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Forecasting the Total Electricity Demand in the City of Malaybalay: Application of Seasonal Autoregressive Integrated Moving Average Model

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ABSTRACT

Power outages remain a significant challenge in Malaybalay as it aims to become a highly urbanized city. Scheduled and unscheduled brownouts exacerbate economic losses across almost all sectors of the economy. This study attempts to examine the trends of the total electricity demand by type of consumer, namely residential, commercial, and industrial, utilizing the 2012 to 2025 monthly data from Bukidnon Second Electric Cooperative (BUSECO). It employed generalized least squares to estimate the demand function for total electricity demand and a seasonal autoregressive integrated moving-average model to forecast electricity demand for 2025 to 2031. The results of the study indicate that a percentage increase in the number of consumers leads to a 1.25 percent increase in total electricity demand, ceteris paribus. Moreover, the SARIMA (1, 1, 1) (1, 0, 1, 12) model has been statistically identified as the best predictive model based on Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) for total electricity demand. Also, the SARIMA (1, 1, 1) (1, 1, 1, 12) model was identified for the residential demand. The SARIMA (0, 1, 1) (0, 1, 1, 12) model for commercial demand, and the SARIMA (1, 1, 1) (1, 0, 1, 12) model for industrial demand. SARIMA model estimates show that total electricity demand could reach 25,859,611.8 kWh kilowatt hours (kWh) in the year 2031, while residential demand is estimated to reach 15,886,455.11 kilowatt hours (kWh), the commercial demand is 6,707,288.70 kilowatt hours (kWh), and industrial demand could reach 16,878,389.31 kilowatt hours (kWh) for the same year. Results highlight the importance of anticipatory planning to ensure a stable electricity supply and promote sustainable growth and development in the city.

Keywords: Forecasting, generalized least squares, total electricity demand, seasonal autoregressive integrated moving average, Malaybalay

INTRODUCTION

Malaybalay City, the capital of Bukidnon Province in Northern Mindanao, has emerged as one of the region's fastest-growing urban centers, driven by population expansion, business investments, and its strategic role as Bukidnon's administrative and economic hub. According to the Philippine Statistics Authority (PSA), the city's population reached 190,712 in 2020, increasing from 174,625 in 2015, with an annual growth rate of 1.87%. This demographic expansion parallels the rise in commercial activities, infrastructure development, and household energy consumption. In recognition of its development performance, Malaybalay City ranked 35th among 114 component cities in terms of economic dynamism in 2023 and earned the Seal of Good Local Governance (SGLG) in 2022, affirming its commitment to sound governance and sustainable development (malaybalaycity.gov.ph; psa.gov.ph).

However, the city's steady economic and population growth has been persistently undermined by recurring scheduled and unscheduled power interruptions, posing significant threats to its economic competitiveness and residents' quality of life. Data from the Bukidnon Second Electric Cooperative (BUSECO) reveal that Malaybalay City has already experienced fifty-nine (59) scheduled and seventy-two (72) unscheduled power outages as of August 7, 2025. These interruptions are attributed to line faults, system maintenance, pole rehabilitation, vegetation clearing, and other technical issues (buseco.coop). While these causes may appear routine, their cumulative effect is economically crippling. The Philippine Institute for Development Studies

(PIDS) estimates that each electricity supply interruption experienced by electric cooperatives can result in losses amounting to ₱10.7 billion nationwide, underscoring the economic gravity of unstable power supply.

Studies conducted in various international contexts consistently demonstrate that reliable electricity supply is a critical driver of economic productivity, business continuity, and overall urban development. Frequent power interruptions are shown to reduce firm output, disrupt supply chains, and discourage investments, particularly in cities with growing commercial sectors. Moreover, electricity demand is strongly correlated with population growth, urbanization, and sectoral economic composition.

Synthesizing these findings, it becomes evident that stable electricity supply is not only a technical requirement but a foundational element of sustained economic growth. However, Malaybalay City presents a distinct context compared to industrialized or highly urbanized cities examined in international studies. Its economy is largely service-oriented and composed of micro, small, and medium enterprises, making it more vulnerable to power disruptions that directly affect daily business operations and household livelihoods. Unlike large industrial firms that may have backup systems, many local establishments in Malaybalay rely solely on continuous grid supply, amplifying the socioeconomic impact of outages. This highlights the need for localized analysis and forecasting approaches that reflect the city's unique economic structure and energy consumption patterns.

Given these realities, forecasting electricity demand becomes a strategic necessity rather than a mere technical exercise. Reliable demand projections will allow utility providers, local planners, and policymakers to anticipate load requirements, optimize energy distribution, and formulate proactive infrastructure investments. This aligns directly with the Philippine Development Plan (PDP) 2023–2028, which envisions a "prosperous, predominantly middle-class society by 2040"—a goal that inherently depends on achieving affordable, accessible, and reliable energy security (pdp.neda.gov.ph). Furthermore, the study contributes to the realization of Sustainable Development Goal (SDG) 7, which seeks to "ensure access to affordable, reliable, sustainable, and modern energy for all," and also Sustainable Development Goal 11, which aims to promote "sustainable cities and communities."

Thus, examining and forecasting the electricity demand of Malaybalay City is not only timely but also essential. The study bridges the gap between economic growth and energy sustainability by providing empirical insights to guide future energy planning. In doing so, it supports both local development priorities and the broader national and global agenda for sustainable and inclusive growth.

Objectives of the Study

The general objective of the study was to estimate the electricity demand function for the city of Malaybalay. Specifically, the study aimed to:

a. present the trends of total electric consumption by types of users: residential, commercial, industrial, and number of consumers in Malaybalay City, Bukidnon; and,

b. forecast electricity demand for the years 2026 to 2031.

REVIEW OF RELATED LITERATURES

Electricity demand forecasting has been widely studied using various econometric and machine learning approaches, each with distinct strengths and limitations. Traditional time-series models such as ARIMA and SARIMA have been extensively applied due to their ability to capture temporal dependencies and seasonal patterns in energy consumption data (Box et al., 2015; Hyndman & Athanasopoulos, 2021). These models are particularly effective when the data exhibit regular periodic fluctuations, as is commonly observed in monthly electricity demand series (Taylor, 2003; Contreras et al., 2003).

In contrast, recent studies have explored advanced forecasting techniques such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and hybrid models combining statistical and machine learning approaches. These models often achieve higher predictive accuracy, particularly in complex and nonlinear environments (Zhang et al., 1998; Hippert et al., 2001; Kong et al., 2017). However, their application typically requires large volumes of high-frequency data, including weather variables, real-time load data, and multiple economic indicators (Fan & Hyndman, 2012; Deb et al., 2017). Moreover, these models often function as "black

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boxes," limiting their interpretability and reducing their practical usefulness for policy-oriented decision-making (Makridakis et al., 2018).

