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An intelligent PID controller tuning for speed control of BLDC motor using driving training-based optimization

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ABSTRACT

Tuning of proportional-integral-derivative (PID) controller remains a matter of great concern for the control engineers as it plays a major role to obtain optimal performance of any system Due to their simplicity and excellent efficiency, metaheuristic algorithms have recently become extremely popular among researchers for handling a wide range of real-world optimization challenges. In order to optimize a PID controller for managing the speed of a BLDC motor, this work proposes a novel application of the driving training-based optimization (DTBO) algorithm, one of the latest and most recent human-based metaheuristic algorithms. The purpose of this present study is to optimize a PID controller for a BLDC motor speed control by DTBO method and evaluate its performance with a similar controller tuned by grey wolf optimization (GWO) method. Additionally, the suggested DTBO-PID controller's robustness analysis is being carried out with BLDC motor parameter modifications as well as a comparison to the GWO-PID controller. The comparison is carried out in MATLAB/Simulink, and the results are based on common step response metrics such rise time, settling time, and maximum overshoot. For easier comprehension, the results are presented in tabular and graphical form. The chosen BLDC motor drive system's selected DTBO-PID controller performs better and is more reliable than the GWO-PID controller, according to the final simulation findings.

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1. INTRODUCTION

One of the emerging motors gaining popularity among researchers is the brushless DC (BLDC) motor owing to its benefits such as excellent efficiency, significant power density, robustness and minimal operating expenses [1]. A proper controller, a predetermined objective function, and an optimization technique are also necessary components of an intelligent drive system [2], [3]. The controller is what makes a system intelligent, and examples include neuro-fuzzy controllers, fuzzy logic controllers, and proportional-integral-derivative (PID) and fractional order PID (FOPID) controllers based on metaheuristics [4]–[6]. The optimization method is intended to be used to formulate the objective or fitness function depending on the desired specifications and restrictions [7].

Metaheuristic or intelligent algorithms are being mostly used in engineering fields with domains including power system [8], [9], electrical drives [5], [7] industrial engineering [10], and mechanical engineering [11], [12]. However, literature review reveals that various optimization algorithms do exist to optimize any controller for solving any real-world application. A wide range of algorithms, including the genetic algorithm (GA) [13], [14] the particle swarm optimization (PSO) [15], [16], the ant colony optimization (ACO) [17], the modified differential evolution [18], the teaching-learning-based optimization (TLBO) [19], the firefly algorithm (FA) [20], the bacterial foraging (BF) [21], the artificial bee colony optimization (ABC) [22], the simulated annealing (SA) [23], the grey wolf optimization (GWO) [24], the whale optimization algorithm (WOA) [25], the flower pollination [26], the salp swarm algorithm (SSA) [27], and the coronavirus optimization algorithm (COA) [28] have been implemented for controller tuning in achieving speed control of a BLDC motor. All of these studies have come to the conclusion that choosing an appropriate optimization algorithm is crucial for improving the control ability of any controller type for a BLDC motor. The goal of the current study is similar to that of the previous ones, but it implements a novel method of controller tuning for BLDC motor drive using the driving training-based optimization (DTBO) algorithm.

One recently proposed meta-heuristic algorithm, DTBO, resembles human driving training mathematically [29]. A number of benchmark functions have been used to successfully assess the performance of the aforementioned optimization, but only a handful of real-life applications, such as those for fuel technological advances [30], computational signal processing [31], and detection of gas leaks [32], has been observed. Following a thorough review of the literature, the authors were unable to locate any appropriate applications of the DTBO algorithm in improving the gain parameters of a PID controller intended to drive a BLDC motor.

In this present study, optimal gain parameters of a PID controller have been determined by means of a very recent DTBO algorithm to regulate a BLDC motor. The results so obtained are then being compared with those obtained by the GWO method, which have proved to be more effective than PSO [24]. The paper, consisting of six sections, starts with introduction and works of literature review. The proposed system model, the mathematical model of the system under consideration, and a thorough explanation of the DTBO approach are all included in the second section. The proposed DTBO-PID controller is implemented in section three in order to manage the speed of the BLDC motor, and the proposed DTBO-PID and existing GWO-PID controllers are compared in section four. Section five of the study includes a robustness examination of the suggested system, and it concludes with a section on conclusion.

2. PROPOSED SYSTEM MODEL

For the current investigation, a BLDC motor is chosen whose speed will be governed by a PID controller. A meta-heuristic optimization approach is used to minimize an objective function as part of the controller tuning process. Block diagram of the closed loop system model is shown in Figure 1, primarily consisting of four subsystems: a BLDC motor for the system plant, a PID controller for the controller, ITAE for the objective function, and DTBO for the metaheuristic algorithm.

