APPLICATION OF ADAPTIVE EEMD METHOD IN VOLTAGE SAG DETECTION

JieSONG
State Grid Shanghai EPRI – China
songjie@sgcc.sh.com.cn

QishiXIAO
State Grid Shanghai EPRI – China
13621872612@163.com

LingPAN
State Grid Shanghai EPRI - China
panling@sgcc.sh.com.cn

Yongjun JIN
Liandi(Nanjing) Information Systems Co., Ltd.-China
jinyj@liandisys.com.cn

Zengyun MA
Liandi(Nanjing) Information Systems Co., Ltd.-China
mazy@liandisys.com.cn

ABSTRACT

In the traditional Ensemble Empirical Mode Decomposition (EEMD) method, the two critical parameters (the amplitude of the added white noise and the number of ensemble trials) are required to be obtained artificially and the added-noise process is non-adaptive. Aiming at the shortcomings of EEMD method, a modified Ensemble Empirical Mode Decomposition (MEEMD) method was proposed. In the proposed method, the added-noise principle of noise assisted decomposition methods were analyzed, and the two parameters: signal-to-noise ratio and correlation coefficient were taken as an evaluation index of decomposition performance, which adaptively determined the optimal amplitude of additive white-noise and number of ensemble trials by calculating the SNR values under different noises and the correlation between obtained components and original components. Furthermore, simulation results show that the proposed method is able to effectively suppress mode mixing and endpoint effects. At last, experiments data measured from the built power quality disturbance platform demonstrate that the proposed method is capable to accurately extract all disturbance parameters of voltage sag, which provides a novel way for power quality disturbance analysis as well.

Keywords：*power quality; voltage sag detection; ensemble empirical mode decomposition; adaptive analysis; disturbance feature extraction*

INTRODUCTION

Current research stated that, with the development of signal processing theory and technology, non-linear and non-steady time-frequency analysis methods have been widely concerned and studied, such as short-time Fourier transform [1], wavelet transform [2] and S transform [3], which increasingly utilized in power quality disturbance detection and analysis. These methods have achieved certain effects in signal detection research, however their processes are still non-adaptive essentially. The reason of which is that after the window function and wavelet basis of the methods are determined, their decomposition scales remain unchanged in the subsequent processing process and have fixed signal analysis ability. However, the signal can be decomposed into a series of adaptive Mode Functions(IMFs) by Empirical Mode Decomposition(EMD) method in the Hilbert Huang transform [4], [5], and the decomposition process only involves the signal itself instead of choosing a complex base function. Therefore, EMD method is a data-driven way to process the non-linear and non-stationary signal.

Inspite of the fact that HHT method has been applied in many fields based on its advantages of adaptive decomposition, such as mechanical fault diagnosis [6], speech signal denoising [7] and harmonic analysis of power system [8]due to the interference of intermittent signals in the application process, modal aliasing effect and endpoint effect appear in the EMD fitting mean curve [9], which reduces the performance of EMD decomposition.

In terms of current issues, Wu proposed Ensemble Empirical Mode Decomposition (EEMD) method [10] by studying the noise auxiliary decomposition method. Compared with the original EMD method, EEMD firstly adds the appropriate controlled noise to the original signal, and then performs EMD decomposition to obtain the intrinsic mode function, which effectively alleviates the modal aliasing and endpoint effect.

In fact, EEMD constructs the controlled Gaussian white noise by selecting appropriate noise adding parameters (the amplitude of adding-noise *A* and ensemble trials *N*), and the modal aliasing and endpoint effect are improved by adding the Gaussian white noise which will affect the distribution of the original signal extreme points. In addition, the amplitude of adding-noise and the number of ensemble trials in the original EEMD method are determined based on experimental experiences. If the amplitude value is small, the noise extreme point cannot affect the distribution of the original signal extreme point, which weakens EEMD method to EMD method and fails to achieve the purpose of improving modal aliasing and endpoint effect. On the contrary, if the amplitude value is larger than normal that the excess residual components and residual noises will be generated. Besides, the ensemble trials is used to eliminate residual noise, which in turns will increase the amount of computation of the algorithm.

