

DESIGN OF AN OPTIMAL PI SPEED CONTROLLER FOR BLDC MOTOR DRIVES USING MODIFIED WHALE OPTIMIZATION ALGORITHM

CH. TRINAYANI¹, RAVI SRINIVAS LANKA²

¹Research Scholar, Department of Electrical and Electronics Engineering,
Jawaharlal Nehru Technological University Kakinada, Kakinada, Andhra Pradesh, India

¹Assistant Professor, Department of Electrical and Electronics Engineering,
Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, Andhra Pradesh, India

²Professor, Department of Electrical and Electronics Engineering,
Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, Andhra Pradesh, India

E-mail: ¹trinayaniceegec@gmail.com, ²lavisrinivas@gmail.com

ABSTRACT

This paper proposes a novel, nature-inspired Modified Whale Optimization Algorithm (MWOA) for the optimal tuning of a Proportional-Integral (PI) speed controller in a Brushless DC (BLDC) motor drive. The IWOA metaphorically models optimization processes based on the transmission dynamics of a virus and the population's immune response, balancing global exploration and local exploitation to minimize the Integral Square Error (ISE) objective function. A detailed dynamic model of the BLDC motor is developed in the MATLAB/Simulink environment to evaluate system performance. The proposed MWOA-tuned PI controller is rigorously tested under various operating conditions, including sudden load changes and step variations in reference speed. Its performance is benchmarked against well-established optimization algorithms, namely Particle Swarm Optimization (PSO) and Differential Evolution (DE), Whale Optimization Algorithm (WOA) for a fair comparison. Simulation results show that the MWOA-based controller has a better dynamic performance. It has faster settling time, less overshoot and is more resistant to disturbances. The results show that the proposed MWOA works to improve drive performance in all of the operational scenarios that were tested.

Keywords: BLDC motor, PI Controller, Speed Deviation, Modified Whale Optimization Algorithm

1. INTRODUCTION

The BLDC motor is an important component in many contemporary industrial and automotive systems. It has a high power/weight ratio and also high efficiency [4], [40]. In spite of these attributes, it can be difficult to achieve high levels of precision with both speed and torque control because the BLDC motor's back-EMF is inherently nonlinear and trapezoidal. As such, traditional proportional-integral-derivative (PID) control methods are still considered by many to be the standard industrial method for speed and/or position control due to their simplicity [29], [30], [45]. A number of recent studies have investigated ways to improve on these basic methods by developing FOPID controllers that allow for a greater degree of flexibility than the classical PID controller by introducing non-integer integration and differentiation orders into the control design. This increased level of flexibility allows for better performance when there are

significant amounts of uncertainty present in the system dynamics [39], [41].

A large number of metaheuristic optimization methods are available in literature to address the limitation of manually adjusting parameters; many nature inspired algorithms are used to automatically adjust PID gains for example Ant Colony Optimization (ACO), [1] Grey Wolf Optimizer (GWO), [24] Particle Swarm Optimization (PSO), [28], [37] to minimize performance metrics such as settling time and peak overshoot. Bio-inspired heuristics such as the Whale Optimization Algorithm (WOA), [17], [35] Cuckoo Search (CS), [31] and Firefly algorithms [34] offer faster convergent rates than traditional gradient-based methods, and utilize the search space's complexity. The use of the JAYA algorithm [8] and adaptive Tabu search [13] indicate potential in both optimizing the design of motors and the performance of their speed controllers simultaneously.

Computational intelligence has extended the limits of BLDC motor drive performance. Engineers have studied Fuzzy Logic Controllers (FLC) in depth because those controllers tolerate parameter changes and do not need a precise mathematical model [2], [19], [23]. For example, the autotuning fuzzy-PID controller [22] and the Adaptive Neuro Fuzzy Inference System (ANFIS) [10], [33] are both hybrid designs. They combine the rule-based approach of fuzzy logic with the training ability of neural networks. These kinds of hybrid systems work well on Electric Vehicle (EV) platforms because they can handle changing load cycles and the needs of regenerative braking [21, 33].

The shift to deep learning and sophisticated neural networks for state estimation and control is also highlighted in recent publications. For stability analysis and real-time speed regulation, Artificial Neural Networks (ANN) and Deep Perceptron models [15], [25], [43], [44] are being used more and more. These models are frequently implemented on inexpensive microcontrollers [36]. In particular, speed estimation in variable-load applications such as fan drives has been enhanced by temporal modelling with Bi-LSTM (Bidirectional Long Short-Term Memory) networks [20]. Additionally, it has been demonstrated that the dynamic behaviour of single-phase motor drives can be stabilized by using Deep Neural Networks (DNN) in conjunction with a mixture-of-experts approach [18].

Sensor less control and fault diagnostics continue to be important research areas to address hardware costs and reliability [3]. Researchers have used second-order active disturbance rejection control (ADRC) to reduce external torque ripples [9] and Luenberger observers for fault detection [27]. Subdomain adaptation networks are increasingly being utilized in conjunction with efficiency-focused methods, such predictive current control [12] and optimal harmonic minimization [11], to achieve complex fault identification [6]. The current frontier for developing high-efficiency, sensorless, and fault-tolerant BLDC motor drives for the upcoming generation of electromechanical systems is represented by this evolution toward hybrid intelligent systems, which is best illustrated by QPSO-CSO techniques [38] and improved gravitational search algorithms [37].

Even with the notable advancements reported in recent research, current control approaches have intrinsic drawbacks that prevent their widespread use. Despite its dependability, traditional PID and

FOPID controllers are not flexible enough to manage the substantial non-linearity and dynamic parameter fluctuations of BLDC motors without requiring frequent human retuning [29], [41]. Although neural network-based and fuzzy logic techniques provide greater flexibility, they are frequently beset by high computational complexity, high memory requirements for real-time implementation, and a significant dependence on large training datasets or expert knowledge [20], [23], and [43]. The sluggish convergence speeds, propensity to become stuck in local optima, and high sensitivity to starting parameter choices of many metaheuristic algorithms used for parameter optimization can also result in uneven control performance in high-precision applications [1], [24].

The Whale Optimization Algorithm (WOA), on the other hand, has unique benefits that solve a number of the drawbacks of existing metaheuristic approaches [17], [35]. WOA's main advantage is its special mathematical model, which imitates humpback whales' bubble-net feeding habit and offers a remarkable balance between the periods of exploration and exploitation. Compared to conventional PSO or Genetic Algorithms, this balance enables WOA to identify optimal PID gains with higher precision and faster convergence rates. Furthermore, WOA is computationally efficient and ideal for real-time implementation due to its simpler structural framework and fewer control parameters to adjust. The controller can maintain stability and decrease settling time even in the face of severe load disturbances and fluctuating operational conditions thanks to its resilience in navigating complicated, multi-modal landscapes.

This study proposes a novel application of the MWOA [18], a recent improved version for the WOA. MWOA demonstrates a robust balance between exploration (global search) and exploitation (local refinement), making it particularly suited for navigating complex, nonlinear search spaces. The core contribution of this paper is the design and implementation of a MWOA-tuned PI controller for the speed regulation of a BLDC motor. The ISE serves as the fitness function for the MWOA to optimize the PI gains. The performance of the proposed MWOA-PI controller is rigorously evaluated in a MATLAB/Simulink environment under various dynamic conditions, including step speed changes and sudden load disturbances. A comprehensive comparative analysis is conducted against controllers tuned by established algorithms like

PSO, DE and WOA. Simulation results conclusively demonstrate that the proposed MWOA-based tuning strategy yields superior transient response, enhanced disturbance rejection, and greater robustness, establishing it as an effective solution for high-performance BLDC motor drives.

