Fault diagnosis of wind turbine bearing based on variational mode decomposition and Teager energy operator

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Abstract: Vibration signal of wind turbine has the non-linear and non-stationary characteristic, thus it is difficult to extract the fault feature. In this study, a novel method based on variational mode decomposition (VMD) and Teager energy operator (TEO) is proposed to diagnose the bearing faults of wind turbine. First, vibration signal is decomposed into several intrinsic mode function (IMF) components by means of VMD, which is a recently proposed signal decomposition method. Then, the most sensitive IMF component is selected according to kurtosis criterion. Moreover, TEO is applied to the most sensitive IMF in order to highlight impact signal. Finally, spectrum is obtained by applying Fourier transform to Teager energy of the selected IMF, thus extracting the fault feature to diagnose bearing fault. The effectiveness of the proposed method for fault diagnosis is validated by simulation and experimental signal analysis results, and comparison studies show its advantage over empirical mode decomposition and conventional spectrum analysis for wind turbine bearing fault diagnosis.

1 Introduction

Owing to the shortage of energy and increasing serious environment problem, renewable energy development has been widely paid attention to in recent years. As one of the most promising new clean renewable energy sources, wind power generation is in large-scale development around the world [1–4]. However, wind turbines are prone to various failures due to long term operation under tough conditions, complex alternating loads and variable speeds [5]. Bearing is a critical component of wind turbine and bearing failures occupy a significant proportion of all failures in wind turbines, which can lead to outage of the unit and high cost of maintenance [6, 7]. Hence, the development of an accurate fault diagnosis method for wind turbine bearing is extremely valuable for improving safety and economy.

So far, a vast amount of signal processing methods have been introduced to diagnose bearing fault for wind turbine, in which time–frequency analysis methods are most commonly used. Time–frequency analysis methods mainly include short-time Fourier transform (STFT) [8], wavelet transform (WT) [9] and Wigner–Vile distribution (WVD) [10]. However, there are various shortages in these methods. For instance, STFT is developed from Fourier transform and has certain limitations in analysing non-stationary signals. WT cannot self-adaptively select the basic function and threshold, so its performance is strongly influenced by artificial factors. WVD suffers from the cross-term interference when processing multi-component signals, thus greatly restricting its application. Consequently, many self-adaptive methods have been proposed and developed in this field. Among these, empirical mode decomposition (EMD) is the most typical method and especially suitable for non-stationary signal analysis, thus it has been widely utilised in fault diagnosis. An et al. [11] proposed a fault diagnosis method based on EMD and Hilbert transform to extract looseness fault feature of direct-drive wind turbine bearing. Feng et al. [12] applied the improved EMD to process vibration signal and further analysis via demodulation to diagnose gearbox fault of wind turbine. Zhang et al. [13] calculated permutation entropy of intrinsic mode functions (IMFs) obtained by EMD to extract fault feature vectors and used support vector machines to classify fault types of bearing. However, EMD still has several inevitable drawbacks such as mode mixing, end effect and sensitivity to sampling, which can lead to interference with fault diagnosis. Recently, a novel self-adaptive signal processing method called variational mode decomposition (VMD) has been proposed by Dragomiretskiy and Zosso [14]. By comparison analysis, it is discovered that VMD can effectively solve the drawbacks of EMD and has better performance than EMD in analysing non-stationary signals [14, 15]. So in this paper, VMD is employed to decompose vibration signal of wind turbine bearing into several IMFs.

In implementation of the method, Teager energy operator (TEO) is utilised to detect impact signal in faulty vibration signal of wind turbine bearing. TEO was first proposed by Kaiser [16] to analyse non-linear speech signal, which is able to accentuate the transient impulse component of vibration signal and significantly suitable for extracting fault feature. Due to the advantages of excellent time resolution and high computational efficiency, TEO has been widely applied in fault diagnosis [17–20]. In addition, kurtosis criterion is proposed to select the most sensitive IMF that contains the richest fault information for spectrum analysis, because the most sensitive IMF of faulty bearing vibration signal should be expected to have the maximum kurtosis.

This paper is organised as follows. The principles of VMD and TEO are, respectively, introduced in Sections 2 and 3. The kurtosis criterion, performance evaluation index and procedure of fault diagnosis method based on VMD–TEO are described in Section 4. The proposed method is illustrated by simulation analysis in Section 5. Diagnostic performance is tested by applying the VMD–TEO method to bearing experimental signal of wind turbine in Section 6. Finally, conclusions are drawn in Section 7.

