Artificial Neural Networks for Intelligent Fault Location on the 33-Kv Nigeria Transmission Line

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***Abstract* — *Transmission lines are generally susceptible to faults, and it is highly desirable and advantageous to locate and clear these faults at the fastest speed. Thus, the aim of this paper is to develop a fault locator using an artificial neural network that will detect, classify and locate a fault when it occurs on the 33-kV Nigeria transmission line network. The network is modeled and simulated in the MATLAB/Simulink environment. The training testing and evaluation of the intelligent locator is done based on a multilayer perceptron feedforward artificial neural network with backpropagation algorithm. The performance of the detector-classifier and each locator was evaluated using Mean Square Error (MSE) and confusion matrix. The developed system is capable of detecting and classifying single line-to-ground faults, double line-to-ground faults, line-to-line faults, all the three lines short circuit faults and no fault condition; and locating line-to-ground, double line-to-ground faults and line-to-line faults. The detector-classifier achieved 91.5 % accuracy and 0.0022 MSE and the locators achieved 100% accuracy each and MSE of 0.000499, 0.000190157 and 0.000783 for single line-to-ground faults, double line-to-ground faults, and line-to-line faults, respectively. The result of the developed system in this work is better in comparison with other similar systems in the literature for locating faults on the Nigeria transmission line.*

Keywords: *Artificial neural networks, Feedforward networks, backpropagation algorithm, fault classifier, fault detector, fault locator, transmission line.*

I. Introduction

An overhead electric power transmission line is a vital link between the generating plants and different substations. They are networks of interconnected electrical conductors exclusively responsible for conveying electrical power from different generating plants to the grid and from the grid to different substations and from one substation to another substation in a varying degree of voltages in order to meet the extremely large number of load demands. This part of the power system network has very lengthy transmission lines which often pass through different environmental topography. Thus, the possibility of experiencing a fault is very high [1]. Transmission line faults are broadly classified into series and shunt faults. Meanwhile, shunt faults are more frequent in occurrence, especially single line-to-ground faults and double line-to-ground faults [1]. Furthermore, any of these faults may be caused by lightning strokes, trees falling across lines, trees growing up to the transmission lines, broken cross arms, bird shorting the lines, and vandalism [2]. Location of fault on overhead electric power transmission lines is imperative to rapid clearance of faults on transmission lines [3]. Thus, for optimal utilization of electric power generated and reliability of electric power supplied, faults on transmission lines have to be detected, classified, and located accurately within the shortest possible time [4]. The artificial neural network is a promising online and offline approach to achieving speedy fault detection, classification, and location in overhead transmission lines [5]. In Nigeria, studies dealing with fault location using intelligent systems on 33-kV Nigeria transmission lines are rare. However, very few papers [6][7] dealt on fault location in 132-kV Nigeria transmission lines. Notwithstanding, there are many fault location techniques that have been in use for fault location on transmission lines [8][9][10]. ANN was employed by [11][12] 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 [13]. The authors used spectral energy information made available through Fast Discrete S-Transform (FDST) for fault identification and classification and for fault location; the fundamental amplitude and phase angle of the two end currents and one end voltage were used. Santos & Senger [14], 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 high-speed faults using neural networks was proposed by [15]. Various other relevant work in the field of fault classification and location using artificial neural networks can be found in [16][17].

In [2], multi-layer perceptron neural network was employed to locate a fault in high voltage transmission lines. The author used back propagation learning principle in training the fault detector-classifier and locator. He designed different ANN structure for each of the classes of faults and as such the research had four different locators. More so, [18] applied a Feed-Forward neural network with backpropagation algorithm based on supervised learning for fault detection and location in extra high voltage transmission lines for high-speed protection. Instantaneous current and voltage magnitudes at the fundamental frequency were used by the author to design a detector and three different fault locators. The locator that used the magnitude of voltage and current gave the best performance. Bashier & Tayeb [19] used multilayer perceptron, back propagation neural network and Neuro Shell-2 software to develop a fault detector, classifier, and locator for a transmission line. In this paper, a single fault detector-classifier and three fault locators are proposed for Nigeria 33-kV transmission line using ANNs. A multi-Layer perceptron feedforward artificial neural network based on the backpropagation algorithm is employed in developing the intelligent fault detector-classifier and locators. In addition, out of extensive simulation and analysis, an approximate means of selecting the number of hidden layers and neurons per layers is provided.

II. The 33-kV Nigeria Transmission Line

The transmission line network consists of 140 km, 33-kV Aluminium Conductor Steel Reinforced (ACSR), conductors with the following properties:

1. Height of pole from ground surface = 28 ft (8.5344 m)
2. Normal cross-sectional areal Alu/Steel = 150/35 mm
3. Approximate overall diameter = 18.1 mm = 0.0181 m
4. Calculated D.C Resistance at 20 ^{0}C = 0.1828 Ohm/km

To assess the performance of the proposed ANN-based fault detector-classifier and locators, the transmission line is modelled using Pi model in MATLAB/Simulink environment. The transmission line model was simulated to acquire through the three-phase measurement block the voltage and current waveforms for different fault types, resistances and fault conditions. Figure 1 depicts the snapshot of the modelled transmission line network used in the whole study.

