Multi-peak MPPT Control Based on Variable Step Disturbance Observation Method and Butterfly Optimization Algorithm

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Abstract: Photovoltaic power generation has attracted more and more attention in the field of new energy applications, and the maximum power point tracking technology is the critical link of the photovoltaic power generation system. In the case of partial shading, the output power curve of the photovoltaic array presents a multi-peak phenomenon, and the traditional MPPT algorithm is easy to fall into the optimal local solution when tracking the maximum power, while the traditional butterfly algorithm has slow convergence and low optimization accuracy in the tracking process. In order to reduce the loss of output power of photovoltaic system, an MPPT control method combining butterfly algorithm with adaptive inertia weight and variable step size disturbance observation method is proposed. In the butterfly algorithm, the population randomly generates the initial solution, and the crossover mutation operation is carried out on the population. The inertia weight is constantly updated with the increase of iteration times, which can reduce the oscillation amplitude in the tracking process, increase the robustness of the algorithm search, and achieve the purpose of global search. Then, the perturbation observation method with variable step size is used to accelerate the convergence speed and accuracy. The simulation results show that compared with the traditional perturbation observation method and butterfly optimization algorithm, the proposed algorithm can find the maximum power point stably, quickly, and accurately in the case of sudden illumination change, which significantly improves the performance of MPPT.

1. Introduction

In modern industrial production and life, the energy demand is increasing, and the supply and quality of energy play a vital role in economic development and social stability. However, using traditional power has endangered the environment and human health. Therefore, the development of clean energy has become a global consensus. Solar energy is one of the primary clean energy sources widely used in power generation. In the photovoltaic power generation system, how to improve the utilization efficiency of solar energy is a vital issue studied by scholars.

The application of MPPT is a fundamental technology that can improve the efficiency and power

generation of solar power generation systems and reduce energy costs. In the actual operation of the photovoltaic power generation system, uneven illumination and sudden change in illumination intensity will lead to the multi-peak phenomenon in the output power curve of a photovoltaic array.^{[1-} ^{2]} Traditional MPPT algorithms, such as constant voltage method, perturbation and observation method(P&O) and incremental conductivity method(INC), are simple and easy to implement, but they are greatly influenced by the environment, so it is difficult to ensure the maximum power generation efficiency of the system.^[3-6] The use of intelligent algorithms makes up for the shortcomings of traditional algorithms to a great extent, including particle swarm optimization algorithm(PSO), genetic algorithm(GA), artificial neural network algorithm(ANN), grey wolf optimization algorithm(GWO), glowworm swarm optimization algorithm(GSO), fuzzy logic control algorithm(FLC), etc. When these algorithms are applied to solar controller, the performance of tracking maximum power is improved.^[5] When PSO is used to track the maximum power point, there are shortcomings such as long optimization time and large power fluctuation.^[7] GA search has the problems of premature algorithm and large fluctuation near the maximum power point, which leads to the inability to output the maximum power accurately and stably.^{9]} When ANN is used to track the maximum power point in a harsh environment, it quickly falls into the optimal local value, and the tracking accuracy decreases.^[15] Although FLC is robust when it is used alone to track the maximum power, it depends on the experience of designers to determine membership functions and fuzzy rules.^[16]

Aiming at the power tracking problem of the photovoltaic array with local shadow, this paper combines the butterfly optimization algorithm (BOA) with variable step size P&O(WBOA-P&O), and applies it to photovoltaic MPPT control. The nonlinear inertia weight factor is introduced into BOA to improve the optimization accuracy. WBOA-P&O algorithm firstly randomly generates the initial solution of butterfly population, selects representative butterflies, and creates new butterflies by cross-breeding the representative butterflies, then introduces random disturbance to increase the diversity of search, and finally uses variable step size P&O to accelerate the convergence speed and improve the final convergence accuracy. Comparing WBOA-P&O with BOA and variable step P&O, the practicability of WBOA-P&O is verified.^[4]

2. Output Characteristics of Photovoltaic Array under Local Shadow

2.1. Mathematical model of photovoltaic cell

The equivalent circuit of photovoltaic cell is shown in Fig.1.



