Proceedings of the 10th International Conference on Structural Health Monitoring of Intelligent Infrastructure, SHMII 10
Porto, Portugal, 30 June - 2 July 2021
A. Cunha, E. Caetano (eds.)

Fault Prognosis for Wind Turbines' Main Bearing based on SCADA data

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ABSTRACT: The rapid growth of large-scale wind turbines (WT) has changed the requirements in terms of operation and maintenance strategies. WTs are required to be safe and profitable systems. A great option is failure prognosis, aiming to reduce maintenance and operating costs, and forecast service life based on condition. In this work, the analysis of the data from the supervisory control and data acquisition (SCADA), already present in industrial sized WTs, and work orders (repair and maintenance data) allows a normality based methodology to be implemented using convolutional neural networks (CNNs). In this work, two years of SCADA data from a real under production wind farm, composed by 12 wind turbines is used. The main bearing failure occurred in one of this wind turbines, and thus it could be used to verify the performance of the proposed strategy in a real life situation. Finally, a proposed indicator helps us pinpoint in advance the occurrence of the fault. The obtained results provide a warning time (alarm) for the main bearing fault up to 5 months in advance.

KEY WORDS: Wind turbine; Fault prognosis; Main bearing; SCADA data; Convolutional neural network.

1 INTRODUCTION

Wind energy is one of the renewable energies that has experienced a dramatic growth in recent years. The reliability requirements of high-value structures, such as WTs, have increased significantly in the search for a lower impact on energy costs [1]. However, this process is not without complexity since these designs often carry inherent the assumption of some uncertainty. Besides, the trend towards larger WTs has significantly increased the repair/replacement cost of their components [2]. On the other hand, and given that the maintenance of WTs is among the factors that most increase the total cost of wind projects, the most effective way to reduce this cost is to monitor their condition continuously. Condition-based maintenance allows early prognosis of WT faults. It facilitates a proactive response, minimizes downtime, and maximizes the wind turbine's life and, therefore, its productivity. However, wind energy technical reports show that some of the currently available monitoring techniques are neither reliable nor suitable for WT applications due to the wind's stochastic nature, hardly affecting the decision-making [3].

The SCADA system is a necessary technical mean for the supervisory control of WTs. SCADA data provides records every 10 minutes of measurements as wind speed, the production of active and reactive power, currents and voltages of the generator, bearings' temperatures, and others). Although SCADA data have not been developed specifically for the purposes of condition monitoring, being able to extract relevant information from it for fault diagnosis would result in rapid deployment and modest set-up cost [4]. It should be noted that in this work, only SCADA data and work order records (repair and maintenance actions) are used; this means that no extra sensors/hardware/equipment or additional information to those mentioned are used.

There are some success stories of using SCADA data for WT condition monitoring. For example, [5] analyzes fault and alarm data from a WT to identify rated and faulty operation periods. Support vector machine (SVM) is applied to detect and diagnose faults taking into account other SCADA data such as temperature, pitch, and rotor data; all analyzed data is known in advance. In [6] a framework is presented to automatically identify faulty operation periods, applying rules to the WT alarm system; they also propose a metric to evaluate the method in a real scenario. In [7] multi-fault detection and classification based on SCADA data is accomplished through multiway principal component analysis and SVM and in [8] the problem of real-time fault detection using SCADA data in wind turbines is addressed.

However, all the aforementioned works require faulty data (historical faulty data). In particular, historical SCADA data must be accurately labelled with the periods when turbines were down due to faults, as well as with the reason for the fault. This is time consuming, error prone and likely to result in a set of labeled vectors with an unbalanced number of classes. By contrast, in this work, there is no need of historical faulty data, thus, the proposed strategy can be applied to any wind farm (even when no faulty data has been yet recorded). In particular, in this work, a normal behaviour model is proposed, that is, the model is build by using normal (healthy) operational data. The main bearing failure is studied, due to its high maintenance and repair cost [9]. To asses the proposed method, a real wind farm composed of 12 WTs is studied, where one WT suffers the failure of interest.

2 Main Bearing Fault

Bearings are widely used in the industry to minimize friction in machine rotating parts. They are a critical component since they have a high percentage of failure compared to other components [10]. Their failure can cause a total breakdown, leading to the machine's failure and, therefore, to the generation of loss in productivity in an unforeseen way for the production facilities [11]. Therefore, it is crucial to consider failure prognosis as an integral part of preventive maintenance procedures, thus increasing their efficiency and reducing the chances of machine downtime.

