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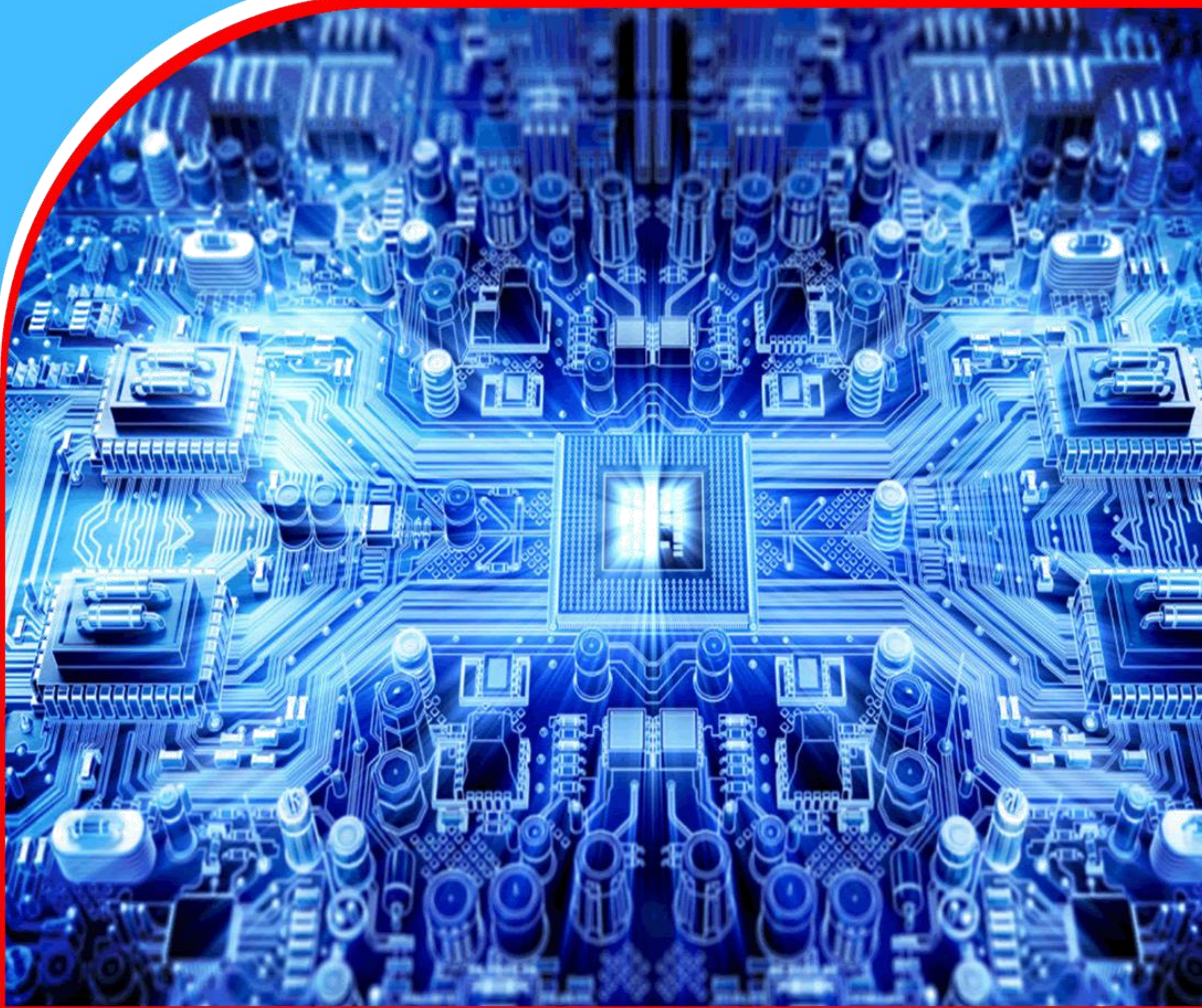

SOLVING ELECTRIC POWER TRANSMISSION LINE FAULTS USING HYBRID ARTIFICIAL NEURAL NETWORK MODULES

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SOLVING ELECTRIC POWER TRANSMISSION LINE FAULTS USING HYBRID ARTIFICIAL NEURAL NETWORK MODULES

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ABSTRACT

Purpose: This paper examined solving electric power transmission line faults using hybrid artificial neural network modules. This paper focuses on detecting, classifying and locating faults on electric power transmission lines.

Methodology: The fundamental principle of the proposed fault diagnosis method is to add to the original network a fictitious bus where the fault occurs. Hence, the bus impedance matrix is augmented by one order. Then, the driving point impedance of the fault bus and the transfer impedances between this bus and other buses are expressed as functions of the unknown fault distance. Based on the definition of the bus impedance matrix, the change of the sequence voltage at any bus during the fault is formulated in terms of the corresponding transfer impedance and sequence fault current.

Results: Findings from this study prove that back propagation neural networks are very efficient when a sufficiently large training data set is available. The regression plots of the various phases such as training, testing and validation indicate that the best linear fit very closely matches the ideal case with an overall correlation coefficient of 0.99329. 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 just 0.836 % which is still acceptable. Thus the neural networks performance is considered satisfactory and can be used for the purpose of three phase fault location as well.

Keywords: *Fault Detection, Electric Power System, Power Protection Systems, Fault Detection Neural Network*

1.0 INTRODUCTION

Huge amount of money and time is lost when faults occur in a power transmission and distribution systems. Also, the timeliness /degree of accuracy with which faults are located in the power systems pose serious challenges especially when the physical dimensions and the size of the transmission lines are considered.

One of the important aspects that this paper concentrates on is the analysis of the transmission line's phase voltages and currents during various fault conditions and how they can be effectively utilized in the design of an efficient fault locator. This work drew its initial motivation from which demonstrates a method that could be used for location of faults in transmission lines using neural fuzzy logic. However, when extensively studied, it can be noted that a fault locator with satisfactorily high accuracy can be easily achieved with the help of hybrid artificial neural-network modules by the use of a large amount of data set for training and the learning process. This eliminates the need for proficiency in power systems which is a necessity when working with expert fuzzy systems (Reddy & Mohanta, 2008). Hence this paper focuses on the design of a fault locator that can be even used by people who aren't experts in the field of power systems.

1.1 Fault Detection in Electric Power System

In an electric power system, a fault is detected by any abnormal electric current flow. For example, a short circuit is a fault in which current bypasses the normal load. An open-circuit fault occurs if a circuit is interrupted by some failure. In three-phase systems, a fault may involve one or more phases and ground, or may occur only between phases. In a "ground fault" or "earth fault", charge flows into the earth. The prospective short circuit current of a fault can be calculated for power systems. In power systems, protective devices detect fault conditions and operate circuit breakers and other devices to limit the loss of service due to a failure (Akke & Thorp, 2016). In a poly phase system, a fault may affect all phases equally which is also called symmetrical fault. If only some phases are affected, the resulting asymmetrical fault becomes more complicated to analyze because the simplifying assumption of equal current magnitude in all phases is no longer applicable. The analysis of this type of fault is often simplified by using methods such as symmetrical components (Das & Novosel, 2013).

A symmetric or balanced fault affects each of the three phases equally. In transmission line faults, roughly 5% are symmetric. This is in contrast to an asymmetrical fault, where the three phases are not affected equally. An asymmetric or unbalanced fault does not affect each of the three phases equally Power transmission and distribution lines are the vital links that achieve the essential continuity of service of electrical power to the end users. Transmission lines connect the generating stations and load centers. Faults are caused either by insulation failures and conducting path failures. Most of the faults on transmission and distribution lines are caused by over voltage due to lighting and switching surges or by external conducting objects falling on over head lines. Birds, tree branches may also cause faults on over head lines. Other causes of faults on over head lines are direct lightning strokes, aircraft, snakes, ice and snow loading, storms, earthquakes, creepers etc. In the case of cables, transformers, generators the causes may be failure of solid insulation due to ageing, heat, moisture or over voltage, accidental contact with earth (Bhalja & Maheshwari, 2011).

The overall faults can be classified into two types:

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www.ajpojournals.org

1. Series faults 2. Shunt faults

A fault if unclear has the following effects on a power system.

Heavy short circuit current may cause damage to equipment or any other element of the power system due to over heating or flash over and high mechanical forces set up due to heavy current.

There may be reduction in the supply voltage of the healthy feeders, resulting in the loss of industrial loads. Short circuits may cause the unbalancing of the supply voltages and currents, there by heating rotating machines. There may be a loss of system stability. The faults may cause an interruption of supply to consumers (Cook, 2015).

1.2 Power Protection Systems

One of the most important components of a power protection system is the relay which is a device that trips the circuit breakers when the input voltage and current signals correspond to the fault conditions designed for the relay operation. Relays in general can be classified into the following categories (Alessandro et al, 1994):

- Directional Relays: These relays respond to the phase angle difference between two inputs to the relay.
- Differential Relays: These relays respond to the magnitude of the algebraic sum of two or more of its inputs.
- Magnitude Relays: These relays respond to the magnitude of the input quantity.
- Pilot Relays: These relays respond to the input signals that are communicated to the relay from a remote location.
- Distance Relays: These relays respond to the ratio of two input phasor signals.

Among the various relays that are used for the protection of electric power lines, distance relays are the most relevant to fault locators. Usually a pair of these distance relays are used for the protection of a two-terminal transmission line (Cook, 2012).

