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Artificial Neural Network Based Fault Classifier for Transmission Line Protection

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Abstract:- This paper presents a method for classification of transmission line faults based on Artificial Neural Network (ANN).Samples of prefault and postfault three phase currents taken at one end of transmission line are used as ANN inputs. 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 confirm the feasibility of the proposed approach.

Keywords:- Fault Classification; Artificial Neural Network; Radial basis function; 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. Various fault classification techniques have been developed by different researchers from time to time. Some of the important fault classification techniques are: (1) wavelet transform based techniques [1]-[4] (2) neural network based techniques [5]-[8] (3) fuzzy logic based techniques [9]-[11]. In this paper, an alternative neural network based fault classification technique 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 [7], [12]-[15] include detection and classification of faults [5],[6], [12]-[14], [16]-[18] and precise location of faults [5],[8],[12]-[14],[16], [17]. 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 [12]-[14],[16]. For such cases the radial basis function (RBF) based neural network is well suited [5],[12]-[14],[16],[19].

A RBF neural network based scheme for classification of transmission line faults is presented in this paper. As many researchers [5],[12],[14],[18] 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. The proposed fault classification scheme is designed to work with only current samples (unfiltered) taken at one end of line. 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' [20] 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. RADIAL BASIS FUNCTION ANN

The architecture of radial basis function neural network (RBFN) with a feed forward structure consisting of three layers is shown in Fig.1. An input layer which consists of source nodes, a hidden layer in which each neuron computes its output using a radial basis function and an output layer which builds a linear weighted sum of hidden neuron output. The hidden nodes are the radial basis function units and the output nodes are used to combine linearly the outputs of hidden neurons. In the hidden layer, each neuron computes its output using a radial basis function. This particular architecture of RBFN directly improves training and performance of the network.

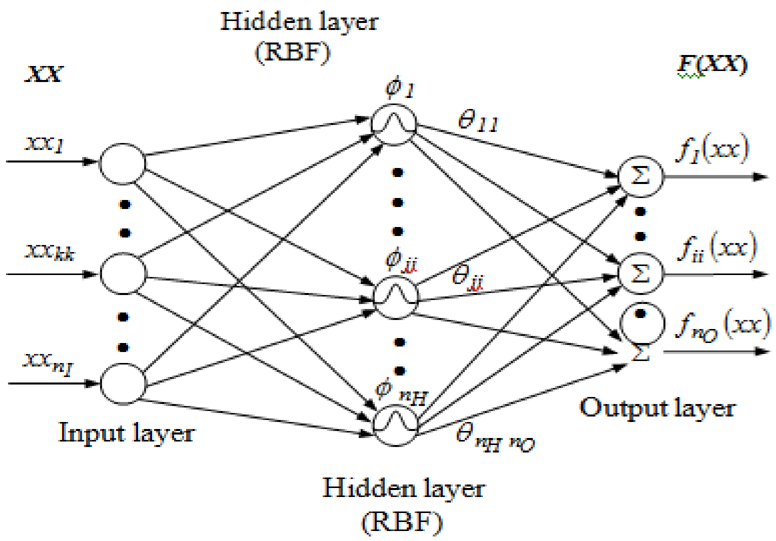

Fig. 1: Architecture of RBF neural network.

Different types of radial basis functions viz. spline, multiquadratic, Gaussian function can be used but the most common is the Gaussian function which has been considered for the proposed application. The RBF network requires less computation time for learning and has a more compact topology in comparison to other types of neural network used for pattern classification like back propagation feedforward networks,. Without altering the already learned mapping, the Gaussian RBF is found suitable in generalizing a global mapping and also in refining local features. To the input xx_{kk} ,the jj^{th} hidden neuron gives the following output:

$$\phi_{jj}(xx_{kk}) = \exp\left(-\frac{1}{\sigma_{jj}^{2}}\left\| xx_{kk} - \mu_{jj}\right\|^{2}\right) \qquad 1 \le jj \le n_H \qquad (1)$$

where μ_{jj} is the center for the jj^{th} hidden neuron and σ_{jj} is the spread of the Gaussian function, $\| \;\|$ denotes the Euclidian norm. The output of the ii^{th} node in the output layer is defined by:

$$f_{ii}(\boldsymbol{XX}) = \sum_{jj=1}^{n_H} \phi_{jj}\left(\left\|\boldsymbol{XX}\text{-}\mu_{jj}\right\|\right)\theta_{jj\,ii} \qquad 1 \le ii \le n_O \qquad (2)$$

Where $\boldsymbol{XX}$ is the input vector and $\theta_{jj\,ii}$ represents the weight from the jj^{th} hidden node to the ii^{th} output node. The performance of a RBF neural network depends on the choice of the values of the centers. Orthogonal least squares (OLS) learning procedure [20]-[22] has been used for determining the RBF centers.

