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Daily Electricity Load Forecasting in Ternate City Using ELM

Andi Muhammad Ilyas [1,a,*]; Muhammad Natsir Rahman[1,b]; Aldi Aswat[1,c]; Faris Syamsuddin[1,d]; Suparman[1,e]; Bayu Adrian Ashad [2,f]; Agus Siswanto[3,g]

[1] *Electrical Engineering, Faculty of Engineering, Khairun University, Ternate, 97718, Indonesia.*
[2] *Electrical Engineering, Faculty of Engineering, Muslim University of Indonesia, Makassar, 90231, Indonesia.*
[3] *Electrical Engineering, Faculty of Engineering, University of August 17, 1945, Cerebon, 45134, Indonesia*
[a] *aamilyas@gmail.com*, [b] *mnrahman@gmail.com*, [c] *aldias@gmail.com*, [d] *faris.syamsuddin@gmail.com*,
[e] *namrap@unkhair.ac.id*, [f] *bayuadrianashad@umi.ac.id*, [g] *asiswanto.untagcrb@gmail.com*,
* *Corresponding author*

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Abstract

The continuously increasing growth of electricity demand necessitates accurate and systematic planning of electric power systems to ensure power flow quality and system reliability. Ternate City, as one of the major activity centers in North Maluku Province, has experienced a substantial rise in electricity consumption, thereby requiring an effective and reliable load forecasting approach. This study aims to predict the daily electricity load in Ternate City using the Extreme Learning Machine (ELM) method. The analysis is conducted using historical electricity load data, which are processed through data preprocessing stages, dataset partitioning into training and testing sets, and ELM-based modeling. The performance of the proposed model is evaluated using the Mean Absolute Percentage Error (MAPE). The results indicate that the MAPE values for the training dataset range from 5.84% to 13.63%, corresponding to very good to good performance categories. Meanwhile, the testing dataset yields MAPE values ranging from 13.45% to 33.09%, which fall within the good to sufficient performance categories. Furthermore, the prediction results are able to accurately capture daily electricity load fluctuation patterns from Monday to Sunday, including peak load periods. Based on these findings, the ELM method demonstrates strong potential as a reliable approach to support electric power system planning and to enhance the quality and reliability of electricity supply in Ternate City.

Keywords: *ELM, Electricity Load Forecasting, Daily Load, Power Quality, Ternate City*

1. Introduction

The demand for electrical energy continues to increase along with population growth, economic development, and the expansion of social and industrial activities. This condition necessitates accurate and systematic planning of electric power systems to ensure power flow quality and system reliability. Ternate City, as one of the major activity and growth centers in North Maluku Province, has experienced a substantial increase in electricity load, thereby requiring appropriate power system planning to support sustainable energy supply and reliable system operation.

Effective electric power system planning is highly dependent on the accuracy of electricity load growth forecasting. Inaccurate load prediction may lead to various technical problems, including voltage quality degradation, increased power losses, and power flow imbalances in distribution networks (Ilyas et al., 2022). Therefore, accurate electricity load forecasting plays a crucial role in supporting decision-making processes related to network development, generation capacity expansion, and improvements in the quality and reliability of electricity services.

Conventional electricity load forecasting methods generally exhibit limitations in modeling nonlinear and complex data patterns (Ilyas et al., 2021), (Brahim et al., 2025), (Said & Ilyas, 2024). With the advancement of computational technologies, artificial intelligence–based approaches, particularly artificial neural networks, have been widely applied to improve prediction accuracy (Caessar & Nrartha, 2024), (Malini et al., 2025). One of the emerging methods is the Extreme Learning Machine (ELM), which is a single hidden-layer feedforward neural network that offers advantages in terms of fast training speed and strong generalization capability. Existing studies predominantly focus on large interconnected systems and long-term forecasting horizons, while investigations on daily load forecasting in small-scale island power systems remain limited.

