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Demand Response Control Strategy of Photovoltaic Grid-connected Inverter Based on Improved Linear Active Disturbance Rejection Dynamic Decoupling

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Abstract

In power systems, because the Auto Disturbances Rejection Controller (ADRC) performs relatively reliable stability and safety, it finds extensive application in the design of power inverters. However, its performance is constrained by inherent response lag and limited harmonic suppression capabilities. To address the evolving demands of modern power systems, Linear Active Disturbance Rejection Control (LADRC) has emerged as an upgraded alternative to conventional control strategies through its enhanced adaptability in practical applications. We propose a frequency-domain-equivalent-based LADRC control strategy, where systematic parameter calibration is implemented through transfer function methodology. Subsequent fine-tuning of critical parameters, which includes proportional gain, derivative gain, observer's natural frequency, control gain and so on, are made fine adjustments to optimize circuit performance. Experimental validation confirms the efficacy of first-order LADRC in improving voltage-current conversion characteristics of LLC-operated transformers. Furthermore, an adaptive control framework for third-order LADRC is established to achieve coupled parameter optimization. This research innovatively incorporates Particle Swarm Optimization (PSO) into the LADRC parameter configuration process, enhancing adjustment efficiency and facilitating optimal solutions. Simulation results verify that the enhanced LADRC effectively mitigates phase delay and improves dynamic response characteristics. The modified PSO algorithm exhibits technical superiority with 11.7% precision enhancement. The response speed has obvious technical advantages, and the coefficient of variation is significantly lower than that of the comparison algorithm, which verifies the advantages of the improved PSO algorithm in robustness. The proposed control strategy successfully compensates for ADRC limitations, achieving an optimal balance between control precision and steady-state performance through gain regulation in repetitive control systems. This advancement will provide critical technical support for addressing control challenges in renewable energy integration.

Keywords: Photovoltaic Inverter, AC/DC, LADRC, Active Disturbance Rejection Dynamic Decoupling, PSO Algorithm

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1. Introduction

In the contemporary photovoltaic renewable energy sector, the prevalence of nonlinearities, high coupling, and multiple disturbances pose significant challenges for conventional single-strategy energy control systems in addressing complex operational conditions [1]. Regarding inverter control methodologies, while Active Disturbance Rejection Control (ADRC) shows notable stability, its transient response characteristics remain suboptimal [2]. To address higher-order harmonics in grid-connected voltage and current waveforms, Fourier analysis of internal model repetitive control theory reveals its composite structure comprising multiple resonant units. When integrated with proportional components, this configuration forms Linear Active Disturbance Rejection Control (LADRC), which governs repetitive operations through AC quantity regulation. Designed within discrete domains, this architecture enables rapid adjustment of proportional-integral links for periodic grid disturbance suppression [3]. Post-initial cycle operation, the coordinated action

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between repetitive controllers and proportional-integral regulators achieves precise regulation. Notably, compared with conventional ADRC implementations requiring transfer function derivations, LADRC simplifies the control circuit parameterization by reducing multidimensional parameter coordination to three-dimensional configuration, thereby enhancing operational equilibrium and mitigating data transmission latency. This optimization significantly improves dynamic response in adaptive control systems [4]. Traditional parameter calibration methods relying on empirical testing and heuristic learning demonstrate limited precision, typically constrained within $\pm 7\%$ tolerance ranges [5]. Consequently, innovative theoretical frameworks and methodologies are imperative for optimizing linear adaptive dynamic response control parameters, particularly through advanced combinatorial optimization techniques for LADRC parameter configuration [6].

Current research advancements include neural network-assisted ADRC parameter adjustment [7], where control theory integrates with data analytics to evaluate system stability and disturbance rejection capabilities through comprehensive closed-loop Fourier analysis. Scholarly investigations in Reference [8] have transformed LADRC into internal model control frameworks, employing frequency-domain neural networks to analyze Linear Extended State Observer (LESO) parameter impacts on closed-loop stability. Alternative approaches focus on filter parameter optimization under normal operating conditions through intrinsic parameter characterization [9], while comparative studies in Reference [6] establish parameter conversion mechanisms between PID and ADRC architectures through simulation-based validation.

