Statistical Modeling Of The Yearly Residential Energy Demand In Nigeria

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Abstract*—In this paper, statistical modeling of the yearly residential energy demand in Nigeria is presented. Specifically, two statistical models were used, namely, the quadratic regression model without interaction and multiple linear regressions with one period l lagged dependent variable. In the study, 46 years data on the yearly residential energy demand in Nigeria was used along with data on temperature and population which are the explanatory variable. The details of the models development process were presented and the regression coefficients were derived based on the case study dataset. The models prediction performances were assessed in terms of R-square value, the sum of square of error (SSE) and the root mean square error (RMSE). The results showed that the R-square value for the multiple linear regression model with one period lagged dependent variable was 0.8525 (85.25%), SSE was 571850 and RMSE was 111.4970. Also, the R-square value for the quadratic regression model without interaction was 0.7265 (72.65%), SSE was 1060100 and RMSE was 151.8083. The multiple linear regression model with one period lagged dependent variable had a better prediction performance. As such it was used to forecast the yearly residential energy demand in Nigeria for the next eleven years (2018 -2028). The forecast result shows that in 2028 the yearly residential energy demand in Nigeria will be 12050.5 MW/h. The results in this study were compared with those obtained in a previous research where only eight years data was used. In that study, the quadratic regression model without interaction was found to be more accurate in the residential energy prediction with very high R-squared value. However, it can be concluded in this study that model prediction performance based on small sample is deceptive; sufficient data is required for effective modeling.

***Keywords*—Statistical Model, Residential Energy Demand, Quadratic Regression Model, Multiple Linear Regressions With One Period L Lagged Dependent Variable, Explanatory Variable**

I. INTRODUCTION

Nigerian residential electric energy consumers have over the years suffered inadequate and recurring epileptic supply from the national grid [1,2,3,4,5,6]. In response, the Nigerian government has in recent years promised to address the challenges faced by the electric power sector [7,8,9,10]. To this end, effort are being made to effectively plan for adequate power supply to all the sectors of the economy.

Importantly, electricity forecasting forms the basis for power system expansion planning, and affects system security and reliability [7,8,9,10]. Forecasting electricity can be generally classified into three categories based on discrete forecast range [11,12,13,14,15]. Firstly, short term forecasting of a few hours ahead to a few days plays an important role in the day-to-day operation and scheduling of generating units [16,17,18]. Secondly, medium term forecasting over a period of a few weeks to a few months, and in some cases to a few years, is mainly useful for fuel allocation and maintenance scheduling [16,17,18,19]. Also, there are also long term forecasts over a period of 5 to 25 years. Therefore, long term forecasts of national electricity consumption assist the government and private sectors in the long term planning' of the electricity industry, such as when and where to build a power plant or when to expand capacity [20,21,22,23]. Consequently, in this paper, statistical modeling and long term forecasting of residential electricity in Nigeria is carried out using two different statistical models, namely, the quadratic regression model without interaction and multiple linear regressions with one period l lagged dependent variable. Existing study in [24] was based on eight years data which was not sufficient for long term forecasting purpose.

Consequently, in this paper, a long term data consisting of 46 years (1970 -2015) data on the residential energy demand in Nigeria was used along with data on the explanatory variables which are temperature and population to model of the yearly residential energy demand in Nigeria. The study became necessary when preliminary study with the two models and the long term data gave slightly different results from the already existing study. The detailed model development are presented along the MATHLAB program computation results and graph plots for the actual and the model predicted yearly residential energy demand in Nigeria. The comparative evaluation of the prediction performance of the two models are also presented along with the forecast of future yearly residential energy demand in Nigeria.

II. METHODOLOGY

A. Model 1: Quadratic Regression Model without Interaction.

With the quadratic regression model without interaction the residential electricity consumption, E_t is expressed as a function of population, P_t and temperature, T_t , as follows;

$$E_t = \alpha_0 + \alpha_1 P_t + \alpha_2 T_t + \alpha_3 {P_t}^2 + \alpha_4 {T_t}^2 + \varepsilon_t \quad (1)$$

Where the error term is $\varepsilon_t$and α_0,α_1 , α_2, α_3 , α_4 and α_5 are regression coefficients. The error term,ε_t, is given as;

$$\varepsilon_t = E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 {P_t}^2 - \alpha_4 {T_t}^2 \quad (2)$$

The of square error, ${\varepsilon_t}^2$ is given as;

$${\varepsilon_t}^2 = \left(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 {P_t}^2 - \alpha_4 {T_t}^2\right)^2 \quad (3)$$

Hence, the sum of square of error denoted as S is defined as;

$$S = \sum_{t=0}^{n}({\varepsilon_t}^2) = \sum_{t=0}^{n}\left(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 {P_t}^2 - \alpha_4 {T_t}^2\right)^2 \quad (4)$$

