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On Retention and Growth Patterns of Abuja Electricity Distribution Company Metered Customers through Times Series Forecasting

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Abstract. This study investigates the long term growth dynamics of metered customers within the Abuja Electricity Distribution Company (AEDC) from 2015 to the first quarter of 2024, using descriptive analytics, trend modelling, and time series forecasting. The descriptive analysis shows a sustained upward trajectory in metering coverage, characterized by policy driven surges during key roll out periods. A linear trend model reveals a highly significant positive slope $\beta = 4,946.69$ and strong explanatory power $(R^2 = 0.94)$, confirming that time is a dominant driver of metering expansion. Annual retention rates further highlight substantial growth in several years, with values exceeding 110% during intensive metering campaigns. In order to forecast future metering performance, multiple ARIMA models were compared, and ARIMA $(1,1,1)$ emerged as the optimal specification based on lowest AIC, BIC, RMSE, and MAPE values. The model's Ljung-Box p-value of 1 indicates that residual autocorrelation is fully addressed which validate its suitability for forecasting. Projections for 2024–2028 indicate continued growth under current operational and policy conditions. Overall, the findings demonstrate strong historical progress and provide a statistically sound basis for future planning and metering investment strategies within AEDC.

Keywords: Forecasting, Growth, Metered, Retention rate

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1. Introduction

Privatisation of the electricity sector in Nigeria started with the enactment of the Electric Power Sector Reform Act, 2005 (EPSR Act) in 2005, which led to the establishment of the legal and regulatory framework for private sector participation and removing of the state monopoly. According to the Bureau of Public Enterprises (BPE), the Nigerian Electricity Regulatory Commission (NERC) was also created with the Power Holding Company of Nigeria (PHCN) as a transitional entity and PHCN was unbundled into six generation companies, one Transmission Company, and eleven distribution companies (Aguda, 2023;

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BPE, 2025). In implementing the Act, PHCN took over the former Nigerian Electricity Power Authority (NEPA) in its assets, liabilities, and functions. The Privatisation reform attained full implementation in 2013 with the generation and distribution value chains were handed over to private investors with intention of improving supply, reliability and improving operational efficiency (Aguda, 2023; BPE, 2005.

Abuja Electricity Distribution Company (AEDC) was among the eleven distribution companies privatised and transferred to private ownership on November 1, 2013. A 60 % equity stake in AEDC held by KANN Utility Limited as a private investor, while the Federal Government of Nigeria retains 40 %. AEDC's distribution franchise spread over 133,000 km^2 across the Federal Capital Territory (FCT), Niger State, Kogi State, and Nasarawa State. AEDC was the fourth of the eleven DISCOs in Nigeria in the roll out of the privatised structure (Adekeye, 2024). It was founded in 1997 and saddled with owning and maintaining the distribution network, installing meters, performing maintenance and billing, organizing consumer credit, and collecting revenues.

AEDC continues to face constant challenges of ageing infrastructure, high technical and non-technical losses, revenue leakage, and a substantive metering gap like other electricity distribution companies in Nigeria (Dahunsi et al., 2021). Metering is recognized as an important operational efficiency lever, supporting billing accuracy, reducing theft, improving revenue collection and customer satisfaction. In the past, Nigeria relied on post-paid meters with manual reads and high error risk; these aforementioned shortcomings led to the introduction of prepaid meters from the middle of 2000s as a solution to controversies around estimated billing, but its uptake remained low due to lack of proper funding and implementation constraints (Dahunsi et al. 2021).

Moreover, NERC introduced the Meter Asset Provider (MAP) Regulations in 2018 to speed up meter roll out by allowing third-party investors to supply, install and maintain meters under regulated amortization structures (Farris, et al., 2010; Nigerian Electricity Regulatory Commission, 2018). Despite this intervention, the metering gap has remained stunted as of April 2025, data from NERC show only $6,274,936$ out of $11,700,422$ active customers were metered which was approximately 53.6%, leaving over 5.4 million unmetered customers (THISDAY Live, 2025). The issue of electricity metering is important to AEDC in the light of several reforms and privatisation processes in the power sector in Nigeria. Many customers still relied on estimated billing due to poor metering infrastructure, which has contributed to consumer frustrations, loss of revenue, and inefficiencies in operations (Dahunsi, et al., 2021). Despite several efforts to introduce MAP scheme by the NERC in solving the metering gap which were unsuccessful due to such factors as insufficient implementation, lack of funds, and regulation bottlenecks. The objectives of transparency, financial sustainability, and the provision of better services to consumers in the power sector is unlikely to be achieved without proper and extensive metering.

