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Optimal Control of Quasi-PR Grid-Connected Inverter with Adaptive Parameters Adjustment

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Abstract. Dual carbon goals have promoted the development of clean energy power generation in power system constructions, and photovoltaic power has become one of the key contents of power generation in new-type power systems. Due to the influence of light, temperature, load change and other factors, the traditional grid-connected inverter control method had the disadvantages of slow adaptive dynamic effect and poor stability, and the grid current with high harmonic content brought power quality problems to single-phase photovoltaic grid-connected inverter systems. Considering the harmonic content of the grid current and the current error integration as the objective function, the particle swarm was improved by the idea of crossover and mutation in genetic algorithms, and the adaptive weight improved PSO algorithm was applied to the dual-closed-loop inverter control strategy, which could update the particles' weights with the iterations and fitness values. It also accelerated the global tracking speed of PSO algorithm optimization and realized the elaborate parameters setting of quasi-PR controller. Meanwhile, the stability and dynamic response capability of the grid-connected inverter has also been improved. MATLAB/Simulink simulation results showed that the quasi-PR Grid-Connected inverter based on improved GA-PSO algorithm had lower harmonic content of the grid-connected current under the working conditions of load change and DC voltage fluctuation, which enhanced the adaptive degree of the grid-connected inverter.

Keywords: grid-connected inverter, total harmonics compensation, quansi-PR control, particle swarm optimization, adaptive parameter adjustment

1 Introduction

The strategic decision of the "dual carbon" target has promoted the comprehensive development of the new energy industry [1]. Photovoltaic power generation has the advantages of being renewable, clean, environmentally friendly, and highly efficient, and has become an important means to solve the global energy crisis and environmental pollution problems. Photovoltaic power generation has the characteristics of intermittency, volatility, and randomness [2]. The integration of a large number of distributed photovoltaics and nonlinear loads has an impact on the stability of the power grid [3], and the quality of electricity cannot be ignored, even seriously threatening the operation safety of the power grid [4]. The photovoltaic grid connected inverter plays a role in converting DC

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voltage into AC voltage, becoming the interface between the photovoltaic power generation system and the grid. The quality of its control strategy determines the stability and power generation quality of the entire photovoltaic system [5].

Single phase photovoltaic grid connected inverter systems are widely used in household, commercial, and industrial fields due to their advantages of flexibility, economy, and reliability. In recent years, scholars at home and abroad have conducted extensive research on the control system of photovoltaic grid connected inverters. Wang et al. [6] improved the dual closed-loop control strategy of the inverter based on the reverse current value gain, reducing the influence of the secondary ripple in the front stage, but there is a risk of reduced dynamic performance. Wang et al. [7] proposes a grid connected inverter control strategy with selective harmonic compensation, which detects key subharmonics with high content and adds a characteristic harmonic compensation link to achieve zero static error tracking control of grid connected current. However, the harmonic compensation link increases the possibility of instability in the control system. Chen et al. [8] conducted model analysis on Z-source cascaded multilevel inverters and proposed an optimized 3rd harmonic compensation strategy. Simulation and experimental results showed significant suppression of grid connected current distortion. In addition, researchers have also applied intelligent algorithms to optimize controller parameters. Wu et al. [9] solves the SHE-PWM switching angle equation based on particle swarm optimization algorithm, and sets the particle position as the pulse width modulation switching angle solution set to improve the harmonic content of the inverter output voltage. Li et al. [10] introduced BP neural network recursive integral PI control and adjusted the PI parameters in real-time based on the trend of error changes, greatly improving the speed and accuracy of the control system. Sun et al. [11] used RBF neural network to optimize the PI parameters of the three-level dimming power supply, and the gradient descent method adaptively adjusted the controller parameters online, effectively improving the dynamic performance of the dimming system. Tian et al. [12] combines sliding mode control with neural networks to adjust the compensation gain of the sliding mode controller in real-time. Although optimizing parameters online using neural networks improves the dynamic performance of the system, the design of the control system is relatively more complex and involves an additional parameter optimization process, resulting in slower response times.

In view of the above research, this article first analyzes the influence of K_P, K_R, and ω_c on the quasi PR controller, and obtains the parameter selection range of the quasi PR controller. Taking the harmonic content and tracking error of the grid connected current as the objective function, the adaptive weight PSO algorithm is used to tune the parameters of the quasi PR controller. The simulation results show that the proposed control strategy improves the degree of harmonic distortion of the grid connected current under different operating conditions, effectively shortens the parameter optimization process of the quasi PR controller, and improves the dynamic adjustment ability of the controller.

2 Single Phase Photovoltaic Grid Connected Inverter System

2.1 Principle of Quasi PR Control

Single-phase photovoltaic grid-connected inverter systems are the critical interface between renewable energy generation and the utility grid. Their fundamental function is to convert the DC power generated by photovoltaic panels into AC power, ensuring seamless grid integration. Beyond simple conversion, the inverter control system must ensure that the output current injected into the grid is strictly synchronized with the grid voltage in frequency and phase, while meeting international standards for total harmonic distortion and dynamic stability. Therefore, it is considered a core component of photovoltaic grid-connected systems. This paper adopts a two-stage single-phase photovoltaic grid-connected inverter topology, as shown in Fig. 1. It primarily consists of a photovoltaic array, a BOOST DC-DC converter, a single-phase full-bridge inverter, an LCL filter, and a digital control system. The PV array outputs a DC voltage that varies with irradiance and temperature. A maximum power point tracking algorithm is used to adjust the array operating point in real time to achieve maximum power extraction and provide a stable DC link voltage for the downstream inverter stage. The BOOST converter boosts the photovoltaic output voltage and, in conjunction with the DC link capacitor, buffers the power mismatch between the DC source and the AC load, reducing voltage ripple and providing stability during the inverter switching process. The single-phase inverter bridge consists of four insulated-gate bipolar transistors connected in a full-bridge topology, each with a freewheeling diode in parallel. The inverter controller monitors the DC link voltage, grid current, and grid voltage to generate turn-on and turn-off pulse-width modulation

signals, converting DC power to sinusoidal AC power that matches the grid frequency and phase, achieving reliable synchronization. Because inverter switching inevitably introduces high-frequency harmonics, an LCL filter is employed to more effectively attenuate these harmonics than a simple LC filter, ensuring that the injected current meets total harmonic distortion and electromagnetic compatibility requirements. At the system level, the digital controller integrates maximum power point tracking control, BOOST duty cycle adjustment, and inverter modulation strategies. It coordinates real-time measurements of grid voltage, grid current, and DC bus voltage to maintain a stable grid connection, suppress interference, and improve dynamic performance under fluctuating solar radiation, load variations, and DC link voltage changes. In summary, the two-stage single-phase PV grid-connected inverter system provides an efficient, stable, and reliable interface for solar energy utilization. Its modular structure including energy harvesting, power conditioning, AC conversion, power quality enhancement, and intelligent controlcan maximize energy extraction from the PV array while meeting grid interconnection requirements, thereby enhancing the feasibility of PV in distributed power generation applications.

