RESEARCH ON PHOTOVOLTAIC SYSTEM'S MAXIMUM POWER POINT TRACKING BASED ON IMPROVED AUTOMATIC BACTERIAL FORAGING METHOD

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Conventional maximum power point tracking algorithms are prone to fall into local optimums when tracking maximum power points. The bacterial foraging method has better global search capability, but the conventional bacterial foraging method converges slowly, resulting in low tracking efficiency. In this paper, the shortcomings of the algorithm are improved by applying the Newton interpolation method to the algorithm and proposing a composite algorithm based on the adaptive bacterial foraging method. The Simulink simulation shows that the improved algorithm is able to find the maximum power point of the PV array faster and more steadily than the traditional algorithm under both static and dynamic shading conditions.

Keywords: local shadow, maximum power point, bacterial foraging method, chemotaxis step, dispersion probability, Newton interpolation method

1. Introduction

In recent years, with the increasing shortage of fossil energy and environmental pollution, the development and utilization of new energy has become an inevitable trend. Among them, solar energy as a widely distributed and abundant clean energy resources have received a lot of attention [1-2]. Photovoltaic power generation is a hot research topic in the field of new energy generation, but at present, photovoltaic cells are vulnerable to the external environment and cannot utilize solar power with maximum efficiency, so the maximum power point tracking technology is especially critical [3]. Under ideal conditions, the external environment is in a uniform light situation and the PV array P-U curve is single-peaked, conventional MPPT algorithms such as perturbation observation method and conductivity increment method can achieve maximum power point tracking. However, in practice, PV arrays are easily shaded

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by trees, buildings, clouds, etc., thus making the PV P-U curve multi-peaked. Therefore, artificial intelligence algorithms need to be used instead of conventional algorithms to achieve maximum power point tracking under complex lighting conditions. In order to improve the maximum power point tracking efficiency of PV arrays under complex lighting, many scholars have proposed improvement strategies for the relevant artificial intelligence algorithms.

Both literature [4] and literature [5] have improved the particle swarm algorithm. The literature [5] proposes a hybrid algorithm of adaptive particle swarm combined with cuckoo search, which effectively overcomes the problem of premature convergence of conventional particle swarm. The firefly algorithm has been improved in literature [6]. The literature [7] proposes an improved firefly algorithm, the use of a fuzzy controller to adaptively adjust the move step factor in the algorithm, which improves the tracking speed in the early stage and avoids system oscillations in the later stage. The chicken flock algorithm has been improved in the literature [8] and [9]. The literature [10] proposes an improvement strategy for the conventional chicken flock algorithm by introducing chaotic sequences for the assignment of initial values in the algorithm and adaptive inertia weights to improve the search strategy of individuals in the population, which improves the search speed and the search accuracy of the algorithm. In the literature [11], an adaptive RBF neural network algorithm is proposed with the main strategy of optimizing the expansion constants and weights with an adaptive linear algorithm, which improves the global search for superiority in the maximum power point tracking process.

In this paper, we propose an adaptive bacterial foraging method (ABFA) based on the theory of the conventional algorithm and introduce Newton interpolation in the termination conditions of the algorithm iterations. The simulation test through Simulink modeling can be concluded that the improved algorithm has better convergence speed and global search ability under local shading conditions, and when the external light distribution changes, the improved algorithm can also find the new maximum power point faster and more accurately.

2. Partially shaded PV array output characteristics

The PV array is composed of numerous PV modules connected in series and parallel, each PV module is equivalent to a nonlinear DC source, and the specific PV module equivalent circuit diagram is shown in Fig. 1.

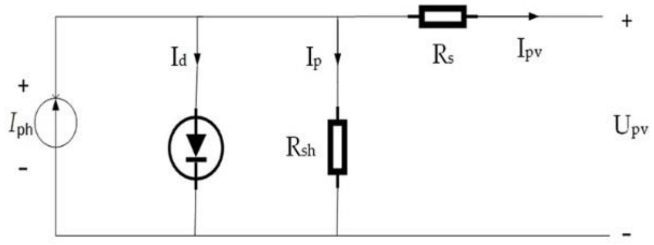


Fig. 1 Equivalent circuit diagram of photovoltaic module

According to Kirchhoff's current law, the output current equation of a single PV module can be expressed as [12]

$$I = I_{ph} - I_0\left\{\exp\left[\frac{q}{nkT}(V + IR_s)\right] - 1\right\} - \frac{V + IR_s}{R_{sh}} \tag{1}$$