This research seeks to provide data driven insights into metered customer retention, and growth by detecting key trends, and forecasting future customer expansion in supporting effective planning and decision making in the electricity distribution sector in Nigeria. In achieving this, the objectives are to: uncover underlying trends of metered customers, estimate the customer retention rate,

and forecast future metered customer growth for 2026 to 2028. Electricity metering brings out fair billing, boosts utility revenue, and reduces energy losses in Nigeria's power sector. The AEDC faces protracted metering, and billing challenges due to structural and regulatory reforms like privatisation and Public-Private Partnerships $(PPPs)$ (Adekeye, 2024). These issues eroding customers' trust and threaten financial stability, given AEDC's strategic role in serving the FCT and nearby states, evaluating its metering performance is very important. This study therefore applies statistical time series analysis to reveal trends, and forecast future metering outcomes. While previous works focused on qualitative reforms, and few quantify metering trends over time. Findings will offer evidence based insights for policymakers to improve programme like MAP and Credit Advance Payment for Meter Implementation $(CAPMI)$ toward universal metering (Ikwuagwu & Ajah, 2023; Oseni, 2015; Oteh, et al., 2021).
On the review of previous study, Time series modelling has long provided a rigorous framework for analyzing and forecasting temporal patterns for utility data. The Box-Jenkins technique remains foundational by combining auto regressive, differencing and moving average components, Autoregressive Integrated Moving Average $(ARIMA)$ models capture autocorrelation and short term variation in a single univariate framework and are widely recommended for short to medium horizon forecasting when a single well measured series contains the signal of interest (Box & Jenkins, 1976; Hyndman & Athanasopoulos, 2018). Modern treatments focus careful identification (p, d, q), stationarity checks, diagnostic testing and rolling forecast evaluation to produce reliable point, forecasts and prediction intervals (Hyndman & Athanasopoulos, 2018. Evidently, ARIMA and hybrid $ARIMA$ machine learning techniques have been used successfully to electricity load and customer count forecasting across contexts, showing that ARIMA often performs well for total short horizon forecasts while machine learning models are improved value when many exogenous predictors are available (Tarmanini, et al. 2023; Enerud, 2024). For metering and subscriber count problems, aggregated Time series models can forecast net customer growth (acquisitions minus attrition), while cohort level methods (survival analysis or Markov chains) better explain retention variability at the individual or segment level (Edgered, 2024). Therefore, combining cohort analyses with ARIMA forecasts produces both operational forecasts and causal insight into retention drivers (Montgomery, et al., 2015).
The Nigerian context presents policy specific considerations despite regulatory interventions such as the MAP Regulations (2018) and the more recent mass metering procurement, the national metering gap has remained substantial, constraining revenue collection and complicating forecasting due to measurement noise from estimated billing and irregular meter roll out (Nigerian Electricity Regulatory Commission, 2018, 2024). Government procurement drives in $2024 - 2025$ such as plans to procure millions of meters which is aimed to close this gap of meter deficit, but implementation lags and structural breaks (policy changes, mass meter installs) can introduce regime shifts that standard ARIMA may fail to capture unless interventions are modelled explicitly (Mohammed, 2024; Proshare Research,2024). Recent empirical studies in Nigeria indicate smart metering and targeted meter programmes can reduce Aggregate Technical, Commercial and Collection $(ATC\&C)$ losses when accompanied by robust

