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A Study of the Stability of an Industrial Robot Servo System: PID Control Based on a Hybrid Sparrow Optimization Algorithm

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Abstract: Industrial robots can cause servo system instability during operation due to friction between joints and changes in end loads, which results in jittering of the robotic arm. Therefore, this paper proposes a hybrid sparrow search algorithm (HSSA) method for PID parameter optimization. By studying the optimization characteristics of the genetic algorithm (GA) and sparrow search algorithm (SSA), the method combines the global optimization ability of GA and the local optimization ability of SSA, thus effectively reducing the risk of SSA falling into local optimum and improving the ability of SSA to find global optimization solutions. On the basis of the traditional PID control algorithm, HSSA is used to intelligently optimize the PID parameters so that it can better meet the nonlinear motion of the industrial robot servo system. It is proven through experiments that the HSSA in this paper, compared with GA, SSA, and traditional PID, has a maximum improvement of 73% in the step response time and a maximum improvement of more than 95% in the iterative optimization search speed. The experimental results show that the method has a good suppression effect on the jitter generated by industrial robots in motion, effectively improving the stability of the servo system, so this work greatly improves the stability and safety of industrial robots in operation.

Keywords: industrial robotics; hybrid sparrow search algorithm; PID optimization; servo system stability

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1. Introduction

With the increasing cost of manual labor in recent years, people are also paying more attention to the working environment and safety, and the demand for industrial robots to replace workers is also increasing. In more and more industrial production, industrial robots have been widely used by people in highly repetitive, environmentally harsh, and complex and dangerous industry positions, such as mechanical and electronic, medical and pharmaceutical, automobile manufacturing, industrial production and aerospace industries. Industrial robots are mainly used for handling, welding, cutting, spraying, grinding, and palletizing [1–4]. As the application scenarios of industrial robots become more and more extensive, the requirements for the service life, operational accuracy, and stability of industrial robots become higher and higher.

The three main technical cores of industrial robots are the controller in the control system, the servo motor in the drive system, and the precision reducer in the mechanical system. As one of the three core technologies, the servo control system of industrial robots has the characteristics of nonlinearity, multiple variables, strong coupling, etc., and to realize closed-loop control, most of the servo control systems use the traditional integer order PID control [5–9]. Therefore, the control of servo motor PID parameters is very important for the operational accuracy and stability of industrial robots. With the deepening of research, more and more intelligent algorithms are being introduced into the classical PID control to obtain more intelligent PID controllers, such as BP neural networks [10–12], particle swarm algorithms [13,14], genetic algorithms [15,16], sparrow algorithms [17,18], and single neuron [19,20] algorithms. Although all these methods make the PID control more intelligent, the mathematical model-based PID self-tuning still has the disadvantages of long identification time and low identification accuracy, which makes the use of self-tuning PID controller algorithms in practice very limited.

A sparrow search algorithm (SSA) is a new intelligent optimization algorithm proposed by Jiankai Xue in 2019 [21]. The principle of the SSA mathematical model is mainly to simulate the behavior of sparrows searching for food and avoiding natural enemies. The SSA searches for the optimal solution by progressively improving the current solution, which is to find a relatively good local optimal solution, and it has a high searching efficiency in problems with a small solution space. However, the SSA only focuses on the local improvement of the current solution and does not maintain the global information, so it is easy to fall into the local optimal solution and not find the global optimal solution. Zhang [22] proposed an improved PID control method for the SSA in order to improve the accuracy of PID and to effectively solve the problem of the SSA easily falling into the local optimal problem. Ouyang [23] proposed an improved SSA to optimize the PID parameters for the problem of the SSA with reduced population diversity that easily falls into the local optimum and, finally, improved the global optimization-seeking ability of the SSA and enhanced the convergence speed and the ability to jump out of the local optimal solution. Liu [24] proposed an improved SSA to optimize the PID for the problem of the SSA with reduced population diversity at the later stage, which easily falls into the local optimum. The optimized PID has better accuracy and stability and can be better applied to engineering projects. Not only do some scholars improve the SSA itself, but some researchers combine the sparrow algorithm with other algorithms. Raj [25] effectively improved the robustness and stability of the PID controller by combining the sparrow with the vulture. Fadheel [26] utilized the grey wolf to assist the sparrow, effectively suppressing the oscillation of the PID parameter changes and improving the stability of the controller. Huang [27] combined the BP neural network and sparrow search algorithm to effectively improve the accuracy and robustness of the PID controller. At present, the research on the stability of the servo system of industrial robots using the sparrow search algorithm is relatively scarce. The strong coupling of industrial robots, the change of friction between the joints, and the change of the end load will cause perturbations to the system so that the servo control system cannot reach a stable state in a very short period.

In order to increase the anti-interference ability of industrial robots, reduce the jitter in the working process, and further improve the stability of the servo system, this paper proposes a hybrid sparrow search algorithm (HSSA) PID parameter optimization method. The main contributions of this paper are twofold:

(1) To address the shortcomings of SSA's insufficient global optimization search capability, the characteristics of GA's strong global optimization search capability are utilized to improve the SSA in a targeted manner and enhance its ability to jump out of the local optimal solution.

(2) In the traditional PID controller, the use of a HSSA to optimize and adjust the PID parameters, so that it can find the optimal solution more quickly, inhibit the jitter of industrial robots during work and, at the same time, improve the stability of the servo system.

The rest of this paper is organized as follows: Section 2 is about the principles and methods of traditional PID controllers. Section 3 is the main principle and method of the algorithm presented in this paper. Section 4 focuses on the experiments and analysis of the servo system stability. Section 5 mainly summarizes the experiments and methods of the servo system stability of industrial robots, as well as the outlook of future work.

2. Study of Conventional PID Control Algorithms

Classical PID control algorithms are widely used in many fields, such as traffic management, robotics, and aerospace exploration due to their simplicity and ease of implementation. The control process consists of the following steps: 1. Real-time feedback signals are obtained from the controlled object through the sensors of the industrial robot, which may include information such as position, speed, angle, etc. 2. The error signal is transmitted between the desired value and the actual value to the PID controller. 3. The PID controller processes and calculates the error signal by using set proportional, integral, and differential parameters, and the calculated control signal passes through the actuator and acts on the controlled object to realize the regulation of its state. 4. Through continuous adjustment and optimization, the actual value of the system output gradually approaches the desired value and, finally, achieves the goal of precise control. This control method has good robustness and adaptability, can be applied to different types of control systems, and has achieved wide success in practice.

