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Pseudo-inverse Matrix Model for Estimating Long-term Annual Peak Electricity Demand: The Covenant University's Experience

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ABSTRACT

One of the major decision problems facing any electrical supply undertaking is the forecasting of peak power demand. A problem therefore arises when an estimate of future electricity demand is not known to prepare for impending possible increase in electricity demand. To overcome this problem, it is therefore imperative to evaluate the precise amount of energy required for a sustainable power supply to customers. In line with this goal, this study established a mathematical model of regression analysis using pseudo-inverse matrix (PIM) method for the assessment of the historical data of covenant University's electric energy consumption. This method predicts a more accurate and reliable future energy requirement for the community, with special consideration for the next one decade. The accuracy of prediction based on the use of PIM method is compared with the forecast result of the least squares model, commonly used by engineers in making long-term forecast. The error analysis result from the mean absolute percentage error and the root mean square error (RMSE) performed on the two models using mean absolute deviation shows that the PIM is the most accurate of the models. Though this method is examined using a University community, it can be further extended to cover the whole country, provided the historical data of the country's past electric energy consumptions is available.

Keywords: Error Analysis, Historical Data, Linear Regression, Peak Demand, Pseudo-inverse Matrix
JEL Classifications: C53, L94, Q47

1. INTRODUCTION

The function of an electrical power system is to supply reliable and least cost electrical energy to electricity users. Electricity demand has increased drastically due to growing population and industrialization in developing countries and therefore it has become important to predict a reliable future energy requirement to meet up with the impending increase in demand for a sustainable energy supply (Abdulkareem et al., 2016, Firsova et al., 2019, Adekitan, 2018). Therefore, estimates of electricity requirements are crucial for appropriate planning of power system expansion, and this begins with a prediction of anticipated future load demands. It is very necessary because there needs to be an accurate picture of the future which many times is based on the past (Cullen, 1999) to prevent shortages in power supply to customers and even to prevent over-generation which will lead to wastage. Accurate models for electricity demand forecasting are crucial to the planning and operation of any organization involved in providing electricity for end-users as it helps the organization's manangement to make valuable decisions on issues concerning power generation, load management and shedding, and development of the power system infrastructure (Feinberg and Genethliou, 2005). Moreover, electricity demand forecasting is important to avoid under generation or over generation of electrical energy. Corporate decision-making mechanisms in energy companies are unavoidably based on predicted electricity demand and pricing (Mahmud, 2011). Excessive or inadequate contracting costs when buying or selling power in the balancing market can result in high financial losses which in extreme cases may lead to bankruptcy.

To improve the accuracy of load predictions in the 20th century, economic factors that are indicators of human activities both, nationally and globally were considered as inputs for long-term prediction of energy demand (Hong and Dickey, 2012). There are different methods and models used in load forecasting. Among them are regression analysis methods (Karpio et al., 2019), Artificial neural network (Kumar and Dixit, 2018), Gaussian process models, time series (Akarsu, 2017), Static state estimation method, Fuzzy logic, hybrid model (Suksawang et al., 2018), machine learning (Preda et al., 2018) and the use of artificial Intelligence (Leith et al., 2004). Linear regression technique is extensively applied in electrical load forecasting from the inception of power system planning and expansion (Heinemann et al., 1966). In addition, different methods have been applied by researchers to handle load forecasting projects. However, with the available variety of mathematical methods needed for calculating electricity demand forecasting, current techniques have certain drawback regarding such calculation. For example, the "method of least squares" has been extensively used by engineers for long-term load forecasting. Although, this method is mathematically accurate, but the accuracy typically obtained using this method is not very reliable for data trends with sudden dip or significant variations because it is based on continuous projection of past trends into the future (Mati et al., 2009). The Time series technique is a regression-based model for forecasting future load trends using previous load pattern as a signal in a time series. However, the use of Time series model for electricity demand forecasting may not be adequate for long-term electricity demand forecast as concluded in the work of (Gross and Galiana, 1987). The quality of any method for forecasting load demand is a function of the availability of historical energy consumption data, and the level of understanding of the effect and influence of each parameter considered on the energy consumption trends (Sachdeva and Verma, 2008).