financing and supply chain arrangements (research on smart metering effectiveness; Research Gate studies 2024–2025).
On customers' satisfaction, Santos et al. (2022) investigated customer satisfaction in residential electricity distribution using structural equation modeling to examine the relationships among service quality, perceived value, trust, and overall satisfaction. Their findings indicate that service reliability, billing transparency, and perceived service fairness significantly influence customer satisfaction, which in utility service research is closely associated with customer loyalty and long-term retention behavior. The study demonstrates that improving operational performance particularly in billing accuracy and service responsiveness that enhances consumer confidence in electricity providers, thereby supporting sustainable customer retention. Although retention growth was not directly modelled as a dependent variable, the authors' empirical evidence provides a strong conceptual and statistical foundation for linking metering quality and service performance to retention outcomes in electricity distribution markets.
Accurate metering is essential for revenue protection, loss reduction, and customer satisfaction in electricity distribution (Dahunsi et al., 2021; Oseni, 2015). Customer's retention depends on reliable metering and billing, often analyzed using cohort or survival methods (Edgered,2024). ARIMA and SARIMA time series models are widely used to forecast customer growth and load demand (Box & Jenkins (1976); Hyndman & Athanasopoulos (2018); Tarmanini et al., 2023). In Nigeria, programmes like MAP and $CAPMI$ aim to improve metering coverage, but significant gaps remain (Nigerian Electricity Regulatory Commission, 2018, 2024). Combining metering assessment with statistical forecasting provides actionable insights for operational and strategic planning in distribution utilities.
Electricity metering has evolved from traditional electromechanical devices to advanced smart meters capable of real-time data acquisition and two way communication, forming a critical component of modern smart grids. Hassan et al. (2022) provides a comprehensive survey and bibliometric analysis of communication technologies for smart meters, including power line communication (PLC), cellular networks, wireless sensor networks (WSN), and low power wide area networks (LPWAN). The study highlights that each technology presents trade-offs in terms of cost, coverage, data rate, and security, suggesting that hybrid communication architectures often offer optimal performance. Key challenges identified include cybersecurity vulnerabilities, interoperability issues, and the need for standardized protocols, emphasizing that reliable meter communication is as vital as accurate measurement. Overall, the study underscores that effective deployment of smart metering systems depends on the integration of appropriate communication technologies, which directly influences operational efficiency, data reliability, and consumer engagement in electricity usage management (Hassan, et al. 2022).
On smart meter, Rind et al. (2023) provided a comprehensive review of smart energy meters from an internet of things (IoT) perspective, emphasizing their role in advanced metering infrastructure (AMI) and smart grid environments. The authors analyzed the architecture of smart meters, including sensing units, microcontrollers, communication modules, and cloud based data management

systems. Their review highlights how smart meters measure active, reactive, and apparent power in real time and transmit consumption data through wireless technologies such as GSM, $Wi-Fi$, $ZigBee$, and internet of thing. The study further discussed cybersecurity concerns, data privacy, interoperability challenges, and integration with renewable energy sources. Overall, the authors conclude that IoT enabled smart meters significantly improve billing accuracy, demand-side management, and energy efficiency, while also supporting predictive analytics and load forecasting in modern power systems.
Jaiswal & Thakre (2022) in Global Transitions Proceedings, focus on the modeling and design of a smart energy meter suitable for smart grid applications. Their work presents the mathematical formulation of power measurement, including computation of instantaneous power$P = VI\cos\phi$, and the digital processing of voltage and current signals using embedded systems. The study demonstrates how microcontroller based designs enhance measurement precision and enable automated billing and remote monitoring. The authors also discuss the hardware configuration and simulation results validating system accuracy. Their findings reinforce the importance of integrating digital metering with communication modules to ensure efficient power consumption monitoring and real-time data transmission within distributed electricity networks.
Avancini et al. (2021) in International Journal of Energy Research, propose an IoT based smart energy meter designed for scalable smart grid deployment. The study introduces a multi-protocol communication framework that supports interoperability across heterogeneous network infrastructures. Through experimental validation, the authors demonstrate the meter's ability to accurately measure consumption data while maintaining secure, low-latency transmission to utility servers. The research further evaluates system reliability, scalability, and integration with energy management platforms. The authors conclude that IoT based smart meters enhance operational transparency, reduce non-technical losses, and provide utilities with actionable consumption data for improved grid optimization and customer engagement.
On the gap addressed by the research, despite reforms and initiatives like MAP and $CAPMI$, there is limited quantitative analysis of metered customer trends and retention in Nigerian distribution utilities (Adekeye, 2024; Nigerian Electricity Regulatory Commission, 2024). Most studies rely on qualitative assessments or cross-sectional data thereby providing limited insight into temporal patterns and forecasting (Dahunsi, et al. 2021). Therefore, there is a lack of time-series-based forecasting studies that combine retention analysis with predictive modeling for future customer expansion (Hyndman & Athanasopoulos, 2018). This gap constrains data driven decision making, strategic planning, and evaluation of metering interventions in the electricity sector (Oseni, 2015).
Methodologically, best practice for a study on AEDC should therefore a combine: $i.$ data on metered customer series such as net counts versus billed accounts; $ii.$ descriptive as well as seasonal decomposition to detect trends and periodicities; $iii.$ ARIMA or Sessional Auto Regressive Integrated Moving Average (SARIMA) modelling with intervention terms with exogenous policy events like MAP and CAPMI occur; $iv.$ cohort or survival analysis of retention estimation; and $v.$ rolling-origin cross-validation and interval forecasting to quantify uncertainty. This mixed approach by Box and Jenkins (1976); Hyndman &

