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# *Review of Power Load Forecasting Methods Based on Deep Learning Algorithms*

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***Abstract:*** As the scale of power systems keeps expanding and load characteristics are growing more complex, precise power load forecasting has emerged as a crucial link in guaranteeing the safe, stable and economical operation of power systems. Deep learning algorithms, with their powerful feature learning and complex non-linear relationship processing capabilities, have achieved remarkable results in the field of power load forecasting. This paper comprehensively reviews the applications of various deep learning algorithms in power load forecasting by combining the characteristics of power systems. It evaluates the accuracy and feasibility of the forecasts, aiming to provide a reference for subsequent research and promote further development in this field.

***Keywords:*** Deep learning algorithms, Power load forecasting, LSTM, CNN

## 1. Introduction

In the current booming development of the power industry, power load forecasting plays a crucial role in guaranteeing the stable operation of power systems and optimizing the allocation of resources. Traditional forecasting methods, such as regression analysis and time-series methods, are limited by the non-linearity and randomness of loads. Moreover, it is difficult for them to comprehensively consider numerous influencing factors, so the forecasting accuracy can hardly meet the growing demands [1]. As deep learning algorithms have gained prominence, their robust feature-learning and data-processing abilities have presented fresh opportunities for power load forecasting. Currently, deep learning has been extensively utilized in this domain. Nevertheless, issues like the complexity of model training and the poor adaptability to non-stationary data still persist. The application scenarios and optimization directions of different models have also become the focus of debate.

This paper reviews the power load forecasting methods based on deep learning algorithms by extensively collecting academic literatures, research reports and other materials in related fields. The objective is to systematically organize the existing research findings, assess the pros and cons of the methods, make the research directions clear, offer a reference for the follow-up research, and facilitate the advancement of power load forecasting technology.

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## 2. Foundations of Deep Learning Algorithms

### 2.1. Long Short-Term Memory Network (LSTM)

LSTM is a special type of Recurrent Neural Network (RNN) designed to address the problems of vanishing gradients and exploding gradients that traditional RNNs encounter when dealing with long-sequence data. As a result, it can effectively learn and remember the dependencies in long-term time series [2].

The unit of LSTM is structured with an input gate, a forget gate, an output gate, and a cell state. The input gate regulates the amount of current input information that gets into the cell state. The forget gate decides whether the information in the cell state from the previous time step should be retained or discarded. The output gate produces an output according to the current cell state and input information. The cell state functions like a conveyor belt, which can transfer long-term information within the time series. This allows LSTM to capture the long-term dependency features in the sequence.

Although LSTM performs well in handling complex time-series data, it is not without flaws. Firstly, the training process of LSTM usually incurs high computational costs. Especially when dealing with large amounts of data, the training time is long and high-performance computing resources are required. In addition, LSTM has relatively poor adaptability to non-stationary data (such as the sudden changes and seasonal variations in power load data), and additional pre-processing steps may be needed to ensure prediction accuracy. Therefore, in practical applications, it is essential to choose an appropriate model in line with the specific problem and integrate it with other methods to make up for the deficiencies of LSTM.

### 2.2. Convolutional Neural Network (CNN)

As a type of deep-learning model, the Convolutional Neural Network (CNN) is mainly designed to process data with a grid-like structure. The architecture of a CNN mainly consists of an input layer, convolutional layers, pooling layers, fully-connected layers, and an output layer. During the data-processing procedure, convolutional kernels are utilized by convolutional layers to conduct feature extraction from the load input matrix. By reducing the data dimension, pooling layers play an effective role in preventing the over-fitting of the model. The fully-connected layers are responsible for aggregating the feature information extracted by the convolutional and pooling layers and then outputting it.

In terms of load forecasting, CNN can capture local and spatial features in the data. With its multi-layer structure, it can extract data features from shallow to deep. At the same time, through parameter sharing and sparse connections, CNN can reduce the number of parameters and the amount of computation while ensuring the performance of the model, thus greatly improving the processing efficiency [3].

## 3. Applications of Deep Learning Algorithms in Power Load Forecasting

### 3.1. Applications of LSTM in Power Load Forecasting

Due to the obvious time-series characteristics of power load and its complex changing trends influenced by various factors, the long-and short-term memory capabilities of LSTM have led to its wide application in power load forecasting. Numerous studies have shown that LSTM is capable of effectively capturing the long-term dependencies within load data and precisely forecasting the load's changing trends.

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LSTM can learn users' daily electricity consumption behavior patterns as well as the seasonal and periodic changes in electricity consumption. The LSTM model can predict the electricity load in the upcoming period by taking historical load data and relevant influencing factors, including temperature, humidity, and date type, as inputs. Reference [4] uses LSTM to predict provincial-level power loads; Reference [5] uses the LSTM model to predict regional short-term power loads. The research results show that the LSTM prediction model with a memory function can better explore the influence relationships in the load time series. Especially for load forecasting during electricity consumption periods that are more sensitive to load changes, it has a higher load forecasting accuracy compared with other methods.

