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DEVELOPMENT OF SHORT-TERM LOAD FORECASTING SYSTEM FOR DEMAND SITE MANAGEMENT OF TRANS-EKULU 33/11KVA DISTRIBUTIVE TRANSFORMER USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

This paper presents the development of an artificial intelligence-based short-term load forecasting system for demand site management of the Trans-Ekulu 33/11KV, 15MVA distributive transformer. Empirical data collection and analysis were performed using Newton Raphson load flow analysis to study feeder performance, and the amount of generated power on a short-term basis (24 hours) was estimated using a unit cost of 5.22 naira per kW. The collected data was used to train an artificial neural network-based load forecasting system, which was then implemented using Simulink. The system was tested through simulation, and the results showed that the algorithm was able to accurately estimate the behavior of the transformer in the next 24 hours, with a regression of 0.9989. The load forecasting system was integrated into the EEDC center for managing the Trans-Ekulu feeder, and the results showed that the behavior of the feeder was correctly estimated by the forecasting system

Keywords: **Power:** load Forecasting; Transformer; Artificial Intelligence; Newton Raphson; Algorithm; Feeder

1. INTRODUCTION

Recognizing the overall amount of power consumption patterns in the future is a vital part of exploring and planning electrical power systems. The quality control and effectiveness of these power system operations heavily depend on accurately forecasting future demand for effective site management. Thus, forecasting the overall power usage per given future time accurately is a mandatory prerequisite for managing power system generation, transmission, and distribution operations. Load forecasting has been an integral part of power system planning since the 19th century and has gained increased research attention worldwide. Accurate load forecasting will help power generation and distribution companies make precise unit commitment decisions regarding voltage control, power supply quality, load switching, network reconfiguration, and infrastructural development. Furthermore, it will ensure low power generation costs and minimize unit costs for consumers, guaranteeing power system reliability.

The importance of load forecasting cannot be overstated. It has received tremendous research focus, aiming to improve accuracy, as the merit derived from the forecasting system depends on the prediction's success. Load forecasting can be classified into three main categories: short-term load forecasting, medium-term load forecasting, and long-term load forecasting. Short-term load demand forecasting predicts for one hour or more but less than 24 hours, medium-term load demand forecasting predicts for 2 days to around 2 weeks or a month, while long-term load forecasting lasts up to 6 months to a year (Ashigwuike et al., 2020).

Traditionally, load forecasting decisions were based on analyzing reports for a case study area. However, this approach is prone to human error and is unreliable. To improve performance, various models such as fuzzy logic, bank Jones algorithm, Kalman filters, expert systems, wavelet technique, and neural network were developed. These approaches have their advantages and disadvantages. However, the use of neural networks offers better success than the counterparts (Zina et al., 2018).

Trans-Ekulu, a place in Enugu, Nigeria, has experienced an influx of people from different parts of the state, resulting in industrial, infrastructural, and economic growth. This population increase has proportionately increased the area's load demand beyond the conventional supply margin. Consequently, the area has experienced poor power supply quality, power outages, fluctuations, and other challenges unsatisfactory to consumers. Developing a load forecasting system to predict the amount of power used by the area can enable better power system planning and improve demand site management.

Over the years, various techniques, including heuristic approaches, machine learning, demand response, among others, have been proposed to develop load forecasting systems for power planning (Maew et al., 2017; Nauru, 2016; Zah et al., 2015; Hana, 2018). However, machine learning has provided better results in terms of forecasting accuracy when compared to the other techniques. Machine learning is a branch of artificial intelligence that can learn by training a dataset and make accurate decisions. Studies by Zah et al. (2015) revealed that neural network-based machine learning algorithms are the most effective solution for power system planning and load forecasting. Thus, we will adopt and use this algorithm to develop a load forecasting model for the EEDC for better demand site management.

