ENGINEERING

ISSN (Print): 24490954
ISSN (Online): 26364972

# LEAST SQUARE REGRESSION METHOD FOR LOAD MANAGEMENT IN ELECTRICITY DISTRIBUTION NETWORK OF A 33 KV FEEDER AT FEDERAL UNIVERSITY OF AGRICULTURE ABEOKUTA, NIGERIA.

***[1]Adebisi O. I. , Adejumobi A. I., Okoye F. E. And [1]Jokojeje R. A.***

*Department of Electrical and Electronics Engineering,*
*Federal University of Agriculture, Abeokuta, Ogun State, Nigeria*
*[1]Department of Electrical and Electronics Engineering,*
*Moshood Abiola Polytechnic, Abeokuta, Ogun State, Nigeria*

**Corresponding Email: adebisi.oluwaseun@yahoo.com*

*Manuscript Received:20/05/2018     Accepted: 30/06/2018     Published: September, 2018*

**ABSTRACT**

A stabilized electricity power system requires that its demand matches its supply. However, in a developing nation such as Nigeria, demand for electric power is continuously growing without comminserate supply s need. Consequently, load management is used to manage this inadequacy. One credible alternative in addressing this shortfall is load forecasting. This research work presents the least square regression method for load management in electricity distribution network using the Federal University Abeokuta (FUNAAB) 33 kV feeder as a case study. Using the five years (2012-2016) load data collected from 132/33 kV Transmission Station at Gboniyi, Abeokuta, Ogun State on the sample network, a polynomial regression model was developed. Adjusted coefficient of determination ($R^2_{adj}$ ) and mean absolute percentage error (MAPE) were respectively used as criteria to diagnostically check and validate the adequacy of the developed model. The obtained results showed that the developed model has good prediction ability with MAPE of 3.01%. Load forecast for further five years (2017-2021) on FUNAAB 33 kV feeder revealed that load growth on the network would increase for the period of study. This suggests that the sample network requires a good load management plan to ensure it performs satisfactorily without being over-loaded.

**Keywords:** *Load management, Load forecasting, Least square regression, Adjusted coefficient of determination and Mean absolute percentage error, Nigeria*

## INTRODUCTION

In developing economy such as Nigeria, demand for electricity is persistently increasing and there is no adequate electricity supply to meet this demand. Consequently, there is a wide supply-demand gap for electric power and this creates the need for load management. Load management facilitates the conservation of the available generated electricity to service the consumers' demands and also ensures efficient planning to meet the future energy demands. In power systems, effective load management cannot be implemented without load forecasting. Load forecast refers to the load or demand behaviour for future. Forecasting is a necessary and important function in virtually every industry including electricity industry as it helps to meet future requirements, reduce unexpected cost and provide a potential input to decision making (Elakrmi and Shikhah, 2016). In any country, great attention is focused on the energy sector as it leads to comfortable life. With the advent of increased civilization and economic development, energy has become a life-sustaining commodity (Elakrmi and Shikhah, 2016). Electricity utilities run the power grid which is regarded as the most complex man-made system to deliver electricity to consumers. One of the major tasking challenges of these utilities is that electricity cannot be massively stored; as a result electricity has to be consumed immediately as it is generated (Espinoza *et al.,* 2007). Hence, at every point in power system, utilities have to ensure that demand for electricity match its supply. In meeting this requirement, the electricity utilities need a tool to anticipate future demand of the consumers in order to plan ahead on meeting this demand. In this respect, load forecasting plays a key role.

Load forecasting is a useful tool for all segments of the electric power industry including generation, transmission, distribution, and retail especially in a deregulation electricity market where the peak demand levels and overall energy consumption patterns have to be projected to support the electric utility's future system and business operations (Mosad, 2015). Load forecast can provide a key input to power system operations, planning, facility expansion issues, system security, maintenance, long-term investments in generation, fluctuating demand, demand of spinning reserve, vulnerability to failures, demand side management, energy management system and infrastructure development among others (Arjun *et al.,* 2015; Mosad, 2015; Hinman and Hickey, 2009). It is therefore very vital for electricity utilities to adopt an appropriate load forecasting technique which is effective and efficient since inaccurate load forecasts can lead to equipment failures or even system-wide blackout (Hong and Shahidehpour, 2015).

