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RESEARCH ARTICLE

Efficient Speed Control for DC Motors Using Novel Gazelle Simplex Optimizer

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ABSTRACT This paper addresses the design of an optimally executed proportional-integral-derivative (PID) controller, tailored for the speed regulation of a direct current (DC) motor. To achieve this objective, we present a novel hybrid algorithm, combining the gazelle optimization algorithm (GOA) with the effective simplex search method known as the Nelder-Mead (NM) technique. The fusion of these algorithms yields an innovative hybridized version, striking the balance between exploration and exploitation. The proposed approach, named the gazelle simplex optimizer (GSO), showcases great promise when applied to the task of controlling the speed regulation of a DC motor using the PID controller. To identify the optimal values for PID gains, we harness the power of a novel objective function as well, which guides the GSO in determining the most favorable controller settings. Rigorous comparative simulations are then undertaken, where we pit the GSO against several other algorithms, namely the reptile search algorithm, prairie dog optimization algorithm, weighted mean of vectors optimization, and the original GOA algorithm. These simulations allow us to assess the system's behavior through various lenses, such as statistical tests, time and frequency domain responses, robustness analysis, and changes in the objective function. The evaluations from these comprehensive tests demonstrate the superiority of the GSO-based PID controlled DC motor speed regulation system. The GSO exhibits better performance than the alternative algorithms, providing solid evidence of its effectiveness. Furthermore, the proposed GSO approach outperforms other reported PID tuning methods, affirming its prowess in achieving superior speed regulation for DC motors.

INDEX TERMS Speed regulation, DC motor, gazelle optimizer, Nelder-Mead simplex method, PID controller.

I. INTRODUCTION

Direct current (DC) motors play a pivotal role in various real-life engineering applications owing to their ease of controllability, high durability, and cost-effectiveness [1], [2]. These versatile motors find extensive use in electric vehicles, machine tools, robotic arms, and cranes, among other industrial applications [3]. In most of these applications, precise speed control is a critical criterion, demanding accurate regulation as DC motors serve as the primary actuation devices in dynamic systems [4].

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To achieve optimal performance, several control structures such as adaptive controllers, fuzzy controllers, sliding mode controllers, and notably, proportional-integral-derivative (PID) controllers have been adopted [5]. The popularity of PID controllers stems from their simplicity, reliability, and cost-effectiveness, with a successful track record of over 80 years in a wide range of industrial applications [6]. However, the tuning of PID gain parameters is crucial for achieving desired performance, a task that may not be effectively handled by traditional techniques for higher-order systems or systems with uncertainties [7].

In response to the challenges posed by traditional tuning methods, metaheuristic algorithms have emerged as promising alternatives, treating problems as "black boxes" and exploring the search space for promising regions [8], [9], [10], [11], [12]. One of the examples of metaheuristic algorithms is the chaotic atom search optimization which is reported in [13]. The related work introduces two optimization algorithms, atom search optimization and its modified chaotic version, are used for determining optimal parameters of a fractional-order PID controller employed in DC motor speed control system. The study evaluates these algorithms against benchmark problems and compares them with other existing controllers, demonstrating their superior performance in DC motor speed control through various analyses. In another study [14], grey wolf optimization is introduced as an alternative to particle swarm optimization for optimizing PID controller parameters. Comparing the two techniques, the study concludes that the grey wolf optimizer-based approach yields superior dynamic performance in brushless DC motor control. Other notable examples of these algorithms for DC motor speed regulation controller design include improved whale optimization algorithm [15], particle swarm optimization [16], artificial bee colony algorithm [17], improved slime mould algorithm [18], flower pollination algorithm [19], and an enhanced stochastic fractal search algorithm [20].

Amidst the landscape of metaheuristic algorithms designed for optimizing PID controllers in DC motor speed regulation, we recognize the need for a new and more effective approach that can deliver promising results surpassing existing methods. Recently, the gazelle optimization algorithm (GOA) has emerged, drawing inspiration from the adaptive qualities of gazelles, which harness agility and speed for solving complex optimization problems [21]. In this context, we introduce the gazelle simplex optimizer (GSO), a pioneering hybrid metaheuristic algorithm that intricately combines the exploratory prowess of GOA with the exploitation capabilities of the Nelder-Mead (NM) technique [22], a renowned derivative-free simplex search approach. This integration enhances the efficiency of PID controller design for DC motor speed regulation, striking a harmonious balance between exploration and exploitation, while simultaneously mitigating computational complexities. Moreover, we propose a novel objective function in this study, further elevating the efficacy of our approach. Through the introduction of the GSO and our innovative objective function, we aim to establish a new frontier in the optimization of PID controllers for DC motor speed regulation, offering a potent and promising alternative to existing methods in the field.

We demonstrate the superior performance of the GSO-based PID controller through extensive simulations and comparisons with other algorithm-based PID controllers. The comprehensive analyses include statistical tests, frequency and time domain responses, robustness, and changes in the objective function, reaffirming the effectiveness of the GSO approach over reptile search algorithm (RSA) [23], prairie dog optimization (PDO) algorithm [24], weighted mean of vectors optimization (INFO) algorithm [25] and gazelle optimization algorithm (GOA) [21].

The statistical analysis demonstrates that the GSO algorithm excels in minimizing the objective function when compared to the GOA, RSA, PDO, and INFO algorithms. The time response analysis reveals that the GSO algorithm outperforms the GOA, RSA, PDO, and INFO algorithms in terms of rise time, settling time, overshoot, and peak time. The frequency response analysis indicates that all the evaluated algorithms, including GSO, GOA, RSA, PDO, and INFO, provide stable PID-controlled DC motor systems with infinite gain margins. The GSO algorithm, in particular, stands out with a wider bandwidth, enabling the system to effectively respond to a broader range of frequencies. The robustness analysis demonstrates that the GSO algorithm consistently delivers competitive and stable performance across different sets of motor parameters compared to the GOA, RSA, PDO, and INFO algorithms. The GSO-based PID controlled DC motor systems exhibit desirable time response metrics, indicating the algorithm's resilience in maintaining stable and efficient control despite fluctuations in motor parameters.

Furthermore, we compare the GSO-based PID controller with other reported state-of-the-art algorithms-based PID controllers (listed in Table 10). The comparison with other reported PID tuning algorithms demonstrates that the GSO algorithm excels in achieving fast response times and minimizing overshoot. It consistently delivers competitive or superior performance in terms of rise time, settling time, overshoot, and peak time compared to a wide range of optimization algorithms. These findings highlight the effectiveness and efficiency of the GSO-based PID tuning algorithm and establish it as a promising choice for optimizing PID control parameters in DC motor control systems. The contributions of this paper can be summarized as follows:

1) A novel hybrid metaheuristic algorithm that combines GOA and NM algorithms is proposed, resulting in a new structure (GSO) that achieves a favorable balance between exploration and exploitation.
2) The proposed GSO is employed to design and implement an efficient PID controller for a DC motor speed control system.
3) A newly developed objective function is introduced, outperforming popular algorithms commonly used for similar purposes.
4) The effectiveness of the GSO is demonstrated through various analyses, including frequency and time domain evaluations, statistical tests, robustness analysis, and objective function changes. These analyses confirm the superiority of the GSO-based PID controllers compared to RSA, PDO, INFO, and the original GOA algorithms-based PID controllers.
5) The efficacy of the proposed GSO-based PID controller is further showcased by comparing it with other state-of-the-art algorithms-based PID controllers, further highlighting its superiority.

The paper's organization is as follows: Sections II and III present the structure of the original GOA and the proposed GSO approaches, respectively. Section IV provides an overview of the mathematical model of the employed DC motor and the PID controller, along with their integration for performing the speed control. The implementation of the proposed algorithm in the PID controlled DC motor system is given in Section V. Extensive analyses are performed to verify the superiority of the proposed algorithm through comparisons with previously reported studies, and the respective results are presented in Section VI. Finally, the paper concludes in Section VII.

