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An Alternative Approach for Location of Transmission Line Faults based on Artificial Neural Network

Preeti Gupta[1], R.N.Mahanty[2]
[1](*Department of Electrical Engineering, National Institute of Technology, Jamshedpur, Jharkhand, India)*
[2](*Department of Electrical Engineering, National Institute of Technology, Jamshedpur, Jharkhand, India)*

***Abstract*:** *This paper describes the application of an artificial neural network (ANN) for location of transmission line faults. Three phase post fault samples of currents and voltages taken at one end of transmission line are used as inputs. Simulation studies have been carried out extensively on two power system models : one in which transmission line is fed from one end and the other in which transmission line is fed from both ends.The models are subjected to different types of faults at different operating conditions for variations in fault location, fault inception angle and fault point resistance. The results presented confirm the feasibility of the proposed scheme.*
Keywords: *Artificial Neural Network, Fault location, Transmission line.*

I. Introduction

Fault location is an important aspect of transmission line relaying. On occurrence of a fault, locating the fault is essential in order to make necessary repairs and to restore power supply as early as possible. Various algorithms for locating faults have been developed and implemented in power systems from time to time. Some of important ones among them are based on traveling wave [1-4], wavelet analysis [5-12], Artificial Neural Network [13-20] and Fuzzy Logic [21]. Fault location methods by combining various techniques viz. neural network, fuzzy logic and wavelet analysis have also been reported [22-25].

An alternative ANN based fault location approach for transmission line protection has been proposed in the present paper.The potential of ANN has been explored for accurate location of transmission line faults. The radial basis function based ANN has been chosen because of its suitability in the area of line relaying over the widely used feedforward network with back propagation algorithm.The ANN approach for fault location is distinctly different from most of the other digital fault location approaches. Whereas, most of the other fault location approaches estimate the distance upto the fault point, the ANN based relays learn from examples presented to them during training and their output corresponding to an input is based on the knowledge acquired during training. Because of their unique principle of operation, the ANN based relays are not affected by the presence of DC offset or harmonics in the voltage/current waveform and hence the possibility of relay overreach/underreach gets minimized. ANN based fault location techniques have been proposed by different researchers [26-34]. Most of these techniques use voltage and current signals in some form or other as the inputs to the network. The ANN based fault locator has one output node which gives the p. u. line length up to the fault point.

A RBF neural network based fault location scheme is presented in this paper. In the fault location scheme presented, samples (unfiltered) of three phase voltages and currents taken at one end of line are used as the inputs to ANN.To validate the proposed scheme, simulation studies have been carried out on two power system models: considering wide variations in the operating conditions. Fault data have been generated using EMTP and using these fault data simulation studies have been carried out by means of a MATLAB program which makes use of MATLAB's 'Neural Network Toolbox' [35].

II. Power System Models

The power system models considered for the simulation study are shown in Fig. 1 and Fig. 2 respectively [17].

Model I: Transmission line fed from one end

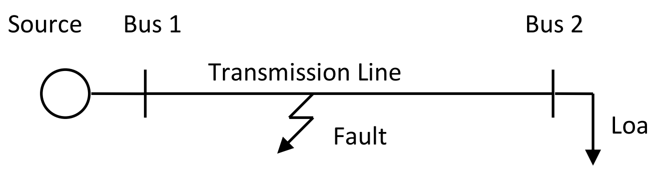

Fig. 1: A Faulted Transmission Line Fed from One End

Line length = 100 km, Source voltage (v_S) = 400 kV
Source impedance (Z_s) = (0.2 + j4.5) Ω per phase,
Positive sequence line parameters: R = 2.34 Ω, L = 95.10 mH, C = 1.24 µF
Zero sequence line parameters: R = 38.85 Ω, L = 325.08 mH, C = 0.845 µF
Load impedance (Z_L) = 500-800 Ω per phase with 0.7-0.9 p.f. lagging