2 Variational mode decomposition

VMD is a recently proposed signal processing method, by which a signal can be decomposed into a set of IMF components. Different from the recursive decomposition pattern of EMD, VMD implements signal decomposition by solving the optimal solution of constrained variational model. Each IMF component obtained by VMD is band-limited and has a respective central frequency.

The goal of constrained variational model is to minimise the sum of each IMF component's bandwidth. The evaluation of bandwidth can be implemented by three steps:

i. Hilbert transform is applied to calculate the analytic signal of each IMF component so that unilateral frequency spectrum can be obtained.
ii. An exponential is used to modulate the estimated central frequency of each IMF component, thus frequency spectrum is shifted to ‘baseband’.

iii. The $H^1$ Gaussian smoothness of the demodulated signal is calculated in order to estimate each IMF component’s bandwidth. Consequently, the mathematical model of constrained variational problem can be given as follows:

$$\min_{u_k} \sum_k \left\{ \sum_i \left| \partial_i (\delta(t) + j/\pi t) * u_k(t)e^{-j\omega_k t} \right|^2 \right\}$$

subject to $$\sum_k u_k(t) = f(t)$$

where $\{u_k(t)\} = \{u_1(t), u_2(t), ..., u_k(t)\}$ represents an ensemble of all IMF components and $u_k(t)$ is $k$th IMF component; $\{\omega_k\} = \{\omega_1, \omega_2, ..., \omega_k\}$ represents an ensemble of central frequencies of all IMF components and $\omega_k$ is the central frequency of $u_k(t)$; $f(t)$ is the input signal.

A quadratic penalty term and Lagrangian multipliers are introduced to convert the constrained variational problem into unconstrained problem. The mathematical model of unconstrained variational problem can be expressed as follows:

$$\Gamma(u_k, \omega_k, \lambda) = \alpha \sum_k \left\{ \sum_i \left| \partial_i (\delta(t) + j/\pi t) * u_k(t)e^{-j\omega_k t} \right|^2 \right\}$$

$$+ \parallel f(t) - u_k(t) \parallel^2 + \{\lambda(t), f(t) - \sum_k u_k(t)\}$$

where $\alpha$ denotes a quadratic penalty term and $\lambda(t)$ denotes Lagrangian multipliers. To solve (2), alternate direction method of multipliers is utilised to find the optimal solution. The update formula of estimated mode $u_k(t)$ is shown as follows:

$$u_k^{n+1}(t) = \frac{f(t) - \sum_{\omega_k} \omega_k(u_k(t)) + (\lambda(n)/2)}{1 + 2\alpha(\omega_0 - \omega_1)^2}$$

(3)

where $f(t), \lambda(n), \omega_k(u_k(t))$ and $u_k^{n+1}(t)$ are Fourier transforms of $f(t)$, $\lambda(t)$, $u_k(t)$ and $u_k^{n+1}(t)$, respectively. It can be discovered from (3) that $u_k^{n+1}(t)$ can be regarded as a Wiener filtering of the current residual $f(t) - \sum_{\omega_k} \omega_k(u_k(t))$. In addition, the inverse Fourier transform can be applied to obtain IMF components in time domain.

The update formula of central frequency $\omega_k$ can be expressed as follows:

$$\omega_k^{n+1} = \frac{\int_{-\infty}^{\infty} \omega_k(u_k(t)) \, d\omega}{\int_{-\infty}^{\infty} |u_k(t)|^2 \, d\omega}$$

(4)

3 Teager energy operator

For any continuous time signal $x(t)$, the TEO $\psi$ is defined as follows:

$$\psi[x(t)] = |\dot{x}(t)|^2 - x(t)\ddot{x}(t)$$

(5)

where $x(t)$ and $\dot{x}(t)$ are the first-order and second-order time differentials of $x(t)$, respectively.

Assuming that linear non-damping vibration system is composed of a mass block and a spring, motion equation of the vibration system is as follows:

$$x(t) = A\cos(\omega t + \phi)$$

(6)

where $x(t)$ is the displacement of block compared with balance position, $A$ is the vibration amplitude, $\omega$ is the inherent frequency and $\phi$ is an initial phase.

At any moment, the instantaneous energy of the vibration system $E$ is given as follows:

$$E = \frac{1}{2}k(x(t))^2 + \frac{1}{2}m(\dot{x}(t))^2 = \frac{1}{2}mA^2\alpha^2$$

(7)

where $k$ is the stiffness of spring and $m$ is the mass of block.

