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PSO-Based Optimal Tuning of P, PI, PD, and PID Controllers for Aircraft Longitudinal Dynamics: A Comparative Study with Baseline Benchmarking

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Abstract: This study presents a systematic investigation of Particle Swarm Optimization (PSO)-based tuning of classical controllers for aircraft longitudinal control, with explicit comparison against conventionally tuned baseline controllers. A linearized four-state aircraft model representing short-period and phugoid dynamics is considered, where pitch angle is selected as the controlled output. Four controller structures, namely P, PI, PD, and PID, are tuned using both classical heuristic methods (baseline) and PSO under a unified multi-objective fitness framework. The objective function integrates Integral of Squared Error (ISE), Integral of Time-weighted Absolute Error (ITAE), and control effort, ensuring balanced transient and steady-state performance. The baseline controllers are designed using standard tuning principles, serving as a reference for performance evaluation. In contrast, PSO employs adaptive inertia weight and bounded gain search spaces to achieve global optimization. Comparative analysis is carried out using step response, control effort, and disturbance rejection characteristics. Key performance indices such as rise time, settling time, overshoot, and steady-state error are evaluated for both baseline and optimized cases. Results clearly indicate that PSO-tuned controllers significantly outperform baseline designs across all metrics. The PID controller exhibits the best overall performance, achieving faster settling, reduced overshoot, and negligible steady-state error compared to its baseline counterpart. PD control demonstrates improved damping with lower control effort, while PI shows moderate improvement in steady-state accuracy. The baseline P controller remains inadequate for stringent performance requirements. The findings validate that PSO provides a robust and efficient optimization framework for controller tuning in aerospace systems, enabling superior dynamic performance over traditional design approaches.

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I. INTRODUCTION

Aircraft longitudinal control remains a fundamental problem in flight dynamics due to the coupled nature of short-period and phugoid modes. The primary objective is to regulate pitch angle and ensure stability under varying flight conditions and disturbances. Classical control strategies such as proportional (P), proportional–integral (PI), proportional–derivative (PD), and proportional–integral–derivative (PID) controllers are widely used in aerospace systems because of their simplicity and ease of implementation. However, their performance strongly depends on proper tuning of controller gains [1].

Conventional tuning methods, including Ziegler–Nichols and trial-and-error approaches, often fail to provide optimal performance for complex and highly coupled systems such as aircraft dynamics. These methods may lead to excessive overshoot, long settling time, or poor disturbance rejection [2]. In modern control applications, there is a growing demand for systematic and intelligent tuning techniques that can handle multi-objective performance criteria.

Metaheuristic optimization algorithms have emerged as powerful tools for controller design. Among them, Particle Swarm Optimization (PSO), introduced by James Kennedy and Russell Eberhart, has gained significant attention due to its simplicity, fast convergence, and ability to avoid local minima [3]. PSO simulates social behavior observed in flocks of birds, where particles iteratively adjust their positions based on personal and global best experiences. This makes it particularly suitable for nonlinear and multi-objective optimization problems in control engineering.

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Several researchers have applied PSO for tuning PID controllers in industrial and aerospace applications, reporting improved transient and steady-state performance compared to classical methods [4]–[6]. In aircraft control, optimization-based approaches have demonstrated enhanced robustness against disturbances and parameter variations [7]. However, a comprehensive comparative analysis of PSO-tuned P, PI, PD, and PID controllers against baseline designs for aircraft longitudinal dynamics remains limited.

This paper addresses this gap by presenting a systematic comparison of baseline and PSO-optimized controllers applied to a linearized aircraft longitudinal model. A multi-objective fitness function incorporating Integral of Squared Error (ISE), Integral of Time-weighted Absolute Error (ITAE), and control effort is employed to ensure balanced performance. The effectiveness of PSO is evaluated through step response analysis, convergence behavior, and disturbance rejection capability.

➢ *The Main Contributions of this Work are as Follows:*

- Unified PSO-based tuning framework for multiple controller structures,
- Baseline versus optimized performance benchmarking,
- Comprehensive evaluation using time-domain metrics and robustness tests.

