Scientific and Social Research, 2026, Volume 8, Issue 3
https://ojs.bbwpublisher.com/index.php/SSR
Online ISSN: 2981-9946
Print ISSN: 2661-4332

Application and Performance Comparison of a CNN–LSTM Hybrid Neural Network for Power Load Forecasting

Wenwen Wang, Hui Zhang

Shandong Labor Vocational and Technical College, Jinan 250300, China

Abstract: Accurate and stable power load forecasting is essential for power system operation and planning. However, traditional single prediction models often exhibit limited performance when modeling complex load data characterized by strong nonlinearity and non-stationarity. To address this issue, this paper proposes a hybrid neural network model that combines a Convolutional Neural Network (CNN) with a Long Short-Term Memory (LSTM) network for short-term power load forecasting. First, considering the temporal dependency and nonlinear characteristics of power load time-series data, both LSTM and CNN–LSTM forecasting models are constructed. Then, the hybrid model is systematically optimized by adjusting the number of convolutional layers, the structure of LSTM hidden layers, and different activation function configurations. Finally, the forecasting performance of the proposed model is evaluated and compared with that of the single LSTM model using root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The experimental results indicate that the CNN–LSTM model achieves higher forecasting accuracy and better generalization performance, and its predicted load curves show greater consistency with actual load variations. The proposed approach provides an effective solution for power load forecasting and offers valuable support for power system dispatching and planning.

Keywords: Power load forecasting; CNN–LSTM; Long short-term memory; Convolutional neural network; Time series prediction

Online publication: April 15, 2026

1. Introduction

In recent years, with the rapid development of deep learning theory and computing capabilities, neural network models have been widely applied in time-series forecasting tasks [1]. Recurrent Neural Networks (RNNs) and their improved variant, Long Short-Term Memory (LSTM) networks, introduce gating mechanisms that effectively alleviate the problems of gradient vanishing and gradient explosion encountered during long-sequence training. As a result, LSTM-based models have achieved promising results in applications such as power load forecasting and wind power prediction [2]. Nevertheless, LSTM networks still exhibit limitations in automatic feature extraction, particularly when handling high-dimensional and multi-scale features, and their forecasting performance requires further improvement [3].

Convolutional Neural Networks (CNNs) demonstrate significant advantages in feature extraction by effectively capturing local patterns through local connectivity and weight-sharing mechanisms. By integrating CNNs with LSTM networks, CNNs can be employed to extract local or spatial features from load data, while LSTM networks model the temporal dependencies of time-series data. Such a hybrid architecture is expected to further enhance the accuracy and stability of power load forecasting [4–5].

Based on the above considerations, this paper systematically analyzes the characteristics of power load data and proposes a CNN–LSTM hybrid neural network model [6]. The network structure is optimized, and extensive comparative experiments are conducted to verify the effectiveness of the proposed model. The study aims to provide a feasible deep learning–based solution for power load forecasting and to support decision-making in power system operation and planning.

2. Related work

2.1. Research status of power load forecasting

Power load forecasting is a critical research topic in power system planning and operation, as forecasting accuracy directly affects generation scheduling, grid security, and electricity market operation. Early studies on power load forecasting were mainly based on statistical theories, including linear regression models and time-series models such as autoregressive (AR) and autoregressive integrated moving average (ARIMA) models. These methods can achieve satisfactory forecasting performance when load patterns are relatively stable and data volumes are limited. However, with the increasing complexity of electricity consumption patterns and the growing penetration of renewable energy sources, power load exhibits stronger nonlinearity and volatility, which gradually limits the prediction accuracy of traditional statistical models in practical applications.

To improve forecasting performance, machine learning methods such as Support Vector Machines (SVM), decision trees, and ensemble learning models have been introduced into power load forecasting. These approaches can partially enhance prediction accuracy by modeling nonlinear relationships in the data. Nevertheless, their ability to capture long-term temporal dependencies and complex nonlinear patterns remains limited, resulting in constrained generalization performance when applied to large-scale or highly dynamic load datasets [7].

In recent years, with the rapid advancement of deep learning technologies, neural network–based load forecasting methods have become a major research focus. Deep learning models are capable of automatically extracting latent features from power load data through multi-layer network structures, demonstrating strong potential in power load forecasting applications.

2.2. LSTM-based power load forecasting methods

Recurrent Neural Networks (RNNs) have been widely applied in power load forecasting due to their inherent capability to process time-series data. However, traditional RNNs suffer from gradient vanishing and gradient explosion problems when modeling long sequence data, which restricts their practical applicability in load forecasting tasks.

