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Modeling Household Electricity Consumption in Kenya using Top-down Approach Method

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Submitted to the School of Mathematics in partial fulfilment for a degree in Master of Science in Social Statistics

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Abstract

Household electricity consumption has been a major contributor to the global energy demand and has increased quickly over the past decades. Therefore, this project attempts to examine the key factors influencing household electricity consumptionin Kenya from a top-down perspective, by reviewing and evaluating previous research work. The study utilized both socio-econmic indicators (e.g. gross domestic product, Number of households connected to the grid), demographic (population) and energy values (electricity tariff). Analysis results found that the gross domestic product and population provide significant impact on household electricity consumption. Nonetheless, the effect of the electricity tariff and the number of households connected to the grid failed to receive a significant support. This implies that future demand for household electricity demand in Kenya will significantly be determined by socioeconomic factors and demographic factors. Thus, these developments should be considered by policy makers in planning for energy in Kenya and developing economies.

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Declaration and Approval

I the undersigned declare that this dissertation is my original work and to the best of my knowledge, it has not been submitted in support of an award of a degree in any other university or institution of learning.

Signature Date

RONO KIPLANGAT CLINTON
Reg No. I56/11273/2018

In my capacity as a supervisor of the candidate's dissertation, I certify that this dissertation has my approval for submission.

Signature Date

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Dedication

I dedicate this project to my parents for their immense support, encouragements and for nurturing me with the importance of education.

Contents

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Rono Kiplangat Clinton

Nairobi, 2020.

1 Introduction

1.1 Background

Electricity is important in all sectors of national economy and it is one of the co-principal of production that satisfys human needs. There are different levels of electricity consumption namely: domestic electricity consumption, small commercial electricity consumption, commercial/industrial consumption, and street lighting

At the domestic level, electricity is used for the following purposes: regulate space's temperature, domestic hot water systems, appliances such as refrigerators, elecctric cookers,TVs, and also for lighting (Swan, L.G. and V.I. Ugursal, 2009).

Domestic electricity consumption accounts for nearly 30 percent of electricity consumed globally (Swan, L.G. and V.I. Ugursal, 2009). Given that the population is rising consistently, demand for household electricity consumption is always on the rise (Vincenzo B. et. al, 2009).

Household electricity consumption patterns are explained by both the economic factors like electricity tariffs, number of households and non-economic factors like public policies. Robust models show that power consumption at the domestic level is strongly associated with power generation, transmission and distribution. Various models have been developed from time series data with electricity demand as a dependent variable using multivariate techniques(Gul,M. et.al, 2011,).

Mariam et al. (2011) presents results of regression models on electricity consumption in Pakistan. Two approaches of analysis were compared. The first approach checked for the correlation between electricity consumed and the following selected variables: population, income per capita and GDP whereby a multiple linear regression model was fitted. The second approach utilized univariate time series to develop a forecasting model. Based on the multiple linear regresseion model, a strong relationship between the dependent variable and the selected variables was reported. the two models were effective in modelling for electricity consumption in Pakistan.

Vicenzo et al. describes how economic and demographic variables influence residential electricity consumption in Italy using linear regression model. The first target of the paper discovered that GDP and GDP per capita is relevant in modelling electricity consumption. However, the findings showed that electricity price is not significant in modeling electricity consumption in Italy.

Chen (2017) examined the factors influencing household electricity consumption in Taiwan and also discovered that electricity price do not receive significant support in modelling electricity consumption. The study however found that gross domestic product, rate of employment, residential space, and the energy labeling schemes had a significant impact on household consumption

Bismark et al.(2016) investigated the causality link of electricity demand and economic growth in Ghana using Cobb-Douglas growth model and Granger Causality test to identfy the direction of the causality. The study considered the following linearly transformed variables: GDP, labor, productivity factorelectricity demand and capital. Study results showed unidirectional causality from GDP to electricity consumption. Additionally, results revealed the electricity conservationdirectly influences the economic growth. Moreover, Daniel W. et al (2011) modelled for household electricity consumption in portugal and estimated the coefficients and the response variable of the model using ordinary least squares. Study results reveal that income directly affect the electricity consumption

Domestic electricity consumption in Kenya has been on an upward trend spearheaded by an increased access rate. This has also been attributed to government's efforts through last mile connectivity program and robust energy policies (Mulea, M. 2011).

Electricity consumption affects many other parties like agriculture, manufacturing, transport and communication hence the need to develop a model which can help generate future scenarios of domestic electricity consumption. By examining the changes at the domestic level, the findings would benefit more the utilities in generation, transmission and distribution and the investors with a more accurate information (Sorasalmi,2012).

There are two methods of modeling electricity consumption namely: Top-down approach and 'Bottom-up approach. These approaches are determined by the data inputs. While top-down approach uses the total energy consumed and other relevant variables to explain the energy consumed within a household, bottom-up approach calculates the amount of energy consumed individually and then generalizes the consumption at the regional level (Swan, L.G. and V.I. Ugursal, 2009.)

This study uses the *top-down approach* method to examine the explanatory factors affecting household electricity demand in Kenya using a time series data from 2000 to 2018. Based on the available data inputs, ageneralized linearmodel that can be used to generate future scenarios and support the decision makers will be developed. The generalized linear model is preferred due to its flexibility.

1.2 Technologies

Electricity consumption

Electricity consumption refers to electricity that has already been consumed. It is measured in kilowatt hours (kWh). There are nine types of electricity consumers. They include:

- Domestic - Lifeline consumer whose energy consumption ranges from 0-100kWh per month
- Domestic and IT (includes water heating) consumes more than 100kWh a month
- small commercial who consume energy ranging 0-15,000 kWh a month
- commercial/Industrial customer who consumes more than 15,000 kWh of energy in a month i.e. manufacturing industries and
- street light customers

Domestic consumers also known residential electricity consumers accounts for electricity consumed at the household level. Domestic consumption varies according to the standard of living of the country, climate, type of residence, income and household appliances. Uses of electricty at the household level include but not limited to the following:

- cooking
- refrigeration
- lighting and charging
- Kettle
- entertainment equipment
- Air conditioners
- laundry/dish washing and warm shower
- Ironing
- water heating
- room heating

Top-down approach

Top-down approach is associated with long term changes within the residential sector. Using historical data, it explains how the data affect the electricity consumption at a national scale. The historical data can either be econometric or technological. Econometric model is attributed but not limited to the following factors: price of an appliance, electricity cost and income while technological model is attributed to appliance ownership or efficiency of the appliances.

