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Artificial Neural Network based Fault Classifier and Locator for Transmission Line Protection

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Abstract: *This paper presents a method for classification and location of transmission line faults based on Artificial Neural Network (ANN). Although for fault classification prefault and postfault three phase currents samples taken at one end of transmission line are used as ANN inputs, for location of faults post fault samples of both current and voltages of three phases are required . Simulation studies have been carried out extensively on two power system models: one in which the transmission line is fed from one end and another, in which the transmission line is fed from two ends. Different types of faults at different operating conditions have been considered for carrying out simulation studies. The simulation results presented confirm the feasibility of the proposed approach.*
Keywords*: Artificial Neural Network, Fault Classification, Fault Location, Transmission Line Protection.*

I. Introduction

For providing the essential continuity of service from generating plants to end users power transmission lines are vital links. Transmission line protection is therefore an important task for reliable power system operation. The identification of the type of fault and the faulty phase/phases is known as fault classification which is an important aspect of transmission line protection. The information provided by classification of fault is necessary for locating the fault and assessing the extent of repair work to be carried out. Various fault classification techniques have been developed by different researchers from time to time. Some of the important fault classification and location techniques are: (1) wavelet transform based techniques [1]-[9] (2) neural network based techniques [10]-[17] (3) fuzzy logic based techniques [18]-[20]. In this paper, an alternative neural network based combined approach for classification and location of transmission line faults has been proposed.

ANN is a mathematical model inspired by biological neural networks. A neural network is an adaptive system changing its structure due to learning phase and responds to new events in the most appropriate manner on the basis of experiences gained through training. The ability of ANNs to learn complex nonlinear input/output relationships have motivated researchers to apply ANNs for solving nonlinear problems related to various fields. ANNs have inherent advantages of excellent noise immunity and robustness and hence ANN based approaches are less susceptible to changing operating conditions as compared to the conventional approaches related to power system engineering. ANNs have been successfully applied to power system protection. ANN applications to transmission line protection [12],[21]-[24] include detection,classification [10],[11],[15]-[17],[21]-[23],[25]-[27] and precise location of faults [10],[13]-[17],[21]-[23],[25],[26]. Although amongst the various available ANN based algorithms, back propagation (BP) training algorithm is the most widely used one, it has some deficiencies including slow training and local minimum which make it unsuitable for transmission line relaying [21]-[23],[25]. For such cases the radial basis function (RBF) based neural network is well suited [10],[21]-[23],[25],[28],[29].

A RBF neural network based scheme for classification and location of transmission line faults is presented in this paper. As many researchers [10],[21],[23],[27] have successfully carried out fault detection using ANN approach, *a priori* knowledge of accurate fault detection has been taken for granted. The previous researchers have generally used both current and voltage samples for fault classification. In the proposed scheme three phase current samples (unfiltered) taken at one end of line are used for classification of faults. However for locating the faults apart from current samples, voltage samples taken at one end of line are also required. Large number of fault data has been generated by means of Electromagnetic Transient Program (EMTP). Using the fault data generated through EMTP, simulation studies have been carried out by means of MATLAB's 'Neural Network Toolbox' [30] taking into account wide variations in fault resistance (R_F), fault inception angle (*FIA*), fault location (α) and load impedance (Z_L) for different types of fault.

II. Power System Models

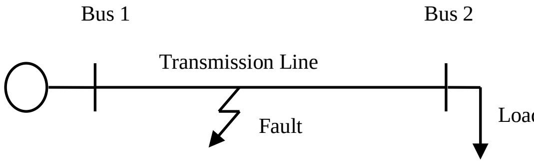

Figure 1: Model I: A faulted transmission line fed from one end

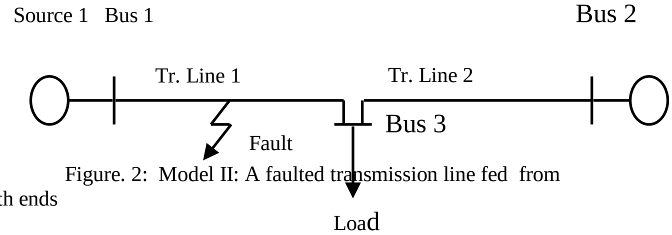

Figure. 2: Model II: A faulted transmission line fed from both ends

The two power system models: Model I and Model II, which have been considered for the development of the fault classification and location algorithms are shown in Fig. 1 and Fig. 2 respectively [10].
As can be seen from the figures each model contains a faulted transmission line. In case of Model I, power is fed to fault from one source, whereas in case of Model II, power is fed to fault from two sources. In each case the fault is associated with a fault resistance and power is fed to fault and load simultaneously. The transmission line parameters and other relevant data for Model-I and Model-II are given below:

2.1 Model I: Transmission line fed from one end

Line length = 100 km ,Source voltage (v_S) = 400 kV,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, Source impedance (Z_S): Positive sequence impedance = (0.45 + j5) Ω per phase and Zero sequence impedance = 1.5× Positive sequence impedance, Load impedance (Z_L) = 800 Ω per phase with 0.8 p.f. lagging

2.2 Model II: 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: $R_2 = 1.3\ R_1$, $L_2 = 1.3\ L_1$, $C_2 = C_1$, 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} = (0.45 + j5) Ω per phase, Z_{S2} = (0.34 + j4) Ω per phase. Zero sequence impedance = 1.5× Positive sequence impedance, for both the sources.

III. The Proposed Fault Classifier

The proposed ANN based scheme for classification of faults is shown in Fig. 3. In the figure, *F*, *D* and *G* represent the presence of fault, the fault direction and the involvement of ground in the fault. *A*, *B* and *C* are the three phases. Simulation studies have been carried out to validate the proposed scheme on two power system models: Model I and Model II, for various types of fault considering variations in operating conditions. Two separate ANNs, one for ground faults and another for phase faults have been used. Hence, the prerequisite of the proposed scheme is that the fault should be detected and also it should be known whether the fault involves ground or not.

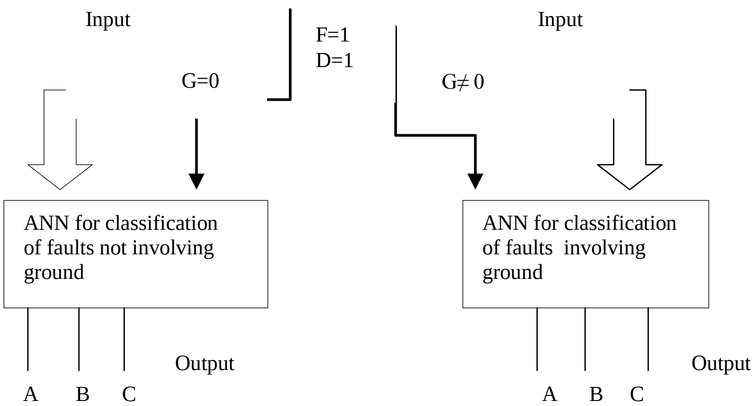

Figure 3: ANN based fault classifier

The various ANNs have been termed as:

- ANN-1 / ANN-3: For classification of faults not involving ground in case of Model I / Model II,
- ANN-2 / ANN-4: For classification of faults involving ground in case of Model I / Model II.

$$\boldsymbol{XX} = \begin{bmatrix} i_{A_1} & i_{B_1} & i_{C_1} \\ i_{A_2} & i_{B_2} & i_{C_2} \\ . & . & . \\ . & . & . \\ i_{A_{n_I}} & i_{B_{n_I}} & i_{C_{n_I}} \end{bmatrix} \quad \text{Inputs}$$

$$\downarrow \qquad \downarrow \qquad \downarrow$$

$$\boldsymbol{F}(\mathbf{XX}) = \begin{bmatrix} A & B & C \end{bmatrix} \quad \text{Outputs}$$

The input data, consisting of normalized absolute values of three pre-fault and four post-fault samples of each of the three phase currents, i_A, i_B, i_C are presented to each of the two ANNs used for fault classification, in the form of multiple input vectors as shown above. This type of batching operation is more efficient than the case when inputs are presented in the form of a single vector [30].

