

Development of An Artificial Neural Network Based Time-Series Fault Predictive Model for Power System

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Abstract
Electrical power is one of the most important forms of energy which is needed in almost every field of human endeavour. However, increase in size of electrical power structure without proper planning has negative effects on power system supplied to end users, thereby increasing the fault level of the network. This research paper therefore, developed an Artificial Neural Network based Time Series (ANN-TS) fault predictive model for forecasting of fault levels in power system. In this paper, ANN-TS model was trained with three years (2015-2017) outage fault frequency and fault duration data obtained from Ayede 132/33 kV transmission substation of Transmission Company of Nigeria (TCN) in Ibadan using Resilient Back-Propagation (RBP) algorithm and simulation was carried out in MATLAB environment using Mean Absolute Percentage Error (MAPE) as performance metric. The model was used to predict yearly fault frequency and fault duration for twenty-three years (2018-2040). The results of the fault frequency forecast showed that monthly forecast graphs were overlapped. Yearly MAPE varied between 0.004 % and 25 %, and the feeders' average MAPE was between 6 % and 10 %. In fault duration, the graphs followed the same pattern in nearly all the paths of the graphs, the yearly MAPE varied between 0.001 % and 25.54 % and the feeders' average MAPE varied between 6 % and 11 %. The model produced a fairly accurate forecast according to the criteria of MAPE. The average overall MAPE of each feeder was between 6 % and 10 % which indicated between 90 % and 94 % accuracy of the model. Therefore the ANN-TS model is effective for fault prediction in reference time series.
Keywords: Electrical Power, Fault, Artificial Neural Network based Time Series, Resilient Back-Propagation, Mean Absolute Percentage Error, Forecasting, Transmission substation.
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1. Introduction

Electrical faults such as short circuit conditions in power systems result in outages which lead to economic losses and reduce the reliability of the electrical system caused by equipment failures such as rotating machines, transformers, human errors and environmental conditions. These faults cause interruption to electric flows, equipment damage and even cause death of humans, birds and animals [1], [4]. Electrical fault is the deviation of voltages and currents from nominal values or states. Under normal operating conditions, power system equipment or lines carry normal voltages and currents which results in a safer operation of the system. When faults occur, excessive high current flow which causes damage to equipment and devices [11], [22].

Electrical power system is not static but changes during operation (switching on or off of generators and transmission lines) and during planning (addition of generators and transmission lines) [1]. In view of this, a fault study is routinely performed by utility engineers. Faults occur in a power system due to insulation failure, flashover, physical damages or human error. These faults are either three phase in nature involving all three phases in a symmetrical manner, asymmetrical in nature where only one or two phases are involved. Faults may be caused by either short circuits to earth or between live conductors, or by broken conductors in one or more phases [10], [17].

Electrical fault in an equipment /apparatus is a defect in the electrical circuit due to short circuit in which current is diverted from the normal path. The nature of a fault implies abnormal condition which causes a decrease in the basic insulation strength between phase conductors or between phase conductors and earth or any earthed screen surrounding the conductors [25]. The reduction of insulation strength is not considered as a fault until it results either in excessive current or in the reduction of the impedance between conductors or between conductors and earth to a value below that of the lowest load impedance normal to the circuit. In an electrical power system comprising of generators, switchgears, transformers, power receivers, transmission and distribution circuits, it is likely that some failures may occur somewhere in the system especially in transmission and distribution lines. This is due to the fact that the electrical power lines are widely branched, have greater length, operate under variable weather conditions and are subject to the action of atmospheric discharges [5], [9], [22].

However, one of the methods employed to monitor the states of some important components in power networks, such as switchgear and transformers, likewise to predict the fault details in generation, transmission and distribution parts of power system is Artificial Neural Network (ANN) [6]. The ANN is trained to detect minor changes to the internal parameters modelled as power system equivalent circuits. The fault details resulting from internal and external changes at sending and receiving ends of the power system can be derived under simulation and then presented to the ANN for training. As some of the internal parameters of the power system do not physically exist, they cannot be measured directly by simple measurement methods. Thus, the application of an intelligent technique, such as an ANN method is required [8], [7], [13], [26].

Fault occurrence on distribution system are on increase, the feeders connected to Ayede 132/33kV transmission substation of Transmission Company of Nigeria (TCN) are not an exception [2], [3], [4]. In view of this, there are high number of fault occurrences which always result in: long period of 'black out' in a large area being supplied by Ayede 132/33kV transmission substation, high magnitude of load and energy losses and this results in economic losses to both energy producer and energy users in the area. In addition, whenever there is fault occurrence, large number of energy users do source for alternative means of energy, these are always diesel and gasoline generators which cause environmental pollutions such as: noise, air, greenhouse gasses and heavy metals which are harmful to the areas being supplied by the substation and the world at large. In view of this, a fault predictive model was developed for forecasting of faults details on Ayede 132/33kV transmission substation of Transmission Company of Nigeria (TCN) using Artificial Neural Network based Time-Series (ANN-TS) model. These fault details forecasting comprise of fault frequency, fault duration and energy loss [3], [4].

1.1. Transmission System

Electrical power transmission system is the bulk movement of electrical energy from a generating site, such as a power plant to an electrical substation. The interconnected lines which facilitate this movement are known as transmission networks [20], [21]. A transmission line is a constituent designed to convey electrical power from the power source over a long distance with minimum losses and with high-voltage three-phase alternating current (AC). Transmission-line voltages are usually considered to be 110 kV and above. Lower voltages, such as 66 kV and 33 kV are usually considered sub-transmission voltages, but are occasionally used on long lines with light loads [15], [19].

The Transmission Company of Nigeria (TCN) is currently being managed by a Management Contractor, Manitoba Hydro International (Canada). Manitoba is responsible for revamping TCN to achieve technical and financial adequacy in addition to providing stable transmission of power without system failure. Currently, the transmission capacity of the Nigerian electricity transmission system is made up of about 5,523.8 km of 330 KV lines and 6,801.49 km of 132 KV lines, 23 km of 330/132 kV sub-stations and 91 km of 132/33 kV substations [16], [23].

1.2. Electrical Substation

An electrical substation is a subsidiary station of an electricity generation, transmission and distribution system where voltage is transformed from high to low or the reverse using transformers. Electric power may flow through several substations between generating plant and consumer and may be changed in voltage in several steps [5], [12]. A substation that has a step-up transformer increases the voltage while decreasing the current, while a step-down transformer decreases the voltage while increasing the current for domestic and commercial distribution. Electrical substations are important part of power system. The continuity of supply depends on the successful operation of substation. It is therefore essential to exercise utmost care while designing and building a substation [19], [27].

According to [20], a substation is a part of an electrical structure: generation, transmission, and distribution system. A substation is an important part of electrical structure [20], [24], [26]. Substations transform voltage from high to low, or the reverse, or perform any of several other important functions. Electric power flow through several substations between generating plant and consumer and its voltage changes in several steps. Substations comprise of switching devices, protection devices, control equipment and power transformers. Distribution circuits are fed from a transformer located in an electrical substation. They divided substation into three groups: Transmission substation, Distribution substation and Distribution feeders [20]. Transmission substation combines the transmission lines into a network with multiple parallel interconnections in order that power can flow freely over long distance from generators to any consumer. Transmission lines operate at voltages above 138kV [7]. The largest transmission substations can cover a large area with multiple voltage levels of many circuit breakers. Today, transmission-level voltages are usually considered to be 110 kV and above. Lower voltages, such as 66 kV and 33 kV, are usually considered sub-transmission voltages, but are occasionally used on long lines with light loads. Voltages above 765 kV are considered extra high voltage and require different designs compared to equipment used at lower voltages. Transmission substations often include transformation from one transmission voltage level to another [9], [27].

