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Online automatic diagnosis of wind turbine bearings progressive degradations under real experimental conditions based on unsupervised machine learning

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ABSTRACT

As a critical component, failures of high-speed shaft bearing in wind turbines cause the unplanned stoppage of electrical energy production. Investigations related to naturally progressed defects of high-speed shaft bearings are relatively scarce and the online assessment in damage severities is rarely available in the literature. In this sense, this paper presents a new online vibration-based diagnosis method for wind turbine high-speed bearing monitoring. The adaptive resonance theory 2 (ART2) is proposed for an unsupervised classification of the extracted features. The Randall model is adapted considering the geometry of the tested bearing to train the ART2 in the offline step. In fact, the time domain, the frequency domain, and the time-frequency domain are investigated for a better bearing fault characterization. Indeed, the use of real measured data from a wind turbine drivetrain proves that the proposed data-driven approach is suitable for wind turbine bearings online condition monitoring even under real experimental conditions. This method reveals a better generalization capability compared to previous works even with noisy measurements.

1. Introduction

Onshore and offshore wind powers are one of the fastest growing sources of electricity generation in the world. By 2015, this growth has reached almost 23 percent in Canada, representing more than 3 billion dollars in investments and 10500 new jobs [1].

Despite its importance in clean energy production, wind turbine generators (WTGs) are subjected under extreme environmental conditions leading to several types of defects and unexpected production stops. Taking also into account the improper maintenance, WTGs often fail prior to their 20-year design life [2]. The damages in WTGs are dominated by failures in gears and bearings [2,3]. In fact, a statistical investigation has shown that gears faults present between 35.55% and 71.11% of all WTG failures [4] and bearings failures account for 64% of all gearbox failures [3,4].

The gearbox, which is a mechanical speed variator that adjusts the speed between the rotor and the generator, consists mainly of gears and bearings. Bearing-related failures (dominated by high-speed shaft bearings (HSSBs)) are about 64% of all gearbox failures, those of gears: (dominated by helical gears) present 25% and the remainder 11% (such as housing and cooling fan) are dominated by lubricants and filtration systems [4].

Recently, the development of load prediction, the reliability of wind gearbox has shown considerable improvement. Despite that, it remains considered as the most sensitive element of the wind turbine system, justifying the need to be well monitored. Due to bearing sensitivity and its high failure rate, one of the fundamental problems currently facing a wide range of industries is how to identify a bearing fault before it reaches a critical level and catastrophic failure [5]. This is important in that a high speed bearing can be replaced "up tower" as a scheduled maintenance event at little cost. A catastrophic failure will likely require a gearbox replacement, with the added cost and time required to marshal a crane.

In this sense, several good surveys on the existing fault diagnosis

Abbreviations: AGWN, Additive Gaussian White Noise; ANN, Artificial Neural Network; ART2, Adaptive Resonance Theory 2; D, degraded state; EEMD, Ensemble Empirical Mode Decomposition; EMD, Empirical Mode; EWMA, exponential weighted moving average; F, failure state; H, healthy state; HSSB, high-speed shaft bearing; IMF, intrinsic mode function; MDVD, Multi-Dimensional Variational Decomposition; SK, Spectral Kurtosis; STFT, Short-Time Fourier Transform; SVM, Support Vector Machines; VMD, Variational Mode Decomposition; WTG, wind turbine generator

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techniques can be found in the literature. Among these surveys we quote the Refs [6–10] and we recommend the reading of the Refs [9,10]. Three different approaches were presented: The physical model developed by experts and validated on large sets, the rule based expert systems and the data-driven model. Authors in Ref [11] have reported that the most suitable approach for the diagnostic and prognostic of bearings is the data-driven one.

Several meaningful data acquisition techniques can be used for wind turbine bearing condition monitoring such as: Acoustic measurement, electrical effects monitoring, power quality, temperature monitoring, oil debris monitoring and vibration analysis. Vibration analysis is the most common technique used in the industry for any kind of rotating equipment and it is an effective tool for the bearing fault diagnosis [9].

Bearing vibration signals can be measured in all industrial systems and it contains the greatest information [5,11]. However, they are considered as non-stationary and non-linear [10]. Consequently, bearing fault diagnosis based on vibration signals needs to be studied by the most effective, robust and sensitive methods.

In this paper, we propose a new data-driven method for WTG diagnosis. For this, a real run-to-failure vibration history of HSSB was used. Our challenge is to define on the first hand, an accurate online technique to determine the health state of the tested HSSB. On a second hand, our challenge is to present an automatic decision capability without any human intervention or expert analysis. As such, three bearing states are defined: The healthy state, the degraded stated and the state of failure. Two steps are considered: The feature extraction step and the unsupervised feature classification step. An advantage of the proposed technique is that it does not need a learning step. In fact the learning and testing steps are done online at the same time as a result of the Adaptive Resonance Theory 2 (ART2) algorithm. An offline step is added to the ART2 neural network using Randall vibration model. This smart steps ensures that the first ART2 decision correspond to the healthy state. Experimental results validate that the proposed method is able to follow sensitively the regularity of bearing degradations even under variable conditions of speed and torque.