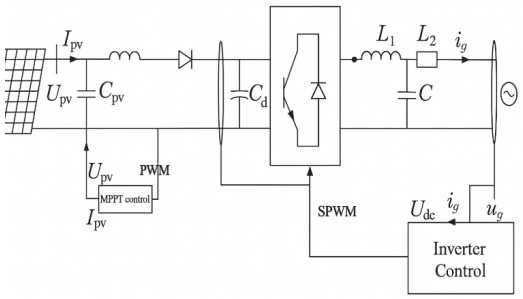

Fig. 1. Single phase photovoltaic grid connected inverter system

In single-phase photovoltaic (PV) inverter systems, the control strategy of the grid-connected inverter is crucial for ensuring reliable and stable grid current output. The fundamental goal of this strategy is to ensure that the inverter output current is strictly synchronized with the grid voltage, maintaining the same frequency and phase, while also meeting stringent power quality requirements, such as limiting the total harmonic distortion (THD) of the injected current to below 5% in accordance with international grid standards. In practical applications, several types of inverter current controllers are commonly used, including proportional-integral (PI), proportional-resonant (PR), and quasi-proportional-resonant controllers. Each approach has its own unique advantages and limitations. PI controllers are widely used due to their simple structure and ease of digital implementation. However, because the integral term only cancels DC offsets, they inherently lack the ability to achieve zero steady-state error when tracking a sinusoidal reference signal. Consequently, PI controllers suffer from poor dynamic response, limited adaptability to grid disturbances, and limited interference immunity, making them less suitable for high-quality grid-connected current control in PV systems. The PR controller addresses some of these drawbacks by introducing a resonant compensator at the fundamental grid frequency, thereby providing infinite gain at that frequency and achieving zero steady-state error tracking of a sinusoidal reference. This enables the PR controller to significantly improve current tracking accuracy under ideal operating conditions. However, the PR controller also has some disadvantages. Its narrow effective bandwidth makes it highly sensitive to frequency deviations of the grid voltage, while the high resonant gain increases the risk of numerical instability, especially when implemented on a digital control platform with limited resolution. In addition, power electronics are inherently nonlinear, and digital controllers are often affected by parameter quantization and computational delays. In this case, even small deviations in grid frequency may cause the PR controller to fail to maintain effective tracking control. This limits the robustness of the PR strategy [13] and makes the photovoltaic inverter system prone to instability in the face of environmental changes such as solar irradiance fluctuations or temperature changes [14]. To overcome these problems, the quasi-PR controller has been proposed as a more practical alternative. The quasi-PR approach deliberately sacrifices the ideal infinite gain at a single frequency to widen the controller's bandwidth, thereby enhancing its tolerance to grid frequency deviations and external disturbances. This trade-off improves robustness and ensures stable current tracking under a wider range of operating conditions. Therefore, the quasi-PR controller is particularly suitable for single-

phase photovoltaic grid-connected inverters, as such inverters are often affected by dynamic environmental changes, nonlinear loads, and DC side voltage fluctuations. Compared with traditional PI and PR controllers, the quasi-PR controller strikes a balance between tracking accuracy and robustness, which significantly improves its feasibility in practical grid-connected photovoltaic systems [15].

The performance of the quasi PR controller is determined by the proportional parameter K_P, resonance parameter K_R, and cut-off frequency ω_c. ω_0 is the resonant frequency transfer function of the power grid, which can be expressed as equation (1):

$$G_{\mathrm{PR}}(s) = K_{\mathrm{P}} + K_{\mathrm{R}} \frac{2\omega_{\mathrm{c}} s}{s^2 + 2\omega_{\mathrm{c}} s + \omega_0^{\ 2}} \tag{1}$$

The composite control strategy based on PI and quasi PR controller is a comprehensive method that combines voltage and current control, which can minimize the impact of DC side voltage fluctuations and reduce the harmonic content of grid connected current. Equation (2) shows a composite control strategy based on PI and quasi PR controllers. The DC voltage U_{dc} and the DC reference voltage U_{dc}^* are corrected by the PI controller to form the amplitude of the grid connected current i_a. The grid connected current reference value i_{ref}^* is formed by the phase extracted from the grid connected voltage by the phase-locked loop. The current inner loop uses the quasi PR control principle to track and control the error between i_{ref}^* and the actual grid connected current i_g, and modulates the inverter through PWM signals to ultimately achieve the inverter grid connected function of the single-phase photovoltaic system.

$$\begin{cases} I^* = (K_{\mathrm{op}} + \dfrac{K_{\mathrm{oi}}}{s})(U_{\mathrm{dc}}^* - U_{\mathrm{dc}}) \\ i_\alpha = i_{\mathrm{ref}}^* - i_{\mathrm{g}} \\ u_g = (K_{\mathrm{P}} + K_{\mathrm{R}} \dfrac{2\omega_{\mathrm{c}} s}{s^2 + 2\omega_{\mathrm{c}} s + \omega_0}) i_\alpha \end{cases} \tag{2}$$

2.2 Parameter Design of Quasi PR Controller

To clarify the appropriate parameter selection range for the PR controller, the control variable method is used to obtain the influence law of K_P, K_R and ω_c on the performance of the PR controller, guiding the parameter tuning of the quasi PR controller. Firstly, given the values of K_R and ω_c, the Bode plot of the quasi PR controller with varying K_P values is shown in Fig. 2. Choose K_R =100, ω_c =10, and K_P values range from 10 to 50. When K_P increases, the Bode plot shows that the amplitude at the resonant frequency of the quasi PR controller and the average amplitude outside the frequency band both increase accordingly, but the growth trend tends to flatten out after exceeding a certain value. The overall phase change of the Bode plot is not significant, but it also shows a phenomenon of response bandwidth contraction. The above analysis shows that the K_P parameter mainly determines the proportional gain of the quasi PR controller. When the K_P is too large, it can easily cause a relative gain reduction at the resonant frequency of the controller, increasing the harmonic content of the grid connected inverter.