2. MATHEMATICAL MODEL OF BLDC MOTOR

Figure 1 depicts a basic three-phase configuration with star-connected stator winding. BLDC motors are a type of permanent magnet synchronous motor (PMSM) characterized by a rotor with permanent magnets and trapezoidal back-electromotive force (back-EMF) waveform. This configuration necessitates a specific drive topology for operation. Typically, a three-phase voltage source inverter (VSI) supplies power to the motor's stator windings. For proper electronic commutation, a rotor position signal is essential to synchronize the inverter's switching sequence with the rotor's magnetic field. This synchronization

enables the six-step commutation (or six-step block) control method. In this scheme, only two of the three phases are energized at any given time, following a precise sequence to generate a rotating magnetic field. For a motor with Hall-effect sensors, the conducting sequence across the inverter's switches (often labelled 1–6) progresses as: 5–6, 1–6, 1–2, 3–2, 3–4, and 5–4, with each phase conducting for 120 electrical degrees. The motor's electromagnetic torque is directly proportional to the phase current. To maximize torque production and efficiency, the supplied rectangular current waveform must be aligned in phase with the trapezoidal back-EMF. The switching block governs this by commutating the current flow through two of the three star-connected windings at a time. The rotor position—obtained via sensors or through sensorless estimation techniques—determines the precise switching instants. Meanwhile, the voltage of the non-conducting (floating) third phase can be monitored and is often utilized in sensorless control algorithms for back-EMF detection.

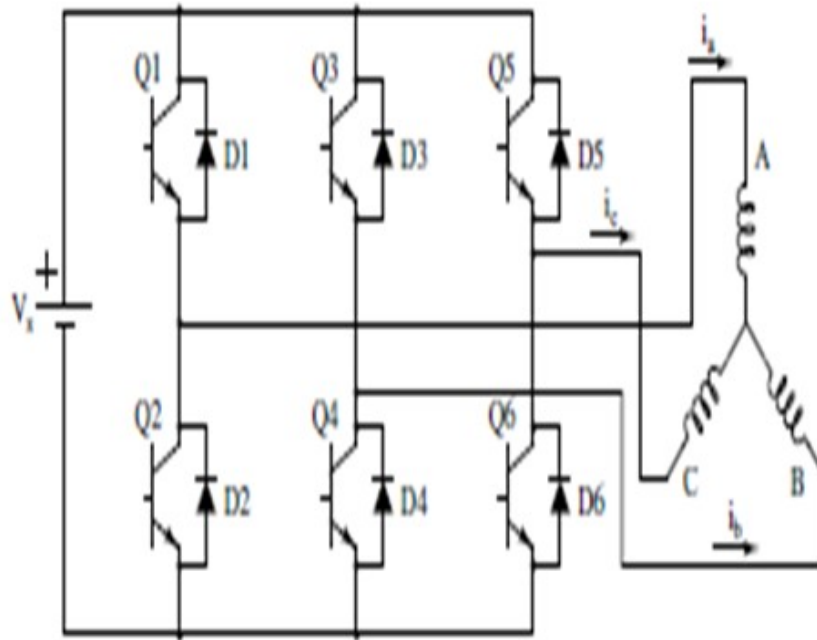


Figure 1: Simplified BLDC Drive Scheme.

The equations given below describes a star connected BLDC motor.

$$v_a = Ri_a + L \frac{di_a}{dt} + e_a \quad (1)$$

$$v_b = Ri_b + L \frac{di_b}{dt} + e_b \quad (2)$$

$$v_c = Ri_c + L \frac{di_c}{dt} + e_c \quad (3)$$

$$T_e = k_f \omega_m + J \frac{d\omega_m}{dt} + T_L \quad (4)$$

The electrical dynamics of the stator are defined by the following per-phase variables and parameters:

Voltages: v_a, v_b, v_c

Currents: i_a, i_b, i_c

Back-EMFs: e_a, e_b, e_c

Parameters: Resistance R and self-inductance L .

The electromagnetic torque developed is T_e . The high-level control strategy for the drive system is depicted in Figure 2. This closed-loop architecture functions as follows: a sensor measures the actual rotor speed (ω), which is then subtracted from the commanded reference speed (ω_{ref}) to produce a speed error signal. This error is processed by a PI controller. The output of the PI controller is a control voltage signal, which acts as the primary command input to the three-phase inverter. The inverter subsequently modulates the power supplied to the motor windings to achieve the desired speed.

The rotor position is estimated using signals from Hall effect sensors. This positional data is then used to generate the appropriate switching signals for the inverter's power electronics. The performance of the speed control loop is heavily influenced by the tuning of the PI controller. This study employs the) to optimize the PI controller gains. The optimization process aims to minimize the ISE, which is used as the objective function to achieve superior control performance.

Table 1 BLDC motor specifications

Motor Specifications	Parametric Values
Voltage	200 volts
Power	1000 W
Nominal Speed	3000 rpm
Current	5.56 A
No. of poles	4
Stator resistance/phase R	3Ω
Stator inductance/phase L	0.001 H
Flux linkages λ	0.175 wb.turn
Moment of inertia J	0.0008 kg-m ² /rad
Viscous coefficient k_f	0.001 N-m/(rad/sec)
Torque constant	1.4 N-m/A
Voltage constant	0.1466 V/rpm

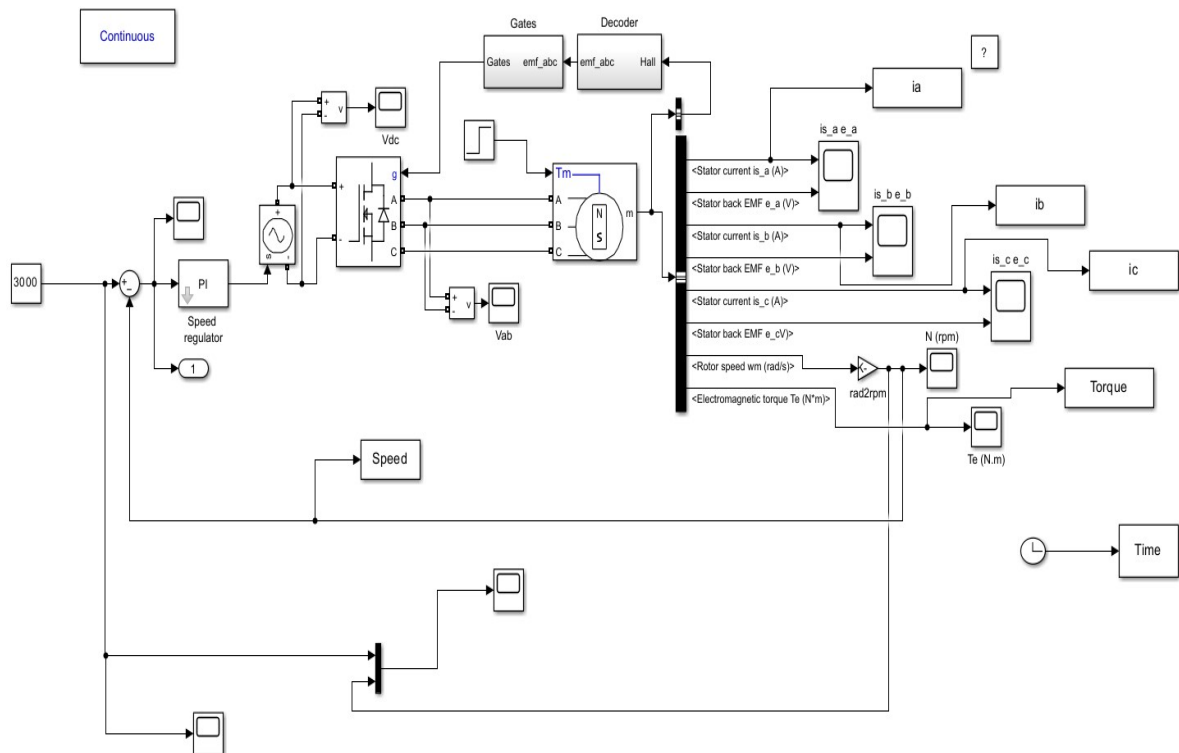


Figure 2: Simulink model for speed control of BLDC motor.

