IDENTIFICATION OF FAULT ZONE IN DISTRIBUTION SYSTEM IN THE PRESENCE OF PV MODULE AND ESD BY DTCWT–STATE VECTOR MACHINE ALGORITHM USING OPTIMALLY PLACED MEASURING DEVICES

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Abstract

In this paper, a novel scheme is suggested for identifying the location of short-circuit faults that occur in distribution system. The proposed genetic algorithm and graph theory–based method is designed such a way that it splits electrical distribution system into protection zones containing buses, protection relays with measuring devices. Proposed methodology also decreases the calculation burden in dealing with large number of data sets. Genetic algorithm–based heuristic search method is used to place measuring devices at optimal location, and it is carried out in MATLAB. A new signal processing technique named dual tree complex wavelets transform is used for feature extraction, and support vector machine–based machine learning classifier is used for pattern recognition. IEEE33 bus radial distribution system and IEEE13 bus feeder test systems are tested for validating the proposed methodology and all the simulation work carried out in MATLAB Simulink.

Key Words

Fault identification, DTCWT, machine learning, power system protection, zone selection

1. Introduction

Electrical distribution system cannot be designed and installed such a way that it never gets any fault, fault in the sense inconvenience occurred in the system through abnormal flow of current in the system. In most of the cases, these faults are unavoidable due to unpleasant weather conditions, interference of birds on overhead lines and chemical pollution. Few faults are not severe in nature, but majority of faults cause huge damage to the distribution system such as production of arc, tripping of switchgear components, insulation damage and components damage. These faults cause blackout in the distribution system and also can harm the living beings. Early detection of faults is the prime goal to the power engineers and researchers in recent days. Many research studies are conducted to detect the various faults that occur in electrical distribution system. Open-circuit faults are the frequent faults that occur in distribution system; it occurs when an interruption occurs in the circuit either by open switch or break in the conductor. Siu Ki Lau *et al.* discussed detection of open-circuit faults in distribution system, and it is mentioned in [1]. Time frequency characteristics of fault waveform–based fault recognition methods in distribution system were carried out by Xue Qin *et al.*, and it is discussed in [2]. In overhead distribution lines, most faults cause arc; the location of these arc faults is identified through radiometry, and it is discussed in [3]. To reduce the errors that occurred in impedance-based fault detection algorithms, S. Das *et al.* introduced a new fault location detection using short-circuit fault current approach, and it discussed in [4]. Based on the busbar-measured voltages, a new short-circuit fault detection algorithm for distribution system is proposed, and further it is discussed in [5]. Nantian Huang *et al.* proposed a new technique to detect and classify the short-circuit faults using empirical wavelet transform; it is given in [6]. Some abnormal faults also occur in distribution system, such as high-impedance fault, which are not detected by the conventional over-current protection scheme; the detailed tutorial on high-impedance fault is discussed in [7]. Short-circuit faults detection and isolation in electric traction system are proposed in [8]. Classification of various short-circuit faults by using probabilistic neural network–based classifier is discussed in [9]. A detailed review on fault location techniques is discussed in [10]. Besides detecting and locating the fault

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Recommended by Dr. Partha Sarathi Subudhi
(DOI: 10.2316/J.2022.203-0336)

in distribution system, isolating the faulty section from the healthy section is also equally important. This scheme of protection is known as "Zone Protection" scheme. In this protection scheme, faulty zone is isolated from the non-faulty zone to ensure the continuous power supply to the non-faulty zone locations. Farhana Ferdous *et al.* proposed a protection zone selection in transmission line by distance relay; it is discussed in [11]. A numerical bus zone protection scheme is proposed for both high-impedance and low-impedance fault measurements; it is discussed in [12]. A transient current–based zone protection scheme using wavelet transform is discussed in [13]. A wide area measurement-based fault location is discussed in [14]; it develops a fault zone identification vector to determine the fault zone. In this paper, a new zone protection scheme is proposed by placing measuring devices (MDs) at optimal location through genetic algorithm–based optimization technique. Graph theory–based search algorithm is used to identify the protection zone, and it is tested on both balanced radial distribution system and unbalanced feeder distribution system, and it efficiently works on both distribution systems. Computation burden is less compared with impedance-based and travelling wave method. Knowledge-based methods have slow response time; this drawback is minimized by this method. The proposed methodology is tested under noise condition. This method is also cost-efficient compared with existed methods.

