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Control Method of Microgrid Grid Connected Inverter Based on Quantum GA-PID

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Abstract

The current trend is towards ever-increasingly rigorous control performance requirements for grid-connected inverters. Therefore, a proportional integral derivative control method of the quantum genetic algorithm and particle swarm optimization was proposed, which can achieve stable and efficient operation of microgrids. The total harmonic distortion of the improved controller was 1. 03%, which was 1. 98% lower than the traditional method and far below the national standard of 5%; The prediction accuracy was on average 82%, 51%, and 54% higher than the other three classic algorithms; After the improvement of sag, the smoothness of microgrid switching was increased, avoiding severe shaking. The convergence time was 68. 3%, 54. 5%, and 35. 5% shorter, and the average convergence algebra was improved by 60. 1%, 67. 2%, and 87. 3%, respectively. The control step response only approached 1. 5 after 0. 4 seconds, which was 75% longer than the improved time, and the overshoot was 0. Accordingly, the proposed method is able to be utilized for the regulation of actual microgrid grid-connected inverters, achieving effective voltage control in dynamic and complex environments.

Keywords: Microgrid, Grid connected inverter, Quantum genetics, PSO, PID

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1. Introduction

With the widespread attention to the concept of sustainable development, countries are conducting relevant research to reduce carbon emissions, among which the application of renewable energy is currently a research hotspot [1]. Micrograds is a new type of renewable energy storage and composite device [2]. As a distributed power source, the performance of microgrid inverters is correlation with the efficient and steady run of microgrids. Proportional integral derivative (PID) controllers have more flexible parameter adjustment control and simpler results, making them more adaptable and robust than traditional controllers [3]. However, the parameter adjustment of traditional PID controller usually depends on experience or trial and error method, which is difficult to adapt to dynamic loading conditions and environmental factors, so its adjustment performance is often unsatisfactory in the face of complex nonlinear systems. Secondly, the traditional tuning method has limited ability to deal with the delay and instability of the system, resulting in large overshoot and slow response time. In addition, with the increase of system scale and complexity, it is difficult for a single PID algorithm to meet the control requirements of multiple-input multiple-output (MIMO) systems, which makes it difficult to effectively optimize and ensure the stability of system performance. Therefore, this study applies PID controller to the control of microgrid grid connected inverters. Applying various algorithms to PID parameter optimization can significantly improve the control performance of microgrid grid connected inverters. Many studies have combined various algorithms to optimize PID parameters and made certain research progress [4].

With the development of machine learning, the combination of PID control and various algorithms has been widely studied. Zhang X et al. (2024) proposed a hybrid algorithm HPSO based on particle swarm optimization (PSO)

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and simulated annealing (SA) for PID controller parameter optimization. This method introduced adaptive weights and dynamic learning factors to improve the global optimization ability of PSO algorithm. Combined with SA mechanism, Metropolis criterion and cooling mechanism were used to guide the population to accept the inferior solution, avoid the local optimal, and enhance the global search ability. The experimental results showed that HPSO algorithm had faster convergence speed and stronger global search ability, and the PID parameters optimized by HPSO algorithm had lower overshoot and better steady-state and dynamic response [5]. Issa M (2023) proposed a hybrid algorithm AOA-HHO based on arithmetic optimization algorithm (AOA) and Harris eagle optimization algorithm (HHO) for PID controller parameter selection. By combining AOA with HHO algorithm with efficient development mechanism, the development ability of AOA in search space was improved, and local optimization was avoided by introducing disturbance and variation factors. The method was applied to select PID parameters to control two engineering applications: DC motor regulation and a three-tank level sequence system. Experimental results showed that AOA-HHO algorithm was superior to AOA and other comparison algorithms in PID parameter optimization [6]. Li X et al. (2025) proposed a proportional-integral-differential (SGD-PID) algorithm based on adaptive stochastic gradient descent to solve practical scenarios where system and channel parameters are difficult to determine. Experimental results showed that the proposed adaptive power control scheme could effectively improve the performance of the system under different channel conditions [7]. Sandeep Y et al. (2024) realized the simulation and control of both arms by combining a PID controller with a transcendence controller to reduce the error of sine wave and periodic trajectory. At the same time, dynamic factors such as buoyancy, gravity and hydrostatic pressure acting on the underwater vehicle were modeled in the integrated SIMULINK model. The study revealed some significant tracks of the left and right fingertips, and employed effective adjustment methods such as Ziegler-Nicholas (Z-N), genetic algorithm (GA), ant colony optimization (ACO) and PSO. By PSO, integrating time multiplied by absolute error standard was used to improve the trajectory tracking accuracy [8]. Patil RS (2023) proposed a systematic review method to comprehensively evaluate the tuning effect of intelligent and naturally inspired algorithms in response to the lack of specific quantitative comparison of PID controller tuning methods in industrial applications. Using intelligent algorithms such as fuzzy logic (FL), artificial neural network (ANN), and adaptive neural fuzzy reasoning system (ANFIS), and evolutionary algorithms such as GA, PSO, differential evolution (DE), ant colony optimization (ACO), artificial bee colony (ABC), firefly algorithm (FA), cuckoo search (CS), harmonious search (HS), gray wolf optimization (GWO), literature comprehensive analysis was conducted. The research results reveal the effectiveness of different tuning methods in industrial applications and provide guidance for practitioners and researchers by comparing the performance of different algorithms [9].

The application of improved algorithms to PID parameter optimization research has also made some progress. He Y et al. (2023) proposed an improved butterfly optimization algorithm (WDBOA) with wind-driven mechanism to address the shortcomings of the butterfly optimization algorithm (BOA) in its ability to balance exploration and utilization. The WDBOA is applied to the parameter optimization of PID controller. Experimental results showed that compared with other PID controllers using GA, pollen propagation algorithm (FPA), cuckoo search (CS) and BOA tuning, the WDBOA-based PID controller had better control performance [10]. Teekaraman Y et al. (2024) proposed a neural fuzzy identification system with partial integral controller (NFISPID), combining selective voltage pulse width modulation and hybrid artificial beehive swarm optimization for the importance of automated control of smart grids. By introducing a secondary controller to deal with abnormal situations in the power grid, this method was tested in the MATLAB environment for efficiency. The results showed that the system had higher efficiency in all parameter values and could stabilize the power grid faster than other existing controllers [11]. Ray P K et al. (2024) proposed a new hybrid algorithm combining PSO and GWO driven PID controller and cascade PI-PD controller to solve the problem of frequency deviation and cross-line power flow deviation in multi-microgrid interconnection systems. Simulation results showed that the proposed PSO-GWO-based PI-PD controller outperformed other technologies on settling time, overshoot and other performance indicators [12]. Pervaiz et al. (2022) suggested a PSO optimized PID with on chaos theory, which utilized chaotic mapping to contribute to the diversity of solutions. This method could effectively optimize the superiority of solutions in complex environments and prevent falling into local optima [13].

In summary, although the application of the prior art in the control of microgrid grid-connected inverters has achieved certain results, there are still some obvious limitations. For example, many algorithms rely on traditional optimization methods (such as PSO, GA, etc.), which may fall into local optimal solutions when dealing with complex nonlinear systems, resulting in unsatisfactory optimization results. Although some improved algorithms (such as HPSO, AOA-HHO, etc.) attempt to improve global search capabilities by combining multiple strategies, they still face challenges when dealing with dynamic environments and system uncertainties. Therefore, simply relying on the superiority of these algorithms can not fully solve many problems in practical applications. Meanwhile, the current research does not pay enough attention to the real-time feedback and adjustment ability under dynamic environment, which leads to the unsatisfactory control effect under high load changes and system disturbances. In the face of these limitations, an improved quantum genetic algorithm (QGA) based on PSO is introduced. The main reason for combining QGA and PSO is that QGA can realize more efficient global search and overcome the limitations of traditional GA by utilizing the superposition and entanglement characteristics in quantum computing, while PSO has good local search ability and fast convergence characteristics. Therefore, the combined QGA-PSO can not only improve the search accuracy and the convergence speed of the algorithm, but also enhance the adaptability and stability of the control system when dealing with complex dynamic environments. The innovation of this study is to introduce PSO into the optimization process of QGA, which can effectively balance the search accuracy, while ensuring convergence accuracy and efficiency. After optimizing the PID parameters, the droop control is improved to achieve smooth and stable switching of the microgrid.

