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Enhanced Real Time and Off-Line Transmission Line Fault Diagnosis Using Artificial Intelligence

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ABSTRACT

This paper is on "Enhanced Real Time and Off-Line Transmission Line Fault Diagnosis Using Artificial Intelligence". The actual implementation and development of the neural networks and their architectures have been achieved for the three different parts of the fault diagnosis process namely fault detection, classification and fault location. This paper also gives an overview of the training and testing processes employed with neural networks. Series of simulation results that have been obtained using MATLAB, Sim Power Systems and the Artificial Neural Networks Toolboxes in Simulink are also presented in detail to emphasize the efficiency and accuracy factors of the proposed fault locator. Several neural networks with varying configurations have been trained, tested and their performances have been analyzed in this work.

Keywords: *Transmission Line Fault, Fault Location, Ground Faults, Power Transmission Line System*

1.0 INTRODUCTION

The increasing complexity of modern power transmission systems makes the search for a reliable and effective scheme for an ideal transmission line fault diagnosis highly indispensable. 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. Moreover, the introduction of new marketing concepts such as deregulation has increased the need for reliable and uninterrupted supply of electric power to the end users who are very sensitive to power outages (Das & Novosel, 2013).

One of the most important factors that hinder the continuous supply of electricity and power is a fault in the power system (Akke & Thorp, 2016). Any abnormal flow of current in a power system's component is called a fault. These faults cannot be completely avoided since a portion of these faults also occur due to natural causes which are beyond human control. Hence, it is very important to have a well coordinated protection system that detects any kind of abnormality in a power system, identifies the type of fault and then accurately locate the position of the fault. Faults are usually taken care of by devices that detect the occurrence and eventually isolate the section from the rest of the power system.

Hence some of the important challenges for the incessant supply of power are detection, classification and location of faults. Faults can be of various types namely transient, persistent, symmetric or asymmetric faults and the fault detection process for each of these faults is distinctly unique in the sense, there is no one universal fault diagnosis technique for all these kinds of faults. The High Voltage Transmission Lines (that transmit the power generated at the generating plant to the high voltage substations) are more prone to the occurrence of a fault than the local distribution lines (that transmit the power from the substation to the commercial and residential customers) because there is no insulation around the transmission line cables unlike the distribution lines. The reason for the occurrence of a fault on a transmission line can be due to several reasons such as a momentary tree contact, a bird or an animal contact or due to other natural reasons such as thunderstorms or lightning. Most of the research done in the field of protective relaying of power systems concentrates on transmission line fault protection due to the fact that transmission lines are relatively very long and can run through various geographical terrain and hence it can take anything from a few minutes to several hours to physically check the line for faults (Eriksson & Rockefeller, 2015).

The automatic location of faults can greatly enhance the systems reliability because the faster we restore power, the more money and valuable time we save. Hence, many utilities are implementing fault locating devices in their power quality monitoring systems that are equipped with Global Information Systems for easy location of these faults. Fault diagnosis techniques can be broadly classified into the following categories (Saha & Rosolowski, 2010):

- Impedance measurement based methods
- Travelling-wave phenomenon based methods
- High-frequency components of currents and voltages generated by faults based methods
- Intelligence based method

From quite a few years, intelligent based methods are being used in the process of fault detection and location. Three major artificial intelligence based techniques that have been widely used in the power and automation industry are:

- Expert System Techniques
- Artificial Neural Networks
- Fuzzy Logic Systems

Among these available techniques, Artificial Neural Networks (ANN) has been used extensively in this dissertation for fault diagnosis on electric power transmission lines. These ANN based methods do not require a knowledge base for the location of faults unlike the other artificial intelligence based methods.

1.2 Transmission Line Fault Diagnosis Techniques

The transmission line fault diagnosis process has been researched for a while and several innovative and efficient techniques have been proposed and analyzed by several authors (Ziegler, 2006). These techniques can be broadly classified as Impedance based methods, travelling wave based methods and Artificial Intelligence based methods. Each of these methods is discussed briefly in the following subsections.

1.2.1 Impedance Based Methods

In the case of Impedance based methods, the operation of the distance relay greatly relies on the fault resistance and is not successful in cases with very high fault resistance (Network

Protection & Automation Guide, 2016). Impedance based methods can be classified into single-ended methods and two-ended methods depending on the number of terminals at which the voltage and current data are collected.

The basic logic behind a single-ended impedance based fault locator is to calculate the location of the fault from the apparent impedance seen looking into the line from one end. Some of the various impedance based methods available in literature are as follows:

1.2.2 Simple Reactance Method

The measured voltage and current values at the terminal are used to calculate the impedance of the line to the fault position as shown in equation (1). Once the line impedance per unit length has been determined, the fault distance can be calculated accordingly as illustrated by equations (2) and (3) (Wright & Christopoulos, 2013).

$$V_A = x.Z_L.I_A + V_f \quad (1)$$

Where VA is the voltage at terminal A, x is the distance to the fault from the terminal A,

IA is the current flowing out of the terminal A,

Vf is the fault voltage and ZL is the line impedance.

$$V_A = x.Z_L.I_A + R_f.I_f \quad (2)$$

Where I_f is the fault current and R_f is the fault resistance as shown in Figure 1, and

$$x = \frac{(V_A/I_A)}{Z_L} - \frac{R_f}{Z_L(I_A/I_f)} \quad (3)$$

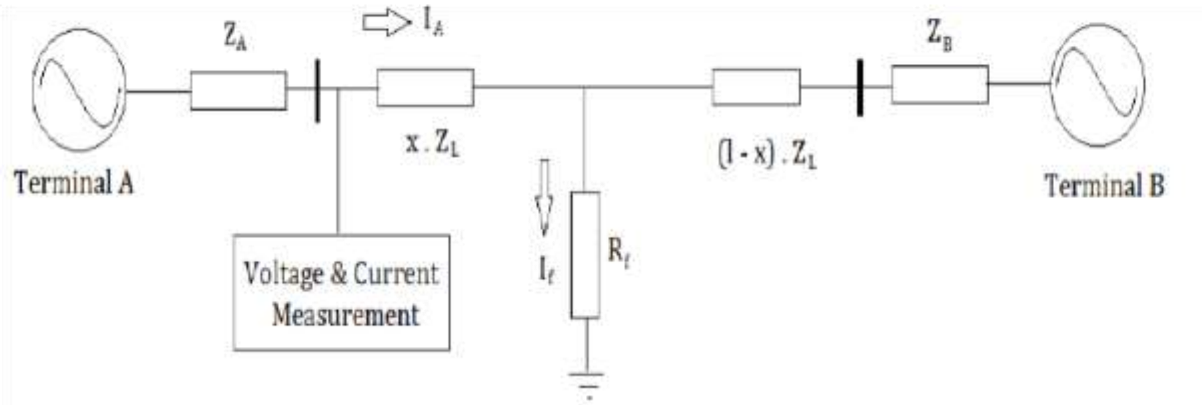


Figure 1: Faulted Transmission Line Illustrating Simple -Reactance Method. (Wright & Christopoulos, 2013).

1.2.3 Takagi Method

The Takagi method is a very simple yet innovative single-ended impedance based Fault diagnosis technique and is illustrated by Figure 2. It requires both the pre-fault and fault data and enhances the simple reactance method by minimizing the effect of fault resistance and reducing the effect of load flow.

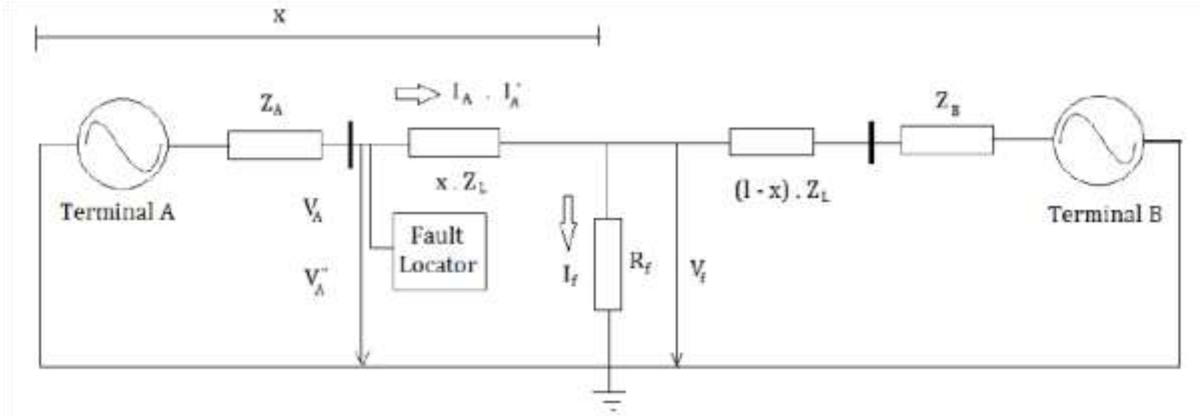


Figure 2: A Single-Phase Circuit Illustrating Takagi Method. (El-Sharkawi & Niebur, 1996)

The Fault Resistance is given by $R_f = \dfrac{V_A - Z_C I_A \tanh \gamma x}{\left(\frac{V_A}{Z_C} \tanh \gamma x - I_A''\right) \psi e^{j\theta}}$ (4)

where V_A is voltage measured at terminal A, I_A is the flowing out of terminal A, γ is the propagation constant, Z_C is the characteristic impedance, Z_L is the line impedance, "I_A" is the superposition current which is the difference between the fault current and the prefault current.

