Application of variational mode decomposition to misalignment fault diagnosis in a wind turbine

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Abstract

Generally, when the misalignment fault occurs in a wind turbine, the vibration signals present the non-stationary and non-linear characteristic nature. The early misalignment fault signal is easily overwhelmed by the strong background signals and noise, making it difficult to detect reliable fault feature. In this paper, a novel variational mode decomposition (VMD) is introduced to address the issue instead of other common adaptive decomposition algorithms such as empirical mode decomposition (EMD) and wavelet transform. VMD is capable of decomposing the fault vibration signal into several stable components and realize the separation of misalignment fault component from background signals. A case study using the fault data from our test rig demonstrate the effectiveness of this method. The characteristic 2X frequency can be extracted from the stable components obtained by VMD efficiently. On the contrary, the fault feature of the components decomposed by the comparative methods is relatively unconspicuous due to the mode mixing and frequency aliasing.

1 Introduction

With the rapid growth of wind power installed capacity, condition monitoring and fault diagnosis has gradually become an important research content in the development of wind power generation technology. As one of the common failure modes in wind turbine, the misalignment fault may cause the vibration of generating set, reduce the reliability of transmission system and even result in the damage of gearbox or bearings [1,2]. Since the couple will be generated by misalignment faults and the shaft neck loads twice forces per round, the 2X frequency will arise when the mechanical chain runs with a high rotation speed. However, the feature of early faults is relatively unconspicuous. With strong background signals and noise, it may be difficult to detect obvious characteristic frequency. The adaptive decomposition approach is a powerful tool to solve this problem which can decompose the raw vibration signal into multiscale components [3]. This technology can achieve the separation of the fault component and other signal components, promoting the accurate early diagnosis.

Wavelet transform has the ability of multi-scale analysis using scaling and translation functions [4], while the frequency aliasing phenomenon may be produced by Mallet algorithm in the process of signal decomposition and reconstruction. In this case, the components will lose the physical meanings and fail to reflect the explicit frequency components in raw signal. Moreover, the appropriate wavelet basis function plays a significant role in acquiring a desired decomposition performance.

Empirical mode decomposition (EMD) is another typical adaptive decomposition method, which utilizes sample interpolation curves to acquire a finite number of component signals called intrinsic mode function (IMF) [5,6]. With its high time–frequency resolution and excellent adaptability, EMD has been extensively studied for fault diagnosis in mechanical system [7]. Nevertheless, because of the defects of this algorithm, the decomposition performance suffers from mode mixing and end effect dramaticly. The mode mixing is defined as several significantly distinguishing component scales exist in single IMF, leading to the meaningless signal components.

Variational mode decomposition (VMD) proposed by Dragomiretskiy and Zosso in 2013 is a novel adaptive decomposition algorithm for the multi-component signal, making use of iterative optimization approach to determine the center frequency and bandwidth of each component [8]. Recently, the emerging VMD has received more and more attention in the field of feature extraction and diagnosis [9-13]. An et al applied VMD to the pedestal looseness fault diagnosis in rotating machinery and successfully extracted the faint fault information, namely the half fractional harmonic component of the rotational frequency [9]. Mahgoun et al compared VMD with ensemble empirical mode decomposition (EEMD) in the application for gear faults detection with variable rotating speed and VMD gave promising results [10]. Yi et al put forward a rolling bearing fault diagnosis scheme based on VMD and particle swarm optimization. The analysis results showed that VMD can enhance the fault feature of rolling bearing so that more high order harmonics of fault characteristic frequency can be detected, significantly outperforming EMD [11]. In this paper, to address the issues mentioned above, a wind turbine misalignment fault diagnosis method based on VMD was presented. It can not only separate the components of fault signal with 2X frequency, background rotating signal and noise from raw vibration signal exactly, but avoid the drawbacks of frequency aliasing and mode mixing in other well existing techniques.

