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Estimation of mode shape in power systems under ambient conditions using advanced signal processing approach

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Abstract: This paper presents a dynamic approach for the monitoring and estimation of electromechanical oscillatory modes in the power system in real time with less computational burden. Extensive implementation of phasor measurement units (PMU) and the utilization of advanced signal processing techniques help in identifying the dynamic behaviors of oscillatory modes. Conventional nonstationary analysis techniques are computationally weak to handle a larger quantity of data in real-time. This research utilizes the variational mode decomposition (VMD) for signal decomposition, which is highly tolerant to noise and computationally more robust. The predefined parameters of the VMD process are assigned using FFT analysis of the signal. The significant decomposed mode resembling the original signal is determined using the correlation coefficient method and used for low-frequency mode estimation. The spectral analysis techniques are used to determine the instantaneous mode shapes, which help to identify the source of oscillation in the power system network. The proposed methodology has been tested using signals obtained from two area Kundur system and actual PMU data recorded from Power System Operation Corporation (POSOCO) Limited of the Indian Power grid. The results confirm the superior viability and adaptability of the proposed approach. The performance comparison with other existing signal processing techniques used to estimate low-frequency modes is also presented to illustrate the effectiveness of the proposed method.

Key words: Cross power spectral density, empirical mode decomposition, mode shape, phasor measurement unit, power spectral density, variational mode decomposition

1. Introduction

Modern power systems face a severe challenge in extracting and quantifying dynamic oscillations. Large-scale integration of renewable energy technologies has resulted in small and large disturbances in the power system network, which led to the reduction in damping of low-frequency power oscillations. Therefore, it is necessary to identify these low-frequency oscillatory modes and their characteristics such as amplitude, frequency, damping ratio, and mode shape or relative phase [1, 2]. These global features aid in the easy and dynamic visualization of the stressed part of the system. Mode shape is defined as the relative magnitude and phase of the oscillation within the system. It is described with respect to the right eigenvectors obtained from a state matrix of the linearized power system model [3]. An extensive review of the existing mode estimation techniques using transient or ringdown and ambient signals are provided in [4]. By analyzing the mode shape in the compass plot or polar plot, immediate remedial actions are initiated to prevent cascading events due to loss of synchronism. Here the length of the phasor represents the oscillatory amplitude. When identifying the oscillation source, the

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generator leading in phase having a smaller damping ratio, acts as the oscillation source [5].

The advancements in wide area monitoring systems (WAMS) and the data driven analysis techniques provide critical information about the oscillatory behaviour of the system. Advanced signal processing algorithms along with high sampling resolution of phasor measurement units (PMUs), enable the system operator to quickly identify the interarea oscillations and take appropriate control actions in near real-time before the cascading occurs. One of the pioneer methods in the field of measurement-based analysis technique is Prony analysis [6, 7]. It involves a polynomial-based approach, and the determination of the polynomial coefficient in the matrix equation leads to the estimation of modal parameters. The drawback of the Prony method is that it is confined to lower-order polynomials [8]. To overcome this drawback, matrix pencil method (MPM) which is effective even in closely spaced modes are used. MPM's most significant disadvantage lies in determining the suitable pencil parameter [9]. The above two techniques are mainly used for the ringdown oscillation studies, whereas the techniques used for ambient oscillation studies are classified as transfer function methods [10, 11] and subspace methods [12–14]. In terms of accuracy, the subspace approach showed promising results; however, transfer function methods require less computation time and are preferred for real-time situational awareness [15].

Most of the research works in this field deal with the stationarity concept. IEEE task force for identifying electromechanical modes in power system has proposed the method of nonlinear nonstationary analysis [16]. Empirical mode decomposition (EMD) has been introduced as the benchmark technique in this kind of research. In combination with the Hilbert transform, EMD produces better results in the mode identification process. However, EMD is challenged due to its mode mixing issues [17, 18]. Based on the de-noising capability, EMD is enhanced to ensemble EMD (EEMD) and complete ensemble EMD. The empirical wavelet transform (EWT) method works well for equally spaced modes in recognising low-frequency modes of nonperiodic and time-varying oscillation but they struggle in separating closely spaced modes [19, 20]. The drawbacks of EMD and EWT are solved in Variational mode decomposition (VMD), a signal decomposition technique with nonrecursive nature proposed by Dragomiretskiy et al. [21]. This methodology has a credible theoretical foundation and exhibits better denoising property. VMD comprises of an adaptive Wiener filter bank that can efficiently decompose the test signal with a center frequency into restricted bandwidths. It uses a nonlinear multi-resolution method for decomposing nonstationary signals through ideal formulation into its constituent modes, ensuring that the spectral separation for each mode is not influenced by the frequency resolution of the sampled signals. However, VMD requires operator intervention to select its initial parameters like the mode number and quadratic penalty terms [22, 23]. A power disturbance analysis method using variational mode decomposition (VMD) is validated on an IEEE 68 bus New England test system [24]. A dynamic approach based on two-stage mode decomposition (TSMD) has been proposed in [25, 26], which uses complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) as the first stage [27] and variational mode decomposition (VMD) as the second stage [28, 29]. Nevertheless, owing to two decomposition stages, mode shape characterization requires more significant computing time. The work presented in this paper proposes a single stage decomposition process using VMD to estimate instantaneous mode shapes of oscillatory modes from a real time PMU data by incorporating a computationally viable method for choosing a suitable mode number. The assumption of mode number is very significant in the performance of VMD because an improper mode number replicates the decomposition modes and therefore affects the computational time. In this work, the appropriate value of mode number is obtained by counting the number of peaks in the FFT of sampled data within the frequency range of 2 Hz [23].

