Comparison of improved EMD entropy and wavelet entropy in vibration signals of circuit breaker

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Abstract

The paper is focusing on extracting the vibration signals of circuit breakers by using Empirical Mode Decomposition (EMD) that improved using least squares to lower the impact on experiment results effectively, which is caused by the EMD inherent end effects. First, work on the EMD and wavelet transform decomposition of both normal and loosening signals, and then to calculate the energy entropy. The results show that the value of improved EMD energy entropy is significantly larger than the wavelet energy entropy. So the improved EMD energy entropy can improve the accuracy of fault diagnosis and provides useful help for the mechanical fault diagnosis based on circuit breakers vibration signals.

Keywords: circuit breakers, vibration signals, energy entropy, EMD, wavelet decomposition

1 Introduction

In traditional vibration, signals analysis theory, some people may totally do signal analysis in time domain, whereas some will do that in frequency domain totally. In order to improve the accuracy of mechanical vibration signals analysis, time- frequency analysis technology is lead up to the fault diagnosis of circuit breaker. For instance, Fourier transform, FFT transform, wavelet transform, wavelet packet transform, and so forth [1]. However, Fourier transform is the fundamental of whether FFT transform or wavelet transform. So it is impossible to get away from the inherence limitations of Fourier transform. That is for the analysis of non-stationary signal, which must be approximated into stationary signal analysis.

Empirical Mode Decomposition (EMD) is a kind of method for the non-stationary signal analysis. According to their own characteristic of time scale to signal decomposition, without setting any base function beforehand. With the base function to automatically generate and self-adaptive multi-resolution feathers, it has the incomparable advantages in the online analysis of non-stationary signal. However, there also exist some self-limitations in EMD, the end effect is the one can't be ignored [2]. In this paper, the EMD was improved, and with the fusion of energy, entropy is applied to fault diagnosis of circuit breaker, to improve the accuracy of diagnosis.

2 End effect

In the EMD, envelope average is a technique to get spline interpolation fitting at the maximum and minimum extreme points of signals and then to calculate the average value of these data. If the endpoints on two ends of the data are not the extreme points, the cubic spline curve which constitutes the upper and lower envelope will produce offset at both ends of the data sequence. Then this will increase the error continuously when we do the spline interpolation and finally generate fitting error in data [3].

During the "screening" process in EMD, due to the uncertainty of extreme value at endpoints, fitting error may be produced in every single spline interpolation and these errors can be accumulated continuously. When we deal with the high-frequency components, end effect will be limited in a very small interval due to a short distance between extreme values and a small time scale. However, when we handle the low-frequency components, situation seems getting worse, because of the large time scale feature existing in low-frequency components, a big fluctuation will occur at the endpoints by the using of cubic spline interpolation. So if we cannot deal with it timely or properly, such fluctuations will "infect", and even cause EMD results in very serious distortion, which led to the failure of EMD [4].

In order to further illustrate the impact on signals of the EMD end effect, here I will build a function to emulate.

$$x(t) = \sin(40\pi t + \pi / 6) + 0.2\sin(20\pi t)\,, \tag{1}$$

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$x_1(t) = \sin(40\pi t + \pi / 6)$

$$x_2(t) = 0.2\sin(20\pi t), \quad (2)$$

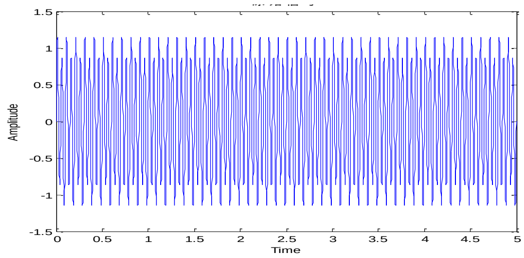

FIGURE 1 Original signal

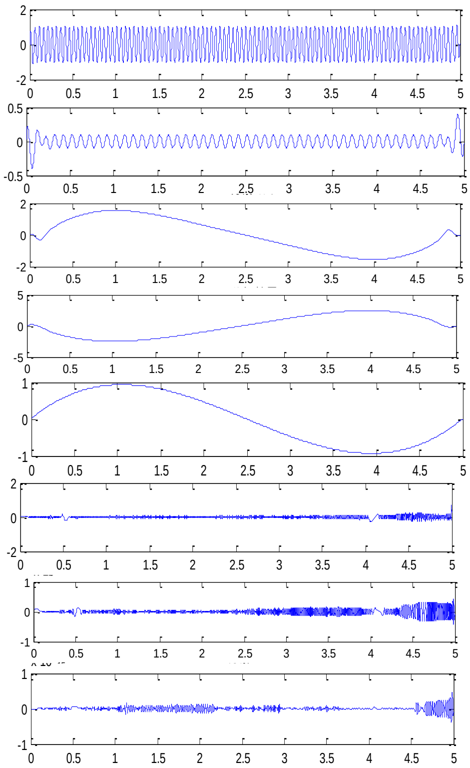
FIGURE 2 The result of Empirical Mode Decomposition

Due to space limitations, only intercept eight IMF components. These eight components are in accordance with the frequency from large to small order. From figure 2, it will be easily noticed that there exist end effect both in IMF2 and IMF3. Waveform aberrance happens both at the left and the right endpoints. Due to the impact of IMF2, the waveform aberrance of IMF3 is getting serious. If we do not deal with these end effects in advance, the Hilbert spectrum will be distorted and the EMD will fail. In this way, we are almost unable to get the correct signal information, which will influence our final judgment.

