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Research on Photovoltaic Power Generation Forecasting Based on a Combined CNN-LSTM Neural Network Model

Ruotong Qiu[1,*], Zhengxin Su[2]

[1]*School of Sciences of SWPU, Southwest Petroleum University, Nanchong, 637001, China*
[2]*College of Electronic Engineering, Chengdu University of Information Technology, Chengdu, 610225, China*
[*]*Corresponding author: 17844566964@163.com*

Abstract: *At present, China's traditional fossil energy is gradually depleted. Among the many new energy sources, solar energy has the advantages of abundant resources and low cost, so photovoltaic power generation has been vigorously promoted and widely used in the world. However, due to the influence of geographical environment, meteorological factors and equipment characteristics, photovoltaic power generation has the characteristics of randomness, fluctuation and anti-peak regulation, which brings many adverse effects to the normal operation and planning of the power system. In order to improve the prediction accuracy of photovoltaic power generation, a CNN-LSTM convolutional neural network prediction model is proposed, which uses a variety of convolution kernels to effectively fuse multiple feature signals to generate higher-level effective features. Taking the dataset as input, the data is filtered through the upper CNN network part, and then the filtered data is mapped to the LSTM long-term and short-term memory neural network part to achieve continuous prediction. Experiments show that the prediction results have high accuracy and stability.*

Keywords: *Photovoltaic Power Generation Prediction, CNN, LSTM, Deep Learning*

1. Introduction

In recent years, renewable resources have been vigorously developed, and solar energy resources are particularly abundant, so photovoltaic power generation has become extremely important. However, due to the influence of geographical environment, meteorological factors and equipment characteristics, photovoltaic power generation has the characteristics of randomness, fluctuation and anti-peak regulation, which brings many adverse effects to the normal operation and planning of the power system. Some scholars have suggested that in addition to our common influencing factors, there are other factors such as $PM_{2.5}$, PM_{10}, SO_2, NO_2, and O_3 that are significantly correlated [1]. At the same time, some scholars have proposed to consider different time periods to predict photovoltaic power generation [2], but the process is complex and inconvenient.

In the face of the harsh environment of energy storage power station voltage, high current and complexenvironment, it is urgent to improve the accuracy of photovoltaic power generation prediction.In terms of photovoltaic power generation prediction, Mr.Li proposed a photovoltaic pow-er generation power prediction model based on TDE-SO-AWM-GRU [3], Mr.Qiu proposed a photovoltaic power generation prediction model based on variational mode decomposition and ensemble learning [4], Mr.Li proposed a short-term photovoltaic power prediction model based on similar daily clustering and PCC-VMD-SSA-KELM model [5], and many scholars pro-posed prediction models with different methods. A PV power combination prediction model using time-varying data augmentation and snake optimization algorithm to optimize the adaptive weighted gated recirculating unit proposed by Mr.LI improves the accuracy by 5.89% and 6.12% in stable and abrupt weather, respectively. The model proposed by Mr.Qiu can improve the accuracy and stability of photovoltaic power generation prediction, and has a faster calculation speed. Looking at the prediction model of Mr.Li, the prediction results are also stable. In order to delicately characterize the uncertainty of photovoltaic output, a new two-modal weather classification method based on photovoltaic power clustering is proposed [6].

In this paper, we will further explore the key technologies and methods of PV fore-casting on the basis of previous research. The aim is to improve the accuracy of PV predic-tion by combining LSTM-

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CNN neural network with LSTM convolutional neural network and CNN long short-term memory neural network. Firstly, the advantages and disadvantages of convolutional neural networks and long short-term memory neural networks and their ap-plicability are understood from multiple aspects, and then a new neural network is con-structed through combination to improve the accuracy of photovoltaic prediction. At the same time, this paper will also focus on the challenges and solutions of PV forecasting in practical applications, in order to provide strong support for the sustainable development of the PV industry.

In summary, photovoltaic forecasting, as an important research direction of the photovol-taic industry, has important theoretical and practical significance.

