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Improved Prediction Approach on Solar Irradiance of Photovoltaic Power Station

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Abstract

Prediction of solar irradiance has great significance to photovoltaic power forecasting and the scheduling plan of power generation. Aim at unsatisfactory prediction accuracy of traditional forecasting methods, this paper presents an approach to predict solar irradiance of photovoltaic power station based on wavelet decomposition and extreme learning machine. With historical irradiance sequence and relative meteorological data as inputs, solar irradiance at intervals 15 minutes is predicted one day ahead. In this approach, historical solar irradiance data is divided through the wavelet decomposition of three layers to obtain detail component and tendency component. Then the prediction models in terms of each component are built based on the extreme learning machine respectively. Finally each prediction value of the component gets final prediction result through wavelet reconstruction. The simulation result coming from the actual measured data of a photovoltaic power station indicates that the proposed model is of higher accuracy in comparison with the traditional ones.

Keywords: *photovoltaic power station, solar irradiance, prediction, wavelet decomposition, extreme learning machine (ELM)*

1. Introduction

The trend toward reducing environmental pollution and easing the energy crisis has accelerated the development of photovoltaic (PV) power generation in power systems [1]. Prediction of PV output power is conducive to dispatching department to make comprehensive arrangement between conventional energy generation and PV generation. It is also used to adjust the generation plan in time and provide the basis for scientific scheduling [2]. Solar irradiance is the main factor which influences the photovoltaic output power. In order to predict the PV output power accurately, the prediction accuracy of irradiance should be improved. At present, neural network method is mainly used to forecast irradiance in PV station. However, the initial value of weight and threshold in neural network model structure is sensitive and their generalization ability is poor [3-5]. A method of forecasting solar irradiance based on blind separation neural network is presented in reference [6]. This method has better prediction accuracy than traditional methods, but the prediction error is obvious in abnormal weather. In reference [7], the irradiance model is built based on seasons by using regression analysis in SPSS statistical software. But it only researched the relationship between solar irradiance and sunshine duration. Nash-Sutcliffe equation is applied in reference [8] to set up multi-models of prediction and confirm the extraterrestrial radiation, sunshine duration, temperature difference as the mainly influencing factors, but the prediction accuracy is kind of low.

Solar irradiance has randomness and periodic, it can be viewed as composition of multiple different frequency components [9, 10]. Each component has strong predictability because its similar frequency characteristic and consistent change rule. So it is an efficient path to improve prediction accuracy by modeling based on respective characteristic of different frequency component. In terms of unsatisfactory irradiance prediction accuracy of traditional prediction methods, this paper presents an approach to predict solar irradiance of photovoltaic power station based on wavelet decomposition and extreme learning machine. Through wavelet decomposition theory, history irradiance sequence can be decomposed into different frequency subsequence. The randomness of irradiance is blunted by analyzing each subsequence to some extent. The defects of slow training speed and easy to fall into local minimum point of the

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neural network can be avoided by means of ELM algorithm. It can achieve faster training speed and higher prediction accuracy. Therefore, prediction method based on wavelet decomposition and extreme learning machine is proposed in this paper.

2. The Analysis on Solar Irradiance of Photovoltaic Power Station

2.1. Change Rule of Irradiance and Selection of Main Predictor

In general the solar irradiance includes two aspects respectively are extraterrestrial irradiance and the surface irradiance. Extraterrestrial irradiance refers to the irradiance beyond the earth atmosphere and will not be influenced by the atmosphere. It has nothing to do with the weather conditions. However, it depends on earth rotation and revolution, and is related to the latitude of location, solar altitude, date and time. During the process of transferring to earth surface from the above atmosphere, solar irradiance will be weakened due to atmospheric absorption, scattering and reflection. Therefore, the surface irradiance is less than corresponding extraterrestrial irradiance. The surface irradiance has great randomness and is related to atmospheric condition. The surface irradiance is employed for denoting the solar irradiance in this paper. The actual measured irradiance form the past is selected as the main predictor.

