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MODELING AND FORECASTING ELECTRICITY CONSUMPTION IN NIGERIA USING ARIMA AND ARIMAX TIME SERIES MODELS

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ABSTRACT
This study compared the extrapolation strengths of two models: Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Integrated Moving Average with an Exogenous Variable (ARIMAX) in the forecast of Nigeria's electricity consumption. Annual data on power generation and consumption from the Central Bank of Nigeria statistical bulletin for 2006 and 2016 over a 51-year period (1970-2020) was used. Industrial and residential electricity consumptions were examined for possible unit roots (non-stationarity) using the Augmented Dickey-Fuller test approach. The ADF test result showed that the time series achieved a stationary state for the variables under consideration at first difference. Akaike Information Criterion (AIC) and Root Mean Square Error (RMSE) were used to assess the performance of each models. Comparing the ARIMA and ARIMAX forecast models, ARIMA(0, 1, 1) emerged for modelling and forecasting industrial electricity consumption in Nigeria while ARIMAX (1, 1, 1) with installation capacity as exogenous variable was suitable for modelling and forecasting residential electricity consumption in Nigeria. The study recommended that for optimal residential electricity consumption in Nigeria, installation capacity and the total power generation in Nigeria should be enhanced.

Keywords: ARIMA, ARIMAX, Electricity Consumption, Forecasting, RMSE, AIC

INTRODUCTION

The first electrical power plant in Nigeria was constructed in 1896 with a 30 kw, 1000 v, 80 cycle supply. A second unit was added in 1902, and by 1909, installed capacity had increased to 120 KW with a documented energy demand of 65 KW (Edomah et al., 2016). The Lagos Marina power station's installed capacity in 1920 was 420 kW. A 3-phase, 4-wire, 50-cycle system was used in 1924 after the Marina site was shut down on November 28, 1923, and the first coal-fired power plant was built and put into service on June 1 of that year with a total installed capacity of 3.6 MW (Edomah et al., 2016). The new power plant's installed capacity increased even more, reaching 13.75 MW. Despite this expansion, Nigeria began to see a fall in the usage of coal for electricity generation between 1944 and 1948 as a result of decreased mining activities and small-scale crude oil discoveries until the large-scale oil discovery in Nigeria in 1956. The Niger Dams Authority (NDA), whose plan included the construction of three hydroelectric and three thermal generating plants, was forced to act because of recurrent outrages (Davidson et al., 2001). Nigeria's population growth was not accompanied by an increase in the amount of power that was accessible. Subsequently, in 1988, available power was increased to 1273 MW. By 1992 population had increased to about 80 million however, the total available power was 3,000 MW (Sule, 2010).

The first Nigerian electrical power plant was built in 1896 comprising of a 30kw, 1000v, 80cycle, single-phase supply, with an additional unit installed in 1902, and by 1909, installed capacity had reached 120KW with a registered energy demand of 65KW (Edomah *et al.,* 2016). In 1920, the installed capacity for the Lagos Marina power station was 420 kW. With a total installed capacity of 3.6 MW and the adoption of a 3-phase, 4-wire, 50-cycle system in 1924 (Edomah et al., 2016), the first coal-fired power station was built and put into service on 1 June 1923 after the Marina site was shut down on 28 November 1923. The installed capacity of the new power plant increased to 13.75 MW. Despite this expansion, Nigeria began to see a fall in the usage of coal for electricity generation between 1944 and 1948 as a result of decreased mining activities and small-scale crude oil discoveries until the large-scale oil discovery in Nigeria in 1956. The Niger Dams Authority (NDA), whose plan included the construction of three hydroelectric and three thermal generating plants, was forced to act because of recurrent outrages (Davidson et al., 2001). Nigeria's population growth was not accompanied by an increase in the amount of power that was accessible. The available power was then expanded to 1273 MW in 1988. Although the population had grown to around 80 million by 1992, the total amount of power available was only 3,000 MW (Sule, 2010). As of August 2013, Nigeria produced 3,183 MW of power nationally and Currently, there are 33 generating stations in Nigeria, of which 14 are fully operational, 4 are not, 14 are only partially operational, and 1 is under construction. The operating generators' total installed capacity of 7,456 MW, which generated 3,375 MW, is much too low in relation to the population of more than 200 million consumers (Okoro & Madueme, 2014). Nigeria's average electricity production increased from 3,655.64 megawatts (MW) reported in the same time of 2022 by 8.6% to 3,970.33 MW in July 2023 (Vanguard Newspaper, 2023). Unfortunately, the majority of Nigerians do not have access to electricity, and those who do, experience intermittent supplies. Major cities in Nigeria still lack consistent power because of limited power generation, despite government efforts to address this issue, which has an effect on consumption and the viability of our sector. In addition, efficient power generation and installation capacity has the potential to improve GDP in Nigeria (Adenomon and Tela, 2017). Nigeria is currently one of the least developed nations in the world, with real consumption falling by 80% short of expectations given the country's population and income levels. Nearly half of all electricity consumed in Nigeria is self-generated, indicating a significant unmet need. Small-scale diesel and gasoline generators have a combined capacity of nearly 14GW. Given this, it is reasonable to believe that Nigeria has a sizable demand gap, but the precise size is debatable. These estimates' notable discrepancies highlight how difficult and crucial it is to forecast demand accurately. If the responsible body or

