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Module Efficiency Improvement Method Based on Gray Wolf Optimization Algorithm in Intelligent Management Environment of Photovoltaic Power Plants

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ABSTRACT

With the gradual depletion of fossil energy resources and the increasingly severe environmental problems, photovoltaic power generation as a typical new energy industry has been highly favored in recent years. In the face of the low efficiency of components often faced by photovoltaic power plants in actual operation, this paper proposes a maximum power point tracking algorithm (IGWO) based on the Gray Wolf optimization algorithm, which optimizes and joins the dynamic weights to expand the search range of the algorithm, and improves the efficiency of solar energy utilization. The gray wolf algorithm is further applied to the optimization of photovoltaic (PV) arrays in power stations, and a PV array reconfiguration algorithm based on the gray wolf optimization algorithm is proposed to randomly generate a radial structure by the broken circle method, and the best reconfiguration scheme is obtained through iterative optimization search. The optimization experiment of photovoltaic power station was carried out, and the photovoltaic array reconstruction algorithm in this paper was used to reconstruct in the static shadow occlusion mode, and the GMPP after reconstruction was significantly improved, and the shadow occlusion mode was increased to 14515.565W, 10626.844W, and 10636.467W, respectively, and the tracking accuracy of the IGWO algorithm in this paper also reached 99.9%, 99.5%, and 99.6%, respectively. The tracking accuracy of the IGWO algorithm in this paper for MPPT tracking control is consistently above 99% level under dynamic shadow shading mode.

Keywords: gray wolf optimization algorithm, maximum power point tracking, photovoltaic array reconfiguration, broken circle method, photovoltaic power generation

1. Introduction

With the rapid development of social industry and economy, people's demand for energy is increasing dramatically [1]. Solar energy as an inexhaustible renewable energy source has undoubtedly become the first choice, and countries around the world have set their sights on the development and

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utilization of solar energy as a sustainable energy strategy [2-4]. However, at present, the problem of conversion efficiency of photovoltaic systems is the main problem that hinders the continued development of the photovoltaic industry, and how to improve the conversion efficiency has become a hot issue in research [5-6].

In solar power systems, PV modules, commonly known as solar panels, are the core part of the system and the most valuable part of the system [7-8]. Their role is to convert the sun's radiant power into electrical energy, either to be sent to the battery for storage or to drive the load [9-10]. Solar cells are excited by sunlight, which causes the transfer of electrons to generate electricity, and the wavelength at which they are excited by sunlight depends on the type of semiconductor [11-12]. In today's market, the main most used cells are crystalline and thin film silicon cells, whose photovoltaic conversion efficiency is generally less than 20%, so this is an important direction to improve the conversion efficiency of the system [13-15].

Solar photovoltaic power generation currently consists of three main forms of application, one is a large-scale grid-connected photovoltaic power plant built in open areas, which directly converts sunlight into electricity for transmission to the power grid [16-17]. The second is urban rooftop grid-connected PV systems, which have a smaller capacity and generate electricity that can first satisfy household use, with excess power that can be fed into the grid, and when the PV system does not generate enough power to support the household demand, the grid will supply power to the household system [18-20]. Thirdly, off-grid PV system, which has a very wide range of applications, can supply power to islands, remote mountain villages, and nomadic families that do not have power grids to meet the basic power needs, and can also supply power to unattended communication base stations, beacon lights, street lights, and traffic command signals, etc. [21-24].

In this paper, the maximum power point tracking and the optimal reconstruction of PV arrays are used to optimize the component efficiency of PV power plants under the intelligent management environment. Firstly, the model of intelligent PV power station system is established, and the composition of intelligent PV power station system is discussed from the aspects of PV modules, PV arrays, PV equipments such as batteries and the working principle of PV power station, and the modeling and output characteristics of PV batteries are proposed, so as to provide the theoretical basis for the subsequent research on the optimization of the efficiency of the components of the PV power station. In the maximum power point tracking problem of photovoltaic power plant, the gray wolf algorithm is introduced, the decreasing mode of the convergence factor of the gray wolf algorithm is optimized, and dynamic weights are added, the original linear decreasing is changed to nonlinear decreasing, and the time of tracking the maximum power point is shortened, so that the maximum power point tracking algorithm based on the gray wolf optimization algorithm is proposed (IGWO). Using the gray wolf algorithm to reconstruct the traditional PV array structure, the broken circle method is used to randomly generate the radial structure as the network structure of the initial solution, randomly generating the radial structure, using the gray wolf algorithm as the framework, step by step iterative searching for the best reconstruction scheme, and the optimal reconstruction algorithm of PV array based on the gray wolf optimization algorithm is proposed. In the pre-optimization phase of the algorithm, the pareto optimal frontier solution set is searched for, and in the post-optimization phase of the algorithm, according to the solution set of the pareto optimal frontier, a set of thresholds of each objective index is determined as the boundaries of the post-optimization phase, and only the solution schemes within the boundaries are allowed to be selected as the better scheme by the direction of search guided by the weighted objective function. Simulation experiments are carried out to test the performance of the maximum power point tracking algorithm based on the Gray Wolf optimization algorithm and the PV array optimization reconstruction algorithm based on the Gray Wolf optimization algorithm, and at the end of the study, the two algorithms are explored through the optimization experiments of the PV power plant to improve the efficiency of the PV power plant components.

2. Smart photovoltaic power plant system modeling

With the society's continuous demand for clean energy and the increasingly urgent need for intelligent energy systems, intelligent photovoltaic (PV) power plants, as a highly efficient renewable energy generation method, have received widespread attention and become part of the energy Internet. As the core component of PV power generation system, PV cell plays a role similar to “heart”, and its performance is directly related to the utilization efficiency and cost control of the whole solar power generation system. In this chapter, we will establish a model of intelligent PV power plant, and elaborate on the power generation of PV power plant and the work of PV cells, so as to provide a basis for the subsequent optimization of the efficiency of components of PV power plant.

2.1. Intelligent photovoltaic power plant system composition

With the environmental problems caused by traditional energy generation becoming more and more serious, solar power generation is highly favored. Solar power generation includes two kinds, one is solar photovoltaic power generation and the other is solar thermal power generation. Solar photovoltaic power generation refers to the direct conversion of solar irradiance into electricity, and solar thermal power generation refers to the conversion of solar energy into heat energy first, and then by the conversion of heat energy into electricity Photovoltaic power generation belongs to the solar photovoltaic power generation, is the use of photovoltaic batteries to convert solar energy into electrical energy system.

2.1.1. Photovoltaic equipment. The relevant equipment in PV intelligent monitoring includes: PV cell monomer, PV module, PV array, controller, battery, inverter.

1) Photovoltaic cell monomer. Photovoltaic cell monomer is the component that converts solar irradiance into electricity, it is the most basic and important unit in the photovoltaic power generation system, and is the core of the photovoltaic power generation system. The working principle of photovoltaic cell monomer is to utilize semiconductor photodiode to absorb solar energy to generate electric potential i.e. electric current, thus realizing the transformation of light energy to electric energy.

2) Photovoltaic Module. Since PV cells alone cannot be used as a separate power source, PV modules are formed by connecting PV cells in series and parallel, and the PV modules can produce a large output current and output voltage, thus outputting high power. PV modules can be used as a separate power source in a PV power generation system and are also referred to as PV modules in many literatures.

3) Photovoltaic arrays. PV modules of the same type are connected in series and parallel to form a PV array, so that the PV array produces a larger output current and output voltage, which in turn produces a larger output power to meet the needs of engineering applications. Photovoltaic array can be used as a large power source, large-scale photovoltaic power plant and roof photovoltaic use of photovoltaic arrays.

4) Battery. The main function of the battery is to store the power generated by the PV power generation system. When the output power of the PV array is not enough to meet the power consumption of the load, the battery can supply power to the load.

5) Controller. The main function of the controller is to ensure the safe and stable operation of the PV equipment. The controller can also control the number of times the battery is charged and discharged, which in turn extends the service life of the battery.

6) Inverter. The inverter is a device that converts the DC power generated by the PV array into AC power, which in turn meets the needs of AC loads in the application.