3.1. Generation of Training Data

An ANN based fault classifier should be trained with sufficient data for different fault situations. But as the data encountered by an ANN based fault classifier is quite large, it is necessary to judiciously decide and consider some representative fault situations and to train the network with data corresponding to these cases such that the ANN gives correct output for all cases.Therefore, each of the ANNs has been trained with different fault data. Fault data have been generated for fault at 5% of the line length from bus 1 of Model I and Model II when the load impedance is 500Ω at 0.8 p. f. lagging. Training sets, for each of the two power system models, have been generated through EMTP simulations for the load impedance as mentioned and by varying fault resistance and fault inception angle. Fault resistances of 5Ω, 50Ω, 100Ω and 300Ω and fault inception angles of 45^0, 135^0 and 225^0 have been considered for training. It is important to select proper values of spread and error goal in designing a RBF neural network.The spread should be smaller than the maximum distance and larger than the minimum distance between the input vectors [29]. After a number of simulations the spreads for the different ANNs have been selected, as indicated below.

ANN-1: Spread = 0.7 , ANN-2: Spread = 0.6 . ANN-3: Spread = 1.0 , ANN-4: Spread = 0.9

Error goal indicates how close the actual output is to the desired one. Lower the error goal, higher is the accuracy and vice versa. After a number of simulation studies, it was decided to fix the error goal for all the ANNs at 0.01. A comparison of the training times, number of epochs (iterations) required for the networks to converge is shown in Table I. Based on this comparison, the ANNs with minimum number of hidden neurons were selected for the proposed fault classifier. The selected values of spread, number of hidden neurons *etc.* for each ANN are highlighted in Table I. The error convergences of the various ANNs during training have been shown in Fig.4- Fig.7.

Table I: Rate of Convergence for various ANN's relating to different RMS errors and spreads

Network	*RMS error*	*Spread*	*Number of hidden neurons*	*Iterations (epochs)*	*Time (sec)*
ANN-1	0.001	0.7	66	66	18.16
	0.01	0.6	45	45	9.907
	0.01	**0.7**	**44**	**44**	**9.461 selected**
	0.01	0.8	Computation incompatible		
ANN-2	0.001	0.5	126	126	81.615
	0.01	**0.6**	**91**	**91**	**45.631 selected**
	0.01	0.7	Computation incompatible		
	0.01	0.8	98	98	52.43
ANN-3	0.001	1.0	75	75	21.77
	0.01	0.8	51	51	12.41
	0.01	0.9	50	50	12.15
	0.01	**1.0**	**50**	**50**	**11.91 selected**
ANN-4	0.001	0.9	141	141	99.446
	0.01	**0.9**	**101**	**101**	**55.07 selected**

0.01	1.0	Computation incompatible		
0.01	1.1	103	103	56.51

After training, each ANN is tested for different types of faults considering wide variations in operating conditions such as R_F (fault resistance), *FIA (*fault inception angle), α *(*fault location) and $Z_{L(}$ pre-fault load). R_F variation of 0-300Ω, *FIA* variation of 0-360^0 , α variation of 0-90% of transmission line length and Z_L variation of 300-1200Ω in per phase load with power factor (lagging) variation of 0.7–0.9 have been considered. Tables II and III contain the test results for various ANNs, which confirm the feasibility of the proposed ANN based fault classification scheme.

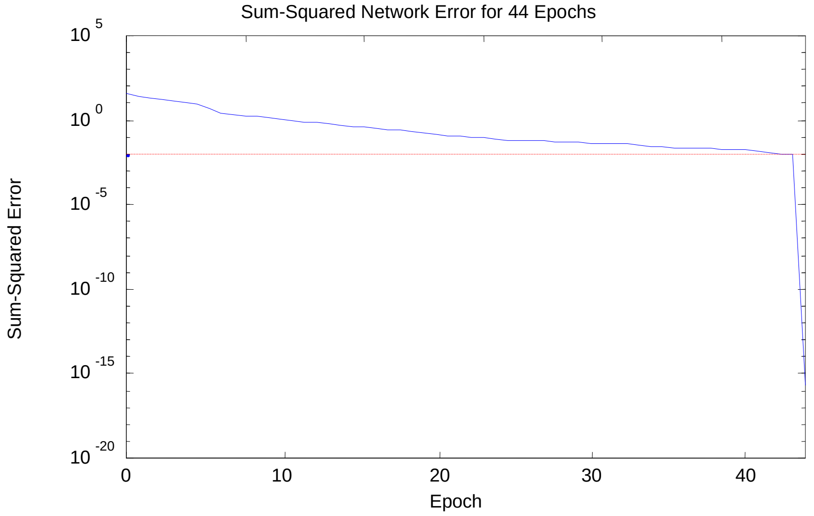

Figure 4: Error convergence of ANN-1 in training.

