Forecasting of Maximum Peak Load Demand of Abuja Region Interconnected Power Network Using Artificial Neural Network

Isaac Alabi* , Abel Airoboman*‡ , Samson Faleye*

* Department of Electrical/Electronic Engineering, Faculty of Engineering and Technology, Nigerian Defense Academy, P.M.B 2109, Kaduna, Nigeria

(airobomanabel@nda.edu.ng)

‡ Corresponding Author; Abel Airoboman, Postal address, Tel: +2347032186403,

airobomanabel@nda.edu.ng

Received: 08.06.2021 Accepted:30.03.2022

Abstract- This paper presents an artificial neural network (ANN) based approach for long-term Maximum Load Demand Forecasting (MLDF) of 33KV substations of Abuja region interconnected network. Historical data were collected from the nine sub stations under Abuja region between 2013 to 2017. The data collated were analyzed using feed forward back propagation of ANN in training, testing and forecasting of load demand. The performance accuracy of ANN was assessed using Mean Square Error (MSE). The simulation results revealed that ANN shows quite good performance as a forecasting tool due to the trends and the large data set available. Further results showed an increase in load demand for all feeders except for Akwanga feeder within 2021-2022. Meanwhile, Apo feeder have the highest maximum demand of 176.43MW closely followed by Central with 167.63MW. Consequently, the lowest maximum demands of 24.94MW closely followed by 39.43 were recorded for Akwanga and Keffi feeders respectively. Generally, Apo feeder recorded the highest maximum load in the year 2021 closely followed by Central Area feeder. In the same vain, the duo of Akwanga and Keffi feeders recorded the lowest maximum demand for the same year. However, an increment in load for all the feeders was observed with respect to their maximum demand except for Akwanga feeder between 2021-2022..

Keywords Abuja, ANN, Forecasting, Load, Network.

1. Introduction

The recent deregulation of the electricity sectors in Nigeria has dramatically influenced its operational philosophies in the direction of better service delivery and efficient delivery of electrical energy to all categories of consumers. The revolution in technology and the regulatory framework have undoubtedly been and will continue to be the dominant driving forces of the change on the organizational system of the electricity. A great deal of effort is required to provide high quality electric power supply to meet the requirements of the various types of customers. Some of the requirements are proper voltage, availability of power on demand, reliability and reasonable cost. By availability of power on demand, we mean to say that power must be available to the consumer in any amount that he may require from time to time. The demands of consumers with regards to nature-controlled demographic, weather and econometric factors has posed the greatest challenges in forecasting coupled with the unpredictable pattern of consumers' demand at any point in time. Power system must be properly planned to ensure adequate and reliable power supply to meet the estimated load demand in both near and distant future. The primary reasons for system planning are to arrive at a realistic estimated result for future demands of power. This concept is a part of load forecasting, load forecast is an intelligent projection of past and present peak load demand patterns to determine future demand load with good prediction reliability. Power system in developing nation like Nigeria is known for its epileptic and unreliable nature partly because of poor planning. This underscores the need accurate load forecasting to aid its operation and planning. Accurate load forecasting holds a significant saving and potential for electric utility company. In [1], Savings are realized when load forecasting is used to control operations and decisions are taking for economic load dispatch, fuel allocation and off-line network analysis.

2. Literature Review

The accuracy of load forecasts has a positive impact on power system operations, as also economy of operations and control of power [2] –[3] in their research identified that both positive and negative forecasting errors lead and cause increased operating costs. Load forecasting could be for long, medium and short term. Srinivasan and Lee, [4] classified load forecasting in terms of the planning horizon's duration: up to 1 day for short-term, 1 day to 1 year for medium-term, and 1-10 years for long-term. Short-term load forecasting is aimed at predicting electric loads for a period of minutes, hours, days, or weeks [5]. Short-term load forecasting plays an important role in the real-time control and the security functions of an energy management system. Short-term load forecasting is applied to the system security assessment problem, especially in the case of increased renewable energy sources penetration in isolated power grids, it can provide, in advance valuable information on the detection of vulnerable situations. Long- and medium- term forecasts are used to determine the capacity of generation, transmission, or distribution system additions, along with the type of facilities required in transmission expansion planning, annual hydro and thermal maintenance scheduling etc. Kazantzakis et al, [5] noted that short-term load forecast for a period of 1- 24 h ahead is important for the daily operations of a power utility since it is used for unit commitment, energy transfer Scheduling and load dispatch. Achieving accurate electric load forecasting is not easy. This is because consumer demands are uncertain and variables that influences consumer demand varies in an unpredictable pattern [6]. Some of these variables or factors include economic factors, time, day, season, weather and random effects. Electricity usage may be, therefore, predicted using data from previous history of load, temperature, humidity, luminosity, and wind speed among other factors. However, accurate models of load forecasting that use all these factors increase modeling complexity without likelihood of a better result. Several methods have been used to perform load forecasting each with its inherent shortfalls.

Time series analysis is a very effective method to create mathematical models for solving a broad variety of complex problems [7] These models are used to identify or predict the behaviours of a phenomenon represented by a sequence of observations. However, creating an accurate model for a time series that represents non-linear processes or processes that have a wide variance is very difficult [7] The trend today, however, is to solve most problems of human using Artificial Intelligence Means (AIM). Artificial intelligence methods for forecasting give better performance in Modeling of time series problems [8] Artificial Neural Networks (ANNs) being one of the artificial intelligence means have been successfully used to solve a broad variety of systems, entailing linear and non-linear processes. The application of ANNs in time series prediction is presented in [9] and in [10]. The success in the application of ANNs lies in the fact that when these networks are properly trained and configured, they are capable of accurately approximating any measurable function. The neurons learn the patterns hidden in data and make generalizations of these patterns even in the presence of noise or missing information. Predictions are performed by the ANN based on the observed data. Load forecasting is clearly a time series problem and an example of a time series problem that can be solved with ANNs is electricity load forecasting . Artificial intelligence or AI is the general term used to describe computers or computer programs which solve problems with "intuitive" or "best-guess" methods often used by humans instead of the strictly quantitative methods usually used by computer [11]. Expert systems, neural networks, fuzzy logic and support vector machines are some of the AIs currently in use today. Programs for some problems such as image recognition, speech recognition, weather forecasting, electric load forecasting, and three-dimensional modelling are not easily or accurately implemented on fixed –instruction-set computers such as 386/i486-based systems [11]. For applications such as these, new computer architecture, modelled after the human brain and which is known as Artificial Neural Network in this study is a novel attempt made to solve the problem of electric power forecasting in the Nigerian power system.

In order to steer the Nigerian electric utility from its current deplorable state, that is characterized by massive power cuts and perpetual suppressed demand, and to achieve a sustainable path towards secure and reliable electricity supply, it is pertinent to focus research effort in this direction using well- established bulk power planning tools and sound operational concepts. Therefore, the research is envisioned at predicting future demand of the Abuja and its environs using ANN. With these overriding goals in mind adequate arrangement would be made to guarantee sufficient energy for future need of the Federal Capital Territory and provide credible demand profile for the load Centres of the Federal Capital Territory (FCT) as required for load allocation by the National Control Centre (NCC).

Stelios et al, [12] uses Kalman used fuzzy logic to forecast hourly load demand. The forecasting was done using one-year data from the large-scale power system. The proposed methodology uses fuzzy rules to incorporate historical load data with time and day. In the specification, day means Weekend or weekdays. The aim of the work was to determine the load curve of a particular day observing one-year data from large-scale Industry. The results obtained shows that this methods is more effective for day to day load forecasting (Short Term) and not long term forecasting. The gap observed in the research was that its only deals with small data and it was short term forecasting method used which will not be accurate for long term forecasting. Box-Jenkins used Auto Regressive Integrated Moving Average ARIMA method and also autocorrelation function for identifying proper ARIMA models the results obtained shows that it is accurate with larger data set, but requires larger computational time. Spectral expansion technique using Fourier series method where load pattern is considered as a number of sine waves with different frequencies was also used. The gap observed in the research was that this method is not accurate for load patterns and also are no perfect periodic time for effective load forecasting [13] Brockmann and Kuthe, [14] proposed several models to forecast electricity usage, from simple statistical models upto hybrid crisp-fuzzy, neuro-fuzzy models based on rules and learning . Their simplest model describes load for an average for the two years 1997 and 1998. This model was later improved by shifting the days of the week. The research focused on the significance of unsupervised learning and its application in the short term load forecasting. Self- organizing feature map network was proposed to illustrate the use of unsupervised learning in load forecasting.The gap observed in the research was, it was still unable to account for holidays that do not occur on same date each year.

Bakirtzis et al, [15] developed an ANN based short- term load forecasting model for the Energy Control Centre of the Greek Public Power Corporation. In the development they used a fully connected three-layer feed-forward ANN and back propagation algorithm was used for the training. Input variables included historical hourly load data, temperature, and the day of the week.

Khotanzad et al, [16] developed neuro fuzzy based a short term load forecast model for deregulated and price sensitive electricity market. In this research, the impact of electricity price on load consumption is considered to design an accurate load forecast model. It is observed that, the load consumption pattern is different between fixed price and price sensitive (PS) electricity market. Forecast model is designed at two stages. ANNSTLF is used in first stage and genetic algorithm is used to optimize the parameters of fuzzy logic rules and membership functions in the second stage. The performance of proposed neuro fuzzy based forecast model is tested on three different types of load. The results show that, the proposed neuro fuzzy based forecast model shows better performance in price sensitive environment than the price-insensitive (PIS) electricity market. The gap in the research was that it focus model on short term forecasting using fuzzy logic model.

Wu et al, [17] proposed a short term load forecast model based on seasonal exponential adjustment method (SEAM) and regression model. In this study, seasonal exponential adjustment method is used to compensate the seasonal variation impact on load demand pattern and regression model is employed for one week ahead load forecast. Furthermore, the simulation results show that, there is significant improvement in forecast accuracy of proposed model for one day ahead load forecast studies than the separate forecast techniques. The research gap on this proposal was that it can only be implemented for one day ahead forecast with small data needed.

Yang et al, [18] proposed a neural network based short term load forecast model with fuzzy logic. Fuzzy logic membership function is designed in such a way that, they will select most Influencing inputs of forecast model. These inputs have great effect on hourly load demand such as air temperature, working or off day, anomalous day and previous correlated load inputs. The output data of fuzzy logic is used to train neural network to forecast working day, off day and special day load demand. By applying fuzzy logic input pre-processing method, the neural network learning time and computational complexity is reduced. A significant improvement in forecast accuracy can be observed by using integrated neural network and fuzzy logic based forecast model than the conventional neural network based forecast model. From the simulation results it also can observed that, the proposed model shows higher forecast MAPE for special days load forecast than the working days due to uncertain load pattern during the special days. The proposal could not only forecast for special days in the year which can cover effective load forecast for long term.

Tripathi et al, [19] developed a generalized regression and probabilistic neural networks based short term load forecast model in order to predict the load demand of Australia's Victoria grid. Therefore, in order to improve the forecast accuracy, electricity prices are included along with previous load and respective weather data as forecast model inputs. Moreover, different case studies are designed to forecast the load demand of week days and weekends. Therefore, proposed model achieve higher forecast accuracy than the comparative techniques. Airoboman et al [20] developed ANN model for prediction of reliability indices of Transmission Company of Nigeria, Benin City, Edo State. The study utilized the back propagation forward feed method. The results showed ANN uniqueness when it comes to predicting reliability variables especially on a large data set.

From the foregoing review, a need arises for the prediction of peak load demand of the Abuja region using ANN to provide adequate information for predicting future load demand, planning and expansion of transmission and make necessary recommendations and suggestions for further research. It can also be said that artificial neural network model is not predominantly used to forecast electric load hence, its utilization in this study. Electric load forecasting is challenging because of the unpredictable characteristics of consumer demand. Vadhera, [21] defines load forecasting as the predicting of electrical power required to meet the short term, medium term and long term demand. Forecasting helps the utility companies in their operation and management of supply to their customers. According to Sarangi et al,

[22] Load forecasting is a technique used by power or energy-providing companies to predict the power/energy needed to meet the demand and supply equilibrium. The accuracy of forecasting is of great significance for the operational and managerial loading of a utility company. Chakrabarti and Halder,

[23] also defined load forecasting as a method of estimating the load for a future time from the available past data. Mill, [24] Electrical load forecasting is important process that can increase the efficiency and revenues for the electrical generating and distribution company. Its helps them to plan on their capacity and operation in order to reliably supply all consumers with required energy. LOAD forecasting can be divided into three main categories which are short term, medium term and long term forecasting. Load forecasting can be classified in terms of the planning horizon’s duration as short, medium or long term forecasting.

