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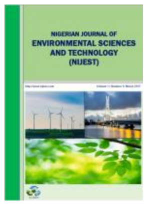

# The Artificial Neural Network Approach for Determining the Futuristic Capacity of Power Supply in the Central Parts of Edo State, Nigeria

Omoroghomwan E. A.[1]*, Igbinovia S. O.[2], and Odiase F. O.[3]
[1,2,3]Department Of Electrical/Electronic Engineering, Faculty of Engineering, University of Benin, Benin City, Edo State, Nigeria
Corresponding Author: * efosaarnoldomoroghomwan@gmail.com

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**ABSTRACT**

*The need for the estimation of the future state of electric power supply in the power system can no longer be avoided. This is due to the inevitable operational, maintenance, planning and expansion obligations of the power sector. In this work, the future trend of power supply by the 33kV feeders that supply power to the customers in the central part of Edo State, Nigeria was forecasted from 2020 to 2030 using Artificial Neural Network. The findings showed that there will be a 13.84% reduction in the power supplied by the utility provider by 2030 if the current trend was sustained. To avoid the adverse impact of such a negative performance by the power supplier, there is a need to increase system capacity by constructing mini grids and implementation of other contingency plans within the study area.*

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**Keywords:** Forecast, Nigeria Power Sector, ANN, Nigeria, NERC, Electric Power Load Forecasting

## 1.0. Introduction

Forecasting is the act of using available historical data to estimate future event or state of a system within an acceptable error margin. The tools and techniques adopted in a specific scenario might differ from another due to the observed pattern of available data (Hong and Fan, 2016). Consequently, a wide range of forecasting techniques have been presented in literature (Hong and Fan 2016). Hence, validation tests of the obtained results from a forecasting technique are usually carried out to ensure the error in the exercise is within an acceptable range.

The duration for which forecasting is carried out determines the descriptive name ascribed to it. The forecast could be very short if the time covered is a few minutes ahead (Pavel, 2022). If the forecast covers between several hours to several days, then it will be seen as a short-term forecast (Jiang *et al.*, 2017). The forecast that covers a period of several hours to several weeks is referred to as medium-term forecasting (Pavel, 2022); while long-term forecasting is an estimation that covers several months to several years (Carvallo *et al*., 2018; Zhixiong and Zhensheng, 2021).

The purposes for which the forecast is required is a major determinant parameter of the duration to be predicted. These purposes include the operational, maintenance and expansion needs in the power system. A very short-term forecast is used to respond to daily load fluctuation (Guan *et al.*, 2013). Short-term load forecast is used to prepare the system for good power quality and high reliability (Pavel, 2022). Medium term forecasting is required for efficient network maintenance planning, setting of prices, and load allocation to customers (Ilseven and Göl, 2017). According to Eke (2003), medium term forecast has the advantage of the ability of easy operational adjustment in case of economic change. Long-term forecast is necessary for future expansion needs (Carvallo *et al*., 2018).

Consequently, load forecasting has become an indispensable tool in the power industry because of the numerous benefits to the sector (Hong and Fan, 2016). It helps the power engineer in effective system expansion plans (Eisa and Hassan, 2011). It is a vital business decision tool in the hands of the system operators (Vasileios, 2022). The future reliability of a power system largely depends on how well the future characteristics of the network has been predicted and how to put the right contingency plans in place (Rouse and kelly, 2011; Sandiford, *et al*., 2015). Forecast is vital for understanding the power supply issues in a broader perspective thereby prompting the responsible institutions to advance means to mitigate the observed lapses. Therefore, the need for future load forecasts in the power system cannot be over-emphasized (Swasti, *et al.,* 2016).

A review of existing literature shows that load forecasting has been done in some parts of Nigeria (Olabode et. al., 2019). Ade-ikuesan *et al.* (2018) applied probabilistic load technique to forecast the load pattern in Ogun State using the energy consumption data for 2016 and 2017 from 2016 to 2017. Akpama, *et al.* (2018) used ANN to Predict the energy consumption of Imo state from 2018 to 2027 using historical data from 2007 through 2016. The data for the study included load demand, gross domestic product (GDP), population, and industrial index production (IPP).