II. GAZELLE OPTIMIZATION ALGORTHM

The gazelle optimization algorithm (GOA) is inspired by the survival abilities of gazelles. It leverages the gazelles' adaptive characteristics for real-world optimization problems [21]. This algorithm utilizes gazelles as search agents which are represented by a randomly initialized $n\times d$ matrix given in (1). To establish the permissible range of values for the population vector, the algorithm integrates the constraints of upper bound (UB) and lower bound (LB).

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,d-1} & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,d-1} & x_{2,d} \\ \vdots & \vdots & x_{i,j} & \vdots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,d-1} & x_{n,d} \end{bmatrix} \tag{1}$$

In (1), X denotes the position vectors matrix (candidate population). Each of $x_{i,j}$, position vector, is generated stochastically using (2) where UB_j and LB_j are the upper and lower bounds, respectively, for the problem whereas $rand$ is a random number. The variables n and d represent the gazelle number and the dimension of the problem, respectively.

$$x_{i,j} = rand \times \left(UB_j - LB_j\right) + LB_j \tag{2}$$

The most promising solution found thus far is identified as the minimum solution after generating candidate solution by $x_{i,j}$ in each iteration. Drawing inspiration from nature, where the fittest gazelles demonstrate remarkable skills in threat detection, alerting others, and predator evasion, we designate the top-performing gazelle as the best-obtained solution. This solution is then utilized in (3) to construct an Elite $n\times d$ matrix, acting as a reference for guiding the gazelles in determining their subsequent steps during the search process.

$$Elite = \begin{bmatrix} x'_{1,1} & x'_{1,2} & \cdots & x'_{1,d-1} & x'_{1,d} \\ x'_{2,1} & x'_{2,2} & \cdots & x'_{2,d-1} & x'_{2,d} \\ \vdots & \vdots & x'_{i,j} & \vdots & \vdots \\ x'_{n,1} & x'_{n,2} & \cdots & x'_{n,d-1} & x'_{n,d} \end{bmatrix} \tag{3}$$

In the present scenario, we denote the position vector of the leading gazelle as $x'_{i,j}$. After each iteration, we dynamically update the Elite matrix whenever a superior gazelle surpasses the current top gazelle. To ensure efficient exploration of the neighboring regions within the domain, we employ a controlled Brownian motion characterized by uniform and regulated steps. This random motion is subject to the Gaussian (normal) probability distribution function, having a variance (σ^2) of 1 and a mean (μ) of 0. The standard Brownian motion [26] can be defined as follows, considering a specific point x.

$$f_B\left(x, \mu, \sigma\right) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)} = \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{x^2}{2}\right)} \tag{4}$$

During grazing, a Brownian motion pattern is modelled for the movement of the gazelles. The mathematical model representing this behavior is given in (5).

$$g_{i+1} = g_i + s \cdot R * \cdot R_B * \cdot \left(Elite_i - R_B * \cdot g_i\right) \tag{5}$$

In the given context, g_{i+1} denotes the solution achieved in the subsequent iteration, while g_i represents the solution obtained in the current iteration. The parameter "s" characterizes the grazing speed of the gazelles. The vector R_B comprises random numbers designed to simulate Brownian motion, whereas R consists of uniform random numbers ranging from 0 to 1. When a predator is detected, the exploration phase commences. During this stage, the GOA adopts a strategy that involves Lévy flight, incorporating a combination of short steps and occasional long jumps. The Lévy distribution is mathematically described as per equation (6) [27].

$$L\left(x_j\right) \approx \left|x_j\right|^{1-\alpha} \tag{6}$$

In here, x_j denotes the flight distance, and α is the power-law exponent, which is restricted within the range (1, 2]. The Lévy stable process, represented as an integral in (7) [21], is defined as follows:

$$f_L\left(x; \alpha, \gamma\right) = \frac{1}{\pi} \int_0^\infty exp\left(-\gamma q^\alpha\right) cos\left(qx\right) \delta q \tag{7}$$

Here, the motion is governed by the distribution index (α), and γ represents the scale unit. GOA generates stable Lévy motion by adopting α values ranging from 0.3 to 1.99, and its formulation is provided in (8) [26].

$$Levy\left(\alpha\right) = 0.05 \times \frac{x}{|y|^{\frac{1}{\alpha}}} \tag{8}$$

The variables α, x, and y are defined as follows: x follows a normal distribution with variance σ_x^2 and mean 0, y follows a normal distribution with variance σ_y^2 and mean 0, and α is set to 1.5. The values of σ_x is calculated as given in (9) and $\sigma_y = 1$ [28].

$$\sigma_x = \left(\frac{\Gamma(1+\alpha)\sin\left(\pi\alpha/2\right)}{\Gamma\left(\left(1+\alpha\right)/2\right)\alpha 2^{((\alpha-1)/2)}}\right)^{1/\alpha} \tag{9}$$

This technique has shown enhanced search capability in optimization studies. The gazelle employs Lévy flight for its escape, while the predator initially adopts Brownian motion before transitioning to Lévy flight. The mathematical description of the gazelle's behavior in spotting the predator is given in (10).

$$\overrightarrow{g_{i+1}} = \overrightarrow{g_i} + S \cdot \mu \cdot \overrightarrow{R} * \cdot \overrightarrow{R_L} * \cdot \left(\overrightarrow{Elite_i} - \overrightarrow{R_L} * \cdot \overrightarrow{g_i}\right) \tag{10}$$

Here, S represents the top speed that the gazelle can achieve, $\overrightarrow{R_L}$ is a Lévy distribution-based vector of random numbers. The mathematical model in (11) describes the behavior of the predator as it chases the gazelle.

$$\overrightarrow{g_{i+1}} = \overrightarrow{g_i} + S \cdot \mu \cdot CF * \cdot \overrightarrow{R_B} * \cdot \left(\overrightarrow{Elite_i} - \overrightarrow{R_L} * \cdot \overrightarrow{g_i}\right) \quad (11)$$

In Eq. (11), CF represents the cumulative effect of the predator, calculated as $CF = (1 - iter/iterMax)^{(2*iter/iterMax)}$. The predator success rate ($PSRs$) has an impact on the gazelle's ability to escape and prevents local minima trapping. The effect of PSR is modeled in (12) where $\overrightarrow{U}$ is a constructed binary vector generated by a random number r from the interval [0, 1], such that $\overrightarrow{U} = 0$ for $r < 0.34$; otherwise $\overrightarrow{U} = 1$. The gazelle matrix contains random indexes of $r1$ and $r2$.

$$\overrightarrow{g_{i+1}} = \begin{cases} \overrightarrow{g_i} + CF\left[\overrightarrow{LB} + \overrightarrow{R} * \cdot \left(\overrightarrow{UB} - \overrightarrow{LB}\right)\right] * \cdot \overrightarrow{U}; \\ \quad if\ r \le PSRs \\ \overrightarrow{g_i} + [PSRs\,(1-r)+r]\left(\overrightarrow{g_{r1}} - \overrightarrow{g_{r2}}\right); else \end{cases} \quad (12)$$

III. PROPOSED GAZELLE SIMPLEX OPTIMIZER

The NM simplex method, known as the NM algorithm, stands as a widely recognized optimization technique, sought after for uncovering the extremum of a multidimensional cost function [29]. Its remarkable efficacy emerges when dealing with nonlinear objective functions devoid of explicit mathematical forms or derivatives. Rooted in the concept of a simplex—a geometric shape extending triangles to higher dimensions—the NM algorithm employs $N + 1$ points in N-dimensional space (N being the number of objective function variables) to construct a convex polytope, each point representing a potential solution. Iteratively, the NM algorithm dynamically refines this simplex toward optimal convergence.

