

Prediction of Residential Electricity Consumption Using Long Short-Term Memory Based Framework

Antara Mahanta Barua

Discipline of Electronics, Krishna Kanta Handiqui State Open University, Guwahati, Assam, India

Email: [antaramah\[at\]gmail.com](mailto:antaramah[at]gmail.com)

Abstract: *Accurate prediction of electricity consumption is vital for the planning and operation of electric utility companies to ensure a balanced supply and demand of power. This study presents a Long Short-Term Memory (LSTM) based neural network model for predicting residential electricity consumption using smart meter data. The dataset consists of three months of electricity usage records collected from 300 households. The proposed model leverages the ability of LSTM networks to capture temporal dependencies and nonlinear patterns inherent in time-series data. To evaluate performance, different activation functions, such as Sigmoid and Hyperbolic Tangent (tanh), were implemented and compared. Model accuracy was assessed using standard evaluation metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The results demonstrate that the LSTM-based approach provides reliable and accurate predictions of residential electricity consumption, highlighting its suitability for short-term load forecasting and smart grid applications.*

Keywords: Electricity Consumption Prediction, Long Short-Term Memory, Smart Meter Data, Forecast Accuracy Metrics.

1. Introduction

Electricity has become an indispensable form of energy in modern society. Rapid population growth, urbanization, and the increasing reliance on electrical appliances have led to a continuous rise in electricity demand. Efficient electricity utilization is crucial not only for consumers and utility providers but also for mitigating environmental challenges such as global warming. As electricity underpins almost every aspect of daily life, ensuring its sustainable generation and consumption has become a global priority. Accurate forecasting of electricity consumption plays a vital role in maintaining the balance between supply and demand. Reliable predictions enable power generation and distribution companies to meet consumer requirements efficiently while minimizing overproduction, operational costs, and energy wastage [1]. Demand forecasting is generally conducted by distribution companies to support efficient load planning and optimal resource allocation. To achieve precise forecasting, electricity usage must be monitored and analyzed regularly. This has been made possible through the deployment of smart metering systems, which provide detailed, real-time consumption data. However, electricity demand is influenced by multiple factors, including weather conditions, occupancy patterns, and the type and usage of household appliances [2]. At the same time, taking all the variables that effect electricity consumption can create an unstable and complex predicted model. There were many methodologies developed for the prediction of the electricity consumption, based on machine learning algorithm. Most of these models use historical data to analyze their techniques for prediction purpose.

In this study, a LSTM framework-based model is presented to predict electricity consumption by using date and temperature data. LSTM is a special kind of Neural Network called Recurrent Neural Networks. It is capable of learning order dependence in sequence prediction problems [3]. The study is based on experiments conducted using the LSTM neural network technique on a smart meter dataset collected from the Smart Meter Data Centre in the northeastern region of India. The proposed model consists of four stages namely,

data retrieval stage, data preprocessing stage, data prediction stage and performance evaluation stage [4]. In data retrieval stage, data is collected from Data Centre and analyzed to validate the model. In the preprocessing stage, some preprocessing operations have been carried out on the data to remove irregularities from the dataset. In the prediction stage, the proposed LSTM model is applied to three months of preprocessed electricity consumption data. The LSTM algorithm is selected for its ability to handle noisy inputs, capture distributed representations, and model continuous time-series data effectively.

For an optimum architecture, the LSTM should have a memory cell which can maintain its state over time and three gates which regulates the information flow into and out of the cell. This model performs effectively without suffering any optimization hurdles as observed in other machine learning algorithms [5]. The performance evaluation of the proposed algorithm is verified by using different statistical measures. The statistical values indicate the accuracy in the prediction of electricity consumption through the model.

2. Related Works

Many researchers have conducted studies with several methods to predict electric power consumption. Initially, statistical methods were applied for prediction but due to the limitations in these techniques, machine learning methods are being explored by several researchers. Some of them are discussed below.

