

# Predictive Modeling of Electricity Load Demand Forecasting Using the CNN-BiLSTM method based on Peak Load in Household Sector Consumers

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**Abstract**—Accurate short-term electricity load forecasting is essential for ensuring reliable energy management and maintaining power system stability, particularly in the household sector where electricity consumption exhibits highly dynamic and nonlinear patterns. Conventional forecasting methods often have limited capability in capturing these complex temporal characteristics. Therefore, this study proposes a hybrid Convolutional Neural Network–Bidirectional Long Short-Term Memory (CNN-BiLSTM) model to forecast 24-hour ahead household electricity demand based on peak load data collected from Mojowarno District, Jombang Regency, Indonesia. The dataset consists of hourly electricity consumption records from January 2024 to January 2025 and was preprocessed through smoothing, outlier handling, and normalization before model training. The proposed model combines CNN for automatic spatial feature extraction and BiLSTM for learning bidirectional temporal dependencies. Experimental results demonstrate excellent forecasting performance with a Test Loss of 0.0024, Test MAE of 0.0562, Test RMSE of 0.0699, MAE of 3.4146 kW, RMSE of 4.2470 kW, and an  $R^2$  value of 0.9889. These findings indicate that the proposed CNN-BiLSTM model effectively captures household electricity consumption patterns and provides accurate short-term peak load forecasting, making it a promising approach for supporting energy management and electricity distribution planning.

**Keywords:** CNN-BiLSTM, electricity load forecasting, household electricity, peak load, deep learning.

## I. INTRODUCTION

Mojowarno District in Jombang Regency has experienced significant economic and population growth, leading to an increased demand for electricity, particularly in households, small industries, and businesses. This results in rapid fluctuations in electricity demand, making accurate short-term load forecasting essential. Inaccurate forecasting can cause supply-demand imbalances, potentially disrupting the grid and increasing operational costs. Household electricity demand is more dynamic and fluctuates due to daily usage patterns and seasonal changes, differing from the more stable consumption patterns in the industrial sector [17].

Household electricity consumption is influenced by factors such as usage times, season, weather conditions, and evolving lifestyles, including the increased use of electronic devices. Due to this complexity, predictive models must account for these variables to ensure accurate and practical energy management [90]. Electricity load forecasting is essential to balance consumer demand with energy supply, ensuring system stability and preventing power outages. Accurate predictions allow system operators to plan effectively, ensuring reliable and sustainable electricity services [13].

One of the most important aspects of electricity load forecasting is peak load, which refers to the highest point of electricity consumption within a certain period, such as a day, week, or month. Information about peak load is crucial for determining the capacity of power plants that need to be prepared to meet demand without shortages. It also plays a key role in the management and distribution of electricity to ensure smooth supply without disruptions or delays [20]. Errors in predicting peak load can have serious consequences, including overloading the electricity distribution network, which can damage essential equipment and cause power outages. This not only disrupts daily activities but also poses significant economic losses, particularly for industries and businesses reliant on stable electricity supply. Therefore, accuracy in forecasting peak load is vital for maintaining the stability and reliability of the power system [18].

Electricity providers are developing forecasting methods that not only ensure accuracy but also capture dynamic patterns and uncertainties in household electricity load data, which can be influenced by various factors. Traditional methods like ARIMA and linear regression, though widely used, struggle with complex, non-linear data and long-term dependencies, making them less effective. Recent advancements in deep

learning offer solutions by automatically extracting important features from raw data and adapting to complex patterns, resulting in more accurate and reliable predictions for managing dynamic power systems [9],[13],[17].

Convolutional Neural Network (CNN) is a type of artificial neural network effective in extracting spatial patterns from data. In time series data such as electricity load, CNN can automatically recognize local and repetitive patterns without human intervention to determine important features. This ability allows CNN to capture hidden variations and trends, making it ideal for analyzing the often complex and dynamic patterns of electricity consumption [20].

