E-ISSN: 1115 – 8492 P-ISSN: 3027 – 0693
MPRI-JNSAR
INTERNATIONAL JOURNAL OF NATURE AND SCIENCE ADVANCE RES.
VOL. 10 NO. 9 OCTOBER-2025

MODELING ELECTRICITY CONSUMPTION RATE IN YOLA ELECTRICITY DISTRIBUTION AND COMPANY (YEDC) JALINGO CENTER, TARABA STATE FROM 2013 TO 2023

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DOI: https://doi.org/10.70382/mejnsar.v10i9.072

Abstract

Predicting electricity consumption has an important role in planning energy strategies for both policy makers and related organizations in any country. This study uses the monthly time series data on electricity consumption in Jalingo, Taraba State from January 2013 to December 2023, to model and forecast the consumption electricity using the ARIMA framework. The study is guided by three objectives and these are: To model the rate of electricity consumption from 2013-2023 over the study period, to estimate the rate of electricity consumption in Jalingo state study period based on the Box-Jenkins ARIMA technique and lastly, to forecast the future units of energy injected in kilowatt (KW) based on the previous years. Based on this research, the study presents the ARIMA (3, 2, 1) model which has the least information criteria with AIC of 2313.17 and BIC of 2327.025, described the patterns observed in the electricity consumption series. The diagnostic tests on the model residuals revealed that the selected model is free from autocorrelation effect, heteroscedasticity and found to be normally distributed, and hence suitable for forecasting electricity consumption in Jalingo. The model was used to forecast the monthly electricity consumption for the next two years (2022-2023) with 95% confidence interval. The selected optimal model, the ARIMA (3, 2, 1) model proves beyond any reasonable doubt that in the next Two years, electricity supply in Jalingo will continue to change due

KEYWORDS:
modelling, electricity, consumption, distribution rate, Jalingo.

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to seasons over time. The study advocates for the liberalization of the electricity power sector in Taraba State in order to pave way for more efficient private investment whose potential is envisaged to adequately meet the existing consumption for electricity. This model is recommended for use until further analysis proves otherwise.

Introduction

Electricity is vital to people's lives, businesses, and organizations, and it plays a crucial role in the growth of nations. It is a crucial metric for assessing the development related well-being of a nation (Okakwu *et al.*, 2019). Since the success of many economic operations and social welfare are strongly related to electricity usage, today's excessive dependence on this resource is undeniable (Da Silva *et al*., 2023). Electrical energy is another name for what is commonly referred to as electricity and the load consumption here is electrical energy.

Estimating future occurrences and situations based on historical data is meant by the term "forecast". Today, the operation and management of electrical energy systems and energy management increasingly depend on energy forecasts. It is the process of estimating the electrical loads required at a given location using historical electrical load demand data (Samuel *et al*., 2017). These forecasts can be just minutes in the future for operational needs or up to five to ten years in the future for planning (Melodi *et al*., 2017). Although forecasting and prediction are frequently conflated, a forecast primarily relies on historical data records. A forecast is thought to be more precise and may include a variety of potential outcomes.

Electric power supply is therefore rated as one of the most essential commodities for any nation's development (Owusu & Sarkodie, 2016). A quick overview on nation building informs that efficient power supply results in quality health care and economic growth to mention a few (Onyeisi Samuel Ogbonna et al 2016). Development results in increase in power demand, which invariably requires planning ahead of time to meet the present and future demand of uninterruptible power supply (Adeshina & Osunmakinde, 2017). Therefore, forecasting of electric energy demand is an important process in the planning of electricity utility companies (Briggs & Ugorji, 2017). In addition, accurate forecast leads to increase reliability of power supply, correct decision making for future development, quality savings in operation and maintenance costs (Almeshaiei & Soltan, 2015). As electric power demand increases, energy consumption assessment becomes imperative which could be carried out either hourly, daily, weekly, monthly or yearly (Fahad & Arbab, 2014). Accurate load forecasting is vital because an overestimation will lead to economic waste since huge investment is needed for the development of excessive power infrastructure,

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while underestimating may result in the degeneration and possible collapse of the existing infrastructure as underinvestment may ensue thereby leading to load shedding or consumer disconnection (Rajakovic & Shiljkut, 2018). The categorization of load forecasting is usually based on usage measured in short, medium and long term. Short term load forecasting is usually deployed when scheduling the generation and transmission of electricity. Medium term load forecasting is employed when scheduling fuel purchase while long term forecasting is used to model power supply and power delivery (Gupta & Pal,2017). Research community is saturated with diverse approach to investigating the best estimate for load forecast for which time series analysis has been adopted as the most prominent.

Statement of the Problem

Electricity is one of the most important commodities for the development of any nation (Ahuja & Tatsutani, (2016) yet electricity shortage still remains a serious problem in Nigeria. This is attributed to the inability of the electricity supply to match consumer demand. For any country, especially developing countries such as Nigeria, electricity demand forecasting is vital for increasing energy productivity. Nigeria is a developing country with a rapidly expanding population and economy, necessitating a rise in energy consumption. Thus, recognizing future energy consumption trends is crucial for designing, running, and exploring any nation's electrical power system (Ade-Ikuesan *et al.,* 2019). As a result, there is need for individuals, academics, nations, and the entire global economy to develop intellectual models for controlling energy consumption processes. Selecting appropriate techniques for evaluating, modelling, and predicting time series of consumption and integrating them with existing information systems for management decisions across individual firms, cities, industries, and states (Kalimoldayev *et al.,* 2020). The focus of this project is to estimate the electricity consumption in Jalingo of Taraba state.

Aim and Objectives of the Study

This research work is aimed at analysing the rate of electricity consumption in Jalingo of Taraba state and the objectives are to:

1. Model the monthly rates of electricity consumption from 2013 – 2023 using time series model.
2. Estimate the rate of electricity consumption in Jalingo, Taraba state from 2013-2023 respectively.
3. Forecast the future units of electricity consumption in Jalingo, Taraba state.

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Significance of the Study

The results from this study will benefit academia and researchers by contributing to existing literature. Appropriate time series models was estimated to forecast the electricity consumption rate figure in the future which will be of concern to the Jalingo Electricity Distribution Company (JEDC) of Nigeria and also serve as a basis for any future research in academia.

Scope of the Study

The study was based on monthly electricity consumption rate Time series modelling and is limited to the data collected from Jalingo Electricity Distribution Company (YEDC), Jalingo Taraba State for a period of ten years (2013 - 2023).

Observations collected from single source generate a univariate time series. Whereas observations collected simultaneously from two or more sources forms a multivariate time series.

