

# Research on power prediction of photovoltaic power station based on similar hour and LM-BP neural network

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**Abstract.** Aiming to solve the problem of low precision of traditional photovoltaic power forecast method under abrupt weather conditions. In this paper, a high-precision photovoltaic power prediction method based on similarity time and LM-BP neural network is proposed. Firstly, the factors affecting the output power of photovoltaic power station are analyzed, and the short-term output power model of photovoltaic power station is established based on similar day and LM-BP neural network. Then, from the perspective of model training efficiency and prediction accuracy, the deficiencies in the short-term power prediction of photovoltaic power stations based on similar days and LM-BP algorithm are analyzed. Secondly, the prediction model of LM-BP neural network based on similar hours is established. Finally, Jiaxing photovoltaic power station is taken as an example for simulation verification. The simulation results show that the proposed method has high accuracy in predicting photovoltaic power under abrupt weather conditions.

## 1 Introduction

Solar radiant energy is the only energy source of photovoltaic power generation system. Due to the influence of day and night, seasonal change, weather change and other factors, photovoltaic power generation has the characteristics of intermittence, randomness and volatility. Therefore, the traditional photovoltaic power station is difficult to predict the power output [1]. Therefore, the output power of photovoltaic grid-connected power system can be predicted accurately. It is of great significance to power grid dispatching, power grid security and stability, and economical and efficient operation.

At present, the short-term output power prediction methods of photovoltaic power station mainly include regression model prediction method, optimization algorithm and artificial neural network method. Artificial neural network algorithm has been widely used because of its strong learning ability and generalization ability. Literature [3] proposed a method to improve the correlation between the training set and the data to be predicted, so as to improve the short-term prediction accuracy of photovoltaic power. Literature [4] established a short-term prediction model for the output power of photovoltaic power generation system based on the mind evolutionary algorithm and the back-propagation BP neural network algorithm, which improved the prediction accuracy of the BP neural network algorithm. Literature [5] proposed a short-term forecasting method for output power of photovoltaic power generation system based on Elman neural network

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model. The results show that the prediction accuracy of the model is higher under sunny conditions. However, under abrupt weather conditions, the prediction results of this model are not ideal. In literature [6], deep learning model was adopted to predict photovoltaic output, but the factors affecting photovoltaic output were not further explored.

In order to improve the prediction accuracy of short-term output power of photovoltaic power station, especially in abrupt weather. In this paper, a short-term power output prediction method based on similar hours and LM-BP neural network is proposed. The results prove that this method can improve the accuracy of PV power prediction.

## 2 Photovoltaic power factor analysis

The photoelectric conversion efficiency of grid-connected power generation system depends on the superposition of the efficiency of each part of the system [7].

### 2.1 Analysis of meteorological factors

Solar radiation intensity is the most important factor affecting the output of photovoltaic power station. When the scale of the solar power station is determined, the power of the photovoltaic power station is proportional to the solar radiation intensity received by the power station. The intermittency and periodicity of the output power of the photovoltaic power generation system are consistent with the solar radiation intensity.

Temperature has a certain influence on the photoelectric conversion efficiency of photovoltaic power station. When the temperature of photovoltaic modules rises, the current in photovoltaic modules will rise, but the voltage will drop, and the voltage will drop more obviously than the current rise. Therefore, when the illumination intensity is consistent, the output power of photovoltaic power station will decrease when the module temperature rises.

The influence of the output power of the humidity photovoltaic power station is reflected in two aspects: firstly, the illumination intensity is weakened to reduce the amount of illumination received by the photovoltaic module per unit area; Secondly, it will affect the heat dissipation of photovoltaic panels, thus reducing the photovoltaic conversion efficiency of photovoltaic panels. When the humidity is high, the power output of the power station is small, and when the humidity is low, the power output of the power station is large.

## 2.2 Weather type

Meteorological factors vary greatly under different weather conditions, which leads to great differences in photovoltaic power under different weather conditions. If the weather conditions in a certain place do not change much in a certain period of time, the output power curve of the photovoltaic power station should be consistent with the change rule of the solar radiation intensity change curve. However, under changeable weather conditions, the main factors affecting solar radiation attenuation will constantly change, making the amount of radiation received by photovoltaic modules fluctuate repeatedly in a certain period of time. At this time, the variation law of photovoltaic power station output power and solar radiation intensity will be greatly different.

