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Comparative Analysis of Objective Functions in PSO-PID Control for BLDC Motor Speed Regulation

Mussaab Alshbib [1*] **Mostafa Darwish [2]**

[1] Associate Professor, Faculty of Informatics Engineering, Idlib University, Idlib, Syria
[2] Graduate Student (M.Sc.), Aleppo University in the liberated areas, Mechatronics Engineering, Syria- Izaz

[*]*Corresponding Author:* e-mail: *dr.mussaab.alshbib@gmail.com*

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***Abstract*—** Brushless DC (BLDC) motors are fundamental in applications such as electric vehicles and robotics, where precise speed regulation is crucial. This study presents a BLDC motor speed control system based on a PID controller optimized using Particle Swarm Optimization (PSO). The system was simulated in MATLAB/Simulink under three speed levels (low, medium, high) and three load conditions (no load, half load, full load), with a comparative evaluation of four objective functions: Integral of Time Absolute Error (ITAE), Integral of Time Squared Error (ITSE), Root Mean Squared Error (RMSE), and a hybrid ITAE+ITSE. A total of 720 experiments were conducted and assessed using five performance metrics: rise time (Tr), settling time (Ts), maximum overshoot (Mp), steady-state error (Ess), and mean value of speed after settling time. Results demonstrated that ITAE outperformed the other objective functions in minimizing rise time, settling time, and steady-state error, achieving a rise time of 0.00087 s at high speed, a settling time of 1.6992 s at medium speed, and a steady-state error of 0.6178% at medium speed. However, other objective functions showed superiority in certain cases for specific performance indices. Overall, RMSE exhibited weaker performance, particularly in settling time and steady-state error. These findings highlight the significance of selecting an appropriate objective function and its impact on the quality of BLDC motor speed control, providing valuable insights for designing efficient PSO-PID controllers for practical applications.

***Keywords*—** BLDC Motor, PID Control, Speed Control, Particle Swarm Optimization PSO, Objective Function.

I. INTRODUCTION

Brushless DC (BLDC) motors have become one of the most prominent choices in modern industrial applications due to their high efficiency, high power density, and low maintenance requirements. They are widely used in electric vehicles, unmanned aerial vehicles, robotics, medical devices, rolling mills, and automation systems [1]. These applications require precise speed control to ensure reliable performance under varying operating conditions. The Proportional–Integral–Derivative (PID) controller is one of the most commonly employed controllers for motor speed regulation because of its simplicity and proven reliability. However, tuning its parameters (Kp, Ki, Kd) using classic methods, such as trial-and-error or the Ziegler–Nichols method, is often ineffective, particularly for nonlinear systems like BLDC motors or systems with time-varying dynamics [2,3]. To overcome these challenges, intelligent optimization algorithms have emerged as effective solutions for tuning controller gains under dynamic conditions. Among them, Particle Swarm Optimization (PSO) has gained significant popularity due to its simplicity, fast convergence, and low computational requirements [4]. This study aims to compare four objective functions (ITAE, ITSE, RMSE, and a hybrid ITAE+ITSE) in terms of their impact on BLDC motor speed control, along with a statistical assessment of the results, The paper is organized as follows: Section 2 describes the adopted methodology, including the design of the PID controller, modeling of the motor equations in the time domain, and implementation of PSO algorithm, Section 3 presents the results, while Section 4 discusses the findings, draws conclusions, and highlights potential directions for future research.

