IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received December 29, 2020, accepted January 14, 2021, date of publication January 19, 2021, date of current version January 29, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3052960

DMPPT Control of Photovoltaic Microgrid Based on Improved Sparrow Search Algorithm

JIANHUA YUAN, ZIWEI ZHAO, YAPING LIU, BAOLIN HE, LIN WANG, BINBIN XIE, AND YANLING GAO

School of Electrical and New Energy, China Three Gorges University, Yichang 443000, China

Corresponding author: Jianhua Yuan (837535990@qq.com)

This work was supported in part by the Open Fund Project of State Key Laboratory of Coal Combustion under Grant FSKLCCA1607, in part by the Key Laboratory Fund Project of Hubei Province for Operation and Control of Cascade Hydropower Stations under Grant 2015KJX07, and in part by the Research Project on the Mechanism of Industry-University-Research Collaborative Training of Graduate Students' Practical Innovation Ability under Grant SDYJ201604.

ABSTRACT There are some problems in the photovoltaic microgrid system due to the solar irradiance-change environment, such as power fluctuation, which leads to larger power imbalance and affects the stable operation of the microgrid. Aiming at the problems of power mismatch loss under partial shading in photovoltaic microgrid systems, this paper proposed a distributed maximum power point tracking (DMPPT) approach based on an improved sparrow search algorithm (ISSA). First, used the center of gravity reverse learning mechanism to initialize the population, so that the population has a better spatial solution distribution; Secondly, the learning coefficient was introduced in the location update part of the discoverer to improve the global search ability of the algorithm; Simultaneously used the mutation operator to improve the position update of the joiner and avoid the algorithm falling into the local extreme value. The results of the model in Matlab showed that the ISSA can track the maximum power point(MPP) more accurately and quickly than the perturbation observation method (P&O) and the particle swarm optimization (PSO) algorithm, and had good steady-state performance.

INDEX TERMS Distributed maximum power point tracking, photovoltaic microgrid, sparrow search algorithm, spatial solution distribution, steady-state.

I. INTRODUCTION

Some research results have been made for the control strategy of photovoltaic microgrid. In the literature [1], a distributed digital controller architecture was developed for controlling the duty ratio of each DPP dc–dc converter in real time. The merits of the proposed algorithm were analyzed from the aspects of communication protocol, control method, tracking efficiency and tracking response time under varying operating conditions. Literature [2] proposed an enhanced maximum power point tracking (MPPT) algorithm, in the operating range near the MPP, a small fixed step size was used to minimize the oscillations at the MPP. In contrast, in the operating range far from the MPP, a variable step size proportional to the slope of the power-voltage curve of PV module was used to achieve fast tracking speed under dynamic weather conditions. Literature [3] proposed a maximum power range estimation method based on the DMPPT technique, which can provide guidance for designing parameters. In the literature [4], a DMPPT method based on the forward converter was proposed for small power module level and sub-module level MPPT applications. The approach achieved a better tracking effect. Literature [5] proposed an advanced searching algorithm (TSPSOEM) for the DMPPT. This applied the basic PSO procedure and incorporated the grouping concept from shuffled frog leaping algorithm (SFLA). The algorithm demonstrated superior results obtained when compared with other conventional methods. This paper proposed a DMMPT control method based on an ISSA. First, the centroid opposition-based learning mechanism was introduced to make the population have a better spatial distribution solution. Second, the learning coefficient and mutation operator were introduced in the location update part to improve the search range and accuracy, and made the photovoltaic power

The associate editor coordinating the review of this manuscript and approving it for publication was Huai-Zhi Wang.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

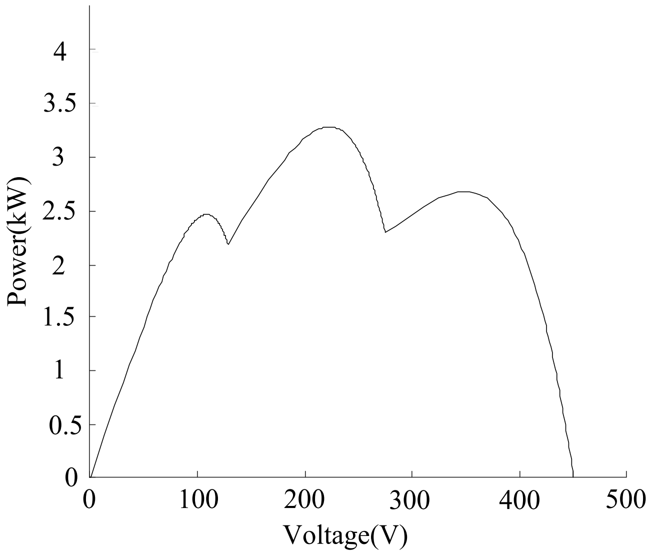

FIGURE 1. P-U characteristic curve under partial shading of photovoltaic array of the photovoltaic microgrid system.

