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Vibration signal analysis of a hydropower unit based on adaptive local iterative filtering

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Abstract

The vibration signals coming from a hydropower unit have strong nonstationary characteristics when strong vortex develops in the hydraulic turbine draft tube. Related to this problem, a new vibration analysis method for a hydropower unit based on adaptive local iterative filtering is proposed. Firstly, adaptive local iterative filtering was used to decompose the complex vibration signal into several intrinsic mode functions. Then, frequency spectrum analysis of these components was performed to obtain the vortex characteristic frequency from the vibration signal. Simulated and real-world signals were used to verify the proposed method. The obtained results show that this method can overcome the problem of mode mixing in the existing empirical mode decomposition method, since it improves the efficiency and accuracy of feature extraction for nonstationary vibration signals from a hydropower unit.

Keywords

Hydropower unit, adaptive local iterative filtering, vibration signal, mode mixing, nonstationary signal

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Introduction

The vibration of a hydropower unit and the pressure fluctuations in a hydraulic turbine are important indicators used while measuring the stability of the running state of the unit.[1–4] Large hydropower units use Francis turbines whose runner blades are fixed. When the unit is running under part-load conditions, the turbine cannot meet the optimum flow conditions of the runner import and export, therefore an unstable eccentric precessing vortex rope will develop in the draft tube of the water turbine.[1] The leading vortex band can damage both the runner and the draft tube, leading to the appearance of cracks therein and, eventually, to their destruction in the most severe cases.[5–7] The precessing vortex rope also causes instability of the unit shaft system, and causes the vibration signals from the unit to exhibit strong nonstationarity.

When a hydropower unit runs in non-steady-state conditions, its vibration signal has a strong nonstationarity. The analysis of nonstationary signals has always been a research focus, as has been noted by many scholars.[8–10] Zheng et al.[8] proposed an adaptive data-driven analysis method known as generalized empirical mode decomposition (GEMD) to process nonstationary signals. For the GEMD method, different baselines are defined and separately subtracted from the original data. This can give different pre-generated intrinsic mode functions (pre-GIMFs). A GIMF is analyzed by using the empirical envelope demodulation method. The analysis results indicate that the proposed method is effective in restraining the boundary effect. It also offers better frequency resolution, more accurate components, and a more accurate time–frequency distribution. To represent the information contained in the nonstationary vibration signals acquired from a working engine, Li et al.[9] used a generalized S-transform to obtain a time–frequency distribution with enhanced energy concentration. They adopted non-negative tensor factorization (NTF) to extract more informative features from the time–frequency matrices. The experimental results verify the validity of the proposed feature extraction method. Gan et al.[10] proposed a multiple-domain manifold (MDM) method to extract representative features based on singular value decomposition

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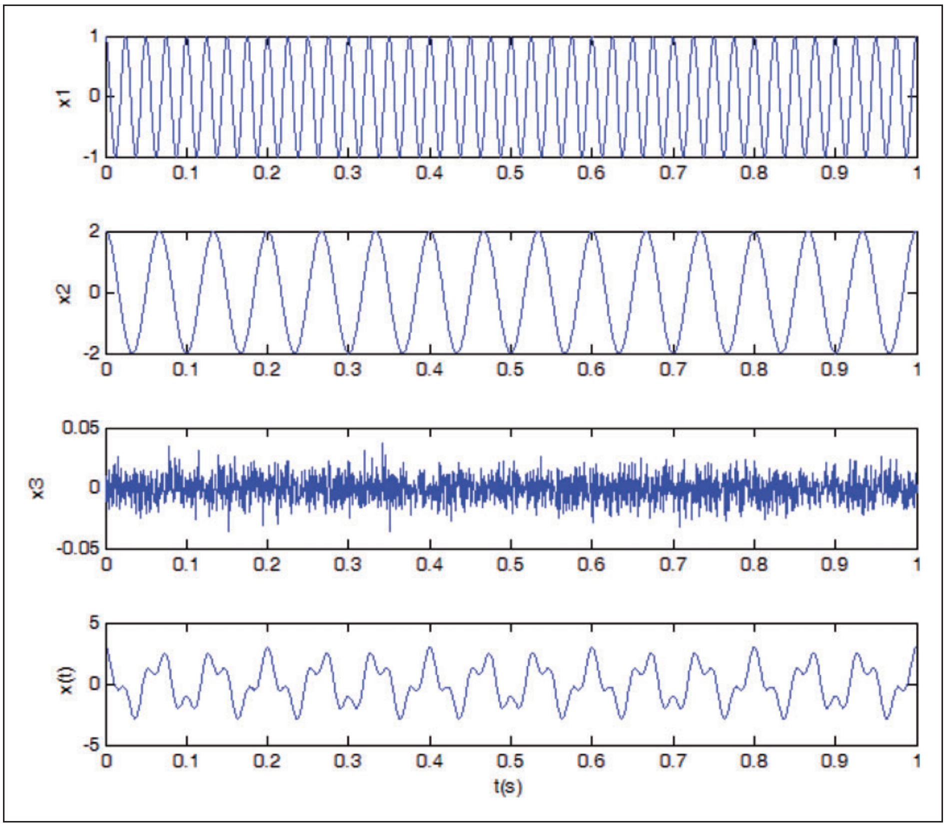

Figure 1. Time domain waveforms of mixed signal $x(t)$ and its components.

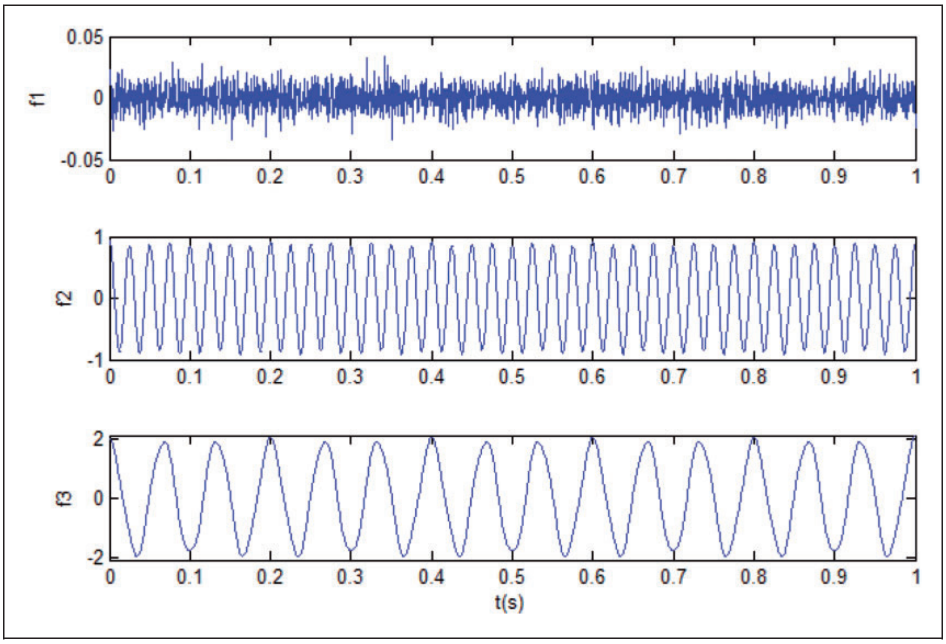

Figure 2. Decomposition results of $x(t)$ by ALIF.

(SVD) and manifold learning. In their method, phase space reconstruction is applied to signals in the time and frequency domains to provide a reconstructed 2D space. In these reconstructed spaces, SVD is used to calculate singular values (SVs). Manifold learning is used to extract MDM features by revising the SVs. The detection of bearing and gear faults confirms the validity of MDM. The most representative adaptative analysis method for nonstationary signals is empirical mode decomposition (EMD).[11,12] This

