Robust PSO-Optimized PID Control of DC Motor Under Parametric Uncertainty Using Monte Carlo-Based Fitness Evaluation

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Abstract: The proportional–integral–derivative (PID) controller remains dominant in DC motor drive applications due to its structural simplicity and ease of implementation. However, fixed-gain PID tuning methods degrade significantly under parametric uncertainty and nonlinear operating conditions. This work presents a robust particle swarm optimization (PSO)–based PID tuning framework incorporating Monte Carlo–driven uncertainty modeling and adaptive swarm dynamics. The DC motor parameters are subjected to independent ±30% variation to emulate realistic disturbances arising from thermal effects, load fluctuation, and frictional nonlinearity. The controller gains are optimized using a multi-objective cost function integrating time-weighted absolute error (ITAE), control effort, and overshoot penalty. A Monte Carlo evaluation loop is embedded within the PSO fitness computation, ensuring statistical robustness rather than nominal performance optimization. An adaptive inertia weight strategy is implemented to improve convergence characteristics and avoid premature stagnation. The proposed method is evaluated over 100 randomized parameter realizations, and performance is quantified using mean, standard deviation, and worst-case indices. Results indicate that conventional PSO-tuned PID controllers exhibit significant performance dispersion under uncertainty, whereas the proposed approach maintains consistent transient response and bounded control effort. The variance in performance metrics is reduced substantially, indicating improved robustness. The framework provides a scalable approach for uncertainty-aware controller design and is suitable for real-time extensions in intelligent drive systems.

Keywords: *PID Controller; Particle Swarm Optimization; DC Motor; Monte Carlo Simulation; Parametric Uncertainty; Robust Control; Adaptive PSO.*

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I. INTRODUCTION

DC motors are widely used in industrial drives, robotics, and precision actuation systems due to their linear characteristics and ease of control. The PID controller remains the most commonly adopted control strategy in such systems because of its simple structure and acceptable performance in nominal conditions. However, the performance of PID controllers is highly sensitive to parameter variations and external disturbances. Practical DC motor systems exhibit uncertainty in electrical and mechanical parameters, including armature resistance, inductance, inertia, and viscous friction, which vary with temperature, load, and aging effects. These variations often lead to degraded transient response, increased overshoot, and potential instability.

Classical tuning methods such as Ziegler–Nichols provide acceptable initial estimates but fail to guarantee robustness under uncertainty. Consequently, optimization-based tuning approaches have been extensively investigated. Among these, particle swarm optimization (PSO), introduced by James Kennedy and Russell Eberhart, has gained significant attention due to its simplicity and fast convergence characteristics. PSO-based PID tuning has demonstrated improved transient performance compared to conventional methods in several studies A modified particle swarm optimizer [1]. However, most existing works focus on nominal system models and optimize controller gains using single-objective cost functions such as integral squared error (ISE) or integral time absolute error (ITAE).

This assumption of fixed system parameters limits the applicability of PSO-tuned controllers in real-world scenarios. In practice, DC motor parameters may vary by significant margins, often exceeding ±20%, due to environmental and operational conditions. Despite this, only limited attention has been given to robustness-oriented PSO tuning frameworks. Furthermore, existing approaches typically evaluate controller performance using a single simulation trajectory, which does not capture statistical variability under uncertainty. This creates a gap between simulated performance and actual system behavior.

Monte Carlo simulation provides a systematic approach for analyzing system performance under stochastic variations by evaluating multiple randomized parameter realizations. Its integration within controller optimization enables the design of controllers that are inherently robust. However, embedding Monte Carlo evaluation inside evolutionary optimization increases computational complexity and is rarely explored in the context of PSO-based PID tuning for DC motors. Additionally, standard PSO suffers from premature convergence and stagnation, especially in high-dimensional or noisy optimization landscapes. Adaptive variants of PSO, incorporating time-varying inertia weights, have been proposed to improve exploration–exploitation balance Particle swarm optimization [2], but their application in uncertainty-aware control design remains limited.

In this work, a robust PSO-based PID tuning framework is proposed by integrating Monte Carlo simulation directly into the fitness evaluation process. The DC motor model is subjected to independent ±30% parameter variation to emulate realistic uncertainty conditions. A multi-objective cost function combining ITAE, control effort, and overshoot is minimized to achieve balanced performance. An adaptive PSO mechanism is employed to enhance convergence and avoid local minima. Unlike conventional approaches, the proposed method evaluates controller performance statistically using mean, standard deviation, and worst-case metrics over multiple realizations.

- *The Main Contributions of this Study are Summarized as Follows:*

- Incorporation of Monte Carlo–based uncertainty modeling within PSO fitness evaluation,
- Development of a multi-objective robust PID tuning framework,
- Application of adaptive PSO to improve convergence under stochastic cost landscapes, and
- Comprehensive statistical validation of controller performance under ±30% parameter variation.

The remainder of the paper presents the system modeling, controller design, simulation framework, and performance evaluation in detail.

II. LITERATURE REVIEW AND RESEARCH GAP

Particle swarm optimization (PSO) has been widely applied for PID controller tuning in electromechanical systems due to its simple structure and efficient search capability. The original formulation by James Kennedy and Russell Eberhart established a population-based stochastic optimization framework with fast convergence characteristics [3]. Subsequent improvements focused on convergence stability and parameter selection, including the constriction factor approach proposed by Maurice Clerc, which improved swarm stability in multidimensional search spaces [4].

