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IMPROVING THE POWER TRANSFER CAPACITY OF 11KVA DISTRIBUTION POWER NETWORK USING ARTIFICIAL NEURAL BASED DEMAND SIDE MANAGEMENT

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Abstract: **This research presented a improving the power transfer capacity of 11KVA distribution network using artificial neural based demand side management technique. The study was embarked on to address the problem of low profit margin experienced in the distribution companies and also the issues of user dissatisfaction on the quality of power supplied. This was addressed using artificial neural network to develop prediction model using data collected from EEDC and then train. The model was implemented with Matlab and deployed for load forecasting and demand response. The result showed that the load forecast accuracy is 94% while the cost estimated accuracy is 97.6%. The implication of this result showed that the model will accurately provides information for better demand response.**

Keyword: **Power transfer capacity, artificial neural network, demand side management technique, 11KVA distribution network, Load forecasting, prediction model.**

I. INTRODUCTION

Electricity is one of the most essential components of the modern human life. It is the main driving forces of the modern world today even though it is taken for granted by some people. On one hand, there are almost 1.3 billion people still not having access to electricity and on the other hand, the demand for electricity is expected to increase significantly over the coming years. Since electricity plays a vital role in the human being society, conservation and appropriate energy management strategies for the grids is a must [1].

Energy management systems are designed to monitor, optimize, and control the smart grid energy market. Demand side management, considered as an essential part of the energy management system, can enable utility market operators to make better management decisions for energy trading between consumers and the operator. In this system, a priori knowledge about the energy load pattern (e.g., day-ahead forecasted load) can help reshape the load and cut the energy demand curve, thus allowing a better management and distribution of the energy in smart grid energy systems [2].

Smart meter is one of the most important devices implemented in the smart grid (SG). With smart meters, electrical data such as voltage and frequency are measured and real-time energy consumption information is recorded. Smart meter supports bidirectional communications between the meter and the central system. Also, the smart meter has the built in ability to disconnect and reconnect certain loads remotely, which can be used to monitor and control the user’s devices and appliances so as to manage demands and loads within the ”smart-buildings” in the future. However the consumers are struggling to manage the increase price and shortage of energy, hence there is need for a smarter approach. This need of smarter energy management systems has led to the development of technologies like demand side management [3].

Demand side management (DSM) can be defined as the selection, planning, and implementation of measures intended to have an influence on the demand or customer side of the electric meter either directly or stimulated indirectly by the utility device [4]. DSM is classified into two main categories which are pricing methods and demand response methods. The pricing methods employ flat rate and tariff techniques for energy management and pricing strategies, while the most recently improved applied method which is the demand response (DR) method is based on load based pricing instead of time base, i.e., electricity tariffs vary proportionally to the power system load as specified in the desired function.

The DR employs programs like peak clipping, Valley filling, Load shifting, Load forecasting, Load building, energy conservation and flexible load shape. Each of these control strategies require to design the incentives or contracts that are proposed to the consumers, while taking into account the consumers’ behaviors and preferences [5]. To achieve these goal DR solutions extensively use artificial intelligence (AI) based solutions.

Recent years have seen an increasing interest in Demand Response (DR) as a means to provide flexibility, and hence improve the reliability of energy systems in a cost effective way. Yet, the high complexity of the tasks associated with DR, combined with their use of large scale data and the frequent need for near real-time decisions, means that Artificial Intelligence (AI) has recently emerged as key technologies for enabling demand side response. AI methods can be used to tackle various challenges, ranging from selecting the optimal set of consumers to respond, learning their attributes and preferences, dynamic pricing, scheduling and control of devices, learning how to incentivize participants in the DR schemes and how to reward them in a fair and economically efficient way and will be reviewed in this research and integrated in the Nigerian national grid.

II. REVIEW OF RELEVANT LITERATURES

Table.1: Shows Summary of Literature Review

AUTHOR	TITLE	TECHNIQUES	METHOD AND MATERIAL	RESEARCH GAP/LIMITATION
[6]	A new mathematical approach and heuristic methods for load forecasting in smart grid	Heuristic method was used	The study used mathematical models to forecast load estimate in grid	The result can be improved with artificial intelligence technique
[7]	Artificial neural network for load forecasting in smart grid	Artificial neural network technique	The study performed long term load forecasting on the distribution system	The accuracy was good but the design of the ANN was complex and that affected the training time
[8]	Short term electric load forecasting using demand side management technique	demand response technique	The study perform load forecasting using demand side management technique for short term power planning in the area	The estimated load usage accuracy can be improved with ANN
[9]	Demand side management using artificial neural networks in a smart grid environment	Artificial neural network	The study performed power system planning on the area using ANN based load forecasting technique	The training time can be minimized with better training algorithm
[10]	A review of residential demand response of smart grid. Renew Sustain Energy Rev	Descriptive analysis	The study reviewed various technique for demand side management	They recommended the use of artificial intelligence technique for future works
[11]	Demand response and smart grid	Demand response technique	The study performed load forecasting on grid	The result can be improved with artificial intelligence
[12]	Demand response forecasting methodology for berkeley lab	Demand side management technique	The study performance load forecasting and sue the result for power system planning	The study can be improved using artificial intelligence technique

[13]	Benefits and challenges of electrical demand response: a critical review	Qualitative analysis	The study overviewed various benefits and challenges of demand response	Artificial intelligence technique was recommended as the best approach in future
[14]	Load forecasting, dynamic pricing and DSM in smart grid: A review,"	demand response technique	The study used DSM to plant the dynamics pricing of power in the grid	The estimated forecasted accuracy need to be improved with artificial intelligence
[15]	Demand response and smart grid	Demand response technique	The study performed load forecasting on grid	The result can be improved with artificial intelligence

III. DESIGN METHODOLOGY

The methods used for the study of the proposed system are characterization, data collection, artificial neural network, training, load prediction. The characterization collected data of the case study 11KVA distribution transformer and analyze the performance for findings such as peak load periods. The artificial neural network is the machine learning algorithm designed and trained to learn the load flow patterns and use the reference model for load forecasting.

3.1 Materials

The materials used for the study of the new system are 11KVA feeder transformer, power cables, ETPA load flow software, Excel software, monitoring PC.

11KVA distribution feeder transformer

This was used to study the consumer load consumption and collected data to analyze and find out peak and off peak time.

Power Cables

These are conductors which serve as channel to transmit the load flow from the feeder to the end users.

ETAP Software

This is software developed with the ability to collect phasor parameters from power system devices and convey to readable format.

Excel software

This software was used to analyze the data collected from the testbed.

Monitoring PC

This is a device which was sued in this research for the supervision of the load flow in the transmission lines.

3.2 Characterization

This research work characterized the Achara layout 11KV distribution feeder from the Enugu Electrical Distribution Company (EEDC) of Nigeria. The essence of this characterization is to determine the actual load capacity of the consumers feed by the 11KV feeder and then use the data to train a neural network that will be used to predict future load capacity and help plan on how to serve the area better.

3.3 How it was done

The characterization was performed remotely from the supervisory data acquisition and control (SCADA) center at the EEDC station. This is was because the inadequate number of meters to supply the customers has read t estimated billing in some areas. The SCADA network was designed to remotely monitor the load performance of the various consumer meters and collect the actual load capacity and price per unit rate for the specified case study time frame for load consumption. The SCADA network consists of monitoring device, Remote Terminal Unit (RTU) which is a device for data collection from the 11KVA feeder, human machine interface, and the monitoring software which converts the data collected using automatic meter reading technology to the interpretable format.