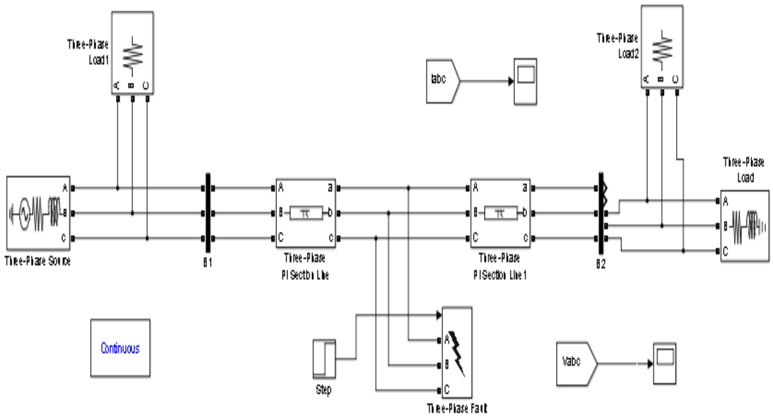

Figure 1: Snapshot of the modelled 33-kV Nigeria transmission line in Simulink/Matlab

A. Sampling and Preprocessing of the Dataset

The Voltage and current signals were generated at 50 Hz and sampled at 1,500 Hz. Thus, there are 30 samples per each cycle. The data obtained were pre-processed for fault detection/classification and location to reduce the overall size of the neural network. The inputs to the neural network for fault detection/classification are the ratios of the instantaneous voltages and currents in each of the phases before and after the occurrence of the fault. For fault location, Fast Fourier Transform was used to extract the magnitude of the fundamental frequency (50 Hz). These pre-processed data were normalized to suit the ANN input data of ± 1. The instantaneous currents and voltages were used to identify/classify the fault while the fundamental phasor magnitude of the voltages and currents signals is used for location estimation. Table 1 and Table 2 shows the target truth table for the ANN and the sample of a scaled voltages and currents for Phase A respectively.

Table 1: The truth table of the detector-classifier for various fault cases

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

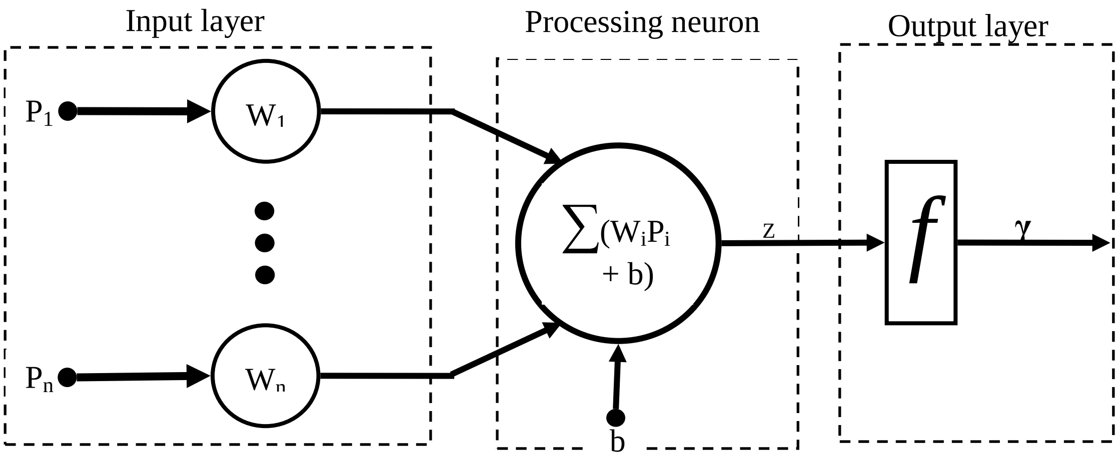

Figure 2: Model of a neuron

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

S/N	V_a	V_b	V_c	I_a	I_b	I_c
1	0.0326	0.7932	0.6076	0.0177	0.0105	0.0083
2	0.0902	0.8032	0.5883	0.0175	0.0107	0.0083
3	0.1498	0.8077	0.5697	0.0171	0.0109	0.0084
4	0.2444	0.8020	0.5444	0.0161	0.0111	0.0086
5	0.3115	0.7872	0.5317	0.0152	0.0111	0.0088
6	0.3966	0.7528	0.5248	0.0139	0.0109	0.0091
7	0.0389	0.7898	0.6116	0.0176	0.0105	0.0083
8	0.0418	0.7905	0.6104	0.0176	0.0106	0.0085
9	0.0448	0.7913	0.6093	0.0177	0.0106	0.0084
10	0.0980	0.8004	0.5909	0.0173	0.0108	0.0087

III. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is modelled after the way and manner biological neural systems work. ANNs consist of many processing elements that are highly interconnected in a particular way in order to perform a particular task[20]. 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. According to [20], the following unique characteristics gave ANN an edge in the artificial intelligent world:

i. ANN is made of massive interconnection of simple processing units thus; information processing can be carried out in a parallel distributed manner.
ii. ANN can be used to solve problems that are inherently nonlinear
iii. ANN approach requires no prior knowledge functions relating the problem variables.
iv. ANN is capable of handling situations of incomplete information and corrupt data.
v. ANN has high noise tolerant