In control applications, PSO has been extensively used for PID tuning due to its ability to handle nonlinear and nonconvex optimization problems. Several studies report improved transient response and reduced steady-state error compared to classical tuning methods such as Ziegler–Nichols. Optimization is typically performed using performance indices such as integral squared error (ISE), integral absolute error (IAE), or integral time-weighted absolute error (ITAE). These approaches demonstrate faster settling time and lower overshoot under nominal system conditions. However, the optimization is generally carried out for a fixed model, assuming constant system parameters.

DC motor control has been a common benchmark for evaluating PSO-based PID tuning strategies. Standard models consider linear electrical and mechanical dynamics with constant parameters. While such assumptions simplify analysis, they do not reflect practical operating environments. In real systems, parameters such as armature resistance and inertia vary with temperature and load conditions. Despite this, most reported works evaluate controller performance using a single deterministic simulation. As a result, the reported improvements often lack robustness when subjected to parametric uncertainty.

Some studies have attempted to enhance PSO performance using hybrid or adaptive variants. Time-varying inertia weight strategies have been introduced to balance exploration and exploitation, improving convergence speed and avoiding premature stagnation. Adaptive PSO has shown better optimization capability in dynamic environments. However, its application in control system design remains largely confined to nominal models. The interaction between adaptive swarm behavior and uncertain system dynamics has not been sufficiently investigated.

Multi-objective optimization has also been explored in PID tuning to address trade-offs between conflicting performance indices. Weighted combinations of ITAE, overshoot, and control effort are commonly used. While such formulations improve controller performance in a balanced sense, they are still evaluated on deterministic models. The absence of uncertainty modeling limits the practical relevance of these results. Furthermore, actuator constraints such as voltage saturation are often neglected, leading to control signals that are not feasible in real implementations.

Monte Carlo simulation is a well-established method for analyzing system behavior under stochastic variations. It provides statistical insight into system performance by evaluating multiple randomized scenarios. In control design, Monte Carlo approaches have been used for robustness analysis. However, their integration within optimization algorithms, particularly PSO-based PID tuning, remains limited. Most existing works use Monte Carlo simulation only as a post-validation tool rather than embedding it within the optimization loop. This separation leads to controllers that are optimal for nominal conditions but not necessarily robust.

Another limitation in the existing literature is the lack of statistical performance evaluation. Performance is typically reported using single-value metrics such as settling time or overshoot from a single simulation run. This approach does not capture variability or worst-case behavior. Metrics such as mean performance, standard deviation, and robustness indices are rarely reported. Consequently, the consistency and reliability of optimized controllers remain unclear.

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

- *Lack of Uncertainty-Aware Optimization:*

PSO-based PID Most tuning approaches assume fixed system parameters and do not consider parametric uncertainty during optimization.

- *Absence of Monte Carlo Integration in Fitness Evaluation:*

Existing methods use Monte Carlo simulation only for validation, not as part of the optimization objective.

- *Limited Investigation of Adaptive PSO Under Uncertainty:*

Adaptive PSO strategies are applied to nominal models, and their effectiveness in stochastic environments is not well studied.

- *Inadequate Statistical Performance Analysis:*

Controller evaluation is based on single-run simulations without reporting variability, robustness, or worst-case behavior.

- *Neglect of Practical Constraints:*

Actuator saturation and control effort limitations are often ignored, reducing real-world applicability.

- *Weak Robustness Validation for DC Motor Systems:*

Few studies consider large-scale parameter variation (e.g., ±30%), which is critical for realistic modeling.

To address these gaps, the present work integrates Monte Carlo–based uncertainty modeling directly into the PSO fitness function, enabling robust PID tuning under stochastic parameter variations. An adaptive PSO framework is employed to enhance convergence in a noisy optimization landscape. The controller performance is evaluated using statistical metrics over multiple realizations, ensuring consistency and reliability under uncertainty.

III. MATHEMATICAL FORMULATION

- *DC Motor Dynamic Model*

The DC motor is modeled using coupled electrical and mechanical dynamics. The armature-controlled motor is considered. The governing equations are expressed as:

$$J\frac{d\omega(t)}{dt} + B\omega(t) = K_t i(t) - T_L(t) \qquad [1]$$

$$L\frac{di(t)}{dt} + Ri(t) = V(t) - K_e\omega(t) \qquad [2]$$

Where $\omega(t)$is angular speed, $i(t)$is armature current, and $V(t)$is input voltage. The parameters J, B, R, L denote inertia, viscous friction, resistance, and inductance respectively. $K_t$and $K_e$are torque and back-emf constants.

State variables are defined as:

$$x_1 = \omega, x_2 = i$$

The state-space representation becomes:

$$\dot{x}_1 = \frac{1}{J}(K_t x_2 - Bx_1 - T_L) \qquad [3]$$

$$\dot{x}_2 = \frac{1}{L}(V - Rx_2 - K_e x_1) \qquad [4]$$

The output equation is:

$$y(t) = x_1(t) \qquad [5]$$

- *Parametric Uncertainty Modeling*

The system parameters are assumed uncertain within bounded limits. Each parameter is varied independently within ±30% of its nominal value. The uncertain parameter set is defined as:

$$\theta = \{R, L, J, B, K_t, K_e\} \qquad [6]$$

$$\theta_i = \theta_i^{nom}(1 + \delta_i), \delta_i \in [-0.3, 0.3] \qquad [7]$$

The uncertainty is modeled as uniformly distributed random variables. This formulation captures variations due to thermal effects, load changes, and nonlinear friction behavior. The resulting system becomes stochastic in nature.