During the 11KV feeder transformer operation, the SCADA was used to monitor the consumer loads recorded from the various smart meters installed at the consumer units. The network structure for the characterized system is presented as shown below;

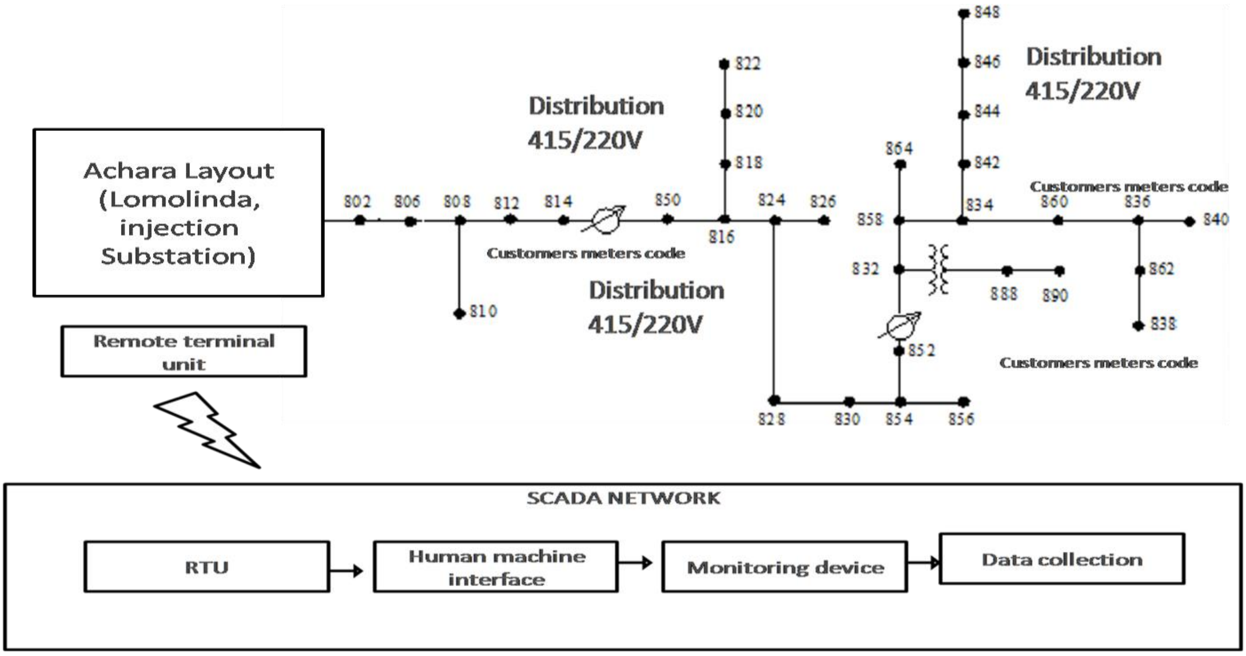


Figure 1: The characterized network

From the SCADA network and the characterized area structured in figure 1 the consumer's consumption rates are identified and monitored remotely using the smart meters installed as shown. Each of the meters is designed using RTU and a communication protocol based on the IEEE 802.11 to collect and transmit \consumer energy consumption characteristics remotely to the control center monitored by the SCADA. This data are collected for 30 different consumers within the scope of the characterized feeder. The data collected contains consumer load consumption characteristics like power consumption rates, tariff units, tariffs rates and average load consumed per hour for the month of September 2020 as shown below at 30.95 rate per unit;

Table 2: Characterized data collected

Prepaid Meter numbers	Average monthly load (Kw/h)	Average daily load (Kw/h)	Monthly tariff (₦)
45-023-333-800	450	15.00	13,927
45-023-333-827	340	11.34	10,523
45-023-333-874	420	14.00	12,999
45-023-333-801	320	10.67	9,9040
45-023-333-877	433	14.44	13,158
45-023-333-863	417	13.90	12,906
45-023-333-860	487	16.24	15,073
45-023-333-857	422	14.07	13,061
45-023-333-807	489	16.30	15,135
45-023-333-879	399	13.30	12,349
45-023-333-866	411	13.70	12,721
45-023-333-867	435	14.50	13,464
45-023-333-864	390	13.00	12,071
45-023-333-832	412	13.74	12,752
45-023-333-816	433	14.44	13,402
45-023-333-803	492	16.40	15,228
45-023-333-870	433	14.44	13,402
45-023-333-869	439	14.64	13,588
45-023-333-818	397	13.24	12,288
45-023-333-884	487	16.24	15,073
45-023-333-873	477	15.90	14,764

45-023-333-854	462	15.40	14,299
45-023-333-875	423	14.10	13,092
45-023-333-812	435	14.50	13,464
45-023-333-818	397	13.24	12,288
45-023-333-884	487	16.24	15,073
45-023-333-873	477	15.90	14,764
45-023-333-854	462	15.40	14,299
45-023-333-875	423	14.10	13,092
45-023-333-812	435	14.50	13,464
Total		**432.88**	**490,759**

The data reported in the table 2 presents the power consumption results collected from the 30 households considered for this study. From the result, it was observed that the total amount generated from the case study feeder is ₦490, 759 within the month of September, with a total of 432.88KW power consumed. The average load consumed by the users for the month is analyzed as shown below;

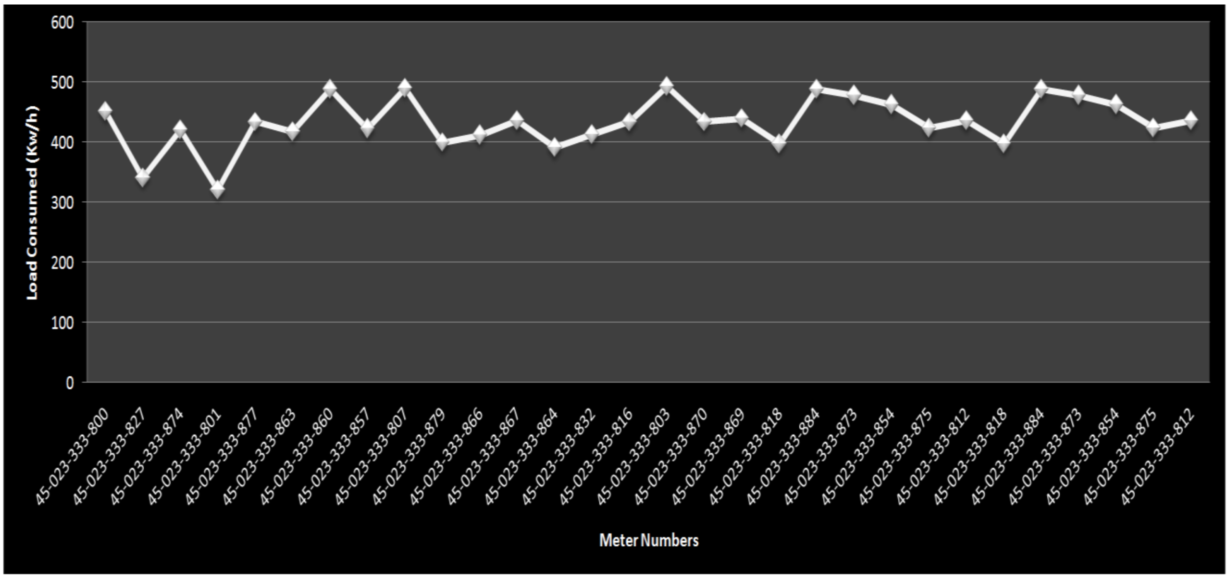


Figure 2: Monthly load consumption performance

The result presented in the figure 2, shows the analyzed for short term power planning and management. It was noticed that the average load consumed by the consumers for the month of September is very dynamic as different days presents different data and will be difficult to manage it accurately by EEDC. Hence there is need for a demand side response design which will be used to estimate this load in the future and hence the result obtained can be used for post planning and energy purchases for future use.