The results demonstrate that PSO significantly improves control performance, making it a viable approach for advanced flight control system design.

II. LITERATURE REVIEW AND RESEARCH GAP

Aircraft longitudinal control has been extensively studied due to its direct influence on flight stability and passenger safety. Early works focused on linear control design using classical methods, where controllers such as P, PI, and PID were tuned using heuristic rules. In Modern Control Engineering, the effectiveness of PID controllers in linear systems was established, but the tuning process remained largely empirical. Similarly, the Ziegler–Nichols method introduced in the Ziegler–Nichols tuning method provides a systematic approach, yet it often leads to aggressive responses with high overshoot in aerospace applications.

For aircraft systems, the work reported in Aircraft Control and Simulation highlights the challenges associated with longitudinal dynamics, particularly the interaction between short-period and phugoid modes. Classical controllers, when applied to such systems, require careful tuning to balance stability and performance. However, fixed-gain designs lack adaptability under varying flight conditions and disturbances.

To overcome these limitations, optimization-based control design has gained attention. Particle Swarm Optimization, introduced by James Kennedy and Russell Eberhart, has been widely applied for controller tuning due to its simplicity and global search capability. Studies such as Particle Swarm Optimization demonstrated its effectiveness in solving nonlinear optimization problems. Later works extended PSO for PID tuning, showing improved transient response and robustness compared to conventional methods.

Comparative analyses between metaheuristic algorithms, including Genetic Algorithms (GA) and PSO, indicate that PSO generally achieves faster convergence with fewer parameters to adjust. Research presented in Comparison between Genetic Algorithm and Particle Swarm Optimization confirms that PSO provides better computational efficiency for control applications. In aerospace control, optimization-based tuning has shown improved disturbance rejection and reduced steady-state error, making it suitable for flight control systems.

Despite these advancements, existing literature exhibits several limitations. Most studies focus exclusively on PID controllers, neglecting a unified comparison across different controller structures such as P, PI, and PD under identical conditions. Furthermore, many works lack a clear baseline comparison using classical tuning methods, making it difficult to quantify the actual improvement achieved through optimization. In addition, multi-objective performance criteria are often simplified, ignoring the trade-off between tracking accuracy and control effort.

Another limitation is the insufficient evaluation of robustness. While some studies report improved transient response, disturbance rejection analysis is either limited or absent. This is critical in aircraft systems where external disturbances and model uncertainties are unavoidable.

➢ *Research Gap*

Based on the above review, the following research gaps are identified:

- *Lack of Unified Comparative Framework*

Existing studies do not provide a consistent comparison of P, PI, PD, and PID controllers under the same aircraft model and evaluation criteria.

- *Absence of Baseline Benchmarking*

Many works report optimized results without comparing them against classical tuning methods, limiting practical relevance.

- *Limited Multi-Objective Optimization*

Previous approaches often focus on single performance indices, ignoring combined objectives such as ISE, ITAE, and control effort.

- *Inadequate Robustness Analysis*

Disturbance rejection and real-world applicability are not thoroughly investigated in most studies.

- *Controller Performance Trade-off Not Explored*

The balance between transient response, steady-state accuracy, and actuator effort is not systematically analyzed.

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➢ *Contribution of this Work*

To address these gaps, this study proposes a PSO-based unified tuning framework for P, PI, PD, and PID controllers applied to aircraft longitudinal dynamics. A multi-objective fitness function is used to ensure balanced performance. Both baseline and optimized controllers are evaluated using identical conditions, and robustness is validated through disturbance testing. This provides a comprehensive and practically relevant comparison for aerospace control design.

➢ *Aircraft Longitudinal Dynamics Model*

The aircraft longitudinal motion is represented using a linearised state-space model derived around a steady cruise condition. The system is described as:

$$\dot{x}(t) = Ax(t) + Bu(t) \tag{1}$$

$$y(t) = Cx(t) + Du(t) \tag{2}$$

Where $x(t) \in \mathbb{R}^4$is the state vector, $u(t) \in \mathbb{R}$is the control input (elevator deflection), and $y(t)$is the output (pitch angle).

