

# A Convolutional Neural Network for Regional Photovoltaic Generation Point Forecast

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**Abstract.** As the rapid growth of photovoltaic (PV) generation capacity, the form of regional PV power integrated by multiple PV plants is becoming more and more common. The changing law of regional PV power is of great significance to control the operation of the power system. This paper presents a novel regional PV power point forecast method that uses the convolutional neural network (CNN) model. In the method, the structure of CNN is applied to extract the nonlinear features between the input data and regional PV power. The forecast of regional PV power in a real power grid is carried out to illustrate the validity of the proposed method. Verification results show that the CNN model can provide more accurate point forecast for regional PV power results than the traditional regional PV power forecast methods.

## 1 Introduction

In recent years, with the aggravation of global energy consumption and the shortage of fossil energy supply, renewable energy utilization technology has developed rapidly. Solar energy plays an important role of renewable energy. As the main way of using solar energy, photovoltaic (PV) power is developing rapidly [1, 2]. At present, the PV power generation has become the priority development direction in the energy field of many countries around the world. The PV power generation has the advantages of cleanliness, sustainable utilization, flexible installed capacity and convenient use. With the rapid development of PV power generation technology in China, the installed capacity of PV power generation is greatly increased.

The input data involved in the power forecast of regional PV plants is large-scale, which includes the numerical weather prediction (NWP) and output power of each PV plant in the region. And there is complex correlation between the input data. Therefore, the key of regional PV power forecast is to efficiently mine effective information from high-dimensional and complex input data [3, 4].

The existing PV power research are relatively few for regional PV power forecast, and the commonly used regional PV power forecast methods are the bottom-up and upscaling methods [5]. The bottom-up method first forecasts the output power of each PV plant in the region separately, and then adds the forecast results of each PV plant to obtain the power forecast result of regional PV

plants [6]. The upscaling method first analyses the correlation of PV plants in the region and selects the representative PV plant in the region, then forecasts the output power of the selected representative PV plant. Finally, the upscaling method obtains the power forecast result of regional PV plants by multiplying the weight coefficient of the representative PV plant [7]-[9]. At present, the bottom-up method is widely used in the power forecast of regional PV plants, which is mainly suitable for small-scale regional PV plants. The forecast accuracy of the bottom-up method is directly affected by the forecast accuracy of each PV plant in the region. Compared with the bottom-up method, the upscaling method does not need to forecast the output power of each PV plant in the region, the upscaling method needs less input information and training time. However, if the selection of representative PV plant is not accurate, the accuracy of regional PV power forecast will be greatly reduced. The contributions of this paper are as follows:

(1) The CNN model is used to forecast the regional PV power. The CNN model can extract features from the input data of each individual PV plant and extract the correlation features between the input data of regional PV plants.

(2) The CNN model is used to forecast the regional PV power generated by ten PV plants in Weifang region of Shandong Province in China. The point forecast method of regional PV power based on the CNN model is compared with the traditional regional PV power forecast methods which includes the bottom-up and upscaling methods. The verification results illustrate that the

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proposed method based on the CNN model has better performance.

The rest of this paper is organized as follows: in Section 2, the CNN model is described in detail. The proposed forecast model of regional PV power forecast is explained in Section 3. Case studies are carried out in Section 4 and Section 5 concludes the paper.

## 2 Deep learning and CNN

Deep learning is the learning process that uses deep neural network (DNN) to realize feature expression. The deep learning can imitate human brain data, such as images,

sounds and words. Deep learning includes multi-layer implicit perceptron, which is the mathematical structure of unsupervised learning [10, 11]. The deep learning can mine the depth and abstract features of input data. The CNN as a typical structure of deep learning is widely used in speech recognition, image processing and other research fields [12]-[13]. In this paper, the CNN is applied to the research field of regional PV power forecast.