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bodies adopt the model with the best performance in projecting Nigeria's electricity consumption, it will address the issue of erratic electricity supply. This research compares time series models namely ARIMA and ARIMAX models for Modelling and forecasting electricity consumption in Nigeria.

In science and technology, there are many issues that arise when a process creates what we may refer to as a family of random variables (stochastic process), where there is a random variable (Xt) for each variable t(time) on some interval T, thereby producing a random function of time. Time series is the term used for such operations (Kotler, 2000). A particular class of stochastic process is the time series. A set of observations made progressively in time on any such measurement is referred to as a time series (X_t) (Morris, 1995). The observations do not stand alone. It consists of a series of observations collected at specific times. These observations are made at equally intervals of time (Chatfield, 1988) or at equally distant places in time. Time series, regression, econometric, decomposition, co-integration, ARIMA, artificial systems like the Artificial Neural Network (ANN), Grey prediction, Input-output, Fuzzy-logic, and bottom-up models are just a few of the models that can be used to forecast energy demand (Haiges, 2016).
The deliberation will be focused on time series multivariate assessment because the data, which includes installed capacity, total generation, residential consumption, and industrial consumption for Nigeria's power generation and consumption from 1973 to 2015, clearly indicates a multivariate time series data. In general, either a multivariate or a univariate strategy can be used to evaluate time series (Haiges, 2016). A multivariate analysis is one in which more than one variable is correlated; a univariate analysis depends only on one variable (Haiges 2016). Due to its straightforward and trustworthy methodology, the Multivariate ARIMA model has amassed a substantial body of work in energy demand projection. It is also thought to be appropriate for long-term projection. Additionally, because it is a widely used method, ARIMA or ARIMAX is suggested in order to prevent an erroneous or invalid forecast.
Adenomon and Madu, (2022), Compared Out-of-Sample Forecast for Inflation Rates in Nigeria using ARIMA and ARIMAX Models. Using the Root Mean Square Error (RMSE) as selection criteria, ARIMAX(0,1,1) with RMSE of 0.6810 emerged as superior model for the in-sample forecast for forecasting inflation rate in Nigeria while ARIMA(1,1,1) emerged as a superior model for the out-of-sample forecast for inflation rate in Nigeria and its forecast for inflation revealed a negative growth in inflation in Nigeria.
Ismail, (2016), worked on modeling and forecasting electricity generation and consumption variables, he considered an additive component model which includes some deterministic and stochastic residual components. The main idea of his approach is that of modeling the generation and consumption of electricity curves, predicting them and finding the intersection of the predicted curves. As benchmark, an ARIMA model was fitted to the scalar time series corresponding to the global clearing generation and consumption points obtained on the curves. As in the first case, results show superior forecasting performance of the functional approach compare to ARIMA.
Cosmo, (2017) worked on modeling and forecasting the Italian electricity price. The research investigates the impact of the 2008 Brent crisis on the determinants of the Italian electricity prices. The structural break in February 2009 was detected after which gas fuel prices and loads resulted to the only determinants of the Italian electricity prices. The data on fuel prices and loads was used to estimate and ARMA-X model with GARCH residuals was used to model this electricity price from 2009 to 2011. Finally, the results jointly with the load forecasts were used to project the Italian power price for the first six months of 2012. The results showed that after the Brent crisis, gas and loads are the best predictor of the Italian electricity price.
Wiwik, et al. (2015), did a research on “Performance Comparisons between ARIMA and ARIMAX Method in Moslem Kids Clothes Demand Forecasting”. They postulated that the Moslem kids clothes demand in Habibah Busana are likely increased at certain times, especially near the Eid holidays, total demands in each year varies and always increase when near the Eid holidays. The result shows that ARIMAX model have better performance than ARIMA method. It is seen from the comparison of AIC, MAPE and RMSE.