And $x = \dfrac{Im(V_A \cdot I_A''^{*})}{Im(Z_L I_A \cdot I_A''^{*})}$ is the distance to the fault from terminal A. (5)

Where $Z_L = \gamma Z_C$ (6)

1.2.4 Zero Sequence Current Method

The modified Takagi method also called the Zero Sequence current method does not require pre-fault data because it uses zero-sequence current instead of the superposition current for ground faults. The location of the fault in this method is given by x in equation (7).

$$x = \frac{Im(V_A . I_R^{*} . e^{-j\beta})}{Im(Z_{1L} . I_A . I_R^{*} . e^{-j\beta})} \quad (7)$$

Where I_R is the zero-sequence current and β is the zero-sequence current angle. The position of the fault 'x' is given by equation (7); VA is voltage measured at terminal A, I_A is the flowing out of terminal A and Z_{1L} is the positive sequence line impedance.

1.2.5 Travelling Wave Based Methods

Travelling wave based methods have been widely used for the purpose of fault diagnosis and are usually based on the correlation between the forward and backward waves travelling along the transmission line as shown in Figure 3. The basic idea is to successively identify the fault initiated by high-frequency travelling waves at the fault locator (Djuric *et al.,* 2016).

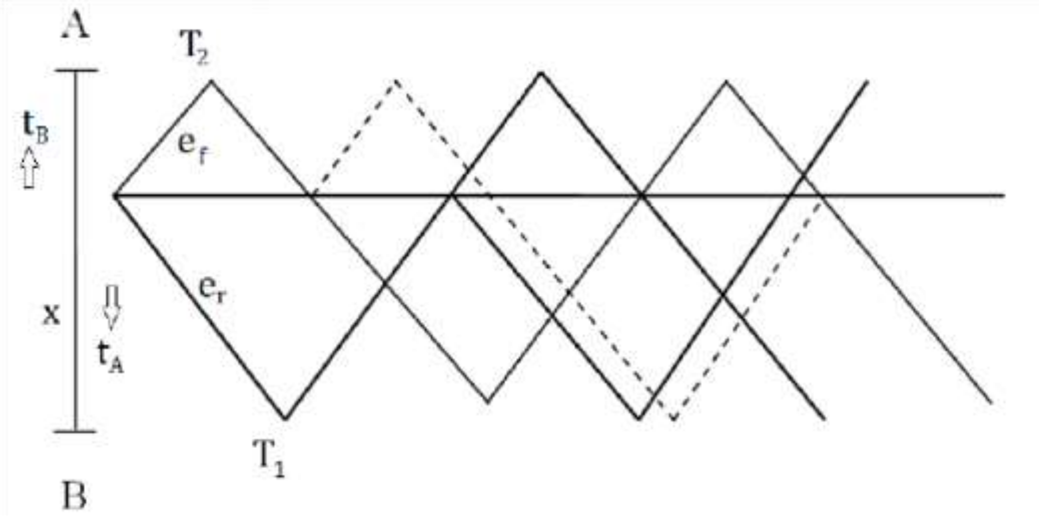


Figure 3: Illustration of Travelling wave based Fault diagnosis. (Djuric *et al.,* 2016)

The time taken by the high frequency components for propagation is used for the location of fault. In Figure 3, a single phase lossless transmission line of length 'l' is considered with a travelling wave velocity of υ, capacitance and inductance per unit length L' and C' and a characteristic impedance of Zc. Assuming the occurrence of a fault at a distance of 'x' from the terminal A, the voltage and current values are given by equations (8) and (9).

$$\frac{\partial e}{\partial x} = -L' \frac{\partial i}{\partial t} \tag{8}$$

$$\frac{\partial i}{\partial x} = -C' \frac{\partial e}{\partial t} \tag{9}$$

Where solutions are given by equations (10) and (11).

$$e(x,t) = e_f(x - vt) + e_r(x + vt) \tag{10}$$

$$i(x,t) = \frac{1}{z_C} e_f(x - vt) - \frac{1}{z_C} e_r(x + vt)$$

(11)

The times taken for the waves to travel from the fault to the discontinuity τ_A and τ_B are to be determined using GPS technology. Once this is done, the fault location "x" can be readily determined by the following equation (12)

$$x = \frac{l - c(\tau_A - \tau_B)}{2}$$

(12)

Where: c is the wave propagation speed of 299.79 m/sec.

2.0 METHODOLOGY AND MATERIALS

2.1 Modeling the Power Transmission Line System

A 500 kV transmission line system has been used to develop and implement the proposed strategy using ANNs. Figure 4 shows a one-line diagram of the system that will be used throughout the research. The system consists of two generators of 500 kV each located on either ends 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 modeled using distributed parameters so that it more accurately describes a very long transmission line.

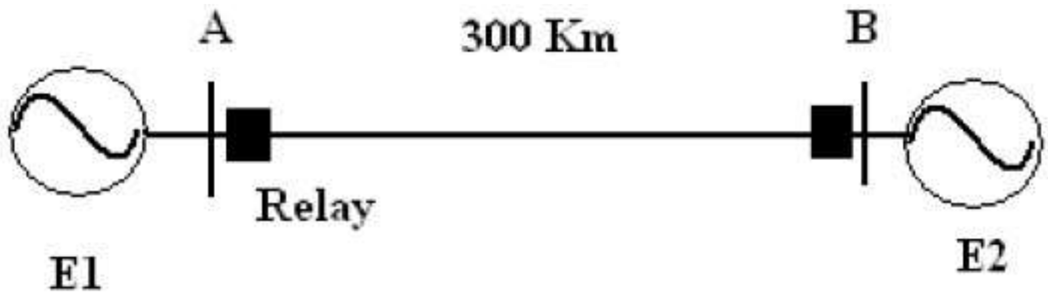
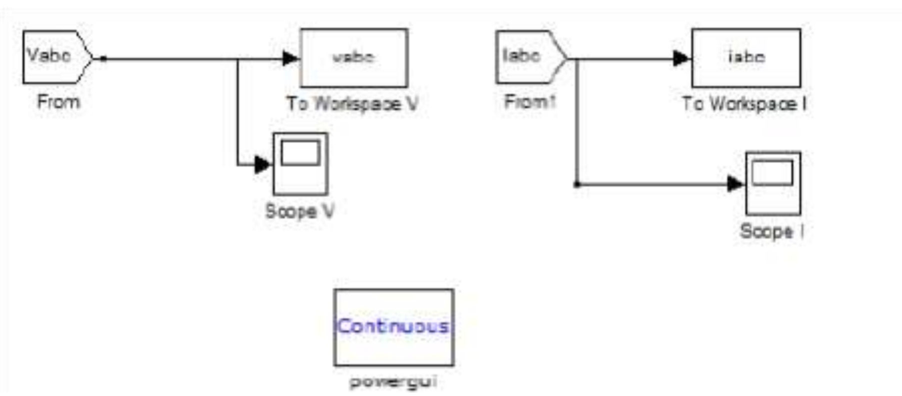


Figure 4: One-line diagram of the studied system.

This power system was simulated using the Sim Power Systems toolbox in Simulink by MathWorks. A snapshot of the model used for obtaining the training and test data sets is shown in figure 5, in which ZP and ZQ are the source impedances of the generators on either side. The three phase V-I measurement block is used to measure the voltage and current samples at terminal A. The transmission line (line 1 and line 2 together) is 300 km long and the three-phase fault simulator is used to simulate various types of faults at varying locations along the transmission line with different fault resistances.



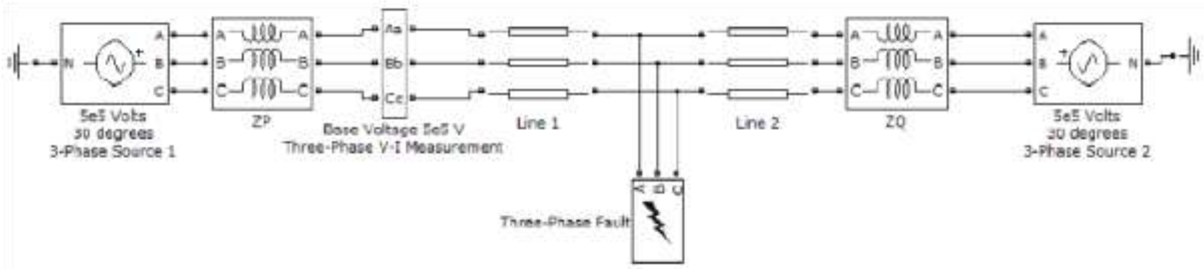


Figure 5: Snapshot of the studied model in SimPower Systems.

The values of the three-phase voltages and currents are measured and modified accordingly and are ultimately fed into the neural network as inputs. The SimPower Systems toolbox 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

There have been 1100 different fault cases simulated for the purpose of fault detection, 1100 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.

2.2 Outline of the Proposed Scheme

Although the basic concept behind relays remains the same, the digital technology has had a significant influence on the way relays operate and have offered several improvements over traditional electromechanical relays.

The main goal of this chapter is to design, develop, test and implement a complete strategy for the fault diagnosis as shown in Figure 6. 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. Once we know that a fault has occurred on the transmission line, the next step is to classify the fault into the different categories based on the phases that are faulted.

