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MODELLING ACCESS TO ELECTRICITY IN UGANDA

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ABSTRACT
This study examines trends and forecasts of access to electricity in Uganda using data from 1995 to 2022 via a quantitative approach based on ARIMA modelling. Balanced time-series data from World Bank is analyzed, with access to electricity as dependent variable, incorporating autoregressive (AR) and moving average (MA) components as independent variables. Parameter estimation is conducted using Maximum Likelihood Estimation (MLE). Results indicate that MA(4) coefficient (0.5847) is positive and statistically significant, suggesting that short-term fluctuations in electricity access are influenced by prior trends, with 58.5% of variations explained by past values. Estimated ARIMA (1, 1, 4) model is both covariance stationary and invertible, making it reliable for forecasting future patterns in electricity access. Projections reveal a steady upward trend, with electricity access expected to increase from 47.1% in 2022 to approximately 65.9% by 2042. These findings highlight the role of sustained infrastructure investment and policy interventions in improving electrification rates. The study recommends prioritizing rural electrification programs, expanding grid infrastructure, and leveraging renewable energy sources.
KEY WORDS: *ARIMA modelling, access to electricity*

INTRODUCTION

Access to electricity is a fundamental prerequisite for economic growth, poverty alleviation, and sustainable development (World Bank 2020). It enhances living standards by improving education, healthcare, and industrialization. Despite its significance, access to electricity remains a major challenge in Uganda, where over 50% of the population lacks electricity (World Bank 2022). This persistent energy deficit highlights Uganda's struggle to meet global targets, such as the Millennium Development Goals (MDGs) and Sustainable Development Goals (SDGs), which emphasize universal access to modern energy services as a catalyst for development (United Nations 2015).

Uganda's electrification rates, particularly in rural areas, have lagged behind international targets. The MDGs aimed to halve the proportion of people without access to modern energy by 2015, while the SDGs further emphasize achieving universal energy access by 2030 (IEA 2021). However, Uganda's rural electrification rates remain disproportionately low, hindering progress toward these goals. As of 2022, only 47.1% of Uganda's population had access to electricity, leaving a significant portion underserved (World Bank 2022).

Limited access to electricity in Uganda is attributed to infrastructural deficits, high connection costs, and economic barriers. Rural areas, where a majority of the population resides, are particularly disadvantaged due to sparse settlements and underdeveloped grids (MEMD 2020). This situation underscores the importance of evidence-based modelling to project trends and inform policies that promote equitable electrification.

This study applies Autoregressive Integrated Moving Average (ARIMA) modelling to analyze trends in Uganda's access to electricity from 1995 to 2022. The use of ARIMA enables effective forecasting and provides insights into future patterns, which are crucial for guiding investment decisions and policy development. By examining historical trends and projecting future access levels, this research aims to support Uganda's electrification efforts and align them with global development targets.

LITERATURE REVIEW

Globally, access to electricity is recognized as a vital component of socio-economic development. According to the IEA (2021), approximately 770 million people worldwide lacked access to electricity as of 2020, with Sub-Saharan

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Africa accounting for nearly 75% of the total. Electrification drives economic growth, facilitates education, and improves health outcomes (World Bank 2020). However, disparities persist between developed and developing nations, highlighting the need for sustainable electrification strategies.

Sub-Saharan Africa remains the most affected region, with an average electrification rate of 46% as of 2020 (IEA 2021). Countries such as Kenya and Rwanda have made significant strides by leveraging renewable energy and off-grid solutions (Blimpo et al. 2019). Despite these advancements, Uganda continues to lag behind its neighbors, emphasizing the need for robust policy frameworks and investments in energy infrastructure.

Uganda's electrification rate stood at approximately 47.1% in 2022, with rural areas facing the greatest challenges (World Bank 2022). Rural electrification programs, such as Rural Electrification Agency, have shown promise but remain constrained by financial and infrastructural barriers (MEMD 2020). Addressing these challenges requires data-driven policies informed by predictive modelling techniques.

This study is grounded in the Diffusion of Innovation Theory (Rogers 2003), which explains how new technologies and practices spread within a society. The theory posits that adoption rates depend on perceived benefits, compatibility, and complexity. In the context of electricity access, affordability, reliability, and infrastructural feasibility influence adoption rates.

The conceptual framework links key variables influencing access to electricity. The dependent variable is access to electricity (% of population), while independent variables are Autoregressive and Moving averages components. ARIMA model is used to assess trends, patterns, and projections, providing insights into future access scenarios.