Bidirectional Long Short-Term Memory (BiLSTM) is a neural network model specifically designed to process time series data by considering information from both the past and the future. This bidirectional approach allows the model to capture long-term dependencies in the data that might be missed by models looking at only one direction of time. In the context of electricity consumption patterns, this ability is crucial, as current consumption is often influenced by both previous and future conditions, enabling BiLSTM to provide deeper insights and more accurate predictions [18].

By combining CNN's strength in extracting spatial patterns with BiLSTM's ability to capture bidirectional temporal information, a hybrid model is created that can accurately predict dynamic household electricity consumption patterns. This model outperforms both individual methods and traditional statistical approaches, offering higher prediction accuracy for energy management [9],[17]. The CNN-BiLSTM model is particularly effective in predicting extreme fluctuations during peak electricity demand, providing highly accurate forecasts even in dynamic and uncertain conditions, making it ideal for short- to medium-term load forecasting.

Several previous studies have demonstrated the effectiveness of deep learning approaches for short-term electricity load forecasting.[2] reported that a CNN-LSTM model achieved higher forecasting accuracy than conventional statistical methods.[13] showed that CNN-BiLSTM effectively captured nonlinear consumption patterns and seasonal variations in residential electricity demand. Similarly,[17] found that CNN-BiLSTM models performed well in forecasting peak electricity loads under highly variable demand conditions.

However, most existing studies focus on urban smart grids, large-scale distribution systems, or datasets collected from developed countries. Limited research has investigated peak load forecasting for household consumers in Indonesian regions, particularly in semi-urban areas such as Mojowarno District. In addition, the characteristics of household electricity consumption in Indonesia may differ from those reported in previous studies due to variations in lifestyle, climate, and electricity usage behavior. Therefore, this study proposes a CNN-BiLSTM model to forecast short-term household electricity demand based on peak load data in

Mojowarno District, Jombang Regency, Indonesia.

Electricity load refers to the total energy consumed by a system, group of consumers, or equipment over a specific period, typically measured in watts (W) or kilowatts (kW) for instantaneous power and kilowatt-hours (kWh) for energy used over time. In households, factors like the number of residents, the type of appliances used, and their usage patterns influence electricity consumption. For instance, high-power devices like air conditioners and water heaters increase demand, while energy-efficient appliances like LED lights have a smaller impact. The simultaneous or continuous use of multiple devices can significantly raise the load.

Peak load is the highest electricity demand recorded during a specific period, such as a day, week, or month, and is crucial for planning power generation and distribution capacity. Accurate estimation of peak load helps prevent system overloads, equipment failure, and power outages while ensuring resource efficiency and cost-effectiveness. Understanding peak load also plays a key role in electricity pricing, energy management strategies, and demand response programs, allowing energy providers to optimize power distribution, use backup generation, and integrate renewable energy sources to maintain a stable and sustainable supply [20].

Electricity load forecasting estimates future energy needs, ensuring a balance between supply and demand to prevent waste or outages. It aids in capacity planning, peak load management, and implementing strategies like demand response and energy storage. Accurate forecasting enhances service quality and customer satisfaction, making it essential for the efficient, reliable, and sustainable operation of the electricity system [13].

Conventional methods like linear regression, ARIMA, moving average, and exponential smoothing are widely used for electricity load forecasting due to their simplicity. However, these methods struggle with non-linear patterns, long-term dependencies, and complex seasonal variations often found in household electricity data. They also require assumptions like data stationarity, which may not always be met. As a result, these methods often fall short in accuracy, highlighting the need for more advanced techniques like machine learning and deep learning [9].

Deep learning is a branch of artificial intelligence that uses multi-layered deep neural networks to extract and learn complex features from data automatically. In contrast to conventional methods that often rely on specific data assumptions and manual feature extraction, deep learning is able to recognize non-linear patterns and complex relationships in big data more effectively.

