International Journal of Soft Computing 12 (1): 72-78, 2017
ISSN: 1816-9503

An Application of Fast Learning Radial Basis Function Networks for an Accurate Estimation of Fault Location in Electrical Distribution Networks

[1, 2]Surender Kumar Yellagoud, [2]Purnachandra Rao Talluri and [1]Gondlala N. Sreenivas
[1]Jawaharlal Nehru Technological University, Hyderabad, India
[2]Formerly in National Institute of Technology, Warangal, India

Abstract: Fault location is one of the important tasks of automated distribution systems. In this research, fast learning Radial Basis Function Neural networks (RBFNs) were employed to automatically locate the faults in distribution networks. The radial basis networks are simpler in structure, faster and more efficient than the conventional multilayer feed forward networks. These are functionally considered equivalent to more successful fuzzy connectionist hybrid models. An IEEE test distribution system was used for analyzing the potential and accuracy ofthese networks in the estimation of fault location information. The distribution network wassimulated and tested in MATLAB/SIMULINK. Three fundamental tasks of this RBFN Models, fault type classification, faulted line section detection and pin pointing of fault location on the faulted line were executed by multiple RBFN Models which were designed in MATLAB environment. All the required fault data for training and testing of the models was generated by triggering various fault scenarios on the simulated distribution network. The test results obtained demonstrate good degree of accuracy. This vital fault location information supplied by RBFNs can greatly support the search efforts of distribution substation repair crew in quickly pin pointing the faulty spot and restoring the power to the affected customers. This reduces the customer service interruption duration and thus contributes in enhancing the power system reliability and quality.

Key words: Fault location, fault classification, distribution networks, artificial intelligence, radial basis function networks, neural network

INTRODUCTION

One of the important objectives of distribution automation is to increase service reliability tothe connected customers. The fault detection, location and isolation of the faulted segment play a vital role in achieving this objective. Automation in fault location facilitates the power distribution engineer to dispatch the repair team to the affected area quickly which can directly reduce the customer service interruption time (Gonen, 2008).

Automated faultlocation in distribution system is technically more difficult than on transmission system, due to inherent complexities in network topology, heterogeneous conductor configuration, numerous laterals and load taps, lack of measuring points and unbalanced loading (Girgis *et al*., 1993; Nouri and Alamuti, 2011). Among the various tool and techniques available today for automated fault location the knowledge based techniques are demonstrating excellent results; more so for distribution networks (Javadian *et al*., 2009; Coser *et al*., 2007; Florez *et al*., 2007). The popular knowledge based methods which were attempted by many researchers are neural networks, fuzzy systems, genetic algorithms and different hybrid combinations of two or more of these (Bedekar *et al*., 2011; Florez *et al*., 2009). Reviews done on the evolution, competency and comparison of various techniques (Saha *et al*., 2002; Awalin1 *et al*., 2012) also declare that the knowledge based techniques are more accurate and highly efficient.

Hybrid combinations of knowledge based techniques are performing better than their individual counter parts. However, radial basis function neural networks which were employed in this stydy are not such hybrid combinations. But, it has single handedly demonstrated good degree of accuracy in pin pointing the locus of the faults in a distribution network. The RBFN has many advantages over its conventional neural networks (Kasabov, 1988) faster training and design of models, efficient generalization, fast convergence properties, no local minima problem and functionally equivalent to fuzzy connectionist hybrid models.

