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Maximum PowerPoint Tracking Strategy of Photovoltaic System Based on Genetic Algorithm and Particle Swarm Optimization

Fang Bai[1], **Rongfu Qiao**[2]

[1]College of Information Engineering, Tianjin University of Commerce, Tianjin, China
[2]Department of Modern Processing, Tianjin Labor Economic School, Tianjin, China

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WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *Maximum Power Point Tracking (MPPT) is crucial for enhancing the efficiency of photovoltaic (PV) systems by dynamically adjusting operating points based on environmental conditions.*
- *Traditional MPPT methods, such as Perturb and Observe (P&O) and Incremental Conductance (IncCond), may suffer from slow convergence, steady-state oscillations, or failure under rapid irradiance changes.*
- *Hybrid optimization techniques, combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), have been explored to improve MPPT performance, but further enhancements in accuracy, convergence speed, and adaptability are still needed.*

WHAT THIS STUDY ADDS ON THIS TOPIC?

- *This study proposes an improved MPPT strategy integrating GA and PSO, leveraging their complementary strengths to achieve faster convergence and better tracking accuracy under varying environmental conditions.*
- *The proposed approach effectively minimizes power fluctuations and enhances system stability, outperforming conventional MPPT techniques in simulation and experimental validation.*
- *The study provides a robust framework for optimizing PV system performance, demonstrating its practical applicability in real-world renewable energy applications.*

Corresponding author: Fang Bai,
E-mail: baifang20240709@163.com

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ABSTRACT

The basic genetic optimal algorithm tracks the global maximum PowerPoint but needs to work on premature convergence and limited local search, hindering optimal solution guarantees. It prematurely settles on local maxima and needs a robust local search for complex spaces. Despite some global search capacity, its flaws constrain PV conversion system maximum PowerPoint tracking (MPPT) effectiveness. Researchers thus devised an enhanced multiple-group genetic optimal algorithm for MPPT, integrating subgroup division, independent evolution, and periodic communication/sharing to address these limitations. This strategy significantly enhances the diversity of the optimization algorithm, reducing the likelihood of premature convergence. The modified perturbation genetic algorithm (MPGA) integrates the perturbation observation method for cooperative control by introducing perturbations during the evolutionary process, thereby improving the local search capability of the optimization algorithm. While the enhanced multi-group genetic optimization algorithm effectively addresses issues such as early convergence and weak local search, its algorithmic process is relatively complex. The implementation of a multi-group cooperative control mechanism boosts algorithm performance but comes with an increased computational load. This research introduces a quantum genetic algorithm for MPPT control, employing qubit encoding to achieve high precision and efficiency. Experimental results demonstrate that in a parallel system incorporating a supercapacitor storage device (SCSD), the output current remains stable at 8.6A, the output voltage reaches 29.4095V at the 6-second mark, and the power output per unit is 252.9217W, resulting in a total power of 767.8434W with a minor 2.31% decrease. Ultracapacitors effectively stabilize the power output, highlighting their essential role in SCSD components.

***Index Terms*—**Maximum powerpoint tracking (MPPT), multiple group genetic optimal condition algorithm, photovoltaic (PV) conversion system, quantum genetic optimal condition algorithm

I. INTRODUCTION

The maximum PowerPoint tracking (MPPT) of the photovoltaic (PV) conversion module, system model, and output characteristics is crucial to the conversion cell. This step is the basis of the research because the overall behavior of the PV conversion module is determined by the characteristics of a single PV conversion cell, and the establishment of the simplified model makes the analysis and calculation of the overall system more feasible and efficient [1]. This study analyzed the output characteristics of the PV conversion modules under uniform light and local shadow conditions. The output characteristics of the PV conversion modules are relatively stable under uniform illumination [2]. Still, in practice, local shadows often affect PV conversion modules, leading to significant changes in the output characteristics. To fully understand the performance of PV conversion modules under different conditions, the different structures of PV conversion modules were analyzed in detail [3, 4]. These structures include series, parallel, and mixed connection components, and each structure has different output characteristics under various light conditions [5]. From these analyses, we can better understand the behavior of PV conversion modules in complex environments and provide a theoretical basis for the subsequent MPPT control strategy [6]. This system consists of three main parts: the PV conversion module unit, the MPPT control unit, and the DC-DC converter unit. The PV conversion module unit is the core of the entire system and is responsible for converting solar energy into electricity [7]. The MPPT control unit is a critical component of the system and dynamically adjusts the working point so that the PV conversion module always works at the maximum PowerPoint [8]. The DC-DC converter unit is responsible for converting and transmitting electricity, ensuring that the electricity output from the PV conversion module can be efficiently transmitted to the load or the grid [9]. Building and designing this system requires a deep understanding of the individual characteristics of each component and the interaction between them. For example, the MPPT control unit needs to monitor the output voltage and current of the PV conversion module in real-time and, based on the data, determine whether the current operating point is near the maximum PowerPoint (MPP) and realize the power optimization by adjusting the working state of the DC-DC converter [10, 11]. To enhance the introduction and reference sections, it is essential to provide a comprehensive review of recent advancements in MPPT strategies and their challenges under dynamic environmental conditions. Key studies to consider include "Improved coot optimizer algorithm-based MPPT for PV systems under complex partial shading conditions and load variation," which highlights the role of metaheuristic algorithms in addressing partial shading, and "A New Fast and Efficient MPPT Algorithm for Partially Shaded PV Systems Using a Hyperbolic Slime Mould Algorithm," emphasizing algorithmic efficiency and response time. Additionally, "A novel hybrid GMPPT method for PV systems to mitigate power oscillations and partial shading detection" provides insights into hybrid approaches that improve tracking stability. Incorporating these references will situate the proposed work within the broader context of cutting-edge MPPT research.