3. Materials and Method

An artificial neural network is an efficient information processing system to perform non-linear modeling and adaptation. It is based on training the system with past and current load data as input and output respectively. The ANN learns from experience and generalizes from previous examples to new ones. Neural networks offer the potential to overcome the reliance on a functional form of a forecasting model. There are many types of neural networks: multilayer perceptron network, self-organizing network, There are multiple hidden layers in the network. In each hidden layer there are many neurons. Inputs are multiplied by weights, and are added to a threshold to form an inner product number called the net function. Advantage of ANN is that no complex mathematical formulation or quantitative correlation between inputs and outputs is required. Another advantage of ANN over statistical models lies in its ability to model a multivariate problem without making complex dependency assumptions among input variables. The Artificial Neutral network ANN It's a simplified model of the central nervous system and a form of artificial intelligence AI used to sole more complex in the areas of Engineering as an example, like Programs for some problems such as image recognition, speech recognition, and weather forecasting. Neural network is an attempt to creating machines that work similar way to the human brain by building these machines using components that behaves like biological neurons.

An artificial neural network called neurons. An artificial neuron tries to mimic the structure and behavior of the natural neuron. A neuron consists of inputs (dendrites), and one output (synapse via axon).The neuron has a function that determines the activation consists of processing units of the neuron. The model of a simple ANN is presented in Figure 1. This model comprises the input, hidden and output layer.

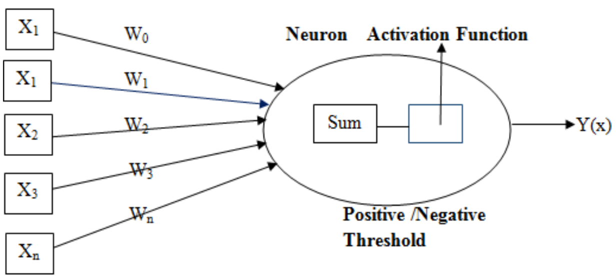


Fig. 1. Model of Artificial Neuron [20], [25]

x_1 ....x_n are the inputs to the neuron. A bias (b) is also added to the neuron along with inputs. Usually bias value is initialized to 1. W_0……W_n are the weights. A weight is the connection to the signal. Product of weight and input gives the strength of the signal. A neuron receives multiple inputs from different sources, and has a single output. The sum is te weighted sum of the inputs multiplied by the weights between one layer and the next. The activation function used is a sigmoid function, which is a continuous and differentiable approximation of a step function. An interconnection of such individual neurons forms the neural network.

$$Y(x) = f \sum [(W_0X_0) + (W_1X_1) + (W_2X_2) + (W_3X_3) +(bn)\ldots\ldots\ldots\ldots..+ (W_nX_n+b_n) \quad (1)$$

The data used for this research work are collected from the nine substation under Abuja sub region namely: Katampe, Apo, Kubwa, Central Area, Karu, Keffi, Akwanga, Suleja and Gwangalada 33kV network from 2013 to 2017. The sample data for daily peak load of Abuja regional network is presented in Table 1.

- INPUT LAYER

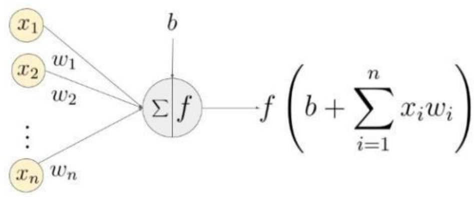
The layer which mathematically is denoted with X(n) for t numbers of input. It contains those units (Artificial Neurons) which receive input from Abuja sub region (nine sub stations) which is express as X(n) using equation (2)

X (n) = *data collate per stations per weeks (∑ sum (d1+d_2 .... d_n)* (2)

- HIDDEN LAYER

These units are in between input and output layers. The function of the hidden layer is to transform the input into information that output unit can use. The hidden layer has 10 neuron which carried the weight with bias. These are used in learning process of the model to achieve the actual output Y (n)

The feed forward equation used for the modeling shown in (3) – (4). The feed forward back propagation was used in this study because literature has shown its efficiency when it comes to analysis of large data set [25]



(3)

$$f\left(b+\sum_{i=1}^{n} x_i w_i\right) \quad (4)$$

Where b1 and b2 = bias at the hidden layers, c1 and c2 bias at the output layers, x = input to neuron, w = weights, n = the number of inputs from the incoming layer, i = a counter from 0 to n,

f(the activation function)= *1 / (1 + e^(-1*z))* (5)

Equations (6) – (11) are used to calculate each feed forward (Z_n) in the next hidden layer using

$$Z_1=f_1\sum[[(W_{11}X_1)+(W_{12}X_2)+(W_{13}X_3)+(W_{14}X_4)+(b_1)] \ldots. + (W_nX_n+b_n)] \quad (6)$$

$$Z_2=f_2 \sum[[(W_{21}X_1)+(W_{22}X_2)+(W_{23}X_3)+(W_{24}X_4)+(b_2)] \ldots\ldots. + (W_nX_n+b_n)] \quad (7)$$

$$Z_3= f_3\sum[[(W_{31}X_1)+(W_{32}X_2)+(W_{33}X_3)+(W_{34}X_4)+(b_3)] \ldots\ldots. + (W_nX_n+b_n)] \quad (8)$$

$$Z_4= f_4\sum[[(W_{41}X_1)+(W_{42}X_2)+(W_{43}X_3)+(W_{44}X_4)+(b_4)] \ldots\ldots. + (W_nX_n+b_n)] \quad (9)$$

$$O_1 = f_5\sum [[Z_1W_1) + (Z_2W_1) + (Z_3W_1) + (Z_4W_1)+ (c_1)]\ldots\ldots\ldots..+(Z_nW_n)+c_{n)}] \quad (10)$$

$O_2=f_6\sum[[(Z_1W_5)+(Z_2W_6)+(Z_3W_7)+(Z_4W_8)+(c_2)]\ldots\ldots\ldots\ldots+(Z_nW_n)+c_{n)}]$ (11)

The above equation can be represented in matric form (n, m).where n represent w is the weight vector of shape number of output neurons (neurons in the next layer). Where x is the input vector of shape (m, 1) where m is the number of input neurons.

The error in propagation can be given as

$E_{(n).} = ½ (\text{Prediction} – \text{Actual})^2$ (12)

Table 1. Weekly Maximum Demand Collated Data from 2013 to 2017 Katampe substation

WEEKS	2013	2014	2015	2016	2017
WEEK 1	76.50	65.00	62.00	75.00	65.50
WEEK 2	75.00	67.30	64.70	78.00	67.70
WEEK 3	78.50	63.50	75.20	78.40	69.90
WEEK 4	69.00	74.50	71.50	77.70	74.60
WEEK 5	47.80	79.00	71.00	76.80	75.00
WEEK 6	60.00	78.30	75.00	87.80	73.60
WEEK 7	66.00	74.00	71.50	89.50	82.20
WEEK 8	53.20	77.50	82.50	86.50	71.60
WEEK 9	68.30	80.50	74.50	92.00	79.70
WEEK 10	69.00	78.90	88.40	87.50	69.70
WEEK 11	72.10	83.50	78.50	74.00	75.20
WEEK 12	57.50	61.00	60.50	69.40	76.40
WEEK 13	70.80	67.50	73.00	80.00	70.50
WEEK 14	75.60	74.00	76.50	81.50	83.00
WEEK 15	68.80	67.00	74.50	77.50	77.50
WEEK 16	81.00	66.50	82.50	80.50	78.70
WEEK 17	78.50	72.00	85.50	87.50	82.30
WEEK 18	76.50	78.50	78.00	82.00	80.30
WEEK 19	75.00	72.50	79.00	72.50	66.40
WEEK 20	78.50	83.30	84.00	62.10	81.00
WEEK 21	69.00	80.50	79.80	82.00	84.60
WEEK 22	47.80	49.00	81.50	76.00	80.70
WEEK 23	60.00	63.50	72.00	62.50	77.90
WEEK 24	66.00	74.50	74.50	60.00	80.50
WEEK 25	53.20	55.00	72.00	70.50	59.30
WEEK 26	68.30	68.00	74.80	58.00	62.00
WEEK 27	69.00	65.00	80.30	69.80	83.00
WEEK 28	63.50	61.50	76.00	66.00	79.30

- OUTPUT LAYER

The output layer contains units that respond to the information about how it's learned any task. This is actual output of the network after serial of back propagation had taken place to reduce the error to the acceptable state. This is denote with Y (n) for t numbers of output and was calculated in accordance with (13) – (15)

$Y(1)=O1$ (13)

$Y(2)=O2$ (14)

Output $Y(n) = Y1 + Y2 + \ldots\ Yn$ (15)

The average of the sum of these errors were minimized using (16)

$$MSE = 2\frac{1}{n}\sum_{i=1}^{n}(Tq - Nq) \quad (16)$$

Where Tq is the target output, Nq is the Network output

Thereafter, the Training and simulation of the defined network was carried with MATLAB 2015 programming language. The codes were defined for the entire nine substations and a sample of the parameters used are presented herewith.

```
% into training, validation and test sets according to timesteps.

% for a list of data division modes type: help nntype_data_division_mode

net.divideMode='value';

% Divide up every value

net.divideParam.trainRatio=80/100;

net.divideParam.valRatio= 10/100;

net.divideParam.testRatio = 10/100;
```

From the above codes written, the model will make use 80% of the whole data for training, use 10% of the data for validation and 10% for test the model for minimal error and prediction for each substation.

Figure 2 represents the flow chart of the ANN process.

The Mean Squared Error (MSE) is a measure of how close a fitted line is to data points. For every data point, you take the distance vertically from the point to the corresponding y value on the curve fit (the error), and square the value the squaring is done so negative values do not cancel positive values. The smaller the Mean Squared Error, the closer the fit is to the data. It is this preference that gave rise to the use of MSE for this study. The MSE has the units squared of whatever is plotted on the vertical axis.

Mean square error the average squared error between the target outputs (Tq) and the network outputs (Nq).Mean square error (MSE) algorithm is an example of supervised training, in which the learning rule is provided with a set of examples of desired network behavior. As each input is applied to the network, the network output is compared to the target. The error is calculated as the difference between the target output and the network output. We want to minimize the average of the sum of these errors.

