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Research on power generation prediction of photovoltaic power station based on improved neural network

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Abstract

The large-scale construction of photovoltaic power plants makes more and more green power connected and utilized, which also brings great impact on the carrying capacity of the power grid. Forecasting the power generation of photovoltaic power plants can better promote the stable regulation of the power grid and promote the consumption of new energy. In this paper, the influence of main environmental factors on photovoltaic power generation is analyzed by Pearson similarity, and a photovoltaic prediction model is established. The model is solved by combining adaptive genetic algorithm and improved Drosophila algorithm to optimize neural network. Finally, the historical sample data of photovoltaic power plants are used for simulation. By comparing the photovoltaic power generation prediction effects of single BP algorithm, GA-BP combined algorithm and GA-FOA-BP intelligent algorithm, it is proved that the method of combining improved Drosophila algorithm to optimize neural network and genetic algorithm to solve the prediction model can reduce the instability of photovoltaic output prediction to some extent and has good application value.

Keywords: PV power forecast, FOA algorithm, GA-BP algorithm

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1. Introduction

In the current situation of global environmental deterioration, the demand for clean and renewable energy becomes more urgent. As a convenient and efficient way to obtain renewable energy, photovoltaic energy has developed rapidly and attracted wide attention. With the rapid development of energy and power economy and technology in China, the introduction of comprehensive green transformation policies and the processive maturity of photovoltaic technology, the photovoltaic industry in China is also advancing in an all-round way [1]. Photovoltaic power station is the core of photovoltaic power generation system, and the exact prediction of its energy generation is crucial to the stable operation of power system and energy management. At the same time, with the cancellation of the photovoltaic subsidy capacity electricity price policy in China, the competition among photovoltaic power generation enterprises is becoming increasingly fierce, and the calculation of power generation capacity is the data basis for its calculation benefits. The expansion of photovoltaic power plant scale and technological progress, combined with the traditional power generation mode to coordinate with each other, optimize the power system, increase the output of solar energy, and precisely forecast the energy generation of photovoltaic power plant are of great help to promote the effective consumption and scientific utilization of new energy[2-4].

The working environment of photovoltaic system is complex. Over time, the surface of the module will accumulate obstructions, and the temperature of the module will increase obviously, and its output voltage and power will decrease [5]. Secondly, clouds, dust, aging and other reasons lead to mismatch between components. For the sake of reduce

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the loss of power generation efficiency of photovoltaic array, it is necessary to adjust its output characteristics to make it show single peak characteristics and avoid multi-peak characteristics. The adverse effects of harsh environment on the output power of photovoltaic power station, such as the impact of ice, dust and sand in winter and storms on the output characteristics of photovoltaic modules, need to accurately predict the photovoltaic power to improve the photovoltaic new quality productivity because of the intermittent, fluctuating and uncertain photovoltaic power generation system [6-8].

Many luminary at power grid system have done a lot of experimental research on photovoltaic energy prediction, and explored the experimental research scheme from different angles. Qiang Zhou et a. [9] propose a flexible measures to forecast the output energy of photovoltaic system based on BP neural network and same kinds situations which is in differents scenes. Using global solar radiation intensity and output power data, the weather types and similar days are classified by using BOM and PCC respectively. Qipeng He et al. [10] propose a step-by-step iterative prediction method based on the combination of weather and electricity big data, and use the intelligent algorithm of Linghou to eliminate outliers that occur in photovoltaic power plants during special weather conditions. Xuejiao Fu et al.[11] give the EMD-PCA-LSTM model to predict the photovoltaic power generation, and combines empirical mode decomposition, ATP and wavelet time transform to model the dynamic time of multivariable characteristic sequence to realize the prediction of photovoltaic power generation. Minghua Chen, Shaoqiang Li, Chen Xiaoxiong [12] propose a variable weight coefficient model based on gray correlation analysis (GRA) and BP neural network combination (GRA-BPNN) to predict photovoltaic output, which has a good forecasting effect on seasonal power generation. Gupta M. et al.[13] use artificial fish swarm algorithm-back propagation neural network to predict photovoltaic power, which has the advantages of high output power accuracy and short training time, but the disadvantage is that the output power will fluctuate greatly in the middle of the prediction result. Abdallah A. et al. [14] use wavelet neural network to create a model and predict the power generation. In this paper, aiming at the intermittence and uncertainty caused by environmental factors, the improved Drosophila neural network is based on GA is for the reason of predicting energy generation of PV large-scale stations. Firstly, Pearson similarity analysis is used to analyze the impact of major constrained variables on photovoltaic energy generation, and a photovoltaic prediction model is established. The strategy is solved in sunny days, rainy days and cloudy days by combining adaptive genetic algorithm and improved Drosophila algorithm to achieve better refinement of prediction forms, which verifies feasibility of the algorithm.