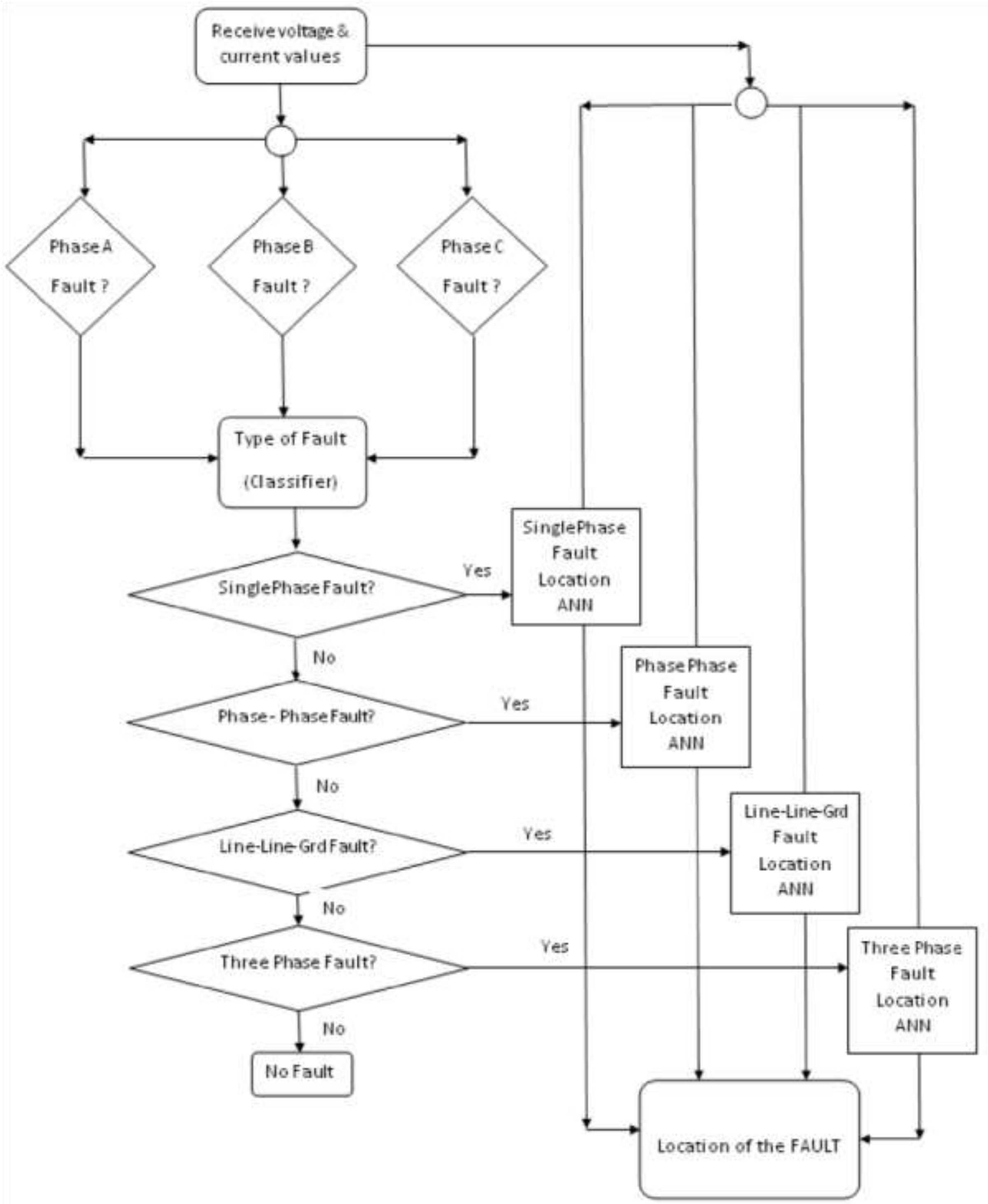


Figure 6: Flowchart depicting the outline of the proposed scheme.

Then, the third step is to pin-point the position of the fault on the transmission line. The goal of this dissertation is to propose an integrated method to perform each of these tasks using hybrid artificial neural-network modules. A back-propagation based neural network has been used for the purpose of fault detection and another similar one for the purpose of fault classification. For each of the different kinds of faults, separate neural networks have been employed for the purpose of fault location. Each of these steps has been depicted in the flowchart shown in Figure 6.

3.0 RESULTS AND DISCUSSIONS

3.1 Testing the Fault Classifier Neural Network

Once the neural network has been trained, its performance has been tested by taking three different factors into consideration. The first of these is by plotting the best linear regression that relates the targets to the outputs as shown in Figure 7. The correlation coefficient in this case was found to be 0.98108 which indicates satisfactory correlation between the targets and the outputs. The dotted line in the figure indicates the ideal regression fit and the red solid line indicates the actual fit of the neural network. It can be seen that both these lines track each other very closely which is an indication of very good performance by the neural network.

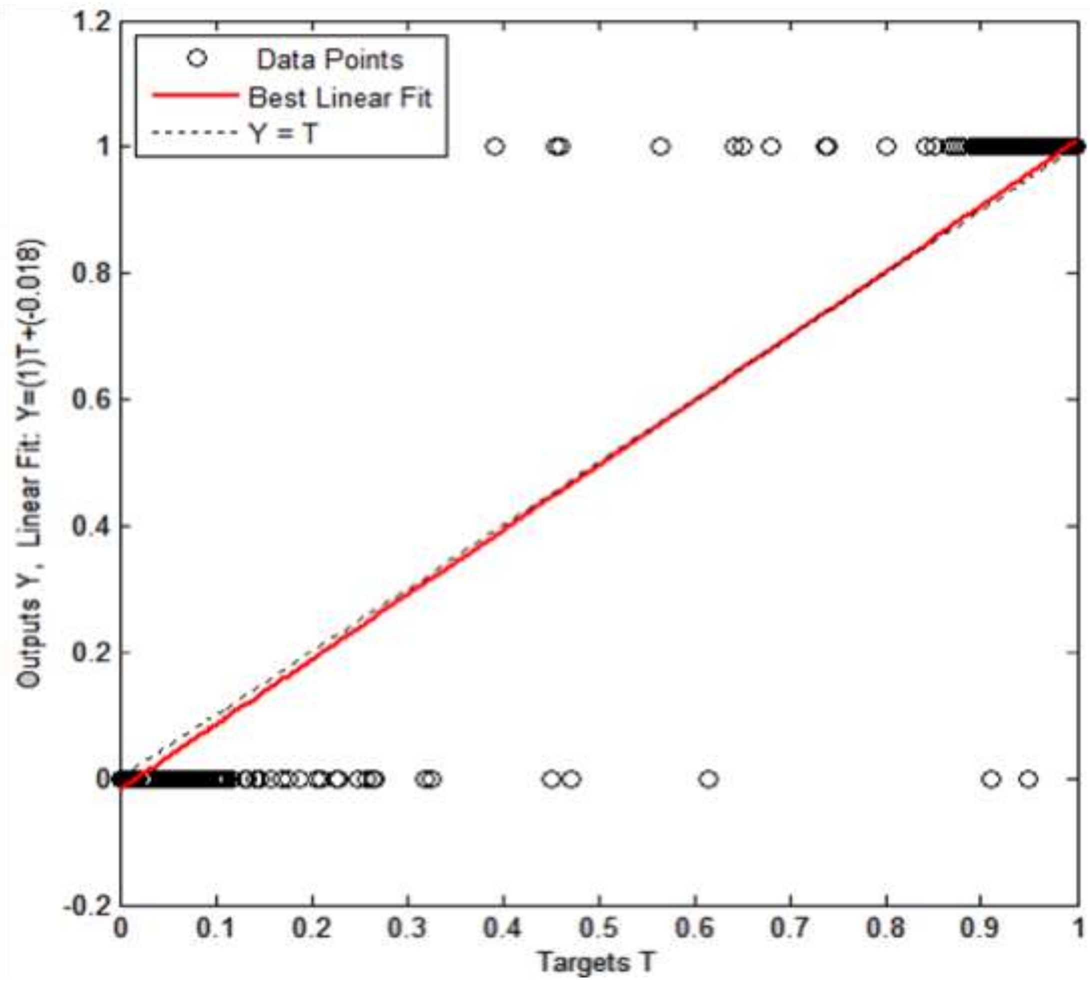


Figure 7: Regression fit of the Outputs vs. Targets of ANN with configuration (6-35-4).

The second factor in the testing process is to plot the Receiver Operating Characteristics curve (ROC). The ROC curves for each of the training, testing and validation phases have been shown in Figure 8 along with the overall ROC curve. The ROC curves are actually plots between the true positive rates (rate of positive classification) and the false positive rates (rate of incorrect classification) of the neural network classifier. Hence, an ideal ROC curve would show points only in the upper-left corner because that is an indication of 100 percent true positivity and 0 percent false positivity in the classification. It is to be noted that the ROC curves plotted in Figure 8 are almost perfect since they all have the lines in the upper-left corner.

