Combining Model-based Monitoring and a Physics of Failure Approach for Wind Turbine Failure Detection

J. Tautz-Weinert[1], S. J. Watson[1]

[1] Centre for Renewable Energy Systems Technology, Loughborough University, Loughborough LE11 3TU, UK

ABSTRACT

Condition monitoring of wind turbines with only operational data has received more attention in the last decade due to the advantage of freely available data without extra equipment needed. Although the operational data recorded by the Supervisory Control And Data Acquisition (SCADA) system are intended for performance monitoring and typically stored only every 10 minutes, information on the turbine's health can be extracted. A major focus is here on the temperature signals of mechanical parts such as drivetrain bearings. Despite the fact that absolute temperatures rise very late in the case of a failure, the temperature behaviour might change well in advance. Model-based monitoring is a tool to detect these small changes in the temperature signal affected by varying load and operation. Data-driven models are trained in a period where the turbine can be assumed to be healthy and represent the normal operation thereafter. Degradation and imminent failures can be detected by analysing the residual of modelled and measured temperatures. However, detecting failures in the residual is not always straightforward due to possibly unrepresentative training data and limited capabilities of this approach. A different way of using SCADA data lies in the estimation of damage accumulation with performance parameters based on the Physics of Failure methodology. A combination of model-based monitoring with damage calculation based on a Physics of Failure approach is proposed to strengthen the failure detection capabilities. The monitoring performance is evaluated in a case study with SCADA data from a wind farm.

Keywords: wind turbines, SCADA, physics-of-failure, condition monitoring, machine learning.

Corresponding author: J. Tautz-Weinert (email: j.tautz-weinert@lboro.ac.uk)

1. INTRODUCTION

With the exponential growth of wind energy in the last decades, the demand for optimised asset management of wind turbines has slowly evolved. In the early days of wind energy, scheduled and corrective maintenance were the appropriate measures for easy-to-access onshore farms and small turbines. With the move offshore and turbine capacities in the multi-MW category in recent years, the more complicated accessibility and significant financial losses for any downtime demand an optimised maintenance strategy. Condition-based or predictive maintenance as a proven strategy in other industries, promises to increase the efficiency of maintenance by optimising the point of intervention based on the condition of the system and risks of imminent failures.

Condition-based maintenance requires adequate measurements and monitoring techniques to reveal the health of the turbine and probabilities of upcoming failures. Due to the complexity of a wind turbine, a single measurement cannot cover the monitoring of all possible structural, mechanical and electrical failures. Failure analyses showed that the gearbox and generator are the most critical subassemblies in terms of failure rate and the corresponding downtime [1,2]. Accordingly, research and industry have focused on condition monitoring of the underlying mechanical failure mechanisms in wind turbine drive trains, although structural health monitoring of the blades, tower and foundation and detection of faults in the power converter, pitch and yaw systems have also been investigated. Potential measurements were found as vibration, acoustic emission, strain, torque, temperatures or oil parameters combined with signal processing techniques such as filtering, synchronous sampling, Hilbert transform, Wavelet transform, Fast Fourier Transform and many others [3,4].

More recently, the use of the operational data recorded by the Supervisory Control And Data Acquisition (SCADA) system has been investigated due the availability of such data without additional sensor installations. While these data are mainly intended for monitoring the performance of turbines in terms of power production, availability, possible misalignment and similar, several different applications to condition monitoring have been identified. Alarm logs in SCADA data might be analysed to find the root causes of events [5,6]. However, the most promising information for drive train condition monitoring lies in the temperature signals as mechanical degradation shows in increased thermal losses [7]. Drive train temperatures in wind turbines fluctuate with changing wind speed, rotational speed and loading. Accordingly, absolute temperature thresholds are known to give late alarms in contrast to vibration-based condition monitoring systems [3]. To overcome this drawback, model-based monitoring can reveal hidden trends in the temperature time series. Due to the complexity of wind turbine systems, data-driven learning is preferred to analytical building of models. Inputs for modelling drive train temperatures might be other temperatures, control signals as the power output or rotational speed or even the history of the target in a partly autoregressive approach. Modelling of the temperatures has been investigated with simple linear sums of inputs [8], artificial neural networks (ANNs) [9,10], adaptive neuro-fuzzy inference systems [11] or state estimation techniques [12]. A previous comparative study of the authors showed that most of the (non-autoregressive) techniques result in similar accurate prediction with slight advantages of ANNs [13].