Long Short-Term Memory (LSTM) networks address these limitations by introducing input gates, forget gates, and output gates, enabling more effective modeling of long-term dependencies in time-series data. Existing studies have demonstrated that LSTM-based models outperform traditional statistical methods and shallow neural networks in short-term power load forecasting in terms of prediction accuracy and stability.

Despite their advantages in temporal dependency modeling, LSTM networks exhibit limited capability in extracting local and multi-scale features from load data. When load variations become highly volatile or exhibit complex patterns, the prediction performance of LSTM models still leaves room for further improvement.

2.3. CNN-based time-series forecasting methods

Convolutional Neural Networks (CNNs) were originally developed for image processing tasks and are well known for their ability to efficiently extract local features through local connectivity and weight-sharing mechanisms. In recent years, CNNs have been increasingly introduced into time-series analysis and have achieved promising results in applications such as financial forecasting, traffic flow prediction, and power load forecasting [8].

In power load forecasting studies, CNNs are typically employed to extract features from load sequences using one-dimensional convolution operations, which can effectively capture local variation patterns in the load data. Related research indicates that incorporating CNN structures can enhance a model's sensitivity to load fluctuations and periodic characteristics [9–10].

However, when CNN models are used independently for load forecasting, they exhibit limitations in modeling long-term temporal dependencies and are therefore insufficient for fully capturing the overall load variation trends [11].

2.4. Research progress on CNN–LSTM hybrid models

To fully exploit the complementary strengths of different deep learning models, researchers have increasingly explored hybrid neural network architectures that combine CNNs and LSTM networks. In such models, CNNs are generally employed to extract local features from load data, while LSTM networks are responsible for modeling long-term temporal dependencies, enabling joint learning of spatial and temporal features.

Previous studies have shown that CNN–LSTM hybrid models achieve higher forecasting accuracy and stronger generalization capability in short-term power load forecasting compared with single CNN or LSTM models. By appropriately designing convolutional layer structures and LSTM hidden-layer parameters, hybrid models can effectively capture load variation patterns and improve forecasting stability.

Nevertheless, existing studies exhibit notable differences in the structural design of CNN–LSTM models. The effects of convolutional layer depth, kernel size, and LSTM architecture configurations on forecasting performance have not yet been systematically analyzed. Therefore, further optimization and comparative analysis of CNN–LSTM hybrid models under specific load data scenarios are still required.

2.5. Research content and contributions of this study

Based on the existing literature, this paper focuses on power load forecasting and constructs both LSTM and CNN–LSTM hybrid neural network models to comparatively analyze their forecasting performance. Compared with previous studies, the main research contributions of this work can be summarized as follows:

(1) LSTM and CNN–LSTM load forecasting models are established according to the temporal and nonlinear characteristics of power load data, ensuring the rationality and fairness of experimental comparisons.

(2) A systematic optimization analysis of the CNN–LSTM hybrid model is conducted by adjusting the number of convolutional layers, the structure of LSTM hidden layers, and the combinations of activation functions

(3) Multiple error evaluation metrics are employed to comprehensively assess forecasting performance, and both quantitative and qualitative analyses are performed to verify the advantages of the proposed hybrid model in power load forecasting tasks.

3. Methodology and experimental design

3.1. Research framework and technical route

Considering that power load data exhibit strong temporal dependency, nonlinearity, and non-stationarity, this study adopts deep learning models as the primary research approach and constructs both an LSTM model and a CNN–LSTM hybrid neural network model for comparative analysis in power load forecasting tasks [12].

The overall research framework is organized as follows. First, the original power load data are preprocessed through data cleaning, normalization, and sample reconstruction to ensure data quality and enhance training stability. Second, a single LSTM-based load forecasting model and a CNN–LSTM hybrid forecasting model are established, and their structural parameters are reasonably configured. Subsequently, the hybrid model is systematically optimized by adjusting the number of CNN convolutional layers, the structure of LSTM hidden layers, and combinations of activation functions. Finally, multiple evaluation metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), are employed to compare the forecasting performance of different models, thereby validating the effectiveness of the CNN–LSTM hybrid neural network for power load forecasting [13].

3.2. Data source and description

The experimental data used in this study are derived from historical load records of a regional power system. The data are sampled at an hourly interval, which can effectively reflect load variation characteristics during typical working days and non-working days. The load series exhibits clear periodicity and volatility, making it suitable for short-term power load forecasting experiments.

