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Sound and vibration-based pattern recognition for wind turbines driving mechanisms

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ABSTRACT

This paper proposes a pattern recognition approach for a Fault Detection and Diagnosis (FDD) system based on the wavelet and the fast Fourier transform. Both techniques are developed in an experimental set that simulates the driving mechanisms housed in the nacelle of a wind turbine (WT) with results being validated in a real wind farm. After a first separate approach of the vibration harmonics and the sound energy, the root mean square error (RMSE) is used to fuse the data into a common pattern. The pattern reveals accurate information for unstable features (e.g. the case of the sound) related to misalignments among other failures. Comparing the experiments with the pattern, it is observed that the pattern is often close to the induced failures with minor exceptions. Relations among all the measured points are also found. The usefulness of the findings lies in the possibility of monitoring inaccessible devices considering this relation. Cost savings based on the strategic placement of the sensors can be intended too. The FDD will ensure the implementation of predictive actions before the occurrence of a catastrophic failure in an area where there is an ongoing challenge for being competitive.

1. Introduction

Wind power technology has experienced an important technological growth in the last decades. This is partly due to the increase of the market share, making companies more competitive; and the specific characteristics of the WTs [25]. Consequently, efforts have been focused on the introduction of new techniques for the condition monitoring (CM) systems to increase the Reliability, Availability, Maintainability and Safety (RAMS) [22]. Often, these efforts involve costs that vary between 20 and 30% of the total life cycle cost of a WT, forcing to consider the economic point of view as another priority [12].

Any current FDD approach is usually based on two basic elements: the abovementioned CM systems and signal processing and simplification methods that extract important information from the original signals [15,18]. This is translated into an early fault detection that help to maximise the productivity performance.

The most common FDD approaches include the study of acoustic emissions [16,35], vibration analysis [42,54], ultrasonic testing [49], thermography [4,71] and oil debris [39,69] among other techniques. Many case studies suggest the application of vibration and acoustic emissions for the analysis of bearings [31,40,58] or blades [11,33].

One of the major problems in the wind energy conversion is related to the generators and the emergence of vibration and noise failures [10,24]. However, researches have concentrated on gearboxes to reduce them for the complete system [36,45,46]. This is the main motivation to propose a novel FDD approach and a subsequent pattern recognition for sound and vibration on a test mechanism consisting of a generator connected to an engine. The choice of the two features is made to contrast with other monitoring systems that usually analyses the results from a single signal (sound, vibration, ultrasound, etc.). Therefore, the set will represent any drive system located in the nacelle of a WT.

The sound has been studied by wavelet techniques. Wavelet transform is an optimal methodology for the detection and diagnosis of particular performances that works with precision when accurate information is required. It is also able to detect particular characteristics as trends, breakdown points or self-similarities. The wavelet transform is selected from previous studies demonstrating its effectiveness and versatility in the area of the renewable energies [21,37,49,51,59,70]. Compared to other techniques, it presents fewer problems suppressing unwanted noise from the raw signal [48,50].

The use of the wavelet transform is not extended to the vibration since there are case studies stating inaccurate identifications in

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generators caused by heavy noises. This situation leads to a previous denoising [9]. Hence, the supporting vibration analysis will be developed from the fast Fourier transform (FFT). The FFT is widely employed for any type of maintenance that involves the existence of rolling elements to find potential defects such as misalignment, looseness, unbalances, etc. The Fourier spectrum shows several harmonics of the rotational speed, more specifically the first and the second, although higher harmonics may also be present in these scenarios [34].

The case study is divided into two phases. The first phase is focused on studying the signals individually to see their trends. The signals are taken from experimental fault modes induced in the set. According to relevant statistical data, over the 60% of the total number of rotating machinery faults belongs to misalignment faults [32,66]. Then, to focus the study on these aspects, apart from other types of faults, is justified. Previously, the quality of the experimental signals is compared with data coming from a wind farm to check that the final conclusions can be extended to real situations appearing in driving mechanisms.

This initial approach bases the results on the RMSE from the harmonics of the vibration and the sound energy. Its conclusions are supported by a statistical study that determines the robustness of the steps performed. Then, in a second phase, data are fused from a shared feature and a pattern recognition is created. The pattern recognition links the information from different sensors and obtains possible deviations depending on distances.

The main advantage of this FDD is the implementation of predictive actions that anticipate the occurrence of failures, even in hardly accessible devices of a real WT. Furthermore, the use of sound sensors can involve a reduction of costs in comparison to the vibration sensors used in current monitoring programs. The diversification of sensors also allows the real-time capture of different types of information.

