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Long-Term Load Forecasting At The End Of The Year Using The Linear Regression Method

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Abstract - This study discusses long-term electricity load forecasting at the end of the year using a linear regression method, applied to the Glugur Substation in Medan. Historical load data from 2021 to 2024 is used as the basis for calculations to forecast electricity loads until the end of 2026. The forecasting process is carried out by modeling the relationship between the increase in time to peak load and monthly energy, using a linear regression approach. The forecasting results show a stable and consistent load increase trend. Model accuracy evaluation is carried out using MAPE, R^2, MAE, and RMSE metrics. The lowest MAPE value is obtained at 1.37% at the Selayang Substation, while the Glugur Substation has a MAPE value of 2.43%, indicating a good level of accuracy for long-term forecasting. This research contributes to supporting the planning of a more reliable and efficient electricity distribution system.

Keywords: *Load Forecasting, linear Regression, Glugur Substation, MAPE, Distribution System, Peak Load.*

1. INTRODUCTION

Human population and activities continue to increase massivelycausing significant technological developments. indirectly,Technology must continue to evolve to meet demandsassisting human activities in many ways. This technological development cannot be separated from the availability of sufficient and stable electrical energy. Already using electricitybecome one of the basic needs in various fields such as business, engineering,socially and culturally. Therefore, appropriate strategies and methods are neededEstimate the power generated and the load required by consumersmaintain system continuity and reliability [1].The importance of generating electricity according to consumer demand is crucial. If the power generated falls short of consumer demand, the system frequency can drop below 50 Hz. This can cause power outages in some locations. Conversely, if too much power is supplied, the system frequency can increase. Therefore, maintaining a balance between power generation and consumer demand is crucial for maintaining electricity system stability.

To address the problems described above, electricity load forecasting is a highly relevant solution. The goal of electricity load forecasting is to predict future power demand. This forecasting minimizes losses for both electricity producers and consumers, while improving the reliability of the electricity system. Highly accurate load forecasting is key to future resource planning. These load estimates are generally based on an analysis of historical load growth trends in the region.

In this study, regression methods such as linear regression were used. Multiple linear regression is a method that combines the response variable (dependent variable) with one or more explanatory variables (independent variables). In long-term situations , estimating workload becomes complex due to the various factors that influence workload patterns in diverse ways. Assessing the impact of each factor separately presents a challenge. Previous research has proposed a workload estimation approach that utilizes historical data on holiday workload patterns. This approach is based on the assumption that future patterns will resemble past data.

Therefore, a long-term electricity load forecasting analysis for 4 years using the Regression method is required. This study will focus on PT PLN (Persero) ULTG Glugur – Medan.with the aim of increasing system resilience and reducing potential losses that may be experienced by electricity producers in Glugur City, especially during the next 4 years.

2. LITERATURE REVIEW

Electric Power System

The electric power system in Indonesia is generally generated by power centers.Electric power such as, Hydroelectric Power Plant (PLTA), Steam Power Plant (PLTU), Gas Power Plant (PLTG), Geothermal Power Plant (PLTP), Gas and Steam Power Plant (PLTGU), Diesel Power Plant (PLTD), and others. Before the electrical energy is transmitted, the voltage must first be increased by a step-up transformer in the transmission substation. Next, the transmitted electrical energy will reach the distribution substation, then the voltage is lowered by a step-down transformer to medium voltage or called primary distribution. After the electrical energy is distributed through the primary distribution network, the voltage of the electrical energy is then lowered again in the secondary distribution to 380/220 volts, then distributed through a low voltage network to be further distributed to customer homes (consumers) [2]. The general electric power system scheme can be seen in Figure 1 below.

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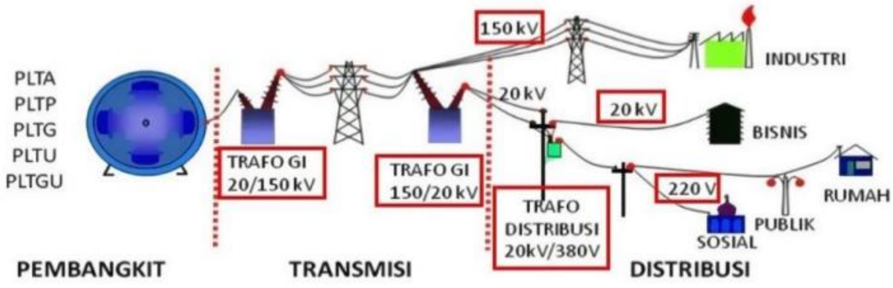

Figure 1. Electrical Power System Schematic

Distribution System Reliability

Reliability is the level of success of the performance of a system or part of an electric power system, to be able to provide better results over a period of time and under certain operating conditions. To be able to determine the level of reliability of a system, an examination must be carried out by means of calculations or analysis of the level of success of the performance or operation of the system being reviewed, over a certain period and then comparing it with previously established standards [4].