When the partial derivative of the sum of square of error is taken with respect to $\alpha_0, \alpha_1, \alpha_2, \alpha_3$and $\alpha_4$then:

$$\frac{\partial S}{\partial \alpha_0} = -2\sum_{t=0}^{n}\left(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 {P_t}^2 - \alpha_4 {T_t}^2\right) \quad (5)$$

Hence,

$$\frac{\partial S}{\partial \alpha_0} = -2\left[\sum E_t - n\alpha_0 - \sum \alpha_1 P_t - \sum \alpha_2 T_t - \sum \alpha_3 {P_t}^2 - \sum \alpha_4 {T_t}^2\right] \quad (6)$$

Equally,

$$\frac{\partial S}{\partial \alpha_1} = -2\sum_{t=0}^{n}(P_t)\left(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 {P_t}^2 - \alpha_4 {T_t}^2\right) \quad (7)$$

$$\frac{\partial S}{\partial \alpha_1} = -2\left(\sum E_t P_t - \alpha_0 \sum P_t - \alpha_1 \sum {P_t}^2 - \alpha_2 \sum T_t P_t - \alpha_3 \sum {P_t}^3 - \alpha_4 \sum {T_t}^2 P_t\right) \quad (8)$$

$$\frac{\partial S}{\partial \alpha_2} = -2\sum_{t=0}^{n}(T_t)\left(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 {P_t}^2 - \alpha_4 {T_t}^2\right) \quad (9)$$

$$\frac{\partial S}{\partial \alpha_2} = -2\left(\sum E_t T_t - \alpha_0 \sum T_t - \alpha_1 \sum T_t P_t - \alpha_2 \sum {T_t}^2 - \alpha_3 \sum {P_t}^2 T_t - \alpha_4 \sum {T_t}^3\right) \quad (10)$$

$$\frac{\partial S}{\partial \alpha_3} = -2\sum_{t=0}^{n}({P_t}^2)\left(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 {P_t}^2 - \alpha_4 {T_t}^2\right) \quad (11)$$

$$\frac{\partial S}{\partial \alpha_3} = -2\left(\sum E_t {P_t}^2 - \alpha_0 \sum {P_t}^2 - \alpha_1 \sum {P_t}^3 - \alpha_2 \sum T_t {P_t}^2 - \alpha_3 \sum {P_t}^4 - \alpha_4 \sum {T_t}^2 {P_t}^2{}_t\right) \quad (12)$$

$$\frac{\partial S}{\partial \alpha_4} = -2\sum_{t=0}^{n}({T_t}^2)\left(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 {P_t}^2 - \alpha_4 {T_t}^2\right) \quad (13)$$

$$\frac{\partial S}{\partial \alpha_4} = -2\left(\sum E_t {T_t}^2 - \alpha_0 \sum {T_t}^2 - \alpha_1 \sum P_t {T_t}^2 - \alpha_2 \sum {T_t}^3 - \alpha_3 \sum {P_t}^2 {T_t}^2 - \alpha_4 \sum {T_t}^4\right) \quad (14)$$

$$\frac{\partial S}{\partial \alpha_5} = -2\sum_{t=0}^{n}(P_t T_t)\left(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 {P_t}^2 - \alpha_4 {T_t}^2\right) \quad (15)$$

$$\frac{\partial S}{\partial \alpha_5} = -2\left(\sum E_t P_t T_t - \alpha_0 \sum P_t T_t - \alpha_1 \sum {P_t}^2 T_t - \alpha_2 \sum P_t {T_t}^2 - \alpha_3 \sum {P_t}^3 {T_t}^2 - \alpha_4 \sum P_t {T_t}^3\right) \quad (16)$$

Then the derivatives in Equation(7) to Equation (16) are set to zero as follows;

$$\frac{\partial S}{\partial \alpha_0} = \frac{\partial S}{\partial \alpha_1} = \frac{\partial S}{\partial \alpha_2} = \frac{\partial S}{\partial \alpha_{13}} = \frac{\partial S}{\partial \alpha_4} = 0 \quad (17)$$

Then;

$$\sum E_t = n\alpha_0 - \alpha_1 \sum P_t - \alpha_2 \sum T_t - \alpha_3 \sum {P_t}^2 - \alpha_4 \sum {T_t}^2 \quad (18)$$

$$\sum E_t P_t = \alpha_0 \sum P_t + \alpha_1 \sum {P_t}^2 + \alpha_2 \sum T_t P_t + \alpha_3 \sum {P_t}^3 + \alpha_4 \sum {T_t}^2 P_t \quad (19)$$

$$\sum E_t T_t = \alpha_0 \sum T_t + \alpha_1 \sum T_t P_t + \alpha_2 \sum {T_t}^2 + \alpha_3 \sum {P_t}^2 T_t + \alpha_4 \sum {T_t}^3 \quad (20)$$

$$\sum E_t {P_t}^2 = \alpha_0 \sum {P_t}^2 + \alpha_1 \sum {P_t}^3 + \alpha_2 \sum T_t {P_t}^2 + \alpha_3 \sum {P_t}^4 + \alpha_4 \sum {T_t}^2 {P_t}^2 \quad (21)$$

$$\sum E_t {T_t}^2 = \alpha_0 \sum {T_t}^2 + \alpha_1 \sum P_t {T_t}^2 + \alpha_2 \sum {T_t}^3 + \alpha_3 \sum {P_t}^2 {T_t}^2 + \alpha_4 \sum {T_t}^4 \quad (22)$$