Time Domain and Frequency Domain

Time domain and frequency domain are two models used in the analysis of any time series dataset. Time domain analysis is used to analyze the dataset over time domain series, the variable is always measured against time which is useful in understanding the pattern behaviour of the time series over time. Whereas, the frequency domain analysis refers to analysing a series with respect to the frequency.

Empirical Study of Time Series

Idoniboyeobu et al. (2018), carried out a study on long term electric load forecasting on the Nigerian power system using the modified form of exponential regression model. The model was used to predict residential, commercial and industrial load demand.

Oyelami and Adewunmi (2014) used GARCH model to estimate the volatility of the marketplace, while Harvey logistic model was used to forecast electricity demand and supply in Nigeria between 2005 and 2026.

Residential Electricity Utilization in Nigeria

Nigeria was modelled and predicted using multiple/quadratic regression models, results showed that the quadratic regression model outperformed multiple regression model (Ezenugu, et al, 2017). Katara, et al (2014) studied electricity demand forecast in Tamale Ghana using ARIMA model. The study employed secondary data spanning from 1990 to

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2013, and the result showed that both domestic and commercial demand were increasing more rapidly than industrial sector demand.

Isaac, et al (2017) carried out a comparative study on medium term load forecasting using Artificial Neural Network, ANN and regression model. Results showed that ANN-model was more superior to the regression model for load forecasting.

Predicting electricity consumption using regression, Kalman filter adaptation algorithm and ANN was investigated in (Ozoh, et al, 2015). The report indicated that Kalman filter adaptation algorithm was best performing in terms of future prediction of electricity consumption.

Electricity Demand and Forecasting Models in Ghana and Pakistan

Prince Yaw Andoh (2021), presented electricity demand and forecasting model for Ghana using average monthly maximum electricity consumption data for a period of ten years. The Auto-Regressive Integrated Moving Average was adopted. The data was reviewed regarding normality, variance equality and stationary conditions. The parameters p, d and q and P, D and Q were determined, and different models were examined. Based on the lowest levels of AIC and BIC, the most suitable model was selected among the models whose overall adequacy was confirmed. ARIMA (1, 1, 1) (0, 1, 2) with the lowest level of AIC was selected as the most adequate model for prediction. Out of this, one year data was selected to validate the model. Regarding the seasonal pattern of TB electricity consumption, Box-Jenkins and SARIMA models are suitable for predicting electricity future consumption.

Yasmeen and Sharif (2014) assessed the time series data of electricity consumption for Pakistan. The Box-Jekins ARIMA methodology was used for forecasting the yearly data collected from 2009 to 2013. Result of the analysis revealed that the series became stationary at first difference. The domestic checking has shown that ARIMA (3,1,2) is appropriate or optimal model based on the Akaike's Information Criterion, the Bayesian Information Criterion (BIC) and Hannan Quinn Criterion (HQ). A five (5) years forecast was made from 2014-2018. The modelling was in three stages, the first was model identification stage, where the series became stationary at the first difference, based on the result provided by the ADF-test. Based on AIC, BIC and H-Q information criteria, ARIMA (3, 1,2) was selected as appropriate model with minimum information criteria. The study can be extended to non-linear models to take care of vitality which may occur in electricity consumption series.

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Application of ARIMA in GDP Forecasting

Musundi et al. (2016), used time series to model and forecast the GDP of Kenya. They employed the Box-Jenkins approach to model and forecast Kenya GDP. The data employed spanned from the year 2005 to the year 2015, and was modelled using the Autoregressive Integrated Moving Average (ARIMA) stochastic model popularized by Box and Jenkins (1976). ARIMA (2, 2, 2) time series model was established as the best for modelling the Kenyan GDP according to the recognition rules and stationary test of time series under the AIC criterion. The results of an in-sample forecast showed that the relative and predicted values were within the range of 5% and the forecasting effect of this model was relatively adequate and efficient in modelling the annual returns of the Kenyan GDP. Finally, they used the fitted ARIMA (2, 2, 2) model to forecast the GDP of Kenya for the next five years.

Forecasting Energy and Gasoline Consumption

Katara et al. (2014), used ARIMA model to forecast electricity demand in Tamale, Ghana. Yearly forecasts were made by utilizing data from 2000 to 2013.

Emmanuel et al. (2018) modelled and forecasted gasoline consumption in Cameroon till 2020 by estimating price and income elasticity's of gasoline consumption using historical data for the period 1994-2010 using a dynamic MLR model. They established a dynamic regression model for forecasting gasoline consumption. Results obtained suggest that price, gross domestic product and income are significant drivers of gasoline consumption in Cameroon. Projected results showed that gasoline consumption will increase by over 7% yearly, reaching 1078 504 m^3 by 2020. Following these findings, they believed their estimation results are consistent and robust.

ARIMA Applications in Oil and Renewable Energy Forecasting

Chukwuemeka O. Omekara (2015), discussed the ARIMA model for crude oil production in Nigeria from January 2013 to March 2015. The multiplicative ARIMA $(1,1,1)(0,1,1)(0,1,1)_{12}$ model was proposed as the best model to be fitted to the crude oil production data. Suat and Feride (2025), developed an ARIMA model to forecast renewable energy and total energy consumption of Turkey from 2016 to 2040 in this study, coal, oil, natural gas, and renewable and total energy consumption data for 1970-2015 was used to forecast energy consumption of Turkey for the next 25 years, using autoregressive integrated moving average (ARIMA) model.

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Time Series Modelling in Financial and Economic Forecasting

Paul et al. (2013), used time series to model and forecast the average daily share price indices for shares of a pharmaceutical company in Bangladesh. Setyo (2017) attempted to predict stock price volatility of equities that are listed on the Indonesia Stock Exchange using the ARIMA model. Jadhav et al. (2017), applied univariate ARIMA techniques to forecast and validate farm prices of cereals in Karnataka state, India. Fattah et al. (2018) sought to model and forecast the sales demand for the products sold by a food company, using a time series approach.

Time Series Application in Renewable Energy and Stock Markets

Alsharif et al. (2019) utilized ARIMA models for both daily and monthly solar radiation in Seoul, South Korea, using solar radiation data. Eke (2019) asserted that the ARIMA (2, 0, 3) is the best fit model for predicting the Nigerian Stock Exchange monthly stock market returns over a ten-year period.

Mustapa & Ismail (2019) sought to develop an appropriate ARIMA model that best fits the S&P 500 monthly stock prices for a 17-year period to enhance portfolio and investment decision making.

Source of Data

The data is a secondary data which was collected from Jalingo Electricity Distribution Company in Jalingo of Taraba state.