Based on the above analysis, in order to improve the adding-noise method, reasonably determine the adding-noise parameters and raise decomposition performance as well as adaptability for the traditional EEMD method, this paper proposes a modified Ensemble Empirical Mode Decomposition (MEEMD) method. Firstly, the research and analysis of noise-adding criterion for the original EEMD method was carried out. The two parameters of Signal-to-Noise Ratio (SNR) and Correlation Coefficient (CC) were introduced. Secondly, the noise amplitude A was adaptively determined by calculating SNR values under different noises. Similarly, the number of ensemble trial was also adaptively obtained via evaluating correlation coefficient values between components and original components. The decomposition process was performed under fixing the acquired two parameters. Furthermore, the simulation experiment results show that the MEEMD method achieves certain improvement effects in modal aliasing suppression and endpoint effect elimination. Finally, MEEMD method was applied to power quality detection of voltage sag, which can detect and analyze the single voltage sag and voltage sag with harmonic interference, accurately locate the moment point of disturbance, and extract parameters such as sag amplitude and phase jump.

EEMD PRINCIPLE

For a given signal $s(t)$, the specific process of EEMD decomposition are defined as follows.

1). Add zero mean gaussian white noise to the origin signal:

$$x^i(t) = s(t) + \xi_0 n^i(t). \tag{1}$$

Where $n^i(t)$ is the ith added white noise, $i = 1, 2, \ldots, N$,N is the ensemble trial, and ξ_0 is the amplitude of add white noise.

2). The signal with noise $x^i(t)$ is decomposed into a set of intrinsic mode functions by EMD method.

$$s(t) + \xi_0 n^i(t) \xrightarrow{\text{EMD}} \sum_{j=1}^{M} imf_j^i(t) + r^i(t). \tag{2}$$

Where $imf_j^i(t)$ is the jth IMF component obtained from the ith ensemble decomposition, $j = 1, 2, \ldots, M$,and $r^i(t)$ is the remaining component of the decomposition.

3). Repeat step (1) and (2) for Ntimes decomposition, and then the obtainedIMF isensemble averaged.

$$\overline{imf_j(t)} = \frac{1}{N} \sum_{j=1}^{M} imf_j^i(t). \tag{3}$$

Where $\overline{imf_j(t)}$ is thefinal jth IMF component decomposed by EEMDmethod.

MEEMD ALGORITHM

In terms of the EEMD method, the added-noise amplitude A and ensemble trial N are both determined artificially in advance, which greatly weakens its adaptability. Reasonable selection of parameters directly affects the quality of decomposition results. Wu and Huang proposed adding noise parameters through a large number of experiments [10]: A generally takes 0.1~0.2 SD (SD represents the standard deviation of the original signal), and N generally takes 100~200 trials.

Based on the above analysis, this paper proposes the MEEMD algorithm, the specific steps are as follows.

Firstly, the power value P_1 of the original signal $s(t)$ is calculated, and the noise with different amplitude is added from 0 SD to 0.5 SD amplitude segment for decomposition. The adding noise interval is 0.01 SD. The SNR value is calculated according to Eq. (4), with the optimal noise amplitude A_i is determined when the residual component IMF is set to 0.

$$SNR = 10\lg(\frac{P_1}{P_2}) = 20\lg(\frac{A_1}{A_2}). \tag{4}$$

Secondly, the optimal ensemble decomposition trial N_i is determined according to Eq. (5):

$$CC = \frac{C(y_i, c_i)}{\sqrt{\sigma(y_i)\sigma(c_i)}}. \tag{5}$$

Where, $C(X, Y)$ is the covariance of X and Y, $\sigma(X)$ is the variance of X, $y_i(t)$ is the signal component, and c_i is the corresponding IMF component obtained by decomposition.

When the ensemble decomposition trial N is changed under the condition of fixing the noise amplitude A_i. In order to speed up the calculation efficiency, the first component of the original signal is usually substituted into the calculation [13].

At last, the controlled Gaussian white noise is constructed to obtain the corresponding IMF components by EEMD decomposition , where the noise amplitude A_i is added to the original signal and the ensemble decomposition trial is fixed as N_i.