Briggs and Ugorji, (2017) used Regression Exponential Method (REM) and Least Square Method (LSM) to predict the expected load consumption of Rivers state from 2018 to 2025. The data utilized in the study was the load consumption from 2011 to 2015. Okelola and Adewuyi (2016) forecasted the load demand of Ogbomoso for July to December 2017 using the power supply data from the Power Holding Company of Nigeria (PHCN), while Idoniboyeobu and Ekanem (2014) used 2006 to 2010 load allocation data from PHCN to forecast the load demand of Uyo, Ikot Ekpene, and Eket towns in Akwa Ibom State. They utilized the least square and regression exponential analysis to arrive at their findings.

These studies have contributed greatly to knowledge around load projection in different parts of Nigeria. However, none of them was conducted in the central part of Edo State. Considering the importance of load forecast in the power system, this study will carry out a long-term forecast of the amount of power that the utility company will likely distribute to the customers in the central part of Edo State based on available data. The customers in this location are fed by the power supplied by Ehor, Ubiaja and Uzebba 33kV feeders from Irrua transmission station.

## 2.0. Methodology

The load to be distributed by the utility company shall be estimated using Artificial Neural Network. This is sequel to the fact that Artificial Neural Network is a very intelligent predictive tool that can be trained to learn the behaviour of a system with the help of historical data (Lemuel et al., 2022). Artificial Neural Network was preferred because it can be used to appropriately model the fluctuating behavior of the feeder's load.

The data used for this study is maximum monthly load data of three (3) 33 kV feeders (Ehor, Ubiaja and Uzebba) obtained between the period of 2015 - 2020 from Irrua Transmission Station as presented in Table 1.

