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A Comparative Study of Harvey Model and Artificial Neural Network Methods for Energy Demand Forecasting in Nigeria

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Abstract: Peak and average load demand are important metrics in the electric power sector as they form a base for energy forecasting and management as techniques to guarantee accurate energy prediction are investigated. In this study, Artificial Neural Network (ANN) has been investigated for peak and average load demand forecast. In comparison with the Harvey Model (HM) which had been previously validated for its superiority in load forecasting, ANN outperformed HM with least errors given the performance metrics of Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). A closer assessment of the results obtained showed that ANN demonstrated a superior performance in forecasting the load demand with minimum errors and will be relevant to stakeholders in energy management as a measure to avoid over and under load demand forecast while making accurate predictions of future energy demand.

Keywords: *Artificial Neural Network; Average Load Demand; Harvey Model; Load forecasting; Peak Load Demand.*

Introduction: Over time, electric power sector has proven to be one of the indispensable economic drivers in promoting national wellbeing of citizenry on a global scale. In order to maintain technological advances and as well promote globalization of economies among other metrics, the challenges faced on the amount of electric energy to be generated and distributed based on existing and future demand has to be surmounted. This in fact places a limit on the decisions reached by the utilities as basic milestones has to be reached in terms of electric power planning, scheduling, power control and load flow analysis. As electric power demand increases, the need for load forecasting becomes significant as it will help in load estimation and consequently, the production and distribution of electric power. Load forecasting has therefore become a tool for energy efficiency management and serves as a technique used in estimating the difference between the actual and predicted values of future load demand in view of optimizing the electrical power system.

According to [1] load flow analysis, scheduling, energy efficiency and management can be investigated via load forecasting while the ensuing outcome must guide against either over-estimation or under-estimation of load demand. The direct consequence of over-estimation may lead to over-investment in power system facilities, installation issues and system efficiency while under-estimation may lead to system overloading and load shedding challenges among others [2]. Load forecasting approaches have been largely classified as statistical techniques and artificial Intelligence techniques. Some of the statistical techniques in use are the Auto-Regression Moving Average (ARMA), Exponential Smoothing Model (ESM), Linear Regression (LR), Stochastic Time Series Technique (STST), Exponential Technique (ET) and Harvey Model among others. The popular among the Artificial Intelligence (AI) techniques in use are Artificial Neural Network (ANN), Fuzzy Logic (FL), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) among others. These AI techniques are beginning to gain huge acceptance in the industry and academia largely due to their adaptive capabilities and ease of manipulation of large and complex dataset, performance accuracy and minimal computational time and cost [3, 4]. In view of the emerging power sector reforms, the electrical industry has become more robust as renewable sources are being explored alongside conventional sources. The underlying factor guiding this degree of robustness has its foundation

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lying on peak and average load demand forecasting. As a matter of fact, assessment of peak load demand is an essential factor that largely determine energy billing, needless to reiterate that the peak load at demand side translate to the price charged for the peak amount of power consumed at any instant of time [5]. Load forecasting has become imperative for power system management as the utilities/consumers depend on its efficient predictions for sustainable power system deployment.

The need for more reliable forecasting technique has spurred research community in investigating novel techniques for load forecasting. Among the contending innovations is the work of [6] in which the authors carried out time series analysis for energy demand forecast in Nigeria by comparing the performances of Harvey, ARMA and ESM for which Harvey Model showed performance superiority. In the work of [7], they studied the effect of modified exponential regression model on long term electric load forecasting in residential, commercial and industrial load demand. Harvey Logistic and Garch Models were used to forecast energy demand and supply in Nigeria [8]. Other statistical models used are the Multiple/Quadratic Regression Model [9] and ARIMA Model [10]. In [11] medium term load forecasting for university based load demand was carried out using ANN and LR Model; ANN outperformed the LR Model. ANN performs prediction by categorizing data into training, validation and testing data, while adopting a number of neurons in the hidden layer as well as iterative algorithm for data training. Authors in [12] proposed a minimum distance based approach for network training and later investigated the effect of ARMA model using Widrow Hoff Delta rule for model parameter update [13]. Alternate expert systems have been explored as well using FL for load forecasting. This approach relies on defining the FL Inference System such that the heuristic properties of the artificial network provide a seamless approach to load forecasting by proposing fuzzy rules and membership functions based on the statistical variation of the load pattern [14]. While hybrid systems of Fuzzy-Neural Networks [15, 16] had been proposed for load forecasting, it is to be noted that FL based systems are more complicated than Neural Network based models for load forecasting with a tradeoff on the cost of defining inputs and model parameters relationship. This article predicts peak and average load demand in Nigeria over a period of twenty (20) years with use of ANN; the performance of ANN was compared with Harvey Model using Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE).