During each iteration, the algorithm assesses the cost function at all $N + 1$ simplex vertices, subsequently sorting them based on their function values. These vertices undergo a sequence of geometric transformations: reflection, expansion, contraction, and shrinkage. By skillfully employing these transformations, the algorithm efficiently explores the objective function landscape.

When a reflected point produces a superior function value to the second-worst vertex, the reflected point is embraced, progressing the algorithm. If the reflected point lies between the second worst and worst vertices, an expansion transformation is initiated, delving further into that direction. Should the reflected point be worse than the worst vertex but superior to all other vertices, a contraction transformation is executed to venture closer to the favorable points. In the event that the reflected point is worse than the worst vertex and all others, a shrinkage transformation ensues, compacting the simplex. Iteratively, the NM algorithm pursues these transformations until predefined convergence criteria are met, such as reaching the maximum iterations or attaining a desired tolerance.

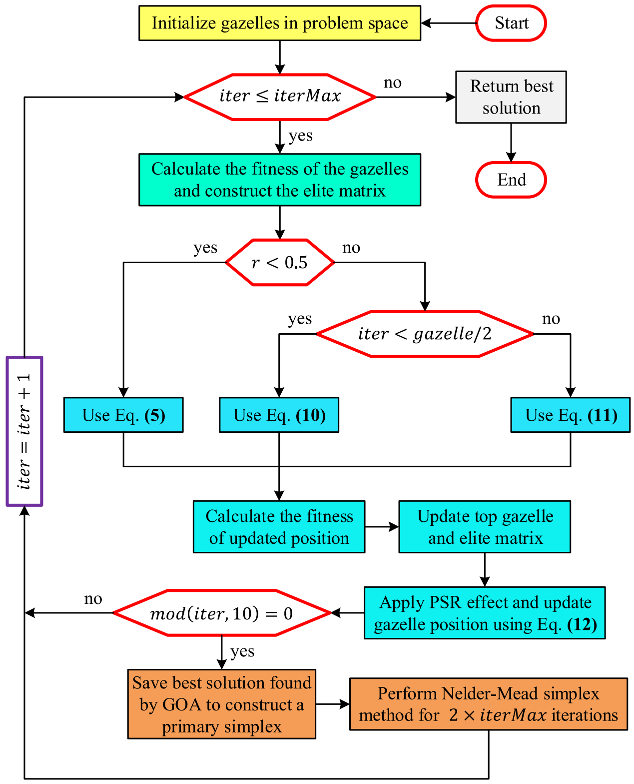

FIGURE 1. Process of gazelle simplex optimizer (GSO).

One of the remarkable aspects of the NM algorithm is its simplicity and robustness, able to handle diverse optimization challenges without requiring objective function derivatives [18]. Recognizing this unique attribute, our study ingeniously employs the NM algorithm as a supporting structure to enhance the exploitation phase of the GOA. In Figure 1, we illustrate the detailed process of gazelle simplex optimizer (GSO), ensuring a seamless integration without incurring significant computational burdens.

In our proposed hybrid version GSO, the original GOA initiates the agent positions' updates. After ten iterations, the acquired solution fosters the creation of a simplex, wherein the NM algorithm takes charge of further refinement. This iterative process of NM advances every ten iterations, performing twice the total number of iterations each time, culminating in a highly efficient and effective algorithm for tuning PID parameters employed in DC motor. This synergistic amalgamation of GOA and NM unlocks new possibilities for optimizing systems with increased precision and computational efficiency.

IV. PID CONTROLLED DC MOTOR SPEED REGULATION

A. OPEN LOOP MATHEMATICAL MODEL OF EXTERNALLY EXCITED DC MOTOR

In this study, we are dealing with a DC motor system, comprising a DC motor and a mechanical load. The main objective is to regulate the motor's speed and torque effectively through a control system. For the purpose of modeling, we have chosen a separately excited DC motor [30]. Figure 2

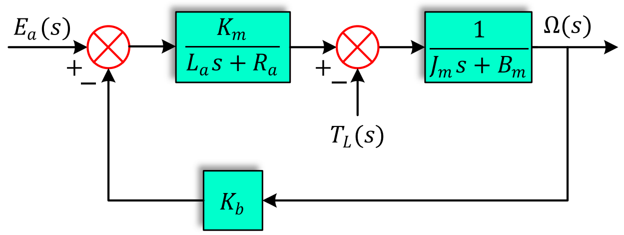

FIGURE 2. Block diagram of DC motor.

depicts the equivalent circuit representing this particular type of DC motor.

To develop a mathematical model of this system, it is considered as a linear time-invariant system and mechanical load is modeled as a constant torque ($T_L(s)$). Besides, the motor is fed with constant voltage input. With these assumptions, the DC motor system can be modeled using a set of differential equations that describe the dynamics of the motor's speed and torque. Let ω denote the motor's angular velocity, and τ denote the motor's torque. The dynamics of the system can be described by $J_m(d\omega/dt) = \tau - B_m\omega$ and $L_a(di/dt) = E_a - R_aI_a - K_b\omega$ where J_m is the motor's moment of inertia, B_m is the motor's damping coefficient, L_a is the motor's inductance, R_a is the motor's resistance, K_b is the motor's back electromotive constant, and E_a is the voltage applied to the motor. I_a is the motor's current, which is related to the torque by $\tau = K_m \cdot I_a$, where K_m is the motor's torque constant. These equations can be simplified by assuming that the motor's internal dynamics are much faster than the mechanical load's dynamics. Under this assumption, the motor's angular velocity ω can be assumed to be constant and equal to the commanded speed. With this simplification, the above equations can be reduced to $I_a = (E_a - K_b\omega)/R_a$ for the current. This equation shows that the motor's current is proportional to the applied voltage and inversely proportional to the motor's resistance. This allows control techniques to be used for designing a control system that regulates the motor's speed and torque by adjusting the applied voltage. Considering this explanation, the open-loop transfer function of a DC motor can be obtained as follows.

$$G(s) = \frac{K_m}{(J_m s + B_m)(L_a s + R_a) + K_m K_b} \tag{13}$$

B. FUNDAMENTALS OF PID CONTROLLER

The PID controller is a widely used feedback control system in engineering and industrial applications. It is designed to maintain a desired setpoint by continuously adjusting a control variable based on the difference between the setpoint and the actual process variable. The PID controller achieves this by considering three components, proportional (K_P), integral (K_I), and derivative (K_D), provided in (14) [6].

$$C(s) = K_P + \frac{K_I}{s} + K_D s \tag{14}$$

The overall PID control action is the sum of the individual proportional, integral, and derivative control actions. The PID controller continuously calculates the control action and adjusts the system output to maintain the process variable close to the desired setpoint, ensuring a stable and accurate control of various industrial processes.