In the context of electrical load forecasting, deep learning offers solutions capable of overcoming the high dynamics and long-term dependencies that exist in electricity consumption data, especially in the household sector. Data containing seasonal fluctuations, changes in user habits, as well as the influence of weather and other external factors are well suited

to be analyzed with this method.

Deep learning models can work directly on raw data or time-series data without the need for complicated pre-processing, thereby speeding up and simplifying the analysis pipeline. In addition, this model can be constantly updated and retrained with new data, so that it is able to adapt to changes in electricity consumption patterns that occur over time.

Some of the popular deep learning architectures in electrical load forecasting are Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) specifically Long Short-Term Memory (LSTM), and a combination of the two such as CNN-BiLSTM which combines the advantages of spatial and temporal feature extraction.

Recent research shows that the use of deep learning significantly improves the accuracy of predictions compared to traditional statistical methods, especially in scenarios involving complex and dynamic data. Therefore, deep learning is the main focus in the development of modern electrical load prediction models [13].

The objectives of this research are to develop a short-term electricity load forecasting model using the CNN-BiLSTM method based on peak load in the household sector in Mojowarno District, Jombang Regency, and to analyze household electricity consumption patterns within a very short time frame (up to 24 hours).

## II. METHODS

### Research Type and Approach

This research uses a quantitative approach with an experimental method focused on developing an electricity load forecasting model using a combination of Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM). This approach is chosen due to its effectiveness in handling time-series data with complex and fluctuating patterns, such as household electricity consumption. CNN extracts important spatial features from historical data, while BiLSTM processes bidirectional temporal information, enabling the model to provide more accurate and adaptive predictions of electricity load patterns [9].

The developed model is tested and evaluated using peak load data from household consumers, which represents the highest electricity load recorded within a specific time period. Peak load data is crucial for planning electricity system capacity and energy distribution. By evaluating the model's performance with this data, the research aims to ensure that the predictions reflect real-world conditions and assist power system managers in effectively anticipating energy demand surges [13].

Additionally, this study emphasizes the importance of the hybrid CNN-BiLSTM approach as a solution to the limitations of conventional forecasting methods, which often fail to capture long-term dynamics and non-linear patterns in household electricity consumption. The combination of CNN and BiLSTM leverages the strengths

of both methods, such as effective local feature extraction and bidirectional temporal dependency modeling, resulting in more stable predictions with lower error rates [17].

### Data Collection

#### Data Collection

The dataset used in this study consists of hourly electricity demand data collected from household consumers in Mojowarno District, Jombang Regency, East Java, Indonesia. The observation period spans from January 1, 2024, to January 31, 2025. The dataset contains historical electricity consumption values and peak load information that are used as input variables for forecasting future electricity demand.

To ensure data quality, several preprocessing procedures were performed, including missing value handling, outlier detection, smoothing, and normalization. These processes help improve data consistency and enhance the learning performance of the deep learning model.

Table 1 summarizes the characteristics of the dataset used in this study.

Table 1. Dataset Characteristics

Parameter	Description
Study Area	Mojowarno District, Jombang Regency
Consumer Type	Household Sector
Observation Period	January 2024 – January 2025
Data Type	Time-Series Electricity Demand
Sampling Interval	Hourly
Forecast Horizon	24 Hours Ahead
Input Features	Historical Load and Peak Load
Output Variable	Future Electricity Demand
Data Processing	Smoothing, Outlier Handling, Normalization

### Data Processing Stages

Preprocessing ensures data quality before model training, addressing issues like missing values, measurement errors, and outliers. Missing values are handled by removal, replacement with mean/median, or imputation, while outliers are detected and removed. Data is then normalized or standardized to ensure consistency, helping deep learning models like CNN-BiLSTM converge faster and improve prediction accuracy.

Data is split into training, validation, and test sets to prevent overfitting and ensure generalization. A common split is 70% for training, 15% for validation, and 15% for testing, though this can be adjusted. In time-series data, a time-based split is used to maintain the temporal order, ensuring the model does not see future data during training.