## 3 Similar day and similar hour selection

### 3.1 Selection of similar day

In order to improve the prediction accuracy of short-term output power of photovoltaic power generation, it is necessary to screen out similar days from historical data, and take the output power of each period of similar days as part of the input of the prediction model.

This article adopts the method of comparison of Euclidean distance to select similar day, the first screening for prediction and same season, the weather types of historical sample set, and one by a historical day and to predict the temperature of the Euclidean distance to determine similar day, will sample concentration and to predict daily temperature history, history of minimum Euclidean distance as a similar day. Temperature data for forecast and historical days are provided by the Weather Forecast and the Optical Power Station Environmental Data Collection Centre respectively. The calculation formula of Euclidean distance is shown in Equation 1:

$$d_i = \sqrt{\sum_{k=1}^{\lambda} (T_{ik} - T_k)^2} \quad (1)$$

Where:  $T_k$  represents the temperature at time  $k$  on the predicted day;  $T_{ik}$  is the temperature at time  $k$  of the historical day  $i$ .

### 3.2 Selection of similar hours

When selecting similar conditions, the temperature alone as a reference quantity cannot be considered for the calculation of Euclidean distance, because temperature fluctuations are usually small in a relatively short period of time when the weather conditions are relatively stable. Therefore, several more parameters need to be considered when selecting similar parameters, such as illumination, humidity and wind speed. However, since their dimensions are different, it is necessary to normalize them before calculating Euclidean distance.

The historical data at the same time nearest 5 days to the date to be predicted are selected from the data set of the corresponding weather type as the sample set. Then Equation (2) is used to calculate the Euclidean distance of the feature vector formed after normalization of the four quantities between the predicted date and the historical date. The historical small moment with the smallest Euclidean distance is selected as the similar hour.

## 4 Similarity day and LM-BP neural network model

### 4.1 LM-BP neural network principle

BP is an information processing algorithm formed by imitating human learning ability and knowledge processing function. The biggest advantage of BP neural network method in predicting the output power of photovoltaic power station compared with other methods is that it does not need to get an accurate mathematical model [8].

The LM (Levenberg-Marquardt) algorithm combines the advantage of fast error reduction of standard BP algorithm in the initial stage of training and the advantage of quasi-Newton algorithm in global optimization when approaching the minimum point of global error. In the L-M algorithm, direct connection is used to approximate  $H^{(k)}$  by the first partial derivative; in the L-M method,  $H^{(k)}$  is approximated by the transpose of the Jacobian matrix multiplied by itself, as shown in Equation (2):

$$H^{(k)} = J^T J \quad (2)$$

Therefore, the weight adjustment formula of L-M algorithm is as follows:

$$w_{k+1} = w_k - [J^T J + \mu I]^{-1} \nabla E(w_k) \quad (3)$$

Where:  $\nabla E(w_k)$  represents gradient;  $J$  is the Jacobian;  $w_k$  represents the network weight;  $\mu$  is the adaptive adjustment value.

### 4.2 Model building

When constructing the prediction model structure of LM-BP neural network, the number of nodes in input layer and output layer, the number of hidden layers and the number of nodes in hidden layer are mainly considered.

Consider day was established by the characteristics of the related factors of simple LM-BP three layer neural network, there are 20 nodes in the input layer (similar to the output power of 13 hours, predict daily maximum temperature, minimum temperature, average temperature, maximum light intensity, the minimum light intensity, and day type quantitative value), the output layer has 13 nodes (to predict the output power of 13 hours). The neural network structure is shown in Fig 1.