In a matrix form the five simultaneous equations becomes;

$$\begin{pmatrix} \sum E_t \\ \sum E_t P_t \\ \sum E_t T_t \\ \sum E_t {P_t}^2 \\ \sum E_t {T_t}^2 \end{pmatrix} = \begin{pmatrix} n & \sum P_t & \sum T_t & \sum {P_t}^2 & \sum {T_t}^2 \\ \sum P_t & \sum {P_t}^2 & \sum T_t P_t & \sum {P_t}^3 & \sum P_t {T_t}^2 \\ \sum T_t & \sum T_t P_t & \sum {T_t}^2 & \sum {P_t}^2 T_t & \sum {T_t}^3 \\ \sum {P_t}^2 & \sum {P_t}^3 & \sum {P_t}^2 T_t & \sum {P_t}^4 & \sum {T_t}^2 {P_t}^2 \\ \sum {T_t}^2 & \sum P_t {T_t}^2 & \sum {T_t}^3 & \sum {T_t}^2 {P_t}^2 & \sum {T_t}^4 \end{pmatrix} \begin{pmatrix} \alpha_0 \\ \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{pmatrix} \quad (23)$$

Let the following terms, R_1, U_1 and a_{c1} be defined as follows;

$$R_1 = \begin{pmatrix} n & \sum P_t & \sum T_t & \sum P_t^2 & \sum T_t^2 & \sum P_tT_t \\ \sum P_t & \sum P_t^2 & \sum T_t P_t & \sum P_t^3 & \sum P_tT_t^2 & \sum P_t^2T_t \\ \sum T_t & \sum T_t P_t & \sum T_t^2 & \sum P_t^2T_t & \sum T_t^3 & \sum P_tT_t^2 \\ \sum P_t^2 & \sum P_t^3 & \sum P_t^2T_t & \sum P_t^4 & \sum T_t^2P_t^2 & \sum P_t^3T_t \\ \sum T_t^2 & \sum P_tT_t^2 & \sum T_t^3 & \sum T_t^2P_t^2 & \sum T_t^4 & \sum P_tT_t^3 \\ \sum P_tT_t & \sum P_t^2T_t & \sum P_tT_t^2 & \sum P_t^3T_t & \sum P_tT_t^3 & \sum P_t^2T_t^2 \end{pmatrix} \quad (24)$$

$$U_1 = \begin{pmatrix} \sum E_t \\ \sum E_tP_t \\ \sum E_tT_t \\ \sum E_tP_t^2 \\ \sum E_tT_t^2 \end{pmatrix} \quad (25)$$

$$a_1 = \begin{pmatrix} \alpha_0 \\ \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{pmatrix} \quad (26)$$

Hence, Equation (23) becomes;

$$R_1(a_{c1}) = U_1 \quad (27)$$

Therefore, the values of the regression coefficients a_{c1} are obtained from the expression given as;

$$a_{c1} = {R_1}^{-1}(U_1) \quad (28)$$

When the case study data on P_t, T_t and E_t are applied, the regression coefficients $\alpha_0, \alpha_1, \alpha_3, \alpha_4$ and α_5 values obtained from Equation (28) are;

$$\alpha_0 = 162.312$$

$$\alpha_1 = 42.11$$

$$\alpha_2 = 5.2133$$

$$\alpha_3 = -1.092$$

$$\alpha_4 = 0.612$$

Eventually, E_t, the residential energy consumption in Nigeria can be modeled according to the quadratic regression model with interaction terms is given as;

$$E_t = 162.312 + 42.11P_t + 5.2133T_t - 1.092{P_t}^2 + 0.612{T_t}^2 \quad (29)$$

B. Model 2 Multiple Linear Regressions with One Period l Lagged Dependent Variable

Multiple Regressions with one period lagged of the dependent variable is a linear regression that represents residential electricity consumption (E_t) in terms of temperature (T), population (P) and residential electricity consumption with one period lagged of the dependent variable as follows;

$$E_t = f(P_t, T_t, E_{t-1}) \quad (30)$$

$$E_t = \alpha_0 + \alpha_1 P_t + \alpha_2 T_t + \alpha_3 E_{t-1} + \varepsilon_t \quad (31)$$

where: α_0, α_1, α_2 and α_4 are regression coefficients and $\varepsilon_t$is the error which can be expressed as;

$$\varepsilon_t = E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 E_{t-1} \quad (32)$$

$$\varepsilon_t^2 = (E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 E_{t-1})^2 \quad (33)$$

