

# De-noising of Power Quality Disturbance Detection Based on Ensemble Empirical Mode Decomposition Threshold Algorithm

Zhang Xuhong<sup>1</sup>, Han Gang<sup>\*2</sup>, Chen Liping<sup>2</sup>

<sup>1</sup>Department of Electronic and Information Technology, Ningxia Polytechnic, Yinchuan  
750021, Ningxia, China

<sup>2</sup>School of Information and Electrical Engineering, China University of Mining and Technology, Xuzhou,  
221116, Jiangsu, China

\*Corresponding author, e-mail: kdhangang@163.com

## Abstrak

Sinyal kualitas daya aktual sering dipengaruhi oleh derau yang mengakibatkan hasil analisis sinyal gangguan yang tidak tepat. Pada paper ini suatu metode yang disebut sebagai metode penghilangan derau ambang berbasis EEMD (Ensemble Empirical Mode Decomposition) dikemukakan untuk meningkatkan kualitas sinyal dengan berbagai tingkat SNR (Signal-to-Noise Ratio). Sebagai perbandingan, digunakan empat ambang, yaitu ambang heuristik, ambang self-adaptive, ambang tetap dan ambang minimax untuk menapis derau pada sinyal kualitas daya. Perbandingan dilakukan melalui analisis dan perbandingan tiga karakteristik sinyal sebelum dan sesudah penghilangan derau, yaitu bentuk gelombang, SNR dan MSE (Mean Square Error), lebih jauh lagi analisis dilakukan pada sifat seketika pada waktu yang berkaitan dengan menggunakan HHT (Hilbert Huang Transform). Hasil simulasi menunjukkan bahwa metode penghilangan derau dengan ambang EEMD dapat menjadikan bentuk gelombang mendekati nilai sesungguhnya. Selain itu diperoleh nilai SNR yang lebih tinggi dan MSE yang lebih kecil dibandingkan dengan menggunakan empat ambang yang lain, serta sifat seketika yang mencerminkan sinyal gangguan aktual secara lebih tepat. Dengan hasil ini dapat dikatakan bahwa algoritma EEMD ambang optimal dapat digunakan untuk penghilangan derau sinyal gangguan pada kualitas daya. Sementara, metode penghilangan derau ambang EEMD dengan sifat adaptif sesuai untuk penghilangan derau sinyal gangguan gabungan.

**Kata kunci:** kualitas daya, penghilangan derau, EEMD, HHT, deteksi gangguan

## Abstract

Actual power quality signal which is often affected by noise pollution impacts the analysis results of the disturbance signal. In this paper, EEMD (Ensemble Empirical Mode Decomposition)-based threshold de-noising method is proposed for power quality signal with different SNR (Signal-to-Noise Ratio). As a comparison, we use other four thresholds, namely, the heuristic threshold, the self-adaptive threshold, the fixed threshold and the minimax threshold to filter the noises from power quality signal. Through the analysis and comparison of three characteristics of the signal pre-and-post de-noised, including waveforms, SNR and MSE (Mean Square Error), furthermore the instantaneous attribute of corresponding time by HHT (Hilbert Huang Transform). Simulation results show that EEMD threshold de-noising method can make the waveform close to the actual value. The SNR is higher and the MSE is smaller compared with other four thresholds. The instantaneous attribute can reflect the actual disturbance signal more exactly. The optimal threshold EEMD-based algorithm is proposed for power quality disturbance signal de-noising. Meanwhile, EEMD threshold de-noising method with adaptivity is suitable for composite disturbance signal de-noising.

**Keywords:** power quality, signal de-noising, EEMD, HHT, disturbance detection

## 1. Introduction

Many domestic and foreign scholars have always been dedicated to the study of power quality problems for many years [1-3]. Extract signal from power system is the first thing for the study of power quality. Due to the complexity of power system structure and interference, the extracted signal of power quality contains noise. If we use it directly, it is difficult to extract information, such as disturbance mutation point, frequency and amplitude. Therefore, the study

of disturbance signal not only requires maximum filtering out noise, but reserving disturbance information as much as possible [4].

