RESEARCH PAPER

A FOPID CONTROLLER BASED BLDC MOTOR SPEED CONTROL USING FIREFLY OPTIMIZATION ALGORITHMS

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ABSTRACT

A lot of industrial and automotive applications employ brushless DC (BLDC) motors because of their great efficiency and accurate control. This work investigates how to enhance BLDC motor speed management by using a Fractional Order PID (FOPID) controller optimized with the Firefly Algorithm (FFA). The FOPID controller improves system dynamics over traditional PID controllers by offering more control flexibility with additional tuning parameters (λ and μ). These settings are optimized by the Firefly Algorithm, which guarantees improved performance under various load scenarios. Simulations using MATLAB/Simulink verify the controller's performance by showing quick reaction times, little overshoot, and lower steady-state error. The suggested method provides dependable speed control, which makes it a viable option for contemporary motor drive systems.

Keywords: Firefly Algorithm, FOPID, BLDC motor, Speed Control, Optimization.

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1. INTRODUCTION

The efficacy, dependability, and precise control capabilities of BLDC motors have led to their enormous rise in popularity in a variety of applications in recent years. EV, robotics, aircraft, and RES all make extensive use of these motors (Shi et al. 2022). Using sophisticated control techniques to effectively regulate the motor's speed and torque is crucial to guaranteeing peak performance. Complex, non-linear systems like BLDC motors within control systems have been successfully handled by sophisticated controllers with optimization algorithms (Aribowo et al., 2021).

2. Structure of FOPID Controller and Firefly Optimization Algorithm

The Fractional Order PID controller is commonly used in motor speed regulation systems and operates as a closed-loop system with a feedback signal. The sensorless BLDC motor speed is controlled by the controller using clever techniques. The PID controller gains are as follows to improve the dynamic characteristics of the FOPID controller: Integral order λ and Derivative order μ are two more Degrees of Freedom parameters that are introduced together with proportional gain Kp, integral gain Ki, and derivative gain Kd. The Kalman filter is used in the sensorless BLDC control approach to estimate the rotor speed. The predicted speed in rpm is sent to the error detector after the reference speed has been manually specified. The error detector generates a difference value that is sent to the FOPID controller. The general block design of a new buck boost converter with a BLDC motor and a traditional inverter adjusted with intelligent controllers is displayed in Figure 1.1.

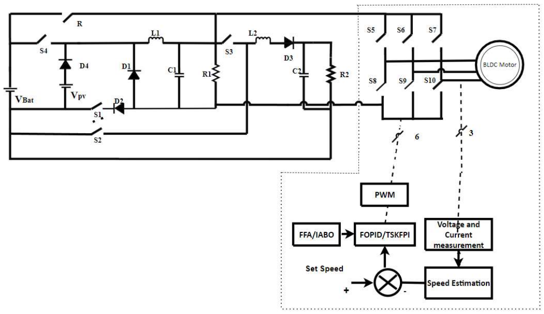

Figure 1.1 Block Diagram of the Proposed System

The controller generates the required tuning parameters, Kp, Ki, Kd, λ, and μ, using an innovative technique based on the Fire Fly Algorithm. The FOPID controller sends the control signal u(t) to the switching logic circuits. The switching logic circuits generate the series of switches that energize the stator winding. To change the firing angle and regulate the voltage to control the motor's speed, a pulse generator generates the PWM signal. Figure 1.2 displays the basic design of the FOPID controller (Mohammed Eltoum et al., 2021).

The optimization method known as the "Fireflies Algorithm" is based on the behavior of fireflies in the wild. In order to tackle optimization problems, this method imitates the way fireflies interact and attract other fireflies using their bioluminescent light. The brightness (intensity of light) of the firefly, which are used to represent issue solutions in this technique, indicates the quality of the solution. Over time, the behavior of fireflies toward brighter fireflies causes them to converge toward the best option. Fireflies transform all of their energy into light through a highly effective chemical reaction. They exchange messages with each other via these light signals. Every one of the more than two thousand species of fireflies has a distinct pattern of light flashing. The intensity of the light drops as two fireflies get farther apart, which limits their communication. As a result, fireflies gravitate toward brighter ones; in the absence of a firefly that is noticeably brighter nearby, they go randomly over the area.

