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Optimization of Smart Building Electrical Load Prediction Using Long Short-Term Memory

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ABSTRACT

The advancement of smart building technologies requires energy management systems that are both efficient and capable of adapting to dynamic operational conditions. A key component of such systems is reliable electrical load forecasting, as building energy demand is affected by environmental conditions, occupancy behavior, and operational activities that exhibit nonlinear and time-dependent characteristics. This study explores the use of the Long Short-Term Memory (LSTM) approach for forecasting smart building electricity consumption based on multivariate time-series data. The input dataset incorporates temporal features, ambient temperature, humidity levels, occupancy-related patterns, and major electrical load components within the building. The research workflow consists of data preprocessing, normalization, time-series construction using a sliding window strategy, LSTM model training, and evaluation of forecasting performance. The findings indicate that the building's electricity demand varies approximately between 6 kW and 17 kW, with an average load ranging from 11 to 12 kW. Performance assessment yields an RMSE of about 3 kW and a MAPE of roughly 25%. The largely symmetric error distribution around zero suggests minimal systematic bias in the predictions, although the model's accuracy during peak demand periods remains limited.

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1. INTRODUCTION

The rapid adoption of smart building technologies has significantly transformed the way electrical energy is monitored, managed, and optimized in modern infrastructures. Smart buildings integrate advanced sensing, communication, and automation systems to improve energy efficiency, operational reliability, and sustainability. However, the increasing penetration of intelligent devices and dynamic user behavior has resulted in highly volatile and non-linear electrical load patterns. These characteristics make accurate electrical load prediction a critical yet challenging task, as reliable forecasts are essential for effective energy management[1], [2], demand response strategies, and optimal operation of smart building energy systems.

Traditional electrical load forecasting approaches, including statistical and regression-based models, have been widely applied in building energy prediction[3], [4], [5], [6]. Although these approaches are relatively simple and easy to interpret, they often lack the capacity to model the complex

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temporal dynamics and nonlinear interactions present in electricity load time-series data. In smart building contexts, power consumption is shaped by numerous time-dependent factors, including occupancy dynamics, environmental variations, and operational scheduling, which give rise to both short-term fluctuations and long-term dependencies. Traditional prediction models typically struggle to capture these patterns effectively, resulting in reduced forecasting accuracy, especially during peak demand periods or sudden shifts in consumption behavior.

Recent advances in artificial intelligence, particularly deep learning techniques, have provided promising alternatives for modeling complex time-series data. The LSTM [6], [7], [8], [9], [10], a specialized form of RNN, has demonstrated superior capability in learning long-term temporal dependencies through its gated memory structure. This architecture effectively addresses the vanishing gradient problem commonly encountered in standard RNNs, enabling more stable and accurate learning processes. Consequently, LSTM has been increasingly adopted for electrical load forecasting applications[11], [12], including those in smart grids and building energy systems.

Although LSTM models offer strong capabilities for time-series forecasting, their prediction accuracy is highly sensitive to proper model design, including network structure, hyperparameter tuning, and the selection of input features. Inadequate parameter configurations can result in overfitting, inefficient training convergence, or limited generalization to unseen data. In addition, the lack of a structured optimization framework may restrict the model's effectiveness in capturing the temporal dynamics inherent in smart building electricity demand. Consequently, enhancing and optimizing LSTM-based load forecasting models remains an important research problem for achieving reliable and robust predictive performance.

Within this framework, the present study introduces an optimized LSTM-based methodology for electricity load forecasting in smart building systems. The proposed approach emphasizes systematic optimization procedures and thorough performance evaluation using established quantitative error indicators. The anticipated contributions include improved forecasting precision and greater adaptability to fluctuating load patterns, thereby supporting intelligent energy management strategies and advancing data-driven solutions for smart building applications.