Corresponding Author: Surender Kumar Yellagoud, Jawaharlal Nehru Technological University, Hyderabad, India

MATERIALS AND METHODS

Radial basis function neural networks: The fundamental idea of RBFNs is developed from the theory of function approximation. Though it is basically a feed forward network but it differs from the conventional multi-layer perceptron networks. RBFNs have attained special distinction in neural computing research domain due to their architectural simplicity, faster learning capabilities, fast and efficient generalization performance. Architecture of radial basis function neural network (Fig. 1) has a very simple three layer profile and basically includes an input layer, one hidden layerand an output layer. Each neuron in the hidden layer contains non-linear radial basis function whose output is inversely proportional to the distance from the center of the neuron and the output neuron contains a linear function. The radial basis functions are radially symmetrical functions like, gaussian, bell-type, Π function, etc.:

$$f(x) = e^{\frac{-(x-M)^2}{2\sigma^2}}$$

where, M and σ are mean and standard deviation of input variable x, respectively. At any particular intermediate node i its radial basis function is centered at a cluster center c_i in then-dimensional input space. The cluster center c_i is represented by the vector (W_{1i}, W_{2i}, ..., W_{1n}) of connection weights between the n input nodes and the hidden node i. The standarddeviation for a particular cluster indicates the range for the corresponding radial basis function. The second layer is connected to the output layer. At each output node a straight summation of weighted outputs from radial basis layer is done with a linear threshold activation function. Training of an RBFN consists of two phases adjusting the RBF of the hidden neurons by applying a statistical clustering method; this represents an unsupervised learning phase applying gradient descent (e.g., the back propagation algorithm) or a linear regression algorithm for adjusting the second layer of connections this is a supervised learning phase. The training of RBFN involves adjustment of the following parameters.

The n-dimensional position of the centers ci of the corresponding radial basis function. Using any of the clustering techniques the number of cluster centers can be identified which fixes the number of hidden neurons this minimizes the distance between the training samples. This adjustment is more important when the volume of training dataset is very large which is usually the case.

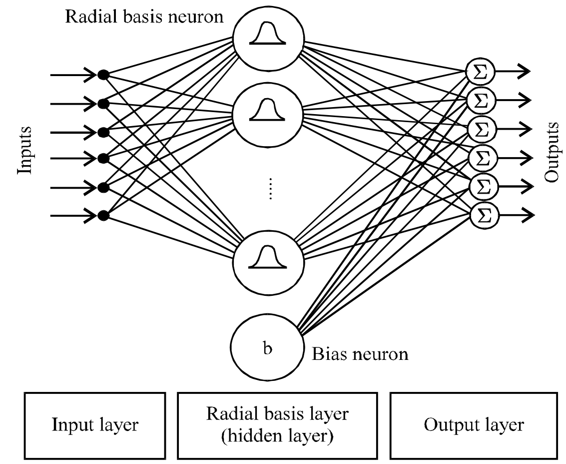

Fig. 1: The basic architecture of radial basis function neural network

The deviation scaling parameter si for every radial basis function it is represented bymean distance to the nearest m-cluster centers:

$$\sigma_i = \left[\frac{\left(\sum\limits_{p=1,\,m}\left(c_i - c_{ip}\right)\right)}{m}\right]^{1/2}$$

where, c_{ip} is the center of the pth cluster near to the cluster i. The weights of the second layer connections.

Outline of RBFN fault location (Fig. 2): In this research, radial basis function neural networks were used to obtain vital fault locationinformation. This vital fault information, estimation of which is the principal objective of this work includes, fault type classification, faulted line section detection and particular faultlocation on that faulted line section. The scheme of work illustrated in Fig. 2 was employed to achieve the objective of this work. Once the fault occurrence is detected, designed RBFN Models are called in sequence to carry out the tasks for which they are dedicated. As per the scheme, first RBFN Model designed for classifying the type of fault is scheduled followed by the detection of faulted line section by another RBFN which is specifically designed and trained for this detection purpose. Each of these two tasks was implemented by a single RBFN. Finally for pinpointing the exact location on the faulted line segment, ten RNFN models were designed. Since, there are 10 line sections in this test distribution system, hence ten RBFNs were