Athanasopoulos (2018); Tarmanini et al. (2023) yields actionable forecasts for planning and policy evaluation while providing evidence on the effectiveness of metering initiatives in improving revenue and reducing losses.
Sosa et al. (2020) investigated long term electricity consumption forecasting using the ARIMA/SARIMA Time series framework applied to monthly kWh sales data from PT. PLN (Persero) in East Java, Indonesia over a ten year period (2008-2017). The study is methodologically sound in its use of Box-Jenkins procedures such as model identification, estimation, diagnostic checking, and forecasting and appropriately justifies ARIMA for univariate linear data. The selected SARIMA $[(1,1,0)(0,1,1)]_{12}$ model achieves a low MAPE (7.97%), indicating good predictive accuracy; however, the negative R^2 value reflects limitations in explanatory power due to data size and variability. While the work contributes practical evidence for ARIMA's applicability in utility demand planning, its reliance on a single univariate series and lack of exogenous variables (for examples, GDP, population, tariffs) constrain the model's robustness for policy and infrastructure decision-making.
Furthermore, Subha & Kowsigan (2023) presented an enhanced ARIMA-based framework for forecasting water demand within an internet enabled smart water distribution network, using long-term monthly consumption data from Austin, Texas. The study was methodologically rigorous in its application of Time series preprocessing, stationarity testing, and automated ARIMA model selection based on the Akaike Information Criterion (AIC), leading to the choice of an $ARIMA(0,0,1)$ model with a non-zero mean. Model performance is evaluated using standard accuracy metrics, including RMSE, MAE, and MASE, which demonstrate acceptable predictive capability for medium term planning. While the integration of ARIMA with smart metering data highlights the model's practical relevance for urban water management, the approach remains limited by its reliance on univariate historical demand without incorporating exogenous drivers such as climate variability, pricing, or population growth, which may restrict its robustness under changing socio-environmental conditions.

2. Materials and Method

2.1 *Study Design and Data Source*

The study focuses on all metered customers of the AEDC across its four operating states which are FCT, Niger, Kogi, and Nasarawa where AEDC serves more than one million customers, its specifically targets residential, commercial, and industrial clients with prepaid or postpaid meters from 2015 to Q1 2024. Instead of sampling individuals, the project utilizes aggregated secondary data from AEDC and NERC thereby effectively conducting a census of the available time-series data. Comparing quarterly and annual metered customer counts ensures comprehensive coverage of AEDC's activities, enabling accurate trend analysis, retention estimation, and forecasting. Using complete population data to improve the reliability of statistical modelling and avoids sampling errors common in survey based studies.