After the decomposition, the power spectral densities (PSD) are plotted for the decomposed modes using the multitaper technique, and the low-frequency modes are identified. The values of PSD and cross power spectrum density (CPSD) are checked, and the relative phase values are calculated [30, 31].

The significant contributions of this paper are:

- A dynamic approach to identify low-frequency oscillatory modes in the power systems, utilising a single decomposition process with less computation time is proposed.
- The proposed method uses VMD and spectral analysis as the major techniques to estimate the mode shape.
- Observed a reduction in computational complexity compared to other reported signal processing techniques, when the proposed method is applied for the real-time PMU data to detect undamped or weekly damped oscillations.

The organization of the article is as follows: Section 2 discusses the basic techniques of VMD, PSD, and CPSD. the proposed approach of estimating the low-frequency oscillatory modes and mode shapes is illustrated in Section 3. Mode shape analysis of the two area Kundur system is presented in Section 4, followed by the mode shape analysis of real-time PMU data obtained from the power system operation corporation (POSOCO) limited in Section 5. Finally, the conclusions are presented in Section 6.

2. Methodology

This section briefly discusses the various techniques used in the proposed approach. It includes the VMD approach, sensitive IMF selection using correlation coefficient, and spectral analysis techniques.

2.1. Variational mode decomposition

VMD is a multi-resolution analytical signal decomposition method based on the concepts of adaptive Wiener filtering, one-dimensional Hilbert transform, and Heterodyne demodulation. VMD's motive is to decompose a real-valued nonlinear nonstationary signal $f(t)$ into a discrete set of quasi-orthogonal intrinsic mode functions (IMF) represented as u_k where K denotes the mode number. This set of IMF signals is amplitude modulated, and frequency signals with a center frequency of ω_k. VMD requires the subsequent computational processes as follows:

1. Hilbert transform [21] is applied to the one-sided spectrum of each of the IMFs to compute its signal characteristics.
2. A multiplication factor of $e^{j\omega_k t}$ is considered to shift the frequency spectrum of mode to baseband.
3. The estimation of bandwidth using gradient of modulated signal based on the $L2$ norm.

The VMD method is assumed as a constrained optimization problem as in Eq. 1

$$\min\left(\omega_k, u_k\right)\left\{\sum_{k=1}^{K}\left\|\delta_t\left[\left(\delta(t)+\frac{i}{\pi t}\right)*u_k(t)\right]e^{-i\omega_k t}\right\|_2\right\} \tag{1}$$

such that $\sum\limits_{k=1}^{K} u_k(t) = f(t)$

The objective function is modified into an unconstrained optimization problem as in Eq. 2:

$$L(\{u_k\},\{\omega_k\},\{\lambda\}) = \alpha \sum_{k=1}^{K} \left\| \delta_t \left[\left(\delta(t) + \frac{i}{\pi t} \right) * u_k(t) \right] e^{-i\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_{k=1}^{K} u_k(t) \right\|_2^2 + \left\langle \lambda, f(t) - \sum_{k=1}^{K} u_k(t) \right\rangle \tag{2}$$

where α is the quadratic penalty term and λ is the Lagrangian multiplier. VMD process calculates these central frequencies and IMFs at these frequencies concurrently using an optimization technique called the alternate direction method of multipliers [32]. The various modes are determined by updating the previous mode and its center frequency as follows

$$\widehat{u}_k^{n+1} = \frac{f - \sum\limits_{i<k} \widehat{u}_i^{\,n+1} - \sum\limits_{i>k} \widehat{u}_i^{\,n} + \frac{\lambda^n}{2}}{1 + 2\alpha(\omega - \omega_k{}^n)^2} \tag{3}$$

$$\widehat{\omega}_k^{n+1} = \frac{\int_0^{\omega} \omega \left| \widehat{u}_k^{n+1}(\omega) \right|^2 d\omega}{\int_0^{\omega} \left| \widehat{u}_k^{n+1}(\omega) \right|^2 d\omega} \tag{4}$$

Once the modes and center frequencies are updated, the Lagrangian multiplier is also restructured as per Eq. 5.

$$\widehat{\lambda}^{n+1} = \widehat{\lambda}^n + \left(f - \sum_k \widehat{u_k}^{n+1} \right) \tag{5}$$

The updation process is performed until the convergence criteria presented in Eq. 6 are satisfied with a tolerance value of ε.

$$\sum_k \frac{\left\| \widehat{u}_k^{n+1} - \widehat{u}_k^{n} \right\|_2^2}{\left\| \widehat{u}_k^{n} \right\|_2^2} < \varepsilon \tag{6}$$

The flowchart shown in Figure 1 represents the stages of VMD process. The number of IMFs extracted depends on the preset value of the mode number. Parameters like fidelity factor (α) and mode number (K) are needed to initialise the VMD operation. These two parameter values are typically allocated randomly, leading to unwanted decomposition stages leading to large processing time. The computational performance of the VMD process is highly dependent especially on the value of mode number. In this work, to avoid the random selection of mode number, the data samples from the PMU have undergone Fourier transform. The number of peaks in the Fourier spectra was identified and assigned as the mode number. With regard to the fidelity factor, typically for low-frequency extraction, higher values of α are preferred. After multiple computer simulation a value of 8000 has been chosen for α, as a further increase in the value has not given any specific improvement in the performance of the VMD process in the work. The selection of appropriate IMF for the mode assessment is discussed in the following subsection.

