

# FAULT IDENTIFICATION SYSTEM FOR ELECTRIC POWER TRANSMISSION LINES USING ARTIFICIAL NEURAL NETWORKS

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**Abstract**— *Electric power transmission line faults hinder the continuity of electric power supplied and increase the system downtime thereby increasing the loss of electric power transmitted. Early fault detection and classification leads to prompt clearance of faults with an attendant effect of improved reliability and efficiency of the power system network. In view of this, this paper develops an artificial neural network (ANN)-based detector and classifier to indicate and classify respectively a fault on Nigeria 33-kV electric power transmission lines. The transmission lines are modeled in Simulink using SimPowerSystems toolbox in MATLAB. Fault simulations are carried out, and the resulting instantaneous values of voltages and currents are used to develop the proposed fault identification system using multilayer perceptron feedforward artificial neural networks with backpropagation algorithm. Results are presented to validate the effectiveness and efficiency of the developed identification system for detecting and classifying faults. The Mean Square Error (MSE), linear regression and the confusion matrix are used as performance evaluators for the system. The ANN-based identification system achieved MSE of  $4.77399e^{-10}$  and an accuracy of 100% for fault detection. This indicates that the performance of the developed ANN-based identification system is highly satisfactory and may be practically implemented on the Nigeria transmission lines.*

**Index Terms**— Artificial neural networks, SimPowerSystems, Backpropagation algorithm, Transmission lines, Fault detector, Fault classifier

## 1 INTRODUCTION

Overhead transmission lines are one of the primary elements in an electric power system transmission network. The electric power transmission line networks consist of interconnected electrical conductors carried on a support which convey electrical power from different generating power station to the grid and from the grid to different substations at varying degree of voltages. In Nigeria, there are four levels of transmission voltages, i.e., 330-kV, 132-kV, 33-kV and 11-kV and these voltage levels use different sizes and/or types of conductors in conveying electrical power [1]. Of these levels of voltages, this paper considers the 33-kV transmission network, which is characterized by very lengthy transmission lines; often it passes through bushes and is more close to the environment compared to 330-kV and 132-kV transmission lines. This makes it more prone to faults hence the possibility of experiencing faults on 33-kV transmission lines is generally higher than in others [2]. Faults on transmission lines are

sudden disturbances that can cause an abnormal flow of current in the line conductors. Faults are widely classified as series faults and shunt faults. The most occurred and severe type of fault is the shunt faults and its analysis is used in the design of protective and relaying equipment [3]. These shunt faults may be caused by lightning strokes, trees falling across lines, vehicle colliding with the poles, trees growing up to the transmission lines, birds short circuiting the lines, etc. When a fault occurs on an electric transmission line, it is imperative to detect and classify it to quicken the necessary arrangement towards restoring the power hence reducing the down time of lack of power to consumers which is part of the main goal of transmission line protection [4].

Therefore, to reduce the downtime of lack of electric power to consumers, a reliable intelligent fault detection and classification system is required to improve identification of the faults on transmission lines. This effort is worthwhile considering the eco-

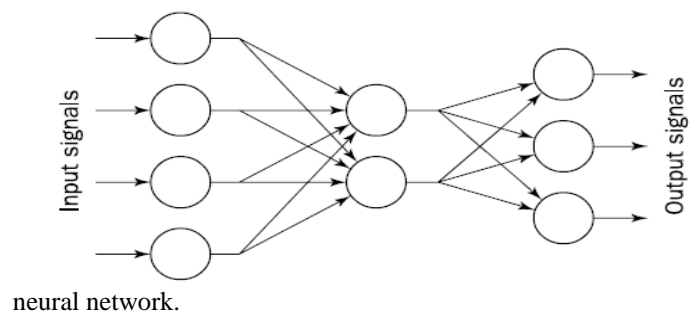
conomic benefits of quick detection and classification of faults [5]. The pattern recognition technique is useful in selecting the faulty and healthy transmission lines in electrical power system transmission network. Its ability is used to differentiate among the three lines which one is experiencing a fault. The ANNs are very powerful in fault identification by pattern recognition. To this end, this paper uses artificial neural networks to develop fault identification system to realize a complete fault detection and classification for all types of shunt faults on the 33-kV Nigeria transmission line.