2.2. The Selection of Secondary Predictors of Irradiance

There are some meteorological factors have great relevance with irradiance. The changing of irradiance can be reflected by them to some degree. As for some meteorological parameters such as cloud form, aerosol, wind speed, wind direction, environment temperature and relative humidity, on one hand, not all historical data can be got due to actual conditions. On the other hand, some meteorological factors are not greatly related to irradiance. It not only brings repeated information but also lead to excessive dimensionality of input vector of model. As a result, the complexity of model will be increased and great difficulty will be brought in for the model by regarding undisposed sequence of multidimensional historical data as predictive factors. Therefore, environment temperature and mean value per hour of relative humidity as secondary predictive factors.

3. Establishment of Irradiance Prediction Model Based on WD-ELM

3.1. Analysis of Irradiance Sequence Based on Wavelet Theory

A mainly function of wavelet theory is that local features of nonlinear signal can be analyzed. It computes the integral of basic wavelet after dilation and translation and the nonlinear signal. S.Mallat describes properties of multi-resolution from aspect of space concept vividly and gives wavelet decomposition algorithm and reconstruction algorithm.

(1) Decomposition algorithm

If C_0 is regarded as discrete signal to be decomposed, according to the decomposition algorithm:

$$\begin{cases} c_{j+1} = Hc_j \\ d_{j+1} = Gd_j \end{cases} \tag{1}$$

In the formula, j=0~J and J is the maximum decomposition layer: H is the low pass filter; G is the high pass filter; c_j and d_j is respectively the low frequency signal and high frequency signal when the original signal is below resolution 2^{-j}, and is the component of original signal at contiguous different frequency. Finally, it will decompose signal to be decomposed to d_1 , d_2 , … , d_j and c_j. This decomposition algorithm adopts two interpolations, and signal data length of every layer is reduced by half than that before decomposition, but the total output data length stays the same as the length of input data c_0. The reduction of signal number is unfavorable for prediction, but the signals decomposed by Mallat algorithm can go through two interpolations re-composition by adopting reconstruction algorithm.

(2) Reconstruction algorithm

The formula of reconstruction algorithm is

$$c_j = H^* c_{j+1} + G^* d_{j+1} \quad (2)$$

In the formula, j=0~J and J is the maximum decomposition layer: H is the low pass filter; G is the high pass filter; c_j and d_j is respectively the low frequency signal and high In the formula: j=J-1 , J-2 , … , 0 : H^* and G^* are dual operators. The number of signals can be increased by reconstructing signals decomposed by wavelet by means of the above formula, and D_1 , D_2 , … , D_j and C_j can be got by reconstructing d_1 , d_2 , … , d_j and c_j. Then:

$$X = D_1 + D_2 + \cdots + D_J + C_J \quad (3)$$

In the formula: D_J:{$d_{1,1}$, $d_{1,2}$…} , … , D_J:{$d_{J,1}$, $d_{J,2}$…} are the high frequency signals reconstructed from layer 1 to layer J; C_J:{$c_{J,1}$, $c_{J,2}$…} are the low frequency signals reconstructed in J layer. In reconstruction algorithm of Mallat, supplement a 0 between neighboring data of input data sequence to make data length increase double so as to recover the data length before two interpolations.

The time frequency window of wavelet transform can be adjusted. When the scale is bigger, the time domain of time frequency window will be wide and the analysis frequency will be low, which is suitable for general view observation; when the scale is smaller, the time domain of the window will be narrow and the analysis frequency will be high, so it is suitable for detail observation and has adaptability to signals. Therefore, the task of analysis of different frequencies by irradiance sequence can be completed by means of wavelet transform.

3.2. Establishment of Irradiance Prediction Model Based on WD-ELM

Extreme learning machine (ELM) algorithm is an effective, easy to use single hidden layer feed-forward neural network learning algorithm [12]. This algorithm will randomly produce link weight of input layer and threshold value of neuron on the hidden layer. Besides, adjustment is not needed during training and the only optimization can be got by just setting neuron number of hidden layer, which overcomes the shortage of traditional neural network [13, 14].