C. PID CONTROLLED SPEED REGULATION OF DC MOTOR

A PID controlled system can be described with the following expression [31].

$$W(s) = \frac{\Omega(s)}{\Omega_{ref}(s)} = \frac{C(s)\,G(s)}{1 + C(s)\,G(s)} \tag{15}$$

In order to comply with earlier reported studies, the DC motor parameters are selected as 0.40Ω for R_a, 2.70 H for L_a, $0.0004 kg{\cdot}m^2$ for J_m, $0.0022 N{\cdot}m{\cdot}s/rad$ for B_m, $0.015 N{\cdot}m/A$ for K_m, and $0.05 V{\cdot}s/rad$ for K_b. Using those values and the transfer function provided in (15), the behavior of the PID controlled system can be characterized as follows.

$$W_{PID}(s) = \frac{15(K_D s^2 + K_P s + K_I)}{1.08 s^3 + (6.1 + 15K_D)\, s^2 + (1.63 + 15K_P)\, s + 15K_I} \tag{16}$$

V. NOVEL PID DESIGN VIA GSO

Initially, the respective engineering problems must be described as minimization problems such that the optimization algorithm can be used. In terms of the description of those systems as minimization problems, the following procedure is adopted in this study so that the parameters of the PID controller can be optimized. Firstly, the problem is represented as $\vec{X} = [x_1, x_2, x_3] = [K_P, K_I, K_D]$ and secondly the following ITAE (integral of time multiplied absolute error) [32] cost function can be adopted for appropriate minimization via GSO.

$$ITAE = \int_0^\infty t \times |e(t)| \times dt \tag{17}$$

In here, $e(t) = \omega_{ref}(t) - \omega(t)$ where $e(t)$ denotes the error signal between the reference speed, $\omega_{ref}(t)$, and the actual speed, $\omega(t)$. Alternatively, another cost function, known as ZLG [33], can also be used as a time domain metrics-based minimization tool. The ZLG cost function is defined as in (18):

$$ZLG = \left(1 - e^{-\varphi}\right) \times \left(e_{ss} + \frac{OS}{100}\right) + e^{-\varphi} \times (t_{st} - t_{rt}) \tag{18}$$

where φ is a balancing factor equals to 1, e_{ss} is the steady state error, OS is overshoot, t_{st} is the settling time and t_{rt} is the rise time. In this study, we aim to exploit the benefit of both ITAE and ZLG, thus, propose a new F objective function provided in (19).

$$F = (1 - \rho) \times ITAE + \rho \times ZLG \tag{19}$$

In here, ρ stands for the balancing coefficient between ITAE and ZLG and its value was set to $\rho = 0.95$. The respective value of the ρ coefficient was determined after extensive

TABLE 1. Control parameters and other settings of the employed algorithms.

Algorithm	Other control parameters
GSO (proposed)	$s \in [0,1]$, $\mu \in [-1,1]$, $S = 0.88$, $PSRs = 0.34$, $\rho = 1$, $\gamma = 2$, $\beta = 0.5$, $\delta = 0.5$
GOA [21]	$s \in [0,1]$, $\mu \in [-1,1]$, $S = 0.88$, $PSRs = 0.34$
RSA [23]	$\alpha = 0.1$, $\beta = 0.1$
PDO [24]	$\rho = 0.1$, $\varepsilon = 2.2204E-16$, $\Delta = 0.005$
INFO [25]	$c = 2$, $d = 4$

evaluations. Meanwhile, the minimization procedure is performed by considering the following constraints for the controller parameters; $10^{-3} \leq K_P, K_I, K_D \leq 25$ [20]. The proposed novel design strategy in this work is illustrated in detail with the bock diagram in Figure 3.

VI. SIMULATION RESULTS AND DISCUSSION

A. COMPARED RECENT ALGORITHMS

In order to provide a fair assessment for the performance evaluation of the proposed GSO, the state-of-the-art algorithms that have recently been reported are employed in this study for comparisons. In this regard, gazelle optimization algorithm (GOA) [21], reptile search algorithm (RSA) [23], prairie dog optimization (PDO) algorithm [24] and weighted mean of vectors optimization (INFO) algorithm [25] are employed for this study. Table 1 lists those algorithms along with their respective control parameters. The related control parameters are chosen with their default values in order to present fair assessment. Apart from those parameters, each algorithm is run 25 individual times using iteration number of 50 and population size of 30 in order to obtain results.

B. STATISTICAL ANALYSIS

Figure 4 presents a comparative boxplot analysis for five different algorithms, namely GSO, GOA, RSA, PDO, and INFO, with respect to their efficacy in minimizing the objective function. The boxplot, given in Figure 4, demonstrates that the worst value obtained by the GSO algorithm is significantly lower than the best values obtained by the other four algorithms (GOA, RSA, PDO, and INFO), thus highlighting the clear superiority of the proposed GSO algorithm in terms of performance.

Table 2 provides a statistical summary of the performance of the different algorithms in minimizing the objective function. The table shows that the GSO outperforms the others in all three metrics. It achieves the lowest minimum value (1.0047E−02), which is significantly better than the minimum values obtained by GOA (1.2889E−02), RSA (1.8543E−02), PDO (2.0484E−02), and INFO (1.4152E−02) algorithms. Similarly, the GSO algorithm also demonstrates superior performance in terms of the maximum objective function value (1.0510E−02), which is remarkably lower than the maximum values of GOA, RSA, PDO, and INFO algorithms. Furthermore, the average objective function value for GSO (1.0227E−02) is notably better than the averages of the other algorithms (GOA: 1.3216E−02, RSA: 1.9067E−02, PDO: 2.1105E−02, INFO: 1.4550E−02). These results indicate that the GSO consistently provides better solutions compared to the other algorithms in terms of the objective function. Table 2 also reveals that the GSO exhibits a significantly lower standard deviation (1.4035E−04) and variance (1.9699E−08) compared to GOA, RSA, PDO, and INFO algorithms. This indicates that the results obtained by the GSO are less dispersed and more stable than those of the other algorithms, further emphasizing its efficacy in optimizing the objective function. The GSO algorithm also achieves a median value of 1.0192E−02, which is better than the medians of GOA, RSA, PDO, and INFO algorithms (1.3184E−02, 1.9002E−02, 2.0991E−02, 1.4495E−02, respectively). This result reinforces the consistent and superior performance of the GSO compared to the other algorithms. Moreover, we assign a rank to each algorithm based on the collective evaluation of the statistical metrics. The GSO secures the top rank (1) among all the evaluated algorithms, signifying its clear superiority. GOA and INFO algorithms follow with ranks 2 and 3, respectively. On the other hand, RSA and PDO algorithms show relatively poorer performance, ranking 4 and 5, respectively.

C. CHANGE OF OBJECTIVE FUNCTION

The convergence curves demonstrating the change of the objective with respect to iteration numbers are presented in Figure 5. As depicted in the figure, the GSO is capable of converging to the lowest objective function value in later iterations, showing its better capability.

Table 3 displays the controller parameters (K_P, K_I,K_P) obtained via GSO, GOA, RSA, PDO and INFO algorithms. Using those parameter values, the transfer functions provided in (20), (21), (22), (23) and (24) can be obtained for GSO, GOA, RSA, PDO and INFO based PID controlled DC motor systems. The analyses presented in the following subsections are performed using those transfer functions.

$$W_{GSO-PID}(s) = \frac{64.95s^2+367.6s+95.47}{1.08s^3+71.05s^2+369.2s+95.47} \tag{20}$$

$$W_{GOA-PID}(s) = \frac{54.48s^2+310.2s+118.6}{1.08s^3+60.58s^2+311.8s+118.6} \tag{21}$$

$$W_{RSA-PID}(s) = \frac{45.29s^2+305.7s+107.2}{1.08s^3+51.39s^2+307.3s+107.2} \tag{22}$$

$$W_{PDO-PID}(s) = \frac{45.52s^2+332.9s+74.88}{1.08s^3+51.62s^2+334.6s+74.88} \tag{23}$$

$$W_{INFO-PID}(s) = \frac{46.91s^2+272.4s+78.23}{1.08s^3+53.01s^2+274s+78.23} \tag{24}$$

D. TIME RESPONSE ANALYSIS

The time response analysis provides valuable insights into the dynamic behavior and performance of PID-controlled DC motor systems. The step responses of different approaches are depicted in Figure 6 which are based on the data presented in Table 4. From Figure 6 and Table 4, it is evident that

