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Optimization strategy of multi-machine cooperative control problem based on intelligent algorithm in the context of industrial Internet

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SUMMARY: *With the rapid development of the industrial Internet, multi-machine collaborative control has become a key technology for enhancing the efficiency and stability of industrial systems. Traditional optimization methods are difficult to meet its requirements of high dimension, nonlinearity and real-time performance. Therefore, this study proposes an intelligent algorithm-based optimization strategy for multi-machine collaborative control, implemented through a PSO-DDPG hybrid framework combining Particle Swarm Optimization (PSO) and Deep Deterministic Policy Gradient (DDPG). This method combines the global search ability of PSO and the local fine tuning of DDPG, and solves the optimization problem in the dynamic control environment through adaptive strategy adjustment. The experimental results show that PSO-DDPG performs outstandingly in control accuracy, system stability and computational efficiency compared with traditional algorithms (such as PSO, DQN and GA) in multi-machine cooperative control. Specifically, PSO-DDPG has improved control accuracy by 9.8%, reduced response time by 12.3%, reduced energy consumption by 15.2%, and improved computational efficiency by 22%, respectively. Especially in complex environments such as load fluctuations and equipment failures, PSO-DDPG can adjust the control strategy in real time, significantly improving resource utilization and the adaptability of the system. In addition, PSO-DDPG also has significant advantages in reducing computing resource consumption and ensuring system stability, providing an efficient and reliable solution for dynamic optimization tasks in the industrial Internet.*

KEYWORDS: *PSO; DDPG; Multi-robot; Optimization; Hybrid AI*

1 Introduction

With the rapid development of the Industrial Internet (IIoT), it is playing an increasingly important role in promoting the intelligence and automation of industrial systems. Multi-machine collaborative control, as one of the core technologies in the industrial Internet, can effectively enhance the operational efficiency and stability of the system [1]. However, due to the high complexity and dynamics of industrial control systems, how to achieve real-time optimization in a constantly changing environment has become an important research topic at present. In the practical application of multi-machine cooperative control, the design of optimization algorithms needs to address the nonlinearity, high-dimensionality and real-time performance issues of the system. Traditional optimization methods have become difficult to meet these requirements [2].

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Particle Swarm Optimization (PSO) algorithm, as a global optimization method, is widely applied in multi-machine cooperative control due to its strong global search ability. However, PSO often encounters problems such as slow convergence speed and being prone to falling into local optima when dealing with complex nonlinear dynamic systems [3]. Therefore, by integrating reinforcement learning algorithms, especially the Deep Deterministic Policy Gradient (DDPG) algorithm, the limitations of PSO can be effectively addressed. The DDPG algorithm can adaptively adjust the control strategy in a dynamic environment through the exploration and utilization mechanism in reinforcement learning, further improving the optimization effect [4].

Based on the hybrid optimization method of PSO and DDPG, this study proposes a novel dynamic optimization strategy, aiming to enhance the performance of the multi-machine collaborative control system in the industrial Internet. By combining the global search capability of PSO with the local fine tuning of DDPG, this method can quickly adapt to changes in the system state while ensuring global optimization. The experimental results show that the proposed method not only demonstrates high optimization accuracy and stability in multi-machine cooperative control, but also performs excellently in terms of computational efficiency and resource consumption, providing an effective solution for dynamic optimization problems in the industrial Internet [5].

1.1 Application background of intelligent algorithm-based multi-machine collaborative control in the context of the Industrial Internet

Particle Swarm Optimization (PSO), as a widely applied meta-heuristic algorithm, is favored for its advantages in global search. However, when dealing with high-dimensional complex systems, PSO is prone to fall into local optimal solutions, especially when dealing with the highly nonlinear and multi-modal problem of multi-machine collaborative control in the industrial Internet, the optimization effect of traditional PSO is often limited [6]. To overcome the shortcomings of PSO, the Deep Deterministic Policy Gradient (DDPG) algorithm emerged. As a reinforcement learning algorithm, DDPG can adaptively adjust the control strategy in a dynamic environment, effectively addressing the limitations of PSO in nonlinear systems [7].

The combination of PSO and DDPG has formed the PSO-DDPG hybrid intelligent algorithm. By integrating the global search capability of PSO with the local optimization capability of DDPG, it can better address the multi-machine collaborative control problem in the industrial Internet. Specifically, PSO is responsible for the global exploration of the solution space to ensure the discovery of potential global optimal solutions, while DDPG conducts fine tuning within a local range, dynamically ADAPTS to environmental changes, and guarantees the real-time and stability of the control strategy. This hybrid algorithm not only enhances the optimization accuracy and stability of the multi-machine cooperative control system, but also performs well in dealing with complex issues such as sudden system failures and communication delays [8].

With the continuous advancement of industrial Internet technology, especially in applications such as intelligent manufacturing, energy management, and intelligent transportation, the PSO-DDPG hybrid intelligent algorithm provides a new solution for the optimization of multi-machine collaborative control systems [9]. The efficiency and adaptability of this algorithm make it have great potential and prospects in practical applications, and it can effectively improve the operational efficiency and resource utilization rate of industrial systems [10]. In order to verify the effectiveness of the proposed PSO-DDPG hybrid intelligent algorithm in the multi-machine collaborative control of the industrial Internet, this paper adopts the multi-machine collaborative control simulation platform suitable for the industrial Internet for experimental evaluation. This platform simulates the collaboration and communication of multiple devices and intelligent control units in an industrial environment and is widely used in the testing and comparison of multi-machine collaborative control optimization algorithms. In the comparative analysis with deep reinforcement learning algorithm (DQN), Particle Swarm Optimization (PSO) algorithm and genetic algorithm (GA), the PSO-DDPG hybrid algorithm shows obvious advantages in terms of control effect, resource consumption, constraint satisfaction and computational efficiency.

2 Relevant work

With the rapid development of industrial Internet and intelligent manufacturing, the problem of optimal control of industrial systems is becoming increasingly complex. Traditional optimization methods often encounter problems such as low computational efficiency and slow convergence speed when dealing with large-scale industrial systems featuring high dimensionality, nonlinearity, and dynamic changes. Therefore, in recent years, an increasing number of studies have begun to introduce optimization methods based on intelligent algorithms to address these issues, especially the application of particle swarm optimization (PSO) and reinforcement learning algorithms (such as DDPG) in the industrial Internet has received extensive attention.