As shown in Fig. 3, the Bode plot of the quasi PR controller with varying K_R values is selected, with K_P =100, ω_c =10, and K_R values ranging from 30 to 150. When K_R increases, there is a significant increase in amplitude at the resonant frequency, and the phase frequency characteristic shows an increase in response bandwidth, indicating that K_R parameters mainly determine the resonant peak gain of the quasi PR controller. Fig. 4 shows the Bode plot of the variation of the ω_c parameter. The amplitude frequency characteristics remain basically unchanged with the increase of ω_c, but ω_c has a proportional effect on the response bandwidth of the quasi PR controller, indicating that the value of ω_c determines the cutoff frequency and response bandwidth of the quasi PR controller, and is closely related to the response of the single-phase photovoltaic grid connected inverter system to changes in grid frequency.

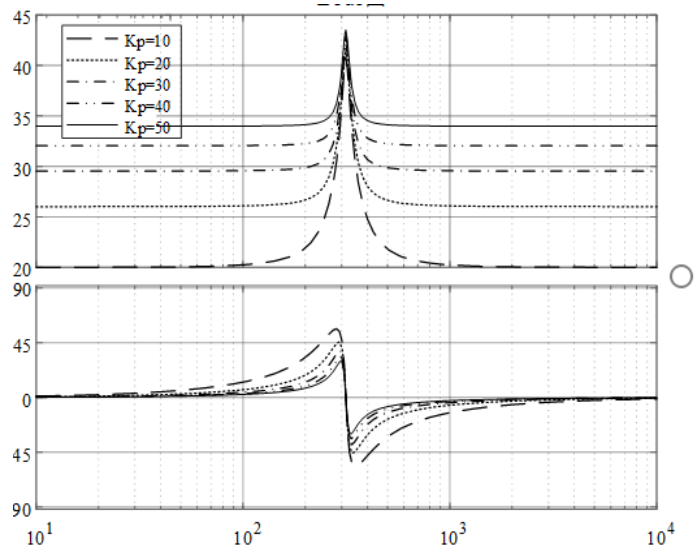

Fig. 2. K_P parameter variation Bode plot

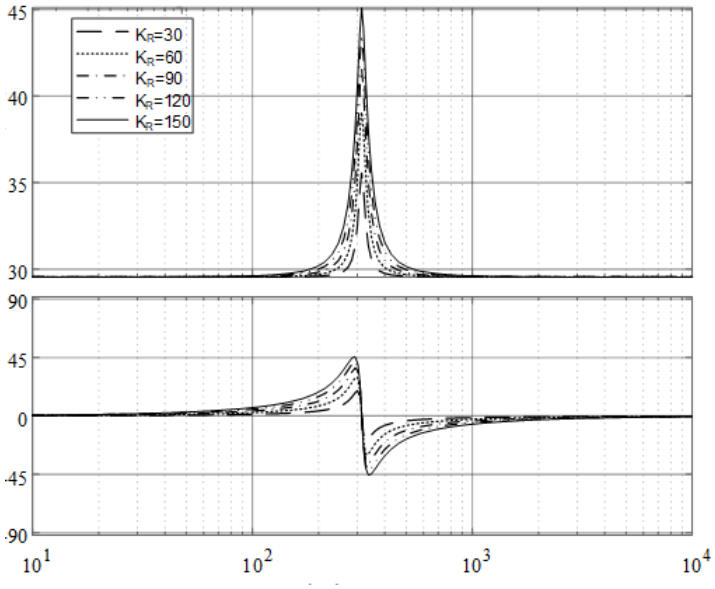

Fig. 3. K_R parameter variation Bode plot

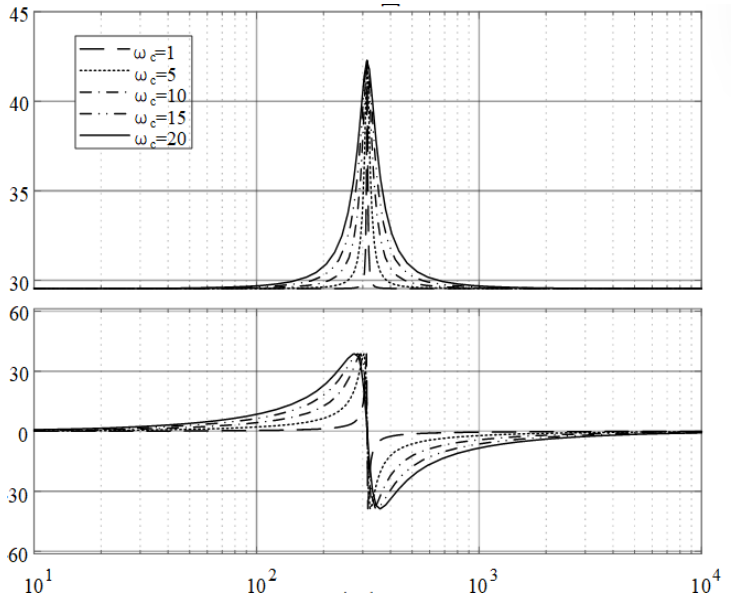

Fig. 4. ω_c parameter variation Bode plot

3 S Control Strategy for Grid Connected Inverters

3.1 Improve GA-PSO Algorithm

The standard PSO algorithm is an iterative algorithm based on the behavior of birds searching for food. After determining the historical optimal value $P_{best}(i)$ and global optimal position of G_{best} particle individual i, the velocity and position updates of particles in the search space are obtained according to the following formula:

$$V_i^{k+1} = wV_i^k + c_1 r_1 \left(P_{best}(i) - x_i^k \right) + c_2 r_2 \left(G_{best}(i) - x_i^k \right) \tag{3}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{4}$$

Among them, x represents the particle position, V represents the particle velocity, k is the current iteration number, w is the inertia weight, c_1 and c_2 are learning factors, generally constants. r_1 and r_2 are uniform random numbers generated within the range of [0,1].