Gowrishanka, *et al* [6] combined the capability of discrete wavelet Transform and artificial neural network to develop a fault detector and classifier in transmission lines. Leite, *et al* [7] developed a new technique for the detection and location of high-speed faults using neural networks. The review of different approach was previewed in [8]. Fault detection and classification for transmission line protection system using artificial neural network was proposed in [9]. Lv and Zhang, [10] employed feedforward artificial neural network with backpropagation algorithm for fault classification on transmission line of 10kV rural power grid. A powerful fault classifier and locator using artificial neural network with supervised learning was proposed in [11]. Silva, *et al.* [12] employed Wavelet Transform and ANN for detection and classification of faults in power transmission lines. A fault detection and location system for high-speed protection in extra high voltage transmission lines using feedforward neural network with the backpropagation algorithm based on supervised learning was applied by [13]. Seema, *et al.* [14] used ANN with gradient descent backpropagation algorithm to implement an intelligent fault identification system. The system realized is capable of detecting only single line-to-ground and double line-to-ground faults. A multilayer perceptron backpropagation neural network combined with Neuro shell-2 software is proposed in [15] to develop a fault detector, classifier, and locator for a transmission line. In this paper, the modeling and simulation of a 33-kV practical electric power transmission system is performed in MATLAB 2015a environment. The results of the simulations formed the input database for the proposed ANN. The multilayer perceptron feedforward artificial neural network with

backpropagation algorithm is employed in the training of two different ANN configurations which are used for fault detection and classification, respectively.

## 2. Artificial Neural Network

Artificial Neural Network (ANN) is a massively interconnected parallel computational system modeled in the way biological neurons work. They are made of several processing elements joined together in a particular way in order to achieve a particular outcome [16],[17]. This makes them more efficient for real-world applications. In addition, its capability to process information in a parallel distributed manner, solve problems that are naturally nonlinear without having prior knowledge functions relating the problem variables and its capability in handling incomplete information and corrupt data, gave it an edge over the other artificial intelligence in fault identification in transmission lines [18]. During training, an artificial neural network learns to produce a desired output based on a given input data. Hence, a training dataset is needed to train any artificial neural network to perform a particular operation [19]. The training of the network is accomplished by sequentially applying input vectors while adjusting network weights accordingly and passing the same through an activation function. The network weight converges gradually as the adjustment of different weights progress to values that will enable each input vector to produce the target [20]. Figure 1 is a simple structure of a feedforward multilayer perceptron artificial



**Figure 1:** Simple Structure of a feedforward Multilayer Perceptron ANN

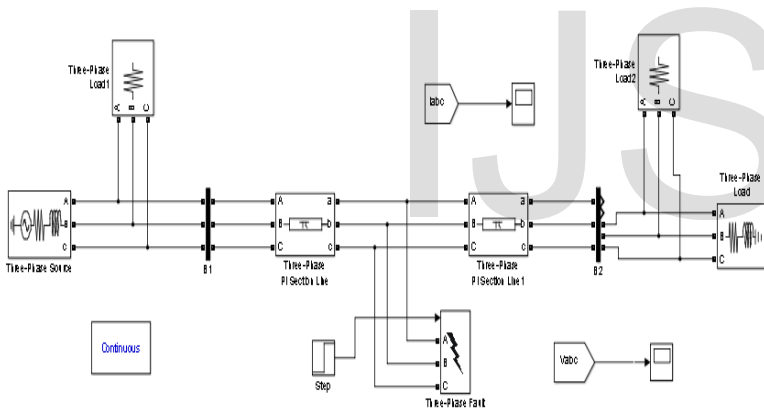
## 2.1 ANN Implementation Steps

The development of the fault identification system using ANN follows these procedures:

- 1 Transmission line simulation, sampling and recording of fault currents and voltages.
- 2 Preprocessing of recorded fault currents and voltages
- 3 Selection of the ANN configuration
- 4 Training of the ANN
- 5 Performance evaluation and validation of the trained ANN to ascertain its capability to generalize.