Model II: Transmission line fed from both ends

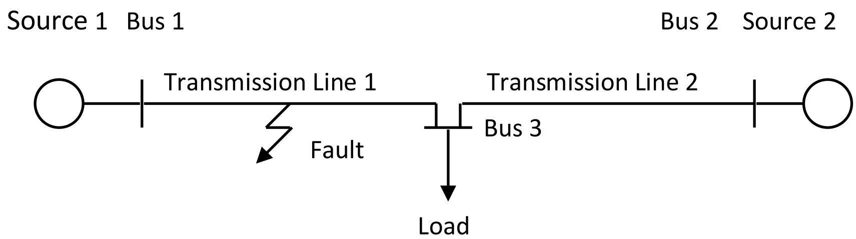

Fig. 2: A faulted transmission line fed from both ends

The parameters of transmission line 1 are same as those considered for transmission line of Model I. The load impedance variations are also same as in case of Model I. The parameters of transmission line 2 and other parameters are as follows:
R_2 =1.3 R_1, L_2 =1.3 L_1, C_2 =C_1, where suffixes 1 and 2 refer to transmission line 1 and transmission line 2 respectively.
v_{S2} = 0.95 v_{S1}, where v_{S1} and v_{S2} are the voltages of source 1 and source 2
δ (Phase difference between v_{S1} and v_{S2}) = 20^0 with v_{S1} leading
Source impedances: Positive sequence impedance: Z_{S1} = (0.2 + j4.5) Ω per phase,
Z_{S2} = (0.34 + j8) Ω per phase.
Zero sequence impedance = 1.5× Positive sequence impedance, for both the sources

III. The Proposed Ann Based Fault Locator

The proposed ANN based fault locator is shown in Fig. 3. The prerequisite of the fault locator is that the fault should be classified before hand .As shown in the figure, for each type of fault, fault locator consists of two ANNs: ANN-I and ANN-II i.e. two ANNs for L-G fault, two ANNs for L-L fault and so on. For training of the ANNs, different values of spread, are used to find the first and second estimates of fault location. The significance of using two ANNs for each fault type is explained in section 3.3.

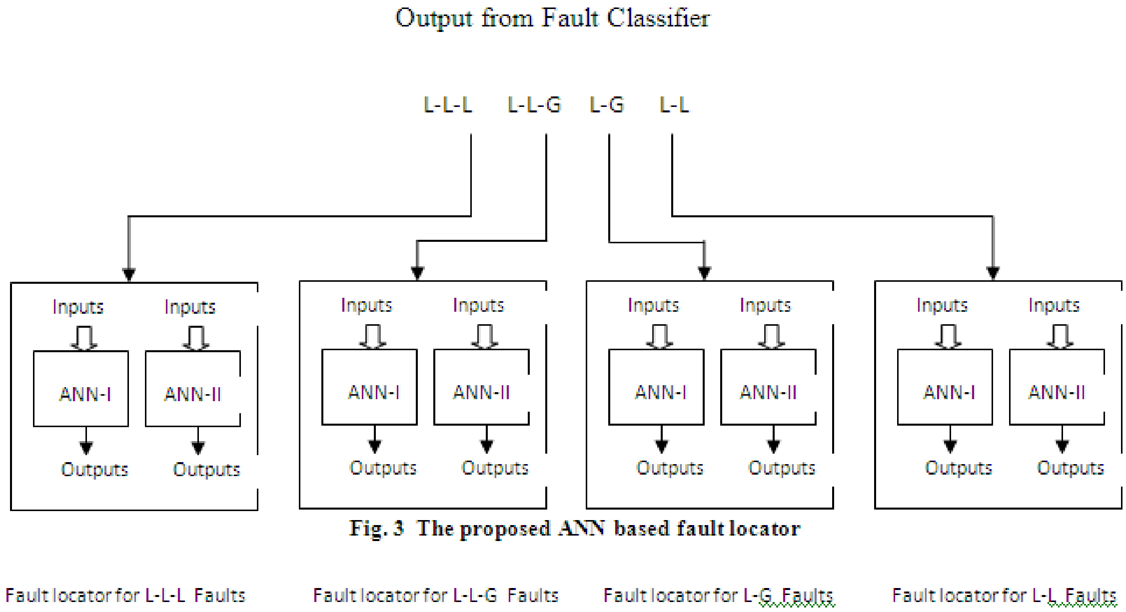

Fig. 3 The proposed ANN based fault locator

Three phases samples of voltages and currents have been used as the inputs to the fault locator. The selection of appropriate ANN pair is made on the basis of the type of fault. For accurately locating the fault, initially the estimate is made by ANN-I depending on the type of fault. Based on the value of this estimate, i.e. if this estimate falls below a certain predetermined value, a second estimate is found out by ANN-II for the particular type of fault. However, there is no need to find the second estimate if the first estimate is equal to or greater than the predetermined value. For the purpose of fault location only the post-fault samples have been found to be suitable. Seven post-fault samples of each of the three phase currents, voltages and zero sequence currents (for faults involving ground only) taken at one end of line have been used as inputs to the proposed ANN based fault locator. The sampling interval is considered as 1 ms. All these samples are normalized and presented in the form of a single input vector. An output is obtained corresponding to the input vector in p.u. of the line length up to the fault point. The input and output in case of line faults are shown below. In case of faults involving ground, samples of zero sequence current are also considered, as already mentioned

