Photovoltaic power prediction method based on similar day and BP neutral network

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Abstract. The Photovoltaic (PV) system output power has intermittency and randomness; thus, it is necessary to find an accurate method for PV system power prediction. This paper describes a practical approach to predict the output power for PV system based on Back Propagation (BP) neutral network and similar days. The global solar radiation intensity and output power data are used to classify the types of weather and similar days by using the Self-Organizing Map (SOM) and the Probabilistic Neural Network (PNN), respectively. The prediction models for different weather type are established. The models have been tested and evaluated by the measured data of the PV systems which is located in Yunnan, RMSE and MAPE values indicate that the method provides reliable output power prediction for PV system under different weather types.

1. Introduction
The output power of the Photovoltaic (PV) system, which is affected by types of weather, temperature, humidity and other factors. These factors lead to the photovoltaic power is intermittent and uncontrollable, and hard to connect to power grid. The PV output power prediction can effectively reduce the adverse impacts on the power grid and improve power system security and stability.

The output power prediction method of PV system based on similar day and BP neural network, which can be achieve higher accuracy by using less training times, it has been widely reported in recent years [1-5]. Wang et al. [6] used the grey correlation method to select similar day, and then used the Radial Basis Function neural network to predict the photovoltaic array output power. Ding et al. [7] reported a prediction model, which based on BP neural network and similar days. The temperature, weather type and season type historic data were used as indicate vectors, and through the calculation of Euclidean distance of data to obtain the corresponding types of weather. The prediction result indicates that the model has high accuracy for power prediction in various weather conditions. Yuan et al. [8] through calculated the Euclidean distance between power generation data of input day and the average power generation data of different weather types to determine the type of similar days and used the BP neural network model to predict the output power of a photovoltaic power station. The present classification method of similar day is base on multiple types of data [9], how to make a simple and effective method to achieve selection of similar days, which is the key of output power prediction.
In this paper, the prediction model which base on BP neural network combine with similar days is proposed. The global solar radiation intensity is used as input parameters, the weather types is determined by using Self-Organizing Map network (SOM) and the Probabilistic Neural Network (PNN) are used for similar day selection. The prediction models under different weather types are established, and the precision are validated and analyzed.

2. Selection of similar days
There is a correlation between the output power of PV system and the global solar radiation intensity. The daily global solar radiation intensity data also reflects the weather type [7, 10], the daily global radiation curve under same weather condition exhibit similar varying tendency. Thus a region of the weather type could be obtained though categorizing the of daily global solar radiation curve data. In this paper, the solar radiation is used as input data, and the types of weather and similar days are selected using Self-Organizing Map and Probabilistic Neural Network, respectively.

2.1. Self-Organizing Map network
When using the BP network model to predict the output power of PV system in order to prevent a single model could not meet precision in different weather types, it should be established the models according to the weather types. For obtaining types of weather which need to get many historical solar radiation intensity data, how to carry on the effective categorizing analysis has become a problem that needs to solve. The SOM network has a function of cluster analysis, which can classify the input curves according to the similar characteristics and it is suitable for classifying daily global solar radiation intensity curves.

The SOM network includes input layer and output layer. The input neurons connect with the output neurons by weights, the neighboring neurons are also connected by the weights, the structure of the SOM network are shown in Figure 1 [11]. Each input sample corresponds to an excited output layer neuron, a category. The matching of input samples with output neuron nodes can be discriminated using Euclidean distance, the function expression is as following:

$$d_j(x) = \sqrt{\sum_{i=1}^{m}(x_i - \omega_{ji})^2}$$

The winning neuron which has the minimum distance, the weights of winning neurons and their neighboring neurons are correct according to Kohonen rule, the formula as shown below:

$$\omega_{ji}(k+1) = \omega_{ji}(k) + \eta(x_i - \omega_{ji}(k))$$

The SOM neural network performs unsupervised learning on the input samples. The inhibition relationship is determined by the distance between output neurons. The statistical distribution of the final connection weights is consistent with the input mode, and then the distribution of the input samples is described.

Fig. 1 The structure of SOM neural network
2.2. Probabilistic Neural Network

The variation curves of solar radiation intensity, which can reflect different weather types are used as target data and use probabilistic neural network to classify similar day. The probabilistic neural network consists of four layers, namely: input layer, hidden layer, pattern layer and output layer, the structure shown in Figure 2 [11].