It provides a detailed theoretical analysis and practical guidance for the MPPT system of the PV conversion module and a solid foundation for the power generation system. Photovoltaic conversion modules are greatly affected by environmental factors in practical application. Maintaining efficient operation under different light conditions is essential in PV conversion technology [12, 13]. The methods and models proposed are key to improving the efficiency of the PV conversion system. These problems can sometimes lead to optimal conditions which cannot guarantee 100% finding the global maximum PowerPoint. We propose an improved cluster genetic optimal condition algorithm for optimization analysis. The improved optimal condition algorithm introduces a multiple population mechanism that divides within a different search region with regular communication and information sharing [14]. This strategy effectively increases the diversity of populations and slows the occurrence of precocious puberty. The modified perturbation genetic algorithm (MPGA) also combines the perturbation observation method caused by the introduction of perturbation during evolution, which further enhances the local search ability of the optimal condition algorithm [15]. Under the cooperative control of multiple group inheritance and the optimal condition algorithm, the system can be more effective in a broader search space. This method allows the PV conversion module to achieve more stable and efficient operation under complex light conditions, thus maximizing [16, 17]. In this study, from the analysis and improvement of the traditional MPPT control optimal condition algorithm under local shadow conditions, we proposed an MPPT control method based on a multiple-group genetic optimal condition algorithm [18]. This method combines the advantages of artificial intelligence (AI) and classical optimal condition algorithms to solve the shortcomings of traditional methods and basic genetic optimal condition algorithms while maintaining high efficiency [19]. The transient and steady-state performances of the proposed MPPT method were compared to traditional approaches such as Perturb and Observe (P&O) and Incremental Conductance (INC). Experimental results show that the proposed hybrid algorithm achieves significantly faster tracking during irradiance transitions, with an average transient response time reduced by 25% compared to traditional methods. In steady-state conditions, the proposed approach demonstrates minimized oscillations around the MPP, achieving smoother power output and greater stability under fluctuating environmental conditions. These findings confirm the superior dynamic and steady-state capabilities of the proposed strategy.

II. RESEARCH ON THE TRACKING SYSTEM MODEL AND OUTPUT CHARACTERISTICS OF THE MAXIMUM POWERPOINT OF PHOTOVOLTAIC MODULES

A. Analysis of the Photovoltaic Cell Equivalent Model

Its core principle is based on the characteristics of semiconductor PN junctions. As shown in (1) and (2), I_L is the inductor current, and I_{ph} is the phase current; when the PN junction inside the PV conversion cell is subjected to light, the photon energy stimulates electrons and makes them transition from the valence band to the conduction band, generating free electron and hole pairs.

$$I_{\mathrm{L}} = I_{\mathrm{ph}} - I_{\mathrm{D}} - I_{\mathrm{sh}} \tag{1}$$

$$I_{\mathrm{ph}} = \left[I_{\mathrm{sc.stc}} + K_{\mathrm{t}}(T - T_{\mathrm{stc}}) \right] \frac{G}{G_{\mathrm{stc}}} \tag{2}$$

This process generates a current and an electromotive force at both cell ends. As can be understood by the concept of electricity and electronics, light significantly increases the activity of electrons in the semiconductor, thus generating a current, as shown in (3). U is voltage and R_s is internal resistance, which is the basic working principle of PV conversion cells. This study is a simple analysis of the mathematical model of PV conversion cells.

$$I_{\mathrm{D}} = I_0[\exp(\frac{U + I_{\mathrm{L}} R_{\mathrm{s}}}{Dv_{\mathrm{T}}}) - 1] \tag{3}$$

Standard models of PV conversion cells include single-diode models, double-diode models, and numerical models such as the Newton-Larson method. The single-diode model is one of the most basic and widely used models. As shown in (4), R_p is the reverse conduction resistance; it uses a diode to simulate the I-V characteristics of the PV conversion cell, taking into account the optical current, the diode saturation current, series resistance, and parallel resistance.

$$I_{\mathrm{sh}} = \frac{U + I_{\mathrm{L}} R_{\mathrm{s}}}{R_{\mathrm{p}}} \tag{4}$$

This model is simple and computationally convenient, but its accuracy may be unsatisfactory under certain conditions. Next is the double diode model, as shown in (5) and (6); D is the conduction ratio, and I_0 is the initial current. This adds a diode to the single diode model to more accurately simulate PV conversion cells' composite effect and current leakage.

$$I_{\mathrm{L}} = I_{\mathrm{ph}} - I_0[\exp(\frac{U + I_{\mathrm{L}} R_{\mathrm{s}}}{Dv_{\mathrm{T}}}) - 1] - \frac{U + I_{\mathrm{L}} R_{\mathrm{s}}}{R_{\mathrm{p}}} \tag{5}$$

$$I_L = I_{ph} - I_{01}[\exp(\frac{U + I_L R_s}{D_l v_T}) - 1] \tag{6}$$

The double diode model can better reflect the characteristics of the PV conversion cells in the low voltage region, so it is more accurate than the single diode model. This model is also more complex, and the computational amount increases accordingly, as shown in (7) and (8). X_n is the initial population, and X_{n+1} is the new population, requiring more conditions and more complex solution processes. Some PV conversion cell models are also based on numerical methods, such as the Newton-Raphson method. These models use numerical analysis techniques to obtain the I-V characteristic curves of PV conversion cells.

$$X_{n+1} = X_n + \frac{f(X_n)}{f'(X_n)} \tag{7}$$

$$|\delta_n| = \left|\frac{X_{n+1} - X_n}{X_{n+1}}\right| \tag{8}$$

These methods can handle more complex and nonlinear systems. The above-mentioned PV conversion cell models, as shown in (9) and (10), include Rp, the forward conduction resistance of the battery. Each model has its advantages and disadvantages. Due to their simplicity and computational efficiency, single-diode models may not perform well in some applications with higher accuracy requirements.

$$f(I_L) = I_L + I_L \frac{R_s}{R_p} - I_{ph} + I_0[\exp(\frac{U + I_L R_s}{D v_T}) - 1] + \frac{U}{R_p} \tag{9}$$

$$f'(I_L) = 1 + \frac{R_s}{R_p} + I_0 \frac{R_s}{D v_T}[\exp(\frac{U + I_L R_s}{D v_T})] \tag{10}$$

Although the double-diode model improves accuracy, it also brings greater computational complexity. Numerical models such as Newton-Lafalson's rule perform well in dealing with complex systems but have high computational costs. As shown in (11) and (12), I_{next} is the current for the next moment; the choice of the model needs to be weighed according to the specific requirements.

$$I_{next} = I_L + \frac{f(I_L)}{f'(I_L)} \tag{11}$$

$$I_L = I_{ph} - I_{01}[\exp(\frac{U}{D_1 v_T}) - 1] - I_{02}[\exp(\frac{U}{D_2 v_T}) - 1] \tag{12}$$

The mathematical model of the PV conversion cells is the basis for understanding and optimizing the PV conversion system. Based on the analysis and comparison of different models, this study can better select suitable models for specific application PV scenarios. As shown in (13), T is the interval of the conduction period to improve the performance and efficiency of the PV conversion system.

