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Fault classification in power systems using EMD and SVM

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KEYWORDS

Fault classification;
Empirical Mode Decomposition (EMD);
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Abstract In recent years, power quality has become the main concern in power system engineering. Classification of power system faults is the first stage for improving power quality and ensuring the system protection. For this purpose a robust classifier is necessary. In this paper, classification of power system faults using Empirical Mode Decomposition (EMD) and Support Vector Machines (SVMs) is proposed. EMD is used for decomposing voltages of transmission line into Intrinsic Mode Functions (IMFs). Hilbert Huang Transform (HHT) is used for extracting characteristic features from IMFs. A multiple SVM model is introduced for classifying the fault condition among ten power system faults. Algorithm is validated using MATLAB/SIMULINK environment. Results demonstrate that the combination of EMD and SVM can be an efficient classifier with acceptable levels of accuracy.

1. Introduction

One of the main problems for the industry and electrical equipment is power quality disturbances such as voltage sag, harmonics. Among all, voltage sag is more dangerous. One of the main causes for voltage sag is short circuit faults such as single line to ground, line to line, and three phase faults. Without proper classification of these faults from healthy conditions, it may cause irrecoverable economic effects. Selecting a proper algorithm for analyzing these system data for faulty conditions in terms of voltage sag is crucial. An algorithm is needed for pre-processing and extracting most significant features from the voltage or current data from system under study. These features can be used for detection of the faulty condition among various possibilities. A classifier is needed for this purpose.

Over the years, wavelet transforms are used for analyzing the fault data. Wavelets and artificial neural networks (ANN) are introduced in power system fault detection in the literature [1]. Online applications of wavelet transforms to power system relaying are presented in the literature [2,3]. Classification of causes for voltage sag using wavelet transform and probabilistic neural network is proposed in the literature [4]. Literature [5] introduces wavelet based combined fuzzy logic classifier for power system faults. In these papers wavelets are used for extracting features from power system data with either ANN or fuzzy logic for classification. Support vector machine is emerged as a new classifying approach besides

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ANN and fuzzy logics in recent years. SVM classifier is introduced as classifier for power system faults in [6]. A combination of wavelet and SVM for fault classification is proposed in [7,8]. Instead of wavelets, EMD with HHT is being used recently for feature extraction stage. Application of HHT and neural networks in detecting power quality disturbances is presented in [9–11]. Various theoretical parameters to be considered for using HHT and EMD for various applications are presented in [12–14].

A combination of EMD and SVM algorithms for feature extraction and classification of power systems fault is discussed in [15]. In this paper, only classification is done among single line to ground, line to line, double line to ground and three phase faults. In this paper, exact classification among faulty phase and fault type among ten faults (*AG*, *BG*, *CG*, *AB*, *BC*, *CA*, *ABG*, *BCG*, *CAG*, and *ABCG*) is calculated. Time of the fault is calculated using instantaneous frequency measurements. Voltage waveforms are obtained for a modal power system under healthy and faulty scenarios by taking varying fault resistance, location of fault and load angles. SimPowerSystems toolbox in SIMULINK environment is used for generating fault data. The data are used for training and testing SVM in MATLAB environment.

2. Methodology

The proposed methodology involves three major stages: feature extraction, feature selection and classification. The block diagram of fault classification system is shown in Fig. 1. Once the voltage waveforms for various scenarios are obtained, they are decomposed into mono component signals called Intrinsic Mode Functions (IMFs). Then Hilbert Huang Transform (HHT) is used for instantaneous amplitude, phase and frequency measurements. The detailed procedure for implementing EMD and HHT is explained in further sections. Unique significant features are extracted for each case which is used for training and testing SVM classifier. Fundamentals of EMD and SVM are provided in sections below.

2.1. Empirical Mode Decomposition

Empirical Mode Decomposition method is based on simple assumption that any data consists of different simple intrinsic mode oscillations [9]. EMD uses sifting process for converting nonlinear and non-stationary signals into mono component and symmetric components. It breaks down given signal into its component Intrinsic Mode Functions (IMFs) [11]. An IMF is defined as an oscillating wave which:

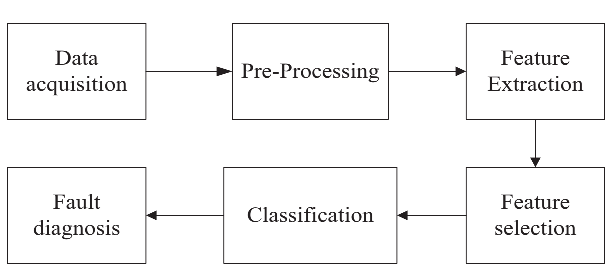

Figure 1 Block diagram of fault classification system.