The method of traditional power quality disturbance signal de-noising includes linear filtering and nonlinear filtering. Linear filtering is mature theory, which usually use FFT. However, when it process the mutation signals, such as transient power quality, it is easy to cause distortion. Nonlinear filtering is a nonlinear mapping of the input signal, which can make the noise signal be zero approximately and maintain the characteristics of the signal. It can overcome the shortcomings of linear filter. In recent years, wavelet transform was gradually applied to denoise the power quality signal[5-7], which includes wavelet decomposition, threshold calculation, threshold processing, reconstruction. The method is simple and the effect of de-noising is better performance. The disadvantage of wavelet transform is that wavelet basis function is not easy to choose, and it does not have the self-adaptability. The method of EMD-based signal de-noising can adaptively decompose the non-stationary signal into different time scales of modal function, which does not need to select basis function [8-10]. In [10], it verifies that the EMD is better performance than wavelet de-noising. But there are some problems, such as end effect and mode mixing problem.

As for mode mixing problem, the Flandrin Group and Huang proposed a method of EEMD(Ensemble Empirical Mode Decomposition), which was assisted analysis method by adding white noise[11]. EEMD can make composite signal decompose into different time scales of modal function. The IMFs which was initially decomposed usually contain noise. It can be directly filtered by space-time filtering method. Then the other IMFs contain noise and disturbance signal, which needs a proper threshold to filter noise at this time. Thus, we can obtain de-noising signal after reasonable reconfigurable signal component. Now many scholars have been successfully applied to the seismic signal containing noise, vibration signals to denoise [12-14]. Therefore, this paper present a EEMD-based threshold de-noising method to filter noise for power quality disturbance signals. Meanwhile, an optimal threshold of each IMF component was proposed, which was based on wavelet threshold de-noising method. Then, we compared four wavelet threshold methods, such as heuristic threshold, adaptive threshold, fixed threshold and mini-max threshold. According to the general evaluation standard, we can take advantage of the waveform, the SNR and MSE to evaluate the effect of noise filtering. Disturbance mutations information need to retain. While considering the de-noising for power quality disturbance signal, we can use HHT to process de-noising signal, and extract start-stop moment of disturbances and obtain the characteristic information of amplitude and frequency. Thus, We can study the feasibility of the EEMD threshold de-noising method by the three indicators of de-noising effect and the two aspects of disturbance characteristics error.

## 2. EEMD and HHT Method

### 2.1. EMD and EEMD Method

#### 2.1.1 EMD Method

When the signal does not satisfy the IMF conditions [15], Empirical Mode Decomposition can be used, as shown in the following steps:

- 1) Strike all the local maximum value and local minimum value of a signal  $s(t)$ , and then use the interpolation function to strike its upper and lower envelopes. The mean value of the upper and lower envelope is recorded as  $m_1$ , the difference value between the signal and  $m_1$  is  $h_1$ , namely:

$$h_1 = s(t) - m_1 \quad (1)$$

- 2) If  $h_1$  satisfies the IMF conditions,  $h_1$  is the first IMF of the signal. If not, then substitute  $h_1$  as a new  $s(t)$  into the equation (1), and repeat (1). When  $h_1$  satisfies the two conditions of the IMF,  $h_1$  is the first IMF of the signal, recorded as  $c_1$ .
- 3) Separate  $c_1$  from the  $s(t)$  to obtain the first allowance  $r_1$ ,

$$r_1 = s(t) - c_1 \quad (2)$$

Regard  $r_1$  as the original signal, repeat the steps 1) and 2), sequentially obtain the second IMF component  $c_2$  of  $s(t)$ , and the third IMF component  $c_3$  of  $s(t)$ , until the  $n$ -th component is a monotonic function. The signal  $s(t)$  is recorded as:

$$s(t) = \sum_{i=1}^n c_i + r_n \quad (3)$$

In (3),  $r_n$  represents the average trend of the residual component signal,  $c_i$  is the different frequency components from high to low of the signal.

The first IMF component is obtained from the original signal.  $c_1$  should contain the finest scale or the shortest period component of the signal. The method of accessing the IMF component of signal is known as 'Sifting'. The sifting process are as follows [16]:

- 1) Set upper and lower envelope for  $u(t)$  and  $v(t)$ , and  $e_1(t)=[u(t)+v(t)]/2$ ,  $e_2(t)=[u(t)-v(t)]/2$ ,  $\sigma(t)=e_1(t)/e_2(t)$ , and it is required to satisfy the ratio of the number and the total duration for at least  $1-\alpha$ , when  $\sigma(t) < \theta_1$ , namely:

$$\frac{\#\{t \in D \mid \sigma(t) < \theta_1\}}{\#\{t \in D\}} \geq 1 - \alpha \quad (4)$$

In (4),  $D$  is the signal duration range,  $\#\{\}$  is the number of collection elements, and as a matter of experience, we set  $\theta_1=0.05, \alpha=0.05$ .