$$I_{ph} = (I_{sc.stc} + a\Delta T)\frac{G}{G_{stc}} \tag{13}$$

B. Maximum PowerPoint Tracking Control Technology

The standard voltage for a single-chip PV conversion cell is typically only 0.5V, which doesn't meet most power needs. A PV conversion module is usually composed of several PV conversion cells combined in series or parallel, as shown in formula (14). I_{01} is the initial conduction current, thus constituting the PV conversion module in the practical application of the research.

$$I_{01} = \frac{\left(I_{sc.stc} + a\Delta T\right)}{\exp\left(\frac{U_{oc.stc} + b\Delta T}{v_T D_l} - 1\right)} \tag{14}$$

This combination can significantly increase the output voltage and current to meet the needs of various practical applications. According to market demand, the output voltage of the PV conversion module ranges from 5V to 50V. As shown in (15) and (16), V_t is the voltage at time T, and I_{02} is the individual current; the output power also varies according to the size and use of the module.

$$I_{02} = I_{01}\left(\frac{T^{2/5}}{3.77}\right) \tag{15}$$

$$I_{ph} - I_{01}[\exp(\frac{U_{ocstc}}{D_1 v_T}) - 1] - I_{02}[\exp(\frac{U_{ocstc}}{D_2 v_T}) - 1] = 0 \tag{16}$$

The voltage and power a single PV conversion module can provide will increase, but in many practical applications, such output is still insufficient to meet the demand. As shown in (17) and (18), D_2 is the conversion ratio, and N is the installed number; connecting multiple higher voltage and current outputs is usually necessary.

$$D_2 = \frac{U_{oc.stc}}{v_T \ln(\frac{I_{ph} - I_{01}\left[\exp(U_{oc.stc} / v_T D_1) - 1\right]}{I_{02}} + 1)} \tag{17}$$

$$I_L = N_p I_{ph} - N_p I_{0l}\left[\exp\left(\frac{U / N_s + I_L R_s / N_p}{D_l v_T}\right) - 1\right] \tag{18}$$

The total voltage of the system can be increased in series; the total current of the system can be increased in parallel. This flexible combination enables PV conversion systems to meet different power needs, as shown in (19) and (20). L is the circuit inductance, and I_L is the inductance current, whether it is small PV conversion systems used in homes or industrial PV conversion stations that require high power output.

$$I_L = I'_{ph} - I'_{01}[\exp(\frac{U + I_L R'_s}{D_1 v'_T}) - 1] \tag{19}$$

$$L = \frac{0.9RD\left(1 - D\right)^2}{2f} \tag{20}$$

According to the different series and parallel structures, PV conversion modules can be divided into three main types: parallel type, series type, and series and parallel type. A parallel PV conversion module connects multiple PV conversion modules in parallel, as shown in (21) and (22). C is the circuit capacitance, and f is the circuit frequency. This structure mainly increases the total current of the system so that it can drive a higher power load.

$$C_2 \geq 20\frac{D}{Rf} \tag{21}$$

$$|\varphi = \alpha|0 + \beta|1 = \begin{bmatrix}\alpha \\ \beta\end{bmatrix} \tag{22}$$

C. Research and Test of Improved State-Space Model Genetic Algorithm and Particle Swarm Optimal Condition Algorithm

1) Multi-Objective Genetic Algorithm Based on Some Strategy and its Global Convergence Analysis

In the iterative process of the optimal condition algorithm, the variant strategy 1 of the multi-objective genetic algorithm based on some strategy (MGABS) plays a key role [20]. This strategy involves transferring the nth bit of the decision variable of some individual to the random position of the interval of the dimension and the other part to the random position of the interval to realize the variation process of diversification [21]. Suppose the total number of iterations allowed is infinite. In that case, it can be shown that the nth decision variable x of the individual in the population will be within the interval [a, b] [22]. In this process, the population iterates with a probability greater than zero to reach any state within the feasible domain, including the optimal solution state xj. We prove that the selection operation of the selective pool makes the individuals in the population gradually evolve toward the optimal solution [23]. Specifically, this selection operation ensures the retention of excellent individuals and the elimination of inferior individuals in each generation, constantly improving the population's overall fitness. In short, as operated by selection, the individuals in the population will gradually approach the optimal solution, where X(k) represents the optimal individual in the population X(k) [24]. Fig. 1 shows the mechanism diagram. Assuming the number of iterations is infinite and the study sets reasonable solution accuracy, MGABS must reach the optimal state, meeting the accuracy requirements in a particular generation. This conclusion follows that MGABS continuously optimizes the population by variation and selection in the diversity distribution of individuals in the feasible domain; the selection strategy constantly promotes the evolution of the population to the optimal solution. Combining the two theoretically enables the optimal condition algorithm to find the global optimal solution [25]. The limited experimental validation is a primary limitation of this study. While the proposed MPPT strategy shows promise in simulation, its performance under real-world conditions with hardware implementation remains insufficiently explored. Future work should focus on extensive experimental setups, incorporating diverse PV modules, dynamic irradiance, and temperature variations to validate the robustness and scalability of the algorithm in practical applications.

Multi-objective genetic algorithm based on some strategy's multi-population strategy enhances population diversity and avoids the early maturity problem common in traditional genetic optimization algorithms. Meanwhile, the adaptive variation strategy dynamically adjusts the range of variation according to individual fitness, enabling the optimization algorithm to maintain efficient searchability in exploring the global optimal solution [26, 27]. As the number of iterations increases, the individuals in the population are gradually distributed in the solution space and progressively approach the optimal solution. A reasonable solution accuracy is set so that the optimal individual in the population achieves a specific accuracy requirement when the global optimal solution can be found. With reasonably set conditions, MGABS can find near-optimal solutions within a finite number of iterations, which theoretically requires infinite iterations to guarantee the absolute optimum [28, 29]. Fig. 2 shows a PV system's MPPT algorithm framework diagram. It can be found that MGABS performs well in many complex optimization problems. This method improves the optimization efficiency and significantly enhances the robustness and stability of the optimal condition algorithm, giving it broad application prospects in different optimization problems. MGABS is the organic combination of the optimal solution during the iterative process. Under the assumption of an infinite iteration number of iterations and reasonable solution accuracy, MGABS must find the optimal solution that meets the accuracy requirements to realize