In Sauhats et al. [6], smart meter based prediction models achieved MAPE below ~10% and RMSE significantly lower than baseline forecasts, showing strong short-term load forecasting accuracy and clustering techniques revealed distinct daily consumption patterns that improved model performance. Hong & Fan [7], provided a comprehensive review of probabilistic electric load forecasting using probabilistic methods and demonstrated that incorporating weather and temporal features significantly improves forecast reliability. Similarly, Wei et al. [8] demonstrated that deep

learning approaches like ANN, CNN, LSTM models achieve higher accuracy than traditional statistical techniques for building energy prediction and reported that weather inputs, feature engineering, and data preprocessing strongly affect prediction performance, with deep learning performing best for complex, large-scale datasets. Likewise, Khalid et al. [9] developed a regression model for predicting the monthly energy consumption patterns and implemented the model using Monte Carlo simulation technique. Furthermore, R. Aras et al. [10] applied artificial neural networks to predict urban building energy consumption and showed that a multilayer perceptron (MLP) and residual network (ResNet) models effectively capture nonlinear relationships between weather, building characteristics, and energy use. S. Devi et al. [11] also confirmed that the ANN achieved low MAPE and RMSE for short-term load forecasting in demand-side management applications. In another study, Kim and Cho [12] proposed a State Explainable Autoencoder (SEA) based deep learning model for electric energy consumption forecasting that captures hidden consumption states while maintaining interpretability. The approach outperformed conventional ANN and LSTM models by achieved lower prediction errors and provided clearer insights into consumption pattern transitions for smart grid applications. Nugaliyadde et al. [13] developed a deep recurrent neural network (RNN) based model for electricity consumption to forecast short, mid, and long term electricity consumption using historical load data. The proposed deep RNN architecture demonstrated improved prediction accuracy compared to traditional machine learning methods by effectively capturing temporal dependencies in time-series energy consumption patterns. Li et al. [14] proposed an Extreme Deep Learning (EDL) approach by integrating deep neural networks with extreme learning machine principles. The model demonstrated higher forecasting accuracy and faster training speed compared to conventional ANN and support vector regression (SVR) models. However, model included only fully-connected layers, so that temporal features were ignored, and it is hard to control the conditions because latent space where the features of data are represented is not defined in the proposed model. The aim of our study is to achieve prediction approach for daily electricity consumption of next month of randomly selected household consumers by using LSTM neural network based framework.

3. Proposed Electricity Consumption Prediction Methodology

Prediction of electricity consumption is very important as it assists the electricity suppliers to minimize wastage of electricity. However, forecasting consumption is challenging due to its dependence on various external factors such as weather conditions, occupancy levels, types of household appliances, and random fluctuations or noise in usage patterns. There are numerous neural network algorithms that have been developed and applied for electricity consumption forecasting. In this study, we propose a methodology based on a Long Short-Term Memory (LSTM) neural network to predict electricity consumption for residential consumers within a smart meter deployment area. The proposed approach consists of four main stages: data retrieval, data preprocessing, data prediction, and model performance

evaluation. Figure 1 shows the block diagram representation of the proposed model.

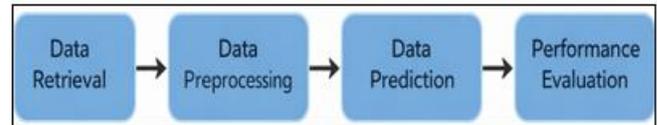


Figure 1: Block diagram of the proposed prediction model

In Data Retrieval stage, the raw data of randomly selected 300 residential consumers from Data Centre of APDCL (Assam Power Distribution Company Limited) is retrieved for preprocessing. To design the prediction model, actual smart meter data were collected from two subdivisions namely Paltanbazar and Ulubari, located in Guwahati city, Assam, over a three-month period from April to June 2024. The dataset includes measurements of voltage, current, power factor, active power (kWh), apparent power (kVA), and frequency (Hz). In this study, the maximum daily temperature was also considered as input data, which was retrieved from the weather database [15].

In the data preprocessing stage, abnormalities such as zero, negative, or missing values were removed from the retrieved dataset. To predict daily electricity consumption, the weighted arithmetic mean of the consumption data for all selected consumers was then calculated on a per-day basis. After the data preprocessing stage, the LSTM neural network was employed to learn the input features and perform the prediction of electricity consumption for residential households. Finally, in the performance evaluation stage, the effectiveness of the proposed model was assessed using standard performance metrics, namely Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The proposed LSTM network utilized time-series data more effectively, as illustrated in Figure 2, which depicted an LSTM neural network architecture consisting of a memory cell along with an input gate and output gate and a forget gate [16].