The basic principle is shown in Figure 1.

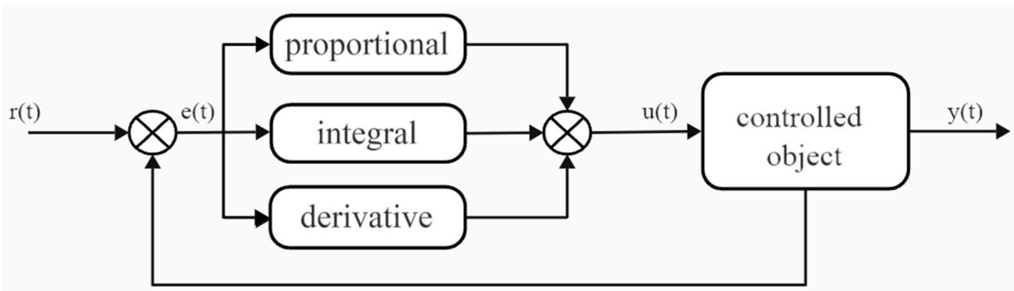

Figure 1. The PID controller structure.

In Figure 1, $r(t)$ denotes the preset desired value, $y(t)$ denotes the actual value of the system output, the control quantity output by the PID controller is $u(t)$, and the error signal is $e(t)$.

$$e(t) = r(t) - y(t) \tag{1}$$

The proportional link, integral link, and differential link are the three core links of the PID classical controller, each having the same importance and a different role. The following three links of the classical PID control algorithm are introduced:

2.1. Proportional Control Link

The proportional control link reflects the sensitivity of the controller to errors and reduces the error $e(t)$ between the desired value $r(t)$ and the actual value of the system output $y(t)$, which is the basic and important control link in the classical PID control algorithm. Assuming that only the proportional control link is used in the controller, the response speed of the system will be faster, but the steady-state error will increase, which will easily lead to oscillations.

2.2. Integral Control Link

In order to maintain and improve the stability and accuracy of the control system, eliminating the steady-state error of the control system is the task of the integral control link, which is the static link of the control system. Assuming that only the integral control link is used in the controller, although the purpose of eliminating the steady-state error can be achieved, the response speed of the system will be reduced, resulting in the occurrence of integral saturation.

2.3. Differential Control Link

The purpose of the integral control loop in the controller is to suppress the oscillations and overshoots of the system, thus improving the dynamic response and immunity to interference. Adding only the differential control link in the controller can suppress the oscillation and overshoot of the system, but it will easily lead to noise interference, impaired system stability, and other problems.

In summary, the three control links of the PID classical controller interact with each other, and the parameters are adjusted according to the specific controlled object and requirements, which can make the system control more accurate. The above-described proportional control link, integral control link, and differential control link linear superposition can be composed of a PID classical control algorithm expression:

$$u(t) = K_P e(t) + K_t \int_0^T e(t)dt + K_D \frac{de(t)}{dt} \tag{2}$$

In Equation (2), $K_D = K_P T_D$, K_D denotes the differential coefficient, and T_D denotes the differential time constant.

Although the traditional PID controller is simple and easy to realize, there are some disadvantages: the parameters of the control algorithm are fixed and cannot be adaptively adjusted to meet the needs of industrial robots under different external factors; control parameters are difficult to adjust and need a certain amount of experience and professional knowledge in order to support the adjustment of the PID parameters; control of nonlinear systems, such as poor and so on, may lead to the consequences of industrial robots, including control accuracy and stability decline, and may even cause economic losses such as industrial product scrap.

In recent years, model predictive control (MPC) has been widely adopted in industrial applications due to its ability to handle multi-variable systems and constraints and anticipate future system states based on a predictive model. Studies such as [28,29] demonstrate MPC's effectiveness in optimizing performance for nonlinear and dynamic systems. However, MPC has significant drawbacks, including high computational complexity, sensitivity to model inaccuracies, and the need for real-time optimization, which can make it less practical for time-sensitive industrial applications such as robotic servo systems.

In contrast, PI control, despite its simplicity, is widely preferred in such scenarios due to its ease of implementation, low computational requirements, and proven effectiveness in stabilizing systems. The proposed HSSA-optimized PID controller enhances traditional PI control by intelligently tuning parameters to handle nonlinearities and disturbances, thereby narrowing the performance gap with advanced control strategies like MPC. This makes the HSSA-optimized PID particularly suitable for real-time industrial applications where computational simplicity and robustness are critical. The experimental results presented in Section 4 confirm that the HSSA significantly improves system stability and response time, underscoring its practical advantages over MPC in scenarios where computational efficiency and real-time performance are paramount.

Therefore, in order to improve the control performance of industrial robots and the adaptability of control algorithms, this paper explores the optimization of PID control algorithms for industrial robots.

3. Research on Hybrid Sparrow Search Algorithm (HSSA)

3.1. Traditional GA

In the 1970s, John Holland in the United States proposed the GA, which is designed based on the laws of biological evolution in nature, and its core idea is to simulate the natural evolutionary process to search for the optimal solution. When solving with a GA, the set of all practical solutions to the problem is called the population, and each solution in the population is called an individual (also known as a chromosome).

The general process of the traditional GA consists of operations such as generating the initialized number of populations N, calculating the individual fitness function values, selection, crossover, and mutation, as shown in Figure 2.

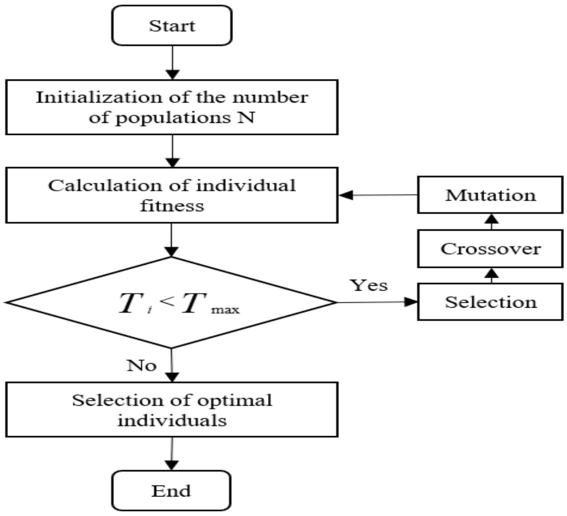

Figure 2. A flowchart of the genetic algorithm.