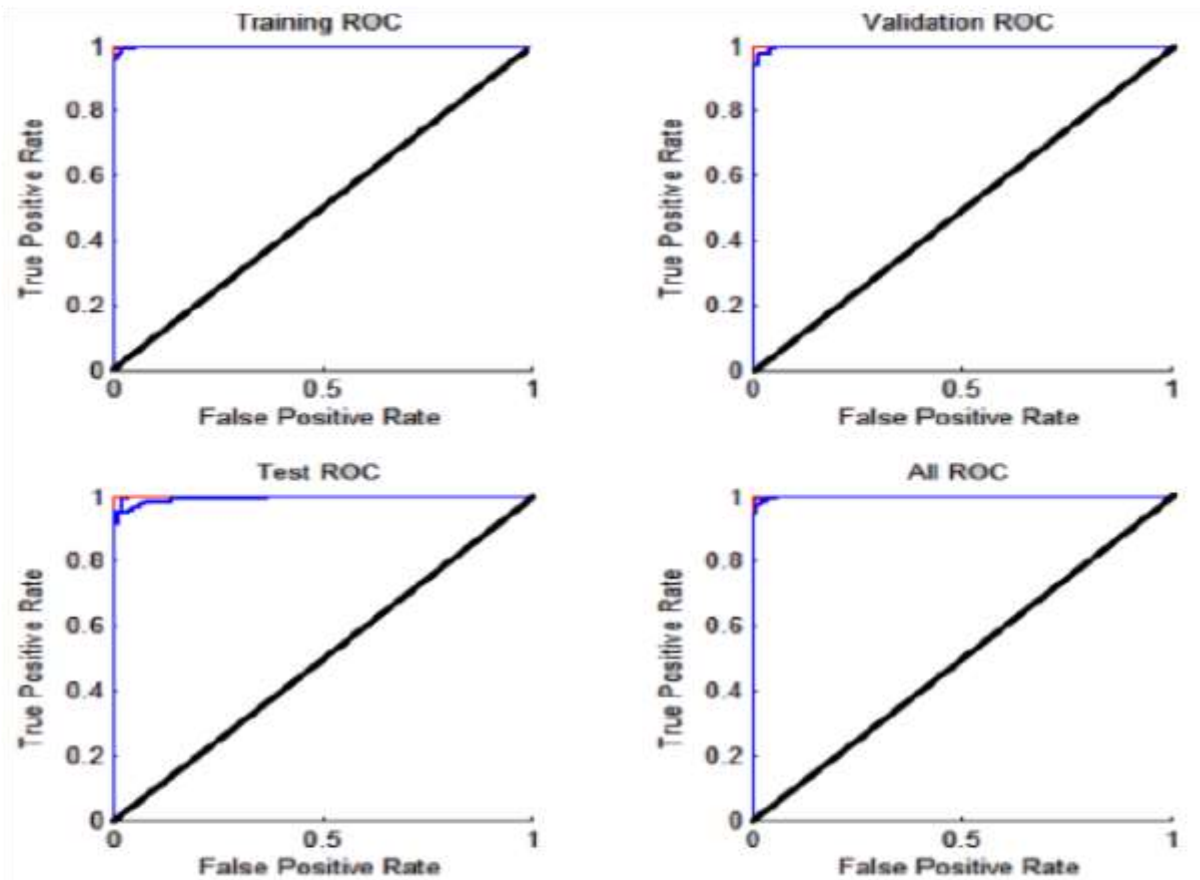


Figure 8: Gradient and Validation performance of the ANN with configuration (6-35-4).

The third step in 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 300 different test cases have been simulated with 550 cases corresponding to different types of faults (about 50 cases for each of the ten faults where the fault resistance and the fault location have been varied in each case). The rest of the 50 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 identify the type of the fault is a 100 percent. Hence the neural network can, with utmost accuracy, differentiate between the ten possible types of faults on a transmission line.

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Figure 9 provides an overview on the neural network and is a screen shot of the training window simulated using the Artificial Neural Network Toolbox in Simulink. Important things to be noted are that the training process converged in about 144 iterations and that the performance in terms of mean square error achieved by the end of the training process was 6.26e-3.

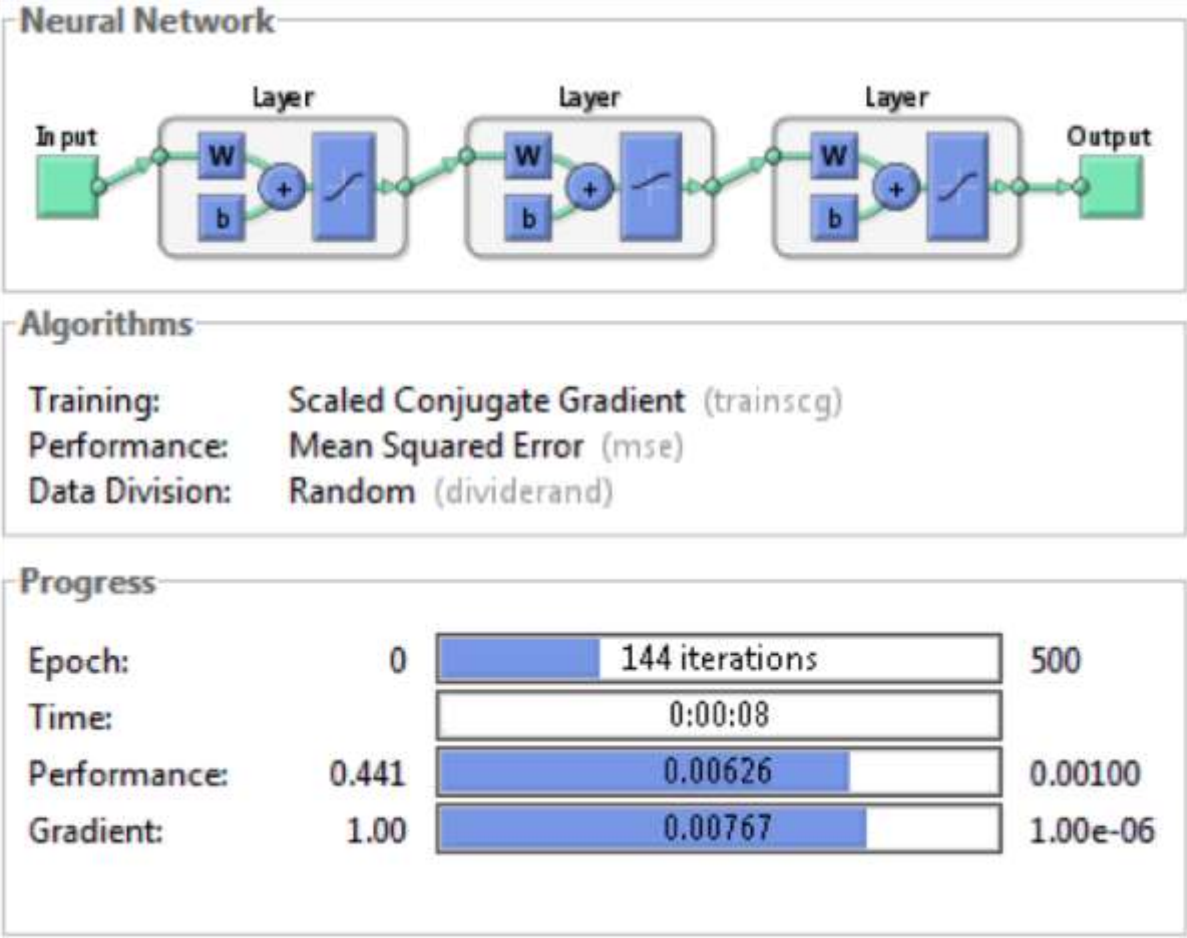

Figure 9: Overview of the ANN with configuration (6-35-4), chosen as fault classifier.

Figure 10 shows the structure of the chosen ANN for the purpose of fault classification and the neural network has 6 neurons in the input layer, 35 neurons in the hidden layer and four neurons in the output layer as shown. Each of the neurons in the output layer would indicate the fault condition on each of the three phases (A, B and C) and the fourth neuron is to identify if the fault is a ground fault. An output of 0 corresponds to no fault while an output of 1 indicates that the phase is faulted.

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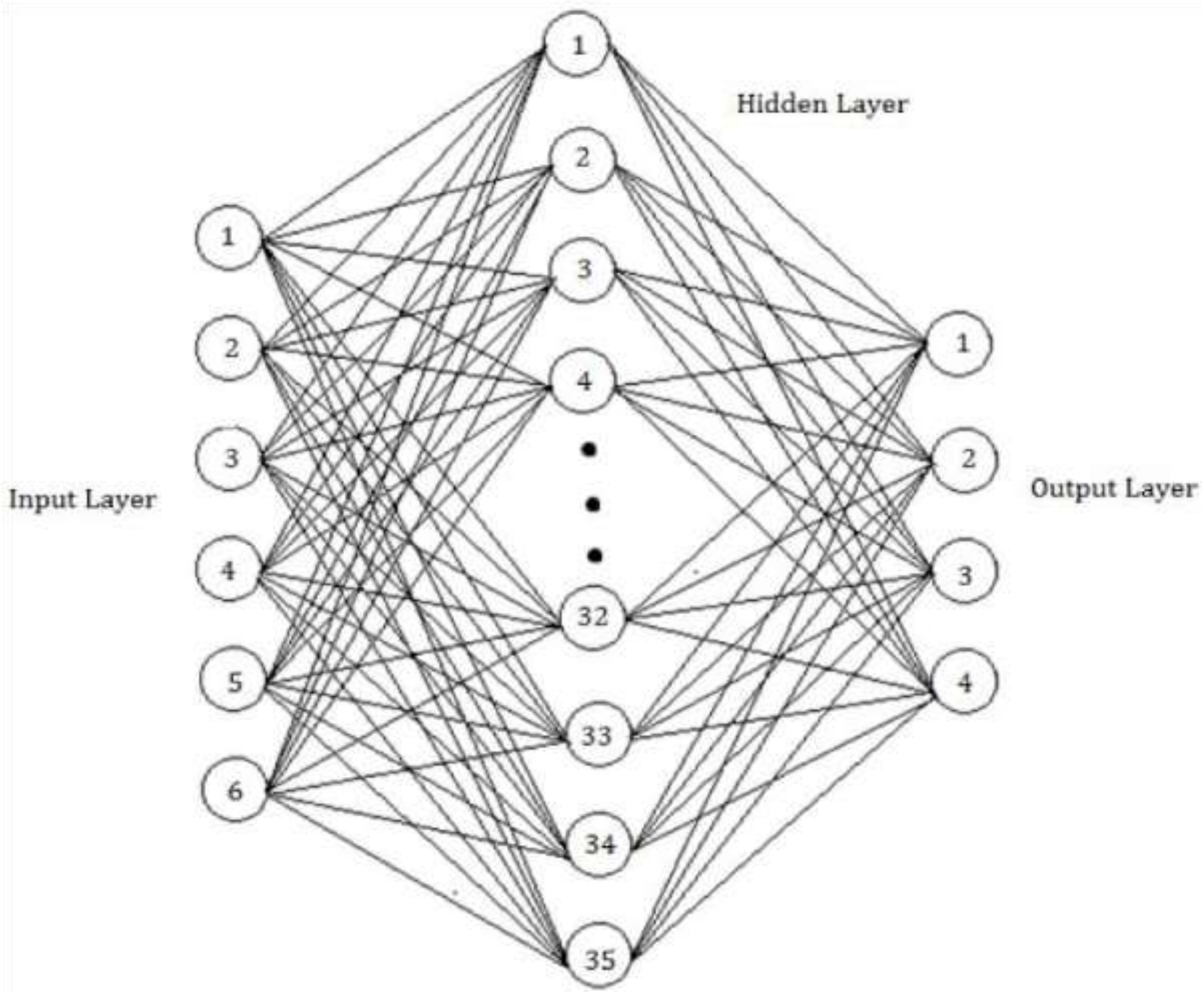

