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An Artificial Neural Network-Based Intelligent Fault Classification System for the 33-kV Nigeria Transmission Line

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Abstract

Electric power Transmission lines are characterized by very lengthy transmission lines and thus are more exposed to the environment. Consequently, transmission lines are more prone to faults, which hinder the continuity of electric power supplied, increases the loss of electric power generated and loss of economy. Quick detection and classification of a fault hastens its Clearance and reduces system downtime thus, improving the security and efficiency of the network. Thus, this paper focuses on developing a single artificial neural network to detect and classify a fault on Nigeria 33-kV electric power transmission lines. This study employs feedforward artificial neural networks with backpropagation algorithm in developing the fault detector- classifier. The transmission lines were modeled using SimPowerSystems toolbox in Simulink and simulation is done in MATLAB environment. The instantaneous voltages and currents values are extracted and used to train the fault detector-classifier. Simulation results have been provided to demonstrate the efficiency of the developed intelligent systems for fault detection and classification on 33-kV Nigeria transmission lines. The performance of the detector-classifier is evaluated using the Mean Square Error (MSE) and the confusion matrix. The systems achieved an acceptable MSE of 0.00004279 and an accuracy of 95.7%, showing that the performance of the developed intelligent system is satisfactory. The result of the developed system in this work is better in comparison with other systems in the literature concerning Nigeria transmission lines.

Keywords: Artificial neural networks, Feedforward networks, Backpropagation algorithm, Transmission lines, Fault detector and classifier

INTRODUCTION

The modern electrical power system is divided into three subsystems namely, generation, transmission, and distribution subsystem. In Nigeria, the generation and distribution subsystems are linked via the transmission subsystem by means of overhead transmission lines. This part of the power system network is characterized by very lengthy transmission lines which often pass through different environmental topography. Therefore, the possibility of experiencing a fault is very high in overhead transmission lines compared to generation and distribution subsystems in the power system network [1]

One of the key factors that hamper the steady supply of electricity is a fault [2]. A fault is an abnormal flow of current in the transmission lines in the power system networks [3]. These faults are broadly classified into series faults and shunt faults. This work focuses on shunt faults which may be caused by lightning strokes, storms, trees falling across lines, trees growing up to the lines, bird shorting the lines, vandalism, etc. [4]. Therefore, for continuity of power supply, the transmission lines must be protected against any form of disturbances by not only disconnecting the faulty section of the system through the protective relays and circuit breakers but also by detecting and classifying the faults [3]. These efforts and interests are based on the safety implications and economic benefits of quickest detection and classification of faults on transmission lines, which speed up fault clearance on transmission lines and hence minimize damage [5]. Therefore, in no small measure, this necessitates the need for an intelligent system that is capable of detecting and classifying faults on the transmission lines [6]. To this end, one of the main challenges facing the Nigeria 33-kV transmission system network today is lack of intelligent fault detectors and classifiers.

There are lots of artificial intelligence techniques i.e., expert systems, neural networks, fuzzy logic systems, genetic algorithms etc., for fault detection and classification [7] but the capability of the artificial neural network (ANN) in classification of fault by pattern recognition is utilized by this paper [6]. Applications of ANNs to power systems fault detection and classification has been demonstrated in the literature. Kumar et al. in [8] employed a feed forward neural network which was trained using the backpropagation algorithm on the studies of fault detection and classification. Gowrishanka et al. [9] used discrete wavelet Transform and artificial neural network approach for fault detection and classification in transmission lines. The authors extracted information from the transient signal both in time and frequency domain using the wavelet transform while the ANN was used for fault classification. A new technique for the detection and location of high-speed faults using neural networks was proposed by [10]. In [11], the feedforward backpropagation approach was deployed. The training algorithm used is the Levenberg Marquardt algorithm. Various other relevant work in the field of shunt faults classification using artificial neural networks can be found in [12] and [13]. Feedforward neural network with the backpropagation algorithm based on supervised learning was applied by [14] to fault detection and location in extra high voltage transmission lines for high-speed protection. The author used instantaneous current and voltage magnitudes at the fundamental frequency to design a detector and a classifier. Seema et al. [15] developed an intelligent fault identification system using feedforward neural network and gradient descent backpropagation algorithm. The developed fault detector was realized in hardware using TMS320C6713. The developed system is capable of detecting single line to ground and double line to ground faults only, for all the three phases. A multilayer perceptron backpropagation neural network together with Neuro shell-2 software was used by [16] to develop a fault detector, classifier, and locator for a transmission line. In this paper, a new approach, using a single ANN system for both fault detection and classification employing multilayer perceptron feedforward artificial neural network with backpropagation algorithm is proposed for efficient and reliable fault detection and classification. The transmission lines are modeled and electrical transient system faults are simulated in MATLAB 2013a. An intelligent ANN fault detector-classifier (IFDC) system is developed for recognition of these faulty patterns. The performance of the developed system is evaluated by simulating the various types of fault.