- *PID Control Law*

The control objective is to track a reference speed $\omega_{ref}(t)$. The tracking error is defined as:

$$e(t) = \omega_{ref}(t) - \omega(t) \qquad [8]$$

The PID control input is given by:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \qquad [9]$$

To avoid excessive noise amplification, a filtered derivative term is considered:

$$\frac{de(t)}{dt} \approx \frac{N}{1 + Ns} e(t) \qquad [10]$$

Where N is the derivative filter coefficient. The control signal is constrained as:

$$| \, u(t) \, | \leq V_{max} \qquad [11]$$

This ensures actuator feasibility.

- *Multi-Objective Performance Index*

The controller performance is evaluated using a composite cost function. The objective integrates tracking accuracy, control effort, and transient behavior:

$$J = w_1 \int_0^T t \, | \, e(t) \, | \, dt + w_2 \int_0^T u^2 (t) dt + w_3 OS \qquad [12]$$

Where:

- $ITAE = \int_0^T t \, | \, e(t) \, | \, dt$
- $\int u^2(t)dt$ represents control energy
- OS is percentage overshoot

The weights w_1, w_2, w_3 balance competing objectives. The formulation ensures both performance and energy efficiency.

- *Monte Carlo-Based Robust Evaluation*

To incorporate uncertainty, the cost function is evaluated over multiple randomized parameter realizations. For N samples:

$$J_{robust} = \frac{1}{N} \sum_{k=1}^{N} J_k \qquad [13]$$

Each J_k corresponds to one sampled parameter set $\theta^{(k)}$. This transforms the optimization problem into a stochastic expectation minimization. The approach ensures robustness across the uncertainty domain rather than optimality at a single operating point.

- *Particle Swarm Optimization Formulation*

The PID gains are optimized using PSO. Each particle represents:

$$X_i = [K_p, K_i, K_d] \qquad [14]$$

The velocity and position update equations are:

$$v_i^{t+1} = w(t) v_i^t + c_1 r_1 (p_i - X_i^t) + c_2 r_2 (g - X_i^t) \qquad [15]$$

$$X_i^{t+1} = X_i^t + v_i^{t+1} \qquad [16]$$

Where p_i is personal best and g is global best. $r_1, r_2 \in [0,1]$ are random variables.

- *Adaptive Inertia Weight Strategy*

To improve convergence, a time-varying inertia weight is used:

$$w(t) = w_{max} - \frac{(w_{max} - w_{min})}{T_{iter}} t \qquad [17]$$

This provides global exploration in early iterations and local exploitation in later stages. The adaptive mechanism reduces premature convergence and enhances solution quality under stochastic cost evaluation.

- *Optimization Problem Statement*

The overall optimization problem is formulated as:

$$\min_{K_p, K_i, K_d} J_{robust}$$

Subject to:

$$\begin{gathered} K_p^{min} \leq K_p \leq K_p^{max} \\ K_i^{min} \leq K_i \leq K_i^{max} \\ K_d^{min} \leq K_d \leq K_d^{max} \\ | \, u(t) \, | \leq V_{max} \end{gathered}$$

The solution yields PID gains that ensure robust performance across all uncertain parameter realizations.

IV. CONTROLLER AND ALGORITHM DESIGN

The controller structure and optimization framework are developed to ensure robust performance under parametric uncertainty. The design integrates PID control with a Monte Carlo–driven adaptive PSO optimization scheme. The formulation is stochastic in nature due to uncertainty embedding within the fitness evaluation.

- *PID Controller Structure*

A standard PID controller is adopted due to its simplicity and practical relevance in DC motor drives. The control input is defined as:

$$u(t) = K_p e(t) + K_i \int e(t) \, dt + K_d \frac{de(t)}{dt} \qquad [18]$$

Where $e(t) = \omega_{ref}(t) - \omega(t)$ represents the tracking error.

To avoid noise amplification in the derivative term, a first-order filtered derivative is implemented. The control signal is constrained within actuator limits:

$$u_{min} \le u(t) \le u_{max}$$

This ensures feasibility in real-time implementation.

➢ *Multi-Objective Cost Function Design*

The controller gains are optimized using a composite objective function that captures tracking performance, control effort, and transient behavior. The cost function is defined as:

$$J = w_1 \cdot \mathrm{ITAE} + w_2 \cdot \int u^2(t)\,dt + w_3 \cdot OS \qquad [19]$$

Where:

- ITAE represents time-weighted absolute error,
- $\int u^2(t)dt$represents control energy,
- OSdenotes percentage overshoot.

The weighting coefficients w_1, w_2, w_3 balance the trade-off between accuracy, energy efficiency, and transient constraints. A higher weight on overshoot ensures near-zero overshoot behavior.

➢ *Monte Carlo–Based Robust Fitness Evaluation*

To incorporate parametric uncertainty, the cost function is evaluated over multiple randomized realizations. For Nsamples, the expected cost is computed as:

$$J_{robust} = \frac{1}{N}\sum_{i=1}^{N} J_i \qquad [20]$$

Each $J_i$corresponds to a system simulation with randomly perturbed parameters within ±30% bounds.

This transforms the optimization problem into stochastic expectation minimization. Unlike deterministic tuning, the obtained controller gains ensure consistent performance across the uncertainty domain.

