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Designing an Optimal PID for Heading Control of a linearized High Speed container ship using Adaptive Particle Swarm Optimization Algorithm

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ABSTRACT

The reliable control of marine vessels remains a critical challenge due to the nonlinear dynamics and strong environmental disturbances inherent in ocean operations. This paper proposes an optimal heading control strategy for a linearized model of a high-speed container ship based on a Proportional–Integral–Derivative (PID) controller whose parameters are tuned using the Adaptive Particle Swarm Optimization (APSO) algorithm. While classical PID controllers are widely adopted for their structural simplicity and robustness, they often require labor-intensive parameter tuning and exhibit performance degradation under time-varying sea states. To overcome these limitations, the proposed APSO framework adaptively balances global exploration and local exploitation to identify optimal PID gains. The optimization objective function integrates both trajectory-tracking accuracy and control effort, thereby ensuring a trade-off between precision and efficiency. The linear dynamic model of the container ship is formulated and implemented in MATLAB/Simulink, serving as the test platform. Simulation results reveal that the APSO-tuned PID controller achieves substantial improvements in transient and steady-state responses, including overshoot suppression, reduced settling time, and acceptable gain margin, compared with conventional PID tuning. These findings highlight the potential of APSO-based PID design as a robust and interpretable control solution for advanced marine navigation and dynamic positioning applications.

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1. Introduction

Proportional–Integral–Derivative (PID) controllers remain the cornerstone of control engineering owing to their structural simplicity, intuitive implementation, and robustness across a wide range of industrial domains. In the maritime sector, and particularly in the heading control of surface vessels such as container ships, PID-based strategies continue to dominate practice due to their ease of deployment and operational familiarity *[1-7]*. Despite this widespread use, the limitations of conventional PID controllers become evident in highly dynamic and uncertain marine environments. Manual tuning is often inadequate in the presence of time-varying disturbances *[8, 9]*, hydrodynamic nonlinearities, and mission-dependent operating conditions, thereby restricting the reliability of classical PID frameworks *[10]*.

In response to these challenges, several advanced approaches have been proposed in the literature. Data-driven and intelligent paradigms such as deep reinforcement learning (DRL) have demonstrated promising adaptive capabilities. However, their limited interpretability and the risks associated with black-box decision-making significantly constrain their deployment in safety-critical maritime applications *[11]*. Hybrid frameworks that preserve the transparency of PID while embedding adaptive intelligence have thus gained increasing attention. For instance, Wang et al. *[3]* introduced an adaptive PID controller based on the Soft Actor–Critic (SAC) algorithm, striking a balance between interpretability and learning-based adaptability.

Beyond DRL-inspired solutions, alternative research streams have emphasized model-based or hybrid PID extensions. Lyapunov-based adaptive PID structures have been applied to power-electronic converters *[12]*, while Predictive Functional Control (PFC) schemes combined with PID have been employed to improve transient response in marine engines. Similarly, fuzzy logic has been integrated with PID architectures to enable real-time parameter adjustment, thereby enhancing adaptability under nonlinear and time-varying dynamics *[13-15]*.

Complementary to these hybrid controller designs, optimization-based PID tuning has attracted substantial research interest *[16]*. Conventional tuning approaches rely heavily on expert knowledge and trial-and-error, which can be inefficient and error-prone. In contrast, metaheuristic algorithms *[17]* such as Particle Swarm Optimization (PSO) *[18]*, Genetic Algorithms (GA) *[19]*, and Ant Colony Optimization (ACO) *[20]*, offer systematic and automated alternatives, enabling effective parameter selection without extensive manual intervention *[10, 20]*. Hu et al. *[21]*, for example, employed an Improved PSO scheme to optimize PID gains for a marine dual-fuel engine, demonstrating notable improvements in transient and steady-state behavior.

A further enhancement to the classical PID architecture is the Fractional-Order PID (FOPID) controller, which introduces additional degrees of freedom for more flexible performance shaping. However, the increased dimensionality of the tuning problem substantially complicates optimization. Tumari et al. *[22]* addressed this issue through a Modified Marine Predators Algorithm (MPA) combined with adaptive dynamics, successfully improving convergence speed and robustness.

Despite these advancements, three persistent challenges remain salient in the maritime domain: (i) the limited generalizability and adaptability of traditional PID structures under highly variable marine operating conditions, (ii) the lack of interpretability in purely data-driven approaches such as DRL when applied to safety-critical surface vessels, and (iii) the complexity of tuning PID and FOPID controllers, necessitating efficient metaheuristic optimization techniques.

