American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-10, Issue-6, pp-147-158
www.ajer.org
Research Paper Open Access

Improvement of Power Systems Protection Using Application of Artificial Neural Network. A Case of Rukpokwu 33kv Port Harcourt Distribution Network

Dieokuma Tamunosiki[1]
Department of Physic, Federal University Otuoke, P.M.B. 126 Yenagoa, Bayelsa State, Nigeria.

Emeruwa Chibuzo[2]
Department of Physic, Federal University Otuoke, P.M.B. 126 Yenagoa, Bayelsa State, Nigeria.

ABSTRACT: *Relative to length, electric power distribution networks are exposed to the environment and hence are more susceptible to faults. The uninterrupted flow of power is disrupted by these flaws. There is also a loss of electricity that is created, which influences the status of the economy. To decrease system downtime, it is vital to include a system that promptly identifies defects in order to expedite their resolution. The efficiency and integrity of the electricity network will increase as a result of this.The artificial neural network presented in this study is intended to identify, categorize and locate faults on the Rukpokwu 33-kV feeder of the Rukpokwu 33-kV feeder of the Rukpokwu 33-kV feeder of the Rukpokwu 33-kV (PHEDC). In the study, fault detectors, classifiers, and locators were used, as well as feed forward back propagation.To model and simulate the distribution network, Matlab Simulink software was utilized. Voltage and current measurements were used to train the model. The suggested network's efficiency in defect detection, categorization, and localization was proved through simulated results. The suggested model's performance was evaluated using the mean square error (MSE) and a confusion matrix. The MSE was 0.00000027736 and the accuracy was 100 percent, which is good.*

KEYWORDS: *Distribution Network, Power Systems, Protection, Artificial Neural Network.*

Date of Submission: 03-06-2021 Date of acceptance: 17-06-2021

I. INTRODUCTION

The demand for electricity in Nigeria is enormous. Fault is one of the challenges that power supply faces. As a result, fault has been a major worry in both the transmission and distribution sectors. So much money and resources are being poured to get infrastructure in working shape. When compared to other sectors, the distribution network has greater power supply interruptions, according to Rahman et al., (2018). The distribution sector is responsible for more than 80% of power outages. Locating a defect is challenging because to the broad nature and dispersion of the distribution network. The distribution industry has been related to both transient and permanent faults. According to the study, around 80% of the defects are temporary, while 20% are permanent.

The use of a system that identifies and classifies defects expedites problem resolution and lowers downtime. As a result, network efficiency will increase. Faults were also identified by Lilik et al. (2014) as the leading cause of power network outages. The study also indicated that defects account for around 75% of all interruptions, thus it's critical to find defects as soon as possible to reduce the system's harm. Currently, the most common methods for locating faults are: High frequency components and traveling wave base method, knowledge based method, which can be classified as Artificial Neural Networks. Using a Hybrid Method and a Matching Approach

In order to improve power system protection, an artificial neural network is used to detect, classify, and locate faults.

II. LITERATURE REVIEW

Faults in Power System

Fault can be described as a deviation of currents and voltages from the acceptable limits. This can occur when there is a bridge between a phase and ground, or between two phases and aground, as well as phase to phase. Short circuit has been identified as the most severe case in fault classification. The attendant result of short circuit faults is seen in the huge flow of charges on the distribution line with the capacity to damage power systems equipment. Faults are categorised as either symmetrical faults or unsymmetrical faults.

Symmetrical Faults

Symmetrical faults are characterised by symmetrical faults currents. These currents are equal with displacement of 120^0. An example of symmetrical fault is a three phase fault. In this type of fault, all the three phases are short circuited, either with the ground or without the ground.

Transient on a Transmission Line

Transient is a fault condition on the distribution in which faults linger for a brief moment. Source of fault could be internal or external.

External Factor

This factor includes: atmospheric disturbances created by direct lightning strokes, side stroke which is lightning discharge that takes place close to the line, atmospheric changes on the distribution line, frictional effects of small particles like dust or dry snow, in addition to the presence of charged clouds nearby. All these factors cause over voltages which could have negative impacts on power quality delivery.

Internal Factor

These over voltages are caused by changes in the operating conditions of the power system. These can be classified as shown below:

1. Switching over voltages or Transient over operation voltages of high frequency: This is caused when switching operation is carried out under normal conditions or when fault occurs in the network. Charging an unloaded long line increases voltage at the receiving end through the principle known as the Ferranti Effect. This in turns causes over voltage in the system. In the same vein, switching on of the primary side of either the transformers or reactors can create over voltage of transient nature occurs.

2. Temporary over voltages: in the event of disconnecting some major load on the line, either during normal or steady state condition, temporary over voltage condition occurs.

Various Protection Schemes

In protecting either the transmission or the distribution network, plants and personnel are also protected. This protection is achieved by disconnecting faulty equipment

Overload Protection

This protection scheme guards against high temperature. Current transformer measures current flowing into the system. The most notable cause of over current is equipment overloads, which can be caused by either short circuits or by ground faults. An overload occurs when equipment is subjected to current above its rated capacity and excessive heat is produced. A short circuit occurs as a result of bridge between phase and earth or phase to phase. Short circuits have the ability to generate temperatures very high temperature. These uninsulated currents can be lethal. Overload protection is classified into instantaneous over current and time over current (T.O.C). Current breaker trips whenever current coming in exceeds the pre-determined level.

Earth Fault Protection

Fault statistic shows that earth faults are common in the distribution network. Hence, so much attention has been given to earth fault protection in the electrical network. The type of earthling method greatly determines the type of earth fault protection to be adopted. Structure of earth fault protection includes: current transformers which is connected in series in the circuit. Generally, the three phase currents are supposed to have the same magnitude. But, in a case where one or two of the phases have direct connection to the earth, it causes a sharp increase in magnitude of their values, hence the circuit becomes imbalance. The circuit is designed to operate if the imbalance exceeds a pre-determined value.

