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Detection and Classification of High Impedance Fault in Nigerian 330 kV Transmission Network using ANN: A Case Study of the Southeast Transmission Network

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Abstract: High Impedance Fault (HIF) occurs when an energized conductor comes in direct or indirect contact with a quasi-insulator. If not detected and eradicated, it would lead to fire outbreak, pose a risk to human lives, and negate the existing environmental friendliness. The transmission lines data of the 330 kV, south east Nigeria network were obtained and modeled in SIMULINK for the detection and classification of the HIF. The transmission lines modeled were from Afam GS (Generating Station) to Alaoji GS, Alaoji GS to Owerri GS, Alaoji GS to Onitsha TS (Transmission Station), and from Onitsha TS to New Heaven TS. The HIF was situated on the 25 km transmission line connecting Afam GS to Alaji GS which was the central part of the Network. The current signal for each of the HIF classes at each location was used as the input data to the Artificial Neural Network (ANN) model with the HIF classification code used as the ANN target. On inserting the developed ANN in the transmission network and testing its performance, it was observed that the maximum HIF classification deviation occurred on the transmission line connecting Alaoji and Onitsha (two phase HIF) at 0.003 (0.15%). This proved that ANN model is capable and suitable in HIF detection and classification on transmission line network in South East.

Keywords: ANN, HIF, HIF Classification, HIF Detection, Simulink

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1. INTRODUCTION

High impedance faults (HIF) emanate when a conductor that is energized with electrical power makes a direct or indirect contact with a quasi- insulating object such as asphalt, building structure, concrete or the conductor falls to the ground [1,2]. The types of faults that occur giving rise to voltage arcing are currently undetectable, constituting high risk to the public and could literally lead to fire outbreak.

Overtime, standard arrangements and reliable methods were proposed and utilized in the identification, classification, and prevention of low impedance faults from cascading and one of the implemented devices currently in use in Nigeria is the conventional relay [1]. In general, high impedance fault are difficult if not impossible to detect and classify with the existing conventional relays [3,4].

In the past decades, various techniques have been proposed for the improvement of the detection of high impedance fault in power transmission and distribution line networks. The proposed methods have been electrical and mechanical methods. The mechanical methods involve mainly the use of equipment to generate low impedance by catching the energized falling conduction. However, as viewed by [3], the installation cost and the maintenance cost of the mechanical equipment is very high. Another proposed method is the electrical method which involves the implementation of proportional relays, Kalman filtering method, and arc detection methods.

Though each of the proposed electrical methods has its own drawbacks but is better preferred than the mechanical methods in terms of cost [5,6,7]. Other occurrences in transmission and distribution line that possess similar characteristics as high impedance fault occurrence are air switching operations, nonlinear loads, capacitor bank operation, starting of induction motor, and transient stability [8,9], hence, the necessity to develop a modern means for HIF detection and classification. Some of the detection and classification methods proposed by previous studies require extensive computation stage for adequate extraction of the input signals which leads to application of strategies to obtain the required detection parameters [10,11].

In [12], the authors used improved Emanuel method for the simulation of HIF under working conditions and utilized DenseNet (a multi scale convolution kernels model) for the implementation of HIF detection and transmission of HIF features effectively and in turn proved the ability of the model to detect the fault occurrence.

Probabilistic neural network model for the detection of the high impedance fault was first utilized in [8]. The outcome was sent to discrete wavelet transform (DWT) for the HIF classification process of which the outcome was displayed at daubechies 6 and at coefficients of d1 to d7 and the purified signal viewed at approximation 7 (a7) which showed the effect of the arc period as a result of HIF occurrence and achieved a classification rate of 94.65 which was high. In [1], the authors modeled a Nigerian 33 kV system with MatLab, introduced the HIF model blocks at various block, used DWT in the detection of the HIF and sent the outcome of the DWT for classification with fuzzy inference system (FIS) and adaptive neuro fuzzy inference system (ANFIS). The essence was to compare both models in terms of their respective success rate and discrimination rates in HIF classification of which ANFIS had a better outcome of 100% success rate and 98.9% discrimination rate outcome respectively as against 72% success rate and 89% discrimination rate outcome presented by fuzzy logic. The authors in [3] utilized wavelet transform for the decomposition of the current and voltage signals for determination of HIF occurrence, the author utilized principal component analysis (PCA) for the feature vector reduction and artificial neural network was utilized for HIF classification. [5] carried out a review on various approaches for the detection of HIF which includes the use of Kalman filtering and pattern recognition, Fractal theorem, wavelet transform, crest factor, fault current flicker, cross winger ville distribution, expert system and Neural networks. Likewise, in [13], the authors carried out HIF detection and classification with hybrid model of gravitational search algorithm and artificial neural network and had a good outcome when compared with other HIF detection and classification methods. In [14], fuzzy logic technique was implemented in the detection of high impedance fault of which the outcome proved to be more accurate in HIF detection when compared with other forms of HIF detection. The authors in [15] embarked on HIF detection, classification, and section identification using extreme learning machines (ELM). Here, the model was used as the HIF identifier base on the arc type occurrence of HIF faults where the randomly selected weights from the simulated HIF occurred network was sent as input to the feed forward neural network model referred to as the ELM of which the outcome was good.

In this paper, five south eastern Nigerian 330 kV stations comprising of two generation stations and 3 load stations were modeled in SIMULINK and simulation carried out to obtain current signals at normal condition and at occurrences of various classes of fault. The current signals were used as inputs to the Artificial Neural Network (ANN) model and the classifier codes were the target data of the model. The developed ANN HIF classifier was inserted in the SIMULINK model network of power system where the effective HIF detection and classifications were tested and reported.

