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Energy Abundance vs Energy Poverty in Nigeria: Empirical Analysis of Access to Clean Cooking Fuels and Technologies

Kagarura Willy Rwamparagi [a], Nahabwe Patrick Kagambo John [a] and Byaruhanga Stephen Rwaheru [a,b*]

[a] Kabale University, Plot 364 Block 3 Kikungiri Hill, Kabale Municipality, P.O Box 317, Kabale, Uganda.
[b] School of Science and Engineering, Atlantic International University, Pioneer Plaza, 900 Fort Street Mall 905, Honolulu, Hawaii 96813, United States of Americ.

Authors' contributions

This work was carried out in collaboration among all authors. Author BSR is the main author of the manuscript. Authors KWR and NPKJ have provided aid in organizing the manuscript. All authors read and approved the final manuscript.

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ABSTRACT

The paradox of energy abundance and energy poverty describes the contradiction where countries endowed with vast energy resources struggle to provide modern energy access to their populations. According to the World Bank, less than 15% of Nigerians have access to clean

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**Corresponding author: Email: sbyaruhanga596@gmail.com;*

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cooking energy, with the majority relying on traditional biomass such as firewood and charcoal, which have adverse health, environmental, and socio-economic implications. This paradox in Nigeria is investigated by analysing access to clean fuels and technologies for cooking, quarterly time-series data from the World Bank spanning 2000 to 2024. The Autoregressive Integrated Moving Average (ARIMA) (p,d,q) modelling framework was employed to analyse and forecast trends in clean cooking energy access. The model incorporates access to clean fuels and technologies for cooking (% of population) as the dependent variable, while autoregressive (AR) and moving average (MA) components serve as independent variables. The study is grounded in the Energy Ladder Theory, which posits that households transition from traditional biomass to cleaner and more efficient energy sources as income and education levels rise. Estimation using Generalised Least Squares (GLS) reveals a statistically significant positive coefficient for MA (4) at 0.4567, suggesting that approximately 46% of current variations in access levels are influenced by past shocks occurring four quarters earlier. Historical data from 2000 to 2024 reveal very low adoption rates of clean cooking fuels, starting below 1% and only reaching about 30.8% by 2024. The ARIMA (1,2,4) model projects a continued but modest upward trend through 2050, with substantial uncertainty surrounding the pace of growth. The study contributes to the expanding discourse on energy justice in resource-rich but energy-poor economies. It affirms that sustainable development in Nigeria depends not only on exploiting energy resources, but on dismantling the structural barriers that hinder equitable access to their benefits. Given the findings, we recommend that policymakers prioritise targeted investments in clean cooking infrastructure, expand public awareness campaigns on the health and environmental benefits of clean fuels, and strengthen regulatory frameworks to encourage private sector participation in clean energy delivery.

Keywords: Autoregressive Integrated moving average; energy abundance; energy poverty; Nigeria, energy ladder theory.

SYMBOLS

AR : Autoregressive
MA : Moving Average
ADF : Augmented Dickey-Fuller Test
GLS : Generalized Least Squares
SDG : Sustainable Development Goal
GDP : Gross Domestic Product
AIC : Akaike Information Criterion
BIC : Bayesian Information Criterion
R^2 : Coefficient of Determination
p : Autoregressive order (number of AR lags)
d : Differencing order for stationarity in ARIMA
q : Moving average order (number of MA lags)
εt : Error term (white noise) at time t
yt : Dependent variable (access to clean fuels at time t)
Ω : Variance-covariance matrix of error terms
SD : Standard Deviation

1. INTRODUCTION

Sub-Saharan Africa (SSA) significantly lags behind in providing clean cooking energy to its population. It is commonly recognised that the cooking methods in the Global South are not sustainable, and at the same time, the share of energy spent on cooking in households is high. For instance, in Kenya, 98% of the energy spent in a household goes on cooking and hot water, whereas for the same activities, a household in Spain spends 50% (Vassiliades et al., 2022; Mewamba-Chekem & Noumessi Fodjou, 2021).

Nigeria is endowed with vast energy resources, including oil, natural gas, coal, and considerable renewable energy potential, such as solar and hydro. Despite this abundance, a significant portion of the Nigerian population continues to suffer from energy poverty, particularly in the form of limited access to clean fuels and technologies for cooking. According to the World Bank (2024), less than 15% of Nigerians have access to clean cooking energy, with the majority relying on traditional biomass such as firewood and charcoal, which have adverse health, environmental, and socio-economic implications. At COP26, Nigeria announced its commitment to carbon neutrality by 2060. Nigeria's Energy Transition Plan (ETP) was unveiled shortly after, highlighting the scale of effort required to achieve the 2060 net-zero target whilst also meeting the nation's energy needs (Nigeria's Energy Transition Plan, 2022; Ekechukwu & Eziefula, 2025).

The paradox of energy abundance amidst persistent energy poverty raises critical questions about the efficiency of energy governance, policy implementation, and infrastructure development in Nigeria. Although the country ranks among the top oil and gas producers in Africa, energy services remain unreliable, unaffordable, and inaccessible for millions, especially in rural and peri-urban areas (IEA, 2022). Women and children are disproportionately affected due to their central roles in household energy use, exposing them to indoor air pollution, respiratory diseases, and time poverty (WHO, 2021).