2. Analysis of photovoltaic power input characteristics

2.1. Environmental impact factors

The factors that affect the actual value of photovoltaic forecasting include weather, light intensity and utilization rate of photovoltaic equipment, humidity, and the comprehensive environment of the location. This article conducts an importance analysis based on the degree of impact on the power generation value, mainly including four primary mandatory reduction variables[15,16].

(1) Solar irradiance. Solar irradiance is restricted by many factors, such as the geographical location of components, weather changes and irradiation angle. Long-term monitoring shows that the variation of irradiance is periodic and basically consistent with the energy generation impacts of solar energy station, and they are positively correlated. Research reflects that irradiance plays important critical role in the energy generation efficiency on photovoltaic system.

(2) Temperature. When the temperature rises, the current on the photovoltaic module increases, but at the same time, the voltage decreases and the overall power decreases. Generally speaking, the increase of temperature will cause the change of output voltage of crystalline silicon battery. When the temperature rises by 1℃, the output voltage of crystalline silicon battery will drop by about 0.5%.

(3) Wind speed. The wind speed will affect the flow speed of air, thus affecting the temperature. When the wind variable factor increases, more factors of the back panel of the photovoltaic module decreases, so that the energy generation efficiency of the module is improved; On the contrary, if its controlling factors becomes smaller, other major element of the back panel of the photovoltaic module will increase, so that the energy generation results in module may be increasing.

(4) Humidity. When the relative humidity of the air increases, the illumination is affected, and the solar energy divergence is reduced by refraction or diffraction, thus affecting the irradiance. At the same time, the humidity will affect the ambient condition to the particular circumstances, so as the increase of air humidity will reduce the ambient temperature. Long-term monitoring shows that there is a negative correlation between environmental humidity and power generation efficiency to some extent.

2.2. Correlation analysis

In this paper, the study of pearson similarity method on forecasting energy generation is used to analyze degree between photovoltaic energy generation data and impact factors. X and Y are used to represent variables, and the ratio of the product of their covariance to the product of their marked differences is the correlation coefficient, specifically:

$$RES = \frac{\sum_{m=1}^{n}\left(D_i - \overline{D}\right)\left(E_i - \overline{E}\right)}{\sqrt{\sum_{m=1}^{n}\left(D_i - \overline{D}\right)^2}\sqrt{\sum_{m=1}^{n}\left(E_i - \overline{E}\right)^2}} \tag{1}$$

According to the calculated Pearson coefficient analysis, solar irradiance has the strongest correlation with photovoltaic output, and it is positively correlated. The correlation between temperature and output is the second, and the correlation of other factors is very weak, as shown in Table 1. The historical data are classified according to sunny, cloudy and rainy weather conditions. At the same time, due to the scarcity of ground light intensity stations and relatively incomplete data at this stage, the solar radiation intensity is taken as the daily average, and the ambient temperature, daily average wind speed, daily average solar radiation intensity and relative humidity are provided to the prediction model as input variables.

