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Vibration Analysis for Large-scale Wind Turbine Blade Bearing Fault Detection with An Empirical Wavelet Thresholding Method

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Abstract

Blade bearings, also termed pitch bearings, are joint components of wind turbines, which can slowly pitch blades at desired angles to optimize electrical energy output. The failure of blade bearings can heavily reduce energy production, so blade bearing fault diagnosis is vitally important to prevent costly repair and unexpected failure. However, the main difficulties in diagnosing low-speed blade bearings are that the weak fault vibration signals are masked by many noise disturbances and the effective vibration data is very limited. To address these problems, this paper firstly deals with a naturally damaged large-scale and low-speed blade bearing which was in operation on a wind farm for over 15 years. Two case studies are conducted to collect the vibration data under the manual rotation condition and the motor driving condition. Then, a method called the empirical wavelet thresholding is applied to remove heavy noise and extract weak fault signals. The diagnostic results show that the proposed method can be an effective tool to diagnose naturally damaged large-scale wind turbine blade bearings.

Keywords: Blade bearing fault diagnosis, low-speed bearing, vibration signal analysis, empirical wavelet transform, wavelet thresholding

1. Introduction

Wind energy is a well-known sustainable and reliable energy source available in nature. It has become one of the major renewable resources for the production of electric energy [1, 2]. The worldwide accumulative installed electricity generation capacity from wind power reached to 486.8 GW by the end of 2016 and it is estimated to be over 800 GW by 2021 [3]. Wind turbines are designed to extract wind energy from available wind flows in the atmosphere. Blade bearings, as the critical parts of wind turbines, are used to pitch blades for optimized outputs or to stop wind turbines for protection if wind speeds are greater than a cut-out speed. In order to pitch blades, blade bearings are driven by electric systems or hydraulic equipment [4–6], as shown in Fig. 1. For the electric pitch system (Fig. 1(a)), blades are adjusted by electric motors driving

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Fig. 1. (a) Blade bearing electrical pitch systems and (b) blade bearing hydraulic pitch systems [7].

geared blade bearings. This type of pitch system is particularly advantageous in saving space. The other hydraulic pitch system is that blade positions are pitched by hydraulic cylinders (Fig. 1(b)). For this type of pitch system, large bearings without gear teeth are used.

Wind turbine blade bearings work in a severer environment because they are exposed in harsh circumstances, such as moisture, sand, wind gusts and lightning strikes. Blade bearing failure leads to poor pitching and aerodynamic imbalance of blades. In serious cases, blades may lose control and crack which cause curtailment in energy productivity. The assemble and repair costs of blade bearings are high; therefore condition monitoring and fault diagnosis (CMFD) of wind turbine blade bearings are often needed in order to increase the wind turbine production and reduce operation and maintenance (O&M) costs [8]. However, CMFD of wind turbine blade bearings is still at an initial stage because of the following challenges:

- The effective vibration data is very limited because blade bearings swing in small angles.
- The fault signals are weak under slow rotation speed conditions (less than 5 rpm). This is because that low rotation results in low kinetic energy according to Newton's law.

To address these issues, vibration analysis is utilized in our project to collect the vibration characteristics of the wind turbine blade bearing, because it is a promising technique for rotating machine CMFD. Moreover, in order to improve the reliability of vibration analysis, various kinds of fault diagnosis methods are developed. According to Ref. [9], fault detection and diagnosis can be divided into two main categories: observer-based diagnosis and signal-based diagnosis. In regard to observer-based approaches, such as sliding

mode observer and Laplace ℓ_1 Huber based filter, they can identify the fault types based on the inconsistency between the model-predicted outputs and the measured outputs of the practical systems [9–12]. Nonetheless, these methods require the dynamic and physical parameters of the bearings which may not be practicable in some cases.