2. LITERATURE REVIEW

Nauru (2016) presented a new mathematical approach and heuristic methods for forecasting in smart grid. The study used mathematical models to forecast load estimate in grid using heuristic method. The result can be improved with artificial intelligence technique. Zah et al. (2015) presented a study on the application of Artificial neural network for load forecasting in smart grid. The study performed long term load forecasting on the distribution system using artificial neural network technique. Hana (2018) researched on short term electric load forecasting using demand site management technique. The study performs load forecasting using demand site management technique for short term power planning in the area using demand response technique. The estimated load usage accuracy can be improved with ANN.

Maew et al. (2017) presented a study on demand site management using artificial neural networks in a smart grid environment. The study performed power system planning on the area using ANN based load forecasting technique using artificial neural networks. The study did not consider cost of the load estimated as a complete analysis and planning. Haider et al. (2016) presented a review on residential demand response of smart grid. The study reviewed various technique for demand site management with the use of descriptive analysis. They recommended the use of artificial intelligence technique for future works. O’connel et al. (2016) presented a study on benefits and challenges of electrical demand response. The study overviewed various benefits and challenges of demand response using a qualitative analysis technique. Artificial intelligence technique was recommended as the best approach in future.

3. MTHODOLOGY

The methodology employed for this paper involved experimental investigation of the Trans-Ekulu 15MVA. 33/11KV feeder using load flow analysis to collect the amount of power consumed by the testbed on short term bases (24Hr). The equivalent cost of the load was also studied. The data collected was used to develop a load forecasting program using artificial neural network and then implement with neural network toolbox in MATLAB.

3.1 Engineering Materials Used

The engineering materials used for the study are laptop which was installed with ETAP load flow analyzer software to read the power consumed by the feeder transformer on daily basis considering active and reactive power parameters. The 15MVA, 11KV feeder transformer was the testbed under study. The price of the load consumed on daily based by the transformer was collected from the EEDC logbook; other instruments used were power meter to measure the overall power flow in the transformer within 24Hr.

3.2 Method of Data Collection

The primary source of data collection is the Enugu State Electricity Distribution Company (EEDC) which provided the data of the testbed. The data collection considers load flow attributes such as active power consumed by the feeder and also the

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equivalent cost which was collected from the account department of the EEDC.

3.3 Investigation of the Trans-Ekulu Feeder Using Newton Raphson Load Flow Analysis

The Newton Raphson load flow analysis in Onah et al. (2019) which consider the bus admittance matrix of the feeder and then used the parameters to compute the Jacobian matrix of the system and formulate the active and reactive power flow of the transfer for the day was used to collect data of the total load on the 19th to 25th March, 2022 for 24Hr of each day.

The total price of the transformer load collected was calculated at the rate of 1Kw unit of energy per hour at 51.22 naira (class B (ie the class the feeder belongs)) in customer traffic plan. The results of the data collection are all reported in chapter four. The data analysis for the overall load consumed and the price are all reported in the chapter four.

3.4 Development of a load forecasting system for the Area

The method used for the development of the load forecasting scheme is the structural method. This method was used due to its ability to model a system in a simple but clearly define the relationships between all the variables put together to achieve the new system. To develop the system, the artificial neural network algorithm was adopted from Arjun et al. (2014). In the paper, the feed forward neural network was modeled using the relationship between the weights, bias and activation function of a single neuron to develop feedforward neural network architecture. The model of the simple feedforward neural network is presented in figure 1 as;