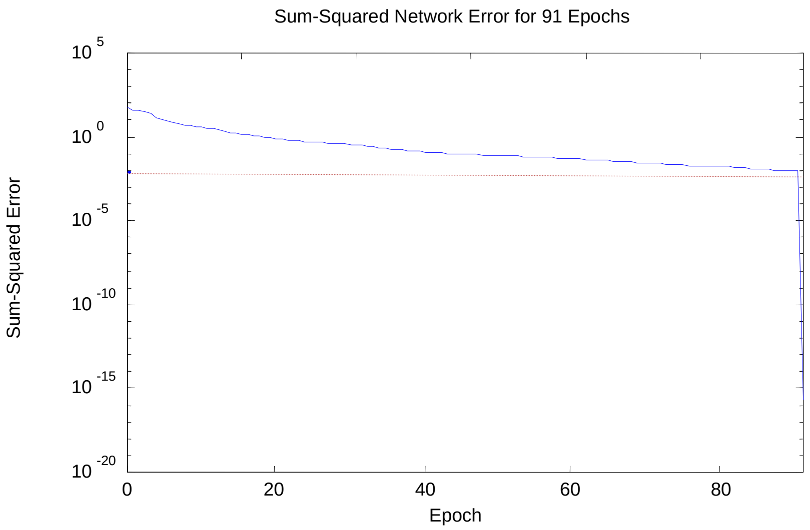

Figure 5: Error convergence of ANN-2 in training.

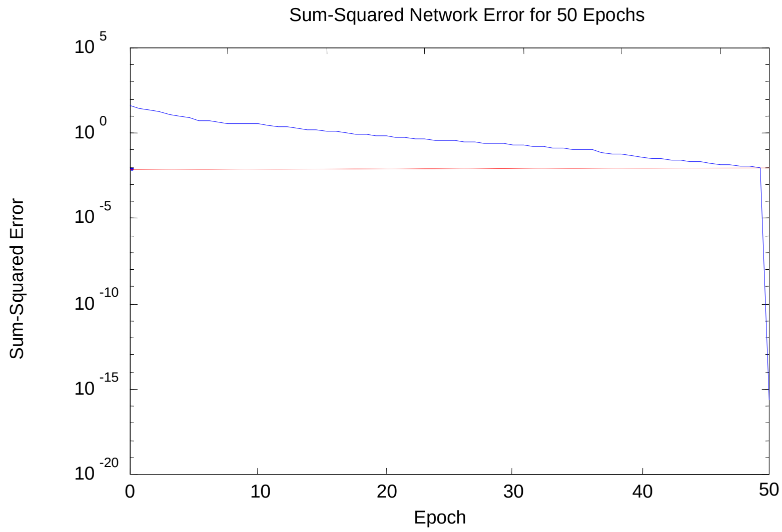

Figure 6: Error convergence of ANN-3 in training

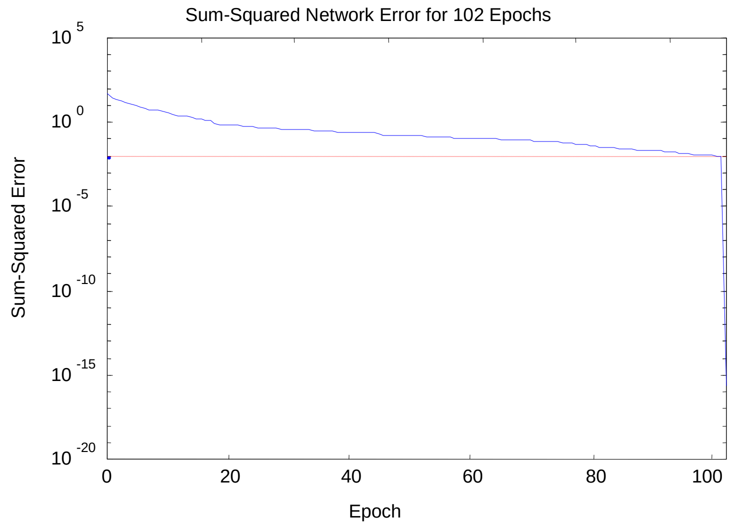

Figure 7: Error convergence of ANN-4 in training.