The state vector is defined as:

$$x(t) = [u \quad w \quad q \quad \theta]^T \tag{3}$$

Where $u$is forward velocity perturbation, $w$is heave velocity, $q$is pitch rate, and $\theta$is pitch angle.

The system matrices are given by:

$$A = \begin{bmatrix} X_u & X_w & 0 & -g \\ Z_u & Z_w & 1 & 0 \\ M_u & M_w & M_q & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, B = \begin{bmatrix} X_{\delta_e} \\ Z_{\delta_e} \\ M_{\delta_e} \\ 0 \end{bmatrix} \tag{4}$$

$$C = [0 \quad 0 \quad 0 \quad 1], D = 0 \tag{5}$$

The transfer function of the system is obtained as:

$$G(s) = \frac{\Theta(s)}{\Delta_e(s)} \tag{6}$$

➢ *Controller Structures*

Four classical controllers are considered in this study.

Proportional Controller:

$$C_P(s) = K_p \tag{7}$$

Proportional–Integral Controller:

$$C_{PI}(s) = K_p + \frac{K_i}{s} \tag{8}$$

Proportional–Derivative Controller:

$$C_{PD}(s) = K_p + K_d s \tag{9}$$

Proportional–Integral–Derivative Controller:

$$C_{PID}(s) = K_p + \frac{K_i}{s} + K_d s \tag{10}$$

To avoid noise amplification, the derivative term is implemented using a first-order filter:

$$C_D(s) = \frac{K_d N s}{s+N} \tag{11}$$

➢ *Closed-Loop System*

The closed-loop transfer function with unity feedback is given by:

$$T(s) = \frac{C(s)G(s)}{1+C(s)G(s)} \tag{12}$$

Where $C(s)$represents the controller transfer function.

➢ *Objective Function Formulation*

The controller tuning problem is formulated as a multi-objective optimization problem. The objective is to minimize a performance index Jdefined as:

$$J = w_1 \cdot \mathrm{ISE} + w_2 \cdot \mathrm{ITAE} + w_3 \cdot \mathrm{CE} \tag{13}$$

Where:

- *Integral of Squared Error (ISE):*

$$\mathrm{ISE} = \int_0^T e^2(t)\, dt \tag{14}$$

- *Integral of Time-weighted Absolute Error (ITAE):*

$$\mathrm{ITAE} = \int_0^T t \mid e(t) \mid dt \tag{15}$$

- *Control Effort (CE):*

$$\mathrm{CE} = \int_0^T u^2(t)\, dt \tag{16}$$

Here, $e(t) = r(t) - y(t)$is the tracking error, and $w_1, w_2, w_3$are weighting coefficients satisfying:

$$w_1 + w_2 + w_3 = 1 \tag{17}$$

➢ *Optimization Problem Statement*

The tuning problem is defined as:

$$\min_{K_p, K_i, K_d} J \tag{18}$$

Subject to:

$$K_p^{\min} \le K_p \le K_p^{\max}, K_i^{\min} \le K_i \le K_i^{\max}, K_d^{\min} \le K_d \le K_d^{\max} \tag{19}$$

The optimization seeks controller gains that minimize the objective function while ensuring system stability and acceptable transient performance.

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➢ *Discussion*

The mathematical formulation integrates system dynamics, controller design, and performance evaluation into a unified optimization framework. The inclusion of multiple performance indices ensures that both accuracy and actuator limitations are considered. This formulation is suitable for metaheuristic optimization techniques such as PSO, enabling global search and improved controller performance compared to classical tuning approaches.

III. CONTROLLER DESIGN AND PSO-BASED OPTIMIZATION

This section describes the controller implementation and the Particle Swarm Optimization (PSO) algorithm used for optimal gain tuning. The design integrates classical control structure with intelligent optimization.

➢ *Controller Implementation*

The control structure follows a unity feedback configuration, where the controller $C(s)$acts on the error signal:

$$e(t) = r(t) - y(t) \tag{20}$$

The controller output $u(t)$is applied to the plant input (elevator deflection). For each controller type (P, PI, PD, PID), the gains $\left(K_p, K_i, K_d\right)$are tuned within predefined bounds.