Synthesizing these findings, it becomes evident that model selection should be context-specific. In highly industrialized or data-rich environments, advanced machine learning models may be preferable due to their ability to capture nonlinear relationships and complex interactions (Kong et al., 2017). However, in localized and data-constrained settings such as Malaybalay City, traditional time-series models remain more appropriate due to their robustness, lower data requirements, and interpretability (Hyndman & Athanasopoulos, 2021). The availability of consistent monthly electricity consumption data, combined with observable seasonal patterns, makes SARIMA a suitable and robust choice for forecasting electricity demand in such contexts.

Despite the growing body of literature on electricity demand forecasting, most studies focus on national or regional levels, with limited attention to city-level analysis, particularly in developing countries such as the Philippines (Almeshaiei & Soltan, 2011; Bianco et al., 2010). This study addresses this gap by providing a localized forecasting model tailored to Malaybalay City, where electricity demand is closely linked to population growth, service-sector expansion, and seasonal consumption behavior. Thus, in data-constrained and policy-oriented contexts, SARIMA remains a preferred approach due to its balance between forecasting accuracy, interpretability, and minimal data requirements.

Scope and Limitations of the Study

This study focuses on forecasting total electricity demand in Malaybalay City, the capital of Bukidnon Province. It specifically examines the electric consumption of all consumer categories—residential, commercial, and industrial—served by the Bukidnon Second Electric Cooperative, Inc. (BUSECO). The analysis used secondary monthly data on electricity consumption from 2012 to 2025, covering 147 months and reflecting the city's recent growth trajectory and electricity consumption.

However, the study is subject to several limitations. First, the analysis is constrained by the availability, accuracy, and granularity of secondary data obtained from BUSECO, which may not fully capture short-term fluctuations or detailed sectoral variations in consumption behavior. Second, while time series and linear regression models can reveal long-term trends, they may not account for nonlinear dynamics or structural shifts driven by unforeseen factors. External shocks such as climate change, typhoons, and El Niño events may significantly influence electricity demand by altering weather patterns, energy usage behavior, and power supply stability. Similarly, policy reforms and technological advancements can abruptly change consumption patterns, potentially causing deviations from forecasted trends.

Given these limitations, future studies are encouraged to incorporate more advanced and flexible modeling approaches to better capture these complex dynamics. Nonlinear models such as Artificial Neural Networks (ANN) and hybrid approaches like ARIMA-CNN may improve forecasting accuracy by accounting for hidden patterns and nonlinear relationships in the data. Additionally, integrating climate variables and other external indicators into forecasting models would provide a more comprehensive understanding of how environmental and structural factors influence electricity demand over time. The study utilizes only one predictor, which minimizes multicollinearity issues but may limit the model's ability to capture other determinants of electricity demand.

Research Design

This study used a descriptive-correlational research design, combined with time-series analysis, to forecast total electricity demand in Malaybalay City, Bukidnon. Data were obtained from the Bukidnon Second Electric Cooperative (BUSECO) and covered 129 months of observation from January 2012 to March 2025. Descriptive statistics were used to present trends in electricity demand by user type and the number of consumers in Malaybalay City, Bukidnon. In correlational research, the study determined the magnitude of the relationship between the number of consumers and total electricity demand. Furthermore, the study used a Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast trends in total electric consumption by user type (residential, commercial, industrial) and the number of consumers in Malaybalay City, Bukidnon. The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is an advanced time-series forecasting method that captures both trend and seasonality, making it highly suitable for electricity demand forecasting.

The selection of the SARIMA model over more complex machine learning or hybrid forecasting techniques is grounded in its balance between accuracy and interpretability. While advanced models may offer marginal improvements in predictive performance, they often function as “black boxes,” limiting their usefulness for policymakers and local planners who require transparent and explainable results. In contrast, SARIMA provides clear parameter structures and interpretable components, enabling stakeholders to understand how past trends and seasonal patterns influence future demand. This transparency is particularly important in the context of public sector decision-making, where accountability and clarity are essential.

Moreover, the study utilized consumer count as the primary predictor of electricity demand due to its reliability and consistent availability in BUSECO records. Although this approach may appear limited compared to models incorporating multiple economic or climatic variables, consumer count serves as a strong and practical proxy for electricity usage, especially in a service-oriented and growing city like Malaybalay. It directly reflects expansion in households and business establishments, which are key drivers of electricity consumption. Given constraints in data availability and consistency for other variables, focusing on consumer count ensures methodological robustness while still capturing the underlying growth dynamics of electricity demand in the city.

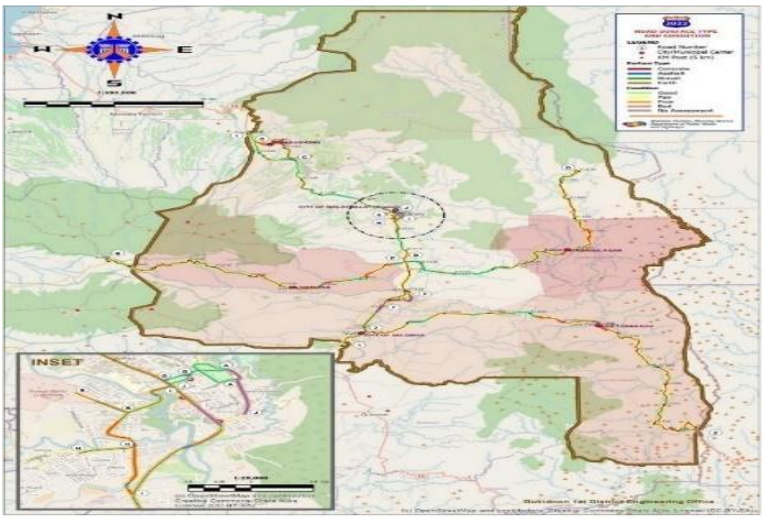
Research Locale

The research locale of this study is Malaybalay City, Bukidnon. The city has a land area of 969.19 square kilometers (374.21 square miles), which constitutes 9.23% of Bukidnon's total area (philatlas.com). Its population, as determined by the 2020 Census, was 190,712, representing 12.37% of Bukidnon province's total population and 3.80% of the Northern Mindanao region's overall population. Based on these figures, the population density is 197 inhabitants per square kilometer, or 510 inhabitants per square mile (philatlas.com).

Malaybalay City ranked 35th out of the 114 component cities in terms of economic dynamism. Economic dynamism is composed of the following indicators: local economy size, local economy growth, local economy structure, safety-compliant business, increase in employment, cost of living, cost of doing business, financial deepening, productivity, and presence of business and professional organizations (Department of Trade and Industry, 2023). Based on the 2023 economic dynamism data, 2023 economic growth ranked 29th among the 114 component cities. Given these developments, the city is expected to become highly urbanized, necessitating higher electricity consumption.

The electricity provider in Malaybalay City is the Bukidnon Second Electric Cooperative (BUSECO). It provides a viable and reliable electricity to its Member-Consumer throughout the ten (10) districts, namely, the City of Malaybalay, Municipality of Manolo Fortich, Sumilao, Impasug-ong, Lantapan, Cabanglasan, Libona, Baungon, Malitbog, and a portion of the Municipality of Talakag and the City of Valencia (nea.gov.ph). The focus of this study is on the city of Malaybalay due to its numerous scheduled and unscheduled power outages and shortages.