Table II: Test Results for Model I.

Fault type	***Fault Conditions***				***ANN Output***		
	α	***FIA***	R_F	Z_L	***A***	***B***	***C***
Normal Condition	-	-	-	$1200\angle 45.57^0$	0.0009	0.0037	0.0067
A-G	0.5	90	300	$400\angle 36.87^0$	0.8876	-0.0218	0.0169
		180	5	$300\angle 45.57^0$	0.9760	0.1189	-0.0216
	0.9	250	200	$1200\angle 45.57^0$	0.8173	-0.0008	0.1321
		360	70	$300\ \angle 25.84^8$	0.8125	0.0549	0.0280
B-C	0.1	60	200	$400\angle 36.87^0$	-0.0032	1.0143	0.9999
		200	20	$400\angle 25.84^0$	-0.0032	1.0091	1.0002
	0.5	90	300	$400\angle 36.87^0$	0.0065	1.0932	0.9997
		300	20	$1200\angle 25.84^0$	0.0453	0.9865	0.9976
C-A-G	0.1	0	0.01	$800\angle 45.57^0$	0.9976	0.1876	0.9876
		200	20	$400\angle 25.84^0$	0.9978	-0.0043	0.9934
	0.9	160	0.01	$800\angle 36.87^0$	0.8698	-0.0056	0.9876
		360	70	$300\angle 25.84^0$	0.8876	0.1698	0.8378
A-B-C	0.1	0	0.01	$800\angle 45.57^0$	0.9986	1.0023	1.0013
		110	70	$1200\angle 45.57^0$	1.1023	0.9995	1.0311
	0.5	90	300	$400\angle 36.87^0$	0.9965	0.8897	0.9786
		300	20	$1200\angle 25.84^0$	1.0743	0.8265	0.9276

Table III: Test Results for Model II.

Fault Type	***Fault Condition***				***ANN Output***		
	α	***FIA***	R_F	Z_L	***A***	***B***	***C***
Normal Condition	-	-	-	$800\angle 25.84^0$	0.0013	-0.0258	0.432
B-G	0.1	60	200	$400\angle 36.87^0$	0.0008	0.9989	-0.0022
		110	70	$1200\angle 45.57^0$	0.1408	0.8667	0.1061
	0.5	90	300	$400\angle 36.87^0$	0.1012	0.8341	0.0876
		180	5	$300\angle 45.57^0$	-0.0008	0.9538	0.0898
C-A	0.5	30	100	$800\angle 45.57^0$	1.0032	-0.0032	1.0543
		180	5	$300\angle 45.57^0$	0.9986	-0.0003	1.0112
	0.9	75	20	$300\angle 45.57^0$	1.0521	1.0321	0.0007
		360	70	$300\angle 25.84^0$	0.9990	0.0021	1.0013
B-C-G	0.1	0	0.01	$800\angle 45.57^0$	0.0765	1.0009	1.0002
		110	70	$1200\angle 45.57^0$	0.0765	1.0563	0.9956
	0.9	250	200	$1200\angle 45.57^0$	0.0108	0.7987	0.7876
		60	70	$300\angle 25.84^0$	0.0028	0.9597	0.9876
A-B-C	0.1	60	200	$400\angle 36.87^0$	0.9456	1.1006	0.9731
		340	50	$300\angle 36.87^0$	1.0075	1.0021	1.0398
	0.5	30	100	$800\angle 45.57^0$	1.0321	0.9786	0.8234
		180	5	$300\angle 45.57^0$	0.9989	1.0043	1.0532

IV. The Proposed Ann Based Fault Locator

The proposed ANN based fault locator is shown in Fig. 8. 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. Similar to fault classification, 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 4.1. The inputs to the fault locator consist of samples of three phase voltages and currents. The selection of appropriate ANN pair is made on the basis of the type of fault. Depending on the type of fault, initially the estimate is made by ANN-I. 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, if the first estimate is equal to or greater than the predetermined value, there is no need to find the second estimate.For the purpose of fault location only the post-fault samples have been found to be suitable.