In (1), I_{ph} denotes photogenerated current, I_0 denotes equivalent diode reverse saturation current, q denotes unit charge, n denotes diode characteristic factor, k denotes Boltzmann constant, T denotes temperature, R_{sh} denotes equivalent parallel resistance, R_s denotes equivalent series resistance, and V and I are the output voltage and output current of the PV module, respectively. Among them, R_{sh} resistance is approximately infinite, and R_s resistance is very small and negligible, so (1) can be simplified as[13]

$$I = I_{ph} - I_0\left\{\exp\left[\frac{qV}{nkT}\right] - 1\right\} \tag{2}$$

The P-U output curve of the PV array is multi-peaked in the case of partial shading. In this paper, we take a 3×1 series PV array as an example and build its engineering model in Simulink, where the PV module model chosen is Solarex MSX60. Under standard test conditions (light intensity of 1000W/m2 and temperature of 25°C), the module of this model has an open-circuit voltage Uoc of 21.5V, a short-circuit current Isc of 9.7A, a peak voltage Um of 17.5V and a peak current Im of 8.58A. Fig. 2 shows the module package of a 3×1 series PV array.

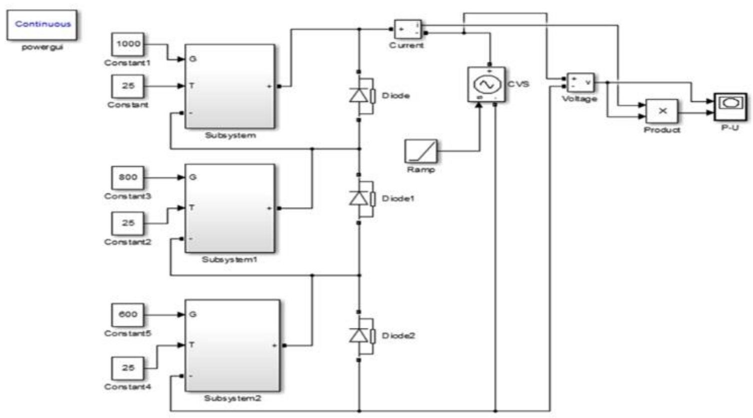
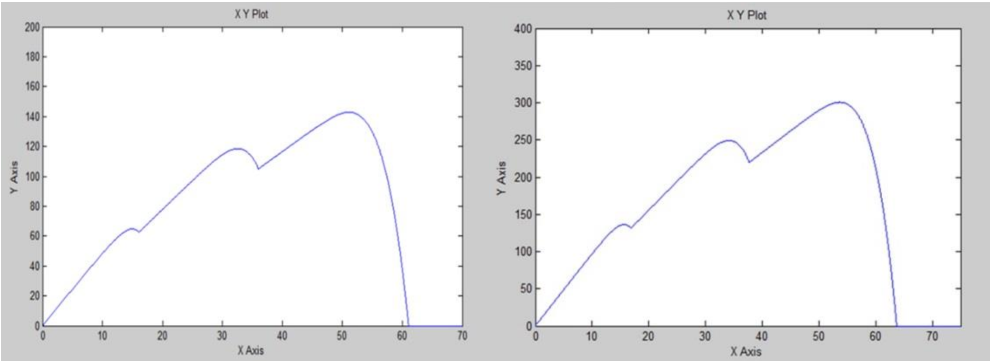


Fig. 2 3×1 series PV array



(a) The first type of light distribution (b) The second type of light distribution
Fig.3 3×1 series PV array P-U curve

Two types of light distribution are set up in the paper to simulate the simulation environment of PV array, the first type is S1=1000W/m2, S2=800W/m2, S3=600W/m2, and the second type is S1=500W/m2, S2=400W/m2, S3=300W/m2. the P-U output curve of PV array under the two shading distribution cases can be represented by Fig. 3.

3.MPPT algorithm strategy

Bacterial foraging algorithm (BFA) have achieved a wide range of applications in the field of intelligent control, and in view of some of the shortcomings of BFA, scholars have continued to improve them. In literature [22] for the disadvantages of slow convergence, inaccurate optimization and poor stability of the BFA. An adaptive diminishing fractal dimension chemotactic step length is designed to replace the fixedstep length to achieve the adaptive step length adjustment, an optimal swimming search method is proposed to solve the invalidsearching and repeated searching problems of the conventional BFA, and the adaptive migration probability is developed to takethe place of the fixed migration probability to prevent elite individuals from being lost in BFA. And apply it to intelligent ship collision avoidance planning. This literature [23] extends the single-peaked bacterial foraging algorithm to establish a multi-colony foraging optimization algorithm for solving multimodal optimization problems and demonstrates that the complexity of the algorithm is lower than its single-peaked form. This literature [24] combines bacterial foraging with Fuzzy synergism, applying it to contrast enhancement, edge & noise detection, noise removal and edge-sharpening (all the four important aspects of dehazing).