Table 1 Load (MW) of the feeders in Uromi Business Unit

| YEAR | FEEDERS | JAN | FEB | MAR | APR | MAY | JUN | JUL | AUG | SEP | OCT | NOV | DEC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2015 | EHOR 33KV FDR | 17 | 22.5 | 20 | 13.9 | 4.3 | 1.9 | 2.4 | 3 | 2.5 | 1.5 | 3.6 | 3.1 |
| | UBIAJA 33KV FDR | 7 | 7.5 | 8.3 | 8.1 | 9 | 7.9 | 13.2 | 7 | 7.2 | 7.5 | 12 | 8 |
| | UZEBBA 33KV FDR | 18 | 17 | 16 | 16.3 | 18 | 15 | 20.4 | 18 | 16 | 17.4 | 16 | 16 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | |
| 2016 | EHOR 33KV FDR | 2.4 | 9.4 | 12 | 12.2 | 11 | 12 | 12 | 13 | 10 | 14.4 | 14 | 7.1 |
| | UBIAJA 33KV FDR | 7.3 | 7.5 | 7.9 | 7 | 12 | 7.1 | 11 | 5.2 | 6 | 6 | 11 | 5.1 |
| | UZEBBA 33KV FDR | 22 | 17 | 6.6 | 6 | 6 | 7.2 | 15.6 | 7.4 | 8.2 | 9 | 13 | 6.6 |
| | | | | | | | | | | | | | |
| 2017 | EHOR 33KV FDR | 12 | 11.8 | 15 | 12.2 | 14 | 13 | 11.6 | 12 | 11 | 11.4 | 6.9 | 11.1 |
| | UBIAJA 33KV FDR | 7.5 | 7.6 | 9.8 | 8 | 11 | 8.5 | 7.6 | 11 | 8.4 | 11.1 | 9 | 8.8 |
| | UZEBBA 33KV FDR | 8.2 | 8.9 | 10 | 10.5 | 7.9 | 9.8 | 7.4 | 9.2 | 8.7 | 9.2 | 9.4 | 8 |
| | | | | | | | | | | | | | |
| 2018 | EHOR 33KV FDR | 12 | 11.9 | 13 | 12.1 | 12 | 12 | 12.1 | 11 | 12 | 11.3 | 12 | 12.4 |
| | UBIAJA 33KV FDR | 8 | 9 | 9.5 | 7.3 | 7 | 8.5 | 11.1 | 6.9 | 6.5 | 8 | 7 | 8.5 |
| | UZEBBA 33KV FDR | 8.6 | 8.8 | 8.4 | 9.1 | 8.9 | 9.9 | 7.6 | 7.8 | 7.6 | 8.4 | 9.7 | 9.8 |
| | | | | | | | | | | | | | |
| 2019 | EHOR 33KV FDR | 12.2 | 12.6 | 13 | 12.7 | 12.2 | 11.8 | 12.9 | 10.9 | 11.3 | 11.2 | 11.9 | 9 |
| | UBIAJA 33KV FDR | 8.4 | 8.8 | 13.8 | 14 | 8.4 | 9.1 | 8 | 7.8 | 8.5 | 10 | 11.1 | 5.6 |
| | UZEBBA 33KV FDR | 8.1 | 8 | 8.9 | 8.5 | 8.3 | 10.2 | 6.2 | 6 | 5.8 | 6.2 | 36 | 10.5 |
| | | | | | | | | | | | | | |
| 2020 | EHOR 33KV FDR | 12.1 | 13.2 | 12 | 12 | 11.41 | 11.4 | 11.1 | 11.9 | 12.5 | 12.6 | 15 | 13.2 |
| | UBIAJA 33KV FDR | 11.1 | 8.8 | 8.2 | 8.5 | 5.85 | 8.6 | 8.2 | 8.1 | 8.9 | 8.7 | 9 | 8.6 |
| | UZEBBA 33KV FDR | 6.5 | 7.7 | 8.6 | 8.4 | 5.26 | 7 | 6.9 | 6.7 | 8.4 | 8.7 | 8.7 | 9.7 |

Table 1 represents the maximum load recorded on each of the feeders in each month. These values do not represent the actual customer load demand but rather the quantum of load delivered by the utility providers within those periods. This is so because the distribution companies may be constrained by system capacity hence the need may arise to regulate the amount of power made available to the customers. This type of forecast is predicated on the need to ascertain the level of system adequacy and the current state of the power system.

### *2.1 Data Pre-Processing*

The data was pre-processed to put the input values in the same scale. The approach here was to normalize the mean and standard deviation of the training set (Bassi, 2006). Neural network training can be made more efficient if certain pre-processing steps are performed on the network inputs and targets (TheMathworks, 2017). This was implemented to normalizes the network inputs and targets so that they will have zero mean and unity standard deviation (Heaton, 2011).

### *2.2 Choice of Neural Network Paradigm*

Feed-forward input-delay back propagation network was used for this application. The input-delayed feed-forward network has a special feature of combining conventional network topology (multi-layer perceptron) with good handling of time dependencies by means of a gamma memory (Lemuel et al., 2022).

### *2.3 Construction of Network Architecture*

Structure of the network affects the accuracy of the forecast. Network configuration mainly depends on the number of hidden layers, number of neurons in each hidden layer and the selection of activation function (Manohar and Reddy, 2008). In each case of choice of network architecture, the network performance shall always be evaluated using mean absolute percentage error (MAPE) defined as:

$$MAPE\ (\%) = \frac{1}{N}\sum_{m=1}^{N} \frac{\left|L_{F(m)} - L_{A(m)}\right|}{L_{A(m)}} \times 100 \tag{1}$$

Where;

$L_{F(m)}$ is the actual load, $L_{A(m)}$ is the forecasted load and N is the number of data (Laouafi, *et al.,* 2015; Al-Shareef, *et al.,* 2008; Param, *et al.,* 2016). The flow chart of all the steps involved in the building of the artificial neural network is presented in figure 1.