Transmission Line under Consideration

The network considered in this study consists of 140 km, 33-kV transmission lines extending between two transformers – one at the sending end and the other at the receiving end. The property of the transmission line conductors useful for its modeling is shown in Table 1.

Table 1: Property of the transmission line under study

Height of pole from ground surface	28 ft (8.5344 m)
Normal cross-sectional areal Alu/Steel	50/35 mm
Approximate overall diameter 1	8.1 mm (0.0181 m)
Calculated D.C Resistance at 20 ^{0}C	0.1828 Ohm/km

The transmission line was modeled using Pi model in Simulink/MATLAB 2013a environment using SimPowerSystems toolbox. Figure 1 depicts the snapshot of the modeled transmission line network used in this study. The model is made up of the three phase fault simulator, the three phase load 1 & 2 representing the transformers respectively and the three phase Pi section lines which represents the transmission lines [17].

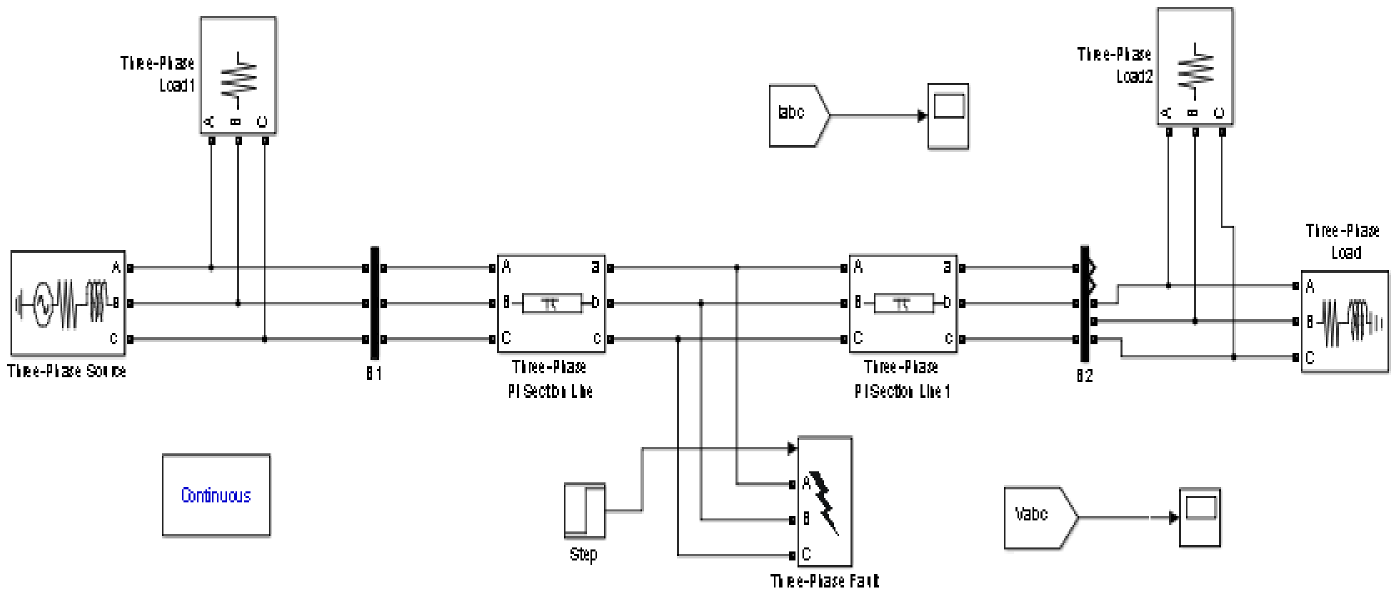

Figure 1: Snapshot of the modeled 33-kV Nigeria transmission line in Simulink/Matlab

This model was simulated in Simulink. The voltage and current signals were measured using the three phase V-I measurement block. The transmission line (line 1 and line 2) together is 140 km long and various shunt faults were simulated between 1 km and 140 km at a step of 2 km. The resistances used are 0.25, 0.5, 0.75, 5, 10, 20, 30 and 50 ohms. The model was used to generate the whole set of data for training the neural network for the development of the IFDC. For the purpose of fault detection and classification, ten (10) fault cases plus no fault case were simulated and 6 x 6,160 sample data were obtained. The three phase voltage and current waveforms were generated and sampled at a frequency of 1.5 kHz. This choice of the sampling frequency was based on the results of series of the experiments carried out using different frequencies that are at least twice the fundamental frequency (50 Hz). Consequently, there are 30 samples per cycle and these samples were not made to be fed into the ANN in its raw state. Hence, it has to undergo a preprocessing stage called feature extraction and scaling [18]. This, in turn, reduces the overall size of the neural network and advances the time performance of the network. Meanwhile, the fault was created at 0.04s which corresponds to the 55th sample. Also, the inputs to the ANN are the ratios of the post-fault and pre-fault voltages and currents in each of the phases, which correspond to the 67th sample and 43rd sample after and before the occurrence of the fault respectively. Table 2 shows the sample scaled Voltage and Current values used with respect to their pre-fault values for phase A at a distance of 60 km from bus B1.