It has been proved that the BFA has good performance in intelligent control. In this paper, the BFA is applied to MPPT control, and in order to solve its shortcomings of slow convergence, this paper combines it with Newton interpolation and proposes a hybrid algorithm with fast convergence and more accurate tracking. The following is a detailed description of the BFA and the hybrid algorithm proposed in this paper.

3.1 Principle of BFA

The BFA is based on the multifunctional foraging behavior of E. coli, which is reflected in the adaptation of bacteria to their environment. In the initial state, all individuals in the bacterial population are freely dispersed in various locations, and the optimal values of individuals in the population are continuously updated through three major motions: convergence, reproduction and migration, so as to find new target functions and eliminate the poorly adapted individuals[14-16]. Among them, the basic principles of convergence operation, reproduction operation and migration operation can be outlined as follows:

1. convergence operation: convergence includes two modes of behavior: flip and forward, flip means that the bacteria adjust their movement direction, forward means that the bacteria move in the current direction, if the individual adaptation value increases, they continue to move in the current direction, and vice versa, they move in the opposite direction.

2. Reproduction: When the number of iterations of bacterial chemotaxis reaches the maximum number, the reproduction operation starts, and the principle of "survival of the fittest and elimination of the unfit" is used to screen out the top 1/2 of the population in terms of fitness and remove the bottom 1/2 of the population in order to ensure the continuous updating and optimization of the population.

3. Migration operation: When the number of iterations of bacterial reproduction reaches the maximum number, the migration operation starts. In order to avoid the algorithm to fall into the local optimum, the bacterial individuals will move to any position in the feasible space with a certain probability to find the optimal. However, the parameters of the formula in the conventional algorithm are fixed, so it is difficult to effectively grasp the magnitude of the step size during the convergence operation, and both good and bad individuals will be dispersed to the rest of the location with the same probability during the migration operation, which makes the global search ability of the algorithm decrease. At the same time, the lack of suitable termination conditions of the algorithm when the bacterial individuals are close to the global optimum point makes the final tracked accuracy value not high[17-18]. Based on the shortcomings in the conventional algorithm, the convergence step formula and migration probability formula in the original algorithm are improved in the paper, and the search ability of the algorithm when approaching the global optimum point is improved by combining the Newton interpolation method.

3.2 Adaptive Bacterial Foraging Algorithm

3.2.1 Convergence step size

In the process of bacterial foraging, chemotaxis is a more critical step, and the selection of its step value has a greater impact on the search ability of individual bacteria in the early stage. In the original algorithm, the bacterial convergence formula can be expressed as

$$\theta_i(j+1,k,l) = \theta_i(j,k,l) + C(i)\omega(i) \tag{3}$$

$$\omega(i) = \frac{\lambda_i}{\sqrt{\lambda_i^T \lambda_i}} \tag{4}$$

In the above equation, *j*, *k*, and *l* denote the number of bacterial tropisms, replications, and migrations, respectively, $C(i)$ denotes the bacterial movement step, and $\omega(i)$ denotes the bacterial movement direction. In the conventional algorithm, the parameter of bacterial convergence step is fixed, and if the value is large, although it improves the search speed of individual bacteria, it will easily lead to oscillation back and forth around the optimal value, which reduces the tracking stability. If the value is small, the search speed is reduced while the stability is improved. Based on the above shortcomings, the convergence step formula of the original algorithm is improved in the paper, and the improved step formula is shown in equation (5).

$$C_i(j) = C(min) + [C(max) - C(min)] \cdot [cos(\frac{j}{m} \cdot \frac{\pi}{2})] \tag{5}$$

where j denotes the number of current iterations, m denotes the total number of iterations, $C(min)$ denotes the minimum value of step size, and $C(max)$ denotes the maximum value of step size. From the adaptive improvement step formula, it can be concluded that in the early stage of the algorithm search, bacterial individuals converge to a larger step value, which can increase the tracking speed in the region far from the optimal value, and when bacterial individuals converge to the optimal value, a small step size can be automatically used to improve the tracking accuracy.

3.2.2 Migration probability

The migration process refers to the search for the optimal solution in which bacterial individuals move from the original region to the new region with a certain probability. In the conventional algorithm, the migration probability of all bacterial individuals is the same, which leads to the migration operation of good individuals and inferior individuals with equal chance, making the search accuracy of the algorithm significantly reduced. Based on the above shortcomings, the migration probability formula of the original algorithm is improved in the paper, and the improved probability formula is shown in equation (6).

$$P_i = [\frac{P_{ed} - F_i}{F_{max}}] P_{ed} \tag{6}$$

Where, P_{ed} denotes the initial migration probability, F_i denotes the fitness of the ith bacteria, F_{max} denotes the maximum fitness value among all bacterial individuals, and P_i denotes the migration probability of the ith bacteria. From equation (6), it can be seen that the less adaptive individual has a larger migration probability value, and the more adaptive individual has a smaller migration probability value, which ensures the excellence of the population evolutionary direction and makes the bacterial individuals continuously converge to the global optimal solution.