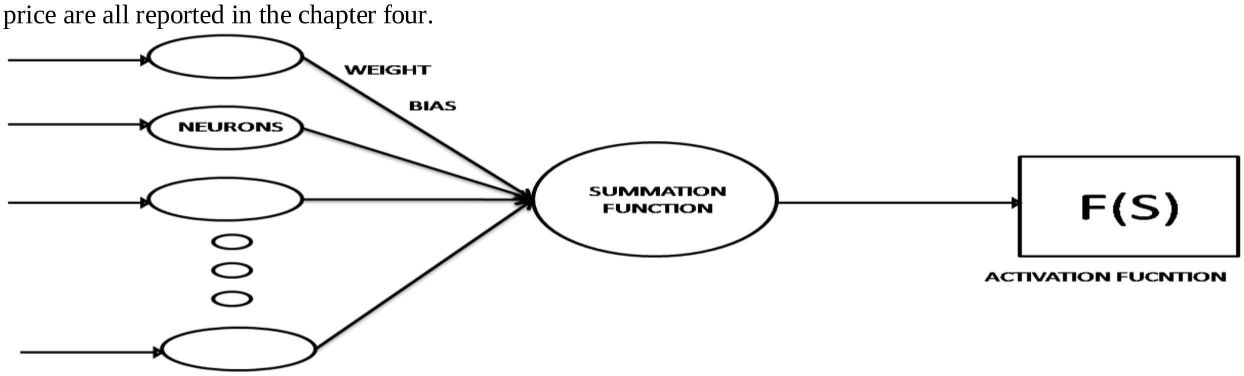

Figure 1: Model of a simple feedforward neural network

The figure 1 presented a simple feedforward neural network architecture configured with the weight, bias, activation function, summation function and the activated output. The model shows how the internal structure of a neural network was modeled with the weight and bis functions incite the neurons as the input. The summation of the input is activated for training to generate the desired load forecasting system. The neural network model in figure 1 was used to develop the neural network architecture used in training the feeder data. The developed model was presented in figure2;

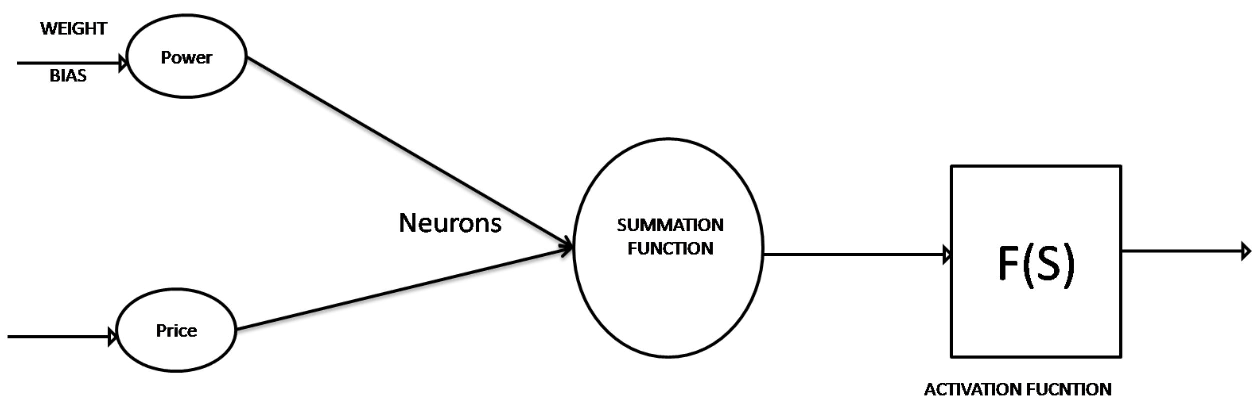

Figure 2: Model of the neural network

The figure 2 presented the model of the neural network developed to train the data collection. The model was developed using considering the number of classes in the data collection which are load and price. These were used to configure the input number to the network. The hidden layers were configured using the training parameter in table 1;

Training Parameters	**Values**
Maximum number of epochs to train	100
Epoch between display	10
Maximum time to train in sec	Infinity
Validation check	6
Initial step size	0.01
Minimum performance gradient	1e-6
Cost horizon	7
Control horizon	2
Number of bias functions	20
Training Iterations	56
Number of hidden layers	20
Number of weights	20
Number of input class	2