2. RESEARCH METHOD

Electrical load prediction in smart buildings is a complex time series forecasting problem due to its nonlinear behavior, temporal dependencies, and sensitivity to various external factors such as occupant activity, environmental conditions, and operational schedules. Conventional statistical methods, including linear regression and autoregressive models, generally rely on linearity and stationarity assumptions, thus limiting their application in the dynamic environment of smart buildings. As data on building energy systems becomes increasingly abundant, data-driven approaches are increasingly being used due to their ability to learn complex patterns directly from historical consumption data. However, CNN [13], [14], [15], [16], [17] lacking temporal memory, are unable to optimally capture long-term dependencies in sequential electrical load data, resulting in inadequate prediction performance. To clarify the research context and characteristics of the data used in developing the prediction model, a summary of the dataset specifications is presented in Table 1.

To overcome these limitations, this study adopted a Long Short-Term Memory (LSTM) neural network as the primary prediction model [6], [7], [8], [18]. Long Short-Term Memory (LSTM) represents an advanced form of Recurrent Neural Networks that addresses the vanishing gradient limitation by employing internal memory units regulated by gating components, specifically the input, forget, and output gates. These mechanisms govern the information flow within the network, allowing relevant historical features to be retained while insignificant data are selectively discarded. Consequently, LSTM is well suited for modeling electrical load time-series data, as it can effectively learn both short-term fluctuations and long-range temporal dependencies. This characteristic makes LSTM particularly well suited for smart building applications, where electricity consumption follows complex daily, weekly, and seasonal behavior that needs to be learned concurrently.

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Table 1. Characteristics of research data

No	Data Parameters	Description
1	Research object	The smart building is a multi-storey academic building consisting of teacher rooms, administration rooms and public areas, with an approximate floor area of ± 2,500–3,000 m²
2	Data source	Smart building energy monitoring system
3	Data types	Multivariate time series data
4	Target variable	Total building electrical load (kW)
5	Input variables	Ambient temperature (°C), humidity (%), number of occupants (occupancy), time indicator (hours), type of day (weekday/weekend)
6	Sampling interval	15 minutes
7	Observation period	3 months
8	Number of data samples	± 8.640 data
9	Electrical load range	6 kW – 17 kW
10	Average electrical load	11 – 12 kW
11	Dominant load system	HVAC, lighting, and office equipment
12	Load characteristics	Nonlinear, fluctuating, influenced by occupancy and environmental conditions

The research methodology used in this study follows a quantitative and data-driven framework aimed at optimizing the performance of LSTM models in electrical load prediction[2], [4], [19], [20]. Historical electrical load data is obtained from a smart building energy monitoring system and recorded at uniform time intervals. In addition to load data, additional variables such as ambient temperature, time of day indicators, and weekday and holiday classifications are included as input features to enrich the information and improve prediction accuracy. These variables represent operational and environmental characteristics that influence energy consumption behavior in smart buildings. Prior to model development, the dataset underwent a comprehensive preprocessing stage. Missing values caused by temporary sensor communication failures were handled using linear interpolation, while abnormal readings resulting from sensor noise or unexpected operating conditions were identified using statistical thresholding and subsequently smoothed. All numerical variables were normalized using min–max scaling to transform data into a comparable range, thereby improving numerical stability and accelerating convergence during LSTM training[21], [22]. A sliding window technique was employed to convert the time-series data into supervised learning sequences, enabling the model to learn temporal dependencies across consecutive observations. To ensure reproducibility and systematic model optimization, this study adopted a grid search-based hyperparameter tuning strategy. Several critical hyperparameters were evaluated, including the number of LSTM units, learning rate, batch size, input window length, and dropout rate. Each configuration was trained and validated using the same data partitioning scheme, and model performance was compared based on validation RMSE. The optimal configuration was selected by balancing prediction accuracy and training stability, ensuring that the final model does not suffer from overfitting or underfitting. The configuration of the optimized LSTM hyperparameters is summarized in Table 2.