2.1.2. Working Principle of Smart PV Power Plant. The photovoltaic effect is the physical process by which a semiconductor photodiode converts absorbed solar energy into electrical energy. Photovoltaic power generation systems can be categorized into two types depending on whether they are ultimately connected to the grid or not: one is off-grid and the other is grid-connected. The off-grid PV power generation system is not connected to the grid and is a separate power generation system; the grid-connected PV power generation system is connected to the grid. Since the grid-connected PV power system has requirements for equipment as well as grid-connection permits, the off-grid type is used in this paper in a smart management environment.

Since most of the PV power systems in engineering applications are large PV power plants or rooftop PV, a large number of PV arrays are used. The PV arrays convert the solar irradiance into DC power through the photovoltaic effect, and the controller deposits the DC power in the battery. The power in the battery can be used directly by DC loads or converted to AC power for AC loads by an inverter.

2.2. Basic Principles of Photovoltaic Power Generation

Nowadays, the production process of PV modules has been improved tremendously, the PV industry chain has been formed rapidly, and the quality and performance of PV modules have been stabilized relatively, and the service life has also been improved tremendously.

Ordinary silicon panels will form a stable structure by sharing electrons between atoms. However, the electrons in this kind of silicon plate are not free, and there is no directional movement to realize power generation. So people began to add material inside the silicon plate, such as adding phosphorus atoms in the silicon plate, phosphorus, the outermost layer of only five electrons, more than one silicon, so that each phosphorus atom more than one electron, together will be more than a lot of electrons, this plate is called N-type plate; and the other side of the boron atoms to join the boron atoms, boron atoms of the outermost layer of only three, less than one silicon, so that each boron atom will have a vacant space, together will be A lot more empty space, this plate is called P-type plate. When the P-type plate and N-type plate together, the homeless electrons quickly in the connection to take up space, the formation of the middle of neither free electrons nor empty space in the stable region, known as the PN junction. When the light shines on the N-type plate, N-type plate to remove free electrons, the original relatively stable electrons also absorb light energy to start active, want to leave the original position. So the N-type plate is more than a lot of free electrons, as long as the external formation of a closed loop, the electrons will run out of madness. PN junction within the original stable electrons will go to supplement the N-type plate within the empty space, P-type plate within the electrons go to supplement the PN junction within the vacant space, so the formation of the electron directional movement, which produces electricity.

2.3. PV Cell Modeling and Output Characteristics

2.3.1. Equivalent modeling of photovoltaic cells. The photovoltaic cell is the smallest component unit of a photovoltaic array. When it is irradiated by a light source, the light energy carried by the light causes the electrons in the N-type silicon plate within the PV cell to become active, and when the load is turned on, they travel along the load to the P-type silicon plate. The PN junction acts as a unidirectional conductor, and ideally can be viewed as a diode.

PCS represents the photocurrent source with an output current of I_{ph}, D represents the effect of the PN junction with a passing current of I_D, R_P represents the current loss with a passing current of I_P, R_S represents the voltage loss of the metal contact, and R represents the connected load.

The output voltage of the photovoltaic cell is V_o and the output current is I_o, where I_{ph}, I_D and I_P can be represented by equations (1), (2) and (3), respectively:

$$I_{ph} = \frac{S}{S_{ref}}\left[1+\alpha(T-T_{ref})\right]I_{ref} \tag{1}$$

$$I_D = I_{Do}\left(e^{\frac{q(R_S I_o + V_o)}{\beta kT}} - 1\right) \tag{2}$$

$$I_P = \frac{R_S I_o + V_o}{R_P} \tag{3}$$

In Eq. (1), S is the test irradiance in W/m^2, S_{ref} is the standard test irradiance, which is usually 1000 W/m^2, α is the temperature impact factor, T is the test temperature, T_{ref} is the standard test temperature, which is usually 25 ℃, and I_{ref} is the photovoltaic current in the standard test environment. In Eq. (2), I_{Do} is the diode saturation current, q is the electronic charge, β is the diode ideality factor, and k is the Boltzmann constant. From Eqs. (1), (2) and (3), it can be seen that only V_o, I_o is unknown in the expressions for I_{ph}, I_D and I_P, and the rest are known quantities or constants.

The expression for I_o can be written as Eq. (4), bringing Eq. (1), Eq. (2) and Eq. (3) i.e., the expression for the IV output characteristics of the PV cell.

$$I_o = I_{ph} - I_D - I_P \tag{4}$$

2.3.2. Output Characteristics of PV Modules. From the equivalent model of PV cell in the previous subsection, it can be found that the light-sensing current I_{ph} is proportional to the irradiance S, which is also affected by the ambient temperature T. Therefore, this subsection will discuss and analyze the trend of the output characteristic curve of the PV module under different irradiances as well as different temperatures.

An increase in the temperature of the PV module leads to a decrease in the output voltage at the maximum power point of the module, and an increase in the irradiance leads to a significant increase in the output current at the maximum power point of the PV module, but this is the variation of the curve in the ideal case. In the real situation, the increase in irradiance will inevitably lead to a rise in the temperature of the PV module, slightly reducing the voltage while the current rises substantially.

3. Maximum power point tracking algorithm based on gray wolf optimization algorithm

The maximum power point tracking (MPPT) control method is to optimize the PV cell output power by adjusting the operating state of the electrical components, so that the PV can be stabilized near the global maximum power point (GMPP) to maximize the electrical energy output, which effectively improves the efficiency of solar energy utilization and the overall performance of the PV power generation system [25].

In this chapter, the principle of maximum power tracking of PV cells will be analyzed, and on the basis of the Gray Wolf Algorithm (GWO), the tracking speed and accuracy will be improved by optimizing and improving the algorithm and applying it to the MPPT, and the improved Gray Wolf Optimization Algorithm (IGWO) will be used for the MPPT control of the PV array, which will improve the efficiency of the power generation of the PV array.

3.1. Principle of maximum power tracking for photovoltaic cells

The principle of maximum power point tracking is to instantly measure the output voltage and current of the PV array, and adjust the current impedance by self-seeking optimal adjustment of the duty cycle of the impedance converter (circuit) through the MPP algorithm, the relationship between the voltage gain of the converter and the duty cycle is not linear, and if the duty cycle of the converter is increased or decreased, the voltage increases or decreases along with it. The duty cycle of the converter is increased or decreased by shifting the operating point to the right or left of the I-U characteristic, so that the equivalent impedance matches the impedance of the PV array, which is known from the maximum power transfer theorem, and the PV array outputs the maximum power at this time. Even if the temperature and light intensity of the PV array change, the output power changes, the system can still work in the best state of the current situation.

R denotes the equivalent internal resistance and R_L denotes the equivalent load, whose output power is maximum only when R and R_L are equal in magnitude. Assuming that the power consumed on the load is P_L, there is:

$$P_L = I^2 R_L = (\frac{U_{pv}}{R_L + R})^2 R_L \tag{5}$$

The derivation of Eq. (5) is obtained:

$$\frac{dP_L}{dR_L} = U_{pv}^2 \times \frac{R - R_L}{(R_L + R)^3} \tag{6}$$

The output power P_L is maximized at $\frac{d}{P_L} dR_L = 0$, i.e., $R_L = R$ in Equation (6).

Even if the temperature and light intensity of the photovoltaic array change so that the output power changes, the system is still able to work in the current situation of the best state. When the light intensity and temperature conditions are determined, the system load on the photovoltaic array maximum power output has a great impact on the normal state of the actual load can not be arbitrarily changed, so between the photovoltaic array and the actual load to join the DC/DC circuit, this paper uses the circuit structure of a simple, stable Boost converter. In this paper, it is assumed that the load of the PV power generation system is purely resistive, and the conversion efficiency of the impedance converter is 100%.

The resistance of the Boost converter is:

$$R' = R_L (1 - D)^2 \tag{7}$$

where: R' is the Boost circuit equivalent load; D is the duty cycle of the switching element; R_L is the actual purely resistive load. The PWM duty cycle of the switching elements of the Boost circuit is generated through voltage closed-loop regulation to match the equivalent load with the impedance of the PV array, thus realizing the maximum power point tracking.