Top-down approach was initiated in 1970s following an energy crisis to understand consumer behavior in-spite of supply and electricity costing. .

Below are the strengths and weaknesses of top-down approach:

- Easy to implement
- It can easily explain a possible or projected change on electricity consumption
- Supports government's efforts in restructuring taxes;
- Draws the impact of various economic backgrounds on power consumption;
- Explain the effects of macroeconomic changes on power consumption and
- The general equilibrium effects

However, it less predicts the impact of new technologies for an informed policy making compared to bottom-up approach. (Swan, L.G. and V.I. Ugursal, 2009)

1.3 Problem statement

Electricity consumption is an essential input for economic growth in Kenya; it is envisaged in vision 2030 as a key deliverable to becoming a middle income economy. Hence a clear understanding on household electricity consumption in Kenya is unavoidable, it directly influence formulation of policies and the need to increase electricity access rate.

There are few comprehensive studies focused on investigating the factors associated with household electricity consumption in Africa using a top-down approach method.In 2018, Kenyan government had to cut its target of expanding electricity output by almost half citing low demand(Tesfamichael, M., Bastille, C., & Leach, M. 2020). This implies that previous electricity forecasts did not provide adequate information on the demand implying that the whole process was over estimated.

Therefore, this study aims to identify the key determinants of the electricity consumption using a top-down approach method in Kenya.

1.4 Objectives

1.4.1 General Objective

The general objective of this study is to model for household electricity consumption in Kenya using generalized linear model

1.4.2 Specific Objective

1. To investigate the factors affecting householdselectricity consumption
2. To evaluate how household electricity consumption pattern has evolved over time.

1.5 Research questions

1. What are the key drivers of electricity consumption in Kenya
2. How has household electricity consumption pattern evolved over time

1.6 Significance

The study will provide detailed analysis analysis on the link between the household electricity consumption and its determinants; it will assist in understanding future developments in the energy sector.

Results from this study will assist in the formulation of policies around household electricity consumption and other related frameworks in Kenya; it will also inform the legislative sector to formulate a decision framework for effective implementation of necessary policies.

The study findings will benefit the energy utilities in power sector planning and development across the country.

1.7 Justification

Investments in the energy sectoras well as electricity access rate and population has been on the rise, however, the household electricity demand and supply gap has been widening. To reduce this gap, this study proposes a methodology to develop a residential electricity consumption model which can be used to generate insights for policy making and power planning.

1.8 Limitations

A main barrier associated with this study is lacking the necessary data on residential/domestic electricity consumption.

1.9 Outline of the Project

This study divides into five chapters: chapter one presents introduction. Chapter two presents and discuss theoretical review, empirical review, conceptual framework and the summary of household electricity consumption literature. Chapter three presents the overall methodologies. in Chapter four analysis and the household electricity consumption model using a top-down approach is presented. In chapter five the conclusion and recommendation.

2 Literature Review

2.1 Theoretical literature Review.

Several theories have been linked to electricity consumption behavior, they include:

Economic theory

Economic theory provides research through theoretical reasoning and explains why and how the economy behaves in a model.

Xiao et al. believes that electricity consumption boost economic growth by supporting capital production, human capital and technology. It is also believed to boost economic social development.

Conventional and behavioral economics

Consumers make decisions based on the cost and benefits of their behavior and principles of utility maximization given certain measures such as income and pricing.(Darnton, 2008a;Jackson, 2005)

This theory has been used to bring out the consumer's preferences in relation to energy efficient appliances. Therefore, economy has been utilized in modeling customer's preferences.

Sociology

Sociology gives weight to external factors and their impact. These factors includes: economy, demography, technology and legislation. Therefore electricity consumed are affected by other factors other than the effect of individual choices. (Karatasou, S. et al 2013)

Theory of Planned behavior

According to Ajzen,1991 behavior is preceded by planned behavior which relies on attitudes towards the behavior, social norms, and perceived behavioral control. Scott et al. measured the association between an individual's attitude and energy saving appliances in British Yorkshire and Humber area. They discovered that the residents had different attitude after using energy-saving appliances. Furthermore, Abrahamse and Steg, 2009 discovered that household electricity consumption is affected by demographic factors. In a nut shell, this implies that energy consumption is affected by psychological factors. (Zhifeng, G. et al 2018)

2.2 Empirical literature Review

While there has been much research on modeling electricity consumption using bottom-up approach, few researchers have taken top-down approach into consideration. Maria and Joao, 2016 conducted a study in Brazil using linear regression model to describe household electricity consumption between 1985 and 2013. The study study found that family income, number of households and electricity tariff have an impact on the electricity consumption.

Chen (2017) examined the factors affecting residential electricity consumption in Taiwan using two approaches; socioeconomic perspective and direct use. The study established that gross domestic product (GDP), employment rates, residential space, and the implementation of energy labeling schemes significantly impacted on residential electricity consumption. Even though energy labeling had an impact, it was negative. Employment rate positively influenced electricity consumption at the household level. Contrary to socio-ecnonomic perspective, Direct use approach varies on the household income level hence not a significant approach. While the two approaches were used to identify key factors affecting electricity consumption, it did not conclusively involve key variables like the electricity tariff.

Praptiningsih et al. (2013) in study analyzing the interrelation between macro indicators using an econometric method developed residential electricity consumption pattern using Multiple Linear Regression method, autoregressive intergrated moving average and autoregressive conditional heteroscedasticty as an empirical representation to the residential electricity consumption condition. From the study, it was established that GDP and inflation rate have a long-standing effect on household electricity consumption.Using Box Jenkins method , analysis results showed that all variables were stationary at first difference with trend and intercept. The study further ARCH/GARCH model predicted for each variable and the outcome revealed that electrification ratio, gross domestic product, inflation, and total energy demand had ARCH effect. Hence the best model in predicting ARCH and GARCH. The study recommended both the ARIMA model and ARCH/GARCH model for forecasting power consumption.

Mulea (2011) in a study investigating the determinants on electricity demand, results indicated that industrial production and kerosene prices had a key impact on electricity consumption. The study applied Ordinary Least Squares and the Error Correction Model for analysis; study resullts crevealed a need to modernize the energy technology and increase supply. However, the study failed to outline the strength capacity of the variables to ascertain its impact on household electricity consumption.