2.2. Sensitive IMF selection stage

IMF selection can be made in different ways such as using correlation coefficient, kurtosis, spectral properties, or as a hybrid method consisting of the above techniques optimized by genetic algorithm (GA) or particle swarm optimization (PSO). The effective determination of dominant frequency modes needs a proper IMF selection strategy with less computational complexity. Therefore, a correlation coefficient based sensitive IMF index formation is considered in this work [33]. The correlation between the primary signal and the decomposed mode functions was checked, and the correlation coefficient $(\delta_{q,x})$ is computed for each IMF according to Eq. 7:

$$\delta_{q_i,x} = \frac{\sum_{i=1}^{N} (x(n) - \overline{x})(q_i(n) - \overline{q_i})}{\sigma_{qi}\sigma_x} \tag{7}$$

where $q_i(n)$ represents the i^{th} decomposed IMF, σ_{qi} and σ_x denote the standard deviations, $\overline{x}$ and $\overline{q_i}$ represent the mean values. In order to identify the most correlated IMF, a sensitive IMF index $S_i(i)$ is calculated as per Eq. 8:

$$S_i(i) = \frac{\delta_{q_i}}{\sum \delta_{q_i}} \tag{8}$$

The index values are determined for all the decomposed modes, and those with the highest index value are selected for mode parameter estimation. The low-frequency modes can be extracted by analysing the selected IMF with power spectral density (PSD) patterns like welch, multitaper, and Yule walker methods [27].

2.3. Spectral analysis technique

Spectral analysis refers to the method of estimating the power content of the frequency component of a signal. Power spectral density (PSD) is an efficient way to describe the amplitude versus frequency content of a random signal. The simple PSD estimation techniques like Welch's method, multitaper method, Burg's method, or Yule-Walker method can be adapted [25]. A random stationary signal $x(m)$ whose PSD is mathematically related to the autocorrelation sequence through Discrete-time Fourier transform (DTFT) can be represented using Eq. 9:

$$P_{xx}(\omega) = \frac{1}{2\pi} \sum_{n=-\infty}^{\infty} R_{xx}(n) e^{-i\omega n} \tag{9}$$

where $R_{xx}(n)$ is the autocorrelation sequence as shown in Eq. 10:

$$\begin{aligned} &R_{xx}(n) = E\left\{x^*(m)x(m+n)\right\} \\ &-\infty < m < \infty \end{aligned} \tag{10}$$

where n denotes the time lag, $E\{.\}$ represents the expectation value, and $*$ represents the complex conjugate operator. For combined random signals $x(m)$ and $y(m)$, cross power spectral density (CPSD) is defined as the DTFT of the cross-correlation function and is represented using the Eq. 11:

$$P_{xy}(\omega) = \frac{1}{2\pi} \sum_{n=-\infty}^{\infty} R_{xy}(n) e^{-i\omega n} \tag{11}$$

Here $R_{xy}(n)$ is the cross-correlation sequence represented as Eq. 12:

$$R_{xy}(n) = E\left\{x(m+n)y^*(n-m)\right\} \tag{12}$$

To find the relative phase between the signals from two PMU stations, the CPSD function $R_{xy}(n)$ is used. It contains the power shared by two signals at a specific frequency known as common mode frequency and the relative phase shift between the signals. The value of $arctan(R_{xy}(n))$ gives the relative phase shift at common mode frequency. Mode shape curves are plotted based on the relative phase shift between the PMU units.

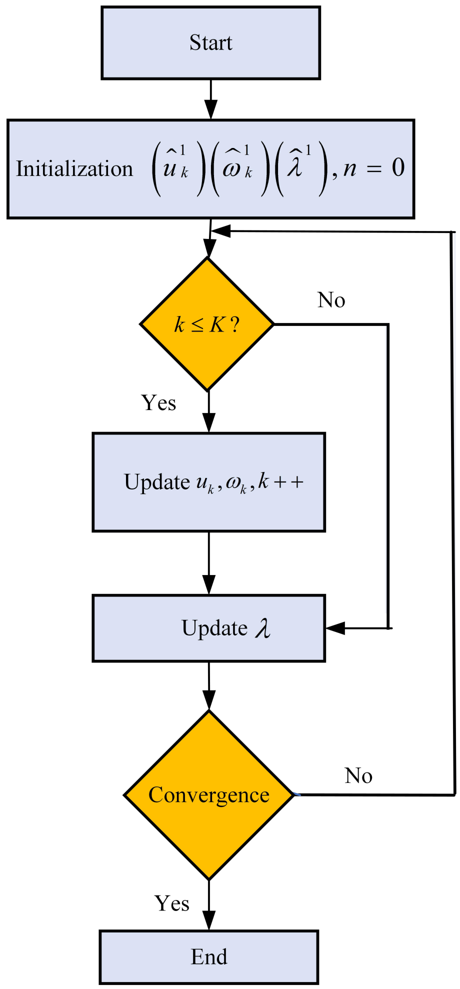

Figure 1. Flowchart of VMD process.