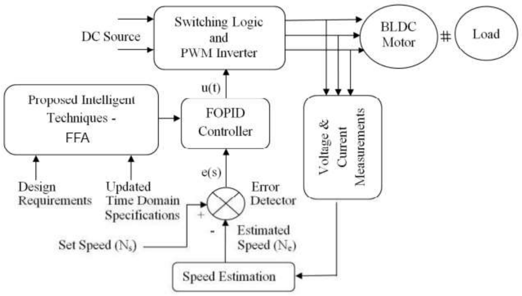

Figure 1.2 Structure of FFA-optimized FOPID Controller – BLDC motor Speed Control

The ten-year-old Firefly algorithm was inspired by the mating and flashing habits of fireflies. This nature-inspired algorithm was created by Xin-She Yang (2021) under the following presumptions:
1. It is believed that all fireflies, male or female, are unisexual and will follow a firefly that appears more intelligent.
2. As two fireflies get farther apart, they become brighter and less appealing.
3. The program's objective is to make a firefly brighter. The Firefly algorithm, which successfully resolves optimization issues, is based on these firefly characteristics. The two key elements of this approach are attraction (β) and light intensity (L).

The level of β is directly related to the L, and the amount is inversely proportional to the distance (r) between fireflies. The flashing light is used to build the goal function that needs to be enhanced. Fireflies I and J are drawn to one another in different ways depending on how far apart they are (r_{ij}). In addition, the inverse square law applies to light intensity.

$$(r) = L_s/r^2 \qquad (\mathbf{1}.1)$$

When the medium is identified, the absorption coefficient (γ) stays constant while the light intensity (L) varies with the distance r. (F. Erdal, 2017)

$$(r) = L_0\, e^{-\gamma r^{2}} \qquad (1.2)$$

There is a clear correlation between the intensity of firefly' light and how attractive they are. At r = 0, the starting intensity is denoted as L_0.

$$\beta = \beta_0 \mathbf{e}^{-\boldsymbol{\gamma} \mathbf{r}^{\mathbf{m}}} \qquad (1.3)$$

Two i and j fireflies placed at coordinates (x_i,y_i) and (x_j,y_j) correspondingly have a Cartesian distance, d_{ij}.

$$r_{ij} = \sqrt{}\sum(x_i,k - x_j,k)^2 \qquad (1.4)$$

The exact location along the kth dimension is indicated by the kth component (x_i,k) of the spatial coordinates xi for the ith firefly. The number of dimensions in the coordinate system is indicated by the variable d. The revised position can be computed as follows if firefly I attracts another effective firefly J:

$$x_i = x_i + \beta_0 e^{-\gamma r^{2}}(x_j - x_i) + \alpha\epsilon \qquad (1.5)$$

In this equation 1.5, the second term accounts for the attraction effect, pulling firefly i toward the more attractive firefly j, where α is the randomization parameter and ε is a vector of randomly generated values derived from a Gaussian distribution. Throughout the search space the n flies uniformly distributed, the fireflies converge to various local optima as the algorithm iterates. The algorithm can eventually attain the global optimum by choosing the best solution from across these local optima. The FOPID controller variables are tuned by the FFA. The implementation of algorithm is separately with three distinct objective functions: J_1, J_2, and J_3, as defined in equations (1.1 – 1.5) respectively.

3. Implementation Steps

The system parameters Kp, Ki, Kd, λ, and μ are first initialized within predetermined bounds in

Step 1: Randomized Initialization. Initial values for parameters such as population size, absorption coefficient, firefly attraction, and the maximum number of iterations used as a termination condition are entered at the start of the process.

Step 2: Population Growth and Fitness Assessment: An initial population is created at random, and the fitness values (ISE, IAE, and ITAE) of each solution in the population are evaluated by identifying the objective functions that correspond to them.

Step 3: Iterative Improvement: Whenever the last criterion—achieving the maximum number of iterations—is met, the subsequent steps are repeated.

Step 3.1: Firefly attraction: For every given xi and xj, where i = 1,...,M and j = 1,...,M, firefly i will begin to migrate in the direction of firefly j if its objective function is greater than firefly i.

Step 3.2: Calculating Attractiveness Equation (5.3) is used to calculate the attractiveness (β).

Step 3.3: Light Intensity Update: After each solution has been updated, the corresponding light intensity (L) for each potential solution in the population is updated.