VERIFICATION OF MEASURED DATA

On the basis of simulation results, in order to verify the actual detection effect of the proposed method, MEEMD method is introduced into the field of power quality voltage sag detection and analysis. The data measured from the built power quality experiment platform are collected for verification. The data acquisition platform is shown in Fig. 1.

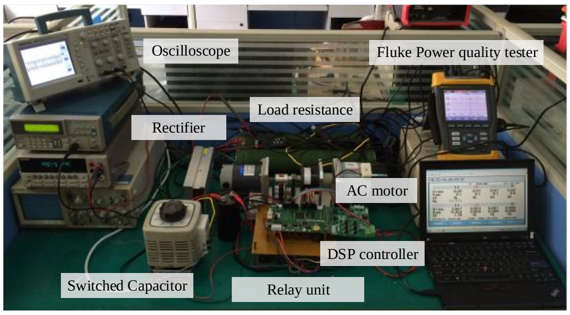


Fig.1. Experiment platform of voltage sag

As shown in Fig. 1, the main experimental devices of the platform include: load resistance (100 Ω, 1000 W), switching capacitance (47 μF), single-phase rectifier bridge(input voltage 220 V, DC output current 10 A), AC voltage regulation (1000 W), AC motor (220 V, 400 W), DSP controller (TMS320F28335), relay groups, oscilloscope and Fluke435 power quality tester.

Single voltage sag experiment verification

In the beginning, the single disturbance experiment of voltage sag is designed. Load resistance and capacitance are suddenly added at t_0 and removed at t_1 by DSP controlling relay groups. And the data is collected by oscilloscope and Fluke power quality tester with a sampling frequency of 15kHz. The measured waveform of single voltage sag is shown in Fig. 2.

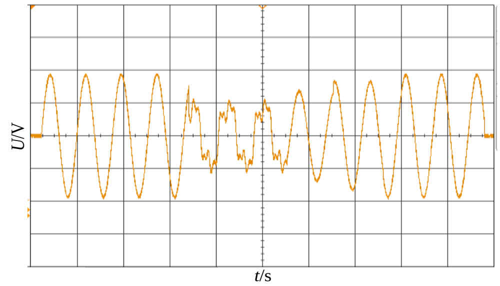
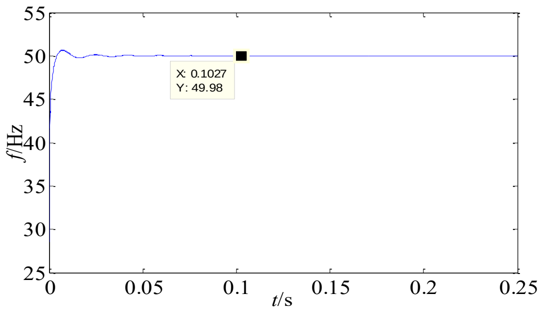
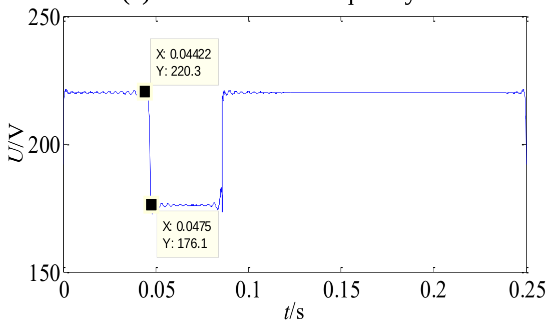


Fig. 2 Measured waveform of single voltage sag

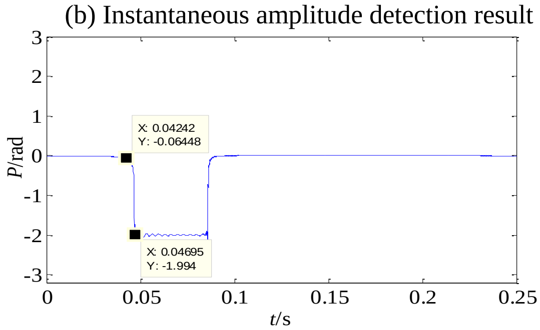
The collected data is imported into MATLAB for analysis and decomposed by MEEMD method. And then, the decomposed IMF components are conducted by Hilbert transformation. The detection results of each characteristic parameter are shown in Fig. 3.