These three gates are composed of a sigmoid neural network layer and a point wise multiplication operation. They are used to control and protect the cell state [17]. The cell is considered as a unit, and the unit can be sequentially connected to each other. The input x_t is passed and added to the h_{t-1} . Here f_t , i_t , g_t , and o_t presents the forget gate, the input gate, the input node, and the output gate respectively.

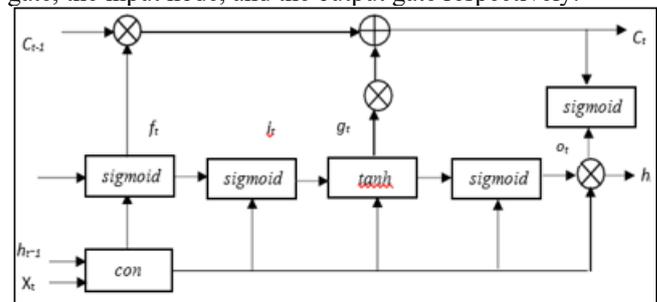


Figure 2: Architecture of LSTM Network
(Source [16])

The values in the cell are used to calculate the output activation of the LSTM. The calculation formulas related LSTM structure of Figure 2 given as: [16]

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (2)$$

$$g_t = \tanh(W_g[h_{t-1}, x_t] + b_g) \quad (3)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (4)$$

$$C_t = C_{t-1} \otimes f_t + g_t \otimes i_t \quad (5)$$

$$h_t = \tanh(C_t) \otimes o_t \quad (6)$$

Where W_f , W_i , W_g , W_o are the corresponding weight matrix connecting the input signal $[h_{t-1}, x_t]$, σ and \tanh represents the sigmoid activation function and hyperbolic tangent function. The cell state C_t remembers the previous values over arbitrary time interval and three gates control the flow of information into and out of the cell. Thus, the LSTM is a suitable neural network for time based prediction problems.

In the performance evaluation stage of the proposed model, the indices MSE, RMSE, MAE, and MAPE are used to compare the actual and predicted values. MSE measures the average squared error and is useful for minimizing the error distribution. RMSE measures the magnitude of the error between predicted and target electricity consumption, while MAPE evaluates the prediction error as a percentage of the actual consumption values [17], [18]. The definitions of these performance metrics are as follows:

$$MSE = \frac{1}{N} \sum_{i=1}^N (A_i - P_i)^2 \quad (7)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (A_i - P_i)^2} \quad (8)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |A_i - P_i| \quad (9)$$

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{A_i - P_i}{A_i} \right| \times 100 \quad (10)$$

Where N is the number of samples, A_i is the i^{th} actual electricity consumption value and P_i is the i^{th} predicted consumption value. These indices provide a single value to measure the accuracy of the output results.

4. Result and Discussion

In the proposed study, energy consumption prediction was performed using two approaches. In the first approach, the model was trained on data from twenty days to predict electricity consumption for the following ten days. In the second approach, the model was trained on two months of data to forecast the average consumption for the subsequent month. The dataset was partitioned in this manner to demonstrate the model's capability for mid-term prediction. According to the first method, the one-month consumption data were divided into a training dataset consisting of the load

consumption of the first 20 days ($20 \times 300 = 6000$ data points). The remaining 10 days of data ($10 \times 300 = 3000$ data points) were used to test the model for predicting the electricity consumption of the last 10 days of that particular month.

In the second method, three months of continuous consumption data were used for the mid-term prediction of average electricity consumption. The data were divided such that the first 50 days of daily consumption ($50 \times 300 = 15,000$ data points) were used as the training set to train the model. The subsequent 11 days of data were used as the validation set, and the remaining 30 days of energy consumption ($30 \times 300 = 9,000$ data points) were used as the testing set. This process continued for 40 iterations, and the loss was measured after each iteration. The proposed LSTM framework was developed using the 64-bit Python 3.12 version. The hardware configuration consisted of a Linux operating system with a 20-core CPU, 64 GB RAM, and a GPU with 11 GB memory. The hyperparameters of the LSTM model that were tested during the experiments are presented in Table 1.

