International Journal of Engineering Inventions
e-ISSN: 2278-7461, p-ISSN: 2319-6491
Volume 15, Issue 1 [January 2026] PP: 97-108

Enhancement of a 4-DOF Industrial Robot via Hybrid PSO-tuned PID Control

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ABSTRACT: *This paper presents an advanced control strategy for industrial robotic manipulators by integrating the conventional Proportional–Integral–Derivative (PID) controller with the Particle Swarm Optimization (PSO) algorithm to enhance overall system performance. Although PID control remains widely adopted due to its simple structure and ease of implementation, its effectiveness often deteriorates in the presence of system nonlinearities, load variations, and environmental disturbances. In the proposed approach, the PSO is employed to automatically tune the PID gains, enabling the controller to adapt more effectively to practical operating conditions without the need for manual adjustment. Simulation and experimental validation results demonstrate that the PSO-tuned PID controller achieves significant improvements in trajectory tracking accuracy, disturbance rejection capability, and closed-loop stability compared with a fixed-gain PID controller. These findings highlight the advantages of combining evolutionary optimization techniques with PID control in industrial robotic systems, contributing to enhanced precision and reliability in real-world applications. This study proposes an optimized control framework for a four-degree-of-freedom (4-DOF) industrial robotic manipulator by integrating a conventional PID controller with a PSO algorithm. While PID controllers are industry standards due to their structural simplicity, they often lack robustness against inherent system nonlinearities, parametric uncertainties, and external disturbances. To address these limitations, a hybrid PSO-PID scheme is developed where the PSO metaheuristic is utilized for the offline/online autonomous tuning of gain parameters (K_P, K_i, K_d). Comparative numerical simulation analyses indicate that the PSO-tuned controller significantly outperforms fixed-gain variants in terms of trajectory tracking precision, settling time reduction, and disturbance rejection. The results validate that the integration of evolutionary heuristics provides a superior balance between transient response and steady-state stability, enhancing the operational reliability of robotic systems in complex industrial environments.*

Date of Submission: 08-01-2026 Date of acceptance: 20-01-2026

I. INTRODUCTION

In the context of advanced automated manufacturing, industrial robotic arms have become an essential component of modern automation systems, capable of executing multi-axis motions to transport materials, tools, or products to predefined locations for repetitive production tasks, thereby enhancing manufacturing efficiency through high-speed operation and superior repeatability. These electromechanical systems are programmed to perform complex tasks that reduce operational costs, increase productivity, and improve product quality. Key characteristics of industrial robots include a high degree of automation, exceptional positioning accuracy, and robust operational durability, which collectively reduce errors, increase processing speed, and enhance production efficiency compared with manual operations in processes such as welding, assembly, material handling, and quality inspection. A typical industrial robot generally consists of a series of interconnected links and joints actuated by drive systems and coordinated by a control unit, enabling the end-effector to execute complex motions in three-dimensional space. This capability represents a fundamental distinction between industrial robots and other fixed automation systems, as robots can be reprogrammed to perform multiple tasks within the same production line.

However, the inherently nonlinear dynamic characteristics and the strong dependence on payload variations, joint friction, and external disturbances make the design of effective controllers for industrial robotic manipulators highly challenging. These robotic systems typically possess multiple degrees of freedom with tightly coupled joint structures, leading to significant interactions among links, especially when time-varying payloads and nonlinear effects such as friction and load imbalance are present. Such characteristics complicate accurate system modeling and directly affect control performance. When the controller is not properly designed, trajectory tracking errors, undesirable transient responses, and increased sensitivity to external disturbances may arise, thereby degrading system stability and operational efficiency. Numerous previous studies have emphasized that strong nonlinearities and variations in dynamic parameters limit the effectiveness of conventional linear control methods, necessitating the adoption of advanced control strategies to address uncertainties and disturbances inherent in robotic systems.

The PID controller is widely regarded as a common choice in industrial robotic control systems due to its simple structure, low implementation cost, and ease of integration into embedded control platforms. Nevertheless, the performance of a PID controller is highly dependent on the proper selection of its gain parameters Kp, Ki and Kd, and the tuning process becomes considerably more challenging in systems exhibiting nonlinear behavior, time-varying disturbances, and payload variations, as typically encountered in robotic manipulators. Conventional tuning methods, such as the Ziegler–Nichols or Cohen–Coon approaches, are based on linear assumptions and often fail to guarantee optimal performance for nonlinear systems or applications requiring a high level of stability, as reported in numerous analytical studies on PID tuning. Comprehensive surveys have shown that these classical methods exhibit inherent limitations under complex operating conditions and are unlikely to yield optimal controller parameters for modern robotic applications, particularly when compared with contemporary optimization-based strategies [1]. To overcome the drawbacks of classical tuning techniques, metaheuristic optimization algorithms, such as Particle Swarm Optimization (PSO), have been extensively investigated and applied for the automatic tuning of PID gains to enhance control performance. In this framework, PSO is integrated with the PID controller to systematically optimize the controller parameters according to performance criteria such as trajectory tracking error, response time, and overall system stability, as demonstrated in PSO-based PID control for robotic manipulators [2]. Other studies have also employed alternative optimization algorithms, including Genetic Algorithms (GA) and hybrid metaheuristic approaches, for PID tuning, revealing substantial performance improvements over manual tuning while providing effective solutions for nonlinear and time-varying systems commonly found in industrial robotics [3]. Consequently, the adoption of automated PID parameter tuning strategies not only reduces reliance on designer experience but also holds significant potential for improving control effectiveness and stability in complex tasks of modern industrial robotic systems [4].