The research problem stems from this disconnection between resource wealth and actual energy service delivery. Several studies have explored electricity generation and grid access in Nigeria; however, fewer have empirically examined access to clean cooking fuels using time-series forecasting approaches. A study indicates that SSA's access to clean fuels and cooking technologies is 44 percentage points lower than the average in Asia, Latin America, and Europe. Economic differences and resource endowments account for approximately 60 per cent of this gap (Malah-Kuete, 2025). This study fills the gap by employing the Autoregressive Integrated Moving Average (ARIMA) model to analyse and forecast access to clean cooking fuels over time. Understanding the dynamics of this access is crucial for designing informed policies aligned with Sustainable Development Goal 7 (Affordable and Clean Energy for All). The rationale for the study lies in its potential to provide empirical evidence that supports targeted interventions and policymaking. By forecasting trends in clean cooking fuel access, the study helps anticipate future challenges and assess the feasibility of Nigeria achieving universal energy access despite its abundant energy endowment. Ultimately, it aims to contribute to the broader discourse on energy justice and sustainable development in resource-rich but energy-poor settings.

2. PROBLEM DESCRIPTION

Despite Nigeria’s vast endowment of energy resources, including oil, natural gas, coal, and abundant renewable potential such as solar and hydro, the majority of its population remains trapped in energy poverty. The contradiction lies in the fact that while Nigeria ranks among the largest oil and gas producers in Africa, less than 15% of households have access to clean fuels and technologies for cooking. Instead, traditional biomass such as firewood and charcoal dominate household energy consumption, particularly in rural and peri-urban communities.

This situation has far-reaching implications: reliance on biomass fuels exposes women and children to household air pollution, respiratory diseases, and significant time poverty from fuel collection. Environmentally, deforestation and greenhouse gas emissions are exacerbated, undermining climate change mitigation efforts. Economically, energy poverty restricts productivity, reinforces poverty cycles, and hinders the attainment of Sustainable Development Goal 7 (affordable and clean energy for all).

The persistence of this paradox is rooted not in resource scarcity but in systemic inefficiencies, weak infrastructure, poor governance, and fragmented policy implementation. Previous research has mainly concentrated on electricity access and generation capacity, leaving a knowledge gap on clean cooking energy dynamics. This research, therefore, addresses this gap by empirically investigating Nigeria’s clean cooking access trends using a time-series forecasting approach (ARIMA), in order to better understand the inertia and structural challenges hindering progress.

3. RESEARCH OBJECTIVES

1. To analyze historical patterns of household access to clean cooking fuels in Nigeria.
2. To apply ARIMA forecasting models to predict future clean cooking adoption trends.
3. To evaluate policy, governance, and institutional barriers affecting energy access expansion.
4. To recommend data-driven strategies for achieving universal clean cooking access in Nigeria.
5. To contribute empirical insights to Nigeria’s progress toward Sustainable Development Goal 7.

4. MATERIALS AND METHODS

We adopt a quantitative, longitudinal research design rooted in time-series econometric analysis. The choice of this design is informed by the objective to examine long-term trends and dynamic patterns in access to clean fuels and technologies for cooking in Nigeria. A longitudinal framework is suitable for assessing the persistence of energy poverty over time, particularly in the context of energy resource abundance. Quantitative methods allow for objective measurement, forecasting, and empirical validation using statistical models (Gujarati & Porter, 2009; Nahabwe & Kagarura, 2025).

We utilise secondary time-series data obtained from the World Bank's World Development Indicators (WDI) database, focusing on Nigeria. The key variable of interest is "Access to clean fuels and technologies for cooking (% of population)", representing the dependent variable. The dataset spans quarterly observations from 2000 to 2024, offering 97 data points for robust time-series modelling.

No sampling is conducted in the conventional sense, as we leverage complete national-level data rather than survey-based microdata. Annual data is transformed into a quarterly format using frequency disaggregation methods, such as the Chow-Lin technique, to enable more detailed temporal analysis (Chow & Lin, 1971; Nahabwe & Kagarura, 2025). This approach ensures the granularity needed for ARIMA model specification and forecasting accuracy.

We employ the Autoregressive Integrated Moving Average (ARIMA) modelling framework, a widely used method for univariate time-series forecasting (Box & Jenkins, 1976; Nahabwe & Kagarura, 2025). ARIMA models are particularly suitable for modelling non-stationary data that exhibit autocorrelation, trends, and seasonality. The modelling process follows four steps: Stationarity testing using the Augmented Dickey-Fuller (ADF) test to determine the order of differencing (Dickey & Fuller, 1979; Nahabwe & Kagarura, 2025). Identification of model parameters (p, d, q) through autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. Estimation of the model parameters using Generalised Least Squares (GLS) to account for potential autocorrelation and heteroskedasticity. Model diagnostics, including residual tests and information criteria (AIC, BIC), to ensure optimal model fit.

The rationale for adopting the ARIMA model lies in its strength in capturing the inertia and memory structure in time-dependent variables, such as clean energy access, where current values are often influenced by historical patterns and past policy interventions (Hyndman & Athanasopoulos, 2018; Nahabwe & Kagarura, 2025).

