ISSN No:-2456 –2165

Single Phase to Ground Fault Location on 415v Distribution Lines using Artificial Neural Network Algorithm

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Abstract:-This paper proposes an algorithm for detecting, classifying and locating single phase to ground faults on electric power 415 volts distribution lines. Feedforward artificial neural networks have been employed along with backpropagation algorithm for each of the three steps in the fault location process which are fault detection, fault classification and fault location. To validate the proposed algorithm, the Michael Okpara University of Agriculture Umudike plant house to new female hostel415 volts distribution line is modelled using Power System Computer Aided Design power systems analysis tool.Simulation results have demonstrated that the fault location method has high accuracy and good robustness. 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 was near precision. The confusion matrices show that the chosen neural network has 100 percent accuracy in fault detection. The artificial neural network chosen for fault detection, fault classification and fault location satisfies the mean square errorgoal of 0.001 by approximately 100 percent. The overall correlation coefficient of the various phases of training, validation and testing for the artificial neural network chosen for fault detection, fault classification and fault location is averagely 99 percent which indicates that the neural network target is able to track the variations in the neural networks outputs very well. The gradient and validation performance plots shows a steady decrease in the gradient and the number of validation fails is zero which indicates smooth and efficient training. This further implies that the neural network can generalize new data fed into it more effectively. The test phase performance shows that the average percentage error obtained for the neural network chosen for fault location for the single phase to ground faults is below 0.5 percent which is very satisfactory and thus the neural network can be used for the purpose of single phase to ground fault location.

Keywords:-Distribution lines, Fault Location, Artificial Neural Network, Single Phase to Ground Fault, PSCAD, MATLAB, ANN, MSE.s

I. INTRODUCTION

The energy progression involves producing the energy, its transmission, and delivering the energy to the end user where the distribution feeders are the latter entities of this energy progression. The significance of the distribution system is no less than the energy production and transmission parts in the electrical power system if not greater. Therefore, numerous economic experts believe that the distribution system should be taken into consideration more earnestly as the entire struggle to generate electrical power is with the purpose of delivering it to the end users. The reliability of the provided electrical energy is one of the provoking and paramount issues of concern to the customer. Also, electric utilities wish to reduce the revenue loss due to outage caused by faults. To achieve this goal, the distribution system has to be highly dependable and effective both under normal and fault situations.

Customer Average Interruption Duration Index induced by faults in the distribution system is one of the factors that influence the reliability index. To be able to improve the reliability, utility companies should be able to detect and identify the fault type and location at short notice after the manifestation of fault. The quicker the fault location is identified or at minimum projected with reasonable certainty, the more hastened the maintenance time to restore normal energy supply.

In conventional methods of locating faults, calls from customers are the fundamental of outage troubleshooting.This means that the utility starts to identify faults when they are briefed by end users about a fallen electric pole, broken cable or when they receive complaints about a cut in power supply. Furthermore, the utility might not receive any callsif the fault occurs during the night-time, which creates a hindrance for the operator in locating the fault.

Fault locating in power systems has been a major subject for power and protection engineers in recent years for the reason of system reliability. Power engineers devote a lot of time to develop different fault locating algorithms in order to overcome this challenge in power systems.Owing to large variations of fault impedance in distribution systems, fault location problem has more complications than in transmission and generation systems.Furthermore, it is not economically viable to equip distribution networks with advanced high-cost protection equipment.

System reliability can be improved by utilizing an accurate fault location program which leads to reduce the average time for the field crew to find and isolate the faults more efficiently. Fault location algorithms may have a huge impact on system reliability by reducing the duration of unexpected outages caused by faults. By reducing unexpected outages in distribution systems due to faults and the average time for the field crew to find and isolate the faults, the cost of maintaining distribution systems is thus minimised.

The aim of this research is to study and successfully design an artificial neural network fault location algorithm that can detect single phase to ground faults on 415V distribution lines. Artificial Neural Network is a knowledge based fault location algorithm which is beneficial when compared to other mathematical approaches because of its capability to map non-linear input data. Its non-deterministic procedure to solve a problem makes artificial neural network a robust tool even when it is presented with unexpected input data.

II. METHODS

The 415volts distribution line from university plant house to new female hostel of Michael Okpara University of Agriculture Umudike, Nigeria is modelled using Power System Computer Aided Design (PSCAD) and fault cases generated. Artificial Neural Network is used to simulate the network for the purpose of fault location. The artificial neural networks toolbox in MATLAB R2014A has been used extensively in order to train and analyse the performance of the neural networks. This neural network is trained with suitable fault parameters. These parameters change regularly with fault type and distance variations.

A. PSCAD Fault Data Simulation

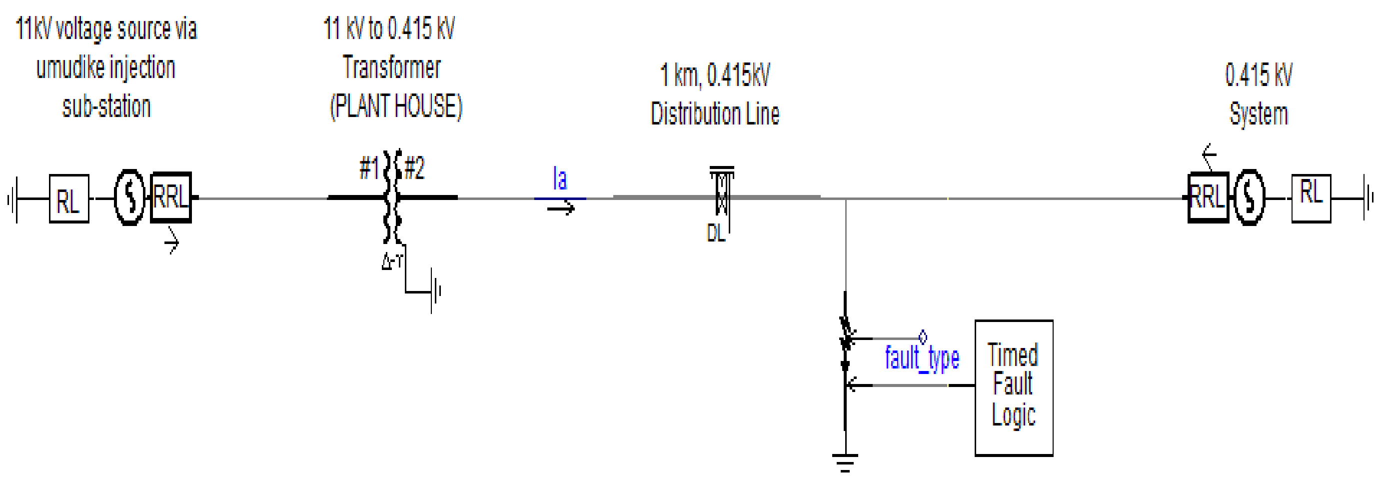


Figure 2.1: Model of the Power Distribution Line Under Study

Figure 2.1 shows the one line diagram of the power distribution line model simulated to obtain the training fault data set. The current present during a fault is among other things, a function of the point on wave at which the fault occurs and the type of fault. The fault types are simulated by changing the fault type parameter in the fault module. The PSCAD is used to simulate the fault types and no fault condition.The multiple runfeatures is used to activate different fault types at different points on the voltage waveform. The fault location was varied by changing the length parameter of the distribution line. Each time a distribution line parameter is changed, the distribution line constants have to be solved and the distribution line batch has to be saved. In simulating various fault locations, distribution line batches with length parameter of 200m, 400m, 600m, 800m and 1000m were saved with different distribution line names. The result of each simulation was saved in a file with distinctive name reflecting the distance and its fault case. The saved file contains data in columns. The first column is run, the second column is time, the third column is the fault type and the fourth is the current output. After all the fault cases were collected, data were extracted and organised for training using MATLAB application software.

B. Fault Location in Distribution Lines

The excellent pattern recognition and classification abilities of neural networks have been utilized in this paper to address the issue of distribution line fault location. Artificial neural network toolbox has been used extensively in order to train and analyse the performance of the neural networks. To achieve the purpose of distribution line fault location, the original problem has been dealt with in three different stages namely fault detection, fault classification and fault location.

ISSN No:-2456 –2165

- The fault resistance has been calculated and varied as: 0.056Ω, 0.112Ω, 0.168Ω, 0.224Ω and 0.28Ω using the formulae R = $\frac{\delta L}{A}$ where δ = Resistivity = 2.8 × $10^{-8}\Omega^{-m}$L=Length of distribution line and A= Cross-Sectional area of the conductor = 100mm^2
- Fault distance has been varied at an incremental factor of every 200m on a 1000m,415 volts distribution line from MOUAU Plant House to New Female Hostel distribution board.