Considering that prediction accuracy typically degrades during peak demand periods, specific strategies were incorporated at the methodological level. Peak load instances were explicitly included in the training dataset to prevent data imbalance. The multivariate input design allows the model to associate sudden load increases with changes in occupancy and environmental conditions. In addition, an early stopping mechanism based on validation loss was implemented to prevent excessive model fitting to extreme values.

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Table 2. LSTM hyperparameter configuration

No	Hyperparameter	Tested Values / Range	Selected Value
1	Model Architecture	Multivariate LSTM	Multivariate LSTM
2	Number of LSTM Layers	1 – 3 layers	2 layers
3	Number of LSTM Units	32, 64, 128	64 units
4	Time Window Length (Window Size)	12, 24, 48	24-time steps
5	Activation Function	Tanh	Tanh
6	Dropout Rate	0.1 – 0.5	0.2
7	Optimizer	Adam	Adam
8	Learning Rate	0.001, 0.0005, 0.0001	0.001
9	Mini-Batch Size	16, 32, 64	32
10	Maximum Number of Epochs	50 – 200	100
11	Early Stopping	Enabled / Disabled	Enabled
12	Optimization Method	Grid Search	Grid Search
13	Loss Function	Mean Squared Error (MSE)	MSE

An electricity load forecasting model based on Long Short-Term Memory (LSTM) is developed by employing a multivariate framework combined with a sliding window technique to effectively learn temporal relationships within the input data. Time-ordered data sequences are provided to one or multiple stacked LSTM layers, allowing internal memory cells to capture and learn long-term patterns from historical electricity consumption. The feature representations generated by the LSTM layers are subsequently forwarded to a dense output layer to produce the predicted load values. To enhance the model's generalization capability and mitigate overfitting, dropout regularization is incorporated during training. Critical architectural settings, including the depth of the LSTM network, the number of hidden units, and the size of the input time window, are selected through empirical performance analysis. Model optimization is conducted by systematically tuning hyperparameters such as learning rate, mini-batch size, training iterations, and the choice of optimization strategy. An adaptive optimizer is utilized to update network parameters efficiently while maintaining training stability. In addition, an early stopping strategy based on validation loss is implemented to prevent excessive training and ensure optimal predictive performance. Multiple experimental configurations are evaluated to determine the most suitable model structure for smart building electricity load forecasting.

The training process involves iterative weight updates using backpropagation through time, with the objective of minimizing the mean squared error between predicted and actual load values. Model performance is continuously monitored using validation data to guide optimization decisions. After training is complete, the optimized LSTM model is evaluated on the testing dataset using standard performance metrics, including RMSE [11], [13], [23], [24], [25], and MAPE. These evaluation metrics offer a thorough measure of forecasting precision and model robustness. The findings confirm the capability of the optimized LSTM framework to effectively learn complex temporal dependencies and to enhance the accuracy of electrical load predictions in smart building contexts. Model accuracy is evaluated using RMSE [23], [26] and MAPE [27], [28], [29], with RMSE measuring the average magnitude of prediction errors in the original data units as follow:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \tag{1}$$

Meanwhile, MAPE is used to express the level of prediction error in percentage form and is formulated as:

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{yi - \hat{y}i}{yi}\right| \tag{2}$$

Beyond numerical performance metrics, the model outcomes are also examined through visual analysis, including comparisons between observed and predicted electricity load profiles, error distribution plots, and cumulative error trends over time. These visual evaluations are intended to offer deeper insight into the model's capability to accurately track smart building load behavior, particularly during peak demand intervals and variations caused by changes in occupancy patterns. By adopting this

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comprehensive evaluation framework, the proposed LSTM model is expected to deliver highly accurate and consistent electricity load forecasts for smart building applications. Such predictions can serve as a reliable foundation for energy management decision-making, including HVAC control optimization, demand response strategies, and overall improvements in energy efficiency. The overall research workflow follows a sequential process consisting of data acquisition, preprocessing, feature normalization, time-series segmentation, LSTM model construction, hyperparameter optimization, model training, and performance evaluation[30], [31]. This structured flow ensures that each stage builds upon the previous one in a systematic manner, allowing the forecasting framework to be clearly understood even without direct reference to the flowchart illustration shown in Figure 1.

