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# Artificial Neural Network Approach of Fault Detection and Identification in 330kV Onitsha-New Haven three Phase Transmission Line

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***Abstract* – This work focuses on the presentation of detection and identification of faults on power transmission line by way of artificial neural network. Power lines are usually liable to faults. It is always expedient to quickly and accurately detect and establish the faults for clearance. ANN identifies faults in large power systems easier than the conventional methods. Onitsha-New haven 330kV Nigerian network was used in this study. The network was modeled and simulated variously in MATLAB environment. The neural network was trained using the values of phase voltages and currents as inputs. The values were scaled with respect to pre-fault values. Analysis of the performance and test of the neural network were carried out. Various possible kinds of faults were examined. Results were gotten for ten (10) fault conditions. The faults were correctly detected and identified. These results show that artificial neutral network is efficient in detection and recognition of power transmission lines' faults.**

***Keywords* – Power Line, Neural Network, Fault Detection, Training Data, Three Phase Fault.**

## I. Introduction

Power transmission systems are always prone and susceptible to faults. The primary aim of a power system is to provide sufficient and uninterrupted quality power supply to the consumers. Unfortunately, this is hardly possible due to unavoidable interruptions and faults that occur on the power system [1]. The lines are mainly responsible for conveying electrical power from different generating plants to the grid, substations and from one substation to another in a varying degree of voltages in order to meet the extremely large number of load demands. Any abnormal flow of current in power system's components is called a fault in the power system. These faults cannot be completely avoided since some of them also occur due to natural causes which are way beyond the control of mankind. Hence, it is very essential to have a well-coordinated protection system that detects any kind of abnormal flow of current in the power system, identifies the type of fault and then accurately locates the position of the fault in the power system. Faults can be due to insulation failures and conducting path failures. The transmission line fault is mainly classified into balanced and unbalanced fault. The balanced faults are three phase faults. However, single lines to ground faults, line to line faults and double line to ground faults are unbalanced in nature. These faults may be caused by lightning strikes, trees falling across lines, trees growing up to the transmission lines, broken cross arms, bird shorting the lines, and vandalism. In the case of cables, transformers and generators, the causes may be failure of solid insulation due to ageing, heat, moisture or overvoltage, accidental contact with earth [2]. Detection of these faults is necessary as it is the first step to clearing the fault [3].The faults are usually taken care of by devices and approaches that detect their occurrences and eventually isolate the faulted section from the rest of the power system. The approach considered by this paper to able to do that accurately within the shortest possible time is Artificial Neural Networks (ANN).

The problem of detecting transmission line faults is as old as the power industry itself. In the beginning, the fault detection was by direct visual inspections of the line [4]. However, the visual inspection of a long line, on foot or by air, is always extremely slow and subject to the terrain circumstances and environmental conditions of the moment. Additionally, visual inspection does not always ensure that the location is found because, in many cases, faults do not leave physical evidence. Fault detection techniques, are ways that seek to detect, with the highest possibly accuracy, those abnormal network conditions that take the current out of its normal course through a transmission line [5]. In power systems, protective devices detect fault conditions and thus operate circuit breakers and other devices to limit the losses. With this, it gives way for protecting the lines from damages [6]. Intelligent, autonomous, online systems have been developed and applied to a significant degree to deal with this type of problem, since they enable fast and accurate diagnosis without the need for human intervention. These fault detective measures have helped in the following ways:

- Expediting service restoration by the utility company.
- Reducing the power outage time.
- Reducing operational cost.
- Reducing the complaints of the customers.

Many industrial processes are not suitable to conventional modeling approaches due to the lack of precise, formal knowledge about the system and strongly nonlinear behavior. In cases where mathematical process models are not available, a nonlinear model can be employed to generate results. One way to build a nonlinear model is to use Artificial Intelligence methods. In transmission lines, neural networks can be an approach for quick prediction of critical clearing time. They are usually used to achieve greater efficiency in fault detection, classification and location. A lot of researches has been conducted and abundantly published in the subject of fault detection.

Jamil et al in [7] modeled a 400kV, 300km transmission line. The system consists of two generators of 400kV each located at both ends of the line along with a three phase fault simulator used to simulate faults at various positions on the transmission line. The line was modeled using distributed parameters. This power system was simulated using the Sim Power Systems toolbox in Simulink by the MathWorks. The values of the three-phase voltages and currents were measured and fed into the neural network as inputs. The Sim Power Systems toolbox has been used to generate the entire set of training data for the neural network in both fault and non-fault cases. However, the result shown was for line to ground fault only. Authors of [8] developed a novel technique for real time fault detection and classification using discrete wavelength transform method and Artificial Neural network respectively. The fault condition was simulated on MATLAB. The fault signals were decomposed up to the fifth detail using discrete wavelength transform to obtain featured extraction. The system is composed of 220 kV transmission circuit with section lengths 200 km (section 1), 120 km (section 2) and110 km (section 3), connected to sources at each end. Although, the wavelet transform is very effective in detecting transient signals generated by faults, it has one main challenge which is the selection of the optimum mother wavelet for applications, if different mother wavelets are used on the same signal, it may yield different results.

