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Research Article

Automated Fault Location on Power Distribution Lines using Artificial Neural Networks

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

Abstract: The work aims to arrive at an accurate estimation of fault location in power Distribution Networks (DNs) using the potentialities of artificial neural networks. For every fault plausible on feeders and distributors of DNs, detailed fault data recording is available only at a common place called distribution substation. In this paper, effort was made to train the Artificial Neural Networks (ANNs) with this plausible common fault data to arrive at an estimation of type of fault and locus of fault. Two ANNs were trained for this task of fault location on an IEEE test case, which was modeled and simulated in MATLAB Simulink. One ANN was dedicated for fault classification to ascertain the specific type of fault; another ANN for detecting the faulted line segment and pinpointing the location on that faulty section. In all, 550 fault combinations were triggered on this simulated IEEE test DN and fault data (voltage and current information) was generated for training and testing of ANNs. The training and testing results clearly demonstrated good degree of accuracy in detecting the correct fault type and faulty section, and locating a closer fault position. This study enables the substation engineer to estimate this fault information sitting in the substation, without actually patrolling or inspecting the affected areas. With this estimation, the maintenance crew can rush to the affected spot with minimum delay to repair and restore the power supply.

Keywords: Artificial intelligence, artificial neural networks, fault location, power distribution networks, power distribution lines, fault classification, soft computing

INTRODUCTION

Background: The electrical power utilities are required to render reliable, continuous and safe electric service to related customers, or to put in today's language, power quality and reliability of electric utilities are mandatory; not merely mandatory, but must for utility's survival too in today's competitive power market. Power quality involves meeting the customer requirements ensuring safety within specified values of voltage and frequency (Gonen, 2008). Obviously the equipment required to shoulder these responsibilities have to be equipped with latest technologies. Once such responsibility, which directly influences the power reliability indices, namely SAIFI (system average interruption frequency index) and CAIDI (customer average interruption duration index), is automated fault location. The power transmission and distribution service interruptions are due to various causes-natural calamities like hurricanes, tornadoes, storms, snow, rain, lightning, falling of big and overhanging trees; contact of birds like cranes, eagles, etc.; contacts of animals like monkeys, kangaroos, etc.; equipment failures, insulation breakdown, defective materials, etc. Other interruptions may be due to certain human actions like fast moving vehicles dashing at the electric poles, vandalism, land excavation machinery damaging the buried power cables, etc. Most of these disturbances are beyond the control of humans and in spite of every effort to minimize these happenings, they do happen again and again. These cited and similar other disturbances have the potential to physically damage the transmission and distribution lines and may result in permanent interruption of power supply to customers concerned. And, utilities have to be prepared to pinpoint the physical locus of these damages on the lines, so that the maintenance/inspection crew can rush with minimum search time to the spot for repair and restoration of service to the affected customers. These exigencies and exercises of the maintenance personnel can be implemented for quick restoration of power supply, if and only the disturbances, or more technically called as power system faults are located quickly and therefore automatically. Herein lay the role of fault location software and hardware, which are designed and developed and updated with latest developments in the field. This updating and upgrading the accuracy offered by these fault local technologies has been continuously undertaken by many researchers, both in academic and industrial departments, through the years, to this day.

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

Still, there is tremendous scope to enhance the accuracy of pinpointing the fault position/location on the affected transmission and distribution lines, so that interruption and restoration times can be minimized and thereby demonstrate greater levels of power quality and reliability.

Initially, automation was applied for fault location on transmission lines only because of its inherent importance and also the labor and time involved in patrolling the lines located at remote areas, especially those in hilly terrains, forest areas, etc. However, the fault location on distribution lines is also receiving more attention and importance to meet the continuously growing customer demands. The de-regulation of power markets world-over is compelling many utilities to compete and comply with the customer demands of uninterrupted availability of power supply. The fault location methods developed for transmission lines are not directly or that easily applicable for distribution lines; because, there are remarkable differences in the network topology and electrical states of transmission lines and distribution lines. These medium and low voltage distribution lines, more specifically feeders, consist of numerous laterals and highly ramifying branches. The prevalence of single phase and three phase loads, which are resistive or inductive and dynamically changing, presence of the load taps along the main feeder and laterals, makes the distribution system and its working characteristics highly non-linear and sufficiently complicated (Nouri and Alamuti, 2011). Fault location methods employed for distribution systems can be grouped into four types (Nouri and Alamuti, 2011): the classical methods, which use fundamental voltages and currents, travelling wave techniques, topology based methods and knowledge-based methods.

LITERATURE REVIEW

To quote, though not the first, but surely among the early classical algorithms developed for fault location, is by Srinivasan and St-Jacques (1989), who employed the concept of simplified distributed parameters for fault location. Here the fault location is the deterministic solution of an equation derived from the circuit model, which compensates for intermediate load taps and end loads. Here the attempt was made to model the variable impedance behavior of loads, which had considerably enhanced the accuracy of fault location. Further developments in these algorithms were done by considering more real time situations, viz. non-homogeneity of distribution feeders, unbalanced conditions, etc. One such attempt was demonstrated by Girgis *et al*. (1991), using apparent impedance approach. Later Zhu *et al*. (1997), developed an algorithm, which searches all sections for faults. The fault location multi-estimation problem, which is unique to distribution system classical algorithms, was solved to some extent using the available data signifying the status of fuses and switching cycles of reclosers' operation.

