

Comparative Performance Analysis of Nature-Inspired Metaheuristic Algorithms for PID Controller Optimization

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Abstract

Tuning PID controllers for diverse dynamic systems remains a fundamental challenge in control engineering due to the conflicting requirements of fast transient response, robustness, and stability. This study presents a comprehensive comparative analysis of eight nature-inspired metaheuristic algorithms—Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Simulated Annealing (SA), Harris Hawks Optimization (HHO), Whale Optimization Algorithm (WOA), Ant Lion Optimizer (ALO), and Differential Evolution (DE)—for optimal PID parameter tuning. The algorithms are evaluated using six benchmark plants representing a wide range of control characteristics, including third-order, high-order, non-minimum phase, unstable, overdamped, and underdamped systems. Optimization performance is assessed based on four integral error criteria (ISE, IAE, ITSE, and ITAE), robustness over multiple independent runs, convergence behavior, and computational efficiency under a fixed computational budget. Comparative results demonstrate that algorithm performance strongly depends on plant dynamics and optimization criteria. Among the evaluated methods, PSO consistently provides the best overall performance by achieving faster convergence and superior solution quality under limited function evaluations, while GWO and WOA exhibit competitive and robust performance across challenging benchmark problems. The findings provide practical guidelines for selecting appropriate metaheuristic optimization algorithms for PID controller design and offer useful insights into the trade-offs between optimization accuracy, robustness, and computational cost in engineering control applications.

Keywords: *PID Controller, Metaheuristic-Based Optimization, Nature-Inspired Algorithms, Control Performance Indices, Robustness Analysis.*

1. Introduction

In modern control engineering, tuning PID controller parameters remains a critical yet challenging task due to nonlinear system dynamics, conflicting performance objectives, and practical constraints. Achieving an optimal balance between stability, robustness, and response speed often requires systematic and efficient optimization strategies [1–5]. The field of intelligent control has grown significantly over the past decade, driven by the increasing complexity of modern systems. As system complexity rises, so does the difficulty of developing accurate mathematical models, which in turn can make control design more challenging. In many cases, highly complex models hinder the effectiveness and practicality of controller

design [6,7]. To enhance control performance and reduce the tuning effort, optimization technologies are increasingly applied to PID controller design problems. Optimization typically involves identifying the optimal set of controller parameters to achieve one or more performance objectives, $f(X)$, such as minimizing overshoot, settling time, or steady-state error, while satisfying system and design constraints, $g(X)$. These constraints—expressed as equalities or inequalities—limit the feasible parameter space and make the search for optimal solutions more complex, especially in nonlinear or time-varying systems. Despite these challenges, the general framework of a mathematical programming model can be described as follows:

$$\begin{aligned} \text{Min or Max: } & f(X) \\ \text{Subject to: } & g_j(X) \leq 0, \quad j = 1, 2, \dots, J \end{aligned} \tag{1}$$

The objective function $f(X)$ and the inequality constraints $g_j(X)$, where X represents the decision variables that form the basis of most engineering design problems [2]. Since engineering designs typically involve constraints [3–5], effective methods are essential to handle these constraints robustly. Optimization approaches that aim to find optimal solutions while satisfying these constraints are broadly categorized into model-based and metamodel-based (or surrogate-based) strategies [8-13].

A remaining gap in comparative PID-tuning studies is the lack of a common, low-function-evaluation framework that evaluates diverse metaheuristics across substantially different plant dynamics while considering solution quality, robustness, and computational cost. Many comparisons emphasize a single plant, a single objective, or unconstrained iteration counts, making it difficult to distinguish algorithmic strengths under a common evaluation budget. To address this gap, the present study compares eight algorithms across six diverse benchmark plants and four integral error criteria using the same population size, a fixed 200-FE budget, ten independent runs, rank-based comparison, and elapsed-time analysis. This design is intended to clarify which search behaviors are most effective for low-budget PID tuning and to provide practical guidance on the trade-off between convergence quality, robustness, and computational cost.

This paper conducts a systematic comparative study of eight advanced metaheuristic algorithms for tuning PID controller parameters applied to six benchmark dynamic plants. The optimizers include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Simulated Annealing (SA), Harris Hawks Optimization (HHO), Whale Optimization Algorithm (WOA), Ant Lion Optimizer (ALO), and Differential Evolution (DE). The goal is to find PID parameters that minimize selected performance indices such as ISE, IAE, ITSE, or ITAE, ensuring high control performance for each plant.

The six benchmark plants represent a variety of practical control challenges, including stable high-order systems, non-minimum phase behavior, and unstable dynamics. This diversity provides a realistic and challenging testbed for evaluating optimizer effectiveness and robustness. The paper extends prior optimization studies from discrete combinatorial problems (e.g., thermistor network design) to continuous nonlinear PID tuning problems, demonstrating the versatility of these metaheuristics.

The remainder of this paper is organized as follows: Section 2 describes the background of the study and discusses benchmark plants and optimization algorithms used. Section 3 formulates the PID tuning problem, presents the experimental setup. Section 4 discusses comparative results with statistical analyses. Section 5 concludes the paper with recommendations and future work.

2. Background of Study

2.1 Benchmark Plants for PID Tuning

To objectively assess the efficacy of the eight metaheuristic optimization algorithms in PID controller tuning, it is imperative to evaluate them across a diverse set of plant models exhibiting distinct dynamic characteristics. Relying on a homogenous set of plants would merely highlight algorithmic performance under specific conditions, failing to reveal true generalization capabilities, robustness, or limitations.

Consequently, this study employs six distinct benchmark plants (G_{s1} to G_{s6}). These models cover a broad spectrum of industrial dynamics, including high-order, integrating, non-minimum phase, unstable, and varying damping characteristics. This comprehensive testbed ensures that the metaheuristics are tested against the multifaceted challenges frequently encountered in real-world control applications. The mathematical formulations and control challenges of these plants are detailed below.