Distribution substation operates at medium voltage levels, between 2.4 kV-33 kV. They deliver electric power energy at once to industrial and home customers as shown in Figure 1 [14]. The input for a distribution substation is typically at least two transmission or sub transmission lines. Input voltage may be 115 kV, or whatever is common in the area. The output is a number of feeders. Distribution feeders transport energy from the distribution substations to the end of consumer's premises. Distribution feeders serve a variety of premises and generally contain many branches on the purchasers' premises. A distribution transformer transforms the distribution voltage to the nominal voltage at once and is utilized in households and commercial plants, typically from 230 to 415V [11], [16], [19]..

In addition, from the primary grid substation, electric power is transmitted at 132 by 3-phase 3 wire to various secondary substations located at the strategic points in the city and sub-urban areas. At secondary substation, the voltage is further stepped down to 33 kV. The 33 kV lines convey electrical power to primary distribution substation/ injection substation where the voltage is further stepped down to 11 kV and in some cases, the 33 kV lines run along the important road sides of the city. Large consumers demanding more than 50 kW do connect to this type of power line [14], [19].

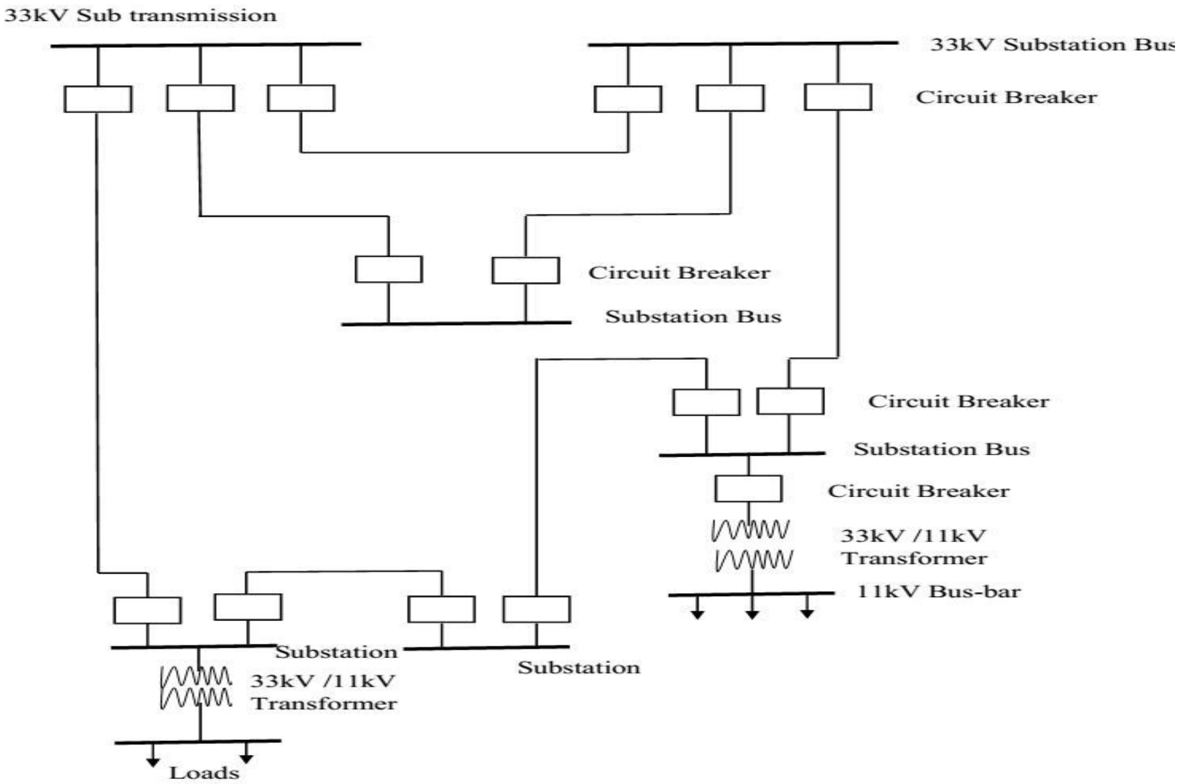

Figure 1: Network form of Electrical Substation

1.3. Electrical Faults

Electrical power systems are designed to perform a required function continuously, except when undergoing preventive maintenance or other planned actions, or due to lack of external resources. Faults occur at any time and at any location of power system items. In power systems consisting of generators, switchgears, transformers, transmission lines and distribution circuits, fault may occur somewhere in the system [13], [18].

A fault is defined as abnormal condition which causes a decrease in the basic insulation strength between phases/ line conductors or phase/ line conductors and earth, or any earthed screens surrounding the conductors. Such decrease in the system insulation is not considered as a fault until it results either in an excess current or in the reduction of the impedance between conductors and earth to a value below that of the lowest load impedance to the circuit [18]. Fault arises due to breakdown of the system insulation by lightning stroke on overhead lines, the connection with earth via an earth wire. Such earth connection occurs when a tree or a man-made object is providing the connecting path between the lines and the earth [14], [23].

The causes of faults can be internal or external, they include the following [1], [6], [7], [22], [23], [26], [27]:

i. **Lightning:** This is a form of visible electric discharge between a rain cloud and the earth or between rain clouds. The discharge is presented in form of a brilliant arc, several kilometers long and stretching between the discharge points. The discharge produces a sound wave that is heard as thunder. Majority of rain clouds are negatively charged at the base and positively charged at the top. There are various hypotheses that explain how polarization occurs, some require ice and some do not. However ice is a necessary factor, because lightning is not usually observed until ice has formed in the upper layers of thundercloud. Many of the electrical faults occurring on overhead power distribution lines are caused by lightning. Installation of arresters on lines has been a better solution to prevent the flashover of insulator assemblies.

ii. **Pollution:** Pollution is always caused by continuous deposit soot or cements dust especially in industrial areas and by salt deposited by wind-borne sea-spray in coastal areas. A high degree of pollution on an insulator assembly reduces the insulation strength of the affected phase, therefore create a path for current to flow across the insulator assembly, which in turn results in excess current or other detectable abnormality.

iii. **Wildfires:** When a wildfire occurs near electrical power line right-of-way (ROW), wood poles can get burnt. Lines carried by steel towers are also vulnerable to heat from wildfire. The conductors on both wood and steel carrying transmission lines are exposed to physical damage from the heat of a wildfire and the damages done to conductor are not repairable. A fire can cause a forced outage of electrical power circuit if it increases the ambient temperature of the air around the conductors above the line's operating parameters. Intense smoke from a nearby wildfire can contaminate an electrical line's insulating medium, which is the air surrounding the conductor. This may result to a phase-to-phase, or phase-to-ground fault due to the ionization of air around the conductor.

iv. **Ageing:** Ageing of electrical insulation system is defined as the irreversible changes of the properties of an electrical insulation system due to action by one or more stresses. The most important part and most ageing sensitive part of electrical equipment, which determines its useful lifetime is electrical insulation system. The total lifetime of the equipment is determined by external and internal factors. The main internal factor is the operating temperature and the external factors are: overvoltage, vibration, humidity, radiation and other factors .Ageing stresses cause intrinsic and extrinsic ageing. Intrinsic ageing is defined as the irreversible changes of basic properties of an electrical insulation system caused by the action of ageing factors on the electrical insulation system. Extrinsic ageing is the irreversible changes of properties of an electrical insulation system caused by action of ageing factors on unintentionally introduced imperfections in the electrical insulation system.