3.4 To determine the network peak and off load period over 24 hours

To determine this, the data of the characterized feeder containing the consumer performance over 24hours was also collected from EEDC and reported as shown in table 3;

Table 3: Load Consumption Report within 24hr

Time (hr)	Load per hour (Kw/h)
0	12.0
1	2.0
2	3.0
3	7.0
4	10.0
5	14.2
6	16.7
7	28.3

8	33.0
9	36.5
10	25.6
11	18.7
12	18.3
13	16.3
14	14.1
15	14.1
16	15.4
17	16.7
18	24.1
19	29.8
20	34.9
21	39.6
22	42.2
23	24.8
24	12.3
Total consumed load	**509.8Kw/h**

The table above presented the result of the daily of load collected from the characterized feeder, from the result it was observed that the total load usage for the date of this data reported is 509.8KW. From the result it was also noticed that the consumption rate varies within certain times of the day and to determine the peak and off load consumption rate within the time frame, the result was analyzed as shown below;

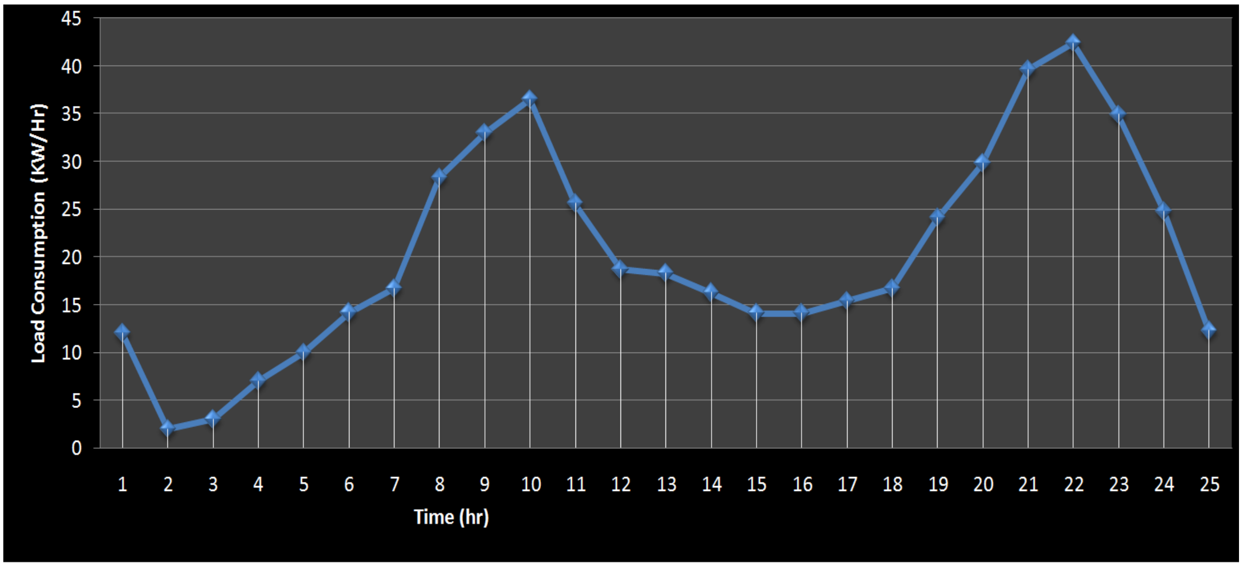


Figure 3: power consumption rate

From the result analyzed using the graph above, it was noticed that the network peak period is at 22hr which is (10:00pm) which recorded the highest consumption of load or the day and off load period is at 2: am.

3.5 To develop a demand side response system using artificial intelligence technique and integrate it into the network characterized

The methods employed for the development of the intelligent demand response system will involve collecting the actual data of the case study Achara layout residential meter system and then feed forward it to an artificial intelligent technique which will be trained and used to predict short term load forecasting of the area in the next month. The forecasted data alongside other feeders forecasted using the proposed system will be used by the EEDC to plan on future load shedding for the particular area. The researcher believed that if the amount in price and rate of energy consumed monthly and yearly for a particular feeder can be determined in future, that will help EEDC to manage the amount of power supplied to that particular area and hence make profit.

3.5.1 Training dataset

The data used for this work consisted of the 30 consumer monthly power consumption results and the amount realized by the EEDC for the zone in the month of September, 2020. The data was used to develop a data model which was feed-forward to an artificial intelligence technique for training and future classification. The data model is presented using the data flow diagram (DFD) below;

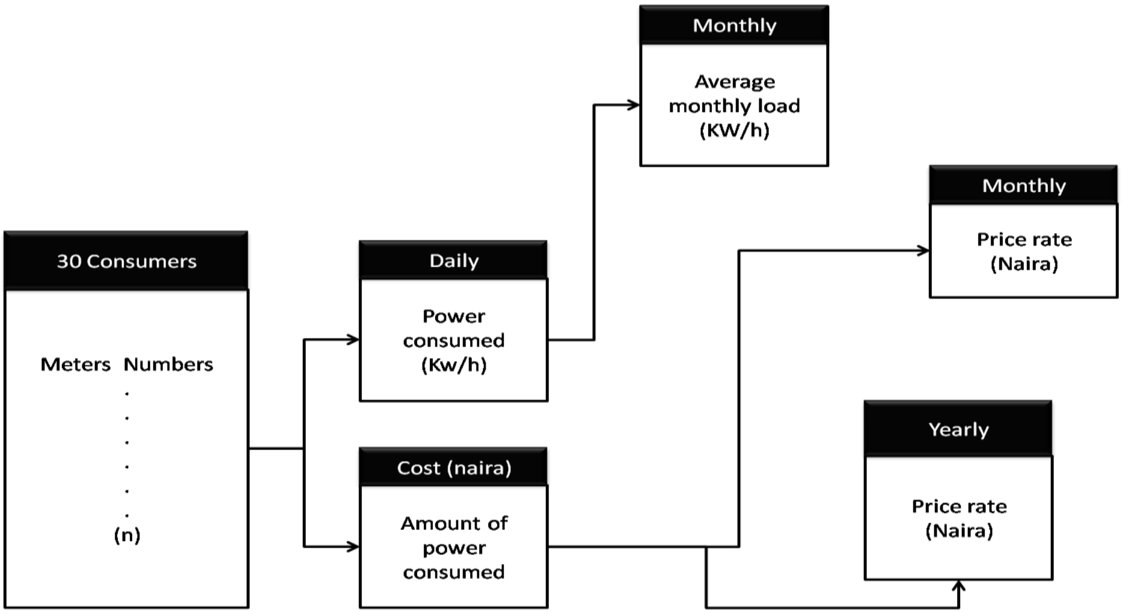


Figure 4: data model (structure of data collected)

The DFD above was used to design the data model which consisted of the data collected for the meters made of power consumption rates and amount realized.

3.5.2 The Artificial intelligence based demand response system

The A.I demand response system which will be used to train the data collected is the artificial neural network. This was designed using the non linear auto regressive moving average model below;

$$y(k+d)=N(y(k),y(k-1),\ldots,y(k-n+1),u(k),u(k-1),\ldots\ldots u(k-n+1)) \quad (3.1)$$

Where u(k) is the system input data from the meters, N is the non linear function (power used and price), and y(k) is the system output

Now that we have defined the system, a neural network is trained to approximate the function (N) using feedback propagation algorithm (see figure 3.6) so as to generate reference predictive model using the training equation as shown below;

$$\hat{}y(k+d)=f(y(k),y(k-1),\ldots,y(k-n+1),u(k-1),\ldots,u(k-m+1))+g(y(k),y(k-1),\ldots,y(k-n+1),u(k-1),\ldots,u(k-m+1))\cdot u(k) \quad (3.2)$$