Materials & Method: The historical load demand data collected from National Control Center in Osun State, Nigeria as found in the work of [6] shown in Table 1 was used. A cursory examination of the collected data shows that trend in both the peak and average load demand increased appreciably as the year’s advances. Of course, the trend observed is expected as the amount of energy demanded can never diminish, it will rather increase due to daily demand for energy to meet up with man’s basic (domestic energy) and social (Commercial and Industrial energy) needs.

Table 1. A Summary of Peak and Average Load Demand from 1998 to 2017.

Year	Peak Load (MW)	Average Load (MW)
1998	2448	2357
1999	2458	2300
2000	2499	2161
2001	2934	2449
2002	3223	3019
2003	3479	3200
2004	3428	3316
2005	3775	3420
2006	3682	3267

2007	3600	3267
2008	3682	3267
2009	3600	3393
2010	3804	3607
2011	4089	3800
2012	4054	3765
2013	4458	4064
2014	4487	4171
2015	4811	4444
2016	5075	4166
2017	5222	4641

(Source: Okakwu *et al.,* 2017)

Both ANN and Harvey Model was employed to make both the peak and average energy prediction over the period of 20 years. The basic description of ANN and Harvey model are described in the following subsections; ANN is one of the mostly used AI techniques for load forecast both for medium and long term basis, its basic principle was founded on the behavior of human neural system. ANN style of solving optimization problems revolves around training of datasets to establish a pattern of what the expected output would be in relation to the input pattern [17], validation and testing of datasets. Authors in [11] described ANN as set of linked input/output units, with every connection having a specified attached weight. ANN is flexible; the associated weight can be adjusted to get a desire output pattern [18]. ANN trains datasets by adjusting the connection weight between layers; training stage is iteratively done [19]. Several approaches have been adopted by researchers to enhance effective datasets training, one of such is Levenberg Marquardt. During the training stage, Levenberg Marquardt combines both the speed of Gauss-newton's method and the stability of error back propagation algorithm [19]. The update rule in Levenberg Marquardt algorithm is governed by eq. 1 given as;

$$W_{k+1} = w_k - (J_K^T J_k + \mu I)^{-1} J_k e_k \qquad \text{eq.1}$$

Where; $\mu =$ Combination Coefficient (Positive Value), $I =$ Identity Matrix, $w =$ weight vector, $e =$ training error and $J =$ Jacobian matrix.

The essential steps in the learning of Levenberg Marquardt was scrupulously detailed in the work of [19, 20] and the astonishing features/advantages and adopted architecture of ANN was painstakingly presented. Summarily, the ANN training parameters used in this work are shown in Table2;

Table 2. The Training Parameters for ANN.

Artificial Neutral Network Training Parameters		
1.0	Design Architecture	2-layer (10 hidden layer and 1 input)
2.0	Training Algorithm	Levenberg Marquardt
3.0	Transfer Function	Tansig, purelin
4.0	Maximum Training Epoch	15
5.0	Performance Function	MSE
6.0	Performance Goal	10^{-5}
7.0	Total No of Neutrons	10

Another viable approach for load forecasting is Harvey Model, its basic mathematical modeling is presented thus;

$$\ln x_k = a \ln X_{k-1} + b + ck + \varepsilon \qquad \text{eq.2}$$

And

$$X_k = X_k - X_{k-1} \qquad \text{eq.3}$$

If;

$$P_j = \ln\left(\frac{X_k}{X_{k-1}}\right) \qquad \text{eq.4a}$$

$$q_j = \ln(X_{k-1}) \qquad \text{eq.4b}$$

Substituting equations (4a) and (4b) into Eqn. (2), the equation is transformed to;

$$P_j = aq_j + b + ck + \varepsilon \qquad \text{eq.5}$$

The error is given in (6)

$$\sum_{j=1}^{m} \varepsilon_j^2 = \sum_{j=1}^{m} \left(P_j - aq_j - b - ck\right)^2 \qquad \text{eq.6}$$