This study focuses on the application of the PSO algorithm for tuning the PID parameters of an industrial robotic manipulator, with the aim of enhancing control quality, improving trajectory tracking performance, and increasing robustness against varying payloads and disturbances typically encountered in manufacturing environments. PSO has been successfully employed to optimize PID parameters in a wide range of robotic and complex mechatronic systems, yielding improvements in response time, steady-state error, and overshoot when compared with conventional, non-optimized PID controllers. In studies on PSO-based PID control for continuum robots, PSO-enabled tuning of PID gains has been shown to significantly reduce response time, overshoot, and settling time relative to fixed-gain PID controllers, resulting in more accurate trajectory tracking along predefined paths in simulation environments [5]. Related investigations have further demonstrated that PSO–PID controllers can enhance the control performance of robotic manipulators and other automated systems, particularly in nonlinear trajectory tracking tasks and under time-varying payload conditions [6]. Moreover, comprehensive reviews on PID tuning for robotic systems indicate that classical tuning methods often fail to achieve optimal performance in complex robotic applications, whereas metaheuristic algorithms such as PSO provide a more effective framework for selecting appropriate Kp, Ki and Kd parameters to meet stringent control performance requirements [7]. Consequently, the PSO–PID controller not only simplifies the parameter tuning process but also improves stability and trajectory tracking accuracy for industrial robots operating under diverse conditions, as reflected in simulation results and comparative performance evaluations against traditional PID controllers [8].

II. OVERVIEW OF PSO-PID CONTROLLERS

In recent years, the application of metaheuristic optimization algorithms, particularly Particle Swarm Optimization (PSO), for tuning PID controller parameters has emerged as a prominent research topic, especially in robotic and mechatronic systems characterized by nonlinear dynamics, time-varying loads, and external disturbances that are difficult to model accurately. Although PID controllers remain widely used due to their simple structure and broad applicability, their performance often degrades significantly under nonlinear and uncertain operating conditions, as conventional tuning techniques are unable to meet stringent optimality requirements. Review studies on PID control for robotic manipulators indicate that classical tuning approaches struggle to achieve a satisfactory balance among stability, trajectory tracking accuracy, and disturbance rejection. This limitation has motivated the adoption of more advanced optimization-based methods to identify suitable controller parameters within large and highly nonlinear search spaces [9].

The PSO algorithm has been employed to directly optimize PID controller parameters, resulting in reduced overshoot, improved settling time, and enhanced trajectory tracking accuracy compared with classical tuning approaches. For instance, in the study by Solihin et al., PSO-based tuning of a PID controller for a DC motor control system significantly decreased overshoot and improved dynamic response characteristics relative to the conventional Ziegler–Nichols method [10]. Similarly, PSO–PID strategies have been applied to the controller design of cable-driven parallel robots (CDPRs), where the PSO algorithm is utilized to automatically search for optimal PID gains without requiring a detailed mathematical model of the system, thereby improving control accuracy and stability [11].

For three-degree-of-freedom robotic manipulators, studies on EOD robotic manipulators employing PSO-optimized PID controllers have demonstrated that PSO is capable of rapidly and effectively tuning control parameters, while achieving significantly improved control performance compared with alternative algorithms such as Genetic Algorithms (GA) or the Whale Optimization Algorithm (WOA), particularly when combined with backpropagation (BP) neural networks for robot control [12]. Other PSO–PID applications to two-wheeled self-balancing robots have further shown that PSO-based tuning not only reduces trajectory tracking errors but also enhances stability and robustness against varying payloads under practical operating conditions [13]. In addition, findings reported in studies on PSO-tuned PID controllers for other control systems, such as First-Order Plus Time Delay (FOPTD) processes, indicate that PSO-based parameter adjustment yields superior performance in terms of faster dynamic response, improved disturbance rejection, and enhanced robustness compared with conventional PID controllers [14]. Collectively, these studies demonstrate that PSO–PID approaches not only simplify the parameter tuning process but also provide substantial improvements across multiple control performance criteria, thereby supporting the selection of PSO as the primary optimization strategy in the present research.

III. ROBOT KINEMATICS

The model of a 4-DOF industrial robotic manipulator is illustrated in Fig. 1. This manipulator is capable of performing flexible motions in three-dimensional space and is widely applied to industrial tasks such as pick-and-place operations, material handling, and trajectory tracking. In order to investigate the control aspect of the system, it is first necessary to establish an accurate mathematical model that captures the relationship between joint motions and the end-effector behavior. Based on the geometric structure depicted in Fig. 1, the modeling process provides a fundamental basis for the subsequent development and analysis of the proposed control strategy.

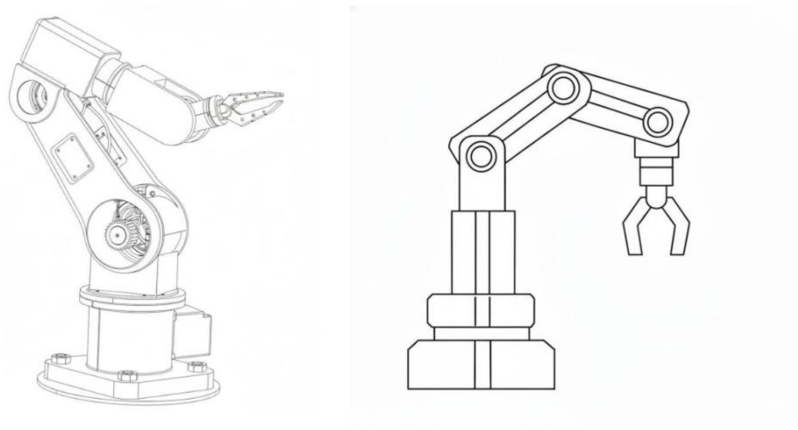

Fig. 1 Robotic manipulator

- The Denavit-Hartenberg (D-H) convention was employed to establish the kinematic parameters of the manipulator a_i; α_i; d_i; θ_i.