- 2) At any moment,  $\sigma(t) < \theta_2$ , while  $\theta_2=10\theta_1$ .

### 2.1.2 EEMD Method

EEMD had some improvement on the basis of EMD, and added white noise to the original signal, and used statistics characteristics of white noise with frequency uniform distribution to eliminate the modal aliasing effect. Meanwhile, it does not depend on the basis functions, while relying on the signal itself features adaptive decomposition, algorithm steps as follows:

- 1) Adding a group of white noise to the original signal  $s(t)$  for the signal  $x(t)$ , and the white noise satisfy the normal distribution for  $(0, (\alpha\sigma)^2)$ , in which  $\sigma$  is the standard deviation of the signal,  $\alpha$  is the noise intensity parameter.
- 2) Decomposed  $x(t)$  by using EMD to obtain IMFs.
- 3) Repeat the above two steps 1) and 2), and each time you add the same noise intensity, then decompose to obtain each component group of IMF.
- 4) The corresponding IMF's averages are the final result for the decomposition.

### 2.2. Hilbert Transform

The Hilbert transform was carried out on IMF which is obtained by the decomposition of EEMD:

$$\hat{c}_i = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{c_i(\tau)}{t - \tau} d\tau \quad (5)$$

The analytic signal is:

$$z_i(t) = c_i(t) + j\hat{c}_i(t) = a_i(t)e^{j\phi_i(t)} \quad (6)$$

The amplitude function and phase function were as follows:

$$\begin{cases} a_i(t) = \sqrt{c_i^2(t) + \hat{c}_i^2(t)} \\ \phi_i(t) = \arctan \hat{c}_i(t) / c_i(t) \end{cases} \quad (7)$$

The instantaneous frequency is:

$$f_i(t) = \frac{1}{2\pi} \frac{d\phi_i(t)}{dt} = \frac{1}{2\pi} \frac{\hat{c}_i' \cdot c_i - \hat{c}_i \cdot c_i'}{\hat{c}_i^2 + c_i^2} \quad (8)$$

By (7) and (8), we can extract the instantaneous amplitude and instantaneous frequency of the disturbance signal to locate the start-stop moment that occurred by disturbances and to describe the characteristics of the disturbance.

### 3. EEMD Threshold De-noising Method

Theoretically, the IMFs noise which is obtained by decomposition of the EEMD has offset each other. And in fact, due to the superposition of noise frequency could not have so much to impact on the program running speed and make the IMFs have noise. The IMFs which is obtained by decomposition of the EEMD before several layers contain large noise energy, and are usually directly filtered out. The noise energy of the IMFs which is obtained later decreases in turn [17], and contains useful signal and noise. By this time, these IMFs need to use the method of threshold de-noising to process noise, the last of the IMFs containing no noise can be retained directly [18]. So, we can use threshold de-noising to process the middle part of the IMFs only, and the signal reconstruction signal expression is:

$$x'(t) = \sum_{i=m_1}^{i=m_2} c_i + \sum_{i=m_2+1}^n c_i \quad (9)$$

The estimation formula of the energy of white noise from the component of  $m_1$  to  $m_2$  is:

$$E_k = \frac{E_{m_1}^2}{\beta} p^{-k}, k = m_1, m_1 + 1, \dots, m_2 \quad (10)$$

In (10),  $p$  and  $\beta$  is the parameters related to sifting cycle times, their values are 2.01 and 0.719 [19]. The threshold can be calculated by the energy of white noise from the component of  $m_1$  to  $m_2$  [20].

$$T = C\sigma_i \sqrt{2 \ln N} \quad (11)$$

In (11),  $N$  represents the signal length,  $C$  represents the coefficient of threshold,  $\sigma_i$  represents the standard deviation of noise containing of the component of  $i$ .

