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Research Article

An Efficient Algorithm for Power Prediction in PV Generation System

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ABSTRACT. Aiming at the existing photovoltaic power generation prediction methods, the modeling is complicated, the prediction accuracy is low, and it is difficult to meet the actual needs. Based on the improvement of the traditional wavelet neural network, a dual-mode cuckoo search wavelet neural network algorithm combined prediction method is proposed, which takes into account the extraction of chaotic features of surface solar radiation and photovoltaic output power. The proposed algorithm first reconstructs the chaotic phase space of the hidden information of each influencing factor in the data history of PV generation and according to the correlation analysis, the solar radiation is utilized as additional input. Next, the proposed algorithm overcomes the limitations of the cuckoo search algorithm such as the sensitivity to the initial value and searchability and convergence speed by dual-mode cuckoo search wavelet neural network algorithm. Lastly, a prediction model of the proposed algorithm is proposed and the prediction analysis is performed under different weather conditions. Simulation results show that the proposed algorithm shows better performance than the existing algorithms under different weather conditions. Under various weather conditions, the mean values of T_{IC}, E_{MAE} and E_{NRMSE} error indicators of the proposed forecasting algorithm were reduced by 43.70%, 45.75%, and 45.41%, respectively. Compared with the Chaos-WNN prediction method, the prediction performance has been further improved under various weather conditions and the mean values of T_{IC}, E_{MAE} and E_{NRMSE} error indicators have been reduced by 25.55%, 27.26%, and 36.83%, respectively.

Keywords: Renewable energy, PV, optimization, chaotic feature extraction, DMCS-WNN

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1. Introduction

With the global energy crisis and environmental pollution intensifying, photovoltaic power generation has developed rapidly as a clean energy source. However, photovoltaic power generation has obvious volatility and randomness. Large-scale grid connections will affect the security and stability of the power grid and economic operation (Sheng et al. 2018). The ultra-short-term forecast of photovoltaic power generation can know its future output power in advance, which helps the grid dispatching department to adjust the scheduling plan in real-time (Zhong et al. 2017), reduce the impact of photovoltaic grid-connected on the system, and enhance the grid's acceptance of photovoltaic power (Liu et al. 2012), (Akhter et al. 2019).

In order to obtain higher economic and social benefits, in recent years, scholars have carried out a lot of research on photovoltaic power generation prediction and achieved certain results, such as improving the PV optimal power flow, energy efficiency and transients optimization (Teng et al. 2019), (Li et al. 2019). Existing prediction methods can be roughly divided into two categories, namely physical methods and statistical methods (Xie et al. 2018), (Das et al. 2018), (Huang et al. 2019). The statistical method is widely used in the short-term/ultra-short-term prediction of photovoltaic power because of the simple modeling and the information required. At present, the commonly used statistical forecasting methods mainly improve the accuracy of forecasting by clustering analysis of various meteorological factors and optimizing the quality of the input of the model by considering new influence factors. Reference (Li et al. 2017) established a short-term forecast model of photovoltaic power generation based on decentralized search and support vector machine regression based on meteorological factor dimensionality reduction processing using probabilistic neural networks to achieve a more accurate forecast of the output power of photovoltaic power plants under various weather types. Taking into account the traditional photovoltaic power generation prediction method based on temperature, wind speed and humidity, sudden weather changes Under the circumstances, there is a problem of low prediction accuracy. In (Liu et al. 2015), the aerosol index was introduced for improvement, and the neural network was used to realize the prediction of power generation, which further improved its prediction performance. Literature (Kang et al. 2011) proposed a method for predicting photovoltaic power using a combination of forwarding selection, K-means clustering analysis and RBF neural

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network, which can significantly reduce the number of input meteorological factors and achieve more accurate prediction. The above method improves the existing method from the perspective of meteorological influence factors. However, the meteorological data often reflects the environmental conditions in a larger area and cannot accurately reflect the environmental information of the photovoltaic panel. As a result, the accuracy of ultra-short-term predictions is limited. Taking into account the impact of external factors on the output power of photovoltaic power generation itself, literature (Munawar et al. 2020) used the results of historical power data wavelet decomposition literature (Saberian et al. 2014) to perform support vector machine classification training and based on autoregressive moving average and neural network models Ultra-short-term prediction of adaptive photovoltaic power generation, but the prediction performance under extreme weather such as cloudy is not analyzed in the simulation. Reference (Du et al. 2019) introduced chaos theory to analyze the historical evolution law of photovoltaic power sequences, and used RBF neural network to learn, and realized the application of chaos prediction theory in the field of photovoltaic power prediction. Reference (Mei et al. 2019) constructed a wavelet neural network (WNN) prediction model based on phase space reconstruction to achieve a more accurate prediction of photovoltaic power generation. However, the sensitivity of WNN's initial value is insufficient, and its accuracy needs to be further improved during periods of large power fluctuations.

Aiming at the existing photovoltaic power generation prediction methods, the modeling is complicated, the prediction accuracy is low, and it is difficult to meet the actual needs. The main contributions of the proposed work is highlighted as follows:

- A DMCS-WNN is proposed which aims to improve the performance of the conventional WNN algorithm, and extract of chaotic features of surface solar radiation and photovoltaic output power.
- The proposed algorithm further improves the accuracy of its prediction under various weather conditions by comprehensively considering the chaotic characteristics of the photovoltaic output power sequence and the impact of surface solar radiation on photovoltaic power generation.
- Compared with the existing NWP-WNN algorithm based on numerical weather forecast data, the proposed algorithm improves its prediction performance during periods of severe power fluctuations.
- The proposed algorithm deploys solar radiation as an additional input factor and improves the traditional CS algorithm based on a dual-mode learning strategy.
- Under its optimization, the convergence speed and optimization ability of the WNN are improved through the proposed algorithm.
- Compared with the Chaos-WNN algorithm, the prediction performance of after using the proposed algorithm is further improved under various weather conditions and the mean values of the T_{IC}, E_{NMAE}, and E_{NRMSE} error indicators have been reduced by 25.55%, 27.26%, and 36.83%, respectively.
- The proposed algorithm can avoid the direct analysis of non-critical external factors through chaotic feature extraction.