The other category is the signal-based diagnostic approach, so fault signal detections are often accomplished by denoising and feature extraction. The conventional signal-based diagnostic method is band-pass filter method, so the filter band determination is a vital process. At present, there are numerous approaches to determine the filter. One of the useful method is the short-time Fourier transform (STFT) which can draw a 3-D plot to specify complex signal amplitude versus frequency and time. Based on this 3-D plot, the optimal frequency band can be determined. However, the calculation speed of this method is often very slow, especially for a large amount of vibration data. To overcome this issue, Antoni proposed the fast kurtogram method which can quickly determine the defect signal frequency range [13], but its resolution is often less than STFT. In recent years, some scholars have utilized SFTF and fast kurtogram to develop tachometer-based or tachometer-less methods which can diagnose the bearing fault types with or without measured rotation speeds [13–18]. However, the drawback of these band-pass filtering methods is that frequency components beyond the determined frequency band are rejected meaning that some fault signals may be degraded which may affect the diagnostic accuracy.

In order to find out the methods that can be applied to blade bearing CMFD, the authors extensively searched Scopus, Sciencedirect, IEEE Xplore, along with an internet search of articles published using a number of keywords: blade bearing, pitch bearing, condition monitoring and fault diagnosis. However, there was no publication for blade bearing CMFD. As blade bearings belong to the type of slewing bearings which are often in large and operated in slow speeds, some works of literature on slewing bearings rather than blade bearings are reviewed here. The publications on slewing bearings' fault diagnosis are found in several applications, such as sewage treatment, metallurgy and pharmacy. Žvokelj *et al.*, [19] proposed a method combining the Ensemble Empirical Mode Decomposition (EEMD) method and the Kernel Principal Component Analysis (KPCA) multivariate monitoring approach called the EEMD-Based multiscale PCA (EEMD-MSKPCA) to identify an inner raceway artificial single defect when the slewing bearing runs at 8 rpm. Žvokelj *et al.*, [20] integrated the Independent Component Analysis (ICA) multivariate monitoring approach with the EEMD to diagnosis a slewing bearing with artificial cracks in the outer raceway at rotation speeds of 1, 4 and 8 rpm. Chen *et al.*, [21] applied the wavelet transform to reduce background noise and diagnose artificial scratch marks in the slewing bearing inner raceway and outer raceway. Guo *et al.*, [22] presented both the wavelet analysis and Hilbert transform to diagnosis an artificial outer ring pitting fault of a mini excavator slewing bearing at speeds of 47 rpm and 60 rpm. Bearing defects of above researches are artificially introduced, which may not simulate natural fault states in practice, especially the incipient fault. However, very few publications extract fault features using natural defects vibration signals. This

is mainly because the bearing takes a long time from normal to fault conditions [23]. Due to experiment limitations, only one publication can be found using the slewing bearing multiple nature defects vibration data, where the Empirical Mode Decomposition (EMD) and the Ensemble Empirical Mode Decomposition (EEMD) methods are used to diagnose outer race and rolling element faults at speeds of 1-4.5 rpm [23]. These bearing faults are produced by using the accelerated life-test method which is closer to the real fault situation.

Drawing on these insights, some concepts and ideas from general slewing bearings can be applied to large-scale wind turbine blade bearing fault detections. The majority techniques used on slewing bearings are either EMD-based or wavelet-based decomposition techniques, because they can separate stationary and non-stationary components from a signal. However, EMD-based methods are based on three specific assumptions [24, 25]. These assumptions may not be held for some applications. In regard to wavelet-based methods, they may need several trials to find a suitable mother wavelet. In this paper, a method called the “empirical wavelet thresholding” is investigated. This method combines the empirical wavelet transform and the wavelet thresholding which denoises extracted modes by thresholding in the wavelet domain. The recently-developed empirical wavelet transform was firstly proposed by Gilles which is based on segmentation of the Fourier spectrum [26]. As a result, the way to segment the Fourier spectrum or to detect the boundaries between noise and fault signals is important. It often relies on different algorithms, such as local maxima [26], lowest minima [27], histogram segmentation [28] and scale space [29]. For the parameter-based approaches (e.g., local maxima, lowest minima), the main difficulty is to choose a suitable amount of boundaries for long sampling time vibration signals. For the parameterless-based algorithm (e.g., histogram and scale space), they can automatically select the number of modes, but the calculation is very slow and complicated and easy out of memory when calculating large-scale data. In this paper, in order to overcome these issues, a novel experimental-based methodology for the spectrum segmentation is investigated. Firstly, the energy distribution of potential fault signals can be analysed in a low noise environment so that the boundaries can be determined based on the properties of fault signals. Secondly, the extracted modes are denoised and reconstructed according to the wavelet thresholding. By utilizing the proposed method, the noise level can be reduced to a minimum, and the defect frequencies can be seen distinctly in the frequency domain of the reconstructed signals.