Maduka, A.C et al (2020) examined the relationship between household electricty consumption and the living standard in Nigeria using ARDL bound cointegration and ordinary least squares for estimation. The study established that there exists a bidirectional causality between household electricty consumption and the standard of living. Furthermore, Gatsi & Appiah (2020) in a study on the relationship among economic growth, population growth, gross savings and energy consumption using autoregressive distributed lag bound test established that there exists a positive relationship energy consumption and economic performance; economic performance measured by the gross domestic product.

Fu et al. (2015) fitted a multiple linear regresssion model in a study to establish the relationship between population and household energy demand. Study results showed that population had a positive effect on household energy demand; though elecricty tariff had a direct impact on the energy consumption it varied based on the geographical location.

In addition, Narayan et al. (2005) investigated the relationship between employment rate, income and electricty demand in Australia. While the three factors under investigation were cointegrated, employment rate and GDP affect electricty consumption in the long run and a weak uninderectional causality from GDP to electricity demand and also from GDP to employment. Ekholm et al. (2010) also observed that income group and cost of other sources of energy affect residential electricty consumption.

Dilaver et al. (2011) in a study investigating the relationship between electricty tariff and household electricity consumption in Turkey, found that the electricty tariff and the underlying electricity consumption trend as key drivers of household electricty consumption. Also, Alberini et al. (2011) fitted a regression model and a static energy demand model to estimate price elasticities of household electricity tariff and gas at a national level; the study observed that electricty tariffs and the living standard as key inputs on energy policies.

Finally, Kenya Institute for Public Policy Research and Analysis (2010), in a study on power consumption in Kenya it established that electricity tariff remains expensive due to over reliance on unclean sources of energy. Results revealed that there is need to increase funding for clean sources of energy reduce electricty tariff. Though the report's intention was to inform on proper policy guidelines, it did not use any statistical model for the analysis hence cannot ascertain how the variables impact the household electricity consumption.

2.3 Conceptual Framework

Based on the existing literatures, figure 1 below shows the top down components key to determinig the factors influencing household electricity consumption at the national level.

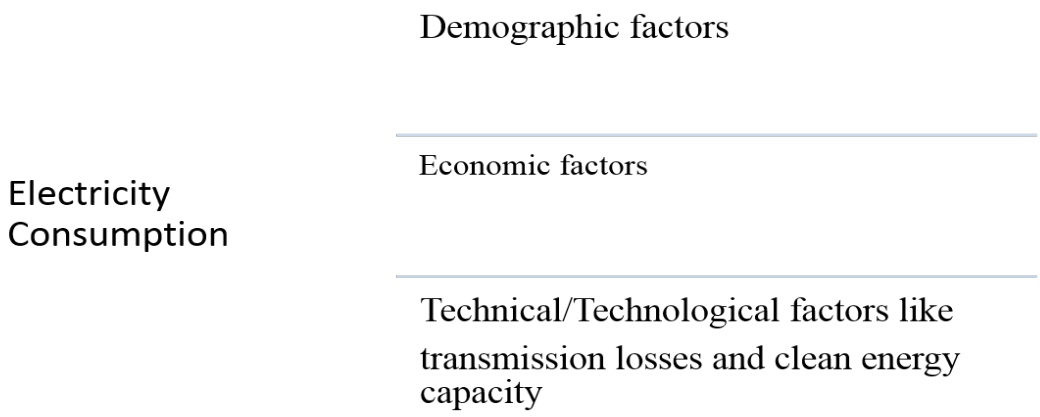

Figure 1. Household electricity consumption conceptual model

2.4 Summary

Based on the literature, various modeling techniques have been used for electricity consumption modeling. These models include but not limited to the following: time series and regression models. Fumo et al. (2015) study established that linear regression analysis is accurate and relatively simple to implement.

3 Methods

3.1 Introduction

The purpose of this chapter is to introduce the research method used for this quantitative grounded study on electricity consumption at the household level. This approach provides a detailed understanding on household electricity consumption at the national scale. The research plan, procedures, analysis method , parameter estimation, model validation/Goodness of fit test, prediction, and the overview are also the primary components of this chapter

3.2 Data and Data Validation

3.2.1 Data and variables

The demographic data from 2000 to 2019 will be obtained from the Kenya National Bureau of Statistics websites while the economic variables data between the year 2000 and 2018 will be obtained from Central Bank of Kenya websites, and the technical and/or technological data from the year 2000 to 2019 will be obtained from the Kenya Power and Lighting Company. Domestic electricity pricing data will be obtained from Stimulus's website.

Lin et. al 2014, argues that the following quantitative variables influence household electricity consumption: population size, GDP and energy resources/supply.(Lin, W. et. al 2014)

To design a model, the researcher will adopt the following variables considered by different authors in the analysis of long range analysis: Demand, supply, GDP, electricity pricing, number of connections, and the population size/number of households.

Dependent variable:- Household electricity consumed (Demand)// Household electricity consumption or demand shows the measures of electricity consumed which is changing over time. The demand is affected by the number of appliances and the efficiency of the appliance within the household. Its notation is **EC** and is measured in gigawatt hours (GWh)

Independent variables are:

- The Gross Domestic Product
  The GDP measures the economic status of a households i.e. household income. It accounts for the uptake of household appliances and efficiency of the appliance. The GDP per capita is measured in billion dollars and its notation is **gdp**

- Population (pop)
  Population is an exogenous variable. It is not affected by an external variable within the electricity sector. It is measured in millions

- Electricity tariff (price)
  Electricity cost affects small consumers of electricity within the residential sector. Electricity cost is mostly affected by the capacity utilization. However a long term increased cost of electricity affects the electricity consumption.Its unit of measure is Kenya shillings per kilowatt hour(Kshs/Kwh)

- Number of household connections (hh)
  It measures the number of households connected to the grid in millions.

3.2.2 Data Validation

Given the model $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \varepsilon$ we can test for the following:

Normality

The residuals follows a normal probality distribution i.e. $\varepsilon/x \sim \mathcal{N}(0, \sigma^2 I)$
. The test hypothesis is :
$H_0 : errorsarenormallydistributed$
$H_1 : errorsdonotfollowanormaldistribution$

We shall test the normality using the Shapiro-Wilk Test given by the formula below

$$W = \frac{\left(\sum_{i=1}^{n} a_i e_{(i)}\right)^2}{\sum_{i=1}^{n} (e_i - \bar{e})^2}, \tag{1}$$

where e_i is related to the i^{th} largest value of the error term and a_i are deducted from the calculation of means, variances, and covariances of the e_i.
The output will then be compared to the tabulated value (Shapiro Wilk Test Table). If W is less than the tabulated value it implies that the residuals are distributed normally else if $W > W_{tabulated}$ distribution is normal.