The remaining of the paper is organized as follows. Section 2 presents the analysis of the chaotic feature extraction and other factors affecting the PV generation. Section 3 explains the proposed algorithm. Section 4 describes the simulation analysis of the proposed research work while Section 5 concludes the paper.

2. Analysis of Chaotic Feature Extraction and Other Factors Affecting PV Generation

2.1 Analysis of Influential Factors of PV Power

There are many external factors that affect the output power of the photovoltaic power generation. According to the process of solar energy transmission and conversion from light energy to electricity (Saberian et al. 2014) **,** the main factors are shown in Figure 1.

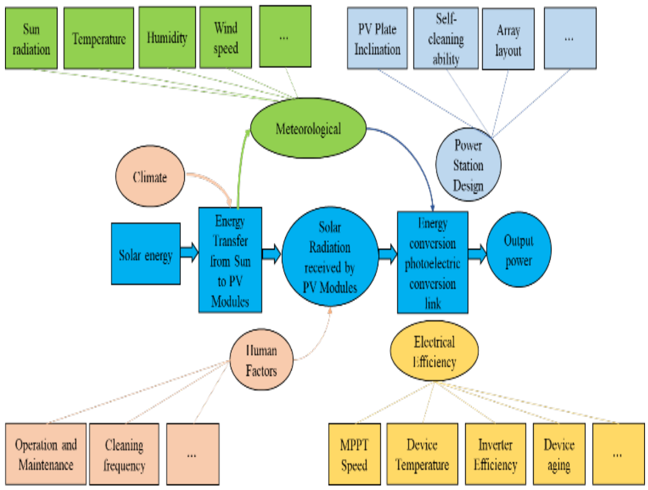

Fig. 1 Illustration of the external factors affecting the output power of the photovoltaic generation.

It can be seen from Figure 1 that without considering climate and human factors, the main influencing factors of photovoltaic power output can be divided into two categories:

- One type is non-meteorological factors that indirectly affect the photoelectric conversion efficiency.
- The other is meteorological factors directly related to the principle of photovoltaic power generation (Brano et al. 2014) .

The first type of influencing factors include the inclination of photovoltaic panels, the conversion efficiency of photovoltaic arrays, and the efficiency of inverters. These factors are numerous and many of them cannot be quantified into specific numerical sequence information. Therefore, many factors cannot be considered comprehensively in the statistical forecast of photovoltaic power by some of the conventional methods, whereas, the statistical methods such as ANN can easily account for that information though not explicitly.

The second type of influencing factors mainly includes surface radiation, atmospheric temperature, humidity, wind speed, wind direction, etc. The influencing factors are numerous and the mechanism is complex. Excessive non-critical considerations will not only increase the difficulty of model training but also are difficult to apply flexibly in practice. The meteorological data of the actual photovoltaic power plant is incomplete, which brings some difficulties to the construction and promotion of the prediction model of photovoltaic power generation based on meteorological data. In order to reduce the limitation of such factors and reduce the mutual interference between various influencing factors, the Pearson correlation coefficient R between the main meteorological factors and the photovoltaic output power is solved, and the correlation analysis is used to extract the key meteorological factors for prediction models Construct. The formula for solving the correlation coefficient is shown in equation (1), and the calculation results are shown in Table 1.

$$R(x,p) = \frac{\operatorname{cov}(x,p)}{\sqrt{\operatorname{cov}(x,x)\operatorname{cov}(p,p)}} \tag{1}$$

where $\operatorname{cov}(\cdot)$ is the covariance solving function; x is the factor to be analyzed; p is the time series of photovoltaic power generation.

Table 1
The correlation coefficient between each meteorological factor and the output power of PV.

Influencing factor	Correlation coefficient
Humidity	-0.65
Temperature	0.65
Sun radiation	0.91
Wind speed	0.10
Wind direction	0.09

Source: (Qiu et al. 2020), (Sun et al. 2016), (Li et al. 2017), (Khan et al. 2017).

It can be seen from Table 1 that photovoltaic power generation has a significant positive correlation with solar irradiance, and its Pearson correlation coefficient is as high as 0.91. In addition to solar radiation, temperature and humidity are also important factors in photovoltaic power generation. Taking cloudy weather as an example, the normalized relationship between temperature, humidity, and solar radiation and the output power of photovoltaic power generation is shown in Figure 2. It can be seen from Fig. 2 that the surface solar radiation has obvious transient changes, which can basically reflect the changing trend of photovoltaic power generation in a short period of time. Temperature and humidity change slowly and have inertial characteristics, which cannot reflect power transients.

