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Detection of Faults in Power System Network to Protect from Cyber Attacks

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***Abstract*—The electrical power grid is a Cyber Physical System (CPS) that forms the lifeline of modern society. The major concern of the electrical network is safe and reliable operation. A cyber attacker in physical power system operation could cause severe damage to the power grid infrastructure and its reliability by stealthily manipulating SCADA operation. Occurrence of fault in different locations in a power system network would change the magnitude of the fault current. This will make a specific relay to operate and any mis-operation of relay may exist if type and location of fault is not identical properly. This work focuses on fault detection ,its classification and identification of faults on electric power transmission lines using neural network. A feed forward neural network is employed, which is trained with back propagation algorithm. The developed neural network is capable of detecting, classifying and location of various types of faults in a transmission line. Simulation is done using MATLAB to demonstrate that artificial neural network based method is efficient in detecting faults on transmission lines and achieve satisfactory performances. An approach for assessing security during the design phase by neural network is investigated in this work. Experimental results show that by training a back propagation neural network to identify attack patterns, possible attacks can be identified from design scenarios presented to it. The performance of the neural network for various types of faults is presented in this work. Neural network is implemented in arduino and fault is identified using LEDs.**

***Index Terms*— Cyber physical system, Fault, Neural network.**

I. INTRODUCTION

In the past several decades, there has been a rapid growth in the power grid all over the world which eventually led to the installation of a huge number of new transmission and distribution lines. Cyber security assessment can be considered as a classification task to detect the security status of the power system operating condition. One of the most important factors that hinder the continuous supply of electricity and power is a fault in the power system. Any abnormal flow of current in a power system's components is called a fault in the power system. These faults cannot be completely avoided since a portion of these faults also occur due to unavoidable natural issues. Hence, protection system which detects any abnormalities is required. Faults may occur due to several reasons like large disturbance, small disturbance and it may exist for a longer period or shorter period.The main objective of this paper is to work on the location and detection of fault with a suitable design.
W.L.Chan et.al[2] have worked on the system which receives informations related to various measurements and fed to their network. Ivan Pavi et al. have worked on identification of fault using Artificial Neural Network (ANN). Seema Singh et al.[12] have also worked on fault detection using neural network with back propagation

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algorithm. Uma Uzubi et al.[13] have analyzed ANN for a unique method of fault detection and location. Implementation of neural network in hardware to detect the fault is not implemented in the literature. In this work Neural network is implemented in arduino and fault identification is observed at remote location. Our previous work, Sheela et.al [14] involved in accessing risk due to cyber attackers. Present work calculates the type and location of fault to distinguish between actual fault and wrong data which is purposely altered by a cyber attacker.

II. Introduction to Neural Networks

An Artificial Neural Network (ANN) can be explained theoretically as a group of neurons which are physically connected and biologically inspired with many layers. The structure of a feed-forward ANN is shown in Fig 2.1. Excitation signals are given as input to the first layer and a weight is attached to each and every neuron and training an ANN is the process of adjusting different weights tailored to the training set. An Artificial Neural Network learns to produce a response based on the inputs given by adjusting the node weights. Hence we need a set of data referred to as the training data set, which is used to train the neural network. ANN comprises of three neuron layers,

- Input layer
- Hidden layer
- Output layer

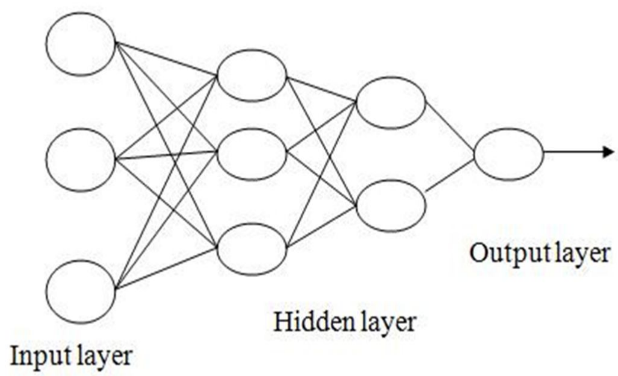

Figure 2.1 Basic Three-Layer Architecture of a Feedforward AN

The bottom layer is known as input neuron network and offers connection point to transmit the input signal to the hidden layer. Hidden layers are the one where the actual processing is done via a system of weighted connections. The in-between input and output layer the layers are known as hidden layers. The topmost layer which give the final output.

