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Energy Loss Pridiction Model Based On Artificial Neural Network Time-Series On Ayede 33 Kv Sub-Station

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Abstract

Electrical power transmission system is the bulk movement of electrical energy from a generating site to an electrical substation. However, due to increasing economical pressures on network operators, the energy loss in the sub-transmission systems is becoming more and more important. The need to minimize these energy losses had been a major concern of utilities and many researchers. Therefore, forecast and estimation on sub-transmission energy losses is a vital task in the daily operation and planning of the power system operators. In this study an energy loss forecasting method based on Artificial Neural Network Time Series (ANN-TS) model was developed and implemented on Ayede 132/33kV sub-transmission station in Ibadan, Oyo State Nigeria. The developed ANN-TS model was trained with three years (2015-2017) daily outage data obtained from Ayede 132/33kV substation using Resilient Back-Propagation (RBP) algorithm to provide a yearly forecast of energy losses for the next twenty-three years (2018-2040) so as to reduce the additional cost related to inaccurate predictions as well as for the possible reduction of energy loss in the system. The simulation was carried out in MATLAB environment and Mean Absolute Percentage Error (MAPE) in the system was investigated. The results showed that yearly forecast graphs of energy loss forecast were overlapped in each feeder. The yearly MAPE varied between 0.1 % and 12 %, and the feeders' average MAPE varied between 6 % and 10 % which indicated between 90 % and 94 % accuracy of the model. Therefore, the developed ANN-TS model produced a fairly accurate energy loss forecast according to the criteria of MAPE.

Keywords: *Electrical Power, Transmission System, Sub-transmission System, Energy Loss Forecasting, Artificial Neural Network Time Series, Resilient Back-Propagation, Mean Absolute Percentage Error.*

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I. INTRODUCTION

Electrical power systems are growing in sizes and complexities in all sectors such as generation, transmission, distribution and load systems. Traditionally, configuration of power system is a chain link that connects generation to distribution via sub-transmission station. A transmission station is a constituent designed to convey electrical power from the power source over a long distance with minimum energy losses and with high-voltage three-phase alternating current (AC) [1], [2]. 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 [6], [17]. However, due to increase in energy demand and size of electrical transmission power structure, transmission system were subjected to inherent technical energy losses which affect their faithful delivery of power transmitted through them to the distribution end of the grid [7], [8].

It needs to be pointed out that, transmission system energy loss alone accounts for 9 % of 40 % of the total energy losses attributed to both transmission and distribution system [6], [20]. This present energy losses on the transmission system in the power sectors is worrisome, to worsen the scenario, human activities in recent time is placing increasing geometrical pressure on power required for running of normal day to day activities of individual and industry [1], [9]. These energy losses overheat power lines, reduce the grids' available transmission capacity, and affect the agreed transaction of energy at the electricity markets. Certain market participants are therefore forced to account for these losses by purchase complementary energy [10], [15].

There are different ways for the evaluation of energy loss in transmission system, but it is difficult to determine the exactly costs regardless of the method used due to the diversity of the losses in an electrical power system. This complexity of the causes of the energy loss presents the difficulty of calculating them [7]. Also, since the size of these losses remain unknown before each operating hour, certain predictions are necessary. Any error between predicted and actual energy loss has to be adjusted during each operating hour. Therefore, power system operators have thus a special interest towards adequate energy loss prediction strategies. Thus, design of energy loss prediction models has become a research priority. However, a majority of these models are mainly designed for energy line loss allocation issues for market applications as opposed to day-ahead predictions for transmission system operator's purposes [13], [16], [19].

There are high number of energy losses occurrences which always result in long period of 'black out' in a large area being supplied by Ayede 132/33kV transmission substation and this results in economic losses to both energy producer and energy users in the area. In view of this, a this study energy loss prediction model based on Artificial Neural Network Time-Series (ANN-TS) was developed for forecasting of energy loss estimation on Ayede 132/33 kV substation for network planning based on readily available data.

1.1 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 [11]. Electric power may flow through several substations between generating plant and consumer, and may be changed in voltage in several steps. 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 [12], [13].

According to Messalti *et al.*, (2013) a substation is a part of an electrical structure: generation, transmission, and distribution system [14]. 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 comprises of switching devices, protection devices, control equipment and power transformers. Distribution circuits are fed from a transformer located in an electrical substation, substation is an important part of electrical structure [14].

Messalti *et al.* (2013) divided substation into three groups: Transmission substation, Distribution substation and Distribution feeders [14]. Transmission substation combines the transmission lines into a network with multiple parallel interconnections in order that power can flow freely over long distances from generators to any consumer. Transmission lines operate at voltages above 138kV. The largest transmission substations can cover a large area with multiple voltage levels, 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], [18], [20].

Distribution substation operate at medium voltage levels, between 2.4 kV-33 kV voltage tiers, and deliver electric powered energy at once to industrial and home customers. 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 [16]. The output is a number of feeders. Distribution feeders transport energy from the distribution substations to the end 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 [10], [18].

1.2 Secondary Substation

Considering Figure 1, from the primary grid substation, electric power is transmitted at 132 by 3-phase 3wire 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 road sides of the city. Large consumers demanding more than 50kW do connect to this type of power line [14].

The components of the secondary substation consists of the following equipment: primary power lines, ground wire, power transformer, disconnecting switch(isolator), switchgear, circuit breakers, current transformer, potential transformer, lightning arrester, bus-bar, control building, protection fence and secondary power lines. The apparatus mentioned were assembled in order to guarantee a successful transportation of electrical power to the consumers [14].