![Fig. 2 The structure of Probabilistic Neural Network](image)

The input layer passes the data to the hidden layer. The number of neurons is same as the length of the input vector. The hidden layer is a radial substratum, and the number of neurons is equal to the number of input data. Each hidden layer neuron has a center point and returns a scalar value by calculating the distance between the input vector and the neuron’s center point. The output probability of neuron in the hidden layer is as following:

$$
\Phi_j(x) = \frac{1}{(2\pi)^d/2}\sigma^d \frac{(x-x_j) \sigma}{\sigma}
$$

Where \(d\) is the spatial dimension of the training data; \(\sigma\) is the smoothing factor; \(X_{ij}\) is the \(j\) central vector of the \(i\) type. For PNN networks, there is one pattern neuron for each category of the target variable. The actual target category of each training case is stored with each hidden neuron; the weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron’s category. The pattern neurons weighted average the output values for the same category neurons in the hidden layer. The probability density function is as following:

$$
\sum_{j=1}^{L_i} \Phi_{ij}
$$

Where \(L_i\) is the number of neurons, the output layer compares the weighted values for each target category accumulated in the pattern layer and uses the largest values to predict the target category.

$$
y = \arg \max(f_i)
$$

3. Design of prediction models

The measurement data obtained from a PV power system, which located in Yunnan province. The peak power of the PV power system is 5.76 kW. The output power data from January to June in 2016 is used for training and verifying the model performance. The corresponding variation curves of solar radiation intensity and weather data are used to classify the weather type and similar day. After removing the anomalous data, the five types of weather are obtained as follows: sunny, cloudy, rain,
sunny to rain and rain to sunny. The number of similar days in different types of weather is shown in Table 1.

| Types of weather      | The number of similar day/d |
|-----------------------|-----------------------------|
| sunny                 | 46                          |
| cloudy                | 45                          |
| rain                  | 31                          |
| sunny to rain         | 27                          |
| rain to sunny         | 24                          |

The BP neural network is widely used to predict the output power of PV system, because of its simplicity of implementation [12-15]. The basic structure of the three-layer BP neural network is used to output power in the article. The structure of BP neural network is shown in Figure 3. There are five prediction models have been built, according to the classification result of weather types. Each model is corresponding to a type of weather. The historical data, which belong to the same weather type are used as samples for training the BP neural network and predicting the output power.

The input parameters of the models include output power data, the highest, the lowest and average ambient temperature of previous day and the highest, the lowest and average ambient temperature of objective day. The number of the neurons of the input layer is 102. After many attempts, it is found that the best number of hidden neurons is 16. The output data of the model is predicted output power for objective day, the number of the parameters is 96.

The predicted output power of the PV system is compared with the measurement data. The prediction accuracy of the model is evaluated by using Mean absolute percentage error (MAPE) and Root Mean Square Error (RMSE). The corresponding expressions as following:

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{P_i - P_{fi}}{P_i} \right| \times 100\%$$

(6)

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (P_i - P_{fi})^2}$$

(7)

where, $P_i$ and $P_{fi}$ are the predicted values and measured values of output power, respectively. The $N$ is the number of the data.
4. Simulation results and discussion
The Figure 4-8 show the predicted results of output power in different types of weather, and the corresponding MAPE and RMSE values are shown in Table 2. The Figure 4 shows the measured and predicted output power curves of the PV system operate in sunny condition. It can be seen from the figure, because there is no cloud cover and meteorological change, the trend of predicted curve coincide with the measured curve. The value of MAPE is 8.92%, and the RMSE value is 0.065 kW. The result indicates that the prediction model of sunny weather exhibits high accuracy.

![Fig. 4 The predicted and measured output power of sunny day](image)

Figure 5 and Figure 6 shows the predicted and measured output power curves in the cloudy and rain weather, respectively. As shown in the Figures, the fitting accuracy of the measured and predicted curves has a significant decline by comparing with the sunny weather. The RMSE values between the prediction result and the measurement result is 0.34 kW and 0.21 kW, and the values of MAPE are 30.91% and 27.51%, respectively.

![Fig. 5 The predicted and measured output power of cloudy day](image)
The performance of the prediction models for sunny to rain and rain to sunny weather are shown in Figure 7 and Figure 8, respectively. As shown in the figures, there is a close relation between prediction accuracy of models and weather types. The fitting results of predicted and measured curves exhibit higher fitting precisions in the period of sunny time, and poor fitness and low accuracy while the rain appear. The MAPE values of the predicted results are 16.84% and 15.29%, respectively.

By comparing the prediction results of the difference meteorological conditions, it can be found that the weather change can be significant decline the prediction accuracy of the models, this is due to the high randomness of the solar radiation intensity is caused by meteorological changes, which makes difficult to accurate predict the trend of output power.
Fig. 8 The predicted and measured output power of the weather changed from rain to sunny

| type of weather       | RMSE/kW | MAPE/% |
|-----------------------|---------|--------|
| sunny                 | 0.06    | 8.92   |
| cloudy                | 0.34    | 30.91  |
| rain                  | 0.21    | 27.51  |
| sunny to rain         | 0.45    | 16.84  |
| rain to sunny         | 0.33    | 15.29  |

5. Conclusion
This paper presents a practical method for output power prediction. The method is based on BP neural network combined with weather types and similar days approach. To verify the predictive ability of the method, the solar radiation intensity data and output power data of a PV system, which located in Yunnan are used to acquire the types of weather and classify similar days by using the SOM and PNN neural network, respectively. The corresponding prediction models are established. The fitting results of the measured and the predicted curves show that the trend of output power is able to describe by using the prediction models. The RMSE and MAPE values indicate that weather change can be significant decline the prediction accuracy of the models. The forecaster performs well in the case of sudden weather changes. The model has good prediction accuracy and has certain practicality and feasibility.

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