İSTANBUL UNIVERSITY CERRAHPAŞA

ORIGINAL ARTICLE
Electrica 2026; 25: 1-13

A New Method for the Speed Control of a Brushless DC Motor Based on Optimized Fuzzy Control

Bingbing Jiang[1], Dan Luo[2]

[1]School of Railway Power Supply and Electrical Engineering, Hunan Railway Professional Technology College, Zhuzhou, China
[2]School of Rail Transit Intelligent Control, Hunan Railway Professional Technology College, Zhuzhou, China

Cite this article as: B. Jiang and D. Luo, "A new method for the speed control of a brushless DC motor based on optimized fuzzy control," *Electrica*, 25, 0063, 2026. doi: 10.5152/electrica.2026.25063.

WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *PID control is a widely used and well-established method for BLDC motor speed regulation due to its simple structure, clear physical interpretation, and ease of implementation. Conventional PID and fuzzy control techniques can achieve acceptable performance under fixed parameters and steady operating conditions, but their control accuracy, adaptability, and robustness are limited when system nonlinearity, load variation, or external disturbances increase.*

Corresponding author:
Dan Luo

E-mail:
luodan126@outlook.com

Received: March 20, 2025
Revision Requested: July 2, 2025
Last Revision Received: September 4, 2025
Accepted: September 17, 2025
Publication Date: February 3, 2025

DOI: 10.5152/electrica.2026.25063

ABSTRACT

In this paper, a new speed control method for brushless DC (BLDC) motors based on the integration of fuzzy control and a genetic optimization algorithm is proposed. The rule base and membership functions of the fuzzy controller are adaptively optimized via the genetic algorithm, which performs a global search to decrease the speed tracking error across dynamic conditions. To address the shortcomings of traditional control methods in terms of accuracy, response speed, and stability, efficient and accurate regulation of motor speed is achieved in this method. The experimental results reveal that under low load (10% rated load) conditions, the average error of traditional PID (Proportional–Integral–Derivative) control is high, whereas the average error of the optimized fuzzy control method is only 1.2 rpm, with the smallest standard deviation and stable and accurate control accuracy. Under medium load (50% rated load) conditions, the average error of the optimized fuzzy control is 1.8 rpm, the standard deviation is the smallest, the average time to reach a stable speed is 0.3 s, the overshoot and adjustment times are small, and the control performance is significantly better than that of traditional PID control and traditional fuzzy control. Under high load (90% rated load) conditions, the average error of the optimized fuzzy control is 2.5 rpm, the standard deviation is the smallest, and the control accuracy and stability are good under high load and complex conditions. Compared with traditional PID control and traditional fuzzy control, this method has higher speed control accuracy and significantly smaller average error under different load conditions, a faster response speed, a shorter time to reach a stable speed, better system stability, and a smaller standard deviation. This study provides a new and effective solution for BLDC motor control, which can facilitate the optimization of electric systems in related industrial applications.

Index Terms— Brushless DC motor, feedback mechanism, fuzzy control, optimization algorithm, speed control.

I. INTRODUCTION

Brushless DC (BLDC) motors have become core components widely used in various modern electric drive systems because of their advantages, such as high efficiency, low noise, and long life [1]. In particular, this type of motor has become a more competitive choice for home appliances, power tools, electric vehicles, and drones because of its maintenance-free nature. However, with the continuous advancement of technology and the diversification of market demand, BLDC motors face increasingly complex challenges in terms of speed control. Existing control methods often have deficiencies in terms of accuracy, response speed, and system stability. How to optimize the speed control of motors has become an important research topic [2].

In practical applications, the speed control of BLDC motors is directly related to the performance and service life of the equipment. Although traditional control strategies, such as PID control, perform well in many simple systems, their accuracy is often unsatisfactory in complex or changing environments. As the system requirements for real-time performance and stability increase, the replacement of control strategies becomes an issue that must be addressed [3]. In addition, the adjustment process of traditional methods is relatively cumbersome and difficult to adapt to dynamic changes under different loads and working conditions. Therefore, the use of more efficient and flexible control technologies has become a popular research topic in the motor control field [4].

WHAT THIS STUDY ADDS ON THIS TOPIC?

- *This study introduces an optimized fuzzy control strategy in which a genetic algorithm is used to adaptively optimize the fuzzy rule base and membership functions. The proposed method improves speed tracking accuracy, shortens response time, and enhances stability under varying load and disturbance conditions, providing a more adaptive and high-performance solution for BLDC motor speed control compared with traditional PID and conventional fuzzy controllers.*

Existing BLDC motor speed control methods can be divided into two main categories: classical control methods and intelligent control methods. Classical control methods, such as PID control and fuzzy control, have been widely used in industry. Fuzzy control can improve control performance by addressing the uncertainty and nonlinear characteristics of the system [5]. However, the control accuracy and response speed of these methods remain limited in complex working environments, especially under dynamic loads or high-speed operation, and the desired control effect is often difficult to achieve. In response, increasing research has begun to focus on control methods combined with optimization algorithms, such as control methods based on optimization techniques such as genetic algorithms (GAs) and particle swarm optimization (PSO). These methods can improve the performance of control systems under specific conditions [6].