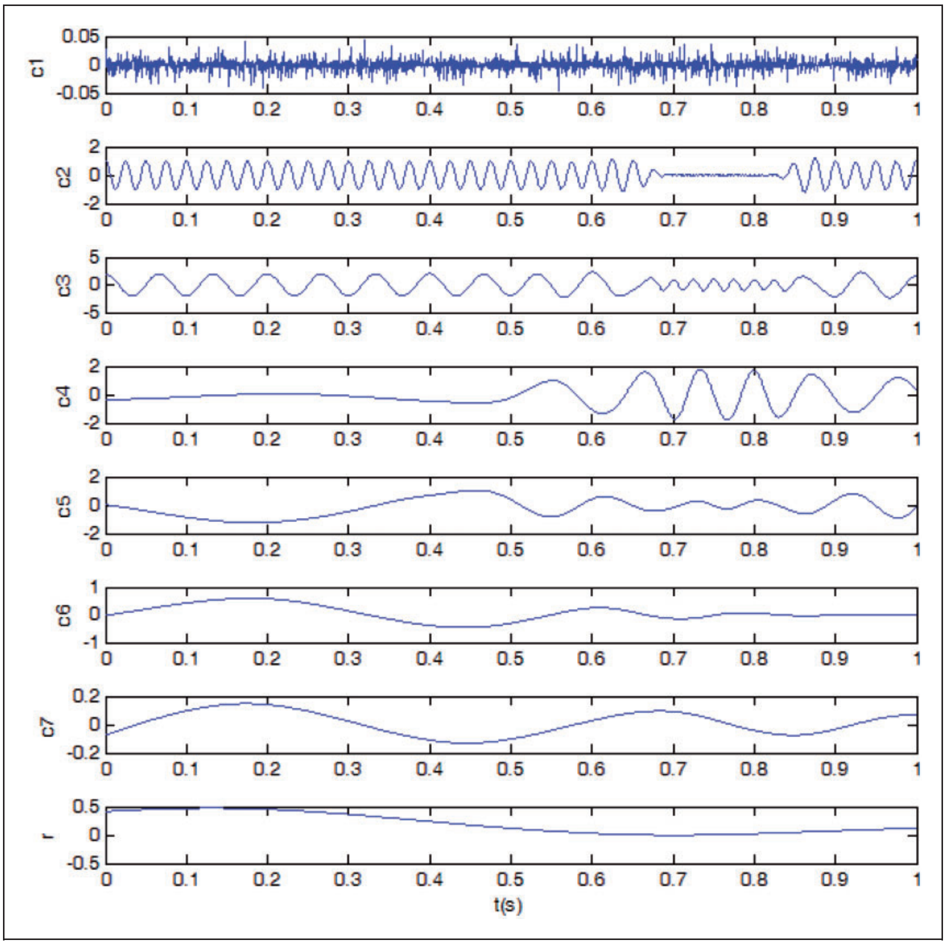

Figure 3. Decomposition results of $x(t)$ by EMD.

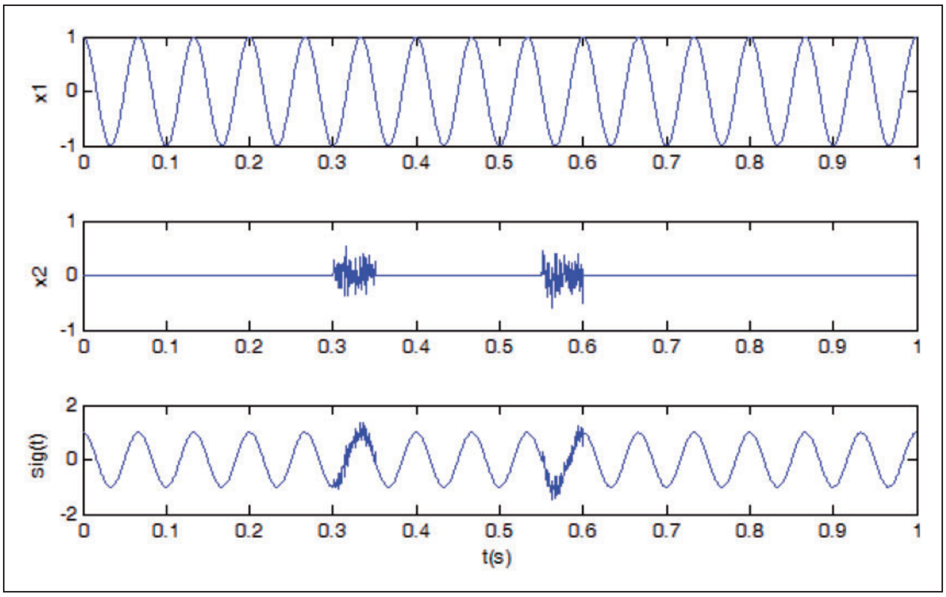

Figure 4. Time domain waveforms of mixed signal $sig(t)$ and its components.

method presents the definition of the intrinsic mode function (IMF) components and gives the instantaneous frequency some physical meaning. This method can adaptively decompose a complex signal into several IMF components; however, EMD suffers from the problems of mode mixing and end effects. Dragomiretskiy and Zosso[13] proposed a fully intrinsic, adaptive, variational mode decomposition (VMD) method: it is an entirely nonrecursive method, can decompose a signal into a discrete number of

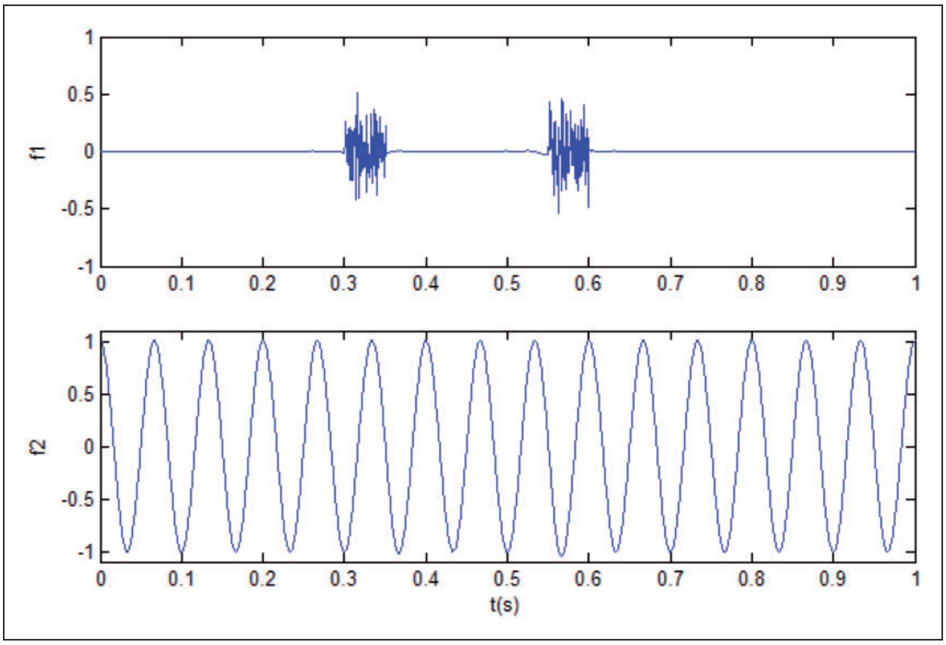

Figure 5. Decomposition results of *sig*(*t*) by ALIF.

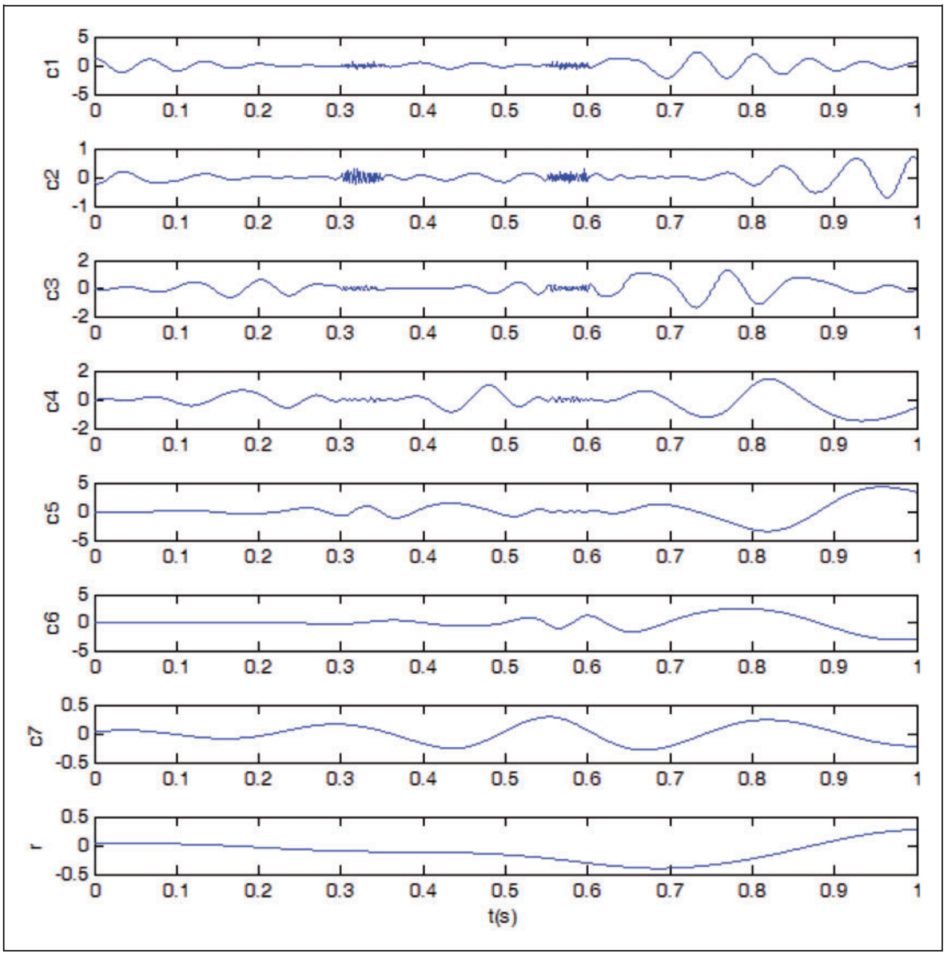

Figure 6. Decomposition results of *sig*(*t*) by EMD.