1. has only one extreme between zero crossings, and
2. has a mean value of zero.

Sifting is implemented iteratively for extracting IMFs from parent signal using following algorithm:

1. Let m_1 be the mean of upper and lower envelopes of given signal $X(t)$, which are determined from a cubic-spline interpolation of local maxima and minima. The first component, h_1 is calculated as shown in (1).
$$h_1 = X(t) - m_1 \tag{1}$$
2. In next step, h_1 is considered as the parent signal, and m_{11} is the mean of h_1's upper and lower envelopes and h_{11} is calculated:
$$h_{11} = h_1 - m_{11} \tag{2}$$
3. Above procedure is repeated n times, until h_{1n} satisfies the conditions of an IMF. Then it is designated first IMF, $I_1 = h_{1n}$, It is then separated from rest of the data using (3).
$$R_1 = X(t) - I_1 \tag{3}$$
4. Now R_1 is considered as main signal and steps 1–3 are repeated for obtaining second IMF.
5. The number of IMFs that can be extracted depends on the signal. The stopping condition is that the R_n becomes monotonic.

2.2. Hilbert Huang Transform

After Empirical Mode Decomposition, HHT is applied on IMF for instantaneous amplitude, instantaneous phase and instantaneous frequency as shown in (4)–(6). First three IMFs are used for feature extraction in this study since most frequency content is present in these IMFs and proved to be sufficient for fault detection [13]. The Hilbert transform of a signal $X(t)$ is $Y(t)$, such that

$$Y(t) = H[x(t)] = \int_{-\infty}^{\infty} \frac{x(\tau)}{\pi(t-\tau)} d\tau \tag{4}$$

$X(t)$ and $Y(t)$ forms analytical signal $Z(t)$

$$Z(t) = X(t) + Y(t) = A(t)e^{j\theta(t)} \tag{5}$$

$$\text{While,} \quad A(t) = \sqrt{X^2(t) + Y^2(t)} \tag{6}$$

$$\theta(t) = \tan^{-1}\left[\frac{Y(t)}{X(t)}\right] \tag{7}$$

$$f(t) = \frac{1}{2\pi}\frac{d\theta(t)}{dt} \tag{8}$$

where $A(t)$ and $\theta(t)$ are instantaneous amplitude and instantaneous frequency respectively.

2.3. Selection of features

The range and changing rate of instantaneous amplitude and phase of voltage signals of a particular phase of the selected line varies dramatically on occurrence of the fault [9]. The energy distribution value also varies considerably once the phase is short circuited. By considering all these parameters, the following three features are selected as most significant features.

(1) Energy distribution of instantaneous amplitude.
(2) Standard deviation of amplitude.
(3) Standard deviation of phase.

Thus three features for each IMF among three IMFs constitute a data set of nine features for each phase. The entire process of feature extraction stage is shown in Fig. 2.

2.4. Support Vector Machines (SVMs)

The SVM evolved from theory to implementation and results, whereas neural networks follow heuristic path from applications to experiments. Also, SVMs are less prone to over fitting problems and give sparse solution when compared to neural and do not depend on input space dimensionality. Many of the classification problems have been addressed by SVM.

Classification using SVM basically involves training and testing data which is composed of many instances. In training set, each instance consists of two attributes (features in this case) and a target value called class label (usually 1 or -1). The aim of this classifier is to create a model which can successfully predict the class label of unknown data or test data instance which consists of only attributes. However, most of the SVM algorithms can classify between only two classes thus making it a two class problem [16–18] i.e., separating the set of training data i.e., $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$, where $x_i \in R_n$ is feature vector and $y_i \in \{-1, +1\}$ class vector. The two classes are separated by a hyperplane as shown in Fig. 3. The dashed lines indicate the margin and the points on the margin are called support vectors. Optimal separating hyperplane is at a distance of $(-b/||w||)$ from origin. ξ is a variable that measures the amount of misclassification in case of non-separable classes. $(-\xi/||w||)$ gives the distance of the misclassification from optimal separating hyperplane.

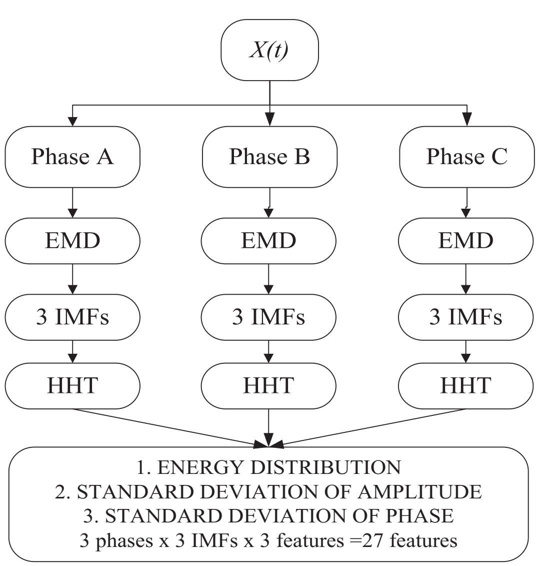

Figure 2 Feature extraction block diagram.

