BJES Basrah Journal for Engineering Sciences

Basrah Journal for Engineering Sciences, Vol. 26, No. 1, (2026), 1-8

Original Article

Journal homepage: https://bjes.edu.iq/bjes
ISSN (Online): 23118385, ISSN (Print): 18146120

IRAQI Academic Scientific Journals

Comparative Performance Evaluation of Classical PID and Optimized PID Controllers for Nonlinear DC Motor Speed Control

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Article Info

Article history:
Received: 2 March 2026
Revised: 1 April 2026
Accepted: 18 April 2026
Published: 28 July 2026

Keywords:
DC motor, PID control, Particle swarm optimization, Nonlinear modeling, Speed control, ITAE.

https://doi.org/10.33971/bjes.26.1.1

Abstract

Traditional Proportional-Integral-Derivative (PID) controllers continue to produce effective performance in controlling DC motors. Nowadays, advancements in optimization techniques are improving control performance. These techniques minimize fluctuations and accelerate convergence. In this study, the Particle Swarm Optimization (PSO) algorithm was applied using the Integral Time Absolute Error (ITAE) objective function. The PSO used to tune PID parameters in MATLAB/Simulink. The resulting PSO-PID performance was compared with that of a conventional PID controller. The findings indicate that the PSO-PID approach reduces peak overshoot errors from 2.1% to 0.5%. Moreover, the PSO-PID substantially decreases the settling time. Despite adding GA, PSO-PID already shows excellent results (0.93 s settling time, compared with 1.85 s in GA and 1.15 s in classical PID). These improvements contribute to smoother actuator voltage. It can also reduce mechanical and electrical issues and enhance long-term system reliability.

1. Introduction

DC motors still play an important role in many industries. These applications are extending to industrial automation, robotics, electric vehicles, and precision positioning systems. DC motors have good torque-speed characteristics and excellent controllability. Precision in controlling speed is highly regarded for stability as well as quality [1]. From a control design perspective, DC motors are typically treated mathematically as linear systems but exhibit nonlinear behavior across a broad range of settings due to magnetic saturation, appropriate nonlinear friction characteristics, parameter uncertainties, and load disturbances [2].

In fact, these nonlinearities degrade the performance of conventional controllers. These degrades struggle to deal with varying operating conditions [3]. The PID controller is still the most widely used algorithm in industrial control applications. However, it is simple and highly effective [4]. However, Ziegler–Nichols tuning is heuristic, and excessive overshoot is noted, and the conventional PID method exhibits limited robustness under nonlinear operating conditions [5], [6]. Because of high controllability and favorable torque-speed characteristics, DC motors are widely used for industrial automation, robotics, electric vehicles, and precision positioning. Though traditional PID controllers are known to be simple and effective, their performance degrades with changes in operating conditions, primarily owing to nonlinearities such as magnetic saturation, nonlinear friction, parameter uncertainties, and load disturbances as shown in Fig. 1.

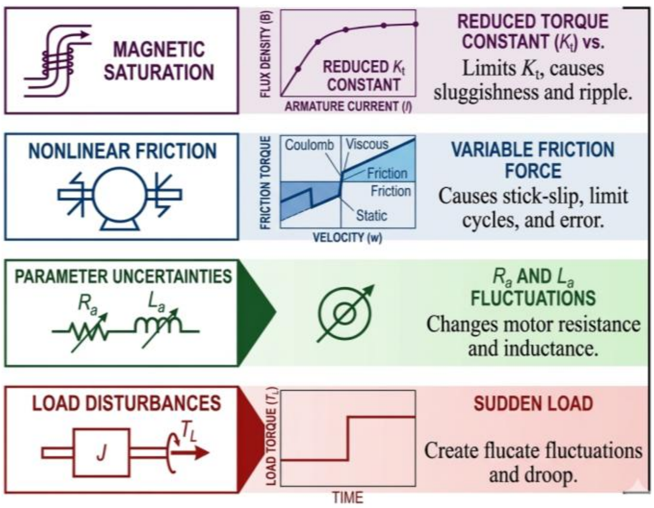

Fig. 1 Degradation mechanisms in traditional PID speed control.