3 The principle of improved EMD

Now, we are using the endpoint extension to solve the EMD end effect. For the extending method, many scholars have done amounts of research at home and abroad. For instance, Daji Huang [5] adopted the mirror extension method. Qifeng Luo [6] adopted the feature wave method. Yongjun Deng [7] used the RBF neural network method. Yushan Zhang [8] adopted the method of support vector regression machines to extend data. All of them have achieved good effect. In this paper, we will extend boundary by using the least-squares method.

Assume that the sampling time of vibration signals are equally spaced. The sampling data is $\{x(k)\},(k=1,2,\cdots,n)$ and the sampling interval is $\Delta t = 1$, so the polynomial function is $\hat{x}(k) = a_0 + a_1 k + a_2 k^2 + \cdots + a_m k^m, k = 1,2,\cdots,n$. We will determine the undetermined coefficient $a_j (j = 0,1,2,\cdots,m)$ of $\hat{x}(k)$ to make the quadratic sum of accumulated error be the smallest, which includes $\hat{x}(k)$ and original data $x(k)$.

$$E = \sum_{k=1}^{n} [\hat{x}(k) - x(k)]^2 = \sum_{k=1}^{n} [\sum_{j=1}^{m} a_j k^j - x(k)]^2 . \quad (3)$$

The following is an equation to guarantee an average value for E.

$$\frac{\partial E}{\partial x} = 2\sum_{k=1}^{n} k^i [\sum_{j=0}^{m} a_j k^j - x(k)] = 0, i = 1,2,...,m, \quad (4)$$

Let us take the partial derivatives respect to a_j in order to obtain $\mathrm{m}+1$ linear equations. We will get the coefficients a_j respect to every term by solving the equations. The m is the order of the polynomial and its values range from 0 to m. Once we set m equal to 0, we can calculate its constant term.

$$\sum_{k=1}^{n} a_0 k^0 - \sum_{k=1}^{n} x(k) k^0 = 0, \quad (5)$$

The constant term is $a_0 = \frac{1}{n}\sum_{k=1}^{n} x(k)$. And the multinomial coefficient is a_j. Next we will obtain the fitting curve of this polynomial. According to the fitting curve and the data length of instantaneous frequency, we will reconsider the value, get the modified instantaneous frequency.

Figure 4 is the graph of improved EMD. Let us compare figure 4 with figure 2. In figure 4, it can be easily found that the end effects in IMF2 and IMF3 have been improved evidently. This strongly proves that end effect impact on original function can be lowered by the introduction of the EMD, which was improved through least squares. After we process the original signals using improved EMD method, it will be helpful to do the waveform analysis and also help a lot to improve the accuracy of fault diagnosis.