Distribution system assurance levels have indices that can be used to compare the performance of distribution systems in providing services to consumers, as a benchmark for progress or to determine projected goals. The following are several types of distribution system assurance levels:

1. SAIFI : *System Average Interruption Frequency Index*
2. SAIDI : *System Average Interruption Duration Index*
3. CAIFI : *Customer Average Interruption Frequency Index*
4. CAIDI : *Customer Average Interruption Duration Index*
5. ASAI : *Average System Availability Index*

In efforts to improve the quality, reliability and service of electricity for consumers, many factors influence the electricity distribution system which follows a number of technical, economic and social reasons so that it can comply with quality standards in the electricity distribution system.

Electrical Load

The load in a region's electric power system depends on commercial and industrial activities, as well as the condition of residential areas, which are also influenced by weather conditions. Religious and social activities also influence certain days, especially national holidays and year-end holidays. Understanding the nature of the load from various customer groups will aid the power system load forecasting process. The electric power system load consists of several customer groups. Each group has unique characteristics [2]. To plan a reliable distribution system, one thing that needs to be considered is the electric load. To determine the electric load, there are several things that need to be considered, such as:

1. Types of electrical loads
2. Load curve
3. Electrical load characteristics
4. Daily load factor

Basic Concepts of Forecasting

Basically, a prediction is an assumption or estimate of what will happen.incidentinti meupcoming. Forecast Cannature qualitative and quantitative. Forecast qualitative Noshapednumber, for example Tomorrow will down Rain, year front will happenwar, next year's sales results will increase, and so on. While the forecastQuantitative forecasts are expressed in the form of numbers or figures. Quantitative forecasts themselves are divided into become two type [8],that is:

1. Single Forecast (*Point Forecast*)
   Forecastsingleconsists ofon Onemarkjust, for example results production company A B Cwillreach 1000unit, profitsalemonthfront will worthRp.250,000.00 where bigusage Power year front will go on5% Andand so on.
2. Interval Forecast

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ForecastHoseconsists ofover several values in an interval bounded by a lower limit value (low forecast)Andlimiton(forecasttall).For example,resultsproductioncompanyA B Cwillachieve800 – 1200 units, next month's sales profit will be worth Rp. 200,000 to Rp.withRp . 250,000,sizeincrease in consumptionPoweryearfront ranges between 5– 10%.

According to the time period, forecasting is divided into 3 periods, according towiththe material he predicted.

1. Long-Term Forecasting *is* a *forecast* thatpredicting the situation in the next few years. The goal is toisForcanprepareavailabilityunitgeneration,systemtransmission, as well asdistribution.
2. ForecastingTermIntermediate(*Mid - TermForecasting*)It isforecastingon a monthly or weekly basis. The goal is to prepare a schedulepreparationAndoperationalsidegenerator.
3. Short-Term Forecasting *is* a *forecast* indaily to hourly timeframes. Commonly used for comparative studiesburdenelectricityestimationwithactual(*real time*).

Linear Regression

Linear regression is a statistical technique that can be used for electricity load forecasting. Linear regression is used to measure the magnitude of the relationship between independent variables and dependent variables and to predict the dependent variable with the independent variable. Regression analysis is the study of the relationship between one variable, called the explained variable, and one or two explanatory variables. The first variable is also called the dependent variable and the second variable is called the independent variable. If there is more than one independent variable, then the regression analysis is called multiple linear regression. This is called so because the influence of several independent variables will be applied to the dependent variable. The objectives of this regression analysis are:

1. Make estimates of the average and value of the dependent variable based on the independent variables.
2. Test the characteristic hypothesis of the dependent variable.
3. Predicting the average value of the independent variable based on the values of the independent variable outside the sample range.

A regression line is a line used to estimate or predict a value on the Y-axis if the value on the X-axis is known. A straight line is called a linear regression line. To create a linear regression line, it is necessary to determine the strength of the relationship between the values on the X- and Y-axis using the correlation coefficient. The coefficient has a minimum value of -1 and a maximum of 1.

