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Research Article

Application of Autoregressive Integrated Moving Average (ARIMA) Model to Forecast Electricity Consumption for Nigeria

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Abstract
The electricity demand relative to supply has increased in the developed and developing economies. Hence, forecasting adequate electricity supply plays a crucial role in driving economic production activities and growth. This is so because electricity supply in relation to demand is vital for future energy planning and policy formulation. Thus, this study employed the Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) model and data on electricity consumption from 1971 to 2014. The result indicates that the ARIMA (1, 1, 2) model is adequate for forecasting and modelling electricity consumption in Nigeria in the short run. Based on this finding, we recommended that researchers and policymakers employ the ARIMA (1, 1, 2) model when forecasting electricity supply in Nigeria.

Keywords: ARIMA; box-jenkins; electricity consumption; forecasting; Nigeria.

Introduction
Electricity power is one of the crucial factors that can drive global economic growth in addition to labour and capital. This is why the Seventh (7) Sustaining Development Goals (SDGs) ensured the provision of sustainable, reliable, affordable, and modern energy, especially for people in low-middle-income countries like Nigeria. According to [1], energy demand relative to supply has increased tremendously worldwide, and its administration is vital for environmental sustainability and future economic prosperity. Hence, forecasting future electricity demand in relation to supply in Nigeria is crucial for energy planning and policy formulation [2]. Nigeria is endowed with an abundance of energy resources, including tide, solar, hydro, coal, lignite, geothermal, wind, biomass, and crude oil. Only natural gas, coal, hydro, crude oil, and electricity are used in their processed forms; wood fuel and solar energy are used in their unprocessed forms [3, 4]

Nigeria has the lowest electricity consumption per capita among the top 5 economies in Africa. For instance, electric power consumption (kwh per capita) in Nigeria was reported at 145toe in 2014 compared to 904toe, 1,363toe, 1,683toe, and 4,198toe for Morocco, Algeria, Egypt and South Africa, respectively[5]. This fact might be traceable to the rapid population estimated to be around 200 million, with a growth rate oscillating between 1.87 per cent and 3.11 per cent from 1951 to 2022 [6]. This growth will increase more into the near future with a dire consequence on energy demand that is expected to double. The best technique for forecasting the occurrence of a particular event using time series data is the ARIMA/ARMA model. A good model for predicting electricity demand requires analyzing calendar, weather, company, and social and historical consumption data within the framework of the Box-Jenkins ARIMA technique [7]. This technique gives different random processes like inflation, stock prices, resource consumption, energy and consumption.

Against this backdrop, this study attempts to forecast electricity demand in Nigeria from 2020 to 2040 with its National Renewable Energy Action Plan (2016), in which 29 per cent of its electricity production will come renewable by 2030 with 13.8GW capacity. This study made three additions to the body of existing literature: (1) to check the stationarity of electricity consumption, (2) to select the appropriate ARIMA model for Nigeria, and (3) to forecast electricity consumption for Nigeria.

Following this introduction, section two examines relevant research on electricity consumption. The third portion then discusses the data and methodology. The results are presented and discussed in part four. part five, which concludes, makes recommendations for the next steps based on the results.

Empirical Literature

The problem of forecasting electricity demand, albeit population growth, has attracted the interest of researchers in recent times. These studies have employed different forecasting models on other countries' time series data of electricity consumption. For example, [8] used the seasonal ARIMA and Neural Network Approach (ANN) models to estimate US household energy usage. The result revealed that the neural network approach is slightly superior to the SARIMA model. However, the study concluded that the SARIMA model is preferred to ANN due to its simplicity.

[9] employed the VARIMAX model to forecast carbon emissions from energy consumption in Thailand's rubber, chemical and petroleum industries from 2000 to 2015. The model is divided into two parts. The first model suggested a 10-year forecast from 2016 to 2025 and ARIMA (2,1,2). The result revealed that the country will have 17.65 per cent more carbon emissions than energy consumption in 2025. On the other hand, the second model suggested a 30-year forecast from 2016 to 2045 and ARIMA (2,1,3). The result showed that the country will have 39.68 per cent more carbon emissions than the energy consumption sectors in 2025. The study concluded that higher carbon emissions from energy consumption negatively affect the environment and economy.

