Electrical Power and Energy Systems 92 (2017) 25–33

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Oscillation mode analysis for power grids using adaptive local iterative filter decomposition

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A R T I C L E I N F O

Article history:
Received 23 July 2016
Received in revised form 18 December 2016
Accepted 13 April 2017

Keywords:
Low-frequency oscillation
Iterative filter
Intrinsic Mode Function (IMF)
Fokker–Planck equation

A B S T R A C T

This study proposes an algorithm based on adaptive local iterative filtering decomposition (ALIFD), which is applicable for the feature extraction of a power oscillating signal in a power system. The ALIFD algorithm uses the Fokker–Planck equation to construct the filter function as well as filter sifting to obtain the intrinsic mode function (IMF) with stable features. This algorithm has a solid mathematical foundation and can effectively avoid the mode-mixing problems in the empirical mode decomposition (EMD) algorithm. In this study, the ALIFD algorithm is initially used to obtain the oscillation component. Subsequently, Hilbert Transformation (HT) of each component is performed, and oscillation characteristic parameters are extracted. Analysis results of the test signal, the simulation signal, and the measured data verify the effectiveness of the proposed algorithm. Meanwhile, the comparative results of the EMD algorithm prove that the proposed method is highly adaptive to extracting the characteristics of power oscillation in a power system.

1. Introduction

The extensive application of power electronic equipment gradually strengthens the nonlinear characteristics of modern electrical power systems [1–3]. Active power oscillation demonstrates non-stationary characteristics after a power system is disturbed under extreme conditions [4–6]. This phenomenon presents new challenges in extracting and analyzing the low-frequency oscillation characteristics of power systems based on measured information.

The traditional modal analysis method calculates the low-frequency oscillation characteristic parameters of a power system by decomposing the characteristics of the state-space model obtained from nearby operating points and then analyzing low-frequency oscillation [7,8]. This method is sensitive to component model precision and system scale, which results in its restricted application in large-scale modern interconnected power systems that consists of power electronic equipment and other nonlinear elements. Therefore, relevant technologies that adopt phasor measurement unit (PMU) measured data and nonlinear digital simulation data as bases and those that use modern signal analysis method and parameter identification method to obtain low-frequency oscillation parameters have rapidly developed in recent years.

The Prony algorithm, the matrix pencil algorithm, and the multidimensional Fourier algorithm are the earliest linear signal analysis methods used for the low-frequency oscillation of power systems [9–12]. The application of these algorithms is based on the premise that the power oscillating signal is stable and linear. Determining the accuracy of the most representative Prony algorithm is considerably affected by the noise of the measured data. Although Prony algorithm has constantly improved, it still cannot fulfill the requirements for the precise extraction of the mode parameters of modern power systems. To eliminate the effect of measured noise and the nonlinear characteristic of the signal on the extraction of low-frequency oscillation parameters, Literature [13] and Literature [14] proposed oscillation frequency and damping ratio identification techniques based on continuous Morlet wavelet transform and digital Taylor–Fourier transformation. However, these techniques require setting the number of modes in a signal before calculation; hence, calculating oscillating signals with strong nonlinear and non-stationary power characteristics is difficult. Literature [15] and Literature [16] used the Kalman filter algorithm and the maximum likelihood estimation algorithm to measure statistical power spectral density and to obtain low-frequency oscillation parameters, respectively. The system transfer function should be predicted before using these methods for

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http://dx.doi.org/10.1016/j.ijepes.2017.04.004
0142-0615/

calculation; thus, it is difficult to obtain the system transfer function in actual power systems.

The Hilbert–Huang transform (HHT) is the most representative nonlinear and non-stationary signal analysis method [17]. This technique has been successfully applied in extracting low-frequency oscillation parameters, with an ideal effect under normal circumstances [18,19]. The HHT low-frequency oscillation parameter extraction algorithm initially uses empirical mode decomposition (EMD) to decompose power oscillating signals into a finite number of IMFs. Subsequently, it conducts Hilbert transformation (HT) of the IMF components and then obtains the low-frequency oscillation parameters. The core of this algorithm is EMD. However, the envelope calculation process of the EMD algorithm is considerably affected by noise, which leads to serious mode-mixing problems in the EMD decomposition results of the noise signal. Although the EMD method the result is improved constantly, the mode-mixing problems remain unsolved. Meanwhile, the EMD algorithm lacks a mathematical basis.

In order to deal with the mode-mixing problems existing in EMD algorithm in the decomposition of power oscillation signal, this paper introduces adaptive local iterative filtering decomposition (ALIFD) and presents a new modal extraction approach based on ALIFD. The iterative filter decomposition (IFD) algorithm uses the filter function to replace the envelope calculation of the EMD algorithm. This algorithm has a solid mathematical foundation and can solve the mode-mixing problems in the EMD algorithm to a certain extent. Literature [20] introduced the Fokker–Planck equation to establish the filter function, proposed ALIFD, and improved the adaptability to signal and noise of ALIFD.

