Short-term prediction of photovoltaic power based on GWPA - BP neural network model

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Abstract

In recent years, due to China's energy crisis and environmental pollution and other increasingly serious, so in recent years to develop renewable energy, solar energy has become one of China's major green energy, and solar photovoltaic power generation has become a solar energy use Main way. However, the photovoltaic power generation is becoming more and more random due to the influence of meteorological factors, and the callability is weak, which makes the photovoltaic power generation forecast more important for the ogrid control strategy, the grid power dispatching and the improvement of the grid power quality. In this paper, we improve the convergence speed and global convergence of wolves algorithm by improving the wolves algorithm (WPA), and propose a GWPA-BP photovoltaic power generation forecasting model based on wolf algorithm optimization BP neural network. Finally, the validity of the proposed method is verified by comparing the predicted data with the measured data.

Keywords

photovoltaic power prediction; wolves algorithm; neural network.

1. Introduction

Based on the numerical data or the measured data, the photovoltaic power prediction is based on the parameterization scheme of the geographical coordinates of the photovoltaic power plant and the specific regional characteristics. The prediction model and algorithm are established to forecast the output power of the PV power plant in the future [1]. From the experience of foreign industry research, photovoltaic power prediction from the forecast method can be divided into two kinds of statistical methods and physical methods [2~3]. Statistical methods for statistical analysis of historical data to find out the inherent law and used to predict; physical methods based on solar radiation transfer equation, PV modules operating equations and other physical equations to predict the need for detailed technical information of photovoltaic power plants and weather and solar radiation data. At present, the methods used to predict the photovoltaic power are mainly used in neural networks, support vector machines and other statistical methods, which is the most widely used BP neural network. However, due to the traditional BP neural network in the training process needs to repeatedly modify the network weights and thresholds, often need hundreds or thousands of iterations it is possible to complete the training to achieve the target error, which led to a larger amount of calculation. In the practical application, if the initial weight of BP neural network, the threshold is not properly selected, then prone to BP neural network convergence speed is slow, easy to fall into the local extreme value of the situation. Therefore, this paper proposes a prediction model (WPA-BP) based on the wolves algorithm to optimize the BP neural network. This method can avoid the blindness of the original selection of network weights and thresholds in order to achieve the efficiency and precision of short-term power prediction.

However, due to the basic wolves algorithm in the iterative update process, will directly eliminate the poor degree of poor individuals, while randomly generating new individuals, this is not conducive to the rapid implementation of the algorithm. Therefore, this paper proposes an improved wolf algorithm based on genetic algorithm operation, called GWPA algorithm, and applies the proposed algorithm to the training of BP neural network, and finally through the optimized BP neural network to carry out the photovoltaic power prediction.

2. Wolves algorithm and its improvement

2.1 Wolves algorithm principle

The wolves algorithm is proposed by simulating the process of prey on wolves. It consists of prey, wolf, wolf and wolf four basic parts, and abstracted out of three acts: walk, summon and siege, and "winner is king" of the first wolf mechanism and "strong survival "Wolves update mechanism of these two mechanisms [4]. The steps of the wolves algorithm are as follows:

1) Initialize. The population size of the wolves is N, the initial evolutionary algebra t = 0, the individual dimension of each wolves is the D dimension variable, that is, the spatial dimension of the search is D, XL and XU are the minimum maximum range of the wolves search space, the maximum number of iterations of the algorithm is M max, then the position of the i-th artificial wolf can be expressed as:

$$X_i = (X_i(1), X_i(2), ...X_i(D)) \quad , i = 1, 2, ..., N$$
$$X_i^t = X^L + rand \times (X^U - X^L), \ i = 1, 2, ..., N \tag{1}$$

Where, X_i^t is the random number in the i-th artificial wolf, $rand \in (0, 1)$ in the t-th population.

2) According to the size of the fitness value, generate the wolf. Through the concrete fitness function to calculate the fitness value of each artificial wolf, select the optimal fitness value of the artificial wolf as the wolf.

