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Prediction of Peak Load Electricity Consumption in Apartment X Building Using Deep Learning with GRU Method

Yusuf[1]*, Ahmad Rofii[1], and Jemie Muliadi[1]
[1] Universitas 17 Agustus 1945 Jakarta, 14350, Indonesia
email: raheemyusuf21@gmail.com

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ABSTRACT – This study presents a predictive framework for daily electricity consumption forecasting in Apartment X using a Recurrent Neural Network (RNN) model with the Gated Recurrent Unit (GRU) method. The dataset consists of daily electricity log sheets containing two main variables: Peak Load Time (WBP) and Off-Peak Load Time (LWBP). The preprocessing stage includes data cleaning, normalization using Min–Max Scaling, and sequence formation through a sliding window approach. The GRU architecture comprises two hidden layers, a dropout layer, and optimization using the Adam optimizer. The model's performance was evaluated using MAE, RMSE, and R^2. The results show that the GRU model achieved an R^2 value of 0.623, indicating a good capability in capturing consumption patterns.

This study contributes to energy forecasting studies in developing countries, emphasizing smart building energy management applications

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Introduction

Electricity consumption in the building sector, particularly apartment complexes, has been increasing due to urban population growth, rising living standards, and the widespread use of electronic devices. According to the International Energy Agency (IEA), the building sector accounts for over 30% of global energy consumption and approximately 28% of direct CO_2 emissions [1]. These conditions highlight the importance of energy efficiency and electricity consumption management to support sustainable development goals (SDGs).

Apartment buildings, which typically operate 24 hours with varying electrical loads, present unique challenges in predicting and managing energy consumption patterns. Fluctuations arise due to seasonal factors, occupant behavior, facility operation hours, and environmental temperature variations [2]. Thus, accurate and adaptive forecasting models are required for non-linear, non-stationary time-series data.

Apartment X, a high-occupancy residential complex, exhibits significant monthly variations in electricity usage. Accurate estimation of power demand is crucial for implementing energy efficiency strategies, managing peak load periods, and planning long-term electrical infrastructure capacity.

This study aims to develop an RNN-based GRU model for predicting daily electricity consumption in apartment buildings.

The study contributes to the field by developing a prediction model for peak-load electricity consumption based on the Gated Recurrent Unit (GRU) architecture. The research implements comprehensive data preprocessing techniques, including feature engineering, to enhance the quality and relevance of input variables for the model. Furthermore, the model's performance is rigorously evaluated using statistical metrics such as the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE), providing a robust assessment of its predictive accuracy.

Literature Review

A. Related Works

Machine learning and deep learning techniques have been widely applied in electricity demand forecasting. Ahmad et al. [1] proposed a hybrid Random Forest–BiLSTM model for short-term load forecasting, improving accuracy by combining feature selection and bidirectional learning. Chen et al. [2] developed a CNN–GRU hybrid model, integrating spatial and temporal feature extraction. Yang and Li [3] introduced an Attention-LSTM model with 6.5% accuracy improvement.

Comparative studies show that GRU offers lower error rates and faster convergence compared to LSTM and vanilla RNN [4][5]. Advanced hybrid approaches, such as SSA–GRU with PSO optimization [6] and CNN–BiGRU [7], demonstrate enhanced performance in complex energy datasets. Ensemble models combining GRU, SVR, RF, and GBDT [8] further improve non-linear relationship modeling.

B. RNN and GRU for Time-Series Forecasting

RNNs are designed for sequential data but often suffer from vanishing gradients. GRU, a simplified LSTM variant, uses update and reset gates to retain temporal dependencies efficiently [12].

C. Peak and Off-Peak Load Systems in Indonesia

Indonesia's electricity pricing system differentiates between Peak Load Time (WBP) and Off-Peak Load Time (LWBP) [14]. WBP (17:00–22:00 WIB) has higher tariffs due to elevated demand. Accurate forecasting aids in load shifting and cost reduction strategies [15].

D. Research Gap

While GRU models have shown strong performance, limited studies focus on apartment buildings in Indonesia. This research fills that gap by implementing an optimized GRU model for WBP forecasting.