2. Methods and Materials

This section constructs a quantum improved QGA, where the adaptive function of the GA is adjusted and applied. Meanwhile, the PID controller has been improved with droop control to enhance the smoothness of grid connected current switching. Finally, PSO is used to optimize the QGA, further adjust the algorithm parameters, and obtain a hybrid algorithm with stronger search performance. The main reason for selecting PSO to enhance QGA is that PSO has strong global search ability and can avoid falling into local optimal solution. Compared with other optimization algorithms, such as GWO algorithm and whale optimization algorithm (WOA), PSO has higher search efficiency in high-dimensional space, and its adaptive adjustment mechanism can better optimize the evolution process of QGA. In addition, PSO has less parameter adjustment requirements and is suitable for combining with QGA, thus improving the overall performance and stability of the algorithm. In terms of computational balance, although PSO will increase the computational complexity, it can effectively improve the solving accuracy through proper parameter configuration and algorithm improvement.

2. 1 Smooth Switching Control Method for Grid Connected Inverters Based on QGA-PID

The control of voltage and current in wind solar energy storage microgrid systems is crucial for the steady of grid connected inverters [14-16]. PID is a classic control method that combines the weighted sum of proportional, integral, and derivative components to control a system [17-19]. The PID controller has adjustable parameters, which makes it easy to implement, but in complex and nonlinear systems in the power grid system, traditional PID controllers may have shortcomings such as long response time and large overshoot [20-22]. Therefore, the study combines quantum improved GA to adaptively adjust the parameters of PID controller and improve the control ability of the model. Quantum computing has been adopted to improve GA by utilizing quantum entanglement properties to optimize complex problems and construct QGA, to enhance the search efficiency. With the research objectives of this section, Figure 1 illustrates the QGA-PID's structure.

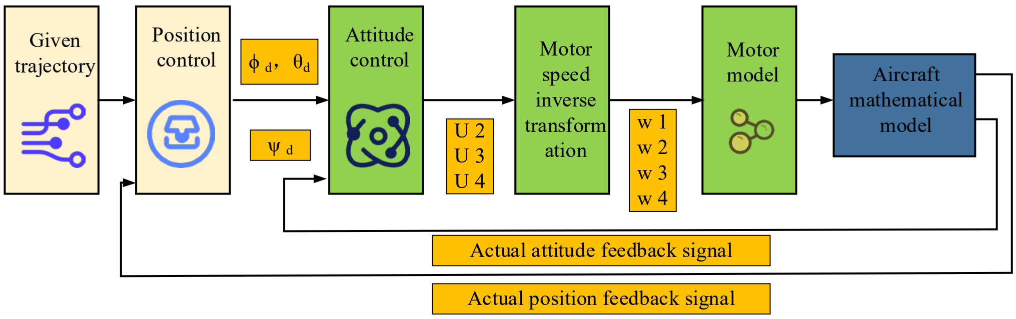

Figure 1. Schematic Diagram of QGA-PID Control Model Structure

Figure 1 shows the flow of a control system. First, a given trajectory is entered, based on which the system performs position control and attitude control. Subsequently, the motor control signal is obtained through the motor speed inverse transformation, and the control signal is further calculated according to the motor model. Next, the aircraft mathematical model is used to predict and correct the control effect. Finally, the system adjusts the control strategy through the actual attitude feedback signal and the actual position feedback signal to ensure that the aircraft runs according to the expected trajectory [23-25]. In the process of global optimization of PID parameters by QGA, it is first necessary to encode representative problems, clarify the PID parameters that need to be optimized, and define them as shown in equation (1).

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \quad (1)$$

In equation (1), $u(t)$ represents the control input; $e(t)$ is the error; K_p, K_i, and K_d are the proportional gain, integral gain and differential gain. After the optimization objective of the PID controller is clarified, QGA is constructed. Firstly, QGA is initialized, and the chromosome encoding is shown in equation (2).

$$|\alpha_i|^2 + |\beta_i|^2 = 1 \quad (2)$$

In equation (2), $|\alpha_i|^2$ and $|\beta_i|^2$ are the probability amplitude of the quantum bit being in the 0 state and 1 state; the sum of the probability amplitude of the quantum bits is 1. Then, through the rotation gate, the quantum individual is updated, and the ground state quantum is adaptively adjusted, iterating towards the optimal direction, as illustrated in equation (3).

$$F = \frac{1}{u(t)} \tag{3}$$

In equation (3), F represents the updated adaptive function, which is inversely proportional to the objective function $u(t)$. To ensure genetic diversity, the genes of the parent chromosome are crossed and mutated to achieve gene exchange and generate new chromosomes. The crossover rate is shown in equation (4).

$$\begin{cases} v^{*} = (v_1, \cdots, v_{k-1}, v_k, v_{k+1}, \cdots, v_n) \\ u^{*} = (u_1, \cdots, u_{k-1}, u_k, u_{k+1}, \cdots, u_n) \end{cases} \tag{4}$$

In equation (4), $u = (u_1, u_2, \cdots, u_n)$ and $v = (v_1, v_2, \cdots, v_n)$ represent two different parental chromosomes, and genes are randomly selected on the parental chromosomes for crossover mutation; u^{*} and v^{*} represent two newly generated chromosomes, respectively; k represents the currently selected chromosome breakpoint, with a breakpoint range of $1 \sim n$. The mutation probability of the genetic operator determines the quality of the next generation of new chromosomes, as shown in equation (5).

$$x_k^{*} = \begin{cases} x_k + \Delta(t, U_{\max}^{k} - v_k), random(0,1) = 0 \\ x_k - \Delta(t, v_k - U_{\min}^{k}), random(0,1) = 1 \end{cases} \tag{5}$$

In equation (5), x_k represents the currently selected chromosome cutting point; $x_k{}^{*}$ represents the new cutting point after crossover mutation; $[U_{\min}^{k}, U_{\max}^{k}]$ represents the currently available range of chromosome cutting points; $random(1,0)$ represents the range of randomly selected cutting points; v_k represents the currently randomly selected cutting points within $[U_{\min}^{k}, U_{\max}^{k}]$ range; $\Delta(t, y)$ represents the arbitrarily distributed data in $[0, y]$. After optimizing the PID parameters, the inverter switching process is smoothed to avoid system impact, as shown in equation (6).

$$u(t) = \frac{u_{\text{start}} + u_{\text{end}}}{2} + \frac{u_{\text{end}} - u_{\text{start}}}{2} \cdot \left(1 - \cos\left(\frac{\pi t}{T}\right)\right) \tag{6}$$

In equation (6), u_{start} and u_{end} represent the control inputs at the initial and end; T represents the switching time. As the main power grid fails, smooth switching of microgrids is the core to ensure stable operation. Sag control is a commonly used method for smooth switching of microgrids, but its sag coefficient cannot be adjusted in real time, resulting in weak anti-interference of the grid. Therefore, QGA-PID is used to improve traditional sag control, as shown in Figure 2.

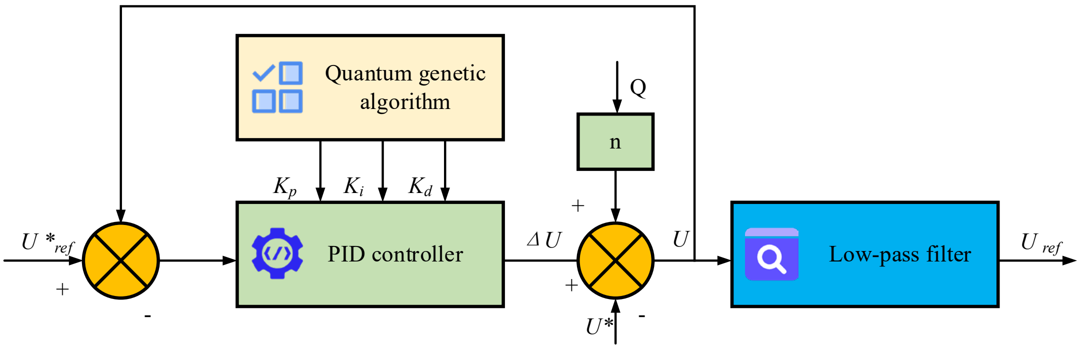

Figure 2. Structure Diagram of Quantum Genetic PID Droop Controller

In Figure 2, the droop controller uses three identical power sources and micrograms in parallel, connected to a transformer and a common point. The difference of the voltage is used as the control input, and the QGA is applied to find out the proper parameter solution as the output. Equation (7) illustrates the proper solution.

$$J(i) = \alpha_p |\ e(i)| + \beta_p |\ de(i)| \tag{7}$$

In equation (7), $J(i)$ represents the optimal parameter solution; α_p and β_p both represent weighting coefficients; $e(i)$ represents overshoot.