Figure 3 The map of Malaybalay City, Bukidnon.



Statistical Analysis

One objective of this paper is to present trends in total electric consumption by user type (residential, commercial, industrial) and the number of consumers in Malaybalay City, Bukidnon. To achieve this, the researchers used Microsoft Excel to display graphs, tables, and descriptive statistics, including the mean, minimum, and maximum.

Further, to determine the best-fitting model for the research study, the researchers explore four functional forms: Linear, Semi-log, Double-log, and Lin-log. Analysis of Variance (ANOVA) was employed to determine the best-fitting model.

To estimate the model's parameters, Ordinary Least Squares (OLS) was used. However, two assumptions of OLS were violated: autocorrelation and heteroscedasticity. Therefore, the study corrected the violations using Generalized Least Squares (GLS). In forecasting electricity demand by user type, we initially used an Autoregressive Integrated Moving Average (ARIMA) model. However, during the visualization of residuals using a correlogram, seasonal spikes in electric consumption were observed every 12 months. Therefore, the study proceeded with the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The SARIMA model is particularly appropriate for this study because electricity consumption data often exhibit both trend and seasonal patterns that are not adequately captured by simple regression or non-seasonal time-series models.

Electricity demand typically fluctuates depending on seasonal factors such as temperature variations, rainfall patterns, and economic activity cycles, as well as long-term trends driven by population growth and industrial expansion. The SARIMA model extends the standard ARIMA framework by incorporating seasonal autoregressive (SAR) and seasonal moving-average (SMA) terms, enabling it to account for periodic seasonal behavior in the data. This makes it highly suitable for modeling the periodic changes observed in monthly or quarterly electricity consumption.

In this study, the use of SARIMA enables robust, data-driven forecasts of electricity demand across different consumer categories in Malaybalay City. Its strength lies in its ability to generate highly accurate short- to medium-term forecasts, which are essential for effective energy planning, load management, and policy formulation. Compared to simpler linear models, SARIMA provides a more comprehensive representation of real-world electricity consumption behavior, accounting for both structural trends and cyclical variations.

Model Identification and Forecasting

Testing for Stationarity

Before the long-run relationship between the number of consumers and total electricity demand can be determined, a univariate analysis is needed. SARIMA (Seasonal Autoregressive Integrated Moving Average) models for univariate time series provide the features of the Box-Jenkins approach. The SARIMA has three stages: 1) the identification stage reports the sample autocorrelation function and the sample partial autocorrelation function that can be inspected to determine a specification for an ARIMA model; 2) the estimation stage estimates the parameters of a SARIMA model and gives diagnostic test for checking the model adequacy and; 3) the Box-Jenkins method is to repeat the identification and estimation stage until a suitable model is found (Harvey [1981]; Judge, Griffiths, Hill, Lütkepohl and Lee [1985]).

Unit Root Test for Stationarity

Augmented Dickey-Fuller Test for Unit Root

A series of tests for the stationarity of the time series was performed. The stationarity of the time series was investigated by employing the unit root test developed by Dickey and Fuller (1979, 1981). The detection of a unit root in a time series indicates non-stationarity, with implications for economic theory and modeling. Test statistics can be based on OLS estimates from a suitably specified regression equation. For a time series Y_t three forms of the “Augmented Dickey-Fuller” regression equations are:

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$$\Delta Y_t = \beta_0 + \beta_1 y_{t-1} \sum_{j=1}^{p} y_j + \varepsilon_t$$

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$$\Delta Y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 t \sum_{j=1}^{p} y_j \Delta y_{t-1} + \varepsilon_t$$

Equation (2) is the random walk, equation (3) is the random walk with a drift, and equation (4) is the mixed process. The number of lagged terms, p, is chosen to ensure the errors are uncorrelated.

The finding that many time series may contain unit roots has spurred the development of the theory of non-stationary time series analysis. Engle and Granger (1987) pointed out that a linear combination of two or more non-stationary series may be stationary. The stationary linear combination is the cointegrating equation and may be interpreted as a long-term equilibrium relationship among the variables; by contrast, if the relationship is not causal, it is spurious. Johansen's cointegration methodology is applied at this point. This approach estimates long-term or cointegration relationships between non-stationary variables using a maximum likelihood procedure that tests for the number of cointegrating relationships and estimates their parameters (Cantavella-Jorda et al., 2002).

Test for Cointegration

An approach to test for cointegration (or evidence of a long-run relationship between non-stationary variables) is to construct test statistics from the residuals of a cointegrating regression. A test for no cointegration for a unit root in the estimated residuals µt. The augmented Dickey-Fuller regression equation is:

$$\Delta \mu_t = \beta \mu_{t-1} + \sum_{j=1} \Phi_j \Delta \mu_{t-j} + V_t$$

The test statistic used the t-ratio test for $\beta = 0$ (the t-test). In addition, the properties for a non-stationary series are the following:

The properties for a non-stationary series are the following:

1) There is no long-run mean to which the series returns
2) The variance is time-dependent and goes to infinity as time approaches infinity
3) Theoretical autocorrelation does not decay, but in finite samples, the sample correlogram dies out slowly

The series is cointegrated if:

1) Both series are non-stationary and related
2) ε_{t-} the residual of the error terms is stationary

Judge et al. (2001) cited a remarkable note for cointegration. First, if the variables are non-stationary and not cointegrated, is there any relationship that can be estimated? In these circumstances, one can investigate whether there is a relationship between the variables after differencing to achieve stationarity. For example, suppose that the two variables y_t and x_t are I (1) variables, and that they are not cointegrated. Since the changes Δy_t and Δx_t are stationary, we can run regressions of the form.

$$\Delta y_t = \beta_1 + \beta_2 \Delta x_t + e_t$$

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Estimating equations like this one provides information about any relationship between changes in the variables. Second, if the one in which yt and xt are stationary, the implicit assumption is maintained for most of the text. In this case, least squares or generalized least squares, whichever is more appropriate, can be used to estimate the relationship between y and x (Judge et al., 1988). However, in the differencing process, the electricity series was already stationary after the first difference. Hence, cointegration cannot be applied.

Moreover, the model's fitness is measured using error metrics, including the Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE).

$$RMSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2$$

where y_t Is the actual value, $y^\wedge{}_t$ is the forecasted value, and n Is the number of observations. A lower RMSE indicates fewer forecast errors and better model fit.

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{(y_t - \hat{y}_t)}{y_t}\right|$$

MAPE expresses the forecast error as a percentage, making it helpful in interpreting accuracy in relative terms. Lower MAPE values suggest higher predictive accuracy.

Lastly, the forecasted values of total electricity demand across the residential, commercial, and industrial sectors have been obtained using the Autoregressive Integrated Moving Average (ARIMA) model.