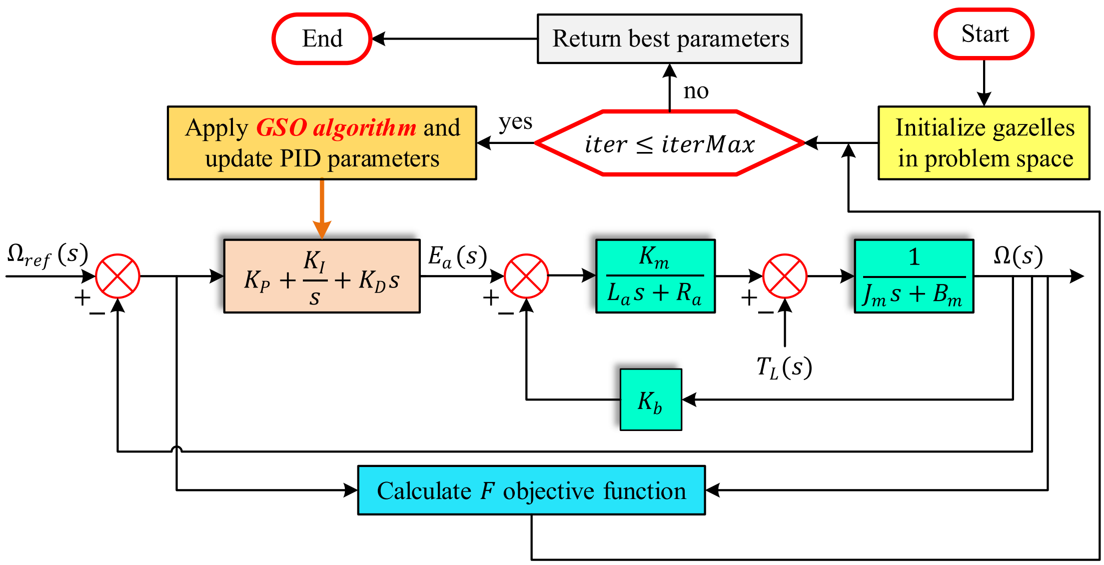

FIGURE 3. Block diagram of proposed GSO-based design for PID controlled DC motor system.

TABLE 2. Statistical performance of different algorithms to minimize objective function.

Statistical metric	GSO	GOA	RSA	PDO	INFO
Minimum	1.0047E−02	1.2889E−02	1.8543E−02	2.0484E−02	1.4152E−02
Maximum	1.0510E−02	1.3912E−02	2.0167E−02	2.2278E−02	1.5392E−02
Average	1.0227E−02	1.3216E−02	1.9067E−02	2.1105E−02	1.4550E−02
Standard deviation	1.4035E−04	2.5832E−04	4.0405E−04	4.6443E−04	3.0873E−04
Variance	1.9699E−08	6.6730E−08	1.6326E−07	2.1569E−07	9.5313E−08
Median	1.0192E−02	1.3184E−02	1.9002E−02	2.0991E−02	1.4495E−02
Rank	1	2	4	5	3

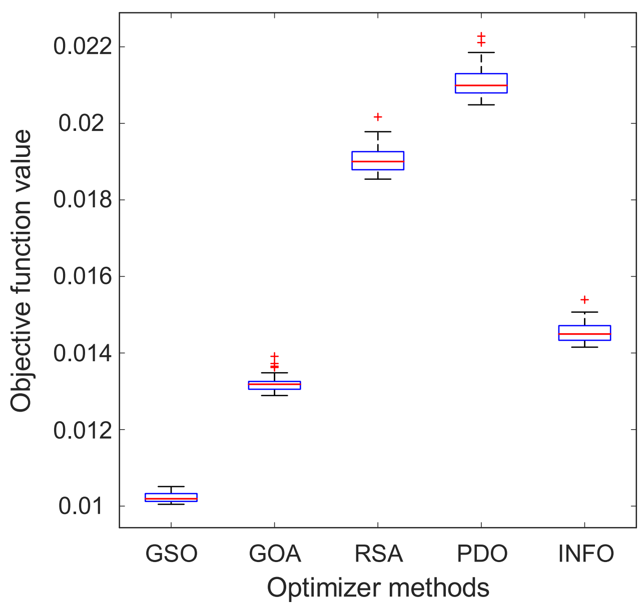

FIGURE 4. Boxplots of GSO, GOA, RSA, PDO and INFO algorithms.

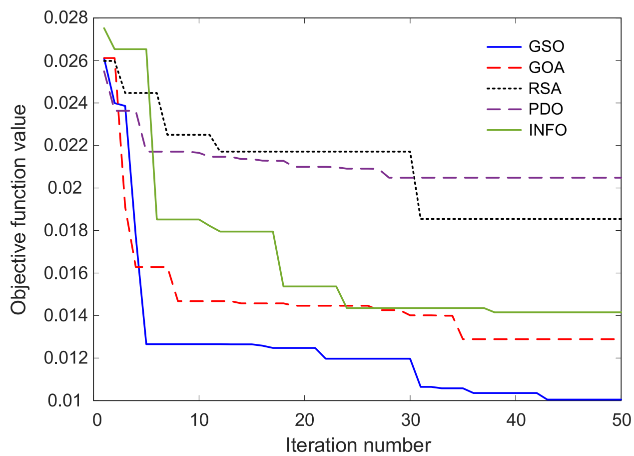

FIGURE 5. Convergence curves showing the change of the objective function values for GSO, GOA, RSA, PDO and INFO.

the GSO-based PID controlled DC motor system exhibits the fastest rise time of 0.0365 seconds among all the algorithms. In comparison, the rise times for the GOA, RSA, PDO, and INFO algorithms are 0.0434, 0.0491, 0.0476, and 0.0501 seconds, respectively. This result highlights the superior dynamic response of the GSO algorithm in achieving a fast rise to the desired output. In addition, the GSO-based PID controlled DC motor system demonstrates the shortest settling time of 0.065 seconds. Comparatively, the settling times for the GOA, RSA, PDO, and INFO algorithms are

TABLE 3. Controller parameters obtained via different algorithms.

Parameter	GSO	GOA	RSA	PDO	INFO
K_P	24.5037	20.6786	20.3786	22.1954	18.1598
K_I	6.3648	7.9084	7.1498	4.9920	5.2156
K_P	4.3300	3.6317	3.0193	3.0346	3.1276

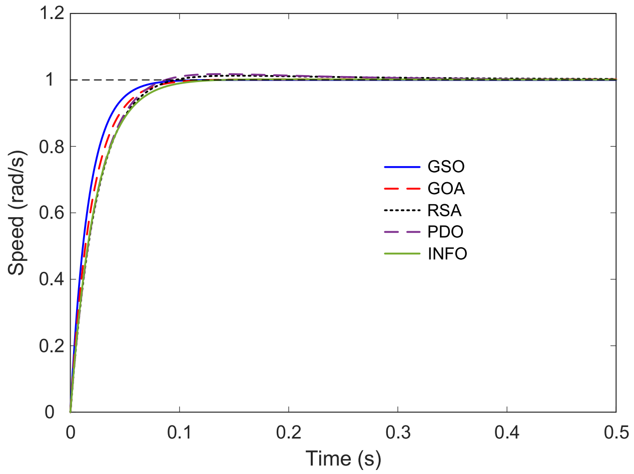

FIGURE 6. Step responses of GSO, GOA, RSA, PDO and INFO based PID controlled DC motor systems.

TABLE 4. Time response metrics for gso, goa, rsa, pdo and info algorithms.