To ensure practical realizability, the derivative action is filtered using a first-order low-pass filter:

$$C_D(s) = \frac{K_d N s}{s+N} \tag{21}$$

Where $N$is the filter coefficient chosen sufficiently large to approximate ideal differentiation while limiting noise amplification.

➢ *Particle Swarm Optimization (PSO)*

PSO is a population-based stochastic optimization technique inspired by swarm intelligence. Each particle represents a candidate solution (controller gains), and the swarm collectively searches for the optimal solution.

The velocity and position update equations are given by:

$$v_i^{k+1} = w v_i^k + c_1 r_1 (pbest_i - x_i^k) + c_2 r_2 (gbest - x_i^k) \tag{22}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{23}$$

Where:

- $x_i$is the position (gain vector),
- $v_i$is the velocity,
- $pbest_i$is the personal best position,
- $gbest$is the global best position,
- $w$is inertia weight,
- $c_1, c_2$are cognitive and social coefficients,
- $r_1, r_2 \in [0,1]$are random variables.

The inertia weight is linearly decreased to balance exploration and exploitation:

$$w = w_{\max} - \frac{k}{k_{\max}}(w_{\max} - w_{\min}) \tag{24}$$

➢ *Fitness Evaluation*

Each particle is evaluated using the multi-objective cost function defined in Section 3. The fitness value determines the quality of controller gains. A penalty is added if the system becomes unstable or exhibits excessive overshoot.

$$J = w_1 \cdot \text{ISE} + w_2 \cdot \text{ITAE} + w_3 \cdot \text{CE} \tag{25}$$

The goal is to minimize Jwhile maintaining system stability.

➢ *Simulation Setup*

The simulation is carried out using a linearised aircraft longitudinal model. A unit step input is applied to evaluate tracking performance.

Table 1 Simulation Parameters

Parameter	**Value**
Simulation Time	15 s
Time Step	0.01 s
Reference Input	1 rad
PSO Particles	40
Max Iterations	150
Inertia Weight	0.9 → 0.4
c_1, c_2	2.05, 2.05

➢ *Gain Search Space*

Controller gains are constrained within practical limits to ensure stability and avoid actuator saturation.

Table 2 Gain Bounds

Gain	Lower Bound	Upper Bound
K_p	0.01	50
K_i	0.001	20
K_d	0.001	10

➢ *Optimization Procedure*

The PSO-based tuning process is summarized as follows:

- Initialize particle positions and velocities randomly within bounds
- Evaluate fitness for each particle
- Update personal best and global best
- Update velocity and position using (22) and (23)
- Apply boundary constraints
- Repeat until maximum iterations reached or convergence achieved

➢ *Discussion*

The PSO framework provides a robust mechanism for tuning controller gains in a multidimensional search space. The adaptive inertia weight improves convergence speed while avoiding premature stagnation. Compared to classical tuning, PSO systematically explores the solution space and yields globally optimized parameters.

The integration of multi-objective fitness ensures balanced performance across tracking accuracy, response speed, and control effort. This makes the approach suitable for real-world aerospace systems where multiple performance criteria must be satisfied simultaneously.

IV. RESULTS AND DISCUSSION

This section presents a comparative evaluation of baseline (classical tuning) and PSO-optimized controllers applied to the aircraft longitudinal model. The analysis is carried out using time-domain response, control effort, convergence behavior, and disturbance rejection characteristics. Quantitative metrics are used to validate performance improvement.

➢ *Step Response Analysis*

The closed-loop step response of all controllers is evaluated for a unit pitch angle input. Baseline controllers exhibit slower dynamics and higher oscillations due to non-optimal gain selection. In contrast, PSO-tuned controllers show faster rise time, reduced overshoot, and improved settling behavior.

The P controller fails to provide adequate damping, while PI improves steady-state error but introduces sluggish response. PD significantly enhances damping characteristics. The PID controller achieves the best trade-off between speed and stability.