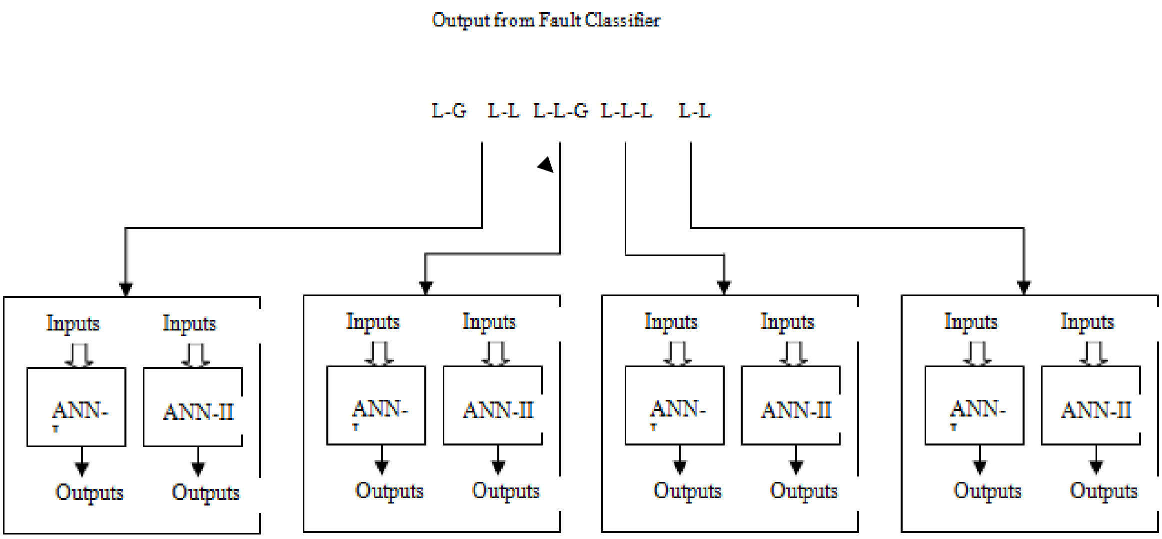

Figure 8: The proposed ANN based fault locator

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.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.

4.1 Generation of Training Data

A fault locator should be able to distinguish between faults occurring at, say, 80% and 85% of the line which implies that number of training data required for a fault locator will be much more than that required for a fault classifie, thus, 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 case.

It has been observed that if two different values of spread are used, one for faults within about 50% of line and another for faults beyond this range, fault location can be estimated more accurately. Therefore, two different values of spread are used. By adopting this technique, 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 Table IV. These values of spread are determined after extensive simulation studies. Table IV 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 V and Table VI. Similar results have been obtained for other load impedance values. As can be seen from Table V, 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 VI.

For fault location, the accuracy required 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 IV: 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

Table V: 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 VI: 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	0.01	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

4.2. Training and Testing of the ANNs

The various ANNs have been trained with the training data as mentioned in section 4.1. 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 Table IV. As can be seen from the table, 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. 9 - Fig. 12 show the error convergence of the various ANNs during training.