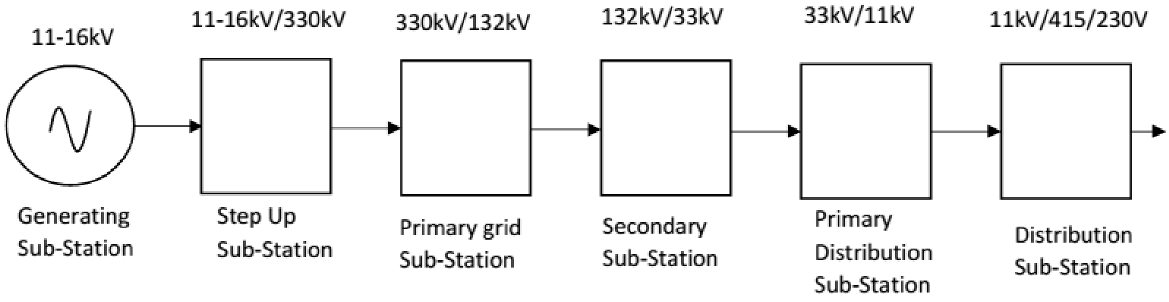

Figure 1: Electric Power Structure

1.3 Ayede Sub-Transmission Station

Ayede 132/33 kV substation is a sub-transmission station of Transmission Company of Nigeria (TCN). Ayede 132/33 kV substation as shown in Figure 2 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 Oluyole feeder [3], [4], [5].

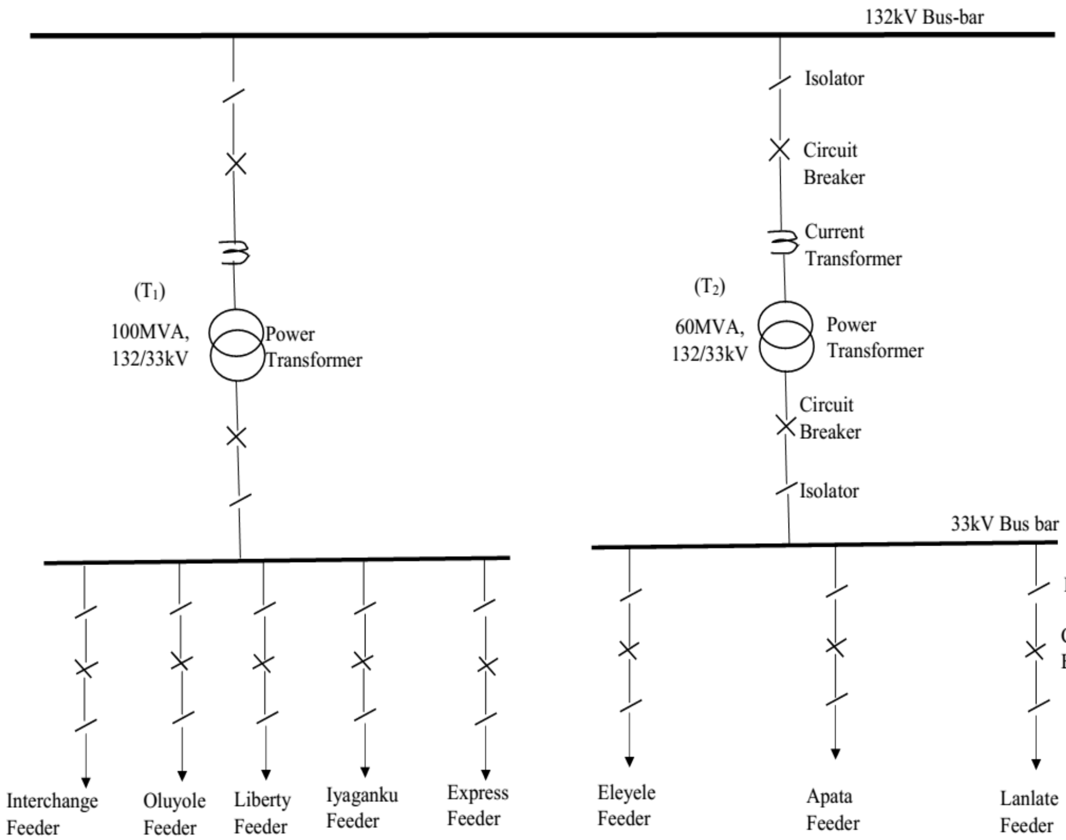

Figure 2: Schematic Diagram of Ayede 132/33kV Transmission Sub-station

1.4 Energy Losses in Power System

Electrical losses are wasteful energy in systems that take a considerable part of the electrical power transmitted and distributed. Electrical losses are classified basically as technical or non-technical energy losses. The technical losses caused by current and resistance (I^2R), hysteresis, eddy currents and dielectric losses (corona). While the non-technical losses are caused by defective meters, errors in meter reading, pilferage and in estimating unmetered supply of energy [2], [19].

Technical losses occurring on transmission lines has resulted in revenue loss, it accounts for 30% of system total losses and the consequence of this scenario is evidently seen in form of limitation on the transfer capabilities of transmission lines [8], [11], [14]. Experiences had shown that all transmission systems are not operated at the same thermal capacity; some are below, some within while others are operating in over loaded condition. This scenario often results in system voltage collapse capable enough of causing system instability thereby reducing their reliability and dependability. No practical system is lossless; losses are inevitable and can only be reduced to minimum. Thus energy loss minimization in power system is an exercise deserving consideration [9], [16], [19].

