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Photovoltaic power forecasting based LSTM-Convolutional Network

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ABSTRACT

The volatile and intermittent nature of solar energy itself presents a significant challenge in integrating it into existing energy systems. Accurate photovoltaic power prediction plays an important role in solving this problem. With the development of deep learning, more and more scholars have applied the deep learning model to time series prediction and achieved very good results. In this paper, a hybrid deep learning model (LSTM-Convolutional Network) is proposed and applied to photovoltaic power prediction. In the proposed hybrid prediction model, the temporal features of the data are extracted first by the long-short term memory network, and then the spatial features of the data are extracted by the convolutional neural network model. In order to show the superior performance of the proposed hybrid prediction model, the prediction results of the hybrid model are compared with those of the single model (long-short term memory network, convolutional neural network) and the hybrid network (Convolutional-LSTM Network) model, and the results of eight error evaluation indexes are given. The results show that the hybrid prediction model has better prediction effect than the single prediction model, and the proposed hybrid model (extract the temporal characteristics of data first, and then extract the spatial characteristics of data) is better than Convolutional-LSTM Network (extract the spatial characteristics of data first, and then extract the temporal characteristics of data).

1. Introduction

As one of the options for humans to solve the fossil fuel problem, renewable energy (RE) will be an important part of the future energy structure. Solar power generation, especially photovoltaic (PV) power generation, plays an important role in RE power generation. In accordance with the Global Future Report 2013 REN21, global solar photovoltaic (PV) power generation capacity may reach 8000 GW by 2050 [1]. However, the volatility and intermittent nature of photovoltaic power generation poses a huge challenge to concentrating it into existing energy systems. Accurate PV prediction is a good way to solve these problems [2].

The PV power forecasting methods are mainly divided into three categories: physical models, statistical models, and machine learning models. The physical model mainly depends on the interaction between the laws of physics and solar radiation in the atmosphere [3]. It consists of three sub-models: numerical weather prediction (NWP) [4], total-sky image (TSI) [5] and satellite image [6]. In the statistical model, five sub-models are included: fuzzy theory [7], grey theory [8], Markov chain (MC) [9], autoregressive (AR) [10] and regression model [11]. These statistical models rely primarily on historical data to obtain the ability to predict future time series. Machine learning, also known as artificial intelligence (AI) models, has the ability to efficiently extract high-dimensional complex nonlinear features and the ability to map directly from input to output [12]. In the machine learning model, there are three sub-models: support vector machine [13], decision tree [14], and artificial neural network (ANN) [15]. Among them, the ANN model is one of the most commonly used methods for predicting time series at present [16,17].

In the early stage of ANN forecasting, people used shallow neural networks and achieved good results. Almonacid F [18] used an ANN model (the multi-layer perceptron (MLP)network developed by the Hahn University Solar and Automated Energy R&D team) to estimate the power generation of PV generators and compared with traditional methods. The results showed that the ANN forecasting model achieved better results than the traditional classical model. Dahmani K [19] applied a forward-propagating MLP to global solar radiation prediction at a certain tilt angle of a short time step (5 min), achieving an average RMSE value of 8.81%, which is a good effect for the short-time step. Lolli F [20] proposed a new neural network (extreme learning machine) for predicting

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intermittent demand. Although its network model is easier to implement, the prediction results are not as good as the back propagation (BP) algorithm. Although the above studies have achieved better results, only one hidden layer has been selected in the structure of the neural network model, and the features contained in the data may not be completely extracted. The reason why only one hidden layer is selected is that for these shallow networks, due to the particularity of the training algorithm, too many hidden layers may cause difficulty in training the neural network, and it is prone to problems such as over-fitting, falling into local minimum value and gradient disappearance [21].

To this end, people have conducted research for more than a decade. Until the introduction of the Deep Belief Network (DBN) [22] in 2006, the deep networks gradually emerged. The DBN network effectively mitigates the two techniques of pre-training and fune-tuning. The problems of training difficulties and gradient disappearance caused by the shallow neural network algorithm are alleviated, and the neural network has been rapidly developed. In the 2012 ImageNet competition, Alex Krizhevsky achieved the first place with a multi-layer convolutional neural network (the classification error rate was only 15%, which was 11% lower than the second place), and since then, deep learning has seen an explosive development [23]. With the continuous improvement of computer hardware and software and big data technology, deep learning networks have been paid attention to and developed, and various deep neural network models have been proposed so far. Current deep neural network models include: deep belief network (DBN) [22], convolutional neural network (CNN) [24], long short-term memory neural network (LSTM) [25], generative adversarial network (GAN) [26], deep residual network (DRN) [27] and so on.

With the rapid development and gradual maturity of deep learning, some scholars have introduced deep neural networks into time series forecasting. In 2014, Takashi Kuremoto [28] first used deep neural networks for time series forecasting. Zhang C Y [29] used the deep belief network to establish a multi-period wind speed forecasting model. The forecasting result is improved by more than 10% compared with other models (such as AR, SVR, etc.), but only wind speed data is used in the input data. Dalto M [30] established an ultra-short-term wind forecasting model based on the deep belief network. The input data also included numerical weather prediction information, and used partial mutual information to reduce the size of the input vector and the parameter complexity of the neural network. The results show that the proposed deep neural network prediction model is better than the shallow neural network. Wan J [31] proposed a DBN-based forecasting method for predicting wind speed. The model forecasting results are also compared with various shallow networks (such as SVR, single hidden layer neural network, multiple hidden layer neural network). The comparison results shows that the DBN-based forecasting model performs better in network performance and prediction accuracy. However, due to the special layer-by-layer training algorithm of the DBN network model, it will lead to excessive training time.