ANN has found wide applications in the areas of load forecasting, fault diagnosis/fault location, economic dispatch, security assessment and transient stability [16]. The model of Figure 1 consists of an input layer, P_1 - P_n representing the input data to the model, a processing neuron and an output layer, γ representing the response of the model. The input is connected to the neuron via the adaptable weights, W_1 - W_n and bias, b. This neuron model can be illustrated by a function that calculates its output as a function of the inputs to it. Thus, the output of the neuron is given as: $Z = \sum W_i X_i + b$ (1)

Afterward, a nonlinear transfer function, f is applied to the weighted sum in equation (1) and this produces the artificial neuron's output, γ as: $\gamma = f(Z)$ (2) The transfer function is one of the major key factors that determine the capability of an artificial neuron 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 [21]. The sigmoid transfer function was chosen for this work because it involves a nonlinear real-world problem. The binary and bipolar sigmoid transfer function can be expressed mathematically as:

$$f(Z) = \frac{1}{1+e^{-\sigma x}} \quad (3)$$

$$f(Z) = \frac{1-e^{-\sigma x}}{1+e^{-\sigma x}} \quad (4)$$

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

IV. Proposed Artificial Neural Network Based Fault Detector-Classifier and Locators

The intelligent fault locator (IFL) is to estimate the actual distance where a fault occurs on transmission lines. The fault detector-classifier (IFDC) is to detect and classify the fault using the instantaneous voltages and currents from the transmission lines, and in consequence, activate the corresponding intelligent fault locator (IFL) to estimate the point at which the fault occurred. The ANN used in developing the IFL uses as inputs the fundamental magnitude of the voltage and current corresponding to the post-fault fundamental frequency (50 Hz). The modular block diagram representing the proposed system is shown in Figure 3.

A. System Design

The study used multilayer perceptron back propagation feed forward neural network with Levenberg Marquardt algorithm. Series of experiments were carried out to arrive at the algorithm, transfer functions combination, the number of hidden layers and the number of hidden neurons. Table 3 shows the parameter values used in generating training dataset and test dataset for the ANN-based IFDC and IFL.

Table 3: **Parameter Values used in Generating Training dataset and Test Dataset**

Training Dataset	
Fault Location (km)	1, 3, 5, …, 139
Fault inception angle $(^0)$	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 $(^0)$	20, 90

Moreover, the developmental process of the ANN-based IFDC and IFL goes through the following procedures:

1. Preparation of appropriate training data set suitable for the ANN to learn.
2. Choosing appropriate ANN configuration

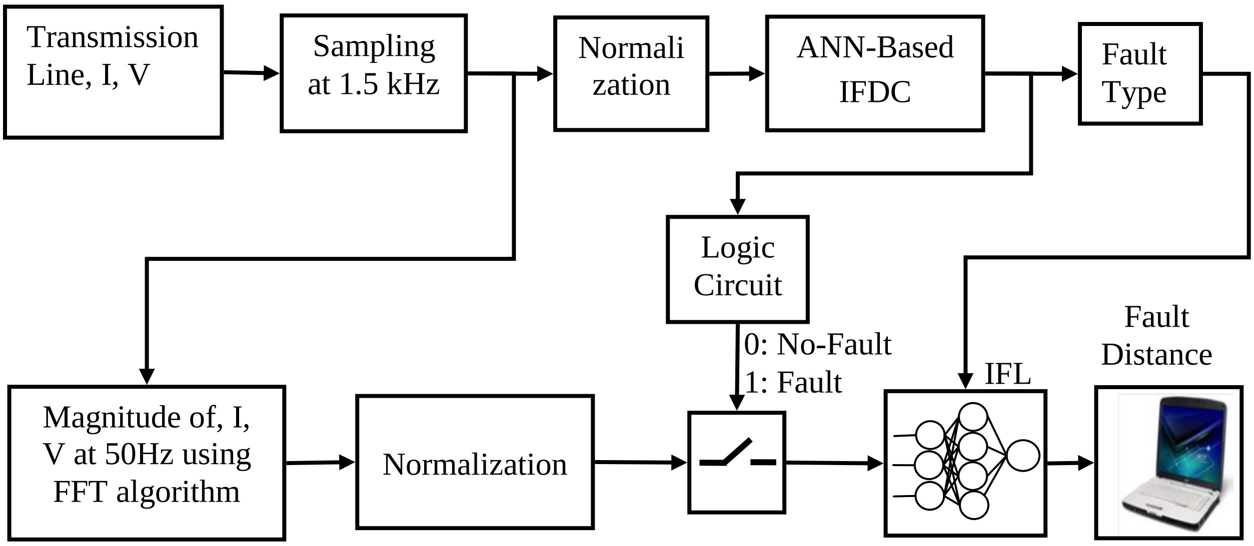

Figure 3: The modular block diagram of the IFLs proposed ANN-Based IFDC and IFLs

for the given application.