3) Walk behavior. In addition to the first wolf, select the best S_num artificial wolf as a wolf and perform walking behavior, until a wolf i detect the prey odor concentration Y_i greater than the wolf's prey odor concentration Y_{lead} or reach the maximum number of walks $T_{\max}$. The location of the wolf i in the d-dimensional space is as follows:

$$X_{id}^p = X_{id} + \sin\left(2\pi \times p / h\right) \times step_a^d \tag{2}$$

In the formula, h represents the number of directions in which the wanderer walks, $step_a$ represents the walking step of the wolf, and p represents the current direction ($p = 1, 2, ..., h$).

4) Raid behavior. The wolf through the howling initiated summons behavior, called around the wolf quickly gathered to the head of the wolf. Wolves according to type (3) the implementation of raids, if the way in the raid, the wolf perceived prey odor concentration $Y_i \rangle Y_{lead}$, then $Y_{lead} = Y_i$, the wolf i instead of the wolf into a new wolf, and re-initiated summon, otherwise, the wolf continue to raid until d_{is} < [5]. When the wolf in the k+1 evolution, in the d-dimensional variable space in which the location as shown in equation (3):

$$X_{id}^{k+1} = X_{id}^k + step_b^d \times (g_d^k - X_{id}^k) / \left| g_d^k - X_{id}^k \right| \tag{3}$$

Where $step_b$ is the length of the raid of the wolf, g_d^k for the k generation of wolves in the d (d=1,2,..., D) dimensional space position.

Determine the distance from the formula (4) calculated:

$$d_{near} = \frac{1}{D \times w} \times \sum_{d=1}^{D} \left| X_d^U - X_d^L \right| \tag{4}$$

Where, w is the distance determination factor.

5) Siege behavior. We look at the position of the wolf as the prey of the mobile position, for the wolves of the k generation, assuming that the prey of the mobile position G_d^k , the wolves siege behavior can be expressed by (5)

$$X_{id}^{k+1} = X_{id}^k + \lambda \times step_c^d \times \left| G_d^k - X_{id}^k \right| \tag{5}$$

Where λ is a random number between $[-1,1]$; $step_c$ is the attack step size; if the wolves are perceived after the siege of the prey odor concentration is greater than the original state of the state of the odor concentration, then update the location of artificial wolves, otherwise, the location of the artificial wolf will remain unchanged. Will be the greatest value of the artificial wolf selected as the first wolf.

Walk step size $step_a$, raid step $step_b$, attack step $step_c$ the relationship between the three as follows:

$$step_a = step_b / 2 = 2 \times step_c = \left| X_d^U - X_d^L \right| / S \tag{6}$$

Where, S is the step factor.

6) Wolves update mechanism. Wolves in accordance with the "survival of the fittest, from strong to weak," the principle of distribution of food, that is, the worst degree of fitness out of the R row of wolves, and then randomly generated R artificial wolf, where R is a random integer between $\left[n/(2\times\beta), n/\beta \right]$ and β is the population update scale factor.

Determine whether the result of the algorithm satisfies the accuracy requirement, or whether the maximum number of iterations $M_{\max}$ is reached. If it is reached, the position of the wolf is the optimal solution of the problem, and the algorithm ends; otherwise, the process is repeated 2) to 5).

2.2 Improved Wolves Algorithm

Through the brief description of the basic principle of the wolves algorithm, we can see that in the last step of the algorithm, the iterative updating mechanism of the wolves is to directly eliminate the individuals with poor fitness value and increase the individuals randomly. Although this can increase the diversity of wolves, but ignored the location of these individuals have reached, reducing the convergence rate of the algorithm [6]. Therefore, in this paper, we propose a new improved wolves algorithm, which integrates the selection, crossover and mutation of genetic algorithm into the last step of the wolves algorithm to improve the convergence speed of the algorithm. The specific operation is as follows:

1) When the wolves are allocated food, the wolves are sorted according to the size of the fitness value. The wolves are divided into three parts, each of which is one-third of the size of the wolves, and the subgroups with the greatest fitness value are Part of the genetic algorithm used in the elite retention strategy, directly retained into the next iteration.