.

$$\begin{bmatrix} v_{A1} \\ \vdots \\ v_{A10} \\ v_{B1} \\ \vdots \\ v_{B10} \\ v_{C1} \\ \vdots \\ v_{C10} \\ i_{A1} \\ \vdots \\ i_{A10} \\ i_{B1} \\ \vdots \\ i_{B10} \\ i_{C1} \\ \vdots \\ i_{C10} \end{bmatrix} \quad \text{Input} \qquad [\ O\ ] \quad \text{Output}$$

Since the number of output is only one in this case, it is not possible to present the input in the form of multiple vectors.

3.1 Generation of Training Data

For accurate location of fault using an ANN based scheme, it is necessary to train the associated network/networks with large number of representative fault cases considering wide variations in fault location, fault resistance, fault inception angle and load impedance for each type of fault. A fault locator should be able to distinguish between faults occurring at, say, 80% and 85% of the line; such precision is not required in case of fault classification. This implies that number of training data required for a fault locator will be much more than that required for a fault classifier.

In order to achieve high degree of accuracy in fault location, large number of training data have been generated using EMTP, considering fault at 10%, 20%, 30%, 40%, 50%, 60%, 70%, 75%, 80%, 85% and 90% of the line. Fault inception angles of 0^0-90^0 at intervals of 18^0 and fault resistances of 0.5Ω, 20Ω, 75Ω and 150Ω have been considered. A per phase load impedance variation of 400-1200Ω at 0.7-0.9 p. f. lagging has also been considered for the training cases.

3.2 Choice of "Spread" and "Error Goal"

It has been observed that fault location can be estimated more accurately if instead of one value of spread for the entire line, two different values of spread are used. Therefore, two different values of spread one for faults within about 50% of line and another for faults beyond this range are used. By adopting the technique of using two values of spread a reduction in fault location error of up to 2-3% or more is obtained, which is significant as far as fault location is concerned.

As already mentioned, this strategy of estimating fault location is implemented by using two ANNs: ANN-I and ANN-II for each type of fault, each of the two ANNs being trained with a different value of spread. The selected values of spread for L-L and L-G faults in case of Model I and Model II are shown in Table1. These values of spread are determined after extensive simulation studies. Table1 also indicates the number of neurons in the hidden layer, the number of epochs (iterations) required for training and the training time of each ANN.

A comparison of results obtained with the two selected values of spread for some typical fault cases corresponding to a load impedance of $400\angle 36.87^0\ \Omega$ and variations in fault location (α), fault resistance (R_F) and fault inception angle (FIA) are presented in Table 2 - 3. Similar results have been obtained for other load impedance values. As can be seen from Table 2, In case of Model I, for L-G faults at 15% of line, results obtained with spread = 0.7 are more accurate than those obtained with spread = 1.3. From the same table, it is clear that, for L-G faults at 82% of line for the same model, results obtained with spread = 1.3 are more accurate as compared to those obtained with spread = 0.7. Thus the use of two values of spread is justified which is also clear from the results shown in Table 3.

The accuracy required in case of fault location is more as compared to that required in fault classification. An output of 0.8 or 0.9 means the same in case of a fault classifier as both indicate a faulty phase, whereas for a fault locator an output of 0.8 means fault occurring at a distance of 80% of line and an output of 0.9 means fault occurring at a distance of 90% of line. To ensure high accuracy in fault location an rms error goal of 0.001 has been considered for all the ANNs of the fault locator.

Table 1: Spreads, number of hidden neurons and training times relating to ANNs of fault locator

	Fault Type	**Network**	**Spread**	**Epochs**	**Number of hidden neurons**	**Training time (min.)**
Model-I	L-L	ANN-I	1.5	475	475	40.20
		ANN-II	0.7	380	380	68.77
	L-G	ANN-I	1.3	521	521	60.79
		ANN-II	0.7	451	451	82.55
Model-II	L-L	ANN-I	1.5	422	422	43.91
		ANN-II	1.0	391	391	52.89
	L-G	ANN-I	0.9	471	471	46.33
		ANN-II	1.4	409	409	66.27

IV. Fault Location Algorithm

The operating principle of the proposed fault locator is as follows:

After the type of fault has been identified, ANN-I dedicated for the particular type of fault, estimates the fault location. In case this estimate is less than 0.45, then a second estimate is found out using ANN-II for the type of fault. In case the first estimate is equal to or greater than 0.45 then there is no need to find second estimate.