Homoscedasticity

Random errors follows a probability distribution where Var(ε/X)=σ^2.

Therefore we are testing for homoscedasticity using Lagranges multipliers test; this is based on the variance function given below

$$Var(Y_i) = \sigma_i^2 = h(\alpha_1 + \alpha_2 Z_{2i} + \alpha_3 Z_{3i} + \ldots + \alpha_s Z_{si} \quad \textbf{(2)}$$

The Z variables might be different from the X variables of the model. We then develop a linear variance function given below

$$Var(Y_i) = \sigma_i^2 = E(\mu_i^2) = \alpha_1 + \alpha_2 Z_{2i} + \alpha_3 Z_{3i} + \ldots + \alpha_s Z_{si} \quad \textbf{(3)}$$

where

$$\hat{\mu}_i^2 = \alpha_1 + \alpha_2 Z_{2i} + \alpha_3 Z_{3i} + \ldots + \alpha_s Z_{si} \quad \textbf{(4)}$$

We then test the hypothesis where
$H_0 : \alpha_1 = \alpha_2 = \ldots = \alpha_s = 0$ $H_1 : \alpha_1 = 0.$
The test statistic used is

$$\chi^2 = n * R^2 \sim \chi^2_{s-1} \quad \textbf{(5)}$$

n is the size of the sample while R^2 is the coefficient of determination.

If $n * R^2 > \chi_{tabulated}$ it implies that heteroscedasticity exists, hence reject the null hypothesis

Suppose we wish to test for heteroscedasticity without a precise knowledge of relevant variables we will use the white test. Breusch-Pagan tests for linear forms of heteroscedasticity (note that as $\hat{y}$ goes up, the error variance goes up) while white test can test for non-linear forms of heteroscedasticity i.e. when error variance increases as x increases in both directions. The assumptions of normality are relaxed. Therefore, White test (a special case of Breusch-Pagan or Lagranges Multiplier test) is a statistical test that seeks to determine if the variance of the errors is constant (heteroscedasticity).

According to *Hal White*, we define the Z variables as equal to X variables. Hence white test variance function is

$$\mu^2 = \alpha_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_2^2 + \alpha_5 X_3^2 + \alpha_6 X_2 X_3 + V \quad \textbf{(6)}$$

We then test for heteroscedasticity for the above equation where:
$H_0 : Homoscedastic$
$H_1 : Heteroscedastic$
and the test statistic is Chi-square given as $\chi^2 = n * R^2$

To mitigate heteroscedasticty in a model, suppose it exists, we will either rebuild the model or transform the variables. Other mitigation methods includes use of standard errors. Ordinary least squares assumes that the errors are independent and identically distributed however the robust standard errors loosens both assumptions.

According to Allison (pg 128), the robust standard errors does not change the parameters however it gives a more accurate value.

Multicollinearity

Multicollinearity exists if the predictors are linearly related, thus violating the assumption that the predictor variables are independent. It not only affects the precision of the coefficient estimates but also weakens the statistical power of the regression model. Furthermore, the coefficient estimates will vary widely when small changes are made on the model.

Consider the model below

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \varepsilon \tag{7}$$

and its auxiliary regression ($\forall X_2$) given as

$$X_2 = \alpha_1 + \alpha_3 X_3 + \alpha_4 X_4 + V \tag{8}$$

where the regressand is one of the regressors from the model; the regressors of the auxiliary equation are all the remaining explanatory variables from the model.

We can then test for collinearity using R^2 and variance inflation factor. The test is constructed as:
H_0: No collinearity
H_1: Collinearity exists

We can also test for collinearity using *Variation Inflation factor* expressed as

$$VIF = \frac{1}{1-R^2} \tag{9}$$

where R^2 is the coefficient of determination of the regression of that explanatory variable on all remaining independent variables.

If $1-R^2$ is close to 1, it implies that little multicollinearity exist; if close to zero the collinearity is high.

VIF shows the extent to which the variance of the parameters are being inflated by collinearity. The $\sqrt{VIF}$ shows how large the standard errors are unlike when collinearity does not exist. A VIF value of 1 indicates the predictor variable is not correlated with other variables, a value of 4 or 5 is considered moderate correlation of the predictor variable with other variables while a value of 10 or more indicates the correlation between the regressor with other predictors is high

To mitigate multicollinearity, we perform either of the following:

1. Drop the redundant variable
2. Increase the sample size
3. Redesign the study or

Auto-correlation (Independence)

Autocorrelation refers to the correlation between the values of the same variables over successive intervals; it can either be positive or negative. The autocorrelation function is used to test for non-randomness in the data. Therefore, if we suspect that there is correlation between μ_t and μ_{t-1} then we model the errors as:

$$\mu_t = p\mu_{t-1} + V_t \tag{10}$$

where $p < 1$ is an unknown parameter and $V_t \sim_{iid} \mathcal{N}(0, \sigma^2)$.

Suppose the equation of interest is

$$Y_t = \beta_1 + \beta_2 X_t + \mu_t \tag{11}$$

then it can be rewritten as

$$Y_t = \beta_1 + \beta_2 X_t + p\mu_t + V_t \tag{12}$$

Therefore, we can test for the first order correlation with the errors using **Durbin Watson test** whereby:

$H_0 : \omega = 0$
$H_1 : \omega \neq 0$
$\omega = 0$, implies that there is no relatuionship between error term in current period and the error term in the previous period i.e.$\mu_t = V_t$. The alternative hypothesis, $\omega \neq 0$, implies that there exists either a positive or negative relationship between the error term in the current period and the previous period.

The Durbin Watson statistic is given as:

$$d = \frac{\sum_{t=2}^{T} (\hat{\mu}_t - \hat{\mu}_{t-1})^2}{\sum_{t=1}^{T} \hat{\mu}_t^2} \tag{13}$$

where μ_t are the least squares residuals.
The Durbin Watson tests varies from 0 to 4 whereby 2 indicates zero correlation. Values ranging from zero to two implies that there exists a positive autocorrelation while negative autocorrelation exists if the values range from two to four.

The output,d, will be compared to the tabulated value (d_c) from the *Durbin Watson* significance table. At $5 percent$ significance level, compare the calculated d against the critical value (d_c); if $d <= d_c$ we reject the null hypothesis and if $d > d_c$ we fail to reject the null hypothesis. Rejecting of the null hypothesis implies that the errors are correlated, autocorrelation exists.

