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Early Detection of Main Bearing Damage in Wind Turbines

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Abstract. According to the European Wind Energy Academy (EAWE), the wind industry has recognized that main bearing failures are a major concern in order to increase the reliability and availability of wind turbines. This is due to the high replacement cost of major repairs and the long downtime associated with main bearing failures. As a result, predicting main bearing failure has become an economically important problem as well as a technological difficulty. This paper presents a data-driven technique based on a closed recurrent unit (GRU) neural network for early failure prediction (months in advance). The main contributions of this work are: (i) The prediction is made exclusively using SCADA (Supervision Control and Data Acquisition) data already present in all industrial wind turbines. Therefore, there is no need to add additional sensors intended for a specific use. (ii) Since the proposed approach only requires healthy data, it can be used in any wind farm even if it has not recorded faulty data. (iii) The suggested algorithm operates under a variety of operational and environmental circumstances. (iv) The methodology is validated in two real in-production wind turbines. production.

Key words

Wind turbine, fault detection, main bearing, SCADA data, GRU neural networks.

1. Introduction

The global energy system is undeniably under transition. The broad adoption and usage of renewable energy is the quickest and cheapest path to increased energy independence following the invasion of Ukraine, and it is the key to combating climate change. Renewables-based electrification, according to the European Commission forecasts, will be critical to achieving climate neutrality in Europe by 2050 [1]. Wind energy is a critical component in achieving this goal, as it is required to account for 50% of the power mix of the European Union, with renewables accounting for 81%. The heart of the issue in the progress of the wind business, however, is the reduction in its levelized cost of energy (LCOE). Wind energy operation and maintenance (O&M) expenses, in particular, account for a large portion (20-25 percent in onshore wind parks and 25-30 percent in offshore wind parks) of the LCOE for this technology [1]. As a result, optimizing maintenance procedures is a critical aspect in achieving low-cost wind energy.

Power generation losses due to downtime (caused by unscheduled equipment repairs) and the costs associated with component replacement can amount to millions of euros per year for any industrial-scale wind farm. Therefore, it is imperative for the wind industry to move from corrective (repairing components after a failure) and preventive (scheduled at regular intervals without considering the actual condition of the asset) to predictive maintenance (planned as needed according asset status).

This research focuses on wind turbine main bearing failures (WT). Indeed, main bearing failures has been identified as a critical issue at the moment of enhancing the reliability and availability of wind turbines by the wind industry, according to the European Wind Energy Academy (EAWE) [2], as they lead to significant repairs with high replacement rate costs and long downtimes.

Since the major function of SCADA (Supervisory Control and Data Acquisition) data is operation and control rather than condition monitoring, using it for this task would be incredibly challenging, but it would also be a cost-effective way of predictive maintenance because it does not necessitate the installation of specially specialized sensors (with the associated costs). Due to continually changing operational conditions induced by environmental changes, SCADA data is very volatile and affected by seasonality (e.g. wind speed and direction, turbulence intensity, ambient temperature, etc.). In addition, SCADA has a very low sampling rate (sometimes 1 Hz, but normally only the 10-minute average is stored for each variable) in contrast to typical condition monitoring systems that have a kHZ frequency, [3].Recent research has concentrated on this approach, and there have been some positive outcomes involving the use of only SCADA data from real WTs for condition monitoring. It should be noted that using SCADA data alone means that no additional sensors are used; however, some work orders information can also be used. For example, in [4], support vector machines (SVM) were used to diagnose and predict WT faults from SCADA data, in [5], is presented a framework that was implemented, using the rules that the turbine alarm follows to perform fault classification, to automatically identify periods of faulty operation, and in [6], an advanced prognostic system based on an artificial neural network was proposed.

The preceding studies used SCADA data to test the technique on genuine WTs; unfortunately, they all required historical fault data denominated as faulty data. In historical SCADA data, the periods when turbines are down due to a failure, as well as the cause of the issue, must be accurately labeled. This is inefficient, error-prone, and almost invariably results in a set of labeled vectors with an uneven number of classes. In this study, however, historical fault data is not required; as a result, the suggested technique may be used to any wind farm, regardless of whether it has recorded faulty data or not. A normal behavior model is presented in this work, which means the model was constructed using data from normal (healthy) operation. The model is trained on a monthly basis. This implies that data from one month is utilized to predict the wind turbine condition the following month. The data from ¾ of the month is utilized for training and the remaining days are used for validation. In this manner, the model does not need to learn varied seasonal fluctuations and provides results tied to the closest season. Finally, the objective of the model is to predict the main bearing temperature of a wind turbine using only data from the two closest neighboring wind turbines.