2.2 *Statistical Analysis*

2.2.1 Trend Analysis

The trend equation is presented in equation (1)

$$\hat{T}_t = \hat{\beta}_0 + \hat{\beta}_1 t \tag{1}$$

Where:

$$\hat{\beta}_1 = \frac{\sum(t-\bar{t})(Y-\bar{Y})}{\sum(t-\bar{t})^2} \tag{2}$$

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{t} \tag{3}$$

Assumptions of the model positioned in equation (1) includes, linearity, homoscedasticity, and residual autocorrelation (Montgomery et al., 2015)

2.2.2 Retention Rate

The customer retention rate (RR) is to assess the proportion of existing customers who remain active over a given period, excluding new acquisitions as positioned in equation (4):

$$RR = \frac{C_t - N_t}{C_{t-1}} \times 100 \tag{4}$$

Where:

$$\begin{aligned} RR &= \text{Retention Rate (\%)} \\ C_t &= \text{Number of customers at the end of the current period} \\ N_t &= \text{Number of new customers acquired during the current period} \\ C_{t-1} &= \text{Number of customers at the beginning of the period} \end{aligned}$$

A higher RR conveys a better loyalty and service efficiency (Edgered, 2024; Farris et al., 2010). RR helps electricity distributors like AEDC in tracking customer stability as well as forecast future retention trends of metered customers (Hyndman & Athanasopoulos, 2018; Oseni, 2015).

2.2.3 Auto Regressive Integrated Moving Average

ARIMA model to predict the metered number of customers that AEDC will have from 2026 to 2028 is presented in equation (5) (Montgomery et al., 2015).

$$M_t = c + \sum_{i=1}^{p} \phi_i M_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{5}$$

If the series is differenced d times, the full ARIMA(p, d, q) model becomes equation (6)

$$\Delta^d M_t = c + \sum_{i=1}^{p} \phi_i \Delta^d M_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{6}$$

Where

$$\begin{aligned}
M_t &= \text{Forecasted number of metered customers at time } t \\
c &= \text{Constant or intercept} \\
p &= \text{Order of the autoregressive (AR) component} \\
d &= \text{Number of times the series is differenced} \\
q &= \text{Order of the moving average (MA) component} \\
\phi_i &= \text{Autoregressive coefficients} \\
\theta_j &= \text{Moving average coefficients} \\
\varepsilon_t &= \text{Random error term at time } t, \quad \varepsilon_t \sim N(0, \sigma^2)
\end{aligned}$$

Source: (Sosa et al. 2020)

3. Results and Discussion

3.1 *Linear Trend Model*

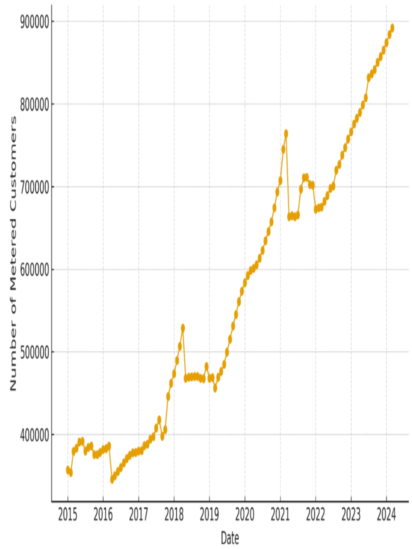

Figure 1: Abuja Electricity Distribution Company Metered Customers between 2015 and First Quarter of 2024

AEDC's metered customers increased steadily from about 350,000 in 2015 close to 900,000 in early 2024 is display in Figure 1. Although, growth was slow and fluctuating between years 2015 to 2017 and there were minor ups and downs but a sharp rise occurred in 2018, followed by a little drop and stabilization in 2019. The trend turned upward as from 2020 with sustained expansions. Major increase occurs around 2021 which was due to increase in metering programme. Generally, the series shows consistent long-term growth with policy-driven surges.

Table 1: Trend Analysis of Metered Customers of Abuja Electricity Distribution Company

Parameter	Estimate	Standard Error	t-Statistic	P-Value
Intercept	286,024.75	7,712.40	37.09	0.000
Trend (t)	4,946.69	119.54	41.38	0.000
R^2	0.94			
Adjusted R^2	0.92			