In addition, mode of operation of power equipment may influence their lifetime [12]. According to [12], the lifetime of electrical equipment is between 20 and 40 years of operation depending on device type, production quality, construction materials and mode of operation [1]. Furthermore, [5] and [12] itemized the following two types of stressors usually considered for ageing:

i. Environmental: They are stressors that exist continuously in the environment surrounding the equipment, whether it is operating or shut down. Examples are; vibration, heat and radiation.
ii. Operational: They are stressors arising from equipment operation. Examples are internal heating from electrical or mechanical loading, physical stresses from mechanical or electrical surges, vibration, and abrasive wearing of parts

1.4. Consequences of Faults

When major fault is left un-cleared, it may result to fire out-break, this can destroy power system equipment, and result in total failure of the entire system. The short circuit fault may have any of the following consequences [18]:

i. An abnormal reduction of the line voltage over a major part of the power system, resulting in major breakdown of the electrical supply to the consumer.
ii. When short circuit occurs, an electrical arc accompanies it resulting in the damaging of apparatus within the system.
iii. Damage to other apparatus in the system due to overheating and mechanical forces
iv. Stability of the electrical system is affected and this may lead to a complete blackout of a given power system.
v. A considerable reduction of voltage on healthy feeders connected to the system having fault can cause abnormal currents to be drawn by motors therefore, causing loss of industrial production.

1.5. Types of Faults

Faults occur in a power system whenever electrical insulation fails due to: flashover, physical damage or human error. These faults may either be three phase when all three phases are short circuited in a symmetrical manner, or asymmetrical when only one or two phases are involved [15]. Generally, power system faults are categorized as shunt faults and series faults. The shunt faults can occur as [20], [26]:

i. Single Line-to-ground fault (SLG): This type of fault occurs when one conductor falls to ground or contacts the neutral wire. It could also be the result of falling trees in a raining storm.

ii. Line-to-Line fault (LL): It is the result of two conductors being short-circuited. As in the case of a large bird standing on one distribution line and touching the other, or if a tree branch falls on top of two of the power lines.
iii. Double Line-to-Ground fault (LLG): This is as a result of a tree falling on two of the power lines.
iv. Balanced three phase fault (LLL): This is a fault condition in which all the three lines/ phases are short circuited. The balanced three phase fault occurs by a contact between the three power lines in many different forms.
v. Line-Line-Line-Ground fault (LLLG): This occurs when a tree falls on three power lines.

According to [23], Series faults occur along the power lines when one or two lines are broken along the distribution network which resulted to unbalanced series impedance. This is referred to as 'single phasing' condition in the power system [10]. Figure 2 shows different types of series faults in power system [13].

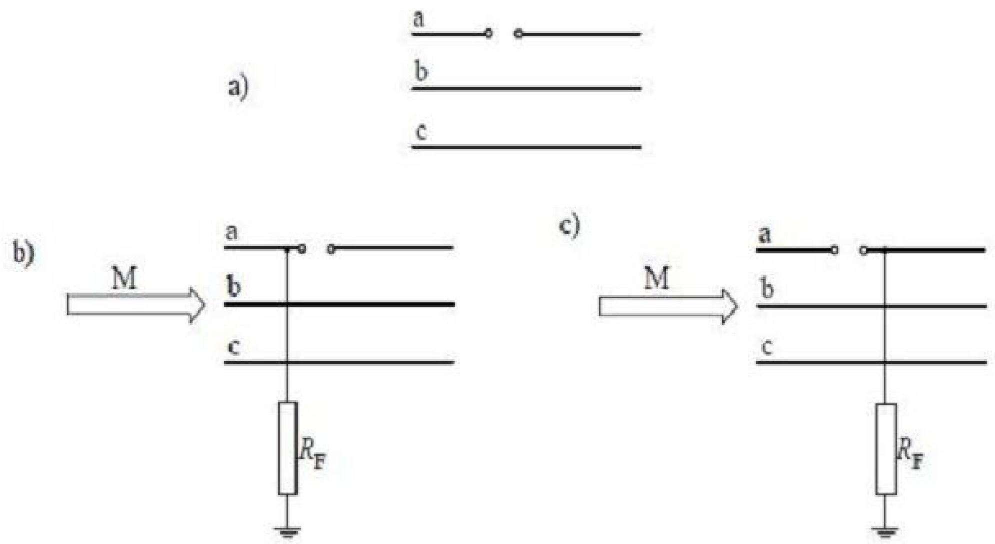

Figure 2: Broken Conductor Faults: (a) Broken Conductor Failure Alone, (b) Line-to-Ground Fault with Broken Conductor, (c) Broken Conductor with Line-to-Ground Fault

1.6. Analysis of Three Phase Symmetrical Faults

In analyzing three phase symmetrical faults using sequence network [8]:

i. Power system operates under balanced steady-state conditions before the fault occurrence. This means that the sequence networks are uncoupled before the fault occurs. During unsymmetrical faults they are interconnected only at the fault location.
ii. Pre-fault load current is neglected: As a result of that, the positive-sequence internal voltages of all feeders are equal to the pre-fault voltage V_F. When neglecting pre-fault load currents, no voltage drops in the pre-fault circuit and thus pre-fault voltage at each bus in the positive-sequence network equals V_F.
iii. Transformer winding resistance, shunt admittances and Δ–Y phase shifts are neglected.
iv. Overhead line series resistance and shunt admittance are neglected.
v. Synchronous machine is simply represented (armature resistance, saliency and saturation are neglected) and all non-rotating impedance loads are neglected.
vi. Induction motors are represented as synchronous machines.
vii. The three lines are represented by Red (R), Yellow (Y) and Blue (B) and their currents are: I_r, I_y and I_b respectively.

1.7. Artificial Neural Network

Artificial Neural Network (ANN) is a machine learning approach inspired by the way in which the brain performs a particular learning task. ANN is modeled on human brain and consists of a number of artificial neurons. In each neuron, the inputs coming to it are added together and this sum is then passed through an activation function which is the transfer function of the neuron [5]. The neural network is a network formed using the neurons and the weights connecting these neurons form the memory of the network. The neurons are connected by links and they interact with each other. The nodes can take input data and perform simple operations on the data. The result of these operations is passed to other neurons. The output at each node is called its activation or node value as shown in Figure 3 [21], [27].

The process by which the ANN is tuned to perform to the particular application is known as training. Once the network is trained with a variety of patterns of input and output combinations, ideally it should be able to predict the correct output when an input pattern is given randomly. ANN are being applied for different optimization and mathematical problems such as classification, object and image recognition, Signal processing, seismic events prediction, temperature and weather forecasting, bankruptcy, tsunami intensity, earthquake and sea level [6]. The success of ANN mostly depends on their design, the training algorithm used and the choice of structures used in training. ANN has the aptitude for random non-linear function approximation and information processing which other methods does not have [5], [9].

In equation (1) below, the neural network plays the role of mapping function Ø.

$$Y = Ø(X) \tag{1}$$

Where; Ø is mapping function of neural network, X is input and Y is output of vectors.