3.2. Traditional SSA

SSA algorithm is a swarm intelligence optimization algorithm proposed by Xue et al. by simulating the foraging mechanism of sparrows, and there are three roles in the optimization model: discoverer, follower, and scout. The discoverer is responsible for searching for the location with sufficient food in the whole search area and providing a foraging area or direction for all the followers. The discoverer is not static in the population; as long as the sparrow can search for a better food location, it can become the discoverer, but the proportion of the discoverers in the whole population is fixed. And the discoverer is affected by predators. There will be two states: when there is no predator around, the discoverer will enter the wide area search; otherwise, all the sparrows will move to the safe area. So in each generation of the search, the position of the discoverer is updated according to Equation (3):

$$X_i^{t+1} = \begin{cases} X_i^t \cdot \exp(\frac{-i}{\alpha \cdot T}), R < ST \\ X_i^t + Q \cdot L, R \geq ST \end{cases} \quad (3)$$

where t denotes the current iteration, and T is the maximum number of iterations and denotes the ith sparrow position at t iterations. α is a random number within (0,1), Q is a random number obeying a normal distribution, L is a 1×D matrix, D is the dimension size where all elements have a value of 1, and R ($R \in [0, 1]$) and ST ($ST \in [0.5, 1]$) are the set alarm and safety values.

The followers will always observe the behavior of the discoverer and adjust their position with the behavior of the discoverer; the position of the followers is updated as shown in Equation (4):

$$X_i^{t+1}\begin{cases} Q\cdot\exp(\frac{X_{worst}^t - X_i^t}{i^2}), i > n/2 \\ X_p^{t+1} + \left|X_i^t - X_p^{t+1}\right|\cdot A^+\cdot L, i \le n/2 \end{cases} \tag{4}$$

where X_{worst}^t denotes the global worst position of the current iteration t, A denotes a 1xD matrix and its elements are randomly assigned to 1 or -1, and A^+ is the pseudo-inverse matrix of matrix A. X_p^{t+1} is the best position found by the discoverer. When a follower fails to compete with a finder when $i \ge n/2$, the follower's food source is insufficient and it needs to search for food in a wider area.

The scout will realize the danger in the population and, thus, adjust its overall position in the sparrow population, which is randomly generated in the whole population, accounting for 10% to 20% of the whole population and updated as per Equation (5) that follows:

$$X_{best}^t = \begin{cases} X_{best}^t + \beta\cdot\left|X_i^t - X_{best}^t\right|, f_i > f_g \\ X_i^t + K\cdot(\frac{\left|X_i^t - X_{worst}^t\right|}{(f_i - f_\omega) + \varepsilon}), f_i = f_g \end{cases} \tag{5}$$

where X_{best}^t denotes the global best position, β is a step control parameter, K is a random number in $[-1, 1]$, f_i is the current individual fitness, and f_g and f_ω are the current global best and worst fitness values. ε is the smallest constant to avoid divide-by-zero error. When $f_g > f_\omega$, it means that the sparrow is at the edge of the population and in a safe state; while $f_g = f_\omega$, it means that the sparrow realizes the danger and needs to move to another position.

3.3. Hybrid Sparrow Search Algorithm (HSSA)

The sparrow search algorithm has advantages in local search problems but limitations in dealing with global optimal problems, while the genetic algorithm has good global search ability and can quickly search out all the solutions in the solution space without falling into the trap of rapid decline of local optimal solutions. Based on the above observations, this paper organically combines SSA and GA to form a two-stage optimization process:

Step one: Global search (GA stage)

In the first stage of the optimization process, the genetic algorithm (GA) is employed to conduct a thorough and systematic global search across the entire solution space. The GA begins by encoding potential solutions as chromosome-like individuals, with the random initialization of a population $P(t)$ represented as:

$$P(t) = \Big\{x_1, x_2, \ldots, x_N), x_i \in R^d \tag{6}$$

Each individual x_i is evaluated using a fitness function $f(x)$, which measures the quality of the solution. The optimization goal is typically formulated as:

$$f(x) \to \max(or\min), i = 1, 2, \ldots, N \tag{7}$$

These individuals are then subjected to a series of biology-inspired operations, including selection. Individuals are selected based on their fitness, often using a roulette-wheel selection scheme. The probability of selecting an individual is proportional to its fitness:

$$probability(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_i)} \tag{8}$$

The fittest individuals are chosen to propagate to the next generation; selected individuals undergo crossover to produce offspring. A common crossover formula is:

$$x_{new} = \alpha x_a + (1 - \alpha)x_b, \alpha \in [0, 1] \tag{9}$$

where x_a and x_b are parent solutions, and α controls the proportion of contribution from each parent. And mutation introduces random variations to enhance diversity and avoid premature convergence. The mutation formula is:

$$x_{new}, i = x_i + \delta, \delta \sim U(-\sigma, \sigma) \tag{10}$$

where σ is the mutation range, and U(−σ, σ) represents a uniform distribution.

Through these iterative steps, GA is capable of efficiently navigating the vast and complex solution space, uncovering regions with high-potential solutions. Its robustness and ability to handle nonlinear and multimodal problems make it particularly effective for large-scale searches. GA's global search capability is crucial for the efficiency of the overall optimization process. GA uses population-based methods that allow for parallel exploration of many potential solutions simultaneously, dramatically reducing the time required to explore vast and high-dimensional search spaces. The evolutionary operators (selection, crossover, and mutation) facilitate broad exploration without becoming trapped in local minima, enabling the algorithm to quickly eliminate suboptimal regions and focus on promising areas. By leveraging these evolutionary strategies, GA not only accelerates the discovery of promising areas but also ensures that the algorithm explores a diverse range of solutions, avoiding being trapped in local optima. This stage serves as the foundation for subsequent optimization, laying the groundwork for more refined and localized searches. The global search phase of GA ensures that HSSA does not fall into the traps of local optimization as it thoroughly explores the entire solution space. By doing so, GA guarantees that the algorithm does not prematurely converge to suboptimal solutions. This broad exploration enhances the optimization accuracy of the HSSA by identifying regions with better potential solutions before transitioning to the SSA phase for further refinement.