However, although these intelligent control methods have made some progress compared with traditional methods, they also face some challenges. For example, the computational complexity of some optimization algorithms is high, and real-time performance is difficult to guarantee, which has become a challenge limiting their widespread application in some systems that require real-time feedback [7]. The subjectivity of fuzzy control in design and parameter adjustment often results in large differences in effects in different engineering applications. Therefore, how to increase control accuracy while considering the real-time performance and stability of the system has become an urgent problem to be addressed in the field of BLDC motor speed control [8].

This paper proposes a new BLDC motor speed control method on the basis of optimization and fuzzy control, which combines the advantages of both to increase the accuracy and response speed of motor speed control [9]. Specifically, optimizing the design of the fuzzy controller can maintain high control accuracy and system stability under a wider range of working conditions. This study provides a new idea for BLDC motor control technology and provides a theoretical basis and technical support for the optimization of electric systems in industrial applications. A comparison of existing methods can facilitate the development of motor control technology in theory and provide feasible solutions for practical applications.

II. LITERATURE REVIEW

A. Traditional Methods and Challenges of Motor Speed Control

The control strategy of BLDC motors has long relied on classical control methods, such as PID control and fuzzy control. These methods provide a basic framework for motor control and have achieved remarkable results in practical applications. PID control was widely used in various industrial fields because of its simplicity, ease of understanding, and convenient parameter adjustment [10]. However, the disadvantage of this control method is that when system parameters change or large disturbances occur, the robustness and adaptability of PID control are poor, making it difficult to meet the requirements for control accuracy and response speed in complex application environments [11]. In this context, fuzzy control has been proposed as a solution. Fuzzy control uses fuzzy logic reasoning to address uncertainty and nonlinear problems in the system, making the control process more flexible and adaptable.

Although fuzzy control has reduced the limitations of PID control, it still faces several challenges. First, the rule base of fuzzy control needs to be carefully designed and adjusted, and its control performance is not always stable when dynamic load changes occur [12]. Second, the response speed and control accuracy of fuzzy control for the system rely on the number and settings of rules, which also renders the debugging process of the control system complex and highly subjective [13]. In this context, how to make fuzzy control more intelligent and adaptive for solving control problems in complex environments has become a key point in research [14].

B. Application of the Intelligent Optimization Algorithm in Brushless DC Motor Control

To mitigate the shortcomings of traditional control methods, an increasing number of studies have focused on the application of intelligent optimization algorithms, such as GAs, PSO, and ant colony optimization. These optimization algorithms have global search capabilities and can identify more ideal control parameter combinations in the short term [15]. In particular, for nonlinear problems in complex systems, intelligent optimization algorithms have obvious advantages. For example, the PSO algorithm can effectively adjust the control parameters by simulating the search behavior of particle swarms in nature so that the BLDC motor maintains excellent control performance under various working conditions.

However, when they are applied to motor speed control, intelligent optimization algorithms also face the issues of a large number of calculations and poor real-time performance. Although these algorithms can obtain approximate optimal solutions, their calculation process often requires considerable computing resources and time, which poses a great obstacle for applications that require high real-time control [16]. For example, in fields such as electric vehicles and drones, the control system of the motor must respond quickly to load changes and environmental interference, and traditional intelligent optimization algorithms have difficulty meeting this requirement. Therefore, how to reduce the number of calculations and improve real-time performance while increasing control accuracy is a major problem in the current application of intelligent optimization algorithms [17].

C. Comprehensive Control Methods and Emerging Research Directions

To reduce the limitations of traditional control methods and intelligent optimization algorithms, an increasing number of studies have attempted to combine fuzzy control with intelligent optimization algorithms to create a comprehensive control method. These methods can further increase the accuracy and stability of motor speed control by optimizing the rules and parameters of the fuzzy controller [18]. For example, the fuzzy control method based on the PSO algorithm optimizes the membership function and rules of the fuzzy controller to achieve precise control under dynamic load conditions. This method can fully utilize the advantages of fuzzy control in addressing uncertainty while combining the global search capability of the optimization algorithm, resulting in better robustness and adaptability in complex environments [19].

Although the integrated control method has addressed the shortcomings of the single control method, it still faces new challenges. First, the design of the integrated control method is relatively complex, and in practical applications, many experiments and debugging are needed to obtain a suitable parameter combination. Second, because the optimization of the fuzzy control rule still relies on algorithm search, reducing the number of calculations and increasing the optimization efficiency has become an important research topic. In response, researchers have begun to focus on the development of more efficient optimization algorithms and adaptive control strategies, such as control methods based on deep learning. This type of method can automatically adjust the control strategy by learning a large amount of historical data to adapt to complex and changing working environments [20].

