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“Maintenance Management in Wind Turbines by Monitoring the Bearing Temperature”

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Chapter 1

Maintenance Management in Wind Turbines by Monitoring the Bearing Temperature

Ana María Peco Chacón, Long Zhang and Fausto Pedro García Márquez

Abstract Wind turbines are increasing in number, size and market share. It is determined whether they are efficient through operating and maintenance costs. Therefore, one of the main objectives of the wind turbines is to increase the service life of the components by applying different methodologies for fault detection. The gearbox is a critical component since it causes the most downtime and failure rate of the wind turbines. The Supervisory Control and Data Acquisition system offers the measurement of several variables, and by a correct analysis it is possible to detect the faults before they occur. This paper analyses the temperature curve of bearing versus wind speed as significant variables of a gearbox failure for fault detection.

Keywords Renewable energy · Wind turbine · Curve power · SCADA · Fault detection

1.1 Introduction

According to the Global Wind Energy Council (GWEC), the cumulative installed wind energy capacity in the world will be more than 800 GW by the end of 2021 [3, 27, 29]. Wind turbines (WTs) have increased in size, therefore, the operation and maintenance costs [24, 26, 30]. It requires to have an efficient and effective condition monitoring system (CMS) to avoid repair costs and wind turbine downtime [13, 14, 23].

WTs suffer adverse climatic conditions, especially those located in the high seas, such as temperature, wind speed, wind shear and random loads [8, 24, 28]. In ad-

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dition, WTs are made up of various complex systems that give rise to a whole, therefore, the failures or damages can occur in various parts of the system [1, 5, 6].

A critical component in wind turbines are bearings, which have been shown to cause more than 50% of gearbox failures [15]. Wind turbine bearing condition monitoring (WTBCM) has been developed to detect premature bearing failures.

Proper bearing maintenance and fault diagnosis are important at an economic level. According to reference [9], a replacement of a 5,000 bearing, can lead to up to 250,000 of loss due to WT downtime, such as the use of cranes, specialized operators, etc. In general, a turbine has an average useful life of about 20 years, with the costs of operation, maintenance and replacement of components being around 10-15% of the total income from energy production.

The Supervisory Control and Data Acquisition (SCADA) system are employed in WTs [22, 31], e.g. it is used by manufacturers such as GE, Siemens and Vestas. The SCADA collects the information from the sensors in the WT during a time interval, usually 10 minutes. They contain statistical characteristics such as maximum and minimum values, standard deviation, etc. The measured variables are mainly temperature, speed, voltage, power, etc. These data need suitable algorithms to be useful for monitoring the WT [7, 10, 19], as well as the prevention and detection of faults before they occur, and not give rise to catastrophic faults. The analysis of SCADA data allows the detection of faults before they occur. However, they have the disadvantage that they are a large amount of data, which makes their analysis and interpretation more difficult [20, 21, 25]. There are numerous techniques and methodologies that are applied to SCADA data, all this to optimize the decision making regarding the maintenance of the components under study.

The condition of gearboxes faces several challenges in the coming years [32], as all approaches require techniques for processing and analysis. SCADA requires methods to predict failures in advance with reasonable time for optimal maintenance of the WT.

Reference [2] proposes to group the components by their failure causes, taking into account the interaction between the components and the consequences of the failure. The aim is to achieve proactive maintenance by means of multi-agent systems. It is a method for condition monitoring WTs due to their complexity and the existing correlations between the components. Therefore, it is important to determine the root cause of the failure in order to optimize the maintenance of WTs.

Kusiak et al. [16] present a method for the prediction of failures in WT using SCADA. The methodology used is based on identifying failures, predict the severity of them, and finally predict the failure. The results showed that the method is able to predict a failure 1 hour before it occurs, but it is important to note that significant information is lost because the SCADA intervals are large. Parameters such as accuracy, sensitivity or failure specification were considered, as well as the use of neural networks to extract information from the method.