Recent years have seen growing interest in the use of optimization algorithms to tune PID/PI controllers in BLDC motor control systems due to their high efficiency and ability to improve control performance. Research has focused on three main areas: PID/PI tuning in BLDC motors, comparison of different optimization algorithms, and improvement of algorithm performance. Several studies have proposed various strategies for tuning controllers using the PSO algorithm. In a study by Sofiane Ben Abdi et al., a hybrid strategy (PSO-ANN) was developed using a hybrid objective function (a*IAE+b*Overshoot) that achieved a reduction in steady-state error and settling time. The study did not mention the effect of changing operating conditions [5], and in a study by Yashi Rani et al., the control performance of a BLDC motor was analyzed by comparing PID and PI strategies using manual tuning, auto-tuning of MATLAB, and the PSO algorithm with an MSE objective function through simulation in MATLAB/Simulink. The study aimed to improve speed response and reduce torque ripple [6]. In a 2016 study, Chookiat Kiree et al. used the PSO algorithm with an SSE objective function to control the PI(D) controller in a BLDC motor, achieving satisfactory speed responses at 800 and 1200 rpm under different load conditions (no load – full load). The results showed the superiority of PSO in terms of settling time and search time compared to GA and TS algorithms [7].In a study by R. Sandip et al. In 2022, the PSO algorithm was used to synthesize a PI controller taking into account the instantaneous acceleration of the BLDC motor. The simulation showed an improvement in speed response and dynamic performance, but without clarifying the objective function used [8]. These studies [5, 6, 7, 8] agree on the effectiveness of the PSO algorithm in improving the control performance of BLDC motors, with different objective functions affecting response speed, control accuracy, and system stability. Other studies have addressed the impact of objective function selection on system performance. In a 2023 study by Mohamed Ahmed Ebrahim Mohamed et al., the performance of PID and FOPID controllers in a hybrid energy system (thermal, wind, hydraulic) was compared using multiple optimization algorithms, including GA, GWO, SCIA, and ASIA. The objective functions used varied between IAE, ITAE, ISE, and ITSE, with the results showing the superiority of ASIA and GWO algorithms, especially when using ITSE and ISE functions in terms of settling time and rise time. Robustness tests were also conducted on the system by changing the system parameters by ±25% and ±50%, confirming the effectiveness and reliability of the proposed optimization techniques in the face of load fluctuations and different operating conditions. This study highlights the importance of selecting the appropriate objective function when tuning controllers to improve the performance of dynamic systems [9], In a study by Seyed Mohammad Hossein Mousakazemi et al., several common objective functions (IAE, ISE, ITAE, ITSE) were compared to improve PID coefficients using a GA algorithm in a PWR nuclear reactor control system The results showed that ISE and ITSE perform better in steady-state regions in terms of response and effectiveness compared to IAE and ITAE, although the latter two are superior in terms of convergence speed towards the optimal solution [10]. Other studies have compared the performance of the PSO algorithm with different optimization algorithms and tuning techniques for PID controller constants to control the speed of BLDC motors. In a 2019 study, Flah Aymen et al used a hybrid objective function (a*ISE + b*Δω) to reduce motor speed fluctuations in high-torque applications where the use of PSO contributed to improving performance stability and increasing control accuracy [11]. In 2014, H.E.A. Ibrahim et al. compared the PSO and BFO algorithms in adjusting the PID controller to control the speed of a BLDC motor using an ITSE objective function, taking into account torque variation. Simulation results in the MATLAB/Simulink environment showed that the PSO algorithm outperformed the BFO algorithm, indicating higher efficiency in searching for optimal PID coefficients [12]. Other studies have focused on improving the performance of the PSO algorithm itself within BLDC motor control systems. In a 2019 study, Manoj Kumar Merugumalla et al presented an improvement to the PSO algorithm using chaotic inertia weight and chaotic constriction factor, which accelerated convergence and improved control accuracy, although the study relied on an objective function representing direct error without analyzing the effect of operating conditions. The results showed the effectiveness of these modifications in reducing oscillations and improving the dynamic response of the system [13]. A 2019 study by Wei Xie et al. focused on improving the convergence speed of the PSO algorithm by modifying the inertia coefficient (w) using five different mathematical formulas to adjust its value and compare them. The simulation results showed the effectiveness of these methods in improving the PI controller tuning for regulating the speed of the BLDC motor, emphasizing the importance of adjusting the inertia coefficient to achieve accurate tuning of the controller constants and accelerate convergence towards the solution [14]. In a 2023 study, Anis Ahmed compared the performance of PSO and GA algorithms in tuning a PID controller for BLDC motor speed control using the ITAE objective function. The results showed that each algorithm has its own advantages in terms of its effect on performance, with the possibility of exploring advanced tuning and control techniques in the future [15]. In 2023, Meenakshi Danu et al. presented a comparative study of the effect of four tuning methods for PID controllers, including automatic tuning in MATLAB, genetic algorithm (GA), particle swarm optimization (PSO), and artificial neural networks (ANN), on the performance of a BLDC motor. The results showed that the PSO algorithm was superior in improving system response, reflecting higher accuracy and stability in motor speed control [16]. Mohamad Ridwan et al. also presented a study that used the PSO algorithm to tune a PI controller while taking into account motor acceleration. They compared several values for the acceleration coefficient (velocity curve slope) and used the algorithm to find the optimal values for Kp and Ki. The simulation results showed that the PSO controller is capable of accurately controlling the speed of the BLDC motor and reaching the reference speed with a stable response [17]. Within the framework of improving the PSO algorithm itself, Nguyen Tien Dat introduced the parallel multiple particles (PMPSO) technique to accelerate the search process and improve the accuracy of PID controller parameter tuning. The study showed the superiority of the PMPSO algorithm over the traditional SPSO version in terms of convergence speed and tuning accuracy [18].

From the previous review, it is evident that most studies agree on the effectiveness of the PSO algorithm in improving system performance in nonlinear applications. However, the majority of these studies did not explicitly address the impact of objective function selection on system behavior. The present study aims to analyze the effect of four objective functions (ITAE, ITSE, RMSE, and a hybrid ITAE+ITSE) on the performance of a PSO-tuned PID controller for BLDC motors. This is achieved through a comprehensive statistical assessment of the dynamic system performance under multiple operating conditions, including variations in speed and torque.

I. Research Methodology:

First: PID Controller Structure, Tuning, and Its Effect on System Behavior:

The Proportional–Integral–Derivative (PID) controller is an effective and widely used control strategy in Brushless DC (BLDC) motor speed applications due to its simplicity and efficiency in achieving precise responses. This controller consists of three main terms: the proportional term (Kp), which responds to the current error between the reference and actual speed; the integral term (Ki), which corrects the accumulated error to reduce steady-state error; and the derivative term (Kd), which enhances system stability by predicting changes in the error. The control action is governed by the following equation[3]:

$u(t) = K_p\, e(t) + K_i \int e(t).dt + K_d \frac{d(e(t))}{dt}$	**(1)**

where: u(t) is the control signal, e(t) is the error signal defined as the difference between the actual and reference speeds, and Figure 1 illustrates the general block diagram of the PID controller with a BLDC motor.

