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Intelligent Shunt Fault Classifier for Nigeria 33-kV Power Lines

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ABSTRACT

This paper presents a new approach to using artificial neural networks (ANNs) in improving the protection of transmission lines. The proposed method uses instantaneous values of voltages and currents during normal and fault conditions on a transmission line as inputs to four different neural network structures. The structures are then aptly combined to yield a system that can detect and classify shunt faults with improved efficiency. The details of the design procedure as well as various simulations carried out are provided in the paper. The performance of the developed system is evaluated using two performance indices, viz., accuracy and mean square error (MSE), and the results show that this approach is capable of detecting and classifying all possible shunt faults on the 33-kV Nigeria power lines in less than 1ms with high level of accuracy.

Key words: Artificial neural network, fault detection, fault classification, transmission line, distance protection

1. Introduction

Electric power systems generally have maintained a sustained rate of development due to increased usage of electrical energy and this has partly given rise to erection and installation of more power lines – both in number and length [1]. The steady and reliable supply of this electrical energy from the power plants to the end users is paramount to utility operators. In conveying the power generated via the power lines, the network sometimes encounters faults. These faults are unavoidable sudden disturbances that can cause an abnormally high amount of current to flow on the appropriate, it may cause severe damage to the entire power system network [2]. This issue has made power system protection, especially on power lines, a key phenomenon to consider [3]. Overhead power line faults could be series or shunt faults. Furthermore, shunt faults can be categorized into symmetrical and asymmetrical faults [4]. In the 33-kV Nigeria power line, the single line-to-ground faults are the most commonly experienced shunt faults. Moreover, these faults may occur as a result of trees growing up to the power lines, phases coming in contact with each other, and so on [5]. The probable occurrence of faults on transmission lines has necessitated the use of a detection and classification system that can aid speedy restoration of power supply on an event of power outage, thereby bringing about optimal utilization of electric power generated and consequent reduction in economic loss. In Nigeria, power outages along the 33-kV power lines (the main link between the 11-kV distribution lines and the 132-kV sub-transmission lines) are very high and it can stay for days or even months before such can be noticed and power restored by the distribution company of Nigeria (DISCO) [6]. This is because the 33-kV Nigerian power network is characterized with long lines which often pass through bushes far off from sight, and there is no system to detect the occurrence of faults on it. To this end, an intelligent system that is capable of detecting and classifying faults is needed.



Over the years, the popularity of ANNs vis-a-vis other methods for fault diagnosis in overhead electrical power lines has steadily increased. ANNs have attained this prominence due to their inherent ability to handle incomplete and corrupt data, highly tolerate noise, process information in a parallel distributed manner, and be easily implemented in hardware. Besides, the typical characteristic of ANNs to capture and retain dynamic changes in the power systems and be retrained online makes any ANN-based relaying protection system insusceptible to system parameter variations [7][8]. A review of the transmission line protection using ANN is given in [5][9]. The use of ANN as distance relaying algorithm is demonstrated in [10], in which an ANN-based scheme is proposed to improve the sensitivity and selectivity of protection systems using samples of current and voltage signals as direct inputs to ANNs as opposed to some other techniques in which preprocessed signals are employed as inputs. A multilayer feed forward ANN is used by [11] to develop a fault detector on transmission lines. The paper employs phase voltage and current signals as input to the neural network. In [7] feed forward ANN with back-propagation algorithm is developed for detection and classification of faults in power transmission lines. The ANN-based algorithm proposed in [12] for transmission lines distance protection, according to the authors, can be used in any transmission line not considering its configuration or voltage level. According to the study presented in [13], an ANN technique for fault detection and classification is capable of identifying faults within 5 to 7 ms, making the technique very suitable for high speed protective relaying. Aggarwal *et al.* [14] develops ten ANNs to identify faults type using current and voltage phasors after fault initiation, with each ANN trained to identify one of the types of faults. Also, in [15], Sanaye-Pasand and Khorashadi-Zadeh train a single ANN to identify different fault types using three samples of current and voltage signals sampled at 800 Hz as inputs to the ANN.

In this paper, a novel method which uses Multilayer Perceptron feed-forward neural network is proposed for shunt faults classification on the 33-kV Nigeria power line. The ANN-based fault classifier in this study uses four ANNs to accomplish its classification task. The preprocessed sampled current and voltage values are used as inputs to each of the ANN.

