Dechang YANG[1], Christian REHTANZ[1], Yong LI[1], Qianjin LIU[2], Kay GÖRNER[1]

Technische University of Dortmund (1), ABB (China) Limited (2)

Denoising and detrending of measured oscillatory signal in power system

Abstract. *This paper presents a novel method for denoising and detrending of oscillatory signal measured from wide area measurement system (WAMS) using empirical mode decomposition (EMD) and time-frequency analysis. First of all, the measured signal is decomposed into a set of intrinsic mode functions (IMFs) by EMD. Next, the IMFs are divided into three parts based on their time and frequency distributions. Then, the noise and higher frequency components, trend components and meaningful oscillation modes are identified respectively. The proposed method are validated by the actual measured signal from WAProtector and the estimated trend is confirmed by comparing with the sliding linear trend estimated method and other nonlinear trend estimated methods.*

Streszczenie. *W artykule zaprezentowano nową metodę usuwania szumu z sygnału okresowego w systemach WAMS. W pierwszej kolejności przeprowadza się dekompozycję sygnału na funkcje, które następnie dzielone są na trzy części w zależności od rozkładu czasowo-częstotliwościowego. (**Usuwanie szumu i trendu w zmierzonym sygnale okresowym systemu WAMS**)*

Keywords: empirical mode decomposition; intrinsic mode functions; signal energy; frequency distribution estimated trend
Słowa kluczowe: szum, trend, WAMS.

Introduction

In recent years, Wide Area Measurement System (WAMS) based Phasor Measurement Units (PMUs) has been built, which provides favorable opportunity to monitor and analyze dynamic features of inter-connected power system near on real time [1,2]. Nevertheless, the information, which contains useful data and captured by WAMS, are polluted by kinds of noise. It requires outstanding techniques to extract and estimate the oscillation modes and parameters of interests.

Denoising and detrending of oscillatory signal is important for several reasons. First, the meaningful oscillation modes are polluted by all kinds of noise. Therefore, denoising is the first step before application of modal identification methods. Secondly, time-varying trends contain useful information on the slow and fast evolution of system dynamics. Detrending can trace the slow dynamic variations in the signal that relate with the load diversification, topological changing and controlling actions. Further, denoising and detrending maybe helpful to isolate and identify events or localized variations in time that cannot be isolated by traditional stationary models.

Formerly, non-stationary time-series models based on both parametric and nonparametric methods have been utilized with varied success for feature extraction and modal identification of time-varying systems. Wavelet-based methods have shown to be effective in nonlinear signal. However the effectiveness depends on the proper choice of a basis wavelet function, because the choice of the wavelet filters determines the trend model. It is necessary to have prior knowledge of the signal. In fact, it is impossible to know the feature of measured signal in advance since power system is a typical time-varying dynamic system. It limits the application of wavelet in analysis of the nonlinear and non-stationary signal [3]. Aiming at the shortcomings of wavelet decomposition, a data-driven technique, empirical mode decomposition (EMD) has shown the merit of producing basis functions from the signal itself. EMD has attracted increasing attention to trend estimation based on its self-adaptive and local ability [4,5]. Paper [4] described the basic principles, decomposition features and results analysis of EMD. As for the trend of nonlinear signal, it is considered as the residue of the traditional EMD. For a single trend, the EMD expressed good performance when it was used to analyze the long term load data and the trend estimate was given by the residue components of the EMD. However, as for the complicated signal, it is obviously that the residue has less meaning with the actual trend according to the definition of the EMD processing. Paper [6] applied an iterative algorithm to identify the trend in PMU data to study electromechanical mode based on the EMD by choosing the accurate high and low frequency.

Traditional EMD technique is presented to identify the trend and to denoise from measured power system oscillations signal. At the beginning, the importance of trend identification is listed. The performances of proposed method are compared with the wavelet shrinkage technique. However, it does not give a reasonable and convincing definition about the trend and noise component [5,7].