2.1. Modelling of BLDC motor

With a good mathematical model comprising all the dynamics of a particular system, it is possible to analyze the system's behavior under different conditions, predict its response to various inputs, and design a controller that can manipulate the system to achieve desired outcomes. A permanent magnet motor with a trapezoidal back electromagnetic field waveform is a BLDC motor. The three-phase inverter, which is thought to be driven in the two-phase conduction mode, uses electronic commutation, which consists of six semiconductor switches (power transistors) [1], [33]. The rotor position required for inverter switching is provided by three Hall effect sensors being attached on the stator and separated by 120 electrical degrees. A typical BLDC motor can be mathematically modelled using a transfer function, differential equation, or state-space equations. However, the transfer function based mathematical model is being considered in the present work as it is frequently employed in automatic control sectors. The back emf and electromagnetic torque mechanisms for each conducted phase winding are identical to those of the conventional brushed DC motor, hence similar analysis techniques can be applied. Figure 2 shows the equivalent electric circuit of a BLDC motor.

The phase voltages of the armature winding are given by (1) to (3).

$$v_a = i_a R + L\frac{di_a}{dt} + e_a \tag{1}$$

$$v_b = i_b R + L\frac{di_b}{dt} + e_b \tag{2}$$

$$v_c = i_c R + L\frac{di_c}{dt} + e_c \tag{3}$$

Where, V_a, V_b and V_c are the terminal phase voltages in volt, i_a, i_b and i_c are the phase currents in ampere, R is the armature phase resistance, L and M are the armature self- and mutual-inductances in henry respectively, and e_a, e_b and e_c are the back emf of motor in volt.

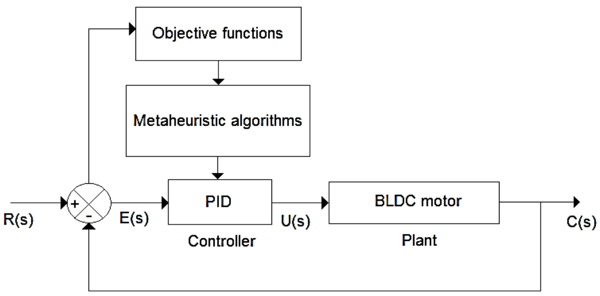

Figure 1. Block schematic of the proposed closed- loop system model

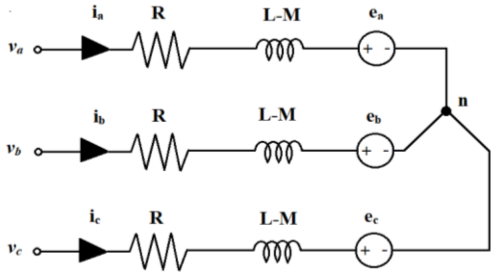

Figure 2. Equivalent electric circuit of BLDC motor

In two-phase conduction mode, either of the two phases *ab* or *bc* or *ca* are excited at a time resulting to simplified equivalent circuit as shown in Figure 3. When the windings of phases *a* and *b* are conducting, then (4) and (5) exists.

$$i_a = -i_b = i \tag{4}$$

$$\frac{di_a}{dt} = -\frac{di_b}{dt} = \frac{di}{dt} \tag{5}$$

Also, ignoring the transient phase (i.e. the trapezoidal sharp border in the back emf profile), the staedy $e_b = - e_a$, the line voltage can be represented by (6).

$$v_{ab} = V_d = i.2R + 2(L - M)\ \frac{di}{dt} + 2e_a = i.R_a + L_a\frac{di}{dt} + K_e\omega \tag{6}$$

Where, V_d represents the voltage of the DC bus in volt, $R_a = 2R$ represents the corresponding line resistance of winding in ohm, $L_a = 2(L\text{-}M)$ represents the corresponding line inductance of winding in henry, K_e represents the back emf constant in V/rads^{-1}, and ω represents the rotor angular speed in rad/s.

Finally, (7) provides the motion equation necessary to construct a comprehensive mathematical model of an electromechanical system.

$$T_{em} - T_l = J_m\frac{d\omega}{dt} + B\omega \tag{7}$$

Where, T_{em} represents electromagnetic torque in Nm, T_l represents load torque in Nm, J_m represents rotor moment of inertia in kgm^2, and B represents viscous friction coefficient in Nm/rads^{-1}.

