Method of Modal Parameter Identification for Power System Low Frequency Oscillation Based on EEMD and Prony Algorithm

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Abstract
Regarding the poor anti-interference and high requirement for input signals of Prony algorithm, we proposed a method for identification of low-frequency oscillation-mode parameters in power systems based on Ensemble Empirical Mode Decomposition (EEMD) and Prony algorithm. First, relying on EEMD's high ability against modal aliasing, we decomposed the original signals based on the size of frequency range, then identified the IMF containing the dominant mode by using the weight of signal energy, finally analyzed the IMF using Prony algorithm and thus obtained the modal parameters of low-frequency oscillation signals. Compared with the traditional Prony algorithm, this algorithm exhibits high noise resistance, a smaller number of orders and higher computing speed. The validity and superiority of this algorithm were validated by applying to modal identification in the noise signals of four-machine two-area systems and in the analog signals of Sichuan power grids.
Key words: LOW-FREQUENCY OSCILLATION, EEMD, PRONY, SIGNAL ENERGY, MODAL IDENTIFICATION

1. Introduction

The scales of power systems in China are expanding along with the rapid development of power industry, which raises the requirements for system monitoring and control. Also along with the expansion of long-distance transmission and weak networking, the poor-damping low-frequency oscillation becomes a bottleneck that restricts the transmission capacity of interconnected power grids [1]. Rapid accurate monitoring and analysis of systematic low-frequency oscillation will facilitate the understanding of systemic dynamic properties and performance and provide a reference basis for prevention and monitoring [2].

Wide-Area Measurement System (WAMS) as a novel stability control technique offers a new information technique platform for monitoring, analysis and control of large-scale power systems. However, the concern for engineering technical personnel is which algorithm can be applied into online identification and rapid accurate alarming of low-frequency oscillation [3-5]. The existing WAMS-based algorithms include real-time fast Fourier transform (FFT), wavelet algorithm, Prony algorithm, and Hilbert-Huang transform (HHT). However, FFT cannot process non-stationary signals or reflect the damping characteristics of oscillation[6]. Wavelet algorithms[7] can reveal the time-varying performance of oscillation, but it is faced with problems of low resolution and difficulty in selection of wavelet basis [8]. Prony algorithm applied into modal analysis of low-frequency oscillation can well identify stationary signals, but it is noise-sensitive and cannot adaptively reflect the time-varying performance of oscillation mode [9]. In response to these disadvantages, various improved Prony algorithms [10-13] have been proposed, but they are still faced with low antinoise performance and difficulty in model order determination. HHT [14] for analysis of nonlinear non-stationary signals applied into modal analysis of low-frequency oscillation can highlight the instantaneous frequency and well identify time frequency [15, 16]. However, the problem faced by Empirical Mode Decomposition (EMD) is the mode confusion. EMD cannot effectively separate 2 modes with a frequency difference within 1-fold [17, 18]. For analysis of low-frequency oscillation in power systems, this limitation is serious because the between-mode frequencies are probably very close. Ensemble Empirical Mode Decomposition (EEMD) [19] can effectively solve this problem.

In this paper, we proposed an algorithm for identification of low-frequency oscillation modal parameters in power systems combining EEMD and Prony algorithm. The core ideas are the pretreatment of actual trajectory using EEMD and the extraction of dominant modal parameters. First, EEMD was used to stabilize non-stationary measured data, thus obtain axisymmetric component IMFs, and identify the IMF of dominant mode using signal energy weight criteria. Then Prony algorithm was used to extract low-frequency oscillation modal parameters from the IMF of the dominant mode. The results show that the pretreatment with EEMD is very rapid and simple, and can largely improve the mode identification precision without enhancing the computation burden.