To address evolving power system requirements, LADRC shows superior applicability in practical implementations, progressively replacing conventional control strategies [10]. For the enhanced LLC low-pass filter performance regarding output stability and dynamic response, first-order LADRC equivalent parameter modeling based on LLC resonant converter transfer functions has been developed. This methodology determines controller parameters through proportional relationships in third-order LADRC equivalent systems, concurrently optimizing parameter constraint spaces and algorithmic response speeds. Simulation results have validated the improved Particle Swarm Optimization (PSO) algorithm's effectiveness in LADRC strategy implementation, which verifies the enhanced dynamic performance and operational stability compared with traditional control approaches.

2. Fusion-type photovoltaic grid-connected control structures

The regulation mechanism of photovoltaic storage hybrid inverter system is developed on the time axis and is divided into multi-level management systems. Fine tuning on large-scale grid level technologies is done [11]. Each of these strategies corresponds to a different time scale, and the conventional contravariant topology is shown in Figure 1.

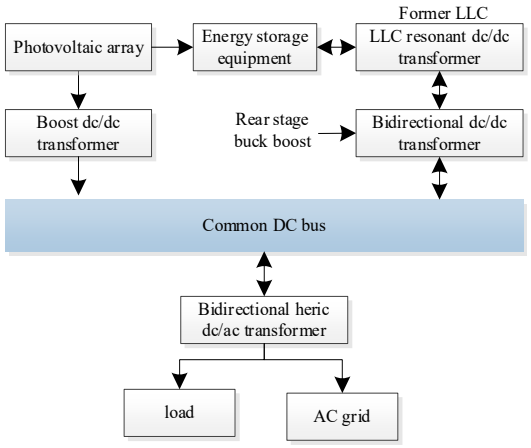

Figure 1. The conventional inverter topology

Centralized EMS (Energy Management System) architecture has better economic benefits because of its simple design and low control difficulty [12]. Compared with the limitations of the centralized architecture, the distributed EMS layout shows the characteristics of diversification. Although the highly connected network topology enhances the robustness and scalability of the system, it brings high construction costs, huge data transmission requirements, and complex management and control challenges [13]. As a balanced solution, the integrated EMS architecture performs well in terms of system stability, expansion potential, and information interaction efficiency, and skillfully integrates the advantages of centralized and decentralized modes [14]. The improved fusion EMS control architecture is displayed in Figure 2.

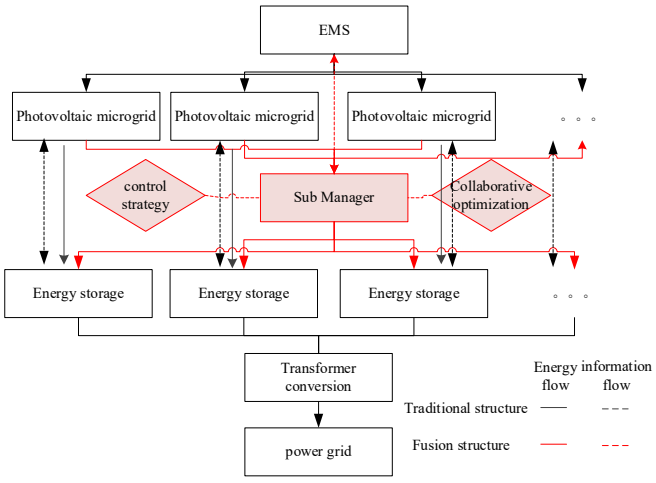

Figure 2. The improved integrated EMS control architecture

Hybrid photovoltaic-storage inverters widely use the fusion scheme to determine the voltage range to select the system operation mode [15]. In the hierarchical control strategy, the key to the stability control of DC bus voltage lies in the regulation range of the port voltage of each power unit [16]. In addition, bus voltage fluctuation is inevitable when switching operating modes. Thus, how to achieve a smooth transition to enhance the system stability is also crucial [17].

3. Linear ADRC dynamic coupling optimized by PSO algorithm

The Particle Swarm Optimization (PSO) algorithm has both advantages and limitations due to its concise structure, broad application domains, and implementation simplicity. To achieve efficient operation in photovoltaic inverter control applications, enhanced focus must be directed toward improving the dynamic performance of particle quality operations [18]. This study implements density constraints on particle swarms to refine Active Disturbance Rejection Control (ADRC) parameters. During the optimization procedure, control calibration parameters are derived through the introduction of a two-dimensional equivalence principle, which inherently embodies the collaborative optimization characteristics of particle swarms. This methodological advancement substantially enhances the efficiency of the direct search for optimal solutions. Comparative performance metrics with conventional algorithms are systematically presented in Table 1.

