Data Insights from an Offshore Wind Turbine Gearbox Replacement

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Abstract. Gearboxes are a complex, yet vital assembly for non-direct-drive offshore wind turbines, which are designed to last for the lifetime of the asset. However, recent studies indicate that they may have to be replaced as early as 6.5 years. Moreover, their contribution to offshore wind farm failures and downtime has been shown to be amongst the three most critical assemblies with the highest material cost required. An improved understanding of these premature failures and the ability to predict them in advance could reduce inspection and maintenance costs, as well as to help overcome many logistical and planning challenges. The objective of this paper is to present the lessons learnt from a gearbox exchange performed in one of the offshore wind turbines at Teesside offshore wind farm, comprising 27 2.3MW wind turbines. The paper takes a condition monitoring perspective and uses the identified spalling at the inner part of the planetary bearing as the governing failure mode. A data management system has been setup, incorporating all the operational data received, including maintenance log information and sensor data. A period of up to 2.5 years, prior to the the gearbox exchange, is examined for this study. SCADA and CMS data of the faulty turbine are compared against the wind farm, using statistical methods and machine learning techniques. Supervised learning models are built, which will help predict similar failures in the future. Results show how different data sources can contribute in gearbox failure diagnosis and help to expedite failure detection for Teesside offshore wind farm and similar wind turbine and gearbox types. This paper will be of interest to wind farm developers and operators to build predictive models from monitoring data that can forecast potential gearbox failures.

1. Introduction

Gearboxes are a critical assembly for offshore wind turbines, which are designed to last for the lifetime of the asset, according to the IEC 61400-4 standards [1]. Nevertheless, a recent study of ~350 offshore wind turbines has indicated that gearboxes might have to be replaced as early as 6.5 years [2]. As wind turbines are increasing in size, gearboxes are physically scaled up, to be able to cope with the larger power output that is required. At the same time, direct drive turbines, i.e. gearless drivetrains, have started to become more popular with offshore wind farm original equipment manufacturers (OEM) [3]. Nevertheless, the vast majority of offshore wind turbines, including the currently largest installed wind turbine in the world, recently upgraded to 9.5MW, are using a geared drivetrain [4]. Studies have compared the reliability of those two types of systems and it was estimated that direct drive generator are expected to have a failure rate up to twice that of gear driven ones [5]. Another study compared five different onshore wind turbine drivetrains, concluding that the lightest and lowest cost solution is the doubly-fed induction generator with a 3-stage gearbox [6]. On the contrary, a recent offshore wind farm study has concluded that direct drive turbines with permanent magnet generators (PMG) have the highest availability, with the lowest operation and maintenance (O&M) costs, followed by PMG with a 2-stage and then a 3-stage gearbox [3]. It should be noted that the results of this study are based on some assumptions that will influence the overall results and conclusion. Primarily, some of the failure rates and repair times were estimated and others used field data, which restricts the direct comparison between the two sets.

Offshore wind turbine gearboxes' failure frequency compared to other assemblies is relatively high. They have been shown to be amongst the three most commonly failed assemblies, with the highest material cost required [2, 7]. Gearboxes can fail due to several different causes, including: (i) Fundamental gearbox design errors, (ii) Manufacturing or quality issues, (iii) Underestimation of actual operational loads, (iv) Variable and turbulent wind conditions, (v) Insufficient maintenance [8, 9].

A short description of the most common gearbox failure modes, along with their root causes are shown below [10, 11]:

- Micropitting; includes fine break-outs on the tooth flanks, resulted by the collapse of lubricant film, experienced by bearings and gears.
- Tooth breakage; caused by high bending stresses on gears.
- Pitting; includes plane surface brake-out, causing fatigue of the material on a gear or a bearing because of exceeding allowable surface pressure.
- Spalling; refers to either extensive surface brake-out of gears or bearings, starting from a pitting in the tooth root area up to the tip or fatigue at low viscosity and high oil temperatures, with the most common root cause being the existence of defective material or debris in the gearbox.
- Scuffing; includes groves in sliding direction and increase of roughness near the tip and the root, resulting to a high sliding velocity and to material transformation. The reason could be high specific load and sliding and the use of inappropriate lubricant on gears or bearings.