Therefore, the sum of square of error, s is given as;

$$S = \sum_{t=0}^{n}(\varepsilon_t^2) = \sum_{t=0}^{n}(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 E_{t-1})^2 \quad (34)$$

The partial derivative of S in terms of $\alpha_0, \alpha_1, \alpha_2$ and α_3 gives:

$$\frac{\partial S}{\partial \alpha_0} = -2\sum_{t=0}^{n}(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 E_{t-1}) \quad (35)$$

$$\frac{\partial S}{\partial \alpha_0} = -2[\sum_{t=0}^{n}(E_t) - (n\alpha_0) - \sum_{t=0}^{n}(-\alpha_1 P_t) - \sum_{t=0}^{n}(\alpha_2 T_t) - \sum_{t=0}^{n}(\alpha_3 E_{t-1})] \quad (36)$$

$$\frac{\partial S}{\partial \alpha_1} = -2[\sum_{t=0}^{n}(P_t)(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 E_{t-1})] \quad (37)$$

$$\frac{\partial S}{\partial \alpha_1} = 2\left[E_tP_t - \alpha_0\sum_{t=0}^{n}(P_t) - \alpha_1\sum_{t=0}^{n}(P_t^2) - \alpha_2\sum_{t=0}^{n}(T_tP_t) - \sum_{t=0}^{n}(\alpha_3 E_{t-1}P_t)\right] \quad (38)$$

$$\frac{\partial S}{\partial \alpha_2} = -2\sum_{t=0}^{n}(T_t)(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 E_{t-1}) \quad (39)$$

$$\frac{\partial S}{\partial \alpha_2} = -2\left[E_tT_t - \alpha_0\sum_{t=0}^{n}(T_t) - \alpha_1\sum_{t=0}^{n}(T_tP_t) - \alpha_2\sum_{t=0}^{n}(T_t^2) - \sum_{t=0}^{n}(\alpha_3 E_{t-1}T_t)\right] \quad (40)$$

$$\frac{\partial S}{\partial \alpha_3} = -2\sum_{t=0}^{n}(E_{t-1})(E_t - \alpha_0 - \alpha_1 P_t - \alpha_2 T_t - \alpha_3 E_{t-1}) \quad (41)$$

$$\frac{\partial S}{\partial \alpha_3} = -2\left[E_{t-1}E_t - \alpha_0\sum_{t=0}^{n}(E_{t-1}) - \alpha_1\sum_{t=0}^{n}(E_{t-1}P_t) - \alpha_2\sum_{t=0}^{n}(E_{t-1}T_t) - \sum_{t=0}^{n}(\alpha_3 E_{t-1}^2)\right] \quad (42)$$

The partial derivatives are then set to zero which results in a set of four simultaneous equations as follows;

$$\frac{\partial S}{\partial \alpha_0} = \frac{\partial S}{\partial \alpha_1} = \frac{\partial S}{\partial \alpha_2} = \frac{\partial S}{\partial \alpha_3} = 0 \quad (43)$$

$$\left.\begin{aligned} \sum E_t &= n\alpha_0 + \alpha_1\sum P_t + \alpha_2\sum T_t + \alpha_3\sum E_{t-1} \\ \sum E_tP_t &= \alpha_0\sum P_t + \alpha_1\sum P_t^2 + \alpha_2\sum T_tP_t + \alpha_3\sum E_{t-1}P_t \\ \sum E_tT_t &= \alpha_0\sum T_t + \alpha_1\sum T_tP_t + \alpha_2\sum T_t^2 + \alpha_3\sum E_{t-1}T_t \\ \sum E_tE_{t-1} &= \alpha_0\sum E_{t-1} + \alpha_1\sum E_{t-1}P_t + \alpha_2\sum E_{t-1}T_t + \alpha_3\sum E_{t-1}^2 \end{aligned}\right\} \quad (44)$$

In a matrix form the four simultaneous equations becomes;

$$\begin{pmatrix} \sum E_t \\ \sum E_t P_t \\ \sum E_t T_t \\ \sum E_t E_{t-1} \end{pmatrix} = \begin{pmatrix} n & \sum P_t & \sum T_t & \sum E_{t-1} \\ \sum P_t & \sum {P_t}^2 & \sum T_t P_t & \sum E_{t-1} P_t \\ \sum T_t & \sum T_t P_t & \sum {T_t}^2 & \sum E_{t-1} T_t \\ \sum E_{t-1} & \sum E_{t-1} P_t & \sum E_{t-1} T_t & \sum {E_{t-1}}^2 \end{pmatrix} \begin{pmatrix} \alpha_0 \\ \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix} \quad (45)$$