Algorithm

1. *Start*
2. *Load training set*
3. *Configure neural network*
4. *Initialize epoch*
5. *Initialize Mean Square Error (MSE)*
6. *Adjust the neural network weights*
7. *Check for least MSE*
8. *If*
9. *Error is true*
10. *Then*
11. *Stop training*
12. *Else*
13. *Next epoch*
14. *Feedback output to input*
15. *Adjust weights*
16. *Check MSE*
17. *Is least MSE = true*
18. *Stop training*
19. *Reference mode*
20. *Stop*

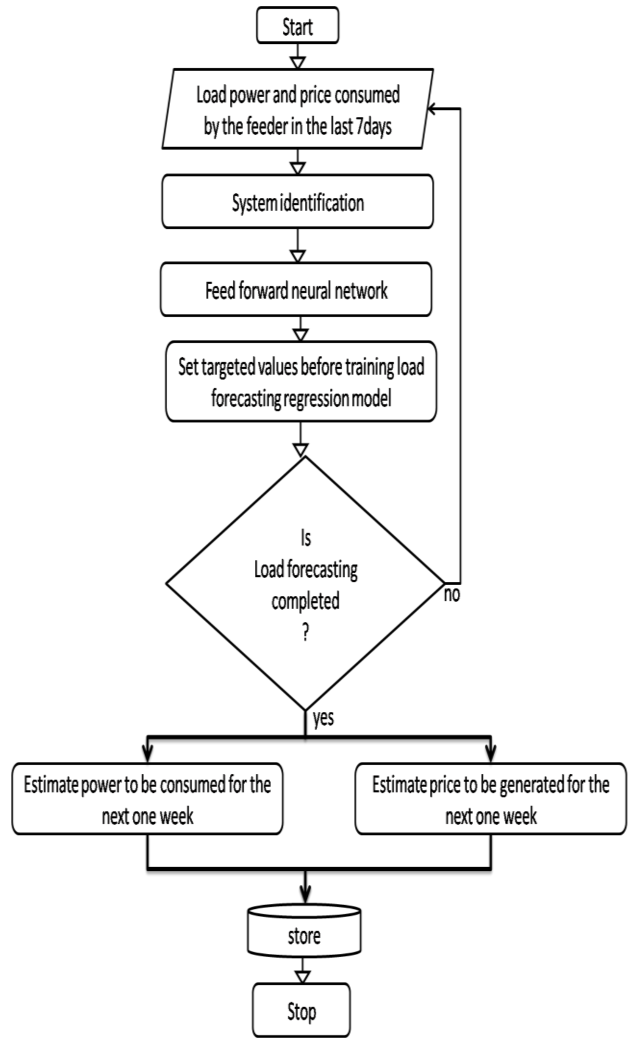

Figure 3: The system flow chart

4 RESULT AND PERFORMANCE ANALYSIS

This section presented the performance of the load forecasting algorithm developed. The result discussed the training performance of the data collection with the neural network algorithm to develop the load forecasting system using MSE and Regression. The result of the algorithm was validated and analyzed. The MSE analysis was presented in figure 4;