Artificial Neural Networks (ANN)

An artificial Neural Network (ANN) is modeled after the way and manner the biological neural systems work [19]. They are parallel computational systems and are made of several processing elements connected together in a particular way in order to perform a particular task [20][21]. ANNs are massively paralleled and have the ability to learn from training data and generalize to new situations. This makes them efficient and robust for real world applications, hence, they are configured to perform tasks analogous to biological brains. According to [15], the uniqueness of ANN that gave it an edge in the artificial intelligent world is based on the fact that, the information processing of ANN can be carried out in a parallel distributed manner because it is made of massive interconnection of elementary processing units, ANN can be used to solve problems that are inherently nonlinear, it requires no prior knowledge functions relating the problem variables and it is capable of handling situations of incomplete information and corrupt data. Moreover, ANN learns to produce an output based on a given input data. The training of the network is accomplished by sequentially applying input vectors while adjusting network weights accordingly [22]. It is in training that the neural network learns to map the input into the output based on a given input data [23]. The network weight converges gradually as the adjustment of different weights progresses (training) to values that will enable each input vector to produce the target [24][25]. The supervised learning which is commonly used in electric power transmission lines fault detection and classification is employed in this study [26]. 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 backpropagation algorithm [27]. Figure 2 depicts a supervised learning approach for a feedforward neural network.

Table 2: Sample of the scaled Voltage and Current values for Phase A

S/N	V_a	V_b	V_c	I_a	I_b	I_c
1	0.3253	0.2693	0.3471	0.4805	0.4861	0.4835
2	0.3979	0.3383	0.3955	0.4336	0.4385	0.4362
3	0.4472	0.3923	0.4380	0.3868	0.3912	0.3891
4	0.5715	0.5604	0.5677	0.1104	0.1114	0.1109
5	0.5755	0.5720	0.5748	0.0604	0.0608	0.0606
6	0.5765	0.5759	0.5765	0.0340	0.0342	0.0341
7	0.5766	0.5767	0.5769	0.0252	0.0253	0.0252
8	0.5768	0.5771	0.5772	0.0183	0.0184	0.0183
9	0.4765	0.4397	0.4906	0.3339	0.3377	0.3361
10	0.4964	0.4599	0.5039	0.3080	0.3115	0.3100

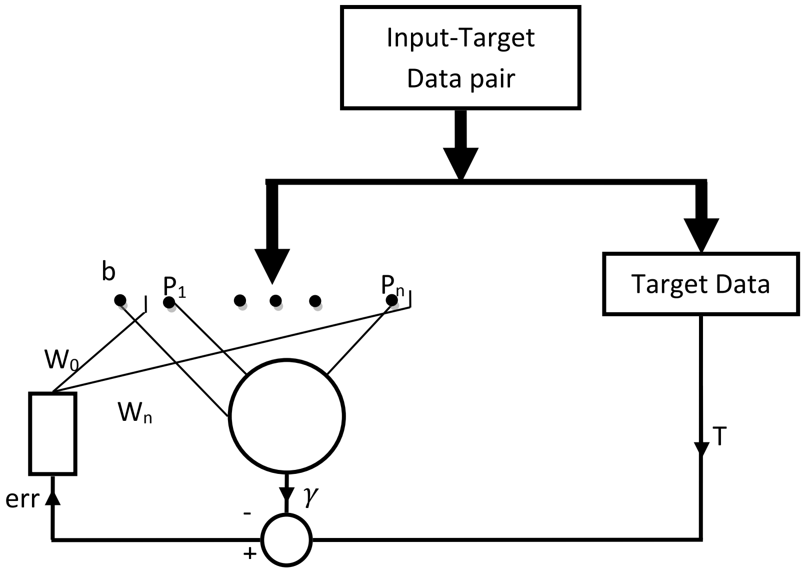

Figure 2: The supervised learning approach for a feedforward neural network

The transfer (activation) function is one of the major key factors that determine the capability of an artificial neural network to approximate functions. The appropriate transfer function is chosen based on the application's requirements. The commonly used types of transfer functions are; linear activation function, sigmoid activation function, and radial activation function. The combinations of sigmoid and linear transfer function were chosen for this work. The binary sigmoid transfer function is expressed mathematically as:

For Binary Sigmoid; $f(Z) = \frac{1}{1+e^{-\sigma z}}$ (1)

For Bipolar Sigmoid; $f(Z) = \frac{1-e^{-\sigma z}}{1+e^{-\sigma z}}$ (2)

where, z = sum of weighted inputs; σ = steepness parameter

System Methodology and Design

The backpropagation feedforward neural network with Levenberg Marquardt algorithm has been chosen. Series of experiments were carried out to arrive at the algorithm, activation functions, the number of hidden layers and number of hidden neurons. The neural network for IFDC takes in six (6) inputs at a time which are the scaled instantaneous voltages and currents for all the three phases for ten (10) different fault cases and no fault case. The training set consist of six thousand, one hundred and sixty (6,160) input-output data set that amounts to five hundred and sixty (560) data set for each case. The proposed IFDC is to use the instantaneous voltage and current values extracted from B1to detect the presence of fault and classifier it accordingly. The truth table for the different types of faults is as shown in Table 3.

