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# Electricity Consumption Forecasting Analysis using Linear Regression Method, DKL 3.2 Method and BaU Scenario

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**Abstract**: Accurate long-term electricity demand forecasting is essential for ensuring reliable power system planning and sustainable energy development. Previous studies have generally focused on the application of a single forecasting approach, such as linear regression, or a limited comparison between two methods, resulting in insufficient evaluation of forecasting performance across multiple sectors and forecasting models. This research addresses this gap by conducting a comparative analysis of three forecasting approaches Multiple Linear Regression, Electricity Demand List Method 3.2 (DKL 3.2), and Business as Usual (BaU) for projecting electricity consumption in the ULP Kencong service area during the 2025–2029 period. The novelty of this study lies in the integration and comparison of these three forecasting methods within a single framework, combined with the utilization of customer growth, connected power capacity, and Land and Building Tax (PBB) indicators as forecasting variables. Forecasting simulations were performed using LEAP software and Microsoft Excel, while forecasting accuracy was evaluated using the Mean Absolute Percentage Error (MAPE). The results indicate that all sectors are expected to experience continuous growth in electricity consumption, with the industrial sector showing the highest increase. Among the evaluated methods, Multiple Linear Regression demonstrated the best forecasting performance, achieving the lowest MAPE values in three of the four analyzed sectors, namely residential (3.49%), business (6.68%), and social (4.77%) sectors. In contrast, DKL 3.2 produced the highest forecasting errors, particularly in the industrial sector (45.98%), while BaU showed moderate and relatively stable performance. These findings support the claim that Multiple Linear Regression is the most suitable and accurate method for long-term electricity consumption forecasting in the ULP Kencong region, providing a reliable basis for future electricity supply planning and infrastructure development.

Keywords: Forecasting, electricity consumption, linear regression, DKL 3.2, Business as Usual

## Introduction

Electricity is one of the most essential forms of energy supporting economic development, industrial growth, public services, and improvements in people's quality of life. Along with rapid population growth, urbanization, technological advancement, and increasing economic activities, electricity demand has continued to rise significantly over the past decades. Electricity has become a fundamental necessity for almost every sector, including residential, commercial, industrial, and public services. Consequently, maintaining a reliable electricity supply has become one of the major challenges faced by power utilities. Inaccurate forecasting of electricity demand may result in either insufficient electricity supply, leading to power shortages and service interruptions, or excessive infrastructure investment that increases operational costs. Therefore, accurate long-term electricity demand forecasting plays a crucial role in supporting sustainable electricity planning, optimizing investment decisions, and ensuring the reliability of power systems[1][2]. Indonesia has experienced a continuous increase in electricity consumption over recent years due to rapid economic development, a growing population, expanding industrial activities, and an increasing electrification ratio. The widespread adoption of digital technologies, the expansion of manufacturing industries, and the development of new residential and commercial areas have further accelerated electricity demand across various sectors. These conditions require PT PLN (Persero), the national electricity company, to continuously

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improve its planning strategies to ensure that electricity generation, transmission, and distribution systems can adequately meet future demand. Consequently, long-term electricity demand forecasting has become an indispensable component of the Electricity Supply Business Plan (RUPTL) and national energy planning policies[3][4]. One of the regions experiencing continuous socio-economic development is the service area of ULP Kencong, which covers the districts of Kencong, Gumukmas, Umbulsari, Jombang, and Puger. This region has shown steady growth in population, commercial activities, public infrastructure, and industrial development. Such development directly contributes to increasing electricity consumption across residential, commercial, industrial, and public sectors. As electricity demand continues to rise, accurate forecasting becomes increasingly important to support infrastructure expansion, improve distribution network reliability, and optimize future electricity investments. Therefore, forecasting long-term electricity consumption in the ULP Kencong service area is essential for supporting sustainable electricity planning and ensuring reliable electricity services for the community[5].