Substituting $T_{em} = K_t i$, where K_t represents the torque constant in Nm/A, and I represent the steady phase current in ampere, in (7), we get (8).

$$K_t i - T_l = J_m\frac{d\omega}{dt} + B\omega \tag{8}$$

Assuming $T_l = 0$ in (8), the current can be found from (9).

$$\mathrm{i} = \frac{J_m}{K_t}\frac{d\omega}{dt} + \frac{B}{K_t}\omega \tag{9}$$

Substituting (9) in (6) and rearranging, we get (10).

$$V_d = \frac{L_a J_m}{K_t}\frac{d^2\omega}{dt^2} + \frac{R_a J_m + L_a B}{K_t}\frac{d\omega}{dt} + \frac{R_a B + K_e K_t}{K_t}\omega \tag{10}$$

The open-loop motor transfer function, which illustrates the relationship between motor angular speed and applied voltage under the ideal no-load condition (i.e., T_l=0), may be represented as (11) using the Laplace transformation of (10).

$$G_p(s) = \frac{\omega(s)}{V_d(s)} = \frac{K_t}{L_a J_m s^2 + (R_a J_m + L_a B)s + (R_a B + K_e K_t)} \quad (11)$$

So, as illustrated in Figure 4, a BLDC motor control system on no-load can be constructed using a transfer function-based framework.

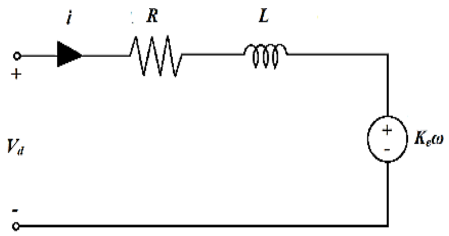

Figure 3. Excited BLDC motor's approximated equivalent circuit with two phase windings

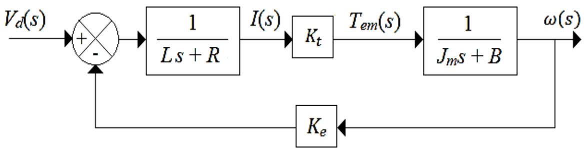

Figure 4. A BLDC motor control system

2.2. PID controller

One of the most prominent feedback controllers used in the field of control engineering is the PID controller [34]. A PID controller's block diagram is presented in parallel form in Figure 5. It has three variables: proportional gain (K_p), integral gain (K_i), and derivative gain (K_d), which provides past, present, and future controls.

The PID controller's output in time domain is represented by (12).

$$u(t) = K_p e(t) + K_i \int_0^t e(t).dt + K_d \frac{d}{dt} e(t) \quad (12)$$

Where, *e(t)* denotes the error signal and *u(t)* denotes the controller output signal.

The transfer function of the controller can be ascertained by applying the Laplace transformation in (12) and is given in (13).

$$G_c(s) = \frac{U(s)}{E(s)} = K_p + \frac{K_i}{s} + K_d.s = K_p \left\{1 + \frac{1}{T_i s} + T_d s\right\} \quad (13)$$

Where, T_i is the reset time (=K_p/K_i) and T_d is the derivative or rate time (=K_d/K_p).

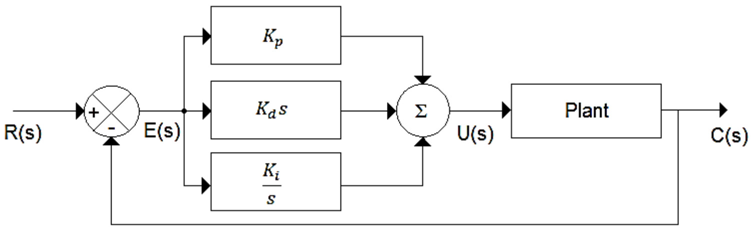

Figure 5. Block diagram of PID controller

2.3. Objective function

It is crucial to establish an objective function (or fitness function) before building an optimization-based PID controller, as this will serve as the foundation for controller tuning. The integral of time multiplied by absolute error (ITAE) [35], which has the mathematical representation (14), is the objective function used in this study.

$$ITAE = \int_0^t t.|e(t)|.dt \quad (14)$$

Where, *t* denotes the run time in second.

The gain parameters of the PID controller's limits serve as the problem constraints. Since the primary objective of an optimization issue is to minimize error, the design problem can be written as an error minimization problem as follows:

$$Objective\ function = Minimize\ (f);\ where,\ f \in ITAE \quad (15)$$

Subject to limitations

$$K_{pmin} \leq K_p \leq K_{pmax} \quad (16)$$

$$K_{imin} \leq K_i \leq K_{imax} \quad (17)$$

$$K_{dmin} \leq K_d \leq K_{dmax} \quad (18)$$

2.4. Metaheuristic algorithm

In the event a PID controller is tuned, its gain values are found in order to produce a rapid output with little variation from the set point and that reacts quickly to disturbances or set point changes with little overshoot. In today's world, metaheuristic optimization algorithms have become popular among research scholars and scientists mainly in different engineering fields. Notable features of such algorithms are simple and easy to implement, no gradient information is required, ability to reach global optima, and inspired from real-world phenomena. The findings of a fairly recent DTBO method for optimizing a PID controller for a BLDC motor are compared with those of the GWO method in this paper.