In contrast to the model-based monitoring investigating temperature signals, the Physics of Failure approach tries to analyse the operational statistics derived from SCADA data in order to estimate the damage accumulation. In a case study with a big farm, it has been demonstrated that turbines with gearbox problems might be identified by their operational statistics [14].

In this paper, a combination of model-based monitoring with statistical analyses as used in the Physics of Failure approach is discussed and tested in a case study with data from an onshore wind farm.

2. MONITORING WIND TURBINE DRIVE TRAINS WITH OPERATIONAL DATA

The SCADA system in wind turbines usually measures multiple parameters with a sampling frequency of 1 Hz. Due to the fact that these measurements are originally intended for long-time performance monitoring, usually only averages and possibly extrema and standard deviations of ten minutes are recorded. The number and selection of measured signals depends on the turbine manufacturer or SCADA system provider, but wind speed and direction, pitch and yaw angles, rotational speed, power output and ambient temperature are always monitored. Additionally, temperatures of parts in the drive train are often measured – although with different levels of detail, e.g. only a generator and a gearbox temperature in one setup or more than twenty temperatures at different locations at the shaft in a more detailed configuration. The numerical SCADA data are supplemented by the alarm log listing all fault events happening during the operation.

2.1. Normal behaviour modelling of SCADA temperatures

Model-based monitoring [8–13] tries to identify anomalies in a system by comparing measured parameters with outputs of a model of the system. This kind of monitoring is able to highlight slight changes in measured signals affected by complex interaction of loading and heat transfers as in the wind turbine drive train. The model needs to predict the fluctuations of the temperature accurately enough to allow the residual of measured and modelled temperature to act as an indicator for possible degradation and imminent failure, as sketched in Figure 1.

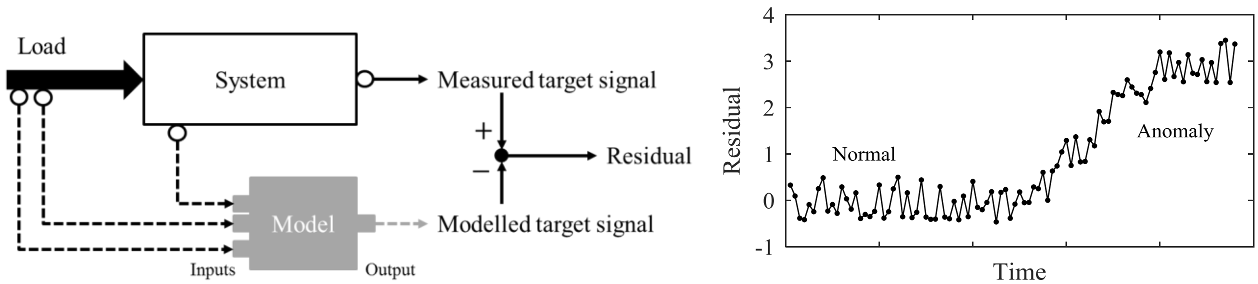


Figure 1.Sketch of model-based monitoring and indication of anomalies in the residual.

Although the basic heat generation in the drivetrain can be traced back to mechanical losses proportional to the acting wind and the rotational speed, the system is affected by more complex interaction of sub-systems, the ambient temperature and cumulative effects which make analytical modelling difficult. In contrast, data-driven modelling requires only a representative training period to learn the relationship. During this training phase the system needs to be in normal condition to enable detecting anomalies thereafter based on the difference to this behaviour. ANNs are a tool to learn and represent non-linear relationships inspired by the human brain. A common feedforward ANN trained by Levenberg-Marquardt backpropagation consists of one input layer, one or more hidden layers with a specified number of neurons and the output layer. Each neuron sums the weighted outputs of the previous layers and uses a non-linear activation function, typically a hyperbolic tangent, to generate an output. For the application of modelling a drivetrain temperature, a single linear output is used.