2. Proposed Methodology

In this proposed methodology, short-circuit faults are detected and located by a genetic algorithm–graph theory search–based method. The basic block diagram of the proposed methodology is shown in Fig. 1:

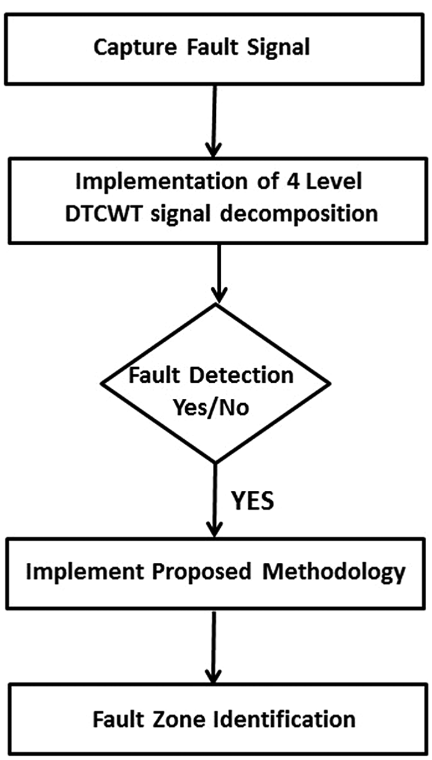

Figure 1. Block diagram of proposed methodology.

2.1 Dual Tree Complex Wavelet Transform (DTCWT)

The drawbacks of conventional wavelet transform are modified by Nick. G Kingsbury *et al.*; they proposed a new wavelet technique named dual tree complex wavelet transform; it is explained in [15]. Therefore, the complex wavelet function is shown in (1).

$$\psi(t) = \psi_i(t) + \psi_j(t) \tag{1}$$

It is known that first stage of decomposition of signal needs one type of filters and later stages need another type of filters for signal decomposition. The design of Q shift filters is based upon choosing low-pass filters with good even length. The low-pass filter $h_{\mathrm{L}}(Z)$ of length 2n with delay that is approximately 1/4 sample is designed with linear-phase low-pass FIR filter $h_{\mathrm{L2}}(Z)$ of length 4n as

$$h_{\mathrm{L2}}(Z) = h_{\mathrm{L}}(Z^2) + Z^{-1}h_{\mathrm{L}}(Z^2) \tag{2}$$

Where H_{L2} has half the desired bandwidth and twice the desired delay. The filters after the first level of decomposition are derived as

$$h_{00\mathrm{A}}(Z) = Z^{-1}h_{\mathrm{L}}(Z^{-1}), \qquad h_{01\mathrm{A}} = h_{\mathrm{L}}(-Z) \tag{3}$$

$$h_{00\mathrm{B}}(Z) = h_{\mathrm{L}}(Z); \qquad h_{01\mathrm{B}} = Z^{-1}h_{\mathrm{L}}(-Z^{-1}) \tag{4}$$

A four-level decomposition is applied to obtain the coefficients of the required signal.

2.2 Optimal Placement of Measuring Devices

The main advantage in this zone protection scheme is to decrease the cost of protection scheme. To achieve this, the number of MDs should be decreased; they should be optimally placed in the power system, and it is done by genetic algorithm [16]. In this optimization problem, IEEE33 bus radial distribution network test system is used. The objective function of optimal placement problem (OPP) is given as

$$P_L = \sum_{i=1}^{n} |i_i|^2 R_i \tag{5}$$

In (5), X denotes the number of MDs and i denotes the bus number, usually $1, 2, 3 \ldots n$. In this OPP, initial population considered is 200. The results are obtained after minimizing the Objective function. Total 11 number of locations are identified as optimal locations for placing the Measuring devices in the IEEE33 bus radial distribution network. The 11 optimal bus locations observed are 2, 3, 5, 9, 14, 17, 19, 22, 24, 26, 30.