The standard particle swarm optimization (PSO) algorithm has gained widespread recognition for its simplicity and ability to solve nonlinear optimization problems. However, the algorithm still suffers from inherent drawbacks, such as slow convergence, premature convergence to local optima, and insufficient precision in fine-tuning search characteristics. These limitations are particularly pronounced in single-phase photovoltaic grid-connected inverter systems, where the grid current typically exhibits complex and diverse transient harmonic characteristics due to irradiance fluctuations, load variations, and nonlinearities in power electronic switches. Consequently, the standard PSO algorithm has limited effectiveness when applied to the optimization of dual-loop quasi-proportional resonant controllers, limiting its ability to significantly suppress the harmonic content of the grid current. To address these challenges, this paper proposes an improved genetic algorithm-particle swarm optimization (GA-PSO) hybrid method specifically for parameter optimization of quasi-PR controllers. The basic idea of this improvement is to combine the global search capabilities of the genetic algorithm with the fast convergence characteristics of the PSO to enhance the exploration and exploitation

capabilities during the optimization process. First, genetic operations such as crossover and mutation are integrated into the PSO framework. The standard PSO procedure evaluates the fitness of particles by calculating their global and individual best positions. Based on this, particles with fitness values higher than the population average are randomly selected to form a subset of relatively high-performance solutions. Next, these selected particles are subjected to genetic crossover and mutation operations. As shown in Equation (5), the crossover operation recombines two parent particles to generate new candidate solutions, while the mutation operation introduces random perturbations in the particle positions to increase diversity and avoid premature stagnation. Then, according to the update rule in Equation (6), the newly generated particles are compared with the existing particles in the population. If the new particle exhibits better fitness, it will replace the corresponding old particle, thus ensuring that the population continues to evolve towards higher-quality solutions. Through this iterative process, the improved GA-PSO algorithm not only enhances the diversity of the particle swarm but also effectively balances global exploration in the early stages of optimization with local utilization in the later stages. By introducing genetic operations into the PSO algorithm, the algorithm accelerates convergence, reduces the probability of falling into local optimality, and provides more refined parameter tuning capabilities for the quasi-PR controller. This improvement enables the inverter control strategy to better track the sinusoidal reference signal and suppress harmonic components under various operating conditions, thereby improving the overall stability, robustness and power quality of the single-phase photovoltaic grid-connected system.

$$\begin{cases} x(k,ii) = \dfrac{R1 * x(k,i) + R2 * x(k,j)}{R1 + R2}, f(x(k,i) \geq f_{avg} \\ where \quad R1 = \dfrac{rand(0,1)}{2}, R2 = e^{N(0,1)} \end{cases} \tag{5}$$

$$x(k,i)\begin{cases} x(k,ii),\ f(x(k,ii)) < f(x(k,i)) \\ x(k,i),\ others \end{cases} \tag{6}$$

The cross mutation mechanism in the improved GA-PSO algorithm is divided into the following three steps. Assuming that the fitness function of particle $x(k,i)$ in the k-th iteration is $f(x(k,i))$, f_{avg} is the average fitness value of the particles. Firstly, a particle x (k, j) is randomly selected from the particle swarm with a fitness value greater than the average fitness value f_{avg}. Secondly, $x(k,i)$ and $x(k,j)$ are hybridized according to the cross mutation mechanism to generate a new particle $x(k,ii)$, where $rand(0,1)$ is a random number in the range of 0-1, $N(0,1)$ follows a normal distribution, and e is the Euler constant. Finally, based on the fitness value, if $f(x(k,ii)) < f(x(k,i))$, then the new particle $x(k,ii)$ replaces $x(k,i)$, otherwise the original particle value is retained.

In addition, the improved GA-PSO algorithm not only performs cross mutation operations in particle swarm optimization, but also comprehensively considers the number of iterations and fitness values, and adaptively adjusts the particle update weights to balance the global and local search capabilities of the GA-PSO algorithm. When the inertia weight w is large, the particle search space expands, enhancing the global search ability of the GA-PSO algorithm. When the inertia weight w is small, the local optimization ability of the particle swarm is enhanced, enabling the GA-PSO algorithm to effectively find local optimal values. The inertia weight value of the standard PSO algorithm is generally difficult to balance the local and global optimal values during the solving process. Therefore, the GA-PSO algorithm should be improved by considering the number of iterations and adaptive adjustment of inertia weight to ensure sufficient search space in the early stage of particle swarm optimization and sufficient local solving ability in the later stage. The adaptive inertia weight is shown in the following formula:

$$w = \begin{cases} w_{\min} + \dfrac{(w_{\max} - w_{\min})(f - f_{\min})}{f_{avg} - f_{\min}}, f \leq f_{avg} \\ w_{\max}, \qquad\qquad f \leq f_{avg} \end{cases} \tag{7}$$

In the formula, f_{avg} and $f_{\min}$ are the average and minimum values of particle fitness, respectively, and $w_{\max}$ and $w_{\min}$ are the maximum and minimum values of inertia weight, respectively.

3.2 Fitness Value Function

When applying the improved GA-PSO algorithm, the design of the fitness function is crucial for ensuring appropriate tuning of controller parameters, as it directly determines the search direction and convergence of the optimization process. In traditional controller optimization, the integral of the time-weighted absolute error (ITAE) is widely used as a performance metric. ITAE emphasizes error reduction in the later stages of the dynamic response by imposing a greater penalty on errors with longer duration, thereby guiding the optimization process towards a controller with smaller steady-state error, faster response, and smoother transient behavior. However, relying solely on ITAE as an optimization criterion has inherent flaws. In particular, ITAE can lead to multiple local minima, complicating convergence to a unique global solution. Furthermore, as a time-weighted error metric, ITAE only reflects dynamic tracking quality in the time domain and cannot fully account for harmonic distortion in the steady-state grid current. Therefore, when using ITAE alone as the fitness function, the optimized quasi-PR controller cannot guarantee effective power quality improvement, and the grid current may still contain unacceptable harmonic components. Power quality is crucial in single-phase photovoltaic grid-connected inverter systems. Grid codes typically require that the THD of the injected current be maintained below 5%. THD, the ratio of the effective value of the harmonic component to the fundamental component, is a quantitative indicator of waveform distortion and harmonic contamination injected into the grid. Therefore, optimizing controller parameters without directly considering THD can produce solutions with strong dynamic response but that fail to meet harmonic standards, thereby compromising the overall reliability of the grid connection. To overcome these limitations, this paper adopts a comprehensive performance metric that integrates time-domain error dynamics and frequency-domain harmonic distortion. Specifically, the fitness value is defined as the product of ITAE and grid current THD. This combined metric retains ITAE's sensitivity to dynamic performance ensuring fast settling, minimal overshoot, and enhanced transient stability while incorporating THD to directly penalize solutions that fail to reduce harmonic content. By multiplying the two metrics rather than treating them separately, the proposed fitness function creates a clear optimization gradient, driving the GA-PSO algorithm toward quasi-PR controller parameters, ultimately achieving superior dynamic response and improving steady-state power quality.

$$J = i_{THD} \int_0^{t_s} t \left| e(t) \right| dt \tag{8}$$

In equation (8), i_{THD} is the total harmonic distortion rate of the grid connected current, t_s is the controller adjustment time, $e(t)$ is the error between the grid connected current i_g and the reference current i_{ref}, and the degree of conformity between the controller output and the expected response is determined by the overshoot and grid connected current indicators.