Table 3: The truth table of the detector-classifier for various fault conditions

S/N	Fault Type	Network Target			
		A	B	C	G
1	A – G	1	0	0	1
2	B – G	0	1	0	1
3	C – G	0	0	1	1
4	A – B – G	1	1	0	1
5	A – C – G	1	0	1	1
6	B – C – G	0	1	1	1
7	A – B	1	1	0	0
8	A – C	1	0	1	0
9	B – C	0	1	1	0
10	A – B – C	1	1	1	0

Moreover, several structures of the artificial neural networks were extensively trained and the performance plot and confusion matrix of the ANN IFDC configuration that gave the best performance is shown in this study. The design and testing process are illustrated in Figure 4 and Figure 5 respectively.

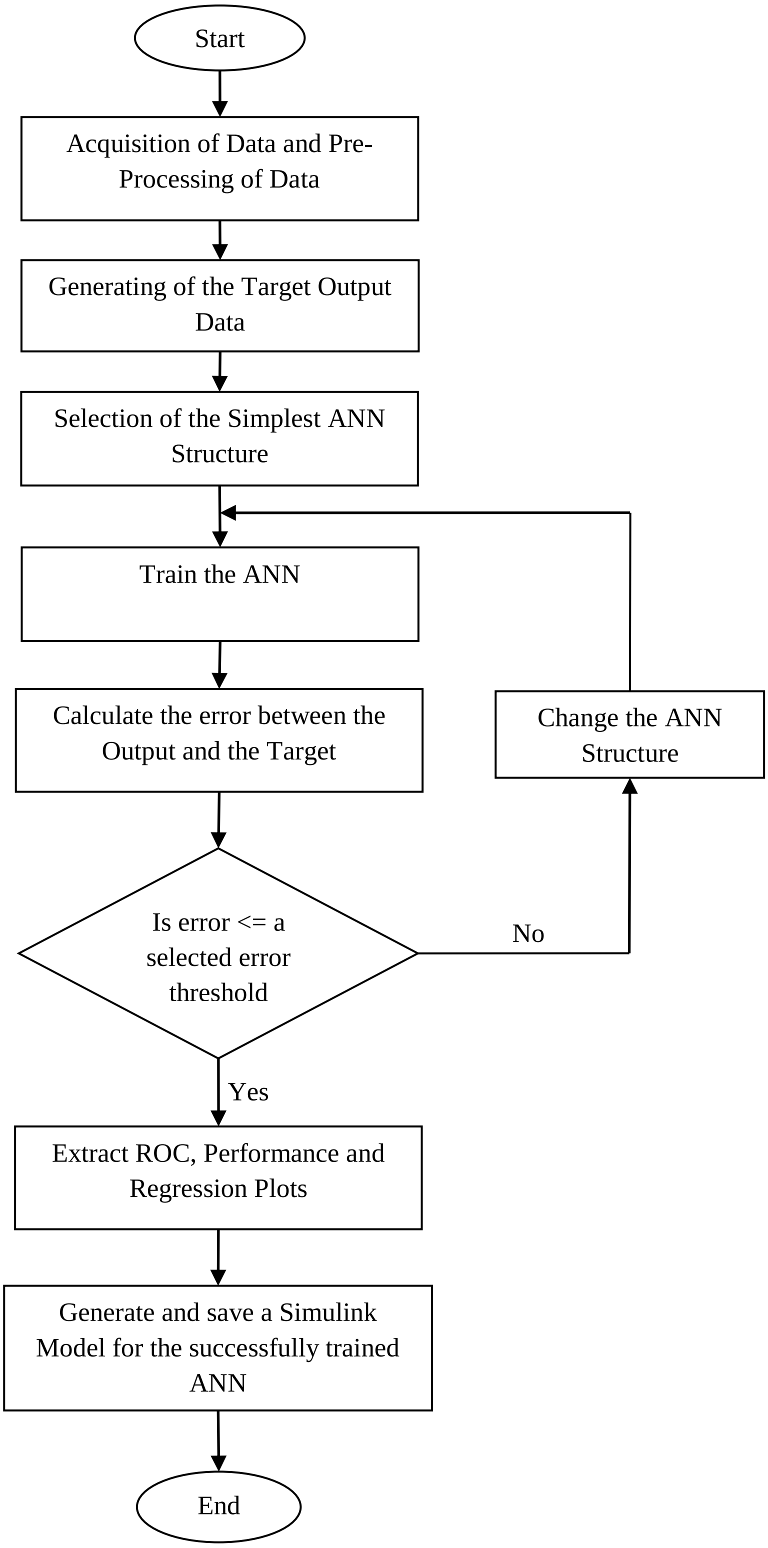

Figure 4: The Flow Chart for developing IFDC

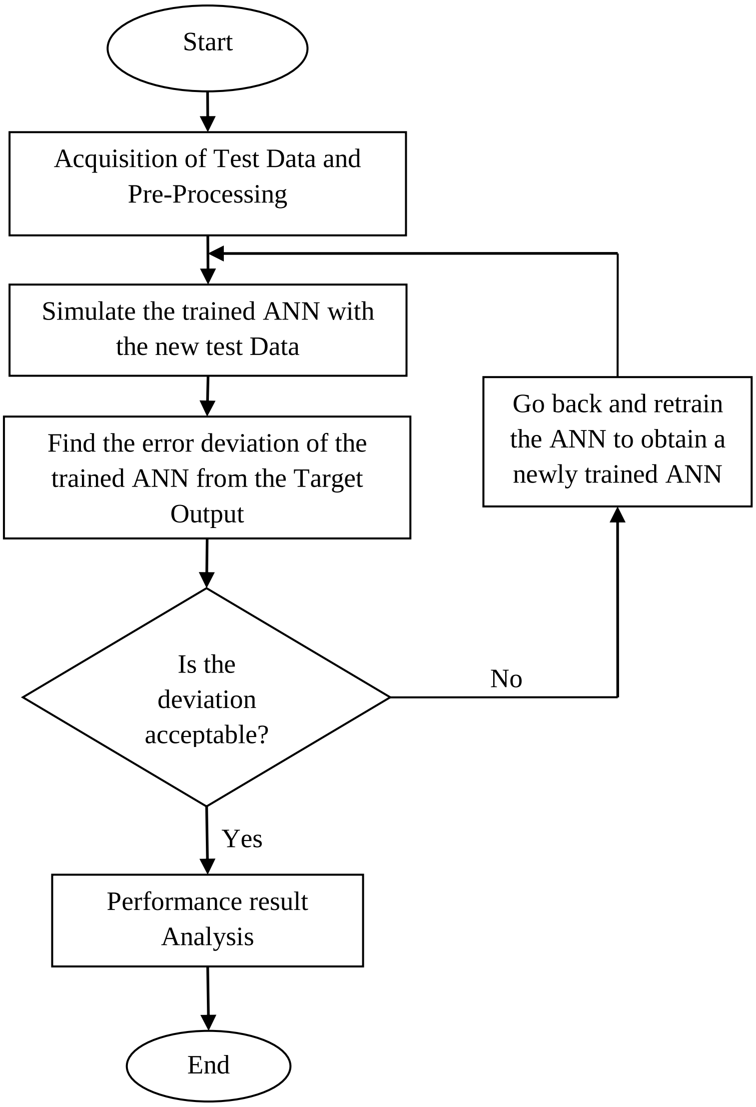

Figure 5: The Flow Chart for Testing the developed IFDC

RESULTS