1) G_{s1} : Third Order Integrating System

The first plant, G_{s1} , represents a third-order integrating process, mathematically described as:

$$G_{s1}(s) = \frac{1}{s^3 + 6s^2 + 7s} \quad (2)$$

This structure—an integrator cascaded with a second-order lag—is characteristic of positional servo systems, such as a motor driving a robotic arm joint to a specific angle [14]. The presence of the pole at the origin naturally eliminates steady-state error for step inputs but introduces an inherent phase lag of -90° . Combined with the lag from the second-order component, the system suffers from a reduced phase margin. The optimization challenge here is to determine PID parameters that leverage integral action for precision while providing sufficient phase leading to prevent low-frequency oscillations.

2) $G_{s2}(s)$: Stable High-Order System

$G_{s2}(s)$ is a fourth-order system characterized by the following transfer function:

$$G_{s2}(s) = \frac{s^2 + 2s}{s^4 + 2s^3 + 5s^2 + s + 0.1} \quad (3)$$

High-order models are often required when simplified second-order approximations fail to capture complex dynamics, such as those found in flexible-link manipulators or cascaded thermodynamic processes [15]. The primary difficulty with $G_{s2}(s)$ is a significant phase roll-off at high frequencies and the presence of complex poles. This makes the closed-loop system sensitive to high-gain derivative action, which can excite high-frequency modes. The metaheuristic algorithms must locate a solution that balances response speed with robust stability, avoiding the excitation of these higher-order dynamics.

3) $G_{s3}(s)$: Non-Minimum Phase (NMP) System

$G_{s3}(s)$ introduces a Right-Half Plane (RHP) zero, classifying it as a Non-Minimum Phase (NMP) system:

$$G_{s3}(s) = \frac{1 - 0.1s}{s^2 + 2s} \quad (4)$$

NMP dynamics are frequently observed in boiler drum level control and aircraft altitude dynamics [16]. RHP zero causes an "inverse response," where the output initially moves in the opposite direction of the steady-state value. This behavior imposes a fundamental limitation on the achievable closed-loop bandwidth. Aggressive tuning to speed up the response typically exacerbates the initial undershoot. Therefore, the optimization goal is to find a set of conservative parameters that minimizes undershoot while maintaining an acceptable settling time.

4) $G_{s4}(s)$: Open-Loop Unstable System

$G_{s4}(s)$ represents a classic open-loop unstable plant:

$$G_{s4}(s) = \frac{1}{s^2 - 1} \quad (5)$$

With a pole in the Right-Half Plane (at $s=1$), this system cannot maintain equilibrium without active feedback control, mimicking dynamics seen in inverted pendulums or magnetic levitation systems [17]. Unlike the previous cases, the primary objective here is stabilization. The optimization landscape is constrained, as many random PID initializations may result in unbounded outputs. The algorithm must first identify the narrow region of stability before optimizing for time-domain performance criteria.

5) $G_{s5}(s)$: Overdamped DC Motor System

$G_{s5}(s)$ models a standard DC motor, encapsulating electrical and mechanical time constants:

$$G_{s5}(s) = \frac{0.01}{0.005s^2 + 0.06s + 0.01} \quad (6)$$

Analysis of the characteristic equation shows that this system is overdamped (real poles). It represents an inherently stable and "well-behaved" plant [18]. While easier to stabilize than $G_{s3}(s)$ or $G_{s4}(s)$, it serves as a baseline to evaluate the convergence speed and precision of the metaheuristics. The optimization challenge is strictly performance-oriented: achieving the fastest rise time and minimum steady-state error without inducing artificial overshoot or controller saturation.

6) $G_6(s)$: Underdamped Robot Joint Dynamics

Finally, $G_6(s)$ represents a simplified model of robot joint dynamics dominated by inertia and damping:

$$G_6(s) = \frac{1}{0.01s^2 + 0.1s + 1} \quad (7)$$

7) While like $G_{s5}(s)$, $G_{s6}(s)$ is characterized by a damping ratio of $\zeta=0.5$ (derived from $\omega_n=10$ rad/s), making it an underdamped system [19]. This mechanical resonance creates a tendency for oscillation. Furthermore, mechanical systems are highly susceptible to noise amplification via the derivative term. Consequently, the metaheuristics must optimize for rapid tracking while suppressing the natural oscillatory tendency of the plant, ensuring a smooth control signal.

2.2 Overview of Metaheuristic Optimization Algorithms

Metaheuristic optimization algorithms are general-purpose search methods designed to obtain optimal or near-optimal solutions for complex problems where exact techniques are impractical [20]. Inspired by natural, biological, physical, or collective-intelligence processes, these algorithms navigate large search spaces by balancing two essential mechanisms: exploration, which diversifies the search to avoid local optima, and exploitation, which intensifies the search around high-quality regions to refine solutions [20]. Effective optimization performance depends on maintaining an adaptive balance between these two behaviors.

The eight algorithms selected for this comparative study, including GA, PSO, GWO, SA, HHO, WOA, ALO, and DE, were chosen to provide a broad and representative cross-section of modern metaheuristic approaches. This set includes established, classical algorithms (GA, PSO, SA, DE) and more recently developed, highly efficient swarm-based techniques (GWO, HHO, WOA, ALO). Their inclusion is

justified by their proven suitability for continuous, unconstrained, and nonlinear optimization problems, such as the PID controller tuning task.

1) *Genetic Algorithm (GA)*

GA is an evolutionary population-based method that improves candidate PID gains through selection, crossover, and mutation, providing broad exploration of the search space [20].

2) *Particle Swarm Optimization (PSO)*

PSO updates candidate PID gains using each particle's personal best and the swarm's global best, providing a direct balance between individual learning and collective exploitation and therefore rapid convergence [21].

3) *Grey Wolf Optimizer (GWO)*

GWO guides the population using the three leading solutions (α , β , and δ), whose combined guidance balances exploration and exploitation around promising regions [22]:

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (8)$$

where X_1, X_2, X_3 are the position updates are derived from the interaction with α , β , and δ , respectively.

4) *Simulated Annealing (SA)*

SA is a single-solution trajectory method that can accept worse solutions early in the search and gradually reduces this probability through the cooling schedule, helping escape local optima before final refinement [23].