III. Application of Neural Network for Fault Analysis in Power System

A fault is any deviations from the actual values of the normal conditions. However, due to sudden external or internal changes in the system, this condition is disrupted. Stabilized power system is not available. Changes will occur due to variations in load, faults occurrence, failure in insulation level, etc. These faults, may either be three phase in nature involving all three phases in a symmetrical manner, or may be asymmetrical where usually only one or two phases may be involved. Faults may also be caused by either short circuits to ground or between live conductors, or may be caused by broken conductors in one or more phases. Sometimes simultaneous faults may occur involving both short-circuit and broken-conductor faults (also known as open-circuit faults). Balanced three phase faults may be analysed using an equivalent single phase circuit. The complex asymmetrical With asymmetrical three phase faults, the use of symmetrical components help to reduce the complexity of the calculations as transmission lines and components are by and large symmetrical, although the fault may be asymmetrical. Fault analysis is usually carried out in per-unit quantities (similar to percentage quantities) as they give solutions which are somewhat consistent over different voltage and power ratings, and operate on values of the order of unity.
Artificial Neural Networks have been used for the protection of power transmission lines. The excellent pattern recognition and classification abilities of neural networks have been cleverly utilized in this project to address

the issue of transmission line fault location. A complete neural-network based approach has been outlined in detail for the location of faults on transmission lines in a power system. To achieve the same, the original problem has been deal with in three different stages namely fault detection, fault classification and fault location.

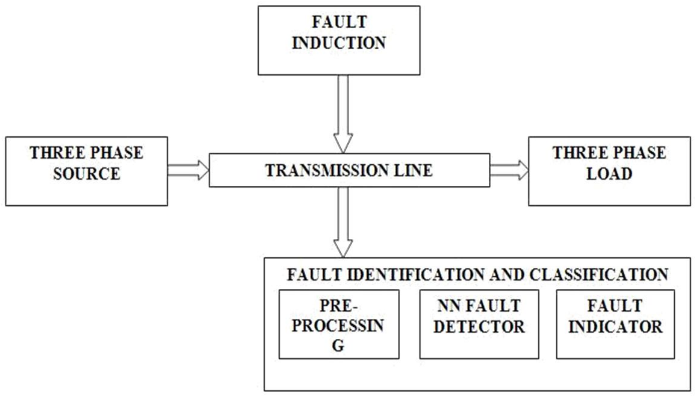

Figure 3.1 Block Diagram of the Fault Analysis

A. Block Diagram

Fault can be identified and classified by various process like preprocessing, neural network detector and fault indicator. At the end transmission line is connected to the three phase load as shown in fig 3.1. A 11 kV transmission line system has been used to develop and implement the proposed strategy using ANNs. The system consists of 11 kV each located of the transmission line along with a three phase fault simulator used to simulate faults at various positions on the transmission line. The line has been modelled using distributed parameters so that it more accurately describes a very long transmission line. A model is created to simulate different types of faults at various locations and the fault current samples are measured. The values of the three-phase currents are measured and modified accordingly and are ultimately fed into the neural network as inputs[10]. The simulation has been used to generate the entire set of training data for the neural network in both fault and non-fault cases.

Faults can be classified broadly into four different categories namely:

- line to ground faults
- line to line faults
- double-line to ground faults
- three-phase faults

10,000 different fault cases are simulated for the purpose of fault detection, 10,000 different fault cases simulated for fault classification and varying number of fault cases (based on the type of fault) for the purpose of fault location.

B. Simulation Results for Various Types of Fault

The three-phase fault simulator is used to simulate various types of faults at varying locations along the transmission line and it is shown in following figures.