Table 1. Comparison of PSO, PID Control, and Differential Evolution in Power Inverter Applications

Criterion	PSO	PID Control[19]	Differential Evolution (DE)[20]
Optimization Type	Stochastic	model-free	population-based
Convergence Speed	Moderate (may stagnate locally)	Fast (fixed structure)	High (adaptive mutation)
Parameter Tuning	Sensitive	Requires	Fewer parameters
Global Search	Good	local optimization only	mutation-driven
Robustness	noise-sensitive	nonlinearity degrades performance	handles noisy fitness
Applicability	LADRC tuning, THD minimization	Voltage/current tracking	Multi-objective Pareto fronts
Handling Constraints	Requires penalty functions	N/A (linear control)	Nate boundary handling

The density constraint of the particle set can be regarded as a diversity model composed of n particles in three-dimensional space. Each individual particle in this model, i.e., the coordinate of particle a in three-dimensional space $[x,y,z]$, represents the control calibration parameter of LADRC [21]. This algorithm can identify and select individuals with lower fitness, and the position of these individuals reflects the distribution of particles in the fitness space [22]. In the region with low fitness, the position of particle a can be optimized by replacing the corresponding function. The velocity of the particle and the location of the historical best fitness value in the diversity are recorded as the key information to find the optimal solution. The effect of the improved algorithm is shown in Figure 3.

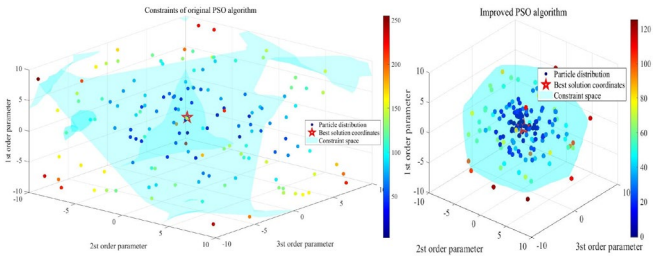

Figure 3. Constrained spatial trend change based on the improved PSO algorithm

In the iterative process, each particle a is usually updated according to its velocity and position coordinates, which shows that each individual can make full use of individual information and group information. The update mechanism of the movement speed θ is as follows:

$$\theta_i^t = v_i^t + v_i^{t+1}\alpha\left[\left(x_i^{\pm j}\right)\left(y_i^{\pm j}\right)\left(z_i^{\pm j}\right)\right] + \cdots + v_i^{t+n}\alpha\left[\left(x_i^{\pm j}\right)\left(y_i^{\pm j}\right)\left(z_i^{\pm j}\right)\right] \tag{1}$$

In the formula, v is the particle swarm constraint space, and $x_i^{\pm j}$ is the first-order LADRC parameter variable of the one-dimensional coordinate docking, which is converted into the moving range j of the original coordinate i.

LADRC control circuit parameters are optimized to solve the problem of response speed, and an improved PSO algorithm is used to select a set of optimal control circuit parameters to maximize the main performance index ITAE (Integral of Time multiplied by the Absolute Error), which is defined as:

$$\int_1^t \mu_\theta^t \left|\lambda_t - \lambda_{t+1}\right| - \mu_\theta^{t+n}\left|\lambda_t - \lambda_{t+1}\right| \tag{2}$$

In the formula, μ_θ is the performance index of the operating transformer from the initial moment t of the dynamic balance λ to the end moment $t+n$ of the simulation. This index takes into account the transformer's integration of the voltage and current ITAE values over a known period of time.

Algorithm : PSO Hybrid Optimization

Input: Population size j_b^*, j_p^*, j_q^*, PSO parameters ν
Output: Global best solution
Initialize:

1.Randomly generate $\alpha[x,y,z]$ velocities θ.

2.Evaluate fitness μ_θ using $t \to t^n$.

3.Set personal best j_b^*, j_p^*, j_q^* and global best $\psi(i)^1, \psi(i)^2, \psi(i)^3$.