If v was assigned as;

$$V = \sum_{j-1}^{m} \varepsilon^2 \qquad \text{eq.7}$$

The Eqn. (8) follows directly from (7)

$$\frac{\partial v}{\partial a} = -2\left[\sum_{j=1}^{m} P_j q_j - a\sum_{j=1}^{m} q_j - b\sum_{j=1}^{m} q_j - c\sum_{j=1}^{m} k_j\right] \qquad \text{eq.7a}$$

$$\frac{\partial v}{\partial b} = -2\left[\sum_{j=1}^{m} P_j q_j - a\sum_{j=1}^{m} q_j - mb - c\sum_{j=1}^{m} k_j\right] \qquad \text{eq.7b}$$

$$\frac{\partial v}{\partial c} = -2\left[\sum_{j=1}^{m} P_j t_j - a\sum_{j=1}^{m} q_j k_j - b\sum_{j=1}^{m} k_j - c\sum_{j=1}^{m} k_j^2\right] \qquad \text{eq.7c}$$

If $\frac{\partial v}{\partial a} = \frac{\partial v}{\partial b} = \frac{\partial v}{\partial c} = 0$ and rearranged in matrix form in (7a, 7b and 7c), this translate to;

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} \sum_{j=1}^{m} q_j^2 & \sum_{j=1}^{m} q_j & \sum_{j=1}^{m} q_j k_j \\ \sum_{j=1}^{m} q_j & m & \sum_{j=1}^{m} k_j \\ \sum_{j=1}^{m} q_j t_j & \sum_{j=1}^{m} t_j & \sum_{j=1}^{m} k_j^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum_{j=1}^{m} P_j q_j \\ \sum_{j=1}^{m} P_j \\ \sum_{j=1}^{m} P_j k_j \end{bmatrix} \qquad \text{eq.8}$$

The solution of (8) gives the constants of the model.

The statistical tools used for performance analysis in this work are the MSE, RMSE, MAE, MAPE and the regression R-value. MSE is the average squared difference between outputs and targets. Lower values are better, with zero connoting no error. Regression R-values measures the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship.

Mean Square Error (MSE);

$$= \frac{\sum_{j=1}^{m} (\hat{x}_k - x_k)^2}{m} \qquad \text{eq.8}$$

Root Mean Square Error (RMSE);

$$= \sqrt{\frac{\sum_{j=1}^{m} (\hat{x}_k - x_k)^2}{m}} \qquad \text{eq.9}$$

Mean Absolute Error (MAE);

$$= \sum_{k=1}^{m} \frac{|\hat{x}_k - x_k|}{m}$$

eq.10

Mean Absolute Percentage Error (MAPE)

$$= \sum_{k=1}^{m} \frac{\left|\frac{\hat{x}_k - x_k}{x_k}\right|}{m} \times 100\%$$

eq.11

Results and Discussion: For this analysis, the datasets was stratified as 70% for data training, 15% for data validation and 15% for data testing. The Neural Network performance measure for average load demand was as shown from Fig. 1 to Fig. 3.

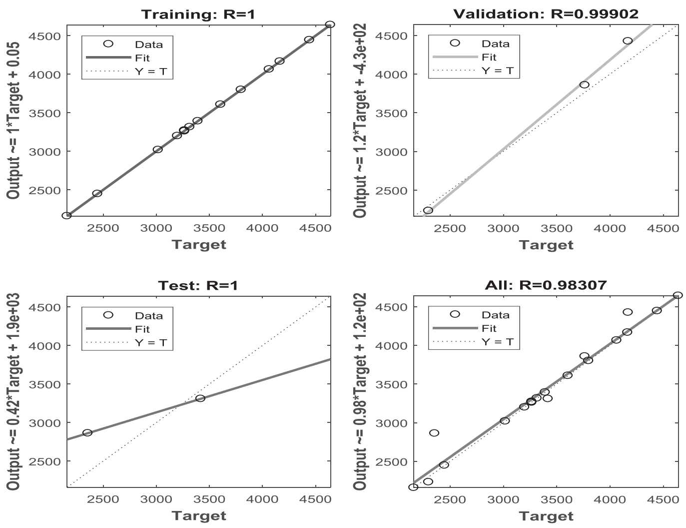

Fig. 1: Correlation between Output And Target Average Load Demand.