As such there are many algorithms developed, which really made extensive attempt to close on to real time scenarios. Aggarwal *et al*. (1997a, b), developed an exhaustive algorithm, which utilized both pre-fault and during-fault values for fault location. Since the fault current in healthy phases should be zero ideally, that particular criterion was used to close on to the actual fault location. At an assumed fault point, admittance into network on either side of it is calculated. This calculated admittance is used to estimate the superimposed fault current in healthy phase(s) and the minima of this fault current along the feeder is identified, which is the estimation fault position of this algorithm. Salim e*t al*. (2008), developed a method for fault diagnosis based on artificial neural networks for finalizing the faulty section and fault detection and classification task is shouldered by wavelet method. An extended impedance based fault location algorithm for a distribution networks was done by Salim *et al*. (2009). An algorithm, which is based on distributed parameters, was developed by Yang *et al*. (2008), for locating faults on underground cables. This algorithm is not much influenced by fault distance and fault resistance fluctuations. Many of the recent works have applied artificial intelligence techniques, which demonstrated highly satisfactory results (Huan *et al*., 2015).

Though all the methods have evolved over the years in increasing the accuracy of estimation, knowledge-based methods have demonstrated overwhelming results, especially in distribution networks. Here is one such effort done using artificial neural networks to estimate the accuracy of fault location in distribution networks. The neural networks were utilized earlier by many researchers for the purpose, however proposed scheme of their application is unique with this work and the results are inspiring and therefore are satisfactory.

ARTIFICIAL NEURAL NETWORKS

Technological revolution: Substation automation to a great extent is achieved with the growth of technology offered by microprocessors. The fault location automation hardware is capable of making precise measurements for system protection, monitoring and regulation. However, the technology could not meet the degree of accuracy required to fulfill the impinging requirements of power quality and security today. And, the alternatives emerged, assuming the name of soft computing, based on pattern-recognition algorithms or decision making approaches that have considerably enhanced the accuracy achieved. This includes artificial

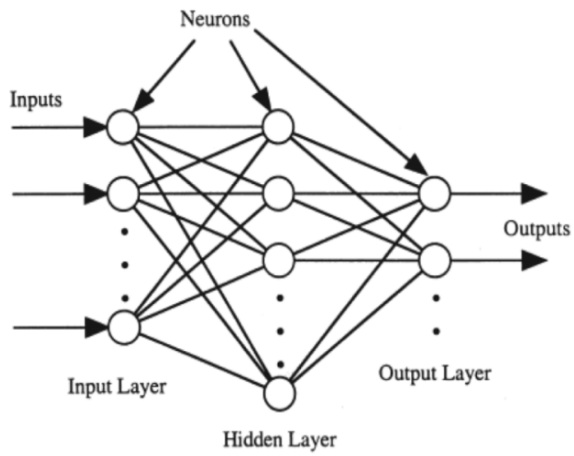

Fig. 1: Feed forward neural network

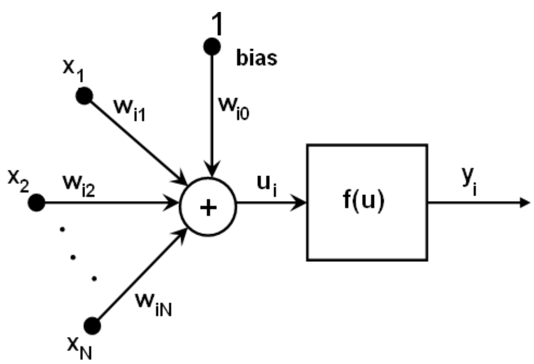

Fig. 2: Neuron with weighted inputs and bias

neural networks, fuzzy logic, expert systems, genetic algorithms, etc. Artificial Intelligence dependent techniques have proved to have remarkable edge over conventional approaches in considerably enhancing the fault location accuracy. Extensive research work is being undertaken by many a research institutions and universities across the world to employ the soft computing techniques for enhancing the accuracy of fault location in power transmission and distribution networks.

Feed forward neural networks: An Artificial Neural Network (ANN) can be trained with a supervised learning algorithm, named popularly as back propagation. These networks are called as feed forward neural networks, which basically comprise of an input layer, where input data is fed to the network, one or more hidden layers and an output layer delivering the output response from the network. The input layer, hidden layer(s) and output layer comprise specified number of neurons (Fig. 1). Every neuron of given layer is connected to the neurons of the previous layer through an adjusting and adapting synaptic weights ‘w’ and biases ‘b’ (Fig. 2). A weight is attached to every neuron and the training involves adjusting of these weights as per the prepared training data. One unique feature of ANN is that they are not dependent on the knowledge base as does the expert systems do. ANNs learn the responses to various inputs contained in the training data by adjusting the weights and biases accordingly. So, it is clear that the ANNs process the information based on the earlier learnt examples. The input layer of ANNs can be fed with either unprocessed input samples, or by features extracted from input samples using data processing techniques. One fundamental issue with the ANNs is that there are no recommended guidelines for selecting number of hidden layers and number of neurons to be considered for every hidden layer. And, one of the principal advantages of ANNs is, their potential to generalize. This generalizing capability enables the ANN to respond to the input data, which was not used during the training of ANN, with remarkable results.