The OLS procedure can be implemented by introducing an error term e in Equation (2), which can be rewritten as

$$\partial_{ii}(\boldsymbol{XX}) = \sum_{jj=1}^{n_H} \phi_{jj}\left(\left\|\boldsymbol{XX}\text{-}\mu_{jj}\right\|\right)\theta_{jj\,ii} + e \qquad 1 \le ii \le n_O \qquad (3)$$

where ∂_{ii} is the desired output of the ii^{th} output node, and then maximizing the error reduction ratio by orthogonal LS principle [5].

III. POWER SYSTEM MODELS

The two power system models: Model I and Model II, which have been considered for the development of the fault classification algorithms are shown in Fig. 2 and Fig. 3 respectively [5].

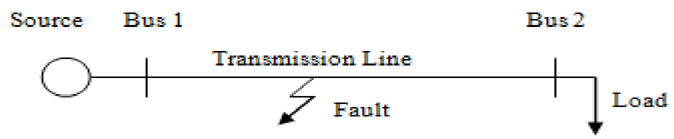

Fig. 2: Model I: A faulted transmission line fed from one end.

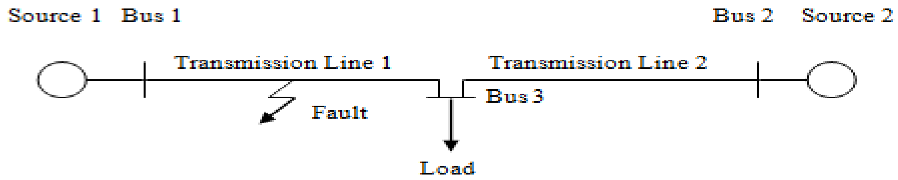

Fig. 3: Model II: A faulted transmission line fed from both ends.

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:

A. 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
Zero sequence impedance = 1.5× Positive sequence impedance
Load impedance (Z_L) = 800 Ω per phase with 0.8 p.f. lagging

B. 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 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} = (0.45 + j5) Ω per phase, Z_{S2} = (0.34 + j4) Ω per phase.

Zero sequence impedance = 1.5× Positive sequence impedance, for both the sources

IV. THE PROPOSED FAULT CLASSIFIER

The proposed ANN based scheme for classification of faults is shown in Fig. 4. 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 fault inception angle, fault location, fault resistance and load impedance.

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.

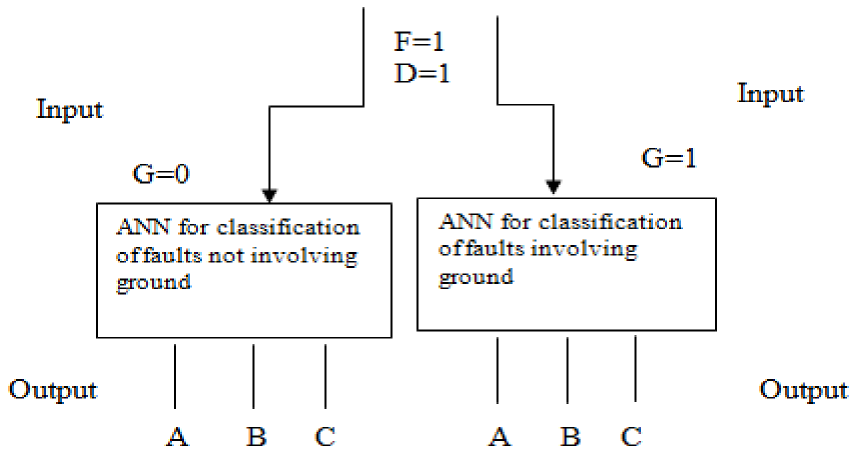

Fig. 4: ANN based fault classifier.

The various ANNs have been termed as:

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

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 below.

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

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

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

This type of batching operation is more efficient than the case when inputs are presented in the form of a single vector [23].

V. GENERATION OF TRAINING DATA

It is necessary to train an ANN based fault classifier with sufficient data for different fault situations. But it is not possible to consider, for training, all the cases that are encountered by an ANN based fault classifier, therefore 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.

In view of the above, each of the ANNs, required for classification of faults for the power system models of Fig. 2 and Fig. 3, has been trained with different fault data. Fault data have been generated for fault at 5% of the line length from bus 1 of the power system models: 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 determines how wide the radial basis functions are. The spread should be smaller than the maximum distance and larger than the minimum distance between the input vectors [23]. 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.5- Fig.8.