5) *Harris Hawks Optimization (HHO)*

HHO alternates between exploration and exploitation according to the prey's escaping energy, transitioning from broader search to more localized improvement as the search progresses [24].

6) *Whale Optimization Algorithm (WOA)*

WOA alternates between global exploration and local exploitation through shrinking encircling and spiral updating, with its control parameters regulating the transition between these behaviors [25].

7) *Ant Lion Optimizer (ALO)*

ALO combines random-walk exploration with attraction toward promising antlion positions and elitist guidance, providing both diversification and convergence pressure [26].

8) *Differential Evolution (DE)*

DE generates trial solutions through differential mutation and binomial crossover, making it effective for continuous search but potentially requiring more evaluations for progressive refinement [27]:

$$V_{i,G} = X_{r1,G} + F \cdot (X_{r2,G} - X_{r3,G}) \quad (9)$$

- 8) Where $r1, r2, r3$ are random distinct indices, and F is the scaling factor. A binomial crossover is subsequently applied to combine the mutant and target vectors, creating a trial vector that replaces the target only if it yields superior fitness [27].

3. Comparative Study

3.1 Problem Formulation

PID controller tuning is inherently a nonlinear, nonconvex, and often multimodal optimization problem, especially for plants exhibiting higher-order dynamics, uncertainty, non-minimum-phase characteristics, or instability. Classical tuning rules, such as Ziegler–Nichols, provide rapid initial estimates but frequently yield suboptimal performance in these scenarios [14], motivating the use of global optimization techniques. To address these limitations, this study formulates PID tuning as a continuous parameter optimization task solvable by nature-inspired metaheuristic algorithms, which have demonstrated strong capability for handling complex control-oriented search landscapes [1].

The objective is to identify the optimal controller gains:

$$\theta = [K_p, K_i, K_d]^T \quad (10)$$

that minimize an integral performance index over the simulation horizon T :

$$\min_{\theta} J(\theta) = \min_{K_p, K_i, K_d} \int_0^T f(e(t), t) dt \quad (11)$$

where $e(t) = r(t) - y(t)$ denotes the tracking error. The study considers four well-established error criteria widely applied in control system optimization [15]:

- Integral of Squared Error (ISE)
- Integral of Absolute Error (IAE)
- Integral of Time-weighted Squared Error (ITSE)
- Integral of Time-weighted Absolute Error (ITAE)

The PID parameter bounds are defined as:

$$K_p \in [0, 10], \quad K_i \in [0, 10], \quad K_d \in [0, 5] \quad (12)$$

This range is selected based on control-theoretic considerations and practical tuning experience. These intervals cover the typical magnitude of PID gains observed in industrial applications while avoiding excessively large values that frequently lead to instability, noise amplification, or actuator saturation, particularly for systems with integrators, non-minimum-phase zeros, or unstable poles [29]. The ranges also maintain a well-conditioned optimization landscape, preventing unnecessary expansion of the search space that would slow convergence without providing meaningful performance benefits [29]. Limiting K_d to a smaller range reflects common engineering practice, as high derivative gains tend to amplify measurement noise and destabilize numerical simulations [14]. Overall, the selected bounds provide a balanced and representative domain for fair and efficient algorithmic comparison.

Eight optimization algorithms are employed to solve the formulated problem. To ensure a fair and unbiased comparison, all algorithms were constrained by an identical computational budget, implemented via a fixed maximum number of function evaluations (FEs). Algorithmic parameter settings were adopted from canonical or recommended values reported in the original literature, ensuring methodological consistency. In this study, a population size of 30 and a maximum of 200 FEs were uniformly applied across all algorithms, as summarized in Table 1.

The 200-FE limit is deliberately used as a stringent, common evaluation budget to assess early-stage optimization efficiency rather than to equalize iteration counts or wall-clock time. Function evaluations are counted at the objective-function level, so every algorithm is allowed the same number of plant simulations, while differences in algorithmic overhead are separately reflected by the measured elapsed time. This FE-based normalization provides a transparent basis for comparing low-budget tuning performance.

Table 1. Parameter settings of the metaheuristic algorithms.

Algorithm	Key Parameters
ALO	- convergence constant $I = 10$ - coefficient = 1 - roulette wheel selection probability = 1.0 - trap radius reduction factor = 0.5.
GWO	a linearly decreases from 2 to 0 - random vectors $A, C \sim U(-a, a)$ - encircling and hunting operators enabled
HHO	- initial escape energy $E_0 = 2$ - escape energy $E = 2 \left(1 - \frac{t}{T}\right)$ - soft besiege threshold = 0.5 - hard besiege threshold = 0.5 - jump strength $J \sim U(0,2)$.
WOA	- spiral coefficient $b = 1$ a decreases from 2 to 0 - exploitation probability $p = 0.5$ - random vector $l \sim U(-1,1)$.
GA	- tournament selection (size = 2) - crossover rate = 0.8 - mutation rate = 0.05 - gaussian mutation variance = 0.02;
PSO	- inertia weight $w = 0.73$ - cognitive/social factors $c_1 = c_2 = 1.49$ - velocity limit = 20% of search range - constriction coefficient $\chi = 0.72$
DE	- scaling factor $F = 0.5$ - crossover rate $CR = 0.9$ - reinitialization probability = 0
SA	- Awareness probability $AP = 0.1$ - light length $fl = 2$ - memory-following probability = 1.0 - perturbation noise amplitude = 1.0

3.2 Performance Metrics

To rigorously quantify the efficacy of the proposed metaheuristic algorithms, this study employs a multi-dimensional assessment framework. The evaluation criteria are categorized into three distinct domains: control accuracy (time-domain performance), statistical robustness (reliability across stochastic runs), and computational efficiency (convergence cost and execution time).