On the basis of previous research, this paper will conduct in-depth research and analysis on the accuracy of the current photovoltaic prediction field, and strive to provide useful reference and reference for the research and practice in related fields.

2. Basic Theory

2.1 CNN Convolutional Neural Networks

As an advanced deep learning algorithm, Convolutional Neural Network (CNN) has attracted wide attention due to its outstanding performance in the field of image processing. CNN gradually extracts hierarchical features in images through hierarchical structure to achieve low-level to high-level feature representation, which is widely used in image classification, object detection, image segmentation and other tasks. The basic structure of a CNN includes multiple parts, including an input layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer [7]. Convolutional layer is the core module of CNN, and its main function is to extract local features from input data through a set of learnable convolutional kernels (filters). These convolution kernels slide over the input data to obtain feature maps through convolution operations, thereby achieving feature extraction and data dimensionality reduction. The introduction of convolutional layers significantly reduces the model parameters and reduces the computational complexity. In addition, the application of activation functions (such as ReLU, Sigmoid, and Tanh) introduces nonlinearity after convolution operations, which enhances the expressiveness of the model and allows the network to fit more complex patterns and data distributions. The pooled layer usually follows the convolutional layer, and its function is to reduce the spatial size of the feature map through downsampling operation, thereby reducing the number of parameters and computational burden, enhancing the robustness of the model, and preventing overfitting. Common pooling operations include maximum pooling and average pooling, which extract the maximum and average values in a local area as output, respectively. The fully connected layer is located in the last few layers of the CNN, which is responsible for flattening the feature map extracted from the previous layers into one-dimensional vectors, and completing the final classification or regression task through a series of fully connected operations. In the fully connected layer, each neuron is connected to all the neurons of the previous layer, forming a dense connection structure, which enables the synthesis and decision-making of high-level features. The structure of the entire CNN model is shown in Figure 1.The design of CNN also makes use of sparse joining and weight sharing mechanism, so that each convolutional kernel is only connected to the local region of the input data, which significantly reduces the number of parameters, and the same convolutional kernel shares weights in different positions, which further improves the training efficiency of the model. These features make CNNs excellent when working with large-scale image data, and can complete complex feature extraction and classification tasks in a relatively short time.

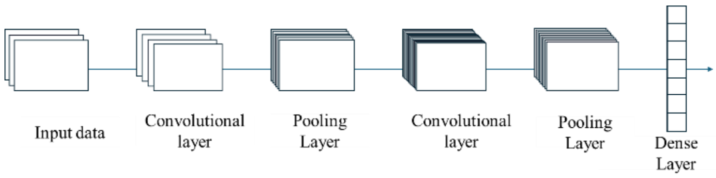

Figure 1: Diagram of CNN Architecture

2.2 LSTM long-term and short-time memory neural network

Long Short-Term Memory (LSTM) neural network is a special type of recurrent neural network (RNN), which is specially designed to overcome the gradient vanishing and gradient explosion problems

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faced by traditional RNNs when processing long sequence data. LSTMs excel when working with time series data by introducing a sophisticated gating mechanism that effectively captures and preserves long-term dependencies in series data. The basic unit of an LSTM neural network is called a cell, which contains a "gate" structure that controls the flow of information. The structure of the cell is shown in Figure 2. The core components of an LSTM network are its unique memory unit and gating mechanism. Each LSTM unit consists of three key gates: an input gate, an oblivion gate, and an output gate. Together, these gates control the transmission and storage of information in the network [8]. The input gate determines the importance of the current input information and selectively writes it to the memory cell; The Forgetting Gate is responsible for sifting through and forgetting unnecessary old information, freeing up storage space and keeping memories dynamically updated; Based on the current memory state and input, the output gate determines which information will be output to the next time step. This design enables the LSTM to flexibly adjust the retention and transfer of information when processing sequence data, which significantly enhances the network's ability to model long-term dependencies. Although LSTMs exhibit strong performance when processing long series of data, their computational complexity and number of parameters increase accordingly. The complex structure of each LSTM unit requires more computing resources for its training and inference process, so in practical applications, it is necessary to select the appropriate model structure and parameter settings according to the requirements of specific tasks and data characteristics to achieve a balance between performance and efficiency. LSTM has a wide range of applications, especially for processing all kinds of data with time series characteristics, such as speech recognition, machine translation, time series prediction, and natural language processing. By flexibly adjusting the gating mechanism, LSTM can effectively capture complex time series relationships in data and provide accurate prediction and classification results. The following picture shows the unit structure of the LSTM long-term and short-time memory neural network.