Considering the local connection and global sharing features of convolutional neural networks can greatly reduce the training parameters and training time of the model, some scholars use convolutional neural networks for time series prediction. He W [32] used the CNN model for short-term power load forecasting. The results show that the CNN model is very flexible and can be applied to time series forecasting tasks. Díaz−Vico D [33] used a convolutional neural network for wind energy and solar irradiance prediction, and the input data came from a numerical weather prediction system. The prediction results show the powerful feature extraction ability of the convolutional neural network. However, the convolutional neural network is mainly used for image processing tasks. The input data is mostly 2 dimensional (2D) data, while the time series data is 1D data. If the 1D time series data is directly used as the input of the CNN, it may not be applicable. Therefore, in order to adapt to the input format of the CNN, Wang H [34], Sezer OB [35], Wang H [36] converted the input data format, and converted the1D time series data into 2D time series data by transformation, and then the transformed data is used as input data of the CNN for prediction. In the output, the 2D data is inversely transformed into 1D data and the predicted output result is obtained. Although converting time series data into 2D format can achieve the expected effect, it introduces a data conversion link, which increases the complexity of the model, and when the convolution kernel traverses the converted 2D matrix, it is easy to generate false information and if the conversion is not appropriate, the prediction result may fail or the effect is not good, which affects the prediction accuracy of the model. The LSTM model is a time recurrent neural network, which is more suitable for solving timing problems. Therefore, some scholars have introduced the LSTM model for time series prediction. Qing X [37] selects weather forecast data and meteorological data as the input of the forecast network, and uses the LSTM model to predict the solar irradiance of the day. Compared with the three methods of presistence method, minimum regression and back propagation, the RMSE values are reduced by 63.7%, 66.9% and 42.9%, respectively, and show less overfitting and wider generalization ability. Srivastava S [38] introduced LSTM for global solar irradiance prediction of solar energy, and the input data increased satellite image data at multiple locations. The predictions show that LSTM is superior to a large number of alternatives with significant differences compared to the persistence method model, with an average predictive skill of 52.2%. Although the introduction of LSTM models can omit the data transformation in CNN, LSTM models are not the best choice when considering the accuracy of the model [39]. In order to reduce the complexity of the prediction model and improve the forecasting accuracy of the model, Wang K [40] and Hong YY [41] introduced a 1D CNN for time series prediction such as wind and PV, which not only reduces the complexity of the model, and the accuracy of the predictive model has also improved.

No network is suitable for all tasks, and deep learning is no exception. Therefore, some researchers have begun to improve the deep learning neural network on the structure (such as cross-layer connection) and the model (such as a mixed model of multiple models). The study found that mixing different deep learning network models to form a hybrid network model can not only overcome the shortcomings of a single neural network, but also utilize the advantages of multiple networks for task analysis, and can achieve better effect than a single network [42].

Given the advantages of hybrid models, hybrid models have also been introduced into time series prediction tasks. Wang H [43] proposed an online reliability time series prediction model combining CNN and LSTM to predict the reliability of future service systems. A series of experiments on historical data were carried out and proved the effectiveness of the method by comparing with other methods. Liu H [44] proposed a new hybrid wind speed forecasting model. Wavelet transform is used to separate the raw data into low frequency and high frequency, CNN extracts high frequency information, and LSTM extracts low frequency information. Compared with multiple models (SVM, BP, GRNN, etc.), the robustness and effectiveness of the proposed model in time series are proved, and when the wind speed changes suddenly, the proposed model has better predictive performance than other models. Qin Y [45], hybrid prediction model (CNN-LSTM) was proposed for wind power production as well as constructional load. Among them, the CNN model is used to obtain the spatial features of the wind field, and the LSTM model is used to obtain the dynamic features of the wind field. The results show that the method has an output error of 5% in short-term predictions (interval less than 1 m). Bao J [46] proposed a space-time deep learning model (ConvLSTM) to predict short-term collision risk across the city. The CNN model extracts spatial features, the LSTM model extracts temporal features, and the ConvLSTM model extracts spatiotemporal features. Compared to some machine learning models, the proposed model performs better. Wen C [47] proposed a space-time expansion (C-LSTME) model for predicting air mass concentration. Advanced spatiotemporal features were extracted through the proposed hybrid model. The results show that the model can predict the air quality at different time and space scales more accurately and stably.

However, since scholars have introduced deep neural networks into time series forecasting, most researchers only migrated the deep learning network directly from other fields to the time series forecasting field, including for wind/PV forecasting, without considering how to mine the association between historical data and combine it with neural networks, even for the most promising hybrid networks. Considering this prediction relationship, we tried to explore a hybrid model suitable for PV power prediction data, and carried out a lot of experimental verification. In the experiment, it is found that for the PV power forecast data, the hybrid model can achieve better results than the single model. Moreover, for the PV forecast data, The sequence of extracting the temporal and spatial features of the data have a great influence on the accuracy of the PV forecasting model. Through a large number of experiments, it is found that considering the temporal features of the PV power prediction data firstly and then considering the spatial features of the PV power prediction data can achieve more accurate results.

Therefore, based on the mechanism characteristics of time series data, a new hybrid model of PV power forecasting is proposed in this paper, namely LSTM-CNN model. The main contributions are as follows: 1) A hybrid photovoltaic power forecasting network considering the temporal-spatio feature extraction order is proposed; 2) Considering the PV data features, the temporal features of the data are first extracted (using the LSTM model) and then the spatial features of the data are extracted (using the CNN model); 3) Select the 1D-CNN model to extracting the spatial features, and the data conversion link is eliminated. The complexity of the model is reduced, and the PV power forecasting is greatly facilitated; 4) Compared with other models (CNN, LSTM, CNN-LSTM), which proves the validity of the model.

The main structure of this paper is as follows: Section 2 introduces the proposed hybrid model framework; Section 3 gives the evaluation indexes of this paper. Section 4 shows the case study experimental results; Section 5 gives the conclusion of the paper.

2. Proposed framework

2.1. Temporal feature learning

Long Short-Term Memory (LSTM) is a time recurrent neural network proposed by Hochreiter & Schmidhuber [25] to learn long-term dependence information. Its internal memory unit and gate mechanism overcome the gradient disappearance and gradient explosion problems in traditional recurrent neural network (RNN) training [48]. The gate mechanism includes forget gate, input gate, update gate, and output gate. The core calculation formula of the LSTM model is as follows:

$$f_t = \sigma\left(w_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

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

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

$$c_t = f_t * c_{t-1} + i_t * g_t \tag{4}$$

$$o_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t * tanh(c_t) \tag{6}$$

where f_t, i_t, g_t, o_t are the output value of the forget gate, input gate, update gate, and output gate respectively. The inputs of the four gates include the LSTM output value h_{t-1} at a former time step $t-1$ and the input data x_t at a present time step. The $w_{f,i,g,o}$ and $b_{f,i,g,o}$ are the weight matrices and bias vectors. c_t is the memory cell. σ is the *sigmoid* activation function. In Ref. [49], Alex Graves gave a general introduction to the LSTM model and derived the forward propagation and backpropagation formulas of the LSTM model. Fig. 1 shows the specific information dissemination of LSTM.