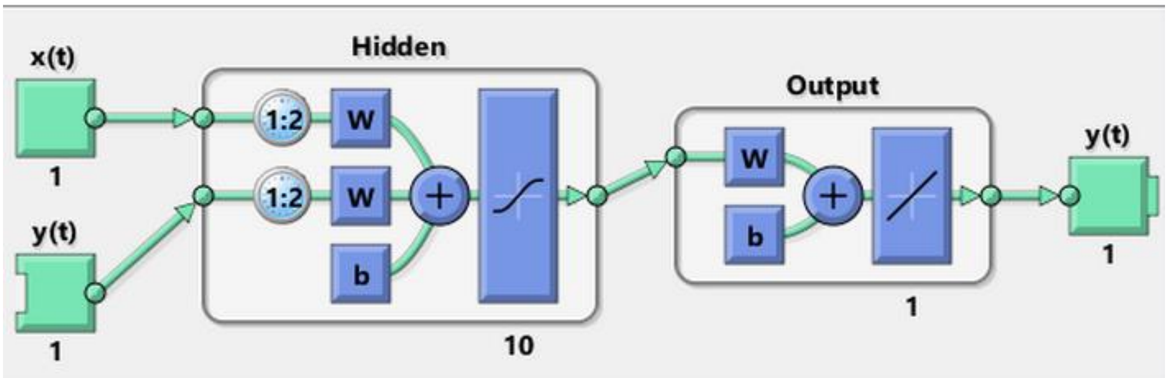


Figure 5: Structure of the artificial neural network

From the model in figure 5, the x(t) is the power consumed while the y(t) is the price realized monthly from the case study area and was used for the training of the neural network. The hidden layers were used to train the network to determine the reference model as shown in the equation 3.3

$$u(k+1) = \frac{y_r(k+d) - f[y(k),\ldots\ldots y(k-n+1), u(k),\ldots\ldots\ldots, u(k-n+1)]}{g[y(k),\ldots\ldots, y(k-n+1), u(k),\ldots\ldots, u(k-n+1)]} \tag{3.3}$$

The model of equation 3.3 presents the model of the neuro controller and will be used to optimize the detection and prediction rate of the proposed system using the feed-forward back propagation algorithm and prediction model below;

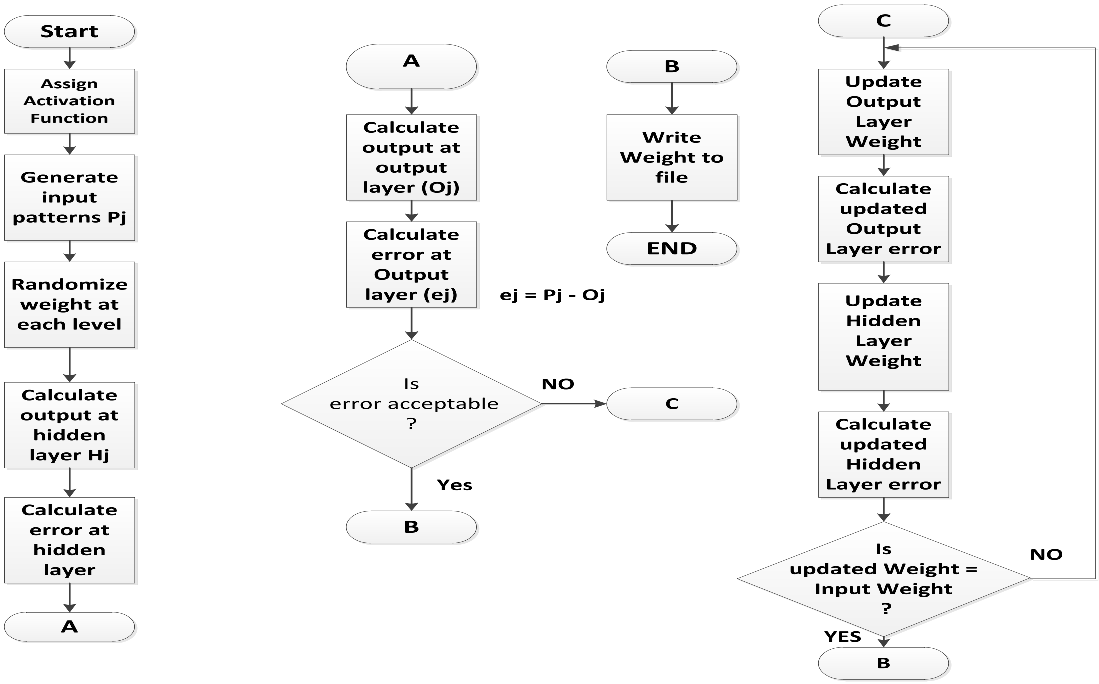


Figure 6: back- propagation algorithm

3.5.3 Prediction model

The neural network predicts the network response over the specified input vector from equation 3.1. The predictor is a numerical optimization programs which determine the feature vectors that minimizes the training performance criterion over the specified horizon as shown below;

$$J = \sum_{j=N1}^{N2}(y_r(t+j) - y_m(t+j))^2 + p\sum_{j=1}^{Nu}(u'(t+j-1) - u'(t+j-2))^2 \tag{3.4}$$

Where N_1, N_2, and N_u define the horizons over which the training error and the prediction features are evaluated. The u′ variable is the tentative feature vectors from equation 3.1, y_r is the desired response, and y_m is the reference model in equation 3.4 which was used for classification. The p value determines the contribution that the sum of the squares of the control increments has on the performance index.

3.6 Implementation of the Model

The models deigned were studied here using Simulink. This model was integrated on the simulink script using neural network toolbox, predictive control toolbox, optimization toolbox and machine learning toolbox. The source codes were presented as shown in section 3.6.1 while the training tool is presented as shown below;

3.6.1 Source codes

```
% load EEDC data from file
folder = 'Data';
data sheet name = 'ISONE CA';
% Import load schedule data for September 2020
if strcmp(sheetname, 'ISONE CA')
   NEData = dataset('XLSFile', sprintf('%s\\2020_smd_hourly.xls',folder,yr), 'Sheet', 'NEPOOL');
else
```

```
NEData = dataset('XLSFile', sprintf('%s\\2020_smd_hourly.xls',folder,yr), 'Sheet', sheetname);
end
% Add a column 'Year for price'
NEData.Year = 2020 * ones(length(NEData),1);
% Import data for monthly price
for yr = 2020
% Read meter data into a dataset array
    x = dataset('XLSFile', sprintf('%s\\%d_smd_hourly.xls',folder,yr), 'Sheet', sheetname);

% Add a column 'Year'
    x.Year = yr*ones(length(x),1);

% Concatenate the datasets together
    NEData = [NEData; x];
end
% train the data
NEData.NumDate = datenum(NEData.Date, 'mm/dd/yyyy') + (NEData.Hour-1)/24;
save([folder '\' genvarname(sheetname) '_Data.mat'], 'NEData');
```

3.6.2 Program block diagram

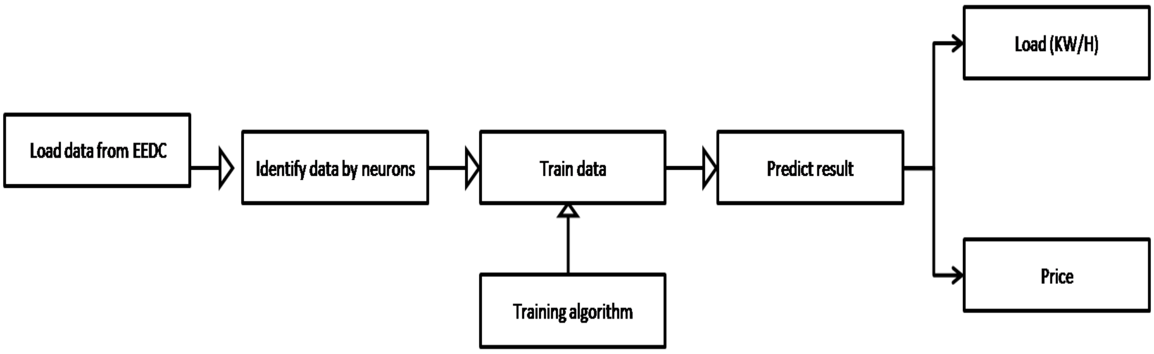


Figure 7: program data flow diagram

The block diagram above was used to develop the program source codes and then implemented using the network training toolbox. Before the training begins, the toolbox automatically splits the data set in test, training and validation sets in the ratio of 70:15:15 and then train and self validate the training performance. This performance are measured considering the regression value, training state, epoch value, validation state among other neural network training evaluation tools. The training tool is presented as shown below, while the training results will be presented and discussed in the next chapter;