Numerous studies have investigated long-term electricity demand forecasting using different forecasting approaches. One of the most relevant studies was conducted by Gozali et al. (2023), entitled *"Electricity Demand Projection Using Multiple Linear Regression at PT PLN (Persero) UP3 Mojokerto for the Period 2022–2027."* The study employed multiple linear regression to forecast electricity demand over a six-year period using variables such as the number of customers, installed capacity, electricity production, and electricity sales. The forecasting model produced relatively low forecasting errors, with Mean Absolute Percentage Error (MAPE) values of 0.23% for customer growth, 0.57% for installed capacity, 1.45% for electricity production, and 1.80% for electricity sales. These results indicate that multiple linear regression provides high forecasting accuracy when historical data exhibit relatively stable linear relationships among variables[6][7]. Unlike statistical regression models, the DKL 3.2 approach incorporates sectoral electricity elasticity, energy intensity, customer growth, and economic indicators into the forecasting process. The study demonstrated that each forecasting method possesses different characteristics and produces varying forecasting results depending on regional electricity consumption patterns and socio-economic conditions [8]. The BaU scenario effectively estimates future electricity demand by extending historical consumption trends without considering substantial technological or policy changes, whereas the DKL method provides a more analytical projection by incorporating electricity elasticity, customer growth, and economic variables. Collectively, these studies confirm that forecasting accuracy depends not only on the selected forecasting method but also on regional characteristics, forecasting variables, and the assumptions underlying each model [9]. Despite the considerable number of studies on electricity demand forecasting, several research limitations remain. First, most previous studies relied on only a single forecasting approach, making it difficult to objectively evaluate which method performs best under specific regional conditions. Second, comparative studies simultaneously evaluating multiple forecasting techniques—particularly Multiple Linear Regression, DKL 3.2, and Business as Usual (BaU)—are still relatively limited, especially at the electricity distribution unit (ULP) level. Third, many previous studies primarily focused on a limited number of variables, such as electricity consumption or customer growth, without integrating other important determinants including installed capacity, land and building tax (PBB), electricity elasticity, and energy intensity. Finally, although several forecasting methods have been proposed, relatively few studies have conducted comprehensive accuracy evaluations using a common performance indicator such as Mean Absolute Percentage Error (MAPE), making direct comparison among forecasting approaches difficult.

These limitations reveal a clear **research gap** in the existing literature. There is still a lack of comprehensive comparative studies evaluating the forecasting performance of statistical, analytical, and trend-based forecasting methods using identical datasets and forecasting indicators. Moreover, little attention has been devoted to evaluating electricity demand forecasting specifically at the distribution service unit level, where local demographic, economic, and infrastructure characteristics significantly influence electricity consumption patterns. Therefore, identifying the most appropriate forecasting approach for a particular service area remains an important research challenge. To address these gaps, this study proposes a comprehensive comparison of three widely used long-term electricity demand forecasting methods: Multiple Linear Regression, DKL 3.2, and Business as Usual (BaU). Unlike previous studies, all three methods are applied to the same historical dataset obtained from the ULP Kencong service area, enabling a fair comparison of forecasting performance. In addition, this study incorporates several forecasting variables, including customer growth, installed capacity, Land and Building Tax (PBB), electricity elasticity, and energy intensity. Forecasting accuracy is evaluated using the Mean Absolute Percentage Error (MAPE), allowing objective assessment of the strengths and weaknesses of each forecasting approach. This comprehensive comparative analysis represents the **novelty** of the present study because it provides practical recommendations regarding the most appropriate forecasting method for regional electricity planning based on identical datasets and evaluation criteria.

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The urgency of this research is closely related to the rapid socio-economic development occurring within the ULP Kencong service area. Continuous increases in electricity demand require more accurate planning to prevent electricity shortages, improve distribution reliability, optimize investment in electrical infrastructure, and support sustainable regional development. Reliable forecasting results are expected to assist PT PLN (Persero) in preparing future electricity supply strategies, expanding distribution networks, planning new substations, increasing transformer capacity, and developing more effective long-term electricity infrastructure plans. Moreover, accurate electricity demand forecasting contributes to national energy security by supporting more efficient resource allocation and sustainable energy management. Based on the aforementioned background, **the objectives of this study** are fourfold: **(1)** to forecast long-term electricity demand in the ULP Kencong service area for the 2025–2029 period using Multiple Linear Regression, DKL 3.2, and Business as Usual (BaU) methods; **(2)** to compare the projected electricity consumption generated by the three forecasting approaches across residential, commercial, industrial, and public sectors; **(3)** to evaluate the forecasting accuracy of each method using the Mean Absolute Percentage Error (MAPE); and **(4)** to identify the most appropriate forecasting method that can support electricity supply planning, infrastructure development, and strategic decision-making for PT PLN (Persero). The findings of this study are expected to contribute both theoretically, by enriching the literature on comparative electricity demand forecasting methods, and practically, by providing reliable recommendations for long-term electricity planning at the regional distribution level.