[10] used historical data spanning 40 years from 1973 to 2013 and a 40-year projection up to 2053 using the autoregressive integrated moving average (ARIMA) technique. The accuracy measurements tests for mean absolute error (MAE) and root mean square error (RMSE) were used in the investigation. Because ARIMA (0,2) was shown to be a more accurate predictor, it was chosen. The ARIMA (1, 0) and ARIMA (0, 2) forecasts did not differ, according to the Diebold-Mariano (DM) test. Policymakers might use the study's findings for intermediate-to long-term energy capacity succession plans, the study's conclusion stated.

In India, [11] forecasted carbon dioxide emissions from different sources of energy consumption. The study employed the linear and PSO algorithm nonlinear regression techniques. The outcome showed that compared to the multiple linear regression model, the PSO model could produce a more accurate estimate. The PSO forecasted carbon emissions from 2017 to 2030. Therefore, the study recommends that necessary steps be taken to reduce carbon emissions, which might affect the environment.

[12] applied the Box-Jenkins technique to Iran's agricultural sector energy consumption from 1988 to 2014. The predicted data is from 2015 to 2026, and the result indicated a downward trend in electricity consumption but is forecasted to go up. Similarly, it found that the ARIMA (4, 1, 2) model is more reliable when forecasting agricultural sector energy demand in Iran. It concluded that the Iranian agricultural sector is approaching sustainability, given the level of energy consumption. Thus, the study recommends that fuel prices be restructured to promote nonrenewable and renewable energy policy and switch to environmentally friendly sources.

[13] used annual data to forecast Morroco's solar and wind energy capacity in 2030. The study applied the additive and multiplicative models to data from 2008 and 2016 to predict an energy consumption estimate between 2017 and 2030. The result revealed that Morroco has potential for renewable energy, particularly wind and solar. The study concluded that the country will reach 52 per cent of installed electricity capacity from renewable energy sources in 2030.

Using the ARIMA model, [14] projected Turkey's energy consumption from 1970 to 2015. Oil, coal, renewable energy, natural gas, and overall energy use were all included in the study. For coal, oil, natural gas, and renewable energy, the results indicated ARIMA (1, 1, 1), ARIMA (0, 1, 0), and ARIMA (0, 1, 2) for total energy consumption. According to the study's findings, the nation's energy consumption will continue to rise through the end of 2040. To be more precise, annual average increases of 4.87 per cent, 1.64 per cent, 3.92 per cent, 4.20 per cent, and 4.87 per cent were projected for coal, natural gas, renewable energy, oil, and overall energy consumption, respectively.

[15] employed three ARIMA models to forecast electricity consumption in China. The study used a synthetic dataset and electricity consumption data for Guangdong province. The result suggested ARIMA (1, 1, 1) because of its precision, stability and suitability for forecasting electricity consumption. The study concluded that forecasting estimates are crucial to managing desired energy demand in the various sectors of an economy.

[16] used data from South Africa to forecast energy consumption from 1998 to 2016. To predict energy consumption from 2017 to 2030, the study used the ARIMA, nonlinear grey (NGM), and nonlinear grey-autoregressive integrated moving average (NGM-ARIMA) models. The result revealed that energy consumption would keep increasing at a growth rate of 7.49 per cent in the next 14 years. The report suggested changing policy to balance energy supply and demand.

[17] compiled data from 1971 to 2011 and used the autoregressive integrated moving average (ARIMA) model to forecast electricity usage in Nigeria. The outcome showed that, notwithstanding the present trend of energy consumption, Nigeria could only catch up to Italy, the twentieth-largest economy in the world, in 2671. Using 2012 as a base year, the study predicted that by 2050 or 2032, yearly increases in electricity usage of 10 to 20 per cent would be reached. The study recommends that an annual electricity consumption of 57 per cent would help achieve the feat in 2020.