The R-Value was seen to approach unity value with average load demand forecast value of 1. This was a good correlation between the output and target and by implication we can conclude that the training was sufficiently done.

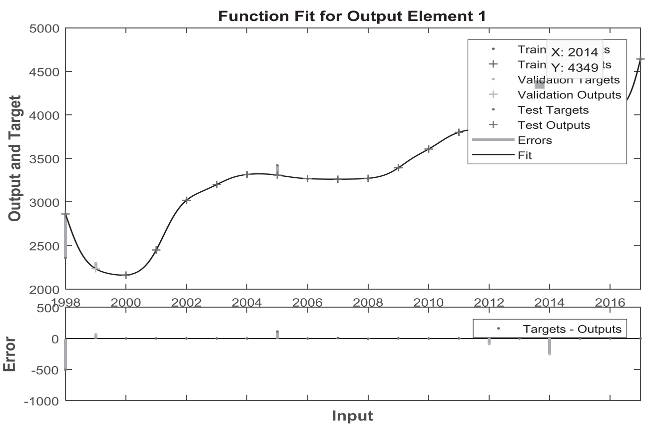

Fig. 2: Correlation between Network Parameters and Error Deviation of the Average Load Demand.

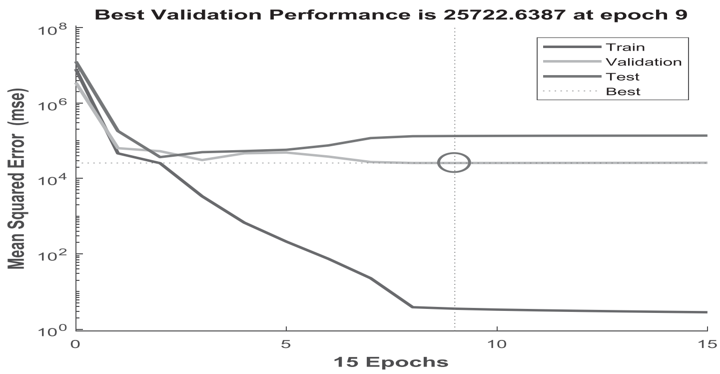

Fig. 3: Mean Squared Error Performance Validation of Average Load Demand.

It was observed from Fig.3 that the best validation performance was found to be 25722.6387 and it occurred at epoch nine (9). A comparison of actual and predicted average load demand obtained with ANN over the period of 20 years was as shown in Fig. 4. As seen from Fig. 4 the predicted values agreed perfectly with actual average load demand, a close examination of the predicted value with ANN was observed to be insignificantly different from the actual average load demand, as a result, for MAPE, MAE and RMSE, ANN model recorded 0.026, 1.3784, 5.5045 and 0.007 respectively.

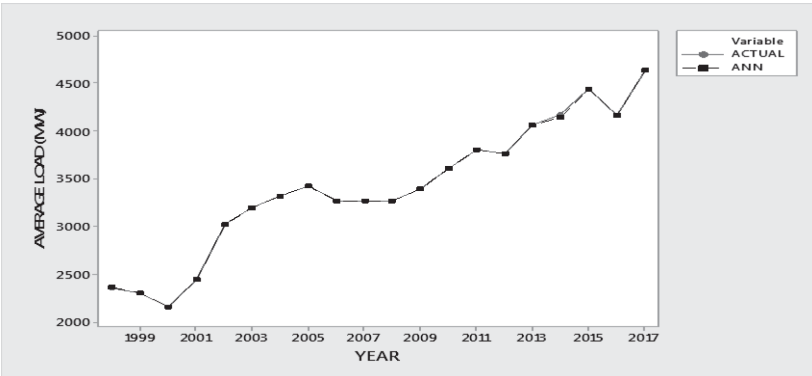

Fig. 4: Comparison of Actual and Average Load Demand Predicted with ANN Model.