1) *Integral Error Indices (Time-Domain Performance)*

The primary objective of the PID tuning process is to minimize the deviation $e(t) = r(t) - y(t)$ where $r(t)$ is the reference setpoint and $y(t)$ is the system output. To evaluate this error over a simulation horizon T , four standard integral performance indices are employed, each emphasizing distinct engineering aspects [30]:

Integral of Squared Error (ISE):

$$J_{ISE} = \int_0^T e(t)^2 dt \quad (13)$$

ISE heavily penalizes large errors due to the squaring operation, making it sensitive to transient deviations such as overshoot or initial spikes. Minimizing ISE encourages rapid convergence toward the setpoint and aggressive error reduction, which is particularly suitable for systems where early transient performance is critical. However, it may tolerate small oscillations during later stages.

Integral of Absolute Error (IAE):

$$J_{IAE} = \int_0^T |e(t)| dt \quad (14)$$

IAE treats all deviations linearly, providing an unbiased measure of cumulative error regardless of magnitude. It offers a balanced assessment between initial transients and steady-state deviations, making it appropriate for systems requiring moderate control effort and overall error minimization without overemphasizing spikes.

Integral of Time-weighted Squared Error (ITSE):

$$J_{ITSE} = \int_0^T t \cdot e(t)^2 dt \quad (15)$$

By weighing the squared error with time, ITSE penalizes late-stage errors more heavily. This directly targets long settling times and steady-state deviations, ensuring that controllers not only respond quickly but also maintain accuracy as the system approaches equilibrium. ITSE is particularly relevant for processes where precise final-state regulation is more critical than rapid transient behavior.

Integral of Time-weighted Absolute Error (ITAE):

$$J_{ITAE} = \int_0^T t \cdot |e(t)| dt \quad (16)$$

Similar in intent to ITSE, ITAE emphasizes long-term accuracy but is less sensitive to short-term peaks due to the linear absolute term. It is widely regarded as the preferred metric for high-precision systems demanding minimal steady-state oscillation, providing an effective balance between settling time and overshoot control.

These four indices collectively enable a holistic evaluation of controller performance [30]. ISE and IAE focus on the magnitude and accumulation of early errors, promoting fast transient response, whereas ITSE and ITAE prioritize steady-state accuracy and long-term stability. Using them together ensures that the tuned PID achieves both responsive and precise control, reflecting real-world engineering priorities.

2) Statistical Robustness Measures

Metaheuristic algorithms are inherently stochastic, relying on random initialization and probabilistic search operators (e.g., mutation and crossover). Consequently, a single simulation run is insufficient for objective evaluation. To address this uncertainty and assess algorithmic reproducibility, a Monte Carlo simulation consisting of $N_{run} = 10$ independent runs are conducted for each optimizer. The following statistical metrics are employed [31]:

Mean Fitness (μ):

The arithmetic mean of the objective function values obtained across the independent runs. This metric indicates the average convergence accuracy (solution quality) of the algorithm and is defined as:

$$\mu = \frac{1}{N_{run}} \sum_{i=1}^{N_{run}} J_i \quad (17)$$

Standard Deviation (σ):

A measure of the dispersion of the results. A lower σ signifies a robust algorithm capable of consistently converging to high-quality solutions, regardless of initial random seed conditions, and can be calculated as:

$$\sigma = \sqrt{\frac{1}{N_{run} - 1} \sum_{i=1}^{N_{run}} (J_i - \mu)^2} \quad (18)$$

To complement the descriptive mean and standard-deviation measures, a non-parametric Friedman test was applied to the paired task-wise ranks across the 24 plant–criterion tasks. When the overall test was significant, pairwise Wilcoxon signed-rank comparisons with Holm adjustment were used to examine whether the rank differences were concentrated in specific algorithm pairs. Because the available comparative summary is expressed as task-wise ranks, this analysis is reported as a rank-based significance assessment, while the ten-run mean and standard deviation remain the measures of stochastic variability.

3) Computational Efficiency Metrics

Assessing computational cost is essential for real-world PID tuning applications, where faster convergence reduces practical implementation time. In this study, we measure the computational efficiency of each optimizer using elapsed time, which records the actual physical execution duration for each independent run.

Let N_{run} denote the number of repetitions for each optimizer M , and $T_{elapsed,i}^{(M)}$ represent the elapsed time of the i -th run. The average elapsed time per run, representing the practical computational cost, is expressed as:

$$\bar{T}_{\text{elapsed}}^{(M)} = \frac{1}{N_{\text{run}}} \sum_{i=1}^{N_{\text{run}}} T_{\text{elapsed},i}^{(M)} \quad (19)$$

Lower values of $\bar{T}_{\text{elapsed}}^{(M)}$ indicate higher computational efficiency. In this study, all optimizers are executed under identical computational settings, ensuring a fair comparison of their temporal performance. This approach effectively captures the overhead of each optimizer, highlighting differences in speed even when they achieve similar control performance.

4. Results and Discussion

This section reports the comparative performance of eight metaheuristic optimizers for PID tuning under a strict budget of 200 objective function evaluations (FEs). In total, 24 plant–criterion tasks (six benchmark plants $\times$ four integral indices) are evaluated, and each task is repeated over ten independent runs to account for stochasticity. The same population size, PID parameter bounds, FE limit, performance criteria, and ten-run protocol are applied to all algorithms, supporting reproducibility and a controlled comparison.

4.1. Overall performance across all tasks

Figure 1 summarizes rank-based outcomes across the 24 tasks (lower rank indicates better final objective value), and Figure 2 shows the average rank and win-rate of all algorithms over 24 tasks under 200 FEs. A consistent performance hierarchy emerges under the low-budget regime. PSO achieves the best average rank across tasks and also attains the highest win frequency, indicating strong “early-to-good” convergence behavior that is particularly advantageous when the evaluation budget is severely limited. GWO and WOA form a closely competitive group, exhibiting consistently high-quality solutions across most plant–criterion combinations.