A number of different approaches have been employed for load forecasting in power systems Some of the basic techniques that have been reported in literature include regression analysis, autoregressive moving average model, time series, static state estimation, fuzzy logic, genetic algorithm, artificial neural network and expert system to name few (Chemetova *et al.*, 2016; Phuangpornpitak and Prommee, 2016; Eroshenko *et al.*, 2014; Fan and Hyndman, 2012; Swaroop and Hussein, 2012; Duan *et al.,* 2011; Hong, 2010; Adepoju *et al.,* 2007; Rashid *et al.,* 2005; Satish *et al.,* 2004; Kivipõld and Valtin, 2003; Al Saba *et al.,*1999; Park *et al.*, 1991). These techniques are very useful, however, they are characterised by varying degree of complexity in terms of functional form and computational procedure. Therefore, the accuracy of the obtained results differs with the individual techniques.

The purpose of this work is to apply least square regression method for load management in electricity distribution network using FUNAAB 33 kV feeder as a case study. Regression analysis is a very useful mathematical approach for determining the statistical relationship or dependence between a change in one variable with respect to another variable(s) (Elakrmi and Shikhah, 2016). The inherent simplicity and flexibility in implementation of the method makes it suitable for this work.

## LOAD FORECASTING IN POWER SYSTEM: TYPES AND APPLICATIONS

Load forecasting is an essential process in electric power system operation and planning. It has become a major field of research in electrical engineering (Espinoza *et al.,* 2007). The electricity utilities require forecasts not only from the production point of view but also for the economical aspect. Accurate tracking of the load by the system generation at all times is a basic requirement in the operation of power systems and must be accomplished for various time intervals. According to literature, the term load forecasting can be described in various ways. It is way of estimating what future electric load will be for a given forecast horizon based on the available information about the state of the system (Kaur, 2017). While Sruthi and Catherine (2015) defined load forecasting as the projection of electrical load that will be required by a certain geographical area with the use of previous load profiles in the said geographical area, Arjun *et al.,* (2015) defined it as a measure of exactness of the difference between the actual and predicted value of future load demand. The convergent point of these definitions is that load forecasting involves anticipation of future load demand. Many economic implications of electricity utilities such as economic scheduling of generating capacity, scheduling of fuel purchases, security analysis, planning of power development, maintenance scheduling and dispatching of generation units are mainly operated based on accurate load forecasting (Phuangpornpitak and Prommee, 2016).

Load forecasting is broadly classified into three categories in literature based on the planning horizon's time frames as short-term load forecasting, medium-term load forecasting and long-term load forecasting (Kaur, 2017; Elakrmi and Shikhah, 2016; Alfares and Nazeeruddin, 2002).

Short-term load forecasting (STLF) aims at projecting electrical hourly loads and energy demand for periods up to some weeks ahead. As reported in Elakrmi and Shikhah (2016), STLF is a very crucial element in the process of power system operational planning that affects the performance of many functions including load flow studies, security and contingency analysis, economic dispatch, unit commitment, hydro-thermal coordination, preventive maintenance plan for the generators, transaction evaluation, reliability evaluation of the power system and trading of power in interconnected systems. The two essential necessities of short term load forecasting are its high accuracy and faster response to study the characteristics of the electrical loads and the various factors affecting them. Such factors may include climatic changes, season and pricing that have a complicated relationship with the loads (Sruthi and Catherine, 2015). The type of the day e.g. weekday, special day, weekend etc. plays also a key role in load forecasting accuracy (Hong and Shahidehpour, 2015).

Mid-Term Load Forecasting (MTLF) is used for predicting the peak load within a span of time. The forecast period ranges from several weeks to 12 months or one year ahead. MTLF is suitable for electricity utilities for maintenance scheduling, power demand management, purchasing planning etc. (Elakrmi and Shikhah, 2016; Sruthi and Catherine, 2015). This type of forecast depends mainly those factors that influence electricity demand such as seasonal variations, addition of new loads, advancement in the technologies used, demand patterns of large facilities, and maintenance requirements of large consumers (Elakrmi and Shikhah, 2016; Sruthi and Catherine, 2015).