The CNN structure has the weight sharing and local connection technology, which can reduce the complexity of the CNN model and reduce the weight parameters. The structure of CNN generally includes the input layer, convolutional layer, pooling layer, fully connected layer and output layer, as shown in figure 1.

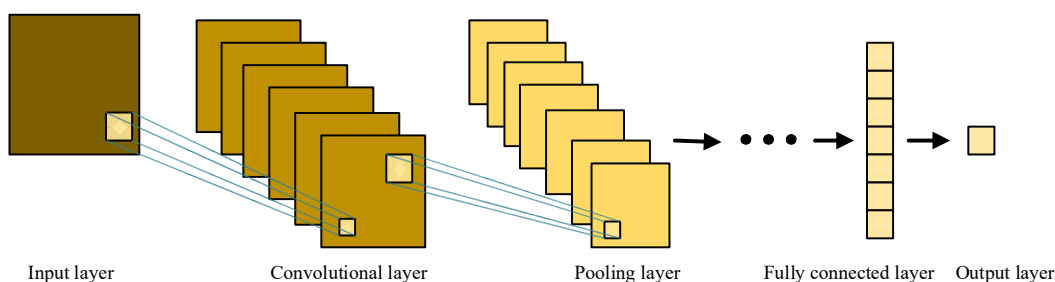


Figure 1. The architecture of CNN.

The functions of each layer of CNN are as follows:

(1) Input layer

The input layer of CNN is used to input data, which is the similar to the input layer of BP neural network (NN).

(2) Convolutional layer

Convolutional layer extracts some features of the upper layer by the fixed size convolutional kernel. The neurons connection of convolutional layer is different from that of BP NN. Each neuron of convolutional layer is only connected with the local neurons of the upper layer, as shown in figure 2. The local connection of neurons in different layers can reduce the parameters in the structure of CNN and improve the training speed.

The convolutional layer is calculated as follows:

$$C_j^l = f\left(\sum_{i \in N_i} I_i^{l-1} \otimes w_{i,j}^l + b_j^l\right) \quad (1)$$

where  $I_i^{l-1}$  is the feature map  $i$  in the  $l-1$ th,  $\otimes$  is the convolutional operation,  $w_{i,j}^l$  is the weights between the feature map  $i$  in the  $l-1$ th and the feature map  $j$  in the  $l$ th,  $b_j^l$  is the bias,  $f()$  is the active function, which selects ReLU function,  $C_j^l$  is the feature map  $j$  in the  $l$ th.

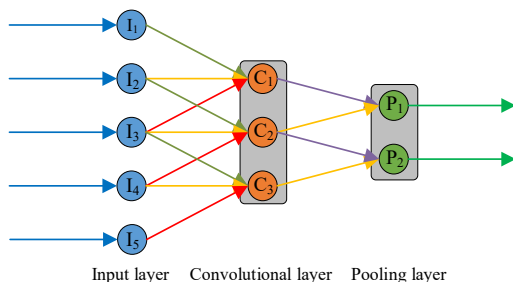


Figure 2. Local connection of neurons in different layers of CNN. (3) Pooling layer

The pooling layer, also known as the down pooling

layer, has the same specific operation as convolutional operation of the convolutional layer. Maximum pooling and average pooling are generally two methods to calculate the matrix value in the pooling kernel. Maximum pooling takes the maximum value in the perception field matrix of the pooling, and the average pooling takes the average value in the perception field matrix of pooling. The pooling layer can extract feature further, which can reduce over fitting of the CNN.

The pooling layer can be calculated as follows:

$$P_j^l = f(\beta_j^l \text{down}(C_i^{l-1}) + b_j^l) \quad (2)$$

where  $C_i^{l-1}$  is the feature map  $i$  in the  $l-1$ th,  $\text{down}()$  is the pooling function,  $\beta_j^l$  is the weights of the feature map  $j$  in the  $l$ th,  $P_j^l$  is the feature map  $j$  in the  $l$ th.