Based on the above principle, the following fault location algorithm has been developed.

1. Ascertain the type of fault by a fault classifier.
2. Select the appropriate ANN pair for the particular fault type.
3. Estimate the fault location (α_e) using ANN-I for the particular fault type.
4. If $\alpha_e < 0.45$, find second estimate using ANN-II.

Table 2: Fault location estimates for different values of spread in case of Model I

α	R_F (Ω)	FIA (^{0})	Network	A-G fault		A-B fault	
				Optimal Spread	α_e	Optimal Spread	α_e
0.15	0.01	0	ANN-I	1.3	0.1698	1.5	0.1401
			ANN-II	0.7	0.1647	0.7	0.1406
		90	ANN-I	1.3	0.1593	1.5	0.1321
			ANN-II	0.7	0.1432	0.7	0.1382
	200	0	ANN-I	1.3	0.1682	1.5	0.1721
			ANN-II	0.7	0.1654	0.7	0.1581
		90	ANN-I	1.3	0.1323	1.5	0.1842
			ANN-II	0.7	0.1498	0.7	0.1702
0.82	0.01	0	ANN-I	1.3	0.8320	1.5	0.8198
			ANN-II	0.7	0.8480	0.7	0.8192
		90	ANN-I	1.3	0.8197	1.5	0.8190
			ANN-II	0.7	0.8012	0.7	0.7986
	200	0	ANN-I	1.3	0.8176	1.5	0.8145
			ANN-II	0.7	0.8164	0.7	0.7947
		90	ANN-I	1.3	0.8157	1.5	0.8082
			ANN-II	0.7	0.7732	0.7	0.7564

α_e= Estimated fault location as a fraction of total line length

Table 3: Fault location estimates for different values of spread in case of Model II

α	R_F (Ω)	FIA (^{0})	Network	A-G fault		A-B fault	
				Optimal spread	α_e	Optimal spread	α_e
0.15	0 0.01	0	ANN-I	0.9	0.1386	1.5	0.1278
			ANN-II	1.4	0.1488	1.0	0.1424
		90	ANN-I	0.9	0.1485	1.5	0.1348
			ANN-II	1.4	0.1505	1.0	0.1387
	200	0	ANN-I	0.9	0.1410	1.5	0.1689
			ANN-II	1.4	0.1487	1.0	0.1592
		90	ANN-I	0.9	0.1378	1.5	0.1645
			ANN-II	1.4	0.1465	1.0	0.1524
0.82	0.01	0	ANN-I	0.9	0.8187	1.5	0.8209
			ANN-II	1.4	0.8098	1.0	0.8176
		90	ANN-I	0.9	0.8094	1.5	0.8187
			ANN-II	1.4	0.8654	1.0	0.8082
	200	0	ANN-I	0.9	0.8156	1.5	0.8071
			ANN-II	1.4	0.8187	1.0	0.7823
		90	ANN-I	0.9	0.7824	1.5	0.7995
			ANN-II	1.4	0.7654	1.0	0.7582

V. Training Of The Anns

The various ANNs have been trained with the training data as mentioned in section 3.1. The error goals of all the ANNs were fixed at 0.001. The spreads of various ANNs for location of L-L and L-G faults and their training times are as indicated in Tables 1 and 2. As can be seen from the tables, the training times are much higher as compared to those in case of ANN based fault classifier. This is because of the large amount of training data that are needed to train the ANNs of the fault locator. Fig. 4 - Fig. 11 show the error convergence of the various ANNs during training.