DATA AND METHODS

This study adopts a quantitative research design to model access to electricity in Uganda from 1995 to 2022. Quantitative methods allow for statistical modelling, trend analysis, and forecasting, which are essential for analyzing time-series data and identifying patterns (Gujarati & Porter 2009). The study employs a time-series approach using the Autoregressive Integrated Moving Average (ARIMA) model, which is widely used for forecasting and analyzing temporal data trends (Box & Jenkins 1976).

The study utilizes secondary data obtained from the World Bank database, specifically focusing on Uganda's annual access to electricity (% of population) from 1995 to 2022. The dataset provides consistent, high-quality, and internationally recognized metrics, ensuring reliability (World Bank 2022). A census sampling approach is used since the data covers the entire population for the specified time frame, eliminating the need for further sampling.

Data analysis follows ARIMA modelling process, which involves three main steps; model identification, parameter estimation, diagnostic checking and forecasting: Assessing stationarity using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller 1981) and visualizing trends to identify appropriate lags for the autoregressive (AR) and moving average (MA) components; estimating model parameters using Maximum Likelihood Estimation (MLE) to ensure precision and minimize errors (Greene 2012); evaluating residuals for white noise and model adequacy using the Ljung-Box Q test and autocorrelation function (ACF) plots (Box & Jenkins 1976); and using the validated ARIMA model to predict trends in access to electricity for the next two decades respectively and generating future policy insights.

ARIMA approach is selected due to its robustness in modelling and forecasting non-stationary time-series data (Hyndman & Athanasopoulos 2018). Its ability to capture trends, seasonality, and irregular variations makes it suitable for analyzing Uganda's electricity access patterns over time. The use of secondary data ensures cost-effectiveness and provides comprehensive coverage, while the reliance on econometric techniques supports the generation of actionable insights for policy makers.

ARIMA (p, d, q) model specification is as follows:

$$Y_t = \mu + \varepsilon_t + \boldsymbol{\phi}_1 Y_{t-1} + \boldsymbol{\phi}_2 Y_{t-2} + \ldots + \boldsymbol{\phi}_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \quad \ldots\ldots\ldots\ldots (1)$$

Where;

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Y_t is the value of the series at time t
μ is the mean of the series
ε_t is white noise
$\boldsymbol{\phi}_1$, $\boldsymbol{\phi}_2$, … $\boldsymbol{\phi}_p$ are the coefficients of the AR (p) component
θ_1, θ_2, … θ_q are the coefficients of the MA (q) component
p is the order of the autoregressive part, representing the number of past values considered
q is the order of the moving average part, indicating the number of past errors considered
d is the number of differences required to make the series stationary (Box & Jenkins 1976)

Maximum Likelihood Estimation (MLE) is used to estimate model parameters, ensuring efficiency and accuracy in predicting (Lütkepohl 2005) electricity access. Maximum Likelihood Estimation process holds that for a given set of observations X = { x_1, x_2, ..., x_n} and assuming they follow a probability distribution with parameter θ, the likelihood function L(θ) is given by:

$L(\theta) = P(X|\theta) = \prod_{i=1}^{n} f(x_1|\theta)$ …… (2)
Where;
$f(x_1|\theta)$ is the probability density function of the observed data point x_i given parameter θ

Thus
$\hat{\theta} = \text{argmax}\,\ell(\theta)$ (Greene, 2012).

Diagnostic tests, such as the Augmented Dickey-Fuller (ADF) test for stationarity (Dickey & Fuller 1979), and the model selection process using the Akaike Information Criterion (AIC) (Akaike 1974), are employed to assess the model's adequacy and ensure its suitability for forecasting. The use of ARIMA modeling in this study is particularly beneficial for analyzing Uganda's electricity access trends, as it enables the evaluation of past behaviors to make reliable projections (Enders 2014).

This approach effectively captures the underlying patterns in electricity access data, thereby providing a robust framework for understanding whether current access levels are sustainable in the long run. Moreover, ARIMA's capacity to handle non-stationary data is particularly well-suited to economic time series, where trends and fluctuations exhibit considerable variation over time (Stock & Watson 2015). The analytical rigor of this model supports drawing meaningful, policy-relevant conclusions about Uganda's electricity access trajectory, offering insights that can guide effective energy policy and planning strategies.

RESULTS

This section presents the results of the study, guided by the research objectives and questions. The findings are based on the analysis of time-series data using ARIMA model and are structured as follows:

Descriptive analysis (Appendix 1), reveals that access to electricity in Uganda has shown a gradual increase from 6.8% in 1995 to 47.1% in 2022. However, the data also highlights fluctuations, particularly between 2000 and 2010, reflecting periods of stagnation and slower growth. These trends underscore the need for strategic interventions to ensure consistent progress.