3. Proposed method

The block diagram shown in Figure 2 depicts the overview of the proposed method to identify the oscillatory mode frequency and corresponding instantaneous mode shape. The obtained raw PMU data is effectively preprocessed before its decomposition. Various methods can be adapted based on the quality of the information. Some techniques are as follows: outlier removal, interpolation, means subtraction, and data parcelling [34]. From the above techniques, outlier removal and means subtraction are used in this work. After the preprocessing, the initial parameters for VMD are selected depending on the FFT peaks as explained in section 2. The selection of proper IMF is made by indexing the IMFs based on the correlation coefficient values. The IMFs having the highest value of the index have been chosen for low-frequency mode estimation by analysing PSD. The CPSD values are utilized to determine the relative phase shift among two PMU stations and the mode shapes are analysed using the compass plot. In this work, VMD is applied to Kundur two area system and real-time PMU data from POSOCO. The proposed method is computationally feasible and accurate when compared to other existing techniques such as TSMD, EEMD, and EMD.

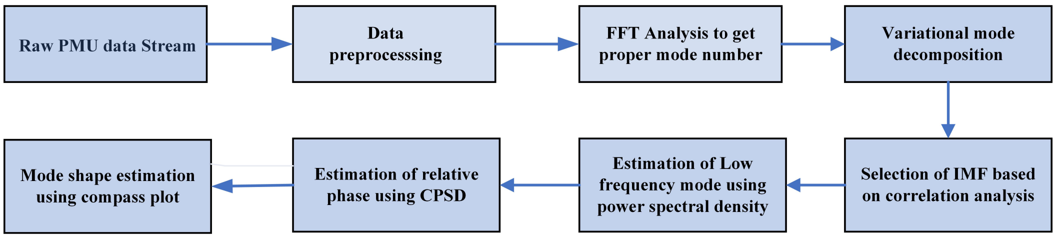

Figure 2. Block diagram of the proposed method.

4. Application of the proposed method in a two area four generator system

The single line diagram of the two area four generator Kundur system is shown in Figure 3. The left area of the system is recognized as Area-1 and the right side as Area-2. This system comprises eleven buses and the two areas are linked by a weak tie-line connecting buses 7 and 9. Two loads are applied to the system on buses 7 and 9 [3]. A three-phase to ground fault is initiated between buses 8 and 9 at 2 s and is removed after 0.3 s. Rotor speed at 60 samples per second is extracted throughout the simulation period of 10 s, and the respective Fourier spectra are shown in Figure 4. White Gaussian noise of signal-noise ratio (SNR) 15dB is added to the rotor speed signal. Three frequencies are identified within the low-frequency region, and hence mode number for the VMD process is three. The fidelity factor is considered as 8000.

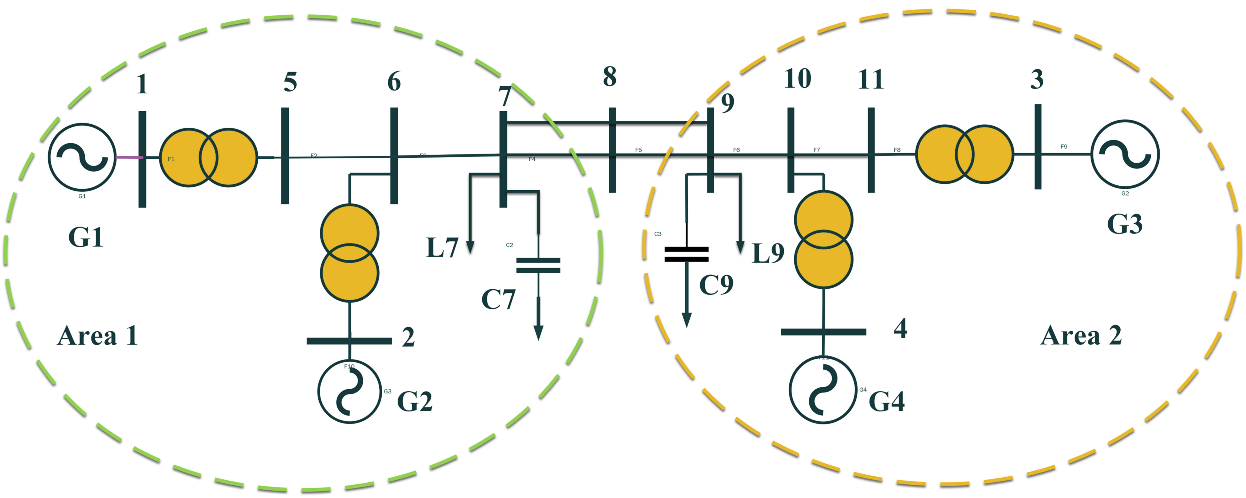

Figure 3. Two area four generator system topology.