The aim of this paper is to diagnose the failure type of the naturally damaged large-scale blade bearing using the vibration signal analysis through an experimental-based empirical wavelet thresholding method. The main contributions are summarized as follows:

- Firstly, the method empirical wavelet thresholding inherits the characteristics of empirical wavelet transform decomposition and wavelet denoising. Compared with the conventional band-pass filtering method, it can extract defect signals distributed in the whole frequency band rather than a single

frequency band; therefore, the weak fault signals can be retained.

- Lastly, to the best knowledge of the authors, no publication on blade bearing fault diagnosis has been found using publicly available information. It is the first attempt to diagnose a naturally damaged blade bearing via vibration analysis.

The remainder of the paper is organized in the following way. In Section 2, the formulas of bearing defect frequencies and empirical wavelet thresholding are presented in details. Section 3 describes the experimental set-up of the wind turbine blade bearing test rig. Section 4 presents a manual rotation case study to investigate fault signals at a very low external noise level so that the boundaries can be determined. Section 5 shows a motor driving case study to diagnose the bearing fault type. Section 6 presents the pictures of the bearing defects which can prove the diagnostic accuracy. Section 7 concludes the current work.

2. Theoretical background

2.1. Bearing defects

Blade bearings are made up of outer races, inner races and rolling elements (e.g., balls). When the irregularity due to faults appears during constant rotation, it will cause a variety of impacts to repeat periodically at a rate known as the fundamental defect frequency [30, 31]. The defect types can be divided as outer raceway defect, inner raceway defect, ball defect and combination defects. Different bearings have different fundamental defect frequencies which relate to their mechanical dimensions. The defect frequencies at the given rotation speed are equivalent to the product of fundamental defect frequencies and the bearing rotation speed [32]. If the vibration signal has one or more dominant frequencies matching one of the defect frequencies, a certain fault can be diagnosed [33]. The formulas for these fundamental defect frequencies are given as below [32]:

$$f_{\text{BPFO}} = \frac{N_b}{2} \left(1 - \frac{d_b}{d_p} \cos \alpha \right) \quad (1)$$

$$f_{\text{BPFI}} = \frac{N_b}{2} \left(1 + \frac{d_b}{d_p} \cos \alpha \right) \quad (2)$$

$$f_{\text{BSF}} = \frac{d_p}{2d_b} \left(1 - \left(\frac{d_b}{d_p} \cos \alpha \right)^2 \right) \quad (3)$$

where f_{BPFO} presents the ball pass frequency multiplier of the outer race. f_{BPFI} is indicated as the ball pass frequency multiplier of the inner race. f_{BSF} is defined as the ball spin frequency multiplier. N_b is the number of rolling elements; d_b is the rolling element diameter; d_p is the pitch diameter and α is the contact angle.

2.2. Empirical wavelet thresholding

The empirical wavelet transform develops from the empirical mode decomposition, which uses a family of wavelets to extract different signal modes adaptively [26]. The empirical wavelet transform ensures that each extracted mode inherits the property of wavelet transform and can be denoised by thresholding in the wavelet domain.

In order to extract different modes, the designed wavelets are equivalent to be a family of filters. The corresponding filters can be better interpreted with the Fourier point of perspective. The normalized Fourier axis having a 2π periodicity is considered and the derivation is limited to $\omega \in [0, \pi]$ because of Shannon criterion. Assuming the Fourier support $\bigcup_{n=1}^N \Lambda_n = [0, \pi]$ is partitioned into N contiguous segments where each segment is expressed as $\Lambda_n = [\omega_{n-1}, \omega_n]$. The way to determine the number of segments N will be introduced in Section 4. The empirical wavelets are built based on the construction of both Littlewood-Paley and Meyer's wavelets which are also defined as a series of bandpass filters on each segment Λ . The Fourier spectrum of the empirical scaling function Φ_0 and the empirical wavelets Ψ_n are defined as follows [26]:

$$\Phi_0(\omega) = \begin{cases} 1 & \text{if } |\omega| \leq (1 - \gamma)\omega_1 \\ \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_1}(|\omega| - (1 - \gamma)\omega_1)\right)\right] & \text{if } (1 - \gamma)\omega_1 \leq |\omega| \leq (1 + \gamma)\omega_1 \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

and

$$\Psi_n(\omega) = \begin{cases} 1 & \text{if } (1 + \gamma)\omega_n \leq |\omega| \leq (1 - \gamma)\omega_{n+1} \\ \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_{n+1}}(|\omega| - (1 - \gamma)\omega_{n+1})\right)\right] & \text{if } (1 - \gamma)\omega_{n+1} \leq |\omega| \leq (1 + \gamma)\omega_{n+1} \\ \sin\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_n}(|\omega| - (1 - \gamma)\omega_n)\right)\right] & \text{if } (1 - \gamma)\omega_n \leq |\omega| \leq (1 + \gamma)\omega_n \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where $\beta(x) = x^4(35 - 84x + 70x^2 - 20x^3)$ and $\gamma < \min_n(\frac{\omega_{n+1} - \omega_n}{\omega_{n+1} + \omega_n})$ are determined to make consecutive filters have less overlaps [26].

Therefore, the approximation coefficients $a(0, m)$ are given by the convolution between the raw vibration signal $f(m)$ and the empirical scaling function:

$$\begin{aligned} a(0, m) &= f(m) * \phi_0(m) \\ &= \sum_{\tau=0}^{\infty} f(\tau) \phi_0(m - \tau) = \mathcal{F}^{-1}(F(\omega) \times \Phi_0(\omega)) \end{aligned} \quad (6)$$

140 where $F(\omega) = \mathcal{F}(f(m))$ and $\phi_0(m) = \mathcal{F}^{-1}(\Phi_0(\omega))$, and $\mathcal{F}(\cdot)$ and $\mathcal{F}^{-1}(\cdot)$ correspond to the discrete Fourier
 141 transform (DFT) and the inverse discrete Fourier transform (IDFT), respectively.

142 In the same way, the detail coefficients $d(n, m)$ are expressed as follows:

$$d(n, m) = \sum_{\tau=0}^{\infty} f(\tau) \psi_n(m - \tau) = \mathcal{F}^{-1}(F(\omega) \times \Psi_n(\omega)) \quad (7)$$

143 where $\psi_n(m) = \mathcal{F}^{-1}(\Psi_n(\omega))$.

144 The next step is to use the wavelet thresholding method to reduce the noise wavelet coefficients to zero.
 145 There are two common wavelet threshold techniques which are hard and soft thresholding where only the
 146 hard-thresholding method has the property to retain the original amplitudes of defect signals without any
 147 distortion which can be used for the bearing fault extraction. The hard-thresholding functions applied to
 148 approximation coefficients and detail coefficients are described as [34]:

$$a_{\text{thres}}(0, m) = \begin{cases} a(0, m) & \text{if } |a(0, m)| > T(0) \\ 0 & \text{if } |a(0, m)| \leq T(0) \end{cases} \quad (8)$$

149 and

$$d_{\text{thres}}(n, m) = \begin{cases} d(n, m) & \text{if } |d(n, m)| > T(n) \\ 0 & \text{if } |d(n, m)| \leq T(n) \end{cases} \quad (9)$$

150 where $T(r), r = 0 \dots n$ is the chosen designed universal threshold [35]

$$T(0) = \frac{\sqrt{2 \log m} \times \text{median}(a(0, m))}{0.45} \quad (10)$$

151 and

$$T(n) = \frac{\sqrt{2 \log m} \times \text{median}(d(n, m))}{0.45} \quad (11)$$

152 **Fig. 2** shows the hard-thresholding rule. Finally, the hard-thresholding coefficients can be reconstructed

Fig. 2. Hard-thresholding rule.