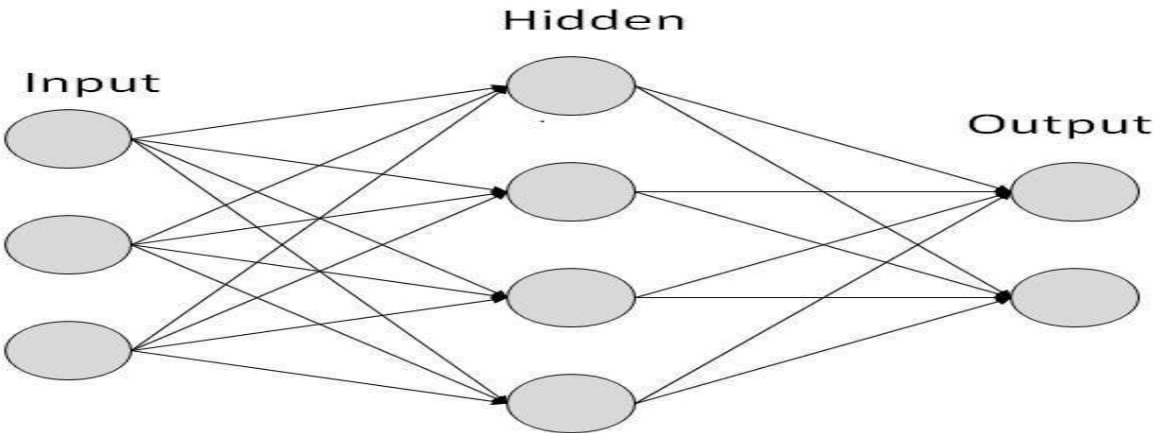

Figure 3: Artificial Neural Network Architecture

2. Materials and Method

Artificial Neural Network based Time-Series (ANN-TS) Fault Predictive model was developed to predict fault details (fault frequency and fault duration) on Ayede 132/33 kV transmission substation of Transmission Company of Nigeria (TCN) shown in Figure 4. The modelling data were data obtained from the performance target measurement sheets of Ayede 33 kV substation for the period of three years (2015-2017). Ayede 132/33 kV transmission substation receives 132 kV electrical supplies from Ayede 330/132 kV transmission station and stepped it down to 33 kV. Eight injection sub-stations take their sources from the secondary side of Ayede 132/33kV power transformers. These feeders include: Apata feeder, Eleyele feeder, Express feeder, Interchange feeder, Iyanganku feeder, Lanlate feeder, Liberty feeder and Oluwole feeder.

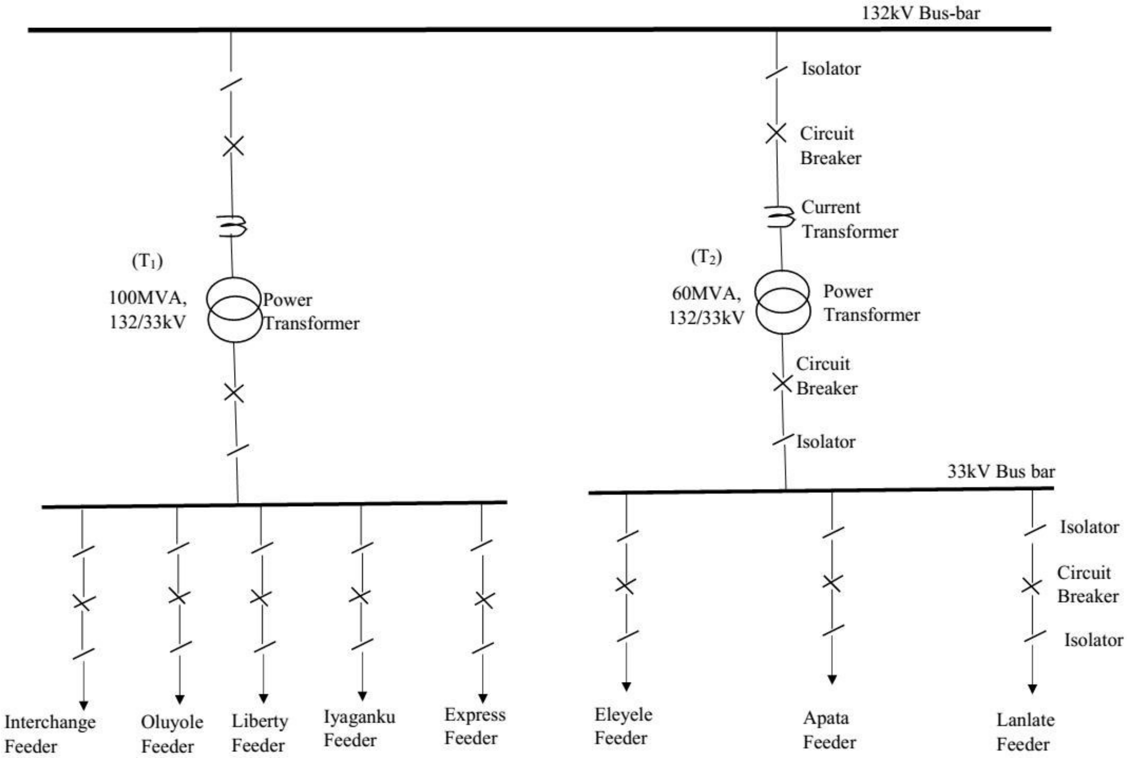

Figure 4: Schematic Diagram of Ayede 132/33kV Transmission Sub-station

2.1 Development of ANN-TS fault predictive model for Ayede 132/33kV substation

Artificial Neural Network based Time Series (ANN-TS) was developed as generalization of mathematical models of human cognition or neural biology based on the following assumptions:

i. Information processing occurs at several simple elements that are called neurons.
ii. Signals are passed between neurons over connection links.
iii. Each connection link has an associated weight, which multiplies the signal transmitted.
iv. Each neuron applies an activation function (usually non-linear) to its net input (sum of weighted input signals) to determine its output signal.

The developed ANN was modelled into three layers: input layer, hidden layer and output layer as shown in Figure 5. Each node in the hidden layer computes $y_j\,(j = 1,2,3,4)$ as shown in equation (2) according to equation (3):

$$f_j \;=\; \sum_1^n x_i w_{ji} \tag{2}$$

A sigmoid function (y_j) is used to transform the output that is limited into an acceptable range. It prevents the output from being too large.