2 Variational mode decomposition

VMD is capable of decomposing the complicated multi-component signal into a discrete number of quasi-orthogonal band-limited intrinsic mode functions (IMFs). The main theoretical framework is to find the optimal solution of a variational problem, adopting constantly iterative optimization strategy to locate the center frequency and bandwidth of each component. For any given non-stationary signal f, the decomposition problem can be defined as follows

$$min_{\{u_k\}\{\omega_k\}}\{\sum_k \left\| \partial_t \left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\} \quad s.t. \sum_k u_k = f \tag{1}$$

where $\{u_k\}=\{u_1,\dots,u_k\}$ are the mode components, $\{\omega_k\}=\{\omega_1,\dots,\omega_k\}$ are their corresponding center frequency and K is the number of decomposed intrinsic modes. To address this constrained variational problem, a quadratic penalty term α and Lagrangian multipliers λ are introduced. The (1) can be transformed into following format

$$L(\{u_k\},\{\omega_k\},\lambda)=\alpha\sum_k \left\| \partial_t \left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2 + \|f(t)-\sum_k u_k(t)\|_2^2 + \langle\lambda(t), f(t)-\sum_k u_k(t)\rangle. \tag{2}$$

Further, the alternate direction method of multipliers (ADMM) is applied to produce different modes and center frequencies during each shifting operation. The estimated modes u_k and the corresponding updated center frequency in the frequency domain can be given as follows:

$$\hat{u}_k^{n+1}(\omega)=(\hat{f}(\omega)-\sum_{i\neq k}\hat{u}_i(\omega)+\frac{\hat{\lambda}(\omega)}{2})\frac{1}{1+2\alpha(\omega-\omega_k)^2}. \tag{3}$$

$$\omega_k^{n+1}=\frac{\int_0^\infty \omega\left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega}{\int_0^\infty \left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega} \tag{4}$$

Summarizing the aforementioned steps, the complete optimization of VMD can be express as:

Initialize $\{u_k^1\},\{\omega_k^1\},\lambda^1, n\leftarrow 0$

Repeat $n\leftarrow n+1$

For $k=1:K$ do

Update u_k for all $\omega\geq 0$ $\hat{u}_k^{n+1}(\omega)\leftarrow(\hat{f}(\omega)-\sum_{i<k}\hat{u}_i^{n+1}(\omega)-\sum_{i>k}\hat{u}_i^n(\omega)+\frac{\hat{\lambda}^n(\omega)}{2})\frac{1}{1+2\alpha\left(\omega-\omega_k^n\right)^2}$

Update ω_k $\omega_k^{n+1}\leftarrow\frac{\int_0^\infty \omega\left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega}{\int_0^\infty \left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega}$

End for

Dual ascent for all $\omega\geq 0$ $\hat{\lambda}^{n+1}(\omega)\leftarrow\hat{\lambda}^n(\omega)+\tau(\hat{f}(\omega)-\sum_k\hat{u}_k^{n+1}(\omega))$ (5)

Until convergence: $\sum_k\left\|\hat{u}_k^{n+1}-\hat{u}_k^n\right\|_2^2/\|\hat{u}_k^n\|_2^2<\varepsilon$.

Detailed introduction of the VMD can be referred in [8], presenting a promising prospect in adaptive decomposition problem.