Distance Protection (Impedance Relay)

In this protection scheme, both voltage and current are detected. According to Yadav & Dash (2014), when there is a deviation in the voltage level, it is an indication of fault condition. At any point in time, impedance along the line is measured. Impedance is the ratio of voltage and current at relay terminals. If this measured impedance is not within acceptable limits, the circuit breaker will operate. The idea being that at fault condition, the comparator compares values at the relay settings with the line impedance from the relay terminal to the point of fault. Any deviation from the acceptable limits is an indication of fault condition. The protection scheme is most effective for long distance distribution network.

Back Up

The significant role of this protection scheme is to disconnect only the affected location of the plant and nothing else. It acts depending upon the output of current and voltage transformers. The station battery is responsible for the circuit breaker trip current. To ensure effective and successful clearing, the battery and the trip coil must be in good condition. Wiring continuity, proper functioning of the circuit breaker, and the closing of the relay trip contact must be of great concern. Back up protection comes to effect when the main protection scheme has failed to clear faults. The backup protection is normally different from main protection and preferably of non-unit type. For instance, over current or distance protection Selectivity is absolute if the protection acts when faults occur within the zone of protection. Whereas, it is relative if it is obtained by grading the settings of protection of several zones which may act when a given fault occurs. Unit system of protection is one with principle of absolute selectivity. Whereas, a system of protection in which selectivity is relative is non-unit systems. Examples are: current time graded protection, distance protection. There are instances a circuit breaker fails to trip when fault occurs. In that scenario, back up protection system will take up responsibility of clearing fault. According to Gabriel (2006), major difference between remote back up protection and local back up protection is that remote back up protection scheme isolates all the system in the event of fault, while local back up protection scheme isolate only the faulty part.

Improved Power System Protection

Power systems protection can be categorized under unit and non-unit protection. Information is fed into the distribution network from one terminal in unit protection. While information is fed through both terminals in non-unit protection. One significant problem with non-unit protection scheme is it inability to differentiate between external faults and internal faults around multi-zone boundaries. Hence, can protect the primary line. Back up protection effectively protect the entire section. In the traditional protection scheme, principle of operation is based on is fundamental frequency phasor in which non- linear ratio between voltages and currents is formed and when compared with threshold, faulted phase can be detected. The study also presented ANN as alternative solution in realising effective fault classification. A similar research by Salat & Osowski (2000) classified faults with boundary protection using self-organised ANN. Results of the study showed effectiveness in using neural network algorithm for solving the problem of classification.

Artificial Neural Network

A neural network constitutes parallel processors used for the storage of trained data, and can use the data in future to determine the health of the network. It adopts the principle of biological neuron in human brains. Study by Yadav & Dash basically classified ANN layers into three.

Artificial neural network has three learning process. This includes supervised, unsupervised and reinforced learning process. There are three learning algorithm associated with neural network, such as supervised learning, unsupervised and reinforced learning. In the supervised learning algorithm, error back propagation is used in tracing faults in the power systems. Training speed and issue of generalization are drawbacks associated with the learning process, hence, unsupervised method was also adopted.

III. MATERIALS AND METHODS

In the study, method used to implement the proposed model is the supervised and unsupervised learning algorithm. The study will describe the process of detecting, classifying and locating fault with the state of the artificial neural network. The distribution systems under consideration is the Rukpokwu 33kV Port Harcourt distribution networks. A model of the work will be simulated using Matlab Simulink.

Considered Power Systems

Rukpokwu 33kV Port Harcourt Distribution network is the proposed network for the study. Matlab Simulink software was used in the modelling and simulation of all components of the network. A three phase circuit breaker block also used and modelled with parameters gotten from the Port Harcourt Distribution Network. Different faults at varied fault resistances were induced with the help of fault block.

Required data for simulation: Line parameters, Single line diagram of the three phase network and Transformer data

Overview of Testing Process

Testing of the trained network is key to ascertaining the reliability of the network. The artificial neural network cannot be put to use without the network being tested to ascertaining the training is valid and can give out the desired output in the event of new data being presented to it. The proposed model can be tested in various ways. One of the many ways is to plot the best linear regression fit between the actual neural network and the expected targets. The nature of the slope will describe the training process. In ideal situation, the slope is expected to be 1.

Another means of testing the network is through the correlation coefficient(r). This method defines the relationship between the outputs and the targets. The performance of the neural network is directly proportional to the correlation coefficient ®. As the value of 'r' approaches 1, it indicates that the network will perform well. Plot confusion matrix is another method of testing the artificial neural network. this method presents a plot that describes the actual number of cases that have been classified positively. The result of the plot is presented in percentage. In an ideal case, 100% means all data has been classified positively and there is no confusion in the classification process. Low percentage classification rate shows that the neural network might perform well in classification. Finally, the most significant means of verifying the reliability of artificial neural network is by feeding new data into it, which is quite different from the dataset used in training it. For the neural network to be reliable and acceptable, the average percentage error must be within the acceptable limits. The algorithm used for the development of the neural network for fault diagnosis is presented in fig 1.