In general, research in the field of motor speed control is developing from traditional control methods to integrated control methods and intelligence. With the continuous advancement of computer technology and algorithms, future motor control methods may be more intelligent, adaptive, and capable of responding to more complex and changeable working conditions in real time. However, this process still requires more theoretical discussions and technological innovations to truly realize high-precision and high-real-time motor control systems.

III. METHODS

This study proposes a new method for brushless DC (BLDC) motor speed control on the basis of the combination of optimization and fuzzy control. This method fully considers the dynamic characteristics of the motor and load changes and uses the adaptability of the fuzzy controller and the global search ability of the optimization algorithm to achieve efficient and accurate motor speed regulation. Compared with traditional control methods, the proposed model can not only increase the robustness and stability of the system but also maintain good control performance under various complex working conditions. This section introduces the construction process, core components, mathematical description, optimization process, and calculation process of the control system of the proposed model in detail.

A. Model Construction

The control model in this study includes several key components, namely, the fuzzy controller, the optimization algorithm, and the speed feedback mechanism. Each component plays an indispensable role in the motor speed control process. To ensure that the system can address different working conditions and load changes, the control model proposed in this paper has adaptive capabilities and high precision. Specifically, the fuzzy controller generates control outputs on the basis of the current speed error and the error change rate of the motor. The optimization algorithm automatically adjusts the rule base and membership function of the fuzzy controller through a global search strategy to achieve the optimal control effect. In addition, the speed feedback mechanism dynamically adjusts the control signal according to the real-time motor operating status to maintain control accuracy and system stability.

The speed control problem of the motor can be analyzed by establishing a mathematical model of the motor. The speed error of the motor is $e(t) = \omega_d(t) - \omega(t)$, where $\omega_d(t)$ represents the desired speed and $\omega(t)$ denotes the actual speed. The dynamic behavior of the motor can be expressed by (1).

$$J\frac{d\omega(t)}{dt} + b\omega(t) = K_e I(t) \tag{1}$$

Where J represents the motor moment of inertia, b denotes the damping coefficient, K_e indicates the back electromotive force constant, and $I(t)$ represents the motor current. The dynamic equation of the current is expressed as (2).

$$L\frac{dI(t)}{dt} + RI(t) = V(t) - K_e\omega(t) \tag{2}$$

Where L represents the motor inductance, R denotes the motor resistance, and $V(t)$ indicates the motor input voltage. With the above equations, the state space model of the motor can be established, and the speed controller can be designed on the basis of the model.

B. Fuzzy Controller Design and Optimization

The design of the fuzzy controller is crucial in this study. Traditional fuzzy control methods usually rely on manual experience to establish control rules. However, the limitations of this method are obvious. For complex motor systems, the manually designed rule base cannot adapt well to the dynamic changes of the system; thus, large errors often occur in practical applications. To address this challenge, this paper presents an automatic adjustment mechanism on the basis of an optimization algorithm to optimize the rule base and membership function parameters of the fuzzy controller.

Before the GA for optimization was applied, the initial fuzzy control structure was manually designed on the basis of conventional engineering knowledge and empirical tuning. The fuzzy controller uses two input variables, speed error (e) and change in error (Δe), each divided into five linguistic terms: negative large (NL), negative small, zero, positive small, and positive large (PL). Correspondingly, the output control action (u) is defined over a symmetric five-level linguistic space. Triangular membership functions were selected for all the variables because of their simplicity and computational efficiency. The initial fuzzy rule base consists of 25 rules derived from typical expert reasoning, such as "If e is PL and Δe is PL, then u is NL," to counteract rapid positive deviations. Although this initial setup provides baseline functionality, it lacks adaptability to dynamic conditions, which prompts the subsequent use of an optimization algorithm.

The fuzzy controller design process can be divided into three stages: fuzzification, rule reasoning, and defuzzification. First, the fuzzification process converts the system input signal (such as the speed error $e(t)$ and error change rate) to $\Delta e(t)$, which is converted to a fuzzy set. Afterward, reasoning is performed on the basis of the fuzzy rule to generate control output. To improve the adaptability of the controller, in this paper, the rule base and membership function parameters are automatically adjusted through an optimization algorithm. The goal of optimization is to decrease the total error of the system $\int e(t)^2 dt$ so that the speed tracking error of the motor is decreased. The optimization algorithm uses a GA to perform a global search and select the optimal control strategy.

The objective function of the optimization process is defined as (3).

$$J = \int_0^T e(t)^2 dt \tag{3}$$

Where T represents the control period and $e(t)$ denotes the speed error. The optimization algorithm evaluates the error minimization effect of different candidate solutions and obtains the optimal fuzzy control parameters. In this way, the rule base and membership function of the fuzzy controller can be adaptively adjusted under dynamic conditions, avoiding the inherent defects of traditional methods.