Among the failures that can be originated in bearings, those that occur most frequently appear in the rolling, the inner ring, the outer ring, and the cage. Figure 1 shows the structure of a bearing to illustrate the aforementioned parts. The failures

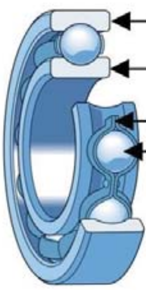

Figure 1. Main components of the rolling bearing [12].

may be due to tread surface damage, fractures, and gouging, or a risk factor.

The most critical failure is that of fracture in the bearing, see Figure 2. When it occurs, the mechanism is unusable. Therefore, the machine in which it is located also remains unusable (fracture is understood as the physical break in any of the bearing components) [13].

In wind energy, a WT main bearing replacement (see Figure 3) has high costs due to machinery, personnel, and downtime; for example, a \$ 5,000 bearing replacement can easily turn into a \$ 250,000 project due to the factors mentioned [15]. For this reason, the prognosis for the main bearing failure leads to great benefits.

Figure 2. Bearing faults: (a) bearing crack on the inner surface; (b) bearing crack on the outer surface, [14].

Figure 3. WT bearing replacement, [16].

3 Wind farm real SCADA data

The wind farm studied is composed by 12 WTs, it is located in Albacete (Spain) with commissioning date in 2006. The WTs are 1500 kW rated power, with 3 blades, a rotor diameter of 77 meters, a rated rotational speed of 18.3 rpm, and a wind swept area equal to 4657 square meters. Figure 4 shows the principal elements of the studied wind turbines.

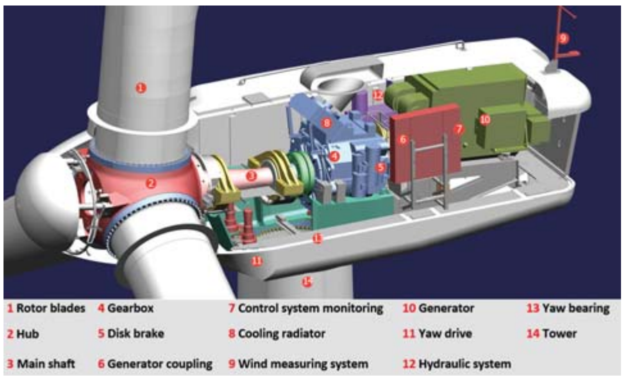

Figure 4. Structure of the studied WTs with its major components, [17].

The SCADA data of the wind farm correspond to operational data between the dates of February 2017 to November 2018. SCADA data includes 43 variables (for each variable, there are measurements of mean, maximum, minimum, and standard deviation) every 10 minutes. In general terms, the variables correspond to environmental measures, temperature of mechanical components, general electrical variables, gen-

Table 1. SCADA variables.

Variable	Description	Units
date_time	Date and time of the sample	-
VelVientoMean	Wind Speed	rpm
VelGenMean	Generator speed	rpm
VelRotorMean	Rotor speed	rpm
PresFrenoMean	Brake pressure	bar
PresAcumGralMean	Accumulated general pressure	bar
PresGHMean	Hydraulic group pressure	bar
TempAceiteGHMean	Hydraulic Group Oil Temperature	bar
PotMean	Active Power	Kw
TotPotReactMean	Reactive power	Kw
SPCosPhiMean	Power factor	-
FrecRedMean	Electric network frequency	Hz
TensRedMean	Phase voltage	V
TempAceiteMultipMean	Gearbox oil temperature	◦C
TempRodamMultipMean	Gearbox bearing temperature	◦C
TempGenMean	Generator temperature	◦C
TempRodamTraseroMean	Rear bearing temperature	◦C
TempCojLAMean	Bearing temperature coupling side	◦C
TempCojLOAMean	Bearing temperature non-coupling side	◦C
TempRadSupMean	Upper gearbox radiator temperature	◦C
TempRadInfMean	Lower gearbox radiator temperature	◦C
TempEjeLento	Low-speed shafft temperture	◦C
TempAmbMean	Ambient temperature	◦C
TempGondMean	Nacelle temperature	◦C
SPPitchMean	Pitch system parameter	-
YawMean	Yaw Angle	◦

eral hydraulic variables, and control variables. Table 1 shows the most relevant 25 SCADA variables with their respective name, description, and measurement unit.