Studies have identified that the most critical gearbox components are the high speed (HS), intermediate shaft (IMS) and planet stage bearings [8, 9, 12–14].

In this study a 2.3MW gearbox from Teesside offshore wind farm is examined, which was replaced on August 24, 2017, located at turbine 14, situated at the middle of the wind farm [15]. The wind farm comprises 27 2.3MW wind turbines and is located 1.5km north of Redcar in the UK. The site has three rows of 9 turbines each. The turbines have a cut-in wind speed of 4 m/s, a cut-out wind speed of 25 m/s and a rated wind speed of 13-14 m/s. The site's average wind speed is around 7.1 m/s. The gearbox is a three-stage planetary-helical design. The high torque stage, is planetary-helical and the intermediary and high-speed stages are normal helical ones. The gearbox is mounted on the main shaft via a shrink disk connection and on the nacelle with rubber bushings. At this gearbox type, planetary stage failures are the most crucial ones, since no in-situ replacement of the failed component can be performed and the whole gearbox needs to be replaced. This is not required for the other two stages.

The paper takes a condition monitoring perspective and uses the identified spalling at the inner part of the planetary bearing as the governing failure mode. The objective of this paper is to present data insights from a gearbox replacement and suggest techniques to diagnose and predict similar future failures. The uniqueness of this study, lays on the fact that the gearbox was replaced at an early stage, since the failure had been identified and it was not let to fail catastrophically, as happens with similar studies. This creates a more realistic and pragmatic scenario when analysing the data, as it allows adequate time for the replacement and investigates early warning signs of component degradation.

2. Methodology

This section describes the data, the pre-processing and the failure detection and diagnosis techniques used to identify the spalling at the inner part of the planet stage bearing.

2.1. Gearbox and Data Description

In order to avoid catastrophic failures of critical components, wind turbines are fitted with remote monitoring systems; this becomes even more critical for offshore wind turbines. Thus, all modern offshore wind turbines have supervisory control and data acquisition (SCADA) systems and most of them also include condition monitoring systems (CMS). The examined offshore wind turbines have both SCADA and CMS installed.

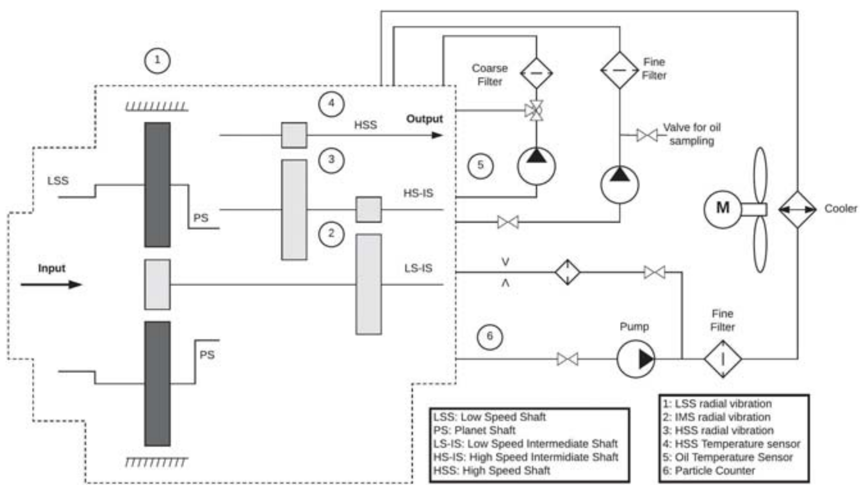

Figure 1. Schematic of the 2.3MW 3-stage planetary/helical gearbox and its cooling system.