1.3 Types of Faults

There are two types of faults which can occur on any transmission lines; balanced fault and unbalanced fault also known as symmetrical and asymmetrical fault respectively. Most of the faults that occur on the power systems are unbalanced faults. In addition, faults can be categorized as shunt faults and series faults (Anderson, 2015). Series faults are those type of faults which occur in impedance of the line and does not involve neutral or ground, nor does it involves any interconnection between the phases. In this type of faults there is increase of voltage and frequency and decrease of current level in the faulted phases. Example: opening of one or two lines by circuit breakers. Shunt faults are the unbalance between phases or between ground and phases. This research only consider shunt fault. In this type of faults there is increase of current and decrease of frequency and voltage level in the faulted phases. The shunt faults can be classified into four types:

1.3.1 Phase to ground fault

In this type of fault, any one line makes connection with the ground.

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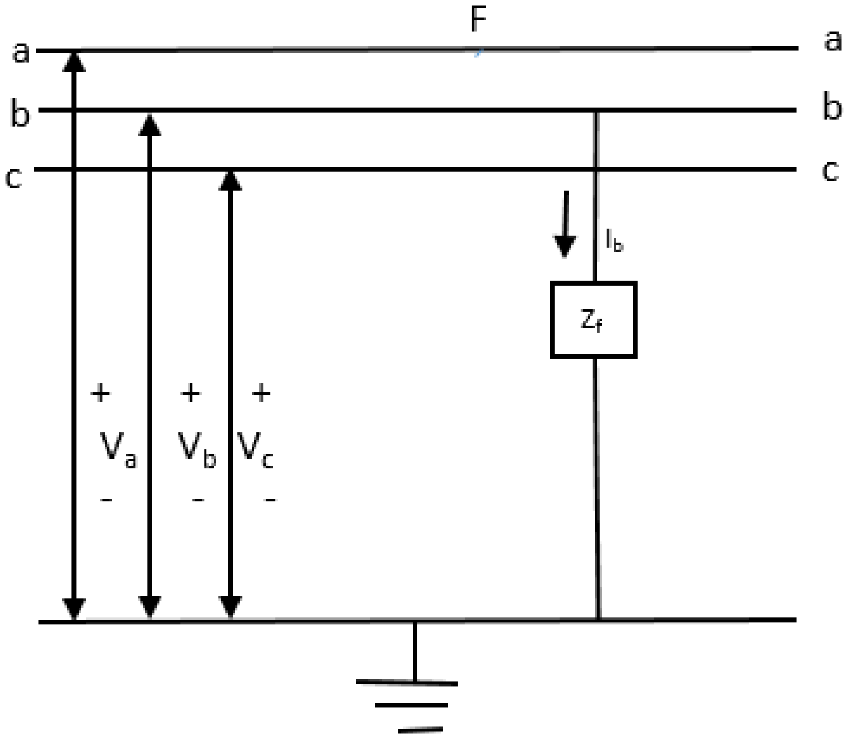


Figure 1: Single Phase to ground fault (Anderson, 2015)

1.3.2 Phase to Phase fault

In this type of fault, there established the connection between the phases.

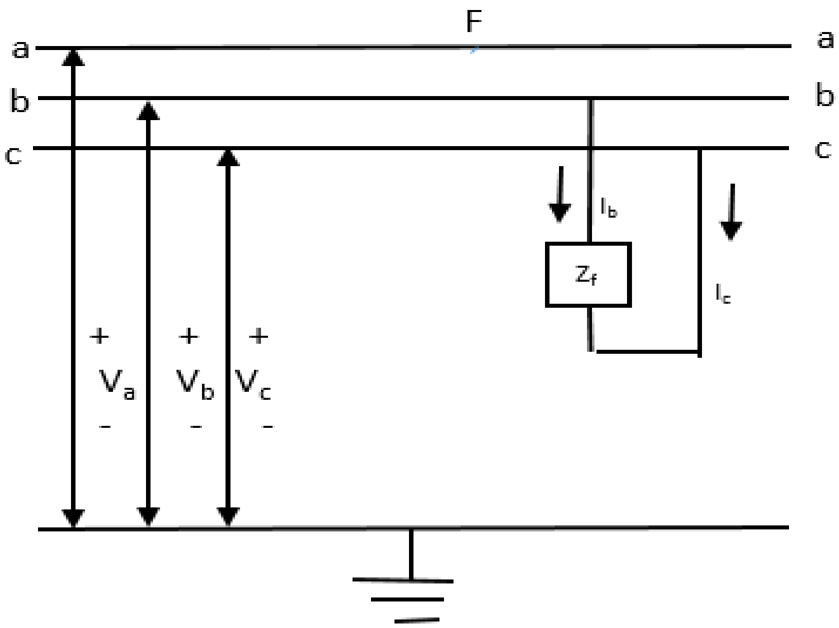


Figure 2: Phase to Phase fault (Silva et al, 2004)

1.3.3. Double Phase to ground fault

In this type of fault, two phases established the connection with the ground.

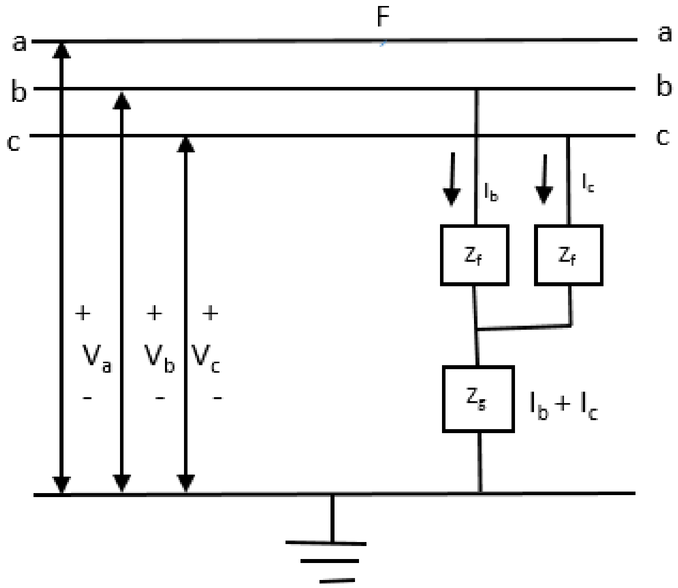
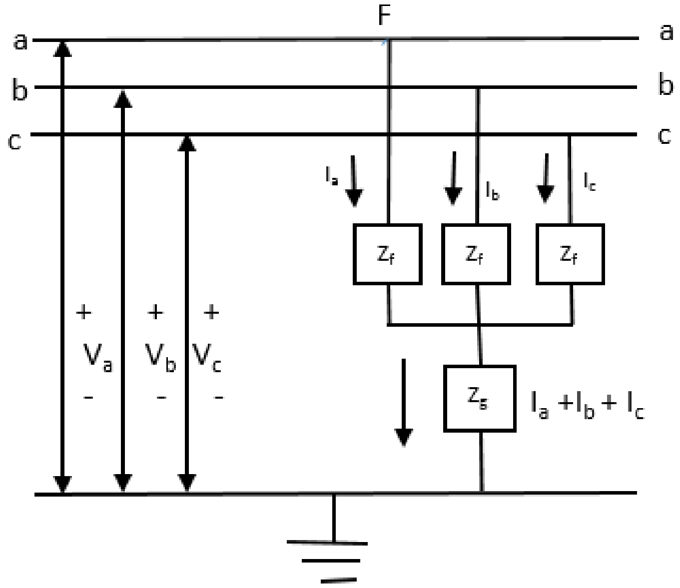


Figure 3: Double phase o ground fault (Anderson, 2015)

1.3.4. Three phase fault

In this type of fault, three phase makes connection with the ground. This is severe fault.



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Vol.1, Issue 1 No.1, pp 1 - 25, 2016
www.ajpojournals.org

Figure 4: 3phase fault (Anderson, 2015)

2.0 MATERIALS AND METHODOS

The fundamental principle of the proposed fault diagnosis method is to add to the original network a fictitious bus where the fault occurs. Hence, the bus impedance matrix is augmented by one order. Then, the driving point impedance of the fault bus and the transfer impedances between this bus and other buses are expressed as functions of the unknown fault distance. Based on the definition of the bus impedance matrix, the change of the sequence voltage at any bus during the fault is formulated in terms of the corresponding transfer impedance and sequence fault current. Depending on the boundary conditions for different fault types, we can obtain the fault location equation using voltage phasors as input.

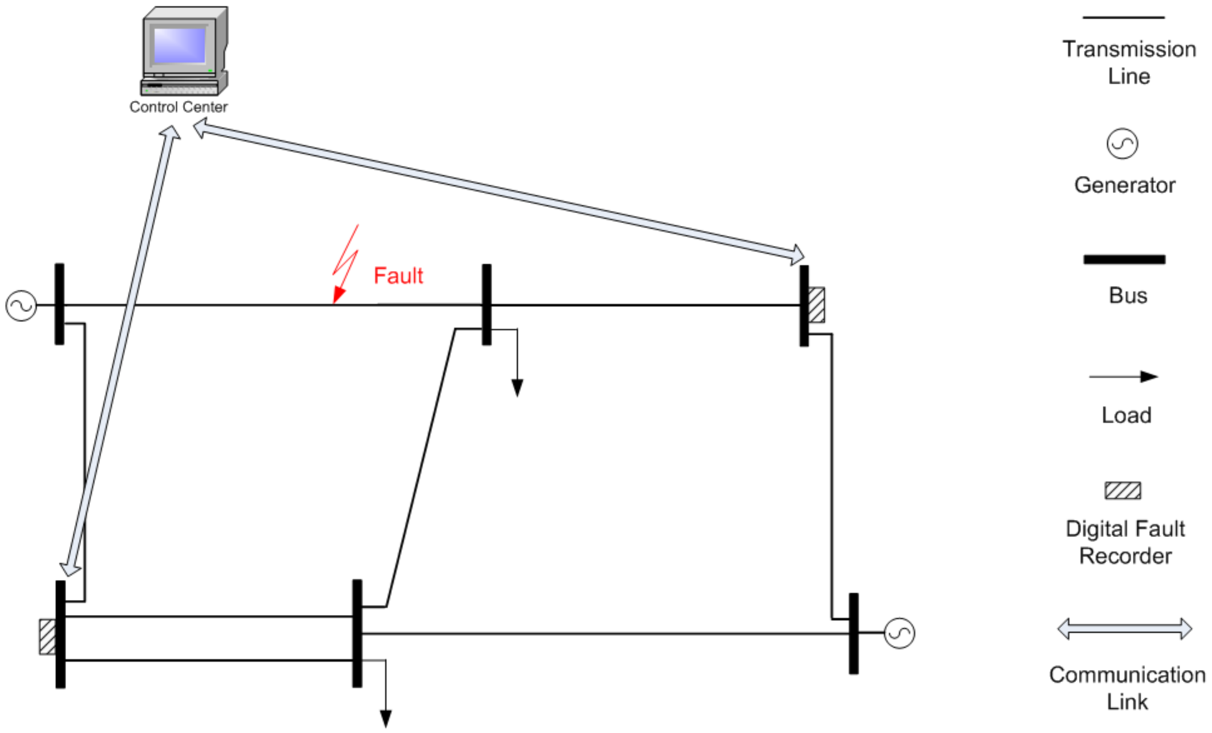

Figure 6: A sample wide area monitoring system.