153 via the wavelet reconstruction method to obtain the empirical wavelet thresholding signal $f_{\text{thres}}(m)$:

$$\begin{aligned}
 f_{\text{thres}}(m) &= \sum_{\tau=0}^{\infty} a_{\text{thres}}(0, \tau) \phi_0(m - \tau) \\
 &+ \sum_{n=1}^N \sum_{\varsigma=0}^{\infty} d_{\text{thres}}(n, \varsigma) \psi_n(m - \varsigma) \\
 &= \mathcal{F}^{-1}(A_{\text{thres}}(0, \omega) \times \Phi_0(\omega)) \\
 &+ \sum_{n=1}^N (\mathcal{F}^{-1}(D_{\text{thres}}(n, \omega) \times \Psi_n(\omega)))
 \end{aligned} \tag{12}$$

154 where $A_{\text{thres}}(\omega) = \mathcal{F}(a_{\text{thres}}(m))$ and $D_{\text{thres}}(\omega) = \mathcal{F}(d_{\text{thres}}(m))$.

155 2.3. Envelope analysis for fault diagnosis

156 After denoising the raw vibration signal via the empirical wavelet thresholding, the next process is to
 157 extract the envelope of the denoised signal and the defect frequencies can be seen in the frequency spectrum
 158 of the envelope. Specifically, the **discrete analytic signal from** the denoised signal $f_{\text{thres}}(m)$ is [36]

$$z(m) = \mathcal{F}^{-1} \{ \mathcal{F} [f_{\text{thres}}(m)] \times u(m) \}, m = 1, \dots, M \tag{13}$$

159 where $z(m)$ **indicates the discrete analytic signal**, and $u(m)$ is defined as:

$$u(m) = \begin{cases} 1, & m = 1, \frac{M}{2} + 1 \\ 2, & m = 2, 3, \dots, \frac{M}{2} \\ 0, & m = \frac{M}{2} + 2, \dots, M \end{cases} \tag{14}$$

Fig. 3. Flowchart of the empirical wavelet thresholding and fault diagnosis method.

The Discrete Hilbert envelope, denoted $e_D(m)$, can be expressed as follows:

$$e_D(m) = \sqrt{\text{Re}[z(m)]^2 + \text{Im}[z(m)]^2} \quad (15)$$

where Re and Im indicate real and imaginary parts respectively. Finally, the frequency spectrum of the Discrete Hilbert envelope $E_D(f) = \mathcal{F}(e_D(m))$ is analysed in order to find bearing defect frequencies. Fig. 3 shows a flowchart of the proposed method.

3. Experiment setup in the laboratory

The normal operations of blade bearings include the starts, constant rotation, stops and direction changes. As can be seen in Fig. 4(a), the blade bearing can be rotated back and forth within 100° . The starting and stopping periods are inconstant and noisy, and only the middle part, e.g., 90° , is constant or quasi-constant. To avoid negative impacts caused by starts and stops, the work of this paper is to investigate whether it is possible to diagnose the blade bearing fault types when non-stationary signals generated from starts and stops are abandoned, and only constant rotation parts are utilized. The blade bearing can be driven by the reciprocal motion to repeatedly collect the vibration characteristics of the same portion (Fig. 4(a3)). The same constant speed short portion collected from each swing can be recombined to extend the data length (Fig. 4(a4) and (a5)).

In order to simulate operations of blade bearings and diagnose blade bearing fault types, a blade bearing test rig is designed at the University of Manchester, as shown in Fig. 5. The outer ring of the bearing is fixed on the test rig, so the inner ring can be rotated for the fault diagnosis. We designed two rotation methods. The first one is the manual rotation and the other is the motor driving. From Fig. 5(a), the bearing can

Fig. 4. Schematics of wind turbine blade bearings (a) field operation, (b) manual rotation operation and (c) motor driving operation.

Fig. 5. Wind turbine blade bearing test rig: (a) manual rotation, (b) motor driving.

be manually rotated by two experimenters. They can use a metal bar as a lever and the bearing can be pushed down in either clockwise direction or pulled up in the anticlockwise direction. The purpose of the manual rotation is to detailedly investigate naturally damaged blade bearing fault characteristics at a very low external noise level without noise caused by driving systems. A natural question for the manual rotation is whether rotation speeds are constant. Therefore, we use a video camera to record manual rotations and then analyze bearing rotation speeds. It is found that speeds are fairly constant except the starting and ending periods which are very similar to real-world conditions. As can be seen in Fig. 4(b), only the middle part is used for further analysis and starting and ending parts are eliminated. For the motor driving rotation, as shown in Fig. 5(b), the kinematic components of the test rig include the three-phase induction motor, gearbox and blade bearing. The motor is able to generate constant rotation speeds in the test conducted. Due to the gearbox, the bearing rotation speed is further reduced. Bearing rotation speeds are controlled by using a motor inverter which can adjust speeds from 0.5 rpm to 10 rpm. To simulate real-world conditions shown in Fig. 4(c), only part of the data is extracted per revolution. The same constant speed short parts collected from each revolution can be recombined to increase the data length (Fig. 4(c4) and (c5)).