Method of Data Analysis

The data was analysed using R and SPSS software and time series models was employed to analyse the data collected.

Components of Time Series

A first vital step in applying the best modelling and forecasting is to consider the type of pattern exhibited by the series from the time series plot. The patterns in the time series data are classified into four main components which are: the trend component, seasonal component, cyclical component, and the irregular component.

Trend Component

Trend is defined as the upward and downward movement in a time series without the influence of seasonality and cyclic fluctuations. The trend of a time series is obtained when both seasonal variation and irregular random variations are eliminated from the time

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series. Trend can be measured by the following methods: graphical method, semi-average method, curve fitting method and moving average method.

Seasonal Component

The time series components used to describe the yearly periodic variations in a given series is known as the seasonal component or variation. Plots used in time series to detect seasonality in a given observed series, includes: A runs sequence plot, seasonal subseries plot, multiple box plot and the autocorrelation plot. Seasonal adjustment is the process of seasonal variation eliminations and the elimination is impact from a time series while a seasonal index is used to compare the average demand for specific period of time compared to the average demand.

Cyclical Component

The oscillation movement with oscillation circle of more than one year is in a time series is known as cyclical variation. The oscillatory movement may be as a result of business cycle. Seasonal variation or seasonality differs from cyclical due to the fact that the seasonal variation has a constant length and curve at regular intervals while cyclical variation varies in length and do not curve at regular intervals in a given year. Measurement of cyclical fluctuations of a time series consists of eliminating the trend and seasonal components and then removing the random component by averaging.

Irregular Component

The irregular fluctuations are what remain when the other time series components have been accounted for. In other words, the residual is obtained when the time series data has been de-trended and seasonality removed through seasonal adjustment and is expected to be noise.

Common Assumptions in Time Series

The common assumptions in many time series techniques especially ARIMA model building is that the data should be stationary. A process (series) is said to stationary given the mean, variance and auto covariance do not depend on time. The mathematical definition of stationary is given as:

1. The mean $\mu = E(X_t)$ (1)
2. The variance $\sigma^2(t) = \text{var}(X_t)$ (2)
3. The auto-covariance (X_{t1}, X_{t2})

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Univariate Time Series

A time series with only one series observation is called a univariate dataset. Univariate time series models usually consider their series as linear combination of its own past value.

Common Univariate Time Series Approach

There are different approaches to modelling a time series dataset. A few of the most common ones are outlined below.

Decomposition

Time series decomposition involves separating a time series into several components such as trends components, seasonal components, and irregular or error term. The decomposition process comprises removing the trend and the seasonality in the time series so as to leave only the irregular fluctuations, which are the main focus of any time series analysis. A typical example of this approach is the Triple exponential smoothing method and also the seasonal loess approach. There are three functional forms that are often used for representing approach. There are three functional forms that are often used for representing a time series, we have;

The additive decomposition

$$Y_t = T_t + S_t + I_t \tag{3}$$

The multiplicative decomposition

$$Y_t = T_t \times S_t \times I_t \tag{4}$$

The log-additive decomposition

$$LogY_t = T_t + S_t + I_t \tag{5}$$

Autoregressive (AR) Models

An autoregressive (AR) model specifies that the variable Y_t is a linear combination of (ρ) previous values $Y_{t-1}, Y_{t-2}, ..., Y_{t-p}$ and a certain random term (shock). It is known as the ρ^{th} order Autoregressive model, defined by

$$Y_t = C + \sum_{i=1}^{p} \varphi_i Y_{t-1} + \varepsilon_t \tag{6}$$

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Where the parameters of the equation (3.1) are $\varphi_i,...,\varphi_p$ is a constant and ε_t is the white noise (error term). The AR (P) Parameter $\varphi_i,...,\varphi_p$ must lie within the stationary bounds -1< φ_i <1 to be wide sense stationary.

Moving average (MA) Models

The moving average (MA) model which was originally invested by Yule in (1927) specifies a univariate time series modelling approach which the output depends linearly on the present and past white noise error terms or random shocks of the series. The phrase moving average (MA) is not the normal moving smoothing methods which consists of arithmetic mean of past historical data, rather the moving average of the error series. The error at each point in the series are assumed to be independent and identically distributed with zero mean and constant variance. The moving average of order (q) is defined by:

$$Y = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_1 \varepsilon_{t-1} \qquad (7)$$

Where (μ) is the mean of the series often assumed to be equal to zero, the parameters of the model are $\theta_1,...,\theta_q$ while $\varepsilon_1,...,\varepsilon_q$ are the white noise error term. The MA (q) must be within the invertibility bound -1< θ_t <1

Autoregressive Moving Average (ARIMA) Models

The approach popularized by Box and Jenkins in 1971, which combines the autoregressive and the moving average approaches together (Box, et al 1994), the model formed as a result of the combination is known as the autoregressive moving average (ARIMA) model, given that the series assumed to be stationary. The autoregressive moving average of order (p,q) is a mixed stochastic process which combines the autoregressive (AR) and the moving average models together is expressed as:

$$Y = c + \varepsilon_t \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{i=1}^{q} \theta_1 \varepsilon_{t-i} \qquad (8)$$

Where all the element of ARIMA (p, q) are as defined in the autoregressive model of order (p) and the moving-average model of order (q). The order of ARIMA (p, q) model is facilitated by simple Autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the time series. The parameter estimates of the autoregressive moving average model which minimizes the error term are derived using the maximum likelihood

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estimation. The autoregressive moving average model can be generalized in other ways, such as the integrated ARIMA models, if the series show evidence of non-stationarity and seasonal effects require differencing. The seasonal autoregressive integrated moving average is expressed as;

$$\Delta^d \Delta_T^D Y_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i y_{t-1} + \sum_{i=12}^{p} \phi_i y_{t-1} + \sum_{i=1}^{q} \varphi_i \varepsilon_{t=1} \sum_{i=12}^{Q} \Theta_t \varepsilon_{t-1} \qquad (9)$$

Stationary and Non-Stationary Time Series

A stationary time series has a zero mean, a constant variance and a constant autocorrelation structure over time with no periodic fluctuations (seasonality). Whereas, non-stationary in a series may follow from the presence of one of these conditions: outliers, random walk, drift, deterministic trend, or non- constant variance. Most economic and business observed time series are not stationary. There are several kinds of stationary stochastic process whose joint probability distribution does not change when shifted in time. A series is believed to be strictly stationary if in addition to a fixed mean and constant variance, it also has a constant auto-covariance structure. While a weak stationary series, also called a second-order stationarity has its mean and variances remain constant over time while the auto-covariance depends on the series lags. A time series data can be non-stationary with respect to the mean or the variance, such series can often be transformed to stationarity by differencing the original series either once (linear trend), fitting a straight line through the series or stabilizing the series variance using either the Log or Square-Root transformation technique.