Table. 1 Denavit–Hartenberg (D-H) kinematic parameters of the manipulator.

i_i	a_i	α_i	d_i	θ_i
1	a_1	0	0	θ_1
2	a_2	0	0	θ_2
3	a_3	0	0	θ_3
4	a_4	0	0	θ_4

Where:

a_i : the distance along the x_i axis between the z_{i-1} and z_i .

α_i : the angle of rotation between the z_{i-1} and z_i axis about the x_i axis

d_i : the displacement along the z_i axis from the x_{i-1} axis to the z_i axis

θ_i : the rotation angle from the x_{i-1} axis to the x_i axis about the z_i axis

General homogeneous transformation matrix for kinematic modeling:

$$ {}^{i-1}T_i = \begin{bmatrix} c(\theta_i) & -s(\theta_i)c(\alpha_i) & s(\theta_i)c(\alpha_i) & a_i c(\theta_i) \\ s(\theta_i) & c(\theta_i)c(\alpha_i) & -s(\theta_i)s(\alpha_i) & a_i s(\theta_i) \\ 0 & s(\alpha_i) & c(\alpha_i) & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{1}$$

Where:

$s(\theta_i) = \sin(\theta_i); s(\alpha_i) = \sin(\alpha_i); c(\theta_i) = \cos(\theta_i); c(\alpha_i) = \cos(\alpha_i)$ The general homogeneous transformation matrix represents the spatial relationship between the base coordinate frame (Frame 0) and the end-effector frame (Frame 4)

$$ {}^{0}_{n}T = \prod_{i=1}^{n} {}^{i-1}_{i}T \tag{2}$$

Robot dynamics

- Determination of total kinetic energy:

$$K = \frac{1}{2}\sum_{i=1}^{n}\left(m_i v_{Ci}^T v_{Ci} + \omega_i^T I_i \omega_i\right) \tag{3}$$

- Computation of the total potential energy:

$$U = \sum_{i=1}^{n} m_i g h_i + U_{ref} \tag{4}$$

- Utilizing the Lagrangian formulation:

$$L(\theta, \dot{\theta}) = K(\theta, \dot{\theta}) - U(\theta) \tag{5}$$

- The Euler–Lagrange equations of motion.

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\theta}}\right) - \frac{\partial L}{\partial \theta} = \tau \tag{6}$$

- Employing the general dynamic equation to derive the mass (inertia), Coriolis/centripetal, and gravitational matrices.

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \tau \tag{7}$$

Where:

q : Represents the generalized coordinates defining the configuration of the robot.

$\dot{q}$: The first time-derivative of the joint coordinates.

$\ddot{q}$: The second time-derivative of the joint coordinates.

τ : The vector of generalized forces or moments acting on the robotic joints.

M : A symmetric, positive-definite matrix representing the system's mass properties.

C : Terms representing velocity-dependent nonlinear dynamic effects.

G : The vector of moments exerted on the joints due to gravity.

IV. CONTROL METHODOLOGY

The Proportional–Integral–Derivative (PID) controller is a fundamental closed-loop feedback control algorithm that is widely used in control engineering and automation to regulate a process variable around a desired reference value. The controller operates by continuously evaluating the error between the measured process output and the setpoint, and then generating an appropriate control signal to reduce this error over time. The PID control mechanism consists of three principal components: proportional (P), integral (I), and derivative (D) actions. The proportional term produces a control response directly related to the instantaneous error, enabling a rapid reaction to deviations; the integral term accumulates the error over time to eliminate steady-state offset; and the derivative term anticipates the future trend of the error by considering its rate of change, thereby mitigating oscillations and improving system stability. The appropriate selection of the control gains Kp, Ki and Kd is a critical step in PID design to achieve the desired control performance, ensuring a balance among stability, minimal error, and acceptable response time. Owing to its simple yet effective structure, the PID controller has become a standard control strategy in a wide range of industrial applications, including temperature, flow, and pressure regulation, motor speed control, and various automated processes [15].

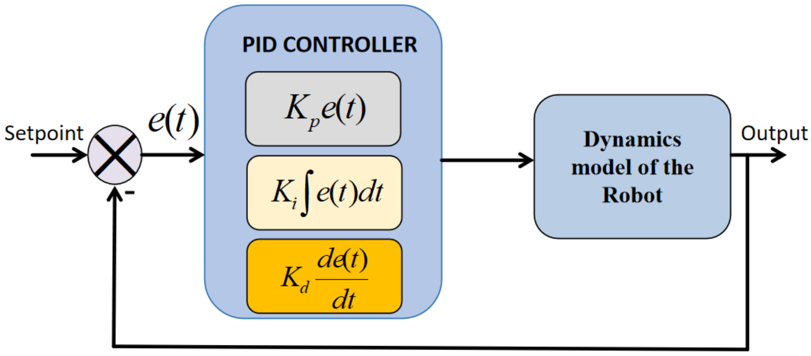

Fig. 2 A PID controller for the robot model

V. PSO ALGORITHM

The PSO is a metaheuristic optimization algorithm belonging to the class of swarm intelligence–based methods and was first introduced by Kennedy and Eberhart in 1995. The fundamental concept of PSO is inspired by the collective foraging behavior observed in flocks of birds or schools of fish, where each individual represents a candidate solution within the search space. The optimization process is carried out through iterative updates of the position and velocity of each particle, guided by both the particle's own best experience (pbest) and the global best experience of the entire swarm (gbest). Through this cooperative information-sharing mechanism, particles progressively converge toward the optimal region of the search space according to a predefined fitness criterion [16].

