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Variational mode decomposition-based power system disturbance assessment to enhance WA situational awareness and post-mortem analysis

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Abstract: This study presents a variational mode decomposition (VMD)-based approach to analyse wide-area (WA) measurements based signals. The commonly used empirical mode decomposition (EMD) has limitations such as sensitivity to noise and sampling rate. However, VMD is an entirely non-recursive algorithm, where the modes are extracted concurrently. These modes help in extracting dynamic patterns of different power system disturbances. The performance of the proposed scheme is extensively validated on the IEEE-39 bus New England test system. The modes generated and the frequency deviation contours of the disturbances including generation loss, fault and line outage are assessed using VMD and the results provide improved performance in terms of decomposition quality compared with the existing EMD technique. Furthermore, a data-mining model known as decision tree is used to classify different power system disturbances based on intrinsic mode functions generated through VMD. The suggested method shows improved decomposition quality and classification accuracy. Thus, the proposed scheme is a potential candidate for improving WA situational awareness along with a post-mortem analysis of real events occurring in a power system.

1 Introduction

Wide-area (WA) monitoring plays a significant role in improving the situational awareness in a power system [1]. Phasor measurement units (PMUs) are backbone of wide-area measurements (WAMs) system, which provide data at a rate of 30 or 60 sample(s) per second. In recent times, information from PMUs are utilised to address many power system problems such as vulnerability assessment, developing catastrophic predictors, wide-area protection, disturbance analysis [2–7]. Analysis of the constituent modes of the real-time data helps in achieving the aforementioned objectives. The nature and severity of the disturbance can be known by observing the frequency and damping of the modes. This information will help in revealing the health of the power system. Furthermore, this will also help in predicting outcome of an evolving contingency. It is reported that most of the recent cascaded outages could have been avoided with better situational awareness [7, 8]. One of the applications of the proposed algorithm is to enhance wide-area situational awareness (WASA). WASA algorithm can assist many applications running in the system control centre. One of such applications is triggering the supervisory protection of transmission lines [7, 8]. A reliable WASA algorithm should be able to differentiate no-fault situations from line faults. Most of the relay mal-operations are caused due to loss of security of the relay. Thus, an efficient WASA algorithm can assist the existing relays in taking the reliable relaying decision.

However, analysis of non-linear and non-stationary power system signals is a subject of in-depth investigation in WA monitoring. Event detection using PMU data is an ongoing research area and it is reported that non-stationary nature of PMU data poses difficulty to traditional disturbance detection techniques [8]. Many PMU measurement-based event detection techniques have been reported in recent times [8–10]. The signals obtained from the PMUs can either be processed by time-domain analysis or through frequency-domain analysis. In case of frequency-domain analysis, Fourier transform (FT) is mostly used to obtain frequency spectrum of the input data. However, FT has its inherent drawback such as incapability in providing time information. Time–frequency analysis has gained its popularity in recent times mainly because of its capability to provide frequency information of the input signal in time domain. The existing time–frequency analysis tools include short-time FT, wavelet transform (WT), S-transform (ST), fast ST, and Wigner–Ville distribution. These techniques are all successfully used in many power system applications such as fault detection, islanding detection, and power quality disturbance detection [8–13]. However, these techniques are having some inherent limitations such as poor time–frequency resolution due to their decomposition basis, sensitivity to noise and sampling [14, 15].

Most recently, empirical mode decomposition (EMD)-based time–frequency analysis methods which have significantly higher time–frequency resolution have also been used in applications such as identifying inter-area oscillations [16], identification of generator coherency [17], and analysis of time-varying waveforms in power quality [18]. The operation in EMD includes recursive detection of local maxima or minima in the input waveform which further predicts the upper or lower envelopes. The average of the envelope is then removed as 'low-pass' centreline. Thus, it isolates the high-frequency oscillations as 'mode' of the input waveform and continues recursively on the remaining 'low-pass' centreline. However, EMD-based techniques have certain limitations such as its sensitivity to noise and sampling [15].

Variational mode decomposition (VMD) technique was reported for the first time in [15]. It is a non-recursive decomposition technique for adaptive and quasi-orthogonal signal decomposition. VMD algorithm can decompose a multicomponent signal into a finite number of band-limited intrinsic mode functions (IMFs) concurrently [15]. In this algorithm, Wiener filtering is embedded directly in Fourier domain to update the mode. Moreover, the VMD technique is reported to be more robust to noise compared with the existing EMD-based decomposition technique. The proposed research work aims to develop VMD-based disturbance analysis scheme to enhance situational awareness in power system. The disturbances may be classified as real power events or reactive power events.

The existing PMUs provide positive sequence voltage and current information along with frequency and rate of change of frequency. Change in real power mostly affects frequency while change in reactive power affects the positive sequence voltage. Thus, VMD can be applied to these two signals to achieve the objective of disturbance analysis. In the proposed paper, frequency deviation information was used to illustrate the effectiveness of the VMD algorithm. The analysis can take place in real time where the signals obtained from the PMUs can be decomposed and important information regarding the system can be retrieved. Furthermore, post-mortem analysis (PMA) following any disturbance can be carried out for the power system. Both the types of analysis are very much essential for modern smart power systems in order to enhance the security and reliability of the system. Furthermore, disturbances such as generator outage, line outage and line fault induce different modes in the frequency or voltage signal. Thus, voltage or frequency waveforms carry unique information with respect to each event. Time–frequency approach-based techniques are improved signal processing algorithms to decompose any signal into time-varying modes. These spectral modes capture time-varying statistical properties of a signal. It is shown that VMD-based analyser helps in extracting accurate modes from the test signal which is further utilised by the decision tree (DT) model to classify different types of power system disturbances.

The remainder of this paper is organised as follows: Section 2 explains the proposed scheme. Section 3 presents the simulation results followed by a discussion on the performance of the proposed scheme in Section 4. Section 5 is the concluding section.

2 Proposed disturbance assessment scheme

EMD was introduced for the first time by Huang *et al.* [19]. It decomposes a signal into principal modes. However, it suffers from drawbacks such as lack of mathematical theory along with its poor performance in the presence of noise [15]. Another class of methods includes use of wavelets. The recent one is called empirical WT [20]. However, the existing decomposition tools such as EMD and WT have the following drawbacks associated with them:

- Poor performance in the presence of noise.
- No provision for backward error correction because of the available recursive sifting in the existing methods.
- Wavelet-based approach has hard band limit.
- If the input signal contains two modes having frequencies, which fall within an octave, then EMD fails to separate these modes.
- The first IMF generated through EMD may be multicomponent if the highest two frequencies present in the input signal comes under one octave and if the input signal comprises a weak component having high frequency along with a strong component of low frequency.