The Differencing Operator

The operator used when dealing with the non-stationary time series is the differencing operator

(∇). It is possible to conveniently express the first and second order non-seasonal differencing terms as:

$$\nabla Y = Y_t - Y_{t-2}$$

$$\nabla^2 Y_t = \nabla(\nabla Y_t) = Y_t - 2Y_{t-1} + Y_{t-2} \qquad (10)$$

The seasonal differencing can be expressed as:

$$Y_t = Y_t - Y_{t-s} \qquad (11)$$

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Unit Root and Stationery

The unit root test is used to determine if a series is non-stationary and require differencing

Augmented Dickey-Fuller (ADF) Unit Root Tests

The dickey-fuller test, investigates the presence of unit root in a time series using a regression expression that nets the mean, the lagged and deterministic time trend term.

$$Y_t - \rho Y_{t-1} + \varepsilon_t$$

Where the variable of interest is Y_t and (t), $(\rho),(\varepsilon_t)$ represent the time index, the parameter coefficient and the residual (error term) respectively. The hypothesis of the ADF test is given as follows:

$$H_o : \rho = 0$$
$$H_1 : \rho < 0$$

The unit root test is carried out under the null hypothesis $\rho = 0$ i.e., the original, series is non-stationary against alternative ($\rho < 0$) i.e. the original series is stationary. The statistic is computed by $DF_t = \frac{\hat{\rho}}{se(\hat{\rho})}$ and compared to the relevant critical value from the Dickey-Fuller table. If the test fails to reject the null hypothesis, differencing is applied until the ACF shows an interpretable pattern with only a few significant autocorrelations.

KPSS Unit Root Test

Kwiatkowski, *et al,* (2018) proposed a procedure for testing stationarity in time series data. The procedure has a null hypothesis of stationary time series. The testing point of the KPSS test is given as $Y_t = \alpha_t + \beta_t + \mu_t$ and instead of the commonly used constant term, a random walk $\alpha_t = \alpha_{t-1} + \varepsilon_t$ is allowed, where (ε_t) is assumed to be normally independent and identically distributed. In all, a p-value less than 0.05 from the result of the KPSS test would be enough to reject the null hypothesis at 5% level of significance while for the ADF test, the p-value of greater than 0.05 would lead to acceptance of the null hypothesis which implies the presence of a unit root in the series and therefore differencing.

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The Principle of Parsimony

The principle of parsimony is a statistical concept which states that in a model selection it is important to employ the smallest possible number of parameters for an adequate representation. By applying this principle to univariate models, a parsimonious univariate model would be a model which contains the maximum number of parameters necessary to yield white noise residuals. The Parsimonious principle is always noted for guiding analyst to choose the smallest models, but care should be taken since making the model too simple might lead to not considering come effect in the time series, especially in the area of intervention analysis.

Box-Jenkins ARIMA Process

The Box-Jenkins (1976) developed a new model which combines the AR and MA process with an integrated term. The ARIMA process was built upon an earlier work done by Yule-walker in 1927. The model was simply denoted as ARIMA *(p, d, q)*, where *(p)* shows the AR process, *(d)* is the integrated term which takes care of non-stationary process and *(q)* represents the MA process. The Box-Jenkins process of fitting and analysing univariate time series can be broadly classified into three iterative stages namely: The model specification stage, parameter Estimation stage and model Diagnostic checking stage.

Box-Jenkins Modelling Approach

There are three iterative stages in Box-Jenkins modelling approach.

Model Identification Stage

Model identification refers to a methodology in identifying the required transformation, such as variance stabilizing transformations, differencing transformation and the proper order of p and q in the model. The first step in developing a Box-Jenkins model is to build the time plot of the observed series to determine the various patterns displayed by the time series data. However, the two most important tools under the model identification stage are the autocorrelation function (ACF) and the partial autocorrelation function (PACF). The ACF of the time series measures the degree of association between current values of a series with earlier values of that same series when the influences of other time lag on the series are held constant. The ACF and PACF are used to perform two major checks at the model identification stage. A check for stationarity and seasonality may be verified from the ACF and PACF plot of the observed time series. If the time plots show that the series oscillate around a finite mean or equivalently, the lags of the ACF and PACF plot rapidly drops to zero or nearer to zero at a faster rate, this indicates the presence of

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stationarity in the series. Also, when the time series data appears to be non-stationary, the lags of the ACF decay slowly or shows a damped sine wave pattern and do not die out to zero while PACF normally shows a high significant spike close to the one at the first lag and subsequently lags quickly decline to zero but do not die out to zero. In practical, time series analysis, a non-stationary time series without seasonality, require a maximum of two consecutive differences to transform the series into a stationary time series. Once that is done, which can either be an autoregressive (AR) model, a moving-average (MA) model or a mixed of the two models the autoregressive moving-average (ARIMA) model. A moving-average model of order *(q)* may be considered, if there are no significant autocorrelation after lag q while a pure autoregressive of order *(p)* may be appropriate if there are no significant partial autocorrelation after lag p. In some situations, a mixture of the two model ARIMA *(p, q)* may be deemed necessary but if the series was differenced to achieve stationarity, the models may be written as IMA *(d, q)*, ARI *(p, q)* or ARIMA *(p, d, q)* respectively. In summary, the behaviour of the ACF and PACF for identifying simple tentative model is presented.

Table 1. Characteristics of the ACF and PACF For various models

MODEL	ACF	PACF
AR *(P)*	Spikes decays towards zero	Spikes cut-off towards zero
MA *(q0)*	Spikes cut-off to zero	Spike decays towards zero
ARIMA *(p, q)*	spikes decay to zero	Spikes decay to zero
ARIMA *(p, d, q)*	spikes do not decay	Spikes do not decay to zero

Model Estimation Stage

The model parameter estimation stage is carried out identifying model for the time series. The Maximum likelihood estimation model is the generally preferred technique to estimating the AR and MA parameters. The three main penalty function statistic used to penalize fitted models with respect to parsimonious principles are the Akaike information criteria (AIC), corrected Akaike information criteria (CAIC) and the Schwarz Bayesian information criteria (BIC). The AICC value as the sample size (n) gets larger converges to AIC and it is recommended to use AICC penalty statistics, if the sample size *(n)* is small or the parameters *(K)* in the model is large (Burnham, K. P. & Anderson, D. R. 2023). These statistics are one of the various criterions used in verifying the adequacy of the chosen model in the model selection stage. Comparatively, models whose residuals follow a white noise process have the smallest penalty statistics. The AIC of the given model is computed as two multiplied by the number of estimated parameters minus two

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multiplied by the maximum value of the likelihood function of the model with AICC is AIC with a correction for finite sample sizes. The BIC of the model is computed as negative two multiplied by the maximum value of the log-likelihood function added to the number of estimated parameters multiplied by then log of the sample size.

$$AIC = 2(K) - 2Ln(L) \quad (12)$$

$$AIC_c = AIC + \frac{2k(k+1)}{n-k-1} \quad (13)$$

$$BIC = 2Ln(L) + KLn(n) \quad (14)$$

Where *(L)* is likelihood function, *(n)* denotes the sample size and *(K)* represent the model parameters.

