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Fault prediction model on electrical power network using artificial neural network-based time series: A case study of Ayede-Eruwa/ Lanlate Feeder

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Abstract

Increase in size of electrical power network usually results in a rise in fault level and consequently in huge economic losses to energy providers and consumers in the distribution systems. Therefore, it is very important to be proactive in dealing with faults on distribution feeder systems not only to reduce financial havoc, but to save lives and improve the quality of life of the people. A case study of Ayede-Eruwa/Lanlate Oyo State, Nigeria 33kV line is considered. An Artificial Neural Network based Time Series (ANN-TS) fault predictive model is developed for forecasting of faults on the above chosen electrical power network. Daily forced outage readings of the substation's feeders for three years were collected and modeled using a three-layer feed-forward network ANN-TS. The results in the frequency of fault prediction show that there is an overlap between the observed and predicted values. The annual Mean Average Percentage Error (MAPE) varies between 0.004% and 25%, and the feeders' average MAPE ranges from 6% to 10%. The fault duration annual MAPE varies between 0.001% and 25.54% while the feeders' average MAPE varies between 6% and 11%. The energy loss prediction follows the same trend with the annual MAPE alternating between 0.01% and 26.75%, andthe feeders' average MAPE between 6% and 10%. The average overall MAPE of each feeder is between 6% and 10% which indicates that the developed model is about 90% to 94% accurate. Although, the model is designed for Ayede-Eruwa/Lanlate feeder, it could be utilized for effective prediction of faults in any power distribution network.

Keywords: Fault prediction; Artificial neural network (ANN); Feeder; MAPE; Distribution

1. Introduction

Electrical power systems are growing in sizes and complexities in all aspects such as generation, transmission, distribution and load systems. Electrical faults such as short circuit conditions in power systems often result to power outages which sometimes reduce the reliability of the electrical system and economic losses 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. Electrical fault is the variation of voltages and currents from nominal values or states. During normal operating conditions, power system equipment carry normal voltages and currents which ensures a safer operation of the system. When fault occurs, excessive high current flows which causes the damage to equipment and devices [1]. Electrical power system is not static but changes during operation (switching on or off generators and transmission lines) and during planning (addition of generators and transmission lines). In the light of these, routine fault analysis is executed by utility

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engineers. Faults occur in a power system due to insulation break down, flashover, physical damages or human error. These faults are either three phases in nature, involving all three phases in a symmetrical manner and 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 [2].

Faults occurrences on distribution system are on increase, the feeders connected to Ayede 132/33kV substation located in Oyo state, southwestern Nigeria are not left out. The high number of faults on this feeder has always escalated to long period of 'black out' in a large area supplied by the substation and the magnitude of the load and energy losses have resulted to financial crisis to service providers and consumers within the region, as well as loss of lives and properties. Whenever a fault occurs, it leads to power outage, the consumers usually look for alternative sources of energy such as the use of diesel or gasoline to power their generators. The carbon dioxide, noise, greenhouse gasses, heavy metals, and other pollutants pose serious threat to our environment and the wellbeing of the people living in the areas covered by the substation.

A fault on electrical power distribution network is an abnormal condition that causes a decrease in the basic insulation strength between phase conductors or between phase conductors and earth or any earthed screen surrounding the conductors. 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 wire to a value below that of the lowest load impedance normal to the circuit. In an electrical power system comprising of transmission, distribution circuits, generators, switchgears, transformers, and power receivers, it is possible 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 subjected to the action of atmospheric discharges [3].

To monitor the states of some useful components in power networks such as switchgear and transformers and to predict the likelihood of faults in generation, transmission and distribution parts of power system, Artificial Neural Network (ANN) is indispensable. The faults details resulting from internal and external changes at sending and receiving ends of the power system can be obtained under simulation and then presented to the ANN for training and validation. Some of the internal parameters of the power system do not physically exist which means they cannot be measured directly by simple measurement methods. As a result, the application of an intelligent technique, such as an ANN-based method is required (Wong *et al.*, 1996). ANN is widely used due to its ability to learn from the training data directly, as well as lesser computational complexity. It is also adaptive, able to handle various nonlinear relationships and can generalize solutions for a new data set [4].

2. Literature review

Many research works have been carried out on Fault Studies on Distribution system. For instance, [5] made a comparison between two methods of fault-location in distribution networks, based on a distributed and a single-ended measurement system, assuming a common distribution system topology, the two methods were applied in order to compare their performances. Results showed that different drawbacks and advantages of two methods, improvements were taken into account, and a possible integration of the two approaches were investigated. Two methods proposed were reviewed and compared using EMTP simulation for a medium voltage network configuration. The complimentary characteristic of two methods suggested the analysis of a hybrid approach considering start-time and wavelet analysis of voltage transients. The paper showed that method A located the lateral where the fault occurred and method B estimated the location of fault on the identified lateral. Hybrid approach resulted in less expensive system compared to method A and more efficient compared to method B.

[6] Employed distributed generation (DG) method to analyze faults in power distribution system. The authors investigated the behaviors of the most significant parameters in power distribution systems, such as voltages, currents and apparent impedances at the substations, based on the values of fault resistance, the power supplied by DG and the relative location of DG and the fault. Different analyses were performed by varying the locations of the DG and the fault, in order to analyze the influence of DG together with the position where the fault has occurred. Application was developed in MATLAB/Simulink that can obtain the electrical and topological data from a database, and that allows to simulate faults in those lines. Two cases were considered to analyze the influence of DG in the location of faults: (a) Short line with DG at the beginning of the line and a single-phase-to-ground fault located at the end of the line. (b) Long line with DG at the ending of the line and a single-phase-to-ground fault located at the beginning of the line. The paper analyzes the impact of distributed generation in the location of faults. Tests performed showed different impacts that exist depending on the relative position of the DG and the fault. The presence of DG in a power distribution system has

a decrease in the value of the apparent reactance seen from the main substation. Thus, the estimate locations calculated by using impedance-based fault location methodologies will be closer than the actual location of the fault.

[7] Outlined impedance-based technique and its application for determining the location of a fault on a distribution system. The practicality of the impedance-based technique in locating a fault was shown by testing it on a Canadian distribution network. The algorithm of the technique was developed and integrated into PSCAD/EMTDC software by using C-interface and FORTRAN Language. Various test cases showed the practicality of the method in locating a fault. The correlation between fault distances and apparent impedance are studied, it showed that as the fault distance increases the sequence apparent reactance also increases. The method was tested using balance and single line to ground faults, the method found the location of fault by analyze the positive and zero sequence reactance part value.