The recently proposed VMD [15] addresses the aforementioned issues. Here, a multicomponent signal can be decomposed into a set of IMFs which are band limited. In other words, discrete number of modes can be obtained from a real-valued input signal. The modes are characterised with specific sparsity properties while regenerating the original input waveform. IMF $v_m(t)$ can be written as

$$v_m(t) = A_m \cos(\varnothing_m(t))) \quad (1)$$

where $v_m(t)$ is the amplitude modulated frequency modulate (AM-FM) signal and $\varnothing_m(t)$ is the non-decreasing function.

It is to be noted that the envelope A_m and the instantaneous frequency $\omega_m(t)$ vary much slower than $\varnothing_m(t)$. In case of VMD, the sparsity characteristics of each mode are selected to be its bandwidth. Thus, each mode m is mostly compact around a central frequency ω_m. The central pulsation ω_m is calculated during the process of decomposition. The bandwidth of a mode is assessed by the following three rules: (i) The analytical signal corresponding to each mode v_m is computed using Hilbert transform. (ii) Each mode's frequency spectrum is shifted to base band. (iii) Finally, H^1 Gaussian smoothness of the demodulated signal is used to estimate the frequency. The final constrained variational problem is defined by [15]

$$\begin{gathered}\min_{\{v_m\},\{\omega_m\}} \left\{ \sum_m \| \partial_t\left[\left(\delta(t) + \frac{j}{\pi t}\right) * v_m(t)\right] \mathrm{e}^{-\mathrm{j}\omega_m t} \|_2^2 \right\} \\ \text{subjected to} \quad \sum_m v_m = f \end{gathered} \quad (2)$$

where v_m is the mth mode and ω_m is the centre frequency around which v_m is mostly constant.

To address (2), the authors in [15] have introduced a quadratic penalty and Lagrangian multiplier. The following equation is used to set the augmented Lagrangian:

$$\begin{gathered}\mathscr{L}(v_m, \omega_m, \lambda) = \alpha \sum_m \| \partial_t\left[\left(\delta(t) + \frac{\mathrm{j}}{\pi t}\right) * v_m(t)\right] \mathrm{e}^{-\mathrm{j}\omega_m t} \|_2^2 + \\ \| f - \textstyle\sum_m^v \|_2^2 + \left\langle \lambda, f - \textstyle\sum_m^v \right\rangle \end{gathered} \quad (3)$$

where α is a balancing parameter.

To solve the variational problem in (3), alternate direction method of multiplier (ADMM) approach is used. Thus, during each shifting operation, different decomposed modes and centre frequency are produced using the ADMM technique. The solutions in spectral domain results into each mode represented as

$$\hat{v}_m = \frac{\hat{f}(\omega) - \sum_{i \neq m} \hat{v}_m(\omega) + \hat{\lambda}(\omega)/2)}{1 + 2\alpha(\omega - \omega_m)^2} \quad (4)$$

There are mainly three steps involved in VMD and are as follows:

(i) modes update
(ii) centre frequency update
(iii) dual ascent update

(i) *Modes update:* In VMD, Wiener filtering is embedded in order to update the mode. The process of updating modes is accomplished in Fourier domain by tuning a filter to the centre frequency ω_m^n

$$\hat{v}_m^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i<m} \hat{v}_i^{n+1}(\omega) - \sum_{i>m} \hat{v}_i^n(\omega) + (\hat{\lambda}^n(\omega)/2)}{1 + 2\alpha(\omega - \omega_m^n)^2} \quad (5)$$

(ii) *Centre frequency update:* the following equation is used to update the centre frequency:

$$\omega_m^{n+1} = \frac{\int_0^\infty \omega \left|\hat{v}_m^{n+1}(\omega)\right|^2 \mathrm{d}\omega}{\int_0^\infty \left|\hat{v}_m^{n+1}(\omega)\right|^2 \mathrm{d}\omega} \quad (6)$$

(iii) *Dual ascent update:* the Lagrangian multiplier is updated using the following equation:

$$\hat{\lambda}^{n+1} = \hat{\lambda}^n + \tau\left(\hat{f} - \sum_m \hat{v}_m^{n+1}\right) \quad (7)$$

The process of signal decomposition continues till

$$\sum_m \| \hat{v}_m^{n+1} - v_m^n \|_2^2 / \| \hat{v}_m^n \|_2^2 < \varepsilon \quad (8)$$

The detailed theoretical and mathematical background of VMD can be obtained from [15].

Let $y(t)$ be the Hilbert transform of IMF $v(t)$, then the analytic signal can be computed by

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$$x(t) = v(t) + \mathrm{i}y(t) = A(t)\exp[\mathrm{i}\varnothing(t)] \quad (9)$$

where $y(t) = (1/\pi)P\int_{-\infty}^{\infty}(v(\tau)/(t-\tau))\,\mathrm{d}\tau$. P is the Cauchy integral value.

The instantaneous frequency (IF) is computed using the following equation:

$$\omega(t) = \frac{1}{2\pi}\frac{v(t)(\mathrm{d}y(t)/\mathrm{d}t) - v(t)(\mathrm{d}v(t)/\mathrm{d}t)y(t)}{v^2(t) + y^2(t)} \quad (10)$$

Instantaneous amplitude (IA) is computed by using the following equation:

$$A(t) = \sqrt{v^2(t) + y^2(t)} \quad (11)$$

VMD produces one IF for each IMF at each time sample. Thus, a multitude of instantaneous frequencies is formed at each time sample. Both IF and IA are function of time. Thus, a three-dimensional space is defined as $[t, \omega(t), A(t)]$. Let

$$G(\omega, t) = \mathrm{Re}\left\{\sum_{i=1}^{k} A_i(t)\,\mathrm{e}^{i\int_i^{\omega}(t)\,\mathrm{d}t}\right\} \quad (12)$$

where k is the number of modes. The 3D space is generalised by converting the two variable function $G(\omega, t)$ into three variables function $[t, \omega(t), A(t)]$ in which, $A(t) = G[\omega(t), t]$. In this manner, the combined time–frequency distribution of the signal is acquired [14].

To show the robustness of VMD-based decomposition in the presence of noise, the following synthetic signal is used as input to both VMD and EMD algorithms:

$$u(t) = \cos 100\pi t + \frac{1}{5}\cos 300\pi t + \frac{1}{14}\cos 500\pi t + \mu \quad (13)$$

As seen from (13), the signal consists of three harmonic components (50 Hz, 150 Hz and 250 Hz) along with Gaussian additive noise (μ) as shown in Fig. 1*a*. The Mode 1, Mode 2 and Mode 3 components estimated using VMD are shown in Figs. 1*b*–*d*, respectively. As shown in figures, all the frequency components are recovered efficiently. The strong low-frequency signal is detected with highest quality.

The same input signal is passed through EMD-based decomposition and as shown in Fig. 2, EMD produces eight estimated modes. It is observed that the first two modes consist of highest-frequency harmonic along with considerable amount of noise. The sixth mode seems to retain most of the low-frequency harmonics. However, this mode is also having significant distortion. Thus, it is observed that VMD-based decomposition is more robust to noise compared with EMD-based technique.