As a result, under nonlinear conditions, metaheuristic optimization methods are used. Particle Swarm Optimization is one such algorithm. It is used to enhance the transient response, robustness, and performance of PID controllers [5], [6].

Influent strides have been made in tuning controller parameters using recent metaheuristic algorithms. Particle Swarm Optimization, as an intelligent optimization technique, offers better global search and better performance optimization [7], [8]. PSO is a robust, population-based

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metaheuristic optimization algorithm. It does not require the objective function to be differentiable [9]. It can be highly effective for tuning PID controllers in non-linear DC motors. The PSO mechanism involves a "swarm" of candidate solutions (as particles). The particles navigate through the tuning parameters Kp, Ki, and Kd. The movement of each particle is governed by two influences: cognitive and social components.

Classical PID tuning methodologies are studied in with channels similar to those of the Modified Ziegler–Nichols, offering reasonable dynamic performance but vulnerable to disturbance and system nonlinearities [10]. In recent years, optimization-based methods have emerged that automate PID parameter tuning. Agarwal et al. [11] investigated different intelligent optimization algorithms, such as Grey Wolf Optimization (GWO) and Sine Cosine Algorithm (SCA). Their study exhibited better transient response characteristics than classical tuning methods. Similarly, Yazgan et al. [12] employed PSO and genetic algorithms (GA) for PID tuning. They stated that PSO offers better stability and dynamic response. Ahmad et al. [13] showed that PID controllers based on the Backtracking Search Algorithm (BSA) had better dynamic. They concluded that there is an enhancement in steady-state responses compared to conventional PID and PSO-based tuning. In parallel, Ibrahim et al. [14] optimized the Fractional-Order PID controllers that were designed using metaheuristic techniques. They used PSO and Ant Colony Optimization (ACO) to reduce errors in classical PID structures.

Moreover, the concepts of intelligent and adaptive control have been incorporated into recent studies. Kumarasamy et al. [15] studied the Advantages of Fractional-Order over Integer-Order PID Controllers in Nonlinear Motor Systems. In their study, they showed that the robustness and flexibility of fractional-order PID controllers are greater than those of integer-order PID controllers. Almawla et al. [16] proposed a combination of PID and fuzzy logic methods. Their developed method is more reliable than classical methods in stability and time response. Likewise, Rahoua et al. [17] showed that fuzzy-PID controllers enhance energy efficiency and the tracking accuracy of the examined systems.

From the literature survey, it is clear that optimization and intelligent control techniques have been widely adopted to compensate for the shortcomings of the conventional PID controller in a nonlinear DC motor system. No direct comparisons of classical vs optimized PID could be located in the literature, and, as such, their corresponding limitations are shown in Table 1. It is evident from Table 1 that the PID tuning method using an optimization technique always outperformed the classical tuning methods in reducing overshoot and settling time. PSO-based controllers have much higher converging and disturbance-tolerant capabilities. However, most existing studies assume linear motor models, neglecting full nonlinear modeling that accounts for magnetic saturation and nonlinear friction. Also, in the benchmarks, a single objective function is usually used, and stability analysis is either not run or left unmentioned. These limitations thus motivate the development of a new integrated nonlinear modeling and ITAE-based optimization framework as presented in this work.

Table 1. Summarizes the main characteristics of the reviewed studies and highlights their methodological differences and limitations.