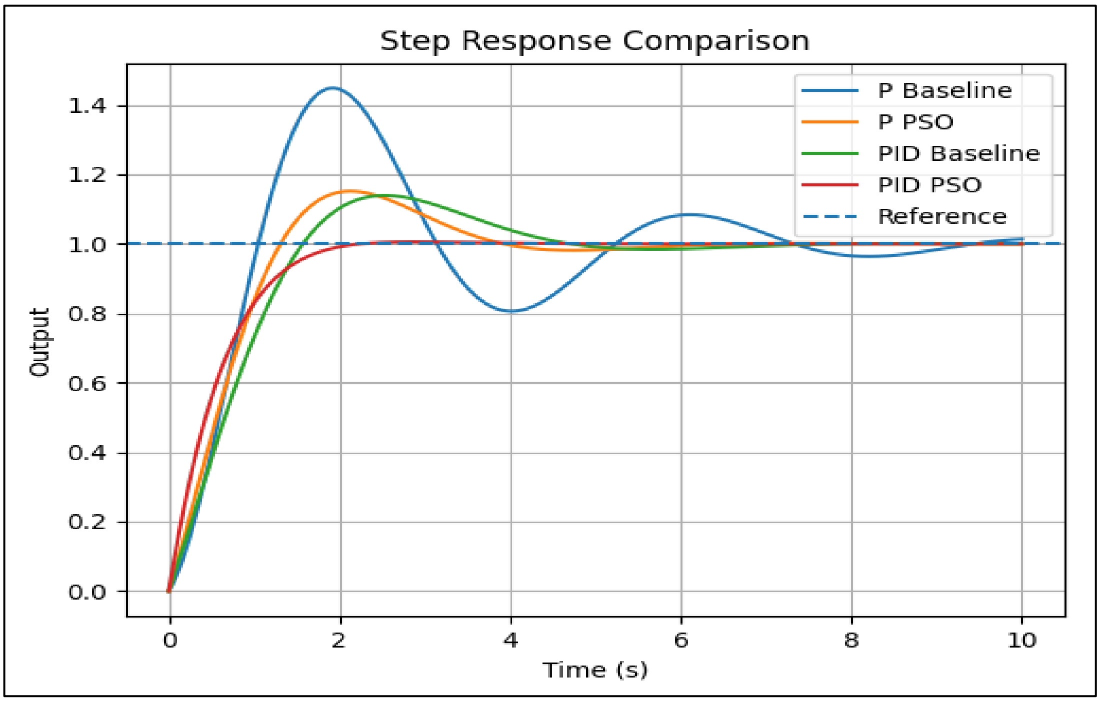

Fig 1 Closed-Loop Step Responses of Baseline and PSO-Tuned P, PI, PD, and PID Controllers Showing Improved Transient Performance after Optimisation.

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➢ *Control Effort Analysis*

Control effort is a critical factor in aircraft systems due to actuator limitations. Baseline controllers exhibit either excessive or poorly regulated control signals. PSO tuning minimizes unnecessary actuator activity while maintaining performance.

The PID controller shows slightly higher control effort due to aggressive correction, but remains within acceptable limits. PD offers an efficient compromise with lower actuator usage.