A schematic diagram of the 3-stage gearbox examined for this study is shown in Figure 1, along with the available fitted sensors. These include three single axis accelerometers, one at each stage of the gearbox and a particle counter, as part of the CMS, as well as two temperature sensors measuring the high speed shaft (HSS) and the oil temperatures, as part of the SCADA system. Moreover, in this study SCADA sensors for the active power and the rotor speed have been taken under consideration. All the available data used in this study are up to 3 years prior to the gearbox replacement. The analysis and interpretation of the SCADA sensor data is usually straight-forward as it is captured in timeseries. The active power and wind speed data analysed are captured in 30-second average sampling and the temperature and rotor velocity data in 10-minute average instances. The CMS data provided are pre-processed by the monitoring equipment and generated in lower sampling frequencies and within a specific time period and active power range. Hence, their sampling rate is dependent on the performance of the turbine and can vary between a few hours and a couple of days. The different analysis methods provided for the CMS data, include:

- Fast Fourier Transform (FFT), which is an algorithm that samples a signal over a period of time and divides it into its frequency components.
- Cepstrum, which is the inverse Fourier transform of the logarithm of the signal's spectrum.

- Envelop, which is generated by passing the time domain signal through a ban-pass filter and then through an enveloper, to extract the repetition rate of the spiky bursts of energy.
- Root mean square (rms), which is the arithmetic mean of the squares of a set of numbers.

CMS are expected to diagnose failures sooner and more precisely than SCADA, in locations where both systems are present. CMS could detect anomalies up to 1 year in advance, whereas SCADA systems up to 3 months prior to failure [5]. This difference is crucial for the O&M planning teams, to schedule the required maintenance operations.

2.2. Data Pre-processing

An integrated database has been created, incorporating the sensor readings from the SCADA, CMS, alarms and maintenance actions, received from the turbines, as presented in [7].

For the wind measurements received from SCADA, only the turbine with the replaced gearbox was investigated, WT14, due to uncertainties in the wind sensor calibration of the other turbines. Initially, certain instances were filtered out, by using conditional statements to remove the equivalent SCADA timestamps, for a duration of 2 years and 9 months, from the information received by the SCADA alarms and the maintenance logs, including: (i) Yaw system, (ii) Pitch system, (iii) Generator faults, (iv) Electrical and grid faults, (v) Sensor failures, (vi) Environmental conditions, (vii) Maintenance operations. This was performed, in order to remove any unrelated time instances. No gearbox related SCADA alarms or maintenance actions, apart from the scheduled routine inspections, had been activated during the lifetime of the faulty wind turbine, only regarding the gearbox oil level. Moreover, in order to examine the data further, the power curves and the rotor velocity data were binned, as indicated by the IEC 61400-1-22 standard [16]. The mean values of the normalized wind speed and normalized power output for each wind speed bin were calculated according to the standard.

CMS data pre-processing is not necessary, as the analysed data are generated and provided by the hardware supplier. They are also provided at different power ranges (0-920, 921-1150,1151-1403, 1404-1656, 1657-1909, 1910-2185, 2186-2415, 2416-3000)kW. For this study, the 2186-2415kW power range has been selectedas it is close to rated power and gives a better indication for the gearbox's degradation. For noisy signals, a SavitzkyGolay filter with a high order number has been applied. This filter fits a set of data points to a polynomial in the least-squares sense.

To maintain confidentiality, the data presented are normalized and some scales have been adjusted. Each figure was normalized individually, so no correlation between figures is possible.

2.3. Failure Detection and Diagnosis

Understanding, diagnosing and predicting the failure modes occurring on critical assemblies is important for reducing lead time for component delivery, as well as increasing asset availability. This is done remotely, by monitoring the information received from the SCADA and CMS. However, an inspection might be required to identify the failure root cause in more detail.

The different SCADA data readings, associated to the gearbox failure diagnosis used are the active power, rotor velocity, HSS temperature and gearbox oil temperature. The oil temperature against the square rotor velocity is also shown, because as indicated by [17], the gear stage inefficiency is proportional to the change in temperature over the squared of the rotor velocity, with the later being equal to the gear velocity at the planetary stage. This means that when a fault occurs on a gear stage, the temperature difference should increase in response to an efficiency reduction. Moreover, the gear oil temperature for different time instances is binned and compared. The SCADA readings can give an initial indication of the failure location, which needs to be further investigated by the vibration data.