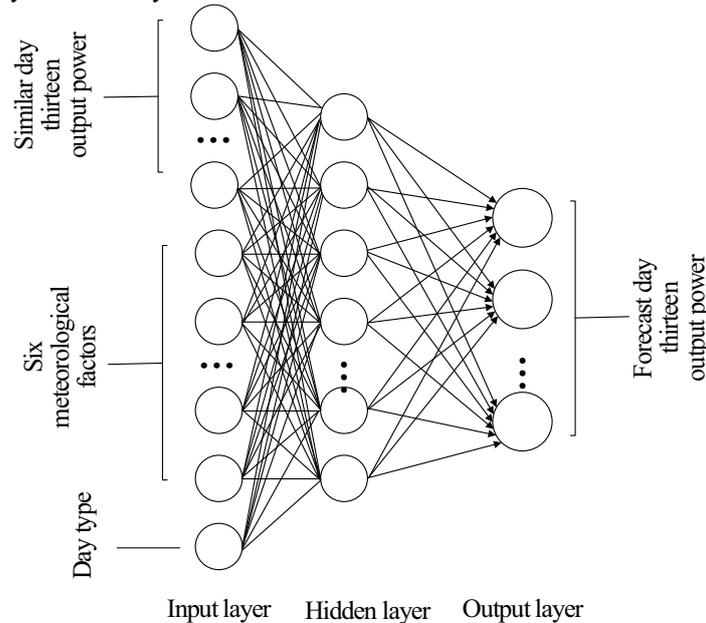


Fig 1 Similarity day and LM-BP neural network model

### 4.3 Performance testing

The historical data of the photovoltaic power station of Jiaxing Power Plant from January 1, 2019 to December 31, 2019 were selected for model training, and the training speed and training error were compared and analyzed. The number of neurons in the hidden layer was

set as 25, the learning rate was set as 0.05, the target error was set as 0.001, and the maximum number of iterations was set as 10000.

The error convergence curve during the training of LM-BP neural network is shown in Fig 2. It can be seen that the pre-set target error can be achieved after 5 iterations.

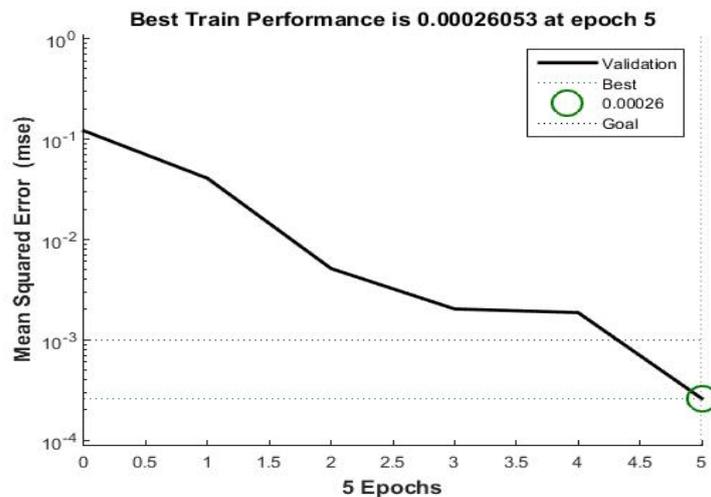


Fig 2 Similarity day and training error of LM-BP neural network

## 5 Photovoltaic power prediction based on similar hour and LM-BP algorithm

### 5.1 Similarity hour and LM-BP model

Categorize historical data by season and weather conditions, and use the classified data to train the

prediction model separately. According to the classification of season, weather and time period, a submodel is built for each time period. According to the actual situation in Jiaxing area, 162 seed models are needed. In winter rain or shine snow three weather, 9 periods a day the power station has output power; Rain or shine rain and snow (fog) four kinds of weather in spring and autumn, the power station has output power in 12 periods every day; There are three kinds of summer rain or shine rain weather, and the power output of the power station is available in 13 periods every day.

The inputs are similar hours of power output and major meteorological parameters including temperature, light and humidity. The output is the predicted hourly output power. So the network structure based on similar hours and LM-BP can be simplified.

In order to simplify the model, a single hidden layer network is also selected. Set the number of hidden layer

neurons to 7. It does not lead to too much time consuming training or error nonconvergence.

The learning rate is set to 0.01, the target error is set to 0.001, and the maximum number of iterations is set to 1000.

### 5.2 Simulation analysis

Taking Jiaxing photovoltaic power station as an example, the abrupt weather situation in winter (2020.03.08 sunny to cloudy) was selected for prediction. Finally, the predicted output power curve and actual output curve of the day are obtained.

The prediction results based on similar days and LM-BP neural network are shown in Fig 3. It can be seen that the prediction accuracy is poor when the weather conditions suddenly change.