3 Case study

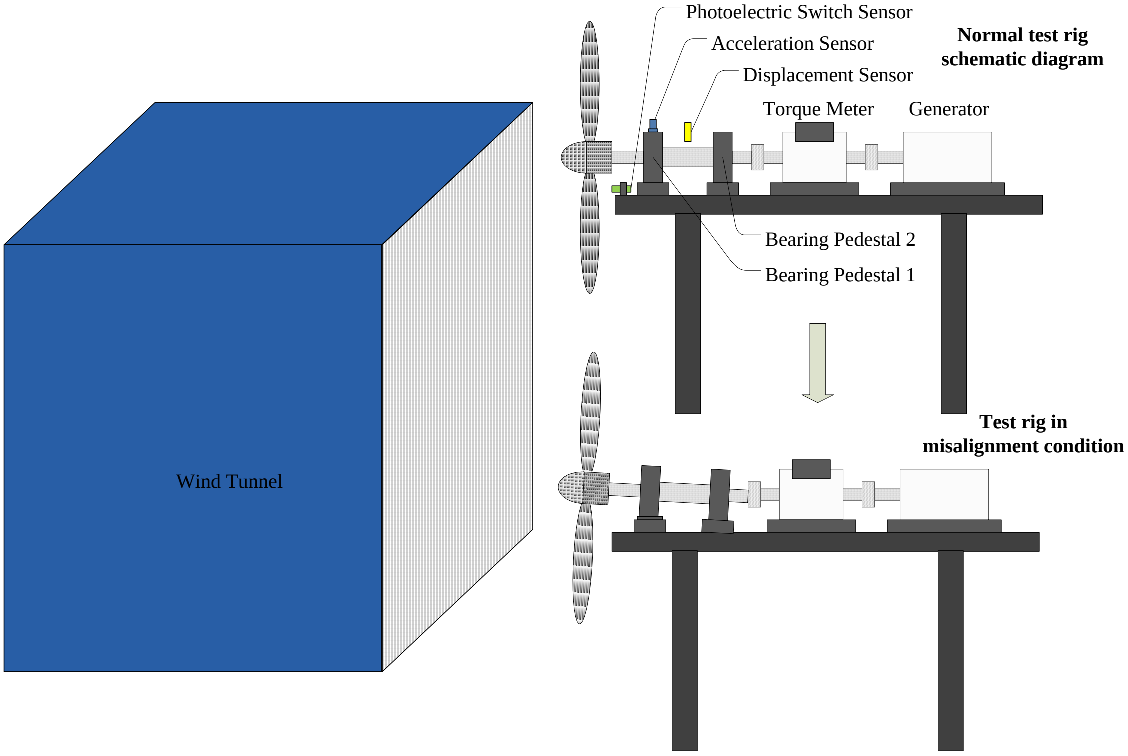

Figure 1. Test rig schematic diagram of direct-drive wind turbine

Figure 2. Test rig of direct-drive wind turbine

To demonstrate the availability of the proposed method for misalignment fault diagnosis, an experimental analysis was performed on the direct-drive wind turbine showed in Figure 1 and 2. The experimental system is introduced in literature [14,15]. The misalignment fault was implemented by inserting a shim (around 2mm) under the front bearing pedestal. Figure 3 gives the time waveform of axial displacement signal in misalignment condition. With the wind speed around 8.0m/s, the rotational speed of main shaft was around 270 rpm. The sampling frequency was 2000 Hz. The frequency spectrum of the vibration signal in Figure 3 is presented in Figure 4. A main peak appears at the rotating frequency X.

However, it is difficult to detect the fault information of misalignment due to the strong background signal and noise. Hence, the adaptive decomposition methods are applied to cope with this problem.

Figure 5 shows the decomposition results via VMD. From the nine obtained component modes, it is clear that the $u_3 \sim u_9$ denoting the noise and high frequency harmonic components are well separated from analytic signal. The attracted components u_1 and u_2 are investigated by frequency analysis. It can be seen that the rotational frequency X and an obvious 2X frequency appear in Figure 6 (a) and (b) respectively. It signifies the vibration signal contains a 2X component and means misalignment faults may occur in the mechanical system, agreeing with the actual status in the test rig. The results show the VMD can separate the real components masked by background signals and noise effectively.

For comparison, the EMD and wavelet transform are also adopted to handle this issue and the decomposition results are illustrated in Figure 7 and 8. In Figure 7, eight IMFs and a residual part are produced by EMD. One can find the distinct mode mixing phenomenon in the IMFs. Meanwhile, from the frequency spectra of $c_4 \sim c_6$ in Figure 8, we only observe the rotational frequency X, whereas no obvious fault characteristic can be detected. The 2X frequency component is total submerged in the decomposed IMFs duo to mode mixing.

As seen in Figure 9, wavelet transform generates seven high-frequency components $D_1 \sim D_7$ and a low-frequency component A_7 from raw signal. Likewise, the $D_1 \sim D_5$ represent the noise and high frequency harmonic. The frequency spectra of attracted components, namely D_6, D_7 and A_7, are illustrated in Figure 10. A main peak 2X frequency component along with several interfering frequencies can be found in Figure 10(b). In Figure 10(c), the rotational frequency X is obvious. Although the component D_7 contains the signal component evincing the misalignment fault and a 2X frequency can be found in its frequency spectrum, in contrast with the results by VMD, one can see the frequency aliasing arises in vibration waveform and frequency spectrum by wavelet transform, affecting the veracity of diagnosis. According to the comparison above, VMD significantly outperforms the conventional EMD and wavelet transform, which demonstrates its excellent adaptive decomposition capacity.