2. TRANSMISSION LINE MODEL AND PERFORMANCE

A transmission line consists of conductors running over steel towers. Transmission lines are usually represented on a per phase basis by their equivalent model with appropriate circuit parameters [16]. Figure 1 show the lumped equivalent circuit model used to define transmission line performance.

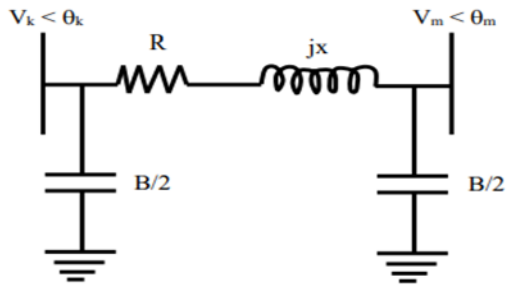

Figure 1. Transmission Line π circuit [17]

The equations of the line are as follow:

$$P_K = V_k^2(g_{km} + g_{k0}) - V_k V_m(g_{km}\cos(\theta_k - \theta_m) + b_{km}\sin(\theta_k - \theta_m)) \quad (1)$$

$$Q_K = -V_k^2(b_{km} + b_{k0}) - V_k V_m(g_{km}\sin(Q_K Q_m) - b_{km} cos(Q_k - Q_m)) \quad (2)$$

$$P_m = V_m^2(g_{km} + g_{m0}) - V_k V_m(g_{km}\cos(\theta_k - \theta_m) - b_{km}\sin(\theta_k - \theta_m)) \quad (3)$$

$$Q_m = -V_m^2(b_{km} + b_{m0}) + V_k V_m(g_{km}\sin(\theta_k - \theta_m) + b_{km}\cos(\theta_k - \theta_m)) \quad (4)$$

where,
P_K - Real power at bus k
Q_K - Reactive power at bus k
P_m - Real power at bus m
Q_m - Reactive power at bus m
V_k - Voltage magnitude at bus k
g_{km} - Conductance from bus k to bus m
g_{k0} - Conductance from bus k to neutral
V_m - Voltage magnitude at bus m
θ_k - Phase angle at bus k
θ_m - Phase angle at bus m
b_{km} - Susceptance from bus k to bus m
b_{k0} - Susceptance from bus k to neutral
g_{m0} - Conductance from bus m to neutral
b_{m0} - Susceptance from bus m to neutral.

3. MODELLING OF HIGH IMPEDANCE FAULT

HIF is a very complex phenomenon, which introduces a highly nonlinear behavior. Stochastic nonlinear current has certain attributes in both transient and steady state parts, which makes it identifiable. The HIF current has four most important and significant characteristics, which are known as build-up, shoulder, non linearity and asymmetry. Build-up and shoulder characteristics exist only before the steady state, after HIF, while the other two characteristics, non linearity and asymmetry exist both before and during the steady state. A HIF current increases until it reaches the steady state value, gradually, which is called build-up. HIF current may stop increasing for a few cycles and then continue to increase again during the build-up stage [18]. The model which is used in this paper includes all HIF signatures, except shoulder, and supports all frequency components. The model simulates first eight cycles of an HIF. In This HIF model, which is based on Emanuel arc model, several arc models are used together to simulate HIF currents and voltage waveforms, similar to the real recorded HIF data from many different experimental tests, on distribution and transmission systems. Figure 2 shows the applied HIF model [18].

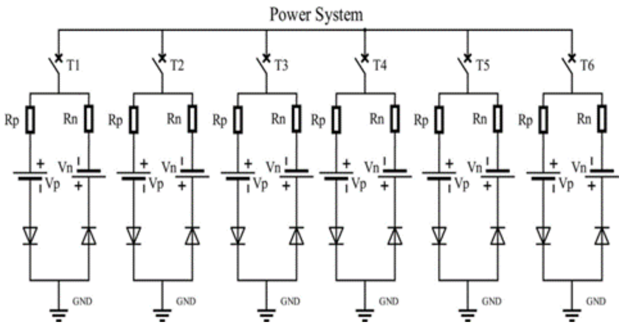

Figure 2. HIF model based on Emanuel arc model [18]

4. SIMULINK MODEL OF THE POWER SYSTEM NETWORK

The high impedance fault detection and classification carried out in this study was done on the south eastern Nigerian 330 kV that runs from Afam generation station (GS) to Alaoji in Imo, Enugu, and Anambra states. The line distance information utilized for the modeling is displayed in Table 1.

Table 1. Transmission line length of 330 kV transmission network in Nigeria

From Bus	To Bus	Line Distance (km)
Afam GS	Alaoji GS	25
Alaoji GS	Onitsha	154
Alaoji GS	Owerri	60
Onitsha	New Heaven	56

Other parameters utilized include the voltage (330kV for all the lines), power rating of the network (a base of 100MW). The power system was modeled with power system environment of SIMULINK in MatLab. The network model is as depicted in Figure 3 which shows the SIMULINK model of the power system network with the slack station from Afam Generation station to Alaoji, from Alaoji to Owerri and Onitsha transmission stations and from Onitsha to New heaven in Enugu all located in South eastern Nigeria (with exception of Afam GS that is located in South southern Nigeria).

Reference to high impedance fault in simulation is to a situation where the results will give low current occurrence and sudden voltage arcing. The study is carried out in simulink, and there is no specification to include impedance value as a fault on its own. The fault block in the simulink has switching sequence of 0 and 1, hence, HIF can be detected when it switches to 1 and also by monitoring the value of the current signal generated without and with the occurrence of fault. Therefore, when it switches or changes to 1, it means that HIF has been activated in the model. A high impedance fault block was introduced into the network on the transmission line connecting Afam GS and Alaoji GS (the location is central to all other locations in the model hence, a HIF occurrence on the transmission line would affect other locations in the model). Data collector and scope showing the current signals of the buses where inserted in the power system model. The current signals for all the classes of faults were exported to the MatLab file which was used as input to the ANN model. A classifier code was generated which formed the target to the ANN model. The input and the target data to the ANN intelligent HIF detector are as displayed in Table 2.