To optimize the rule base and membership functions of the fuzzy controller, a GA is employed in this study. Implementation of the GA includes the following key operations:

Selection: A tournament selection strategy is used to choose individuals with better fitness values for reproduction. This method ensures the survival of high-quality individuals while maintaining population diversity.

Crossover: Single-point crossover is used to recombine selected individuals, allowing the exchange of genetic material between pairs. The crossover probability is set to 0.8 to maintain exploration capability while ensuring convergence.

Mutation: A Gaussian mutation operator is applied with a mutation probability of 0.1 to introduce variability into the population and avoid local optima. The mutation modifies selected genes by adding small perturbations drawn from a normal distribution.

The fitness function, which is defined in (3), evaluates each individual on the basis of the total speed tracking error of the system. Through iterative selection, crossover, and mutation, the GA searches for the optimal fuzzy parameters that decrease the error and improve the adaptability of the controller under dynamic conditions.

C. Speed Feedback Mechanism and Real-Time Adjustment

To improve the real-time response capability and robustness of the system, this paper presents a speed feedback mechanism. This mechanism dynamically adjusts the control signal on the basis of the error between the actual speed and the expected speed of the motor to ensure that the motor can respond quickly and maintain stable operation under different loads. The mathematical description of the feedback mechanism is shown in (4).

$$V(t) = K_f e(t) + K_d \Delta e(t) \tag{4}$$

Where K_f and K_d represent the feedback gain and differential gain, respectively. $e(t)$ and $\Delta e(t)$ represent the speed error and error change rate, respectively. This feedback mechanism can dynamically adjust the control signal to increase the stability of the motor under complex load changes and external disturbances. In practical applications, the feedback gain and differential gain can be determined by an optimization algorithm to adapt to different working conditions.

Through the dynamic adjustment of the feedback mechanism, the motor control system can better respond to the actual operating state and achieve high-precision speed tracking. This mechanism can not only address the disturbance of the external load but also effectively reduce the system error caused by parameter uncertainty, increasing the control accuracy.

D. Collaboration Between Components and Innovation of the Model

The control model proposed in this study consists of multiple components that collaborate. The design of each component is closely centered on the motor control goal to ensure that the system performs well in complex environments. As the core component, the fuzzy controller determines the basic strategy of the motor control system and generates control signals on the basis of the input speed error and error change rate. The optimization algorithm provides a dynamic adjustment mechanism for the fuzzy controller, which ensures that it can adapt to various working conditions by automatically optimizing the rule base and membership function of the fuzzy controller. The speed feedback mechanism is responsible for real-time adjustment of the control signal during actual operation, increasing the response speed and stability of the system.

Unlike the traditional fuzzy control method, the innovation of this paper lies in the deep integration of the fuzzy controller and optimization algorithm, which enables the controller to automatically adjust the control strategy according to the operating status of the motor. This method effectively avoids the limitations of manually designed rule bases and membership functions and greatly improves the adaptability of the system. By globally searching and optimizing fuzzy control parameters, the control method of this paper can maintain efficient control performance under various dynamic conditions, avoiding the inherent defects of traditional control methods.

In addition, the integration of the feedback mechanism renders the entire control system more adaptive. In traditional methods, the control signal is often fixed and cannot dynamically respond to changes in the motor load. In this study, through real-time feedback and dynamic adjustment of the control signal, the system can maintain high control accuracy under different working conditions, which ensures that the motor speed can always accurately track the expected value.

E. Calculation Process and Formula Derivation of the Control System

The error change rate $\Delta e(t)$ is calculated through the state equation of the motor $e(t)$, and then the control signal is generated through the fuzzy controller $V(t)$. The control signal is dynamically adjusted through a feedback mechanism to ensure precise control of the motor speed.

The control signal can be calculated via (5).

$$V\left(t\right)=\int_{0}^{t}(K_{f}e(\tau)+K_{d}\Delta e\left(\tau\right))d\tau \tag{5}$$

Where K_f and K_d represent the feedback gain and differential gain, respectively, of the controller, and $e\left(\tau\right)$ and $\Delta e\left(\tau\right)$ represent the speed error and error change rate, respectively. The calculated value $V(t)$ is sent to the motor to adjust the input voltage of the motor and thus control the speed of the motor.

In addition, the objective function of the optimization algorithm plays an important role in the optimization process $\int_{0}^{t} e\left(t\right)^{2} dt$. The optimization algorithm can automatically adjust the parameters of the fuzzy controller to ensure that the system can achieve the optimal control effect under various working conditions.