The sliding window technique is used to transform time-series data into a format suitable for CNN and BiLSTM models. Data is segmented into fixed-size windows, allowing CNN to extract spatial features and BiLSTM to capture temporal dependencies. This transformation enables the

model to effectively learn both local and temporal patterns, enhancing prediction accuracy, especially for seasonal and fluctuating data.

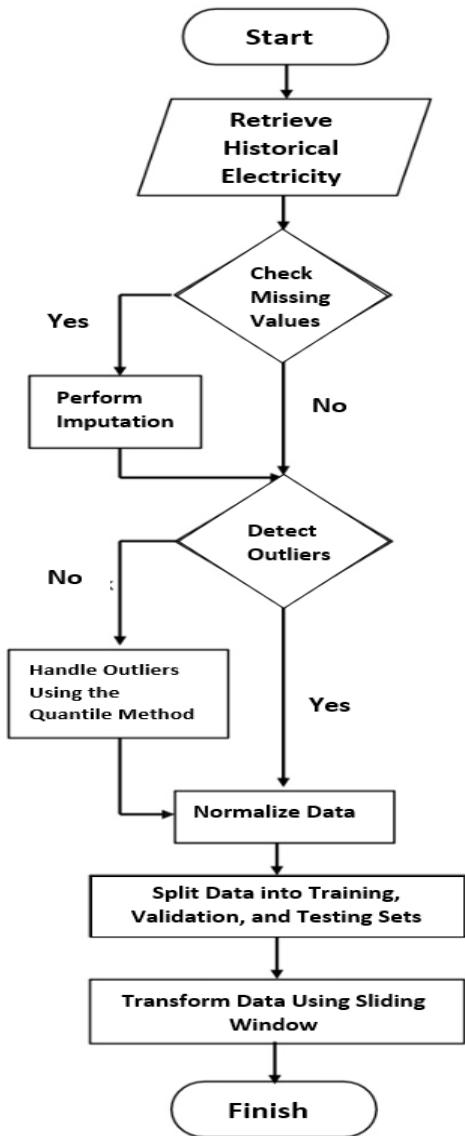


Figure 1 Data Processing Stage

### CNN-BiLSTM Model Design

The model developed in this study consists of several key layers working together to effectively process time-series electricity consumption data. The Convolutional Neural Network (CNN) layer acts as a spatial feature extractor, using convolutional filters to automatically learn and identify local patterns, such as recurring spikes or drops in electricity usage over time. This helps reduce data complexity while highlighting the important features that represent electricity consumption patterns.

Next, the feature outputs from the CNN layer are passed to the Bidirectional Long Short-Term Memory (BiLSTM) layer. BiLSTM captures bidirectional temporal patterns, modeling long-term dependencies and temporal context both from past to future and vice versa. This allows the model to understand complex time relationships, such as how past electricity usage influences future periods.

Finally, the processed data from the BiLSTM layer is fed into a Fully Connected (Dense) layer, which combines all

temporal features to generate the output prediction, such as the estimated peak load for a given period. The model is trained using the Adam optimization algorithm, which adapts the network weights using the advantages of stochastic gradient descent and momentum. The Mean Squared Error (MSE) loss function is used to minimize the squared differences between predicted and actual values, ensuring that the model's predictions are accurate and stable.

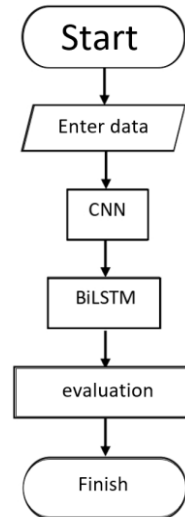


Figure 2 Architecture Model

Model training is performed iteratively over several epochs until convergence is reached, indicated by minimal reduction in validation loss. To avoid overfitting, dropout is used to randomly deactivate neurons during training, promoting better generalization. Hyperparameters, such as the number of filters in the CNN layer, kernel size, LSTM units, and learning rate, are adjusted based on validation results through hyperparameter tuning, ensuring the model achieves optimal performance.