Figure 1: Equivalent circuit of photovoltaic cell

The current I can be expressed by the following equation:

$$I = I_{pv} - I_d \left[\exp\left(\frac{q(U+IR_s)}{nKT}\right) - 1 \right] - \frac{U+IR_v}{R_{vh}}$$
(1)

In Eq. (1), I_{pv} represents photocurrent; I_d represents the reverse current of the diode; I_d represents equivalent series resistance; R_{vh} stands for equivalent parallel resistance; K is the temperature when the photovoltaic cell works; T is the amount of electron charge.

2.2. Mathematical model of photovoltaic array

In this paper, [1×5] photovoltaic array is taken as the research object, and the equations of output power P_{pv} and output voltage U_{pv} of photovoltaic module are as follows:

$$P_{pv} = I_{pv}U_{pv}\left\{1 - Cexp\left(\frac{-U_{mp}}{D}\right)p\left[exp\left(\frac{U_{pv}}{D} - 1\right)\right]\right\}$$
$$C = 1 - \frac{I_{mp}}{I_{pv}} \qquad D = U_{oc} \bullet \frac{U_{mp}lnC}{U_{pv}}$$
(2)

In Eq. (2), U_{oc} is the open circuit voltage; I_{mp} is the current at the maximum power point; U_{mp} is the voltage at the point of maximum power.

2.3. Multipeak output characteristic

In this paper, five photovoltaic cells are connected in series in turn, and the light intensity (W/m^2) received by each photovoltaic cell is shown in Table 1. The photovoltaic array is switched from working condition 1 to working condition 2 at 0.5s. The output curves of the photovoltaic array in both cases are shown in Fig.2. The maximum power under working condition 1 is 4607W, and the maximum power under working condition 2 is 5768W (Fig.2).



Table 1: Working condition of photovoltaic array



3. Improved Strategy of Butterfly Optimization Algorithm

3.1. Traditional butterfly optimization algorithm

BOA is a meta-heuristic intelligent algorithm. Inspired by the mating behavior of butterflies, the algorithm receives, senses and analyzes the odor in the air to determine the potential direction of mating partners. Butterfly will produce a certain intensity of fragrance related to its adaptability, that is, when the butterfly moves from one position to another, its adaptability will change accordingly. When a butterfly senses that another butterfly is emitting more fragrance in this area, it will approach. This stage is called global search. On the other hand, when the butterfly can't perceive the fragrance larger than itself, it will move randomly, and this stage becomes a local search.^[8]

In BOA, fragrance is a mode, which is expressed as a function of the physical intensity of the stimulus, as shown in the Eq. (3), where c is a sensory mode, with a value between [0,1], and it is introduced to distinguish odor from sound, light, temperature and other forms; I is the intensity of stimulation, and its size is related to the adaptability of butterflies; a is a power exponent, with a value between [0,1]. Experiments show that with the enhancement of stimulation, the sensitivity of insects to stimulus changes becomes lower and lower, so the parameter a is a response compression state, that is, when I increases, f grows slower than I.^[9]

$$f = cI^a \tag{3}$$

In each iteration of BOA, all butterflies in the solution space move to new positions, and then their fitness values are re-evaluated. First, the butterfly will use Eq. (3) to generate fragrance in its own position, and then carry out global and local search. In the global search stage, the butterfly moves towards the most suitable butterfly. At this time, the solution of the butterfly can be expressed by Eq. (4), where g^* is the optimal solution among all the solutions in the current iteration, f_i is the fragrance of the *i* butterfly, and r is the random number in [0,1]. The local search can be expressed by Eq. (5), where x_i^t and x_k^t are randomly generated random solutions in the solution space.^[10]

$$x_i^{t+1} = x_i^t + (r^2 \times g^* - x_i^t) \times f_i$$
(4)

$$x_{i}^{t+1} = x_{i}^{t} + (r^{2} \times x_{j}^{t} - x_{k}^{t}) \times f_{i}$$
(5)