After training several ANN structures, the ANN with 6-10-10-10-4 configuration had the overall performance of 0.00004279 and accuracy of 95.7%, hence it was chosen as the ANN IFDC for this study. Moreover, the validation performance plot, linear regression plot, confusion matrix, Receiver Operating Characteristics (ROC) plot and simulation with a new set of data outside the one used for training were used to ascertain the performance of the developed ANN IFDC [7]:

Figure 6 is the performance plot of the IFDC in terms of training, testing and validation. It can be seen that the best MSE performance of this neural network is 0.00004279.

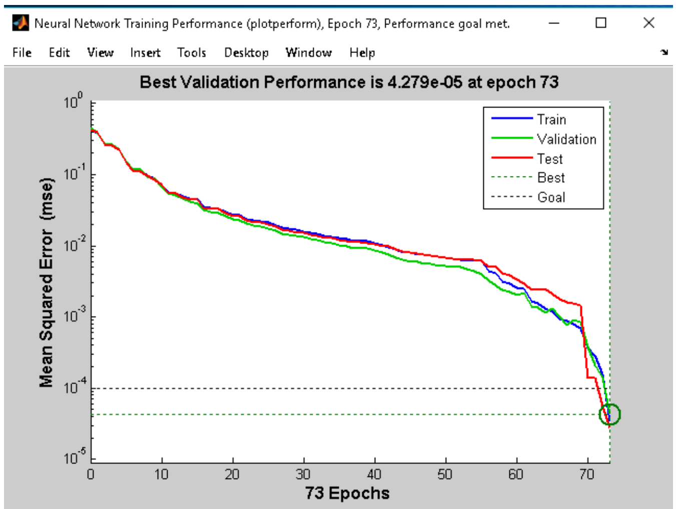

Figure 6: Performance Plot for three hidden layers with 6-10-10-10-4 Configuration

Figure 7 is the correlation coefficient (r) plot which measures how well the neural network's targets can track the variations in the outputs.