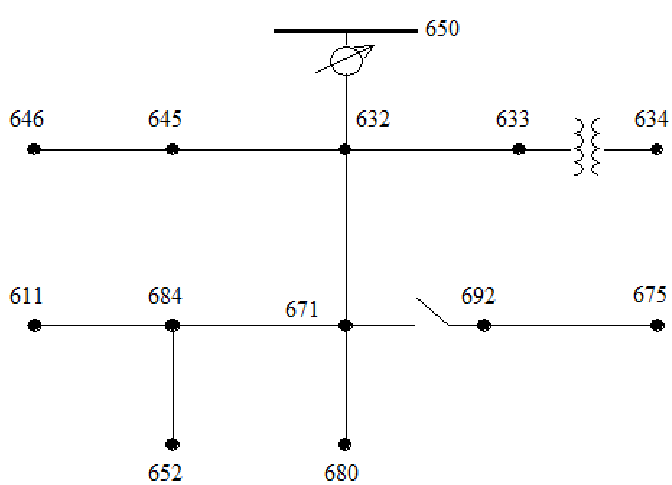

Fig. 3: IEEE 13 node distribution network

MATERIALS AND METHODS

IEEE 13 node test case: A 13 node IEEE power distribution network (Fig. 3) is considered for studying application of ANN for automating location of triggered faults on this distribution network (DN). The DN has 10 actual line segments (Table 1) and other details in Table 2 to 4.

Matlab simulation and data generation: The simulink model for the above DN with the cited specification and load distribution was developed in MATLAB Simulink using block sets of Sim Power System. All the eleven faults, viz. 3 phase-to-phase faults, 3 single-line-to-ground faults, 3 double-line-to-ground faults and two three-phase-short circuit faults (with and without ground), were triggered on all line segments. The five locations were chosen on each line segment, all the eleven faults were planted at each chosen location using three phase fault block of Sim Power System. In all, 550 fault-data (voltage and current information) files were generated for these cited fault combinations. About 80% of this data is used for training the ANNs. Two ANNs were used for accomplishing task of fault location on this DN. One is ANN_CLASSIFIER, which is dedicated for the purpose of fault type classification; and the other is ANN_LOCATOR dedicated for faulted line segment detection and pinpointing fault position on that segment. The scheme of fault location using these two ANNs is illustrated in Fig. 4.

RESULTS AND DISCUSSION

Data processing: The fault data collected from various fault combinations can be transformed or processed into a suitable form to feed into the input layer of ANN concerned for proposed training. There are various data processing techniques line-up in the literature of the day, to treat the raw data available from real time data acquisition centers of actual power distribution system. To quote a few, clarke's transformation, fast fourier transform, continuous wavelet transform, discrete wavelet transform, principal component analysis, etc. All these data processing techniques will extract the required features, which stand as a representative of whole data and will facilitate the ANN for an accurate and fast convergence towards the final results. The data processing/preparation techniques when applied to raw data available will greatly influence the results of ANN. The data processing will not only extract the features required, but also reduce the quantum and complexity of data available and thereby simplify the task ahead without compromising the accuracy of data. However, the IEEE test DN, which is considered here is a very typical sort of DN standing very close to the actual real time DN scenarios, but data generated doesn't involve such complexities and disturbances, which is plausible in real time actual DNs. Hence, three cycles of post fault current and voltage information is extracted from

Table 1: Line segment data

Node A	Node B	Length (ft.)	Config.
632	645	500	603
632	633	500	602
633	634	0	XFM-1
645	646	300	603
650	632	2000	601
684	652	800	607
632	671	2000	601
671	684	300	604
671	680	1000	601
671	692	0	Switch
684	611	300	605
692	675	500	606

Table 2: Transformer data

Transformer	kVA	kV-high	kV-low	R-%	X-%
Substation:	5,000	115 - D	4.16 Gr. Y	1	8
XFM -1	500	4.16 -Gr.W	0.48- Gr.W	1.1	2

Table 3: Spot load data

Node	Load Model	Ph-1 kW	Ph-1 kVAr	Ph-2 kW	Ph-2 kVAr	Ph-3 kW	Ph-3 kVAr
634	Y-PQ	160	110	120	90	120	90
645	Y-PQ	0	0	170	125	0	0
646	D-Z	0	0	230	132	0	0
652	Y-Z	128	86	0	0	0	0
671	D-PQ	385	220	385	220	385	220
675	Y-PQ	485	190	68	60	290	212
692	D-I	0	0	0	0	170	151
611	Y-I	0	0	0	0	170	80
	Total	1158	606	973	627	1135	753

Table 4: Distributed load data

Node A	Node B	Load Model	Ph-1 kW	Ph-1 kVAr	Ph-2 kW	Ph-2 kVAr	Ph-3 kW	Ph-3 kVAr
632	671	Y-PQ	17	10	66	38	117	68