The work in [9] developed an intelligent system for fault detection and classification on a 33kV Nigerian transmission line. The performance of the detector-classifier was evaluated using the Mean-Square Error (MSE) and the confusion matrix. The line was modeled using PI-model and run in Simulink / MATLAB 2013 environment using Sim-power systems toolbar. The instantaneous voltage and current values were extracted and used to train the fault detector-classifier. In [10], a 200km, 400kV transmission line was modeled and used implement an artificial neural network. The system consists of two generators 11kV each located on either end of the line along with a 3-phase simulator to simulate faults at mid position of it. The line was modeled using MATLAB2009a and simulated using the sim power system toolbox in Simulink. Among all the types of faults, it is only the single line to ground fault that was shown.

ANN was employed by [11] in fault identification, fault classification, and fault location. A current differential method for detecting, classifying and locating of faults on transmission line was proposed by [12]. The authors used spectral energy information made available through Fast Discrete S-Transform (FDST) for fault identification, classification and location; the fundamental amplitude and phase angle of the two end currents and one end voltage were used. Santos and Senger in [13] presented an artificial neural network based algorithm for transmission lines distance protection. The algorithm developed was used by the authors in transmission line regardless of its voltage level. A new technique for the detection and location of faults using neural networks was proposed by [14]. However, in the operation of the technique, fault inception angle was not considered. Palanichamy in [15] proposed ANN to identify faults in electrical machine and power system lines while in operation to ensure uninterrupted dependable power system operation. In the work, vibration and acoustic outflow signals were used to identify deficiencies and imminent disappointments in running machine and system.

In the case of Bermegjo and others in [16], an exact review of the use of Artificial Neural Network when predicting energy production and its behavior in terms of reliability from chosen renewable energy resources was carried out. The paper wrote up various applications of ANN models for better renewable energy prediction and understanding assets' reliability concern. Boujoudar and colleagues in [17] proposed an intelligent controller based energy management for stand-alone power system by using artificial neural network. The Artificial Neural Network Controller (ANNC) controls DC/DC Bidirectional Converter (DBC) that connects battery (Li-ion) with the DC Bus of the Stand-alone Power System (SPS) utilizing the signal used for training the network with the signal having adequate information about the modeled system. ANN is the best approach having been quite successful in determining the correct type of fault. It has high degree of robustness, ability to learn and capability to work with incomplete and unforeseen input data. No researcher to the best of knowledge of the author has addressed fault detection on the 330kV Onitsha - New Haven three phase transmission line of the Nigerian power network with approach of Artificial Neural Network (ANN) using phase voltages and currents to find various kinds of faults due the line's radial nature and its interconnections. This point in question is plainly treated in this paper.

MATLAB/Simulink Sim power systems toolbox was used to simulate the transmission line model. Feed-forward networks were employed along with back-propagation algorithm for each of the three phases in the fault location process. Analysis on neural networks with varying number of hidden layers and neurons per hidden layer was provided to validate the choice of the neural networks in each step. Simulation results were used to demonstrate that artificial neural network based method is efficient in detecting and identifying faults on transmission lines and achieves satisfactory performances.

## II. Materials and Method of ANN

2.1. *Modeling of the Power Transmission Line System*

The 330kV transmission line from Onitsha to New Haven was modeled in this study. It consists of two 330/132kV transformers each located on either end of the transmission line. The line is 96km long and the three-phase fault simulator was used to simulate various types of faults at varying locations along the line with different fault resistances. In transmission line, faults are classified as single line to ground fault, line to line fault, double line to ground fault and three phase fault. The line was modeled using distributed parameters and these parameters were obtained from [18].

The line was modeled and simulated using the Sim Power Systems toolbox in MATLAB Simulink. The model of the line is shown in Figure 1 and was used for obtaining the training and test data sets. The three phase V-I measurement block was used to measure the voltage and current samples at the terminal A.