According to Chaleampong and Tapanee (2013), they did a research on Autoregressive Integrated Moving Average with Explanatory Variable (ARIMAX) Model for Thailand Export. Their paper examined the forecasting performance of ARIMAX and ARIMA models for Thailand export data. They also examined the direct and indirect approaches of forecasting. They found that, for country-level data, ARIMAX model outperforms ARIMA model only in some principal trade partners; Japan, USA, EU and Australia.

MATERIALS AND METHOD
The study population includes all 36 of Nigeria's states as well as the Federal Capital Territory, Abuja. The 51-year span under consideration was from 1970 to 2020. Only the generation and consumption of electricity were sampled in the study. While the consumption aspect encompasses both industrial and residential usage, the power generation aspect consists of installed capacity and total generation. Kilo Watts (KW) measurements of electricity production and consumption were made annually. ARIMA and ARIMAX time series models were implemented utilizing E-View and R statistical software.

Specification and Estimation of ARIMA and ARIMAX Models.
ARIMA modeling or the Box-Jenkins method was named after the two statisticians who introduced this approach in 1976 (Box & Jenkins, 1976; Adenomon, 2017). ARIMA is the combination of the autoregressive and moving average models. The series Y_t is said to be ARIMA (p,d,q) if

$$\phi(L)(1-L)^d Y_t = \theta(L)\varepsilon_t \qquad (1.1)$$

The mathematical formula for an ARIMA model can be expressed as follows:

$$Y_t - \phi_1 Y_{t-1} - \ldots - \phi_p Y_{t-p} = \varepsilon_t + \theta_1\varepsilon_{t-1} + \ldots + \theta_q\varepsilon_{t-q}$$
$$Y_t = \phi_1 Y_{t-1} + \ldots + \phi_p Y_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \ldots + \theta_q\varepsilon_{t-q}$$
$$y_t = \sum_{i=1}^{p} \phi y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \qquad (1.2)$$

The ARIMAX modeling, is the ARIMA modeling with an exogenous variable (Adenomon & Madu, 2022) given as :

$$\phi(L)(1-L)^d Y_t = \Theta(L)X_t + \theta(L)\varepsilon_t \qquad (1.3)$$

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A few fundamental principles, including stationarity, invertibility, and parsimony, are fundamental to ARIMA modeling (Chaleampong & Tapanee, 2013). The series is said to be stationary if its mean, variance, and covariance do not change over time. This can be accomplished using logarithmic transformation and differentiation of either order I(0) or I(1) of integrated integration. According to Box and Jenkins, sparse models outperform over-parameterized models with extra coefficients that might alter the degrees of freedom in forecasting (Alagidede, 2008). The measured variable yt must exhibit a convergent autoregressive process or be represented by a finite order moving average, which is another implicit criterion in ARIMA.2017 (Zafer & Lestor, 2017). According to Box and Jenkins, there are three stages to ARIMA modeling: identification, estimation, and diagnostic checking (Ratnadip & Agrawal, 2013).

Nigeria's Generation and Consumption historical Time series data from 1970 to 2020.

This section focused on the description of the data used in this study.