Electricity demand forecasts can be classified based on the time horizon which is taken into consideration in the forecast analysis as short-term, medium-term and long-term forecasts. The short-term forecast is mostly used for hydro scheduling, unit commitment, assessment of power system security and trading on the spot market. Medium term forecast: Are run usually for about a week to a year. It is useful for maintenance planning and scheduling of the fuel supply. The long-term forecast is usually longer than a year. They are applied mainly for power system planning (Adoghe et al., 2013, Paravan, 2003) and for developing the power supply and delivery system which comprises the generation, transmission, and distribution systems.

Therefore, the purpose of this research is to perform a long-term energy demand forecast by establishing a regression mathematical model via the PIM method. This PMI method and the popular least squares model (LSM) method are practically implemented using covenant University's electricity consumption data covering the previous years 2007-2016 as a basis for predicting the future energy consumption. The results of the mean absolute percentage error (MAPE) analysed for PMI and LSM methods are 10.29% and 21.51% respectively, hence the PMI gives a more reliable and accurate prediction of future energy requirement for the community. This present study establishes reliable data for both demand and future energy requirements that can be used to structure objective decisions and policy formulation about the upgrade or possible replacement of the existing electrical power infrastructure for higher capacity. The data will also be used as a guide for further expansion and for establishing procurement policies for construction capital.

2. METHODS AND DATA

The foundation of this work which is the collection of relevant data and the historical data, shows one visible trend from 2007 to 2016. The available data of the Covenant University's Annual Peak Electricity Consumption from 2007 to 2016 is then analysed and arranged as shown in Table 1.

From Table 1, the peak or maximum load (ML) is the maximum amount of measured electrical power consumed in the whole year, annual growth (AG) is the arithmetic difference between the load of 2 consecutive years, and AG rate (AGR) is the proportion of the AG to the ML expressed as a percentage before the year of the AG and calculated using equation (1):

$$\text{Annual growth rate} = \frac{\text{Annual growth}}{\text{Maximum load before year of annual growth}} \times 100 \tag{1}$$

The historical data of the annual peak electricity consumption from 2007 to 2016 is presented in Figure 1.

2.1. Pseudo-Inverse Mathematical Model of Electricity Demand Forecasting

The feasibility of using inverse matrix method for electricity forecasting was demonstrated by (Islam et al., 2013) by applying the inverse matrix Technique to forecast the energy demand of an isolated island in Bangladesh.

For the pseudo-inverse mathematical model, we examine the set of data points given as

$$(X_1,Y_1)\ (X_2,Y_2)\ldots(X_n,Y_n)$$

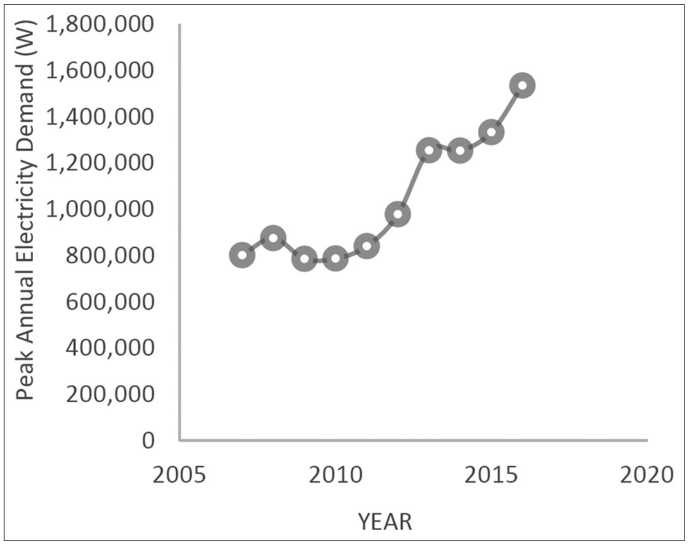
We evaluate a function $F(x)$ so that

$$Y_i = F(x) + \alpha \tag{2}$$

Table 1: Covenant university's annual peak electricity consumption from 2007 to 2016