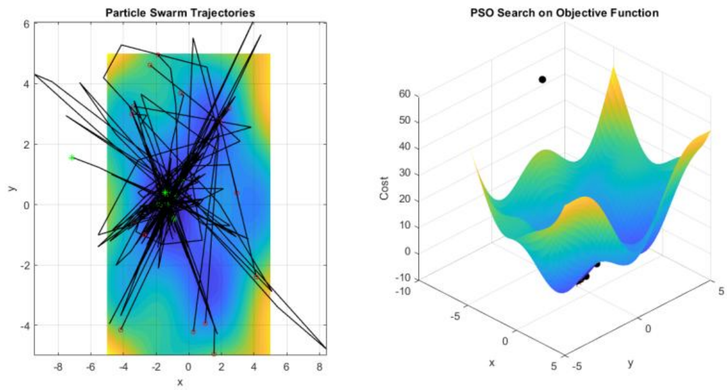

Fig. 3 Iterative convergence and global best selection in particle swarm optimization

In PSO, each particle moves through the search space with a velocity that is influenced by two main components: one driving the particle toward its personal best position and the other directing it toward the global best position of the swarm. Achieving an appropriate balance between exploration of new regions in the search space and exploitation of existing high-quality solutions is a key factor determining the effectiveness of the algorithm. The PSO does not require gradient information or a detailed mathematical model of the optimization problem, which allows it to be efficiently applied to a wide range of nonlinear, multimodal, and large-scale optimization problems in engineering and computer science. Consequently, PSO has been widely adopted in applications such as control optimization, job scheduling, controller parameter tuning, system design, and other approximate solution search problems [17].

Stochastic velocity update law:

$$v_i^{k+1} = wv_i^k + c_1 r_1 \left(pbest_i - x_i^k \right) + c_2 r_2 \left(gbest - x_i^k \right) \tag{8}$$

Spatial position update rule:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{9}$$

Where:

$x_i^k ; v_i^k$: he position and velocity vectors of the i particle at iteration k, respectively.

$pbest_i$: The personal best position achieved by particle throughout its historical trajectory.

$gbest$: The global best position attained by the entire swarm.

w The inertia weight factor, which balances the algorithm's exploration and exploitation capabilities.

$c_1 ; c_2$: The acceleration coefficients, representing the cognitive and social scaling factors.

$r_1 ; r_2$: Uniformly distributed random variables within the range [0;1]

Algorithm flowchart:

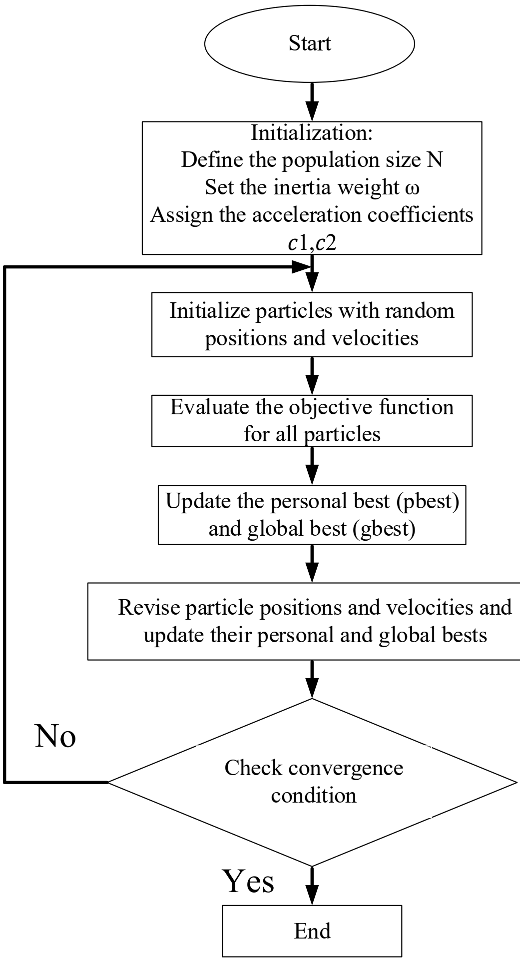

Fig. 4 A flowchart of the PSO algorithm

The PSO is an optimization method based on the collective behavior of a population of candidate solutions, referred to as particles, within the search space. Initially, each particle is randomly initialized with a position and a velocity, while the population size and acceleration coefficients are predefined. At each iteration, the fitness value of each particle is evaluated using the objective function of the problem. Based on this evaluation, each particle records the best position it has encountered so far (pbest), and the entire swarm identifies the current global best position (gbest).

The velocity and position update process of the particles is designed such that each individual is influenced by both its own experience and that of the entire swarm, thereby achieving a balance between exploration of the search space and exploitation of promising regions. The updated velocity of each particle is computed based on three components: the inertia term, the cognitive component directing the particle toward its personal best position (pbest), and the social component guiding it toward the global best position (gbest). After the velocity update, the particle's position is adjusted accordingly, and the new fitness value is re-evaluated.

The algorithm iteratively performs fitness evaluation, updates the pbest and gbest values, and adjusts particle velocities and positions until a predefined stopping criterion is satisfied, such as reaching a maximum number of iterations or achieving a target error threshold. By incorporating both individual experience and collective knowledge into the update mechanism, the PSO is able to converge efficiently toward optimal or near-optimal solutions in a wide range of complex optimization problems.