Let the following terms, R_2, U_2 and a_{c2} be defined as follows;

$$R_2 = \begin{pmatrix} n & \sum P_t & \sum T_t & \sum E_{t-1} \\ \sum P_t & \sum {P_t}^2 & \sum T_t P_t & \sum E_{t-1} P_t \\ \sum T_t & \sum T_t P_t & \sum {T_t}^2 & \sum E_{t-1} T_t \\ \sum E_{t-1} & \sum E_{t-1} P_t & \sum E_{t-1} T_t & \sum {E_{t-1}}^2 \end{pmatrix} \quad (46)$$

$$U_2 = \begin{pmatrix} \sum E_t \\ \sum E_t P_t \\ \sum E_t T_t \\ \sum E_t E_{t-1} \end{pmatrix} \quad (47)$$

$$a_{c2} = \begin{pmatrix} \alpha_0 \\ \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix} \quad (48)$$

Hence, Equation (45) becomes;

$$R_2(a_{c2}) = U_2 \quad (49)$$

Therefore, the values of the regression coefficients a_{c2} are obtained from the expression given as;

$$a_{c2} = {R_2}^{-1}(U_2) \quad (50)$$

When the case study data on P_t, T_t and E_t are applied, the regression coefficients $\alpha_0, \alpha_1, \alpha_3, \alpha_4$ and α_5 values obtained from Equation (50) are;

$$\alpha_0 = 0.4786$$

$$\alpha_1 = 0.00025$$

$$\alpha_2 = 0.0180$$

$$\alpha_3 = 0.7583$$

Eventually, E_t, the residential energy consumption in Nigeria can be modeled according to the multiple linear regressions with one period lagged of the dependent variable is given as;

$$E_t = 0.4786 + 0.00025P - 0.0180T + 0.7583E_{t-1} \quad (51)$$

III. RESULTS AND DISCUSSION

The graph plot showing the actual yearly residential energy demand in Nigeria and the predicted residential energy demand based on the quadratic regression model without interaction is presented in Figure 1. Also in Figure 1 are the graph plots for the explanatory variables, namely, temperature and population. The R-square value for the quadratic regression model without interaction is 0.7265 (72.65%), the sum of square of error (SSE) is 1060100 and root mean square error (RMSE) is 151.8083.

The graph plot showing the actual yearly residential energy demand in Nigeria and the predicted residential energy demand based on the multiple linear regression model with one period lagged dependent variable is presented in Figure 2. Also in Figure 2 are the graph plots for the explanatory variables, namely, temperature and population. The R-square value for the multiple linear regression model with one period lagged dependent variable is 0.8525 (85.25%), the sum of square of error (SSE) is 571850 and root mean square error (RMSE) is 111.4970. Essentially, the multiple linear regression model with one period lagged dependent variable has a better prediction performance. As such it was used to forecast the yearly residential energy demand in Nigeria for the next eleven years (2018 -2028), as shown in Figure 3 and Table 1. The forecast result shows that in 2028 the yearly residential energy demand in Nigeria will be 12050.5 MW/h.

In a similar study published in 2017 [24] the study eight years (2007 – 2014) data for the model development and the models had very high prediction performance with R-squared value of over 0.93 for both models. However, the quadratic regression model without interactions had a higher R-squared value of over 0.9389 and was then selected as the best model for charactering the yearly residential energy demand in Nigeria. On the other hand, in this study which used 46 years (1970 – 2015) data the R-squared value for the two models dropped and the multiple linear regression model with one period lagged dependent had a better prediction performance than the quadratic regression model without interactions. In essence, the small sample of data used in the previous study was not sufficient to effectively characterize the yearly residential energy demand in Nigeria.

