Pressure fluctuation signal analysis of pump based on ensemble empirical mode decomposition method

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Abstract: Pressure fluctuations, which are inevitable in the operation of pumps, have a strong non-stationary characteristic and contain a great deal of important information representing the operation conditions. With an axial-flow pump as an example, a new method for time-frequency analysis based on the ensemble empirical mode decomposition (EEMD) method is proposed for research on the characteristics of pressure fluctuations. First, the pressure fluctuation signals are preprocessed with the empirical mode decomposition (EMD) method, and intrinsic mode functions (IMFs) are extracted. Second, the EEMD method is used to extract more precise decomposition results, and the number of iterations is determined according to the number of IMFs produced by the EMD method. Third, correlation coefficients between IMFs produced by the EMD and EEMD methods and the original signal are calculated, and the most sensitive IMFs are chosen to analyze the frequency spectrum. Finally, the operation conditions of the pump are identified with the frequency features. The results show that, compared with the EMD method, the EEMD method can improve the time-frequency resolution and extract main vibration components from pressure fluctuation signals.

Key words: pressure fluctuation; ensemble empirical mode decomposition; intrinsic mode function; correlation coefficient

1 Introduction

Pressure fluctuations, which are inevitable in the operation of pumps, have a strong non-stationary characteristic and contain a great deal of important information representing the operation conditions (Shen et al. 2000; Yuan et al. 2009). Therefore, monitoring and analysis of pressure fluctuations are essential for ensuring the stable and safe operation of hydropower units. In order to perform further analysis, some conventional signal processing methods have been introduced to extract the features of pressure fluctuation signals, including fast Fourier transform (FFT), short-time Fourier transform (STFT), and wavelet transform (WT) (Al-Badour et al. 2011). However, these methods are not self-adaptive signal processing

methods by nature and are not suitable for non-stationary signals.

In recent years, a new signal processing method, the empirical mode decomposition (EMD) method, has been proposed to analyze non-stationary signals (Huang et al. 1998; Flandrin et al. 2004; Feng and Chu 2005; Donghoh and Hee-Seok 2009). The EMD method can decompose the original signal into a number of intrinsic mode functions (IMFs) which represent the natural oscillatory mode embedded in the signal. Furthermore, the frequency components involved in each IMF not only relate to the sampling frequency, but also change with the original signal. Therefore, the EMD method is a self-adaptive signal processing method and has been widely used in the analysis of vibration signals. However, it has a shortcoming, which is the mode mixing problem. Mode mixing can be defined in two ways: a single IMF contains the oscillatory modes with different scales, or the same frequency resides in different IMFs. In order to solve the mode mixing problem, the ensemble empirical mode decomposition (EEMD) method was developed (Wu and Huang 2009; Lei et al. 2011; De Ridder et al. 2011). In this study, with an axial-flow pump as an example, the EEMD method was used to extract the time-frequency features of pressure fluctuation, and the results were compared with those of the EMD method.

In section 2 of this paper, the EMD method is briefly reviewed. In section 3, the EEMD method and its comparison with the EMD method are described in order to show the advantages of EEMD in signal purification and shaft orbit reconstruction. In section 4, the EEMD method is used to analyze the pressure fluctuation captured from an axial-flow pump, and the results of EEMD and EMD are compared to show the advantages of EEMD in detecting the pressure fluctuation. Finally, the experimental results are summarized.

2 EMD method

The EMD method is based on the simple assumption that any complicated multi-component signal can be decomposed into different simple intrinsic modes of oscillations (Tanaka and Mandic 2007). Each mode should be independent of the others and satisfy the following conditions:

(1) Across the whole data set, the number of extrema and the number of zero crossings must either be equal or differ at most by one.

(2) At any point, the mean value of the upper envelope and lower envelope is zero.

With these conditions, any signal $s(t)$ can be decomposed through the following steps:

(1) Identification of the local extrema and generation of the the upper and lower envelopes by interpolation of the local minima and maxima, respectively.