## 3. Power System Transmission Line Modeling

The snapshot of the Simulink model of 33-kV transmission line of Isolo transmitting station is shown in Figure 2. It consists of 140 km length of 33-kV transmission line. A source is located at one end and a load attached at the other end. The transmission lines are modeled in Simulink/MATLAB 2015a environment



using Pi model.

**Figure 2:** Snapshot of the modeled 33-kV Isolo transmission line in Simulink/Matlab

The sampling frequency of the model is 1.5 kHz. The simulation time is set to 0.02 second. In the model, the current and voltage measurements are carried out at bus B1. The instantaneous values of voltages and currents obtained are used for fault detection and classification. Ten different faults scenario were simulated at varying distance and resistance values. The transmission line characteristics and parameters used for the model are:

Line Length = 140 km

Positive- and zero-sequence resistances (Ohms/km):

[0.18446 0.39072]

Positive- and zero-sequence inductances (H/km):

[0.0010981 0.0024668]

Positive- and zero-sequence capacitances (F/km):

[1.0865e-08 6.6177e-09]

Fault Starting = 0.020 seconds

Duration in fault = 0.03 Seconds

Type Conductor = ACSR

### A. Simulation and Preprocessing of data

The system model is first set up in Simulink, and then the three-phase V-I measurement block is used to measure the instantaneous values of voltages and currents signals. The three section pi-section line 1 and 2 together is 140 km long. Ten different shunt faults plus no fault condition are simulated between 1 km and 140 km at a step of 2 km. The values of resistances and fault inception angle used are shown in Table 1. These faults are simulated one after another and the three phase voltage and current waveforms generated are sampled at a frequency of 1.5 kHz. Hence, there are thirty (30) samples per cycle. These samples are preprocessed to obtain a suitable input data set for the ANN [21]. In all, a total of 6 x 6,160 sample data set is obtained for this study.

**Table 1:** Parameter Values used in Generating the Training and Test Dataset

Training Dataset	
Fault inception angle ( $^{\circ}$ )	30, 60
Fault Resistance (Ohms)	0.25, 0.5, 0.75, 5, 10, 20, 30 and 50
Test Dataset	
Fault Location (km)	8, 16, 24, ..., 138
Fault Resistance (Ohms)	15, 25
Fault inception angle ( $^{\circ}$ )	20, 90

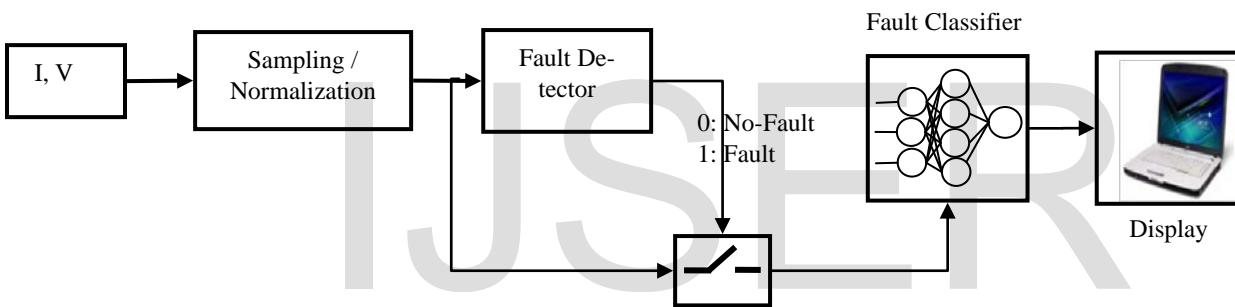
## 4. The Proposed Fault Identification System