Substituting (6) into (5), we can obtain (8) which is shown as follows:

$$\psi[x(t)] = \psi[A\cos(\omega t + \phi)] = A^2\omega^2$$

(8)

By comparing (7) and (8), it can be discovered that there is only one difference $m/2$ between the TEO and the instantaneous energy $E$. Therefore, the TEO is able to track the energy of vibration signal $E$ very effectively.

For a discrete time signal $x(n)$, the TEO can be redefined by replacing differential with difference as follows:

$$\psi[x(n)] = |x(n)|^2 - x(n-1)x(n+1)$$

(9)

As shown in (9), the numerical value of TEO could be obtained by calculating only three consecutive samples of the measured signal, so it has high time resolution to instantaneous change of signal and simplicity in application.

4 Fault diagnosis method of bearing based on VMD–TEO

4.1 Kurtosis criterion

Kurtosis is a non-dimensional parameter that measures the deviation of probability density function of a random signal $x(t)$ from the Gaussian distribution [21]. It is defined as the following equation:

$$K = E(x - \mu)^4/\sigma^4$$

(10)

where $K$, $\mu$ and $\sigma$ are the kurtosis, mean value and standard deviation of signal $x(t)$, respectively.

Vibration signal approximately obey the Gaussian distribution and has a kurtosis of 3 when bearing is in normal operating state [22]. However, when a defect occurs in bearing, vibration signal containing the impact components caused by failure obviously deviates from the Gaussian distribution and has a greater kurtosis. Thus, kurtosis has been successfully used to indicate the proportion of impact components in vibration signal. Different frequency component caused by failure are contained in each IMF. Among them, the IMF with the maximum kurtosis contains the most abundant fault information, from which fault feature can be more effectively extracted. Therefore, the IMF with the maximum kurtosis obtained by VMD is selected for further spectrum analysis to extract fault feature.

4.2 Performance evaluation index

To quantitatively evaluate the performance of different methods, an evaluation index $P$ is introduced in this section. $P$ is defined as the ratio of fault characteristic components’ energy to total energy in spectrum. It can be given as follows:

$$P = \frac{\sum |A_f|^2}{\sum |A_f|^2 + \sum |A_f|^2} \times 100\%$$

(11)

where $f$ is the fault characteristic component and $A(f)$ is the amplitude of $f$ in spectrum; $f'$ is the interference component and $A(f')$ is the amplitude of $f'$ in spectrum.

Equation (11) indicates that the greater the value of evaluation index $P$, the higher proportion the energy of fault characteristic components accounts for, and the less the interference components impact on fault diagnosis. Thus, spectrum with greater evaluation index can extract more obvious fault feature and performs better in fault diagnosis.
i. **Vibration signal acquisition**: Setting the mounting position of vibration sensors and sampling rate, vibration signal of wind turbine bearing is acquired through signal acquisition system.

ii. **VMD analysis**: Variational decomposition method is applied to decompose vibration signal into a group of IMF components.

iii. **Extracting the most sensitive IMF**: Kurtosis of each IMF can be calculated by (10) and the IMF with the maximum kurtosis is selected as the most sensitive IMF.

iv. **Spectrum analysis**: In order to accentuate transient impulse, the TEO is utilised to process the most sensitive IMF component. Then, the Teager energy of the most sensitive IMF is analysed by Fourier transform to obtain the spectrum.

v. **Fault diagnosis**: By comparing the prominent component in spectrum with the fault characteristic, bearing fault can be diagnosed.

### 5 Simulation analysis

In this section, the proposed method is utilised to analyse vibration signal with inner race fault simulated by the typical bearing fault model.

#### 5.1 Bearing fault model

Randall *et al.* [23] proposed a rolling bearing fault model in 2001, which comprehensively takes into account the effects of bearing structure, manufacturing tolerance, amplitude modulation, random slide of balls, surface abrasion and so on. It has been successfully applied to simulate vibration signals with bearing fault [24, 25]. The formula of bearing fault model can be given as follows:

\[
\begin{align*}
  x(t) &= \sum A_i(t) \cdot \left( p(t - iT - \tau_i) + n(t) \right) \\
  A_i(t) &= A_0 \cdot \cos(2\pi f_i t + \varphi_0) + C_A \\
  p(t) &= \exp(-Br) \cdot \cos(2\pi f_n t + \varphi_0)
\end{align*}
\]

where \(A_i(t)\) is the factor function of amplitude modulation, \(p(t)\) is an impact signal caused by defect, \(n(t)\) is a Gaussian white noise, \(T\) is the time period of impact signals and \(\tau_i\) is the slight time fluctuation of the \(i\)th impact relative to mean period \(T\).