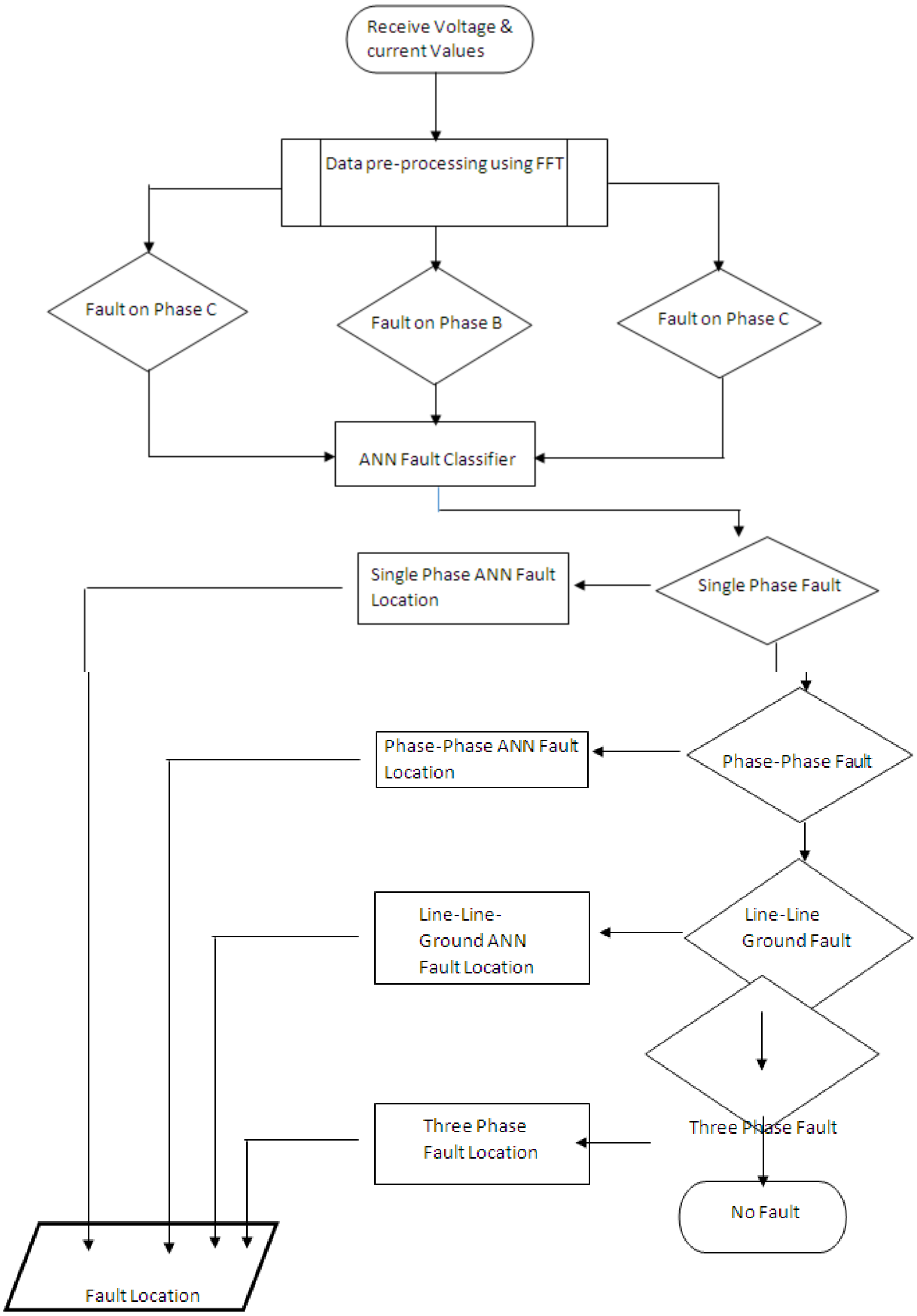


Fig1 flowchart of ANN Fault Diagnostic Algorithm

Performance Evaluation

Data is the key parameter in the neural network. The training dataset should be able to cover the distribution network is would be implemented. The amount of data is this case is directly proportional to the complex nature of the network to which it should be applied. The proposed study requires large dataset to meet the growing challenges in the distribution network to which it is to be implemented. The performance function is expressed as shown in equation (1)

$$F(x) = -\sum_{q=1}^{Q} \sum_{I=1}^{SM} t_{i,q} ln \frac{a_{i,q}}{t_{i,q}} \quad (1)$$

The regression characteristics is used to analyse the output of the trained network and the corresponding targets in the fault locator section. The expression that relates the actual outputs and the targets are given in equation (2)

$$a_q = mt_q + c + \varepsilon_q \quad (2)$$

m=slope, C=offset, t_q = target a_q = actual output, ε_q = the residual error of the regression.

The correlation coefficient between (R) between t_q and a_q is expressed as shown in equation (3)

$$R = \sum_{q=1}^{Q}(t_q - \bar{t})(a_q - \bar{a}) \quad (3)$$

Where $S_t = \sqrt{\frac{1}{Q-1}\sum_{q-1}^{Q}(t_q - \dot{t})}$ (4)

and $S_a = \sqrt{\frac{1}{Q-1}\sum_{q=1}^{Q}(a_q - \bar{a})}$ (5)

Clustering with Self Organized Neural Network Algorithm

Self-organising function of neural network takes cognizance of similar properties of the signals fed into it. It takes in input signals at the same time and comparatively analyse the various output patterns with respect to their mutual characteristics. Clustering involves training a neural network based on pattern such that it presents patterns that reflect common properties of the topology. The same input data for both fault detector and locator are also used as input to the network. In this learning process, no room is made for targets in the algorithm.

In order to ensure the trained neural network can generalize well, several plot were generated. These plots S.O.M topology, S.O.M neighbour distances, S.O.M input planes, S.O.M sample hits and S.O.M weight positions.

Table 1: Parameters Used in Generating Training and Testing Dataset

Data for Training	
Fault Location (km)	2,4,6,…………….100
Fault Resistance (Ω)	0.25, 0.5, 0.75, 5, 10, 20, 30, 50

Table 2: PHEDC Fault Data for Testing the Designed ANN

S/No	Ia	Ib	Ic	Va	Vb	Vc	Fault Types
1	0.0128	0.0125	0.0122	0.9990	0.995	0.9989	No fault
2	1.5570	0.0385	0.0386	0.3701	1.0930	1.1357	A-G
3	0.0725	1.142	0.0321	1.3100	0.5660	1.0820	B-G
4	0.0320	0.0720	1.1520	1.0802	1.2220	0.2443	C-G
5	1.0160	1.6940	0.0780	0.2776	0.3132	1.1050	A-B-G
6	1.0941	0.0207	1.9475	0.3103	1.3000	0.2801	A-C-G
7	0.0935	1.9842	1.6950	1.2800	0.2872	0.3094	B-C-G
8	2.0726	2.4835	0.0436	0.5287	0.5352	1.0050	A-B
9	0.0237	2.1620	2.4844	1.0100	0.5295	0.5348	B-C
10	2.3892	0.0137	2.0235	0.5360	1.0050	0.5310	A-C
11	1.6358	1.2008	1.1999	0.2074	0.2089	0.2107	A-B-C-G

Table 1 describes parameters used in generating dataset used for training the proposed ANN and testing of the neural network. The fault location was varied between 2 and 100km at intervals of 2. Fault resistance was also varied as shown in the table.