The fault identification system being proposed is designed to detect the presence of a fault and afterward classify the fault. The developed system has two stages – the detection stage and the

classification stage. The Figure 3 shows the modular block representing the proposed system while the stages involved in the developmental process are as follows:

1. Acquisition and Pre-Processing of input Data set
2. Preparation of appropriate target data set suitable for the ANN to learn
3. Choose ANN configuration
4. Train the ANN
5. Calculate the performance MSE
6. Evaluate the trained ANN using the Performance MSE, confusion matrix, Regression Plot and a new set of data outside the one used for training.
7. Generate and save a Simulink Model for the best performed ANN based on the test matrix.

data which means 560 samples for each of the faults considered and No-fault case. This invariably forms an input-output pattern of set of six (6) inputs and an output pair. Several configurations of the ANN with varying number of neurons are extensively trained and the results of the structure that gives the best satisfactory performance are presented. The performance MSE, confusion matrix, regression plot and the generalization capability are used as performance indicators. Table 2 shows the truth table of the fault state of the lines.



**Figure 3:** The modular block diagram of ANNFD

#### 4.1 Fault Detector

The proposed ANN-Based fault detector (ANNFD) is designed using the preprocessed instantaneous current and voltage data set generated to indicate the absence or presence of a fault on the 33-kV Nigeria electric transmission lines [22]. In consequence, if the ANNFD detects a fault, it activates the corresponding ANN-Based fault classifier (ANNFC) for classification of the detected fault. The ANNFD uses one-terminal line datum extracted at bus B1 and takes in six (6) inputs at a time which are the preprocessed instantaneous voltages and currents for the ten (10) different fault cases and no-fault case simulated. A total of six thousand, one hundred and sixty (6,160) input data set is extracted, scaled and used as input data for training the ANNFD. Hence, the training set consists of 6 x 6,160 input data set and 1 x 6,160 target output

**Table 2:** The Target Truth Table for the ANNFD

	Fault Type										
	A	B	C	A-	A-	B-	A	A	B	A-	No-Fault
	-	-	-	B-	C-	C-	-	-	-	B-	No-Fault
	G	G	G	G	G	G	B	C	C	C	
<b>Line Status</b>	1	1	1	1	1	1	1	1	1	1	0

#### Results and Discussion

The ANN structure with 6-5-1 configuration having activation function combination of purelin/logsig/tansig for the input layer, one hidden layers and output layer respectively gave the best satisfactory performance among several structures considered. Furthermore, the developed ANNFD confusion matrix, validation performance plot, and linear regression plot are presented in Fig-

ure 7, Figure 8, and Figure 9, respectively and are used to ascertain the capability of the ANNFD to generalize [6].