2) That the second part of the fitness value, that is, the second part of the genetic algorithm used in the cross operation. In order to obtain high-precision weight, in this paper, the individual is used in real coding, so cross-method operation using real cross method. The cross-operation of the k-th gene X_k and the l-th gene X_l in the j-th position is as follows:

$$\begin{cases} X_{kj} = X_{kj}(1-b) + X_{lj} b \\ X_{lj} = X_{lj}(1-b) + X_{kj} b \end{cases} \tag{7}$$

Where b is a random number between $[0,1]$.

3) The smallest part of the fitness value, that is, the third part of the genetic algorithm used in the mutation operation. The mutation operation selects the j-th gene of the i-th individual for mutation operation, as follows:

$$X_{ij} = \begin{cases} X_{ij} + (X_{ij} - X_{\max}) f(g), r \geq 0.5 \\ X_{ij} + (X_{\min} - X_{ij}) f(g), r < 0.5 \end{cases} \tag{8}$$

$$f(g) = r_2 (1 - \frac{g}{M_{\max}}) \tag{9}$$

Where $X_{\max}$ and $X_{\min}$ are the upper and lower bounds of the factor X_{ij}; r is the random number between $[0,1]$; r_2 is a random number; g is the current iteration number.

The improved wolf algorithm is called GWPA algorithm, the specific algorithm flow shown in Figure 1.

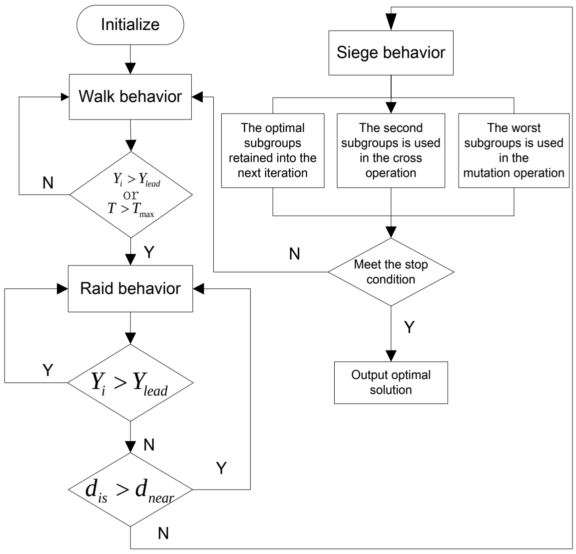

Figure 1 GWPA algorithm flow chart

3. GWPA-BP power prediction model

Although the BPNN multi-layer sensor has a strong nonlinear learning ability and therefore has a wide range of applications in photovoltaic power prediction, there are still many defects. For example: the standard BP algorithm convergence speed is slow and easy to fall into the local extreme, training time is too long and other shortcomings. In this paper, a GWPA algorithm is proposed to optimize the parameters of BP neural network, and the GWPA-BP power prediction model is established to improve the accuracy of prediction [7]. Wolves algorithm optimization BP neural network specific process is as follows:

1) Encoding. The improved Wolves algorithm (GWPA) is an integer coding method, and the parameters of the BP neural network are encoded as a whole parameter. Each individual contains all the weights and thresholds of BP and can represent a BP neural network structure.

2) Initialize the parameters. The position X_i of the individual wolves in the wolves, the population size N, the maximum number of iterations $M_{\max}$, the maximum number of walks $T_{\max}$, the walking step length $step_a$, the attack step size $step_b$, the attack step size $step_c$, the distance determination factor W, the update scale factor β and the step size factor S.

3) The fitness function is set to the reciprocal of the mean square error function, and the fitness value is an important index to evaluate the pros and cons of the population.

4) GWPA algorithm to optimize the initial weights and thresholds of BP neural networks. According to the above steps 1) - 4), the iterative optimization of the optimal individual is performed.