3. Training the ANN.
4. Performance evaluation of the trained ANN using the following test matrix
   i. the plot of the best linear regression fit
   ii. the plot of the performance MSE
   iii. the plot of the confusion matrix
   iv. the plot of the Receiver Operating Characteristics (ROC)
   v. to present the ANN with a new set of data outside the one used for training

Finally, the above developmental process is illustrated in Figure 4.

B. ANN-Based Fault Detector-Classifier

The fault detector-classifier task can be formulated as a pattern recognition problem. The MLP ANN feed forward with back propagation algorithm was used to develop an intelligent detector-classifier system. The neural network for detector-classifier 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 (i.e. A-G, B-G, C-G, A-B-G, A-C-G, B-C-G, A-B, A-C, B-C and A-B-C), 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) dataset for each case. Several structures of the artificial neural networks were extensively trained using the input-output dataset [22][23]. As the training progresses, the ANN minimizes the performance function (Mean Square Error) and the outputs of the training in this work will be the fault condition (1 – Fault or 0 – No-fault) and the type of fault (A-G, B-G, etc).

C. Results and Discussions

After several extensive training of different ANN structure, the ANN with two hidden layers having 6-15-5-4 configuration produced the best performance. The activation function combination is logsig/purelin/tansig for two hidden layers and output layer respectively while the input transfer function is linear. Figure 5 is the performance plot of the developed detector-classifier. It can be seen that the best validation performance MSE by the end of the training process is 0.00229587. Also, from the confusion matrix of Figure 6, this ANN configuration achieved an accuracy of 91.9%.