#### 5.2 Simulation and results analysis

According to the bearing fault model shown in (12), vibration signal with inner race fault is simulated for analysis. Simulation parameters are set as follows: the shaft rotational frequency \(f_s\) is 12 Hz; the fault characteristic frequency (FCF) of inner race \(f_n = 1/T\) is 57 Hz; the resonant frequency of rolling bearing \(f_0\) is 4000 Hz; the initial value of amplitude \(A_0\) is 2 and attenuation constant \(B\) depending on bearing designation \(B = 800\). In addition, the sampling frequency \(f_s\) is set to 23 kHz and the signal-to-noise ratio of simulation signal added with noise is −12 dB.

Fig. 2 shows time domain waveform and envelope spectrum of simulation signal. Comparing Fig. 2a with 2b, we can discover that impact signal is almost completely drowned by strong background noise. As shown in Fig. 2c, none of frequency components obviously have greater amplitude in envelope spectrum. Therefore, it is difficult to extract fault feature by time domain analysis and envelope spectrum.

The VMD method is utilised to analyse simulation signal and five IMF components are obtained. Time domain waveforms and frequency spectrum of IMF components are shown in Figs. 3a and b, respectively. It could be discovered from Fig. 3b that each IMF component has different frequency band and compact frequency support around a central pulsation. Then, in order to select the most sensitive IMF, kurtosis of five IMFs are calculated and results show that component C2’s kurtosis is maximum. So, component C2 is picked out as the most sensitive IMF for further Teager spectrum analysis. Figs. 4a and b present the Teager energy waveform and Teager energy spectrum of component C2. From Fig. 4b, we can find three clear peaks at 57, 114 and 171 Hz, which, respectively, correspond to the FCF of inner race \(f_n\), two times of \(f_n\) and three times of \(f_n\). Consequently, the fault feature of rolling bearing is effectively extracted by the VMD–TEO method.

To validate the advantage of the proposed method in fault diagnosis domain, EMD is introduced to analyse the simulation...
signal mentioned above and TEO is used for further analysis. Then, we can obtain the Teager energy spectrums of each IMF components and select the best spectrum to compare with the result analysed by VMD–TEO. Fig. 5a shows the time domain waveforms of eight IMF components obtained by EMD. Correspondingly, frequency spectrums of the first five IMF components C1–C5 are shown in Fig. 5b. By comparison, we can find that the Teager energy spectrum of component C1 has the best effect and is the only one which extracts the FCF, as shown in Fig. 4c. However, compared with Fig. 4b, the amplitude of FCF \( f_i \) and two times of \( f_i \) in Fig. 4d are not prominent. Furthermore, lots of interference frequency components also exist in Fig. 4d. Table 1 shows the performance contrast of different analysis methods. From Table 1, it can be seen that the evaluation index \( P \) of VMD–TEO is greater than other fault diagnosis methods. In conclusion, the VMD–TEO method performs better than EMD and conventional spectrum analysis.

**6 Experiment**

To validate the practicability and effectiveness of VMD–TEO in fault diagnosis, bearing fault experiments are conducted in wind turbine test rig, which is shown in Fig. 6. The test rig is composed of wheel hub, main shaft, gearbox and generator. The main shaft is supported by two rolling bearings, which bear mainly the radial and also certain axial load. An acceleration sensor, X&K AD500T, is mounted on bearing pedestal to acquire vibration signals and the sampling frequency is 10 kHz. Parameters of X&K AD500T are as follows: measuring range of 25 g (\( g = 9.8 \text{ m/s}^2 \)), sensitivity of 500 mV/g, frequency range of 0.3–12,000 Hz and resolution of 0.004 g. To simulate the typical faults of wind turbine bearing, spark erosion technique is utilised to seed a pit in inner race and outer race.

### 6.1 Fault identification under constant speed condition

During the constant speed experiment, the rotational speed of main shaft is 140 rpm. Computational formulas of FCF with inner race and outer race [26] are given in (13) and (14), respectively

\[
\begin{align*}
    f_i &= \frac{1}{2} \left[ 1 + \frac{d}{D} \cos \beta \right] f_r Z \\
    f_o &= \frac{1}{2} \left[ 1 - \frac{d}{D} \cos \beta \right] f_r Z
\end{align*}
\]

(13)

where \( f_i \) is the FCF of inner race, \( f_o \) is the FCF of outer race, \( f_r \) is the shaft rotational frequency, \( D \) is the pitch diameter, \( d \) is the ball diameter, \( \beta \) is the contact angle and \( Z \) is the number of the balls. Substituting parameters of rolling bearing into above formulas, we can obtain that the FCF of inner race \( f_i \) is 77.9 Hz and FCF of outer race \( f_o \) is 52.7 Hz.