Table 2. Current signal HIF classification values for transmission line from Onitsha to New heaven

Current Signals (A)			Classification type (to ground)	Classification value
Phase A	Phase B	Phase C		
-127.6000	-129.7000	136.1000	Normal	0
-218.7000	-134.3000	79.7900	A-g	1
-8.4970	-56.2300	142.1000	B-g	2
-471.3000	-131.1000	134.7000	C-g	3
-102.6000	-60.3800	83.3700	AB-g	4
-550.0000	-135.5000	80.3800	AC-g	5
-400.0000	-55.8700	140.6000	BC-g	6
-480.1000	-59.8700	83.8800	ABC-g	7

The current signals in Tables 2, 3, and 4 are the summation of the current signals for each phase at the occurrences of various classes of faults at Onitsha-New heaven, Alaoji-Onitsha, and Alaoji-Owerri respectively. The phase current signals were the input to the ANN model while the classification values were the targets to the code.

Table 3. Current signal HIF classification values for transmission line from Alaoji to Onitsha

Current Signals (A)			Classification type (to ground)	Classification value
Phase A	Phase B	Phase C		
-133.4000	-129.8000	157.7000	Normal	0
-37.2000	-134.0000	93.0400	A-g	1
113.5600	-56.5000	164.6000	B-g	2
-181.2000	-131.6000	15.7000	C-g	3
-9.0600	-6.2700	97.1300	AB-g	4
-6.2000	-135.5000	9.3400	AC-g	5
-49.4000	-156.4500	16.5000	BC-g	6
-4.20	-6.0800	7.3600	ABC-g	7

Table 4. Current signal HIF classification values for transmission line from Alaoji to Owerri

Current Signals (A)			Classification type (to ground)	Classification value
Phase A	Phase B	Phase C		
-133	-127.9	130.1	Normal	0
-29.5	-130.2	78.91	A-g	1
163.9	-56.94	135.1	B-g	2
-119	-130.6	17.5	C-g	3
18.54	-8.89	81.57	AB-g	4
-16	-132.7	7.15	AC-g	5
-156	-56.8	12.4	BC-g	6
-18	-9.66	8.79	ABC-g	7

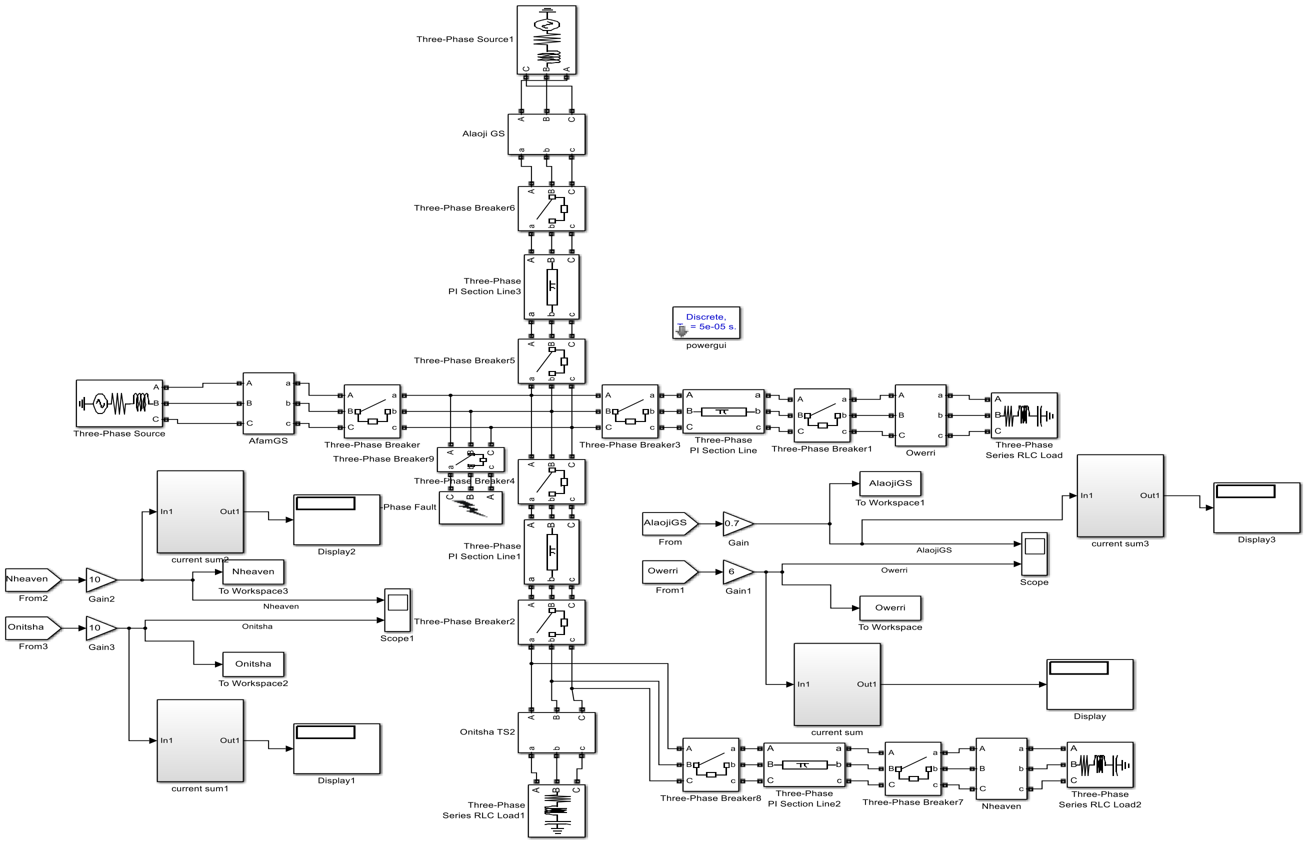

Figure 3. SIMULINK model of the power system Network with fault applied on the transmission line connecting Afam GS to Alaoji GS

5. ANN MODEL OF THE HIF DETECTION AND CLASSIFICATION

The inputs and the targets data in Tables 2, 3, and 4 were exported into the ANN model environment as shown in the ANN environment snapshot in Figure 4.