The paper is structured as follows: Section 2 introduces a brief overview of the wavelet transform and the FFT and their different uses. Section 3 describes the case study and the results of a first analysis to relate the experimental information obtained from a test bench to a real WT. Section 4 sets an approach to a pattern recognition method and a based fault classification including the remarkable results. Finally, the last section presents the conclusions.

2. Wavelet transform and fast Fourier transform

The wavelet transform distinguishes and identifies local characteristics of a signal in the time and frequency domain, e.g. spectral features, unusual temporary files and other properties related to the lack of stationary [13]. Traditional filter based methods can loss part of the frequency details [27], while wavelet transforms considers this useful information during the denoising [45].

Wavelets transforms are generated from the translation and scale change from a same wavelet function $\psi_{s,\tau}(t)$, called *mother wavelet*, which is given by Eq. (1).

$$\psi_{s,\tau}(t) = \left(\frac{1}{\sqrt{s}}\right)\psi\left(\frac{t-\tau}{s}\right) \tag{1}$$

where s is the scale factor, and τ is the translational factor.

The wavelet transform $W_f(s,\tau)$ of a function $f(t)$ is the decomposition of $f(t)$ in a set of functions forming a base with the conjugate of $\psi_{s,\tau}(t)$. It is defined in Eq. (2) [52,63]:

$$W_f(s,\tau) = \int f(t)\psi^*_{s,\tau}(t)\mathrm{d}t \tag{2}$$

The use of the energy spectrum is suggested to reduce calculations when the signal processing is complex [65]. The energy spectrum is based on Parseval's energy theorem [17]:

$$\sum_{t=0}^{N-1}|x(t)|^2 = \frac{1}{N}\sum_{g=0}^{N-1}\left|A_j(g)\right|^2 + \sum_{j\le J}\left[\frac{1}{N}\sum_{g=0}^{N-1}\left|D_j(g)\right|^2\right] \tag{3}$$

where $x(t)$ is the signal in the time domain, g is the discrete signal of the Fourier transform, N is the sampling period and, A and D are approximated and detailed coefficients of the wavelet.

The most recurrent wavelet transform families are Haar [23], Symlet [3] or Daubechies [14,56,62]. Daubechies wavelets are employed in the case study due to its good results when working with discrete wavelet transforms [8,19,44,45,64]. The use of the wavelet transform has been popularised focused on the diagnosis and detection of mechanical faults in centrifugal pump [37], gears [51,65], rotors [6,59], stators [68] or bearings [60]. Other areas where its application can be found are the health monitoring of structures [47,55], power transformers [28,57] or chemical process installations [61].

On the other hand, the FFT calculates the discrete Fourier transform and its inverse. The sequence of N complex numbers (x_0, …, x_{N-1}) is transformed into a periodic sequence of complex numbers according to Eq. (4) [7]:

$$X_k = \sum_{n=0}^{N-1} x_n \cdot e^{-i2\pi kn/N} \tag{4}$$

where i is the imaginary unit and $e^{\frac{i2\pi}{N}}$ is the N$^{\text{th}}$ root.

The use of the FFT is typically related to the analysis of signals in the frequency domain [41] when periodic patterns are required [2] or a fault origin and its severity must be determined [29]. FFT is often considered to find incipient misalignment and unbalances in rotating machines [38,43,53,67] from the appearance of frequency peaks [1,20].

3. Case study

3.1. Experimental system and relevant components in WTs

A pattern recognition will be employed to extract useful information from the signals. Properties from measurable and comparable parameters will be set. FDD approaches assign categories based on sharing a common characteristic that is distinguishable from the rest in order to recognise the patterns. Three basic steps will be followed to obtain the final results [26]:

1. A CM system will be set on the testing bench (Fig. 1).
2. An extraction of features, sound and vibration, using specific algorithms and a decision making will be introduced.
3. A classification to obtain the pattern recognition employing FFT and wavelet transforms methods will be developed.

The case study presents a CM system for a mechanism based on an engine and a generator linked by a coupling joint (Fig. 1). The system is designed to represent some of the drive systems located on a WT, generally in the nacelle, e.g. cooling devices (generators, gearboxes), electric motors for service crane, yaw motors, pitch motors (depending on the configuration) or pumps (oil, water) according to the sub systems configurations, ventilators, etc.

The system board operates with sound and vibration sensors with a current of 13 A at 2890 rpm and a velocity of 1500 rpm. The motor is powered by 3 × 380VAC with a velocity ranging from 1435