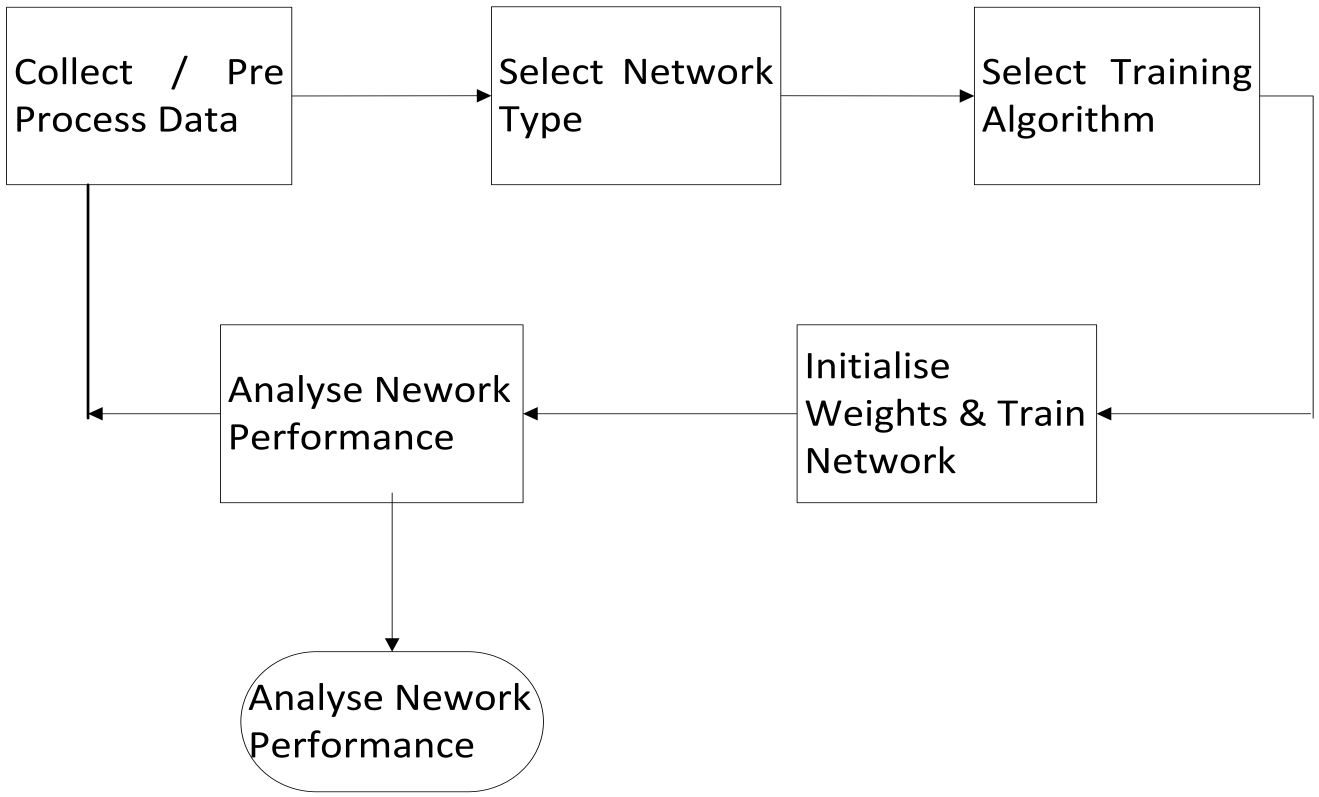


Figure 2.2: Block Diagram of Neural Network Training Procedure

Figure 2.2 is the block diagram of neural network procedure which describes the training procedure employed by artificial neural network for training of neural network input data.

C. Training and Test Data

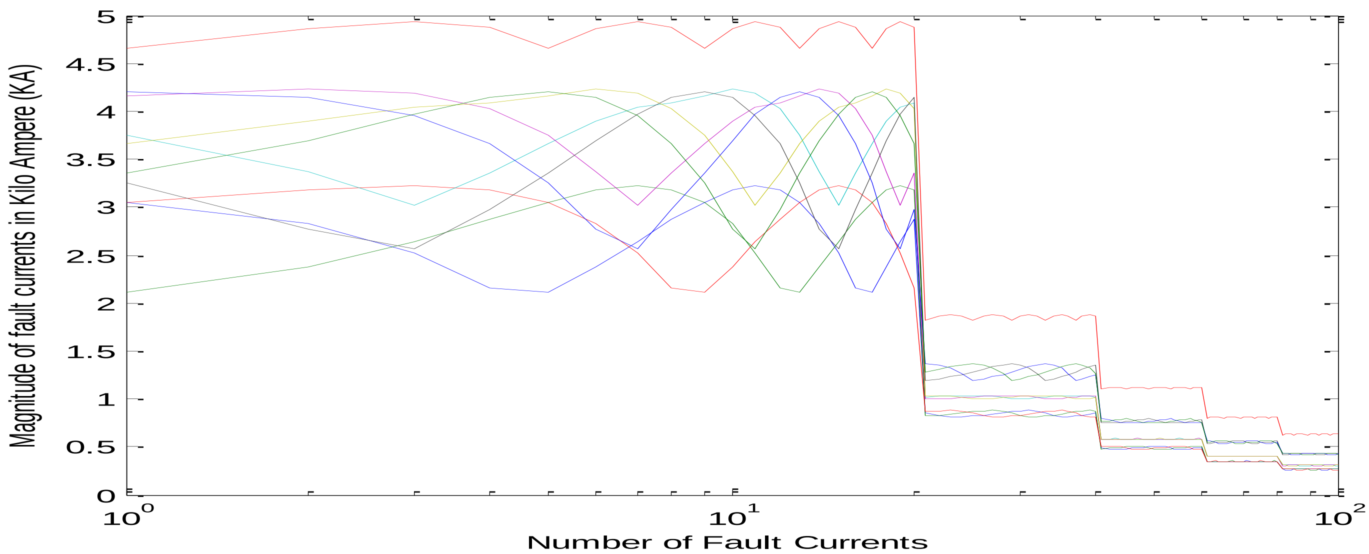
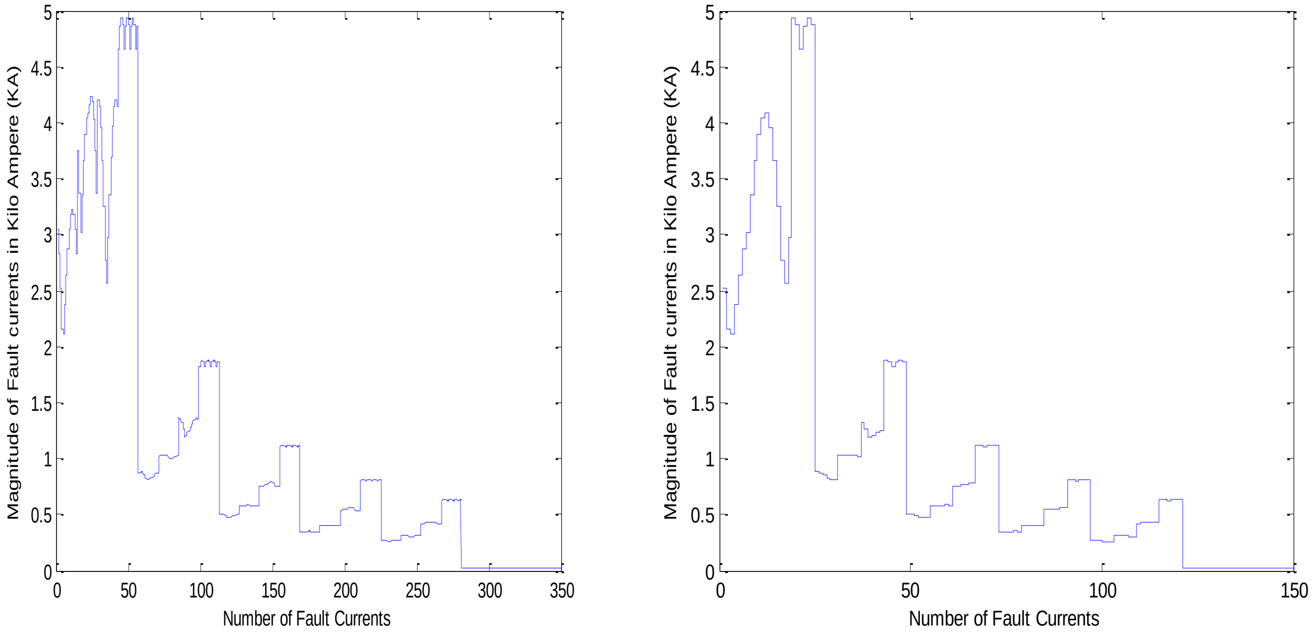