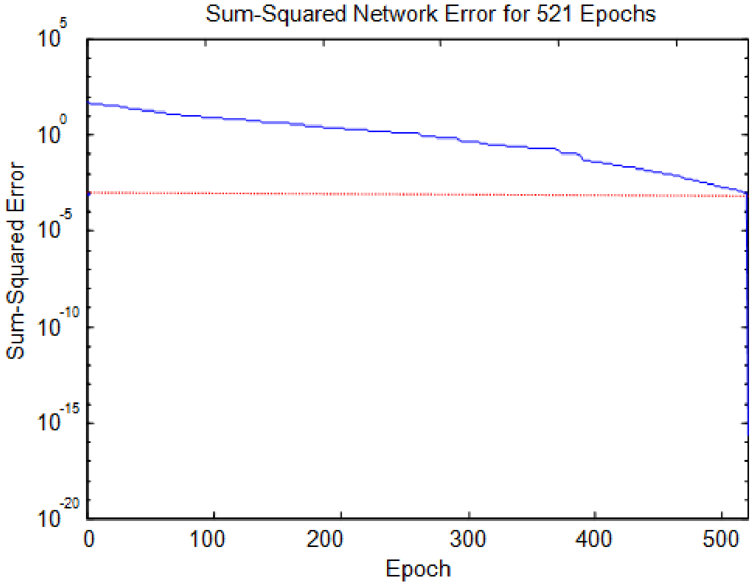

Figure 9: Error convergence of ANN-I (Model I) for L-G faults in training

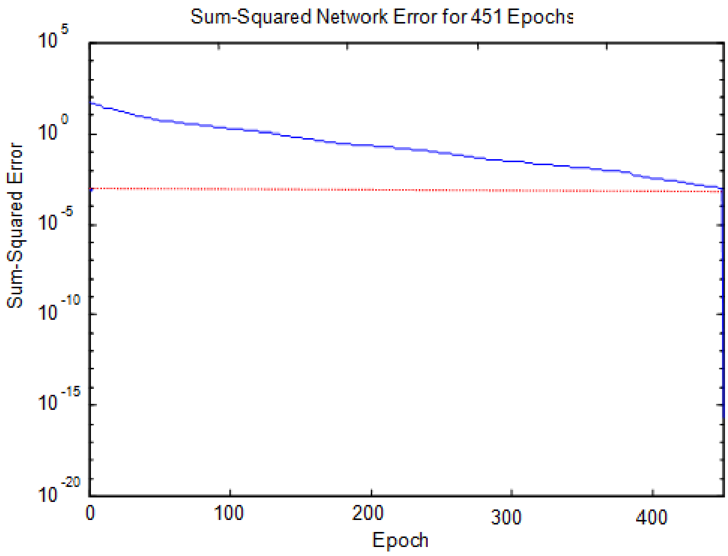

Figure 10: Error convergence of ANN-II (Model I) for L-G faults in training

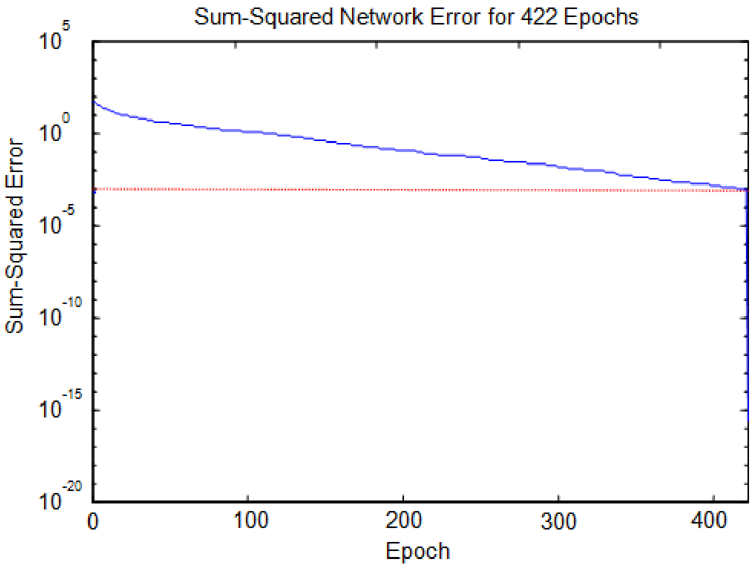

Figure 11: Error convergence of ANN-I (Model II) for L-L faults in training

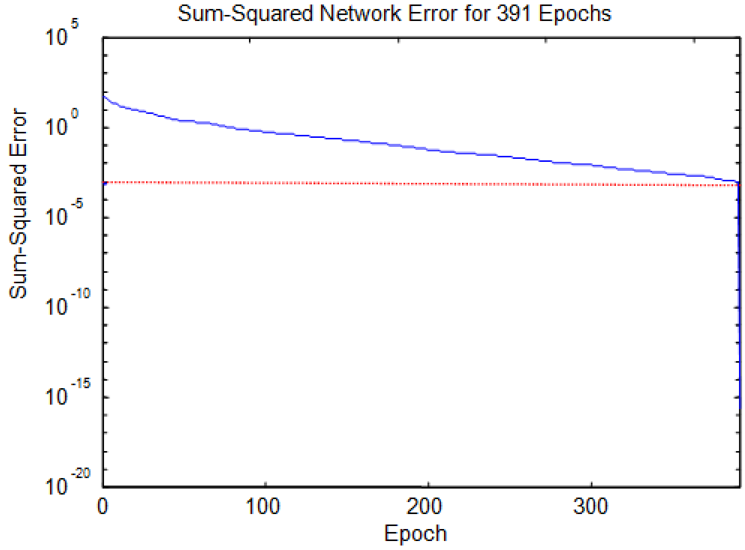

Figure 12: Error convergence of ANN-II (Model II) for L-L faults in training

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 VII-Table X. 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 VII: Test Results for A-G Fault for Model-I

