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Performance Evaluation of ANN-Based Fault Classifier on Nigerian 330kV-Transmission System

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Abstract— Modern power system is known to be a complex and large interconnected network of generators, transmission lines, and other power equipments. Consequently, occurrence of faults on transmission lines are inevitable. Thus, the need to carry out performance evaluations of various faults in a transmission network becomes imperative. In this work, transmission line parameters used for modelling were obtained from Transmission Company of Nigeria (TCN), Osogbo and the power model obtained was simulated using MATLAB version 2016a. The Back-propagation Feed-forward Neural Network architecture was trained using Levenberg-Marquardt (trainlm) algorithm. The performance of the proposed single Artificial Neural Network architecture for detection and classification was evaluated using sensitivity, specificity and accuracy as performance metrics. The implementation of this research will be of great significance to power system operations and planning.

Index Terms— Detection, Classification, Faults, Artificial Neural Network (ANN), Power network, Sensitivity

1 Introduction

IN recent times, power system consists of complex, highly integrated and very large systems known as grid system. Fortunately, the study of power system does not require a real-world interconnected network approach [1]. It requires simple model systems to understand the basic functioning of the power system. These functional areas include; generation, transmission, and distribution and they have various parameters or components by which they are described [2]. Most engineering scholars believe that transmission sector is the backbone of electrical power system in the world at large, as it serves as the link between the generation and the distribution sector. The high voltage transmission in Nigeria is separated into two; the 330 kV high voltage transmissions and the 132 kV high voltage transmissions. The 330 kV-transmission is from the generating stations to the sub-transmission system [3]. These transmissions are done through majorly using overhead transmission lines which spans several kilometers. The frequent occurrence of blackout experienced of recent in some developing and developed countries have posed a great challenge to power system utilities. Nigerian 330kV is not left out from the incessant supply due to continous increase in load demand. When faults occurs on a power network, the aftermath could be to distrupt transmission of electric power and thereby leading to unplanned outages of power supply, equipment damage, and occasional fatality. Hence, it is of optimum importance to have a protective system to detect and classify faults at the shortest possible time, to shorten fault rectification time and manage resources well. To tackle this problem, a considerable number of authors have proposed diverse techniques in the open literature. For instance, detection and classification of faults on electric power using artificial neural Network based fault detector and classifiers, feed-forward network along with backpropagation algorithm was presented in [7] and [8], respectively. Different ANN structures were used for fault detection and classification of faults in the literature, however, they are considered to be complex and occupy more space on industrial computer in case of application. Some algorithms based upon ANN for location of faults and relay architecture for protection of transmission line are also suggested by [9], [10], [11]. Although, the research done by some of these authors were quite insightful, however, much attention has not been given to detection and classification of faults on a practical power system such as Nigerian 330kV grid system. Therefore, this work aimed at detection and classification of faults using Artificial Neural Network (ANN), taking Nigerian 330-kV grid system as a case study. In this paper, we proposed an architecture feed-forward back-propagation algorithm based upon ANN for fast and reliable fault detection and classification. This will reduce complexity and storage for industrial applications compared to other works reviewed. The various processes of modeling, training, simulations and testing were also implemented on Nigerian 330-kV transmission network.

The remainder of this paper are organized as follows: Section 2 shows a brief description of the Nigerian 330kV grid system. Details system methodology and design are presented in section 3. Section 4 presents results of simulations obtained and the discussion. The conclusion of the work is presented in section 5.

2. DESCRIPTION OF THE TEST CASE STUDY

The Nigerian 330-kV transmission network considered in this study consists of 240 km, 330-kV transmission lines extending

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between two transformers (one each at the sending end and the receiving end). The necessary parameters of the transmission line conductors useful for its modeling were obtained from Transmission Company of Nigeria, Osogbo. The relay on the line can only display 10 readings of fault per time, with some type of faults not catered for and type of fault not reflecting in some cases, the sample is shown in Table 1. Therefore, the transmission line was represented by distributed parameters and the frequency dependence of the line parameters is taken into account. A three phase fault simulator was used to simulate faults at various positions on the transmission line. The line has been modelled using transmission parameters so that it accurately describes a long transmission line. The snapshot of the modelled transmission line is shown in Figure 1.