IV. OUTLINE OF THE PROPOSED SCHEME

The main goal of this work is to design, develop, test and implement a complete strategy for the fault diagnosis as shown in Fig 4.1 Initially, the entire data that is collected is subdivided into two sets namely the training and the testing data sets. The first step in the process is fault detection and the next step is to classify the fault into the different categories based on the phases that are faulted. Then, the third step is to pin-point the position of the fault on the transmission line.

The goal of this project is to propose an integrated method to perform each of these tasks using artificial neural networks. A back-propagation based neural network has been used for the purpose of fault detection and another

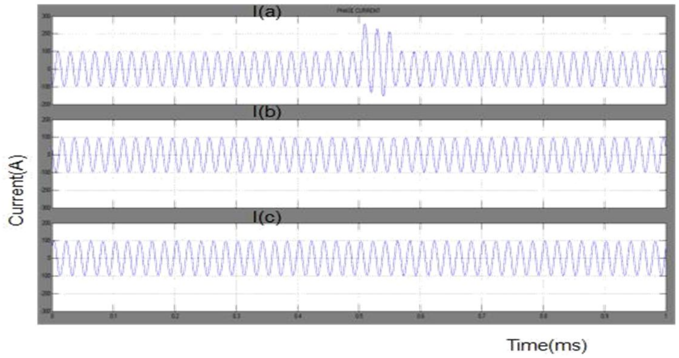

Figure 3.2(a) Single Phase to Ground Fault(A-G)

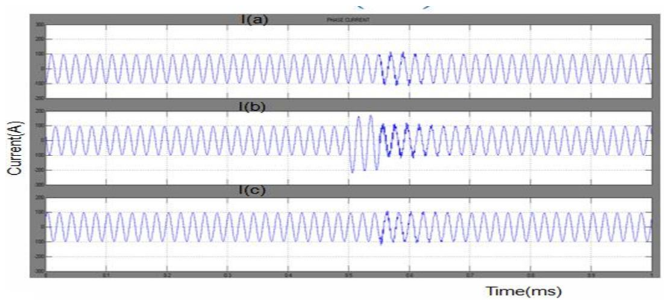

Figure 3.2(b) Single Phase to Ground Fault(B-G)

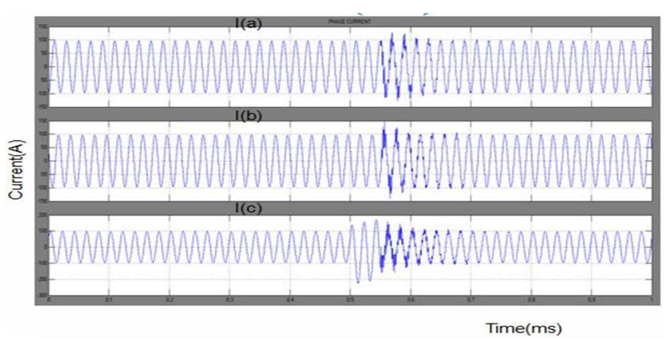

Figure 3.2(c) Single Phase to Ground Fault(C-G)

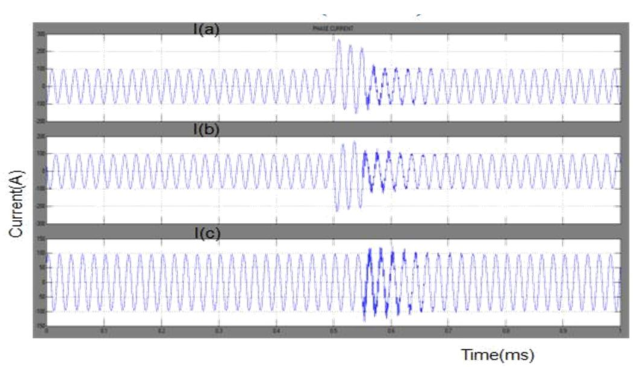

Figure 3.2(d) Double Phase to Ground Fault(A-B-G)