Long-Term Load Forecasting (LTLF) is intended for applications in capacity expansion and long-term capital investment return studies (Elakrmi and Shikhah, 2016). The forecast period usually ranges from 1 year to 15-20 years ahead. This type of load forecasting is used in providing the peak load and energy projection for the coming years of the study period that suitably meet planning requirements.

Of the forecast types highlighted above, the interest of this work is on long-term load forecasting since a long-term projection of future demand or consumption is very essential for better operation, planning and economical utilization of power systems. More so, long-term load projection on electricity distribution feeders such as the FUNAAB 33 kV feeder serving many important areas in Abeokuta, one of which is the Federal University of Agriculture, Abeokuta will go a long way towards assisting the electricity distribution utility in managing this feeder in discharging its responsibility efficiently.

## MATERIALS AND METHODS

The theoretical background to least square regression model and the test of adequacy of the model are presented as follows:

### Least Square Regression Analysis

As reported by Adebisi *et al.,* (2016), the least square regression method is the most suitable for long term prediction of stochastic events of which power system load can be categorized. It is therefore adopted as the modeling technique for this work. In using a regression method for load prediction, the load data are assumed to fit a pre-defined function or model that has unknown parameters (Elakrmi and Shikhah, 2016). The technique is then applied to obtain an optimum set of these unknown parameters that make the known data and the forecasted data result in the minimum sum of squared errors. Since power system loads exhibit non-linear characteristics in most cases, it is imperative to adopt a regression model that best reflect these characteristics, hence, the choice of polynomial regression.

The pthorder polynomial regression model which gives a non-linear relationship between a given set of n-paired data points $(X_1,Y_1)$, $(X_2,Y_2)$,…, $(X_n,Y_n)$ processed using least square regression method is expressed by equation (1) which is further modified into matrix notation expressed by equation (2) (Rawlings et al., 1998):

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \cdots + \beta_p X_i^p + \varepsilon_i, \quad p < n \quad ........(1)$$

where

***$Y_i$ is the n×1 column vector of dependent variables (predicted values);***

***$X_i$ is the n × (p+1)matrix of the independent variables;***

***β is the (p+1)× 1 vector of regression parameters or coefficients***

*to be estimated;*
*$\epsilon$ is the n × 1 vector of random errors;*
*i is the observational unit 1, 2, 3, …, n;*
*n is the sample size;*
*p is the polynomial order.*

$$\begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix} = \begin{bmatrix} 1 & X_1 & X_1^2 X_1^3 & \cdots & X_1^p \\ 1 & X_2 & X_2^2 X_2^3 & \cdots & X_2^p \\ \vdots & \vdots & \vdots\ \vdots & & \vdots \\ 1 & X_n & X_n^2 X_n^3 & \cdots & X_n^p \end{bmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{pmatrix} + \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{pmatrix} \quad .......(2)$$

(n×1) (n×(p+1)) ((p+1)×1) (n×1)

As earlier stated in this section of the research work, the main objective of the regression theory is to minimize the sum of errors squared ($S_{es}$) at each data point as it gives a measure of goodness of fit. This requirement results in a condition expressed by equation (3) (Adebisi *et al.,* 2016):

$$S_{es} = \sum_{i}^{n} \epsilon_i^2 = \sum_{i}^{n} \left\{ Y_i - \left( \beta_0 + \sum_{p=1}^{j} \beta_p t_i^p \right) \right\}^2 = minimum \quad ..(3)$$

Evaluation of the values of the independent variables $Y_i$ in equation (1) requires that the regression parameters $\beta_0, \beta_1, \beta_2 ...... \beta_p$ must be known and are obtained by partial differential manipulation of equation (3). This results in equation (4) (Adebisi *et al.,* 2016):

$$\begin{array}{ccc} A & Z & B \\ \begin{pmatrix} n & \sum X_i & \sum X_i^2 & \cdots & \sum X_i^j \\ \sum X_i & \sum X_i^2 & \sum X_i^3 & \cdots & \sum X_i^{j+1} \\ \sum X_i^2 & \sum X_i^3 & \sum X_i^4 & \cdots & \sum X_i^{j+2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sum X_i^j & \sum X_i^{j+1} & \sum X_i^{j+2} & \cdots & \sum X_i^{j+j} \end{pmatrix} & \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_j \end{pmatrix} = & \begin{pmatrix} \sum Y_i \\ \sum X_i Y_i \\ \sum X_i^2 Y_i \\ \vdots \\ \sum X_i^j Y_i \end{pmatrix} \end{array} \quad .......(4)$$