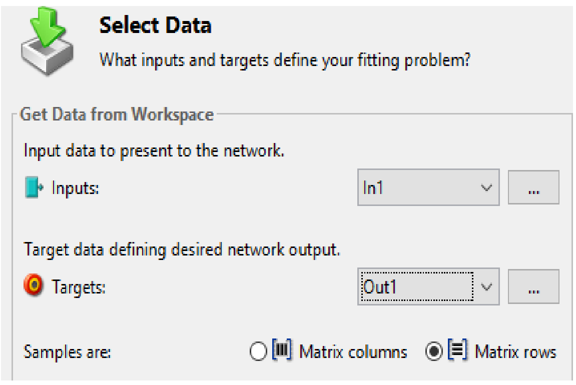

Figure 4. Data selection for ANN model

The 'In1' in Figure 4 represents the current signal of the transmission line while the out1 is the HIF classification code which was utilized as the target to the code. The same was done for all the transmission line locations under review. Levenberg Maquart's back propagation algorithm was used for the training of the network and the system data was split to 50%, 25%, 25% (50% used as train data, 25% used as test data and 25% used as validation data). Five (5) hidden neurons were selected for the training of the system. The system architecture of the network is shown in Figure 5. The inputs to the ANN models are the current phases of the transmission lines. The "out" is the classification and the number of hidden neurons selected are 5 with Log-Sigmoid model deployed for each of the hidden neurons. The weights and biases are utilized in tuning the inputs and hidden neurons so as to achieve an "out" that has less error deviation from the target. The ANN model is modeled for the three transmission locations. The input and target data are shown in Tables 2, 3, and 4. Table 2 is the first location (transmission line) from Onitsha to New Heaven with phase A, B, and C which are the inputs, while the classification value is the target. Table 3 is for ALaoji to Onitsha while Table 4 is for Alaoji to Owerri.

Figures 6-9; 10-13; 14-17 depict the results of the mean square error performance, training state, error histogram, and regression of coefficient plot respectively of the ANN training and testing phase for Onitsha - New Heaven transmission line. 10-13 depict the results of the mean square error performance, training state, error histogram, and regression of coefficient plot respectively of the ANN

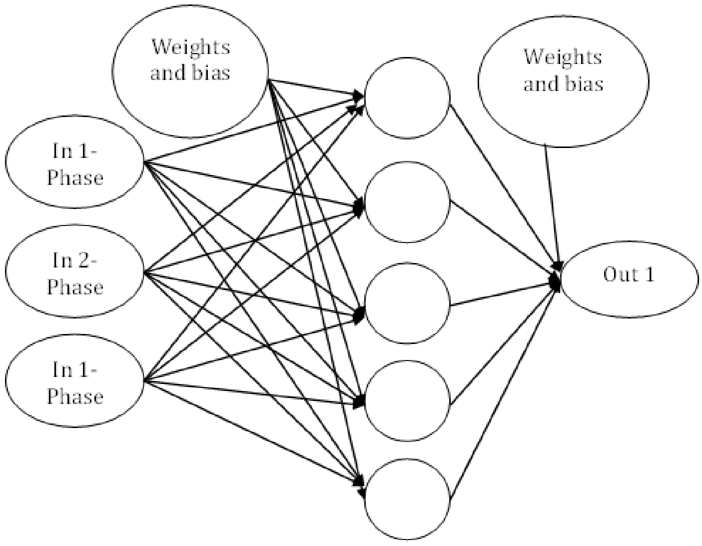

Figure 5. ANN architecture

training and testing phase for Alaoji - Onitsha and 14-17 depict the results of the mean square error performance, training state, error histogram, and regression of coefficient plot respectively of the ANN training and testing phase for Alaoji - Owerri.

6. OPTIMIZATION METHOD FOR ANN ARCHITECTURE

Levenberge Maquart's Back Propagation Algorithm is selected for the training of the network. Embedded in this algorithm is the Log-Sigmoid curves which are used for the hidden neurons. There is no form of model for the input neurons. The input is just to specify the number of inputs on its own and select the best neuron to be represented. The output neuron is linear model as shown in Figures 9, 13, and 17.

Generally, Artificial Intelligence are not known to have a standard mathematical model. Most AI, e.g, Surface Vector Machine, Neural Network, Adaptive Neuro Fuzzy Inference System, Random Forest, Decision Trees etc, have their different schematic system of representation, hence, no specific equation in the x and y domain. In the case of ANN, the graphs in Figures 8, 9, 12, 13, 16, and 17 represent the relationships between the inputs and the targets. Linear equations could be derived though from the graphs, but there are no known mathematical formula linking the inputs to the targets, reason being that in ANN, the hidden neurons utilizes the Log-Sigmoid curve whose relationships cannot automatically represents what happens from the input to the output. All it shows is the effects when the input neurons comes into the hidden neurons. Therefore, one cannot adequately produce a relationship between the inputs and the targets in the case of neural networks using any specific form of mathematical model. The only form of linear model is shown by the sides of the regression plots of Figures 9, 13, and 17.

