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Vibration-based bearing fault detection for operations and maintenance cost reduction in wind energy

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Critical mechanical faults in wind turbine systems lead to considerable downtime and repair costs. Improving the detection and diagnosis of such faults thus brings about significant cost reductions for operations and maintenance (O&M) and electricity production. One of the most common defects in drivetrains are rolling element bearing faults. Detecting the faults in their incipient phase can prevent a more catastrophic breakdown and save a company time and money. This paper focuses on separating the bearing fault signals from masking signals coming from drivetrain elements like gears or shafts. The separation is based on the assumption that signal components of gears or shafts are deterministic and appear as clear peaks in the frequency spectrum, whereas bearing signals are stochastic due to random jitter on their fundamental period and can be classified as cyclostationary. A technique that recently gained more attention for separating these two types of signals is the cepstral editing procedure and it is investigated further in this paper as an automated procedure. The performance of the developed methods is validated on experimental data from the National Renewable Energy Laboratory (NREL) in the context of the wind turbine gearbox condition monitoring round robin study.

1. Introduction

Wind turbines are exposed to strong dynamic excitation events such as varying wind speeds, electricity grid events, or sea waves (for offshore wind turbines) [1]. The production cost of electricity by wind turbines is strongly influenced by the reliability of the wind turbine systems [2]. The downtime and repair costs significantly contribute to the economic impact of faults. In particular gearboxes in wind turbines exhibit substantial downtime in case of failure [3] and bearings turn out to be the most critical component in wind turbine gearboxes [4,5]. In general, rolling element bearings are one of the most used components in wind turbine drivetrains. According to the statistics provided by the NREL gearbox reliability database, more than half (76%) of wind turbine gearbox failures are caused by bearings, with gear faults being the second major cause for failure (17.1%). It is estimated that overall more than 90% of all rotating machines [6] contain rolling element bearings. Unfortunately, they are susceptible to a multitude of premature deficiencies and less than 10% of rolling element bearings reach their expected basic L10 life, the life at which ten percent of the bearings can be expected to have failed due to normal fatigue failure for that particular application. These observations imply a need for an improved comprehensive condition-based maintenance program. However, there are still some hurdles to be overcome before such an exhaustive program becomes fully feasible. One of these problems is the detection of characteristic bearing fault frequencies that are masked by high energy harmonic signals originating from other machine elements like shafts or gears. Separating the bearing fault signals from other masking signal content of such elements is thus a valuable endeavor. The separation is based on the assumption that bearing fault signals are stochastic due to random jitter on their fundamental period and can be categorized as cyclostationary whereas gear or shaft signals are deterministic and appear as distinct peaks in the amplitude spectrum. An important factor to the success of a method is its robustness to noise. In addition to removing harmonic content, the method should not decrease the signal-to-noise ratio of potential faults [7,8].

Recently there have been a number of developments concerning the topic of discrete components removal (DCR). Time-synchronous averaging (TSA) [9] is a well-known technique primarily used when deterministic signal components are the main

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interest. It essentially averages over all the fundamental periods of a specific shaft or gear in a signal, producing a clean averaged vibration signal of one period of the component. However, it can also be used for deterministic component removal. By removing all of the obtained averaged deterministic signals, the residual signal consists mainly out of stochastic signal content.

Another method frequently used for discrete component removal is the self-adaptive noise cancellation method (SANC) [10]. This method is an adaptation of adaptive noise cancellation (ANC) which uses an adaptive filter to remove corresponding components between two signals mixed in a primary signal based on a reference signal. The SANC method replaces the reference signal with a slightly delayed version of the primary signal. This constitutes the removal of the deterministic components and produces a residual signal, retaining the stochastic content. A method based on the same approach as the SANC technique was developed by Antoni & Randall [10] and was called the discrete/random separation technique (DRS). A transfer function is calculated between the input signal and its delayed version. This transfer function filters out the deterministic content by fast convolution in the frequency domain.

An alternative approach is to model the deterministic components using past values of the vibration signal. By subtracting the predictable signal model from the full signal, the stochastic unpredictable signal content is obtained. This method is called linear prediction filtering (LPF) [11].

A more recent technique edits the real cepstrum [12] for the purpose of discrete component removal. It is this preprocessing technique that is investigated further in this paper as it shows great potential in separating cyclostationary bearing signals from discrete components. Qualitative studies conducted by Kilundu et al. [13] and Randall et al. [12] compare cepstral editing to the other aforementioned methods. These studies indicate through experimental tests that the cepstrum editing procedure (CEP) can outperform the other methods.

