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Short-Term Power Forecasting of Photovoltaic Power Generation Based on Similar Day and Improved Principal Component Analysis

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Abstract. Aiming at the problem of the accuracy of short-term photovoltaic power forecasting, in this paper, a short-term photovoltaic power forecasting method with dual correlation selection of similar day and improved principal component analysis is proposed. First, based on the traditional similar day selection method, a dual correlation method combining weighted Euclidean distance and weighted gray correlation degree is introduced to select similar days with higher similarity. Then, logarithmic processing is performed on the principal component analysis method to increase the principal component factor contribution rate, thereby improving the accuracy of the prediction model. Taking the historical data of a photovoltaic power station in Qinghai as an example, the short-term power forecasting method for photovoltaic power generation using the dual correlation selection similarity day and improved principal component analysis is compared with the method using the traditional similarity day and principal component analysis and the method using dual correlation selection of similarity day and principal component analysis. The results show that the prediction accuracy of the proposed method in this paper is higher.

Keywords: dual correlation, photovoltaic power generation, short-term power prediction

1 Introduction

In recent years, with the adjustment of China's energy structure, solar energy has developed rapidly as a clean and renewable new energy source, and it is gradually developing from an independent system to large-scale grid connection [1-2]. However, photovoltaic power generation has large fluctuations and randomness, and these characteristics will cause a certain degree of adverse effects on the grid [3-4]. Therefore, it is necessary to study a more accurate output power prediction method, which can promote coordinated dispatch of the power grid and improve the safety and stability of power system operation.

In recent years, more and more algorithms have been applied to the field of prediction, which has made the accuracy of predictions constantly improve. In Literature [5], a combination prediction model based on rough sets was proposed. Firstly, three single prediction models based on similar day, support vector machine and continuous method are established, and then the combined weight of the single prediction model is determined according to the method of determining the importance of attributes in rough set theory. However, this method ignores the importance of the influence of various meteorological factors on the photovoltaic output when calculating the correlation degree. Literature [6] proposed a

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photovoltaic power generation prediction model based on genetic algorithm-fuzzy radial basis neural network. By calculating Euclidean distance to select similar days, the solar radiation intensity and temperature on similar days were used as input variables of the prediction model. But this method ignores the shortcoming that Euclidean distance can only be used to characterize the distance between two sample points. Literature [7] used principal component analysis to process the original data, and the selected principal components were used as the input of the neural network. Although this method reduces the dimensionality of the input quantity, its dimensionality reduction effect still needs to be improved.

In order to make up for these shortcomings that the influence degree of meteorological factors on photovoltaic output will be ignored when selecting traditional similar days, only considering the degree of similarity between the historical day and the forecast day in space distance or curve shape, there are more input dimension of BP neural network in modeling prediction, and so on. This paper uses the historical output data and meteorological data of a photovoltaic power station in Qinghai Province to directly predict the power generation. A short-term photovoltaic power generation prediction method based on the dual correlation method to select similar days and improved principal component analysis is proposed, and the method is verified in combination with the actual case. The results show that the prediction accuracy of the proposed method in this paper is higher than that of the traditional method of similar day selection and principal component analysis.

2 Select Similar Days

2.1 Weight Calculation

There are many factors that affect the prediction of photovoltaic power generation and the power output of photovoltaic power generation is greatly affected by external factors, mainly including irradiance, temperature, humidity, and wind speed. However, each influencing factor has a certain degree of influence on the amount of photovoltaic power generation. For example, irradiance is the most influential compared to other influencing factors [8]. Therefore, a reasonable weight distribution is the basis for accurately selecting similar days.

The methods of determining weights are mainly divided into subjective empowerment and objective empowerment. Subjective empowerment has a large subjective arbitrariness and is easily restricted by the completeness of expert knowledge and experience. Objective weighting is to determine weights based on the objective relationship between data, which overcomes the shortcomings of subjective randomness of subjective empowerment. The entropy method is one of the most widely used methods for objectively determining weights. Therefore, this paper uses the entropy weight method to determine the weight of each meteorological parameter.