Table 1: The hyperparameters of LSTM model

Layers	Neurons	Optimizer	Batch size	Epoch
Input	3	Adam	32	40
Hidden	5			
Output	1			

The proposed LSTM model consisted of three layers with 50 LSTM units, and the final layer included a dense layer before generating the output. The number of training iterations (epochs) was set to 40, and a batch size of 32 was used in the experiments to obtain optimal results. The Adam optimizer was employed to achieve the highest prediction accuracy.

The characteristics of the average electricity consumption for the analyzed period were illustrated in Figure 3. In this plot, the days of a month were considered along the x-axis, and electricity consumption in kilowatt-hours was considered along the y-axis. It has been observed that in the month of April, the maximum consumption occurs in the first and fourth week when highest temperature of the month (37.8°C) was recorded in April 24, 2024. The increased load during this period is primarily attributed to the usage of household appliances such as fans, lights, refrigerators, and other cooling equipment driven by the rising ambient temperature. From the average load curve of May 2024, it has been observed load gradually increases from the first week through the third week of the month, reflecting a consistent rise in electricity demand. The maximum electricity consumption was recorded during the fourth week of the month and the highest temperature of 40.1°C was recorded on May 25, 2024. The consumption shows a declining trend towards the end of the month.

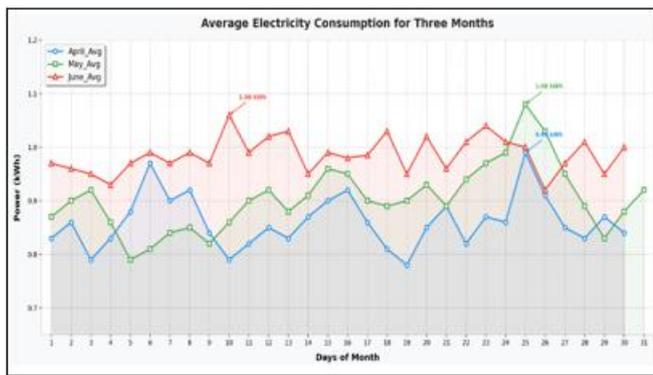


Figure 3: Average daily electricity consumption from April to June 2024

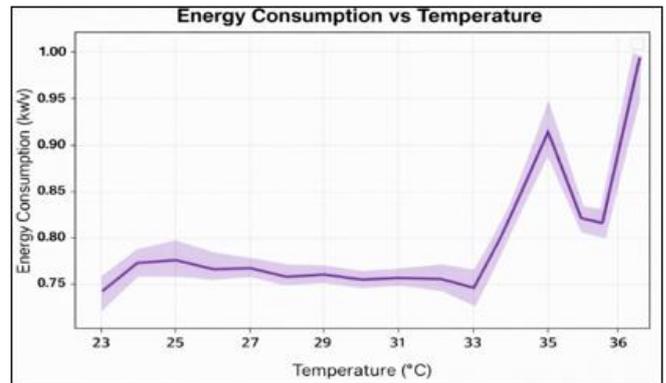


Figure 4: Electricity consumption versus temperature plot for April, 2024

From the average load curve plotted over the period of June 1 to June 30, 2024, it has been observed that the electricity consumption gradually increases during the first ten days of the month, reaching its maximum recorded value of 1.06 kWh on June 10, 2024. Following this peak, the consumption shows a gradual declining trend through the mid of the month, dropping to lower values around the fourth week. However, a slight recovery is observed towards the end of the month, with consumption rising again near June 30, 2024. Overall, the June load curve reflects a single-peak consumption pattern with steady but variable electricity demand highlighting the need for efficient load management strategies during peak consumption periods.

In this model, since the prediction was carried out based on date and temperature, the relationship between electricity consumption and the maximum temperature of the predicted month of April was illustrated in the graph shown in Figure 4. In this figure, temperature (in degrees Celsius) was plotted along the x-axis, while power consumption (in kWh) was plotted along the y-axis. It was observed that the electricity consumption for April 2024 initially increased gradually with rising temperature, followed by a sharp increase at around 34°C. Thereafter, a slight decrease was noted, and the consumption again increased, reaching a maximum value at approximately 37°C. These observations indicate that daily electricity consumption over the month was influenced by temperature variations. Higher temperatures led to increased electricity usage for some consumers, primarily due to greater demand for cooling to maintain comfortable environmental conditions.