2.2. Spatial feature learning

Different from the traditional fully connected neural network, local connection and weight sharing are two major characteristics of convolutional neural networks. Common CNN mainly includes convolutional layer, pooled layer, and fully connected layer. Convolution is the core concept of CNN, which is mainly used to extract local features of images. It is a common mathematical calculation method. In the convolution layer, the feature graph of the previous layer interacts with the convolution kernel to form the output feature graph j of the convolution layer. Each output feature graph j may contain convolution with multiple input feature graphs. The convolution layer is calculated as follows:

$$y_j^{(l)} = \left(\sum_{i \in C_j} t_i^{l-1} \otimes w_{i,j}^{(l)}\right) + b_j^{(l)} \tag{7}$$

$$t_j^l = f\left(y_j^{(l)}\right) \tag{8}$$

where t_j^l is the feature graph of convolution layer l, C_j represents a set of input feature graphs, $b_j^{(l)}$ is the bias, $y_j^{(l)}$ is the output of convolution, and $w_{i,j}^{(l)}$ is the convolution kernel。 f is the activation function. In this paper, Rectified linear unit (Relu) is used as the activation function, and the formula is as follows:

$$f(x) = \max(0, x) \tag{9}$$

Pooling layer, also known as the downsampling layer, mainly reduces the number of parameters by reducing the size of the image, including average pooling and maximum pooling, etc. In this paper, maximum pooling is mainly adopted. Fig. 2 shows the mainly basic structure of CNN and the specific operation process of convolution and pooling. Kernel is the size of the convolution kernel, stride is the step length,* represents the convolution operation.

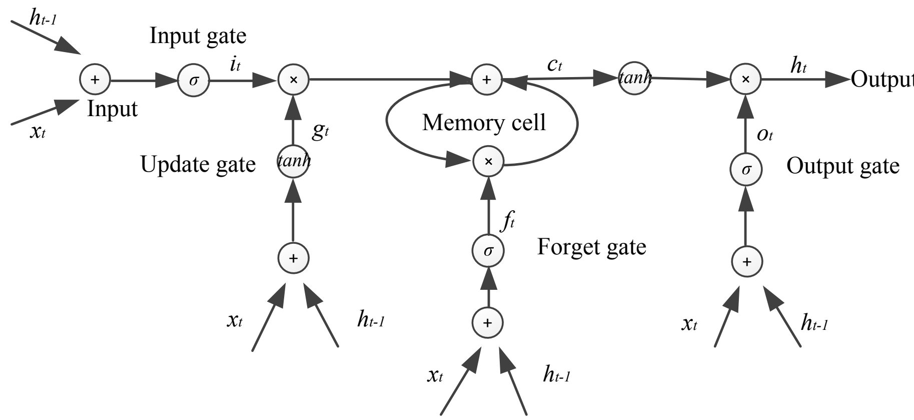

Fig. 1. The specific information dissemination of LSTM.

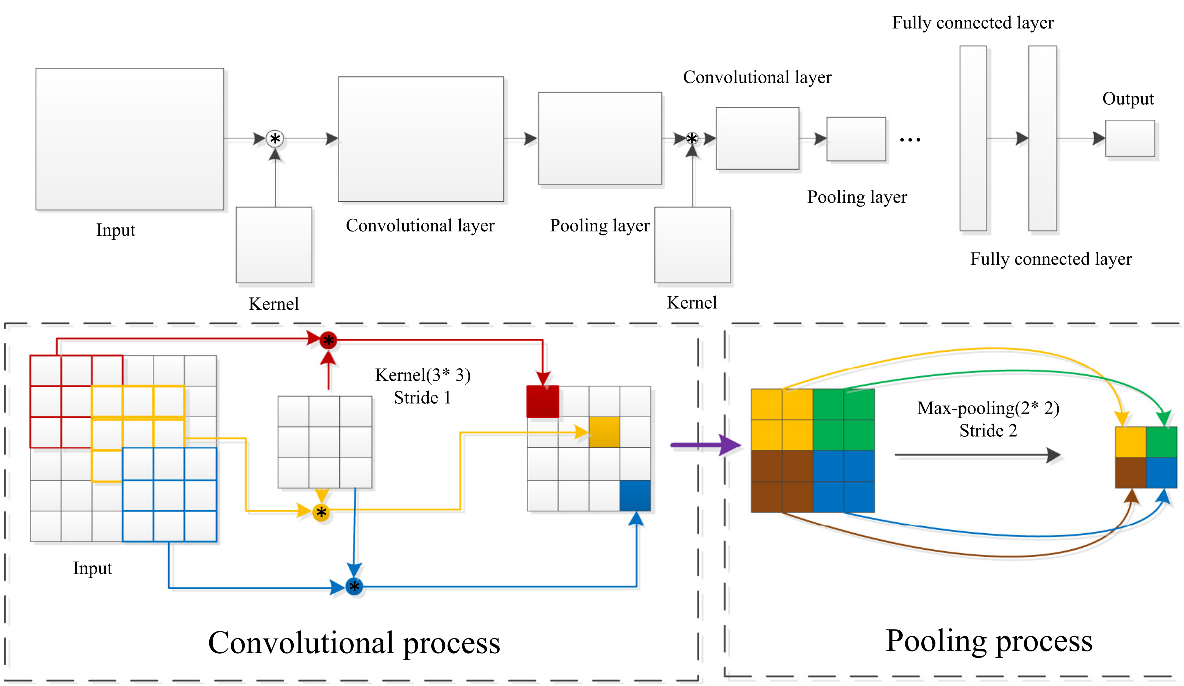

Fig. 2. The basic structure of CNN.

2.3. LSTM-Convolutional Network structure

Hybrid model tend to performs better than a single model [46,50,51]. Therefore, a hybrid PV power forecasting model is proposed in this paper. The LSTM model is used to extract the temporal feature information of the history data, and the CNN is used to extract the spatial feature information of the history data. Fig. 3 shows the structure diagram of the proposed model. It can be seen from Fig. 3 that the obtained historical data is first transmitted to the LSTM model as an input of the LSTM model, and the temporal feature information of the data is acquired by using the advantage of the LSTM model to process the time series data, and then the obtained temporal feature information is used as the input of a convolutional neural network model to extract the spatial feature information of the data, and then get the output result. To prevent model overfitting, the dropout layer is added to the model. Fig. 4 shows the block-diagram for the framework.

3. Evaluation indexes

In this paper, some evaluation indexes are selected to evaluate the model. They are: MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), RMSE (Root Mean Square Error), and SDE (Standard Deviation of Error). The promoting percentages of the MAE (PMAE), MAPE (PMAPE), RMSE (PRMSE) and SDE (PSDE) in Ref. [52] were also selected in this paper to evaluate the performance of the model and can be expressed as follows:

$$\mathrm{MAE} = \frac{\left(\sum_{i=1}^{N} |y(i) - \widehat{y}(i)|\right)}{N} \tag{7}$$

$$\mathrm{MAPE} = \frac{\left(\sum_{i=1}^{N} |y(i) - \widehat{y}(i)/y(i)|\right)}{N} \tag{8}$$