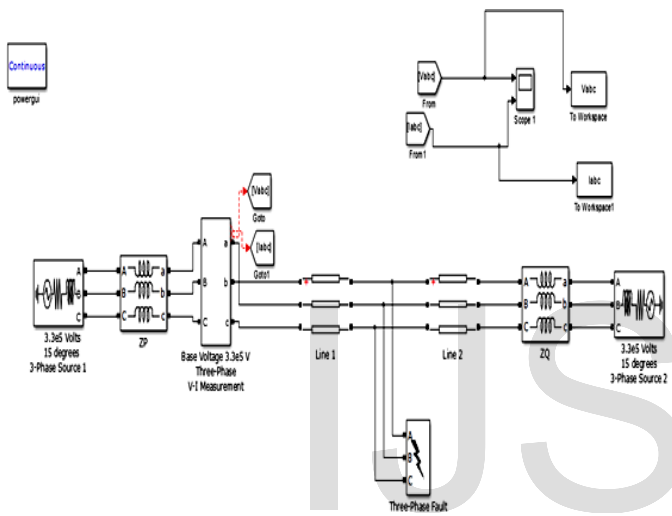

Figure 1: The snapshot of the modelled transmission line.

TABLE 1

Samples of Relay Data fault voltages and current for the three phases

V_{af} (kV)	V_{bf}(kV)	V_{cf}(kV)	Iaf(A)	Ibf(A)	Icf(A)	Type of fault
73.6100	28.1431	108.6251	1.1449	-9.4163	1796.9880	CG
180.5430	118.0630	-46.1361	336.9890	-19.9656	997.7581	CG
183.1286	114.2850	-50.8926	343.9110	13.61548	889.1493	CG
69.1091	-99.0207	-90.3572	724.5722	245.5486	144.1229	AG
130.6284	-95.6287	-34.3178	787.0480	185.9840	616.9635	AC
125.7992	-79.0719	-73.9845	370.0378	43.1368	-203.0250	AG
197.4000	-94.2727	-95.9438	-8.2342	1056.5800	-152.3050	Nil
128.7871	-39.2494	-90.8961	943.1424	1060.3300	127.9254	AB
-36.5350	-20.7246	145.9905	141.5476	939.1581	-96.3403	Nil
181.5999	-24.7750	100.7040	-798.724	-2769.28	-97.4677	BG

3. SYSTEM METHODOLOGY AND DESIGN

3.1 Artificial neural network

The feed forward neural network type is one of the most common neural networks in use and it is suitable for many types of applications. Feed forward neural networks are often trained via simulated annealing, genetic algorithms, or via one of the propagation techniques like back-propagation. It has no feedback connection hence, the information travel is unidirectional. They are the simplest neural networks. A feed-forward network with N0 as input and KR as output signals are shown in Figure 2. [8]. First, the network was trained by feeding learning patterns into the solution and by adjusting the weights according to some learning rules known as the supervised learning, unsupervised learning and reinforcement learning. The supervised learning or training has both the inputs and the expected target values known prior to the training of ANN. We then applied this techniques to fault detection and classification in a power system

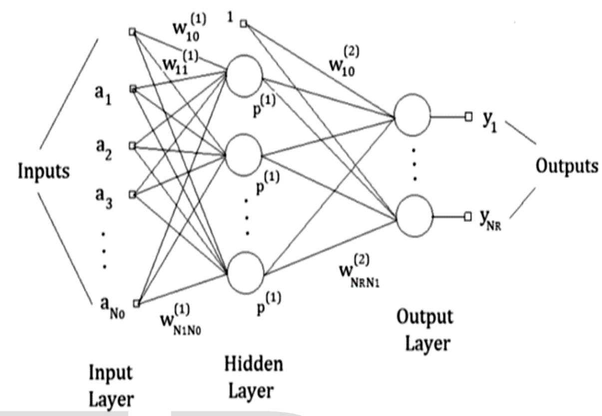

Figure 2: Structure of a two-layered feed-forward network. [8]