Table 1. Table of correlation coefficient between meteorological factors and photovoltaic output

Program	Solar irradiance	Temperature	Wind speed	Humidity
correlation coefficients	0.78	0.62	0.26	-0.27
correlation	strong	medium	weak	weak

2.3. Data preprocessing

In order to more accurately analyze that the forecasting error of photovoltaic power station is controlled in a lower range and influenced by different environmental factors, the first task is to preprocess the historical data and delete the singular data. The formula for normalization is:

$$Z_n = \frac{Z_n - Z_{\min}}{Z_{\max} - Z_{\min}} \tag{2}$$

Where: Z_n, $Z_{\max}$ and $Z_{\min}$ are the upper and lower limits of various parameter values in the fruit fly algorithm for predicting photovoltaic power generation.

3. Establishment of adaptive genetic algorithm prediction model

3.1. Adaptive genetic algorithm

Adaptive genetic algorithm is a re-optimization for a series of scale animal bionics of basic genetic algorithm [17]. If the population achieves a certain optimal solution, the population will carry out genetic operation, so that the population will evolve in the direction of swimming solution, and every reasonable photovoltaic calculation in the system will tend to be consistent. Once the population converges to the optimal solution, the individuals with strong performance around the optimal solution will be destroyed. To solve this problem, we should carry out in-depth optimization after protecting the optimal individual, and the adaptive genetic algorithm came into being. The method can make P_c and P_m automatically change with the fitness of the population, and its adjustment formula is:

$$P_c = \begin{cases} \dfrac{k_1\left(f_{\max} - f_{czd}\right)}{f_{\max} - f_{qpj}} & f_{czd} \geq f_{qpj} \\ k_2 & f_{czd} < f_{qpj} \end{cases} \tag{3}$$

$$P_m = \begin{cases} \dfrac{k_{1*}\left(f_{\max} - f_{czd}\right)}{f_{\max} - f_{qpj}} & f_{czd} \geq f_{qpj} \\ k_{2*} & f_{czd} < f_{qpj} \end{cases} \tag{4}$$

Where k1, k1*, k2, k2*⩽1 and greater than or equal to 0. $f_{\max}$ and f_{qpj} are the limit values based on photovoltaic verification values for different sequences respectively. f_{czd} is the one with greater fitness among the two strings used for crossing.

When P_c is large, new individuals will enter the population. If P_c is too large, the crossover operation will be destroyed faster than the new optimal individuals, making it difficult for the population to evolve. On the contrary, if P_c is too small, in the process of searching, the speed is very slow, and the search cannot be promoted normally. Proper selection of crossover probability can greatly improve the search speed in population evolution, and the general P_c value is (0.5 ~ 1). Although the mutation operator plays a small role, it can also enhance the change of the population and ensure that the search surface of the algorithm can cover all points in the problem space. However, its mutation rate is high, which is similar to random search, so the research P_m is selected as (0.1 ~ 0.5). In the application of the algorithm, adjust k1 and k1* reasonably to ensure that P_c and P_m are within a reasonable range.

3.2. Establishment of forecasting model

Drosophila neural network is depend on about usual three-layer BP neural network bus, and takes Drosophila is inject to the forecast energy structure, so as to further solve the photovoltaic prediction model by scisntific forecast algorithm results. Drosophila algorithm is used to transform and nonlinear map the input data to extract time-frequency features, and its topological structure is shown in Figure 1. Where, m_{onode} is the total generation node number in the output storey, n is the total generation node number in the hidden storey, and l_{inode} is the total generation node in the input storey.