Year No.	Year	Annual peak Load	Annual growth	Annual growth rate (%)
1	2007	801,876		
2	2008	875,980	74,104	9.2
3	2009	786,000	−89,980	−10.27
4	2010	787,450	1,450	0.184
5	2011	840,874	53,424	6.78
6	2012	978,654	137,780	16.38
7	2013	1,255,162	276,508	28.25
8	2014	1,253,800	−1,362	−0.11
9	2015	1,333,788	79, 988	6.38
10	2016	1,535,340	201,552	15.11

Figure 1: Peak annual electricity demand for 2007 to 2016



for i =1, 2,………. n
α is defined as a small approximation error.

Assume the function $F(x)$ has the form of a linearly weighted sum such that

$$F(x) = \sum_{k=1}^{m} C_k f_k(x) \quad (3)$$

Where m is the number of summands, and the specific basis function f_k is given by

$$f_k = x^{k-1} \quad (4)$$

Which means (implying from Equation 3) that

$$F(x) = C_1 + C_2X^1 + C_3X^2 + \ldots\ldots\ldots + C_mX^m \quad (5)$$

Equation (5) is a polynomial of degree m-1 in X. i.e.,

$$A = \begin{bmatrix} f_1(x_1) & f_2(x_1) & \cdots & f_m(x_1) \\ f_1(x_2) & f_2(x_2) & & f_m(x_2) \\ \vdots & & \ddots & \vdots \\ f_1(x_n) & f_2(x_n) & \cdots & f_m(x_n) \end{bmatrix} = a_{ij} \quad (6)$$

Represent the matrix of values of basic functions at the specified points; $a_{ij}=f_j(x_i)$.

Let $C=C_K$ represent the required m-vector of coefficients of Equation (5), therefore

$$A_c = \begin{bmatrix} f_1(x_1) & f_2(x_1) & \cdots & f_m(x_1) \\ f_1(x_2) & f_2(x_2) & & f_m(x_2) \\ \vdots & & \ddots & \vdots \\ f_1(x_m) & f_2(x_m) & \cdots & f_m(x_m) \end{bmatrix} \begin{bmatrix} C_1 \\ C_2 \\ C_m \end{bmatrix} = \begin{bmatrix} F(X_1) \\ F(X_2) \\ F(X_m) \end{bmatrix} \quad (7)$$

The vector of the predicted values of y is presented in equation (7).

And $\alpha=A_c-y$ is the n-vector of approximation errors. Therefore, the least squares solution which minimizes the approximation error (α) is given by $C=[(A^TA)^{-1} A^T]y$.

Which implies that $C=[A^*]y$

Where $A^*=[A^TA]^{-1}A^T$ and it is termed the pseudo–inverse of matrix A.

2.2. Computation of Mathematical Model

With respect to the annual peak load data presented in Table 1, we can now find the function of the form:

$$y=C_1+C_2X^1+C_3X^2+C_4X^3+\ldots\ldots+C_{10}X^9 \quad (8)$$

Equation (8) is the least squares fit for the observed data points. Therefore, we can evaluate the yearly peak load and growth for ten additional years as determined below:

Based on the data given, matrix A is defined below:

$$A = \begin{bmatrix} 1 & X_1 \\ 1 & X_2 \\ 1 & X_3 \\ 1 & X_4 \\ 1 & X_5 \\ 1 & X_6 \\ 1 & X_7 \\ 1 & X_8 \\ 1 & X_9 \\ 1 & X_{10} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \\ 1 & 5 \\ 1 & 6 \\ 1 & 7 \\ 1 & 8 \\ 1 & 9 \\ 1 & 10 \end{bmatrix}$$

$$A^T A = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \\ 1 & 5 \\ 1 & 6 \\ 1 & 7 \\ 1 & 8 \\ 1 & 9 \\ 1 & 10 \end{bmatrix}$$

$$A^T A = \begin{bmatrix} 10 & 55 \\ 55 & 385 \end{bmatrix}$$

Also,

$$(A^T A)^{-1} = 1/det \begin{bmatrix} 385 & -55 \\ -55 & 10 \end{bmatrix} = \frac{1}{825} \begin{bmatrix} 385 & -55 \\ -55 & 10 \end{bmatrix}$$

Recall that, $A^*= [A^TA]^{-1}A^T$.