3.2. Variable step size duty cycle disturbance observation method

The problem of oscillation and misjudgment will occur in the maximum power point tracking of fixed step P&O, resulting in unnecessary energy loss. Variable step-size P&O can better solve the contradiction between speed and accuracy in the process of maximum power tracking, which ensures the tracking speed and reduces the vibration amplitude and energy loss. Therefore, this paper uses the method of step-by-step approximation with duty ratio to search for the maximum power point. Observing the absolute value change of the slope dP/dU of the PV array P-U curve shows that the absolute value of dP/dU decreases monotonically until zero during the process of gradually approaching the maximum power point, according to this characteristic, the duty cycle perturbation is shown in Eq. (6), where μ is the variable step speed factor and is a positive number. ΔD has a prescribed upper and lower limit, when $\Delta D \ge \Delta D_{max}$, $\Delta D = \Delta D_{max}$; when $\Delta D \le \Delta D_{min}$, $\Delta D = \Delta D_{min}$. The duty cycle change expression is shown in Eq. (7).

$$\Delta D = \mu (dP/dU). \tag{6}$$

$$D_{ref} = \begin{cases} D_{ref} + \mu(dP/dU), \ \Delta D_{min} < \Delta D < \Delta D_{max} \\ D_{ref} \pm \Delta D_{max}, \qquad \Delta D \ge \Delta D_{max} \\ D_{ref} \pm \Delta D_{min}, \qquad \Delta D \le \Delta D_{min} \end{cases}$$
(7)

Obviously, the accuracy of variable-step P&O is greatly improved during the search process, which makes the system stabilize at the maximum power point as soon as possible. Although the performance of variable-step P&O is much improved compared to fixed-step P&O, it still has poor response to external environmental changes and is only applicable to environments with small changes in light intensity.^[10-11]

3.3. Improved butterfly optimization algorithm

3.3.1. Nonlinear inertia weight

To address the shortcomings of the basic butterfly algorithm for complex functions convergence speed is slow, low accuracy of the search, this paper in the global search phase to introduce a non-linear decreasing inertia weight with the increase of evolutionary algebra, inertia weight function as Eq. (8).

$$w = \frac{1}{\left[(t+1)^{(\alpha+\beta)}\right]^3} \cdot \left(\frac{\alpha \cdot t^{\alpha}}{N_{iter}{}^{\alpha}} + \frac{\beta \cdot t^{\beta}}{N_{iter}{}^{\beta}}\right)$$
(8)

where α and β are weight coefficients and $\alpha = 2$ and $\beta = 3$. The inertia weight w is between [0,1], and in the early stage of evolution, w is larger and BOA has a strong global search ability and a large detection range, which is conducive to jumping out of the local optimum, and w decreases in the later stage, when the butterfly performs a fine search near the optimum, making the algorithm converge faster. The improved global search is represented by Eq. (9).

$$x_i^{t+1} = w \cdot x_i^t + (r^2 \times g^* - x_i^t) \times f_i$$
(9)

3.3.2. Composite control strategy

In order to reduce the oscillation at the late stage of algorithm search and improve the convergence accuracy, this paper proposes a control strategy that combines WBOA with variable step P&O. The first part of the composite control is the WBOA search process, and the second part is the variable-step P&O tracking process.^[12] The control schematic is shown in Fig.3. The specific steps are as follows:

• Initial inertia weight w, number of iterations t, butterfly position update x_i^{t+1} , stimulus intensity I, and adaptation degree. Any 10 duty cycles between [0,0.8] are chosen as individual butterflies.

• Measure the output current and voltage of the system, calculate the power (fitness) of each butterfly at the current position, and find out the position of the butterfly with the largest fitness, assign it to g^* , and judge whether the maximum distance of the current butterfly group is less than 0.06.

• If the result of step (2) is no, the BOA search is performed. Given a switching probability p of 0.6, a random number r is generated from within [0,1]. If r is greater than p, the butterfly performs a local flight and updates the position according to Eq. (5); if r is less than p, the butterfly performs a global flight and updates the position according to Eq. (9).