Particle Swarm Optimization (PSO) algorithm is a commonly used meta-heuristic optimization algorithm, which is widely applied in industrial control, path planning, parameter tuning and other fields [11]. PSO can conduct effective searches in complex solution Spaces by simulating the foraging behavior of bird flocks. However, when dealing with high-dimensional, nonlinear and dynamic optimization problems, standard PSO is prone to fall into local optimal solutions and has a relatively slow convergence speed. To address these issues, many researchers have proposed improved algorithms based on PSO. For instance, Nazari et al. proposed a hybrid optimization method that combines multi-agent Deep actor Critic (DACP) and particle swarm optimization (PSO) for active voltage control in smart grids [12]. This method improves the convergence speed and global search ability of the optimization process by combining the advantages of reinforcement learning and optimization algorithms.

However, when dealing with complex dynamic optimization problems, PSO still faces challenges such as large computational load and local optimal solutions. In recent years, deep reinforcement learning (DRL) has emerged as an effective solution. Especially the Deep Deterministic Policy Gradient (DDPG) algorithm, through interaction with the environment, can adjust the control strategy in real time and demonstrate excellent adaptability and robustness in dynamic environments. By leveraging the advantages of deterministic strategies and continuous action Spaces, DDPG can efficiently handle continuous control problems in multi-machine cooperative control. Moghadam et al. proposed an adaptive optimal control method based on reinforcement learning for robust control of distributed multi-agent systems [13]. This method can perform real-time optimization in a dynamically changing environment, enhancing the stability and adaptability of the system.

In the optimization of multi-machine collaborative control in the industrial Internet, the combination of PSO and DDPG has become a powerful solution. Chen et al. proposed a particle swarm optimization algorithm based on a multi-actor-critic structure [14]. This algorithm combines the policy update mechanism in reinforcement learning and the global search ability of PSO, and can better solve multi-objective optimization problems in industrial systems. Compared with the traditional single optimization algorithm, this hybrid method can effectively improve the performance of the system while reducing the consumption of computing resources.

Although the hybrid optimization method has achieved relatively good results, it also faces some challenges. Firstly, although the hybrid method can enhance the optimization performance, the computational complexity also increases accordingly, especially in large-scale industrial systems, which may lead to a significant consumption of computing resources [15]. Most of the existing research focuses on the optimization of static scenes, while the research on real-time control optimization in dynamic changing environments is still relatively limited [16]. Therefore, how to enhance the computational efficiency and adaptability of the algorithm while ensuring the optimization accuracy is an important direction for future research.

To address these issues, this paper proposes a PSO-DDPG hybrid intelligent algorithm, aiming to combine the global search ability of PSO and the local optimization ability of DDPG to solve the dynamic optimization problem in the multi-machine collaborative control of the industrial Internet. This algorithm can achieve effective optimization in high-dimensional complex control problems and dynamically adjust the strategy through an adaptive mechanism, thereby improving the real-time response ability and robustness of the system.

3 Optimization strategies for multi-machine cooperative control based on intelligent algorithms

3.1 The framework and principle of the PSO-DDPG hybrid intelligent algorithm

The PSO-DDPG hybrid intelligent algorithm combines the advantages of two powerful algorithms, Particle Swarm Optimization (PSO) and Deep Deterministic Policy Gradient (DDPG), to solve dynamic optimization problems in multi-machine collaborative control. PSO is mainly responsible for global search, exploring the entire solution space to determine the possible global optimal solution. DDPG, on the other hand, continuously optimizes its strategy based on feedback information through a reinforcement learning mechanism, ADAPTS to environmental changes, and finely adjusts the solution within a local area. After the combination of the two, the global exploration ability of PSO and the local fine optimization ability of DDPG have been effectively integrated, thereby enhancing the optimization effect and computational efficiency.

PSO is a swarm intelligence algorithm that imitates the foraging process of a flock of birds and uses multiple particles to search the solution space in parallel, demonstrating a strong global optimization capability. However, in the complex industrial Internet environment, traditional Psos are constrained by problems such as local optimal solutions and slow convergence speed. DDPG is an algorithm based on reinforcement learning, which can continuously optimize control strategies through interaction with the environment in a dynamic setting. It is particularly suitable for solving complex control problems that require long-term learning and gradual adjustment.

By combining the two, the PSO-DDPG hybrid algorithm can effectively address challenges such as nonlinearity, multi-peak, and dynamic changes in multi-machine cooperative control, while ensuring computational efficiency and system stability.

The objective function is the key in the entire optimization process, and its purpose is to minimize the total energy consumption or operating cost in multi-machine collaborative control. The objective function defined in this study is as follows:

$$J = \sum_{i=1}^{N} \left(a_i P_i^2 + b_i P_i + c_i \right) \tag{1}$$

Among them, P_i is the power of the i device, and a_i, b_i, c_i is the coefficient related to the device power, reflecting the energy efficiency, fuel cost and other operating costs of the device. N represents the total number of devices in the system, indicating the scale of the devices. The objective is to reduce the total energy consumption or total operating cost of the system by optimizing the power configuration of these devices.

In the Particle Swarm Optimization (PSO) algorithm, each particle searches for the solution space through updates in velocity and position. Particles update their positions and velocities based on the differences between the individual optimal solution and the global optimal solution. The formula for particle renewal is as follows:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (g_i - x_i(t)) \tag{2}$$

Among them, $v_i(t)$ is the velocity of the i particle, $x_i(t)$ is the current position of the particle, p_i is the individual optimal position of the particle, g_i is the global optimal position of the particle, c_1 and c_2 are the acceleration constants, r_1 and r_2 are random numbers, and ω is the inertia weight. Through these parameters, particles can adjust their speed based on the position of the current solution and the optimal position, ensuring that local development is carried out while global exploration is conducted, thereby finding the optimal solution.