Study/Year	Method	Model Type	Objective Function	Key Results	Main Limitation
Rahoua et al.	Fuzzy-PID vs Classical PID	Nonlinear (BLDC)	ZN tuning & Fuzzy inference	Improved tracking accuracy, reduced error, higher efficiency	Limited comparison with other optimization algorithms
Almawla et al.	PID / SMC / Fuzzy Logic	Nonlinear DC model	Comparative time-domain evaluation	SMC showed better stability and faster response	Classical PID performance limited under uncertainty
Kumarasamy et al.	IOPID vs FOPID Review	Nonlinear BLDC	Optimization-based tuning	FOPID improved robustness and flexibility	Review-based, lacking unified benchmarking
Ibrahim et al.	PSO-FOPID / ACO-FOPID	Nonlinear DC Motor	ITAE minimization	Faster settling and lower error indices	Higher overshoot under some conditions
Ahamed et al.	PID tuned with BSA & PSO	DC Motor (comparative)	Optimization algorithms	BSA-PID showed better dynamic and static performance	Tested under limited operating scenarios
Yazgan et al.	PSO vs GA vs Classical PID	DC Motor	Metaheuristic tuning	PSO achieved superior overall performance	No advanced nonlinear modelling
Agarwal et al.	GWO-PID vs SCA-PID	DC Motor	Intelligent optimization	GWO improved rise time and overshoot	Limited experimental validation
Hassan et al.	Classical PID tuning methods	PMDC Motor (practical)	Modified ZN, CHR, Tyreus-Luyben	Modified ZN gave acceptable dynamic response	Limited robustness for nonlinear systems

While there have been many studies on DC motor speed control with classical PID and various optimization-based methods, numerous limitations exist in the current literature. Earlier literature primarily assessed either individual optimization algorithms or specific intelligent controller methods. These literatures do not present a clear comparison with classical PID and optimized PID controllers. While PSO-based PID tuning is commonplace in DC motor applications, this paper provides a benchmark framework for comparing the performance of classical PID versus PSO-tuned PID controllers in a nonlinear operating region. Using performance indices such as rise time, settling time, overshoot, and ITAE, the framework is suitable for reproducible assessment and enables transparent quantification of improvements over classical PID approaches.

Furthermore, there are studies that intend only PSO, GA, GWO, or fuzzy-based approaches to enhance performance for a particular system model, and do not make a comparative assessment on the same system model with similar tuning criteria, or based on similar simulation assumptions, making it impossible to directly compare the performance of such works. Moreover, several works rely solely on intelligent controllers or structures of fractional order, but there is no clarity on how much improvement over a classical PID controller has been achieved in an identical nonlinear DC motor environment. Thus, this systematic review indicates a clear research gap that should be bridged by providing an unbiased comparative performance evaluation of classical PID vs optimal PID controllers for nonlinear DC motor speed control, achieved using common performance indices and under uniform operating conditions. Bridging this gap is essential to obtain concrete information on the effectiveness of the control and to determine which control strategy will be optimal when implemented in the nonlinear motors of their eventual real-world applications.

2. Mathematical modeling

The mathematical model of the nonlinear DC motor considered in this paper is introduced in this section. This section explains the modeling method: partitioning the system into electrical and mechanical subsystems, then extracting transfer functions, and finally addressing nonlinearity to better reflect the actual motor performance. To increase readability while remaining somewhat academic, there is a brief description before each subsection.

2.1. Electrical subsystem modeling

The electrical subsystem defines the relationship between the voltage applied to the armature and the current armature [18]. According to Kirchhoff's voltage law, the voltage across the armature inductance and resistance, as well as the back-emf from rotation, must be overcome by the applied voltage. Armature voltage equation and back electromotive force (Back-EMF) is proportional to the motor angular speed, can be written as:

$$e_b(t) + R_a\, i_a(t) + \frac{di_a(t)}{dt}\, aL = V_a(t) \tag{1}$$

Where $e_b(t)$ is the back electromotive force (Back-EMF) in (V) proportional to rotor angular speed and given in equation (2). R_a is armature resistance in Ohm (Ω), $i_a(t)$ is armature current in Amber (I), L is armature inductance in Henry (H), $di_a(t)/dt$ is rate of change of armature current in (A/s), and $V_a(t)$ is applied armature voltage in (V).

Back electromotive force (back-EMF) is proportional to the motor angular speed, given by:

$$e_b(t) = K_e w(t) \tag{2}$$

Where $w(t)$ is rotor angular speed in (rad/s).