$\hat{y}_{t+h}|_t = \mu + \Sigma\ \varphi_i\ \hat{y}_{t+h-i}|_t + \Sigma\ \Phi_j\ \hat{y}_{t+h-js}|_t + \Sigma\ \theta_i\ \varepsilon_{t+h-i}|_t + \Sigma\ \Theta_j\ \varepsilon_{t+h-js}|_t$

RESULTS

Trend of Residential Electric Consumption in Malaybalay City, 2012-2024

The city faces frequent power outages, affecting both economic activities and public services. Forecasting electricity demand would enable the Bukidnon Second Electric Cooperative (BUSECO) to implement more effective policies and ensure a reliable supply to support the growing population, thereby contributing to sustained economic productivity and development.

As shown in Figure 4, the electric consumption of residents in Malaybalay City has increased from January 2012 to March 2025, averaging 517,317.12 kWh per annum, from 3.3 million kilowatt-hours in 2012 to around 7.6 million kilowatt-hours in 2025. Moreover, the highest residential consumption from 2012 to 2025 occurred in the 4th quarter of 2024, with 7,786,702.07 kWh. Guo et al. (2017) noted that residential electricity consumption is directly related to household appliances and population. Further, Urrutia et al. (2019) noted that the last quarter of the year typically sees the highest electricity consumption due to festivities and celebrations such as Christmas and New Year.

Trend of Commercial Electric Consumption in Malaybalay City, 2012-2024

Another type of electric user is a commercial one. These types of electricity users refer to business and commercial activities. The trend of commercial electric consumption from 2012 to 2025 in Malaybalay City is shown in Figure 5. The graph indicates that the business sector has been consuming more electricity throughout the years, from 2 million kilowatt-hours in 2012 to about 2.6 million kilowatt-hours in 2025. The average commercial electric consumption is recorded as 149,161.59kWh per annum.

However, it can be observed that commercial electric demand suddenly dropped in the second quarter of 2020, from 1,818,805.01 kWh to 1,548,214.61 kWh. This situation is due to the city's total lockdown on commercial

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and business activities. In the exact figure, it can be observed that in the first quarter of 2025, the demand for electricity in the commercial sector increased from 2,503,256.32 kWh to 2,603,908.65 kWh.

This situation is due to many new businesses operating in the city, leading to higher electricity demand. Katara et al. (2014) explained that new business operations can lead to increased electricity demand. Moreover, according to the data from the Business Permit and Licensing Office, there were 6,303 registered Micro, Small, and Medium Enterprises (MSMEs) in Malaybalay City as of 2025.

Furthermore, the upward trajectory of commercial electricity consumption reflects not only the expansion of businesses but also the growing adoption of energy-intensive technologies and services in Malaybalay City.

Trend of Industrial Electric Consumption in Malaybalay City, 2012-2024

Regarding industrial electricity consumption in Malaybalay City, Figure 6 shows a significant increase in the industrial sector, with an average annual consumption of 517,317.12 kWh. However, in some quarters of 2020 and 2021, a slight decrease in industrial electricity consumption has been recorded.

This slight decrease is explained by the pandemic, which led to lockdowns. However, in the middle of the second quarter of 2020, industrial electricity consumption substantially increased again. By the second quarter of 2021, COVID-19 pandemic restrictions had been lifted, leading to the recovery of various businesses and services. Consequently, this led to higher electricity demand. This result is consistent with the study by Delima (2019), which found that after pandemic restrictions were lifted, industrial, commercial, and residential electric consumption returned to its pre-pandemic trend.

Total Electric Demand in Malaybalay City, 2012-2024

The total electricity demand is the sum of the three user types: residential, commercial, and industrial. Figure 7 shows the trend of total electricity demand in Malaybalay City from the first quarter of 2012 up to the first quarter of 2025.

The graph shows a significant increase in electricity demand in the city from 2012 to 2025, although fluctuations are observed in several quarters each year. These trends are closely linked to the city's economic structure, particularly the dominance of the service sector, which accounts for 95.87% of establishments. Unlike industrial-heavy cities where demand is largely driven by manufacturing activities, Malaybalay's electricity consumption is highly influenced by commercial operations such as retail stores, restaurants, and small service-oriented enterprises. As a result, demand patterns tend to fluctuate based on business activity, consumer behavior, and operating hours within this sector.

As explained earlier, the pandemic situation led to a decline in the city's electric consumption. However, electricity demand regained momentum as the local economy gradually reopened following the lifting of travel restrictions.

Another reason for the decline in total electricity demand in the city was the problem encountered by the Mindanao power grid in early 2014 (Torion, 2014). Preventive maintenance activities on the grid resulted in scheduled power interruptions in Malaybalay, temporarily reducing electricity consumption. These outages had direct implications on local livelihoods, particularly for small businesses such as sari-sari stores, retail shops, and other microenterprises that rely heavily on continuous electricity for daily operations. Interruptions not only reduced consumption but also disrupted income-generating activities at the community level.

This situation was further exacerbated by insufficient power supply across the entire Mindanao grid, affecting electric cooperatives that serve the city, such as BUSECO.

Number of Electric Consumers in Malaybalay City, 2012-2024

The total number of consumers connected to Bukidnon Second Electric Cooperative (BUSECO) is shown in Figure 8. As observed, the number of consumers has grown steadily from 2012 to 2025, averaging 7,477 per year.

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Figure 4 Trend of Residential Electric Consumption in Malaybalay City, 2012 to 2025

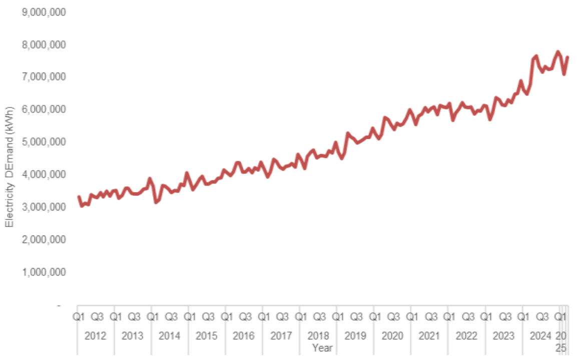


Figure 5 Trend of Commercial Electric Consumption in Malaybalay City, 2012 to 2025

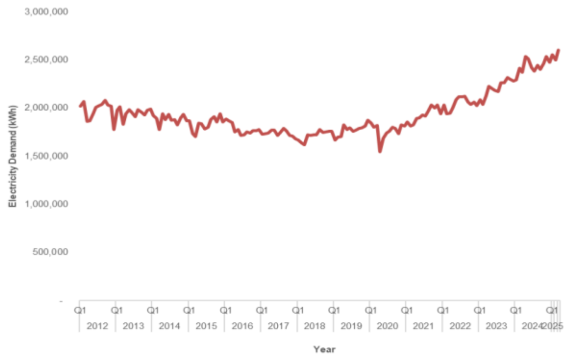


Figure 6 Trend of Industrial Electricity Consumption in Malaybalay City, 2012 to 2025

