African Journal of Mathematics and Statistics Studies
ISSN: 2689-5323
Volume 7, Issue 2, 2024 (pp. 183-191)
www.abjournals.org

MODELING THE ACCESSIBILITY TO ELECTRICITY IN NIGERIA USING TIME SERIES TECHNIQUE

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Cite this article:

Oguntola T. O., Adesina O. A., Oke S. A., Oladimeji L. A. (2024), Modeling the Accessibility to Electricity in Nigeria using Time Series Technique. African Journal of Mathematics and Statistics Studies 7(2), 183-191. DOI: 10.52589/AJMSS-JYWHCHDQ

Manuscript History

Received: 28 Feb 2024

Accepted: 1 May 2024

Published: 7 Jun 2024

ABSTRACT: *Access to electricity in Nigeria has been a major issue for the country for many years. With a rapidly growing population and an increasing demand for electricity, the country has struggled to provide a reliable and sustainable source of power. This work focuses on modeling access to electricity in Nigeria spanning 1990 to 2020 extracted from the World Bank database. The data was subjected to Augmented Dickey-fuller test and the Box-Jenkins ARIMA time series methodology was used for analysis. The time plot showed a continuous fluctuation of access to electricity in an upward trend direction and the result of the augmented Dickey-Fuller (ADF) unit root test suggested that the series is not stationary at original level, but the model incorporates first differencing. The electricity accessibility series was modeled and predicted using the Autoregressive Integrated Moving Average Model (ARIMA). ARIMA (0,1,1) was selected as the appropriate optimal model based on the Akaike's Information Criterion and Bayesian Information Criterion. Likewise, from the result of the forecast the access to electricity in Nigeria will continue to rise for the next 10 years. It was recommended that the government should make efforts to address the issue by implementing reforms, privatizing the electricity sector, and investing in renewable energy sources such as solar and wind power.*

KEYWORDS: Electricity Accessibility, ARIMA, Differencing.

Article DOI: 10.52589/AJMSS-JYWHCHDQ
DOI URL: https://doi.org/10.52589/AJMSS-JYWHCHDQ

INTRODUCTION

Families need energy to generate services like pumping water and speeding up the process of cooking healthy food, as well as to light up places, which improves educational outcomes and helps establish new enterprises. Utilizing electricity also facilitates the reallocation of time between day and night, increasing the amount of labor hours that may be used. Electricity is one of the key inputs used by businesses to speed up production. In modern times, any significant growth opportunity must first provide access to electricity. Electricity is helpful for learning. Africa's connection to the global economic system is made possible by electricity. In practical terms, one's standard of living depends on having access to power. All around the world, it is an essential source of sustenance for human survival (Kamaludin, 2013).

Electricity is a key infrastructural element for economic growth. It is a multidimensional "energy currency" that drives an extensive range of goods and services that enhance living standards, boost labor productivity, and promote entrepreneurship. More than 600 million people in Africa lack access to electricity and over 80% of those living in rural regions do not have electricity at all (Kwakwa, 2012). Less than 40% of people in West African nations were able to access electricity. This rate is lower than the 87% global average (Ouedraogo, 2013). In 2018, almost 85% of Ghana's population has access to electricity (World Bank Development Indicators, 2016). Following are nations like Senegal, Cote d'Ivoire and Nigeria, where roughly 62%, 66%, and 54% of the people, respectively, have access to electricity (Shahsavari, 2018). It is commonly acknowledged that having access to energy services that are reliable, cost-effective, and modern is a crucial and irrefutable tool for growth in the economy.

This work was motivated by the current issue people are facing to access the use of electricity. The need for energy has increased quickly in West Africa as a result of population growth and a rapidly expanding economy, notably in recent years and in metropolitan areas. The population of Africa is thought to be extremely young and expanding quickly (Odhiambo, 2009). Akinlo (2008) shows that there is a strong correlation between population growth and energy demand. As population grows, it is often associated with high acquisition and heavy usage of energy consuming gadgets and equipment. As a result, population growth has a direct relationship with energy demand, such that as a population grows, it directly leads to a growth in energy demand. Again, economic growth is argued to equally have a direct relationship with energy consumption.