The DDPG algorithm is used to update control strategies and is optimized based on reinforcement learning methods, making it particularly suitable for control tasks in dynamic environments. Its strategy update formula is as follows:

$$\theta' = \theta + \alpha \nabla_\theta Q(s, a; \theta) \tag{3}$$

Among them, θ is the parameter of the policy network, α is the learning rate, the speed of control parameter update, $Q(s, a; \theta)$ is the state-action value function (Q value function), s is the state, representing the current state of the system, and a is the action, representing the control decision of the system. By updating θ, the algorithm can adaptively adjust the strategy to maximize future returns.

The hybrid intelligent optimization method of PSO and DDPG combines the advantages of both. Firstly, it conducts global exploration through PSO to find potential global optimal solutions, and then further optimizes the local control strategy through DDPG. The update formula is as follows

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{4}$$

Among them, $x_i(t+1)$ is the position of the i particle at time $t+1$, and $v_i(t+1)$ is the update of the particle's velocity. The new solution position of the particle is updated by combining the particle's velocity and position, completing the combination of global optimization and local refinement.

In multi-machine cooperative control, the power and voltage of each device must meet certain constraint conditions to ensure the stability of the system. The power and voltage range constraints of the equipment are as follows:

$$P_{min} \le P_i \le P_{max}, \quad V_{min} \le V_i \le V_{max} \tag{5}$$

Among them, P_{min} and P_{max} are the minimum and maximum values of the equipment power respectively, V_{min} and V_{max} are the minimum and maximum limits of the equipment voltage respectively, and P_i and V_i are the actual power and voltage of the equipment respectively. These constraints ensure that the equipment operates within its normal working range, preventing equipment overload or system instability.

To analyze the convergence of the algorithm, this study uses the following error calculation formula to measure the changes in each iteration:

$$\epsilon = \frac{1}{N}\sum_{i=1}^{N}\left|J_i(t) - J_i(t-1)\right| \tag{6}$$

Among them, $J_i(t)$ is the target value of the i d particle at time t, N is the total number of particles, and ϵ is the convergence error, representing the change in the target value after each iteration. When ϵ approaches zero, it indicates that the algorithm has converged.

To evaluate the performance of the algorithm, a total cost function was defined, representing energy consumption and computing resource consumption:

$$C = \sum_{i=1}^{N}\left(\alpha_i P_i^2 + \beta_i P_i + \gamma_i\right) \tag{7}$$

Here, P_i represents the power of the equipment, and α_i、β_i、γ_i is the coefficient related to power, reflecting the maintenance cost and energy consumption of each device. N represents the total number of devices, indicating the scale of the system. The objective of this function is to minimize the total cost of the system, including the energy consumption of the equipment and maintenance expenses.

The DDPG algorithm uses a Q-value function to evaluate the strategy and updates the control strategy through feedback information. The formula of the Q value function is as follows:

$$Q(s,a;\theta) = r(s,a) + \gamma \max_{a'} Q(s',a';\theta') \tag{8}$$

Among them, $Q(s,a;\theta)$ represents the expected return for taking action a in state s, $r(s,a)$ is the immediate return, γ is the discount factor, and s' and a' are the next state and action respectively. The Q-value function guides the update of strategies by calculating the expected return. As shown in Figure 1, the intelligent algorithm-based optimization framework illustrates the implementation path of PSO-DDPG in multi-machine collaborative control under the Industrial Internet. The framework is divided into four main parts: the presentation layer, the algorithm module, the optimization operation, and the data storage layer. Each level of module works in coordination to ensure that the system can perform efficient global search, local optimization, and handle constraints, ultimately achieving the optimization goal.