3.2. Principles of the Gray Wolf Algorithm

The Gray Wolf Algorithm (GWO) is inspired by the hierarchical management system of gray wolf populations within nature and the trapping mechanism adopted by gray wolf packs during hunting [26]. The gray wolf optimization algorithm has fewer parameters to be adjusted, only the number of individual gray wolves and the maximum number of iterations, so it has an advantage over other group intelligence optimization algorithms when the program needs to be designed quickly. Moreover, the gray wolf optimization algorithm has been shown to significantly outperform classical metaheuristic algorithms such as particle swarm algorithms and differential evolutionary algorithms in terms of solution accuracy and robustness. In view of its excellent performance on the optimization problem of multi-polar functions, the Gray Wolf optimization algorithm has attracted wide attention from experts and scholars, and has been successfully applied to many fields such as photovoltaic, wind turbine, thermodynamic system, large-scale photovoltaic power plant system, smart grid, etc.

3.2.1. Mathematical Model of Gray Wolf Optimization Algorithm. Assuming that there is N_w gray wolf distributed in the search space, in order to simulate the hierarchical management system of the wolf pack, the GWO algorithm considers the best three solutions at the end of each iteration as α, β and δ in turn, and the rest of the solutions are considered as ω. The following mathematical models of the wolf pack's searching, encircling, pursuing and attacking the prey are given below, which together form the mathematical model of the Gray Wolf Optimization Algorithm.

1) Mathematical model of prey encirclement. After the scouting wolf finds the whereabouts of the prey, the distance between each gray wolf and the prey is firstly calculated by equation (8), and then each gray wolf makes corresponding adjustments according to the position of the prey and the distance between itself and the prey to realize the encirclement, as shown in equation (9):

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)| \tag{8}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{9}$$

where $\vec{X}_p$ and $\vec{X}$ are the position vectors of the prey and the gray wolf, respectively, $\vec{D}$ is the distance between the gray wolf and the prey, t is the current iteration number, and vectors $\vec{A}$ and $\vec{C}$ are both parameter vectors, which need to be computed by the following equation:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{10}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{11}$$

where $\vec{a}$ is the convergence factor that decreases linearly from 2 to 0 during the optimization process, r_1 and r_2 are random numbers within [0, 1]. And the number of iterations t also changes linearly (increasing from 1 to the maximum number of iterations $t_{\max}$ one by one), so in this paper, we have used t to express $\vec{a}$, and we have to solve the following equations:

$$\begin{cases} 2 = k*1+b \\ 0 = k*t_{\max}+b \end{cases} \tag{12}$$

The expression for $\vec{a}$ can be obtained as:

$$\vec{a} = \frac{2}{1-t_{\max}}t + \frac{-2t_{\max}}{1-t_{\max}} \tag{13}$$

2) Mathematical modeling of prey pursuit. In the abstract search space, in fact, all gray wolves do not know the location of the prey (the globally optimal solution), but since α, β and δ (the best three solutions) are closest to the prey and thus can be assumed to have a better knowledge of the potential location of the prey. Therefore, when updating the position of the gray wolves in each iteration, the positions of the current best three solutions are kept unchanged, and the other individual gray wolves (i.e., ω) are updated with positions based on the current best three solutions. In other words, the first three best solutions are utilized to guide the wolves to discover the location of their prey:

$$\vec{D}_a = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right| \tag{14}$$

$$\vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right| \tag{15}$$

$$\vec{D}_5 = \left|\vec{C}_3 \cdot \vec{X}_5 - \vec{X}\right| \tag{16}$$

$$\vec{X}_1 = \left|\vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha\right| \tag{17}$$

$$\vec{X}_2 = \left|\vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta\right| \tag{18}$$

$$\vec{X}_3 = \left|\vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta\right| \tag{19}$$

$$\vec{X}(t+1) = (\vec{X}_1 + \vec{X}_2 + \vec{X}_3)/3 \tag{20}$$

where $\vec{x}_\alpha, \vec{x}_\beta, \vec{x}_\delta, \vec{X}$ denotes the position vector of $\alpha, \beta, \delta, \omega$, respectively, and both α, β and δ have their own independent $\vec{A}$ and $\vec{C}$ parameter vectors as well as their distance $\vec{D}$ from the prey.

3) Mathematical model of attacking prey (local search). When the prey gives up running away due to physical exhaustion, the wolves begin to attack the prey thus completing the hunt. From Eq. It can be seen that when the value of $|\vec{A}|$ is in [0, 1], the next position of the gray wolf will appear anywhere between its current position and the position where the prey is located. And from Eq. $\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a}$, it can be seen that $\vec{A}$ is a random number within $[-\vec{a}, \vec{a}]$, so this process of attacking the prey can be simulated by decreasing the convergence factor $\vec{a}$. It can be seen that the attacking behavior makes the grey wolf optimization algorithm has a good local search ability.

4) Mathematical model for searching prey (global search). Wolves will disperse outwards when searching for prey, a process that is opposite to the behavior of gray wolves that gather towards the prey location when attacking the prey. In the pre-iteration period, since $|\vec{A}|$ is greater than 1, it can force the gray wolves to turn their backs on the prey (the current local optimal solution) to explore and discover a more suitable prey (the global optimal solution). In other words, the GWO algorithm focuses more on global search in the pre-search phase. Another vector $\vec{c}$ further improves the global search capability of the algorithm. As can be seen from Eq. (8), $\vec{c}$ serves to randomly increase $(|\vec{c}|>1)$ or decrease $(|\vec{c}|<1)$ the ease with which the gray wolf approaches the prey, which increases the randomness of the algorithm and thus avoids falling into a local optimum. It is worth noting that $\vec{C} = 2 \cdot \vec{r_2}$ and $\vec{c}$ do not decrease linearly during the iteration process but always provide random values, this is to be able to strengthen the global search throughout the optimization process, especially at the end of the iteration, which solves the problem that the algorithm is prone to fall into the local optimum due to the decrease of $\vec{A}$.

3.2.2. Implementation steps of the basic gray wolf optimization algorithm in PV MPPTs. In summary, the implementation process of the gray wolf optimization algorithm in PV MPPT is as follows:

1) Set the wolf pack size N_p and the maximum number of iterations $t_{\max}$;

2) Initialize a, A, C and the position of the gray wolf, in this algorithm, the position of the gray wolf is the duty cycle, and the larger the output power corresponding to the duty cycle is, the higher the level of the corresponding gray wolf in the hierarchical management system;

3) Calculate the output power corresponding to each gray wolf;

4) Compare and rank all the output powers and determine the three best current solutions X_a, X_β and X_δ;

5) Calculate the values of a, A and C;

6) updating the position of each individual gray wolf;

7) If the maximum number of iterations is reached, terminate the program while stabilizing the duty cycle at the global optimum; otherwise go to 3).

8) Restart the program if an abrupt change in light is detected.

3.3. Improved algorithm for maximum power tracking based on gray wolf optimization algorithm

The Gray Wolf algorithm has obvious advantages over other intelligent algorithms, and the calculation results are more competitive, but there are some areas for improvement in itself. In this paper, the improved gray wolf algorithm (IGWO) is applied to track the maximum power.

The convergence factor a of the basic gray wolf algorithm is linearly decreasing, but the algorithm is not linear in the iteration process. So the linear decreasing strategy of the convergence factor does not fully reflect the superiority of the algorithm, for which a new nonlinear decreasing method is applied in this paper:

$$a = 2 - 2\left(\frac{1}{e-1} \times (e^{\frac{t}{m}} - 1)\right) \tag{21}$$

where e is the base of the natural logarithm; t is the current number of iterations; m is the maximum number of iterations.