(4) Fully connected layer

Each neuron in the fully connected layer is fully connected with the neurons in the upper layer. The fully connected layer is used to integrate the features extracted from the convolutional layer and the pooling layer for further forecast. The fully connected layer can be calculated as:

$$F_j^l = f\left(\sum_{i \in l-1} w_{i,j}^l N_i^{l-1} + b_j^l\right) \quad (3)$$

where  $N_i^{l-1}$  is the neuron  $i$  in the  $l-1$ th,  $w_{i,j}^l$  is the weights between the neuron  $i$  and the neuron  $j$ ,  $F_j^l$  is the neuron  $j$  in the  $l$ th.

(5) Output layer

The function of the output layer is basically the same as that of BP NN, which is used to output the forecast results of CNN.

### 3 CNN model for regional PV power forecast

The output PV power, solar irradiance and temperature of each PV plant in the region are used as the input data for the regional PV power forecast. The input data of regional PV power forecast is large and complex. Therefore, in-depth mining of input data and extraction of key features is very important to obtain more accurate regional PV power forecast. As an efficient data mining method, deep learning has been widely used in many fields.

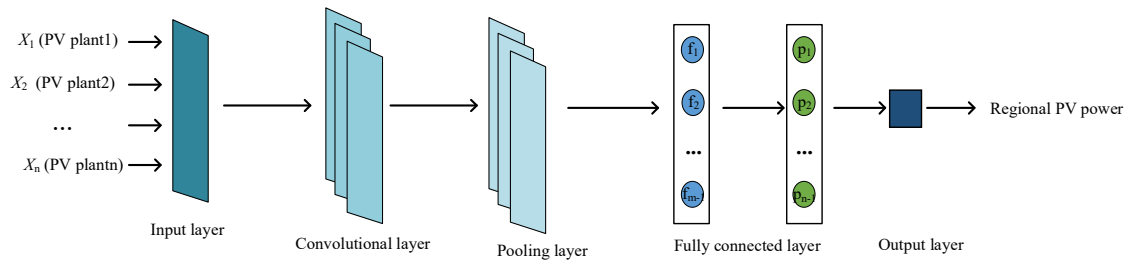


Figure 3. Regional PV power forecast model based on CNN.

In this paper, the CNN model is applied to the point forecast of regional PV power, and structure of the forecast model is shown in figure 3. Firstly, the data matrix consists of historical power, solar irradiance and temperature data of PV plants, which are input into the CNN model by the input layer. Then the dimension of input data is reduced and the feature is extracted by the convolutional layers and pooling layers. And then the extracted features are integrated into a vector and input into the fully connected layer to forecast the output power of regional PV plants. Finally, the point forecast results of regional PV power are output by the output layer.

### 4 Case study

In this paper, the mean absolute error (MAE) and root mean square error (RMSE) are selected as the point forecast of regional PV power evaluation criteria, which can be described as:

$$RMSE = \frac{1}{N} \sqrt{\sum_{i=1}^N \left( \frac{y_i^* - y_i}{C_i} \right)^2} \quad (4)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N \left| \frac{y_i^* - y_i}{C_i} \right| \quad (5)$$

where  $N$  denotes the number of samples,  $y_i^*$  and  $y_i$  denote the actual regional PV power and the forecasted regional PV power of the  $i$ th sample respectively,  $C_i$  denotes the nominal capacity of the regional PV plants where the  $i$ th sample is located.

#### 4.1 Data description and pre-processing

The data used in the case study are historical data from ten PV plants in Weifang Shandong Province. The data ranges from October 1, 2017 to March 31, 2018, with 15-minute resolution. Data of each PV plant in the region includes solar irradiance, temperature, and output power of PV plant.

Before the regional PV power forecast, it is necessary to normalize the data in order to eliminate the errors caused by different data dimensions. The output power of PV plants is normalized by:

$$\bar{y} = \frac{y}{y_N} \quad (6)$$

where  $y$  is the real PV power,  $\bar{y}$  is the normalized output power of PV plant,  $y_N$  is the installed capacity of PV plant.