(a) Instantaneous frequency result



(b) Instantaneous amplitude detection result



(c) Instantaneous phase detection result

Fig. 3. Test results of single voltage sag

As shown in Fig.3, given the single voltage sag experiment, the instantaneous amplitude *U*, frequency *f* and jump phase *phi* can be effectively extracted by Hilbert transform after the measured data are decomposed by MEEMD method.

Afterwards, in order to accurately locate the disturbance point of voltage sag, the data in Fig. 3 are used to detect the starting t_b and ending disturbance time t_d by the second derivative. The disturbance detection results are shown in Fig. 4.

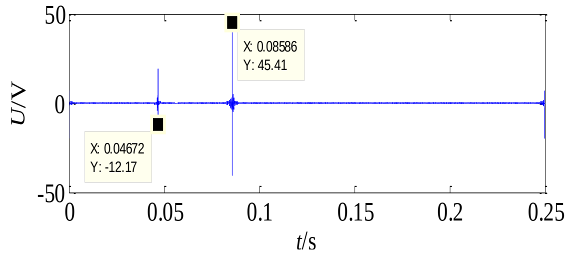


Fig. 4.Disturbance time detection results of single voltage sag

From the Fig. 4, aiming at the voltage sag disturbance with amplitude hopping, the moment of mutation can be accurately located by directly deriving the instantaneous amplitude. Finally, for the purpose of comprehensively comparing the detection results of different methods, the specific detection values of each characteristic parameter are given in Tab. 1.

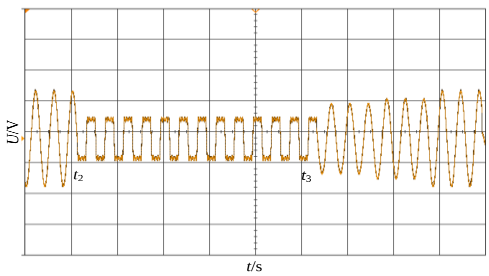
Tab.1 Test results comparison of single voltage sag

Method	t_b(s)	t_d (s)	*U*(V)	*phi*(rad)
EEMD	0.0404	0.0920	46.998	-1.994
MEEMD	0.0467	0.0859	47.900	-1.982
Fluke	0.0466	0.0861	47.111	-2.112

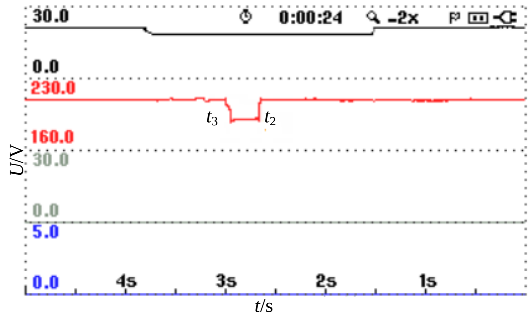
It can be seen from Tab.1 that the detection effect of EEMD and MEEND methods are similar to Fluke without the interference of other intermittent signals. The above two methods not only accurately extract the sag characteristic parameters, but also locate the disturbance moments.

Voltage sag with harmonics verification experiment

In this phase, the voltage sag with harmonics interference experiment is designed. Meanwhile, the motor drive module is controlled by DSP, and the AC motor and rectifier bridge are put into operation at t_2 and cut off at t_3.The measured voltage waveform and the voltage sag waveform are shown inFig.5(a) and Fig.5(b)



(a) Harmonic voltage sag measured waveform



(b) Harmonic voltage sag waveform

Fig. 5.Acquisition waveform of voltage sag with harmonic

The same method is adopted for analysis, and the actual data collected are decomposed by MEEMD method. The decomposition results are shown in Fig.6.