If autocorrelation exists, then the following remedial measures will be applied:

1. Investigate the ommision of one or more of the explanatory variables
2. Apply differencing to all temporal independent variables in the dataset and rerun the regression or
3. Include Include AR(1) model

3.3 Empirical Model

Studies show that there is a positive relationship between electricity consumption and GDP. It is classified as a short run equilibrium as it explains rate at which the preceding disequilibrium is being corrected. The relationship is not spurious.

Mozumder and Marathe claims that per capita gross domestic product causes per capita energy consumption. Using vector error correction model Mashih, and Mashih also found that income has a direct impact on electricity consumption in Indonesia and bi-directional causality exists in Pakistan.

Yang(2000) in his investigation on the relationship between electricity consumption and GDP in Taiwan found that there exists a bidirectional impact between the demand and the GDP.

Few studies have also considered electricity tariff as a factor of electricity consumption at the household level due to its magnitude of elasticity. Electricity tariff varies on the customer groups and per consumption level in Kenya. The higher the consumption the higher the electricity price. Other studies consider the pricing as an endogenous variable as it is affected by other factors like source of clean energy and cost of power production.

Literature claims that the population is an important variable which shows the trend. It further claims that the increase in residential electricity consumption increases with an increase in population. It is an exogenous variable as it is not affected by the system.

Studies also assert that advancement in the supply sector reduces the cost of production which increases the profits. Few studies have associated the cost of electricity to the consumer and the source of energy, whether renewable or non-renewable.

In Kenya, the population has been on the rise which implies that the number of households in also increasing. Increased population implies that there is an increase in electricity connection.

Increased number of electrified households triggers the economy. This gives the investors an opportunity to do investments in clean sources of energy which is cheaper compared non-modern methods. Furthermore, it also triggers the cost of electricity which has an direct impact on the consumption.

Power efficient appliances are also associated to electricity consumption however not covered in this study.

Therefore **EC**=$f(gdp, pop, price, hh)$

3.4 Parameter Estimation

Gujarati, 2000 suggests that linear regression is fit when modeling household electricity consumption from top-down approach. R software statistical package will be used to perform the regression analysis.

3.4.1 Multiple Linear regression analysis

Linear regression models the relationship between the dependent and the independent variable(s). To fit a statistical model, we will use a multiple linear regression which is designed for two or more explanatory variables. The equation below will be used to model for the household electricity consumption in Kenya.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \varepsilon \tag{14}$$

Where:

- Y is the annual electricity consumed
- X_i denote population (pop), Number of connection(hh), Electricity pricing(price), Gross Domestic Product (GDP)
- β_i is the corresponding regression coefficient and
- ε is the statistical error

$$Y = X\beta + \varepsilon \tag{15}$$

where Y denotes the dependent variable, X denoting the independent variables and β denoting the parameters then

$$Y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} ,X = \begin{pmatrix} 1 & x_{11} & x_{12} & \dots & x_{1n} \\ 1 & x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \dots & \vdots \\ 1 & x_{n1} & x_{n2} & \dots & x_{nn} \end{pmatrix},$$

$\beta = (\beta_0, \beta_1, \beta_2, \ldots, \beta_n)^T$, and $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n)^T$.

Therefore the coefficients or the parameters of the independent variables can be obtained as $\hat{\beta} = (X^T X)^{-1}(X^T Y)$

Multiple linear regression model assumptions

Multiple linear regression considers several key assumptions listed below:

1. Linear relationship; regressor regressand relationship linear
2. Multivariate normality; this assumption implies that all variables should be normal. $\varepsilon/x \sim \mathcal{N}(0, \sigma^2 I)$
3. No or little multicollinearity. No associations among the regressands. Also, the error of the mean is uncorrelated i.e. the standard mean error of the dependent variable is independent from the independent variables.
4. Homoscedasticity; constant variance $Var(\varepsilon/X) = \sigma^2 I$
$Var(\varepsilon/X) = \sigma^2$
$Cov(\varepsilon_i, \varepsilon_j = 0$

Ordinary least squares

$$-2\sum_{i}^{n}(y_i - (\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k))^2 = a \tag{16}$$

Hence determine the partial derivatives of a with respect to

$$\beta_i$$

where

$$\beta_i; i = 0, 1, 2, 3 \ldots k$$

i.e.

$$-2\sum_{i}^{n}(y_i - (\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k)) = \frac{\partial a}{\partial \beta_0} \tag{17}$$

$$-2\sum_{i}^{n}(x_1(y_i - (\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k))) = \frac{\partial a}{\partial \beta_1} \tag{18}$$

$$-2\sum_{i}^{n}(x_k(y_i - (\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k))) = \frac{\partial a}{\partial \beta_k} \tag{19}$$

This implies that we will have k+1 normal equations as shown below.

when i=0

$$\sum y_i = n\beta_0 + \beta_1 \sum x_1 + \beta_2 \sum x_2 + \ldots + \beta_k \sum x_k \tag{20}$$

when i=1

$$\sum x_i y_i = \beta_0 \sum x_1 + \beta_1 \sum x_1^2 + \beta_2 \sum x_1 x_2 + \ldots + \beta_k \sum x_1 x_k \tag{21}$$

and when i=k then

$$\sum x_k y_i = \beta_0 \sum x_k + \beta_1 \sum x_k x_i + \beta_2 \sum x_k x_2 + \ldots + \beta_k \sum {x_k}^2 \tag{22}$$

3.4.2 Generalized Linear Model (GLM)

Suppose the data exhibits a non constant variance then we will apply a generalized linear model outlined below. GLM comprises of:

1. Random component which specifies the distribution of an independent variable given the explanatory variables
2. Linear predictor- Linear function of regressors given as $y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_k X_{ik}$. Also presented as $X_i' \beta = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_k X_{ik}$
3. link function which transforms the expectation of a response variable to a linear predictor. $\mu_i = \mathbb{E}(Y_i)$
   $g(\mu_i) = X_i^{-1} \beta$
4. the link function $g(\mu_i)$ is often nonlinear

Therefore, $f(y_i, \theta_i)$ is an exponential function given as

$$f(y_i, \theta_i) = exp[y_i \theta_i + b(\theta_i) + c(y_i)] \tag{23}$$

GLM model assumptions

The *glm* method has the following assumptions:

1. The regressand needs not to be distributed normally
2. The regressand can be non-linear transformations
3. Homogeneity of the variance does not need to be satisfied
4. The observations are independently distributed
5. Generalized linear model presumes a linear relationship between the transformed response variable and the predictor variables.