Reference [33] shows a new index called ALI to determine the abnormal level of the condition. A generalized model has been created to detect anomalies in WTs, using SCADA data and with the implementation of fuzzy synthetic evaluation mod-

els. It is common to use SCADA data in components: temperature, power and speed. The results show to be more effective than traditional methods based on thresholds.

According to reference [18], the decreasing in reliability over time the WT is mainly caused by mechanical components. A method based on the Hidden-Markov model was proposed, where the degradation of the performance of WT components is studied. The results demonstrated that they can be a guide for the safety operation of similar WT components. It has the advantage of using small sample data as opposed to traditional reliability analysis methods that need more data.

A multi-level hybrid strategy is proposed in [17], following a single- and multi-turbine approach to building fault indicators. In this paper is considered a SCADA database with data collected every 10 minutes for four years. The results demonstrated the effects of changes in environmental and operating conditions.

Section 1.2 introduces the temperature monitoring bearing. The case study is presented in section 1.3, where the main results are analysed. Finally, the paper finalizes with the main contributions.

1.2 Temperature Monitoring in Bearings

Temperature measurements provide relevant information about the state of the WT. The temperatures of the WT components or subsystems must be between certain values and may not be exceeded during normal operating conditions. An abnormal temperature by outliers may indicate a malfunction of the WT, such as rotor over-speed, short circuits, lubrication failure, etc. For these reasons, techniques based on temperature control have been commonly applied in the diagnosis of faults in gearboxes, bearings, generators and power converters.

Reference [4] employs the bearing temperature as an indicator of the aging of the main bearing of the WT. Because the temperature data of the main bearing provides information about the state of the WT. The abnormal temperature can indicate the presence of bearing defects, problems with the lubricating oil, electrical current of the shaft, variability of external loads, etc. The condition of the gearbox bearing is an effective indicator of the service life of the WT. During its operation it will suffer wear and, therefore, the properties of the lubricating oil will change due to aging, this can cause fatigue loads. The bearing is, therefore, not efficient, and entails a loss of energy in the bearing operation, that is shown in a thermal way, i.e. increases the temperature.

A temperature increase can be caused by many factors, sometimes it is difficult to identify the root cause of the temperature variation. If a sensor measures the temperature of a component by a failure of other components nearby can cause an increase in the temperature of this sensor, making it difficult to determine the cause. It is used complex techniques for the interpretation of SCADA data, to rule out false alarms or failures in the measurement.

A degradation model of the bearings is used as a method to predict the real-time remaining useful life (RUL) [12]. This method consists in using the SCADA data of

the WT bearings temperature and calculating the relative temperature by means of a moving average. The performance degradation model is established by means of the Wiener process with linear fluctuations. The parameters of this model are obtained by the maximum likelihood estimation method. The results showed that online RUL prediction is more effective than the traditional method. The first value outside the bearing temperature warning threshold it is established based on an inverse Gaussian distribution, that allows to improve WT operation and maintenance strategies.

The relationship between WT bearing temperature residues and Gaussian (GP) processes was studied by Herp et al. [11]. It was shown that failure prediction is possible due to overheating of the bearing. The results showed that it is possible to predict one month before the appearance of a real failure, although in the future it is important to work with more historical data. They demonstrated that Bayesian inference is useful to predict the WT states, as the calculations offer a compensation between model performance and computational efficiency.

1.3 Case Study

Data mining is employed in this paper to extract information from the system and create patterns of behaviour. Data mining is used in the SCADA dataset to 3 turbines. The data were collected for two consecutive years measured at intervals of 10 minutes.

This paper proposes the use of historical data to create a simple model to identify outliers to detect faults.

Fig. 1.1 presents the power curves for the three WTs, more than 100,000 data points for 2 years, 2013 and 2014. The model considers these data together with the temperature of the bearing.

There are many studies on the power versus wind speed curve, but not on temperature of the bearing. Fig. 1.2 shows the bearing temperature versus wind speed curve. Zone 1 is omitted because the turbine is stopped. When the wind speed increases, the temperature of the mechanical components increase (Region 2). Once the wind speed exceeds the nominal speed, the WT must set its nominal output power and the temperature of the components will not change due to the wind speed

Fig. 1.1 Power Curve, years 2013-2014

(Region 3). If there was an error in setting the upper limit of the nominal output power, the temperature of the mechanical components would continue rising and it could lead to a catastrophic failure.