[8] Presented a state-of-the-art article review of various approaches to analyze fault detection in power system. The author discussed most appropriate method for fault detection in the power system after investigating different types of approaches such as Bridge circuit method, Surface wave, Petri nets, Wavelet transform approach, Neural network approach, Artificial intelligence (Fuzzy, Genetic), Graph methodology Real-time, Statistical methodology) and their area of applications. The author concluded that the fault detection in power system must be fast when fault occurred in the transmission line, transformer, or anywhere in the electricity system.

[9] Analyzed mega volts ampere (MVA) method for symmetrical three phase faults, analysis of power systems during fault conditions provided information for circuit breaker selection, relay setting and the stability of the system operation. The study provided the values of voltages and currents during faulted conditions, in order to set protective devices to a vaues so as to minimize the harmful effects of such contingencies. The author highlighted the causes of faults as: insulation failure, a conducting material comes in contact with a bare conductor, lightning, and trees falling on the electric wires, vehicular collision with the poles or towers. He compared the results with two other methods: Ohmic conversion and Per-Unit conversion methods and concluded that MVA method was easier and recommended for industrial power system short circuit calculations.

[10] Developed an algorithm that distinguished between overload current and short circuit fault currents, the algorithm was simulated in MATLAB before field deployment. The hardware parts of the system consist of embedded system that reports abnormal conditions to the Distribution Control Center (DCC) using wireless communication. The system recorded the transformer loading and reports to the control center periodically. Recorded information is analyzed and diagnoses to determine the status of the network. Integration of real time diagnostic system to the EPDS improves the power availability.

[11] Employed MATLAB approach to analyze fault situations. In their work, a single line diagram for standard IEEE 11 bus and IEEE 30 bus system was used as a case study. Load flow study was carried out using the Newton- Raphson to determine the voltage magnitude, phase angle, real power and reactive powers at each bus of the transmission lines. Results of the load flow obtained showed that the voltage magnitude is within the tolerance ranges of ± 10%. Pre-fault parameters calculations were done, three phase short circuit fault was simulated on the 11 bus system, total fault current, fault voltage magnitude, fault voltage phase angle at each bus were calculated, fault current flows in the lines, SCMVA ratings based on the fault currents on each bus and lines were also calculated and the corresponding Circuit Breakers ratings were chosen.

[12] Carried out a fault analysis of 33kV distribution system using Ekiti state as a case study. Based on the available statistical data, Ekiti State suffers from severe shortages of electric power due to dilapidated and outdated electrical power infrastructures. Conditions of all relevant electrical facilities for distributing power at the 33kV level were assessed. Power availability in the 33/11kV injection stations in the state was considered by collecting energy supplied data, faults and other outages. Outcome of the research indicated that the probability of having two consecutive hours of power was less than 25% in a year for most of the feeders. The distribution networks were characterized by leaning poles or crooked structures, shattered insulators, broken or decayed cross-arms and vegetation encroachment. These were responsible for faults experienced on the 33kV distribution network of Ekiti State district.

[13] Developed a microcontroller-based protection system for electric distribution system for the purpose of effective monitoring and control of distribution system. It consisted of GSM networking, designed to send data from Distribution system to a Sub-station, a MATLAB GUI system was developed to show the data. A system was developed for the user to easily recognize the status of distribution transformer whether safe or unsafe and the distribution line that is suffered by fault. Its function is to monitor the distribution line status continuously and to detect the fault on distribution line due to the constraints such as overvoltage, under voltage, SLG, DLG faults. If any of these occurs, a message will be sent

to a designated controlling unit or substation. A MATLAB GUI consists of transformer, microcontroller ATMEGA16, GSM module and bridge rectifier, the circuits were designed and simulated in PROTEUS. GSM based microcontroller protection system is reliable and cost-effective solution for monitoring and controlling the electric distribution system.

[14] Designed a reclosing mechanism for permanent or temporary fault. Timer Integrated circuit IC-555 was used to give the time duration of fault. Circuit breaker was employed for disconnecting the line at fault occurrence and reconnect on clearance of fault. Reclosing mechanism resets the supply after small interruption in the event of temporary fault but it remained in tripped condition in case of permanent fault. MATLAB software was used to simulate the system. Circuit breaker was used for opening at fault instant and closing at fault clearance. Model fault time was given by the Signal builder. Ideal switch was connected with signal builder, when signal was given to the switch, it closed and fault occurred in the system and at that instant, circuit breaker is operated and disconnected the system from faulty part.

According to [15], symmetrical components were used to simulate symmetrical and asymmetrical operation of power systems. The paper described an approach based on symmetrical components theory to calculate short-circuit currents as a result of simultaneous SLG and BLL-F. The advantages of the new equivalent circuit developed were as follows. It is used to calculate a single line-to-ground fault and a bolted line-to-line fault. Also, it is used for calculating a combination of simultaneous faults in the same location in small and large power systems.

[16] Presented an intelligent based on cognitive systems for fault prognosis in power transformers. The system combined evolutionary and connectionist mechanisms into a hybrid model that became essential tool in the development of a predictive maintenance technology to actuate when any equipment fault occurred and to prevent or reduce unplanned reactive maintenance. The system was tested on a generic architecture for modeling cognitive systems. The generic architecture allowed the introduction of other knowledge based applications and is flexible to allow for changes or improvements in the techniques employed in the symbolic and connectionist layers. The results showed that the system predicted correctly not only the type of fault but also when that fault is expected to occur. The prediction is useful for System Health Management.

[17] Examined the effects of faults on system stability in power system. IEEE 14 bus power system model was used as a case study. The author used different types of faults to examine the behaviors of IEEE 14 bus model. The paper modeled an interconnected system created a fault which resulted in oscillations whose occurrence creates unbalanced currents in lines therefore affect the stability of the system. Voltage level decrease was noticed due to instability as a result of transient oscillations. The authors concluded that: a fault in any part of the subsystem in an interconnected electrical power system, will affect system voltages and system currents,and therefore must be improved otherwise it will be creating fault component of circuit parameters to other lines. Therefore, transient stability and fault analysis are very important in power network.

[18] Introduced a smart Global System for Mobile Communications (GSM) based system for accurately fault detection and location. The unit has a shorter response time for technical crew to rectify faults and thus save transformers from damages. The system used a current transformer,avoltage transformer, Programmable Intelligent Computer (PIC 16F877) Microcontroller, RS-232 connector, and a Global System for Mobile Communications (GSM) modem. Fault details are transmitted to the control room for appropriate action. The system provided a reduction in the time required to locate a fault by automatically providing accurate fault location information especially in the radial system. It allowed operators such as GRIDco to correctly detect and locate faulted segments on their transmission lines and, therefore, minimized power disruptions to distribution substations and help save expensive transformers.