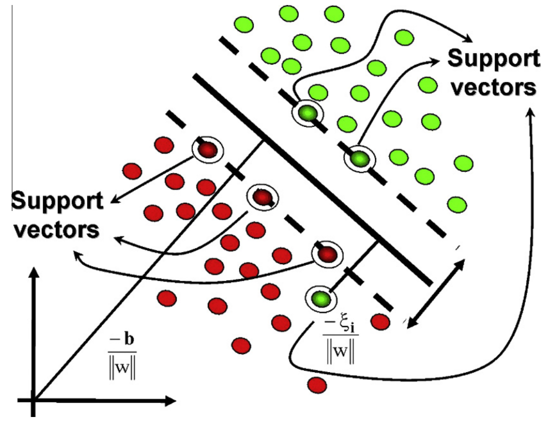

Figure 3 Example of Support Vector Machine.

Hyperplane, $g(x)$ which accurately separates the data into its corresponding classes as in [17] is given by (9)

$$W^T x_i + b = 0 \tag{9}$$

where W is a vector with real values and b is a constant. Their values should be derived in such that the unknown data are classified accurately. This is possible by maximizing the separation margin between the classes which is defined as shown in (10) [17].

$$m = \frac{2}{\|W\|} \tag{10}$$

For maximizing m, W should be minimized. According to [17], for a given set of linearly separable data, this can be formulated as quadratic optimization problem as shown in (11).

$$\min \frac{1}{2}\|W\|^2 \tag{11}$$

$$\text{subject to } y_i(W^T x_i + b) \geqslant 1 \tag{12}$$

It can also be solved in terms of Lagrange multipliers, α_i, as shown in (13) [17]

$$\max L(\alpha) = \sum_{i=1}^{N} \alpha_i + 2^{-1} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle \tag{13}$$

$$\text{subject to } \alpha_i x_i = 0 \tag{14}$$

where $\langle x_i, x_j \rangle$ is an inner product.

In this case, support vectors are designated by α_i^*, where $\alpha_i^* > 0$ and W and b are obtained by (15 and 16) [17]:

$$W^* = \sum_{i=1}^{N} \alpha_i^* x_i y_i \tag{15}$$

$$b^* = y_{sv} - \sum_{i=1}^{N} \alpha_i^* y_i \langle x_i, x_{sv} \rangle \tag{16}$$

Now the optimal function is given by (17) [17]:

$$f(x) = \text{sign}\left(\sum_{i \in SV} \alpha_i^* y_i \langle x_i, x_{sv} \rangle + b^* \right) \tag{17}$$

In case if data cannot be separated linearly then (W^*, b^*) does not exist. Then the input data should be mapped first from n-dimensional space (R^n) to higher dimensional feature space (F^m) [17]:

$$\phi : R^n \rightarrow F^m x_i \rightarrow \phi(x_i) \tag{18}$$

Then another function f is used to map the data from feature space to decision space (Y^2) [17]:

$$f : F^m \rightarrow Y^2\phi(x_i) \rightarrow f(\phi(x_i)) \tag{19}$$

An SVM classifier separating two nonlinearly separable classes is shown in Fig. 4.

Usually kernel functions are used for mapping nonlinearly separable data into higher dimensional feature space. Thus Eq. (17) can be modified as follows [17]:

$$f(x) = \text{sign}\left(\sum_{i\in SV}\alpha_i^* y_i \cdot k(x_i, x_{sv}) + b^*\right) \tag{20}$$

where $k(x_i, x_{sv})$ is kernel function. Equation of k for Radial Basis Function (RBF) is given as in (21) [17]:

$$k(x, y) = \exp\left(-\frac{||x - y||^2}{2\sigma^2}\right) \tag{21}$$

Various kernel functions are available, while Gaussian RBF kernel is proved to be reliable kernel functions for this purpose [15]. In this paper Gaussian RBF kernel is used.

3. System under study

A simple three phase power system is modeled in SIMULINK environment. It includes three lines, 500 km, 200 km and 150 km with impedance values per km (R, X, C) for zero sequence is (0.3064, 0.9654, 7.751×10^{-6}) and for positive sequence is (0.01273, 0.2026, 12.74×10^{-6}) respectively. The power system network is shown in Fig. 5. Fault is applied on 500 km line at various locations. Three parameters of the selected system are varied: (1) Load Angle (10°, 20° and 30°), (2) Fault location (varied from 10 km to 100 km in intervals of 20 km from source) and (3) Fault Resistance (0.1 and 100 ohms). Thus a total of 450 cases are taken into study, out of which 400 cases are used for training SVM and 50 cases are used for testing SVM.