2.3 Graph Theory–Based Protection Zone Selection

The main reason behind in choosing graph theory for protection zone selection is to simplify complex power system. The graph theory–based expert system is furthermore discussed in [17]. The graph theory–based search method basically involves the following steps:

Table 1
Graph Theory Search Method Results on IEEE33 Bus

Zone	Bus Numbers
Zone 1	1, **2**, **3**, **19**, 20, 21, **22**, 23, **24**, 25
Zone 2	4, **5**, **26**, 27, 28, 29, **30**, 31, 32, 33.
Zone 3	7, 8, **9**, 10, 11, 12, 13, **14**, 15, 16, **17**, 18

N Samples	Predicted YES	Predicted NO
Actual YES	Truly YES (TY)	False NO (FN)
Actual NO	False YES (FY)	Truly NO (TN)

Figure 2. Typical confusion matrix.

Step 1: Check the number of buses.
Step 2: Initial node or bus is treated as a basic zone.
Step 3: The bus that is neighbour to the basic zone is added, and treat this as a new zone.
Step 4: Continue step 3 until all the zones reach the number of buses in the power system.
Step 5: Eliminate the duplicate zones, which have common buses.
Step 6: Group the buses in three-zone protection scheme.
Step 7: Stop the process if it satisfies step 6, if not, go to step 2.

The above steps of search method are programmed in MATLAB; the results obtained from testing the IEEE33 radial distribution bus system are shown in Table 1.

As shown in Table 1 bold values are optimal locations to place measuring devices. Like 2,3,19,22 and 24 in Zone 1 5,26,30 in Zone 2 9,14 and 17 in Zone 3. This search method ensures minimum number of MDs in each and every zone.

2.4 Pattern Recognition

In this paper, a machine learning–based classifier is used for the pattern recognition. A supervised machine learning–based technique, named as "Support Vector Machine (SVM)" learning technique, is used for pattern recognition. It is more discussed in [18].

The gradient search method is used to minimize the support vectors and to find the optimal hyperplane in the classification problem, and it is discussed in [19]. Confusion matrix is a table that describes the performance of the classification problem. The typical confusion matrix of binary classification problem is shown in Fig. 2.

The feature extraction–based confusion matrix for classification problems is briefly discussed in [20]. The accuracy of the classification problem is given as

$$\text{Precision} = \frac{TY}{TY + FN}, \qquad \text{Accuracy} = \frac{TY + TN}{TY + FN + FY + TN} \tag{6}$$

3. Results and Discussions

In this paper, an 11 kV balanced radial distribution system is used to test the proposed methodology. Standard IEEE33 bus test system is selected for detecting the location of short-circuit faults and isolating it from the healthy zones. The block diagram of IEEE33 bus system with optimally placed MDs is shown in Fig. 3.

Case 1: L-G fault occurred between bus number 28 and bus number 29

In this, L-G fault is applied to the IEEE33 bus balanced radial distribution test system at proposed case location. The L-G fault is applied at time interval of 0.5–0.7 s at the proposed location, and the necessary simulation work is carried out in MATLAB Simulink. The fault signal is captured, and it is shown in Fig. 4.

The fault signal data is collected at MDs located at bus numbers 5, 26 and 30. The non-fault signals are collected at other remaining MDs. These signals are decomposed by the dual tree complex wavelet transform–based signal processing technique. The total numbers of samples (N) considered in this classification problem are 400. These collected data are huge in number. In this huge data, only few data give the better analysis of the signal. This feature selection from the huge data is known as feature detection. In this paper, Chi-square feature detection method is used to reduce the data. In this, all the data compared with observed and expected value and the data which have high Chi-square value are more dependent on the response. These selected signals have high Chi-square value. The formula for Chi-square is given as

$$X_c = \sum \frac{(0_i - E_i)^2}{E_i}$$

where c = degrees of freedom
O = observed value
E = expected value

The confusion matrix after training the data in SVM is shown in Table 2.

In the Table 2, out of 140 fault signal data, 135 data signals are predicted correctly and classified in to Zone-2 with 96.42% accuracy. The overall accuracy of the classification problem is 95.0%.

Case 2: L-L-G fault occurred between bus number 3 and bus number 23

In this case, the L-L-G fault is applied between bus number 3 and bus number 23. The fault is applied at time duration from 0.5 to 0.7 s; the captured fault signal at bus number 23 is shown in Fig. 5.