Based on the same augmented bus impedance matrix, Voltage and Current Relation (VCR) are employed. Now the change of the current at any branch can be expressed as a function of the relevant fault current and the transfer impedance terms associated with the two ends of the branch.

Fault location model takes fully into account the shunt capacitance. With different boundary conditions for the various fault types, the unknown fault location can be obtained by properly formulating the fault currents and voltages at the fault point. Two subroutines assuming that the fault occurs on either side of the series compensator are developed. A prescription to distinguish the correct fault location from the erroneous one is provided.

American Journal of Computing and Engineering
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Vol.1, Issue 1 No.1, pp 1 - 25, 2016

Tests were done on figure 7 which is a single three phase transmission line system having two generators. Phasor voltage and current are assumed to be available from both ends of a single transmission line.

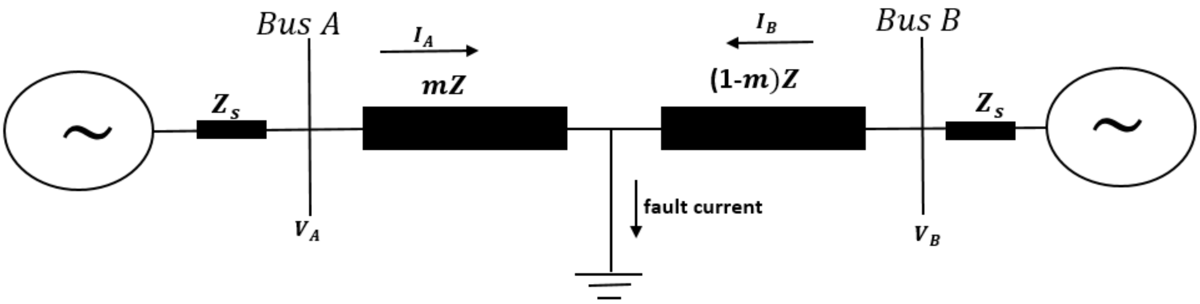

Figure 7: Faulted three phase transmission line

Fault locators are assumed to be located on both ends of the transmission line. When faults occurred, recorded phasor voltages and currents were taken from both ends. The power system was designed in special software for simulation and analysis of transient in power system. Algorithms of the hybrid artificial neural network method were written in MATLAB. Different fault types were made at different locations on transmission lines. Fault voltages and fault currents from were taken and given as input to MATLAB which gives the fault distance.

The transmission lines of length 300Km were modeled in SimPowerSystems. The aerial mode current samples waveform was given as input to MATLAB. In MATLAB, the sampled waveform are decomposed into detail and approximation coefficients wavelets using high pass filter and low pass filters respectively.

The set of input-output pairs that are used to train the neural network are obtained prior to the training process either by using physical measurements or by performing some kind of simulations. Figure 8 show that the teacher teaches the neural network to modify its weights according to the error ‘e’ between the outputs and the targets. The weights of the neural network are then modified iteratively according to equation (2). The general idea behind supervised learning and the mathematics involved has been adopted from Edmund (2016).

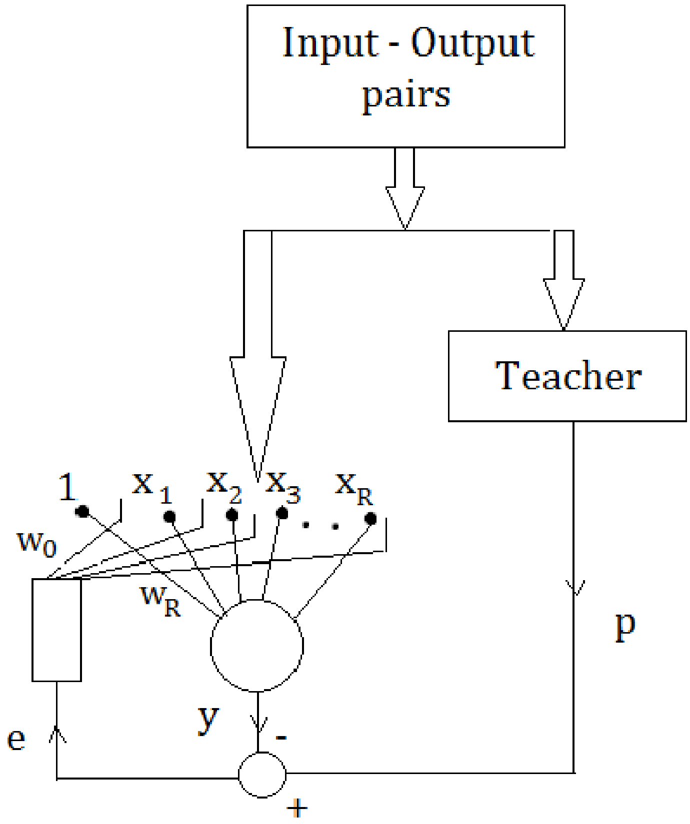

Figure 8: Scheme of supervised learning.

$$w_{ji}(n+1) = w_{ji}(n) + \Delta w_{ji}(n) \quad (1)$$

Where: wji(n) and wji(n+1) are the previous and the modified weights connected between the ith and the jth adjoining layers. Δwji(n) stands for the correction or modification factor and n stands for the number of iteration. Considering the jth neuron in a single layer neural network, the training efficiency is enhanced by minimizing the error between the actual output of the jth neuron and the output that has been dictated by the teacher. Let yj(n) and pj(n) be the actual and the teacher-requested outputs for the jth neuron in the nth iteration. Then the error value of that iteration is given by: equation (2),

$$e_j(n) = p_j(n) - y_j(n) \quad (2)$$

The vector **e** (n) that stores the values of all the errors is also a function of the weights **w**(n) for the corresponding layers' inputs. The value by which the weighing coefficients change (also called the correction factor) is given by the following equation (3.3),

$$\Delta w_{ji}(n) = \eta e_j(n) x_i(n) \quad (3)$$

Where: xi is the ith input signal and η is the rate at which the learning process takes place. As mentioned earlier, learning process aims at the minimization of the error function. The same criterion can also be achieved by the usage of a Least Square Method (LSM).

Hence, if there are L neurons in a particular network, the cost function to be ultimately minimized is given by (3.4),

$$S_2(\boldsymbol{w}) = \frac{1}{2}\sum_{j=1}^{L}\left(p_j - y_j\right)^2 \quad (4)$$

If the number of learning pairs with an input vector x(n) and an output vector d(n) of the form (x(n),d(n)) are P in the training set, then during the nth iteration of the learning process, then:

$$S_2(\boldsymbol{w}(n)) = \frac{1}{2}\sum_{n=1}^{P}\sum_{j=1}^{L}\left(p_j(n) - y_j(n)\right)^2 \quad (5)$$

Since the activation functions that are employed are more than often non-linear, minimization of the above equation (5) is a non-linear problem. Several numerical methods that can handle non-linear functions effectively are available and are based on the steepest-decent method. The steepest-decent method is an extension to the Laplace's method of integral approximation where the contour integral in a complex plane is deformed to approach a stationary point in the direction of the steepest decent. The back-error-propagation learning technique is based on the steepest-decent method and is usually widely applied in a version known as the Levenberg-Marquardt algorithm.

The back-error-propagation algorithm chooses random weights for the neural network nodes, feeds in an input pair and obtains the result. Then the error for each node is calculated starting from the last stage and by propagating the error backwards. Once this is done, the weights are updated and repeat the process with the entire set of input/output pairs available in the training data set. This process is continued till the network converges with respect to the desired targets. The back-error-propagation technique is widely used for several purposes including its application to error functions (other than the sum of squared errors) and for the evaluation of Jacobian and Hessian matrices. The correction values are calculated as functions of errors estimated from the minimization of equation (5). This process is carried out layer by layer throughout the network in the backward direction. This algorithm is pictorially depicted in Figure 9.