The photovoltaic power sequence itself has chaotic characteristics (Du et al. 2019), (Wang et al. 2018) and its highly autocorrelated fluctuation characteristics imply various external factors. The chaotic phase space reconstruction is performed on it, and the information of the influencing factors contained in it can be recovered through the chaotic attractor trajectory, which lays the foundation for ultra-short-term prediction of photovoltaic power generation. Therefore, in order to avoid direct analysis of influencing factors, based on the chaotic feature extraction of photovoltaic power data, consider only using solar radiation that can reflect power transients as additional input factors to further improve the prediction effect

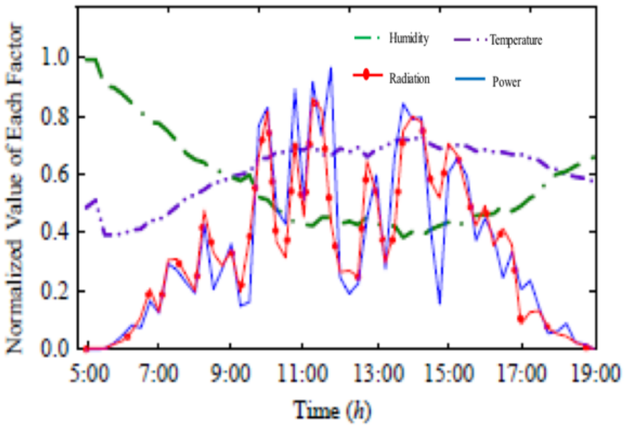

Fig. 2 Illustration of the impact of meteorological factors on the output power of PV generation.

2.2 Chaotic Feature Extraction of output Power of PV generation

During the process of phase space reconstruction parameters of PV power generation, it is of great significance to properly select the delay time τ and the embedding dimension m. The selection of these two parameters will directly affect the quality of phased space reconstruction, which in turn affects the impact of prediction. Considering that the selection of m and τ is closely related, the C-C method has the characteristics of strong anti-noise ability, requires less number of computations and utlizes the improved algorithm to solve the phase space reconstruction parameters (Kiml et al. 1999).

For the photovoltaic power sequence $p_i(i = 1.2, \dots, N)$, let the correlation integral of the embedded time series be

$$C(m,N,r,\tau) = \frac{\sum_{1\le i<j\le M} 2H(r - \|p_i - p_j\|)}{M(M-1)} \tag{2}$$

Where τ denotes delay time, N is the total number of data points; M is the number of delay vectors which is used to predict the PV energy values; r is the defined spatial distance; $H(\cdot)$ is the step function; P_i and P_j are two points embedded in the reconstructed phase space of the photovoltaic power sequence.

Using a statistical approach to identify the order of significance from the correlation function of equation (2), the construction test statistics are expressed as

$$S_1(m,N,r,\tau) = C(m,N,r,\tau) - C^m(1,N,r,\tau) \tag{3}$$

For high accuracy and improved prediction, let the total number of data points $N \to \infty$, and using the block averaging algorithm, equation (3) can be rewritten as

$$S_2(m,r,\tau) = \frac{1}{\tau}\sum_{S=1}^{\tau}[C_S(m,r,\tau) - C_S^m(m,r,\tau)] \tag{4}$$

Now, we select the largest and smallest two radii r, and define the statistics of how fast $S_1(m,r,\tau)$ changes to r under the same m and τ. That is, the statistic of the change of r is $\Delta S_1(m,\tau)$ which is expressed as

$$\Delta S_1(m,\tau) = \max\left(S_1(m,r_j,\tau)\right) - \min\left(S_1(m,r_j,\tau)\right) \tag{5}$$

To estimate a reasonable value of τ, we take taking $N = 3000$, $m = 2,3,4,5$, $r_j = i\frac{\sigma}{2}$, $i = 1,2,3,4$, $\sigma = std(x)$ (σ is the series standard deviation) and construct and calculate the new test statistics shown in equation (6) according to the Brock-Dechert-Scheinkman (BDS) statistical theorem

$$\begin{cases} \Delta\bar{S}_1(\tau) = \frac{1}{4}\sum_{m=2}^{5}\Delta S_1(m,\tau) \\ \bar{S}_1(\tau) = \frac{1}{16}\sum_{m=2}^{5}\sum_{i=1}^{4} S_1(m,r_i,\tau) \\ \bar{S}_2(\tau) = \frac{1}{16}\sum_{m=2}^{5}\sum_{i=1}^{4} S_2(m,r_i,\tau) \end{cases} \tag{6}$$

Select the delay corresponding to the first local minimum of $\Delta\bar{S}_1(\tau)$ as the optimal delay time τ. Find the period of $|\bar{S}_1(\tau) - \bar{S}_2(\tau)|$ as the optimal embedding window l. The embedding dimension m is obtained from the formula $m = INT(l/\tau) + 1$.

According to the required reconstruction parameters, the initial one-dimensional photovoltaic power time series is reconstructed into the m-dimensional phase space by using the delayed coordinate reconstruction method to recover the chaotic attractor trajectory containing the information of each influencing factor, and it's matrix expression as follows

$$\boldsymbol{P} = \begin{bmatrix} p_1 & p_{1+\tau} & \cdots & p_{1+(m-1)\tau} \\ p_2 & p_{2+\tau} & \cdots & p_{2+(m-1)\tau} \\ \vdots & \vdots & \ddots & \vdots \\ p_M & p_{M+\tau} & \cdots & p_{M+(m-1)\tau} \end{bmatrix} \tag{7}$$

3. Proposed Algorithm

3.1 Optimized WNN by Cuckoo Search Algorithm

Based on the traditional neural network topology, the compact wavelet neural network uses the mother wavelet base as the hidden layer excitation function to avoid human subjective factors in the traditional network hidden layer design. Wavelet analysis has local characteristics of time and frequency and can extract local information of input quantities on multiple scales. Neural networks have self-adaptation and self-learning capabilities. Combining the two and introducing scaling factors and translation factors can improve the generalization ability and convergence speed of the network. It has a more flexible function fitting efficiency (Rosato et al. 2017). However, the initial weights and wavelet factors of the wavelet neural network are randomly generated. In order to make up for the lack of sensitivity of the initial values, Cuckoo algorithm (Yang et al. 2009) is used to optimize its initial parameters in order to expand the search range and improve the network's fault tolerance Ability and convergence speed, further reducing the negative impact of initial parameters on the learning ability of the WNN network. The specific process is shown in Figure 3.