[19] Modeled and simulated MATLAB software to analysis and identified faults on 300km/440kV EHV transmission lines. The paper itemized different types of faults: L-G fault, 2L-G fault, 3L-G fault and three line short circuits. The paper discussed methods used to ascertain types of fault detection, direction estimation and faults distance location as: transient signals-based methods, power frequency components-based methods and superimposed components-based methods. Simulation was done using MATLAB simulation in computer. Maximum voltage transmission line faults were easily detected and analyzed. The paper finally established the use MATLAB software along with the Sim-power system toolbox in Simulink for detection and analysis of faults distance on 300km/440 kV supply on long transmission line.

[20] Studied the performance and optimal allocation analysis of resistive type superconducting fault current limiters (SFCLs) of a power system using UK network standards. Two models were developed to assess the impact of incorporating SC material on the performance of SFCLs. Firstly; operation of SFCL was modeled using a Heaviside function. Secondly, a realistic model was used to simulate the operation of an SFCL, taking into consideration the proper E–J characteristics of the superconducting material and dynamic temperature evolution. The two models were used

independently and the authors proved that SFCLs effectively improved the damping characteristics of generation system, and mitigated voltage dips at the grid. The comparison led to a conclusion that adequate physical properties for the electro-thermal dynamics of the SC materials has to be considered in order to accurately predict behavior of SFCLs inside a power system.

[21] Applied 'fault tree analysis' to estimate power system reliability; analysis of power flows was developed and implemented for power system reliability assessment. Approximate DC load flow model was used, simulation of single line failures was done and corresponding power flows were accounted during fault trees construction. The work was tested on the IEEE reliability test system consisting of: 24 substations, 20 load buses, 7 generator buses with total 32 generators, 38 power lines, among them 14 with common cause failure (CCF). The method allowed more precise and analytical approach for estimation of grid disturbances, therefore improved input data for Probabilistic Safety Assessment (PSA) analysis of specific plant.

Considering the aforesaid, most of the previous researches were centered on different aspects of faults analysis such as use of simulation module to analyze different types of faults, use of distribution generation method to analyze faults in power distribution system, development of an algorithm to differentiate between overload current and short circuit current, examine different types of sags caused by different types of faults, presentation of intelligent based system for fault prognosis, comparative study of faults on distribution system, design of a reclosing mechanism for permanent and temporary faults, evaluation of fault current and voltage in a symmetric power system, and other related topics. Authors adopted different approaches and methods to obtain their results, none of the research is focused on development and application of faults prediction model for electrical distribution system. In view of this, this research work develops an ANN-TS fault predictive model to predict fault occurrences, fault durations, and electrical energy losses in electrical distribution system, with emphasis on Ayede – Lanlate/ Eruwa 33kV feeder. It will help in the future planning and smooth operation of the substation and encourage concerned authority to take adequate steps to guard against the likelihood of faults in the substation.

3. Overview of electric power system in Nigeria

The Nigerian power network consists of a few generating stations mostly sited in remote locations near the sources of fuel and are usually connected to the load centers by long transmission lines. The transmission capacity of the Nigerian Electricity Transmission system is made up of about 5,523.8km of 330kV lines and 6,801.49km of 132kV lines, 23 numbers of 330/132kV sub-stations and 91 numbers of 132/33kV sub-stations [22]. Nigerian transmission lines are interconnected and overloaded, the switchgears are obsolete while most of power transformers lack adequate maintenance.

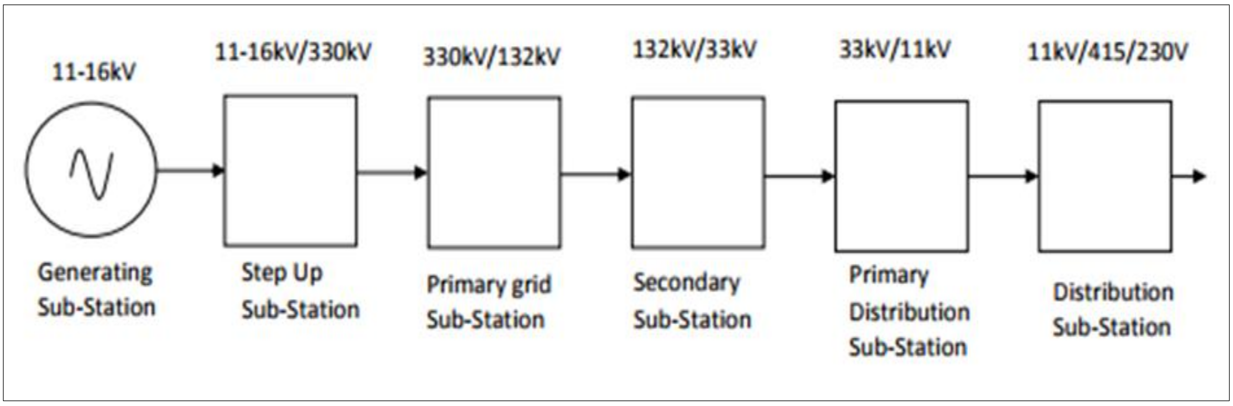

Figure 1 A block diagram of electric power structure in Nigeria

A block diagram of electric power structure in Nigeria is shown in Figure 1. From the primary grid substation, electric power is transmitted at 132kV 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 33kV. The 33kV lines convey electrical power to primary distribution substation/ injection substation where the voltage is further stepped down to 11kV, and in some cases, the 33kV lines run along the important roadsides of the city. A number of consumers demanding more than 50kW do connect to this type of power line [23].

4. Faults in Electrical Power System

The consequences of faults on a power system may be catastrophic, hence it is intolerable. There are many factors responsible for faults in any power system. First, lightning is one of the major causes of faults on our distribution network. It is a form of visible electric discharge between a rain cloud and the earth or between rain clouds [24]. Installation of lightning arresters to lines has been a solution to prevent the flashover of insulator assemblies. A ZnO gapless incorporated suspension type arrester is reliable in surge absorption with no delay in discharge [25]. Pollution is another cause of faults resulting from the dirt deposit 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, thereby creating a path for current to flow across the insulator assembly which in turn results in excess current or other detectable abnormality [1].In most remote areas, wildfires contribute massively to the number of faults occurrence. This happens near electrical power line right-of-way (ROW) when 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 [26]. 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 conductors [27].

Moreover, ageing is also a factor contributing to power outage on power distribution system. It 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 [28].

When major fault is left unclear, it may result to fire outbreak; 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:

- 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.
- An electrical arc that may lead to damaging of apparatus within the system.
- Damage to other apparatus in the system due to overheating and mechanical forces.
- Stability of the electrical system is affected and this may lead to a complete blackout of a given power system.
- 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 [29].

There are many types of faults that may occur on 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 [11]. Generally, power system faults are categorized as shunt faults and series faults. The shunt faults can occur as:

4.1 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 as represented in Figure 2(a).

4.2 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 fall on top of the two of the power lines as represented in Figure 2(b).