Figure 10: Chosen ANN for Fault Classification (6 – 35 – 4).

3.2 Fault Location

This section talks about the design, development and the implementation of the neural network based fault locators for each of the various types of faults. This forms the third step in the entire process of fault location after the inception of the fault. The following subsections deal with the various kinds of faults and their error performances individually.

3.2.1 Single Line – Ground Faults

Now that we can detect the occurrence of a fault on a transmission line and also classify the fault into the various fault categories, the next step is to pin-point the location of the fault from either ends of the transmission line. Three possible single line – ground faults exist (AG, B-G, C-G), corresponding to each of the three phases (A, B or C) being faulted.

Feed forward back – propagation neural networks have been surveyed for the purpose of single line – ground fault location, mainly because of the availability of sufficient relevant data for training. In order to train the neural network, several single phase faults have been simulated on the transmission line model. For each of the three phases, faults have been simulated at every 3 Km on a 300 Km long transmission line.

Along with the fault distance, the fault resistance has been varied as mentioned earlier in section 3.4. Hence, a total of 2400 cases have been simulated (100 for each of the three phases with each of the eight different fault resistances as 0.25, 0.5, 0.75, 1, 5, 10, 25 and 50 ohms respectively). In each of these cases, the voltage and current samples for all three phases (scaled with respect to their pre-fault values) are given as inputs to the neural network. The output of the neural network is the distance to the fault from terminal A. Firstly, a few of the various neural networks (with varying combination of hidden layers and number of neurons per hidden layer) that performed reasonably well are presented along with their respective error performances and then the chosen neural network is shown with all its characteristics depicted in detail. Efficiency of each of the trained networks is analyzed based on their regression performance and their performance in the testing phase. The test performance plots are obtained by simulating various faults on different phases at varying locations and calculating the error in the output produced by the Neural Network. Figures 11 – 18 show the error performance and regression plots of neural networks with 1 and 2 hidden layers.

Figure 11 plots the best linear regression fit between the outputs and the targets of the neural network with 6 neurons in the input layer, 2 hidden layers with 5 and 5 neuron in them respectively and 1 neuron in the output layer (6-5-5-1). The correlation coefficient (r) as mentioned earlier is a measure of how well the neural network relates the outputs and the targets. The closer the value of r is to 1, the better the performance of the neural network. The value of r in this case is found to be 0.99799. In order to test the performance of this network, 12 different single phase faults have been simulated on different phases with the fault distance being incremented by 25 Km in each case and the percentage error in calculated output has been calculated. Figure 12 shows the results of this test conducted on the neural network (6-5-5-1). It can be seen that the maximum error is almost 4.5 percent.

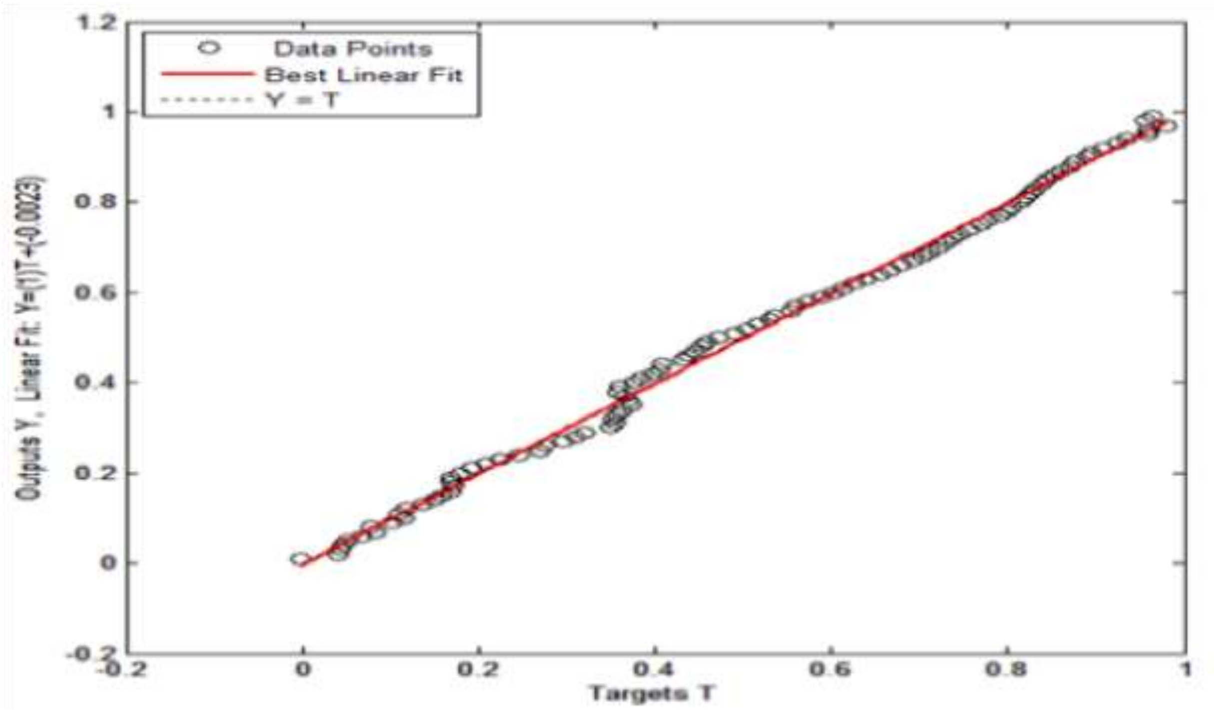

Figure 11: Regression fit of the Outputs vs. Targets with configuration (6-5-5-1).

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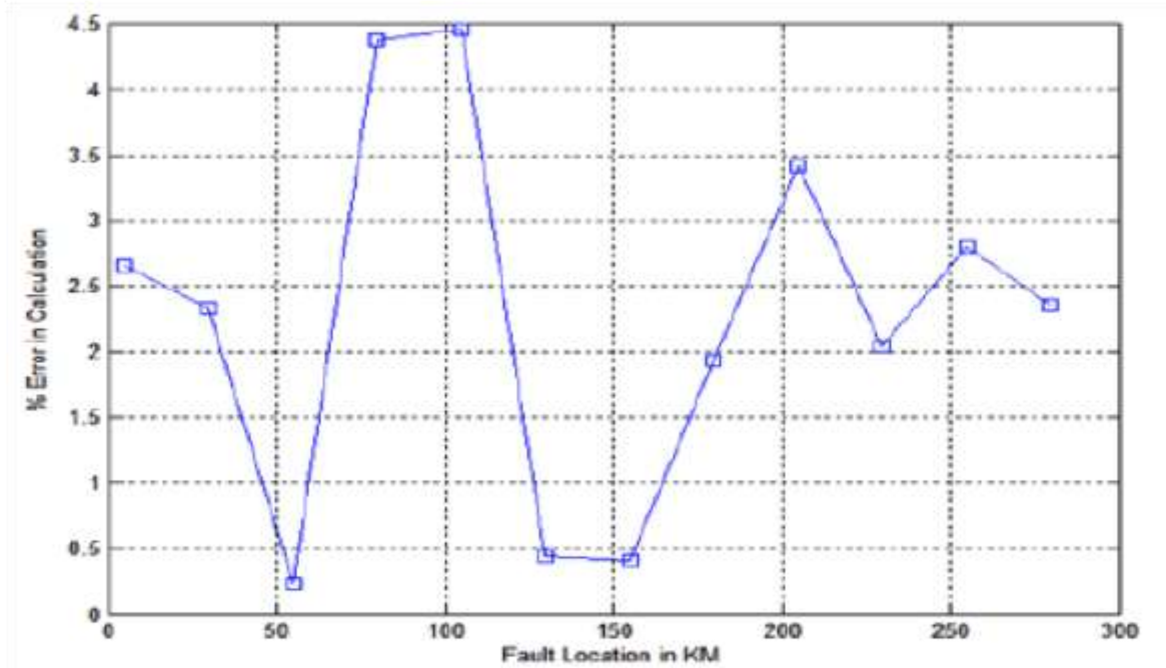

Figure 12: Test Phase performance of the Neural Network with configuration (6-5-5-1).