Addressing this research gap, the present study applies the Extreme Learning Machine (ELM) to predict daily electricity load in the island power system of Ternate City, with particular emphasis on capturing weekday–weekend demand variations and peak load characteristics. The novelty of this study lies in demonstrating the effectiveness of ELM for short-term daily load forecasting in a geographically isolated power system, where load patterns are strongly influenced by local activity cycles. By focusing on detailed daily fluctuation behavior rather than aggregated long-term demand, this research provides practical insights to support operational planning and reliability enhancement in small-scale island electricity systems.

The results of this study are expected to contribute to more reliable decision-making in electric power system operation and planning in island regions, as well as to enrich the body of knowledge on the application of machine learning techniques for electricity load forecasting in isolated and developing power systems

2. Method

This study employs a quantitative approach using an artificial intelligence-based forecasting method, namely the Extreme Learning Machine (H. Wang et al., 2024), to predict electricity load growth in Ternate City. The research methodology is systematically structured, beginning with data collection and preprocessing, followed by model design, training, and testing phases, and concluding with the evaluation of prediction results in relation to power flow quality.

2.1 Research Data

The data used in this study consists of historical electricity load data for Ternate City obtained from the Kastela Substation. The dataset includes daily load values recorded from January to December 2023. These historical data serve as the primary input for the training and testing processes of the Extreme Learning Machine (ELM) model.

2.2 Extreme Learning Machine

Extreme Learning Machine (ELM) is a neural network–based learning approach employing a *Single Hidden Layer Feedforward Neural Network* (SLFN) architecture, which was developed to address the limitations of conventional training methods (Morais, 2022), (H. Wang et al., 2024), (Zhao et al., 2022). In ELM, the input-to-hidden layer weights and bias terms are randomly assigned and remain fixed during the training phase, while the output layer weights are analytically determined using the Moore–Penrose pseudoinverse method (Kızıldağ et al., 2024), (de Mattos Neto et al., 2021), (Sun et al., 2023). This training strategy significantly reduces computational complexity and training time, while preserving the model's generalization capability in capturing nonlinear relationships within the data. Owing to these advantages, ELM has been widely applied in prediction and forecasting tasks, including electrical load forecasting, where it demonstrates reliable accuracy and computational efficiency for power system applications.

The forecasting process based on the Extreme Learning Machine (ELM) method comprises three principal stages, namely the random initialization of input weights and bias terms, the computation of hidden layer outputs, and the analytical estimation of the output weights. This formulation avoids iterative weight adjustment, thereby improving computational efficiency (Morais, 2022), (J. Wang et al., 2022), (J. Wang et al., 2022). The learning speed of conventional feedforward neural networks is further enhanced through the ELM framework, as reported in previous studies (Ilyas et al., 2021), Accordingly, the architectural design of the ELM model applied in this study is presented as follows.

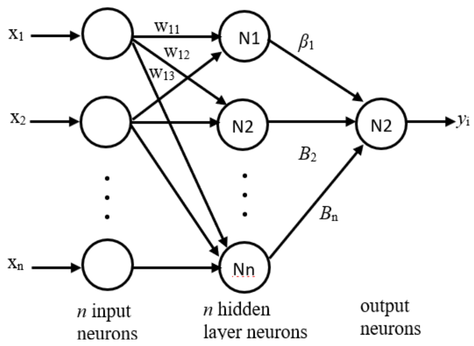

Figure 1. Extreme Learning Machine (ELM) Architecture

2.3 Mathematical Model of the Extreme Learning Machine (ELM)

The mathematical model of the Extreme Learning Machine (ELM) is designed to enhance the training efficiency of Single Hidden Layer Feedforward Neural Networks (SLFN). The model achieves high computational speed through a simplified training mechanism in which input-to-hidden weights are randomly initialized and kept fixed during learning (Kireyna Cindy Pradhisa & Yotenka, 2024). Accordingly, an ELM model with m units in a single hidden layer is formulated as follows.

$$\hat{X}_t = \sum_{i=1}^{m} \beta_i \, g \, (w_i \, . x_j + b_i) \quad (1)$$

Where:
$\hat{xt}$ = prediction data,
βi = weight connecting the hidden neuron to the output neuron,
wi = weight connecting the input neuron to the hidden neuron,
xj = input data vector,
bi = bias weight to the hidden neuron.