(2) Calculation of the mean of the upper and lower envelopes, $m_1(t)$.

(3) Calculation of the difference between $s(t)$ and $m_1(t)$, that is:

$$h_1(t) = s(t) - m_1(t) \tag{1}$$

If $h_1(t)$ is an IMF, then $h_1(t)$ is the first IMF of $s(t)$. Otherwise, $h_1(t)$ will be

treated as a new $s(t)$ and the process above will be repeated until $h_1(t)$ is an IMF. The sifting process can be described as

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t) \tag{2}$$

where k is the number of iterations. The final $h_{1k}(t)$ is redefined as $c_1(t)$, which is the first IMF. In absolute terms, $c_1(t)$ is the high-frequency component of the signal.

(4) Separation of $c_1(t)$ from $s(t)$, and definition of the difference as

$$r_1(t) = s(t) - c_1(t) \tag{3}$$

here $r_1(t)$ should be treated as a new $s(t)$. Repeating the process above, $c_2(t)$, $c_3(t), \cdots, c_n(t)$ are obtained, where $c_n(t)$ is the nth IMF of $s(t)$. Then, we have

$$\begin{cases} r_2(t) = r_1(t) - c_2(t) \\ r_3(t) = r_2(t) - c_3(t) \\ \qquad \vdots \\ r_n(t) = r_{n-1}(t) - c_n(t) \end{cases} \tag{4}$$

Step (4) can be stopped when $r_n(t)$ is a monotonic function.

(5) Finally, formulation of the original signal as

$$s(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{5}$$

$c_1(t), c_2(t), \cdots, c_n(t)$ contain different frequency bands ranging from high to low, which are defined as IMF1, IMF2, $\cdots$, IMFn, while $r_n(t)$ represents the central tendency of the signal.

Thus, the EMD method provides a complete and orthogonal decomposition of the inspected signal without missing information or introducing any additional information. However, the major disadvantage of EMD is the mode mixing problem. This is a result of signal intermittency. To illustrate the mode mixing problem existing in EMD, a simulation signal is considered in this section. $x(t)$ is a sine wave of 8 Hz attached by small impulses. EMD decomposed $x(t)$ into three IMFs, and the performance of EMD is shown in Fig. 1. Mode mixing problems occurred in IMF1 and IMF2, and IMF1 simultaneously contained the sine wave and the impulse. IMF3 was the false component.
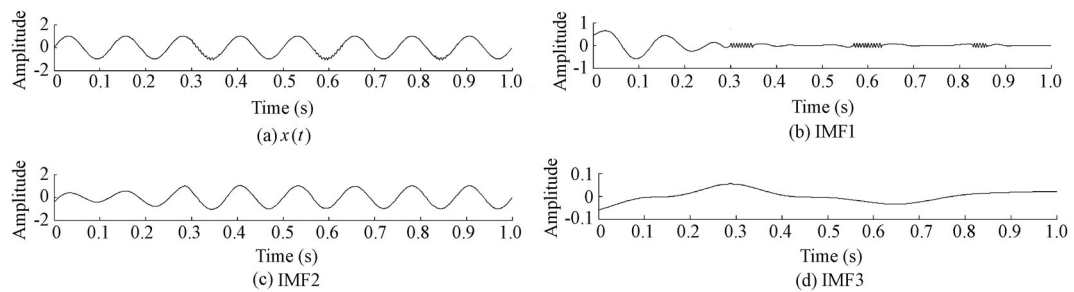

Fig. 1 EMD of simulation signal $x(t)$

3 EEMD method

EEMD was developed to solve the mode mixing problem existing in EMD. It is a noise-added data analysis (NADA) method, which is a method based on the insight from studies of the statistical properties of white noise, showing that the decomposed different-scale components of the signal should be automatically projected onto the corresponding scales of white noise in the background when the added white noise is uniformly distributed across the whole time-frequency domain (Li and Ji 2009; Huang et al. 2011). Using EEMD, the white noise in each iteration is different, while the noise can be canceled out by extracting the ensemble mean of IMFs. Then, the final results are the ensemble mean of IMFs.