Step two: Localized search (SSA stage)

Once the global search phase is completed, the optimization process transitions into a more focused stage involving the sparrow search algorithm (SSA). This stage is specifically designed to perform localized searches, refining the solutions identified in the GA phase, and the solutions obtained from the GA stage are used to initialize the sparrow population:

$$X(t) = \{x_1, x_2, \ldots, x_N\} \tag{11}$$

The best solution found so far is denoted as x_{best} .

Discoverers are responsible for global exploration. Their positions are updated as follows:

$$x_i(t+1) = \begin{cases} x_i(t) \cdot \exp(\frac{-i}{\beta \cdot T}), R_1 < p_s \\ x_i(t) + K \cdot (x_i(t) - x_{best}), R_1 \geq p_s \end{cases} \tag{12}$$

where $R_1 \in [0, 1]$ is a random number; p_s is the safety threshold for detecting danger; β controls the step size; T is the current iteration; K is a random step size factor.

Followers adjust their positions based on the discoverers' locations and their relative fitness:

$$x_i(t+1) = x_i(t) + S \cdot (x_{best} - x_i(t)) + L \cdot (x_{worst} - x_i(t)) \tag{13}$$

where S and L are random factors controlling the step size; x_{worst} represents the least-fit individual.

To simulate danger awareness, sparrows can adjust their behavior dynamically when the safety threshold p_s is exceeded:

$$x_i(t+1) = x_{best} + \gamma \cdot |x_i(t) - x_{best}| \tag{14}$$

where γ is a random factor controlling the degree of adjustment.

The SSA operates by modeling the behavior of sparrows in a flock where individuals adjust their positions dynamically based on both local information (positions of nearby individuals) and global information (the overall distribution of the population). This dual-layered strategy allows SSA to balance exploration and exploitation effectively, covering a broad search space while honing in on regions with high potential for optimal solutions. The SSA phase improves the computational efficiency of the overall algorithm by focusing the search on promising regions identified by GA. Unlike traditional exhaustive searches, SSA's adaptive mechanism allows it to exploit local information effectively, optimizing solutions with fewer iterations. This reduces the need for broad exploration and, thus, decreases the total computational burden. SSA's ability to self-organize and adjust search intensity based on fitness values further ensures that it refines solutions with a minimal computational cost.

The adaptability of the SSA flock is a key strength of this algorithm. By continuously updating their positions through intelligent interactions, sparrow individuals ensure that no promising area is overlooked. This phase complements the global search by focusing on fine-tuning and narrowing down the search space to achieve high precision in identifying the best possible solutions. Furthermore, the SSA's ability to self-organize and adjust its search intensity makes it particularly suitable for large-scale optimization problems where efficient exploration and exploitation are critical for success. The SSA phase significantly improves the accuracy of the solutions obtained from the GA phase. While GA ensures that the solution space is explored thoroughly, SSA's localized search allows for fine-tuning of solutions, adjusting parameters to maximize their performance. This dual-layered optimization approach guarantees that solutions are not only optimal in their broader regions but are also precise and well-suited to the specific problem.

The combination of GA's global search and SSA's localized search forms a hybrid optimization process that offers both enhanced algorithm efficiency and optimization accuracy. The global search phase (GA) rapidly narrows down the potential solution space, identifying promising areas while maintaining computational efficiency. The localized search phase (SSA) then fine-tunes the solutions, ensuring that the results obtained are not only close to the global optimum but also precise and well-adjusted.

By integrating these two powerful algorithms, HSSA ensures a highly efficient and accurate optimization process, which is critical for solving complex and large-scale problems, such as those encountered in industrial robot servo systems. The efficiency of the GA phase ensures that the algorithm quickly converges to promising regions of the solution space, while the accuracy of the SSA phase ensures that the optimal solutions are finely tuned and highly precise.

This hybrid approach significantly improves both the efficiency of finding solutions and the accuracy of the final optimized outcomes. The overall performance of the algorithm is superior to the individual contributions of GA or SSA alone as it takes advantage of both global exploration and local exploitation. The specific workflow for the localized search phase is visually represented in Figure 3, providing a clear and structured overview of its implementation process