Maximum Likelihood Estimates

Maximum likelihood estimator estimates the coefficients of a glm model as it yields the best estimator with larger sample and is straight forward compared to OLS.

The likelihood function is a joint density of y's, denoted by $L(\beta,\sigma^2)$. We try to determine the values of $\hat{\beta}$ and σ^2 that maximizes $L(\beta,\sigma^2)$ given y and x values in the sample. Therefore if $\varepsilon/x \sim \mathcal{N}(X\beta,\, \sigma^2 I)$ where X is $m*(n+1)$ of rank $n+1<m$, the mle of β and σ^2 are:

$$\hat{\beta} = (X^TX)^{-1}(X^Ty)$$
$$\sigma^2 = \tfrac{1}{n}(y-X\hat{\beta})^{-1}(y-X\hat{\beta})$$

The

$$L(y_i;\beta,\sigma^2) = f(y;\beta,\sigma^2) = \frac{1}{(2\pi\sigma^2)^{n/2}}e^{-(y-X\beta)/2\sigma^2} \quad (24)$$

Since y_i's are independent , then $L(\beta,\sigma^2)$ can be obtained as

$$\Pi_{i=1}^{n} f(y;\beta,\sigma^2) \quad (25)$$

as shown below

$$lnL(y_i;\beta,\sigma^2) = -\frac{n}{2}ln(2\pi) - \frac{1}{2\sigma^2}(y-X\beta)^T(y-X\beta) \quad (26)$$

Taking partial derivatives of $lnL(\beta,\sigma^2$ with respect to $\hat{\beta}$ and σ^2 and equating to zero gives $\hat{\beta} = (X^TX)^{-1}(X^Ty)$.

The σ^2 will biased since $E(\hat{\sigma}^2) = \frac{1}{n}\sigma^2$ while the unbiased has a denominator of $\frac{1}{m-n-1}$ such that $s^2 = \frac{1}{m-n-1}(y-X\beta)^T(y-X\beta)$, hence unbiased estimator.

3.5 Evaluating goodness of fit

3.5.1 R-squared and the adjusted R-squared

The accuracy of the model will be assessed using R square and the goodness of fit established using the adjusted coefficient of determination (R square adjusted).

$$R^2 = Cor(Y,\hat{Y})^2 = 1 - \frac{\sum(y_i - \bar{y})^2}{\sum(y_i - \bar{y})^2}$$

R^2 (coeficient of determination) varies from 0 to 1. However, large value does not necessarily indicate that the model fits the data well hence need for a more detailed analysis. Adjusted R square is given by the formula below

$$R^2_{adj} = 1 - (1 - R^2)\frac{n-1}{n-k}$$

3.5.2 Residual analysis

We will also use the root mean squared error (RMSE) parameter to test the scatter of the data around the model. We will estimate the error variance (σ^2) as shown below: $\sigma^2 = Var(e_i) = \mathbb{E}(e_i^2)$
where

$$e_i = Y_i - \hat{Y}_i$$

$e_i = Y_i - (\beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n)$ and the unbiased estimator of the σ^2 is given by

$$\hat{\sigma}^2 = \frac{\sum \hat{e}_i^2}{n-k}$$

k is the number of parameters including the intercept.
Therefore, RMSE = $\sqrt{\sigma^2}$

Lower RMSE indicate a better fit.

3.5.3 Deviance Statistic

We will the model goodness of fit using the deviance test where:

H_0: null model is better fit
H_1: fitted model is better fit.

Let $l(\hat{\mu},\phi;y)$be the log likelihood maximized by β for a fixed value ϕ. The discrepancy can be rewritten as

$$\sum 2w_i(y_i(\tilde{\theta}_i-\hat{\theta}_i)-b(\tilde{\theta}_i)+b(\hat{\theta}_i))/\phi = D(y;\hat{\mu})/\phi \quad (27)$$

$D(y;\hat{\mu})$ is the deviance for the current model since $D(y;\hat{\mu}) = D(y;\hat{\mu})/\phi$. For the normal distribution it is given as

$$\sum(y-\hat{\mu})^2 \quad (28)$$

The degree of freedom (p) is the number of predictors. The test statistic follows a chi-squared distribution. We reject the null hypothesis if the p-value$<<$ than 5% significance level; a small p-value indicates a significant fit..

3.6 Overview

This chapter's aim was to outline the research method used to answer the research questions. A detailed explanation on the procedures, data gathering, statistical analysis and test the goodness of fit of the model outlines how the study will be conducted. Multiple linear regression analysis will be used to develop a domestic electricity consumption model in Kenya. Chapter will provide the study results by demonstrating the methodology discussed in this chapter.

4 Results and Discussion

4.1 Introduction

This chapter presents the data analysis, presentation and interpretation of the study. Statistical tools for Microsoft excel and R were used for data input and analysis.

Household electricity consumption

Based on the analysis, figure 2 the chart below shows electricity consumption patterns in Kenya from the year 2000 to 2018

