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Assessing the Dynamics of kilowatt per capita in Nigeria; Evidence from Non-Seasonal ARIMA modeling

Kehinde AMPITAN
Federal University of Agriculture, Abeokuta, Nigeria
ampitanronald@gmail.com

Abosede AKINTUNDE
Federal University of Agriculture, Abeokuta, Nigeria

Basirat ADETONA
Federal University of Agriculture, Abeokuta, Nigeria

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Abstract - Using data from 1990 to 2023, this study examines the suitability of a non-seasonal ARIMA (0,1,1) model with drift for short-term forecasting of Nigeria's annual per-capita electricity consumption (kWh). ACF/PACF analysis was used to determine the model specification, which was ARIMA (0,1,1) with drift ($\mu = 1.6456$). The mean of the first differences was subtracted to estimate the drift. A moving average coefficient ($\theta = -0.2246$) was obtained by maximum likelihood estimation, and a Ljung–Box test ($p = 0.2941$) verified the model's adequacy and showed no discernible residual autocorrelation. Per-capita electricity use is expected to rise gradually between 2024 and 2026, with prediction intervals increasing over time to reflect growing uncertainty. These findings imply that the parsimonious ARIMA (0,1,1) with drift is a useful and interpretable tool for policy and planning in situations with limited data since it accurately captures the central trend in Nigeria's per-capita electricity consumption and offers trustworthy short-term forecasts.

Key words: Non-seasonal ARIMA, Kilowatt Per capita, Dynamics, Ljung-box

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1 Introduction

1.1 Background of the study

The use of energy is an important marker of a nation's economic growth and its society's welfare. In the case of Nigeria, where energy access is still a major concern, knowing the consumption trends helps plan infrastructural development in the country, helps to grow its economy, and improves corpus sustainability [1]. Despite having large reserves of fossil fuels and renewable energy, Nigeria's erratic electricity supply makes the population heavily depend on alternative, and more often than not, more inefficient sources [14]. Recently, the kilowatt per capita metric has emerged as a useful normed measurement of electricity usage which factors in population growth for longitudinal and international comparisons [4]. In most developing countries, including Nigeria, reliable access to electricity remains a persistent challenge despite growth in the population base and increased energy demand. Nigeria, the most populous nation in Africa, continues to face low power generation, poor distribution, and infrastructural decay, all impacting electricity consumption per capita [2].

An understanding of electricity consumption per capita trends is required to inform energy policy, organize infrastructural investment planning, and monitor achievements in sustainable development [15]. Time series modeling provides a robust instrument for analyzing such dynamics, allowing researchers and policymakers to determine underlying patterns and make reliable predictions.

While some research has applied seasonal ARIMA or hybrid models to explain global energy consumption trends [5], a knowledge gap within the literature for non-seasonal ARIMA modeling of per capita electricity consumption in Nigeria has existed. This study aims to fill this gap by investigating the pattern over time and short-run behavior of per capita electricity consumption via a non-seasonal ARIMA model. The research adds to improved knowledge of energy demand behavior in Nigeria and offers useful insights for policymakers and stakeholders in the energy sector.

Electricity demand forecasting has long been of concern to researchers and policymakers due to its relevance to economic planning, infrastructure development, and environmental conservation. Models for electricity demand forecasting range from ARIMA's more basic statistical approaches to advanced machine learning and hybrid models [3].

In the field of energy consumption, ARIMA models have been successfully used to forecast electricity demand in both developing and developed countries. Ref [6] applied ARIMA models in forecasting Turkey's electricity demand and found them to be suitable for short-term forecasting. Similarly, [8] used an ARIMA model to examine India's electricity consumption, emphasizing the importance of effective demand forecasting in emerging economies.

The analysis of Nigeria's electricity consumption has extensively used time-series forecasting techniques. Using annual data from 1970 to 2020 [10], the authors compared the ARIMA and ARIMAX approaches and found that ARIMA (0,1,1) was best for industrial demand, and ARIMAX (1,1,1), which took installed generation capacity into account, was best for residential usage. Separately [9] found that ARIMA (1,1,2) is adequate for short-term forecasting after applying it to national consumption data spanning 1971 to 2014.