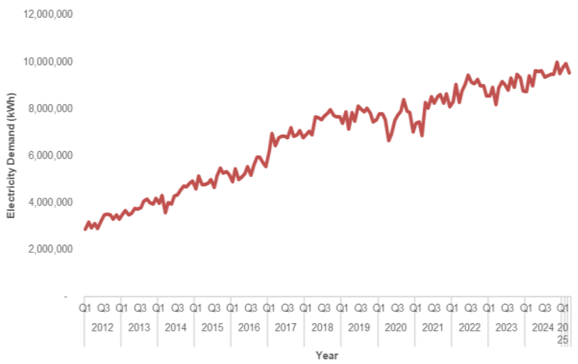


Figure 7 Trend of Total Electricity Demand in Malaybalay City, 2012-2025

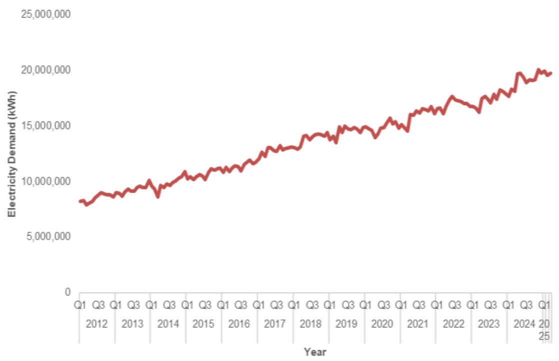
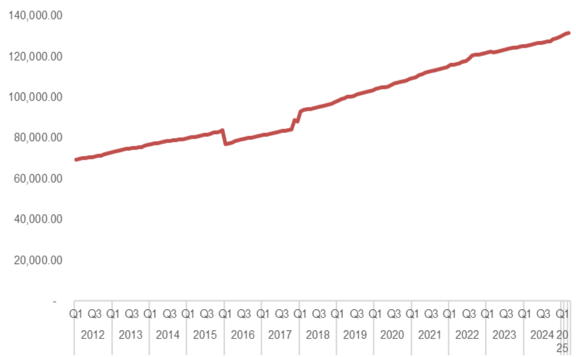


Figure 8 Electricity Consumer Trend in Malaybalay City, 2012 to 2025



However, a sudden drop in consumer numbers was observed from the fourth quarter of 2015 through the first quarter of 2016 due to the policy implementation of 'no payment, no electric connection.

The city's growing population also contributes significantly to the increase in electricity users. As Malaybalay continues to grow, household formation and urban expansion naturally lead to greater demand for electricity to support daily living and emerging community needs (Urrutia et al., 2018).

Total Electricity Demand In Malaybalay City

Diagnostic Test for OLS and GLS Assumptions

The four functional forms were empirically tested in this study: linear-linear, log-linear, linear-log, and double-log models to determine the best fit for forecasting total electricity demand in Malaybalay City.

Table 1 GLS Estimates

Regression Models				
Variables/Statistics	Model 1 (Linear-Linear)	Model 2 (Log-Linear)	Model 3 (Linear-Log)	Model 4 (Log-Log)
Intercept	-2,555,300* *(-887,500)* [0.00]	6.60* *(-0.04)* [0.00]	-168,060,000* *(-10,020,000)* [0.00]	0.91* *(0.12)* [0.00]
Number of Consumers	165.95* *(8.91)* [0.00]	0.00* *(0.00)* [0.00]	36,484,000* *(-2,013,000)* [0.00]	1.25* *(0.03)* [0.00]
R^2	0.98	0.99	0.98	0.94
σ^2	416,780	0.01	416,550	0.01

Legend: Values in parentheses () are the standard error of estimates.

Values in brackets [ ] are p-values

* significant at 5%

ns- not significant at the 5-percent level of significance.

The double log model was identified as the most appropriate based on its overall model variance (Table 1). Also, the coefficient of determination is 0.93, indicating that the consumer variables explain 93.61% of the total variability in electric demand.

Furthermore, for every 1 percent increase in the total number of BUSECO consumers, total electricity demand in Malaybalay increases by 1.25 percent per month, holding other factors constant. Donatos and Mergos (1991) found that in Greece, the number of consumers was a significant determinant of residential electricity demand. Moreover, the variable number of consumers is statistically significant at the 1% level in affecting total electricity demand. These results are similar to other related studies conducted in the Philippines that associate increased electricity consumption with growth in consumers (Gumaru, 2019).

In the ordinary least squares estimation, certain assumptions were violated, such as the homoscedasticity and no autocorrelation assumptions, leading to inefficient results. To improve parameter estimation efficiency, Generalized Least Squares (GLS) was employed. Table 2 shows the analysis of variance, where the variation left unexplained by the model is only 0.02, and the total sum of errors is 1124.6. The p-value of the model is 0.000, meaning the model is significant and can be used for interpretation.

Table 2 ANOVA test results of double-log model

ANALYSIS OF VARIANCE - FROM ZERO				
	SS	DF	MS	F
REGRESSION	1,124.6	2.	562.31	5,041,980.83

ERROR	0.02	156.	0.00	P-VALUE
TOTAL	1,124.6	148.	7.11	0.00

Autoregressive Integrated Moving Average Model

After identifying the best model, which is the double-log, we initially tested ARIMA to forecast electric demand per type of user. During model selection, the correlogram showed a pattern of spikes in total electric demand by user type. According to Hyndman and Athanasopoulos (2021), when a dataset exhibits a seasonal spike pattern, a Seasonal Autoregressive Integrated Moving Average (SARIMA) model can be appropriately applied. Seasonal Autoregressive Integrated Moving Average (SARIMA) improves the accuracy and robustness of electricity demand forecasting. The ARIMA model enabled the researchers to capture the underlying patterns in the time-series data that static regression models could not fully address. Table 3 shows the ARIMA model results for total electric demand in the city.

Table 3 ARIMA Model Results Electricity Demand Series

Model	Log-Likelihood	AIC	BIC	Residual Q-test (40 lags)
ARIMA(1,1,1) Total Demand	472.68	-937.37	-925.12	Q = 79.27, p = 0.00
ARIMA(1,1,1) Residential Demand	420.57	-833.16	-820.91	Q = 366.52, p = 0.00
ARIMA(0,1,1) Commercial Demand	444.52	-883.05	-873.87	Q = 29.45, p = 0.88
ARIMA(1,1,1) Industrial Demand	380.68	-753.37	-741.12	Q = 73.51, p = 0.00

The ARIMA model is statistically appropriate for capturing both short-term dynamics and overall variability of electricity demand across all sectors. For total demand, the AR (1) and MA (1) parameters are highly significant, reflecting strong influences of past values and short-term shocks, with low error variance of $\sigma = 0.01$ indicating high forecasting accuracy. Residential demand shows significance in both AR(1) and MA(1), suggesting the combined effects of historical consumption and seasonal household behaviors. In contrast, commercial demand is primarily driven by short-term fluctuations in MA(1). Industrial demand is sensitive to unexpected short-term shocks MA (1), rather than past values, with the highest error variance of $\sigma = 0.02$ indicating greater volatility.