Figure 2.3: Plot of the Entire Generated Fault Data

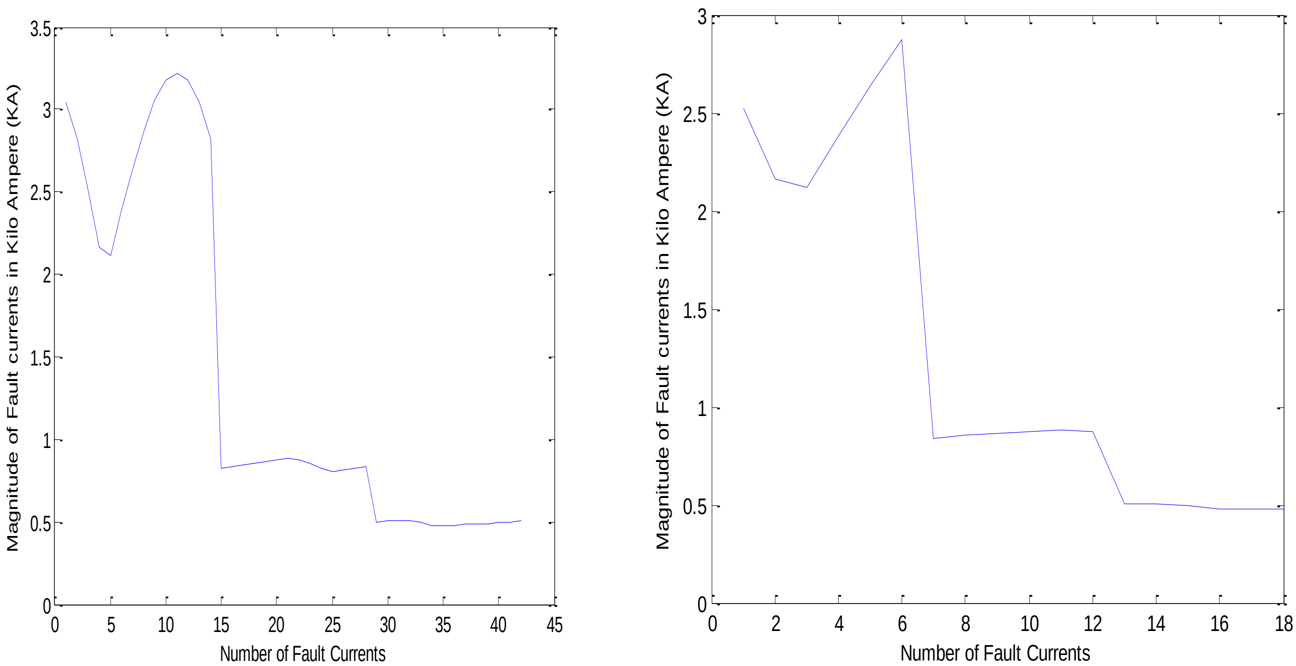
Figure 2.3 shows the plot of the entire generated fault data. The horizontal axis indicates the number of fault currents generated for each fault type over a distribution line of 1000m with a separation of 200m each on the line and the vertical axis represents the magnitude of fault currents.



(a)Training data (b) Test data

Figure 2.4: Plots of the Training and Test Data for Fault Detection Neural Network

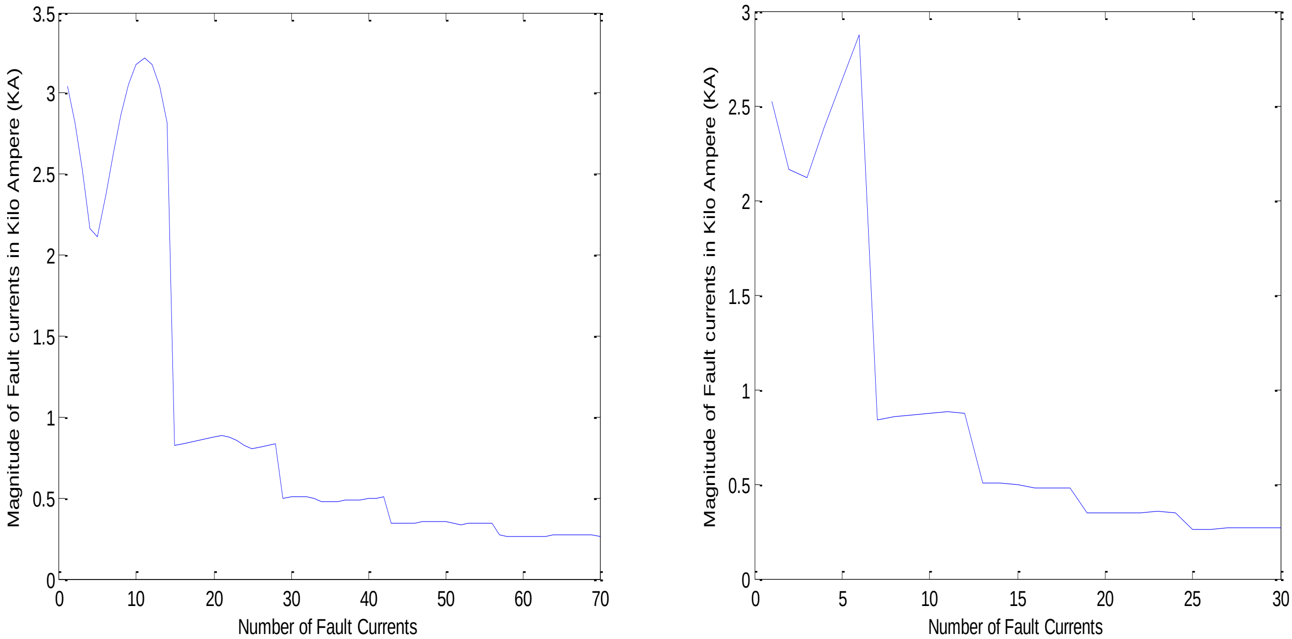
Figure 2.4 shows the plots of the artificial neural network training and test data for fault detection. The horizontal axis represents number of fault currents and the vertical axis represents the magnitude of fault currents.



(a) Training data (b) Test data

Figure 2.5:Plots of the Training and Test Data for L-G Fault Classification Neural Network

Figure 2.5 shows the plots of the training and test data for single phase to ground fault classification artificial neural network. The horizontal axis represents number of fault currents and the vertical axis represents the magnitude of fault currents.



(a) Training data (b) Test data

Figure 2.6:Plots of the Training and Test Data for L-G Fault Location Neural Network

Figure 2.6 shows the Plots of the training and test data for single phase to ground fault location artificial neural network. The horizontal axis represents number of fault currents and the vertical axis represents the magnitude of fault currents.

III. RESULTS

In this section, the results of the Artificial Neural Network (ANN) training and testing is elaborated and analysed with respect to single phase to ground fault location on distribution lines. This section is subdivided into fault detection, fault classification and fault location.

A. Fault Detection Results

a). Training of the Fault Detection Neural Network

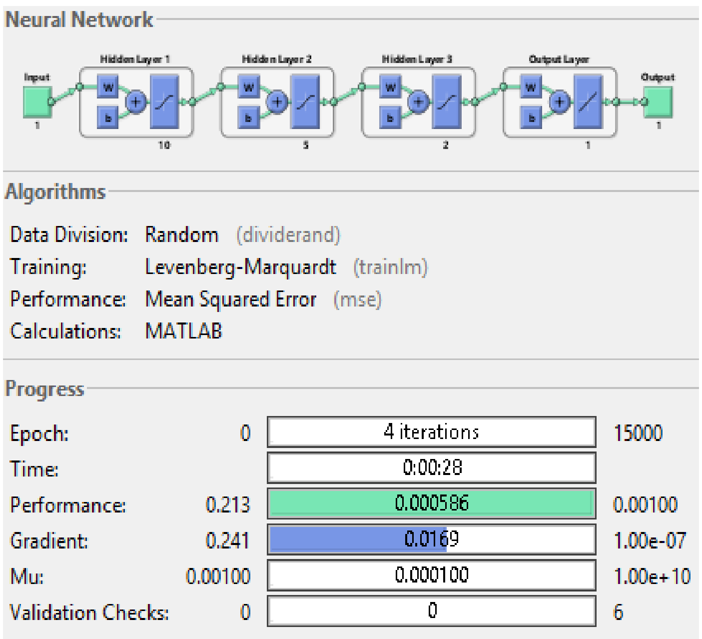


Figure 3.1: ANN Chosen for Fault Detection(1-10-5-2-1)

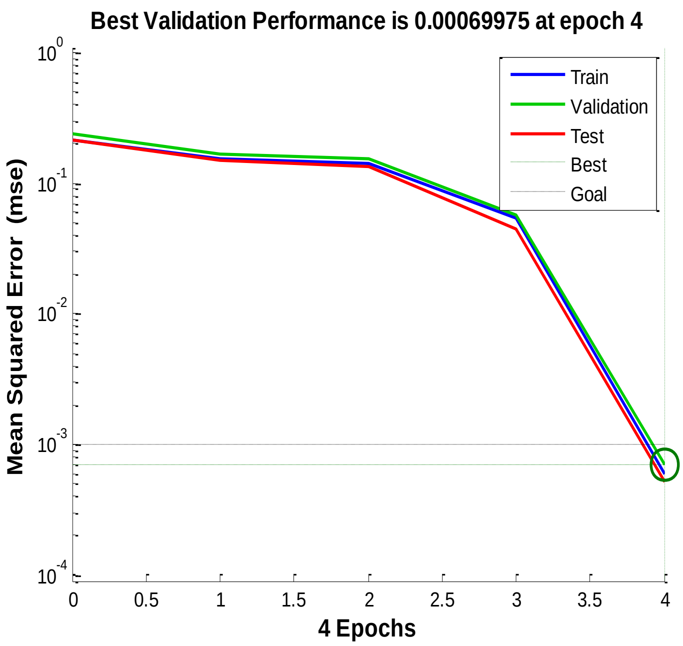


Figure 3.2: MSE Performance of the Network (1-10-5-2-1)