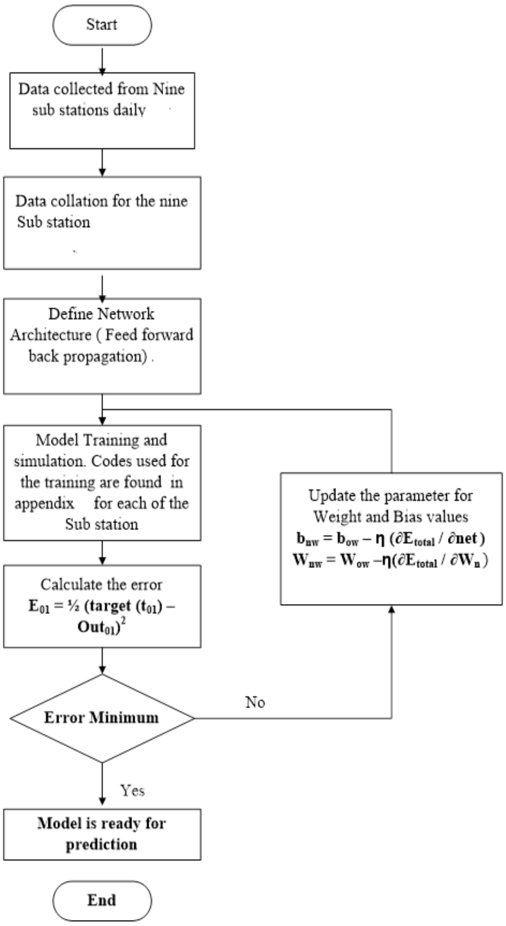


Fig. 2. Flowchart for the Model neural network

4. Results and Discussion

Table 2. Central Area weekly forecast for 2018-2022

YEAR	2018	2019	2020	2021	2022
Week 1	55.81	53.95	53.17	57.05	55.60
Week 2	64.83	56.27	57.12	59.40	74.88
Week 3	62.80	49.70	52.42	60.52	80.29
Week 4	60.74	53.87	56.56	73.60	72.02
Week 5	59.15	52.82	55.35	69.94	78.89
Week 6	56.13	62.38	59.35	67.84	70.56
Week 7	57.73	59.85	57.01	64.62	77.26
Week 8	59.57	55.82	62.00	68.17	77.64
Week 9	59.85	56.77	61.73	54.91	88.58
Week 10	60.68	60.66	56.70	62.04	80.28
Week 11	59.67	63.37	60.72	58.20	79.20
Week 12	59.01	62.04	63.59	51.54	78.20
Week 13	59.12	60.21	63.18	58.13	75.88
Week 14	59.08	59.55	63.68	63.01	79.32
Week 15	59.70	60.98	64.05	55.91	77.40
Week 16	59.98	62.04	63.16	61.20	78.23
Week 17	59.92	61.67	63.60	63.89	78.10
Week 18	59.97	60.98	64.23	54.74	77.18
Week 19	59.79	60.77	64.33	56.67	78.10
Week 20	59.83	61.39	64.40	62.18	77.45
Week 21	59.98	61.86	64.47	54.92	77.75
Week 22	60.06	61.81	64.40	56.96	77.80
Week 23	60.22	61.55	64.45	64.21	77.53
Week 24	60.26	61.50	64.58	57.63	77.80
Week 25	60.29	61.78	64.66	56.24	77.60
Week 26	60.34	62.03	64.71	63.28	77.67
Week 27	60.37	62.07	64.76	57.33	77.70
Week 28	60.45	61.99	64.79	54.13	77.62
Week 29	60.53	62.01	64.84	62.65	77.70
Week 30	60.59	62.16	64.89	59.18	77.64
Week 31	60.67	62.32	64.95	54.38	77.65
Week 32	60.71	62.39	65.00	62.76	77.66
Week 33	60.77	62.40	65.05	60.59	77.64
Week 34	60.83	62.44	65.09	53.41	77.66
Week 35	60.89	62.54	65.14	61.23	77.64
Week 36	60.95	62.66	65.19	61.27	77.64
Week 37	61.01	62.73	65.24	53.06	77.64
Week 38	61.07	62.77	65.28	60.43	77.63
Week 39	61.13	62.83	65.33	62.76	77.64
Week 40	61.19	62.92	65.38	53.52	77.63
Week 41	61.24	63.01	65.42	59.26	77.63
Week 42	61.30	63.08	65.47	63.43	77.63
Week 43	61.36	63.14	65.52	53.62	77.62
Week 44	61.41	63.21	65.56	57.63	77.62
Week 45	61.47	63.28	65.61	63.99	77.62
Week 46	61.52	63.36	65.66	54.55	77.62
Week 47	61.58	63.44	65.70	56.44	77.61
Week 48	61.63	63.50	65.75	64.48	77.61
Week 49	61.68	63.57	65.79	55.69	77.61
Week 50	61.74	63.64	65.84	54.94	77.60
Week 51	61.79	63.72	65.88	64.34	77.60
Week 52	61.84	63.79	65.92	56.93	77.60
Week 53	61.89	63.86	65.97	53.61	77.60

Table 3. Karu weekly forecast for 2018-2022

YEAR	2018	2019	2020	2021	2022
Week 1	65.84	53.91	68.36	75.80	68.28
Week 2	68.83	61.47	81.07	78.27	133.55
Week 3	74.89	64.83	84.98	87.33	141.52
Week 4	77.22	62.57	80.02	90.63	53.43
Week 5	67.07	76.92	67.47	95.93	128.19
Week 6	67.84	79.09	44.81	109.81	83.57
Week 7	78.09	86.14	71.99	96.32	36.42
Week 8	77.59	95.59	68.02	91.32	96.22
Week 9	69.90	102.11	69.21	102.59	100.41
Week 10	71.60	99.09	89.71	120.72	108.70
Week 11	77.61	110.52	87.88	103.13	126.39
Week 12	78.13	112.97	88.71	107.97	106.37
Week 13	73.19	108.69	91.19	112.19	100.28
Week 14	72.08	112.64	89.73	111.86	148.94
Week 15	76.15	114.88	92.86	102.73	82.92
Week 16	77.88	110.32	83.14	110.70	104.46
Week 17	74.48	110.47	76.03	108.90	167.63
Week 18	72.18	112.76	66.75	107.64	63.17
Week 19	74.23	110.72	57.87	106.17	94.31
Week 20	76.49	108.63	59.06	111.14	158.98
Week 21	75.15	111.07	60.52	107.50	55.60
Week 22	72.61	111.49	75.78	108.45	90.35
Week 23	73.46	109.05	87.27	108.62	148.41
Week 24	75.67	110.75	88.43	110.25	55.86
Week 25	75.58	112.45	91.81	107.74	98.70
Week 26	73.53	110.88	95.12	109.64	152.13
Week 27	73.05	111.15	97.02	109.25	64.26
Week 28	74.61	113.03	95.17	109.71	106.68
Week 29	75.20	112.62	87.60	108.72	159.55
Week 30	73.77	111.81	77.55	110.23	69.06
Week 31	72.70	113.16	65.08	109.44	106.04

Week 32	73.53	113.61	56.09	109.91	161.59
Week 33	74.56	112.61	53.15	109.63	66.76
Week 34	73.98	113.15	56.86	110.45	101.25
Week 35	72.83	114.00	72.95	109.80	159.30
Week 36	73.05	113.46	87.18	110.39	63.91
Week 37	74.04	113.35	89.13	110.24	99.02
Week 38	74.02	114.17	92.25	110.66	158.69
Week 39	72.98	114.20	96.61	110.33	64.34
Week 40	72.57	113.84	98.35	110.86	98.89
Week 41	73.23	114.36	96.96	110.69	161.66
Week 42	73.57	114.74	89.15	110.99	65.76
Week 43	72.88	114.48	78.04	110.88	96.86
Week 44	72.24	114.65	64.99	111.26	164.91
Week 45	72.59	115.12	55.48	111.13	65.09
Week 46	73.17	115.09	52.78	111.41	91.60
Week 47	72.91	115.06	56.62	111.38	165.60
Week 48	72.22	115.42	73.13	111.64	62.98
Week 49	72.19	115.59	88.09	111.59	86.19
Week 50	72.69	115.54	90.23	111.84	164.75
Week 51	72.70	115.74	93.24	111.85	61.74
Week 52	72.06	115.99	97.23	112.04	83.79
Week 53	71.72	116.02	98.66	112.06	165.61

Table 4. Katampe weekly forecast for 2018-2022

WEEKS	2018	2019	2020	2021	2022
Week 1	70.5	73.44	72.17	78.81	74.11
Week 2	70.26	76.12	77.80	74.80	71.73
Week 3	66.93	74.03	109.35	69.53	87.50
Week 4	67.65	73.66	101.45	77.51	83.66
Week 5	69.82	68.90	84.52	75.30	107.45
Week 6	73.07	75.67	75.87	76.13	77.26
Week 7	72.11	78.00	83.76	78.29	77.87
Week 8	73.54	76.51	65.69	78.51	73.48
Week 9	74.99	72.94	66.97	77.82	72.15
Week 10	73.67	74.64	74.35	80.55	84.56
Week 11	71.91	71.26	69.63	81.00	121.40
Week 12	72.28	71.17	74.61	82.06	90.67
Week 13	71.38	73.45	68.27	83.74	108.86
Week 14	70.47	72.94	70.97	84.61	73.67
Week 15	71.44	73.18	72.02	85.74	92.85
Week 16	71.44	73.18	72.02	85.74	92.85
Week 17	71.03	72.05	73.76	85.54	111.67
Week 18	71.92	72.72	72.45	84.83	123.15
Week 19	71.92	72.72	72.45	84.83	123.15
Week 20	71.39	72.56	75.02	84.28	75.75
Week 21	71.95	71.01	71.75	84.10	77.59
Week 22	71.84	72.78	72.67	84.25	89.51
Week 23	71.30	72.31	72.08	84.53	109.01
Week 24	71.74	71.25	72.85	85.09	115.48
Week 25	71.70	72.57	73.98	85.66	136.88
Week 26	71.28	72.49	71.86	86.09	77.76
Week 27	71.67	71.28	72.63	86.41	85.39
Week 28	71.69	72.65	72.81	86.54	77.99
Week 29	71.33	72.39	72.94	86.48	107.77
Week 30	71.65	71.46	73.33	86.38	110.87
Week 31	71.68	72.58	72.16	86.28	144.68
Week 32	71.35	72.47	72.80	86.24	77.88
Week 33	71.60	71.52	73.07	86.34	103.33
Week 34	71.63	72.66	72.85	86.52	72.21
Week 35	71.34	72.41	72.99	86.76	105.20
Week 36	71.55	71.66	72.47	87.01	105.53
Week 37	71.59	72.66	72.92	87.22	143.23
Week 38	71.34	72.45	73.08	87.35	76.53
Week 39	71.51	71.74	72.79	87.43	110.61
Week 40	71.56	72.76	72.89	87.46	71.97
Week 41	71.33	72.42	72.72	87.48	104.40
Week 42	71.47	71.87	72.97	87.51	102.85
Week 43	71.52	72.79	73.02	87.58	141.95
Week 44	71.32	72.45	72.79	87.67	75.61
Week 45	71.44	71.96	72.90	87.79	114.81
Week 46	71.49	72.89	72.88	87.90	72.14
Week 47	71.30	72.43	72.98	87.99	106.05
Week 48	71.40	72.10	72.97	88.06	100.86
Week 49	71.45	72.94	72.84	88.12	141.54
Week 50	71.28	72.46	72.94	88.16	74.79
Week 51	71.37	72.21	72.95	88.20	118.90
Week 52	71.41	73.02	72.97	88.24	72.24

Table 5. Apo weekly forecast for 2018-2022

YEAR	2018	2019	2020	2021	2022
Week 1	113.60	117.23	118.29	131.07	128.52
Week 2	115.25	115.77	128.53	124.79	158.27
Week 3	112.39	126.22	126.06	131.39	166.83
Week 4	113.47	123.74	126.10	129.76	137.64
Week 5	111.79	112.88	134.89	137.18	158.29
Week 6	111.98	112.59	131.04	131.96	176.43
Week 7	113.95	116.53	141.83	137.67	159.29
Week 8	112.85	116.23	131.38	137.59	141.81
Week 9	113.68	119.77	118.06	139.20	163.80
Week 10	114.17	116.66	133.54	134.08	169.05
Week 11	113.86	119.09	117.00	132.99	167.32
Week 12	114.11	120.48	132.12	131.57	165.44
Week 13	113.81	122.45	118.98	131.57	164.91
Week 14	113.82	121.42	135.47	130.84	166.68
Week 15	113.75	122.81	121.59	131.25	166.24
Week 16	113.50	123.86	136.46	130.95	165.95
Week 17	113.61	125.04	121.29	130.98	165.98
Week 18	113.53	124.63	134.80	130.82	166.09
Week 19	113.51	125.42	119.89	130.87	166.25
Week 20	113.57	126.06	134.28	130.74	166.21
Week 21	113.55	126.62	120.40	130.74	166.26
Week 22	113.59	126.33	135.77	130.68	166.32
Week 23	113.59	126.77	121.83	130.65	166.37
Week 24	113.58	127.15	136.84	130.59	166.42
Week 25	113.60	127.37	122.12	130.57	166.45
Week 26	113.57	127.17	136.54	130.52	166.50
Week 27	113.56	127.44	121.56	130.48	166.54
Week 28	113.55	127.68	136.31	130.44	166.59
Week 29	113.54	127.77	121.63	130.40	166.63
Week 30	113.53	127.66	137.06	130.36	166.67
Week 31	113.52	127.86	122.35	130.33	166.71
Week 32	113.52	128.03	137.91	130.29	166.75
Week 33	113.52	128.08	122.74	130.25	166.79
Week 34	113.52	128.03	138.16	130.21	166.83
Week 35	113.52	128.20	122.61	130.17	166.87
Week 36	113.51	128.33	138.23	130.13	166.91
Week 37	113.51	128.36	122.62	130.09	166.95
Week 38	113.51	128.37	138.69	130.06	166.99
Week 39	113.50	128.50	122.99	130.02	167.02
Week 40	113.50	128.60	139.34	129.98	167.06
Week 41	113.50	128.64	123.33	129.95	167.10
Week 42	113.50	128.68	139.76	129.91	167.13
Week 43	113.50	128.79	123.42	129.87	167.17
Week 44	113.49	128.87	140.01	129.83	167.20
Week 45	113.49	128.91	123.49	129.80	167.24
Week 46	113.49	128.97	140.37	129.76	167.27
Week 47	113.49	129.07	123.73	129.73	167.30