The required fault signal data is collected at MDs located at 2, 3, 19, 22 and 24. The remaining signals data are collected at other MDs situated at different locations. Total 400 data signals are collected by DTCWT-based signal decomposition at level-4. The confusion matrix after training the data is given in Table 3.

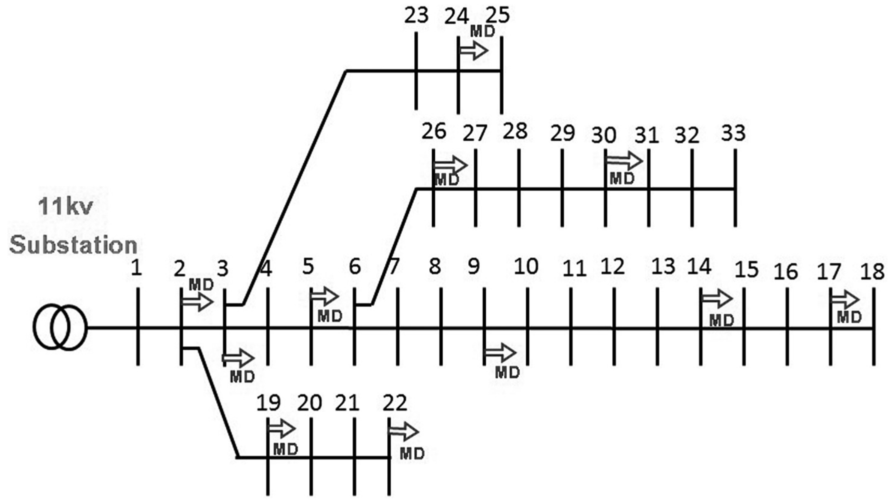

Figure 3. Block diagram of IEEE-33 RDN with optimally placed measuring devices (MDs).

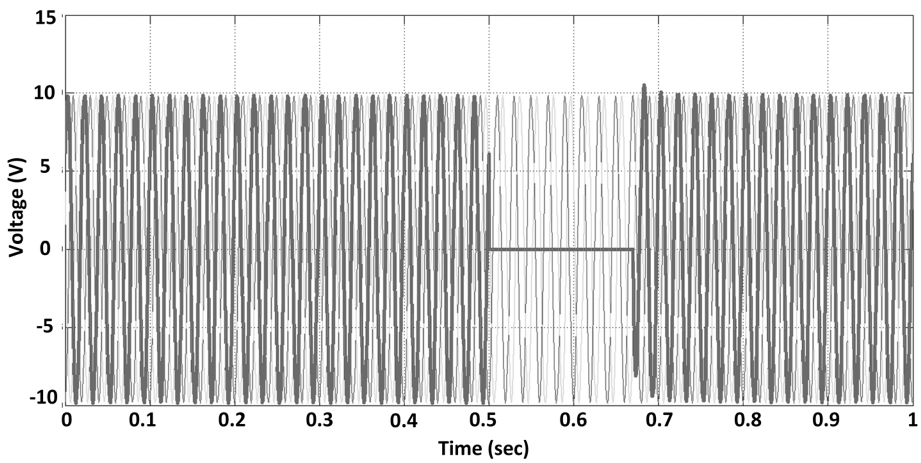

Figure 4. L-G fault signal at bus number 28 to bus number 29.

Table 2
Confusion matrix for Case-1

$N = 400$	Predicted			Percentage
		Zone 1	Zone2	Zone3	
Actual	Zone1	**125**	2	5	94.69%
	Zone2	3	**135**	2	**96.42%**
	Zone3	3	5	**120**	93.75%
		131	142	127	**95.0%**

In Table 3, out of 145 fault signals, 140 signals are predicted as fault signals located at Zone-1. The SVM classifier trained the data and located the fault location at Zone-1 with 96.55% efficiency. The overall efficiency of the classification problem is 96.25%.

Case 3: L-L-L fault occurred between bus number 12 and bus number 13

In this case, the L-L-L fault is applied between bus number 12 and bus number 13; the fault signal captured at bus number 13 at time interval from 0.5 to 0.7 s is shown in Fig. 6.

The fault signal data are collected at MDs located at bus numbers 9, 14 and 17. The overall data signals obtained are 400. These total signals are trained in SVM-based classifier. The confusion matrix obtained after training the signals data is tabulated in Table 4.