Figure 3.1 presents the trained ANN with the 1-10-5-2-1 configuration chosen for fault detection.Figure 3.2 shows the Mean Square Error(MSE) performance plot of the neural network 1-10-5-2-1 chosen for fault detection.

b). Testing the Fault Detection Neural Network

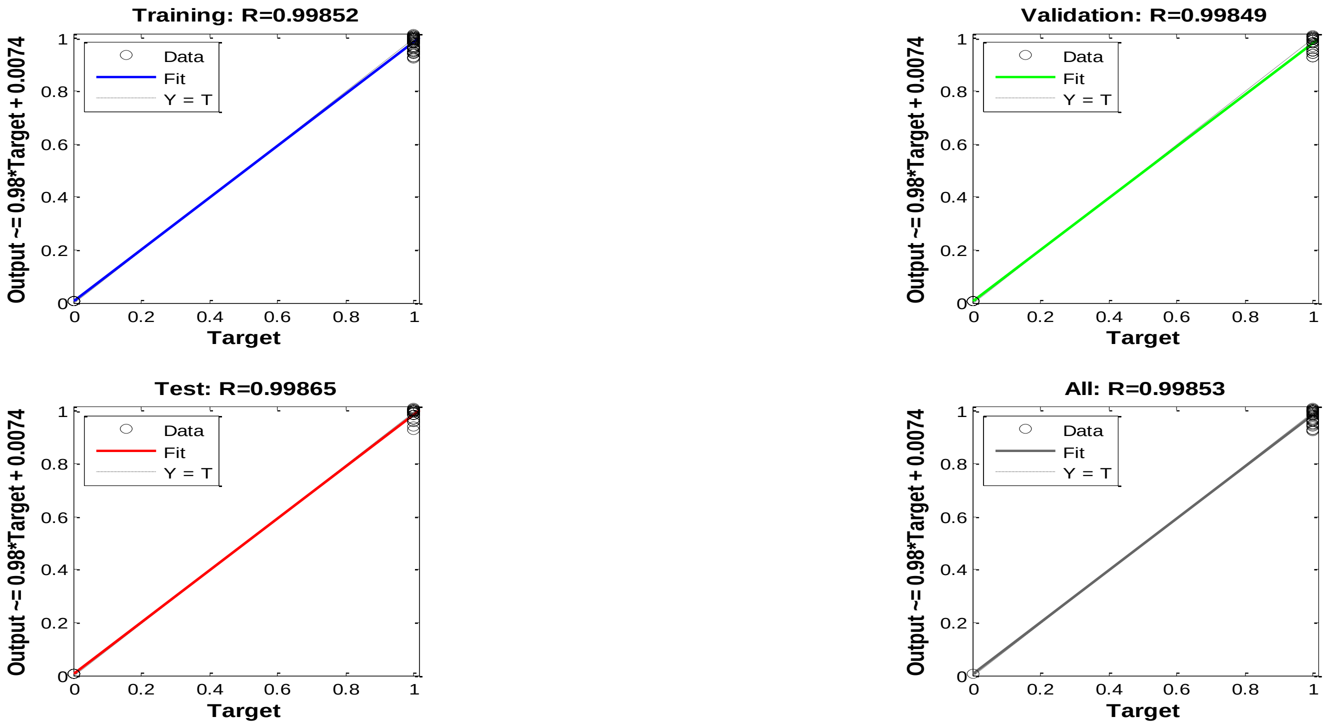


Figure 3.3:Regression fit of the Outputs vs. Targets for the Network (1-10-5-2-1)

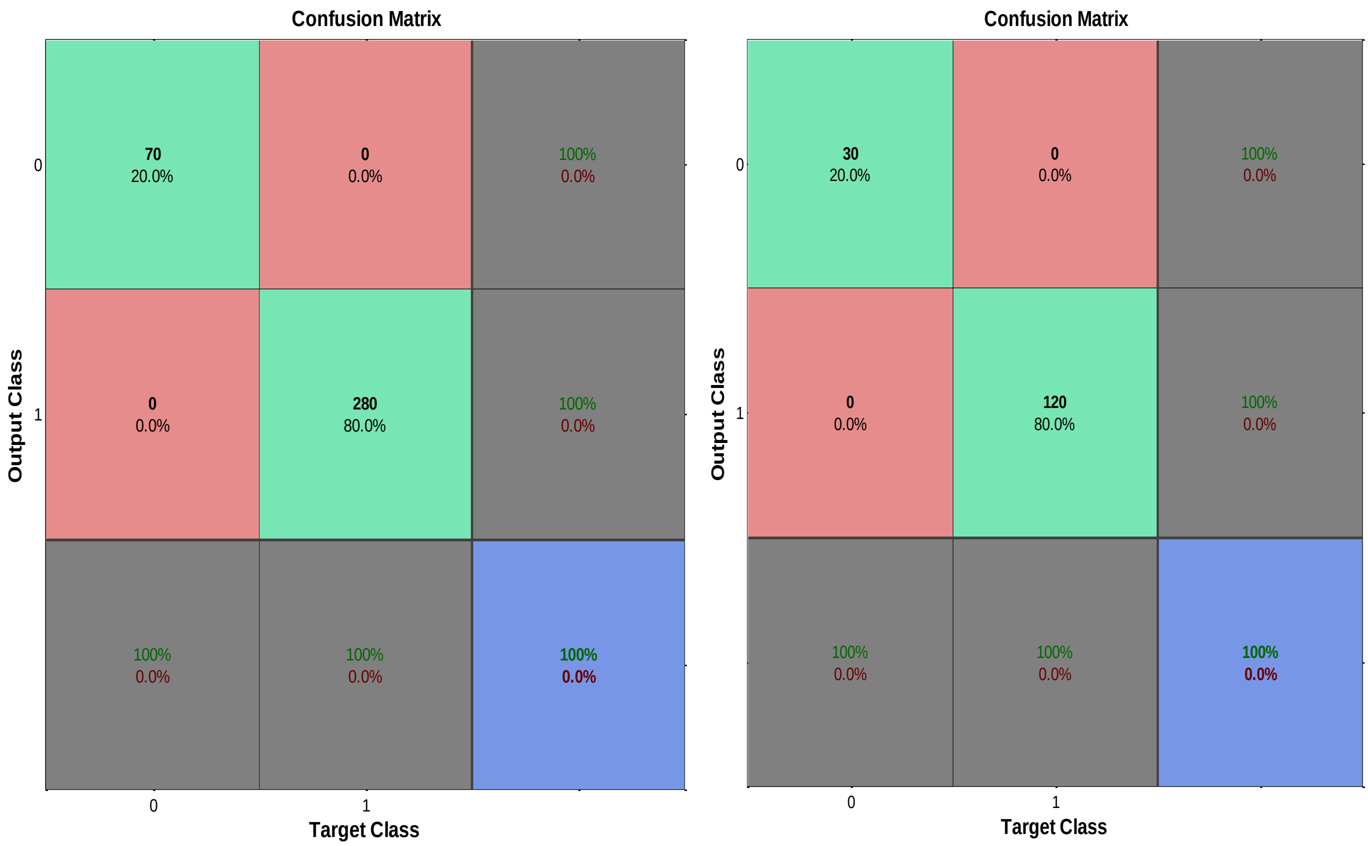


Figure 3.4: Confusion Matrix for the Training and Test Phase for the Network (1-10-5-2-1)

Figure 3.3 presents the regression fit of the outputs vs. targets for the network (1-10-5-2-1) and figure 3.4 presents the confusion matrix for the training and test phase for the network (1-10-5-2-1) chosen for fault detection.

B. Fault Classification Results

Type of Fault	A	B	C	Ground
No fault	0	0	0	0
A-G Fault	1	0	0	1
B-G Fault	0	1	0	1
C-G Fault	0	0	1	1

Table 3.1 Fault Classifier Artificial Neural Network Outputs for Various Faults.

Table 3.1 presents the fault classifierartificial neural network outputs for various single phase to ground faults.

a). Training the Fault Classifier Neural Network for Single Phase to Ground Faults.