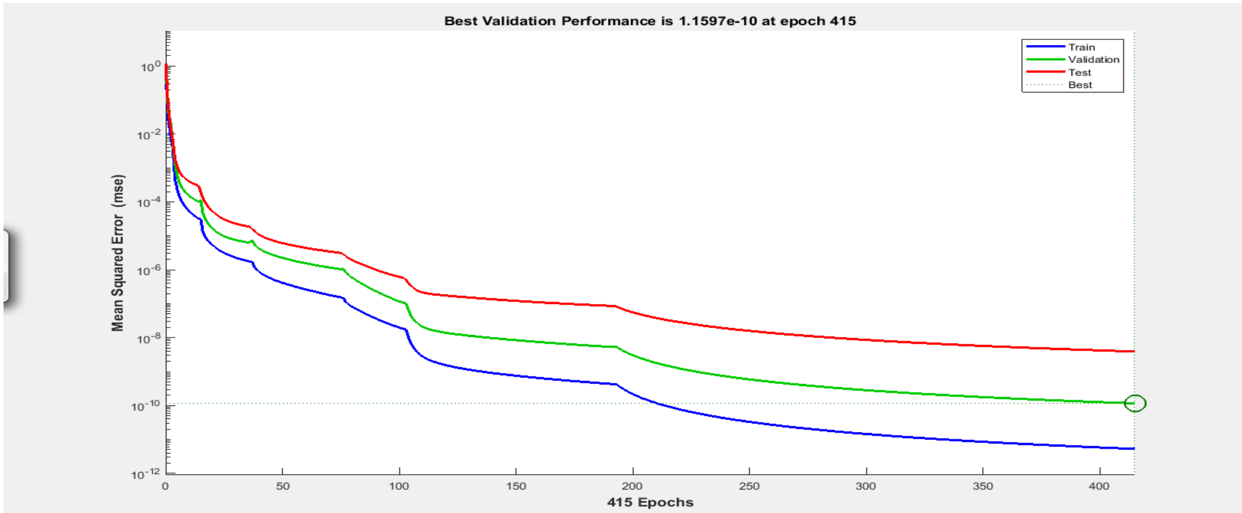

Figure 4: MSE result of the algorithm

The result of the MSE in figure 4 was used to measure the error which occurred in the neural network during the training process. The idea was to achieve error of zero or approximately zero. From the result it was observed that the MSE result is 1.1597E-10 at epoch 415. The implication of this result showed that the error which occurred during the training process is minimal and hence indicated that the learning process was good and the algorithm was able to predict the transformer behavior on a day time series. The next result presented the regression performance as in figure 5;