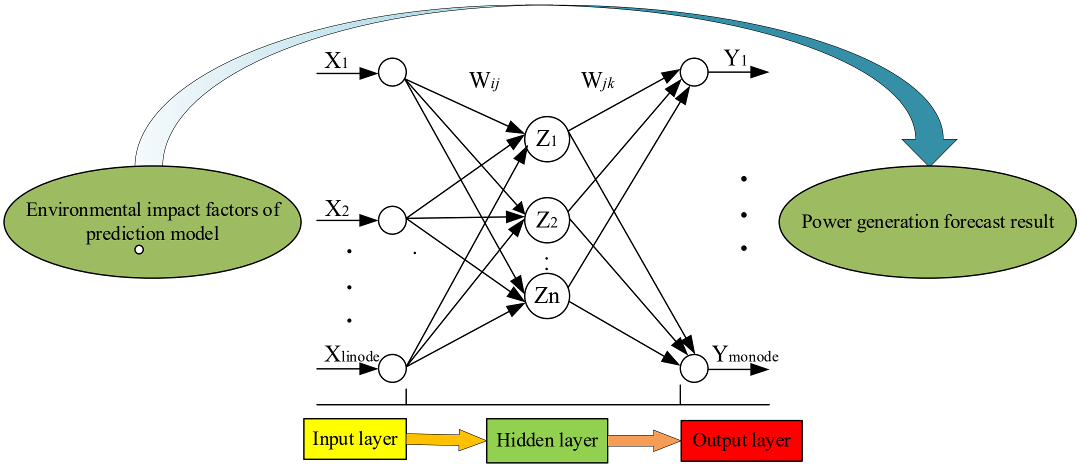

Figure 1. Topological structure of Drosophila neural network

Four real-time data of solar irradiance, ambient temperature, instantaneous wind speed and air humidity are input, so the alternative ways of solvation in the input layer is 4. The output data is only one real-time data of power generation, and the number of nodes in the output layer is one. The available solar factor nodes of hidden storey can be calculated from formula (5), and the optimal place of structure in the hidden storey is 10 according to the simulation experiment. The forecasting model of photovoltaic power generation is as follows:

$$n = \sqrt{l_{inode} + m_{onode}} + a \tag{5}$$

Where: A is the adjustment coefficient, which is an arbitrary constant between [1,8].

4. Research on power generation prediction of photovoltaic power station based on genetic algorithm and drosophila neural network

4.1. Improved drosophila algorithm

The fruit fly algorithm is a cross innovation algorithm in the field of predicting photovoltaic power generation, gradually beginning to be applied in the joint solution of multiple constraint factors in short-term photovoltaic power forecasting using multiple intelligent algorithms. Studying the living habits of fruit flies, we aim to highlight their biomimetic characteristics. They have excellent auditory and map memory functions, as well as strong memory for the tastes of other animals around them. Specifically, firstly, sensitive components around the target location are collected through smell, and the target values are gathered step by step. The direction of food and companions gathering is located through the eyes, and finally the victory fruit is found through the optimal travel route. The stronger the odor of food, the stronger the perception of fruit flies. Of course, the intensity of the flavor is directly related to the sensitivity of fruit flies to their favorite foods, which means that fruit flies decide their route based on their own habits and preferences, and ultimately achieve their own goals and pursuits. The travel route of fruit flies is not straight, which means it is not smooth sailing. Fruit fly algorithms generally cannot directly obtain the optimal photovoltaic prediction value, and need to be constantly verified and corrected. By verifying the error between the predicted value and the actual value, the final path of fruit fly detection is determined. Drosophila algorithm is mainly based on the cooperation mechanism of Drosophila colony and information sharing mechanism to determine the optimal solution, which is The prediction of continuous and naturally solvable photovoltaic data has a fine tuned and controllable effect, but for complex climate electricity prediction, its understanding has biased oscillation photovoltaic characteristics, which is prone to recurrence in long search time and low efficiency. In view of the above shortcomings, the following improvements are made:

(1) Improvement of step size selection. In Drosophila algorithm, the selection of step size parameters It can effectively determine the starting value of photovoltaics by drosophila algorithm. In order to improve abnormal results of new shoot of the algorithm and prevent algorithm oscillation, Step update, that is, the coupling verification of step weight, try to correct the photovoltaic prediction structure weight and iteration time. The step size update formula is as follows:

$$\begin{cases} L = L_0 - \dfrac{L_0(g-1)}{\mathrm{T}_{\max}} \\ w = w_0 \times a^g \end{cases} \tag{6}$$

Where: L_0 represents the original step size, g reflects the current foraging algebra, and $\mathrm{T}_{\max}$ glasses the upper limit of foraging iterations, w is the weight updating coefficient, which is determined by the initial setting coefficient w_0 and iteration times g, and the value of a is (0,1).