$$y_j \;=\; \frac{1}{1+e^{-f_j}} \tag{3}$$

Lastly, Y in the node of the output layer in Figure 5 was obtained by equation (4)

$$Y = \sum_{j=1}^{4} y_j w_j \tag{4}$$

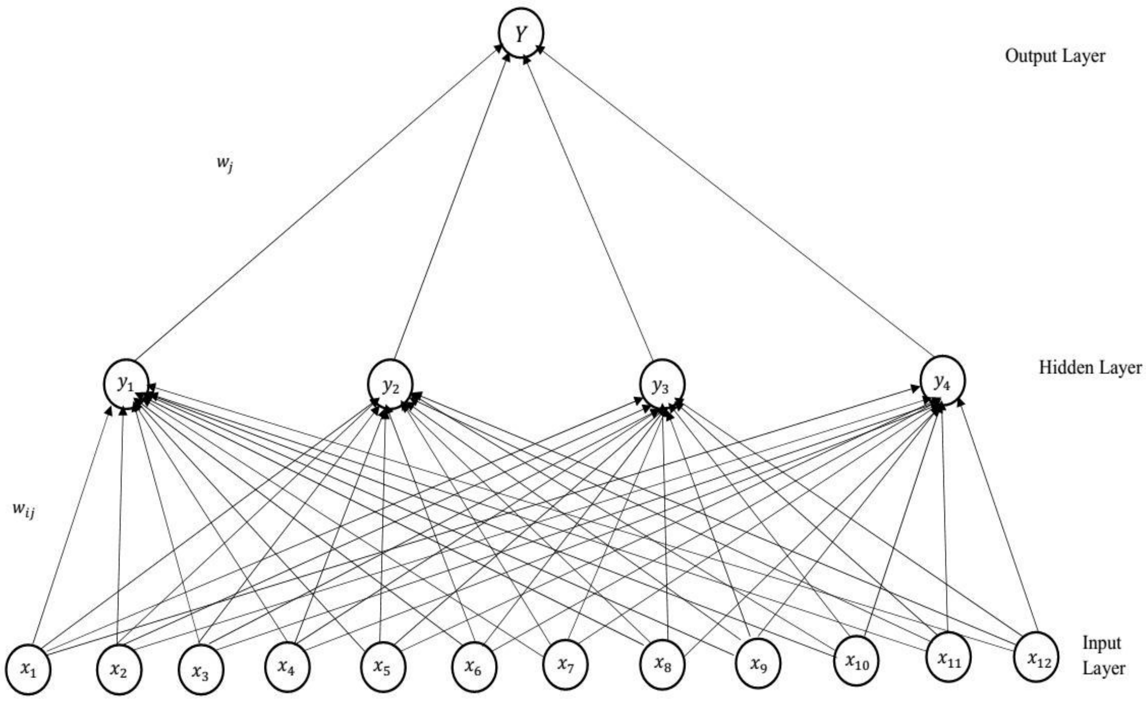

Figure 5: Three Layer Artificial Neural Network Time Series Fault Predictive Model Network for Ayede 33kV Substation

In this study, the Resilient Back-propagation (RBP) was adopted due to its speed, early convergence, stability and production of fairly good results. The learning process involves the following steps:

Step 1: Assign random numbers to the weights

Step 2: For every element in the training set, calculate the output using the summation functions embedded in the nodes

Step 3: Compare computed output with observed values

Step 4: Adjust the weights and repeat steps (2) and (3). If the result from step (3) is not less than a threshold value, alternatively, this cycle can be stopped early by reaching a predefined number of iterations, or the performance in a validation set does not improve.

Step 5: Repeat the above steps for other elements in the training set.

The ANN model developed in this research paper is the standard three-layer feed-forward network. Since the one-step-ahead forecasting is considered only, one output node was employed. The activation function for hidden nodes in the logarithm function is given as:

$$\lfloor Logsig \rfloor: \quad f(y) = \frac{1}{1+e^{(-x)}} \tag{5}$$

and for the output node the identity function (pure linear function):

$$\lfloor Lin \rfloor: \quad f(x) = x \tag{6}$$

Where x is the input signal (fault frequency, fault duration)

Bias terms were used in both hidden and output layer's nodes. The fast Resilient Back-propagation algorithm provided by the MATLAB neural network toolbox was employed in the training process. The ANN was randomly initialized with weights and bias values. The selected architecture consists of 12 input nodes in the entrance layer, 4 hidden nodes in the second layer and one node in the output layer (1–12; 4; 1) as shown in Figure 5. The input of the model consists of the 12 previous numbers corresponding to the last 12 months fault data. The output is the predicted faults for the next month.

The data set was divided in a sub-set for training, a sub-set for validation and a sub-set for testing. The data set between January and December of the previous year was used for training. Several training sessions for each identified situation was performed with different initial weights. From this number of training sessions, the ANN obtained was retrained to obtain better forecast results in each situation under the validation set. The set was used for early stop training if the Root Mean Square Error (RMSE) does not decrease in a number of five training iterations.

Developed ANN-TS fault predictive model for computing a forecast of $Y_{(t)}$ using selected past observations (data) is stated as:

$$Y_t = b_{2,i} + \sum_{j=1}^{n} w_j \ f\left(\sum_{j=1}^{m} W_{ij} y_{t-i} + b_{1,j}\right) \tag{7}$$

Where: m *is* the number of input nodes, n is the number of hidden nodes, f *is* a sigmoid transfer function such as the logistic, used in the hidden layer nodes,{w_j, j = 0, 1, 2, ……n} is a vector of weights from the hidden to output nodes, {W_{ij}, i =0,1,…..m; j=1,2……,n} are weights from the input to hidden nodes, $b_{2,1}$ and $b_{1,j}$ are the bias associated with the nodes in output and hidden layers, respectively.

The output of the developed ANN-TS is governed by the minimum Root Mean Square Error (RMSE) in the training set. The minimum RMSE between the observed and predicted values are used as the agreement index. RMSE is as shown in equation (8).

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(A_t - Y_t)^2}{n}} \qquad (8)$$

Where; A is the observed value, Y is the prediction value, and n is the total number of observations.

The other agreement index used is the coefficient of correlation ($r_{A.P}$) between the observed and predicted values and is as shown in equation (9).

$$r_{A.P} = \frac{\sum_{t=1}^{n}(A_t - \overline{A})(Y_t - \overline{Y})}{\sqrt{\sum_{t=1}^{n}(A_t - \overline{A})^2 (Y_t - \overline{Y})^2}} \qquad (9)$$

2.2 Algorithmic Method of Initializing Weight of ANN-TS model for Ayede 132/33kV

i. Calculate the maximum $\max(x_i)$ and minimum $\min(x_i)$ for all input variables x_i where *i= [1, …, N]*.

ii. Calculate the maximum distance between two points of the input space D^{in}, D^{in} is given by:

$$D^{in} = \sqrt{\sum_{i=1}^{N}[\max(x_i) - \min(x_i)]^2} \qquad (10)$$

where i is the number of input neurons

iii. Calculate the w_{max} to define the interval $[-w_{max}, w_{max}]$ from which the random weights for the hidden layer will be drawn.

$$w_{max} = \frac{0.72}{D^{in}}\sqrt{\frac{8}{N}} \qquad (11)$$

iv. Evaluate the centre of the input space C^{in} using the following equation:

$$C^{in} = \left(\frac{max(x_1) + min(x_1)}{2}, \frac{max(x_2) + min(x_2)}{2}, \dots, \frac{max(x_n) + min(x_n)}{2}\right) \qquad (12)$$

v. Calculate the threshold w_{ji} given by: $$w_{ji} = -\sum_{j=1}^{n} c_i^{in} w_{ji} \qquad (13)$$

vi. Calculate the v_{max} to define the interval $[-v_{max}, v_{max}]$ from which the random weights for the output layer, v_{max} is given by: $v_{max} = \frac{11.10}{H}$, where H is the number of node in the hidden layer.

vii. Evaluate the threshold v_{j0} of the output layer given by:

$$v_{j0} = -0.5 \sum_{j=1}^{H} v_{ji} \qquad (14)$$

This method of initializing weights was employed for the proposed algorithm in this study. The stepwise for the proposed algorithm is as follows:

Step 1: Choose network, apply initialized weights.
Step 2: Select a sample to process
Step 3: For each node in the hidden layer calculate the linear (1) and non-linear (2) output.
Step 4: For each node in the output calculate the Linear (1) and non-linear (2) outputs, Non-linear (7) and linear error (10)
Step 5: For each node in the hidden layer, calculate the linear (12) and non-linear error (13)
Step 6: Update the weights using equation (3.10)
Step 7: Repeat the step 3 - 6 for all patterns
Step 8: Evaluate the error of the network and evaluate the stopping criteria. If stopping criteria is not reached repeat Steps 2-5.