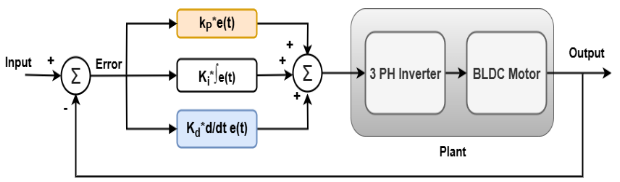

Figure 1: PID Controller Diagram with BLDC Motor

Table 1 illustrates the effect of increasing each PID gain on the signal performance metrics, which is crucial for analyzing the system's behavior [19].

Table 1: Effect of Increasing PID Controller Gains on Signal Metrics

Parameter	Rise Time (T_r)	Overshoot (Mp)	Settling Time (Ts)	Steady State Error (Ess)	Peak Time (Tp)
Increase Kp	Decrease in rise time	Increase in Overshoot	A little change in the settling time	Decrease Steady State Error	Decrease in peak time
Increase Ki	Decrease in rise time	Increase in Overshoot	Increase in Settling Time	Eliminate Steady State Error	Decrease in peak time
Increase Kd	A small decrease in rise time	Decrease in Overshoot	Decrease in Settling Time	Didn't affect the Steady State Error	Maybe cause a small increase in peak time

Second: BLDC Motor and Its Mathematical Model:

In this paper, the BLDC motor operates using the 6-Step Commutation method, a widely used technique that sequentially switches the phase voltages among the three phase pairs (A-B-C) over six steps within each electrical cycle. The switching timing is determined based on the rotor position, which is typically sensed using Hall sensors, enabling continuous rotation with relatively simple implementation compared to other commutation methods. Figure 2 illustrates the electrical structure of the motor along with the three-phase inverter drive circuit.

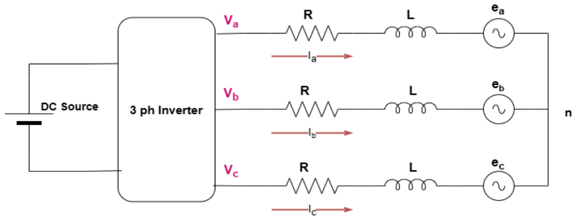

Figure 2: BLDC Motor Structure

The mathematical model of the BLDC motor is constructed from a set of differential equations that describe the electrical and mechanical behavior of the motor. These equations can be divided into two main categories [20, 21]:

First: Electrical Equations:

The three-phase voltages can be represented by the following equations:

$$V_a = R_s i_a + L_s \frac{i_a}{dt} + e_a$$
$$V_b = R_s i_b + L_s \frac{i_b}{dt} + e_b$$
$$V_c = R_s i_c + L_s \frac{i_c}{dt} + e_c \quad (2)$$

Where:

- Vx is the phase voltage,
- Ix is the phase current,
- Rs is the winding resistance (assumed equal for all three phases),
- Ls is the phase inductance (assumed equal for all three phases),
- ex is the back electromotive force (EMF) generated by rotation (mutual inductance between energized windings is neglected), and it's expressed by the following equations (3):

$$e_a = 0.5K_e\omega_m f(\theta_e)$$
$$e_b = 0.5K_e\omega_m f\left(\theta_e - \frac{2\pi}{3}\right)$$
$$e_c = 0.5K_e\omega_m f\left(\theta_e - \frac{4\pi}{3}\right) \quad (3)$$

Where K_e represents the back EMF constant, ω_m is the rotor angular speed, θ_e is the electrical angle, and $f(\theta_e)$ denotes the back EMF function (trapezoidal waveform) given by the equation (4):

$$f(\theta_e) = \begin{cases} 1 & , \quad 0 \le \theta_e < \frac{2\pi}{3} \\ 1 - \frac{6}{\pi}\left(\theta_e - \frac{2\pi}{3}\right) & , \quad \frac{2\pi}{3} \le \theta_e < \pi \\ -1 & , \quad \pi \le \theta_e < \frac{5\pi}{3} \\ -1 + \frac{6}{\pi}\left(\theta_e - \frac{5\pi}{3}\right) & , \quad \frac{5\pi}{3} \le \theta_e < 2\pi \end{cases} \quad (4)$$

Second: Mechanical Equations:

The electromagnetic torque generated by the motor (T_e) is given by the following equation (5):

$$T_e = K_e(e_a i_a + e_b i_b + e_c i_c) \quad (5)$$

The mechanical angular velocity of the rotor is given by the following equation (6):

$$\frac{d}{dt}\omega_m = \frac{1}{J}(T_e - T_L - B\omega_m) \quad (6)$$

Where:

- J is the moment of inertia,
- B is the viscous friction coefficient,
- Tl is the applied load torque.

The electrical angle is related to the mechanical angle by the following equation (7):

$$\theta_e = p\theta_m \quad (7)$$

Where:

- θ_e is the electrical angle,
- θ_m is a mechanical angle,
- p is the number of pole pairs.