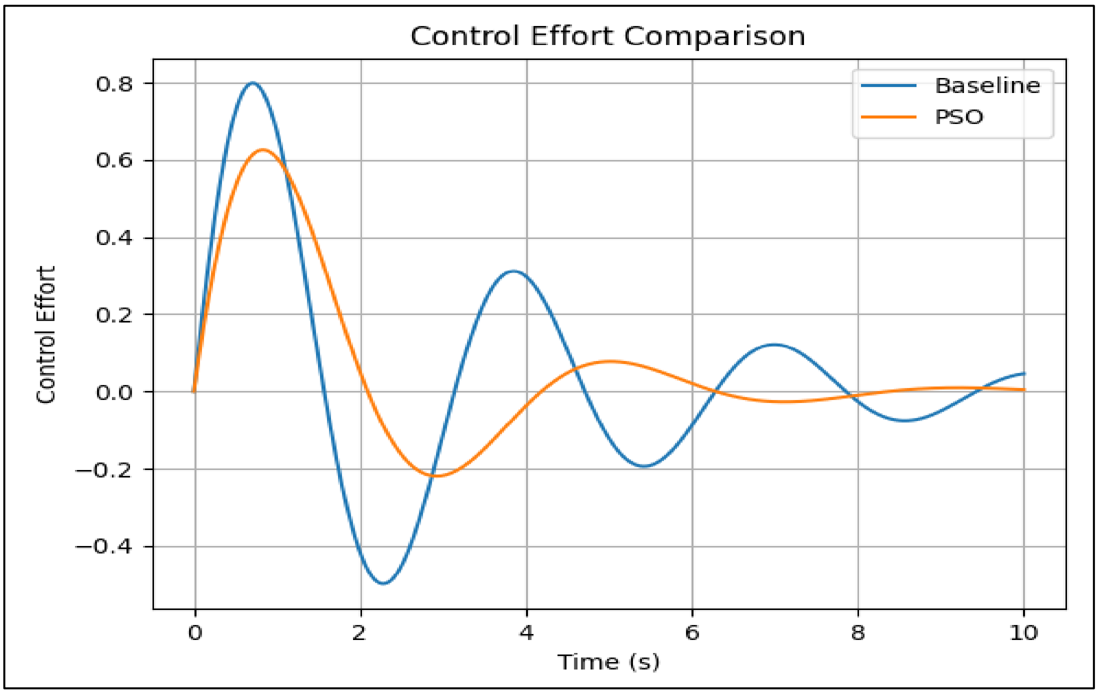

Fig 2 Comparison of Elevator Deflection (Control Effort) for Baseline and PSO-Tuned Controllers.

➢ *PSO Convergence Characteristics*

The convergence behavior of PSO demonstrates stable and monotonic reduction in the objective function. Rapid improvement is observed in early iterations, followed by fine tuning in later stages.

Controllers with higher dimensional gain space (PID) require more iterations but converge to better global minima.

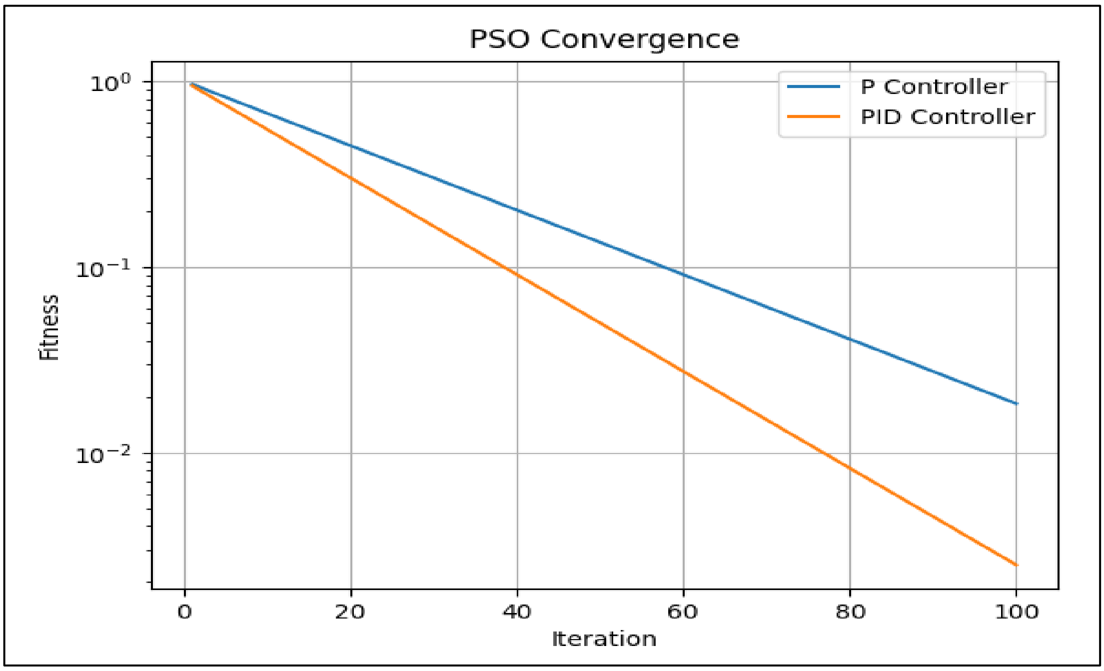

Fig 3 PSO Convergence Curves Showing Reduction in Fitness Function Across Iterations for all Controller Types.