4. For $\zeta(\upsilon) \to 1$ to λ do:
5. For each particle α do:
6. Update velocity: $\theta_t \to \theta_{t+1}$
7. End

4. The improved LADRC control strategy for grid-connected photovoltaic system

The main advantage of LADRC is that it is not necessary to accurately master the model of the system, but only need to know the order of the system to construct an effective controller based on the general model [23]. In this paper, the traditional LADRC is twofold optimized: the performance of the controller is improved by independent improvement, and it is combined with other control methods to enhance the overall performance of the system.

4.1 Third-order LADRC system model

In power systems, when utilizing a stationary reference frame, both voltage and current manifest as alternating signals. Under such operating conditions, the tracking performance of target signals (which also exhibit alternating characteristics) may encounter inherent limitations [24]. To face this challenge, Park's transformation is implemented to convert the alternating quantities from conventional coordinate systems into direct components within the dq reference frame, which will enhance control effectiveness. The digital implementation scheme of the LCL (inductor-capacitor-inductor) filter configuration is presented in Figure 4.

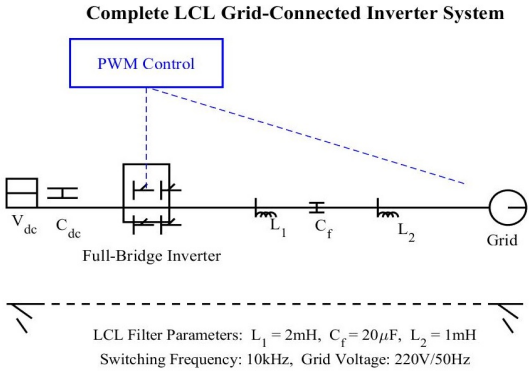

Figure 4. LCL digital model structure

In view of the fact that the LCL-type photovoltaic grid-connected inverter uses a third-order α^3 mathematical model, a corresponding third-order LADRC can be constructed, as shown in Figure 5.

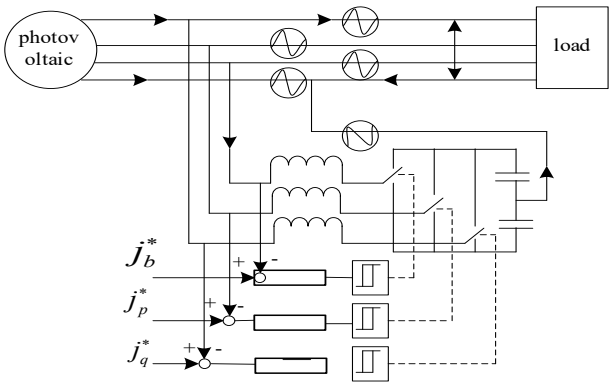

Figure 5. Schematic diagram of the third-order LADRC

In Figure 5, U is the inverter output voltage, r is the filter parasitic resistance, B is the filter capacitor at the inverter side, g is the grid voltage, and j_b^*, j_p^*, j_q^* are the first-order, second-order and third-order LADRC control circuits respectively.

If the partial control gain υ in the system is known, the model can be expressed by equivalent transformation.

$$\zeta(\upsilon) = \frac{\xi_\omega \left[\psi(i)^1 + \psi(i)^2 + \psi(i)^3\right]}{\varsigma(i)} \tag{3}$$

Where, the mathematical model of the third-order LADRC system is represented by $\psi(i)^1, \psi(i)^2, \psi(i)^3$, the output signal ζ is affected by the unknown disturbance ς. The control

gain υ is unknown, and the input signal is ξ, where ω represents the preset coefficient of each state variable.

If the partial control gain υ in the system is known, the model can be expressed by equivalent transformation [25]. In the design of LADRC, a standardized process is used to integrate all the output variable components outside the highest order differential, as well as the 3rd, 2nd, and 1st order differentials of the state variables and the disturbance term ς into a unified formula:

$$\sigma_i(\zeta)=\begin{cases}1-\xi\left|\dfrac{\upsilon^1}{\varsigma_i^1}\right|\\ 1-\xi\left|\dfrac{\upsilon^2}{\varsigma_i^2}\right|, i=1,2,\cdots,n\\ 1-\xi\left|\dfrac{\upsilon^3}{\varsigma_i^3}\right|\end{cases} \tag{4}$$