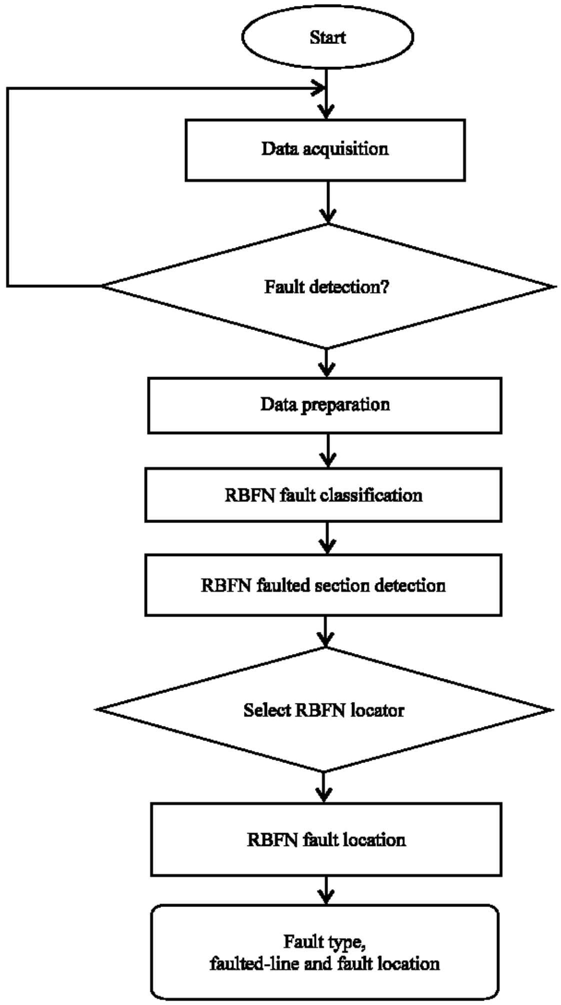

Fig. 2: Flowchart for fault location using RBFNs

developed, one RBFN for each line section. After detecting the faulted line section the corresponding RBFN fault locator is selected for performing the fault location task. A total of 12 RBFNs were developed for achieving the objective of this research.

MATLAB simulation, data generation and data preparation: A typical 13 node IEEE power distribution network with ten line sections (Fig. 3) developed by IEEE PES distribution system analysis subcommittee's distribution test feeder working group (IEEE distribution planning working group Report in 1991 (Kersting, 2000) was used in this research. The simulink model of this network was developed and tested in a MATLAB simulink environment. All the ten hunt type of faults were considered for data generation-3 phase-to-phase faults, 3 single-line-to-ground faults, threedouble-line-to-ground

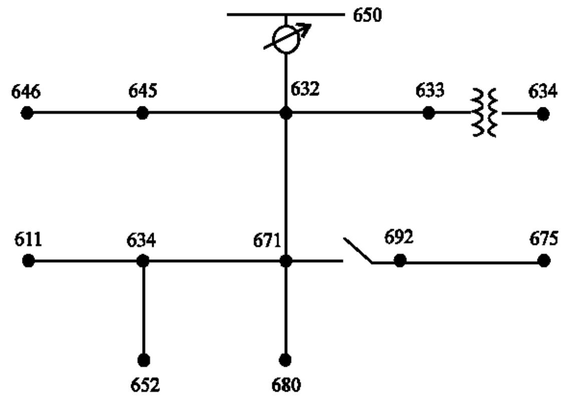

Fig. 3: IEEE 13 node distribution network

faults, one three-phase-short circuit fault. About 1500 fault scenarios were triggered on this test network for generating fault data which was used for training and testing of designed RBFN Models. The generated data includes the pre-fault and post-faultcurrent samples. The current samples were collected at a sampling frequency of 1 KHz. Thepost-fault RMS current values (Ghani *et al*., 2009) are calculated from the three cyclepost-fault current data and they are normalized using pre-fault RMS values. The RBFN Models used in this work are trained and tested with this normalized data.

RBFN fault classification model: A single RBFN Model was designed and trained for the task of fault type classification. All the ten types of faults are designated with integer values from 1-10 (Table 1 and 2) for the RBFN training. The normalized 3-phase RMS currents are the three inputs to the RBFN Model and its one output is one of the ten possible fault types. The RBFN Model developed for the task is presented in Fig. 4 and the model details are given in Table.