Step 3.4: Finding a better solution: After ranking the fireflies, the best option as of right now is determined.

Step 4: Optimal PID Controller Gains Output: At the end of the iterative procedure, the algorithm outputs the optimal PID controller gains.

4. Optimal parameters of FOPID controller with FFA

The controller determines the optimal values of λ, μ, and PID gains for a range of BLDC motor operating situations. The computation time and associated objective function values for the FOPID optimum parameters Kp, Ki, Kd, λ, and μ under various load situations are displayed in Table 1.1.

Table 1.1 Ideal FOPID Controller Parameters with FFA

Varying load Conditions	**Controller Parameters - FOPID**				
	K_p	K_i	K_d	λ	μ
No load (T_L = 0 Nm)	2.7135	1.5129	0.081	0.4853	0.3485
25% load (T_L = 1.25 Nm)	2.7135	1.5096	0.080	0.4853	0.3485
50% load (T_L = 2.5 Nm)	2.6352	1.4124	0.076	0.5574	0.4165
75% load (T_L = 3.75 Nm)	2.6068	1.3587	0.065	0.6385	0.6291
100% load (T_L = 5 Nm)	2.5405	1.3012	0.054	0.8599	0.8364

4 Results

The FOPID optimized with FFA controller for controlling the speed of the sensorless BLDC motor and it has been implemented in the MATLAB environment using suitable toolboxes. The Simulink model is made up of a three-phase VSI, a 3φ BLDC motor, a FOPID controller, a PWM inverter, switching logic and blocks for input parameter monitoring. There are separate Simulink models for the pulse generator, comparator, 3 AND & NOT gates that make up the switching logic and PWM generator. Another variant uses a FOPID controller with FFA to optimize the controller's settings. To further measure motor characteristics including position of the rotor, back EMF, electromagnetic torque, speed, and current in the stator at each phase are developed (Bae et. al. 2020).

This section’s results are obtained through simulations using the MATLAB/Simulink toolbox. The sensorless BLDC motor speed response is analysed under different conditions, including constant and varying load conditions, and varying set speed scenarios. The FOPID controller optimized with FFA is utilized to sensorless speed control, and various time domain performance parameters (Das et. al. 2020) are extracted from the simulations.

4.1 Speed Response under No Load and Full Load

The simulation was conducted with a no load for a reference speed of 1500 rpm. From the obtained results, various speed response parameters such as Settling time t_s, Peak time t_p, Rise time t_r, and Steady-state error e_s were analysed. The speed response of the BLDC motor under no load condition is shown in Figure.1.3 with very small value of ripple. The three phase stator voltage a, b & c are shown in Figure 1.4 under no load condition. The Figure 5.8 shows the speed response under full load conditions with reference speed of 1500 rpm. The Figure 1.5 & 1.6 shows the electromagnetic torque of BLDC motor under no-load (0Nm) and full load (5Nm) conditions. The settling time of BLDC motor under full load condition is 0.238s and for the no load condition is 0.362s. It shows that compare to no load condition the BLDC motor takes more time to settle compare with full load condition and both are less than 1 second. The steady state error is also lesser than 1%.