2. 2 Optimized QGA-PSO Microgrid Control Method

In the previous section, the construction and optimization process of QGA-PID were detailed, achieving stable, precise, and global control of photovoltaic microgrid inverters [26-28]. However, due to the large number of nonlinear and real-time changing nonlinear parameters in actual optical storage systems, the control process is very complex. Simple QGA-PID control has limitations in accuracy, response time, and adaptability when dealing with complex working conditions [29]. Therefore, this study introduces PSO to further optimize QGA, to obtain a more powerful global optimization algorithm. The PSO exhibits superior global search capabilities and a more rapid convergence rate in comparison to the conventional QGA. Its process is shown in Figure 3.

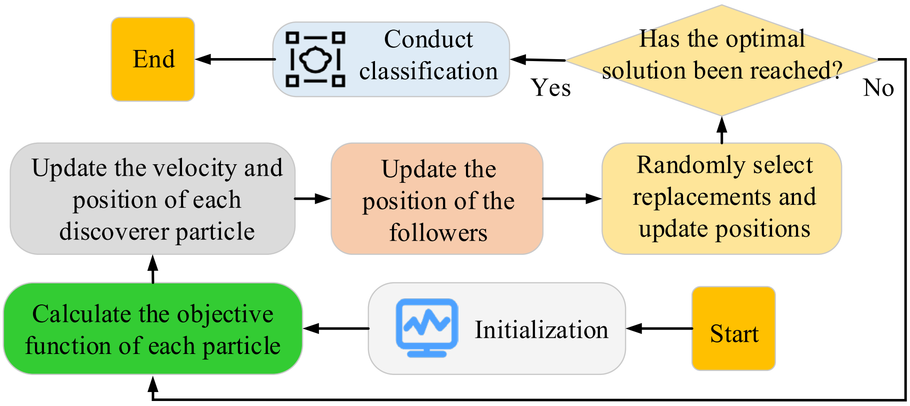

Figure 3. Schematic Diagram of PSO Flow

Figure 3 shows the flow of PSO. The first step is initialization, setting the initial position and speed for each particle. Then, the objective function of each particle is calculates, the velocity and position of each discoverer particle is updated based on the objective function value. The following particle then updates the position of the followers based on the motion of the exploring particle. During this process, some particles are randomly selected as replacements and their positions are updated. Has the optimal solution been reached? Has the optimal solution been reached? If yes, then classify, otherwise continue iterating. Finally, the process ends [30-31]. The first step in its construction process is to initialize the controller parameters obtained by the QGA-PID algorithm, providing initial optimization space for PSO. The process of parameter selection of optimization algorithm includes the initialization stage, the definition of fitness function, the updating of particle velocity and position, the selection and mapping of alternative particles, and the setting of iteration and termination conditions. In the initialization stage, the number of particles, initial position and speed are set to lay the foundation for the search process. The fitness function is used to evaluate the effect of the algorithm and guide the selection of the best parameters. The particle speed and position update mechanism ensure the exploration and utilization of the algorithm, and enhance the optimization efficiency. Selecting and replacing poorly performing particles can increase the diversity and avoid the algorithm falling into local optimality. Through several iterations, the PID parameters are continuously optimized to achieve higher control performance. The initialization of the location and speed of the particle swarm is illustrated in equation (8).

$$\begin{cases} x_i(0) = x_{\min} + rand(0,1) \times (x_{\max} - x_{\min}) \\ v_i(0) = v_{\min} + rand(0,1) \times (v_{\max} - v_{\min}) \end{cases} \tag{8}$$

In equation (8), $x_i(0)$ and $v_i(0)$ respectively represent the location of the i th particle; $x_{\min}$ and $x_{\max}$ respectively are the upper and lower limits of the control parameters; $v_{\min}$ and $v_{\max}$ are the upper and lower limits of the velocity. There is a discrepancy of the predicted and actual response values of the PSO to the power grid system. The framework of the control model is shown in Figure 4.

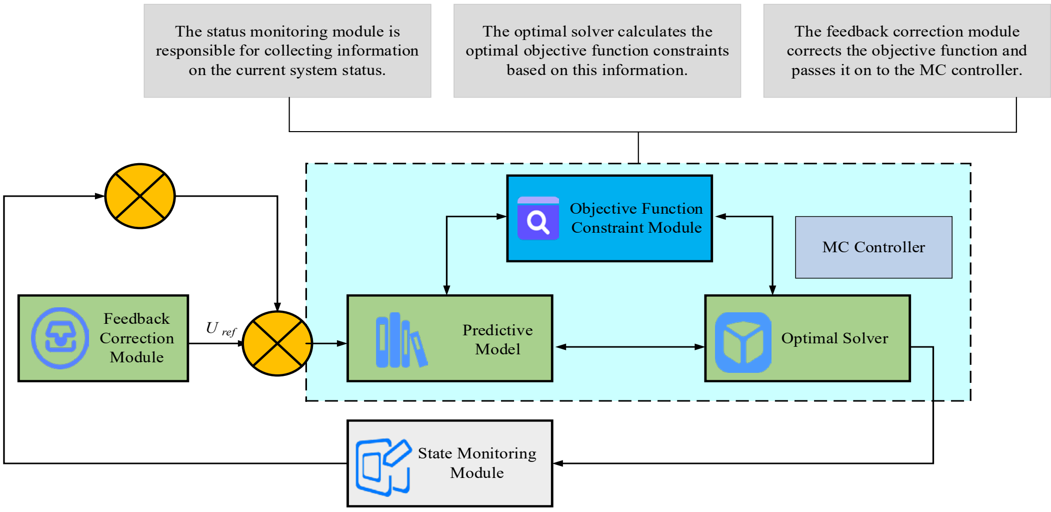

Figure 4. Schematic Diagram of QGA-PID Control Model Optimized by PSO

Figure 4 shows the schematic diagram of the QGA-PID control model optimized by PSO. The model's state monitoring module is responsible for collecting information about the current state of the system in real time to provide a basis for subsequent processing. Using this information, the optimal solver computes the optimal objective function constraints. The feedback correction module then corrects the objective function according to the resulting constraints and passes the optimized result to the MC controller. The whole process also includes a predictive model to enhance the predictive power of the system and ensure the accuracy of the control effect. Through the collaboration of these modules, the model can be effectively optimized to achieve better performance. The calculation of particle fitness is shown in equation (9).

$$f_i = w_1 \times \mathrm{ISE} + w_2 \times \mathrm{IAE} + w_3 \times \mathrm{ITAE} \quad (9)$$

In equation (9), f_i is the fitness value of the i th particle; w_1, w_2, and w_3 all represent weight factors; ISE, IAE, and ITAE are the integral squared error, absolute error, and time absolute error. The fitness value function can be combined with multiple performance indicators to comprehensively evaluate the quality of particles. The weights are adaptively adjusted, as shown in equation (10).

$$\omega(t^*) = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{t^*_{\max}} \times t^* \quad (10)$$

In equation (10), $\omega(t^*)$ is the inertia weight at time t; $\omega_{\max}$ and $\omega_{\min}$ represent the inertia weight's largest and smallest value; $t^*_{\max}$ and t^* are the largest iteration and the current iteration. As the inertia coefficient decreases, the search accuracy of the algorithm gradually improves. The speed update is shown in equation (11).