The EEMD algorithm can be described as follows:

(1) The number of the ensemble M and the ratio of the standard deviation of white noise to the standard deviation of the original signal N_{std} are initialized, and the number of trials m is set to 1.

(2) The mth trial for the signal added with the white noise is implemented.

(a) The white noise is added to the original signal $s(t)$, that is

$$s_m(t) = s(t) + n_m(t) \tag{6}$$

where $n_m(t)$ is the mth added white noise, and $s_m(t)$ is the noise-added signal of the mth trial.

(b) The signal $s_m(t)$ is decomposed into l IMFs c_{im} $(i = 1, 2, \cdots, l; \ m = 1, 2, \cdots, M)$ with the EMD method, where c_{im} is the ith IMFs of the mth trial.

(c) If $m < M$, then $m = m + 1$ and steps (a) and (b) are repeated until $m = M$, with different white noises each time.

(3) The ensemble mean of M trials for the ith IMF, C_i, is calculated, that is

$$C_i = \frac{1}{M} \sum_{m=1}^{M} c_{im} \tag{7}$$

(4) C_i $(i = 1, 2, \cdots, l)$ is considered the final ith IMF.

M was suggested to be 100 by Wu and Huang (2009), and N_{std} ranges from 0.01 to 0.4.

To demonstrate the EEMD performance in overcoming the mode mixing problem, the simulation signal in Fig. 1 was decomposed again with the EEMD method, where $M = 100$ and $N_{std} = 0.01$. The results are shown in Fig. 2. It can be concluded that the sine wave and impulse components of the original signal are clearly separated. IMF1 represents the impulse component and IMF2 represents the sine wave. Therefore, the EEMD method is capable of solving the mode mixing problem and extracting the more precise decomposition results.
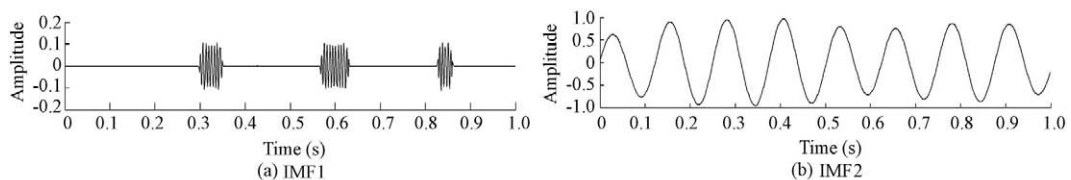

Fig. 2 EEMD of simulation signal $x(t)$

4 Application of two methods to pressure fluctuation analysis

The test facility is illustrated schematically in Fig. 3. The test bed consisted of two motors, two electric valves, four butterfly valves, a head tank, a draft tank, two supply pumps, and a test pump. Various impellers and diffusers could be installed in the test section to test their steady state performance. The instantaneous flow rate was measured with an electromagnetic flowmeter installed in the pipeline. The pressure fluctuations were measured with pressure transducers. The instantaneous torque and rotational speed were measured with a torque meter.
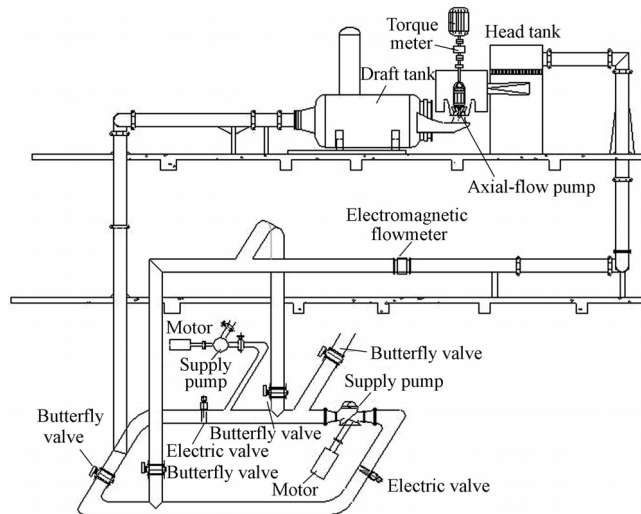