The back-EMF term describes the coupling between the motor's electrical and mechanical dynamics, i.e., electromechanical coupling.

2.2. Mechanical subsystem modeling

The mechanical subsystem models the motor shaft's rotational behavior [19]. As defined by Newton's second law of rotational motion, electromagnetic torque must overcome inertia, viscous friction, and external load torque.

The mechanical dynamics can be described as:

$$T_L(t) - K_t i_a(t) = B_w(t) + \frac{d_w(t)}{dt} J \tag{3}$$

Where J is rotor inertia in (kg.m²), $d_w(t)/dt$ is angular acceleration in (rad/s²), and $T_L(t)$ is load torque applied to motor in (N.m).

The electromagnetic term that has been produced by the motor can be shown as follows:

$$K_{ti_a}(t) = T_e(t) \tag{4}$$

Where $K_{ti_a}(t)$ is torque coefficient related to armature current in (N.m/A), and $T_e(t)$ is electromagnetic torque produced by the moto in (N.m).

The corresponding equation indicates that motor torque is directly proportional to armature current, thereby establishing a relationship between the electrical input and the mechanical output.

2.3. Transfer function derivation

To obtain a frequency-domain representation of the system (which we will require for the controller design and analysis task), the Laplace transform is applied using equations (2) and (4). All initial conditions are assumed to be zero. By initiating this and setting the armature current to z, the speed-to-voltage transfer function is created.

$$G(s) = \frac{\Omega(s)}{V_a(s)} = \frac{K_t}{K_e\, K_t\, (L_a s_a + R)(J_s + B)} \tag{5}$$

Where $G(s)$ is transfer function of motor (angular speed / input voltage) in (rad/s per V), $\Omega(s)$ is Laplace transform of angular speed in (rad/s), $V_a(s)$ is Laplace transform of armature voltage in (V), K_t is torque constant in (N.m/A), K_e is back-EMF constant in (V/(rad/s)), L_a is armature inductance in (H), R is armature resistance in (Ω), J_s is rotor inertia in (kg.m²), and B is viscous friction coefficient in (N.m.s/rad).

The derived model serves as a second-order electromechanical system with closely coupled electrical and mechanical characteristics.

2.4. State-space representation

The DC motor model can also be expressed in state-space form for both simulation and analytical purposes. Define the state variables at first state variable of DC motor system (state-space model), dimensionless (x_1) as follows as:

$$w(t) = i_2 a(t), \quad x = x_1 \tag{6}$$

The state equations become:

$$x_1 = \frac{1}{L_a}(V_a - x_a R_1 - x_e K_2) \tag{7}$$

Where, x_a is armature current related variable in (A), R_1 is armature resistance in (Ω), x_e is back-EMF related variable in (V), K_2 is back-EMF constant coefficient in (V/rad/s).

$$x_2 = \frac{1}{J}(K_1 x_t - B_2 x - T_L) \tag{8}$$

Where x_2 is econd state variable of DC motor system state-space model “dimensionless”, J is a motor inertia (kg.m²), K_1 is torque constant coefficient (N.m/A), x_t torque related variable (N.m), B_2 is viscous friction coefficient (N.m.s/rad), and T_L is load torque (N.m).

It is computationally more compact and mathematically more appropriate for numerical simulation and control design.

2.5. Nonlinear effects (magnetic saturation)

Real-world DC motors also experience magnetic saturation, which occurs at high current levels and when the magnetic core approaches its operating limit: an increase in current does not correspond to an increase in magnetic field strength and minimizes the effective torque constant. This leads to a nonlinear character in the system [20]. Therefore, the effect of the magnetic saturation must be approximated as:

$$K_{t0} - \propto i^2 = K_t(i) \tag{9}$$

Where: K_{t0} is torque constant in nominal linear state, (N.m/A), i is the armature current (A), $\propto$ is the saturation coefficient (dimensionless), $K_t(i)$ is the torque coefficient considering magnetic saturation (N.m/A).