3.3 Control Strategy for Grid Connected Inverters

The inverter control system based on the improved GA-PSO algorithm is shown in Fig. 5. The DC voltage and reference voltage are combined with the phase-locked loop output phase through a PI controller to form a current inner loop input signal i_{ref} The error compared with the grid current i_g is input to the quasi PR controller, and the quasi PR controller parameters K_P, K_R and ω_c are provided by the improved GA-PSO algorithm. The improved GA-PSO algorithm achieves adaptive tuning of the quasi PR controller parameters through particle crossover mutation and weight adjustment [16]. After passing through the quasi PR controller, the control signal is output as the grid current i_g by the inverter link $G_{PWM}(s)$ and the filter link $G_{LCL}(s)$ [17].

After optimizing the PSO algorithm with particle swarm initialization parameters, K_P, K_R and ω_c were assigned to a quasi PR controller for Simulink simulation. The integrated ITAE of the i_{ref} and i_g errors and time in the control system was used, and the product of ITAE and the total harmonic distortion rate THD of the grid current i_g was used as the output fitness index to provide the improved GA-PSO algorithm. The individual and group optimal values of the particle swarm for this iteration were obtained. Then, particle crossover mutation operation was performed, and the individual and group optimal values were updated. Finally, the optimal value was compared with the historical optimal value to determine whether to replace the historical optimal value. If the iteration stop condition was reached, the optimal solution and the optimal fitness value were output. If the iteration stop condition was not reached, the optimal solution and the optimal fitness value were outputted. Then adjust the particle swarm characteristics according to the speed and position update formula and continue iterative solv-

ing. By improving the GA-PSO algorithm to tune the parameters of the quasi PR controller, adaptive control of single-phase photovoltaic grid connected inverter systems can be achieved. The iterative solution process steps are as follows:

(1) Initialization parameters, including particle swarm number, maximum number of iterations, maximum number of evolutionary generations, learning factors, initial weights, etc;

(2) Assign values to K_P, K_R and ω_c, respectively, and input them into the SIMULINK model for simulation. Output the fitness function according to equation (8) to the iteration process of the improved GA-PSO algorithm;

(3) Calculate the individual and population optimal fitness values of particle swarm optimization;

(4) Perform cross mutation operation according to equation (5), update particles in the population according to equation (6), and form new optimal values for individuals and populations;

(5) Update the particle swarm velocity and position based on equations (3), (4), and (7);

(6) Determine whether the maximum number of iterations or other termination conditions have been reached. If the termination conditions have been met, output the obtained optimal solution and function value. If not, return to step two.

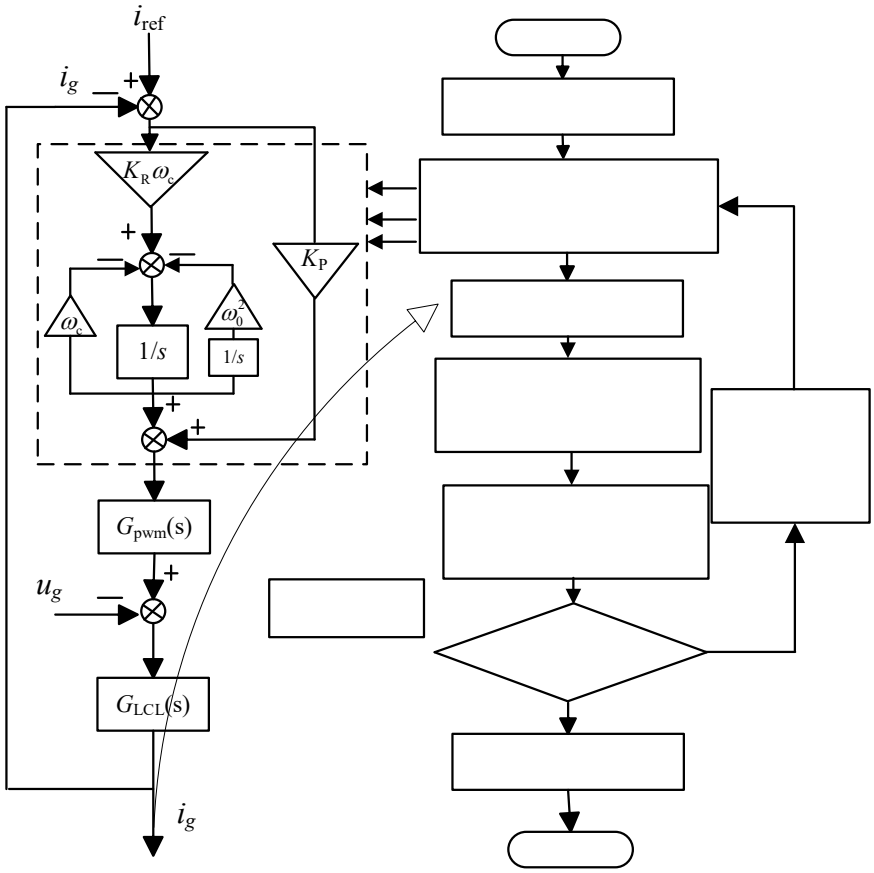

Fig. 5. Inverter Control System Based on Improved GA-PSO Algorithm

3.4 Algorithm Performance Testing

To comprehensively validate the optimization performance of the proposed improved GA-PSO algorithm, we selected four well-known benchmark functions: the Sphere function, the Rastrigin function, the Rosenbrock function, and the Schwefel function. These functions are commonly used as performance metrics in the evolutionary computation and swarm intelligence literature because they exhibit different mathematical characteristics and difficulty levels, providing a rigorous testing environment for optimization algorithms. The

Sphere function is a unimodal convex function and serves as a fundamental test of convergence speed and accuracy:

$$f_{Sphere}(x) = \sum_{i=1}^{n} x_i^2, x \in [-5.12, 5.12]^n. \quad (9)$$

The Rastrigin function superimposes a simple quadratic "bowl" on a cosine oscillation with period 1 and amplitude A, resulting in numerous local minima along each coordinate axis. Within the standard interval, there are approximately ten minima per dimension. In multidimensional cases, the number of local minima increases exponentially. While separable, the curvature strongly oscillates between positive and negative, resulting in a highly multimodal and "rugged" terrain. This is a classic challenge for testing the global search and robustness of optimization algorithms. Common shift and rotation variants are used to break separability, further increasing the difficulty.