1.5 Determination of Energy Loss

The determination of energy loss of a network can be done in many ways. The methods distinguish each other in terms of complexity, data acquisition, accuracy and whether the period under review is in the past or future [11], [12], [16], [18]:

i. **Measurement of Energy Loss:** Measuring the energy loss is simple task for existing networks, but it can only be applied to past periods. The sold energy has to be subtracted by the bought energy to obtain the energy loss. The difficulty remains in the data acquisition for a specific date. This method cannot be applied to network planning since only the past can be reviewed.

ii. **Computation of Energy Loss with a Network Simulation Program:** The computation of the energy loss is done by dividing the time period under review into time segments, obtaining the data for the loads for each time segment and computing the power loss for each time segment with a network computation program. The power loss is multiplied by the considered time segment and summed up, which yields the energy loss. The summation approaches the integral of the power loss of the time period under review.

iii. **Energy Loss Estimation Method:** The energy loss estimation method is based on the approximation of the loss factor by the load factor. For the approximation only information about the peak power, average power and power loss at peak load is needed. After all, only one load flow calculation has to be performed for the load losses and one for the no-load losses. This makes it easy to estimate the energy loss caused by technical losses with available data and in a very short time.

However, for the purpose of this study Artificial Neural Network (ANN) with Time Series model was employed to verify the results of the developed loss estimation method.

1.6 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. 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 [2], [7], [15].

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. 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 [8], [10].

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

$$Y = \text{Ø}(X) \tag{1}$$

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

The neural network is a massively parallel distributed processor that store knowledge and make it available for use. It resembles the human brain in the following three forms:

(i) The knowledge stored is acquired by the network through a learning process. Just as brain learns and acquire the knowledge through learning.

(ii) Inter nervous correction strengths, known as synaptic weights are used to store the knowledge acquired, just like synapse in the biological neuron.

(iii) The network is capable of generalization.

II. MATERIALS AND METHOD

Artificial Neural Network based Time-Series (ANN-TS) model was developed to predict energy loss on Ayede 132/33 kV substation using modelling data obtained from the performance target measurement sheets for the period of three years (2015-2017). The developed ANN was modelled into three layers: input layer, hidden layer and output layer. Bias terms were used in both hidden and output layer's nodes. Resilient Back-Propagation (RBP) 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 3.

The input of the model consists of the 12 previous numbers corresponding to the last 12 months energy loss data. The output is the predicted loss for the next month. From this number of training sessions, the obtain ANN was retrain to obtain better forecast results in each situation under the validation set. Validation of the developed model with the test set was achieved with the use of Mean Absolute Percentage Error (MAPE).

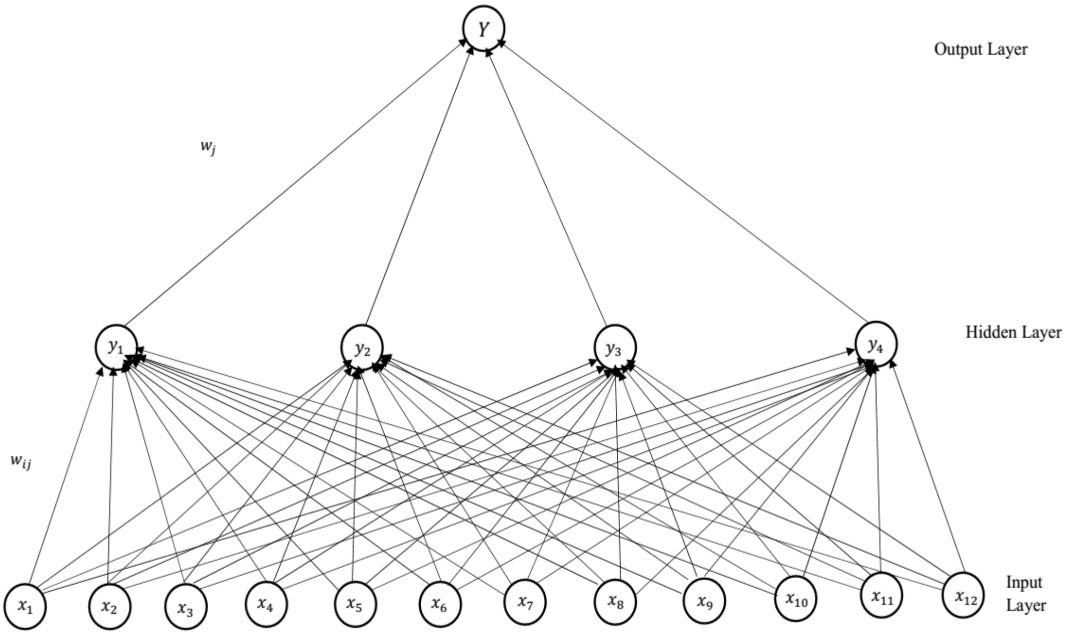

Figure 3: Three Layer ANN-TS Energy Loss Model for Ayede 33kV Substation

From Figure 3, each node in the hidden layer $y_j (j = 1,2,3,4)$ is computed as:

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

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

$$y_j = \frac{1}{1+e^{-f_j}} \quad (3)$$

Lastly, Y in the node of the output layer in Figure 3 is obtained by equation (4)

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

The activation function for hidden nodes in the logarithm function is given as:

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

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

$$[Lin]: f(x) = x \quad (6)$$

where; x is the input signal energy loss.

