Identifications of Power System Dominant Low-Frequency Eletromechanical Oscillations Using Hilbert Marginal Spectrum

Maja Muftić Dedović(✉) and Samir Avdaković

Faculty of Electrical Engineering, University of Sarajevo, Sarajevo, Bosnia and Herzegovina
maja.muftic-dedovic@etf.unsa.ba

Abstract. Identification of low-frequency electromechanical oscillations (LFEOs) in a power systems is an important aspect of modern systems for monitoring, control and protection. Generally, available signals from power systems are nonlinear and non-stationary, and their treatment requires adequate mathematical techniques. One of the most popular technique for time-frequency signal analysis is the Hilbert-Huang transform, with a very successful application in different fields of science. In this paper, the Hilbert marginal spectrum (HMS) obtained by the Empirical Mode Decomposition (EMD), which separates the signal into several Intrinsic Mode Functions (IMFs), is applied for the identification of the dominant LFEOs in a power system. Results of the HMS approach are tested in two examples and compared with the results obtained using the global wavelet spectrum (GWS) approach.

Keywords: Power system · Low-Frequency electromechanical oscillations Empirical mode decomposition · Hilbert marginal spectrum

1 Introduction

Power system low-frequency electromechanical oscillations (LFEOs) are the result of various events [1]. The LFEOs are mostly damped in character, but in certain situations these oscillations can be undamped in the power system and can lead to the system collapse. Therefore, special attention is paid to the identification of these oscillations, with a special focus on the inter-area oscillations. In literature, the LFEOs are mostly divided into local and inter-area oscillations, with frequencies going up to 5 Hz. Because of the power systems' characteristics available signals are generally nonlinear and non-stationary, and their processing requires appropriate mathematical techniques. A special focus is placed on the time-frequency signal processing techniques, whose results can yield useful conclusions, like the commencement of the disturbance, the dominant frequency, the amplitude, etc. [1, 2]. There are several time-frequency techniques such as the Short-Time Fourier transform (STFT), the Continuous and the Discrete Wavelet Transform (CWT and DWT), the Hilbert-Huang Transform (HHT), which are often used in order to analyze the available signal. A practical application of various techniques of identifying and analyzing the LFEOs, readers can find in [3]. One

M. Hadžikadić and S. Avdaković (eds.), *Advanced Technologies, Systems, and Applications II*, Lecture Notes in Networks and Systems 28,
https://doi.org/10.1007/978-3-319-71321-2_17

of the most popular techniques for the analysis of non-stationary and nonlinear signals and time series in the last fifteen years is the HHT, and in this paper the HHT is used for practical analyses [3–12]. In Refs. [4, 5] two different analytical approaches are presented, with the first being the empirical mode decomposition (EMD) of measured power system oscillations and the second is based on the wavelet analyses. When the same features appear in both techniques at the same time, they have similar, correct results and it is recommended to use these two approaches to analyze rapid variations in non-stationary systems with transitory incorrect occurrence. Also, the comparison between those nonlinear and non-stationary techniques and conventional approaches is given. In [6], the CWT and the HHT are applied to identify aspects of the system's dynamic behavior, even in cases where a power system dynamic characteristics change several times due to load shedding and generation tripping operations [6].

Browne et al. [7] applied comparative assessment of the two techniques for solving the dynamic power system modal identification problem. The first is Prony analysis and assumes stationary signals, and the HHT, which is able to identify non-stationary system behavior. They yield similar results for the stationary signal, but it is recommended that the two techniques complement each other [7]. Laila et al. use refined HHT to characterize time varying, multicomponent inter-area oscillations. This characterization of temporal behavior can be applied to a wide-variety of signals found in large time-variant systems [8].

Applications of the HHT approach for denoising and detrending of measured oscillatory signal is presented in [9]. The measured signal is decomposed into a set of intrinsic mode functions (IMFs) by the EMD. Next, the IMFs are divided into three parts according to the energy relations between IMFs and appropriate distribution in the frequency domain, which considers the features of signal both in time and frequency domain [9]. On the other hand, Nilanjan [10] uses instantaneous phase differences in inter-area oscillations to track generator coherency using the HHT. The EMD calculates the instantaneous phase differences between dominant inter-area modes. This technique has reflection in the application of the reduction of large dynamical systems using empirical method with limited understanding of the system. Also, movements of low frequency electromechanical oscillations (LFEOs) are presented in [11] for the identification of power system areas with coherent generator groups, applying the CWT and the HHT approaches [11].

In this paper, the Hilbert marginal spectrum (HMS) is used for the identification of dominant LFEOs, which represents the distribution of the total amplitude (energy) depending on the frequency. With respect to [12, 13], it can be concluded that this approach has the higher resolution ratio and a clearer frequency presentation of the analyzed signal with respect to the Fourier spectrum. The results obtained in practical analysis are compared with Global Wavelet Spectrum aspect [6]. The Matlab codes based on Refs. [14, 15, 17] are used for calculations.