4.3 Double Line-to-Ground fault (LLG)

This is as a result of a tree falling on two of the power lines as shown in Figure 2(c).

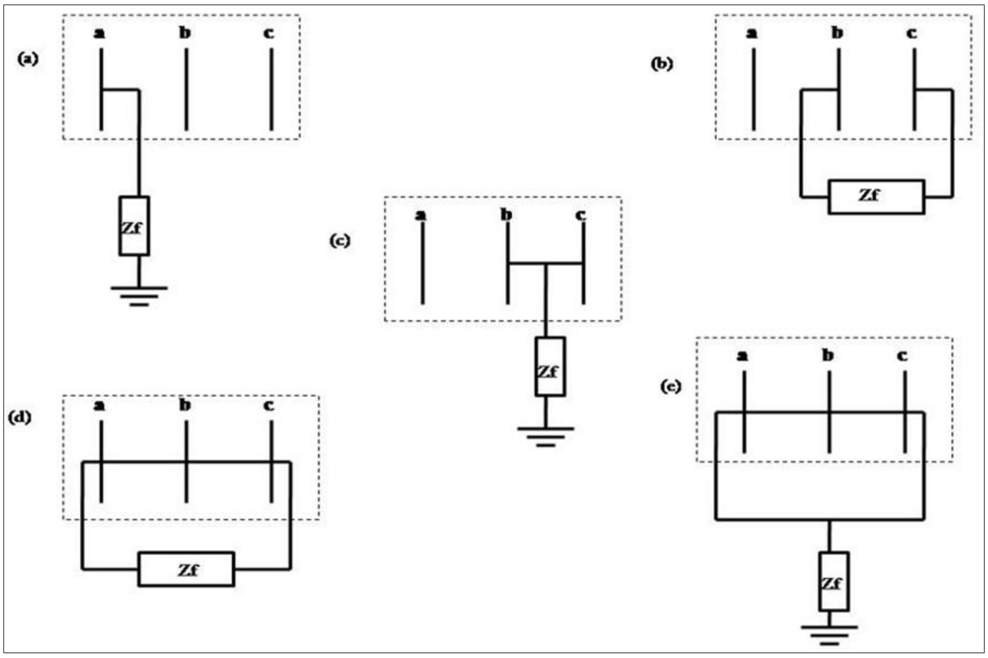

Figure 2 Shunt Faults (a) L-G (b) L-L (c) L-L-G (d) L-L-L (e) L-L-L-G

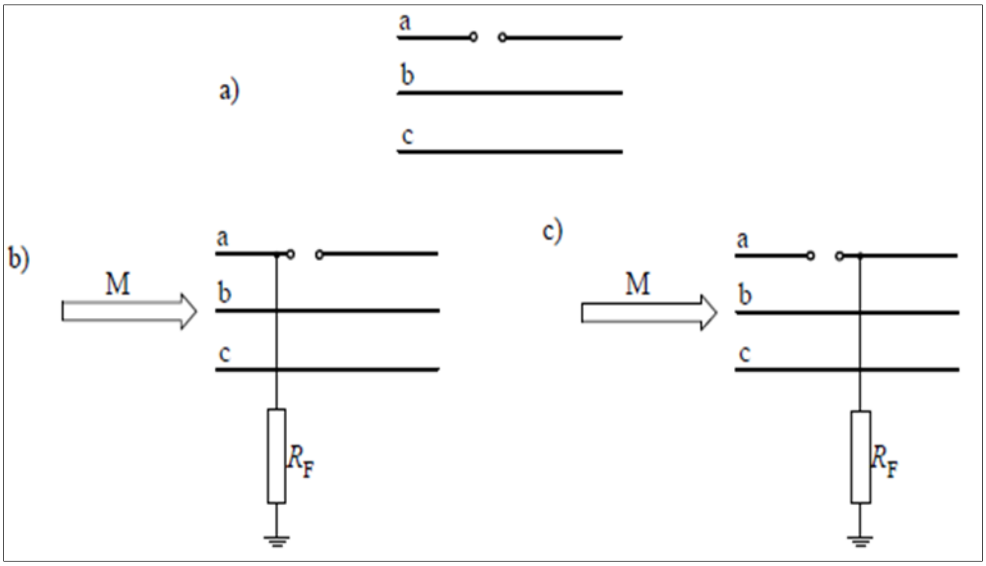

Figure 3 Broken conductor faults: (a) Broken conductor failure alone, (b) Line-to-Ground fault with broken conductor, (c) Broken conductor with Line-to-Ground fault

4.4 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 is shown in Figure 2(d), which occurs by a contact between the three power lines in many different forms.

4.5 Line-Line-Line-Ground fault (LLLG)

This occurs when a tree falls on three power lines as shown in Figure 2(e).

According to [3], Series faults occur along the power lines when one or two lines are broken along the distribution network which results to an unbalanced series impedance. This is referred to as 'single phasing' condition in the power system [30]. Figure 3 shows different types of series faults in power system.

5. Methodology

This study developed an ANN-TS based fault predictive model to predict fault parameters (fault frequency, fault duration and energy loss) on the transmission/distribution network/ feeder. Electrical power substation investigated is Ayede-Eruwa/Lanlate 33kV feeder in Oyo state, south-west Nigeria. Direct patrol and inspection of Ayede-Eruwa/Lanlate 33kV feeders as well as personal visits to substation for on–the-spot assessment of the state of equipment and installations of the substations was carried out. Forced outage readings of the feeder between January 2016 and December 2019 were taken. Daily faults occurrences on the feeder were extracted and used as modeling data as shown in Table 1.

Table 1 Modeling Data of Fault Frequencies, Fault Durations & Energy Loss Prediction for Ayede – Eruwa/ Lanlate 33kV feeder

	Eruwa/ Lanlate Feeder Faults Frequency			**Eruwa/ Lanlate Feeder Faults Duration**			**Eruwa/Lanlate feeder Energy Loss**		
	2015	2016	2017	2015	2016	2017	2015	2016	2017
January	28	9	25	28	38.3	43	235	191	109
February	26	19	55	39.1	49.4	60.2	117	75.9	343
March	21	26	49	18.4	123	175	219	747	965
April	0	15	54	0	130	47.3	0	212	227
May	21	17	56	19.1	13.3	68.3	222	29.2	286
June	30	12	59	43.9	70.2	128	244	172	697
July	27	25	62	34.8	21.2	107	280	59.2	725
August	50	31	36	89.7	76.1	26.9	766	467	160
September	18	37	42	16.9	121	94.9	178	573	714
October	30	13	55	43.2	130	106	235	674	494
November	50	36	45	89.7	46.8	79.1	766	448	404
December	32	24	48	43.6	25.5	37.7	291	38.8	391

According to [31], ANN-TS is developed as generalizations of mathematical models of human cognition or neural biology based on the following assumptions:

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

ANN consists of processing elements called neurons and nodes. Neurons are connected to one another through communication links. Each connection has an associated weight. The weights are the parameters of the model used by the network to solve a problem. ANN in this work is modeled into three layers: input, hidden and output. Where each node in the hidden layer represented by $y_j (j = 1,2,3,4)$is expressed using equation (1)

$$y_j = \frac{1}{1+e^{-f_j}} \quad (1)$$

Where

$$f_j = \sum_1^n x_i w_{ji} \quad (2)$$

A sigmoid function (y_j) is used to transform the output that is limited into an acceptable range because it limits the output to acceptable size.