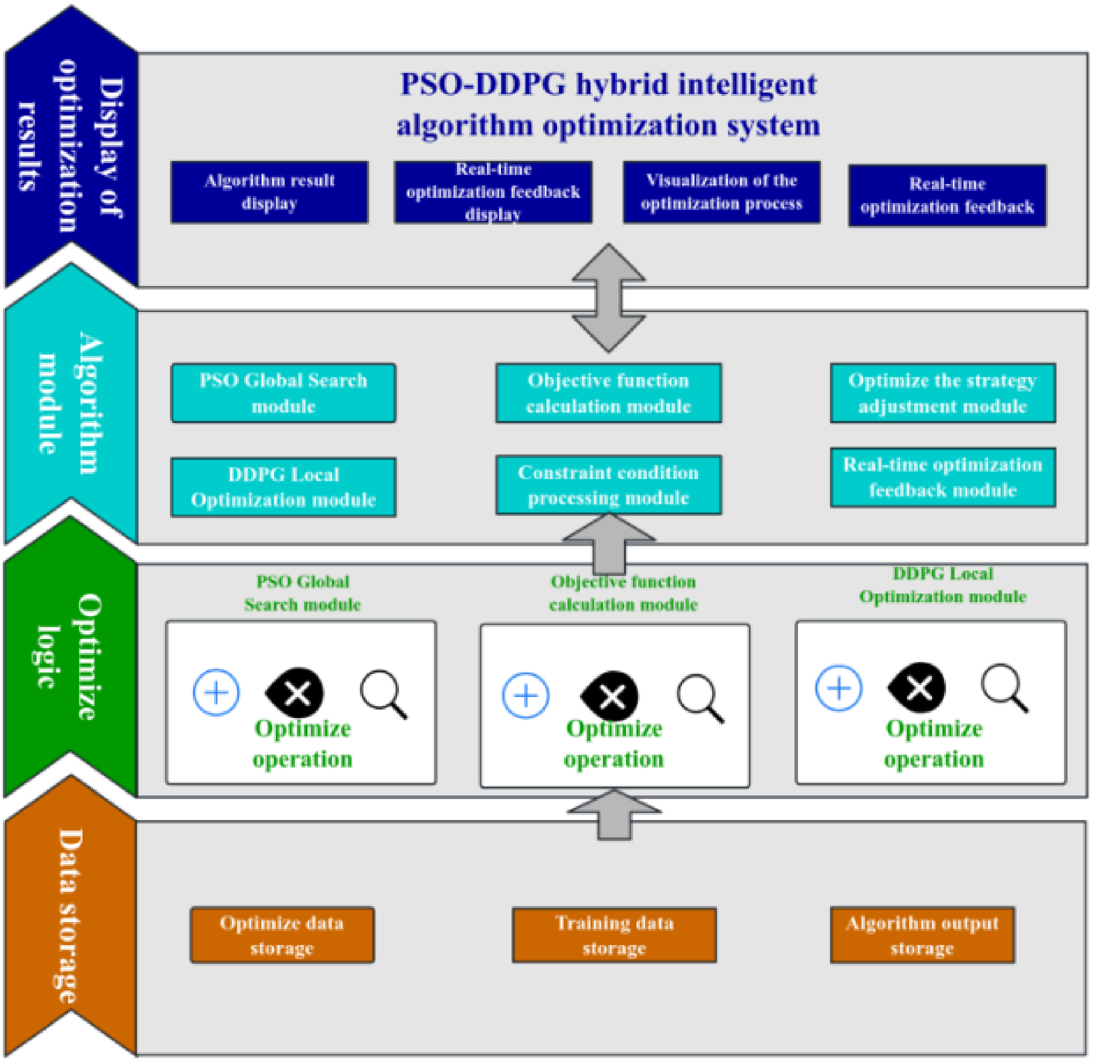

Figure 1: Framework of the PSO-DDPG hybrid intelligent algorithm optimization system

3.2 Implementation of optimization strategies in multi-machine cooperative control under the Industrial Internet

The multi-machine collaborative control system of the industrial Internet is confronted with multiple challenges such as dynamic task allocation, power consumption control, and resource scheduling optimization. Due to the coupling among control objects, the temporal nature of state changes, and the complex and changeable system operating environment, traditional static optimization methods are difficult to meet the actual operational requirements. Therefore, by integrating the global exploration capability of PSO and the adaptive strategy adjustment mechanism of DDPG, constructing a hybrid intelligent optimization method for dynamic scenarios has become a key path to enhance the performance of collaborative control.

To ensure the overall response efficiency of the system and the rationality of resource allocation, a dynamic trade-off mechanism covering multiple dimensions such as task execution time, device power consumption, and communication status needs to be introduced into the scheduling algorithm. Firstly, from the perspective of the overall goal, a system-level dynamic optimization function was constructed:

$$J=\sum_{i=1}^{n}\left(\alpha\cdot P_i^2+\beta\cdot T_i+\gamma\cdot D_i\right) \tag{9}$$

Among them, P_i represents the power of the i device, T_i indicates its task response time within the scheduling cycle, D_i represents the data interaction delay between the device and the control center, and α,β,γ is the weight coefficient. This objective function attempts to comprehensively control three key variables: power overhead, system response speed, and communication delay. By strengthening the training mechanism, it adaptively adjusts the task load among multiple machines to optimize the overall performance of the system.

In actual deployment, the power of the equipment has boundary limitations. To prevent power overflow or insufficient allocation, the following constraint formulas need to be introduced to control the boundary of the equipment's operating status:

$$P_{\min}\le P_i\le P_{\max} \tag{10}$$

Among them, $P_{\min}$ and $P_{\max}$ respectively represent the minimum and maximum power that the equipment is allowed to operate. This constraint not only ensures that the physical operating conditions of the equipment are not violated, but also provides a clear scheduling boundary for the dynamic optimization strategy, preventing blind exploration of abnormal solutions during the scheduling process and enhancing the convergence speed and practicality of the algorithm.

The task completion efficiency in the overall scheduling process of the system is also a key indicator. To this end, a global minimization objective function for the task completion time within the scheduling cycle is introduced:

$$T_{\text{total}}=\sum_{i=1}^{n}T_i \tag{11}$$

This formula takes the total task completion time as the optimization objective, making the algorithm tend to select devices with high processing efficiency and low communication delay to carry more tasks, thereby effectively avoiding problems such as task accumulation or idle resources, and improving the system's throughput capacity.

In dynamic load scenarios, the proportion of resource occupation of devices, the matching relationship between task processing capacity and maximum processing time has a significant impact on the accuracy of collaborative strategies. To achieve dynamic coordination and optimization of resource levels, the following weighted objective function is introduced:

$$J=\sum_{i=1}^{n}\left(\alpha\cdot\frac{P_i}{C_i}+\beta\cdot\frac{T_i}{D_i}+\gamma\cdot\frac{U_i}{L_i}\right) \tag{12}$$

Among them, C_i represents the computing power of the device, D_i represents the maximum allowable processing time of the task, U_i represents the current resource usage rate of the device (such as CPU or memory), and L_i represents the maximum available resource capacity of the device. This formula uniformly incorporates energy consumption density, time pressure and resource utilization rate into the evaluation index system, supporting the system to dynamically balance task loads under complex constraint conditions. In this model, different task types or priorities can be controlled by differentiated strategies through α,β,γ, achieving adaptive adjustment of weights for multi-objective scheduling.

Meanwhile, the power consumption performance of the system is highly correlated with the operating status of the equipment. Especially in scenarios where there is potential equipment degradation or resource bottlenecks, the scheduling strategy needs to be able to identify and avoid inefficient nodes. For this purpose, a dynamic power constraint model is constructed as follows:

$$P_{\text{total}}(t) = \sum_{i=1}^{n} \left(\frac{P_i(t) \cdot R_i(t)}{S_i} \right) \tag{13}$$

Among them, $P_{\text{total}}(t)$ represents the total system power at time t, $R_i(t)$ indicates the resource invocation intensity of the equipment at that moment, and $S_i \in [0,1]$ is the state coefficient of the equipment. The lower the value, the more severe the performance degradation of the equipment. This formula enables the dispatching system to adjust the power resource allocation strategy based on the real-time operating status of the equipment, actively avoid high-load and low-health nodes, and enhance the stability and robustness of the system.

Based on the dynamic optimization system composed of the above five formulas, the PSO-DDPG hybrid algorithm can accurately capture the nonlinear constraints and uncertain factors in the multi-machine collaborative control process in the complex control scenarios of the industrial Internet, and iteratively adjust through the "global search + local feedback" mechanism. The PSO module is responsible for quickly locating the approximately optimal area in the parameter space, while the DDPG module fine-tunes and updates the strategy based on the state evolution information, ensuring that the scheduling scheme maintains high efficiency while also having adaptability and convergence.