Developed ANN-TS energy loss forecasting of $Y_{(t)}$ model is given as:

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

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 developed ANN-TS model was validate using 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.

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

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

III. RESULTS AND DISCUSSION

The results of ANN-TS energy loss forecasting model on Ayede 33kV substation were observed in each substation feeder. In view of this, the predicted data of ANN-TS model of each feeder were compared with the observed values for twenty-three years (2018-2040). It is important to note that the observed data is the original data of the time series and was never seen by the ANN-TS model in the phase. To validate the model, the criteria of MAPE between the observed and the predicted values is calculated using equation (8).

Figure 4 to 11 showed monthly energy loss forecasting graphs of energy loss on each feeder. The graphs showed the observed and predicted time series for each feeder. As expected, the model predicted better, except in few cases where the predicted value overshot the observed value and vice-visa. The graphs took the same pattern in each feeder. Yearly MAPE varied between '0.1 %' and '12 %', and feeder average MAPE varied between '6 %' and '10 %'. Energy loss is the product of power loss and down time on the feeders, this was forecasted to provide likely energy loss on each feeder and this will enable the energy provider to avert these occurrences.

The comparison summary statistics of the out-of-sample data used as the validation set for forecasting performance of the model were given in Figure 12. 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 in Lewis (1982), 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.

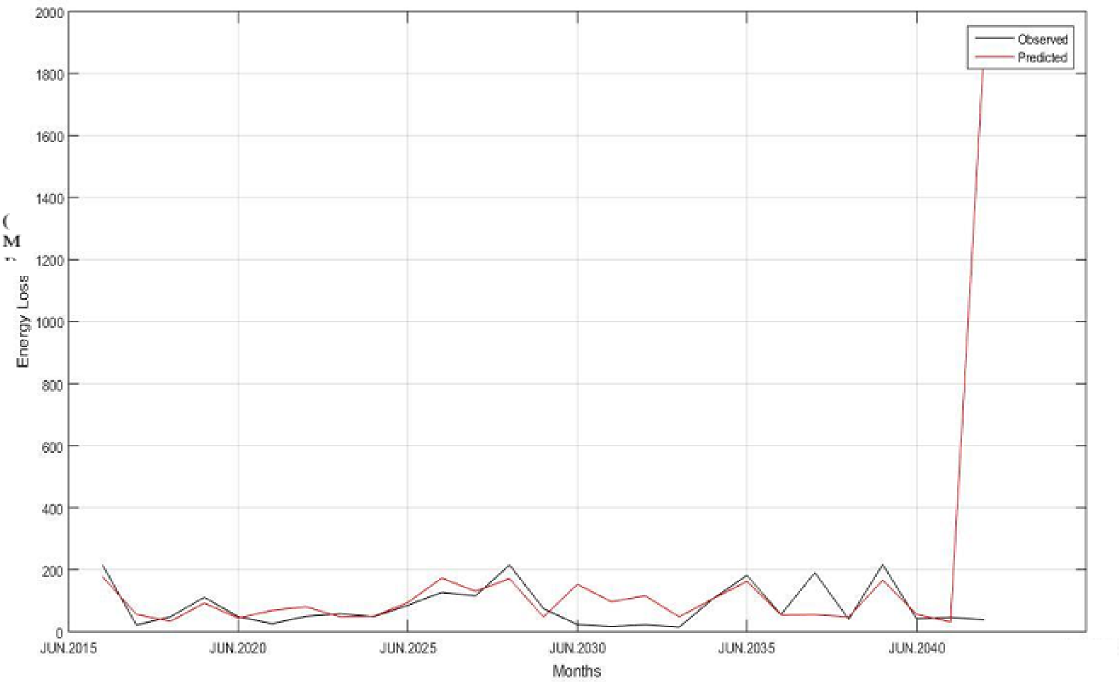

Figure 4: Monthly Energy Loss Forecasting on Apata Feeder from 2018:01 – 2040:12.