In addition, there is information about the work orders (maintenance and repair actions) to which the WTs are subjected to. These data provide the time of the failure, description of the problem, component replaced, and comments from different personnel, among other data. With these available information, and the SCADA data, a failure prognosis procedure is proposed using a CNN, based on healthy data. The proposed methodology is a normal behaviour model, that is, the model is build by using normal (healthy) operation data. Thus, there is no need of historical faulty data, thus, the proposed strategy can be applied to any wind farm (even when no faulty data has been yet recorded).

4 Fault Prognosis Methodology

Different techniques have been used to monitor bearing failures [18], [19]. The main problem with classical techniques is that they require the supervision of an expert to extract features, so advanced engineering is needed, which implies greater human effort [20]. Currently there are new techniques and tools, such as deep learning, that allow the automatic extraction of features simplifying the final solution and considerably improving precision [21]. Furthermore, this type of methodology can be easily generalized or transferred to a different context [22].

This work is focused on developing a method to prevent the main bearing failure in WTs. Consequently, it is proposed a normality method, analyzing SCADA data from WTs using a CNN. Besides, an indicator is implemented based on a threshold, in order to minimize the number of false positives.

As previously mentioned, the wind farm is composed by 12 WTs. In this work, the notation WT1, WT2, and so on will be used to refer to each one of the WTs in the wind farm. The work orders show that WT2 presents the main bearing failure on May 21, 2017. The main challenge of this research is to predict the failure several months in advance. The strategy is to use the data between the dates of February 2017 until December 2017 for the training and validation of CNN. Then, data from 2018 (up to November 2018) is used for testing (making predictions). In figure 5 a graph with the explained dates is shown.

Figure 5. WT2 detailed training, validation, test data and date of failure.

5 DATA PREPROCESSING

The SCADA variables selected to develop the normality model are shown in Table 2 with their units. The variable Pot is measured before the electrical energy reaches the electrical network; therefore, it is considered the power delivered to the network; this variable is sensitive to wind variations. The TempAmb variable measures the ambient temperature, which affects the temperature of several mechanical components of the WT. TempCojLA and TempCojLOA variables correspond to the temperatures of the coupling side of the bearing and the non-coupling side of the bearing, respectively. TempEjeLento measures the slow shaft temperature, which is close to the main bearing. Variables TempGen and TempRodamMultip correspond to the generator temperature and the gearbox bearing temperature. Finally, the VelRotor control variable has been used; this variable measures the rotor speed.

The real SCADA data has noise, such as outliers and missing data caused by faulty sensors, communication problems, maintenance, or WT repairs. To solve these problems data cleaning is a must. First, the outliers have been eliminated by range filtering, see Table 2. For example, it is known that the ambient temperature can range from -5 degrees to 40 degrees, thus data out of this range has been eliminated; this procedure is carried out for the other variables.

This procedure leads us to another problem. As we remove the invalid values, we increase the number of missing values, so data imputation is needed. In this work, simple imputation is proposed for intermediate data; this procedure is performed using piecewise cubic interpolation (pchip), thus preserving the trend and shape of the data, see Figure 6. Finally, the extreme missing data (initial and final values) have been filled with the repetition of the last closest real data.

Table 2. Selected SCADA variables used to develop the normality model, its description, range of possible values, and units.

Variable	Description	Range	Units
Pot	Generated real power	[0, 2000]	kW
TempAmb	Ambient temperature	[−5, 40]	°C
TempCojLA	Bearing coupling side temperature	[0, 120]	°C
TempCojLOA	Bearing non-coupling side temperature	[0, 120]	°C
TempEjeLento	Low-speed shaft temperature	[0, 120]	°C
TempGen	Generator temperature	[0, 175]	°C
TempRodamMultip	Gearbox temperature	[0, 120]	°C
VelRotor	Rotor speed	[0, 50]	rpm