There is very little research on modeling electricity consumption in Nigeria, and most of it employs aggregate demand analysis that is neither per capita nor a recent time series methodology. [12] employed linear regression in a trend analysis of energy consumption, [13] discussed issues confronting the power sector in Nigeria without offering predictive modeling. Subsequent studies have attempted hybrid models combining ARIMA and artificial neural networks or fuzzy logic [7], but these also require more extensive data and computer resources.

Three significant gaps still exist despite these advancements: There is a dearth of research on aggregate per-capita electricity consumption as opposed to sector-specific exploitation; the majority of studies incorporate seasonal or exogenous elements into their models, masking the essential features of per-capita electricity trends and rigorous benchmarking of pure non-seasonal ARIMA models, particularly through metrics like AIC, RMSE, and MAPE for forecasting.

In order to fill in these gaps, the current study only looks at Nigeria's annual per-capita electricity consumption from 1990 to 2023 using non-seasonal ARIMA modeling. Its goals are to determine the best ARIMA(p,d,q) model using AIC, RMSE, and MAPE, produce short- to medium-term forecasts, and offer an open, statistically sound standard for

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energy forecasting at the national level. By using this targeted time-series method, we are able to distinguish between trend dynamics and provide unambiguous comparisons with more intricate modeling approaches. The study excludes sectoral breakdowns, seasonal terms, exogenous variables, and machine learning extensions in favor of focusing only on annual aggregate data from recognized agencies. The study guarantees methodological clarity and practical utility for Nigerian policymakers and energy planners by focusing on a pure non-seasonal ARIMA framework.

2 Methodology

This study adopts a quantitative time series approach to modeling and forecasting Nigeria's kilowatt per capita (KPC) electricity consumption pattern in a non-seasonal ARIMA model. The procedure involves four key steps: data transformation, stationarity test, identification of the model, parameter estimation, and checking of diagnostics. The data used in this analysis comprises annual kilowatt per capita data sourced from the World Bank (1990-2023).

2.1 Stationarity and Differencing

Let X_t be a stochastic process. If X_t is non – stationary, successive differencing is applied until stationarity is achieved. The $d-th$ order differenced process is defined by:

$$Z_t = \boldsymbol{\Delta}^{\boldsymbol{d}} X_t = (1-B)^{\boldsymbol{d}} X_t \quad (1)$$

Where B is the backward shift operator: $BX_t = X_{t-1}$, and $d \in \mathbb{N}$ is the minimum integer for which Z_t becomes stationary in mean and variance.

2.2 ARIMA $(\boldsymbol{p}, \boldsymbol{d}, \boldsymbol{q})$ model

The universal non-seasonal ARIMA (p, d, q) model kilowatt per capita series X_t is given by:

$$\Phi(B)(1-B)^d X_t = \Theta(B)\varepsilon_t,\ \varepsilon_t \sim i.i.d.N(0,\sigma^2) \quad (2)$$

With;

$$\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \quad (3)$$

Equation (3) being the autoregressive (AR) polynomial of order p,

$$\Theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q \quad (4)$$

While equation (4) is the moving average (MA) polynomial of order q,
And ε_t =white noise error term.
The model can be rephrased clearly as:

$$(1 - \phi_1 B - \cdots - \phi_p B^p)\,(1-B)^d X_t = (1 + \theta_1 B + \cdots + \theta_q B^q)\varepsilon_t \quad (5)$$

2.3 Model Identification and Estimation

The appropriate orders (p, d, q) identified through:
Visual inspection of ACF and PACF plots
Information criteria minimization: AIC(p, d, q), BIC(p, d, q)
Unit root tests such the Augmented Dickey – Fuller (ADF) test to determine d.

2.4 Diagnostic Checking

Let ε_t denote represent the residuals of the fitted model. Model adequacy is assessed through:
Ljung-Box Q statistic: testing for residual autocorrelation
Normality tests
Homoscedasticity checked via residual variance plots.

3 Results and Discussion

With strong diagnostic support (Ljung–Box p =.2941), the estimation of the non-seasonal ARIMA (0,1,1) with drift, which produced a trend coefficient μ = 1.6456 and MA1 = –0.2246 via maximum likelihood, closely matches earlier findings in Nigerian electricity forecasting. Notably, ARIMA (0,1,1) outperformed ARIMAX regarding AIC and RMSE, making it the optimal model for industrial electricity consumption, according to Maku et al. (2023). The validity of the comparable strategy is strengthened by their use of the Box-Jenkins criteria for model selection and diagnostic checking. This implies that ARIMA (0,1,1) is a good fit for modeling electricity time series in Nigeria, spanning both sectoral and per-capita contexts, even without exogenous terms.