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (g - x_i(t)) \quad (11)$$

In equation (11), $v_i(t+1)$ is the speed of the i th particle at $t+1$; ω represents inertia weight; c_1 and c_2 respectively represent particle acceleration constants; r_1 and r_2 respectively represent random numbers, ranging from [0, 1]; p_i represents the historical optimal location of the i th particle; g represents the global optimal position. The particle position is adjusted with the updated particle velocity, and the resulting position update is expressed in equation (12).

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (12)$$

In equation (12), $x_i(t+1)$ is the position of the i th particle at time $t+1$; $x_i(t)$ is the location of the i th particle at time t. Better QGA-PID control parameters are searched. To determine whether the algorithm needs to be terminated, the convergence condition of the algorithm is shown in equation (13).

$$\left| f_{\mathrm{best}}(t+1) - f_{\mathrm{best}}(t) \right| < \varepsilon \quad (13)$$

In equation (13), $f_{\mathrm{best}}(t+1)$ and $f_{\mathrm{best}}(t)$ represent the optimal fitness values obtained by the algorithm at $t+1$ and t, respectively; ε is the pre-set convergence threshold in the algorithm. When the absolute value of the fitness difference between adjacent time steps is less than the preset threshold, the current solution is the optimal solution, as shown in equation (14).

$$K_p^*, K_i^*, K_d^* = g \quad (14)$$

In equation (14), K_p^*, K_i^*, and K_d^* respectively represent the PID controller parameters optimized by PSO. By utilizing the local search capability of PSO to optimize the

QGA-PID controller, the performance is further improved, as shown in equation (15).

$$U = a \times Q + (1 - a) \times P \quad (15)$$

In equation (15), U represents the parameter values obtained by QGA and PSO mixed optimization; Q represents the parameter update values obtained by QGA; P represents the parameter update values obtained by PSO; a represents the mixed weight coefficient, which aims to update the step size ratio. The mixed optimization flowchart of QGA-PSO for PID controller is shown in Figure 5.

Figure 5 shows the optimization process based on PSO and neural network. First, neural network architecture is designed as the basis of the entire system, defining the structure and hierarchy of the network. The PSO is then initialized to explore the optimization space. The global optimization step of PSO is to calculate the fitness value of each particle and update the individual optimal solution and the population optimal solution according to the fitness value. To enhance the searching ability, the adaptive mutation operation is introduced to make the particles jump out of the local optimal solution. Then, it will check whether the iteration is complete, and if not, it will continue the optimization process. After each round of optimization, the first M particles with the best fitness are selected and passed to the neural network for local optimization to further fine-tune the network parameters. Finally, the best result is selected as the final optimization result. By combining global optimization and local optimization, the performance and accuracy of neural network in complex audio signal recognition can be effectively improved. In practical applications, hardware limitations and challenges posed by computing requirements must also be taken into account. Specifically, the complexity and real-time computing capability of the algorithm require the system to have high processing performance and computing resources, especially in MIMO systems and dynamic environments, which need to quickly process large amounts of data and perform complex calculations. In addition, the hardware implementing this optimization method needs to support high-frequency data acquisition and processing to ensure that the control strategy can respond to system changes in a timely manner. Therefore, in practical applications, dealers and operators need to evaluate the corresponding hardware configuration during the system design phase to ensure the effective implementation of the algorithm and meet the performance requirements. This will help to promote the practical application of QGA-PSO method in microgrid grid-connected inverters, and improve its feasibility and practical value.

In the above optimization process, QGA and PSO achieve efficient PID parameter tuning through synergistic effect. First, QGA uses the superposition and entanglement properties of qubits to encode PID parameters and generate a diverse solution space through global search, which helps avoid stalling at locally optimal solutions. The PSO then fine-tuned the search process by introducing a collaborative mechanism for its particle population, with each particle updating its speed and position according to its historical best position and global best position. The global search capability provided by QGA is combined with the local search capability of PSO to optimize the objective function, ensuring that the particles quickly adapt and converge to the optimal control parameters in a complex dynamic environment. This structured interaction not only improves the optimization speed and accuracy, but also enhances the stability of the algorithm when dealing with nonlinear and uncertain problems, making the final tuned PID controller show better performance in microgrid-connected inverters.

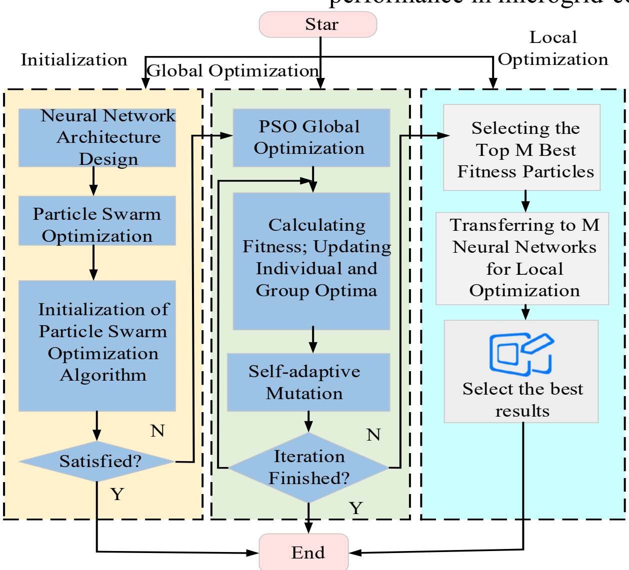

Figure 5. QGA-PSO Hybrid Optimization Flow Chart

3. Results

The control performance of QGA-PID proposed by the research was tested, and Total Harmonic Distortion (THD), response error, convergence accuracy, and speed of grid connected current were used as evaluation indicators. Other traditional algorithms were compared and analyzed, and the actual control effect was compared with the PID controller before improvement.

3. 1 Performance Testing of Smooth Switching Control for Grid Connected Inverters Based on QGA-PID

The parameters of the research model were selected as follows: the sampling rate of the audio signal was set to 44.1 kHz, and the audio depth was set to 16 bits, which can balance the resolution and processing efficiency of the signal to meet the needs of most audio signals. The threshold for note recognition was set to 0.01. The minimum note length was set to 80 ms to ensure that sustained information about the note is captured while avoiding excessive noise misjudgment. The learning rate of the neural network model was set to 0. 001. The population size in the PSO was set to 50 and the maximum number of iterations was 100. To test the controller constructed by the proposed method, a simulation was conducted on the microgrid system. The experimental equipment used Intel Core i5 2. 80 GHz CPU, 2.96 GB of memory, and Windows 7 operating system. Firstly, the application effect of the improved QGA-PID controller in microgrid systems was verified, while the traditional QGA-PID controller was used for comparative analysis, and system stability was adopted as the evaluation index. The results of the frequency dependent THD of the grid connected current in the power grid system were shown in Figure 6. In Figure 6 (a), the THD of traditional QGA-PID was 3. 01%. In Figure 6 (b), the THD of the improved QGA-PID was 1. 03%, which was 1. 98% lower than the traditional method and far below the national standard of 5%. The results indicated that the proposed method could decrease the THD value and had high superiority in improving current quality, with better harmonic control capability than traditional methods.