$\text{Y}_t = 286{,}024.75 + 4{,}946.69\,t$(7) Parameters estimates of trend analysis of equation (1) displayed in Table 1 is fitted as equation (7) being estimated trend model for the metered customers. The intercept $\beta_0 = 286{,}024.75$ indicates the estimated value of the series at the starting point of the study period (when $t = 0$). The slope coefficient $\beta_1 = 4{,}946.69$ shows that, on average, the variable increases by 4,946.69 units per year, indicating a strong upward trend over time. The associated t-statistics for both parameters are very large: $t = 37.09$ for β_0 and $t = 41.38$ for β_1, with p-values approximately equal to zero, confirming that the trend is statistically significant at the 5% level. This implies that time is a strong predictor of changes in the series, and the variable exhibits a consistent and significant growth pattern over the study period. The p-value of 0.000 for $\hat{\beta}_1$ indicates the upward trend is highly statistically significant. Together, these results show a clear and consistent long-term increase in metered customers. Statistically, the model provides strong evidence that time is a major driver of AEDC's metering growth. An R^2 of 0.94 means the model explains 94% of the variation in metered customer growth, indicating an excellent fit. The Adjusted R^2 being 0.92 shows that the model's explanatory power remains strong even after adjusting for the number of predictors (Raykov & DiStefano, 2025). This high alignment confirms that time is a very reliable predictor of AEDC's metering expansion.

3.2 *Retention Rate*

Table 2: Annual Retention Rate of Abuja Electricity Distribution Company Metered Customers

Year	Start	End	Return (%)
2015	357,045	378,248	105.9
2016	381,592	378,416	99.2
2017	380,118	462,048	121.6
2018	473,457	482,508	101.9
2019	468,223	573,134	122.4
2020	583,619	693,622	118.8
2021	707,333	701,781	99.2
2022	672,571	757,733	112.7
2023	766,077	864,970	112.9
2024	874,029	892,028	102.1

The annual data in Table 2 shows significant variability in customer growth and retention across the years. From 2015 to 2024, AEDC generally experienced rising customer numbers, with strong expansion in years like 2017, 2019, and 2020, where retention rates exceeded 118%, indicating substantial net additions. Years such as 2016 and 2021 show retention rates slightly below 100%, suggesting minor declines or slow turnover in metered customers. The sharp increases in 2020 and 2023 reflect periods of aggressive metering programs and improved customer capture. Meanwhile, 2022 shows a strong rebound after a dip in 2021, highlighting recovery in customer acquisition efforts. Overall, the table demonstrates a mostly positive long-term trajectory with intermittent dips, driven by operational changes, policy interventions, and metering roll out intensity. On model identification and selection, by considering the stochastic dynamics of the series, several ARIMA (p,d,q) specifications were estimated following first-order differencing d=1 to achieve stationarity. The competing models are ARIMA(1,1,1), ARIMA(0,1,1), and ARIMA(2,1,1) which were evaluated using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Root Mean Square Error (RMSE). These criteria jointly assess model parsimony, goodness-of-fit, and predictive accuracy. On ARIMA (1,1,1), differencing equation (4) yields equation (5) which incorporate one autoregressive term and one moving average term on the first differenced series. The inclusion of both autoregressive of order 1 (AR(1)) and Moving Average 1 (MA(1)) components implies that the current change in the series depends not only on its immediate past change but also on past random shocks. This dynamic structure captures both persistence and short-term shock adjustments, which is particularly suitable for economic or utility-related time series exhibiting gradual growth and stochastic disturbances.

3.3 *Forecasting*

Table 3: Auto Regressive Integrated Moving Average (ARIMA) Candidate Models

p	d	q	AIC	BIC	RMSE
1	1	1	2447.83	2455.93	37,443.90
0	1	1	2454.53	2459.93	37,722.90
2	1	1	2455.58	2466.38	37,626.20

On model identification and selection, Table 3 present the stochastic dynamics of the series, several ARIMA (p, d, q) specifications were estimated following first-order differencing $(d = 1)$ to achieve stationarity. The competing models are ARIMA(1,1,1), ARIMA(0,1,1), and ARIMA(2,1,1), which were evaluated using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Root Mean Square Error (RMSE). These criteria jointly assess model parsimony, goodness-of-fit, and predictive accuracy. For ARIMA(1,1,1), differencing equation (5) yields equation (6), which incorporates one autoregressive term and one moving average term on the first differenced series. The inclusion of both autoregressive of order 1 (AR(1)) and moving average of order 1 (MA(1)) components implies that the current change in the series depends not only on its immediate past change but also on past random shocks. This dynamic structure captures both persistence and short-term shock adjustments, which is particularly suitable for economic or utility-related time series exhibiting gradual growth and stochastic disturbances as presented in equation (8)

$$\Delta M_t = c + \phi_1 \Delta M_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t \tag{8}$$