When the convergence factor is changed to nonlinear, the algorithm starts to approach the target gradually and searches slowly: when the middle is close to the target, the search step is increased to save time; finally, when the optimal target has been found, the step is slowed down again. This way of searching not only saves a lot of time, but also does not easily miss the optimal target. The nonlinear convergence factor in the multi-peak function can avoid falling into the local optimum, thus enhancing the ability to find the global optimum, and the convergence speed is also greatly improved. With the number of iterations, the ω-wolf continuously approaches the three wolves, but the degree and direction of its approach to each wolf is different, so based on this, a dynamic weight adjustment method is introduced to solve the relationship between global search and local search. According to equation (22) can be obtained:

$$\begin{aligned} w_1 &= \frac{|X_1|}{|X_1| + |X_2| + |X_3|} \\ w_2 &= \frac{|X_2|}{|X_1| + |X_2| + |X_3|} \\ w_3 &= \frac{|X_3|}{|X_1| + |X_2| + |X_3|} \end{aligned} \tag{22}$$

where w_1, w_2, w_3 is the learning rate of ω wolves to α, β, δ three wolves, respectively, then the final iteration is:

$$X(t+1) = \frac{(w_1 X_1 + w_2 X_2 + w_3 X_3)}{3} \tag{23}$$

Improve the application of the Gray Wolf algorithm to different problems without making any special changes to the structure of the algorithm. The reason it is easy to apply to different problems is that it treats the problem primarily as a black box. In other words, only the inputs and outputs of the system are important to the algorithm. Therefore, all that is needed is to know how to represent the problem in terms of the algorithm. The Improved Gray Wolf algorithm is more inclined to stochastic optimization problems than other optimization methods. The optimization process starts with a stochastic solution and there is no need to compute the derivatives of the search space to find the optimal solution.

In the IGWO algorithm, the duty cycle of the converter is used as a position parameter to describe each gray wolf, i.e., the gray wolf position parameter is X. According to the gray wolf position, the power of the real-time sampled PV array is calculated. When the standard deviation between the individual gray wolves is less than a preset threshold or reaches a preset number of iterations the position of α wolves is taken as the final optimization result; if the standard deviation between the individual gray wolves is not less than a preset threshold and does not reach a preset number of iterations, return to the gray wolf position X, re-calculate the real-time power, select the optimal value, the second best value, and then the positions of the wolves corresponding to α wolves, β wolves, and δ wolves to continue with the iterative step, respectively.

To better understand how IGWO solves the tracking problem, the following points should be noted.

1) The social hierarchy proposed by IGWO preserves the best solution during the iterative process.

2) The proposed surround mechanism defines a circular neighborhood around the solution that can be extended to higher dimensional hyperspheres.

3) Random parameters A and C assist the candidate solutions to obtain hyperspheres with different random radii.

4) The proposed hunting method allows the candidate solutions to find the possible locations of the prey.

5) The adaptive values of a and A ensure the approximate direction of search and survey.

6) The adaptive values of parameters a and A allow the IGWO to smoothly transition between survey and search.

7) With the reduction of A, half of the iterations focus on surveying $(|A|\geq 1)$ and the other half on exploring $(|A|<1)$.

8) Only two main parameters need to be adjusted (a and C).

3.4. *Experimentation and Analysis*

In this section, the MPPT of PV arrays under different environmental conditions is carried out by using P&O, PSO, GSO, GWO with the Gray Wolf Optimization Algorithm (IGWO) proposed in this chapter, respectively, and the simulation results are compared and analyzed exhaustively.

The experiments are simulated by MATLAB and the data are tested on the V-SUN-S4000 practical training platform, which is mainly composed of PV power supply system, inverter and load system, and monitoring system, and its main parameters are shown in Table 1.

Table 1. Experimental parameters

Parameters	Parameter value
Rated power	20W
Rated voltage	17.6V
Rated current	1.14A
Open circuit voltage	21.7V
Short circuit current	1.26A

3.4.1. Maximum power point tracking simulation test for standard operating conditions. Firstly, the most basic uniform invariant light simulation test is carried out for the PV array using the Gray Wolf Optimization (IGWO) algorithm proposed in this chapter. The PV array consists of four PV cells connected in series, and each PV cell is subjected to a light intensity of 1000W/m^2 and a temperature of 25℃. The P-U output curve of the PV array is shown in Fig. 1, from which it can be seen that at this time the P-U curve of the PV array has only one maximum value, which is 999.6W.

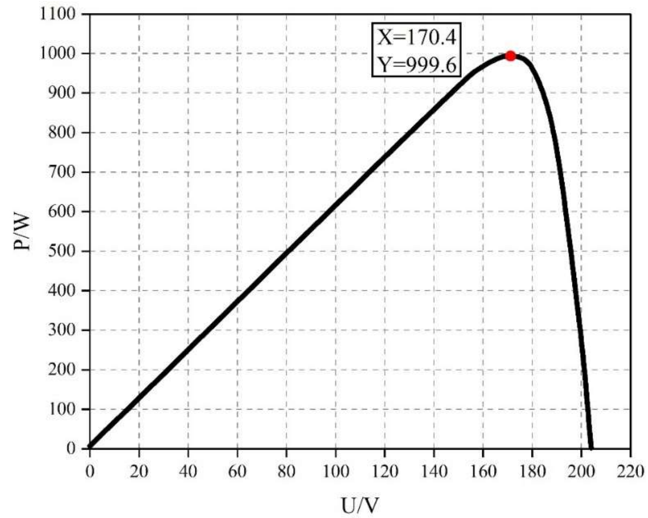


Fig. 1. P-U output curve of photovoltaic array under standard operating conditions

The MPPT simulation results of the IGWO algorithm under uniform constant illumination are specifically shown in Fig. 2. According to the simulation results in the figure, it can be seen that the curve carries out irregular back and forth oscillation before 0.06s, and climbs steadily between 0.06s and 0.15s, and tracks to the maximum power after 0.15s. The maximum power tracked by the IGWO algorithm proposed in this paper is 978 W, which is basically in line with the actual maximum power of the PV array, indicating that the designed Gray Wolf Optimization-Perturbation Observation method is theoretically feasible and can be effectively applied to the maximum power point of the PV array.

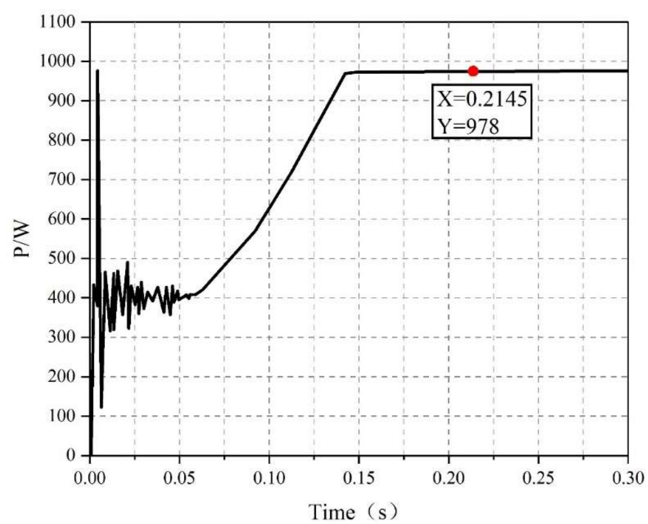


Fig. 2. MPPT simulation under uniform illumination

3.4.2. Multi-peak maximum power point tracking simulation test. In order to verify the tracking control effect of the IGWO algorithm on the maximum power point of the PV array under static shading conditions, in this section, the light intensity of the 4*1 series structure PV array model is set to $500W/m^2$, $1000W/m^2$, $800W/m^2$, and $600W/m^2$, respectively, and the temperature is 25°C, at which time the output curve of the PV array is shown in Fig. 3.