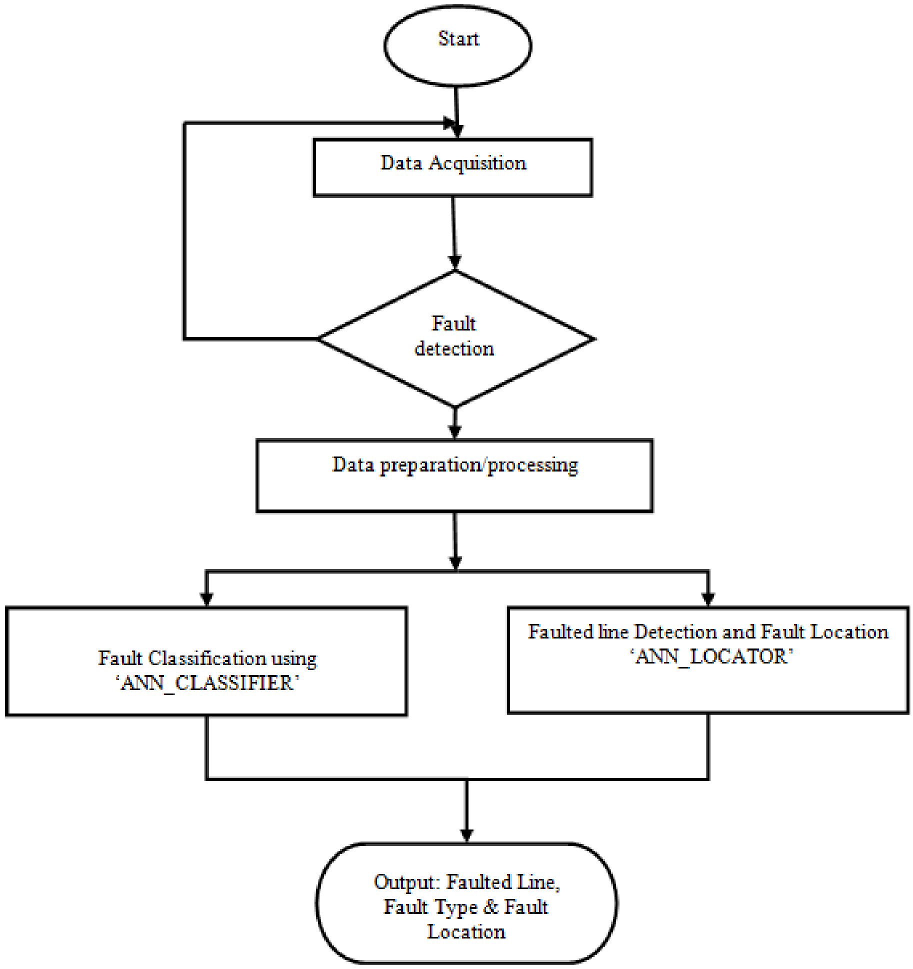

Fig. 4: Scheme of Fault location

Table 5: Final training data of ANN_CLASSIFIER

Network	Multilayer Feed forward network
Number of hidden neurons	10
Number of Epochs	230
Training	Bayesian regularization back propagation
Data division	Random
Performance	0.000302
Gradient	0.000481

fault-data, which was generated by triggering faults on simulink model of IEEE test DN considered. The extracted three cycle post fault data (voltages and currents) were normalized with the pre-fault values (voltage and current) and used as input vectors to the input layer of ANNs for he training rigmaroles.

Training of ANN_CLASSIFIER: A separate ANN is dedicated exclusively for the task of fault classification. As cited this ANN is required to identify the fault type from among the 11 types of faults, when they are individually presented to ANN after due training. This ANN titled, 'ANN_CLASSIFIER' is subjected to rigorous training schedules to achieve this challenging fault classification task. The performance results of final phase of training, which demonstrated reasonably good convergence to the proposed task, are presented here in Table 5, Fig. 5 to 8. The regression plots for training and testing clearly indicate that, regression value is closer to an ideal value of unity, viz. 0.99934 and 0.80519, respectively. Due rounding of output ANN values for the fault types of almost all the fault combinations was done and all the ANN values could be equated with actual values. When compared, for many line segments, the results are significantly correct (Sarvi and Torabi, 2012; Nouri and Alamuti, 2011).

Training of ANN_LOCATOR: The task of detecting the faulted line segment among the 10 line segments of the test DN and estimated fault location on the faulted line segment, is shouldered by the neural network designated as, ANN_LOCATOR. This task is still more challenging than the fault classification. Rigorous training schedules were conducted on this ANN and results of the final phase of training, where satisfactory

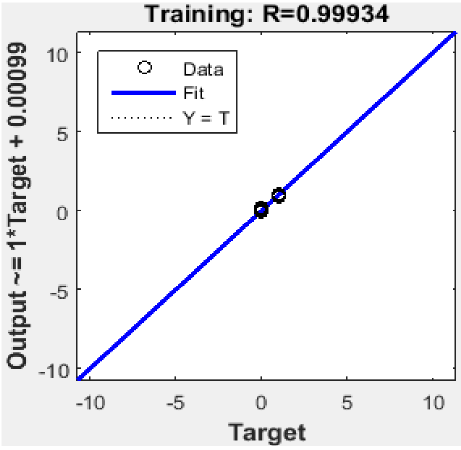

Fig. 5: ANN_CLASSIFIER Regression plot (training)