The paper is organized as follows: Sect. 2 briefly presents the HHT method and calculation of the HMS. The practical analysis of the test system and the signals from the real European system is presented in Sect. 3, while the conclusions are presented in Sect. 4.

2 Background

In this section, a brief review of the approach is based on [12–14]. The HHT performs signal decomposition or the time series on a finite number of components. After application of the EMD, the Hilbert transform is applied on every component of a signal, and the instantaneous frequency is obtained. The EMD decomposes signal to a finite number of Intrinsic Mode Functions (IMFs). The IMFs must meet two requirements:

(i) For a full set of data the number of extreme and the number of zero-crossings must either be equal or different by one at most.
(ii) The mean value envelope defined by the local maxima and the envelope, which is determined by local minimum is zero at any point.

Process of extracting an IMF is given with the following algorithm:
STEP-1: For original signal $x(t)$ identifies the extremes (both maxima and minima). Because of physicality of the LFEOs in the power system, signals $x(t)$ selected for practical analyses are oscillations of active power and frequency and best represent the dynamic electromechanical processes in an electric power system.

STEP-2: Use cubic spline functions for connecting local maxima and local minima and thus generate the upper and lower envelopes, $u(t)$ and $d(t)$, respectively.
STEP-3: Determine the local mean:

$$m_1(t) = (u(t) + d(t))/2 \tag{1}$$

STEP-4: IMF should have zero local mean:

$$h_1(t) = x(t) - m_1 \tag{2}$$

STEP-5: If $h_1(t)$ do not meet conditions of IMFs, procedure is repeating and $h_1(t)$ is concerned with a new signal. Determinate $h_{11}(t)$:

$$h_{11}(t) = x(t) - m_{11} \tag{3}$$

where m_{11} is mean of the upper and lower envelope of the signal $h_1(t)$.
STEP-6: Procedure is repeated k times, or until component $h_{1k}(t)$ is obtained, which meets the conditions for the IMF.

In that case $h_{1k}(t)$ is designated as the first IMF component $c_1(t)$, derived function contains the highest frequency occurring in the analyzed signal. After identifying the first IMF, it is subtracted from the original signal. The result of subtraction is residual and proceeding EMD procedure is treated as the original signal, which is subject to the same process of filtering. The procedure is repeated until you find all the components (final residue should be constant or monotonic function), or until a pre-defined condition is fulfilled. At the end of the decomposition, the original signal has the following form:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{4}$$

where,

$c_i(t)$—ith IMF, n is the number of intrinsic modes;

$r_n(t)$—final residual.

Having obtained the IMF component of analyzed signal, perform the Hilbert transform on each component. If $H[c_i(t)]$ denotes HHT of ith IMF component, then the analytical form of the signal $c_i(t)$ is formed by:

$$z_i(t) = c_i(t) + jH[c_i(t)] = a_i(t)e^{j\phi_i(t)} \tag{5}$$

$$a_i(t) = \sqrt{c_i(t)^2 + H[c_i(t)]^2} \tag{6}$$

$$\phi_i(t) = \arctan\frac{H[c_i(t)]}{c_i(t)} \tag{7}$$

The instantaneous frequency is as shown:

$$w_i(t) = \frac{d\phi_i(t)}{dt} \tag{8}$$

If $a_i(t)$, $\theta_i(t)$ and $\omega_i(t)$ denote amplitude, phase and instantaneous frequency of signal $z_i(t)$ respectively, original signal is as shown:

$$x(t) = H[\omega, t] = \text{Re}\left\{a_i(t)\exp(j \cdot \int \omega_i(t)dt)\right\} \tag{9}$$

This denotes to The Hilbert-Huang spectrum. For this The Hilbert-Huang spectrum Hilbert marginal spectrum is defined as:

$$h(\omega) = \int_0^T H[\omega, t]dt \tag{10}$$

where, T is the duration of the signal.

The Hilbert-Huang spectrum produces time-frequency distribution of amplitude, while the Hilbert marginal spectrum represents distribution of amplitude (energy) depending on the frequency [12–14]. Having in mind the research presented in Refs. [12, 13], we can conclude that this approach has the higher resolution ratio and a clearer presentation of the analyzed signal frequency components compared to the Fourier spectrum.