Among the necessary equations for modeling the motor are the phase current equations in the star (Y) connection configuration, which are derived by substituting and rearranging the set of fundamental equations (8):

$$\frac{d}{dt}i_a = \frac{1}{3L_s}\left(2V_{ab} + V_{bc} - 3R_s i_a + p\Phi_m\omega_e(\Psi_c + \Psi \Psi_a)\right) \quad (8)$$

$$\frac{d}{dt}i_b = \frac{1}{3L_s}\left(V_{bc} + V_{ab} - 3R_s i_b + p\Phi_m\omega_e(\Psi_a + \Psi_c - 2\Psi_b)\right)$$

$$i_c = -i_a - i_b$$

Where:

- V_{ab}, V_{bc} is the voltage difference between two phases,
- Φ_m is the permanent magnet flux,
- Ψ_c , Ψ_b, Ψ_a represent the magnetic flux of each phase.

Third: Particle Swarm Optimization (PSO):

The PSO algorithm is one of the Nature-Inspired Algorithms inspired by the behavior of swarms in nature. It is used to find optimal or near-optimal solutions of nonlinear problems, making it suitable for tuning PID controllers in nonlinear systems such as BLDC motors [22].

How does the PSO algorithm work?

PSO relies on a set of particles, where each particle represents a set of PID parameters (Kp, Ki, Kd). The position and velocity of each particle in the search space are updated based on two factors:

- Best individual solution (PBest): The best position reach the particle itself.
- Best global solution (GBest): The best location reached l group of particles as a whole.

The two basic equations for updating speed and location (equations used in Standard PSO). Equation (9) expresses the particle speed equation, and equation (10) expresses the particle location equation.

$v_i^{t+1} = w\,v_i^t + c_1.r_1\,(PBest_i - x_i^t) + c_2.r_2\,(GBest - x_i^t)$	**(9)**
$x_i^{t+1} = x_i^t + v_i^t$	**(10)**

Where:

v_i^t: velocity of particle i at iteration t,

x_i^t: position of particle i at iteration t,

w: inertia coefficient,

c_1, c_2: acceleration coefficients,

r_1, r_2: random adjustment coefficients between 0 and 1.

Figure 3 shows the flowchart of the steps for implementing the PSO algorithm.

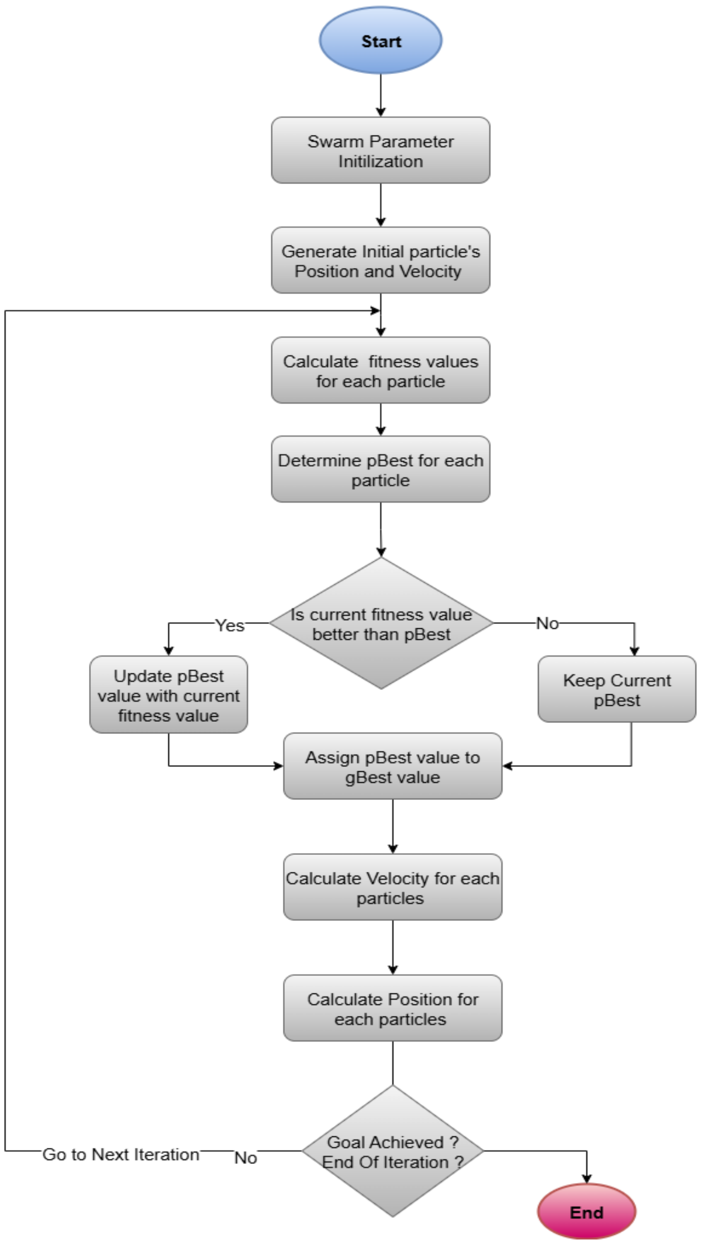

Figure 3: Flowchart of the steps for implementing the PSO algorithm

Advantages and disadvantages of the PSO algorithm:

The PSO algorithm has a set of characteristics and ongoing research to improve it and resolve its weaknesses. Table 2 shows its most prominent advantages and disadvantages [23, 22].