VI. OPTIMIZATION OF PID CONTROL PARAMETERS VIA PARTICLE SWARM METAHEURISTIC

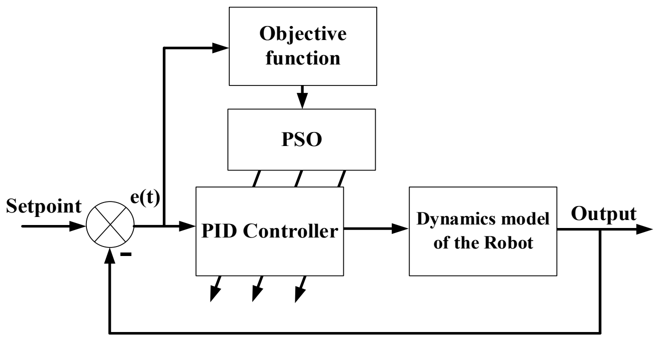

Fig. 5 Optimization of PID controller gains using PSO

In practical control systems, the performance of a PID controller is highly dependent on the appropriate selection of the parameters Kp, Ki, and Kd in order to achieve the desired transient response, steady-state error, and overall stability. Manual tuning of these parameters is often time-consuming and may fail to deliver optimal performance, particularly for nonlinear systems or systems operating under significant disturbances and load variations. Therefore, the PSO is adopted as an automated approach to determine the optimal PID parameter set by treating Kp, Ki, and Kd as decision variables and searching for their most suitable combination according to a predefined performance criterion.

Specifically, PSO initializes a population of particles, each representing a feasible combination of Kp, Ki, and Kd within the search space. The quality of each particle is evaluated using the integral of time-weighted absolute error (ITAE), which is employed in this study to assess the control performance of an industrial robotic manipulator by penalizing tracking errors over time. This criterion assigns greater weight to errors that persist for longer durations, thereby encouraging faster convergence and more stable system responses. The optimization process focuses on adjusting the PID parameters to minimize the ITAE value over the entire simulation interval, resulting in a favorable trade-off between trajectory tracking accuracy and oscillation suppression. During the iterative process, each particle retains its personal best position (pbest), while the swarm collectively identifies the global best position (gbest). Particle velocities and positions are then updated by considering both pbest and gbest, ensuring a balanced exploration and exploitation of the search space. The algorithm proceeds until a stopping condition is met, such as reaching the maximum number of iterations or achieving an error value below a predefined threshold. The application of PSO for PID parameter tuning demonstrates a significant improvement in control performance compared with conventional tuning methods.

VII. NUMERICAL SIMULATION RESULTS

Table. 2 Initialization of algorithm parameters

The core configuration settings for the optimization routine.	PID Controller
The total number of parameters to be optimized	12
The total number of particles (individuals) within the swarm.	100
The predefined termination criterion based on the total generational cycles.	100
Also referred to as the individual learning factor.	1.5
Also referred to as the collective learning factor.	1.5

The factor used to control the impact of the previous velocity on the current one.	0.09

Table. 3 PID controller parameters optimized via the PSO algorithm

PSO for PID Controller	ITAE
K_{p1}	202.9870
K_{i1}	63.4039
K_{d1}	47.9111
K_{p2}	164.8549
K_{i2}	43.4333
K_{d2}	26.0514
K_{p3}	74.8497
K_{i3}	57.8722
K_{d3}	8.3091
K_{p4}	168.2827
K_{i4}	45.2190
K_{d4}	22.7250

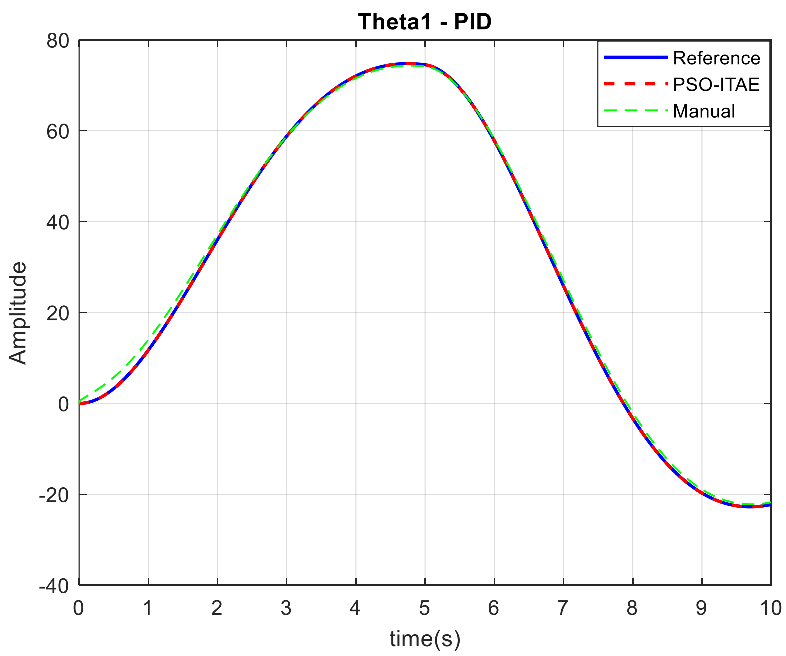

Fig. 6 Simulation results for the Theta 1 angle

Table. 4 Quality evaluation parameters for the Theta 1 angle

Controller	Performance Evaluation via the Objective Function ITAE1			
	Overshoot (±)	Rise Time (S)	Settling Time (S)	ITAE1
PID	7.5	2.8	6.8	0.6813
PID-PSO	5.5	2.5	6.2	0.6407

The simulation results demonstrate that the PID controller optimized via the PSO algorithm achieves superior tracking performance compared to the manual tuning method. As observed from the response plots, the system output under PSO-based control follows the reference trajectory more closely, particularly during the transient phase. The maximum overshoot for the PSO-tuned controller is approximately 5.5%, which is a significant improvement over the 7.5% observed with the manually tuned PID, indicating a substantial reduction in signal oscillation.