$\sigma_i$  can be estimated by (10) [21], and the standard deviation of noise containing of the layer of  $m_1$  is:

$$\sigma_{m_1} = \frac{\text{median}(|c_{m_1}|)}{0.6745} \quad (12)$$

Because of the noise energy of the component from the  $m_1$  to the  $m_2$  gradually decrease, accordingly, the threshold coefficient  $C$  of the layers will gradually reduce. In this paper, the selection of the threshold of the components was shown in (13):

$$C_{m_1} = 0.9 \times \frac{\max(|c_{m_1}|)}{\sqrt{E_{m_1}} \sqrt{2 \ln N}} \quad (13)$$

$$C_{n+1} = C_n / 2 \quad (n = m_1 + 1, L, m_2 - 1)$$

By (10)-(13), the threshold expression of each IMF can be obtained as follows:

$$T = CE_{m_1} \sqrt{\frac{P^{-k}}{\beta}} \sqrt{2 \ln N} \quad (14)$$

In the threshold processing, the threshold coefficient is associated with the size of the signal and the way of threshold processing. The wave peaks of Transient power quality disturbance signal have high frequency part of discharge phenomenon. Soft threshold is relatively smooth processing method, and make the waveform smooth and easy to cut off the details information, while hard threshold can preserve more detail information. So this paper adopts hard threshold of the EEMD. The result evaluation standards of signal de-noising processing generally have SNR (signal-to-noise ratio) and MSE (the reconstruction of the signal mean square error). The calculation formula of SNR and MSE are as follows:

$$\gamma_{SNR} = 10 \lg \frac{\sum_{i=1}^{i=N} s^2(i)}{\sum_{i=1}^{i=N} (\hat{s}(i) - s(i))^2} \quad (15)$$

$$\varepsilon_{MSE} = \frac{1}{N} \sum_{i=1}^N (\hat{s}(i) - s(i))^2 \quad (16)$$

In (15)-(16),  $s(i)$  is the original signal value of the  $i$  point,  $\hat{s}(i)$  is the de-noising processed value of the  $i$  point.

In this paper, the method steps of EEMD threshold de-noising, as follows:

- (1) We use the method of EEMD to decompose the noise signal  $x(t)$ , to obtain the IMFs.
- (2) Choose the appropriate  $m_1$  and  $m_2$ . According to (12)-(14), we need to IMFs from  $m_1$  to  $m_2$  to energy evaluation and threshold calculation .
- (3) Each component which used threshold de-noising reconstructs to obtain de-noising signal.

## 4. Simulation and Analysis

### 4.1. EEMD Threshold and Four Wavelet Thresholds De-noising

In this section, we will add different SNR noise to voltage sag signal in MATLAB environment and use the EEMD threshold and the heuristic threshold, the self-adaptive threshold, the fixed threshold and the minimax threshold to filter the noises.

The voltage sag signals is:

$$s(t) = [1 - \alpha \square_s(t_2 - t_1)] \sin \omega_0 t \quad (17)$$

In (17),  $\alpha$  is the amplitude of sags,  $\alpha=0.1 \sim 0.9$ ,  $(t_2 - t_1)$  is the duration of mutation,  $0.5T < t_2 - t_1 < 0.3s$ .

In this paper, voltage sag parameter is selected:  $\alpha=0.35$ ,  $t_1=0.11$ ,  $t_2=0.19$ ,  $\omega_0=100\pi$ . In order to analyze the EEMD threshold de-noising under different thresholds methods, and 5, 10, 20, 30, 40, 50db of the SNR will superimposed on the sag signal orderly to obtain the SNR  $\gamma_{SNR}$  and MSE  $\varepsilon_{MSE}$  after de-noising the signal .Whereas under the same SNR value, simulation result maybe has a little differences, therefore, we use the average value of 20 experiments. Superpose signal with different SNR (5, 10, 20, 30, 40, 50db), we use EEMD threshold and four wavelet thresholds (the heuristic threshold, the self-adaptive threshold, the fixed threshold and the minimax threshold) to denoise. After denoising, we can calculate  $\gamma_{SNR}$ ,  $\varepsilon_{MSE}$  by Eqs. (15)-(16).  $\gamma_{SNR}$ ,  $\varepsilon_{MSE}$  are as follows in Figure 1.