• If the result of step (2) is yes, the variable-step P&O search is performed, and the step size is updated using Eq. (7), and when the adaptation of two adjacent iterations meets the algebraic condition, the best duty cycle is output and the search is ended. Otherwise, the P&O search is repeated

(Fig 3).



Figure 3: Composite control schematic diagram

4. Simulation and Analysis of Results

4.1. Simulation

The PV power generation system is modeled in Simulink as shown in Fig.4. The model is selected as a conventional boost circuit with circuit parameters set to $C_1 = 500\mu F$, $C_2 = 25\mu F$, L = 8.5mH, and $R_{load} = 100\Omega$. The PV module parameters selected in this paper are $U_{oc} = 36.3V$, $I_{sc} = 7.84A$, $I_{mp} = 7.35A$, and $U_{mp} = 29V$. The maximum number of BOA and WBOA-P&O iterations is set to 15.



Figure 4: Schematic diagram of photovoltaic power generation system

To verify that WBOA-P&O performs better than variable-step P&O and BOA on MPPT, the model performs multiple simulations of these three types of algorithms under shading conditions in working condition one and working condition two, and compares the performance indexes of these three algorithms, including tracking accuracy, tracking speed, and oscillation conditions, based on the simulation results. Firstly, variable-step P&O is used to track the maximum power, and its simulation results are shown in Fig.5. Secondly, the maximum power is tracked based on BOA, and the process is shown in Fig.6. Finally, the maximum power is tracked using WBOA-P&O, and the simulation graph is shown in Fig.7.



Figure 5: The tracking process of variable-step P&O



Figure 6: The tracking process of BOA



Figure 7: The tracking process of WBOA-P&O

4.2. Analysis of results

Table 2: Performance of three algorithms under working condition 1

Algorithm	Average maximum power (w)	Difference from maximum power (W)	Convergen ce time (s)	Tracking accuracy (%)	Oscillation situation
P&O	4593.5	13.5	0.035	99.7	Micro oscillation
BOA	4602.5	4.5	0.45	99.9	Large oscillation
WBOA-P&O	4607	0	0.22	100	Small oscillation

A	Algorithm	Average maximum power (w)	Difference from maximum power (W)	Convergence time (s)	Tracking accuracy (%)	Oscillation situation
F	°&O	5227	541	0.045	90.6	Micro oscillation
F	BOA	5018	750	0.4	86.9	Micro oscillation
V F	WBOA- P&O	5768	0	0.18	100	Small oscillation

Table 3: Performance of three algorithms under working condition 2

From Table 2 and Table 3, it can be seen that the tracking accuracy of both variable-step P&O and BOA reaches more than 95% under working condition 1. The oscillations in the tracking process of variable-step P&O are tiny and the convergence speed is extremely fast, while the oscillations in the tracking process of BOA are large and the convergence time is longer. Due to the transient change of working conditions, the average maximum power point tracked by variable-step P&O and BOA differs greatly from the standard maximum power point under working condition 2, and the tracking accuracy decreases significantly although the oscillation amplitude in the tracking process is extremely small. In contrast, WBOA-P&O is able to track 100% of the standard maximum power point in both working condition 1 and working condition 2, and the oscillation amplitude is very small. As a result, when the light condition changes rapidly, the variable-step P&O and BOA tracking can easily fall into the local optimal situation and cannot find the global optimal power point, while MBOA-P&O can quickly adapt to the environmental changes and can quickly and accurately find the global optimal value for the next working condition.^[13-14]

5. Conclusion

This paper proposes a composite MPPT algorithm based on the combination of WBOA and variable-step P&O for the PV array output characteristic curve with multiple extreme points under partial shading, and a PV power generation system model is built for comparison experiments with BOA and variable-step P&O method. The introduction of nonlinear inertia parameters in BOA can better balance the ability of global search and local search, avoid falling into the optimal local solution to some extent, and make BOA have better convergence and find the optimal solution quickly. Variable-step P&O adjusts itself in the iteration process, reducing the decision space and improving the search efficiency, in which the duty cycle starts to change continuously for local search, improving the stability and robustness of the search process. Through simulation experiments, it can be found that WBOA-P&O significantly reduces the oscillation amplitude, accelerates the convergence speed, and dramatically improves the search accuracy during the search process, thus reducing the power loss of PV cell power generation and improving the utilization efficiency of PV power generation, which reflects good adaptability to environmental changes and has engineering application conditions.