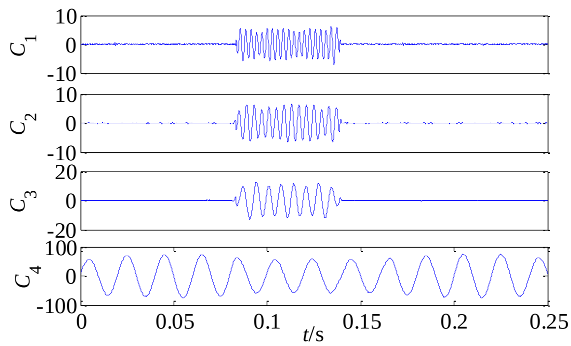


Fig. 6. Decomposition result of voltage sag with harmonic

It can be seen from Fig. 6 that three harmonic components C_1~C_3 are detected in addition to the fundamental frequency in the complex perturbation with harmonics experiment. Therefore, Hilbert transform is utilized to extract the components of the decomposed IMFs. The detection results are shown in Fig. 7.

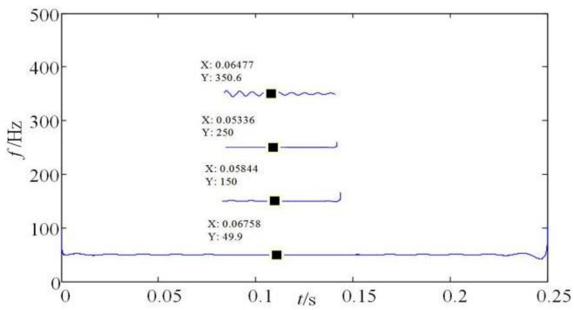
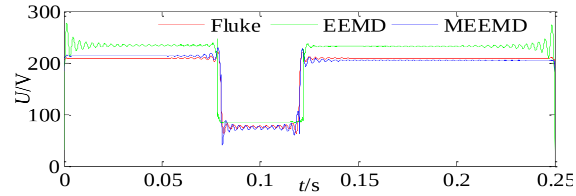
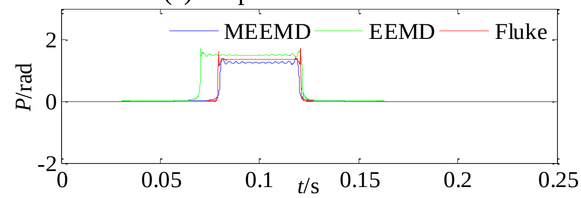


Fig. 7. Detection result of harmonic components

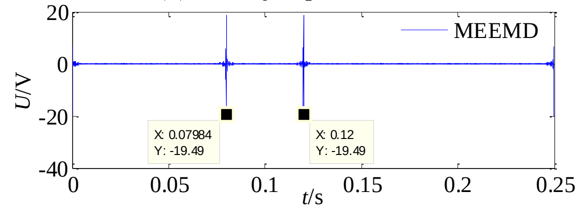
From Fig. 7 we can see, there are 50 Hz fundamental wave and 3~7 odd harmonic components from the result. Furthermore, Fig. 8 shows the detection results of each sag characteristic parameter in the case of harmonic interference.



(a) Amplitude detection result



(b) Phase jump detection result



(c) Disturbance moment detection result

Fig. 8. Detection result of voltage sag with harmonic

Finally, the specific characteristic parameters of voltage sag of each method under harmonic interference are given in Tab. 2.

Tab.2 Test results comparison of voltage sag with harmonic

Method	t_b(s)	t_d (s)	U(V)	*phi*(rad)
EEMD	0.0579	0.1075	100.98	1.458
MEEMD	0.0789	0.1200	129.78	1.287
Fluke	0.0768	0.1213	127.75	1.235

From Fig. 8 and Tab. 2, in the case of complex disturbance, the proposed method is relatively accurate in extracting characteristic parameters containing harmonic voltage sag, and the tracking performance is similar to the detection results of Fluke instrument. The positioning error of disturbance time point are 2.71 %, 1.07 %, and the sag amplitude and phase jump error are 1.59%, 4.2%, which meets the requirements of voltage sag detection error.