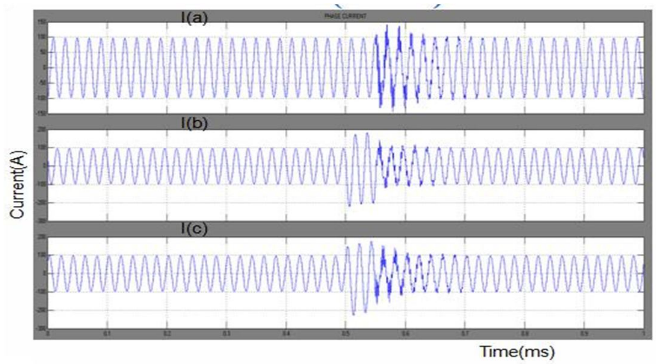

Figure 3.2(e) Double Phase to Ground Fault(B-C-G)

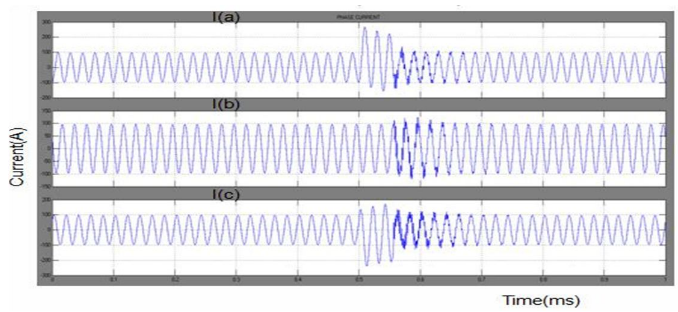

Figure 3.2(f) Double Phase to Ground Fault(C-A-G)

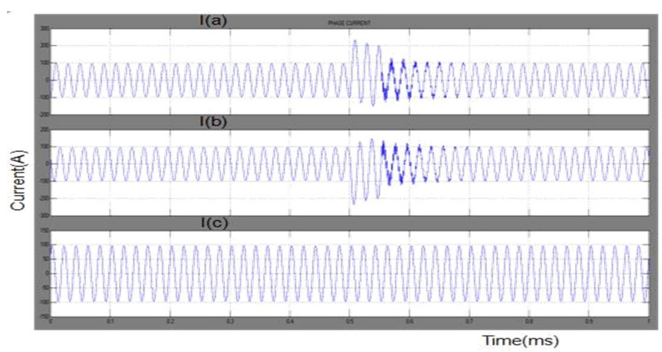

Figure 3.2(g) Double Phase Fault(A-B)

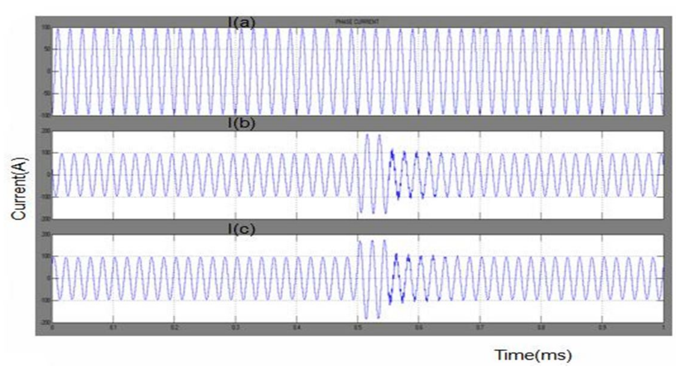

Figure 3.2(h) Double Phase Fault(B-C)

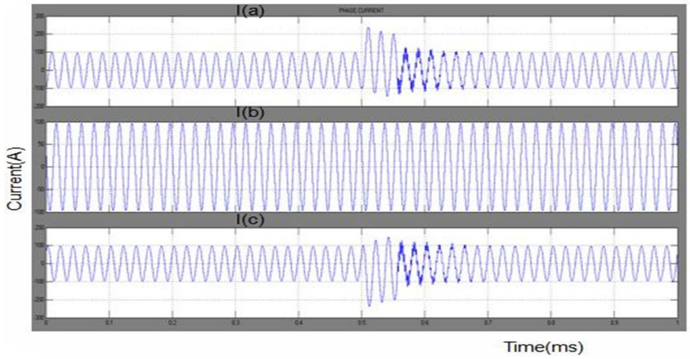

Figure 3.2(i) Double Phase Fault(C-A)