The test wind turbine blade bearing manufactured by Rollix was operational on a wind farm for over 15 years. The defects of this bearing are produced under real wind turbine working conditions. The weight is 261 kg and its geometric parameters are listed in Table 1. According to Table 1 and Eqs. (1) to (3), the fundamental defect frequencies can be calculated which are shown in Table 2. As shown in Fig. 5(a), the vibration data is acquired from the accelerometer mounted at the bottom of the outer ring surface. The accelerometer is Hansford HS-100-type sensor and the parameters are as follows: the sensitivity of 1000 mV/g, the frequency response of 2 Hz-10 kHz and the bias voltage of 10-12 V_{DC}. The vibration module HS-551 is used to power the sensor, strip off the bias voltage and output vibration signals. Meanwhile, the

Table 1

Geometric parameters of the test blade bearing.

Outer diameter	Pitch diameter	Ball Diameter	Ball Numbers	Contact angle
$d(\text{mm})$	$d_p(\text{mm})$	$d_b(\text{mm})$	N_b	α
1129	1000	54	60	50°

Table 2

Defect frequencies of the test blade bearing.

Rotation speeds	f_{BPFI}	f_{BPFO}	f_{BSF}	Comments
(rpm)	(Hz)	(Hz)	(Hz)	
1	0.5173	0.4826	0.1541	Fundamental defect frequency
1.2	0.6208	0.5791	0.1850	Manual rotation
2.1	1.0863	1.0135	0.3236	
4.1	2.1209	1.9787	0.6318	
3.19	1.6502	1.5395	0.4916	Motor driving
3.05	1.5778	1.4719	0.4700	

power supply module HS-570-20 provides constant 24 V direct voltage for the vibration module HS-551. The vibration module HS-551 is connected to a high-speed data acquisition device. In this paper, we use 50 kS/s as the sampling rate. The data is collected using the DAQami software and hardware systems.

4. Case 1: manual rotation and spectrum segmentation

4.1. Raw vibration data collected at different manual rotation speeds

In order to investigate the bearing fault characteristics at a very low noise level, we designed a manual rotation experiment to maximumly avoid external mechanical and electrical noise. First of all, the bearing inner ring is manually rotated by two experiments in the clockwise direction at rotation speeds of 1.2 rpm, 2.1 rpm and 4.1 rpm, respectively, and the quasi-constant speed rotation angle is 45° . As can be seen in Fig. 6(a), there are a number of small spikes and several large spikes in each test. These spikes may indicate fault signals. As the bearing is naturally damaged, the extents of the faults inside the bearing are noticeably different. The amplitudes of weak fault signals are smaller than 0.1 volts, but the amplitudes of severe fault signals are greater than 0.25 volts. However, because of the noise generated from the bearing itself, more representative or useful information cannot be observed in the raw data. Therefore, the frequency spectrums of these three tests are presented in Fig. 6(b) using the FFT method. It can be seen in Fig. 6(b), these three tests have similar frequency distributions and dominant frequency components are concentrated in the

frequency range from 0 to 3600 Hz. From Figs. 6(c) and 6(d), due to the noise, the defect frequencies listed in Table 2 cannot be observed in the frequency spectrum of raw data. Therefore, we need to remove these noise with the aim of extracting fault features in the following subsections.

4.2. Spectrum segmentation

For the empirical wavelet transform, segmentation of the Fourier spectrum is a vital procedure as it provides the adaptability with respect to the raw vibration data. If the number of segments N is small, the amount of extracted modes will be limited meaning that the noise and fault signals cannot be separated. Whereas, if N is large, the extracted modes will distort the fault signals; furthermore, the calculation requires large memory resulting in slow computing speed. For this reason, we propose to use a novel experimental-based spectrum segmentation approach to quickly determine the boundaries.