4. Combined three SVM model

In this paper, a multiple SVM model is employed which constitutes three SVMs. *SVM-A*, *SVM-B* and *SVM-C* are trained to detect fault in A, B and C phases respectively. In testing phase each SVM classifies the fault as class 1 if the fault is detected in corresponding phase; otherwise, it is classified as class −1. Fault is determined using the combination of results from all the three SVMs according to the logic sequences shown in Table 1.

Special case corresponds to a situation where the model cannot classify between double line to ground faults and three phase faults. In such case the following procedure is followed for classifying between *ABG*, *BCG*, *CAG* and *three phase* faults.

1. Check each phase for voltage lag or voltage rise using peak values of voltages in each phase using instantaneous amplitude values.
2. Drop in instantaneous amplitude during a particular period (fault period) in all the three phases indicates three phase faults.
3. Drop in two phases and rise in third phase indicate double line to ground fault.

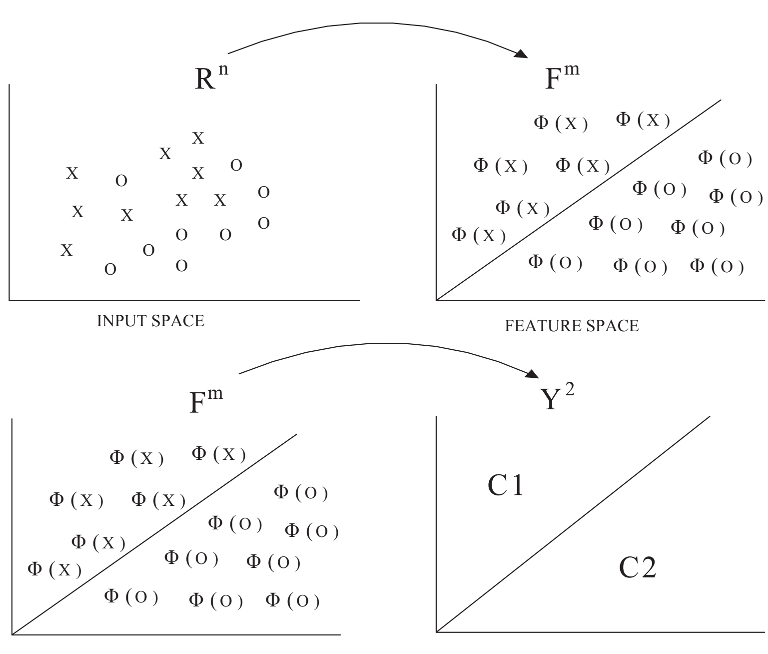

Figure 4 Nonlinearly separable classifier.

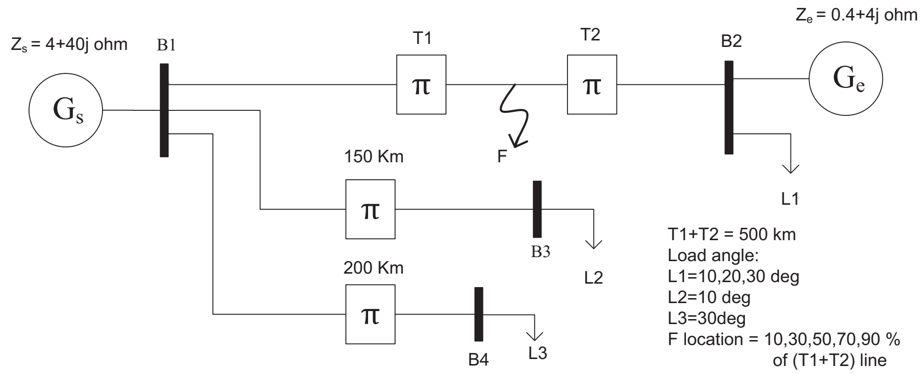

Figure 5 Power system network.

Table 1 Multiple SVM logic for fault classification.

SVM 'A'	SVM 'B'	SVM 'C'	Fault type
1	−1	−1	AG
−1	1	−1	BG
−1	−1	1	CG
1	1	−1	AB
−1	1	1	BC
1	−1	1	CA
1	1	1	Special case

The overall Multiple SVM model can be represented as shown in Fig. 6.