American Journal of Computing and Engineering
ISSN xxxx-xxxx (Paper) ISSN XXXX-XXX (Online)
Vol.1, Issue 1 No.1, pp 1 - 25, 2016

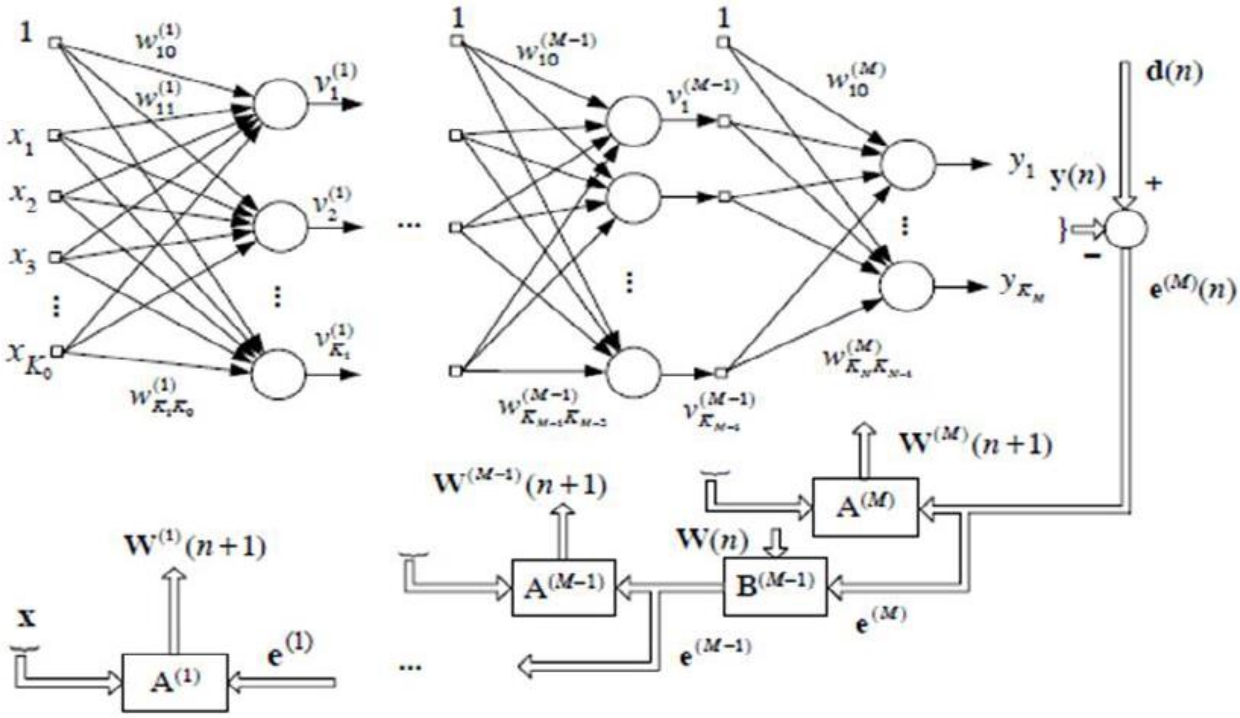

Figure 9: Structure of back-error-propagation algorithm

The corresponding weighing vectors are shown in blocks A $^{(M)}$, A$^{(M-1)}$,…, A$^{(1)}$ and the errors that are propagated to the lower layers are calculated and stored in the blocks B$^{(M-1)}$, B$^{(M-2)}$,…, B$^{(2)}$. The back-error-propagation algorithm has been implemented in many ways but the basic idea remains the same. The only thing that changes in each of these implementations is the method used for the calculation of the weights that are iteratively upgraded when passed backward from layer to layer in the neural network. The modifications involved are also used in the training process of recurrent networks. The rate at which the learning process takes place can be estimated by keeping a check on the correction values in successive stages. The total number of iterations required to achieve satisfactory convergence rate depends on the following factors:

- size of the neural network
- structure of the network
- the problem being investigated
- the learning strategy employed
- size of the training/learning set

The efficiency of a chosen ANN and the learning strategy employed can be estimated by using the trained network on some test cases with known output values. This test set is also a part of the learning set. Hence the entire set of data consists of the training data set along with the testing data set. The former is used to train the neural network and the latter is used to evaluate the performance of the trained artificial neural network.

American Journal of Computing and Engineering
ISSN xxxx-xxxx (Paper) ISSN XXXX-XXX (Online)
Vol.1, Issue 1 No.1, pp 1 - 25, 2016
www.ajpojournals.org

3.0 RESULTS AND DISCUSSION

3.1 Fault Detection

For the purpose of fault detection, various topologies of Multi-Layer Perceptron have been studied. The various factors that play a role in deciding the ideal topology are the network size, the learning strategy employed and the training data set size.

After an exhaustive study, the back-propagation algorithm has been decided as the ideal topology. Even though the basic back-propagation algorithm is relatively slow due to the small learning rates employed, few techniques can significantly enhance the performance of the algorithm. One such strategy is to use the Levenberg-Marquardt optimization technique. The selection of the apt network size is very vital because this not only reduces the training time but also greatly enhance the ability of the neural network to represent the problem in hand. Unfortunately there is no thumb rule that can dictate the number of hidden layers and the number of neurons per hidden layer in a given problem.

3.1.1 Training the Fault Detection Neural Network

In the first stage which is the fault detection phase, the network takes in six inputs at a time, which are the voltages and currents for all the three phases (scaled with respect to the pre-fault values) for ten different faults and also no-fault case. Hence the training set consisted of about 1100 input output sets (100 for each of the ten faults and 100 for the no fault case) with a set of six inputs and one output in each input-output pair. The output of the neural network is just a yes or a no (1 or 0) depending on whether or not a fault has been detected. After extensive simulations it has been decided that the desired network has one hidden layer with 10 neurons in the hidden layer. For illustration purposes, several neural networks (with varying number of hidden layers and neurons per hidden layer) that achieved satisfactory performance are shown and the best neural network has been described further in detail. Figures 10 – 11 show the error performance plots of neural networks with 1 and 2 hidden layers respectively. The chosen network has been depicted in Figure 16 and the various error performance plots have been shown in Figures 11 – 16.

Figure 10 shows the training performance plot of the neural network 6-10-1 (6 neurons in the input layer, 1 hidden layer with ten neurons in it and one neuron in the output layer). It can be seen that the network did not achieve the desired Mean Square Error (MSE) goal by the end of the training process.

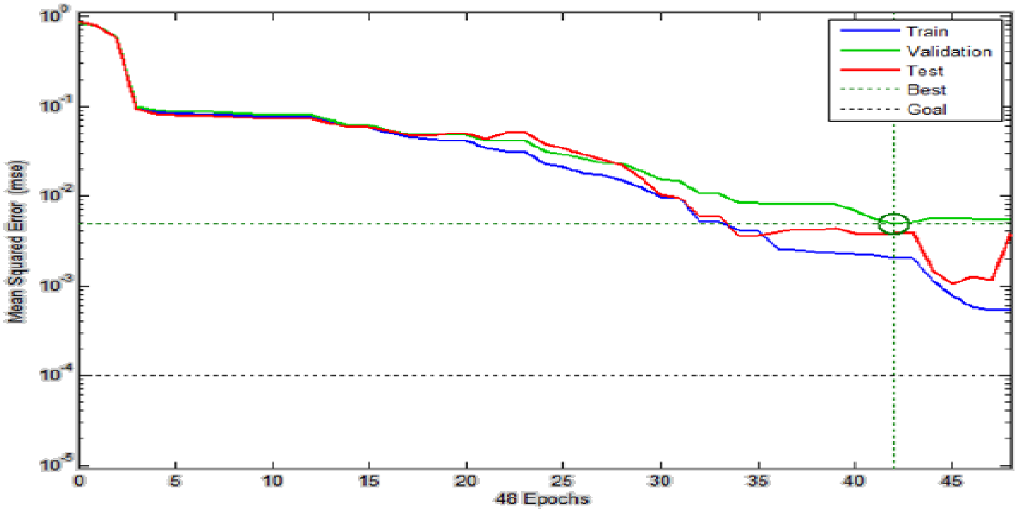

Figure 10: Mean-square error performance of the network (6-10-1).

Figure 11 shows the training performance plot of the neural network with 6-10-5-1 configuration (6 neurons in the input layer, two hidden layers with 10 and 5 neurons respectively and one neuron in the output layer). It is to be noted that the neural network could not achieve the MSE goal of 0.0001 by the end of the training process.

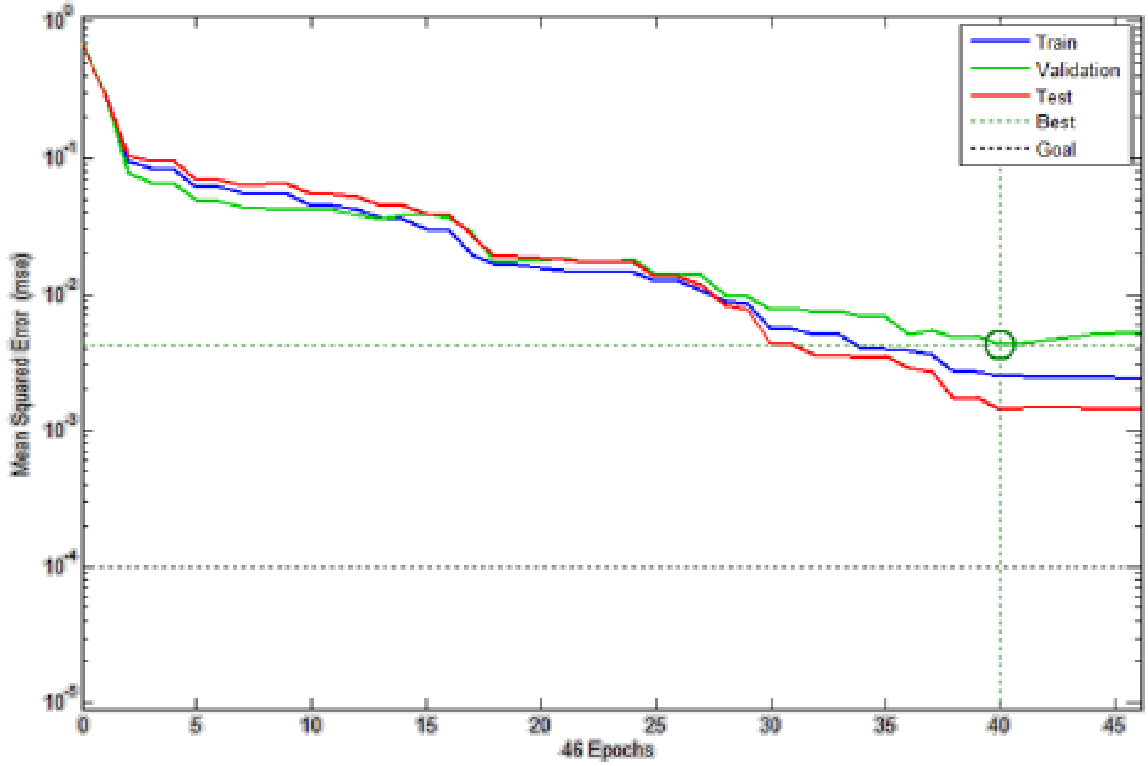

Figure 11: Mean-square error performance of the network (6-10-5-1).