Table 1: Descriptive Statistics

	IC	TG	INDUS	RESI
Mean	5123.482	1726.375	237.5431	720.5825
Median	4548.600	1724.900	235.3000	518.0000
Maximum	12522.43	6180.000	434.4200	1869.840
Minimum	670.6000	176.6000	91.40000	53.90000
Std. Dev.	3198.538	1100.653	85.33642	551.7935
Skewness	0.736573	1.304755	0.692640	0.792570
Kurtosis	3.236467	6.545042	3.202178	2.405624
Jarque-Bera	4.730412	41.17583	4.164742	6.090144
Probability	0.093930	0.000000	0.124634	0.047593
Sum	261297.6	88045.10	12114.70	36749.71
Sum Sq. Dev.	5.12E+08	60571861	364115.2	15223803
Observations	51	51	51	51

IC: Installation Capacity; TG: Total Power Generation; INDUS: Industrial; RESI: Residential

Within the period under study, the average Installation Capacity, Total Power generation, Industrial Electricity consumption and Residential Electricity Consumption are 5123.4 MW, 1726.4 MW, 237.5 MW and 720.6 MW respectively. All the series considered have positive skewness while Total Power generation and Residential Electricity consumptions where not normally distributed ($p<0.05$). all the series exhibited moderate kurtosis.

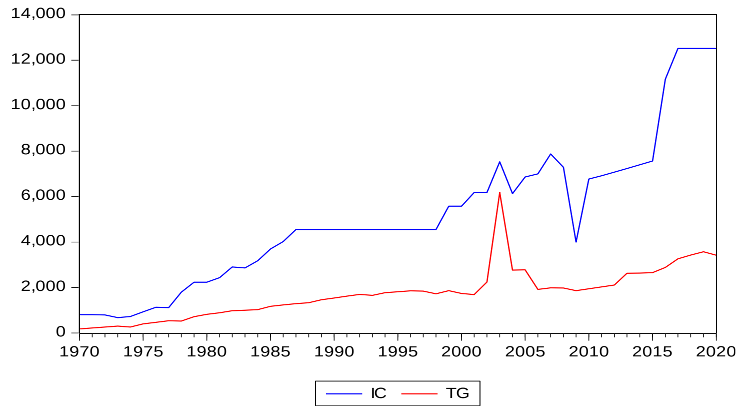

Figure 1: Plot of Installation Capacity (IC) and Total Power Generation (TG) in Nigeria from 1970 to 2020

The Fig 1 above shows the plot of Installation capacity (IC) and Total Power Generation (TG) in Nigeria from 1970 to 2020. Although installation capacity is higher that total power generation in Nigeria, the margin is not wide between 1970 to 2009. But widen margin was seen from 2011 to 2020.

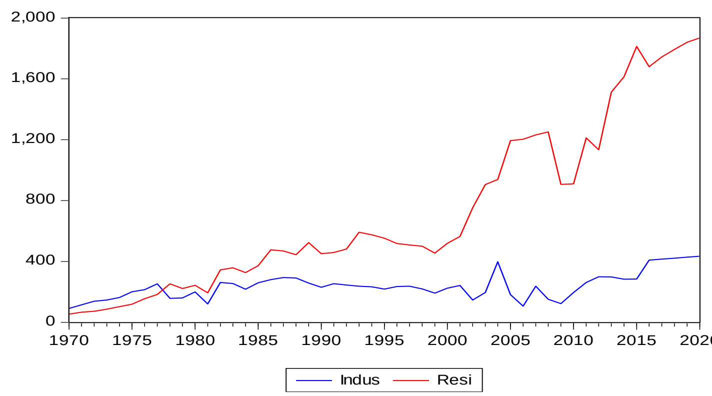

Figure 2: Plot of Industrial (Indus) and Residential (Resi) Electricity Consumption in Nigeria from 1970 to 2020

The Fig 2 above shows the plot of Industrial (Indus) and Residential (Resi) Electricity consumption in Nigeria from 1970 to 2020. Between 1970 to 1977, Industrial Electricity consumption in Nigeria was higher but from 1978 to 2020 residential electricity consumption was higher in Nigeria.

RESULT AND DISCUSSION

Results will appear in the following sub-headings: (1) Identification (2) Estimation (3) Diagnostic check and (4) Forecast performance validation.

Identification.

At this stage is the process to ensure data series is stationary for industrial consumption & residential consumption, Unit root test usually is a test for checking whether a time series data is stationary or not. This research adopted the use of Augmented Dickey-Fuller (ADF, 1979) test approach. Stationary time series data are prerequisite for developing and testing an ARIMA or ARIMAX model. Therefore, the collected data were processed, and the first difference was applied to the make the data stationary. The variables are labeled as lnINDUS and lnRESI for the natural logarithmic series and Δ lnINDUS and ΔlnRESI after undergoing

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first difference. The results of the ADF test on the two series are presented in Table 2 below.