3. PROPOSED MWOA

Maintaining an effective balance between exploration and exploitation is essential for heuristic algorithms to achieve global solutions in complex engineering problems. During the exploitation phase, particles converge toward local best solutions, while in the exploration phase, they search more broadly to identify the global best solution. WOA [46], as noted by its developer S. Mirjalili, has a limitation: its solution updates depend heavily on either the previous iteration's solution or the current best solution. If the current best solution is not near the true global optimum, subsequent solutions may follow this suboptimal path, potentially causing the algorithm to converge prematurely to a local optimum. This reliance reduces WOA's ability to consistently locate the global best solution. Mirjalili suggests that enhancing the exploitation capability of WOA could strengthen its overall performance. Since the convergence behaviour of WOA is guided by the best solutions found so far, inaccuracies in these solutions can prevent the algorithm from reaching the global optimum. To overcome this drawback, a MWOA is introduced in this work. In MWOA, a weighting factor is incorporated into the position-updating mechanism to improve exploitation and enhance search efficiency. This factor decreases linearly from 0.9 to 0.4 throughout the optimization process. The primary role of this weighting factor is to regulate the influence of the current best solution, preventing premature convergence to local optima. This adjustment helps achieve a more balanced transition between exploration and exploitation, ultimately increasing the likelihood of locating the global optimum. This modification represents the key enhancement from WOA to MWOA. The fundamental motivation for employing MWOA to optimize the pi controller gains is its inherent ability to balance global search capability with local convergence, achieved through dynamically adjusting the transmission rate and immunity threshold. Additionally, MWOA operates with a minimal set of control parameters, enhancing its usability and reducing computational overhead compared to algorithms such as PSO, DE, and WOA. The effectiveness of balancing exploration and exploitation phases has been demonstrated in preliminary studies across various optimization benchmarks. Given the complex, nonlinear nature of BLDC motor control, MWOA's adaptive search mechanism is particularly well-

suited for tuning the pi controller parameters to achieve optimal dynamic performance. MWOA is applied to optimize the proportional (kp) and integral (ki) gains for BLDC motor speed control. The step-by-step procedure for implementing MWOA is outlined below. The updated position of each search agent is determined using the following equations.

STEP 1: Initialization of Control Variables

The algorithm was configured with a population size of 40 individuals and was run for a total of 100 generations. The proportional and integral gains of the PI controller are defined as the variables to be optimized. The initial set of candidate solutions is generated randomly using the following formula.

$$M_{ji}^0 = M_j^{min} + rand.(M_j^{min} - M_j^{max}) \quad (5)$$

The control variable is denoted as M . For each design parameter indexed by j (where $j = 1, 2, \dots, Z$), allowable values are bounded by a minimum (M_j^{min}) and a maximum (M_j^{max}). Here, Z represents the total count of design parameters to be optimized. The optimization uses a population of candidate solutions, with Y indicating the total population size. Each candidate is indexed by i (where $i = 1, 2, \dots, Y$). Furthermore, $rand$ is a random number uniformly distributed in the range $[0, 1]$.

Step 2: Objective function evaluation

In this research, the MWOA is employed to tune the gains of a PI controller, using the ISE as the primary performance metric. The core objective is to minimize the ISE by reducing the deviation between the desired reference speed and the system's actual speed over time. This objective is mathematically expressed by the following equation.

$$ISE = \int_0^T [e(t)]^2 dt \quad (6)$$

Where t is the time for the system to reach steady state and $e(t)$ is the error between reference speed and actual speed.

Step 3: Shrinking encircle mechanism for updating of search agents (exploration phase)

In this approach, the gain parameters of the PI controller serve as the search agents in the optimization process. The MWOA is applied to iteratively refine these parameters toward an optimal configuration. Since the true optimal solution is not known a priori, the best-performing candidate identified so far based on the objective function evaluation is designated as the target or a near-optimal reference. Once this leading agent is determined, the remaining agents adjust their positions accordingly to improve the collective search.

$$\vec{M}_{ji}(t+1) = \vec{w} \cdot \vec{M}_{ji}^*(t) - \vec{Y} \cdot \vec{V} \quad (7)$$

$$\text{Where } \vec{V} = |\vec{F} \cdot \vec{M}_{ji}^*(t) - \vec{M}_{ji}(t)| \quad (8)$$

Where t is the present iteration, $\vec{Y}$, $\vec{V}$ are the coefficients vectors, $\vec{M}_{ji}^*$ is finest solution attained

until now, $\vec{M}_{ji}$ is the position vector, $\|$ is absolute value and $\cdot$ shows multiplication between elements.

Here, $\vec{Y}$, $\vec{V}$ are given by

$$\vec{Y} = 2\vec{y} \cdot \vec{r} - \vec{y} \quad (9)$$

$$\vec{F} = 2 \cdot \vec{r} \quad (10)$$

Here the range of $\vec{Y}$ is between $-y$ and y , where y alters between 2 and 0 throughout process of optimization. The values of y , Y , F are updated for each search agent and updates its position by Eq.7,

if the value of $\vec{Y}$ is less than 1.

Step 4: Updating particles via a spiral mechanism

Humpback whales employ a distinctive hunting tactic, moving in a contracting circular pattern while simultaneously following a spiral-shaped trajectory toward their prey. This dual motion is mathematically modeled to replicate the whale's helical approach. All search agents within the algorithm update their positions according to the following equation, which encapsulates this combined spiral and encircling behavior.

$$\vec{M}_{ji}(t+1) = \vec{V}^b \cdot e^{bl} \cdot \cos(2\pi l) + \vec{w} \cdot \vec{M}_{ji}^*(t) - \vec{Y} \cdot \vec{V} \quad (11)$$

Where

$$\vec{V}^b = |\vec{w} \cdot \vec{M}_{ji}^*(t) - \vec{M}_{ji}(t)| \quad (12)$$

The vector $\vec{V}^b$ defines the distance from the whale (search agent ij) to the target prey (best-known solution). The coefficient l is a uniform random number within the range $[-1,1]$, and b is a constant parameter that sets the form of the spiral trajectory. In the simulation model used for this study, the algorithm selects between the two movement strategies with equal likelihood 50% probability each. Consequently, the search agent updates its position according to the equations below:

$$\vec{M}_{ji}(t+1) = \vec{w} \cdot \vec{M}_{ji}^*(t) - \vec{Y} \cdot \vec{V} \text{ if } \delta \leq 0.5 \quad (13)$$

$$\vec{M}_{ji}(t+1) = \vec{w} \cdot \vec{V}^b \cdot e^{bl} \cdot \cos(2\pi l) + \vec{w} \cdot \vec{M}_{ji}^*(t) - \vec{Y} \cdot \vec{V} \text{ if } \delta \geq 0.5 \quad (14)$$

where, δ is a random number in $[0,1]$.

Step 5: Search for prey (exploitation phase)

If $\vec{Y}$ is larger than 1, the search agent's exploitation phase location is updated using a randomly picked search agent rather than the best search agent. The following equation is followed by the search agent.

$$\vec{M}_{ji}(t+1) = \vec{w} \cdot \vec{M}_{ji} \text{ rand} - \vec{Y} \cdot \vec{V} \quad (15)$$

$$\vec{V} = |\vec{F} \cdot \vec{M}_{ji} \text{ rand} - \vec{w} \cdot \vec{M}_{ji}(t)| \quad (16)$$

Where $\vec{M}_{ji} \text{ rand}$ is the arbitrary number changes while iterations are going.

4. SIMULATION RESULTS AND DISCUSSIONS

The BLDC motor drive and its associated control system were modeled and simulated within the MATLAB/Simulink (2024) environment. The key motor parameters used for the simulation studies are detailed in Table 1. To rigorously evaluate the performance of the closed-loop speed control system, its dynamic response was tested under various transient load conditions. To validate the efficacy of the proposed controller, the performance of the MWOA-tuned PI controller was

benchmarked against two established bio-inspired optimization algorithms: PSO, DE, and WOA. The comparative analysis used the ISE as the common objective function for optimization. The specific algorithmic parameters configured for PSO, DE, WOA and the novel MWOA in this study are provided in Table 2. For a fair comparison, the population size and the maximum number of iterations were maintained at identical values across all three algorithms. Each algorithm was executed independently to convergence, and the resulting optimal PI gain parameters obtained from PSO, DE, WOA and MWOA are compiled in Table 3.