[18] projected Nigeria's long-term household electricity demand from 2015 to 2029 using linear and quadratic regression models with a moderating term. The outcome showed that in 2029, home power consumption will amount to 6521.09 MW/h. Furthermore, research demonstrated that population is relevant and positive for both short- and long-term forecasting. Thus, the study concluded that quadratic models with moderating effects are more accurate in forecasting electricity demand because it has the highest coefficients compared to linear models.

Similarly to this, [19] examined historical data on Covenant University, Ota, Nigeria's electric energy consumption using the pseudo-inverse matrix (PIM) technique. The result revealed that the model's electricity consumption forecast was accurate for the study period from 2017 to 2016. Furthermore, the study concluded that the PIM technique predicted more precise and reliable future energy requirements for the university compared to the ordinary least squares model. Therefore, the study recommended the PIM technique to forecast a country's electricity demand, given historical data on past electricity consumption.

[2] employed the Harvey, Autoregressive and Markov chain models to forecast electricity generation and consumption in Nigeria using data from 1990 to 2017. The projection period for the study was from 2018 to 2037, and the maximum likelihood estimation technique was employed. The result revealed that the Markov chain technique best predicted electricity generation. Conversely, the Harvey technique predicted the best than others. Therefore, the study recommends the Markov-Harvey technique to forecast electricity generation and consumption for 20 years.

Methodology

Autoregressive Integrated Moving Average (ARIMA) Model

To predict energy consumption, numerous forecasting models have been employed in the literature to date. However, the most straightforward models seem to be those that rely on time series [1]. Time series models are suitable for observing past events to predict future outcomes. When predicting energy consumption using time series-based data, one of the methods most frequently used is the autoregressive integrated moving average (ARIMA) model. ([20]; [14]; [1]). Box and Jenkins created the ARIMA technique in 1976 to analyse a time series variable's characteristics objectively and determine which model best fits it. This procedure does not require an explanatory variable but depends on its past realization to predict future values. Thus, ARIMA models leverage autocorrelation procedures to forecast [14].

Three distinct random processes are combined into an ARIMA model; each effect is denoted by ARIMA (p, d, q). where MA(q) is the moving average method's order, I(d) is the integration process' order, and AR (p) is the autoregressive process' order. The sample data is not stationary, in which case the I(d) process of the model is applied. When the series is stationary at the first difference, d=1, if it is stationary at the level, and so on. The variable was believed to depend linearly on the past and current values of an error component in the moving average method. As described in the research of [14], the generalised baseline univariate ARIMA (p, d, q) model is represented as follows:

$$Y_t = \mu + \alpha_1 Y_{t-1} + \ldots + \alpha_p Y_{t-p} - \theta_1 \varepsilon_{t-1} - \ldots - \theta_q \varepsilon_{t-q} \qquad [1]$$

where α and θ are unknown parameters, ε is an independent identically distributed error term with zero mean, and Y_{t-1} is the differenced time series value. The moving average (MA) process is represented as q, while the lag autoregressive (AR) process is marked as p. Step 1 is identification, Step 2 is estimation, Step 3 is diagnostic checking, and Step 4 is forecasting. These steps were taken into consideration by the Box-Jenkins technique. Finding the model specification parameters p, d, and q is necessary for the identification process. The two main elements of the identification process are the autocorrelation function (ACF) and the partial autocorrelation function (PACF). To facilitate identification, the outcomes of ACF and PACF are shown against their lag length on a correlogram [17].