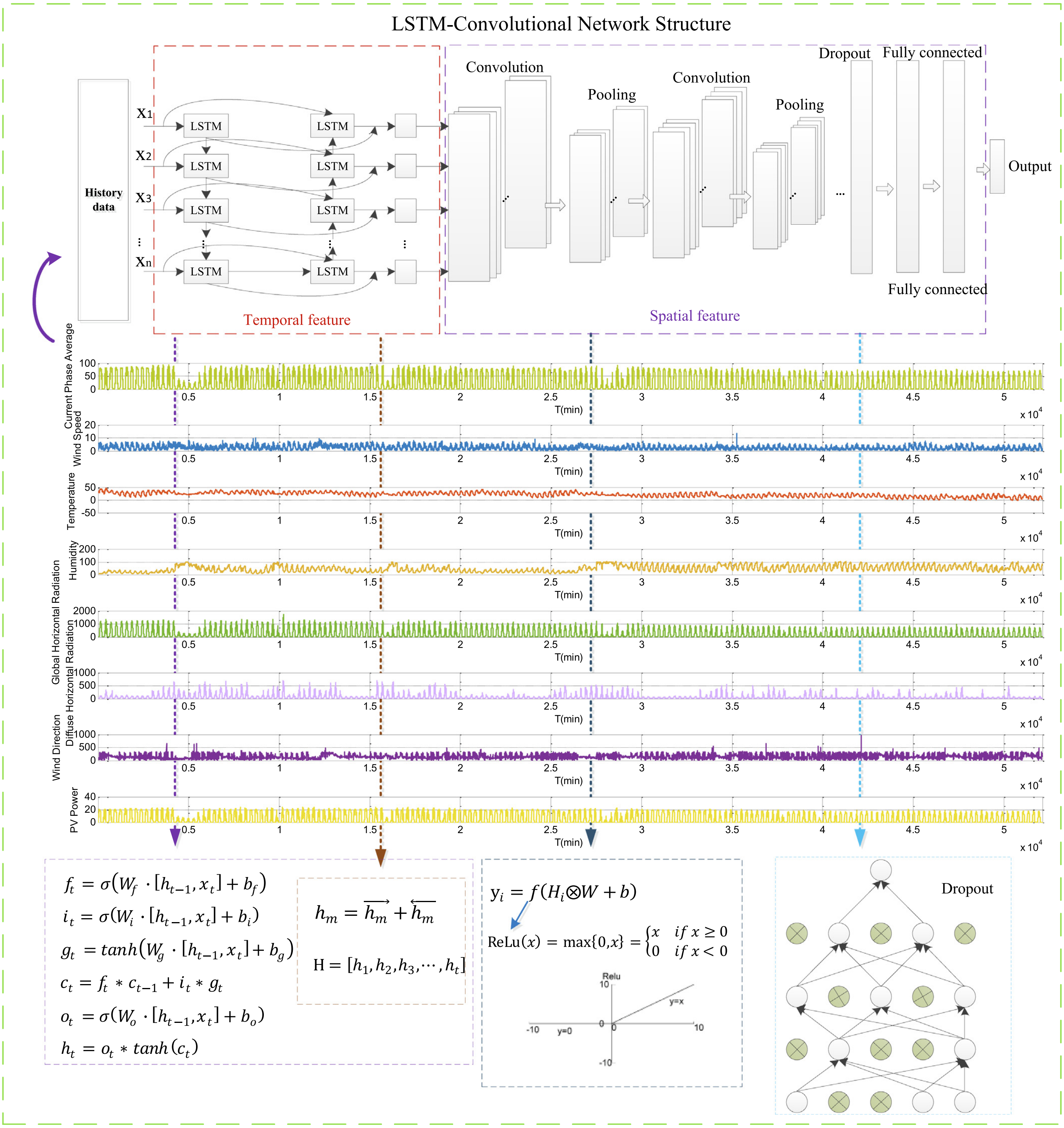

Fig. 3. The LSTM-Convolutional network structure.

$$\text{RMSE} = \sqrt{\frac{\left(\sum_{i=1}^{N}[y(i) - \hat{y}(i)]^2\right)}{N-1}} \tag{9}$$

$$\text{SDE} = \sqrt{\frac{\left(\sum_{i=1}^{N}\left[y(i) - \hat{y}(i) - \sum_{i=1}^{N}(y(i) - \hat{y}(i))\Big/N\right]^2\right)}{N}} \tag{10}$$

$$\text{PMAE} = \left|\frac{MAE_1 - MAE_2}{MAE_1}\right| \tag{11}$$

$$\text{PMAPE} = \left|\frac{MAPE_1 - MAPE_2}{MAPE_1}\right| \tag{12}$$

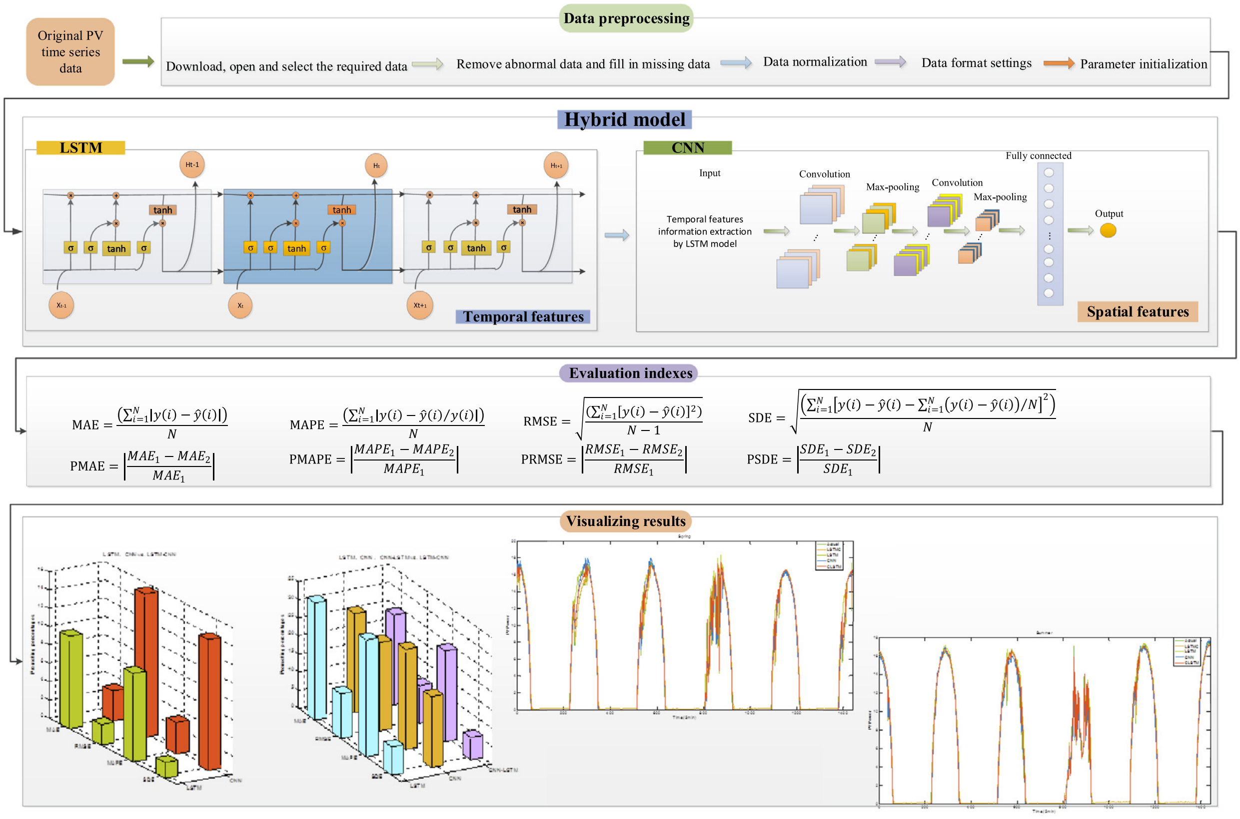

Fig. 4. The block-diagram for the framework.