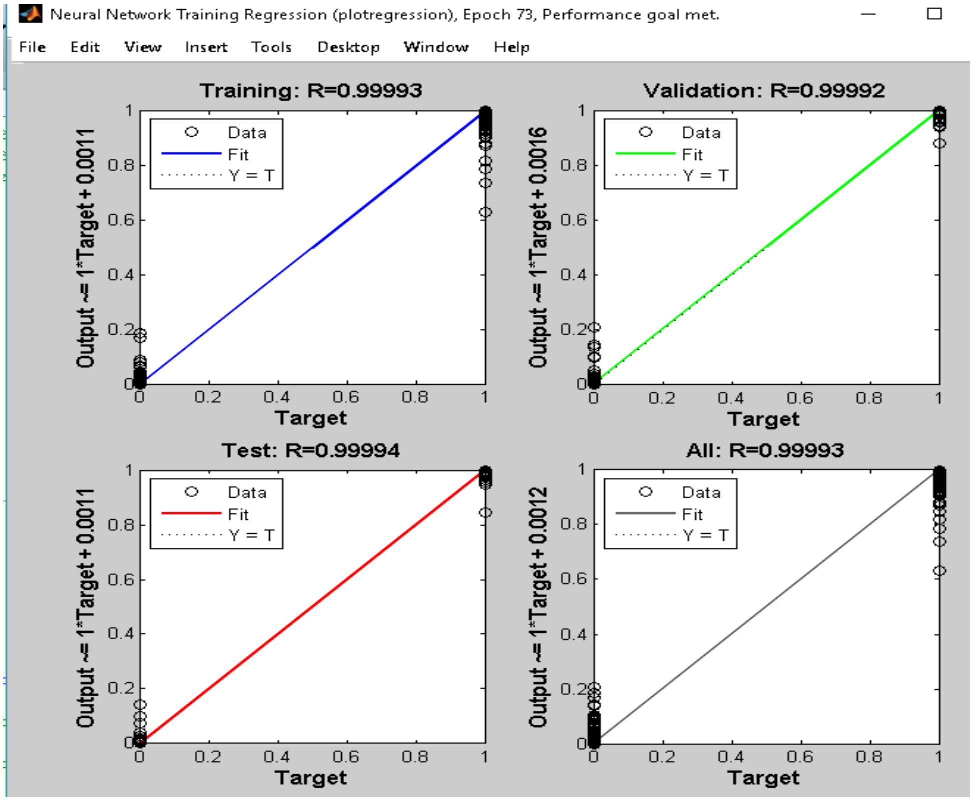

Figure 7: The Regression Plot for the IFDC with 6-10-10-10-4 Configuration

Figure 8 is the confusion matrix of the chosen ANN IFDC with 6-10-10-10-4 configuration.

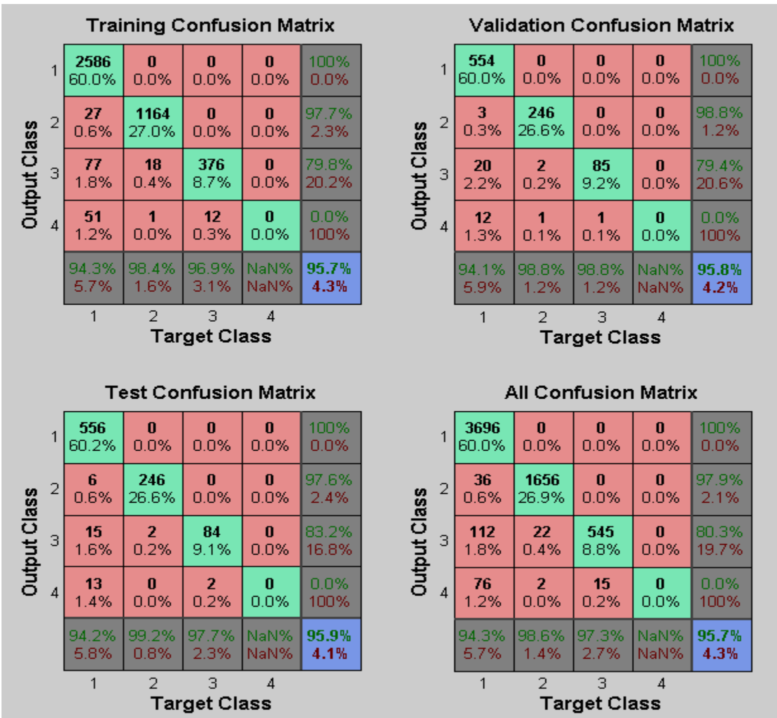

Figure 81: Confusion Matrix for three hidden layers with 6-10-10-10-4 Configuration

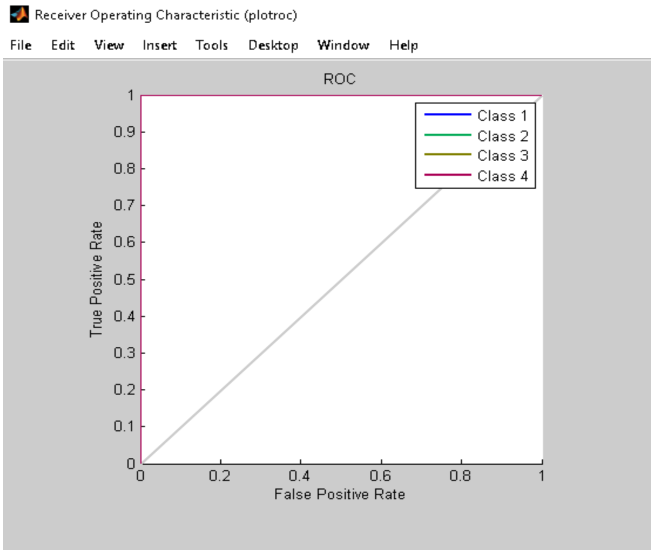

Figure 9: The ROC for IFDC with 6-10-10-10-4 Configuration

Figure 9 represents the plots between the rate of positive classification and the rate of incorrect classification of the developed ANN IFDC classifier.