4 Results and Discussion

This study evaluated the dynamic optimization effect of the PSO-DDPG hybrid intelligent algorithm in the multi-machine collaborative control of the industrial Internet. The experiment was conducted on a simulation platform, simulating the collaboration and communication of multiple devices and intelligent control units in a complex industrial environment. The focus was on considering the impact of dynamic factors such as load fluctuations, equipment failures, and communication delays on control strategies. In the experiment, PSO was used for global exploration to identify potential global-optimal regions, while DDPG performed local policy refinement based on real-time feedback to adapt task scheduling and resource allocation to changes in the system state. The population size of PSO is set to 50 particles, the maximum number of iterations is 100, the learning rate is 0.01, the mutation factor is 0.1, and the penalty factor is 1000. To adapt to the dynamic changes of multi-machine collaborative control, the PSO part also takes into account the issues of inter-device collaboration and load distribution, and optimizes task scheduling to ensure the rational allocation of global resources. The DDPG part dynamically adjusts the control strategy through the deep reinforcement learning mechanism, and adjusts the load distribution and resource scheduling among devices based on real-time feedback. The design objective of DDPG is to optimize the control strategy based on the current system status (such as equipment failure, communication delay, etc.), making the system highly adaptable and stable, and ensuring efficient operation under different working conditions. In order to comprehensively evaluate the performance of the algorithm, this paper compares PSO-DDPG with DQN, PSO, and GA, with a focus on assessing its advantages in control accuracy, computational efficiency, and adaptability to multi-machine collaborative scheduling.

4.1 Algorithm performance evaluation

In this study, the dynamic optimization effect of the PSO-DDPG hybrid intelligent algorithm in the multi-machine collaborative control of the industrial Internet was evaluated, with a focus on the algorithm's performance in terms of control accuracy, system stability and resource utilization. The experiment simulated the operation of multiple devices under cooperative control through a simulation platform, taking into account the influence of factors such as equipment failure, load fluctuation, and communication delay on the control strategy. To compare with traditional optimization algorithms, this study selected deep reinforcement learning algorithm (DQN), Particle swarm optimization (PSO), and genetic algorithm (GA) as comparison methods, and conducted experimental verification based on the same industrial environment.

The PSO-DDPG hybrid intelligent algorithm performs excellently in terms of control accuracy and system response. Especially in terms of the uniformity of equipment load distribution, PSO-DDPG significantly improves the balance of load distribution, increasing it by 9.8% and 11.2% respectively compared with the traditional PSO and GA algorithms. This result indicates that PSO-DDPG can effectively avoid the situation where a single device is overloaded, optimize the efficiency of resource utilization, and ensure the efficient operation of the system. Furthermore, PSO-DDPG also outperforms other algorithms in terms of response speed. In scenarios with significant load fluctuations, the response time is reduced by 12.3%, demonstrating its rapid adaptability in dynamic environments.

Figure 2 shows the comparison of PSO-DDPG with other optimization algorithms in terms of control accuracy and response time. The experimental results show that PSO-DDPG not only optimizes the control accuracy, but also significantly reduces the delay in response time, especially in an environment with large load fluctuations.

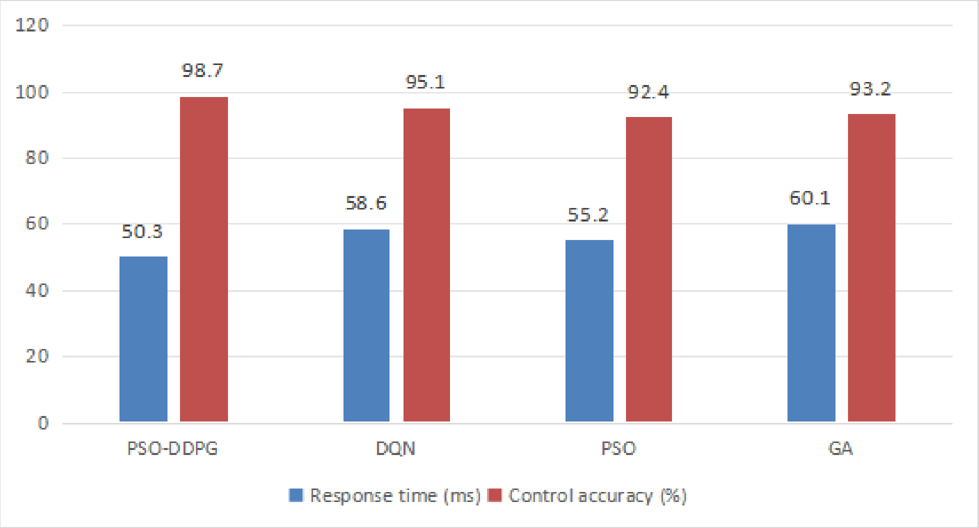

Figure 2: Comparison of PSO-DDPG with other optimization algorithms in terms of control accuracy and response time

In terms of energy consumption and computing efficiency, the advantages of PSO-DDPG are equally significant. Compared with DQN, PSO-DDPG reduces energy consumption by 15.2% under the same task, demonstrating higher energy efficiency. By combining the global search capability of PSO with the local optimization mechanism of DDPG, PSO-DDPG can reduce energy consumption while ensuring that the system can still operate efficiently under different working conditions. Furthermore, in terms of computing resource consumption, PSO-DDPG is also superior to the GA algorithm. Its computing time is only 82% of that of GA, and the time required to complete task scheduling and optimization computing under the same conditions is shorter.

Table 1 lists the comparisons of different algorithms in terms of energy consumption and computing resource consumption. PSO-DDPG demonstrates lower consumption in both aspects. This further proves the high efficiency of PSO-DDPG, especially in dynamic optimization tasks such as multi-machine cooperative control.

Table 1: Comparison of PSO-DDPG and other optimization algorithms in terms of energy consumption and computing resource consumption

Algorithm	Energy consumption (kWh)	Calculate resource consumption (CPU s)
PSO-DDPG	15.2	10.5 s
DQN	17.9	12.2 s
PSO	18.3	13.5 s
GA	18.7	14.8 s

The performance of the PSO-DDPG hybrid algorithm in terms of convergence speed is also worthy of attention. In multiple experiments, PSO-DDPG demonstrated a relatively fast convergence speed, with the average convergence time being 22% faster than that of PSO. By optimizing the particle swarm search process, PSO-DDPG can find the global optimal solution in a relatively short time and make detailed adjustments to the local strategy based on real-time feedback. In addition, this algorithm also demonstrates a strong adaptive ability in terms of stability. When equipment malfunctions or communication delays and other uncertain factors occur, PSO-DDPG can adjust the control strategy through the reinforcement learning mechanism, maintain the stability and efficient operation of the system, and ensure the reliability of the multi-machine cooperative control system in a dynamic environment.