3.3 Improved adaptive bacterial foraging algorithm (IABFA)

When the bacterial population has gradually approached the optimal solution through continuous convergence, replication and migration operations, a reasonable termination condition of the algorithm should be established. In the conventional BFA, the termination condition of the algorithm is once per iteration, that is, the fitness of all bacteria individuals are sorted in descending order, assuming that the total number of bacterial populations is n. When the output power error between the first bacteria and the nth bacteria is less than the threshold ε, the current system is considered to have found the maximum power point. However, the conventional termination condition tends to cause the algorithm to iterate for too long, making the system unstable. Therefore, in the paper, the two sides of the global optimal point are sampled, and the approximate curve fitting is performed by Newton interpolation, and the MPP point is found directly according to the parabolic extremum formula, which effectively avoids the system oscillation caused by too many iterations of the algorithm[19].

In the case of constant external temperature and light intensity, the shape of the P-U output curve of the PV system will not change, specifically as a parabola with a downward opening, in which the curve segment near the MPP point is partially characterized by a quadratic function, and the voltage value of the maximum power point can be calculated by x=-b/2a. In the paper, three voltage sampling points P_0 (x_0, $f(x_0)$), P_1 (x_1, $f(x_1)$), P_2 (x_2, $f(x_2)$) are selected on the left and right sides of the MPP point, where the three sampling points are selected to meet certain conditions, and the relationship between P_0, P_1 and P_2 is shown in equation (7).

$$\begin{gathered}(P_1 > P_0, P_1 > P_2) \&\& (U_0 > U_1 > U_2) \\ (P_1 > P_0, P_1 > P_2) \&\& (U_0 < U_1 < U_2)\end{gathered} \tag{7}$$

As it can be seen from equation (7), the three sampling points after adding the constraints can be guaranteed to be distributed on the left and right sides of the MPP point and used as Newton interpolation sample points to fit the curve. When the number of bacterial migration iterations tends to saturate, it can be approximated that the current working point has been located in the neighborhood of MPP point, at this time, three individuals that meet the above-mentioned law are selected from the bacterial population, which are noted as P_0 (x_0, $f(x_0)$), P_1 (x_1,

$f\ (x_1)$), P_2 (x_2, $f\ (x_2)$), and then the Newton interpolation polynomial can be expressed as [20-21]

$$L(x) = l_0(x) \cdot f(x_0) + l_1(x) \cdot f(x_1) + l_2(x) \cdot f(x_2) \tag{8}$$

where $l_0(x)$, $l_1(x)$, and $l_2(x)$ can be represented by the following metric, respectively

$$l_0(x) = \frac{(x-x_1)(x-x_2)}{(x_0-x_1)(x_0-x_2)} \tag{9}$$

$$l_1(x) = \frac{(x-x_0)(x-x_2)}{(x_1-x_0)(x_1-x_2)} \tag{10}$$

$$l_2(x) = \frac{(x-x_0)(x-x_1)}{(x_2-x_0)(x_2-x_1)} \tag{11}$$

Combining equation (9) - equation (11), the general polynomial of equation (8) can be obtained as

$$L(x) = ax^2 + bx + c \tag{12}$$

where a, b, and c can be expressed respectively as

$$a = \frac{f(x_0)}{(x_0-x_1)(x_0-x_2)} + \frac{f(x_1)}{(x_1-x_0)(x_1-x_2)} + \frac{f(x_2)}{(x_2-x_0)(x_2-x_1)} \tag{13}$$

$$b = \frac{f(x_0)(x_1+x_2)}{(x_0-x_1)(x_0-x_2)} + \frac{f(x_1)(x_0+x_2)}{(x_1-x_0)(x_1-x_2)} + \frac{f(x_2)(x_0+x_1)}{(x_2-x_0)(x_2-x_1)} \tag{14}$$

$$c = \frac{f(x_0)x_1x_2}{(x_0-x_1)(x_0-x_2)} + \frac{f(x_1)x_0x_2}{(x_1-x_0)(x_1-x_2)} + \frac{f(x_2)x_0x_1}{(x_2-x_0)(x_2-x_1)} \tag{15}$$

By interpolating three sample points P_0 (x_0, $f\ (x_0)$), P_1 (x_1, $f\ (x_1)$), P_2 (x_2, $f\ (x_2)$) for output voltage detection and output power acquisition, the corresponding functions are shown in Eqs. (16)-(18).

$$P(x_0) = ax_0{}^2 + bx_0 + c = f(x_0) \tag{16}$$

$$P(x_1) = ax_1{}^2 + bx_1 + c = f(x_1) \tag{17}$$

$$P(x_2) = ax_2{}^2 + bx_2 + c = f(x_2) \tag{18}$$

The solutions of a, b, and c can be found by substituting x_0, x_1, x_2, and $f(x_0)$, $f(x_1)$, and $f(x_2)$ into the expressions of a, b, and c. The current MPP point voltage, which is the global optimum searched by the BFA, is found by the quadratic extremum solution formula x = -b/2a.