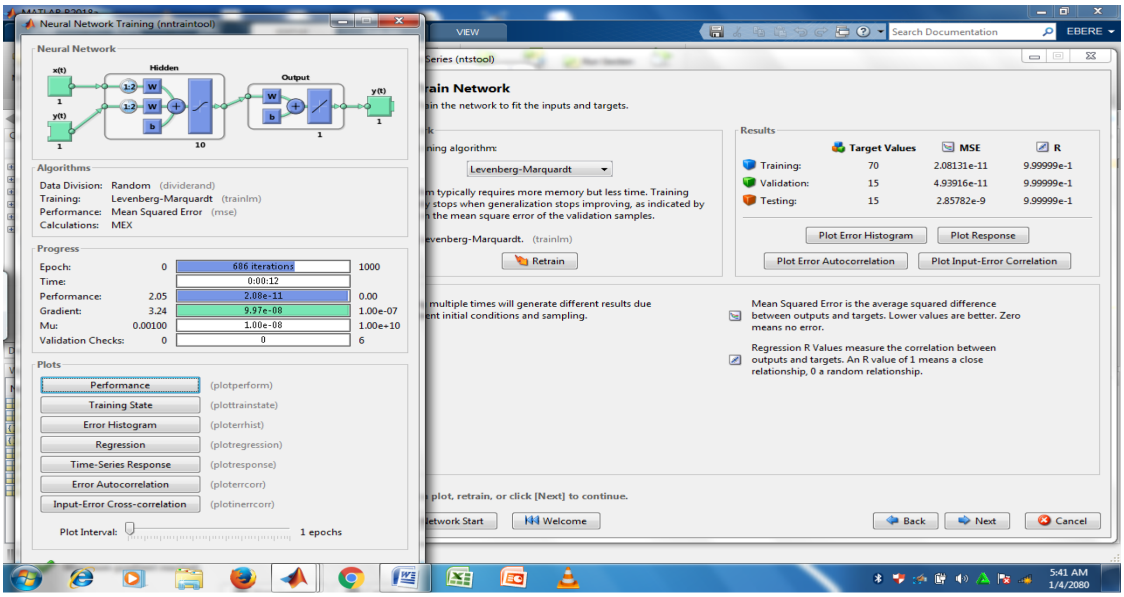


Figure 8: neural network training tool

From the toolbox above, the data was feed to the neural network using the data model designed in figure 4 and then trained using the training tool above with the training parameters in table 3.; the training dataset was collected from EEDC with the inputs load and cost (see appendix B) for the dataset.

Table 4: Neural Network Parameters

Parameters	Values
Controller Training epochs	10
Size of hidden layers	10
Controller training segments	30
No. delayed reference input	2
Maximum plant output	3.1
Maximum plant input	15
Number of non hidden layers	2
Maximum interval per sec	2
No. delayed controller output	1
No. delayed plant output	2
Minimum reference value	-0.7
Maximum reference value	0.7

IV. RESULTS AND DISCUSSIONS

This chapter will discuss the results of the simulations performed. This will be done using the neural network training tool box to generate the necessary training performance tools and evaluate the results using discussions. The result of the integrated new system will also be evaluated considering the estimated power consumption rate and price. Then the work will be validated using comparative analysis.

4.1 Result of Characterization

This section presented the performance of the characterization performance and the amount of power used at the 11KV feeder on daily and monthly bases. The result is presented in figure 9 and 10