Figure 12 shows the training process of the neural network with 6-10-5-3-1 configuration (6 neurons in the input layer, 3 hidden layers with 10, 5 and 3 neurons in them respectively and one neuron in the output layer).

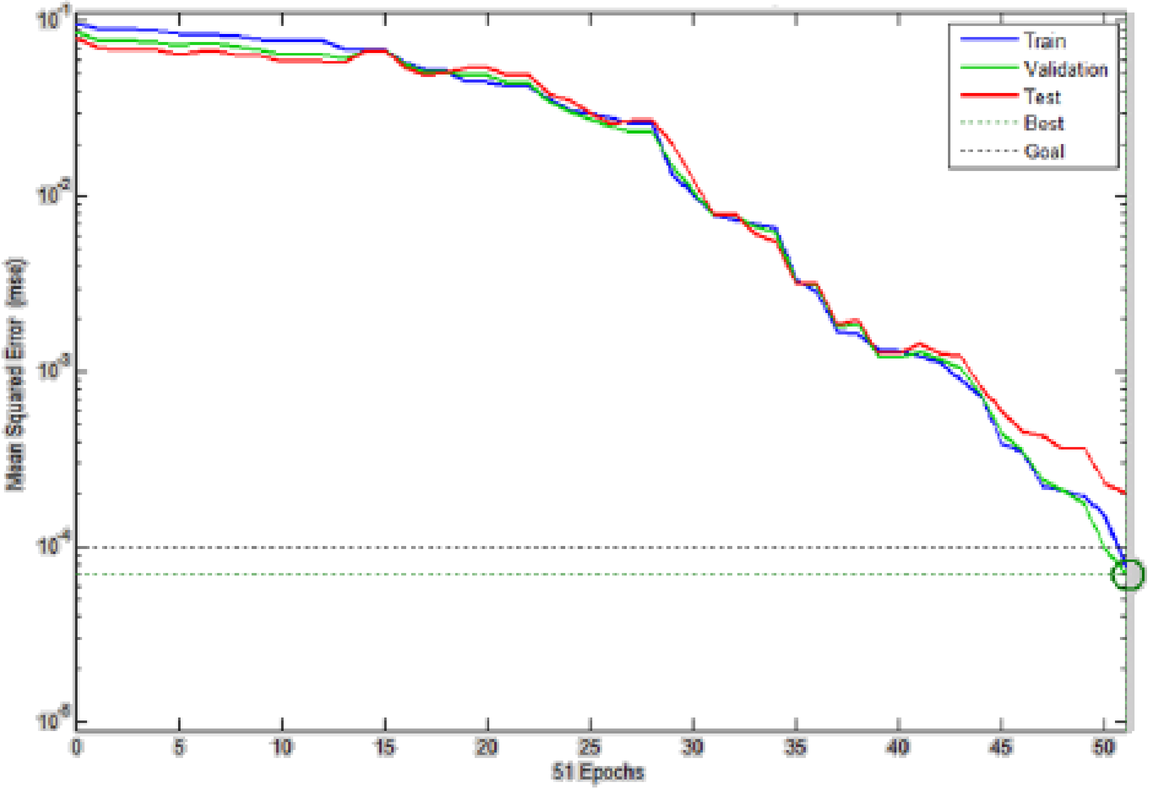

Figure 12: Mean-square error performance of the network (6-10-5-3-1).

From the above training performance plots, it is to be noted that very satisfactory training performance has been achieved by the neural network with the 6-10-5-3-1 configuration (6 neurons in the input layer, 3 hidden layers with 10, 5 and 3 neurons in them respectively and one neuron in the output layer). The overall MSE of the trained neural network is way below the value of 0.0001 and is actually 6.9776 e-5 by the end of the training process. Hence this has been chosen as the ideal ANN for the purpose of fault detection.

3.1.2 Testing the Fault Detection Neural Network

Once the neural network has been trained, its performance has been tested by three different factors. The first of these is by plotting the best linear regression that relates the targets to the outputs as shown in Figure 13.

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Vol.1, Issue 1 No.1, pp 1 - 25, 2016
www.ajpojournals.org

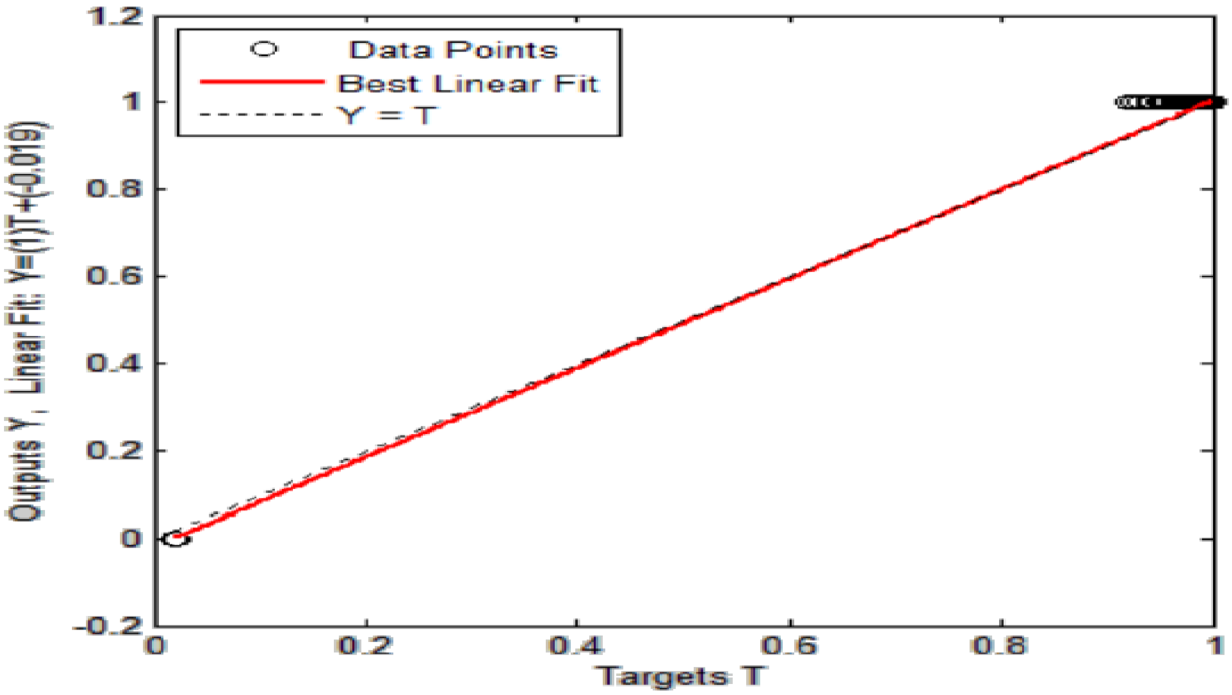

Figure 13: Regression fit of the outputs vs. targets for the network (6-10-5-3-1).

The correlation coefficient (r) is a measure of how well the neural network's targets can track the variations in the outputs (0 being no correlation at all and 1 being complete correlation). The correlation coefficient in this case has been found to be 0.99967 in this case which indicates excellent correlation.

The second means of testing 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. Figure 14 plots the confusion matrix for the three phases of training, testing and validation. The diagonal cells in green indicate the number of cases that have been classified correctly by the neural network and the off diagonal cells which are in red indicate the number of cases that have been wrongly classified by the ANN. The last cell in blue in each of the matrices indicates the total percentage of cases that have been classified correctly in green and the vice-verca in red. It can be seen that the chosen neural network has 100 percent accuracy in fault detection.