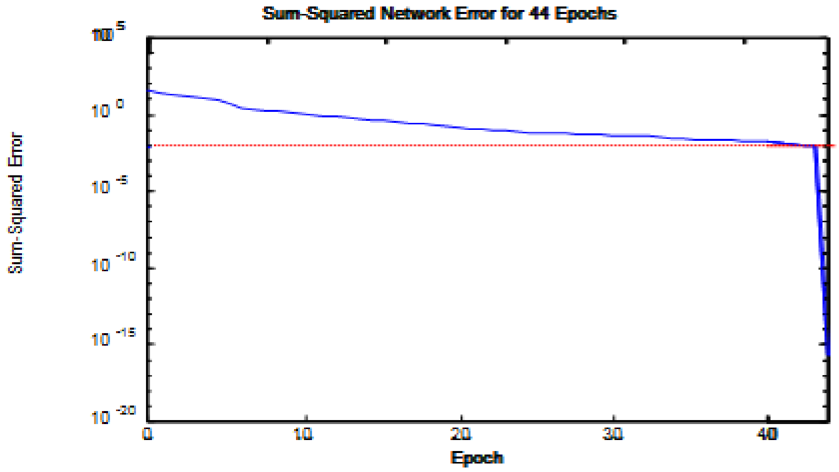

Fig. 5. Error convergence of ANN-1 in training.

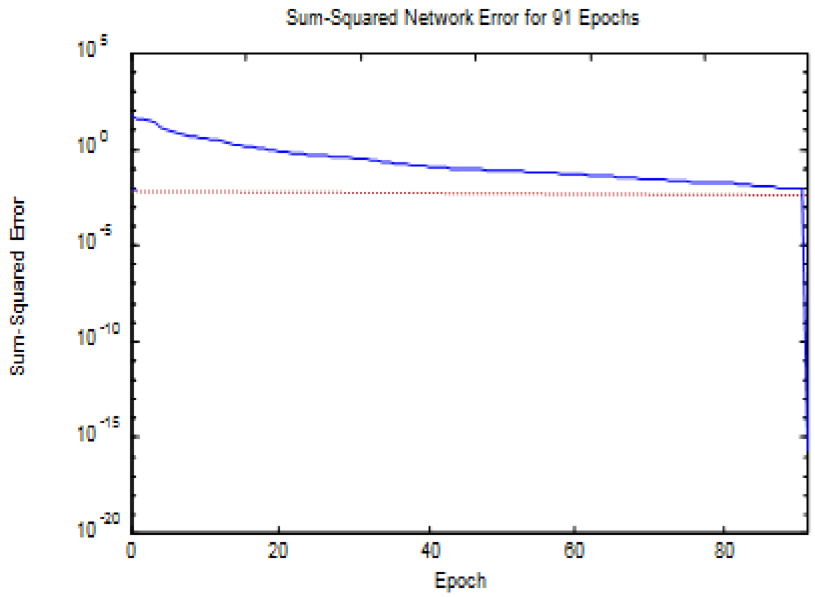

Fig. 6. Error convergence of ANN-2 in training.