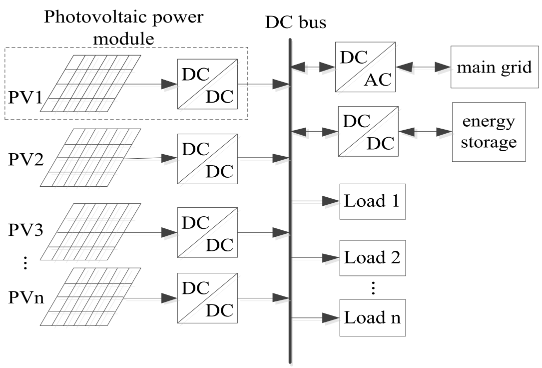

FIGURE 2. The structure of the photovoltaic DC microgrid system.

station work at the MPP. The simulation showed that the proposed algorithm can track the global MPP quickly, accurately and reliably under different environmental conditions.

II. THE OUTPUT CHARACTERISTICS OF PHOTOVOLTAIC POWER SUPPLY UNDER PARTIAL SHADOW AND THE STRUCTURE OF MICROGRID

Due to the influence of the weather, the photovoltaic array in the photovoltaic power station will produce partial shading, which causes the P-U output characteristic of the photovoltaic array to be non-linear and produce multiple peaks [6], [7]. For example, sets the short-circuit current of the photovoltaic array $I_{sc} = 9.2$A, open circuit voltage $U_{oc} = 43.7$V, maximum working voltage $U_m = 35$V, maximum working current $I_m = 8.95$A, under the condition that the light intensity is 1000W/m^2, 800W/ m^2 and 300 W/ m^2, the P-U characteristic curve of the photovoltaic array in the photovoltaic power station is shown in Fig. 1.

In order to optimize the power supply of photovoltaic microgrid composed of more partially shaded photovoltaic power modules, a control strategy with global maximum power tracking is required [8], [9]. Since photovoltaic cells initially generate direct current, generally multiple photovoltaic power sources form a direct current photovoltaic microgrid [10]. The global maximum power tracking control strategy of DC photovoltaic microgrid is generally implemented based on the DC-DC converter of each photovoltaic power module [11]; Then configure the energy storage device to adjust the power supply when the microgrid operates independently, and connect to the main grid through the grid-connected inverter on the PCC side [12], [13]. The structure of the photovoltaic DC microgrid system is shown in Fig. 2.

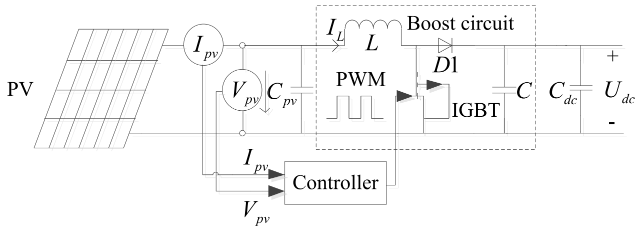

FIGURE 3. DMPPT control system in each photovoltaic power module.

III. PHOTOVOLTAIC POWER MODULE HARDWARE COMPOSITION AND OUTPUT CONTROL

The peak output of the photovoltaic power supply changes with the change of light and temperature in the external environment. The DC-DC converter that implements the maximum power tracking uses a Boost circuit [14], By adjusting and controlling its duty cycle to change the equivalent output impedance, the photovoltaic power supply can work at the MPP [15]–[17]. The Boost circuit structure of DMPPT in photovoltaic DC microgrid is shown in Fig. 3.

In the figure, V_{pv} is the output voltage of the photovoltaic cell, I_{pv} is the output current of the photovoltaic cell, I_L is the current flowing through the inductor, C_{dc} is the equivalent capacitance of the DC bus, and U_{dc} is the voltage of the DC bus.