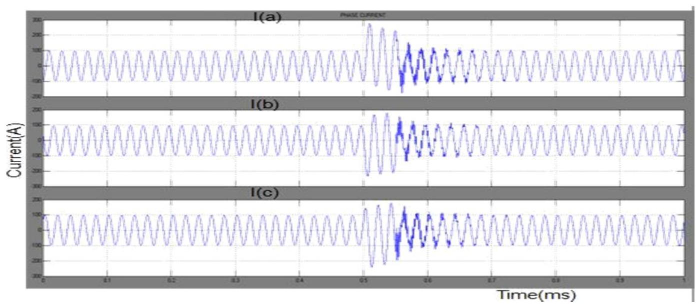

Figure 3.2(j) Three Phase Fault(A-B-C)

similar one for the purpose of fault classification and location. Each of these steps has been depicted in the flowchart shown in Fig 4.1.

V. Training the Fault Classifier Neural Network

The neural network has four outputs, each of them corresponding to the fault condition of each of the three phases and one output for the ground line. Hence the outputs are either a 0 or 1 denoting the occurrence of the fault on the line (A, B, C or G). The proposed design distinguishes between the ten possible categories of faults. Table 1.1 represents the faults and the ideal output for each of the faults.

TABLE 1.1 FAULT CLASSIFIER FOR ANN OUTPUTS FOR VARIOUS FAULT

S.NO	TYPES OF FAULT	NETWORK OUTPUT			
		A	B	C	G
1	A-G	1	0	0	1
2	B-G	0	1	0	1
3	C-G	0	0	1	1
4	A-B	1	1	0	0
5	B-C	0	1	1	0
6	C-A	1	0	1	0
7	A-B-G	1	1	0	1
8	B-C-G	0	1	1	1
9	C-A-G	1	0	1	1
10	A-B-C	1	1	1	0
11	NO FAULT	0	0	0	0

VI. Training and Testing the Neural Network for Fault Location

To train the neural network, several faults have been simulated on the transmission line model. Along with the fault, distance has been varied. Hence, various cases have been simulated (10000 for each of the three phases with each of the eight different fault distances as 25,75,125,175,50,100,150,200 km respectively). In each of these cases, the current samples for all three phases (scaled with respect to their pre-fault values) are given as

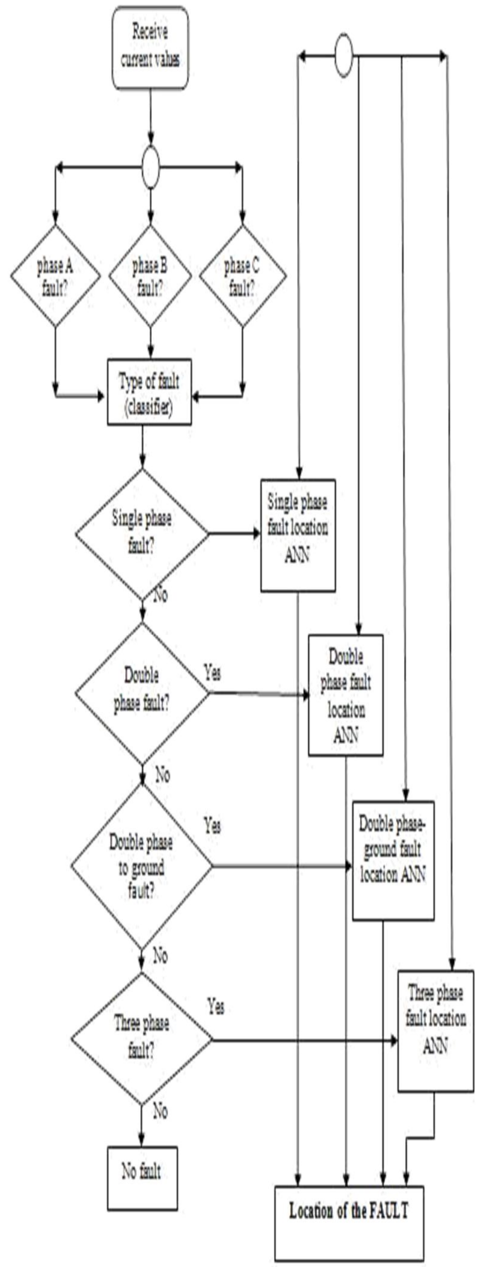

Figure 4.1 Flowchart of the Proposed Scheme

inputs to the neural network. The output of the neural network is the distance to the fault from terminal A. Efficiency of each of the trained networks is analyzed based on their regression performance and their performance in the testing phase. The closer the value is to 1, the better the performance of the neural network. The percentage error in calculated for various types of fault has been calculated.