Varieties of suitable techniques are available for solving equation (4). Application of Gaussian Elimination method to equation (4) results in equation (5) as:

$$Z = A^{-1} * B \quad ...............(5)$$

**Diagnostic Check for Model Adequacy**

The purpose of diagnostic checking or testing of the adequacy of the regression model is to determine how well the model best fits the data or put in another way is to protect against being misled by the random variation in the estimates (Rawlings *et al.,* 1998). Adequacy of the regression model can be checked by different methods (Rawlings *et al.,* 1998) but the approach adopted in this work is statistical test where the coefficient of determination, $R^2$ was used as a criterion to judge the quality of fit. Mathematically, coefficient of determination, $R^2$, is expressed by equations (6) to (8) (Adebisi *et al.,* 2016):

$$R^2 = 1 - \frac{RSS}{TSS} \quad ..........(6)$$

$$RSS = \text{Residual Sum of Squares} = \sum_{i=1}^{n} (Y_i - \breve{Y}_i)^2 \quad ......(7)$$

$$TSS = \text{Total sum of squares} = \sum_{i=1}^{n} (Y_i - \bar{Y})^2 \quad .........(8)$$

where

$Y_i$ = Sample data

$\breve{Y}_i$ = Theoretical $Y_i$ value corresponding to $X_i$ (estimated through the regression model)

$\bar{Y}$ = Mean value of all $Y_i$ values

The value of $R^2$ lies in the range $0 \le R^2 \le 1$ and the closer the value is to 1, the better the fit.

Another important diagnostic check of the adequacy of the regression model is the adjusted $R^2$, $R^2_{adj}$, which is expressed by equation (9) (Adebisi *et al.,* 2016):

$$R^2_{adj} = 1 - \left\{ \frac{RSS}{n-(m+1)} \bigg/ \frac{TSS}{n-1} \right\} \quad ...............(9)$$

The significance of $R^2_{adj}$ is not different from $R^2$. The closer the value of $R^2_{adj}$ is to 1, the better the fit. However, since $R^2_{adj}$ takes in to account both the deviations and the numbers of degrees of freedom, it should be considered as a criterion for diagnostic checking of the adequacy of the model.

Having used the model adequacy checks expressed by equations (6) and (9) to determine the polynomial regression model that best fits the data set, the accuracy of the selected model as a forecasting method was further validated by Mean Absolute Percentage Error (MAPE). MAPE is one of the most popular measures of the forecast accuracy and it is mathematically expressed by equation (10) (UmmulKhair *et al.,* 2017; Kim and Kim, 2016):

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{Y_i - \breve{Y}_i}{Y_i} \right| \quad .............(10)$$

where $Y_i$ and $\breve{Y}_i$ assume their usual meaning as given in equation (7).

The regression equations (1) to (5) and the model adequacy check equations (6) to (9) along with the model accuracy validation equation (10) were extended to this work by representing the dependent variables $Y_i$ with load data in MW and independent variables $X_i$ with the time period or duration for which the loads are consumed while all other parameters retain their usual meaning.

**Collection of Load Data**

The data on peak monthly load consumed on FUNAAB 33 kV distribution feeder used as a case study in this work for five-year periods from 2012 to 2016 were collected from 132/33 kV Transmission Station located at Gbokoniyi, Onikolobo, Abeokuta, Ogun State through personal contact with the appropriate personnel and departments in the Station. FUNAAB 33 kV distribution feeder is one of the 33 kV feeders served by the Transmission Station and is maintained by Ibadan Electricity Distribution Company (IBEDC) IjeunTitun Business Hub in Abeokuta, Ogun State.

## RESULTS AND DISCUSSION

The analyzed five-year monthly peak load data on FUNAAB 33 kV distribution feeder from 2012 to 2016 in this work are presented in Table 1.