American Journal of Computing and Engineering
ISSN xxxx-xxxx (Paper) ISSN XXXX-XXX (Online)
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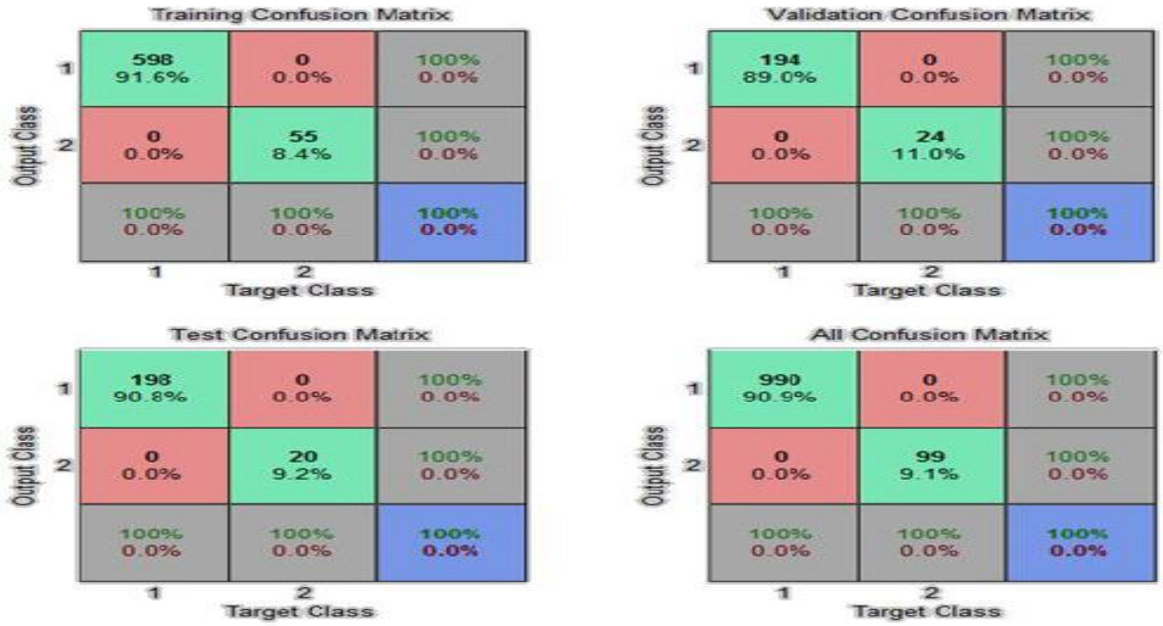
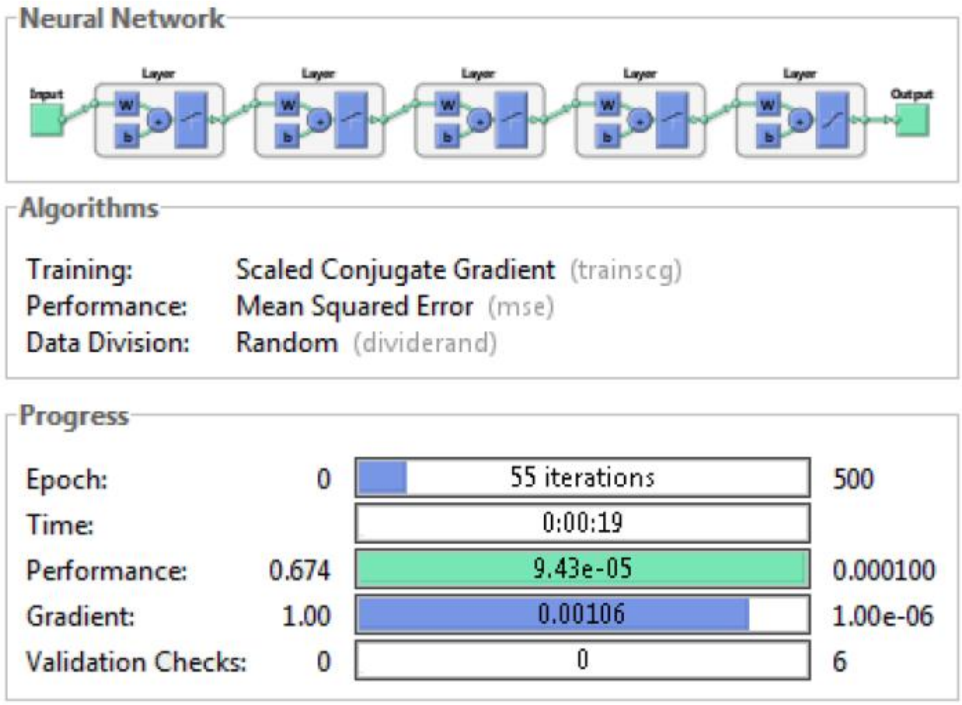


Figure 14: Confusion matrices for Training, Testing and Validation Phases.

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 200 cases corresponding to different types of faults (about 20 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 100 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 a 100 percent. Hence the neural network can, with utmost accuracy, differentiate a normal situation from a fault condition on a transmission line.



American Journal of Computing and Engineering
ISSN xxxx-xxxx (Paper) ISSN XXXX-XXX (Online)
Vol.1, Issue 1 No.1, pp 1 - 25, 2016

Figure 15: Overview of the ANN (6-10-5-3-1) chosen for fault detection.

Figure 15 presents a snapshot of the trained ANN with the 6 – 10 – 5 – 3 – 1 configuration and it is to be noted that the number of iterations required for the training process were 55. It can be seen that the mean square error in fault detection achieved by the end of the training process was 9.43e-5 and that the number of validation check fails were zero by the end of the training process.

The structure of the chosen neural network for fault detection is shown in Figure 16 with the input layer, hidden layers and the output layer labeled. It is to be noted that there are 6 neurons in the input layer, 3 hidden layers with 10, 5 and 3 neurons in them respectively and one neuron in the output layer.

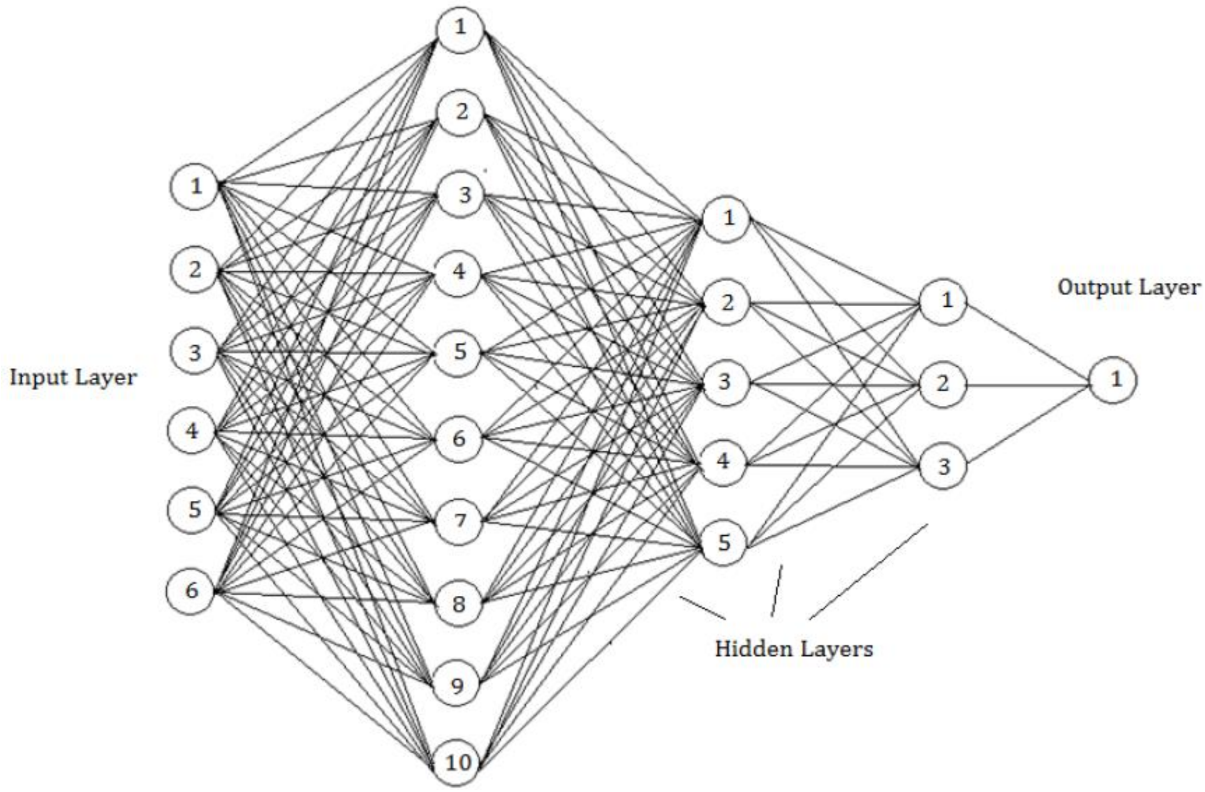


Figure 16: Chosen ANN for Fault Detection (6 – 10 – 5 – 3 – 1)

3.2 Fault Classification

Once a fault has been detected on the power line, the next step is to identify the type of fault. This section presents an analysis on the fault classification phase using neural networks. A review of the different neural networks that were analyzed is provided which is followed by the chosen network.

Fault classifiers based on neural networks have been extensively proposed and used in the past and almost all of these classifiers made use of multilayer perceptron neural network and employed the back-propagation learning strategy. Although back propagation learning

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Vol.1, Issue 1 No.1, pp 1 - 25, 2016 www.ajpojournals.org

strategy is inherently slow in learning and poses difficulty in choosing the optimal size of the network, it is undoubtedly the ideal strategy to be employed when there is a large training set available because back-propagation algorithm can provide a very compact distributed representation of complex data sets.

3.2.1 Training the Fault Classifier Neural Network

The same process that was employed in the previous section is also followed in this section in terms of the design and development of the classifier neural network. The designed network takes in sets of six inputs (the three phase voltage and current values scaled with respect to their corresponding pre-fault values). 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 absence or presence of a fault on the corresponding line (A, B, C or G where A, B and C denote the three phases of the transmission line and G denotes the ground).

Hence the various possible permutations can represent each of the various faults accordingly. The proposed neural network should be able to accurately distinguish between the ten possible categories of faults. The truth table representing the faults and the ideal output for each of the faults is illustrated in Table 1.

American Journal of Computing and Engineering
ISSN xxxx-xxxx (Paper) ISSN XXXX-XXX (Online)
Vol.1, Issue 1 No.1, pp 1 - 25, 2016

Table 1: Fault classifier ANN outputs for various faults.