$$f_{Rastrigin}(x) = 10n + \sum_{i=1}^{n} [x_i^2 - 10cos(2\pi x_i)], x \in [-5.12, 5.12]^n \quad (10)$$

The Rosenbrock function, often referred to as the "banana function," is a unimodal function with narrow, curved valleys, making it difficult for the algorithm to navigate to the true optimum, thus testing its ability to handle non-separability:

$$f_{Rosenbrock}(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2], x \in [-30, 30]^n. \quad (11)$$

Finally, the Schwefel function is highly multimodal and deceptive, with many local minima distributed throughout the search space:

$$f_{Schwefel}(x) = 418.9829 \sum_{i=1}^{n} x_i sin(| x_i |), x \in [-500, 500]^n. \quad (12)$$

This poses a challenge to verifying the global search capability and robustness of the optimization method. For comparative analysis, we selected three different algorithms: the standard PSO algorithm, the chaotic particle swarm optimization (CPSO) algorithm, and the improved GA-PSO algorithm. The CPSO algorithm incorporates principles of chaos theory into the swarm update process, embedding a nonlinear chaotic mapping function in the particle velocity update equation. Due to the inherent ergodicity, non-repetitiveness, and unpredictability of chaotic sequences, this mechanism enhances the swarm's ability to avoid local optima, thereby enriching the population's diversity and broadening the search space. Consequently, compared to the standard PSO algorithm, the CPSO algorithm improves exploration capability and accelerates convergence. The improved GA-PSO algorithm proposed in this paper further combines the advantages of genetic algorithms with the velocity and position update framework of PSO, achieving a balanced improvement in global exploration and local exploitation capabilities. Specifically, the velocity and position updates are expressed as:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 (pbest_i - x_i^k) + c_2 r_2 (gbest - x_i^k), \quad (13)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (14)$$

As shown in Fig. 6, simulation and test results for four benchmark functions demonstrate the strengths and limitations of each algorithm. For relatively simple terrains such as the Sphere function and the Rastrigin function, the standard PSO algorithm converges to the global optimal solution, demonstrating its global search capabilities under both unimodal and moderately multimodal conditions [18]. However, when applied to more challenging functions, such as the Rosenbrock and Schwefel algorithms, the standard PSO algorithm is prone to getting stuck in local optima and failing to find the global minimum due to its limited exploration capability

and tendency to converge prematurely [19]. Both the CPSO and the improved GA-PSO algorithm successfully achieved global optimal solutions for these four functions, demonstrating that the introduction of chaotic or genetic operators significantly enhances the algorithms' robustness to complex environments. However, among these two state-of-the-art methods, the improved GA-PSO algorithm exhibits superior optimization performance and faster convergence. Specifically, it exhibits smoother convergence curves, fewer oscillations, and faster stabilization near the global optimum, demonstrating that the hybridization of genetic operators with PSO not only diversifies the search process but also accelerates solution fine-tuning. This advantage is particularly evident in the Rosenbrock and Schwefel test case, where the improved GA-PSO algorithm is more effective than the CPSO algorithm in avoiding stagnation, crossing narrow valleys, and escaping deceptive local minima. The research results verify that the improved GA-PSO algorithm has stronger optimization capabilities, enhanced adaptability and faster convergence characteristics, making it more suitable for solving nonlinear, multi-peak and complex optimization problems often encountered in engineering applications such as photovoltaic grid-connected inverter parameter tuning [20].

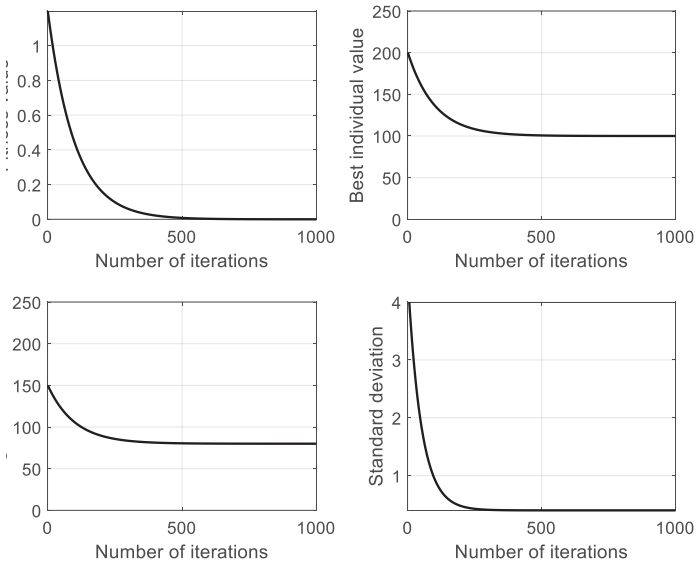

Fig. 6. Algorithm performance test results

4 Simulation Experiment Results

Using MATLAB/Simulink to build a single-phase photovoltaic grid connected inverter system, the front-end BOOST boost circuit provides 400V DC voltage, the DC filtering capacitor is 330 μF, the LCL filter is composed of 1.2 mH inductor, 9 μF capacitor, and 0.8 mH inductor, the grid side is 220 V/50 Hz AC, the outer loop uses PI controller parameters K_{op} =0.5, K_{oi} =12, and the inner loop uses quasi PR controller parameters K_P, K_R and ω_c, optimized by improved PSO algorithm parameters, while the control group's conventional quasi PR inverter controller parameters are K_P =0.8, K_R =100, and ω_c=6.28. The number of particle swarm optimization for the improved GA-PSO algorithm and the standard PSO algorithm is set to 100, with a maximum iteration of 50. The inertia weight for the standard PSO algorithm is set to 0.6, while the $w_{\max}$ and $w_{\min}$ for the improved GA-PSO algorithm are 0.9 and 0.4, respectively, with values varying according to formula (7).