For the CMS data, the planet bearing readings are used for the analysis. It is difficult to understand if the signal represents a faulty or healthy turbine, without the exact machine frequencies and amplitudes held by the OEM. Thus, the different dates need to be plotted in order to understand the signal trending and how the failure is progressing in a waterflow diagram for the envelope and FFT spectrums of the planet stage. Moreover, the cepstrum rms of the planet stage and particle counting signals are examined.

2.4. Data-Driven Models
As there was no SCADA generated alarm related to any gearbox component, it would be interesting to investigate the possibility of creating warnings from the SCADA sensor readings that can trigger further investigation in similar future situations. Due to the nature of the data, different classification learning algorithms were selected and trained, including support vector machine (SVM), ensemble classifiers, decision trees and k-nearest neighbours (KNN). The applied algorithms can be found at [18,19]. The input data used for the models include the active power, wind speed, rotor velocity, HSS temperature and gear oil temperature. The data were labelled as "healthy" or "warning" states based on the data generated before and after the gearbox replacement. For the different states, the training data were randomly selected on a 75/25% of training/test data, as suggested by [21]. The output of the models is the performance of the difference classifiers.

In terms of CMS signals, the only indication for degradation was noticed at the cepstrum rms values of the planet bearing readings. Thus, it was selected for further analysis and model predictions. An autoregressive model was used for predicting the future trend of the rms signal [20]. The model's parameters are estimated using variants of the least-squares method, by only using a historical data series. 700 time instances have been used for training, with the last 300 instances representing the forecasted and actual future data that were generated.

3. Results
This section presents the results from the detection, diagnosis and data-driven models of the investigated gearbox failure.

3.1. Failure Detection and Diagnosis
The results for the failure detection and diagnosis from SCADA and CMS data are shown below.

3.1.1. SCADA The original and filtered power curves are shown in Figures 2 and 3 respectively. The power curve information was filtered further to reflect a period of 5 months prior to the gearbox replacement and the same period 2 years before, as shown in Figure 4. As can be seen, there is no clear underperformance of the turbine at this stage, just a slight deviation to the right for the 2017 data. The binned power curve is visualized in Figure 5. By following this method it is more evident that the turbine is underperforming a few months before replacement, for the wind speeds from 0.3 to 0.55. It was chosen to compare the power curve characteristics of the turbine, with a previous healthy state of the same or a neighbouring turbine, as the provided OEM's power curves might not be representative. Similarly, active power was binned and plotted against rotor velocity data, Figure 6, leading to the same conclusion, of turbine underperformance for the period in 2017. Moreover, as the rotor is directly connected to the gearbox's planetary stage, an initial assumption can be made for the failure location. The different gearbox temperatures have been compared at different time periods, before and after the gearbox replacement, as seen in Figures 7-11. The oil temperature against the square rotor velocity is presented in Figure 9. All the temperature related Figures indicate that there is a significant temperature increase, caused by the faulty gearbox. In Figures 8 and 9, the temperature increase is seen at the lowest active power and rotor velocity values, which makes it hard for an alarm system to capture them, but it is still not totally clear, when comparing all the previous and after replacement

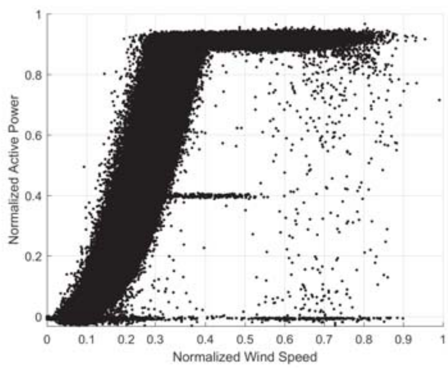

Figure 2. Normalized 30-sec average power curve for 2 years and 9 months.

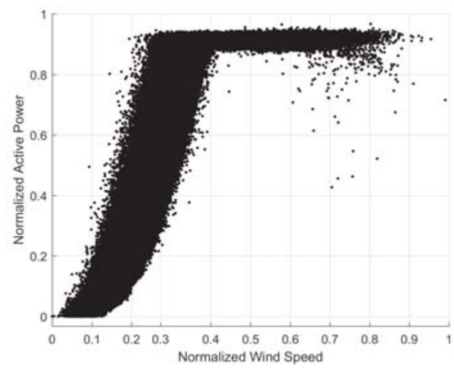

Figure 3. Normalized filtered 30-sec average power curve for 2 years and 9 months.