Table 2 Algorithm Parameters

Algorithm	Parametric Values
PSO	Size of the Populations= 50 Number of iterations =100 $C_1 = 2, C_2 = 2$ Weighing factor, $w=(0.9-0.4)$
DE	Size of the Populations= 50 Mutation constant, $F = 0.5$ Cross over constant, $C.R = 0.8$
WOA	Size of the Populations= 50 Number of iterations=100 Constant, y =varies between 2 & 0
MWOA	Size of the Populations= 50 Number of iterations=100 Constant, y =varies between 2 & 0, W = varies between 0.9 & 0.4

Table 3 Global best values of PI controller gains obtained

Tuning Algorithm	K_p	K_i
PSO	0.012	10.012
DE	0.013	12.123
WOA	0.16	17.036
MWOA	0.89	19.45

The system's dynamic performance was examined under various reference speed settings, as seen in the step-response characteristics shown in Figure 3. At intervals of 0–0.3–0.6–0.9 s, respectively, the target speed values of 1500–2000–2500–3000 rpm are applied to test the tracking

capability of the various optimization techniques. Across all transitions, the MWOA consistently outperformed PSO, DE, and WOA in terms of time-domain specification. The MWOA, in particular, had the fastest rise time and a substantially shorter settling time, reaching each new setpoint in around 0.02 seconds with minimal oscillation. While conventional PSO and DE algorithms tracked the reference speed, they had a slower transient response and longer settling times.

The robustness and superiority of the proposed MWOA-PI controller were investigated through three distinct operational scenarios:

Case 1: Under load Operation (50% of full load)

Under this condition, the BLDC motor is commanded to track a reference speed of 3000 rpm while 50% full rated load torque i.e., 1.59 Nm is applied applied at 0.5 sec. The comparisons of the BLDC motor speed response with the suggested approach and other existing methods are shown in Figure 4. The figure presents a detailed comparative analysis of rotor speed control performance using different optimization-based tuning methods. The plot specifically focuses on the transient response period between 0.5 and 0.6 seconds, which is critical for evaluating system dynamics after a change in the reference speed command. The curves compare the reference speed (target) against the actual speed achieved by controllers tuned with PSO, DE, WOA, and MWOA. The purpose is to visually assess which algorithm provides the best tracking in terms of response speed, overshoot, settling time, and stability. Typically, in such studies, the MWOA curve is expected to demonstrate superior performance, showing the fastest convergence to the reference with minimal overshoot and oscillation, followed by WOA, with PSO and DE likely showing slower and more oscillatory responses. This figure serves as empirical evidence that the proposed improvement in the WOA yields tangible benefits in control precision and dynamic response. The time response specifications are shown in table 4.

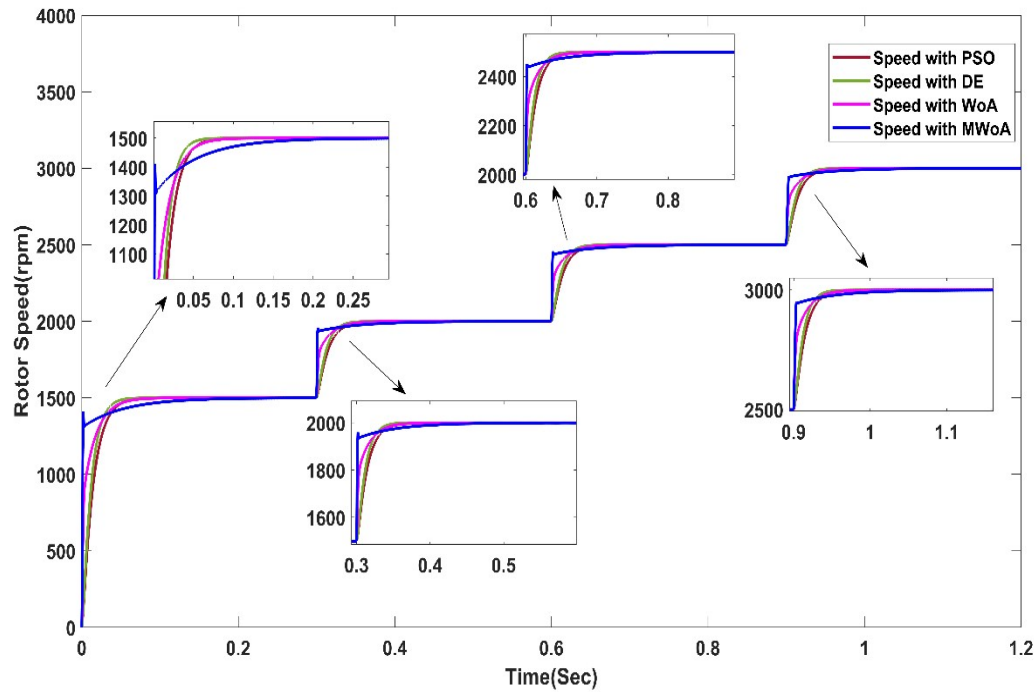


Figure 3: Speed response of BLDC motor for speed variations.

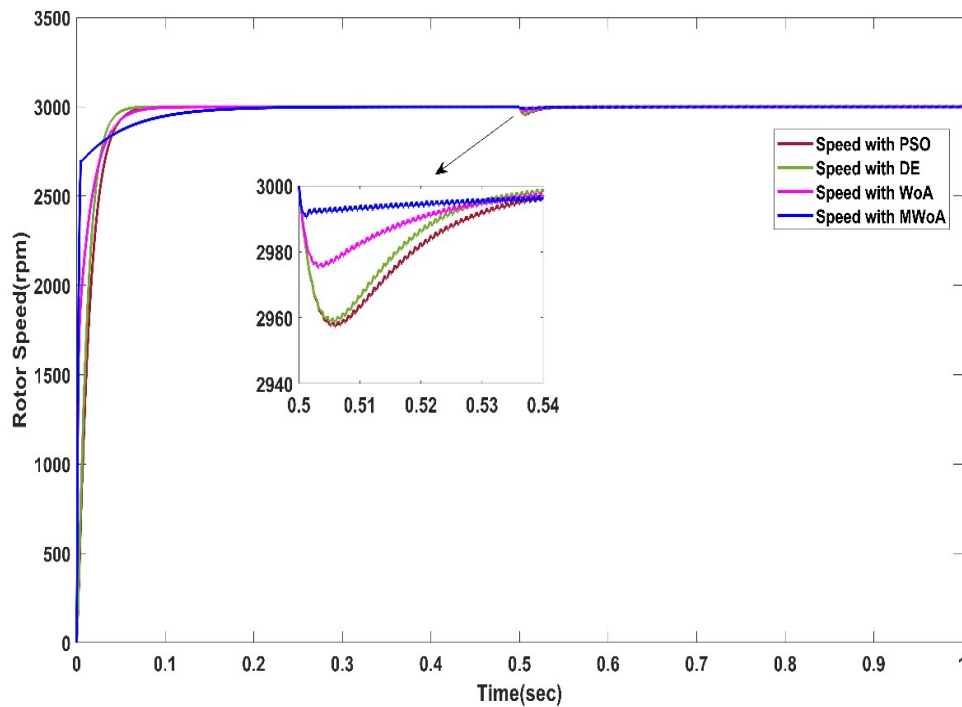


Figure 4: Speed response of BLDC motor at under load condition.

