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Analysing RMS and peak values of vibration signals for condition monitoring of wind turbine gearboxes

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ABSTRACT

Wind turbines (WTs) are designed to operate under extreme environmental conditions. This means that extreme and varying loads experienced by WT components need to be accounted for as well as gaining access to wind farms (WFs) at different times of the year. Condition monitoring (CM) is used by WF owners to assess WT health by detecting gearbox failures and planning for operations and maintenance (O&M). However, there are several challenges and limitations with commercially available CM technologies – ranging from the cost of installing monitoring systems to the ability to detect faults accurately. This study seeks to address some of these challenges by developing novel techniques for fault detection using the RMS and Extreme (peak) values of vibration signals. The proposed techniques are based on three models (signal correlation, extreme vibration, and RMS intensity) and have been validated with a time domain data driven approach using CM data of operational WTs. The findings of this study show that monitoring RMS and Extreme values serves as a leading indicator for early detection of faults using Extreme value theory, giving WF owners time to schedule O&M. Furthermore, it also indicates that the prediction accuracy of each CM technique depends on the physics of failure. This suggests that an approach which incorporates the strengths of multiple techniques is needed for holistic health assessment of WT components.

1. Introduction

The availability and the consequent O&M costs of WFs are influenced by the failure and downtime of WT components such as the gearbox. In offshore WFs, where repair procedures are complex and logistics are influenced by extreme weather conditions, the impact of component failure can lead to even longer WT downtimes [1,2]. These O&M issues have spurred the need for remote condition monitoring and assessment capabilities for WT components to detect faults early enough in order to be able to plan O&M activities and minimise downtime. CM is gradually becoming the state-of-the-art approach for meeting this need in large multi-megawatt and offshore WT applications after being requested by certification bodies after series of catastrophic WT failures in the early 1990s [3]. Yet the adoption of CM technologies for commercial WF applications has not been without challenges. On the one hand, installing purpose-built CMS, which typically do not accompany WTs except in few offshore applications, is very expensive. On the other hand, even though most large WTs have Supervisory Control and Data Acquisition (SCADA) systems, SCADA systems also have issues with prediction reliability and accuracy [3].

This study proposes a perspective of WT gearbox O&M through the use of CM for early fault detection, enabling WF owners time to plan O&M well in advance and save costs by reducing downtime as a consequence. This maintenance approach is called condition based maintenance (CBM) [4,5]. Unlike preventive maintenance (PM) [6], a CBM approach takes the condition of the monitored component into account when making O&M decisions. This provides the opportunity for both the effective planning and scheduling of maintenance actions [7]. PM takes into account the previous failure and service history, factoring these as risk parameters when calculating the interval between the current operating period and the next wear-out or failure time [6]. Conversely, with CBM there is no need for previous failure history. O&M planning is achieved by monitoring key parameters that would be indicative of

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any deterioration in a WT's health, so as to detect failures at their early stage. The success of CBM depends on the type and accuracy of the CM technique used, the analysis methods and the interpretation of results.

In the CBM approach presented in this study, three models (signal correlation, extreme vibration, and RMS intensity) are proposed and validated based on a data driven time-domain approach addressing the key limitation and issues that have been identified in literature [3,8,9]. For this, a three stage approach was used, they are: data pre-processing, modelling and validation. The models are validated using data from operational and failed turbines, seeking to show how sensitive the models are in detecting different types of failure modes in wind turbine gearbox. Operational turbines with healthy gearboxes are used to show the normal response for each model while faulty gearboxes with some of the common gearbox failure modes are used to show the detectability of each model for different types of failures.

The main contributions of this paper are in two parts:

- The improvement of known techniques of using RMS values of vibrations [8,10] and application to monitor WT gearbox health.
- The development and validation of a novel approach for detecting abnormal WT gearbox operation using the extreme value theory.

The outline of the article is as follows: In Section 2, a brief review of literature on CM and CBM is done by identifying the main techniques and the limitations of current approaches. In Section 3, the three models proposed to meet the limitations are developed. Section 4 presents the results after data from 10 WT gearboxes were used to validate the proposed models. A comparison of healthy versus faulty gearboxes was made for each model and a case study for detecting three common failure modes of the gearbox high speed module is also done. Finally, in Section 5, the findings are summarised and a view into future research directions is presented.