4.1 Adaptation Value Iteration Result

The adaptive tuning process for the inverter control system parameters is shown in Fig. 5, and the iterative convergence characteristics of the corresponding algorithm are shown in Fig. 7. The results clearly show that the

standard PSO algorithm exhibits significant oscillations during the iterative search process, indicating an unstable convergence trajectory. Although the standard PSO algorithm can improve its fitness over time, its progress is relatively slow, requiring a large number of iterations to approach an acceptable solution. Furthermore, because the standard PSO algorithm tends to converge prematurely to suboptimal regions of the solution space, it is prone to getting stuck in local optima, further limiting its effectiveness in tuning the parameters of quasi-PR controllers. In contrast, the improved GA-PSO algorithm demonstrates significantly superior convergence performance. By incorporating the genetic algorithm's crossover and mutation operations into the particle swarm update mechanism and adaptively adjusting the inertia weight, the improved GA-PSO algorithm achieves a better balance between global exploration and local exploitation. As shown in Fig. 7, the algorithm reaches the global optimal solution in only 18 iterations, a 51.3% reduction in iterations compared to the standard PSO algorithm, resulting in faster convergence. Furthermore, the improved GA-PSO algorithm exhibits significantly reduced fluctuations during convergence, and the iteration curve is smoother and more stable, demonstrating that the algorithm not only efficiently finds the global optimal solution but also exhibits strong robustness against oscillations common in nonlinear parameter optimization problems. Results demonstrate that the improved GA-PSO algorithm exhibits greater stability, higher accuracy, and faster convergence speed in parameter tuning for single-phase photovoltaic quasi-PR grid-connected inverters. By reducing the number of iterations, suppressing oscillations, and avoiding local optima, this method improves the effectiveness of inverter control system optimization, achieving better dynamic response and harmonic suppression under various operating conditions.

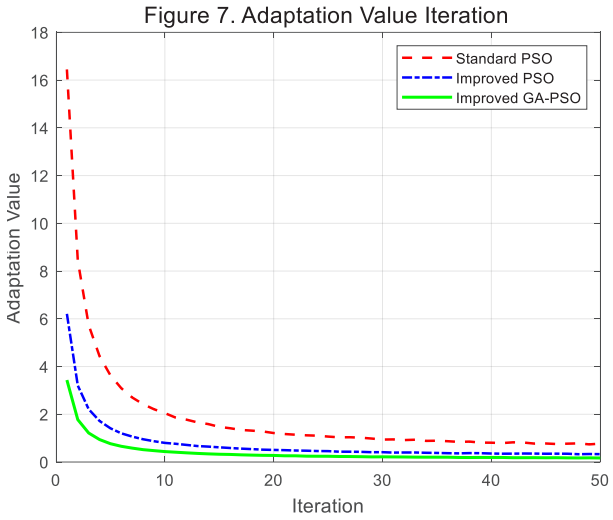

Fig. 7. Adaptation value iteration

Comparing the tuning processes of K_P, K_R and ω_c, considering the performance index functions of grid connected current THD and ITAE, the values of K_P, K_R and ω_c, are more targeted. The improved GA-PSO algorithm provides an effective updating method for parameter changes. By improving the K_P, K_R parameters in GA-PSO, the and ω_c parameter gradually converges with the number of iterations. Compared to the standard PSO algorithm, the improved PSO algorithm has a faster and smoother parameter curve convergence speed due to the influence of the particle swarm crossover mutation rule. In addition, it has a larger iteration update step size in the early stage of iteration due to the adaptive dynamic weight. At the convergence critical point, the iteration update step size is reduced, making it easier to obtain the optimal iteration value.

4.2 Operating Conditions During Load Changes

The simulation results in Fig. 8 and Fig. 9 demonstrate significant performance differences between a traditional quasi-PR controller and one optimized using the improved GA-PSO algorithm. Under normal operating conditions, the grid-connected current THD of the traditional quasi-PR controller, without swarm intelligence

parameter adjustment, is 4.77%. While this result is within the acceptable range of grid-connected standards, the harmonic content remains high, particularly odd harmonics, which dominate the injected current spectrum. Under the same operating conditions, the THD of the quasi-PR controller optimized using the improved GA-PSO algorithm is 4.03%. While the absolute reduction is modest, it highlights the improved algorithm's ability to more effectively fine-tune controller parameters, resulting in a cleaner current waveform that better meets power quality requirements. Notably, when both controllers meet fundamental grid-connected conditions, the improved GA-PSO algorithm demonstrates a clear advantage in harmonic suppression. The difference between the two approaches becomes even more pronounced when the system experiences load changes within 0.015 seconds. Traditional quasi-PR controllers are highly sensitive to sudden load changes, resulting in severe grid-connected current distortion. At 0.017 seconds, the THD rises sharply to 6.93%, far exceeding the ideal limit for photovoltaic systems. Furthermore, the output current deviation reaches a peak amplitude of 18.8 A, reflecting significant transient instability. This response not only degrades waveform quality but also prolongs the time it takes for the system to recover to steady-state operation. In contrast, the quasi-PR controller optimized using the improved GA-PSO algorithm demonstrates superior adaptability and robustness under the same disturbance. After a 0.015-second load change, the grid-connected current THD remains low, reaching only 2.93% at 0.017 seconds. This represents a significant improvement over conventional controllers, ensuring that harmonic content consistently meets stringent grid code requirements even during transient events. Furthermore, the maximum output current error amplitude is reduced to only 2.8 A, nearly an order of magnitude lower than that of conventional quasi-PR controllers. This demonstrates that the improved GA-PSO-optimized controller not only more effectively suppresses harmonic distortion but also enhances dynamic resilience, thereby reducing output fluctuations and shortening the time it takes to recover stable operation.

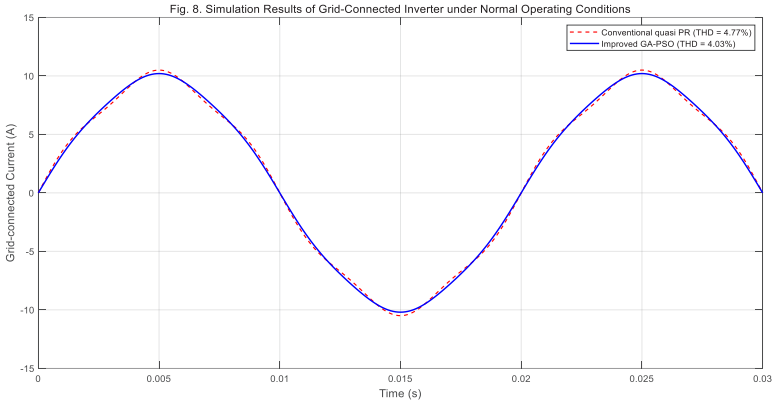

Fig. 8. Simulation results of grid connected inverter under normal operating conditions