(2) Improvement of concentration judgment value. Due to the fact that fruit flies sometimes encounter special questions that affect their judgment when determining direction based on sensation, they may obtain the optimal solution in advance and deviate from realityphenomenon, so the corresponding action factor g is introduced into the concentration judgment value formula, which makes S_i increase and further increases the search range of the algorithm. The formula is:

$$S_i = 1/D_i + g \times D \tag{7}$$

Where: g obeys the uniform distribution of [-1,1], and D_i is the first starting point of fruit flies, that is, the initial action position.

(3) Improvement of visual choice. By optimizing the strategies for fruit flies to enter different scenarios, analyzing the optimal values for photovoltaic prediction under different climate conditions, determining the optimal population, and searching for the most accurate fruit fly odor marker values under forward, reverse, or any degree of freedom conditions, it can better reduce the errors caused by special odors and weather conditions on the prediction results, and adopt appropriate manual corrections to reduce iterations, get rid of the worst taste seeking results, and improve system adaptability.

4.2. Implementation steps of photovoltaic power generation prediction algorithm

Take into account of the progressive BP neural network forecast form has the shortcomings of less than ideal forecast correctness and convenient to go into useful approach, the Drosophila algorithm is introduced to promote the structure of above new pattern, and then the optimized network parameters are given to the adaptive genetic algorithm for optimization, so as to minimize the global error. The flow chart of energy forecast of PV energy station based on genetic algorithm and Drosophila new pattern is shown in Figure 2.