$$\text{PRMSE} = \left| \frac{RMSE_1 - RMSE_2}{RMSE_1} \right| \tag{13}$$

$$\text{PSDE} = \left| \frac{SDE_1 - SDE_2}{SDE_1} \right| \tag{14}$$

where $y(i)$ is the actual PV power data, $\hat{y}(i)$ is the forecasted data, and N is the number of $y(i)$.

4. Case studied

4.1. Data sets

The 1B DKASC, Alice Springs PV system data is selected for the following research in this paper [53]. The data includes current phase average(A), active power (KW), wind speed (m/s), weather temperature celsius (°C), weather relative humidity (%), global horizontal radiation ($w/m^2 \times sr$), diffuse horizontal radiation ($w/m^2 \times sr$), wind direction (°),etc. The resolution of the data is 5-minues, and half year data (53280samples) is selected in this paper. The history data is divided according to Ref. [54], as shown in Fig. 5.

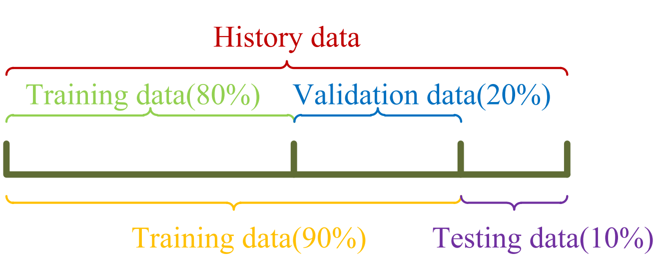

Fig. 5. The specific division of the history data.

4.2. Experimental

The hybrid model (LSTM-CNN) is proposed in this paper for PV power forecasting. The LSTM model in the hybrid model contains two hidden layers, each of which has 64 and 128 neurons. The CNN model in the hybrid model mainly consists of two layers of convolutional layers and two layers of pooling layers. The number of convolution kernels is 64 and 128, respectively and the max-pooling is selected in the pooling layers. There are two layers of fully connected layers in the hybrid model, and the number of neurons is 2048 and 1024, respectively. The specific parameter settings of the model are shown in the following Table 1 and all designed by the trial and error method. In order to demonstrate the good performance of the proposed model, the results obtained by the proposed model are compared with other models (LSTM, CNN, and CNN-LSTM). The parameter settings of each model are the same as the proposed model settings in this paper.

Table 2 shows the results of the different forecasting model. As can be seen from Table 2, among all the models, the prediction effect of the hybrid model (CNN-LSTM, LSTM-CNN) is better than that of the single model (LSTM, CNN). For the CNN-LSTM hybrid model, the MAE value is 0.294, RMSE value is 0.693, MAPE value is 0.056, and SDE value is 0.677. In addition, the prediction effect of LSTM-CNN hybrid model is better than that of CNN-LSTM hybrid model. For the LSTM-CNN hybrid model, the MAE value is 0.221, which is 0.073 lower than that of CNN-LSTM model; RMSE value is

Table 1
The specific parameters settings of the proposed model.

Models	Configuration			
LSTM-CNN	LSTM	Units1	Units1 = 64	Epoch = 100 Batch-size = 600
		Units2	Units2 = 128	
	CNN	Convolution	filters = 64; kernel_size = 3; stride = 1	
		Max-pooling	kernel size = 2; stride = 2	
		Convolution	filters = 128; kernel_size = 3; stride = 1;	
		Max-pooling	kernel size = 2; stride = 2;	
	Dropout	dropout = 0.1		
	Fully connected	neurons = 2048		
	Fully connected	neurons = 1024		

Table 2
The results of the forecasting model.

Models	Results			
	MAE	RMSE	MAPE	SDE
LSTM [37]	0.327	0.709	0.062	0.689
CNN [55]	0.304	0.822	0.058	0.790
CNN-LSTM [40]	0.294	0.693	0.056	0.677
LSTM-CNN	0.221	0.621	0.042	0.635

0.621, which is 0.072 lower than that of CNN-LSTM model; MAPE value is 0.042, which is 0.014 lower than that of CNN-LSTM model; SDE value is 0.635, which is 0.042 lower than that of CNN-LSTM model. For the single model of CNN, the values of MAE and MAPE are smaller than those of LSTM, while the values of SDE and RMSE are larger than those of LSTM.

The comparison of promotion percentages between different models is shown in Table 3. Table 3 shows the promotion percentages between a single model (LSTM, CNN) and different hybrid models (CNN-LSTM, LSTM-CNN) and between the hybrid model (CNN-LSTM) and the hybrid model (LSTM-CNN). It can be seen from Table 1 that: 1) PMAE, PRMSE, PMAPE and PSDE values of LSTM model vs. CNN-LSTM model are 10.092%, 2.257%, 9.677%, 1.742%, respectively; PMAE, PRMSE, PMAPE and PSDE values of LSTM model vs. LSTM-CNN are 32.416%, 12.412%, 32.258%, and 7.837%, respectively; the PMAE, PRMSE, PMAPE, and PSDE values of the CNN model vs. the CNN-LSTM model were 3.289%, 15.693%, 3.448%, and 14.304%, respectively; the PMAE, PRMSE, PMAPE, and PSDE values of the CNN model vs. the LSTM-CNN model were 27.303%, 24.453%, 27.586%, and 19.620%, respectively; therefore, the hybrid model was more accurate than the single model. 2) The PMAE, PRMSE, PMAPE and PSDE values of the CNN-LSTM model vs. the LSTM-CNN model are 24.830%, 10.390%, 25.000%, and 6.204%, respectively; the LSTM-CNN model is more accurate than the CNN-LSTM model. 3) Under the evaluation indicators PMAE and PMAPE, the promotion percentages of the LSTM model compared to the hybrid model (CNN-LSTM, LSTM-CNN) is higher than that of the CNN model, while the evaluation index PRMSE and PSDE, the LSTM model compared to the hybrid model (CNN-LSTM, LSTM-CNN) is lower than the CNN model; different single models can be selected under different evaluation indicators. 4) The LSTM and CNN models are compared with the hybrid models CNN-LSTM and LSTM-CNN respectively. The results show that the hybrid model LSTM-CNN has a higher percentage of promotion, which indicates that LSTM-CNN performs better on PV power forecasting. To more intuitively show the promotion percentages between different models, Fig. 6 gives the histogram of the promotion percentages between the different models.