Week 48	113.49	129.14	140.86	129.69	167.34
Week 49	113.49	129.18	124.03	129.65	167.37
Week 50	113.49	129.25	141.29	129.62	167.40
Week 51	113.49	129.33	124.23	129.58	167.44
Week 52	113.49	129.39	141.60	129.55	167.47
Week 53	113.49	129.45	124.40	129.51	167.50

Table 6. Kubwa weekly forecast for 2018-2022

YEAR	2018	2019	2020	2021	2022
Week 1	51.54	54.21	52.08	60.66	50.75
Week 2	59.48	58.40	36.36	61.83	71.89
Week 3	61.69	60.89	47.16	70.07	106.55
Week 4	65.38	60.58	59.56	75.44	75.66
Week 5	64.62	53.47	62.05	76.01	66.56
Week 6	64.48	54.14	61.79	77.05	74.28
Week 7	63.19	48.29	67.24	72.22	79.16
Week 8	61.94	54.39	65.69	69.17	80.32
Week 9	60.86	46.08	60.80	64.82	48.78
Week 10	58.85	55.33	67.19	67.10	84.36
Week 11	58.76	57.34	64.38	65.95	83.62
Week 12	58.34	63.04	61.83	67.49	81.39
Week 13	59.36	60.06	66.95	69.78	81.52
Week 14	60.44	66.27	66.16	70.44	80.47
Week 15	61.49	61.26	61.56	71.99	96.49
Week 16	62.49	60.40	67.33	71.13	85.74
Week 17	62.59	53.84	65.72	71.58	83.02
Week 18	62.75	53.91	62.18	70.73	88.59
Week 19	62.34	49.11	66.64	70.05	89.54
Week 20	62.04	50.43	66.50	70.03	89.59
Week 21	61.63	51.95	61.95	69.25	81.68
Week 22	61.29	56.49	66.74	69.88	86.77
Week 23	61.21	58.49	66.36	69.57	91.11
Week 24	61.15	62.01	62.42	70.12	84.96
Week 25	61.37	62.41	66.00	70.35	83.96
Week 26	61.54	62.51	66.76	70.34	86.07
Week 27	61.78	59.10	62.23	70.76	89.59
Week 28	61.94	56.91	65.76	70.41	86.24
Week 29	62.03	52.91	66.69	70.68	83.25
Week 30	62.07	51.21	62.59	70.42	87.26
Week 31	62.03	49.90	64.96	70.42	88.73
Week 32	62.01	52.03	66.93	70.48	85.92
Week 33	61.96	54.20	62.48	70.31	84.35
Week 34	61.94	57.90	64.45	70.57	86.74
Week 35	61.94	59.79	66.88	70.42	88.73
Week 36	61.96	61.91	62.77	70.62	85.62
Week 37	62.00	60.84	63.55	70.62	84.67
Week 38	62.03	59.86	67.03	70.63	87.00
Week 39	62.07	56.27	62.78	70.76	87.96
Week 40	62.10	54.21	62.85	70.65	85.83
Week 41	62.13	51.11	66.95	70.79	84.89
Week 42	62.15	51.06	63.06	70.71	86.98
Week 43	62.16	51.08	61.90	70.77	87.73
Week 44	62.18	54.19	66.99	70.80	85.69
Week 45	62.19	55.99	63.18	70.77	85.28
Week 46	62.21	59.43	61.16	70.87	86.90
Week 47	62.22	59.61	66.79	70.82	87.44
Week 48	62.24	60.95	63.50	70.91	85.78
Week 49	62.25	58.08	60.29	70.91	85.45
Week 50	62.27	57.24	66.61	70.93	86.92
Week 51	62.29	53.19	63.71	70.98	87.17
Week 52	62.30	52.77	59.69	70.96	85.82
Week 53	62.31	50.24	66.17	71.03	85.66

Table 7. Keffi weekly forecast for 2018-2022

YEAR	2018	2019	2020	2021	2022
Week 1	19.36	19.67	19.00	22.69	17.93
Week 2	18.32	16.78	19.87	38.08	15.47
Week 3	21.05	16.67	24.08	38.93	18.70
Week 4	18.28	18.17	19.75	22.23	13.14
Week 5	18.25	18.01	23.79	15.21	19.34
Week 6	19.39	21.23	30.07	8.80	25.57
Week 7	19.50	20.18	26.18	6.00	8.17
Week 8	19.01	18.57	27.27	23.02	15.57
Week 9	20.07	19.54	25.95	6.13	21.00
Week 10	19.29	22.21	23.21	27.14	30.24
Week 11	19.25	21.72	28.53	23.93	28.93
Week 12	19.53	22.41	29.23	29.86	36.74
Week 13	19.64	22.13	29.41	24.85	15.54
Week 14	19.54	21.65	29.38	20.73	25.64
Week 15	19.88	22.02	28.17	12.55	28.09
Week 16	19.72	22.90	27.56	18.36	28.40
Week 17	19.73	22.69	28.79	26.45	29.47
Week 18	19.83	22.81	28.96	24.39	39.43
Week 19	19.89	22.80	29.45	24.78	21.95
Week 20	19.90	22.69	29.38	25.38	29.24
Week 21	20.03	22.81	29.03	21.29	27.89
Week 22	20.03	23.08	28.90	18.15	27.55
Week 23	20.06	23.04	29.10	22.39	28.28
Week 24	20.12	23.07	29.22	27.35	36.36
Week 25	20.16	23.11	29.45	26.80	25.91
Week 26	20.20	23.11	29.47	24.94	30.79
Week 27	20.27	23.15	29.43	20.50	27.74
Week 28	20.30	23.26	29.41	17.09	27.54
Week 29	20.34	23.27	29.46	21.15	28.01
Week 30	20.39	23.29	29.53	26.99	31.75
Week 31	20.43	23.33	29.63	26.56	27.51
Week 32	20.47	23.35	29.67	25.83	30.63
Week 33	20.52	23.39	29.70	22.35	28.16
Week 34	20.56	23.44	29.73	17.95	28.10
Week 35	20.60	23.46	29.77	19.44	28.19
Week 36	20.64	23.49	29.82	26.30	29.46
Week 37	20.68	23.52	29.87	27.05	28.14
Week 38	20.72	23.55	29.91	26.04	29.81
Week 39	20.76	23.58	29.95	23.55	28.55
Week 40	20.80	23.61	29.99	19.26	28.61
Week 41	20.84	23.64	30.03	18.78	28.52
Week 42	20.88	23.67	30.07	25.09	28.88
Week 43	20.92	23.70	30.11	27.35	28.45
Week 44	20.95	23.72	30.15	26.32	29.23
Week 45	20.99	23.75	30.19	24.53	28.72
Week 46	21.03	23.78	30.23	20.53	28.83
Week 47	21.06	23.80	30.26	18.73	28.76
Week 48	21.10	23.83	30.30	23.84	28.84
Week 49	21.14	23.85	30.34	27.36	28.68
Week 50	21.17	23.88	30.38	26.56	29.00
Week 51	21.21	23.90	30.41	25.25	28.82
Week 52	21.24	23.92	30.45	21.80	28.90
Week 53	21.28	23.95	30.48	19.21	28.88

Table 8. Akwanga weekly forecast for 2018-2022

YEAR	2018	2019	2020	2021	2022
Week 1	19.12	21.00	19.51	18.12	19.25
Week 2	21.07	20.88	16.37	23.72	13.59
Week 3	20.68	19.89	16.50	18.91	21.58
Week 4	20.92	21.95	13.61	14.91	24.94
Week 5	21.00	21.60	14.99	22.87	19.63
Week 6	21.56	20.77	14.13	10.96	24.81
Week 7	21.54	23.39	11.70	11.77	22.99
Week 8	23.54	23.14	13.73	11.88	22.48

Week 9	23.81	22.86	23.22	7.37	20.49
Week 10	24.26	24.17	23.26	12.94	22.59
Week 11	24.30	24.77	23.50	20.05	22.01
Week 12	26.01	24.20	25.40	19.41	21.03
Week 13	26.85	24.93	20.36	25.89	21.53
Week 14	27.79	24.88	24.86	24.32	21.30
Week 15	28.32	24.49	29.81	27.44	21.41
Week 16	29.10	24.81	25.43	32.19	21.48
Week 17	29.80	24.88	27.88	32.67	21.26
Week 18	29.21	24.69	29.16	32.23	21.37
Week 19	28.56	24.88	26.12	35.78	21.39
Week 20	27.57	24.98	28.56	33.53	21.36
Week 21	26.52	24.88	31.39	32.68	21.40
Week 22	25.31	24.97	29.24	35.21	21.38
Week 23	24.72	25.05	30.81	33.74	21.39
Week 24	25.31	25.01	33.53	32.04	21.41
Week 25	26.19	25.05	31.99	35.89	21.41
Week 26	27.09	25.13	33.46	33.61	21.42
Week 27	27.93	25.13	37.14	32.47	21.43
Week 28	28.84	25.15	36.35	35.77	21.43
Week 29	29.85	25.21	37.37	34.08	21.45
Week 30	30.55	25.22	41.11	31.86	21.45
Week 31	30.75	25.24	40.48	36.27	21.46
Week 32	30.44	25.29	39.46	33.80	21.47
Week 33	29.78	25.31	41.91	32.01	21.48
Week 34	28.75	25.33	41.54	36.17	21.49
Week 35	27.32	25.36	37.66	34.24	21.49
Week 36	25.93	25.39	38.57	31.44	21.50
Week 37	25.29	25.41	40.52	36.68	21.51
Week 38	25.65	25.44	35.84	34.06	21.52
Week 39	26.54	25.46	34.50	31.46	21.53
Week 40	27.55	25.48	40.49	36.67	21.54
Week 41	28.51	25.51	38.17	34.46	21.55
Week 42	29.50	25.53	33.07	30.86	21.55
Week 43	30.69	25.55	40.93	37.17	21.56
Week 44	31.76	25.57	41.57	34.37	21.57
Week 45	32.23	25.59	34.09	30.75	21.58
Week 46	31.98	25.61	38.52	37.27	21.59
Week 47	31.26	25.63	42.60	34.73	21.60
Week 48	30.26	25.65	36.10	30.10	21.61
Week 49	28.91	25.67	33.46	37.79	21.61
Week 50	27.23	25.68	43.10	34.72	21.62
Week 51	25.86	25.70	39.67	29.84	21.63
Week 52	25.73	25.72	30.41	38.01	21.64
Week 53	26.59	25.73	41.63	35.05	21.65