In the node of the output layer, Y is obtained according to equation (3)

$$Y = \sum_{j=1}^{4} y_j w_j \qquad (3)$$

In this work, the Resilient Back-propagation method is adopted because of its fast convergence, stability, and remarkable performance. The learning process involves the following stages:

- Random numbers assigned to the weights.
- Calculate every element in the training set output using the summation functions embedded in the nodes.
- Observed values are Compared with computed output.
- Weights Adjusted and steps (2) and (3) repeated, if the result from step (3) is not less than a threshold value. Alternatively, this cycle maybe stopped early by reaching a predefined number of iterations, or if the performance in a validation set does not improve.
- Above steps were repeat for other elements in the training set.

The ANN model developed in this study uses the standard three-layer feed-forward network. Since the one-step-ahead prediction is considered, only one output node is employed. The activation function for hidden nodes is the logarithm function given by equation (4)

- $$\lfloor Logsig \rfloor: \quad f(y) = \frac{1}{1+e^{(-x)}} \qquad (4)$$

and the output node is defined using the identity function (pure linear function described using equation (5).

$$\lfloor Lin \rfloor: \quad f(x) = x \qquad (5)$$

where$x$ is the input signal (fault frequency, fault duration, energy loss)

In addition, 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 used in the training process. The ANN was randomly initialized with weights and bias values. In selecting the architecture, various experiments with different architectures were carried out by training and testing, and the fairly better architecture was selected according to the results in a validation set using hundreds of training sessions. The architecture consists of 12 input nodes in the entrance layer, 4 hidden nodes in the second layer and one node in the output layer (12; 4; 1). The input of the model is 12 previous numbers which correspond to the last 12 months fault data while the output is the predicted faults for the next month. The model had twelve nodes at the input-layer, four neurons at the hidden-layer and one at the output-layer. The model had a logarithm activation function at the hidden-layer and was trained using the Resilient Back-propagation algorithm. Extracted data were divided into 50%, 30%, and 20% for training, testing and validation purposes respectively. The data were applied to the developed model for forecasting possible fault details. Simulation was done using MATLAB R2015a. The data obtained between January and December of the previous year is used for training. In the training process of an ANN different end point is achieved, though with similar performance for different initial values.Hence, several training sessions for each identified situation is performed with different initial weights. From this number of training sessions, the ANN is 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 squared error (RMSE) does not decrease in a number of five training iterations. This early stop training condition prevents over-fitting of the training data by ANN-TS without improvements in a data not used in the training phase.

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

$$Y_t = b_{2,i} + \sum_{j=1}^{n} w_j \, f\left(\sum_{j=1}^{m} W_{ij} y_{t-i} + b_{1,j}\right) \qquad (6)$$

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, $\{w_j, j = 0, 1, 2, \dots\dots.n\}$ is a vector of weights from the hidden to output nodes,$\{W_{ij}, i = 0, 1, \dots\dots.m : j = 1, 2 \dots\dots n\}$are weights from the input to hidden nodes, and $b_{2,1}$and $b_{1,j}$are the bias associated with the nodes in output and hidden layers, respectively.