Average percentage of the population with access to electricity is approximately 18.07%. This indicates that, on average, about 18% of the population has access to electricity across the studied areas. Median value is 13%, meaning that half of the data points are below this percentage, and half are above it. The median is lower than the mean, suggesting a skew towards lower access to electricity.

Highest observed value for electricity access is 47.1%, indicating that in some areas, nearly half of the population has access to electricity. Lowest value for electricity access is 2.81%, highlighting regions where very few people have access to electricity. Standard deviation of 13.80% shows considerable variability in access to electricity across the population. A higher standard deviation suggests that access to electricity is uneven, with some areas having very low access and others achieving much higher levels.

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Positive skewness (1.00) indicates that the distribution of electricity access is right-skewed. There are more observations with lower electricity access, but the distribution has a tail extending towards higher values, indicating a few areas with significantly better access. The kurtosis of 2.60 suggests a moderate peak in the distribution, slightly platykurtic (flatter than a normal distribution). This implies that the data has fewer extreme values compared to a normal distribution.

Jarque-Bera Statistic is 4.89, assesses whether the data follows a normal distribution. Its Probability is 0.0868 which is greater than 0.05, implying that the data does not significantly deviate from normality. Thus, the null hypothesis (that the data is normally distributed) cannot be rejected, suggesting that the distribution of electricity access is approximately normal.

The total electricity access across all 28 observations is 506.03%. This is the sum of the access percentages for all the observed years. Sum of squares of deviations is 5144.33 which indicates the total squared deviations of the observed data from the mean, providing a measure of the overall spread or variability in electricity access. The sample includes 28 observations, representing 28 different years or data points on access to electricity.

Stationarity tests (Appendix 2 and Appendix 3) are conducted using Augmented Dickey-Fuller (ADF) test to check for stationarity. Results indicate that the original series was non-stationary in level ($p > 0.05$). After first difference, the series achieved stationarity ($p < 0.05$), justifying the use of ARIMA model.

ARIMA (1, 1, 4) model was identified as the best, based on Akaike Information Criterion (AIC = 5.555052) and Schwarz Criterion (SC = 5.747028). Parameter estimates include: AR(1) = 0.030377 ($p = 0.8706$); MA(4) = 0.584749 ($p = 0.0133$). Accordingly, the coefficient of MA(4) is statistically significant, while that of AR(1) is statistically insignificant.

Diagnostic checks confirm the adequacy of the model. The residuals are white noise, as confirmed by the Ljung-Box Q test ($p > 0.05$), and the autocorrelation function (ACF) plots show no significant patterns, validating the model's robustness. Forecasts for the next 20 years suggest a steady rise in access to electricity, reaching approximately 65.9% by 2042. This projection aligns with Uganda's strategic goals but highlights the need for accelerated interventions to meet the universal access targets outlined in the Sustainable Development Goals (SDGs). Results are summarized as follows:

Results of the ARIMA (1, 1, 4) model (Appendix 4)

$$\widehat{Electricity}_t = 1.184201 + 0.030377\text{AR}(1) + 0.584749\text{MA}(4) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Hence

$$\hat{\theta} = \begin{bmatrix} 1.184201 \\ 0.030377 \\ 0.584749 \end{bmatrix}$$

Constant term (1.184201) represents the baseline level of Uganda's access to electricity, independent of the autoregressive (AR) and moving average (MA) components.

AR(1) coefficient of 0.030377, though positive, is statistically insignificant. This suggests that the autoregressive component has little to no meaningful effect on the access to electricity in Uganda in the current model.

MA(4) coefficient of 0.584749, being both positive and statistically significant, indicates that the fourth-order moving average component significantly influences electricity access in Uganda, with its impact being substantial.
Sigma-Squared value of 10.57924 reflects the variance of the model's residuals, providing an estimate of the error variance in predicting Uganda's electricity access.

Adjusted R-squared value of 0.167058 indicates that the model explains approximately 16.7% of the variance in electricity access, suggesting a relatively low level of explanatory power. This may imply that other factors not included in the model could better explain variations in electricity access.

Durbin-Watson statistic of 1.912710 suggests no significant autocorrelation in the residuals, as the statistic is close to the ideal value of 2. This supports the assumption that the residuals are not correlated over time.

Histogram of residuals for the ARIMA (1, 4) model (Appendix 7) shows a kurtosis value of 2.36, a Jarque-Bera statistic of 1.1, and a p-value of 0.58. These results suggest that the residuals are approximately normally distributed, which indicates that the model is robust and appropriate for forecasting electricity access trends in Uganda.