The modes obtained through VMD are further utilised to classify different power system events such as generator outage, line outage and line fault. A data-mining model known as DT is used to accomplish the above task. The reason behind the selection of DT as a classifier is its capability to provide transparent solution. DT has been successfully applied to many recent power system applications such as fault classification, dynamic security assessment, fault detection [2, 3, 7, 21]. The flowchart of the proposed disturbance assessment scheme is shown in Fig. 3. As shown in the figure, the IMFs resulted due to VMD are passed through a DT model. The DT model is trained to classify different power system events. Furthermore, if any poorly damped modes are observed following VMD analysis, then the corresponding damping controller can be activated to damp-out those oscillations. The detailed results corresponding to mode extraction is discussed in Section 3 and the disturbance classification part is detailed in Section 4.

3 Test cases and result analysis

The proposed VMD-based disturbance analysis scheme has been tested on the New England 39-bus system (Fig. 4). Siemen's commercial simulation software package named Power System Simulation for Engineering (PSS/E) is used for modelling the test system. The dynamic and sequence component data required for simulation in PSS/E environment are obtained from [22]. Disturbances such as sudden generator outage, line outage, and fault on transmission lines are simulated in PSS/E. The simulation window considered for the proposed study is 3 s (362 numbers of samples). The disturbances are applied at 1 s (sample no. 124). As the governors take almost 2 s to participate in controlling the system frequency [8], the simulation considers the post disturbance time frame of 2 s into account which is considered as natural response of the system. Thus, the total time frame of study becomes 3 s. The frequency deviation signals are stored in an excel file. The data are further used as input to VMD algorithm which is coded in MATLAB 2015(b) environment. The algorithm is tested for different types of disturbances which includes generator outage, line outage, and fault on the transmission line. Both EMD- and VMD-based techniques are used to process the input signal. The test results are discussed as follows:

(i) *Generator outage on bus-33:* New England 39-bus test system consists of 10 generators. Generator outage may create stressed condition in the power grid. Thus, it is essential to identify any generator outage condition, and it should be followed by the necessary control action. To study the effect of generator outage, the generator at bus-33 is tripped at 1 s (at sample no. 124), and the frequency deviation at bus-19 is monitored as shown in Fig. 5*a*. The reason behind observing frequency deviation at bus-19 is that this bus is closest to the disturbance location. The frequency deviation signal obtained through PSS/E simulation is passed through both VMD and EMD decomposition algorithm. The three modes obtained through VMD are shown in Fig. 5*b* and the seven EMFs obtained through EMD are shown in Fig. 6*a*. The contours of the reconstructed composite signal after VMD and EMD decomposition are shown in Figs. 5*c* and 6*b*, respectively. The results reveal that frequency deviation contour gives improved resolution compared with EMD-based decomposition. This shows the efficient local decomposition quality of VMD. Owing to the presence of Wiener filtering which updates the mode directly in Fourier domain, the VMD-based scheme is more robust to noise.

(ii) *Line outage of 16–19:* Sudden line outage is also one of the large disturbances which might occur in the power transmission system. Line outage may also induce stressed condition in the power system. To study the effect of line outage, lines 16–19 of the test system is tripped at 1 s (sample no. 124) and the corresponding frequency deviation signal is shown in Fig. 7*a*. The frequency deviation signal is analysed through both VMD and EMD algorithms. The three modes obtained from VMD are shown in Fig. 7*b* and the seven EMFs obtained through EMD are shown in Fig. 8*a*. The contours of the reconstructed composite signal after VMD and EMD decomposition are shown in Figs. 7*c* and 8*b*, respectively. Once again it is observed that it is easier to distinguish disturbance from healthy power system condition using VMD compared with EMD. This feature will be very much useful for modern days PMU-based WA monitoring system to enhance situational awareness in the power system.

(iii) *Fault on 16–19:* Transmission line faults are most common disturbance those occur in the power transmission system. Distance relays are generally used to identify and isolate the faulty transmission line in the power system. To study the effect of fault, a three-phase bolted fault is incepted on lines 16–19 at 1 s (sample no. 124) and the corresponding frequency deviation is measured at bus-16 as shown in Fig. 9*a*. The three modes obtained through VMD is shown in Fig. 9*b* and the seven EMFs obtained through EMD is shown in Fig. 10*a*. The contours of the reconstructed composite signal after VMD and EMD decomposition are shown in Figs. 9*c* and 10*b*, respectively. Similarly, the time–frequency instantaneous spectrum for both the methods is given in Figs. 9*d* and 10*c*, respectively. It is inferred from the simulation results that the IMFs obtained through EMD of the faulted signal are all distorted. Thus, it is difficult to judge the contribution of each IMF which ultimately makes the signal analysis more complex. However, the three modes obtained using VMD clearly indicates