Therefore;

$$A^* = 1/825 \begin{bmatrix} 385 & -55 \\ -55 & 10 \end{bmatrix} * \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 \end{bmatrix}$$

Using MATLAB to compute the matrix A^* yields:

$$A^* = \begin{bmatrix} 0.4000 & 0.3333 & 0.2666 & -0.1336 & 0.1332 \\ -0.0546 & -0.0425 & -0.0304 & -0.0183 & -0.0062 \end{bmatrix} \begin{bmatrix} 0.0665 & -0.0002 & -0.0669 & -0.1336 & -0.2003 \\ 0.0059 & 0.0180 & 0.0301 & 0.0422 & 0.0543 \end{bmatrix}$$

But $C=[A^*]Y$ where $Y = \begin{bmatrix} 801,876 \\ 875,980 \\ 786,000 \\ 787,450 \\ 840,874 \\ 978,654 \\ 1,255,162 \\ 1,253,800 \\ 1,333,788 \\ 1,535,340 \end{bmatrix}$ and $C = \begin{bmatrix} 5.86905*10^5 \\ 0.81231*10^5 \end{bmatrix}$

So, we have obtained values for C_1 and C_2 from the matrix C above.

Therefore C_1=5.8691*10^5 and $C_2=0.81231*10^5$.

Thus, the mathematical model for the annual peak load for Covenant University is given as:

$$Y=(5.86905*10^5)+(0.81231*10^5)x \text{ Watts} \quad (9)$$

Based on the model i.e., equation (9), the annual peak load for the next ten years is estimated. The variable x represents time and can hence be replaced by t. Therefore, equation (9) becomes

$$Y=(5.86905*10^5)+(0.81231*10^5)t \text{ Watts} \quad (10)$$

2.3. Linear Regression Analysis

The linear regression statistical method that summarizes and studies relationships between two continuous (quantitative) variables was employed to validate the degree of accuracy of PIM (Firsova et al., 2019). Regression analysis is referred to as Time series analysis when the only predictor variable is time period. In the study by (Ahmad and Chen, 2019), a model was developed for predicting energy usage requirement using random forest, nonlinear and stepwise regression analysis. To ensure that regression analysis gives an accurate forecasting method for the data in question, the dependent variable and the independent variable are measured at the continuous level and the data for this study satisfies this criterion such that a linear relationship exists between the dependent and independent variables. In this manner, the coefficient of determination (R^2) and the coefficient of correlation were calculated, and their values obtained were 83.62% and 0.91 respectively. The basic model of the time series regression is shown in the equation (11):

$$Y=a+bt \quad (11)$$

Where Y=Annual peak electricity demand and t=Time.

The values of a and b are calculated using the following formulae:

$$a = \frac{\sum Y}{n} - b\left(\frac{\sum t}{n}\right) \quad (12)$$

$$b = \frac{n\sum tY - \left(\sum Y\right)\left(\sum t\right)}{n\sum t^2 - \left(\sum t\right)^2} \quad (13)$$