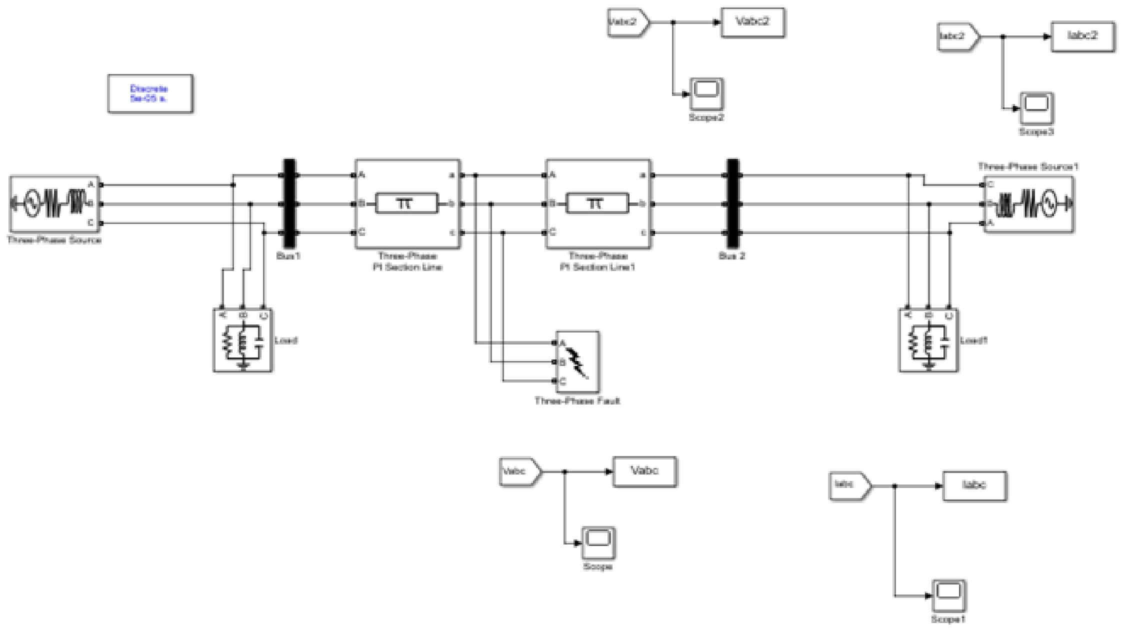


Fig. 1. Model of the 330kV Transmission Line in Matlab/Simulink.

## 2.2. *The Artificial Neural Network*

The learning or training of the neural network is one of the basic concepts behind the successful application of the neural network in any field and it is used to determine the weights to achieve the desired target. The Artificial Neural Network can be trained using two basic types of learning process; the supervised learning process and the unsupervised learning process. In supervised learning, the network weights are modified iteratively with the aim of minimizing the error between a given set of input data and their corresponding target values using backward propagation algorithm. This process which is commonly used in electric power transmission lines fault detection and classification was employed in this study. 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 and performing some kind of simulations. The neural network was trained to modify its weights according to the error ‘e’ between the outputs and the targets. However in the case of unsupervised learning, the relationship between the inputs and the target values are unknown. The neural network is trained with a training data set where the input values are known. It is important to choose the right set of examples for efficient training. These examples are usually chosen using some sort of a similarity principle. The supervised learning strategy for a feed forward neural network is shown in the Figure 2.

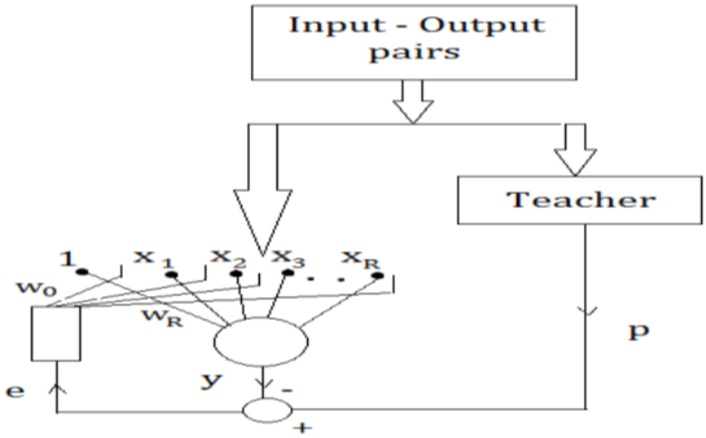


Fig. 2. An illustration of the supervised learning scheme.

The weights are reduced, increased or even the same. The change in weight is as expressed in equation (1),

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

where $w_{ji}(n)$ and $w_{ji}(n+1)$ are the previous and the modified weights connected between the $i_{th}$ and the $j_{th}$ adjoining layers. $\Delta w_{ji}(n)$ stands for the correction or modification factor and n stands for the number of iteration. Considering the $j_{th}$ neuron in a single layer neural network, the training efficiency is enhanced by minimizing the error between the actual output of the $j_{th}$ neuron and the output that has been dictated by the training data. Let $y_j(n)$ and $p_j(n)$ be the actual and the teacher-requested outputs for the $j_{th}$ neuron in the nth iteration.

Then the error value of that iteration is given by:

$$\mathrm{e_j(n) = p_j(n) - y_j(n)} \tag{2}$$

The vector $e_j(n)$ 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 equation,

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

where $x_i$ is the $i_{th}$ 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 use of a Least Square Method (LSM). Hence, if there are L neurons in a particular network, the cost function, $S_2(w)$, to be ultimately minimized is given by equation (4),

$$\mathrm{S_2(w)} = \frac{1}{2} \sum_{J=1}^{L} \left(\mathrm{p_j - y_j}\right)^2 \tag{4}$$

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:

$$\mathrm{S_2\big(w(n)\big)} = \frac{1}{2} \sum_{n=1}^{P} \sum_{j=1}^{L} \Big(\mathrm{p_j(n) - y_j(n)}\Big)^2 \tag{5}$$

where $P_j$ is the desired output and $y_j$ is the output at layer j for nth training pattern. Since the activation functions employed are more than often, minimization of equation (5) is a non-linear problem. Several numerical methods that can handle non-linear functions effectively are available and are based on 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 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 shown in Figure 3.