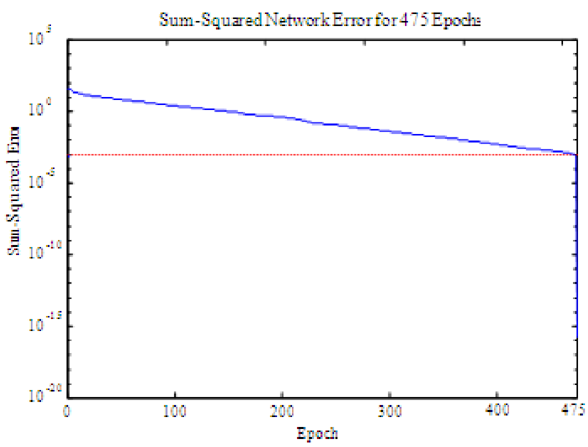

Fig. 4 Error convergence of ANN-I (Model I) for L-L faults in training

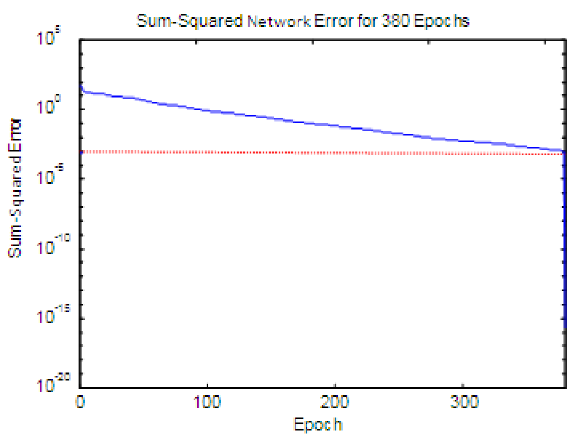

Fig. 5 Error convergence of ANN-II (Model I) for L-L faults in training

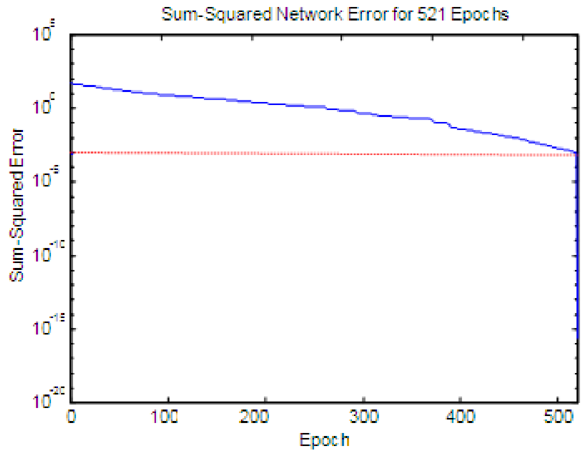

Fig. 6 Error convergence of ANN-I (Model I) for L-G faults in training

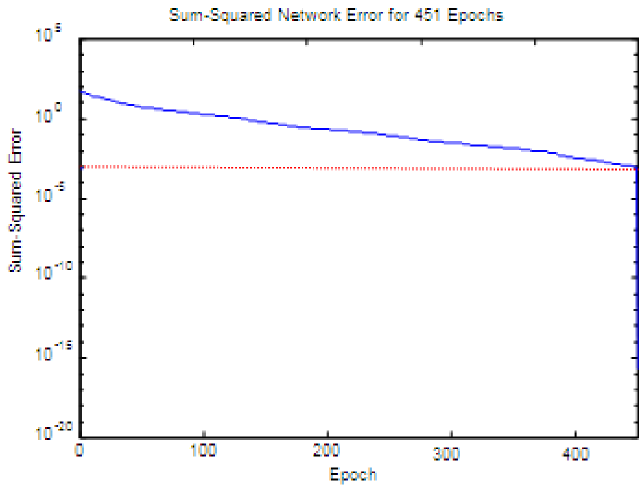

Fig. 7 Error convergence of ANN-II (Model I) for L-G faults in training

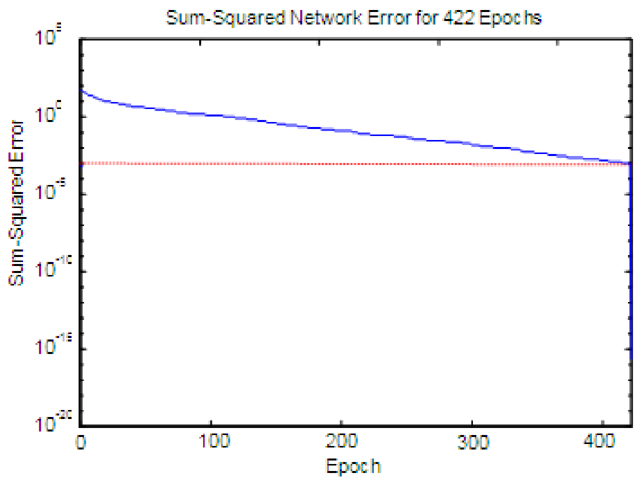

Fig. 8 Error convergence of ANN-I (Model II) for L-L faults in training

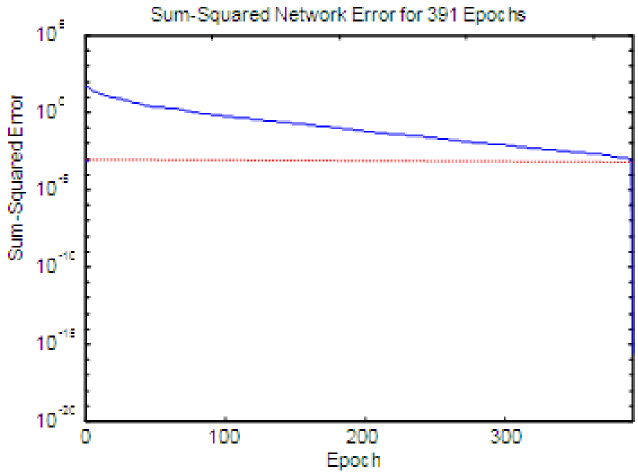

Fig. 9 Error convergence of ANN-II (Model II) for L-L faults in training

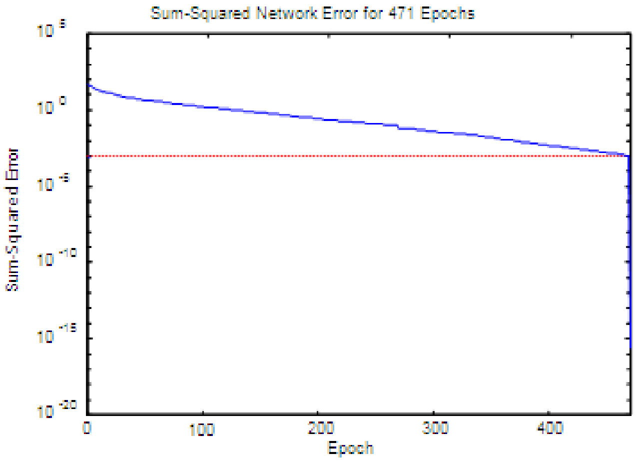

Fig. 10 Error convergence of ANN-I (Model II) for L-G faults in training