Substituting values in equation. (13), gives

$$b = \frac{n\sum tY - \left(\sum Y\right)\left(\sum t\right)}{n\sum t^2 - \left(\sum t\right)^2} = \frac{(643.09)-(365.694)}{(10*385)-(35^2)}$$

b=0.1057

Substituting values in equation (12), gives

$$a = \frac{\sum Y}{n} - b\left(\frac{\sum t}{n}\right) = \frac{10.4484}{10} - 0.1057\left(\frac{35}{10}\right)$$

a=0.6749

Therefore, substituting the values of a and b into the regression equation, the following equation is obtained:

$$Y=0.6749+0.1057t \quad (14)$$

3. RESULTS AND ANALYSIS

In this section, the PIM mathematical model is used to develop a regression equation and the conventional Least-Squares Model is also used to model another regression equation for comparison with the results of the first. Therefore, the practical implementation of the PIM mathematical model of equation (10) and the experimentation of the LSM representation of equation (14) were simulated on the ten-year data collected. Thus, the mathematical model for the Annual Peak Electricity Demand for Covenant University as calculated for PIM using the mathematical model of equation (10) is as presented in Table 2 and Figure 2 below.

Recall equation (10):

$$Y=(5.86905*10^5)+(0.81231*10^5)t$$

$(0.81231*10^5)t$ infers that the peak annual electricity demand increases at a rate of 81,231 Watts per year. The value $5.86905*10^5$ is the estimated annual peak load when t=0. That is, the estimated annual peak load for 2006 (the base year) is 586,905 Watts.

The AGR of the peak annual electricity demand is calculated for all the years using the following equation:

$$\text{AGR} = \frac{\text{Annual growth}}{\text{Maximum load before year of annual growth}} *100 \quad (15)$$

and the average per unit growth rate was calculated to be 3.64% using the formula below:

$$P = P_0 e^{\propto(t-t_0)} \quad (16)$$

Where
P is the peak annual electricity demand for a period of ten years;
P_0 is the peak annual electricity demand at time t=0;
$\propto$ is the average per unit growth rate;
t_0 is time period of zero; and
t=10-year time.

For the LSM, based on the model of equation (14), the annual peak electricity consumption for the next ten years is again estimated. The result of the annual peak load forecast obtained from the Least squares mathematical model of equation (14) is as presented in Table 3 and Figure 3.

From equation (13), the value 0.1057 infers that the annual peak load increases at a rate of 0.1057 megawatts or 105,700 watts per year. The value 0.6749 is the estimated annual peak load when t = 0. That is, the estimated annual peak load for 2006 (the base year) is 0.6749 Megawatts or 674,900 watts.

3.1. Evaluation of Prediction Interval

The prediction interval is a range of values at which the estimated values of peak annual electricity consumption are expected to fall into. All good forecast models have methods of calculating an upper value and a lower value. This is the prediction interval within which the forecasted value as a specified level of probability is expected to remain. This specified level of is the confidence level. Therefore, for the PMI method, the prediction intervals for the range within which the estimated values of peak annual electricity consumption are expected to fall are as shown in Table 4 and Figure 4.

Table 2: PMI estimated annual peak load for the period 2017-2026

Year No.	Year	Annual peak load (W)	Annual growth	Annual growth rate (%)
11	2017	1,480,446	−54894	−3.575
12	2018	1,561,677	81231	5.49
13	2019	1,642,908	81231	5.2
14	2020	1,724,139	81231	4.94
15	2021	1,805,370	81231	4.71
16	2022	1,886,601	81231	4.49
17	2023	1,967,832	81231	4.31
18	2024	2,049,063	81231	4.13
19	2025	2,130,294	81231	3.96
20	2026	2,211,525	81231	3.81

Table 3: LSM forecasted annual peak load for years 2017-2026

Year No.	Year	Annual peak load (W)	Annual growth	Annual growth rate (%)
11	2017	1.8376	0.3023	19.69
12	2018	1.9433	0.1057	5.75
13	2019	2.049	0.1057	5.44
14	2020	2.1547	0.1057	5.16
15	2021	2.2604	0.1057	4.9
16	2022	2.3661	0.1057	4.67
17	2023	2.4718	0.1057	4.47
18	2024	2.5775	0.1057	4.27
19	2025	2.6832	0.1057	4.1
20	2026	2.7889	0.1057	3.94

For the LSM model, the prediction intervals for the range within which the estimated values of peak annual electricity consumption are expected to fall are as shown in Table 5 and Figure 5.