Fig. 7(a) displays the frequency spectrums of three manual rotation vibration signals from 0 to 4000 Hz where nine spike groups can be seen clearly for each test. As a result, in the frequency domain, different rotation speeds change the spectrum amplitudes. However, no significant changes are reflected in frequency components. This situation is due to the fact that the variations of different speeds are very small. Therefore, for different slow rotation speed tests, the same boundaries can be used to remove noise and extract fault features.

Based on the spike group distributions shown in Fig. 7(a), the boundaries make a trial of $B_1 = 310$ Hz, $B_2 = 590$ Hz, $B_3 = 908$ Hz, $B_4 = 1290$ Hz, $B_5 = 1744$ Hz, $B_6 = 2318$ Hz and $B_7 = 3856$ Hz. As can be seen in Fig. 7(b), these seven boundaries have separate the whole frequency band into eight portions. Φ_0 is the scaling function and $\Psi_n(n=1..7)$ indicates empirical wavelets.

4.3. Empirical wavelet thresholding

In order to quantify the fault signals in each mode, kurtosis is used in this paper as it is an indirect method to evaluate defect signal-to-noise ratio. The high kurtosis value can indicate that the signal has a high amount of spikes caused by bearing faults. The equation of the kurtosis is expressed as follows [37]:

$$\text{Kurt} = \frac{\frac{1}{n} \sum_{i=1}^n (X_i - \mu)^4}{\left(\frac{1}{n} \sum_{i=1}^n (X_i - \mu)^2 \right)^2} \quad (16)$$

where X indicates the input signal and n is the signal length; μ is defined as the mean value of X . As can be seen in Fig. 8(c), kurtosis values are very small for Mode 1 and Mode 2; therefore, there are very few fault signals distributed below 590 Hz. From Mode 3 to Mode 8, many large fault signals and weak fault signals are reflected, especially for Mode 5, Mode 6, Mode 7 and Mode 8.

Fig. 6. (a) The raw vibration data plots, (b) the frequency spectrum plots, (c) 0-100 Hz frequency spectrum plots and (d) 0-10 Hz frequency spectrum plots.

Fig. 7. Segmentations of frequency spectrums at (a1) 1.2 rpm (a2) 2.1 rpm (a3) 4.1 rpm and (b) empirical wavelet filter bank in the normalized Fourier axis.

To further extract the small and large fault signals from each Mode and minimize the noise interferences, the decomposed modes can be denoised via the hard-thresholding. As shown in Fig. 8(c), red dash lines in each mode indicate the universal threshold value calculated by Eqs. (10) and (11). For each mode, all wavelet coefficients within the upper threshold and the lower threshold will be set to zero. Finally, thresholded modes can be reconstructed to get the denoised signals presented in Fig. 8(b). Compared with the raw signal displayed in Fig. 8(a), the denoised signal can clearly present the compound fault signals with extremely low noise disturbances and the kurtosis value improves from 246.8 to 545.0. As a result, the empirical wavelet thresholding can not only use defect signals distributed in the whole frequency band, but also denoise the extracted modes by thresholding. Therefore, the bearing fault signals are retained and the noise level is reduced.

5. Case 2: vibration signals collected by motor driving

In this case, the bearing is driven by a motor in the clockwise direction. Fig. 9(a) shows the raw data in the time domain at 3.19 rpm and Fig. 9(b) illustrated the recombined signal with three 90° portions vibration data. Each part is extracted from each revolution and they have similar vibration characteristics. In the same way, Fig. 10(a1) displays the recombined signal at the rotation speeds of 3.05 rpm. Consequently, FFT is applied to the recombined signals in order to get the frequency spectrum distributions. Fig. 10(b) displays the frequency spectrums of the recombined data. Comparing with Fig. 7(a) and Fig. 10(b), the frequency distributions below 2318 Hz for two situations are very similar which have 8 spike groups. Above 2318 Hz, the amplitudes in Fig. 10(b) become small due to external mechanical and electrical noise. Therefore, the

Fig. 8. (a) raw vibration signal at 4.1 rpm and (b) empirical wavelet thresholding signal and (c) modes extracted by the empirical wavelet transform.