A test of statistical significance using the t-test is carried out on each estimated parameters in the model to test whether any of the parameters are significantly different from zero. The t-value of the test is computed from the ratio of each parameter estimate to its standard error. A parameter is considered statistically significant if the absolute value of the t-ratio is greater that the critical value (|t|) with (n-k) degrees of freedom and significant level of 0.05. The basic rule is that all parameters which are not maintained while parameters which are not significant are trimmed from the model. Furthermore, the estimated AR *(p)* and MA *(q)* parameters must also conform to the boundary conditions. The t-test statistic for the parameters estimates are expressed as:

$$t = \frac{\varphi_p}{se(\varphi_p)} \quad (15)$$

$$t = \frac{\theta_p}{se(\theta_p)} \quad (16)$$

Where φ_p denotes the parameter estimate coefficient of the AR *(p)* and θ_p denotes the parameter estimate coefficient of the MA *(q)* while $se(\varphi_p)$ and $se(\theta_p)$ denotes the standard errors of their coefficients in the above equation.

Diagnostic Checking

The diagnostic stage is used to examine whether the fitted model satisfies all the basic assumptions that is the residuals series are uncorrelated random shocks with zero mean and constant variance (white noise). These assumptions are verified by testing whether any of the autocorrelation values (r_k) are significantly different from zero one at a time using the student t-test statistic. An alternative approach to testing the significance of the autocorrelation values (r_k) one at a time, is using the Ljung-Box portmanteau (Ljung &

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Box, 2020). The Ljung-Box test which is modified version of the portmanteau test statistic developed by Pierce and Box (2020), is a test-statistic used for testing whether any group of autocorrelations are statistically different from zero. Instead of testing randomness at each distinct lag in the series, it tests the "overall randomness based on the number of lags being considered". The Ljung-Box test statistic has a distribution closer to the chi-square distribution which is considered better than the portmanteau test statistic proposed by Pierce and Box (2020). The Ljung-Box Q-statistic is normally used to test the adequacy of the model whether the residual have a zero mean, a constant variance and serially uncorrelated (white noise). The Ljung-Box test statistic is expressed as:

$$Q = n(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^{\,2}}{(n-k)} \tag{17}$$

Where (n) denotes the sample size, ($\hat{\rho}_k^{\,2}$) is the square of the autocorrelation at lag k and (h) is the maximum lag being tested. The hypothesis to be tested is formulated as:

H_0: The residuals are independently distributed

H_1: The residuals are not independently distributed

For significance level (α), the critical region for rejection of the hypothesis of randomness, using the chi-square distribution is given as $Q > \chi^2{}_{\alpha(h-p-q)}$. Where the level of significance (α) is taken to be 0.05, *(h)* is the maximum number of lags being tested which is usually around 20 while the order of the AR and MA models are *(p)* and *(q)* respectively. It is important to check whether the residuals of the chosen models are normally distributed with zero mean and constant variance by using the residuals plot against time or Shapiro-Wilk Normality test expressed as:

$$W = \frac{\left(\sum_{i=1}^{n}\alpha_i x_i\right)^2}{\sum_{i=1}^{n}(x_i - \hat{x})^2} \tag{18}$$

Where (x_i) is the i^{th} order statistic, $\bar{x} = (x_i + \ldots + x_n)/n$ is the sample mean and a = $(\alpha_i + \ldots + \alpha_n)$. The decision of the Shapiro-Wilk normality test (Shapiro & Wilk, 1965) is based on the p-value against the chosen level of significance (0.05). The hypothesis for the Shapiro-Wilk normality test is given as:

H_0: The residuals are normally distributed

H_1: The residuals are not normally distributed

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The null hypothesis is rejected if the chosen level of significance is greater than the p-value from the Shapiro-Wilk normality test. Otherwise, it's not rejected. While Langrange multiplier (LM) test proposed by Engle, 1982 in order to test for the existence of Autoregressive Conditional Heteroscedasticity behaviour based on the regression in a time series data set. The ARCH-LM test statistics is expressed as:

$$ARCH - LM = TR^2 \quad (19)$$

Where (R) is the sample multiple coefficients computed from the regression $\varepsilon_t^2, \varepsilon_{t-1}^2, \ldots, \varepsilon_{t-q}^2$ on a constant and T is the sample size. The ARCH-LM hypothesis to be tested is expressed as:

H_0: The residuals are Homoscedasticity

H_1: The residuals are not Homoscedasticity.

Under the null hypothesis that there is no ARCH effect, the test statistic is asymptotically distributed as chi-square distribution with *(q)* degrees of freedom. If the model fails to pass the entire diagnostic test, it is advised to restart the model building cycle unit a more appropriate model is obtained for the observed time series.

ARIMA Forecasting Model

A view into the future is one of the main objectives of model building. In this study the forecast estimation function for optimal *(h)* periods ahead is expressed as:

$$\hat{y}_{T+h/T} = -\theta_1 \hat{\varepsilon}_{T+h-1/T} \quad (20)$$

The error is the difference between the actual consumption rate series values and the fitted values from the chosen model in the study. The forecast error $\hat{\varepsilon}_t$ (h) at lead time is given by:

$$\hat{\varepsilon}_t = y_{T+h} - \hat{y}_{T+h/T} \quad (21)$$

Where y_{T+h} represent the actual hypertension series value at $T + h$.

Visualize the Time series

Figure 1 shows the monthly time series plots of Electricity Consumption Rate, Jalingo, Nigeria from 2013-2023. The plot of the observations displays the series on the y-axis against the time interval on the x-axis showing the patterns in the data over time.