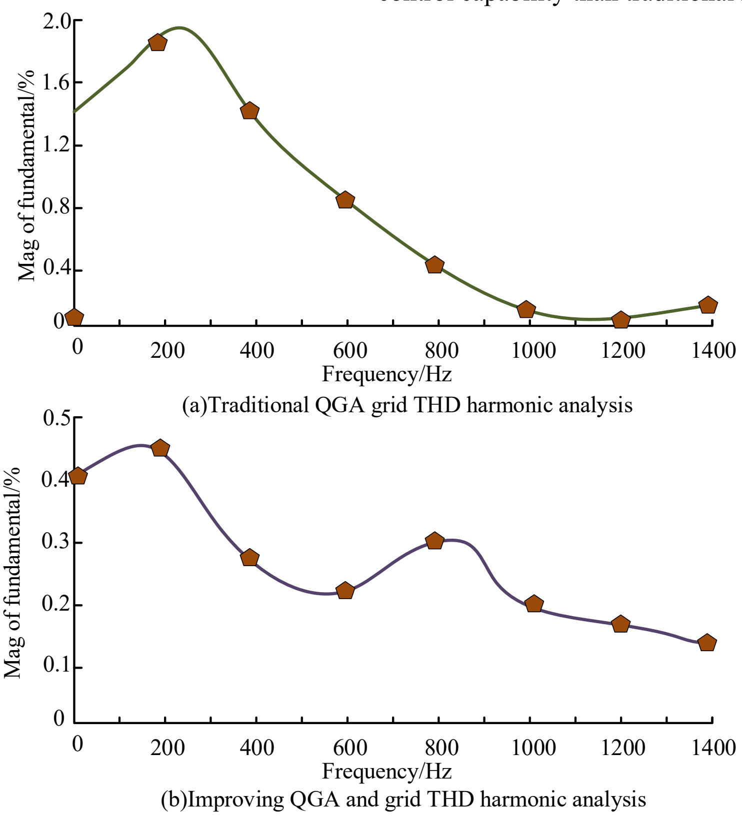

Figure 6. Analysis of QGA Current Harmonic Control Before and After Improvement

To verify the response accuracy of the proposed QGA, three similar algorithms, Adaptive GA (AGA), Standard GA (SGA), and Optimized GA (OGA) were used for comparative analysis. The discrepancy of the predicted response value and the true response value of PID control parameters was used as an evaluation index. The stability of voltage control response of the power grid system applied to PID parameter control with various algorithms varied with control time. In Figure 7 (a), the proposed method had the highest prediction accuracy, with the predicted value coinciding with the true height, with a difference of only 2%. In Figure 7 (b), AGA performed the worst with a prediction error of 84%. The error values of SGA and OGA in Figures 7 (c) and 7 (d) were at an intermediate level, at 53% and 56%, respectively. The prediction accuracy of the proposed method was 82%, 51%, and 54% higher than the average of AGA, SGA, and OGA. Therefore, the proposed algorithm had superiority in predicting PID control parameters and controlling the voltage response of microgrids.

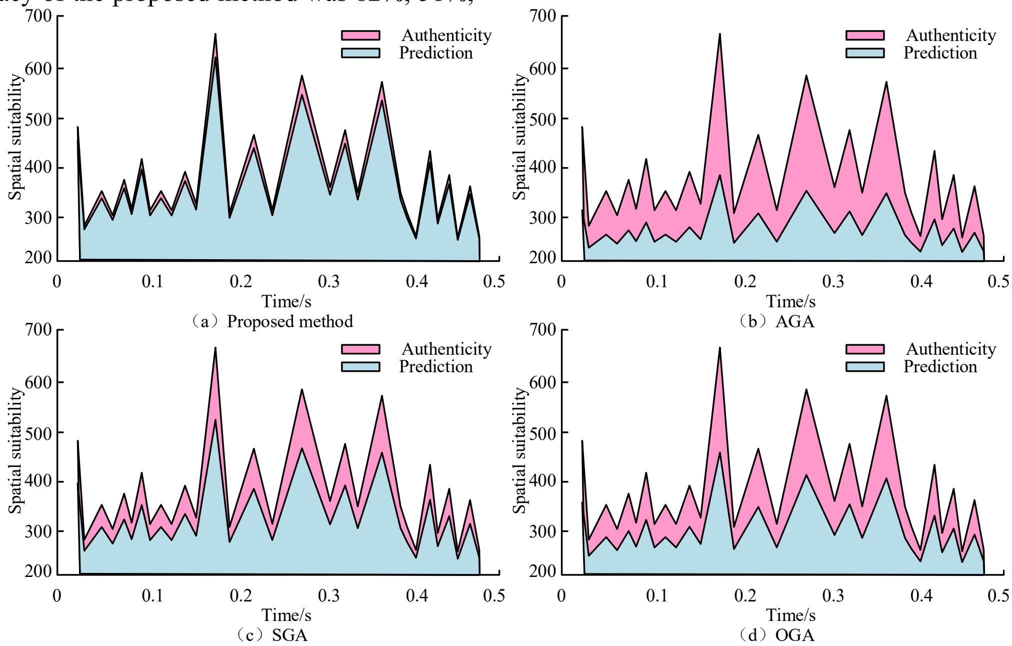

Figure 7. Comparative Analysis of Prediction Accuracy of Various Algorithms

The smoothness of voltage and power curves was adopted as evaluation indicators. The QGA-PID control methods before and after improvement were compared and analyzed. In Figure 8 (a), before and after the 1. 7s microgrid switching, after the improvement of droop control, the smooth switching voltage always fluctuated within the range of [-250, 250] without severe shaking; However, the conventional voltage curve showed sharp fluctuations, with two extreme points of -300 and 300 respectively. In Figure 8 (b), the power was divided into photovoltaic power supply, battery, and load voltage. The photovoltaic and load voltages remained constant at 4.5 kW and 5 kW, respectively, without significant fluctuations. The battery remained at -6.5kW from 0-0.5s, and at two time points beyond 0.5s and 2s, the power rapidly increased, taking over some of the power supply, but there was no significant fluctuation and remained in a steady increasing trend. Therefore, after the sag improvement, the steady and power quality of the microgrid connected system could be effectively controlled.

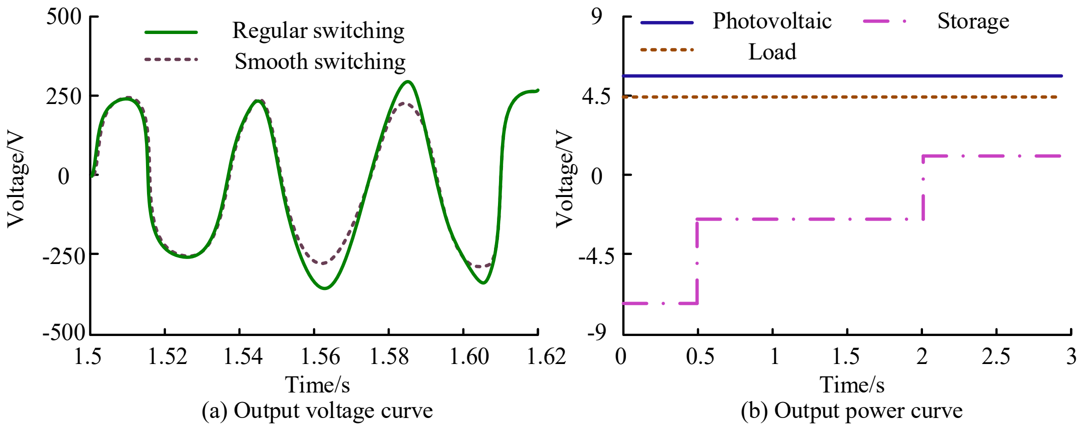

Figure 8. Comparison of Switching Control Effects of Microgrids Before and After Sag Improvement

3. 2 Analysis of the Practical Application Effect of QGA-PID Controller Optimized by PSO

To verify the superiority of the improved PSO, WOA was adopted, and three different datasets, Iris, Wheat, and Wine, were used for comparative analysis. In Figure 9, the proposed method converged to the optimal solution at a faster rate in different datasets, and the convergence curve was always below WOA. In Figure 9 (a), the proposed method began to converge to 0.02 after 58 iterations. In Figure 9 (b), the convergence effect of the two methods was slightly poor, and the proposed method started to slowly converge to 0. 1 when the number of iterations reached 65. In Figure 9 (c), the proposed method converged to 0.18 after 78 iterations.