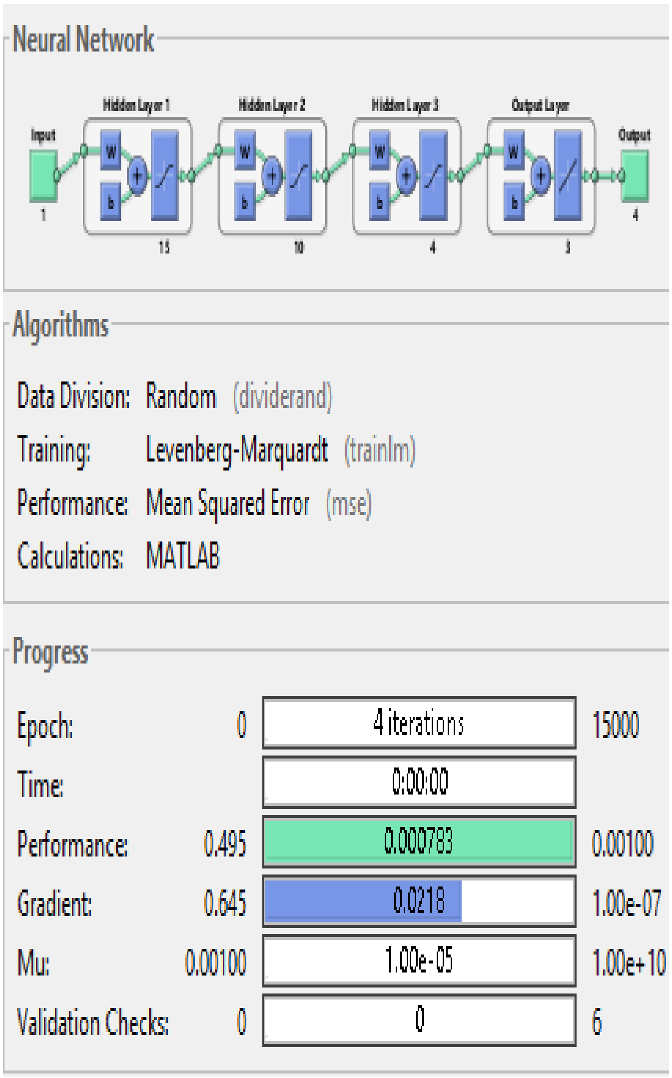


Figure 3.5: ANN with configuration (1-15-10-4-4)

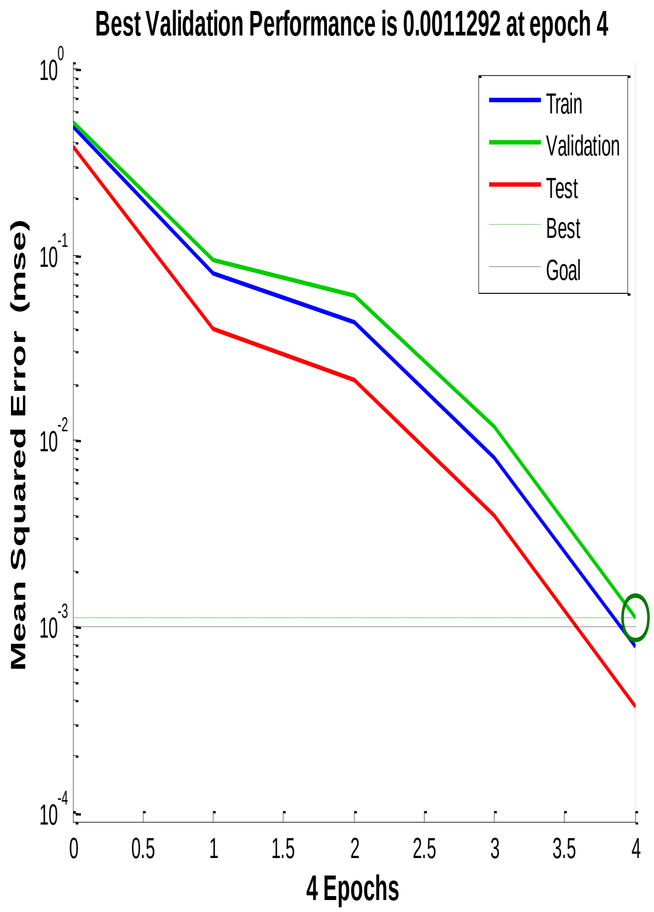


Figure 3.6: M.S.E performance of the chosen as fault classifier network with configuration (1-15-10-4-4)

Figure 3.5 provides an overview of the neural network chosen for single phase to ground fault classification. Figure 3.6 presents the mean square error performance plot of the chosen ANN for single phase to ground fault classification.

ISSN No:-2456 –2165

b). Testing the Fault Classifier Neural Network for Single Phase to Ground Faults

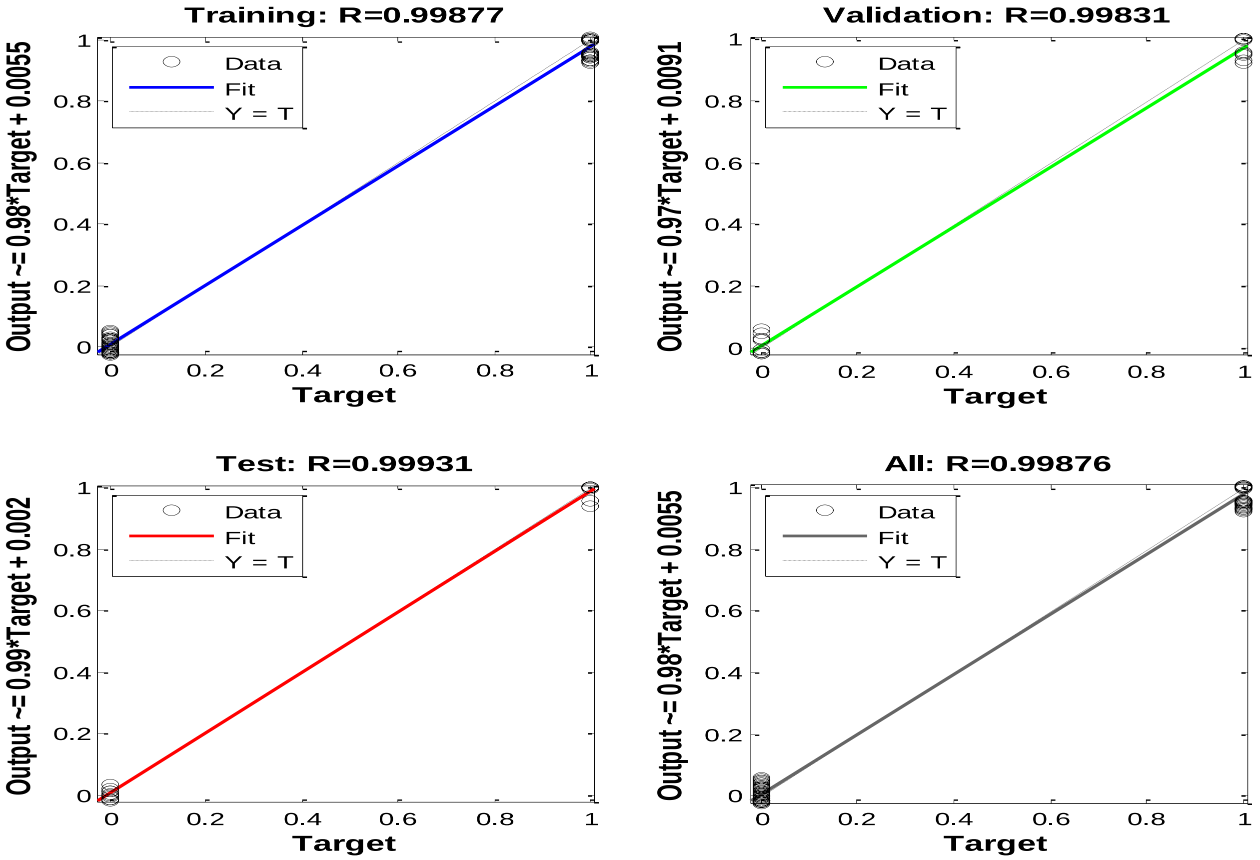


Figure 3.7:Regression fit of the Outputs vs. Targets of ANN (1-15-10-4-4)