Given the objective of forecasting and analysing the temporal behaviour of clean cooking fuel access, ARIMA is the most appropriate model due to its parsimonious structure and strong predictive power. Unlike structural models that require multiple explanatory variables, ARIMA focuses on the internal dynamics of the series, making it ideal when explanatory data are limited or where policy shifts are reflected in the historical trends of the target variable (Lütkepohl, 2005; Nahabwe & Kagarura, 2025). Additionally, GLS estimation ensures that serial correlation and variance issues do not bias the results, thereby improving model efficiency and accuracy. The general form of an ARIMA (p,d,q) model is expressed as:

$$Y_t = c + \sum_{i=1}^{p} \boldsymbol{\phi}_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \ldots\ldots (1)$$

Where;

Y_t is Access to clean fuels and technologies for cooking (% of population), at time t
cis constant term
ε_t is white noise at time t
$\boldsymbol{\phi}_i$ are the coefficients of the autoregressive terms
θ_j are the coefficients of the moving average terms
p = Number of lagged AR terms
d = Number of differences required to make the series stationary
q = Number of lagged MA terms (Box & Jenkins 1976; Wooldridge, 2013; Nahabwe & Kagarura, 2025)

Generalised least squares (GLS) estimation is selected for its ability to effectively handle time-series data that exhibits serial correlation and heteroscedasticity, thus providing more reliable and efficient parameter estimates compared to Ordinary Least Squares (OLS) in this context. The GLS procedure adjusts for potential correlations and non-constant variances in the error terms, which are common in time-series data (Wooldridge 2016; Nahabwe & Maniple, 2025). The GLS estimator for the regression coefficients is given by the following formula:

$$\hat{\beta} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where:

$\hat{\beta}$is a column matrix of coefficients
X is the matrix of independent variables
y is the column vector of the dependent variable
Ω is the variance-covariance matrix of the error terms, accounting for both heteroscedasticity and autocorrelation in the residuals (Wooldridge, 2013; Nahabwe & Maniple, 2025).

Prior to modelling, the dataset is visually inspected for trends and seasonality. Stationarity is assessed using the Augmented Dickey-Fuller (ADF) test, and differencing is applied where necessary to achieve stationarity. The optimal ARIMA model is identified using autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, followed by selection based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Diagnostic checks are performed, including the Ljung-Box Q test for autocorrelation, and residual analysis to ensure white noise characteristics.

The ARIMA model is chosen for its robustness in handling time-dependent data, especially in situations where no clear explanatory variables are involved beyond the behaviour of the series itself (Lütkepohl, 2005; Nahabwe & Kagarura, 2025). Given that the objective is to examine trends and predict future performance of nuclear energy, ARIMA's strength in producing reliable short- to medium-term forecasts makes it highly suitable. Furthermore, this method allows for empirical insights that are directly relevant to policy discourse on the environmental sustainability of energy systems, without the confounding influence of external variables.

5. THEORETICAL BACKGROUND

Globally, access to clean fuels and technologies for cooking remains a significant development challenge. According to the International Energy Agency (IEA, 2022), over 2.3 billion people still rely on traditional biomass, coal, or kerosene for cooking. This lack of clean cooking access contributes to nearly 3.2 million premature deaths annually due to indoor air pollution (WHO, 2021). While progress has been made in regions like East Asia and Latin America, Sub-Saharan Africa continues to lag significantly, with access rates stagnating or even declining in some countries. Sustainable Development Goal 7 (SDG 7) emphasises the need for universal access to affordable, reliable, sustainable, and modern energy by 2030. However, achieving this goal is constrained by issues such as affordability, infrastructure deficits, weak policy enforcement, and low investment in clean cooking technologies (ESMAP, 2020).

In Sub-Saharan Africa, the paradox of energy abundance and energy poverty is stark. Despite hosting vast reserves of fossil fuels and renewables, the region has the lowest rate of access to modern energy services globally (IEA, 2022). Countries like Angola, Nigeria, and Ghana are oil-rich, yet a significant portion of their populations lack access to clean cooking energy. Regional studies emphasise that clean cooking solutions remain largely unaffordable for poor households, and efforts to transition are often hampered by weak policy coordination and limited access to finance (Brew-Hammond, 2010; Pachauri et al., 2013). Moreover, cultural preferences and a lack of awareness further hinder adoption. Efforts such as the African Clean Cooking Energy Solutions (ACCES) initiative have been established, yet adoption remains slow due to limited scalability and localised implementation challenges (UNDP, 2025).

Nigeria presents a compelling case of energy resource wealth juxtaposed with widespread energy poverty. Despite being Africa's largest oil producer and having considerable natural gas reserves, over 80% of the population relies on traditional biomass for cooking (World Bank, 2024). National efforts such as the Nigeria Energy Transition Plan and the National Clean Cooking Policy have aimed to improve access, yet implementation has been weak due to funding constraints, poor inter-agency coordination, and limited stakeholder engagement (NESP, 2022). Scholars have critiqued Nigeria's energy governance as fragmented and overly reliant on grid-based electrification, with insufficient emphasis on decentralised and clean cooking solutions (Aklin et al., 2018). The urban-rural divide further exacerbates inequality in access, with rural households being the most disadvantaged (Oyedepo, 2012). Moreover, previous empirical studies in Nigeria have primarily focused on electricity access and supply, with minimal focus on clean cooking energy from a time-series forecasting perspective, thus creating a research gap that this study addresses.

The study is grounded in the Energy Ladder Theory, which posits that households transition from traditional biomass to cleaner and more efficient energy sources as income and education levels rise (Leach, 1992; Kagarura et al., 2025). The theory explains energy consumption behaviour and has been widely applied in studies examining fuel-switching dynamics in developing countries. However, critics argue that the transition is not always linear due to fuel stacking, where households use multiple energy sources simultaneously (Masera et al. 2000). Despite its limitations, the Energy Ladder Theory provides a useful lens for understanding barriers to clean fuel adoption in resource-rich but energy-poor settings like Nigeria.

