

Long-Term Peak Load Estimate and Forecast: A Case Study of Uyo Transmission Substation, Akwa Ibom State, Nigeria

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To cite this article:

Clement Effiong, Simeon Ozuomba, Udem John Edet. Long-Term Peak Load Estimate and Forecast: A Case Study of Uyo Transmission Substation, Akwa Ibom State, Nigeria. *Science Journal of Energy Engineering*. Vol. 4, No. 6, 2016, pp. 85-89.

doi: 10.11648/j.sjee.20160406.16

Received: October 25, 2016; **Accepted:** December 10, 2016; **Published:** January 24, 2017

Abstract: This paper presents an approach for long-term estimation and forecasting of electric peak load. A 10-year peak load forecast is performed on Uyo transmission substation in Akwa Ibom State, Nigeria. The peak loads of the past ten years (from 2006 to 2010) are used as input data used to develop the model for forecasting the peak load demand in Uyo metropolis. Particularly, Multiple Linear Regression (MLR) method is used to model the annual peak load. The explanatory variables, namely, temperature, population and gross domestic product are used in the analysis. The peak load model parameters are estimated using only the data of the year 2006 to the year 2012, which accounts for 70% of the entire dataset for training and 30% (that is, 2013 to 2015) of the data are used for cross validation. The results show that with respect to the training dataset the prediction model has Mean Absolute Percentage Error (MAPE) of 0.00613%, Mean Absolute Deviation (MAD) of 0.277743 and Coefficient of Determination (R^2) value of 0.99184 which shows that about 99.184% of the peak load are explained by the explanatory variables used in the prediction. Furthermore, with respect to the validation dataset (2013 to 2015) the prediction model has RMSE of 1.038042 and percentage error of less than 2% which shows that the proposed peak-load-demand model can effectively predict the peak load demand for Uyo.

Keywords: Peak load, Multiple Linear Regression Model, Load Estimation, Load Forecasting, Population, Temperature, Gross Domestic Product (GDP)

1. Introduction

The frequent electrical power outages experienced in Akwa Ibom State and in other states of the federation is traced to various defects in the electricity distribution system and inability to perform regular load analysis on the existing injection and distribution substations by Port Harcourt Electricity Distribution Company (PHED). To overcome this, every stakeholder such as the Generation Company, GENCO, Transmission Company, TRANSCO, Distribution Company DISCO and Retail Company (RETAILCO) need load forecast inputs to prepare new schemes of extension or enhancements or capacity additions or infrastructure development. Moreover, network and system planning is always based on load requirements, and electric peak-load forecasting is always employed for effective and efficient planning of a power system.

More so, the existing load demand forecast for the case study site has been focusing on time series analysis and that

does not consider the explanatory variables that may contribute to the variations in load demand. Interestingly, there has been radical increase in infrastructural development as well as rapid growth in population and a significant improvement in the gross domestic product (GDP) in Akwa Ibom State in the last decades.

Furthermore, the present administration of Akwa Ibom State is focusing on expansion in the industrial sector, a move that will require adequate power supply for its success. Therefore, peak load demand model and forecast is very essential for estimating and forecasting the peak load demand in Akwa Ibom State. In this paper, the focus is on the peak load in Uyo which is the capital of Akwa Ibom state and also the part of the state that has witnessed the tremendous transformation in terms of population and infrastructural development.

2. Review of Related Works

Electric load forecasting or simply put, load forecasting, according to [1], means estimating active load at various load buses ahead of actual load occurrence. However, [2], defined electric load forecasting as a phenomenon of knowing what may happen to a system in the next coming time periods. Similarly, [3] added that electric load forecasting is a method to estimate the load for a future time point from the available past data. [4], stated more comprehensively and acceptably that electric load forecasting is an intelligent projection of past and present demand patterns to determine future ones with sufficient reliability. The term load according to [4] is a device or conglomeration of devices that taps energy from the power system network. Load is a general term meaning either demand or energy, where demand is time rate of change of energy.

According to [5], there are many factors that affect load forecasting, and these factors include, Time factors, such as: Hours of the day (day/night), Day of the week (week day/weekend) and Time of the year (season), Weather conditions (temperature and humidity), Class of customers (residential, commercial, industrial, agricultural, public, etc.), Special events (TV programmes, public holidays, etc.), Population, Economic indicators (per capita income, Gross National Product (GNP), GDP, etc., Trends in using new technologies, Electricity price etc.