3.2. Evaluation of Forecast Accuracy

The measure of degree of accuracy for the two forecast techniques employed in this study was evaluated based on the following equations (17) to (19) and their results of accuracy is as shown in Table 6.

$$\text{MAD} = \frac{\sum |y_i - f_i|}{n} \tag{17}$$

Figure 2: PMI forecasted peak annual electricity demand for 2017 to 2026

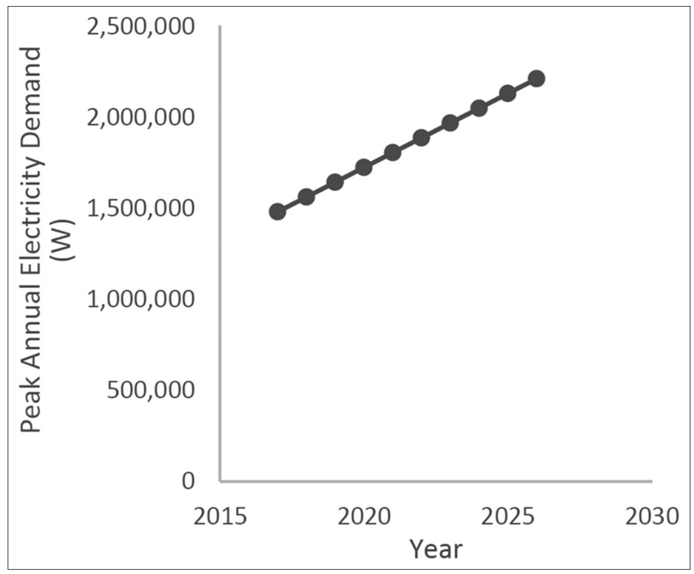
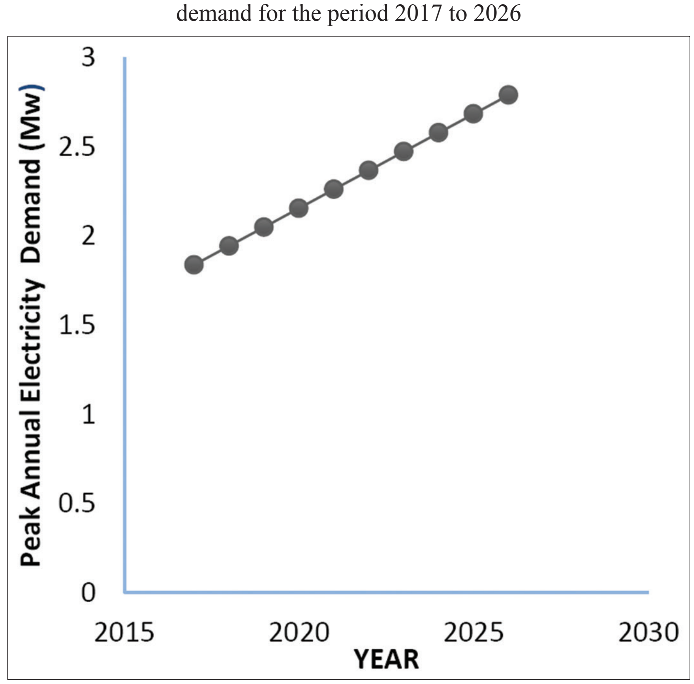


Figure 3: Least squares model forecasted peak annual electricity demand for the period 2017 to 2026



$$\text{RMSE} = \sqrt{\frac{\sum |y_i - f_i|^2}{n}} \quad (18)$$

$$\text{MAPE} = \frac{100}{n} \sum \left| \frac{y_i - f_i}{y_i} \right| \quad (19)$$

Figure 4: Historical and forecasted annual peak loads showing lower and upper confidence intervals (PMI)