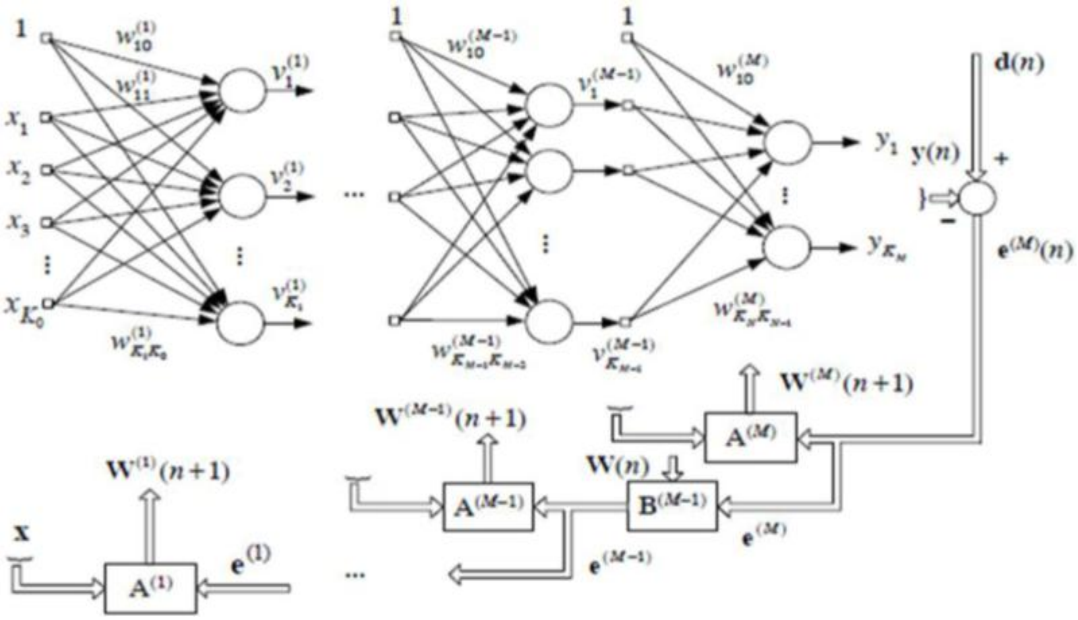


Fig. 3. Structure of back-error-propagation algorithm [7].

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.

### 2.3. *Training of Artificial Neural Network*

In training the neural network, series of tests were carried out on the transmission line using MATLAB Simulink to generate the input data needed to train the neural network. The input data with its corresponding output were fed into the network thus teaching it what its output should be at any particular input. The ANN thus learned from the inputs and outputs and adjusted its weight. It slowly developed the ability to generalize upon the data.

The ANN took six inputs which comprised the voltage and current of the three phases at a particular time. The voltages and current were scaled with respect to the corresponding voltage and current values before the occurrence of the fault. The training set consisted of 1100 input-output data sets. 100 data sets were gotten for each of the 10 fault cases and another 100 data set was collected for the no fault case thus making it a total of 1100 training data set. A sample of the input training data set for the various fault cases is shown in the Table 1.

Table 1. Samples of inputs to the neural network for various fault cases.

| S/N | Va(pu) | Vb(pu) | Vc(pu) | Ia(pu) | Ib(pu) | Ic(pu) | Fault Type |
|---|---|---|---|---|---|---|---|
| 1 | -0.3486 | -0.0527 | 0.9270 | -0.7126 | -0.4890 | 0.3227 | Phase A to Ground |
| 2 | -0.7168 | -0.0982 | 1.0675 | 0.3561 | -2.0463 | 0.0452 | Phase B to Ground |
| 3 | -0.7968 | -0.4437 | 0.2203 | 0.4983 | -0.4370 | 8.9684 | Phase C to Ground |
| 4 | -0.0980 | -0.1824 | 1.0721 | -7.1159 | -0.8401 | 0.0396 | Phase A & B to Ground |
| 5 | 0.0834 | -0.3611 | 0.0475 | -8.7726 | -0.4623 | 10.6410 | Phase A & C to Ground |
| 6 | -0.7109 | 0.0504 | 0.0990 | 0.4260 | -3.5251 | 9.6127 | Phase B & C to Ground |
| 7 | -0.4937 | -0.5781 | 1.0717 | -3.1572 | 3.0846 | 0.1056 | Phase A to B |
| 8 | 0.1976 | -0.3593 | 0.1617 | -9.4466 | -0.5201 | 9.9670 | Phase A to C |
| 9 | -0.7124 | 0.3320 | 0.3805 | 0.4145 | -6.7757 | 6.3620 | Phase B to C |
| 10 | 0.0401 | -0.0443 | 0.0042 | -8.5631 | -2.2873 | 10.8504 | Phase A to B to C |
| 11 | -0.7123 | -0.3757 | 1.0719 | 0.4148 | -0.5186 | 0.1038 | No Fault |