The conceptual framework underpinning this study is structured around the relationship between energy resource endowment and access to clean fuels and technologies for cooking, mediated by policy, infrastructure, economic, and behavioural variables. The dependent variable is the percentage of the population with access to clean fuels and technologies for cooking. Independent variables are past access trends captured through autoregressive and moving average terms. The framework assumes that despite resource abundance, systemic inefficiencies and policy failures perpetuate energy poverty, particularly in clean cooking access. The ARIMA modelling approach is thus used to forecast access trends and quantify inertia in energy poverty reduction.

6. RESULTS AND DISCUSSION

Descriptive analysis of access to clean fuels and technologies for cooking (% of population) in Nigeria reveals persistent energy poverty over the study period (2000–2024). The mean access rate is 7.91%, suggesting that, on average, fewer than 8% of Nigerians had access to clean cooking energy. The median value of 2.5% is substantially lower than the mean, indicating a positively skewed distribution and that, for much of the period, access remained very low. The maximum value of 30.8% and the minimum of 0.9% reveal wide disparities, while a standard deviation of 9.36 shows substantial variability.

The skewness value of 1.18 and kurtosis of 2.92 reflect moderate right skew and near-normal peakedness. The Jarque-Bera test statistic of 22.50 ($p = 0.000013$) rejects the null hypothesis of normality, confirming that the data is non-normally distributed, a feature that validates the use of time series techniques like ARIMA, which do not rely on normality assumptions.

Stationarity tests using Augmented Dickey-Fuller show the original series is non-stationary ($p>0.05$) in level and first difference achieves stationarity upon second differencing ($p<0.05$). Consequently, the ARIMA (1,2,4) model is identified as the best fit based on model selection criteria (AIC=-4.087729; SC=-4.007080; H-QC = -4.055141). Inferential statistics using model output are estimated as follows:

Results of ARIMA (1,2,4) model (Appendix 6)

$$\widehat{ACCESS\_TO\_CLEAN\_FUELS}_t = 0.006588 - 0.023206AR(1) + 0.456719MA(4) \ldots\ldots\ldots(3)$$

Hence,

$$\hat{\beta}_{GLS} = \begin{bmatrix} 0.006588 \\ -0.023206 \\ 0.456719 \end{bmatrix}$$

The constant term (0.006588) is statistically insignificant, suggesting no systematic upward or downward drift in access trends independent of past values or shocks.

The AR(1) coefficient of –0.0232 is also statistically insignificant, indicating weak or negligible autoregressive behaviour after second differencing. In essence, past values (lag 1) do not strongly influence current access levels.

The MA(4) coefficient is 0.4567 and statistically significant, indicating that approximately 46% of current variations in access to clean cooking fuels are attributable to shocks that occurred four quarters earlier. This finding confirms a high degree of inertia in Nigeria’s clean cooking energy access trends highlighting that past disruptions, policy delays, or implementation gaps continue to influence outcomes well into the future.

The model’s Adjusted R-squared of 0.2779 implies that approximately 28% of the variability in the differenced access series is explained by the model, a reasonable outcome for univariate time series forecasting in public policy contexts (Gujarati & Porter, 2009; Nahabwe & Kagarura, 2025).

Regarding model diagnostics, the normality test (Appendix 8) rejects the null hypothesis of normally distributed residuals ($p < 0.05$). However, the Ljung-Box Q-test (Appendix 6) yields p-values greater than 5%, implying that residuals behave like white noise, i.e., they are uncorrelated and homoscedastic. This confirms that the model is not mis-specified and has captured the underlying structure in the data adequately. Furthermore, the ARIMA structure analysis (Appendix 7) confirms that both autoregressive and moving average roots lie within the unit circle, satisfying the conditions for stationarity and invertibility, which are essential for the model's stability (Hamilton, 1994; Nahabwe & Kagarura, 2025).

Appendix 9 shows that historical data from 2000 to 2024 reveal very low adoption rates of clean cooking fuels, starting below 1% and only reaching about 30.8% by 2024. The ARIMA (1,2,4) model projects a continued but modest upward trend through 2050, with substantial uncertainty surrounding the pace of growth. These findings empirically validate the paradox of energy abundance and energy poverty in Nigeria: despite its vast oil and gas reserves, access to clean cooking fuels remains extremely limited and characterised by strong temporal inertia. The significant MA(4) component further highlights the prolonged influence of past shocks, suggesting that progress in expanding clean energy access is often delayed, reactive and fragmented, a pattern consistent with earlier observations by Aklin et al. (2018) and Oyedepo (2012).

Unlike prior cross-sectional or descriptive studies, this research applies a robust time-series forecasting approach, offering novel insights into the temporal dynamics of energy poverty. While previous studies like Brew-Hammond (2010) and Pachauri et al. (2013) emphasise structural and governance failures, this study quantifies how policy lags and implementation shocks propagate over time, thus hindering access expansion.

Furthermore, the findings align with the Energy Ladder Theory (Leach, 1992; Kagarura et al., 2025), which posits that households transition to cleaner fuels as incomes rise. However, our results also support critiques of the linearity of this model (Masera et al., 2000), given that clean cooking access remains stagnant even as national GDP has grown, suggesting that economic growth alone is insufficient without targeted interventions.