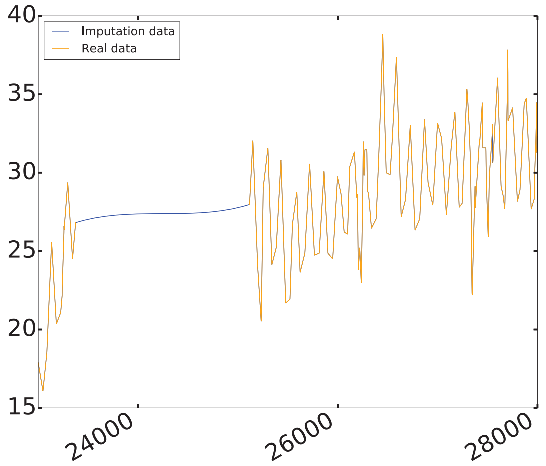

Figure 6. Imputation in the ambient temperature data (SCADA variable TemAmb).

5.1. Data split

To develop the prediction model, deep learning methods divide the available data into sets of training, validation, and testing. The training data set is the data set used to train the CNN model (make adjustments to the model). The validation dataset is used to provide an unbiased assessment of the fit of the model in the training dataset while fitting the hyperparameters of the model. In this work, the data for training and validation corresponds to the data between dates from February 6, 2017 to December 31, 2017. These data have been divided as follows: 90% for training and 10% for validation, see Figure 5. In other words, there are 42624 samples for training and 4752 samples for validation.

Test data allows evaluating whether the answers obtained from the model are correct or not. The data reserved for the test (predictions) corresponds to data between January 1, 2018, until November 31, 2018. Thus, in total, there are 47808 samples.

5.2. Data normalization

The main reason for data normalization is to improve the neural network training process's efficiency, which significantly reduces the number of epochs required for the network to learn and thus leads to a better predictor. The SCADA data studied comes from different types of sensors and, thus, with different magnitudes. The strategy implemented is the min-max scaling in each SCADA variable separately.

5.3. Data reshape

The data conversion strategy converts the time-series information available in the SCADA data to spatial information. The transformation is carried out individually for each of the seven SCADA data; in such a way, arrays with 144 samples can be obtained (this corresponds to one day of data). The arrays obtained in this process have a size of 12×12. The SCADA data mentioned correspond to the seven SCADA variables shown below, where t represents a time instant.

- TempAmbMean(t-143, t-142, t-141, ···, t)
- TempRodamMultipMean(t-143, t-142, t-141, ···, t)
- TempCojLAMean(t-143, t-142, t-141, ···, t)
- TempCojLOAMean(t-143, t-142, t-141, ···, t)
- TempGenMean(t-143, t-142, t-141, ···, t)
- PotMean(t-143, t-142, t-141, ···, t)
- VelRotorMean(t-143, t-142, t-141, ···, t)

The arrays obtained from the data reshape can be represented as grayscale images. Figure 7 shows an example.

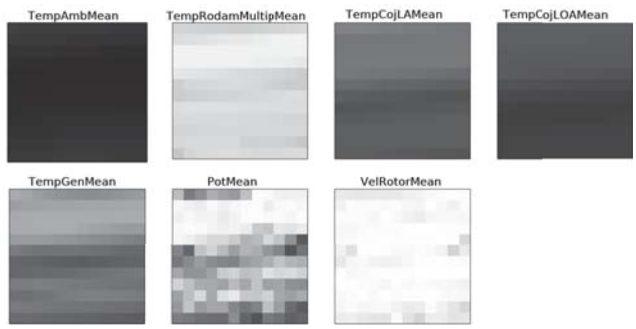

Figure 7. Input arrays shown as gray scale images.

The CNN output is the SCADA variable TempEjeLento at instant t. That is, the variable TempEjeLento at time t is approximated by the CNN using the information of the other aforementioned variables at times t-143, t-142, t-141, ···, t.

6 Convolutional Neural Network

The proposed CNN architecture is shown in Figure 8 and the most relevant characteristics are given in Table 3. Initially, input arrays have dimension $12 \times 12 \times 7$, as there are seven

SCADA variables. These data go trough the first convolution module; this module is composed by 14 filters (kernel 3×3) with padding and stride equal to 1, thus, as result it is obtained a $12 \times 12 \times 14$ output size. The second and third convolutions have the same kernel, padding and stride settings, with results of $12 \times 12 \times 21$ and $12 \times 12 \times 7$ output size respectively. Next, there are three fully connected layers with sizes 200, 84, and 1. Finally, note that all the connected layers have a ReLu activation function. The parameters have been optimized with Adam, which is an adaptive learning rate method. This method is easy to implement, is computationally efficient, needs low memory requirements, and the hyper-parameters are intuitive to interpret and generally require a little adjustment. The values of the selected hyper-parameters are an initial learning rate of $\alpha_0 = 0.00001$, a gradient decay factor of $\beta_1 = 0.9$, a squared gradient decay factor of $\beta_2 = 0.999$, and a $\varepsilon = 10^{-8}$.