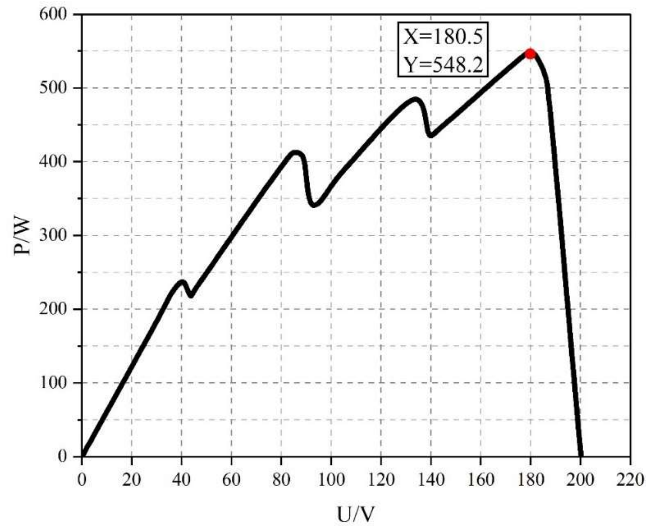


Fig. 3. P-U output curve of multi-peak photovoltaic array

The IGWO algorithm of this paper is simulated in comparison with the GWO algorithm and the simulation results are shown in Fig. 4. From the simulation results, it can be seen that the maximum power tracked based on the IGWO algorithm is 547.3W, and the maximum power tracked by the GWO algorithm is 488.2W, which indicates that the GWO algorithm is applied to the tracking of the maximum power point of multiple peaks and the algorithm will fail, which reflects the shortcomings of the traditional GWO algorithm in terms of slow convergence speed and poor stability, while this paper's IGWO algorithm has better performance.

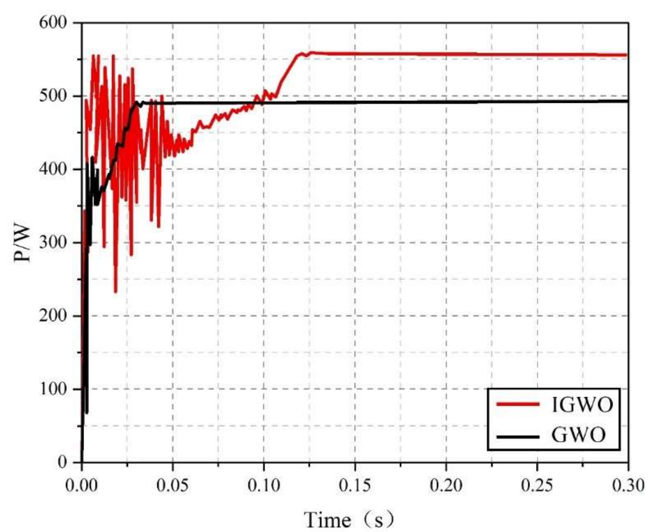


Fig. 4. Comparison of MPPT control simulation results

4. Optimal reconfiguration algorithm for photovoltaic arrays based on gray wolf optimization algorithm

PV plants are often located in complex environments and are susceptible to PSCs, which can cause their P-V output characteristic curves to show multi-peak patterns. This not only reduces the output power of the system, but also may damage the PV modules. The multi-peak phenomenon also interferes with the MPPT control and affects the power generation efficiency of the PV system. In this chapter, the traditional PV array structure will be reconstructed using the Gray Wolf optimization algorithm to improve the reliability, safety, and economy of PV power plant operation [27].

4.1. Combination of circle-breaking method and depth-first search

The solution of the reconstructed model in this paper consists of switching variables and power variables. Its switching variables are handled by the broken circle method and depth-first search [28]. Where the broken circle method obtains the random radial structure and the depth-first search obtains the node traversal order. The node traversal order according to the depth path type is in line with the characteristics of the PV power plant system forward back generation trend calculation.

Steps of depth-first search algorithm:

1) Mark all nodes as "unvisited" for any $v \in V(G)$;

2) If v has no "unvisited" neighbor node, go to (5);

3) Select a neighboring node u with v "not visited", and mark u as "visited";

4) Assign u to v and return to step (2);

5) If there is still a node "not visited", the node visited before v will be assigned to v (back), return to step 2).

Steps of broken circle method:

1) Given a connectivity graph containing m loop as the initial network structure;

2) Divide all branches into m branch sets according to the m loops;

3) Randomly remove one edge from each branch set respectively, and the network structure graph formed by the remaining branches is the radial shape.

In the algorithm optimization search process, before calculating the trend information, the depth-first search determines whether the iterative solution is a connected graph or not, and determines the type of network structure, whether it is a loop solution, a solution containing isolated nodes, or a radial solution, and generates the node traversal order; the radial solution is retained, and the loop in the loop solution is opened, and the loop-breaking method generates a random radial solution to replace the disjointed solution containing isolated nodes. Application flow of depth-first search based on the broken-loop method:

1) Given a connectivity graph containing m loop as the initial network structure graph;

2) Divide all the branches into m branch sets according to the paths of the m loops.

3) Randomly remove one branch from each branch set respectively, and the structure formed by the remaining branches is radial;

4) Traverse the paths of its nodes obtained by depth-first search

5) Output the final network structure and its node traversal paths.

4.2. Multi-objective optimization and its decision making

In a multi-objective decision problem, each objective is the object of finding the minimum/maximum value. Let the decision variable be $x_1, x_2, \ldots, x_n$ and the multi-objective problem function is modeled as:

$$\min f_1(x_1,x_2,\ldots,x_n)\min f_2(x_1,x_2,\ldots,x_n)\ldots\min f_p(x_1,x_2,\ldots,x_n)$$
$$s.t.\begin{cases} g_1(x_1,x_2,\ldots,x_n)\geq 0 \\ \ldots\ldots \\ g_m(x_1,x_2,\ldots,x_n)\geq 0 \end{cases} \tag{24}$$

It can be abbreviated as:

$$\begin{cases} \min F(f_1(X), f_2(X),\ldots, f_p(X)) \\ \quad g_i(X)\geq 0, i=1,2,\ldots,m \end{cases} \tag{25}$$

where: $x_1, x_2, ..., x_n$ is the decision variable, $X=(x_1,x_2,...,x_n), F(f_1(X), f_2(X),..., f_p(X))$ represents the objective function $f_1(X), f_2(X),..., f_p(X)$ equally minimized composite function, abbreviated as

$\min F(X)$. The minimization of the composite function consists of two meanings, what value of the function of the multi-objective problem can make the original problem to get the most satisfactory solution and what value of the decision variable can make the original problem to get the most satisfactory solution.

For the multi-objective optimization problem, different decision makers have different preferences for each objective, and the decision-making scheme is also different, so it is necessary to sort or optimize the objectives according to certain rules, and such rules are the principles that need to be followed in decision-making.

Define the constraint set $R=\{X \mid g_i(X)\geq 0, i=1,2,\ldots,m\}$. We call X^1 a non-inferior solution if, for any two feasible solutions $X^1, X^2 \in R$, there exists $f_1(X^1)\leq f_1(X^2), f_2(X^1)\leq f_2(X^2),\ldots,$ $f_p(X^1)\leq f_p(X^2)$ and at least one $f_p(X^1)< f_p(X^2)$ in the form of a composite function that can be abbreviated as $F(X^1)\leq F(X^2)$, when none of the p objective values of the scheme X^1 is worse than the p objective values of the scheme X^2 and at least one of the objective values is better. For a non-inferior solution, its solution is not the worst, there are worse solutions than it. For a multi-objective optimization problem, there are often multiple optimal non-inferior solutions in its set of non-inferior solutions, called Pareto optimal frontiers.

The decision-making method in this paper is as follows.

1) In the early stage of the optimization algorithm, the solution set of Pareto optimal frontier is found first.

2) In the later stage of the optimization algorithm, there are two criteria: setting the weights of different objectives, and selecting the best solution in the solution set of Pareto-optimal frontier according to the comprehensive optimization objective function, so as to determine the optimal solution that satisfies the decision maker. The setting of the weights of different objectives reflects the different preferences of the decision maker, i.e. the size of the comprehensive optimization objective function. Then according to the solution set of Pareto optimal frontier, a set of thresholds of each objective index is determined as the boundaries of late optimization, and only the solution solutions within the boundaries are allowed to be selected as the better solution.