Figure 13 plots the best linear regression fit between the outputs and the targets of the neural network with 6 neurons in the input layer, 25 neurons in the hidden layer and 1 neuron in the output layer (6-25-1). The value of the correlation coefficient r in this case is found to be 0.9959. In order to test the performance of this network, 12 different single phase faults have been simulated on different phases with the fault distance being incremented by 25 Km in each case and the percentage error in calculated output has been calculated. Figure 14 shows the results of this test conducted on the neural network (6-25-1). It can be seen that the maximum error is around 7 percent which is not very satisfactory.

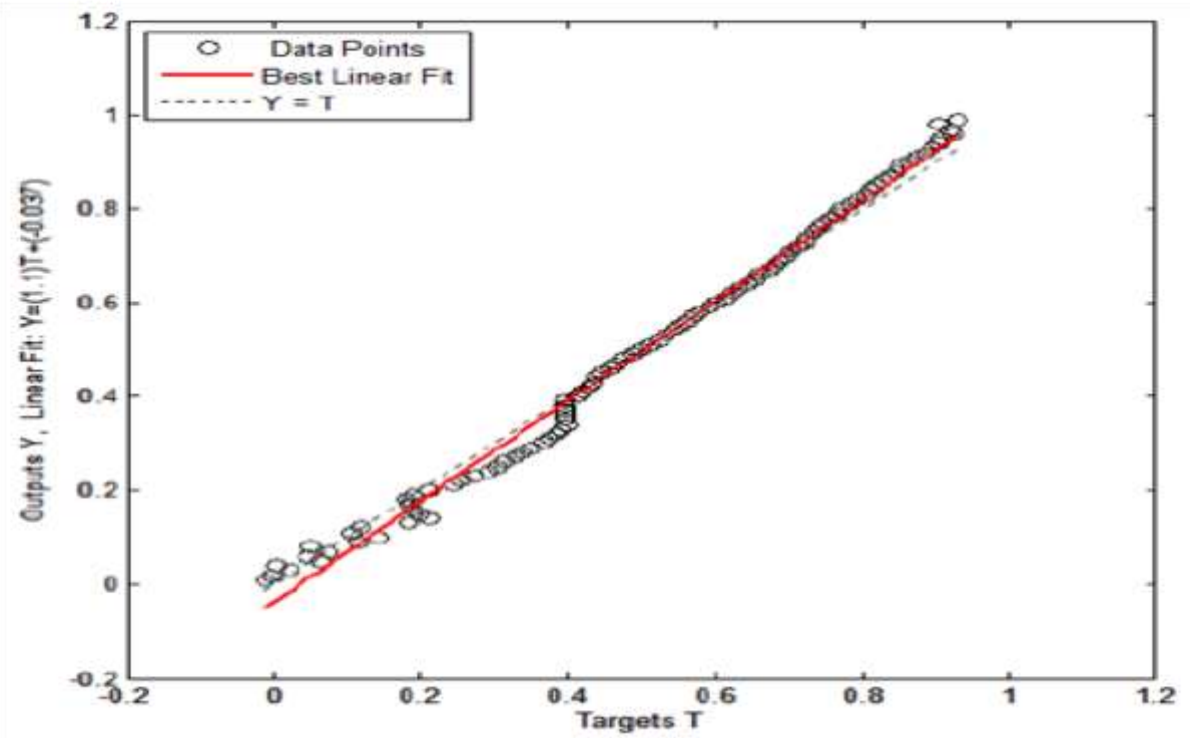

Figure 13: Regression fit of the outputs versus targets with configuration (6-25-1).

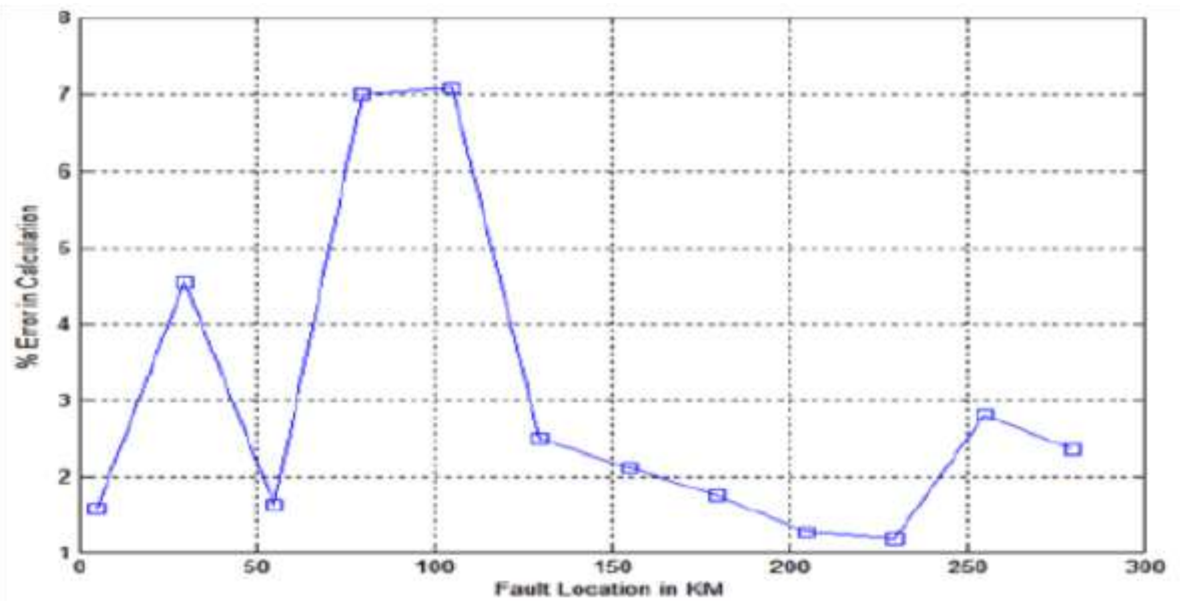

Figure 14: Test phase performance of the ANN with configuration (6-25-1)

Figure 15 plots the best linear regression fit between the outputs and the targets of the neural network with 6 neurons in the input layer, 16 neurons in the hidden layer and 1 neuron in the

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output layer (6-16-1). The value of the correlation coefficient r in this case is found to be 0.99906.

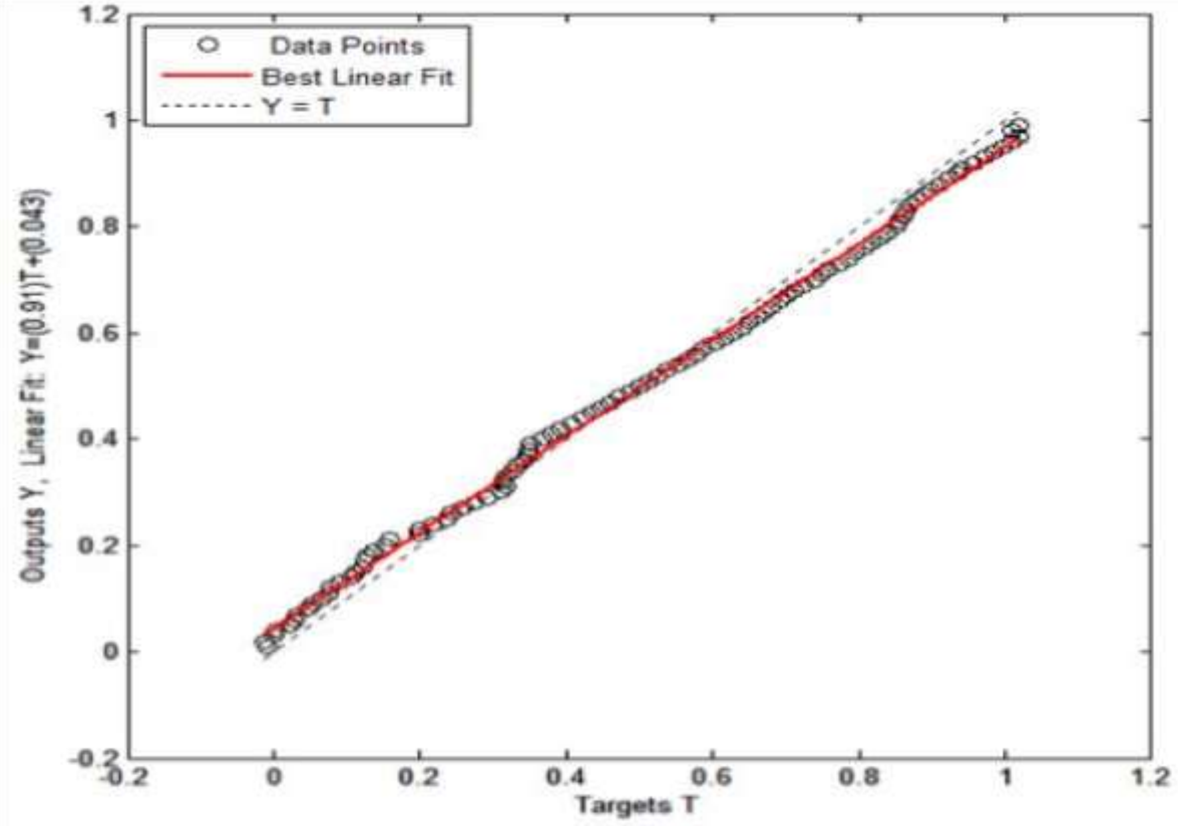

Figure 15: Regression fit of the outputs versus targets with configuration (6-16-1).