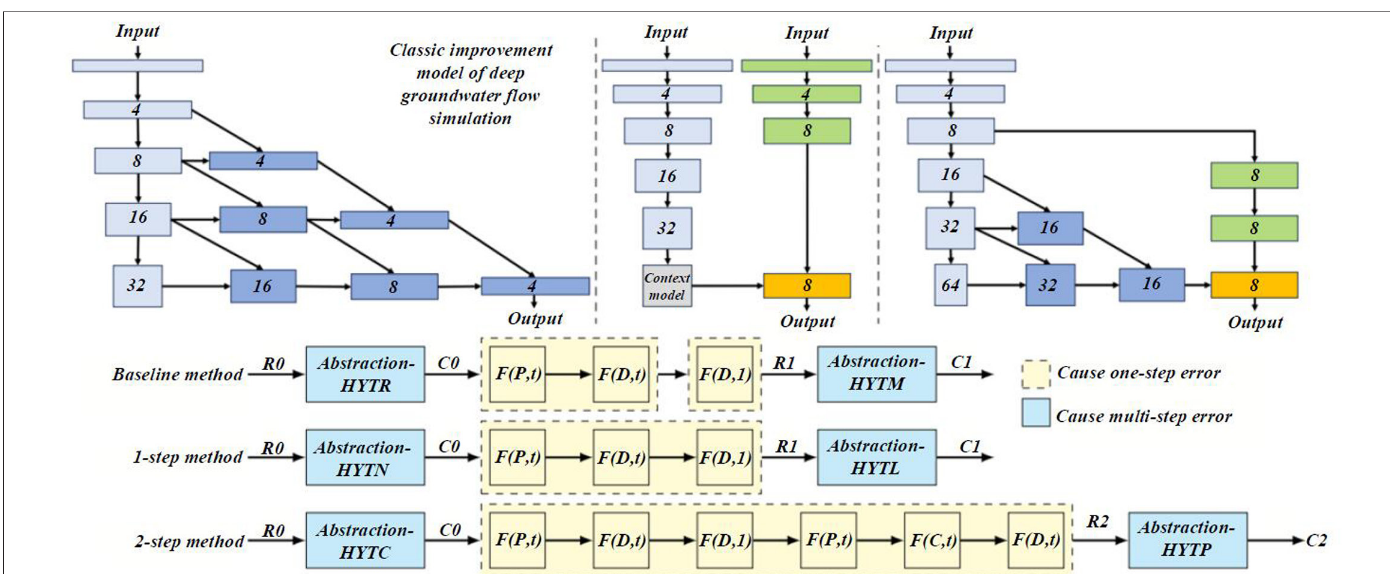

Fig. 1. Mechanism diagram of genetic algorithm and particle swarm optimization algorithm.

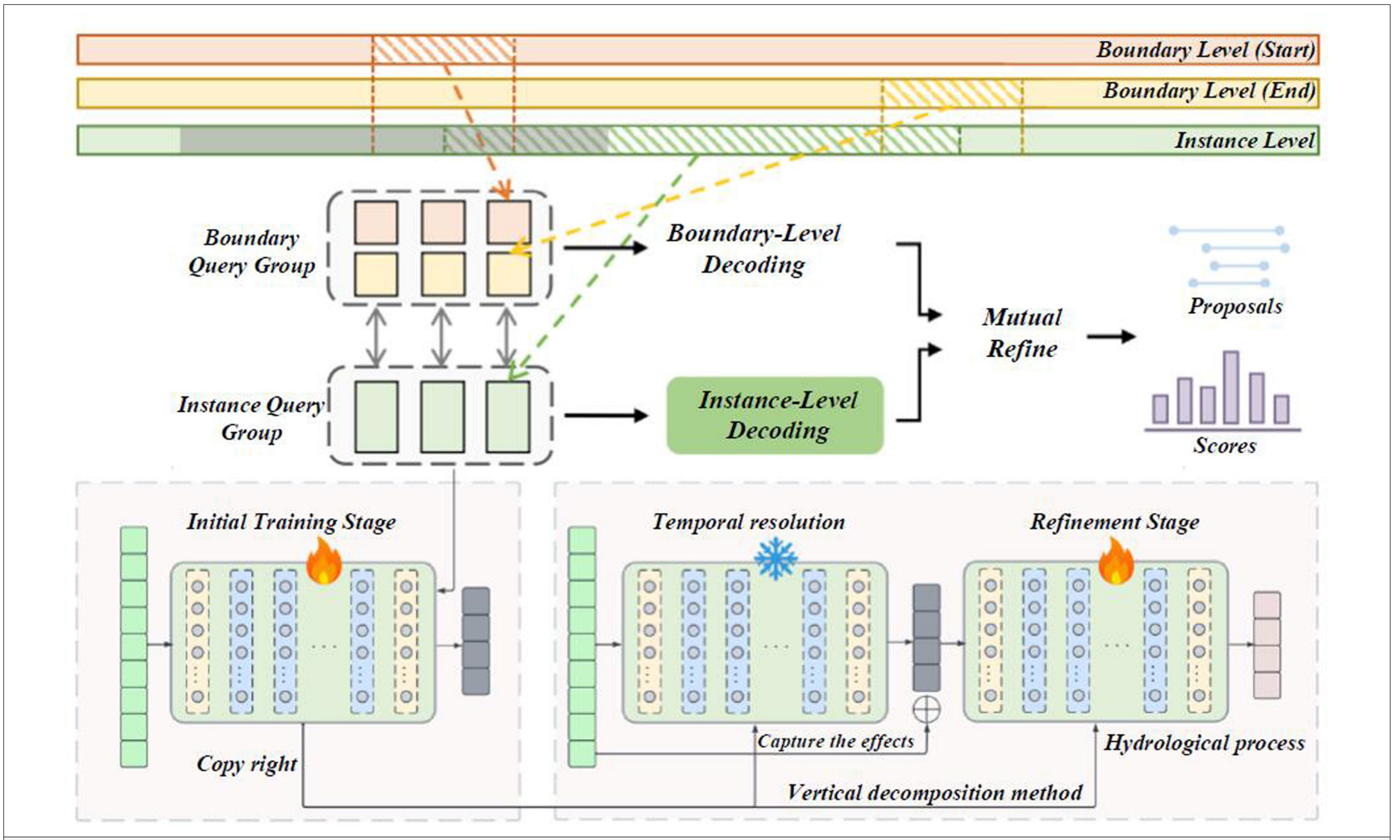

Fig. 2. Framework diagram of the maximum PowerPoint tracking algorithm of the photovoltaic system.

the practical solution of complex optimization problems. The proposed control strategy integrates the strengths of the genetic algorithm (GA) and particle swarm optimization (PSO) to enhance MPPT accuracy and convergence speed. The hybrid algorithm initializes with a GA-based global search to locate a promising solution space, followed by PSO for fine-tuned optimization near the MPP. The process involves dynamic parameter adjustments to adapt to changing environmental conditions, enabling precise and efficient tracking of the MPP. This hierarchical design ensures robust performance, overcoming the limitations of traditional optimization-based MPPT methods.