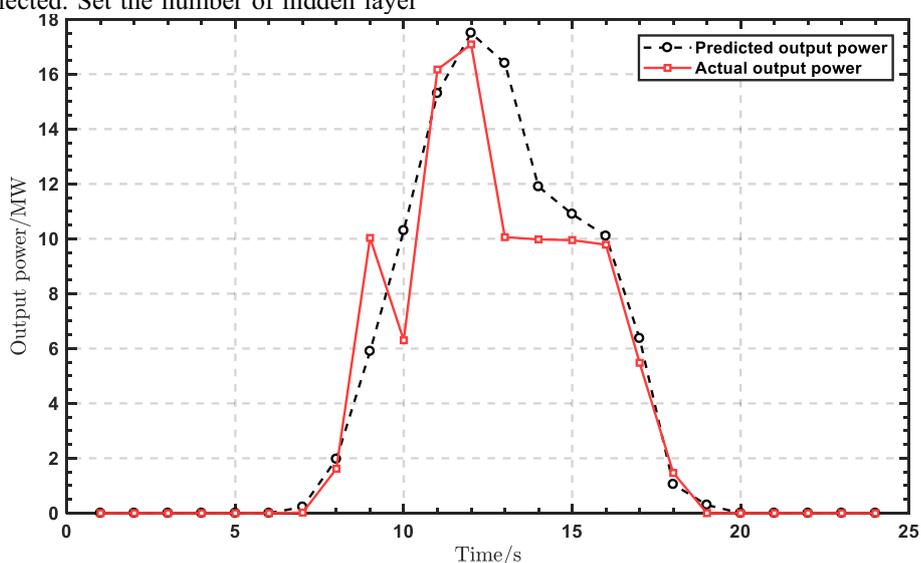


Fig 3 Similar days and LM-BP prediction results

The prediction results based on similar hours and LM-BP neural network are shown in Fig 4. It can be seen

that the prediction accuracy is greatly improved when the weather changes abruptly.

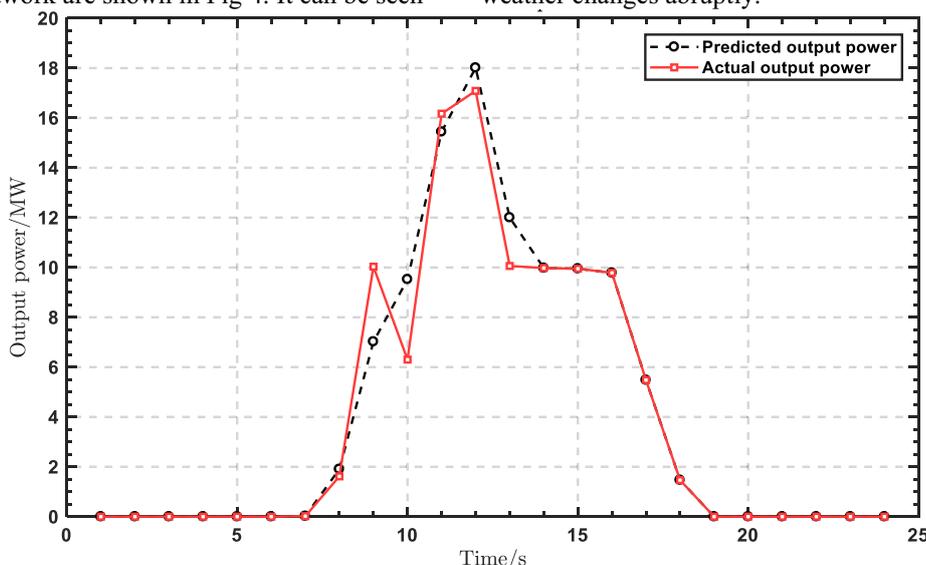


Fig 4 Similar hours and LM-BP prediction results

By comparing Fig 3 and Fig 4, it can be seen that MAPE of similar hour and LM-BP neural network model in abrupt weather is reduced to less than 10%, reaching a very high precision standard.

## 6 Conclusion

In this paper, a similar hour LM-BP neural network photovoltaic power prediction model is proposed. Taking the photovoltaic power station of Jiaying Power Plant as an example, the abrupt weather is simulated and predicted. The simulation results show that this method has high precision in predicting photovoltaic power in abrupt weather, and has high engineering application value. When the output power of morning and evening power stations is small, how to improve the prediction accuracy of photovoltaic power is the focus of the next research.

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