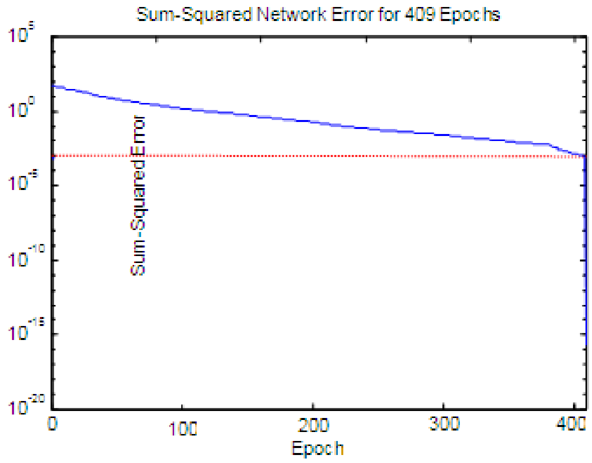

Fig. 11 Error convergence of ANN-II (Model II) for L-L faults in training

VI. Testing Of The Anns

After the training phase was over, each ANN was tested for different types of faults considering wide variations in fault location (α), fault resistance (R_F), fault inception angle (FIA) and load impedance (Z_L). Some representative test results for the two most common types of fault viz. L-L and L-G faults are presented in Table 4-Table 7. Test results corresponding to two values of load impedance viz. $400\angle 36.87^0$ Ω and $1200\angle 45.57^0$ Ω have only been shown. Similar results have been obtained for other loading conditions. The test results confirm the feasibility of the proposed ANN based fault location scheme.