2.4.1. Driving training-based optimization (DTBO)

DTBO is a population-based technique that was very recently introduced in [29]. It was motivated by how people learn to drive in driving schools and by the instructor-training programmers. A student driver has the choice to select an instructor from a variety of available ones at the driving school. The selected instructor then instructs the novice driver in a variety of techniques. The student driver follows the instructor's recommendations when driving based on the tactics and skills they have gained. Additionally, self-practice could aid in enhancing the trainee driver's driving abilities. The researchers were motivated to create a mathematical model for carrying out optimization based on these intelligent human interactions between a learner driver and the instructor. The following two steps make up the entire algorithm.

- Reset the population's positions

The population matrix described in (19) is used to model the DTBO members, which are driving instructors and learners, as potential candidate solutions.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{NXm} = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{Nm} \end{bmatrix}_{NXm} \quad (19)$$

Where, *m* represents the total count of problem variables, *N* represents the population size, *X* represents the population matrix, X_i represents the i^{th} candidate solution, $x_{i,j}$ represents the j^{th} variable value estimated by the i^{th} candidate solution, and so forth.

However, using (20), the member spots are initialised at random.

$$x_{i,j} = lb_j + r.(ub_j - lb_j), i = 1,2,\ldots,N, j = 1,2,\ldots,m \quad (20)$$

Where, *r* is an arbitrary integer between [0,1], ub_j and lb_j are the respective upper and lower limits of the j^{th} problem variable.

- Specify and assess the objective function

Each potential solution is given a specific value, and it is this value that is used to assess the problem's objective function. Each potential solution's corresponding values of the objective function are calculated and represented into a vector using (21).

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{NX1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{NX1} \quad (21)$$

Where, F_i stands for the objective function's value corresponding to the i^{th} candidate solution and F stands for the objective function's vector.

Among all the computed values so obtained from (21), the member with the greatest fitness score of the objective function is regarded as the best candidate solution (X_{best}). The next three distinct phases must each be applied to the best member in order to improve and update it.

i) Phase 1: Instructor-led driving training (exploration)

The selection of an instructor from the population comes first, followed by the beginner's learning in the first phase of the DTBO update. The population's best members are classified as driving teachers, while the others as trainee drivers. Learning the instructor's driving techniques causes population members to roam throughout the search environment, boosting DTBO's exploration capabilities and helping to identify the ideal location. The objective function values are compared at each iteration, and the matrix of driving instructors is built with N members as illustrated in (22).

$$DI = \begin{bmatrix} DI_1 \\ \vdots \\ DI_i \\ \vdots \\ DI_{N_{DI}} \end{bmatrix}_{N_{DI}Xm} = \begin{bmatrix} DI_{11} & \cdots & DI_{1j} & \cdots & DI_{1m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ DI_{i1} & \cdots & DI_{ij} & \cdots & DI_{im} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ DI_{N_{DI}1} & \cdots & DI_{N_{DI}j} & \cdots & DI_{N_{DI}m} \end{bmatrix}_{N_{DI}Xm} \quad (22)$$

Where, DI represents the matrix of driving instructors, DI_i represents the i^{th} driving instructor, $DI_{i,j}$ represents the j^{th} dimension of i^{th} driving instructor; also $N_{DI} = [0.1 \times N \times (1-t/T)]$ gives the count of driving instructors, where, t represents the present iteration, and T represents the maximum iteration count.

Using (23), the revised locations for each member are determined.

$$x_{i,j}^{P1} = \begin{cases} x_{i,j} + r.(DI_{k_i,j} - I.x_{i,j}), F_{DI_{k_i}} < F_i; \\ x_{i,j} + r.(x_{i,j} - DI_{k_i,j}), otherwise, \end{cases} \quad (23)$$

Where, $x_{i,j}^{P1}$ denotes the i^{th} candidate's new value estimated in phase 1, I denotes an arbitrary integer within {1,2}, r is a random integer between [0,1], DI_{k_i} denotes a randomly chosen driving instructor to teach the i^{th} candidate, where, k_i is randomly chosen from $\{1,2,\ldots,N_{DI}\}$, $x_{i,j}$ denotes the j^{th} dimension of i^{th} candidate in phase 1, $DI_{k_i,j}$ denotes its j^{th} dimension, and $F_{DI_{k_i}}$ denotes the value of its objective function.