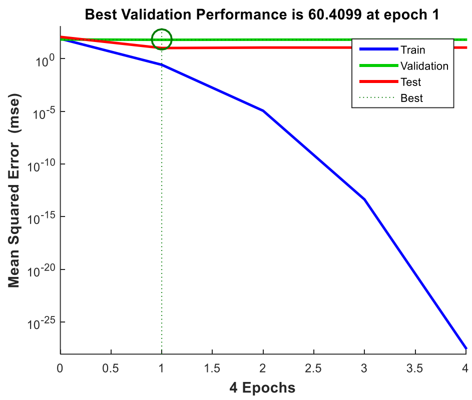

Figure 6. Mean square error performance

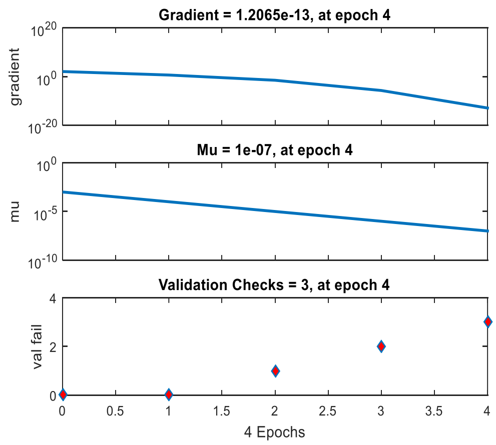

Figure 7. Training state

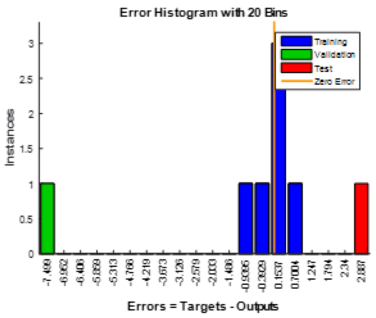

Figure 8. Error histogram

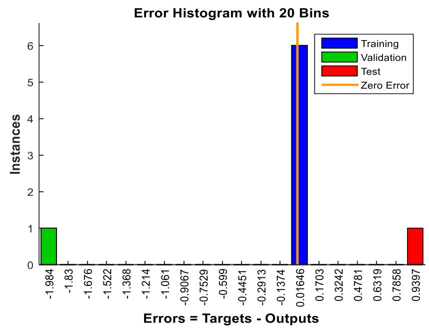

Figure 12. Error histogram

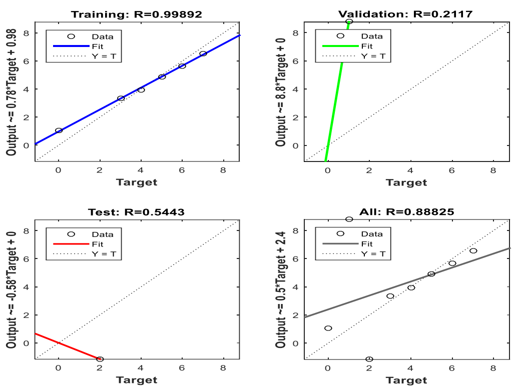

Figure 9. ROC (Regression of coefficient) plot

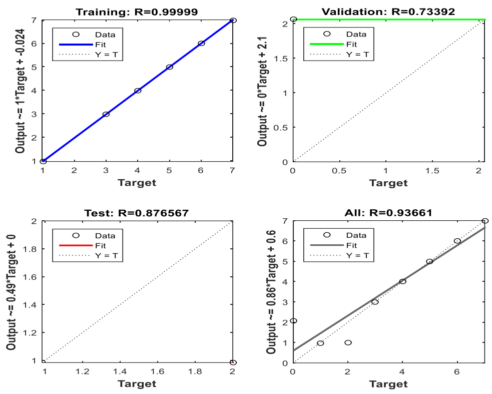

Figure 13. ROC (Regression of coefficient) plot

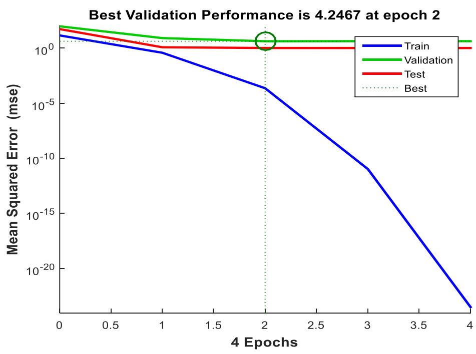

Figure 10. Mean square error performance plot

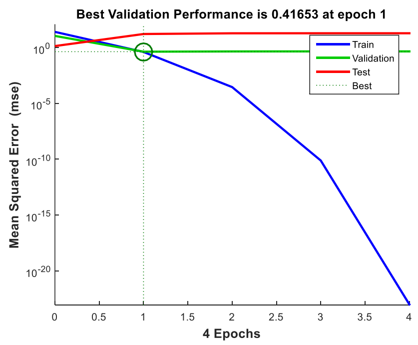

Figure 14. Mean square error performance plot

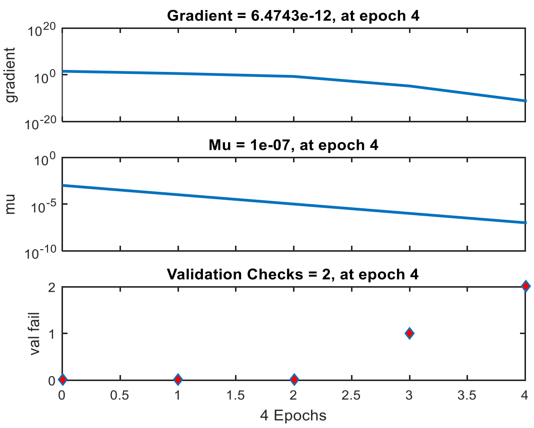

Figure 11. Training state

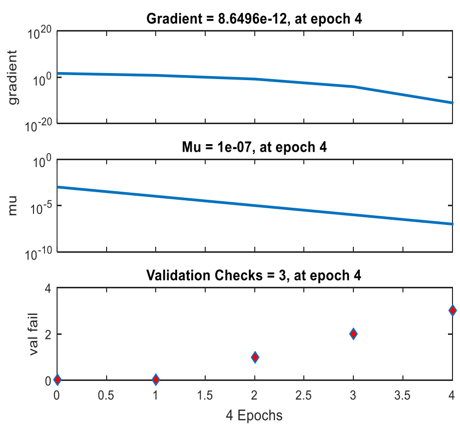

Figure 15. Training state

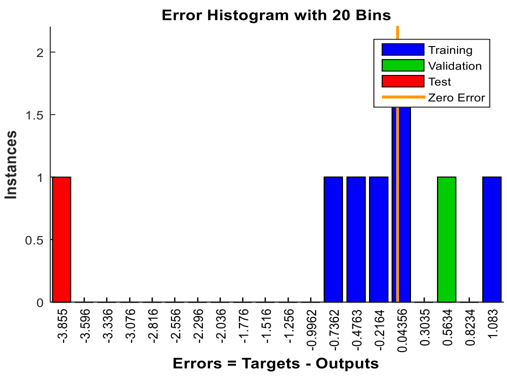

Figure 16. Error histogram

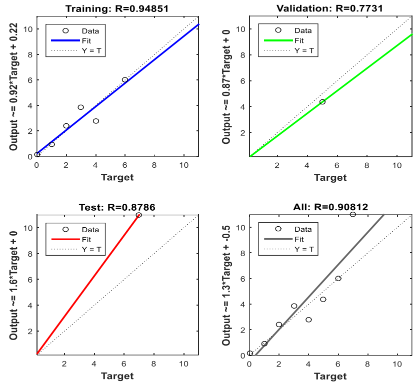

Figure 17. ROC (Regression of coefficient) plot

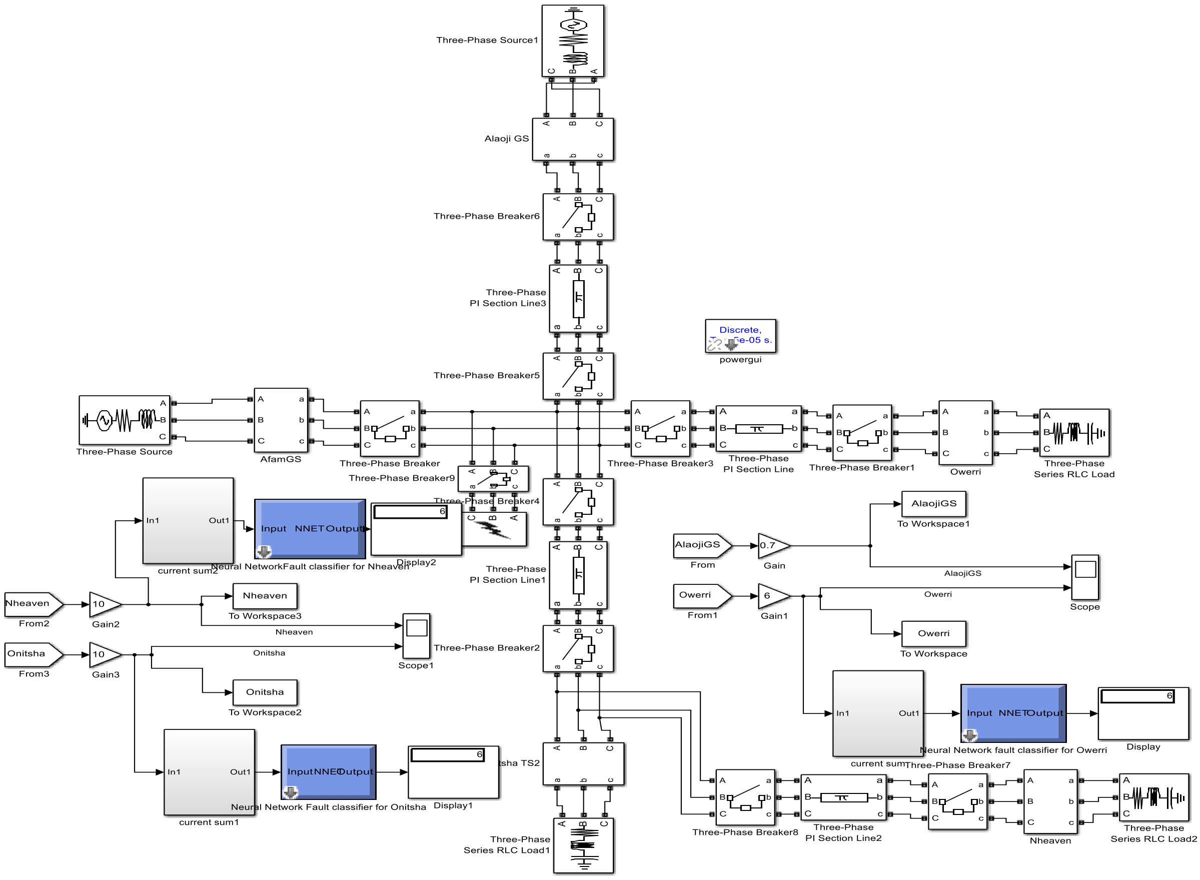

Figure 18. Power system model with ANN HIF detector and classifier with fault applied at the transmission line connecting Afam GS and Alaoji GS

7. RESULTS AND DISCUSSION

In this section, the conditions of the classes of the occurrence of the HIF are presented ranging from when the system operated at normal condition to the occurrence of the single phase HIF (at phase C), occurrence of double phase HIF (at phase B and C) and occurrence of three-phase HIF. These were carried out for each of the transmission line locations. The current signal for the system at normal condition (without faults) for each of the transmission line location are displayed in Figure 20. These are the current conditions at normal conditions without any fault occurrence. Each of the phases operated at normal condition. The current signal for the occurrence of HIF on a single phase is displayed in Figure 21. The HIF fault majorly occurred on phase C which current signal's arcs are seen at the startup of other phases but normalized afterwards with a reduced amplitude. The current signals for two phase HIF of the transmission line for each of the locations are displayed in Figure 22. The effect of the HIF occurrence can be seen on phases B and C. It reduced the current signal of these phases leaving an arc at the startup of phase A that normalized afterwards. The current signal for the three phases of the transmission lines with HIF for each of the location are shown in Figure 23. The HIF three phase occurrence and its effects on the current signals transmitted are shown. The effect commenced from the onset and generated an arc before transmitting low signal as expected of a system with HIF occurrence. ANN model was inserted in the affected locations and the HIF classification performance was presented. The ANN prediction code for the network is displayed in Table 5.