band-separated modes, where the modes are extracted concurrently and each mode has limited bandwidth in the spectral domain. The VMD method, however, has two important limitations: one is its boundary effects, and sudden signal onset in general, another is the required explicit (manual) selection of the number of active modes in the decomposition. Gilles[14] proposed empirical wavelet transform (EWT) that can build an

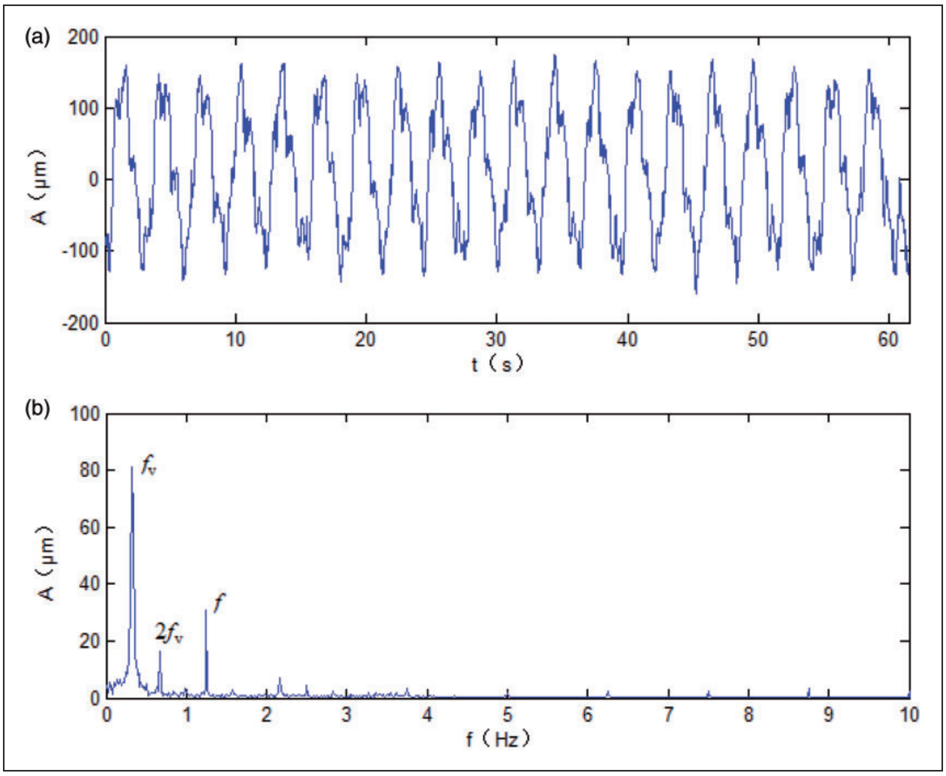

Figure 7. Waveform and amplitude spectrum of the shaft vibration signal at the generator upper guide bearing of the hydropower unit: (a) signal waveform; (b) amplitude spectrum of signal.

adaptive wavelet basis to decompose a given signal into adaptive sub-bands. However, this method has the requirement of pre-defining filter bank boundaries and requires the manual selection of the number of decomposition modes. Cicone et al.[15] proposed the adaptive local iterative filtering (ALIF) method to solve this problem. This ALIF method uses an iterative filtering strategy together with an adaptive and data-driven filter length selection to achieve signal decomposition. The purpose of presenting the ALIF method is to design a local, adaptive and stable iterative filtering method.

This research proposed an ALIF-based method of analysis for nonstationary vibration signals arising from hydropower units. Firstly, the ALIF approach was used to decompose the complex signal into a series of intrinsic mode functions (IMFs). Then, a frequency spectrum analysis of each IMF component was undertaken to obtain the characteristics of the hydropower unit vibration signal in the situation when the hydraulic turbine draft tube was under the influence of a strong vortex.

Adaptive local iterative filtering method

ALIF method is based on Iterative filtering (IF)[16] technique. The main differences between ALIF method and IF technique are that ALIF method can compute adaptively the filter length and the filters can be chosen from Fokker–Planck equations[15] to compute the moving average of the signals. ALIF method is described as follows:

ALIF method IMF = ALIF(f)
  IMF = {}
  while the number of extrema of $f \geqslant 2$ **do**
    $f_1 = f$
    while the stopping criterion[15] is not satisfied **do**
      compute the filter length $l_n(x)$[15] for $f_n(x)$
      $f_{n+1}(x) = f_n(x) - \int_{-l_n(x)}^{l_n(x)} f_n(x+t)w_n(x,t)\mathrm{d}t$
      $n = n + 1$
    end while
    IMF = IMF $\cup \{f_n\}$
    $f = f - f_n$
  end while
IMF = IMF $\cup \{f\}$

In the proposed method, $w_n(x,t)$, $t \in [-l_n(x), l_n(x)]$, is the filter at point x for the signal $f_n(x)$, and its length is $2l_n(x)$. The ALIF method has two iterations: one capturing a single IMF and another producing all the IMFs. The former is called the inner iteration, the latter is called the outer iteration. The updating step of the inner iteration is

$$f_{n+1}(x) = f_n(x) - \int_{-l_n(x)}^{l_n(x)} f_n(x+t)w_n(x,t)\mathrm{d}t \qquad (1)$$

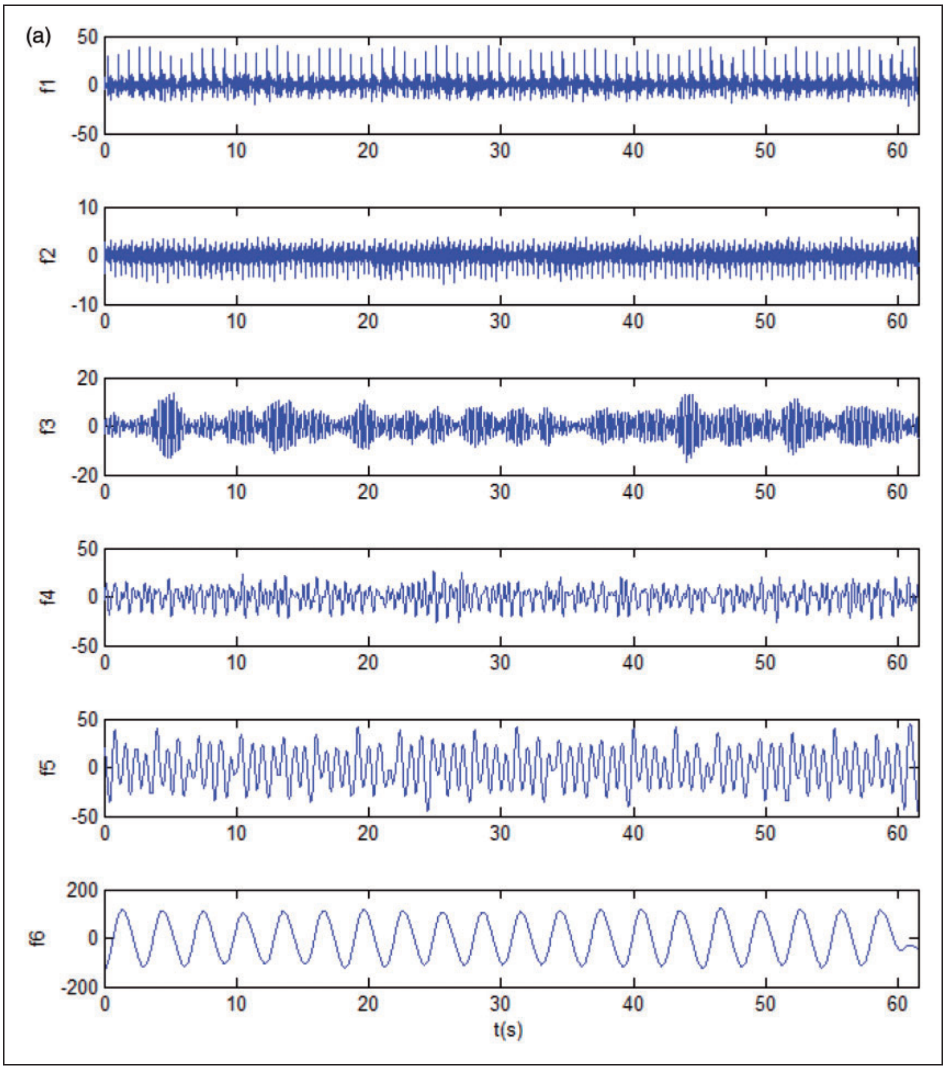

Figure 8. Decomposition results and frequency spectra found using the ALIF method on a shaft vibration signal taken from the generator upper guide bearing: (a) decomposition results; (b) frequency spectrum of the components; (c) frequency spectrum of components f3 to f6.