		α_e = 15%		α_e = 55%		α_e = 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 VIII: Test Results for A-B Fault for Model-I

		α_e =15%		α_e =55%		α_e =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)= $1200\angle 45.5$ 7^0**
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=	0.01	0.1298	0.1443	0.5464	0.5523	0.8194	0.8123

90^0	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 IX: Test Results for A-G Fault for Model-II

		α_e =15%		α_e =55%		α_e =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	0.1486	0.1352	0.5981	0.5489	0.8172	0.8226
	10	0.1872	0.1623	0.5504	0.5487	0.8256	0.8118
	50	0.1506	0.1456	0.5527	0.5397	0.8187	0.7982
	100	0.1609	0.1481	0.5566	0.5362	0.8221	0.8118
	200	0.1509	0.1497	0.5543	0.5398	0.8176	0.7918
FIA= 45^0	0.01	0.1263	0.1314	0.5871	0.5681	0.8171	0.8237
	10	0.1365	0.1521	0.5874	0.5612	0.8564	0.8325
	50	0.1567	0.1398	0.5980	0.5547	0.8121	0.8165
	100	0.1441	0.1359	0.5987	0.5655	0.8182	0.7986
	200	0.1411	0.1543	0.5547	0.5345	0.7979	0.7863
FIA= 90^0	0.01	0.1508	0.1432	0.5416	0.5521	0.7989	0.8157
	10	0.1783	0.1621	0.6012	0.5944	0.8592	0.8182
	50	0.1476	0.1346	0.5425	0.4998	0.8176	0.7976
	100	0.1487	0.1383	0.5452	0.5199	0.8118	0.7869
	200	0.1465	0.1291	0.5313	0.5545	0.7952	0.7998

Table X: Test Results for A-B Fault for Model-II

		α_e =15%		α_e =55%		α_e =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

V. Comparison With Some Of The Existing Schemes

The salient features of some of the existing RBF neural network based fault classification and location schemes and those of the proposed algorithms are described below. The proposed scheme has several advantages: (a)For classification of faults range of fault resistance R_F varies from 0-300 Ω which is high as compared to that proposed by Song et al.,[21]; Dash et al.[23]; Lin et al.[25] and Mahanty et al.[10] (b)Unlike Song et al.[21] which require SCR firing angle[21], the proposed one requires only current samples as inputs for fault classification and voltage and current samples as ANN inputs for fault location (c) filtering of the signals not required (d)The range of FIA is similar to other schemes (e) Zero sequence currents which have been considered by Mahanty et al.[10] has been ignored in the proposed scheme. As a result of this, the network size and training time get reduced without affecting the accuracy for fault classification.For locating faults, although network is complicated resulting in an increase in number of iterations, accuracy as compare to method suggested by Mahanty et al.[10] is more.The error is reduced from 6-7% to 2-3%.

VI. Conclusions

A methodology for classification and 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. Whereas most of the previous researchers have generally used both voltage and current samples, the proposed scheme is designed to work with only current samples as inputs for classifying faults. Unfiltered samples of both currents and voltages of the three phases have been considered as inputs for ANNs of the fault locator . Both pre-fault and post-fault samples of three phase currents are considered as inputs in order to be able to distinguish between the current waveforms of healthy and faulty phases. Two separate ANNs, one for LG & LLG faults and another one for LL & LLL faults in the proposed scheme have been used, thus making the classification of faults easier. For fault location, two ANNs: one to locate faults occurring within about 50% of the line and the other one to locate faults occurring beyond this range have been used. For locating faults, two different values of spread are used for training of ANN's so as to obtain accurate estimates of fault location. The proposed scheme has been validated by considering wide variations in operating conditions such as fault location, fault inception angle, fault resistance and load impedance. The simulation results confirm the feasibility of the proposed schem**e.**

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