2. Related works

Antecedent research in CM of WT gearboxes has covered a wide variety of applications ranging from standard techniques such as vibration and oil debris analysis [1,11–16] to others such as acoustic emissions [17] and SCADA analysis [7–9,18–22] etc. While the first three are purpose-built CMS for monitoring specific parameters and detecting incipient failures, SCADA systems were primarily installed on WTs for measuring operational parameters such as wind speed, ambient temperature, component temperature and generator power [3,5]. However, because they are readily available, SCADA systems are now also used for CM. This has been achieved by creating models and trends from SCADA data which when interpreted, are used to assess the condition of WT components [1,8,20,23,24]. A good example of such technique that does not rely on traditional CMS can be found in Ref. [25], where angular velocity measurements from the gearbox input shaft and output shaft to the generator were used to define an error function for detecting gear and bearing damage. It is also worth noting that previous works on WT gearbox CM have focused on two main strands: (1) CM algorithm development, validation and improvement, such as [16,25–28], and (2) CM technology assessment and development, for example [11,15,29,30].

Irrespective of the technique and/or technology applied for CM, the capability of CM depends on two factors [30]: (a) the number and type of sensors and (b) the associated signal processing and simplification methods, with the latter being relevant to this study. The number and types of sensors are generally determined by the type of commercial CMS or SCADA systems used and are beyond the scope of this article. According to [30], some examples of signal processing methods used for CM include: Statistical Analysis, Time Domain Analysis, Cepstrum Analysis, Wavelet Transformation etc. In Ref. [31], three CM methods applied to SCADA analysis were discussed, they are: Signal Trending, Artificial Neural Networks and Physical Modelling. All these methods have the tendency to lead to false alarms or erroneous predictions if models used for detection are not accurate or sophisticated enough [8,23]. Moreover, more sophisticated models require more complicated algorithms which are computationally intensive and more difficult to develop [27]. Although most purpose-built CMS come with built-in detection algorithms, they are expensive to install and have not been fully justified economically [24,32]. SCADA systems on the other hand are already part of most large WTs and hence no extra costs are incurred to use SCADA for CM. On the downside, analyses of SCADA parameters are prone to high rate of false alarms. This is due to the following fundamental issues with SCADA:

- SCADA has a low 10 min sampling rate which has been considered too low for accurate fault diagnosis when conventional CM techniques are used [3,8].
- Models generated from are relatively poor since SCADA training data are noisy [1].
- SCADA data values varies over a wide range of operating conditions [8]. Consequently, a change in SCADA data does not necessarily mean a fault has developed; it can simply be as a result of a change in operating conditions. This brings additional complexity in analysing SCADA data since developed models would have to normalise the variability and seasonality of operating conditions in order to improve accuracy [7].

Of the three issues, only the first two are unique to SCADA data. The issue with the variability of operational conditions also has an effect on several monitored parameters obtained from commercial CMS, such as vibrations. A good example of this is how pitch control of WTs induces variability in monitored CM parameters. This is because pitch control limits the aerodynamic power of the turbine in order to control the power output [33], hence leading to nonlinearities in the behaviour of the turbine [8]. CM parameters such as gearbox vibrations and temperature, often vary over wide ranges [8] and a change in their levels does not necessarily indicate the occurrence of a fault, but a fault may lead to changes in these values [3,8,34].

The issues identified above have some influence on several analysis techniques commonly used in literature, especially if insufficient effort is made in data pre-processing and in normalising operational variability. Two good examples which illustrate this are: the pitfalls in comparing similar and/or neighbouring turbines through signal trending (see Figs. 1–3), and the effect of seasonality on the physical models based on gearbox energy balance (see Figs. 4 and 5). First, whilst comparing operating parameters of neighbouring turbines has proven useful in determining outliers [31], it does not always show the true picture and can be misleading. This is because different WTs and their components, even though identical in design, may have different response in terms of the CM parameters used for trending (Figs. 1–3 illustrate this). Second, the use of gearbox oil and bearing temperatures are also examples of common parameters used for monitoring the health of wind turbine components [1,8,23,35]. This approach has been used to model the energy balance of the gearbox, i.e. energy is either transmitted by the gearbox as output power or dissipated as heat energy in the form of temperature rise. Here, a loss in efficiency of the gearbox would be signalled by an increase in energy loss which consequently indicates a fault. However, seasonality of ambient temperature influences the accuracy of the approach if not