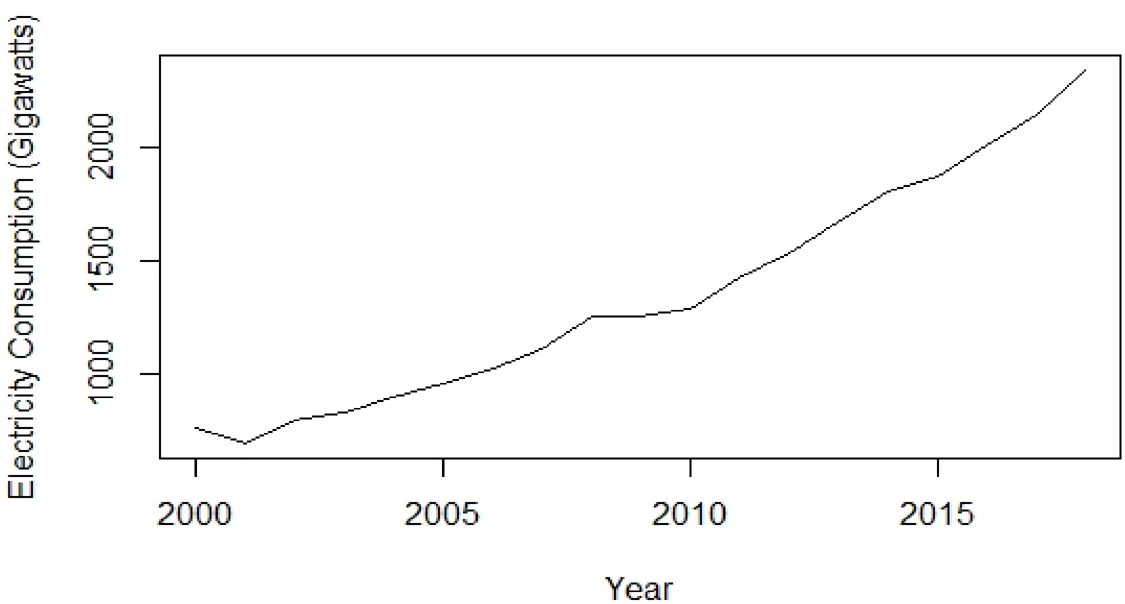

Figure 2. Household electricity consumption trend

4.2 Data validation

Normality test

Table 1. Normality test

Shapiro-Wilk normality test
W = 0.91875, p-value = 0.1073

At 5% significance level, the p-value is greater than 0.05 implying that the distribution of the errors are not significantly different from normal distribution.

Homoscedasticity

In line with the previous chapter, we used Breusch-Pagan that has χ^2 to test for homoscedasticity.

Table 2. Test for Homoscedasticity

studentized Breusch-Pagan test
BP = 1.6748, df = 4, p-value = 0.7953

As per the results, the p-value is less than the significance level of 0.05,this implies that we fail to reject the null hypothesis that the data is homoscedastic.

Autocorrelation

We tested for correlation between the values of the same variables over successive intervals using durbin-watson test.

Table 3. Test for autocorrelation

Durbin-Watson test
DW = 2.1289, p-value = 0.3421

Given that the number of parameters is 5 and the sample size is 20, the critical values are $d_L = 0.792$ and $d_U = 1.991$. The $DW = 2.1289$ is greater than $d_U = 1.991$ hence we fail to reject the null hypothesis implying that the error terms are not auto-correlated.

Multicollinearity

Table 4. Test for multicollinearity

Variance Inflation Factor	
Households connected to the grid	13.51855
Population	56.75583
GDP	84.09198
Electricty Tariff	25.19686

We tested for multicollinearity using Variance Inflation Factor (VIF). If VIF is greater than 10, it implies that multicollinearity exists. The Analysis results found that there exists a strong relationship between the independent variables.

4.3 Parameter Estimation

4.3.1 Multiple Linear Regression Model

Table 5. Linear regression output

Coefficients	Estimate	Std. Error	t value	$Pr(> \|t\|)$
(Intercept)	-124.236	238.580	-0.521	0.61069
hh	35.817	16.602	2.157	0.04884
pop	21.252	9.645	2.203	0.04482
gdp	12.185	3.236	3.766	0.00209
Price	3.587	11.967	0.300	0.76877

The linear equation of the model is given as

$$EC = -124.236 + 35.817hh + 21.252pop + 12.185gdp + 3.587price \quad (29)$$

The p-value of the model is less than the significance level of 0.05 which it implies that the model is significantly fit. The residual standard error is 35.57 on 14 degrees of freedom; this implies that the average household electricty consumption that varies from the predicted value given by the regression line is 35.57 gigawatt hours.

The p-value column in table 5 shows the association between the depedent variable-electricity consumption- and the independent variables. Results indicate that there is a statistically significant association between the household electricity consumption and the population, households connected to the grid and gross domestic product. The raltionship between household electricty consumption and electricty tariff is not statistically significant at the significance level of 0.05.

4.3.2 Generalized Linear Model

We fitted a generalized linear model using normal distribution, identity link on R software and the results are as shown in table 6 below.

Table 6. Generalized linear model results

Coefficients	Estimate	Std. Error	t value	$\Pr(>\|t\|)$
(Intercept)	-124.236	238.580	-0.521	0.61069
hh	35.817	16.602	2.157	0.04884
Pop	21.252	9.645	2.203	0.04482
gdp	12.185	3.236	3.766	0.00209
Price	3.587	11.967	0.300	0.76877

The p-value of the number of households connected to the grid(0.04884) and the gross domestic product(0.04482) are significant in modelling household electricity consumption at 0.001 significance level while the country's population is significant in modeling electricity consumption at 0.01 significance level. Contrary, the p-value of the electricity tariff ($0.76877 > 0.05$) indicates that it is not significant in modelling for household electricty consumption.

The standard errors explain the percentage variation of the coefficients from the true value. The variation number of households connected to the grid is 16.6 percent from the true mean; percentage variation of the country's population from the true mean is 9.645 percent; percentage variation of gross domestic product from the true mean is 3.2 percent while percentage variation of electricity tariff from the true value is approximately12 percent.

The model is given as

$$EC = -124.236 + 35.817hh + 21.252Pop + 12.185gdp + 3.587price \tag{30}$$

where hh is the number of households connected to the electricity, pop is the country's population, gdp is the country's gross domestic product and price is the electricity tariff.

The model can be interpreted as :

- Households
  Adjusting for population, gross domestic product and electricity tariff, one million

increase on the number of households connected to grid increases electricity consumption by 35.817 GWh

- Gross domestic product
  Adjusting for population, number of households connected with electricity and electricity tariff,one billion Kenyan shillings increase in GDP increases electricity consumption by 12.185 GWh

- Population
  Adjusting for gross domestic product, number of households connected with electricity and electricity tariff,a million increase in population increases the electricity consumption by 21.252 GWh

- Electricity tariff
  Though the electricty tariff is not significant in modelling for household electricity consumption, the models suggests that adjusting for population, number of households connected with electricity and gross domestic product, one shilling increase in electricity price decreases the electricity consumption by 3.587GWh

4.4 Model goodness of fit

4.4.1 R-squared and the adjusted R-squared

The coefficient of determination for the data is 0.9960843 implying that 99.6% of the data fit the model. We used the adjusted R squared to evaluate the goodness of fit of the model; given that the Adjusted R-squared is 0.995, it implies 99.5% variation of household electricity consumption is explained by the number of households connected to the grid, country's population and gross domestic product. Electricity tariff is not significant in modelling for household electricity consumption as its p-value is greater than the critical value of 0.05.

4.4.2 Residual analysis

The Root mean squared error which indicates the standard deviation of the unexplained variance in the data is $7.3632 * 10^{-6}$. Given that the RMSE is small, it is implies that the model is significantly fit.