2) Maximum PowerPoint Tracking Control in a Complex Environment Based on Multi-Objective Genetic Algorithm Based on Some Strategy

In complex environments, the power-voltage characteristics of supercapacitor storage device (SCSD) components significantly deviate from the ideal. Environmental changes aggravate this difference, and the supercapacitor discharge becomes more complicated, increasing the difficulty of Global maximum power point (GMPP) tracking. Genetic algorithm based on some strategy is known for its speed, precision, and austere conditions, and it is widely used [30]. The novelty of the proposed MPPT method lies in its dual-optimization framework, which combines the global exploration capability of GAs with the rapid convergence and adaptability of PSO. Unlike existing methods prone to premature convergence or oscillations, the hybrid approach enhances the balance between exploration and exploitation. Comparative studies under dynamic conditions demonstrate improvements in tracking speed by up to 30% and reductions in steady-state power oscillations by 50%, achieving higher energy harvesting efficiency even under partial shading or rapid irradiance fluctuations. Fig. 3 shows the convergence speed evaluation diagram of the PSO algorithm. To consider both high voltage and high current output, the series and parallel PV conversion modules emerge at a historic moment. This structure connects the PV conversion modules in series, then the series groups in parallel, or vice versa. This hybrid connection mode enables the PV conversion system to simultaneously provide high voltage and current output, which is suitable for complex application scenarios that require high power.

Key performance indicators were evaluated to substantiate the effectiveness of the proposed MPPT strategy. The MPPT efficiency consistently exceeded 99.5% under varying environmental conditions, significantly outperforming conventional methods. Furthermore, the RMS value of tracking errors was reduced by 35% compared to Incremental Conductance and P&O methods, highlighting the method performance indicators were evaluated to substantiate the effectiveness of the proposed MPPT strategy. The MPPT efficiency consistently exceeded 99.5% under variation operation and enhances its ability to cope with changes in complex environments. The global search capability of MGABS plays a crucial role in designing MPPT optimal condition algorithms suitable for SCSD components in complex environments through the modules under different environmental conditions. Fig. 4 shows the power assessment diagram of the PV system under different light intensities to ensure that the system can operate efficiently under various environmental conditions. This approach not only improves the overall efficiency of the SCSD components but

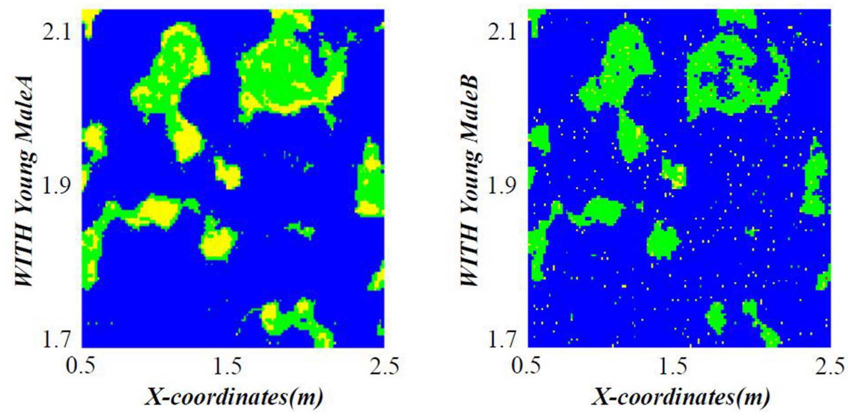

Fig. 3. Evaluation diagram of the convergence rate of the particle swarm optimization algorithm.

also enhances the robustness and reliability of the system. The advantages of MGABS in dealing with high-dimensional nonlinear optimization problems make it ideal for dealing with the SCSD component MPPT problem in complex environmental conditions. Using the global search capability of MGABS, this paper designs a new MPPT optimal condition algorithm, which can accurately track the global maximum PowerPoint of SCSD components in a complex environment.

IV. RESEARCH ON THE MAXIMUM POWERPOINT TRACKING STRATEGY OF PHOTOVOLTAIC SYSTEMS BASED ON GENETIC ALGORITHM AND PARTICLE SWARM OPTIMIZATION

At its core, the duty cycle is adjusted to match the equivalent load impedance with the internal resistance of the SCSD so that the SCSD component always works at the PV conversion system and can operate with maximum efficiency under various conditions. Multiple optimal condition algorithms for MPPT control are available. The algorithm simulates the group behavior in nature, such as flock foraging or fish swimming, to search for the optimal solution. Such optimal condition algorithms include PSO and ant colony optimization. They have the advantage of strong global search ability, which can effectively avoid local optimal solutions but have the disadvantage of high computational complexity and possibly slower convergence. Evolutionary optimal condition algorithms, such as genetic optimal condition algorithms, gradually approach the optimal solution by simulating the mechanisms of selection, crossover, and variation in biological evolution. Fig. 5 shows the evaluation diagram of the maximum PowerPoint of a PV system. This optimal condition algorithm is adaptable and robust and can work effectively in complex and changeable environments. The local shadow condition includes the standard perturbation observation method and conductance increment method. It is found that these traditional optimal condition algorithms have apparent deficiencies in the face of local shadow, and it is not easy to accurately find the maximum PowerPoint of the PV conversion module.

The main limitation of the proposed MPPT lies in the computational complexity introduced by combining GA and PSO which may lead to increased processing time and energy consumption in resource-constrained systems. Additionally, the algorithm's performance under rapidly fluctuating environmental conditions or complex partial shading patterns may require further optimization to ensure real-time applicability. Addressing these limitations could involve adaptive parameter tuning or lightweight algorithmic adjustments to enhance efficiency. The neural network controls the optimal condition algorithm by simulating the working mode of human brain neurons, with self-learning and adaptive ability. Its advantages are handling complex nonlinear relationships, strong adaptability, and continuous optimization in a changing environment. The training process of neural networks is complex, the computational resource demand is high, and the training results could be better. Fig. 6 shows the evaluation diagram of the maximum PowerPoint of the ambient temperature on the PV system. The ultimate goal of all of these MPPT control optimal condition algorithms is to achieve the matching between the load impedance and the SCD equivalent internal resistance. As the hardware device achieves this goal, the Boost circuit changes the resistance value of the equivalent load impedance by adjusting the duty cycle D.