An equivalent formulation of the updating step is used to establish the convergence theorem for the ALIF method. The scaling function can be linear as $g_n(x, y) = l_n(x)\, y/L$, or cubic as $g_n(x, y) = l_n(x)\, y^3/L^3$. The function $g_n(x, y)$ is used to change the right-hand side in equation (1) to

$$\int_{-l_n(x)}^{l_n(x)} f_n(x+t) w_n(x,t)\mathrm{d}t = \int_{-L}^{L} f_n(x+g_n(x,y)) W(y)\mathrm{d}y$$

So equation (1) can be rewritten as

$$f_{n+1}(x) = f_n(x) - \int_{-L}^{L} f_n(x+g_n(x,y)) W(y)\mathrm{d}y \qquad (2)$$

where $W(y)$, $y \in [-L, L]$, is a fixed filter.

A new operator T is defined as $T_{w,l}(f) := \int_{-l(x)}^{l(x)} f(x+t)w(x,t)\mathrm{d}t$. The convergence theorem for the inner iteration of ALIF method is

Let $f(x)$, $x \in R$, be continuous and $f(x) \in L^\infty(R)$. Let

$$\varepsilon_n = \frac{\| T_{w_{n+1},l_{n+1}}(f_{n+1}) \| L^\infty}{\| T_{w_n,l_n}(f_n) \| L^\infty}, \quad \delta_n = \frac{\| T_{w_{n+1},l_{n+1}}(|f_{n+1}|) \| L^\infty}{\| T_{w_n,l_n}(|f_n|) \| L^\infty} \qquad (3)$$

If $\prod_{i=1}^n \varepsilon_i \to 0$, $\prod_{i=1}^n \delta_i \to c > 0$, as $n \to \infty$, then $\{f_n(x)\}$ converges to an IMF.

The convergence theorem for the outer iteration of the ALIF method is:

Let $f(x)$, $x \in R$, be continuous and differentiable and let $f(x)$ have a finite number of extreme points in any compact interval. So $f(x)$ has at most k

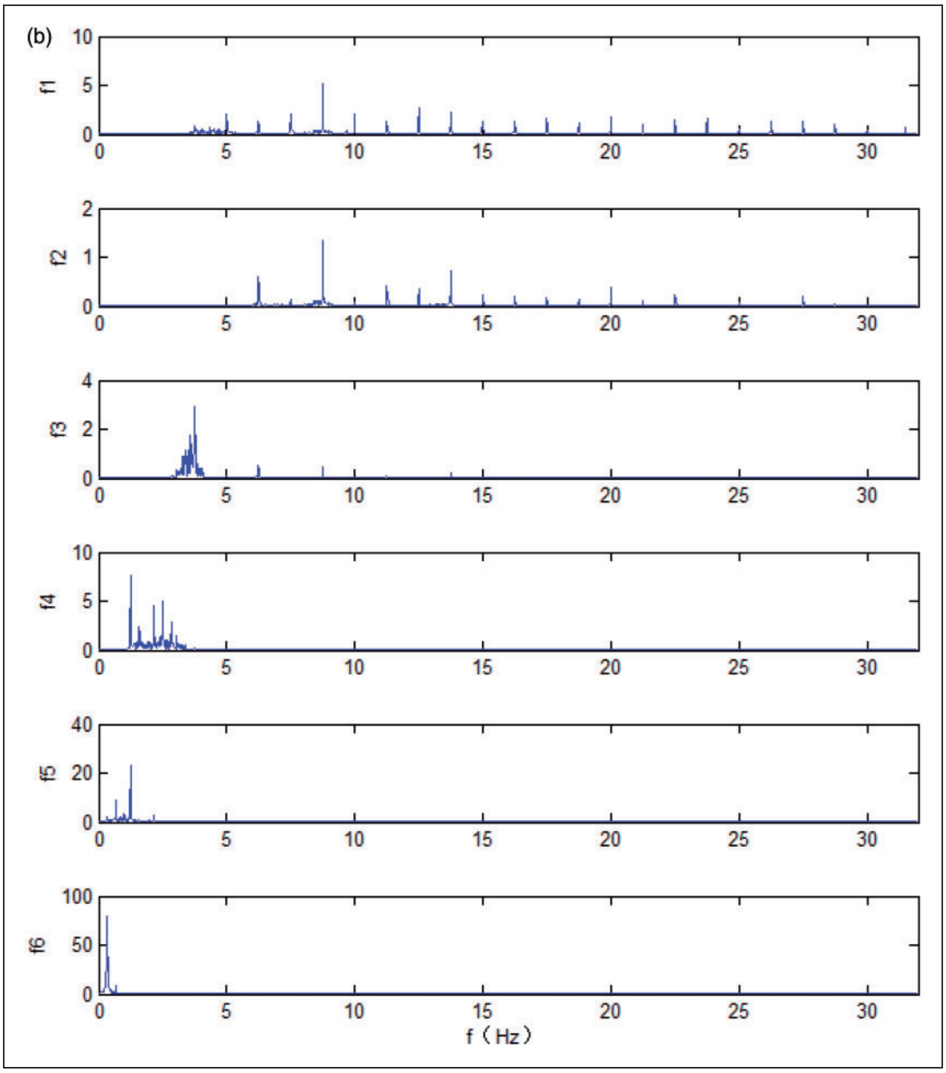

Figure 8. Continued.

countable extreme points. Let x_i, $i = 1, 2, \ldots, k$, be the extreme points of $f(x)$. Assume that $f(x)$ is strictly monotonic in $[x_i, x_{i+1}]$, $i = 1, 2, \ldots, k-1$. The functions $c_n^{(1)}(x)$ and $c_n^{(2)}(x)$ are defined using $f_n(x)$ as

$$\begin{aligned} c_n^{(1)}(x) &= \int_{-L}^{L} [f_n'(x) - f_n'(g_n(x,y) + x)]W(y)\mathrm{d}y \\ c_n^{(2)}(x) &= \int_{-L}^{L} [f_n'(x) - f_n'(g_n(x,y) + x)]h(y)W(y)\mathrm{d}y \end{aligned} \tag{4}$$

The function $f(x)$ is assumed to be a differentiable function with properties as described above. Equation (2) is used, if the scaling function is separable, i.e. $g_n(x, y) = l_n(x)h(y)$ and for every $n \in N$

$$\begin{aligned} c_n^{(1)}(x) + l_n'(x)c_n^{(2)}(x) > 0 \quad \text{when } f_n'(x) > 0 \\ c_n^{(1)}(x) + l_n'(x)c_n^{(2)}(x) < 0 \quad \text{when } f_n'(x) < 0 \end{aligned} \tag{5}$$

Then the number of extreme points of $f(x) - \lim_{n\to\infty} f_n(x)$ is at most the number of extreme points of $f(x)$ if $\lim_{n\to\infty} f_n(x)$ exists.

A detailed algorithm of ALIF method are given in Cicone et al.[15]

Simulation signal analysis

To show the ability of the ALIF method in alleviating the problem of mode mixing, this research compared the performance of the EMD[5,6] and ALIF methods. The EMD method is widely used for non-stationary vibration signal analysis. In this part of the research, two examples were used to demonstrate the performance of the ALIF method.