Ljung-Box Q statistic/test results (Appendix 5) show that we fail to reject the null hypothesis, indicating that the residuals of the ARIMA (1, 1, 4) model are white noise. This suggests that there is no autocorrelation within the residuals, further validating the adequacy of the model.

Further diagnostics of the ARIMA (1, 1, 4) structure (Appendix 6) reveal that the AR and MA roots are covariance stationary and invertible, as they lie within the unit circle. This condition is essential for the model's reliability in forecasting future trends.

Finally, forecasts of electricity access for the next two decades are provided in Appendix 7 and Appendix 8, offering a projected outlook on the country's electricity accessibility.

DISCUSSION

Findings of this study on modelling access to electricity in Uganda provide valuable insights into accessibility and trends. The baseline level of electricity access, represented by the constant term (1.184201), indicates a relatively low starting point in Uganda's electricity provision, which aligns with previous studies that have highlighted country's struggles with energy access (World Bank 2023). This low baseline is consistent with Uganda's ranking among countries with limited rural electrification (Karekezi & Kithyoma 2002).

AR(1) coefficient of 0.030377, although positive, is statistically insignificant, suggesting that past values of electricity access have little impact on the current electricity access level. This contrasts with findings from other studies in Africa, where autoregressive terms were found to be significant in modelling electricity access, particularly in countries with higher electricity grid penetration (Deichmann et al. 2011). Lack of statistical significance in this study could point to Uganda's unique context, where access to electricity may be more influenced by other external factors such as infrastructure development, political stability, or donor funding rather than historical trends in electricity provision.

In contrast, MA(4) coefficient of 0.584749 is found to be statistically significant. This indicates a significant moving average effect, suggesting that shocks from previous periods (such as government policies or infrastructure projects) continue to influence electricity access. This is consistent with the findings of Blimpo et al. (2019), who demonstrated that policy decisions and external interventions significantly shape long-term electricity access in Sub-Saharan Africa. The positive value of the MA component is a unique finding in this study, highlighting the importance of such interventions in shaping the trajectory of electricity access in Uganda.

The relatively low Adjusted R-squared value of 0.167058 indicates that the model's explanatory power is modest. This aligns with other studies in developing countries, where access to electricity is often influenced by a wide array of complex socio-economic and infrastructural factors, many of which may not be fully captured in a simple time-series model (Nichiforov et al. 2017). Furthermore, the low explanatory power suggests the need for further exploration of additional variables, such as socio-economic status, urbanization rates, and regional policy variations, to improve the model's predictive accuracy.
The Durbin-Watson statistic of 1.912710, indicating no autocorrelation in the residuals, supports the model's reliability and is consistent with findings from previous studies employing ARIMA models in energy access research (Tiwari, et al. 2022. Lack of autocorrelation suggests that the residuals are independent and that the model is appropriately specified.

Histogram of residuals (Appendix 7), showing a kurtosis value of 2.36 and a Jarque-Bera statistic of 1.1 (p-value = 0.58), indicates that the residuals are approximately normally distributed. This finding is consistent with other studies

that have found ARIMA models to be robust in forecasting electricity access trends (Tiwari et al., 2022). The normality of the residuals also suggests that the model's assumptions are met, making the results more reliable for forecasting future trends in Uganda.

Finally, the Ljung-Box Q statistic results (Appendix 5) confirm that there is no significant autocorrelation in the residuals, validating the adequacy of the ARIMA (1, 1, 4) model. This further supports the use of the ARIMA model as a reliable tool for time-series forecasting in electricity access studies, as seen in similar applications in developing countries (Sharma & Mishra 2023).

A unique finding in this study is the identification of significant moving average effects in Uganda, suggesting that interventions from the government and external actors, such as international aid or infrastructure development, have a lasting impact on electricity access. This insight adds to the growing body of literature that emphasizes the role of external shocks and interventions in shaping energy access patterns in low-income countries.

LIMITATIONS

While this study provides valuable insights into the modelling of electricity access in Uganda, several limitations are acknowledged, which may have influenced the findings.

The study employs an ARIMA time-series model to forecast electricity access in Uganda. While ARIMA models are powerful tools for capturing patterns and trends in time-series data, they may not fully account for the complexities of the factors influencing electricity access, such as socio-political influences, infrastructure development, and policy interventions. The exclusion of these additional variables in the model may limit the comprehensiveness of the findings. Future studies could consider incorporating a broader range of explanatory variables, such as GDP growth, urbanization, and policy changes, to capture more nuanced dynamics (Tiwari et al. 2022).