The inputs for modelling can be chosen based on the understanding of the system (also called domain knowledge) or based on the properties of the signals, e.g. the correlation of signals. Although using partly autoregressive modelling might increase the accuracy of prediction, this will not necessary improve the anomaly detection capability as the prediction is influenced by the target signal and could adapt to changes in the behaviour.

Wind turbine drivetrains usually consist of main bearings, main shaft, a gearbox build of a planetary and two parallel stages, the generator shaft and generator and multiple bearings. All possible target temperatures have to be monitored as behavioural changes might not only show up in the nearest sensor, but also in other signals.

Any significant maintenance or replacement will alter the behaviour of the system. Accordingly, normal behaviour models need to be re-trained after such events.

The model-based monitoring of drivetrain temperatures aims to detect slow degradation due to mechanical wear in bearings and gears. Early identification of these problems will enable the operator to optimise the maintenance scheduling and prevent long downtimes. However, challenges in representative training and limited detection capabilities result in significant uncertainties of this monitoring approach.

2.2. Physics of Failure

The Physics of Failure approach [14] aims to estimate damage accumulation based on a simplified physical model and operational statistics derived from SCADA data. Maintenance is to be targeted based on probabilities of failures. The basis of a Physics of Failure approach is a system analysis which includes a detailed system definition, potential failure modes with their causes and damage driving operating conditions. A damage accumulation model has to be built for each of the identified potential failure modes. Gray and Watson [14] gathered failure root causes of wind turbine gearboxes and derived several performance parameters from SCADA data to identify failure modes in a case study. The farm-wide comparison of the parameters such as average wind speed, rated power hours, brake application count, yaw movement, low speed and high power and rated speed hours, rotor starts and power dynamic, indicated that the failing turbines were affected by ‘high cycle fatigue due to poor contact between roller and raceway occurring at conditions of high stationary power’ [14]. A bearing damage model based on Lundberg-Palmgren’s bearing life formulae and linear Palmgren-Miner damage accumulation was proposed and applied using the SCADA signals power and rotational speed to approximate the bearing load. The damage model was only calibrated with the observed failures, but the resulting damage values of the failing turbines were clearly higher than the 75% percentile of the farm. However, in terms of indicating problems in certain turbines, the farm-wide comparison of the rated power hours gave similarly helpful information. Accordingly, evaluating performance parameters can be prioritised over developing full damage models.

3. CASE STUDY

In this study, data from 12 turbines in an onshore UK wind farm with a capacity of approx. 1-3 MW are analysed. The SCADA records are available from a period of 2.5 years and consist of signals in 10 minute resolution as listed in Table 1, available as averages (mean) and partly maximums (max), minimums (min) and standard deviations (std). No detailed specification of sensor types or locations is available. The temperature signals are numbered, but lack a descriptive labelling.

Table 1: Case study SCADA signals

Parameter	**Signal**
Wind speed	Mean, max, min, std
Wind, nacelle and relative direction	Mean
Pitch angle	Mean
Generator speed	Mean, max, min, std
Electrical power	Mean, max, min, std
Power factor, frequency	Mean
Voltage and current per phase	Mean
16 temperatures	Mean
Active time for line, turbine, wind, ambient temperature, yaw motion	Seconds of 600

The investigated turbines were affected by several drivetrain subassembly or part replacements, which are gathered from a commented stoppage list as the only maintenance documentation. Five gearbox replacements, three generator replacements and six bearing replacements took place. Sufficient details to describe the failure are only given for one gearbox replacement, where gear teeth broke on the intermediate speed stage gear. Only three of the investigated turbines did not undergo any major replacement.