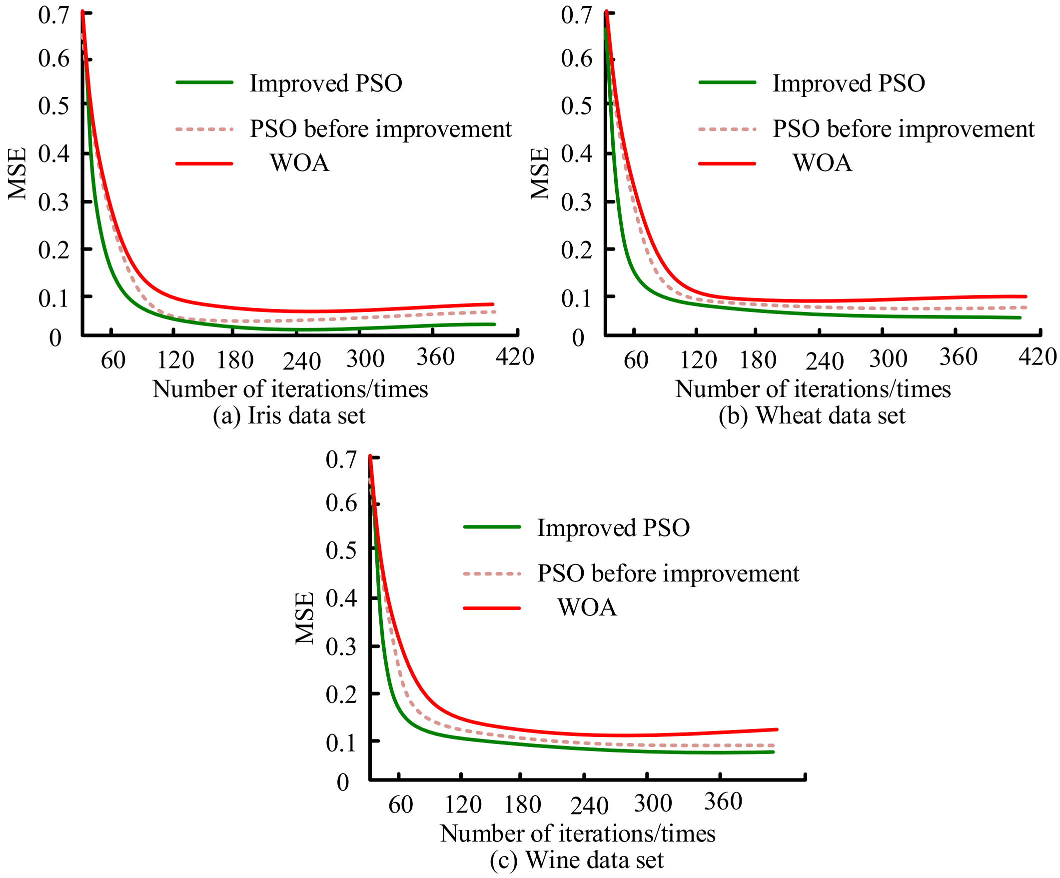

Figure 9. Comparison of MSE Convergence Curves of Various Algorithms

To verify the superiority of PSO over QGA improvement, PSO with Local Dynamic Inertia Weight (PSO-LDIW), Adaptive Weight PSO (AWPSO), and PSO with Inertia Control (PSO-IC) with local dynamic inertia weight were used for comparative analysis. Four algorithms were applied to two functions for performance testing, and the average generation values of each algorithm were used as evaluation indicators. In Figure 10 (a), in the f1 test function, when the iteration increased, the average convergence algebra of the proposed method was the lowest, at 64, while the average convergence algebras of PSO-LDIW, AWPSO, and PSO-IC were 78, 94, and 167, respectively, which were 60.1%, 67.2%, and 87.3% higher than the proposed algorithm. In Figure 10 (c), the proposed algorithm had the fastest convergence speed with a convergence time of 1.23, which was 68.3%, 54.5%, and 35.5% shorter than the convergence times of PSO-LDIW, AWPSO, and PSO-IC, respectively. In Figures 10 (b) and 10 (d), the average convergence algebra and convergence time trends of each algorithm in the f2 test function remained unchanged compared to those in the f1 test function. Therefore, the proposed method had high global search capability and solving efficiency.

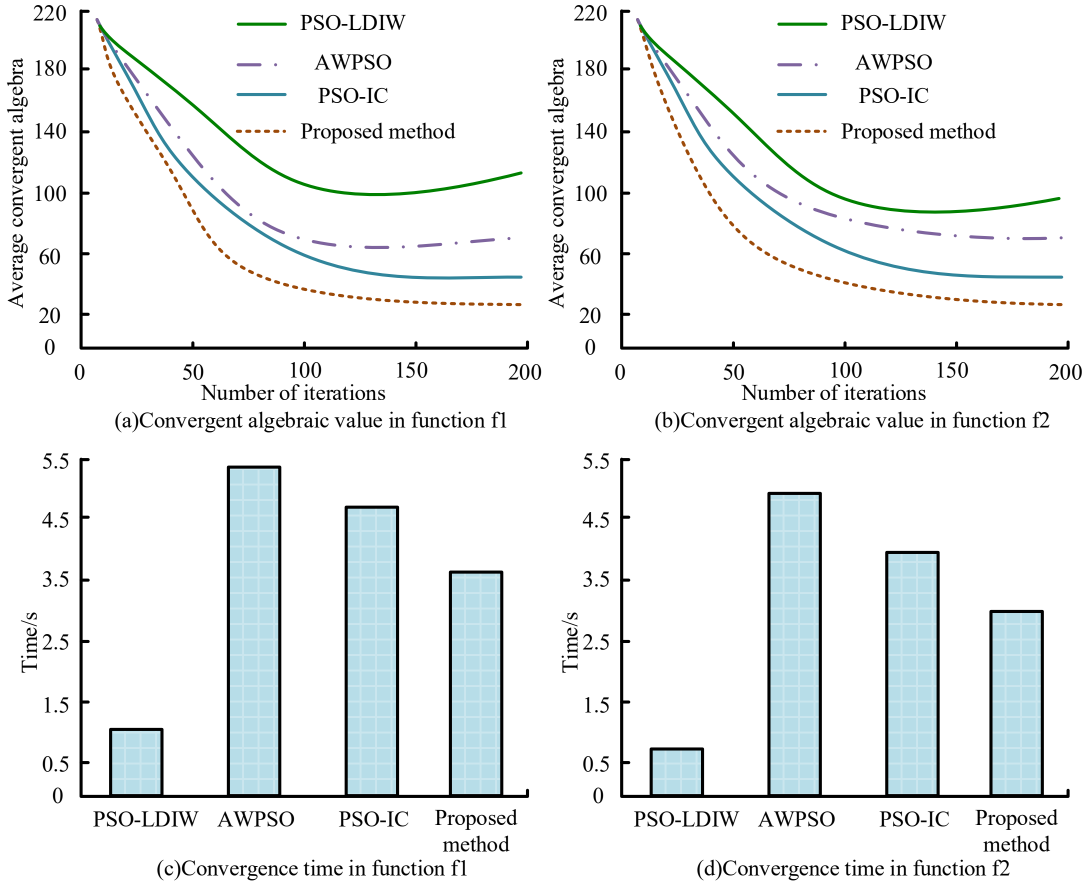

Figure 10. Comparative Analysis of Solution Performance of Various Algorithms

The Improved Whale Optimization Algorithm (IWOA) and the Nelder Mead Whale Optimization Algorithm (NMWOA) were used for comparative analysis. Each algorithm was applied to four different functions and repeated experiments were conducted at population sizes of 50 and 150, respectively. The convergence accuracy of each algorithm was used as an evaluation metric. In Figure 11 (a), under a population size of 50, the proposed algorithm showed the best convergence performance in all four tests. Among them, the convergence accuracy of the test function f1 reached the highest 97%, which was 5% and 9% higher than IWOA and NMWOA, respectively. In Figure 11 (b), under a population size of 150, the proposed algorithm still had the best convergence accuracy among all functions. Compared with the test results of a population size of 50, the difference was within 5%. Thus, the proposed method had high convergence accuracy and reliability in different test functions.