Furthermore, the developed IFDC was tested with a total of 6 x 187 test data which was not part of the data set used in the training. The test data set contains seventeen (17) cases each corresponding to the different conditions of shunt faults and no-fault condition. The fault resistance was taken as 0.75 Ohms while the fault location was varied from 8 to 140 in steps of 8. Tables 4 to 7 show side-by-side the target and the ANN IFDC output under each fault condition.

Table 4: Test Result of the ANN IFDC with New Data Set for L-G

K m	**IFDC O/P AG**				**TARGET**				**IFDC O/P BG**				**TARGET**				**IFDC O/P CG**				**TARGET**			
1	1	0	0	1	1	0	0	1	2e-13	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
2	1	0	0	1	1	0	0	1	6E-7	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
3	1	0	0	1	1	0	0	1	7e-08	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
4	1	0	0	1	1	0	0	1	6e-10	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
5	1	0	0	1	1	0	0	1	1e-08	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
6	1	0	0	1	1	0	0	1	2e-09	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
7	1	0	0	1	1	0	0	1	9e-10	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
8	1	0	0	1	1	0	0	1	1e-15	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
9	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
10	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
11	1	0	0	1	1	0	0	1	0	1	1e-13	1	0	1	0	1	0	0	1	1	0	0	1	1
12	1	0	0	1	1	0	0	1	0	1	1e-07	1	0	1	0	1	0	0	1	1	0	0	1	1
13	1	0	0	1	1	0	0	1	0	1	1-05	1	0	1	0	1	0	0	1	1	0	0	1	1
14	1	0	0	1	1	0	0	1	0	1	1e-08	1	0	1	0	1	0	0	1	1	0	0	1	1
15	1	0	0	1	1	0	0	1	3e-10	1	6e-13	1	0	1	0	1	0	0	1	1	0	0	1	1
16	1	0	0	1	1	0	0	1	5e-3	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
17	1	0	0	1	1	0	0	1	1e-05	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1

Table 5: Test Result of the ANN IFDC with New Data Set for L-L-G

S/N	IFDC O/P ABG				TARGET				IFDC O/P ACG				TARGET				IFDC O/P BCG				TARGET			
1	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
2	1	1	0	0.9	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
3	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
4	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
5	1	1	0	0.9	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
6	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
7	1	1	0	0.9	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
8	1	1	0	0.9	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
9	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
10	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
11	1	1	1e-16	0.9	1	1	0	1	0.9	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
12	1	1	5e-15	0.9	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
13	1	1	5e-17	1	1	1	0	1	0.9	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
14	1	1	3e-14	1	1	1	0	1	0.9	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
15	1	1	1e-12	0.9	1	1	0	1	0.9	0	1	1	1	0	1	1	0	1	1	0.9	0	1	1	1
16	1	1	0	0.9	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	0.9	0	1	1	1
17	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	0.9	0	1	1	1

Table 6: Test Result of the ANN IFDC with New Data Set for L-L

S/N	IFDC O/P AB				TARGET				IFDC O/P AC				TARGET				IFDC O/P BC				TARGET			
1	1	1	4e-3	9e-08	1	1	0	0	1	0	1	0	1	0	1	0	5e-17	1	1	0	0	1	1	0
2	1	1	5e-4	5e-10	1	1	0	0	1	0	1	0	1	0	1	0	1e-10	1	1	0	0	1	1	0
3	1	1	1e-05	3e-10	1	1	0	0	1	0	1	0	1	0	1	0	1e-13	1	1	0	0	1	1	0
4	1	1	1e-07	2e-09	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1	0
5	1	1	2e-09	5e-08	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1	0
6	1	1	1e-10	1e-06	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1	0
7	1	1	7e-11	1e-05	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	3e-13	0	1	1	0
8	1	1	1e-10	5e-05	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	7e-10	0	1	1	0
9	1	1	8e-10	7e-05	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	4e-08	0	1	1	0
10	1	1	1e-08	3e-05	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	1e-07	0	1	1	0
11	1	1	1e-07	2e-06	1	1	0	0	1	1e-12	1	0	1	0	1	0	0	1	1	8e-09	0	1	1	0
12	1	1	4e-06	3e-08	1	1	0	0	1	3e-07	1	0	1	0	1	0	0	1	1	2e-11	0	1	1	0
13	1	1	1e-4	1e-11	1	1	0	0	1	1e-4	1	0	1	0	1	0	0	1	1	7e-15	0	1	1	0
14	1	1	2e-3	5e-17	1	1	0	0	1	3e-4	1	0	1	0	1	0	4e-12	1	1	0	0	1	1	0
15	1	1	3e-3	0	1	1	0	0	1	8e-05	1	0	1	0	1	0	7e-05	1	1	0	0	1	1	0
16	1	1	1e-09	0	1	1	0	0	1	6e-06	1	0	1	0	1	0	2e-3	1	1	9e-16	0	1	1	0
17	1	1	0	0	1	1	0	0	1	4e-07	1	0	1	0	1	0	5e-17	1	1	0	0	1	1	0