From above analysis, the main problems in underlying components estimation are summarized as follows: (1) there is no consistent definition about trend. There are many special definitions in different application area. Moreover, the trend relates with the time scale. (2) Most of the mentioned methods analyzed just based on the time domain and neglected the distribution in frequency domain and relationships between different oscillation modes. (3) as we know, there is no paper to analy the IMFs both from time and frequency domain.

Aiming at these problems, a novel method of denosing and detrending of measured oscillatory signal form WAMS is presented in this paper. First of all, measured information is decomposed into a set of IMFs by EMD. Next, the IMFs are classified into three parts according to the energy relationships among IMFs and their corresponding distributions in frequency domain. Then, the flow chart of proposed method is introduced and the validity and feasibility of the proposed method are evaluated by the actual measured signal from WAProtector.

Empirical Mode Decompostion (EMD)

The EMD is an iterative process which decomposes a time dependent signal $x(t)$ into its own IMFs. The algorithm diagram of the EMD can be seen in Fig.1 [4].

Fig.1 shows two iterations in the process of EMD. The internal iteration loop is sifting, which is used to extract the IMFs while the external loop is the main iterations, which is used to define the numbers of IMFs and to end the processing of decomposition.

The nonlinear and non-stationary signal can be decomposition into a set of IMFs based on the EMD. The decomposed results can be expressed as follows:

(1)
$$x(t) = \sum_{j=1}^{n} c_j(t) + r(t)$$

$c_j(t)$ is the IMFs; n is the number of IMFs; $r(t)$ means the residue of the signal.

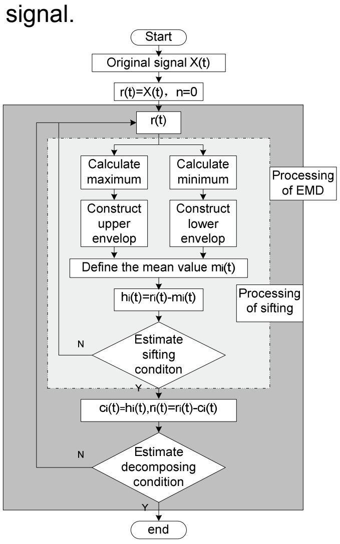

Fig. 1 The flow chart of EMD

Time-frequency analysis of IMFs

In this section, a novel method to determine the oscillatory meaningful modes contained in the measured data is proposed based on the time-frequency analysis. As for the time domain, it is clear that the meaningful components have higher energy than the higher frequency components or noises. Further more, Huang has pointed that although the results of EMD cannot be proved orthogonal in theory, the practical decomposition result usually is near orthogonal. Therefore, the energy of the original signal is equals to the sum of IMFs' energies and residue's energy.

In paper [8], the author proposed a method to calculate the energy of signal. The basic principles of this method are introduced in this part.

For a specified signal $\delta(t)$, the energy criterion is described as follows:

(2)
$$E_0 = \int_{t_1}^{t_2} \delta^2(t)dt$$

E_0 is the energy of original signal; t_1 is the start time; t_2 is the start time.

The discretized form of (2) can be expressed as:

(3)
$$E_0 = \sum_{i=1}^{N} \delta^2(i)$$

After the EMD, the original signal $\delta(t)$ is decomposed as several IMFs and one residue. Then,

(4)
$$E_{sum} = E_r + \sum_{i=1}^{n} E_{imf}(i)$$

E_{sum} is the total energy of IMFs and residue; E_r is the energy of the residue; $E_{imf(i)}$ is the energy of the i th IMF.

(5)
$$\varepsilon = \frac{E_n - E_0}{E_0} \times 100\%$$

ε is the energy decomposition error. Actually ε is can be used to indicate the orthogonality of EMD, if ε equals to zero, it means the IMFs are fully orthogonal.