In Table 4, 146 fault signals out of 148 signals data are predicted that they are located at Zone-3. The proposed zone protection pattern recognition predicted that fault signals belong to Zone-3 with 97.33% accuracy. The overall accuracy of the classification problem is 98.00%.

3.1 Integration of Distributed Generation in Radial Distribution System

To attach this distributed generation (DG) in power system, it is required to know the voltage and power profile of distribution system at each and every bus. In this paper, backward/forward sweep load flow analysis is used. The load flow analysis is carried out in MATLAB. The power flow problem converged, and it reached the convergence value of less than 0.001. The result from the power flow carried out is obtained; bus number 18 is observed at a low

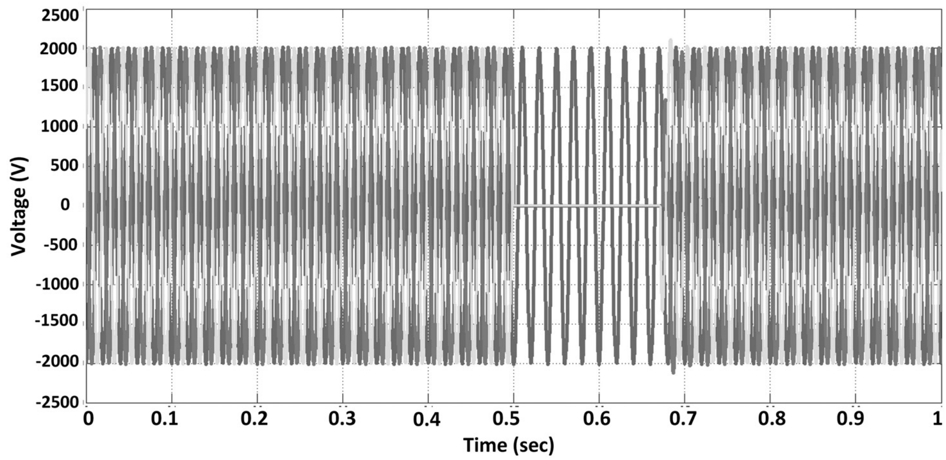

Figure 5. L-L-G fault signal at bus number 23.

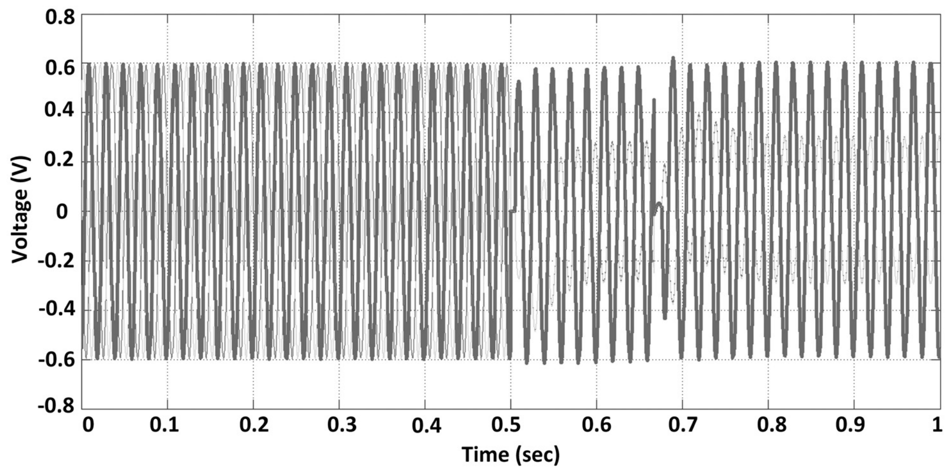

Figure 6. L-L-L fault signal at bus number 13.