IV. PHOTOVOLTAIC POWER OUTPUT CONTROL BASED ON THE SPARROW SEARCH ALGORITHM

The sparrow search algorithm (SSA) obtains the optimal solution by imitating the specific behavior of the sparrow [18]. First, establish the discoverer-joiner sparrow population model, and randomly select some sparrows as guards. The discoverer is responsible for providing foraging directions and areas for the sparrow population. Joiners will follow the discoverer for food, monitor the discoverer and snatch food from the discoverer. When the vigilant realizes the danger, the sparrow population will immediately make anti-predation behavior. Finally, through multiple iterations of the locations of discoverers and joiners, the most adaptive location for the entire population is found.

Introduce the SSA into the DMPPT control strategy, consider the position of the discoverer based on the duty cycle of the DC/DC converter, the duty cycle is used to control the output voltage. The output power $P = UI$ in the photovoltaic array is the objective function, and the foraging amount found by the discoverer is regarded as the output power.

The sparrow population is in the space of $N \times D$, N is the total number of sparrows, D is the spatial dimension, Then the position of the i-th sparrow in space is $X_i = (x_{i1}, x_{i2}, \cdots, x_{id})$, $i \in [1, N]$, $d \in [1, D]$, x_{id} represents the position of the i-th sparrow in the d-dimensional space.

Discoverer location update formula:

$$x_{id}^{t+1} = \begin{cases} x_{id}^{t} \cdot \exp\left(\dfrac{-i}{\alpha \cdot T}\right), & R_2 < ST \\ x_{id}^{t} + Q \cdot L, & R_2 \geq ST \end{cases} \tag{1}$$

Among them, t represents the current number of iterations; T is the maximum number of iterations; α is a uniform random number between (0, 1]; Q is a random number with normal distribution; L is a matrix whose elements are all 1, and the size is $1 \times d$; $R_2 \in [0, 1]$ Represents the warning value; $ST \in [0.5, 1]$ represents the safety value.

When $R_2 < ST$, it means that the population is not in danger and the discoverer continues to search; When $R_2 \geq ST$, it means that the vigilant detected the predator and immediately issued an alarm to other sparrows. The population immediately made anti-predation behavior and flew to a safe area for food.

Joiner location update formula:

$$x_{id}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{x_{worst\ d}^{t} - x_{id}^{t}}{i^2}\right), & i > \dfrac{N}{2} \\ x_{best\ d}^{t+1} + \frac{1}{D}\sum\limits_{d=1}^{D}\left(rand\left(-1, 1\right) \cdot \left|x_{id}^{t} - x_{best\ d}^{t+1}\right|\right), & i \leq \dfrac{N}{2} \end{cases} \tag{2}$$

Among them, $x_{worst\ d}^{t}$ represents the global worst position at the t-th iteration; $x_{best\ d}^{t+1}$ represents the global best position at the t+1th iteration.

When $i > \frac{N}{2}$, it means that the i-th joiner has not obtained food and needs to fly to other places for food. When $i \leq \frac{N}{2}$, it means that the i-th joiner is close to the global optimal position and randomly foraging around.

The update formula of the vigilant position:

$$x_{id}^{t+1} = \begin{cases} x_{worst\ d}^{t} + \beta\left(x_{id}^{t} - x_{worst\ d}^{t}\right), & f_i \neq f_g \\ x_{id}^{t} + K\left(\dfrac{x_{id}^{t} - x_{worst\ d}^{t}}{|f_i - f_w| + e}\right), & f_i = f_g \end{cases} \tag{3}$$

Among them, β represents the step length control parameter, which is a random number subject to a normal distribution with a mean value of 0 and a variance of 1; K represents the moving direction of the sparrow, and the value is a random number in the interval $[-1, 1]$; e is a constant with a very small value; f_i represents the fitness of the i-th sparrow; f_g represents the optimal fitness of the current sparrow population; f_w represents the worst fitness of the current sparrow population.

When $f_i \neq f_g$, it means that the i-th sparrow is at the edge of the population and is easily attacked by predators; when $f_i = f_g$, it means that the i-th sparrow is in the center of the population, and because it is aware of the threat, it needs to be close to other sparrows to reduce the catch risk.