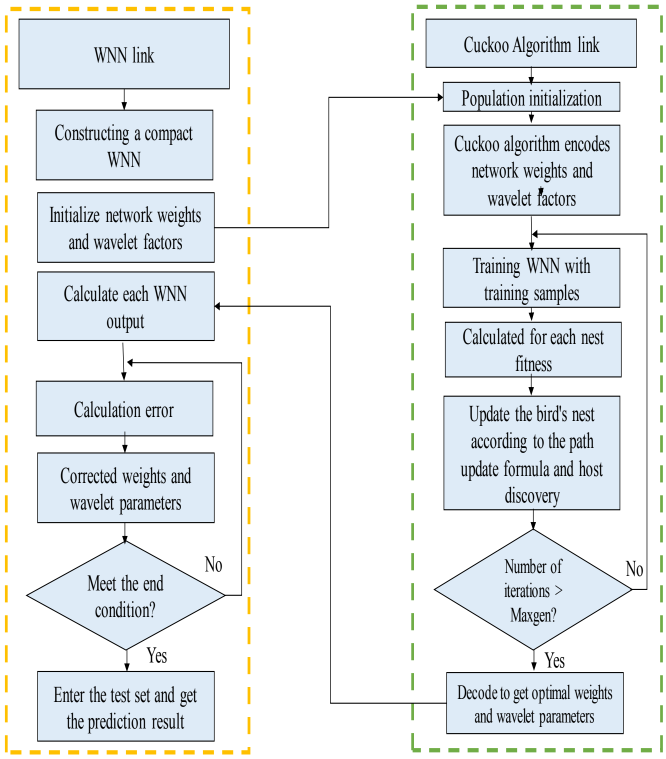

Fig. 3. Optimized WNN by Cuckoo Search Scheme.

Among them, the compact wavelet neural network is designed with a three-layer structure, and the specific structure is shown in Figure 4. The number of nodes in the network input layer I is determined according to the predicted input vector dimension. The number of output layer nodes is O. The number of nodes in the hidden layer is M_{hid}. First, the approximate range is determined according to the empirical formula $M_{\text{hid}} < \sqrt{(I+O)} + a$ (a is a constant between 0 and 10), and then determined by trial and error. When the traditional cuckoo algorithm improves the wavelet neural network, the bird's nest update rate p_{disc} is a fixed value, so that its global and local search capabilities are maintained at a constant level, and it is easy to obtain the optimal solution.

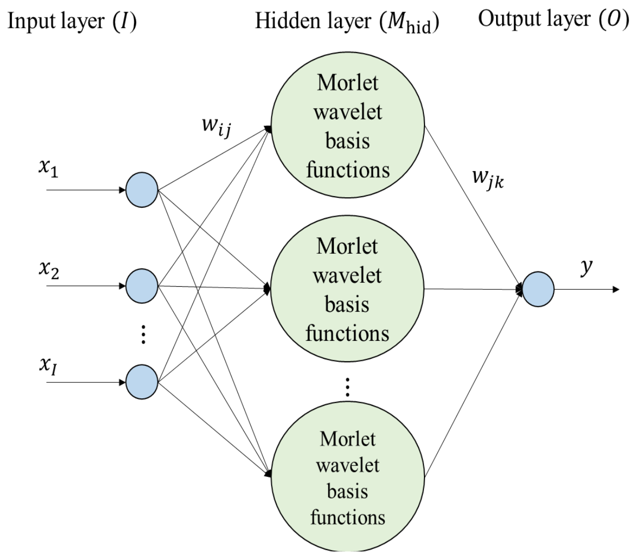

Fig. 4. WNN Structure.

In addition, the similar search behavior of Levi's flight can lead to the loss of search space diversity, and once it falls into a local optimum, it cannot escape. In view of this, the traditional CS algorithm is improved based on the dual-mode learning scheme (Chen et al. 2009).

3.2 Improvement of Cuckoo Search Algorithm

The improved cuckoo search algorithm realizes the online trade-off between local and global search by setting the development and exploration mode. In the exploration mode, the DMCS adds a global search to prevent the algorithm from falling into a local optimum. In the development mode, local search is enhanced to improve the convergence speed, and new evolution operators are used to realizing information sharing between populations, enhance the randomness of the entire optimization process, and better develop and avoid local optimization. The specific process is shown in Figure 5.

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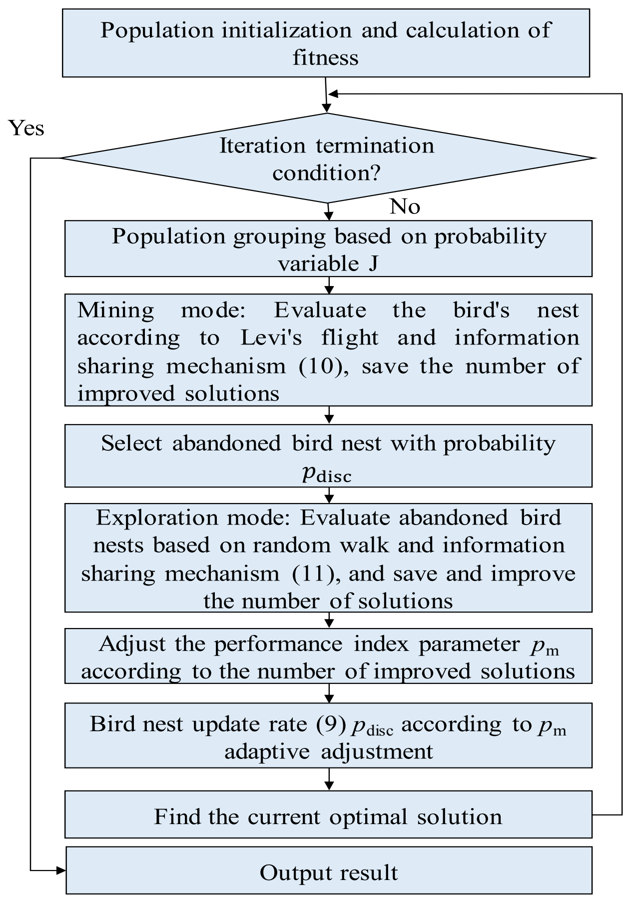

Fig. 5 Illustration of the flowchart of the dual-mode cuckoo search scheme.