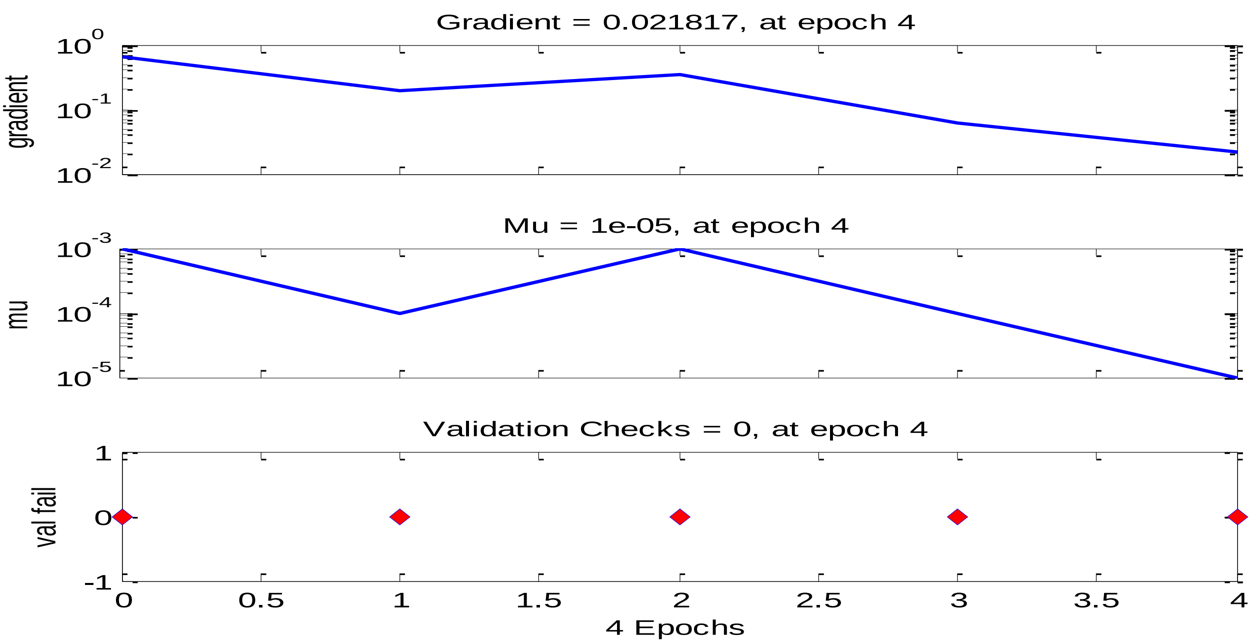


Figure 3.8:Gradient and Validation Performance of the ANN(1-15-10-4-4)

Figure 3.7 presents the plot of the best linear regression that relates the targets to the outputs for each of the phases of training, validation and testing of the ANN chosen for fault classification. Figure 3.8 present the gradient and validation performance plot of the chosen artificial neural network of the ANN chosen for fault classification.

C. Fault Location Results

a). Training the Neural Network for Single Phase to Ground Fault Location

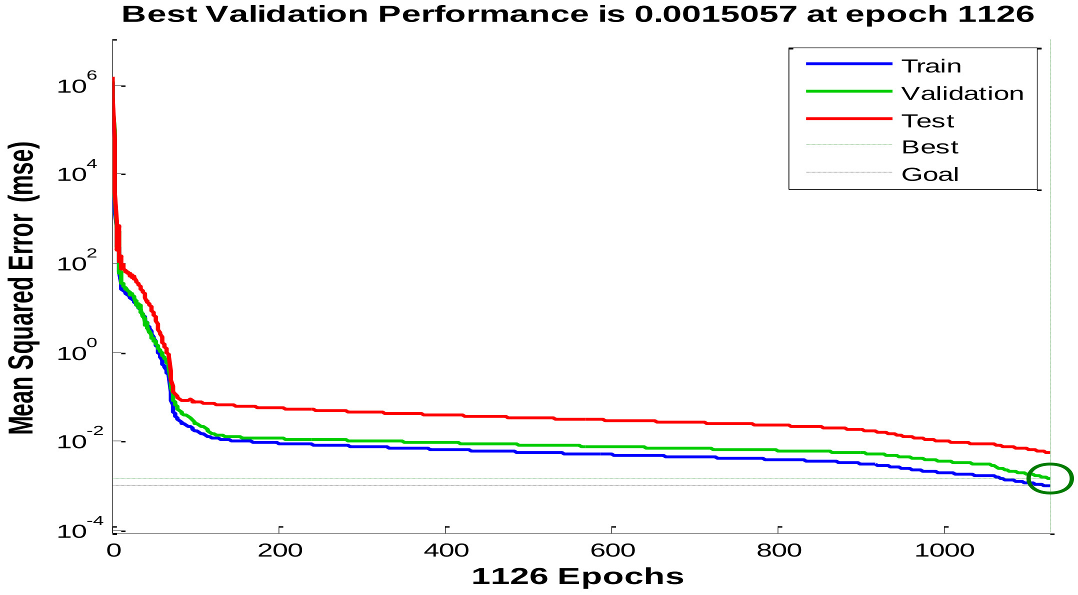


Figure 3.9: M.S.E of the Network (1-20-20-10-1)

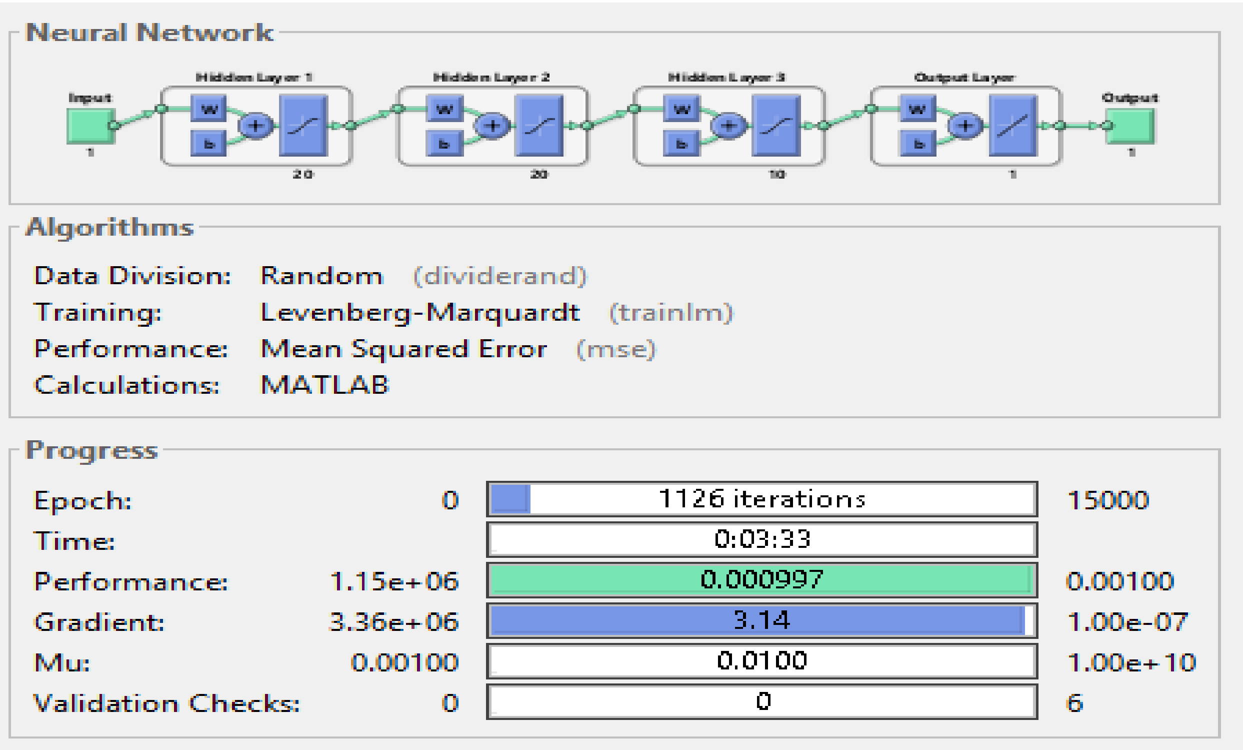


Figure 3.10: Chosen ANN with Configuration(1-20-20-10-1)

Figure 3.9 presents the mean square error performance of the trained fault location network for single phase to ground fault location with configuration (1-20-20-10-1). Figure 3.10 shows the chosen neural network for single phase to ground fault location.