Table 4: Test results for A-G fault for Model-I

		α_e					
		15%		55%		82%	
	R_F (Ω)	Z_L (Ω) $400\angle 36.87^0$	Z_L (Ω) $1200\angle 45.57^0$	Z_L (Ω) $400\angle 36.87^0$	Z_L (Ω) $1200\angle 45.57^0$	Z_L (Ω) $400\angle 36.87^0$	Z_L (Ω) $1200\angle 45.57^0$
FIA= 0^0	0.01	0.1621	0.1452	0.5055	0.5359	0.8489	0.8318
	10	0.1308	0.1562	0.5713	0.5453	0.8221	0.8096
	50	0.1790	0.1495	0.5588	0.5341	0.8157	0.7989
	100	0.1719	0.1482	0.5518	0.5091	0.8120	0.8204
	200	0.1796	0.1508	0.5590	0.5297	0.8192	0.8017
FIA= 45^0	0.01	0.1640	0.1354	0.5383	0.5289	0.8677	0.8267
	10	0.1289	0.1543	0.5827	0.5608	0.8232	0.8301
	50	0.1711	0.1396	0.5584	0.5503	0.8241	0.8174
	100	0.1591	0.1443	0.5284	0.5235	0.8183	0.8199
	200	0.1528	0.1459	0.5098	0.5385	0.8063	0.7985
FIA= 90^0	0.01	0.1411	0.1399	0.5373	0.5509	0.8185	0.8049
	10	0.1573	0.1569	0.5327	0.5789	0.8184	0.8093
	50	0.1429	0.1376	0.5211	0.4996	0.8138	0.8189
	100	0.1484	0.1416	0.5188	0.5178	0.8204	0.8662
	200	0.1428	0.1428	0.5186	0.5117	0.8096	0.7987

Table 5: Test results for A-B fault for Model-I

		α_e					
		15%		55%		82%	
	R_F (Ω)	Z_L (Ω) $400\angle 36.87^0$	Z_L (Ω) $1200\angle 45.57^0$	Z_L (Ω) $400\angle 36.87^0$	Z_L (Ω) $1200\angle 45.57^0$	Z_L (Ω) $400\angle 36.87^0$	Z_L (Ω) $1200\angle 45.57^0$
FIA= 0^0	0.01	0.1401	0.1342	0.5502	0.5507	0.8187	0.8177
	10	0.1687	0.1787	0.5720	0.5386	0.8145	0.8198
	50	0.1487	0.1423	0.5397	0.5621	0.8013	0.7986
	100	0.1504	0.1505	0.5321	0.5732	0.8098	0.7998
	200	0.1634	0.1453	0.5643	0.5432	0.8176	0.7992
FIA= 45^0	0.01	0.1287	0.1376	0.5476	0.5394	0.8165	0.8095
	10	0.1545	0.1665	0.5243	0.5238	0.8191	0.8207
	50	0.1654	0.1765	0.5721	0.5654	0.8125	0.8197
	100	0.1556	0.1785	0.5865	0.5865	0.8654	0.8564
	200	0.1609	0.1321	0.5121	0.5138	0.7987	0.7897
FIA= 90^0	0.01	0.1298	0.1443	0.5464	0.5523	0.8194	0.8123
	10	0.1476	0.1434	0.5518	0.5397	0.8189	0.8297
	50	0.1512	0.1509	0.5502	0.5611	0.7976	0.8078
	100	0.1445	0.1665	0.5598	0.5776	0.8321	0.8265
	200	0.1687	0.1397	0.5521	0.5232	0.8187	0.7988

Table 6: Test results for A-G fault for Model-II

		α_e					
		15%		55%		82%	
	R_F (Ω)	Z_L (Ω) $400\angle 36.87^0$	Z_L (Ω) $1200\angle 45.57^0$	Z_L (Ω) $400\angle 36.87^0$	Z_L (Ω) $1200\angle 45.57^0$	Z_L (Ω) $400\angle 36.87^0$	Z_L (Ω) $1200\angle 45.57^0$
FIA= 0^0	0.01	0.1393	0.1312	0.5472	0.5456	0.8197	0.8188
	10	0.1500	0.1665	0.5500	0.5275	0.8167	0.8089
	50	0.1676	0.1485	0.5122	0.5381	0.8011	0.7897
	100	0.1286	0.1196	0.5149	0.5228	0.8013	0.7886
	200	0.1556	0.1426	0.5287	0.5546	0.7976	0.7898
FIA= 45^0	0.01	0.1521	0.1408	0.5469	0.5408	0.8232	0.8180
	10	0.1385	0.1698	0.5545	0.5326	0.8176	0.8372
	50	0.1721	0.1843	0.5350	0.5625	0.8312	0.8193
	100	0.1421	0.1657	0.5765	0.5213	0.8221	0.8514
	200	0.1724	0.1603	0.5621	0.5233	0.8091	0.8300
FIA= 90^0	0.01	0.1298	0.1443	0.5454	0.5390	0.8165	0.8098
	10	0.1576	0.1424	0.5549	0.5411	0.8207	0.8217
	50	0.1243	0.1486	0.5089	0.5416	0.7986	0.7878
	100	0.1311	0.1512	0.4976	0.5323	0.8097	0.8162
	200	0.1512	0.1213	0.5502	0.5291	0.7987	0.7873