The ANN used the instantaneous voltage and current of the lines to determine if there was a fault on the transmission line. The output of the neural network is either a 1 or 0 which represents YES or NO depending on whether there is a fault on the line or not. Table 2 depicts the truth table of the detector-identifier for various cases of fault.

Table 2. Truth table of detector-identifier for various fault cases.

| Fault | Phase/ Network Target | | | |
|---|---|---|---|---|
| | A | B | C | G |
| A – G | 1 | 0 | 0 | 1 |
| B – G | 0 | 1 | 0 | 1 |
| C – G | 0 | 0 | 1 | 1 |
| A – B – G | 1 | 1 | 0 | 1 |
| A – C – G | 1 | 0 | 1 | 1 |
| B – C – G | 0 | 1 | 1 | 1 |
| A – B | 1 | 1 | 0 | 0 |
| A – C | 1 | 0 | 1 | 0 |
| B – C | 0 | 1 | 1 | 0 |
| A – B – C | 1 | 1 | 1 | 0 |

The Neural Network toolbox in Simulink divided the entire set of data provided into three different sets namely; the training set, validation set and the testing set. The training data set was used to train the network by computing the gradient and updating the network weights. The validation set was provided to the network during the training process and the error in validation data set was monitored throughout the training process. When the network started over fitting the data, the validation errors increased and when the number of validation fails increased beyond a particular value, the training process stopped to avoid further over fitting the data and the network was returned at the minimum number of validation errors. The test set was not used during the training process but used to test the performance of the trained network. If the test set reaches the minimum value of Mean-Square Error (MSE) at a significantly different iteration than the validation set, then the neural network will not be able to provide satisfactory performance.

After some simulations, a neural network with 3 hidden layers was chosen for the desired. The neural network has 10 neurons in its first hidden layer, 5 neurons in the second hidden layer and 3 neurons in its 3$^{rd}$ hidden layer. The neural network has a network configuration of 6-10-5-3-1 with five layers.

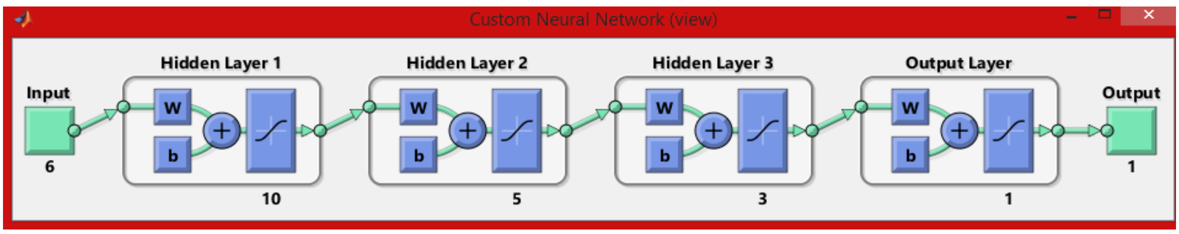


Fig. 4. Developed neural network model in simulink.

The neural network achieved a satisfactory result by giving an output within the Mean-square Error (MSE) goal.

## III. Results and Analysis

### 3.1. *Fault Simulation Results*

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The transmission line modeled on MATLAB Simulink was simulated with the various fault cases and the values of the current and voltage for three phases obtained. The waveforms for the fault cases were viewed from the scope. The waveforms for Single line-to-ground fault (SLG), Line-to-line fault (L-L), double line-to-ground fault (2LG) and three phase faults are shown in Figures 5, 6, 7 and 8 respectively.