Type of Fault	Network Outputs			
	A	B	C	G
A-G fault	1	0	0	1
B-G fault	0	1	0	1
C-G Fault	0	0	1	1
A-B Fault	1	1	0	0
B-C Fault	0	1	1	0
C-A Fault	1	0	1	0
A-B-G fault	1	1	0	1
B-C-G Fault	0	1	1	1
C-A-G Fault	1	0	1	1
A-B-C Fault	1	1	1	0

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Hence the training set consisted of about 1100 input output sets (100 for each of the ten faults and 100 for the no fault case) with a set of six inputs and one output in each input-output pair. Back-propagation networks with a variety of combinations of hidden layers and the number of neurons per hidden layer have been analyzed. Of these, the ones that achieved satisfactory performance are shown followed by the best neural network which has been described further in detail. Figures 17 – 21 show the error performance plots of neural networks with 1 and 2 hidden layers respectively.

Figure 17 shows the training performance plot of the neural network 6-5-5-31-4 (6 neurons in the input layer, 3 hidden layers with 5, 5 and 31 neurons in them respectively and four neurons in the output layer). It can be seen that the best validation performance in terms of the Mean Square Error (MSE) by the end of the training process is 0.01289.

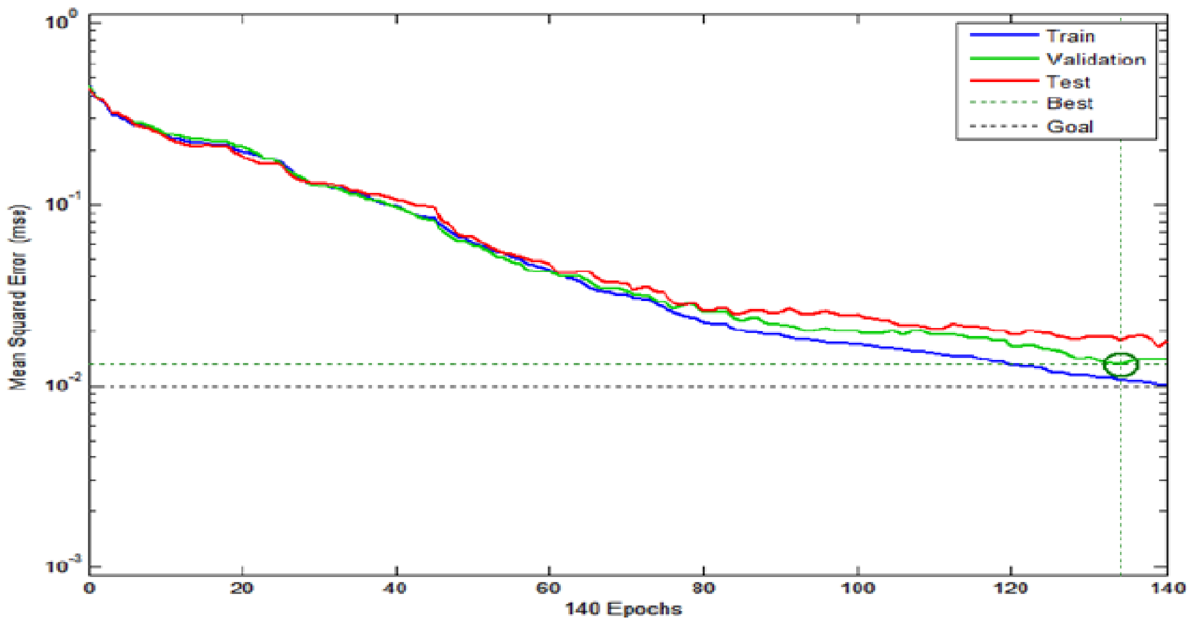

Figure 17: Mean-square error performance of the network with configuration (6-5-5-31-4).

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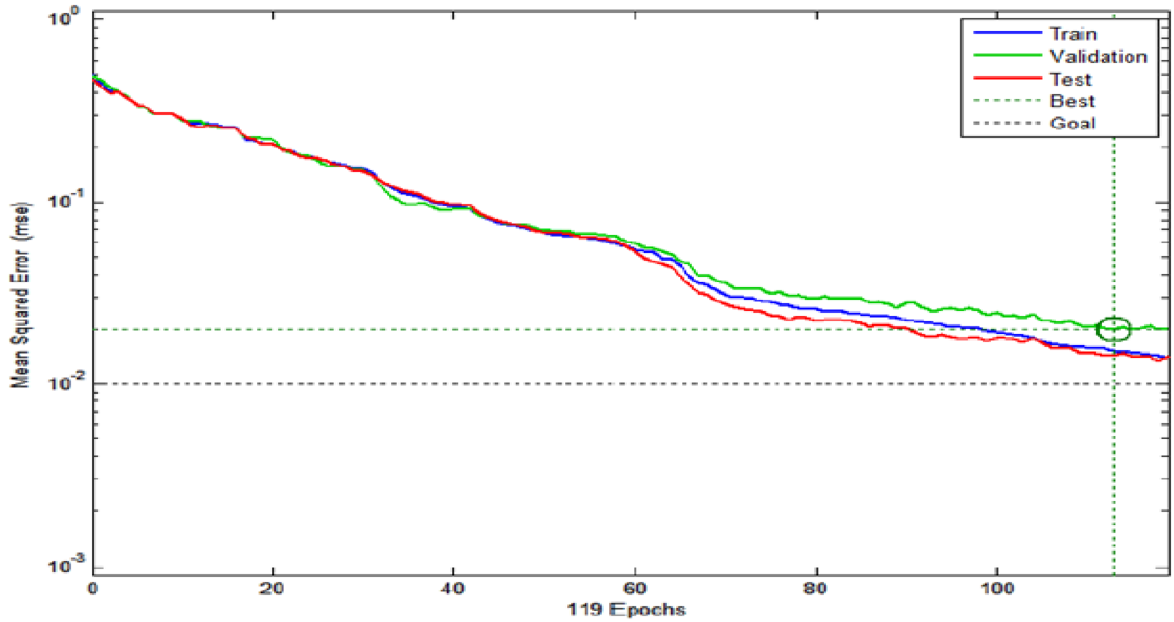

Figure 18: Mean-square error performance of the network with configuration (6-5-31-4).

Figure 18 shows the training performance plot of the neural network 6-5-31-4 (6 neurons in the input layer, 2 hidden layers with 5 and 31 neurons in them respectively and four neurons in the output layer). It can be seen that the best validation performance in terms of the Mean Square Error (MSE) by the end of the training process is 0.019773.

Figure 19 shows the training performance plot of the neural network 6-5-4 (6 neurons in the input layer, 1 hidden layer with 5 neurons in it and four neurons in the output layer). It can be seen that the best validation performance in terms of the Mean Square Error (MSE) by the end of the training process in this case is 0.029578.

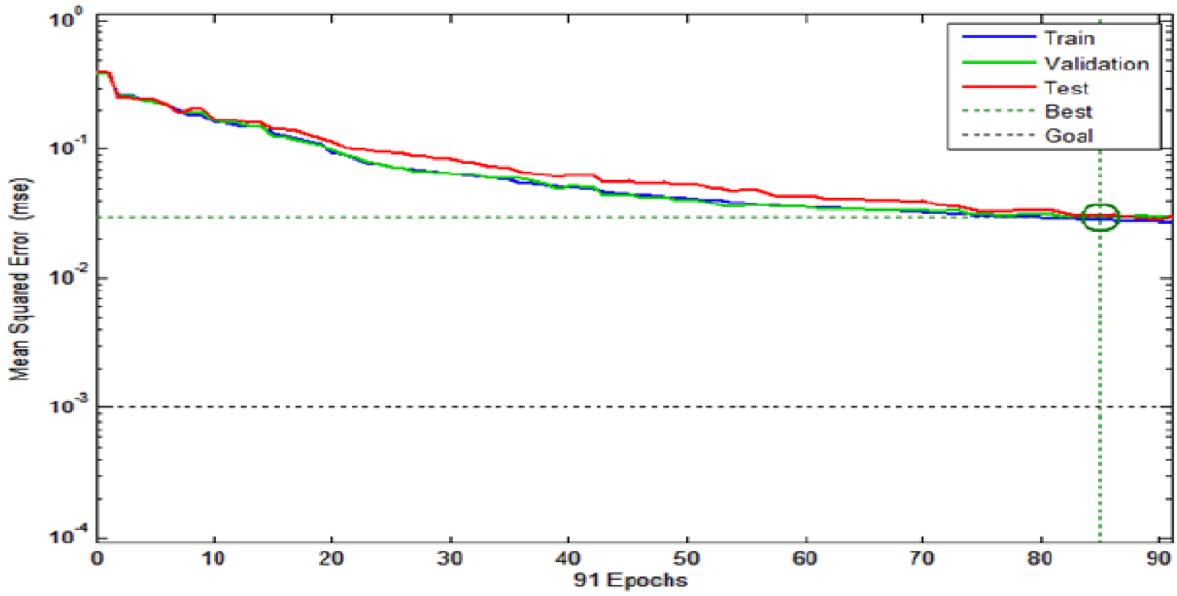

Figure 19: Mean-square error performance of the network with configuration (6-5-4).

Figure 20 shows the training performance plot of the neural network 6-10-4 (6 neurons in the input layer, 1 hidden layer with 10 neurons in it and four neurons in the output layer). It can be seen that the best validation performance in terms of the Mean Square Error (MSE) by the end of the training process in this case is 0.0077.