## Method

This study builds on previous research, namely, "Electricity Demand Projection Using the Multiple Linear Regression Method at PT PLN (Persero) UP3 Mojokerto from 2022 to 2027." This study used a single method, namely linear regression, with a forecasting period of six years. The results showed errors in the number of customers of 0.23%, installed capacity of 0.57%, electricity production of 1.45%, and electricity sold of 1.80%. The subsequent study was entitled "Analysis of Projected Electricity Demand in Temanggung Regency Based on Load Growth." This study uses two methods, namely the DKL 3.2 method and simple linear regression with a forecasting period of 5 years[10][11]. The output of this research is expected to support the decision-making process in energy infrastructure development and policy. Through these contributions, the study fills the existing research gap by providing a systematic comparison of forecasting methods and identifying the most accurate model for long-term electricity demand forecasting at the utility service-unit level. The findings demonstrate that Multiple Linear Regression produces the lowest forecasting errors in most sectors, thereby establishing its superiority over DKL 3.2 and BaU methods for forecasting electricity consumption in the ULP Kencong service area.

### A. Forecasting Factor

Forecasting factors are variables used in simulations and calculations of estimated electrical energy consumption. After grouping the data, calculations and simulations are performed using the three methods according to the variable criteria.

Table 1. Forecasting Factor Results

| Forecasting Factor | Value |
|---|---|
| PBB Growth | 0,14% |
| Household customer growth | 0.18% |
| Business customer growth | 0.72% |
| Industrial customer growth | 0.93% |
| Social customer growth | 0.25% |
| Household customer factor | 1.27 |
| Business customer factor | 5.04 |
| Industrial customer factor | 6.51 |
| Social customer factor | 1.78 |
| Household electricity consumption growth | 0.33% |
| Business electricity consumption growth | 1.06% |
| Industrial electricity consumption growth | 1.49% |
| Social electricity consumption growth | 0.65% |
| Household energy elasticity | 2.29 |
| Business energy elasticity | 7.00 |
| Industrial energy elasticity | 10.44 |
| Social energy elasticity | 4.57 |
| Household connected power growth | 0.28% |

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| | |
|---|---|
| Business connected power growth | 0.10% |
| Industrial connected power growth | 1.14% |
| Social connected power growth | 0.67% |
| Household electricity intensity | 0.14 |
| Business electricity intensity | 0.34 |
| Industrial electricity intensity | 0.55 |
| Social electricity intensity | 0.40 |

**B. Analysis Regression**

Linear regression is a technique used to determine the causal relationship between independent variables (X) and a dependent variable (Y)[12], [13], [14]. The purpose of this method is to obtain a regression equation that describes the relationship between the dependent and independent variables. If the dependent variable is related to two or more independent variables, the appropriate method is multiple linear regression. Linear regression is generally divided into two types: simple linear regression and multiple linear regression. In this study, used the multiple linear regression analysis method. The general formula for multiple linear regression is as follows:

$$\boldsymbol{y = a + (b_1x_1) + (b_2x_2)}$$

To calculate the values of the regression coefficients ($b_1$ and $b_2$) as well as the constant a, the following equations are used:

$$\boldsymbol{\alpha = \frac{(\sum y) - (b_1 \times \sum x_1) - (b_2 \times \sum x_2}{n}}$$

$$\boldsymbol{b_1 = \frac{[(\sum x_{2^2} \times \sum x_1 y) - (\sum x_2 y \times \sum x_1 x_2)]}{[(\sum x_{1^2} \times \sum x_{2^2}) - (\sum x_1 \times x_2)^2}}$$

$$\boldsymbol{b_2 = \frac{[(\sum x_{1^2} \times \sum x_2 y) - (\sum x_1 y \times \sum x_1 x_2)]}{[(\sum x_{1^2} \times \sum x_{2^2}) - (\sum x_1 \times x_2)^2}}$$

**C. DKL 3.2**

The DKL 3.2 method is the result of combining various approaches, including econometrics, trend analysis, and analytical methods[15] [16] [17]. The data used in this model is derived from PLN consumer electricity consumption over the past ten years[18][19][20]. In this model, the approach to estimating electricity demand is carried out by dividing consumers into four sectors: the household sector, the business sector, the public sector, and the industrial sector[21].

**D. Business as Usual (BaU)**

The Business as Usual (BaU) method for forecasting electricity consumption is an approach that assumes energy usage or growth patterns will remain consistent with current or historical conditions, disregarding significant changes in policy, technology, or economic trends[22][23][24]. In the BaU context, projections are based on historical trends such as population growth, economic activity, or past energy consumption, without accounting for factors like energy efficiency policies or shifts toward renewable energy sources[25][26][27].