In order to better show the forecasting results of the proposed model in this paper, Figss. 7–10 shows the PV power forecasting results of different models in different seasons. It can be seen from the figure that the forecasting results of all models have the same trend with the actual values. The hybrid model has a higher similarity, especially the LSTM-CNN model, whose forecasting results is the closest to the actual value.

The simulation process are accomplished in a personal computer in Python3.6, 64 bit operating system, 8.00 GB of RAM, and Intel(R) Core (7M) i5-8400 CPU@2.8GHZ 2.81GHZ and Table 4 shows the operating time (including the training time and running time of the model) of the different model in this paper. As can be seen from Table 4, the training time of the LSTM model is the shortest, which is 70.490s. The training time of the CNN is 787.494s. The training time of the hybrid model is the longest among which the training time of CNN-LSTM is 983.701s and the training time of LSTM-CNN is 871.606s. This is mainly because for the hybrid model, not only the temporal features of the data need to be extracted but also the spatial features of the data need to be extracted, so training time is long, which is understandable. However, when the model training is completed, the running time is greatly reduced. The LSTM model requires 5.439s running time. Although the training time of the CNN model is longer than the LSTM, the running time is actually less than the running time of the LSTM, which is 5.425s. The running time of the hybrid model is also greatly reduced. It only takes 8.692 s s for CNN-LSTM and 7.196s for LSTM-CNN. Although the training time of the mixed model is much longer than that of the single model, with the improvement of the hardware environment, the training time will be correspondingly reduced in the practical application, which is acceptable in the practical application of PV power prediction.

5. Conclusion

In this paper, considering the mechanism characteristics of photovoltaic data, a hybrid photovoltaic power forecasting model, namely LSTM-CNN network model, is proposed. The hybrid model

Table 3
The comparison of promotion percentages between different models.

	LSTM vs. CNN-LSTM	CNN vs. CNN-LSTM	LSTM vs. LSTM-CNN	CNN vs. LSTM-CNN	CNN-LSTM vs. LSTM-CNN
PMAE	10.092%	3.289%	32.416%	27.303%	24.830%
PRMSE	2.257%	15.693%	12.412%	24.453%	10.390%
PMAPE	9.677%	3.448%	32.258%	27.586%	25.000%
PSDE	1.742%	14.304%	7.837%	19.620%	6.204%

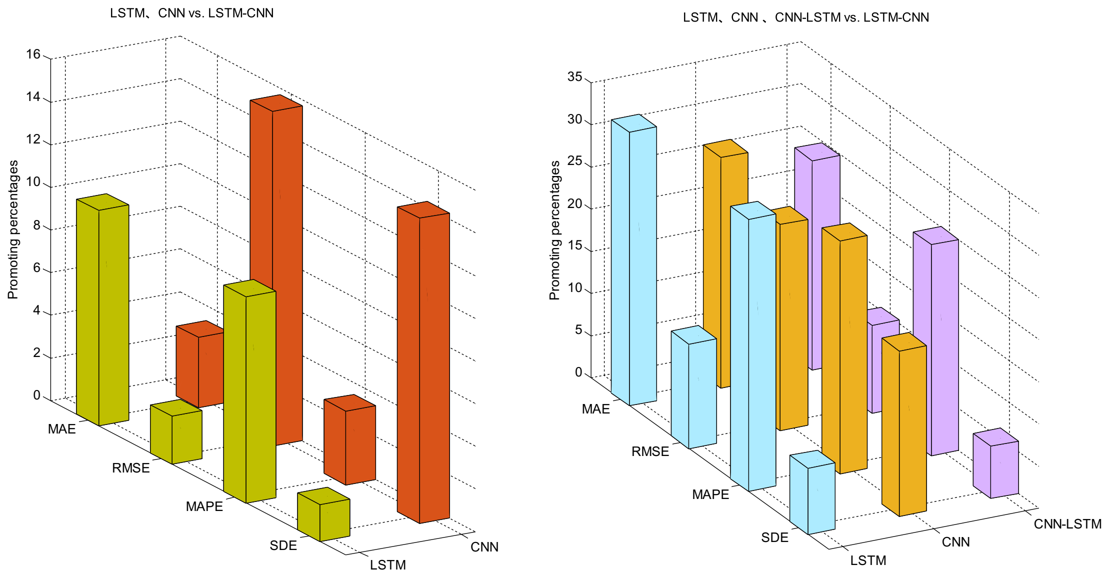

Fig. 6. The histogram of the promotion percentages between the different models.

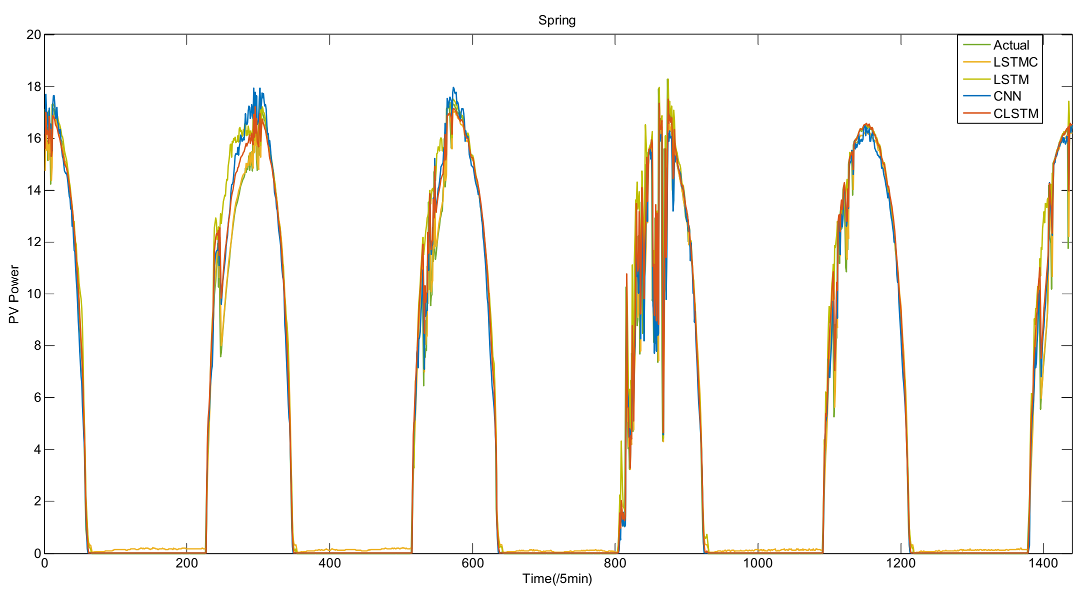

Fig. 7. The forecasting results of the different model and actual PV power in spring in this paper.