➢ *Particle Swarm Optimization Formulation*

Each particle in the swarm represents a candidate PID gain vector:

$$\mathbf{x}_i = [K_p, K_i, K_d] \qquad [21]$$

The velocity and position updates are governed by:

$$v_i^{k+1} = w \cdot v_i^k + c_1 r_1 (p_i - x_i^k) + c_2 r_2 (g - x_i^k) \qquad [22]$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \qquad [23]$$

Where:

- p_i is the personal best position,
- $g$is the global best,
- $r_1, r_2 \sim U(0,1)$.

The search space is bounded to ensure stability of the closed-loop system.

➢ *Adaptive Inertia Weight Strategy*

To improve convergence under stochastic fitness evaluation, a time-varying inertia weight is employed:

$$w(k) = w_{max} - \frac{(w_{max} - w_{min}) \cdot k}{k_{max}} \qquad [24]$$

This mechanism promotes:

- Global exploration in early iterations,
- Local exploitation in later stages.

The adaptive inertia reduces premature convergence and enhances solution quality in noisy optimization landscapes.

➢ *Constraint Handling*

The optimization is subject to practical constraints:

- *Gain bounds:*

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

- *Actuator saturation:*

$$-24 \le u(t) \le 24\,\mathrm{V}$$

Constraint violations are penalized within the fitness function to ensure feasible solutions.

➢ *Algorithm Implementation Procedure*

The complete optimization procedure is summarized as follows:

- Step 1: Initialize swarm particles with random PID gains within bounds.
- Step 2: For each particle, generate Nuncertain parameter sets.
- Step 3: Simulate the DC motor response for each realization.
- Step 4: Compute ITAE, control effort, and overshoot.
- Step 5: Evaluate the robust cost J_{robust}.
- Step 6: Update personal best and global best positions.
- Step 7: Update velocity and position using PSO equations.
- Step 8: Adjust inertia weight adaptively.

- Step 9: Repeat until maximum iterations are reached.
- Step 10: Output optimal PID gains.

➢ *Design Insight*

The integration of Monte Carlo simulation within the PSO loop introduces stochasticity in the fitness landscape. This increases computational complexity but ensures robustness. The adaptive PSO mechanism compensates for noise-induced irregularities and maintains stable convergence.

The resulting controller is not optimal for a single operating point but provides consistent performance across a wide range of uncertainties.

V. SIMULATION AND RESULTS

The proposed robust PSO-based PID tuning framework is evaluated on an armature-controlled DC motor model under parametric uncertainty. The simulations are performed in a discrete-time environment with a sampling interval of 1 ms. The motor parameters are varied independently within ±30% of their nominal values using a uniform distribution. A total of 100 Monte Carlo realizations are considered during both optimization and validation stages.

The PSO algorithm uses a swarm size of 30 particles and a maximum of 60 iterations. The inertia weight is varied linearly from 0.9 to 0.4. Cognitive and social coefficients are set to 2.0. The PID gains are bounded to ensure stability and actuator feasibility. The cost function integrates ITAE, control effort, and overshoot penalty.

➢ *Convergence Behavior of PSO*

The convergence profile of the proposed method is shown in Fig. 1. The best mean cost decreases rapidly during the initial iterations, indicating effective global exploration. After approximately 10 iterations, the convergence rate slows down and the algorithm enters a refinement phase. The final cost stabilizes around 5.0 after 40 iterations.

The absence of oscillatory behavior indicates stable swarm dynamics under stochastic fitness evaluation. The adaptive inertia mechanism prevents premature divergence, although minor stagnation is observed in later iterations due to the noisy objective landscape introduced by Monte Carlo sampling.