The selected mode number and fidelity factor are used to decompose each rotor speed signal for the VMD process. A detailed analysis is presented here on the speed signal obtained from generator 3. The VMD application to rotor speed signal of generator 3 produces three IMFs as shown in Figure 5 where IMF1 is a trend signal which can be eliminated. The spectral densities of IMF2 and IMF3 are analysed, and the repetition of low-frequency modes is observed in IMF2. Hence IMF2 has been selected for further analysis and the power spectral density of IMF2 is as shown in Figure 6. IMF selection can also be done by calculating sensitive

IMF index and is presented in Table 1. IMF2 having a higher index value is selected for further analysis. Three low-frequency oscillatory modes of 0.73 Hz, 1 Hz, and 1.35 Hz are identified from the PSD pattern of IMF2. In these low-frequency modes, 0.73 Hz is considered as the inter-area oscillatory mode, and the mode shape analysis is focused on 0.73 Hz. The proposed VMD method is compared with TSMD, EEMD, and EMD method statistically using SNR versus standard deviation plot and is represented in Figure 7. In terms of accuracy perspective, root mean square error (RMSE) values can be estimated and plotted against standard deviation as shown in Figure 8. Hence the denoising power and the accuracy in error terms are calculated for the proposed method and compared with the existing algorithms. It is observed that VMD is more robust than other algorithms.

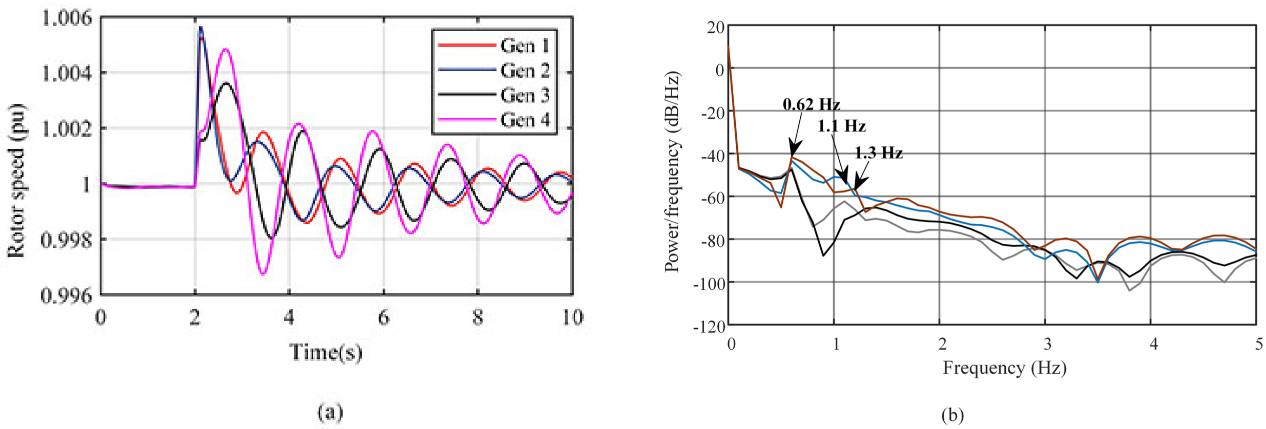

Figure 4. Rotor speed signals (a) waveform (b) Fourier spectra.

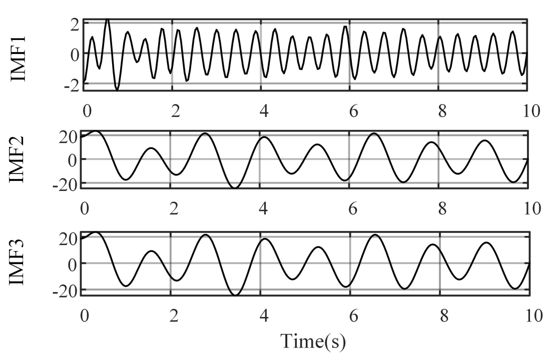

Figure 5. Decomposed IMFs after VMD process for the rotor speed signal of generator 3.

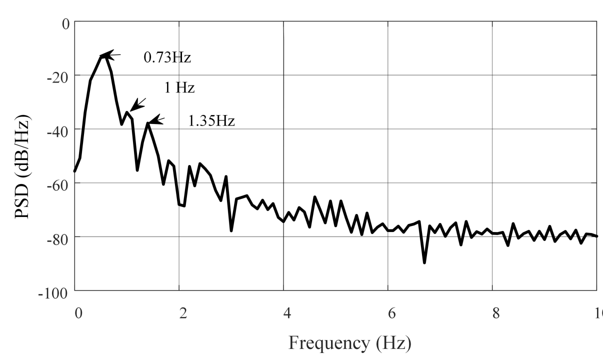

Figure 6. Power spectral density of IMF2.

Table 1. Sensitive IMF index values corresponding generator 3.

IMF	Index value
1	0.085
2	0.156
3	0.142

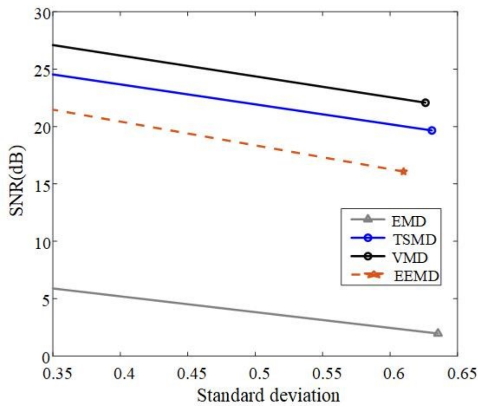

Figure 7. SNR vs. standard deviation.