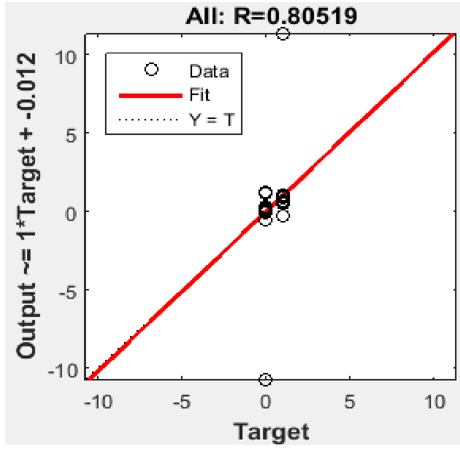

Fig. 6:ANN_CLASSIFIER Regressionplot (overall)

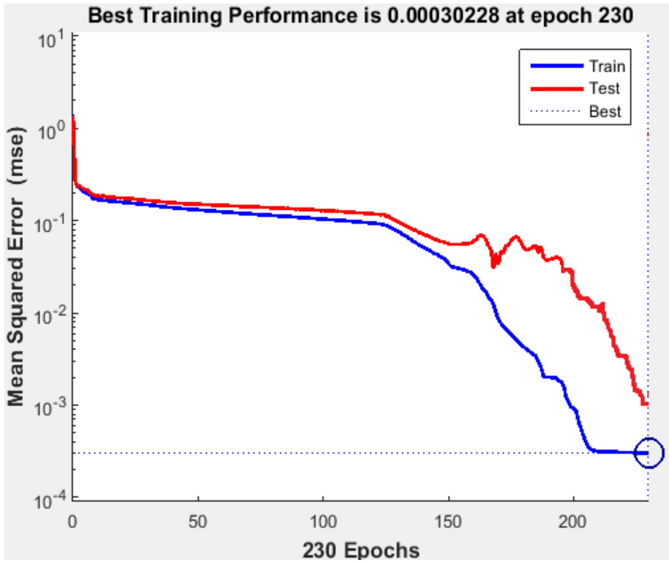

Fig. 7: ANN_CLASSIFIER Performance plot

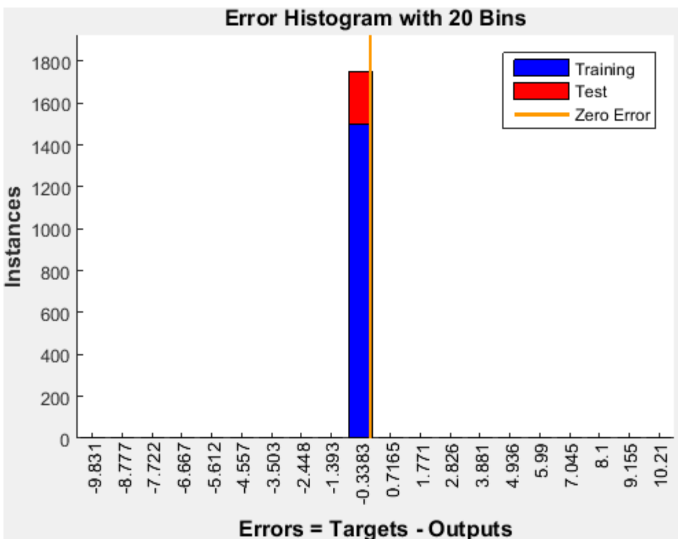

Fig. 8: ANN_CLASSIFIER Histogram

Table 6: ANN_ LOCATOR final training data

Network	Multilayer Feed forward network
Number of hidden neurons	15
Number of Epochs	247
Training	Bayesian regularization back propagation
Data division	Random
Performance	0.00026313
Gradient	0.00562
Network	Multilayer Feed forward network

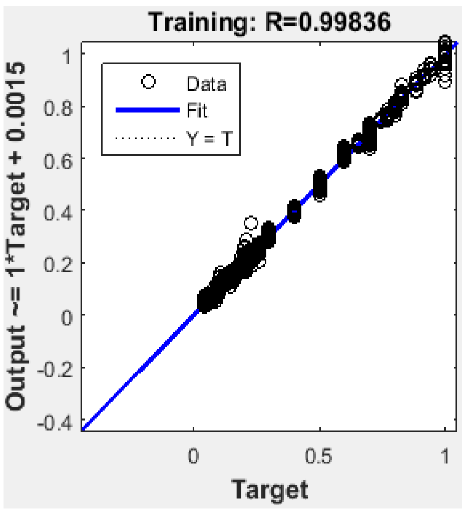

Fig. 9: ANN_LOCATOR Regression Plot (training)

convergence was noticed, are presented in Table 6, Fig. 9 to 12. The regression plots and performance plots for training and testing can be best appreciated against the results published in papers (Sarvi and Torabi, 2012; Nouri and Alamuti, 2011; Huan *et al*., 2015).