Table 2: Advantages and disadvantages of the PSO algorithm

Advantages of PSO	Disadvantages of PSO
Ease of implementation	Early convergence in some cases
Low computational resources	Sensitivity to algorithm constants
Stable performance with different initial values	Slow convergence in advanced stages

In this paper, PSO is used to find the PID controller constants for controlling the speed of the BLDC motor. Several objective functions were used in the controller tuning process for comparison purposes:

- ITAE (Integral of Time Absolute Error): $ITAE = \int t.|e(t)|\,dt$
- ITSE (Integral of Time Square Error) :

- hybrid objective function (ITAE+ ITSE)

The above functions were chosen as objective functions because they describe the system response in several ways:

- ITAE reduces late errors and enhances long-term signal stability.
- ITSE reduces large momentary errors and enhances short-term system stability.
- RMSE provides a comprehensive measure of tracking because it describes the energy of the error.
- A composite cost function (ITAE + ITSE) was also adopted, trying to achieve a balance between response speed and temporal stability.

Figure 4 shows the relationship between iteration and the value of the objective function. We observe in various cases the convergence of the solution at different cost functions.

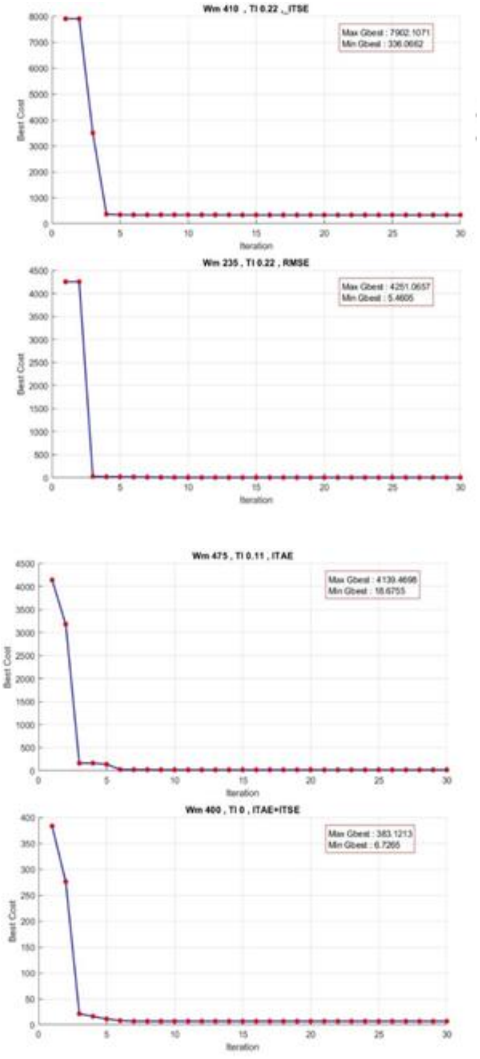

Figure 4: Algorithm convergence curves towards the optimal solution

As mentioned, one of the disadvantages of the algorithm is local solutions, so some cases in which the algorithm failed to find the required solution were excluded, and a test was conducted for specific cases (4 cases), and the values of the controller constants were found repeatedly (10 times for each case). A line was drawn to show the average value of the target function values for the ten repetitions, as shown in Figure 5.

The results of ten attempts for the same speed and torque conditions for four different cases show that the target function values vary within an acceptable range in most cases, which allows for a single experiment to suffice. However, there were cases of very large values, indicating that the algorithm failed in that case, which requires repeating the experiment and excluding the value for that experiment.

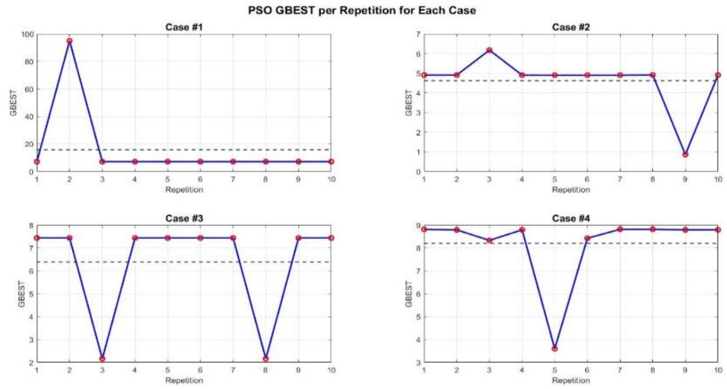

Figure 5: Repetition diagrams for specific cases (speed - torque)

1.1. Data Acquisition and Dataset Creation:

A dataset was created using MATLAB/Simulink, where the BLDC motor speed range was divided into three levels: low speed, medium speed, and high speed. For each speed level, three torque conditions were tested: zero torque (no load), 50% of maximum load, and 100% of load. For each speed and torque condition, the optimal values for the PID controller constants were determined using the particle swarm optimization (PSO) algorithm, ensuring that the motor performance was covered under various operating conditions. The data was generated using four different objective functions (Objective Functions).
The data was organized in a database, which was generated using MATLAB software to analyze the results and evaluate the quality of each signal based on the following criteria:

- Rise Time
- Overshoot%
- Settling time
- Steady-state error (%)
- Average speed signal values after stabilization

II. Results and Discussions:

To compare the performance of the objective functions (ITAE, ITAE+ITSE, ITSE, RMSE) and their effect on the tuning of PID controller constants in the BLDC motor speed control system, a statistical description of 720 experiments covering three speed cases (low, medium, high) and three load torque cases (no load, half load, full load). During this process, the average of five performance indicators was calculated: rise time, settling time, maximum overshoot, steady-state error, and average after settling.