Furthermore, the rise time of the system using the PSO algorithm decreased from 2.8s to 2.5s, enabling a faster response to setpoint variations. The settling time was also shortened from 6.8s to 6.2s, reflecting the system's ability to reach a steady state more rapidly with attenuated post-transient oscillations. These enhancements suggest that the PSO algorithm identified a more optimal set of PID parameters, establishing an effective balance between response speed and system stability.

Regarding the Integral of Time-weighted Absolute Error (ITAE) criterion, the PSO-optimized PID controller outperformed the manual tuning approach. Specifically, the ITAE value was reduced from 0.6813 to 0.6407 upon applying the PSO algorithm. This decrease indicates that tracking errors were suppressed not only in magnitude but also throughout the entire transient period, thereby validating the improved overall control quality of the PID–PSO scheme for the Theta 1 angle.

In robotic manipulator control applications, minimizing overshoot and oscillations is critical for mitigating mechanical vibrations and enhancing setpoint tracking accuracy. Consequently, the obtained results demonstrate that the application of the PSO algorithm for PID parameter optimization yields a marked improvement over conventional manual tuning methods

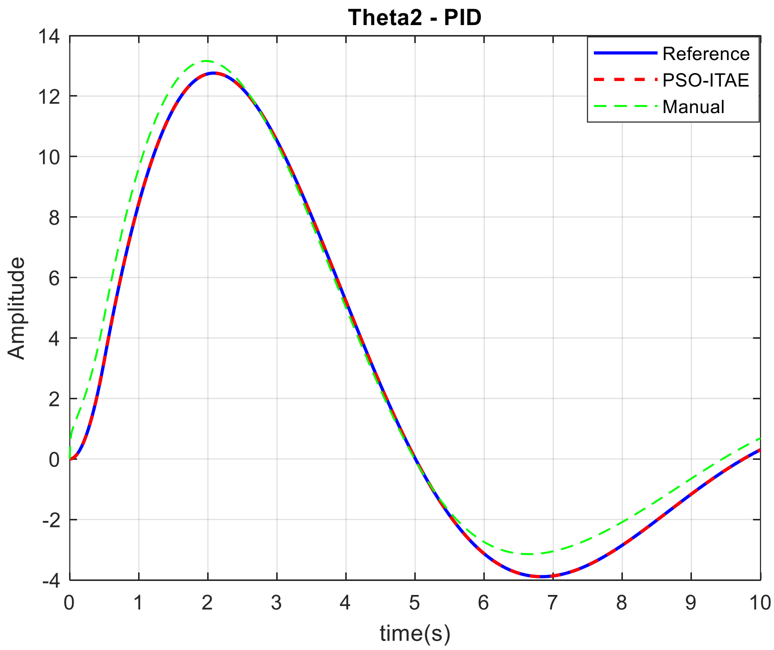

Fig. 7 Simulation results for the Theta 2 angle

Table. 5 Quality evaluation parameters for the Theta 2 angle

Controller	Performance Evaluation via the Objective Function ITAE2			
	Overshoot (±)	Rise Time (S)	Settling Time (S)	ITAE2
PID	10.2	1.85	6.40	0.4226
PID-PSO	7.5	1.60	5.80	0.4032

For the second joint Theta 2 , the simulation results indicate that the PID controller tuned via the PSO algorithm provides a superior response compared to the manual parameter selection method. Observation of the response plots reveals that the system trajectory under PID–PSO control follows the setpoint more closely throughout the entire motion profile. The maximum overshoot was reduced from 10.2% to 7.5%, demonstrating a clear mitigation of the overshoot phenomenon.

Furthermore, the rise time of the system utilizing the PSO-optimized PID decreased from 1.85 s to 1.6 s, reflecting a faster response to variations in the reference signal. The settling time was also shortened from 6.4 s to 5.8 s; concurrently, the post-transient oscillations exhibited smaller amplitudes compared to the manually tuned PID case. This proves that the PID parameter set identified by the PSO algorithm enables the system to reach a steady state earlier and maintain a smoother response.

Regarding the Integral of Time-weighted Absolute Error (ITAE) metric for the Theta 2 joint, the manually tuned PID yielded an ITAE value of 0.4226, whereas the PSO-optimized PID achieved a lower value of 0.4032. This improvement indicates that the PSO algorithm effectively reduced the cumulative tracking error over time and enhanced the overall control quality of the system, aligning with the observations derived from the response plots.