(6)
$$\eta(i) = 100\% \times E_{imf}(i) \Big/ \sum_{i=1}^{n} E_{imf}(i)$$

$\eta(i)$ is the energy coefficient of IMFi. This parameter is used to describe the energy relations among IMFs. Obviously, the energies of IMFs which stands for the meaningful oscillation modes are higher.

According to the theory in paper [9,10], the mean values of IMFs contians help information in determing the noise and interesting oscillation mode. By decomposition, the number of extrema decreases when going from one residual to the next, thus guaranteeing that the complete decomposition is achieved in a finite number of steps. However, different sifting stop criterions will affect the numbers of IMFs and their corresponding mean values. Here, the mean values are proposed as a supplemental criterion to calculate the number of IMFs which contain the plentiful oscillatory information.

A key property of the EMD is its ability to act as a filter. Actually, the processing of EMD can be considered as the separation of different frequency components. First, the Higher Frequency Components (HFCs) or noises are extracted and they are denoted as the fore IMFs. Then, the meaningful components which are polluted by noise in original signal are identified and they are saved as the middle IMFs. Next, the Artificial Components (ACs) or Ultra Low Frequency Components (ULFCs) are left. And the last extracted function is usually monotone, or has one extrema. It is called as the residue.

For the frequency domain, it has been obviously proved that the range of the low frequency is $0.1Hz$-$2.5Hz$. Therefore, the frequencies of IMFs which located fully or partially in mentioned range can be considered as the physically meaningful components.

According to above desicripition and the principles of EMD, the decomposition results of complex measured data can be rewritten as the general form [5]:

(7)
$$x(t) = \sum_{j=1}^{n} c_j(t) + r(t) = \underbrace{\sum_{i=1}^{p} c_i(t)}_{Noise+HFCs} + \underbrace{\sum_{k=p+1}^{r} c_k(t)}_{\text{Physically meaningful components}} + \underbrace{\sum_{l=r+1}^{n} c_l(t)}_{ACs+ULFCs} + r(t)$$

$c_i(t)$ is the HFC or noise and p is corresponding number; $c_k(t)$ is the IMF contains the meaningful components and r-p is the number; $c_l(t)$ is the AC or ULFC and n-r is the corresponding number. $r(t)$ is the residue. By denoising the HFC or noise and by detrending the ULFC or AC as well as redidue, the underlying phenomena of interest can be selected as the oscillatory modes.

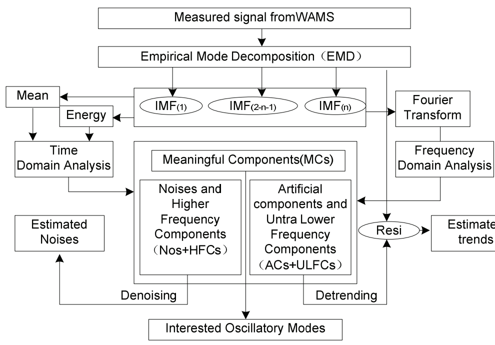

Fig.2 The sketch diagram of proposed method

Proposed method

From above analysis, there are three criterions imposed on the decomposed results of EMD. The energy and mean value are the evaluation indexes in time domain while the frequency distribution is the criterion in frequency domain. The flow chart of the proposed method used for detrending and denoising is shown in Fig.2.

Actual application to measured data from WAProtector

Generally, it is difficult to get the real-time operation data from transmission level because of the consideration of business benefit and competition. Therefore, the measured information from distribution side is helpful to analyze the oscillation dynamic and trend. Here, the WAProtector system [11] is used for presentation of real-time measured data obtained from WAMS, real-time calculated values and archived data. The locations of PMUs in UCTE (Union for the Coordination of Transmission of Electricity) are installed as Fig.3.