Example 1. A mixed signal $x(t)$ was analyzed; $x(t)$ can be written as

$$x(t) = x_1(t) + x_2(t) + x_3(t) \tag{6}$$

where $x_1(t) = \cos(80\pi t)$, $x_2(t) = 2\cos(30\pi t)$, $x_3(t)$ is random noise whose mean is zero, whose values are normally distributed, and $t \in [0, 1]$. The time domain

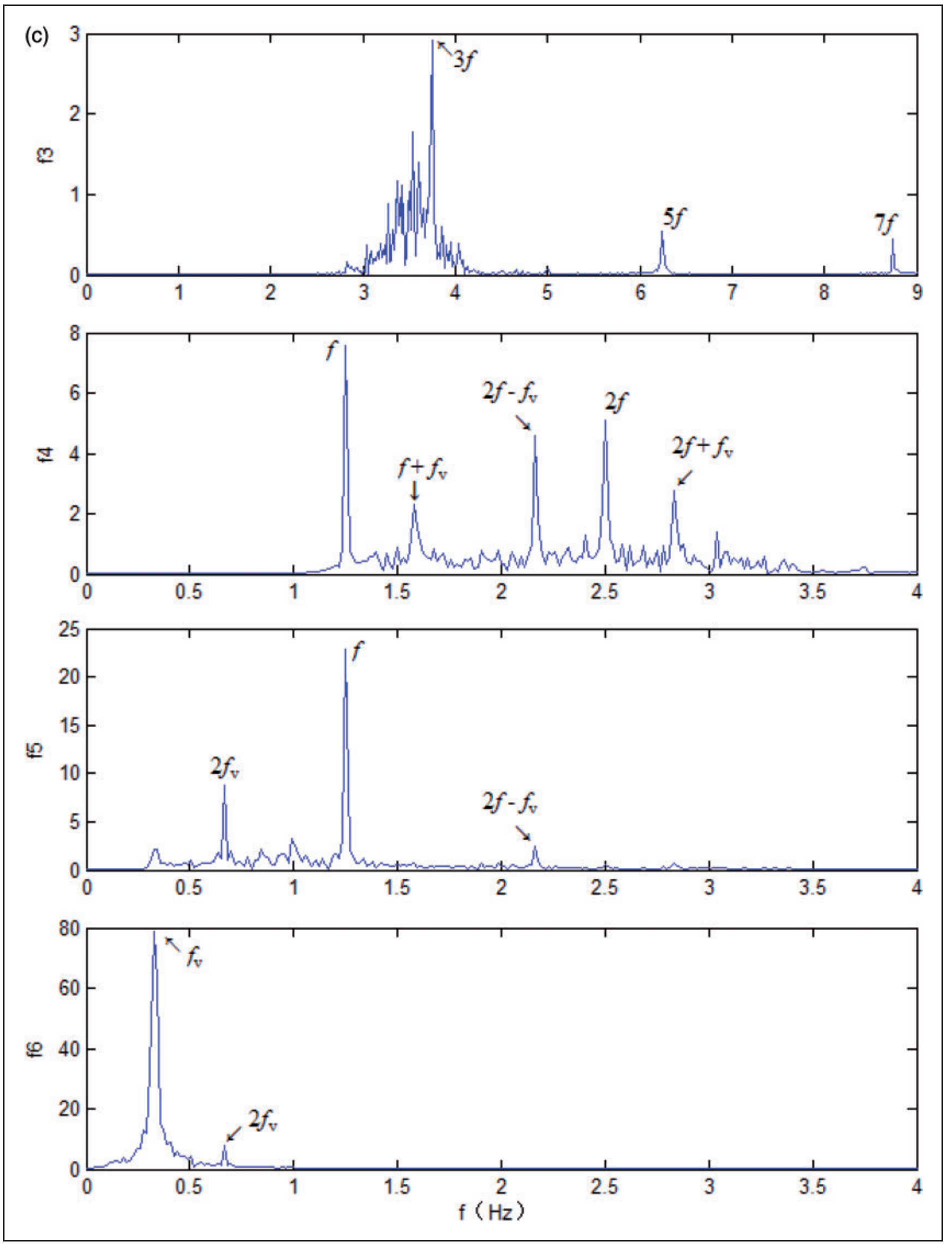

Figure 8. Continued.

waveform of the mixed signal and its components are shown in Figure 1.

The ALIF and EMD methods are respectively used to decompose the mixed signal $x(t)$. The decomposed results of both methods are shown in Figures 2 and 3, respectively. The ALIF results of mixed signal $x(t)$ are shown in Figure 2: the ALIF method produced three components. The EMD results from mixed signal $x(t)$ are shown in Figure 3: the EMD method produced seven components and a residual. It can be seen from Figure 3 that, due to noise interference, the EMD results seemed to suffer more severely as a result of the mode mixing problem. The differences between the obtained and real components were large, however, the ALIF method can effectively alleviate the problem of mode mixing, and the obtained components were closer to the real components. The f2 and f3 components of the ALIF results respectively corresponded to the real components $x_1(t)$ and $x_2(t)$, and the f1 component represented the noise, making the decomposition suitable for this purpose. The simulation results, using the aforementioned signal, showed that the ALIF method was able to alleviate the problem of mode mixing when it was caused by noise interference.

Example 2. An example of mode mixing (which in this case was caused by intermittent signals) was also analyzed. The mixed signal $sig(t)$, which was

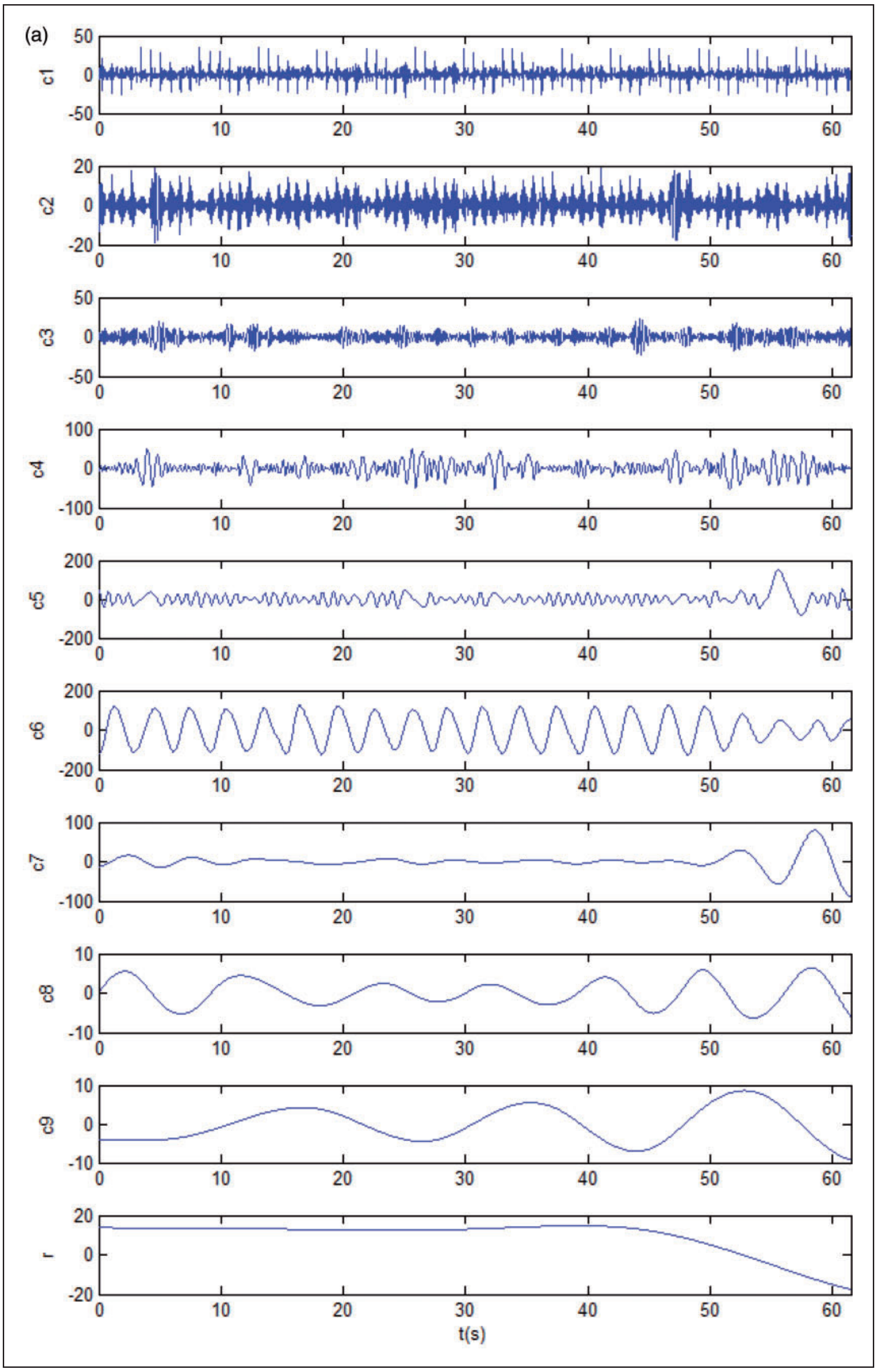

Figure 9. Decomposition results and frequency spectra found using the EMD method on a shaft vibration signal taken from the generator upper guide bearing: (a) decomposition results; (b) frequency spectrum of the components; (c) frequency spectrum of components c3 to c6.

composed of a high-frequency intermittency signal and a sinusoidal signal, can be written as

$$sig(t) = x_1(t) + x_2(t) \tag{7}$$

where $x_1(t) = \cos(30\pi t)$, $x_2(t)$ consists of two intermittent signals, and $t \in [0, 1]$. The mixed signal was composed of a high-frequency intermittent signal and a cosine signal whose frequency was 15 Hz. Its time domain waveform is shown in Figure 4.