2.3. Prediction of Fault Details (Fault Frequency and Fault Duration)

The fault data (fault frequency and fault duration) extracted from Ayede 132/33kV transmission substation for the period of three years were divided into three in ratio 50 % : 30 % : 20 %; fifty percent of the data in each case was used for training of the developed model, thirty percent for testing and twenty percent of the data for validation. Flow chart in Figure 6 showed the step by step process of ANN-TS prediction system for Ayede 132/33kV transmission substation. Validation of the developed model with the test set was achieved with the use of Mean Absolute Percentage Error (MAPE). MAPE is a statistical measure of how accurate a forecast system is. It measures this accuracy as a percentage and is calculated as average absolute percentage error for each time period minus actual value divided by actual value.

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{N}\left|\frac{Y_t - A_t}{A_t}\right| \tag{15}$$

Where; n is the total number of data considered, Y_t is the forecast/ predicted value, and A_t is the actual value / observed value.

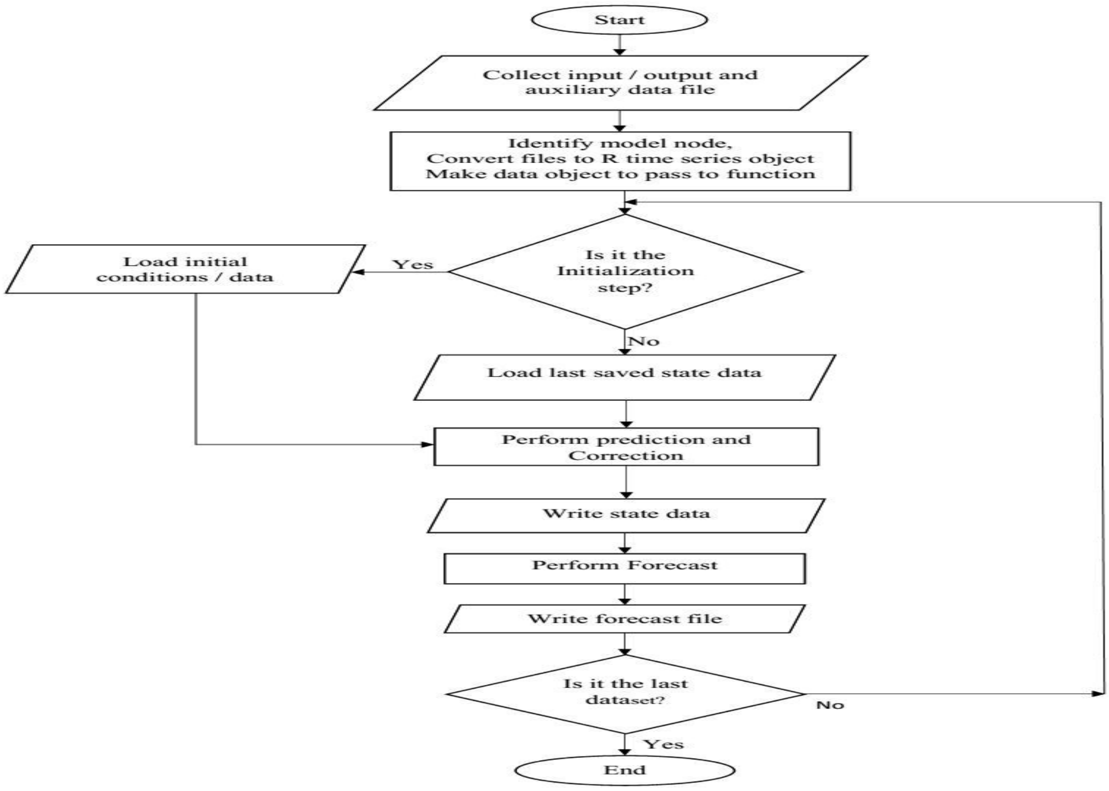

Figure 6: Flow Chart of ANN-TS Fault Predictive Model for Ayede 132/33kV

3. Discussion of Results.

The results of ANN-TS model under the test set were observed for fault frequency and fault duration. In view of this, the predicted data of ANN-TS model of each feeder were compared with each other for twenty-three years (2018-2040). The selection process of the ANN predicted value is governed by the minimum Root Mean Square Error (RMSE). The model was validated using MAPE.

3.1 Forecasting of Fault Frequency on the Feeders

The developed predictive model was applied to the three years faults frequency modelling data of each feeder for forecasting. Modelling data for various feeders in Ayede transmission substation were used to train the model, when the epoch were reached and weight data were obtained, the new data were used to train and retrain and new weight data were obtained, this was repeated and several output were obtained as predicted data of fault frequencies. The model was used to predict the possible faults occurrences on each feeder for the period of twenty three years (2018-2040).

Figure 7 presented the yearly fault frequency forecasting graph results obtained for the prediction of faults frequency on each feeder of Ayede 132/33 kV substation. The graphs for predicted data overlaps in almost all the feeders considered. MAPE demonstrated that the yearly percentage error varied between 0.01 % and 15 % and the feeder average MAPE range between 6 % and 10 %, indicating accuracy of about 90 % of the developed ANN-TS fault predictive model. This showed that the predictive model performed satisfactorily. Fault frequency is the number of fault occurrences on a feeder within a specific period, it is worth forecasting in order to prevent its future occurrences.

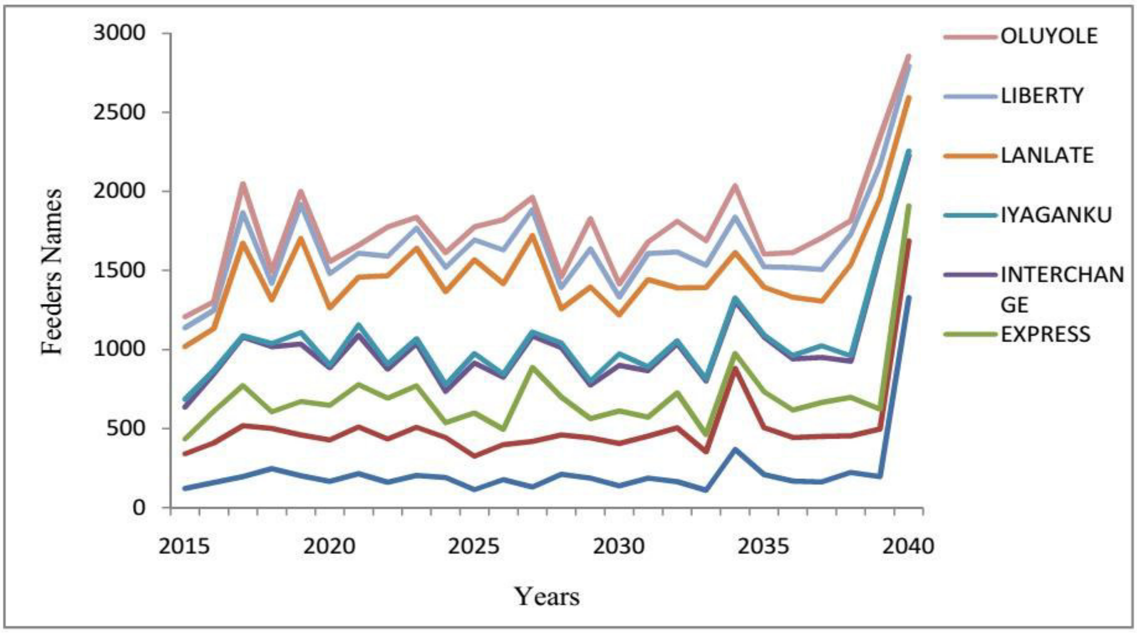

Figure 7: Yearly Fault Frequency Forecasting on Ayede Substation Feeder from 2018 – 2040