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MATERIALS AND METHODS

The study relied basically on secondary data obtained from the World Bank database which covers access to electricity during the period of 31 years (1990 – 2020). The ARIMA model has been extensively used in forecasting economics, stock prices, marketing, social problems, and industrial production, among others (Arowolo et al., 2022). We employed the Moving Average Model (MA).

Time Series Modeling

The primary objective of time series analysis is to develop mathematical models that provide reasonable descriptions for sample data. To provide a statistical setting for describing the character of data that seemingly fluctuate in a random fashion over time, we defined time series as a collection of random variables taken at equal intervals of time. Let $\{w_t\}$ be electricity accessibility which is a stochastic process.

Stationarity Concept

To develop a time series model that is effective for forecasting, stationarity is a prerequisite. The electricity accessibility series is not stationary at original level, but the model incorporates first differencing. A time $\{w_t, t = 0, \pm 1, ...\}$ is said to be stationary if it has statistical properties similar to those of the time-shifted series $\{w_{t+b}\}$, for each integer b.

White Noise

Let $w_t \sim WN\left(0, \sigma_w^2\right)$ be white noise where mean is zero and variance σ_w^2

Differencing

The idea of making a non-stationary series to become a stationary one is called differencing of the time series. Differencing can help stabilize the mean of the time series by removing changes in the level of a series and so eliminating (or reducing) trend. It is done by subtracting the previous observation from the current observation more formally.

Model Representation

Autoregressive Model (AR)

A stationary time series (w_t) is said to be an autoregressive process of order p if it satisfies

$$w_t = \phi_1 w_{t-1} + ... + \phi_1 w_{t-p} + \varepsilon_t$$

where w_t is the time series, $\phi_i, i = 1, 2, ..., p$ are the autoregressive parameters, ε_t is white noise process usually independent and identically distributed normal random variable. In order for the model to remain stationary, the roots of its characteristic's polynomial must lie outside of the unit circle i.e. |B| > 1.

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Moving Average Model (MA)

The Stochastic process (w_t) is said to be a moving average process of order 'q' if it satisfies the difference equation.

$$w_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_1 \varepsilon_{t-q}$$

Where $\theta_i, i = 1, 2, \ldots, q$ are the moving average parameter of the model, ε_t is a white noise process with mean zero and variance σ^2. For MA (q) process invertibility condition holds.

Autoregressive Moving Average Model (ARMA(p,q))

A time series Z_t is said to follow an autoregressive moving average model of order ARMA (p,q) if it satisfies

$$w_t - \phi_1 w_{t-1} - \ldots - \phi_1 w_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_1 \varepsilon_{t-q}$$

$$\Phi(B) w_t = \theta(B) \varepsilon_t$$

Both stationarity and invertibility conditions are required for an ARMA (p,q) process

Autoregressive Integrated Moving Average (ARIMA)

In time series analysis, an autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model.

RESULTS AND DISCUSSIONS

The result emanates from the applied time series techniques in reference to data collected on electricity accessibility in the 31 years from 1990 to 2020. A discussion on data analysis related to this finding is found in the next section. The data descriptive statistics were computed and presented in Table 3.1.

Table 3.1: Descriptive Statistics of the Data

Statistic	Min	Median	Mean	Range	Variance	Std. Deviation	Max
Electricity Accessibility	27.30	47.61	46.88	32	61.15	7.82	59.30

Table 1 above shows the descriptive statistics of the variable used in the analysis. The average electricity accessibility is 46.88. The minimum and maximum of electricity accessibility is (27.30, 59.30). Time plot was used to visualize the data; time series was the tool used for the analysis, and ARIMA model was used to fit the trend line and forecast for the next 10 years.