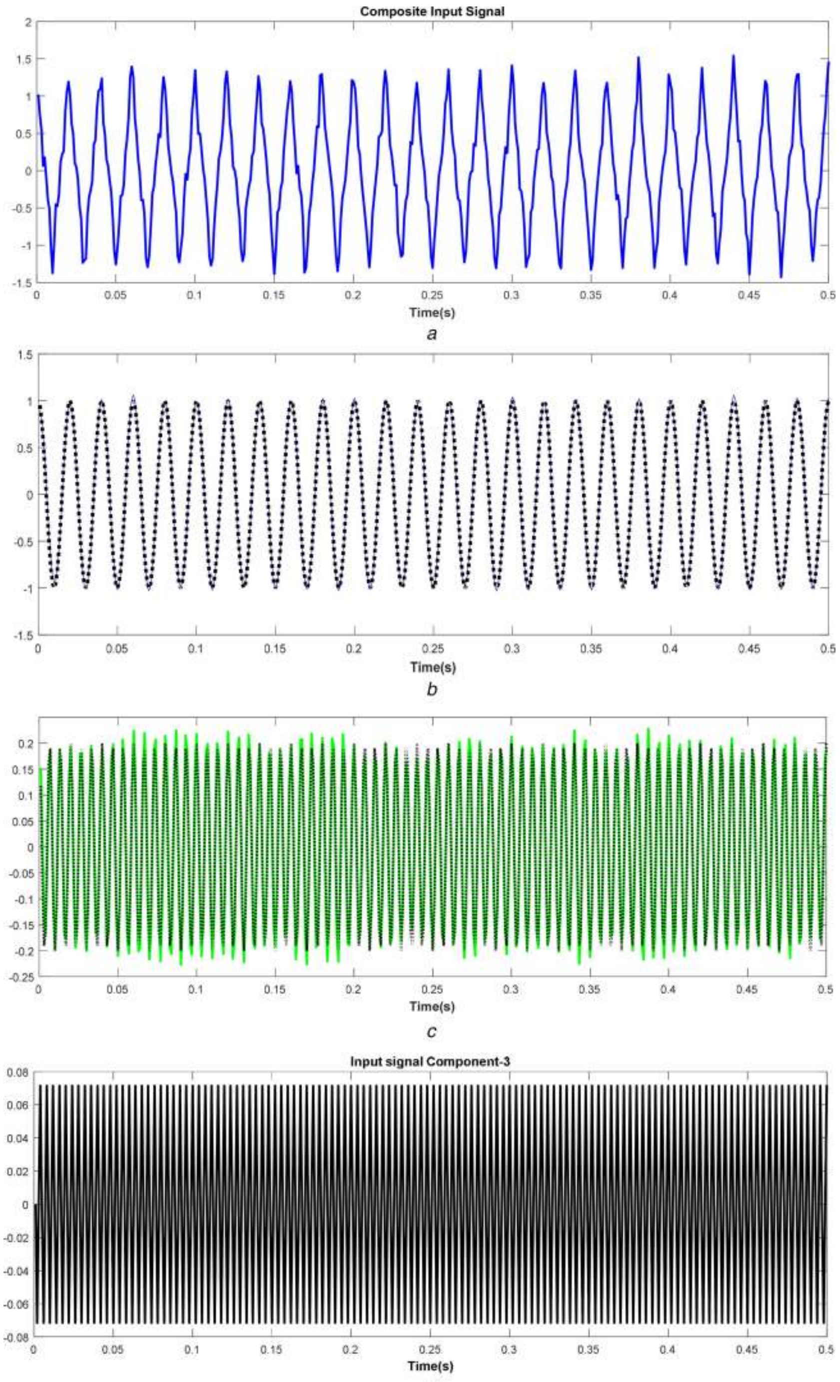

Fig. 1 *Results of VMD based decomposition for a synthetic signal*
(a) Composite input signal with noise,
(b) Mode 1 extracted by VMD, ***(c)*** Mode 2 extracted by VMD, ***(d)*** Mode 3 extracted by VMD

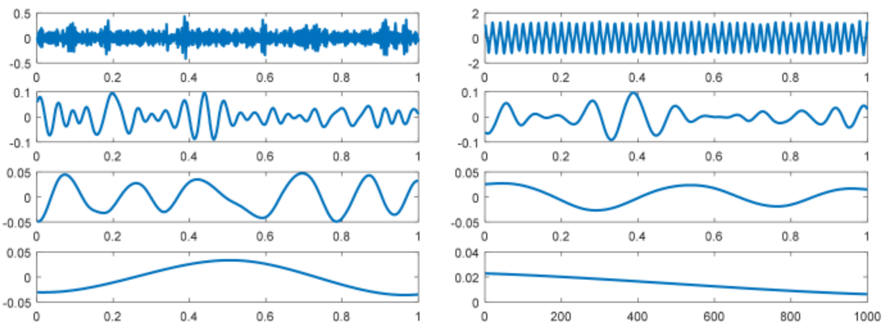

Fig. 2 *Result of EMD decomposition*

each frequency component present in the faulted signal and thus, the signal analysis becomes easier. The time–frequency resolution of VMD is also better than that of EMD. This will help in localising and detecting the disturbances efficiently. Thus, the

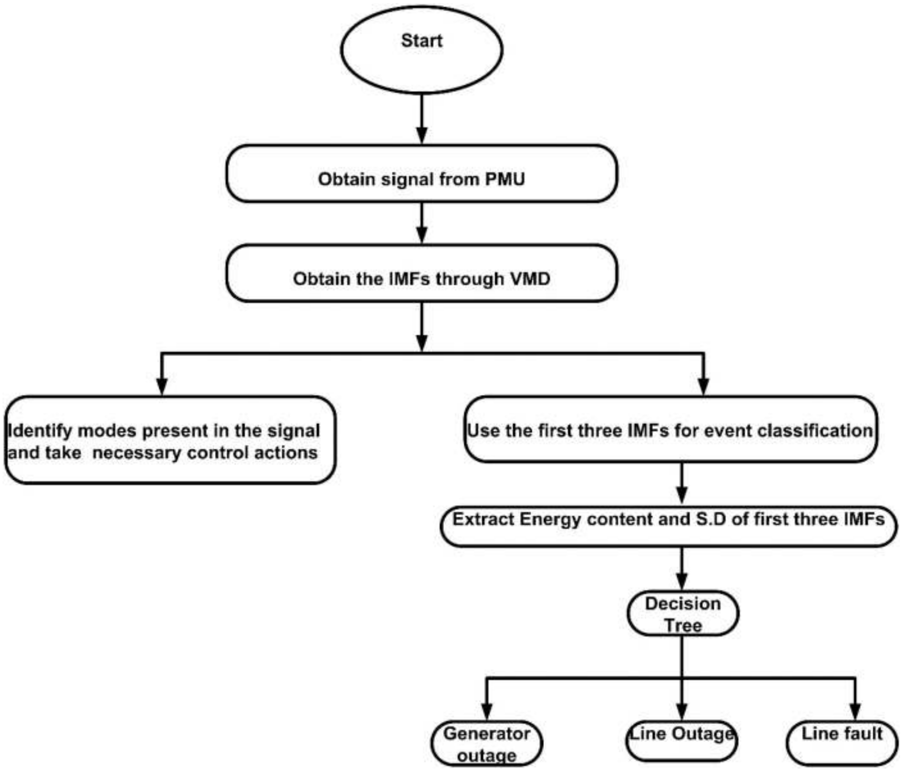

Fig. 3 *Flowchart of the proposed disturbance assessment scheme*

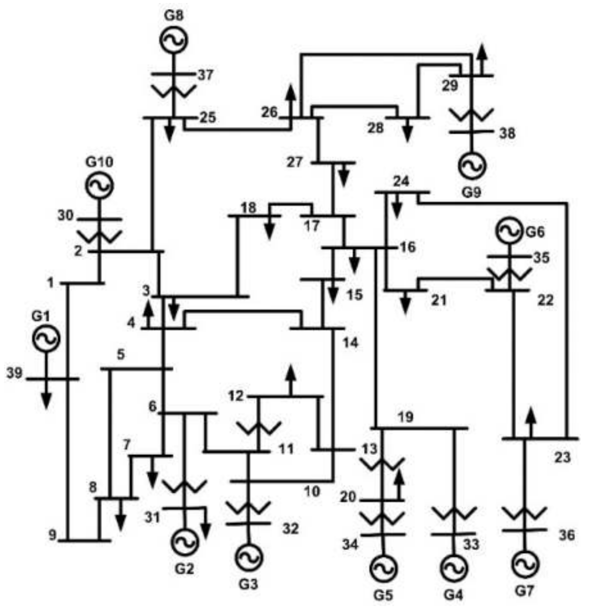

Fig. 4 *IEEE-39-bus system*

process of efficient tone detection is shown using VMD. Furthermore, the noise robustness of VMD makes it a suitable candidate for real-time disturbance analysis in the power transmission system.