3.2 Forecasting of Faults Duration on the Feeders

Fault duration is the total period in which the system is down and unable to make energy available for the customers supplied. The ANN-TS fault predictive model was applied to the modelling data of the fault duration data obtained for the period of three years (2015-2017). The model was used to forecast the possible faults duration on each feeder for the period of twenty three years (2018-2040). Figures 8 showed the yearly fault duration forecasting graphs of the fault duration forecasting results obtained on the feeders. The results followed the same pattern in nearly all the portion of the graphs in each feeder, yearly MAPE is between '0.01 % and '17 %', and average MAPE varied between '6 %' and '11 %'. Fault durations on feeders were predicted to provide expected down-time on each feeder in order to prevent the future occurrence.

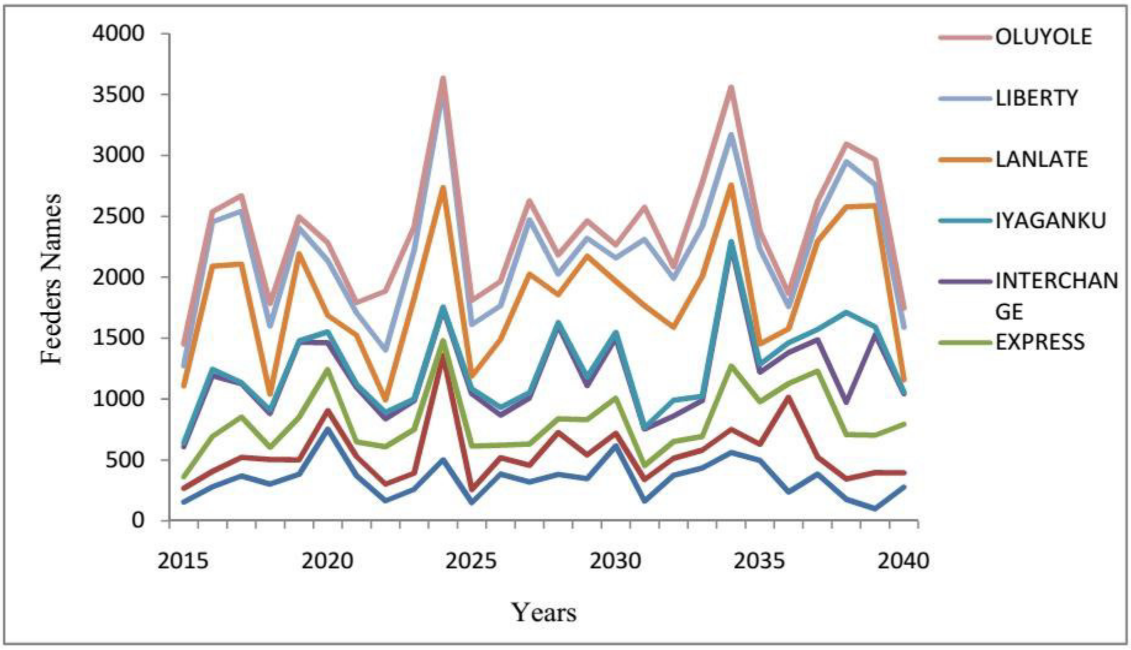

Figure 8: Yearly Fault Duration Forecasting on Ayede Substation Feeder from 2018 – 2040

3.3 Performance Measure of ANN-TS Fault Predictive Model using MAPE

The statistical summary of the out-of-sample (data used as the validation set) forecasting performance of the model were given in Tables 1A, 1B, 2A and 2B. In almost all the forecast, the graphs took the same pattern in each feeder. Yearly MAPE varied between 0.01 % and 26.75%, and feeder average MAPE varied between 6 % and 10 %. Judged by the average overall accuracy measures of each feeder, it was observed that the forecasting performance of the model is good. Therefore, according to the criteria of MAPE for model evaluation, the predicted data with the selected model has a highly accurate forecast because the average overall result of each feeder is lower than 10 %. This indicated accuracy of between 90 % and 94 % of the model. Figure 7 and 8 displayed the predicted graphs of time series for entire sequence.

Table 1A: Fault Frequency Forecasting Error Measures for Root Mean Square

YEAR	APATA RMSE	ELEYELE RMSE	EXPRESS RMSE	INTERCHANGE RMSE	IYAGANKU RMSE	LANLATE RMSE	LIBERTY RMSE	OLUYOLE RMSE
2018	66.58	0.005	2.857	30.23	0.633	0.032	7.716	0.332
2019	0.01	6.393	4.246	34.42	2.441	0.016	0.014	2.498
2020	5.949	0.026	4.079	8.182	0.625	5.324	4.949	0.015
2021	0.049	7.895	4.915	5.592	2.373	3.346	6.508	5.497
2022	9.462	0.064	6.809	5.782	0.613	53.23	10.17	5.565
2023	0.013	25.73	3.368	6.560	1.054	5.177	4.847	2.041
2024	9.483	0.032	3.710	5.783	2.675	8.756	4.995	2.735
2025	5.510	7.692	3.243	22.85	2.366	0.126	5.572	1.984
2026	8.006	4.908	3.709	2.188	0.734	5.177	28.77.	1.925
2027	0.004	9.113	76.15	5.138	1.087	0.012	6.051	1.898
2028	54.62	8.183	5.127	22.29	0.069	52.24	4.713	0.009
2029	9.106	8.064	6.164	4.492	1.034	0.077	7.453	1.566
2030	6.355	7.721	4.776	4.811	2.405	60.80	5.159	2.897
2031	3.895	7.216	2.266	8.121	1.163	64.23	6.454	6.034
2032	1.611	13.25	0.035	4.476	0.616	7.266	6.030	2.00
2033	5.568	6.884	1.545	5.691	0.128	9.528	4.784	29.32
2034	56.74	70.28	3.741	0.645	0.607	1.900	5.494	1.982
2035	8.213	12.09	10.95	5.677	1.041	3.888	4.784	1.950
2036	5.722	10.06	16.51	0.043	0.629	22.21	4.627	2.560
2037	11.62	7.402	24.03	6.697	3.429	2.926	6.520	0.627
2038	27.00	3.392	6.717	5.713	0.620	7.421	3.785	2.929
2039	9.755	38.03	2.018	13.40	2.670	2.006	2.245	3.265
2040	32.75	4.067	3.910	0.146	1.009	3.738	3.941	1.99