With Harvey model, the average load demand obtained is significantly higher in magnitude compared to both the predicted values obtained using ANN and the actual average load demand. For MAPE, MAE and RMSE, Harvey model recorded the following values; 2.3579, 9.1095, 111.0188 and 0.0156 respectively. Fig.5 presents a line graph comparison of predicted values obtained with Harvey and ANN model. A closer examination shows the value obtained with ANN model agreed wholesomely with the actual values in the collected data.

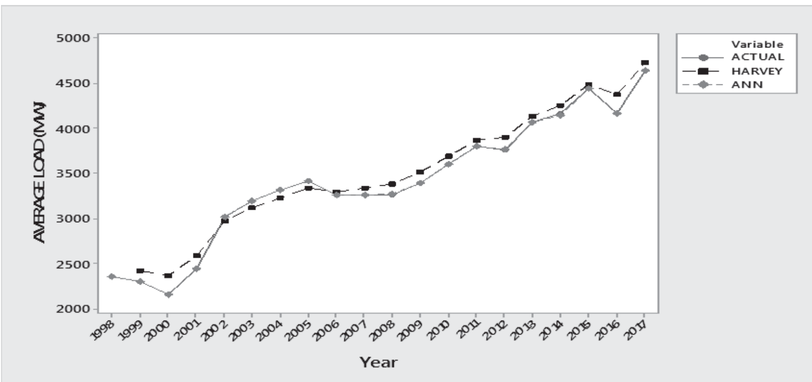

Fig.5: Comparison of Predicted values for Average Load Demand obtained with ANN and Harvey Model.

The Neural Network performance measure for peak load demand was as shown from Fig. 6 to Fig. 8. The R-value was seen to approach unity value; this demonstrated high correlation between the target and the output, for the validation R stood at 0.97053 which is also a strong correlation coefficient, for testing R values was found to be 0.99961 while for all, R was found to be 0.98645. We can conclude that the ANN was sufficiently trained.

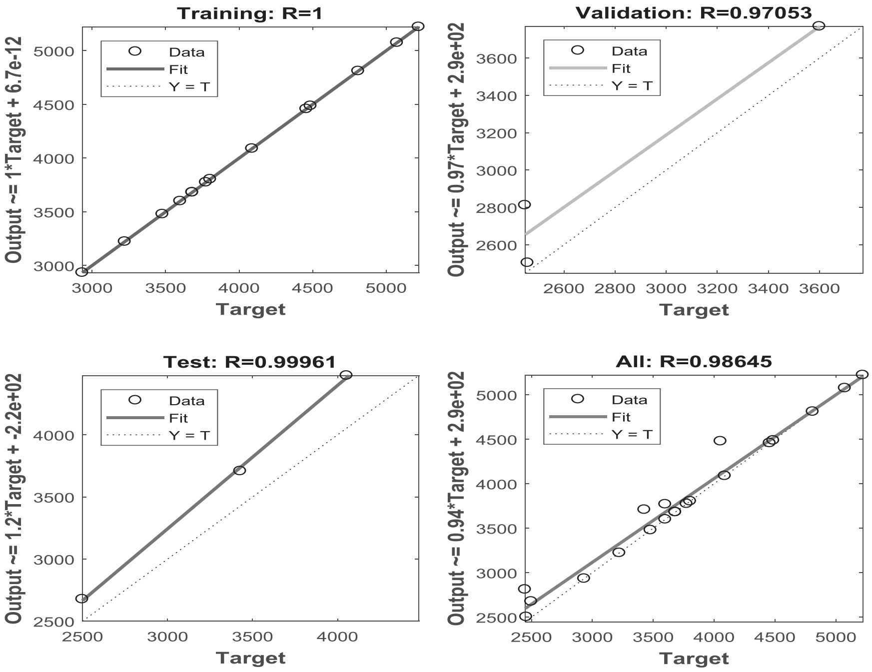

Fig.6: Correlation between Output and Target Peak Load Demand.