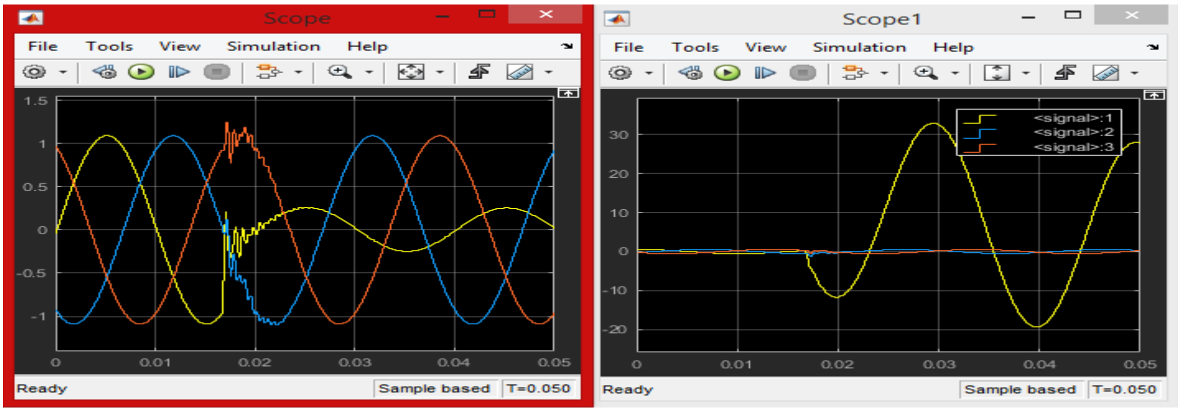


Fig. 5. Voltage and current waveforms for single line to ground fault.

In Figure 5, a fault occurred between phase A and the ground. From the scope, there was a sudden drop in the line voltage of phase A and a corresponding increase in the current of the phase up to 10 times the normal current.

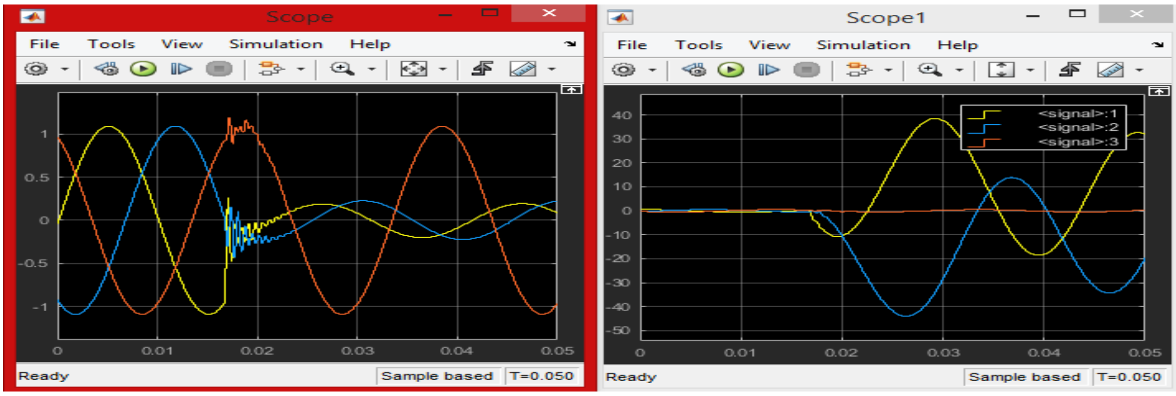


Fig. 6. Voltage and current waveforms for double line to ground fault.

From Figure 6, there was a fault between phase A, Phase B and the ground. There was also a sudden drop in the voltage of the two lines and an increase in the phase currents.

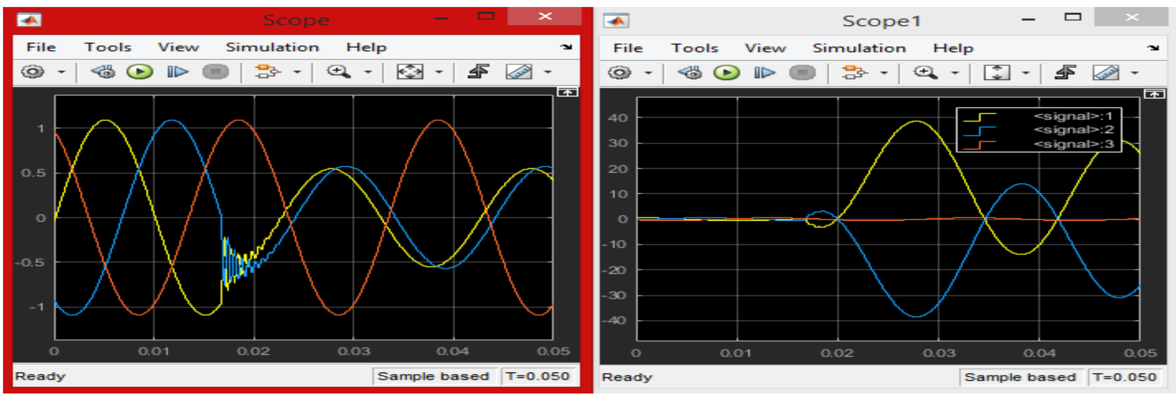


Fig. 7. Voltage and current waveforms for line to line faults.

From Figure 7, there was a fault between phase A and phase B. There was a drop in their respective voltages and an increase in their current. Phase C was roughly unaffected.