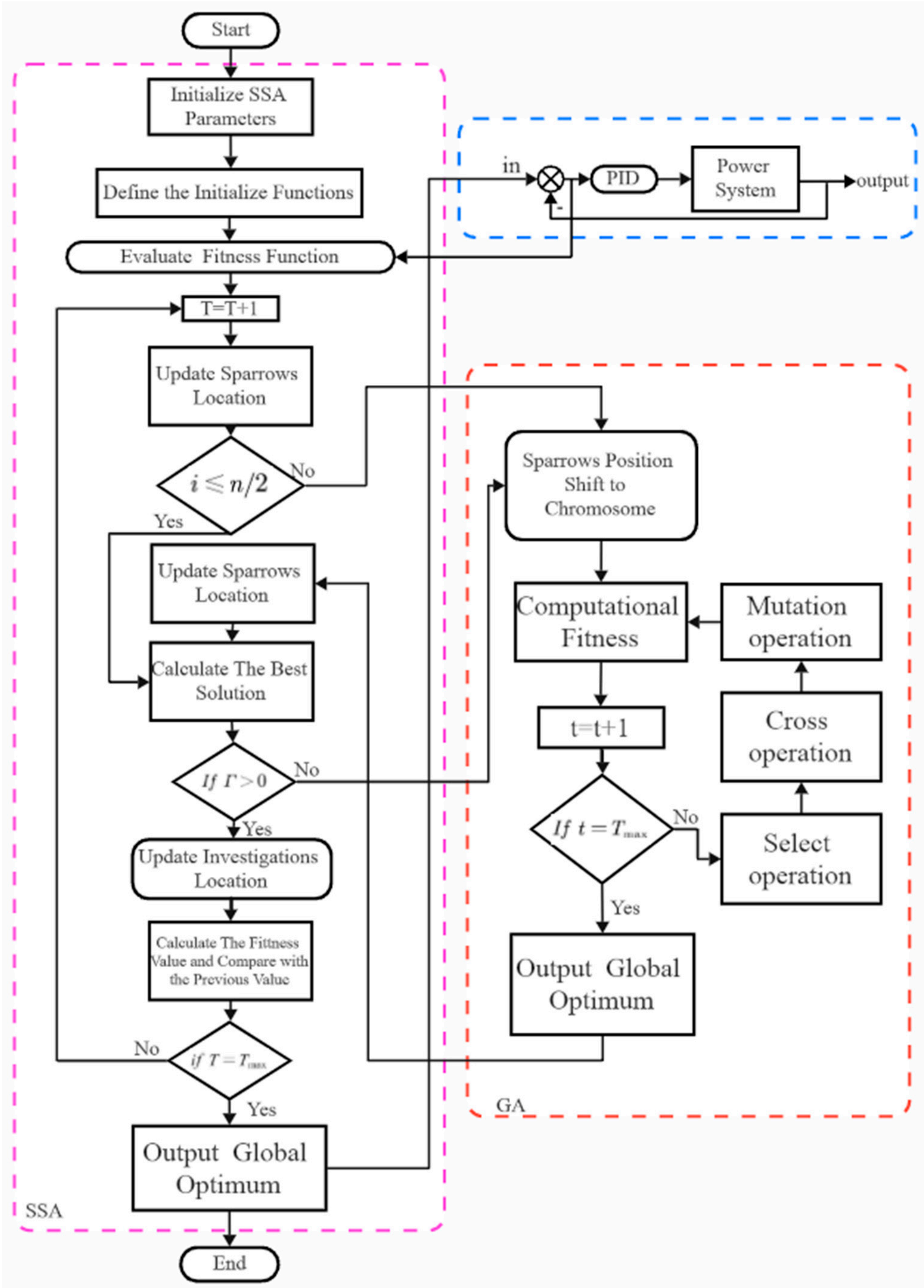

Figure 3. A flowchart of the HSSA.

Figure 3 illustrates the workflow of the hybrid sparrow search algorithm (HSSA) and its integration with the PID control system for optimizing the stability of industrial robot servo systems. The figure highlights the dual-phase optimization process: the global search phase (conducted by the GA) and the localized search phase (handled by the SSA). The optimization process outputs dynamically tuned PID parameters (Kp, Ki, Kd), which are provided to the PID controller to minimize the system error (e(t)) and improve performance metrics such as rise time, overshoot, and steady-state error. The GA phase initializes and explores a wide range of candidate solutions, identifying regions with high potential for optimization. These solutions are then fine-tuned in the SSA phase where discoverers and followers iteratively refine parameters by balancing global and local information. The optimized control signal (u(t)) is applied to the servo motor to correct deviations caused by nonlinearities, external disturbances, and load changes. This hybrid approach addresses the nonlinear, multivariate, and strongly coupled characteristics of industrial robot servo systems, enhancing both computational efficiency and optimization accuracy. The annotated workflow in Figure 3 clarifies the input error signal (e(t)) to the PID controller and the output control signal (u(t)), which ensures precise and stable motion of the servo system.

4. Analysis of Experimental Data and Results

In order to prove that the HSSA algorithm in this paper has a better effect on optimizing the PID parameters and, at the same time, can better improve the stability of the servo system of industrial robots, this paper carries out comparison experiments from two aspects. The first aspect is the simulation experiment of the algorithm performance, comparing the results of the algorithm in the dimensions of iterative convergence and step response and analyzing the performance differences of different algorithms to highlight the superiority of this paper's HSSA algorithm in terms of performance. The second aspect is the application of this paper's algorithm in industrial robots through the monitoring oscilloscope to compare the results of the industrial robots before and after the addition of the HSSA in the two dimensions of pulse smoothness and pulse tracking error with and without load, to analyze the effect of this paper's algorithm on the suppression of industrial robot jitter.

4.1. Experimental Environment

To complete the various comparative experiments mentioned above, the experimental environment used in this paper is shown in Table 1.

Table 1. The hardware and software configuration.

Hardware	Processor	12th Gen Intel(R) Core (TM) i7-12490F 3.0 GHz(Chengdu, China)
	RAM	16 GB (15.8 GB available)
Software	Operating System	Windows 11 (64-bit operating system)
	Simulation Tool	MATLAB R2023a

Experiments used in the six-axis industrial robot, model SYB0805A (5 KG) (SanYi Intelligent Robotics, Yibin, China), are shown in Figure 4. In this paper, all industrial robot control experiments will be set up to complete the industrial robot above. The industrial robot joints and the range of motion and the movement of each joint at the maximum speed are shown in Table 2.

Figure 4. A six-axis industrial robot.

Table 2. Joint motion parameters.

Joint	Range of Motion (°)	Maximum Speed (*/s)
J1	−170~170	220
J2	−90~+90	220
J3	−90~+90	220
J4	−170~170	290
J5	−120~120	337
J6	−360~360	540

4.2. Experimental Analysis and Discussion

4.2.1. Algorithm Performance Analysis

To evaluate the algorithm's performance, a second-order control system model is utilized as the testbed, given by:

$$G(s) = \frac{\omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2} \tag{15}$$

This model accurately reflects the dynamics of robotic servo systems, incorporating parameters such as natural frequency (ω_n) and damping ratio (ξ) to simulate real-world conditions. The experimental parameters used for this analysis are summarized in Table 3. The results of the simulation experiments are illustrated in Figures 5 and 6. These figures compare the iterative convergence speed and step response time of the HSSA with those of PID, GA, and SSA. The HSSA demonstrates significantly improved performance, achieving faster convergence and shorter response times, thereby validating its superior optimization capability.

Table 3. The experimental parameters.