The ALIF and EMD methods were respectively used to decompose the mixed signal $sig(t)$. The results are shown in Figures 5 and 6. Figure 5 shows results based on the ALIF method, from

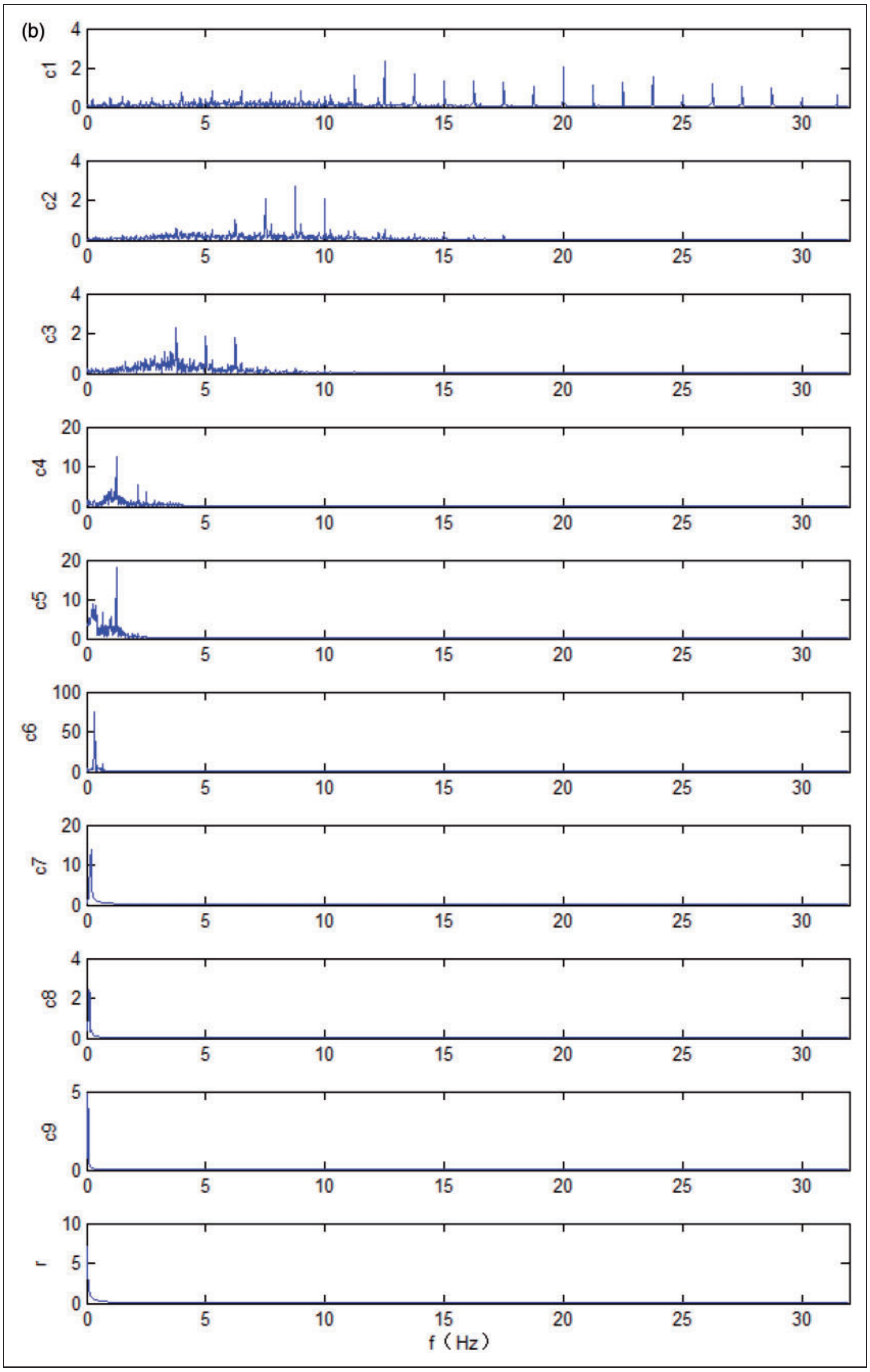

Figure 9. Continued.

which two components were obtained. Figure 6 shows results based on the EMD method, from which seven IMF components and one residual part were obtained. It can be seen from Figure 5 that ALIF can effectively inhibit mode mixing. f2 component corresponds to $x_1(t)$ and f1 represented the noise part. The decomposed results were acceptable. It can be seen from Figure 6 that, due to interference from the intermittent signal, the decomposed results (which are based on EMD) exhibited serious mode mixing.

The analysis of the two aforementioned simulation signals showed that the ALIF method was an effective way of processing nonstationary signals. It can effectively inhibit the mode mixing caused by high-frequency intermittent and random noise. The ALIF-based components were superior to the EMD-based components.

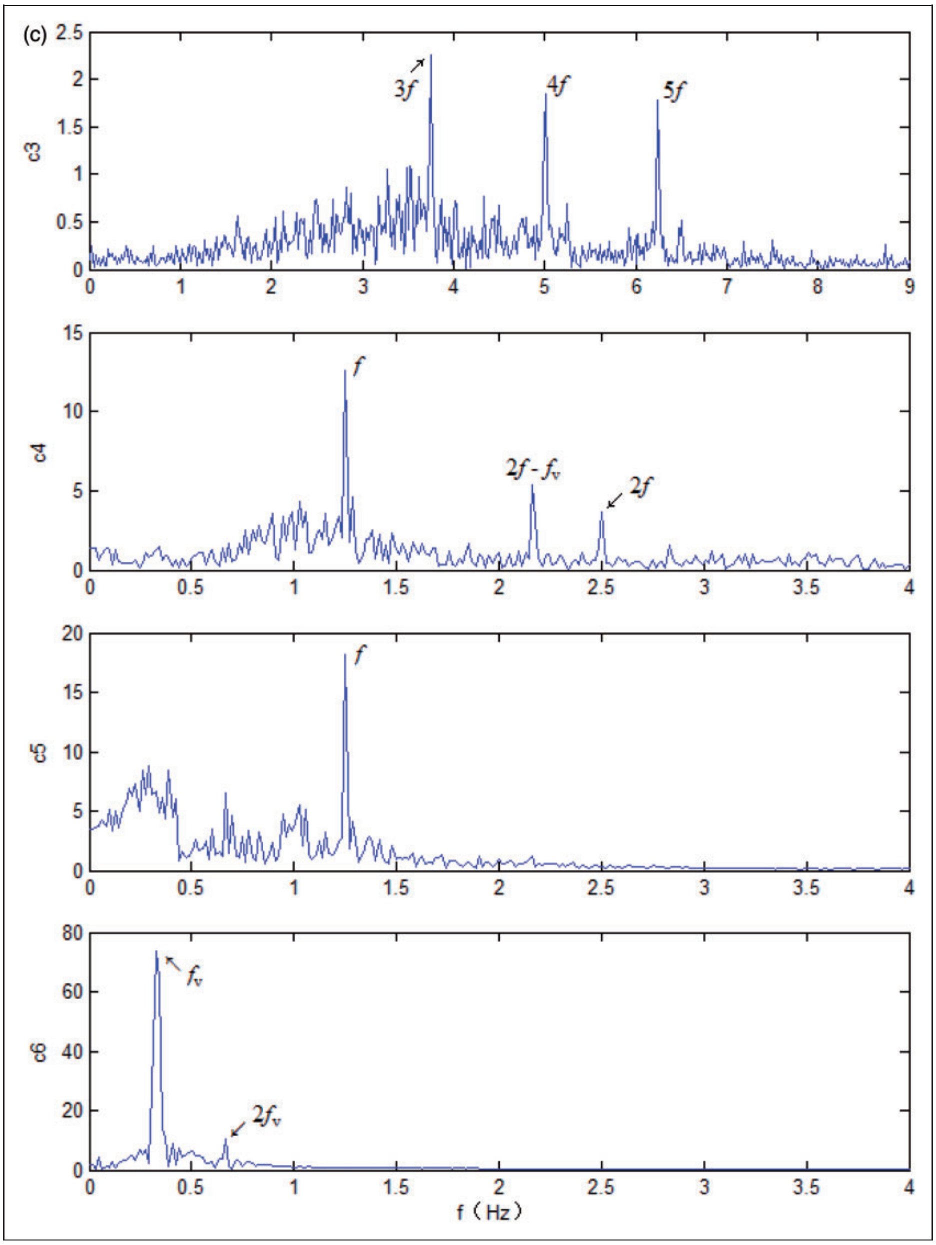

Figure 9. Continued.