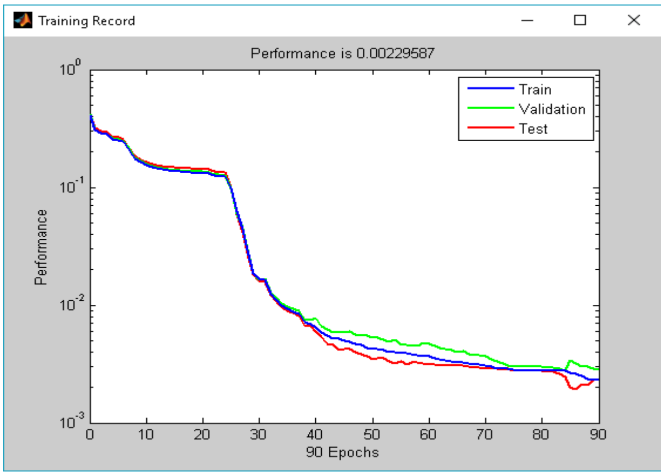

Figure 5: Performance Plot for two hidden layers with 6-15-5-4 configuration

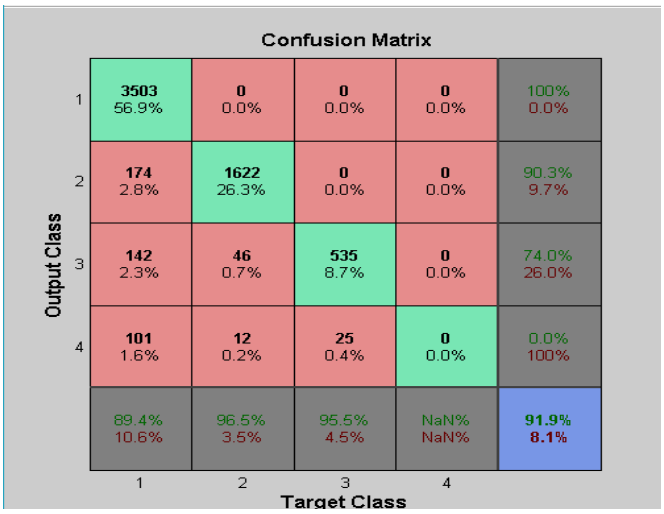

Figure 6: Confusion Matrix for ANN-Based IFDC with 6-15-5-4 configuration

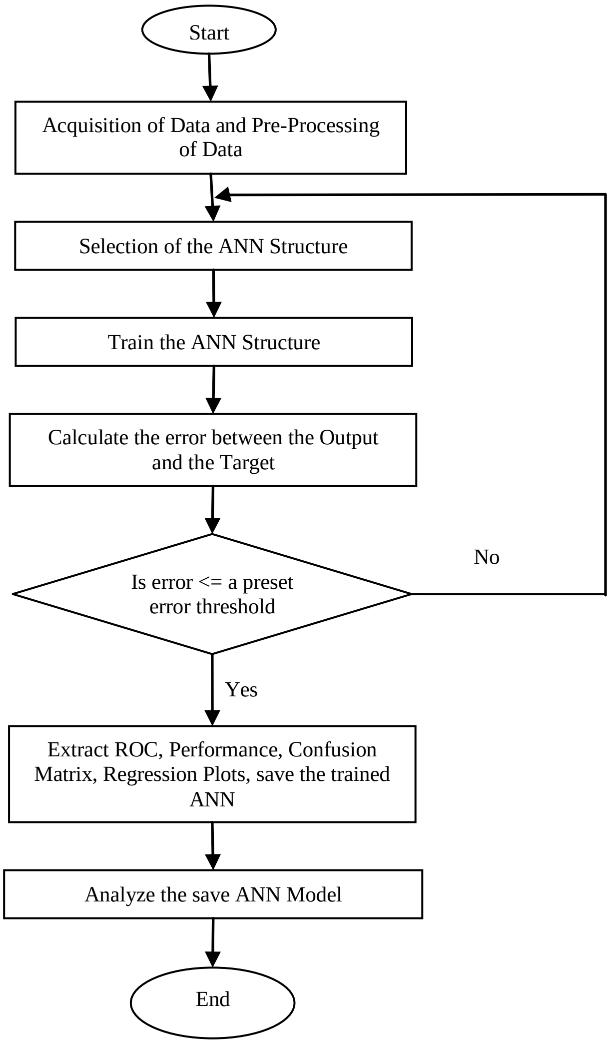

Figure 4: The developmental process of the ANN-based IFDC and IFL

D. Performance Evaluation

The IFDC was tested with a total of 6 x 187 dataset. Seventeen (17) cases each corresponds to different conditions of shunt faults and No-fault condition. The fault resistance was taken as 15 Ohms while the fault location was varied from 8 to 140 in steps of 8.

Table 4: Performance test result for ANN-Based IFDC

Km	**IFDC OUTPUT**				**TARGET**				**IFDC OUTPUT**				**TARGET**				**IFDC OUTPUT**				**TARGET**			
	A-G								**B-G**								**C-G**							
8	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
16	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
24	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
32	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
40	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1
	A-B-G								**A-C-G**								**B-C-G**							
48	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
56	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
64	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
72	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
	A-B								**A-C**								**B-C**							
80	1	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1	0
88	1	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1	0
96	1	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1	0
104	1	1	0	0	1	1	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	1	0
	A-B-C								**No-Fault**															
112	1	1	0.9	0	1	1	1	0	0	0	0	0	0	0	0	0								
120	1	1	0.9	0	1	1	1	0	0	0	0	0	0	0	0	0								
128	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0								
136	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0								

Table 4 shows the selected output of the ANN-based IFDC for each fault condition and the corresponding target. Additionally, if the result table should be scaled to the next whole number, the output of the ANN-based IFDC will be exactly the same with the target, representing a satisfactory result. Also, the detector-classifier developed in this study used only one ANN structure to do detection and classification as against what is in [2] and other related literature. The system achieved an accuracy of 91.9%, which is worthwhile. This developed model is significant because it will help in reducing the computational burden, energy usage and memory utilization on systems. Hence, improving the speed and reliability of the power system, which is very vital in power system protection and security [4]

V. ANN-Based Intelligent Fault Locators (IFL)

Three different locators were developed, one for each of the three classes of asymmetrical faults, namely, line-to-ground (L-G) faults, line-to-line-to-ground (L-L-G) faults and line-to-line (L-L) faults. The target of the ANN is the actual points in km were the faults occur and for this study, the target is taken from 1 km to 140 km in steps of 2 km. When the ANN had been trained, its output is the estimation of the fault location in the transmission lines.

A. Structure of the ANN IFL

A multi-layer perceptron feedforward neural network with backpropagation algorithm was used for the training. The number of hidden layers was selected empirically after several experiments. In this paper, three fault locators are presented. The first locator (L-G IFL) is to locate line-to-ground faults only, the second locator (L-L-G IFL) is to locate double line-to-ground faults only and the third locator (L-L IFL) is to locate line-to-line faults only. All the locators use the magnitude of the fundamental frequency of voltages ($|V_a|$, $|V_b|$, $|V_c|$) and currents ($|I_a|$, $|I_b|$, $|I_c|$) after the sixth cycle. Extraction was done using Fast Fourier Transform (FFT). The configuration of each locator corresponds to the number of neurons at the input layer (which equals the number of input variables), hidden layers and output layer (which equals the number of output variables). There are six neurons in the input layer and single neuron at the output layer for all the locators. The number of hidden layers and neurons for each locator was determined after several of experiments. Moreover, it was found that two hidden layers with 15-19 neurons and 15-20 neurons for L-G and L-L-G respectively and three hidden layers with 10-15-20 neurons for L-L faults lead the best performance in their respective category. The output layer of each IFL contains one neuron to guesstimate the fault location. In summary, the structures or configurations of the ANN IFL were 6-15-19-1 with activation function combination of tansig/logsig/purelin for hidden layers and output layer, in that order for L-G IFL, 6-15-20-1 with activation function combination of logsig/tansig/purelin for hidden layers and output layer, in that order for L-L-G IFL and 6-10-15-20-1 with activation function combination of logsig/logsig/tansig/purelin for hidden layers and output layer for L-L IFL respectively.