RBFN faulted line section detection model: All the 10 line sections along with their respective lengths and designated integer values are given in Table 3. The 3-phase RMS currents are the 3 inputs and one output is the faulted line section. The RBFN Model developed for the task is presented in Fig. 5 and themodel details are given in Table 4.

RBFN fault location model: There are 10 line sections present in the IEEE test distribution network and accordingly ten RBFN fault location models were designed and developed for the fault location task. Once the faulted line section is detected by the designated

Table 1: Fault type's representation for anfis training

Fault fault type on three phases (A, B and C)	Numeral value for ANFIS
Phase-to-phase fault between A and B	1
Phase-to-phase fault between B and C	2
Phase-to-phase fault between A and C	3
Three-phase fault	4
Single-line-to-ground fault on A	5
Single-line-to-ground fault on B	6
Single-line-to-ground fault on C	7
Double-line-ground fault between A and B	8
Double-line-ground fault between B and C	9
Double-line-ground fault between A and C	10

Table 2: RBFN fault classification model information

Parameter	Values
Number of inputs	3 (three-phase RMS currents)
Number of output (s)	1 (fault type)
Number of hidden neurons	451
Performance goal	0.05
Spread constant	0.05

Table 3: Details of line sections

Line section	Length (m)	Numeral value for RBNN
650-632	606.1	1
632-633	151.5	2
632-645	151.5	3
645-646	90.9	4
632-671	606.1	5
692-675	151.5	6
671-684	90.9	7
864-652	242.4	8
684-611	90.9	9
671-680	303.0	10

Table 4: RBFN fault classification model information

Parameters	Value
Number of inputs	3 (three-phase r.m.s currents)
Number of output (s)	1 (fault type)
Number of hidden	406 neurons
Performance goal	0.075
Spread constant	0.025

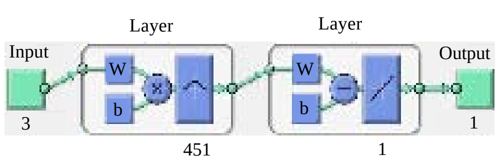

Fig. 4: RBFN fault classification model

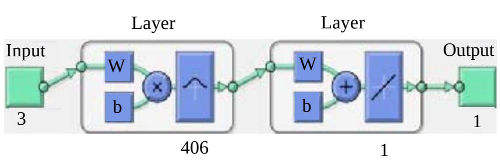

Fig. 5: RBFN faulted line section detection

model that particular line section dedicatedfault location model is selected and the specific location (in meters) is estimated. One of theseten models, i.e., model for line

Table 5: RBFN fault location model for line section (632-633)

Parameter	Values
Number of inputs	RMS currents
Number of output (s)	1 (fault type)
Number of hidden neurons	57
Performance goal	2.0
Spread constant	0.05

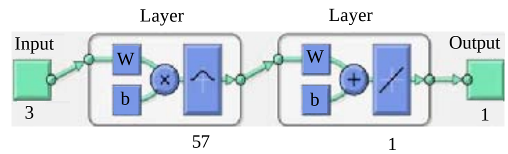

Fig. 6: RBFN fault location model

section (632-633) is considered here for presentation. This RBFN Model is shown in Fig. 6 and the model details are given in Table 5.

RESULTS AND DISCUSSION

Training of all the RBFN Models was done using fault current data generated from about 1000 fault scenarios. Training performance curves for all the three tasks, viz. fault type classification, faulted line section detection and fault location (on the faulted line section) are presented in Fig. 7-9. The trained RBFN Models were tested for their accuracy inperforming their designated tasks. The estimated values of the respective RBFN Models arepresented in Table 6-8.