Normality

The normality graph shown in figure 3 below indicate the plots follow a straight line implying that the residuals are normally distributed.

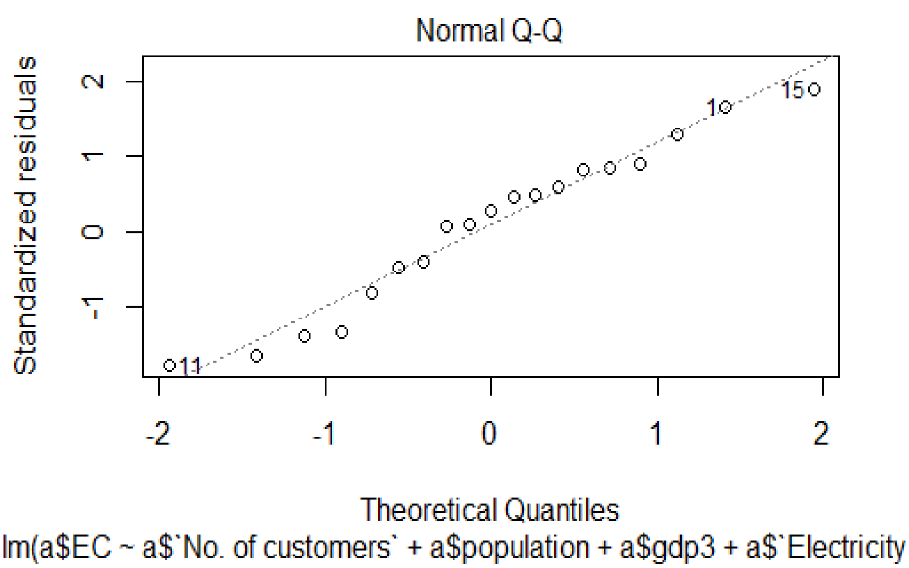

Figure 3. Normality of the residuals

Residuals vs fitted plots

The linearity test output shown in figure 4, indicate that the plotted points are symmetrically distributed regression around the horizontal line.

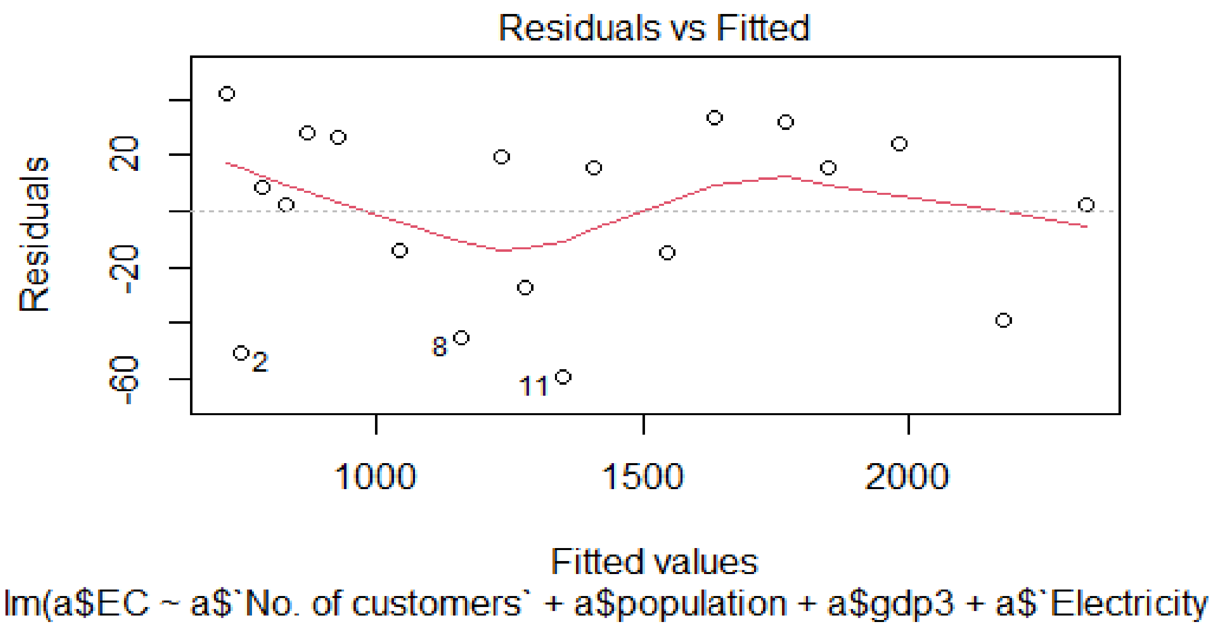

Figure 4. Linearity test

4.4.3 Deviance Statistic

We compared two models; the saturated model also known as the complex model and the fitted also known as the null model. The results are as shown in table 7 below

Table 7. Model goodness of fit

Res.	Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	18	4524250				
2	14	17716	4	4506534	890.34	< 2.2e-16

The p-value<0.05 implying that the saturated model is significantly fit in modelling for household electricity consumption.

5 Conclusion and Recommendation

The study analyzes the impact of the factors influencing household electricity consumption while exploring on the trends and behaviors of the household electricity consumption in Kenya. The study applied a generalized linear model to fit for household electricity consumption in Kenya. Data was obtained from Kenya Power reports and government institution websites. The models uses annual data from the year 2000 to 2018.

The basics for simple and multiple linear regression analysis were applied in the analysis. From the analysis, it was discovered that the observations satisfied three linear assumptions of a model. The data violated the multicollinearity assumption where Population, Number of households connected to the grid and gross domestic product were highly correlated. The study compared the saturated model and fitted model to establish the goodness of fit.

Study results reveal that population, number of households connected to the grid, gross domestic product are significant in modeling for household electricity consumption. The electricity tariff, however, is not significant as expected based on the previous studies in the litrature review.

Absence of similar studies in Kenya restricted our study to compare our findings with other studies outside the country. In Australian context, Fan et al. (2015) found out that many factors-varied and complex-affects electricity consumption. The model used showed a reasonable performance in forecasting electricity consumption of individual household though studying household electricity consumption is complex and requires integration of disciplines.

In our study, results suggests that generalized linear method can be used to better understand household electricity consumption and how decision makers can influence them. The model can be improved further by introducing new variables which influence electricity consumption. Another model can be developed to model daily or monthly electricity consumption at the household level. Therefore, it would be important to do region-specific studies to understand more on the impact of the factors influencing household electricity consumption using top-down approach.

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