B. Tests and Results

A separate data set was created to investigate the performance of the developed ANN-based IFLs. The total of 6 x 51 test dataset was generated and scaled accordingly for L-G faults, L-L-G faults, and L-L faults. The fault resistance was taken as 25 Ohms while the fault location was varied from 8 to 140 in steps of 8. Table 5 shows the results of the ANN-based IFLs outputs. The first column on the left indicates the target (km) and the other columns on the right indicate the outputs of the ANN-based IFL corresponding to the three categories of fault locators, namely, L-G IFL, L-L-G IFL and L-L IFL, respectively.

Table 5: Result for the ANN IFLs with New Dataset

TARGET	ANN L-G IFL OUTPUT			ANN L-L-G IFL OUTPUT			ANN L-L IFL OUTPUT		
	A-G	B-G	C-G	A-B-G	A-C-G	B-C-G	A-B	A-C	B-C
8	8.008	7.976	8.076	7.997	7.997	7.973	8.003	8.000	8.001
16	16.050	16.010	15.932	16.028	16.033	16.011	15.997	16.038	15.979
24	23.966	23.997	24.043	23.999	23.983	23.998	23.972	23.983	23.990
32	31.987	31.995	32.014	31.966	31.998	31.989	31.993	32.013	32.018
40	39.979	40.020	40.030	40.068	39.981	40.043	39.991	39.993	40.035
48	47.980	48.004	48.010	47.999	47.990	47.991	48.018	47.990	48.021
56	55.986	56.001	56.022	55.994	55.989	56.015	56.029	56.000	55.978
64	63.990	64.000	64.004	63.988	63.999	64.011	64.054	63.994	63.994
72	71.988	72.005	72.006	72.005	71.996	72.003	72.050	71.976	72.025
80	79.985	80.006	80.026	80.013	79.998	80.015	80.022	80.006	79.996
88	87.982	87.996	88.015	88.002	88.011	88.008	88.011	88.009	87.994
96	95.999	96.010	96.002	96.012	96.015	95.987	96.017	95.973	96.003
104	103.986	104.004	104.006	103.980	104.008	103.993	103.998	103.952	103.968
112	112.036	112.007	112.005	111.988	111.993	112.012	111.972	111.956	111.940
120	119.994	120.005	119.994	120.006	120.004	119.985	119.970	119.948	119.974
128	127.986	127.987	128.007	128.012	128.011	127.992	127.977	127.994	127.994
136	136.020	135.974	136.026	135.999	135.992	136.000	136.054	136.095	136.095

For ease of analysis, the error in fault location (km) is evaluated using the following mathematical relationship:

$$\text{Error (km)} = \left|\text{ANN output - Target}\right|, \qquad (5)$$

where 'ANN output' is the output (km) of the ANN fault locator and 'Target' is the real distance where the fault occurred in the transmission line (km). More so, the performance of the fault locators are evaluated using the percentage error expressed mathematically as:

$$\%\ \text{Error} = \left[\frac{\text{Error}}{\text{length of the line}}\ \text{X}\ 100\ \%\right], \qquad (6)$$

The Figure 7, Figure 8 and Figure 9 are the graph of the error (km) against the target (km) of the L-G IFL, L-L-G IFL, and L-L IFL respectively. From the graphs, the minimum errors for all the locators are zeros (0) and the maximum errors of the fault locators are 0.076 km, 0.068 and 0.095 for L-G IFL, L-L-G IFL, and L-L IFL in that order. Again, from Figures (10, 11 and 12), the percentage errors are 0.0543%, 0.0486% and 0.0679% for L-G IFL, L-L-G IFL, and L-L IFL respectively, showing a considerable satisfactory result.