For stationarity, either a formal unit root test or a visual inspection of the correlogram is performed. If the variable is not stationary, the data is differenced until stationarity is attained. The values of p, d, and q are then calculated for the ARIMA estimation based on the order of stationarity. The predicted coefficient is then put through a diagnostic to ensure that it fits well. By extracting the estimation residual and determining if the ACF or PACF is significant, the variable fitness is obtained. On the other hand, if they don't matter, it will be assumed that the residuals are random and the estimated ARIMA model fits the data well. If not, an appropriate specification for the ARIMA model is used, and forecasting is carried out using the fitted model.

Data

Data on Nigeria's energy consumption from 1971 to 2014 was gathered for this analysis from the World Bank Development Indicator. Table 1 lists the sources and descriptions for the variable.

Table 1. Variables description and sources.

Variables	Code	Description	Source
Electricity consumption	ELC	Electric power consumption KWh per capita	World Bank(2022), WDI

ELC-electricity consumption

Results and Discussion

Finding the optimal ARIMA (p, d, q) specification is the first step in the Box and Jenkins 1976 ARIMA process. To accomplish this, Figure 1 displays the correlogram of electricity use with 20 lags. However, before the identification procedure, the data were subjected to the Augmented Dickey-Fuller unit root test. The unit root result in Table 2 revealed that electricity consumption (ELC) is stationary after the first difference, thus suggesting an ARIMA model. Furthermore, the correlogram result at the level showed that ACF begins from a high value of 0.865 at one lag and declines slowly to about ten lags. This implies that the ACF spikes are outside the 95 per cent confidence interval the broken lines represent. Thus, it is significantly different from zero. On the other hand, the PACF showed that other values are not significant after the first lag at 0.865. Thus, there is enough evidence of non-stationarity of the electricity consumption (ELC) data at the level.

When stationarity is not attained at the level, the identification process demands that the variable be differenced; as a result, the first differenced correlogram was performed to make electricity consumption (ELC) stationary. The outcome is shown in Figure 2. The pattern observed in Figure 2 suggests that electricity consumption (ELC) is stationary after the first difference. However, stationarity was achieved because the spikes for ACF and PACF remained within the 95% confidence interval the broken lines represented. Similar to this, the ACF and PACF displayed a damped sine wave pattern with good exponential decay. Because of their similar patterns, ACF and PACF are both statistically significant at Lag 1, suggesting the existence of an ARIMA process. The ARIMA (1, 1, 2) model was therefore applied.

Table 2: The ADF unit root test result.

Variable and Period	Level		First Difference	
Electricity Consumption (ELC)	t-Statistics	Prob.	t-Statistics	Prob.
Adjusted Sample: 1973 to 2014	-3.048456	0.1316	-8.728272	0.0000***
Test Critical Values: 1% = -4.186481; 5% = -3.518090; 10% = -3.189732				

Note: *** indicates significance at 1%, 5% and 10% levels; Prob.= Probability

Date: 07/25/22 Time: 01:10
Sample: 1971 2014
Included observations: 44

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.865	0.865	35.216	0.000
		2	0.770	0.088	63.820	0.000
		3	0.670	-0.054	86.004	0.000
		4	0.537	-0.198	100.58	0.000
		5	0.452	0.079	111.19	0.000
		6	0.384	0.058	119.02	0.000
		7	0.326	0.028	124.85	0.000
		8	0.240	-0.205	128.08	0.000
		9	0.187	0.037	130.10	0.000
		10	0.120	-0.052	130.95	0.000
		11	0.028	-0.125	131.00	0.000
		12	-0.003	0.095	131.00	0.000
		13	-0.024	0.084	131.04	0.000
		14	-0.039	0.013	131.14	0.000
		15	-0.028	0.010	131.20	0.000
		16	0.000	0.079	131.20	0.000
		17	0.016	0.022	131.22	0.000
		18	0.021	-0.042	131.25	0.000
		19	0.030	-0.051	131.32	0.000
		20	0.009	-0.064	131.33	0.000

Figure 1. Correlogram of electricity consumption at level.