The results presented in Table 3 for ARIMA(1,1,1) produced the lowest AIC (2447.83) and BIC (2455.93) values, alongside the smallest RMSE (37,443.90). Since lower AIC and BIC values indicate a better trade-off between model complexity and fit, the ARIMA(1,1,1) specification demonstrates superior explanatory and forecasting performance relative to the alternative models. The relatively small difference between AIC and BIC further suggests that the selected model achieves parsimony without unnecessary parameter inflation. The superior performance of ARIMA(1,1,1) indicates that the series follows a stochastic trend process with short-run dependence. The first differencing confirms that the original series is integrated of order one, $I(1)$, implying non-stationarity in levels but stationarity in first differences. Consequently, forecasts derived from this model incorporate both deterministic growth through the differencing structure and stochastic adjustments via AR and MA components, making it robust for medium-term projections. From a policy and planning perspective, the model suggests that variations in the number of metered customers are influenced by both momentum effects captured by the AR term, and temporary shocks captured by the MA term. This provides empirical evidence of dynamic adjustment behavior in the metering expansion process. Considering the ARIMA(0,1,1) model, it is expressed as a first-differenced moving average process of order one (MA(1)) without autoregressive dynamics as shown in equation (9)

$$\Delta M_t = c + \theta_1 \varepsilon_{t-1} + \varepsilon_t \tag{9}$$

Although the model is simpler, it yielded higher AIC (2454.53) and RMSE (37,722.90) values, indicating reduced predictive efficiency. Similarly, the ARIMA(2,1,1) model is presented in equation (7); despite incorporating an additional autoregressive parameter, it did not improve model performance, instead resulting in higher AIC (2455.58) and BIC (2466.38) values. This suggests potential overparameterization without commensurate improvement in explanatory power is positioned in equation (10)

$$\Delta M_t = c + \phi_1 \Delta M_{t-1} + \phi_2 \Delta M_{t-2} + \theta_1 \varepsilon_{t-1} + \varepsilon_t \tag{10}$$

Where M_t, q, ϕ_i $(i = 1, 2)$, θ_j $(j = 1)$, and $\varepsilon_t \sim N(0, \sigma^2)$ are as defined in equation (2).

Overall, based on information theoretic criteria, and forecast accuracy measures, ARIMA(1,1,1) is selected as the optimal specification. The model achieves a balance between parsimony and predictive performance, and its stochastic structure adequately characterizes the temporal evolution of the series.

The Figure 2 compares the actual number of AEDC metered customers with the fitted values from the ARIMA(1,1,1) model across 2015-2024. The actual series shows a strong upward trajectory with noticeable jumps around 2018, 2020, and 2021, reflecting periods of intensified metering programs. The ARIMA fitted line closely tracks the actual data throughout the entire period, indicating that the model captures both the long-term growth trend and short-term fluctuations effectively. Although there is an initial dip at the beginning typical of differencing in ARIMA models, the fit stabilizes quickly and aligns tightly with the real observations. Overall, the plot demonstrates that ARIMA(1,1,1) provides a reliable representation of the customer growth pattern, validating its suitability for forecasting AEDC's future metering levels.

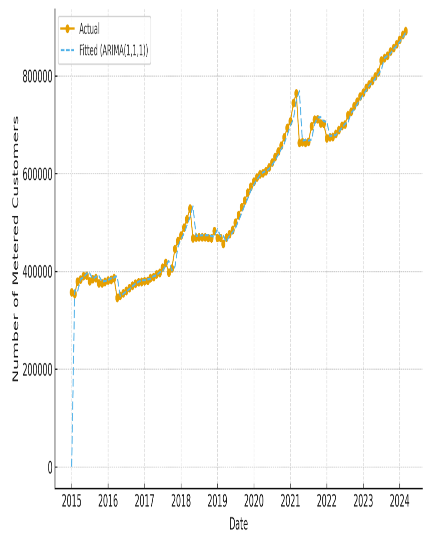

Figure 2: Actual Versus Fitted of ARIMA (1,1,1)