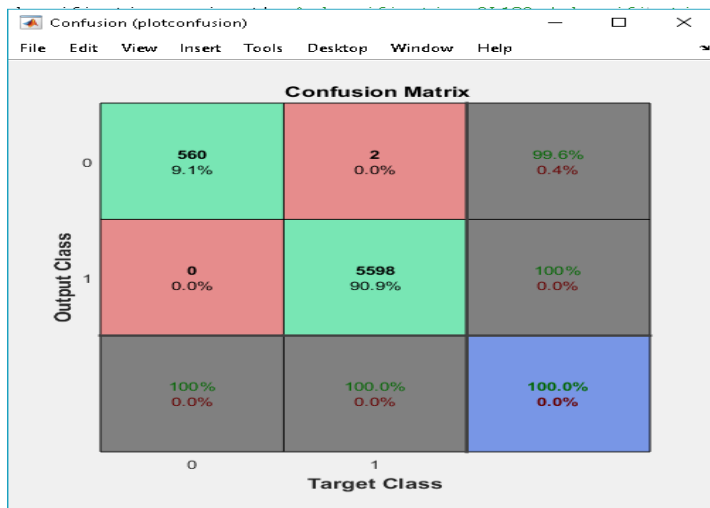


Figure 7: Confusion Matrix for ANN-Based FD with 6-14-4 configuration

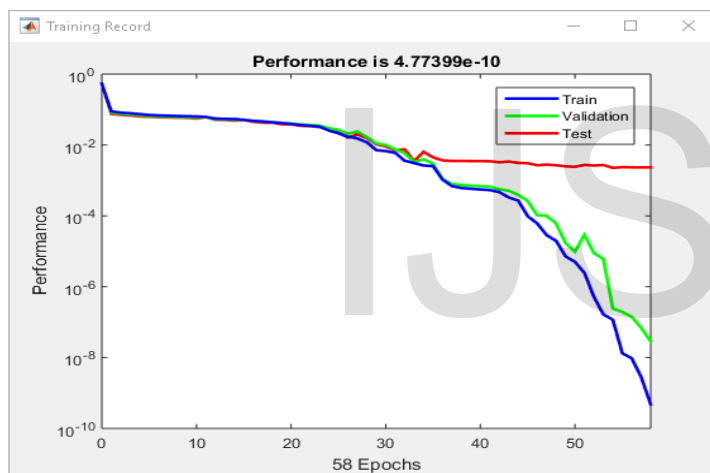


Figure 8: Performance Plot for one hidden layers with 6-14-4 configuration

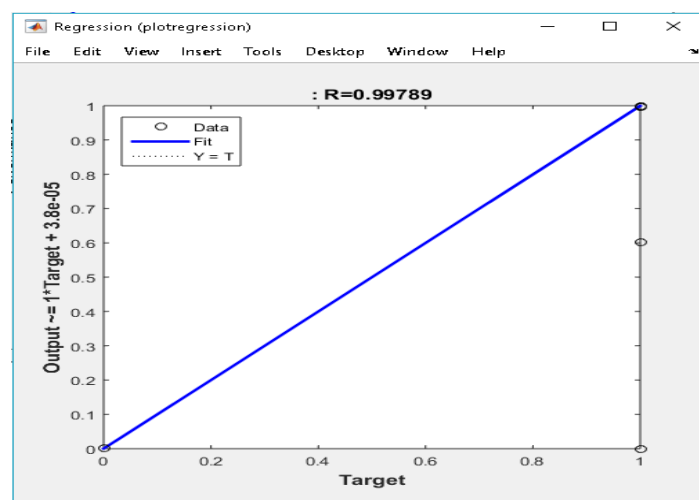


Figure 9: The ROC for ANNFD with 6-14-4 Configuration.

It can be seen from the blue square box of Figure 7 that the performance of the developed fault identification system is 100%, showing that there is no confusion in detecting all the faults tested. In addition, the performances plot (Figure 8), shows that the best validation performance MSE is  $4.77389e-10$  which is below the preset MSE goal of 0.0001 and finally, the linear regression fit (Figure 9) shows the relationship between the actual neural network's outputs and the desired targets. However, from Figure 9, the correlation coefficient, R is 0.99789 which is very close to the ideal value (1), thus indicating an excellent correlation. Therefore, the performance of the developed system is said to be satisfactory and the system can be said to have very good training, validation, and testing. Hence, the developed ANNFD can be deployed to the 33-kV Nigeria transmission line.