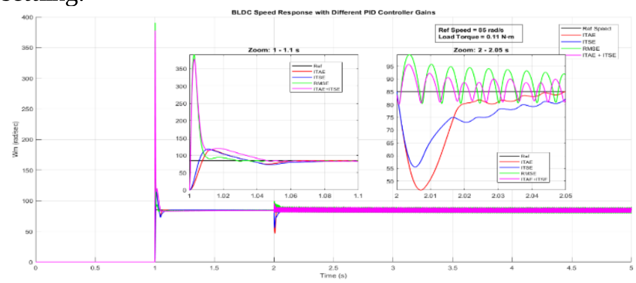

Figure 6-a: Comparison of speed signals Wm:85 rad/sec | Tl:0.11 N.m

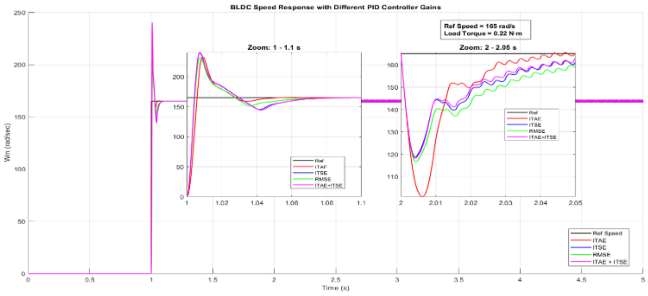

Figure 6-b: Comparison of speed signals Wm:165 rad/sec | Tl:0.22 N.m

Figure 6-a compares the speed response with time for a BLDC motor at a reference speed of 85 rad/sec and 50% of the nominal torque, and Figure 6-b compares the speed response at a reference speed of 165 rad/sec and 100% torque using PID constants tuned by the PSO algorithm with different objective functions.

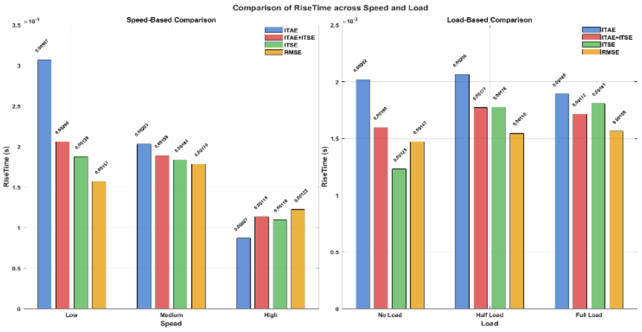

Figure 7: Comparison of rise time under Different Speeds and Conditions

Figure 7 compares the rise time of the objective functions across different speed and applied torque conditions, highlighting the superior performance of ITAE with a rise time of 0.00087 seconds at high speed. It also shows the superiority of ITAE in achieving a low rise time (0.000869981 seconds at high speed), showing a fast response to the BLDC motor. In contrast, RMSE recorded a higher rise time (0.001563627 seconds at full load), indicating a slower response. This makes ITAE ideal for BLDC applications that require fast dynamic response.

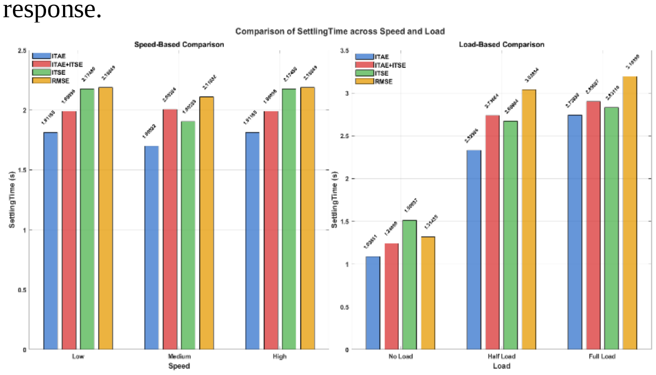

Figure 8: Comparison of Settling Time under Different Speed Load Conditions

Figure 8 compares the settling time of the objective functions, showing the superior performance of ITAE, which achieved a settling time of 1.81165 s at medium speed, providing fast stabilization for the BLDC motor. In contrast, RMSE recorded the longest settling time (2.18849 s at low speed), indicating lower efficiency under certain conditions. These results support the use of ITAE in applications that require fast stabilization.