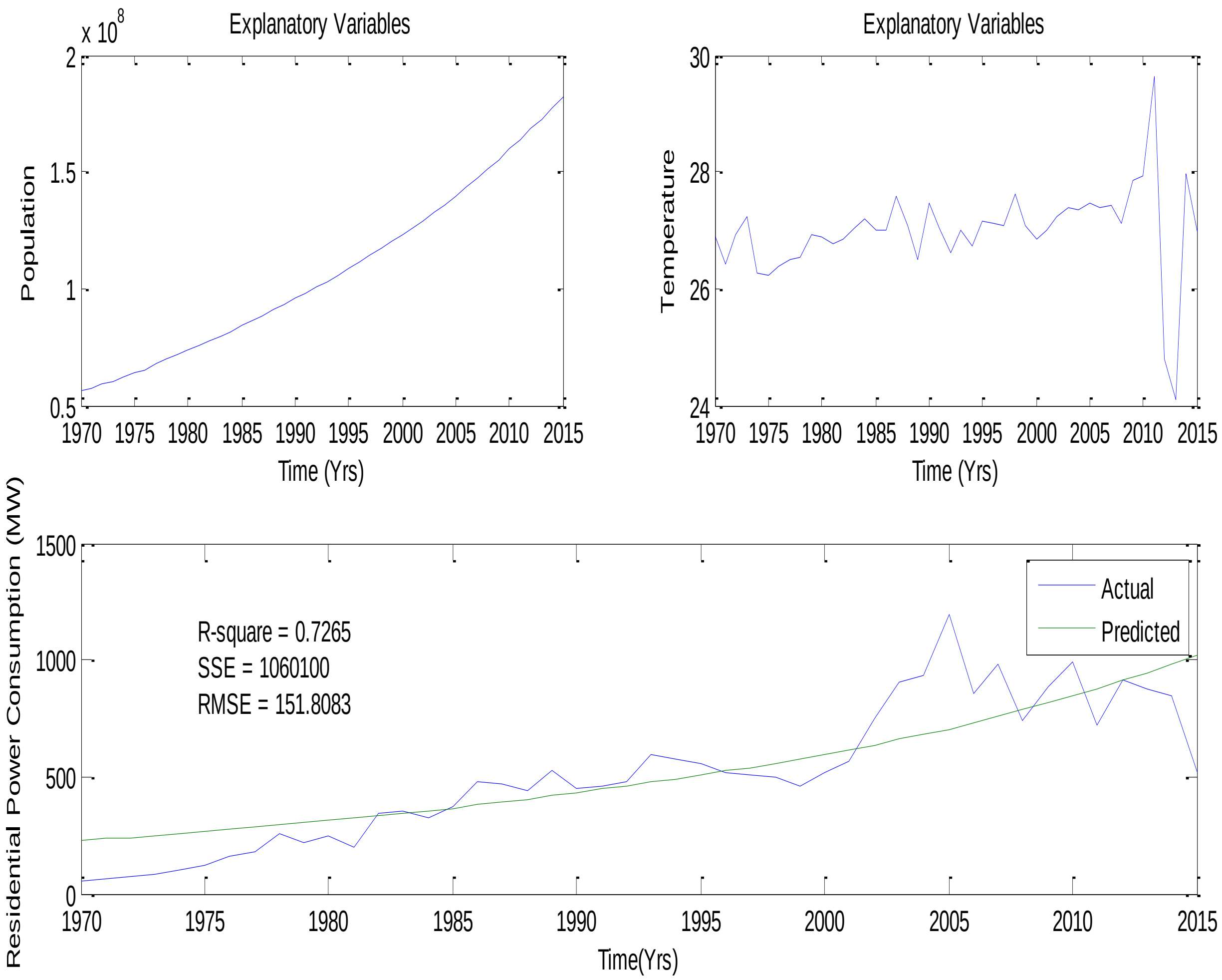

Figure 1: Plot of residential power consumption with quadratic regression model without interaction

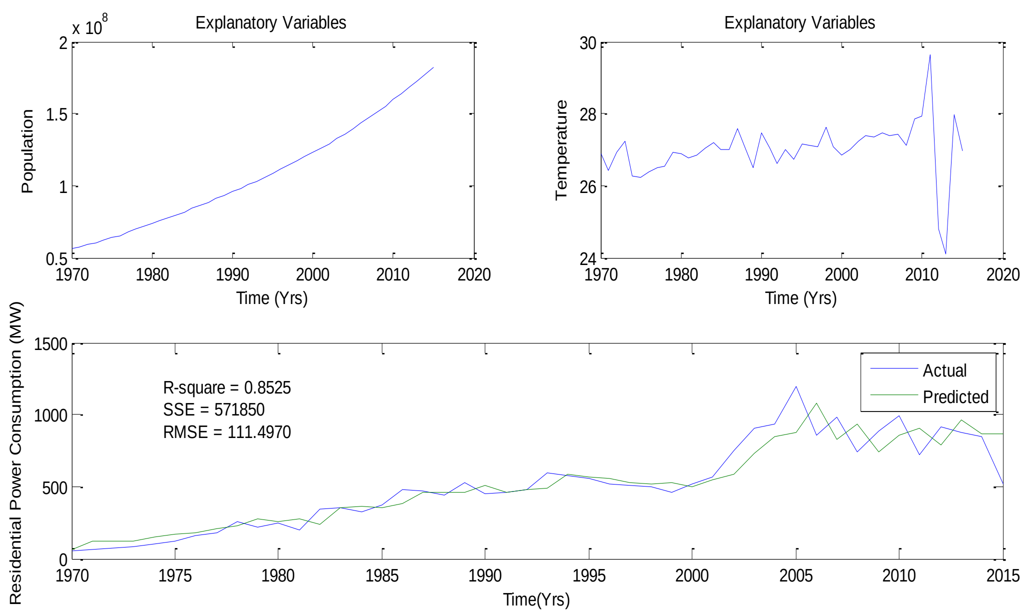

Figure 2: Plot of residential power consumption with the multiple linear regression model with one period lagged dependent variable

Table 1: The **yearly residential energy demand forecast using the multiple regression model with one period lagged dependent variable (MW/h)**