The specific improvement points are as follows:

a) Adaptively adjust the update rate p_{disc}.

DMCS regularly collects fitness function information throughout the optimization process to adaptively select the best search mode (i.e. development or exploration).

The specific algorithm search mode is defined as follows:

$$u = \begin{cases} 1, & 0 \le p_m \le 0.5 \\ 0, & 0.5 \le p_m \le 1 \end{cases} \tag{8}$$

where 1 is the development mode; 0 is the exploration mode. $p_m = S_{\mathrm{improve}/}S_{\mathrm{total}}$, S_{improve} is the number of improved solutions in a certain cycle. S_{total} evaluates the total number of solutions for a cycle.

DMCS uses p_m to evaluate the search performance of the algorithm. If the performance has been enhanced (or remains the same), it decides whether to continue the search using exploration mode or switch to development mode to improve search capabilities. Therefore, p_m can provide the necessary learning information for the adaptive adjustment of the update rate p_{disc} to achieve the online trade-off of the search pattern. The update process of p_{disc} in each search, the model is shown in equation (9).

$$p_{\mathrm{disc}} = \begin{cases} \max(0, p_m - \xi\,), & \text{if } u = 1 \\ \min(1, p_m + \xi\,), & \text{if } u = 0 \end{cases} \tag{9}$$

Where $\pm\xi$ is the increase/decrease speed of p_{disc}. When the DMCS shows poor performance, choose a development mode and reduce the update rate. Otherwise, select the exploration mode and increase the update rate.

b) Information sharing mechanism between populations.

When Levi flight is realized by the Mantegna algorithm, its similar search behavior will lead to the loss of diversity in the search space. Once the optimal solution falls into a local optimum, it cannot escape. Therefore, a crossover and mutation operator with different characteristics is proposed to enhance its diversity through information sharing between populations. First, according to the probability variable J, the bird nests to be optimized are randomly divided into 3 groups. Then, the bird's nest to be optimized is updated according to its current grouping and the corresponding update rules of the group. Equations (10) and (11) give specific grouping strategies and corresponding update rules for the DMCS population, respectively.

$$x_i^{t+1} = \begin{cases} x_i^t + \alpha \oplus (x_i^t \oplus le'vy(\beta) - x_i^t), \delta < J \\ x_i^t + \alpha \oplus \left(x_j^t - x_i^t \oplus le'vy(\beta)\right), J \le \delta < 1 - J \\ x_i^t + \alpha \oplus \left(x_j^t - x_i^t\right) \oplus le'vy(\beta), \delta \ge 1 - J \end{cases} \tag{10}$$

$$= \begin{cases} x_i^t + H(p_{\mathrm{disc}} - \varepsilon) \oplus \left(x_j^t \oplus \gamma - x_i^t\right), \delta < J \\ x_i^t + H(p_{\mathrm{disc}} - \varepsilon) \oplus \left(x_j^t - x_i^t \oplus \gamma\right), J \le \delta < 1 - J \\ x_i^t + H(p_{\mathrm{disc}} - \varepsilon) \oplus \left(x_j^t - x_i^t\right), \delta \ge 1 - J \end{cases} \tag{11}$$

where x_i^t and x_j^t are 2 random bird nests; α is the step size; $\oplus$ is the point multiplication operation; $le'vy(\beta)$ is a random search path. $H(v)$ is Heaviside function; γ, δ, and ε are random numbers subject to a uniform distribution. $J \in [0,1]$ is a probability-based variable that is responsible for assigning the elements to be optimized in each bird's nest to a certain group. When defining the update rules, each part of the equations (10) and (11) plays different roles in the search process. In equation (10):

- Update the bird's nest to be optimized according to its own information and encourage it to follow Levi's flight to find new solutions x_i^t.
- Enable the nest to be optimized to explore its surrounding area and attract it to the position of the new solution x_i^t in the search space.
- An information-sharing method is presented to attract solutions to x_i^t. The partial online balance enables the algorithm to effectively use the information of nearby populations, making the DMCS more random throughout the optimization process. Equation (11) explores the search space by a simple random walk in the same way.

c) Application of DMCS-WNN algorithm in PV power prediction

There are many external factors affecting photovoltaic power generation, such as the geographic layout of the power station, the inclination of the panel, the conversion efficiency of the array, the surface solar radiation and the atmospheric temperature.

In order to fully consider the various external influence factors of photovoltaic power generation, and further take advantage of the improved WNN algorithm to solve the nonlinear problem, based on the chaotic dynamic feature extraction of photovoltaic power generation, a new type of photovoltaic power generation with additional solar radiation input factors is proposed.