4 Discussion

The main focus of this paper is to introduce a new signal decomposition technique named VMD for enhancing WASA along with PMA. It is reported that most of the recent blackouts including four major North American blackouts and the 2012 Northern India blackout were due to the lack of situational awareness [23, 24]. Thus, efficient situational awareness can help in avoiding cascaded outages in the system. Furthermore, extracting dynamic patterns from WA measurement signals is part of PMA following any disturbance in the system. In the proposed study, two statistical features are extracted to locate the dominant IMF and to observe the effect of different disturbances on the extracted parameters. The features are further utilised to classify different power system events. The two features are

(i) energy content of the IMF (ECI)
(ii) standard deviation of the IMF (SDI).

Deviation in energy content of an IMF (ΔECI) is defined as the difference in ECI after and before the disturbance. ΔECI is derived as follows:

$$\Delta \text{ECI} = \left\{ \sum |y_i|^2 \right\}_a - \left\{ \sum |y_i|^2 \right\}_b \tag{14}$$

Standard deviation is derived as follows:

$$\text{SDI} = \text{standard deviation of } y_i \tag{15}$$

where y_i is the discrete-time analytic signal of IMF i. In the present study, 'i' is considered to be 1, 2, and 3. That means only first three IMFs are considered for building the DT model. The reason for choosing first three IMFs comes from the experience and also by assuming that most frequency content lies in the first three modes of oscillation. In this paper, three types of power system disturbances such as generator outage (C-I), line outage (C-II), and line fault (C-III) are considered. ΔECI and SDI values corresponding to each test cases are depicted in Table 1. It is observed that IMF_1 is the dominating IMF having maximum energy content among the three IMFs produced through VMD. Furthermore, the ΔECI and SDI corresponding to Case-III (fault case) is maximum when compared with other disturbances. This information can help in differentiating fault from other power system disturbances. Thus, the first three IMFs are used as input to the DT model. Here, the target outputs are divided into three classes. Rattle software package is used to develop DT-based classifier [21, 25–27]. Thus overall, six features are extracted. To classify different disturbances in the power system, the PMU information corresponding to generator buses are used. This is a feasible option because generator buses are usually less in numbers compared with total number of buses. Post disturbance one cycle data is utilised for the analysis. Total 10,117 test cases are

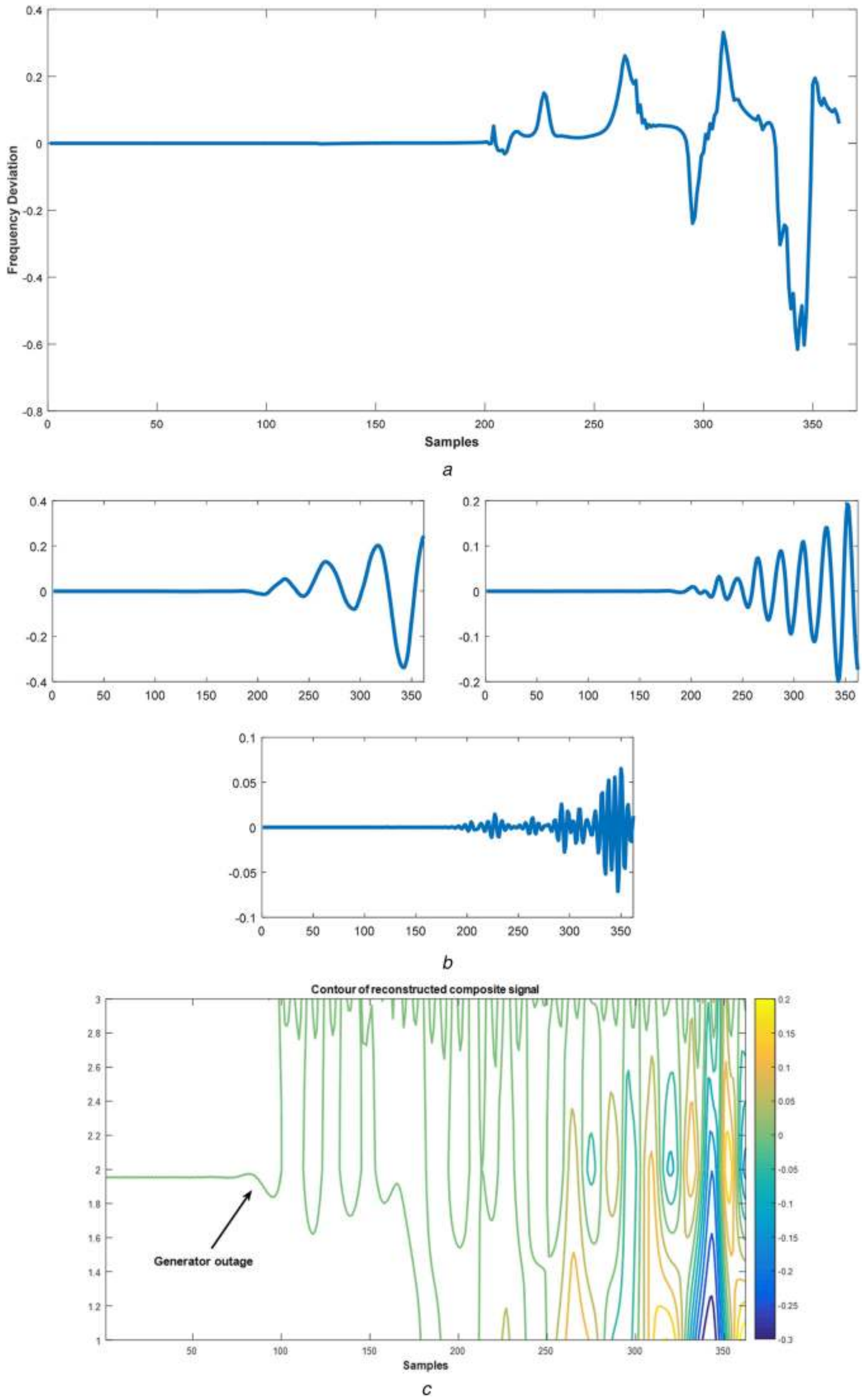

Fig. 5 *Performance of VMD for generator outage*
(a) Frequency deviation (generator 33 outage),
(b) Three modes obtained after VMD decomposition (generator 33 outage),
(c) Frequency deviation contour after VMD decomposition (generator 33 outage)

considered out of which 70% cases are used for training the DT and rest 30% are used for testing. The test cases also include different types of fault with variations in fault parameters such as fault resistance, fault location, fault inception angle. Ten generator outage cases along with 46 line outage cases are included in the input file. The test data sheet also includes signals with noise of SNR 20 dB. Table 2 depicts the confusion matrix generated after testing period. All total, 3000 fault scenarios, four generator outage scenarios, and 31 line outage scenarios are used as test cases. The results show that the data-mining model provides a classification accuracy of close to 99%. The proposed scheme is compared with some of the existing signal processing tools such as WT, ST, and EMD. To have a balanced comparison, the classifier DT is kept constant. The performance comparison is tabulated in Table 3. It is observed that the better decomposition quality of VMD helps in achieving an improved classification accuracy.