Fig. 4 shows the mathematical model of Newton interpolation method for solving the extreme values.

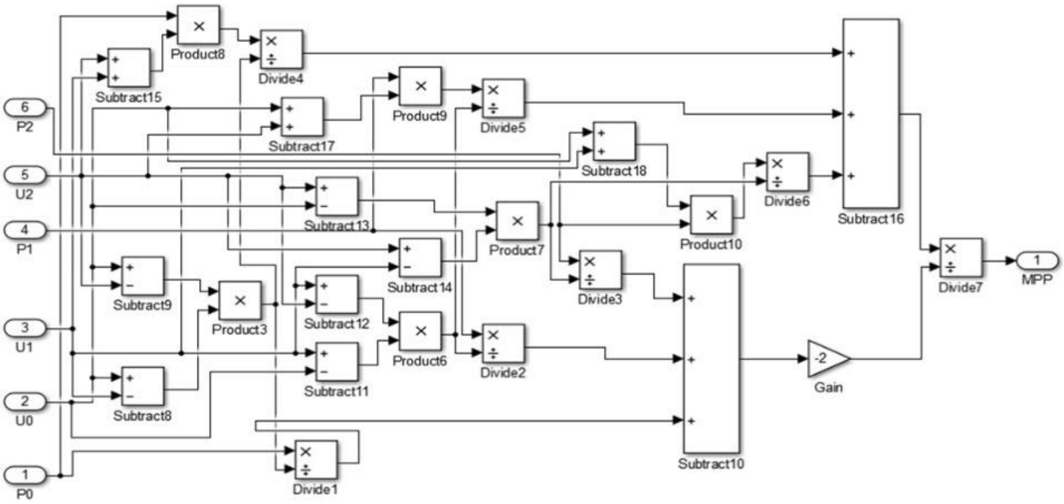


Fig.4 Newton interpolation simulation model

It can be seen that the introduction of Newton interpolation in the termination condition of the BFA prevents system oscillations caused by multiple iterations and accurately calculates the global optimal point voltage in one step, which effectively improves both tracking stability and tracking accuracy.

When using the ABFA for PV array maximum power point tracking, the position of each bacteria is noted as the PV array output voltage value and the adaptation of the bacteria is the PV array output power value, and the basic execution steps of the algorithm are as follows.

1. Initialize each parameter, including the population size n, the maximum number of convergence m, the maximum number of replication p, the maximum number of migration q; and the maximum step value of bacterial convergence C(max), the minimum step value C(min), and the initial migration probability Ped of bacteria.

2. If the current number of convergence $j < m$, the convergence cycle is carried out, and the current number of iterations is updated to $j = j + 1$ for each cycle, and continue to judge whether j is less than m. If the result is yes, then continue to execute step 2, if the result is no, then execute step 3, the specific convergence step formula is shown in equation (5).

3. If the current replication number $k < p$, the replication cycle is carried out, and the current iteration number is updated to $k = k + 1$ for each cycle, and continue to judge whether k is less than p. If the result is yes, continue to execute step 3, and if the result is no, execute step 4 to sort the bacteria in order of their adaptability from largest to smallest, and screen out the top 1/2 individuals for reproduction, while eliminating the bottom 1/2 individuals.

4. If the current migration number $l < q$, the migration cycle is carried out, and the current iteration number is updated to $l = l + 1$ for each cycle, and continue to judge whether *l* is less than q. If the result is yes, continue to execute step 4, and if the result is no, execute step 5, and the specific migration probability formula is shown in equation (6).