#### 4.2 Model verification

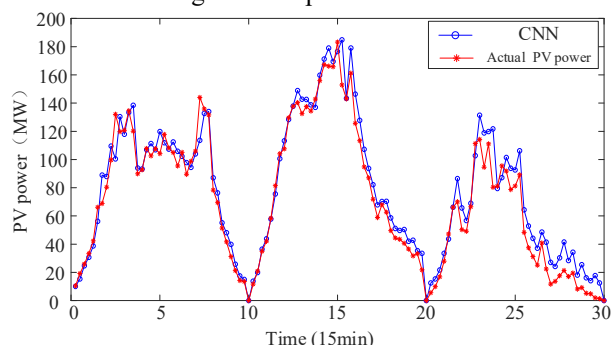
In this section, the historical data of ten PV plants in Weifang Shandong Province is used to verify the validity of the regional PV power forecast method based on the CNN model. Data of PV plant include historical output power, solar irradiance and temperature as input data. The input data has been pre-processed and normalized. The historical data of regional PV plants are divided into two parts: the training set (data from October 2017 to February 2018) and the verification set (data of March 2018).

Based on the deep learning algorithm, the CNN model is applied to the point forecast of regional PV power. Firstly, the pre-processed data is input into the CNN model through the input layer, and then the dimension is reduced and the feature is mined through the convolutional layers and the pooling layers. Then the extracted feature is integrated into a vector and input into the fully connected layer. Finally, the point forecast result of regional PV power is output by the output layer.

Through many experiments, the structure of CNN model of regional PV power forecast is set. The convolutional layers is set as three layers, the convolutional kernel in convolutional layer is set as  $2 \times 2$ , and the pooling layers are set as three layers, the pooling kernel in pooling layer is set as  $2 \times 2$ , and the pooling function in pooling layer selects the maximize pooling, and the fully connected layers are set as two layers, the activation function selects the ReLU function, the training method is random gradient descent method.

Figure 4 shows the point forecast results curve of regional PV power in three days ahead based on the CNN model, the blue curve in the figure 4 is the forecast results

of regional PV power, and the red curve is the actual value of regional PV power. It can be seen from the figure 4 that the trend of regional PV power forecast curve is basically the same as the curve of actual regional PV power, which shows that the CNN model proposed in this paper is effective in the regional PV power forecast.



**Figure 4.** Regional PV power forecast based on CNN model.

### 4.3 Comparison with different forecast models

In order to further illustrate the effectiveness of the CNN model of regional PV power forecast, the proposed method is compared with the regional PV power point forecast methods, which includes the bottom-up method and upscaling method.

The regional PV power forecast method based on the bottom-up method uses support vector machine (SVM) and BP NN to forecast the PV output power of individual PV plant. The structure of the individual PV power forecast in this section is set as follows: Gaussian function is used as kernel function in SVM, BP NN structure includes one input layer, two hidden layers and one output layer, sigmoid function is selected as activation function in BP NN model, and random gradient descent method is used as training method of BP NN model. The power forecast results of each PV plant in the region are added to obtain the point forecast results of regional PV power based on the bottom-up method. The upscaling method firstly analyses the correlation between PV plants in the region and selects PV plant 5 as the representative PV plant in the region. And then the SVM and BP NN are used to forecast the output power of the representative PV plant. Finally, the point forecast results of regional PV plants based on the upscaling method are obtained according to the weight coefficient.