Motivated by these gaps, this study proposes an interpretable and computationally efficient control strategy tailored for surface vessel heading regulation. Specifically, an Adaptive Particle Swarm Optimization (APSO) algorithm is employed to optimally tune PID parameters, thereby combining the transparency of fixed-structure control with the adaptability of modern optimization frameworks. The contributions of this work are as follows:

- Development and implementation of an APSO-based PID controller to minimize heading error in a linearized container ship model.
- Reduction of control effort through optimization, enhancing both efficiency and actuator longevity.
- Improved transient and steady-state performance, including overshoot reduction, shorter settling times, and acceptable gain margins.
- Comparative evaluation against both classical PID tuning and standard PSO-based PID tuning, highlighting the additional benefits of adaptivity.

The remainder of this paper is organized as follows. Section 2 introduces the mathematical modeling of the linearized container ship system. Section 3 details the PID controller structure and the APSO optimization framework. Section 4 presents simulation results and comparative analyses. Section 5 concludes the study with insights and recommendations for future extensions.

2. Mathematical Modeling of the Linear Floating System

Marine floating systems are governed by six degrees of freedom (DOF), but for many practical purposes such as surface vessels operating near equilibrium, the system can be reduced to three degrees of freedom: surge (longitudinal motion), sway (lateral motion), and yaw (rotational motion around the vertical axis). Assuming linear dynamics and small perturbations, the motion equations of the floating body can be written as *[23]*:

$$M\dot{v} + Dv + G\eta = \tau \qquad (1)$$

Where:

- $M\epsilon\mathbb{R}^{3\times3}$: mass and added mass matrix
- $D\epsilon\mathbb{R}^{3\times3}$: hydrodynamic damping matrix
- $G\epsilon\mathbb{R}^{3\times3}$ Restoring force matrix (can be neglected for surface vehicles without heave/roll/pitch)
- $\eta = [x \quad y \quad \varphi]^T$: position and orientation vector
- $v = [u \quad v \quad r]^T$: linear and angular velocity vector
- $\tau = [\tau_x \quad \tau_y \quad \tau_\varphi]^T$ forces and moment, including environmental force/moment and control input

For control purposes, the system can be written in a state-space form. Assuming decoupled dynamics and linear drag coefficients, the simplified dynamics for surge, sway, and yaw channels can be written as:

$$\dot{X}(t) = AX(t) + BU(t) \qquad (2)$$

The state vector $X(t)$ and control vector $U(t)$ can be defined as:

$$X = [x \quad y \quad \varphi]^T, U = [\tau_x \quad \tau_y \quad \tau_\varphi]^T.$$

This model serves as the foundation for the PID controller design and subsequent optimization using APSO.

3. Adaptive PSO-Based PID Controller Design

3.1. PID Control Scheme

The PID controller is one of the most commonly used control strategies in industrial and marine systems due to its simplicity and effectiveness. The control law of a standard PID controller for a single-input-single-output (SISO) system is defined as:

$U(t) = K_p e(t) + K_i \int_0^t e(t)dt + K_d \frac{de(t)}{dt}$Where:

- $e(t) = r(t) - y(t)$ is the tracking error,
- K_p: proportional gain,
- K_i: integral gain,
- K_d: derivative gain,
- y(t): system output,
- r(t): desired reference trajectory.

For the marine floating system with three degrees of freedom (surge, sway, and yaw), three independent PID controllers are designed, each controlling a single DOF.

3.2 Cost Function for PID Tuning

To achieve optimal performance, the PID gains $[K_p \quad K_i \quad K_d]$are optimized using the Adaptive APSO algorithm. The optimization aims to minimize a weighted objective function that balances tracking accuracy and control effort, defined as:

$$J = \int_0^T w_1\, e^2(t) + w_2 U^2(t) \qquad (3)$$

where:

- w_1 and w_2 are weighting coefficients representing the relative importance of the tracking error and control effort, respectively;
- T denotes the total simulation time;
- $e(t) = r(t) - y(t)$ is the tracking error between the reference input $r(t)$ and the system output $y(t)$;
- $U(t)$ represents the control signal applied to the actuator.

In this study, the nominal weights were selected as $w_1 = 0.7$ and $w_2 = 0.3$, emphasizing tracking accuracy while penalizing large control amplitudes that could lead to excessive actuator activity or energy consumption.