There are m historical day sample data, and each historical day has n meteorological parameters, forming an $m \times n$ meta-data matrix $A = \left[a_{ij}\right]_{mn}$, which a_{ij} represents the value of the j th meteorological parameter in the i th historical day. The formula for calculating the entropy of the j th meteorological parameter is as shown in equation (1):

$$E_j = k \cdot \sum\nolimits_{i=1}^{m} b_{ij} ln b_{ij}, j = 1, 2, \ldots, n . \tag{1}$$

where $k = -\dfrac{1}{\ln m}; b_{ij} = \dfrac{a_{ij}}{\sum\nolimits_{i=1}^{m} a_{ij}}$.

When $b_{ij} = 0$, order $b_{ij} \ln b_{ij} = 0$. The formula for calculating of the weight of the j th meteorological parameter is as shown in equation (2):

$$\omega_j = \frac{1 - E_j}{\sum\nolimits_{j=1}^{n} (1 - E_j)} . \tag{2}$$

where $\omega_j \in [0,1]$, $\sum_{j=1}^{n} \omega_j = 1$.

2.2 Weighted Euclidean Distance and Weighted Grey Correlation

Calculation of weighted Euclidean distance. Calculate the weighted Euclidean distance between the meteorological parameters of the i th historical day and the forecast day, and the calculation formula is as shown in equation (3).

$$D_i = \sqrt{\frac{1}{n}\sum_{j=1}^{n} \omega_j \left[a_{0j} - a_{ij} \right]} . \tag{3}$$

Where D_i is the Euclidean distance between the meteorological parameters of the i th historical day and the forecast day; a_{0j} is the j th meteorological parameter of the forecast day; ω_j is the weight of the j th meteorological parameter.

Calculation of weighted grey correlation. Calculate the correlation coefficient of the j th meteorological factor between the i th historical day and the forecast day, and the calculation formula is as shown in equation (4) [9].

$$\delta_{ij} = \frac{\min_i \min_j \left| a_{0j} - a_{ij} \right| + \rho \max_i \max_j \left| a_{0j} - a_{ij} \right|}{\left| a_{0j} - a_{ij} \right| + \rho \max_i \max_j \left| a_{0j} - a_{ij} \right|} . \tag{4}$$

Where, δ_{ij} is the correlation coefficient of the j th meteorological factor between the i th historical day and the forecast day; ρ is the resolution coefficient, $\rho \in \left[0,1\right]$, it is usually taken as $\rho = 0.5$.

Calculate the weighted gray correlation degree of the eigenvectors of the meteorological parameters between the i th historical day and the forecast day, and the calculation formula is as shown in equation (5).

$$G_i = \frac{1}{n}\sum_{j=1}^{n} \omega_j \delta_{ij} . \tag{5}$$

Where G_i is the weighted gray correlation degree of the eigenvectors of the meteorological parameters on the i th historical day and the forecast day; ω_j is the weight of the j th meteorological parameter; δ_{ij} is the correlation coefficient of the j th meteorological parameter between the i th historical day and the forecast day.

2.3 Select Similar Days by Dual Correlation Method

Since the weighted Euclidean distance can only represent the spatial distance of meteorological parameter curve between the historical day and the forecast day, the weighted gray correlation degree can only indicate the similarity of shape of meteorological parameter curves between the historical day and the forecast day. In order to select similar days with higher similarity, this paper uses the dual correlation method to select similar days, and sets the objective function of dual correlation method as:

$$F_i = \alpha D_i + \beta G_i . \tag{6}$$

According to a large number of sample data experiments, the coefficients of the weighted Euclidean distance and the weighted association degree are respectively determined as $\varphi = 0.5, \beta = 0.5$. Solve the composite objective function and select all historical days with F_i values greater than 0.85 as similar day sets.