The unique contribution of this study lies in its use of ARIMA forecasting to highlight inertia and volatility in clean cooking access trends. It underscores the urgency of adopting forward-looking, data-driven energy policies that can anticipate and smooth out these lags. Additionally, the low adjusted R-squared and residual behaviour signal that non-economic and institutional variablessuch as political will, policy coordination, and household preferences a crucial role and should be integrated into future models.

7. CONCLUSION

We set out to interrogate the persistent contradiction between Nigeria's immense energy resource endowment and the widespread inaccessibility to clean fuels and technologies for cooking. Anchored in a time-series forecasting framework, the research has illuminated the inertia, volatility, and structural gaps characterising Nigeria's progress toward clean energy access. While Nigeria possesses sufficient natural resources to ensure universal modern energy services, the country remains trapped in a condition of energy poverty, an issue that is both preventable and policy-contingent.

The study reinforces the understanding that energy poverty is not merely a function of resource scarcity, but a product of governance inefficiencies, institutional weaknesses, and policy inertia (Aklin et al., 2018; Brew-Hammond, 2010). The failure to convert resource wealth into equitable and sustainable access to clean cooking fuels exemplifies the broader structural disconnect within Nigeria's energy policy landscape. The challenge is not one of technological feasibility, but rather of prioritisation, inclusion, and sustained political commitment.

Moreover, the analysis underscores that addressing clean cooking energy poverty requires more than aggregate economic growth. It calls for deliberate and inclusive policy frameworks that integrate behavioural, social, and infrastructural dimensions of energy access particularly in contexts where rural populations and women are disproportionately affected (WHO, 2021; UNDP, 2025). Empirical evidence presented here offers a call to action for policymakers, development practitioners, and scholars to reorient Nigeria's energy strategy from a supply-centric to a people-centred approach.

Our study contributes to the expanding discourse on energy justice in resource-rich but energy-poor economies. It affirms that sustainable development in Nigeria depends not only on exploiting energy resources, but on dismantling the structural barriers that hinder equitable access to their benefits. Bridging this gap is not just a policy imperative; it is a moral and developmental necessity.

8. LIMITATIONS

While this study offers critical empirical insights into the paradox of energy abundance and energy poverty in Nigeria, several limitations are acknowledged in relation to its design, data, and analytical approach. We employed a univariate time-series design using the ARIMA modelling framework. Although this method is appropriate for forecasting and capturing the historical dynamics of clean cooking fuel access, it does not account for multivariate interactions with explanatory factors such as income levels, urbanisation, education, energy prices, or policy interventions. This constraint limits the explanatory power of the model and may omit important structural determinants of energy poverty (Gujarati & Porter, 2009; Lütkepohl, 2005; Kagarura et al., 2025). A multivariate approach, such as Vector Autoregression (VAR) or Structural Equation Modelling (SEM), might have provided deeper causal insights but was outside the scope of this study.

We relied exclusively on secondary data from the World Bank's World Development Indicators, transformed from annual to quarterly frequency using interpolation methods. While frequency disaggregation improves temporal resolution, it may introduce estimation error or mask abrupt changes due to shocks or policy changes (Chow & Lin, 1971). Furthermore, national-level data obscure intra-country disparities, particularly the rural-urban divide and regional heterogeneities in clean energy access (IEA, 2022). Thus, the results may not fully reflect localised experiences of energy poverty, especially in Nigeria's underserved northern and riverine communities.

Additionally, the lack of disaggregated demographic data such as gender, income quintiles, or household-level behavior limits the ability to conduct distributional analysis or explore equity dimensions of energy access. This is especially relevant given that women and children bear the brunt of energy poverty due to their roles in cooking and fuel collection (WHO, 2021).

The ARIMA(1,2,4) model used in the study assumes linearity and stationarity after differencing. While diagnostic tests confirmed the model's validity (stationary roots, white noise residuals), the non-normality of residuals (Jarque-Bera $p < 0.05$) suggests potential mis-specification or the presence of unmodeled nonlinearities (Hamilton, 1994; Nahabwe & Kagarura, 2025). Moreover, the relatively low adjusted R-squared (0.2779) indicates that a large portion of the variability in access trends remains unexplained, potentially due to omitted variables or structural breaks not captured in the ARIMA framework.

The use of Generalised Least Squares (GLS) improves estimation efficiency, but the absence of real-time policy variables, fuel pricing data, or technological adoption rates restricts the model's policy sensitivity. As a result, the findings should be interpreted as indicative rather than definitive forecasts.

9. RECOMMENDATIONS

We propose the following recommendations, drawing from our findings and the persistent paradox of energy abundance alongside energy poverty in Nigeria, in the areas of policy, programming, and research:

The Federal Government should prioritise a comprehensive and enforceable national policy on clean cooking access that includes specific, measurable targets aligned with SDG 7. This policy should go beyond generic electrification plans and directly address clean cooking infrastructure, affordability, and distribution (IEA, 2022).

Existing fossil fuel subsidiesparticularly on kerosene and petrolshould be gradually reallocated to subsidise clean cooking technologies such as LPG, ethanol, biogas, and improved cookstoves. Targeted subsidies will help bridge affordability gaps for low-income and rural households (Pachauri et al., 2013; UNDP, 2025).

Improved coordination is needed between the Ministries of Energy, Environment, Women's Affairs, and Health to integrate clean cooking into broader development planning. Establishing a dedicated Clean Cooking Task Force under the National Council on Energy could enhance accountability and coherence in implementation.