Table 2 also describes fault parameter. This parameter was gotten from PHEDC. these parameters were used to ascertain the applicability of the proposed model to Port Harcourt Distribution network.. This data was keyed into the network and the output was compared to the target output.

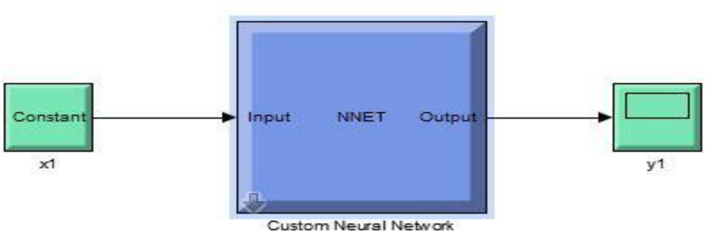


Fig 2: Simulink Model of the Developed Network

Fig 2 represents a developed model of the artificial neural network after a successful and satisfactory training is done, and a satisfactory performance is achieved. This developed Simulink model is realized with a 'gensim' function to enable it to be used with other blocks in the simulation model.

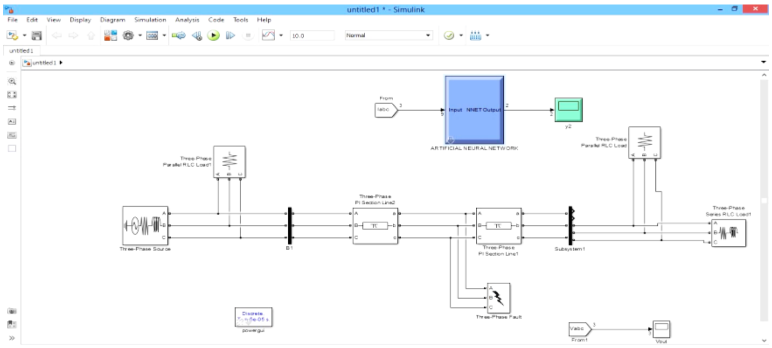


Fig 3: Snapshot of the Modelled 33-kV Transmission Line in Matlab/Simulink

Simulation Set-Up and Hardware Implementation

Fig 3 describes the set up for transmission line comprising the 3 phase source and load, three phase fault and neural network-based fault detection simulation model to test the efficacy of the proposed method. Transmission line model is generated with discrete state and pi section line. Sampling time of this model is Ts= 5e-5s and simulation is done for 3 seconds. With these specifications, the current and voltage vectors consist of 50 samples. This simulation model of transmission line with various fault cases is used to create training data which was used to train neural network. A feed forward neural network with 1 hidden layers is used for fault detection purpose. The number of neurons in the hidden layer can be varied to get the optimum performance. Satisfactory result preferred for the hardware was 1 hidden layer with 4 neurons, which contains 16 weights and 5 biases. Hence, a total of 21 values are required, which is easier for hardware implementation and able to detect faults successfully. The neural network was also trained to change inputs from floating point to the binary form. For instance, input in floating points ranging from 0.01to 0.99 are changed into 0 in binary form; whereas inputs ranging from 1to 10 are changed into 1 in binary form. Hence, the proposed model changed analogue inputs into digital output.

TRAINING PROCESS OF THE FAULT DETECTOR

During the training of fault detector, various topologies of multi-layer perception were considered. To decide which topology was ideal, factors such as network size, learning strategy employed and the size the training data set were given due consideration. After extensive study, the back-propagation algorithm was adopted as ideal topology. Although the basic back-propagation algorithm is relatively slow due to the small learning rates employed, Levenberg-Marquardt optimization technique was also incorporated in order to improve performance of the algorithm. Also, in order to enhance the ability of the neural network to represent the problem at hand as well as reduce training time, it was necessary to select suitable network size. During training process, dataset was divided into training data, testing data as well as validation data. 70% of the data was used for training, 15% was used for testing and 15% was used for validation. The neural network gives out an output of either 1 or 0. 1 is an indication of the presence of fault, whereas 0 indicates the absence of fault. Three fault detectors were designed taking cognizance of currents and voltages values. Training set constituted 5,500 inputs output set (500 for each set of faults and 500 for the non-fault case) with a set of six inputs and one output in each input-output pair.

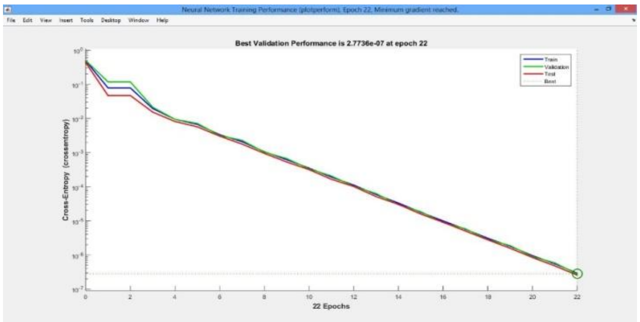


Fig 4: Mean-square error performance of the network (6-7-10-3-1).

Fig 4 shows the training performance plot of the neural network with 6 neurons at the input, three hidden layers with the first having 7 neurons, the second layer having 10 neurons and the third layer having 3 neurons; the output has just one neuron. After extensive training with variations in number of layers and neurons at the input, hidden layer and output to ascertain best performance, it was decided that neural network with six neurons at the input, one hidden layer with ten neurons in it and one neuron at the output achieved the desired Mean Square error of 0.00000027736, which is comparatively insignificant when compared to 0.001 set as the threshold. The trained network has gas high performance with high probability of meeting its target.