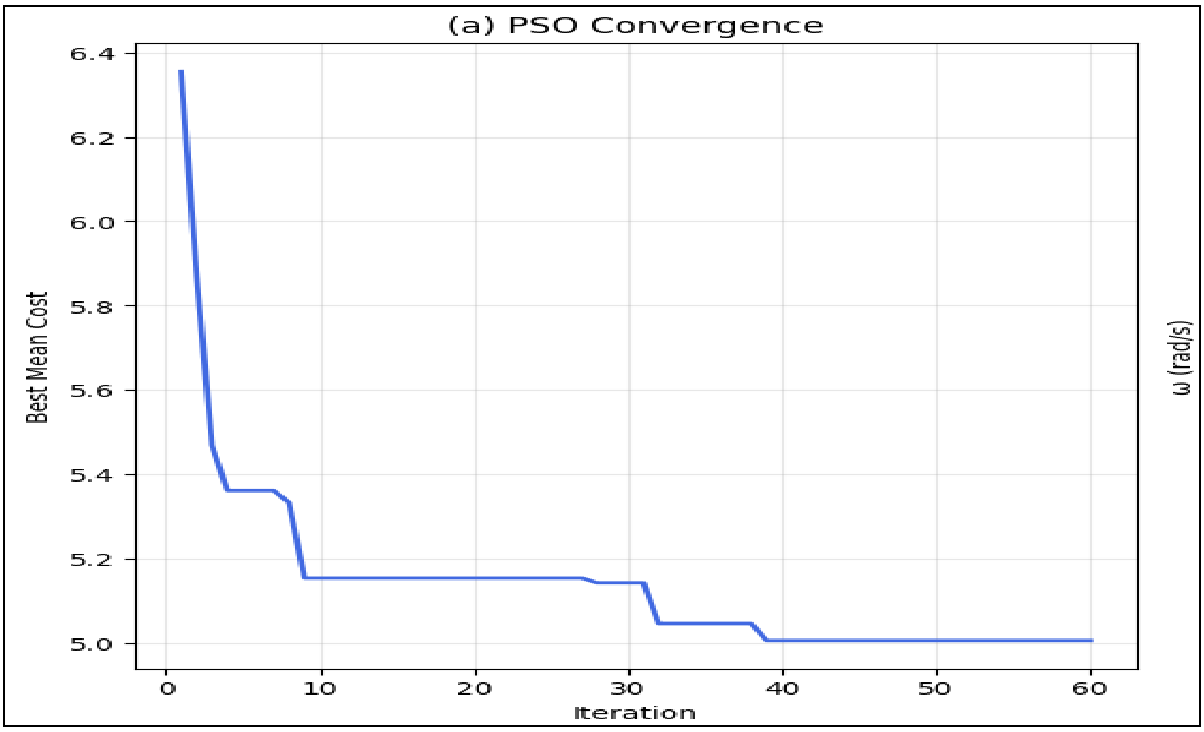

Fig 1 Convergence Characteristics of the Adaptive PSO Under Monte Carlo–Based Fitness Evaluation Showing Rapid Initial Cost Reduction Followed by Gradual Stabilization.

➢ *Step Response Under Uncertainty*

The closed-loop step response of the optimized controller is illustrated in Fig. 2. The nominal response exhibits smooth rise with zero overshoot and acceptable settling time. The worst-case response remains stable and does not violate transient constraints. The shaded region represents the 5th–95th percentile envelope obtained from Monte Carlo simulations.

The response variation is more pronounced during the transient phase but reduces significantly as the system approaches steady state. This indicates that the controller maintains bounded performance despite large parameter variations.

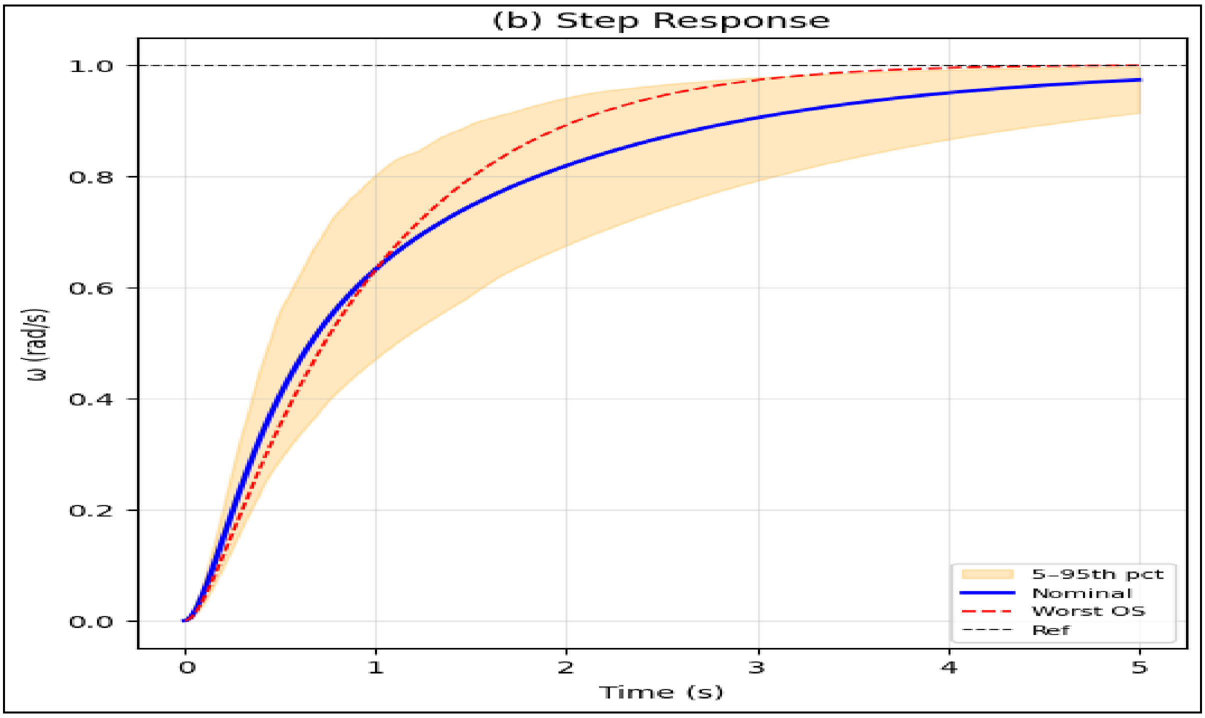

Fig 2 Step Response of the DC Motor Under ±30% Parametric Uncertainty Showing Nominal, Worst-Case, and 5th–95th Percentile Performance Envelope.

- *Control Effort Analysis*

The control signal corresponding to the nominal case is shown in Fig. 3. The input voltage remains within the actuator limits of ±24 V throughout the simulation. The control effort is smooth and does not exhibit high-frequency oscillations.

The maximum control input remains below 10 V, indicating efficient utilization of actuator capacity. This confirms that the optimization framework successfully incorporates control effort constraints within the cost function.