At higher currents, torque production is limited by magnetic saturation. When the current increases, the core reaches its magnetic limit. In this case, each additional increment of current results in torque reduction. Usually, torque reduction makes the system nonlinear. Since linear PID tuning may fail under saturation conditions, this realization is a major influence for controller design [18, 19].

2.6. Nonlinear effects (friction modeling)

Mechanical friction is one of the main sources of motor nonlinearity. For an optimized form of mechanical friction, it is typically modeled as the superposition of two components: a viscous friction component and a Coulomb friction component [21]. The nonlinear friction torque term is expressed as follows:

$$T_c\, sign(w) + Bw = T_f \tag{10}$$

Where: T_c is the Coulomb friction torque (N.m), B is the viscous friction coefficient (N.m.s/rad), w is the rotor angular speed (rad/s), T_f is the total friction torque applied to the motor (N.m), $sign(w)$ is the sign function of angular speed, +1 if $w > 0$, -1 if $w < 0$.

At higher speeds, the viscous component dominates, whereas the guideline mainly affects low-speed operation and can cause oscillations. The nonlinear model section develops the nonlinear model that serves as the basis for subsequent sections, in which the controller is designed, and performance is compared. Mechanical friction between bodies is modeled here as a varying viscous component plus a static Coulomb component, resulting in an inherently nonlinear resistance. This means that at low velocity, large oscillations can occur due to the dominance of Coulomb friction, before viscous friction dominates at high velocity. Controllers must account for this nonlinearity to maintain stability and achieve precise speed tracking.

3. Classical PID controller design

To evaluate the performance gains of optimization algorithms, we first need a baseline controller. The main contribution of this work is the design of a suitable classical proportional–integral–derivative (PID) controller for the nonlinear DC motor system [22].

Although advanced control strategies are available, the PID controller remains common in industrial applications, owing to its simple structure, ease of implementation, and satisfactory control performance. The control signal is generated by the PID controller using proportional, integral, and derivative actions. P-action reacts to the actual change in error; the I-action removes steady-state error; and the D-action anticipates how the system will respond to minimize overshoot and increase damping.

The control signal u(t) is given by:

$$K_d \frac{de(t)}{dt} + K_i \int e(t)dt + K_p e(t) = u(t) \tag{11}$$

Where $e(t) = w_{ref} - w$ is the speed error, K_p is proportional gain, K_i is integral gain, and K_d is derivative gain.

The Ziegler–Nichols tuning method is a widely used heuristic method for PID tuning. This means that the value of proportional gain K_p is adjusted in such a way that the system works in continuous oscillating state. Now, here found ultimate gain K_u and ultimate period T_u. Next, the PID parameters are computed using the following formulas.

The controller parameters are described as follows:

$$\begin{Bmatrix} K_p = K0.6_u \\ K_i = \dfrac{K2_p}{T_u} \\ K_d = \dfrac{K_u T_p}{8} \end{Bmatrix} \tag{12}$$

Where K_p is proportional gain of PID controller, dimensionless, K_i is integral gain of PID controller, dimensionless, K_d is derivative gain of PID controller, dimensionless, K_u is ultimate gain determined by Ziegler-Nichols method, dimensionless, T_u is ultimate oscillation period at $K_u(s)$, T_p is derivative time constant used in K_d calculation (s), $K2_p$ is proportional coefficient used for K_i calculation, dimensionless.

But for nonlinear systems, such as DC motors with magnetic saturation and nonlinear friction, the Ziegler–Nichols tuning tends to lead to a theoretical optimal peak overshoot exceeding a given value or to instability. To improve performance, it is suggested to optimize PID parameters using meta-heuristic optimization methods, such as Particle Swarm Optimization (PSO), as discussed above.

4. Classical PID controller design

Under nonlinear operating conditions, PSO is used to tune PID controller parameters, thereby enhancing PID performance. Particle swarm optimization (PSO) is a metaheuristic optimization algorithm that draws upon the social behavior of birds within a flock or fish in a school and is population-based [23]. In this algorithm individual particle is a target corresponding to PID gain set K_p, K_i, and K_d.