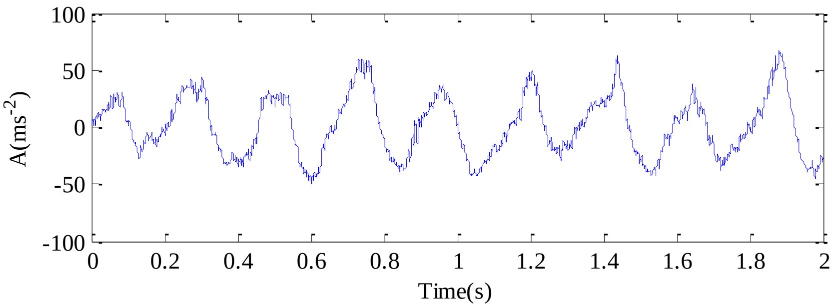

Figure 3. Time waveform of vibration signal with misalignment fault

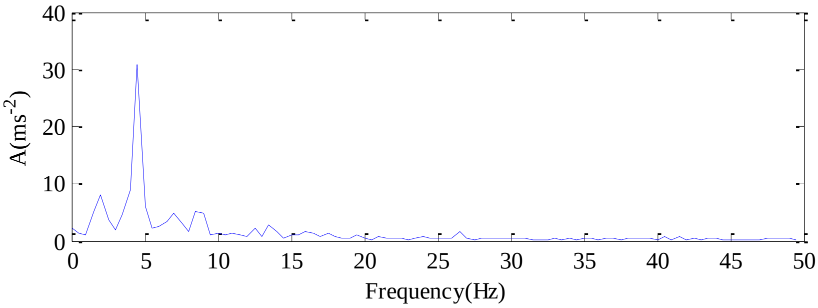

Figure 4. Frequency spectrum of fault signal

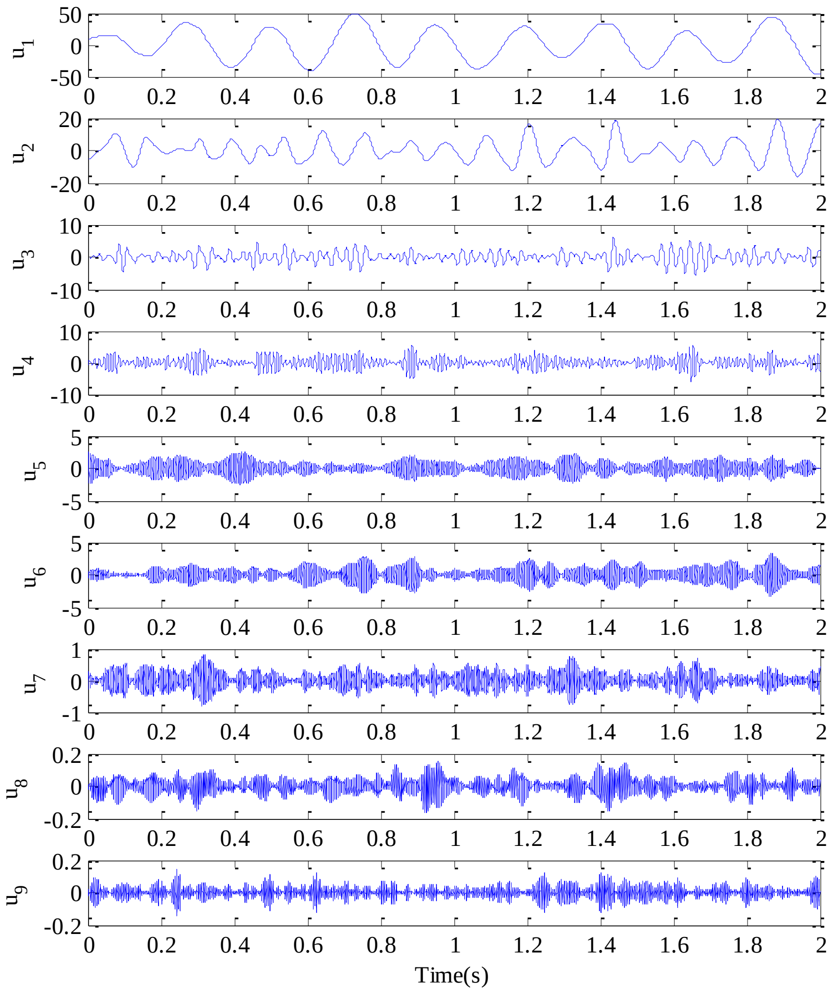