**E. Mean Absolute Percentage Error (MAPE)**

To determine the accuracy of the projected electricity demand generated by the LEAP program, a method is needed to measure the level of accuracy. This study uses MAPE (Mean Absolute Percentage Error) to assess the accuracy of the projections. Although the simulation results are not exactly the same as the actual data, this indicates that the system's

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accuracy and economic aspects can still be maintained. The error in the forecasting results can be calculated using the following formula:

$$Error = \frac{actual - forecasting}{actual} \times 100\%$$

## Results And Discussion

### A. Electricity Consumption Forecasting Results Using the Linear Regression Method

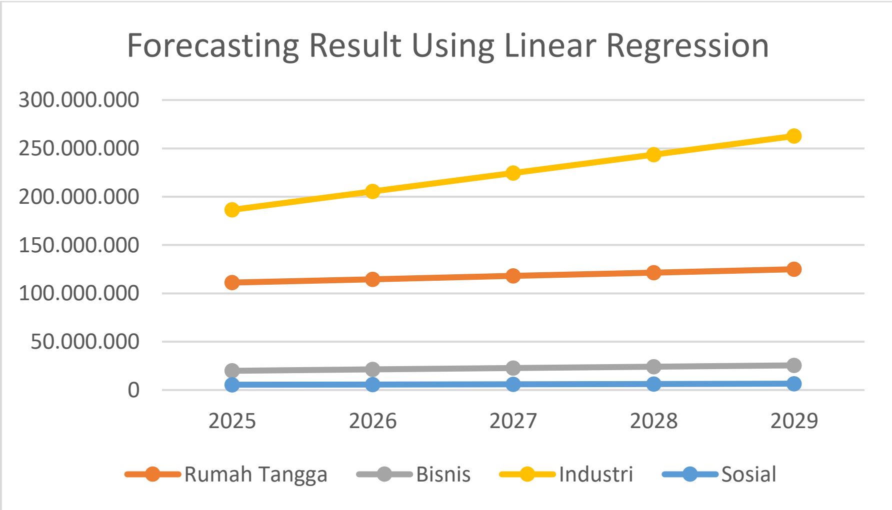


Figure 1.Forecasting Result Using Linear Regression

Based on the projected electricity consumption table for the social sector from 2025 to 2029, there is a gradual increase in consumption each year. Total consumption rises from 5,503,080 kWh in 2025 to 6,569,986 kWh in 2029. The average monthly growth rate is recorded at 0.37%, while the annual growth rate reaches 4.5%. This increase indicates a positive trend in electricity usage for social purposes, which may reflect the expansion and growing activity of social services such as educational institutions, healthcare facilities, and places of worship from year to year.

### B. Electricity Consumption Forecasting Results Using the DKL 3.2 Method

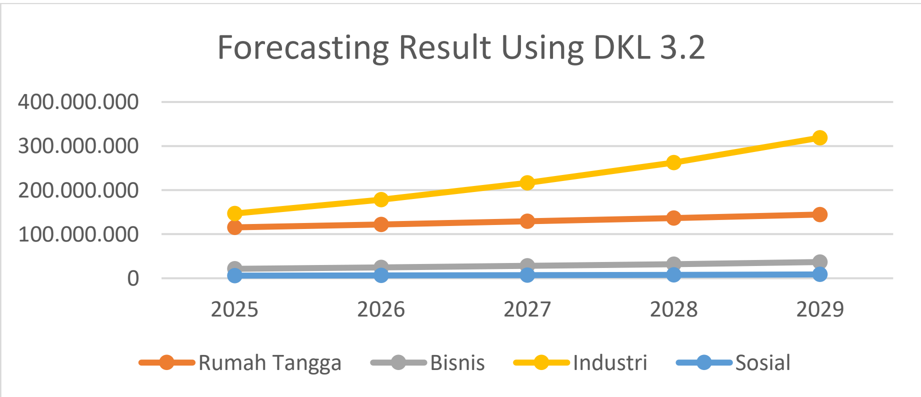


Figure 2.Forecasting Result Using DKL 3.2 Method

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Based on the projected electricity consumption using the DKL 3.2 method, each sector exhibits significantly different consumption patterns. The industrial sector shows the highest growth, averaging 1.6% per month, indicating an expansion in manufacturing and production activities that require substantial energy supply. This increase remains consistent throughout the year with a stable pattern, reflecting a continuously rising energy demand in line with industrial infrastructure development.