Due to the missing temperature labels in this case study, the different failing parts cannot be targeted directly by normal behaviour modelling. Instead, all temperature signals are analysed and possibly helpful targets identified. Pre-processing is applied in terms of a validity check and removal of a complete sample if invalid values are found. ANN models with 20 neurons in one hidden layer are trained with data representing 3 months. Five inputs are automatically selected on the basis of the strongest correlation in the training phase. Re-training of models after major replacements or obvious system modifications is implemented. Residuals are filtered for steps > 5°C in the target, model prediction or residual. To reduce the fluctuations, residuals are smoothed by calculating the median of each 288 samples (two days). Warnings are generated based on a threshold representing 2% exceeding probability derived from a fitted Gaussian distribution to the residual from the training period. Alarms are raised only if more than 3 of possibly 10 warnings occur in a moving window.

As a first step of the Physics of Failure approach, performance parameters are defined as given in Table 2. Due to the distribution of replacements in time, analysing statistics of the whole data as done in [14] would not be helpful. In contrast, the parameters are calculated for each month accumulating all data up to this date. Adequate normalisation is chosen to enable comparing of parameters from different data size. It has to be noted that the small number of turbines in this case study impedes any statistical analysis.

Table 2: Definition of performance parameters for failure analysis. All parameters (except TUS) are calculated for operation only by requiring power mean > 10%.

Parameter	**Definition**	**Normalisation / scaling**
Wind speed (WS)	Average of wind speed mean	1.0 to 1.5 rated wind speed
Turbulence (TU)	Average of wind speed std	0 to 1.5 rated wind speed * 10
Turbulence in standstill (TUS)	Average of wind speed std (power < 10%)	0 to rated wind speed * 10
Rated power (RP)	Count if power mean > 90%	Ratio: divide by sample size
High wind speed (HW)	Count if wind speed max > rated wind speed	Ratio: divide by sample size
Power factor inverse (PF)	1 – average of power factor mean	*100
Power dynamic (PD)	Average of power std	0 to rated power * 10
High rotational speed (HS)	Count if generator speed mean > 90%	Ratio: divide by sample size

4. RESULTS

4.1. Model-based monitoring

Two temperatures are identified to relate to gearbox failures. The advance detection of problems is demonstrated in Figure 2 and 3. Gearbox problems are detected 39, 66, 75, 78 and possibly 492 days in advance for the five gearbox replacements, respectively. However, if the approach is applied to all turbines, a significant number of alarms is issued without known gearbox problems, see Figure 4. The alarms might be false or indicate other unreported problems. If the generator failures are to be detected, using another temperature shows good indication for the two replacements in the same turbine. However, the number of alarms in other turbines without generator replacement is high, see Figure 5. The alarm distribution over time indicates here a seasonal pattern visible in most turbines. Additionally, it seems possible, that some alarms might indicate gearbox problems. No clear alarm pattern is found in any of the temperatures for the bearing replacements.

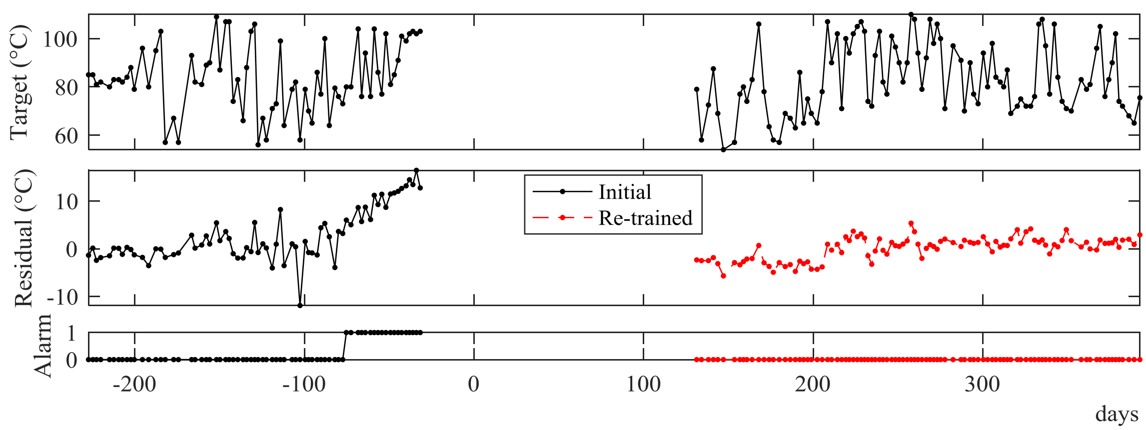


Figure 2. Detection of a gearbox problem with the time axis referring to the replacement date (temperature A, turbine 12).