2. The ensemble empirical mode decomposition

2.1 Intrinsic mode function (IMF) and Ensemble Empirical Mode Decomposition (EEMD)

Location EMD was modified to EEMD to solve modal aliasing [20]. The principle is that since Gaussian white noise is homogeneously distributed, white noise can be added to make signals continuous at different scales and reduce modal aliasing. The specific decomposition steps and principles are as follows [21]:

(1) Repeatedly add white noise $n_i(t)$ into the original signal $x(t)$ (standard deviation [SD] of white noise is 0.1- to 0.4-fold of that of original signal) with mean 0 and constant amplitude SD:

$$x_i(t) = x(t) + n_i(t) \tag{1}$$

where $x_i(t)$ is the Gaussian white noise added at the *i*-th time. The size of the added white noise will directly affect the signal EEMD and avoid modal aliasing.

(2) Decompose $x_i(t)$ using EMD to obtain IMF $c_{ij}(t)$ and a remainder term $r_i(t)$. where $c_{ij}(t)$ is the *j*-th IMF decomposed after the addition of the *i*-th Gaussian white noise.

(3) Repeat steps 1 and 2 N times. Since the

statistical average of uncorrelated random series is 0, the above corresponding IMFs were used in EEMD to alleviate the effects of multiple Gaussian white noise on real IMF, and the IMF after EEMD is:

$$c_j(t) = \frac{1}{N}\sum_{i=1}^{N} c_{ij} \tag{2}$$

where $c_j(t)$ is the j-th IMF after the original signal is decomposed using EEMD. A larger N will make the sum of IMFs closer to 0. Then the EEMD result is:

$$x(t) = \sum_j c_j(t) + r(t) \tag{3}$$

where $r(t)$ is the final residual component, reflecting the average trend of signals. With EEMD, any signal $x(t)$ can be decomposed into the sum of several IMFs and a residual component. The eigenmode component $c_j(t)(j=1,2,......)$ reflects the components from high to low frequency, and each frequency range contains specific frequency components, which change with the variation of oscillation signal $x(t)$.

2.2 Dominant mode recognition using EEMD

According to Parseval's theorem in signal spectrum analysis [22-23], we can obtain the energy of IMF-component signal $E_{imf,i}$:

$$E_{imf,i} = \int_0^T \left| f_{i,j}(t_j) \right|^2 dt = \sum_{j=1}^{m} \left| x_{i,j} \right|^2 \tag{4}$$

where $x_{i,j}$ (i=number of IMF components; j is the number of scattered sampling points) is the amplitude of scattered point of IMF component $f_{i,j}(t_j)$.

The dominant oscillation mode was searched for using the energy weights of all IMF components:

(1) Find the signal energy $E_{imf}(i)$ of each IMF, and also:

$$E_{IMF} = \sum_{i=1}^{n} E_{imf}(i) \tag{5}$$

(2) Since the low-frequency oscillation of power systems is mostly in compound mode, we concern the dominant mode with the smallest damping ratio and large oscillation amplitude. In this paper, with the maximum IMF oscillation energy as the index for qualitative analysis, we extracted from the EMD results the IMF with large energy weight as the dominant mode, while ignored the other components with low energy. The weight of IMF energy is expressed as follows:

$$\eta_i = \frac{E_{imf}(i)}{E_{IMF}} \times 100\% \tag{6}$$

3. The classic Prony analysis

With Prony algorithm, the linear combination of p complex exponential functions with random amplitude, phase, frequency and attenuation factor was used to fit uniformly-spaced sampling data x(1)……x(N):

$$\hat{x}(n) = \sum_{i=1}^{p} b_i z_i^n \tag{7}$$

where $b_i = A_i e^{j\theta_i}$, $z_i = e^{(\alpha_i + j2\pi f_i)\Delta t}$; A_i, θ_i, α_i, and f_i are the amplitude, phase, attenuation factor and frequency; $\hat{x}(n)$ is the estimated value of $x(n)$, Δt is the sampling interval, and p is the number of orders.