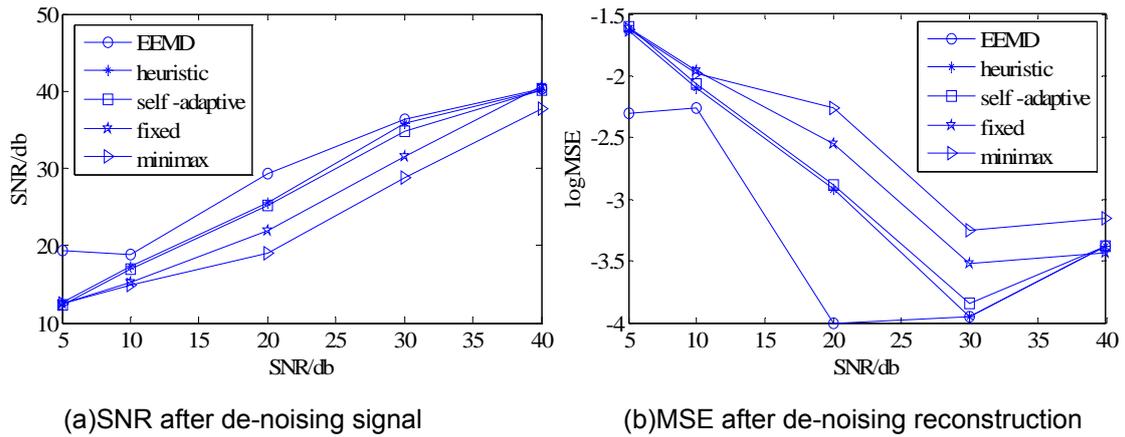


Figure 1. SNR and MSE after de-noising sag signal

Figure 1 shows that the  $\gamma_{SNR}$  and  $\epsilon_{MSE}$  of the heuristic threshold de-noising is almost coincident with the  $\gamma_{SNR}$  and  $\epsilon_{MSE}$  of the self-adaptive threshold de-noising. The  $\gamma_{SNR}$  of the fixed threshold and the minimax threshold de-noising are very small, but the  $\epsilon_{MSE}$  is very large. While by using the EEMD threshold de-noising, the  $\gamma_{SNR}$  is larger and the  $\epsilon_{MSE}$  is smaller than four wavelet thresholds de-noising. Simulation result shows that the EEMD threshold de-noising is better than four wavelet thresholds de-noising.

When SNR of the sags signal is 20db that the noise pollution is more serious, the resulted signal by using EEMD threshold and four methods of wavelet thresholds de-noising are separately as shown in Figure 2 (a), and the instantaneous amplitude which is obtained by HHT are as shown in Figure 2 (b), Localization of the starting and ending times (start-end moment) and detection of relative error are as shown in Table 1. And we can see that by using EEMD threshold de-noising, the resulted signal's relative error is minimum.

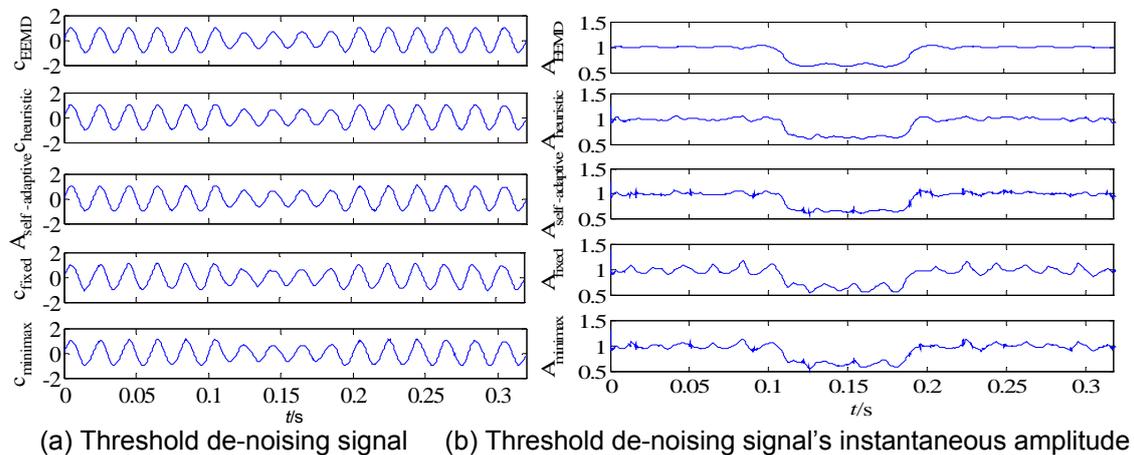


Figure 2. Threshold de-noising signal

Table.1 Detection error of various threshold

	EEMD		Heuristic		Self-adaptive		Fixed		Mini-max	
	Detection /s	Error %	Detection /s	Error %	Detection /s	Error %	Detection /s	Error %	Detection /s	Error %
t <sub>1</sub>	0.1098	0.18	0.1066	3.09	0.0998	9.28	0.1028	6.55	0.1028	6.55
t <sub>2</sub>	0.1898	0.11	0.1974	3.89	0.1944	2.32	0.1999	5.21	0.1948	2.53

The starting time of the actual setting voltage disturbance is  $t_1, t_1=0.11s$ , and the end time is  $t_2, t_2=0.19s$ .