However, different classes of load forecasting make use of different models to meet the entire specific objectives of the application. These methods have been further defined according to their different uses. Short-term forecasts are used to ensure the stability of a system. Medium (mid-term) forecasts for generation optimization and long term forecasts for investment planning [6].

Generally, load forecasting methods are mainly classified into two categories: classical approaches and ANN based techniques. Classical approaches are based on statistical methods and forecast future value of a variable by using a mathematical combination of the historic information [7]. For instance with time series model of auto regressive integrated moving average (ARIMA) which incorporates the knowledge of experienced human operators short term load forecasting is carried out by using a linear combination of the past values of the variable [7]. In [8, 9] long-term and midterm electric load forecasting is presented which incorporates daily and weekly simple linear regression models with annual load growth to predict the future load demand. Meanwhile, for different residential areas by using ANN based techniques short and long term load forecasting is performed in [10, 11, 12-13] and in [14] respectively.

In the aforementioned studies, the results obtained from different approaches are compared and discussed.

3. Data and Methodology

In this paper, long term peak load estimate and forecast is performed for the city of Uyo with the Multiple Linear Regression (MLR) based method and using the annual peak

load, GDP, population and temperature data from 2006 to 2015. Data on the population (2007 – 2015) of Uyo is collected from the Ministry of Economic Development Uyo, Akwa Ibom Stat., Data on annual peak-load is collected from the transmission Company of Nigeria (TCN), Uyo 132/33KV transmission substation and data on temperature of Uyo is collected from [15].

About 70% of the dataset is used as the training data for generating the prediction model whereas the remaining 30% of the dataset is used for cross validation of the model. More so, the model parameters are determined, error analysis is carried out, the model is developed and future peak load forecast are made. The Multiple Linear Regression (MLR) for the peak load is given as;

$$P_L = \beta_0 + \beta_1(GDP) + (\beta_2POP) + \beta_3(TEMP) \quad (1)$$

Where:

P_L ; is the peak load demand; DP is the Gross Domestic Product; POP is the Population and TEMP is the Temperature. $\beta_0, \beta_1, \beta_2, \beta_3$ are the regression parameters to be determined. For simplicity of mathematical expressions, the following substitutions will be made

$P_L = Y$; $GDP = X_1$; $POP = X_2$ and $TEMP = X_3$. Therefore, equation (1) can be rewritten as:

$$Y_i = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 \quad (2)$$

Using matrix notations, equation (2) can be rewritten as:

$$Y_i = [1 \ X_1 \ X_2 \ X_3]_i \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix}; i = 1 \dots \dots m \quad (3)$$

Where ‘m’ is the number of observations available from past data history

$$Y = X\beta \quad (4)$$

Where X is an n x 4 matrix; Y is an n x 1 column vector and β is a 4 x 1 column vector . The least square error method is used to minimize the sum of squared errors or residuals. The sum of squared residuals is given by;

$$SS_{Res} = \sum_1^n e_i^2 \quad (5)$$

Where ‘e’ is the error: the difference between the actual value and the predicated value.

$$e = (Y - \hat{Y}) \quad (6)$$

$$SS_{Res} = \sum_1^n e_i^2 = e'e = (Y - \hat{Y})'(Y - \hat{Y}) \quad (7)$$

$$\text{but } \hat{Y} = \hat{\beta} X \text{ (matrix form)}$$

$$SS_{Res} = (Y - \hat{\beta} X)'(Y - \hat{\beta} X) \quad (8)$$

$$SS_{Res} = Y'Y - Y'\hat{\beta} X - \hat{\beta}'X'Y + \hat{\beta}'X'X\hat{\beta} \quad (9)$$

$$SS_{Res} = Y'Y - 2\hat{\beta}'X'Y + \hat{\beta}'X'X\hat{\beta} \quad (10)$$

Taking partial derivative of SS_{Res} with respect to $\hat{\beta}$: $\frac{\partial SS_{Res}}{\partial \hat{\beta}} = 0$

$$\frac{\partial SS_{Res}}{\partial \hat{\beta}} = -2X'Y + 2\hat{\beta}X'X = 0 \quad -2X'Y + 2\hat{\beta}X'X = 0 \quad (11)$$

Solving for $\hat{\beta}$:

$$\hat{\beta} = (X'X)^{-1} X'Y \quad (12)$$

4. Results and Discussion

4.1. Dataset Used for the Peak Load Model

Table 1 shows that 10 years data used in the study. The data consist of 2006 to 2015 Peak load demand in megawatt, Population, GDP and temperature in °C.