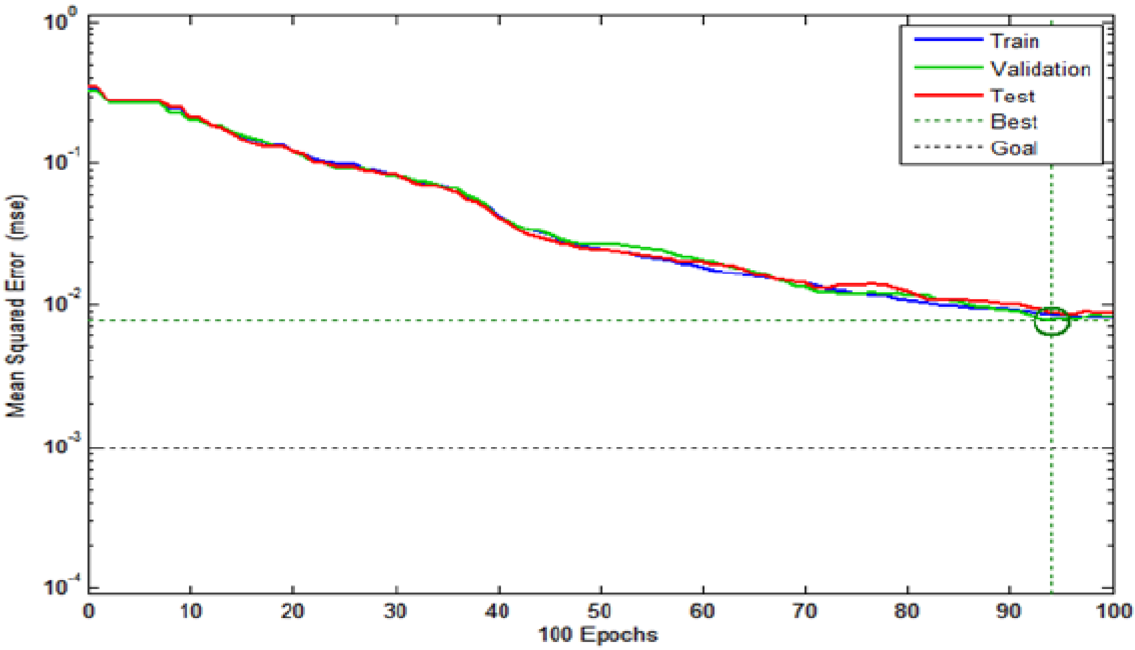

Figure 20: Mean-square error performance of the network with configuration (6-10-4).

Figure 21 shows the training performance plot of the neural network 6-20-4 (6 neurons in the input layer, 1 hidden layer with 20 neurons in it and four neurons in the output layer). It can be seen that the best validation performance in terms of the Mean Square Error (MSE) by the end of the training process in this case is 0.0093975.

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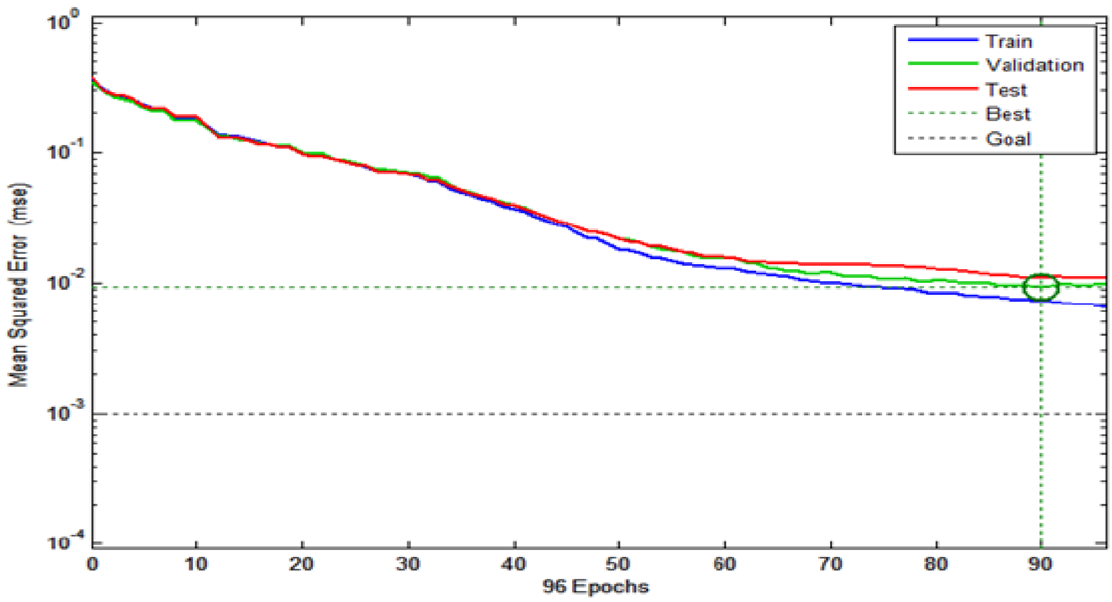

Figure 21: Mean-square error performance of the network with configuration (6-20-4).

Figure 22 shows the training performance plot of the neural network 6-35-4 (6 neurons in the input layer, 1 hidden layer with 35 neurons in it and four neurons in the output layer). It can be seen that the best validation performance in terms of the Mean Square Error (MSE) by the end of the training process in this case is 0.00359.

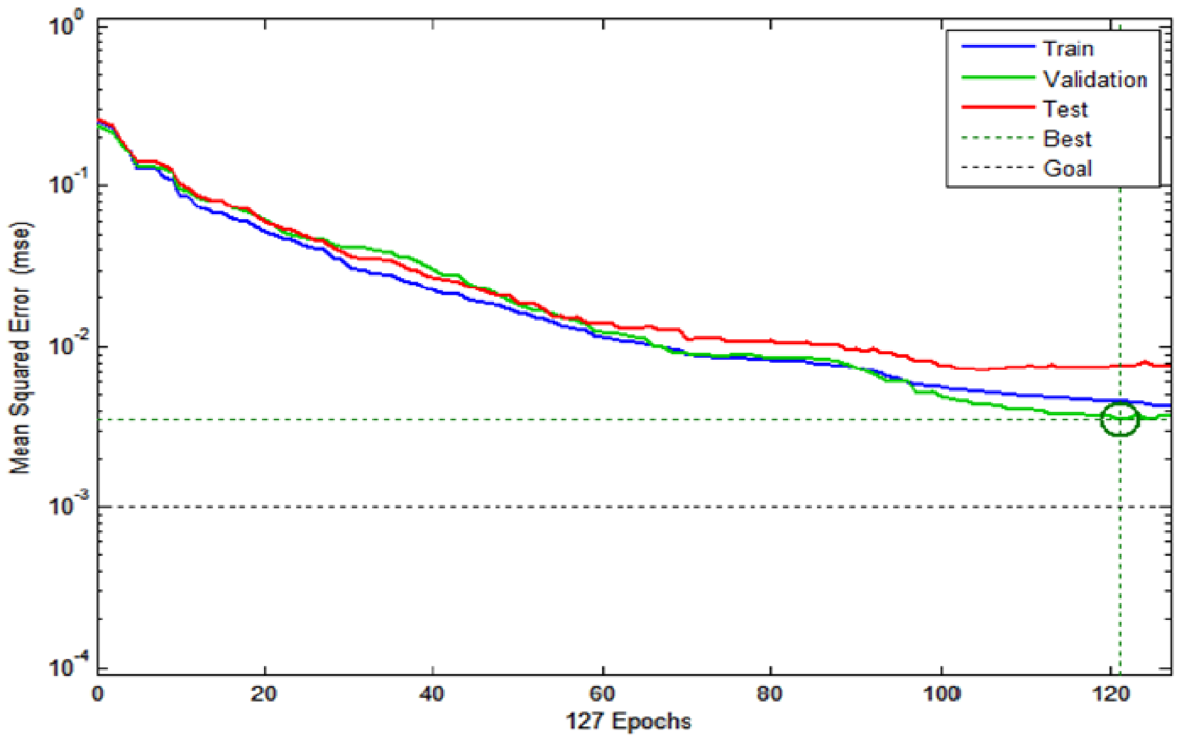

Figure 22: Mean-square error performance of the network with configuration (6-35-4).

From the above training performance plots, it is to be noted that satisfactory training performance has been achieved by the neural network with the 6-35-4 configuration (6 neurons in the input layer, 35 neurons in the hidden layer and one neuron in the output layer). The overall MSE of the trained neural network is 0.0035986 and it can be seen from Figure 22 that the testing and the validation curves have similar characteristics which is an indication of efficient training. Hence this has been chosen as the ideal ANN for the purpose of fault classification.

4.0 CONCLUSIONS

This paper has studied the usage of hybrid neural networks as an alternative method for the detection, classification and location of faults on transmission lines. The methods employed make use of the phase voltages and phase currents (scaled with respect to their pre-fault values) 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 separate ANNs have been proposed for each of these faults.

All the neural networks investigated in this paper belong to the back-propagation neural network architecture. A fault diagnosis scheme for the transmission line system, right from the detection of faults on the line to the fault location stage has been devised successfully by using hybrid artificial neural-network modules.

The present study made significant contribution to knowledge by developing an enhanced back error-propagation algorithm as the basic algorithm in which the neuron weights are adjusted in consecutive steps to minimize the error between the actual and the desired outputs. This process is known as supervised learning. Since back propagation neural networks are very efficient when a sufficiently large training data set is available, it has been chosen for all the three steps in the fault location process namely fault detection, classification and fault location.

As a possible extension to this work, it would be quite useful to analyze all the possible neural network architectures and to provide a comparative analysis on each of the architectures and their performance characteristics. The possible neural network architectures that can be analyzed apart from back propagation neural networks are radial basis neural network (RBF) and support vector machines (SVM) networks.

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