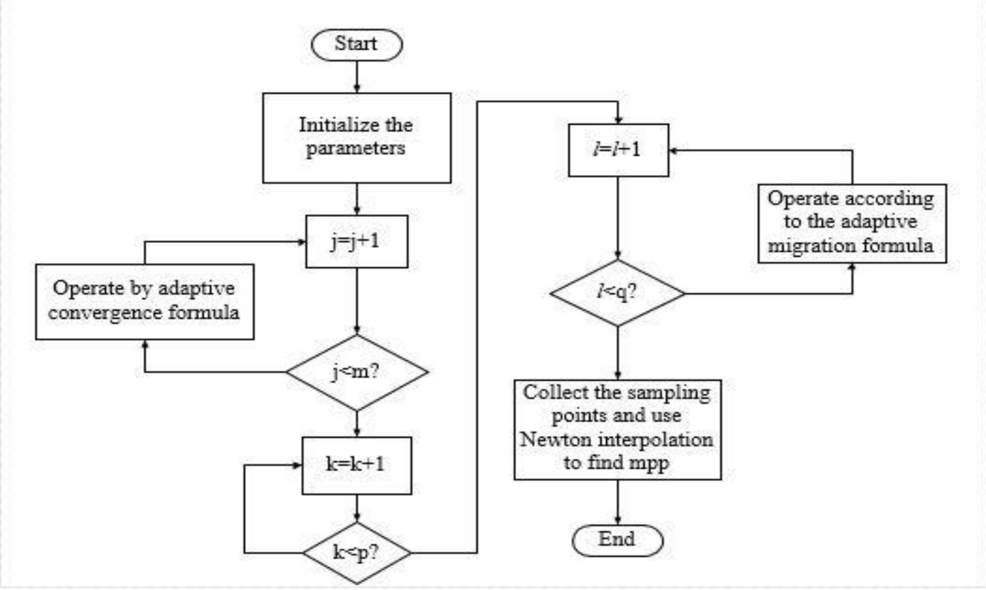


Fig.5 Flow chart of the improved algorithm

5. After the bacterial population performs a series of convergence, replication and migration operations, three sampling points on either side of the global optimum are selected and the MPP point voltage is calculated directly using Newton's interpolation method and the program is terminated. The flow block diagram of the improved ABFA is shown in Fig. 5.

In addition, when the external light intensity changes drastically, the algorithm restart condition needs to be set up to track the new global optimum point. In general, the BFA restart judgment formula is as follow

$$\varepsilon = \frac{|P_{real} - P_{max}|}{P_{max}} \tag{19}$$

The threshold value ε is 0.1, P_{real} is the actual output power of PV array, and P_{max} is the maximum output power of PV array. When the system index reaches the minimum threshold value, it indicates that the external shadow distribution has changed significantly, and then the algorithm will be restarted automatically for maximum power point tracking.

4. Simulink simulation analysis

In this section, a Boost circuit model is built in MATLAB/Simulink as shown in Fig. 6. The circuit model contains three series-connected PV module package modules, a bacterial foraging algorithm module, a PWM pulse signal converter, a MOSFET tube, a boost inductor L, a filter capacitor C, and an external load R. The bacterial foraging algorithm integrator generates a PWM pulse sequence by capturing the output voltage and output current of the PV module and inputting the two signals as inputs to the internal integrator for computation, whose output modulated waveform interacts with the carrier waveform within the PWM pulse modulator. At the same time, the PWM pulse sequence is converted into a duty cycle signal D to control the switching tubes. By changing the magnitude of the duty cycle D, the equivalent load of the Boost circuit can be adjusted to match the optimal output load, thus controlling the PV array to maintain the optimal output state. The inductor L is 11mH, the filter capacitor C1 is 300uF, the filter capacitor C2 is 100uF, the external load resistance is 50Ω, and the PWM frequency is set to 30KHz. The parameters of BFA were selected as follows: population size n=6, maximum number of convergence m=5, maximum number of replication p=4, maximum number of migration q=3, initial migration probability Ped=0.75, maximum convergence step value C(max)=1, minimum convergence step value C(min)=0.3, where the fixed convergence step value of conventional BFA was based on C(max)=1, and fixed migration The probability value was uniformly taken as Ped=0.75. In this simulation test, the Solarex MSX60 PV module is used as the research object to simulate and analyze the maximum power point tracking under two external conditions, static shadow distribution and dynamic shadow distribution, respectively.