Hyperparameter tuning can be done using methods like grid search, which exhaustively searches all predefined combinations, random search, which selects combinations randomly for greater efficiency, and Bayesian optimization, which uses probabilistic models to minimize trials and find the optimal configuration more effectively than grid or random search.

The developed model is evaluated using key metrics such as Mean Absolute Error (MAE), which measures the average absolute difference between predicted and actual values, Root Mean Square Error (RMSE), which penalizes larger errors, and Mean Absolute Percentage Error (MAPE), which expresses prediction error as a percentage of the actual values. The CNN-BiLSTM architecture was selected because it combines the strengths of convolutional neural networks in extracting local features and Bidirectional Long Short-Term Memory networks in learning temporal dependencies from time-series data. This hybrid approach is particularly suitable for household electricity demand forecasting, where consumption patterns are highly dynamic and influenced by various temporal factors.

After training and evaluation, the model is implemented in a simulation system to predict real-time electricity load demand and test its performance in various scenarios. Validation is done by comparing predictions with unseen data, ensuring the model's ability to generalize over time. Integrated into an

energy management system, the model supports faster decision-making, improving scheduling and peak load reduction for more efficient electricity load management in households.

This research uses Python for its flexibility and strong support for AI and machine learning. TensorFlow and PyTorch are used for developing the CNN-BiLSTM model, with TensorFlow excelling in deployment and PyTorch offering flexibility for experimentation. Libraries like pandas, numpy, and matplotlib are employed for data preprocessing, numerical operations, and visualization, ensuring efficient and clear data handling. This combination enables structured, accurate, and replicable research.

### III. RESULT AND DISCUSSION

This study utilizes Python for its flexibility and strong support in AI and machine learning. TensorFlow and PyTorch are used to develop the CNN-BiLSTM model, with TensorFlow excelling in deployment and PyTorch offering flexibility for experimentation. Pandas, numpy, and matplotlib are used for data preprocessing, numerical operations, and visualization, ensuring efficient and clear data processing. This combination allows for structured, accurate, and reproducible research.

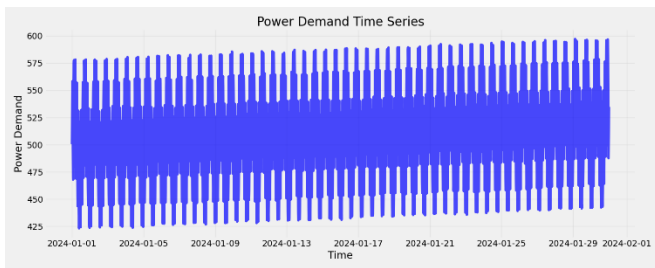


Figure 3 visualized through a time series

The household electricity demand dataset collected from Mojowarno District, Jombang Regency, covers the period from January 2024 to January 2025 with an hourly sampling interval. Figure 3 illustrates the temporal variation of electricity demand throughout the observation period. The data exhibit clear daily fluctuations, where electricity consumption increases during the morning and evening hours and decreases during late-night periods. These recurring patterns indicate the presence of strong temporal dependencies that are suitable for deep learning-based time-series forecasting.

The observed fluctuations also demonstrate that household electricity demand is influenced by residents' daily activities and electricity usage behavior. Such nonlinear and dynamic characteristics make conventional statistical forecasting methods less effective, thereby motivating the use of hybrid deep learning models capable of learning complex temporal relationships.