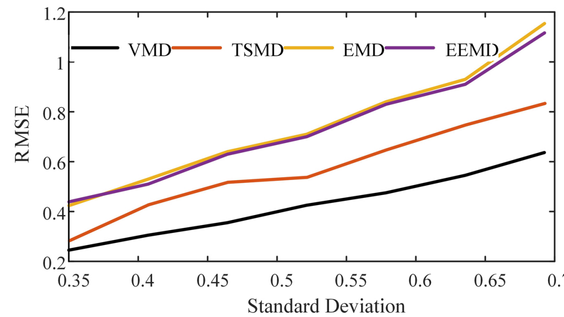

Figure 8. RMSE vs. standard deviation.

After estimating low-frequency modes, instantaneous mode shapes are drawn based on the low-frequency mode. To obtain the mode shape, CPSD values for different rotor speed signals are evaluated. Similarly, IMF selection is done for the remaining rotor speed signals of generators and IMF2 is selected generously after the VMD process. A reference waveform as shown in Eq. 13, is generated based on the common mode frequency of 0.73 Hz.

$$x(t) = \sin 2\pi(0.73)t \tag{13}$$

The magnitude of CPSD is determined and the phase difference is computed according to Eq. 14.

$$\text{Phase difference}, \phi = \arctan(R_{xy}(0.73)) \tag{14}$$

where x represents the reference signal, and y represents the speed signal. The CPSD values estimated for all rotor speed signals corresponding to IMF2 are shown in Table 2. The mode shape plot corresponding to 0.73 Hz is shown in Figure 9.

The simulation was carried out using a machine with 2.3 GHz dual core intel i5 8 GB RAM. The CPU time and memory usage were identified using MATLAB commands. The computational strength of the proposed method is compared with that of other methods with spectral analysis procedure in terms of the number of modes, processing time, and memory usage and are presented in Table 3 and it is evident that the proposed method requires fewer iterations and memory usage than other methods.

Table 2. CPSD values corresponding to 0.73 Hz.

Machine number	CPSD value	IMF level
1	0.723 + 0.267i	2
2	0.675 + 0.352i	2
3	–0.632–0.278i	2
4	–0.687–0.318i	2

5. Application of actual PMU data

This section describes the mode shape determination in a real power system using real-time PMU data from different stations at a sampling rate of 25 Hz. There are five regional grid networks in the Indian grid market,

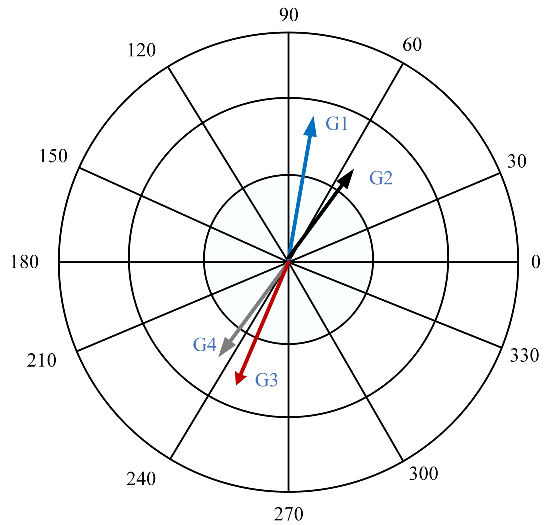

Figure 9. Mode shape of two area four generator system using the proposed method.

Table 3. Comparison of computational strength among different algorithms.

Parameter	**Proposed method**	**TSMD**	**EEMD**	**EMD**
Number of modes	2	4	7	9
Processing time or CPU time (ms)	45	62	63	72
Memory usage (MB)	350	421	452	486

enabling electricity transmission between states in each region. Real-time frequency data is obtained from the POSOCO Limited Bangalore. Around thousand samples of PMU station data from the Ballia unit are taken as the reference. It has been observed that a 5% to 95% deviation in active power generation from Kahalgaon thermal power plant on 17th March 2018 resulted in ambient oscillations across the grid. As a preliminary study, such a massive change in generation may be the reason behind the low-frequency oscillations. The PMU data from Durgapur, Farakka, Jamshedpur, and Vindhyachal are considered the analysis. Geographically Vindhyachal and Ballia are at a distance of 200 km. Also, Durgapur, Farakka, and Jamshedpur are approximately 210 km apart. The frequency data is analysed for the duration of 40 s which includes the major oscillation event of ambient nature.

The real-time PMU signals from POSOCO are represented in Figure 10, and the critical disturbance is noted within the range of 27–32 s. The Fourier spectra of the signals are shown in Figure 11 where two prominent low-frequency peaks were observed. As specified by the preprocessing step a median filter is used to remove the outliers. Then the mean value of the test signals is calculated and a detrended value is formed which is the difference between the initial signal and its mean. After the preprocessing procedure, test signals are subjected to the VMD process. The mode number is given a value of 2 depending on the Fourier spectra of PMU data processed. Two decomposition modes are obtained, and IMF2 is selected for the low-frequency oscillation mode analysis. The CPSD plot of different PMU units corresponding to IMF2, exhibited three low-frequency modes, 0.39 Hz, 0.585 Hz, and 1.563 Hz as shown in Figure 12.