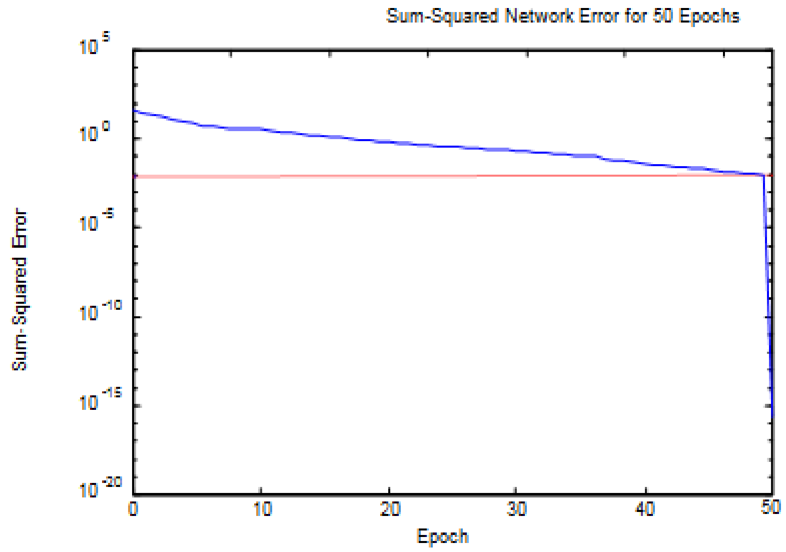

Fig. 7 Error *convergence of ANN-3 in training*

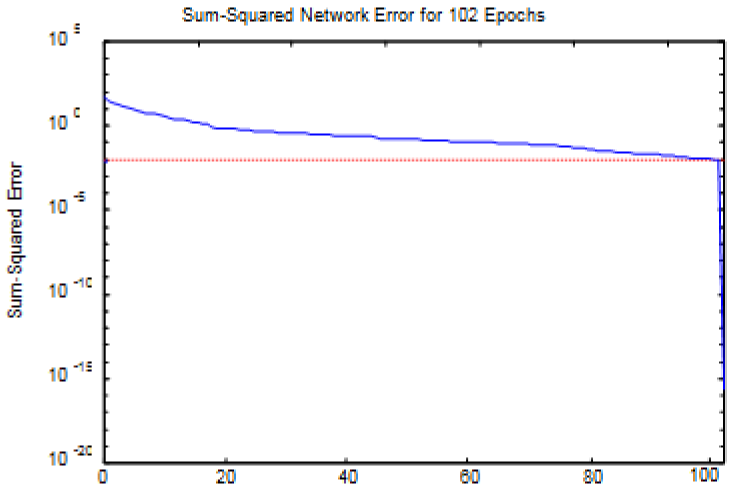

Fig. 8. Error convergence of ANN-4 in training.

After training, each ANN is tested for different types of faults considering wide variations in operating conditions such as fault resistance, fault inception angle, fault location and 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.

VI. COMPARISON WITH SOME OF EXISTING SCHEMES

A comparison of some of the existing RBF neural network based fault classification schemes with the proposed one has been carried out. The advantages of the proposed scheme are: (a) Range of fault resistance R_F varies from 0-300 Ω which is high as compared to that proposed by Song et al.,[12]; Dash et al.[14]; Lin et al.[16] and Mahanty et al.[5] (b) Zero sequence currents which have been considered by Mahanty et al.[5] has been ignored in the proposed scheme. As a result of this, the network size and training time get reduced without affecting the accuracy of fault classification (c) Only current inputs are required.

VII. CONCLUSIONS

A methodology for classification 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 fault classification scheme is designed to work with only current samples as inputs. 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. 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 show that the proposed scheme is suitable for classification of transmission line faults including the high impedance ones.

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Table I: CONVERGENCE RATES RELATING to DIFFERENT RMS ERRORS and SPREADS

Network	RMS error	Spread	Number of hidden	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		
	0.01	0.9	44	44	9.615
	0.01	1.0	45	45	8.586
ANN-2	0.001	0.5	126	126	81.615
	0.01	0.4	93	93	47.71
	0.01	0.5	Computation incompatible		

	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**
	0.01	1.1	53	53	14.015
	0.01	1.2	55	55	14.54
ANN-4	0.001	0.9	141	141	99.446
	0.01	0.7	107	107	60.35
	0.01	0.8	Computation incompatible		
	0.01	**0.9**	**101**	**101**	**55.07 selected**
	0.01	1.0	Computation incompatible		
	0.01	1.1	103	103	56.51

Table II. TEST RSULTS for MODEL- I.