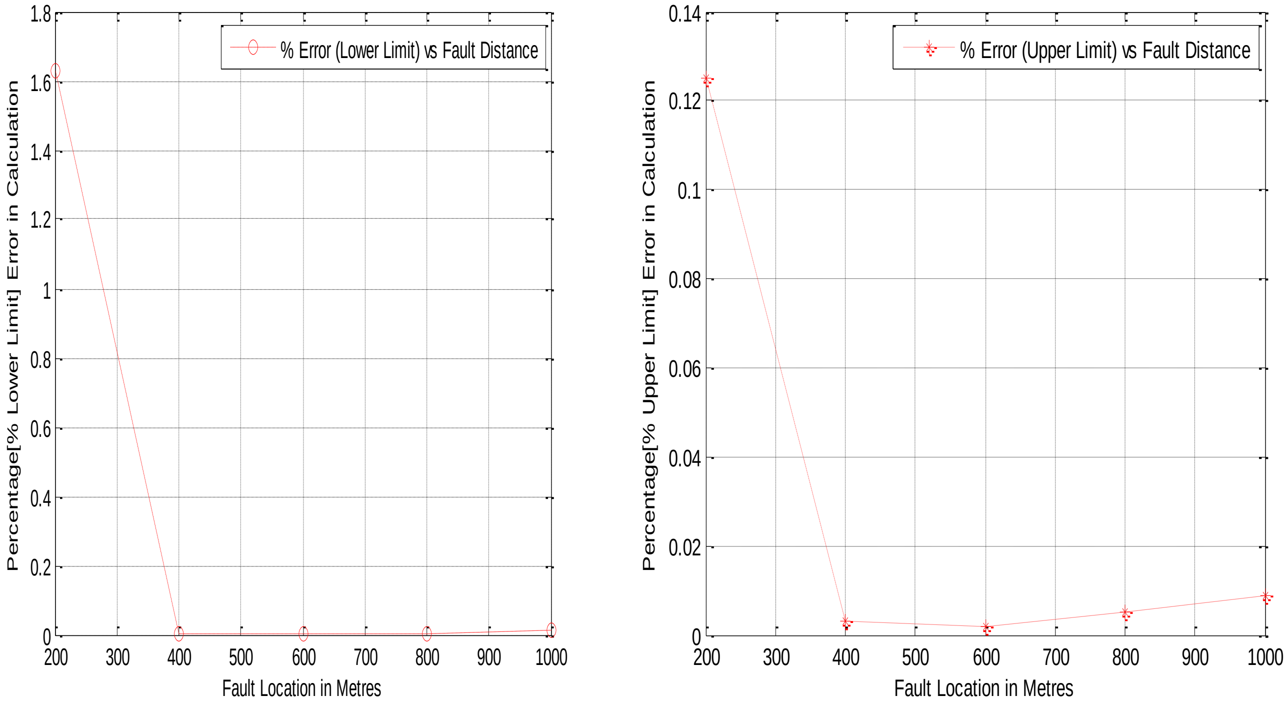


Figure 3.11: Lower and Upper Limit Test Phase Performance of the ANN (1-20-20-10-1)

Figure 3.11 shows the lower and upper limit test phase performance of the ANN with configuration (1-20-20-10-1) chosen for single phase to ground fault location.

b). Testing the Neural Network for Single Phase to Ground Fault Location

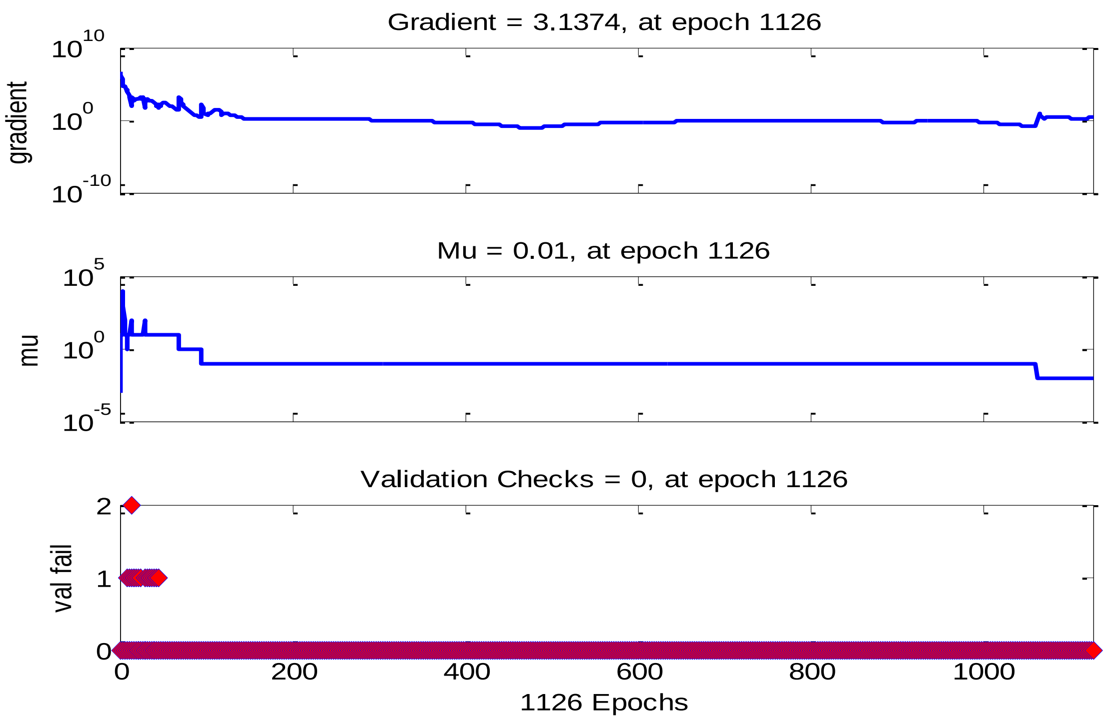


Figure 3.12: Gradient and validation Performance of the Network (1-20-20-10-1)

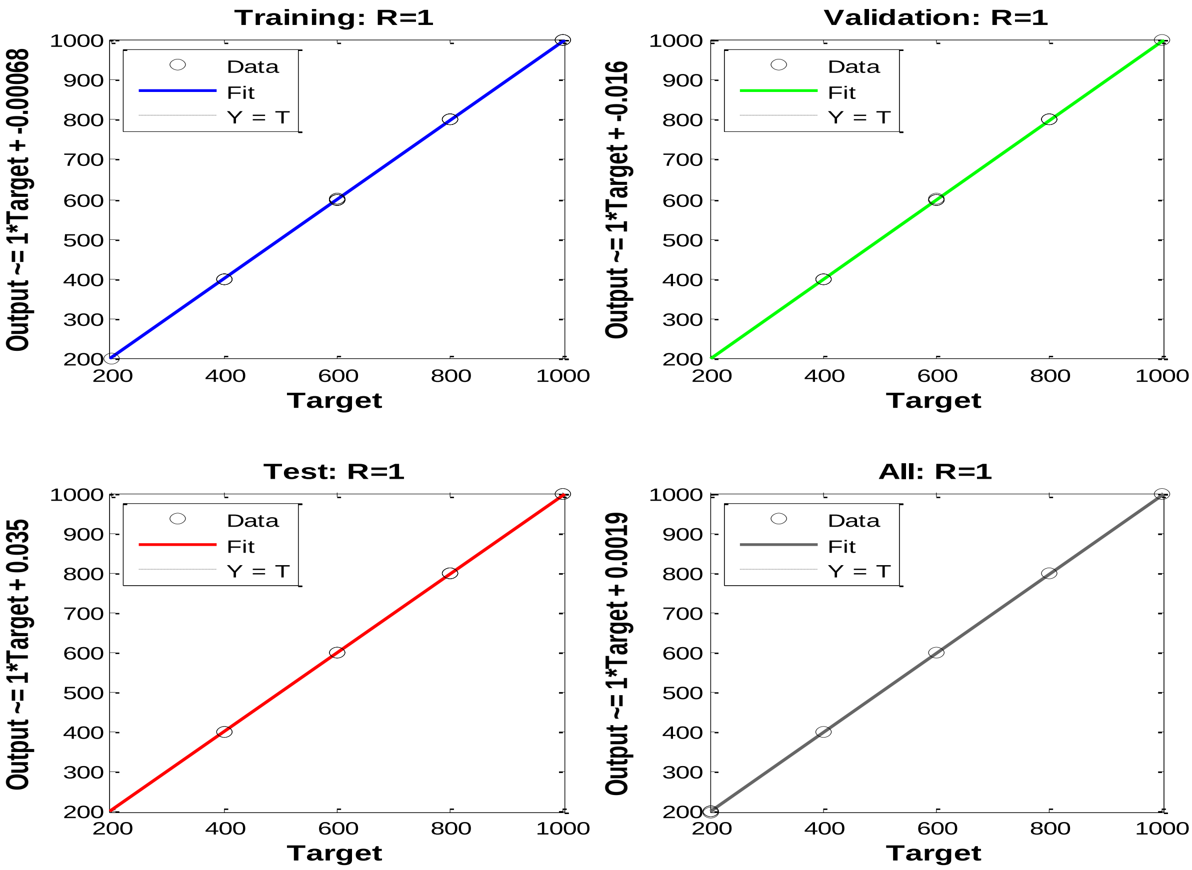


Figure 3.13:Regression plots of the various phases of learning of the ANN (1-20-20-10-1)

Figure 3.12 present the gradient and validation performance plot of the chosen artificial neural network chosen for single phase to ground fault location and figure 3.13 presents the plot of the best linear regression that relates the targets to the outputs for each of the phases of training, validation and testing of the chosen artificial neural network with the configuration (1-20-20-10-1).

	% Error vs Fault Distance (Lower Limit)			**% Error vs Fault Distance (Upper Limit)**		
Serial No:	Fault Distance (m)	Simulated Fault Location	Percentage Error	Fault Distance(m)	Simulated Fault Location	Percentage Error
1	200	196.74	1.630	200	200.25	0.125
2	400	399.99	0.003	400	400.01	0.003
3	600	599.99	0.002	600	600.01	0.002
4	800	799.96	0.005	800	800.04	0.005
5	1000	999.87	0.013	1000	1000.09	0.009
Average			0.33			0.03

Table 3.2: Percentage Errors for the ANN Chosen for L-G Fault Location

Table 3.2 shows the percentage errors for the artificial neural network chosen for single phase to ground fault location.