The study uses data from a relatively small sample size of 28 observations, which may not be sufficient to generalize the findings to a larger population. With a limited number of data points, the statistical power of the model is reduced, which could have led to biased or imprecise estimates, especially for the autoregressive and moving average components. Larger and more diverse datasets could provide more reliable results and allow for a more robust analysis (Nichiforov et al. 2017). Additionally, the study focuses solely on national-level data for Uganda, potentially overlooking regional variations in electricity access that might present different trends and patterns (Blimpo et al. 2019).

Availability and quality of data are significant constraints in this study. The data on electricity access in Uganda was sourced from secondary databases, which might be subject to reporting errors, inconsistencies, or lack of granularity. The study does not account for seasonal fluctuations or structural breaks in the data that could affect electricity access trends. Moreover, the absence of high-frequency data may have limited the model's ability to capture short-term changes and shocks that can significantly impact electricity access, such as natural disasters or major policy changes (World Bank 2023). Future studies could benefit from more detailed and higher-frequency datasets to better understand the dynamics of electricity access.

The study employs ARIMA modelling to assess electricity access trends. While ARIMA models are commonly used for forecasting time-series data, they assume stationarity in the data, which may not always hold in practice. Although diagnostic tests were conducted to check for autocorrelation and stationarity, other advanced techniques such as structural breaks tests or cointegration analysis could have been used to better account for potential non-stationarity or long-term equilibrium relationships in the data (Karekezi & Kithyoma 2002). Additionally, ARIMA models may not fully capture the impact of exogenous shocks or non-linear relationships between the variables, which could lead to omitted variable bias. Other advanced econometric techniques, such as Vector Autoregressive (VAR) models or machine learning approaches, could provide more comprehensive insights into the factors influencing electricity access in Uganda (Sharma & Mishra 2023).

The study focuses on Uganda's national-level electricity access trends and does not explore regional differences or temporal shifts in the distribution of electricity access. Regional disparities in electricity infrastructure, socio-economic development, and policy implementation may lead to different electricity access trajectories (Deichmann et

al. 2011) within Uganda. Further research could consider a regional analysis to understand the local dynamics that contribute to the overall electricity access trends. Additionally, the time period covered by the study (specific years) may not fully capture the long-term evolution of electricity access, and future studies could extend the time horizon for a more comprehensive understanding.

ARIMA model assumes that the residuals are normally distributed and independent, which is crucial for the validity of the forecasts. Although diagnostic tests suggest that the residuals are approximately normal and white noise, there remains a possibility of heteroscedasticity or other violations of model assumptions that could affect the results. The assumption of linearity in the ARIMA model may not adequately represent the complex, non-linear relationships that may exist between electricity access and other socio-economic factors (Tiwari et al. 2022) in Uganda.

CONCLUSION

This study has explored the dynamics of electricity access in Uganda by employing ARIMA time-series modelling to forecast future trends and assess the factors influencing access to electricity. Findings have highlighted the significant potential of ARIMA models in understanding electricity access, providing valuable insights into the long-term trajectory of electricity provision in Uganda.

The research finds that Uganda's electricity access follows a discernible trend over time, with a generally upward trajectory in the proportion of the population gaining access to electricity. Despite this, certain limitations in data quality and sample size could have somewhat constrained the precision of the forecasts. The study also reveals that factors such as government policies, infrastructure investment, and socio-economic dynamics play a crucial role in shaping electricity access, even though they were not directly incorporated in the ARIMA model. Future studies that integrate these variables into more complex modelling frameworks may yield a deeper understanding of the drivers of electricity access.

While ARIMA model is effective in capturing essential trends and producing reliable forecasts, the study recognizes the importance of addressing model limitations. Incorporating additional socio-economic factors and exploring more advanced econometric methods could enhance the model's robustness. Furthermore, the findings underscore the importance of continuous data monitoring and the need for high-frequency data to refine future models and forecasts.

In conclusion, this study contributes to the body of knowledge on electricity access in Uganda, highlighting the importance of reliable modelling techniques and a deeper understanding of underlying factors influencing electricity distribution. The projections provide valuable insights for policy makers, development agencies, and energy planners to make informed decisions on expanding electricity access in the country, which remains crucial for economic growth and improved living standards. However, the study's limitations also present avenues for further research, particularly in terms of expanding the data scope and incorporating broader factors affecting electricity access.

RECOMMENDATIONS

Based on the findings of this study, several recommendations are presented to enhance electricity access in Uganda, focusing on policy, programs, and further research.