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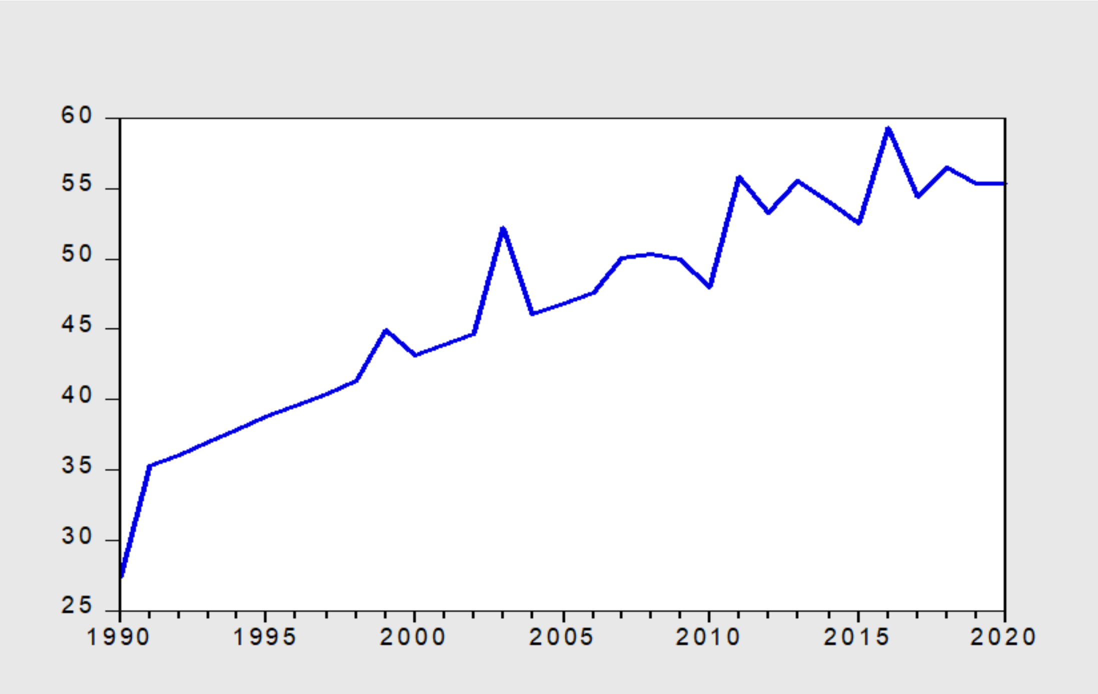

Figure 3.1: Time Plot of Electricity Accessibility

Time series are not stationary as depicted in Figure 3.1. It can be observed from the depicted time plot that the series has an upward trend; hence, continuous fluctuation of access to electricity from 1990 upwards.

Stationarity Test for Electricity Accessibility

$H_0: There\ is\ \ no\ unit\ root$

$H_1: There\ is\ unit\ root$

Table 3.1.1: Stationarity Test and the Difference for Electricity Accessibility

Process	**Test Statistics**	**P-value**
ADF	-2.562861	0.1133

Table 3.1.2: The Difference Series for Stationarity Test

Process	**Test Statistics**	**P-value**
ADF	-4.8556862	0.0006

Table 3.1.1 and 3.1.2 show the result for the stationarity tests and its difference respectively. Since the $p > \alpha$ at level in Table 3,1.1, we fail to reject the null hypothesis and conclude there is no unit root in the series (series is not stationary). We subjected the series to differencing to obtain Table 3.1.2 which gives the stationarity tests of electricity accessibility using Augmented Dickey Fuller.

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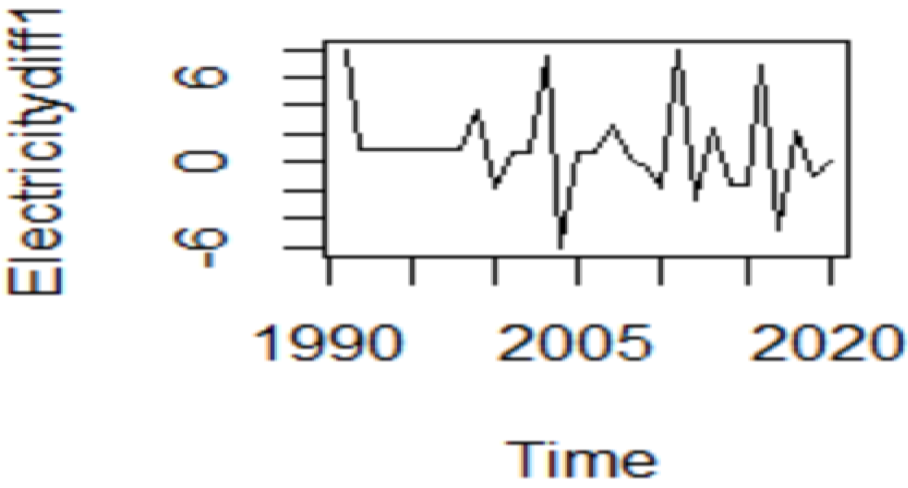