The ADF test result showed that the series has achieved a stationary state, with hypothesis stated as follows:

H_0: The time series data (INDUS/RES) has unit root.
H_1: The time series data (INDUS/RES) has no unit root.

The result in Table 1 below indicates that the logs of industrial & residential consumption is non-stationary at level but become stationary at first difference, since the p= 0.0000 <0.05. Therefore, the null hypothesis was rejected at 0.05 significant level.

Table 2: The ADF test results on natural logarithmic level, and first differenced natural logarithmic series

Variable	t-statistics	p-value	Order	Remark
InINDUS.	-1.541025	0.5045	I(0)	Not stationary
∆ InINDUS	-10.07296	0.0000	I(1)	Stationary
InRESI.	-2.316185	0.1710	I(0)	Not Stationary
∆ InRESI.	-7.793359	0.0000	I(1)	Stationary

Note: InINDUS = Natural logarithm of Industrial consumption
InRESI = Natural logarithm of Residential consumption.

Estimation

Different ARIMA and ARIMAX models were estimated at this stage to obtain the optimal model using Alkaike Information Criterion (AIC), RMSE, significant coefficients, normality of residuals and Ljung Box to adjudge the competing models for comparison. The Q-Q plots of each model were carefully analyzed to see how the data set behaved in terms of distribution. The AIC is utilized as a measure to identify the plausible (optimal ARIMA & ARIMAX) models with the best fit since AIC is found to be more consistent in selecting a model for better forecast (Bell & Hillmer 1983).
The following models were selected

Table 3: Optimal ARIMA model for Modelling Industrial Electricity Consumption in Nigeria
ARIMA(0,1,1)

Coefficient	Estimate	Std Error	z-value	p-value	Remark
MA1	-0.5488	0.1215	-4.5179	6.247e-06	S
Constant	0.0276	0.0176	1.5639	0.1178	NS

S: Significant; NS: Not Significant

Among the competing ARIMA models for modelling industrial electricity consumption in Nigeria, ARIMA (0,1,1) model emerged as the superior model. As shown in table 3 above, only the moving average coefficient was significant (p<0.05). This further suggest that industrial electricity consumption in Nigeria follows a Moving Average process.

Table 4: Optimal ARIMAX model for Modelling Industrial Electricity Consumption in Nigeria
ARIMAX (0,1,1)

Coefficient	Estimate	Std Error	z-value	p-value	Remark
MA1	-0.5634	0.1166	-4.8342	1.337e-06	S
Constant	2.6624	4.6559	0.5718	0.5674	NS
IC	44.3754	49.6477	0.8938	0.3714	NS
TG	20.3511	40.4424	0.5032	0.6148	NS

S: Significant; NS: Not Significant; IC: Installation Capacity; TG: Total power Generation

Among the competing ARIMAX models for modelling industrial electricity consumption in Nigeria, ARIMAX (0,1,1) model emerged as the superior model. As shown in table 4 above, only the moving average coefficient was significant (p<0.05). This further suggest that Installation capacity and Total power generation does not provide sufficient evidence to improve the forecast of industrial electricity consumption in Nigeria.

Table 5: Optimal ARIMA model for Modelling Residential Electricity Consumption in Nigeria
ARIMA(1,1,1)

Coefficient	Estimate	Std Error	z-value	p-value	Remark
AR1	-0.6433	0.4646	-1.3845	0.1662	NS
MA1	0.5310	0.5099	1.0414	0.2977	NS
Constant	0.0708	0.0202	3.5058	0.0005	S

S: Significant; NS: Not Significant

Among the competing ARIMA models for modelling Residential electricity consumption in Nigeria, ARIMA (1,1,1) model emerged as the superior model. As shown in table 5 above, only the constant coefficient was significant (p<0.05).