Field case study

To verify the superiority and practicality of the proposed method, the real-world hydropower unit's vibration signals (the shaft vibration signal at the generator upper guide bearing of the hydropower unit and the shaft vibration signal at the generator lower guide bearing thereof) were selected for analysis.

The steps in the ALIF-based vibration signal analysis were as follows:

1. In accordance with a certain sampling frequency, the vibration at different locations on the hydropower unit in a hydropower plant was tested. The vibration signals of the unit were acquired.
2. The ALIF method was used to decompose each vibration signal into a finite number of simple components.
3. The frequency spectrum analysis of each component was undertaken separately: this can provide frequency information about the original signal.
4. According to the frequency information, the effect of the hydraulic turbine's draft tube vortex on the hydropower unit's vibration signals was assessed.

The apparatus used a hydropower unit from the Three Gorges hydropower plant. The test data were non-stationary due to the fact that the unit was operating in a condition in which its hydraulic turbine draft tube was suffering from the effects of a strong vortex. The sampling frequency used in the test was

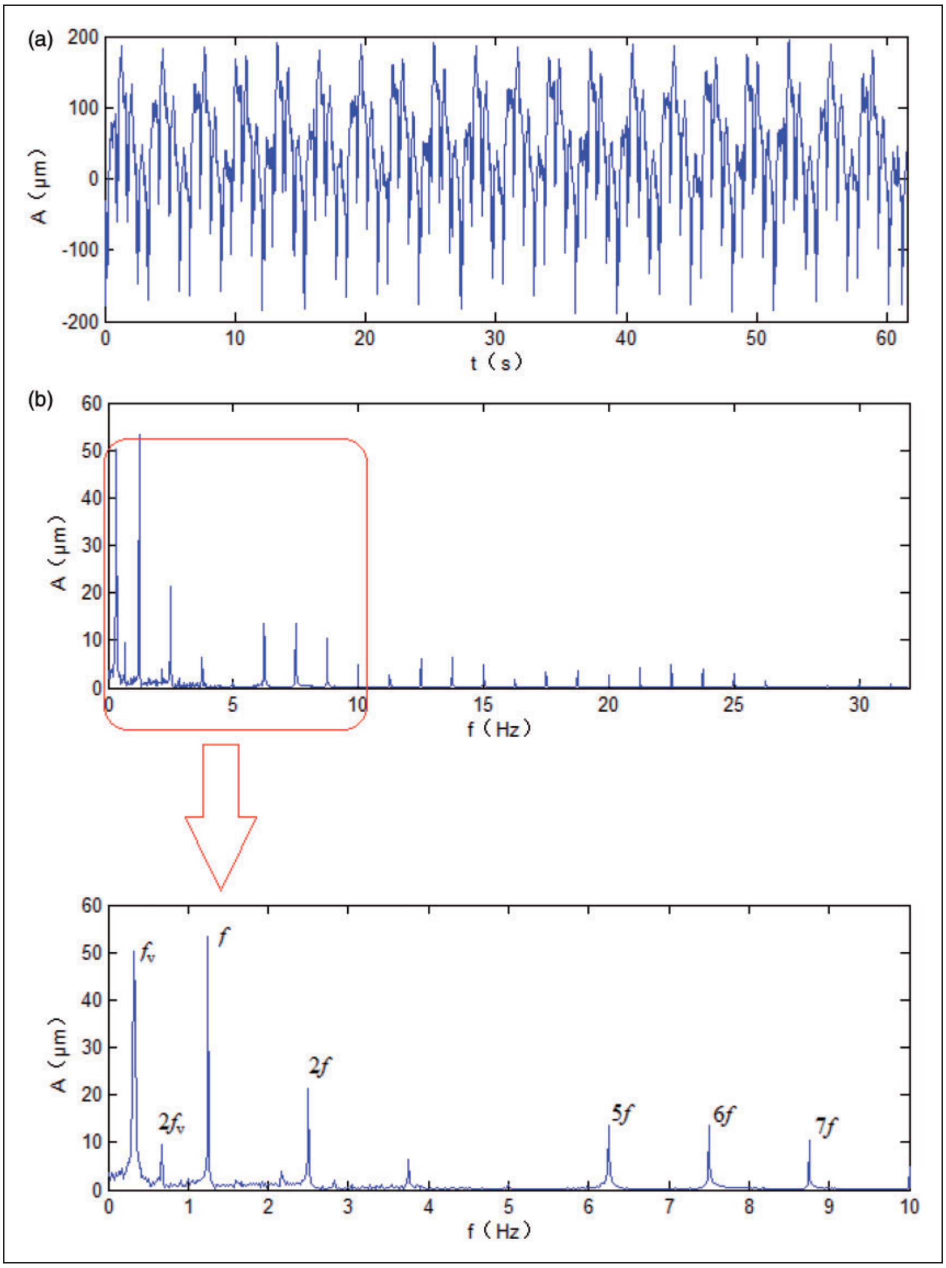

Figure 10. Waveform and amplitude spectra of the shaft vibration signal taken from the generator lower guide bearing of the hydropower unit: (a) signal waveform; (b) amplitude spectrum of signal.

64 Hz. The unit's rated output was 710 MW, its rated speed was 75 r/ min, the maximum head of water across the device was 113 m, the minimum head of water across it was 61 m, and the rated head of water was 85 m.

When the hydropower unit output was 560 MW, the working head of water was 102.19 m, therefore the precessing vortex rope in the draft tube was a serious issue. The waveform of the shaft vibration signal at the generator upper guide bearing of the hydropower unit is shown in Figure 7(a), and its frequency spectrum in Figure 7(b). As seen from Figure 7(b), the main frequencies of the shaft vibration signal at the generator upper guide bearing were f_v, $2f_v$, and f, where f_v is the vortex frequency of the hydraulic turbine's draft tube, f_v is $1/4f$–$1/3f$, and f is the rotational frequency of the unit. Other frequency information from this signal is not obvious: the frequencies f_v and $2f_v$ are caused by the vortex in the draft tube of the hydraulic turbine. Under a strong vortex condition in such a hydraulic turbine, the main frequency components of most signals (vibration and pressure fluctuation signals) show information about the frequency of the vortex, and the amplitude of the frequency is larger. As the intensity of the vortex in the draft tube gradually decreases, the frequency of the vortex in these signals (vibration and pressure fluctuation) gradually decreases until the vortex disappears.