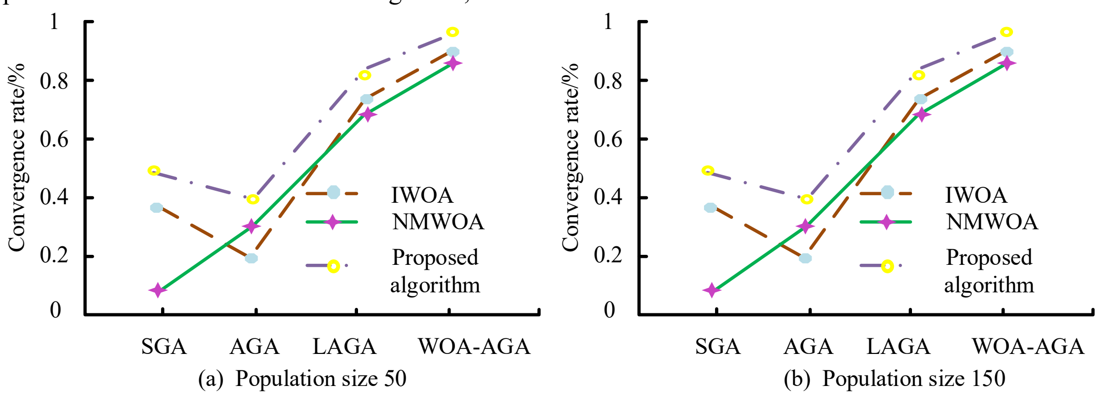

Figure 11. Comparative Analysis of Convergence Accuracy of Various Algorithms in Different Test Functions

To test the improved PID controller, a comparative analysis was conducted on the PID controller before and after improvement under four different operating conditions. The rotation angle step size was adopted as an evaluation index. As the testing time increases, the step response curves of PID control before and after improvement are illustrated in Figure 12. In Figure 12 (a), the rotation angle step size of the proposed method began to converge to 1 at 0. 1s and remained stable with increasing testing time; The control step response of the PID before improvement only approached 1.5 at 0.4s, which was 75% longer than the time after improvement. In addition, there was a sudden change in the rotation angle step size at 0.4s, and the overshoot reached 14.3%, which only stabilized after more than 1s. In Figures 12 (b), 12 (c), and 12 (d), the test results of the two methods in operating conditions 2, 3, and 4 were consistent with operating condition 1, and the trend of the step response curve did not change significantly, with a difference of less than 3%. As a result, the improved PID controller had superior performance compared to before, with higher response speed and smaller overshoot.

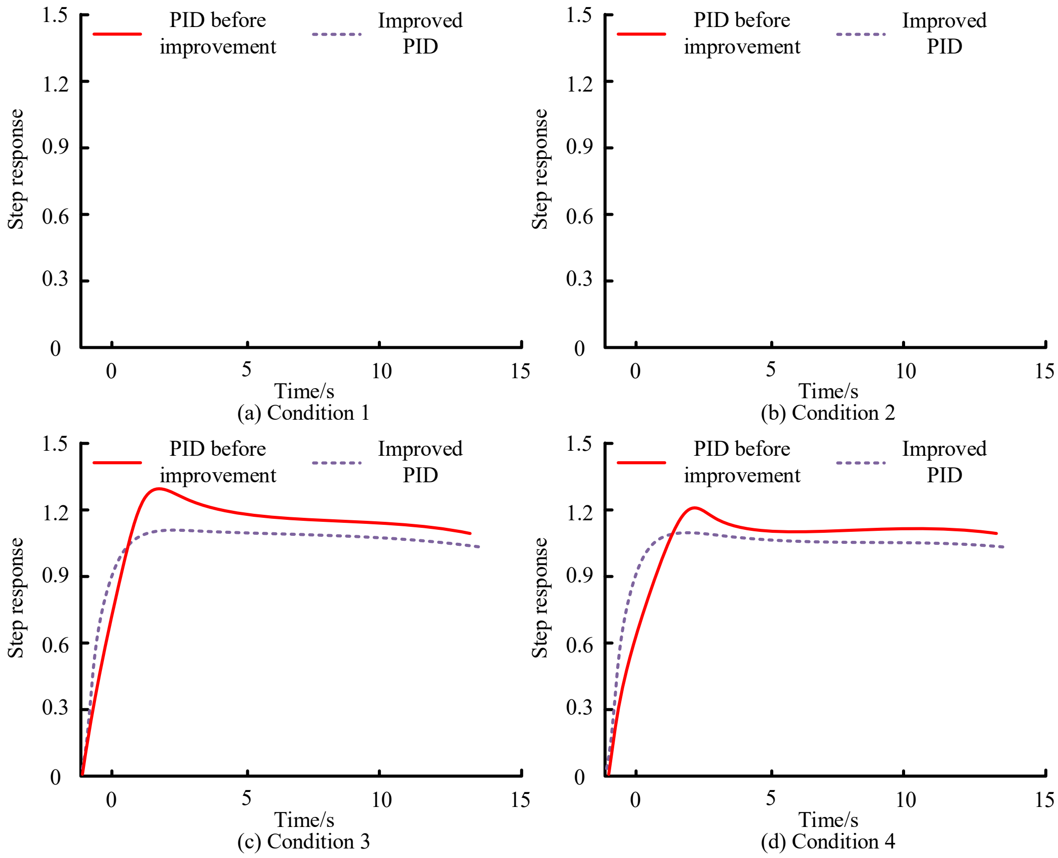

Figure 12. Comparison of PID Control Performance Before and After Improvement

4. Discussion and Conclusion

To improve the control performance of microgrid connected inverters, a control method combining PSO and QGA-PID was proposed to optimize the algorithm's search capability, stability, and accuracy for optimal parameters. The THD of the improved QGA-PID controller was 1.03%, which was 1. 98% lower than the traditional method and far below the national standard of 5%; The prediction accuracy of control parameters was 82%, 51%, and 54% higher than the average of AGA, SGA, and OGA; After the improvement of droop, the smooth switching voltage always fluctuated within the range of [-250, 250], and the photovoltaic and load voltages remained at 4.5kW and 5kW respectively. The battery remained at -6.5kW from 0-0.5s without severe shaking; The proposed method began to converge to 0.02 after 58 iterations, which was 0.03 and 0.08 higher than the PSO and WOA before the improvement, respectively; The average convergence algebras of PSO-LDIW, AWPSO, and PSO-IC were 78, 94, and 167, respectively, which were 60.1%, 67.2%, and 87.3% higher than the proposed algorithm; The convergence accuracy was 5% and 9% higher than IWOA and NMWOA, respectively; The control step response of the PID before improvement only approached 1.5 at 0.4s, and the control step response only approached 1.5 at 0.4s, which increased the time by 75% compared to the improved time, and the overshoot was 0. Therefore, the QGA-PSO optimization method proposed in this study can significantly improve the control performance of microgrid-connected inverters, especially in dynamic environments with frequent fluctuations. Its efficient PID parameter tuning not only improves the response speed and stability of the system, but also reduces the total harmonic distortion (THD) below the safety standard, ensuring improved power quality. For practical applications, this means being able to better cope with the instability brought about by renewable energy access, thereby enhancing the ability of microgrids to contribute to the grid. At the same time, the reliability and adaptability of the method make it widely used in different microgrid configurations and operating conditions, and improve its market acceptance and implementation economy.

The proposed method had significant advantages over other classical algorithms in the PID parameter optimization process. In practical applications, compared with using GA or PSO methods alone, the improved QGA-PSO utilized the global search capability of quantum computing and the local optimization ability of PSO to achieve local refinement search while also improving global solving ability. It could effectively reduce steady-state errors and achieve higher output voltage accuracy. Compared to traditional WOA, it had more diversity in convergence speed, reduced the possibility of falling into local optima, and had a higher convergence rate [32]. In terms of control stability, the proposed method, improved by droop control, had faster response time and response stability compared to the hybrid algorithm of fuzzy logic and differential evolution [33]. In terms of PID control performance, the proposed method had higher adaptability to dynamic and complex environments compared to neural network-based PID controllers, and the training process of the algorithm was simpler, resulting in faster search speeds. Therefore, the proposed method outperformed other traditional and hybrid methods in terms of control accuracy, convergence speed, stability, and response time, and could be effectively applied in practical control scenarios of grid connected inverters. The proposed QGA-PSO optimization method shows significant performance advantages in theory, but it may still face many challenges and limitations in practical grid-connected inverter applications. First of all, the dynamic characteristics and uncertainties of the microgrid may make it difficult for the control algorithm to work stably in real-time applications, especially in the face of instantaneous load fluctuations or fault events, the response time and accuracy of the control strategy will be tested. Second, in terms of hardware implementation, the need for computing resources may limit the roll-out of the approach in resource-poor or cost-sensitive environments. In view of the above limitations, future research can focus on the following directions. Firstly, how to extend the QGA-PSO optimization algorithm to deal with the dynamic characteristics and uncertainties of microgrid should be discussed. Considering the feasibility of hardware implementation, more lightweight algorithm implementation can be studied to meet the needs of resource-poor or cost-sensitive environments. The introduction of advanced machine learning technology for intelligent decision-making will help optimize control strategies under more complex operating conditions, ensuring the reliability and practicality of microgrids.