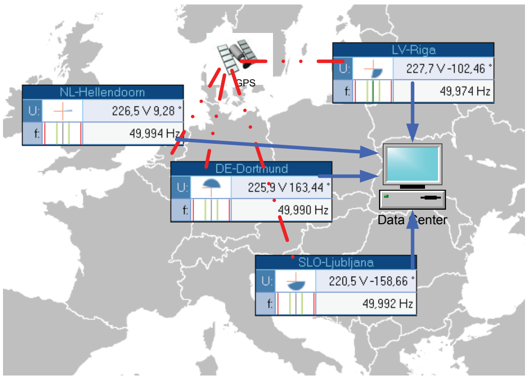

Fig.3 Simplified geographical scheme of studied system

From 23:58:00, Feb, 23, 2011 to 00:20:00, Feb, 24, 2011, there was an obvious dynamic oscillation during this period. The frequency signal in Dortmund is shown in Fig.4.

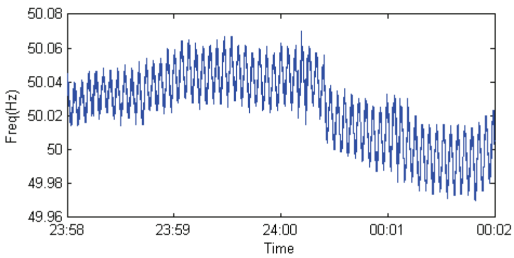

Fig.4. The frequency signal in Dortmund during recorded time

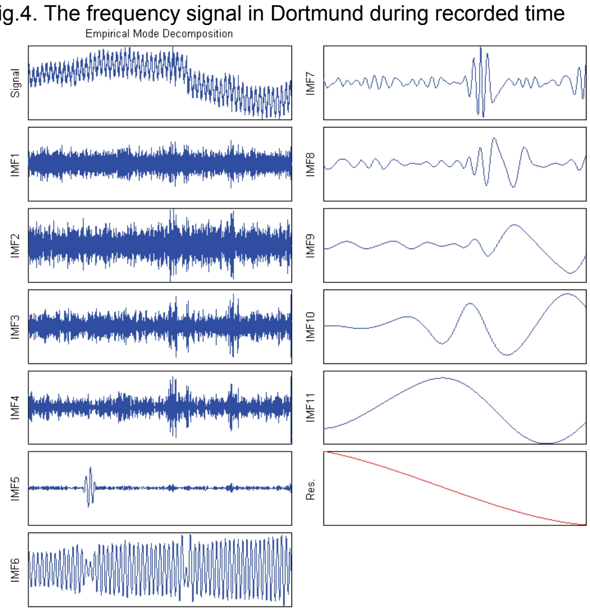

Fig.5 Decomposition results of measured signal

From Fig.4, it is clear that the measured signal has typical nonlinear and nonstationary characteristics. It is heavily polluted by all kinds of noises, including the small burrs and near Gauss white noises. Then, the proposed signal is employed to denoise and detrend. Firstly, EMD is used to decompose measured signal into a set of IMFs and one residue. The decomposed results is shown in Fig.5.

From the decomposed results in Fig.5, it is clear that there are 11 IMFs and one residue. This residue is monotone and it just stands for the simple direction of the original signal. Obviously, it is not reasonable when the residue is only considered as the trend of the signal. Moreover, the trend in measured signal has direct relations with the time scale. In Fig.4, we can see that the trend is increasing from 23:58 to 24:00 while it is decreasing from 24:00 to 00:01. There is an abrupt descend near 24:00 and an obvious protuberance near 00:01 respectively.

From the time domain analysis, the energy coefficient of every IMFs are calculated based on (2-6). The results are shown in Fig.8

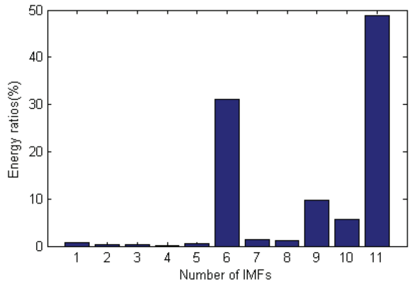

Fig.6 The energy coefficient of IMFs

The last IMF contains the most energy and the value is near 50% of total energies of IMFs. Next, the energy of IMF6 is near 33%. Furthermore, IMF9 and IMF10 also have obvious energies. The energies of other IMFs are small.