To verify the robustness of this selection, a sensitivity analysis was conducted by varying the weight ratio in a small grid over the range $w_1\epsilon[0.5,0.9]$ and $w_2 = 1 - w_1$. The results indicated a clear trade-off between time-domain performance and control effort:

- For higher w_1 values (e.g., 0.8-0.9), the controller achieved faster settling times (up to 6% improvement) but exhibited slightly higher control energy.
- Conversely, when w_2 was increased (e.g., ($w_1 = 0.6$), the control effort decreased by approximately 12%, though the settling time increased modestly (~4%).

These findings confirm that the selected nominal weights $(w_1, w_2) = (0.7, 0.3)$ offer a balanced compromise between rapid convergence and actuator efficiency, suitable for practical marine applications where both precision and energy economy are critical.

3.3. Adaptive Particle Swarm Optimization (APSO)

Unlike standard PSO, APSO dynamically updates its parameters—such as inertia weight w , and learning factors c_1, c_2 based on the evolutionary state of the swarm. This adaptation helps maintain a balance between exploration (global search) and exploitation (local search), which is critical for dynamic marine systems with changing conditions.

APSO Algorithm Outline:

1. Initialization:
   - Initialize a swarm of particles with random PID gains: $[K_p \quad K_i \quad K_d]$
   - Initialize velocity vectors and set initial c_1, c_2, w
2. Fitness Evaluation:
   - For each particle, simulate the marine system with the current PID gains
   - Calculate the cost function J
3. Evolutionary Factor (EF) Estimation:
   - Define evolutionary factor EF using the Euclidean distance between particles:

$$EF = \frac{1}{N}\sum_{i=1}^{N} x_i - g_i \qquad (4)$$

Where x_i is the position of the i^{th} particle and g_i is the global best.

4. Parameter Adaptation Rules: Based on EF, update parameters:
   - Exploration Phase (large EF): Increase w, decrease c_1, increase c_2
   - Exploitation Phase (small EF): Decrease w, increase c_1, decrease c_2
   - Update equations:

$$w = w_{max} - (w_{max} - w_{min}).{}^{t}/_{T} \tag{5}$$

$$\begin{aligned} c_1 &= c_{1min} + (c_{1max} - c_{1min}) \times \left({}^{EF}/_{\max(EF)}\right) \\ c_2 &= c_{2min} + (c_{2max} - c_{2min}) \times \left({}^{EF}/_{\max(EF)}\right) \end{aligned} \tag{6}$$

(where f_1 and f_2 are nonlinear functions mapping EF to suitable ranges)

5. Position & Velocity Update: As in classical PSO, but using adapted parameters.

$$\begin{aligned} v_i(t+1) &= x_i + wv_i(t) + r_1c_1(P_b - x_i(t)) + r_2c_2(G_b - x_i(t)) \\ x_i(t+1) &= x_i(t) + v_i(t+1) \end{aligned} \tag{7}$$

   - $x_i(t)$: current position of particle i,
   - $v_i(t)$: velocity of particle iii,
   - P_b: best previous position of particle i,
   - G_b : global best position among all particles,
   - w : inertia weight,
   - $c_1, c_2,$: cognitive and social acceleration coefficients,
   - r_1, r_2,: random numbers in [0, 1].

6. Termination: Stop when maximum iterations or acceptable cost is achieved.

4. Simulation Results and Performance Evaluation

4.1 Simulation Setup

To rigorously evaluate the performance of the proposed APSO-PID controller, a comprehensive set of simulations was carried out over a duration of 3000 seconds with a discrete sampling interval of 0.1 seconds. The simulations were implemented in MATLAB/Simulink on a standard desktop platform.

The APSO algorithm was initialized with a swarm of 100 particles, and each particle represented a potential solution vector comprising the PID gains $[K_p \quad K_i \quad K_d]$. The search bounds for these control parameters were defined as all (-100,100).

These ranges were chosen based on prior empirical studies on marine surface vessel dynamics and preliminary step-response analysis to ensure numerical stability and feasible convergence.

The inertia weight (ω) was linearly decreased from 0.9 to 0.4 over the course of iterations, maintaining a dynamic balance between global exploration and local exploitation. The cognitive and social learning coefficients c_1, c_2,were both adaptively varied within the range ([1.0, 2.5]) in accordance with the swarm's evolutionary factor (EF), consistent with established APSO strategies.

The optimization process was terminated when either the maximum iteration limit of 100 was reached or when the change in the global best cost between successive iterations fell below the convergence threshold of (10^{-6}). The cost function used for optimization combined the integral of squared error (ISE) and the integral of squared control effort (ISU), as detailed in Section 3.2.