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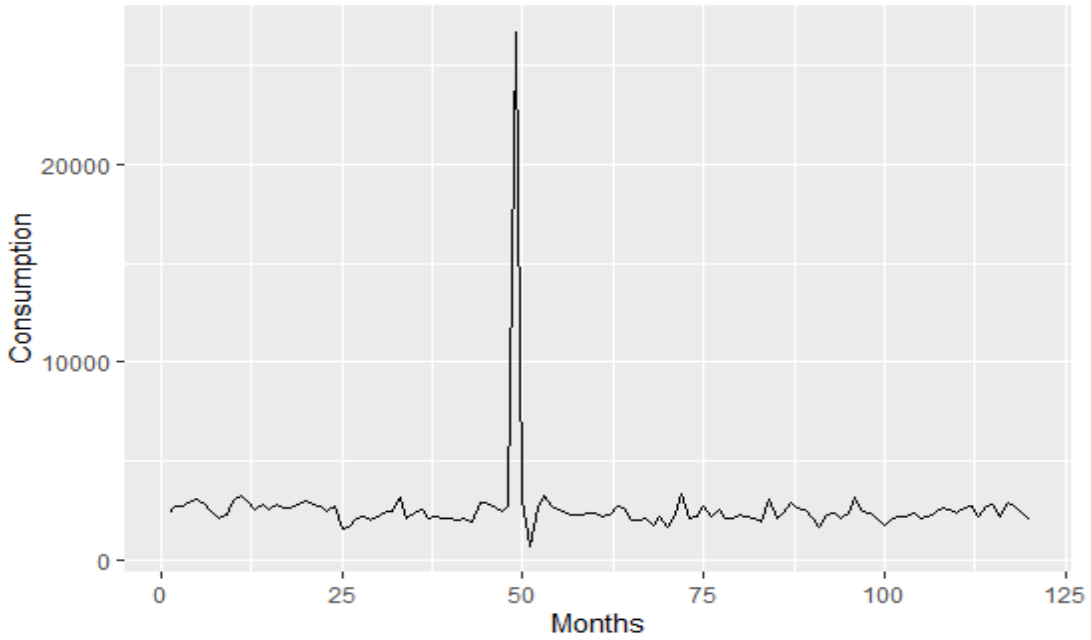


Figure 1: Monthly Electricity Consumption of Jalingo, Nigeria, from 2013-2023.

The plot of the series reveals several fluctuations across the months indicating significant variation over time, which shows that our time series is not stationary with the Augmented Dickey-Fuller Test (Dickey-Fuller = -2.9533, Lag order = 4, p-value = 0.1807). Since the p-value is greater than the significant level at 0.05 we therefore fail to reject the null hypothesis that the electricity consumption rate data is not stationary. In order to perform any successive modelling on our time series, our time series must be stationary: that is, the mean, variance, and covariance of the series should all be constant with time. We need to stationaries the time series by differencing the data.

Stationaries the Time series

The electricity consumption rate data attains stationary after the second difference, with the Augmented Dickey-Fuller Test (Dickey-Fuller = -21.943, Lag order = 0, p-value = 0.01). Since the p-value is less than 0.05, we therefore reject the null hypothesis and accept the alternative hypothesis that the time series data for electricity consumption rate is stationary

Model Identification

Since the electricity data became stationary at the second lag difference, it means that the model to be considered is of this form ARIMA (1,2,3).

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In Figure 2, the plots of the autocorrelation and partial autocorrelation function of the stationary time series data are examined. The ACF decay exponentially after lag 1 suggesting an MA (1) and the PACF dies off after significantly lag 5, suggesting an AR (5) and the corresponding ARIMA Model is (5,2,1).

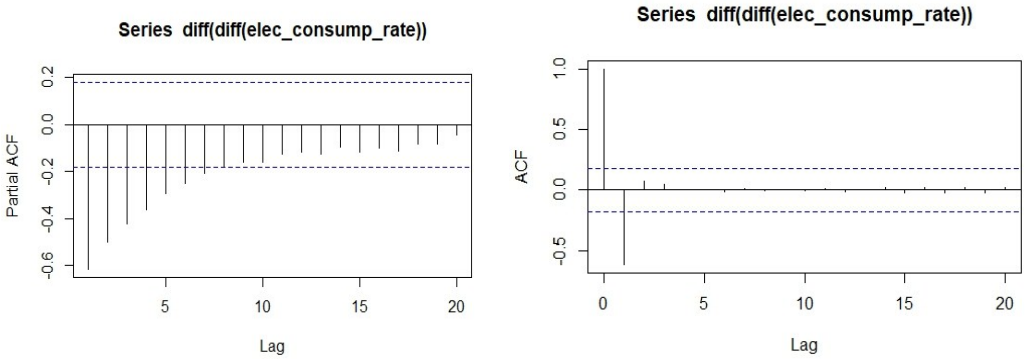


Figure 2: ACF and PACF of the second differenced of Electricity Consumption data

Model Estimation

Our findings in the ACF/PACF section suggest that, one among the four models i.e ARIMA (5,2,1), ARIMA (5,2,2), ARIMA (5,2,3), ARIMA (6,2,2) might be the best fit. These tentative ARIMA models are assessed by choosing the least AIC, log likelihood and BIC criteria to serve as the best ARIMA model.

Table 2: Goodness of fit test and selection of optimal ARIMA model for Electricity Consumption data

ARIMA Model	RSME	AIC	BIC
ARIMA (5,2,1)	3861.823	2274.18	2293.570
ARIMA (5,2,2)	2939.264	2223.00	2245.167
ARIMA (5,2,3)	2504.903	2198.40	2223.331
ARIMA (6,2,2)	2844.363	2218.73	2243.671

The results in Table 2 indicates that, among the four models suggested by ACF/PACF, ARIMA (5,2,3) is the best model, since it has the smallest values of AIC and BIC. However, we conducted a random experiment using an built-in function in R software called ‘’autoregressive model analysis.’’ to search for parameters, until we find the optimal parameters that yield the lowest AIC/BIC. ARIMA (3,2,1) was found to be the optimal model. Therefore, we can use ARIMA (3,2,1) for forecasting of our future values.

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Table 3: Best ARIMA (3,2,1) Model for Electricity Consumption data using ''auto. Arima'' in R

	AR(1)	AR(2)	AR(3)	MA(1)
Coefficients	-1.4091 .	-1.1300	-0.4879	-1.0000
Standard Error	0.0798 .	0.1101	0.0788	0.0217
Sigma^2	2256619			
log likelihood	-1151.59			
AIC	2313.17			
BIC	2327.025			

The parameters of ARIMA (3, 2, 1) from the result in Table 3 of the analysis are $\phi_3 = -1.4879$, $\phi_2 = -1.1300$, $\phi_1 = -1.4091$ $\theta_1 = -1.0000$.