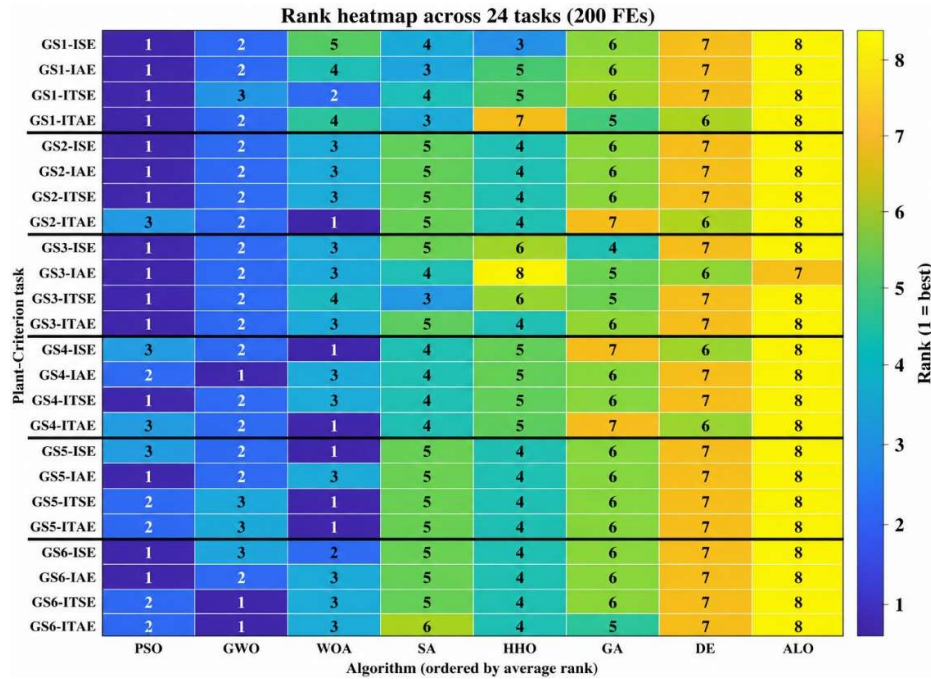


Figure 1. Rank-based performance comparison across 24 plant–criterion tasks under a 200-FE budget

The observed hierarchy is also consistent with the search mechanisms of the algorithms. PSO directly exploits personal-best and global-best information, which can produce rapid movement toward promising

PID regions and is advantageous when only 200 FEs are available. GWO maintains guidance from multiple leading solutions, while WOA alternates encircling and spiral search behaviors; these mechanisms can preserve useful population guidance while retaining exploration, helping explain their comparatively robust performance across the challenging GS3 and GS4 tasks [21,22,25].

The Friedman test on the 24 task-wise rank vectors indicates a statistically significant difference among the eight algorithms ($\chi^2(7) = 149.764$, $p < 0.001$). Post-hoc Wilcoxon signed-rank comparisons against PSO, with Holm adjustment, also show significant rank differences for GWO (adjusted $p = 0.0282$), WOA (adjusted $p = 0.0240$), and the remaining algorithms (adjusted $p < 0.001$). Thus, the overall ranking pattern is unlikely to be explained solely by random variation at the task level.

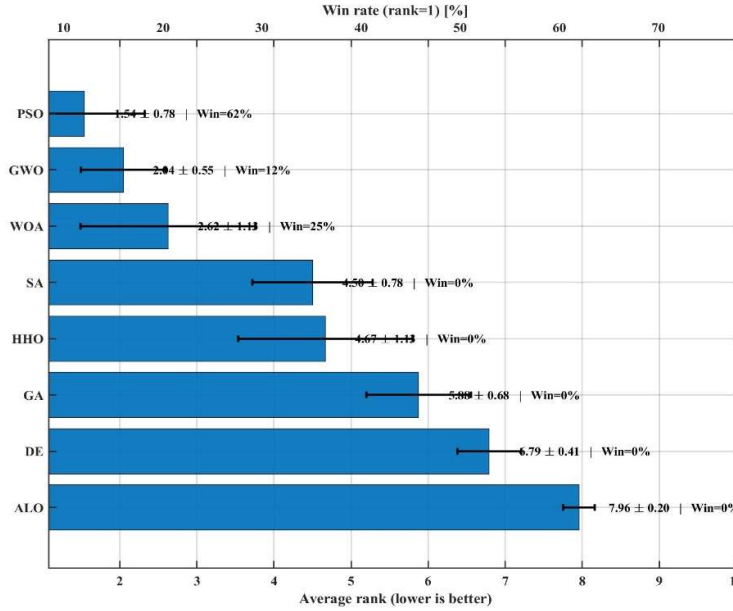


Figure 2. Average rank and win-rate of all algorithms over 24 tasks under a 200-FE budget.

In contrast, DE does not demonstrate a systematic advantage within 200 FEs. While DE can be competitive on selected tasks, its overall ranking remains inferior to PSO/GWO/WOA, suggesting that the refinement-oriented search dynamics of DE are less likely to fully manifest under stringent evaluation truncation.

4.1.1. Influence of plant dynamics

Algorithm performance is strongly modulated by plant dynamics. For well-behaved or moderately damped systems, multiple optimizers can reach satisfactory solutions within 200 FEs, resulting in smaller rank separation. However, for more challenging dynamics, particularly the non-minimum phase plant GS3 and the open-loop unstable plant GS4, the performance gap becomes more pronounced.

These two plants impose fundamentally different difficulties: GS3 exhibits inverse response constraints due to the right-half-plane zero, whereas GS4 requires stabilization of an open-loop unstable pole. Under such conditions, the feasible region yielding stable and well-damped closed-loop behavior is narrower, and low-budget optimization becomes more sensitive to fast convergence and robust population guidance. Consequently, PSO remains highly competitive due to rapid initial improvement, while GWO and WOA often display strong robustness across runs on these difficult cases, for instance, see Figures 3 and 4.