Time response related performance metric	GSO	GOA	RSA	PDO	INFO
Rise time (s)	**0.0365**	0.0434	0.0491	0.0476	0.0501
Settling time (s)	**0.0650**	0.0765	0.0782	0.0735	0.0873
Overshoot (%)	**0**	0.0867	1.2753	1.7590	0.1440
Peak time (s)	**0.1218**	0.1453	0.1518	0.1378	0.1693

0.0765, 0.0782, 0.0735, and 0.0873 seconds, respectively. The shorter settling time for the GSO algorithm signifies its ability to stabilize the system's output faster and reduce transient oscillations effectively.

Moreover, the GSO-based PID controlled DC motor system has zero overshoot, providing a perfect response to the step input. In contrast, the overshoot values for the GOA, RSA, PDO, and INFO algorithms are 0.0867%, 1.2753%, 1.759%, and 0.144%, respectively. This result shows that the GSO algorithm delivers a superior control action with no overshooting and better control precision. Lastly, it can be observed that the GSO-based PID controlled DC motor system achieves the shortest peak time of 0.1218 seconds. The peak times for the GOA, RSA, PDO, and INFO algorithms are 0.1453, 0.1518, 0.1378, and 0.1693 seconds, respectively. This result further emphasizes the GSO algorithm's capability to expedite the system's response and reach the peak output faster.

E. FREQUENCY RESPONSE ANALYSIS

In this section, we perform a frequency response analysis of PID-controlled DC motor systems using different optimization algorithms. The Bode diagrams of these systems are depicted in Figure 7 (which is obtained from open-loop transfer function), and the corresponding frequency response metrics are presented in Table 5. From Table 5, we can observe that all algorithms have an infinite gain margin, signifying that the PID controlled DC motor systems are inherently stable under varying gain levels for all the evaluated optimization algorithms. In addition, the GSO-based PID controlled DC motor system has a phase margin of 89.9898°. Similarly, the phase margins for the GOA, RSA, PDO, and INFO algorithms are 89.9469°, 88.5266°, 87.7976°, and 89.7942°, respectively. These values indicate that all algorithms provide high phase margins, ensuring stable system responses even with slight phase lag.

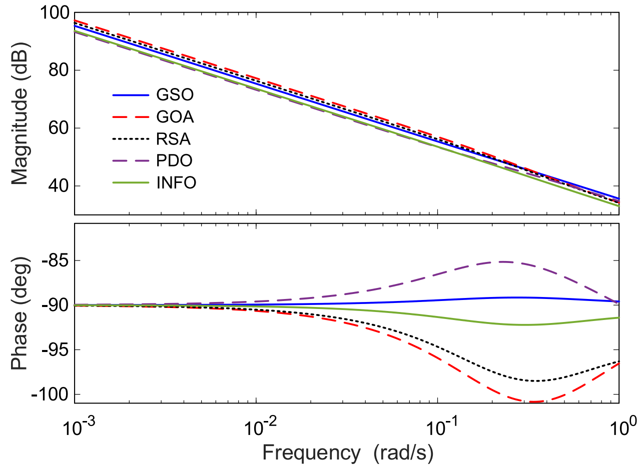

FIGURE 7. Bode diagrams of GSO, GOA, RSA, PDO and INFO based PID controlled DC motor systems.

TABLE 5. Frequency response metrics for GSO, GOA, RSA, PDO and INFO algorithms.

Frequency response related performance metric	GSO	GOA	RSA	PDO	INFO
Gain margin (dB)	**Inf.**	**Inf.**	**Inf.**	**Inf.**	**Inf.**
Phase margin (°)	**89.9898**	89.9469	88.5266	87.7976	89.7942
Bandwidth (rad/s)	**60.0087**	50.3594	43.0393	43.8810	43.5089

Moreover, we can observe that the GSO-based PID controlled DC motor system exhibits the widest bandwidth of 60.0087 rad/s among all the algorithms. The wider bandwidth of the GSO algorithm signifies its ability to handle a broader range of frequencies and respond more effectively to different input signals.

F. ROBUSTNESS ANALYSIS

In this section, we conduct a robustness analysis of the PID-controlled DC motor systems with respect to variations in motor parameters. Specifically, we investigate the

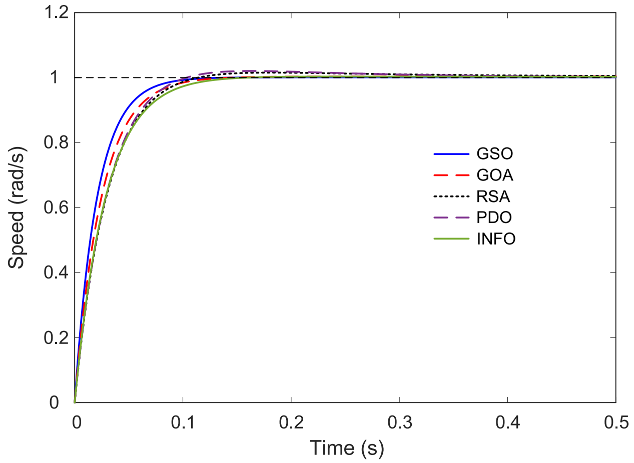

FIGURE 8. **Comparison of output speed responses for K_m= 0.012 and R_a= 0.30.**

TABLE 6. **Numerical results of time response analysis for K_m = 0.012 and R_a= 0.30.**

Time response related performance metric	GSO	GOA	RSA	PDO	INFO
Rise time (s)	0.0455	0.0541	0.0605	0.0583	0.0623
Settling time (s)	0.0804	0.0942	0.0946	0.1784	0.1071
Overshoot (%)	0.0382	0.2576	1.5485	2.0457	0.3077
Peak time (s)	0.1523	0.1818	0.1804	0.1636	0.2120

performance of the systems for four sets of motor parameters: (1) K_m= 0.012 and R_a= 0.30, (2) K_m= 0.018 and R_a= 0.30, (3) K_m= 0.012 and R_a= 0.50 and (4) K_m= 0.018 and R_a= 0.50. The comparison of output speed responses and the numerical results of time response analysis for each case are presented in Figures 8 to 11 and Tables 6 to 9, respectively.

Figure 8 illustrates the comparison of output speed responses for K_m= 0.012 and R_a= 0.30 set of motor parameters. From Table 6, it can be observed that the GSO-based PID controlled DC motor system achieves a rise time of 0.0455 seconds, a settling time of 0.0804 seconds, an overshoot of 0.0382%, and a peak time of 0.1523 seconds. Comparatively, the GOA, RSA, PDO, and INFO algorithms yield slightly different time response metrics for the same motor parameters. The GSO algorithm demonstrates competitive performance with other optimization algorithms, indicating its robustness in handling variations in motor parameters.

Figure 9 displays the comparison of output speed responses for K_m= 0.018 and R_a= 0.30 set of motor parameters. Table 7 presents the corresponding numerical results of the time response analysis. The GSO-based PID controlled DC motor system achieves a rise time of 0.0304 seconds, a settling time of 0.0539 seconds, no overshoot, and a peak time of 0.1015 seconds. The GSO algorithm consistently shows superior performance in terms of rise time and overshoot, while maintaining competitive settling and peak times with other algorithms. This performance demonstrates the robustness

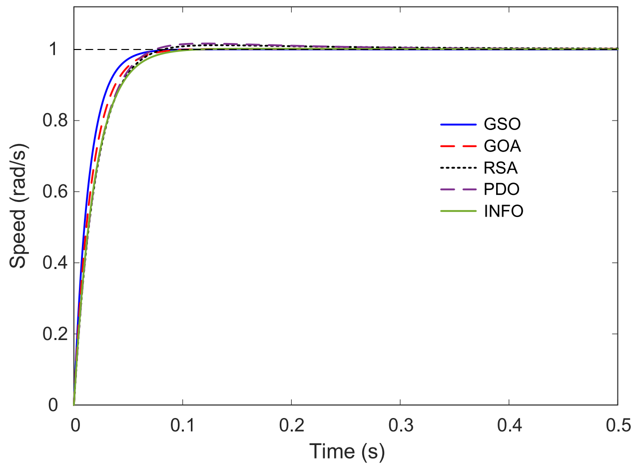

FIGURE 9. **Comparison of output speed responses for K_m= 0.012 and R_a= 0.50.**

TABLE 7. **Numerical results of time response analysis for K_m= 0.018 and R_a= 0.30.**