V. DMPPT OPTIMIZATION CONTROL BASED ON IMPROVED SPARROW SEARCH ALGORITHM

A. IMPLEMENTATION OF POPULATION INITIALIZATION BASED ON CENTROID OPPOSITION-BASED LEARNING

The standard SSA uses random initialization to generate the initial sparrow population. For the intelligent algorithm of population iteration, the quality of the initial population has a certain impact on the final convergence accuracy. In this paper, centroid opposition-based learning (COBL) is used to generate the initial population of the SSA, which ensures the uniformity and diversity of the initial population, and improves the fitness of the initial population.

Define 1 Center of gravity. Let $(X_1, \cdots X_n)$ be n points with unit mass in the D-dimensional space, the expression of the overall center of gravity is:

$$M = \frac{X_1 + \cdots + X_n}{n} \tag{4}$$

Then:

$$M_j = \frac{\sum\limits_{j=1}^{D} x_{i,j}}{n}, i = 1, 2, \cdots, n \tag{5}$$

Define 2 reversal point of center of gravity. If the center of gravity of a discrete uniform whole is M, the opposite point of X_i at a certain point in the whole is defined as:

$$\bar{X}_i = 2 \times M - X_i, i = 1, 2, \cdots, n \tag{6}$$

The reverse point is in a search space with a dynamic boundary, denoted as $x_{i,j} \in \left[a_j, b_j\right]$. The change of the dynamic boundary puts the reversal point in a shrinking space that is constantly changing. The expression of the dynamic boundary is:

$$a_j = \min\left(x_{i,j}\right), b_j = \max\left(x_{i,j}\right) \tag{7}$$

If the reverse point exceeds the range of the dynamic boundary, the reverse point is recalculated, and its expression is:

$$\bar{x}_{i,j} = \begin{cases} a_j + rand\left(0, 1\right) \times \left(M_j - a_j\right), & if\,\bar{x}_{i,j} < a_j \\ M_j + rand\left(0, 1\right) \times \left(b_j - M_j\right), & if\,\bar{x}_{i,j} > b_j \end{cases} \tag{8}$$

The steps of implementing population initialization based on centroid opposition learning are as follows:

Step 1: Randomly generate the D-dimensional vector $X_i = (x_{i1}, x_{i2}, \cdots, x_{id})$ of the numerical component in (0, 1),among them, $i \in [1, N]$, $d \in [1, D]$, according to the above five formulas, $2N$ vectors are generated for population initialization.

Step 2: Map the j-th component to interval $\left[\min_j, \max_j\right]$ according to $z_{ij} = \min_j + x_{ij} \times \left(\max_j - \min_j\right)$, among them, $i \in [1, N], j \in [1, D]$.

Step 3: Evaluate the fitness of each sparrow, and select the position of the sparrow with higher fitness as the position of the initial population.

B. POSITION UPDATE BASED ON LEARNING COEFFICIENT AND MUTATION OPERATOR

Aiming at the problem that the traditional SSA is easy to fall into the local extremum, this paper uses learning coefficients and mutation operators to improve the search ability of the SSA.

The discoverer has a strong foraging ability. When the discoverer falls into a local extreme, it will cause the entire algorithm to fall into a local optimal solution. This paper introduces learning coefficients into the discoverer's location update formula to improve the discoverer's global search ability. When the joiner is $i > \frac{N}{2}$, it shows that these joiners have weak foraging ability and easily fall into local extremes. In this paper, mutation operator is introduced into the position update formula of joiners to improve the ability of some joiners to jump out of local extremes.

The formula for updating the location of the discoverer after improvement:

$$x_{id}^{t+1} = \begin{cases} v(t)\, x_{id}^{t} \cdot \exp\left(\dfrac{-i}{\alpha \cdot T}\right), & R_2 < ST \\ v(t)\, x_{id}^{t} + Q \cdot L, & R_2 \geq ST \end{cases} \tag{9}$$

Among them, $v(t)$ is the learning coefficient of the discoverer.

The expression of $v(t)$ is:

$$v(t) = v_{\min} + (v_{\max} - v_{\min}) \times \sin\left(\frac{t}{T}\pi\right) \tag{10}$$

Among them, $v_{\max}$ and $v_{\min}$ are the maximum and minimum learning coefficients respectively.

The formula for updating the location of the joiner after improvement:

Among them, δ is the degree of control of variation; $Cauchy(t)$ is a random variable subject to Cauchy distribution.