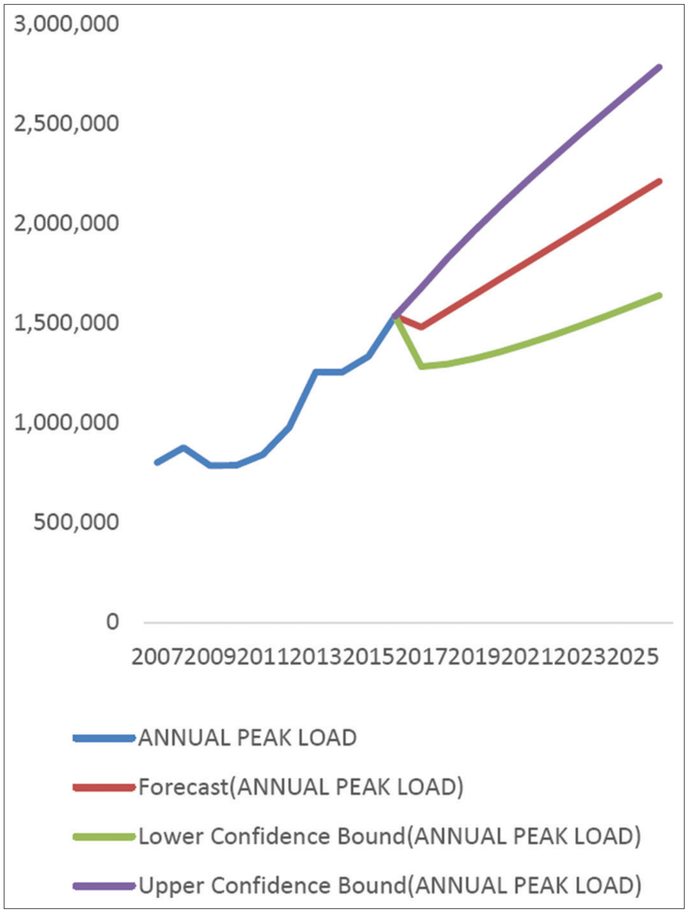
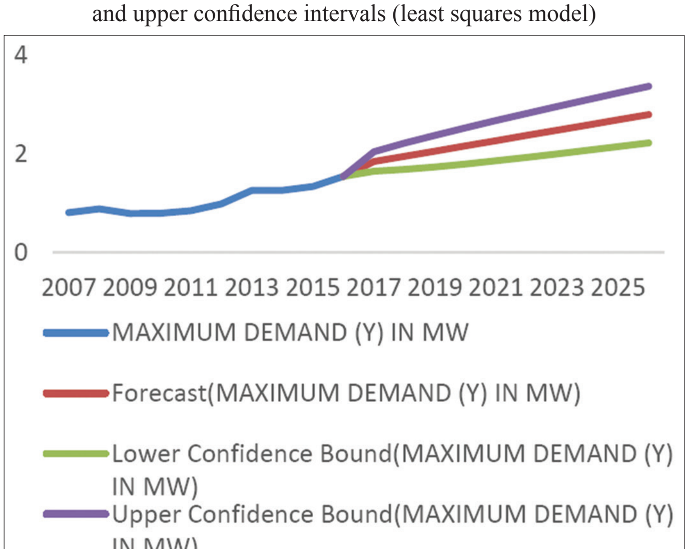


Figure 5: Historical and forecasted annual peak loads showing lower and upper confidence intervals (least squares model)



3.3. Software and Simulation

The Minitab statistical software was used to simulate a regression analysis for the historical data which was similarly applied by (Ulkareem et al., 2018). The results obtained were reasonably close to that obtained when the PIM Model is used. The results obtained from the simulation are shown in Figure 6.