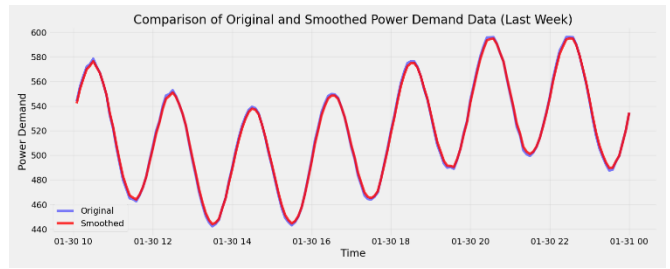


Figure 4 Smoothing Comparison

Prior to model training, the raw electricity demand data were preprocessed through smoothing, outlier handling, and normalization to improve data quality. Figure 4 compares the original and smoothed datasets. The smoothing process successfully reduced high-frequency noise while preserving the overall consumption trend, enabling the model to learn representative temporal patterns more effectively.

Figure 5 presents the dataset after outlier handling. Extreme values that could potentially degrade prediction performance were successfully identified and corrected without altering the intrinsic characteristics of the data. Consequently, the processed dataset provides a more reliable representation of household electricity consumption and improves model robustness during training.

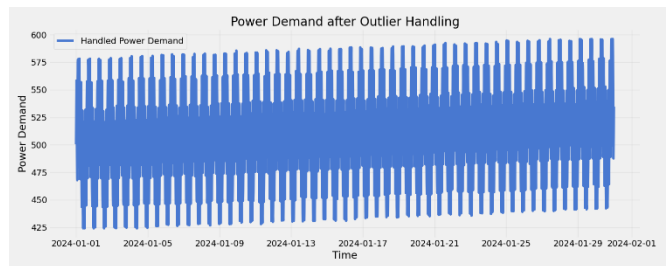


Figure 5 post-outlier handling data visualization

The post-outlier handling data visualization, shown in, displays electricity demand from January 1 to February 1, 2024, after outliers have been removed or corrected. The demand fluctuates between 425 and 575, with recurring peaks and valleys reflecting varying energy needs at different times. The graph highlights significant seasonal fluctuations, with higher demand during peak hours or increased energy requirements. By removing outliers, the data presents a clearer and more accurate view of real demand patterns, which is crucial for energy planning, enabling electricity providers to better predict demand and plan for resource distribution more efficiently.



Figure 6 Loss During Training

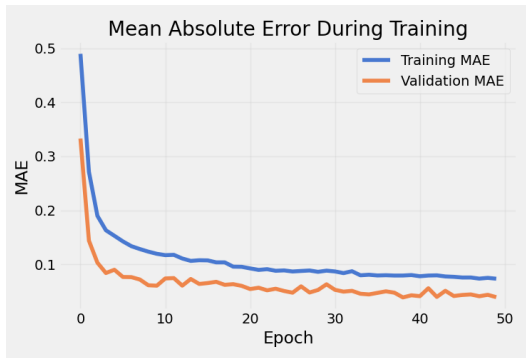


Figure 7 MAE Training

The CNN-BiLSTM model was trained using the processed electricity demand dataset to predict household electricity load for the next 24 hours. Figure 6 illustrates the evolution of training loss and validation loss during model optimization. Both curves decrease rapidly during the initial epochs and gradually converge to stable values after approximately 35 epochs.

The absence of a significant gap between the training and validation loss indicates that the proposed model does not suffer from overfitting and possesses good generalization capability. The convergence behavior also demonstrates that the selected CNN-BiLSTM architecture effectively learns both local spatial features and long-term temporal dependencies contained in household electricity demand data.

Similarly, Figure 7 shows the Mean Absolute Error (MAE) during the training process. Both training and validation MAE consistently decrease as the number of epochs increases, indicating continuous improvement in prediction accuracy. The stabilization of MAE at a low value confirms that the proposed model successfully minimizes forecasting errors throughout the learning process.