In general, the response of the Theta 2 joint exhibits distinct differences between the two tuning methods, particularly during the transient phase where variations are most pronounced. The PSO-optimized PID controller not only suppresses the overshoot but also ensures that the system response remains proximal to the reference trajectory throughout the operation. These results suggest that the PID parameters determined by the PSO algorithm are more compatible with the dynamic characteristics of the Theta 2 joint, thereby enhancing the stability and reliability of the control system

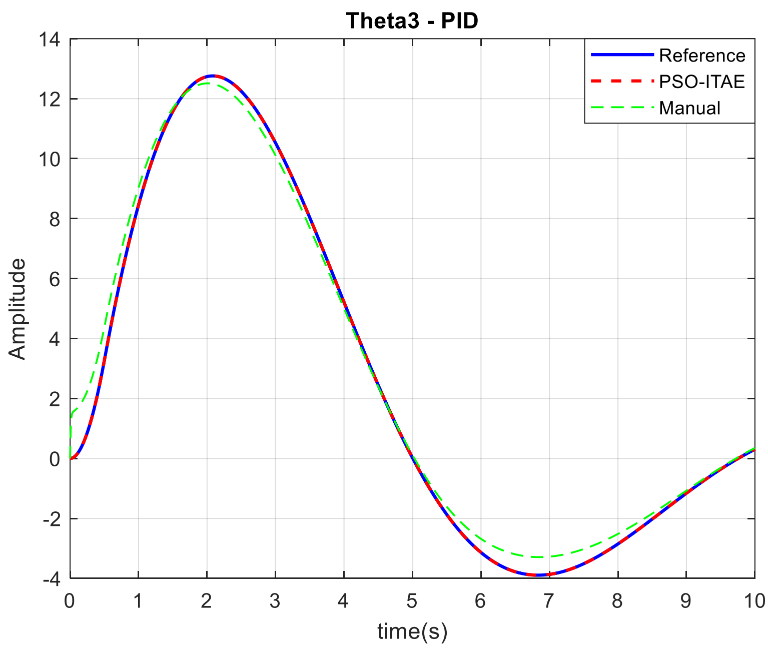

Fig. 8 Simulation results for the Theta 3 angle

Table. 6 Quality evaluation parameters for the Theta 3 angle

Controller	Performance Evaluation via the Objective Function ITAE3			
	Overshoot (±)	Rise Time (S)	Settling Time (S)	ITAE3
PID	8.6	1.75	5.90	0.2454
PID-PSO	6.3	1.55	5.35	0.2201

For the Theta 3 joint angle, the PID controller optimized via the PSO algorithm demonstrates simultaneous improvements in both response speed and system stability compared to the manual tuning method. As illustrated in the simulation plots, the system response under PID–PSO control tracks the reference trajectory more accurately throughout the motion profile, particularly at the trajectory peaks and troughs where tracking errors typically manifest. The maximum overshoot was reduced from 8.6% to 6.3%, indicating a significant mitigation of the overshoot phenomenon.

Furthermore, the rise time of the system decreased from 1.75 s to 1.55 s, reflecting a faster response to control signals. The settling time was also shortened from 5.9 s to 5.35 s, while the post-transient oscillation amplitudes were smaller than those observed with the manually tuned PID. These results suggest that the PID parameters identified by the PSO algorithm facilitate a smoother response and maintain minimal error during the setpoint tracking process.

For the Theta 3 joint, the ITAE value of the manually tuned PID was 0.2454, whereas the PID–PSO achieved a lower value of 0.2201. The reduction in the ITAE index confirms that the PSO-optimized controller provides superior long-term tracking performance, particularly during prolonged transient phases. This finding further validates the efficacy of the PSO algorithm for PID parameter optimization across robotic manipulator joints.

Since the Theta 3 joint plays a critical role in refining the position and trajectory of the end-effector, enhancing the control response directly contributes to improved motion accuracy and stability. The simulation results demonstrate that the PSO algorithm serves as an effective methodology for the PID parameter optimization problem in robotic joint control.

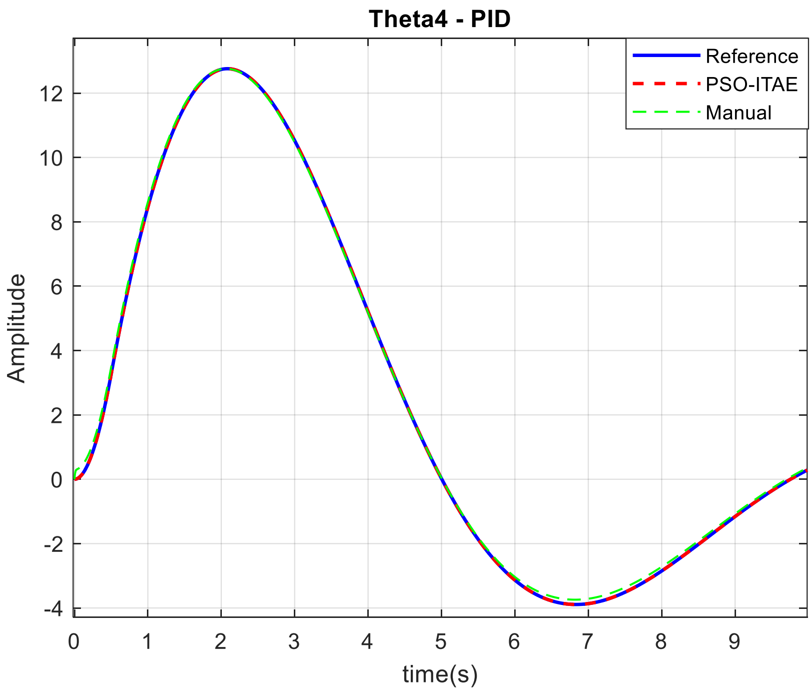

Fig. 9 Simulation results for the Theta 4 angle

Table. 7 Quality evaluation parameters for the Theta 4 angle

Controller	Performance Evaluation via the Objective Function ITAE4			
	Overshoot (±)	Rise Time (S)	Settling Time (S)	ITAE4
PID	9.1	1.70	6.00	0.07721
PID-PSO	6.7	1.55	5.50	0.07127

For the Theta 4 joint angle, the application of the PID controller optimized via the PSO algorithm ensures that the system response tracks the setpoint more accurately throughout the motion profile, particularly at the trajectory peaks and troughs. The maximum overshoot was reduced from 9.1% to 6.7%, indicating a significant mitigation of the overshoot phenomenon compared to the manual tuning approach.