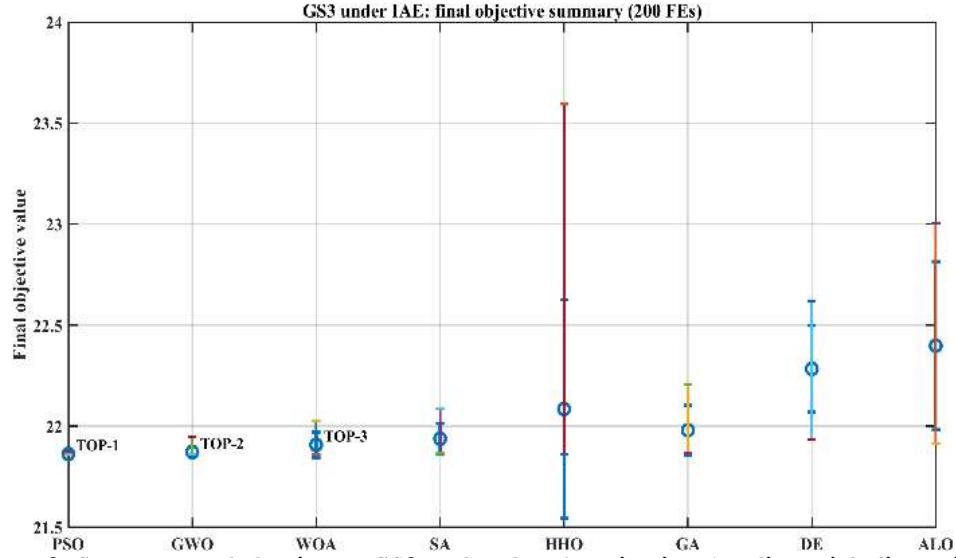


Figure 3. Convergence behavior on GS3 under the IAE criterion (median with dispersion).

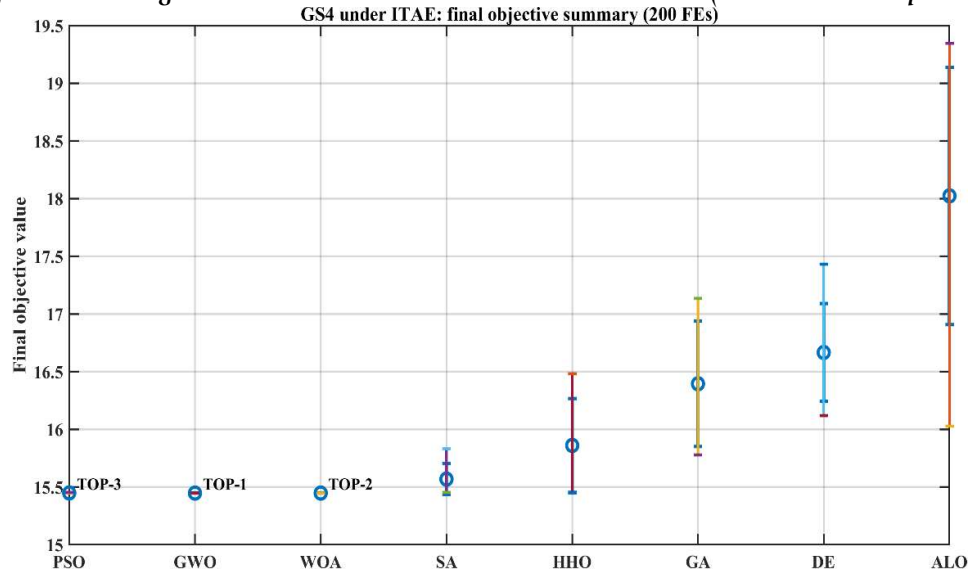


Figure 4. Convergence behavior on GS4 under the ITAE criterion (median with dispersion).

4.1.2. Sensitivity to performance criteria

The choice of performance index further shapes algorithm behavior. Time-weighted criteria (ITSE/ITAE) penalize late-stage residual error more heavily and therefore amplify the importance of reaching a high-quality region of the search space early. Under the 200-FE constraint, optimizers that can rapidly reduce the objective value and stabilize progress (notably PSO, GWO, and WOA) tend to benefit most from time-weighted indices. Conversely, methods that typically require longer horizons to exploit late-stage refinement may exhibit inferior settling characteristics when the budget is insufficient to activate their full exploitation potential.

4.1.3. Reliability and rank distribution

While average rank provides a global performance indicator, the reliability of an optimizer under repeated stochastic runs is equally important in practical tuning scenarios. Figure 5 reports the aggregated rank distribution across all 24 plant–criterion tasks and ten independent runs. A clear contrast can be observed among the algorithms. PSO, GWO, and WOA concentrate a large proportion of probability mass in the top-ranked positions, indicating a high likelihood of achieving near-optimal solutions within the 200-FE

budget. These algorithms frequently attain top 1 and top 3 ranks across tasks, reflecting strong consistency under limited evaluations.

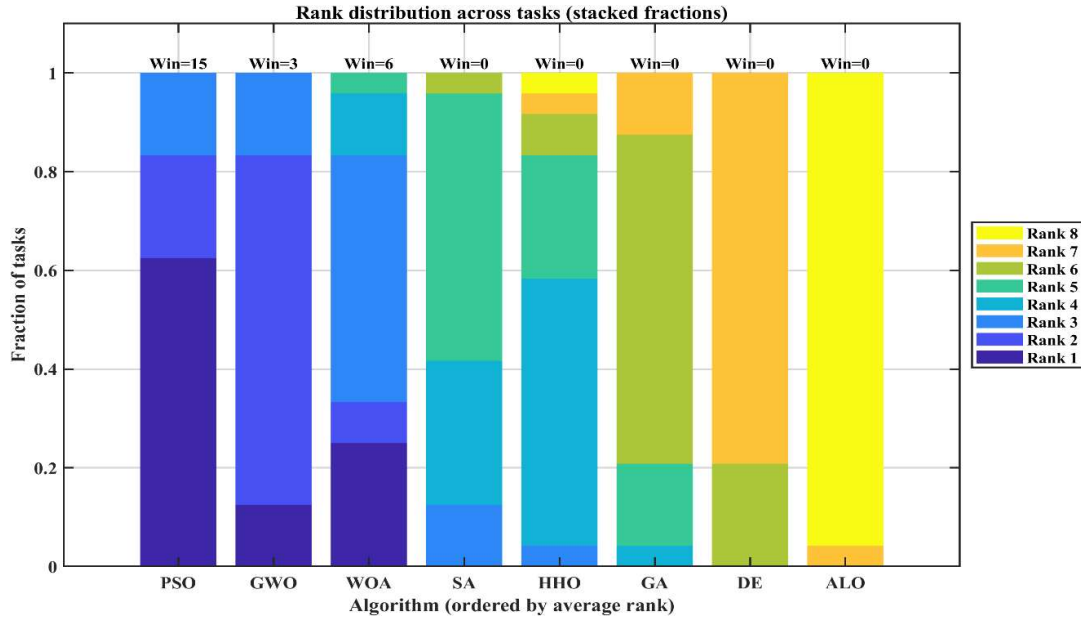


Figure 5. Aggregated rank distribution across all tasks and runs (probability mass over ranks).