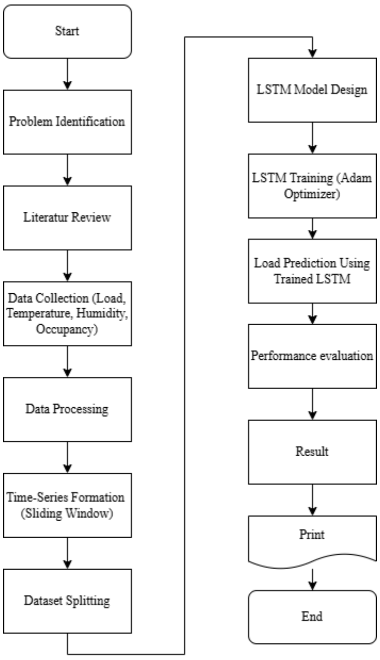

Figure 1. Research flowchart

3. RESULTS AND DISCUSSION

Experimental results of smart building electrical load prediction using the Long Short-Term Memory (LSTM) method based on multivariate time series data. The results are visualized in several graphs representing the characteristics of the initial data, the normalization process, the model's prediction performance, and the prediction error analysis. These graphs aim to provide a comprehensive overview of building energy consumption patterns, the relationship between environmental variables and occupancy, and the LSTM model's ability to learn the temporal dynamics of electrical load. The total electrical load profile of the smart building during the observation period, which shows significant fluctuations due to occupant activity and building operational conditions, is shown in Figure 2. Next, graphs of the normalized environmental and occupancy data are displayed to demonstrate the relative variation between the input variables used in model training. Normalization ensures all variables are on a comparable scale, allowing the neural network to learn stably and efficiently, as shown in Figure 3.

The main results of the study are demonstrated through a comparison graph between the actual electrical load and the LSTM prediction results. This graph provides an initial indication of the model's accuracy in following the actual electrical load pattern shown in Figure 4. In addition, a scatterplot between the actual and predicted values is presented, which is used to evaluate the closeness of the predicted results to the ideal values shown in Figure 5. To complete the analysis, a graph of the prediction error and error distribution is presented to assess the stability of the model and detect any bias or systematic deviations shown in Figure 6. By presenting this series of graphs, this section provides a

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visual basis for further discussion of the performance of the LSTM model, the advantages achieved, and the limitations that still exist in the context of smart building electrical load prediction.