A positive relationship generally has the characteristic of an increase in value on the X axis being proportional to an increase in value on the Y axis, while a negative relationship states that an increase in value on the X axis is inversely proportional to a decrease in value on the Y axis. If the relationship between X and Y is weak, there is no relationship between an increase or decrease between the values on the X and Y axes, then it can be called a weak relationship or no relationship.

The regression line equation can be formulated as follows:

$$\hat{Y} = a + b\,X \quad (2.1)$$

$$y = \alpha + b_1 X_1 + b_2 X_2 + b_n X_n \quad (2.2)$$

$\hat{Y}$ = Dependent variable
a = constant
b = Coefficient of variable X
X = Independent variable
α= Fixed coefficient
b_n = Regression coefficient
X_n = Independent variable or predictor variable

To calculate the values of a and b, you can use the following formula:

$$a = \mu_y - (b_1 .\mu_{x1} + b_2 .\mu_{x2} + \ldots + b_n .\mu_{xn}) \quad (2.3)$$

$$b = \frac{(\sum XY) - (\sum X)(\sum Y)}{n(\sum X^2) - (\sum X)^2} \quad (2.4)$$

$$b_1 = \frac{\sum_{i=1}^{n} (x_{1i} - \mu_{x1})(y_1 - \mu_y)}{\sum_{i=1}^{n} (x_{1i} - \mu_{x1})^2} \quad (2.5)$$

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3. RESEARCH METHODS

Time and Place of Research

This research began in October 2024 with a research topic search and literature review. The final project research location was PT PLN (Persero) ULTG Glugur, Medan.

Data and Equipment Required

The data used in this study is data obtained fromPT PLN (Persero) ULTG Glugur - Medan. The data and equipment used in this study are as follows:

1. Historical data of monthly electricity load in 2021-202 4
2. Monthly peak load data from 2021-202 4
3. Microsoft Excel

Observed Variables

The variables observed in this study are:

1. Monthly electricity usage in 2021-202 4
2. Monthly peak load in 2021-202 4 .

Research Procedures

The procedures used in this research are as follows:

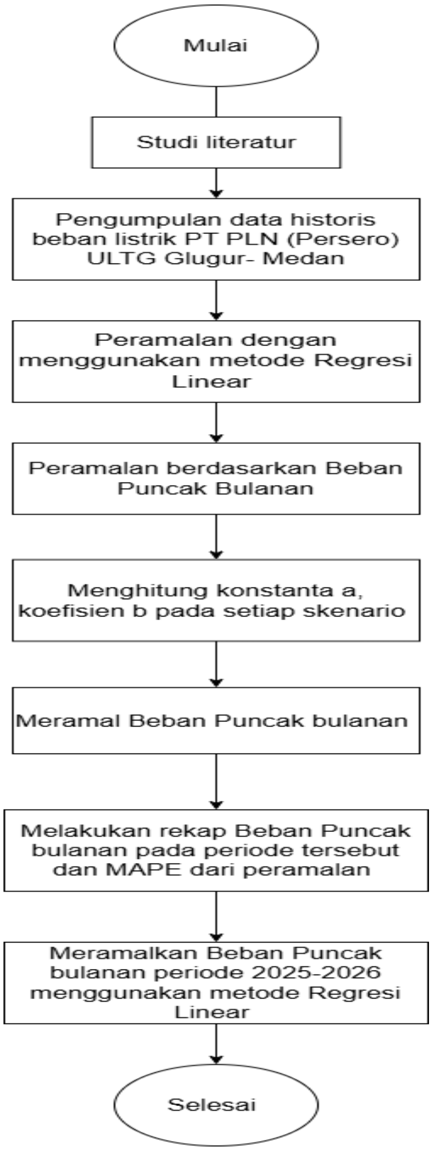

Figure 2. Research Flow Diagram

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4. RESULTS AND DISCUSSION

Forecasting Using Linear Regression Method

In forecasting using the linear regression method, we first model the data we have into the form of variables X and Y. Where X is the dependent variable in a data, in this study the independent variable is the increase in the year from 2021-2024. For variable Y is the dependent variable or the variable that is influenced, in this study the variable that is influenced is the increase in Peak Load for the same month from 2021-2024.