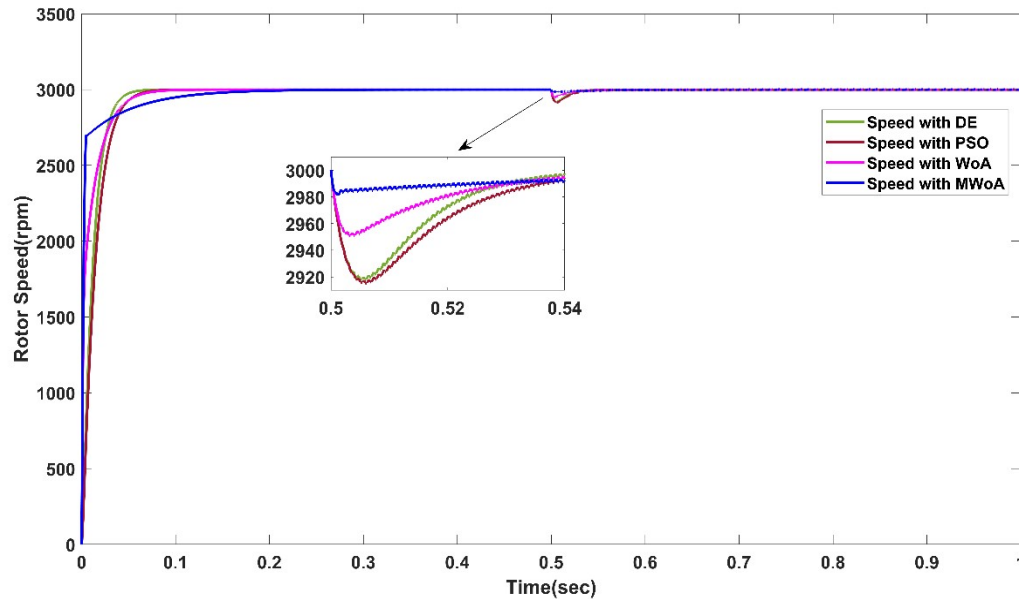


Figure 5: Speed response of BLDC motor at full load condition.

Table 4 Time response specifications for case 1

Algorithm	Rise Time (sec)	Settling Time (sec)	Maximum Speed Drop (rpm)	Recovery Time
PSO	0.08	0.15	45	0.045
DE	0.065	0.12	40	0.04
WOA	0.045	0.08	23	0.035
MWOA	0.015	0.05	7	0.015

Case 2: Full Load Operation

The BLDC motor was tested under a set-point speed of 3000 rpm. To evaluate dynamic performance, a load disturbance of 3.18 Nm was introduced at 0.5 seconds. Figure 5 illustrates the resulting speed transients, comparing the response achieved with the proposed approach against those of established benchmark methods.

The comparative analysis of the time-domain specifications, summarized in Table 5, demonstrates the efficacy of the proposed optimization techniques in regulating rotor speed. All four algorithms i.e., DE, PSO, WOA, and MWOA successfully achieve a steady-state speed of 3000 rpm with zero steady-state error and no peak overshoot, indicating a robustly damped control law. In terms of transient behaviour, WOA exhibits the most efficient startup trajectory,

reaching the reference speed in approximately 0.08 s. While MWOA shows a rapid initial rise to 2700 rpm within the first 0.01 s, it adopts a more gradual approach to the final setpoint, resulting in a slightly longer total rise time. The $t = 0.5$ s the load disturbance is applied. The MWOA algorithm demonstrates superior disturbance rejection capabilities, limiting the speed dip to only 15 rpm (a 0.5% deviation) and achieving recovery in approximately 0.01 s. In contrast, PSO and DE experience significantly deeper drops of 85 rpm and 80 rpm, respectively, with recovery times nearly seven times slower than MWOA. These results suggest that while WOA provides a balanced initial response, the MWOA optimization yields a higher degree of controller stiffness and dynamic stability, making it the most suitable choice for high-precision applications under varying load conditions.

Table 5 Time response specifications for case 2

Algorithm	Rise Time (sec)	Settling Time (sec)	Maximum Speed Drop (rpm)	Recovery Time
PSO	0.14	0.11	85	0.07
DE	0.12	0.09	80	0.06
WOA	0.08	0.06	50	0.04
MWOA	0.25	0.05	15	0.01

Case 3: Over load operation (150% of full load)

The BLDC motor's target speed was configured at 3000 rpm. A load torque disturbance of 4.77 Nm was introduced at 0.5 seconds. Figure 6 provides a comparative visualization of the motor's speed response, contrasting the performance of the proposed method with that of other established techniques. This report analyzes a comparative performance chart of rotor speed control, where the controller parameters are tuned using four different metaheuristic optimization algorithms: PSO, DE, WOA, and an MWOA. The time response specifications are shown in table 6. The dynamic response of the rotor speed was evaluated across four optimization strategies: PSO, DE, WOA, and MWOA. The results indicate that MWOA achieves the most efficient time-domain performance, characterized by the shortest rise time and settling time with negligible overshoot. Furthermore, the analysis at $t = 0.5$ s demonstrates that MWOA provides superior disturbance rejection, maintaining a maximum undershoot of only 20 rpm, compared to the significantly higher drops of 125 rpm observed in PSO and DE. While all algorithms eventually achieve a steady-state error of zero, MWOA consistently exhibits higher robustness and faster recovery, making it the most effective

candidate for high-precision rotor speed control under varying load conditions.

Table 6 Time response specifications for case 3

Algorithm	Rise Time (sec)	Settling Time (sec)	Maximum Speed Drop (rpm)	Recovery Time
PSO	0.12	0.25	125	0.055
DE	0.11	0.24	120	0.05
WOA	0.06	0.18	70	0.035
MWOA	0.025	0.15	20	0.01

To test the robustness of the controller, the motor is started at no load and a load of 1.59 Nm is applied at 0.3 s and a load of 3.18 Nm is applied at 0.6 s. Figures 7 and 8 compare speed and torque responses of the machine in which the PI controller is tune different algorithms. Figure 7 shows the speed dips occurring with a disturbance in load and it also shows that the speed is quickly regained by the controls. Figure 8 shows the torque responses of drives with additional load using various algorithms. Figures 9, 10, 11, 12 shows the stator current variation during load variations with PSO, DE, WOA and MWOA respectively.

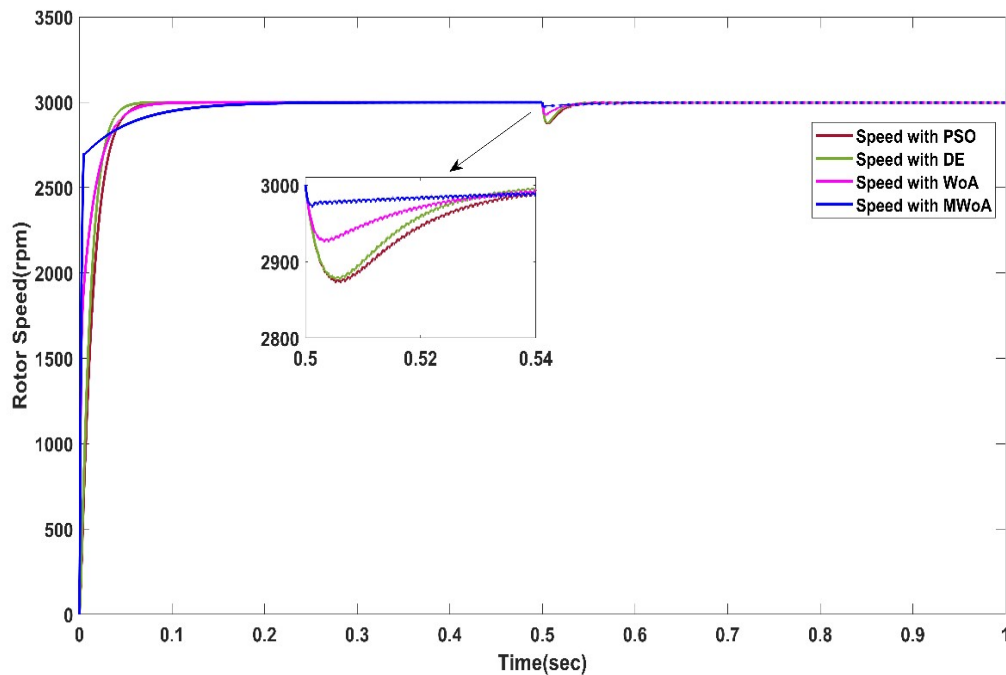


Figure 6: Speed response of BLDC motor at over load condition.