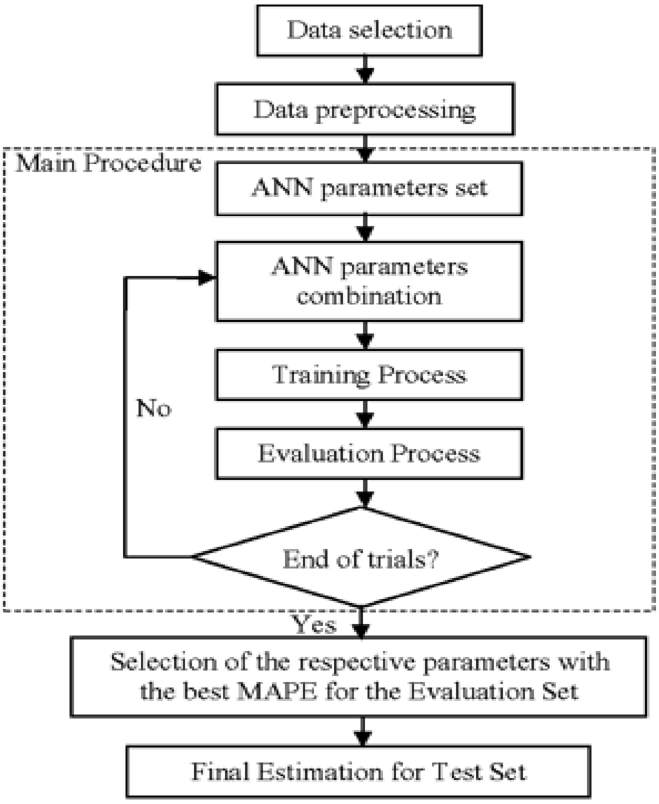


Figure 1: Flowchart of the artificial neural network set-up

*2.4 Network Training*

The network was trained with samples of the research data so that it can recognize the hidden pattern of the load data. Five years data (i.e., 2015-2019) out the six years collected data (i.e., 2015-2020) was used in training the Artificial Neural Network. Testing and validation were done using the last year data (i.e., 2020). Two training styles exist viz: Incremental training in which the weights and biases of the network are updated each time an input is presented to the network, and batch training wherein the weights and biases are updated only after all the inputs are presented to the network (Benlembarek, *et al.,* 2010; Adamowski, 2008).

*2.5 Training Algorithms*

Several training algorithms are known and used in training feed-forward networks which are basically back-propagation networks. Some of the training algorithms suffer the problem of slow rate of convergence and will not be considered for this research (Guan, *et al.,* 2013; Senjyu, *et al.,* 2002). Scaled conjugate gradient algorithm proposed by Polak-Ribiere was used (TheMathworks, 2017) as shown in Figure 2.