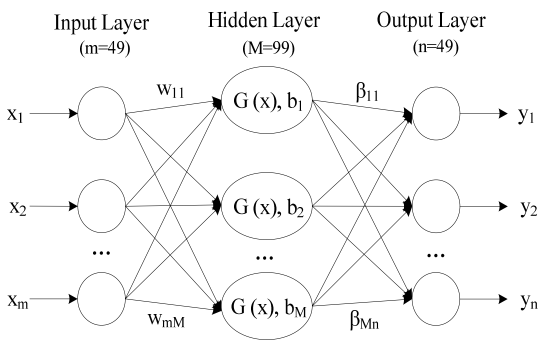

Figure 1. Prediction Model of Approximation Composition

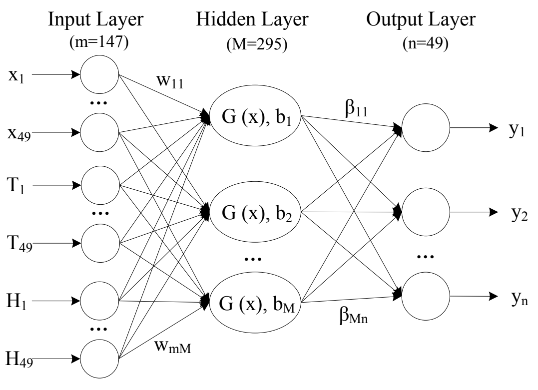

Figure 2. Prediction Model of Detail Composition

Three-layer decomposition on historical irradiance sequence is conducted by using wavelet transform to obtain low-frequency approximation signal and high-frequency detail signal. Models of the decomposed sequence are respectively established by adopting extreme learning machine. Feed-forward single hidden layer structure is employed in the network training models of extreme learning machine shown in Figure 1 and Figure 2.

Assume that m, M, n respectively refer to the node number of network input layer, hidden layer and output layer. G(x) is the activation function of hidden layer neuron, bi is threshold value. ω is the link-weight between network input layer and hidden layer and β is the link-weight between network hidden layer and output layer. X refers to the historical irradiance decomposition sequence of the day before and Y refers to the predicted sequence of the following day. T and H mean temperature and relative humidity respectively.

Every sequence can be trained and predicted through this method, and then each result will be reconstructed to get complete prediction result. The prediction steps are shown in Figure 3. The prediction method of WD-ELM can be given as follows.

(1) First of all, the historical irradiance sequence is divided into detail compositions and approximation compositions of varying length through three-layer wavelet decomposition.

(2) Then prediction models for each divided component are built respectively based on extreme learning machine.

(3) After that, predicted value of solar irradiance is obtained after wavelet reconstruction of predicted results.

(4) At last, simulation is made with the measured date in a photovoltaic power station in China's Gansu Province.

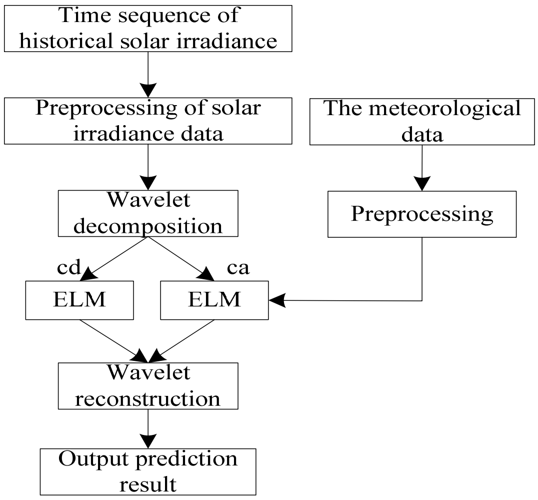

Figure 3. Block Graph of Solar Irradiation Prediction Process

4. Results and Analysis

4.1. Simulation Data

This paper makes simulation with a photovoltaic power station of Gansu as example. The photovoltaic power station makes real-time recording of solar irradiance, temperature, relative humidity and value of output power every day from its operation. The historical data of solar irradiance recoded in 1-12 months of 2012 is chosen as samples, solar irradiance time sequence of one month selected randomly to be tested, then to predict solar irradiance of photovoltaic power station one day ahead with intervals of 15 minutes. As irradiance changes as sun rises and falls, the historical irradiance sequence will be made by the data of 7:00-19:00 and the time period without irradiance in the night will be omitted.