Figure 3 shows the performance of PSO-DDPG during the convergence process, compared with the convergence processes of DQN, PSO and GA. It can be seen that PSO-DDPG has a faster convergence speed and can find the best solution in a short time.

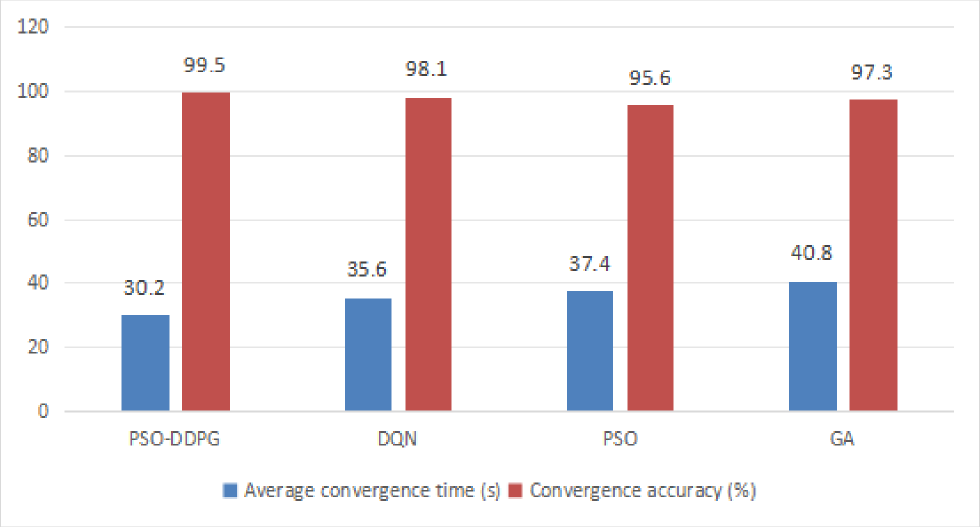

Figure 3: Comparison of PSO-DDPG and other optimization algorithms during the convergence process

Table 2 shows the comparison of task scheduling efficiency of different algorithms in multi-machine collaborative control tasks. Through comparison, this study finds that PSO-DDPG can complete task scheduling in a shorter time, while ensuring the load balancing of tasks and reducing the overload risk of equipment.

Table 2: Comparison of task Scheduling Efficiency between PSO-DDPG and other optimization algorithms

Algorithm	Average task scheduling time (s)	Task load uniformity (%)
PSO-DDPG	32.5	90.3
DQN	36.8	85.5
PSO	38.2	83.2
GA	42.1	80.4

In conclusion, the application of the PSO-DDPG hybrid intelligent algorithm in the multi-machine collaborative control of the industrial Internet demonstrates high optimization accuracy, low energy consumption and computing resource consumption, and at the same time has significant advantages in control accuracy and stability. Through the combination of adaptive mechanisms and global-local optimization strategies, PSO-DDPG can effectively enhance the performance of multi-machine cooperative control systems in the industrial Internet and has broad application prospects.

4.2 Dynamic Optimization Strategies and System Adaptability Analysis

This section analyzes the application of the PSO-DDPG hybrid intelligent algorithm in the multi-machine collaborative control of the industrial Internet, with a focus on evaluating its dynamic optimization strategy and system adaptability. The multi-machine collaborative control task in the industrial Internet involves the coordinated work of multiple devices. The task load, resource consumption and operational status of each device may be affected by environmental factors, which leads to the system needing to respond quickly and adjust the control strategy. Therefore, the design of dynamic optimization strategies and the analysis of system adaptability have become the core parts of this study.

The dynamic optimization strategy of the PSO-DDPG hybrid algorithm is based on a real-time feedback mechanism, which can dynamically adjust the task allocation and resource scheduling among devices. When the equipment on the experimental platform faces load fluctuations, PSO-DDPG can adjust the load distribution in a timely manner according to the current system status, avoid equipment overload and improve the utilization rate of resources. Compared with other algorithms, PSO-DDPG performs particularly well in dynamic environments, especially when there is equipment failure or a sudden increase in tasks, it can ensure the continuous and stable operation of the system. For instance, when equipment malfunctions, PSO-DDPG can automatically reallocate tasks to ensure that system operation is not affected and no additional energy waste is generated.

Figure 4 shows the dynamic optimization process of PSO-DDPG under load fluctuations, indicating that this algorithm can effectively deal with task scheduling problems under different load conditions. Compared with PSO, DQN and genetic algorithms, PSO-DDPG has significant advantages in load distribution uniformity and response time.