Figure 3.2: Time Plot of the Difference Electricity Accessibility

Model Identification for Electricity Accessibility

Doing ACF and PACF analysis for Electricity Accessibility, most of the time, comparison of these estimated autocorrelations with some theoretical autocorrelation is used regarding the selection of some tentative time series model.

Table 3.3 displays the electricity accessibility's Autocorrelation function (ACF) and the Partial Autocorrelation Function (PACF).

Estimation of ARIMA model

Any number of time series models fit to the data were used to do the model comparison using the AIC (Akaike 1974). This is a criterion for measuring the deviation of the fitted model from the actual one. A contending model refers to a time series model with the minimum AIC value.

Table 3.3: Estimation of the parameters

	Coefficient	*Std. Error*	*Z*	*p-value*
Constant	0.824778	0.129368	6.375	<0.0001
θ_1	−0.757621	0.148764	−5.093	<0.0001

Mean dependent var	0.936667	S.D. dependent var	3.325282
Mean of innovations	0.936667	S.D. of innovations	2.591063
R-squared	0.907865	Adjusted R-squared	0.907865

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Log-likelihood	−71.55685	Akaike criterion	149.1137
Schwarz criterion	153.3173	Hannan-Quinn	150.4585

Fitting an ARIMA(p,d,q) model to Table 3.3, where p stands for the number of autoregressive parameters, d is the number of differences, and q is the number of moving average parameters. Most of the time a series might best be described by an ARIMA model. The model with the minimum Akaike Information Criterion (AIC) will bring the univariate best model, ARIMA(0,1,1). Therefore, the ARIMA model will be:

$$y_t = 0.824778 + 0.757621\varepsilon_{t-1}$$

Box- LJung Test

To determine whether or not the residuals are correlated, the Box-LJung test is used in this instance.

H_0: The residuals are uncorrelated.

H_0: The residuals are correlated.

Table 3.4: Box- LJung Test Result

Process	**Box Test**	**Df**	**P-value**
Electricity Accessibility	0.0013104	1	0.9711

Table 3.5: Comparison of The Model for Electricity Accessibility forecasted data

Model	AIC	BIC
ARIMA(0,1,1)	149.11	153.32

Table 3.6 displays the minimum AIC and BIC used to determine the best time series model taken into consideration.

Forecast

The projections in the table below show the sequence of increasing electricity accessibility. Using ARIMA, we obtained a 10-years forecast (2021 to 2030) for Electricity Accessibility.

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Table 3.5 Forecast Table for Electricity Accessibility

Year	ARIMA Forecast
2021	58.43717
2022	59.26194
2023	60.08672
2024	60.9115
2025	61.73628
2026	62.56106
2027	63.38584
2028	64.21062
2029	65.0354
2030	65.86018

CONCLUSION

Accurate prediction about the demand of electricity helps in proper planning for generation of electricity and planning of resources required to generate electricity in the form of fuel. Furthermore, it helps in planning for future electricity needs. The time plot of electricity accessibility is another helpful tool to track the advancements done by a particular region in granting access of electricity to its people. Consideration needs to be extended on this, however, more still needs to be done to ensure each and every individual can access electricity. The analysis of the electricity in Nigeria gave us an ARIMA (0, 1, 1) as the best model for the period 1990-2020 and could forecast the accessibility for the year 2021-2030 based on time series data that is available. Electricity accessibility in Nigeria is non-random. As can be seen in Figure 2, the pattern is indicative of a trend with no distinct seasonal component. In other words, short-term noise or shocks in data could represent current levels of access.

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