Table 3
Confusion Matrix for Case-2

$N = 400$	Predicted				Percentage
		Zone 1	Zone2	Zone3	
Actual	Zone1	**140**	2	3	**96.55%**
	Zone2	2	**125**	2	96.42%
	Zone3	3	3	**120**	93.75%
		145	130	125	**96.25%**

voltage of 0.9136 p.u, and bus number 33 is also observed at 0.917 p.u. These buses are treated as weak busses, and distributed generators can be injected to meet the load demand. The basic objective function for optimal DG's sizes is given as

$$\text{Minimize} \quad P_L = \sum_{i=1}^{n} |i_i|^2 R_i$$

Subjected to

Table 4
Confusion Matrix for Case-3

$N = 400$	Predicted				Percentage
		Zone 1	Zone2	Zone3	
Actual	Zone1	**126**	1	1	98.43%
	Zone2	1	**120**	1	98.36%
	Zone3	2	2	**146**	**97.33%**
		129	123	148	**98.00%**

$$\begin{aligned} &|V_{\mathrm{i\,min}}| \leq |V_{\mathrm{i}}| \leq |V_{\mathrm{i\,max}}| \\ &|I_{\mathrm{ij}}| \leq |I_{\mathrm{ij\,max}}| \end{aligned} \tag{7}$$

Where P_{L} is power loss, where power loss should be minimized. I_{i} is the current flowing through the i^{th} branch and R_{i} is resistance of the i^{th} branch. Here it is considered that the optimal locations for placing DG are bus number 18 and bus number 33. particle swarm optimization (PSO)-based optimization technique is used to optimize the DG sizing problem. IEEE33 bus radial distribution test system is used for solving this optimization problem. The DG size and power loss obtained after optimization are given in Table 5.

Table 5
DG Sizing

Bus Number	Voltage Profile before DG	Voltage Profile after DG	Power Loss	DG Size
33	0.917	0.967	90.3 kw	1.2 MW
18	0.9136	0.963	90.3 kw	0.65 MW

PV module integrated with battery is used as DG source in this paper. The power loss is minimized from 203 to 90.3 KW. The total power saved through this DG size placement is 113 kW. PV rating installed at bus 33 is 1.2 MW, and PV rating installed at bus 18 is 0.65 kW These DG sources are injected at bus numbers 18 and 33. The weak buses 16, 17, 18 and 31, 32, 33 are marked in red colour in the block diagram. The block diagram of IEEE33 radial distribution system with DG is shown in Fig. 7.

The PV module integrated with battery source is designed and simulated in MATLAB Simulink.

Case 4: L-G fault occurred between bus number 31 and bus number 32

In this case, L-G fault occurred between bus number 31 and bus number 32 in IEEE33 radial distribution system with distributed generators connected at bus number 18 and bus number 33. The L-G fault is applied at the time interval from 0.5 to 0.7 s through a breaker. The confusion matrix of Case 4 is shown in Table 6.

In Table 6, out of 140 fault signals, 137 fault signals are grouped such that they belong to Zone-2 with 97.85% accuracy. The overall accuracy of the pattern recognition problem is 96.25%.

Case 5: L-L-L fault occurred between bus number 15 and bus number 16

In this case, the L-L-L fault is applied between bus number 15 and bus number 16; the fault signal is captured at bus number 15 at time interval from 0.5 to 0.7 s.

Table 6
Confusion Matrix for Case 4

$N = 400$	Predicted				Percentage
		Zone 1	Zone2	Zone3	
Actual	Zone1	**127**	2	3	96.21%
	Zone2	2	**137**	1	**97.85%**
	Zone3	3	4	**121**	93.75%
		132	143	125	**96.25%**

The state of charge of the battery during the fault is observed at the integrated PV battery DG connected at bus number 18. The observed state of charge of the battery is shown in Fig. 8.

The fault signals are measured at MDs located at bus numbers 9, 14 and 17. The non-fault signals are collected at other MDs located at optimal locations. The fault signal and non-fault signals are decomposed by dual tree complex wavelet transform, and features extracted from these signal are sent to pattern recognition. In total, 400 signal data are collected at various MDs located at optimal location. The confusion matrix of Case 5 is tabulated in Table 7.

In Table 7, out of 150 fault signal data, 147 signal data are grouped as fault signal and located at Zone-3 with 98.00% accuracy. The overall accuracy of the SVM-based pattern recognition is 98.25%.

Case 6: Unbalanced feeder system

In this case, IEEE13 feeder bus unbalanced system is considered to validate the proposed methodology. It is a simple test system to analyse the distribution system. The operating voltage of this test system is 4.16 kV. It is highly loaded system with voltage regulator. A shunt capacitance is placed between bus 671 and bus 692. An inline transformer is there between bus 633 and bus 634. It is heavily loaded Un Balanced System.