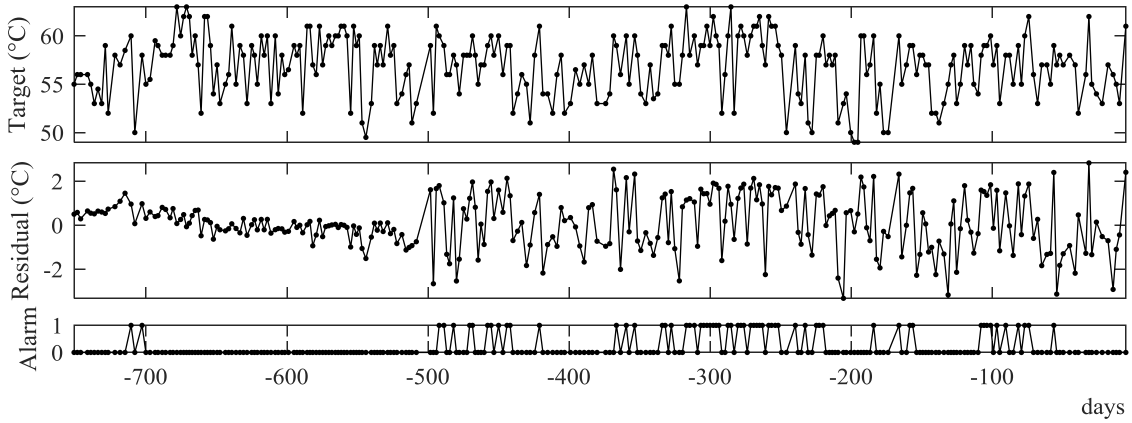


Figure 3. Detection of a gearbox problem with the time axis referring to the replacement date (temperature B, turbine 2).

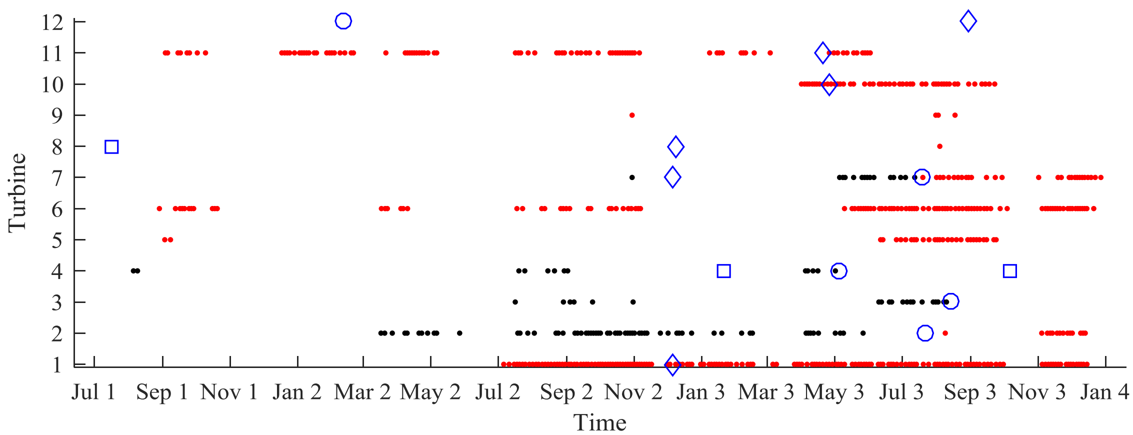


Figure 4. Alarms for gearbox problems in all turbines based on temperature B. Unrelated alarms are marked red, gearbox replacements with a circle, generator and bearing replacements with a square and asterisk, respectively.