is mainly used to extract the temporal-spatio features of the photovoltaic data for photovoltaic power forecasting, wherein the long short-term memory network model is used to extract the temporal features of the photovoltaic data, and the convolutional neural network model is used to extract the spatial features of the photovoltaic data. In order to evaluate the performance of the proposed hybrid model:

First, the forecasting results of the hybrid model (CNN-LSTM, LSTM-CNN) are compared with the forecasting results of a single model (long short-term memory network, convolutional neural network). The results show that the prediction results of the hybrid forecasting model (CNN-LSTM, LSTM-CNN) are better than the forecasting results of the single model (long short-term memory network, convolutional neural network). The PMAE value of the LSTM vs. hybrid model is 10.000%–33.000%, the PRMSE value is 2.000%–13.000%, the PMAPE value is 9.000%–33.000%, and the PSDE value is 1.000%–8.000%. The CNN vs. hybrid model has a PMAE value of 3.000%–28.000%, a PRMSE value of 15.000%–25.000%, a PMAPE value of 3.000%–28.000%, and a PSDE value of 14.000%–20.000%.

Secondly, by comparing the proposed hybrid model (LSTM-CNN) with another hybrid model (CNN-LSTM), it can be find that the model that first extracting the temporal features of the data and then extracting the spatial features of the data is preform better than the model that extracting the spatial features of the data first, and then extracting the temporal features of the data. The values of PMAE, PRMSE, PMAPE and PMAPE of CNN-LSTM vs. LSTM-CNN were 24.830%, 10.390%, 25.000% and 6.204%, respectively. This may be because temporal features dominate the time series.

In the experiment, the training time and running time of the model are also counted. The results show that the training time and running time of the hybrid model are longer than the single model,

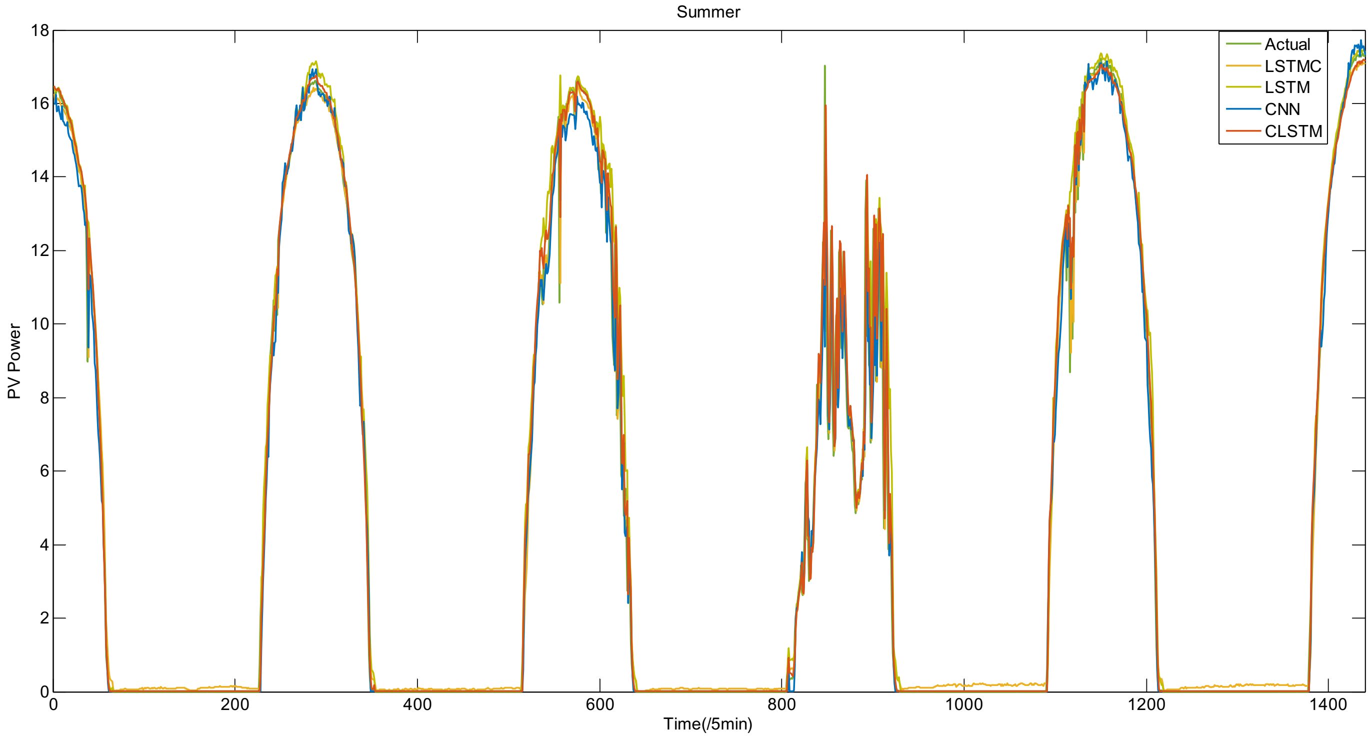

Fig. 8. The forecasting results of the different model and actual PV power in summer in this paper.