Diagnostic Checking

The diagnostic checking analyses the residuals as well as model comparisons. The Standardized residuals are independent identically distributed sequence with zero mean and variance one. The ACF and PACF of the standardized residuals show no significant lags. Also, the Lung Box result (Q^*=3.695, d f = 6, p-value =7.705e-06) shows that the residuals are stationary and constitute white noise. Thus, the selected model is appropriate to represent the series and it is a good fit.

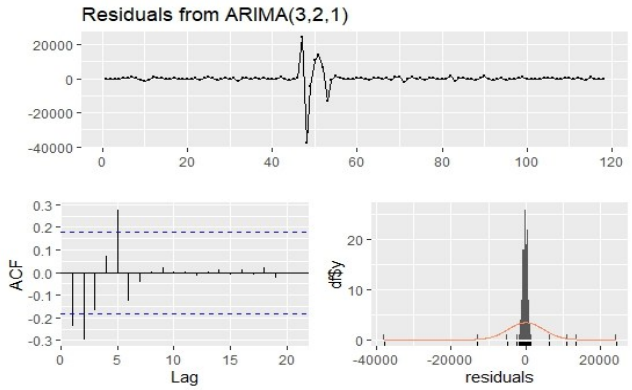


Figure 4. (a) The standardised residual plot, (b) ACF and (c) Histogram of the residuals of the series after a second-order non-seasonal difference and second-order seasonal difference.

Forecasting Electricity Consumption Rate in ATC Jalingo

The parameters of ARIMA (3, 2, 1) from the result in Table 3 of the analysis are $\phi_3 = -1.4879$, $\phi_2 = -1.1300$, $\phi_1 = -1.4091$ $\theta_1 = -1.0000$. The parameters are used to modelled the electricity consumption rate. ARIMA (3,2,1) model can be obtained from as follows;

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$$Y_t = \phi_3 Y_{t-3} + \phi_2 Y_{t-2} + \phi_1 Y_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1}$$

$$Y_t = \text{-}0.4879\, Y_{\text{t-3}} \text{ -}1.1300\, Y_{t-2} \text{ -}1.4091\, Y_{t-1} + \varepsilon_t - 1.0000\, \varepsilon_{t-1}$$

Future Electricity Consumption rate in ATC Jalingo Taraba State, Nigeria can be forecasted using the equation above

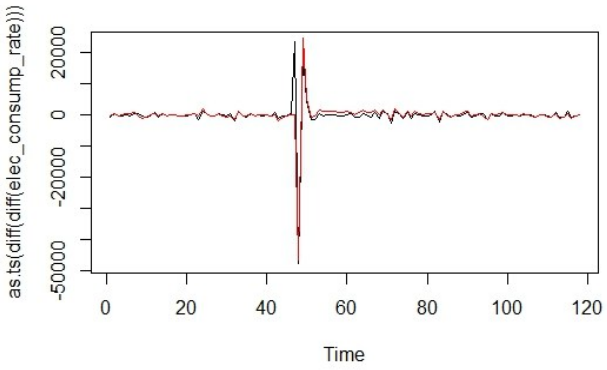


Figure 5: Time series plot of the actual and predicted Electricity consumption rate data

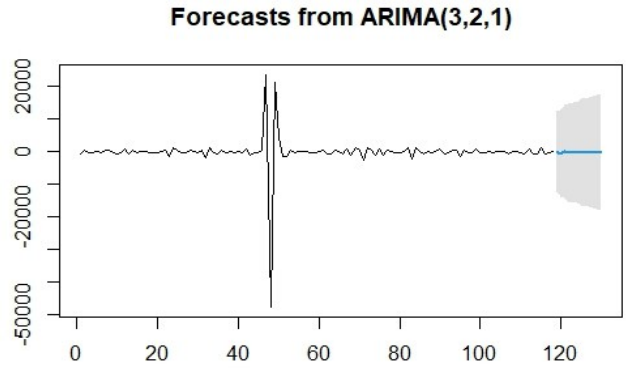


Figure 6: Time series Plot of the Electricity consumption rate data in Jalingo centre and its Forecast

Summary

In this study, we presented the time series plot of the Electricity consumption rate data recorded at Jalingo Electricity Distribution Company, A T C office. The time series plot indicated that the mean and variance were not constant, hence the need for differencing of the observed data to attain stationary. The data attain stationary after the second difference. ARIMA (3,2,1) was selected as the best optimal model which has the lowest value of AIC/BIC. The root mean square error (RMSE) was used to assess the predictive capability of the optimal model.

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Conclusion

The ARIMA model could be applied to effectively predict the electricity consumption rate.

Recommendations

The study advocates for the liberalization of the electricity power sector in Taraba State in order to power way for more efficient private investment whose potential is envisaged to adequately meet the existing consumption for electricity. This model is recommended for use until further analysis proves otherwise.

References

Ade-Ikuesan, O. O., Oyedeji, A. O. and Osifeko, M. O. (2019). Linear regression long-term energy demand forecast modelling in Ogun State, *Nigeria. Journal of Applied Sciences and Environmental Management, 23(4), 753–757.*

Adeshina, Y.A and Osunmakinde, I.O. (2017). Short-term multiple forecasting of electric energy loads for sustainable demand planning in smart grids for smart homes*Journal of Sustainability*, 9: 1-27.

Ahuja, D. and M. Tatsutani, (2016). Policies Enhancing Renewable Energy Development and Implications for Nigeria. *Sustainable energy*. *Vol. 4 No.* 1, 7-16

Almeshaiei, E and Soltan, H. (2015). A methodology for electric power load forecasting. *Alexandria Engineering Journal*, 50: 137-144.

Alsharif, M.H.; Kim, J.; Kim, J.H. Green (2019) sustainable cellular base stations: An overview and future research directions. *Energies* 2017, 10, 587

Akoli & Adoms (2023). Regulatory Impact of Informality on gasoline Consumption Efficiency in Africa: *A proposal two – part complementary hypothesis test vol 140, December*

2024 Box, and Jenkins, (2015). *Time Series Analysis: Forecasting and Control*. John Wiley & Sons, 7th edition. Consumption in Turkey: *Energy Market and Regulatory J*. 1(1) (2010) Box, Jenkins and Reinsel (1994): *Time Series Analysis: Forecasting and Contro* 7th

Edition Box, and Jenkins, (1976). ARIMA (2,2,2) *Forecasting, Structural Time Series Model and the Kalman Filter.* By Andrew C.