Table 7: Test Result of the ANN IFDC with New Data Set for L-L-L and No fault

S/N	IFDC O/P ABC				TARGET				IFDC O/P NO FAULT				TARGET			
1	1	1	1	0	1	1	1	0	0.02	6e-6	1e-3	3e-3	0	0	0	0
2	1	1	1	0	1	1	1	0	0.02	6e-6	1e-3	3e-3	0	0	0	0
3	1	1	1	0	1	1	1	0	0.02	6e-6	1e-3	3e-3	0	0	0	0
4	1	1	0.9	0	1	1	1	0	0.02	6e-6	8e-4	3e-3	0	0	0	0
5	1	1	0.9	0	1	1	1	0	0.02	6e-6	9e-4	3e-3	0	0	0	0
6	1	1	0.9	3e-15	1	1	1	0	0.02	6e-6	9e-4	3e-3	0	0	0	0
7	1	1	0.9	6e-14	1	1	1	0	0.01	5e-6	8e-4	3e-3	0	0	0	0
8	1	1	0.9	2e-13	1	1	1	0	0.01	5e-6	9e-4	3e-3	0	0	0	0
9	1	1	0.9	4e-13	1	1	1	0	0.01	5e-6	8e-4	3e-3	0	0	0	0
10	1	1	0.9	2e-13	1	1	1	0	0.01	5e-6	9e-4	3e-3	0	0	0	0
11	1	1	0.9	9e-14	1	1	1	0	0.01	4e-6	1e-3	3e-3	0	0	0	0
12	1	1	0.9	1e-14	1	1	1	0	0.01	4e-6	1e-3	3e-3	0	0	0	0
13	1	1	0.9	3e-16	1	1	1	0	0.01	4e-6	1e-3	4e-3	0	0	0	0
14	1	1	0.9	0	1	1	1	0	0.01	4e-6	1e-3	4e-3	0	0	0	0
15	1	1	0.9	0	1	1	1	0	0.01	3e-6	1e-3	4e-3	0	0	0	0
16	1	1	1	0	1	1	1	0	0.01	2e-6	2e-3	4e-3	0	0	0	0
17	1	1	1	0	1	1	1	0	0.01	2e-6	1e-3	5e-3	0	0	0	0

DISCUSSION

The performance plot and the confusion matrix of the ANN IFDC in terms of training, testing and validation (Figure 6 and Figure 8) show that the developed ANN IFDC achieved a significant accuracy of 95.7% and performance (MSE) of 0.00004279 which is above the preset MSE goal of 0.0001. These values are an indication that the developed system is very efficient. Again, it is worthwhile to mention that the correlation coefficient, R, (Figure 7) is 0.99993. This value indicates excellent correlation since it is near the ideal value (1). The dotted lines in this figure indicate the ideal regression fit while the blue, red and grey solid lines indicate the actual fit of the neural network. It can be seen that the solid lines superimposed the dotted lines in the three cases, indicating a very good performance by the developed ANN IFDC. More so, from Figure 9, all the curves are well fitted into the upper-left corner, which is an indication of 100 percent true positivity and 0 percent false positivity. Moreover, looking at the results of Tables 4 to 7, it can be seen that if the output results of the IFDC are approximated to the nearest whole number, it will be exactly the same with the target. Hence, the developed ANN IFDC for the 33-kV Nigeria transmission line is capable of detecting and classifying accurately all the line-to- ground (L-G) faults (Table 4), line-to-line-to-ground (L-L-G) faults (Table 5), line-line (L-L) faults (Table 6), all the three phase short circuit (L-L-L) faults and no fault condition (Table 7). Finally, these results affirm clearly the efficiency of the proposed fault detector-classifier and its ability to generalize the situation from the given data and are better than the result in [22].

CONCLUSIONS

The reliability of electric power transmission is in no small measure affected by Faults. The longer it takes utility operators to detect and classify, the longer it takes to clear and the less reliable the system becomes. Hence, early detection, fast clearance and speedy restoration of power system become paramount. In this work, the application of artificial neural networks for the fault detection and classification on three phase transmission lines was extensively studied. The developed systems in this paper utilized as inputs the instantaneous voltage and current values which were normalized for fault detection and classification. In addition, results were shown for ten different conditions of faults for detection and classification, of which nine are asymmetrical faults and the remainder, is a symmetrical fault. The entire shunt faults tested is detected and accurately classified. The results achieved prove that the neural network architecture and configuration used are efficient.

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