Time response related performance metric	GSO	GOA	RSA	PDO	INFO
Rise time (s)	0.0304	0.0361	0.0412	0.0400	0.0417
Settling time (s)	0.0539	0.0636	0.0662	0.0625	0.0726
Overshoot (%)	0	0.0993	1.2073	1.6652	0.1735
Peak time (s)	0.1015	0.1211	0.1315	0.1204	0.1411

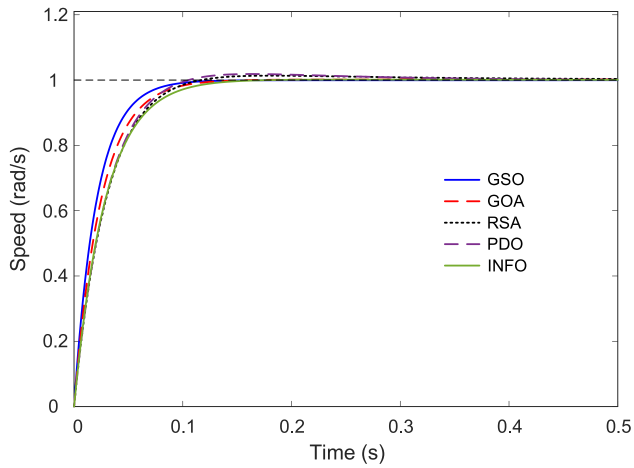

FIGURE 10. **Comparison of output speed responses for K_m= 0.018 and R_a= 0.30.**

of the GSO algorithm in handling different motor parameter values.

Figure 10 depicts the comparison of output speed responses for K_m= 0.012 and R_a= 0.50 set of motor parameters. Table 8 presents the corresponding numerical results of the time response analysis. The GSO-based PID controlled DC motor system achieves a rise time of 0.0457 seconds, a settling time of 0.0818 seconds, no overshoot, and a peak time of 0.1521 seconds. Similar to previous cases, the GSO algorithm consistently exhibits competitive performance in

TABLE 8. Numerical results of time response analysis for K_m= 0.012 and R_a= 0.50.

Time response related performance metric	GSO	GOA	RSA	PDO	INFO
Rise time (s)	0.0457	0.0544	0.0608	0.0586	0.0627
Settling time (s)	0.0818	0.0960	0.0959	0.0896	0.1094
Overshoot (%)	0	0.0792	1.3493	1.8515	0.1037
Peak time (s)	0.1521	0.1814	0.1814	0.1632	0.2116

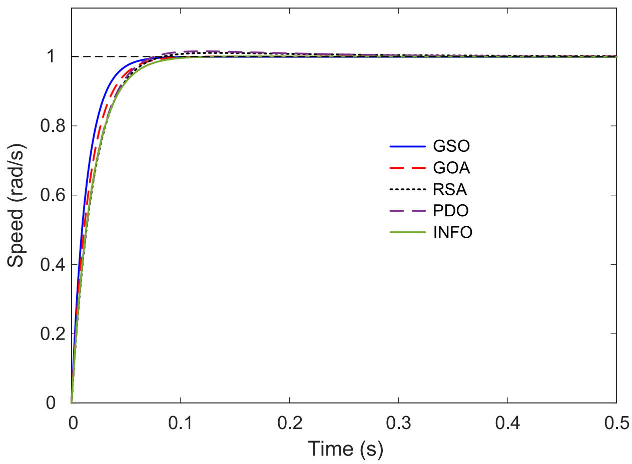

FIGURE 11. Comparison of output speed responses for K_m= 0.018 and R_a= 0.50.

TABLE 9. Numerical results of time response analysis for K_m= 0.018 and R_a= 0.50.

Time response related performance metric	GSO	GOA	RSA	PDO	INFO
Rise time (s)	0.0305	0.0363	0.0414	0.0402	0.0419
Settling time (s)	0.0545	0.0644	0.0669	0.0630	0.0736
Overshoot (%)	0	0	1.0715	1.5325	0.0355
Peak time (s)	0.1014	0.1210	0.1322	0.1202	0.1408

all time response metrics, indicating its robustness to variations in motor parameters.

Figure 11 illustrates the comparison of output speed responses for K_m= 0.018 and R_a= 0.50 set of motor parameters. Table 9 provides the corresponding numerical results of the time response analysis. The GSO-based PID controlled DC motor system achieves a rise time of 0.0305 seconds, a settling time of 0.0545 seconds, no overshoot, and a peak time of 0.1014 seconds. The GSO algorithm again displays superior performance in terms of rise time and overshoot, while remaining competitive in settling and peak times, further showcasing its robustness in handling variations in motor parameters.

G. COMPARISONS WITH OTHER REPORTED PID TUNING ALGORITHMS

In this section, we compare the performance of the GSO-based PID tuning algorithm with various other reported PID tuning algorithms listed in Table 10. The comparison is based on key time response metrics, namely rise time, settling time, overshoot, and peak time. To allow the repeatability tests by the readers, the controller parameters obtained by the respective algorithms are also provided in the table.

The GSO demonstrates competitive performance across the time response metrics compared to other reported PID tuning algorithms. It achieves a rise time of 0.0365 seconds, a settling time of 0.065 seconds, zero overshoot, and a peak time of 0.1218 seconds. The GSO outperforms hybrid SFS in all time response metrics, showing significantly faster rise and settling times, and no overshoot. It exhibits comparable or slightly better performance compared to LFDNM and LFD in terms of rise time, settling time, and overshoot. The GSO also achieves faster rise and settling times with zero overshoot, showcasing its superior performance over CS, GA, and hASO-SA. Moreover, it demonstrates faster rise and settling times with no overshoot, surpassing GWO, SCA, and ASO algorithms. Besides, the proposed GSO exhibits competitive performance with SMA, ISCA, and IWO in terms of rise time, settling time, and overshoot. Lastly, the GSO consistently outperforms PSO, CMA-ES, AOA, AOA-HHO, SFS, HHO, HGSO, OBL/HGSO, IKA, MMPA, MPA, GOA, WOA, EOA, and JAYA algorithms with notably faster rise and settling times and no overshoot.

H. DISCUSSION

In this study, we conducted a comprehensive analysis of the GSO's efficacy in tuning PID control parameters for DC motor systems. We compared the performance of the GSO with various other optimization algorithms, namely GOA, RSA, PDO, and INFO. The analysis encompassed statistical analysis, time response analysis, frequency response analysis, and robustness analysis to gain a comprehensive understanding of the GSO algorithm's capabilities.

The statistical analysis of the objective function minimization revealed that the GSO excels in providing superior values compared to the other algorithms. It consistently achieved the lowest minimum and maximum objective function values, as well as the best average, standard deviation, and variance. The ranking of the algorithms based on various statistical metrics also confirmed the GSO's top performance. These results emphasize the efficacy of the GSO in achieving optimal solutions for the PID control parameters, making it a compelling choice for DC motor control optimization.

The time response analysis further substantiated the GSO's efficacy. Across different sets of motor parameters, the GSO-based PID controlled DC motor systems consistently exhibited faster rise and settling times, zero overshoot, and shorter peak times compared to other algorithms. These results demonstrate the GSO's ability to generate stable and responsive control actions, indicating its superiority in optimizing PID parameters for dynamic DC motor systems.