A.1 Linear Regression Forecasting based on Peak Load

To relate the effect of annual increases on peak load, historical peak load data for the same month is required. Therefore, a graph of the relationship between annual increases and peak load must be created. The resulting relationship is represented by annual increases on the "X" axis and peak load on the "Y" axis. In the following table, data from the Glugur substation contains three transformers. We determine the X and Y variables from the daily peak load summary data for the January and December periods from 2021 to 2024, which we will use to forecast peak load at the end of 2026.

Table 1Peak Load Data 2021-2024 Glugur Substation Trafo 1

Year (X) / Month (Y)	**2021 (MW)**	**2022 (MW)**	**2023 (MW)**	**2024 (MW)**
Januari	36.4	35.9	37.7	38.5
Februari	38.7	38.2	32.1	39.3
Maret	32.1	41.5	31.6	46.6
April	35.2	37.8	39.7	45.0
Mei	36.8	38.9	42.5	45.0
Juni	35.5	35.7	42.5	44.5
Juli	36.2	40.4	39.1	39.8
Agustus	29.5	40.4	36.1	40.1
September	-	36.1	31.8	38.1
Oktober	39.6	39.6	34.2	46.6
November	36.3	27.8	0.0	43.2
Desember	34.3	30.8	31.1	44.2

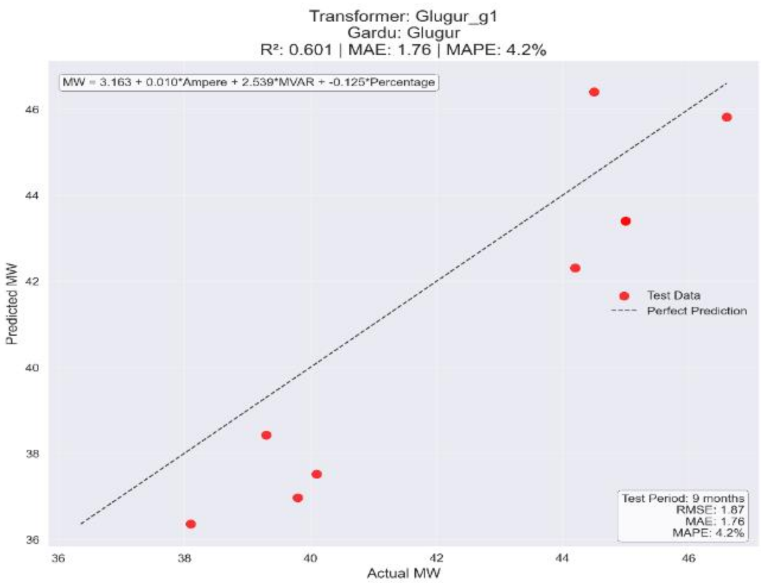

Figure 2, Glugur Substation

The graph in Figure 3 shows the distribution of the actual peak load value (X-axis) against the peak load value predicted by the linear regression model (Y-axis) for Transformer 1 at the Glugur Substation. The dotted line indicates the ideal condition "Actual = Predicted", so that points close to the line indicate good prediction accuracy. From the test results over a 9-month test period, the coefficient of determination (R^2) value was obtained at 0.601,

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MAE 1.76 MW, and MAPE 4.2%, which indicates that the linear regression model is able to capture the load increase pattern with a relative average error below 5%. The presence of several points that deviate above or below the ideal line indicates seasonal load fluctuations or external disturbances that have not been fully accommodated by the regressor variables.

The results of the forecast data for the increase in the load on the Glugur Main Substation (Transformer 1) can be seen in Table 2.

Table 2. Summary of Regression Method Forecasting Results in the Load Increase Scenario

Actual (MW)	Forecastad (MW)	Percentage Error (%)
44.2	42,30984	4.276374918
39.3	38.42678	2.221937637
46.6	45,81511	1.684310614
45	43,39851	3.558868463
45	43,39851	3.558868463
44.5	46.39706	4.263052916
39.8	36.96882	7.11352068
40.1	37,51315	6.451041593
38,1	36,35599	4.577448288

Table 2 displays a summary of the actual peak load values, the peak load values predicted by the linear regression model, and the error percentage for each test period at Transformer 1 of the Glugur Substation. From the eight test data sets, it can be seen that the difference between the actual and predicted values ranged from 1.68% to 7.11%. The highest error occurred at the actual value of 39.8 MW with an error percentage of 7.11%, which was likely caused by sudden load fluctuations or external factors such as extreme weather conditions during that month. Meanwhile, the lowest error (1.68%) was observed at the actual value of 46.6 MW, indicating that the model was quite accurate when the load entered the highest peak range. The average error percentage (MAPE) for the entire test data was 4.2%—this value is still below the 5% tolerance threshold commonly used in electricity load forecasting—confirming that the linear regression model used was able to represent the peak load increase pattern well. These results support the use of the model in capacity planning and operational strategies of substations, particularly for predicting future power requirements.