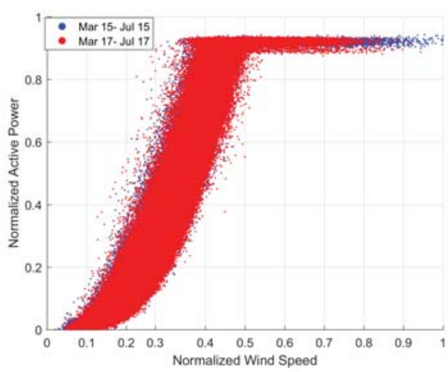

Figure 4. Normalized 30-sec average power curve for March- July 2015 and 2017.

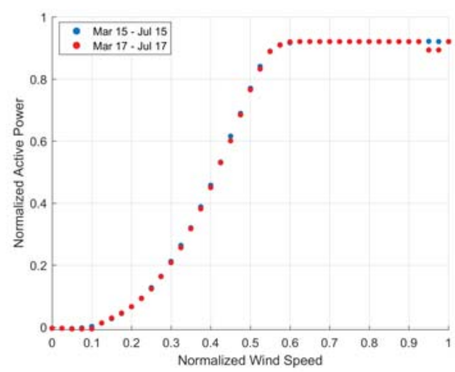

Figure 5. Normalized binned power curve for March- July 2015 and 2017.

curves. In the case of the HSS temperature, Figure 7, the temperature increase is more clear throughout the whole power range, showing a 3-4 ^{o}C temperature difference, but keeping it still within the SCADA alarm limits, as no such alarms have been triggered. Figure 10 shows a bar plot with the different temperature bins. Although a difference can be noticed for the before and after replacement values, there is a temperature increase at high temperatures, for 2 months after replacement, which is due to the highest energy production during that period. Figure 11 makes this difference more apparent, as the environmental conditions were very similar during those instances. Although there is an evident temperature increase at the different gearbox temperature data shown and a reduction in the rotor velocity, the exact location of the failure cannot be precisely identified by only investigating the SCADA data.

3.1.2. CMS Figures 12 and 13 show a three dimensional representation of the envelope and FFT values at different time instances. As it can be seen, no obvious changes in the component's frequency response and no visible, critical sidebands are building up.

By examining the signal from the cepstrum analysis, a more pronounced increase in amplitudes can be observed. The filtered rms signal of it is shown in Figure 14, where an increasing trend can be seen after March 2017, which is a sign of degradation.

A constant increase in the particle counting can be noticed in Figure 15, by comparing the slopes after and before the replacement. This increase is most indicative when the particle counting against the cumulative energy generation of the turbine is examined. This could provide an early indication of the fault, revealing that material breakout is present.

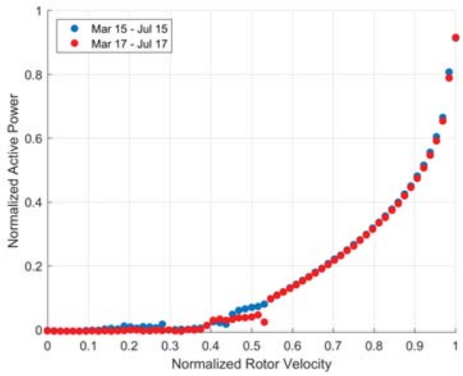

Figure 6. Normalized active power against rotor velocity.

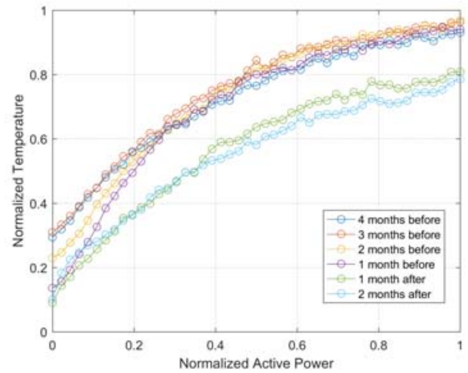

Figure 7. Normalized gearbox high speed stage temperature against active power.