5. Results and discussion

All the data for training and testing phase are acquired by simulating the sample model (Fig. 5) using SimPowerSystems toolbox in SIMULINK environment (R2009b). The proposed algorithm is implemented using Matlab 7 software on a Windows 7 operating system with Intel core i3-870 system

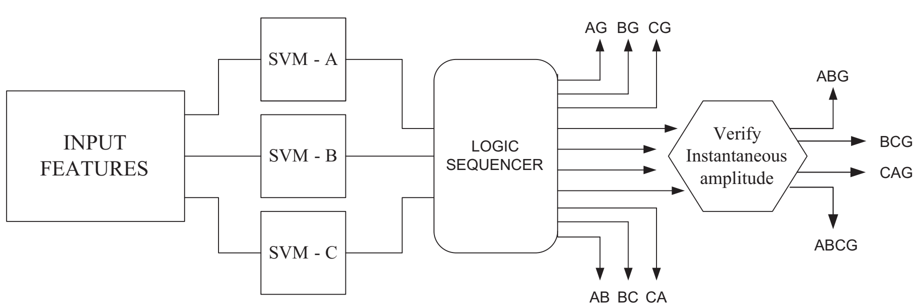

Figure 6 Implementation of multiple SVM model.

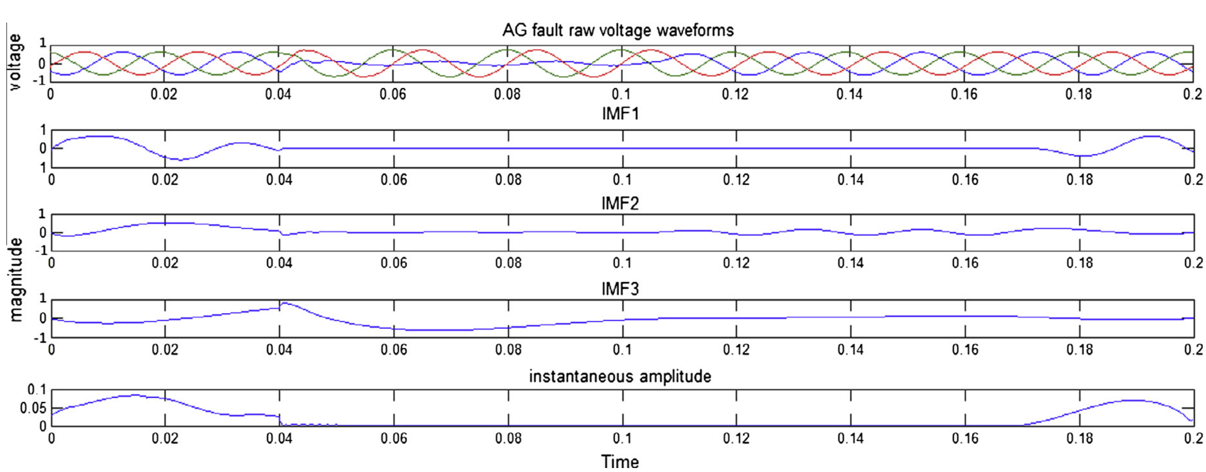

Figure 7 AG fault: voltage waveforms, IMF1–3 and instantaneous amplitude of phase A.

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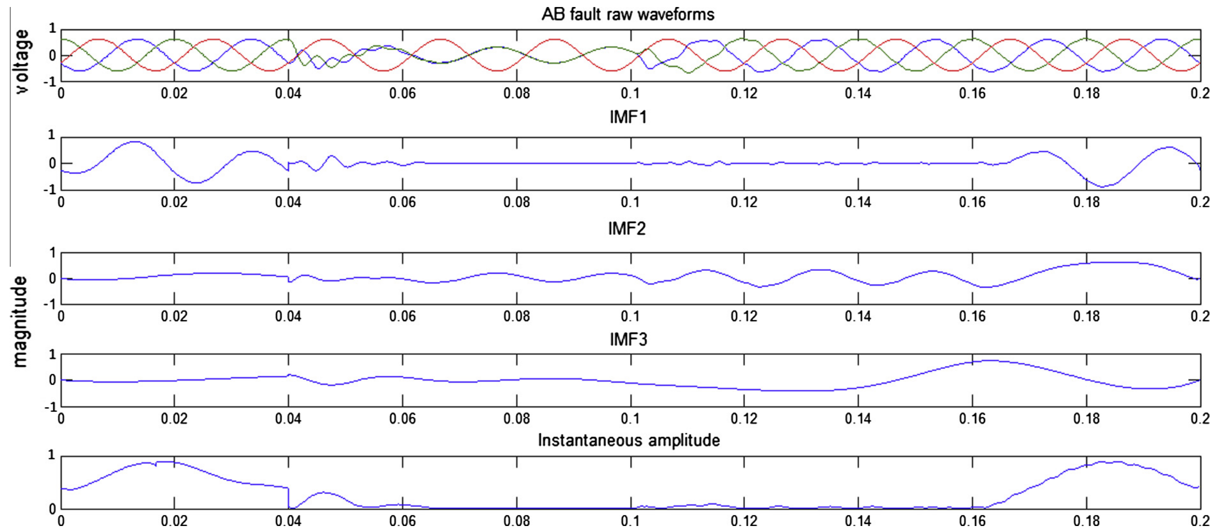

Figure 8 AB fault: voltage waveforms, IMF1–3 and instantaneous amplitude of phase A.