To make the fitted signal utmost approach the original signal, with the principle of least square error:

$$\min(\varepsilon = \sum_{n=0}^{N-1} \left| x(n) - \hat{x}(n) \right|^2) \tag{8}$$

When N>2p, from Eq. (8), we can compute the amplitude, phase, attenuation factor and frequency, which is an issue of solving nonlinear least squares problem. When z_i is regarded as the root of a linear constant-coefficient difference equation, then z_i satisfies a characteristic equation:

$$\psi(z) = \sum_{i=0}^{p} a_i z^{p-i} = 0 \tag{9}$$

Equation (7) is the homogeneous solution of a constant-coefficient linear difference equation, which can be deduced from a series of mathematical transformations:

$$\hat{x}(n) = -\sum_{i=1}^{p} a_i \hat{x}(n-i)\quad (p \le n \le N-1) \tag{10}$$

Equation (10) can be unfolded to the form of matrix:

$$-\begin{bmatrix} \hat{x}(p) & \cdots & \hat{x}(0) \\ \hat{x}(p+1) & \cdots & \hat{x}(1) \\ \vdots & \cdots & \vdots \\ \hat{x}(N-1) & \cdots & \hat{x}(N-p-1) \end{bmatrix} \begin{bmatrix} 1 \\ a_1 \\ \vdots \\ a_p \end{bmatrix} = \begin{bmatrix} \hat{x}(p) \\ \hat{x}(p+1) \\ \vdots \\ \hat{x}(N-1) \end{bmatrix} \tag{11}$$

From Eq. (11), then we can solve a_i; by substituting to Eq. (8), then we solve z_i and substitute it to Eq. (7), thus identifying the following parameters:

$$\begin{cases} \alpha_i = \ln|z_i| / \Delta t \\ f_i = \arctan\left[\mathrm{Im}(z_i)/\mathrm{Re}(z_i)\right] / 2\pi\Delta t \\ A_i = |b_i| \\ \theta_i = \arctan\left[\mathrm{Im}(b_i)/\mathrm{Re}(b_i)\right] \end{cases} \tag{12}$$

4. Identification of low-frequency oscillation mode based on EEMD and Prony

During identification of low-frequency oscillation mode, though the traditional and improved Prony algorithms can be used as a filter [11-13], they are noise-sensitive. When noise is > 40 dB, no accurate results can be obtained [24]. Then scattered Kalman filtering [25] and low pass filtering [3] pretreatment algorithms were proposed. However, a system model is needed by Kalman filtering, while the real inputted signals are mostly non-stationary and their real characteristics are largely unknown. To use a low-pass or band-pass filter, we first need transformation between time domains or frequency domains, and pre-determine the filter's cutoff frequency and signal broadband, which make it difficult to determine the filter's parameters and the required system model if only depending on the real inputted signals. EEMD can effectively isolate the noise from the real signals, extract the similar low-frequency oscillation modes, and find the IMF containing the dominant mode depending on the weights of IMF energy. Finally, Prony algorithm was used to extract low-frequency oscillation modal parameters from the IMF containing the dominant mode.

The algorithm combining EEMD and Prony algorithm for analysis of low-frequency oscillation modes of power systems is showed in Figure 1.

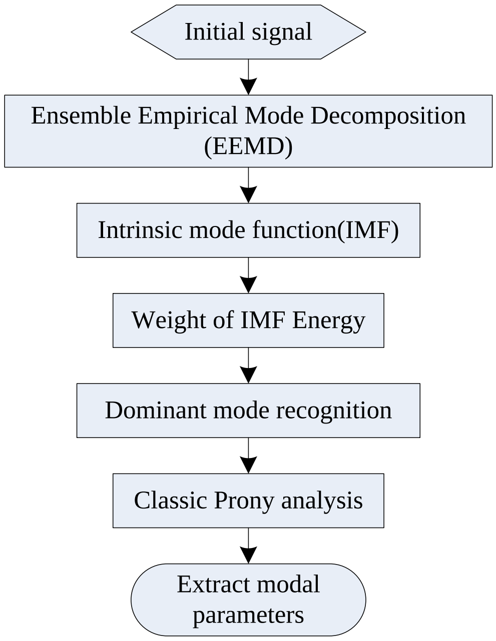

Figure 1. Flow chart of mode analysis based on EEMD and Prony

5. Simulation study

5.1 Four-machine two-area system

With an 11-node system as example, the application of EEMD/Prony into identification of low-frequency oscillation in power systems based on noise-like signals was validated via simulation. The system's connection diagram is showed in Figure 2 and the specific parameters were introduced in Ref. [1]. A simulation system based on Matlab platform was built; the terminal of generator set G1 was added with reactive power disturbance of 20 Mvar at 0.5 s and relieved after 0.5 s, with reference power of 1000 MW. The generator's electromagnetic power fluctuated greatly when the simulation proceeded for more than 24 s, leading to increasing oscillation, gradual loss of synchronization with the system, and finally to system splitting.