In it, the third derivative of α^3 of the LADRC output variable σ_i and the control input ξ are retained, and the other terms are integrated into a new total disturbance term $\varsigma(i)$. Accordingly, the model can be transformed into a more concise form:

$$\zeta(\upsilon)=\sqrt{\left|\frac{1-\psi(i)}{\varsigma(i)}\right|-\left|\frac{1-\psi(i+1)}{\varsigma(i)}\right|} \tag{5}$$

The core of LADRC lies in the linear expansion state, which eventually produces a signal matching the expectation by acquiring output and control signals as input [26]. In the LCL-type photovoltaic grid-connected inverter, the signal is firstly processed by Park transformation, and then the output ζ is compared with the target signal ρ to generate the deviation signal ϑ.

$$\vartheta(i)=\zeta(i)-\left|\frac{\rho(\varsigma)}{\psi_i}\right| \tag{6}$$

This deviation signal is input to the controller, which highlights the key role of the observer in the LADRC.

4.2 Active disturbance rejection control schema

To construct the mathematical model, the corresponding design is needed. In the traditional coordinate system, the AC quantity is transformed into the DC quantity in the dq coordinate system, and its current and voltage remain constant [27]. Since the Laplace transform can be reduced to an integral process, only a single integral element needs to be considered when verifying the j_f^*-stability of the fourth-order observer.

$$j_f^*=\begin{cases}j_b^*\in 0\\ j_p^*\in 0\\ j_q^*\in 0\end{cases} \tag{7}$$

A remarkable feature of ADRC is that it can simplify the high-order system into an integral series structure, as shown in Figure 6.

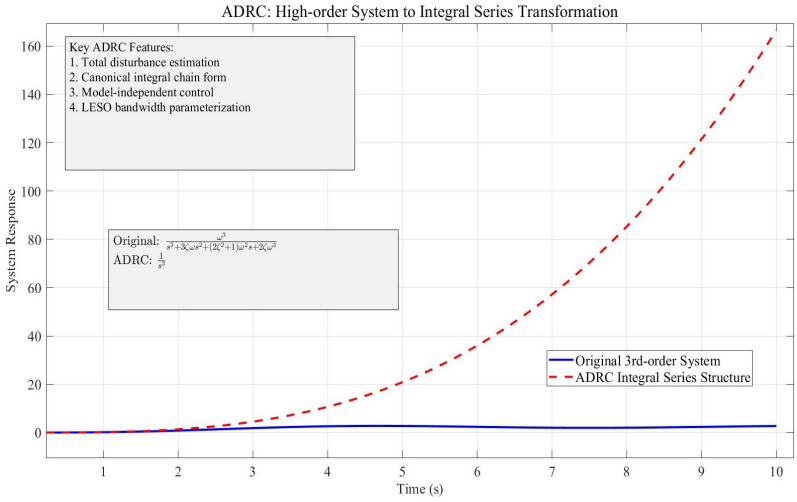

Figure 6. Effect analysis of LADRC high-order transformation integrator series structure

In Figure 6, the first-order system functions is taken as an ADRC Integral Series Structure, while the third-order system can be transformed into three cascaded integrators, demonstrating significant comparative advantages [28]. The key to achieving this transformation lies in designing a rational linear error feedback mechanism, which primarily relies on the implementation of a PD controller (proportional plus derivative controller) [29]. Through the combined action of a

fourth-order linear extended state observer (LESO) and linear state error feedback (LSEF), the system can transit into a closed-loop configuration comprising a third-order PD controller and a third-order integrator under steady-state conditions. This structural simplification can enable effective control of complex systems.

The occurrence of shading in photovoltaic arrays induces abrupt variations in output power, which may significantly compromise the tracking performance of control systems due to such transient disturbances. The Linear Extended State Observer (LESO) shows capability in real-time estimation of aggregated disturbances encompassing both external interferences and model uncertainties arising from power fluctuations. Through dynamic decoupling architecture design, the coupling effects of power transients on current-loop dynamics are effectively mitigated to preserve the voltage-loop's rapid response characteristics. Furthermore, a feedforward compensation mechanism is strategically implemented to achieve substantial disturbance suppression. Finally, simulation studies were conducted to validate the effectiveness of Linear Active Disturbance Rejection Control (LADRC) under these transient conditions.