The study highlights the importance of improving electricity access in Uganda, which requires substantial investment in electricity infrastructure. It is recommended that the Ugandan government prioritize the development of electricity generation, transmission, and distribution infrastructure, particularly in rural areas where access remains limited. Increasing investments in renewable energy sources, such as solar and wind, can complement traditional grid expansion and improve energy security (Karekezi & Kithyoma 2002).

A key policy recommendation is the development of inclusive energy policies that consider the diverse needs of urban and rural populations. Policymakers should aim to create a balanced approach to ensure that both areas receive adequate attention. Specifically, the government should encourage off-grid energy solutions, which can be more cost-effective for remote areas, while still expanding the national grid in urban centers (Deichmann et al. 2011). Additionally, energy policies should be designed to integrate socio-economic factors, such as income levels and education, as they significantly influence electricity access.

Given the financial constraints faced by many households, especially in rural areas, it is recommended that government provides targeted subsidies or incentives for electricity consumption. This could include subsidies for low-income households or tax incentives for companies investing in energy access initiatives. Targeted subsidies would help mitigate the financial barriers that hinder electricity access for the poor, thereby promoting inclusive economic development (Karekezi & Kithyoma 2002).

Uganda's electricity access could benefit from stronger regional cooperation and the establishment of cross-border electricity grids. Integrating Uganda into regional power pools could help stabilize supply and reduce electricity costs. This will not only enhance access but also promote economic integration within East Africa (Blimpo et al. 2019).

We recommend that Uganda implements community-based energy programs to support local solutions for electricity access. These programs can foster the development of small-scale, renewable energy projects such as solar microgrids or biogas plants. Encouraging community participation in energy projects ensures that local needs are met and empowers communities to take ownership of their energy future (World Bank 2023).

Programs focused on raising awareness about the importance of electricity access and energy efficiency should be launched. Educating the population on the benefits of energy access, particularly in rural areas, will help create demand for electricity and ensure that communities understand how to maximize the potential of electricity for economic and social development (Tiwari et al. 2022).

Ugandan government should foster partnerships with the private sector to enhance energy access. Private companies, particularly those in the renewable energy sector, can contribute to the expansion of electricity access by providing innovative solutions. Public-private partnerships (PPPs) can be particularly effective in financing and implementing off-grid and mini-grid energy projects (Tiwari et al. 2022.

Future research should explore the impact of socio-economic factors such as income levels, urbanization, and education on electricity access. A more comprehensive model that integrates these factors will provide a deeper understanding of the challenges and opportunities for increasing electricity access (Nichiforov et al. 2017). Further studies could investigate the long-term impact of policy interventions on electricity access, especially in terms of rural electrification. Research should focus on evaluating the effectiveness of current energy policies and their implementation across different regions of Uganda to identify best practices and areas for improvement (Deichmann et al. 2011).

Future research should focus on improving the quality and scope of data on electricity access in Uganda. Increased data granularity, including regional and seasonal variations, will allow for more robust models and better forecasts. Additionally, integrating advanced econometric methods, such as cointegration analysis or machine learning techniques, could provide more accurate insights into the factors influencing electricity access (Sharma & Mishra 2023).

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APPENDICES

Appendix 1: Descriptive statistics

	ELECTRICITY (% of Population)
Mean	18.07251
Median	13
Maximum	47.1
Minimum	2.811104
Std. Dev.	13.80329
Skewness	1.004091
Kurtosis	2.604648
Jarque-Bera	4.887284
Probability	0.086844
Sum	506.0304
Sum Sq. Dev.	5144.332
Observations	28

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Appendix 2: Unit root test, ELECTRICITY (in Level)

Null Hypothesis: ELECTRICITY has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=6)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.695163	0.9897
Test critical values:	1% level	-3.699871	
	5% level	-2.976263	
	10% level	-2.627420	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ELECTRICITY)
Method: Least Squares
Date: 12/23/24 Time: 22:09
Sample (adjusted): 2 28
Included observations: 27 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ELECTRICITY(-1)	0.041490	0.059684	0.695163	0.4934
C	0.787370	1.261969	0.623922	0.5383

R-squared	0.018964	Mean dependent var	1.492593
Adjusted R-squared	-0.020278	S.D. dependent var	3.861337
S.E. of regression	3.900291	Akaike info criterion	5.631166
Sum squared resid	380.3067	Schwarz criterion	5.727154
Log likelihood	-74.02075	Hannan-Quinn criter.	5.659709
F-statistic	0.483252	Durbin-Watson stat	2.409056
Prob(F-statistic)	0.493364		