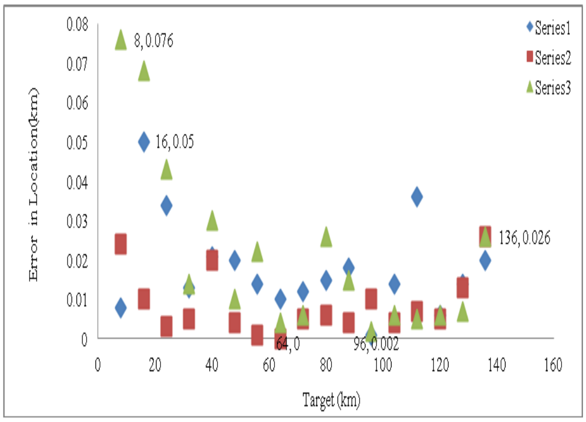

Figure 7: Test Result of ANN-Based L-G IFL

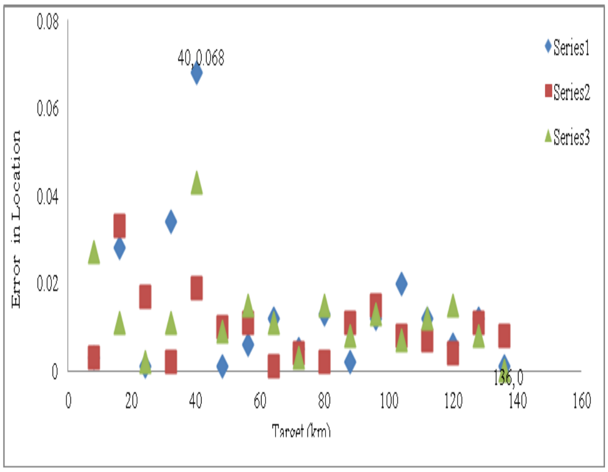

Figure 8: Test Result of ANN-Based L-L-G G IFL

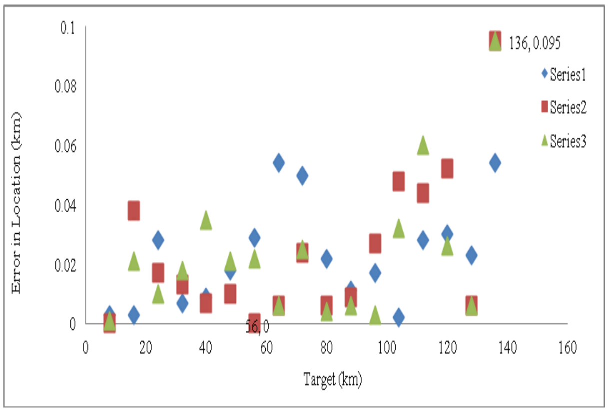

Figure 9: Test Result of ANN-Based L-L IFL

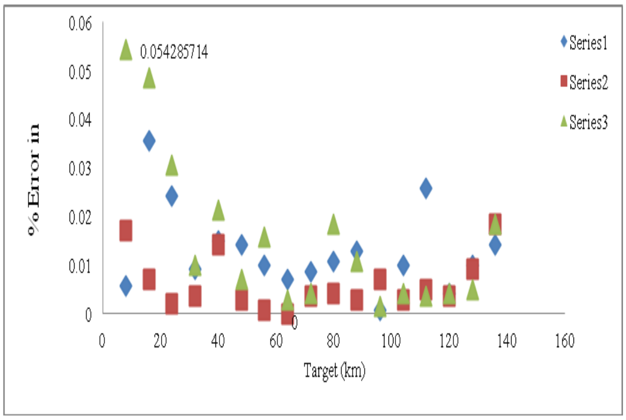

Figure 10: % Error Result of L-G IFL

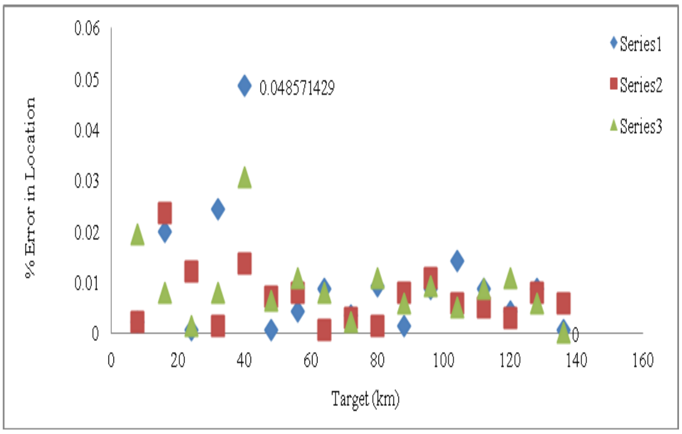

Figure 11: % Error Result of L-L-G IFL

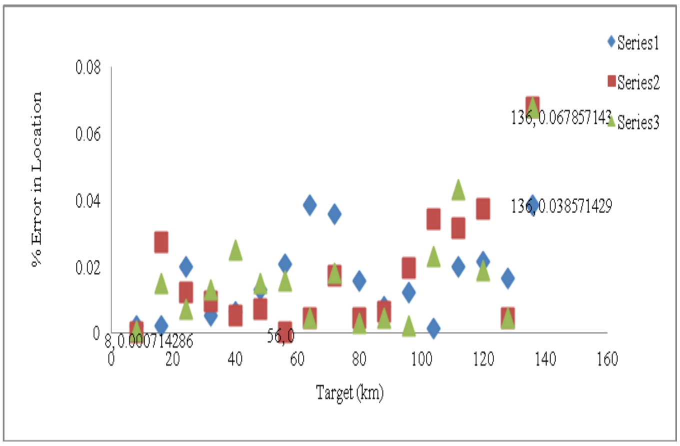

Figure 12: % Error Result of L-L IFL

VI. Conclusion

An artificial neural network based fault detector-classifier for easy protection of Nigeria 33-kV transmission line and three ANN-based intelligent fault locators for faults location in 33-kV Nigeria transmission line using multilayer perceptron feedforward neural network with backpropagation algorithm have been proposed in this paper. It uses the instantaneous values of voltages and currents as inputs to the artificial neural network (ANN) for fault detection and classification and the magnitude of the fundamental frequency for fault location. The transmission line was modeled using SimPowerSystems toolbox and simulated in Simulink/MATLAB 2013a environment. A single detector-classifier was developed to detect and classify ten (10) different shunt faults and three different locators were developed to location single line-to-ground faults, double line-to-ground faults, and line-to-line faults. The test results presented demonstrate highly satisfactory performance and precision of the developed ANN intelligent fault detector-classifier and locators. In general, ANN proves to be reliable in developing a classifier and locator for Nigeria 33-kV transmission line.