Furthermore, a recapitulation of peak load data for the Glugur Trafo 2 Substation for the 2021–2024 period is presented in Table 3 below.

Table 3data 2021-2024 GI Glugur transformer 2

Year (X) / Month (Y)	2021 (MW)	2022 (MW)	2023 (MW)	2024 (MW)
January	15.9	29.7	26.9	27.8
February	28.4	31.8	38.8	32.8
March	27.4	32.5	33.5	39.1
April	40.6	31.0	22.9	39.2
Mei	33.9	31.9	33.8	39.2
Juni	33.6	30.0	33.8	36.8
Juli	15.1	35.3	48.4	26.5
Agustus	28.3	35.3	45.1	39.5
September	-	23.4	33.1	38.0
October	27.9	31.7	27.7	23.2
November	32.0	28.3	0.0	24.0
December	29.4	22.6	29.0	31.4

From the monthly peak load data of Glugur Transformer 2 Substation for the period 2021–2024, a consistent annual increase in load is seen, for example, in January it increased from 15.9 MW (2021) to 27.8 MW (2024) as

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well as seasonal spikes in April and May, reflecting the influence of weather patterns and consumption; although there is a data gap in September 2021, the overall trend is similar to Transformer 1, so these results can be used as a basis for calibrating forecasting models and formulating more appropriate capacity planning policies and maintenance schedules.

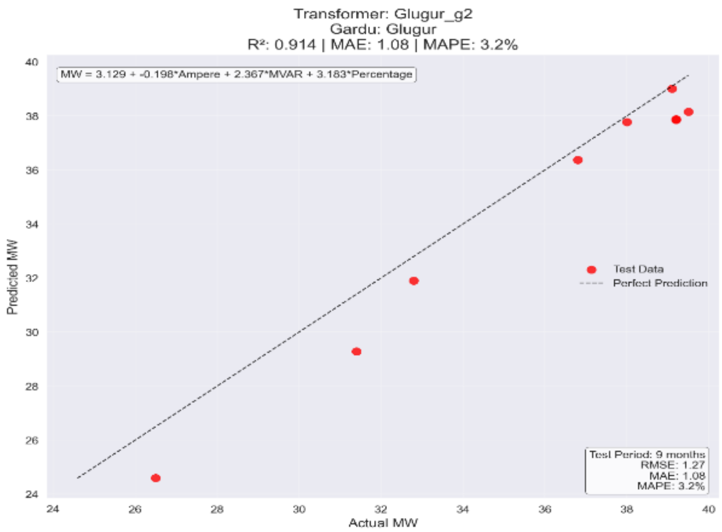

Figure 4. Actual Monthly Peak Load Forecast Results – Transformer 2, Glugur Substation

The graph in Figure 4 shows the distribution of the actual peak load value (X-axis) against the peak load value predicted by the linear regression model (Y-axis) for Transformer 2 at the Glugur Substation. The dotted line indicates the ideal condition "Actual = Predicted", so the red dots adjacent to the line represent high prediction accuracy. During the 9-month testing period, the model achieved a coefficient of determination (R^2) of 0.914, MAE of 1.08 MW, and MAPE of 3.2%, indicating an average relative error well below the 5% tolerance threshold. Several points that are slightly away from the ideal line indicate seasonal fluctuations or external factors that have not been fully captured by the regressor variables. Overall, these results confirm that linear regression provides reliable peak load predictions for Transformer 2, making it suitable for supporting capacity planning and substation maintenance.

As for the regression line equation, $y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_n X_n$ shows the relationship between variables X and Y. After the graph is formed, to make a forecast we must determine the values of coefficients a and b using formula (2.3). Where the values of coefficients a, b1, b2, b3 are obtained, can be seen in Table 4.