Fault type classification: Figure 7 shows the training performance of the fault type classification and the sloping profile of the curve clearly indicates the faster training and convergence capabilities of the RBFN approximation networks towards the preset goal. One thousand datasets were used for training the network. Table 6, actual, estimated and rounded values for fault type classification of three line sections are presented. The estimated RBFN values were rounded to nearest integer and it is justified, since the intermediate values (estimated by RBFN) lurking between the integers (allocated for fault types from 1-10, Table 1 for RBFN training) have no significance without rounding of figures. The fault classification performance of thethree line sections demonstrated correct results for all 10 fault types; except for one fault type (phase-to-phase fault between phases b and c) on line section (684-652) where the RBFN model misfired (shown as shaded).

Faulted line section detection: The training performance of the RBFN faulted line section detection model is depicted in Fig. 8. The preset performance goal is achieved in 400 epochs with 1000 training datasets. The test results for three faulted line sections (2, 5 and 9) for 10 fault scenarios are given in Table 7. The integer values of 1-10 are allocated to 10 line sections for RBFN training (Table 3). The RBFN Model misfired for three fault scenarios (shown as shaded).

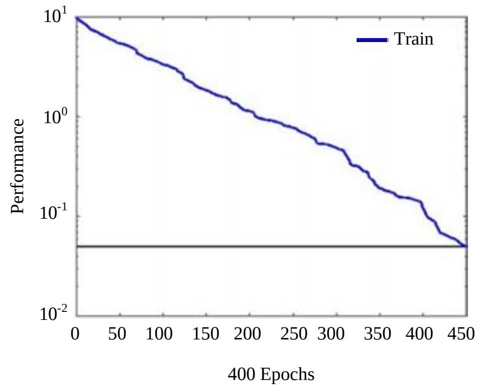

Fig. 7: Performance curve for RBFN fault type classification model

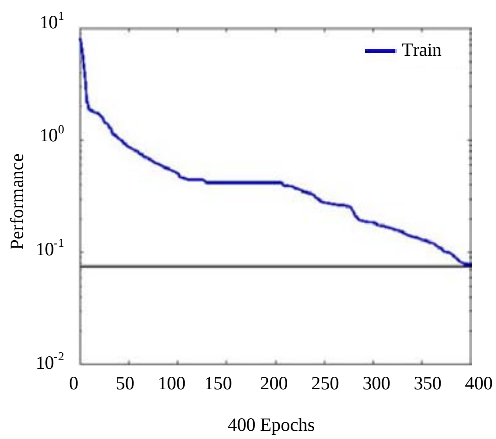

Fig. 8: Performance curve for RBFN faulted line section detection model

Fault location on faulted line section: The training performance of the most vital and final task of pinpointing fault location orposition in meters on the detected faulted line section is presented in Fig. 9. Since, it is notpossible to present the results for all the line sections, line section, i.e., line section 2 (632-633) is chosen for illustrating the RBFN performance. In about 50 epochs the RBFN converged tothe preset goal when 110 training datasets were presented to the network model. The fault location results of the designated RBFN are demonstrated in Table 8. The actual and RBFN estimated values for 20 fault scenarios are presented along with their error values. The error values are within the range of 4 m and therefore can be conveniently concluded as highly satisfactory performance.

The research presented in this study is unique in its strategy and application of radial basis function neural networks and more so involving a specific IEEE test distribution network. Hence, it is not proper

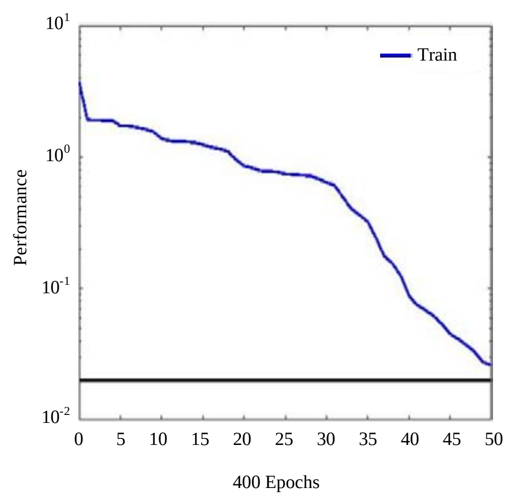

Fig. 9: Performance curve for RBFN fault location model of line section (632-633)