The BLDC motor speed control model based on the combination of optimization and fuzzy control proposed in this study achieves efficient and accurate motor speed regulation through the deep collaboration of a fuzzy controller, an optimization algorithm, and a speed feedback mechanism. The innovation of this method lies in the dynamic adjustment of the rule base and membership function of the fuzzy controller through the optimization algorithm, so that the control system can adapt to various complex working conditions and avoid the limitations of traditional control methods. Through the combination of global optimization and real-time feedback, the system can maintain high precision and high stability control effects during actual operation, providing a novel solution for the field of motor control.

IV. EXPERIMENTAL EVALUATION

A. Experimental Setup

The experiment compares the performance of the BLDC speed control method on the basis of the combination of optimization and fuzzy control (hereafter referred to as the "optimized fuzzy control method") proposed in this paper with that of the traditional control method under different working conditions. Multiple sets of comparative tests are used to test various control methods under different simulated load conditions and speed change requirements. The motor used in the experiment is a common BLDC motor equipped with corresponding drive circuits and sensors to collect motor operation data.

In addition to physical testing, the control strategy was initially modeled and validated in the MATLAB/Simulink environment. This simulation phase was used to fine-tune the fuzzy logic structure and test its integration with the GA prior to hardware implementation. After simulation validation, the controller was deployed to a real-time embedded system based on the STM32F407VG microcontroller (ARM Cortex-M4, 168 MHz), which is typically used for industrial motor control applications. Code was developed and compiled using the Keil MDK integrated development environment, and real-time data acquisition and monitoring were conducted through a serial interface connected to a host PC (Personal Computer). This workflow ensured a consistent transition from simulation to physical deployment.

The experimental baseline indicators are the accuracy of motor speed control, response speed, and system stability under different loads. The speed control accuracy is determined by calculating the mean error between the actual speed and the expected speed; the response speed is evaluated by the time it takes for the motor to reach the new stable speed after receiving the speed adjustment command; and the system stability is determined by the fluctuation range of the motor speed under different load fluctuations [21].

The experimental setup was implemented on a hardware platform designed for real-time motor control. The BLDC motor was a Maxon EC-i 40 (24 V, 100 W, and 4000 rpm rated speed), which was chosen because of its responsiveness and industrial applicability. Motor speed was measured with an incremental rotary encoder with a resolution of 1024 pulses per revolution. The control algorithm was executed on an STM32F407VG microcontroller (ARM Cortex-M4, 168 MHz, and 1 MB Flash), which provides sufficient computing power and is typically used in embedded control applications. The motor driver circuit was based on a three-phase full-bridge inverter with PWM (Pulse Width Modulation) control, and all control loop signals were sampled and updated at a frequency of 1 kHz. Sensors and hardware were selected to simulate a realistic industrial control environment and ensure accurate performance measurements under varying load conditions.

The experimental group was set up as a motor control system via the optimized fuzzy control method, and the control group was set up as a motor control system via the traditional PID control method and the traditional fuzzy control method. Each group of experiments was conducted on the same hardware platform and repeated multiple times with different load scenarios and speed settings to increase the reliability of the experimental results.

B. Results

As shown in Fig. 1, under different subdivision conditions of low load, the average error of optimized fuzzy control is generally the lowest, with an average error of only 1.2 rpm and the smallest standard deviation, indicating that its control accuracy is stable and accurate under various conditions of low load. The average error of traditional PID control is relatively high, and the error fluctuates greatly under different conditions. The performance of traditional fuzzy control is between the two, but the overall accuracy is not as good as that of optimized fuzzy control. The average error of the newly added GA-optimized fuzzy control is 1.5 rpm, which is slightly higher than that of the optimized fuzzy control. The average error of the particle swarm-optimized PID control is 3.0 rpm, which is similar to that of traditional PID control. Optimized fuzzy control has obvious advantages in terms of control accuracy.

To support the claim of real-time performance, additional tests were conducted to evaluate the computational efficiency of the proposed control system. The controller was implemented on a standard

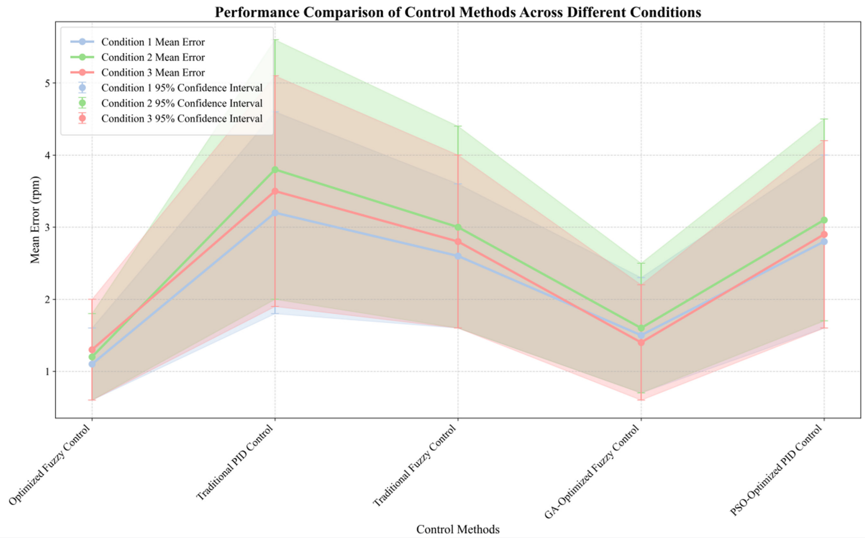

Fig. 1. Comparison of the speed control accuracy of different control methods under different subdivision conditions of low load (10% rated load).