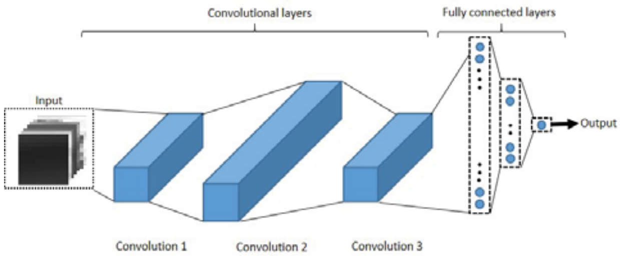

Figure 8. CNN architecture.

7 Fault Prognosis Indicator

With the trained model, we can compare the predicted TempEjeLento with respect to the real (target) SCADA data for that variable. For example, taking WT2 as an example, it can be observed in Figure 9.

From the result shown in Figure 9, the absolute value of the actual values T^{el} and predicted values $\hat{T}^{el}$ is computed, see Equation (1). The result is shown in Figure 10.

$$dif = |T^{el} - \hat{T}^{el}| \tag{1}$$

The CNN model may not be able to keep up with the rapid change in turbine operating conditions such as turbine start or incorrect sensor measurements. Therefore, it is normal that the difference increases to a high level and returns to normal in a short time. If the indicator is based on the single value of the difference, there would be too false positives, as can be seen in Figure 10.

Therefore, it would be better to use long-term values of the difference above a certain threshold. The threshold equal to the mean plus six times the standard deviation has been defined, see Equation (5). It should be noted that the mean and standard deviation (see Equation (3) and Equation (4)) are obtained in each SCADA variable from the training and validation data sets as a whole (2017 data).

$$dif_{2017} = |T^{el} - \hat{T}^{el}| \tag{2}$$

$$\mu = \text{mean}(dif_{2017}) \tag{3}$$

$$\sigma = \text{std}(dif_{2017}) \tag{4}$$

$$\text{threshold} = \mu + 6\sigma \tag{5}$$

For each week, the number of times in which a data is greater than the threshold is counted (n_{over}). A minimum function is implemented in the indicator to give a value of 0 if no sample exceeds the threshold and a value of 1 if at least 216 samples exceed the threshold (that is more than a day and a half of samples are over the threshold). Equation (6) shows the implemented indicator.

$$\text{Indicator} = \min\left(1, \frac{n_{over}}{216}\right) \tag{6}$$

8 Results

Figure 12 shows the results obtained throughout the wind farm. Recall that WT2 suffers the main bearing failure on May 21, 2018. The graph corresponding to WT2 clearly shows two peaks in the indicator, the first in February and the second peak in May (date where the failure occurs). The alarm activates five months in advance, in February, when the indicator passes the value of 0.5 (note that the indicator values are always between 0 and 1). At the other WTs, the indicator remains at zero or only small peaks appear (as in WT6, WT 10, and WT11) but they do not generate an alarm warning (as they do not surpass the value 0.5).

Figure 11 shows a flow diagram of the proposed normality model and indicator. First, the healthy data from the wind turbine is processed, normalized, and reshaped. Then, the CNN is trained with the proposed architecture and ends with the indicator developed to warn if there is a risk of failure in the WT.

9 Conclusions

In this work, a strategy based on a normality model is proposed using a CNN. The approach is tested in a real wind farm under operation composed by 12 WTs where one WT suffers the failure of interest, and the others are healthy. The contribution of this work consists of the cleaning and imputation of the SCADA data, followed by normalization, reshape to arrays and the design of a deep CNN. The proposed indicator allows us to obtain weekly results and warns us when a failure is close by (the indicator exceeds the value of 0.5).

The conceived methodology can be easily applied to other WTs since labels are not needed beforehand. In the analyzed wind farm, an excellent precision of 100% is achieved with no false positives. These results are promising and future work will be carried out with other types of fault and other wind farms data.