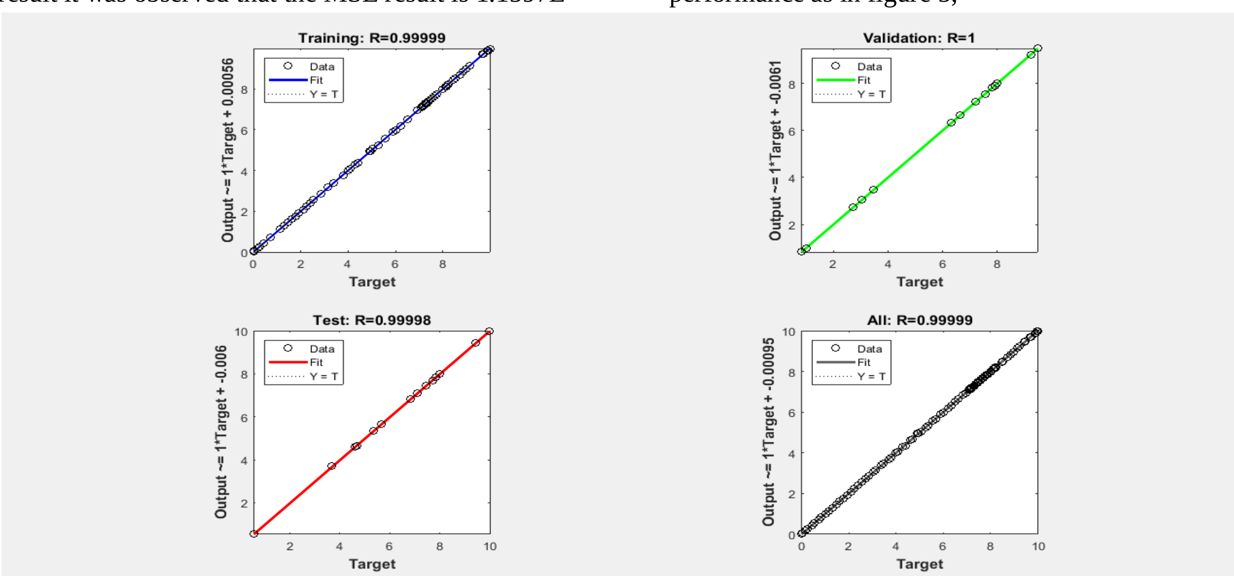

Figure 5: Regression Performance

TABLE 2: VALIDATION RESULT OF THE ALGORITHM

S/N	MSE	Regression
1	1.1597E-10	0.9999
2	1.2597E-10	0.9679
3	1.1897E-10	0.9939
4	1.1297E-10	0.9899
5	1.2297E-10	0.9879
6	1.1387E-10	0.9309
7	1.1597E-10	1.0000
8	1.1997E-10	0.9879
9	1.1447E-10	0.9934
10	1.1397E-10	0.9952
Average	1.1537E-10	0.98469

The table2 presented the result of the validation performance and it was observed that the MSE value is 1.1537-E which is approximately zero thus indicating good training performance. The result of the regression was also validated and the result of 0.98469 was achieved, which is also very close to the ideal regression value of 1. The result of the system integration presented the impact of the algorithm on the EEDC system for the load forecasting of the feeder performance in the next 24hrs. The result is presented in the table 3;

TALE 3: FORECASTED DATA OF THE FEEDER IN THE NEXT 24HRS.

Time (Hr)	Average daily load (Kw/h)
1	14.98
2	10.56
3	16.29
4	16.11
5	14.39
6	14.39
7	14.32
8	13.14
9	13.14
10	11.22
11	13.62
12	15.29
13	15.28
14	13.58
15	16.13
16	13.78
17	12.46
18	13.57
19	14.38
20	16.97
21	14.29
22	15.78
23	15.78
24	13.51
Total	340.52
Cost kW/Hr	17,441.4344
Cost Kw/day	418,594.426

The result of the table 3 presented the performance of the algorithm when used to forecast the load consumption of the transformer in the next 24hrs. The estimated amount generated per hour and total amount expected from the feeder in the next 24Hr was presented which is 418,594.426. The result showed that the transformer will consume 340.52kW of power.

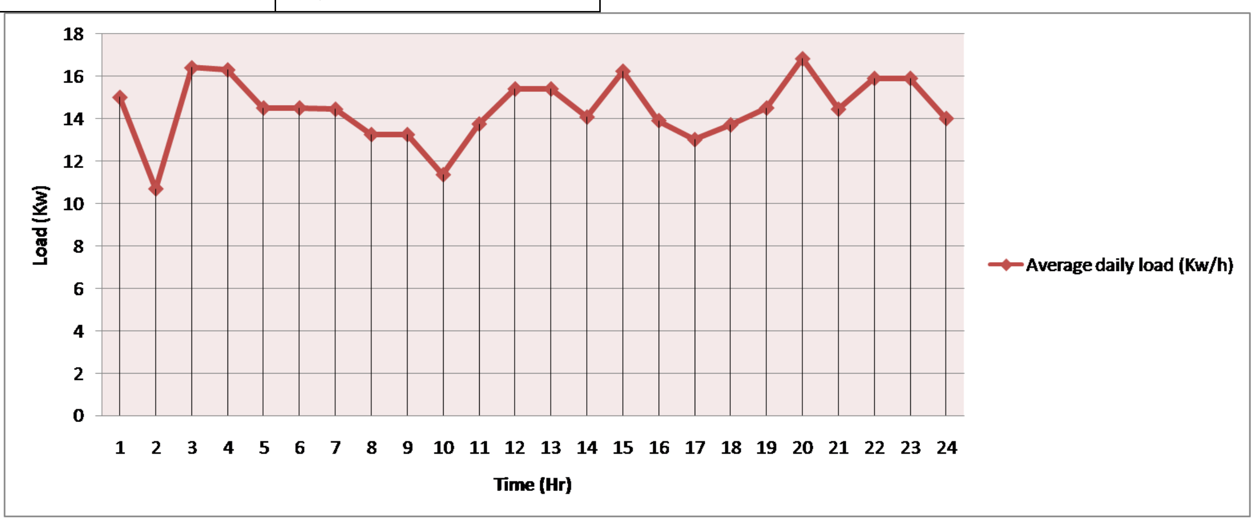

Figure 6: Estimated behavior of the feeder with ANN

The figure 6 presented the load forecasted behavior of the transformer showing estimated load consumption performance of the system in the next 24Hr. The result showed that the estimated peak period is 8pm (20:00) while the off-peak period is 2:00 am.