In order to explore the features of IMFs more clearly, the mean values of IMFs are calculated and the results are shown in Fig.7.

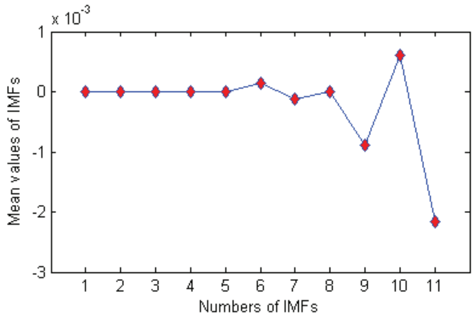

Fig.7 The computed means of IMFs

It can be seen from Fig. 7 that: (1) the mean value of IMF is becoming bigger and bigger with the further decomposition; (2) the mean values of IMF1-IMF4 is smaller comparing with other IMFs; (3) IMF5 can be considered as the knot or knee of the calculated values.

According to the principles of EMD, each IMF can be considered as one AM-FM signal and has special frequency distribution in frequency domain. Here, Fast Fourier Transform (FFT) is utilized to analyze the frequency distribution of every IMF. The calculated frequency spectrums of original signal and IMFs are shown in Fig.8. The logarithmic form is employed in order to display the results more clear in the low frequency area.

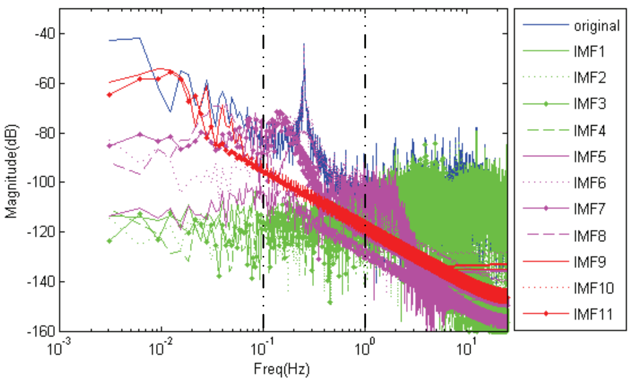

Fig.8. Frequency distributions of IMFs

In Fig.8, we can see that the frequency distributions of all the IMFs can be divided into three parts: *1-10Hz, 0.1-1Hz* and *0.003-0.1Hz*. The frequencies of IMF1-IMF4 are all in the high frequency range. They are the same as the higher frequency distribution of original signal. Therefore, they are considered as the higher frequency components or noises. The frequencies of IMF8-IMF11 are in the range of *0.003-0.1Hz*. They are considered as the lower frequency components in the original signal. Actually, the frequency range of low frequency oscillation is *0.1-1Hz*. From Fig.8, the frequencies of IMF5, IMF6 and IMF7 are located in the same frequency as the range of low frequency oscillation. All of them are taken as the meaningful components in the nonlinear and nonatationary signal.

Detrending and denoising identification

Detrending and denoising processes can be implemented based on the time and frequency domain. According to (7), the analyzed signal can be rewritten as:

$$x(t)=\sum_{i=1}^{4} IMF_i(t)+\sum_{k=5}^{7} IMF_k(t)+\sum_{l=8}^{11} IMF_l(t)+r(t)$$

Then, the noises or HFCs and the extracted oscillatory modes are shown in Fig 9.