Fig. 7a displays the inner race fault signal waveform of wind turbine bearing, from which few regular impact components can be observed. Fourier transform is applied to obtain amplitude spectrum, as shown in Fig. 7b. It can be discovered from this figure that the energy of fault signal is evenly distributed in wide frequency band. Moreover, envelope spectrum is shown in Fig. 8.
in which there is no component with prominent amplitude. Thus, it can be concluded that the fault feature of inner race cannot be effectively extracted by Fourier transform and envelope spectrum analysis.

VMD is utilised to decompose the inner race fault signal into seven IMF components, in which kurtosis of component C2 is maximum. According to kurtosis criterion, component C2 is selected as the most sensitive IMF for further Teager spectrum analysis. Teager energy waveform of component C2 is shown in Fig. 8a. Compared with Fig. 7a, impact signals in component C2 are obviously highlighted and the effect of noise is effectively restrained. Fig. 8b depicts the Teager energy spectrum of component C2. From Fig. 8b, the FCF of inner race $f_0$ (78 Hz), two times of $f_0$ (156 Hz) and three times of $f_0$ (234 Hz) can be clearly detected. Therefore, it can be judged that damage exists in the inner race of wind turbine bearing, which is in agreement with the fact.

Similarly, EMD is applied to analyse the fault signal and the best Teager energy spectrum is selected to compare with the result analysed by VMD–TEO. The fault signal is decomposed into ten IMF components, in which the Teager energy spectrum of component C1 has the best effect. Figs. 8c and d show the Teager energy waveform and Teager energy spectrum of component C1. As one can see from Fig. 9d, the FCF of inner race is not prominent and surrounded by lots of interference frequency components. The evaluation index values of different analysis methods are shown in Table 2, which indicates the evaluation index $P$ of VMD–TEO has the greatest value. Therefore, it can be concluded that the VMD–TEO method is superior to other analysis method in extracting fault feature of inner race.

### Table 1: Performance contrast in diagnosing simulation fault

<table>
<thead>
<tr>
<th>Analysis method</th>
<th>Evaluation index $P$, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>amplitude spectrum</td>
<td>0.08134</td>
</tr>
<tr>
<td>envelope spectrum</td>
<td>0.5291</td>
</tr>
<tr>
<td>Teager energy spectrum analysed by EMD</td>
<td>9.526</td>
</tr>
<tr>
<td>Teager energy spectrum analysed by VMD–TEO</td>
<td>46.72</td>
</tr>
</tbody>
</table>

6.2 Fault identification under varying speed condition

In this section, the experiment is conducted under varying speed condition to further validate the effectiveness of VMD–TEO in analysing non-stationary signal. The rotational speed of main shaft increases from 80 to 140 rpm during the experiment.

According to (13) and (14), it can be found that the FCF changes with the shaft rotational frequency $f_r$. So, the FCF is not constant under varying speed condition. However, geometry parameters ($D$, $d$, $\beta$ and $Z$) of rolling bearing are all fixed. Hence, fault characteristic order (FCO) obtained by dividing FCF by $f_r$ is only related to bearing structure and not affected by shaft speed.
In implementation of order analysis, angular resampling is introduced to pre-process the raw vibration signal. By resampling vibration signal at a constant angle increment, time domain signal is transformed into angular domain signal. Then, the VMD–TEO method is applied to angular domain signal to calculate the order spectrum, from which FCO can be extracted to diagnose bearing fault.

The FCOs of inner race and outer race can be calculated by the following formulas:

\[
O_{\text{inner}} = \frac{f_i}{f_r} = \frac{Z_1}{Z_2}\left(1 + \frac{d}{D}\cos\beta\right)
\]  
\[
O_{\text{outer}} = \frac{f_o}{f_r} = \frac{Z_1}{Z_2}\left(1 - \frac{d}{D}\cos\beta\right)
\]

Substituting parameters of rolling bearing into (15) and (16), we can obtain that the FCO of inner race \(O_{\text{inner}}\) is 33.4 and FCO of outer race \(O_{\text{outer}}\) is 22.6.