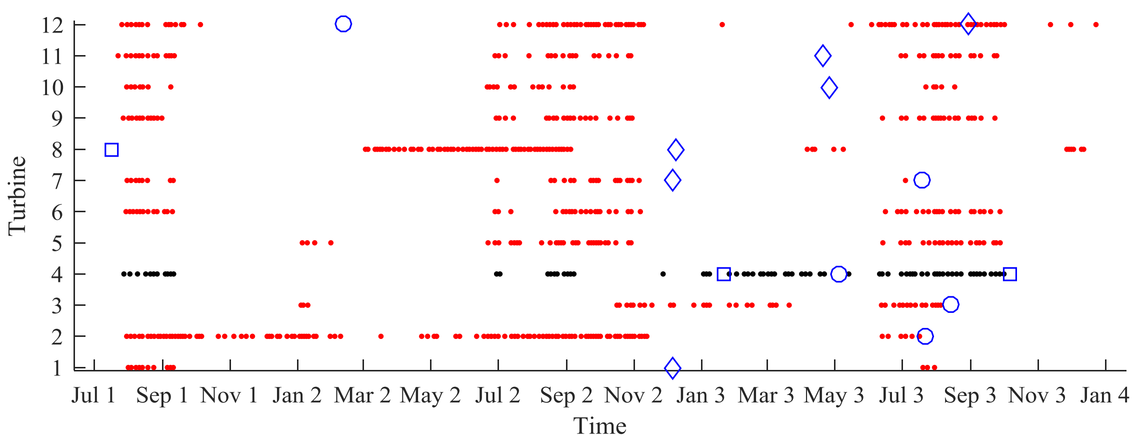
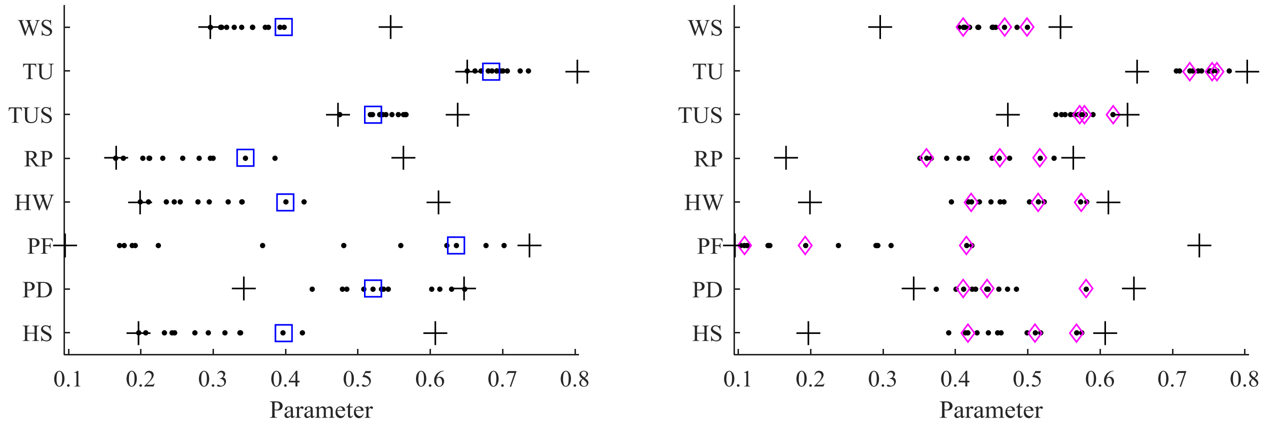


Figure 5. Alarms for generator problems in all turbines based on temperature C. Unrelated alarms are marked red, generator replacements with a square, gearbox and bearing replacements with a circle and asterisk, respectively.