Table 9. Seluja weekly forecast for 2018-2022

YEAR	2018	2019	2020	2021	2022
Week 1	39.96	41.67	38.13	45.31	41.41
Week 2	43.10	37.65	38.43	38.01	42.20
Week 3	44.65	41.94	40.35	45.40	45.97
Week 4	42.54	41.91	40.35	49.00	48.45
Week 5	41.36	36.42	40.40	45.18	43.73
Week 6	42.84	41.49	40.28	56.74	42.47
Week 7	41.22	36.95	41.37	50.37	37.94
Week 8	37.68	38.40	39.47	46.15	38.57
Week 9	38.12	40.42	37.81	46.63	34.94
Week 10	39.17	34.59	37.51	57.85	47.31
Week 11	37.31	40.75	41.52	49.63	50.58
Week 12	37.41	35.23	43.26	39.30	50.28
Week 13	40.46	36.88	39.68	32.15	43.84
Week 14	40.82	44.05	38.05	34.54	46.31
Week 15	39.83	34.34	41.47	36.96	46.70
Week 16	41.44	38.82	42.88	36.65	49.60
Week 17	42.42	36.39	42.06	41.71	50.36
Week 18	40.53	36.39	38.78	56.74	50.90
Week 19	39.60	46.84	38.52	64.73	49.69
Week 20	40.63	32.66	40.80	53.95	50.01
Week 21	39.46	34.80	42.47	45.77	49.67
Week 22	37.36	39.13	41.45	40.04	49.76
Week 23	38.47	34.01	38.75	35.93	49.74
Week 24	39.63	45.71	39.38	34.73	50.11
Week 25	38.50	32.38	41.88	35.44	50.05
Week 26	38.93	34.28	43.07	37.35	50.11
Week 27	41.00	47.32	40.50	43.52	50.06
Week 28	40.67	32.01	38.19	57.03	50.07
Week 29	39.45	35.45	40.74	65.03	50.00
Week 30	40.48	32.43	42.39	54.21	50.04
Week 31	40.72	36.39	42.18	46.03	50.04
Week 32	38.65	51.11	39.00	39.26	50.07
Week 33	38.23	32.50	37.98	34.94	50.08
Week 34	39.51	30.79	41.20	34.99	50.11
Week 35	38.66	40.81	42.88	35.52	50.10
Week 36	37.68	34.53	40.46	37.27	50.11
Week 37	39.49	45.82	38.15	43.22	50.11
Week 38	40.28	31.95	39.88	57.11	50.12
Week 39	39.00	33.67	42.54	65.55	50.13
Week 40	39.51	49.11	42.98	55.71	50.14
Week 41	40.81	31.33	39.10	46.45	50.15
Week 42	39.48	34.69	37.77	39.23	50.16
Week 43	38.18	32.67	41.25	34.39	50.16
Week 44	39.42	35.94	42.93	35.12	50.17
Week 45	39.26	51.74	40.30	35.52	50.18
Week 46	37.49	31.73	38.07	36.89	50.19
Week 47	38.40	30.08	39.65	42.32	50.19
Week 48	39.95	42.75	42.62	55.75	50.20
Week 49	38.83	34.07	43.00	65.99	50.21
Week 50	38.48	44.54	38.94	58.29	50.22
Week 51	40.38	31.79	37.76	47.34	50.22
Week 52	39.95	35.62	41.50	40.08	50.23
Week 53	38.08	50.59	43.10	33.69	50.24

Table 10. Gwagwalada weekly forecasts for year 2018 to 2022

YEAR	2018	2019	2020	2021	2022
Week 1	33.39	34.19	33.07	32.68	34.04
Week 2	35.57	40.51	33.19	35.06	38.29
Week 3	35.46	40.78	33.98	32.76	42.75
Week 4	38.30	38.87	31.95	33.97	49.38
Week 5	35.13	40.02	33.24	33.35	32.35
Week 6	36.97	38.63	32.12	39.23	30.33
Week 7	35.52	34.37	32.99	37.69	27.96
Week 8	34.06	33.34	34.40	36.10	45.21
Week 9	34.23	35.66	41.81	40.83	49.76
Week 10	32.93	39.16	44.17	39.93	47.96
Week 11	34.21	37.85	39.49	39.47	35.59
Week 12	34.12	38.73	42.93	40.10	32.63
Week 13	34.85	38.59	42.65	36.62	33.21
Week 14	35.66	37.55	38.88	40.50	40.32
Week 15	35.59	36.84	40.14	36.77	44.44
Week 16	36.11	37.26	41.15	37.68	44.60
Week 17	35.67	37.31	39.00	40.68	37.38
Week 18	35.53	37.58	39.80	35.11	34.84
Week 19	35.23	38.15	41.08	40.46	35.00
Week 20	34.82	38.38	39.86	39.22	38.48
Week 21	34.85	38.22	40.13	38.57	41.16
Week 22	34.74	38.15	41.14	40.68	41.63
Week 23	35.02	38.08	40.37	35.62	38.00
Week 24	35.24	37.97	40.31	40.63	36.16
Week 25	35.45	38.03	41.05	39.72	35.99
Week 26	35.69	38.22	40.63	37.09	37.79
Week 27	35.71	38.36	40.48	40.74	39.34

Week 28	35.74	38.47	41.02	36.26	39.73
Week 29	35.63	38.56	40.85	40.33	38.02
Week 30	35.52	38.59	40.68	40.55	36.86
Week 31	35.44	38.57	41.07	36.36	36.62
Week 32	35.37	38.59	41.04	40.78	37.52
Week 33	35.41	38.64	40.89	37.39	38.38
Week 34	35.47	38.70	41.16	39.99	38.63
Week 35	35.58	38.79	41.20	40.68	37.85
Week 36	35.69	38.89	41.09	36.21	37.18
Week 37	35.78	38.96	41.27	40.80	36.97
Week 38	35.84	39.01	41.35	39.07	37.40
Week 39	35.84	39.06	41.28	39.62	37.85
Week 40	35.83	39.10	41.40	40.69	38.00
Week 41	35.80	39.15	41.49	37.28	37.64
Week 42	35.78	39.21	41.46	40.74	37.27
Week 43	35.78	39.28	41.54	40.19	37.12
Week 44	35.79	39.35	41.64	39.56	37.31
Week 45	35.84	39.42	41.63	40.67	37.54
Week 46	35.89	39.48	41.69	38.84	37.62
Week 47	35.95	39.54	41.78	40.61	37.44
Week 48	36.00	39.60	41.79	40.43	37.24
Week 49	36.03	39.65	41.84	39.82	37.14
Week 50	36.05	39.71	41.93	40.63	37.21
Week 51	36.06	39.77	41.95	40.00	37.32
Week 52	36.06	39.84	42.00	40.49	37.35
Week 53	36.07	39.90	42.08	40.48	37.27

Figures 3 - 6 shows the plots of the weekly demand prediction for Katampe sub station for year 2018 to 2022. The average (MW), maximim (MW) and minimum (MW) result are listed. The results show an average weekly prediction of 71.39MW, maximum demand prediction 74.99MW and minimum demand Prediction of 69.53MW

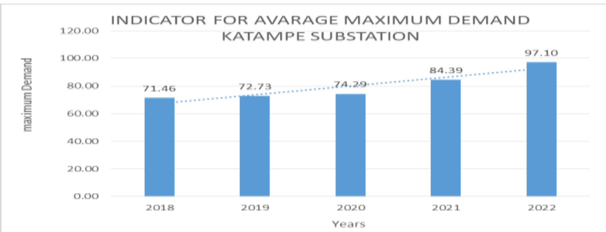


Fig. 3. Plot of indicator for average maximum demand of katampe sub-station

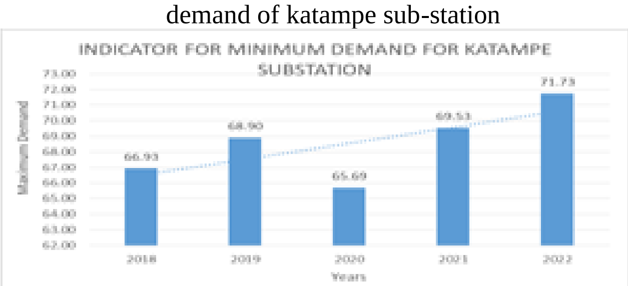


Fig. 4. Plot of indicator for average minimum demand of katampe sub-station

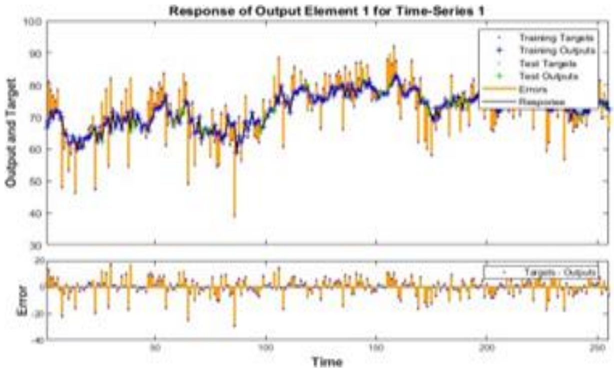


Fig. 5. Plot of Figure of Output, Target and Error for Katampe Sub-station

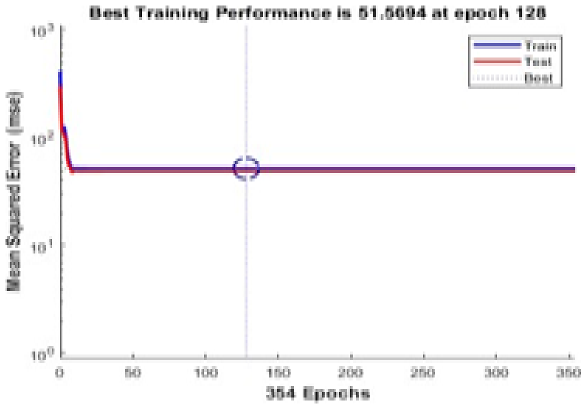


Fig. 6. Plot of Training Performance for Katampe Sub-station

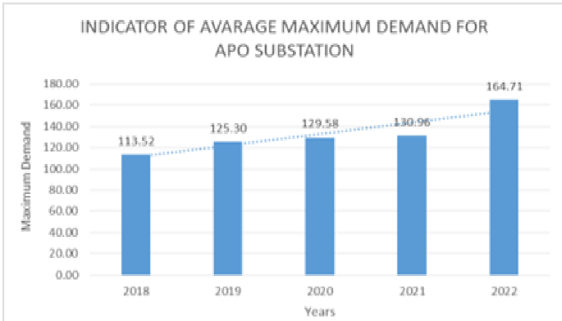


Fig. 7. Plot of indicator for average maximum demand of Apo sub-station

Figures 8 - 10 shows the plots of the weekly damand prediction for Apo sub station respectively for year 2018 to 2022. The average (MW), maximim (MW) and minimum (MW) result are listed. The results show an average weekly prediction of weekly prediction of 113.52MW, maximum prediction of 115.25MW and minimum Prediction of 111.79MW.

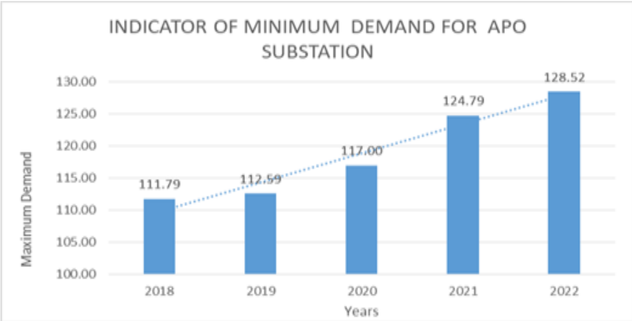


Fig. 8. Plot of indicator for minimum demand of Apo sub-station

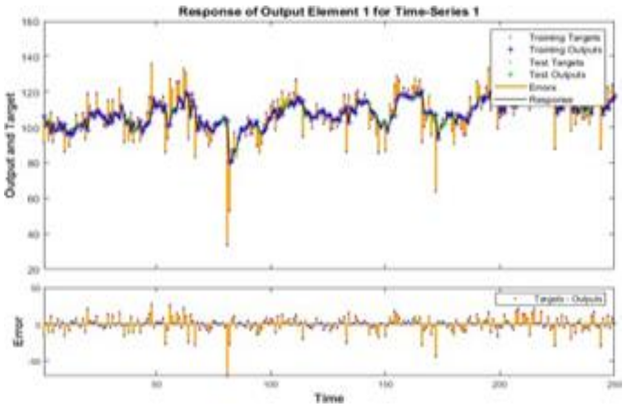


Fig. 9. Plot of Output, Target and Error for Apo Sub-station

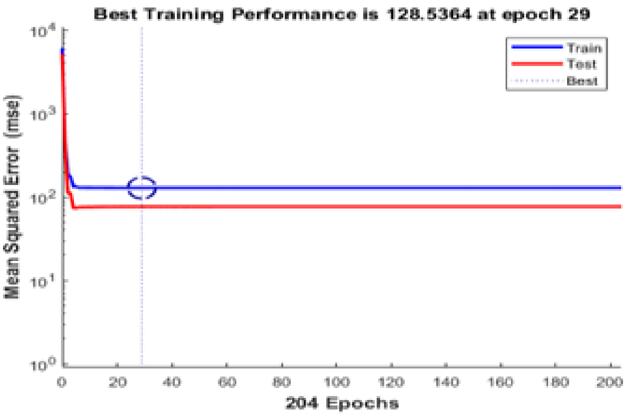


Fig. 10. Plot of Training Performance for Apo Sub-station

Figures 11-14 shows the plots of the weekly damand prediction for Kubwa sub station respectively for year 2018 to 2022. The average (MW), maximim (MW) and minimum (MW) result are listed. The results show an average weekly prediction of weekly prediction of 61.65MW, maximum prediction of 65.38 and minimum Prediction of 51.54MW.