The phase of the particular mode with respect to reference station Ballia is determined. Accurate determination of the relative phase is influenced by sampling noise and traveling of a specific mode. The

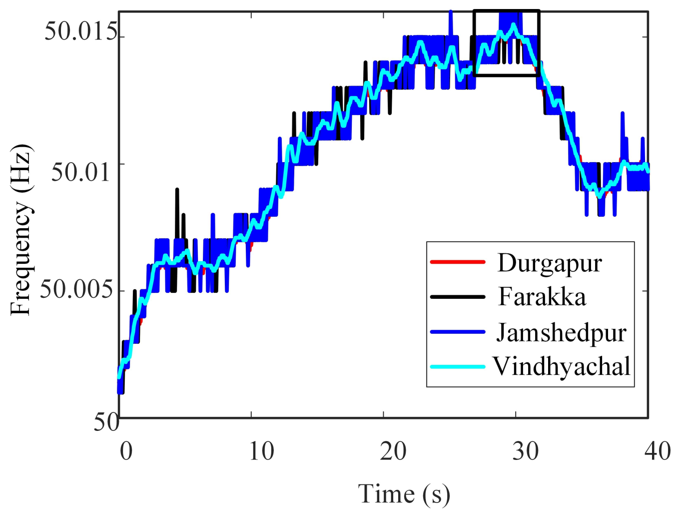

Figure 10. PMU data from POSOCO.

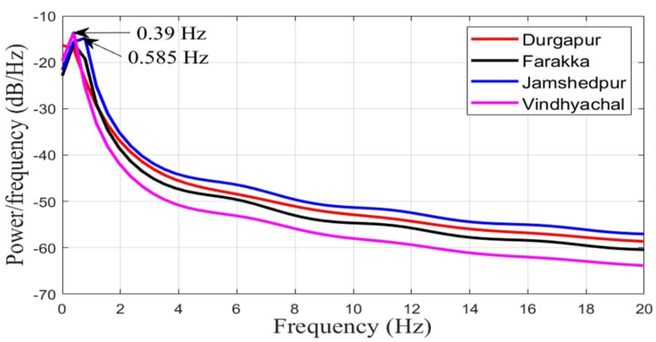

Figure 11. Fourier spectra of PMU data.

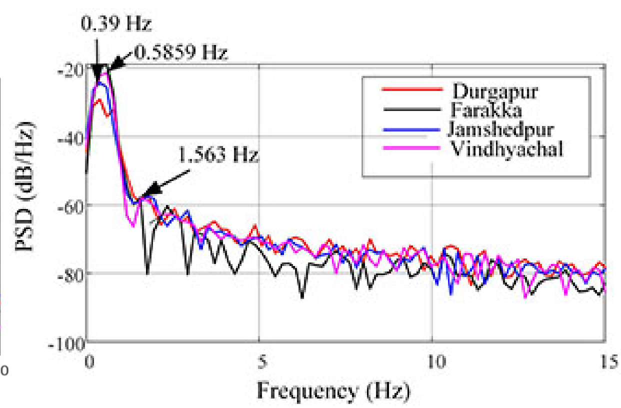

Figure 12. Magnitude of CPSD values corresponding to IMF2.

instantaneous mode shape can be plotted in real-time based on the CPSD values. CPSD value from the decomposed component gives the relative phase and hence the mode shape curve along the corresponding frequency modes. This instantaneous mode shape helps the system operator to determine the real-time variation in a single-window procedure. The mode shape curve at the instant of 20 s and 40 s corresponding to 1.563 Hz, 0.585 Hz, and 0.39 Hz are presented in Figure 13, Figure 14, and Figure 15, respectively. It is confirmed from the instantaneous mode shape curve that 1.563 Hz corresponding to the local area mode of oscillation and the other two low-frequency modes correspond to inter area mode of oscillation. With the help of the proposed method, an operator can easily identify the power system oscillation status in real time through the visualisation of instantaneous mode shape curves and can act immediately for an event happening in the power grid. These low-frequency points are already validated with POSOCO reports. The CPU time and memory usage are estimated for the whole process including the decomposition and spectral analysis procedure and are shown in Table 4. The proposed method supersedes other algorithms and shows better computational strength compared to other techniques. The existence of these modes is confirmed in the POSOCO reports [35].