2.3.1 Mathematical Model of ELM Training

Training data represent a subset of the complete dataset utilized in the construction and parameter adjustment of the machine learning model. These data provide the basis for the learning algorithm to identify patterns and relationships within the dataset. The mathematical formulation used to compute the hidden layer output during the training phase is expressed as follows:

$$H_{init\ ij} = \left(\sum_{k}^{n} = 1 \, w_{jk} \, . x_{ik}\right) + \, b_j \quad (2)$$

Where:
H_{init} = Hidden layer output matrix,

i = [1, 2, …, N], where N is the total number of data,
j = [1, 2, …, $\tilde{N}$], where $\tilde{N}$ is the total number of hidden neurons,
n = Number of input neurons,
w = Input weight,
x = Input data used,
b = Bias value,

The following mathematical expression is used to analytically compute the output weight values.

$$\beta = H^{+}T \tag{3}$$

Where:
β = Output weight matrix,
H+ = Moore-Penrose matrix, generalized inverse of matrix H,
T = Target matrix.

2.3.2 Mathematical Model of ELM Testing

The testing model constitutes a portion of the dataset used to evaluate the generalization capability of the machine learning model developed during the training phase. These data are employed to assess the accuracy and performance of the model in predicting previously unseen data. The mathematical expression used to compute the output layer values is presented as follows:

$$y = H\,\beta \tag{4}$$

Where:
y = Output layer, which is the prediction result,
H = Output weight value obtained from the training process,
β = Output in the hidden layer calculated using the activation function.

2.3.3 Data Denormalization Process

The data denormalization stage aims to restore the predicted values that have undergone normalization to their original data scale. This process is necessary to ensure that the prediction results can be directly interpreted according to the original measurement units. The equation employed in the denormalization process is expressed as follows:

$$d = d'(\max - \min) + \min \tag{5}$$

Where:
d'= normalized predicted value,
d = predicted value after conversion to the original scale,
min = minimum value in feature data set X,
max = maximum value in feature data set X

2.3.4 ELM Performance Evaluation

The performance of the prediction model is evaluated using several error metrics, namely the Mean Absolute Percentage Error (Román et al., 2024), (Abbas et al., 2025), (Hussain et al., 2025), Mean Squared Error (Jain & Gupta, 2024), (Yu, 2024), and Root Mean Squared Error (Shafiullah et al., 2021), (Alsalem, 2025). The formulation of these performance evaluation metrics is presented in the following equations.

a. Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \times 100\,\% \tag{6}$$

b. Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{7}$$

c. Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \tag{8}$$

Where:
n = number of test data,
Y_i = actual value of the i-th electrical load,
$\hat{Y}_i$ = predicted value of the i-th electrical load

Lower values of Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) indicate smaller prediction errors and, consequently, higher model accuracy. Therefore, the employed model can be considered to exhibit more optimal performance in forecasting electrical load growth. Furthermore, the following table presents the commonly used interpretation of MAPE value thresholds as a reference in related studies.

Table 1. Interpretation of Mean Absolute Percentage Error (MAPE) Values

MAPE Value (%)	Accuracy Interpretation
< 10	Very good
10 – < 20	Good
20 – < 50	Fair
≥ 50	Poor

3 Results And Discussion

3.1 Daily Load Forecasting

Daily electrical load forecasting from Monday to Saturday is conducted to identify load variation patterns associated with the characteristics of community activities on each day. Each day exhibits a distinct load profile influenced by the level of activity in the residential, office, and commercial sectors. This analysis aims to evaluate the model's capability to capture hour-by-hour load fluctuation patterns for each day, as well as to assess the consistency and accuracy of the employed method in forecasting variations in electrical demand over the considered period. A more detailed discussion of the daily load forecasting results is presented in the following sections.

3.1.1 Monday's Electricity Load Forecast

The electrical load profile for Monday is presented to illustrate the pattern of load variations over 24 hours and to compare the forecasted values with the actual data as a basis for evaluating the performance of the proposed model.