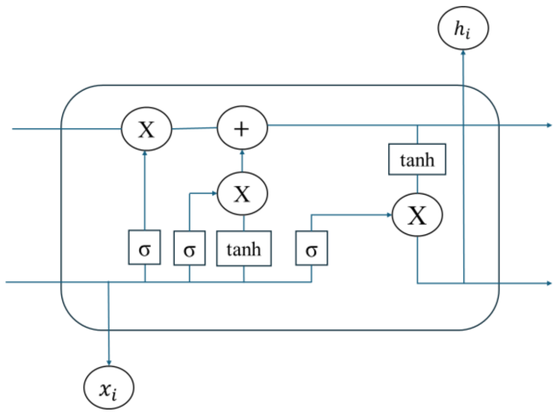

Figure 2: Neural Unit for LSTM

2.3 CNN-LSTM combinatorial neural network

The CNN-LSTM model is an advanced deep learning model that combines convolutional neural network (CNN) and long short-term memory (LSTM), which is designed to process complex spatiotemporal data. The model makes full use of the advantages of CNN and LSTM in their respective fields to realize the joint modeling of spatial and temporal information [9]. In the CNN-LSTM model, the CNN is first responsible for capturing the spatial local features of the input data. Through a series of convolutional layer and pooling layer operations, CNNs are able to extract important features from the input data, such as edges, textures, and shapes. These features can not only effectively represent the spatial structure of the original data, but also reduce the dimension of the data and reduce the complexity of subsequent processing. Specifically, the convolutional layer calculates local features through the sliding of the convolution kernel, while the pooling layer reduces the size of the feature map through downsampling operations while retaining key information, thereby enhancing the effectiveness of feature extraction. The extracted spatial features are then fed into the LSTM section for further processing. At the heart of LSTM is its unique gating mechanism, including input, forget, and output gates, which allows LSTM to effectively capture long-term dependencies in sequence data. The input gate controls the degree to which new information is introduced, determining which new inputs will be added to the current memory unit; The forgetting gate is responsible for sifting through and forgetting unnecessary old information, so as to dynamically update the memory state; Based on the current state of memory and input, the output gate determines which information will be passed on to the next moment. This design allows the LSTM to flexibly adjust the retention and transfer of information when processing sequence

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data, so as to effectively capture complex time series relationships. The structure of the entire CNN-LSTM model is shown in Figure 3.The combination of CNN and LSTM enables the CNN-LSTM model to process spatial and temporal information at the same time, and realizes efficient modeling of complex spatiotemporal data. CNN is responsible for extracting rich spatial features from the input data, while LSTM is responsible for modeling and predicting these features in the time dimension. This organic combination of spatial and temporal features makes the CNN-LSTM model have significant advantages when processing complex time series data, and can achieve higher accuracy and better generalization ability.