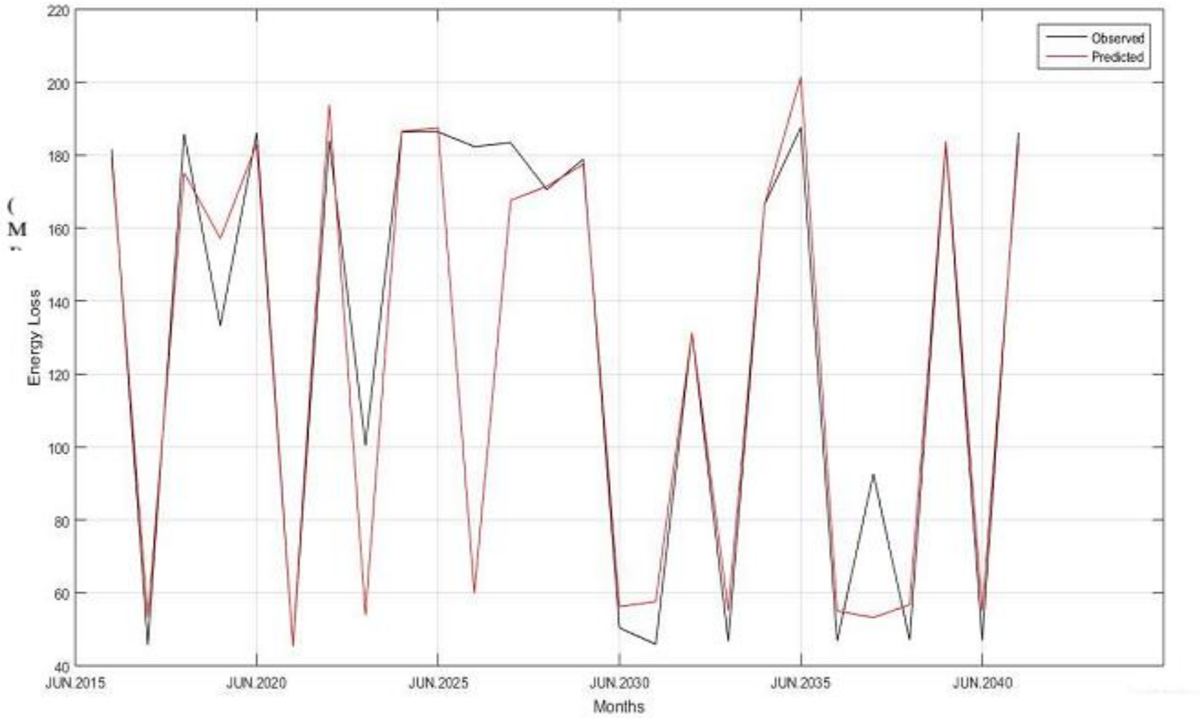

Figure 5: Monthly Energy Loss Forecasting on Eleyele Feeder from 2018:01 – 2040:12.

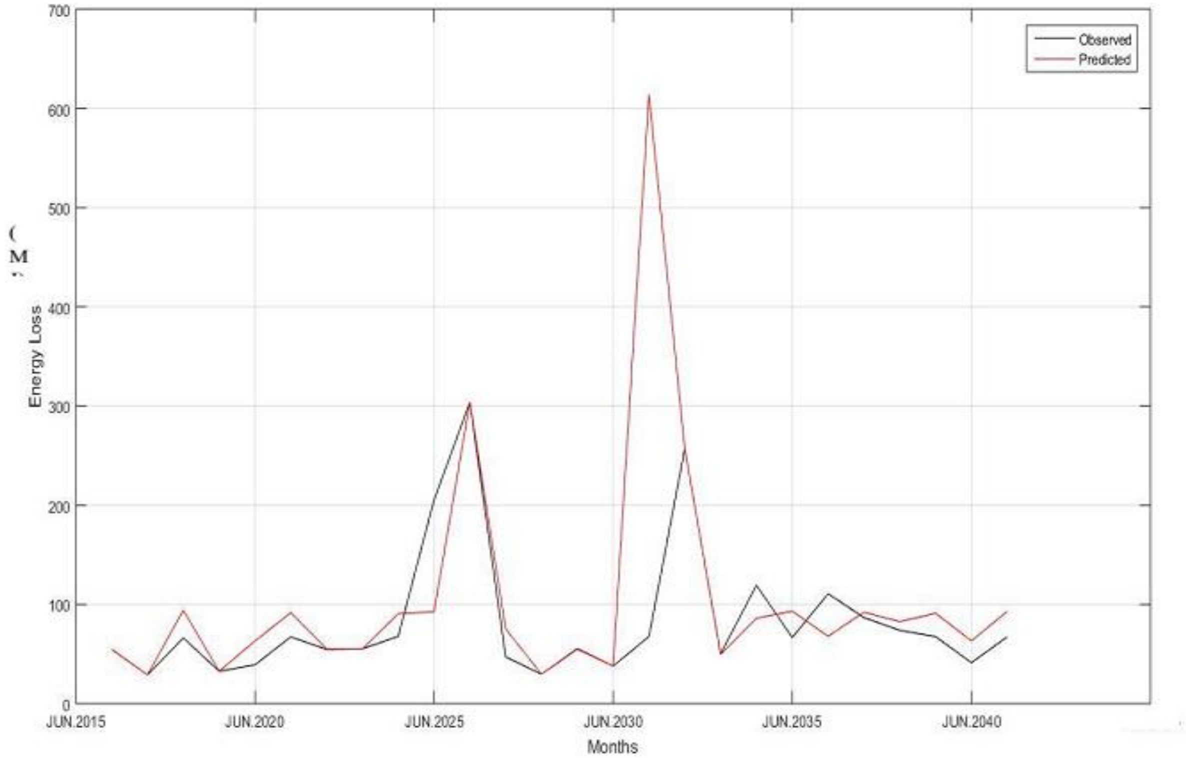

Figure 6: Monthly Energy Loss Forecasting on Express Feeder from 2018:01 – 2040:12.