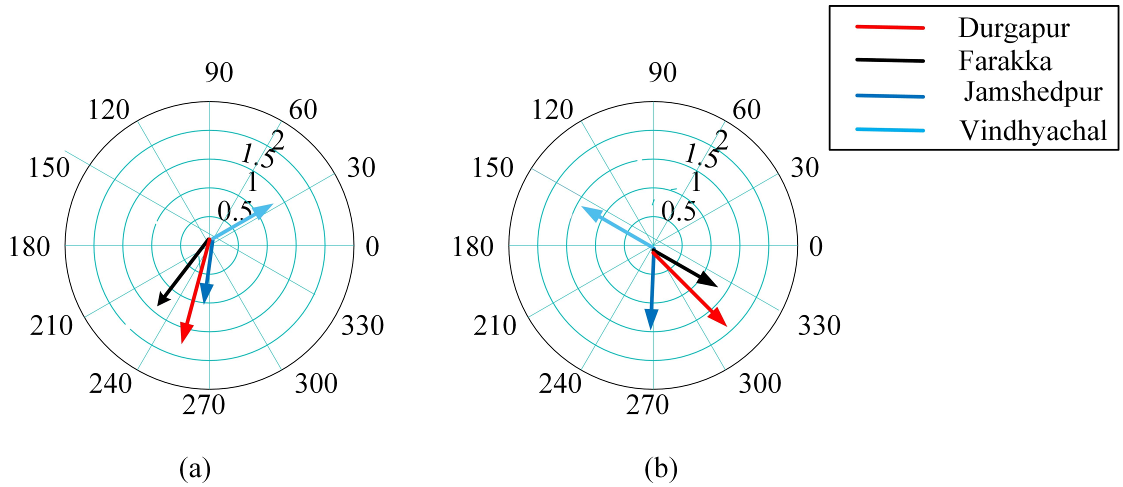

Figure 13. Instantaneous mode shape for 1.563 Hz mode through spectral analysis (a) at 20 s, (b) at 40 s.

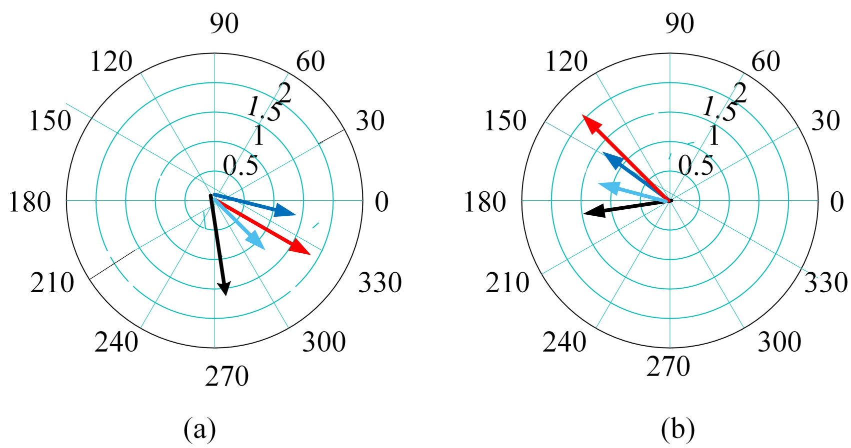

Figure 14. Instantaneous mode shape for 0.585 Hz mode through spectral analysis (a) at 20 s, (b) at 40 s.

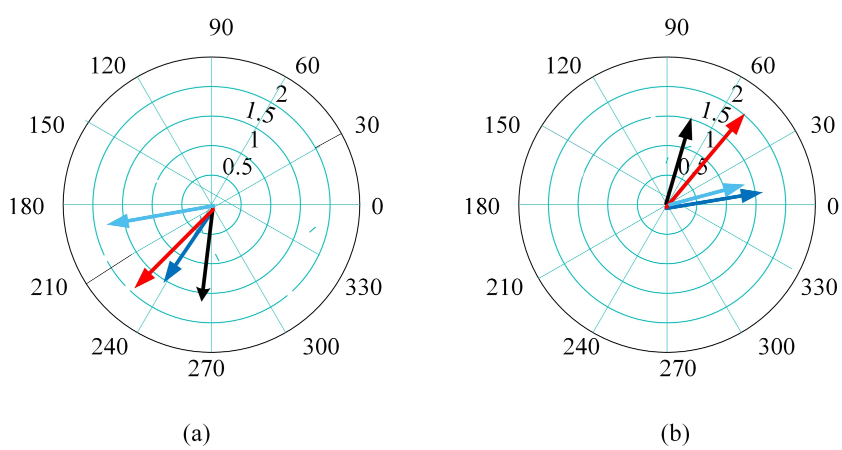

Figure 15. Instantaneous mode shape for 0.39 Hz mode through spectral analysis (a) at 20 s, (b) at 40 s.

Table 4. Comparison of computational strength of different algorithm on PMU data.

Parameter	Proposed method	TSMD	EEMD	EMD
Number of modes	2	3	8	11
Processing time or CPU time (ms)	91	130	152	180
Memory usage (MB)	376	452	466	496

6. Conclusion

This paper introduces a robust dynamic approach for identifying low-frequency oscillatory modes and determining instantaneous mode shape in real-time PMU signals with minimum computational complexity. The major drawback of the conventional low-frequency mode identification method is its lower accuracy and computational burden. The conventional approaches had mode mixing problems, low SNR values, computational complexities, multi-stage mode estimation process, and inaccuracy in determining low-frequency modes. In this paper, VMD and spectral analysis are combined to provide an effective strategy to identify the oscillatory modes and the mode shape characterization. The proposed approach has been compared with the conventional methods such as TSMD, EEMD, and EMD and is found to be computationally more robust and tolerant to noise. The methodology is illustrated using the simulated data from Kundur two area system and real time PMU data from POSOCO Limited and highlighted the superiority of the proposed work in instantaneous mode shape estimation. As a future scope, the signal decomposition strategy can be enhanced by considering the data quality issues such as missing data problems and intrusions.

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