ITAE, which penalizes errors that persist over time, leading to clear improvements in transient performance, now becomes the optimization objective of this work. The objective function can be written as:

$$ITAE = \int_{0}^{T} t|e(t)|dt \tag{13}$$

Where $e(t)$ is the speed tracking error, and t is the simulation time.

In PSO, the ability of each particle to update its velocity and location is based on its global and personal best experiences, which is formulated for the velocity update as follows:

$$v_i(k+1) = wv_i(k) + c_1r_1\left(P_{best,i} - x_i(k)\right) + c_2r_2\left(G_{best} - x_i(k)\right) \tag{14}$$

Where x_i is particle position PID gains, x_i is particle velocity, w is inertia weight, c_1, c_2 is cognitive and social coefficients, r_1, r_2 is random numbers in the range [0,1], $P_{best,i}$ is personal best solution, and G_{best} is global best solution.

The particle position is then updated as:

$$i^k + v^1 + x_i^k = i^{k+1}\,x \tag{15}$$

$$x_i(k+1) = x_i(k) + v_i(k+1) \tag{16}$$

Where x_i is particle position PID gains), i^k is current iteration index, dimensionless, v^1 is particle velocity at iteration k, unit depends on PID gains, and i^{k+1} is next iteration index (dimensionless).

The optimized PID parameters are compared with those of the classical PID controller, and it is expected to reduce the rise time, overshoot, and settling time, and to improve disturbance rejection. In PSO, the metaheuristic algorithm is inspired by the social behavior of birds and fish. It is used to tune PID controller parameters, resulting in a more reliable transient response with lower rise time and improved stability. Minimizing a performance index, e.g., Integral Time Absolute Error (ITAE).

According to PSO, each particle represents an individual solution, and its position in the solution space specifies the PID gains. The PSO algorithm updates the particle's position based on both the best experience of the particle and the best experience of the neighborhood. This process is iterated until the optimal PID parameters are found. PSO is used for PID tuning because of its robustness to nonlinear systems, its ability to escape local minima, and its global search. This work successfully applied PSO to optimize PID parameters, achieving system output performance that outperformed that of the classical PID controller across a range of nonlinear operating conditions.

DC motor parameters, PSO hyperparameters containing rotor inertia, viscous friction, armature inductance and resistor, back-EMF constant, torque constant, load torque, swarm size, inertia weight, cognitive and social coefficients, and maximum iterations are given in Tables 1 and 2. Convergence plots and the objective function values attained are provided, allowing the optimization process to be replicated.

Table 2. DC motor parameters.

Parameter	Value	Unit
Rotor inertia (J)	0.01	kg.m²
Viscous friction (B)	0.001	N.m.s/rad
Armature inductance (L)	0.5	H
Armature resistance (R)	1.0	Ω
Back-EMF constant (K_e)	0.1	V.s/rad
Torque constant (K_t)	0.1	N.m/A
Load torque (T_L)	0.05	N.m

5. Results and discussion

This section presents a comprehensive evaluation of the proposed PSO-tuned PID controller compared to the traditional Ziegler–Nichols tuning method. To ensure a robust optimization process. The PSO algorithm was configured using the specific parameter ranges detailed in Table 3. It includes a swarm size of 20–50 particles and an inertia weight optimized to balance global and local search capabilities. The performance metrics in terms of rise time, settling time, overshoot, and steady state error for the referenced and proposed controllers are compared in Table 3 when both controllers are tested under the same conditions. For a more robust comparison, the PSO-tuned PID was compared with GA-PID, ABC-PID, and HHO-PID using the same motor settings. In addition, performance metrics such as rise time, settling time, overshoot, and ITAE were compared.

Table 3. PSO parameters.