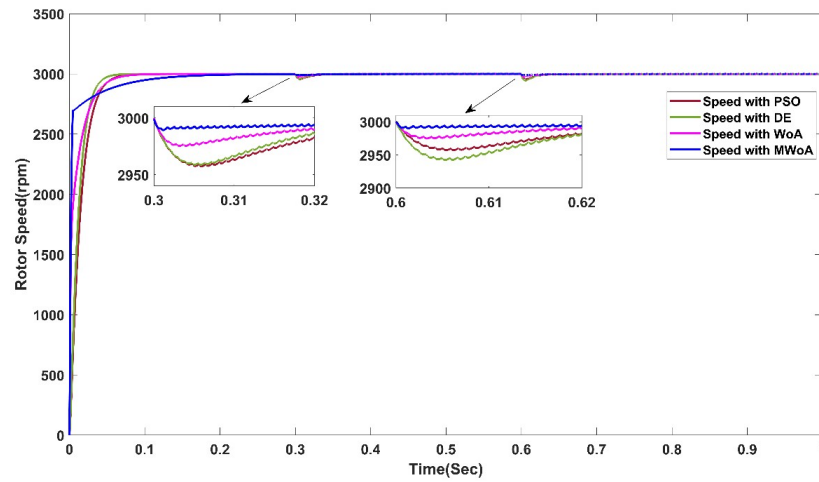


Figure 7: Speed response for load variations.

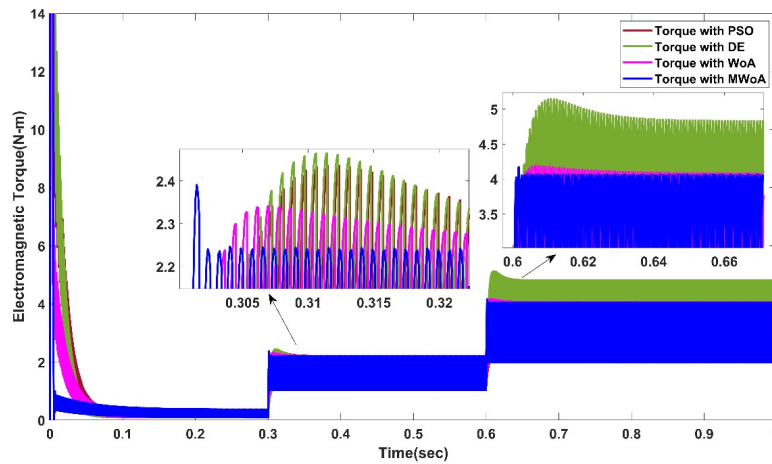


Figure 8: Torque response for load variations.

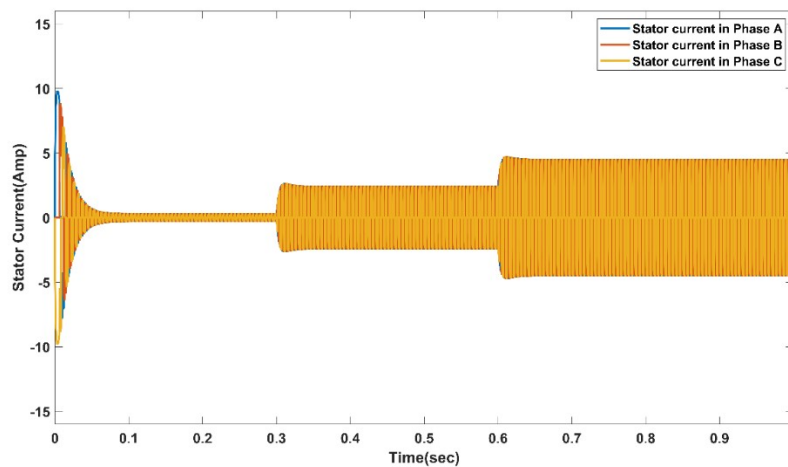


Figure 9: Stator current with load variation using PSO.

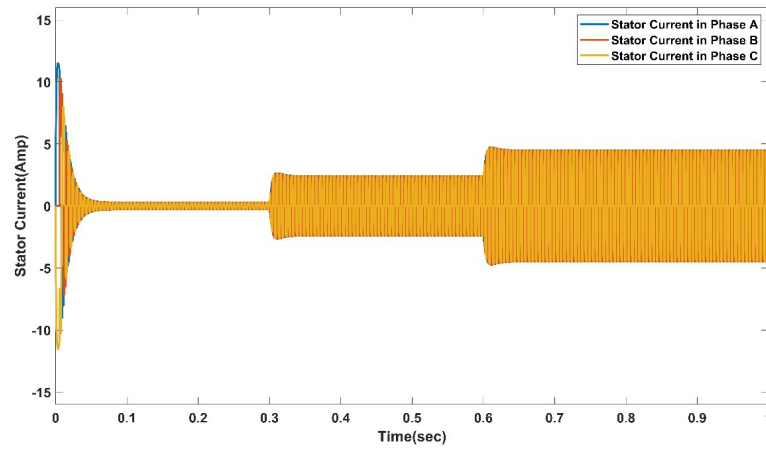


Figure 10: Stator current with load variation using DE.

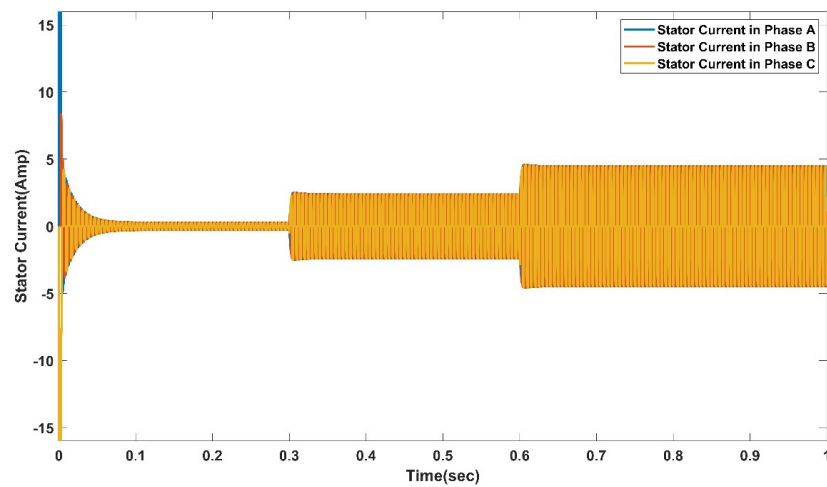


Figure 11: Stator current with load variation using WOA.

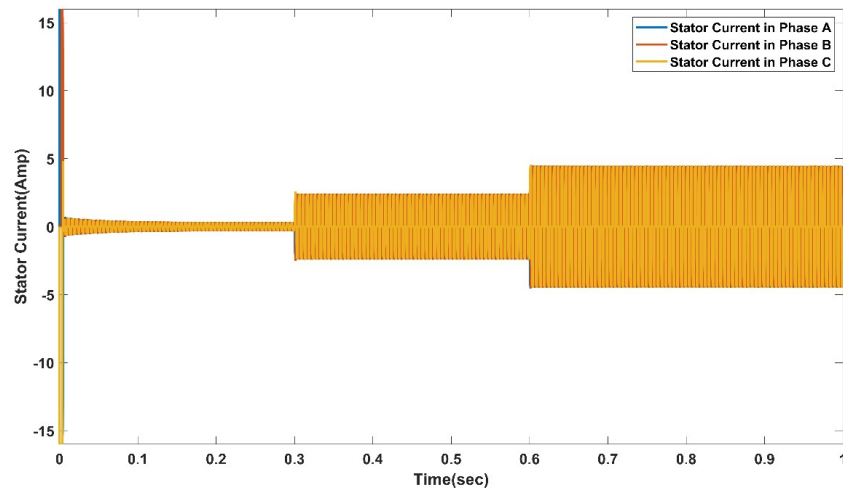


Figure 12: Stator current with load variation using MWOA.