Date: 07/25/22 Time: 00:11
Sample: 1971 2014
Included observations: 43

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.322	-0.322	4.7906	0.029
		2	-0.120	-0.250	5.4751	0.065
		3	0.254	0.148	8.5934	0.035
		4	-0.184	-0.081	10.277	0.036
		5	0.043	0.022	10.370	0.065
		6	-0.118	-0.213	11.093	0.086
		7	0.102	0.067	11.647	0.113
		8	-0.058	-0.093	11.833	0.159
		9	-0.012	0.054	11.841	0.222
		10	0.039	-0.072	11.930	0.290
		11	0.001	0.078	11.930	0.369
		12	-0.128	-0.221	12.953	0.373
		13	-0.006	-0.052	12.955	0.451
		14	-0.021	-0.211	12.984	0.528
		15	-0.059	-0.016	13.223	0.585
		16	0.057	-0.101	13.457	0.639
		17	0.008	0.075	13.462	0.705
		18	0.008	-0.104	13.467	0.763
		19	0.061	0.128	13.765	0.797
		20	-0.041	-0.147	13.904	0.835

Figure 2. Correlogram of electricity consumption at first difference.

Estimation

The second stage in the ARIMA procedure is estimating the AR(1) and MA(2) models selected for this study. The D(ELC) represents the first difference values for electricity consumption. In the sequel to the conclusion in step one, the model to be estimated is specified as:

$$D(ELC)_t = \delta + \beta_1 D(ELC)_{t-1} + \mu_t$$

[3]

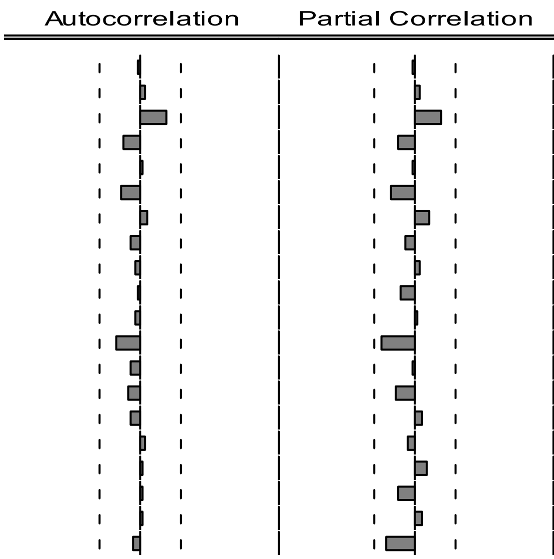
Estimating equation 3 gives the result below:

D(ELC) = 2.75825426338 + [AR(1)=-0.346829762604,MA(2)=-0.276431239389 [4]

Diagnostic Checking

Using a correlogram to assess the goodness of fit, diagnostic tests are run on the residuals derived from equation 3 in the third step of the ARIMA process. Figure 3 presents the ACF and PACF results.

Date: 07/25/22 Time: 03:55
Sample: 1971 2014
Included observations: 43
Q-statistic probabilities adjusted for 2 ARMA terms



	AC	PAC	Q-Stat	Prob
1	-0.021	-0.021	0.0200	
2	0.038	0.038	0.0892	
3	0.193	0.195	1.8983	0.168
4	-0.129	-0.126	2.7209	0.257
5	0.010	-0.010	2.7256	0.436
6	-0.147	-0.183	3.8517	0.426
7	0.045	0.102	3.9629	0.555
8	-0.068	-0.081	4.2154	0.648
9	-0.031	0.041	4.2684	0.748
10	-0.017	-0.100	4.2854	0.830
11	-0.045	0.014	4.4064	0.883
12	-0.177	-0.255	6.3558	0.785
13	-0.077	-0.012	6.7352	0.820
14	-0.083	-0.152	7.1982	0.844
15	-0.078	0.051	7.6172	0.868
16	0.030	-0.061	7.6834	0.905
17	0.011	0.082	7.6925	0.936
18	0.022	-0.120	7.7316	0.956
19	0.016	0.055	7.7511	0.972
20	-0.053	-0.206	7.9842	0.979