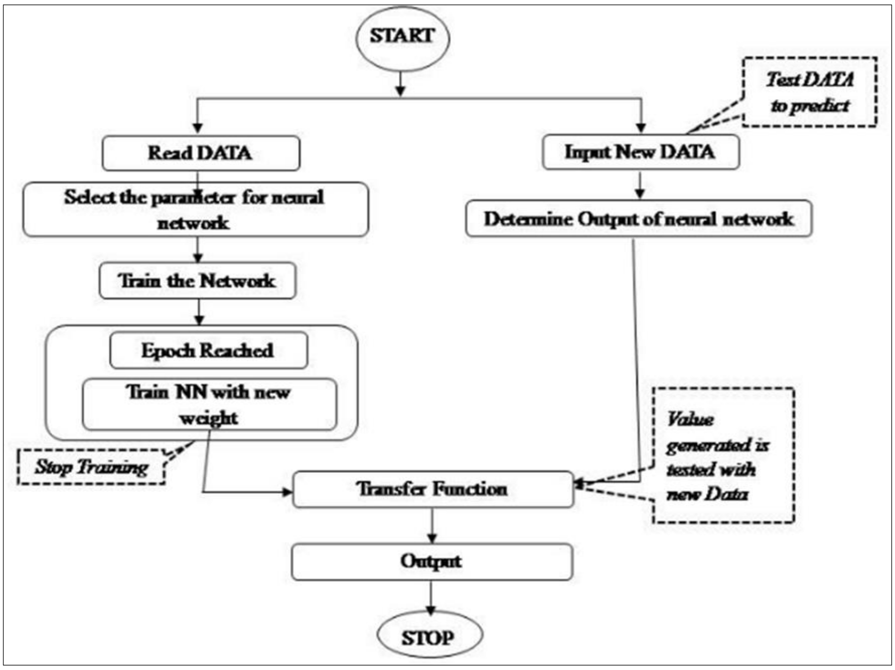

Figure 4 The Activity Diagram for Fault Prediction System Using ANN-TS Model

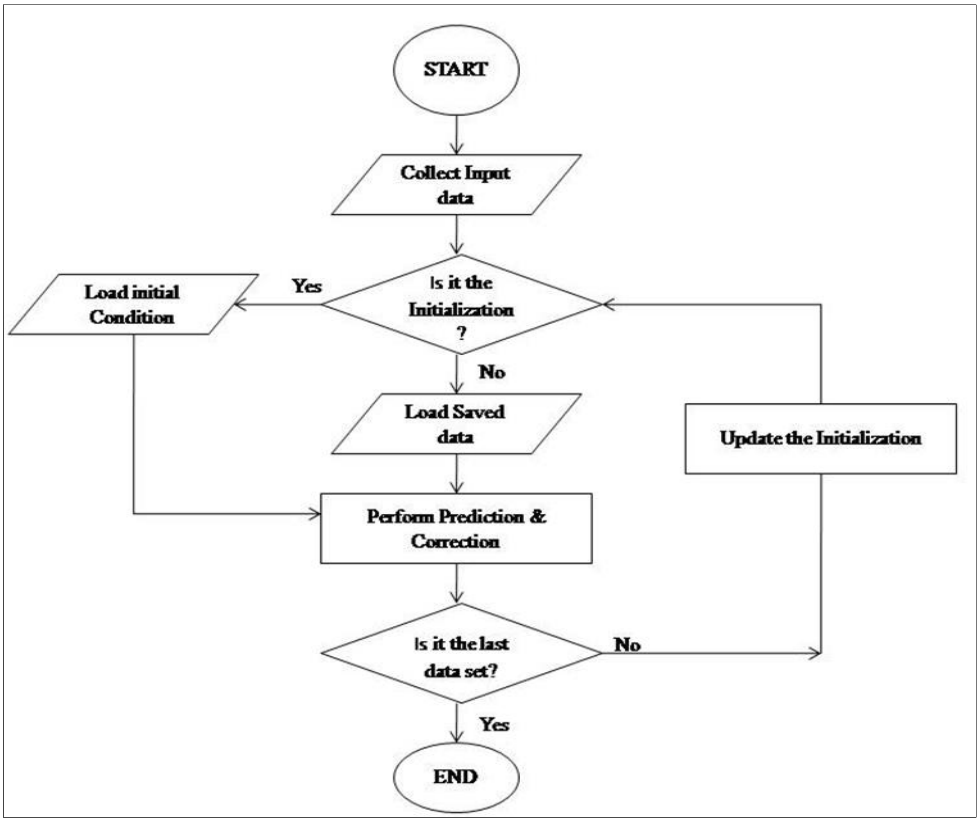

Figure 5 Flow Chart For ANN-TS Fault Predictive Model

The results of each ANN-TS under the test set which is the predicted data were compared with the observed values for the last three years (2015, 2016, and 2017). The output of the developed ANN-TS is governed by the minimum 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 7 [31].

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - Y_t)^2}{n}} \quad (7)$$

where A_t is the observed value,Y is the predicted value, and n is the total number of Observations. Validation of the developed model is achieved with the use of MAPE, which is a statistical measure of how accurate a prediction system is. It measures accuracy as a percentage and is calculated as average absolute percentage error for each time period minus actual value divided by actual value According to equation 8.

$$MAPE = \frac{1}{n}\sum_{t=1}^{N}\left|\frac{Y_t - A_t}{A_t}\right| \quad (8)$$

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.

Figures 4 and 5 show the activity diagram and flow chart of ANN-TS fault predictive model.

6. Results and discussion

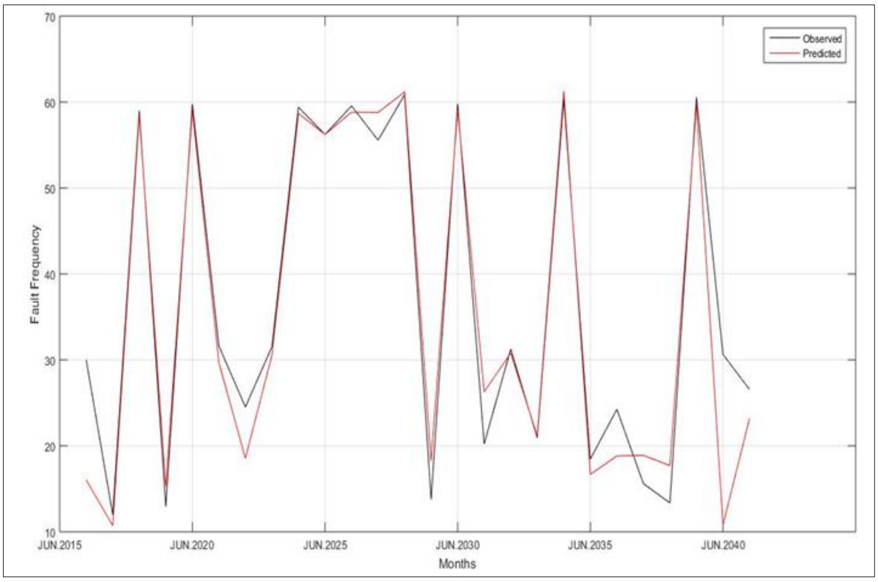

Figure 7 Monthly Fault Frequency Forecasting on Eruwa/Lanlate Feeder from January 2018 to December 2040

Fault frequency is the number of fault occurrences on a feeder within a specific period. Fault duration is the period in which the system is down and unable to make energy available to the customers supplied. Energy loss is the product of power loss and down time on the feeders. The results for monthly fault frequency, fault duration and energy loss results are presented in Tables 2, 3, and 4, respectively while the graphical representation are shown in Figures 7, 8, and 9, respectively. In Figure 7,it can be observed that the monthly fault frequency predicted values and the observed data overlap. The MAPE reveals that the yearly percentage error varies between 0.01% and 15% and the feeder average MAPE ranges between 6% and '10%, indicating an accuracy of about 90% of the developed fault prediction model. Figure 9 shows the monthly energy loss prediction on Eruwa/Lanlate Feeder from January 2018 to December 2040 and similar pattern is followed by the results in Figure 8. The yearly MAPE varies between 0.1 % and 12 %, and feeder average MAPE varies between 6 % and 10 %.The results showed that the observed values and predicted values had almost the same values except in few cases when there are little differences.