The mid-term prediction for the last 10 days of a month was performed using the input dataset from the first 20 days of that month. The prediction results, after the proposed LSTM model was trained, were plotted in Fig. 5(a), Fig. 5(b), and Fig. 5(c). The electricity consumption data of 300 consumers for the first 20 days of April 2024 were used as training data to train the proposed LSTM model, and the consumption for the last 10 days of the same month was predicted. The model was trained on 6000 sample training data and 3000 sample testing data. Fig. 5(a) showed the actual consumption pattern after the model was trained to predict the last 10 days of April 2024. Fig. 5(b) indicated the predicted consumption pattern for the same period. In Fig. 5(c), the actual and predicted results were considered together.

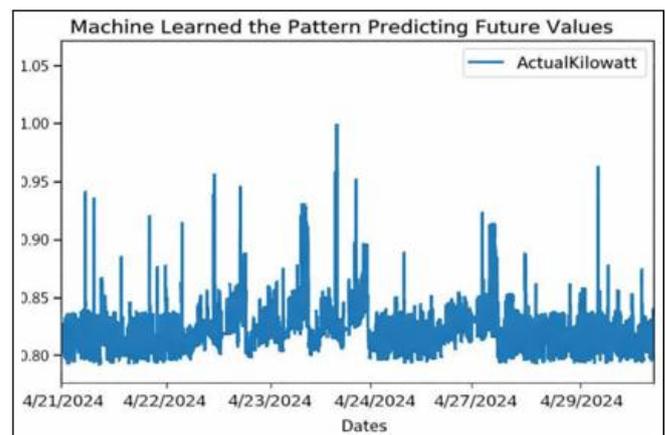


Figure 5(a): Representation of actual consumption pattern for last 10 days of April, 2024

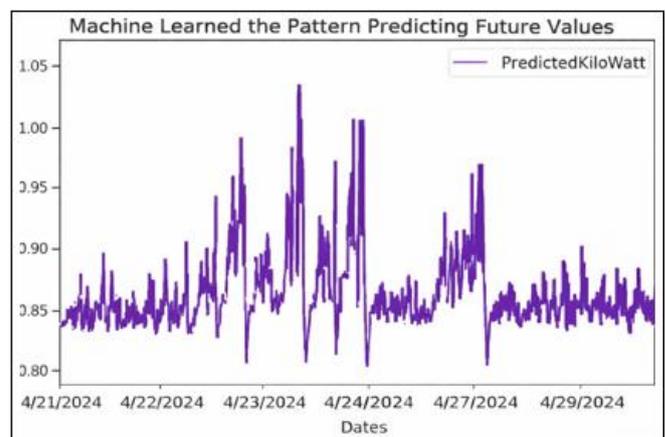


Figure 5(b): Predicted consumption pattern for the last 10 days of April 2024.

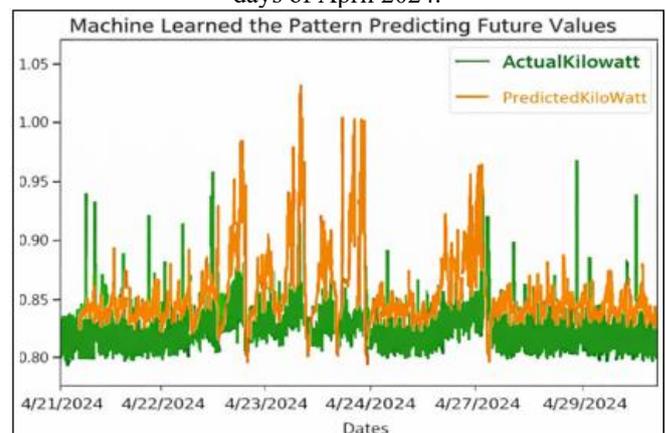


Figure 5(c): Actual and predicted results using the LSTM technique

The performance of the proposed model was assessed using performance metrics. The error metrics quantified the difference between the predicted values and the actual values. The metrics used to evaluate the model performance were MSE, RMSE, MAE, and MAPE. Table 2 summarized these metrics for the LSTM model algorithm.