To ensure the generality and reproducibility of the experimental results, only load data from a continuous time period are selected for model construction and analysis.

3.3. Data preprocessing methods

3.3.1. Data cleaning

During actual data acquisition, power load data may contain missing values and outliers. To reduce the impact of abnormal data on model training and forecasting results, the original load data are first subjected to data cleaning procedures. For a small number of missing values, interpolation using adjacent time points is applied for data completion. For outliers that significantly deviate from the normal range, mean-value substitution is adopted for correction, ensuring the continuity and rationality of the load data sequence [14].

3.3.2. Data normalization

Since power load data typically has a wide numerical range, directly feeding raw data into the model may lead to training instability and slow convergence. Therefore, min–max normalization is applied to the load data to map the original values into the range of [0,1][0, 1][0,1]. The normalization process is defined as follows:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where xxx denotes the original load value, $x_{\max}$ and $x_{\min}$ represent the maximum and minimum values of the sample data, respectively. Through normalization, the influence of different data scales on model training is effectively reduced, thereby improving the stability and convergence of the forecasting models.

4. Experimental results and analysis

4.1. Overall analysis of forecasting results

Based on the experimental design and parameter settings described in Chapter 3, both the LSTM-based load forecasting model and the CNN–LSTM hybrid neural network model were constructed to perform load forecasting experiments on the same test dataset. To ensure the comparability of experimental results, the two models were trained and tested under identical datasets and experimental environments.

From the overall forecasting results, both models are able to effectively capture the general variation trends of power load, and their predicted curves maintain a high degree of consistency with the actual load curves over most time periods. However, during periods with relatively large load fluctuations—particularly during rapid load increases or decreases—the single LSTM model exhibits a certain degree of prediction lag. In contrast, the CNN–LSTM hybrid model demonstrates greater stability in capturing load variation trends [15].

4.2. Comparative analysis of forecasting curves

To visually compare the forecasting performance of different models, the actual load values and predicted values on the test dataset were plotted for curve comparison. The results indicate that during relatively stable load periods, both the LSTM and CNN–LSTM models can accurately fit the actual load variations. However, during periods with significant load changes—such as the onset of the morning electricity consumption peak—the forecasting curve produced by the CNN–LSTM model shows closer alignment with the actual load curve.

In particular, around the 30th to 45th sampling points, corresponding to the transition period from load valley to peak, the CNN–LSTM model more accurately captures the upward trend of the load. Its predicted values remain highly consistent with the actual load changes. This observation suggests that the introduction of the CNN structure enhances the model's ability to extract local features from the load sequence, thereby improving overall forecasting performance.

4.3. Comparative analysis of error evaluation metrics

To further quantitatively evaluate the forecasting performance of different models, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were employed to assess the prediction results of the LSTM and CNN–LSTM models.

The CNN–LSTM hybrid model outperforms the single LSTM model across all three evaluation metrics. Specifically, the CNN–LSTM model achieves significantly lower RMSE and MAE values, indicating superior performance in terms of overall prediction stability and error control. The reduction in MAPE further demonstrates that the CNN–LSTM model also achieves improved performance in controlling relative prediction errors.

Overall, these results confirm that the incorporation of CNN structures enables more comprehensive feature extraction from load sequences, providing more informative input representations for the LSTM layers and thereby enhancing forecasting accuracy.

4.4. Impact of model structure on forecasting performance

During the construction of the CNN–LSTM hybrid model, the design of the convolutional layer structure plays a crucial role in forecasting performance. Experimental results indicate that when the convolutional structure is overly simple, the model's ability to extract local load features is limited, and the improvement in forecasting performance is not significant. As the number of convolutional layers is appropriately increased, forecasting accuracy gradually improves.

However, it is also observed that increasing the number of convolutional layers does not always lead to better performance. When too many convolutional layers are introduced, the model complexity and parameter scale increase substantially, resulting in higher training difficulty and a greater risk of overfitting. This can ultimately lead to degraded forecasting performance. Therefore, in practical applications, the number of convolutional layers and related parameters should be carefully selected according to the characteristics of specific load datasets.

4.5. Discussion of results

Based on the comprehensive analysis of forecasting curves and error evaluation metrics, it can be concluded that the CNN–LSTM hybrid neural network exhibits clear advantages over the single LSTM model in power load forecasting tasks. The primary reason for this improvement lies in the CNN's ability to effectively extract local features and variation patterns from load sequences, thereby providing richer feature representations for the LSTM layers to model long-term temporal dependencies.