2. The Modeled Power System

The studied power system network in this paper is the 33-kV power line, which is approximately 140 km length, running from Isolo sub-transmitting station to NEPA axis in Lagos, Nigeria. Modeled in MATLAB 2015a, the single line diagram and parameters of the network are depicted in Figure 1 and Table 1, respectively. S_1 has a reference voltage of 33 kV, while S_2 has a reference voltage of 11 kV.

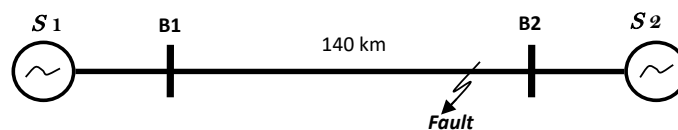


Figure 1: Studied Power System Single Line Diagram [16]

The input data (currents and voltages) for training the ANN are extracted from the power system by simulation due to insufficient real-time data. Since Nigerian power lines operate at a standard frequency of 50Hz, all signals are sampled at a sufficient frequency of 1.5 kHz (i.e. 30 samples/cycle). In the model, the current and voltage measurements are carried out at B1 (see Figure 1). The instantaneous values of voltages and currents obtained are preprocessed and transmitted to MATLAB to build an ANN-based system for fault detection and thus classification. Ten different fault scenarios are simulated at varying distance and

resistance values. Moreover, the values of the parameters used in generating the data for the proposed ANN-based intelligent shunt fault classifier are shown in Table 2.

Table 1: Line Parameters of the studied system

S/N	Line Property	Value
1	Line Length (km)	140
2	Positive- and zero-sequence resistances (Ohms/km)	[0.18446 0.39072]
3	Positive- and zero-sequence inductances (H/km)	[0.0010981 0.0024668]
4	Positive- and zero-sequence capacitances (F/km)	[1.0865e-08 6.6177e-09]
5	Fault Starting	0.020 seconds
6	Type Conductor	ACSR

Table 2: Training and Test Data Generation Parameters

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

3. The Proposed Intelligent Shunt Fault Classifier

The developed intelligent shunt fault classifier (ISFC) is designed to detect the presence of a fault and afterward classify the fault using four different modular artificial neural networks. The developed system has two stages – the detection stage and the classification stage. The three-phase fault detectors (IFD_R, IFD_Y, and IFD_B) are to indicate the presence (1) or the absence (0) of shunt faults on lines R, Y, and B respectively, while the detector IFD_G is to signify the involvement of ground. For ease, accuracy, and efficiency of fault classification, the logic behind the proposed system (as shown in Figure 3) is to use a single ANN to detect a fault on each phase in combination with a ground ANN to show if the ground line is affected. The result is that if the outputs of the four ANNs read ‘RYBG: 0 0 0 0’, then the system is in a normal state; otherwise, the system is in an abnormal state, and the outputs indicate which lines are responsible for the abnormality (i.e., fault). By this method, the occurrence/non-occurrence of faults and the type of faults are captured precisely. For instance, a readout of ‘RYBG: 1 0 0 1’ implies an occurrence of a line (Phase R)-to-ground fault, while a readout of ‘RYBG: 0 1 1 0’ means a line-to-line fault has occurred on Phase Y and Phase B.

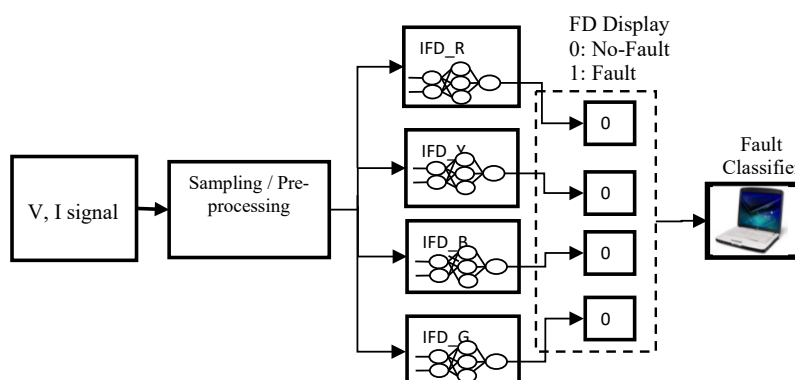


Figure 3: Modular Block Diagram of ISFC in a No-fault State

Figure 4 is a flowchart showing the developmental process involved in developing ISFC