The remainder of this paper is organized as follows: a short literature review of bearing fault diagnosis based on vibration analysis is presented in Section 2. In Section 3, we detail the different steps of the proposed method. In this section, the feature extraction procedure is presented and the basic principles of the ART2 neural network are detailed. Experimental results are provided in the Section 4. Also, in this section a comparison of the performances of the proposed method with previous methodologies in literature is given. Finally, our conclusions and prospects are provided in Section 5.

2. Brief discussion of the reported diagnosis methods

To reduce the operating and maintenance costs of WTGs, reliable and effective bearing fault detection techniques are needed. In this sense, several efforts were presented in the literature using vibration monitoring. Most existing works tried to detect effectively the fault characteristic frequencies [10]. However, the passage from the time-domain to the frequency-domain requires the hypothesis of the stationary of the mechanical vibrations [12]. Unfortunately, HSSB vibration signals are considered non-stationary since WTG gearboxes often exhibit some speed and load variations in practice due to: tower shadow/wind shear, the variation of the speed and the quality of the wind (turbulence) [13,14].

To avoid this problem, Saidi et al. proposed to decompose bearing vibration signals into a number of stationary intrinsic mode functions (IMFs) based on the Empirical Mode Decomposition (EMD) method [12]. The first IMF is then used to compute the bi-spectrum and to detect the fault characteristic frequencies. The idea of this work was impressive despite that the authors haven't justified the use of the first IMF vs. other IMFs. Additionally, the experimental validation of the proposed method was based on Case Western Reserve University (CWRU) bearing data benchmark where the recordings were made at constant speed and load.

To deal with a wide range of speed and load fluctuations, authors in Ref [15] proposed a new method called Multi-Dimensional Variational Decomposition (MDVD). In fact, the Variational Mode Decomposition (VMD) is incorporated into convolutional Blind-Source Separation (BSS) to arrange with the load and speed variations. Experimental results based on some bearings with axial cracks in the outer race showed that the proposed method has great potential for WTG bearing fault diagnosis.

In addition to the problem of non-stationary, noises present a serious trouble in the study of bearing vibration signals [10]. In reality, these signals are always affected by the much stronger signals associated with the gears, shafts and rotor bars. In other words, bearing vibration signals are relatively weak (10e-3 gs) compared to other unintentionally recorded signals (10 s gs) [5]. To overcome this problem and to detect incipient faults at an early stage despite the high background noise, the cyclic bispectrum is used in [16]. By inheriting the advantages of the cyclic bispectrum, an alternative approach based on bispectrum and cyclostationarity analysis wad proposed. Despite all the efforts of authors, this method was not very sensitive to noises.

In [17], the fast kurtogram was combined with the genetic algorithm for resonance demodulation. Initial estimates and final optimization were more accurate than classical methods for the detection of fault characteristic frequencies. However, it is still very hard to distinguish incipient faults when vibration signals are smaller than the noise measurements. Also, this method, like the other works already quoted, requires an expert intervention analyze inthe frequency spectra. Thereby, the sensitivity and the specificity results of these works are highly dependent on the experience of the user.

Alternatively, several works suggest that bearing fault diagnosis is mainly a problem of pattern recognition [18]. The use of artificial intelligence techniques provides an expert system for automatic incipient fault detection without any human intervention [5]. In so doing, Artificial Neural Network (ANN) was used in [19] to classify some extracted features and to analyze ball bearing faults. The feature extraction step was based on the combination of EMD and Hilbert transform methods. The proposed strategy was interesting, that achieved high fault classification accuracy. Similarly, ANN has proved its effectiveness for bearing fault diagnosis in [5]. Time-domain and time-frequency domain features were extracted and initially evaluated using a statistical criterion. Then, the selected features were classified online to define the state of health of the studier bearing.

In [20], the curvilinear component analysis was used to select the most significant time-domain features on a first hand. The nonlinear behavior of the extracted features is visualized and well interpreted and explained physically. On a second hand, a hierarchical neural network was used to perform online the classification stage. This work has presented a powerful method even in different operating conditions. Similarly, the importance of the combination of time-domain features and ANN was validated also in [21].

In [22], a combination of higher order spectral features and Support Vector Machines (SVM) was presented. Authors initially computed the bi-spectrum of the recorded vibration signals and then extracted statistical frequency-domain features. Then, a "one-against-all" SVM strategy was adopted to classify the extracted features. The potential of this method has the processing capability to extract and classify the meaningful information coming from vibration signals with different frequency ranges and even with small energy.

Although that previously cited works have attempted to present a robust strategy for online bearing fault diagnosis, they suffer, with respect, from two common drawbacks:

- The feature extraction process was not justified. Three domains could be investigated: the time-domain, the frequency-domain and the time-frequency-domain. Unfortunately, previous works have