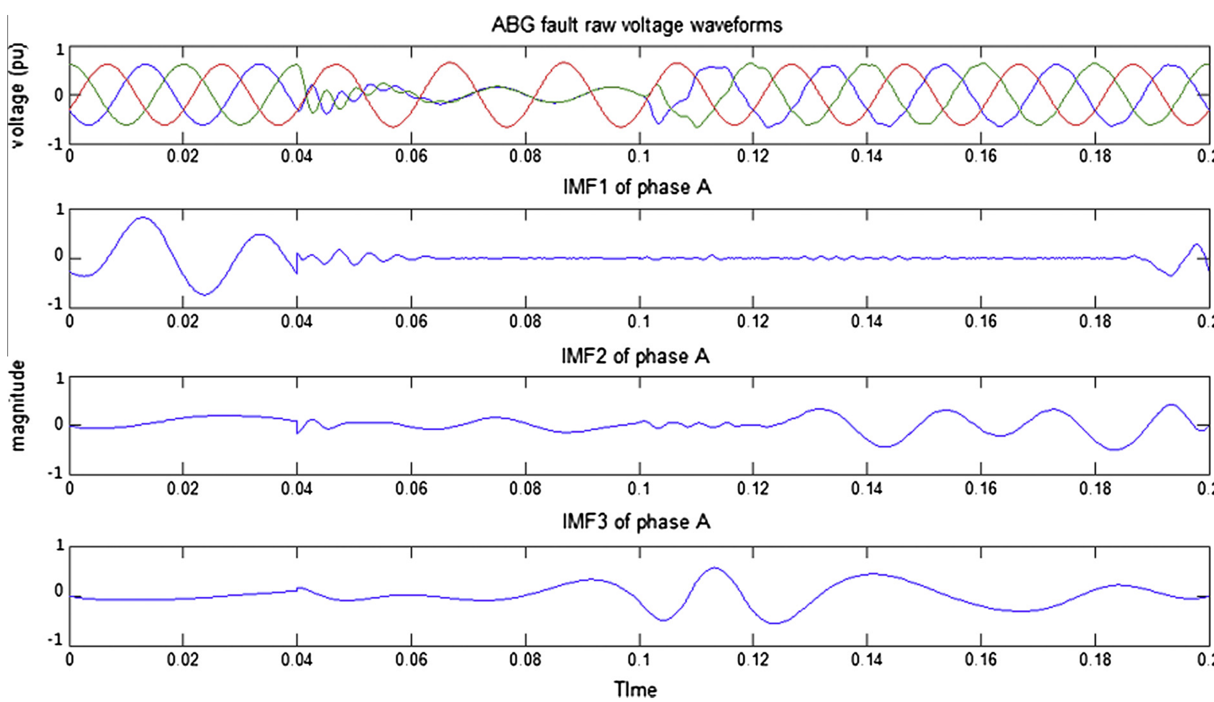

Figure 9 ABG fault: voltage waveforms, IMF1–3 and instantaneous amplitude of phase A.

and the methodology takes the computational time of 1.92 s for classifying a typical fault. This computation time varies from case to case analysis of the chosen test system. Voltage waveforms for one single line to ground fault case (AG), one line to line fault case (AB), one double line to ground (ABG) and one three phase fault condition are shown in Figs. 7–10 along with $IMF1$–3 and instantaneous amplitude for phase-A. For ABG fault and ABCG fault, instantaneous amplitudes of IMF1 of all the three phases are shown separately in Figs. 11 and 12. For ABG fault (Fig. 11) the instantaneous amplitude for phase-A and B is decreased throughout the fault situation, while for phase-C, instantaneous amplitude is raised once fault is occurred. For three phase faults (Fig. 12), in all the three phases instantaneous amplitude is diminished upon occurrence of fault. This property is used for classifying between double line to ground fault and three phase faults under special condition shown in Table 1. All the three SVMs are trained rigorously using the data obtained by varying parameters of the sample mode. SVM toolbox of MATLAB software is used for this purpose. A combination