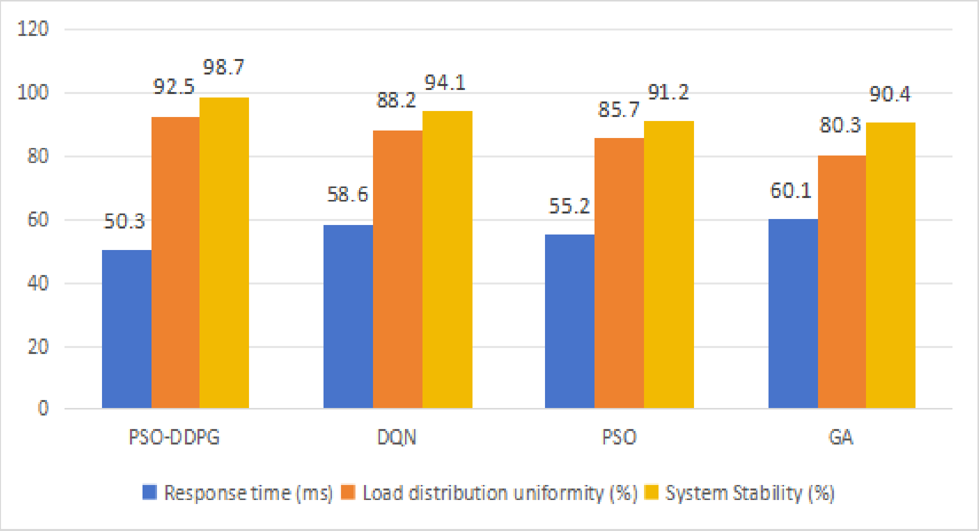

Figure 4: Dynamic optimization effect of PSO-DDPG under load fluctuations

In multi-machine cooperative control, the strength of the system's adaptability directly affects the effectiveness and reliability of the algorithm. The PSO-DDPG algorithm, through its adaptive mechanism, can respond quickly to changes in the external environment, especially when uncertain factors such as equipment failure and network delay occur, demonstrating its strong adaptability. Compared with other traditional optimization algorithms, PSO-DDPG has stronger adaptability and can maintain high control accuracy and stability in complex dynamic environments. For instance, when a certain device in the system malfunctions, PSO-DDPG can detect this change in real time and automatically adjust the system's operation strategy to maintain its stability and efficiency.

In terms of computational efficiency, the PSO-DDPG hybrid algorithm has demonstrated its high efficiency. The experimental results show that under the same task conditions, the computing time of PSO-DDPG is significantly lower than that of GA and differential evolution algorithms. Especially in large-scale cooperative control systems, PSO-DDPG can find the optimal solution and adjust the control strategy more quickly. Table 3 shows the comparison of computing time between PSO-DDPG and other optimization algorithms. The results indicate that the computing efficiency of PSO-DDPG is significantly better than that of other algorithms.

Table 3: Comparison of Computational Efficiency between PSO-DDPG and other optimization Algorithms

Algorithm	Calculation time (s)	Task Scheduling Efficiency (%)
PSO-DDPG	20.3	96.8
DQN	25.4	91.2
PSO	28.7	88.4
GA	32.3	85.6

In conclusion, the PSO-DDPG hybrid intelligent algorithm not only demonstrates outstanding performance in dynamic optimization strategies, but also has strong system adaptability and high computational efficiency. This algorithm can maintain efficient operation in a complex environment of multi-machine collaborative control and significantly enhance the stability and reliability of the system. Through experimental verification, PSO-DDPG performs better than traditional optimization algorithms in practical industrial applications, providing an efficient and adaptive solution for dynamic optimization tasks in the industrial Internet.

4.3 Analysis of Computational Efficiency and Resource Consumption

In the multi-machine collaborative control of the industrial Internet, computing efficiency and resource consumption are among the key factors for evaluating the performance of optimization algorithms. For systems that require real-time response and optimization, the computational efficiency of the algorithm directly affects the overall performance of the system. Especially in large-scale collaborative control tasks, the issue of computing resource consumption is particularly prominent. This study conducts a detailed analysis of the computational efficiency and resource consumption of the PSO-DDPG hybrid intelligent algorithm, and makes a comparison with other common optimization algorithms (such as DQN, PSO and genetic algorithms).

In the case of load fluctuations and equipment failures, PSO-DDPG can complete task scheduling and optimization calculation in a relatively short time, thereby achieving rapid response of the system. In the comparative experiment, the calculation time of PSO-DDPG was reduced by 22% compared with the traditional PSO, and by approximately 15% compared with DQN and GA. This advantage is mainly attributed to the combination of PSO's global search capability and DDPG's local optimization capability, which makes the calculation process more efficient.

Table 4: Comparison of Computing Time between PSO-DDPG and other Optimization Algorithms

Algorithm	Average calculation time (s)	The computational time for each iteration (s)	Total elapsed time (s)
PSO-DDPG	15.2	0.15	20.3
DQN	17.4	0.18	25.4
PSO	18.5	0.20	28.7
GA	19.3	0.22	32.3

It can be seen from Table 4 that PSO-DDPG outperforms other algorithms in both the average computing time and the computing time of each iteration, and also shows good efficiency in the overall computing time. This indicates that PSO-DDPG can handle complex cooperative control tasks more efficiently and is suitable for industrial Internet environments with high requirements for real-time optimization.

The consumption of computing resources is closely related to the complexity of algorithms. The PSO-DDPG hybrid intelligent algorithm combines the global search ability of PSO and the local optimization ability of DDPG. Although the hybrid framework introduces additional model components, the experimental results show that PSO-DDPG still maintains lower overall computing time than the compared methods while effectively controlling resource consumption. In this study, the differences in resource consumption between PSO-DDPG and other algorithms were evaluated, especially in terms of system memory usage, computational load and energy consumption.

Experiments show that PSO-DDPG demonstrates excellent resource consumption control capabilities in large-scale industrial control tasks. Although the computing time of PSO-DDPG is slightly longer, its memory usage and CPU utilization rate are significantly lower than those of GA and DE algorithms. Compared with the Genetic Algorithm (GA) and Differential Evolution (DE) algorithms, PSO-DDPG can complete more efficient task scheduling and optimization with lower consumption of computing resources. Table 5 shows the comparison of different algorithms in terms of resource consumption. PSO-DDPG outperforms GA and DE in both memory usage and CPU utilization.

Table 5: Comparison of Resource Consumption between PSO-DDPG and other Optimization Algorithms

Algorithm	Memory usage (MB)	CPU utilisation (%)	Energy consumption (kWh)
PSO-DDPG	120	60	12.5
DQN	130	65	13.0
PSO	140	70	14.2
GA	150	75	15.5

Through the analysis in this section, it can be seen from this study that the PSO-DDPG hybrid intelligent algorithm demonstrates significant advantages in terms of computational efficiency and resource consumption. Although its computing time is slightly longer, compared with other optimization algorithms, PSO-DDPG performs well in terms of computing resource consumption and memory usage, and is particularly suitable for industrial control systems that require real-time optimization and rapid response. Furthermore, the resource consumption optimization strategy of PSO-DDPG further enhances its application prospects in large-scale multi-machine cooperative control, providing an efficient and resource-friendly solution for dynamic optimization tasks in the industrial Internet.