The plot of MSE against the epoch shows that the best validation performance was found to be 54490.877 and this occurred at epoch eight (8) as seeen in Fig. 10. Presented by Fig. 11 is the function fit for the output element.

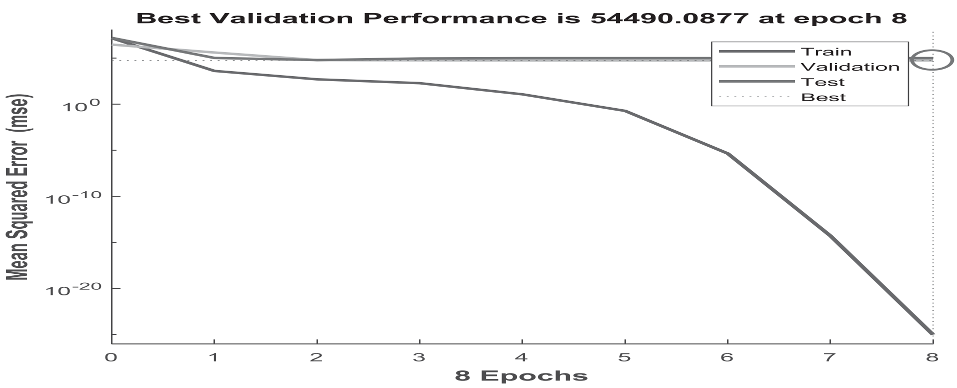

Fig. 7: Mean Squared Error Performance Validation of Peak Load Demand

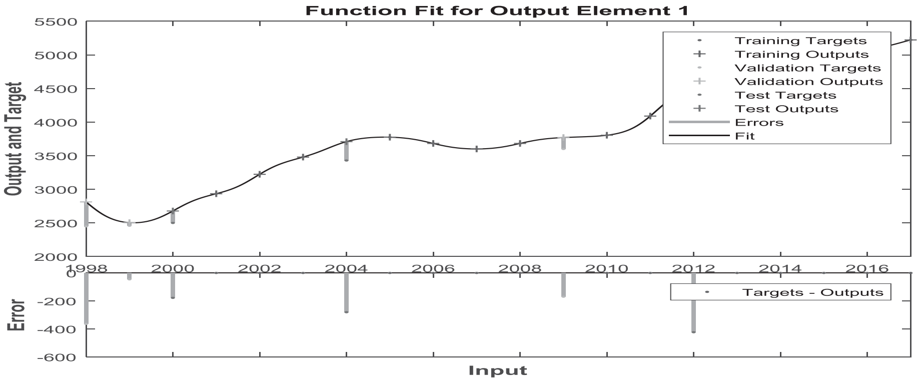

Fig. 8: Correlation between Network Parameters and Error Deviation of the Peak Load Demand.

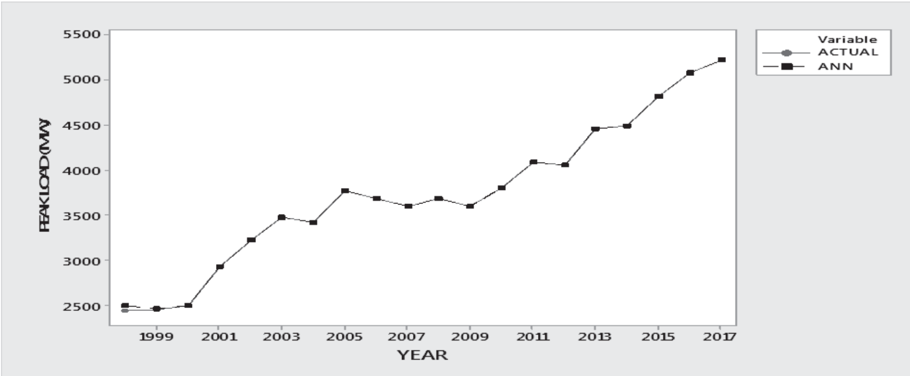

Fig. 9: Comparison of Actual and Peak Load Demand Predicted with ANN Model.