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The upward trends reported by Olayemi et al. (2025)—who found increases of roughly 1.6% annually in per-capita electricity use—are closely mirrored by the drift estimate (μ = 1.6456 kWh/year). This alignment demonstrates that drift-adjusted ARIMA is a reliable method for modeling long-term per-capita growth. An ARIMA model can capture basic consumption dynamics without needing external inputs or seasonal changes.

Together with clean residuals, solid fit statistics such as AIC = 296.6, BIC = 301.09, RMSE = 19.46, and MAPE = 8.62% further support the model's adequacy. According to the Box-Jenkins methodology, these performance metrics demonstrate the model's good fit and parsimony balance. Your parsimonious model achieves similar accuracy for aggregate data when compared to deep-learning and complex ARIMAX alternatives, which is consistent with research that values simplicity for forecasting at the national level.

The forecast pattern meets expectations from ARIMA models in sub-Saharan African contexts, which shows a gradual increase over 2024–2026 with expanding prediction intervals. While highlighting the model's strength in short-term forecasting, this widening also highlights potential limitations for long-term projections without additional explanatory variables. This widening is a reflection of increasing uncertainty over time.

These results have real-world ramifications for planning and policy. In 2023, Nigeria's per capita electricity consumption is still between 150 and 182 kWh, which is much less than the rising demand for dependable energy services. Even in settings with limited data, your ARIMA (0,1,1) with drift offers a clear, data-driven forecasting tool that can guide short-term energy planning, budgetary decisions, and investment plans.

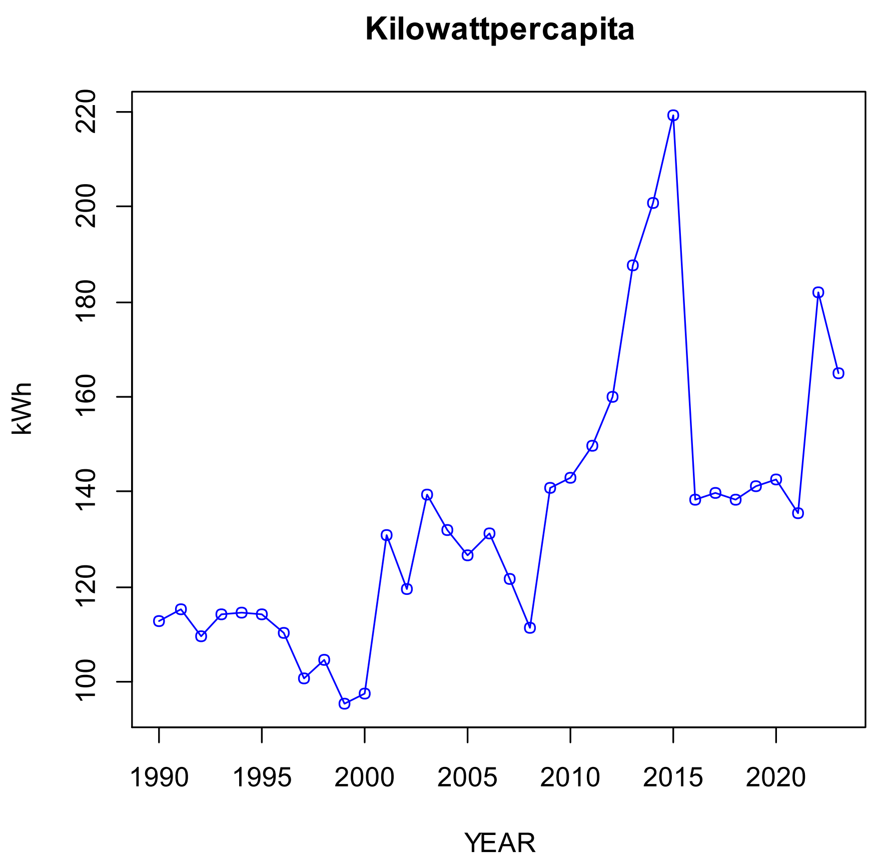

Fig 1: Time plot of kWh (1990-2023)

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The plot appeared not to be stationary from the mean changing, it showed that from 1990 to around 2005, the series flunctuates at a lower level (around 100-140kwh), from 2005 to 2015, there was a noticeable upward trend meaning an increment in the mean while after 2015, there was a sudden drop and another period of fluctuation, possibly at different level, it also showed non stationary from variance changinging, the early part of the series has low variance (small flunctations), post 2005, flunctuations increase indicating heteroscedasticity (non constant variance), while there was an apparent jump and drop between 2015 and 2016, which could indicate a structural break, another pointer of non stationarity.