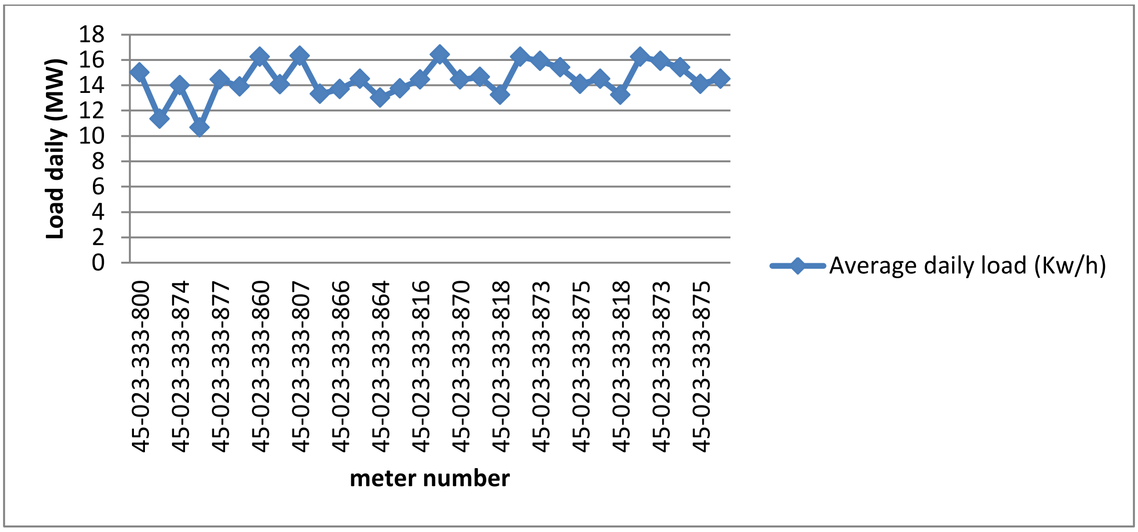


Figure 9: daily power used at the 11KV feeder

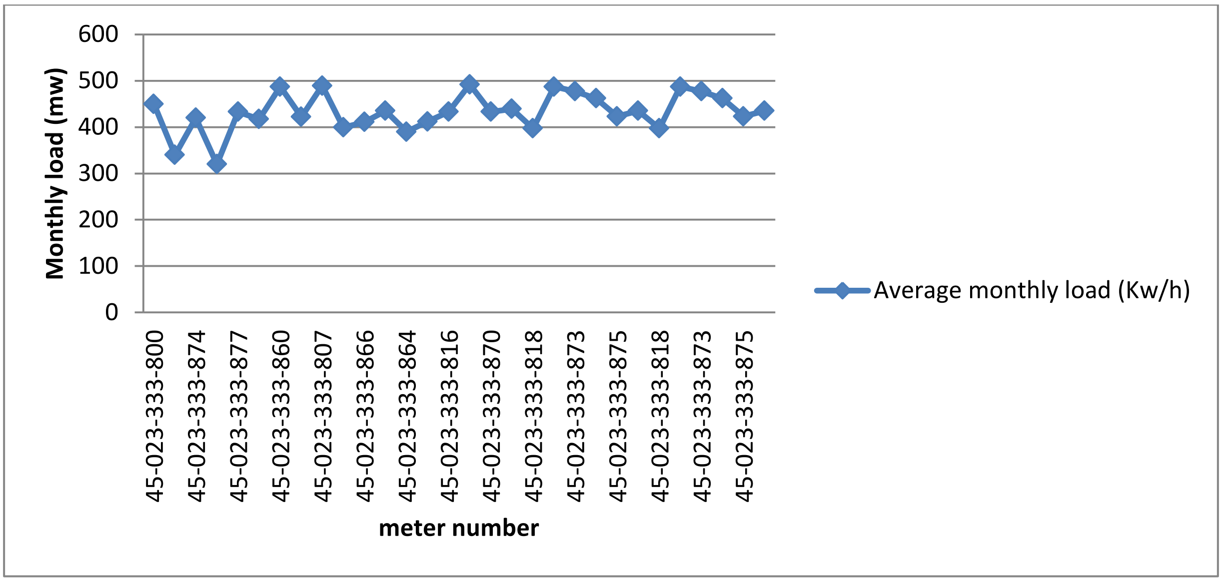


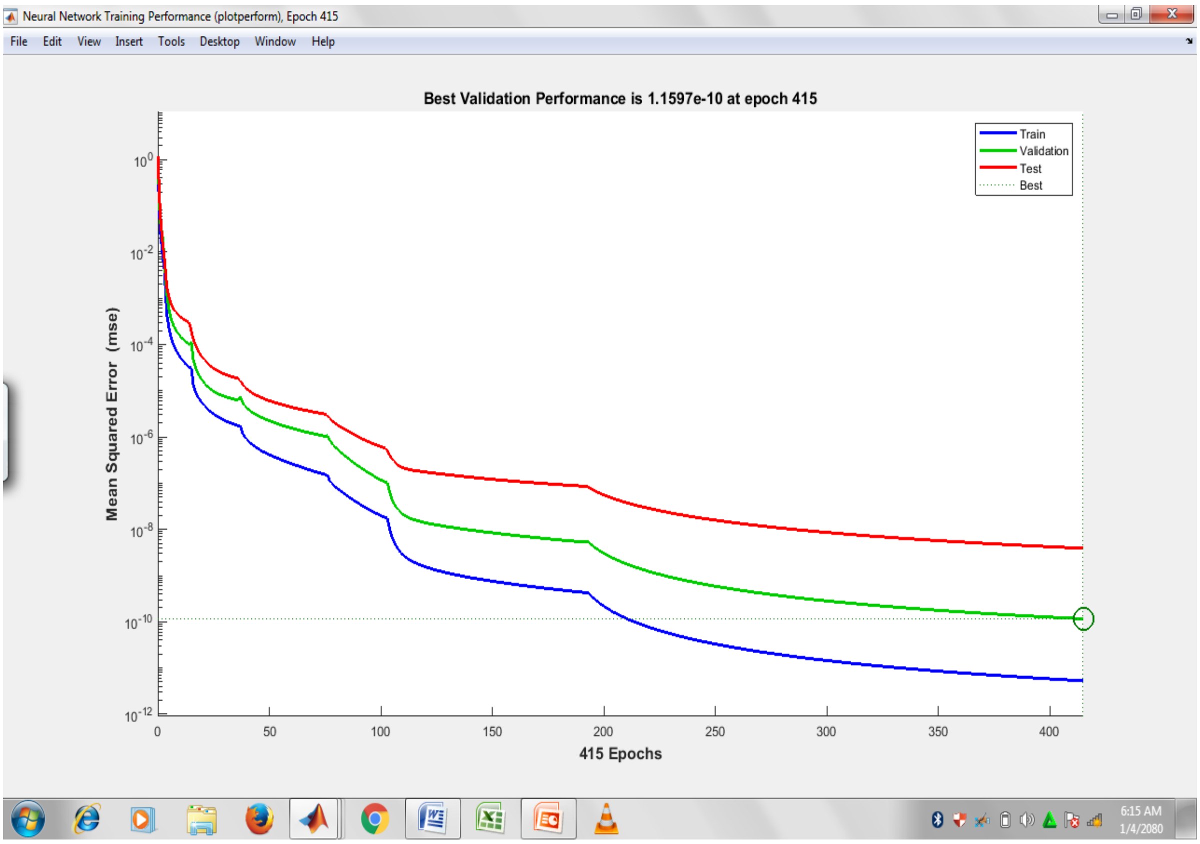
Figure 10: Power consumed on monthly basis

The result in figure 9 and 10 presented the actual power consumed by the 11KV distribution transformer. This data was used to train the neural network to able to forecast time series behavior of this feeder and the result achieved is presented in the next section.

4.2 Result of other works done

4.2.1 Training Results of the ANN

The neural network training toolbox automatically train, test and validate the training features and the training performance is monitored as shown below;



From the result presented in Figure 11: Neural network training performance

Figure 11, the performance of the neural network is presented for both the test, training and validation sets respectively. As the training process proceeds, this tool is used to monitor the response using the various epoch values until the epoch at which the least error and best validation performance is achieved which is at epoch 415. Also the aim of the tool is to monitor the training patterns of the sets. From the result it was observed that the three sets are correlated with similar pattern structure. The implication shows that the training process is perfect with an auto correlation error value of 1 as shown in figure 10.

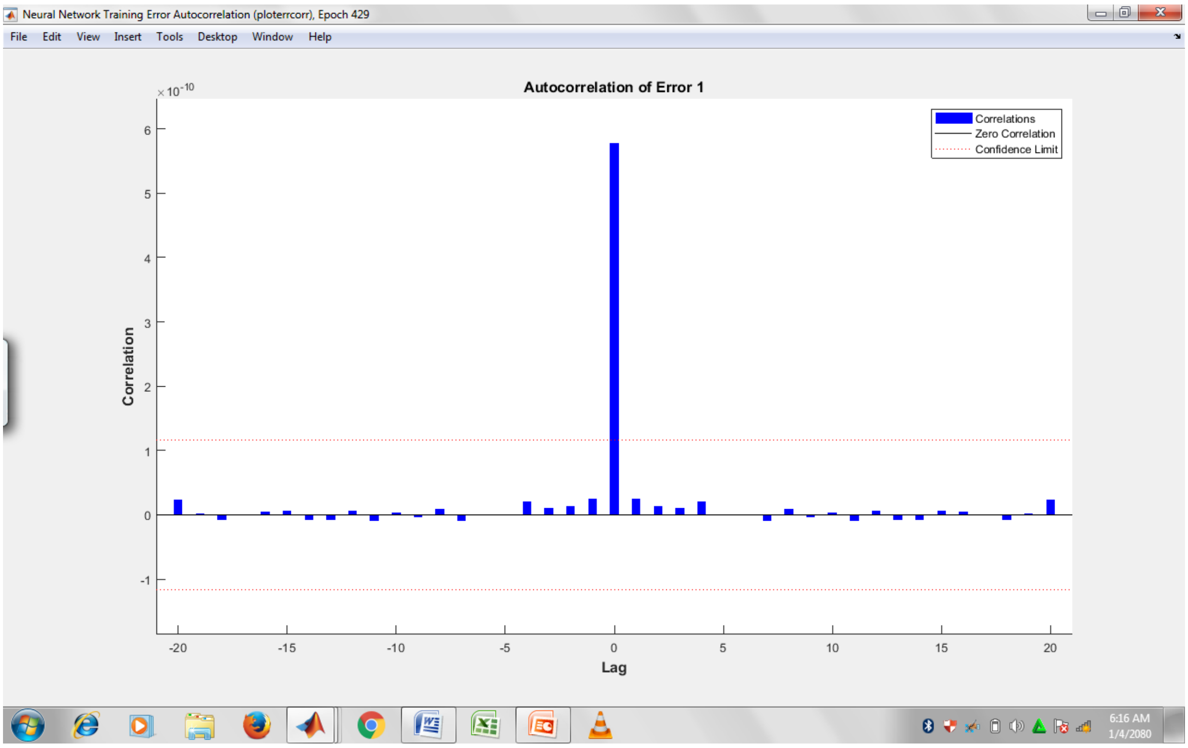


Figure 12: training auto correlation result

The next result is used to present the relationship between the correlations errors of the input and output targets. The result employs a regression value to represent the relationship between the zero correlations value and confidence limit. The aim is to achieve a confidence value greater than zero to imply that the training result is perfect as shown below;