Table 1B: Fault Frequency Forecasting Error Measures for MAPE

YEAR	APATA MAPE	ELEYELE MAPE	EXPRESS MAPE	INTERCHANGE MAPE	IYAGANKU MAPE	LANLATE MAPE	LIBERTY MAPE	OLUYOLE MAPE
2018	5.53	0.004	12.70	2.41	8.15	0.25	12.00	0.54
2019	0.009	8.085	5.40	4.00	7.31	0.08	0.17	6.44
2020	12.44	0.019	3.72	1.09	11.11	3.94	8.07	0.65
2021	0.044	7.586	5.66	5.41	6.92	4.51	2.67	13.54
2022	10.96	0.042	12.85	5.61	14.25	23.53	2.36	13.67
2023	0.011	12.05	3.91	8.34	14.41	2.50	15.41	11.36
2024	10.95	0.024	12.10	5.30	10.98	9.10	12.98	7.14
2025	8.054	13.95	3.29	10.43	11.95	0.61	13.88	10.62
2026	11.77	7.772	11.79	2.51	13.26	3.43	3.18.	7.35
2027	0.007	10.43	7.40	6.27	8.54	0.05	12.04	13.33
2028	4.64	9.846	6.49	10.06	0.742	4.26	10.26	0.03
2029	12.57	13.75	10.19	7.95	25.00	0.35	12.06	3.06
2030	12.91	10.03	7.78	3.91	16.08	3.53	13.12	17.18
2031	5.934	7.906	7.22	7.40	2.99	5.81	11.89	6.93
2032	2.945	12.91	0.39	3.52	10.86	8.05	12.53	7.25
2033	7.089	9.604	3.88	4.43	1.49	9.07	13.86	6.11
2034	4.69.	7.34	12.17	0.47	7.82	2.67	12.27	7.50
2035	11.94	17.56	13.46	3.92	3.70	5.49	11.50	6.58
2036	13.68	13.75	10.14	0.30	9.32	10.32	11.75	12.22
2037	12.28	9.700	12.04	8.72	24.34	3.10	11.57	0.82
2038	3.652	4.589	13.27	8.87	13.60	4.95	11.76	10.57
2039	9.505	11.67	7.20	4.39	1.20	2.02	3.80	5.63
2040	2.897	7.179	4.92	0.84	20.07	3.46	13.18	5.46

Table 2A: Fault Duration Forecasting Error Measures for Root Mean Square

YEAR	APATA RMSE	ELEYELE RMSE	EXPRESS RMSE	INTERCHANGE RMSE	IYAGANKU RMSE	LANLATE RMSE	LIBERTY RMSE	OLUYOLE RMSE
2018	0.001	21.23	9.15	1.48	0.68	10.50	24.15	12.76
2019	0.002	6.05	0.001	34.82	0.01	73.44	8.23	1.72
2020	11.21	15.95	8.70	13.93	8.02	18.54	0.02	4.36
2021	0.102	3.76	5.17	11.85	0.004	23.69	0.08	1.50
2022	9.63	3.06	746.7	7.68	11.20	21.73	13.27	8.43
2023	14.94	3.7	12.08	14.58	0.07	36.39	17.47	13.01
2024	26.11	24.26	1.32	7.21	0.28	17.60	18.50	6.43
2025	39.54	4.44	10.57	14.80	2.36	11.32	5.89	8.87
2026	0.69	5.24	0.83	5.06	1.96	24.12	36.34	12.79
2027	18.26	38.55	12.37	16.93	1.85	3.82	1.84	10.66
2028	0.012	945.1	0.36	17.17	0.79	62.74	5.55	5.09
2029	20.33	11.69	6.72	3.44	5.52	1.10	5.62	1.61
2030	12.97	8.04	19.23	2.59	2.58	26.82	1.33	1.64
2031	1.76	1.87	0.14	0.20	0.24	0.99	36.18	18.80
2032	17.75	58.53	5.28	4.10	20.20	22.55	26.53	1.64
2033	15.51	6.82	0.03	13.26	2.10	1.18	10.96	35.54
2034	53.12	20.57	3.97	20.31	0.34	1.51	70.40	85.91
2035	26.81	4.76	9.95	4.46	5.52	20.50	17.30	2.30
2036	20.88	22.00	6.90	2.53	6.26	3.08	0.50	1.38
2037	0.40	0.40	75.6	5.13	7.91	63.93	3.11	1.21
2038	1.52	3.21	17.8	0.27	1.98	46.64	5.29	4.51
2039	15.73	43.35	5.51	17.6	2.11	21.31	2.37	0.62
2040	16.3	4.88	10.93	0.003	0.74	34.53	11.76	5.01

Table 2B: Fault Duration Forecasting Error Measures for MAPE

YEAR	APATA MAPE	ELEYELE MAPE	EXPRESS MAPE	INTERCHANGE MAPE	IYAGANKU MAPE	LANLATE MAPE	LIBERTY MAPE	OLUYOLE MAPE
2018	0.01	12.33	12.83	1.70	7.72	20.41	13.38	14.45
2019	0.01	15.22	0.001	8.19	0.02	25.54	9.78	1.90
2020	20.95	12.28	6.52	6.80	9.51	20.32	0.009	12.40
2021	0.37	2.90	7.48	9.92	0.043	7.59	0.16	1.67
2022	12.54	7.31	10.37.	3.96	10.08	9.73	3.97	6.15
2023	9.42	3.46	8.82	12.61	0.61	13.27	8.52	6.36
2024	12.29	12.20	3.90	7.43	3.45	4.12	14.18	11.75
2025	5.2	10.58	8.85	4.50	21.12	2.81	3.42	7.87
2026	0.25	13.06	1.28	3.06	13.10	8.23	12.07	14.82
2027	8.08	5.94	12.17	17.78	14.04	0.83	1.33	6.14
2028	0.05	5.48	0.41	4.45	6.50	10.39	8.22	14.90
2029	11.26	16.85	7.29	3.61	10.76	0.189	11.30	3.88
2030	11.2	15.44	11.52	1.41	3.39	10.67	1.88	1.28
2031	2.18	1.53	0.2	0.21	2.26	0.21	10.60	10.53
2032	18.46	12.83	7.29	2.55	22.75	10.07	10.94	1.31
2033	6.13	10.71	0.06	12.38	12.89	0.26	2.31	8.94
2034	9.81	12.43	12.05	16.02	4.55	0.50	7.39	9.33
2035	12.00	5.31	6.39	2.40	10.37	22.86	17.73	5.99
2036	13.06	13.10	23.04	1.73	6.29	6.91	1.05	1.73
2037	0.20	0.59	4.24	4.87	12.19	24.15	6.45	2.54
2038	1.78	4.89	12.4	0.19	6.61	18.61	1.42	11.55
2039	9.20	7.07	5.44	9.36	4.33	10.20	4.88	0.36
2040	12.22	10.28	9.73	0.003	10.44	10.79	3.44	13.79

4. Conclusion

This research paper has developed an Artificial Neural Network Time Series (ANN-TS) predictive model for the purpose of prediction of fault frequency and fault duration on Ayede 132/33 kV substation feeders. The time series was used in the logarithmic transformed data. The series were separated into three sets of data: a training data set to train the neural network, a validation data set to stop the training process earlier and a test data set to examine the level of prediction accuracy. The model has four (4) neurons in the hidden layer with the logarithm activation function and was trained using the Resilient Back-Propagation (RBP) algorithm. The analysis of the output forecast data of the selected ANN model showed reasonably close results compared to the target data. The developed model is then considered adequate for the purpose of prediction in the reference time series.

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