Table 1: Monthly peak load on FUNAAB 33 kV Distribution Feeder from 2012 to 2016 (TCN, 2017)

| Month | Load in MW | | | | |
|---|---|---|---|---|---|
| | Year 2012 | Year 2013 | Year 2014 | Year 2015 | Year 2016 |
| January | 345.5 | 346.5 | 269.9 | 250.3 | 260. 7 |
| February | 327.6 | 296.3 | 246. 7 | 210.8 | 251.4 |
| March | 292.9 | 370.6 | 231.6 | 203.1 | 235.9 |
| April | 298.3 | 292.9 | 232.9 | 220.0 | 243.1 |
| May | 309.5 | 294.0 | 266.9 | 212.9 | 222.6 |
| June | 351.6 | 301. 7 | 247.2 | 255.9 | 184.3 |
| July | 376. 7 | 319.1 | 253.0 | 252.1 | 223.1 |
| August | 371. 7 | 296.5 | 262. 7 | 268.4 | 247.4 |
| September | 401.9 | 257.2 | 155. 7 | 246.9 | 252.9 |
| October | 367. 7 | 250.9 | 150.2 | 271.3 | 280.4 |
| November | 347.4 | 246.1 | 252.1 | 256.3 | 223.9 |
| December | 338.6 | 286.2 | 228.9 | 252.4 | 256.2 |
| Total | 4129.4 | 3558.0 | 2798.0 | 2900.4 | 2881.9 |

The analysis was done in such a way that a polynomial regression model was developed using the yearly total peak load from 2012 to 2016 in Table 1 with regression equations (1) to (5). Considering that the load data fit the pre-defined polynomial model in equation (1) with orders 2, 3 and 4 respectively assumed, model adequacy checks presented in equations (6) and (9) were applied to judge which of the polynomial orders best modelled the load data. The obtained results are presented in Table 2.

Table 2: Model Adequacy Checks

| **Criterion** | **Polynomial order** | | |
|---|---|---|---|
| | **Order 2** | **Order 3** | **Order 4** |
| $R^2$ | 0.96 | 0.96 | 1.0 |
| $R^2_{adj}$ | 0.91 | 0.82 | Undefined |

The results in Table 2 revealed that the polynomial regression model of order 4 leads to an over-fit condition for the load data which is never desired for any load prediction technique. The choice between order 2 and order 3 polynomial models revealed that the load data are best modelled by the order 2 polynomial model since $R^2_{adj}$ value of 0.91 was higher than that of order 3 polynomial model which was 0.82.

Hence, the developed polynomial regression model for the load data in this work is

$$Y=5183.4-1158.8X+140.6X^2$$

where Y represents the loads in MW and X represents the years for which the loads were consumed.

The performance of the developed polynomial regression model is depicted graphically as presented in Figure 1 and the accuracy of the model was further validated by the MAPE calculated in Table 3 using equation (10). The obtained MAPE was 3.01% which was lower than maximum 5% error required for such model (Chemetovaet al., 2016). This clearly indicates that the developed polynomial regression model is feasible and suitable for long-term load forecasting in electricity distribution network such as for FUNAAB 33 kV distribution feeder.

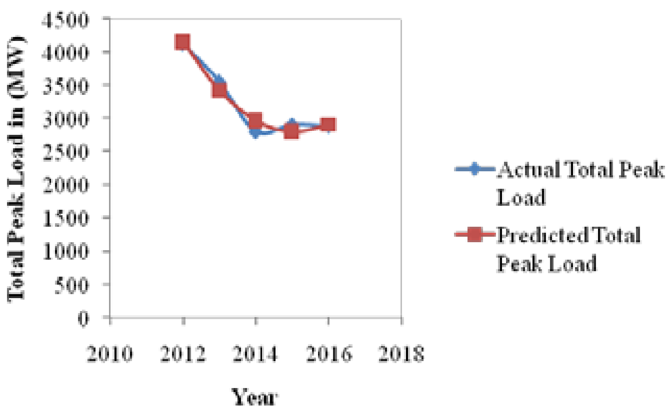


Figure 1: Plot of the actual total peak load and the predicted total peak load from 2012 to 2016 using developed the polynomial regression model.