5) To determine whether to meet the termination conditions, if satisfied, the output of the desired solution of the optimal solution - the location of the wolf is the optimal solution to be optimized; otherwise the implementation of step 4.

6) Output the global optimal solution, that is, the location of the space where the wolf. The spatial position of the wolf is used as the initial weight and threshold of the BP neural network and the training BP neural network is used to predict.

4. Simulation experiment

In this paper, the UQ Solar project's previous PV data and the corresponding meteorological data are used as experimental samples. The atmospheric temperature, light intensity and output power of the PV power station from April 2015 to June 2015 are selected as the sample set, The data from April 25th to June 2nd is the training sample set, and finally the GWPA-BP model is used to predict the PV output power at eleven hour points from 7:00 to 5:00 on June 3, and the unmodified BP prediction model. The prediction results for the current day are compared with the actual measured data as shown in Fig.2.

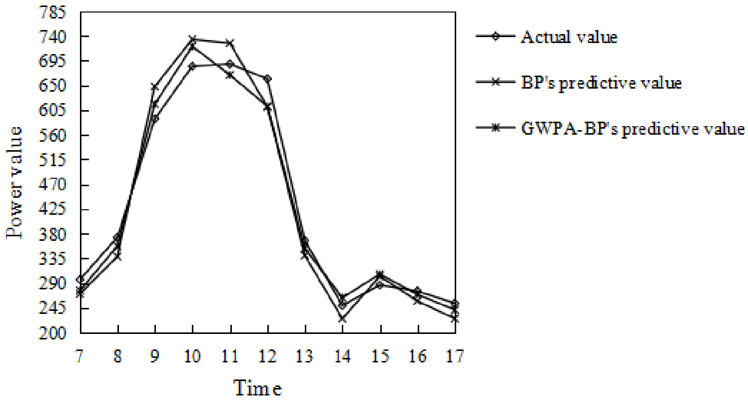

Figure 2. Comparison of predicted power values for both models

Table 1 gives the classical BP model, GWPA-BP model of the respective power prediction results and relative error. Table 2 gives a comparative analysis of the relative error of the two models.

Table 1. Comparison of two predictive model predictive results

Time	Actual power value (kw)	BP model		GWPA-BP model	
		Predictive value (kw)	Relative error (%)	Predictive value (kw)	Relative error (%)
7:00	296	270	8.5	276	6.8
8:00	373	338	9.3	357	4.5
9:00	589	648	-10.1	616	-4.5
10:00	685	734	-7.2	721	-5.4
11:00	689	727	-5.6	669	3
12:00	662	611	7.8	612	7.6
13:00	367	340	7.5	353	4
14:00	249	225	9.9	263	-5.8
15:00	286	302	-5.9	306	-7
16:00	275	257	6.9	269	2.2
17:00	253	225	11.2	241	5.1

Table 2. Comparison of two prediction model errors

Forecasting model	Minimum relative error (%)	Maximum relative error (%)	Average relative error (%)
BP model	5.6	11.2	8.17
GWPA-BP model	2.2	7.6	5.08

It can be seen from the above figure and table that the average relative error of the classical BP network model is 8.17% and the average relative error of the GWPA-BP model is 5.08%. Therefore, the improved wolf algorithm improves the BP neural network, the prediction error is gradually reduced and the prediction accuracy is improved accordingly. It is proved that the GWPA-BP model can predict the PV output power more accurately.

5. Conclusion

As the wolves algorithm has the shortcomings of slow convergence, this paper uses the genetic algorithm to improve the wolves algorithm, the improved algorithm is called GWPA algorithm. And the GWPA algorithm is applied to optimize the parameters of BP neural network, a new model GPWA-BP is proposed. The simulation results show that the GPWA-BP model can effectively predict the PV output power at a certain time. Compared with the unpredictable classical BP prediction model, the prediction accuracy is greatly improved, and the short - term PV power can be predicted well, and it is widely used in the power system with high accuracy.

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