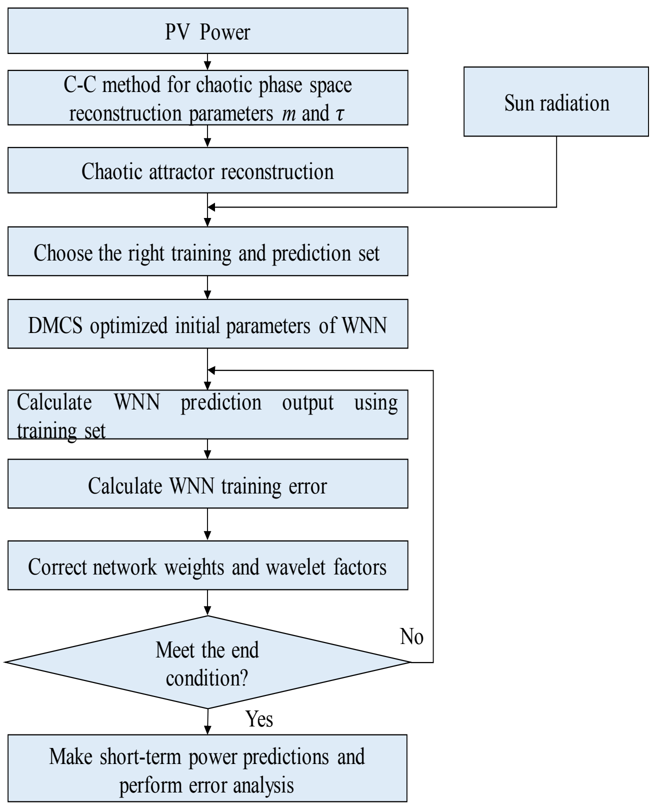

Fig. 6 Flow chart of the proposed dual-mode cuckoo search wavelet neural network algorithm.

Power combination prediction method. The specific process is shown in Figure 6. It can be seen from Figure 6 that, first, the proposed prediction algorithm uses chaos theory to extract the chaotic dynamic characteristics of PV power generation to restore the evolution law of chaotic attractors and extract various external factors that affect PV power generation. Then select the surface solar radiation that can reflect the power transient situation as an additional input factor and use DMCS-WNN to predict the photovoltaic power generation. Finally, the Hill inequality coefficient T_{IC}, normalized mean absolute error (E_{NMAE}), and normalized root mean square error (E_{NRMSE}) were used to evaluate and analyze the simulation results to illustrate the effectiveness of the proposed algorithm (Nespoli et al. 2019).

The expressions are:

$$T_{\mathrm{IC}} = \frac{\sqrt{\frac{1}{N_{\mathrm{total}}}\sum_{i=1}^{N_{\mathrm{total}}}(\hat{y}_i - y_i)^2}}{\sqrt{\frac{1}{N_{\mathrm{total}}}\sum_{i=1}^{N_{\mathrm{total}}}\hat{y}_i^2} + \sqrt{\frac{1}{N_{\mathrm{total}}}\sum_{i=1}^{N_{\mathrm{total}}}y_i^2}} \tag{12}$$

$$E_{\mathrm{NMAE}} = \frac{1}{N_{\mathrm{total}}}\frac{1}{P_{\mathrm{inst}}}\sum_{i=1}^{N_{\mathrm{total}}}|y_i - \hat{y}_i| \times 100\% \tag{13}$$

$$E_{\mathrm{NRMSE}} = \frac{1}{P_{\mathrm{inst}}}\sqrt{\frac{1}{N_{\mathrm{total}}}\sum_{i=1}^{N_{\mathrm{total}}}(y_i - \hat{y}_i)^2 \times 100\%} \tag{14}$$

In the formula: N_{total} is the number of predicted points; P_{inst} is the installed capacity of PV power generation system; y_i is the measured value; $\hat{y}_i$ is the predicted value.

4. Results and Analysis

This section provides the experimental analysis and comparative evaluation of the proposed algorithm. We select a 65-day power data and corresponding weather information of a PV power system in the first quarter of 2017 were selected for simulation analysis, including sunny-to-cloudy (13 days), sunny (12 days), cloudy-to-sunny (12 days), and cloudy (12 days) and cloudy (14 days) typical weather types (http://www.solar.uq.edu.au/ 2017). The sampling period is 5:00-19:00 every day, the sampling resolution is 5 min, and 168 sample points are collected every day. In order to verify the effectiveness of the proposed prediction algorithm, the power generation of photovoltaic under sudden and non-abrupt weather conditions is simulated in MATLAB 2017a. The time series of the measured raw power generation of photovoltaic is shown in Figure 7.

The improved C-C method is used to determine the chaotic phase space reconstruction parameters. The results of each statistic are shown in Figure 8. It can be seen from Figure 8 that the first local minimum of the $\Delta\bar{S}_1(\tau)$ statistic appears at time x = 35. The period τ^* of $|\bar{S}_1(\tau) - \bar{S}_2(\tau)|$ is 168, so the delay time of the studied data sample is $\tau = 35$, and the average trajectory period is optimally estimated to be $l = 168$, which is obtained by $m = \mathrm{INT}(l/\tau) + 1$ and embedding dimension is 5.

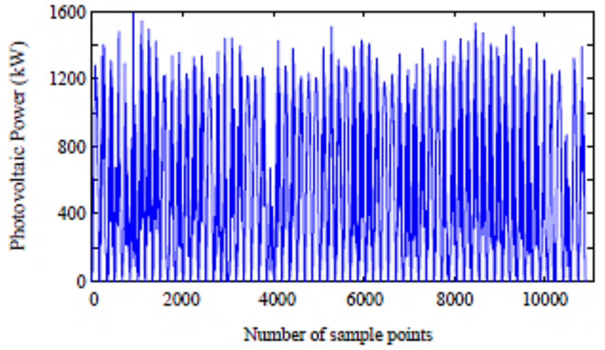

Fig. 7. PV power under a different number of sample points.

