gearbox exchanges revealed that the calibration did not work properly as high alarm levels occurred.

4 Conclusion

Different modelling techniques and anomaly detection techniques have been discussed and compared with the aim of condition monitoring of wind turbine drive trains.

The application of NBM algorithms in a case study shows that temperature prediction with a mean error of approx. 1° C is feasible with two model inputs for all investigated modelling techniques except linear ARX. Indeed, NSET performs with a prediction error approx. ten times smaller.

Using the residual of measured and modelled temperature for fault detection is not as straightforward as might be assumed. The calibration of the thresholds of the different anomaly detection techniques with one turbine in the farm did not result in reliable fault detection for all turbines. This might be due to various reasons including the unaccounted seasonal effect, suboptimal configuration of modelling techniques and anomaly detection algorithms or even incomplete maintenance records and poor data quality. However, the successful detection of a gearbox failure in one turbine up to 35 days in advance shows promise for LINI, ANNFF, ANNLR and ANFIS modelling, in particular using RAW and DAILY anomaly detection. The poor failure detection performance using ARX modelling techniques including NSET indicate, that although the target temperature is accurately predicted, the model parameters are adapting to new behaviour associated with incipient failure so no change in residual behaviour is observed. The ALI fuzzy alarm generation has not been implemented in a comparable manner to the other detection techniques, but the challenges of finding only true alarms have been visible here as well.

Further research needs to address the seasonal effect, optimal input selection, suitable calibration of anomaly thresholds, dedicated anomaly detection techniques for ARX techniques and additional ways to achieve reliable failure detection.

Acknowledgement

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 642108 (Advanced Wind Energy Systems Operation and Maintenance Expertise, http://awesome-h2020.eu/).

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