The overview of the neural network is shown in fig 6.1. From the above training, performance plots is shown in fig 6.2. It is to be noted that very satisfactory training performance has been achieved by the neural network with the 3-6-4 configuration (3 neurons in the input layer, 6 hidden layers and 4 neuron in the output layer). Hence this has been chosen as the ideal ANN for the purpose of fault detection.

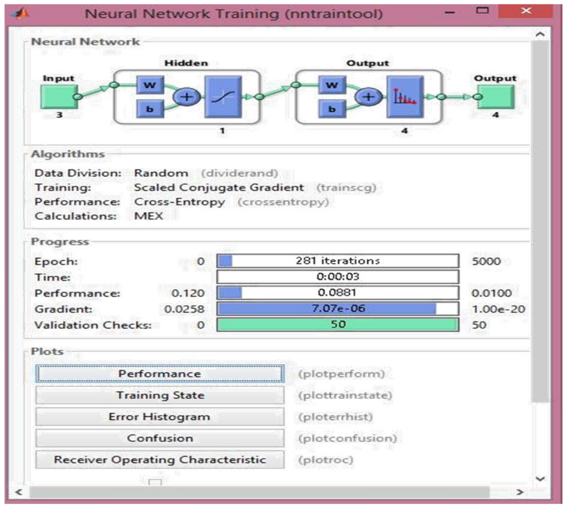

Figure 6.1 Overview of the NN Fault Detection

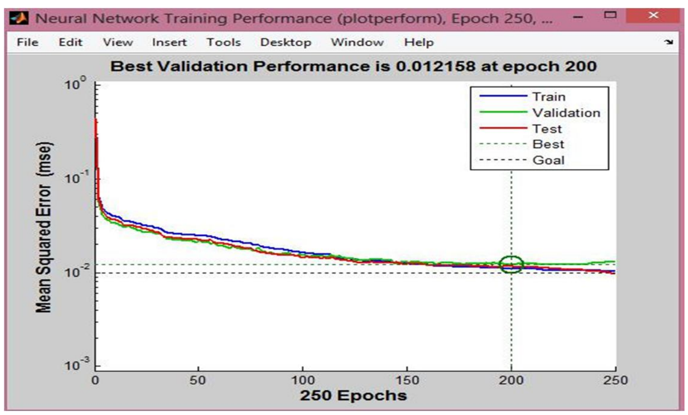

Figure 6.2 Mean Square Error Performance of the Network

After the testing process, the performance of the neural network is to plot the confusion matrices for the various types of errors that occurred for the trained neural network. It can be seen that the chosen neural network has 100 percent accuracy in fault detection from fig 6.3 confusion matrix.

Fig 6.4 plots the receiver operating characteristics for the three phases of training, testing and validation. The testing process is to create a separate set of data called the test set to analyze the performance of the trained neural network. A total of 10000 different test cases have been simulated with different types of faults. The rest of the cases correspond to the no-fault situation. After the test set has been fed into the neural network and the results obtained, it was noted that the efficiency of the neural network in terms of its ability to detect the occurrence of a fault is around 90 percent.

Figure 6.5 shows the neural network output obtained for a 3 phase fault at a distance of 25 km.

Tables 1.2 (a-d) illustrates the percentage errors in fault location for different types of faults as a function of fault distance. Hence, the performance of the neural network in this case illustrates its ability to generalize and react upon new data. It is to be noted that the average error in this case is very satisfactory. Thus the neural networks performance is considered satisfactory and can be used for the purpose of all types of fault location.