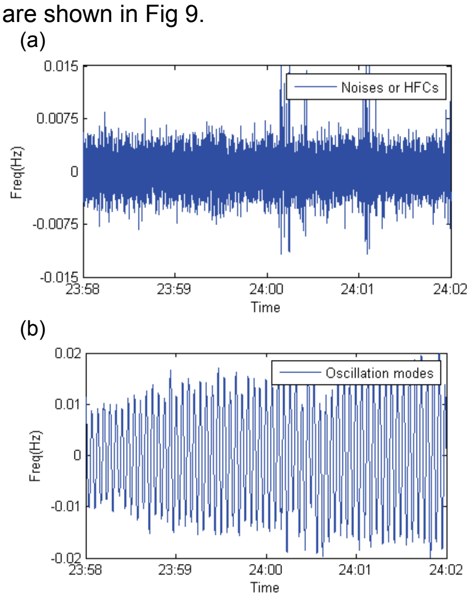

Fig.9 Identification results by proposed method. (a) noise or HFCs; (b) meaningful oscillation modes

In order to evaluate the performances of the proposed method in estimating the trend, the trends identified by sliding detrend function , wavelet decomposition and local mean method are compared.

In paper [12] the function of *detrend.m* is described. This method is used to identify a straight line, which can fit the original waveform best. The trend is identified by subtracting the detrend signal from the original waveform. It can be observed that the *detrend.m* is just suitable for the linear signal. It could omit some major trend features in nonlinear and nonstationary original waveform. In order to deal with the nonlinear signal, we proposed a sliding detrend method. First of all, the signal is broken into several segments and the linear trends for each segment are calculated. Then the averaging means of these trends are located and smoothed by sliding window. The smoothed line is considered as the trend of whole signal. In fact, the size of window should be adjusted according to the features and time scales of original. Here, the size of window is set as 500 (the length of time span is 10s) and the estimated trend is shown in Fig.10.

Wavelet shrinkage can be selectively used to approximate the original signal to any order of accuracy and leads to a finer reconstruction of system motion. For the selected signal, a decomposition level of 10 is chosen for the wavelet shrinkage approach and the 'db4' is chosen as the specific wavelet. The 8th level reconstruction of signal is also shown in Fig.10.

According to the theory proposed by A.R. Messina in paper [7], the local means of the first sifting step of IMF1 (or the time average of the first sifting step of IMF1 and first sifting step of IMF2) also is approximated as the trend of the original signal. However, the selected signal is heavily polluted by the noises, it is not correct if we extract the local means of the first sifting step as the trend. From the energy and frequency distribution analysis, IMF1 to IMF4 are all extracted as the noises or HFCs. Hereby, the left signal components is reset as the new signal. Then the calculated time average of local means both the first sifting step of IMF1(the IMF5 of original signal)and the first sifting step of IMF2 (the IMF6 of original signal) is approximately thought as the trend and the results is also shown in Fig.10.

From the analysis in both time and frequency domain, IMF8, IMF9, IMF10 and IMF11 are divided into the trend part. Therefore, the estimated trend is extracted and shown in Fig.10 based on the proposed technique.

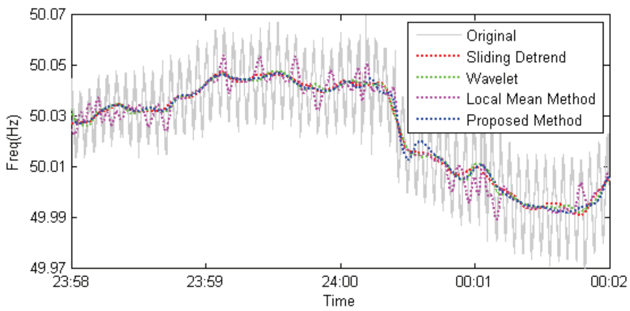

Fig.10.Comparisons of estimated trends

According to the trends estimation, the main conclusions are summarized as follows: (1) All the mentioned methods can be used to extract the trend from nonlinear and nonstationary signal. (2) The performances of sliding detrend method depends on the size of window. It is necessary to have plentiful knowledge about the signal in advance. (3) Local Mean method can be used to extract the trends. However, the performance is easily affected by the noise. It can be used to analyze the measured signal from the simulation model. (4) Both the wavelet shrinkage and the proposed method have the good performances in determine the trend. The wavelet shrinkage relates with the wavelet function and the decomposition level while the proposed method is based on the energy of the signal which is more reasonable to explore the dynamic features of signal. It is obvious that the proposed method presents a powerful choice to separate the trend and oscillation mode under the noise polluted circumstance.