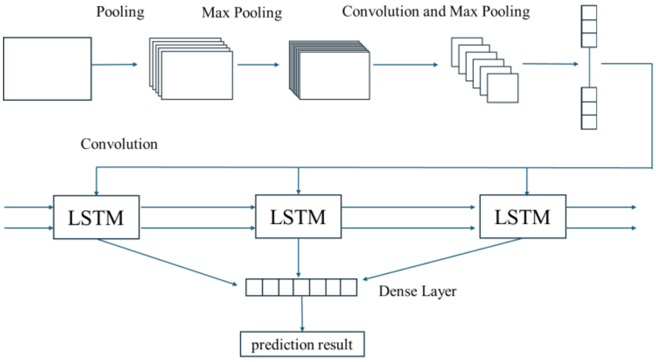

Figure 3: CNN-LSTM Combination Model

3. Model establishment

3.1 Data Processing

In this paper, photovoltaic power stations in a certain region are selected as prediction samples to verify the accuracy of the proposed CNN-LSTM model in photovoltaic power generation prediction. The study period was from January to December 2018, during which the meteorological data were averaged at 10-minute sampling intervals and entered into the meteorological database at 2-minute intervals. All data is used as a training set, except for the required test day data. In the process of data preprocessing, the statistical method Z-score is used to detect anomalies in the abnormal data in the dataset. Specifically, the Z-score value of each data point is calculated, and whether it is abnormal data is judged according to the set threshold. For the detected abnormal data, the adjacent non-abnormal data is replaced and supplemented, that is, the values of the previous and next non-abnormal data are used to fill in. For the processing of missing data, the interpolation method is used for filling. The interpolation method uses the relationship between known data points to deduce the reasonable value of the missing data, so as to ensure the integrity and continuity of the data set. In this way, the processed dataset can provide reliable data support for subsequent model training and prediction. Through the above data processing and model training steps, this study aims to evaluate the performance and accuracy of the proposed CNN-LSTM model in photovoltaic power generation prediction, and explore its feasibility and superiority in practical application.

3.2 Normalization

In view of the fact that photovoltaic power generation data is affected by many factors, there may be significant differences in the value range of different features, which may lead to the difficulty of convergence of the model during the training process, or lead to the extension of the training time. To solve this problem, we use the following formula to normalize the data to reduce the impact of anomalous data on the accuracy of the neural network model.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x' is the normalized feature; x is the actual feature; x_{max} and $x_{\min}$ are the maximum and minimum values of x respectively.

With the above normalization formula, we scale the feature data to the interval range of ([0,1]) to ensure that different features have the same scale. In the process of practical application, normalization can not only accelerate the convergence of the model, but also improve the stability and prediction

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accuracy of the model. Specifically, the normalized data can eliminate the adverse effects of magnitude differences between different features, so that the model can learn the relationship between features more effectively, thereby improving the overall performance.

3.3 Construct a CNN-LSTM neural network model

The CNN layer is designed primarily for extracting spatial features from images. A typical CNN layer consists of convolution operations, activation functions, and pooling operations. The mathematical expression for the convolution operation is as follows:

$$S(t) = (I * K)(t) = a = \sum_{a=-\infty}^{\infty} I(a)\, K(t-a) \tag{2}$$

I is the input image, K is the convolution kernel, S is the convoluted feature map, t is the current position, and a is the input image position covered by the convolution kernel.

Through convolution operations, CNNs are able to extract local features in an image, such as edges, corners, and textures. Activation functions, such as ReLU, introduce nonlinearity, allowing the model to learn more complex features. Pooling operations, such as maximum or average pooling, are used to reduce the size and computational complexity of feature maps while preserving the most important features.

After the spatial features are extracted, the LSTM layer is constructed to process the feature sequences extracted from the CNN. The LSTM layer is designed to handle timing data, and at its core lies the gating mechanism, including the input, forget, and output gates. The following is a formula for the status of these gates and LSTM cells:

$$\text{Input Gate:} i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \tag{3}$$

$$\text{Forget Gate:} f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \tag{4}$$

$$\text{Cell State:} \widetilde{C_t} = \tan h(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \tag{5}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t} \tag{6}$$

$$\text{Output Gate:} o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \tag{7}$$

$$h_t = o_t \odot \tan h\,(C_t) \tag{8}$$

x_t is the input of the current moment, h_{t-1} is the output of the previous moment, C_t is the state of the LSTM unit, i_t, f_t , o_t are the outputs of the input, forget, and output gates, respectively, σ is the sigmoid function, $\odot$ represents the multiplication of elements bit by bit, and W and b are the learnable weights and biases [10].

Through these gating mechanisms, the LSTM can effectively control the flow of information, maintain long-term memory, adapt to complex timing features, and finally connect the CNN layer and the LSTM layer. Flatten the last feature map of the CNN layer or perform other appropriate transformations to match the input requirements of the LSTM layer. Then, the output of the CNN is taken as the input of the LSTM.