Table 2 Monthly Faults Frequency Forecasting of Eruwa/ Lanlate Feeder

	Faults frequency																									
	2015	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**	**2026**	**2027**	**2028**	**2029**	**2030**	**2031**	**2032**	**2033**	**2034**	**2035**	**2036**	**2037**	**2038**	**2039**	**2040**
JAN.	28	9	25	9.931	25.76	21.55	10.91	29.52	25.4	43.9	25.55	25.57	26.86	160.39	25.8	2135	29.258	25.87	46.78	12.07	12.91	10.9	10.35	26.2	22.9	29.2
FEB.	26	19	55	19.93	55.76	44.2	18.76	27.53	55.4	44.9	55.55	55.42	56.86	20.865	55.8	21.86	29.215	26.85	46.72	20.22	16.59	20.73	14.34	31.4	28.6	27.2
MAR.	21	26	49	26.93	49.76	22.63	27.86	22.51	31.49	54	49.55	49.6	50.86	27.915	49.8	30.53	131.61	16.77	50.69	27.22	27.67	34.87	27.31	50	21.6	22.2
APR.	0	15	54	15.93	54.76	1.621	18.04	184.3	54.4	54.4	54.99	38.27	55.86	16.917	54.8	20.1	1.3446	20.62	55.69	16.22	16.71	17.6	16.36	55	0.64	1.37
MAY	21	17	56	17.93	56.76	22.62	19.99	22.56	57.19	53.9	56.55	56.51	57.86	18.911	56.8	20.72	22.258	22.48	57.69	18.22	18.69	16.4	18.35	60	21.6	26
JUN.	30	12	59	12.93	59.76	31.62	24.51	31.53	59.4	56.2	59.55	55.56	60.86	13.783	59.8	20.22	31.261	20.94	60.34	18.45	24.25	15.6	13.36	60.6	30.6	26.6
JUL.	27	25	62	25.93	62.76	28.61	26.88	28.53	62.4	43.8	62.55	62.52	63.86	26.908	62.8	28.84	28.253	27.87	63.89	26.21	26.7	26.73	26.43	63.1	25	29
AUG.	50	31	36	32.04	36.71	51.62	32.91	51.53	36.4	45.4	36.55	41.12	37.86	32.925	36.5	41.21	51.252	50.87	37.69	34.72	32.7	35.23	40.51	41.7	50.6	51.2
SEP.	18	37	42	37.93	42.76	19.62	38.91	44.04	42.41	42.3	42.57	42.57	43.9	1762.7	42.8	19.05	19.274	18.92	23.39	38.22	38.7	38.73	38.35	43.1	18.6	19.2
OCT.	30	13	55	13.93	55.76	31.62	18.76	31.53	55.4	56.2	55.55	55.53	56.86	15.083	55.8	20.01	29.215	20.4	46.72	14.22	16.59	14.13	14.34	55.7	28.6	31
NOV.	50	36	45	36.93	45.76	51.62	37.9	51.53	45.4	45.4	45.55	41.11	46.86	37.889	45.8	55.7	51.248	50.87	38.06	34.72	44.38	35.23	37.35	41.7	50.6	51.2
DEC.	32	24	48	24.93	48.76	33.62	25.92	33.53	48.41	48.8	48.55	48.54	49.86	25.907	48.8	27.31	127.48	32.87	49.69	25.22	25.71	102.2	25.3	49.1	32.6	21.8

Table 3 Monthly Faults Duration Forecasting of Eruwa/Lanlate Feeder

	Faults duration																									
	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039	2040
JAN.	28	38.3	43	43.4	29.3	28.5	29.2	85.1	40	43.7	42.8	29.3	41.9	38.31	40.9	46.7	44.9	29.9	43.2	28.2	146	38.5	241	77.8	43.3	38.6
FEB.	39.1	49.4	60.2	61	40.6	39.5	40.5	97.7	53.1	103	62	40.3	61.3	53.93	61.9	34	62.1	40.9	60.4	39.3	59.9	44.98	78.6	75	73.9	49.7
MAR.	18.4	123	175	536	20	598	19.9	177	138	176	206	19.7	176	131.3	177	31.8	177	72.1	175	18.7	123	122.7	8.42	45.1	160	123
APR.	0	130	47.3	59.9	1.65	0.6	1.3	54.3	53.8	4.16	49.4	1.27	48.5	47.59	49.1	38.7	52.7	1.81	47.6	0.23	127	130.5	17.8	42.5	87.3	131
MAY	19.1	13.3	68.3	68.6	274	19.7	20.5	77.3	101	68.7	70.3	20.4	69.4	108.6	70	21.7	69.4	79.4	70.3	19.3	8.36	13.57	15.7	89	98.6	100

JUN.	43.9	70.2	128	128	45.4	44.4	44.9	106	39.8	129	130	45.1	116	129	130	30.4	130	45.7	128	44.1	70.8	48.91	74.6	73.3	93.7	70.5
JUL.	34.8	21.2	107	64.6	37.1	35.1	36.2	92	119	108	136	36.1	108	150.7	109	47.8	109	36.5	107	35	22	23.01	41.2	84.7	83.3	21.6
AUG.	89.7	76.1	26.9	27.3	66.9	90.2	9.03	54.6	18.2	27.4	28.9	91	27.9	28.27	28.6	56.9	28.9	91.6	27.1	90	76.8	75.88	68.9	62.3	37	76.4
SEP.	16.9	121	94.9	95.2	18.5	17.6	18.4	75.3	108	95.5	96.9	18.2	96	102.1	96.7	20.5	96.9	18.8	95.2	11.9	825	10812	17.2	95.5	90.1	121
OCT.	43.2	130	106	94	43.9	43.5	44.6	104	37	107	108	38.2	107	114.5	108	23.4	108	45.1	106	43.4	131	51.22	36.3	72.4	87.2	130
NOV.	89.7	46.8	79.1	78.7	91.3	90.2	91.1	55.1	80.3	79.7	81.1	91	80.1	78.28	80.8	22.3	81.1	91.5	83.1	89.9	47.5	47.49	74	73.9	89.8	47.1
DEC.	43.6	25.5	37.7	37.9	45.2	323	45	39.3	40	38.2	41.7	128	40.8	21773	39.4	45.3	39.6	45.4	37.9	43.8	26.1	50.27	48.1	72.8	50.9	108

Table 4 Monthly Energy Loss Forecasting of Lanlate Feeder

	Energy loss																									
	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039	2040
JAN.	235	191	109	191	110	192	209	140	192	596	192	193	3089	191	234	119	266	105	166	192	127	428	506	273	108	254
FEB.	117	75.9	343	76.2	344	76.5	32.8	485	77.6	78.4	77.6	70.1	76.4	72.2	197	535	520	536	345	86.7	371	357	119	163	411	343
MAR.	219	747	965	747	967	748	748	967	272	748	748	749	748	711	252	966	684	967	966	748	966	970	219	220	586	569
APR.	0	212	227	213	228	213	262	215	214	214	214	214	4233	213	3.31	224	227	228	196	6661	204	229	14	1.43	232	229
MAY	222	29.2	286	29.5	288	29.8	5.6	513	30.9	58.1	30.6	35.7	32	31.6	223	329	311	342	236	26.2	284	308	221	241	585	210
JUN.	244	172	697	172	698	173	357	680	487	180	508	165	176	173	256	692	890	678	697	173	693	417	244	192	579	773
JUL.	280	59.2	725	59.5	726	59.8	726	481	61.1	100	60.1	64.2	62.6	64.6	201	493	511	499	724	371	729	524	280	279	710	630
AUG.	766	467	160	468	162	468	429	160	469	469	469	521	467	468	659	162	160	156	167	7002	131	162	483	765	160	136
SEP.	178	573	714	573	716	573	575	716	575	570	574	574	581	573	372	715	715	700	715	575	718	680	338	179	1516	674
OCT.	235	674	494	675	495	675	680	1292	676	676	561	676	666	675	96.3	495	493	501	1437	358	494	518	236	389	578	496
NOV.	766	448	404	448	405	448	298	407	450	443	449	449	450	416	670	4812	4201	405	538	441	411	566	765	615	404	411
DEC.	291	38.8	391	39.1	393	39.4	232	500	40.8	3.87	40.3	39.8	37.3	36	218	351	361	363	410	48.2	367	327	102	242	337	194