4.1 COMPARATIVE ANALYSIS

In this section, the data acquired after the implementation of the algorithm was compared with the actual data collected on the date and the to determine the system reliability and the results are presented in table 4;

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TABLE 4: COMPARATIVE RESULT OF THE TRANSFORMER DAILY DATA

Time (Hr)	Estimated Load	Actual Load
1	14.68	15.00
2	10.46	10.67
3	16.19	16.40
4	16.11	16.30
5	14.29	14.50
6	14.39	14.50
7	14.12	14.44
8	13.14	13.24
9	13.14	13.24
10	11.22	11.34
11	13.52	13.74
12	15.29	15.40
13	15.28	15.40
14	13.58	14.07
15	16.13	16.24
16	13.78	13.90
17	12.46	13.00
18	13.57	13.70
19	14.28	14.50
20	16.67	16.83
21	14.29	14.44
22	15.78	15.90
23	15.78	15.90
24	13.51	14.00
Total	340.52	344.46
Cost kW/Hr	17,441.4344	17,643.2412
Cost Kw/day	418,594.426	423,437.789

The result in the table 4 presented the performance of the comparative performance of the transformer using the actual and estimated data. The result showed that the estimated total load consumed by the transformer is 340.53kW as against 344.46kW. The implication of the result showed that the load forecasting algorithm was able to closely estimate the transformer load. The graphical analysis was used to read other behavior of the transformer as shown in figure 7;