Table 4 ARIMA Parameter Estimates for Electricity Demand Series

Series	Parameter	Coefficient	Std. Error	z-value	p-value
Total Demand	_cons	0.00*	*(0.00)*	9.87	[0.00]
	AR(1)	0.40*	*(0.10)*	4.05	[0.00]
	MA(1)	-0.86*	*(0.06)*	-13.84	[0.00]
	/sigma	0.01*	*(0.00)*	20.18	[0.00]
Residential Demand	_cons	0.00*	*(0.00)*	7.69	[0.00]
	AR(1)	0.33*	*(0.12)*	2.63	[0.00]
	MA(1)	-0.85*	*(0.07)*	-11.47	[0.00]
	/sigma	0.01*	*(0.00)*	22.62	[0.00]

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Commercial Demand	_cons	0.00 ns	*(0.00)*	0.84	[0.40]
	MA(1)	-0.43*	*(0.07)*	-5.59	[0.00]
	/sigma	0.01*	*(0.00)*	26.88	[0.00]
Industrial Demand	_cons	0.00*	*(0.00)*	3.30	[0.00]
	AR(1)	-0.12 ns	*(0.17)*	-0.71	[0.47]
	MA(1)	-0.39*	*(0.17)*	-2.25	[0.02]
	/sigma	0.02*	*(0.00)*	20.43	[0.00]

Legend: Values in parenthesis () are standard error of estimates.

Values in bracket [ ] are p-values

* significant at 5%

ns- not significant at the 5-percent level of significance.

As shown in Table 3, the residual Q-test results for each user type indicate the presence of autocorrelation, which means that the electric demand in a given month is influenced by its values in previous months. Therefore, the model needs to be adjusted or corrected to account for this autocorrelation. The SARIMA model is appropriate for capturing seasonality in both the short-term dynamics and the overall variability of electricity demand across all sectors.

Seasonal Autoregressive Integrated Moving Average (SARIMA) Procedure

Model Selection

After applying the Autoregressive Integrated Moving Average (ARIMA) model, the analysis revealed significant seasonal patterns in the dataset. Recognizing the presence of these recurring fluctuations, the study employed the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to improve the accuracy and robustness of electricity demand forecasting.

To test the stationarity of the time series data, the Augmented Dickey-Fuller test was performed. The p-value for the test without differencing is 0.73, as shown in Table 5, indicating that the data are non-stationary. First differencing was applied to investigate whether the data would become stationary. After the first differencing, the p-value was 0.00, indicating that the time series data is already stationary.

Table 5 Augmented Dickey Fuller Test for First Difference of Total Electricity Demand

Test without Differencing		**With First Differencing**	
Test Statistics	P-Value	Test Statistics	P-Value
-1.05	0.73	-17.95	0.00

Table 6 shows the Akaike Information Criteria, Bayesian Information Criteria (AIC/BIC), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) criteria for model selection. These were used to compare several SARIMA model specifications and identify the most accurate forecasting models in each category of electricity demand. Our analysis indicates that the SARIMA(1,1,1)(1,0,1,12) model is the most

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suitable for modeling total electricity demand, as it yields the lowest AIC (-963.65) and BIC (-945.28), as well as the lowest RMSE (13.59) and MAPE (0.86).

Moreover, for residential demand, the SARIMA(1,1,1)(1,1,12) model produced the best forecasts, whereas the SARIMA(0,1,1)(0,1,1,12) model produced slightly more variable forecasts. The SARIMA(1,1,1)(1,0,1,12) model best represented the industrial sector but had superior RMSE (17.01) and MAPE (1.49), indicating greater volatility.

Table 6 Model Selection criteria of SARIMA Electricity Demand (Total, Residential, Commercial and Industrial).

Variable	Model	Log Likelihood	AIC	BIC	RMSE	MAPE
Total Demand	SARIMA(1,1,1)(1,0,1,12)	487.82	-963.65	-945.27	13.59	0.86
	SARIMA(1,1,0)(0,1,1,12)	440.56	-873.13	-861.20	14.88	0.94
Residential	SARIMA(1,1,1)(1,1,1,12)	448.53	-885.07	-867.17	9.09	0.87
	SARIMA(0,1,1)(0,1,1,12)	447.42	-886.84	-874.91	9.18	0.87
	SARIMA(1,1,0)(1,1,0,12)	430.76	-853.53	-841.60	10.04	0.96
Commercial	SARIMA(0,1,1)(0,1,1,12)	404.57	-801.14	-789.21	7.57	1.03
	SARIMA(1,1,0)(1,1,0,12)	388.35	-768.70	-756.76	9.05	1.17
	SARIMA(1,1,1)(0,1,1,12)	409.45	-808.90	-793.98	7.90	1.05
Industrial	SARIMA(1,1,1)(1,0,1,12)	401.46	-790.92	-772.54	17.01	1.49
	SARIMA(0,1,1)(0,1,1,12)	367.75	-727.51	-715.58	17.82	1.52
	SARIMA(1,1,0)(1,1,0,12)	348.59	-689.19	-677.26	20.41	1.63

The model selection results presented in Table 6 indicate that, for each electricity demand sector, the best-fitting SARIMA models are those with the lowest AIC and BIC values, reflecting strong model performance without unnecessary complexity. As shown in Table 6, the SARIMA (1,1,1)(1,0,1,12) model for total electricity demand provides the lowest AIC (–963.65) and BIC (–945.27), and also records the lowest Mean Absolute Percentage Error (MAPE), confirming its suitability and forecasting accuracy for total demand.

For the residential sector, the SARIMA (1,1,1)(1,1,1,12) model yields the lowest AIC (–885.07) and BIC (–867.17), making it the most statistically appropriate choice. In the commercial sector, the SARIMA (0,1,1)(0,1,1,12) model produces the lowest AIC (–801.14) and BIC (–789.21), suggesting it best captures both seasonal and non-seasonal variations in demand. Meanwhile, for the industrial sector, the SARIMA (1,1,1)(1,0,1,12) model yields the lowest AIC (–790.92) and BIC (–772.54), further confirming its suitability relative to competing specifications.

To enhance clarity and interpretation, the results should also be complemented by comparative graphical presentations (e.g., Figures 10–12), where residential, commercial, and industrial electricity demand forecasts are presented side by side. Such visual comparisons allow for a clearer understanding of sectoral differences in growth patterns, seasonal fluctuations, and relative contributions to total electricity demand in Malaybalay City.

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Parameter Estimation

The parameter estimation results indicate that the identified SARIMA models apply to the short-term, seasonal, and trend components of electricity demand across all sectors. For total demand, all SARIMA (1,1,1) (1,0,1,12) parameters were significantly high, indicating strong dependence on past values and seasonal influences, and high forecasting accuracy.