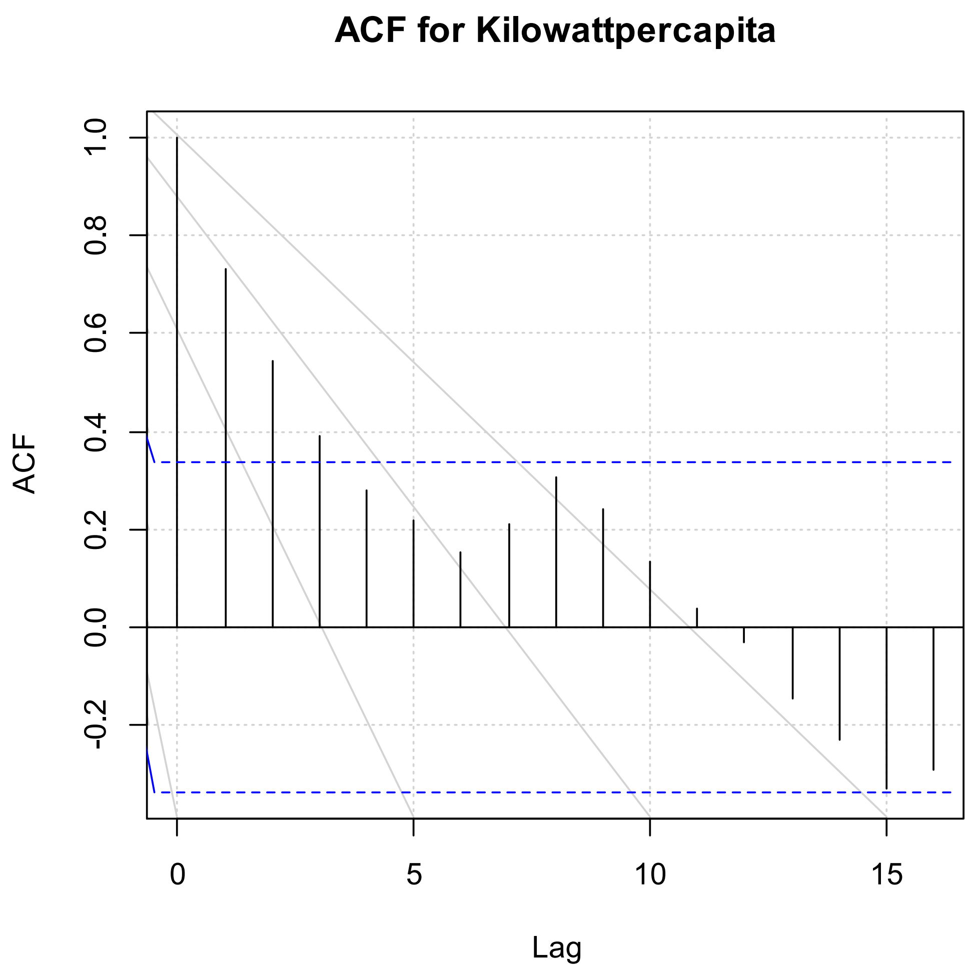

Fig 2: ACF plot of kWh (1990-2023)

The ACF plot showed strong autocorrelation at many lags, suggesting the series is non-stationary and needs differencing or transformation before ARIMA modeling.