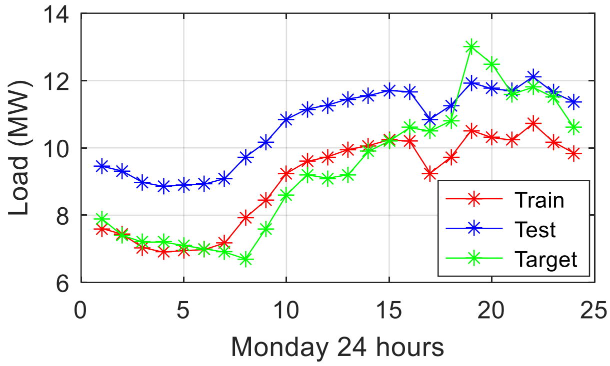

Figure 1. Electricity Load Graph for Monday

Figure 1 illustrates that the electrical load profile tends to be lower during the early morning to morning hours, followed by a substantial increase starting in the afternoon and reaching a peak in the late afternoon to evening period, approximately between 18:00 and 20:00. The test curve generally lies above the training and target curves, while the target data represent actual load fluctuations with a pronounced peak during peak-demand hours. Overall, the figure indicates that the modeled results successfully capture the typical daily load trend observed on working days.

3.1.2 Tuesday Load Forecasting

The electrical load profile for Tuesday is presented to illustrate the pattern of load variations over 24 hours and to compare the forecasted results with the actual data as a basis for evaluating the performance of the proposed model, as shown below.

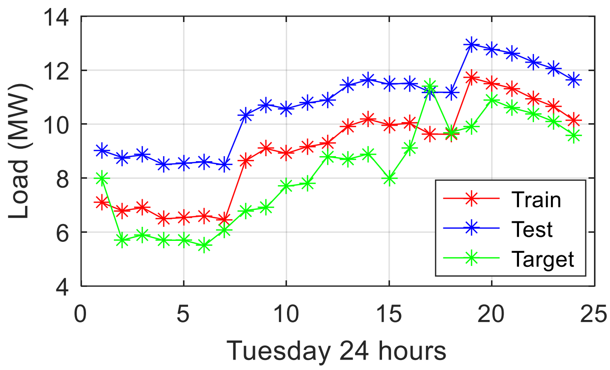

Figure 2. Grafik Electricity Load Graph on Tuesday

Figure 2 presents the 24-hour daily electrical load profile for Tuesday, comparing the training data, testing data, and actual load values. The electrical demand remains relatively low during the early morning hours, then gradually increases from morning to midday, and reaches its peak in the evening period, approximately between 19:00 and 21:00, before declining thereafter. Overall, the predicted results closely follow the actual load pattern, indicating that the model is capable of representing the daily electrical load characteristics, although minor deviations are observed at certain hours.

3.1.3 Wednesday Load Forecasting

The electrical load profile for Wednesday is presented to illustrate the pattern of load variations over 24 hours and to assess the level of agreement between the predicted results and the target data as a basis for evaluating the model performance, as shown in the following figure.

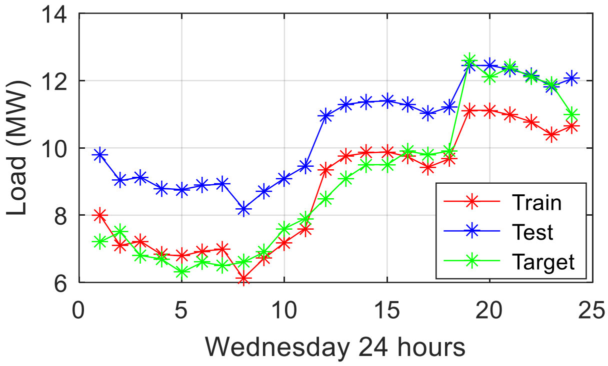

Figure 3. Wednesday's load graph

Figure 3 illustrates the 24-hour daily electrical load profile for Wednesday, comparing the training data, testing data, and actual load values. The electrical demand remains relatively low during the early morning hours, followed by a gradual increase from morning to midday, and reaches its peak in the evening period, approximately between 19:00 and 21:00, before declining thereafter. The close agreement between the predicted results and the actual data indicates that the model is able to adequately represent the daily electrical load characteristics, although some discrepancies are observed at certain time intervals.