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References

^[1] Jalil Mohd Faisal, Khatoon Shahida, Nasiruddin Ibraheem, Bansal R. C. Review of PV array modelling, configuration

and MPPT techniques[J]. International Journal of Modelling and Simulation, 2022, 42(4).

[2] Gayathri Monicka Subarnan, Karthikeyan Madhu, Manimegalai Damodaran. A Review on Investigation of PV Solar Panel Surface Defects and MPPT Techniques[J]. Recent Advances in Electrical & Electronic Engineering, 2022, 15(8).

[3] Saidi K, Maamoun M, Bounekhla M. A new high performance variable step size perturb-and-observe MPPT algorithm for photovoltaic system[J]. International Journal of Power Electronics and Drive Systems, 2019, 10(3):1662.

[4] Lv Guanxi, Bai Di. Research on MPPT control strategy based on the Perturbation observation method[J]. Journal of Physics: Conference Series, 2023, 2474(1).

[5] Mishra Jyotismita, Das Subhadip, Kumar Deepak, Pattnaik Monalisa. A novel auto-tuned adaptive frequency and adaptive step-size incremental conductance MPPT algorithm for photovoltaic system[J]. International Transactions on Electrical Energy Systems, 2021, 31(10).

[6] Priyanka Singh, Nitin Shukla, Prerna Gaur. Modified variable step incremental-conductance MPPT technique for photovoltaic system[J]. International Journal of Information Technology, 2020, 13(6).

[7] Ahmadi S H S, Karami M, Gholami M, et al. Improving MPPT Performance in PV Systems Based on Integrating the Incremental Conductance and Particle Swarm Optimization Methods[J]. Iranian Journal of Science and Technology, Transactions of Electrical Engineering, 2022(1):46.

[8] Sundareswaran K, Kumar V V, Palani S. Application of a combined particle swarm optimization and perturb and observe method for MPPT in PV systems under partial shading conditions[J]. Renewable Energy, 2015, 75.

[9] Yang B, Yu T, Zhang X, et al. Dynamic leader based collective intelligence for maximum power point tracking of PV systems affected by partial shading condition[J]. Energy Conversion and Management, 2019, 179:286-303.

[10] Debnath D, Soren N, Pandey A D, et al. Improved Grey Wolf assists MPPT Approach for Solar Photovoltaic System under Partially Shaded and Gradually Atmospheric Changing Condition[J]. International energy journal, 2020(1):20.

[11] Qais, Mohammed H. Hasanien, Hany M. Alghuwainem, Saad. Enhanced whale optimization algorithm for maximum power point tracking of variable-speed wind generators[J]. Applied Soft Computing, 2020, 86.

[12] Karthikeyan M, Manimegalai D. Jellyfish Search Algorithm for MPPT in Photovoltaic Systems Under Partial Shading Conditions [J]. Fluctuation and Noise Letters, 2023, 22(02).

[13] Kececioglu O F. Design of type-2 fuzzy logic controller optimized with firefly algorithm for maximum power point tracking of photovoltaic system based on super lift Luo converter [J]. International journal of numerical modelling: Electronic networks, devices and fields, 2022(4):35.

[14] Fathi M, Parian J A. Intelligent MPPT for photovoltaic panels using a novel fuzzy logic and artificial neural networks based on evolutionary algorithms[J]. Energy Reports, 2021, 7(31):1338-1348.

[15] Touil S A, Boudjerda N, Boubakir A, et al. A sliding mode control and artificial neural network based MPPT for a direct grid-connected photovoltaic source[J]. Asian Journal of Control, 2019.

[16] Bisht R, Sikander A. An improved method based on fuzzy logic with beta parameter for PV MPPT system[J]. Optik, 2022, 259.