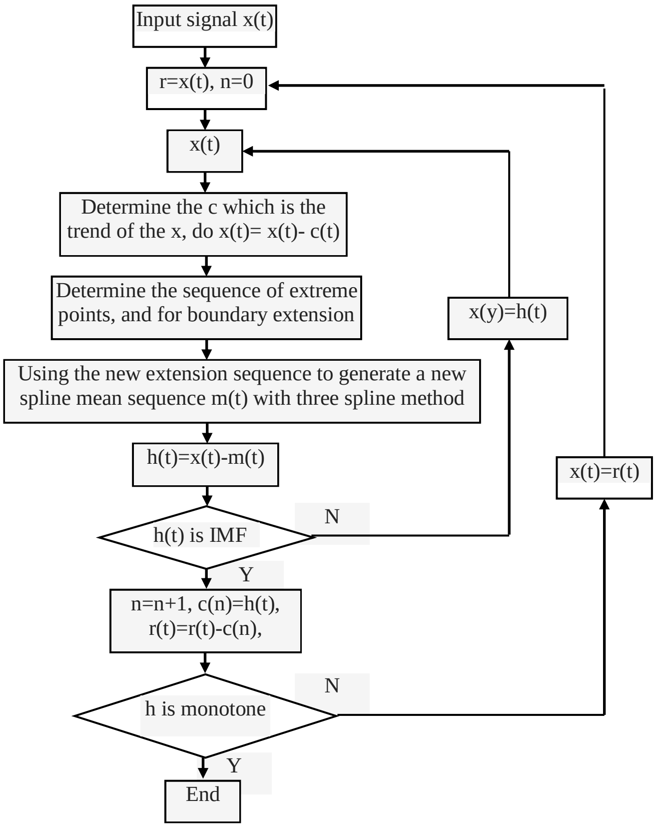

FIGURE 3 The steps of improved EMD method

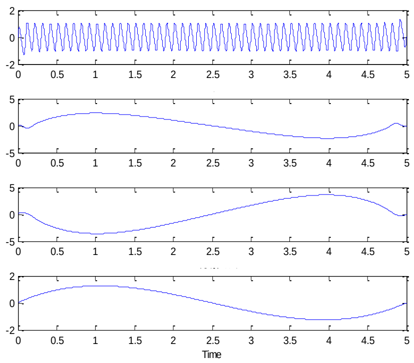

FIGURE 4 The graph of improved EMD

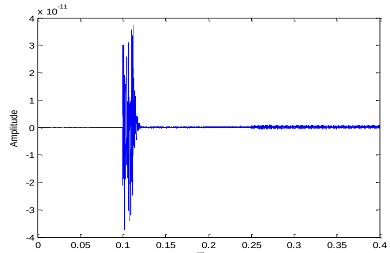

FIGURE 5 original vibration signals

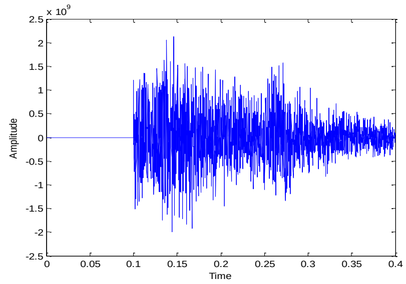

FIGURE 6 Loosening vibration signals

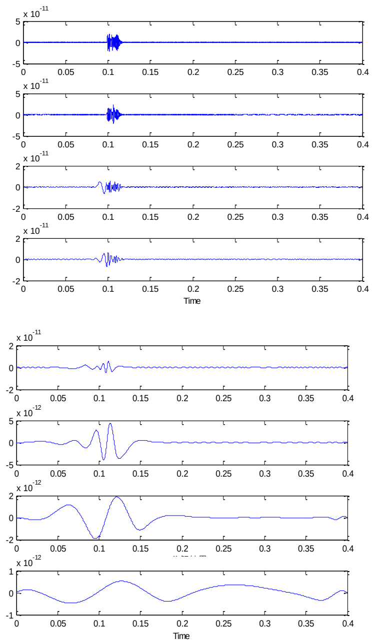

FIGURE 7 Applying the improved EMD to decompose normal signals

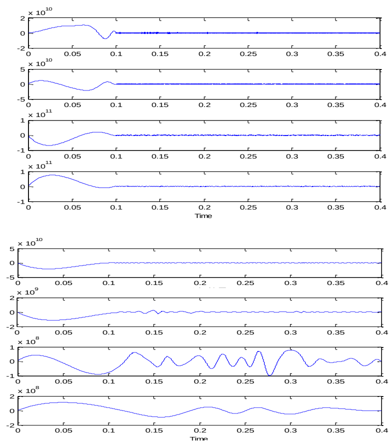

FIGURE 8 Applying the improved EMD to decompose loosening signals

4 The analysis of vibration signals using improved EMD

The original waveform of vibration signals is showing in Figure 5, while the graph of Figure 6 is showing the original waveform of loosening signals. We are able to see that there is some obvious difference in the waveform of the normal and the loosening situation showing on the two time domain graphs. However, we have lots of difficulties in finding out the specific situation and the types of faults just through the comparison in time domain graphs. Therefore, we need to apply the improved EMD method to decompose the normal and the loosening signals separately. The IMF results are showing in both Figure 7 and Figure 8.

After the decomposition, we get 11 IMF components. Here we only list the 8 components in front. In the vibration signal, the key signal mainly concentrated in the high frequency parts, which are the first few components of the IMF.

5 Applying wavelet decomposition to the analysis of vibration signals

The principle of wavelet transform won't be displayed here. We did five wavelet decompositions to obtain the high-frequency components of normal and loosening signals that was shown in Figure 9 and Figure 10 respectively. For an easy observing, we increase the time to 10^4 times of the normal. From Figure 9 we can clearly see that vibration happens at 0.1s, whose signal ends up at 0.12s and the measure of it lasts 1s. However, the vibration continues to 0.5s in Figure 10. The huge denoising function of wavelet transform shows good results in the vibration signals processing.