Table 6: Optimal ARIMAX model for Modelling Residential Electricity Consumption in Nigeria
ARIMAX (1,1,1)

Coefficient	Estimate	Std Error	z-value	p-value	Remark
AR1	-0.7128	0.2596	-2.7455	0.0060	S
MA1	0.5545	0.2993	1.8530	0.0639	S at 10%
Constant	0.0507	0.0202	2.5088	0.0121	S
IC	0.2488	0.1323	1.8801	0.0601	S at 10%
TG	0.1084	0.1029	1.053	0.2923	NS

S: Significant; NS: Not Significant; IC: Installation Capacity; TG: Total power Generation

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Among the competing ARIMAX models for modelling residential electricity consumption in Nigeria, ARIMAX (1,1,1) model emerged as the superior model. As shown in table 6 above, AR1 and constant are significant at 5% (p<0.05) while the MA1 and IC coefficients are significant at 10% (p<0.1). This further suggest that Installation capacity has some level of potential to improve the forecast of residential electricity consumption in Nigeria.

Diagnostic Check
This section focused on testing for the adequacy of the optimal model and the selection between ARIMA model and ARIMAX model.

Table 7: Diagnostic check on the optimal models for industrial Electricity consumption

Model	JB Test	Adequacy Test		RMSE	AIC
		Lag 12	Lag 24		
ARIMA(0,1,1)	P=0.1823	Adequate	Adequate	0.2657	16.72
ARIMAX (0,1,1)	P=0.0021	Adequate	Adequate	56.3896	556.49

The result in table 7 above shows that both ARIMA and ARIMAX model were adequate at lag 12 and lag 24. The ARIMA (0,1,1) passed the normality test (see Fig 3 at the appendix) while ARIMAX (0,1,1) failed the normality test (see Fig 4 at the appendix). Using the RMSE and AIC means of selection, ARIMA(0,1,1) emerged as the superior model for modelling industrial electricity consumption in Nigeria.

Table 8: Diagnostic check on the optimal models for residential Electricity consumption

Model	JB Test	Adequacy Test		RMSE	AIC
		Lag 12	Lag 24		
ARIMA(1,1,1)	P=0.4686	Adequate	Adequate	0.1516	-37.71
ARIMAX (1,1,1)	P=0.8935	Adequate	Adequate	0.1429	-39.63

The result in table 8 above shows that both ARIMA and ARIMAX model were adequate at lag 12 and lag 24. The ARIMA (1,1,1) passed the normality test (see Fig 5 at the appendix) while ARIMAX (1,1,1) also passed the normality test (see Fig 6 at the appendix). Using the RMSE and AIC means of selection, ARIMAX (1,1,1) emerged as the superior model for modelling residential electricity consumption in Nigeria.

Forecast Validation
Forecast validation can be achieved using the RMSE and AIC values, which means model with the least value of RMSE and AIC emerged as superior forecasting model. In this present study, using the RMSE and AIC means of selection, ARIMA(0,1,1) emerged as the superior model for modelling industrial electricity consumption in Nigeria. also, Using the RMSE and AIC means of selection, ARIMAX (1,1,1) emerged as the superior model for modelling residential electricity consumption in Nigeria.

Conclusion and Recommendation
The study compared the extrapolation strengths of two models: Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Integrated Moving Average with an Exogenous Variable (ARIMAX) in the forecast of Nigeria's electricity consumption. Annual data on power generation and consumption from the Central Bank of Nigeria statistical bulletin for 2006 and 2016 over a 51-year period (1970-2020) was used. Industrial and residential electricity consumptions were examined for possible unit roots (non-stationarity) using the Augmented Dickey-Fuller test approach. The ADF test result showed that the time series achieved a stationary state for the variables under consideration at first difference as against what they were at levels. Using the Akaike Information Criterion (AIC) and Root Mean Square Error (RMSE) were used to assess the performance of each models. Comparing the ARIMA and ARIMAX forecast models, ARIMA (0,1,1) was excellent for modelling and forecasting industrial electricity consumption in Nigeria while ARIMAX (1, 1,1) with Installation capacity as exogenous variable was suitable for modelling and forecasting residential electricity consumption in Nigeria. This study recommended that for optimal residential electricity consumption in Nigeria, the installation capacity in Nigeria must be enhanced.

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Appendix

Table 9: Data on Generation and Consumption of Electricity in Nigeria from 1970 to 2020.