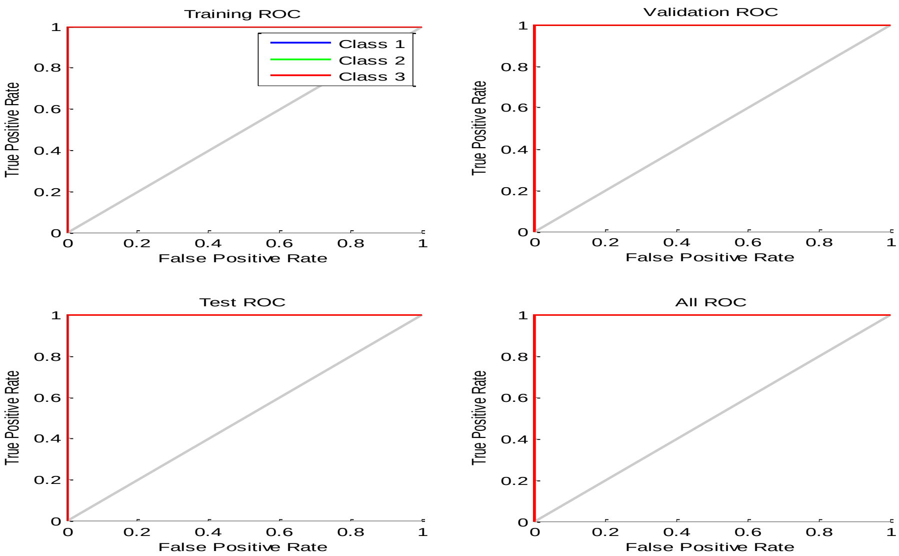


Fig 5: Receiver Operating Characteristics of Fault Detector using Current and Voltage Values

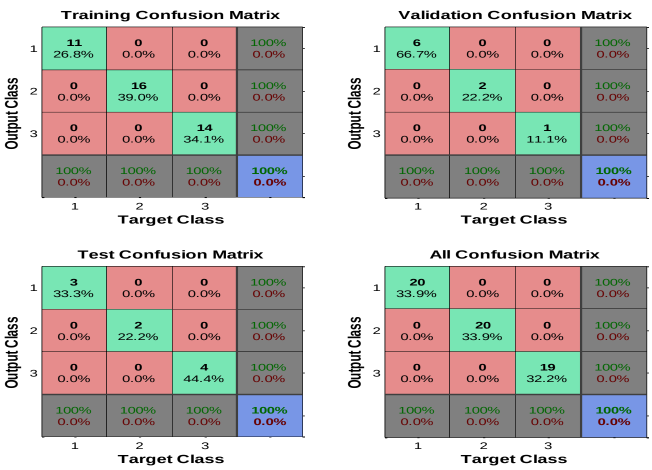


Fig 6: Confusion Matrix of Fault Detector Network Current and Voltage Values

Discussion of Figures for A.N.N. Fault Detector

The figure 6 is a curve for each of the training, testing and validation phases. Also, overall receiver operating characteristics curve fault detector is presented. The curves illustrate the actual plots between true positive rates (rate of positive classification) and false positive rate (rate of incorrect classification) of the proposed network classifier. The deviation between target and output is represented by the coloured line occurring in each axis. Since no deviation occurs as shown in the figure, it therefore means that the output is a perfect correspondence to the target. The figures also indicate 100 percent true positivity and 0 percent false positivity in the classification. As shown in the figure, the ROC curves plotted in Fig 5 are almost perfect since they all have the lines in the upper-left corner.

Fig 6 is a plot of confusion matrix that illustrates various types of errors present in the proposed trained network. This matrix gives information about performance of the proposed network. From the plots, the proposed network can classify fault correctly as represented in the cell coloured green. The red coloured square indicate the number cases incorrectly classified. The cell coloured blue indicates total percentage of cases correctly classified. The proposed model recorded 100 percentage fault detection accuracy. In summary, high number in green cell indicates high accuracy of classification and a zero value indicates that no misclassification occurred.

Structure and Training of Fault Locator

Fault locator was developed with approximate function algorithm, incorporated with backpropagation for the purpose of training the network. Voltage and current were inputs data at 50Hz. Trial and error method was used in selecting number of neurons in both input and hidden layers. Various network topologies were obtained, but appropriate network that gave satisfactory performance was chosen. Levenberg-Marquardt and Scaled Conjugate Gradient algorithm was used as optimization techniques. Current and voltage values were used to design the fault locators. The output has one neuron, which represents the estimated fault location.

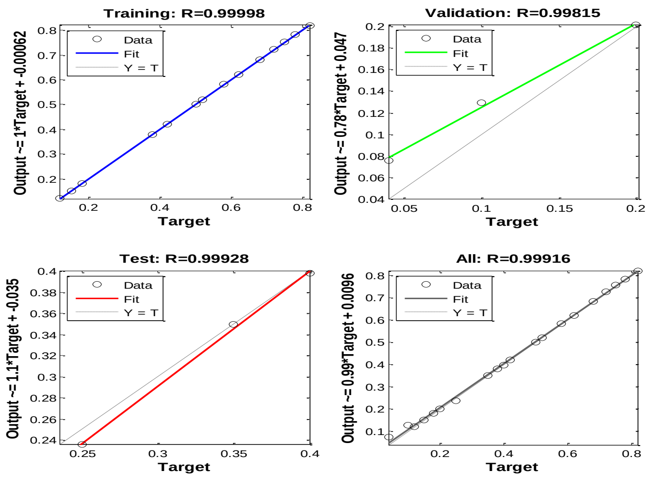


Fig 7: Regression Fit for Fault Locator using Voltage and Current Values

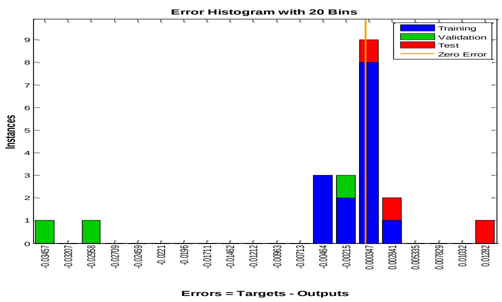


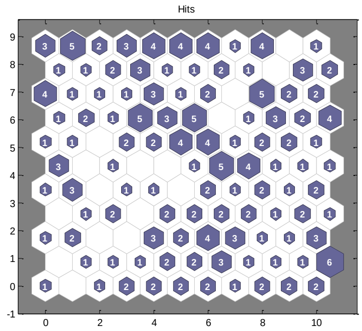
Fig 8: Error Histogram for Fault Locator using Voltage and Current Values

Discussion of Plots from A.N.N. Fault Locator

Fig 8 is a graph that shows regression fit for intelligent fault locator. This plot was used to confirm the applicability of the network after training was done. The plot describes how the actual output relates to the targets. Ideally, the regression (R) should be 1. Since the values of R ranges between 0.99815 and 0.99998,

which is approximately 1, it therefore indicates that an excellent result was obtained from the trained network. In principle, the value of R is directly proportional to the performance of the network.
Fig 8 is a plot of error histogram. The error as shown in the figure is much less than 0.002, which is an indication of a good network with high performance.