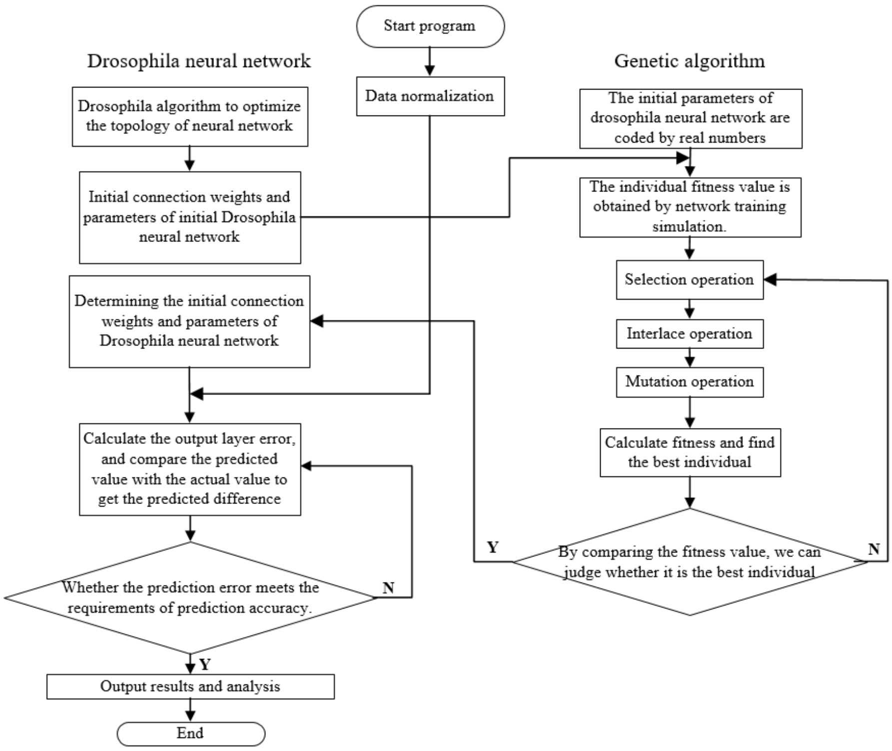

Figure 2. Flow chart of GA-FOA-BP new pattern PV energy forecast mode

5. Example analysis

Based on the historical data and meteorological data of photovoltaic power station in Zhangjiakou, Hebei Province, the simulation and error of photovoltaic power generation prediction are studied. The photovoltaic power generation data from April to June, 2018 is selected as the input sample of the forecasting model. Firstly, the data are divided into three categories based on different types of weather with different properties, and 20 groups of data are selected for each category. Then, the classified samples are trained by using Intelligent factors that can be optimized model, GA-BP neural network model and FOA-GA-BP neural network model, and the power generation is continuously predicted and tested, so that the test value approaches the expected value. It is worth noting that considering that the photovoltaic output is limited by time, the working time of the photovoltaic power station is set between 7: 00 and 18: 00, that is, every 7: 00 ~ 18: 00, with a period of 30min, 23 environmental temperature data and photovoltaic output data are collected, in addition to daily average solar irradiation intensity, daily average wind speed and relative humidity. Finally, the sample data is imported into the tested network to get the final predicted value. The number of hidden layer nodes of BP neural network and GA-BP is 12, the population size of genetic algorithm is 10, and the maximum iteration number is 30. The crossover probability and mutation probability are selected in Literature [18].

This paper reflects the size of power generation through the size of power generation efficiency. Comparing the BP neural network, GA-BP and GA-FOA-BP forecasting models, the power curve of each moment in sunny days is shown in Figure 3.

As can be seen from Figure 3, the predicted values of the three models in Figure 3 are consistent with the actual values, reaching the peak at around 12: 00. With the gradual sunset, the solar irradiance decreases and the power generation efficiency shows a downward trend.

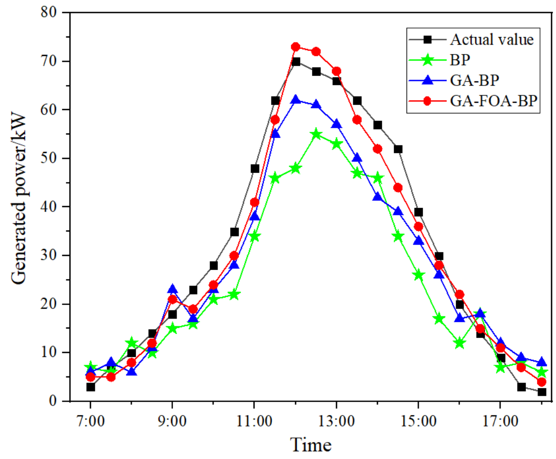

Figure 3. Comparison of power prediction in sunny days

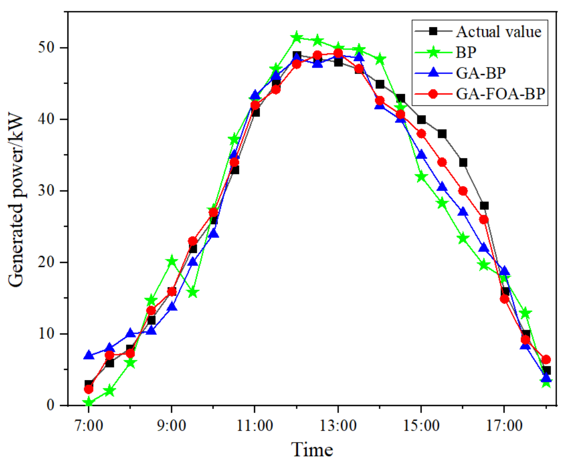

Figure 4. Comparison of power prediction in cloudy days

The curve of power generation and relative error prediction value at each time in cloudy days is shown in Figure 4. In Figure 4, the power generation of each model is lower than that in sunny days, and the power generation is more stable, and the difference between the maximum power and the minimum power is lower than that in sunny days.