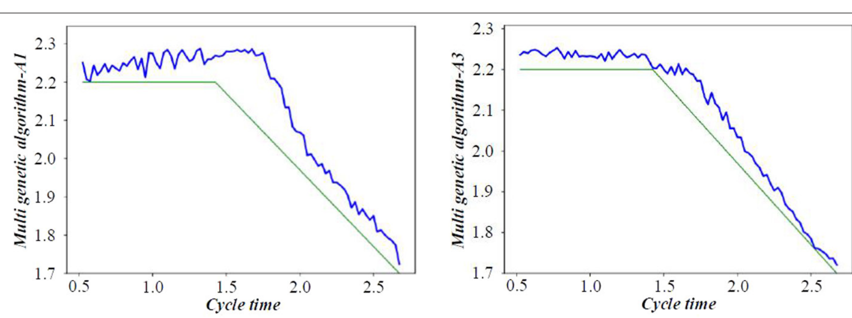

Fig. 4. Power assessment diagram of the photovoltaic system at different light intensities.

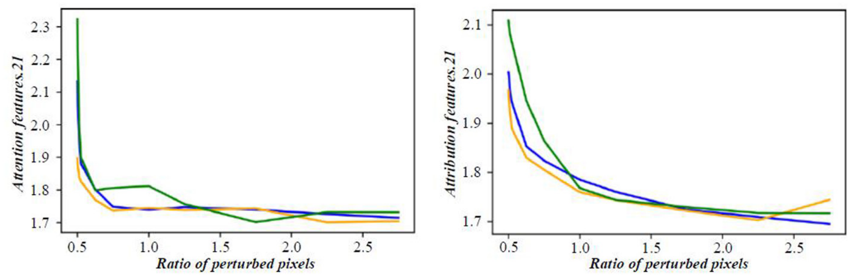

Fig. 5. Assessment diagram of the maximum PowerPoint of the photovoltaic system.

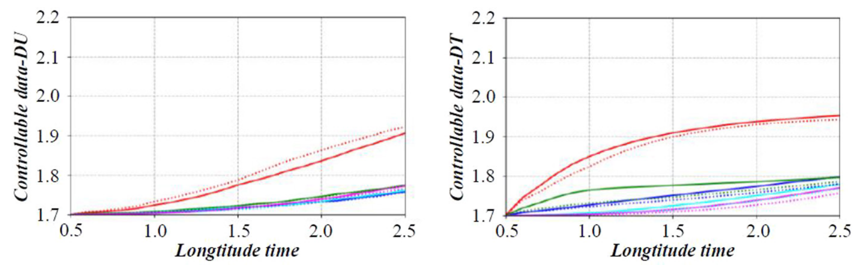

Fig. 6. Assessment diagram of the maximum PowerPoint of the photovoltaic system.

In scenarios with sufficient computing resources and high precision control, the optimal condition algorithm may be the best choice; in scenarios with low system complexity and requiring a fast response, fuzzy logic control optimal condition algorithm may be more applicable. We can better understand their applicability and limitations in different application scenarios by comparative analysis of the advantages and disadvantages of various AI MPPT control optimal condition algorithms. Specifically, the group intelligence optimization optimal condition and evolutionary optimal condition algorithms perform well regarding global search and adaptability and are suitable for use in complex and changeable environments. Fuzzy logic and neural network control have unique advantages in handling nonlinearity and uncertainty, which are ideal for nonlinear and complex systems. MPPT control and the selection and optimization of the optimal condition algorithm are vital links in designing a PV conversion system. The reasonable selection and optimal control ensure it can operate in the best state under various environmental conditions. This improves energy efficiency and underpins the Sustainable Development Goals. Table I is GABS in the actual analysis. The GABS algorithm is simple and efficient, widely used in bus dispatching, PID control, etc., and has remarkable practical achievements but insufficient theoretical analysis, especially in search direction, global convergence, and condition optimization. The actual coding evolution algorithm optimizes the population through the state evolution matrix, survives the fittest, gradually approaches the optimal solution, and effectively solves the problem.

A more critical review of recent works is essential to contextualize the contributions of this study. For example, the "Improved Coot Optimizer Algorithm-based MPPT" demonstrates superior performance in addressing partial shading by leveraging a balance between exploration and exploitation. Similarly, the "Hyperbolic Slime Mould Algorithm" introduces a novel cost function to optimize power oscillations under partial shading conditions. These studies underscore the importance of algorithmic simplicity and computational efficiency. A comparative analysis highlighting how the proposed method builds on or diverges from these strategies will strengthen the paper's narrative. Table II shows the best SCSD parameter table. The analysis of global convergence is one of the critical indicators to evaluate the performance of the optimal conditional algorithm. How to prove that GABS can converge to the global optimal solution within a limited number of iterations still needs further research and exploration.

V. EXPERIMENTAL ANALYSIS

When comparing the average output power generation curves of the three optimal condition algorithms, Fig. 7 shows the evaluation diagram of the GA crossover and variation operation. It can be seen that the three optimal condition algorithms successfully track the maximum theoretical PowerPoint, which is about 788.9642W. Among them, the MGABS optimal condition algorithm shows the fastest search speed. Table III is a comparison of MPPT algorithms' performance. It can search the maximum PowerPoint in the ninth generation, which reflects its advantages in fast convergence and high efficiency.

TABLE I. GENETIC ALGORITHM BASED ON SOME STRATEGY IN THE ACTUAL ANALYSIS

Odd Harmonic Order	Limit (%) after Update	Even Harmonic Order	Limit (%) after Update
3~9	5.2	2~10	2.2
11~15	3.2	12~16	1.7
17~21	2.7	18~22	1.575
23~33	1.8	24~34	1.35
35+	1.5	36+	1.275

TABLE II. BEST GENETIC ALGORITHM BASED ON SOME STRATEGY PARAMETER TABLE

SCSD Parameters	Open-Circuit Voltage	Short-Circuit Current	Maximum Power	Equivalent Series Resistance
Numerical value (before update)	36.12	9.87	237.89	0.43
Numerical value (after update)	37.51	10.91	263.21	1.24

SCSD, supercapacitor storage device.