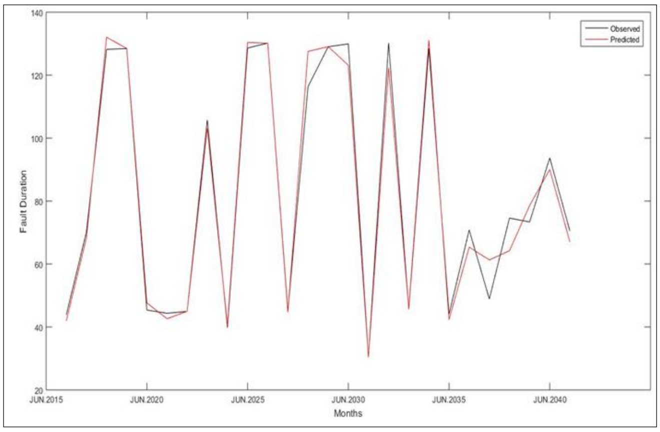

Figure 8 Monthly Fault Duration Forecasting on Eruwa/Lanlate Feeder from January 2018 to December 2040

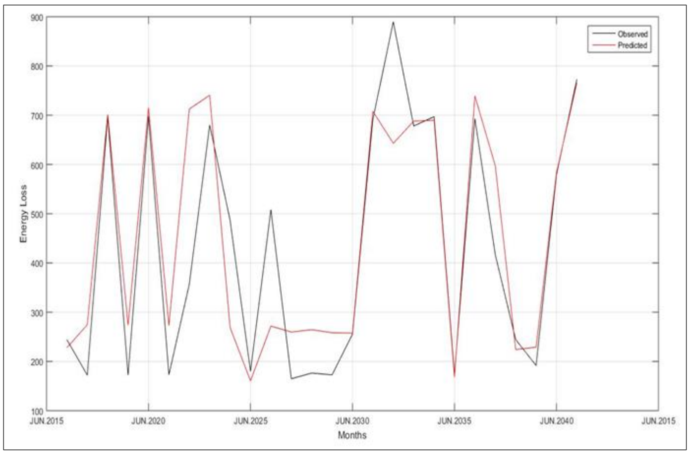

Figure 9 Monthly Energy Loss Forecasting onEruwa/Lanlate Feeder from January 2018 to December 2040

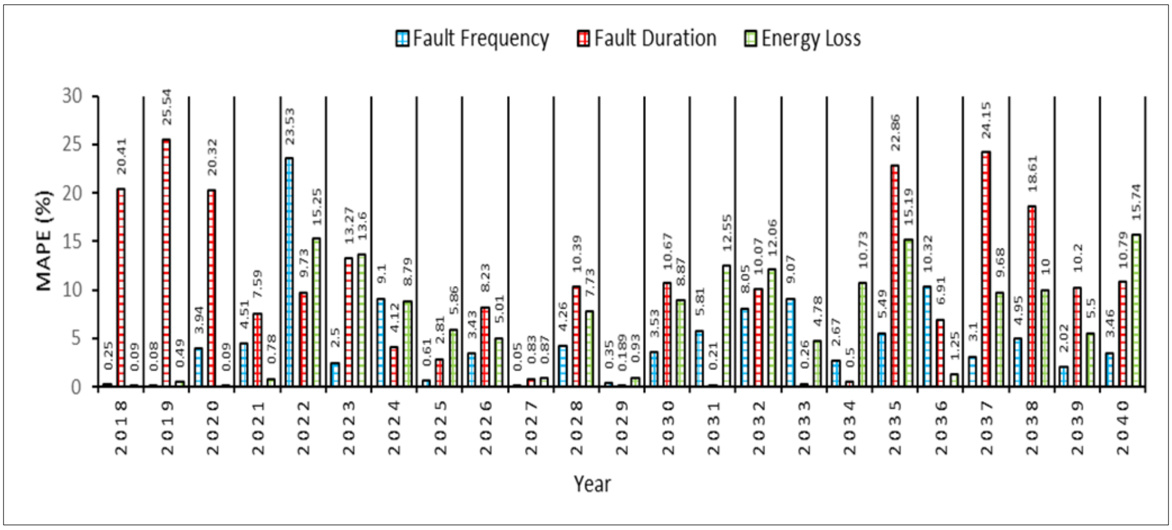

Figure 10 Measures of Prediction Error

The results of the error in the prediction model is illustrated in Figure 10. It can be observed that the yearly MAPE varies between 0.05 and 23.53 %, 0.189 and 25.54 %, and 0.09 and 15.74 %, for fault frequency, fault duration, and energy loss, respectively. The feeder average MAPE for fault frequency, fault duration, and energy loss are 4.83 %, 4.1 %, and 7.21 %, respectively. This demonstrates the accuracy of the model in fault prediction on the feeder.

7. Conclusion

This work has developed and applied a fault prediction model for electrical power network using Artificial Neural Network for predicting the fault occurrence frequency, duration, and energy loss on Ayede - Eruwa/Lanlate 33kVfeeder, in Oyo state southwestern Nigeria. A logarithmic-based time series was used for data transformation. The data were separated into three data sets: a training to train the neural network, a validation to stop the training process earlier, and a test to examine the level of prediction accuracy. The model has four neurons in the hidden layer with the logarithm activation function and was trained using the Resilient Back-propagation algorithm (a variation of back-propagation algorithm) as well as twelve preceding values as the input. The results showed a reasonably close result to the target data, according to the values of Mean Absolute Percentage Error obtained demonstrating the accuracy of the prediction model. Therefore, the developed model is considered adequate for the purpose of prediction in the reference time series.

The following can be concluded from the developed prediction model:

- Although, the prediction model in this work was developed using modeling data obtained from Ayede 132/33 kV substation, it could be deployed on any electrical fault analysis on both transmission and distribution network based on the accuracy of the model.
- To ensure adequate and uninterrupted power supply along Ayede-Eruwa/Lanlate feeder, all wooden poles and cross-arms need to be replaced with concrete poles and steel cross-arms, respectively.
- Energy provider and all players in the energy sector need to be proactive enough in envisaging the effects of energy loss and its economic implications in the sub-station as well as a more innovative and pragmatic approach in minimizing the possibility of losses.
- Eruwa/Lanlate feeder is too long leading to higher energy losses. Hence, the use of FACT devices will be of tremendous benefits to mitigate these losses.
- It is imperative to ensure constant clearing of the "right-of-way, lowering of the footing resistance, and using multiple shielding wires and differential protection for better system efficiency in Ayede- Eruwa/Lanlate 33kV feeders.

Compliance with ethical standards

Disclosure of conflict of interest

We all agreed to the publication of this research work.

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