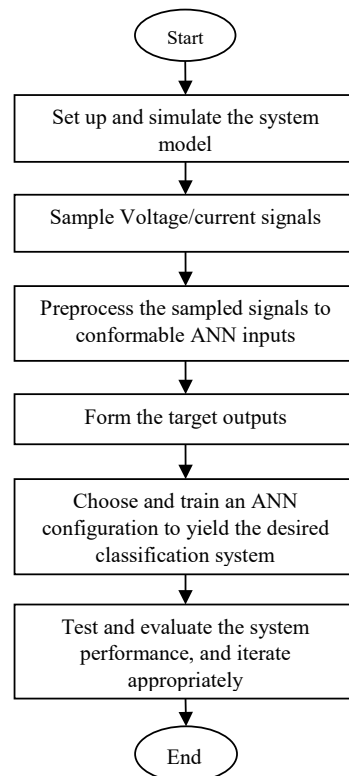


Figure 4: Developmental Process of the Proposed ISFC

3.1. Data Generation and Pre-processing

The proposed ANN-based ISFC is designed using a multilayer perceptron feed forward neural network with Levenberg Marquardt algorithm. Each ANN has six inputs, which correspond to the number of phase voltages and currents, and one output (either 0 or 1), which corresponds to the number of target outputs. Also, the number of hidden layers, the number of hidden layer neurons and the activation functions are all determined experimentally. As given in Table 3, all fault scenarios (ten cases of shunt fault and one no-fault case) are considered. For each fault scenario, the power network is simulated severally by varying the fault distance, resistance and inception angle so as to realize sufficient data for training and testing the ANNs. The training set consists of 6 x 6,160 input data sets and 1 x 6,160 target output data. This together forms a 6 x 1 input-output pattern for each of the module. It is important to note that, before they are presented to the ANN, the generated instantaneous current and voltage values are preprocessed and normalized to match the ANN input pattern of 0's and 1's. This is an essential stage in the development of the classifier which involves the reduction of the size of the input data sets to correspond to the neural network input pattern. It reduces the magnitude of the input data to the neural networks to a maximum value of + 1 and a minimum value of -1, hence improving the rate of the training process [16].

Table 3: The Target Truth Table for the ANN-Based ISFC

Module Code	Fault Type										
	R-G	Y-G	B-G	R-Y-G	R-B-G	Y-B-G	R-Y	R-B	Y-B	R-Y-B	No-Fault
ANN_R	1	0	0	1	1	0	1	1	0	1	0
ANN_Y	0	1	0	1	0	1	1	0	1	1	0
ANN_B	0	0	1	0	1	1	0	1	1	1	0
ANN_G	1	1	1	1	1	1	0	0	0	0	0

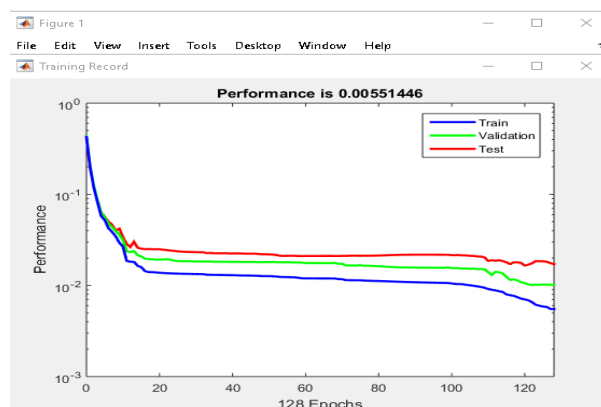
4. Results and Evaluation

The supervised learning is employed in training extensively several configurations of the ANN with varying number of hidden layers, hidden layers neurons and activation functions for each of the modular ANNs with their corresponding target outputs. It is observed after series of training and testing of various combinations of hidden layers that the ANN with two hidden layers results in the best performance for all the ANN modules. The results of the configurations are summarized in Table 4.