Year	Yearly residential energy demand forecast using the multiple regression model with one period lagged dependent variable (MW/h)
2018	11010.3
2019	11117.7
2020	11246.7
2021	11369.7
2022	11466.5
2023	11581.1
2024	11691.0
2025	11775.8
2026	11879.7
2027	11966.9
2028	12050.5

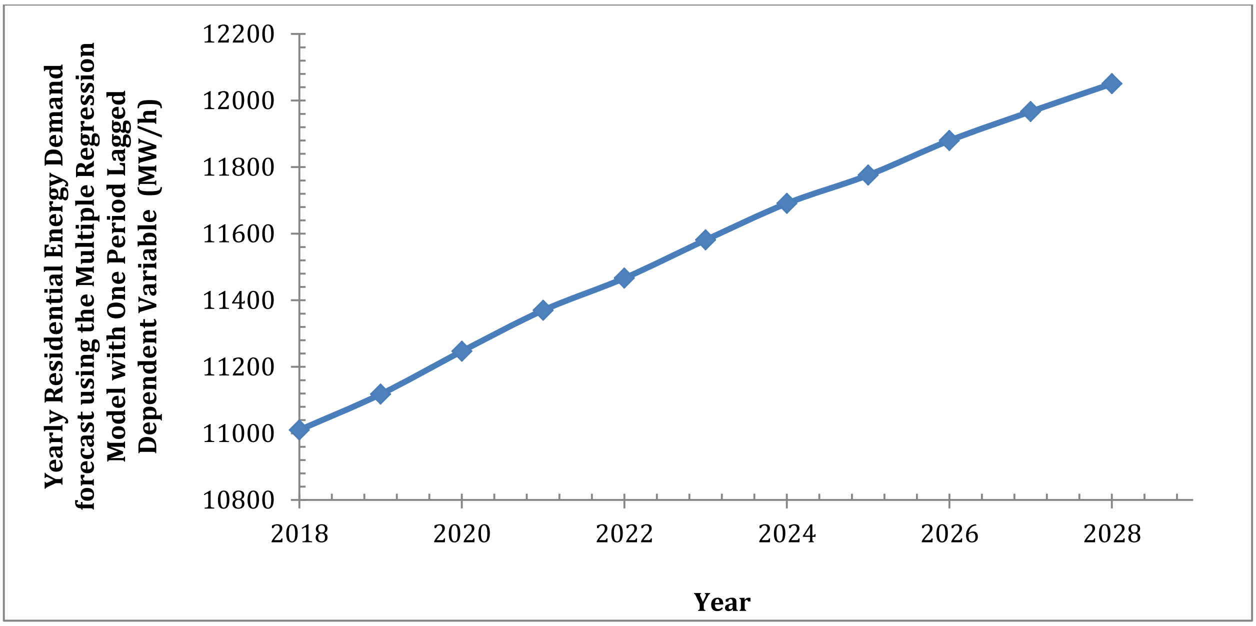

Figure 3: The yearly residential energy demand forecast using the multiple regression model with one period lagged dependent variable (MW/h)

IV. CONCLUSION

The yearly residential energy demand in Nigeria is analyzed using two statistical models, namely, the quadratic regression model without interaction and multiple linear regressions with one period l lagged dependent variable. The study used 46 years data on residential energy demand as well as data on temperature and population which are the explanatory variable. The analysis showed that the multiple linear regressions with one period l lagged dependent variable is more accurate in predicting the yearly residential energy demand than the quadratic regression model without interaction. As such the multiple linear regressions with one period l lagged dependent variable is used to forecast the yearly residential energy demand in Nigeria for the years 2018 to 2028. The results in this study were compared with those obtained in a previous research where only eight years data was used. In that study, the quadratic regression model without interaction was found to be more accurate in the residential energy prediction with very high R-squared value. However, when that model was subjected to the long term data used in this study, the model prediction performance dropped significantly and the multiple linear regressions with one period l lagged dependent variable was found to be more accurate. In all, it can be concluded in this study that sufficient data is required for effective modeling and model prediction performance based on small sample is deceptive.