The organization of the rest of this paper is described below. In section 2, a brief description of wind turbines is presented. In Section 3, the methodology proposed in this work is described. Section 4 is to present the results obtained and their discussion. Finally, Section 5 draws conclusions and describes future work.

2. Wind Turbine Overview

In this work, the SCADA data from two wind turbines with a diameter of 101 meters and a nominal capacity of 2300 kW are used. The main components of the WT are shown in Figure 1. At a wind speed of 3 m/s, the energy generation begins, at a wind speed of 12 m/s, the WT achieves its rated power, and when the wind speed reaches 20 m/s or higher, the WT uses its braking system to automatically stop. The technical specifications of the turbine are summarized in Table I.

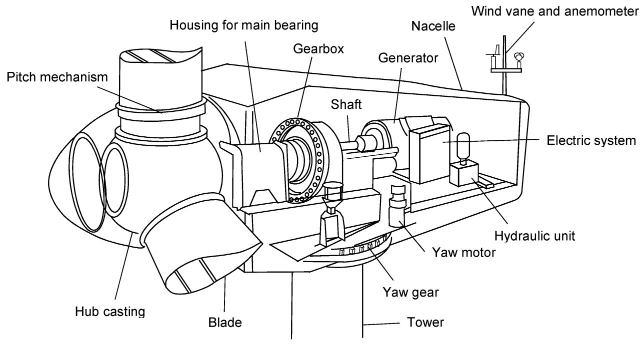

Fig. 1: Wind turbine components.

Table I. Park WTs technical specifications.

Technical specification	Value
Number of blades	3
Nominal power	2300 kW
Rotor diameter	101 m
Wind class	IEC IIb
Swept area	8012 m
Cut-in wind speed	3 m/s
Rated wind speed	12 m/s
Cut-out wind speed	20 m/s

The data are collected from January 1, 2018 to August 31, 2018 and represent continuous operation of the WT every 10 minutes. The SCADA data are made up of environmental, electrical, hydraulic, and control variables. In addition, components' temperatures are obtained and stored in the SCADA data. For these variables, the mean, maximum, minimum, and standard deviation of the 10-minute averaging period of 1 Hz sampled data are accessible. Finally, in addition to SCADA data, information on maintenance and repair actions (work orders) for the studied WT is available. The following information is provided by this data: failure type, failure date, work order date, affected subsystems, and the description of the action that was performed. This data is used in this study to model and test whether the suggested methodology can forecast the occurrence of main bearing faults months ahead of time.

3. Fault Detection Methodology

This section describes the proposed fault detection methodology, which is a normal behavior model (NBM). NBM will learn the patterns related to the healthy state by training only with historical sensor data from all normal modes of operation of the asset. A model that has learned the normal operation of an asset will be able to indicate when it is beginning to act abnormally, which is often a sign of imminent failure or suboptimal operation. The following steps will be comprehensively explained. First, the data imputation and normalization is sated. Then, the used SCADA variables and the proposed GRU network are given as well as the data split into training, validation, and testing sets. Finally, the proposed fault prognosis indicator (FPI) is stated in Section 3-D, which employs a moving daily average strategy to reduce the number of false alarms.

A. Data imputation and normalization

Because real data is messy, a data cleaning approach is necessary. For missing data, a data imputation methodology is employed in this study. Techniques based on statistical variables such as mean, median, and mode are not taken into account because they may induce bias in the data's mean and deviation [7]. Alternatively, the piecewise cubic Hermite interpolating polynomial is suggested [8]. This interpolation provides a continuous first derivate function that keeps its shape and is monotonic. The nearest value is used to fill in missing data at the beginning and end of the dataset.

On the other hand, each of the variables that will be utilized in the model must be normalized. Otherwise [9], the output of the model may be skewed toward large-scale data. Machine/deep learning approaches frequently recommend scaling the data in order to improve the efficiency of the optimization procedure. In this work, data are scaled using the Min-Max approach, which uses a linear transformation from the initial set's range to scale data in the [0,1] range (the minimum value is transformed to 0 and the maximum value is transformed to 1). As a result, this technique produces data that is standardized to the same interval for all variables [10].