Connecting the CNN layer with the LSTM layer allows you to take full advantage of the advantages of both. Flatten the last feature map of the CNN layer and perform other appropriate transformations to match the input requirements of the LSTM layer. The output of the CNN is then used as the input of the LSTM. Through this connection, the model can achieve a seamless transition between spatial feature extraction and time series information processing, thereby improving the prediction accuracy of photovoltaic power generation. The application of hybrid models combining CNN and LSTM in photovoltaic power generation forecasting can not only capture the spatial features in image data, but also deal with dynamic changes in time series data. This method has high predictive and generalizable capabilities, and can provide accurate and reliable prediction results in the volatile photovoltaic power generation environment, which in turn provides strong support for the management and optimization of smart grids.

4. Simulation results and analysis

When constructing a CNN-LSTM model, it is necessary to consider the model structure, the number of hidden layers, the number of training units, the optimization algorithm, and the error function. In this

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paper, the ambient temperature and irradiance, battery power, photovoltaic module temperature and voltage are taken as input variables, the hidden layer is the most important component of the model, the data of the input person is completed in the hidden layer, and the output layer is to obtain the prediction result of the model output, that is, the predicted value of photovoltaic power generation. When constructing a CNN-LSTM model, many key factors need to be considered, including the overall structure of the model, the number of hidden layers, the number of training units in each layer, the selection of optimization algorithms, and the setting of error functions. Each choice has a significant impact on the model's performance and ultimately the predictions. In this study, the input layer of the combined model first performs preliminary processing of the input data to ensure that the data format and scale are suitable for subsequent model training and prediction. Specifically, the ambient temperature, irradiance, battery power, temperature of the photovoltaic module, and its voltage are selected as input variables. These variables are the key factors affecting photovoltaic power generation, and through deep learning of these data, the accuracy of photovoltaic power generation prediction can be effectively improved. The hidden layer is the most core part of the model structure, and its main function is to gradually transform the input data into a feature representation with a high degree of abstraction and discriminant power through multi-level calculation and feature extraction. In the classical CNN-LSTM model, the convolutional layer (CNN layer) is responsible for extracting the spatial features of the input data, while the long short-term memory network layer (LSTM layer) is used to capture the time series features in the time series data. The advantage of this structure is that it can process multi-dimensional data and time series data at the same time, thus providing a richer information base for forecasting tasks. The data after a series of nonlinear transformations in the hidden layer is summarized and processed in the output layer, and the result of the output layer is the final predicted value of the model. In this study, the task of the output layer is to generate a forecast value of photovoltaic power generation, which is the result of complex calculations based on input variables.

In this paper, python3.11 is used to construct the CNN-LSTM neural network, and five groups of influencing factors are inputted: ambient temperature, irradiance, battery power, photovoltaic module temperature and voltage, and the data of five columns of influencing factors are input into the convolutional layer without setting a sliding window when training the model and prediction, and the feature map obtained by the convolutional layer is input to the maximum pooling layer for pooling operation, and the feature matrix with a size of 5×1 is obtained. The pooled feature matrix is input to the LSTM layer for time series modeling and prediction. The LSTM level has two hidden levels, the first containing 32 units and the second containing 64 units. The LSTM processes the time series data through the input gate, the forgetting gate and the output gate mechanism, and the eigenvector output of the LSTM layer is input to the fully connected layer for the final photovoltaic power generation prediction. There are 10 nodes in the fully connected layer. For the number of convolution kernels in CNN is 64, the size of the convolution kernel is 3×3, and the step size of the convolution kernel is 1, and the convolutional layer extracts the local features of the input data through the convolution operation. During the training process, the maximum number of iterations is set to 1000 times, and the initial learning rate is 0.01. The Adam (Adaptive Moment Estimation) is selected for the optimization algorithm, the Mean Squared Error (MSE) is selected for the error function to minimize the gap between the predicted value and the actual value, and the reference value and default value are used for the rest of the parameters.