The proposed methodology is applied on the IEEE13 bus system. The zones are separated through the genetic

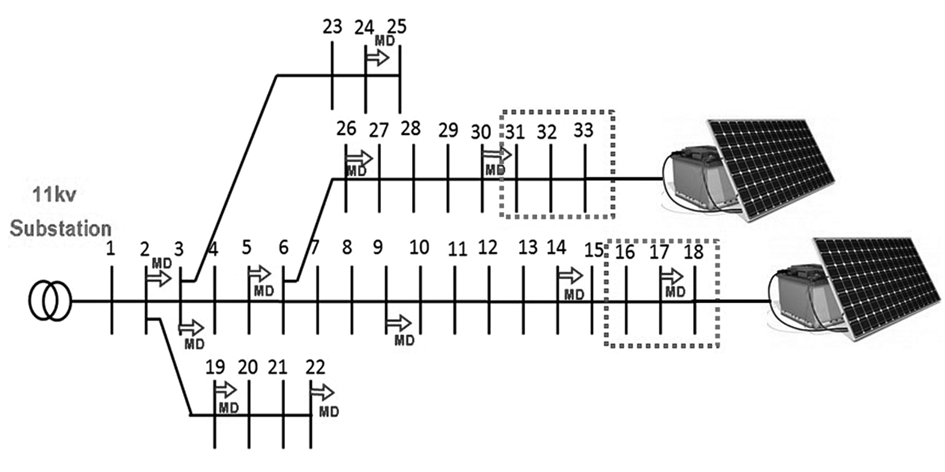

Figure 7. Block diagram of IEEE33 bus with distributed generation.

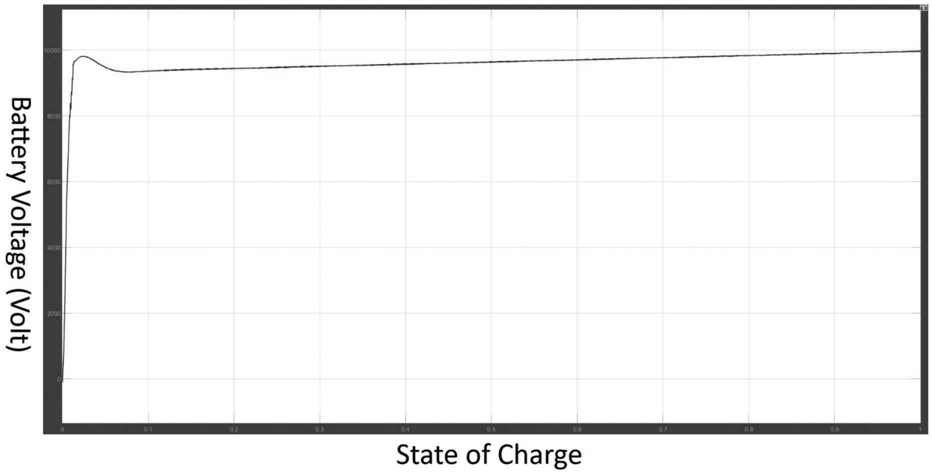

Figure 8. State of charge of battery at bus 18.

Table 7
Confusion Matrix for Case 5

$N = 400$		Predicted			Percentage
		Zone 1	Zone2	Zone3	
Actual	Zone1	**126**	1	1	98.43%
	Zone2	1	**120**	1	98.36%
	Zone3	1	2	**147**	**98.00%**
		128	123	149	**98.25%**

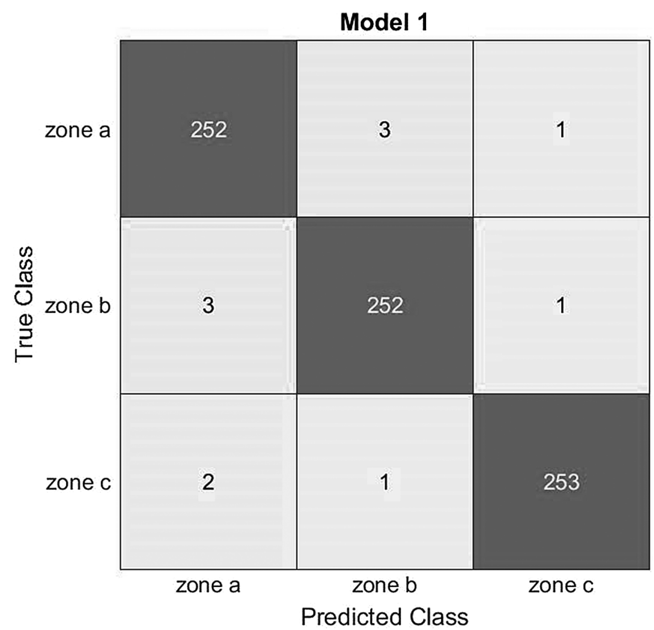

Figure 9. Confusion matrix for Case 6.