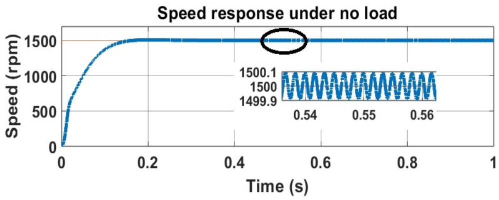

Figure 1.3 Speed Response under no-load condition

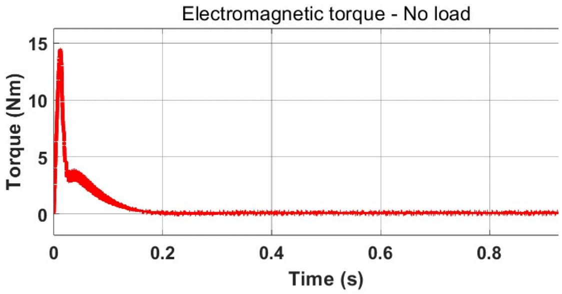

Figure 1.4 Electromagnetic Torque under no-load

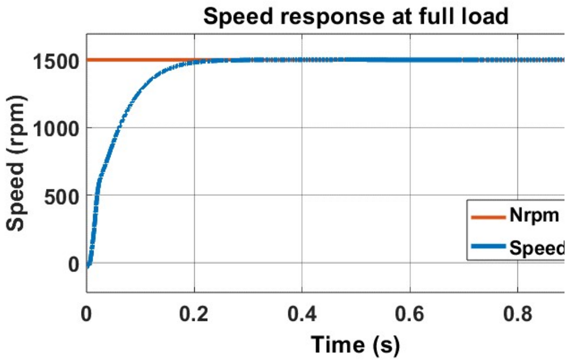

Figure 1.5 Speed Response at T = 5Nm

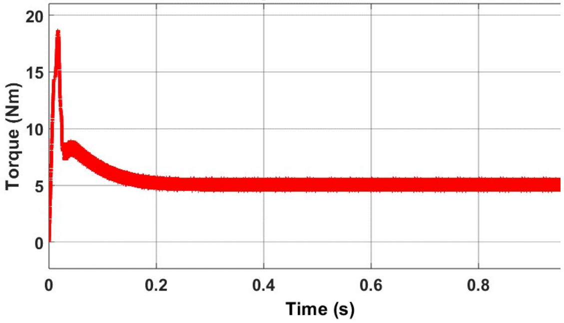

Figure 1.6 Electromagnetic Torque under Full load condition

4.2 Speed Response for Varying Load Condition

Tests were performed on an BLDC motor with a 1500rpm set speed under different load circumstances (25%, 50%, 75%, and 100% load) to evaluate the efficiency of the controller. In each load condition, the system's response in the temporal domain was observed. The test results confirm that the controller for the BLDC motor speed regulation of the functions effectively within all respects. When the motor load increases or decreases, the controller shows no undershoot or overshoot. The speed response and electromagnetic torque of BLDC motor under varied load circumstances is shown in Figure 1.7 & 1.8. Furthermore, the proposed controller seems to be suitable for drives functioning in changing load conditions. The time domain parameters for the speed performance across various loads are shown. The settling is slightly increasing by increasing the load and the steady state error is from 0.27% for 25% load and 0.8% for 100% load which is under the objective level of lesser than 1%.

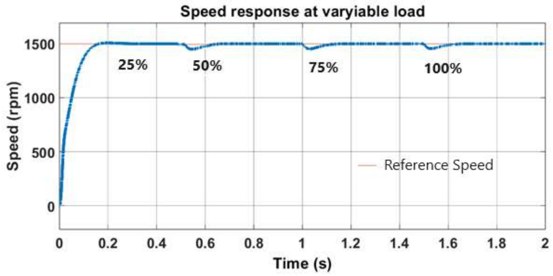

Figure 1.7 Variable load - Speed response

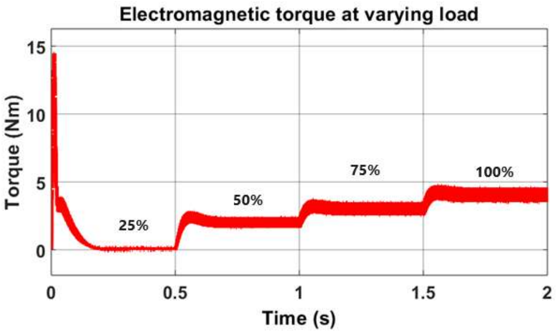

Figure 1.8 Electromagnetic torque

4.3 Speed Response under Varying Set Speed Condition

BLDC motor is utilized in variable-speed drive systems. The time domain characteristics are examined to verify the effectiveness of the FOPID controller under varying set speed conditions for speed control of sensorless BLDC motor. Different cases involving various set speed changes are analysed and described below.

- Case 1: Speed changes from 500rpm to 1000rpm
- Case 2: Speed changes from 1000rpm to 1500rpm
- Case 3: Speed changes from 1500rpm to 1000rpm
- Case 4: Speed changes from 1500rpm to 500rpm

In case 1, the performance evaluation of the FFA-optimized FOPID controller is carried out by varying the set speed from 500rpm to 1000rpm in two steps. In the first stage, the configured speed shifts from 0 to 500 rpm from 0 to 1 second interval. The speed can be adjusted from 500 rpm to 1000 rpm during a time period of 1 to 2 seconds in the second step. In this case 1, it clearly shows that settling time for 500rpm is 0.163s and for 1000rpm is 1.182s with steady state error is lesser than 1%

Simulation results and time domain parameters under different speed conditions are illustrated in Figure 1.9 respectively. The BLDC motor stator current in Phase a, b & c under different speed conditions shown in Figure 1.10 with a maximum value of 10.2A during transition period from 500rpm to 1000rpm. The observations from the Figure and the table indicate that the FFA-optimized FOPID controller performs with quick settling time and lesser steady state error value.