Table 6: RBFN fault type classification model test results

Fault classification on line section (632-633)			Fault classification on line section (645-646)			Fault classification on line section (684-652)		
Actual	RBFN	Rounded	Actual	RBFN	Rounded	Actual	RBFN	Rounded
1	0.76	1	1	0.96	1	1	0.80	1
2	2.00	2	2	1.81	2	2	1.49	1
3	3.00	3	3	2.38	3	3	2.87	3
4	3.90	4	4	4.07	4	4	4.31	4
5	5.17	5	5	5.01	5	5	4.98	5
6	6.07	6	6	6.05	6	6	5.96	6
7	7.19	7	7	6.99	7	7	6.98	7
8	7.93	8	8	7.75	8	8	7.94	8
9	9.00	9	9	8.90	9	9	9.00	9
10	10.48	10	10	9.21	10	10	10.03	10

Table 7: RBFN faulted line section detection model test results

Fault classification on line section-2 (632-633)			Fault classification on line section-5 (632-671)			Fault classification on line section-9 (684-611)		
Actual	RBFN	Rounded	Actual	RBFN	Rounded	Actual	RBFN	Rounded
2	1.99	2	5	5.04	5	9	8.87	9
2	2.02	2	5	4.65	5	9	9.18	9
2	2.12	2	5	4.96	5	9	8.89	9
2	2.15	2	5	4.95	5	9	9.48	9
2	2.03	2	5	5.49	5	9	9.18	9
2	2.05	2	5	3.67	4	9	9.01	9
2	1.98	2	5	4.36	4	9	9.08	9
2	1.95	2	5	4.92	5	9	9.02	9
2	2.26	2	5	5.07	5	9	9.31	9
2	1.91	2	5	5.12	5	9	8.37	8

Table 8: RBFN fault location on faulted line section-2(632-633)*

	Fault location values in meters			
Type of fault	Actual	RBFN	Error	Error (%)
Phase-to-phase fault between A and B	61.0	60.9	-0.1	-0.07
Phase-to-phase fault between B and C	76.0	75.9	-0.1	-0.07
Phase-to-phase fault between A and C	91.0	90.6	-0.4	-0.26
Three-phase faults on A, B and C	106.0	105.7	-0.3	-0.20
Single-line-to-ground fault on A	121.0	122.6	1.6	1.06
Single-line-to-ground fault on B	61.0	61.3	0.3	0.20
Single-line-to-ground fault on C	76.0	76.8	0.8	0.53
Double-line-ground fault between A and B	91.0	91.3	0.3	0.20
Double-line-ground fault between B and C	106.0	104.9	-1.9	-0.73
Double-line-ground fault between A and C	121.0	119.3	-1.7	-1.12
Phase-to-phase fault between B and C	61.0	59.7	-1.3	-0.86
Phase-to-phase fault between A and C	75.7	75.0	0.7	-0.46
Three-phase faults on A, B and C	91.0	91.7	0.7	0.46
Single-line-to-ground fault on A	106.0	106.9	0.9	0.60
Single-line-to-ground fault on B	121.0	117.8	-3.2	-2.10
Single-line-to-ground fault on C	61.0	59.8	-1.2	-0.80
Double-line-ground fault between A and B	76.0	76.5	0.5	0.33
Double-line-ground fault between B and C	91.0	91.2	0.2	0.13
Double-line-ground fault between A and C	106.0	107.8	1.8	1.20
Phase-to-phase fault between A and B	121.0	118.6	-2.4	-1.60

*Length of the line section-2(632-633) = 151.5 m

to compare these results with any other previous works (Zayandehroodi *et al*., 2011). However, the accuracy achieved can greatly expedite the search effortsof distribution substation repair crew in reaching the faulty spot.