If the updated position enhances the objective function value, it replaces the old one by using (24).

$$X_i = \begin{cases} X_i^{P1}, F_i^{P1} < F_i; \\ X_i, otherwise, \end{cases} \quad (24)$$

Where, X_i^{P1} denotes the i^{th} candidate's new solutions estimated in phase 1, and F_i^{P1} denotes its objective function value.

ii) Phase 2: Modelling of the instructor's skills for the student driver (exploration)

The student driver develops skills in the second phase of the DTBO update by copying the instructor's tactics and gestures. Candidates are forced to move to various locations in the search space in this case, improving their ability to explore. The mathematical representation of this is (25).

$$x_{i,j}^{P2} = P. x_{i,j} + (1 - P). DI_{k_i,j} \quad (25)$$

Where, $x_{i,j}^{P2}$ denotes the i^{th} candidate's new value estimated in phase 2, while $P=0.01+0.9(1-t/T)$ represents the patterning index.

If the updated position enhances the objective function value, it replaces the old one by using (26).

$$X_i = \begin{cases} X_i^{P2}, F_i^{P2} < F_i; \\ X_i, otherwise, \end{cases} \quad (26)$$

Where, X_i^{P2} denotes the i^{th} candidate's new solutions estimated in phase 2, and F_i^{P2} denotes its objective function value.

iii) Phase 3: Individual practice (exploitation)

The trainee driver's self-practice to improve his driving abilities is part of the third phase of the DTBO update, and it helps him achieve his personal best by finding a better position based on a local search around his current position. Thus, this stage demonstrates DTBO's ability to take use of local search. Using (27), a position is first generated over each population member in order to represent this mathematically.

$$x_{i,j}^{P3} = x_{i,j} + (1 - 2r). R. \left(1 - \frac{t}{T}\right). x_{i,j} \quad (27)$$

Where, $x_{i,j}^{P3}$ denotes the i^{th} candidate's new value estimated in phase 3, and R=0.05.

If the updated position enhances the objective function value, it replaces the old one by using (28).

$$X_i = \begin{cases} X_i^{P3}, F_i^{P3} < F_i; \\ X_i, otherwise, \end{cases} \quad (28)$$

Where, X_i^{P3} denotes the i^{th} candidate's new solutions estimated in phase 3, and F_i^{P3} denotes its objective function value.

The population members are updated following the first through third phases, resulting in the endpoint of a single DTBO iteration. The members are updated through (22) to (28) up to the maximum iterations permitted by the algorithm before moving on to the next one. The final step is the presentation of the solution, which is the best candidate solution discovered throughout the execution of the full DTBO algorithm. Figure 6 displays the DTBO algorithm's pseudo-code.

```
Start DTBO.
    Input: The information of optimization problem.
    Adjust N and T.
    Initialize the DTBO population position and evaluate
    the objective function.
    For t = 1 to T
        For i = 1 to N
        Phase 1: Training by the driving instructor (exploration).
            Determine the driving instructor matrix based on comparison
            of objective function values.
            Select a driving instructor at random from the matrix DI.
            Calculate the new position of the ith DTBO member
            using Equation (23).
            Update position of the ith DTBO member using Equation (24).
        Phase 2: Patterning of the instructor skills of the student
        driver (exploration).
            Calculate the patterning index P.
            Calculate the new position of the ith DTBO member
            using Equation (25).
            Update position of the ith DTBO member using Equation (26).
        Phase 3: Personal practice (exploitation).
            Calculate the new position of the ith DTBO member
            using Equation (27).
            Update position of the ith DTBO member using Equation (28).
        End.
        Update the best obtained candidate solution.
    End.
    Output: The best candidate solution obtained by DTBO.
End DTBO.
```

Figure 6. DTBO algorithm's pseudo-code

3. IMPLEMENTATION OF DTBO-PID CONTROLLER FOR SPEED CONTROL OF BLDC MOTOR

Table 1 contains a list of the BLDC motor's specifications [36] that were employed in this study. The open-loop motor transfer function $G_P(s)$ can be found by replacing the values in Table 1 in (11), which is represented by (29).

$$G_p(s) = \frac{0.84}{1.376e-06s^2 + 6.4017e-03s + 0.7136} \tag{29}$$

A personal computer with an Intel®i5 2.5 GHz processor and 8.00 GB RAM is used to simulate the drive's transient response using the DTBO algorithm on the MATLAB/Simulink (version R2020a) platform. The proposed system's Simulink model with DTBO-based PID tuning for the ITAE performance measure is depicted in Figure 7. The Simulink model displayed in Figure 7 has been utilized for evaluating the DTBO-PID approach in MATLAB. The proposed DTBO algorithm's various parameter values are listed in Table 2. Figure 8 shows the convergence graph of ITAE objective function using the DTBO technique to determine the PID controller's optimal gain values. The acquired DTBO-based PID controller gain values after the optimization procedure has been successfully completed are K_p = 8.4131, K_i = 961.421, and K_d = 1.97e-08. The transfer function of the PID controller is shown in (30), obtained by substituting these gain values in (13).