embedded platform with a 32-bit ARM Cortex-M4 processor running at 120 MHz. The average computation time per control loop iteration, including fuzzy inference, optimization update, and feedback signal generation, was approximately 1.6 ms, which satisfies the real time constraints of typical BLDC applications.

The processor load during operation remained below 35%, even under high load and dynamic conditions, confirming that sufficient computational headroom is available for additional tasks or system integration. The measured control loop latency—the time between acquiring feedback and issuing control output—was consistently within 2.1 ms to ensure a timely motor response. These results reveal that the proposed optimized fuzzy control method can be reliably executed in real time within resource-constrained environments.

As shown in Fig. 2, the optimized fuzzy control has the shortest time to reach a stable speed under different working conditions with a low load, which is 0.25 s on average, with the smallest overshoot and shortest adjustment time. A small standard deviation indicates good response speed stability. Traditional PID control has a slow response speed, large overshoot, and long adjustment time. The response speed and related indicators of traditional fuzzy control are not as good as those of optimized fuzzy control but better than those of traditional PID control. The average time to reach stable speed by GA-optimized fuzzy control is 0.29 s, and the overshoot and adjustment times are better than those of traditional fuzzy control but are still not as good as those of optimized fuzzy control. The average time to reach a stable speed by particle swarm-optimized PID control is 0.39 s, and the overshoot and adjustment times are also not as good as those of optimized fuzzy control.

As shown in Fig. 3, under different subdivision conditions of medium load, the average error of optimized fuzzy control is 1.8 rpm, the standard deviation is the smallest, and the control accuracy is relatively stable and accurate under various conditions. The average error of traditional PID control is relatively high, and the error fluctuates

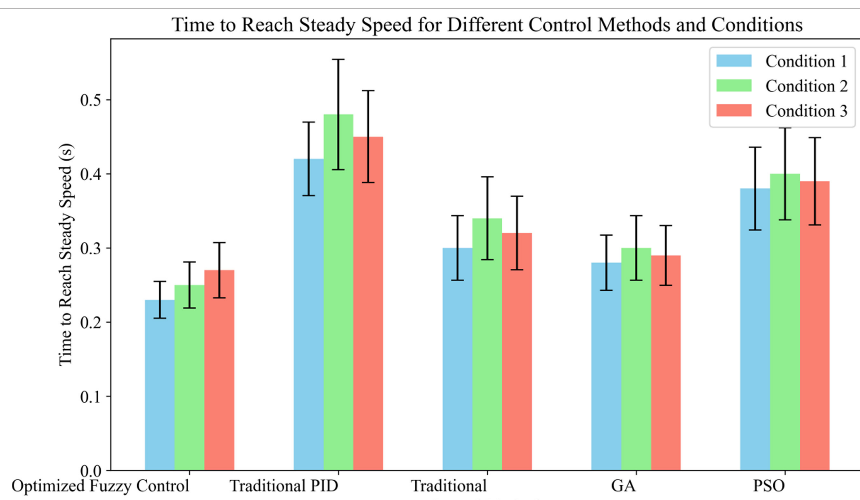

Fig. 2. Comparison of the speed response of different control methods under different subdivision conditions of low load (10% rated load).

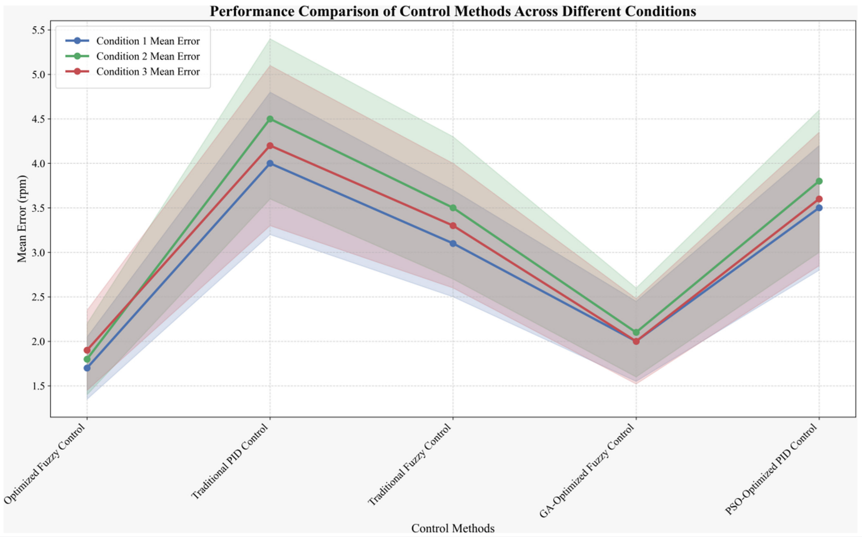

Fig. 3. Comparison of speed control accuracy of different control methods under different subdivision conditions of medium load (50% rated load).