Table 1. Dataset used for Estimate and Forecast of Peak Load.

Year	Peak Load (MW)	Population	GDP	Temperature
2006	38	305961	8545	27
2007	39	316364	9126	27
2008	41	327120	9701	27
2009	42	338242	10370	26
2010	43	349742	11179	27
2011	45	361634	11727	26
2012	46	373929	12231	26
2013	48	386643	12891	26
2014	50	399789	13704	26
2015	51	413381	14019	26

4.2. The Peak Load Model and Its Prediction Performance

The peak load model parameters are estimated using only the data of the year 2006 to the year 2012, which accounts for 70% of the entire dataset for training and 30% (that is, 2013 to 2015) of the data are used for cross validation. This is done to avoid over-fitting or over training of the entire dataset and to see how good the model can predict out of sample data. The estimated value for the regression parameters for the peak-load-demand model are;

$$\begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} = \begin{bmatrix} 8.484966 \\ 0.000119 \\ -0.0000546 \\ -0.23631 \end{bmatrix}$$

Hence, the peak-load-demand model is given as;

$$Y_i = 8.484966 + 0.000119X_1 - 0.0000546X_2 - 0.0000546X_2 - 0.23631X_3 \quad (13)$$

Table 2 gives the predicted peak-load demand for the years 2013 to 2015 and the percentage error of the prediction. With RMSE of 1.038042 and percentage error of less than 2%, it can be said that the cross validation results in Table 2 shows that the peak-load-demand model can effectively predict the peak load demand for Uyo.

Table 2. Model Validation.

Year	Actual Peak Load (MW)	Predicted Peak Load (MW)	% error	Error ²
2013	48	47.67234258	0.68262	0.107359
2014	50	49.19316539	1.613669	0.650982
2015	51	50.79428936	0.403354	0.042317
RMSE	1.038042			0.51661

Table 3 gives the predicted peak-load demand for the entire 10 years, 2006 to 2015 and the percentage error of the prediction. Again, the RMSE value of 0.75 is evident that the model effectively predicted the peak load for the 10 years data. The highest percentage error occurred in 2014 with a value of 1.613% The graph of the actual and the predicted peak load is given in figure 1.

Table 3. Predicted Peak-Load with the Percentage Errors.

Year	Actual Peak Load (MW)	Predicted Peak Load (MW)	% error	Error ²
2006	38	38.067	-0.1763	0.031092
2007	39	39.2739	-0.7023	0.493253
2008	41	40.5232	1.16302	1.352611
2011	45	44.7582	0.53728	0.288668
2012	46	46.1946	-0.423	0.178963
2013	48	47.6723	0.68262	0.46597
2014	50	49.1932	1.61367	2.603928
2015	51	50.7943	0.40335	0.162694
RMSE				0.754302

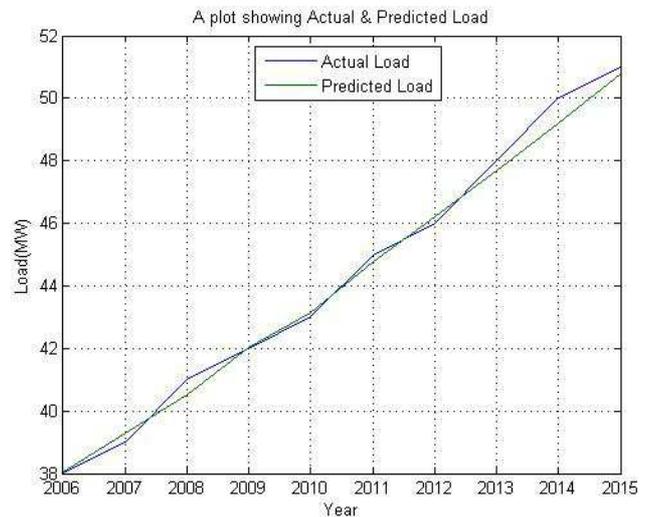


Figure 1. A plot showing Actual and predicted peak load for the year 2006 to 2015.