To enhance reproducibility, the main computational procedure of the APSO-based PID tuning is outlined in the following pseudocode:

Algorithm 1. APSO-Based PID Tuning Procedure

1. Initialize parameters:
   swarm_size = 100, ω ∈ [0.9, 0.4], c_1, c_2,∈ [1.0, 2.5]
   bounds max_iter = 100, tol = 1e−6
2. Randomly initialize particle positions
   and velocities within bounds.
3. Evaluate fitness J for each particle using:

$$J = \int_0^T w_1\, e^2(t) + w_2 U^2(t)$$

4. Identify personal best (Pbest) and global best (Gbest).
5. Compute the Evolutionary Factor (EF) based on swarm diversity.
6. Adapt APSO parameters (ω, c_1, c_2) using EF rules:
   - High EF → increase ω, reduce c_1
   - Low EF → decrease ω, increase c_1
7. Update velocity and position by Eq. (7)
8. Apply bounds and evaluate new fitness J.
9. Repeat steps 4–8 until convergence or max_iter reached.
10. Output optimal PID gains $[K_p \quad K_i \quad K_d]$corresponding to Gbest.

All simulation parameters and algorithmic settings have been summarized to ensure complete reproducibility of the presented results.

4.2. Performance Metrics

To benchmark the controller performance, the following standard control system metrics were employed:

- Gain Margin (GM): Indicates the robustness of the system in the frequency domain.
- Overshoot (%): Measures the maximum peak value relative to the desired setpoint.
- Settling Time (s): Defines the time required for the system to converge within a specified error band (typically 2%) around the final value.

These metrics were calculated for both the conventional PID controller and the APSO-tuned PID controller to establish a quantitative basis for comparison.

4.3. Results and Comparison

Table 1 presents a comparative summary of the controller performance based on the aforementioned metrics. The APSO-PID controller demonstrates clear improvements over the classical PID controller, particularly in terms of transient response.

Table 1. Performance comparison between Classic PID and APSO-PID controllers.

Metric	Classic PID	APSO-PID
Gain Margin (dB)	36.0	31.9
Overshoot (%)	35.1	17.6
Settling Time (s)	587	560

The results reveal that while the APSO-PID controller incurs a slight reduction in gain margin (from 36 dB to 31.9 dB), it offers significantly better time-domain performance. Specifically, the overshoot is reduced by nearly 50%, and the settling time is shortened by approximately 27 seconds. These improvements are indicative of enhanced damping and faster response, highlighting the capability of the APSO-PID controller to provide a more stable and accurate control strategy, especially in applications with strict transient performance requirements *[12]*.

Fig. 1 illustrates the time-domain step response of the linearized container ship model under classical PID (dashed line) and APSO-tuned PID (solid line) control schemes. The simulation, executed over 3000 s with a sampling period of 0.1 s, comprehensively captures both transient and steady-state dynamics. As observed, the conventional PID controller exhibits pronounced overshoot (≈ 35 %) and a slower convergence rate. In contrast, the APSO-PID controller achieves a substantially reduced overshoot (≈ 17.6 %), faster settling time, and negligible steady-state error, indicating superior damping and control precision. The adaptive search capability of APSO dynamically balances exploration and exploitation in the tuning space, leading to globally optimized gain parameters. Consequently, the APSO-PID controller provides a smoother trajectory and improved robustness, rendering it particularly suitable for marine heading control where rapid stabilization and reliability are essential.