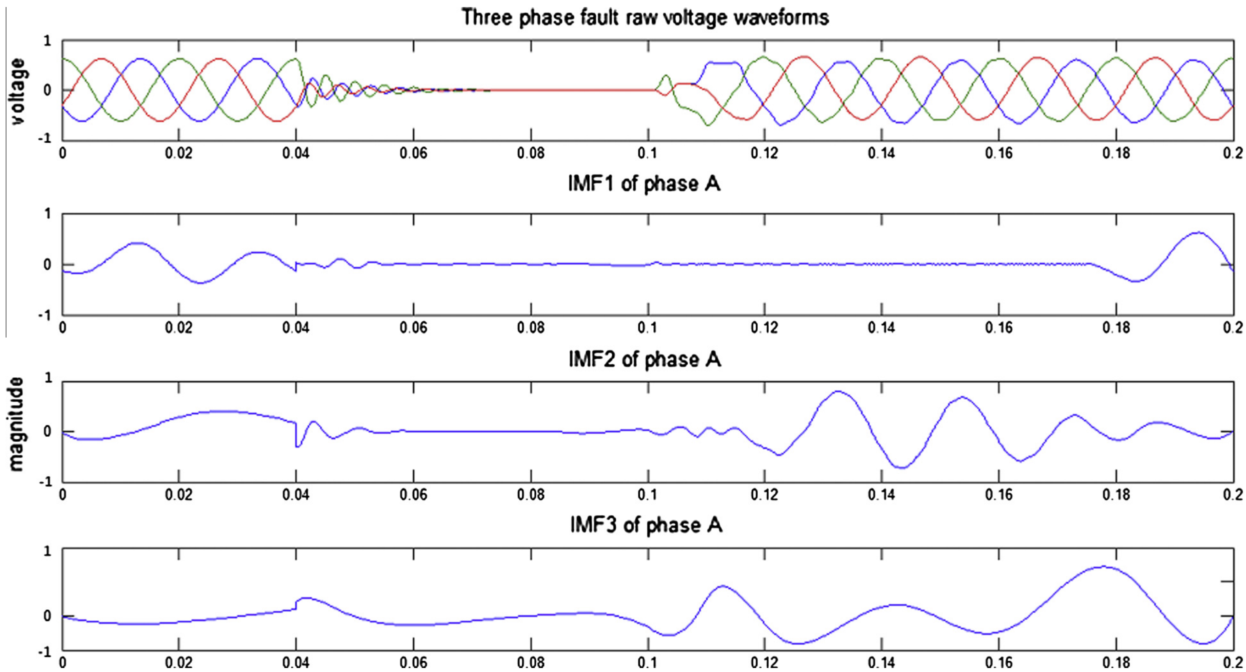

Figure 10 ABC fault: voltage waveforms, IMF1–3 and instantaneous amplitude of phase A.

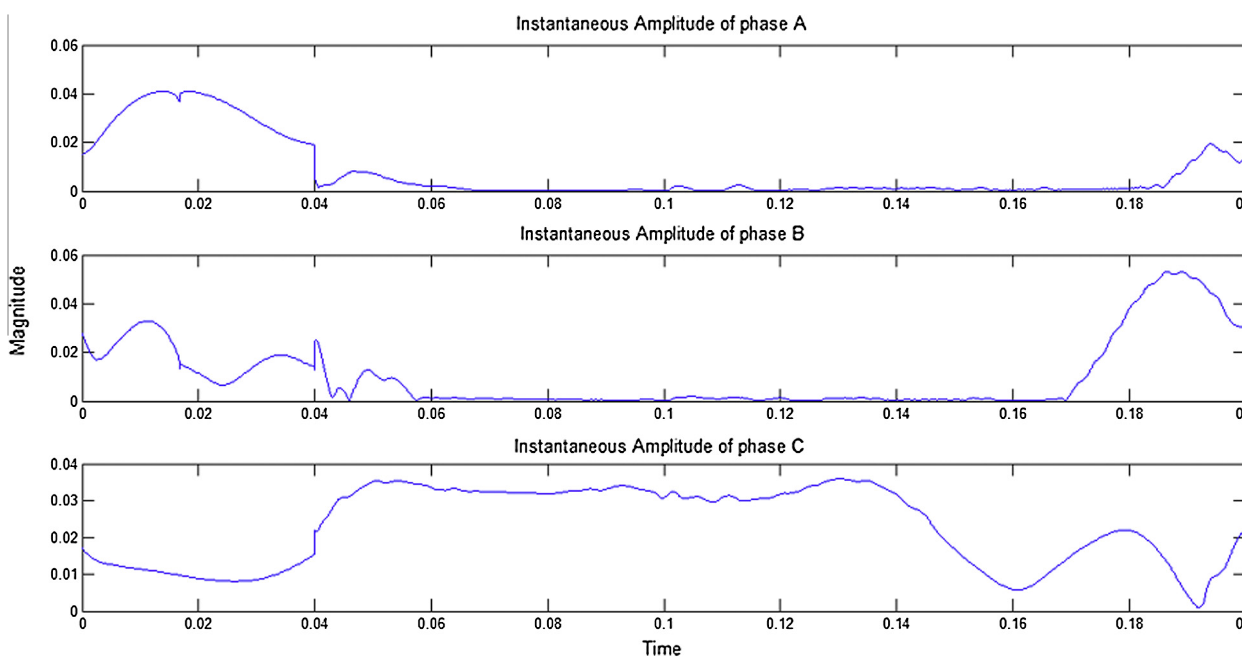

Figure 11 Instantaneous amplitude of IMF1 of phase A–C for ABG fault.