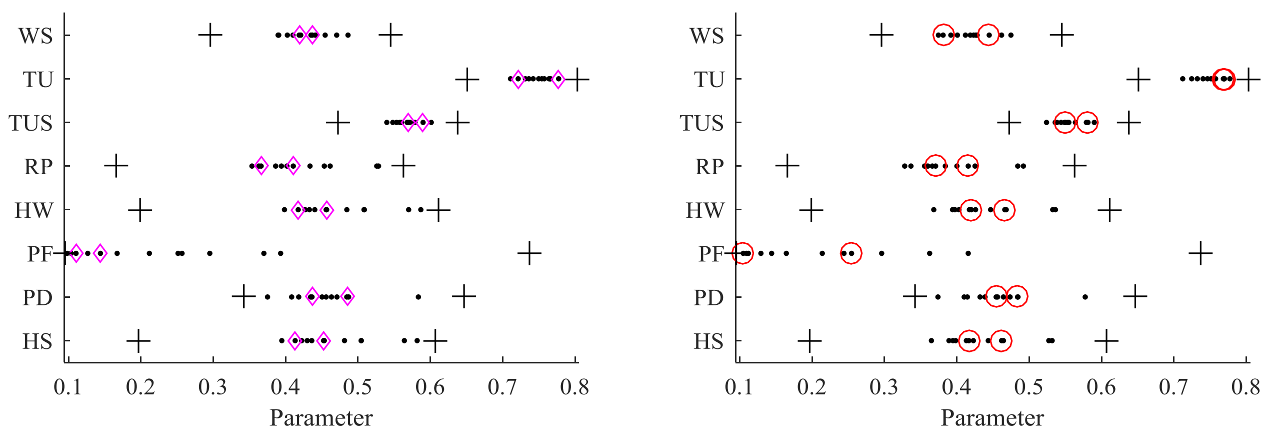
4.2. Operational statistics

The analysis of the defined performance parameters showed that the whole farm is affected by changing operation during the whole 2.5 years of data as the parameter values from all turbines clearly vary with time. As there is no common pattern, it is most likely that the reported replacements of gearboxes, generators and bearings have diverse causes and failure modes. Examples are given in Figure 6 and 8 for selected dates with highlighted replacements happening in this month. The generator problem in turbine 4, Figure 6a, seems to be related to relative high wind speed and accordingly rated power operation and high speed. Noticeably, the reactive power generation was exceptionally high in this time in several turbines including the failing one (average power factor of 0.9947). The bearing replacements, Figure 6b and Figure 7a, are found with various parameter values. Although most of the replacements show low or average parameter values, some are linked to high turbulence in operation. A high turbulence could also be the driver of the two gearbox replacements in Figure 7b.



(a) (b)

Figure 6. Performance parameters for all turbines in July year 1 (a) and December year 2 (b). Generator and bearing replacements marked with square and diamond, respectively. The extrema of the parameters from all months are marked with a plus symbol.



(a) (b)

Figure 7. Performance parameters for all turbines in April year 3 (a) and July year 3 (b). Bearing and gearbox replacements marked with diamond and circle, respectively. The extrema of the parameters from all months are marked with a plus symbol.

5. CONCLUSION

Operational data from wind turbines could build an alternative and complement of dedicated vibration measurements. Model-based monitoring is a way to detect anomalies in the behaviour of wind turbine drive train temperature signals to detect mechanical degradation and possible failures. In contrast, the statistical analysis used in the Physics of Failure approach tries to identify turbines at risk by evaluating the damage drivers with performance parameters. A combination of the two approaches is proposed to increase the reliability of monitoring.

In a case study, both approaches are applied with the aim of finding early indications for several gearbox, generator and generator bearing replacements. In the model-based monitoring with ANNs and thresholds based on the residual distribution from training, early alarms for all gearbox replacements are issued. Similarly, generator problems in one turbine show up if using another temperature signal. However, many unrelated or possibly false alarms in turbines without reported problems of this type reveal challenges in getting reliable monitoring. The evaluation of the performance parameters results in the conclusion that different damage drivers and failure modes were involved. Particular high values in turbulence, reactive power generation and wind speed are found to correlate with some of the failed turbines. Although the properties of the case study limit the capabilities of both approaches, it can be seen that the combination of model-based monitoring and statistical analysis of SCADA data increases the knowledge of the system's condition.