The mathematical analysis in Section 2 followed by the simulation results in Section 3 of this paper reveals the following facts regarding VMD:

- VMD scheme has better tone detection, tone separation, and noise robustness qualities compared with EMD.
- Lack of mathematical foundation of EMD is its biggest drawback. However, this is not an issue for VMD.
- One of the most important features of VMD is that the IMFs obtained through VMD are concurrent.
- The use of Wiener filter in VMD makes it a noise robust algorithm.

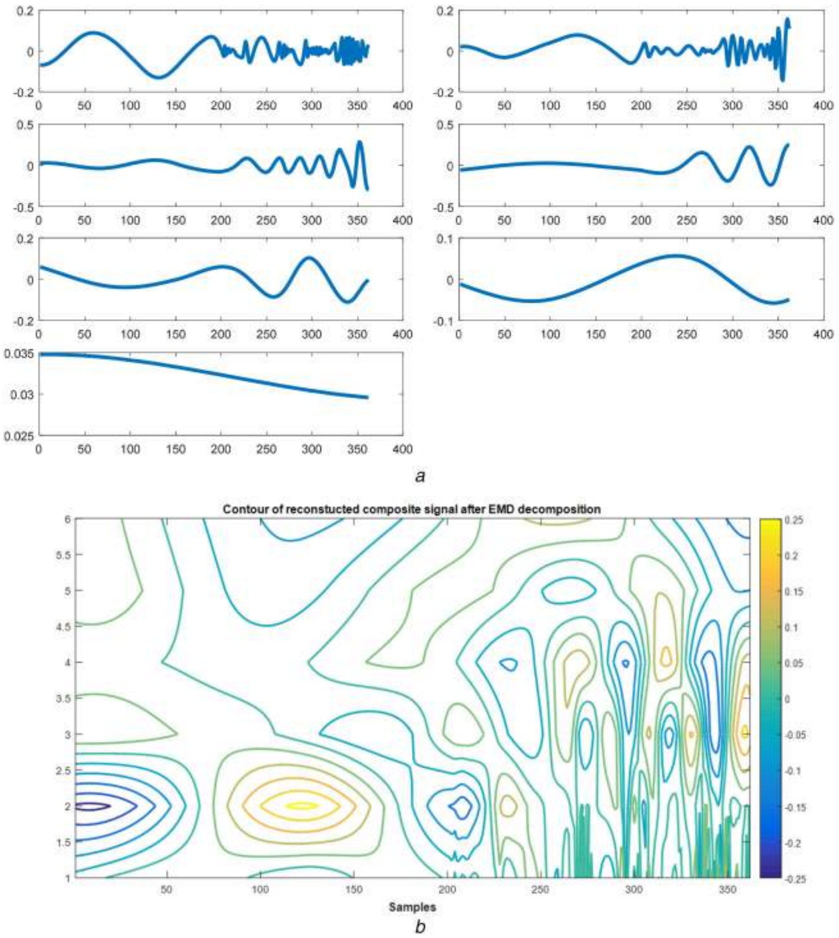

Fig. 6 *Performance of EMD for generator outage*
(a) Seven IMFs obtained after EMD decomposition (generator 33 outage),
(b) Frequency deviation contour after EMD decomposition (generator 33 outage)

- VMD is also robust to sampling.
- The IMF generated through VMD is compact around a centre pulsation. Thus, each IMF contains the information on the local characteristics of the input signal.
- The instantaneous frequency spectrum following VMD reveals the spectral characteristics of the various reflections with much more clarity than the corresponding EMD results.

The authors see two kinds of application for the proposed scheme.

(i) VMD algorithm can be incorporated in modern days PMUs, so that real-time disturbance analysis can be achieved. The inherent noise robustness quality of VMD along with its ability to extract meaningful information from the raw input data in the time as well as in time–frequency domains makes it a potential candidate for disturbance analysis.
(ii) The second application is the PMA of any real world event using wide-area information. This can be accomplished in the system protection centre (SPC) where information from all the PMUs are coming. Tasks such as cascading failure analysis are part of such application.

5 Conclusions

In this paper, a VMD-based disturbance analysis scheme is proposed. The ability of VMD to extract useful information in both time and time–frequency domain is very much useful in WAMs-based assessment of disturbance records. VMD shows very strong local decomposition capability along with its immunity to noise. It produces band-limited IMFs with specific sparsity property. This property is very much useful in analysing the non-stationery and non-linear power system signals. Furthermore, the instantaneous frequency spectra obtained through VMD shows much better time–frequency resolution than that of EMD. Disturbances such as generator outage, line outage, and transmission line fault are analysed through VMD. A DT-based disturbance classification scheme is proposed. The modes obtained through VMD are utilised to build the disturbance classifier. A classification accuracy of close to 99% is achieved through the proposed scheme. The proposed scheme can help in improving WASA in modern power transmission system.