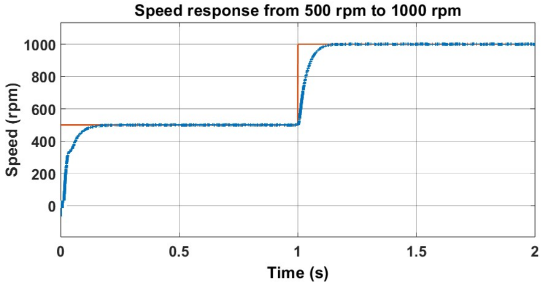

Figure 1.9 Case 1: Speed response from 500 rpm to 1000 rpm

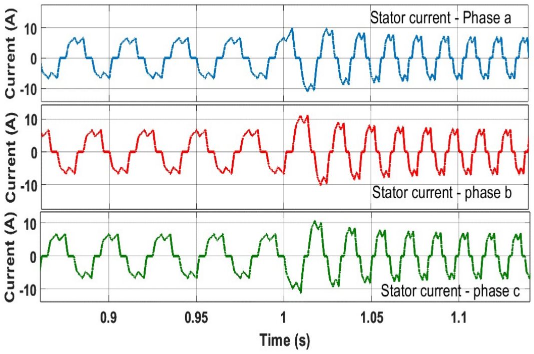

Figure 1.10 Case 1: Stator current – Phase a, b & c

In Case 2, the performance evaluation of the FFA-optimized FOPID controller is carried out by varying the set speed from 1000 to 1500rpm. In the first step, the set speed will have varied up to 1000 rpm from initial 0 rpm during the period of 0 to 1 second with a settling time of 0.172s and steady state error is 0.8%. In the second step, the 1000 rpm to 1500 rpm speed variation will take place during the period from 1 to 2 seconds with settling time of 1.219s and steady state error is 0.54%. The simulation results and time domain parameters for the set speed under varying conditions are illustrated in Figure 1.11. The stator current is raised up to maximum of 10.2A as shown in Figure 1.12. In case 2, the raise time is 0.116s to attain 1000rpm from initial 0 rpm with peak value of 992rpm and it indicates that the FFA-optimized FOPID controller performs well under these conditions. Initially the steady state error is raised up to 0.8% and then reduced to 0.54% respectively.

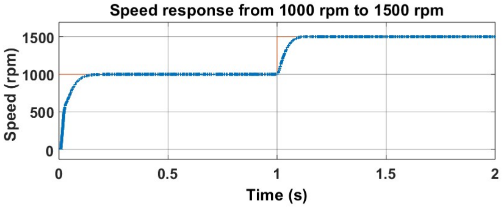

Figure 1.11 Case 2: Speed response from 1000 rpm to 1500 rpm

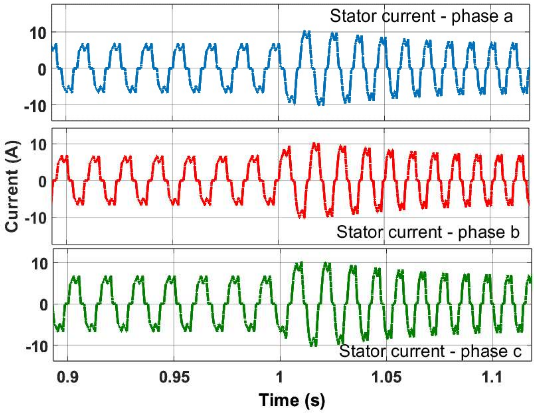

Figure 1.12 Case 2: Stator Current of BLDC for speed response from 1000 rpm to 1500 rpm

In case 3, the FOPID controller performance evaluation is carried out by varying the set speed from 1500 to 1000rpm. In the first step, the 1500 rpm is varied based on set speed during the period up to 1 second. In the second step, the speed reduced to 1000 rpm from 1500 rpm during the period from 1 to 2 seconds. The simulation results and time domain parameters are illustrated in Figure 1.13, for various set speed conditions respectively. The system attains its rated speed 1500rpm at 0.206s settling time with steady state error value of 0.54% and system attains Settling time at 1.176s with steady state error value of 0.3% for the speed response from 1500 to 1000rpm respectively.