Fig. 3 Schematic view of test system

The experimental data of pressure fluctuations were captured from an axial-flow pump. The pressure transducers were installed in the vicinity of the impeller inlet, the impeller outlet, and the outlet conduit. The number of blades was three. The rotational speed of the electric motor was 1 250 r/min. The advanced data acquisition and analysis system EN900 supported by the ENVADA Company in Beijing was used to collect the signal. The sampling frequency was 256 times the rotational frequency, and 1 024 points were collected every time. Taking the pressure fluctuation signal in the vicinity of the impeller outlet as an example, the time domain waveform is shown in Fig. 4.
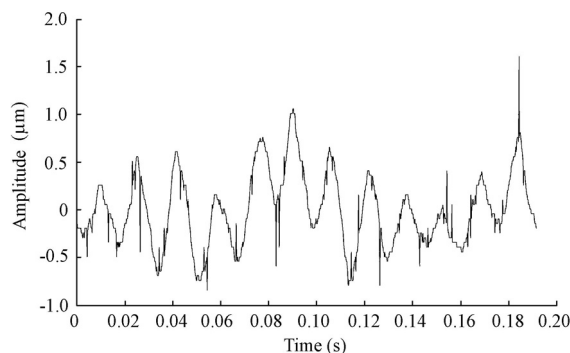

Fig. 4 Time domain waveform of pressure fluctuation

The EMD and EEMD methods were employed to decompose the pressure fluctuation signal into seven IMFs from high frequency to low frequency, as shown in Fig. 5 and Fig. 6. $M = 100$ and $N_{std} = 0.01$ for the EEMD method.
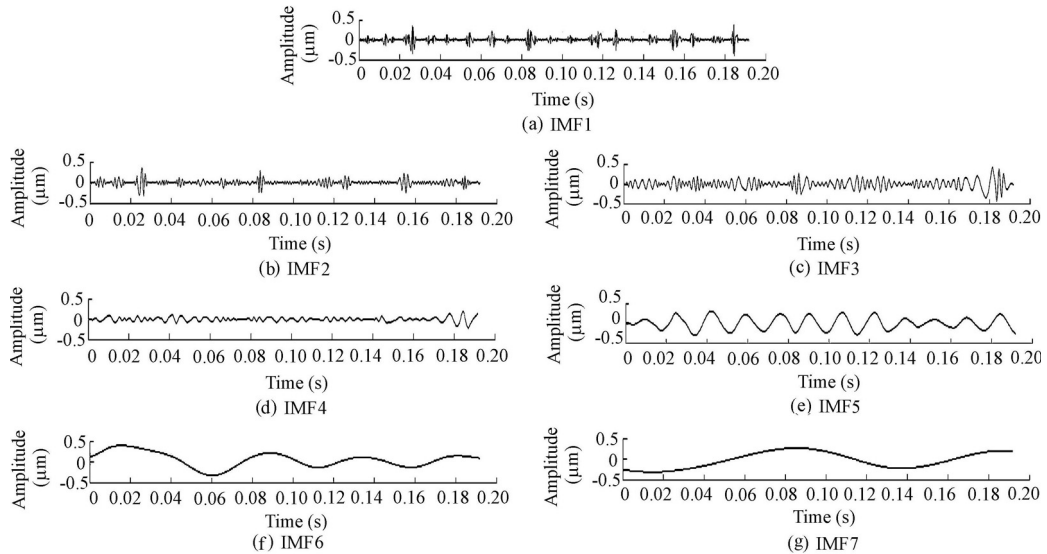