Table 3: Calculation Mean Average Percentage Error Associated with the Developed Polynomial Regression Model

| Year | Actual Total Peak Load | Predicted Total Peak Load | Absolute % Error |
|---|---|---|---|
| 2012 | 4129.4 | 4165.2 | 0.87 |
| 2013 | 3558.0 | 3428.2 | 3.65 |
| 2014 | 2798.0 | 2972.4 | 6.23 |
| 2015 | 2900.4 | 2797.7 | 3.54 |
| 2016 | 2881.9 | 2904.2 | 0.77 |
| MAPE | 3.01 | | |

The developed polynomial regression model for long-term load projection on FUNAAB 33 kV electricity distribution feeder was used to forecast load demand on the feeder for further five years from 2017 to 2021 to examine the demand pattern. The obtained results are presented in Table 4.

Table 4: Load Projection on FUNAAB 33 kV Electricity Distribution Feeder from Years 2017 to 2021

| **Year** | **Forecasted Total Peak Load in MW** |
|---|---|
| 2017 | 3291.9 |
| 2018 | 3960.7 |
| 2019 | 4910.7 |
| 2020 | 6141.9 |
| 2021 | 7654.2 |

The results in Table 4 showed that there would be an increase in the load growth on FUNAAB 33 kV electricity distribution feeder for the period of year 2017 to 2021. This implies that for the feeder to rise to its responsibility of supplying electricity to the areas it serves, the utility in charge of the feeder needs to put in place a good load management strategy to plan and monitor the activities on the feeder to ensure its optimal performance without being over-stressed.

## CONCLUSION

Load forecasting is a useful tool for all segments of the electric power system and a key component for effective load management in the system. In this work, least square regression approach was used to develop a polynomial model for long-term load prediction in electricity distribution network with FUNAAB 33 kV feeder considered as a case study. The obtained results showed that the developed polynomial regression model has good prediction ability with minimum error. The mean absolute percentage error obtained in using the model for load prediction on FUNAAB 33 kV electricity distribution feeder was 3.01% which was lower than maximum 5% error required from such a mode. With the model, it was also revealed that the load growth on FUNAAB 33 kV feeder between the period of year 2017 to 2021 would increase and this is an eye-opener for the electricity utility in charge of the feeder to implement a good load management plan to monitor the activities of the feeder to ensure its optimal performance when loaded. More so, further work is on-going to use other methods such as artificial neural network, fuzzy logic, hybrid technique etc. for load forecasting in electricity distribution network and compare the results with the least square regression model for better inferences on these techniques.

## REFERENCES

AdebisiO.I., AdejumobiI.A., Jokojeje, R.A. and Amusa, K.A. (2016). Reliability Assessment of Electrical Distribution Network Using Least Square Regression Approach; FUNAAB 33 kV Feeder as a Case Study. *Umudike Journal of Engineering and Technology, 2(1)*: 120-126.

AdepojuG.A, OgunjuyigbeS.O.A, and AlawodeK.O. (2007).Application of Neural Network to Load Forecasting in Nigerian Electrical Power System.*The Pacific Journal of Science and Technology,8(1):* 68-72.

Alfares, H.K., and Nazeeruddin, M. (2002). Electric Load Forecasting: Literature Survey and Classification of Methods. *International Journal of Systems Science, 33(1)*: 23-34.

Al Saba, T. and El-Amin, I. (1999).Artificial Neural Networks as Applied to Long-Term Forecasting. *Artificial Intelligence in Engineering, 13:* 189-197.

Arjun, B., Kumar, G. and SudhansuK.M. (2015).A Review of Short-Term Load Forecasting Using Artificial Neural Network Models. Proceeding of Inter-Science Institute of Management and Technology International Conference on Intelligent Computing, Communication and Convergence, 48: 121-125.

Chemetova, S., Santos, P. and Neves, M.V. (2016).Load Forecasting in Electrical Distribution Grid of Medium Voltage.7thIFIPWG 5.5/SOCOLNET Advanced Doctoral Conference on Computing, Electrical and Industrial Systems, Costa de Caparica, Portugal, April 11-13, 340-349.

Duan, P., Xie, K., Guo, T. and Huang, X. (2011).Short-Term Load Forecasting for Electric Power Systems Using PSO-SVR and FCM Clustering Techniques.Energies, 4: 173-184.