3 Improved Principal Component Analysis

3.1 General Steps for Principal Component Analysis

Principal component analysis is a statistical method that reduces the dimension of the original variable and transforms a set of possible related variables into a set of linear uncorrelated variables by orthogonal transformation. The converted set of variables is called the principal component. Assuming that the number of samples size of the original variable is m and each sample has n observations, the expression of the original variable matrix A is

$$A=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}. \quad \textbf{(7)}$$

Where a_{ij} is the observation of the j th indicator in the i th sample.

The principal component analysis steps are as follows:

Eliminate the influence of different original variables and large numerical differences, and normalize the original variables to obtain the expression of matrix Y .

$$Y=\begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix}. \quad \textbf{(8)}$$

Where y_{ij} is the normalized calculation result of observations of the j th indicator in the i th sample.

The expression of y_{ij} is

$$y_{ij}=\frac{a_{ij}-\overline{A_j}}{\sqrt{var(A_j)}}\left(i=1,2,\cdots,m; j=1,2,\cdots,n\right). \quad \textbf{(9)}$$

Where $\overline{A_j}$ is the average of the index variable A_j ; $\mathrm{var}(A_j)$ is the variance of A_j .

The expressions of $\overline{A_j}$ and $\mathrm{var}(A_j)$ are

$$\overline{A_j}=\frac{1}{m}\sum_{i=1}^{m}a_{ij}\ . \quad \textbf{(10)}$$

$$\mathrm{var}(A_j)=\frac{1}{m-1}\sum_{i=1}^{m}\left(a_{ij}-\overline{A_j}\right)^2\ . \quad \textbf{(11)}$$

The correlation coefficient matrix of the matrix Y is established as

$$R=\begin{bmatrix} 1 & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}. \quad \textbf{(12)}$$

Where r_{ij} is the calculation result of the j th indicator in the i th sample.

The expression of r_{ij} is

$$r_{ij} = \frac{1}{m-1}\sum_{t=1}^{m} Y_{ti}Y_{ti}, (i, j = 1, 2, \cdots, n). \tag{13}$$

where Y_{ti} is the normalized calculation result of the observation value of the i th index in the t th sample.

The eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n \geq 0$ of the matrix R and the corresponding eigenvectors are obtained by calculation.

$$c_i = (c_{i1}, c_{i2}, \cdots c_{in})^T, (i = 1, 2, \cdots n). \tag{14}$$

The choice of the number of principal components. The variance contribution rate and the cumulative variance contribution rate of the principal component are respectively

$$\eta_i = \frac{\lambda_i}{\sum_{d=1}^{n} \lambda_d}, (i = 1, 2, \cdots, n; d = 1, 2, \cdots n). \tag{15}$$

$$\eta(i) = \frac{\sum_{d=1}^{i} \lambda_d}{\sum_{d=1}^{n} \lambda_d}. \tag{16}$$

where λ_i is the i th eigenvalue of the matrix R; $\sum_{d=1}^{n} \lambda_d$ is the sum of all the eigenvalues of the matrix R. $\sum_{d=1}^{i} \lambda_d$ is the sum of the first i eigenvalues of the matrix R.

Generally, the o principal components $(o \leq n)$ corresponding to the eigenvalues $\lambda_1, \lambda_2, \cdots, \lambda_o$ whose cumulative variance contribution rate is greater than 85%.

The principal component expression is

$$\begin{cases} Z_1 = c_{11}A_1 + c_{12}A_2 + \cdots + c_{1n}A_n \\ Z_2 = c_{21}A_1 + c_{22}A_2 + \cdots + c_{2n}A_n \\ \cdots \\ Z_o = c_{o1}A_1 + c_{o2}A_2 + \cdots + c_{on}A_n \end{cases}. \tag{17}$$

where c_{on} is the n dimensional eigenvector corresponding to the o th eigenvalue of the original variable matrix. $(A_1, A_2, \cdots, A_n)^T$ is initial input variable for n dimension.