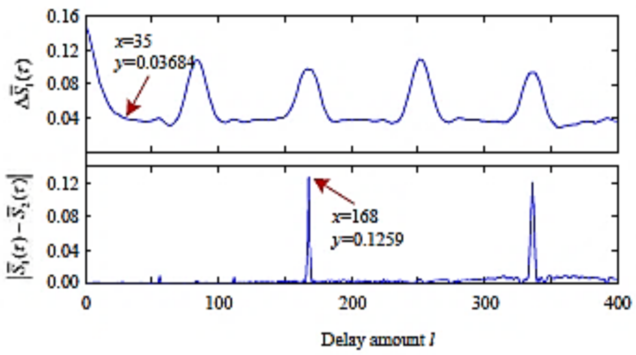

Fig. 8. Illustration of the deployment of the improved C-C algorithm for phase space reconstruction

The key parameters of the study are set as follows: The number of WNN training is 100, the weighting factor learning efficiency is $\eta_1 = 0.01$, the wavelet smoothing and scaling factor learning efficiency is $\eta_2 = 0.001$, the birds nest discovery probability is $p_{\mathrm{disc}} = 0.25$, the rate of increase and deceleration $\xi = 0.25$, and the number of initial nests is $N_{\mathrm{nest}} = 80$. The maximum number of iterations is $M_{\max} = 100$. In order to verify the proposed DMCS optimization performance, the average absolute error between the predicted value and the actual value is used as the fitness. The CS algorithm and the DMCS algorithm are compared and analyzed in Figure 9.

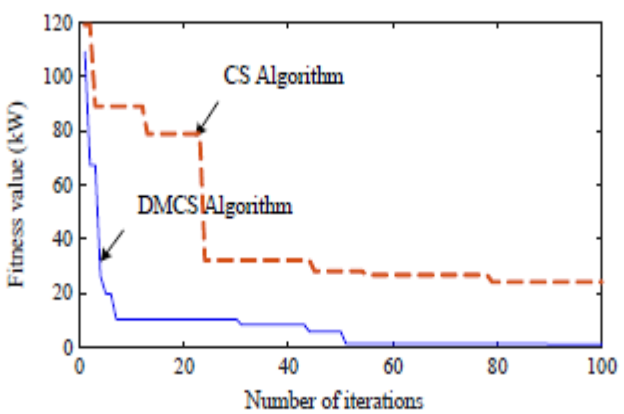

Fig. 9. Comparison of the fitness value of the proposed DMCS algorithm and traditional CS algorithm under a different number of iterations.

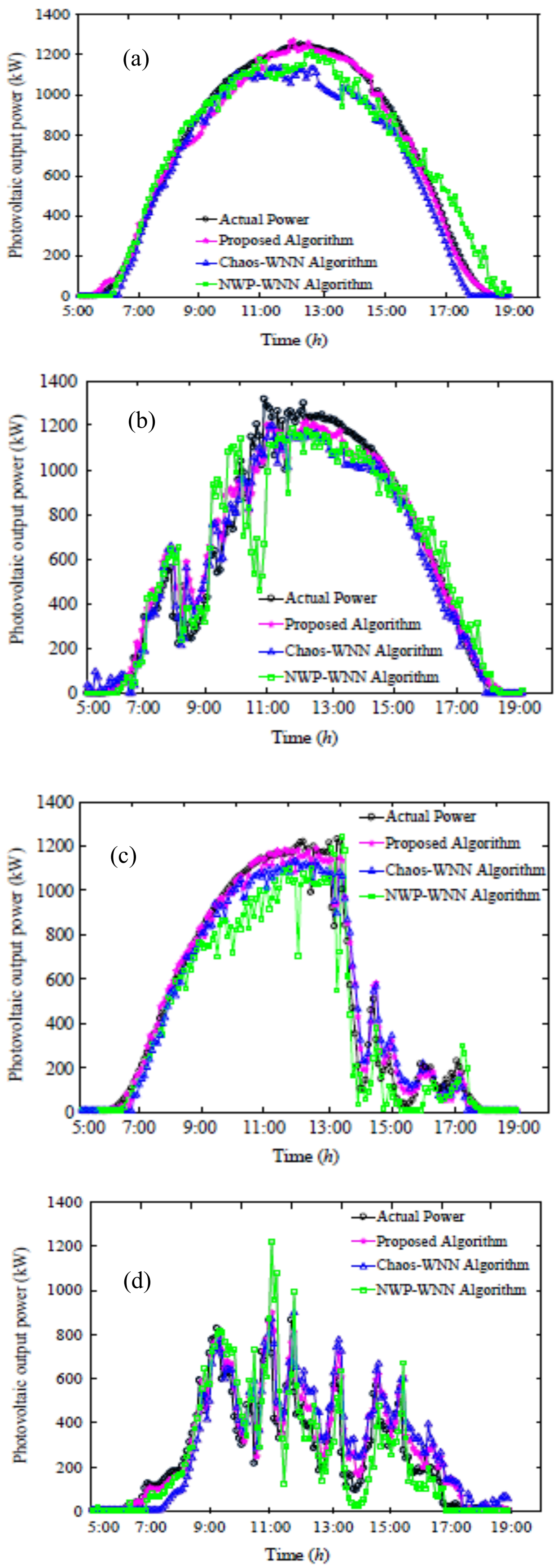

Fig. 10. Comparison of the PV output power of algorithms under different weather conditions. (a) sunny weather; (b) from cloudy to sunny; (c) sunny to cloudy; (d) cloudy.

It can be seen from Figure 9 that by adaptively adjusting the update rate p_{disc} and increasing the information-sharing mechanism, the improved DMCS algorithm has a faster initial convergence rate than the CS algorithm, and the latter algorithm makes the optimization problem out of the local optimum after the 50th generation.