3.1 Problem formulations

Following the method as shown in the flowchart of Figure 3, the input is the simulated data obtained from high voltage transmission line Simulink model and are analyzed for eight types of faults and no fault conditions. One hundred (100) set of data were obtained for each of the cases mentioned. The data obtained was normalized as a preprocessing operation. Generally, to normalize a range of data of a quantity X;

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

In application, the normalized value of Line 'a' voltage and current are given in Equation 2 and 3 as;

$$V_{an} = \frac{V_a - V_{a\min}}{V_{a\max} - V_{a\min}} \tag{2}$$

$$I_{an} = \frac{I_a - I_{a\min}}{I_{a\max} - I_{a\min}} \tag{3}$$

where X_n is the normalized value of quantity X, X_{min} is the minimum value of X in the data bank and X_{max} is the maximum value of X.

The data set was divided into two set, 60 sets for training and testing (train data) and 40 sets for testing and evaluating per-

International Journal of Scientific & Engineering Research, Volume 8, Issue 2, February-2020
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formance (test set). BPNN supervised trained FFNN with two hidden layers of 18 neurons in the first hidden layer and 15 neurons in the second hidden layer was chosen and its training with Levenberg-Marquardt optimization technique was the network created for classification.

The training data set was used to train the network. The network adjusts the weights and bias to attain the thresholds stated for the various types of fault or no fault situation. The validation set is provided by the network during the training process (this implies the inputs data without the outputs) and the error in validation data set is monitored throughout the training process. The Mean Square Error (MSE) tells how efficient the neural network training is, and the MSE for each output in each iteration is calculated by;

$$MSE = \frac{1}{N}\sum_{1}^{N}\left(E_i - E_0\right)^2 \tag{4}$$

where N is number of iterations, Ei is actual output and Eo is output of the model.

The correlation coefficient 'R' for training, validation and testing was also used as evaluation for training effectiveness. When 'R' is very close to 1 and there is similarity between testing and validation curves, it indicates efficient training.

The Parameter metrics used in the analysis are therefore expressed in the equations (5) to (7)

$$Sensitivity = \frac{TP}{TP + FN} \tag{5}$$

$$Specificity = \frac{TN}{TN + FP} \tag{6}$$

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \tag{7}$$

where TP, FN, TN and FP, represent True Positive, False Negative and False Positive respectively and are defined as follows:

TP: It is when the classifier gives the correct classification of fault at the presence of fault.

FP: It is when the classifier gives a type of fault at no fault condition.

TN: When the classifier say there is no fault at no fault condition.

FN: When the classifier says there is no fault when fault is present.

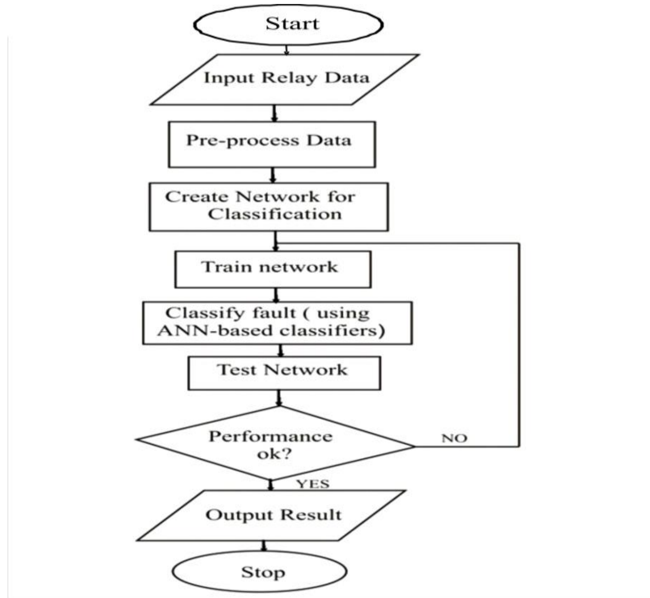

Figure 3: Flow chart for ANN-based fault detection and classification

4. SIMULATION RESULTS AND DISCUSSION

Table 2, shows the normalized fault voltage and current sample values for all the various types of faults and also during the no fault case. V_{an}, V_{bn} and V_{cn} are the normalized voltages on line A, line B and line C respectively while I_{an}, I_{bn} and I_{cn} are the corresponding normalized current.