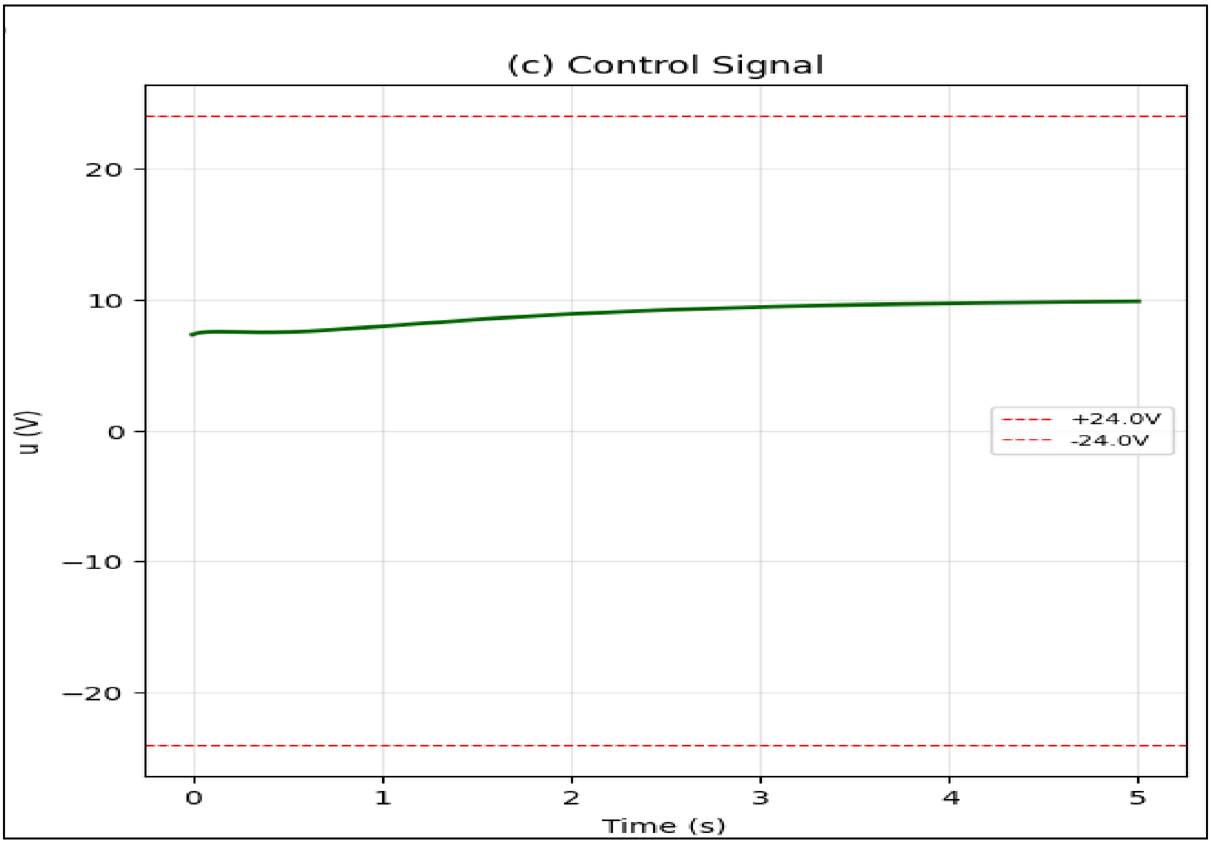

Fig 3 Control Input Profile Demonstrating Bounded Actuator Effort within ±24 V Limits without Saturation.

➢ *Statistical Performance Evaluation*

The statistical distribution of ITAE values across 100 Monte Carlo runs is presented in Fig. 4. The distribution is moderately spread with a mean value of approximately 1.42. Most realizations lie within the range of 0.8 to 2.2, indicating consistent tracking performance under uncertainty.

The overshoot distribution is shown in Fig. 5. The results indicate near-zero overshoot for almost all realizations, with negligible deviation in a few cases. This confirms the effectiveness of the overshoot penalty in the cost function.