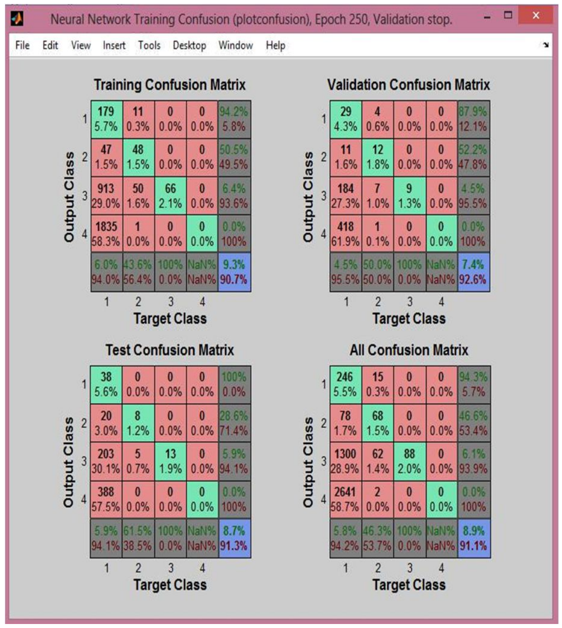

Figure 6.3 Confusion Matrix

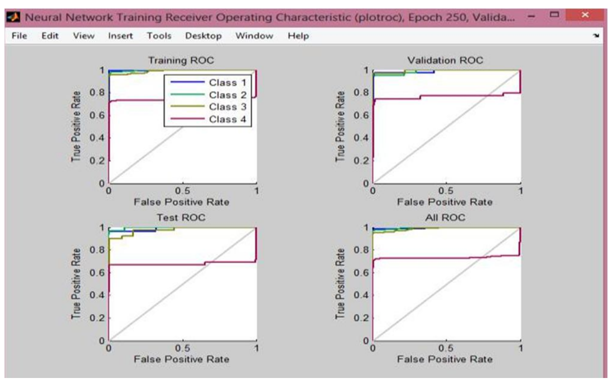

Figure 6.4 Receiver Operating Characteristics

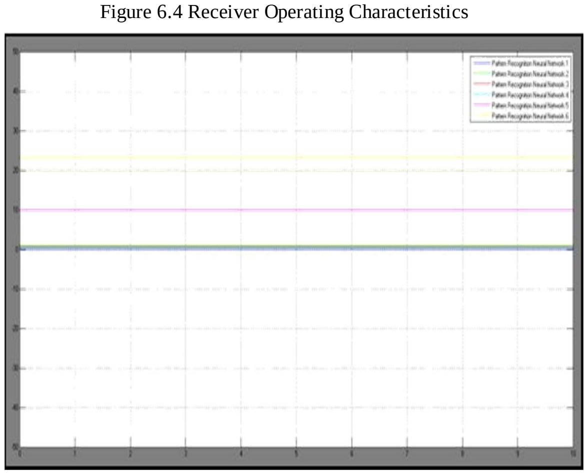

Fig 6.5 Neural Network Output for Three Phase Fault @ 25 km

TABLE 1.2(A) PERCENTAGE ERRORS AS A FUNCTION OF FAULT DISTANCE FOR THE ANN CHOSEN FOR SINGLE PHASE TO GROUND FAULT LOCATION

S.NO	%ERROR VS FAULT DISTANCE		
	FAULT DISTANCE(km)	MEASURED FAULT LOCATION	PERCENTAGE ERROR
1	25	25.49	1.96
2	75	75.58	0.77
3	125	125.12	0.09
4	175	175.09	0.05
5	50	50.56	1.12
6	100	100.02	0.02
7	150	150.03	0.02
8	200	200.67	0.33
		Average	0.54

TABLE 1.2(B) PERCENTAGE ERRORS AS A FUNCTION OF FAULT DISTANCE FOR THE ANN CHOSEN FOR DOUBLE PHASE TO GROUND FAULT LOCATION