**4.2 .Detection and positioning for the de-noised disturbance signal**

Based on experimental results in 4.1, we use the EEMD threshold method to denoise for the composite disturbance signal (including oscillatory transients, third harmonic, voltage interruption and swell), and the composite disturbance signal is superimposed 20db of SNR. Then, we can calculate  $\gamma_{SNR}$  is 18.9405 and  $\epsilon_{MSE}$  is 0.0079. The composite disturbance signal and components of de-noising reconstruction are shown in Figure 3. Figure 3 shows that the self-adaptive threshold of the EEMD can filter out noise basically. The instantaneous amplitude of the transient, the instantaneous frequency and amplitude of the third harmonic, the frequency amplitude of voltage interruption and voltage swells can be obtained by using the HHT. The instantaneous feature of IMFs are shown in Figure 4. And we can detect starting and ending times of the disturbance and calculate for the average frequency amplitude. The results are shown in Table 2. Table 2 shows that the starting and ending times, frequency and amplitude of the disturbance signal. The error of the frequency and amplitude are very small by using the method of EEMD threshold.

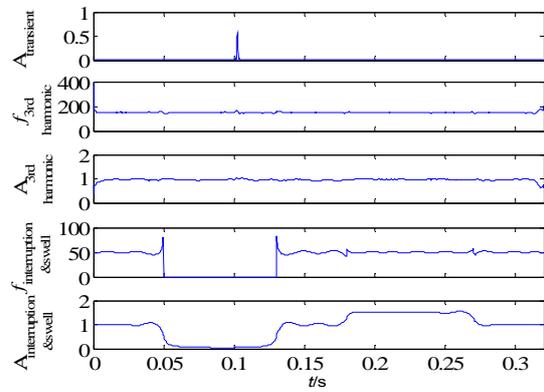
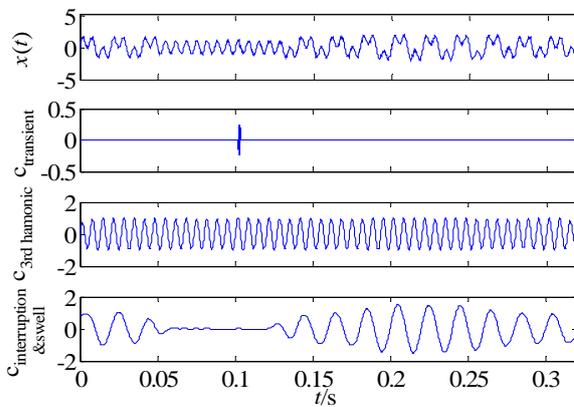


Figure.3 Components of EEMD decomposition

Figure 4. The instantaneous feature of IMFs

Table 2. Detection error of instantaneous feature

	Transient		Third harmonic		interruption		Swell	
	Detection	Error%	Detection	Error %	Detection	Error %	Detection	Error %
amplitude	0.5712	14.24	0.9539	4.6	----	----	----	----
frequency /Hz	----	----	150.4661	0.31	----	----	----	----
$t_1/s$	0.1	2	----	----	0.0498	0.4	0.1802	0.11
$t_2/s$	0.1054	2.3	----	----	0.1302	0.15	0.2698	0.074

starting and ending times: transient is 0.102s, 0.103s; interruption is 0.05s, 0.13s; swells is 0.18s, 0.27s.

**5. Conclusion**

This paper present a EEMD threshold de-noising method based on the filtering characteristics of Ensemble Empirical Mode Decomposition and the energy distribution regularity of the IMF component. Compared with four wavelet thresholds, EEMD threshold de-noising method has a better performance to denoise the voltage sag signal which was superimposed different signal-to-noise ratio. Simulation results show that EEMD threshold de-noising method can make the waveform close to the actual value. The SNR is higher and the MSE is smaller than four wavelet thresholds. Meanwhile, the instantaneous characteristics of each IMF component can be obtained by Hilbert-Huang transform after using the EEMD adaptive

threshold de-noising to process the composite disturbance signal which was superimposed noise signal. Therefore, It can accurately process composite disturbance signal for power quality, which will can significantly enhance power system safety and will in turn bring great economical benefits.