REFERENCES

1. Alphonsus, O. N. (2016). AN EXAMINATION OF THE CHALLENGES OF POWER SUPPLY IN NIGERIA IN POST-PRIVATIZATION ERA, 2013—2016. *Asian Journal of Basic and Applied Sciences Vol*, *3*(1).
2. Ijewere, A. A. (2011). The Management of Electricity Power Supply in Nigeria: Problems and Prospects. *Journal of Research in National Development*, *9*(2), 173-185.
3. Okafor, E. E. (2008). Development crisis of power supply and implications for industrial sector in Nigeria. *Studies of Tribes and Tribals*, *6*(2), 83-92.
4. Emodi, N. V., & Yusuf, S. D. (2015). Improving electricity access in Nigeria: obstacles and the way forward. *International Journal of Energy Economics and Policy*, *5*(1), 335-351.
5. Onochie, U. P., Egware, H. O., &Eyakwanor, T. O. (2015). The Nigeria electric power sector (opportunities and challenges). *Journal of Multidisciplinary Engineering Science and Technology*, *2*(4), 494-502.
6. Sambo, A. S., Garba, B., Zarma, I. H., &Gaji, M. M. (2012). Electricity generation and the present challenges in the Nigerian power sector. *Journal of Energy and Power Engineering*, *6*(7), 1050-1059.
7. Ezirim, G., Onyemaechi, E., & Freedom, O. (2016). The Political Economy of Nigeria's Power Sector Reforms: Challenges and Prospects, 2005-2015. *Mediterranean Journal of Social Sciences*, *7*(4), 443.
8. Ezema, I. C. (2015). *Profiling the environmental sustainability of residential buildings in Lagos, Nigeria using life cycle assessment* (Doctoral dissertation, PhD Thesis, Covenant University, Ota, Nigeria).
9. Eneh, O. C. (2011). Nigeria's Vision 20: 2020-issues, challenges and implications for development management. *Asian Journal of Rural Development*, *1*(1), 21-40.
10. Okedu, K. E., Uhunmwangho, R., &Wopara, P. (2015). Renewable energy in Nigeria: The challenges and opportunities in mountainous and riverine regions. *International Journal of Renewable Energy Research (IJRER)*, *5*(1), 222-229.
11. Malik, A. S., &Kuba, C. (2013). Power generation expansion planning including large scale wind integration: a case study of Oman. *Journal of Wind Energy*, Volume 2013, Article ID 735693, 7 pages. Available at: downloads.hindawi.com/archive/2013/735693 .pdf Accessed on 23th November 2018
12. Kim, J. Y., & Kim, K. (2018). Integrated Model of Economic Generation System Expansion Plan for the Stable Operation of a Power Plant and the Response of Future Electricity Power Demand. *Sustainability*, *10*(7), 2417.
13. Zeljko, M. (2008, January). Generation expansion planning in the open electricity market. In *International Conference on Deregulated Elactricity Market Issues in South-Eastern Europe, 22-23 September 2008, Lefkosia, Cyprus*.
14. Lu, M., Dong, Z. Y., &Saha, T. K. (2005). A framework for transmission planning in a competitive electricity market. In *2005 IEEE/PES Transmission & Distribution Conference & Exposition: Asia and Pacific* (pp. 1-6). IEEE.
15. Osório, G., Lotfi, M., Shafie-khah, M., Campos, V., &Catalão, J. (2019). Hybrid Forecasting Model for Short-Term Electricity Market Prices with Renewable Integration. *Sustainability*, *11*(1), 57.
16. Campos, V., Osório, G., Shafie-khah, M., Lotfi, M., &Catalão, J. P. (2018, December). Short-Term Hybrid Probabilistic Forecasting Model for Electricity Market Prices. In *2018 Twentieth International Middle East Power Systems Conference (MEPCON)* (pp. 962-967). IEEE.
17. Bunnoon, P., Chalermyanont, K., &Limsakul, C. (2012). Mid-term load forecasting: Level suitably of wavelet and neural network based on factor selection. *Energy Procedia*, *14*, 438-444.
18. Botterud, A., Wang, J., Miranda, V., &Bessa, R. J. (2010). Wind power forecasting in US electricity markets. *The Electricity Journal*, *23*(3), 71-82.
19. Moustris, K. P., Zafirakis, D., Alamo, D. H., Medina, R. N., &Kaldellis, J. K. (2017). 24-h ahead wind speed prediction for the optimum operation of hybrid power stations with the use of artificial neural networks. In *Perspectives on Atmospheric Sciences* (pp. 409-414). Springer, Cham.
20. Dilaver, Z., & Hunt, L. C. (2011). Modelling and forecasting Turkish residential electricity demand. *Energy Policy*, *39*(6), 3117-3127.

21. Teixeira, J., Macedo, S., Gonçalves, S., Soares, A., Inoue, M., &Cañete, P. (2017). Hybrid model approach for forecasting electricity demand. *CIRED-Open Access Proceedings Journal*, *2017*(1), 2316-2319.
22. Citroen, N., Ouassaid, M., &Maaroufi, M. (2015, March). Long term electricity demand forecasting using autoregressive integrated moving average model: Case study of Morocco. In *2015 International Conference on Electrical and Information Technologies (ICEIT)* (pp. 59-64). IEEE.
23. Kaboli, S. H. A., Fallahpour, A., Selvaraj, J., & Rahim, N. A. (2017). Long-term electrical energy consumption formulating and forecasting via optimized gene expression programming. *Energy*, *126*, 144-164.
24. Ezenugu, I. A., Nwokonko, S. C., &Markson, I. (2017). Modelling and Forecasting of Residential Electricity Consumption in Nigeria Using Multiple Linear Regression Model and Quadratic Regression Model with Interactions. *Mathematical and Software Engineering*, *3*(2), 173-182.