4.2. Simulation Result

Establish the prediction model of WD-ELM as shown in Figure 1. Firstly, make three wavelet decompositions for historical irradiance sequence of one month and predict the decomposed low frequency components ca_1, ca_2, ca_3 and high frequency components cd_1, cd_2, cd_3 by using extreme learning machine (recorded as ELM1……ELM6). Then, reconstruct the output data of six websites and get complete predictive irradiance which is recorded as model I. As low frequency component has obvious day property, ELM1-ELM3 takes decomposed low frequency sequence and relative meteorological data as input and the rest three websites just takes various layers of high frequency sequence as input. The result of three layers of wavelet decomposition for historical irradiance is shown in Figure 4.

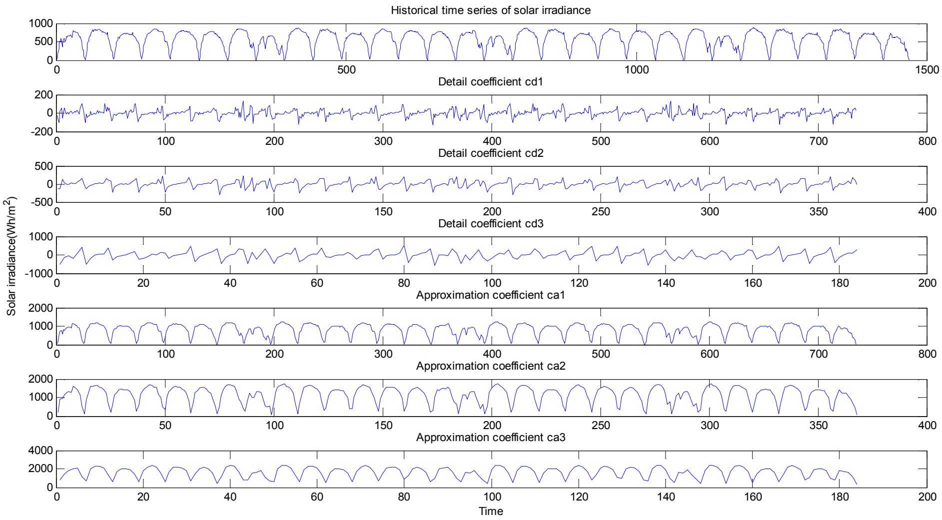

Figure 4. Wavelet Decomposition of Solar Irradiance in One Month

In order to verify the efficiency of the proposed method more objectively, the feed-forward neural network trained with BP algorithm (recorded as model II) is here compared, which is also trained with plenty of historical samples from Jan. to Dec. to predict solar irradiance during 7:00-19:00 one day in advance. The respective irradiance results predicted by Model I and Model II are shown in Figure 5 and Figure 6.