#### 4.2. Fault Classification

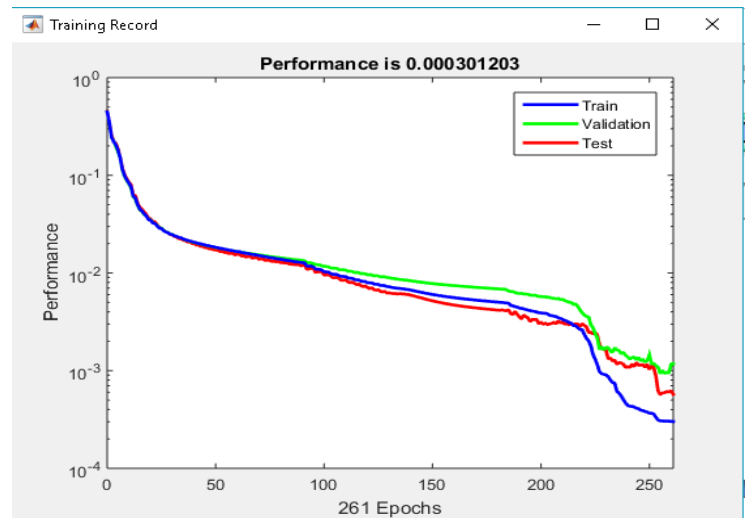
The process of developing artificial neural network based fault classifier (ANNFC) employed for ANNFD. The ANN takes in a set of  $6 \times 6,160$  as input data set as earlier emphasized and  $4 \times 6,160$  target output which in turn forms an input-output pattern of six (6) inputs and four (4) output pair. The four output target of the neural network corresponds to the fault state of each of the three lines and the ground line. To this end, the various permutation of the fault state of the lines with the ground is shown in Table 3. Moreover, it is expected that the developed system should be able to accurately classify the ten possible categories of faults and the No-fault case. The training data set holds total of 6,160 inputs data set and a corresponding output target i.e. 560 for each of the fault type and No-fault condition. The MLP feedforward Back-propagation neural networks with combinations of different hidden layers, number of neurons in each hidden layer and transfer function are thoroughly and exhaustively investigated. As before, the mean square error of the trained network, confusion matrix, linear regression and receivers operating characteristics are used as performance matrix to test the proposed system.

**Table 3:** The Target Truth Table for the ANNFC

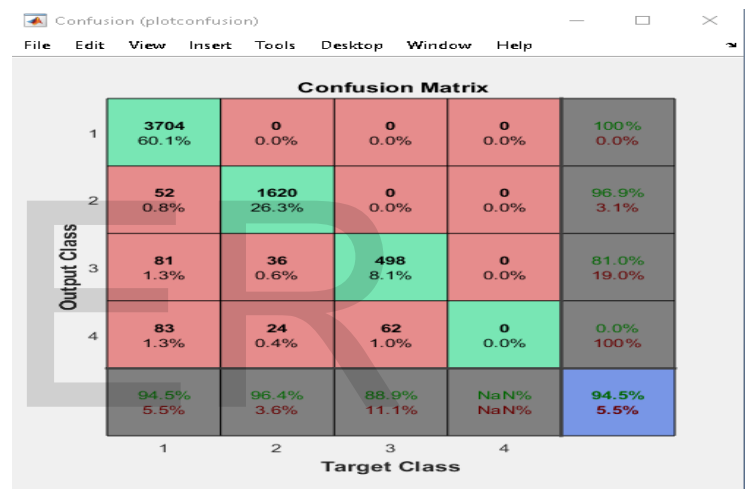
Line	Fault Type										
	A	B	C	A-	A-	B-	A	A	B	A-	No-Fault
	-	-	-	B-	C-	C-	-	-	-	B-	
G	G	G	G	G	G	B	C	C	C		
A	1	0	0	1	1	0	1	1	0	1	0
B	0	1	0	1	0	1	1	0	1	1	0
C	0	0	1	0	1	1	0	1	1	1	0
G	1	1	1	1	1	1	0	0	0	0	0