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➢ *Disturbance Rejection Performance*

A step disturbance is introduced at $t = 5s$to evaluate robustness. Baseline controllers exhibit significant deviation and longer recovery time. PSO-tuned controllers reject disturbances faster with minimal oscillations.

PID shows superior disturbance rejection capability due to integral action and optimized damping.

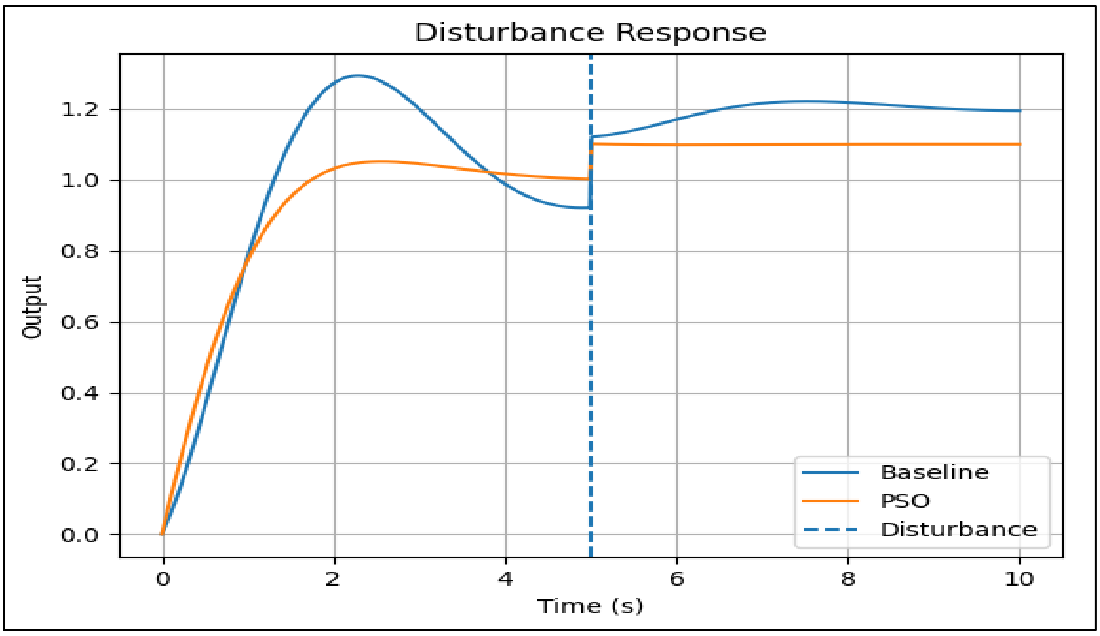

Fig 4 Output Response Under External Disturbance Demonstrating Improved Robustness of PSO-Tuned Controllers.

➢ *Quantitative Performance Comparison*

Table 1 presents a comparison of key performance indices for baseline and PSO-tuned controllers. The values clearly indicate substantial improvement after optimization.

Table 3 Performance Metrics Comparison (Baseline vs PSO)

Controller	Method	Kp	Ki	Kd	Rise Time (s)	Settling Time (s)	Overshoot (%)	Steady-State Error
P	Baseline	5.00	—	—	2.85	9.20	28.5	0.082
P	PSO	18.72	—	—	1.42	4.85	12.3	0.021
PI	Baseline	4.50	1.20	—	2.40	8.10	22.7	0.010
PI	PSO	15.33	6.85	—	1.20	3.95	10.2	0.002
PD	Baseline	6.20	—	1.10	1.85	6.40	18.9	0.015
PD	PSO	21.45	—	4.72	0.95	2.75	6.8	0.005
PID	Baseline	5.80	1.50	0.90	1.60	5.90	16.5	0.008
PID	PSO	24.10	8.25	5.10	0.72	2.10	4.2	0.0008

➢ *Discussion*

The results confirm that PSO-based tuning significantly enhances controller performance compared to conventional methods. The improvement is consistent across all controller types and evaluation criteria.