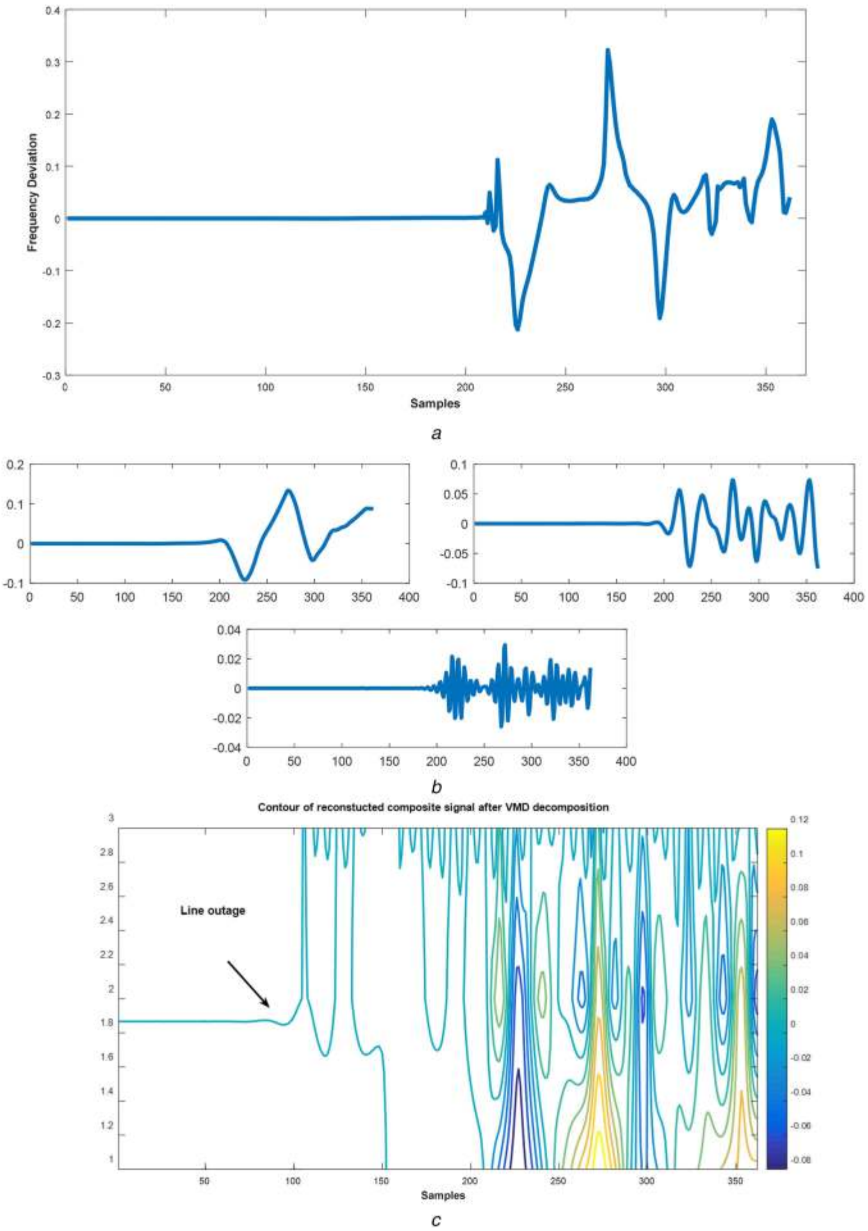

Fig. 7 *Performance of VMD for line outage*
(a) Frequency deviation (lines 16–19 outage),
(b) Three modes obtained after VMD decomposition (lines 16–19 outage),
(c) Frequency deviation contour after VMD decomposition (lines 16–19 outage)

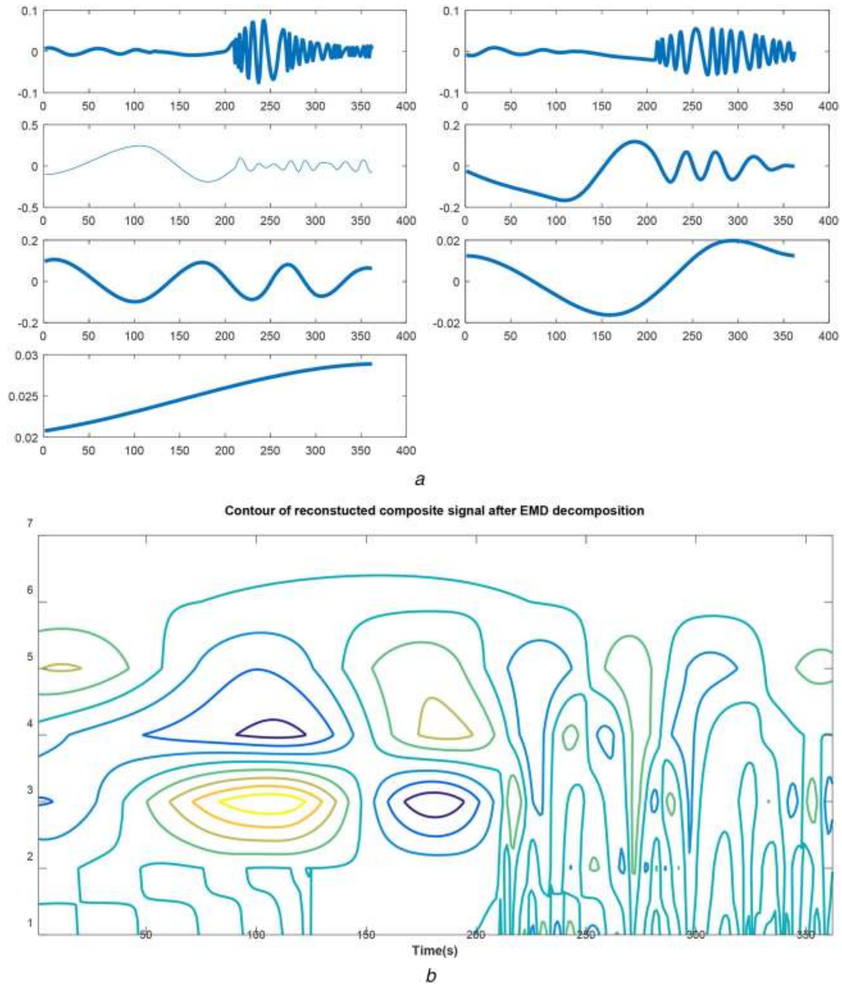

Fig. 8 *Performance of EMD for line outage*
(a) Seven IMFs obtained after EMD decomposition (lines 16–19 outage),
(b) Frequency deviation contour after EMD decomposition (lines 16–19 outage)