In the frequency response analysis, the GSO continued to demonstrate its prowess. The GSO-based PID controlled DC motor systems exhibited infinite gain margins, high phase margins, and wider bandwidths, showcasing the algorithm's

TABLE 10. Performance evaluation with respect to other reported pid tuning algorithms.

Reference	Tuning algorithm	PID parameters			Time response-related performance metric			
		K_P	K_I	K_D	Rise time (s)	Settling time (s)	Overshoot (%)	Peak time (s)
Proposed	GSO	24.5037	6.3648	4.3300	**0.0365**	**0.0650**	**0**	**0.1218**
[34]	Hybrid SFS	6.6315	0.212	0.5993	0.1505	0.4801	6.2369	0.3171
[5]	LFDNM	19.5593	5.1566	3.4097	0.0462	0.0813	0.0324	0.1549
	LFD	17.2099	4.3981	3.0808	0.0516	0.0927	**0**	0.1708
	CS	13.9287	8.0760	2.1747	0.0683	0.1085	1.4751	0.2245
	GA	8.8569	6.0605	1.4641	0.1021	0.1620	1.8870	0.3854
[35]	hASO-SA	18.4258	3.3082	3.1755	0.0494	0.0866	0.0178	0.1667
[36]	GWO	6.8984	0.5626	0.9293	0.1388	0.2052	1.5062	0.3241
[37]	SCA	11.3163	0.5544	1.8072	0.0833	0.1382	0.1920	0.2359
[13]	ASO	11.9437	2.0521	2.4358	0.0692	0.1535	**0**	0.8885
[38]	SMA	18.6458	2.5235	3.1921	0.0491	0.0857	0.0163	0.1744
[39]	ISCA	18.8156	4.7628	3.3181	0.0476	0.0846	**0**	0.1590
[40]	IWO	1.5782	0.4372	0.0481	0.4189	1.2533	6.9759	0.8544
	PSO	1.5234	1.3801	0.0159	0.3560	1.8028	24.2406	0.8498
[41]	CMA-ES	17.3347	10.9710	0.2140	0.0799	0.8893	44.8522	0.1963
	AOA	17.057	4.8488	0.2917	0.0821	0.7138	37.7541	0.1957
	AOA-HHO	14.435	0.1636	1.7620	0.0743	0.2508	2.8376	0.1832
[42]	SFS	1.6315	0.2798	0.2395	0.5436	1.4475	**0**	8.5689
[43]	HHO	15.8581	3.6963	2.7732	0.0568	0.1003	**0**	0.1905
[44]	HGSO	13.4430	1.2059	2.2707	0.0684	0.1186	**0**	0.2187
	OBL/HGSO	16.9327	0.9508	2.8512	0.0546	0.0946	**0**	0.1749
[45]	IKA	17.8728	6.4852	3.7256	0.0445	0.0922	**0**	0.2089
[46]	MMPA	20	0.7448	1.7395	0.0635	0.2793	7.0059	0.1516
	MPA	20.5123	0.0468	1.3215	0.0675	0.2878	11.7809	0.1573
	GOA	18.8298	6.9433	1.5404	0.0675	0.3188	8.8271	0.1624
	WOA	19.7780	0.0017	1.8436	0.0627	0.2702	5.9537	0.1503
	EOA	19.9952	0.0630	1.7572	0.0634	0.2758	6.7823	0.1502
	JAYA	20	0.001	1.7387	0.0636	0.2766	6.9365	0.1515

robustness in handling a broad range of frequencies and maintaining stability in the control system. The GSO's exceptional performance in frequency domain analysis further underscores its efficacy in optimizing PID control parameters for varying motor dynamics.

The robustness analysis examined the GSO's performance under different motor parameter variations. The GSO-based PID controlled DC motor systems consistently delivered desirable time response metrics, demonstrating the algorithm's resilience to parameter changes. The ability of the GSO algorithm to provide stable and efficient control despite fluctuations in motor parameters enhances its suitability and reliability for real-world applications.

The comparison with a wide range of reported PID tuning algorithms highlighted GSO's superiority. The GSO outperformed or displayed competitive performance against other optimization algorithms across all key time response metrics. Its consistently faster rise and settling times, coupled with zero overshoot, set the GSO apart as an effective and efficient choice for PID parameter optimization.

Considering all the analyses performed in this study, it is evident that the GSO excels in optimizing PID control parameters for DC motor systems. Its ability to consistently provide superior objective function values, fast response times, stable control actions, and robust performance against parameter variations highlights its efficacy. The GSO offers significant advantages in terms of control system stability, responsiveness, and precision, making it a powerful tool for optimizing PID control parameters in dynamic systems.

In conclusion, the GSO's effectiveness in PID tuning for DC motor systems is demonstrated through comprehensive analyses and comparisons. Its consistent superiority over other optimization algorithms indicates its potential as a valuable tool for engineering applications where PID control is crucial. The GSO presents a promising avenue for enhancing control system performance, reducing operational costs, and achieving higher efficiency in various engineering domains.

VII. CONCLUSION

In this study, we conducted a thorough investigation into the efficacy of the GSO (a hybrid version of GOA and NM with improved capability) in tuning PID control parameters for speed regulation of DC motor. Through comprehensive analyses and comparisons with other state-of-the-art optimization algorithms, we sought to assess the GSO's capabilities and its potential as a valuable tool for engineering applications. The statistical analysis of the objective function minimization demonstrated that the GSO consistently outperforms other algorithms. It provided lower minimum and maximum objective function values, better averages, and reduced dispersion, establishing its proficiency in delivering optimal solutions for PID control parameter tuning. In the time response analysis, the GSO-based PID controlled DC motor systems exhibited superior performance with faster rise and settling times, zero overshoot, and shorter peak times compared to other algorithms. These results emphasized the GSO's effectiveness in generating stable and responsive control actions, making it a promising choice for dynamic DC motor control optimization. In the frequency response analysis, the GSO algorithm showcased its robustness and stability by achieving infinite gain margins, high phase margins, and wider bandwidths. This capability enables the GSO to optimize PID parameters for varying motor dynamics, enhancing its suitability for a wide range of control applications. Furthermore, the robustness analysis revealed the GSO's reliability and adaptability in handling parameter variations. The GSO-based systems consistently delivered desirable time response metrics, further enhancing the algorithm's attractiveness for real-world applications where parameter uncertainty is prevalent. The comparison with other reported PID tuning algorithms across various time response metrics established the GSO as a frontrunner, consistently outperforming or displaying competitive performance. The GSO's consistent superiority in terms of stability, responsiveness, and control precision underscored its potential as an effective and efficient choice for PID parameter optimization.

In conclusion, this study has demonstrated the remarkable efficacy of the GSO in tuning PID control parameters for the speed regulation of DC motor systems. The GSO's consistent outperformance of other algorithms across a range of metrics highlights its potential as a powerful tool for engineering applications. Its ability to provide optimal solutions, stability, responsiveness, and robustness even in the face of parameter variations positions it as a significant contribution to the field of control optimization. As we look ahead, several potential avenues for future research emerge. One promising direction could involve the application of the GSO in more complex and multifaceted control systems, exploring its adaptability to different types of motors and diverse operational conditions. Additionally, investigating the integration of the GSO with advanced machine learning techniques or exploring its use in real-time control systems could further enhance its capabilities. Furthermore, the extension of this work to address multi-objective optimization problems and the incorporation of hardware experiments to validate the algorithm's performance in practical scenarios represent exciting opportunities for future research. These potential avenues hold the promise of advancing the state-of-the-art in control optimization and strengthening the GSO's position as a transformative tool for engineers and researchers in various domains.

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