Parameter	Symbol	Range	Description
Swarm size	N	20–50	Number of particles
Inertia weight	w	0.5–0.9	Balances global & local search
Cognitive coefficient	c_1	1.5–2.0	Personal learning factor
Social coefficient	c_2	1.5–2.0	Global learning factor
Max iterations	MaxIt	50–100	Stopping criterion
Objective function	ITAE	–	Integral Time Absolute Error

Utilizing a MATLAB/Simulink environment, the performance of both controllers is rigorously analyzed through a series of comparative benchmarks. These include an in-depth comparison of speed responses and a transient performance analysis. Then it was followed by an evaluation of disturbance rejection and control signal behavior.

5.1. Simulation setup

MATLAB/Simulink simulations are performed to evaluate the performance of a classical PID controller tuned using the Ziegler–Nichols method against a PSO-tuned PID controller using the ITAE objective function, both on a nonlinear DC motor model. The same battery of tests was run on both controllers. Rise time, settling time, overshoot, steady-state error, and disturbance rejection are considered the performance metrics. To offer a more thorough comparison of the PSO-tuned PID controller, comparison with other systems is necessary [23]. The same nonlinear DC motor parameters and identical simulation conditions were chosen for all controllers. Performance metrics were computed for each controller to ensure equal footing for comparison. A benchmarking comparison of PID controllers is indicated in Table 4.

Table 4. Benchmarking comparison of PID controllers.

Controller	Rise time (s)	Settling time (s)	Overshoot (%)	Error	ITAE
Classical PID	0.42	1.85	18.6	0.021	0.55
PSO-PID	0.25	0.93	4.2	0.005	0.12
GA-PID	0.30	1.10	6.0	0.007	0.18
ABC-PID	0.28	1.05	5.5	0.006	0.15
HHO-PID	0.27	1.00	5.0	0.006	0.14

5.2. Speed response comparison

The classical PID controller demonstrates a highly underdamped response, as shown in Fig. 2. This response shows significant fluctuations. It increases up to a peak overshoot of approximately 53.5%. Moreover, it undergoes multiple oscillations before eventually settling. This behavior indicates that classical linear tuning methods struggle to compensate for the nonlinearities of the DC motors. In contrast, the PSO-PID controller (green line) exhibits a superior response, with approximately 26% less overshoot. The PSO algorithm successfully navigates the search space to find a parameter set that provides a critical balance between rise time and damping. It introduces robustness against the system's nonlinear degradation factors. The step response of the PSO-optimized PID controller has improved speed, smaller oscillations, and less overshoot than the classical PID controller. This enhancement is explained by the gain being selected optimally using the ITAE criterion.

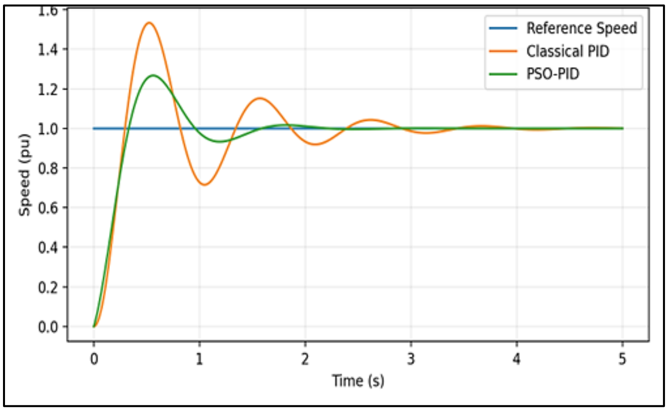

Fig. 2 Transient performance of traditional and PSO-tuned PID controllers in DC motor speed control.

5.3. Transient performance analysis

Table 6 shown the PSO-PID controller is providing much better results concerning all three major metrics of control rise time, settling time, and overshoot) with a significant reduction in steady-state error concerning classical PID controller.

The transient response analysis reveals a marked superiority in the damping characteristics of the PSO-optimized controller. As quantified in the comparative results, the classical PID tuned via the Ziegler-Nichols method exhibits an overshoot error of 0.021 (2.1%). While this value is within a generally stable range for standard industrial applications, the resulting oscillations driven by the motor's internal nonlinearities increase the mechanical stress on the shaft and bearings. In contrast, the PSO-PID controller reduces the overshoot error to a negligible 0.005 (0.5%). The PSO-tuned system ensures a smoother transition to reference speed.