$$G_c(s) = 8.4131 + \frac{961.421}{s} + 1.97e-08s \tag{30}$$

By multiplying the transfer functions of the controller (PID) and plant (BLDC motor), the transfer function of forward path open-loop system is obtained and stated in (31).

$$G_F(s) = G_c(s) * G_p(s) = \frac{1.6548e-08s^2 + 7.067s + 807.5936}{1.376e-06s^3 + 6.4017e-03s^2 + 0.7136s} \tag{31}$$

Finally, the transfer function of closed-loop DTBO-PID based BLDC motor system with unity feedback (*H(s)=1*) is determined by (32).

$$G_{CL}(s)_{DTBO-PID} = \frac{1.6548e-08s^2 + 7.067s + 807.5936}{1.376e-06s^3 + 6.4017e-03s^2 + 7.7806s + 807.5936} \tag{32}$$

Table 1. Specifications of BLDC motor

Parameter	Value	Unit
Number of phases	3	-
Number of poles	6	-
Stator phase resistance	8	Ω
Stator phase inductance	1.72	mH
Rotor moment of inertia	0.0008	kgm^2
Friction co-efficient	0.001	Nms
Torque constant	0.84	Nm/A
Back emf constant	0.84	$V/rads^{-1}$

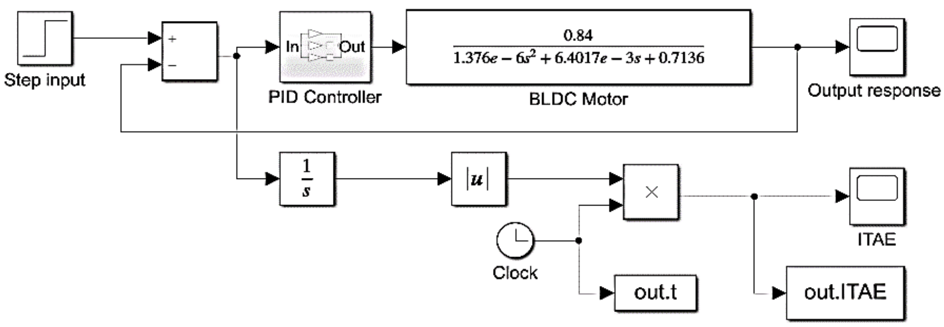

Figure 7. Model of BLDC motor in Simulink with PID controller and ITAE objective function

Table 2. Values for DTBO algorithm's parameters

Parameters	Values
Dimension count (m)	3
Population size (N)	50
Maximum iteration count (T)	100
Constant (R)	0.05
Lower limit among [K_p; K_i; K_d]	[0; 0; 0]
Upper limit among [K_p; K_i; K_d]	[10; 1000; 0.1]

4. COMPARATIVE ANALYSIS

The transient response output of the proposed controller is compared with those of an existing controller [24] on some well-known optimal criteria of the step responses in the time domain specifications, such as rise time (t_r), settling time (t_s), and maximum overshoot (M_p). This is performed in order to validate optimal control performance and efficient system operation. The GWO algorithm is executed on MATLAB using the fundamental parameter values specified in Table 3, and the PID controller's optimal gain values are achieved, as shown in Table 4. Figure 9 displays the GWO algorithm's convergence graph for minimizing the chosen objective function. Figures 8 and 9 show that the best optimal value of the proposed DTBO algorithm for computing the ITAE objective function is 6.832e-09 and is only attained at iteration number 42, while the same value is found to be 1.442e-07 at iteration number 95 by the GWO approach. Therefore, it can be said that the suggested DTBO algorithm, in contrast to the GWO method, is able to generate a more accurate fitness value with a quick convergence rate without stalling in a local minimum. Figure 10 compares the performance of the proposed DTBO-PID and the existing GWO-PID [24] controllers for the BLDC motor's unit step responses. As can be observed from the figure, the suggested controller has a superior temporal response than the existing one.