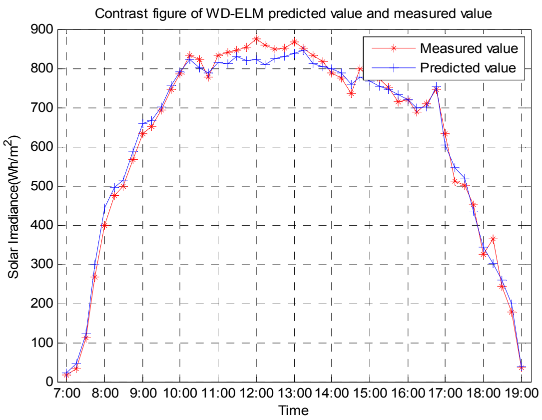

Figure 5. Result Comparison of Irradiance Predicted by WD-ELM

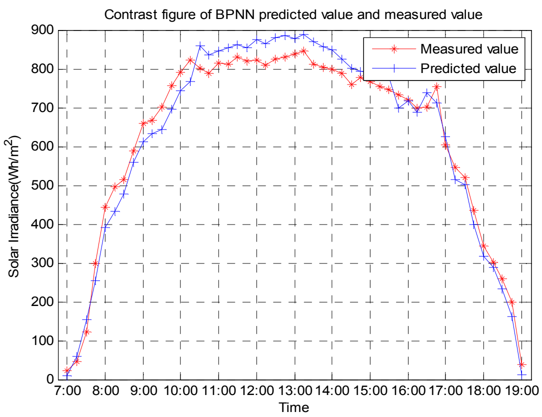

Figure 6. Result Comparison of Irradiance Predicted by BPNN

4.3. Error and Analysis

Two methods on WD - ELM and BP neural network to predict the solar irradiance one day in ahead, respective prediction errors between predicted value and actual value were shown in Figure 7 and Figure 8.

In order to quantitatively judge the optimal prediction method, in this paper, two ways of evaluation and comparison are made by using MAE and MAPE. Suppose that I_M is actual prediction value of irradiance, I_P is the number of prediction points and the error is defined as:

Mean absolute error:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |I_M - I_P| \tag{5}$$

Mean percentage error:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{I_M - I_P}{I_M}\right| \times 100\% \quad (6)$$

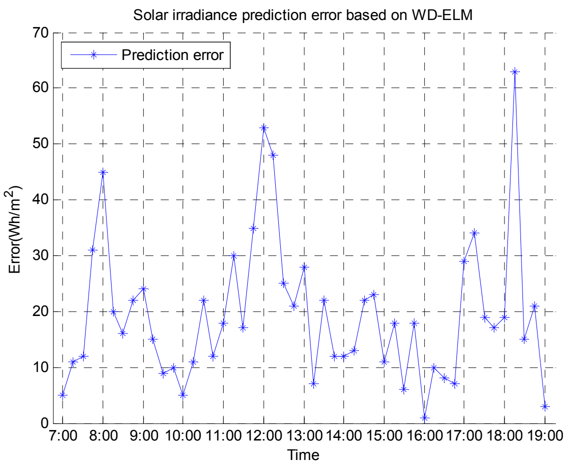

Figure 7. Error of Irradiance Predicted by WD-ELM

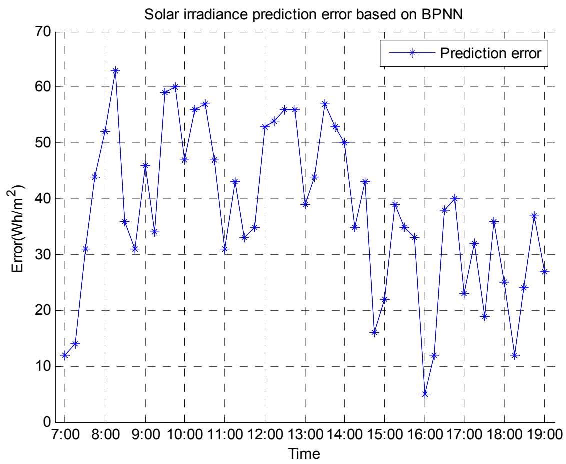

Figure 8. Error of Irradiance Predicted by BPNN

Table 1. Comparison of Prediction Errors Corresponding to the Two Prediction Methods

Prediction Methods	MAE(Wh/m^2)	MAPE(%)
Model I : The method of WD-ELM	19.4849	5.0363
Model II : The method of BPNN	37.6735	14.4462

From Table 1, the prediction result by using the model in this paper is more accurate than the traditional prediction model of neural network, MAE is only 19.4849Wh/m^2 and MPE is reduced to 5.0363%. WD-ELM algorithm can use wavelet transform to make irradiance projected to different scales and decomposed into periodic signals under multi-scale, and as each component uses different processing methods, the accuracy of component prediction during the irradiance period will surely be improved.

5. Conclusion

The prediction method of solar irradiance based on wavelet decomposition combine extreme learning machine algorithm is proposed in this paper. The simulation result coming from the actual measured data of a photovoltaic power station indicates that the proposed model is of higher accuracy in comparison with the traditional neural network methods. Therefore, the approach of WD-ELM is more applicable to the prediction on solar irradiance of photovoltaic power station. It has broad prospect in engineering application.

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