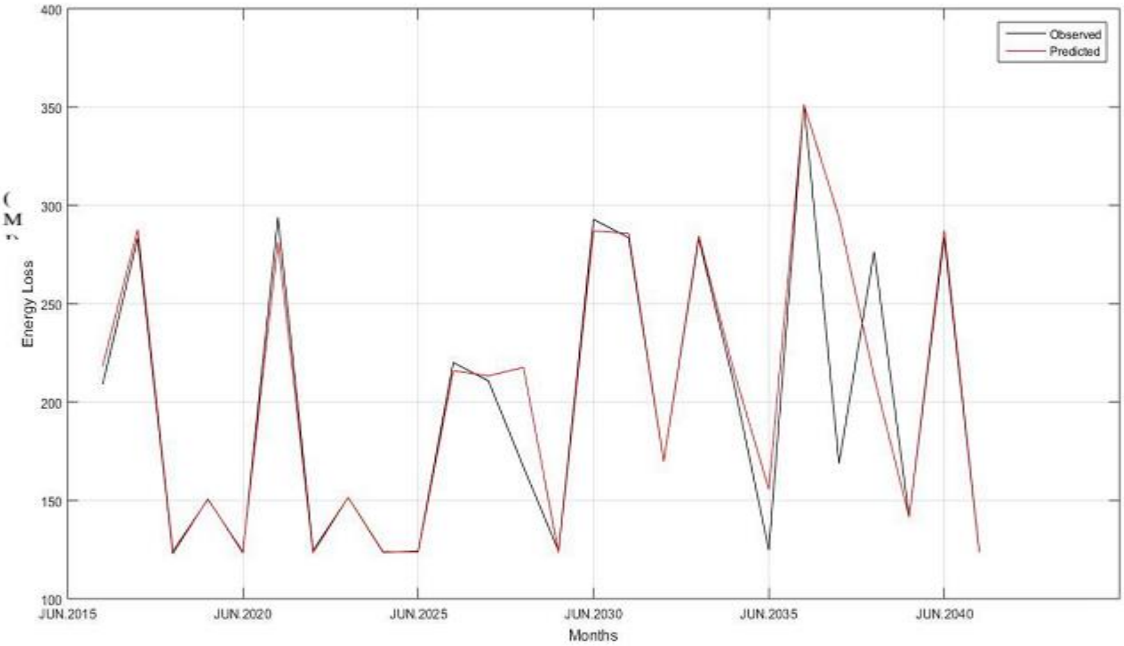

Figure 7: Monthly Energy Loss Forecasting on Interchange Feeder from 2018:01 – 2040:12.

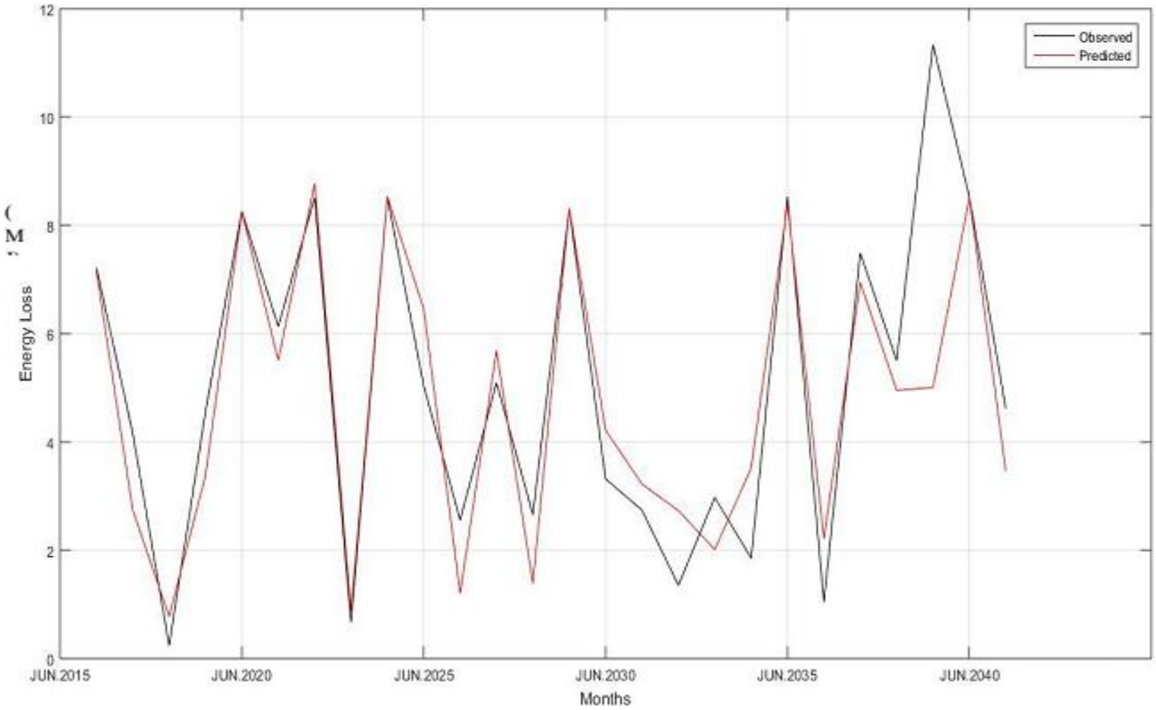

Figure 8: Monthly Energy Loss Forecasting on Iyaganku Feeder from 2018:01–2040:12.