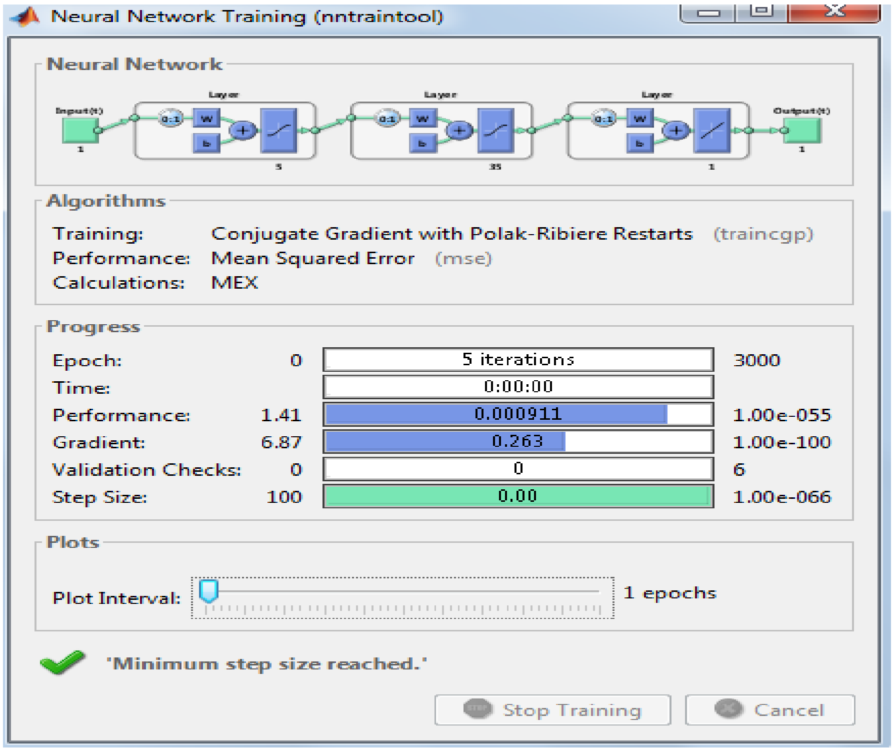


Figure 2: Neutral Network Training Tool

*2.6 Back-propagation Implementation Strategy*

Back-propagation is one of the best algorithms for training a supervised neural network (Yi, 2008). The implementation of back-propagation algorithm and the equations used to calculate various intermediate values and error terms are explained with the help of the figure 3.

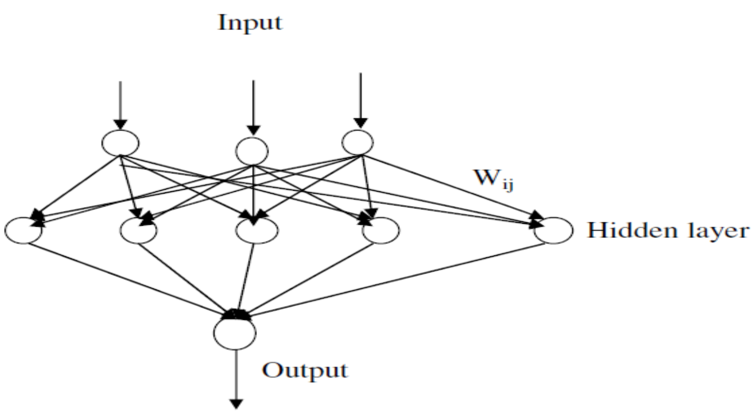


Figure 3: Structure of a three-layered feed-forward Type of ANN

A typical performance function that is used for training a feed-forward neural network is the mean sum of the squares (mse) of the network errors represented as;

$$F = mse = \frac{1}{N}\sum_{i=1}^{N} (e_i)^2 = \frac{1}{N}\sum_{i=1}^{N} (t_i - a_i)^2 \qquad (2)$$

It is possible to improve generalization if we modify the performance function by adding a term that consists of the mean of the sum of squares of the network weights and biases (TheMathworks, 2017) as;

$$msereg = \gamma mse + (1 - \gamma) msw \qquad (3)$$

And

$$msw = \frac{1}{n}\sum_{j=1}^{n} W_j^{\ 2} \qquad (4)$$

$Where$
$F \ is \ the \ Performance \ Function$
$mse \ is$ the Mean Square Error
$msereg \ is \ the \ Mean \ Square \ Error \ with \ regulation$
$N \ is \ the \ Total \ numbers \ of \ months$
$msw \ is$ the Mean square weight
$e \ is \ the \ Error$
$W \ is \ the \ Weight$
$j \ is \ the \ Notation \ indicating \ a \ starting \ point$
$\gamma \ is \ the \ performance \ ratio$

### *2.7 Model Parameters*

The parameters used for the load prediction in the artificial neural network are presented in Table 2. The prediction of the load to be supplied by each of the feeders till the year 2030 were eventually done based on these parameters. The average annual forecasted load obtained from the monthly values are presented in Table 3 and the implications were discussed in Section 3 of this work.