Table 4: The ANN modular architecture

ANN Module	Layer Neurons				Activation Function Combination	Performance MSE
	Input	Hidden layer 1	Hidden layer 2	Output		
ANN_R	6	10	10	1	tan-sigmoid/purelin/log-sigmoid	0.00551
ANN_Y	6	10	12	1	Log-sigmoid/tan-sigmoid/tan-sigmoid	0.000638
ANN_B	6	10	12	1	log-sigmoid/purelin/tan-sigmoid	1.888e-8
ANN_G	6	10	18	1	tan-sigmoid/log-sigmoid/log-sigmoid	0.00381

More so, the performance MSE, confusion matrix, regression plot and the generalization capability are used as performance indicators for the trained ANNs. Figure 5 to Figure 7 show the performance MSE, confusion matrix and regression plot respectively for ANN_R.

**Figure 5:** Performance Plot for ANN_R model

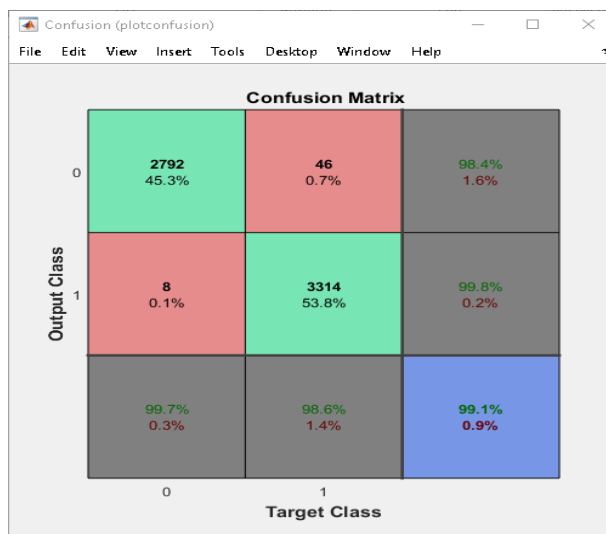


Figure 6: The Confusion Matrix of ANN_R model

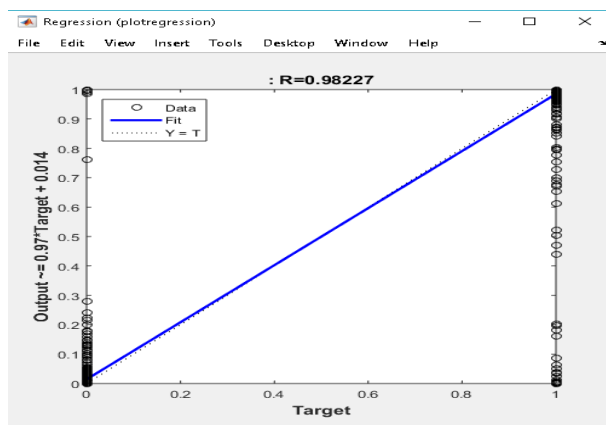


Figure 7: The Regression plot of ANN_R model

Furthermore, Figure 8 to Figure 10 depicts the performance MSE, confusion matrix and regression plot respectively for ANN_Y.