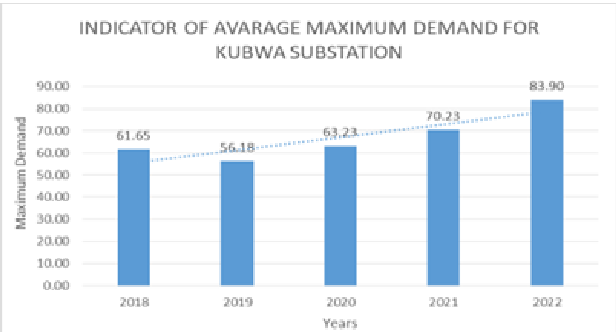


Fig. 11. Plot of indicator for average maximum demand of Kubwa sub-station

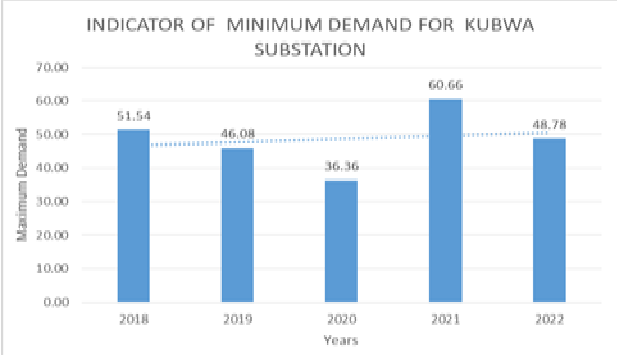


Fig. 12. Plot of indicator for minimum demand of Kubwa sub-station

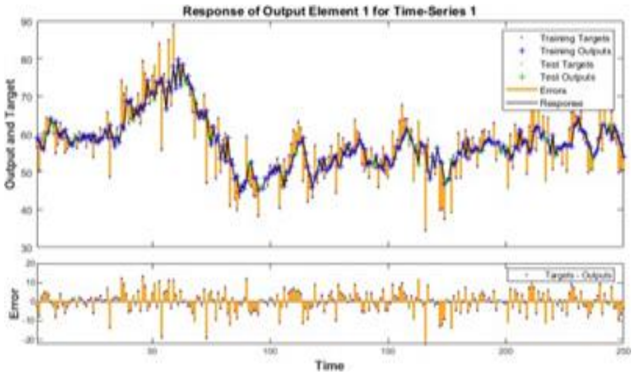


Fig. 13. Plot of Output, Target and Error for Kubwa Sub-station

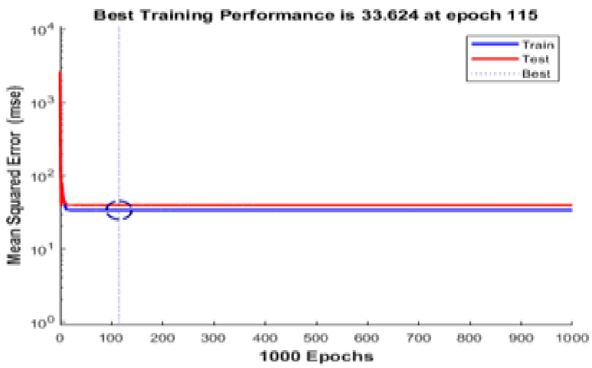


Fig. 14. Plot of Training Performance for Kubwa Sub-station

Figures 15-18 show the plots of the weekly damand prediction for Central area sub station respectively for year 2018 to 2022. The average (MW), maximim (MW) and minimum (MW) result are listed. The results show an average weekly prediction of weekly prediction of 73.4MW, maximum prediction of 78.13MW and minimum Prediction of 65.84MW.

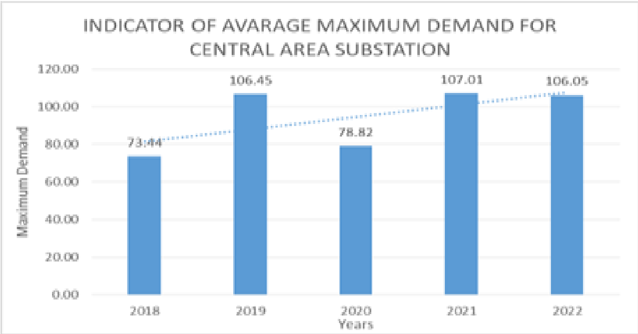


Fig. 15. Plot of indicator for average maximum demand of Central Area sub-station

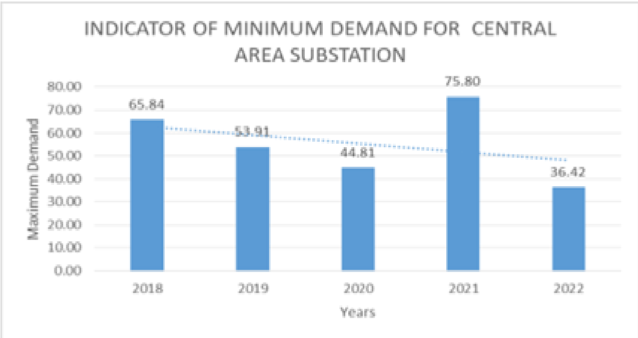


Fig. 16. Plot of indicator for minimum demand of Central Area sub-station

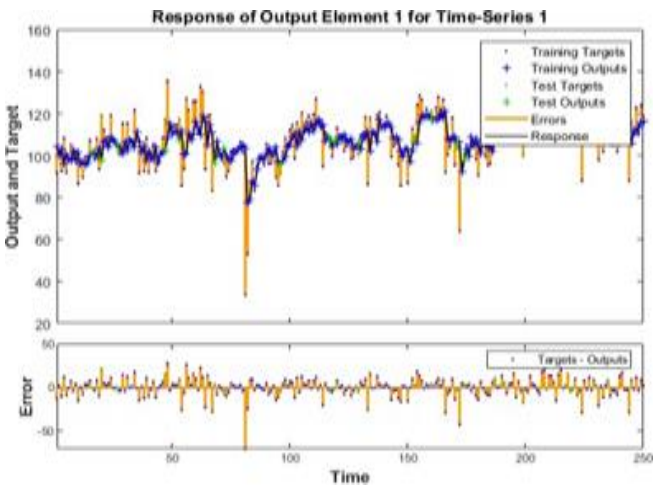


Fig. 17. Plot of Output, Target and Error for Central Area Sub-station

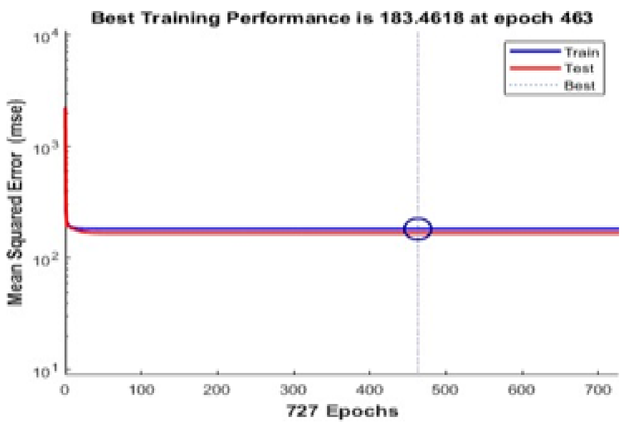


Fig. 18. Plot of Training Performance for Central Area Sub-station

Figures 19-22 show the plots of the weekly demand prediction for karu sub station respectively for year 2018 to 2022. The average (MW), maximim (MW) and minimum (MW) result are listed. The results show an average weekly prediction of weekly prediction of 60.49MW, maximum prediction of 64.83MW and minimum Prediction of 55.81MW.

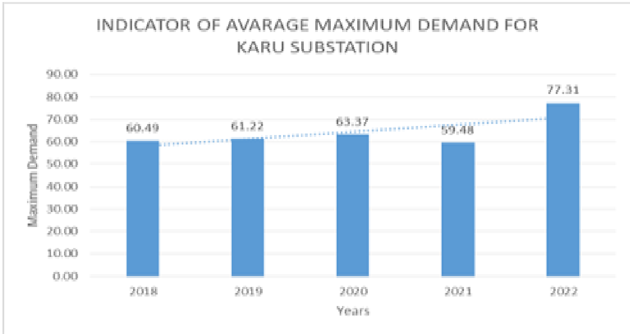


Fig. 19. Plot of indicator for average maximum demand of Karu sub-station

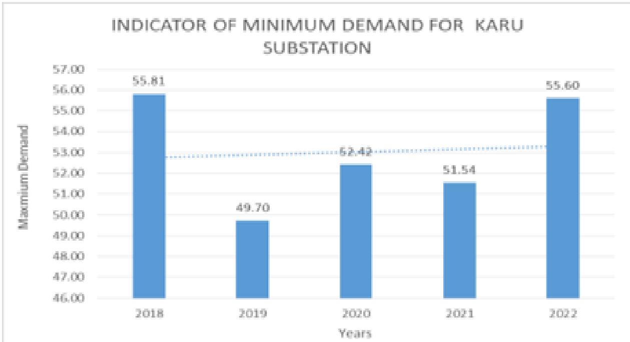


Fig. 20. Plot of indicator for minimum demand of Karu sub-station

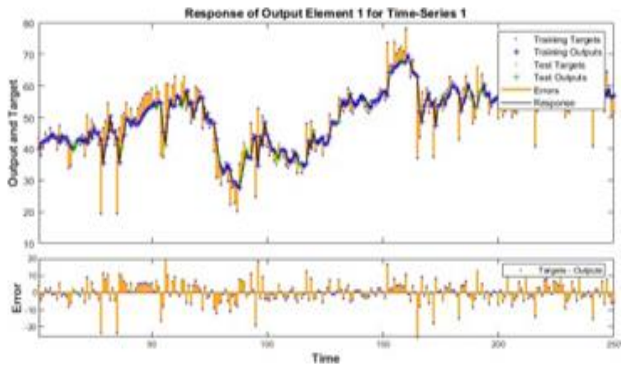


Fig. 21. Plot of Output, Target, Error and for Karu Sub-station

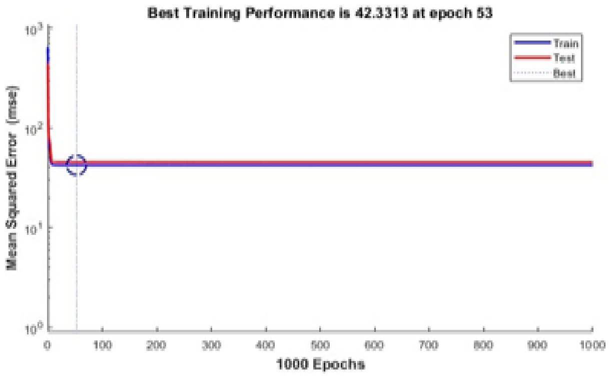


Fig. 22. Plot of Training Performance for Karu Sub-station

Figures 23 – 26 shows the plots of the weekly damand prediction for keffi sub station respectively for year 2018 to 2022. The average (MW), maximim (MW) and minimum (MW) result are listed. The results show an average weekly prediction of weekly prediction of 20.21MW, maximum prediction of 21.28MW and minimum Prediction of 18.25MW.