4.3. Reconstruction Strategy Based on Improved Gray Wolf Algorithm

The innovations of this paper to improve the reconfiguration strategy of the gray wolf algorithm are mainly two:

1) Combining the loop-breaking method and depth-first search to apply the microgrid reconfiguration optimization problem. In the optimization process, the depth-first search is used to identify and judge the type of network structure obtained by the Gray Wolf iterative formula, the loops in the connected network structure containing loops are opened, and the disconnected network structure is topped by the random network structure generated by the loop-breaking method, and then the node or branch traversal order of the radial network structure with feasible solutions is obtained by the depth-first search. After the disconnected structures are replaced, these new network structures are introduced, and their fitness is only added to the population if it is better than the solution of the corresponding individual of the previous generation. In this way, the introduction of solutions with new "genes" increases the diversity of the population and enhances the global search capability of the gray wolf algorithm in the reconstruction problem, especially in the early stage.

2) The method of shielding unsatisfactory solutions according to the threshold value of each target indicator in the multi-objective decision-making process is proposed. When hunting, the gray wolf pack chases more than one prey group in the early stage, and after screening by the gray wolf leaders at all levels, the prey gradually decreases in the later stage until a frail and sickly prey is locked as the only prey to be chased, and the prey is finally captured. If each prey is regarded as an objective function,

then this is the multi-objective decision-making process of the gray wolf. Inspired by this, the decision-making process of multi-objective optimization of the gray wolf algorithm is divided into two phases: pre and post. In the early stage, the four objective functions of the reconstruction model are simultaneously looking for the extreme value, searching for Pareto, finding the optimal frontier set of Pareto, and completing the pre-optimization; in the late stage of optimization, the search scope is enlarged and the programs outside the threshold of each objective index are shielded, and the better method is selected according to the comprehensive objective function, and the best program is found in the end. In the later stage, enlarging the search scope and shielding the programs outside the threshold of each objective index can somewhat solve the problem that the multi-objective gray wolf algorithm is easy to fall into the local optimum.

After obtaining the real-time information of the system state, the calculation procedure of the reconfiguration strategy of the improved gray wolf algorithm in this paper starts to be executed, and after obtaining the optimal reconfiguration scheme, adjustment commands are issued for the micro-sources, adjustable loads and network switches in the system.

4.4. *Experimentation and Analysis*

In order to verify the effect of the PV array optimization reconfiguration algorithm based on the Gray Wolf optimization algorithm proposed in this chapter in the reconfiguration of PV array, the PV modules are built to form a 6×6 TCT PV array, and the simulation of the shadow shading situation is specifically shown in Fig. 5.

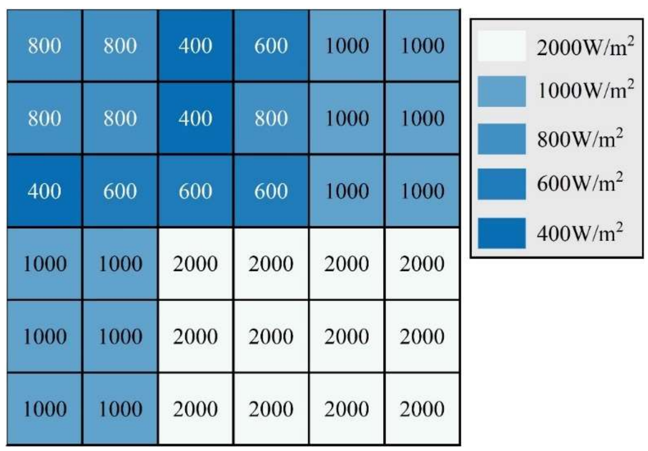
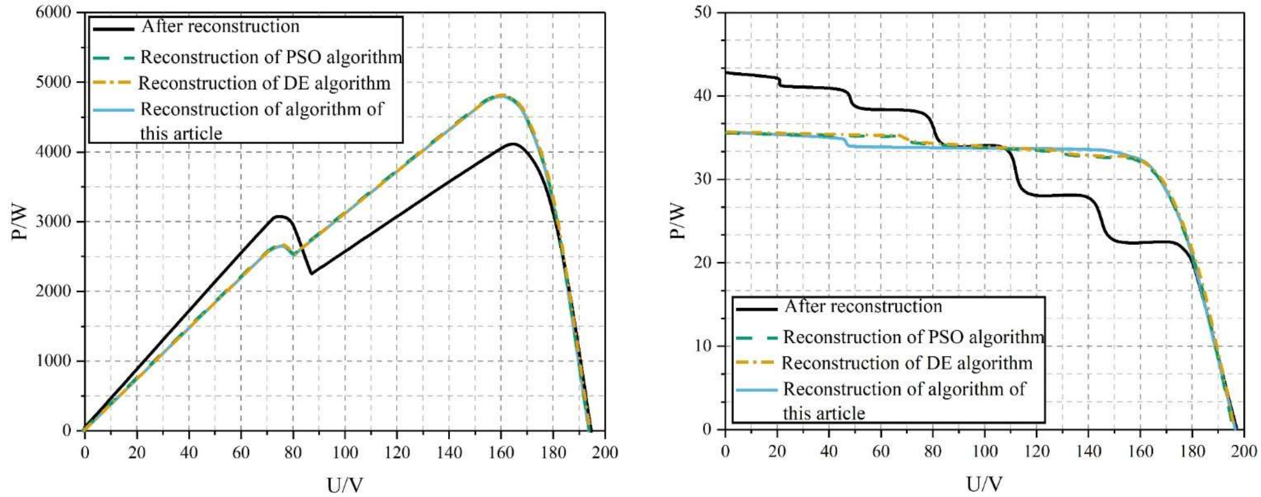


Fig. 5. Shading mode of photovoltaic array

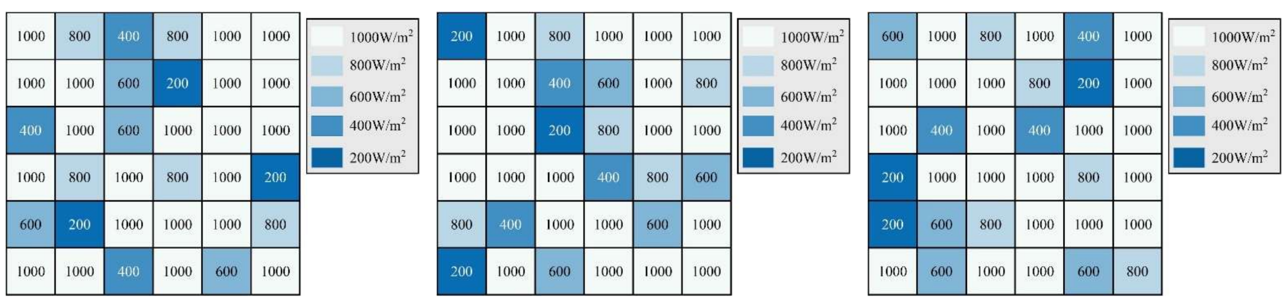
PSO algorithm and DE algorithm are chosen to compare with the algorithm of this paper, and the P-U curve and I-U curve before reconstruction are specifically shown in Fig. 6. Figures (a) and (b) show the P-U curve and I-U curve, respectively. As can be seen from the figures, the P-U curve before reconstruction has multiple peaks and the I-U curve has multiple steps, while the P-U curve after reconstruction can be approximated as having only one peak point and the I-U curve is obviously smoother.



(a)P-U curve (b)I-U curve

Fig. 6. P-U curve and I-U curve

The shadow distribution of PSO algorithm, DE algorithm and this paper's algorithm after reconstruction is specifically shown in Fig. 7. Figures (a)~(b) show the PSO algorithm, this paper's algorithm and DE algorithm, respectively. It can be seen that all three algorithms effectively realize the dispersion of the shadow region. However, the effect of DE and PSO is slightly lower than this paper's algorithm, and the characteristic curves of the first two are basically overlapped, and the reconstruction effect is the same. PSO and DE can also play a good effect on the optimization of PV arrays, but the optimization effect is still affected by the shadows, and this paper's algorithm will have a better effect on the reconstruction of the PV arrays under the complex shadowing method.