Figure 5. Decomposed modes of misalignment fault signal using VMD

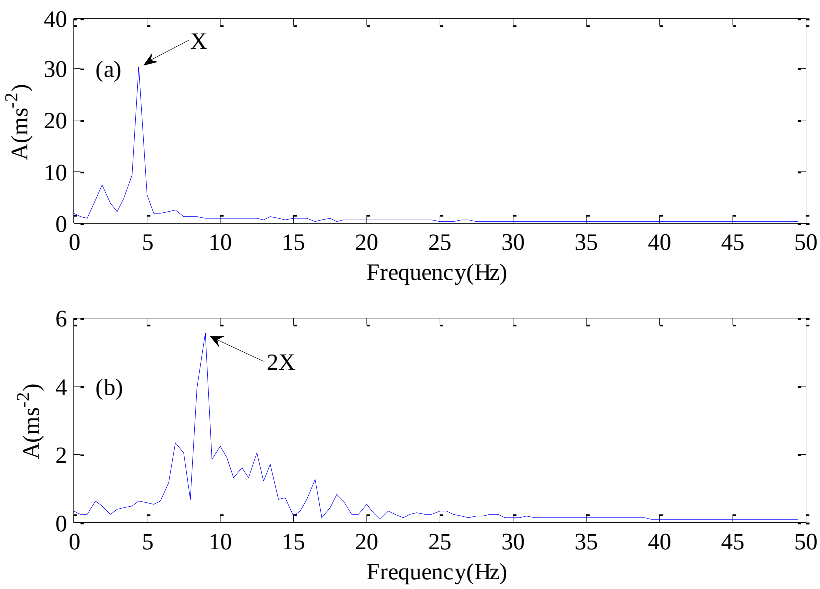

Figure 6. Frequency spectra of valuable components. (a) Frequency spectrum of u_1; (b) frequency spectrum of u_2.