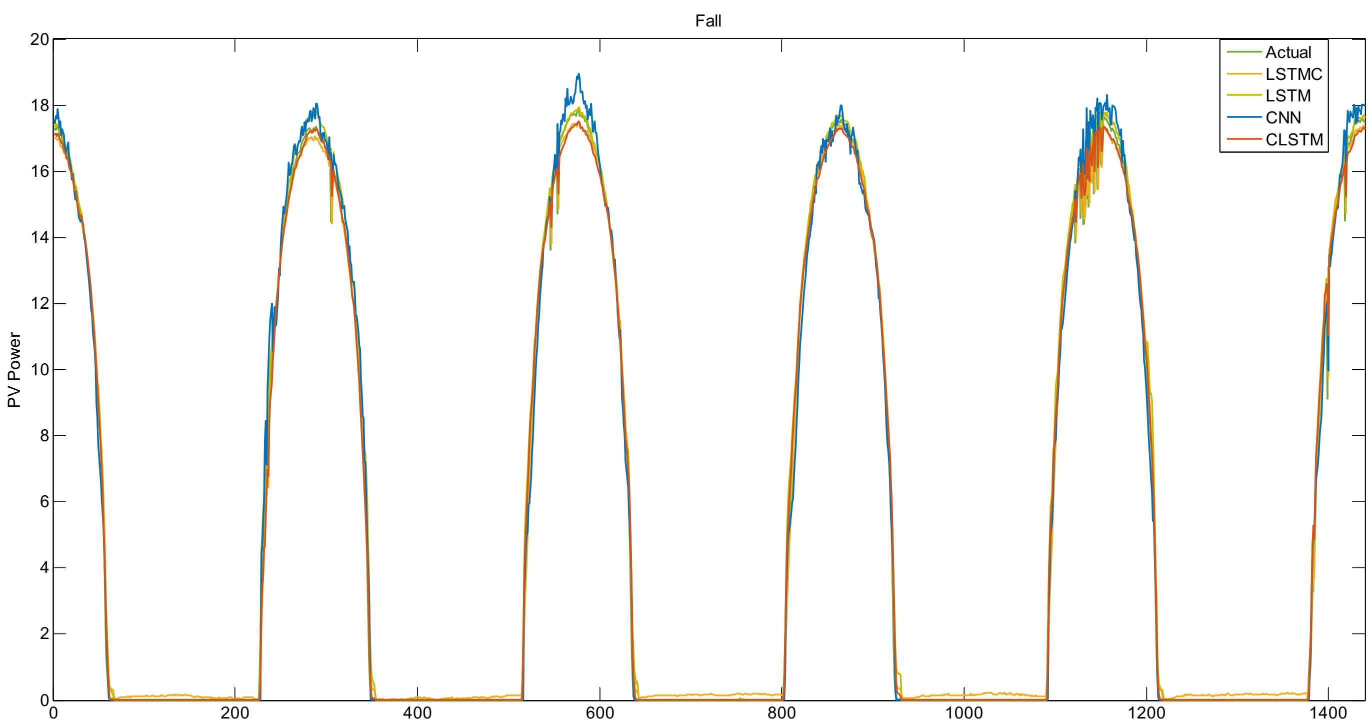

Fig. 9. The forecasting results of the different model and actual PV power in fall in this paper.

and the training time is 1.5–13.5 times of the single model. This is because the hybrid model must extract the dual characteristics (temporal and spatial features) of the data, so the training time is longer than the training time of the single model. However, it is found from the running time of the model that although the running time of the hybrid model is higher than the running time of the single model, the difference between the two is only 2–4 s and the accuracy of the hybrid model is higher than that of the single model. Moreover, with the improvement of hardware and software environment and code optimization, the training time will be

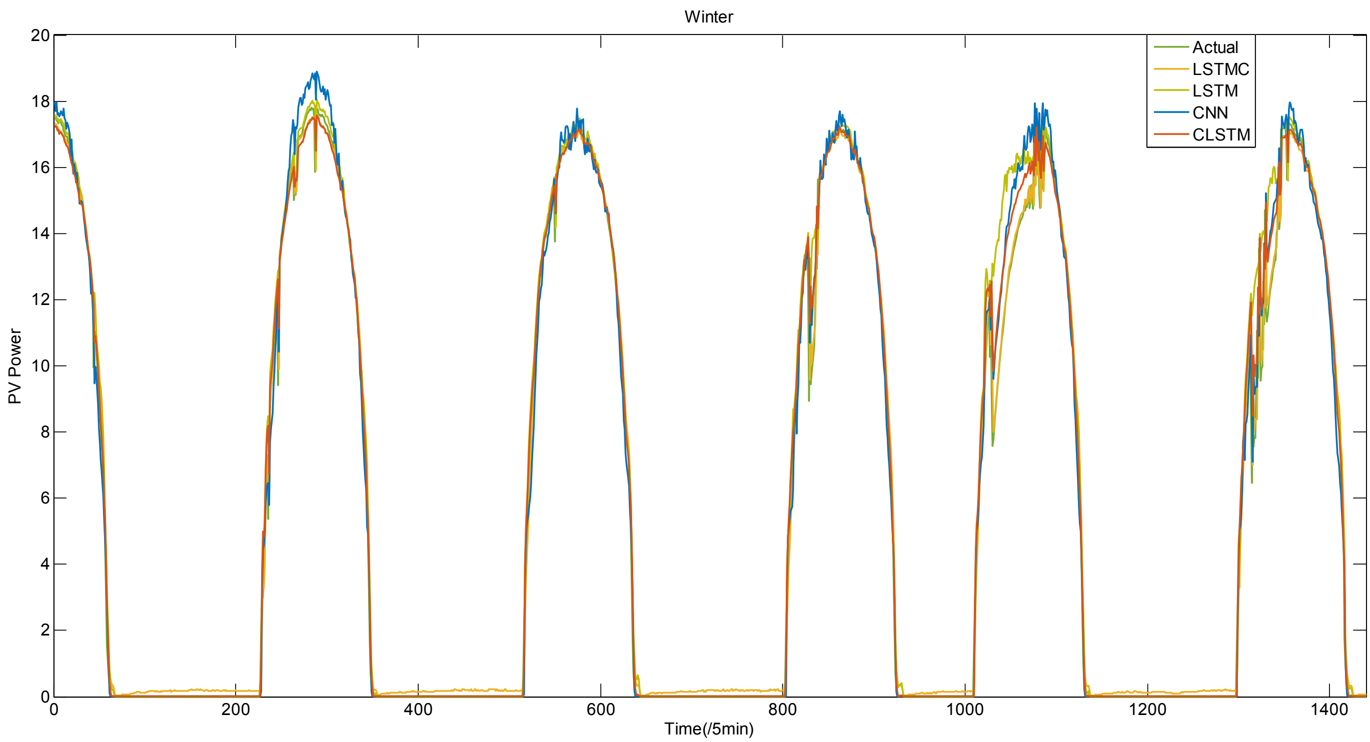

Fig. 10. The forecasting results of the different model and actual PV power in winter in this paper.

Table 4
The operating time of the different model in this paper.

	LSTM	CNN	CNN-LSTM	LSTM-CNN
Training time(s)	70.490	787.494	983.701	871.606
Running time(s)	5.439	5.425	8.692	7.196

greatly reduced, which is very helpful for the prediction of photovoltaic power in practical applications.

In a word, this paper starts from the mechanism characteristics of time series data and considers the influence of the connection mode of hybrid model on the forecasting results. The LSTM-CNN model is proposed for PV power prediction. Using long short-term memory network and convolutional neural network models to extract the temporal and spatial characteristics of historical data to mine the relationship between historical data and combine with neural networks, avoiding the usual practice of simply migrating deep learning models from other fields to the field of time series forecasting. The choice of PV power forecasting model becomes more clear and has important guiding significance for practical engineering applications. The contribution of this work towards the research community is also introduced in the introduction and conclusion in more detail.

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