(a)PSO (b)Algorithm of this article (c)DE

Fig. 7. Shadow distribution after reconfiguratio

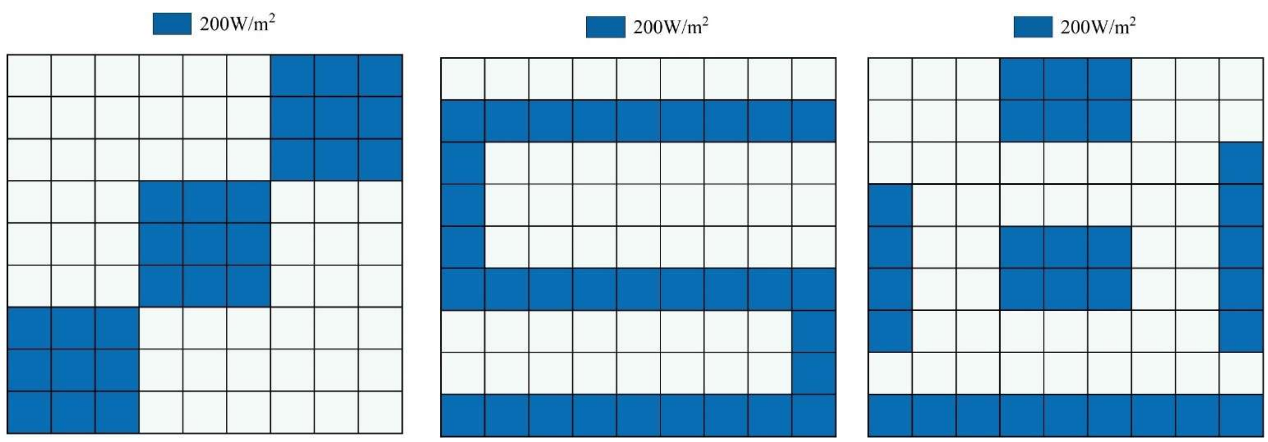
5. Optimization experiment of photovoltaic power plant based on gray wolf optimization algorithm

In the previous chapters, this paper proposed the maximum power point tracking algorithm (IGWO) based on the gray wolf optimization algorithm to optimize the PV MPPT control and enhance the efficiency of PV power generation, and the PV array optimization and reconstruction algorithm based on the gray wolf optimization algorithm is used to dynamically reconstruct the PV arrays, which effectively improves and enhances the output power of PV power generation. In this chapter, the above two algorithms will be applied simultaneously, firstly, the maximum power point tracking algorithm is applied to reconstruct the PV array structure, and secondly, the PV array optimization reconstruction algorithm is used to perform MPPT tracking control of the reconstructed PV power generation system, which further improves the performance of the smart PV power plant system.

5.1. Simulation Setup

5.1.1. 9×9 simulation modeling. In order to be able to fully study and analyze the feasibility of array reconfiguration and MPPT control of PV power generation systems under local shading conditions using the IDBO algorithm, this section builds a 9 × 9 TCT PV array composed of the lower PV module under the MATLAB/Simulink environment, which is commonly used for modeling actual PV power generation systems and can more realistically react to the shadow shading when the This model is commonly used to model real PV power generation systems, which can more realistically reflect the array operation when shadowing.

5.1.2. Shadow Masking Mode. In the experiment, the influence of other factors on PV arrays besides irradiance is ignored, and six types of PV array shadow shading situations are constructed as shown in Fig. 8, so as to simulate the type of shading on PV arrays caused by buildings, trees, stains, clouds, etc., to a certain extent, and these three shading modes simulate the shading situation suffered by the PV arrays in the static situation.



(a)Shadow occlusion pattern 1 (b)Shadow occlusion pattern 2 (c)Shadow occlusion pattern 3

Fig. 8. Schematic diagram of the shadow occlusion pattern of the 9×9 PV array

5.2. Simulation results and analysis under different shadow masking modes

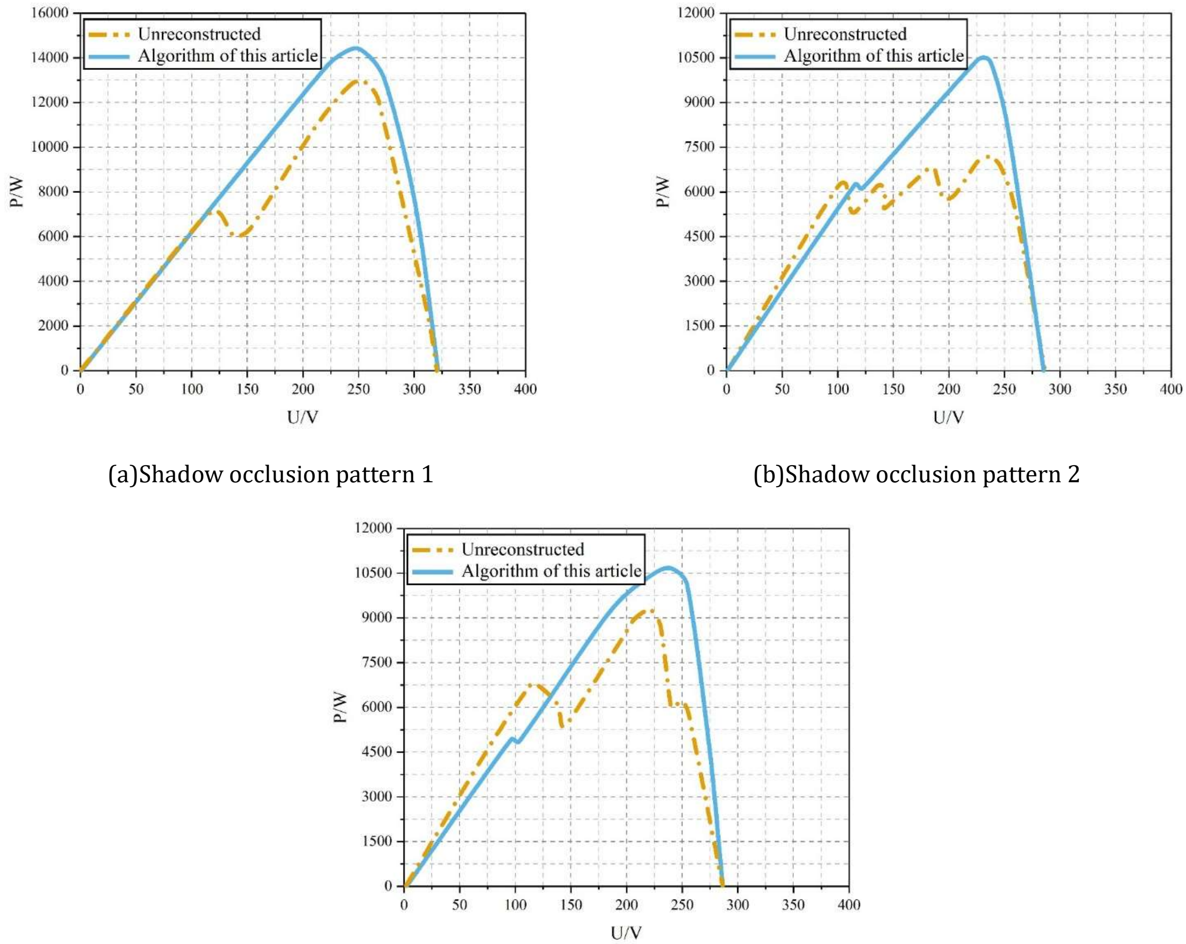
5.2.1. Static Shadow Occlusion Mode:

1) Analysis of the effect of PV array optimization and reconstruction. Using the PV array optimization reconfiguration algorithm based on the gray wolf optimization algorithm proposed in this paper, the PV array of the PV power plant is reconfigured. The P-V characteristic curves of PV arrays under three shading modes are specifically shown in Fig. 9. Figures (a) to (c) correspond to the shadow shading modes 1 to 3, respectively.