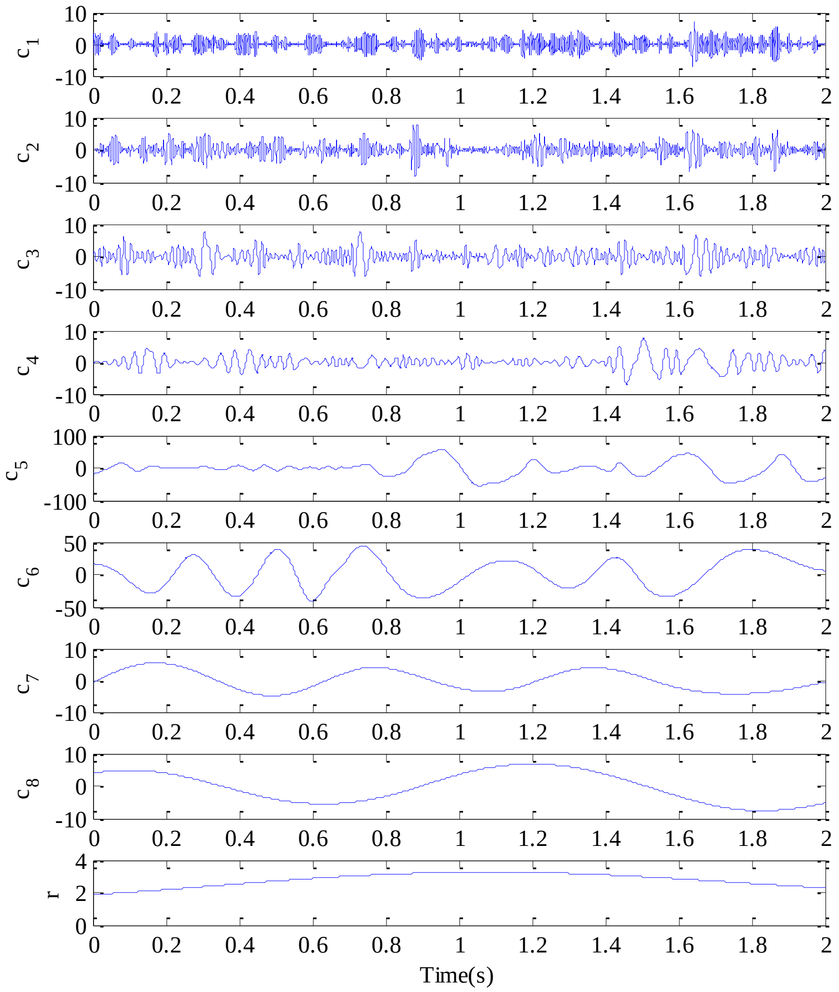

Figure 7. Gained IMFs of misalignment fault signal using EMD

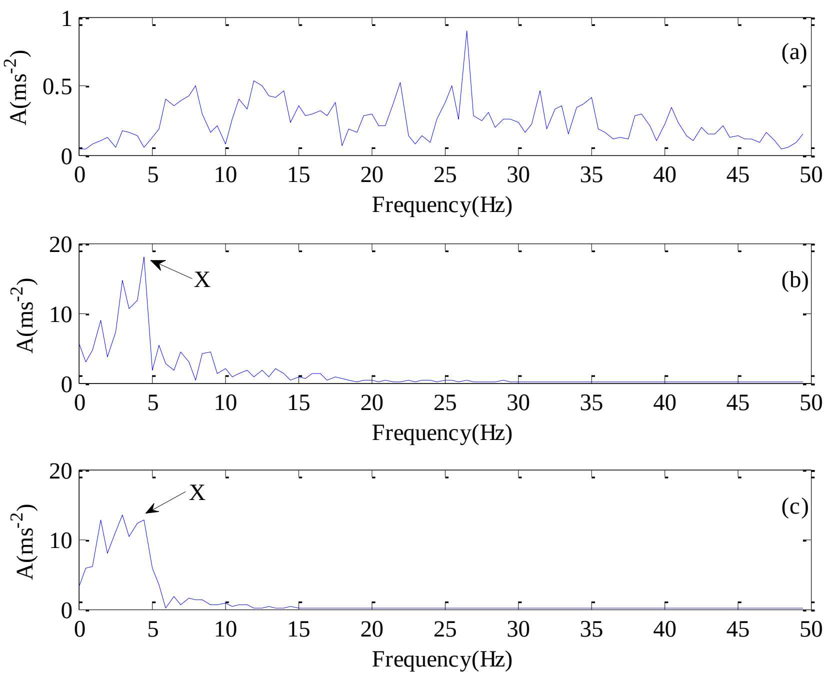

Figure 8. Frequency spectra of valuable components. (a) Frequency spectrum of c_4; (b) frequency spectrum of c_5; (c) frequency spectrum of c_6