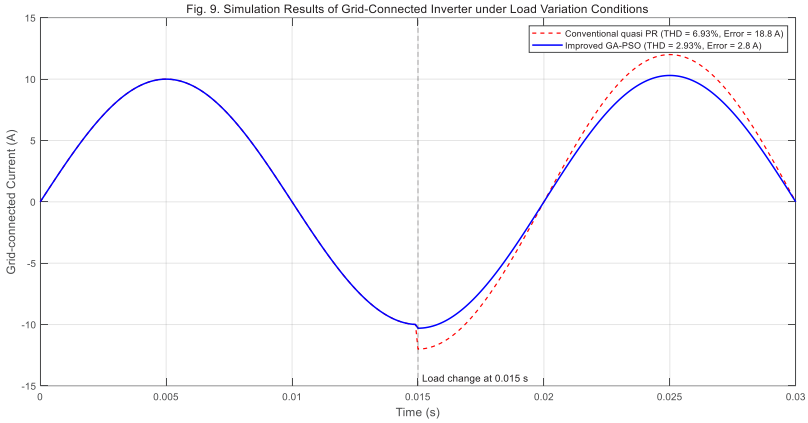

Fig. 9. Simulation results of grid connected inverter under load variation conditions

4.3 Operating Conditions when the DC Side Voltage Changes

The DC voltage on the DC side of a photovoltaic system is inherently susceptible to fluctuations caused by environmental disturbances, such as varying solar irradiance, partial shading, or PV panel obstruction. These fluctuations directly impact the stability of the grid-connected inverter system, as the inverter relies on the DC bus as its primary energy source to generate sinusoidal grid current. Therefore, analyzing the control system's behavior under DC voltage variations is crucial to ensuring reliable and continuous grid connection. As shown in Fig. 10, the DC bus voltage drops sharply at 0.25 seconds. When controlled using a traditional quasi-PR controller, this sudden voltage drop can severely destabilize the grid current. Oscillations immediately follow the disturbance, indicating that the controller is unable to effectively compensate for the sudden change in supply voltage. At 0.29 seconds, the THD of the output current rises sharply to 11.19%. This high distortion exceeds the permitted limits set by grid regulations, causing the inverter to lose synchronization with the grid and fail to maintain the required frequency and phase alignment between the inverter output and the grid voltage. This performance reflects the limitations of traditional controllers, namely their lack of robustness and adaptability to fast voltage transients. In contrast, the improved GA-PSO-optimized quasi-PR controller demonstrated greater adaptability under the same conditions. After a 0.25-second DC-side voltage sag, the controller effectively adjusted its internal parameters and stabilized the grid-connected current. At 0.29 seconds, despite the system disturbance, the THD of the grid current was only 4.87%, well below the required grid-connection limit. Furthermore, the inverter maintained frequency and phase synchronization with the grid voltage, enabling reliable grid connection even under severe DC voltage fluctuations. This result confirms that the improved GA-PSO-optimized regulation strategy not only suppresses harmonic distortion more effectively than traditional methods but also ensures system adaptability to rapid voltage variations. In summary, the results in Fig. 10 demonstrate that the improved GA-PSO-optimized quasi-PR controller exhibits greater adaptability and robustness than the traditional quasi-PR controller. It is capable of maintaining reliable grid connection under a variety of operating conditions, including load variations, DC-side voltage sags, and other environmental disturbances. This capability significantly improves the overall stability, dynamic performance, and power quality of single-phase PV grid-tied inverter systems, making them a promising solution for practical applications where environmental variations and uncertainties are inevitable.

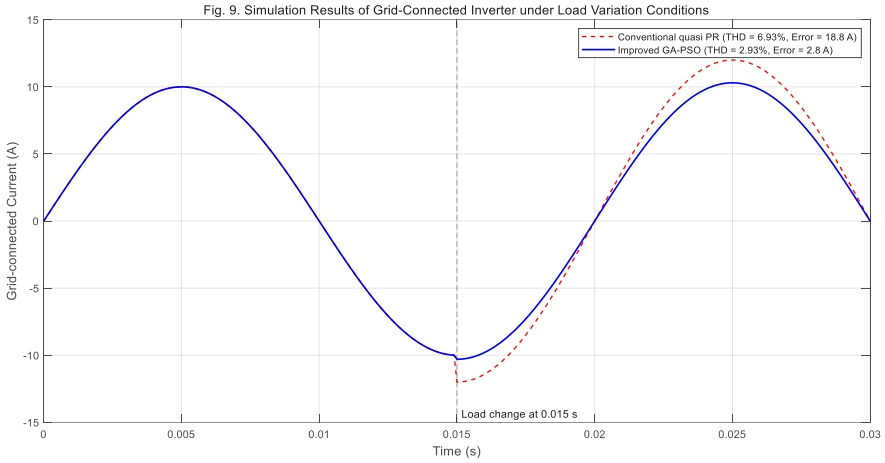

Fig. 10. Simulation results of grid connected inverter under DC side voltage variation conditions

5 Conclusion

This paper investigates the control strategy for a single-phase photovoltaic grid-connected inverter system, focusing on the adaptability and dynamic performance of a quasi-proportional resonant controller. First, a systematic analysis is conducted on the impact of controller parameters on the transient response and dynamic behavior

of the quasi-proportional resonant structure, clarifying how inappropriate parameter values affect current quality and response speed. Based on this, an adaptive parameter tuning method is proposed that comprehensively considers the harmonic content of the grid-connected current and the time-domain error as performance indicators. By comprehensively considering these two aspects, the tuning objective is more comprehensive, ensuring that the controller not only achieves fast and stable dynamic tracking but also meets power quality standards. To further improve optimization efficiency, a particle swarm optimization method is combined with a genetic algorithm, introducing a crossover mutation mechanism and a dynamically adjusted inertia weight factor. This improved hybrid algorithm is applied to the tuning of the quasi-proportional resonant controller in the inverter control strategy. This algorithm simultaneously considers fitness evaluation and iteration progress during the iterative optimization process, effectively balancing early global exploration with later local optimization, accelerating optimization convergence, improving parameter tuning accuracy, and alleviating the problem of local optimal stagnation. These improvements significantly enhance the grid-connected inverter's ability to dynamically respond to disturbances and maintain stable operation under various operating conditions. Simulation experiments validate the effectiveness of this approach. Results show that the improved hybrid algorithm-optimized quasi-proportional resonant controller maintains low grid-connected current harmonic distortion even under sudden load changes or DC power supply voltage fluctuations. Compared with traditional controllers, the improved approach achieves smaller output error amplitude, faster steady-state recovery, and reliable synchronization with the grid voltage. This demonstrates that the proposed control strategy not only enhances the robustness and adaptability of single-phase photovoltaic grid-connected inverter systems but also provides a valuable reference for the broader development of adaptive dynamic performance improvement methods and controller parameter adjustment strategies in photovoltaic power generation applications.

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