The business sector experiences considerable growth at 1.1% per month, suggesting an increase in economic activities that rely on electricity-based technologies. The household sector shows the most stable growth at 0.4% per month, reflecting a gradual rise in consumption aligned with the growth in the number of households and the ownership of electronic appliances. The social sector, with a growth rate of 0.8% per month, indicates a rising energy demand for public facilities such as schools, hospitals, and government buildings.

The DKL 3.2 forecasting model also predicts increasing electricity demand across all sectors. However, unlike regression analysis, DKL incorporates customer growth, electricity elasticity, energy intensity, and economic growth into the forecasting process. Consequently, the projected growth rates differ among customer categories. The industrial sector again exhibits the highest projected growth (approximately 1.6% per month), followed by the commercial sector (1.1%), public sector (0.8%), and residential sector (0.4%).

These findings suggest that the DKL method is more responsive to changes in macroeconomic indicators than statistical regression models. While DKL provides detailed sector-specific projections, its dependence on several forecasting assumptions may increase uncertainty when actual economic conditions deviate from projected trends.

**C. Electricity Consumption Forecasting Results Using the BaU Method**

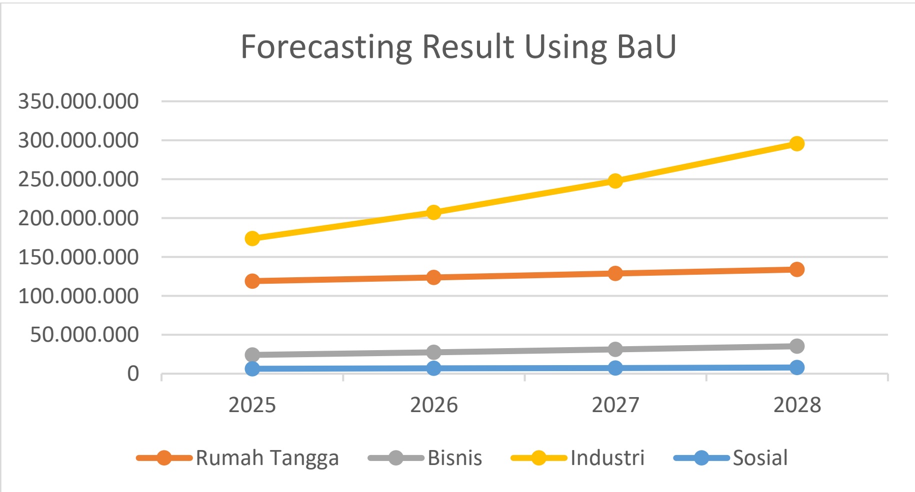


Figure 3.Forecasting Resul Using the BaU Method

Based on the projected electricity consumption using the Business-as-Usual (BaU) method for the 2025–2029 period, different growth patterns are observed across sectors. The industrial sector shows the highest growth, averaging 1.49% per month, with consumption increasing from 145.4 million kWh in 2025 to 295.4 million kWh in 2029. This exponential rise reflects intensified manufacturing and production activities that require a substantial energy supply, in line with the expansion of the industrial sector.

The business sector records significant growth at 1.06% per month, with consumption rising from 21.2 million kWh to 35.2 million kWh. This surge indicates rapid development in commercial activities, including business digitalization and the growth of small and medium enterprises (SMEs). The household sector grows more steadily at 0.33% per month, with consumption increasing from 114.4 million kWh to 133.8 million kWh, reflecting a rise in the number of households and greater use of electronic appliances.

The social sector shows a growth rate of 0.65% per month, with consumption rising from 5.8 million kWh to 8.0 million kWh, indicating an increasing energy demand for public facilities such as schools and hospitals. The Business as Usual

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scenario assumes that future electricity demand follows historical consumption trends without considering major technological, regulatory, or economic changes. The projection indicates continuous growth across all customer sectors throughout the study period.

Industrial electricity consumption increases from approximately 145 million kWh to nearly 295 million kWh, while commercial demand rises from approximately 21 million kWh to 35 million kWh. Residential electricity consumption increases steadily from approximately 114 million kWh to 134 million kWh, whereas public sector consumption grows from approximately 5.8 million kWh to 8 million kWh. The BaU model effectively represents long-term consumption trends under stable economic conditions. However, because it ignores future policy interventions, technological innovations, and energy efficiency improvements, the method may overestimate electricity demand when significant structural changes occur.