Fig. 9. raw and recombined vibration data at 3.19 rpm.

boundaries for the recombined signals can be the same as [Section 4.2](#) which are $B_1 = 310$ Hz, $B_2 = 590$ Hz, $B_3 = 908$ Hz, $B_4 = 1290$ Hz, $B_5 = 1744$ Hz, $B_6 = 2318$ Hz and $B_7 = 3856$ Hz.

[Fig. 11\(c\)](#) shows the extracted modes at 3.19 rpm. For Mode 8, the noise type is different from other modes, which is asymmetry to the x-axis. Therefore, the calculated threshold value (red dash line) for Mode 8 is manually modified to 0.07 V (blue dash line) in order to minimize the noise influence. [Fig. 11\(a\)](#) and [Fig. 11\(b\)](#) indicate the raw vibration data and the empirical wavelet thresholding signal. Similarly, [Fig. 12](#) presents both the time domain signal and the empirical wavelet thresholding signal at 3.05 rpm. It is clearly seen that the proposed method can extract fault signals under slow rotation speed conditions.

After that, FFT is applied to demodulated Hilbert envelopes, as presented in [Fig. 13](#), to find defect frequencies in the frequency domain. As can be seen, the dominant frequencies are 1.630 Hz at 3.19 rpm and 1.553 Hz at 3.05 rpm. [Table 3](#) list the defect frequency matching error which is the ratio between the identified dominant frequency and the calculated defect frequency. The equation is as follows:

$$\text{Error} = (|f_{\text{rotation}} - f_{\text{fault}}| / f_{\text{fault}}) \times 100\% \quad (17)$$

where f_{rotation} indicates the experimental dominant frequencies and f_{fault} can be chosen as f_{BPFI} , f_{BPFO} and f_{BSF} shown in [Table 2](#). After comparing defect frequencies listed in [Table 2](#) and diagnosis matching error shown in [Table 3](#), the bearing fault most likely happens in inner raceway with an average matching error of 1.39%.

6. Damage evidence

After inserting an endoscope into the bearing, some cracks in the inner raceway are clearly seen in several positions. [Fig. 14\(a\)](#) presents one large crack with dimensions of over 5 mm wide and 9 mm long. From

Fig. 10. The recombined vibration signals plot at (a1) 3.05 rpm (a2) 3.19 rpm and the frequency spectrums plot at (b1) 3.05 rpm (b2) 3.19 rpm.

Table 3

Defect frequencies matching error at 3.19 rpm and 3.05 rpm.

Rotation speed	Matching error		
	Inner race fault	Outer race fault	Ball fault
3.19 rpm	1.20%	5.84%	232.65%
3.05 rpm	1.58%	5.50%	230.43%
Average	1.39%	5.65%	231.54%

Fig. 11. (a) raw vibration signal at 3.19 rpm and (b) empirical wavelet thresholding signal and (c) modes extracted by the empirical wavelet transform.

Fig. 12. (a) raw vibration signal at 3.05 rpm and (b) empirical wavelet thresholding signal.

Fig. 13. Defect frequencies at (a) 3.19 rpm, (b) 3.05 rpm.

Fig. 14. Visible inner race defects (a) first position and (b) second position.

Fig. 14(b), some smaller cracks with different dimensions are presented. Furthermore, the balls and outer raceway are also checked with no significant damages. Therefore, the endoscope inspection confirms that the proposed method is accurate.

7. Conclusions

In this paper, the vibration signals of a large-scale wind turbine blade bearing are collected by two cases which are the manual rotation and motor driving. For the manual rotation case, it can simulate the real-world blade bearing working condition at a very low external noise level. Therefore, this case can easily study severe fault and weak fault characteristics so that the frequency boundaries of fault signals can be determined. For the motor driving condition, the limited vibration signals are recombined in order to improve the diagnostic accuracy. This procedure can effectively solve the lack of data issue at constantly rotating speeds for field tests of wind turbine blade bearing CMFD. The empirical wavelet thresholding method is applied to denoise the recombined signals and the envelope analysis is implemented to diagnose the bearing fault. The endoscope inspection confirms that the analysis is accurate.

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