	GENERATION		CONSUMPTION	
YEAR	INSTALLED CAPACITY (MW)	TOTAL GENERATION (MW)	INDUSTRIAL CONSUMPTION (MW)	RESIDENTIAL CONSUMPTION (MW)
1970	804.70	176.60	91.40	53.90
1971	804.70	215.40	114.90	66.20
1972	786.70	255.40	138.20	72.90
1973	670.60	299.70	146.10	86.60
1974	721.00	261.10	163.20	103.00
1975	926.20	395.10	200.40	118.30
1976	1125.20	468.70	214.60	155.20
1977	1114.20	538.00	253.00	182.70
1978	1793.70	522.70	157.70	253.20
1979	2230.60	710.70	160.30	221.90
1980	2230.50	815.10	199.70	243.10
1981	2430.00	887.70	121.00	193.60
1982	2902.10	973.90	262.00	344.50
1983	2858.80	994.60	254.40	358.00
1984	3178.00	1025.50	217.20	326.60
1985	3695.50	1166.80	259.80	372.00
1986	4016.00	1228.90	280.50	476.60
1987	4548.00	1286.00	294.10	468.60

1988	4548.00	1330.40	291.10	443.80
1989	4548.00	1462.70	257.90	523.60
1990	4548.00	1536.90	230.10	450.80
1991	4548.00	1617.20	253.70	459.30
1992	4548.00	1693.40	245.30	481.60
1993	4548.60	1655.80	237.40	592.40
1994	4548.60	1772.90	233.30	575.00
1995	4548.60	1810.10	218.70	552.60
1996	4548.60	1854.20	235.30	518.00
1997	4548.60	1839.80	236.80	508.30
1998	4548.60	1724.90	218.90	500.00
1999	5580.00	1859.80	191.80	455.10
2000	5580.00	1738.30	223.80	518.80
2001	6180.00	1689.90	241.90	564.50
2002	6180.00	2237.30	146.20	752.80
2003	7530.00	6180.00	196.00	905.60
2004	6130.00	2763.60	398.00	938.50
2005	6861.60	2779.30	182.30	1194.30
2006	6997.90	1914.50	106.20	1203.10
2007	7876.90	1982.30	237.10	1231.20
2008	7292.10	1975.00	151.60	1251.80
2009	4000.00	1859.90	122.30	906.80
2010	6774.60	1941.70	195.40	910.10
2011	6919.90	2023.50	261.30	1211.80
2012	7074.10	2105.70	299.50	1134.50
2013	7234.00	2628.60	297.70	1512.60
2014	7398.10	2634.80	283.40	1613.70
2015	7564.70	2655.90	284.50	1812.80
2016	11165.86	2881.74	409.06	1680.62
2017	12522.43	3260.27	415.40	1744.03
2018	12522.43	3428.31	421.74	1793.65
2019	12522.43	3568.04	428.08	1841.27
2020	12522.43	3416.44	434.42	1869.84

Source: CBN bulletins and Website

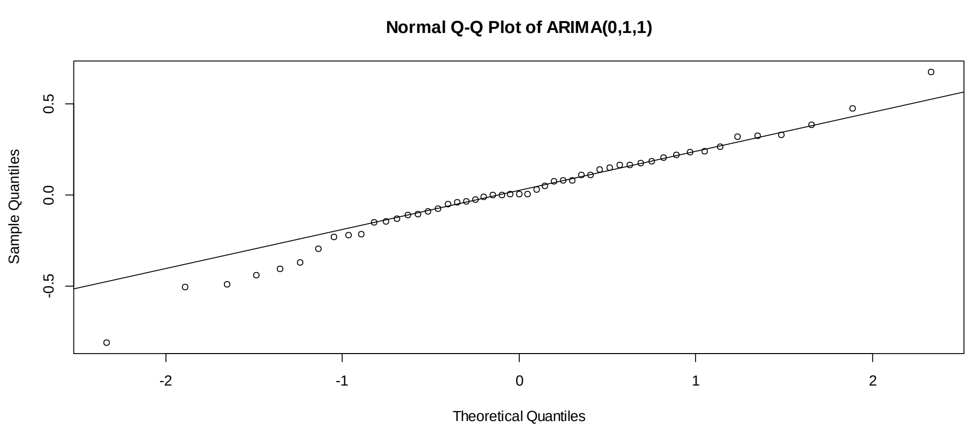

Figure 3: Q-Q Plot for normality of ARIMA (0,1,1) for Industrial Electricity Consumption in Nigeria