The unreconstructed GMPP under shadow shading mode 1 is 12928.267 W, and the GMPP after reconstruction is 14515.565 W. It can be concluded that this paper's PV array optimization reconstruction algorithm based on the Gray Wolf optimization algorithm has a significant enhancement of the maximum output power, and the reconstructed P-V characteristic curves can be approximately regarded as single-peak-like.

The reconstructed GMPP is 10626.844W in shadow masking mode 2, and the array output characteristic curve before reconstruction shows a four-peak multi-peak pattern, while the reconstructed array output characteristic curve shows a double-peak, which indicates that the PV array optimization reconstruction algorithm based on the Gray Wolf optimization algorithm achieves good dispersion of the shadow distribution of the array, and greatly enhances the output power of PV arrays.

In shadow shading mode 3, the reconfigured PV array output power changes from 8961.858 W to 10636.467 W. The PV array optimization reconfiguration algorithm based on the Gray Wolf optimization algorithm achieves a significant increase in power.



(a)Shadow occlusion pattern 1

(b)Shadow occlusion pattern 2

(c)Shadow occlusion pattern 3

Fig. 9. P-V characteristic curve

2) Analysis of the optimization effect of MPPT control. The convergence time of the algorithm is recorded as the time when the maximum power is tracked and the power fluctuation range is <5% or when the power is stable. The tracking time and accuracy of the maximum power point tracking algorithm (IGWO) based on gray wolf optimization algorithm proposed in this paper with GWO algorithm, PSO algorithm, and ACO algorithm in three different shading modes are shown in Table 2. From the table, it can be seen that the tracking accuracy of this paper's IGWO algorithm in shadowing modes 1, 2, and 3 reaches 99.9%, 99.5%, and 99.6%, respectively, and the tracking accuracy is better than that of other compared algorithms. Meanwhile, the IGWO algorithm in this paper is also ahead of other comparative algorithms in convergence time under the premise of ensuring the optimal tracking accuracy, with the tracking time of 0.094s in shaded mode 1, and the tracking time of 0.11s in shaded modes 2 and 3.

Table 2. Test results

Shadow occlusion pattern	Algorithm	Tracking accuracy(%)	Tracking time(s)
Shadow occlusion pattern 1	IGWO	99.9	0.094
	PSO	98.9	0.138
	ACO	97	0.137
	GWO	96.2	0.17
Shadow occlusion pattern 2	IGWO	99.5	0.11
	PSO	99	0.133
	ACO	89.8	0.152
	GWO	89.7	0.186
Shadow occlusion pattern 3	IGWO	99.6	0.11
	PSO	97.1	0.129
	ACO	99.7	0.155
	GWO	95.7	0.183

No matter in what kind of shading mode, the proposed PV array optimization reconfiguration algorithm based on Gray Wolf optimization algorithm has outstanding reconfiguration effect, and the GMPP finding performance of maximum power point tracking algorithm based on Gray Wolf optimization algorithm is excellent, which can effectively improve and enhance the performance of the smart PV power plant.

5.2.2. Dynamic Shadow Occlusion Mode. The dynamic shadows are varied one by one according to the arrangement of shadow shading mode 1, shadow shading mode 2, and shadow shading mode 3, and each shading situation is kept for 1s, and the MPPT tracking control of 9×9 TCT PV arrays is carried out by using four algorithms, namely, the IGWO algorithm, the GWO algorithm, the ACO algorithm, and the PSO algorithm, in this paper. The specific operation of each algorithm under dynamic shadow variation is shown in Table 3. Under dynamic shading change, in the first stage, i.e., shading mode 1, each algorithm plays basically the same as its static and mode, but with the dynamic change of shading mode each algorithm's GMPP effect has decreased. The IGWO algorithm in this paper has the smallest decrease, and its tracking accuracy remains at 99.966% and 99.451% in the second and third stages, with the smallest decrease.The tracking accuracies of the ACO, GWO and PSO algorithms also decrease, while the tracking efficiency of the ACO algorithm has a larger decrease, and its lowest working efficiency reaches 96.341%.

Table 3. Results of MPPT tracking control

Simulation time	Shadow occlusion pattern	Index	IGWO	GWO	PSO	ACO
0-1s	Shadow occlusion pattern 1	Maximum output power (W)	8123.762	8103.379	8093.873	8097.972
		Tracking efficiency (%)	99.981	99.942	99.947	99.885
1-2s	Shadow occlusion pattern 2	Maximum output power (W)	13881.36	13862.57	13618.33	13754.55
		Tracking efficiency (%)	99.966	99.112	98.173	99.124
2-3s	Shadow occlusion pattern 3	Maximum output power (W)	10551.35	10518.13	10516.34	10437.38
		Tracking efficiency (%)	99.451	98.165	98.125	96.341

The performance analysis of static and dynamic shading modes shows that the proposed PV array optimization reconstruction algorithm based on the Gray Wolf optimization algorithm can effectively reconstruct the PV array dynamically and achieve effective dispersion of shading distribution to reduce the power mismatch between the array components. The maximum power point tracking algorithm based on the gray wolf optimization algorithm proposed in this paper can effectively improve the MPPT control capability of PV arrays in the case of localized shading, and reduce the power loss of PV modules while realizing the increase of output power. The enhancement effect of module efficiency of PV power plant is obvious.

6. Conclusion

In order to realize the component efficiency improvement of PV power station under the intelligent management environment, this paper starts from the maximum power point tracking (MPPT) control and PV array structural reconstruction, introduces the gray wolf algorithm and carries out the targeted optimization, and puts forward the maximum power point tracking algorithm based on the gray wolf optimization algorithm (IGWO), and the PV array optimization reconstruction algorithm based on the gray wolf optimization algorithm, respectively. The algorithm performance experiments are carried out separately, and the maximum power tracked by the IGWO algorithm in this paper is 978W under uniform and constant illumination, which is basically in line with the actual maximum power of PV arrays. Compared with the traditional GWO algorithm, the maximum power tracked by this paper's IGWO algorithm is 547.3W, while the GWO algorithm is only 488.2W, and this paper's IGWO algorithm obviously has better performance. In the performance experiments of the PV array optimization reconstruction algorithm based on the Gray Wolf optimization algorithm, the P-U curve and I-U curve of this algorithm, PSO algorithm and DE algorithm are significantly smoother after the PV array optimization. This algorithm is better than PSO algorithm and DE algorithm in the dispersion of shaded areas, and it is more effective in the reconstruction of PV arrays under complex shading methods.

The IGWO algorithm and the PV array optimization reconstruction algorithm based on the Gray Wolf optimization algorithm are jointly applied to the optimization of PV power plants, and the application practice is carried out to build a 9×9 TCT PV array composed of the following PV modules and set up three kinds of shadow shading modes. Under the static shadow shading mode, the PV array optimization reconstruction algorithm based on the Gray Wolf optimization algorithm is applied to reconstruct the PV array of the PV power plant. The GMPP in shadow shading mode 1 is increased from 12928.267W to 14515.565W, the GMPP in shadow shading mode 2 is increased to 10626.844W, and the output power of the PV array in shadow shading mode 3 is changed from 8961.858W to 10636.467W, all of which achieve a significant increase in power. In terms of the optimization effect of MPPT control, the tracking accuracy of the IGWO algorithm in this paper reaches 99.9%, 99.5%, and 99.6% in the shading modes 1, 2, and 3, respectively, and the convergence time is 0.094s, 0.11s, and 0.11s, respectively, which outperforms the comparative GWO algorithm, PSO algorithm, and ACO algorithm in terms of the performance of tracking accuracy and convergence time. In the dynamic shadow masking mode, the tracking accuracy of the IGWO algorithm in this paper reaches 99.981%, 99.966%, and 99.451% in the first, second, and third phases, respectively, which is always above 99%, and the decrease is smaller than that of the GWO algorithm, ACO algorithm, and PSO algorithm. In conclusion, the PV array optimization reconfiguration algorithm based on the Gray Wolf Optimization Algorithm and the maximum power point tracking algorithm based on the Gray Wolf Optimization Algorithm proposed in this paper have obvious effects on the component efficiency improvement of PV power plants, and the output power improvement is achieved at the same time of reducing the component power mismatch and power loss.

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