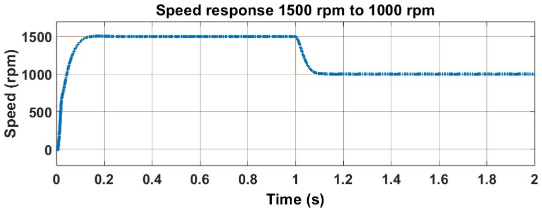

Figure 1.13 Case 3: Speed response from 1500 rpm to 1000 rpm

The Figure 1.14 shows the stator current of BLDC motor which is sharply reduced 3A during speed reduction from the maximum value of 8A from speed response from 1000rpm to 1500rpm.

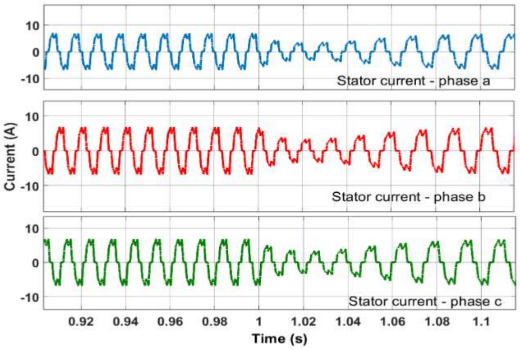

Figure 1.14 Case 3: Stator Current of BLDC for speed response from 1500 rpm to 1000 rpm

In case 4, the performance evaluation of FFA-optimized FOPID controller is carried out by reducing the speed from 1500 rpm to 500 rpm. In the first step, the speed is at 1500 rpm during the time period from 0 to 1 second. In the second step, the speed is changed from 1500 rpm to 500 rpm during the time period from 1 to 2 seconds. The simulation results and time domain parameters for different speed conditions are illustrated in Figure 1.15. During the time period 0 to 1s the motor settled at 0.204s to attain 1500rpm from its initial state with steady state error value of 0.54%. Further reducing the speed from 1500 to 500rpm, the motor settles at 1.194s with steady state error value of 0.6%. During this case the system perform better with reduced steady state error lesser than 1% and lesser settling time.

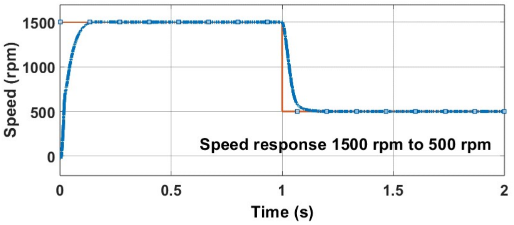

Figure 1.15 Case 4: Speed response from 1500 rpm to 500 rpm

The Figure 1.16 illustrates the stator current of BLDC motor for speed response from 1500 rpm to 500 rpm. It clearly shows that the current is considerably reduced to minimum value during transition period.

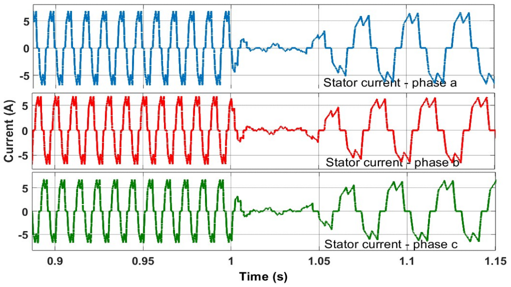

Figure 1.16 Case 4: Stator Current of BLDC for speed response from 1500 rpm to 500 rpm

Conclusion

The BLDC motor speed control performance is greatly improved by the FFA-optimized FOPID controller, which guarantees accurate regulation under dynamic load situations. The controller successfully reduces steady-state error while attaining quicker settling times, according to simulation data. The suggested approach exhibits more robustness and adaptability than traditional techniques, which qualifies it for use in industrial and automotive settings. The Firefly Algorithm is a successful optimization method for adjusting controller parameters, which improves system efficiency and stability. Real-time implementation and comparison with other metaheuristic algorithms for additional optimization may be part of future research.

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