algorithm and graph theory–based method. The observed zones are categorized. Bus 611, bus 684, bus 671, bus 652 and bus 680 are grouped as Zone 1. In Zone 1, MD is at bus 684. Bus 633, bus 634, bus 675 and bus 692 are grouped as Zone 2. In Zone 2, MDs are placed at bus 634 and bus 675. Bus 646, bus 645, bus 632 and bus 650 are grouped in Zone 3. In Zone 3, MDs are placed at bus 645, bus 632 and bus 650. The LLL short circuit fault is given between bus 611 and 684. The fault data is collected at each and every MD. The collected samples are analysed through four-level DTCWT-based signal processing techniques. The confusion matrix after the data is trained in the SVM-based algorithm is given in Fig. 9.

In the above table, out of 256 fault signal data, 252 signal data are grouped as fault signal and located at Zone-1 with 98.43% accuracy. The overall accuracy of the SVM-based pattern recognition is 98.56%. Prediction speed of the classification problem is 27,000 obs/s. Response time of simulation is observed as 0.0764 s. The above obtained results are analysed and tabulated in Table 8.

As shown in Table 8, the L-G fault that occurred in Case-1 is located at Zone-2 and is predicted correctly by proposed methodology with fault detection efficiency of 96.42% and the overall efficiency is 95.00%. The L-L-G fault that occurred in Case-2 is located at Zone-1 and is predicted correctly by proposed genetic algorithm–graph theory–based protection zone selection method with fault detection efficiency of 96.55%, and the overall efficiency is 96.25%. The L-L-L fault that occurred in Case-3 is located at Zone-3 and is predicted correctly by proposed zone protection methodology with fault detection efficiency of 97.33%, and the overall classification problem efficiency is 98.00%. The DG source is placed at buses 18 and 33. The L-G fault occurred in Case-4; it is located at Zone-2 and is predicted correctly by proposed methodology with 97.85%. The L-L-L fault occurred in Case-5, it is located at Zone-3, and it is predicted correctly with 98.00%. In Case 6, it is observed that fault zone is identified correctly. The fault is located between bus 611 and bus 682, categorized in Zone 1, and proposed methodology identified the fault location accurately with 98.43% accuracy, and overall classification accuracy is 98.56%.

4. Conclusion

In this article, a novel fault zone detection algorithm using voltage signal is proposed for balanced and unbalanced

Table 8
Overall Performance Analysis

Case	DG Allocation	Fault Type	Actual Zone	Predicted Zone	Fault Zone Detection Efficiency (%)	Overall Efficiency (%)
1	Without DG	L-G	Zone 2	**Zone 2**	96.42	95.00
2		L-L-G	Zone 1	**Zone 1**	96.55	96.25
3		L-L-L	Zone 3	**Zone 3**	97.33	98.00
4	With DG	L-G	Zone 2	**Zone 2**	97.85	96.25
5		L-L-L	Zone 3	**Zone 3**	98.00	98.25
6	With DG	L-L-L	Zone 1	**Zone 1**	98.43	98.56

distribution systems. According to the proposed technique, a new zone protection scheme is proposed by placing MDs at optimal location which is based on the genetic algorithm. The proposed technique is applied on IEEE 33 bus balanced system as well as on highly loaded unbalanced feeder system. This method is also validated in the presence of energy storage device and DG. The overall efficiency of the methodology is 96–98% which is shown in the result analysis part. The conclusions made from this paper are listed below

1. The proposed methodology assures at least one or more MDs in each zone.
2. The proposed methodology is cost-efficient compared with other zone protection systems that are discussed in the literature review.
3. Memory size is decreased through this proposed methodology.

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Biographies

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