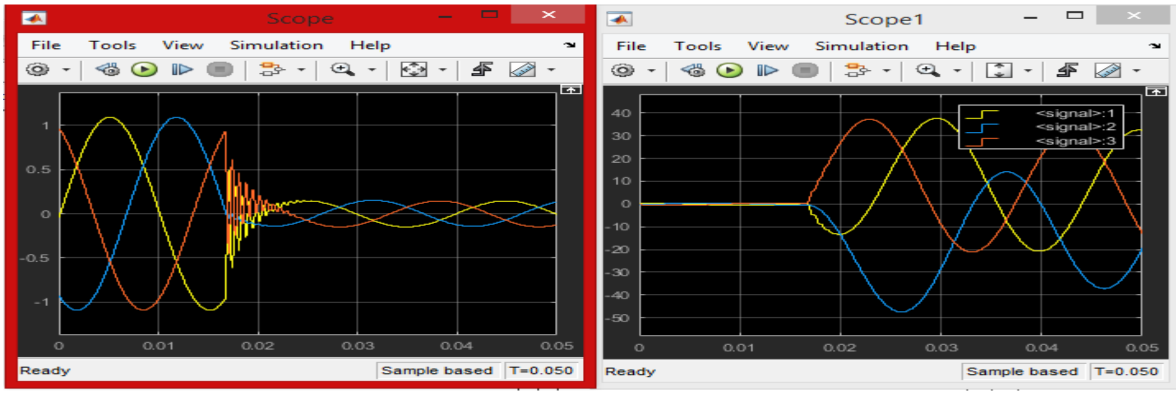


Fig. 8. Voltage and current waveforms for three phase faults.

In Figure 8, there was a fault between the three phases. All the phase voltages and currents were affected. The currents increased to a high extent while there was a great drop in the voltages.

### 3.2. *Analysis of Training Performance of the Neural Network*

After some series of tests with neural networks of different configurations, the 6-10-5-3-1 was chosen because it gave a satisfactory performance. The training performance plot of the network is shown in Figure 9.

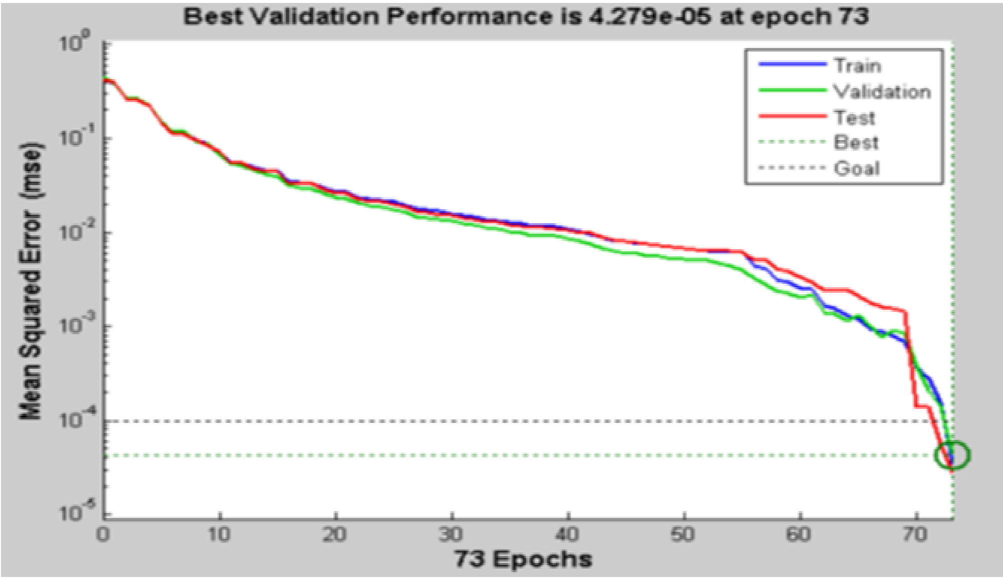


Fig. 9. Performance Plot of neural network with 6-10-5-3-1 Configuration.

From the training performance plot shown in Figure 9, it was seen that a satisfactory training performance was achieved with the neural network using 6-10-5-3-1 Configuration. The overall mean square error (MSE) of the trained network is below 0.0001 and is actually 0.00004279. Therefore, the trained neural network was chosen as the ideal network for the detection of fault.

### 3.3. *Testing of the Trained Neural Network*

After the training of the neural network, the next step was to test the performance of the neural network. The performance was determined by two methods;

- The regression plot.
- Creating a separate set of data to analyze the network's performance.

### 3.3.1. *The Regression Plot*

The Regression Plot was gotten by plotting the best linear regression that relates the targets to the outputs. It shows how well the target of the neural network can track the variations in the output. The Regression plot is shown in Figure 10.