Material and Methods

A. Research Design

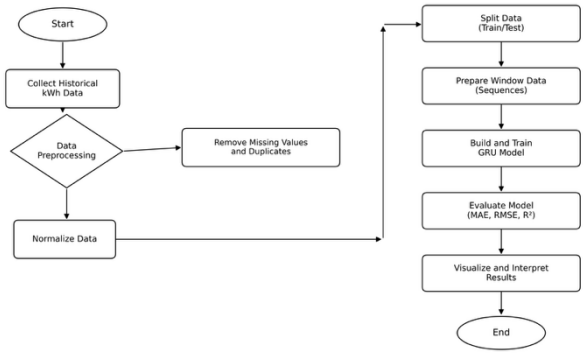

Figure 1. Research workflow including data collection, preprocessing, GRU model development, training, and evaluation stages.

This experimental quantitative study applies RNN-GRU architecture for daily electricity consumption forecasting. The workflow includes data collection, preprocessing, GRU modeling, hyperparameter optimization (Optuna), training, validation, and evaluation.

B. Data Source and Characteristics

Data were obtained from daily log sheets of Apartment X, containing electricity consumption in kWh during WBP and LWBP.

C. Data Preprocessing

Data cleaning (removal of duplicates and missing values via linear interpolation), outlier detection (IQR), feature engineering (day, month, lag variables), and normalization (Min–Max Scaling) were performed. The dataset was split: 70% training, 15% validation, 15% testing.

D. GRU Model Architecture

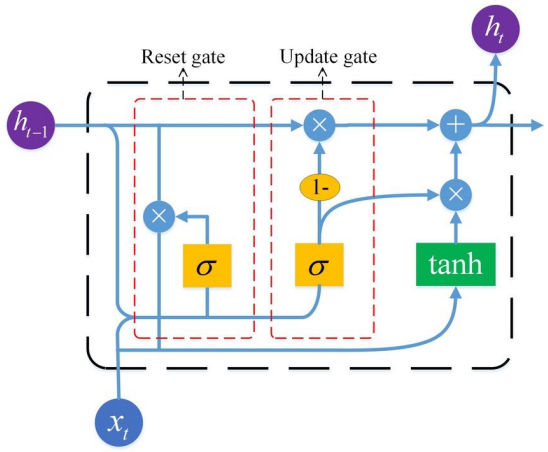

Figure 2. GRU Architecture

The GRU network includes two hidden layers, dropout regularization, ReLU activation, and a dense output layer. Training used Adam optimizer and MSE loss.

E. Hyperparameter Optimization (Optuna)

Optuna's Bayesian optimization tuned learning rate, neuron count, dropout rate, batch size, and epochs. The configuration with minimal validation loss (MSE) was selected.

F. Model Training and Validation

Implemented in TensorFlow-Keras with early stopping. Adaptive learning rates improved convergence.

G. Evaluation Metrics

Model performance was assessed via MSE, RMSE, and R^2. An $R^2 \geq 0.8$ indicates strong explanatory power.

Results and Discussion

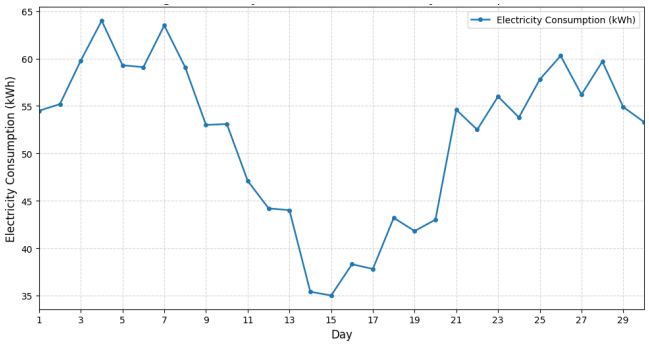

Figure 3. Daily electricity consumption fluctuation patterns (raw data before preprocessing).

A. Data Description and Preprocessing Summary

Figure 3 depicts the daily electricity consumption pattern before data preprocessing. Fluctuations in consumption reflect different user activities between weekdays and weekends, as well as peak and off-peak hours. This irregular pattern justifies the use of the GRU model, which is designed to capture non-linear temporal dependencies.

The figure also shows that raw data contain occasional outliers and seasonal trends, both of which were addressed during the preprocessing stage through normalization and feature engineering.

The dataset includes WBP and LWBP consumption with added temporal and lag features. Preprocessing improved feature richness and model interpretability.