Appendix 3: Unit root test, ELECTRICITY (in First difference)

Null Hypothesis: D(ELECTRICITY) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=6)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.084019	0.0000
Test critical values:	1% level	-3.711457	
	5% level	-2.981038	
	10% level	-2.629906	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ELECTRICITY,2)
Method: Least Squares

Date: 12/23/24 Time: 22:12
Sample (adjusted): 3 28
Included observations: 26 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(ELECTRICITY(-1))	-1.171855	0.192612	-6.084019	0.0000
C	1.957236	0.796133	2.458427	0.0216

R-squared	0.606656	Mean dependent var	0.226496
Adjusted R-squared	0.590267	S.D. dependent var	5.923257
S.E. of regression	3.791502	Akaike info criterion	5.577205
Sum squared resid	345.0117	Schwarz criterion	5.673982
Log likelihood	-70.50366	Hannan-Quinn criter.	5.605073
F-statistic	37.01529	Durbin-Watson stat	2.012708
Prob(F-statistic)	0.000003		

Appendix 4: Results of the ARIMA (1, 1, 4) model

Dependent Variable: D(ELECTRICITY)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 12/23/24 Time: 22:29
Sample: 2 28
Included observations: 27
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.184201	1.074121	1.102484	0.2817
AR(1)	0.030377	0.184372	0.164762	0.8706
MA(4)	0.584749	0.217923	2.683286	0.0133
SIGMASQ	10.57924	3.888418	2.720705	0.0122

R-squared	0.263167	Mean dependent var	1.492593
Adjusted R-squared	0.167058	S.D. dependent var	3.861337
S.E. of regression	3.524075	Akaike info criterion	5.555052
Sum squared resid	285.6394	Schwarz criterion	5.747028
Log likelihood	-70.99320	Hannan-Quinn criter.	5.612136
F-statistic	2.738219	Durbin-Watson stat	1.912710
Prob(F-statistic)	0.066667		

Inverted AR Roots	.03			
Inverted MA Roots	.62+.62i	.62+.62i	-.62-.62i	-.62-.62i

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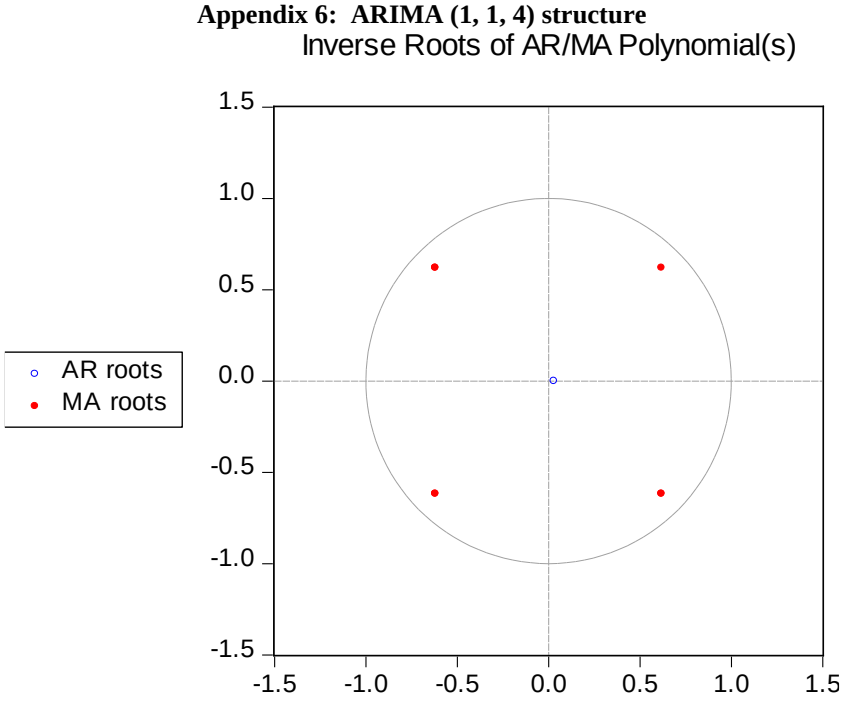
Appendix 5: Ljung-Box Q statistic/ test