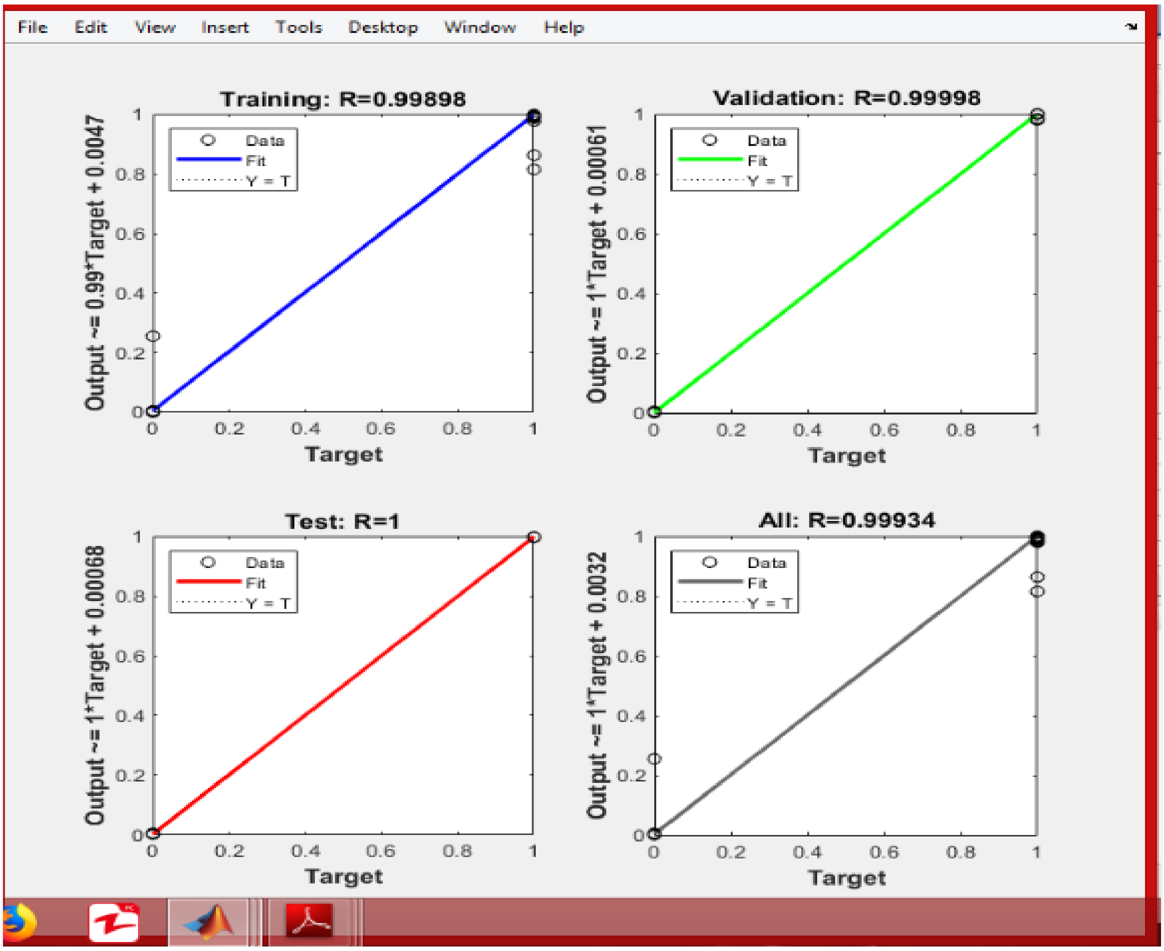


Fig. 10. Regression plot of the network with 6-10-5-3-1 Configuration.

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 for the training process was found to be 0.99898; the coefficient for testing was 1 while validation was 0.99934. With these values, it can be said that the correlation is excellent.

### 3.3.2. *Creating a Separate Set of Data to Analyze the Network's Performance*

The second 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 110 different test cases have been simulated with 100 cases corresponding to different types of faults (about 10 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 10 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 was very high. Hence the neural network can, with utmost accuracy, differentiate a normal situation from a fault condition on a transmission line.

## IV. CONCLUSIONS

This work on the use of an Artificial Neural Network for the purpose of detecting faults in a transmission line was carried out successfully. The Onitsha-New Haven 330kV transmission line was used as a case study. The transmission line was modeled using MATLAB Simulink toolbox. The neural network was trained using values of phase voltages and currents as the inputs to the network. The training data set used for the work was simulated using MATLAB along with the Sim Power Systems toolbox in Simulink. In performing the training and analyzing the performance of neural network, the Artificial Neural Networks Toolbox was used extensively. The value was scaled with respect to the pre-fault values. Various possible kinds of faults such as the single line to ground, line to line, double line to ground and three phase faults were taken into consideration.

Results were gotten for the ten fault conditions and the faults were accurately detected. This results shows that the neural network is an efficient method for the detection of faults on the transmission lines.

## V. RECOMMENDATION

As possible extension to this work, it will be useful to analyze other possible neural network architectures such as radial basis function neural network (RBF) and the support vector machines (SVM) networks as well as providing a comparative analysis on each of the architectures and their performance characteristics with regard to the transmission line in question. It will also be very necessary to check and analyze the advantages of a particular neural network structure and learning algorithm before chosen for any application.

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