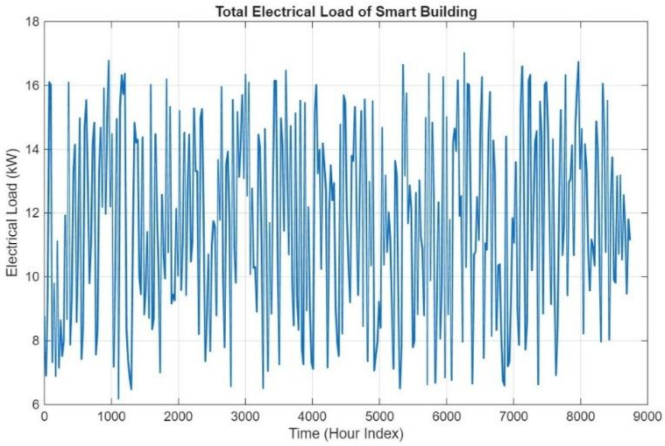

Figure 2. Total electrical load of smart building

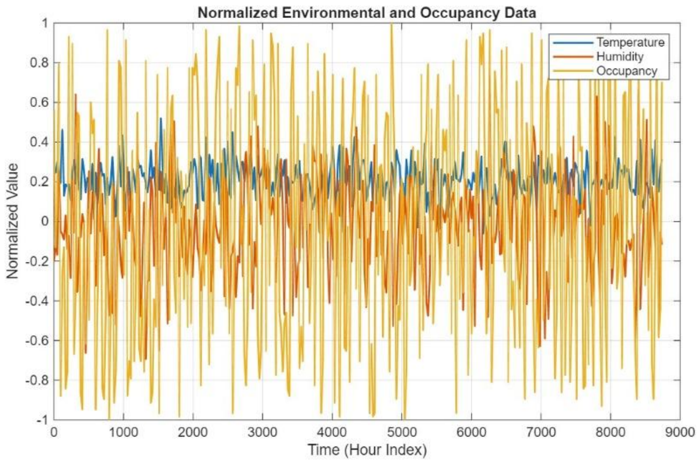

Figure 3. Normalized environmental and occupancy data

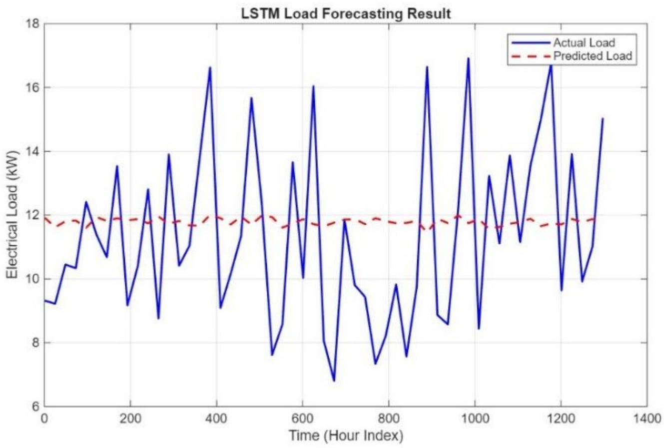

Figure 4. LSTM load forecasting result

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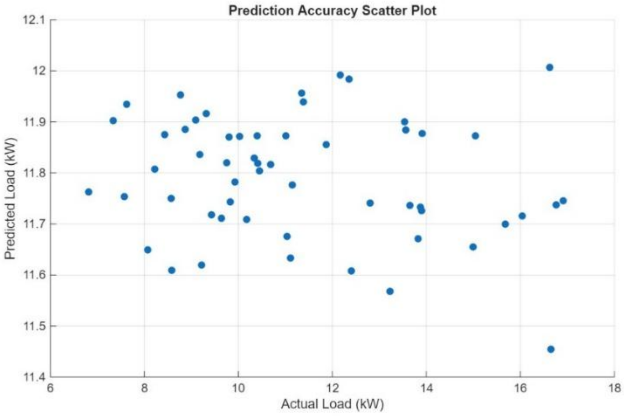