B. Input and output data to the GRU network

The objective of the GRU network is to predict the main bearing temperature of a wind turbine using data from the two closest neighboring wind turbines. Since the three WTs receive the same wind flow, their energy production will be related. By having a related energy production, the internal variables of each WT will also be related to its neighbors. From this, it is possible to build a normality model on the variable main bearing temperature and detect abnormal temperatures that indicate a fault in the main bearing. The variables used as input are the main bearing temperature and the gearbox oil temperature of the two closest neighboring wind turbines.

Because the work uses data that can be affected by seasonality, such as the change in temperature throughout the year, the model is trained with a monthly frequency. This means that data from one month is used to predict the next month. For this, the data of ¾ of the month is used for training (that is, 22 or 23 days depending on the month) and the remaining ¼ for validation. With this approach, the model does not adjust for different seasonal temperature changes and provides results tied to the closest season. In addition, the ambient temperature is removed from all temperatures.

C. GRU proposed architecture

The GRU architecture requires a different set of hyperparameters depending on the problem at hand to achieve optimal performance. This section describes the selected hyperparameters in detail.

First, the number of hidden layers; this hyperparameter define the layers of the network that exist between the input and output and contain the GRU cells, is specified. In this work, it is defined as a single hidden layer, since testing with two layers did not improve the early failure detection performance and therefore did not justify the additional computational effort.

Second, the hidden size determines the number of entities in the hidden state. In other words, it defines the number of neurons or GRU cells in the hidden layer. This hyperparameter determines the learning ability of the model. In this paper, 128 hidden-state neurons are chosen due to the amount of samples the model needs to process.

Third, the batch size is chosen to be 128, an initial learning rate set to 0.001, and 50 epochs used to train the network.

Finally, a loss function must be defined. In this work, the loss function chosen is the mean square error (MSE) because large errors are more important (may represent a defect) compared to small errors (possibly due to model errors).

D. How is the fault prognosis indicator (FPI) structured?

In this work, an indicator is needed to recognize when a prediction indicates that the current temperature of the main bearing is abnormal and the WT will fail. For this task, a FPI is defined using a residual and establishing a detection threshold. The natural residual to be used would be the absolute difference between the actual temperature of the SCADA main bearing and the one predicted by the model. However, using this approach would lead to an overwhelming number of false alarms.

To avoid this problem, the initial residual is filtered using a moving daily average (MDA). With this filter, the long persistence in time of the residual above the threshold is taken into account, which allows false alarms to be discriminated from real failure detection alarms.

After the filter, a threshold is defined using the training data. The FPI should indicate when a residual does not behave normally, so using the mean μ and standard deviation σ of the filtered training and validation residual should indicate what the normal behavior is. So the threshold is defined as:

$$\text{threshold} = \mu + \kappa\sigma, \quad (1)$$

where κ is a constant that sets the threshold value. In this work, the value of κ is 9.

4. Results and Discussion

This section presents and discusses the results obtained by applying the suggested failure prediction approach on two wind turbines. To do this, the absolute difference between the predicted and SCADA value is plotted for the two WTs of interest: one healthy and one faulty; where the fault is a main bearing failure on June 11, 2018.

Figures 2 and 3 shows the GRU predictions on the test data sets from January to August 2018. Figures 2 (a) and (b) show the estimated value generated by the model on the test sets and the SCADA value of a healthy and a defective WT, respectively. In Figure 2 (a), the prediction is close to the target value, with only a few disparate values. It is different in Figure 2 (b); it shows some disparate values, and the samples during the failure and a month later show a large difference from the real value.