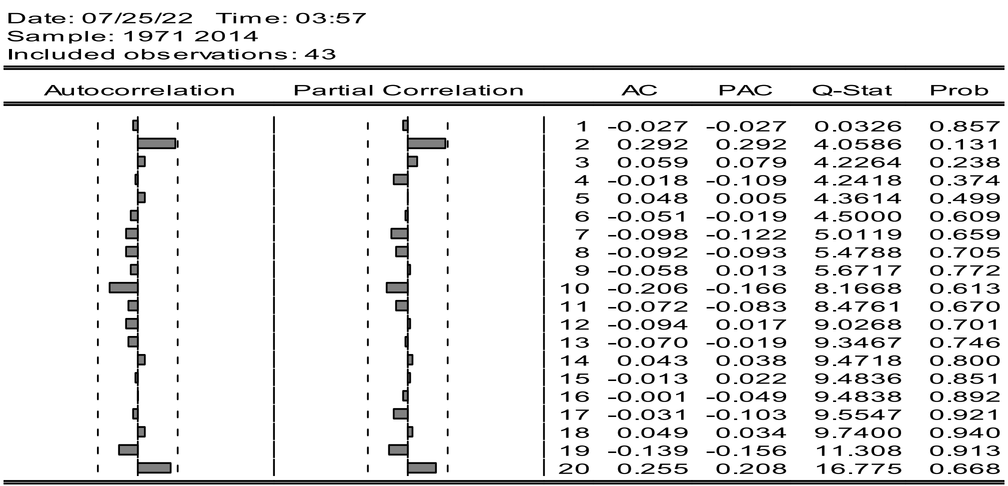
Figure 3. Correlogram of residuals.

Figure 3 presents the result of the correlogram of residuals for the Adjusted ARIMA Model obtained after estimating the ARIMA (1, 1, 2) model. The findings indicate that there is no significant difference between the lags of ACF and PACF because the spikes are flat and fall under the 95 per cent confidence interval, as indicated by the broken lines. This suggests that the residuals from the calculated model are stochastic, as shown by the diagnosis correlograms for both AC and PAC. Thus, the ARIMA (1, 1, 2) model specified for this study is adequate for forecasting electricity consumption in Nigeria.

Ljung-Box Test for Correlation

Forecasted model

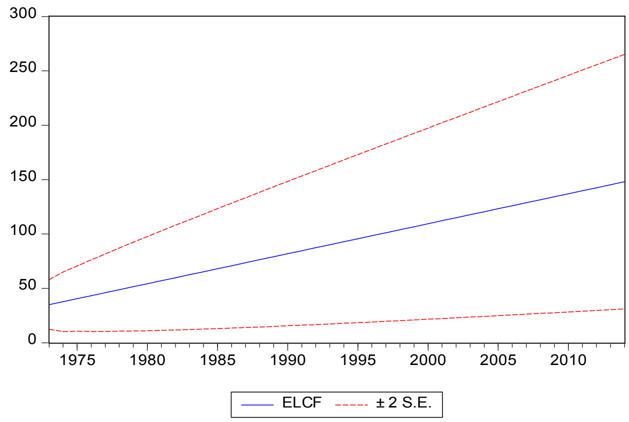
After obtaining the appropriate ARIMA model for electricity consumption in Nigeria, we further estimated and forecasted the trends between the forecast (ELCF) and the actual (ELC) data. Tables 5 and 6 present the results of the electricity demand forecast for Nigeria we obtained using the ARIMA (1, 1, 2) model. The result obtained shows that the chosen model is adequate for modelling and forecasting electricity consumption in Nigeria. This result runs counter to the research conducted by [15] and [12]. Thus, future forecasts can add to the existing historical data and apply the same model.