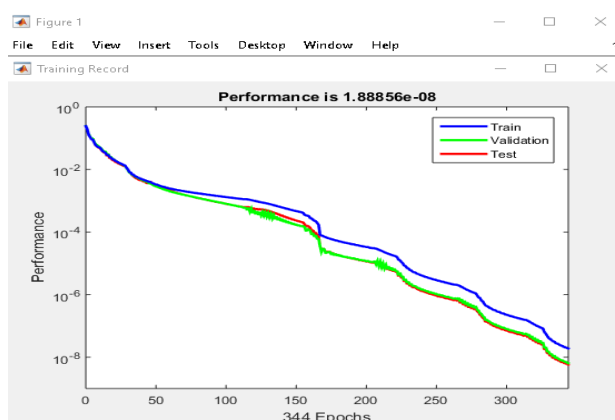


Figure 8: Performance Plot for ANN_Y model

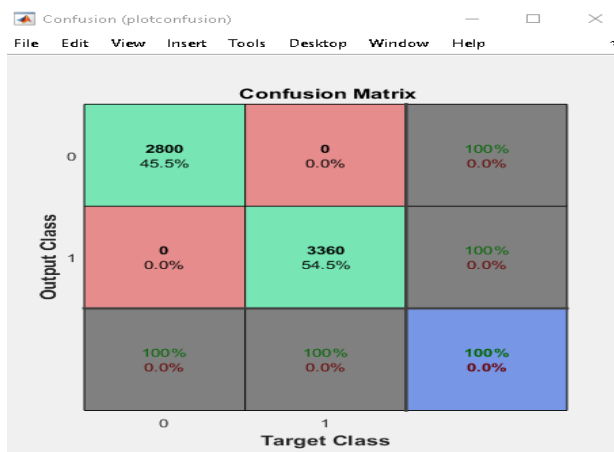


Figure 9: The Confusion Matrix of ANN_Y model

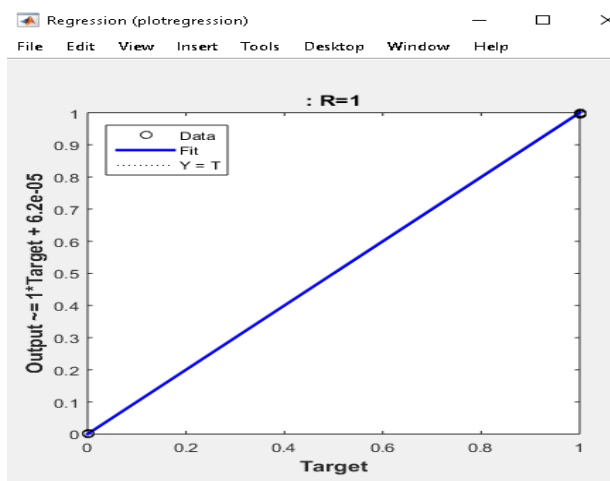


Figure 10: The Regression plot of ANN_Y model

Figure 11 to Figure 13 illustrates in that order the performance MSE, confusion matrix, and regression plot for the trained ANN_B.

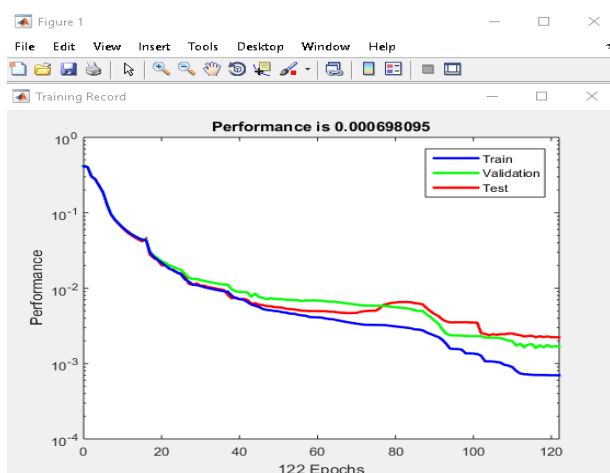


Figure 11: Performance Plot for ANN_B model

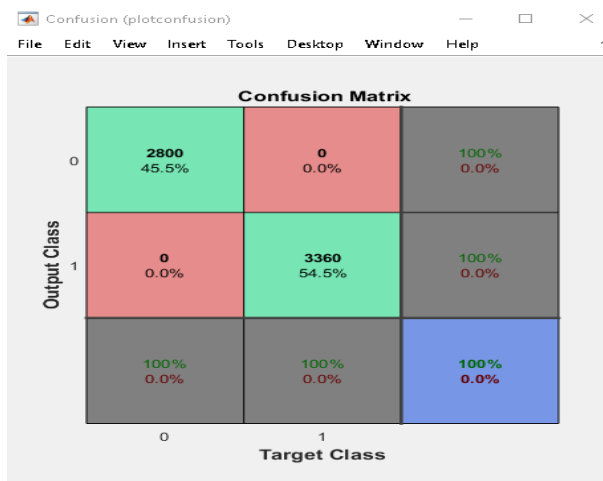


Figure 12: The Confusion Matrix of ANN_B model

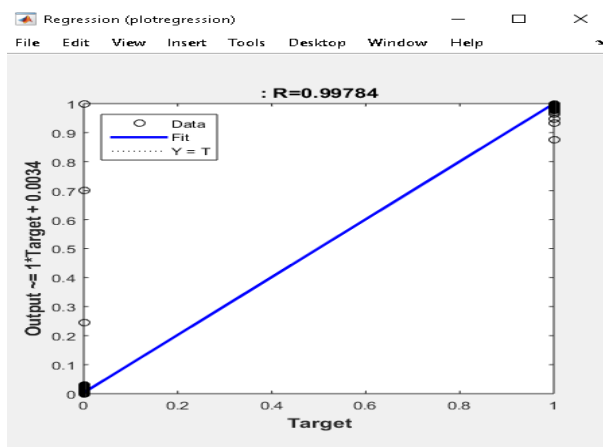


Figure 13: The Regression plot of ANN_B model

The performance MSE, confusion matrix and the regression plot for ANN_G is shown in Figure 14 to Figure 16.