Conclusions

As the first step of dealing with the measured signal from WAMS, detrending and denoising have significant importance in extracting the meaningful information and oscillatory modes. In this paper, a novel detrending and denoising method which considers the features of signal both in time and frequency domain is proposed. Signal energy algorithm is proposed to calcualte the energy of each IMF in time domain, while the FFT is used to analyze the frequency distribution. The complex nonlinear and nonstaionary signal is divided into three parts based on proposed technique.

The proposed method are validated by the actual measured signal from WAProtector and the estimated trend is confirmed by comparing with the sliding linear trend estimated method and other nonlinear trend estimated methods.

REFERENCES

[1] Kamwa I, Beland J, Trudel G, et al. Wide-area monitoring and control at Hydro-Quebec: Past, present and future. Proceedings of IEEE Power Engineering Society General Meeting, Montreal, Canada, 2006.

[2] A.G. Phadke, R.M. de Moraes, The Wide World of Wide-Area Measurement, IEEE Power and Energy Magazine, 6(2008), No.5, 52-65

[3] Tona R, Benqlilou C, Espuna A, et al. Dynamic data reconciliation based on wavelet trend analysis, Industrial & Engineering Chemistry Research, 44(2005), No. 12, 4323-4335.

[4] Huang N. E, Shen Z, Long S. R. The empirical mode decomposition and Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society of London, 454(1998), 903-995.

[5] Messina A.R, Vittal V, Heydt G. T et al. Nonstationary Approaches to Trend Identification and Denoising of Measured Power System Oscillations IEEE Trans. Power systems , 24 (2009),No. 4, 1798-1807.

[6] Zhou N, Trudnowski D, Pierre J. W. et al.An Algorithm for Removing Trends from Power-System Oscillation Data. Proceedings of IEEE power Engineering Society General Meeting, 2008.

[7] Messina A R. Inter-area oscillations in power systems a non-linear and non-stationary perspective. Berlin, Springer Press, 2009.

[8] Mu G, Shi K, An J, et al．Signal energy method based on EMD and its application to research of low frequency oscillation. Proceedings of the CSEE, 28(2008), No.19, 36-41. (in chinese)

[9] Flandrin P, Rilling G, Gonçalvés P. Empirical mode decomposition as a filter bank. IEEE Signal Process. Lett, 11(2004), No.2, 112-114.

[10] Flandrin P, Gonçalvés P, Rilling G. Detrending and denosing with empirical mode decompositions. Proceedings of the European Signal Processing Conference (EUSIPCO '04), Aalborg,Denmark ,2004.

[11] Babnik Tadeja, Gabrijel Uros, Mahkovec Bojan，et al. Wide Area Measurement System in Action. 2007 IEEE Lausanne Power Tech, Lausanne, Switzerland. 2007.

[12] Matlab User's Guide, version 7.0.4.365, The MathWorks, Inc., Jan 2005.

***Authors**: M.-Sc.Dechang Yang.Institute of Power Systems and Power Economics, Emil-Figge-Str. 70, 44227 Dortmund, Germany. Email:yang.dechang.cau@gmail.com;*
Prof. Dr.-Ing. Christian Rehtanz.Institute of Power Systems and Power Economics, Emil-Figge-Str. 70, 44227 Dortmund, Germany. Email: Christian.Rehtanz@tu-dortmund.de

The Correspondence address and the E-mail are:

Dechang Yang,
Raum 2.16
Gebäude BCI-G2. 2. Etage
Emil-Figge-Straße 70
Dortmund 44227, Germany
Phone: +49 2317554318
E-mail: yang.dechang.cau@gmail.com