3.2 Improvement of Principal Component Analysis

Principal component analysis is a linear dimensionality reduction technique. It normalizes the original data so that the covariance matrix becomes a correlation coefficient matrix. The correlation coefficient matrix reflects the positive correlation of the correlation degree between indicators. However, in practical problems, if the number of indicators is large, the contribution rate of the first principal component is usually unsatisfactory. At this time, it is necessary to select more principal components to meet the requirement that the cumulative contribution rate reaches the target level. This makes it easy to make the dimensionality reduction effect of the principal component analysis insignificant. In addition, most of the original indicators are nonlinear, the linearization improvement of the nonlinear function of the original indicators can be considered to realize the linearization processing of the PCA's input data.

Principal component analysis performs log-centered processing on the original data to extract non-linear features of the original data. The contribution rate of the extracted first principal component is high and that can contain most important information in the data. The specific method is:logarithmic transformation is performed on the original data.

$$a'_{ij} = \ln a_{ij} - \frac{1}{n}\sum_{l=1}^{n} \ln a_{il}. \tag{18}$$

Where a_{ij} is the observation of the j th indicator of the i th sample. $i = 1, 2, \cdots, m$; $j = 1, 2, \cdots, n$; $l = 1, 2, \cdots, n$.

The calculation process of improved principal component analysis is shown in Fig. 1.

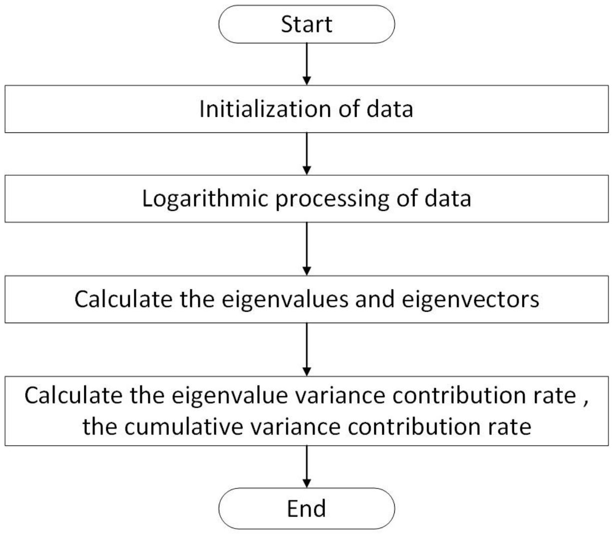

Fig. 1. Improved Calculation Process of Principal Component Analysis

4 Establish BP Neural Network Prediction Model

4.1 Predictive Model Design

Artificial neural networks have been widely used in power load forecasting and wind power forecasting, and are also considered as an effective method for predicting solar radiation intensity and output power of photovoltaic power generation systems. BP neural network is currently one of the more mature and widely used artificial neural network models. It is a multi-layer forward network for single propagation with capabilities of good nonlinear mapping, learning and adaptive.

The BP neural network chosen in this paper is a 3-layer neural network. The number of input layer nodes corresponds to the input variables of the prediction model. The number of hidden layers is one. The choice of the number of units in the hidden layer has a greater impact on the result. The number of hidden layer units has a direct relationship with the problem requirements and the number of input / output units, if the number is too small, the network will obtain too little information; if the number is too large, it will increase the training time, resulting in too long learning time, and the error may not be the best. In this paper, we use empirical formula (19) and make multiple attempts to select 11 nodes in the hidden layer.

$$\mathrm{e}_1 = \sqrt{e + g} + h. \tag{19}$$

Where: e_1 is the number of hidden layer units, e is the number of input units; g is the number of output units; h is a constant between [1, 10], determined $h = 7$ according to a large number of sample tests.