5. CONCLUSION

This study has successfully proposed and validated a novel IWOA for the optimal tuning of a PI speed controller in a BLDC motor drive. Inspired by viral transmission dynamics and immune response mechanisms, MWOA effectively balances global exploration and local exploitation to minimize the ISE objective function, ensuring precise and robust motor control. Through comprehensive simulations conducted in MATLAB/Simulink under various operational conditions including sudden load changes and step reference speed variations the MWOA-tuned PI controller consistently demonstrated superior dynamic performance when benchmarked against established optimization algorithms such as PSO, DE, and standard WOA. These results confirm that the proposed MWOA is not only theoretically sound but also practically effective in enhancing the performance of BLDC motor drives. The algorithm's ability to optimize controller parameters in a dynamic and uncertain environment makes it a promising tool for industrial motor control applications, offering a pathway toward more efficient, responsive, and reliable electromechanical systems. Future work may explore the implementation of MWOA in real-time embedded systems and its extension to other types of motors and multi-objective optimization frameworks.

REFERENCES:

- [1] E. Çelik and M. Karayel, "Effective speed control of brushless DC motor using cascade IPDf-PI controller tuned by snake optimizer," *Neural Computing and Applications*, vol. 36, pp. 7439–7454, 2024, doi: 10.1007/s00521-024-09470-y.
- [2] F. Shafique, M. S. Fakhar, A. R. Butt, and M. A. Khan, "Analyzing the performance of metaheuristic algorithms in speed control of brushless DC motor: Implementation and statistical comparison," *PLOS ONE*, vol. 19, no. 10, e0310080, 2024, doi: 10.1371/journal.pone.0310080.
- [3] S. S. A. Naqvi, H. Jamil, N. Iqbal, S. Khan, D.-I. Lee, Y. C. Park, and D. H. Kim, "Multi-objective optimization of PI controller for BLDC motor speed control and energy saving in electric vehicles: A constrained swarm-based approach," *Energy Reports*, vol. 12, pp. 402–417, 2024, doi: 10.1016/j.egy.2024.06.019.
- [4] N. Prabhu, R. Thirumalaivasan, and B. Ashok, "Design of sliding mode controller with improved reaching law through self-learning strategy to mitigate the torque ripple in BLDC motor for electric vehicles," *Computers and Electrical Engineering*, vol. 118, art. no. 109438, 2024, doi: 10.1016/j.compeleceng.2024.109438.
- [5] Z. Li, X. Fan, Q. Kong, J. Liu, and S. Zhang, "Torque ripple suppression of BLDCM with optimal duty cycle and switch state by FCS-MPC," *IEEE Open Journal of Power Electronics*, vol. 5, pp. 381–391, 2024, doi: 10.1109/OJPEL.2024.3368221.
- [6] C. Zeng, Z. Wan, S. Huang, and J. He, "Torque ripple suppression in non-commutation interval of the coreless brushless DC motor based on unipolar PWM predictive control," *IET Power Electronics*, vol. 17, pp. 1621–1631, 2024, doi: 10.1049/pel2.12719.
- [7] L. Sun, Y. Li, J. Zhao, and C. Mi, "Commutation torque ripple suppression method for brushless DC motors with minimum phase shift angle," *International Journal of Circuit Theory and Applications*, vol. 52, no. 10, pp. 5144–5165, 2024, doi: 10.1002/cta.3997.
- [8] U. Hari Krishna and P. P. Rajeevan, "Multi-level voltage space vector structure based control strategy with reduced torque ripple for open-end winding BLDC motor drives," *IEEE Access*, vol. 12, pp. 74524–74538, 2024, doi: 10.1109/ACCESS.2024.3405978.
- [9] M. Akrami, E. Jamshidpour, B. Nahid-Mobarakeh, S. Pierfederici, and V. Frick, "Sensorless control methods for BLDC motor drives: A review," *IEEE Transactions on Transportation Electrification*, 2024, doi: 10.1109/TTE.2024.3387371.
- [10] B. Saha and B. Singh, "Sensorless BLDCM drive using an improved DSOGI-PLL observer for solar-PV-assisted LEV," *IEEE Transactions on Power Electronics*, vol. 40, no. 1, pp. 1636–1644, 2025, doi: 10.1109/TPEL.2024.3425914.
- [11] K. Kroičs and A. Būmanis, "BLDC motor speed control with digital adaptive PID-fuzzy controller and reduced harmonic content," *Energies*, vol. 17, no. 6, art. no. 1311, 2024, doi: 10.3390/en17061311.
- [12] E. Maheswari, B. N. Kommula, K. Rajesh, and S. Sharma, "Optimized maximum power point tracking for PV fed hybrid DC-DC converter-based BLDC motor driven electric vehicles,"

- Electrical Engineering, vol. 107, no. 1, pp. 965–986, 2025, doi: 10.1007/s00202-024-02561-y.
- [13] J. Sevugan Rajesh, R. Karthikeyan, and R. Revathi, “Analysis and control of grid-interactive PV-fed BLDC water pumping system with optimized MPPT for DC-DC converter,” *Scientific Reports*, vol. 14, art. no. 25963, 2024, doi: 10.1038/s41598-024-77822-8.
- [14] A. Dutta and A. Panda, “Torque ripple minimization of BLDC motor using dual predictive control for EV application,” in *Proc. 2024 IEEE 4th Int. Conf. Sustainable Energy and Future Electric Transportation (SEFET)*, 2024, doi: 10.1109/SEFET61574.2024.10718139.
- [15] S. B. Pandya, P. Jangir, M. Mahdal, K. Kalita, J. S. Chohan, and L. Abualigah, “Optimizing brushless direct current motor design: An application of the multi-objective generalized normal distribution optimization,” *Heliyon*, vol. 10, no. 4, art. no. e26369, 2024, doi: 10.1016/j.heliyon.2024.e26369.
- [16] P. Saiteja, B. Ashok, B. Mason, and P. S. Kumar, “Assessment of adaptive self-learning-based BLDC motor energy management controller in electric vehicles under real-world driving conditions for performance characteristics,” *IEEE Access*, vol. 12, pp. 40325–40349, 2024, doi: 10.1109/ACCESS.2024.3375753.
- [17] W. Chen, L. Zhu, X. Li, Z. Wang, et al., “Variable conduction mode control method to reduce torque ripple for symmetrical winding multi-phase brushless DC motor,” *IEEE Transactions on Power Electronics*, vol. 40, no. 1, pp. 638–651, 2025, doi: 10.1109/TPEL.2024.3472644.
- [18] L. Wang, Z.-Q. Zhu, X. Sun, F. Wei, and D. Liang, “A 12-step asynchronous PWM scheme for high-speed brushless DC drives with commutation compensation,” *IEEE Transactions on Industrial Electronics*, vol. 71, no. 10, pp. 11936–11947, 2024, doi: 10.1109/TIE.2024.3355524.
- [19] Y. Qu, Z. Liu, and L. Cai, “High-order state-filtering system design and its application to feedback control of a three-phase BLDC motor,” *IEEE Transactions on Industrial Electronics*, vol. 72, no. 3, pp. 2948–2957, 2025, doi: 10.1109/TIE.2024.3433421.
- [20] A. Dehestani Kolagar, A. Entezari, and M. R. Alizadeh Pahlavani, “Direct power control in BLDC motor drives using finite control set model predictive control to reduce torque ripple and speed fluctuation and improve harmonic distortions,” *Journal of Control*, vol. 17, no. 4, pp. 1–19, 2024, doi: 10.61186/joc.17.4.1.
- [21] “Analysis of control methods for BLDC motors in electric vehicle powertrain systems,” in *Proc. 2024 IEEE Int. Conf. Power Electronics, Drives and Energy Systems (PEDES)*, 2024, doi: 10.1109/PEDES61459.2024.10961105.
- [22] “Confirmatory check of 1 kW BLDC motor for use in electric vehicle application,” in *Proc. 2024 IEEE 3rd Int. Conf. Electrical Power and Energy Systems (ICEPES)*, 2024, doi: 10.1109/ICEPES60647.2024.10653463.
- [23] R. Inan, “An improved model predictive current control of BLDC motor with a novel adaptive extended Kalman filter-based back EMF estimator and a new commutation duration approach for electric vehicle,” *International Journal of Circuit Theory and Applications*, 2025, doi: 10.1002/cta.4407.
- [24] R. Shenbagalakshmi, S. K. Mittal, J. Subramaniyan, V. Vengatesan, D. Manikandan, et al., “Adaptive speed control of BLDC motors for enhanced electric vehicle performance using fuzzy logic,” *Scientific Reports*, vol. 15, art. no. 12579, 2025, doi: 10.1038/s41598-025-90957-6.
- [25] A. Kumar, M. V. Naik, R. Kumar, et al., “Design and analysis of BLDC motor speed control for electric vehicles powered by solar PV and grid supply,” *Discover Electronics*, vol. 2, art. no. 60, 2025, doi: 10.1007/s44291-025-00097-4.
- [26] N. Prabhu, T. Rajaram, and B. Ashok, “Design of sliding mode model predictive dual-loop control through self-learning strategy to mitigate the torque ripple in BLDC motor for electric vehicles,” *Scientific Reports*, vol. 15, art. no. 45617, 2025, doi: 10.1038/s41598-025-29445-w.
- [27] Y.-T. Shieh, G.-T. Liou, S.-L. Jeng, W.-H. Chieng, J.-S. Lai, and E.-Y. Chang, “Copolar synchronous switching method for BLDC motor control in EV application,” *IEEE Access*, vol. 13, pp. 116729–116744, 2025, doi: 10.1109/ACCESS.2025.3584259.
- [28] M. Karabacak, D. Hrvanovic, E. Ipek, E. Blazhevskaya, N. Köster, H. Haberl, and G. Prochart, “Accurate BLDC modeling and interleaved control for multi-motor powertrains with improved FOC to mitigate battery current and torque ripples,” *IEEE Access*, vol. 13, pp.