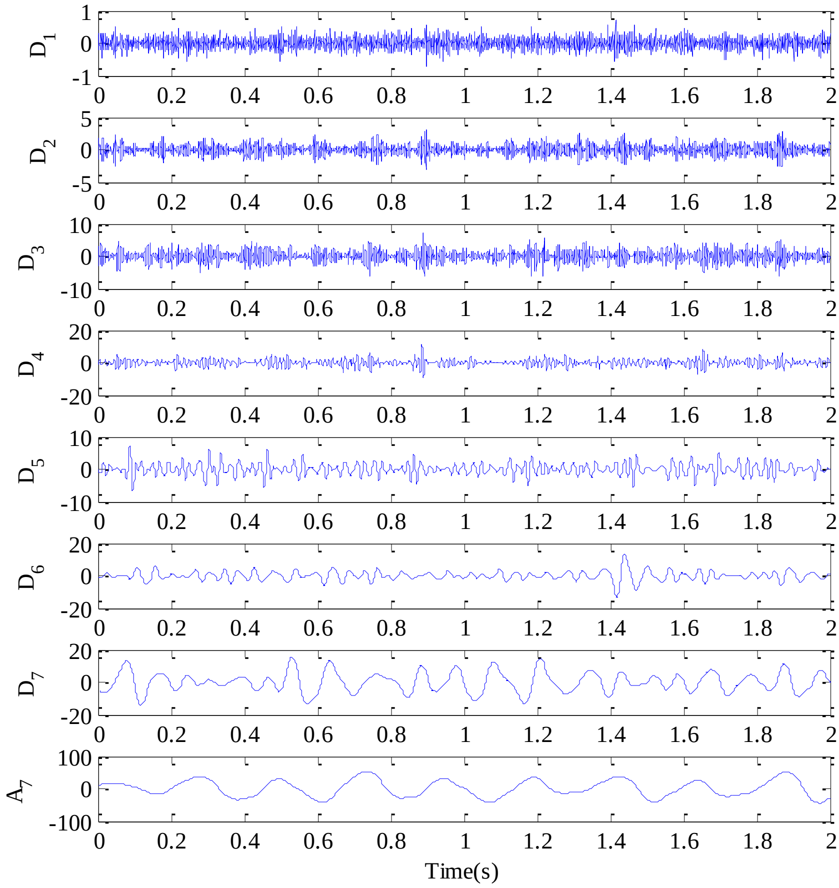

Figure 9. Decomposition result of misalignment fault signal using wavelet transform

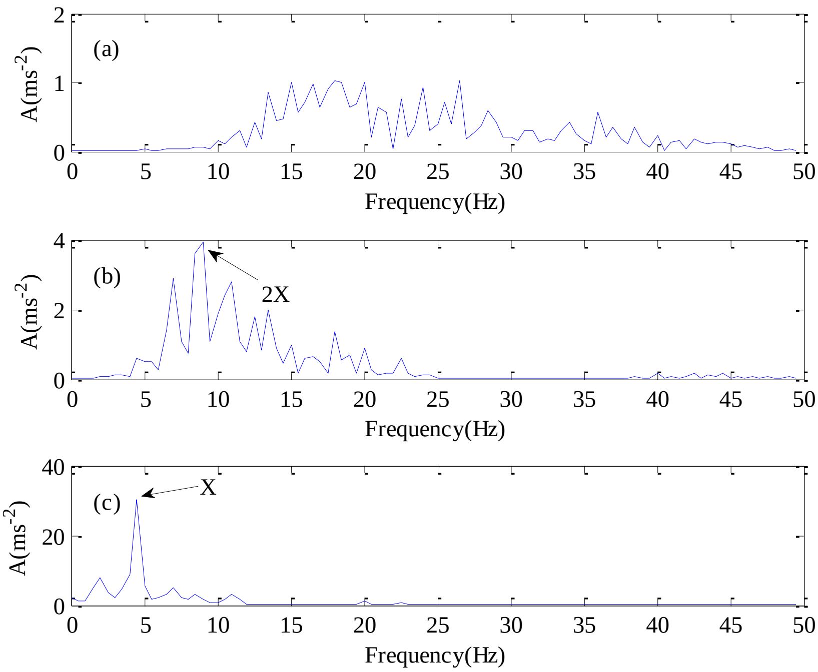

Figure 10. Frequency spectra of valuable components. (a) Frequency spectrum of D_6; (b) frequency spectrum of D_7; (c) frequency spectrum of A_7

4 Conclusions

As a novel adaptive decomposition algorithm, VMD adopts the iterative optimization strategy to decompose the multi-component signal, instead of the circular recursion and screening in other traditional approaches. For the difficulty of early diagnosis of misalignment fault, VMD was introduced to diagnose this type of fault in wind turbine. The case study using the data from our test rig shows that VMD is capable of separating the fault characteristic component from the strong background signal and noise effectively. This can achieve the feature extraction of weak fault when the misalignment fault occurs. The decomposed components by VMD have a precise physical meaning and contribute to judge the status of mechanical system. As a contrast, the decomposition performances by EMD and wavelet transform suffer from mode mixing and frequency aliasing respectively, leading to the ambiguous diagnosis results.

Acknowledgments – additional information

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