Table 2 training results

Epoch	Loss	MAE
41	0,0049	0,0761
42	0,005	0,0766
43	0,0048	0,0756
44	0,0047	0,0741
45	0,0047	0,0747
46	0,0045	0,0736
47	0,0045	0,0731

The results of the deep learning model training over several eras are shown in table 1, using two main metrics to evaluate the model's performance: Loss and MAE (Mean Absolute Error). Loss measures the difference between the model's prediction and the actual value, with a lower value indicating higher accuracy. In the table, Losses consistently decreased from 0.0049 in epoch 41 to 0.0045 in epoch 47, indicating an increase in prediction accuracy over time. Similarly, the MAE, which measures the mean absolute difference between predicted and actual values, decreased from 0.0761 in age 41 to 0.0731 in age 47. The consistent decline in Loss and MAE reflects an increase in prediction accuracy and model generalization capabilities, with smaller errors as the number of times increases.

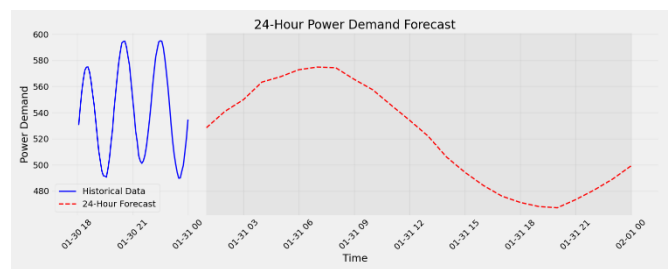


Figure 8 Ahade forecast

Figure 8 compares historical electricity demand with the predicted demand for the following 24 hours. The predicted values closely follow the actual consumption pattern, indicating that the CNN-BiLSTM model successfully captures the nonlinear behavior of household electricity demand.

The forecasting results demonstrate that the proposed model accurately identifies peak demand periods while maintaining stable predictions during off-peak hours. This capability is particularly important for electricity providers because accurate peak load forecasting enables better generation scheduling, demand management, and operational planning.

Model evaluation on the testing dataset produced a Test Loss of 0.0024, Test MAE of 0.0562, Test RMSE of 0.0699, MAE of 3.4146 kW, RMSE of 4.2470 kW, and an R<sup>2</sup> value of 0.9889. The high coefficient of determination indicates that the proposed model explains approximately 98.89% of the variance in household electricity demand, demonstrating excellent forecasting capability.

The experimental results confirm that combining CNN and BiLSTM provides substantial advantages for short-term household electricity load forecasting. CNN effectively extracts local consumption features from historical data, whereas BiLSTM captures long-term bidirectional temporal dependencies that cannot be modeled efficiently by conventional statistical approaches.

Compared with previous studies, the obtained forecasting accuracy is consistent with the findings reported by Chen et al. [2], Liu et al. [13], and Singh et al. [17], who also demonstrated

that hybrid CNN-based recurrent neural networks outperform traditional forecasting methods in modeling nonlinear electricity demand. However, unlike previous studies that mainly focused on smart grids or urban electricity systems, the present study evaluates the CNN-BiLSTM model using household peak load data collected from a semi-urban area in Indonesia. Therefore, the proposed model contributes additional evidence regarding the applicability of deep learning techniques for residential electricity demand forecasting under local consumption characteristics.

#### IV. CONCLUSION

This study developed a hybrid Convolutional Neural Network–Bidirectional Long Short-Term Memory (CNN-BiLSTM) model for short-term household electricity load forecasting based on peak load data collected from Mojowarno District, Jombang Regency, Indonesia. The proposed model successfully captured the nonlinear and temporal characteristics of household electricity consumption, resulting in high forecasting accuracy with a Test Loss of 0.0024, Test MAE of 0.0562, Test RMSE of 0.0699, MAE of 3.4146 kW, RMSE of 4.2470 kW, and an R<sup>2</sup> value of 0.9889. These results demonstrate that the CNN-BiLSTM architecture is effective for predicting short-term household electricity demand and can support peak load management, electricity distribution planning, and energy management. Nevertheless, this study was limited to historical electricity consumption and peak load data from a single study area. Future research should incorporate additional influencing factors, such as weather conditions, public holidays, and socioeconomic variables, and evaluate the proposed model using datasets collected from multiple regions to further improve forecasting accuracy and model generalization.

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