Parameter	PID	GA	SSA	HSSA
Initial population (N)	-		200	
Maximum number of iterations	-		500	
Damping ratio (ξ)		0.7		
Natural frequency (ω_n)		5 rad/s		
Kp	5.0			
Ki	1.0			
Kd	0.01			
Upper bound			[100, 10, 1]	
Lower bound			[0, 0, 0]	
Dim		3		3
Cross rate		0.6		0.6
Mutation rate		0.05		0.1
Discovery rate (p_s)			0.7	0.7
Vigilance rate (p_v)			0.2	0.2
Safety threshold (τ)			0.6	0.6

The experimental parameter settings in Table 3 were selected to balance optimization performance and computational efficiency, ensuring the HSSA effectively optimized the PID parameters for the industrial robot servo system. The initial population size of 200 was chosen to provide sufficient diversity in the solution space, facilitating effective global exploration while maintaining computational feasibility. The maximum number of iterations, set to 500, was determined through preliminary tests, ensuring the algorithms achieved convergence without unnecessary computational overhead. The damping ratio (ξ = 0.7) and natural frequency (ω_n = 5 rad/s) were selected to align with the typical dynamics of second-order robotic systems, promoting stable operation and minimizing overshoot. PID parameter ranges (Kp, Ki, Kd) were defined with initial values of 5.0, 1.0, and 0.01, respectively, and upper bounds of [100, 10, 1] to accommodate the nonlinear behavior of the servo system and provide ample flexibility for optimization. The dimensionality of the search space was set to 3, corresponding to the three PID parameters. Algorithm-specific settings included a crossover rate of 0.6 and a mutation rate of 0.05 for GA, ensuring genetic diversity and avoiding premature convergence. For the SSA, a discovery rate of 0.7, a vigilance rate of 0.2, and a safety threshold of 0.6 were used to balance exploration and exploitation effectively. These parameter values were validated through preliminary experiments and tailored to address the nonlinear, multivariate, and strongly coupled characteristics of the system, ensuring robust and efficient optimization.

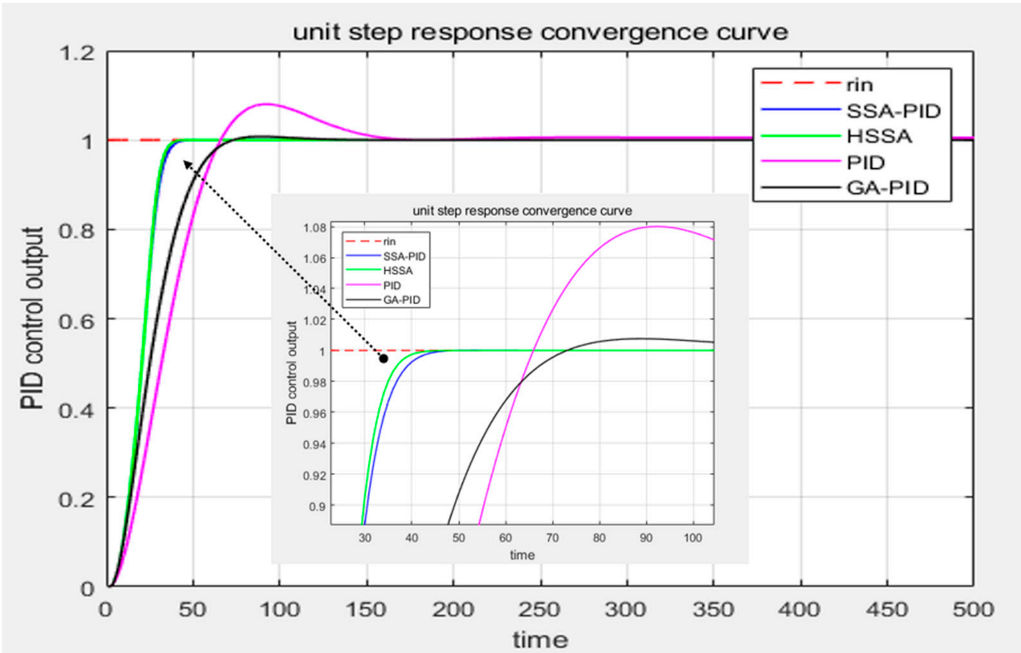

Figure 5. A simulation of the step system response.

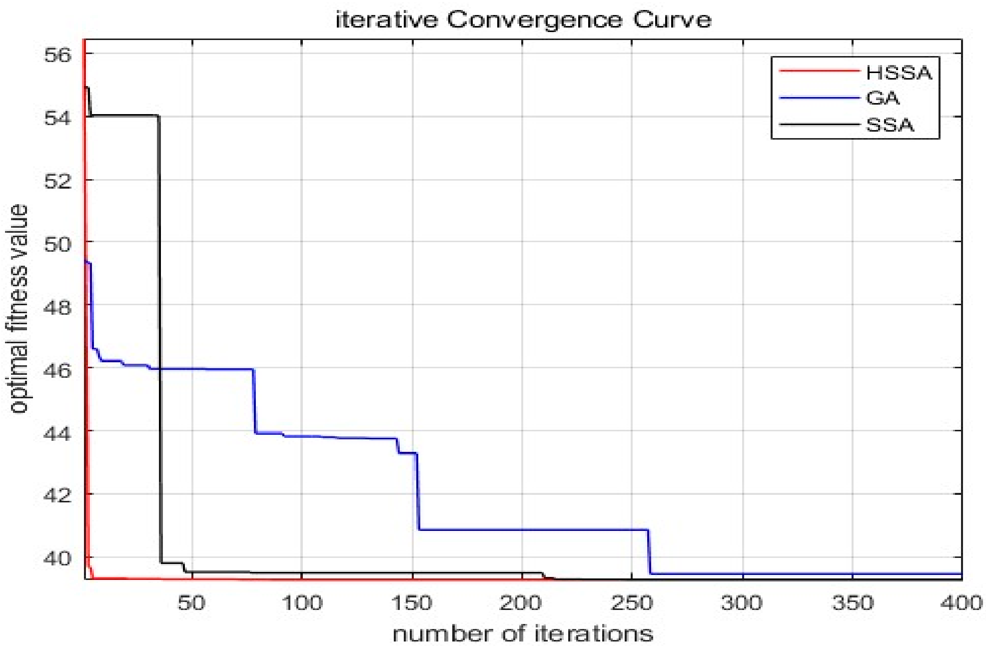

Figure 6. Iterative convergence curves.