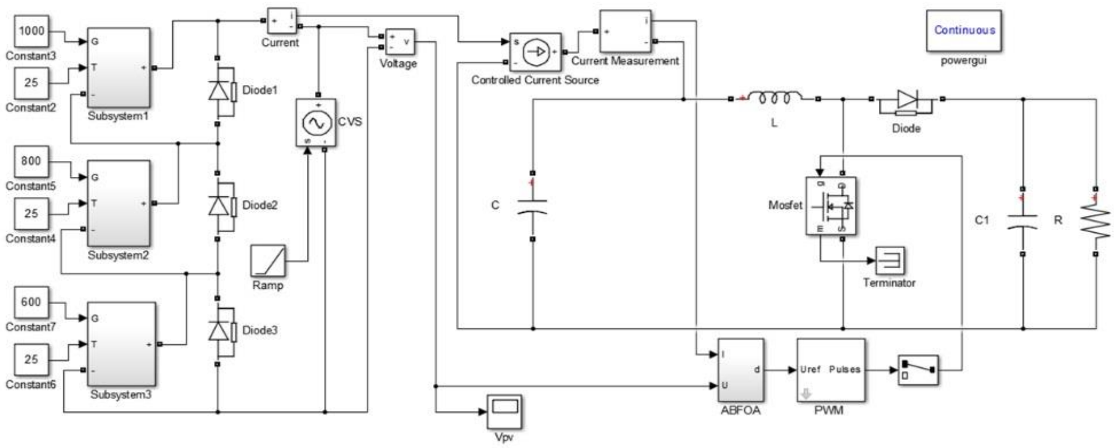


Fig.6 Boost circuit simulation model

In this paper, we choose the simulation solver type as variable-step ode45, set the maximum step and minimum step adjustment method as automatic mode, and simulate the conventional BFA, ABFA and IABFA in MPPT under the external conditions of shadow distribution type I (S1=1000W/m2, S2=800W/m2, S3=600W/m2 and the temperature is 25°C). The environment is changed from shading distribution type I to shading distribution type II(S1=500W/m2, S2=400W/m2, S3=300W/m2 and the temperature is 25°C), and the global peak power of PV array is changed from 300 W to 150 W as shown in Fig. 3(a) and (b). The power tracking waveforms of the three algorithms are shown in Fig. 7, 8 and 9.