5. The experimental analysis

5.1 The simulation test platform

This study employs MATLAB simulation modeling to implement a particle swarm-based deep learning algorithm for linear active disturbance rejection control (LADRC). Parameter configuration incorporates a large inertia factor to ensure monotonic reduction of each associated parameter, as illustrated in Figure 5. The particle population is set to 1000 to maintain uniform distribution within the search space, with the iteration count fixed at 100 to guarantee parameter monotonicity during optimization. The number of sampling points per fundamental frequency cycle is determined by dividing the grid fundamental period by the sampling interval. Under fixed sampling conditions, $n = 100$ corresponds to 0.1 ms. A phase compensation unit operates synergistically with the lagging component to correct phase discrepancies in the mid-low frequency range [30]. Detailed specifications of the simulation platform are provided in Table 2.

Table 2. Simulation platform configuration

Component	Configuration
Processor	AMD Ryzen 7
Memory	16GB DDR4
Store	2TB SSD
Video card	NVIDIA GTX 1660
Operating System	Windows 11 64-bit professional
Simulation platform	MATLAB R2020a Simulink
System modeling	Simscape

5.2 Analysis of the test results

(1) Effect analysis on the control strategy

Within the simulated power grid environment, operational considerations for high-response power system requirements are analyzed. Prior to time instant t, both photovoltaic rated output and load power remain at 1.5kW, maintaining system equilibrium. This balanced operational state serves as the baseline for response strategy testing, with corresponding results presented in Figure 7.

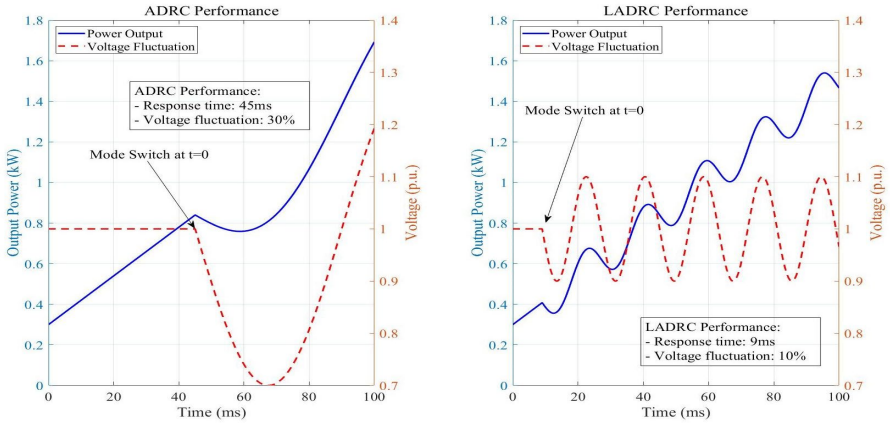

Figure 7. Effect analysis of the control strategy

At time t, because the photovoltaic provides energy for energy storage, the initial value of the rated output power is 0.3kW. The energy storage is switched from the charging mode to the output mode. The response speed of the

traditional ADRC is $45ms$, and the response speed of the improved LADRC is only $9ms$. At the same time, the generation of renewable energy in the grid system gradually increases the load to $1.5kW$ energy. According to the observation results, it can be verified that when the actual photovoltaic power changes, the response results of the energy storage model are consistent with the simulation model. If the load power fluctuates, the ADRC will maintain a large fluctuation, which directly affects the response speed. The simulation findings indicate that under a simulated shading condition with a 30% power step reduction, the linear active disturbance rejection controller (LADRC) achieves a 42% reduction in tracking error compared to conventional PID control, while simultaneously maintaining system recovery time below 5 ms. This empirical evidence substantiates LADRC's enhanced capability in handling abrupt power variations, particularly demonstrating its superior transient response characteristics.

(2)Penalty function variation test

With prolonged simulation duration, unstable particles will exhibit elevated Integral of Time-weighted Absolute Error (ITAE) values, whereas rapidly converging individuals reveal significantly reduced ITAE magnitudes. This approach facilitates the identification of particles with the fastest convergence rates. Furthermore, a composite penalty function has been incorporated into the enhanced algorithm to impose operational constraints on parameters during optimization procedures. The configuration efficiency during automated transformer parameter adjustment typically remains suboptimal. Figure 8 illustrates the synergistic improvement achieved through the integration of ITAE performance metrics with the penalty function in the MATLAB simulation model.