Date: 12/23/24 Time: 22:33
Sample: 1 28
Included observations: 27
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	-0.004	-0.004	0.0006	
. |* . |	. |* . |	2	0.086	0.086	0.2298	
.**| . |	.**| . |	3	-0.260	-0.261	2.4399	0.118
. | . |	. | . |	4	0.027	0.026	2.4652	0.292
. *| . |	. *| . |	5	-0.168	-0.135	3.4719	0.324
. | . |	. | . |	6	0.013	-0.057	3.4782	0.481
. | . |	. | . |	7	0.011	0.050	3.4829	0.626
. *| . |	.**| . |	8	-0.114	-0.212	4.0194	0.674
. | . |	. | . |	9	0.008	0.014	4.0224	0.777
. | . |	. | . |	10	0.038	0.053	4.0883	0.849
. | . |	. | . |	11	0.067	-0.039	4.3085	0.890
. *| . |	. *| . |	12	-0.121	-0.112	5.0676	0.887

Appendix 6: ARIMA (1, 1, 4) structure



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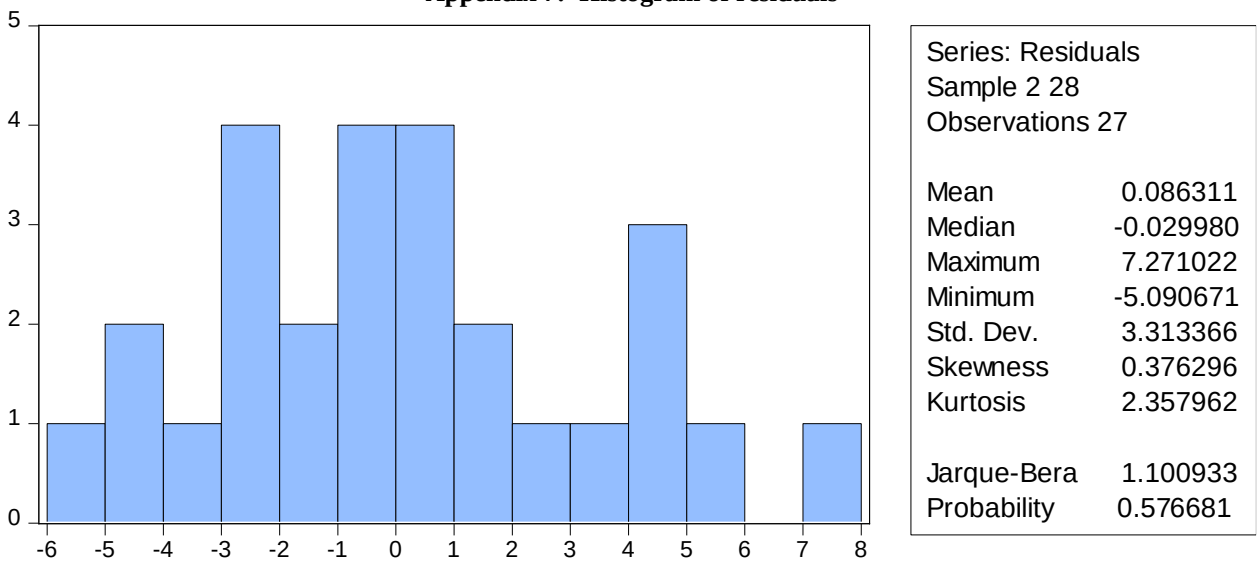
Appendix 7: Histogram of residuals



Appendix 8: Uganda's ELECTRICITY and ELECTRICITY forecast results

1995	6.8	6.8
1996	2.811104298	2.811104298
1997	3.94494772	3.94494772
1998	5.0747118	5.0747118
1999	6.199634075	6.199634075
2000	7.4	7.4
2001	8.6	8.6
2002	7.8	7.8
2003	10.5	10.5
2004	11.6	11.6
2005	8.9	8.9
2006	9	9
2007	14.8	14.8
2008	15.9	15.9
2009	10	10
2010	12.1	12.1
2011	14.6	14.6
2012	20.5	20.5
2013	13.9	13.9
2014	20.4	20.4
2015	18.5	18.5
2016	26.7	26.7
2017	32.4	32.4
2018	41.9	41.9
2019	41.3	41.3
2020	42.1	42.1
2021	45.2	45.2
2022	47.1	47.1
2023		**48.05032169**
2024		**47.55414221**

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2025		**47.3302452**
2026		**47.04430145**
2027		**48.18384274**
2028		**49.36668669**
2029		**50.55084606**
2030		**51.73504539**
2031		**52.91924594**
2032		**54.10344652**
2033		**55.2876471**
2034		**56.47184768**
2035		**57.65604827**
2036		**58.84024885**
2037		**60.02444943**
2038		**61.20865001**
2039		**62.3928506**
2040		**63.57705118**
2041		**64.76125176**
2042		**65.94545234**

Appendix 9: Graph showing Uganda's ELECTRICITY and ELECTRICITY forecast results