Elarkrim, F. and Shikhah, N.A. (2016).Electricity Load Forecasting-Science and Practices.Retrieved September 30, 2017 from https://pdfs.semanticscholar.org.

Eroshenko, S.A., Vinokurov, K.V. and Smolina, A.Y. (2014).Electrical Load Forecasting.WIT Transactions on Ecology and the Environment, 190: 299-305.

Espinota, M., Suykens, J.A.K., Belmans, R. and De Moor, B. (2007). Electric Load Forecasting Using Kernel-Based Modeling for Non-Linear System Identification.IEEE Control Systems Magazine, 43-57.

Fan, S. and Hyndman, R.J. (2012). Short-Term Load Forecasting Based on a Semi-Parametric Additive Model. IEEE Transactions on Power Systems, 27(1): 134-141.

Hinman J. and Hickey E. (2009).Modeling and Forecasting Short-Term Electricity Load Using Regression Analysis. Retrived September 30, 2017 from https://irps.illinoisstate.edu/downloads/research/documents/LoadForecastingHinman-HickeyFall2009.pdf

Hong T. (2010). Short Term Electric Load Forecasting.PhD Dissertation, Graduate Program of Operation Research and Department of Electrical and Computer Engineering, North Carolina State University, Raleigh, NC, USA.

Hong, T. and Shahidehpour, M. (2015). Load forecasting Case Study. Eastern Interconnection States' Planning Council (EISPC) and National Association of Regulatory Utility Commissioners (NARUC).

Kaur, A. (2017). Load Forecasting. Retrieved September 30, 2017 from http://cseweb.ucsd.edu/~trosing/lectures/load_forecast.pdf

Kim, S. and Kim, H. (2016).A New Metric of Absolute Percentage Error for Intermittent Demand Forecast. *International Journal of Forecasting, 32(3)*: 669-679.

Kivipõld T. and Valtin J. (2013).The Use of Regression Analysis of Time Series for Forecasting Electricity Consumption of Consumers and the Proposal of an Algorithm for Calculating the Electricity Price. *International Journal of Energy and Environment,* 5 (7): 221-228.

Mosad, A. (2015). Introduction to Electric Load Forecasting Methods.*Journal of Advanced Electrical and Computer Engineering, 2(1)*:1-12.

Park, D.C., El-Sharkawi, M.A. and Marks II, R.J. (1991). Electric Load Forecasting Using Artificial Neural Network.*IEEE Transactions on Power Engineering,* 6: 442-449.

Phuangpornpitak, N. and Prommee, W. (2016).A Study of Load Demand Forecasting Models in Electric Power System Operation and Planning.*GMSARN International Journal,* 10:19-24.

Rashid T. and Kechadi T. (2005).A Practical Approach for Electricity Load Forecasting.In the proceeding WEC'05, The 3rd World Enformatika, Isanbul, Turkey, ACTA Press, 5: 201--205.

Rawlings O. J., Sastry G. P. and Dickey A. D. (1998).Applied Regression Analysis: A Research Tool.Retrived September 24, 2017 from http://web.nchu.edu.tw/~numerical/course992/ra/Applied_Regression_Analysis_A_Research_Tool.pdf

Satish B., SwarupK.S., Srinivas S. and Hanumantha A. R. (2004).Effect of temperature on short term load forecasting using an integrated ANN. Electric Power Systems Research, 72, 1(15): 95-101.

Sruthi J. And Catherine R.L.H. (2015).A Review on Electrical Load Forecasting in Energy Management. *International Journal of Innovative Science, Engineering and Technology, 2*(3): 670-676.

Swaroop, R. and Hussein, A.A. (2012). Load Forecasting for Power System Planning and Operation Using Artificial Neural Network at Al Batinah Region, Oman. *Journal of Engineering Science and Technology, 7(4)*: 498-504.

TCN (2017).Monthly Peak Load on FUNAAB 33 kV Distribution Feeder from 2012 to 2016. Data Collected from 132/33 kV Transmission Station located at Gbokoniyi, Onikolobo, Abeokuta, Ogun State.

UmmulKhair, Hasanul, F., Sarudin, A. and Robbi, R. (2007). Forecasting Error Calculation with Mean Absolute Deviation and Mean Absolute Percentage Error. *Journal of Physics: Conference series 930 012 002*.