Figure 5 illustrates the step response of different algorithms, showcasing the superior performance of the HSSA in adjusting PID parameters. To enhance readability, Table 4 summarizes the specific step response times, highlighting the improvements achieved by the HSSA. The HSSA achieves a maximum improvement in response time of approximately 73% compared to traditional PID. Notably, the traditional PID and GA-PID algorithms exhibit overshooting, while the HSSA effectively eliminates overshooting and achieves faster convergence. Compared to the SSA-PID, the HSSA not only has a shorter response time but also converges more quickly, demonstrating its better global optimization capability and its ability to suppress servo system jitter.

Table 4. Step response time comparison.

Algorithm	Response Time (s)	Overshoot (%)	Improvement over PID (%)
PID	120	10	-
GA-PID	95	7	20.8%
SSA-PID	75	0	37.5%
HSSA	32	0	73.3%

Figure 6 presents the iterative convergence curves, comparing the performance of the HSSA, GA, and SSA in terms of convergence speed and optimal solution quality. To provide more concrete insights, Table 5 summarizes the number of iterations required for convergence and the quality of the optimal fitness value achieved. The HSSA shows a 95% improvement in the speed of iterative convergence over GA and achieves a better optimal value compared to GA and SSA. This underscores HSSA's superior ability to jump out of local optima and improve servo system stability.

Table 5. Iterative convergence speed and optimal value comparison.

Algorithm	Iterations to Convergence	Optimal Fitness Value	Improvement Over GA in Iterations (%)
GA	210	55	-
SSA	260	49	50%
HSSA	5	40	95%

The results confirm that the HSSA converges the fastest and achieves the best optimal fitness value, demonstrating its efficiency and robustness in PID parameter optimization.

4.2.2. Algorithm Application Analysis

This section focuses on the practical application of the HSSA algorithm to an industrial robot (model SYB0805A (SanYi Intelligent Robotics, Yibin, China)), which has six degrees of freedom (DoFs). For the experiments, Joint 3—responsible for vertical motion—was selected for analysis as its movement is critical for ensuring overall stability and performance during industrial tasks. The experiments evaluated the robot's performance in two dimensions: pulse smoothness and pulse tracking error, both with and without load. Using a monitoring oscilloscope, the motion of the robot joints was analyzed before and after deploying the HSSA-optimized PID parameters.

The input to the robot during these experiments was a sinusoidal trajectory signal with an amplitude of 30° and a frequency of 0.5 Hz. This input was chosen to simulate typical operational movements and evaluate the ability of the HSSA algorithm to handle dynamic and variable-speed conditions. The evaluation focused on assessing improvements in stability, jitter suppression, and tracking precision.

Figures 7 and 8 show the pulse smoothness experiments for Joint 3 before and after deploying the HSSA algorithm. The y-axis (speed) is measured in °/s, while the x-axis (time) is measured in seconds. Before the HSSA deployment (Figure 7), the robotic joint exhibited irregular and jagged pulse outputs, resulting in significant jitter and instability during operation. After the HSSA deployment (Figure 8), the pulse outputs became noticeably smoother, demonstrating the algorithm's ability to optimize PID parameters and enhance stability. These results confirm the HSSA's effectiveness in ensuring consistent and smooth joint motion, reducing vibrations, and improving control performance.

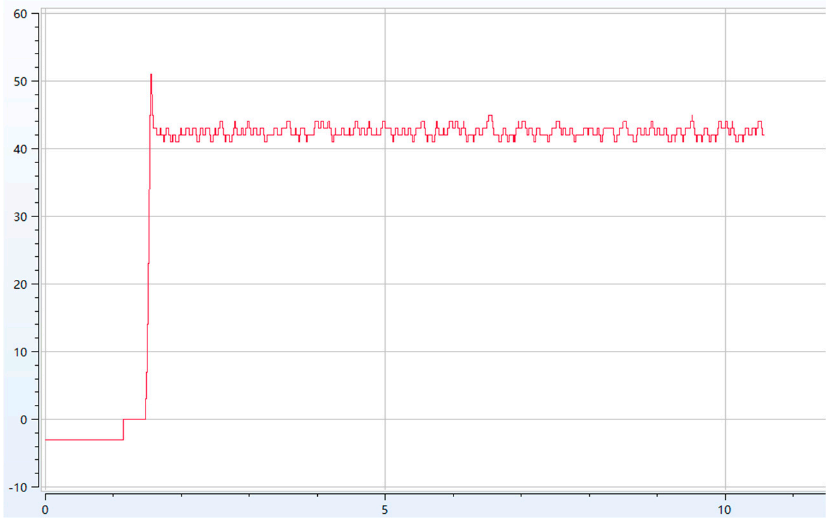

Figure 7. Movement speed of the robotic arm before the HSSA deployment.

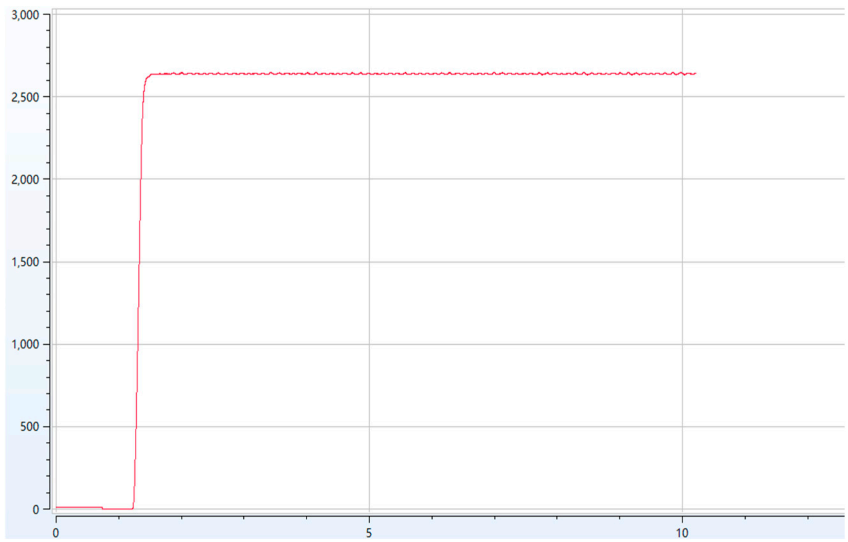

Figure 8. Movement speed of the robotic arm after the HSSA deployment.