C. ALGORITHM CONTROL PROCESS

The specific steps are as follows:

Step 1: Initialize the sparrow population.

Step 2: Optimal population based on centroid opposition learning.

Step 3: The generation of discoverers and joiners. Evaluate the fitness of all sparrows to their current positions. Choose *pNum* sparrows with the highest location adaptability as discoverers, and other sparrows as joiners.

Step 4: Update the location of the discoverer according to formula (9).

Step 5: Update the position of the joiner according to formula (11), as shown at the bottom of the next page.

Step 5: Update the position of the vigilant according to formula (3).

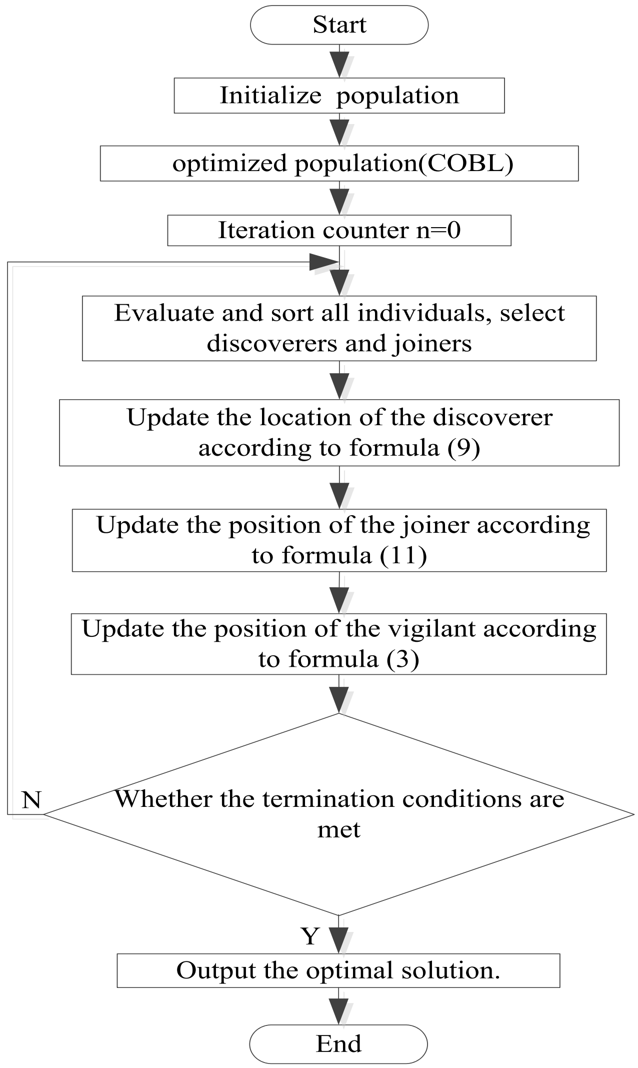

FIGURE 4. DMPPT control flow based on ISSA algorithm.

Step 6: Determining whether the termination condition is satisfied. If the current optimal value is better than the optimal value of the previous iteration, continue to update the location, otherwise iterate until the conditions are met.

Step 7: Output the optimal solution.

VI. SIMULATION AND ANALYSIS

In order to verify the reliability of the method proposed in this article, this paper builds a photovoltaic microgrid model based on the Matlab simulation platform, uses the boost circuit model shown in Figure 3, inductance $L = 1\mu$H, capacitance $C = 100\mu$F, and sets the light intensity of the photovoltaic module as shown in Figure 1. This article uses the P&O in the traditional DMPPT control, the general PSO algorithm and the ISSA algorithm shown in Fig. 4 of this article to perform maximum power tracking. The total simulation time is 3s.

It can be seen from Fig. 5 that when the photovoltaic array produces local shadows, the traditional P&O cannot

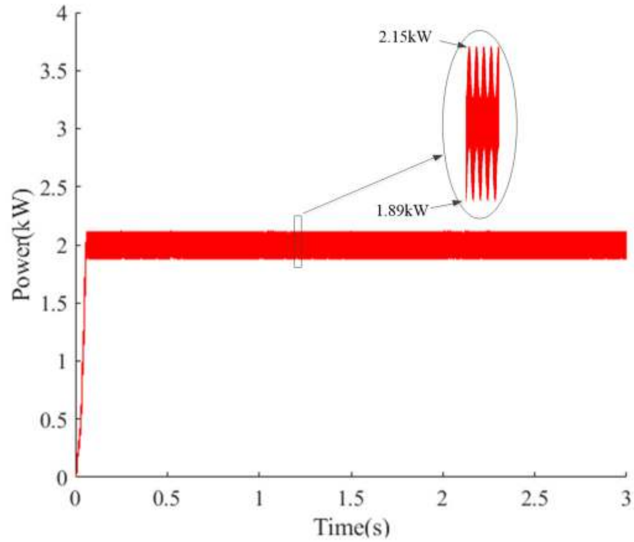

FIGURE 5. Output power curve of p&o.