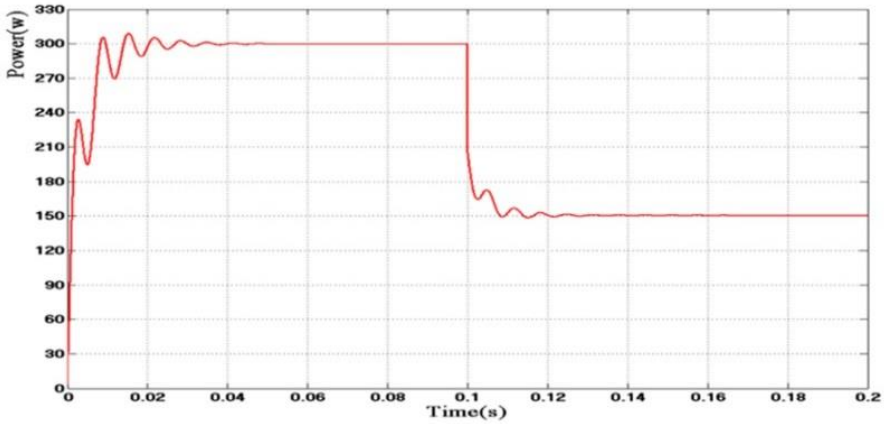


Fig.7 BFA power tracking waveforms

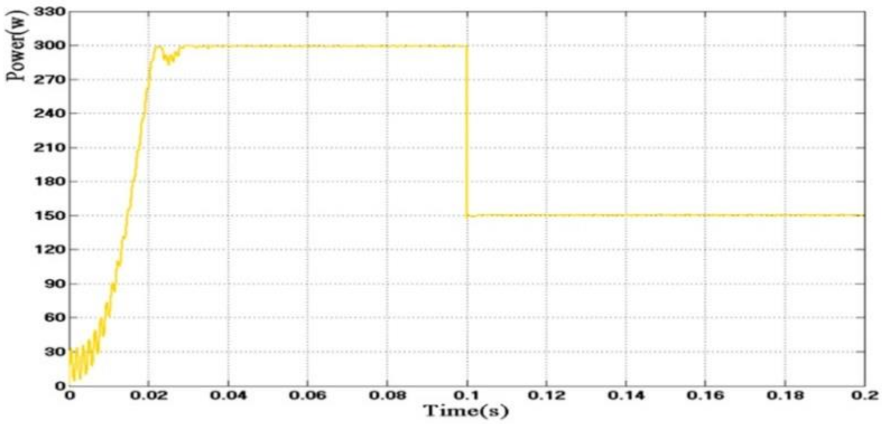


Fig.8 ABFA power tracking waveforms

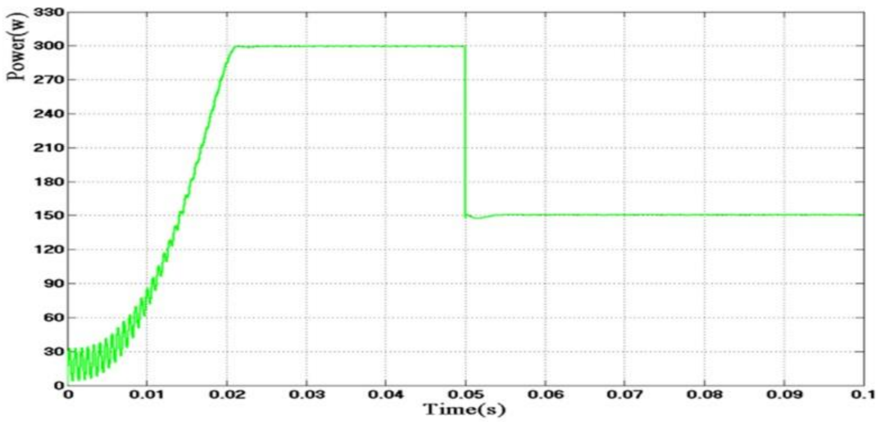


Fig.9 IABFA power tracking waveforms

From the analysis of Figs. 7, 8 and 9, it can be seen that the ABFA has a smoother tracking waveform and a smaller steady-state oscillation rate than the conventional BFA. And the optimal output power is about 297.7W. The conventional BFA has a large power fluctuation near the maximum power point, and the optimal output power is about 295.4W.This is due to the fact that the convergence step value of bacterial individuals is fixed at the early stage of tracking, which prevents bacterial individuals from adaptively adjusting the step size according to the current environment, while at the later stage of tracking, some superior and inferior individuals are transferred to the rest of the feasible space for optimal solution search with equal probability, which makes the overall tracking efficiency of the algorithm decrease. The adaptive bacteria foraging combined with Newton interpolation algorithm tracking stability is significantly better than the first two algorithms, and the optimal output power is 300W with the highest tracking accuracy. This is due to the fact that the MPP point voltage is calculated directly by using Newton interpolation in the late stage of algorithm tracking, which can avoid the high frequency oscillation caused by multiple iterations of the algorithm, reduce the system energy loss, and improve the search accuracy at the same time.

Observe the second half of the waveform in Figs. 7, 8 and 9, it can be concluded that when the external environment is in a dynamic shadow distribution situation, the convergence speed and stability of the ABFA are significantly improved compared to the conventional BFA. From the simulated waveform, the ABFA quickly converges and stabilizes at about 148.5W after the sudden change of light intensity, with very little waveform oscillation during the period, while the conventional BFA lacks a suitable step adjustment factor and a flexible migration probability formula, and there is a more violent power oscillation, and the final output power is about 147.3W. Re-observation of IABFA, the proposed hybrid algorithm is significantly better than the other two algorithms in all aspects, whether in terms of convergence speed, stability or search accuracy, and its final output power is 150 W. Therefore, the composite algorithm has better dynamic response capability when the external environment is in a complex and variable situation. From Figs. 7, 8 and 9, we can obtain Table I. Comparison of the tracking time of the algorithm in the two stages.

Table I

Time consumption comparison table

types / projects	CBFA	ABFA	IABFA
Time spent in the first stage of tracking	0.04	0.03	0.02
Time consumption reduction ratio		25%	50%
Time spent in the second stage of tracking	0.02	0.004	0.003
Time consumption reduction ratio		80%	85%

By comparing the data in Table I for one time use, it can be obtained that the conventional BFA, the ABFA and IABFA take less and less time in tracking time when the light intensity is constant, and the ABFA reduces the tracking time by 25% compared with the conventional BFA, IABFA reduces the tracking time by 50% compared with the conventional BFA. It is demonstrated that the proposed algorithms have higher performance when the light intensity is constant.

By comparing the data of secondary time use in Table I, it can be obtained that the re-tracking performance of BFA is much worse than that of the ABFA and IABFA when there is a sudden change in light intensity, and both of them reduce the re-tracking time by 80% compared with the traditiona.

5. Conclusion

In response to the phenomenon that the P-U curves of photovoltaic arrays show multiple peaks under complex illumination, an adaptive bacterial foraging algorithm is proposed in the paper based on the original bacterial foraging method by improving the convergence step of bacterial individuals and the migration probability formula. Simulink modeling and simulation tests show that the adaptive bacterial foraging method is able to find the maximum power point faster and more steadily than the conventional bacterial foraging method in both dynamic and static shadow distributions. In order to further improve the search accuracy of the algorithm near the maximum power point, the paper introduces the Newton interpolation method in the termination condition of the adaptive bacterial foraging method and proposes a composite algorithm, which can also be tested by MPPT simulation, and it can be concluded that the composite algorithm converges faster and has a lower steady-state oscillation rate than the previous two algorithms, regardless of the dynamic shadow distribution or static shadow distribution, and the actual tracked maximum power point is almost error-free. Based on the proposed bacterial foraging combined with Newton interpolation algorithm in the paper, the MPPT efficiency of the PV system under partial shading is improved to some extent, and the utilization rate of PV power is improved at the same time.

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