After the CNN-LSTM modeling is completed, the data and model are put into the program, and the results are shown in the Figure below.

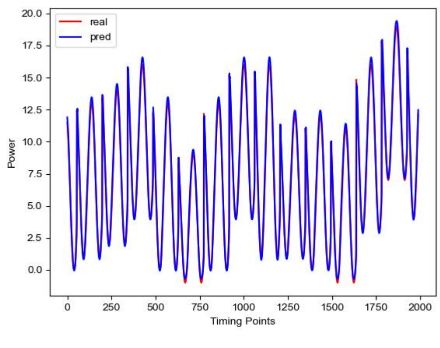

Figure 4: Prediction results of CNN-LSTM neural network model

As can be seen from the Figure 4, the CNN-LSTM neural network model has excellent performance

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in the prediction of photovoltaic power generation and has high prediction accuracy. By comparing the original data and the forecast data, it can be clearly seen that the predicted value of the CNN-LSTM model is very close to the actual data, which indicates that the model can effectively capture the change trend of photovoltaic power generation and make accurate predictions. The CNN-LSTM model makes full use of the spatial feature extraction ability of Convolutional Neural Network (CNN) and the temporal feature capture ability of Long Short-Term Memory Network (LSTM) when processing complex photovoltaic power generation data. The CNN layer is able to identify local patterns and important features in the input data, while the LSTM layer is able to handle long-term dependencies in the time series data. This combination makes the CNN-LSTM model show strong adaptability and prediction accuracy in the face of the multi-dimensional and time-series characteristics of photovoltaic power generation data.

In order to comprehensively evaluate the performance of the CNN-LSTM model in the prediction task, the results and variance of each model were calculated by comparing the single LSTM model, the CNN model and the common BP model [11]. The results of the evaluation indicators of each model are shown in the table.