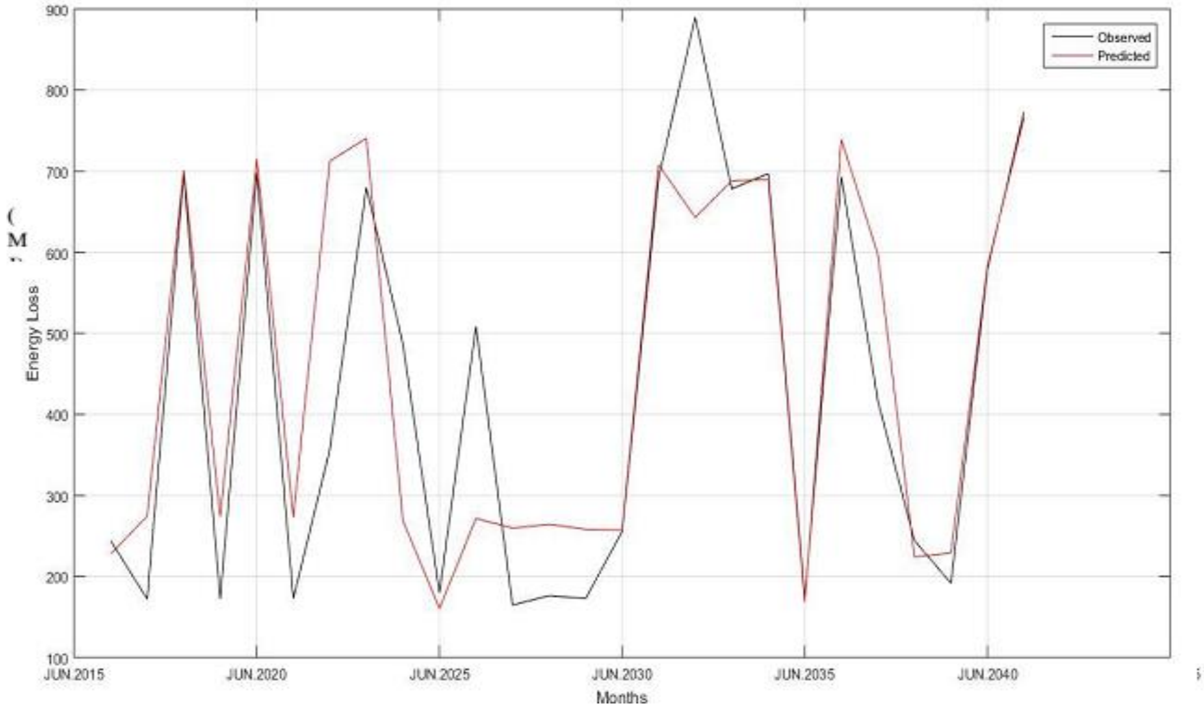

Figure 9: Monthly Energy Loss Forecasting on Lanlate Feeder from 2018:01 – 2040:12.

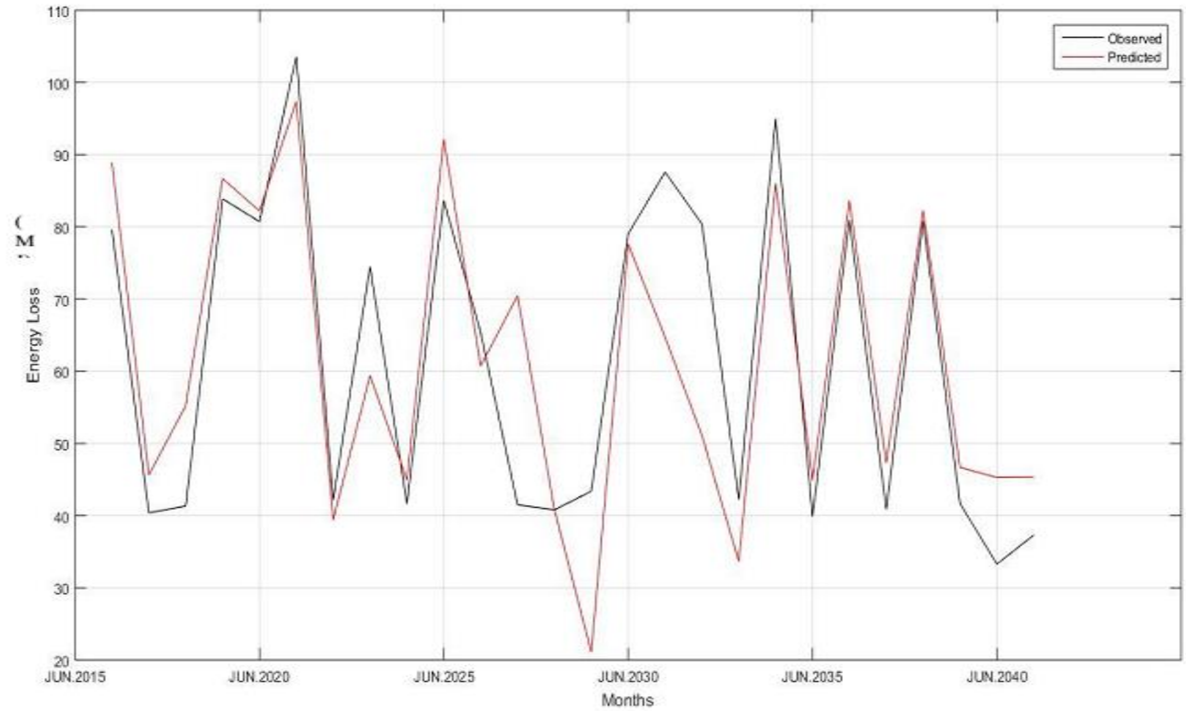

Figure 10: Monthly Energy Loss Forecasting on Liberty Feeder from 2018:01 – 2040:12.