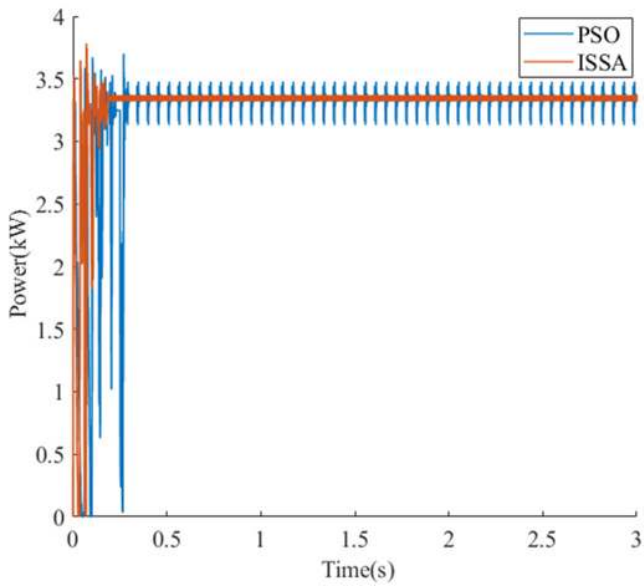

FIGURE 6. The output power curve of the PSO and ISSA algorithms when the illumination is constant.

accurately track the global MPP and falls into the local MPP, and there is a large power fluctuation after reaching the steady state.

It can be seen from Fig. 6 that in the case of partial shadows, the DMPPT control based on the PSO algorithm tracks the global MPP after 0.28s. The tracking speed is slow,

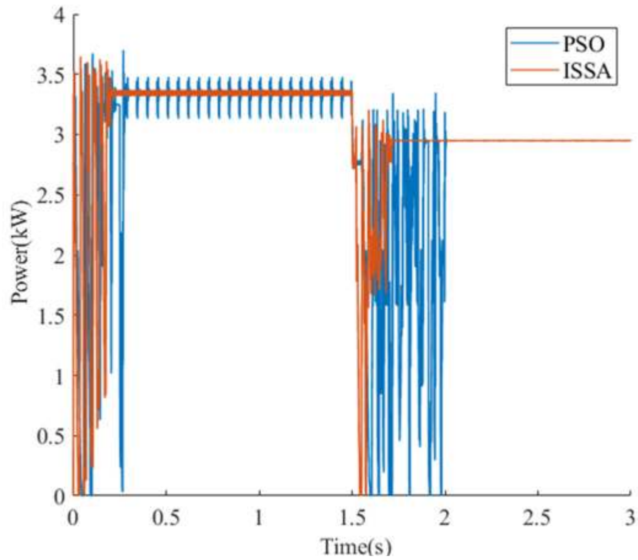

FIGURE 7. The output power curve of the PSO algorithm when the illumination changes.

the tracking process is unstable, and there are large power fluctuations in the steady state. The DMPPT control based on the ISSA algorithm proposed in this article tracks to the global MPP after 0.21s, has a higher tracking speed, and the tracking process is more stable, and the power fluctuation is smaller in the steady state.

This paper simulates the photovoltaic microgrid under varying light intensity set the initial light intensity of the photovoltaic module as shown in Fig 1. Change the light intensity to 1000W/m^2, 700W/m^2 and 500 W/m^2 at 1.5s, the total simulation time is 3s.

It can be seen from Fig. 7 that in the case of partial shadows, the DMPPT control based on the PSO algorithm restarts slower than ISSA when the illumination changes, and the global MPP is tracked after 0.51s. The DMPPT control based on the ISSA algorithm proposed in this article quickly traced the global MPP after 0.23s.