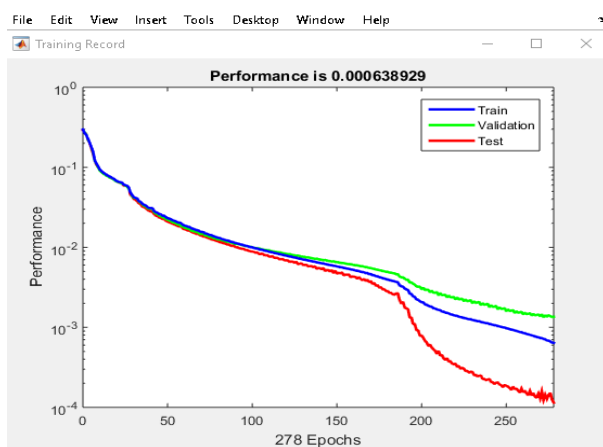


Figure 14: Performance Plot for ANN_G model

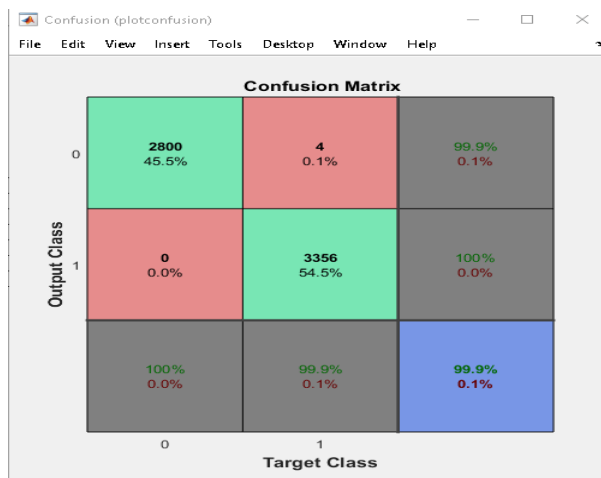


Figure 15: The Confusion Matrix of ANN_G model

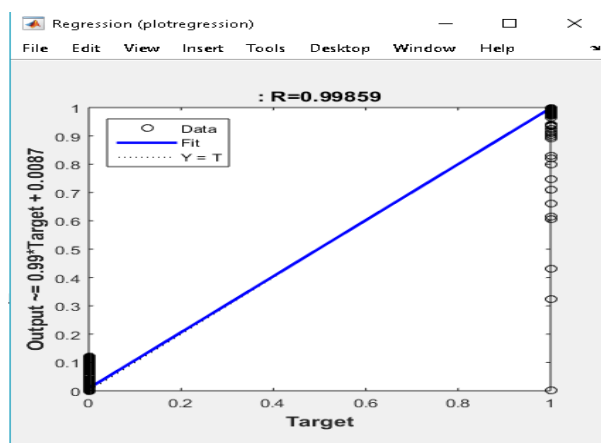


Figure 16: The Regression plot of ANN_G model

Moreover, the developed ISFC capability to generalize is tested with 10 new fault instances for each fault type, amounting to 110 new fault scenarios. Figure 17 to Figure 20 represent the Simulink models that show the responses of the developed intelligent shunt fault classifier for some selected fault types.