Simulation Results for Fault Classification via Self Organizing Map Function



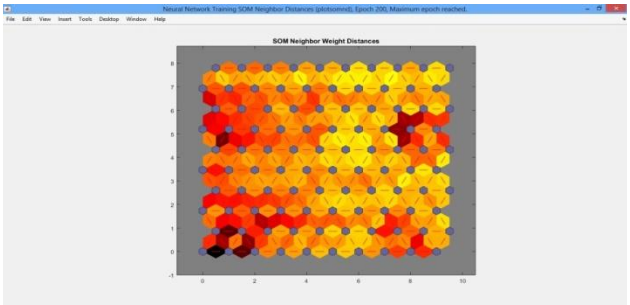


Fig 9: Plot of S.O.M Sample Hits

Fig. 10: Plot of S.O.M Neighbour Weight Distance

Discussion of Results of Fault Classification via Self Organising Map Function
Fig 9 is a plot that illustrates various samples of different fault classes that fall within each cluster. Each of these samples represents each fault type. The plots also show four major clusters constituting four fault types (L-G, L-L-G, L-L, L-L-L-G).
Fig 9 presents the neighbour weight distance plot consisting of 100 neurons. The plot is made of different colours which illustrates cluster of similar fault types. The bright colour describes faults whose faults values are almost the same, such single line to earth fault, double line to earth faults faults. The fairly dark cluster also describes faults of almost the same values too, such as phase to phase fault. The dark colour describes faults samples that were not properly classified.

Performance Evaluation of Intelligent Fault Detector-Classifier (IFDC)
Factors used to evaluate the performance of intelligent fault locator include the confusion matrix, the plot receiver operating characteristics and imputing data different from the data set used for training of the network. These factors help in determining the efficacy of the proposed network.

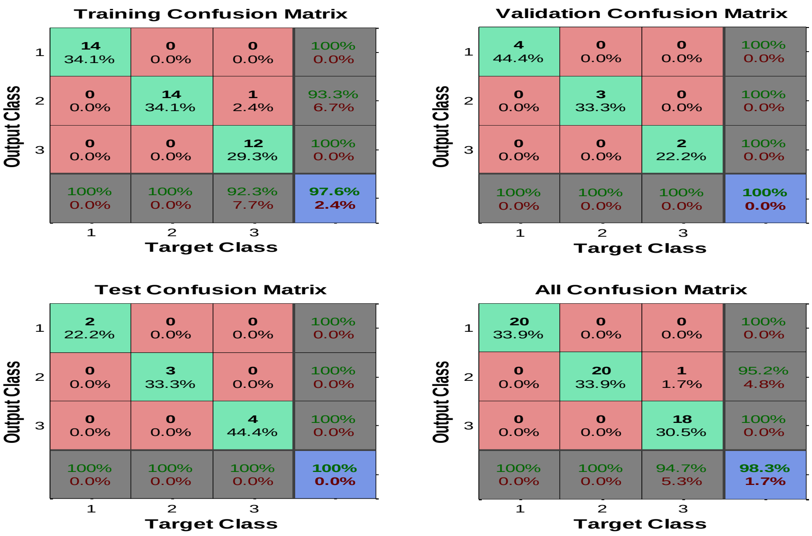


Fig 11: Confusion Matrix Plot for ANN-Based with 6-7-10-1

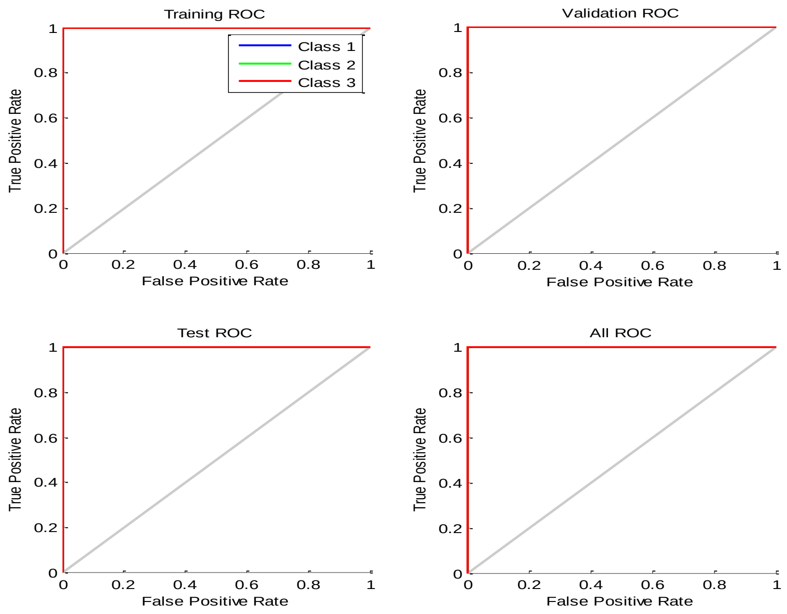


Fig 12: Receiver Operating Characteristics for ANN-Based IFDC

Table 3: 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
	A-B-G								B-C-G								A-C-G							
32	1	1	0	1	1	1	0	1	0	1	1	1	0	1	1	1	1	0	1	1	1	0	1	1
40	1	1	0	1	1	1	0	1	0	1	1	1	0	1	1	1	1	0	1	1	1	0	1	1
48	1	1	0	1	1	1	0	1	0	1	1	1	0	1	1	1	1	0	1	1	1	0	1	1
	A-B								B-C								A-C							
56	1	1	0	0	1	1	0	0	0	1	1	0	0	1	1	0	1	0	1	0	1	0	1	0
64	1	1	0	0	1	1	0	0	0	1	1	0	0	1	1	0	1	0	1	0	1	0	1	0
72	1	1	0	0	1	1	0	0	0	1	1	0	0	1	1	0	1	0	1	0	1	0	1	0
	A-B-C								NO FAULT															
80	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0								
88	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0								
96	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0								

Fig 11 presents a confusion matrix which illustrates how the trained network was able to detect and classify faults correctly. Result of the plot shows very high accuracy as indicated in the high numbers on the green cells. Incorrect classification is also seen in the cells colour red. The green cells have values ranging between 90% and 100% which shows high performance in fault detection and classification. The proposed model achieved an accuracy of 98.3%, which is worthwhile.