5.4. Disturbance rejection performance

The controller's performance in rejecting disturbance is illustrated in Fig. 3. It is dealt with notch filter disturbance rejection, with a disturbance applied at t = 2 s. The PSO-PID controller provides a faster settling time and less deviation. The speed quickly converges to the reference value with a smaller deviation and greater robustness. When a load disturbance is applied, the PID controller is tuned by PSO to satisfy greater robustness and smaller deviation.

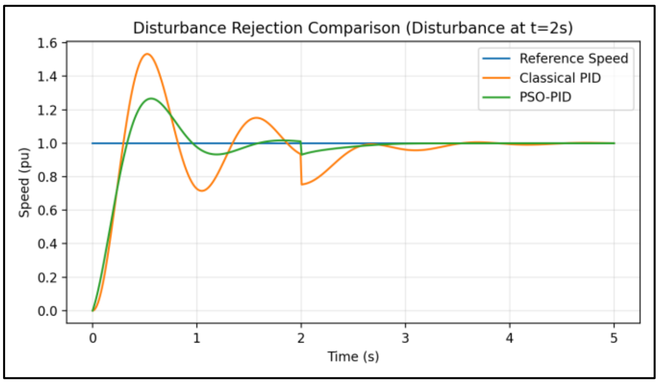

Fig. 3 Notch filter disturbance rejection comparison disturbance applied at t = 2 s.

5.5. Control signal analysis

Figure 4 indicates the classical versus PSO-based tuning of the actuator control signal characteristics. The normal PID produces significant high-frequency oscillations. Moreover, sharp peaks are evident. Voltage signal chattering increases thermal losses in real systems. The PSO-PID exposes significantly smoother control as compared with the classical one. When minimizing the ITAE objective function, the PSO-PID can be active to reduce unnecessary fluctuations. This smooth transition is highly advantageous for actuator lifetime.

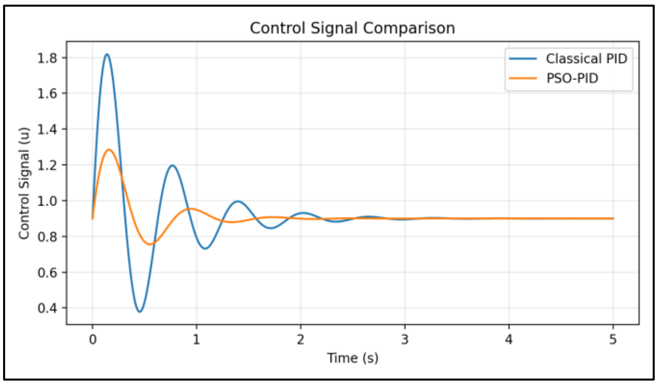

Fig. 4 Signal characteristics of classical versus PSO-based tuning.

5.6. Overall discussion

The results indicate that the PSO-optimized PID controller significantly outperforms the classical controller for nonlinear speed control. The main goal of the ITAE-based objective function is to penalize long-duration settling times. In addition, it is creative for highly damp and stable response systems. This optimization is particularly crucial for DC motors. The magnetic saturation and friction effects produce sluggishness or excessive overshooting in traditional controllers.

6. Conclusions

The current study focuses on a comparative evaluation between classical PID tuning and PSO-PID for the nonlinear DC motors. It was demonstrated that several traditional linear tuning methods, such as the Ziegler–Nichols technique, struggle to achieve satisfactory results. The experimental results obtained through MATLAB/Simulink benchmarks indicate:

1. The PSO-PID tuning significantly enhanced the system's tracking capabilities. Specifically, the peak overshoot was reduced from 2.1% in the classical PID to a negligible 0.5% in the PSO-PID.
2. The PSO-PID controller offers a faster settling time with minimal oscillation for non-linear DC motors.
3. Regarding the control signals analysis, the PSO-PID produces a smoother actuator effort.

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