3.1.4 Thursday Electrical Load Forecasting

The electrical load profile for Thursday is presented to illustrate daily load fluctuations over 24 hours and to compare the predicted results with the target data as a basis for evaluating the model performance, as shown in the following figure.

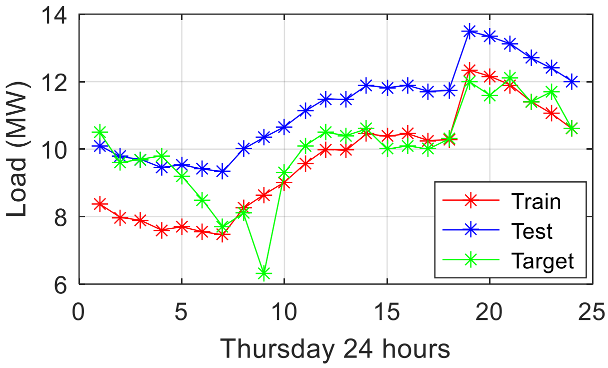

Figure 4. Electricity Load Graph for Thursday

Overall, Figure 4 shows that the electrical load tends to be lower during the early morning to morning hours, then increases from the afternoon and reaches a peak in the late afternoon to evening period, approximately between 19:00 and 21:00. The test curve generally lies above the training and target curves, indicating higher estimated values, while the target curve represents the actual load pattern used as a reference. This figure illustrates the comparative performance of the model against the actual data in forecasting daily electrical demand.

3.1.5 Friday Electrical Load Forecasting

The electrical load profile for Friday is presented to illustrate the pattern of load variations over a 24-hour period and to serve as a basis for evaluating the agreement between the predicted results and the actual data, as shown in the following figure.

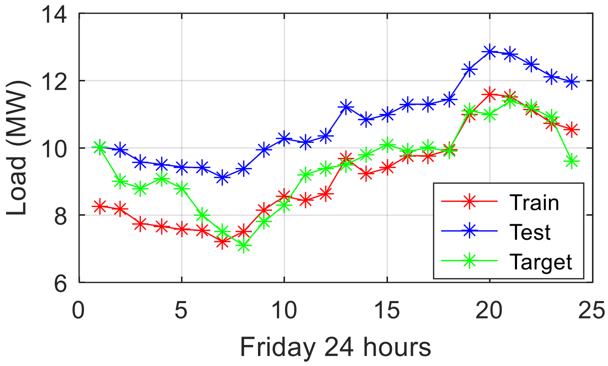

Figure 5. Electricity Load Graph for Friday

Figure 5 illustrates that the electrical load remains relatively low from the early morning to the morning hours, then gradually increases from the afternoon and reaches its peak during the late afternoon to evening period, approximately between 19:00 and 21:00. The test curve tends to lie above the training and target curves, indicating higher estimated values, while the target curve represents the actual daily load pattern. Overall, the figure demonstrates a strong consistency between the modeled results and the actual data in forecasting daily electrical demand.

3.1.6 Saturday Electrical Load Forecasting

The electrical load profile for Saturday is presented to illustrate the characteristics of electrical demand over a 24-hour period and to evaluate the performance of the forecasting model based on the agreement between the predicted results and the actual data, as shown in the following figure.

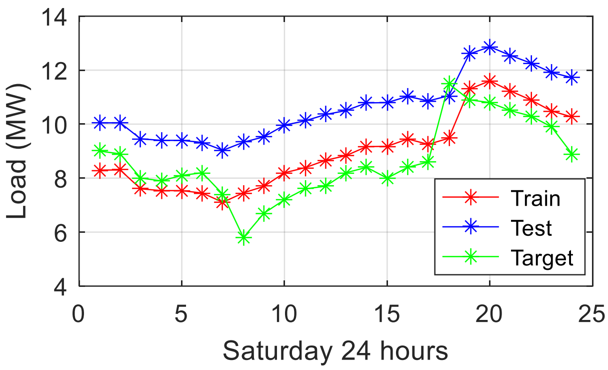

Figure 6. Saturday's Electricity Load Graph

Overall, the electrical load remains relatively low from the early morning to the morning hours, then gradually increases from the afternoon and reaches its peak during the late afternoon to evening period, approximately between 18:00 and 20:00. The test curve tends to lie above the training and target curves, while the target curve represents the actual load pattern. This figure demonstrates a consistent trend between the modeled results and the observed daily electrical load conditions.