Table 3. Values for GWO algorithm's parameters

Parameters	Values
Dimension count	3
Population size	50
Maximum iteration count	100
Lower limit among [K_p; K_i; K_d]	[0; 0; 0]
Upper limit among [K_p; K_i; K_d]	[10; 1000; 0.1]

Table 4. Gains for DTBO-PID and GWO-PID controllers and criteria for transient response

Controller types	Controller gains			Transient response criteria		
	K_p	K_i	K_d	t_r (s)	t_s (s)	M_p (%)
DTBO-PID (proposed)	8.4131	961.421	1.97e-08	0.0015	0.0025	0
GWO-PID	7.6539	988.4761	2.7718e-04	0.0017	0.0028	0.8483

As can be seen in Table 4 that both rise and settling times are less along with zero overshoot in case of the proposed DTBO based PID controlled system than the GWO based system. Hence, in achieving speed regulation of a BLDC motor, the proposed DTBO-PID controller proves its excellence in giving best transient response results as compared to the GWO-PID controller.

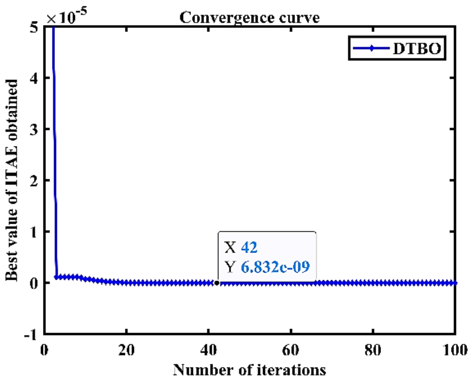

Figure 8. DTBO algorithm's convergence graph for ITAE objective function

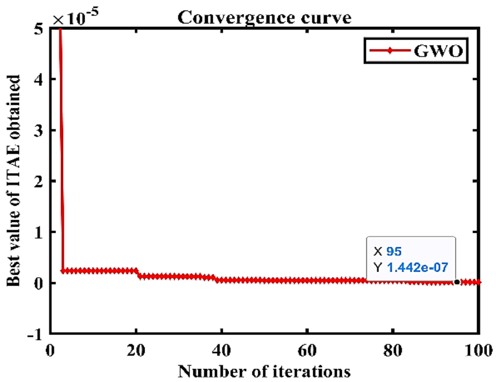

Figure 9. GWO algorithm's convergence graph for ITAE objective function

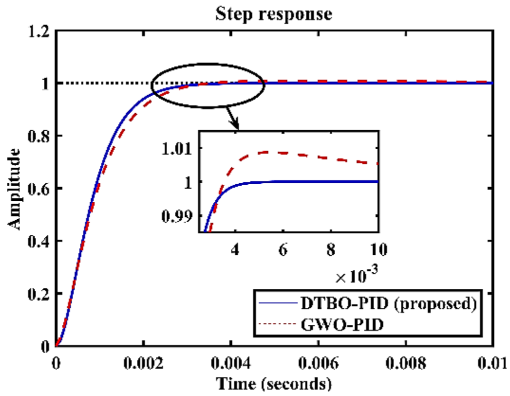

Figure 10. Comparison of BLDC motor's step responses with DTBO-PID (proposed) and GWO-PID controllers

5. ROBUSTNESS ANALYSIS

A system is said to be robust if it happens to remain in stable state even in case of certain uncertainties. Robustness analysis of the proposed system is performed by observing the system behavior with changes in electrical phase resistance (R_a) by $\pm 30\%$ and torque constant (K_t) by $\pm 40\%$. These changes lead to four possible operating cases as shown in Table 5 and thereafter comparative analysis have been carried out. Tables 6 through 9 presents, accordingly, the comparative simulation results of the transient response analysis in time domain in each of the four cases. Figures 11 to 14 also display the corresponding comparative speed for unit step response plots.

Table 5. Different operating cases for BLDC motor

Motor parameter	Case A	Case B	Case C	Case D
R_a (in Ω)	5.6	5.6	10.4	10.4
K_t (in Nm/A)	0.504	1.176	0.504	1.176

Table 6. Transient response outcome in case A

Controller types	t_r (s)	t_s (s)	M_p (%)
DTBO-PID (proposed)	0.0018	0.0031	**0**
GWO-PID	**0.0016**	**0.0026**	0.2267

Table 7. Transient response outcome in case B

Controller types	t_r (s)	t_s (s)	M_p (%)
DTBO-PID (proposed)	**0.0017**	**0.0027**	0.0105
GWO-PID	0.0022	0.0039	**0**

Table 8. Transient response outcome in case C

Controller types	tr (s)	ts (s)	Mp (%)
DTBO-PID (proposed)	**0.0032**	**0.0059**	**0**
GWO-PID	0.0033	0.0059	0

Table 9. Transient response outcome in case D

Controller types	tr (s)	ts (s)	Mp (%)
DTBO-PID (proposed)	**0.0015**	**0.0027**	**0**
GWO-PID	0.0017	0.0032	0

It is seen that the proposed DTBO-PID controller has the smallest rise and settling times in all the cases except in case A where it has zero overshoot while GWO-PID has the smallest rise and settling times only in case A along with some percentage of overshoot. Moreover, the DTBO-PID controller has zero overshoot in all the three cases except in case B (negligible percentage) where GWO-PID has zero overshoot.