Fault type	***Fault Conditions***				***ANN Output***		
	α	***FIA* (^{0})**	***R_F* (Ω)**	***Z_L* (Ω)**	***A***	***B***	***C***
Normal Condition	**-**	**-**	**-**	**$1200\angle 45.57^0$**	**0.0009**	**0.0037**	**0.0067**
	0.1	**0 110**	**0.01 70**	**$800\angle 45.57^0$ $1200\angle 45.57^0$**	**1.0028 0.9195**	**-0.0447 0.0341**	**-0.0012 -0.0311**
A-G	**0.5 0.9**	**90 180 250 360**	**300 5 200 70**	**$400\angle 36.87^0$ $300\angle 45.57^0$ $1200\angle 45.57^0$ $300\angle 25.84^0$**	**0.8876 0.9760 0.8173 0.8125**	**-0.0218 0.1189 -0.0008 0.0549**	**0.0169 -0.0216 0.1321 0.0280**
	0.1	**60 200**	**200 20**	**$400\angle 36.87^0$ $400\angle 25.84^0$**	**-0.0032 -0.0032**	**1.0143 1.0091**	**0.9999 1.0002**
B-C	**0.5**	**90 300**	**300 20**	**$400\angle 36.87^0$ $1200\angle 25.84^0$**	**0.0065 0.0453**	**1.0932 0.9865**	**0.9997 0.9976**
	0.9	**5 250**	**100 200**	**$400\angle 36.87^0$ $1200\angle 45.57^0$**	**0.0465 0.0532**	**1.0123 0.9995**	**1.0055 0.9907**
	0.1	**0 200**	**0.01 20**	**$800\angle 45.57^0$ $400\angle 25.84^0$**	**0.9976 0.9978**	**0.1876 -0.0043**	**0.9876 0.9934**
C-A-G	**0.5**	**30 300**	**100 20**	**$800\angle 45.57^0$ $1200\angle 25.84^0$**	**0.9345 0.9995**	**-0.0367 0.0013**	**0.8687 0.9797**
	0.9	**160 360**	**0.01 70**	**$800\angle 36.87^0$ $300\angle 25.84^0$**	**0.8698 0.8876**	**-0.0056 0.1698**	**0.9876 0.8378**
	0.1	**0 110**	**0.01 70**	**$800\angle 45.57^0$ $1200\angle 45.57^0$**	**0.9986 1.1023**	**1.0023 0.9995**	**1.0013 1.0311**
A-B-C	**0.5**	**90 300**	**300 20**	**$400\angle 36.87^0$ $1200\angle 25.84^0$**	**0.9965 1.0743**	**0.8897 0.8265**	**0.9786 0.9276**
	0.9	**75 250**	**20 200**	**$300\angle 45.57^0$ $1200\angle 45.57^0$**	**0.9932 0.8865**	**0.9421 0.8789**	**0.9887 0.9765**

Table III: TEST RSULTS for MODEL II

Fault type	***Fault Condition***				***ANN Output***		
	α	***FIA*** (^{0})	R_F (Ω)	Z_L (Ω)	***A***	***B***	***C***
Normal Condition	**-**	**-**	**-**	**$800\angle 25.84^0$**	**0.0013**	**-0.0258**	**0.432**
	0.1	**60** **110**	**200** **70**	**$400\angle 36.87^0$** **$1200\angle 45.57^0$**	**0.0008** **0.1408**	**0.9989** **0.8667**	**-0.0022** **0.1061**
B-G	**0.5** **0.9**	**90** **180** **75** **250**	**300** **5** **20** **200**	**$400\angle 36.87^0$** **$300\angle 45.57^0$** **$300\angle 45.57^0$** **$1200\angle 45.57^0$**	**0.1012** **-0.0008** **-0.0012** **-0.0031**	**0.8341** **0.9538** **0.9436** **0.7326**	**0.0876** **0.0898** **0.0118** **0.0065**
	0.1	**0** **110**	**0.01** **70**	**$800\angle 45.57^0$** **$1200\angle 45.57^0$**	**0.9564** **0.9998**	**-0.0021** **-0.0012**	**0.9612** **1.01213**
C-A	**0.5**	**30** **180**	**100** **5**	**$800\angle 45.57^0$** **$300\angle 45.57^0$**	**1.0032** **0.9986**	**-0.0032** **-0.0003**	**1.0543** **1.0112**
	0.9	**75** **360**	**20** **70**	**$300\angle 45.57^0$** **$300\angle 25.84^0$**	**1.0521** **0.9990**	**1.0321** **0.0021**	**0.0007** **1.0013**
	0.1	**0** **110**	**0.01** **70**	**$800\angle 45.57^0$** **$1200\angle 45.57^0$**	**0.0765** **0.0765**	**1.0009** **1.0563**	**1.0002** **0.9956**
B-C-G	**0.5**	**30** **180**	**100** **5**	**$800\angle 45.57^0$** **$300\angle 45.57^0$**	**-0.0056** **-0.0432**	**1.0987** **0.9943**	**0.9765** **0.9765**
	0.9	**250** **60**	**200** **70**	**$1200\angle 45.57^0$** **$300\angle 25.84^0$**	**0.0108** **0.0028**	**0.7987** **0.9597**	**0.7876** **0.9876**
	0.1	**60** **340**	**200** **50**	**$400\angle 36.87^0$** **$300\angle 36.87^0$**	**0.9456** **1.0075**	**1.1006** **1.0021**	**0.9731** **1.0398**
A-B-C	**0.5**	**30** **180**	**100** **5**	**$800\angle 45.57^0$** **$300\angle 45.57^0$**	**1.0321** **0.9989**	**0.9786** **1.0043**	**0.8234** **1.0532**
	0.9	**5** **160**	**100** **0.01**	**$400\angle 36.87^0$** **$800\angle 36.87^0$**	**0.9954** **1.0223**	**1.0223** **0.9998**	**0.8543** **1.0346**