The aforementioned techniques have proven their worth in the past, but they have their disadvantages and the cepstral editing procedure also provides some advantages that the other methods lack. The TSA method, for example, requires the application of the TSA method for every different shaft or gear, making this process quite laborious. Afterward, the signal has to be reverted back from the angular domain to the time domain. The TSA method only removes harmonics of the signal and does not eliminate their modulation sidebands. It also modifies the full spectrum and cannot be performed for certain frequency bands only. When using linear prediction filtering for removal of discrete frequency content, one has to take care when choosing the model order. The order has to be smaller than the bearing fault impulse spacing and should maximize the impulsiveness of the residual signal. Sometimes criteria such as the Akaike Information criterion is used for selecting the optimum model order. Since both the SANC and DRS method are based on the same approach they have similar drawbacks. They both require the discrete signal components to have longer correlation lengths than the used delay, while the stochastic bearing signal content is assumed to have a short correlation length. These assumptions can limit the practical use of these methods for complex machinery. They also might treat low-frequency harmonics belonging to the bearing signal as discrete signal content and filter them out mistakenly. The cepstrum editing procedure (CEP) has the advantage that it is able to selectively remove certain harmonics by editing the corresponding components in the real cepstrum. This is a fairly straightforward operation and can tolerate some speed variation making order tracking often unnecessary. It can also remove modulation sidebands and operate on a smaller frequency band instead of the full spectrum. Lastly, it also does not require any filter optimization, iterative process or model order choices.

The ambition of this paper is to validate the performance of the cepstrum editing procedure by applying it to the well-documented experimental vibration data, provided by the *National Renewable Energy Laboratory* in light of a past *wind turbine gearbox condition monitoring round robin study*. While the cepstrum editing procedure takes care of the discrete/random separation, a number of other processing methods are applied to alleviate some other problems and enhance the fault detection. More in particular, order tracking, band-pass filtering, and envelope analysis are utilized as well. Inspection of the results indicates that the cepstrum editing procedure performs well in removing masking high-energy discrete frequency components from experimental vibration data. Cepstrum editing can thus prove to be a useful pre-processing tool before envelope analysis and can be easily included in extensive condition monitoring schemes [14].

The structure of this paper is as follows: Section 2 discusses the main processing methods used in this study. Section 3 provides details regarding the general characteristics of the test setup and the installed wind turbine components like the gearbox and bearings. Section 4 examines the results for the observable bearing faults. Finally, section 5 discusses the found results and conclusions.

2. Overview of the processing algorithms

Since the measured data originates from a complex machine, the full processing procedure consists of multiple steps. Fig. 1 shows a diagram containing the main processing stages used in this paper.

While NREL provides a tacho signal for the high-speed shaft (HSS) in the healthy measurements of the wind turbine gearbox, only a speed estimate in rotations per minute (RPM) is provided for the HSS data of the damaged gearbox. This means that an order tracking method is used for resampling the vibration in the angular domain based on extracting a virtual encoder signal (see Section 2.1).

The second processing step entails the separation of the vibration signal into deterministic signal components originating from the gears and shafts, and stochastic components coming from the bearings. A cepstrum editing procedure is used to attain this separation (see Section 2.2).

The third processing stage involves bandpass filtering the residual cepstrum edited signal in order to increase the bearing signal-to-noise ratio before demodulation (see Section 2.4). This step makes use of the kurtogram [15] and thus the optimal demodulation band is considered to be the frequency band with the highest kurtosis. The actual analysis of the data was performed both on the bandpass filtered data and on the unfiltered, full bandwidth data. Consequently, in some cases this processing step is not displayed when demodulating the full frequency band of the data showed higher values for the bearing fault frequencies.

The final processing stage calculates the squared envelope spectrum (SES) of the residual signal after cepstrum editing and bandpass filtering. Envelope analysis is probably one of the most used tools in bearing fault analysis and a lot of research has been done in the past improving the technique and understanding the full potential of it [16].

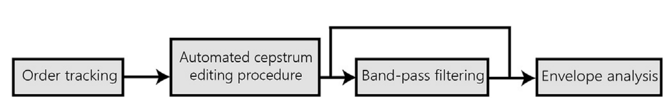

Fig. 1. Schematic diagram of the used processing steps.