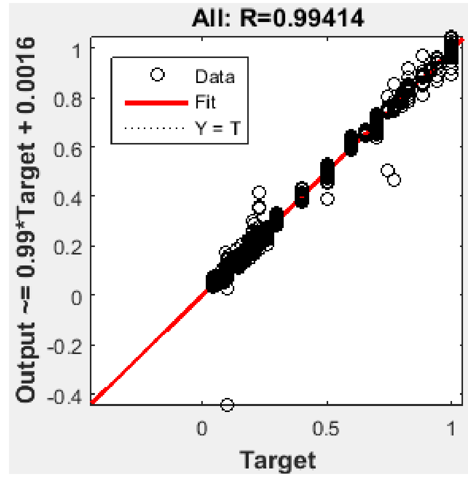

Fig. 10: ANN_LOCATOR Regression Plot (overall)

Fault classification and fault location: Two trained ANNs were thoroughly tested using the 20% remaining fault data, which was segregated solely for the purpose of testing. This data is not used for training any of these two ANNs. These trained ANNs were rigged into the scheme illustrated in Fig. 4. As was done for training purpose, the three cycle post fault feature data of the current and voltage was extracted and input vectors were prepared for testing the ANNs positioned into the proposed scheme. This data contains the fault information related to all the 10 line segments of the IEEE test case. Though it is not feasible to present all the test results here, attempt is made to illustrate few of them (Table 7 to 10 and Fig. 13 to 14). It is understood that fault location cited is in meters and is measured from the beginning of the faulted line segment. It

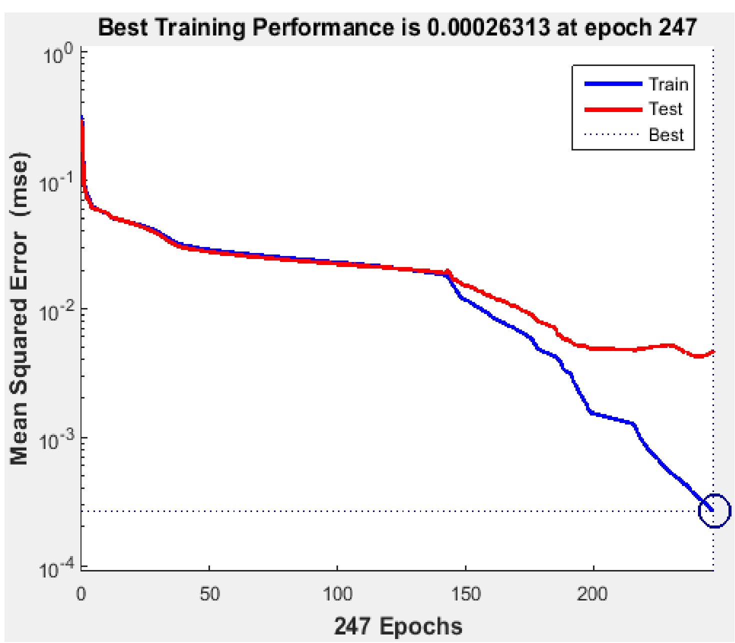

Fig. 11: ANN_ LOCATOR Performance plot

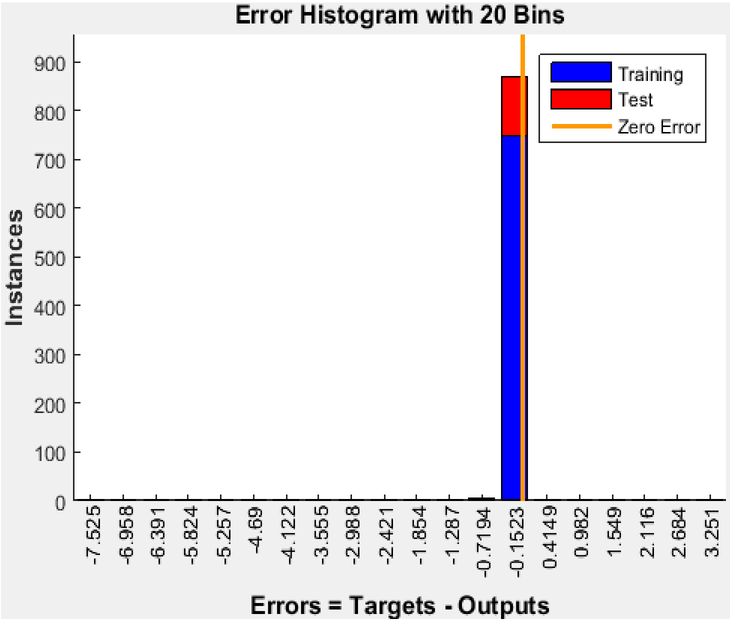

Fig. 12: ANN_LOCATOR Histogram

Table 7: Percentage fault location error on line segment 650-632

	Actual values			ANN values			
S. No.	Faulted line	Fault type	Fault location in meters	Faulted line	Fault type	Fault location in meters	%Error
1	650-632	Phase-to-phase fault between A and B	348	650-632	Phase-to-phase fault between A and B	348	0
2	650-632	Phase-to-phase fault between B and C	348	650-632	Phase-to-phase fault between A and B	348	0
3	650-632	Phase-to-phase fault between A and C	348	650-632	Phase-to-phase fault between A and B	348	0
4	650-632	Three-phase-short without ground	348	650-632	Three-phase-short without ground	348	0
5	650-632	Single-line-ground on phase A	348	650-632	Single-line-ground on phase A	348	0
6	650-632	Single-line-ground on phase B	348	650-632	Single-line-ground on phase B	349	0.16
7	650-632	Single-line-ground on phase C	348	650-632	Single-line-ground on phase C	349	0.16
8	650-632	Double-line-ground between A and B	348	650-632	Double-line-ground between A and B	348	0
9	650-632	Double-line-ground between B and C	348	650-632	Double-line-ground between B and C	578	37.9
10	650-632	Double-line-ground between A and C	348	650-632	Double-line-ground between A and C	348	0
11	650-632	Three-phase-short with ground	348	650-632	Three-phase-short with ground	349	0.16