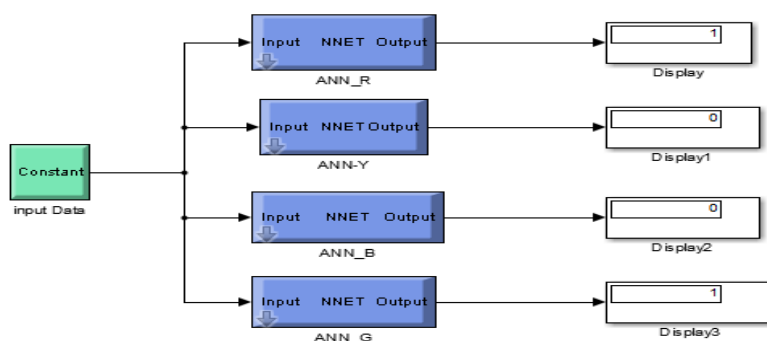


Figure 17: ISFC output for R-G fault with fault occurring at 48 km

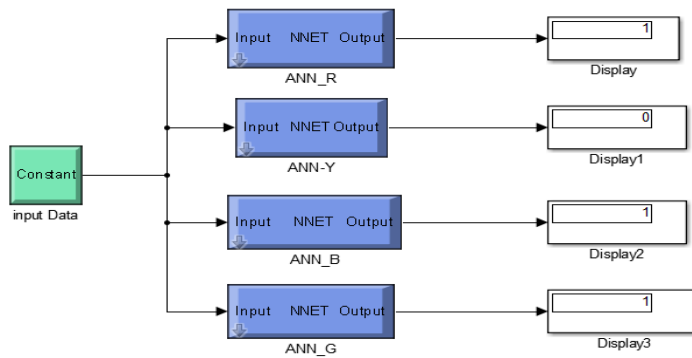


Figure 18: ISFC output for Line-line-to-ground fault for R-B-G fault with fault occurring at 56 km

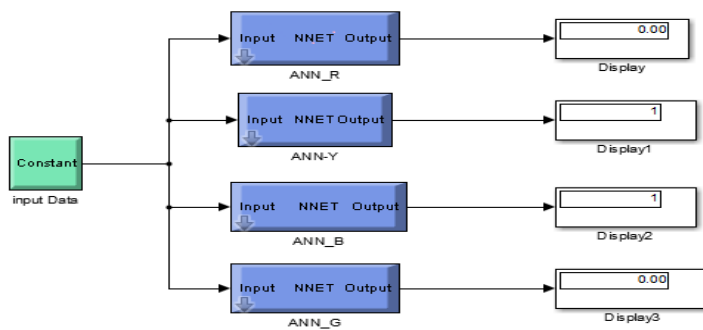


Figure 19: ISFC output for line-to-line fault for Y-B fault with fault occurring at 48 km

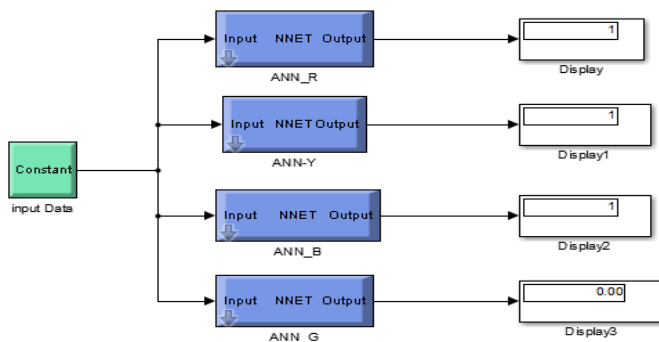


Figure 20: ISFC output for three lines shunt fault (R-Y-B) with fault occurring at 72 km

It can be seen from the performance plots (Figure 5, Figure 8, Figure 11 and Figure 14) which show the mean square error, that the testing and the validation curves have similar characteristics. Hence, it can be said that the ISFC has an efficient training, testing and validation. The satisfactory accuracy (Figure 6, Figure 9, Figure 12 and Figure 15) and the accurate correlation (Figure 7, Figure 10, Figure 13 and Figure 16) shown by the confusion matrixes and the regression plots respectively by the developed ISFC proof that this system can be deployed for the purpose for which it is developed. Finally, based on the results presented, the ISFC developed can effectively and efficiently classify all the ten possible types of shunt faults and No-fault condition considered on the 33-kV Nigeria transmission line. The Simulink results presented demonstrate the ability of the intelligent shunt fault classifier to accurately indicate and classify all shunt fault types in all the considered simulation tests.

5. Conclusion

A new approach for shunt fault classification has been demonstrated in this paper. The model employs preprocessed and normalized instantaneous values of currents and voltages generated from one terminal datum as inputs to four independent ANN modules corresponding to the three phases and the ground, respectively of an electric power transmission line. After suitably training the modules (ANN_R, ANN_Y, ANN_B, and ANN_G), their outputs are appropriately gated to visually indicate the fault types. The performance of the system, when tested under various shunt fault types with varying resistances and distances, shows that the system can be used to improve distance line protection in 33-kV Nigeria power line.

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