In future works, the performance parameter values of this farm shall be compared to farms with similar settings. However, a thorough evaluation of the benefit of combining the two monitoring approaches will need better case data with a bigger farm size, more fault-free turbines and sufficient documentation.

ACKNOWLEDGEMENTS

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 (project AWESOME, http://awesome-h2020.eu/).

REFERENCES

[1] Carroll, J., McDonald, A., McMillan, D. (2015) Failure rate, repair time and unscheduled O&M cost analysis of offshore wind turbines. Wind Energy 17:1107–19. doi: 10.1002/we.1887.

[2] Reder, M., Gonzalez, E., Melero, J.J. (2016) Wind Turbine Failure Analysis - Targeting current problems in Failure Data Analysis. J Phys Conf Ser 753. doi: 10.1088/1742-6596/753/7/072027.

[3] Tchakoua, P., Wamkeue, R., Ouhrouche, M., Slaoui-Hasnaoui, F., Tameghe, T.A., Ekemb, G. (2014) Wind Turbine Condition Monitoring: State-of-the-Art Review, New Trends, and Future Challenges. Energies 7:2595–630. doi: 10.3390/en7042595.

[4] Qiao, W., Lu, D. (2015) A Survey on Wind Turbine Condition Monitoring and Fault Diagnosis - Part II: Signals and Signal Processing Methods. IEEE Trans Ind Electron 62:6546–57. doi: 10.1109/TIE.2015.2422394.

[5] Qiu, Y., Feng, Y., Tavner, P., Richardson, P., Erdos, G., Chen, B. (2012) Wind turbine SCADA alarm analysis for improving reliability. Wind Energy 15:951–66. doi: 10.1002/we.513.

[6] Gonzalez, E., Reder, M., Melero, J.J. (2016) SCADA alarms processing for wind turbine component failure detection. J Phys Conf Ser 753. doi: 10.1088/1742-6596/753/7/072019.

[7] Feng, Y., Qiu, Y., Crabtree, C.J., Long, H., Tavner, P.J. (2013) Monitoring wind turbine gearboxes. Wind Energy 16:728–40. doi: 10.1002/we.1521.

[8] Schlechtingen, M., Ferreira Santos, I. (2011) Comparative analysis of neural network and regression based condition monitoring approaches for wind turbine fault detection. Mech Syst Signal Process 25:1849–75. doi: 10.1016/j.ymssp.2010.12.007.

[9] Bangalore, P., Tjernberg, L.B. (2015) An Artificial Neural Network Approach for Early Fault Detection of Gearbox Bearings. IEEE Trans Smart Grid 6:980–7. doi: 10.1109/TSG.2014.2386305.

[10] Sun, P., Li, J., Wang, C., Lei, X. (2016) A generalized model for wind turbine anomaly identification based on SCADA data. Appl Energy 168:550–67. doi: 10.1016/j.apenergy.2016.01.133.

[11] Schlechtingen, M., Santos, I.F., Achiche, S. (2013) Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 1: System description. Appl Soft Comput 13:447–60. doi: 10.1016/j.asoc.2013.09.016.

[12] Wang, Y., Infield, D. (2012) Supervisory control and data acquisition data-based non-linear state estimation technique for wind turbine gearbox condition monitoring. IET Renew Power Gener 7:350–8. doi: 10.1049/iet-rpg.2012.0215.

[13] Tautz-Weinert, J., Watson, S.J. (2016) Comparison of different modelling approaches of drive train temperature for the purposes of wind turbine failure detection. J Phys Conf Ser 753:72014. doi: 10.1088/1742-6596/753/7/072014.

[14] Gray, C.S., Watson, S.J. (2010) Physics of Failure approach to wind turbine condition based maintenance. Wind Energy 13:395–405. doi: 10.1002/we.360.