Fig. 1.2 Graph of the bearing temperature as wind speed

Fig. 1.3 shows the linear regression of the temperature curve of the bearing against the wind speed, studying the regression in intervals of one unit of speed (m/s). The three turbines have a similar behaviour into three zones. The first zone is set until the wind speed reaches approximately 5 m/s. The temperature of the bearing depends fundamentally on the ambient temperature, therefore, it can increase but lower than that of zone 1 because it is able to dissipate heat. In the range of 3 to 9 m/s, the growth of the wind speed causes the bearing increasing almost linearly and with great slope. It is due to the fact that the wind speed increases and, therefore, the wind turbine speed increases, generating greater friction between the mechanical components of the gearbox and the bearing. Finally, Zone 3, the wind speed increases and the bearing temperature is almost constant because the rotor of the wind turbine speed does not increase.

The temperature of the bearing in turbine 1 differs from turbine 2 and 3. It is higher in Zone 1, but lower in zone 2, probably because there are less friction in the bearing, the lubrication is better.

Fig. 1.4 shows the same approach to Figure 3 applied to the power versus wind speed curve. The three turbines have a similar power curve because they are in the same location and with the same technical characteristics.

Fig. 1.5 presents the behaviour of the bearing temperature versus wind speed in the different seasons of the year (winter, spring, summer and autumn). The main conclusions are:

Fig. 1.3 Linear Regression in intervals of 1 unit of bearing temperature curve

Fig. 1.4 Linear regression of power curve versus wind speed

- WT 1 has a lower temperature in most cases, therefore, its heat dissipation is better and / or there is less friction between components. WT 2 and 3 have a similar performance.
- April shows irregularities in Zone 3, probably due the turbines have been stopped several times, a defected sensor, maintenance tasks, etc.
- January presents the most stable response in Zone 3.

The quadratic mean error (RMSE) has been used by the Eq. (1.1).

Fig. 1.5 Linear regression of bearing temperature versus wind speed in different seasons of the year

It is a statistical measure that is used in the quantitative study of model. p_i is the temperature of the actual bearing and $\hat{p}_i$ is the temperature of the predicted bearing, where n is the number of data points.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (p_i - \hat{p}_i)^2} \quad (1.1)$$

The results obtained show that the non-linear fit that best fits the model is the grade 9 polynomial, given by eq. (1.2), where $x = 6.453$, normalized by , and $\sigma = 3.785$.

$$F(x) = p_1x^9 + p_2x^8 + p_3x^7 + p_4x^6 + p_5x^5 + p_6x^4 + p_7x^3 + p_8x^2 + p_9x + p_{10}. \quad (1.2)$$

Table 1.1 shows the RMSE values for different degrees of polynomials.

Table 1.1 RMSE values

	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6	Grade 7	Grade 8	Grade 9
RMSE	6.595	5.377	5.253	4.892	4.865	4.833	4.809	4.809	4.808

It is recommended to use the grade 7 polynomial due to the computational cost. Fig. 1.6 shows the optimum regression of the bearing temperature versus wind speed curve with 95% confidence limits.

Fig. 1.6 Bearing temperature versus wind speed curve fitting

1.4 Conclusions

The gearbox is the mechanical component that causes the most downtime to the wind turbine. Bearing temperature analysis is a variable for failure prevention and detection in gearboxes. Failure analysis is done in this paper using historical data of the temperature curve versus wind speed. A 95% confidence interval is established, and outliers are identified in real time to indicate that a fault or measurement error appears. Bearing and gearbox failures are identified before they occur, and catastrophic failures can be avoided. It is proposed to study the correlation of other variables with the bearing temperature for failure detection, and the study of the causes of temperature changes in the bearing, such as dissipation capacity, friction between mechanical components and the quality and quantity of oil for optimum lubrication.

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