Furthermore, the rise time of the system decreased from 1.70 s to 1.55 s, reflecting the system's enhanced responsiveness to control signals. The settling time was also shortened from 6.0 s to 5.5 s; concurrently, the post-transient response exhibited smoother characteristics with attenuated oscillations. This suggests that the PID parameters identified by the PSO algorithm facilitate simultaneous improvements in both response speed and system stability.

Beyond temporal performance indices, the Integral of Time-weighted Absolute Error (ITAE) criterion further demonstrates the superiority of the PSO-based optimization. Specifically, the ITAE value for the manually tuned PID was 0.07721, whereas the PID–PSO achieved a lower value of 0.07127. The reduction in the ITAE index reflects a decrease in tracking error in terms of both magnitude and duration, thereby confirming the efficacy of the PSO algorithm in enhancing the control quality for the Theta 4 joint.

FUNDING STATEMENT

This research is funded by Electric Power University under research 2025. Project Granted number DTNH.23/2025.

REFERENCES

[1]. V. K. Singh và S. K. Sud, “Metaheuristic algorithms for PID controller parameters tuning: review, approaches and open problems,” Heliyon, vol. 8, no. 5, p. e09399, 2022. https://doi.org/10.1016/j.heliyon.2022.e09399

[2]. N. Bounouara, M. Ghanai, and K. Chafaa, “Metaheuristic Optimization of PD and PID Controllers for Robotic Manipulators,” IIETA Journal of Engineering Science and Applications, vol. 54, no. 6, pp. 835–845, 2021. https://www.iieta.org/journals/jesa/paper/10.18280/jesa.540605

[3]. F. Hashim, “Design of a Predictive PID Controller using Particle Swarm Optimization,” International Journal of Electronics and Telecommunication, 2020. https://ijet.pl/index.php/ijet/article/view/10.24425-ijet.2020.134035

[4]. “A Particle Swarm Optimization tuned nonlinear PID controller with improved performance and robustness,” Results in Control and Optimization, vol. 12, 2023. https://doi.org/10.1016/j.rico.2023.100289

[5]. N. Bounouara, M. Ghanai và K. Chafaa, Metaheuristic Optimization of PD and PID Controllers for Robotic Manipulators, IIETA Journal of Engineering Science and Applications, vol. 54, no. 6, pp. 835–845, 2021. https://www.iieta.org/journals/jesa/paper/10.18280/jesa.540605

[6]. A. K. Hamoudi, Optimum Setting of PID Controller Using Particle Swarm Optimization for a Position Control System, Al-Nahrain Journal for Engineering Sciences, vol. 20, no. 1, pp. 292–297, 2017. https://nahje.com/index.php/main/article/view/105

[7]. J. Li, Analysis And Comparison of Different Tuning Method of PID Control in Robot Manipulator, Highlights in Science, Engineering and Technology, vol. 71, pp. 28–36, 2023. https://doi.org/10.54097/hset.v71i.12373

[8]. N. Bounouara, M. Ghanai & K. Chafaa, Metaheuristic Optimization of PD and PID Controllers for Robotic Manipulators, IIETA Journal of Engineering Science and Applications, 2021. https://www.iieta.org/journals/jesa/paper/10.18280/jesa.540605

[9]. Jiyan Li, Analysis And Comparison of Different Tuning Method of PID Control in Robot Manipulator, Highlights in Science, Engineering and Technology, 2023. https://doi.org/10.54097/hset.v71i.12373

[10]. M. I. Solihin, L. F. Tack & M. L. Kean, Tuning of PID Controller Using Particle Swarm Optimization (PSO), International Journal on Advanced Science, Engineering and Information Technology, vol. 1, no. 4, pp. 458–461, 2011. https://doi.org/10.18517/ijaseit.1.4.93

[11]. Dinh Ba Pham et al., “Application of Particle Swarm Optimization for PID Controller Parameter Tuning in Parallel Cable-Driven Robotic Systems,” Journal of Maritime Science and Technology, 2021. https://jmst.vimaru.edu.vn/index.php/tckhcnhh/article/view/68

[12]. Yunkang Zhou et al., Research on the Optimization of the PID Control Method for an EOD Robotic Manipulator Using the PSO Algorithm for BP Neural Networks, Actuators, vol. 13, no. 10, 386, 2024. https://www.mdpi.com/2076-0825/13/10/386

[13]. N. Hasanah, -. Alrijadjis & B. Sumantri, Modified Particle Swarm Optimization Based PID for Movement Control of Two-Wheeled Balancing Robot, International Journal on Advanced Science, Engineering and Information Technology, vol. 9, no. 4, pp. 1154–1162, 2019. https://doi.org/10.18517/ijaseit.9.4.9485

[14]. A Particle Swarm Optimization tuned nonlinear PID controller with improved performance and robustness for First Order Plus Time Delay systems, Results in Control and Optimization, vol. 12, 100289, 2023. https://doi.org/10.1016/j.rico.2023.100289

[15]. “Proportional–Integral–Derivative controller,” Wikipedia. Provides a general definition, operating principles, and main components of the PID controller. Available at: https://en.wikipedia.org/wiki/Proportional%E2%80%93integral%E2%80%93derivative_controller

[16]. “Particle Swarm Optimization,” Wikipedia. Describes the fundamental principles and operational mechanism of the PSO algorithm. Available at: https://en.wikipedia.org/wiki/Particle_swarm_optimization