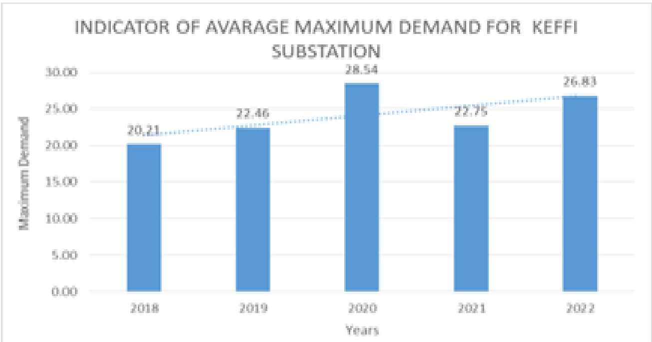


Fig. 23. Plot of indicator for average maximum demand of Keffi sub-station

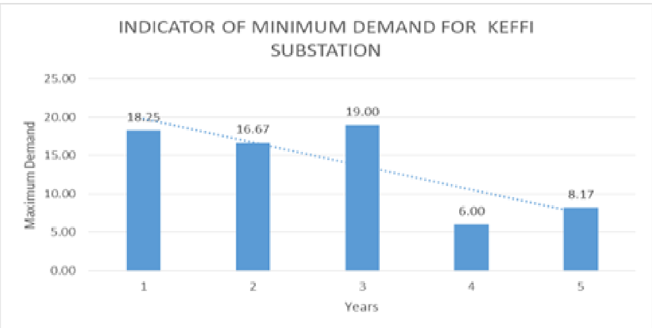


Fig. 24. Plot of indicator for minimum demand of Keffi sub-station

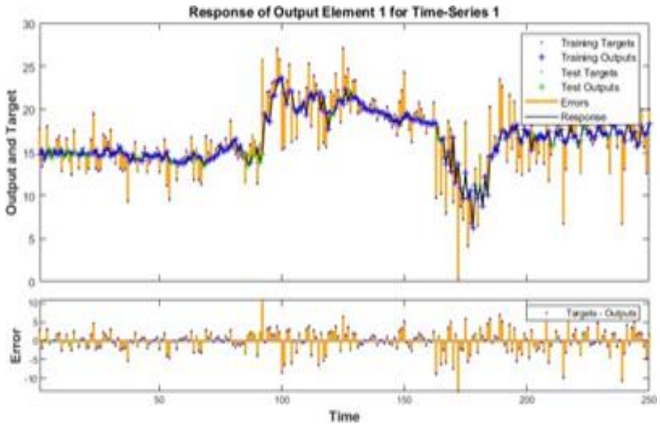


Fig. 25. Plot of Output, Target and Error for Keffi Sub-station

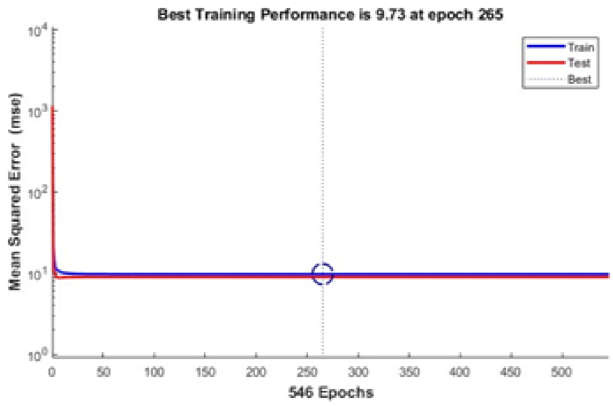


Fig. 26. Plot of Training Performance for Keffi Sub-station

Figure 27-30 shows the plots of the weekly damand prediction for Akwanga sub station respectively for year 2018 to 2022. The average (MW), maximim (MW) and minimum (MW) result are listed. The formula used in arriving at the average (MW), maximim (MW) and minimum (MW) result are shown above in equation (1), (2), (3) and (4) respectively. The results show an average weekly prediction of weekly prediction of 26.90MW, maximum prediction of 32.23MW and minimum Prediction of 19.12MW.

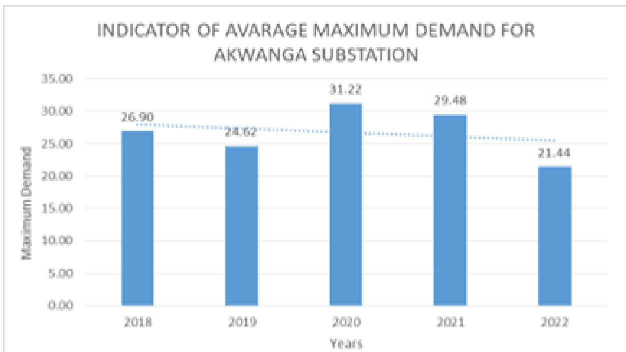


Fig. 27. Plot of indicator for average maximum demand of Akwanga sub-station

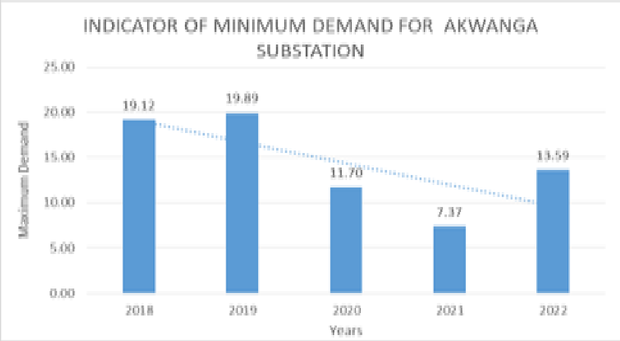


Fig. 28. Plot of indicator for minimum demand of Akwanga sub-station

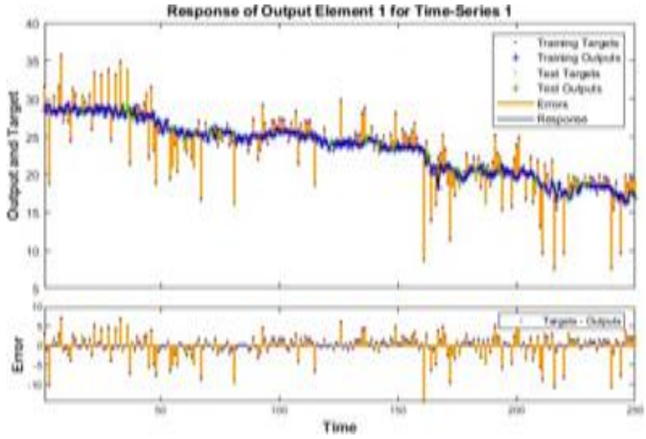


Fig. 29. Plot of Output, Target and Error for Akwanga Sub-station

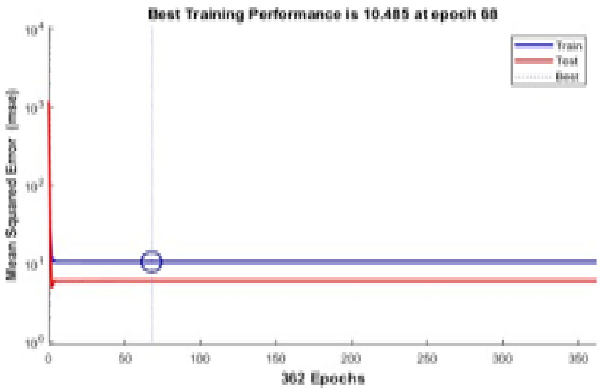


Fig. 30. Plot of Training Performance for Akwanga Sub-station

Figure 31-34 shows the plots of the weekly demand prediction for Suleja sub station for year 2018 to 2022. The average (MW), maximim (MW) and minimum (MW) result are listed. The results show an average weekly prediction of weekly prediction of 39.73MW, maximum prediction of 44.65MW and minimum Prediction of 37.31MW.