Table 8: Percentage fault location error on line segment 632-645

	Actual values			ANN values			
S. No.	Faulted line	Fault type	Fault location in meters	Faulted Line	Fault type	Fault location in meters	% Error
1	632-645	Phase-to-phase fault between A and B	100	632-645	Phase-to-phase fault between A and B	101	0.660066
2	632-645	Phase-to-phase fault between B and C	100	632-645	Phase-to-phase fault between B and C	100	0
3	632-645	Phase-to-phase fault between A and C	100	632-645	Phase-to-phase fault between A and C	101	0.660066
4	632-645	Three-phase-short without ground	100	632-645	Three-phase-short without ground	98.7	-0.85809

Table: 8: Continue

5	632-645	Single-line-ground on phase A	100	632-645	Single-line-ground on phase A	109	5.940594
6	632-645	Single-line-ground on phase B	100	632-645	Single-line-ground on phase B	104	2.640264
7	632-645	Single-line-ground on phase C	100	632-645	Single-line-ground on phase C	100	0
8	632-645	Double-line-ground between A and B	100	632-645	Double-line-ground between A and B	101	0.660066
9	632-645	Double-line-ground between B and C	100	632-645	Double-line-ground between B and C	101	0.660066
10	632-645	Double-line-ground between A and C	100	632-645	Double-line-ground between A and C	96.7	-2.17822
11	632-645	Three-phase-short with ground	100	632-645	Three-phase-short with ground	99.5	-0.33003

Table 9: Percentage fault location error on line segment 632-671

	Actual values			ANN values			
S. No.	Faulted line	Fault type	Fault location in meters	Faulted line	Fault type	Fault location in meters	% Error
1	632-671	Phase-to-phase fault between A and B	409	632-671	Phase-to-phase fault between A and B	410	0.164989
2	632-671	Phase-to-phase fault between B and C	409	632-671	Phase-to-phase fault between B and C	405	-0.65996
3	632-671	Phase-to-phase fault between A and C	409	632-671	Phase-to-phase fault between A and C	408	-0.16499
4	632-671	Three-phase-short without ground	409	632-671	Three-phase-short without ground	412	0.494968
5	632-671	Single-line-ground on phase A	409	632-671	Single-line-ground on phase A	406	-0.49497
6	632-671	Single-line-ground on phase B	409	632-671	Single-line-ground on phase B	407	-0.32998
7	632-671	Single-line-ground on phase C	409	632-671	Single-line-ground on phase C	407	-0.32998
8	632-671	Double-line-ground between A and B	409	632-671	Double-line-ground between A and B	411	0.329979
9	632-671	Double-line-ground between B and C	409	632-671	Double-line-ground between B and C	412	0.494968
10	632-671	Double-line-ground between A and C	409	632-671	Double-line-ground between A and C	423	2.30985
11	632-671	Three-phase-short with ground	409	632-671	Three-phase-short with ground	407	-0.32998

Table 10: Percentage fault location error on line segment 684-652

	Actual values			ANN values			
S. No.	Faulted line	Fault type	Fault location in meters	Faulted line	Fault type	Fault location in meters	% Error
1	684-652	Phase-to-phase fault between A and B	64	684-652	Phase-to-phase fault between A and B	63.8	-0.08251
2	684-652	Phase-to-phase fault between B and C	64	684-652	Phase-to-phase fault between B and C	61.9	-0.86634
3	684-652	Phase-to-phase fault between A and C	64	684-652	Phase-to-phase fault between A and C	62.9	-0.4538
4	684-652	Three-phase-short without ground	64	684-652	Three-phase-short without ground	66.0	0.825083
5	684-652	Single-line-ground on phase A	64	684-652	Single-line-ground on phase A	64.5	0.206271
6	684-652	Single-line-ground on phase B	64	684-652	Single-line-ground on phase B	64.0	0
7	684-652	Single-line-ground on phase C	64	684-652	Single-line-ground on phase C	64.4	0.165017
8	684-652	Double-line-ground between A and B	64	684-652	Double-line-ground between A and B	64.1	0.041254
9	684-652	Double-line-ground between B and C	64	684-652	Double-line-ground between B and C	55.1	-3.67162
10	684-652	Double-line-ground between A and C	64	684-652	Double-line-ground between A and C	61.7	-0.94884
11	684-652	Three-phase-short with ground	64	684-652	Three-phase-short with ground	62.0	-0.82508