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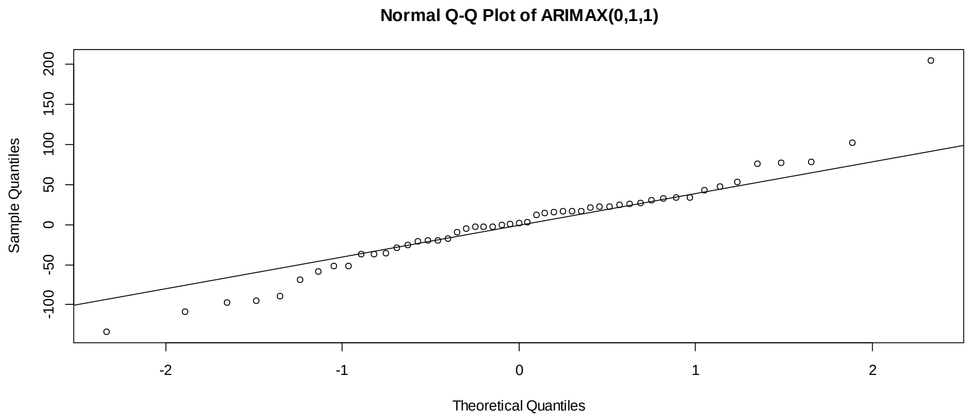

Figure 4: Q-Q Plot for normality of ARIMAX (0,1,1) for Industrial Electricity Consumption in Nigeria

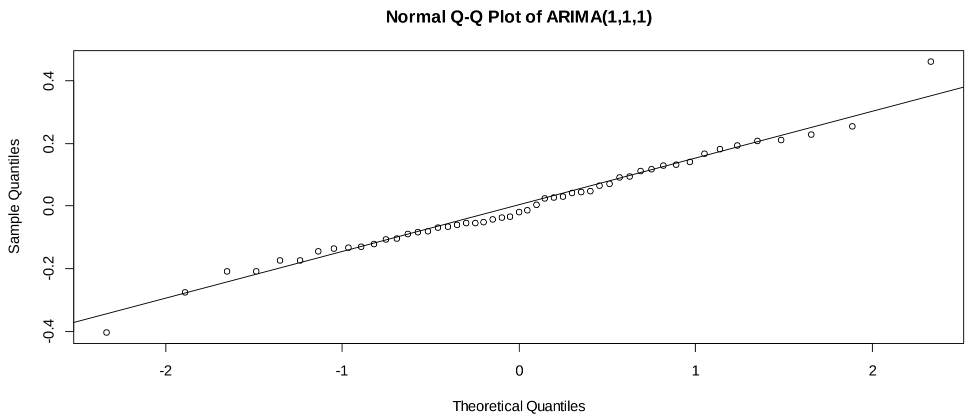

Figure 5: Q-Q Plot for normality of ARIMA(1,1,1) for Residential Electricity Consumption in Nigeria

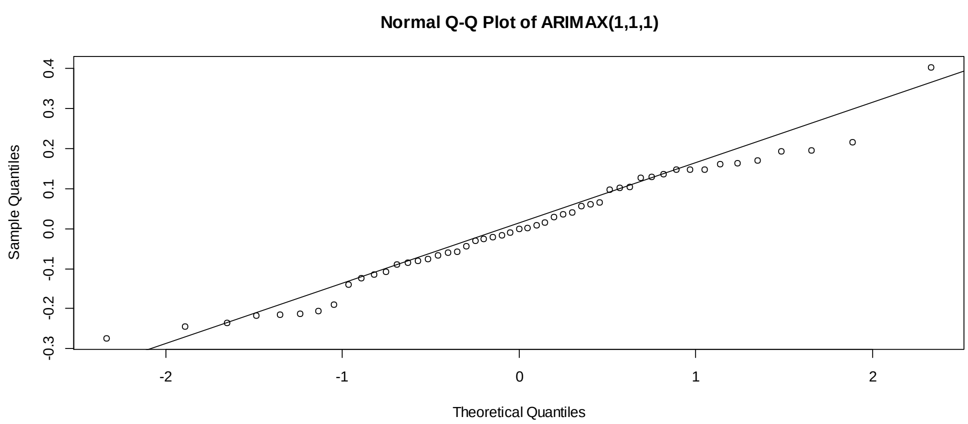

Figure 6: Q-Q Plot for normality of ARIMAX (1,1,1) for Residential Electricity Consumption in Nigeria