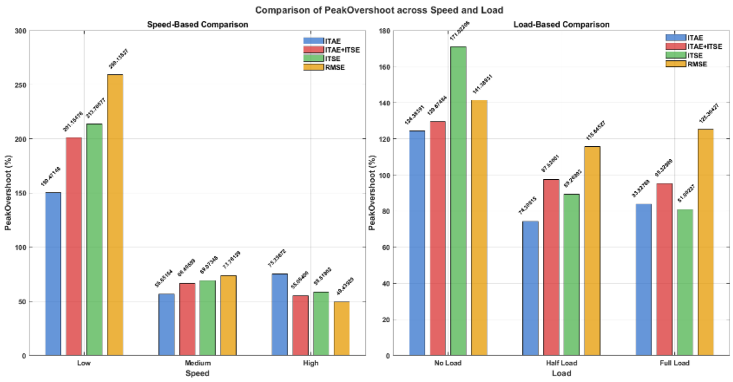

Figure 9: Comparison of overshoot under Different Speeds and Load Conditions

Figure 9 illustrates that the maximum overshoot varies depending on the objective function and operating conditions ITAE achieved the lowest overshoot at medium speed (56.65%) and in some load cases, while RMSE excelled at high speed (49.44%) and recorded the highest values at low speed (259.14%), these results indicate that there is no single objective function that minimizes overshoot in all conditions, which requires balancing the requirements of response speed and peak overshoot reduction.

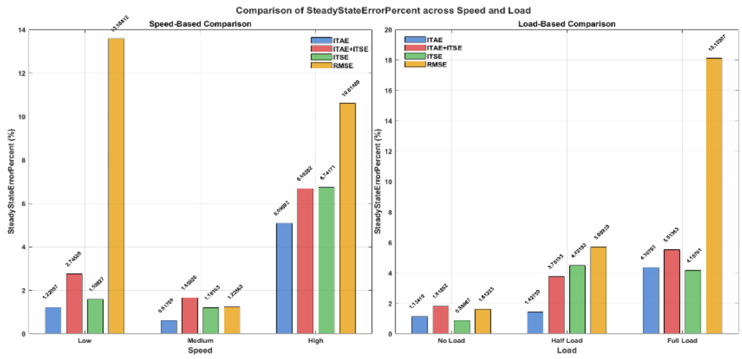

Figure 10: Comparison of steady-state error under Different Speeds and Load Conditions

Figure 10 compares the steady-state error of the target functions, highlighting the accuracy of ITAE with the lowest error (0.6178% at medium speed) in BLDC motor control, and shows that ITAE's superiority in reducing steady-state error reflects high accuracy in BLDC motor control. In contrast, RMSE recorded the highest error (13.5881% at low speed), limiting its suitability for high-precision applications. These results confirm the superiority of ITAE for PID control in BLDC motors.

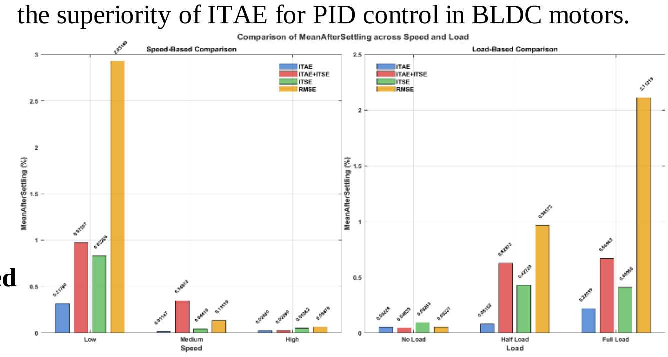

Figure 11: Comparison of mean after settling under Different Speeds and Load Conditions

Figure 11 compares the mean after settling value of the speed signal after stabilization for the objective functions (ITAE, ITAE+ITSE, ITSE, RMSE), showing an RMSE reduction of 2.1122% at full torque. This shows that ITAE significantly reduces the speed signal vibration after stabilization compared to RMSE, which recorded a high value. This difference reflects the ability of ITAE to achieve smoother stabilization of the

BLDC motor speed. These results support the use of ITAE in applications that require stable motor speed control with minimal oscillations.

III. Future Work

The study demonstrated that the ITAE objective function provided the best performance for tuning the PID controller of a BLDC motor, achieving the shortest rise time, the fastest settling time, and the lowest steady-state error. In contrast, RMSE showed the weakest performance, particularly in terms of overshoot and average settling speed oscillations, limiting its suitability for applications requiring high precision and stability. The ITSE function exhibited balanced performance without clearly outperforming ITAE, making it an acceptable choice when a trade-off between response speed and accuracy is needed. Meanwhile, the composite function (ITAE+ITSE) did not demonstrate a significant advantage over the individual functions. The analysis further revealed that the effectiveness of each objective function varies with operating speed and load torque, highlighting the importance of aligning the selection of the objective function with the operating conditions. Based on 720 simulation experiments, a comprehensive database has been developed, enabling future training of intelligent neural networks capable of predicting optimal PID parameters for diverse operating scenarios, paving the way for more adaptive and effective BLDC motor control systems.

For future work, it is proposed to train neural networks using the optimal PID values under different operating conditions, to compare PSO against well-known optimization algorithms such as GA, GWO, ACO, DE, and BFO when applied to BLDC motors, and to investigate the design of composite objective functions with weighted terms for enhanced performance, the current dataset can also be utilized to develop a scheduling controller.