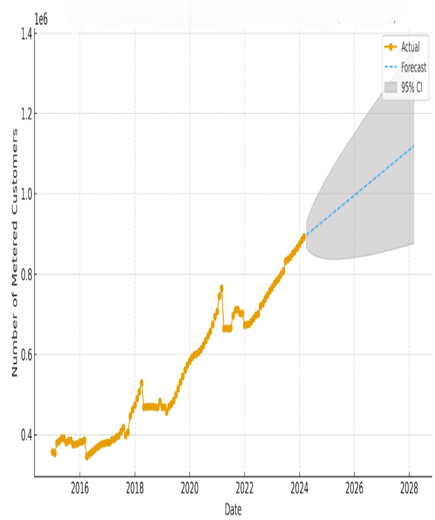

Figure 3: ARIMA Forecast (2024-2028)

The ARIMA forecast for 2024-2028 projects a continued upward growth in AEDC's metered customers, extending the strong trend observed in the historical data as presented in Figure 3. The forecast line likely shows a smooth increase, reflecting the model's expectation that metering expansion will persist at a steady pace if current conditions remain unchanged. The confidence intervals around the forecast widen gradually over time.
This is normal and indicates increasing uncertainty the further the model projects into the future. Despite this uncertainty, the central forecast still suggests substantial customer growth, consistent with past installation patterns and policy driven metering programs. Overall, the figure signals a positive outlook

for AEDC's metering coverage, supporting long-term planning for infrastructure, resources, and operational expansion.

Table 4: Model Validation Summary

Model	R^2	AIC	BIC	RMSE	MAPE (%)	Ljung–Box p-value
Trend	0.94	2671.39	2676.81	39,988.20	6.61	–
ARIMA(1,1,1)	–	2447.83	2455.93	37,443.90	2.54	1

The validation results in Table 4 show that while the Trend model performs reasonably well with an R^2 of 0.94, it is clearly outperformed by the ARIMA(1,1,1) model across key accuracy metrics. The ARIMA model achieves substantially lower AIC and BIC values, indicating a better overall model fit with fewer penalties for complexity. Its RMSE (37,443.90) and particularly the very low MAPE (2.54%) demonstrate that ARIMA predicts the number of metered customers far more accurately than the Trend model.
Furthermore, the Ljung–Box p-value of 1 confirms that the residuals of the ARIMA model exhibit no significant autocorrelation, suggesting that the model adequately captures the underlying dynamics of the data. In contrast, the Trend model does not provide such diagnostic verification. Overall, the ARIMA(1,1,1) model emerges as the superior forecasting tool based on model fit, forecast accuracy, and statistical reliability.

4. Conclusion

The analysis demonstrates a consistent and substantial expansion in AEDC's metered customer base from 2015 to early 2024, driven primarily by policy-supported metering initiatives and operational improvements. The descriptive trend shows steady long-term growth with notable surges during intensive roll-out periods, particularly in 2018, 2020, and 2021. The linear trend model confirms this upward trajectory statistically, with a highly significant slope and strong explanatory power ($R^2 = 0.94$), indicating that time is a strong determinant of metering growth.
Retention rate patterns further reinforce the company's positive customer acquisition performance, with several years recording retention rates above 110%, reflecting effective expansion efforts despite occasional short-term fluctuations. The forecasting analysis identifies ARIMA(1,1,1) as the most robust model, outperforming alternative specifications through lower AIC, BIC, RMSE, and a very low MAPE. In addition, its residuals successfully pass the Ljung–Box test, confirming that the model adequately captures both the underlying trend and short-term stochastic dynamics in the series.
Overall, the results indicate that AEDC has achieved substantial and sustained growth in metered customers over the past decade. The ARIMA(1,1,1) model further provides reliable evidence that this upward trajectory is likely to persist in the medium term. These findings therefore offer a solid empirical basis for planning future metering targets, improving resource allocation, and designing effective policy interventions aimed at sustaining metering expansion.

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