## References

- [1] IEEE Standard. 1159-195. *IEEE Recommended Practice for Monitoring Electric Power Quality*. New York: IEEE Press; 1995, 1-36.
- [2] Gupta M, Kumar R, Gupta A. Neural network based indexing and recognition of power quality disturbances. *TELKOMNIKA Telecommunication Computing Electronics and Control*. 2011; 9(2): 227-236.
- [3] YANG H T, LIAO C C. A de-noising scheme for enhancing wavelet-based power quality monitoring system. *IEEE Trans on Power Delivery*. 2003; 16(3): 353-360.
- [4] Feng Yu, Tang Yi, Shi Yanhui. Survey on research method of power quality analysis and parameter estimation. *Proceeding of the CSU-EPSCA*. 2010; 22(3): 78-84.
- [5] Kim CH, Aggarwal R. Wavelet transforms in power systems-Part 2 Examples of application to actual power system transients. *Power Engineering Journal*. 2001; 15(4): 193-202.
- [6] Cunping Wang Xianggen Yin; Minghao Wen. An improved ip-iq reactive and harmonic current detecting method. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(7): 1629-1636.
- [7] Zhang Quanming, Liu Huijin, Zhou Xinqi. Wavelet Soft-threshold de-noising method of power quality signal. *High Voltage Engineering*. 2006; 32(1):99-101.
- [8] Tianrui Feng, Sen Ouyang. Design of a distribution network power quality monitoring system based on metering automation systems and its application. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(7): 1547-1553.
- [9] Yannis Kopsinis, Stephen McLaughlin. Development of EMD-Based De-noising Methods Inspired by Wavelet Thresholding. *IEEE Transactions on Signal Processing*. 2009; 57 (4): 1351-1362.
- [10] Sun Jinbao, Zhu Yongli, Liu Liqing. Study on de-nosing method based on EMD used in insulator leakage current. *Journal of North China Electric Power University*. 2010; 37(6): 1-5.
- [11] Zhaohua WU, Norden E. Huang. Ensemble Empirical Mode Decomposition: A Noise-assisted Data Analysis Method. *Advances in Adaptive Data Analysis*. 2009; 1(1):1-41.
- [12] Shi Heng, Li Guilin, Wang Wei. Random noise attenuation based on ensemble empirical mode decomposition. *Progress in Geophysics*. 2011; 26(1):71-78.
- [13] Zhao Mingsheng, Liang Kaishui, Luo Yuanfang. Application of EEMD in blasting vibration signal de-noising. *Blasting*. 2011; 28(2):17-22.
- [14] Wei Limin, Sun Jinbao, Zhu Yongli. A de-noising method based on EEMD for insulator leakage current. *Journal of North China Electric Power University*. 2012; 39(2): 17-22.
- [15] N. E Huang. *The empirical mode decomposition and the Hilbert spectrum for non-linear and non-stationary time series analysis*. Proc. R. Soc. London. 1998: 454: 903-995.
- [16] Rilling G, Flandrin P, Goncalves P. *On empirical mode decomposition and its algorithms*. IEEE-EURASIP Workshop on Nonlinear Signal and Image Processing. Grado, Italy: 2003:1-5.
- [17] WU Z H, HUANG N E. A study of the characteristics of white noise using the empirical mode decomposition method. *Proceedings of the Royal Society A*. 2004; 460(2046): 1597-1611.
- [18] P Flandrin, G Rilling, P Goncalvès. EMD equivalent filter banks, from interpretation to applications. *World Scientific*. 2005(2): 57-74.
- [19] Kopsinis Y, McLaughlin S. Development of EMD-based denoising methods inspired by wavelet thresholding. *IEEE Transactions on Signal Processing*. 2009; 57(3):1351-1362.
- [20] Max, Zhou C, Kemp I J. Automated wavelet selection and thresholding for PD detection. *IEEE Electrical Insulation Magazine*. 2002;18(1): 37-47.
- [21] Yannis K, Stephen M. Development of EMD-based de-noising methods inspired by wavelet thresholding. *IEEE Transactions on signal Processing*. 2009; 57(4):1351-1362.