Appendices:

1. Table of motor constants and equation symbols
2. Table of PSO algorithm parameters
3. Final database
4. Table of experimental results analysis

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest.

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Human Participants

This paper does not involve human participants.

Originality Note

The authors confirm that the manuscript is their original work, and if others' works are used, they are properly cited/quoted.

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Appendices

Table of motor constants :

Used Motor: RS Pro Brushless DC Motor Stock No: 536-6046

Rs	**0.65 Ω (line-to-line Resistance)**
Ls	2.1 mH (line-to-line Inductance)
pm	0.063 Wb (≈ torque constant)
p	2 Pole pairs
Ke	0.0595 V·s/rad
J	1.19*〖10〗^(-5) kg·m²
B	1*〖10〗^(-4) N·m·s/rad (assumed)
Rated Speed	4000 rpm (≈485 rad/sec)
Rated Torque	0.22 N · m
Max Peak Torque	0.68 N · m
Supply Voltage	36 V
Max Peak Current	9.8 A

Table of PSO constants:

Problem Dimension	nVar = 3 (Kp, Ki, Kd)
Search Space Upper Limit	[90, 450, 30]
Search Space Lower Limit	[0, 0, 0]
Number of particles	20
Max Iteration	30
Inertia Weight Bound	Wmax=1 , Wmin =0.1
Personal Acceleration Coefficient	C1= 1.49618
Global (Social) Acceleration Coefficient	C2= 1.49618

Objective Function	Speed	Rise Time	Settling Time	Peak Overshoot	Steady State Error Percent	Mean After Settling
ITAE	Low	0.003068333	1.8116	150.4714823	1.2210%	0.3179%
ITAE+ITSE	Low	0.002059304	1.9910	201.1547576	2.7452%	0.9730%
ITSE	Low	0.001876602	2.1748	213.7007664	1.5863%	0.8329%
RMSE	Low	0.00156924	2.1885	259.138268908406	13.5881%	2.9314%
ITAE	Medium	0.002033026	1.6992	56.65154212	0.6178%	0.0115%
ITAE+ITSE	Medium	0.00188702	2.0038	66.40599467	1.6563%	0.3488%
ITSE	Medium	0.001838908	1.9036	69.07347618	1.1916%	0.0442%
RMSE	Medium	0.001785447	2.1108	73.7612881	1.2357%	0.1352%
ITAE	High	0.000869981	1.8116	75.39671773	5.0909%	0.0248%
ITAE+ITSE	High	0.001136977	1.9910	55.06399516	6.6828%	0.0230%
ITSE	High	0.001100031	2.1748	58.51901568	6.7417%	0.0528%
RMSE	High	0.001224894	2.18849	49.43928604	10.6149%	0.0647%

Objective Function	Load	Rise Time	Settling Time	Peak Overshoot	Steady State Error Percent	Mean After Settling
ITAE	no Load	0.002016986	1.0855	124.3839114	1.1342%	0.0523%
ITAE+ITSE	no Load	0.001596499	1.2405	129.67484	1.8185%	0.0464%
ITSE	no Load	0.001230941	1.5094	171.0220569	0.8807%	0.0926%
RMSE	no Load	0.001470742	1.3144	141.3893065	1.6122%	0.0534%
ITAE	Half Load	0.002062448	2.3299	74.30815358	1.4276%	0.0815%
ITAE+ITSE	Half Load	0.001771691	2.7368	97.62001384	3.7519%	0.6287%
ITSE	Half Load	0.001775589	2.6699	89.26892991	4.4819%	0.4274%
RMSE	Half Load	0.001545211	3.0383	115.6452679	5.6984%	0.9657%
ITAE	Full Load	0.001891905	2.7399	83.82767718	4.3679%	0.2204%
ITAE+ITSE	Full Load	0.001715112	2.8987	95.32989354	5.5138%	0.6696%
ITSE	Full Load	0.001809011	2.8311	81.00227151	4.1570%	0.4099%
RMSE	Full Load	0.001563627	3.1940	125.3042687	18.1281%	2.1122%

About the authors

Mussaab ALSHBIB received the B.Sc. degree in electrical and electronic engineering from the University of Aleppo, Aleppo, Syria, in 2002, the M.Sc. degree in electrical engineering from electrical drive department, Aleppo University, Syria, in 2009, and the Ph.D. degree in electrical engineering from electrical drive department, Aleppo University, Syria, in 2015. My research interests are in the areas of electric drive and digital control systems. A reviewer in many international Journals, such as Wiley and Springer ones.

Mostafa Darwish is a mechatronics engineer who earned a B.Sc. in Mechatronics Engineering (2021) from the University of Aleppo. He is currently pursuing a Master's degree in Mechatronics Engineering at the same university, where his research centers on improving the performance of Brushless DC

(BLDC) motors through adaptive Artificial Neural Networks (ANNs). His research interests focus on the design and development of intelligent control and drive systems for BLDC motors. In addition to his academic work, he has practical experience in renewable energy systems and control circuit design, supporting a strong blend of theoretical and applied engineering skills. Mostafa has also been actively engaged in research activities, with contributions to several scientific conferences, reflecting his commitment to advancing knowledge and sharing research outcomes within the engineering community.