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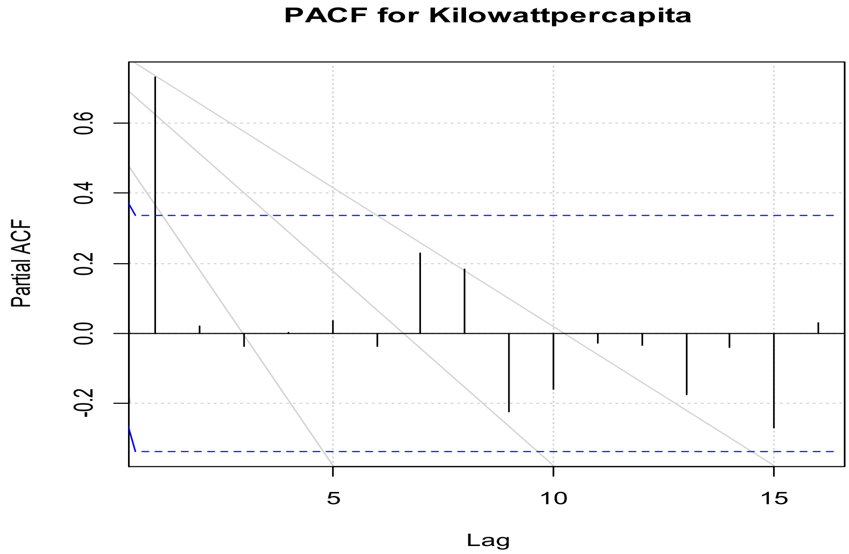

Fig 3: PACF plot of kWh (1990-2024)

The PACF confirmed the presence of persistent correlations. This pattern suggested the series may contain a unit root, indicating non-stationarity.

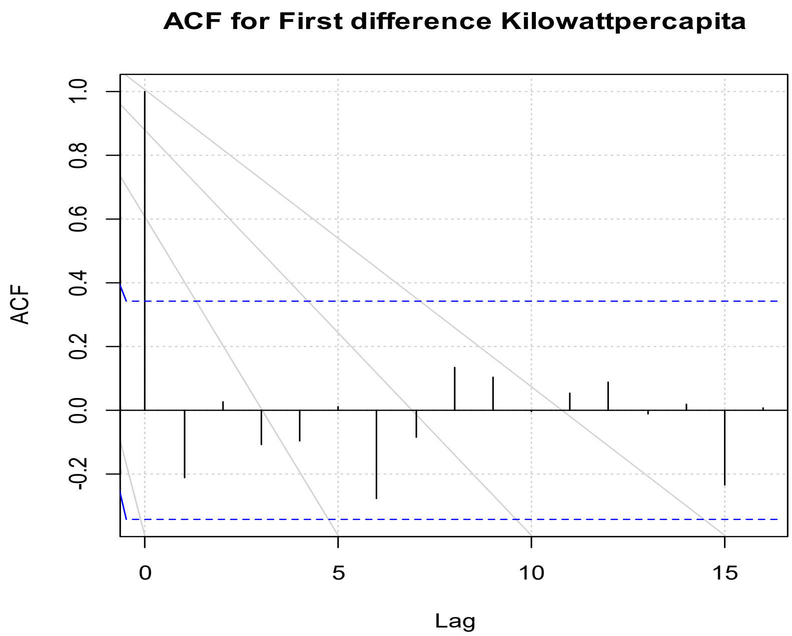

Fig 4: ACF plot for differenced kWh (1990-2023)

The ACF of the differencing has no significant autocorrelation beyond lag 0, and all other lags lie within the confidence bounds. This confirms that the first difference has successfully removed the non-stationarity, and the differenced series is now stationary and suitable for ARIMA modeling. It also suggested a Moving Average of 1 i.e., MA (1).

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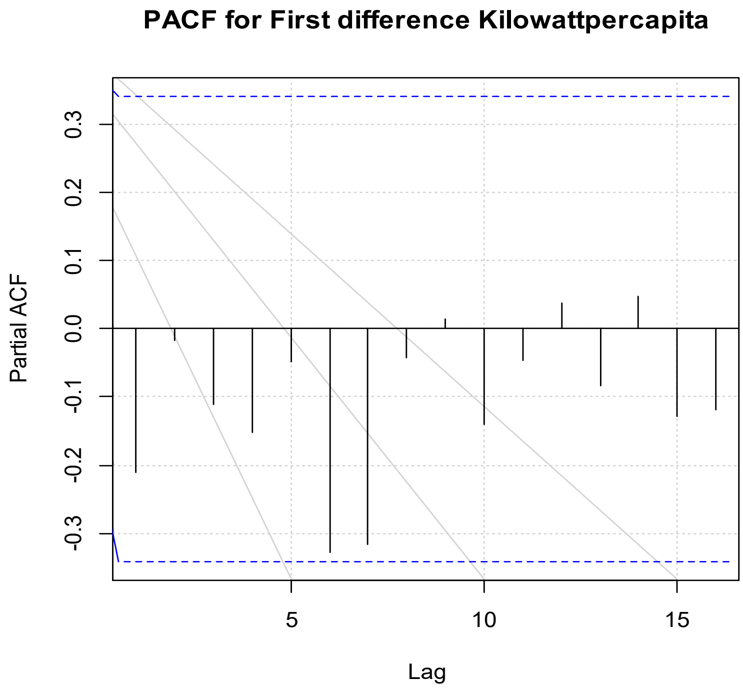