S.NO	%ERROR VS FAULT DISTANCE		
	FAULT DISTANCE(km)	MEASURED FAULT LOCATION	PERCENTAGE ERROR
1	25	25.04	0.16
2	75	75.18	0.24
3	125	125.01	0.008
4	175	175.6	0.34
5	50	50.81	1.62
6	100	101.12	1.12
7	150	152	1.33
8	200	200.8	0.4
		Average	0.65

TABLE 1.2(C) PERCENTAGE ERRORS AS A FUNCTION OF FAULT DISTANCE FOR THE ANN CHOSEN FOR DOUBLE PHASE FAULT LOCATION

S.NO	%ERROR VS FAULT DISTANCE		
	FAULT DISTANCE(km)	MEASURED FAULT LOCATION	PERCENTAGE ERROR
1	25	25.03	0.12
2	75	75.09	0.12
3	125	125.7	0.56
4	175	175.4	0.23
5	50	50.17	0.34
6	100	100.2	0.2
7	150	151.3	0.86
8	200	201	0.5
		Average	0.37

TABLE 1.2(D) PERCENTAGE ERRORS AS A FUNCTION OF FAULT DISTANCE FOR THE ANN CHOSEN FOR THREE PHASE FAULT LOCATION

S.NO	%ERROR VS FAULT DISTANCE		
	FAULT DISTANCE(km)	MEASURED FAULT LOCATION	PERCENTAGE ERROR
1	25	25.06	0.24
2	75	75.07	0.09
3	125	125.20	0.16
4	175	175.06	0.03
5	50	50.04	0.08
6	100	100.2	0.2
7	150	150.7	0.46
8	200	201.08	0.54
		Average	0.22

VII. IMPLEMENTATION OF NEURAL NETWORK USING ARDUINO

Implementation of neural network using arduino for various types of fault like single phase to ground fault, double phase to ground fault, double phase fault and three phase fault. With MATLAB support package for arduino, the arduino is connected to a computer running MATLAB, processing is done on the computer with MATLAB. With Simulink support package for arduino, algorithm is developed in Simulink and deployed to the arduino using code generation, processing is then done on the arduino. After processing is done 4 LED's are connected in breadboard. 4 LED's represent A phase, B phase, C phase and ground. When LED is glown it shows fault has occured in that phase. Figure 7.1 shows output for single phase fault indicated by LED.

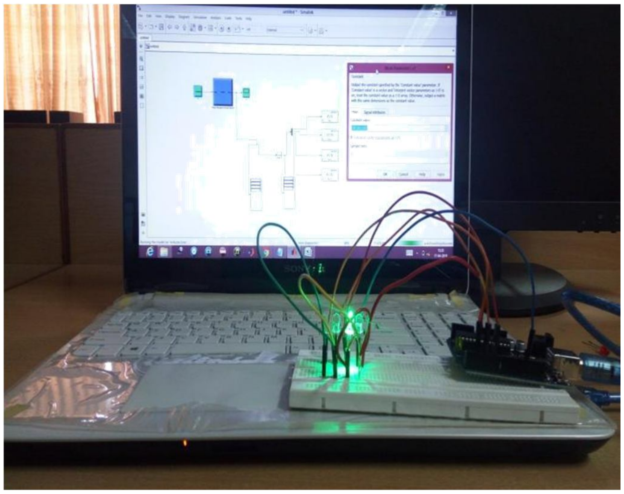

Fig.7.1 Implementation of Neural network for single phase fault

VIII. CONCLUSION

Neural networks as an effective method for the detection, classification and location of faults on transmission lines. The methods employed make use of the phase currents as inputs to the neural networks. Various possible kinds of faults namely single line-ground, line-line, double line-ground and three phase faults have been taken into consideration into this work and also occurrence of the faults is considered at different locations. A fault location scheme for the transmission line system, right from the detection of faults location stage has been devised successfully by using artificial neural networks. The simulation results obtained prove that satisfactory performance has been achieved. Depending on the application of the neural network and the size of the training data set, the size of the ANN keeps varying. To simulate the entire power transmission line model and to obtain the training data set, MATLAB has been used to train and analyze the performance of the neural networks. Arduino is used here to implement neural network. Mitigation of faults due to cyber attacks will be our future work.

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