Given the disproportionately low access in rural communities, government and development partners should invest in community-based clean cooking programmes, including micro-financing schemes, awareness campaigns, and rural distribution channels. These programmes should leverage local cooperatives and women's groups for outreach and adoption (Brew-Hammond, 2010; WHO, 2021).

Policy tools such as tax incentives, start-up grants, and import duty waivers for clean cooking technology manufacturers and distributors should be expanded. Encouraging local innovation and entrepreneurship in the clean cooking value chain will reduce costs and increase adoption rates (Aklin et al., 2018).

Existing social programs, such as the National Social Investment Program (NSIP) should include clean cooking as part of household support packages. This approach will increase penetration while protecting vulnerable populations from harmful indoor air pollution.

Future research could employ multivariate econometric and panel data models that incorporate socio-economic, cultural, and policy variables to better understand the drivers of clean energy adoption in Nigeria's diverse regions (Lütkepohl, 2005).

Empirical evaluations of past interventions as the National Clean Cooking Policy (NESP, 2022) are needed to identify best practices, implementation bottlenecks, and replicable models. Mixed-method studies combining quantitative and qualitative insights would be particularly valuable.

Enhanced ARIMA or machine learning-based models incorporating behavioural, climatic, and demographic indicators can improve long-term access forecasting and guide strategic planning (Hyndman & Athanasopoulos, 2018; Nahabwe & Kagarura, 2025).

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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APPENDICES

Appendix 1. Descriptive statistics

	Access to clean fuels and technologies for cooking (% of population)
Mean	7.911856
Median	2.5
Maximum	30.8
Minimum	0.9
Std. Dev.	9.355397
Skewness	1.179137
Kurtosis	2.91788
Jarque-Bera	22.5048
Probability	0.000013
Sum	767.45
Sum Sq. Dev.	8402.251
Observations	97

Appendix 2. Unit root test, Access to clean fuels and technologies for cooking (% of population) (in Level)

Null Hypothesis: ACCESS_TO_CLEAN_FUELS has a unit root
Exogenous: None
Lag Length: 5 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.656869	0.8562
Test critical values:	1% level	-2.590622	
	5% level	-1.944404	
	10% level	-1.614417	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ACCESS_TO_CLEAN_FUELS)
Method: Least Squares
Date: 07/13/25 Time: 15:34
Sample (adjusted): 2001Q3 2024Q1
Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ACCESS_TO_CLEAN_FUELS(-1)	0.000554	0.000843	0.656869	0.5130
D(ACCESS_TO_CLEAN_FUELS(-1))	1.016087	0.081373	12.48671	0.0000
D(ACCESS_TO_CLEAN_FUELS(-2))	-0.001197	0.110972	-0.010785	0.9914
D(ACCESS_TO_CLEAN_FUELS(-3))	-0.001197	0.110972	-0.010785	0.9914
D(ACCESS_TO_CLEAN_FUELS(-4))	0.686764	0.110972	6.188635	0.0000
D(ACCESS_TO_CLEAN_FUELS(-5))	-0.718135	0.088297	-8.133196	0.0000

R-squared	0.992959	Mean dependent var	0.328571
Adjusted R-squared	0.992545	S.D. dependent var	0.324071
S.E. of regression	0.027981	Akaike info criterion	-4.250931
Sum squared resid	0.066549	Schwarz criterion	-4.085380
Log likelihood	199.4174	Hannan-Quinn criter.	-4.184142
Durbin-Watson stat	2.047714		

Appendix 3. Unit root test, Access to clean fuels and technologies for cooking (% of population) (in First difference)

Null Hypothesis: D(ACCESS_TO_CLEAN_FUELS) has a unit root
Exogenous: None
Lag Length: 4 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.365926	0.5502
Test critical values:	1% level	-2.590622	
	5% level	-1.944404	
	10% level	-1.614417	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ACCESS_TO_CLEAN_FUELS,2)
Method: Least Squares
Date: 07/13/25 Time: 15:33
Sample (adjusted): 2001Q3 2024Q1
Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(ACCESS_TO_CLEAN_FUELS(-1))	-0.002514	0.006870	-0.365926	0.7153
D(ACCESS_TO_CLEAN_FUELS(-1),2)	0.005433	0.079595	0.068252	0.9457
D(ACCESS_TO_CLEAN_FUELS(-2),2)	0.005433	0.079595	0.068252	0.9457
D(ACCESS_TO_CLEAN_FUELS(-3),2)	0.005433	0.079595	0.068252	0.9457
D(ACCESS_TO_CLEAN_FUELS(-4),2)	0.693393	0.079595	8.711480	0.0000

R-squared	0.454184	Mean dependent var	0.007143
Adjusted R-squared	0.428797	S.D. dependent var	0.036900
S.E. of regression	0.027888	Akaike info criterion	-4.267846
Sum squared resid	0.066887	Schwarz criterion	-4.129887
Log likelihood	199.1870	Hannan-Quinn criter.	-4.212188
Durbin-Watson stat	2.008991		

Appendix 4. Unit root test,Access to clean fuels and technologies for cooking (% of population)(in Second difference)

Null Hypothesis: D(ACCESS_TO_CLEAN_FUELS,2) has a unit root
Exogenous: None
Lag Length: 3 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.005179	0.0436
Test critical values:	1% level	-2.590622	
	5% level	-1.944404	
	10% level	-1.614417	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ACCESS_TO_CLEAN_FUELS,3)