The historical data and meteorological data of the photovoltaic power plant are processed, the processed data is used to train the BP neural network, and the trained neural network model is used to predict the short-term output of the photovoltaic power station.

4.2 Training and Prediction of BP Neural Network

The training of BP neural network uses the error back propagation learning algorithm [10], with P training samples, T is the maximum number of trainings; w is the connection weight; $w(t)$ is the weight of the t th iteration; $\vartriangle w(t)$ is the weight change of the t th iteration according to the traditional BP learning algorithm; $E(t)$ is the total network error for the t th iteration; ε is the allowable error for the system; η is the learning rate. The algorithm flow is:

(1) Initialize the weight w, set currently the t th iteration;

(2) Input P samples in turn, set the current input is the p th sample, calculate the output and back propagation error of each layer.

(3) If $p < P$, then $p = p + 1$, go to step (2), otherwise go to step (4).

(4) Adjust the connection weight of each layer according to the weight adjustment formula.

(5) According to the new connection weight, calculate the output, back-transmission error and total error $E(t)$ in each layer. If $E(t) < \varepsilon$ or $t > T$, terminate the training process. Otherwise $t = t + 1$, go to step (2) for a new round of training.

According to the method of determining the input and output data, the designed BP neural network is trained. The output power data of the similar day, the weather parameters and the weather parameters of the forecast day are taken to predict the output of the forecast day after the training.

5 Forecast Examples and Results Analysis

5.1 Forecast Examples

Example 1. Using historical data from spring 2015 (March 1, 2015-May 31, 2015), the original data in this article is from a photovoltaic power station in Qinghai Province. Taking into account the geographic location of the photovoltaic power plant where the data originates, historical data shows that the generation power from 19:00 to 8:00 in the next day is basically 0, so select the generation data from 8:00 a.m. to 19:00 in similar day, recorded every 15 min. The total generation power of 45 generation time series is used as the 45 inputs of the prediction model; the meteorological parameters of similar day and prediction day are selected as the other 8 inputs of the prediction model. In order to verify the effectiveness of the proposed prediction method, experiments were programmed in Matlab 2016a. First of all, because the units are different for different variables and the order of magnitude are very different, so the data is normalized as shown in formula (20) [11].

$$f^{'} = \frac{f - f_{\min}}{f_{\max} - f_{\min}}. \tag{20}$$

Where $f^{'}$ is the normalized data; f is the input raw data; $f_{\max}$ and $f_{\min}$ are the maximum and minimum values of the original data.

May 15, 2015 was selected as the forecast day, and the weather forecast parameters for that day are shown in Table 1. Historical data of similar days of photovoltaic power generation and corresponding meteorological parameters were selected as training samples. First, the dual correlation method combining weighted Euclidean distance and weighted correlation is used to select similar days, the results are shown in Table 2.

Table 1. Forecast daily weather parameters

Forecast day	irradiance	temperature	wind speed	humidity
2015-05-15	655w/m2	-2.665℃	3.25m/s	31.125%

Table 2. Similar day selection results

data	2015-04-24	2015-05-14	2015-04-22	2015-04-30
Similarity	0.99	0.98	0.92	0.89

An improved principal component analysis was performed on the input 53 factors (45 generating power and 8 meteorological factors), and the characteristic values, variance contribution rate and cumulative contribution rate of each factor were calculated. Generally, the principal components corresponding to the eigenvalues whose cumulative variance contribution rate is greater than 85% basically cover all the information of the original variable [7]. As can be seen from Table 3, the cumulative contribution rate of the first three principal components is 86.9%> 85%. A new input variable is calculated from equation (16).