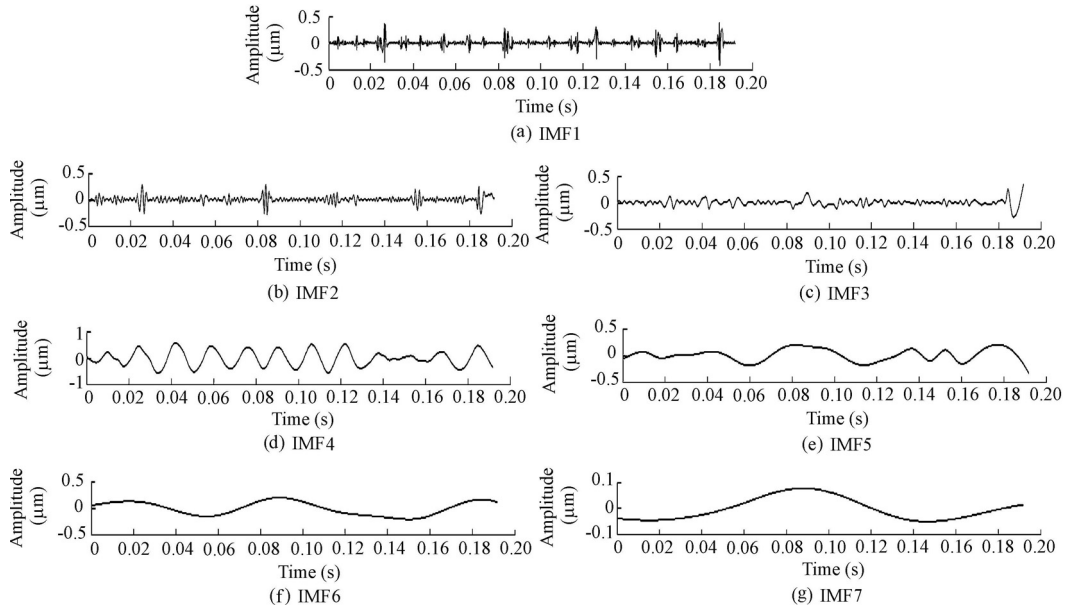**Fig. 5** Decomposition results of pressure fluctuation signal with EMD method

Fig. 6 Decomposition results of pressure fluctuation signal with EEMD method

The most sensitive IMFs can be chosen according to the correlation coefficients between IMFs produced by the EMD and EEMD methods and the original signal (Hu and Yang 2007). The correlation coefficients were calculated and are listed in Table 1. According to the results of Table 1, IMF5, IMF6, and IMF7, produced by the EMD method, are the most sensitive IMFs, while IMF4, IMF5, IMF6, and IMF7, produced by the EEMD method, are the most sensitive IMFs.

Table 1 Correlation coefficients between IMFs produced by EMD and EEMD methods and original signal

Method	Correlation coefficient						
	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7
EMD	0.055 3	0.091 9	0.069 2	0.100 3	0.802 9	0.263 4	0.384 6
EEMD	0.109 4	0.080 1	0.209 4	0.795 3	0.471 5	0.488 2	0.393 4

Spectrum analysis was then applied to the most sensitive IMFs and the results are shown in Fig. 7 and Fig. 8. With the EMD method, 62.5 Hz and 10.4 Hz were extracted clearly. As mentioned before, the rotational speed was 1 250 r/min, so the rotational frequency f_0 was 20.83 Hz. As shown in Fig. 7, the frequencies of IMF5, IMF6, and IMF7 were $3f_0$, $0.5f_0$, and $0.5f_0$, respectively. The frequency $3f_0$ results from the influence of the number of impellers, which was three, while the frequency $0.5f_0$ is the result of the irregular movements of turbulence. However, the rotational frequency f_0 cannot be extracted separately. In addition, IMF6 and IMF7 represent the same frequency component. In order to extract more precise decomposition results, EEMD was preformed. As shown in   Fig. 8, the frequencies of IMF4, IMF5, IMF6, and IMF7 were $3f_0$, f_0, $0.5f_0$, and $0.25f_0$, respectively. It can be concluded that not only the rotational frequency (f_0) but also the new frequency ($0.25f_0$) can be identified clearly. The frequency $0.25f_0$ is also the result of the irregular movements of turbulence. The movements become stronger when the flow is reduced to a certain degree. Therefore, the decomposition results of the pressure fluctuation based on the EEMD method are much better than those based on the EMD method.