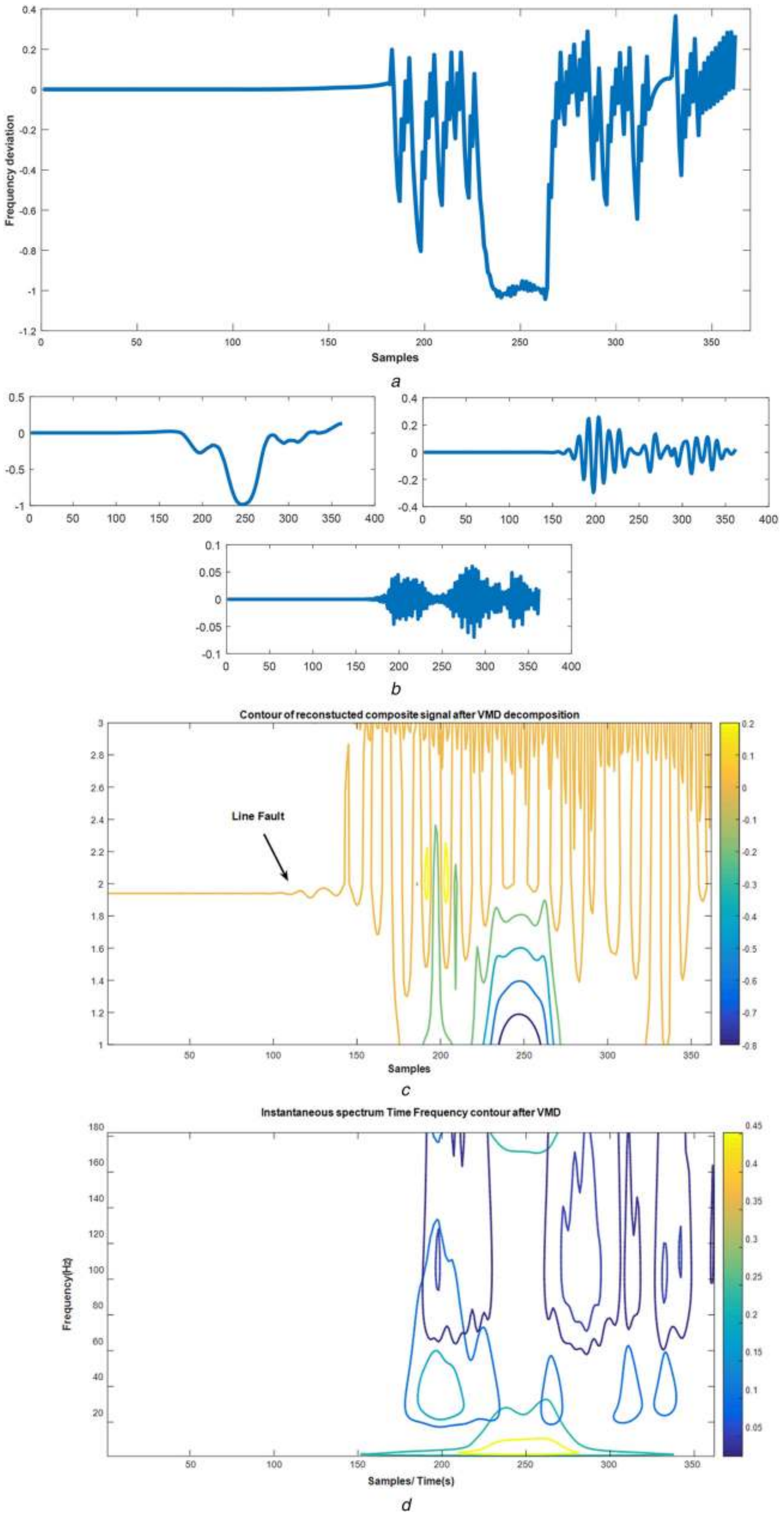

Fig. 9 *Performance of VMD for line fault*
(a) Frequency deviation (fault on lines 16–19),
(b) Three modes obtained after VMD decomposition (fault on lines 16–19),
(c) Frequency deviation contour after VMD decomposition (fault on lines 16–19), ***(d)*** Instantaneous spectrum time–frequency contour after VMD decomposition (fault on lines 16–19)

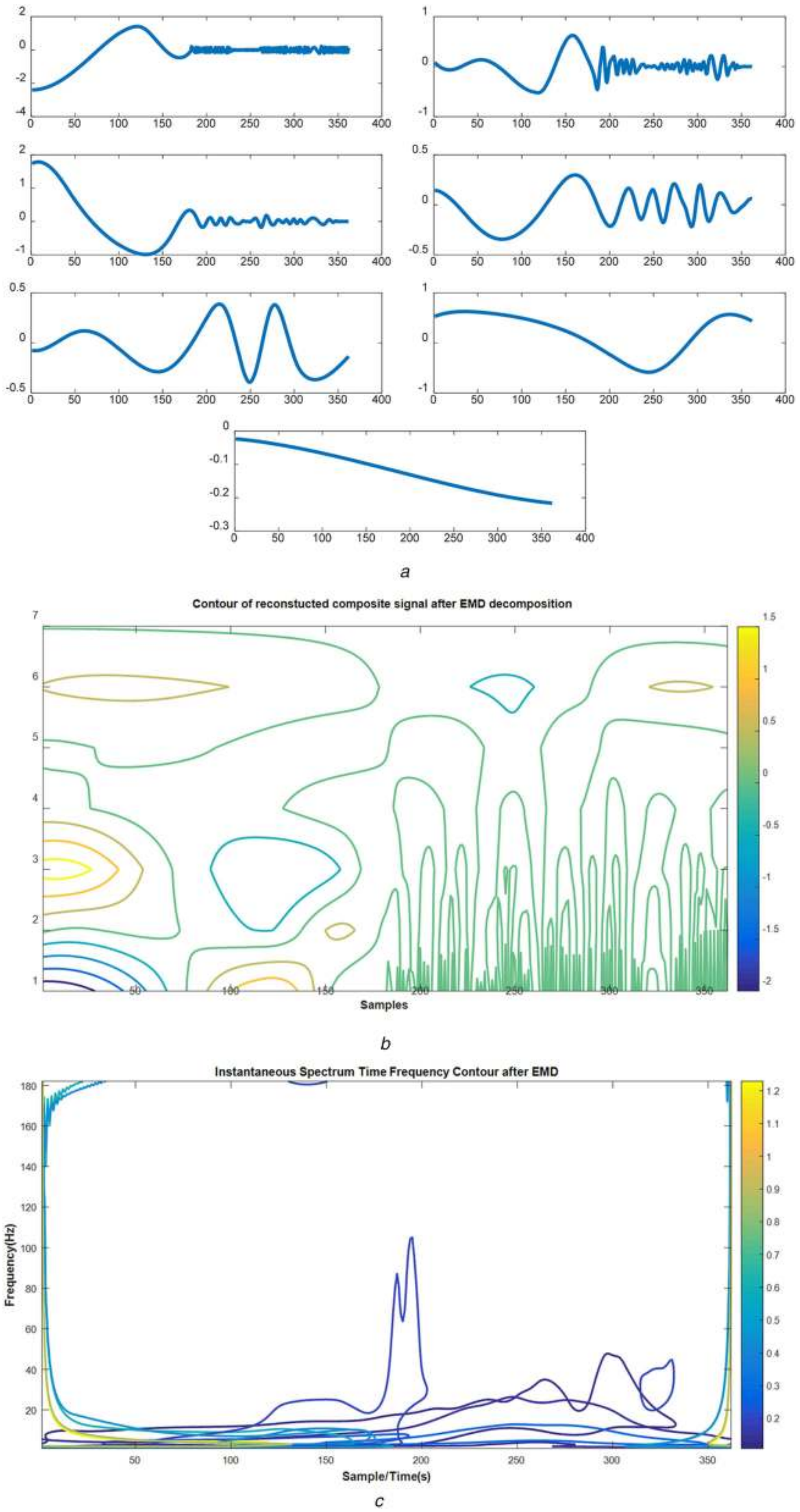

Fig. 10 *Performance of EMD for line fault*
(a) Seven modes obtained after EMD decomposition (fault on lines 16–19),
(b) Frequency deviation contour after EMD decomposition (fault on lines 16–19),
(c) Instantaneous spectrum time–frequency contour after EMD decomposition (fault on lines 16–19)

Table 1 Energy content and standard deviation comparison

Disturbance	C-I	C-II	C-III
ΔECI			
IMF_1	*2.2689*	*1.1174*	*7.5629*
IMF_2	1.3197	0.6328	1.8347
IMF_3	0.3211	0.1730	0.4737
SDI			
IMF_1	*0.0823*	*0.0291*	*0.1705*
IMF_2	0.0543	0.0229	0.074
IMF_3	0.0147	0.0071	0.0189

Italic values indicate higher magnitude compared to other values

Table 2 Confusion Matrix generated after testing period

Cases	C-I (actual)	C-II (actual)	C-III (actual)
C-I (predicted)	4		31
C-II (predicted)		31	
C-III (predicted)			2969
classification accuracy, %	100	100	98.96

Table 3 Classification accuracy (%) comparison with different signal processing tools

Cases	EMD and DT	WT and DT	ST and DT	Proposed scheme
C-I	100	100	100	100
C-II	87	80.64	83.87	100
C-III	92.15	88.19	91.12	98.96

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