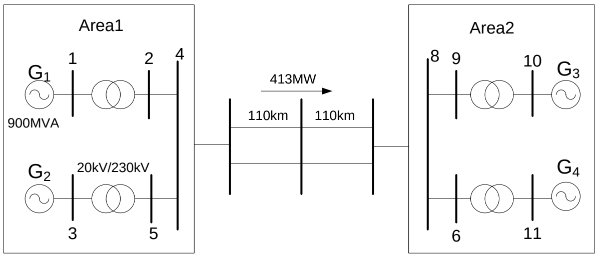

Figure 2. Four-machine two-area system wiring diagram.

To simulate the small-amplitude random disturbance in a real power system, we randomly injected at all load sites with small-disturbance power signals, which were obtained from Gaussian white noise using a low-pass filter. The active power curve outputted by G3 is showed in Fig. 3; the oscillation information was extracted via the EEMD/Prony algorithm to validate its accuracy and antinoise performance.

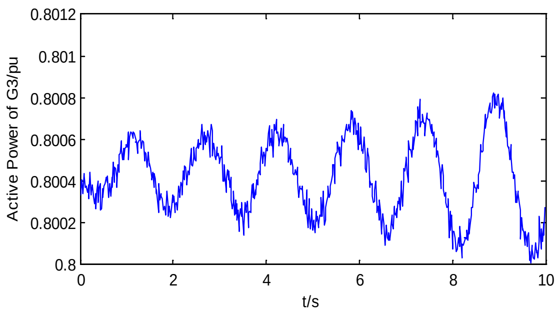

Figure 3. Active power noise signal of G3 output

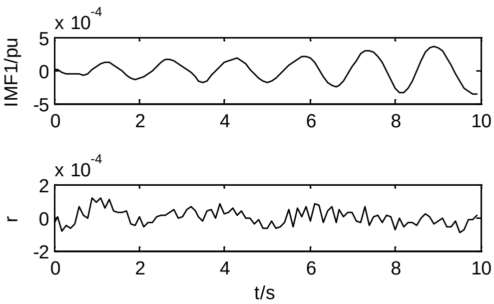

Figure 4. EEMD decomposition of the active power noise signal

The decomposed results (Fig. 4) show that the first IMF component displayed the largest amplitude and highest frequency, and then the amplitude and frequency both gradually decreased. Also IMF1 showed that the decomposition with EEMD could satisfactorily inhibit the noise.

One significant characteristic was that the major signal components could be extracted via decomposition with EEMD, because the power oscillation trajectory was generated via the interaction of multiple oscillation modes. In a previous article [17], when IMF1 with the largest amplitude was compared with the original oscillation signal (after direct current components were removed), the consistence between curves confirmed that IMF1 contained the information with the most significant oscillation signals, which unfortunately complicated the identification. In this paper, the IMF containing the dominant oscillation mode was identified via comparison of energy weights, thus achieving similar effects, facilitating the digitization of results, and avoiding artificial factors (Table 1).

Table 1. Stat. result of signal energy analysis

IMF	Signal Energy $E_{\mathrm{imf}}(i)$	Weight of IMF Energy(%)	E_{IMF}
IMF1	$2.89e^{-6}$	93.59	$3.09e^{-6}$
r	$1.98e^{-7}$	6.41	

Clearly, the energy weight of IMF1 was 93.59%, while the remaining energy weight was 6.41% (Table 1), indicating that IMF1 contained the dominant oscillation characteristics of real signals. Thus, it is practical to identify the dominant oscillation mode via comparison of energy weights.

The Prony algorithm was analyzed by inputting the original signal and IMF1 separately

(Table 2).