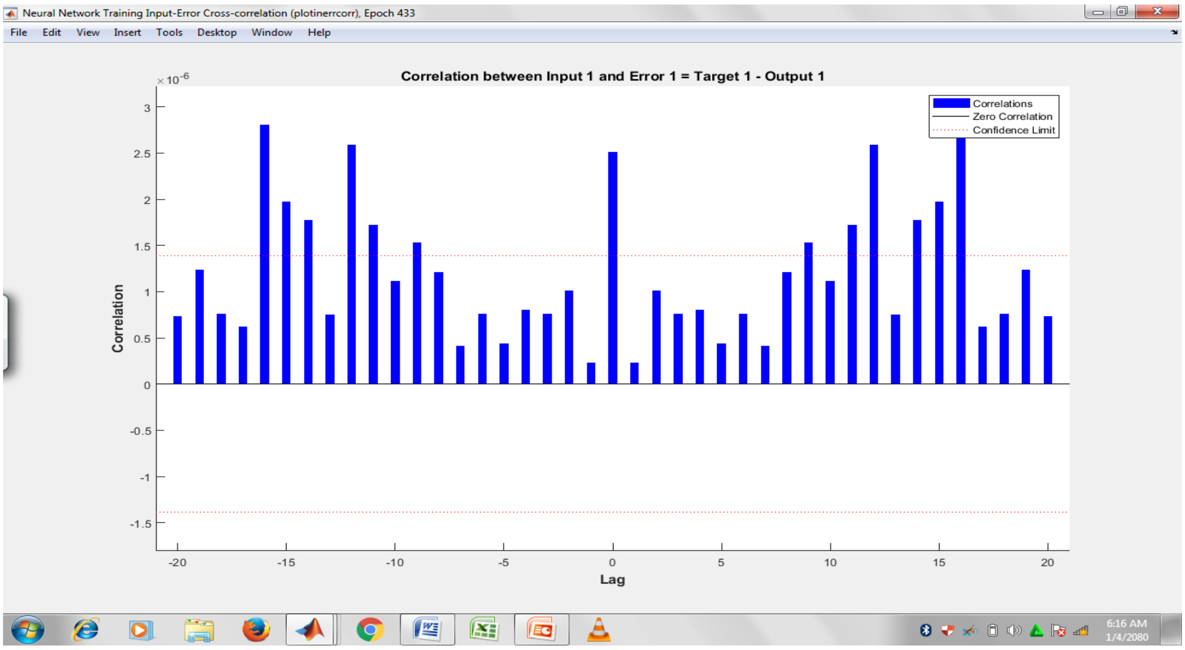


Figure 13: input error cross correlation result

From the result presented in figure 13, it reveals that the correlations between the input errors are in the confidence zone (greater than one) showing that a least error margin is realized during the training.

The regression analyzer below is used to evaluate the training performance for the test, train, validation and overall cross validation result of the neural network training process using a regression value as shown below;

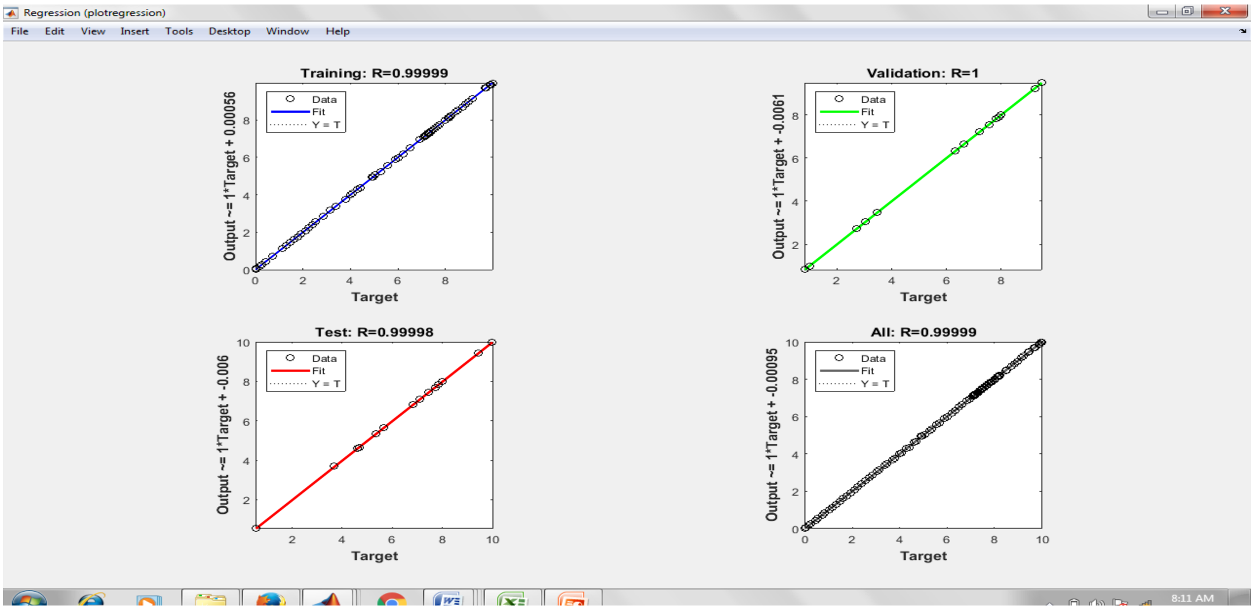


Figure 14: regression result

From the result presented in figure 14, the training performance of the neural network has been presented using the regression analyzer. In the result, it was observed that the overall regression value is 0.98. The implication of this result shows that the system will be able to estimated future time series vectors of the consumer behavior at 98% accuracy rate.

Result when integrated on the case study Areas

In this section, the performance of the integrated power system network was used to estimate the consumption rate of the 30 selected consumers for the next month and also the amount to be realized as shown below;

Table 5: The Estimated load forecasted for next month

Meter numbers	Average monthly load (Kw/h)	Average daily load (Kw/h)
45-023-333-800	441	14.7
45-023-333-827	333	11.1
45-023-333-874	417	13.7
45-023-333-801	314	10.5
45-023-333-877	409	13.7
45-023-333-863	408	13.1
45-023-333-860	457	14.2
45-023-333-857	412	13.7
45-023-333-807	414	15.9
45-023-333-879	317	12.1
45-023-333-866	405	12.8
45-023-333-867	415	13.4
45-023-333-864	370	12.6
45-023-333-832	402	12.7
45-023-333-816	413	14.1
45-023-333-803	472	15.4
45-023-333-870	423	13.9
45-023-333-869	419	13.4

45-023-333-818	317	12.6
45-023-333-884	477	15.3
45-023-333-873	422	14.7
45-023-333-854	442	14.2
45-023-333-875	413	13.1
45-023-333-812	415	13.3
45-023-333-818	361	12.2
45-023-333-884	467	15.4
45-023-333-873	447	14.5
45-023-333-854	432	14.0
45-023-333-875	413	13.2
45-023-333-812	415	12.3

The result presented in table 5 presented the estimated power to be consumed by the case study consumes over the next month. The equivalent price estimated to be realized from this area is also estimated and presented as shown below;

Table 6: Estimated tariff for the next month

Meter numbers	Monthly tariff (₦)
45-023-333-800	13648
45-023-333-827	10317
45-023-333-874	12739
45-023-333-801	9706
45-023-333-877	12999
45-023-333-863	12618
45-023-333-860	14882
45-023-333-857	12904
45-023-333-807	14879
45-023-333-879	12044
45-023-333-866	12510
45-023-333-867	12201
45-023-333-864	11982
45-023-333-832	12508
45-023-333-816	12044
45-023-333-803	14901
45-023-333-870	13033
45-023-333-869	13301
45-023-333-818	12022
45-023-333-884	14804
45-023-333-873	14520
45-023-333-854	14022
45-023-333-875	12991
45-023-333-812	13011
45-023-333-818	12101
45-023-333-884	14983
45-023-333-873	14502
45-023-333-854	14011
45-023-333-875	12803
45-023-333-812	13195