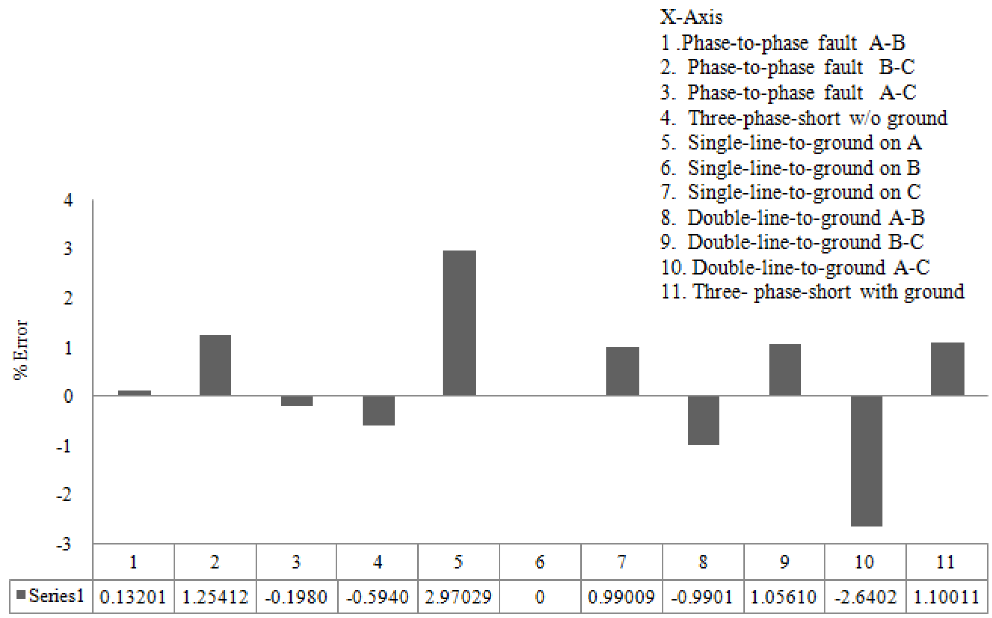

Fig. 13: Percentage fault location error for all fault types on line segment (632-633) at 73meters

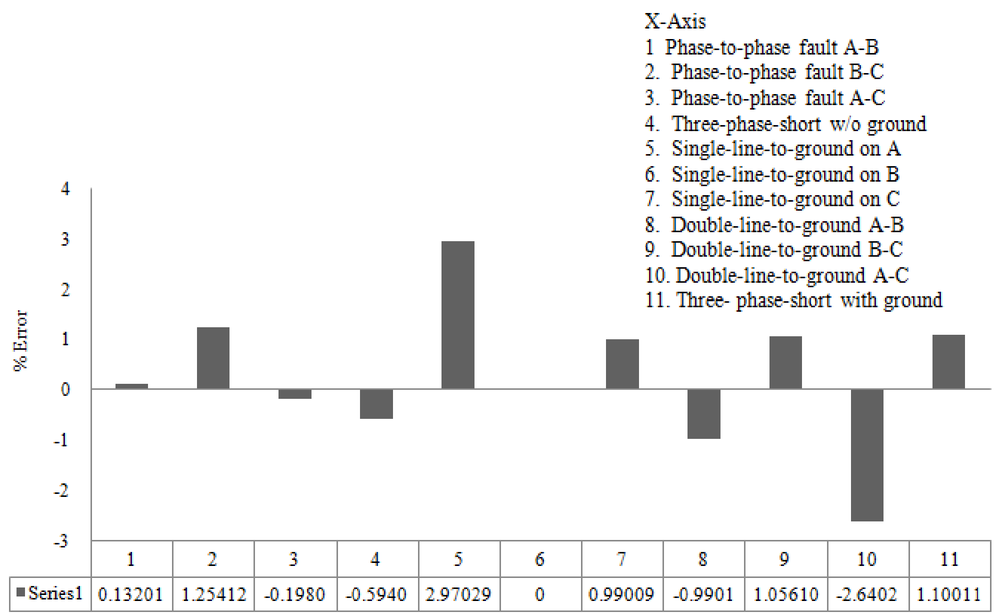

Fig. 14: Percentage fault location error for all fault types on faulted line (645-646) at 52meters

will be reiterated that ANN_CLASSIFIER outputs the type of fault involved and ANN_LOCATOR outputs faulted line segment along with the particular fault location on that line segment. The error calculation is done using the following formula:

$$fl_{error} = \frac{l_{ANN} - l_{actual}}{l_{total}} \times 100$$

where,
l_{total} = Total length of the faulted line
l_{actual} = Actual fault location in meters
l_{ANN} = Estimated fault location in meters
fl_{error} = Percentage fault location error

CONCLUSION

A MATLAB simulink model for an IEEE 13 node test case of DN was developed. All the eleven types of faults were triggered on all line segments of test DN. In all 550 fault combinations were planted and related fault data (voltage and current information) was generated. Three cycles of post fault voltage and current samples for all these combinations were extracted/processed for ANN training and testing. Two ANNs were trained and tested using the data. Neural network tool box of MATLAB was used for rigorous training of the ANNs. Some of the results of the ANNs are duly illustrated in this paper. All the illustrations are self-explanatory and demonstrate the accuracy achieved by the ANNs. It goes without saying that the results obtained are inspiring and therefore satisfactory.

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