5 Conclusion

This study proposes an optimization strategy for multi-machine collaborative control based on intelligent algorithms in the context of the Industrial Internet and realizes it through a PSO-DDPG hybrid framework. By combining the global search ability of Particle Swarm Optimization (PSO) and the local optimization ability of Deep Deterministic Policy Gradient (DDPG), this algorithm can effectively solve complex problems such as nonlinearity, high dimensionality, and dynamic changes in multi-machine cooperative control. The experimental results show that PSO-DDPG not only outperforms traditional algorithms (such as PSO, DQN and GA) in terms of optimization accuracy and stability, but also performs well in terms of computational efficiency and resource consumption. This method ensures the efficient operation of the system under uncertain factors such as equipment failure, load fluctuation and communication delay by dynamically adjusting the control strategy, demonstrating strong adaptability and robustness. Compared with traditional optimization algorithms, PSO-DDPG effectively reduces computing time and resource consumption while ensuring system stability, and has high practical application value. Future research will further expand the PSO-DDPG algorithm and explore its application in larger-scale and more complex industrial Internet environments, especially in fields such as intelligent manufacturing, energy management, and intelligent transportation. In addition, machine learning methods will be integrated to enhance the adaptive optimization capability of the algorithm, providing more intelligent solutions for the efficient operation and resource optimization of the industrial Internet.

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References

[1] Yin S, Jin M, Lu H, et al. Reinforcement-learning-based parameter adaptation method for particle swarm optimization[J]. Complex & Intelligent Systems, 2023, 9(5): 5585-5609. https://doi.org/10.1007/s40747-023-01012-8

[2] Zhang Y, Ding M, Zhang J, et al. Multi-UAV pursuit-evasion gaming based on PSO-M3DDPG schemes[J]. Complex & Intelligent Systems, 2024, 10(5): 6867-6883. https://doi.org/10.1007/s40747-024-01504-1

[3] Y Sun, J Yao, X Li, S Fan, Z Wang. Optimizing the Multi-Objective Discrete Particle Swarm Optimization Algorithm by Deep Deterministic Policy Gradient Algorithm [J]. Journal on Artificial Intelligence, 2022, 4(1): 47728. https://doi.org/10.32604/jai.2022.027839

[4] Zeng H, Huang Y, Zhan K, et al. Multi-Agent DDPG-Based Multi-Device Charging Scheduling for IIoT Smart Grids[J]. Sensors, 2025, 25(17): 5226. https://doi.org/10.3390/s25175226

[5] Guo Z, Li Z. Distributed auto disturbances rejection resilient control of permanent magnetic maglev trains based on the optimized deep deterministic policy gradient algorithm[J]. IET Control Theory & Applications, 2024, 18(11): 1383-1397. https://doi.org/10.1049/cth2.12673

[6] PENG K, YIN X, LIU X, et al. A strategy search method based on particle swarm optimization and deep reinforcement learning[J]. Computer Engineering & Science, 2023, 45(04): 718. http://joces.nudt.edu.cn/EN/Y2023/V45/I4/718

[7] Pan Z, Ma Y, Feng Y, et al. DDPG-Based Resilient Control for CACC Under Communication Delays and DoS Attacks[C]//2025 Joint International Conference on Automation-Intelligence-Safety (ICAIS) & International Symposium on Autonomous Systems (ISAS). IEEE, 2025: 1-6. https://doi.org/10.1109/ICAISISAS64483.2025.11051360

[8] Perera M, Fattah S, Mistry S, et al. Reinforcement Learning Controlled Adaptive PSO for

Task Offloading in IIoT Edge Computing[C]//Companion Proceedings of the ACM on Web Conference 2025. 2025: 1249-1253.https://doi.org/10.1145/3701716.3715559

[9] Ibrahim O, Aziz M J A, Ayop R, et al. Integrated DDPG-PSO Energy Management Systems for Enhanced Battery Cycling and Efficient Grid Utilization[J]. Energy Nexus, 2025: 100448.https://doi.org/10.1016/j.nexus.2025.100448

[10] Kumar R, Sharma D, Sadu A. A hybrid multi-agent based particle swarm optimization algorithm for economic power dispatch[J]. International journal of electrical power & energy systems, 2011, 33(1): 115-123.https://doi.org/10.1016/j.ijepes.2010.06.021

[11] Du S, Fan W, Liu Y. A novel multi-agent simulation based particle swarm optimization algorithm[J]. Plos one, 2022, 17(10): e0275849. https://doi.org/10.1371/journal.pone.0275849

[12] Nazari E , Nazari N , Semnani S H ,et al.A hybrid multi-agent deep actor-critic learning and particle swarm optimization algorithm for active voltage control in smart grids with renewable energies[J].e-Prime - Advances In Electrical Engineering, Electronics And Energy, 2025, 13(000).https://doi.org/10.1016/j.prime.2025.101075

[13] Moghadam R, Modares H. Resilient adaptive optimal control of distributed multi-agent systems using reinforcement learning[J]. IET control theory & applications, 2018, 12(16): 2165-2174.https://doi.org/10.1049/iet-cta.2018.0029

[14] Chen H, Shen L Y, Wang C, et al. Multi Actors-Critic based particle swarm optimization algorithm[J]. Neurocomputing, 2025, 624: 129460. https://doi.org/10.1016/j.neucom.2025.129460

[15] Na Y, Li Y, Chen D, et al. Optimal energy consumption path planning for unmanned aerial vehicles based on improved particle swarm optimization[J]. Sustainability, 2023, 15(16): 12101. https://doi.org/10.3390/su151612101

[16] Hanna L, Cagan J. Evolutionary Multi-Agent Systems: An Adaptive and Dynamic Approach to Optimization[J].Journal of Mechanical Design, 2009, 131(1):011010-011017. https://doi.org/10.1115/1.3013847

[17] Yassami M, Ashtari P. A novel hybrid optimization algorithm: Dynamic hybrid optimization algorithm[J]. Multimedia Tools and Applications, 2023, 82(21): 31947-31979. https://doi.org/10.1007/s11042-023-14444-8

[18] Jia L, Pei Y. Recent Advances in Multi-Agent Reinforcement Learning for Intelligent Automation and Control of Water Environment Systems[J]. Machines, 2025, 13(6): 503.https://doi.org/10.3390/machines13060503