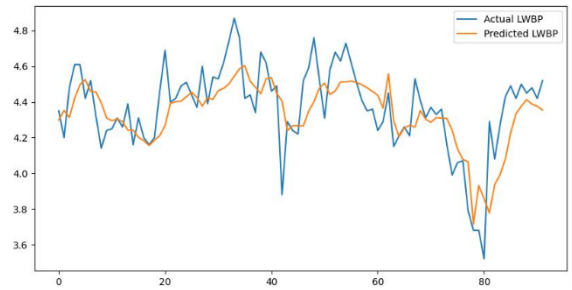

Figure 4. Predicted versus actual daily electricity consumption during off-peak hours (LWBP).

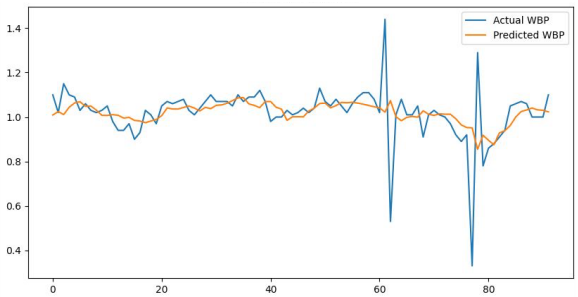

Figure 5. Predicted versus actual daily electricity consumption during peak hours (WBP).

Figure 4 and Figure 5 shows the comparison between actual and predicted electricity consumption for the Off-Peak Load (LWBP) and Peak Load (WBP) periods, respectively. Both figures show that the predicted values closely follow the actual consumption trend, indicating that the GRU model effectively learns temporal dependencies in the data. Minor deviations occur in periods of sudden load spikes, likely due to unmodeled external factors such as temperature variations, equipment usage schedules, or occupancy patterns.

The relatively consistent alignment between prediction and actual curves demonstrates that the model generalizes well for short-term load forecasting, maintaining reliable performance across both load categories. Model Training and Hyperparameter Tuning.

Two GRU layers (128, 64 units) with dropout 0.3 and L2 regularization were used. Optuna optimization achieved best validation performance.

B. Model Performance Evaluation

Table 1. Performance evaluation metrics of the GRU-based prediction model.

Metric	Value
RMSE	0.129
MAE	0.101
R^2	0.623

Table 1 summarizes the predictive performance of the GRU-based model in forecasting electricity consumption. The RMSE of 0.129 and MAE of 0.101 indicate that the average prediction error remains relatively low, confirming that the model can approximate the actual consumption values with satisfactory accuracy. In addition, the coefficient of determination (R^2) of 0.623 shows that the model explains a moderate proportion of the variability in the observed data. This finding suggests that the GRU architecture is effective in learning the underlying temporal structure of electricity consumption patterns, although some discrepancies remain, particularly during abrupt load changes. Therefore, the proposed model can be considered sufficiently reliable for short-term forecasting applications, while further improvement may be achieved by incorporating additional external variables and more diverse training data.

C. Comparative Analysis

Table 2. Comparison of experimental results showing trade-offs between accuracy and generalization.

Experiment	RMSE	MAE	R^2	Notes
1.	0.129	0.101	0.623	Balanced performance
2.	0.061	0.039	0.339	Low error, poor generalization
3.	0.061	0.040	0.340	Similar to Exp 2

Table 2 compares the performance of three GRU model configurations with different hyperparameter settings. Experiment 1 achieved the most balanced result, with an R^2 of 0.623 and low RMSE and MAE values, indicating consistent generalization and minimal overfitting.

Experiments 2 and 3 yielded lower error rates but significantly reduced R^2 values, implying that while they achieved closer fits during training, their generalization ability on unseen data was weaker. This comparison highlights the importance of selecting hyperparameters that ensure a balance between accuracy and stability rather than minimizing loss alone.

D. Discussion and Insights

GRU demonstrated effective pattern recognition but struggled with outliers. Future studies may integrate hybrid CNN–GRU, ensemble methods, or external features (e.g., temperature, holidays) to improve accuracy beyond $R^2 \geq 0.8$.