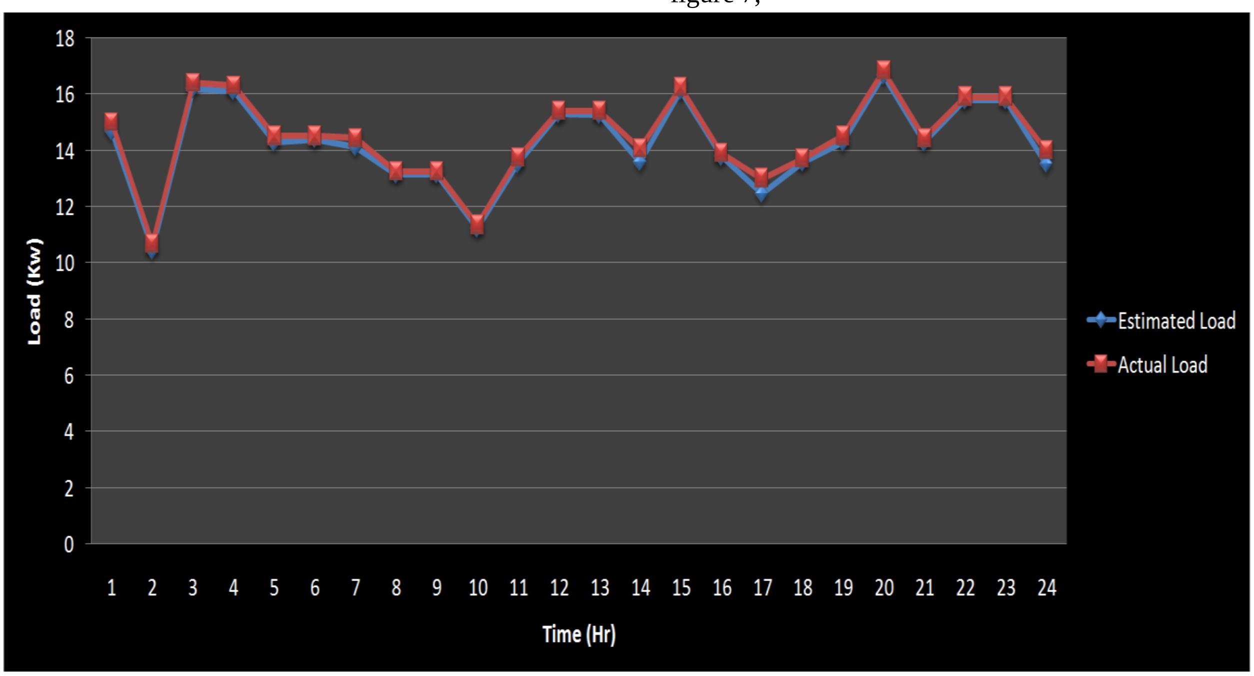

Figure 7: Comparative transformer behavior

The figure 7 presented the comparative result of the load forecasting algorithm as against the actual data. From the result, it was observed that the algorithm was able to estimate that the actual peak and off-peak period and other load behavior. The result also estimated the amount of load consumed by the transformer and the actual load consumed as presented in the figure 8;

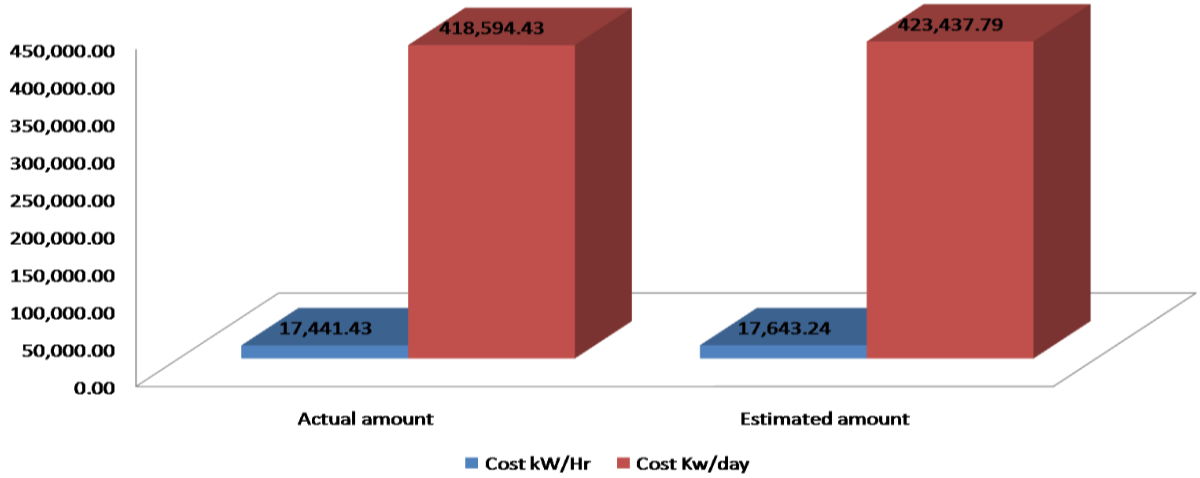

Figure 8: Comparative cost analysis

The figure 8 presented the comparative feeder performance in term of cost. The result estimated the amount of load consumed by the transformer on hourly basis and also on daily basis. The result showed that the load flow analysis system was able to correctly estimate the amount of power consumed from the load. The idea is to know which is expected from the feeder at the end of the day and then compare with the actual cost realized from the feeder. This will help in better demand site management.

4. CONCLUSION

From the experimental investigation conducted on the load flow of the 11kV feeder, it was uncovered that the behavior of the transformer varies on daily basis and as a result there is need for a smart strategy for demand site management. This solution was developed in this research using artificial neural network to develop an algorithm for load forecasting. The algorithm developed was tested, validated and deployed at the EEDC for the management of the Trans-Ekulu feeder. The result showed that the system developed was able to correctly estimate the performance of the load for seven consecutive days and also determine the total amount expected to be generated from the feeder.

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