Fig 12 presents receiver operating characteristics of IFDC. The plot is used to illustrate the performance characteristics of the network. Deviation between the actual output and the target is represented by the coloured line. The curve shows 100% sensitivity, which indicates that 100% detection and classification of faults. It is also observed that there was no deviation in the plot which also affirms that actual output tracked target perfectly

Table 3 presents actual output of the IFDC and the target. Data used for implementation was obtained from Rukpokwu 33kV feeder. Total number 6 x 132 dataset was used to test the applicability of the network. Twelve (12) cases each represents different fault and no fault conditions. The output values are almost the same as the target, representing a satisfactory result.

Table 4: Result for ANN-Based IFLs with Fault Data from PHEDC

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	B-C-G	A-C-G	A-B	B-C	A-C
8	8.006	7.972	8.070	7.998	7.998	7.975	8.005	8.000	8.002
16	16.048	16.010	15.950	16.030	16.025	16.015	15.998	16.042	15.985
24	23.936	23.995	24.000	23.998	23.998	23.997	23.978	23.984	23.993
32	31.982	31.995	32.020	31.997	31.997	31.989	31.996	32.016	32.020
40	39.984	40.050	40.049	40.068	39.984	40.045	39.995	39.994	40.038
48	47.986	48.008	48.045	47.995	47.995	47.996	48.008	47.992	48.030
56	55.982	56.005	56.002	55.995	55.986	56.020	56.032	56.000	56.000
64	64.006	64.000	64.004	63.998	63.999	64.012	64.048	63.995	63.998
72	71.993	72.000	72.005	72.002	71.995	72.002	72.055	71.982	72.025
80	80.006	80.004	80.036	80.015	79.998	80.015	80.020	80.005	80.000
88	87.984	67.998	88.020	88.002	88.015	88.006	88.013	88.007	87.996
96	96.010	96.050	96.002	86.015	96.020	95.995	96.017	96.000	96.002

Table 4 describes the activity of intelligent fault locator. The table contains column for target and actual output and their various locations of occurrence. Results show that the proposed model was able to locate fault at approximate points of occurrence. The difference between the target and actual output was insignificantly small. Error in fault location (Km) can be expressed as:

$$\text{Error (km)} = [\text{ANN Output} - \text{Target}] \qquad (6)$$

From equation (6), ANN output is the output in (km) of the ANN fault locator and the target is the actual distance where the fault occurred on the transmission line. More so, the performance of the fault locators is evaluated using the percentage error expressed mathematically as:

$$\%\ \text{Error} = \left[\frac{Error}{Length\ of\ the\ Line} \times 100\%\right] \qquad (7)$$

The Table shows slight variations in fault location between the actual distances on the transmission line and the ANN output distance. The minimum error in (km) is zero (0) and maximum is 0.070 for L-G fault, minimum of 0.001 and maximum of 0.068 for L-L-G fault and minimum of zero (0) and maximum of 0.055 for L-L fault. Since error lies between 0 and 0.070, the Artificial Neural Network Intelligent fault locator has high performance with great reliability.

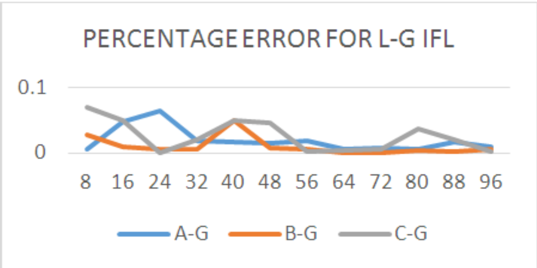


FIG 13: %Error Result of L-G IFL

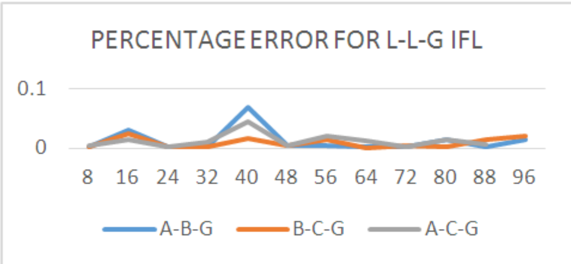


FIG 14: %Error Result of L-L-G IFL

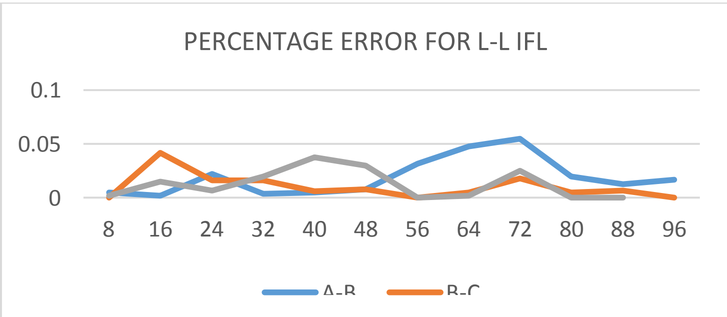


FIG 15: %Error Result of L-L IFL

Fig 13, 14 and 15 are graphs showing percentage error against target for L-G IFL, L-L-G IFL, and L-L IFL. It is observed that percentage error for L-G IFL is 0.070%; L-L-G IFL is 0.068% and L-L is 0.055%. These values, which are much less than 1% are indication of satisfactory results.

IV. CONCLUSION

On the Rukpokwu 33kV, an artificial neural network was used. For defect detection, categorization, and localization, Port Harcourt Distribution was implemented. The results suggest that the neural network can efficiently operate on the Port Harcourt Distribution network. The model performed well in terms of fault identification, classification, and localization, with low error. Furthermore, the findings reported for the ten (10) distinct fault instances examined reveal that the suggested network has been created to be efficient and trustworthy.