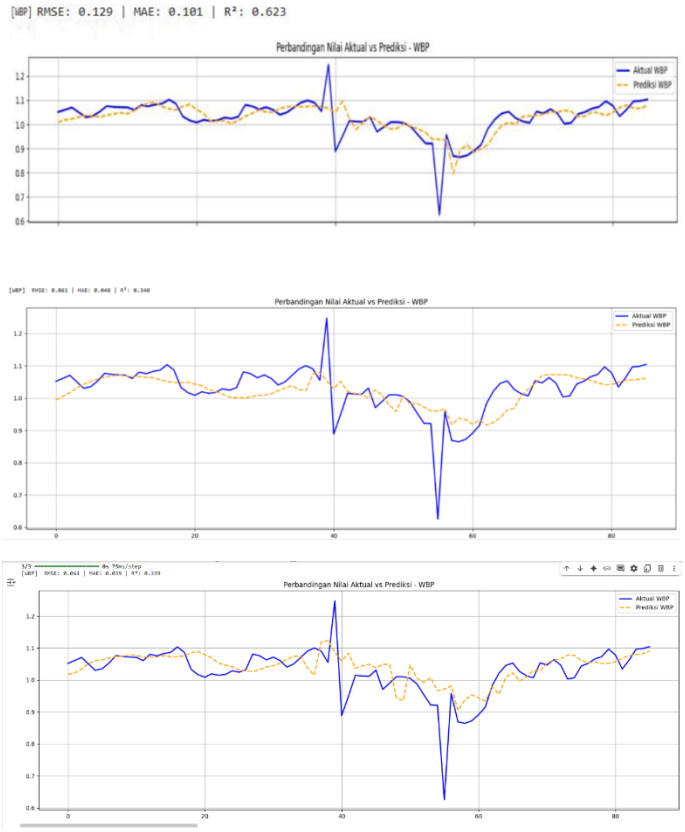

Figure 6. Model performance comparison during training and testing phases, showing convergence and stability.

Figure 6 shows the convergence behavior of the GRU model during the training and testing phases. The training and validation loss curves gradually decrease and stabilize after several epochs, indicating that the model successfully learns data patterns without overfitting. The minimal gap between both curves signifies robust model generalization, confirming that the chosen network depth, dropout rate, and learning rate were appropriate. This result also demonstrates that the Optuna-based hyperparameter optimization effectively improved training efficiency and prevented divergence, ensuring a reliable predictive performance.

Conclusion

This study developed and evaluated a Recurrent Neural Network (RNN) model employing the Gated Recurrent Unit (GRU) architecture to predict daily electricity consumption during Peak Load Time (WBP) in Apartment X. The model achieved a coefficient of determination (R^2) of **0.623**, a Root Mean Square Error (RMSE) of **0.129**, and a Mean Absolute Error (MAE) of **0.101**, demonstrating its capability to effectively model the temporal patterns and seasonal trends of daily electricity usage. These results indicate that the GRU model can capture general consumption behaviors and recurring load variations with reasonable accuracy. However, its ability to predict extreme fluctuations or sudden spikes remains limited, primarily due to the absence of external influencing variables such as temperature, occupancy rate, and holiday schedules that often drive non-linear changes in consumption patterns.

Despite these limitations, the GRU-based forecasting approach offers a computationally efficient and reliable framework for short-term electricity demand prediction in apartment buildings. The model's strength lies in its capacity to learn sequential dependencies and maintain stability during the training process, making it well-suited for applications in energy management systems. By providing more accurate short-term forecasts, building operators and energy managers can implement demand response strategies, optimize peak load operations, and reduce overall energy costs.

To enhance future model performance, the inclusion of feature augmentation—such as weather data, occupancy information, and special event indicators—could improve prediction precision, particularly for irregular load events. Furthermore, developing hybrid deep learning architectures that integrate GRU with Convolutional Neural Networks (CNN-GRU) or Attention Mechanisms may further strengthen the model's ability to recognize complex, non-linear consumption patterns. Expanding the model for multi-step forecasting across several days ahead could also support longer-term energy planning and decision-making. In addition, training with larger and more diverse datasets from multiple buildings is expected to improve the generalization capability and robustness of the model.

In summary, the GRU-based RNN model presents a promising approach for intelligent energy forecasting in residential buildings, offering a balance between accuracy, efficiency, and scalability. With further refinement and integration into smart building systems, this approach has the potential to significantly contribute to sustainable energy management, cost optimization, and the realization of smart grid initiatives in urban apartment complexes.

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Competing Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper. The research was conducted independently, and no financial or commercial

relationships were involved that could be construed as a potential conflict of interest.

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