Varvey Burnham, K. P. & Anderson, D. R. (2023): Model Selection and Multimodel Inference: *A practical information theoretic approach. Springer, Cambridge.*

Briggs, T. A. and Ugorji, K. (2017). Assessment of electricity demand and prediction model for the future: River's State. *European Journal of Mechanical Engineering Research*, 4: 1-23,

Da Silva, D. G.; M. T. B. Geller; M. S. dos Santos Moura; and A. A. de Moura Meneses (2022). Performance evaluation of LSTM neural networks for consumption prediction. *E-Prime-Advances in Electrical Engineering, Electronics and Energy*, 2, 100030.

Eke, C. N. (2019). Time Series Analysis on Monthly Stock Market Returns of the Nigerian Stock Exchange: An Arima Modeling Approach. *Asian Journal of Economics, Business and Accounting,* 11(4), 1-9.

Emmanuel F.S, Jean G.T, Salome N.E, Francis D.K and Donatien N (2018). Modeling and Forecasting Gasoline Consumption in Cameroon using Linear Regression Models. *International Journal of Energy Economics and Policy.*

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

Ettet (2012): Techer beliefs and Technology integration Practice

Ezenugu, I. A., Nwokonkwo and I. Markson, I. (2017). Modelling and forecasting of residential electricity consumption in Nigeria using Multiple and Quadratic regression models. *American Journal of Software Engineering and Applications*, 6: 99-104.

Fahad, M. U. and Arbab, N. (2014). Factors affecting short term load forecasting", *Journal of Clean Energy Technologies,* 2: 305-309.

Fattah (2018): Forecasting of demand using ARIMA model –*sage journals*

Gupta, V and Pal, S. (2017). An Overview of Different Types of Load Forecasting Methods and the Factors Affecting the Load Forecasting. *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*, 5: 729733.

Idoniboyeobu, D. C., Ogunsakin, A. J. and Wokoma, B. A. (2018). Forecasting of electricity energy demand in Nigeria using modified form of exponential model. *American Journal of Engineering Research*, 7: 122-135.

Isaac, A. S., Adetiba, E., Odigwe, I. A., and Felly-Njoku, F. C. (2017). A Comparative study of regression analysis and artificial neural network methods for medium-term load forecasting, *Indian Journal of Science and Technology*: 10: 1-7.

Jadhav V, Chinnappa Reddy B V and Gaddi G M (2017) Application of ARIMA Model for Forecasting Agricultural Prices [J]. *Journal of Agricultural Science and Technology* 5(12) 981-992

Kalimoldayev, M.; Drozdenko, A.; Koplyk, I.; Marinich, T.; A. Abdildayeva and T. Zhukabayeva. (2020). Analysis of modern approaches for the prediction of electric energy consumption. *Open Engineering*, 10(1), 350–361.

Katara, S., Faisal, A. and Engmann, G. M. (2014). A Time Series Analysis of electricity demand in Tamale, Ghana. *International Journal of Statistics and Applications*, 4: 269-275.

Kwiatkowski (2018): KPSS test for Functional time series

Ljung and Box (2020): On a measure of lack of fit in time series models. Biometrika, 65(2), 297-303. doi:10.1093/biomet/65.2.297

Melodi, A. O.; S. T. Adeniyi and R. H. Oluwaniyi. (2017). Long-term load forecasting for Nigeria's electric power grid using ann and fuzzy logic models. 2017 IEEE 3rd *International Conference on Electro-Technology for National Development* (NIGERCON), 962–968.

Mustapa and Ismail (2019): Modeling and Forecasting S & P 500 Stock price using hybrid ARIMA – Garch model Musundi Sammy Wabomba, M'mukiira Peter Mutwiri and Mungai Fredrick. (2016) Modeling and Forecasting Kenyan GDP Using Autoregressive: *International Journal of Statistics and Applications.* 4 (6): 283 -291.

Onyeisi S. O. (2016). Power Generation Capacity and Economic Growth in *Nigerian: European Journal of Business and Management ISSN 2222-1905 (paper) ISSN 2222-2839 (Online) Vol.8, No. 32, 2026*

Omekara (2015): Neuroscience Letters 546 (2015) page 67-70

Okakwu, I. K.; E. S. Oluwasogo; A. E. Ibhaze and A. L. Imoize. (2019). A comparative study of time series analysis for forecasting energy demand in Nigeria. *Nigerian Journal of Technology*, 38(2), 465–469.

Owusu, P. A. and Sarkodie, S. A. (2016). A review of renewable energy sources, sustainability issues and climate change mitigation. *Cogent Engineering*, 3: 1-14.

Oyelami, B. O. and Adewunmi, A. A. (2014). Models for forecasting the demand and supply of electricity in Nigeria. *American Journal of modelling and optimization*, 2: 25-33, 2014.

EDITOR-IN-CHIEF
Prof. E. Mclenna [Australia]

Pierce and Box (2020): On a measure of lack of fit in time series models

Ozoh P., S. Abd-Rahman and J. Labadin (2015). Predicting electricity consumption: A comparative analysis of the accuracy of various computational technique, 9th International Conference on IT in Asia, Kuching, Malaysia. 2015

Andoh P.Y. (2021). Forecasting Electricity Demand in Ghana. *Journal of Engineering and Technologies Science*, Vol 3(1) 2021: 1-9

Pual (2013): African journals online

Rajakovic, N.L and Shiljkut, V.M. (2018). Long-term forecasting of annual peak load considering effects of demand-side programs. *Journal of Modern Power Systems and Clean Energy*, 6: 145-157.

Samuel, I. A.; A. Emmanuel; I. A. Odigwe and F. C. Felly-Njoku. (2017). A comparative study of regression analysis and artificial neural network methods for medium-term load forecasting. *Indian Journal of Science and Technology*, 10(10), 1–7.

Sene (2012). Microbial Ecology Volume 63 Number 2, February 2012 Pierce and Box (2020): On a measure of lack of fit in time series models.

Setyo T. W. (2017). The ARIMA Model for the Indonesia Stock Price: *International Journal of Economics and Management 11 (S1): 223-236 (2017)*

Suat and Feride (2018): Forecasting Energy Consumption of Turkey by ARIMA model, *Journal of Asian scientific Research.*

Suat Ozturk and Feride Ozturk, (2016). Forecasting Energy Consumption of Turkey by Arima Model, 4(2) 64-73. *Journal of Asian Scientific Research: Vol. 8 No. 2(2018)*

Wahyudi (2017): *Journal of Technology and science Education*

Yasmeen, F. and M. Sharif, (2014). Forecasting electricity consumption for Pakistan. *International Journal of Emerging Technology and Advanced Engineering*, 4(4): 496 – 503.

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