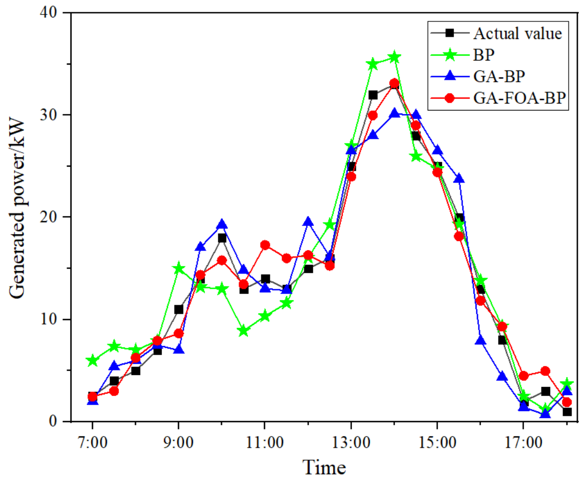

Figure 5. Comparison of power prediction in rainy days

As shown in Figure 5, the curve between the generated power and the predicted value of relative error at each time in rainy days shows that the variation trend of the generated power is complicated and greatly influenced by environmental factors, and the fitting degree between each model and the actual value is not as good as that in the first two weather environments, and the peak value of its power output also shows obvious lag effect compared with the first two weather environments. By analyzing and comparing the three models, the accuracy of the prediction model is analyzed and reflected by the average absolute percentage error and root mean square error. The prediction error results of the three prediction models are shown in Table 2.

Table 2. Prediction error results of three prediction models

Weather regime	BP		GA-BP		GA-FOA-BP	
	EMAP	ERMS	EMAP	ERMS	EMAP	ERMS
Sunny day	11.2	7.3	9.6	6.3	7.1	5.5
Cloudy day	16.3	8.2	15.2	7.5	13.5	6.9
Rainy day	19.5	9.6	18.9	8.7	16.7	7.3

In three kinds of weather, through the comparison of error data, the three models have better prediction effect in sunny days, because the light intensity is large at noon and small in the morning and evening on sunny days, and the output power curve is approximately normal distribution. In cloudy days, due to the shading effect of clouds and the uncertainty of cloud movement, the photovoltaic output power fluctuates. The forecast effect of rainy days is the worst, because it is influenced by multiple factors such as rainfall and cloud changes, and more factors need to be considered to make the model forecast more accurate.

According to the error comparison, the FOA-AGA-BP neural network prediction model has higher accuracy than the GA-BP neural network prediction model. There are obvious errors in the results of the classical BP neural network prediction model. Although the relationship between photovoltaic output and meteorological factors can be found through historical data, the prediction model based on the classical neural network training method has obvious defects. Although the prediction effect can be improved by repeatedly adjusting parameters, even so, it is difficult to train the best state.

In three kinds of weather, the average absolute error and root mean square error of GA-FOA-BP neural network prediction model are obviously smaller than other models, and the prediction error is 7.41% in sunny days, while the other two models are 11.2% and 9.6%. It can be seen that compared with GA-BP prediction model which only optimizes the weights and thresholds of neural network, the prediction accuracy is improved to some extent. This shows that only optimizing the initial weights and values of BP neural network can not greatly improve the forecasting ability of BP neural network, but optimizing the connection structure and weight threshold of BP neural network can better make up for the shortcomings of BP neural network in forecasting.

6. Conclusion

In this paper, for the sake of solving the problem of inaccurate forecasting of PV energy generation and fluctuation of forecasting results under various meteorological factors, a forecasting of PV energy generation based on scientific mode, Drosophila neural network, is proposed. Firstly, the study of pearson similarity method on forecasting the impact of actual factors of continuous change factors on photovoltaic energy generation, and historical data are normalized, and then a photovoltaic forecasting model is further studied and built. The model is solved by combining adaptive genetic algorithm and improved Drosophila algorithm to optimize the neural network. Finally, listing a series sample actul messages of PV energy station in Zhangjiakou by way of illustion, the simulation analysis is used successfully. By comparing the photovoltaic power generation prediction effects of single BP algorithm, GA-BP combined algorithm and GA-FOA-BP intelligent algorithm, it is concluded that the GA-FOA -BP prediction model established by optimizing BP neural network can better reduce the error in photovoltaic power generation prediction under different environmental conditions and has good application value.

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