The area and also the actual amount and the forecasted amount to be realized from the area as shown in the table below. From the result presented in table 6, the estimated price expected to be realized from this case study feeder in the next month is presented as shown. With this result the EEDC can plan for the area and design the best load shedding plan which will suit the consumer load and also the amount realized from the region. The next result will present the comparative analysis comparing the actual load and the forecasted load for

Table 7: Comparative result of load consumed for a month

Meter numbers	Actual characterized power consumed (Kw/h)	Estimated power (Kw/h)
45-023-333-800	450	441
45-023-333-827	340	333
45-023-333-874	420	417
45-023-333-801	320	314
45-023-333-877	433	409
45-023-333-863	417	408
45-023-333-860	487	457
45-023-333-857	422	412
45-023-333-807	489	414
45-023-333-879	399	317
45-023-333-866	411	405
45-023-333-867	435	415
45-023-333-864	390	370
45-023-333-832	412	402
45-023-333-816	433	413
45-023-333-803	492	472
45-023-333-870	433	423
45-023-333-869	439	419
45-023-333-818	397	317
45-023-333-884	487	477
45-023-333-873	477	422
45-023-333-854	462	442
45-023-333-875	423	413
45-023-333-812	435	415
45-023-333-818	397	361
45-023-333-884	487	467
45-023-333-873	477	447
45-023-333-854	462	432
45-023-333-875	423	413
45-023-333-812	435	415

The result in table 7 presents the actual power consumed by the customers and the estimated power consumed. The result showed that the average monthly load forecasted is 408.7kw against 432.8kw. From the result, a comparative graph is used to shows that relationship between the data generated as shown below;

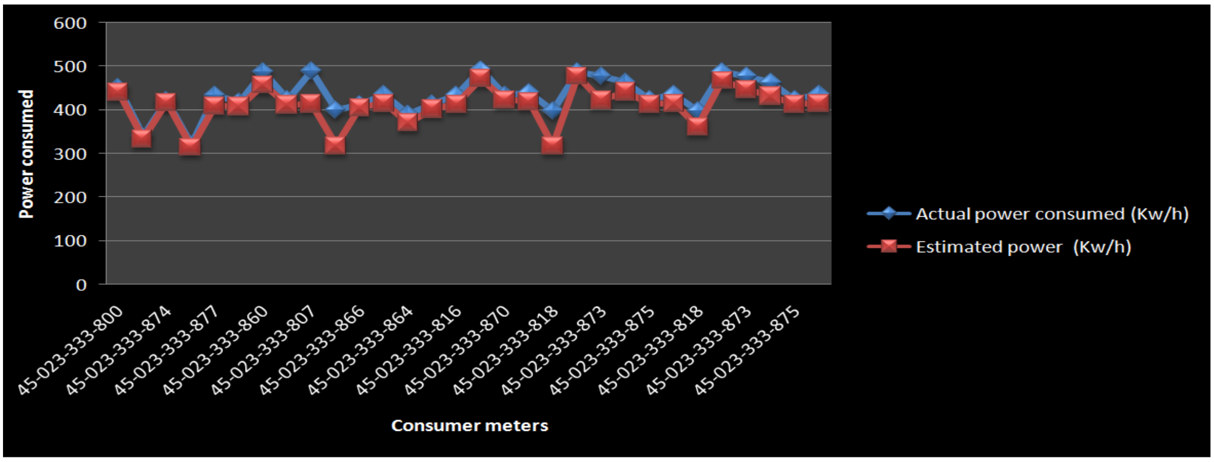


Figure 15: Comparative power consumed for the month

Table 8: Comparative analysis for the estimated daily load consumption

Meter numbers	Actual daily characterized load (Kw/h)	Estimated daily load (Kw/h)
45-023-333-800	14.7	15.00
45-023-333-827	11.1	11.34
45-023-333-874	13.7	14.00
45-023-333-801	10.5	10.67
45-023-333-877	13.7	14.44
45-023-333-863	13.1	13.90
45-023-333-860	14.2	16.24
45-023-333-857	13.7	14.07
45-023-333-807	15.9	16.30
45-023-333-879	12.1	13.30
45-023-333-866	12.8	13.70
45-023-333-867	13.4	14.50
45-023-333-864	12.6	13.00
45-023-333-832	12.7	13.74
45-023-333-816	14.1	14.44
45-023-333-803	15.4	16.40
45-023-333-870	13.9	14.44
45-023-333-869	13.4	14.64
45-023-333-818	12.6	13.24
45-023-333-884	15.3	16.24
45-023-333-873	14.7	15.90
45-023-333-854	14.2	15.40
45-023-333-875	13.1	14.10

The result in table 8 presents the performance of the new load forecasting system and then the characterized. The result showed that the mean forecasted load per day is 13.5kw against the characterized 14.3kw. The percentage accuracy is 94%.

The results presented in table 9 shows the comparative result for the actual characterized and estimated price generated by the integrated system designed as show below;

Table 9: Comparative price estimated

Meter numbers	Actual Characterized Monthly tariff (₦)	Estimated Monthly tariff (₦)
45-023-333-800	13,927	13648
45-023-333-827	10,523	10317
45-023-333-874	12,999	12739
45-023-333-801	9,904	9706
45-023-333-877	13,158	12999
45-023-333-863	12,906	12618
45-023-333-860	15,073	14882
45-023-333-857	13,061	12904
45-023-333-807	15,135	14879
45-023-333-879	12,349	12044
45-023-333-866	12,721	12510
45-023-333-867	13,464	12201
45-023-333-864	12,071	11982
45-023-333-832	12,752	12508
45-023-333-816	13,402	12044
45-023-333-803	15,228	14901
45-023-333-870	13,402	13033
45-023-333-869	13,588	13301

45-023-333-818	12,288	12022
45-023-333-884	15,073	14804
45-023-333-873	14,764	14520
45-023-333-854	14,299	14022
45-023-333-875	13,092	12991
45-023-333-812	13,464	13011
45-023-333-818	12,288	12101
45-023-333-884	15,073	14983
45-023-333-873	14,764	14502
45-023-333-854	14,299	14011
45-023-333-875	13,092	12803
45-023-333-812	13,464	13195

From the amount forecasted in the new system which is averagely N13072 per month for each meter, against the characterized cost of 13387 per month for each meter, this implies a cost prediction accuracy of 97.6% which is very good and will help the distribution companies make better planning.

V. CONCLUSION

The management of power system in Nigeria has been very challenging over the past decade as the number of consumers keeps increasing while the load average power generated and distributed remains static due to poor investment in power generation. Secondly the high tariff rates imposed on the consumers have become a major problem, despite the lack of satisfaction reported generally be the power consumers. As a result power system management have become a major challenge and has lead to the adoption of various demand side management technique to help manage the consumer load consumption rate, pricing, and other power system planning methodologies.

Demand side management have to do with the proper management of power system from the consumer to the supply end to satisfy the demand and also ensure desired income is generated by the distribution companies. Conventionally smart meters have been used, but due to the fact that meters are vandalized in some places, and also due to the fact that most localities still depends on estimated bills makes the energy management process difficult. This work provides an artificial intelligence based demand response technique which estimates the load and equivalent amount to be realized for each feeder and then the data generated will be used by the EEDC or other distribution company for power system planning, load shedding and other power management services.

5.1 Contribution to Knowledge

- A neural network predictive model was developed to forecast load with accuracy of 94% load forecast accuracy
- The system was able to forecast price at 97.6% accuracy

5.2 Recommendation

Having successfully completed this research work, the following are recommended;

i. Loss is one of the major challenges affecting the power system in Nigeria, hence loss minimization schemes should be designed and integrated into the system for better quality of power

ii. The training dataset can be improved so as the system can be used for the national grid

iii. Weather report can also be integrated on the data model to help improve prediction accuracy

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