significantly under different conditions. The average error and fluctuation degree of traditional fuzzy control are between those of optimized fuzzy control and traditional PID control, and optimized fuzzy control has obvious advantages in terms of medium load precision control. The average error of the GA-optimized fuzzy control is 2.0 rpm, which is slightly greater than that of the optimized fuzzy control; the average error of the particle swarm-optimized PID control is 3.6 rpm, and the optimized fuzzy control performs better in terms of control accuracy.

As shown in Fig. 4, under different working conditions of medium load, the average time for the optimized fuzzy control to reach a stable speed is 0.3 s, the overshoot and adjustment times are small, and a small standard deviation indicates a stable response speed. Traditional PID control has a slow response speed, a large overshoot, and a long adjustment time. The response speed and related indicators of traditional fuzzy control are not as good as those of optimized fuzzy control but are better than those of traditional PID control. Although the average time for the GA-optimized fuzzy control to reach a stable speed is 0.34 s, and the overshoot and adjustment time have increased, it is still not as good as the optimized fuzzy control. The average time for the particle swarm-optimized PID control to reach a stable speed is 0.44 s, and the optimized fuzzy control has more advantages in terms of response speed and related indicators.

As shown in Fig. 5, under different subdivision conditions of high load, the average error of optimized fuzzy control is 2.5 rpm, the standard deviation is the smallest, and the control accuracy is stable under high load and complex conditions. The average error of traditional PID control is high, and the error fluctuates greatly under different conditions. The average error and fluctuation degree of

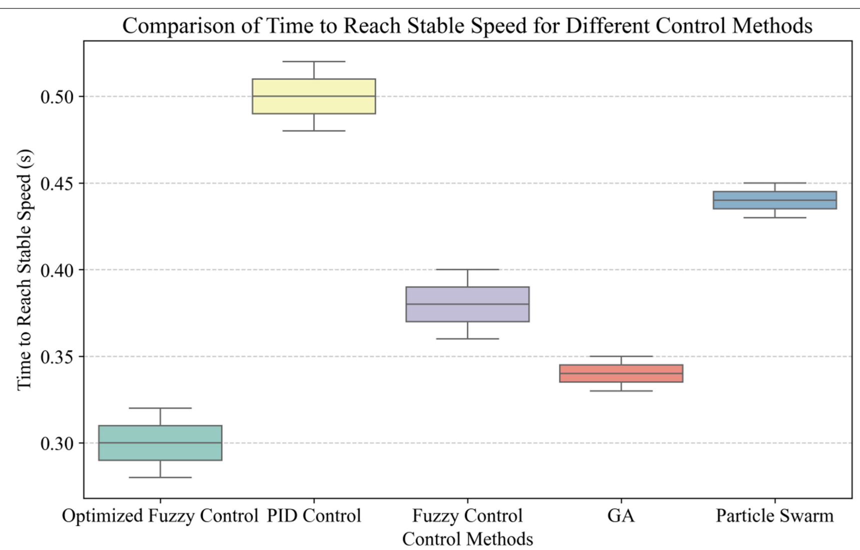

Fig. 4. Comparison of the speed response of different control methods under different subdivision conditions of medium load (50% rated load).