Table 4 shows some other prediction performance measures used to assess the prediction accuracy of the model. Namely, Mean absolute percentage error (MAPE), Mean absolute deviation (MAD) and Coefficient of Determination (R²). The R² value of 0.99184 shows that about 99.184% of the peak load are explained by the explanatory variables.

Table 4. Model Prediction Performance Measures.

Mean absolute percentage error (MAPE)	0.00613
Mean absolute deviation (MAD)	0.277743
Sum of Square Error (SSE)	1.224572
Coefficient of Determination (R^2)	0.99184

4.3. The Peak Load Forecasting

An individual forecast with the Multiple Linear Regression model of equation 13 is performed. The peak load forecasts for years 2016 to 2024 are presented in Table 5.

Table 5. Peak Load Forecasts for Years 2016 To 2024.

Year	POP	GDP	Temperature	Forecasted Peak Load (Mw)
2016	427436	13730	26	52.48352779
2017	441969	15035	26	54.14262275
2018	456996	15613	26	55.90024084
2019	472534	16191	26	57.71870099
2020	488600	16769	26	59.60002733
2021	505213	17348	26	61.54642745
2022	522390	17926	26	63.56003469
2023	540151	18504	26	65.64317573
2024	558516	19082	26	67.79823186

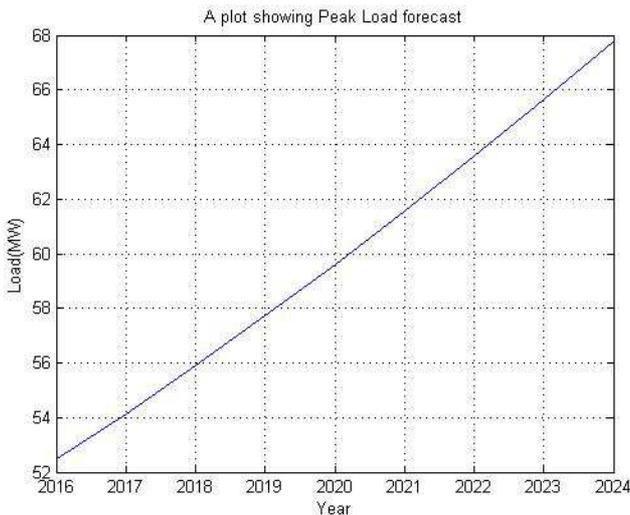


Figure 2. Peak Load Forecasts For Years 2016 To 2024.

From the plot, it is evident that the peak load demand will prevail in the forthcoming years, having a stable growth rate. It is equally observed that, the projected or extrapolated peak load demand will reach approximately 67.798MW in 2024, having an increase of about 32.93% when compared to the actual peak load in 2015. Therefore, compared to the 2015 power demand, at least additional 32.93% electric power production will be required in the next 10 years to meet the near future electric power demand.

5. Conclusion and Recommendation

5.1. Conclusion

Long term peak load forecast is an important tool that is

required for effective and efficient planning of power systems. This paper presents the results of a study on long-term electric peak load estimate and forecast of Uyo transmission substation up to 2024. The study also takes into account some of the factors that affect peak load demand, namely: GDP, population growth and temperature data from 2006 to 2015. MLR method is used to model the annual peak load. The model estimation demonstrates a huge success as the mean absolute error is approximately 0.61%, and coefficient of determination of over 99%.

Finally, the projected or extrapolated peak load demand will reach approximately 67.798MW in the year 2024, having an increase of about 32.93% when compared to the actual peak load in 2015. Therefore, additional electric power production will be required in the near future to meet the excessive electric power demand in the Uyo metropolis.

5.2. Recommendation

This paper only considers three explanatory variables; population, GDP and temperature. Other explanatory variables should be considered as well, such as; the power system losses (LOSS), the load factor (LF), the unit cost of electricity, etc to see the effects these factors will have on the peak load estimates and forecasts.

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