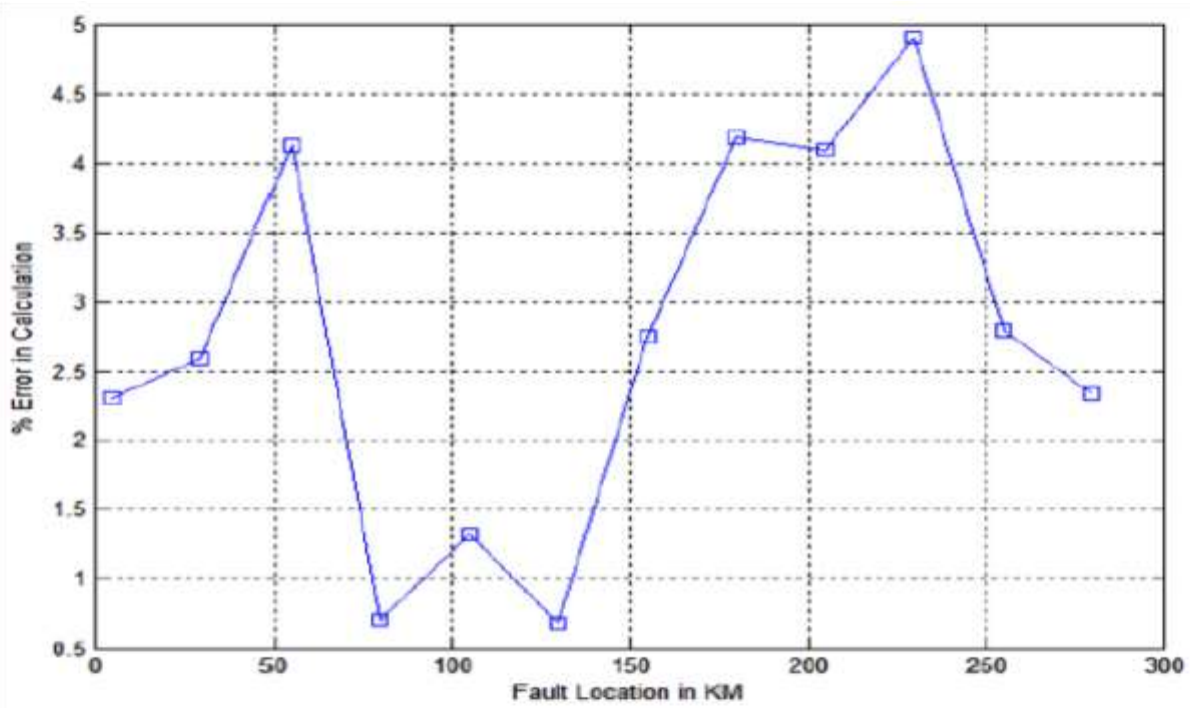

Figure 16: Test phase performance of the neural network with configuration (6-16-1).

In order to test the performance of this network, 12 different single phase faults have been simulated on different phases with the fault distance being incremented by 25 Km in each case and the percentage error in calculated output has been calculated. Figure 16 shows the results of this test conducted on the neural network (6-16-1). It can be seen that the maximum error is around 4.75 percent.

Figure 17 plots the best linear regression fit between the outputs and the targets of the neural network with 6 neurons in the input layer, 7 neurons in the hidden layer and 1 neuron in the output layer (6-7-1). The value of the correlation coefficient r in this case is found to be 0.99924 which is by far the best and the closest to one.

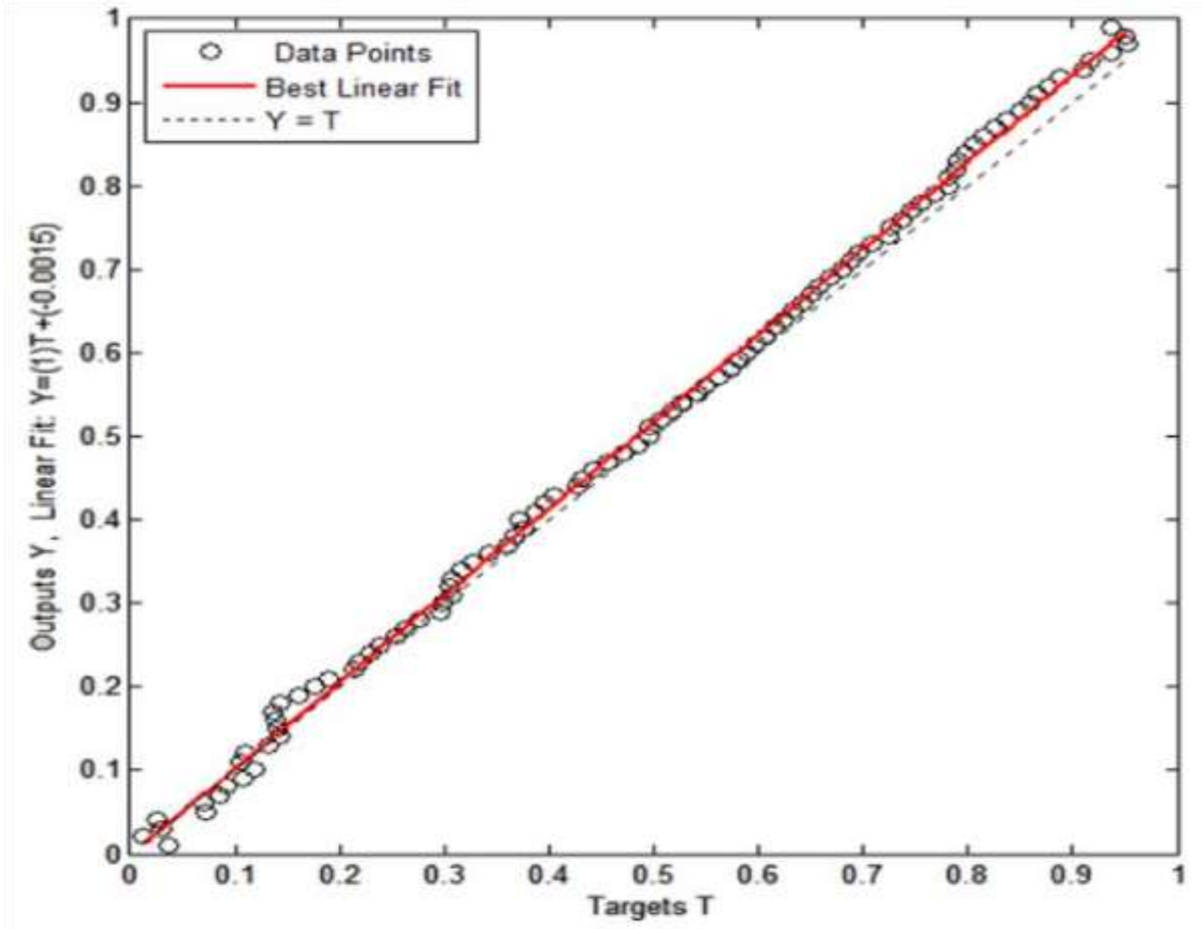

Figure 17: Regression fit of the outputs versus targets with configuration (6-7-1).

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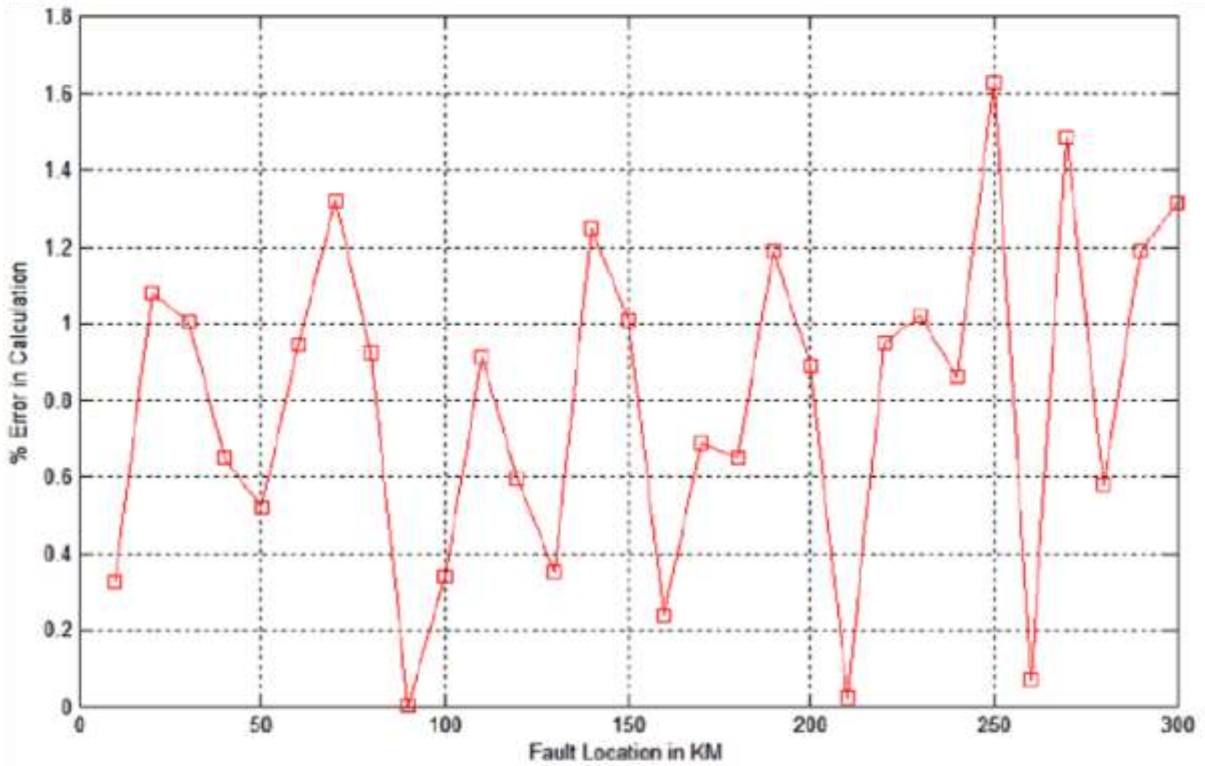

Figure 18: Test phase performance of the ANN with configuration (6-7-1).