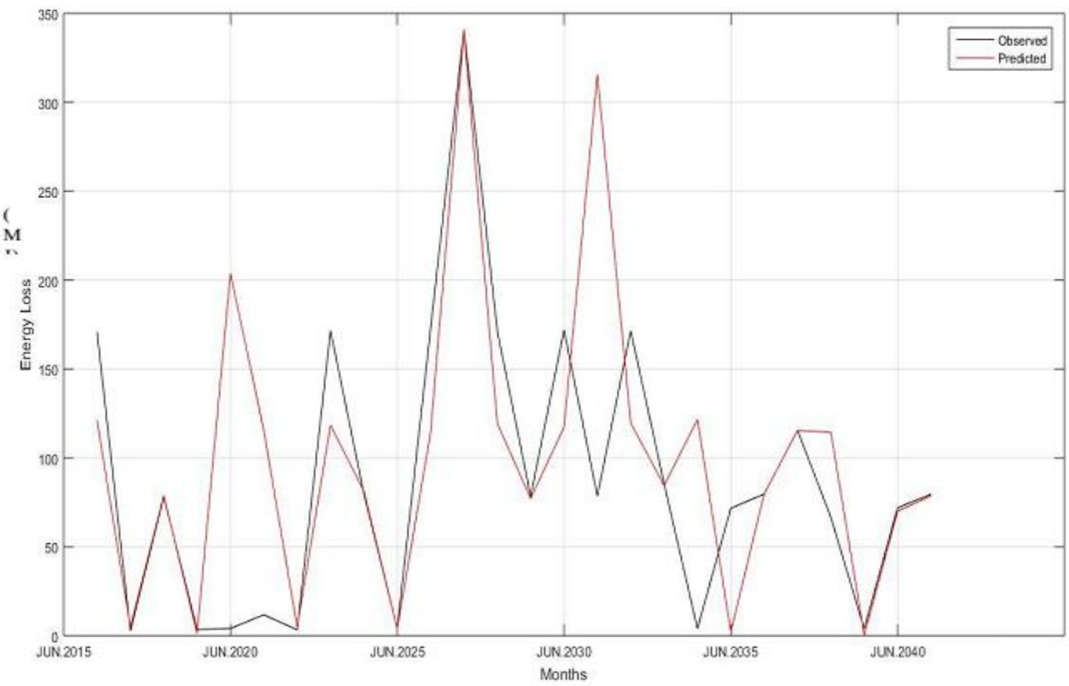

Figure 11: Monthly Energy Loss Forecasting on Oluyole Feeder from 2018:01 – 2040:12.

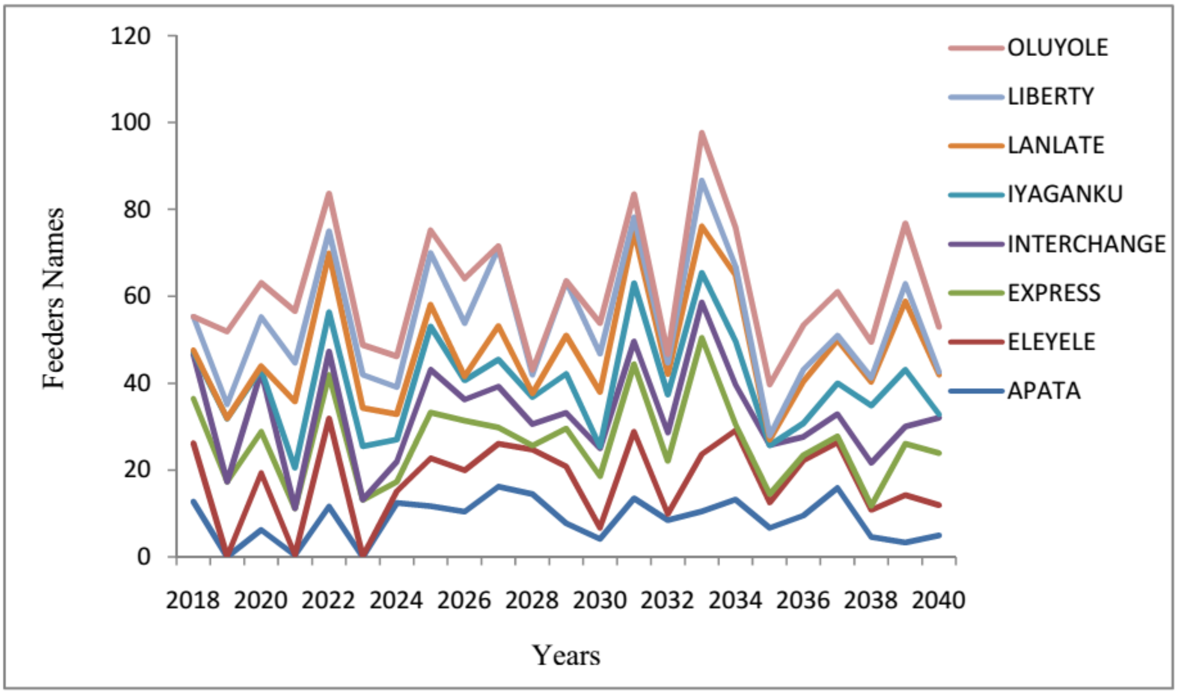

Figure 12: Energy Loss Forecasting Error Measures of Ayede 33kV substation

IV. CONCLUSION

The importance of forecasting increases energy loss in power system is not only during operation of power system, but also in the system planning process. This task has to be performed in a reasonable time while having the needed data available, especially the reduction of energy loss for a network expansion is of interest. This study therefore developed an Artificial Neural Network Time Series (ANN-TS) energy loss prediction model on Ayede 132/33kV 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 ANN model has the twelve (12) preceding values as the input. The analysis of the output forecast data of the selected ANN model showed reasonably close results compared to the target data, that is, the model produced, according to the criteria of Mean Absolute Percentage Error (MAPE) an accurate forecast. With the developed model, the power network operators and planner can quickly give reliable results with the energy loss forecasting model during the network planning process. Therefore the developed model is considered adequate and sufficiently good for the purpose of energy loss prediction in the reference time series.

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