- 209328–209355, 2025, doi: 10.1109/ACCESS.2025.3640284.
- [29] V. Tadivalasa, P. K. Biswas, U. Das, S. B. Thanikanti, et al., “Optimized PV fed sensorless BLDC motor control system using Q-recurrent adaptive controller and Levy-enhanced circular search mechanisms,” *Scientific Reports*, vol. 15, art. no. 42701, 2025, doi: 10.1038/s41598-025-26884-3.
- [30] M. A. Khan, D.-Z. Baig, H. Ali, et al., “Torque and speed prediction of a brushless direct current motor using nonlinear autoregressive with exogenous inputs and neural network,” *Scientific Reports*, vol. 15, art. no. 27191, 2025, doi: 10.1038/s41598-025-11296-0.
- [31] S. Wang, D. Li, and B. Tan, “A novel sensorless commutation technique for BLDC motors: Phase-delay elimination and enhanced error compensation,” *International Journal of Circuit Theory and Applications*, vol. 53, no. 12, pp. 6962–6973, 2025, doi: 10.1002/cta.4520.
- [32] Z. Feng, E. S. Tahim, J. Zhang, R. R. Ramesh, et al., “Extended operation of brushless DC motors beyond 120° under torque ripple reduction control,” *IEEE Transactions on Energy Conversion*, vol. 40, no. 4, pp. 3071–3083, 2025, doi: 10.1109/TEC.2025.3565219.
- [33] H. Krishna U. and P. P. Rajeevan, “A direct torque control scheme with integrated commutation torque ripple reduction for BLDC motor drives with open-end windings,” *IEEE Open Journal of Power Electronics*, 2025, doi: 10.1109/OJPEL.2025.3545738.
- [34] A. Kardeş, M. Çavdar, and Ö. Üstün, “A high-performance driver design for brushless DC motors in E-scooter speed control,” in *Proc. 2025 16th Int. Conf. Electrical and Electronics Engineering (ELECO)*, 2025, doi: 10.1109/ELECO69582.2025.11329217.
- [35] R. K. Verma and R. Kumar, “Speed control of single stage solar PV fed BLDC motor-driven water pumping,” in *Proc. 2025 4th Int. Conf. Power, Control and Computing Technologies (ICPC2T)*, pp. 994–999, 2025, doi: 10.1109/ICPC2T63847.2025.10958757.
- [36] S. Karyś and P. Stawczyk, “High-efficiency BLDC motor regenerative braking system with new single-switched transistor control algorithm,” *International Journal of Electrical Power & Energy Systems*, vol. 166, art. no. 110565, 2025, doi: 10.1016/j.ijepes.2025.110565.
- [37] A. Gopalakrishnan and R. Thottungal, “Enhancing power efficiency in BLDC motor drives for drones using multiview learning with hybrid optimization algorithms,” *Scientific Reports*, vol. 15, art. no. 28021, 2025, doi: 10.1038/s41598-025-13420-6.
- [38] A. I. Abouseda, R. O. Doruk, and A. Amini, “Parameter identification and speed control of a small-scale BLDC motor: Experimental validation and real-time PI control with low-pass filtering,” *Machines*, vol. 13, no. 8, art. no. 656, 2025, doi: 10.3390/machines13080656.
- [39] A. Venkatesh, S. Nalinakshan, S. Phani Kumar, S. S. Kiran, and K. Akash, “Optimized control strategies for BLDC motor in sustainable energy systems: Enhancing stability and performance through intelligent controllers, filtering techniques and internal model control,” *Global Energy Interconnection*, 2025, doi: 10.1016/j.gloi.2025.09.004.
- [40] D. Sudarno Putra, W. Purwanto, Risfendra, J. O. Abratiguin, A. Baharudin, and T. Huda, “Design and simulation of BLDC motor control using MATLAB Simulink: A detailed approach,” *Mechanical Engineering for Society and Industry*, vol. 5, no. 2, pp. 399–412, 2025, doi: 10.31603/mesi.13370.
- [41] M. Şen and M. Mutluer, “A review of BLDC motors: Types, application, failure modes and detection,” *Energies*, vol. 18, no. 24, art. no. 6402, 2025, doi: 10.3390/en18246402.
- [42] D. M. Hojati, S. C. Mukhopadhyay, R. Han, and F. Taghizadeh, “Torque ripple and vibration reduction in BLDC motors using a bilayer stator structure,” *IEEE Transactions on Industrial Electronics*, 2026, early access, doi: 10.1109/TIE.2026.3697473.
- [43] D. Luo and B. Jiang, “A new method for the speed control of a brushless DC motor based on optimized fuzzy control,” *ELECTRICA*, vol. 26, pp. 1–13, 2026, doi: 10.5152/electrica.2026.25063.
- [44] S. M. Dawood, Z. M. Alhakeem, Q. Q. Thabit, et al., “Brushless DC motor optimum speed control using TSA-PID strategy,” *Journal of Engineering and Applied Science*, vol. 73, art. no. 364, 2026, doi: 10.1186/s44147-026-01230-0.
- [45] D. S. Purushothaman and K. R. Santha, “Neural network based optimization of FOPID controller for speed regulation of a sensorless BLDC motor drive,” *Journal of Vibration Engineering & Technologies*, vol. 14, art. no. 305, 2026, doi: 10.1007/s42417-026-02505-9.

- [46] V. Kumarasamy, M. Paramasivan, G. Chandrasekaran, J. Thangavel, S. Muthusamy, J. Giri, M. Kanan, C. K. Chan, S. Singh, D. Varshney, and N. Naik, "Machine learning technique based optimized fractional order PID controller of Brushless DC motor in Electric Delta Type Recumbent Tricycle applications," Results in Control and Optimization, vol. 23, art. no. 100705, 2026, doi: 10.1016/j.rico.2026.100705.