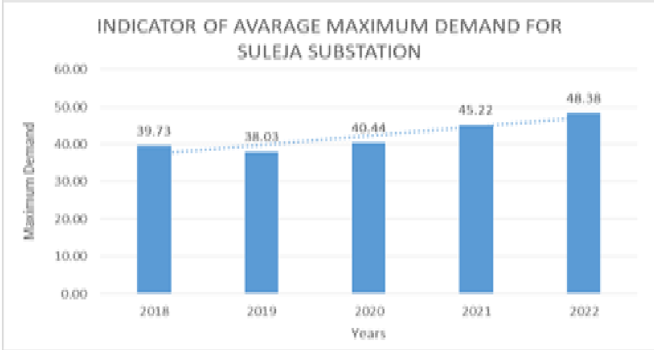


Fig. 31. Plot of indicator for average maximum demand of Suleja sub-station

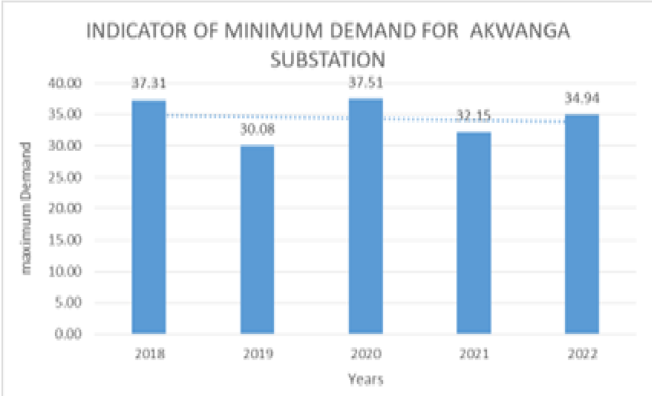


Fig. 32. Plot of indicator for minimum demand of Suleja sub-station

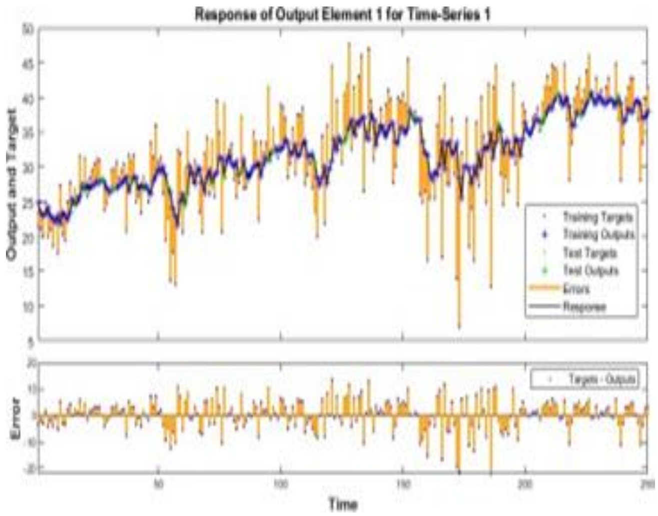


Fig. 33. Plot of Output, Target, Error and for Suleja Sub-station

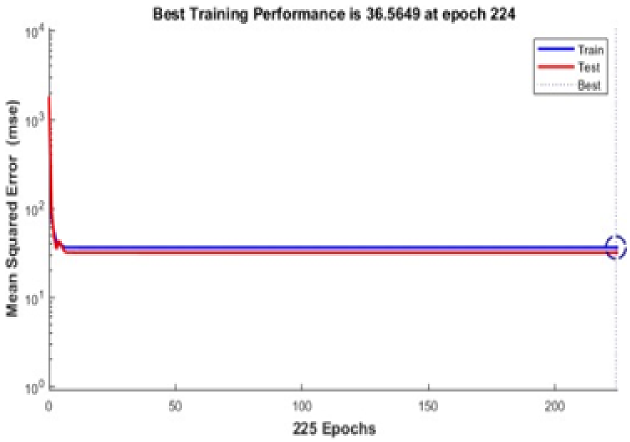


Fig. 34. Plot of Training performance for Suleja Sub-station

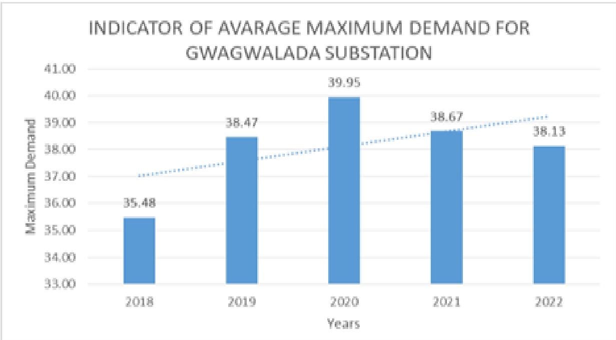


Fig. 35. Plot of indicator for average maximum demand of Gwagwalada sub-station

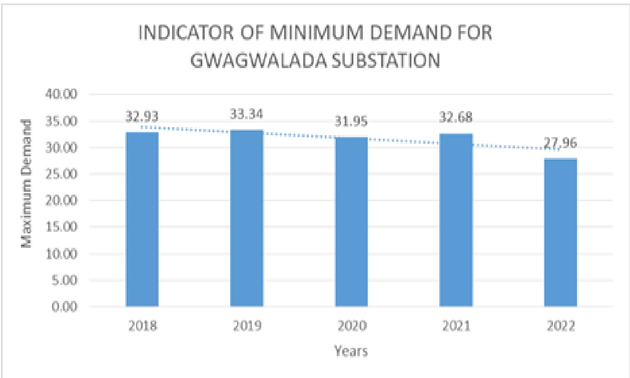


Fig. 36. Plot of indicator for minimum damand of Gwagwalada sub-station

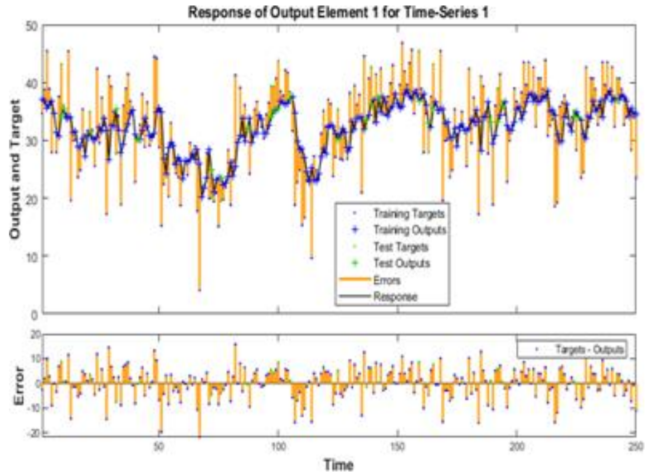


Fig. 37. Plot of Output, Target and Error for Gwagwalada Sub-station

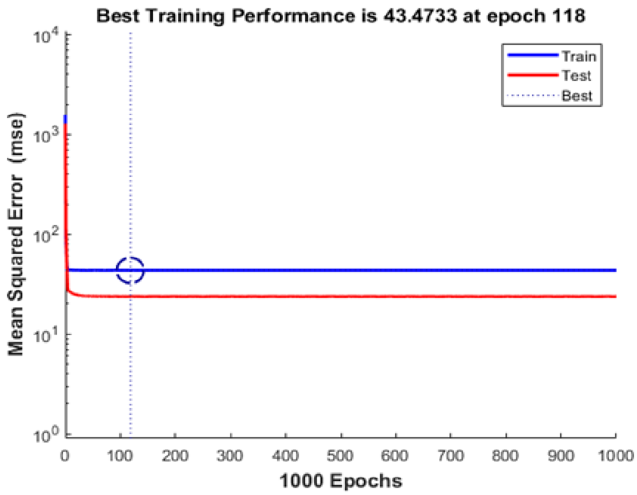


Fig. 38. Plot of Training Performance for Gwagwalada Sub-station

In Tables 2-10 the results of the weekly forecasting for a period of four (4) years 2018-2022 are presented. These results have been interpreted graphically as shown in Figures 3 – 38. The Figures show the plot of the average maximum demand and minimum demand in addition to the training performance, the number of iterations represented as epoch, output, target and error of all the 33kV feeders radiating from the Abuja region of the FCT. The results in Tables 2-10 are summarily presented in Tale 11.

Table 11. Summary of Maximum and Minimum Load Demand

Feeders	Prediction indicator	2018	2019	2020	2021	2022
Katampe	MAXIMUM DEMAND PER YEAR	74.99	78.00	109.35	88.24	144.68
	MINIMUM DEMAND PER YEAR	66.93	68.90	65.69	69.53	71.73
Apo	MAXIMUM DEMAND PER YEAR	115.25	129.45	141.83	139.20	176.43
	MINIMUM DEMAND PER YEAR	111.79	112.59	117.00	124.79	128.52

Kubwa	MAXIMUM DEMAND PER YEAR	65.38	66.27	67.33	77.05	106.55
	MINIMUM DEMAND PER YEAR	51.54	46.08	36.36	60.66	48.78
Central Area	MAXIMUM DEMAND PER YEAR	78.13	116.02	98.66	120.72	167.63
	MINIMUM DEMAND PER YEAR	65.84	53.91	44.81	75.80	36.42
Karu	MAXIMUM DEMAND PER YEAR	64.83	63.86	65.97	73.60	88.58
	MINIMUM DEMAND PER YEAR	55.81	49.70	52.42	51.54	55.60
Keffi	MAXIMUM DEMAND PER YEAR	21.28	23.95	30.48	38.93	39.43
	MINIMUM DEMAND PER YEAR	18.25	16.67	19.00	6.00	8.17
Akwanga	MAXIMUM DEMAND PER YEAR	32.23	25.73	43.10	38.01	24.94
	MINIMUM DEMAND PER YEAR	19.12	19.89	11.70	7.37	13.59
Suleja	MAXIMUM DEMAND PER YEAR	44.65	51.74	43.26	50.90	65.99
	MINIMUM DEMAND PER YEAR	37.31	30.08	37.51	32.15	34.94
Gwangalada	MAXIMUM DEMAND PER YEAR	38.30	40.78	44.17	40.83	49.76
	MINIMUM DEMAND PER YEAR	32.93	33.34	31.95	32.68	27.96

The results from the summary show that by the year 2022, the Apo feeder will have the highest maximum demand of 176.43MW closely followed by Central with 167.63MW. Consequently, the lowest maximum demands of 24.94MW closely followed by 39.43 were recorded for Akwanga and Keffi feeders respectively. Similarly, Apo feeder also recorded the highest maximum load in the year 2021 and also closely followed by Central Area feeder. In the same vain, the duo of Akwanga and Keffi feeders recorded the lowest maximum demand for the same year.

However, an increment in load for all the feeders was observed with respect to their maximum demand except for Akwanga feeder between 2021-2022. The results shown is an indicator that there is electric power shortage in Abuja region. The power within the city centre happen to have the highest maximum demand, meanwhile, the contrary is this case for the satellite towns. There is, therefore, a need for the appropriate authority to ensuring last mile connection of electricity with the region.

5. Conclusion

The Problem of suppressed demand and the need for planning to accommodate future rise in the demand in Abuja and its surrounding communities give led to this research work. This is imperative in order to avoid system black out in most of the city as the capital of the country. Sequel to the collection of relevant data, the ANN model was built for the nine substations selected, simulation was carried out and results was obtained for predictions. The major area of contribution to knowledge through this research are the determination of forecast model that can be easily design and deployed for the Generation and network expansion planning.

This paper can therefore serve as a useful guide for the purpose of network expansion and planning.

References

[1] D.W. Bunn, and E. D. Farmer, Review of load Forecasting Methods in the Electric Power Industry, New York: Wiley, pp13-30, 2008.

[2] H. K. Alfares, and M. Nazeeruddin, “Electric Load Forecasting” Literature survey and classification of methods”, International Journal of System Science, Vol. 33(1), pp. 23-34, 2002

[3] T. Haida, and S. Muto, Electric Regression based Peak Load Forecasting Using a Transformation Technique, IEEE Transactions on Power Systems, Vol.9, pp.1788-1794, 2005

[4] D. Srinivasan, and M. A. Lee, Survey of Hybrid Fuzzy Neural Approaches to Electric Load Forecasting, Proceedings of IEEE International Conference on Systems, Man and Cybernetics, Part 5, Vancouver, BC, pp. 4004-4008, 2005.

[5] K. Kalaitzakis, G. S. Stavrakakis, E. M. Anagnostakis, “Short-term load forecasting Based on artificial neural networks parallel implementation”, Electric Power Systems Research 63, pp.185-196, 2002.

[6] D. Bassi, and O. Olivares, “Medium Term Electric Load Forecasting Using TLFN Neural Networks”, International Journal of Computers, Communications and Control Vol. 1 N0. 2. pp. 23- 32., 2006.

[7] D. O. Arroyo, M.K. Skov, and Q. Huynh, “Accurate Electricity Load Forecasting with Artificial Neural Networks”, Proceedings of the 2005 International Conference on Computational Intelligence for modelling, control and Automation, and International conference on Intelligent Agents, Web Technologies and Internet Commerce, 2005

[8] M.M. Yi, K.S. Linn, and M. Kyaw, “Implementation of Neural Network Based Electricity Load Forecasting”, World Academy of Science, Engineering and Technology, 42, 2008

[9] K. Chakraborty, Mehrota, K., Mohan, C. K., and Ranka, S., Forecasting the Behaviour of Multivariate Time Series Using Neural Networks, vol5 pp.961- 970, 2002

[10] T. Kolarik, and G. Rudorfer, Time Series Forecasting Using Neural Networks,Proceedings of the International Conference on APL., Antwerp, Belgium, pp.86-94, 2007.

[11] V. H. Douglas, Microprocessor and Interfacing: Programming and Hardware, (2ndedn.), Tata McGraw-Hill Publishing Company Ltd, New Delhi, 2010.

[12] S. A. Markoulakis, G. S. Stavrakakis, T. G. Nikolaou, "Short-term load Forecasting based on the Kalman filter and the neural-fuzzy network (ANFIS)", Proceedings of the 2006 IASME/WSEAS International Conference on Energy & Environmental Systems, Chalkida, Greece, May 810, 2006 (pp189-193)

[13] H. Nie, G. Liu, X. Liu, Y. Wang, "Hybrid of ARIMA and SVMs for Short- Term Load Forecasting", 2012 International Conference on Future Energy, Environment, and Materials, Energy Procedia 16 (2012) 1455–1460

[14] W. Brockmann, and S. Kuthe, “Different Models to Forecast Electricity Loads”, EUNITE competition. Available: http://neuron.tuke.sk/competition/index.php

[15] A. G. Bakirtzis, V. Petridis, S. J. Kiartzis, M. C. Alexiadis, and Maissis, A. H.: “A neural Network Short-Term Load Forecasting Model for the Greek Power System’, IEEE Transactions on Power Systems, 11, pp.858-863, 1996.

[16] A. Khotanzad, E. Zhou, H. A. Elragal, Neuro-fuzzy approach to short-term load forecasting in a price-sensitive environment. IEEE Trans Power System 2002; 17:1273–82.

[17] J. Wu, J. Wang, H. Lu, Y. Dong, X. Lu, Short term load forecasting technique based on the seasonal exponential adjustment method and the regression model. Energy Convers Manag 2013; 70:1–9.

[18] K. Yang, L. Zhao, Load forecasting model based on amendment of mamdani fuzzy system. In: Proceedings of 5th international conference on wireless communications, networking and mobile computing, WiCom'09: IEEE; 2009.p. 1–4

[19] M. Tripathi, K. Upadhyay, S. Singh, Short-term load forecasting using generalized regression and probabilistic neural networks in the electricity market.Electr J 2008;21:24–34

[20] A. E. Airoboman, A. A. Ahmad, N. S. Idiagi, and A. Aderibigbe, “A Medium Term Prediction of Feeder Trip Profile on Power Systems Network using Artificial Intelligenc” IEEE PES Power Africa Conference, Nairobi, Kenya. pp. 1-5, 2020.

[21] S. S. Vadhera, Power System Analysis and Stability, Khana Publishers, NaiSarak, Delhi, 2004.

[22] P. K. Sarangi, N. Singh, R. K. Chanhan, and R. Singh, “Short Term Load Forecasting Using Artificial Neural Network: A Comparison with Genetic Algorithm Implementation”, Asian Research Publishing Network (ARPN) Journal of Engineering and Applied Sciences Vol. 4 (9), November 2009.

[23] A. Chakrabarti and S. Halder, Power system Analysis. Operation and Control, (2ndedu), PHI learning Private Ltd, New Delhi, 2008.

[24] S. Mill, Publish Articles on blog on Electrical load forecasting 2016

[25] A. E. Airoboman and N. S. Idiagi “Reliability Prediction in the Nigerian Power Industry using Neural Network” Journal of Electrical and Electronics Engineering (JEEE). Vol. 13, No.2, pp. 17-22, 2020.