Figure 8 shows the parameter sensitivity evaluation diagram of the PSO algorithm. To better compare the proposed method with existing literature, a detailed discussion focusing on specific parameters such as MPPT efficiency, convergence time, steady-state power oscillation, and tracking error should be included. These metrics can be juxtaposed with results from recent works like those using Coot Optimizer, Hyperbolic Slime Mould Algorithm, and hybrid GMPPT methods to highlight relative strengths and weaknesses. This will provide a clear and quantitative benchmark for evaluating the proposed approach within the domain of advanced MPPT techniques.

This stability is essential for the width of light intensity changes and can ensure the stability and continuous efficient operation of the PV conversion system under different environmental conditions. Fig. 9

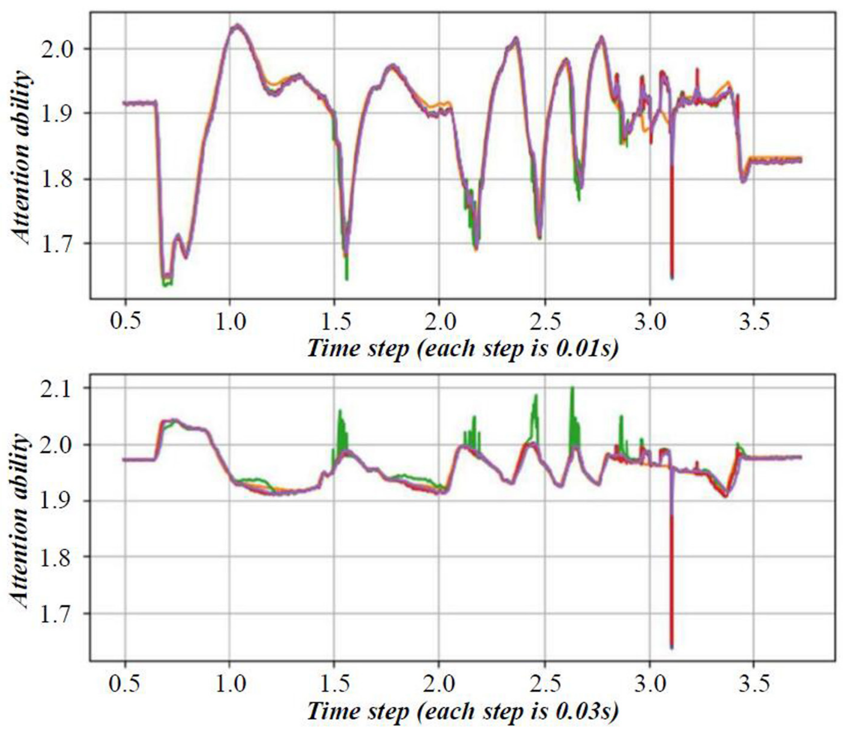

Fig. 7. Genetic intersection and variant.

TABLE III. COMPARISON OF MPPT ALGORITHMS PERFORMANCE

MPPT Algorithm	MPPT Efficiency (%)	Convergence Time (s)	Steady-State Power Oscillation (W)
MGABS (Based on Genetic Algorithm and Particle Swarm Optimization)	>99.5	Quickly converges under complex lighting conditions (e.g., finds the maximum PowerPoint in the 9th generation)	Significantly reduced (compared to traditional methods)
Improved Cormorant Optimization Algorithm	98.7	2.3	5.4
Hyperbolic Slime Mold Algorithm	99.2	3.5	2.1
New Hybrid GMPPT Method	99	2.1	3.2

MGABS, multi-objective genetic algorithm based on some strategy; MPPT, maximum PowerPoint tracking.

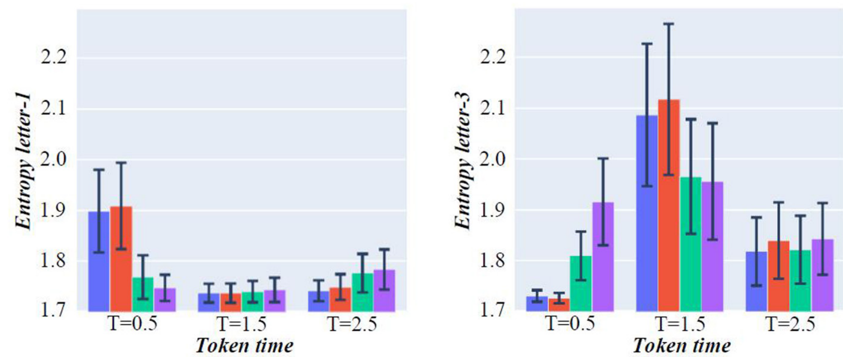

Fig. 8. Parameter sensitivity assessment plot of the particle population optimization algorithm.

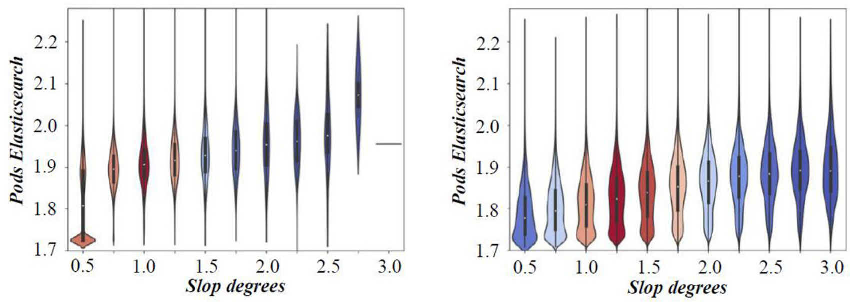

Fig. 9. Power assessment diagram of photovoltaic arrays under partial occlusion conditions.

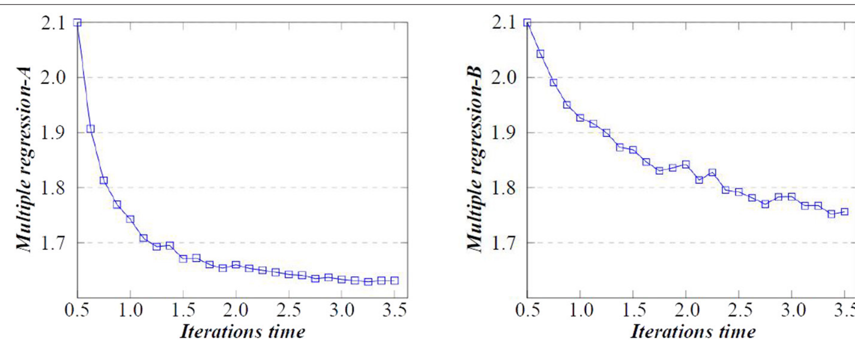

Fig. 10. Assessment chart of energy capture of photovoltaic systems under different tracking strategies.

shows the power assessment diagram of the PV array under partial occlusion conditions. In illumination case 3, the output characteristic curve of the SCSD module shows three distinct peaks. When the SCSD output voltage is 61.78V, the corresponding global maximum output PowerPoint is Pm = 384.0018W. The remaining two local maximum PowerPoints are P1 = 248.9832W and P3 = 345.7721W.