Figure 5. Prediction accuracy scatter plot

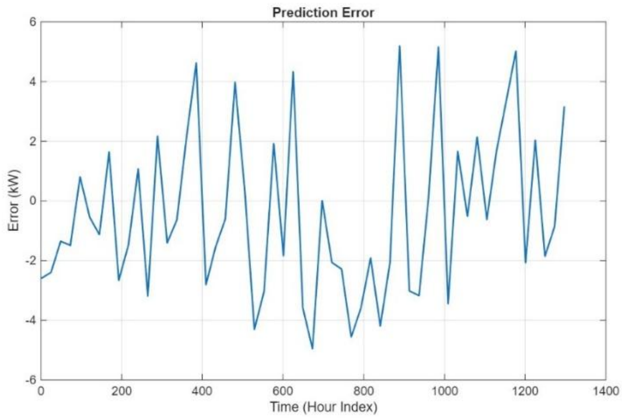

Figure 6. Prediction error

Based on Figure 2 above, energy consumption exhibits a fairly complex fluctuation pattern with significant daily variations. The electrical load ranges from approximately 6 kW to 17 kW, with an average value of 11–12 kW. This fluctuation pattern reflects the typical characteristics of smart buildings, where the electrical load is strongly influenced by occupancy levels, HVAC system usage, and other operational activities. The wide variation in load between the minimum and maximum values indicates high energy consumption dynamics over time. This situation emphasizes that a simple linear model-based prediction approach will struggle to accurately capture load dynamics, thus utilizing a Long Short-Term Memory (LSTM) model becomes relevant for modeling nonlinear relationships and long-term temporal dependencies.

Figure 3 shows that each input variable varies over time, with a normalized value ranging from –1 to 1. The occupancy variable exhibits the largest fluctuation compared to temperature and humidity, indicating that human activity plays a dominant role in changes in the building's electrical load. This variation provides a crucial source of information for the LSTM model to study the nonlinear relationship between environmental conditions and energy consumption. The LSTM prediction results shown in Figure 4 demonstrate that the model is able to follow the general trend of the actual electricity load quite well, with the average predicted value being around 11.7–11.9 kW. However, there are still quite clear differences at peak load points, especially when the actual load increases above 15 kW. This indicates that extreme load spikes due to sudden changes in occupancy or certain intensive activities still pose a challenge for the model. Figure 5 shows a distribution of points that is relatively close to the diagonal line, indicating a positive correlation between the predicted results and the actual values. Most points are concentrated in the load range of 8–14 kW, although there are some deviations at high loads. The still quite wide distribution of points indicates that the prediction accuracy is not yet fully optimal.

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This is reinforced by Figure 6, which shows alternating positive and negative errors with error values ranging from around –5 kW to +5 kW.

To provide a more thorough assessment of the Long Short-Term Memory (LSTM) model's performance, the forecasting outcomes are examined through several visualization-based analyses, including the error distribution illustrated in Figure 7, the cumulative absolute error presented in Figure 8, the comparison between measured and predicted load profiles over a selected time interval shown in Figure 9, and the quantitative evaluation metrics summarized in Figure 10. These visual representations are employed to evaluate model stability, analyze the nature of prediction errors, and examine the capability of the LSTM model to accurately track the dynamic behavior of smart building electricity demand. This evaluation approach extends beyond average accuracy metrics by also investigating how prediction errors evolve over time and across different load operating conditions.