The 61-day data is selected as the training set, and one day is selected as the test set from the next 4 days (non-abrupt weather represented by sunny days and sudden weather represented by cloudy to sunny, sunny to cloudy, cloudy, etc.). Based on the idea of single-step circular scrolling and using weather-wavelet neural network prediction method (NWP-WNN), chaos-wavelet neural network prediction method (Chaos-WNN), and the proposed prediction method to perform 30 independent simulation comparison analysis, the results are shown in Figure 10. It can be seen from Figure 10 that the traditional NWP-WNN prediction method based on meteorological information such as solar radiation, temperature, humidity, and wind speed has the worst tracking performance under various weather conditions. Especially in the abrupt weather conditions represented by cloudy to sunny, sunny to cloudy, and cloudy, because the influencing factors of photovoltaic power generation cannot be fully considered, during the period of severe power fluctuations, the deviation between the predicted value and the actual value is large, and the range of forecast error fluctuation is too big. The Chaos-WNN prediction method based on the chaotic phase space reconstruction of photovoltaic power generation is used to improve the prediction performance to a certain extent. However, at noon during cloudy weather and sunny conditions, the delay effect and tracking effect are relatively poor. Compared with such algorithms, the proposed algorithm comprehensively considers various factors affecting the output power of PV power generation and the improvement of traditional WNN, and its tracking effect is the best, and the range of error fluctuation is small.

Table 2
Prediction performance comparison of various algorithms under different weather conditions.

Weather Condition	Prediction Algorithm	T_{IC}	E_{NMAE} (%)	E_{NRMSE} (%)
Sunny day	NWP-WNN	0.054	4.517	3.510
	Chaos-WNN	0.059	4.765	3.807
	Proposed	0.022	1.809	1.322
Cloudy to clear	NWP-WNN	0.108	8.277	5.320
	Chaos-WNN	0.063	4.775	3.754
	Proposed	0.057	4.437	2.912
Sunny to cloudy	NWP-WNN	0.115	7.272	4.956
	Chaos-WNN	0.065	4.327	3.185
	Proposed	0.052	3.531	2.212
Partly cloudy	NWP-WNN	0.199	7.205	4.437
	Chaos-WNN	0.172	6.472	5.003
	Proposed	0.135	5.019	3.502
Mean	NWP-WNN	0.119	6.181	4.556
	Chaos-WNN	0.090	5.085	3.937
	Proposed	0.067	3.699	2.487

In order to accurately and intuitively evaluate the prediction performance of each algorithm, T_{IC}, E_{NMAE}, E_{NRMSE} are selected to perform error analysis on the prediction results of different weather conditions. The results are shown in Table 2. From Table 2, it can be seen that the prediction effect of each prediction method under non-abrupt weather conditions represented by sunny days is better than that of abrupt weather conditions, and it can be seen that the severity of weather changes has a certain impact on the prediction effect. In addition, under various weather conditions, the proposed forecasting method, compared with the other two methods, achieves a further improvement in forecasting accuracy by comprehensively considering various factors that affect the output power of photovoltaic power generation and the improvement of traditional wavelet neural networks. Compared with the Chaos-WNN prediction method, by using the DMCS algorithm to improve the traditional wavelet neural network and additional surface solar radiation input factors, the error of the proposed prediction method is reduced. In several typical weather conditions, the mean value of the T_{IC}, E_{MAE} and E_{NRMSE} error indicators are reduced by 25.55%, 27.26% and 36.83% respectively. Compared with the NWP-WNN prediction method based on numerical weather forecast data, through the chaotic feature extraction and wavelet neural network improvement, the average values of the T_{IC}, E_{NMAE}, and E_{NRMSE} error indicators of the proposed prediction method are reduced by 43.70% and 45.75 in several typical weather conditions, respectively. %, 45.41%. In addition, when forecasting under different weather conditions, the proposed forecasting method does not show obvious error fluctuations and has certain adaptability.

5. Conclusion

Aiming at the existing photovoltaic power generation prediction methods, the modeling is complicated, the prediction accuracy is low, and it is difficult to meet the actual needs. Based on the improvement of the traditional wavelet neural network, a DMCS-WNN combined prediction method is proposed, which takes into account the extraction of chaotic features of surface solar radiation and photovoltaic output power. By analyzing the simulation results of the proposed prediction method in non-abrupt and abrupt weather, the following conclusions are drawn:

The proposed prediction algorithm further improves the accuracy of its prediction under various weather conditions by comprehensively considering the chaotic characteristics of the photovoltaic output power sequence and the impact of surface solar radiation on photovoltaic power generation. Compared with the NWP-WNN prediction algorithm based on numerical weather forecast data, it improves its prediction performance during periods of severe power fluctuations. Under various weather conditions, the mean values of the T_{IC}, E_{NMAE}, and E_{NRMSE} error indicators of the proposed forecasting algorithms were reduced by 43.70%, 45.75%, and 45.41%, respectively. The proposed prediction algorithm uses solar radiation as an additional input factor and improves the traditional CS algorithm based on a dual-mode learning strategy. Under its optimization, the convergence speed and optimization ability of the wavelet neural network are improved. Compared with the Chaos-WNN prediction method, the prediction performance has been further improved under various weather conditions and the mean values of the T_{IC}, E_{MAE} and E_{NRMSE} error indicators have been reduced by 25.55%, 27.26%, and 36.83%, respectively.

The proposed prediction method can avoid the direct analysis of non-critical external factors through chaotic feature extraction. The prediction is simple and convenient for engineering practice. It lays a theoretical foundation for the application of ultra-short-term prediction results to photovoltaic power generation smoothing. The limitations of the proposed work are that when two complicated algorithms are combined, then the computational complexities of the proposed algorithms will increase. So, the potential improved of the proposed work is to focus on the possibilities of reduction in the computation complexities and improve the accuracy of prediction by accumulating more data.

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