Table 4. Regression Coefficients for Load Forecasting Model at Glugur Substation

Transformer	Intercept (a)	Coef_Ampere (b_1)	Coef_MVAR (b_2)	Coef_Percentage (b_3)
1	3,613	0,0104	2,5393	-0,1253
2	3.1292	-0.1979	2.3671	3.1829
3	3.3034	-97.6489	3.5289	1691.3552

So based on Table 4, the regression equation for 3 transformers at the Glugur Substation is obtained. Where the values of Intercept (α), Coef_Ampere (b_1), Coef_MVAR (b_2), Coef_Percentage (b_3) are obtained. Then the value of y can be found using formula (2.3), namely:

$y = \alpha + b_1 X_1 + b_2 X_2 + b_n X_n$

$y = 3.613 + 0.0104 X_1 + 2.5393 X_2 + -0.1253 X_3$

Table 5. Performance of Regression Model with evaluation of regression model performance at Glugur Substation

Transformer	R2	MAE (MW)	RMSE (MW)	MAPE (%)
1	0,601	1,76	1,87	4,2%
2	0,914	1,08	1,27	3,2%
3	0,04	3,22	3,63	8,8%

Based on Table 5, the results of the regression model performance evaluation for electrical load forecasting in various transformers can be seen using the statistical indicators R², MAE, RMSE, and MAPE. Of the three

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transformers analyzed, Transformer 2 showed the best performance with an R^2 value of 0.914 which indicates the model is able to explain 91.4% of the variability of peak load data. The MAE value of 1.08 MW and RMSE of 1.27 MW in Transformer 2 indicate a very low level of prediction error, with a MAPE of only 5.2% which is still within acceptable tolerance limits for electrical load forecasting applications.

Transformer 1 performed quite well with an R^2 of 0.901, but had a slightly higher RMSE (1.67 MW) despite the same MAE (1.08 MW). The MAPE of 4.2% for Transformer 1 was even better than that for Transformer 2, indicating good prediction consistency. In contrast, Transformer 3 performed very poorly with the lowest R^2 (0.04), indicating the model was only able to explain 4% of the load data variability. The very high MAE and RMSE values for Transformer 3 (3.22 MW and 3.63 MW) and the MAPE of 8.3%, which exceeded the tolerance limit, indicated that the linear regression model was not suitable for the load characteristics of the transformer.

This significant performance difference indicates that each transformer has unique load characteristics. Transformers 1 and 2, with more stable and predictable load patterns, performed satisfactorily, while Transformer 3, with its high load fluctuations or non-linear pattern, required a more complex modeling approach.

By using a linear regression model, the load for the next 24 months can be predicted.

Table 6. Load Forecasting Data Results at the Glugur Main Substation

No	Date	Forecasted (MW)
1	2025-01-31	36.38918521
2	2025-02-28	36.42237823
3	2025-03-31	36.45557124
4	2025-04-30	36.48876425
5	2025-05-31	36.52195726
6	2025-06-30	36.55515028
7	2025-07-31	36.58834329
8	2025-08-31	36.6215363
9	2025-09-30	36.65472931
10	2025-10-31	36.68792232
11	2025-11-30	36.72111534
12	2025-12-31	36.75430835
13	2026-01-31	36.78750136
14	2026-02-28	36.82069437
15	2026-03-31	36.85388738
16	2026-04-30	36.8870804
17	2026-05-31	36.92027341
18	2026-06-30	36.95346642
19	2026-07-31	36.98665943
20	2026-08-31	37.01985245
21	2026-09-30	37.05304546

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22	2026-10-31	37.08623847
23	2026-11-30	37.11943148
24	2026-12-31	37.15262449

5. CONCLUSION

The conclusions that can be drawn from the research that has been conducted are as follows:

1. The results of long-term electricity load forecasting at the end of 2026 using the linear regression method, the model at the three substations shows a moderate and consistent upward trend. Transformer 1 is projected to increase from 36.39 MW in January 2025 to 37.15 MW in December 2026 (an increase of 2.23%), Transformer 2 from 37.80 MW to 38.60 MW (2.11%), and Transformer 3 from 47.03 MW to 48.03 MW (2.14%). This nearly linear growth pattern confirms that linear regression is able to adequately capture long-term load trends, even though the load characteristics of each transformer are different—with the highest reliability at Transformer 2 and the most variable at Transformer 3.
2. The forecasting results show that Transformer 2 has the best accuracy with a MAPE of 3.2%, followed by Transformer 1 at 4.2%, and Transformer 3 with the highest value of 8.8%. All MAPE values are still below the 10% tolerance threshold for long-term forecasting, so that peak load predictions at the three substations are suitable as a basis for capacity planning and operational strategies—with the note that more caution is needed for Transformer 3 to consider additional modeling approaches to increase its accuracy.

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