Table 2: LSTM Performance for Last 10-Day Prediction

MSE (kWh)	RMSE (kWh)	MAE (kWh)	MAPE (%)
0.0396	0.1992	0.1703	12.25

The statistical values shown in Table 2 indicated the accuracy of the model's performance, and the LSTM network achieved an average root mean square error of 0.1992 kWh.

The mid-term prediction for the next month was performed using the input dataset from the previous three months. The prediction results, after training the LSTM model, are presented in Figure 6. The x-axis represented the dates of the month, while the y-axis showed the day-wise average power consumption of both actual and predicted values for 300 consumers. It was observed that the differences between the actual and predicted power consumption were minimal across all maximum samples during the testing of the LSTM model.

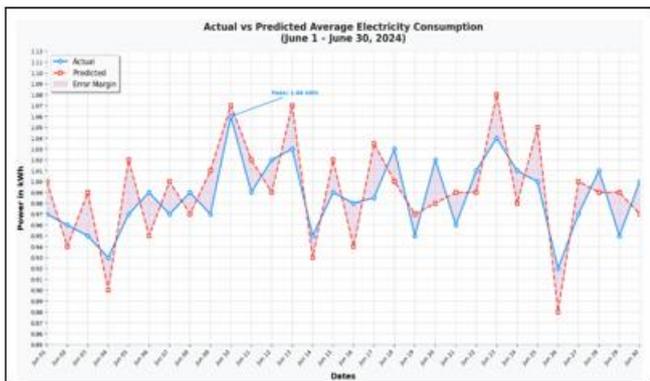


Figure 6: Comparison of Actual and Predicted Average Power Consumption for June 2024

The prediction results were evaluated using performance metrics. These metrics were calculated from Equations 7 to 10. Table 3 summarizes the values of these error metrics for the one-month average consumption prediction.

Table 2: LSTM Prediction Errors for One-Month Average Consumption

MSE (kWh)	RMSE (kWh)	MAE (kWh)	MAPE (%)
0.0158	0.125	0.1006	11.12

Comparing the prediction errors in Table 2 and Table 3, it was observed that the next-month prediction results yielded lower error values compared to the 10-day energy prediction for a month. The comparative analysis of the proposed model's performance for the two prediction methods using the same dataset is presented in Table 4. The MSE and RMSE values were recorded as 0.0396 kWh and 0.1992 kWh for the last 10-day prediction, whereas for the next-month prediction, these values were 0.0158 kWh and 0.0125 kWh, respectively.

Table 2: Comparison of Performance Metrics for Two Prediction Methods

Prediction Method	MSE (kWh)	RMSE (kWh)	MAE (kWh)	MAPE (%)
Last 10 days of a month	0.0396	0.1992	0.1703	12.25
Next month	0.0158	0.125	0.1006	11.12

5. Conclusion and Future Scope

Electricity consumption prediction modeling was a challenging task due to inherent randomness and noise in the data. This study focused on developing a model to predict electricity consumption for residential consumers. Initially, the dataset underwent data retrieval and preprocessing procedures. Subsequently, the prediction algorithm was applied, and the model's performance was evaluated.

The prediction results of both methods were evaluated using four performance metrics: MSE, RMSE, MAE, and MAPE. For Method 1, the values were 0.0396, 0.1992, 0.1703, and 12.25, while for Method 2, they were 0.0158, 0.125, 0.1006, and 11.12, respectively, for the LSTM model. These results demonstrated that the LSTM model was capable of predicting next-month average electricity consumption with higher accuracy.

In future work, predictions could be extended to cover the next six months or a full year. This approach could also be applied to other neural network models to compare prediction performance. In the present study, day and maximum temperature were considered as independent input variables. The work could be further extended by incorporating additional input parameters, such as time, location, number of family members, number of smart appliances etc. With consumption readings available at periodic intervals, the methodology could enable more accurate predictions of electricity consumption during peak load demand.

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