In this paper, the HMS obtained by the EMD is applied for the identification of the dominant LFEOs in a power system and results of the HMS approach, tested in two examples, are compared with the results obtained using the global wavelet spectrum (GWS) approach. Detailed mathematical elaboration of the CWT and the GWS readers can find in [11, 17], so it will not be presented in this paper. Generally, the CWT of discrete signal is defined as the time series or a signal convolution with a scaled and translated version of the complex conjugate of a wavelet function [11]. The Morlet function is selected for practical analyses, because it provides a great balance between time and frequency localization. As a results of the CWT analysis, wavelet power spectrum (WPS) of a signal x is obtained and presented on the time-frequency maps, providing a lot of useful information. After obtaining the WPS, it is very practical to show that information as an average value of result on the range of a scale or time by defining the GWS [11, 17].

3 Results from the Test System and Signals from Real System

The Kundur two-area test system is selected as a first example of practical analysis and identification of the LFEOs ([4], pp. 813). This system consists of four generating units, where 400 MW transmits from one area to another through two parallel lines. In the analysis generators are equipped with automatic voltage regulators (AVR). The results of the LFEOs for different control device characteristics are presented in [1], which is confirmed by the modal analysis too. Results of modal analysis will not be presented in this paper, but it should be noted that in this test system inter-area mode frequency is around 0.5 Hz. After the simulation of outage of the transmission line between Bus 7 and Bus 8 (one of the parallel lines), the oscillations occurred through the system. The active power oscillation in p.u. is presented in Fig. 1, where the base power of the test system is 100 MVA. Results of the signal processing using two selected approaches are presented in Fig. 2. Using the CWT with the Morlet wavelet function, the GWS result as time-averaged wavelet spectrum is presented in Fig. 2a, and it clearly identifies the dominant oscillatory mode at about 0.5 Hz, which confirms the expected results. Further, the results of the HMS approach are shown in Fig. 2b, where it can also be concluded that the HMS approach for signal from Fig. 1, clearly identifies the dominant oscillatory mode of 0.5 Hz.

The second example is the analysis of signal frequencies obtained after the disturbance in the Turkey power system in 2010 (Fig. 3). The signals are measured in different parts of the European power system and obtained via implemented European wide area monitoring system. Over the same signals different analysis are presented in [11, 16].

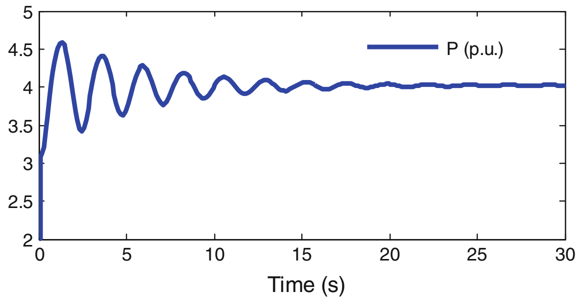

Fig. 1. An active power oscillation on transmission line 7–8 after tie-line tripping

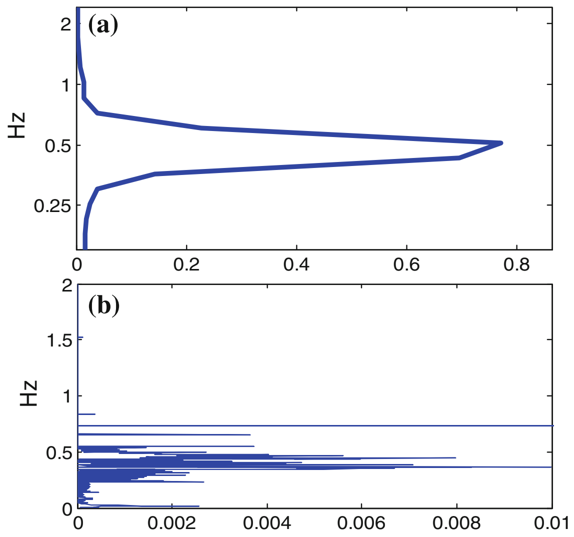

Fig. 2. **a** GWS and **b** HMS results of a signal analysis from Fig. 1

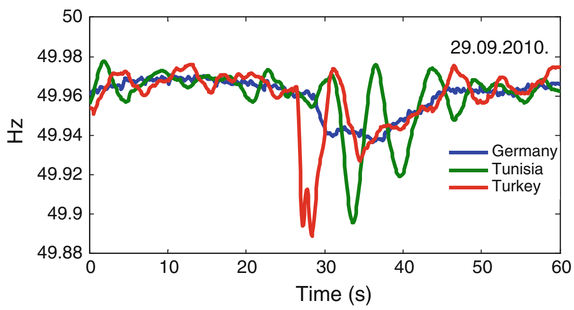

Fig. 3. Frequency oscillations during outage of the generation unit in the Eastern Turkey [11, 16]

After disturbances in the system (outage of the generator) an imbalance of active power has occurred and frequency oscillations in different points of interconnection can be seen in Fig. 3. After a time interval of a few seconds, disturbance is propagated through the system and affected other parts of the interconnection. In addition to the frequency changes in Turkey, the frequency changes in Germany and Tunisia are also presented (Fig. 3). The analysis is performed on the frequency signals (which are synchronously measured through existing Wide Area Monitoring System), and the results are presented in Fig. 4.