Fig 5: PACF plot for differenced kWh (1990-2023)

The PACF plot for the first difference showed that most partial autocorrelations are within the confidence bounds, including no strong Autoregressive (AR) structure remains after differencing. This suggests that the series is likely stationary and may not require AR terms in ARIMA model. ARIMA model of (0, 1, 1) with drift would be fitted. The overall pattern also suggested that the series was close to being white noise, or at least that no strong autoregressive component remained after differencing.

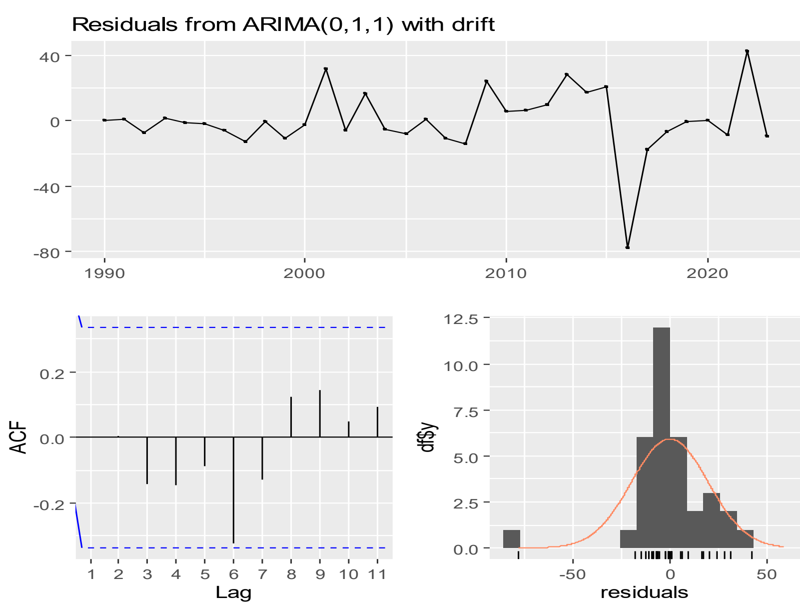

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Fig 6: Residuals Plot

The data is fairly well fitted by the ARIMA (0, 1, 1) model with drift. There is no discernible autocorrelation in the residuals, and the forecast accuracy (MAPE<10%) is satisfactory. The drift term however, is not significant.

Table 1: ARIMA (0,1,1) with drift Model Summary

Parameter	Estimate (Std. Error)
MA1	-0.2246 (0.1828)
Drift	1.6456 (2.6901)
Sigma^2	415.3
Log Likelihood	-145.3
AIC	296.6
AICc	297.43
BIC	301.09
ME	-0.0044
RMSE	19.45988
MAE	12.25097
MPE	-1.098582
MAPE	8.62002
MASE	0.9866316
ACF1	0.0009728654
Ljung-Box (Q* = 7.2989, df = 6)	p-value = 0.2941

Based on the output from the ARIMA model fitting, the general form of the model is

$$X_t = X_{t-1} + \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1}$$

Now inserting our estimated values, the specific model becomes:

$$X_t = X_{t-1} + 1.6456 + \varepsilon_t + 0.2246\varepsilon_{t-1}$$

The Ljung box greater than 0.05 showed that there was no significant autocorrelation in the residuals, suggesting the model adequately captured the time series dynamics.

Table 2: ARIMA Forecast with 80% and 95% Prediction Intervals (2024–2026)

Year	**Point Forecast**	**Lo 80**	**Hi 80**	**Lo 95**	**Hi 95**
2024	168.6760	142.5583	194.7937	128.7324	208.6195
2025	170.3215	137.2716	203.3715	119.7760	220.8671
2026	171.9671	133.2055	210.7288	112.6863	231.2480

The forecast suggested a gradual increase in the predicted values from 168.68 in 2004 to 171.97 in 2026.