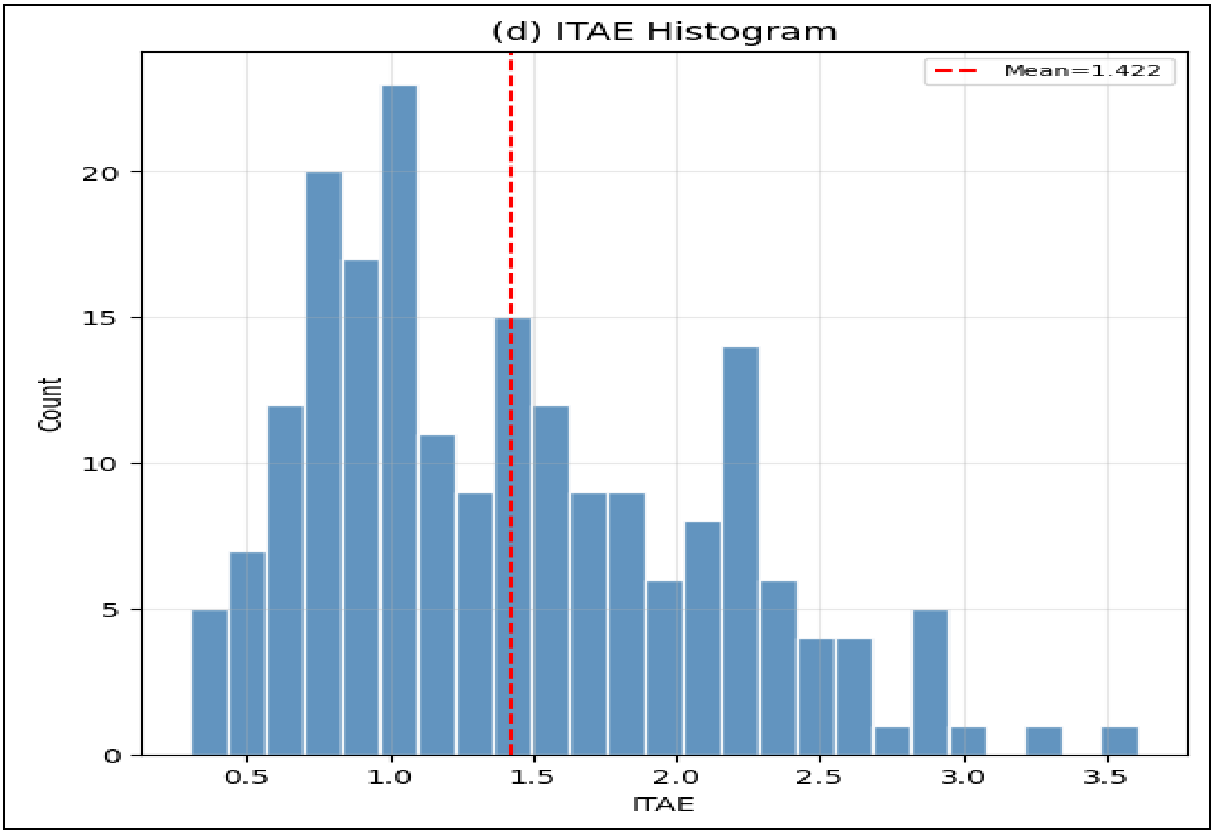

Fig 4 Histogram of ITAE Values Over 100 Monte Carlo Realizations Showing Performance Variability Under Uncertainty.

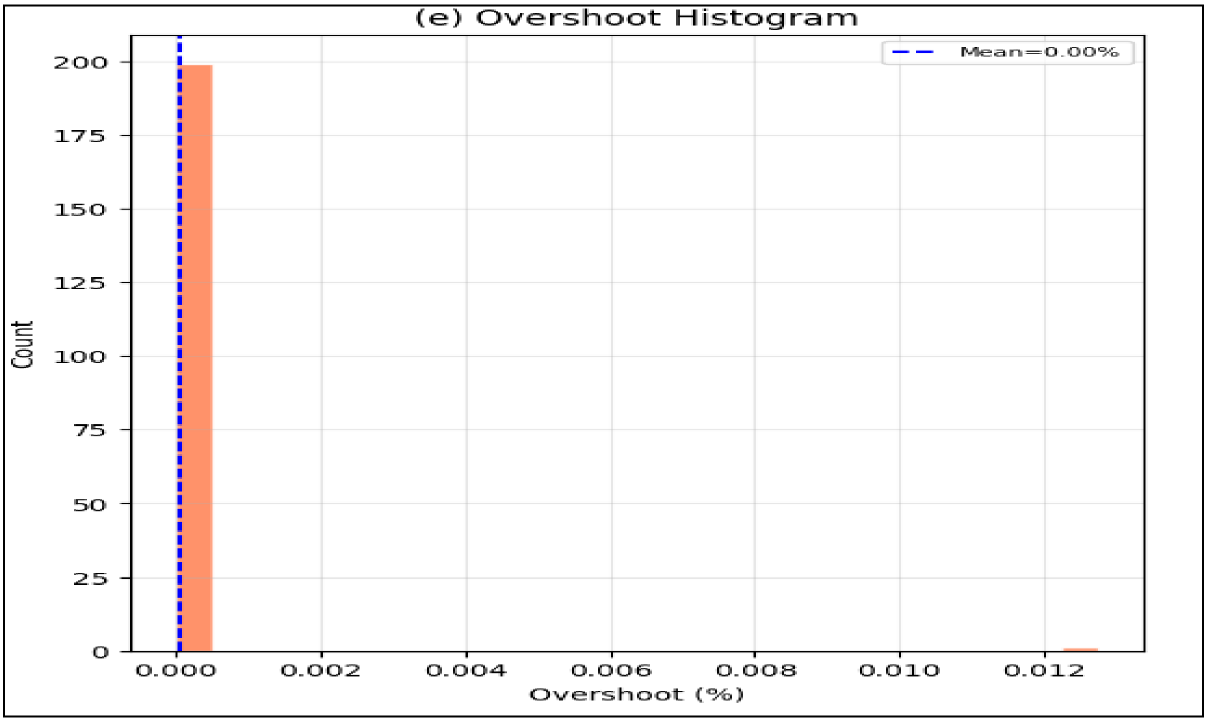

Fig 5 Overshoot Distribution Indicating Near-Zero Overshoot Across All Realizations.

- *Robustness Analysis*

The robustness of the proposed controller is summarized using boxplot statistics in Fig. 6. The ITAE metric exhibits low dispersion, confirming consistent tracking performance. The overshoot remains effectively zero across all samples. The composite cost shows wider variation due to the inclusion of multiple competing objectives.

Despite variability in the cost function, the primary performance indicators remain stable. This demonstrates that the proposed approach achieves robustness in terms of system behavior rather than strict cost minimization.