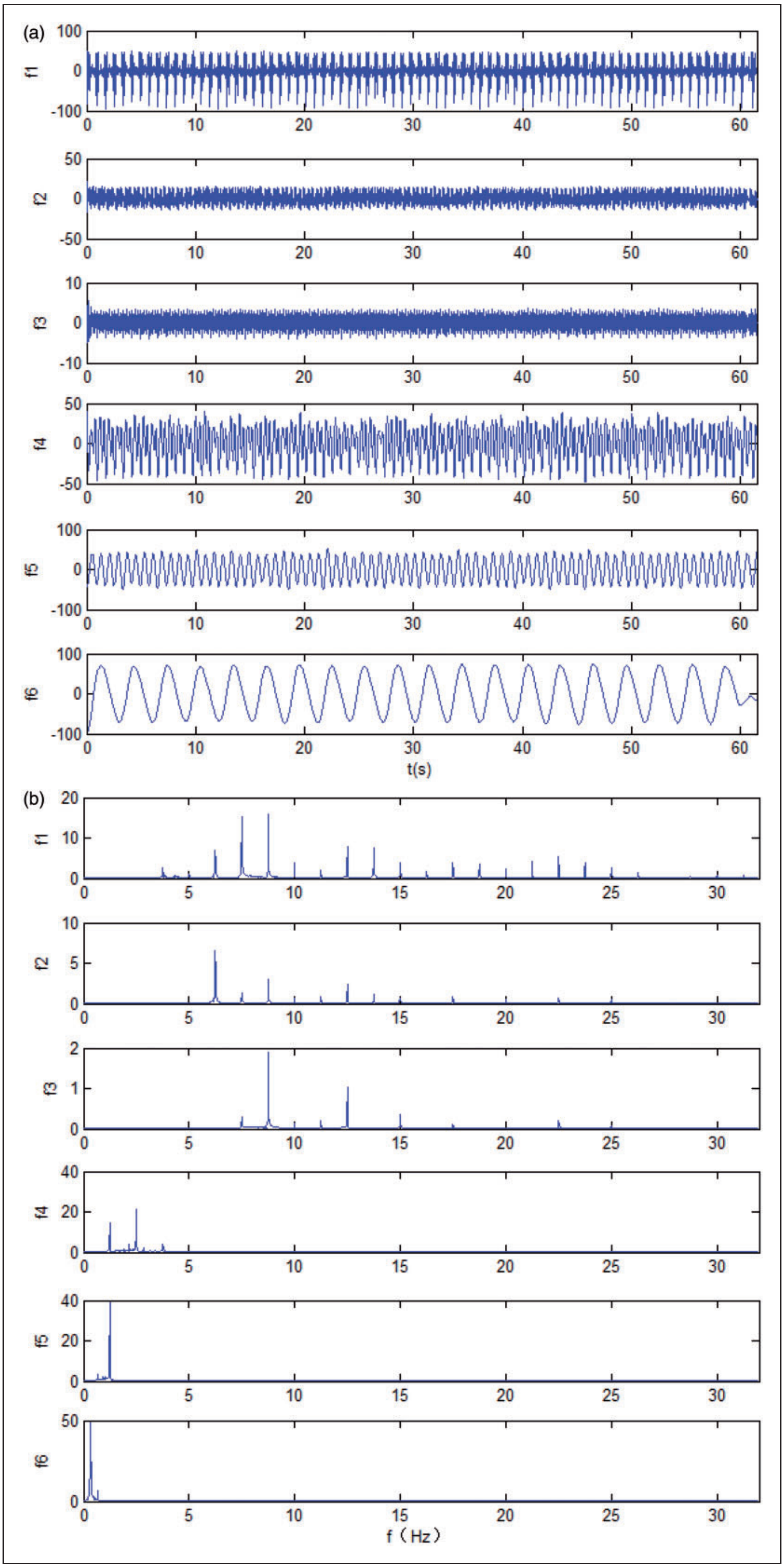

Figure 11. Decomposition results and frequency spectra found using the ALIF method on a shaft vibration signal taken from the generator lower guide bearing: (a) decomposition results; (b) frequency spectrum of the components; (c) frequency spectrum of components f4 to f6.

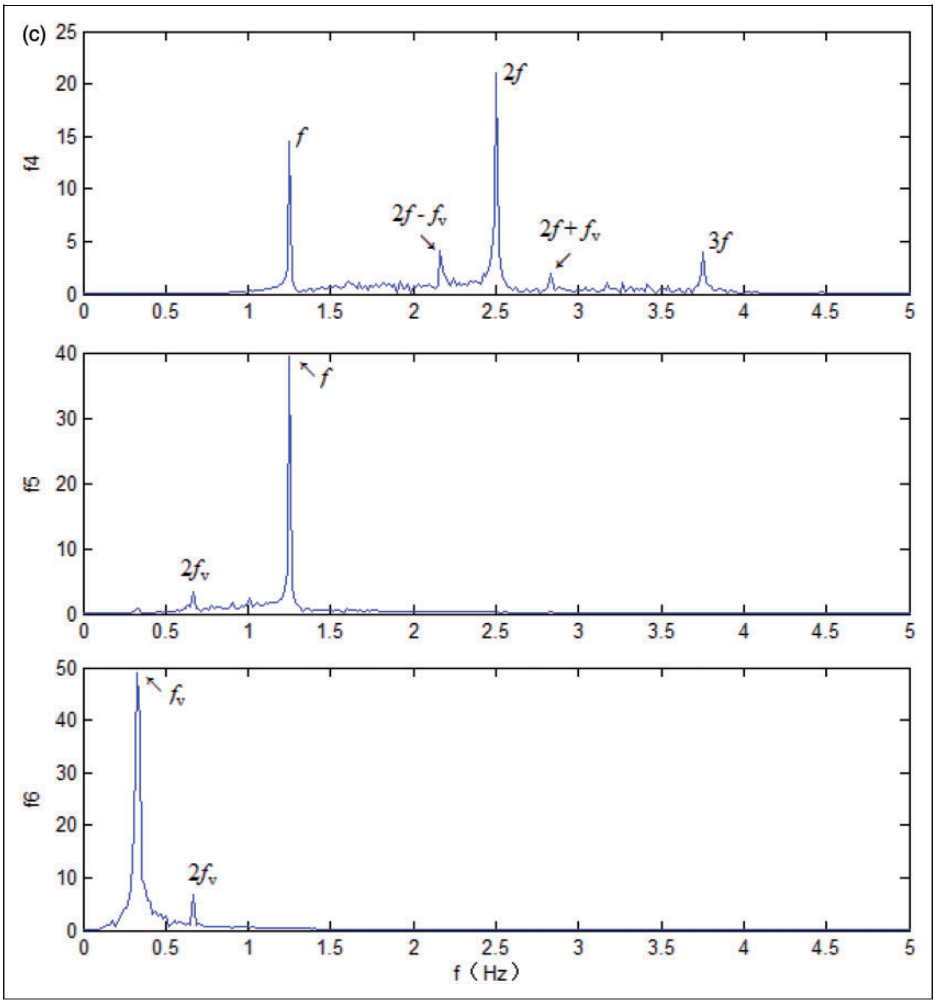

Figure 11. Continued.

The rotational frequency f is caused by a rotor imbalance in the hydropower unit.

The ALIF method was used to decompose the shaft vibration signal at the generator upper guide bearing into six components, as shown in Figure 8(a). Their frequency spectra are shown in Figure 8(b) and (c). It can be seen from Figure 8 that components f1 and f2 corresponded to the multiple frequencies of the unit's rotational frequency (f), component f3 corresponded to $3f$, $5f$, and $7f$, component f4 corresponded to f, $f + f_v$, $2f - f_v$, $2f$, and $2f + f_v$, component f5 had significant $2f_v$, f, and $2f - f_v$ frequencies, and component f6 contained significant f_v and $2f_v$ frequencies. It can be seen that some important frequency information ($3f$, $5f$, $7f$, $f + f_v$, $2f - f_v$, $2f$, and $2f + f_v$) can be revealed by using the ALIF method to decompose the shaft vibration signal at the generator upper guide bearing. This frequency information cannot be found in Figure 7(b).

The EMD method is used to decompose the same signal (Figure 7(a)) to compare the decomposition performances of each method. The results, and their frequency spectra, are shown in Figure 9. It can be seen from Figure 9(a) that significant mode mixing occurred in several components. From Figure 9(c), it can be seen that only the coupling frequency $2f - f_v$ of the rotational frequency of the unit can be found. Other coupling frequencies cannot be found.

The waveform of the shaft vibration signal at the generator lower guide bearing of the hydropower unit is shown in Figure 10(a), and its frequency spectrum is shown in Figure 10(b). It can be seen from Figure 10(b) that the main frequencies of the shaft vibration signal were f_v, $2f_v$, f, $2f$, $5f$, $6f$, and $7f$, where f_v is the vortex frequency of hydraulic turbine's draft tube, and f is the rotational frequency of this unit. Other frequency information about this signal was not obvious.

The ALIF method was used to decompose the shaft vibration signal at the generator lower guide bearing into six components, as shown in Figure 11(a). The component frequency spectra are shown in Figure 11(b) and (c). It can be seen from Figure 11 that components f1 to f3 corresponded to the multiple frequencies of the unit's rotational frequency (f), component f4 corresponded to f, $2f - f_v$, $2f$, $2f + f_v$, and $3f$, component f5 had significant $2f_v$

and f frequencies, and component f6 contained significant f_v and $2f_v$ frequencies. It can be seen that some important frequency information ($2f - f_v$, $2f + f_v$) can be revealed by using the ALIF method to decompose the shaft vibration signal: such information cannot be found in Figure 10(b).

In summary, it can be seen from the vibration signal analysis of a hydropower unit shaft vibration at the generator upper and lower guide bearings that the decomposition results from the ALIF method were superior to those found when using the EMD method. The ALIF method was validated using both numerically simulated data and real test signals from a hydropower unit. It can acquire more frequency information, which was deemed useful when analyzing the coupling relationship between a vortex in the draft tube and hydropower unit vibrations.

Conclusions

ALIF is a new nonlinear and nonstationary signal analysis method. This method uses an iterative filtering strategy together with an adaptive and data-driven filter length selection algorithm to achieve its decomposition. The vibration signals from a hydropower unit have strong nonstationary characteristics when a strong vortex occurs in the hydraulic turbine draft tube. To tackle this problem (nonstationary signal), a new vibration analysis method for a hydropower unit based on ALIF has been proposed. The analysis of simulated and real signals showed that the ALIF method can inhibit the mode mixing inherent to the existing EMD method. The proposed method can effectively and accurately extract the features of a nonstationary vibration signal from a hydropower unit.

Declaration of Conflicting Interests

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