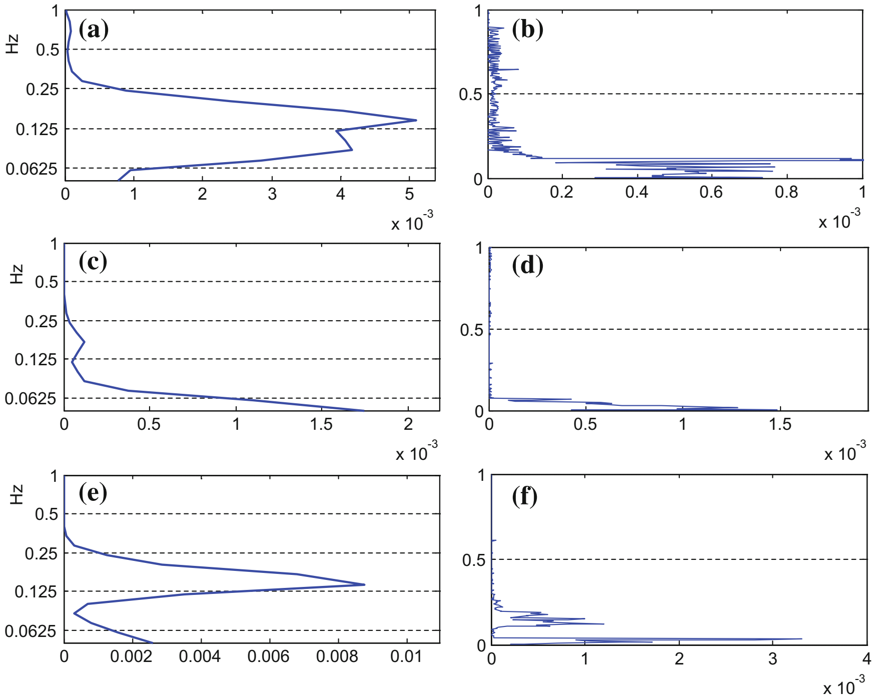

Fig. 4. Result comparison for GWS and HMS approach: **a** GWS Turkey, **b** HMS Turkey, **c** GWS Germany, **d** HMS Germany, **e** GWS Tunisia and **f** HMS Tunisia

Analyzing the results obtained from the processing signal frequency oscillations in Turkey, it can be concluded that the dominant oscillatory modes for both approaches are identified in the frequency range of up to 0.25 Hz. (Figure 4a, b). Both approaches identify the same frequencies at about 0.14 and 0.09 Hz. The amplitude of the 0.14 Hz frequency for both approaches is higher compared to the amplitude of 0.09 Hz frequency. Time scope of occurrence of these frequencies and length of their duration can be identified at the time-frequency maps (time-frequency representation) for both approaches, but in this paper due to the large number of figures, these results are not presented. By analyzing the signal measured in Germany using the GWS approach, it can be concluded that the dominant frequency is identified at about 0.17 Hz. A more detailed analysis of the time-frequency map found that this frequency occurred immediately after the disturbance and soon disappeared. The HMS approach identified the frequencies around 0.09 Hz (Fig. 4d) and in this case results based on the GWS approach are different compared to the HMS approach. The higher oscillations after disturbance propagation through the observed power system are identified in Tunisia, which is evident in Fig. 3. It is clear, for both approaches, that the dominant frequencies are about 0.14 Hz (Fig. 4e, f). Generally from previous analyses, it can be concluded that the HMS approach for analyzing signals from the real power system and comparing them with the GWS approach, correctly identified the dominant oscillatory modes.

4 Conclusion

In this paper, the HMS approach is applied to identify the dominant LFEOs. The results obtained from the HMS approach are compared to the results of the GWS approach. By practical signal analysis using the test system and the signal measured in real power system, the HMS approach correctly identified the dominant oscillatory modes. In general, both approaches (the CWT and the HHT) are excellent mathematical tools for analyzing non-stationary and nonlinear signals and are very effective tools for the localization of the frequency and amplitude of the observed signal in time. In the context of identification and analysis of the LFEOs, with special attention to inter-area oscillations, both approaches in a time-frequency presentation of results, identify the beginning of a certain disturbance, and from the CWT coefficients or the IMFs, the frequencies and their damping can be identified. The GWS and the HMS approaches clearly distinguish dominant oscillation modes and can provide very useful information for the operators of a power system

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