In addition, the CNN–LSTM model demonstrates greater stability during periods of large load fluctuations, indicating stronger adaptability when dealing with complex load variation scenarios. This characteristic is of significant practical value for power system operation and dispatching, where accurate and stable load forecasting is essential for reliable decision-making.

5. Conclusion

This study conducted a comparative experimental analysis of an LSTM-based model and a CNN–LSTM hybrid neural network model for power load forecasting. The experimental results demonstrate that although both models are capable of capturing the overall load variation trends, the CNN–LSTM model outperforms the single LSTM model in terms of forecasting accuracy, stability, and generalization capability.

The findings further confirm the effectiveness of incorporating convolutional neural network structures into power load forecasting models. By enhancing local feature extraction from load sequences, the CNN–LSTM hybrid model provides more informative representations for temporal modeling, thereby improving overall forecasting performance. These results offer experimental support for subsequent model optimization and practical applications in power system operation and planning.

Disclosure statement

The authors declare no conflict of interest.

References

[1] Han Y, Hou ZM, 2026, BO-CNN BiLSTM Attention Analysis and Peak Scenario Simulation of Carbon Emissions in Resource-based Cities in China Based on RF-RFECV Feature Selection. Environmental Science, 47(3): 1433–1448. https://doi.org/10.13227/j.hjkx.202501278

[2] Tan Z, Zhang WM, Yin ZL, et al., 2025, Short Term Power Load Forecasting Model Based on Deep Learning and Optimization Algorithms. Microcomputer Applications, 41(12): 28–31 + 35.

[3] Qiao YH, Lin X, Cao DY, et al., 2025, Ship Power Load Forecasting Method Based on Variational Mode Decomposition and Hybrid Neural Network. Ship and Sea Engineering, 54(6): 127–133.

[4] Zhao RX, Gu H, and Meng QY, 2026, Short-Term Power Load Forecasting Based on CNN-LSTM and Dual Attention Mechanism. Information & Computer, 38(1): 29–32.

[5] Qi XF, 2025, Research on Energy Saving and Loss Reduction Technology of Power Transmission and Distribution Lines Based on Deep Learning. Electrical Technology & Economy, 2025(12): 57–60.

[6] Cao T, 2025, Research on Power System Load Forecasting Models Based on Deep Learning. Electrical Technology & Economy, 2025(12): 18–20 + 23.

[7] Chen YT, Chen JJ, Lv HX, et al., 2025, The Current Application Status of Artificial Intelligence Technology in Power System Load Forecasting. Energy Conservation, 44 (11): 157–160.

[8] Hou PP, Liu B, Xie J, et al., 2025, Research on Intelligent Algorithm-based Power Load Forecasting and Optimization Method. Electrical Era, 2025(11): 80–82.

[9] Ding WF, Zhou ZZ, Xie ZH, et al., 2025, Low Voltage Substation Load Forecasting Based on Temporal Convolutional Neural Network and Cross Algorithm. Power System Protection and Control, 53(21): 156–165.

[10] Qi SJ, Li RH, Duan MH, 2025, Research on Power Load Forecasting Based on Backpropagation Neural Network Algorithm. Shanxi Electric Power, 2025(5): 9–14.

[11] Li HT, 2025, Research on Power Load Forecasting Considering New Energy and Joint Scenarios, thesis, Shijiazhuang Railway University.

[12] Geng JT, 2025, Research on Intelligent Power Load Forecasting Based on Deep Learning. Automation Application, 66(20): 34–36. DOI: 10.19769/j.zdhy.2025.20.009.

[13] Suo Zhigang. "Research on Data Analysis and Forecasting Technologies in Intelligent Photovoltaic Power Generation Systems." Science & Technology Information, vol. 23, no. 20, 2025, pp. 208–210. https://doi.org/10.16661/j.cnki.1672-3791.2412-5042-0597

[14] Zhang Q, Li ZH, Fan YP, et al., 2025, A Tilted Sample Prediction Algorithm Based on LSTM and CNN in a Novel Power System. Telecommunications Science, 41(10): 211–221

[15] Rui LX, 2024, Research on Residential Load Forecasting Based on Spatiotemporal Graph Neural Networks, thesis, Nanjing University of Posts and Telecommunications.