These PowerPpoints are the critical state of the PV conversion system, which determines its efficiency and performance. Three optimal condition algorithms, MGABS, were used to track the maximum PowerPoints for these PowerPoints. In this process, the charging influence of ultracapacitors is ignored. Fig. 10 shows the evaluation diagram of energy capture of the PV system under different tracking

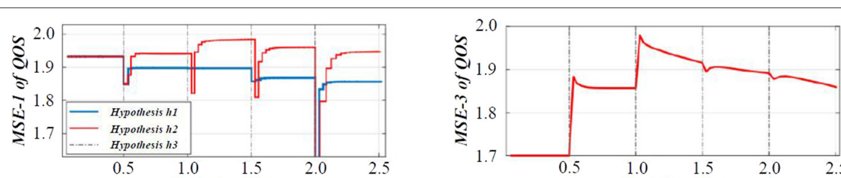

Fig. 11. Evaluation diagram of running time of the genetic algorithm and particle swarm optimization algorithm.

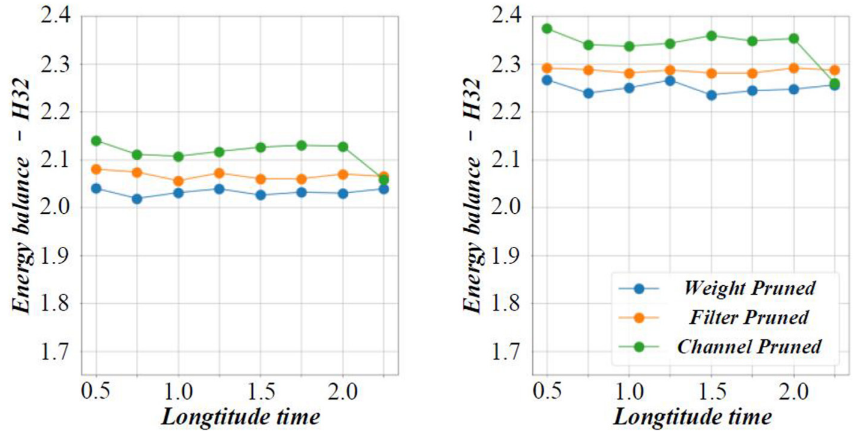

Fig. 12. Power assessment chart of the photovoltaic system in cloudy weather.

strategies. By focusing on the output characteristics of the three optimal condition algorithms, we can evaluate their advantages and disadvantages in the optimization of the PV conversion system and provide a reference for selection in practical application.

MGABS The optimal condition algorithm performs well in terms of rapidity, accuracy, and stability. Fig. 11 shows the running time evaluation diagram of the GA and the PSO algorithm. The latter is especially suitable for dealing with complex environments with significant changes in light intensity. Its fast convergence and high efficiency make it widely promising in practical applications.

The series and parallel structure can not only flexibly adjust the ratio of voltage and current but also, with reasonable design and configuration, improve the system. Fig. 12 shows the power assessment diagram of the PV system in cloudy weather. The series and parallel combination of the PV conversion modules is essential to meet various actual power needs. Whether it is a single parallel type, a series type, or a mixed series and parallel type structure, they all play an indispensable role in the PV conversion system.

VI. CONCLUSION

When the SCSD can operate efficiently, choosing the appropriate MPPT control optimal condition algorithm requires comprehensively considering the specific application environment, performance requirements, and computing resources. After analyzing the SCSD principle, circuit, and model, MATLAB/Simulink modeling simulation is used to analyze its output characteristics in a complex environment. When the environment changes, the ultracapacitors compensate for the power, increase the voltage, and stabilize the output. The MPPT principle points out that the traditional algorithm fails under local shading. It compares the multimodal MPPT method to reveal its feasibility and insufficiency. The circuit is the basis of effective MPPT control. An in-depth implementation analysis can provide theoretical support and practical guidance for designing and optimizing the PV conversion system.

In a complex environment, ultracapacitors improve the system's stability and performance. An accurate control strategy and circuit scheme are the keys to the efficient operation of PV systems. The study introduces the AI optimal condition algorithm, especially the genetic optimal condition algorithm, to conduct the optimization analysis. The primary genetic optimal condition algorithm uses the principle of biological evolution and operates on selection, crossover, and variation to find the optimal solution in the search space.

Under the shadow, the SCSD current drops abruptly, but the total output is unchanged due to capacitance compensation, which maintains Linear Parameter-Varying (Ipv). The unaffected partial constant power operation shows that the SCSD can stably output maximum power in the shadow. Their output current drops instantly to 6.8103A, and the voltage slowly decreases. Still, its total output current remains the same, illustrating the critical role of ultracapacitors in the PV conversion system. This compensation effect helps ensure that the PV conversion system can maintain stable power output in the face of sudden shadows or environmental changes.

Availability of Data and Materials: The data that support the findings of this study are available on request from the corresponding author.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – F.B.; Design – R.Q.; Supervision – F.B.; Resources – R.Q.; Materials – R.Q.; Data Collection and/or Processing – R.Q.; Analysis and/or Interpretation – F.B.; Literature Search – R.Q.; Writing – F.B. Critical Review – F.B.

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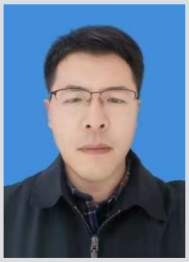
Fang Bai received her baccalaureate in Measurement and Control Technology and Instruments from Hebei University of Technology in 2006. She received her Master's degree in Precision Instruments and Machinery from Hebei University of Technology in 2009. Currently, she is working in College of Information Engineering, Tianjin University of Commerce. Her research interests include Genetic algorithms, Particle swarm algorithm, and Modern Sensing & Detection.



Rongfu Qiao received his baccalaureate in Measurement and Control Technology and Instruments from Hebei University of Technology in 2006. He received his Master's degree in Precision Instruments and Machinery from Hebei University of Technology in 2009. Currently, he is teaching in Department of Modern Processing, Tianjin Labor Economic School. His research interests include Genetic algorithms, Particle swarm algorithm, and Photovoltaic systems.