Reference

[1] Liu Y, Cao B, Li H. Improving ant colony optimization algorithm with epsilon greedy and Levy flight. Complex & Intelligent Systems, 2021 , 7(4):1711-1722.

[2] Usman A M, Abdullah M K. An Assessment of Building Energy Consumption Characteristics Using Analytical Energy and Carbon Footprint Assessment Model. Green and Low-Carbon Economy, 2023, 1(1): 28-40.

[3] Stodola P. Hybrid ant colony optimization algorithm applied to the multi-depot vehicle routing problem. Natural computing, 2020 , 19(2):463-475.

[4] Wellendorf A, Tichelmann P, Uhl J. Performance Analysis of a Dynamic Test Bench Based on a Linear Direct Drive. Archives of Advanced Engineering Science, 2023, 1(1):55-62.

[5] Zhang X, Yang Y. Optimization of PID controller parameters using a hybrid PSO algorithm. International Journal of Dynamics and Control, 2024, 12(10): 3617-3627.

[6] Issa M. Enhanced arithmetic optimization algorithm for parameter estimation of PID controller. Arabian journal for science and engineering, 2023, 48(2): 2191-2205.

[7] Li X, Xia Y, Gui L, Li H, Lang L. Enhanced Real-Time Multiuser Uplink UWOC System Based on Hybrid Multiple Access and SGD-PID Power Control Algorithm. Lightwave Technology, Journal of, 2025, 43(1):190-197.

[8] Sandeep Y, Sunil K, Manoj G. Trajectory control and optimization of PID controller parameters for dual-arms with a single-link underwater robot manipulator. Journal of the Chinese Institute of Engineers, 2024, 47(7):830-840.

[9] Patil R S, Jadhav S P, Patil M D. Review of intelligent and nature-inspired algorithms-based methods for tuning PID controllers in industrial applications. Journal of Robotics and Control (JRC), 2024, 5(2): 336-358.

[10] He Y, Zhou Y, Wei Y, Luo Q, Deng W. Wind driven butterfly optimization algorithm with hybrid mechanism avoiding natural enemies for global optimization and PID controller design. Journal of Bionic Engineering, 2023, 20(6): 2935-2972.

[11] Teekaraman Y, Kuppusamy R, Indragandhi V. Investigations on the effect of micro-grid using improved NFIS-PID with hybrid algorithms. Computing, 2024, 106(8): 2541-2559.

[12] Ray P K, Bartwal A, Puhan P S. Load frequency control in interconnected microgrids using Hybrid PSO–GWO based PI–PD controller. International Journal of System Assurance Engineering and Management, 2024, 15(8): 4124-4142.

[13] Pervaiz S, Bangyal WH, Ashraf A, Nisar K, Haque MR, Ibrahim A, Ag AB, Chowdhry B, Rasheed W, Rodrigues JJ. Comparative research directions of population initialization techniques using PSO algorithm. Intelligent Automation & Soft Computing, 2022, 32(3):1427-1444.

[14] Zhang H, Thompson J, Gu M, Jiang XD, Cai H, Liu PY, Shi Y, Zhang Y, Karim MF, Lo GQ, Luo X. Efficient on-chip training of optical neural networks using genetic algorithm. Acs Photonics, 2021, 8(6):1662-1672.

[15] Minh HL, Khatir S, Rao RV, Abdel Wahab M, Cuong-Le T. A variable velocity strategy particle swarm optimization algorithm (VVS-PSO) for damage assessment in structures. Engineering with Computers, 2023, 39(2):1055-1084.

[16] Rad I S, Alinezhad M, Naghibi S E, Kamarposhti M A. Detection of internal fault in differential transformer protection based on fuzzy method. International Journal of Physical Sciences, 2011, 6(26): 6150-6158.

[17] Shokouhandeh H, Ahmadi Kamarposhti M, Asghari F, Colak I, Eguchi K. Distributed generation management in smart grid with the participation of electric vehicles with respect to the

vehicle owners' opinion by using the imperialist competitive algorithm. Sustainability, 2022, 14(8): 4770-4770.
[18] Pozna C, Precup RE, Horváth E, Petriu EM. Hybrid particle filter–particle swarm optimization algorithm and application to fuzzy controlled servo systems. IEEE Transactions on Fuzzy Systems, 2022, 30(10):4286-4297.
[19] Kamarposhti M A, Colak I, Shokouhandeh H, Iwendi C, Padmanaban S, Band S S. Optimum operation management of microgrids with cost and environment pollution reduction approach considering uncertainty using multi-objective NSGAII algorithm. IET Renewable Power Generation, 2025, 19(1): e12579.
[20] Shokouhandeh H, Ahmadi Kamarposhti M, Colak I, Eguchi K. Unit commitment for power generation systems based on prices in smart grid environment considering uncertainty. Sustainability, 2021, 13(18): 10219.
[21] Shishavan ST, Gharehchopogh FS. An improved cuckoo search optimization algorithm with genetic algorithm for community detection in complex networks. Multimedia Tools and Applications, 2022, 81(18):25205-25231.
[22] Kamarposhti M A, Khormandichali S M M, Solyman A A A. Locating and sizing of capacitor banks and multiple DGs in distribution system to improve reliability indexes and reduce loss using ABC algorithm. Bulletin of Electrical Engineering and Informatics, 2021, 10(2): 559-568.
[23] Kamarposhti M A, Alinezhad M. Comparison of SVC and STATCOM in static voltage stability margin enhancement. system, 2009, 3(2): 297-302.
[24] Chotikunnan P, Chotikunnan R. Dual design PID controller for robotic manipulator application. Journal of Robotics and Control (JRC), 2023, 4(1):23-34.
[25] Makahleh F M, Amer A, Manasrah A A, Attar H, Solyman A A, Kamarposhti M A, Thounthong P. Optimal management of energy storage systems for peak shaving in a smart grid. Computers, Materials and Continua, 2023, 75(2): 3317-3337.
[26] Eslami E, Ahmadi Kamarposhti M. Optimal design of solar–wind hybrid system-connected to the network with cost-saving approach and improved network reliability index. SN Applied Sciences, 2019, 1(12): 1742.
[27] Saleh B, Yousef AM, Ebeed M, Abo-Elyousr FK, Elnozahy A, Mohamed M, Abdelwahab SA. Design of PID controller with grid connected hybrid renewable energy system using optimization algorithms. Journal of Electrical Engineering & Technology, 2021, 16(6):3219-3233.
[28] Suseno EW, Ma'arif A. Tuning of PID controller parameters with genetic algorithm method on DC motor. International Journal of Robotics and Control Systems, 2021, 1(1):41-53.
[29] Ma'arif A, Setiawan NR. Control of DC motor using integral state feedback and comparison with PID: simulation and arduino implementation. Journal of Robotics and Control (JRC), 2021, 2(5):456-461.
[30] Çelik E, Öztürk N, Arya Y, Ocak C. (1+ PD)-PID cascade controller design for performance betterment of load frequency control in diverse electric power systems. Neural Computing and Applications, 2021, 33(22):15433-15456.
[31] Guzmán JL, Hägglund T. Tuning rules for feedforward control from measurable disturbances combined with PID control: a review. International Journal of Control, 2024, 97(1):2-15.
[32] Ghith ES, Tolba FA. Design and optimization of PID controller using various algorithms for micro-robotics system. Journal of Robotics and Control (JRC), 2022, 3(3):244-256.
[33] Lin P, Wu Z, Fei Z, Sun XM. A generalized PID interpretation for high-order LADRC and cascade LADRC for servo systems. IEEE Transactions on Industrial Electronics, 2021, 69(5):5207-5214.