REFERENCES

[1]. Abdulkareem, A. C., Awosope, O. A., Adoghe, A. U. and Alayande, S. A. (2016). Investigating the Effect of Asymmetrical Faults at Some Selected Buses on the Performance of the Nigerian 330-kV Transmission System. International Journal of Applied Engineering Research, vol. 11, no. 7, pp. 5110-5122.

[2]. Abdulkareem, A. C.,Awosope, O. A., and Awelewa, A. A. (2016). The use of three-phase fault analysis for rating circuit breakers on Nigeria 330 kV transmission lines. Journal Engineering and Applied Sciences, vol. 11, no. 12, pp. 2612-2622.

[3]. Aggarwal, R. K. (2012). A Feedforward Artificial Neural Network Approach to Fault Classification and Location on a 132kV Transmission Line Using Current Signals Only. In the Proceedings of the Upper Penisula Environmental Coalition,2012.

[4]. Awasthi, I. and Ahmed, A. (2012). "Protection of Transmission Lines Using Artificial Neural Network," International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 2, No. 7, Pp. 70–73.

[5]. Chebbi, S.& Meddeb, A. (2015). ''Protection plan medium voltage distribution network in Tunisia''. International scholarly and scientific Research & Innovation, Vol. 9, Issue 2, Pp. 1307- 6892.

[6]. Chen, C. and Yao, T. (2013). Evolutionary design of constructive multilayer feedforward neural network.*Journal of Electrical Engineering and Technology* vol. 19, no. 16, pp. 2413–2420.

[7]. Cifuentes, Chaves, H., Mora, Florez J., Perez, Londoris S. (2017). ''Time Dormain Analysis for Fault Location in Power Distribution System Considering the Load Dynamics'', Electrical Power System Research, Vol. 146, Pp. 331-340

[8]. Daisy, M. and Dashti, R. (2016). Single Phase Fault Location in Electrical Distribution Feeder Using Hybrid Method, Journal on Energy, Vol 103, Pp. 356-368

[9]. Gabriel Benmou yal (2006). The Protection of Synchronous Generators: In Electric Power Engineering Handbook-Electric Power Generation, Transmission, and Distribution. CRC press.

[10]. Hagan, M. T. and M. H. Beale, M. H. (n.d). Neural Network Design. 2nd edition,ebook

[11]. Horowitz, S. H. (2006). Transmission Line Protection. In Electric Power Engineering Handbook-Electric Power Generation, Transmission, and Distribution. CRC Press.

[12]. Jayaprakash, J., Mercy, P. A., Jothi, L. and Juanola, P. (2016). ''Planning and Coordination of Relay in Distribution system using E-TAP'', Pakistan Journal of Biotechnology. Vol. 13, (special issue on Innovation in information embedded and communication system), Pp. 252-256.

[13]. Kothari, A., Nagrath, I.. J. (2003). Modern Power System Analysis,3rd ed.,Mc Graw-Hill Companies inc. Li, K. K., Lai, L. L. and David, A. K. (2000). Application of artificial neural network in faul location technique.*In Proceedings of the Electric Utility Deregulation and Restructuring and Power Technologies*. Pp. 226–231.

[14]. Lilik Jamilatul Awalin ,Hazlie Mokhlis , Ab Halim Abu Bakar (2012). ''Recent Development in Fault Location Methods for Distribution Networks'', Przegląd Elektrotechniczny, ISSN 0033-2097, R. 88 NR 12a/2012

[15]. Linus, O. I., Awosope, C.D. A, and Ademola, A. (2013). ''A review of PHCN Protection Schemes, International journals of Engineering Research & Technology (IJERT), Vol. 5, No. 8, Pp. 2278-8181.

[16]. Madueme, T. C. and Wokoro, P. G. (2015). "The Use of Artificial Neural Networks In The Theoretical Investigation of Faults in Transmission Lines," Nigerian Journal of Technology, Vol. 34, No. 4, Pp. 851–860.

[17]. Mazen, A. S., Ahamed, A.R.K.& Mohamed, H. (2015). ''Improvement of Protection Coordination for a Distribution System Connected to a Micro Grid Using Unidirectional Fault Current Limiter. Ain shames Engineering Journal, Vol. 5, Issue 2, Pp. 1-10, http; // doi; 10. /016/jasej.

[18]. Salat, R. and Osowski, S. (2000). Fault Location in Transmission Line Using Self-Organizing Neural Network.*Signal Process. Proceedings 2000,. WCCC-ICSP 2000. 5th Int. Conf.*, vol. 3, pp. 1585–1588 vol.3.

[19]. Sarangi, P., Sahu, A., and Panda, M.(2013). A Hybrid Differential Evolution and Back-Propagation Algorithm for Feedforward Neural Network Training. *Int. J. Comput. Appl.*, vol. 84, no. 14, pp. 1–9.

[20]. Usman I.A, (2015). ''A design of protection schemes for AC Transmission lines considering a case study'', International Journal of Electrical and Electronics Engineers, Vol. 7, Issue 2, Pp. 2286-6197

[21]. Yadav, A. and Dash, Y. (2014). An Overview of Transmission Line Protection by Artificial Neural Network : Fault Detection , Fault Classification , Fault Location , and Fault Direction Discrimination. In proceedings of Hindawi Publishing Coporation Advances in Artificial Neural Systems.

[22]. Yadav, A. and Thoke, A. S. (2011). Transmission line fault distance and direction estimation using artificial neural network.*Int. J. Eng. Sci. Technol.*, vol. 3, no. 8, pp. 110–121.

[23]. Zheng, Z. (2012). Fault Location and Type Identification on Transmission Line Using a Novel Traveling Wave Method. In the proceedings of the 2012 International Conference on High Voltage Engineering and Application,Shanghai,China, pp. 0–3.

Dieokuma Tamunosiki, et. al. "Improvement of Power Systems Protection Using Application of Artificial Neural Network. A Case of Rukpokwu 33kv Port Harcourt Distribution Network."*American Journal of Engineering Research (AJER)*, vol. 10(6), 2021, pp. 147-158.