Fig. 9 shows the comparison of predicted value obtained with ANN for the peak load demand and the actual peak load demand collected over the period of 20 years. It was observed from the line graph that the values obtained with ANN were almost of the same order of magnitude when compared with the actual peak load demand collected. Based on the peak load predicted with ANN, ANN achieved 136.350, 11.677, 0.120 and 3.05 for MSE, RMSE, MAPE and MAE respectively.

Presented in Fig. 10 was the comparison of predicted values obtained with ANN and Harvey Model, the values obtained with Harvey showed a significant overshoot, this account for the magnitude of values obtained for the MSE, RMSE, MAPE and MAE which are13790.862, 117.435, 17.010 and 10.183 respectively.

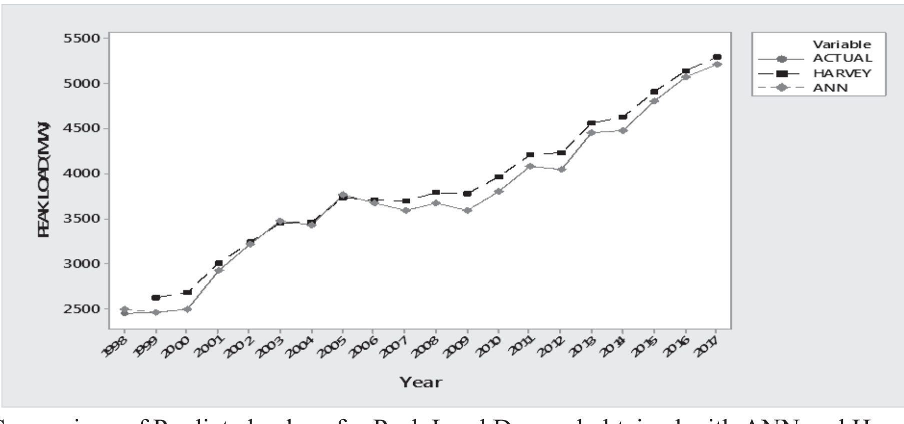

Fig. 10: Comparison of Predicted values for Peak Load Demand obtained with ANN and Harvey Model.

Presented in Table 3 and Table 4 was the summary of performance evaluation of ANN and Harvey Model used to predict both the average and peak load demand.

Table 3. Performance Measure for Predicted Average Load Demand.

MODEL	MSE	RMSE	MAPE	MAE
ANN	30.300	5.505	0.050	1.9000
HARVEY	12325.174	111.019	2.358	9.1095

Table 4. Performance Measure for Peak Load Demand.

MODEL	MSE	RMSE	MAPE	MAE
ANN	136.350	11.677	0.120	3.05
HARVEY	13790.862	117.435	17.010	10.183

The performance metrics shown in Table 3 and Table 4 revealed that ANN predicts the load demand with least error in comparison with Harvey Model for all statistical tools adopted for evaluation. From the Tables of comparison, ANN gave the best performance with MSE of 136.350, RMSE of 11.677, MAPE of 0.120 and MAE of 3.050 for Peak load demand and MSE of 30.300, RMSE of 5.505, MAPE of 0.050 and MAE of 1.9000 for average load demand. On a general scale, ANN shows well over 1000% performance increase over Harvey Logistic Model. The validation of findings with respect to Harvey Model further revealed that ANN forecast better based on the average and peak load demand.

Conclusions: Presented in this work is artificial neural network-based load forecasting in Nigeria: an approach to energy efficiency. Average and peak load demand data for the period of twenty years was collected from National Control Center in Osun State, Nigeria. The data collected was analyzed with the ANN and Harvey Model to predict the load demand for the periods under consideration. Levenberg Marquardt algorithm was employed to enhance the training of ANN. For all cases examined, ANN showed superiority with least mean squared error in comparison with Harvey Model. A closer examination showed that the values obtained with ANN for both the average and peak load demand exhibited a high correlation with the actual data collected for both the peak and average load demand. It is therefore, not an overstatement that the adoption of the Neural network in predicting load demand in the investigated area will assist in future planning, expansion and energy management of the power system infrastructure in the area under study while impacting the national grid positively towards providing sustainable energy. Hybrid of ANN and GA is proposed for further studies.

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