Table 2: ANN Model Parameters Used

| **Parameter** | **Value** |
|---|---|
| Architecture/Structure | 5-35-1 |
| Epochs | 3000 |
| Performance Ratio | 0.01 |
| **Activation function used** | |
| • In hidden layers | Tansigmoid |
| • In the outer layer | Purelin |
| • Error tolerance | 0.0001 |
| Stopping Criteria | No. of iterations >=epochs or network error<=tolerance |
| Training Algorithm | Conjugate gradient algorithm using Polak-Ribiere restart technique |
| Learning rate | 0.001 |
| Momentum constant | 0.75 |
| Validation checks | 6 |
| **Number of neurons** | |
| • First layer | 5 |
| • Second layer | 35 |
| • Third layer | 1 |

### *2.8 Validation of The ANN Results*

The presented parameter utilized by the ANN tool as presented in Table 2 showed that the error tolerance was set to 0.0001 which means the accuracy level is very high. To affirm this, the forecasted results were validated by comparing the forecasted values with the actual values of 2020 to see the average percentage errors for all the feeders using equation 5.

$$Prediction \ Error \ (\%) = \left(\frac{V_A - V_F}{V_A}\right) * 100 \qquad (5)$$

$V_A$ is Actual Value
$V_F$ is Forecasted Value

The results which are presented in Table 3 revealed that the average error percentage are -1.45%, -2.51%, and -6.60% for Ehor, Ubiaja and Uzebba respectively. According to Ogujor, and Kuale (2007), These values are within acceptable error margin. Hence, the model is good enough for this study.

Table 3: ANN forecast results validation values

| Months | Original Data | | | Predicted Values | | | % Error | | |
|---|---|---|---|---|---|---|---|---|---|
| Jan-20 | 12.10 | 11.10 | 6.50 | 12.19 | 11.31 | 7.27 | -0.73 | -1.89 | -11.87 |
| Feb-20 | 13.20 | 8.80 | 7.70 | 13.50 | 8.91 | 8.27 | -2.24 | -1.26 | -7.45 |
| Mar-20 | 12.00 | 8.20 | 8.60 | 12.04 | 8.40 | 8.26 | -0.32 | -2.49 | 3.90 |
| Apr-20 | 12.00 | 8.50 | 8.40 | 12.96 | 8.70 | 8.27 | -7.98 | -2.40 | 1.59 |
| May-20 | 11.41 | 5.85 | 5.26 | 11.19 | 6.11 | 6.27 | 1.97 | -4.36 | -19.06 |
| Jun-20 | 11.40 | 8.60 | 7.00 | 11.81 | 8.91 | 7.26 | -3.61 | -3.62 | -3.73 |
| Jul-20 | 11.10 | 8.20 | 6.90 | 11.71 | 8.43 | 7.47 | -5.47 | -2.83 | -8.25 |
| Aug-20 | 11.90 | 8.10 | 6.70 | 10.22 | 8.30 | 7.34 | 14.11 | -2.50 | -9.59 |
| Sep-20 | 12.50 | 8.90 | 8.40 | 12.71 | 9.01 | 8.81 | -1.66 | -1.24 | -4.94 |
| Oct-20 | 12.60 | 8.70 | 8.70 | 12.89 | 8.91 | 9.47 | -2.34 | -2.41 | -8.84 |
| Nov-20 | 15.00 | 9.00 | 8.70 | 15.59 | 9.10 | 8.25 | -3.97 | -1.13 | 5.18 |
| Dec-20 | 13.20 | 8.60 | 9.70 | 13.88 | 8.79 | 9.26 | -5.16 | -2.16 | 4.54 |
| Average % Error | | | | | | | -1.45 | -2.51 | -6.60 |

## 3.0 Results and Discussion

The future quantity of the power that will be distributed from the Ehor, Ubiaja and Uzebba 33kV feeders were predicted in the methodology section. The Artificial Neural Network was used for the load growth forecast and the obtained results are as presented in Tables 4.