The improvements in pulse smoothness are summarized in Table 6. After deploying the HSSA, the pulse stability index increased by 17%, and the peak jitter was reduced by 13%, highlighting the algorithm's superior stability performance.

Table 6. A comparison of pulse smoothness.

Parameter	Before HSSA Deployment	After HSSA Deployment	Improvement
Pulse Stability Index	75%	92%	+17%
Peak Jitter (%)	18%	5%	−13%

Figures 9 and 10 illustrate the tracking error experiments for Joint 3, both with and without load. The y-axis (tracking error) is measured in millimeters (mm), and the x-axis (time) is measured in seconds. Before deploying the HSSA algorithm (Figure 9), the robot exhibited significant and irregular tracking errors, particularly under load conditions. After deploying the HSSA algorithm (Figure 10), the tracking errors were greatly reduced and smoothed, even under load. This demonstrates the HSSA's superior ability to optimize PID parameters, improve trajectory tracking precision, and maintain robustness in varying operational conditions.

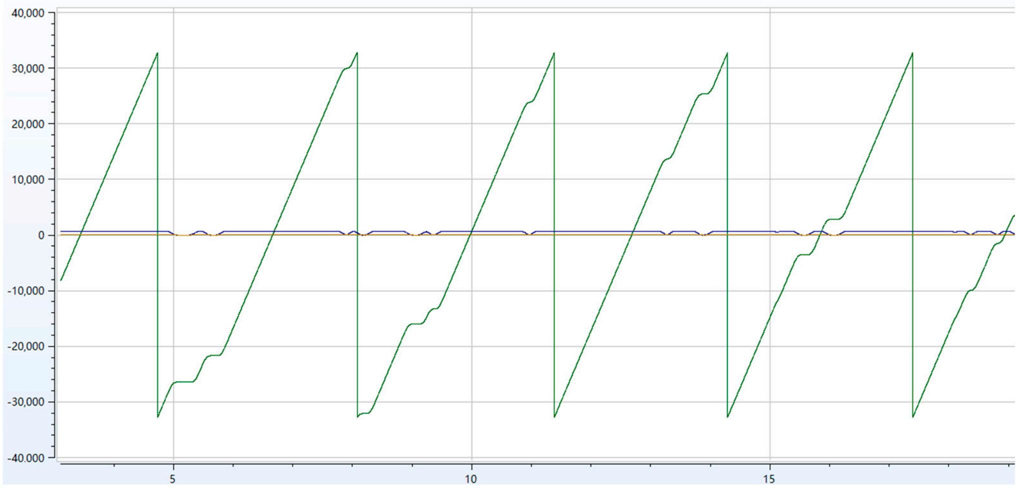

Figure 9. The robotic arm tracking error before the HSSA deployment.

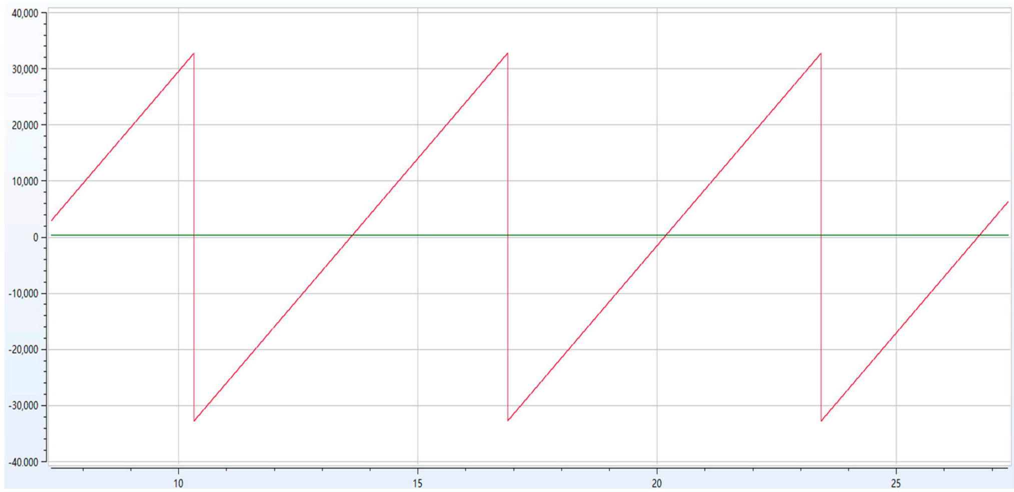

Figure 10. The robotic arm tracking error after the HSSA deployment.

The improvements in the tracking error are summarized in Table 7. The tracking error without load was reduced by 68%, while the error under load was reduced by 76%, highlighting the robustness and universality of the HSSA algorithm.

Table 7. A comparison of tracking error.

Condition	Before HSSA Deployment	After HSSA Deployment	Improvement
Tracking Error (No Load)	±2.5 mm	±0.8 mm	68%
Tracking Error (With Load)	±5.0 mm	±1.2 mm	76%

5. Conclusions

In order to eliminate the jittering of the robotic arm caused by the instability of the servo system due to the friction between the joints and the change in the end load of the industrial robots during operation, this paper designs a PID parameter optimization method with a hybrid sparrow search algorithm (HSSA). By studying the optimization characteristics of the genetic algorithm (GA) and sparrow search algorithm (SSA), the method combines the global optimization ability of the GA and the local optimization ability of the SSA, thus effectively reducing the risk of SSA falling into local optimum and improving the ability of SSA to find global optimization solutions. Through the experimental results, we find that the HSSA in this paper has better convergence speed and optimization ability compared with GA, SSA, and traditional PID, and the response time is maximally improved by about 73% in the comparison experiment of the step system response, and the speed of the iterative optimization is maximally improved by more than 95% in the comparison experiment of the iterative convergence. The experiment effectively proves that HSSA has a good suppression effect on the jitter generated by industrial robots in motion, effectively improves the stability of the servo system, and effectively ensures the stability and safety of industrial robots at work. Finally, due to time reasons, we did not carry out the simulation experiment of adding interference and the comparison experiment of industrial robots under complex working conditions. The next step will be to carry out experiments in unknown environments; at the same time, we will carry out more in-depth research on the influence of interference and external factors.

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