Date: 07/25/22 Time: 03:57
Sample: 1971 2014
Included observations: 43

	AC	PAC	Q-Stat	Prob
1	-0.027	-0.027	0.0326	0.857
2	0.292	0.292	4.0586	0.131
3	0.059	0.079	4.2264	0.238
4	-0.018	-0.109	4.2418	0.374
5	0.048	0.005	4.3614	0.499
6	-0.051	-0.019	4.5000	0.609
7	-0.098	-0.122	5.0119	0.659
8	-0.092	-0.093	5.4788	0.705
9	-0.058	0.013	5.6717	0.772
10	-0.206	-0.166	8.1668	0.613
11	-0.072	-0.083	8.4761	0.670
12	-0.094	0.017	9.0268	0.701
13	-0.070	-0.019	9.3467	0.746
14	0.043	0.038	9.4718	0.800
15	-0.013	0.022	9.4836	0.851
16	-0.001	-0.049	9.4838	0.892
17	-0.031	-0.103	9.5547	0.921
18	0.049	0.034	9.7400	0.940
19	-0.139	-0.156	11.308	0.913
20	0.255	0.208	16.775	0.668

Figure 4. Ljung-box test for autocorrelation.



Forecast: ELCF
Actual: ELC
Forecast sample: 1971 2014
Adjusted sample: 1973 2014
Included observations: 42

Root Mean Squared Error	14.68306
Mean Absolute Error	11.76256
Mean Abs. Percent Error	14.34219
Theil Inequality Coefficient	0.075608
Bias Proportion	0.000078
Variance Proportion	0.024869
Covariance Proportion	0.975053
Theil U2 Coefficient	1.162208
Symmetric MAPE	14.09011

Figure 5. Electricity demand forecast.

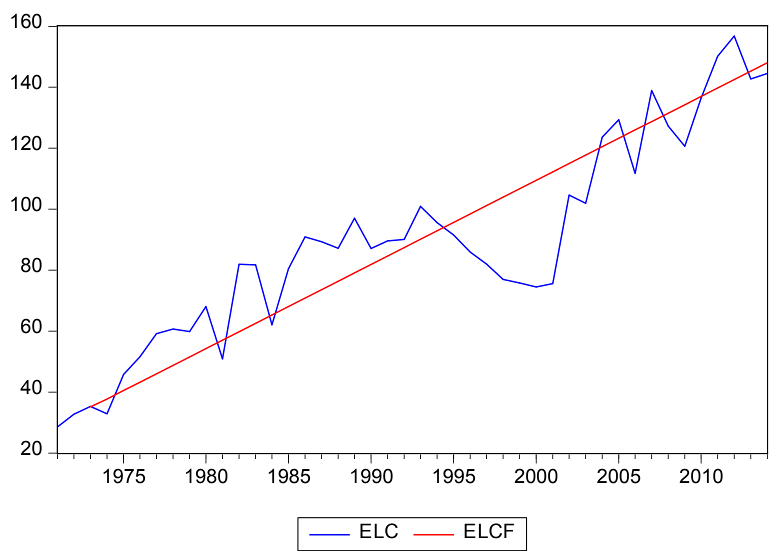


Figure 6. Electricity demand forecast

Conclusions

Electricity demand forecasting is vital for energy supply and macroeconomic policy modelling. Integrating demand forecasting with other policy objectives can help economies plan. As a result, we used the Box-Jenkins ARIMA model to estimate Nigeria's electricity consumption. The research collected historical electricity consumption data spanning from 1971 to 2014. The outcome demonstrated that the ARIMA (1,1,2) model is suitable for modelling and predicting Nigeria's electricity consumption. We advise academics and policymakers to use the ARIMA (1, 1, 2) model for projecting Nigeria's energy supply in light of this conclusion.

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Authors' contributions: James Tumba Henry conceptualized, prepared the original draft, supervised, analysed the data; Amade Peter contributed to data interpretation and literature review; All authors read and approved the final manuscript.

Data availability statement: Data supporting this manuscript will be provided upon reasonable request from the corresponding author.

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