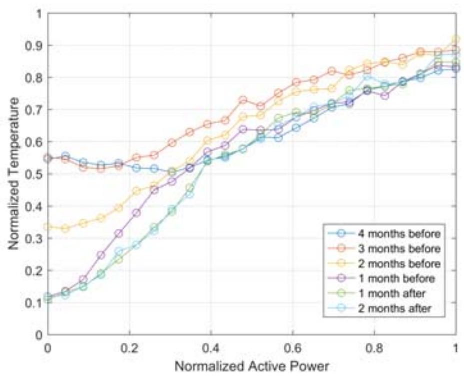

Figure 8. Normalized gearbox oil temperature against active power.

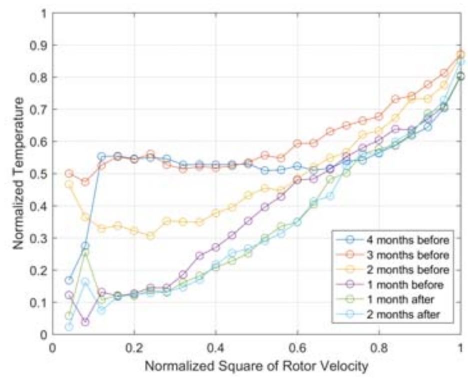

Figure 9. Normalized gearbox oil temperature against square of rotor velocity.

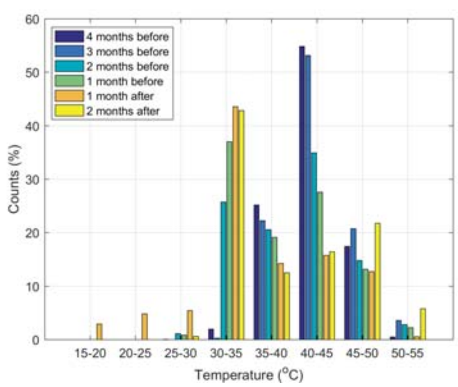

Figure 10. Gear oil temperature bins for different months.

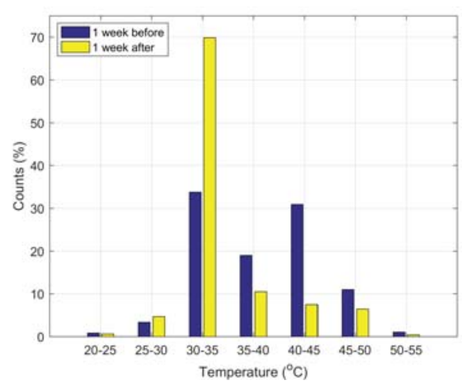

Figure 11. Gear oil temperature bins for a week before and after replacement.

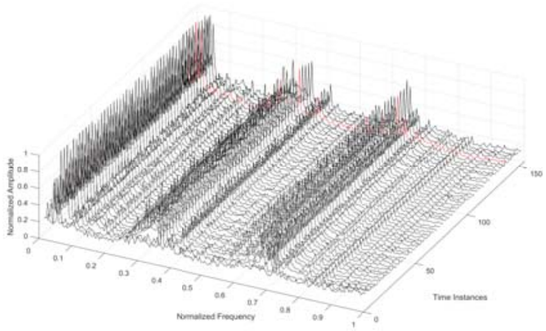

Figure 12. Waterflow representation of planet bearing envelope spectrum (annotated line represents the gearbox replacement date).

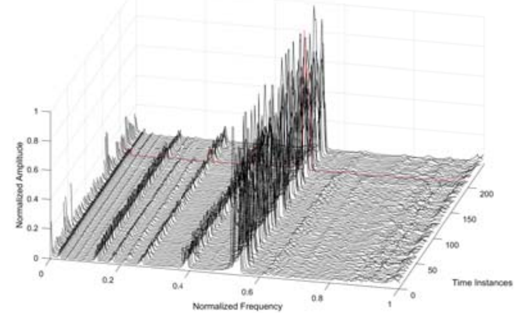

Figure 13. Waterflow representation of planet bearing FFT spectrum (annotated line represents the gearbox replacement date).