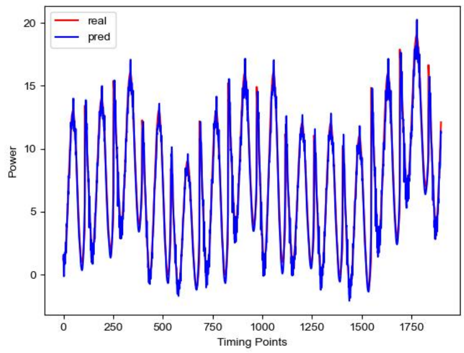

Figure 5: BP neural network prediction results

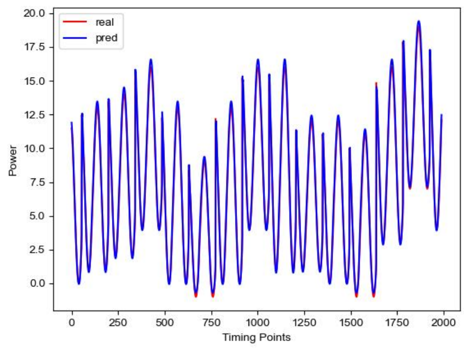

Figure 6: LSTM prediction results

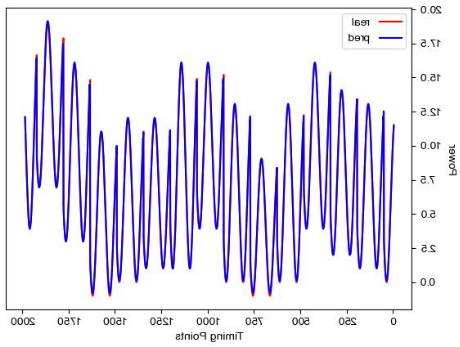

Figure 7: The results of CNN predictions

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Table 1: RMSE of each model

Models	RMSE	R^2
CNN-LSTM	0.438	0.978
BP	1.014	0.914
LSTM	0.795	0.911
CNN	0.774	0.937

As can be seen from the Figures 5-7, the prediction results of the CNN or LSTM model fluctuate up and down compared to the data of the prototype monitoring data. However, with the passage of time and the prediction time, the gap between the predicted value and the prototype monitoring value gradually widened. This phenomenon reveals the possible limitations of single models in dealing with long-term series predictions, as they may not be able to effectively memorize and utilize earlier data information. However, the CNN-LSTM model, with its unique structural design, is able to memorize longer time series information and dig deeper into the intrinsic correlation between data sets. This capability enables the CNN-LSTM model to make full use of historical data in the prediction process and improve the accuracy of prediction. This proves that the CNN-LSTM model can memorize longer time series and mine the correlation between data sets, which significantly improves the accuracy of its power generation prediction. As shown in Table 1, the comparison and analysis of the prediction accuracy evaluation index RMSE of several models shows that the CNN-LSTM model has lower RMSE and higher prediction accuracy than the single LSTM, CNN model and BP model. According to the prediction results, the CNN-LSTM model can accurately track the changes of the actual data during the peak and trough periods of photovoltaic power generation, showing high stability and high efficiency. Compared with traditional single models, such as models that only use LSTM or CNN, CNN-LSTM models are more efficient and accurate when dealing with nonlinear and non-stationary data. In this view, the CNN-LSTM model greatly improves the prediction accuracy of photovoltaic power generation and verifies its applicability in photovoltaic power generation prediction.

5. Conclusion

In order to significantly improve the accuracy of the prediction model for photovoltaic power generation, this paper deeply explores and proposes an advanced combined prediction model that integrates Convolutional Neural Network (CNN) and Deep Learning Long Short-Term Memory Network (LSTM), namely the CNN-LSTM model. The model cleverly combines the respective advantages of CNN and LSTM, and brings a new breakthrough in the field of photovoltaic power generation prediction by using the spatial feature extraction ability of CNN in image recognition and the time-dependent learning ability of LSTM in sequence data processing. In the construction of the model, we took into account a number of key factors, including variables such as ambient temperature, irradiance, battery power, PV module temperature, and voltage, which are critical to the impact of PV power generation. In order to fully capture the dynamic changes in the process of photovoltaic power generation, we have carried out preprocessing operations such as standardization of these input data, aiming to improve the quality of the data, enhance the stability of the model, and promote the convergence speed of the training process. After the preprocessing was completed, we built and trained the CNN-LSTM model. During the training of the model, the model gradually adjusts the parameters by learning a large amount of historical data to continuously optimize its prediction performance. The experimental results show that the CNN-LSTM model shows excellent performance in the prediction of photovoltaic power generation. Specifically, compared with the single LSTM model and CNN model, the combined model not only has higher prediction accuracy, but also shows better adaptability and robustness in dealing with the complexity and variability in the process of photovoltaic power generation. The convolutional layer of CNN can effectively extract the local spatial features in the input data and identify the important patterns in the photovoltaic power generation data, which are difficult to capture by a simple time series model. The LSTM layer is able to handle the time dependencies in the sequence data and capture the long-term dependencies and trend changes in the PV generation data. Through this combination of spatial characteristics and time dependence, the CNN-LSTM model can more comprehensively understand the change law of photovoltaic power generation, so as to improve the accuracy of prediction. In addition, our experimental results further show that the CNN-LSTM model can provide high-precision prediction results in a variety of different photovoltaic power generation scenarios. Whether it is sunny or cloudy, whether it is the peak or trough period of photovoltaic power generation, the CNN-LSTM model shows excellent stability and adaptability. This achievement not only proves the applicability and reliability of the model, but also provides new ideas and methods for future research on photovoltaic power generation prediction.

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The CNN-LSTM combined prediction model proposed in this paper shows significant advantages in the field of photovoltaic power generation prediction. By combining the powerful functions of CNN and LSTM, the model performs well in handling complex and changeable photovoltaic power generation data, and provides strong technical support for the optimization and management of photovoltaic power generation systems. Looking ahead, further research and optimization are expected to enable the model to play a greater role in the field of smart grids and renewable energy, and promote the development and popularization of photovoltaic power generation technology. Overall, the CNN-LSTM model brings new possibilities for PV power generation prediction, and its efficiency and accuracy will provide a solid foundation for continuous innovation in the PV power generation industry.

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