**D. Forecasting Error**

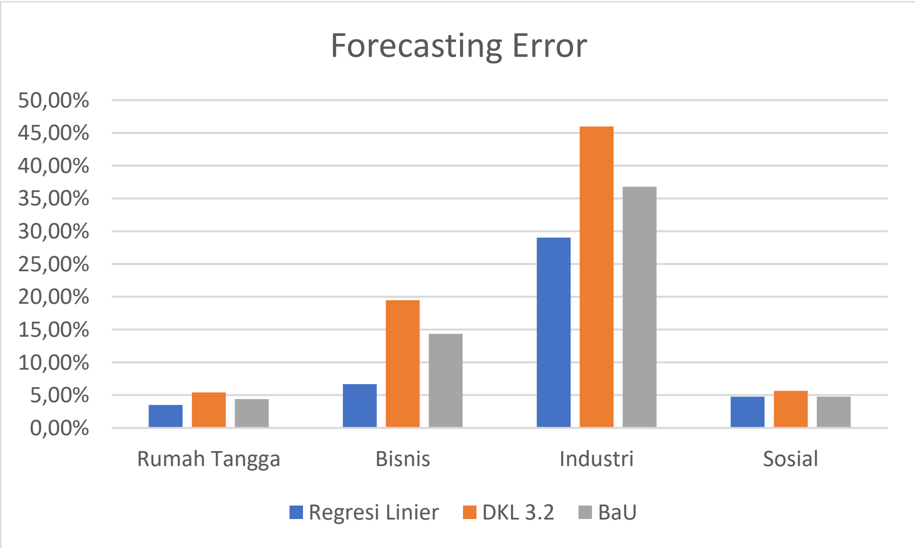


Figure 4. Forecasting Error

Based on the data, each projection method shows different levels of accuracy across sectors. In the household sector, Linear Regression has the lowest error (3.49%), followed by BaU (4.41%) and DKL 3.2 (5.41%), indicating that Linear Regression is the most accurate. In the business sector, Linear Regression again performs better with an error of 6.68%, while DKL 3.2 and BaU show higher errors of 19.49% and 14.36%, respectively. The industrial sector records the highest errors across all methods—Linear Regression (29.04%), BaU (36.79%), and DKL 3.2 (45.98%)—suggesting challenges in predicting industrial demand due to non-linear fluctuations or external factors. In the social sector, Linear Regression and BaU yield similar results with errors of 4.77% and 4.78%, while DKL 3.2 is slightly less accurate at 5.67%.

## Conclusions

This study successfully projected long-term electricity consumption in the ULP Kencong service area for the 2025–2029 period using three different forecasting approaches: Multiple Linear Regression, Electricity Demand List Method 3.2 (DKL 3.2), and Business as Usual (BaU). The results indicate that electricity consumption is expected to increase across all customer sectors, including residential, business, industrial, and social sectors. Among these sectors, the industrial sector is projected to experience the highest growth in electricity consumption, reflecting the increasing expansion of industrial activities and production capacity in the region. The forecasting accuracy evaluation using Mean Absolute Percentage Error (MAPE) demonstrates that the Multiple Linear Regression method provides the most accurate and consistent results compared with DKL 3.2 and BaU. The regression model achieved the lowest forecasting errors in the residential (3.49%), business (6.68%),

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and social (4.77%) sectors. In contrast, all methods produced relatively high forecasting errors in the industrial sector, indicating that industrial electricity demand is influenced by more dynamic and complex factors that require additional forecasting considerations. This study also confirms that integrating customer growth and connected power capacity can improve the reliability of long-term electricity demand projections. Furthermore, the novelty of this research lies in the comprehensive comparison of three forecasting methods within the same case study area, namely ULP Kencong, enabling a more thorough assessment of forecasting performance and method suitability. Based on the findings, Multiple Linear Regression can be recommended as the most suitable forecasting method for long-term electricity demand projection in the ULP Kencong service area. The results of this study are expected to serve as a valuable reference for PLN and policymakers in planning electricity supply, developing power generation facilities, and expanding electricity infrastructure to ensure a reliable, efficient, and sustainable power system in the future. Therefore, future studies are recommended to integrate socioeconomic indicators, renewable energy policies, and climate variables into forecasting models while comparing conventional statistical approaches with advanced machine learning algorithms.

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