TABLE 2

Samples of input Data (normalized values of voltages and current)

Case number	Type of fault	V_{an}	V_{bn}	V_{cn}	I_{an}	I_{bn}	I_{cn}
1	AG	0.8481	-0.0075	0.3376	0.2197	0.2605	0.2250
2	BG	0.5166	0.1057	0.0187	0.0518	0.8469	0.0419
3	CG	0.9540	0.0577	-0.0739	0.0170	0.2834	0.0207
4	ABG	0.8546	0.0117	0.1530	0.0413	0.4935	0.0296
5	BCG	0.3257	0.0323	-0.0012	0.0202	0.9447	0.0076
6	ACG	-0.0349	0.0663	0.0490	0.0844	0.9897	0.0736
7	ABCG	0.0010	0.0382	0.0383	0.0278	0.9980	0.0165
8	NO FAULT	0.0081	0.0140	0.0181	0.0246	0.9994	0.010

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A satisfactory training performance was achieved by the neural network with the 6-18-15-4 configuration (6 neurons in the input layer, 2 hidden layers with 18 and 15 neurons in them respectively and 4 neurons in the output layer) as shown in Figure 3. The overall MSE of the trained neural network doing training is 0.0817, which is the closest to zero, compared to other configurations tested. Hence, 6-18-15-4 has been chosen as the ideal ANN for the purpose of fault detection and classification. The ANN-based model (6-18-15-4) for the classifier is shown in Plate 1.

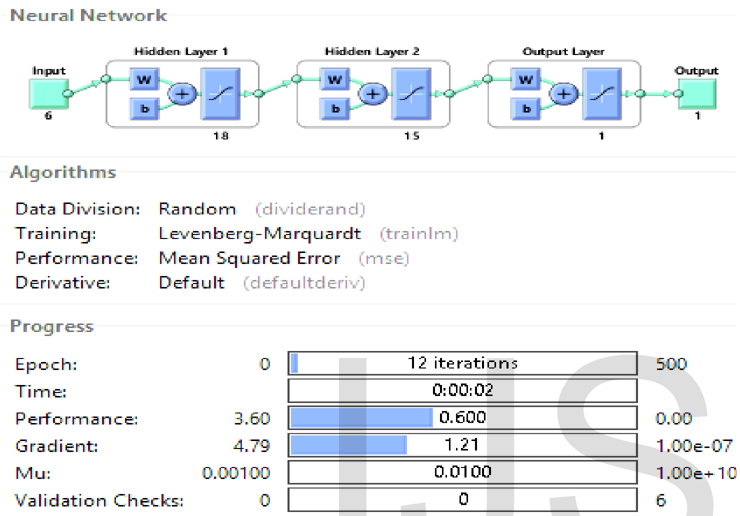

Plate 1: Snapshot during ANN-based FFNN classifier training session

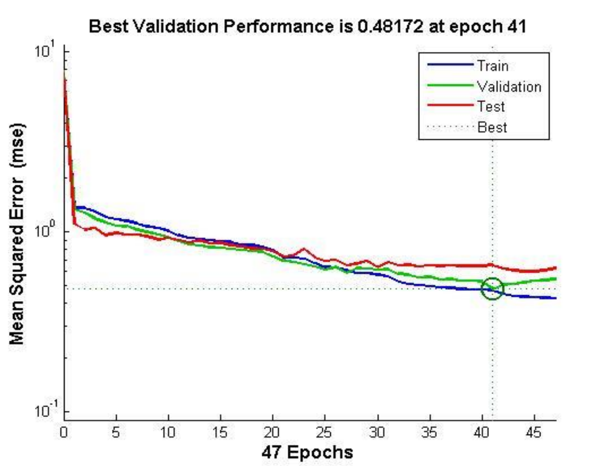

Figure 3: Training performance plot of the neural network 6-18-15-4

Figure 4 shows the curve of regression Fit for the outputs versus targets of the proposed ANN. The correlation of the 6-18-15-4 ANN is 0.96836 for training which indicates very good correlation between the targets and the outputs.