In order to test the performance of this network, 100 different single phase faults have been simulated on different phases with the fault distance being incremented by 10 Km in each case and the percentage error in calculated output has been calculated. Figure 18 shows the results of this test conducted on the neural network (6-7-1). It can be seen that the maximum error is around 1.65 percent which is very satisfactory. It is to be noted that the average error in fault location is just 0.89 percent.

Figure 19 shows an overview of the chosen ANN and it can be seen that the training algorithm used is Levenberg - Marquardt algorithm. The performance function chosen for the training process is mean square error. Figure 20 plots the mean-square error as a function of time during the learning process and it can be seen that the achieved MSE is about 0.0005056 which is way below the MSE goal of 0.01.

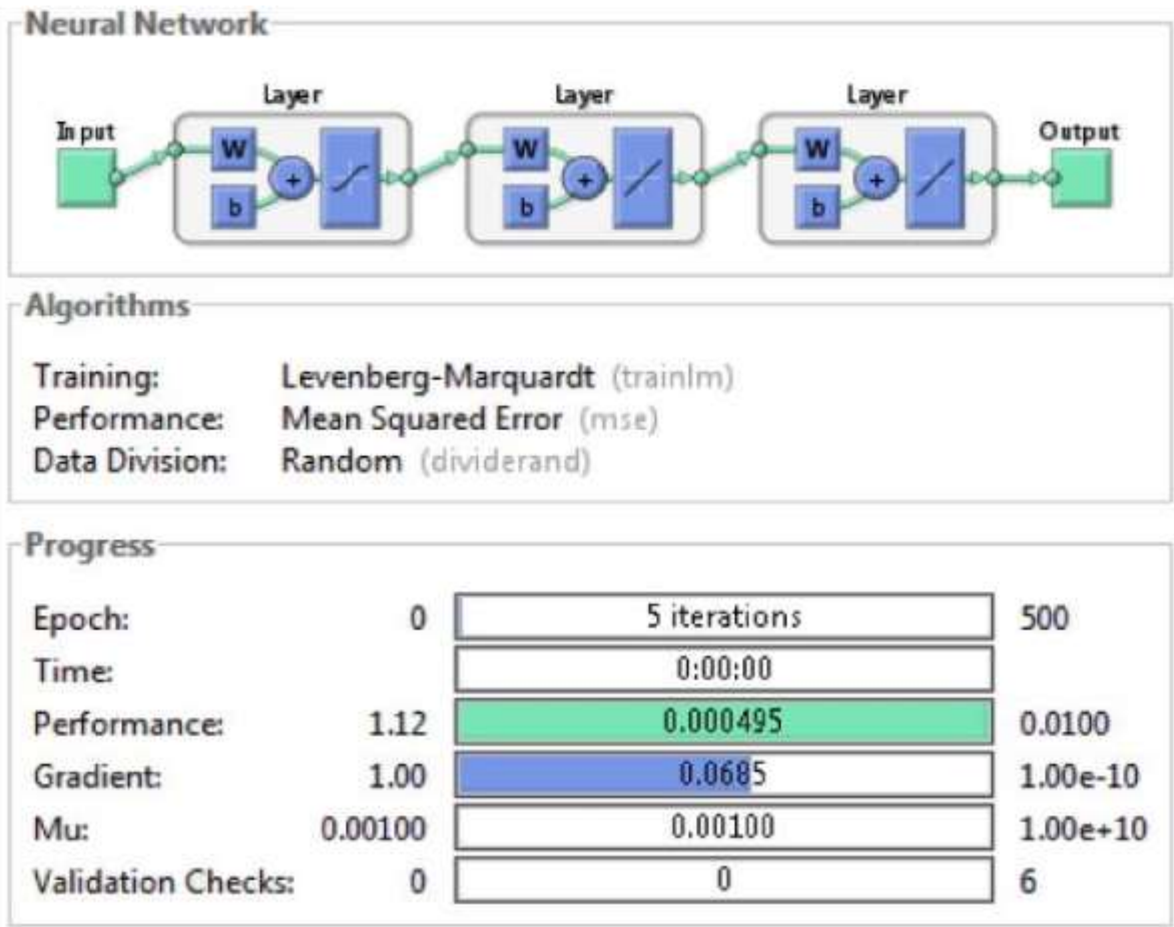

Figure 19: Overview of the chosen ANN with configuration (6-7-1).

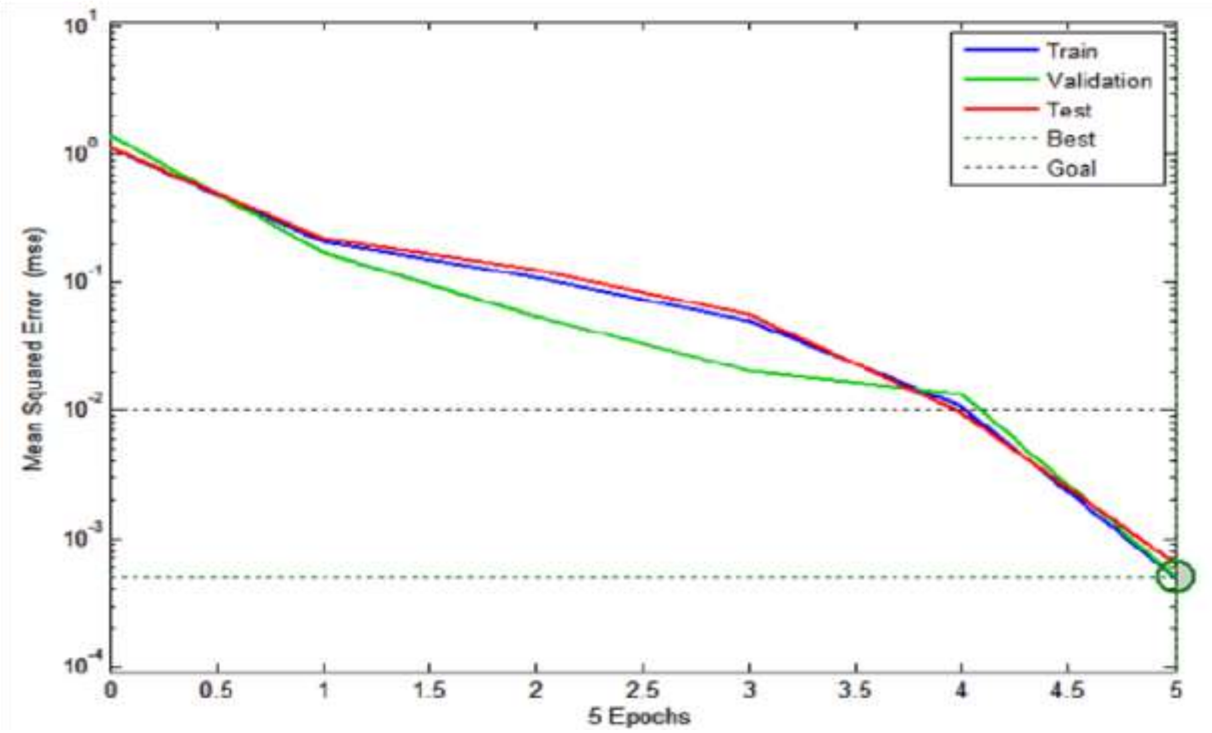

Figure 20: Mean-square error performance of the network with configuration (6-7-1).

4.0 CONCLUSIONS

The simulation results obtained prove that satisfactory performance has been achieved by all of the proposed neural networks in general. As further illustrated, depending on the application of the neural network and the size of the training data set, the size of the ANN (the number of hidden layers and number of neurons per hidden layer) keeps varying. The importance of choosing the most appropriate ANN configuration, in order to get the best performance from the network, has been stressed upon in this work. The sampling frequency adopted for sampling the voltage and current waveforms in this dissertation is just 720 Hz which is very low compared to what has been used in the literature (a major portion of the works in literature utilized 2 kHz – 5 kHz).

To simulate the entire power transmission line model and to obtain the training data set, MATLAB R2010a has been used along with the Sim Power Systems toolbox in Simulink. In order to train and analyze the performance of the neural networks, the Artificial Neural Networks Toolbox has been used extensively.

Some important conclusions that can be drawn from this dissertation are:

- Neural Networks are indeed a reliable and attractive scheme for an ideal transmission line fault diagnosis scheme especially in view of the increasing complexity of the modern power transmission systems.
- Back Propagation neural networks are very efficient when a sufficiently large training data set is available and hence Back Propagation networks have been chosen for all the

three steps in the fault diagnosis process namely fault detection, classification and fault location.

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