In comparison, DE exhibits a noticeably broader rank distribution, with a larger fraction of outcomes falling into lower-ranked positions. This dispersion suggests higher sensitivity to initialization and a reduced probability of converging to high-quality solutions when the evaluation budget is severely constrained. From a practical perspective, the rank distribution analysis highlights that PSO, GWO, and WOA not only perform well on average but also offer superior reliability, which is critical when repeated tuning attempts are infeasible or costly.

4.1.4. Performance–time trade-off

Under a fixed evaluation budget, computational time reflects algorithmic overhead rather than extended search depth. Figure 6 illustrates the trade-off between optimization performance (average rank) and runtime across all algorithms under the 200-FE constraint.

The results show that superior performance does not require increased computational time. PSO, GWO, and WOA achieve consistently lower average ranks without incurring disproportionate runtime costs, indicating efficient utilization of the limited evaluation budget. In contrast, DE does not translate its computational effort into improved ranking performance under the same constraint, highlighting a mismatch between runtime expenditure and solution quality.

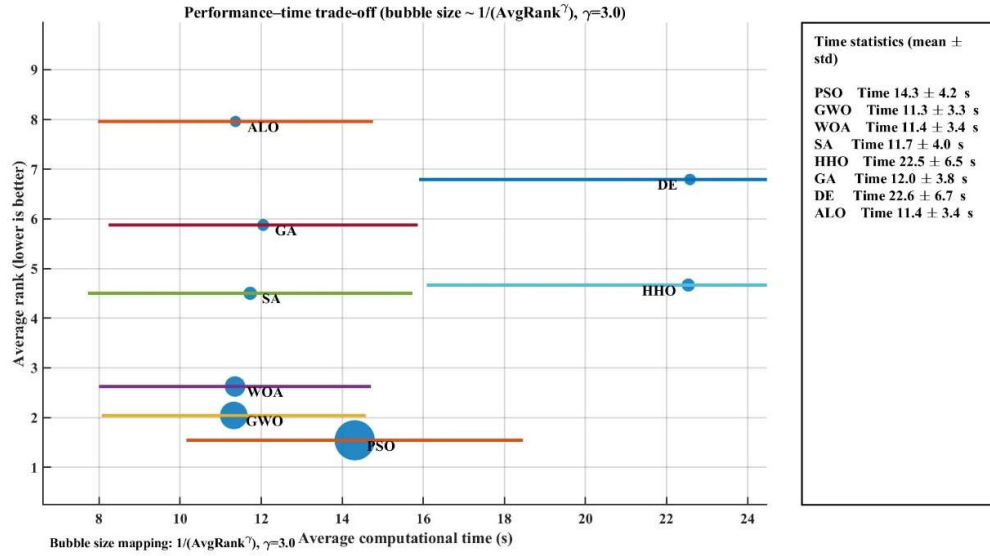


Figure 6. Trade-off between optimization performance and computational time under 200 function evaluations.

These observations suggest that, when the number of function evaluations is capped, algorithmic efficiency in exploiting early search information is more critical than raw computational time. From an engineering standpoint, PSO, GWO, and WOA therefore offer a more favorable performance–time balance for low-budget PID tuning applications.

4.1.5. Control level validation

Rank-based and convergence analyses provide optimization-level indicators of solution quality; however, it is essential to confirm that these advantages translate into meaningful closed-loop responses. Therefore, step-response validation is performed on the two most challenging plants, GS3 (non-minimum phase) and GS4 (open-loop unstable). For each plant–criterion task (GS3 under IAE and GS4 under ITAE), representative controllers are selected as the best-performing run among ten trials for PSO, GWO, WOA, and DE, and their closed-loop unit-step responses are compared in Figure 7.