**Table 1.** Evaluation criteria of different point forecast methods.

Method	MAE	RMSE
SVM-bottom-up	0.014	0.032
BP NN-bottom-up	0.109	0.029
SVM-upscaling	0.120	0.031
BP NN-upscaling	0.116	0.027
CNN	0.074	0.015

It can be seen from table 1 that the evaluation criteria MAE and RMSE of point forecast results of regional PV power based on the CNN model are far less than the bottom-up and upscaling methods. Therefore, the forecast

accuracy of the CNN model is higher than that of the bottom-up and upscaling methods. Although the input data of the regional PV power forecast has strong randomness and volatility, the forecast results of regional PV power based on the CNN model still has high accuracy. Therefore, the CNN model is suitable for the regional PV power forecast, and this method can improve the accuracy of regional PV power forecast.

## 5 Conclusion

Due to the large-scale input data and complex internal correlation of regional PV power forecast, the CNN model is applied to the forecast of regional PV power forecast in this paper. The CNN has the advantages of weight sharing and local connection in high-dimensional data. The CNN can deeply mine the effective information in the input data and fully extract the key features. In this paper, the real data of ten PV plants in Weifang of Shandong Province are used for case studies. The proposed method in this paper is compared with the bottom-up and upscaling methods that use SVM and BP NN model to forecast the individual PV plant. The forecast accuracy of the CNN forecast model is higher than the bottom-up and upscaling methods, which proves that the CNN has better performance in data mining of regional PV power forecast.

Generally speaking, the point forecast of regional PV power based on the CNN model can effectively achieve depth data mining and improve the accuracy of regional PV power forecast results.

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## References

1. Yona, A. Senjyu, T. Funabashi, T. (2013) Determination method of insolation prediction with fuzzy and applying neural network for long-term ahead PV power output correction. *IEEE Trans. Sustain. Energy*, 4: 527-533.
2. Li, Y. Su, Y. Shu, L. (2014) An ARMAX model for forecasting the power output of a grid connected photovoltaic system. *Renewable Energy*, 66: 78-89.
3. Zhang, X. Li, Y. Lu, S. (2019) A solar time based analog ensemble method for regional solar power forecasting, *IEEE Trans. Sustain. Energy*. 10 : 268-279.
4. Mathiesen, P. Kleissl, J. (2011) Evaluation of numerical weather prediction for intra-day solar forecasting in the continental United States, *Solar Energy*. 85: 967-977.
5. Antonanzas, J. Osorio, N. Escobar, R. (2016) Review of photovoltaic power forecasting, *Solar Energy*. 136: 78-111.

6. Junior, T. Oozeki, H. Ohtake, T. (2015) Regional forecasts of photovoltaic power generation according to different data availability scenarios: a study of four methods, *Progress in Photovoltaics Research & Applications*. 23: 1203-1218.
7. Pierro, M. De Felice, M. Maggioni, E. (2017) Data-driven upscaling methods for regional photovoltaic power estimation and forecast using satellite and numerical weather prediction data, *Solar Energy*. 158: 1026-1038.
8. Saint-Drenan, Y. M. Good, G. H. Braun, (2016) Analysis of the uncertainty in the estimates of regional PV power generation evaluated with the upscaling method, *Solar Energy*. 135: 536-550.
9. Saint-Drenan, Y. M. Good, G. H. Braun, M. (2017) A probabilistic approach to the estimation of regional photovoltaic power production, *Solar Energy*. 147: 257-276.
10. Wang, Z, Li, Q. Wang, G. (2017) Deep learning based ensemble approach for probabilistic wind power forecasting, *Applied Energy*. 188: 56-70.
11. Pierro, M. De Felice, M. Maggioni, E. (2017) Data-driven upscaling methods for regional photovoltaic power estimation and forecast using satellite and numerical weather prediction data, *Solar Energy*. 158: 1026-1038.
12. Gu, J. Wang, Z. Kuen, J. (2018) Recent advances in convolutional neural networks' *Pattern Recognition*. 77: 354-377.
13. Hiary, H. Saadeh, H. Saadeh, M. (2018) Flower classification using deep convolutional neural networks, *IET Computer Vision*. 12: 855-862.