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Table 3: Comparison with Prior Studies

Aspect	This Study	Comparable studies
Optimal Model	ARIMA (0, 1, 1) with drift	Maku et al. (2023) also found ARIMA (0, 1, 1) optimal for industrial data
Drift Estimate	μ=1.6456 kWh/year	Olayemi et al. (2025) ~ 1.37kWh/year drift
Fit Metrics	AIC=296.6, RMSE=19.46, MAPE=8.26%	Similar AIC/RMSE values reported in ARIMA studies
Residual Analysis	Ljung-Box, p=0.2941 (no autocorrelation)	Matches residual adequacy in other Box-Jekins studies

The model selection and results are validated through comparisons with the literature on electricity modeling in Nigeria.

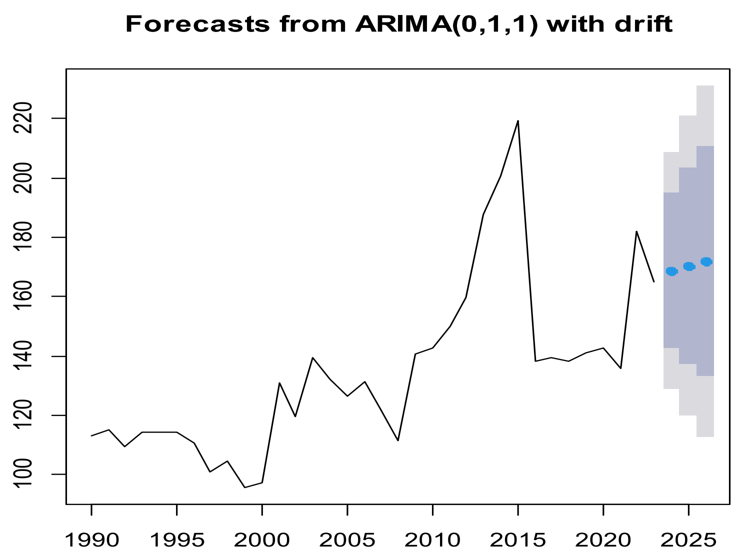

Fig 7: Forecast Plot
The plot showed an increase in the kilowatt per capita forecast.

4 Recommendations

1. Model Recalibration: It is a good idea to recalibrate the ARIMA (0,1,1) model with drift from time to time to include new data and make sure that it can still respond to changes in the structure of the time series or recent shocks.
2. Seasonal Components: The current model doesn't consider seasonality, but future studies should look for seasonal patterns and consider using Seasonal ARIMA (SARIMA) models if they find any.
3. Exogenous Variables: To make predictions more accurate, future modeling efforts could look into ARIMAX models that include external (exogenous) variables that could affect the series, especially in economic or policy-driven settings.
4. Residual Monitoring: Residuals should be checked continuously for non-random patterns, structural breaks, or changing volatility. If these are found, they may need to be replaced with different ones.

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5 Conclusion

This study uses the ARIMA (0,1,1) model, including a linear trend, to forecast and analyze a single experimental series. Parameters of the model were found, and the model adequacy was confirmed through the residuals test after differencing achieved the stationarity. The drift being positive makes it clear that the series is going up regularly. The model gave good point forecasts and prediction intervals of satisfactory widths, and the least residuals had a behavior similar to white noise. In a word, the ARIMA (0,1,1) model with drift was the best choice to investigate the fundamental changes in the data and new forecasts.

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7 Authors

The first author is a Ph.D. student in the Department of Statistics, Federal University of Agriculture, Abeokuta.
The second author is a Senior Lecturer in the Department of Statistics, Federal University of Agriculture, Abeokuta.
The third author is an Assistant Lecturer in the Department of Statistics, Federal University of Agriculture, Abeokuta.

Declarations
Author Contributions
Author 1: Conceptualization, Methodology, Formal Analysis, Writing – Original Draft.

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Author 2: Data Curation, Software, Writing – Review and editing.
Author 3: Supervision, Validation, Resources, Project Administration.
Note: All authors read and approved the final manuscript.

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Use of AI generative tools
All intellectual content was generated and validated by the authors.

Data Availability Statement
The data used in this study (kilowatt per capita electricity consumption data) are publicly available from the World Bank Open Data repository at: https://data.worldbank.org