ISSN No:-2456 –2165

IV. DISCUSSION

In this section, the results of the artificial neural network training and testing are discussed with respect to single phase to ground fault location on distribution lines.

A. Fault Detection Discussion

a). Training of the Fault Detection Neural Network

The designed network takes in sets of eleven inputs for ten different fault conditions and the no fault condition with a set of one input and one output in each input-output pair. The output of the artificial neural network is a yes or no (1 or 0) depending on if or not a fault has been detected. Figure 3.1 shows the artificial neural network chosen for fault detection. As indicated in figure 3.1,the training process converged in about 4 iterations. It can be seen that the mean square error in fault detection achieved by the end of the training process is 0.000586 and that the number of validation fails is zero by the end of the training process.

Figure 3.2 shows the mean square error performance plot of the neural network 1-10-5-2-1 (1neuron in the input layer, 3 hidden layers with ten, five, two neurons in it and one neuron in the output layer). From the mean square error performance plot of figure 3.2, it is to be noted that very satisfactory training performance has been achieved by the neural network with the 1-10-5-2-1configuration (1neuron in the input layer, 3 hidden layers with 10,5,2 neurons in it respectively and one neuron in the output layer). The overall mean square error of the trained neural network is below the mean square error goal of 0.001 and is actually 0.000586 by the end of the training process. Also, it can be seen from figure 3.2 that the testing and the validation curves have a similar characteristic which is an indication of efficient training. Hence, this neural network has been chosen as the ideal artificial neural network for the purpose of fault detection.

b). Testing of the Fault Detection Neural Network Discussion

As can be seen from the regression plot of figure 3.3, the slope of the regression plots of each of the phases of training, validation and testing is 1 which indicates excellent performance of the neural network. 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). It can be seen that the best linear fit matches the idealcase with an overall correlation coefficient of 1.

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 3.4 shows the plots of the confusion matrix for the training and test phase. 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 indicates the total percentage of cases that have been classified correctly in green and the vice-versa in red. It can be seen that the chosen neural network has 100 percent accuracy in fault detection.

The third step in the testing process is to create a separate set of data called the test data set to analyse the performance of the trained neural network. 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 absolute accuracy differentiate a normal situation from a fault condition on a distribution line.

B. Fault Classification Discussion

Once 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.

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 ten inputs for ten different fault conditions with a set of one input and four outputs in each input-output pair. 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 distribution 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 and classify the single phase to ground fault.

a). Fault Classifier Neural Network For Single Phase to Ground Faults

Three possible single phase to ground fault conditions exist (A-G, B-G, C-G), corresponding to each of the three phases (A, B or C) beingfaulted.

b). Training the Fault Classifier Neural Network Ft for Single Phase to Ground Faults

The training set consists of three inputs for three different single phases to ground fault conditions with a set of one input and four outputs 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 analysed.

Figure 3.5 provides an overview of the artificial neural network and is a screen shot of the training window simulated using the artificial neural network. As indicated in

figure 3.5, the training process converged in about 4 iterations and the performance in terms of mean square error achieved by the end of the training process is 0.000783.
Figure 3.6 presents the mean square error performance plot. It is to be noted that satisfactory training performance has been achieved by the neural network with 1-15-10-4-4 (1 neuron in the input layer, 29 neurons in the hidden layer and four neurons in the output layer. The mean square error of the trained neural network is 0.000783 and it can be seen from figure 3.6 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 single phase to ground fault classification.

c). Testing the Fault Classifier Neural Network for Single Phase to Ground Faults

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 for each of the phases of training, validation and testing as shown in Figure 3.7. The Overall correlation coefficient in this case was found to be 0.99876 which indicates satisfactory correlation between the targets and the outputs. The dotted line in the figure indicates the ideal regression fit and the coloured 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.

The second factor in the testing process is provided by Figure 3.8, which is the gradient and validation performance plot. It can be seen that there is a steady decrease in the gradient and also that the number of validation fails are 0 during the entire process which indicates smooth and efficient training because the validation and test phases meets the mean square error goal at the same time approximately.

The third step in the testing process is to create a separate set of data called the test set to analyse the performance of the trained neural network. 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 almost 100 percent. Hence the neural network can with absolute accuracy differentiate and classify the single phase to ground fault faults on a distribution line.

C. Fault Location Discussion

This forms the third step in the entire process of fault location after the inception of the fault. As mentioned earlier, the threshold used for the fault simulation with respect to the fault location distances are 200m, 400m, 600m, 800m and 1000m respectively.

a). Single Phase to Ground Fault Location

The neural network detects the occurrence of a fault on a distribution line and also classifies the single phase to ground fault; the third step is to pin-point the location of the fault from the distribution sub-station.Three possible single phase to ground faults exist (A-G, B-G, C-G), corresponding to each of the three phases (A, B or C) being faulted. The faults are detected according to the fault classifier artificial neural network outputs for various faults as indicated in Table 3.1.

b). Training the Neural Network for Single Phase to Ground Fault Location

In order to train the fault location neural network, several single phase faults have been simulated on the distribution line model. For each pair formed by the three phases, faults have been simulated at every 200m on a 1Km long distribution line. Along with the fault distance, the fault resistance has been varied as mentioned earlier. In each of these cases, the current samples for all the three phases are given as inputs to the neural network. The output of the neural network is the distance to the fault from the distribution sub-station. Therefore, each input output pair consists of three inputs and one output.

The performance function chosen for the training process is mean square error. Figure 3.9 shows the performance of the neural network (in terms of training, testing and validation) and it can be seen that the achieved mean square error is about 0.000997 which is below the mean square error goal of 0.001 (denoted by the black dotted line). Figure 3.10 shows the chosen neural network for single phase to ground fault location with all its characteristics depicted in detail.

As shown in figure 3.11, the training process converged in about 1126 iterations and the performance in terms of mean square error achieved by the end of the training process is 0.000997 which is satisfactory.

c). Testing the Neural Network for Single Phase to Ground Fault Location

Once the neural network has been trained, its performance has been tested by taking three different factors into consideration. One key factor that evaluates the efficiency of the artificial neural network is the test phase performance illustrated in Figure 3.12. As shown in figure 3.12, the maximum error is 1.6 percent for lower limit and 0.125 percent for upper limit. Also, the average error in fault location for upper limit is 0.03 percent and the average error for lower limit is just 0.33 percent. The average and the maximum error percentages are in tolerable ranges and hence the network’s performance is considered satisfactory.

Another form of analysis is provided by Figure 3.13, which is the gradient and validation performance plot. It can be seen that there is a steady decrease in the gradient and also that the maximum number of validation fails did not exceed 1 during the training process which indicates smooth and efficient training. This indicates efficient training because the validation phase follows the test phase closely if the number of validation fails is low. This further implies that the neural network can generalize new data fed into it more effectively.

The third factor that is considered while evaluating the performance of the network is the correlation coefficient of each of the various phases of training, validation and testing. Figure 3.14 shows the regression plots of the various phases such as training, testing and validation. It can be seen that the best linear fit matches the ideal case with an overall correlation coefficient of 1.

Table 3.2 illustrates the percentage errors in fault location as a function of fault distance and fault resistance. Two different cases have been considered (shown in adjacent columns) for the lower and upper limit respectively. The average error for the lower limit is 0.33% and the average error for the upper limit is just 0.03% which is still very satisfactory. Thus the neural networks performance is considered satisfactory and can be used for the purpose of single phase to ground fault location.

V. CONCLUSION

This research paper onsingle phase to ground fault location on 415 volts distribution lines using artificial neural network algorithm has been successfully carried out. The usage of artificial neural networks as an alternative method for the detection, classification and location of single phase to ground faults on distribution lines has been investigated in this paper.

Phase currents are used as inputs to the neural network in the methods employed. All the artificial neural networks studied in this paper belong to the feed forward back propagation neural network architecture. A single phase to ground fault location algorithm for the distribution line system, right from the detection of faults on the line to the fault location stage has been devised successfully by using artificial neural networks. Satisfactory performance has beenachieved by all of the proposed artificial neural networks as validated from the simulation results obtained.

Power system computer aided design transient simulation tool has been used to simulate the power distribution line model and to obtain the training fault data set. The artificial neural networks toolbox in MATLAB R2014A has been used extensively in order to train and analyse the performance of the neural networks. In view of the increasing complexity of the modern power distribution systems, neural networks are indeed a reliable and attractive scheme for an ideal distribution line fault location scheme and are therefore recommended for fault location on distribution lines. The major subsections for the development of the fault location algorithm include the following:

- Fault Detection
- Fault Classification
- Fault Location

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