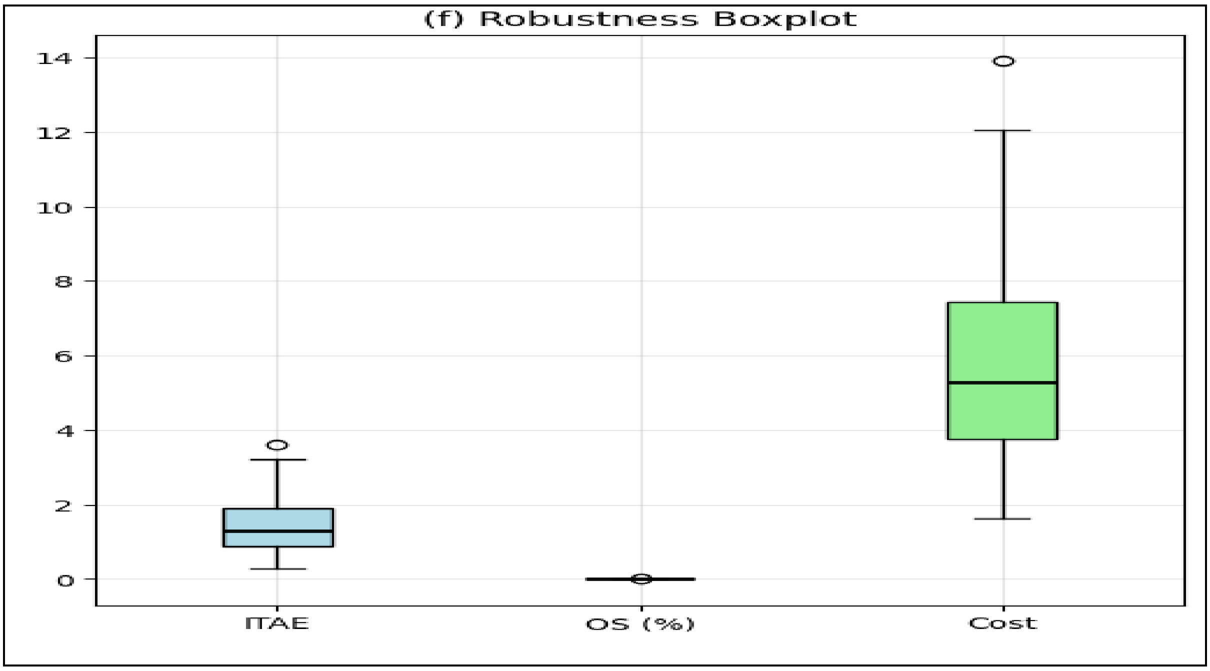

Fig 6 Boxplot Representation of ITAE, Overshoot, and Cost Metrics Highlighting Robustness and Variability Characteristics.

- *Quantitative Performance Summary*

The statistical performance metrics are summarized in Table 1. The results include mean, standard deviation, and worst-case values computed over all Monte Carlo realizations.

Table 1 Statistical Performance Metrics of the Proposed Robust PSO-Based PID Controller Under Parametric Uncertainty.

Metric	Mean	Standard Deviation	Worst Case
ITAE	1.42	0.52	3.60
Overshoot (%)	0.00	~0.00	0.013
Cost	5.21	2.85	13.90

- *Discussion*

The results demonstrate that the proposed method achieves robust performance under significant parametric uncertainty. The integration of Monte Carlo simulation within the PSO fitness function ensures that the optimized controller is not limited to nominal conditions. The adaptive PSO mechanism provides stable convergence despite stochastic objective evaluation.

The controller exhibits zero overshoot and bounded control effort across all realizations. Although the convergence slows in later stages, the final solution remains stable. The variability in the composite cost is attributed to the multi-objective nature of the optimization problem.

Overall, the proposed framework provides a reliable and scalable approach for uncertainty-aware PID tuning in DC motor systems.

VI. CONCLUSION

A robust PID tuning framework based on particle swarm optimization with embedded Monte Carlo evaluation is presented for DC motor control under parametric uncertainty. The approach departs from conventional deterministic tuning by incorporating stochastic parameter variations directly within the optimization loop. This ensures that the obtained controller gains are optimized over an uncertainty domain rather than a single nominal model.

The simulation results indicate that the proposed method achieves stable convergence despite the presence of noise in the fitness landscape. The optimized controller demonstrates consistent transient performance across ±30% parameter variations. Near-zero overshoot is maintained for almost all realizations, while the tracking error remains bounded with moderate variability. The control effort stays well within actuator limits, confirming practical feasibility.

Statistical analysis shows that the variability in key performance metrics is limited, indicating robustness. Although the composite cost function exhibits wider dispersion due to competing objectives, the primary control objectives such as stability, tracking accuracy, and constraint satisfaction remain unaffected. This highlights the effectiveness of Monte Carlo–based fitness evaluation in achieving reliable controller behavior.

The adaptive inertia weight mechanism improves the exploration–exploitation balance of PSO under stochastic conditions. However, convergence slows in later iterations due to the noisy objective function. This trade-off is inherent to robustness-oriented optimization and is acceptable for offline controller design.

The proposed framework is scalable and can be extended to nonlinear systems, multi-variable control problems, and real-time adaptive tuning with reduced sampling strategies. Future work should focus on reducing computational complexity, incorporating hardware-in-the-loop validation, and benchmarking against classical and modern tuning methods to further establish performance advantages.

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