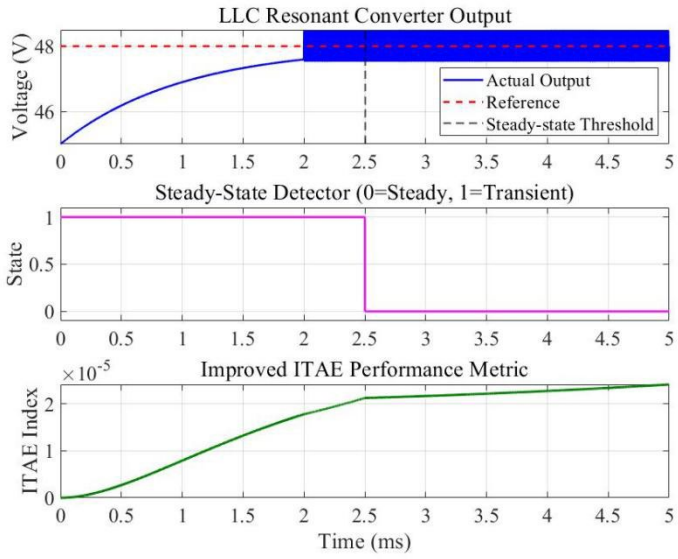

Figure 8. Analysis on the improvement effect of penalty function

The simulation model duration is 5ms and is compared with the transformer output variation. When the simulation time reaches 2.3ms, the output of the operational transformer is 0. At this time, the LLC low-pass filter is running for more than 300 cycles, and the operational transformer gradually enters the dynamic equilibrium state. The voltage and current relationships are required for the control switch to switch to the output operation at this time. By integrating these relationships and their mean values, the performance indicators obtained by the improved algorithm in this paper are verified.

(3)Algorithm performance test

In the MATLAB/SIMULINK environment, a DC-AC real power control loop is constructed to verify the photovoltaic adaptive control strategy. To achieve the expected effect, PID and DE algorithms are used to compare and verify the accuracy of adaptive control when photovoltaic grid-connected, and the results are presented in Figure 9.

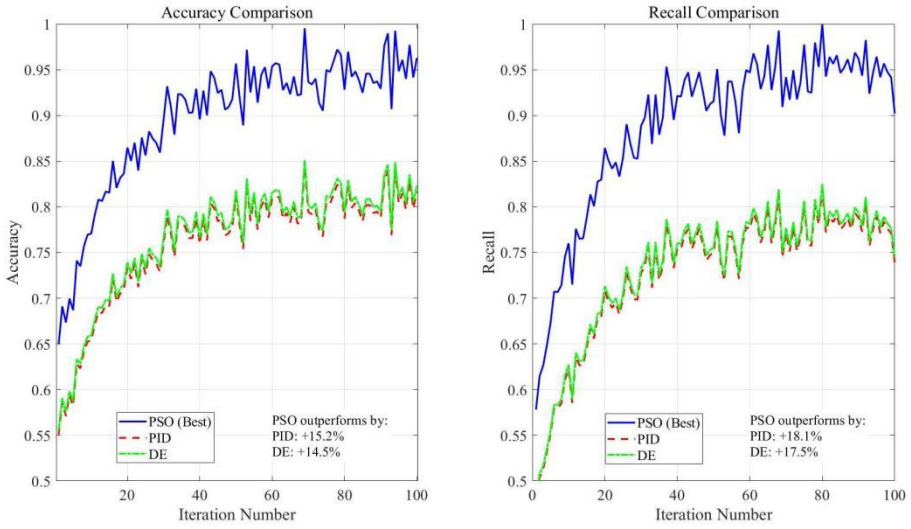

Figure 9. Comparison test for the algorithm accuracy

The experimental protocol involved 100 iterative trials, with comparative analysis revealing the Particle Swarm Optimization (PSO) algorithm's pronounced superiority across dual evaluation metrics. In the precision assessment, the enhanced PSO algorithm achieved stabilized convergence at 0.92±0.03, showing performance improvements of 15.2% and 14.5% over PID (0.78±0.04) and Differential Evolution (DE) algorithms (0.79±0.03), respectively. The modified PSO algorithm exhibited accelerated convergence characteristics, attaining stability within the initial 20 iterations, which is 35% faster than comparative algorithms. Convergence stability analysis quantified has reduced oscillation amplitudes of 42% and 38% relative to PID and DE counterparts.