Table 7 Final Estimates of SARIMA Model Parameters for Electricity Demand

Variable	Model	Parameter	Coefficient	Std. Error	t/z-Stat	p-value
Total Demand	SARIMA (1,1,1) (1,0,1,12)	Constant	0.00*	*(0.00)*	4.53	[0.00]
		AR(1)	0.45*	*(0.11)*	3.90	[0.00]
		MA(1)	-0.84*	*(0.07)*	-10.72	[0.00]
		Seasonal AR(12)	0.98*	*(0.03)*	24.85	[0.00]
		Seasonal MA(12)	-0.88*	*(0.14)*	-6.31	[0.00]
		Sigma (σ)	0.01*	*(0.00)*	15.03	[0.00]
Residential Demand	SARIMA (1,1,1) (1,1,12)	Constant	0.00^{ns}	*(0.00)*	0.86	[0.38]
		AR(1)	0.21^{ns}	*(0.18)*	1.16	[0.24]
		MA(1)	-0.61*	*(0.14)*	-4.15	[0.00]
		Seasonal AR(1)	0.12*	*(0.10)*	1.26	[0.20]
		Seasonal MA(1)	-0.91*	*(0.15)*	-5.75	[0.00]
		Sigma (σ)	0.01*	*(0.00)*	13.12	[0.00]
Commercial Demand	SARIMA (0,1,1) (0,1,12)	Constant	0.00*	*(0.00)*	2.24	[0.02]
		MA(1)	-0.52*	*(0.08)*	-5.99	[0.00]
		Seasonal MA(12)	-0.86*	*(0.11)*	-7.55	[0.00]
		Sigma (σ)	0.01*	*(0.00)*	18.43	[0.00]
Industrial Demand	SARIMA (1,1,1) (1,0,1,12)	Constant (drift)	0.00^{ns}	*(0.00)*	1.66	[0.09]

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		AR(1)	0.18^{ns}	*(0.19)*	0.96	[0.33]
		MA(1)	-0.59*	*(0.14)*	-4.01	[0.00]
		Seasonal AR(12)	0.97*	*(0.03)*	25.74	[0.00]
		Seasonal MA(12)	-0.84*	*(0.13)*	-6.37	[0.00]
		Sigma (σ)	0.01*	*(0.00)*	17.24	[0.00]

Legend: Values in parenthesis () are standard error of estimates.

Values in bracket [ ] are p-values

* significant at 5%

ns- not significant at the 5-percent level of significance.

In the case of residential demand, moving-average terms are important for short-term shocks and annual variations, whereas past consumption has little influence.

The strong performance of the SARIMA models across all sectors, as indicated by low MAPE and RMSE values, suggests that electricity demand in Malaybalay City is largely driven by predictable temporal patterns, rather than highly volatile or nonlinear dynamics. This reinforces the appropriateness of SARIMA in this context, as the city's electricity consumption is closely tied to population growth, expansion of service-oriented businesses, and recurring seasonal consumption cycles, rather than complex real-time fluctuations requiring advanced machine learning approaches.

In particular, the dominance of the service sector in Malaybalay (95.87% of establishments) implies that electricity demand is influenced by routine business operations and seasonal consumer behavior, which are effectively captured by SARIMA's seasonal structure.

Model Diagnostic

The credibility of the SARIMA models was assessed using a Portmanteau (Q) test to determine whether the residuals behaved as white noise, indicating that the models were adequate.

Table 8 Diagnostic Test: Portmanteau (Q) Test for White Noise Residuals

Variables	**p-value**
Total Electricity Demand	0.34
Residential Electricity Demand	0.78
Commercial Electricity Demand	0.59
Industrial Electricity Demand	0.95

All the models deliver p-values greater than 0.05: 0.34 for total demand, 0.78 for residential, 0.59 for commercial, and 0.95 for industrial, indicating that the residuals are random and do not exhibit autocorrelation. These findings confirm that both SARIMA models are statistically valid and that all sectors can effectively predict electricity demand.

Forecast Of Electricity Demand In Malaybalay City (2025 To 2031)

Forecast for Residential Electric Demand

Forecasts of residential electricity demand in Malaybalay City from 2025 to 2031 are provided in Figure 10. In December 2026, residential electricity demand was 9,431,287.849 kWh, and it is forecast to increase to 15,886,455.11 kWh in December 2031.

The forecasted increase in residential electricity demand in Malaybalay City reflects not only rising consumption but also underlying socio-economic changes, particularly population expansion and urban migration. As more households settle in the city due to its growing economic opportunities, residential electrification continues to expand. The increase from 9,431,287.849 kWh in December 2026 to over 15,886,455.11 kWh by 2031 indicates a substantial rise in household demand driven by higher appliance ownership, improved living standards, and increased access to electricity. These findings suggest the need for policies focused on sustainable urban planning, residential energy efficiency programs, and the expansion of distribution networks to accommodate the growing number of households.

Forecasted Commercial Electric Consumption

The forecasted commercial electricity demand in Malaybalay City, Bukidnon, for the next five years (2026–2031) is shown in Figure 11. In December 2026, commercial electricity demand was 3,126,446.49 kWh, and it is forecast to increase to 6,707,288.70 kWh in December 2031.

The forecast indicates that commercial electricity demand in Malaybalay City will rise sharply over the next decade. This growth reflects the expansion of the city's service-oriented economy, with increasing numbers of retail establishments, restaurants, and small enterprises. Moreover, fluctuations and peaks in commercial demand can be interpreted in relation to seasonal business cycles, such as holidays, festivals, and peak retail periods, when economic activity intensifies. These patterns highlight how electricity consumption is closely tied to consumer behavior and commercial activity. From a policy perspective, the findings emphasize the importance of ensuring a stable and reliable power supply during peak seasons, as well as investing in grid resilience and capacity expansion to support the city's growing commercial sector.

Forecasted Industrial Electric Consumption

Shown in Figure 12 is the forecasted demand for industrial electricity in Malaybalay City for the next five years. In December 2026, industrial electricity demand was 11,082,965.98 kWh, and it is forecast to increase to 16,878,389.31 kWh in December 2031.

The forecast indicates that industrial electricity demand in Malaybalay City will continue to grow steadily over the next five years. Although the industrial sector represents a smaller share of the city's overall economic structure compared to the service sector, the increasing demand signals the gradual emergence and expansion of manufacturing and processing activities in the area. This trend reflects improving economic diversification and rising production output. From a policy standpoint, the forecasted rise in industrial demand suggests the need for targeted grid expansion, particularly in designated or emerging industrial zones, to ensure that future energy requirements are met without compromising supply reliability. Strategic infrastructure investments and long-term energy planning will be crucial to support sustained industrial growth and attract further investments into the city.

Scenario Forecasts for Total Electric Demand in Malaybalay, 2025 to 2031

The forecast of total electricity demand for Malaybalay City for 2026 to 2031 under three scenarios is shown in Figure 13. First, the actual forecasting of the total electricity demand in Malaybalay City, Bukidnon; second, with a lower bound of 95% confidence interval; and lastly, the upper bound of 95% confidence interval.

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In December 2026, total electricity demand was 21,625,591.5 kWh, and it is forecast to increase to 25,859,611.8 kWh in December 2031 under the first scenario.

Assumptions:

<u>Forecast 1</u> uses actual forecasts of total electricity demand in Malaybalay City, Bukidnon.

<u>Forecast 2</u> uses a lower bound of a 95% confidence interval

<u>Forecast 3</u> uses an upper bound of a 95% confidence interval

In the second scenario, total electricity demand is forecasted to be 19,424,393.86 kWh by December 2026, and 20,795,247.47 kWh by December 2031. In the third scenario, the total electricity demand is forecasted to increase to 24,076,231.69 kWh in December 2026 and 32,157,324.65 kWh in December 2031.