CONCLUSION

The fast learning radial basis function neural networks were employed in this work for anaccurate estimation of fault location in an IEEE test electrical distribution network. Three fundamental tasks of this estimation, fault type classification, faulted line section detection and pin pointing of fault location on the faulted line were executed by multiple RBFN Models. These models were simple in design with very few parameters to be optimized and faster intraining involving less number of epochs. They have demonstrated accurate results for many fault scenarios, except at very few scenarios where they mis fired. The results achieved can greatly support the search efforts of distribution substation repair crew in quickly pin pointing the faulty spot and restoring the power to the affected customers. This reduces the customer service interruption time and thus contributes in enhancing the power system reliability and quality.

REFERENCES

Awalin, L.J., H. Mokhlis and A.H.A. Bakar, 2012. Recent developments in fault location methods for distribution networks. Przeglad Elektrotechniczny, 88: 206-212.

Bedekar, P.P., S.R. Bhide and V.S. Kale, 2011. Fault section estimation in power system using Hebb's rule and continuous genetic algorithm. Intl. J. Electr. Power Energy Syst., 33: 457-465.

Coser, J., D.T.D. Vale and J.G. Rolim, 2007. Design and training of artificial neural networks for locating low current faults in distribution systems. Proceedings of the IEEE International Conference on Intelligent Systems Applications to Power Systems ISAP, November 5-8, 2007, IEEE, Toki Messe, Niigata, ISBN:978-986-01-2607-5, pp: 1-6.

Florez, J.M., G.M. Espana and S.P. Londono, 2009. Learning-based strategy for reducing the multiple estimation problem of fault zone location in radial power systems. IET. Gener. Transm. Distrib., 3: 346-356.

Florez, J.M., V.B. Nunez and G.C. Caicedo, 2007. Fault location in power distribution systems using a learning algorithm for multivariable data analysis, power delivery. IEEE. Trans., 22: 1715-1721.

Ghani, A.M.R.A., A. Mohamed and H. Shareef, 2009. ANFIS approach for locating precise fault points with coordinated geometries in a test distribution system. Eur. J. Sci. Res., 35: 461-473.

Girgis, A.A., M. Fallon, M. Christopher and D.L. Lubkeman, 1993. A fault location technique for rural distribution feeders. IEEE Trans. Indus. Appl., 29: 1170-1175.

Gonen, T., 2008. Electric Power Distribution Systems. 2nd Edn., CRC Press, ?Boca Raton, Florida,.

Javadian, S.A.M., A.M. Nasrabadi, M.R. Haghifam and J. Rezvantalab, 2009. Determining fault`s type and accurate location in distribution systems with DG using MLP neural networks. Proceedings of the International Conference on Clean Electrical Power, June 9-11, Capri, pp: 284-289.

Kasabov, N.K., 1988. Foundations in Neural Networks, Fuzzy Systems and Knowledge Engineering, a Bradford Book. The MIT Press, Marylebone, England, Pages: 284.

Kersting, W.H., 1991. Radial distribution test feeders. IEEE Trans. Power Syst., 6: 975-985.

Nouri, H. and M.M. Alamuti, 2011. Comprehensive distribution network fault location using the distributed parameter model. IEEE. Trans. Power Delivery, 26: 2154-2162.

Saha, M.M., R. Das, P. Verho and D. Novosel, 2002. Review of fault location techniques for distribution systems. Proceedings of the Conference on Power Systems and Communications Infrastructures for the Future, September 23-27, 2002, CD-ROM Publisher, Beijing, China, pp: 1174-1179.

Zayandehroodi, H., A. Mohamed, H. Shareef and M. Mohammadjafari, 2011. An automated protection method for distribution networks with distributed generations using radial basis function neural network. Proceedings of the 5th IEEE International Conference on Power Engineering and Optimization (COPEO), June 6-7, 2011, IEEE, Shah Alam, Malaysia, ISBN:978-1-4577-0355-3, pp: 255-260.