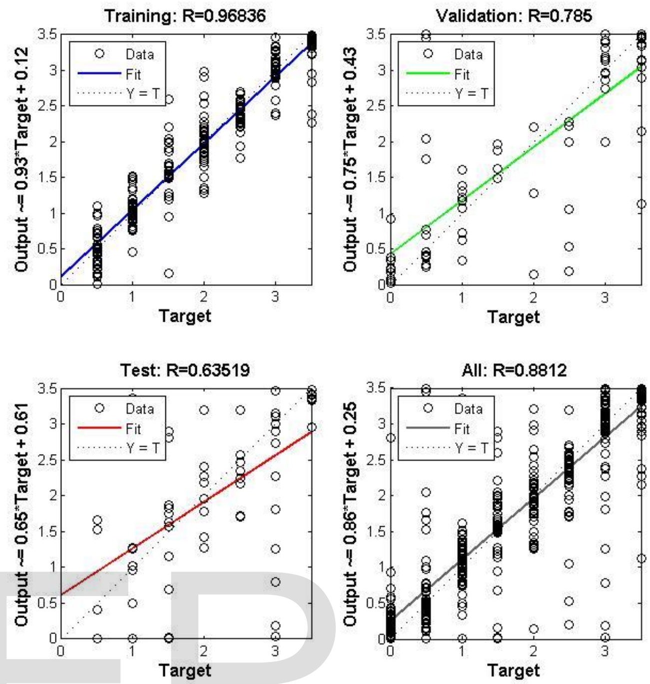

Figure 4: Plot of the linear regression of FFNNN Classifier that relates the targets to the outputs

The ANN fault classifier was tested with two data sets; training data set (60 for each fault conditions and no fault condition on the modelled transmission line). Table 3 shows the classification output when the training data was used to test the network performance. It gave 100% accuracy showing that the network was well trained. [7], explains that the efficiency and best performance of a developed ANN and the optimum learning method can be estimated by using the final trained network by testing with testing dataset.

Owning to this fact, the test data set (consisting of 40 various fault records each for the 7 types of fault mentioned early and no fault conditions) was used to test the 6-18-15-4 ANN classifier. Various observations were made and its relevance to the efficiency of the neural network is determined using sensitivity, specificity, and accuracy as performance metrics. The performance of the network was tested based on its behaviour with the trained data set and the test data set. The three performance matrices selected (sensitivity, specificity, and accuracy) has something to do with true positive (TP), false posi-

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tive (FT), true negative (TN) and false negative (FN), which are defined in Equations 5- 7.

Table 3:
Output of Classification using training data set to test

A	B	C	G	FAULT TYPE
1	0	0	1	AG
0	1	0	1	BG
0	0	1	1	CG
1	1	0	1	ABG
1	0	1	1	ACG
0	1	1	1	BCG
1	1	1	1	ABCG
0	0	0	0	No fault

For test data, 40 sets were considered for each type of fault and no fault condition. This means 280 data represents fault conditions while 40 represent no fault condition. Number of actually positive samples (P) is 280; number of actually negative samples (N) is 40. Results shows that TP is 220 (i.e. the classifier gives the correct classification of fault at the presence of fault 220 times). FP is 2 (i.e. the classifier gave a type of fault at no fault condition twice.), TN is 38 (i.e. the classifier say there is no fault at no fault condition 38 times.) and FN is 60 (i.e. the classifier says there is no fault when fault is present 60 times), as shown in Table 3. Using equations 5 – 7, sensitivity is equal to 78.6%, Specificity equals 95.0% and accuracy equals 81.3%

5. CONCLUSION

This paper explored the use of ANN to detect and classifier fault on transmission lines. Various kinds of faults namely, single line-ground, double line-ground and three phase faults to ground have been taken into consideration in this work and the same ANNs have been proposed for each of these faults. It has been proven that fault classification and detection on a transmission line can be done at once using a 2-layer (6-18-15-4 configuration) BPNN, trained by a supervised training method, using the Levenberg-Marquardt optimization technique. This gives room for a more suitable, less complex and faster classification. The output of this research is a smart system that is capable of detecting and classifying faults on Nigerian 330-kV power transmission system, using a single ANN architecture. The implementation of which will be of great significance to power system operations and planning.

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