Table 4: Forecasted annual peak load showing rediction intervals for PMI

Year	Forecasted annual peak Consumption (MW)	Lower prediction interval (MW)	Upper prediction interval (MW)
2017	1.8376	1.6400	2.0400
2018	1.9433	1.6800	2.2100
2019	2.0490	1.7300	2.3700
2020	2.1547	1.7900	2.5200
2021	2.2604	1.8500	2.6700
2022	2.3661	1.9200	2.8100
2023	2.4718	1.9900	2.9500
2024	2.5775	2.0600	3.0900
2025	2.6832	2.1400	3.2300
2026	2.7889	2.2200	3.3600

Table 5: Forecasted annual peak loads for year 2017-year 2026

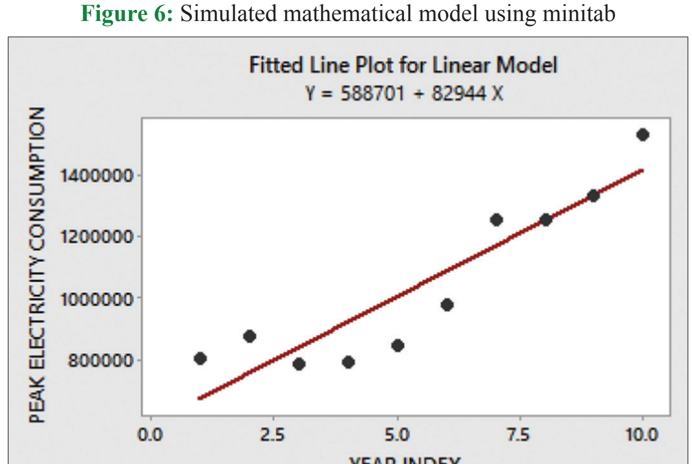
Year No.	Year	Forecasted annual peak load (MW)	Annual growth (MW)	Annual growth rate (%)
11	2017	1.8376	0.3023	19.69
12	2018	1.9433	0.1057	5.75
13	2019	2.0490	0.1057	5.44
14	2020	2.1547	0.1057	5.16
15	2021	2.2604	0.1057	4.90
16	2022	2.3661	0.1057	4.67
17	2023	2.4718	0.1057	4.47
18	2024	2.5775	0.1057	4.27
19	2025	2.6832	0.1057	4.10
20	2026	2.7889	0.1057	3.94

Table 6: MAD, RMSE and MAPE for the two models

Method	MAD	RMSE	MAPE%
Pseudo-inverse model (PMI)	0.0985	0.1105	10.29
Least-square model (LSM)	0.2156	0.2451	21.51

MAD: Mean absolute deviation, MAPE: Mean absolute percentage error

Figure 6: Simulated mathematical model using minitab



The linear regression equation obtained from the Minitab software is:

$$Y=588701+82944t \quad (20)$$

Comparing equation (20) obtained from the Minitab software with equation (10) obtained using the PMI model, it is observed that they are almost the same. This further proves the accuracy of the PMI model for long-term electricity demand forecasting.

4. CONCLUSION

The present effort mainly focuses on the long-term forecasting of covenant University's electricity demand using mathematical model approach known as PMI. The forecast of electricity consumption obtained from the model was accurate for the study from 2017-2026. The study conducted forecast accuracy test or error analysis that validates the accuracy of the results of the peak annual electricity demand obtained in the work. From the error analysis performed on the two methods, the PMI method has been proven to be mathematically superior and a more accurate method than the LSM which, like most time series model, proved to be inaccurate for a long-term forecast in view of saturation of the series. Moreover, the results of the Minitab statistical software used to simulate a regression analysis for the covenant historical data, were reasonably close to that obtained using the PMI Model which further confirmed the high degree of accuracy of the results obtained in the study. The PMI provides a valuable and accurate tool that can be used by Covenant University to make reliable energy management policies and to plan for future expansion of the existing electrical energy infrastructure. However, for a higher level of accuracy, an AG of between 81,231Watts (as obtained from PMI) and 105,700 Watts (as obtained from LSM model) per year would be an innovative approach for a reasonable growth range thereby complementing the drawback of each of the techniques.

Based on the level of accuracy of this study, this method can be used for the modelling of country's electricity demand provided the historical data of the country's past electric energy consumptions is available. The suggested further work may include the application of using a multi-variate regression analysis that will take micro-economic variables into consideration that could also be influencing variables of the electrical energy consumption.

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