Table 3. Improved eigenvalues and contribution rates of principal component analysis

Ingredient	Initial eigenvalue		
	eigenvalue	Variance contribution rate/%	Cumulative contribution rate/%
1	2.303	41.9	41.9
2	1.265	23.2	65.1
3	1.197	21.8	86.9
4	0.234	4.3	91.2
53	0.003	0.037	100

In order to verify the effectiveness of the prediction methods mentioned in this paper, several combination methods are given for comparison: Method 1 represents the combination of the traditional similar day method and principal component analysis method; Method 2 represents the combination of dual correlation selection of similar day method and principal component analysis method; Method 3 represents the combination of the dual correlation selection of similar day method and improved principal component analysis (the method mentioned in this paper), and the prediction results of these three methods are compared with the actual values, as shown in Fig. 2. As can be seen from the figure, method 1 has the largest fluctuation and the lowest accuracy compared with the actual value. In method 3, compared with the actual value, the fluctuation between 10:00-12:00 is small and the prediction accuracy is high. From the perspective of the total prediction time, compared with the other two methods, the volatility of the method 3 is significantly reduced. In summary, it can be seen that the accuracy of the method in this paper is the highest.

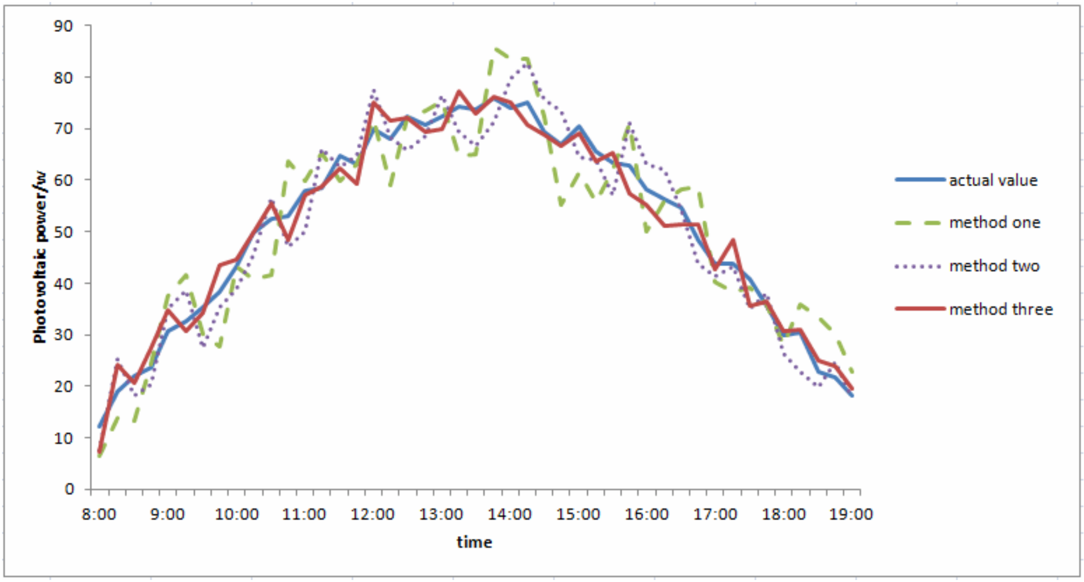

Fig. 2. Photovoltaic Power

5.2 Error Analysis

Usually, the Mean Absolute Percent Error (MAPE) and Root Mean Squared Error (RMSE) are selected as the error evaluation indicators. In MAPE, the situation of positive and negative phase cancellation will not occur because the deviation is absolute value, and it can better reflect the prediction error. RMSE strengthens the role of large numerical errors, improves flexibility, and reflects the extent to which predicted values deviate from the actual photovoltaic output. MAPE is shown in formula (21), and RMSE is shown in formula (22) [12-13]. The calculation results of average relative error and root mean square error are shown in Table 4.

Table 4. Prediction error

method of prediction	MAPE/%	RMSE
Method 1	14.43	1.33
Method 2	11.49	1.14
Method (method of this paper)	7.58	0.94

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\frac{|S_i - B_i|}{S_i}\times 100\% . \quad \textbf{(21)}$$

$$\text{RMSE}=\sqrt{\frac{1}{m}\sum_{i=1}^{m}(S_i - B_i)^2} . \quad \textbf{(22)}$$

Where S_i and B_i are the predicted value and actual measured value of the i data point, respectively; m is the data length used for verification.