Method: Least Squares
Date: 07/13/25 Time: 15:31
Sample (adjusted): 2001Q3 2024Q1
Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(ACCESS_TO_CLEAN_FUELS(-1),2)	-0.312039	0.155617	-2.005179	0.0481
D(ACCESS_TO_CLEAN_FUELS(-1),3)	-0.687961	0.134768	-5.104777	0.0000
D(ACCESS_TO_CLEAN_FUELS(-2),3)	-0.687961	0.110038	-6.252050	0.0000
D(ACCESS_TO_CLEAN_FUELS(-3),3)	-0.687961	0.077808	-8.841734	0.0000

R-squared	0.736645	Mean dependent var	3.85E-17
Adjusted R-squared	0.727564	S.D. dependent var	0.053164
S.E. of regression	0.027749	Akaike info criterion	-4.288268
Sum squared resid	0.066991	Schwarz criterion	-4.177901
Log likelihood	199.1162	Hannan-Quinn criter.	-4.243742
Durbin-Watson stat	2.000000		

Appendix 5. Results of ARIMA(1,2,4) model

Dependent Variable: DDACCESS_TO_CLEAN_FUELS
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 07/13/25 Time: 15:45
Sample: 2000Q3 2024Q1
Included observations: 95
Convergence achieved after 34 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006588	0.004429	1.487417	0.1403
AR(1)	-0.023206	0.104248	-0.222599	0.8243
MA(4)	0.456719	0.096434	4.736082	0.0000

R-squared	0.293235	Mean dependent var	0.006842
Adjusted R-squared	0.277871	S.D. dependent var	0.036135
S.E. of regression	0.030707	Akaike info criterion	-4.087729
Sum squared resid	0.086748	Schwarz criterion	-4.007080
Log likelihood	197.1671	Hannan-Quinn criter.	-4.055141
F-statistic	19.08528	Durbin-Watson stat	2.000231
Prob(F-statistic)	0.000000		

Inverted AR Roots	-.02			
Inverted MA Roots	.58+.58i	.58+.58i	-.58-.58i	-.58-.58i

Appendix 6. Ljung-Box Q statistic/ test

Date: 07/13/25 Time: 15:49
Sample (adjusted): 2000Q3 2024Q1
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |. |	. |. |	1	-0.000	-0.000	2.E-05	
. |. |	. |. |	2	-0.025	-0.025	0.0598	