Figure 10 Forecasted Residential Electric Consumption, 2025-2031

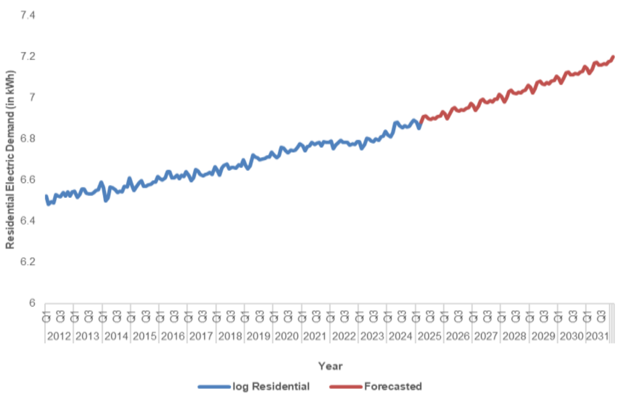


Figure 11 Forecasted Commercial Electric Consumption, 2025-2031

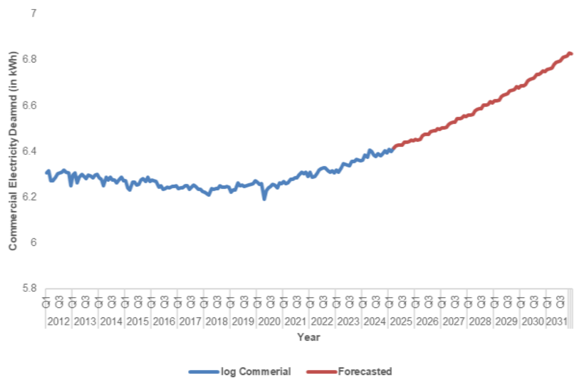


Figure 12 Forecasted Industrial Electric Consumption, 2025-2031

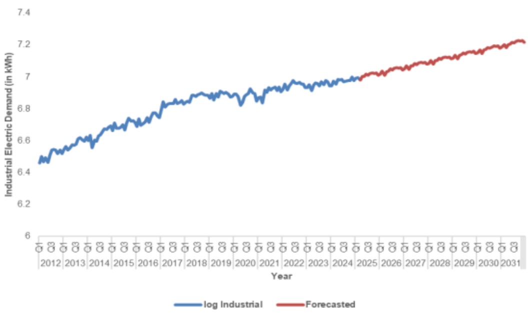
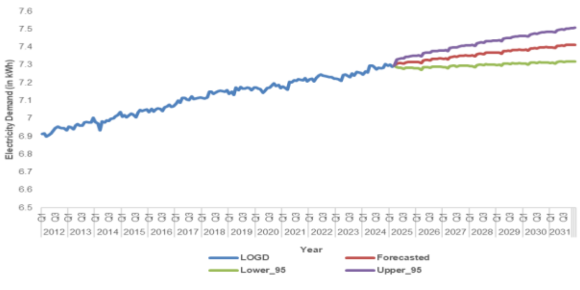


Figure 13 Historical and forecasted monthly electricity demand in Malaybalay City under three consumer growth scenarios, 2012 to 2031



The forecasted total electricity demand shows an increasing trend in the first and third scenarios. However, the second scenario shows the most evident decrease among all scenarios, since it uses a lower bound of the 95% confidence interval; thus, it is expected to decrease compared to other scenarios. This result is expected since the number of consumers in Malaybalay City is increasing. Since Malaybalay City, Bukidnon, has been identified as one of the cities with robust economic growth and development due to its rising population and business opportunities, it is also expected that the number of electricity consumers will continue to rise (malaybalaycity.gov.ph). Furthermore, the first scenario provides a more reliable forecast than the other two, as it uses the actual monthly growth rates derived from historical data on total electricity demand in Malaybalay City from 2012 to 2025.

CONCLUSION & RECOMMENDATIONS

Electricity consumption across user types, particularly residential, commercial, and industrial, consistently increased. Residential demand steadily increased as the number of consumers grew, driving higher electricity use. Meanwhile, commercial demand continues to rise as more businesses flourish in the city, creating more establishments and employment opportunities. Industrial consumption fluctuated more due to production cycles but showed an overall upward trend. Together, these sectoral patterns contributed to a consistent rise in total electricity demand.

The researchers also established the relationship between the number of consumers and electricity demand using the Generalized Least Squares (GLS) method. The study concludes that the number of consumers has a significant, positive effect on both sectoral and total electricity demand in the city.

Further, the study applied the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast electricity demand across all sectors and in total. The model successfully captured both seasonal fluctuations and long-term trends in residential, commercial, and industrial consumption, while also reflecting short-term variations. Forecasts indicated a continued increase in electricity demand across sectors and in total, confirming that sectoral growth and the expanding number of consumers jointly influenced future electricity requirements. In general, all models have shown statistically significant and reliable coefficients, demonstrating their ability to predict electricity demand across sectors. These results provided reliable projections that could guide energy planning and management in the city.

The findings confirm that SARIMA is not only statistically robust but also practically suitable for localized electricity demand forecasting in data-constrained environments such as Malaybalay City

Based on the results and conclusions of this study, the researchers recommend:

1. The electric provider, BUSECO, should prioritize the development and modernization of the power distribution system to ensure sufficient electricity supply in the future. In particular, grid capacity should be expanded progressively—such as through a targeted annual increase in capacity—to match the forecasted growth in electricity demand. Investments in transmission lines, substations, and related infrastructure must be aligned with projected sectoral and total demand to maintain efficiency, reliability, and stability in the city's electricity network.

2. The city of Malaybalay should actively promote the diversification of energy sources to reduce reliance on unstable power supply. This includes expanding the use of renewable energy such as solar, hydropower, and biomass, which are suitable for the local context. The local government may also encourage public-private partnerships (PPPs) for renewable energy development projects in Malaybalay City to accelerate investment and technology adoption.

3. Demand-side management programs should be implemented to optimize electricity consumption and reduce peak load pressures. These may include time-of-use pricing schemes, energy efficiency campaigns, and incentives for adopting energy-saving technologies among households, commercial establishments, and industries. Such measures will not only help manage rising demand but also improve overall system efficiency and consumer awareness of energy use.

4. Future studies and energy planning should consider incorporating additional variables, such as weather conditions, income levels, electricity pricing, technological adoption, and supply-side factors, while also exploring complementary forecasting methods, including machine learning techniques. Incorporating these variables and approaches will enhance the accuracy of electricity demand projections and provide stronger guidance for long-term planning.

5. The findings of this study should be integrated into both short-term and long-term energy planning frameworks at the city and provincial levels. In the short term, policies should focus on stabilizing supply, reducing outage frequency, and improving operational efficiency. In the long term, policymakers are

encouraged to align electricity demand forecasts with broader economic and development strategies, ensuring that infrastructure expansion, renewable energy integration, and technological modernization are systematically implemented to prevent demand-supply imbalances.

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