In summary, the DMPPT control method based on the ISSA algorithm has faster tracking speed and higher accuracy. It can respond and restart the DMPPT control quickly and timely after the illumination changes, track the global MPP quickly, and reduce the mismatch loss of the photovoltaic microgrid.

VII. CONCLUSION

Aiming at the problem of system mismatch caused by power loss in the photovoltaic microgrid under the change of

$$x_{id}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{x_{worst\ d}^{t} - x_{id}^{t}}{i^2}\right) + \delta \times Cauchy\,(t)\,, & i > \dfrac{N}{2} \\ x_{best\ d}^{t+1} + \dfrac{1}{D}\sum\limits_{d=1}^{D}(rand\,(-1,1) \cdot \left|x_{id}^{t} - x_{best\ d}^{t+1}\right|), & i \le \dfrac{N}{2} \end{cases} \tag{11}$$

external environment, this paper introduced centroid opposition learning, learning coefficient and mutation operator into the SSA, which increased the diversity of the population and avoids falling into local extreme values. The Matlab simulation showed that the ISSA algorithm proposed in this article has better tracking effect than the traditional P&O and general PSO algorithm. In the process of external light changes, it has the characteristics of fast speed, high accuracy, and stable reliability, which effectively solves the problem of traditional DMPPT control that is easy to fall into local MPP and cause power loss in photovoltaic microgrids.

REFERENCES

[1] J. Biswas, A. M. Kamath, A. K. Gopi, and M. Barai, "Design, architecture, and real-time distributed coordination DMPPT algorithm for PV systems," *IEEE J. Emerg. Sel. Topics Power Electron.*, vol. 6, no. 3, pp. 1418–1433, Sep. 2018, doi: 10.1109/JESTPE.2017.2756698.

[2] H.-S. Lee and J.-J. Yun, "Advanced MPPT algorithm for distributed photovoltaic systems," *Energies*, vol. 12, no. 18, p. 3576, Sep. 2019, doi: 10.3390/en12183576.

[3] G. Zhou, Q. Tian, M. Leng, X. Fan, and Q. Bi, "Energy management and control strategy for DC microgrid based on DMPPT technique," *IET Power Electron.*, vol. 13, no. 4, pp. 658–668, Mar. 2020, doi: 10.1049/iet-pel.2019.0383.

[4] M. E. Basoglu, "Forward converter-based distributed global maximum power point tracking in partial shading conditions," *Social Netw. Appl. Sci.*, vol. 2, no. 2, pp. 1913–1921, Jan. 2020, doi: 10.1007/s42452-020-2027-6.

[5] M. Mao, L. Zhang, P. Duan, Q. Duan, and M. Yang, "Grid-connected modular PV-converter system with shuffled frog leaping algorithm based DMPPT controller," *Energy*, vol. 143, pp. 181–190, Jan. 2018, doi: 10.1016/j.energy.2017.10.099.

[6] F. Wang, T. Zhu, F. Zhuo, H. Yi, S. Shi, and X. Zhang, "Analysis and optimization of flexible MCPT strategy in submodule PV application," *IEEE Trans. Sustain. Energy*, vol. 8, no. 1, pp. 249–257, Jan. 2017.

[7] K. L. Lian, J. H. Jhang, and I. S. Tian, "A maximum power point tracking method based on perturb- and-observe combined with particle swarm optimization," *IEEE J. Photovolt.*, vol. 4, no. 2, pp. 626–633, Mar. 2014.

[8] L. Xi, J. Chen, Y. Huang, Y. Xu, L. Liu, Y. Zhou, and Y. Li, "Smart generation control based on multi-agent reinforcement learning with the idea of the time tunnel," *Energy*, vol. 153, pp. 987–997, Jun. 2018, doi: 10.1016/j.energy.2018.04.042.

[9] L. Xi, L. Yu, Y. Xu, S. Wang, and X. Chen, "A novel multi-agent DDQN-AD method-based distributed strategy for automatic generation control of integrated energy systems," *IEEE Trans. Sustain. Energy*, vol. 11, no. 4, pp. 2417–2426, Oct. 2020, doi: 10.1109/TSTE.2019.2958361.

[10] H. Wang, Y. Liu, B. Zhou, C. Li, G. Cao, N. Voropai, and E. Barakhtenko, "Taxonomy research of artificial intelligence for deterministic solar power forecasting," *Energy Convers. Manage.*, vol. 214, Jun. 2020, Art. no. 112909, doi: 10.1016/j.enconman.2020.112909.