Table 7: Test results for A-B fault for Model-II

		α_e					
		15%		55%		82%	
	R_F (Ω)	Z_L (Ω) $400\angle36.87^0$	Z_L (Ω) $1200\angle45.57^0$	Z_L (Ω) $400\angle36.87^0$	Z_L (Ω) $1200\angle45.57^0$	Z_L (Ω) $400\angle36.87^0$	Z_L (Ω) $1200\angle45.57^0$
FIA= 0^0	0.01	0.1393	0.1312	0.5472	0.5456	0.8197	0.8188
	10	0.1500	0.1665	0.5500	0.5275	0.8167	0.8089
	50	0.1676	0.1485	0.5122	0.5381	0.8011	0.7897
	100	0.1286	0.1196	0.5149	0.5228	0.8013	0.7886
	200	0.1556	0.1426	0.5287	0.5546	0.7976	0.7898
FIA= 45^0	0.01	0.1521	0.1408	0.5469	0.5408	0.8232	0.8180
	10	0.1385	0.1698	0.5545	0.5326	0.8176	0.8372
	50	0.1721	0.1843	0.5350	0.5625	0.8312	0.8193
	100	0.1421	0.1657	0.5765	0.5213	0.8221	0.8514
	200	0.1724	0.1603	0.5621	0.5233	0.8091	0.8300
FIA= 90^0	0.01	0.1298	0.1443	0.5454	0.5390	0.8165	0.8098
	10	0.1576	0.1424	0.5549	0.5411	0.8207	0.8217
	50	0.1243	0.1486	0.5089	0.5416	0.7986	0.7878
	100	0.1311	0.1512	0.4976	0.5323	0.8097	0.8162
	200	0.1512	0.1213	0.5502	0.5291	0.7987	0.7873

VII. Comparison With Some Of The Existing Schemes

The salient features of some of the existing RBF neural network based fault location schemes and those of the proposed algorithms are described below. The proposed scheme has several advantages: (a) Unlike many other methods which require frequency[33] and SCR firing angle[32] the proposed one requires only voltage and current samples as ANN inputs (b) filtering of the signals not required (c) covers wider range of R_F as compared to **many** other schemes and hence suitable even under high impedance fault conditions (d)The range of firing angle is similar to other schemes (d) although network is complicated resulting in an increase in number of iterations but more accurate as compare to method suggested by Mahanty et al.[17].The error is reduced from 6-7% to 2-3%.

Table 8: RBF neural network based fault location schemes

Scheme suggested by:	Input data (filtered / unfiltered)	Fault locator Inputs	R_F range	FIA range
Song et al. [33]	Unfiltered	Samples of 3-phase v, i, v^2, i^2, SCR firing angle	0.5Ω fixed	0^0-90^0
Dash et al. [34]	Filtered	Samples of 3-phase v, i,i_0 , f	0-100Ω	0^0-90^0
Mahanty et al. [18]	Unfiltered	Samples of 3-phase v, i ,i_0	0-200Ω	0^0-90^0
Proposed scheme	Unfiltered	Samples of 3-phase v, i ,i_0		

VIII. Conclusions

A methodology for location of transmission line faults based on RBF neural network has been presented. The use of RBFNN has been found to be very effective as it can overcome the deficiencies associated with BP algorithm. Unfiltered samples of both currents and voltages of the three phases have been considered as inputs for ANNs of the fault locator. For each fault type, the fault locator consists of two ANNs: one to locate faults occurring within about 50% of the line and the other one to locate faults occurring beyond this range. Two different values of spread are used for training of ANN's so as to obtain accurate estimates of fault location. To validate the proposed scheme simulations studies have been carried out for two most common types of fault viz. L-L and L-G faults by considering wide variations in fault inception angle, fault location, fault resistance and load impedance. It may be noted that the sizes of the ANNs are quite large. This is because of the use of the radial basis function ANNs and the large amount of data needed to train them. The size of ANNs can be reduced if filtered data are used instead of unfiltered data as inputs.

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