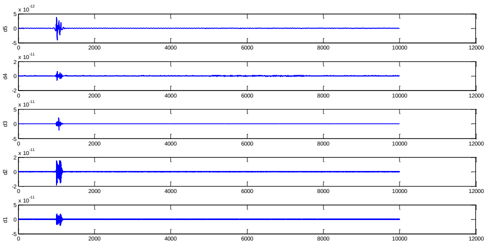

FIGURE 9 Wavelet decomposition of normal waveform

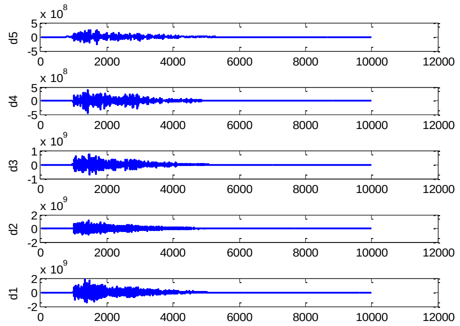

FIGURE 10 Wavelet decomposition of loosening waveform

6 Vibration signals analysis through power entropy and the EMD

Information entropy is described mathematically like this: Assume that $p(p_1, p_2, \cdots, p_n)$ is an uncertain probability distribution and k is an arbitrary constant, so the information entropy of this distribution is

$$s(p) = -k\sum_{i=1}^{n} p_i \ln p_i \,. \tag{6}$$

After a calculation, we know that if the system information entropy $s = 0$, it will be a certain system. No events will happen except the ones that had happened. The probability of event occurrence is strongly not uniform, so the uncertainty is 0 [9].

The power frequency distributions of vibration signals are different, which are generated in different status of different circuit breakers. Even in the same status, due to the changeable environment, there is difference in this distribution. We need a standard to value the amount of power. So the concept of power entropy is coming up. When we apply the EMD method to decompose a signal, different frequency terms will be included in the n IMF components. The energy is $E_1, E_2, \cdots E_n$, and it's a partition in frequency domain. The definition of EMD power entropy is

$$H_E = -\sum_{i=1}^{n} p_i \ln p_i \,. \tag{7}$$

The p_i in this equation is the percentage of power in the i^{th} IMF component, that is $p_i = E_i / E$, and $E = \sum_{i=1}^{n} E_i$. According to the definition of information entropy, the more uniform the distribution of p_i is, the larger the H_E value will be, whereas the smaller.

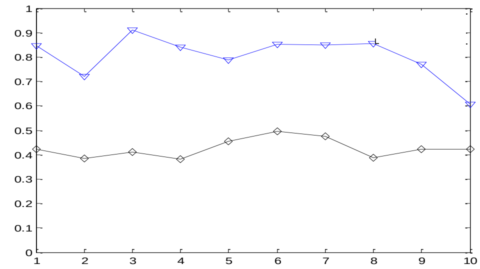

FIGURE 11 The graph of comparison of wavelet power entropy

Let us work on the calculation of the power entropy value after applying the EMD method and wavelet transform decomposition to normal and loosening signals. Power entropy values for ten groups signals by using wavelet transform decomposition are shown in Figure 11. The above line represents loosening signals, while the following one is for normal signals [10].

Power entropy values for normal and loosening signals by using improved EMD method are shown in Figure 12.

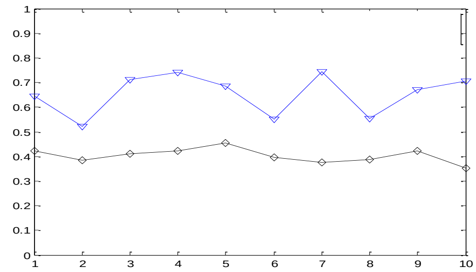

FIGURE 12 Graph of the comparison of improved EMD power entropy

When we compare the Figure 11 with Figure 12, we can find that the switching signals in normal status are smaller than that in fault status and they are relatively centralized. The mechanical fault vibration signals of circuit breakers are often at high frequency, and resonance is hard to happen. So the power signals are relatively uniform and centralized. Power entropy can be used as the fingerprint for circuit breaker fault.

Now we are going to get the average value of the signals that we measured to obtain the improved EMD and wavelet transform entropy value both under normal and loosening situations. Wavelet entropy under normal state is 0.403 and under loosening situations is 0.656. The improved EMD entropy under normal state is 0.426 and under loosening situations is 0.803.

It tells us that the entropy value of improved EMD under loosening situation is larger than that we get under the normal situation. Meanwhile, the result is much more obvious than that by using wavelet. The bigger entropy value exists in these two statuses, the easier it can be distinguished. From this point, we can realize that the improved EMD method is better than the wavelet transform evidently. This kind of entropy value analysis method gives us a lot of convenience for training once the data permits later.

Using the improved Empirical Mode Decomposition to process the original signal, we can effectively reduce the influence of end effect on the decomposition results and overcome the inherent disadvantages of EMD. Therefore, we combined it with energy entropy to do the analysis of vibration signals and achieved good effect.

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