<table>
<tr><td>. |. |</td><td>. |. |</td><td>3</td><td>-0.019</td><td>-0.019</td><td>0.0964</td><td>0.756</td></tr>
<tr><td>. |** |</td><td>. |** |</td><td>4</td><td>0.226</td><td>0.226</td><td>5.2894</td><td>0.071</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>5</td><td>-0.021</td><td>-0.023</td><td>5.3333</td><td>0.149</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>6</td><td>-0.027</td><td>-0.018</td><td>5.4077</td><td>0.248</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>7</td><td>-0.015</td><td>-0.007</td><td>5.4311</td><td>0.366</td></tr>
<tr><td>. |**** |</td><td>. |*** |</td><td>8</td><td>0.492</td><td>0.464</td><td>31.049</td><td>0.000</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>9</td><td>-0.013</td><td>-0.019</td><td>31.068</td><td>0.000</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>10</td><td>-0.026</td><td>-0.007</td><td>31.140</td><td>0.000</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>11</td><td>-0.025</td><td>-0.012</td><td>31.208</td><td>0.000</td></tr>
<tr><td>. |. |</td><td>.*|. |</td><td>12</td><td>0.018</td><td>-0.198</td><td>31.245</td><td>0.001</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>13</td><td>-0.029</td><td>-0.009</td><td>31.340</td><td>0.001</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>14</td><td>-0.030</td><td>-0.013</td><td>31.446</td><td>0.002</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>15</td><td>-0.029</td><td>-0.019</td><td>31.545</td><td>0.003</td></tr>
<tr><td>. |. |</td><td>**|. |</td><td>16</td><td>0.026</td><td>-0.244</td><td>31.626</td><td>0.005</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>17</td><td>-0.037</td><td>-0.026</td><td>31.784</td><td>0.007</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>18</td><td>-0.038</td><td>-0.033</td><td>31.961</td><td>0.010</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>19</td><td>-0.041</td><td>-0.034</td><td>32.161</td><td>0.014</td></tr>
<tr><td>.*|. |</td><td>. |. |</td><td>20</td><td>-0.125</td><td>-0.025</td><td>34.069</td><td>0.012</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>21</td><td>-0.038</td><td>-0.022</td><td>34.253</td><td>0.017</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>22</td><td>-0.037</td><td>-0.023</td><td>34.422</td><td>0.023</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>23</td><td>-0.037</td><td>-0.021</td><td>34.599</td><td>0.031</td></tr>
<tr><td>. |. |</td><td>. |* |</td><td>24</td><td>-0.056</td><td>0.101</td><td>35.012</td><td>0.039</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>25</td><td>-0.038</td><td>-0.012</td><td>35.201</td><td>0.050</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>26</td><td>-0.038</td><td>-0.009</td><td>35.390</td><td>0.063</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>27</td><td>-0.040</td><td>-0.009</td><td>35.602</td><td>0.078</td></tr>
<tr><td>.*|. |</td><td>. |. |</td><td>28</td><td>-0.106</td><td>-0.030</td><td>37.158</td><td>0.072</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>29</td><td>-0.032</td><td>-0.011</td><td>37.298</td><td>0.090</td></tr>
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<tr><td>. |. |</td><td>. |. |</td><td>31</td><td>-0.031</td><td>-0.015</td><td>37.569</td><td>0.132</td></tr>
<tr><td>.*|. |</td><td>.*|. |</td><td>32</td><td>-0.079</td><td>-0.131</td><td>38.486</td><td>0.138</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>33</td><td>-0.029</td><td>-0.023</td><td>38.607</td><td>0.164</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>34</td><td>-0.028</td><td>-0.027</td><td>38.722</td><td>0.192</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>35</td><td>-0.028</td><td>-0.027</td><td>38.840</td><td>0.223</td></tr>
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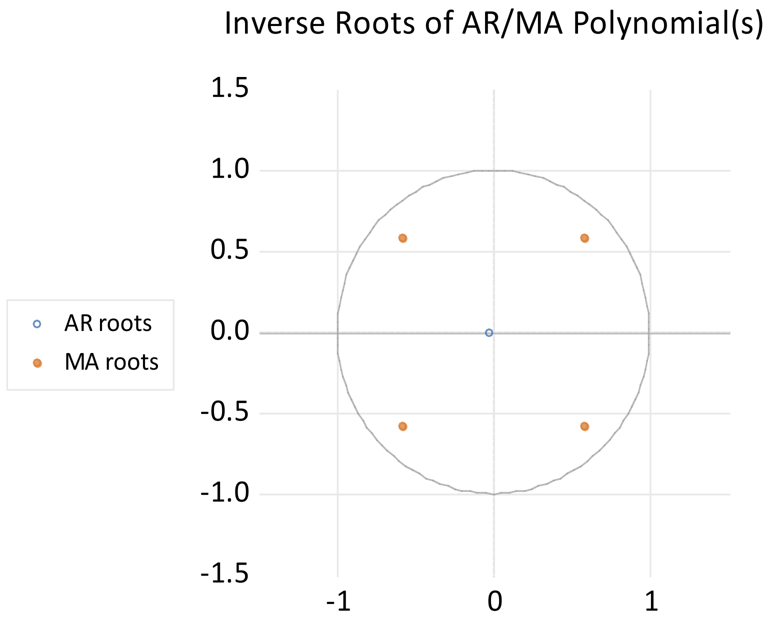
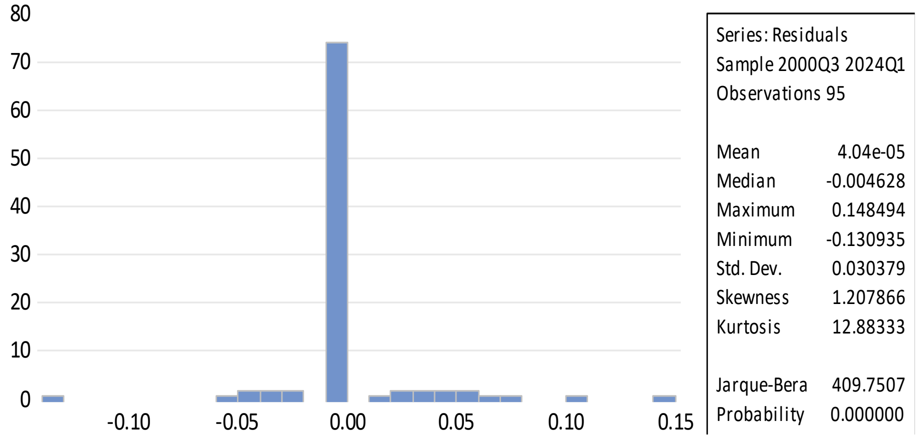
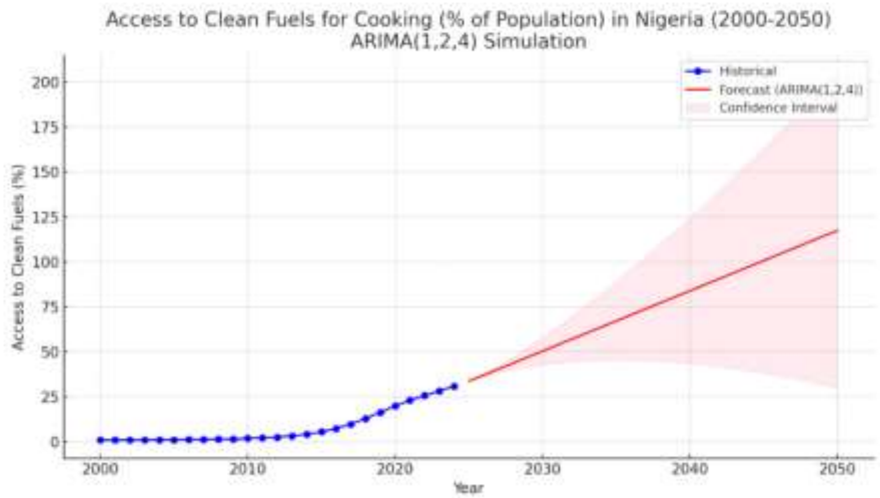


Appendix 7. ARIMA(1,2,4) structure



Appendix 8. Histogram of residuals



Appendix 9. Graph showing Nigeria's Access to clean fuels for cooking 2000-2050

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