As can be seen from Table 4, compared by method 3 and method 2, the method using improved principal component analysis to predict short-term photovoltaic power generation, the absolute average error percentage of that can be increased by about 4 percentage points and the root-mean-square error of that is reduced by 0.2; Compared by method 2 and method 1, it can be seen that the use of the dual correlation method to select similar days has a significant improvement over the traditional method for selecting similar days. The absolute average error percentage of that can be increased by about 3 percentage points, and the root mean square error is reduced by 0.19.

Example 2. In order to fully prove the superiority of the method in this paper, a set of data is randomly selected to predict the photovoltaic power generation of one day. Based on historical data from June 1 to August 20 in 2015, 45 points were forecast for the full day of August 21, 2015. And the actual values are compared with the prediction results of the three methods in example 1 respectively, the predicted power curve and the actual power curve are shown in Fig. 3 and the specific prediction error is shown in Table 5.

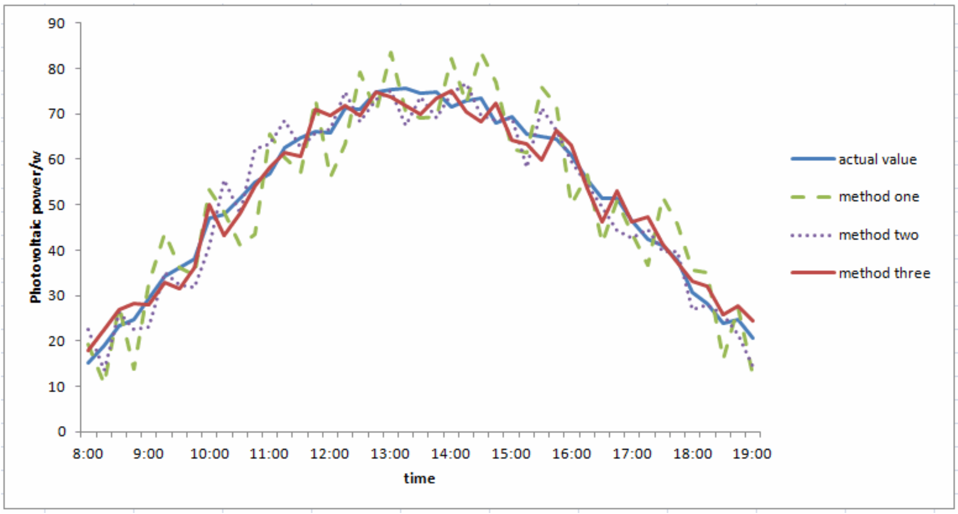

Fig. 3. Photovoltaic Power

Table 5. Prediction error

method of prediction	MAPE/%	RMSE
Method 1	15.09	1.47
Method 2	12.29	1.24
Method (method of this paper)	7.74	0.96

6 Conclusion

Aiming at the different meteorological factors affecting photovoltaic power generation, this paper first uses the entropy weight method to obtain the weights of various meteorological factors affecting photovoltaic power generation. Then, a dual correlation method combining weighted Euclidean distance and weighted gray correlation is used to select similar days, so that the meteorological conditions on similar days are more consistent with the meteorological conditions on the forecast day. In order to increase the contribution rate of the principal component factor, a logarithmic processing principal component analysis method is proposed. In the analysis results, the principal component factor whose cumulative contribution rate is greater than 85% is selected as the input factor of the BP neural network. Finally, a BP neural network prediction model is established to complete the prediction. The experimental results show that the improvement of similar day and principal component analysis greatly improves the accuracy of the prediction model. In the future, other parameters of the BP neural network can be optimized to further improve the accuracy of the prediction model.

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