of Coupled Simulated Annealing (CSA) and a standard simplex method is used for optimizing the following two parameters of SVM: (1) Regularization parameter, γ which determines the trade-off between the training error, minimization and smoothness, and (2) squared bandwidth, σ^2. Initially CSA is used to calculate good starting values and they are passed to the simplex method in order to fine tune the result. The optimized values of γ and bandwidth are shown in Table 2. The results show that out of 50 cases chosen randomly among 450 for validating the proposed methodology, the classifier identifies accurately with efficiency of 95% and above.

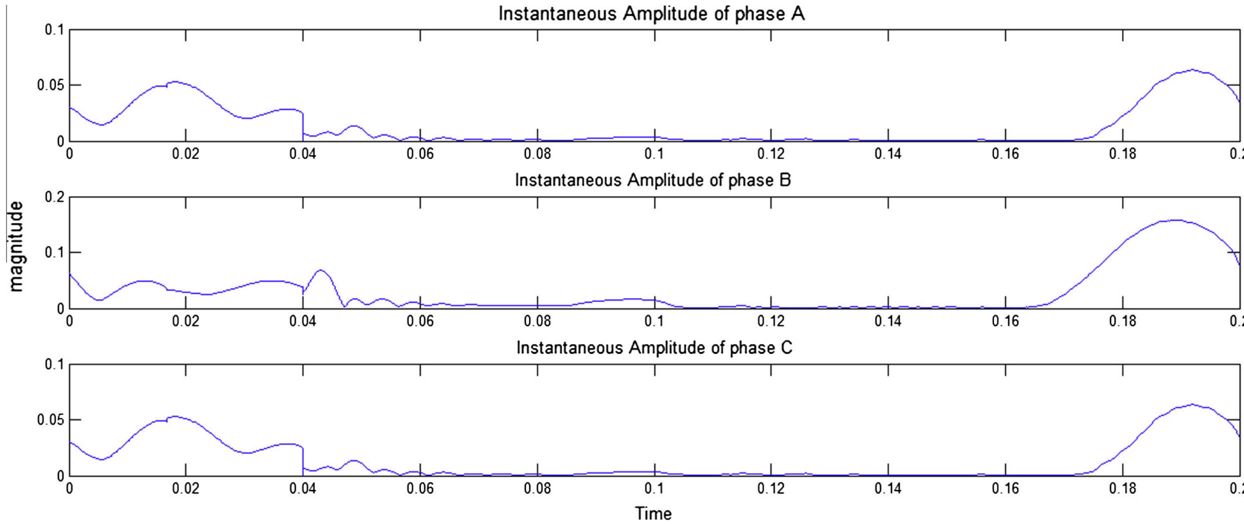

Figure 12 Instantaneous amplitude of IMF1 of phase A–C for three phase faults.

Table 2 SVM classifiers parameters and performance.

SVM	RBF kernel parameters	No. of testing cases	No. of cases classified accurately	Efficiency of classifier (%)	Overall efficiency
SVM-A	$\gamma = 23$ $\sigma^2 = 0.4$	50	48	96	
SVM-B	$\gamma = 26$ $\sigma^2 = 0.4$	50	49	98	95.33%
SVM-C	$\gamma = 23$ $\sigma^2 = 0.4$	50	46	92	

6. Conclusion

In this paper, a hybrid algorithm to classify the power system fault is proposed. The proposed technique uses multiple SVM model with features extracted using Empirical Mode Decomposition and Hilbert Huang Transform algorithms. Classification is done among ten fault cases with rigorous training and testing phases. Accuracy and feasibility of the proposed methodology are demonstrated by results obtained. The main contribution of the proposed algorithm is the possibility of its application to any transmission line, no matter the line configuration, with no need for re-training at different load values, voltage levels and fault resistances. In this paper, a simple power system network is trained and tested for evaluating the algorithm. From the results it has identified that the algorithm is producing good results on fault classification. However, the algorithm functionality does not depend on number of buses or complexity of the network. Hence the proposed algorithm is expected to work for any number of buses if training is done accordingly. The classification efficiency does not depend upon fault resistance, location of fault or the load value.

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