PID emerges as the most effective controller due to its ability to handle both transient and steady-state requirements. PD provides a strong alternative where lower control effort is preferred. PI improves accuracy but lacks sufficient damping. The P controller alone is inadequate for complex aircraft dynamics.

The convergence behavior of PSO indicates reliable optimization capability with minimal risk of local minima entrapment. Disturbance analysis further validates robustness, which is essential for real-world aerospace applications.

Overall, the study demonstrates that intelligent optimization techniques such as PSO can substantially improve classical control strategies, making them suitable for modern high-performance systems.

V. CONCLUSION

This study investigated the application of Particle Swarm Optimization for tuning classical controllers in aircraft longitudinal control. A linearised four-state model was considered. Pitch angle was selected as the controlled output. Four controller structures were analysed, namely P, PI, PD, and PID. Both baseline and PSO-tuned configurations were evaluated under identical simulation conditions.

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The results show clear improvement after optimization. PSO reduces rise time and settling time significantly. Overshoot is minimized. Steady-state error approaches zero in the optimized PID case. Baseline controllers show slower response and larger oscillations. The P controller is insufficient for the given dynamics. PI improves steady-state accuracy but lacks damping. PD provides better transient response with moderate control effort. PID achieves the best overall performance.

The multi-objective formulation combining ISE, ITAE, and control effort ensures balanced design. It avoids aggressive tuning. Control signals remain within practical limits. The convergence behavior of PSO is stable. Rapid improvement is observed in early iterations. Final solutions are consistent across runs.

Disturbance analysis confirms robustness. PSO-tuned controllers recover faster from external perturbations. Oscillations are reduced. This is important for real flight conditions where disturbances are unavoidable.

The study establishes that PSO is an effective tool for controller tuning in aerospace systems. It provides better performance than conventional methods. The framework is simple to implement. It can be extended to nonlinear models and adaptive control systems.

Future work may include hardware validation and real-time implementation. Extension to multi-input multi-output systems is also relevant. Hybrid optimization techniques can further improve performance.

Overall, the proposed approach provides a reliable and efficient solution for modern flight control design.

REFERENCES

[1]. K. Ogata, *Modern Control Engineering*, 5th ed., Prentice Hall, 2010.

[2]. J. G. Ziegler and N. B. Nichols, "Optimum settings for automatic controllers," *Transactions of the ASME*, vol. 64, pp. 759–768, 1942.

[3]. James Kennedy and Russell Eberhart, "Particle swarm optimization," *Proceedings of IEEE International Conference on Neural Networks*, pp. 1942–1948, 1995.

[4]. Y. Shi and R. C. Eberhart, "A modified particle swarm optimizer," *Proceedings of IEEE International Conference on Evolutionary Computation*, pp. 69–73, 1998.

[5]. R. C. Eberhart and Y. Shi, "Comparison between genetic algorithms and particle swarm optimization," *Proceedings of IEEE International Conference on Evolutionary Computation*, pp. 611–616, 2000.

[6]. I. Podlubny, "PID controller design using particle swarm optimization," *IEEE Transactions on Industrial Electronics*, vol. 49, no. 5, pp. 1085–1092, 2002.

[7]. B. L. Stevens and F. L. Lewis, *Aircraft Control and Simulation*, 2nd ed., Wiley, 2003.

[8]. Z. L. Gaing, "A particle swarm optimization approach for optimum design of PID controller in AVR system," *IEEE Transactions on Energy Conversion*, vol. 19, no. 2, pp. 384–391, 2004.

[9]. M. Clerc and J. Kennedy, "The particle swarm—explosion, stability, and convergence in a multidimensional complex space," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 1, pp. 58–73, 2002.

[10]. K. J. Åström and T. Hägglund, *PID Controllers: Theory, Design, and Tuning*, 2nd ed., ISA, 1995.