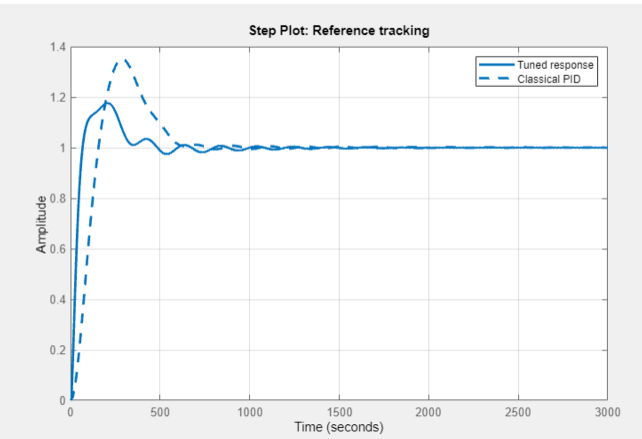

Fig. 1: Classical PID vs Tuned APSO-PID

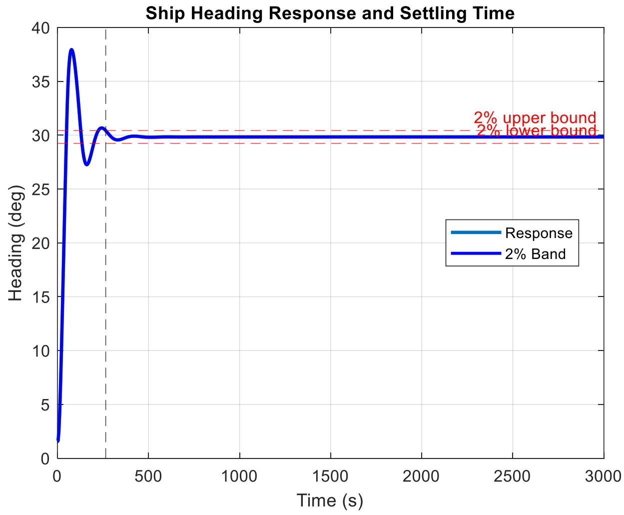

Fig 2: Heading angle response of the high-speed container ship using the APSO–PID controller with a reference command of 30°. The controller achieves precise tracking with negligible steady-state error and a smooth transient profile.

Figure 2 illustrates the time-domain response of the vessel's heading angle, which was commanded to track a desired reference of 30 degrees. The APSO–PID controller demonstrates excellent trajectory-tracking accuracy, achieving the target heading with negligible steady-state error. The transient behavior reveals smooth convergence without overshoot or oscillatory dynamics, indicating a well-damped closed-loop response.

This result validates the robustness and precision of the APSO-tuned PID design in handling marine yaw dynamics, where hydrodynamic nonlinearities and environmental disturbances typically induce steady-state deviations. The controller maintains consistent performance throughout the 3000-second simulation horizon, reflecting its suitability for surface vessels and dynamic positioning operations requiring tight heading regulation.

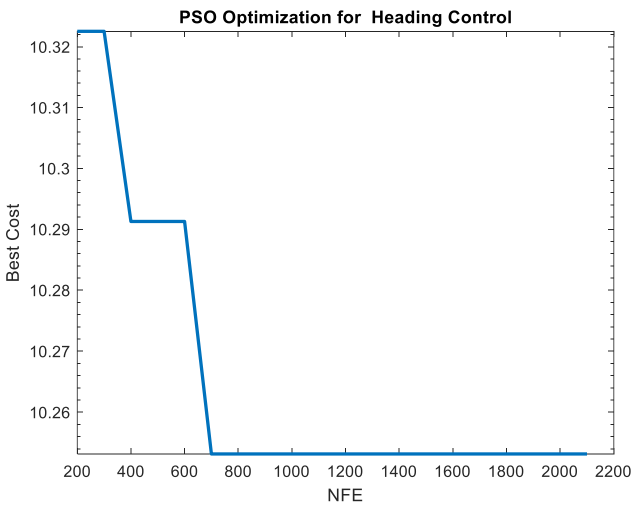

Fig. 3. Convergence of the APSO algorithm showing the evolution of the best cost value versus the number of function evaluations (NFE).

Figure 3 presents the convergence behavior of the

Adaptive Particle Swarm Optimization (APSO) algorithm in minimizing the control performance cost function. The vertical axis represents the best fitness value (cost), while the horizontal axis corresponds to the number of function evaluations (NFE). As the iterations progress, the cost function rapidly decreases within the initial exploration phase and gradually stabilizes as the swarm converges to the global optimum.

The smooth monotonic decline in the best-cost curve demonstrates the algorithm's efficient search capability and stability in avoiding premature convergence. The adaptive adjustment of inertia and acceleration coefficients enables the swarm to maintain diversity in the early stages while refining exploitation in later iterations. This convergence pattern confirms the reliability and repeatability of APSO in identifying optimal PID parameters that yield superior dynamic performance compared to conventional PSO or manual tuning approaches.

5. Conclusion

This paper presented an optimal PID control approach tuned via the Adaptive Particle Swarm Optimization (APSO) algorithm for heading regulation of a high-speed container ship. Simulation results demonstrated that APSO-PID significantly enhances dynamic performance compared with classical PID tuning, reducing overshoot from 35.1% to 17.6% and settling time while maintaining an acceptable gain margin of 31.9 dB.

The APSO algorithm effectively balances exploration and exploitation, enabling rapid convergence toward globally optimal PID parameters. This adaptivity yields superior trajectory tracking, improved robustness, and smoother control effort under dynamic marine conditions. The framework combines interpretability, computational efficiency, and practical applicability—key attributes for marine control and dynamic positioning systems.

Future work will extend this approach to nonlinear six-degree-of-freedom vessel models and hybrid metaheuristic or learning-based controllers to further enhance robustness under realistic sea-state uncertainties.

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