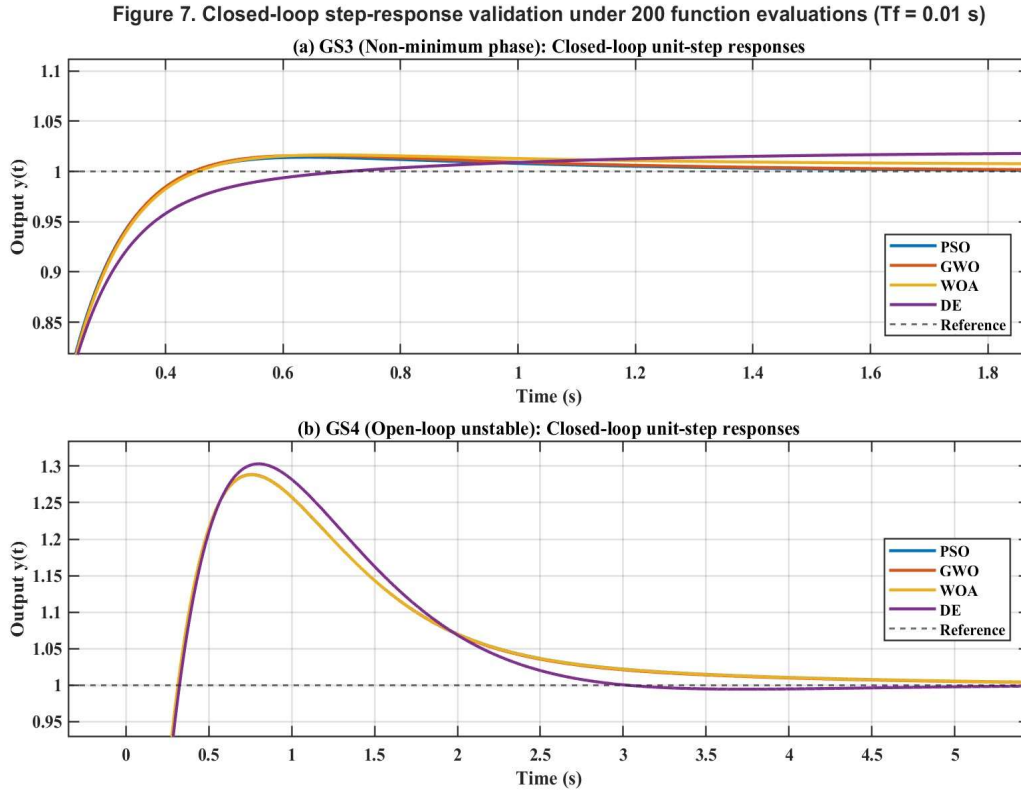


Figure 7. Closed-loop step-response validation on challenging benchmark plants under the 200-FE tuning regime. (a) GS3 (non-minimum phase) and (b) GS4 (open-loop unstable) unit-step responses obtained using PID controllers tuned by PSO, GWO, WOA, and DE. Controllers correspond to the best-performing run among ten trials for the respective plant–criterion task (GS3–IAE and GS4–ITAE). On GS3, all controllers stabilize the system with relatively small overshoot; PSO/GWO/WOA exhibit closely aligned transients, whereas DE shows a longer settling tail. On GS4, all controllers stabilize the plant but overshoot is more pronounced; PSO, GWO, and WOA achieve more favorable transient behavior, while DE remains stable but inferior in transient performance.

The GS3 responses confirm that, for non-minimum phase dynamics, the achievable transient improvement is inherently constrained; nevertheless, PSO/GWO/WOA achieve similarly well-damped responses consistent with their strong optimization ranks, while DE exhibits slower decay to steady state (settling tail), aligning with its weaker low-budget convergence profile. For GS4, the larger overshoot reflects the increased difficulty of stabilizing an unstable open-loop pole under limited evaluations; within this regime, PSO/GWO/WOA again yield more competitive transients, whereas DE remains stable but with degraded overshoot/settling characteristics. Overall, Figure 7 verifies that the optimization-level differences are faithfully reflected at the control-performance level, strengthening the practical relevance of the comparative conclusions.

4.2. Summary of Findings

This study presented a systematic comparison of eight metaheuristic algorithms for PID controller tuning under a strict computational budget of 200 function evaluations. Across 24 plant–criterion tasks covering diverse dynamics and four integral performance indices, results were evaluated over ten independent runs to account for stochastic variability.

Overall, PSO delivers the strongest average performance under the low-budget regime, indicating that rapid early convergence is a decisive advantage when evaluations are severely limited. GWO and WOA consistently form a highly competitive group and frequently attain top-tier outcomes, particularly on challenging dynamics and time-weighted criteria where robust population guidance and balanced exploitation are beneficial. In contrast, DE does not show systematic superiority within 200 evaluations, suggesting a budget–algorithm mismatch in which its refinement strength is unlikely to fully emerge under strict truncation.

Control-level validation on the most challenging plants (GS3 non-minimum phase and GS4 open-loop unstable) confirms that optimization-level advantages translate into improved closed-loop transient behavior. From an engineering standpoint, PSO provides a strong default choice for severely constrained tuning scenarios, with GWO and WOA serving as robust alternatives, especially for difficult plant dynamics and time-weighted objectives. Future work will extend the comparison to higher evaluation budgets and additional control metrics (e.g., robustness margins and control effort) to clarify budget-dependent algorithm selection strategies.

5. Conclusion

This study presented a comparative evaluation of eight metaheuristic algorithms for PID controller tuning across six benchmark plants with diverse dynamics under a limited budget of 200 function evaluations. The results show that algorithm effectiveness is highly dependent on both plant characteristics and computational constraints. Among the methods, PSO consistently achieved the best overall performance due to its rapid convergence, making it particularly suitable for low-budget optimization scenarios. GWO and WOA also demonstrated strong and reliable performance, especially for challenging systems such as non-minimum phase and unstable plants. In contrast, DE and some other algorithms showed weaker performance under the restricted evaluation budget, indicating a mismatch between their strengths and short optimization horizons. The findings further highlight that time-weighted performance criteria (ITSE and ITAE) favor algorithms capable of early convergence, and that optimization results are consistent with improved closed-loop control behavior.

Overall, PSO is recommended as a practical default choice for constrained PID tuning, with GWO and WOA as robust alternatives. Future work will explore higher evaluation budgets, hybrid strategies, and additional control performance metrics. Future research will investigate algorithm performance under different problem settings and extended optimization horizons to better understand their convergence behavior. The development of hybrid and adaptive optimization strategies, combining the fast convergence of algorithms like PSO with the strong exploration capabilities of methods such as GWO, WOA, or DE, could further enhance PID tuning performance across diverse plant dynamics. Moreover, future studies can extend the framework to more complex and realistic scenarios, such as time-delay systems, nonlinear and time-varying plants, and multi-objective PID tuning formulations. The integration of constraint-handling techniques and surrogate-assisted optimization could also improve scalability for computationally expensive systems.

Declarations

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Author Contributions

All authors contributed to the conceptualization, methodology, investigation, analysis, and preparation of the manuscript. All authors reviewed and approved the final version of the manuscript.

Data Availability Statement

This study did not involve the collection or use of experimental datasets. The research was conducted through computational simulations, and the relevant methodology, simulation settings, and results are presented in the manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest.

Ethical Statement

This study was based on computational simulations of benchmark dynamic systems and did not involve human participants, human data, or animal subjects. Therefore, ethical approval was not required.

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