**A. Results and Discussion**

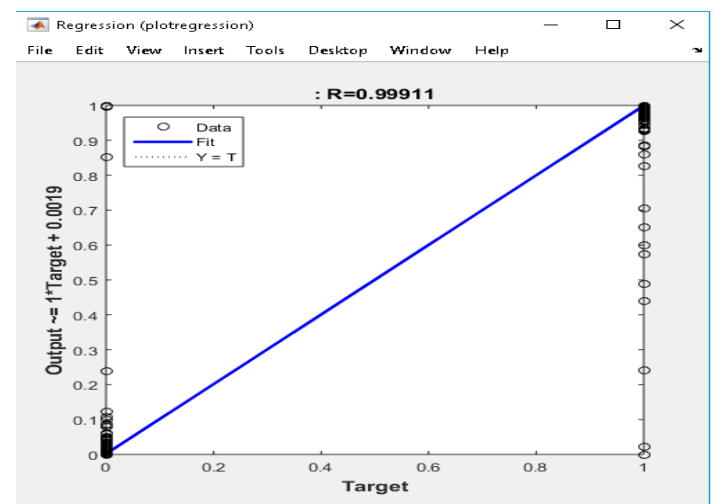
After training several ANN structures with different configurations, the ANN structure with 6-16-4 configuration having activation function combination of purelin/logsig/tansig for the input layer, one hidden layer and output layer respectively gave the best satisfactory performance. Figure 10 – Figure 13 show the performance matrix used in determining the performance of the developed ANNFC. From Figure 10, it can be said that the ANNFC is efficient since the testing and the validation curves have similar characteristics and the validation performance MSE is 0.000301203 which is below the preset MSE of 0.001. Also, an accuracy of 94.5% as seen in Figure 11 and the correlation coefficient of 0.99911(Figure 12) which shows how much the network output was able to track the target further proves the satisfactory performance of the developed ANNFC. From the ROC plot (Figure 13) which expresses the percentage of true positivity and false positivity, it can be seen that all the line are well fitted in the upper-left corner which expresses a 100% true positivity and 0 percent false positivity of classification. Based on the results, this study concluded that the ANNFC developed can effectively and efficiently differentiate among all the ten possible types of faults considered and No-fault condition on the 33-kV Nigeria transmission line.



**Figure 10:** Performance Plot for one hidden layer with 6-16-4 configuration



**Figure 11:** Confusion Matrix for ANNFC with 6-16-4 configuration



**Figure 12:** The Regression Plot for the ANNFC with 6-16-4 Configuration



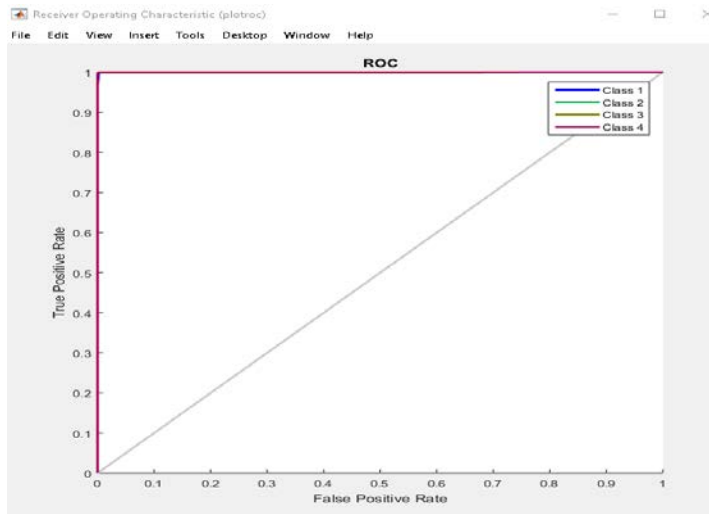


Figure 13: The ROC for ANNFC with 6-16-4 Configuration

## Conclusions

The longer faults stay on a transmission line, the more damage it is likely to cause to the transmission network which will eventually lead to loss of economy. To this end, artificial neural networks have been employed in this paper in designing a fault identification system for fault identification and classification on the 33-kV Nigeria electric transmission line. The developed system uses as inputs data to the ANN the preprocessed instantaneous values of voltages and currents sampled at a frequency of 1.5 kHz. Moreover, all the single line-to-ground faults, double line-to-ground faults, and line-to-line faults tested have been accurately detected and classified. More so, results presented for the ten (10) different fault cases analyzed shows that the developed identification system is efficient and reliable enough to be implemented on the 33-kV Nigeria electric power transmission line.

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