Table 4: Load (MW) forecast for Ehor, Ubiaja and Uzebba feeders

| | YEAR | Ehor | Ubiaja | Uzebba | Total |
|---|---|---|---|---|---|
| AVAILABLE DATA | 2015 | 7.93 | 8.56 | 16.95 | 33.44 |
| | 2016 | 10.83 | 7.72 | 10.34 | 28.89 |
| | 2017 | 11.83 | 9.04 | 8.97 | 29.83 |
| | 2018 | 11.93 | 8.11 | 8.72 | 28.75 |
| | 2019 | 11.81 | 9.46 | 10.23 | 31.49 |
| | 2020 | 12.37 | 8.55 | 7.71 | 28.63 |
| FORECASTED DATA | 2021 | 10.66 | 9.02 | 9.66 | 29.34 |
| | 2022 | 10.15 | 9.03 | 9.66 | 28.84 |
| | 2023 | 10.09 | 9.05 | 9.66 | 28.79 |
| | 2024 | 10.08 | 9.06 | 9.66 | 28.80 |
| | 2025 | 10.08 | 9.06 | 9.66 | 28.80 |
| | 2026 | 10.08 | 9.06 | 9.66 | 28.81 |
| | 2027 | 10.08 | 9.06 | 9.66 | 28.81 |
| | 2028 | 10.08 | 9.06 | 9.66 | 28.81 |
| | 2029 | 10.08 | 9.06 | 9.66 | 28.81 |
| | 2030 | 10.08 | 9.07 | 9.66 | 28.81 |
| | VARIATION (%) | 27.11 | 5.93 | -42.99 | -13.84 |
| | TREND | | | | |

Table 4 represents the forecasted supplied electrical power by the utility company from each of the feeders. The result showed that the distributed load on Ehor feeder increased from 7.93MW in 2015 by 27.11% to 10.08MW by 2030. The supplied power on Ubiaja increased by 5.93% while Uzebba reduced by -42.99% 2030. Consequently, the supplied electrical power in the study area reduced from 33.4MW in 2015 to 28.81MW in 2030. This represents a 13.84% reduction in power supply.

Though the load demand was expected to increase based on the existing studies (NACOP, 2016) nevertheless, historical and forecasted records as presented in Table 4 showed that the capacity of the distributed power by the utility provider declined with time. This load decline is like what happened in Eastern Australia from 2009 to 2014 (Sandiford, et al., 2015). However, the underlying factors responsible for such situation cannot be verified to be same in both scenarios. The decline in Australia was because of improved energy efficiency management by the customers. They replaced their electrical gadgets with more energy efficient gadgets thereby reducing load demand on the system. In the case of our study, the load reduction in our study area from 33.44MW in 2015 to 28.63MW in 2020 was most probably due to power system inadequacies. In this wise, our findings contradict earlier works in Nigeria that were not influenced by such system inadequacies. This can be found in the projected load trend for Ekiti state (Omoroghomwan, 2012), Elebu community in Kwara state (Oladeji and Sule, 2015) and the national load requirement (Ezeolisah, 2015).

## 4.0 Conclusions

Load forecast is a major tool for power system Engineer for planning and operational purposes. This involves a systematic observation of the past events with appropriate tools to estimate the likely behaviour of the system in the future with minimal deviation. This study has presented the future capacity of electric power that will be supplied by the utility providers to the customers in the central part of Edo state, Nigeria based on past records. The result showed a negative trend that needs to be attended to if the benefits of adequate power supply is to be of the priority of the regulatory agency of the power sector. Therefore, there is a need to construct mini grids in strategic locations within the network. There is also a need to extend the existing power infrastructure to areas that are currently not connected to the power supply system. It is believed that this study has helped to present the power supply status in the central part of Edo state, Nigeria. This will help guide investors, power system regulators and customers in the areas of intervention, policy formulation and contingency analysis purposes.

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