Based on these findings, it can be said that the proposed DTBO-PID controller proves to be robust than the GWO-PID controller at regulating the speed of a BLDC motor.

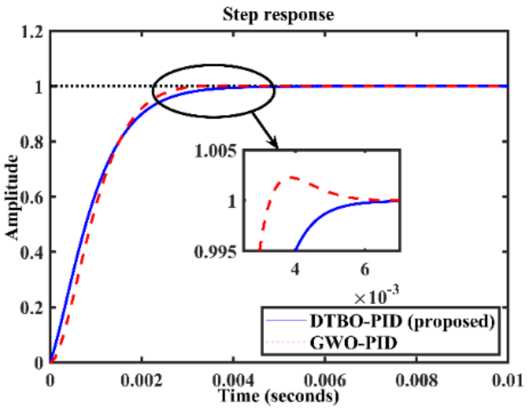

Figure 11. Speed for step responses in case A

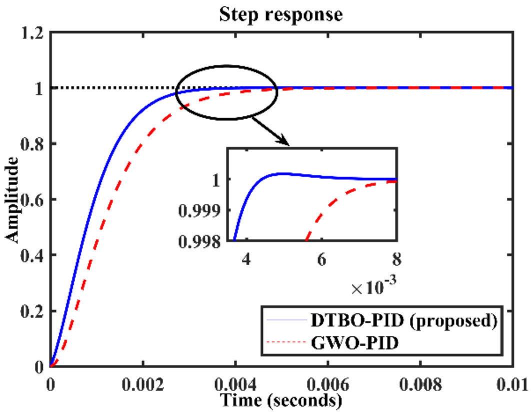

Figure 12. Speed for step responses in case B

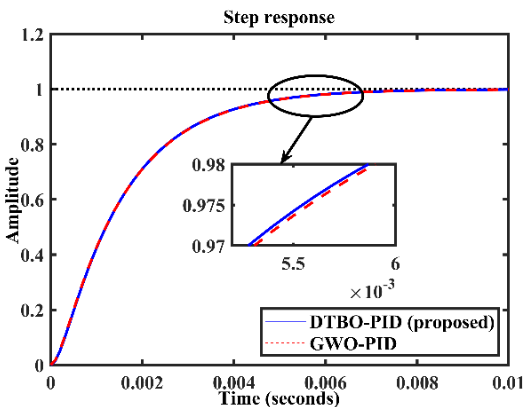

Figure 13. Speed for step responses in case C

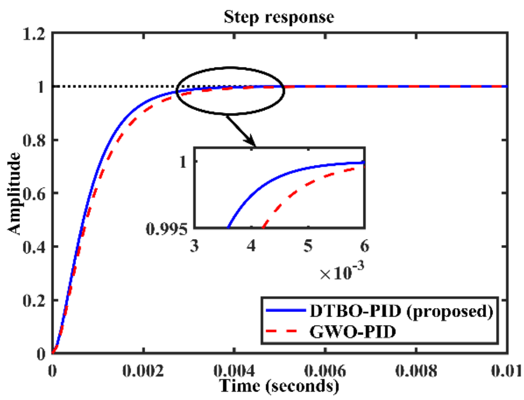

Figure 14. Speed for step responses in case D

6. CONCLUSION

Optimization plays a very important role in increasing any system's efficiency. The system used in this present work is a BLDC motor drive system which is being controlled by a PID controller. In the present investigation, a novel method for determining the optimal gain values for this PID controller in regulating the speed of the BLDC motor drive system has been provided. The PID controller is tuned using a relatively recent DTBO algorithm by reducing the ITAE objective function. On the basis of time domain requirements including rise time, settling time, and peak overshoot, the system performance is compared using the ITAE performance index. Furthermore, to show the efficiency of the proposed method, it is being compared in terms of performance characteristics with the GWO method with the same objective function. According on the simulation results, the suggested DTBO-PID controller performs better than the GWO-PID controller. Additionally, robustness assessment of the proposed system has been performed by changing some motor parameters. Upon doing the comparative analysis, it has been concluded that the proposed DTBO-PID controller proves to be more robust than GWO-PID controller in majority of the operating cases. These performance evaluations of DTBO based PID controller optimization technique will add a new degree of complexity to the controller structure for a BLDC motor drive system.

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