3.1.7 Sunday Electrical Load Forecasting

The electrical load profile for Sunday is presented to illustrate the pattern of load variations over a 24-hour period and to assess the level of agreement between the predicted results and the target data as a basis for evaluating the model performance, as shown in the following figure.

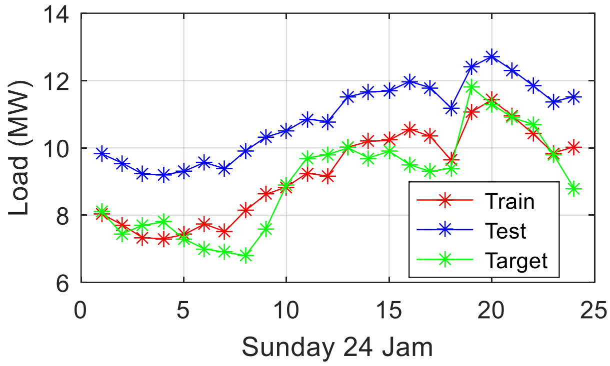

Figure 7. Sunday Electricity Load Graph

Figure 7 illustrates that the electrical load remains relatively low from the early morning to the morning hours, then increases gradually from midday and reaches its peak during the evening period, approximately between 19:00 and 21:00. The Test curve generally lies above the Train and Target curves, indicating higher estimated values, while the Target curve represents the actual daily load pattern. Overall, the graph demonstrates a similar trend between the modeled results and the actual data in forecasting the daily electrical load during the weekend.

3.1.8 Mean Absolute Percentage Error (MAPE) in Load Forecasting

The following table summarizes the daily Mean Absolute Percentage Error (MAPE) values obtained from the training and testing results using the Extreme Learning Machine (ELM) method for load forecasting.

Table 2. MAPE Results of Electrical Load Forecasting Using the Extreme Learning Machine

Day	MAPE Training (%)	Accuracy Category	MAPE Testing (%)	Accuracy Category
Monday	7.3863	Very Good	17.8172	Good
Tuesday	13.6250	Good	33.0897	Fair
Wednesday	6.4549	Very Good	19.5864	Good
Thursday	7.9836	Very Good	13.4451	Good
Friday	6.0657	Very Good	14.2526	Good
Saturday	9.9366	Very Good	25.0318	Fair
Sunday	5.8390	Very Good	21.7693	Fair

Table 2 summarizes the MAPE results for both training and testing datasets. The training data exhibit consistently low MAPE values across all days, ranging from 5.8390% to 13.6250%, which fall within the very good to good accuracy categories. These results indicate that the Extreme Learning Machine (ELM) model is capable of learning daily electrical load patterns with high accuracy. For the testing data, the MAPE values range from 13.4451% to 33.0897%, corresponding to good to fair accuracy levels. The highest MAPE is observed on Tuesday, suggesting the presence of more complex load variations on that day. Overall, the evaluation results demonstrate that the Extreme Learning Machine method provides satisfactory performance in daily load forecasting, with an acceptable level of generalization when applied to unseen data.

4 Conclusions

Based on the results of the daily electrical load forecasting study conducted in Ternate City, several conclusions can be drawn as follows:

1. The Mean Absolute Percentage Error (MAPE) values obtained from the training dataset range from 5.84% to 13.63%, which fall within the very good to good accuracy categories. These results indicate that the proposed model is able to effectively learn and represent daily electrical load patterns.
2. For the testing dataset, the MAPE values range from 13.45% to 33.09%, corresponding to good to fair accuracy levels. The highest prediction error occurs on Tuesday, suggesting the presence of more complex and dynamic load variations on that particular day.
3. Overall, the Extreme Learning Machine (ELM) method can be considered a reliable approach for supporting power system planning and enhancing the quality of electrical power flow management in Ternate City.

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