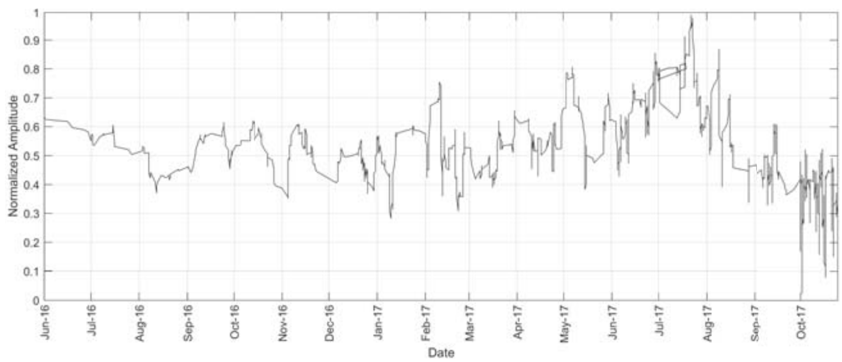

Figure 14. Normalized cepstrum rms of the planet bearing against the different dates.

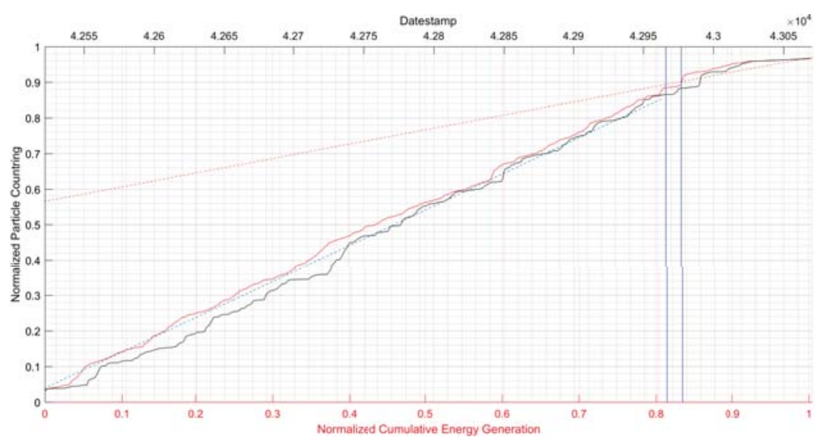

Figure 15. Normalized particle counting against date (top x-axis and black line) and normalized cumulative energy generation (bottom x-axis and red line). The vertical blue line indicates the replacement interval. The dotted blue and orange lines indicate the slopes of the particle counting against energy generation lines before and after replacement respectively.

3.2. Data-Driven Models

For the SCADA readings, different algorithm features have been varied until the highest accuracy is met, with the top five shown in Table 1. The SVM Gaussian algorithm can provide the largest number of true positive values. For all the algorithms, the percentage of true positive values for the "warning" state is lower, meaning that there is at least 8% chance for the algorithm not to flag the warning cases. SVM quadratic algorithm was the least accurate and most time consuming one, due to its high complexity.

Table 1. Supervised learning algorithms tested with their accuracy.

Algorithm	Specifications	True Positive Rate (Healthy)	True Positive Rate (Warning)
SVM	Gaussian, Scale:0.26	97%	92%
Ensemble	Bagged Trees, Split: 10, learners: 30	96%	91%
KNN	Mahalanobis, NN=10	96%	92%
Decision Tree	Gini's index, max number of splits: 400	95%	86%
SVM	Quadratic, box constraint: 1	93%	81%

An example of the model's outputs for the cepstrum rms of the planet bearing can be seen in Figure 16. The model was able to predict the future trend, with a high level of accuracy, for the replaced gearbox turbine. The predicted and actual curves for the 300 time instances modelled, that represent 5 months, have the same slope value. The model was tested for all of Teesside's turbines, giving similar results for 26 out of the 27 turbines. The model requires a Savitzky-Golay filter, in order to yield suitable predictions.