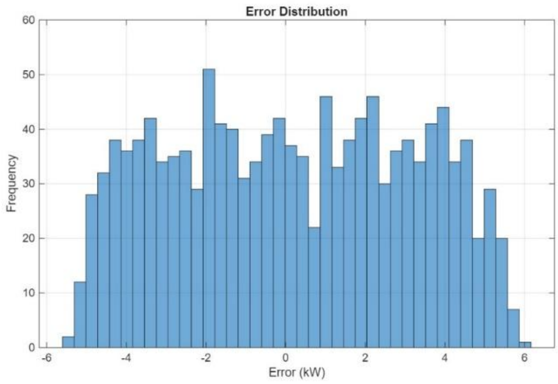

Figure 7. Error distribution

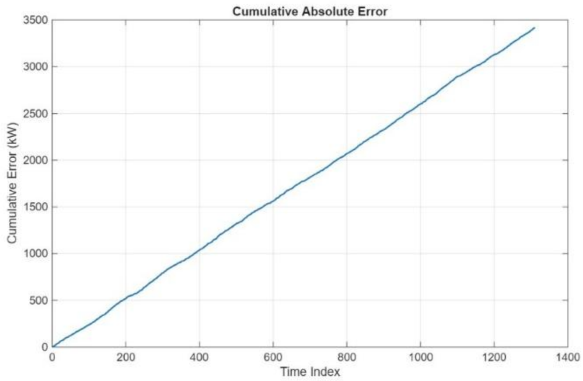

Figure 8. Cumulative absolute error

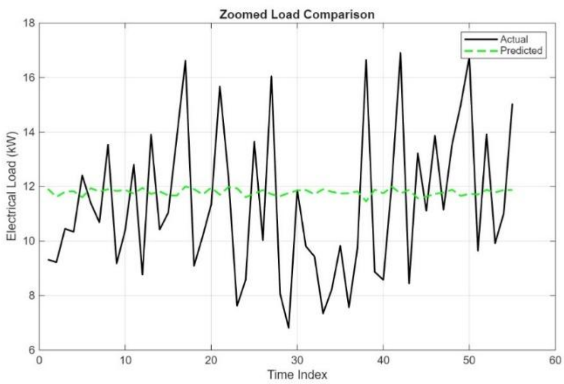

Figure 9. Zoomed load comparison

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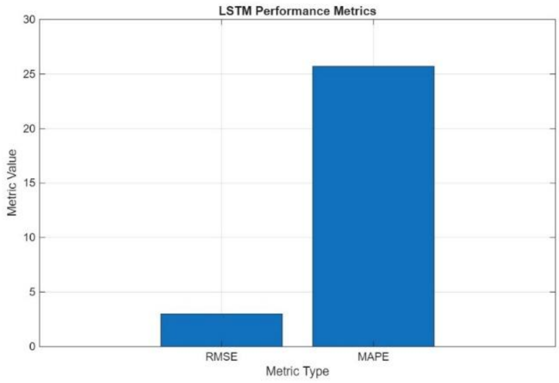

Figure 10. LSTM performance metrics

As shown in Figure 7, the forecasting errors are centered near zero and fall within an approximate interval of −6 kW to +6 kW, suggesting that the model does not exhibit a pronounced systematic bias. This relatively symmetric error pattern indicates that the LSTM-based predictor neither consistently overpredicts nor underpredicts the building's electricity demand. In addition, the cumulative absolute error illustrated in Figure 8 increases in a nearly linear manner, indicating that prediction inaccuracies are distributed uniformly throughout the testing horizon rather than being concentrated in particular time segments. The comparative results presented in Figure 9 further reveal that the LSTM model is able to follow the general trend of the measured electrical load with reasonable accuracy. However, reduced sensitivity is observed during peak demand periods, where rapid and sharp increases in load occur. This limitation reflects the challenge of modeling abrupt load variations caused by sudden changes in occupancy levels and building operational activities. The quantitative assessment shown in Figure 10 reports a RMSE of approximately 3 kW and a MAPE of around 25%. These metrics demonstrate that the proposed approach achieves a satisfactory level of accuracy for short-term load forecasting, while also indicating opportunities for further refinement to improve performance under extreme operating conditions.

To strengthen the analysis, supplementary visualizations are provided to describe the behavior of the main input variables used in the smart building load prediction framework. These include occupancy dynamics presented in Figure 11, the HVAC power consumption profile shown in Figure 12, and ambient temperature variations during the monitoring period illustrated in Figure 13. Examining these variables offers valuable insight into their temporal characteristics and their influence on the overall electricity demand of the building. A clear understanding of the patterns and interactions among these inputs is critical, as the quality, variability, and representativeness of the input data strongly determine the capability of the Long Short-Term Memory (LSTM) model to capture complex temporal dependencies and nonlinear relationships between environmental factors, human behavior, and electrical load demand.