(a) IMF5

(b) IMF6

(c) IMF7
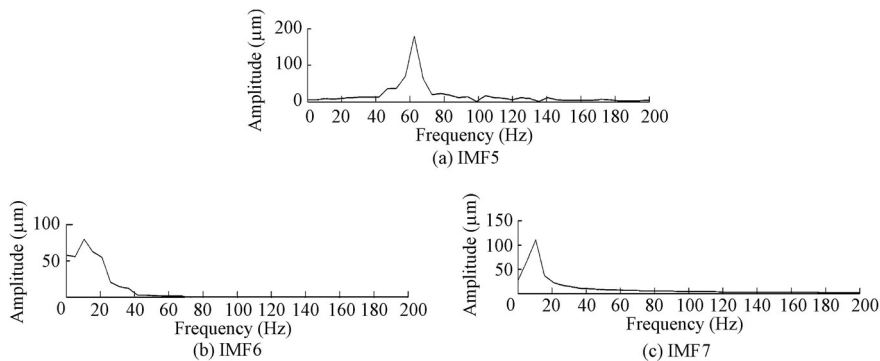
Fig. 7 Spectrum analysis of IMFs produced by EMD method

(a) IMF4

(b) IMF5

(c) IMF6

(d) IMF7
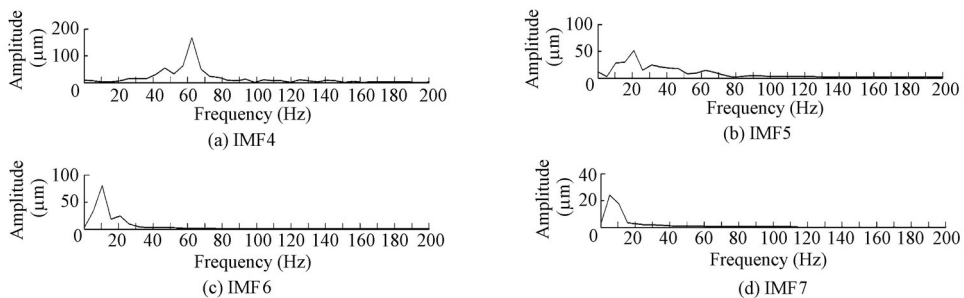
Fig. 8 Spectrum analysis of IMFs produced by EEMD method

From the experiment, it can be found that the EEMD method can effectively resolve the mode mixing problem existing in the EMD method and achieve more precise decomposition results than the EMD method. However, there are some problems that need to be resolved before EEMD operation, such as parameter settings and IMF post-processing. The values of the ensemble number and the ratio of the standard deviation of white noise to the standard deviation of the original signal have a large influence on the accuracy of EEMD. Until now, there has not been a specific principle to provide guidance for the choice of the parameters. Before wide application of EEMD can be achieved, there are a lot of problems that need to be studied further.

5 Conclusions

In this paper, the EEMD method is introduced and applied to analysis of the frequency characteristics of pressure fluctuations. In order to select the number of IMFs, the EMD method was used first. Then the signal was decomposed by the EEMD method with the number of IMFs determined by the EMD method. This approach avoids interference from other false components and is essential for selection of sensitive IMFs. It overcomes the mode mixing problems that occurs with the EMD method. Furthermore, EEMD provides a better decomposition performance for the lower frequency components. The experimental results indicate that the EEMD method is effective for multi-component signals. However, there are still some problems that need to be studied further to improve the stability and validity of the EEMD method.

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