References

[1] W. P. Davis, *Analysis Of Faults In Overhead Transmission Lines*, (California State University, Sacramento, 2012).

[2] S. B. Ayyagari, *Artificial Neural Network Based Fault Location for Transmission Lines*, (University of Kentucky Master's Theses, 2011). Paper 657. http://uknowledge.uky.edu/gradschool_theses/65.

[3] S. K. Kumar, M. Swamy, and V. Venkatesh, Artificial Neural Network Based Method for Location and Classification of Faults on a Transmission Lines, *Int. J. Sci. Res. Publ.*, 4(1), pp. 2250–3153, 2014.

[4] M. Kezunovic, "Fundamentals of Power System Protection," in *The Electrical Engineering Handbook*, 2005, pp. 787–803.

[5] J. C. S. Souza, M. A. P. Rodrigues, M. T. Schilling, and M. B. Do Coutto Filho, "Fault location in electrical power systems using intelligent systems techniques," *IEEE Trans. Power Deliv.*, vol. 16, no. 1, pp. 59–67, 2001.

[6] O. E. Obi, O. A. Ezechukwu, and C. N. Ezema, An Extended ANN-Based High Speed Accurate Transmission Line Fault Location for Double Phase to- Earth Fault on Non-Direct-Ground, *International Journal of Engineering Science Technologies*, 1(1), pp. 31–47, 2017.

[7] V. C. Ogboh and T. C. Madueme, "Investigation of Faults on the Nigerian Power System Transmission Line Using Artificial Neural Network, *International Journal of Research in Management, Science & Technology* 3(4), pp. 87–95, 2015.

[8] C. Ji, *Impedance-Based Fault Location Methods for Transmission Line*, (Clemson University, TigerPrints. All Theses Theses. Paper 1543, 2012).

[9] A. G. Shaik and R. R. V. Pulipaka, "A new wavelet based fault detection, classification and location in transmission lines," *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 35–40, 2015.

[10] K. Hosseini, Short Circuit Fault Classification and Location in Transmission Lines Using a Combination of Wavelet Transform and Support Vector Machines, *International Journal on Electrical Engineering and Informatics*, 7(2), pp. 353–365, 2015.

[11] M. Jamil, S. K. Sharma, and R. Singh, "Fault detection and classification in electrical power transmission system using artificial neural network," *SpringerOpen Journal*, 4:334 DOI 10.1186/s40064-015-1080-x, 2015

[12] H. P. Amorim and L. Huais, "Faults location in transmission lines through neural networks," in *2004 IEEE/PES Transmision and Distribution Conference and Exposition: Latin America (IEEE Cat. No. 04EX956)*, pp. 691–695, 2004.

[13] K. R. Krishnanand, P. K. Dash, and M. H. Naeem, "Detection, classification, and location of faults in power transmission lines," *Int. J. Electr. Power Energy Syst.*, vol. 67, pp. 76–86, 2015.

[14] R. C. Dos Santos and E. C. Senger, "Transmission lines distance protection using artificial neural networks," *Int. J. Electr. Power Energy Syst.*, vol. 33, no. 3, pp. 721–730, 2011.

[15] M. T. Hagh, K. Razi, and H. Taghizadeh, "Fault classification and location of power transmission lines using artificial neural network," in *Power Engineering Conference, IPEC 2007 International*, pp. 1109–1114. *2007.*

[16] M. Tarafdar Haque and A. Kashtiban, "Application of Neural Networks in Power Systems; A Review," *International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering* Vol:1, No:6, 2007.

[17] P. Chandra Sekhar, B. V. Sanker Ram, and K. S. Sarma, "Fast computing neural network modeling for fault diagnosis in power systems," *J. Eng. Appl. Sci.*, 2010.

[18] T. Bouthiba, "Fault Location in Ehv Transmission Lines Using Artificial Neural Networks," *Int. J. Appl. Math. Comput. Sci.*, vol. 14, no. 1, pp. 69–78, 2004.

[19] E. Bashier and M. Tayeb, "Faults Detection in Power Systems Using Artificial Neural Network," *Am. J. Eng. Res.*, vol. 2, pp. 2320–847, 2015.

[20] S. Singh, K. R. Mamatha, S. Thejaswini, "Intelligent Fault Identification System for Transmission Lines Using Artificial Neural Network," *IOSR J. Comput. Eng.*, vol. 16, no. 1, pp. 23–31, 2014.

[21] T. Kocak, "Sigmoid Functions and Their Usage in Artificial Neural Networks," *Univ. Cent. Florida*, p. 29, 2015.

[22] S. Kesharwani and D. K. Singh, "Simulation of Fault Detection for Protection of Transmission Line Using Neural Network," *International Journal of Science, Engineering and Technology Research (IJSETR)*, Vol 3, no. 5, pp. 1367–1371, 2014.

[23] S. Ekici, S. Yildirim, and M. Poyraz, "Energy and entropy-based feature extraction for locating fault on transmission lines by using neural network and wavelet packet decomposition," *Expert Syst. Appl.*, 34(4), pp. 2937–2944, 2008.