[11] H. Tian, F. Mancilla-David, K. Ellis, E. Muljadi, and P. Jenkins, "A cell-to-module-to-array detailed model for photovoltaic panels," *Sol. Energy*, vol. 86, no. 9, pp. 2695–2706, Sep. 2012.

[12] D. Xu, Q. Wu, B. Zhou, C. Li, L. Bai, and S. Huang, "Distributed multi-energy operation of coupled electricity, heating, and natural gas networks," *IEEE Trans. Sustain. Energy*, vol. 11, no. 4, pp. 2457–2469, Oct. 2020, doi: 10.1109/TSTE.2019.2961432.

[13] T. Wang, D. O'Neill, and H. Kamath, "Dynamic control and optimization of distributed energy resources in a microgrid," *IEEE Trans. Smart Grid*, vol. 6, no. 6, pp. 2884–2894, Nov. 2015.

[14] Y. C. Xue, B. Li, and S. R. Wang, "An improved MPPT algorithm based on power quadratic differential for photovoltaic system," *Adv. Power Syst. Hydroelectr. Eng.*, vol. 31, no. 6, pp. 117–123, 2015.

[15] Y.-H. Liu, S.-C. Huang, J.-W. Huang, and W.-C. Liang, "A particle swarm optimization-based maximum power point tracking algorithm for PV systems operating under partially shaded conditions," *IEEE Trans. Energy Convers.*, vol. 27, no. 4, pp. 1027–1035, Dec. 2012.

[16] I. R. Balasubramanian, S. I. Ganesan, and N. Chilakapati, "Impact of partial shading on the output power of PV systems under partial shading conditions," *IET Power Electron.*, vol. 7, no. 3, pp. 657–666, Mar. 2014.

[17] S. Moballegh and J. Jiang, "Modeling, prediction, and experimental validations of power peaks of PV arrays under partial shading conditions," *IEEE Trans. Sustain. Energy*, vol. 5, no. 1, pp. 293–300, Jan. 2014.

[18] J. Xue and B. Shen, "A novel swarm intelligence optimization approach: Sparrow search algorithm," *Syst. Sci. Control Eng.*, vol. 8, no. 1, pp. 22–34, Jan. 2020, doi: 10.1080/21642583.2019.1708830.

JIANHUA YUAN was born in Dongkou, Hunan, in 1978. He received the Ph.D. degree in power system and automation from Shandong University, China, in 2011. He currently works with the Automation Department, School of Electrical and New Energy, China Three Gorges University. His current research interests include research on photovoltaic microgrid energy management system, research on new power electronic technology applied to new energy grid-connected power generation, and wireless laser energy transmission.

ZIWEI ZHAO was born in Liaocheng, Shandong, in 1997. He received the bachelor's degree in 2019. He is currently pursuing the master's degree in electrical engineering with the School of Electrical and New Energy, China Three Gorges University. His current research interests include photovoltaic microgrid energy management system research and optoelectronic technology.

YAPING LIU was born in Yantai, Shandong, in 1997. She received the bachelor's degree in 2020. She is currently pursuing the master's degree in energy and power with the School of Electrical and New Energy, China Three Gorges University. Her current research interests include photovoltaic power generation research and UAV energy supply technology.

BAOLIN HE was born in Dazhou, Sichuan, in 1995. He received the bachelor's degree in electrical engineering and automation in 2018. He is currently pursuing the master's degree in energy power with China Three Gorges University. His current research interest includes photovoltaic power generation efficiency control strategies.

LIN WANG was born in Handan, Hebei, in 1997. She received the bachelor's degree in electrical engineering and automation in 2020. She is currently pursuing the master's degree in control science and engineering with China Three Gorges University. Her current research interest includes remote energy supply for drones.

BINBIN XIE was born in Wuhan, Hubei, in 1997. He received the bachelor's degree in electrical engineering and automation in 2019. He is currently pursuing the master's degree in energy power with China Three Gorges University. His current research interest includes short-term forecasting of photovoltaic system power generation.

YANLING GAO was born in Binzhou, Shandong, in 1995. She received the bachelor's degree in electrical engineering and automation in 2019. She is currently pursuing the master's degree in control science and engineering with China Three Gorges University. Her current research interests include drone flight control and path planning.