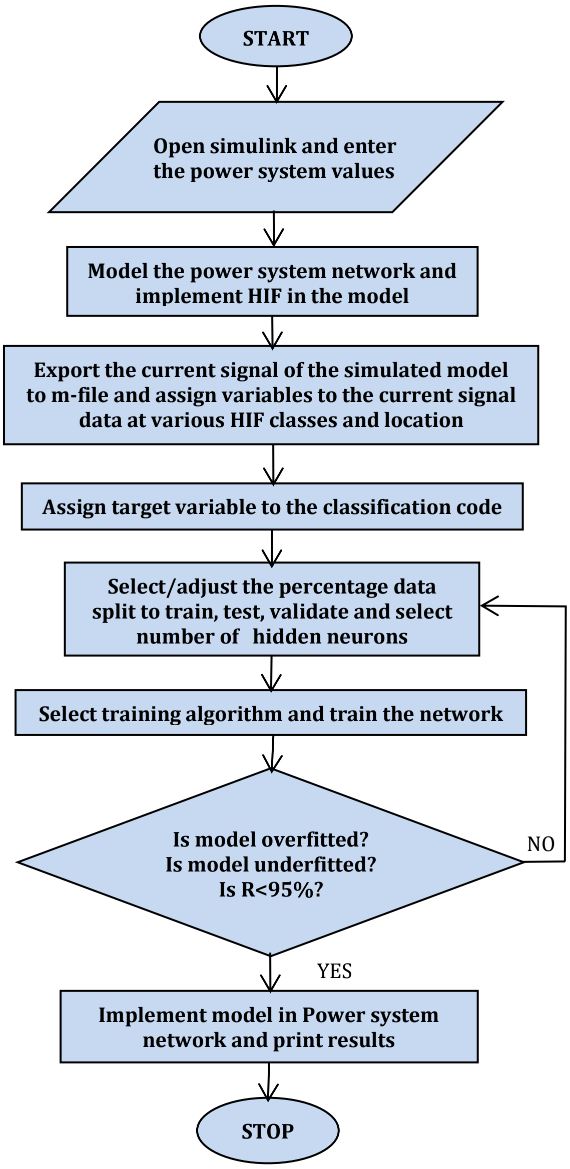

Figure 19. Flow chart of the modelling and simulation

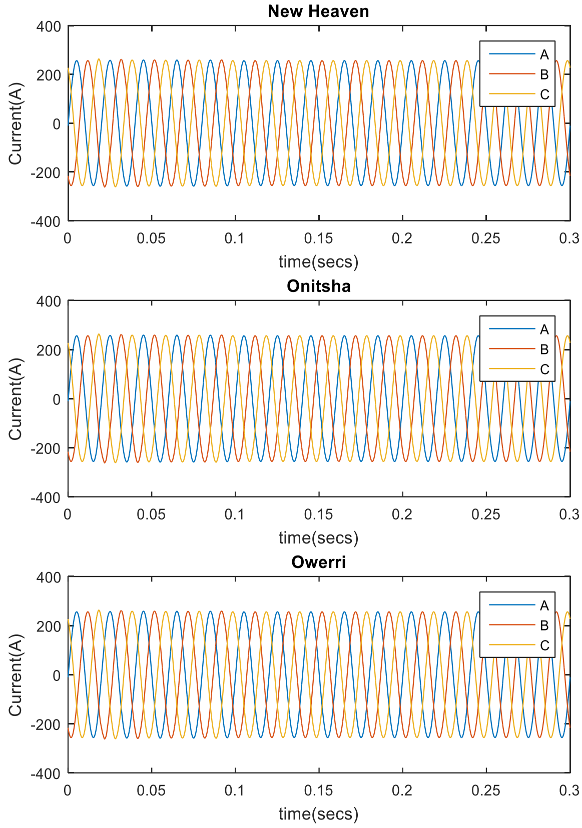

Figure 20. Current signal at Normal conditional

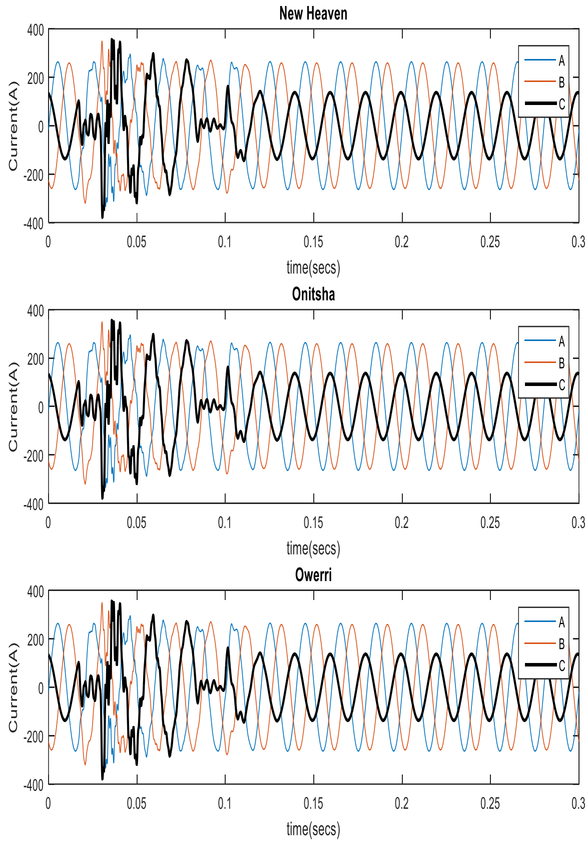

Figure 21. Current signal of HIF fault on a single phase

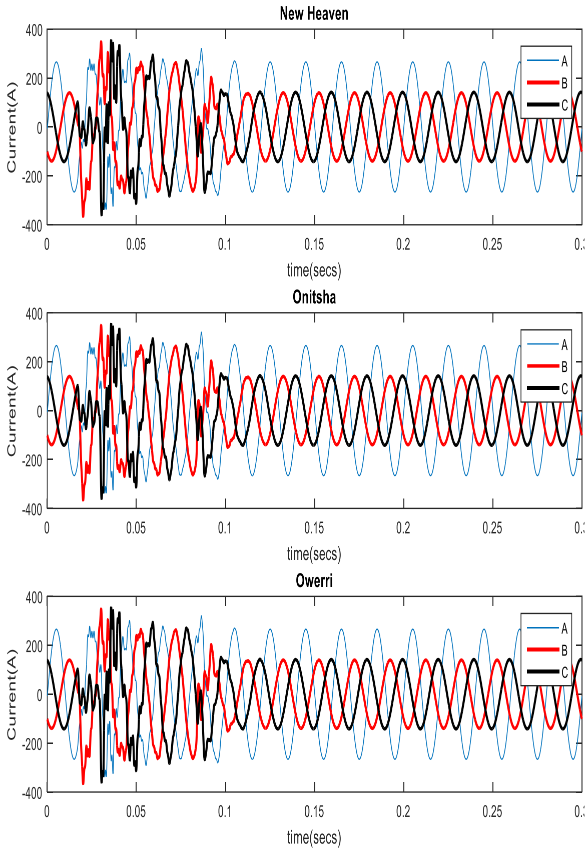

Figure 22. Two phase high impedance fault on the transmission line for each of the locations

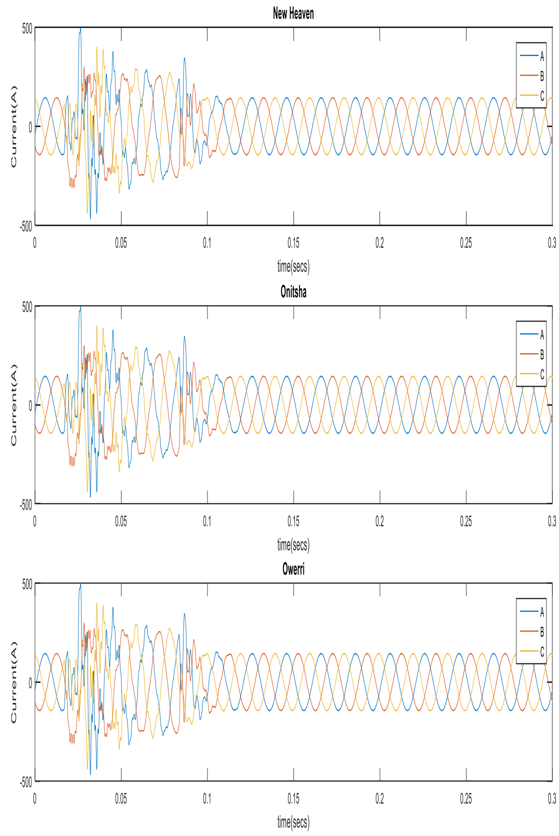

Figure 23. Three phase HIF on the transmission line network

Table 5. ANN HIF detection and classification

HIF class	Actual HIF class code	ANN predicted class code		
		Onitsha-New Heaven	**Alaoji-Onitsha**	**Aloaji-Owerri**
Normal	0	0.0002176	-0.0007733	-0.001272
A-g	1	1	1.001	1
B-g	2	2.001	2.003	2.001
C-g	3	2.998	3.002	3.001
AB-g	4	4	4	4
AC-g	5	5	5	5
BC-g	6	6	6	6
ABC-g	7	7	7	7

Table 5 shows the HIF classification values predicted with ANN. This predicted classification values have little and tolerable errors whose maximum value can be seen on the single-phase line B-g along Alaoji-Onitsha transmission line with percentage error of 0.15% implying that ANN should be utilized in the HIF prediction and classification.

8. CONCLUSION AND RECOMMENDATIONS

This paper outlines the detection and classification of HIF occurrence using ANN model in the South eastern Nigerian 330 KV network on the following transmission line; Alaoji GS to Owerri TS, Alaoji GS to Onitsha and from Onitsha TS to New Heaven TS. The power system network was modeled in SIMULINK/MatLab with the HIF model block situated between Afam GS to Alaoji GS which represents the central part of the network. The current signal for each of the classifications were obtained and sent to the ANN model as the input data and the target data was the HIF classifier values. The HIF classification outcome presented after inserting the ANN model in the power system model indicated a perfect HIF classification as shown in Table 5. It is therefore obvious that ANN model has the capability and reliability to be utilized for HIF detection and classification on the 330 kV transmission lines in Nigeria. Certainly, other models such as Surface Vector Machine, Neural Network, Adaptive Neuro Fuzzy Inference System, Random Forest, Decision Trees etc, have their degree of accuracy when implemented. Further studies will be carried out to implement these models and their reliabilities explored for effective utilization in the HIF classification and detection.

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