The remainder of this paper is organized as follows. Section 2 briefly reviews the IMF and the sifting process. Section 3 introduces core theory and the basic decomposition process of the adaptive local iterative filtering algorithm. Section 4 presents the oscillation parameter identification algorithm based on HT. The proposed method is used to analyze the low-frequency oscillation of the test signals, the digital simulation results, and the measured signals in Section 5. Finally, Section 6 concludes the study.

2. IMF sifting process

The EMD algorithm provides a new method for nonlinear and non-stationary signal analysis. Similarly, variational mode decomposition [21], empirical wavelet transform [22], and synchrosqueezed wavelet transform algorithms [23] have been consecutively proposed. These algorithms aim to obtain the IMF step by step, with each mode satisfying the following conditions:

$$\begin{cases} c_1(t) = \lim\limits_{n\to\infty}\chi_1^n(y(t)) \\ c_k(t) = \lim\limits_{n\to\infty}\chi_k^n(y(t) - \sum\limits_{i=1}^{k-1} c_i(t)) \end{cases}, \tag{1}$$

where $y(t)$ is a given nonlinear and non-stationary signal, χ is the fluctuant operator capturing the fluctuation part, κ is set as the moving operator which is a moving average of the signal $y(t)$, and $\chi(y(t)) = y(t) - \kappa(y(t))$.

Furthermore, the IMF can be obtained through the following selection process.

***Step* 1.** The moving operator $\kappa(y(t))$ of a given non-stationary and nonlinear signal $y(t)$ is calculated.

***Step* 2.** The fluctuant operator χ is obtained by subtracting the moving operator from the original signal $y(t)$ as follows:

$$\chi(y(t)) = y(t) - \kappa(y(t)). \tag{2}$$

***Step* 3.** Whether the wave operator χ satisfies the IMF conditions of Formula (1) is determined. If it does not satisfy the IMF conditions, then Steps 1 and 2 are repeated for the fluctuant operator χ; if it satisfies the IMF conditions, then the IMF component $c_i(t) = \chi$ can be obtained.

***Step* 4.** m components are subtracted from the signal $y(t)$ to obtain the residual component $r(t)$ as follows:

$$r(t) = y(t) - \sum_{i=1}^{m} c_i(t), \tag{3}$$

where $r(t)$ is set as the original signal to repeat Steps 1–3 until the residual component $r(t)$ becomes the trend component.

After finite decomposition, the IMF components with different frequencies in the original signal can be obtained. Then, the original signal can be described as the sum of N IMF components and the remaining components as follows:

$$y(t) = \sum_{i=1}^{N} c_i(t) + r(t). \tag{4}$$

The main difference in various decomposition algorithms lies in the different methods used to calculate the sliding factor κ. In EMD, the moving operator is the mean value of the upper and lower envelope lines of the signal, i.e.,

$$\kappa(y(t)) = \frac{1}{2}(E_u(x) + E_l(x)), \tag{5}$$

where $E_u(x)$ and $E_l(x)$ are the upper and lower envelope lines of the signal $y(t)$, respectively.

3. Adaptive local iterative filter decomposition algorithm

3.1. Iterative filter decomposition (IFD)

The EMD algorithm adopts the cubic spline interpolation algorithm to generate envelope lines, and then uses Formula (5) to calculate the sliding operator. Subsequently, it inhibits the high-frequency components of the signal to certain extent, and results in the situation in which signal decomposition is significantly affected by noise. The results of this algorithm are incomplete. L. Lin and Y. Wang et al. constructed a low-pass filter function to replace the envelope-based sliding operator of EMD and proposed an IFD algorithm [24].

In the iterative filtering algorithm, the moving operator is calculated through the convolution of a given signal $y(t)$ and a filter function $\omega(t)$; that is,

$$\begin{cases} \kappa(y(t)) = \int_{-l(y)}^{l(y)} y(t+s)\omega(s,\ t)ds \\ \int_{-l(y)}^{l(y)} \omega(s,\ t)ds = 1 \end{cases}, \tag{6}$$

where $l(y)$ is the filter length, which can be obtained using Formula (7) as follows:

$$l(y) = 2\left[\frac{S\tau}{m}\right], \tag{7}$$

where τ is the set parameter, which is between 1.6 and 2.0; m is the number of extreme points in the decomposed signal; and S is the signal length.

Performing actual calculation when n in Formula (1) approaches infinity is difficult because of the limited calculation time. When the actual situation is considered, Formula (8) can be used to describe the characteristics of IMF as follows:

$$\begin{cases} |(e_{\min} + e_{\max}) - e_0| \leqslant 1 \\ \frac{E_u(t)+E_l(t)}{2} = 0 \end{cases}, \tag{8}$$