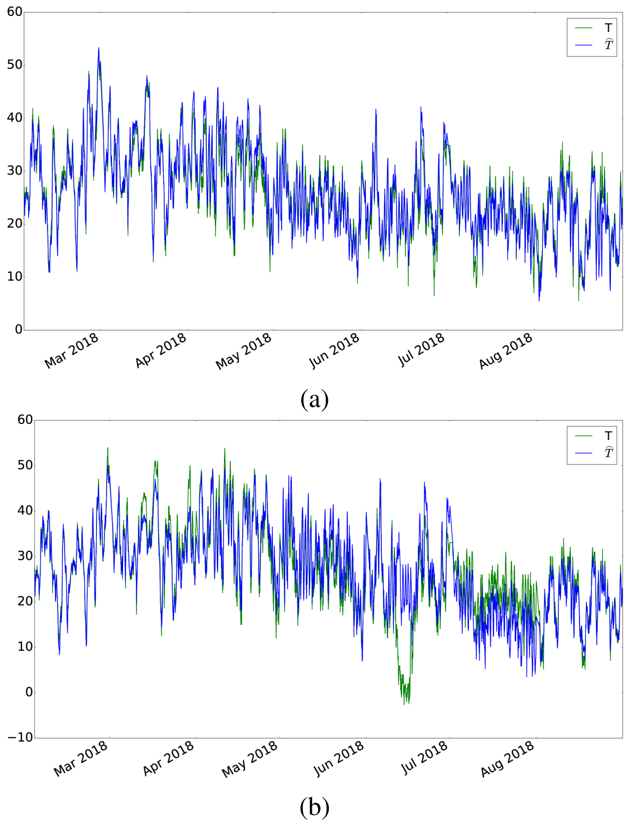

Fig. 2: (a) GRU estimated $\widehat{T}$, and SCADA real T, for WT1 over the test set. (b) GRU estimated $\widehat{T}$, and SCADA real T, for WT2 over the test set.

Finally, Figures 3 (a) and (b) show the difference between the prediction and the target value in the test set using a daily moving average. These last values are used to trigger an alarm when a fault occurs.

Applying a daily moving average on the forecast errors transforms the data into a time-persistence function that measures the behavior and trend of the data. In this way, the number of false positives is reduced, increasing the reliability of the model. In addition, a threshold is defined for when an alarm should be triggered.

Since one month's forecast is obtained by the trained model using the previous month as input, it is reasonable to use statistical estimators of the previous month to define when a forecast sample is out of range. Therefore, $\mu + 9\sigma$ is defined as the threshold.

Figure 3 (a) shows three times when the samples are outside the threshold. This occurs in July and August. Instead, Figure 3 (b) has some samples outside the running threshold that represents the June fault informational alarm.

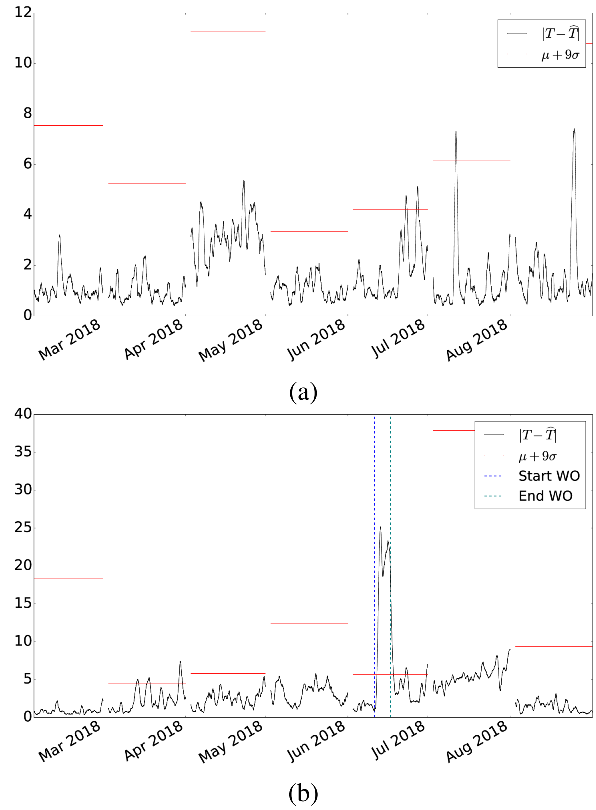

Fig. 3: (a) Error absolute value, $|T - \widehat{T}|$, with moving daily average for WT1 over the test set. (b) Error absolute value, $|T - \widehat{T}|$, with moving daily average for WT2 over the test set.

5. Conclusions

In this work, an early detection methodology for main bearing damage in WTs is proposed. The results show that the time it takes to generate an early prognosis is several months in advance, giving the plant operator enough time to schedule maintenance. Furthermore, the described technique works in the various operational and environmental situations that WTs face. Finally, the methodology is validated in two real in production wind turbines.

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