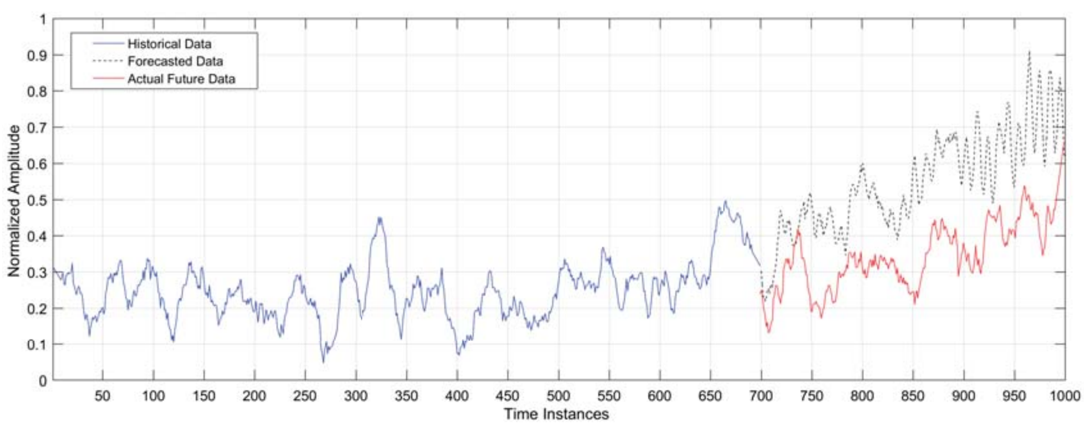

Figure 16. Normalized cepstrum rms of the planet bearing, with forecasted and actual sensor values for 300 time instances.

4. Discussion and Conclusion

Temperature readings have aided in identifying early warning signs of the gearbox's components. However, a limitation of this analysis is that the environmental temperature has not been taken into account, as it is expected to have little influence to the findings, when the power output is taken under consideration, but it will be included in future analysis. Moreover, it was made clear that it is not possible to detect the exact fault location from SCADA temperature sensors and a more detailed analysis of the vibration signals is required, which can also be done for cross-validation. The different waterflow representations of the envelope and FFT spectrums show only a very minor increase in the signal sidebands, which does not necessarily represent an evident failure. Thus the cepstrum rms was used to better visualize the vibration signal increase. This is not always easy, as those systems are in different platforms and inhomogeneous formats, which creates a problem in interpreting and analysing the data in time. This paper also investigated different data-driven models for the SCADA and CMS systems, with a high level of accuracy, which could be further tested in order to increase the confidence levels in the results, to reduce unnecessary warnings.

To conclude, this paper has examined a planetary stage bearing spalling on a 3-stage 2.3MW gearbox. Literature has identified this failure mode as one the most common ones. Similar studies have been performed in the past, mainly investigating catastrophic failures of gearbox's components, whereas in this case the fault was identified well in advance and the gearbox was replaced at an earlier stage. The paper has tried to identify and diagnose the failure by examining the SCADA and CMS on the wind turbine. The importance of this study is that it investigated a pragmatic scenario of a gearbox replacement, with early stage warnings. It was shown that an integrated analysis of the temperature, vibration and particle counter signals, creates a clearer view on the current gearbox condition, which could reduce the possibility of triggering unnecessary inspections and false alarms. The data-driven models presented could lead to a more efficient monitoring system that can be used for diagnosing and indication of early stage warnings on future failures, which can be automated and ease the role of the reliability and condition monitoring personnel.

Future work will include further investigation and real time implementation of the data-driven models presented in Section 6, correlation of environmental conditions with the SCADA system readings, as well as investigation of different failure modes. Moreover, the root cause of the failed gearbox and any relationships with the wakes generated by the other turbines will be examined.

Acknowledgments

The authors would like to thank the Energy Technology Institute and the Research Council Energy Programme for funding this research as part of the Industrial Doctoral Centre for Offshore Renewable Energy (IDCORE) programme (grant EP/J500847), as well as the European Unions Horizon 2020 research and innovation programme under the grant agreement No 745625. Moreover, the authors would like to thank EDF Renewables UK for providing access to the data and the anonymous reviewers for their valuable comments and suggestions to improve the quality of the paper.

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