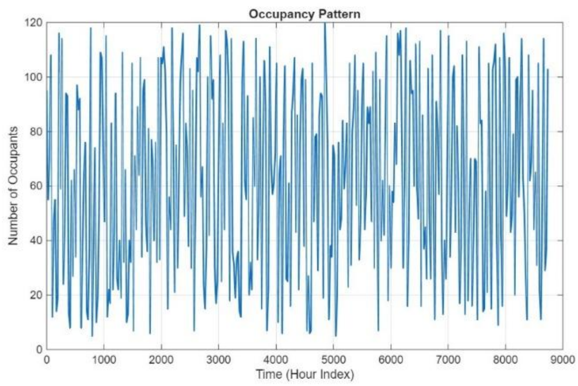

Figure 11. Occupancy pattern

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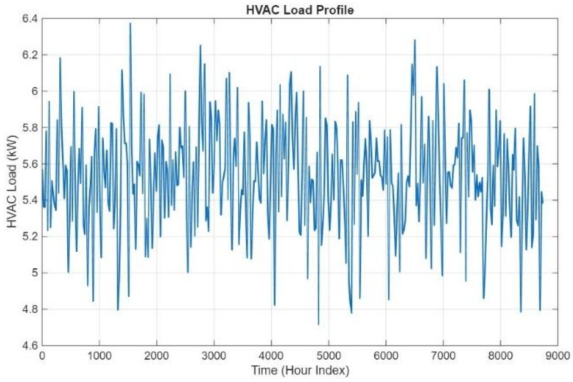

Figure 12. HVAC load profile

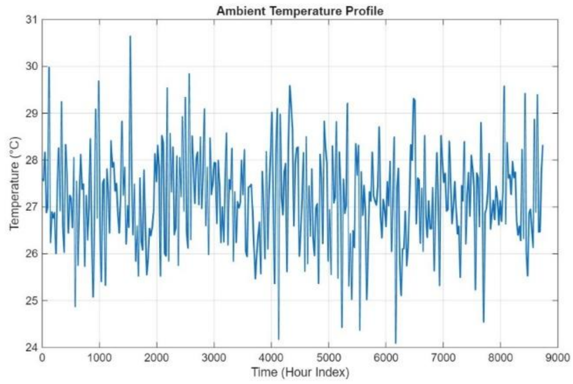

Figure 13. Ambient temperature profile

Based on the occupancy pattern graph, a fairly high fluctuation in the number of occupants is seen with a range of around 5 to 120 people, reflecting variations in human activity over time. The HVAC load profile shows a more stable change but still fluctuates in the range of 4.8 to 6.3 kW, which is influenced by temperature conditions and occupancy levels. Meanwhile, the ambient temperature graph shows a temperature variation between 24 °C and 30 °C with a relatively consistent daily pattern. The combination of these three variables explains the main source of variation in the building's electrical load and emphasizes the importance of a multivariate approach based on LSTM to capture the simultaneous influence of environmental factors and occupant behavior on energy consumption.

4. CONCLUSION

This study demonstrates that electricity load forecasting in smart building environments is inherently complex due to the combined influence of environmental conditions, occupancy behavior, and operational dynamics. The observed load profile exhibits significant variability, with demand ranging from approximately 6 kW to 17 kW and an average consumption of 11–12 kW, confirming the nonlinear and time-dependent nature of smart building energy usage. By applying a multivariate Long Short-Term Memory (LSTM) framework with systematic hyperparameter optimization, this research contributes a data-driven forecasting approach capable of learning both short-term fluctuations and long-term temporal dependencies. The experimental results indicate that the optimized model achieves a RMSE of approximately 3 kW and a MAPE of around 25%, reflecting a satisfactory level of prediction accuracy for short-term building-level load forecasting. From a practical perspective, the forecasting results can support intelligent energy management applications, such as predictive HVAC control, load scheduling, and demand response planning. Accurate short-term load predictions enable building operators to anticipate peak demand periods and implement proactive control strategies to improve energy efficiency and operational reliability. Despite these strengths, the model shows reduced accuracy during peak load conditions caused by abrupt occupancy changes and intensive operational activities. This limitation highlights opportunities for future research, including the integration of hybrid deep

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learning architectures, attention mechanisms, or real-time occupancy sensing to enhance peak load responsiveness. Overall, the proposed approach provides a robust foundation for smart building energy forecasting and opens avenues for further development toward adaptive and resilient energy management systems.

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