CONCLUSION

This paper proposed a modified Ensemble Empirical Mode Decomposition (MEEMD) method, which will solve the problem of the selection of adding noise parameters for standard EEMD method which largely relied on the determination of human experience and the non-adaptability of noise adding process.

Based on the research of the standard EEMD method, Signal to Noise Ratio and correlation coefficient are introduced as the evaluation indexes of noise decomposition performance, and the noise parameters A and N are determined adaptively.

The simulation results show that the proposed method achieves certain improvement effects on modal aliasing, endpoint effects and suppression of false components.

In conclusion, MEEMD method is applied in the field of voltage sag detection and analysis. Combine Hibert transform with MEEMD method and the result shows that it is possible to effectively extract the amplitude and jump phase of voltage sag and accurately locate the disturbance moment. The detection effect is equivalent to the actual power quality instrument, which verifies the effectiveness and feasibility of the method.

REFERENCES

[1] ZHAO Feng-zhan, YANG Ren-gang. Voltage sag disturbance detection based on short time fourier transform [J].Proceedings of the CSEE,2007,7(10):28-34(in Chinese).

[2] Thirumala K, Umarikar A C, Jain T. Estimation of Single-Phase and Three-Phase Power-Quality Indices Using Empirical Wavelet Transform[J]. IEEE Transactions on Power Delivery, 2015, 30(1):445-454.

[3] ZHANG Zhiyu, MAN Weishi, XI Lei, et al. Application of Fast S-Transform in Power Quality Analysis[J]. Power System Technology, 2013, 37(05):1285-1290.

[4] Huang N E, Shen Z, Long S R, et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis[J]. Proceedings Mathematical Physical & Engineering Sciences, 1998, 454(1971):903-995.

[5] Huang N E. A New Method for Non-linear and Non-stationary Time Series Analysis: The Hilbert Spectral Analysis[J]. Proceedings of SPIE - The International Society for Optical Engineering, 2000, 4056:197-209.

[6] ZHENG Jinde, CHENG Junsheng. Improved Hilbert-Huang Transform and Its Applications to Rolling Bearing Fault Diagnosis[J]. Journal of Mechanical Engineering, 2015, 51(1):138-145.

[7] Molla K I, Hirose K, Minematsu N, et al. Voiced/Unvoiced Detection of Speech Signals Using Empirical Mode Decomposition Model[C]// International Conference on Information and Communication Technology. IEEE, 2007:311-314.

[8] LI Tian-yun, CHENG Si-yong, YANG Mei, et al. Power System Harmonic Analysis Based on Hilbert-Huang Transform[J]. Proceedings of the CSEE, 2008, 28(4): 109-113.

[9] Tang Baoping, Dong Shaojiang, Ma Jinghua.Study on the method for eliminating mode mixing of empirical mode decomposition based on independent component analysis[J]. Chinese Journal of Scientific Instrument, 2012, 33(7):1477-1482.

[10] Zhaohua Wu, Norden E. Huang. Ensemble empirical mode decomposition: a noise-assisted data analysis method[J]. Advances in Adaptive Data Analysis, 2011, 1(01):1-41.

[11] LEI Y, LI N, LIN J, et al. Fault diagnosis of rotating machinery based on an adaptive ensemble empirical mode decomposition [J]. Sensors, 2013, 13(12): 16950-16964.

[12] KONG De-tongs, LIU Qing-chaos, LEI Ya-guo, et al. The improved EEMD method and its application [J]. Journal of Vibration Engineering, 2015, 28(6):1015-1021.

[13] Xue X, Zhou J, Zhang Y, et al. An improved ensemble empirical mode decomposition method and its application to pressure pulsation analysis of hydroelectric generator unit[J]. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 2014, 228(6): 543-557.

[14] Zheng J, Cheng J, Yang Y. Partly ensemble empirical mode decomposition: An improved noise-assisted method for eliminating mode mixing[J]. Signal Processing, 2014, 96:362-374.

[15] ZHU Wenlong, ZHOU Jianzhong, XIAO Jian, et al. Voltage sag disturbance detection based on short time fourier transform [J].Proceedings of the CSEE,2013, 33(29):95-101.(in Chinese).