Table 2. Results of low frequency oscillation modes based on noise signal

Method	Mode order	Mode Type	Frequency/ (Hz)	Damping
EEMD/Prony	11	1	0.64	0.11
		2	1.3	-0.81
Prony	29	1	0.63	0.18
		2	1.5	-0.94
Ideal Value	7	1	0.64	0.11
		2	1.3	-0.86

We conclude from Table 2 that: use of Prony algorithm alone into processing of noise-like signals resulted in relatively large errors and a larger number of computation orders, thus complicating the identification of dominant mode. In comparison, the use of EEMD/Prony improved the accuracy in identification of modal parameters and largely reduced the Prony-induced effect of non-dominant mode.

5.2 Case study of power grids

Figure 5 shows the active-power time-domain simulated curves of Hong-Ban Line (Honggou substation - Banqiao substation) and Huang-Wan Line (Huangyan substation - Wanzhou substation) obtained from BPA stability calculation program at sampling interval of 0.01 s when transient ground fault occurred at the Jianshan high-voltage side of Sichuan power grids.

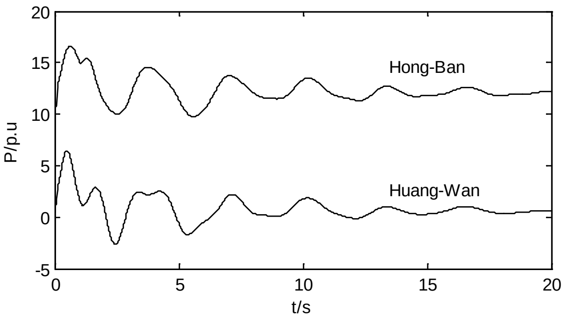

Figure 5. Active-power curves of Hongban Line and Huangwan Line

Table 3. Results of oscillation modes on Hongban Line based on EEMD/Prony

Amplitude/*pu*	Frequency /Hz	Damping	Energy
3.2	0.31	-0.12	110
1.0	0.14	-0.39	15
0.63	0	-4	0.18
0.35	0.58	-0.14	1.1
…	…	…	…
Mode order p=31			

Table 4. Results of oscillation modes on Huangwan Line based on EEMD/Prony

Amplitude/*pu*	Frequency /Hz	Damping	Energy
4.1	0	-0.4	55
2.5	0.31	-0.13	63
2.0	0.1	-0.12	4.4
0.5	0.73	-0.38	24
…	…	…	…
Mode order p=31			

Table 5. Results of oscillation modes on Huangwan Line based on EEMD/Prony

Amplitude/*pu*	Frequency /Hz	Damping	Energy
3.8	0.32	-0.13	130
2.7	0	-3.8	3.4
0.89	0.12	-0.13	7.3
0.69	1.5	-1.1	0.58
…	…	…	…
Mode order p=41			

Clearly, both Hong-Ban Line and Huang-Wan Line contained oscillation frequency of 0.31 Hz (Tables 3 and 4), indicating that such oscillation frequency is the regional oscillation mode strongly associated with Sichuan and Chongqing power grids. The systemic attenuation factors or the real parts of systemic eigenvalues were all negative, indicating that the systems were stable then, which was also reflected from the power oscillation curves. The joint use of EEMD and Prony in extraction of dominant mode greatly reduced the number of computation orders, which helps to rapidly determine the dominant mode and dominant frequency (Table 4 and 5).

6. Conclusion

The combination of EEMD and Prony was used to identify the low-frequency oscillation mode of power systems. With this approach, we can identify a system's low-frequency oscillation modal parameters directly using the data measured at the end, without considering the single or multiple mechanisms generating low-frequency oscillation. When the system is normal operating or the disturbance is small, we first used EEMD to obtain the stable signals containing the dominant mode, and then used Prony algorithm to obtain the corresponding low-frequency oscillation modal parameters. The case study showed that the Prony algorithm after pretreatment with EEMD reduced the number of computation orders and more accurately approached the real oscillation curve.

Along with the wide application of WAMS, this approach with high operation speed and high parameter identification precision will provide new clues and algorithms for study on low-frequency oscillation of power systems.

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