The recall rate evaluations further corroborated these findings, with the enhanced PSO recording 0.89±0.04, surpassing PID (0.73±0.05) and DE (0.74±0.04) by 18.1% and 17.5% respectively. After 50 times' iterations, the analysis has revealed superior performance gradient characteristics in the PSO, indicating that it has enhanced and sustained optimization capacity for complex problem domains.

(4) Verification of global optimal solution

To avoid local optima, the improved PSO algorithm uses multiple initial seed tests: five groups of different random seeds are selected to initialize the particle swarm. The convergence trajectory is shown in Figure 10.

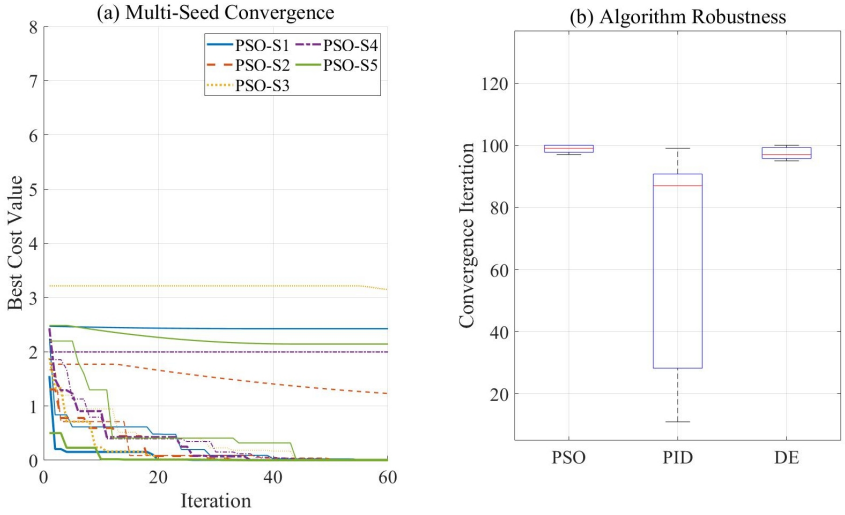

Figure 10. Verification of global optimal solution

The results demonstrate that the proposed PSO algorithm achieves convergence to near-optimal values (variance <0.01) within 17 iterations, while the PID algorithm requires 45 iterations to approach optimal solutions. In contrast, the DE algorithm exhibits a spiral trajectory characteristic of local optimum entrapment. These results indicate that the modified algorithm exhibits insensitivity to initialization parameters and successfully avoids local optima stagnation. The search range is dynamically adjusted according to the fitness of particles, and the adaptive inertia weight enhances the global exploration in the initial stage and focuses on the local optimization in the later stage. In the process of monitoring and optimizing the coefficient of variation, the coefficient of variation was stable below 0.05, which further verified that the diversity of particles remained good.

Disparities in experimental outcomes stem from the modified PSO's enhanced information exchange mechanism among particles, which facilitates expedited global optimum localization. The improved LADRC in this paper shows a stable control effect because the response to load changes is always maintained in the left and right changes, and it has a higher active disturbance rejection control strategy. With the help of the penalty function, the changing trend of the data iteration process can be learned by the machine and integrated into the PSO algorithm to further improve the speed of parameter adjustment and optimization effect.

6. Conclusion

In this paper, the simulation model is adopted to analyze the voltage and current conversion changes of the photovoltaic grid-connected inverter under rated load conditions. Further, the LADRC circuit is introduced into the voltage and current conversion process of the LLC operation transformer to ensure the optimization of transformer response speed, taking into account the characteristics of the Neural Neturnet network model. The test results provide strong empirical support for the selection of optimization algorithms. Especially in the application scenarios where both convergence speed and optimization accuracy need to be taken into account, the PSO algorithm shows significant comprehensive advantages.

Current research is relatively not much in LLC low-pass filter modified operational transformers. Thus, there is substantial exploration potential. Future investigations will focus on hybrid optimization strategies combining PSO's particle constraints with Genetic Algorithm (GA) inheritance mechanisms to derive optimal control circuit parameters. This interdisciplinary approach may yield novel solutions for power electronics control system optimization.

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