6.2.1 Inner race fault identification: The collected signal with inner race fault is shown in Fig. 9a, from which it can be discovered that the amplitude of vibration signal increases obviously with speed variation. The amplitude spectrum and envelope spectrum are presented in Figs. 9b and c, and both of them are invalid to fault diagnosis.

The collected signal is pre-processed by angular resampling and further analysed by VMD–TEO method. Fig. 10a displays the Teager energy waveform of sensitive IMF in angular domain. The order spectrum is shown in Fig. 10b which reveals two clear peaks at the FCO of inner race \(O_{\text{inner}}\) (22.6) and two times of \(O_{\text{inner}}\) (45.2). Hence, it can be diagnosed that there is a fault on the inner race of bearing, and results indicate that the VMD–TEO method is capable of diagnosing bearing fault under varying speed condition.

For comparison, the analysis results of EMD method are presented in Figs. 10c and d. One can see from Fig. 10d that the peaks at FCO are not prominent as in Fig. 10b and there are a lot of interference components. As shown in Table 3, the evaluation index \(P\) of VMD–TEO is 54.39% and much greater than others.

### Table 2: Performance contrast in diagnosing inner race fault under constant speed condition

<table>
<thead>
<tr>
<th>Analysis method</th>
<th>Evaluation index P, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>amplitude spectrum</td>
<td>0.1835</td>
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<tr>
<td>envelope spectrum</td>
<td>0.7429</td>
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<tr>
<td>Teager energy spectrum analysed by EMD</td>
<td>8.344</td>
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<tr>
<td>Teager energy spectrum analysed by VMD–TEO</td>
<td>59.72</td>
</tr>
</tbody>
</table>

Fig. 7 Inner race fault signal of wind turbine bearing under constant speed condition
(a) Time domain waveform, (b) Amplitude spectrum, (c) Envelope spectrum

Fig. 8 Analysis results of inner race fault signal under constant speed condition
(a) Teager energy waveform of sensitive IMF analysed by VMD–TEO, (b) Teager energy spectrum of sensitive IMF analysed by VMD–TEO, (c) Teager energy waveform of sensitive IMF analysed by EMD, (d) Teager energy spectrum of sensitive IMF analysed by EMD

Fig. 9 Inner race fault signal of wind turbine bearing under varying speed condition
(a) Time domain waveform, (b) Amplitude spectrum, (c) Envelope spectrum

Fig. 10 Analysis results of inner race fault signal under varying speed condition
(a) Teager energy waveform of sensitive IMF analysed by VMD–TEO, (b) Teager energy spectrum of sensitive IMF analysed by VMD–TEO, (c) Teager energy waveform of sensitive IMF analysed by EMD, (d) Teager energy spectrum of sensitive IMF analysed by EMD

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Comparison results indicate that the performance of VMD–TEO is better than other analysis methods in diagnosing inner race fault under varying speed condition.

6.2.2 Outer race fault identification: Figs. 11a–c show time waveform, amplitude spectrum and envelope spectrum of the outer race fault signal. Similarly, neither amplitude spectrum nor envelope spectrum can extract obvious fault feature. Analysis results of outer race fault signal by the VMD–TEO method are shown in Figs. 12a and b. As shown in the order spectrum (Fig. 12b), three clear peaks can be easily recognised at the FCO of outer race $O_{outer}$ (22.6), two times of $O_{outer}$ (45.2) and three times of $O_{outer}$ (67.8). Figs. 12c and d display the analysis results of EMD method. Performance contrast in diagnosing outer race fault is shown in Table 4. Similar to the above analysis results, VMD–TEO outperforms EMD in diagnosing outer race fault.

7 Conclusion

This paper presents a novel fault diagnosis method for wind turbine bearing based on VMD and TEO. VMD is a recently proposed signal decomposition method and can effectively solve the drawbacks of EMD, which is utilised to decompose bearing vibration signal into several IMFs. Moreover, TEO has good...
performance in detecting impact signal and is very suitable for processing non-stationary signal. In addition, kurtosis criterion is proposed in order to select the most sensitive IMF for spectrum analysis and an evaluation index is introduced to quantitatively evaluate the fault diagnosis performance.

The simulation and experimental signal analyses show that the VMD–TEO method can successfully extract fault feature. Both inner race and outer race defects of wind turbine bearing have been identified by applying the proposed method. Compared with EMD and conventional spectrum analysis, the VMD–TEO method has obvious advantages in diagnosing wind turbine bearing fault.

8 Acknowledgment

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9 References