Although LSTM shows outstanding performance when dealing with time-series data and is capable of effectively grasping the long-term dependencies within load data, it also has certain limitations. In particular, its computational complexity is relatively high when dealing with large-scale data. To make up for this deficiency, the Convolutional Neural Network (CNN), as another deep-learning algorithm, has gradually been introduced into power load forecasting due to its successful application in the field of image processing. Through local feature extraction and spatial information fusion, CNN can process multi-source information and effectively improve the prediction accuracy in the spatial dimension.

### 3.2. Applications of CNN in Power Load Forecasting

The application of CNN in power load forecasting is mainly based on its powerful feature extraction capabilities. When dealing with power load data, CNN can transform the load time series into a format suitable for convolutional operations. Through multiple layers of convolution and pooling operations, it can automatically extract local and global features from the data.

In regional load forecasting, CNN can integrate multi-source information such as geographical information and meteorological data to extract features from load data at different locations within the region. By combining spatial and temporal information, CNN can uncover the changing patterns of the load in both spatial and temporal dimensions, thus more accurately predicting the changing trends of the regional load. Reference [6] proposes a short-term power load forecasting model that combines a three-channel (historical, temporal, and meteorological environment) LSTM with CNN. By combining CNN and LSTM, CNN is responsible for extracting the spatial and local features of the load data, while LSTM focuses on learning the long-term dependencies of the time series. Complementing each other's advantages, the two can capture the features of the load data more comprehensively, thereby achieving more accurate load forecasting.

## 4. Model Performance Evaluation and Comparison

### 4.1. Evaluation Metrics

To accurately evaluate the performance of deep learning models in power load forecasting, multiple evaluation metrics are usually adopted. Commonly used ones include Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Coefficient of Determination ($R^2$).

MAE represents the average size of the absolute difference between the predicted values and the actual values. A lower MAE value indicates that the prediction outcomes are nearer to the true values. MAPE represents the prediction error in the form of a percentage, which can intuitively reflect the relative magnitude of the prediction error and is convenient for comparison under different data scales and prediction scenarios. RMSE takes into account the sum of the squared errors, is more sensitive to the fluctuations of the errors, and can more comprehensively evaluate the stability of the prediction model. R2 serves as a metric to evaluate how well the model fits the data. Its value lies within the

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range of 0 to 1. The nearer the value of R2 is to 1, the superior the model's fit to the data is, and the more robust its predictive capability becomes.

### 4.2. Performance Comparison

In practical applications, the performance of different deep learning algorithms in power load forecasting varies.

LSTM has an advantage in handling time-series data with long-term dependencies and can better capture the periodic and trend changes of load data. However, when dealing with large-scale data, LSTM has a high computational complexity and a long training time.

CNN, on the other hand, is good at extracting local and spatial features of data and performs well in handling load forecasting problems with multi-source data fusion. However, when it comes to capturing long-term dependencies in time-series, CNN has relatively limited capabilities. Therefore, in practical applications, it is imperative to pick appropriate deep-learning algorithms or combinations of such algorithms in accordance with the particular features of the load data and the prediction demands.

## 5. Challenges in Research

Although deep learning has achieved remarkable results in power load forecasting, it still faces the challenge of data quality issues in practical applications. Meeting the requirement for a vast quantity of high-quality data is frequently challenging. Especially in power systems, data is often restricted by collection and annotation. Problems such as data missing and noise interference are widespread. This not only reduces the training effect of the model but may also significantly affect the prediction accuracy. Reference [7] proposes a method to decompose the load according to the technological and power-consumption characteristics, which solves the problem of noise interference during the data pre-processing.

## 6. Conclusions and Prospects

This paper, based on the analysis of current literature, summarizes how deep-learning algorithms are applied and their advantages in power load forecasting, especially in improving prediction accuracy and handling complex non-linear relationships. However, despite the progress made in a large number of studies, current challenges, such as data quality, computational efficiency, and model interpretability, still restrict the widespread application of this technology. Therefore, future research should focus on the following aspects:

1. Data Processing and Quality Improvement: Further research on data pre-processing techniques, such as more effective data cleaning, missing value imputation, and noise suppression methods, to improve data quality. Meanwhile, explore multi-source data fusion techniques, making full use of various data resources both inside and outside the power system, such as meteorological data, economic data, user behavior data, etc., to provide more abundant information for deep learning models and enhance prediction accuracy [8].
2. Research on Model Interpretability: Conduct research on the interpretability of deep learning models, explore how to combine the prediction results of deep learning models with the physical principles and operation mechanisms of the power system, develop visualization tools and interpretive methods, making the prediction process and results of the model easier to understand and explain, and enhancing the credibility and application value of the model in practical engineering.

3. Computational Efficiency Optimization: Explore more efficient deep-learning model architectures and training algorithms. For instance, employ lightweight models, distributed computing technology, and model compression technology. These measures aim to decrease the computational complexity of the model, accelerate the model's training and prediction speed, thereby fulfilling the requirements of real-time load forecasting in large-scale power systems.
4. Construction of General-Purpose Models: In view of the differences in power load characteristics in different regions, carry out research on deep learning models based on regional characteristics. Combine factors such as geographical information, climatic conditions, and industrial structures to build general-purpose load forecasting models, and enhance the adaptability and prediction precision of the models in different scenarios.

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