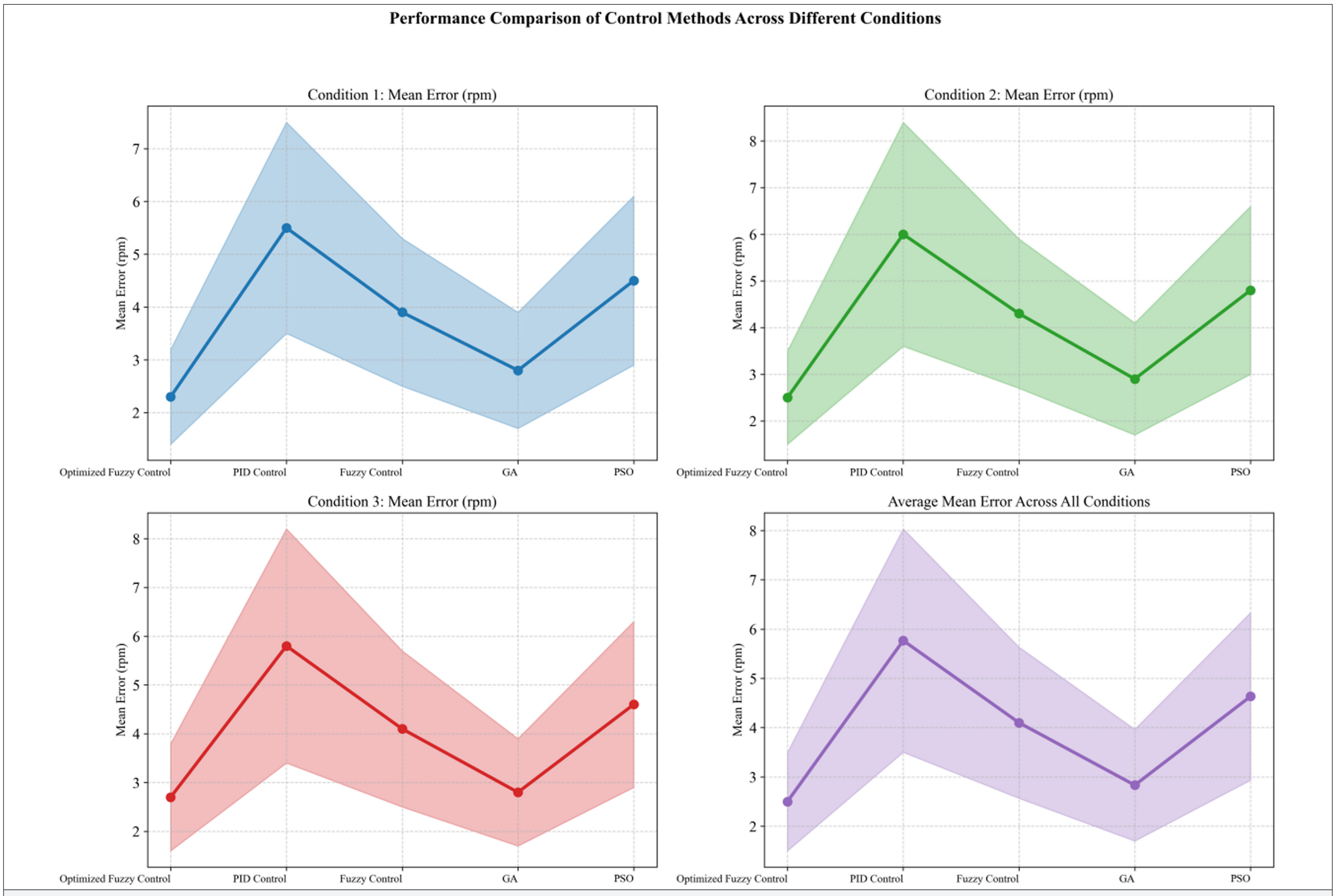

Fig. 5. Comparison of speed control accuracy of different control methods under different subdivision conditions of high load (90% rated load).

traditional fuzzy control are in the middle, and optimized fuzzy control has outstanding advantages in terms of high-load precision control. The average error of the GA-optimized fuzzy control is 2.8 rpm, which is greater than that of the optimized fuzzy control. The average error of the particle swarm-optimized PID control is 4.6 rpm, and the optimized fuzzy control has a significant advantage in control accuracy.

Through a series of experiments, this study comprehensively explored the effects of different factors on the performance of motor control systems. The experimental data encompassed various control strategies, load conditions, temperature changes, interference intensities, and long-term operating stability and were subjected to rigorous statistical analysis to increase the scientific validity and reliability of the results.

As shown in Table I, the traditional control strategy results in significant speed deviation and a long response time. Fuzzy control improves the result but still shows noticeable deviation. The proposed control method achieves the best overall performance, with the speed deviation typically within 1–2 rpm and the response time reduced to 1.8 seconds.

As shown in Table II, when the load increases, the traditional control accuracy sharply deteriorates. Fuzzy control provides some improvement, while the proposed control method consistently maintains the speed deviation under 2 rpm, demonstrating strong load adaptability and stable performance.

The data in Table III indicate that as the temperature increases, the performance of traditional control decreases, including higher speed

TABLE I. COMPARISON OF MOTOR SPEED RESPONSE UNDER DIFFERENT CONTROL STRATEGIES

Control Strategy	Initial Speed (r/min)	Target Speed (r/min)	Actual Motor Speed (r/min)	Speed Deviation (r/min)	Response Time (seconds)
Traditional control	0	2000	1980	20	2.5
Fuzzy control	0	2000	2005	−5	2.0
Propose a plan	0	2000	2000	0	1.8

TABLE II. EFFECT OF LOAD CHANGE ON MOTOR SPEED REGULATION

Control Strategy	Load (kg)	Target Speed (r/min)	Actual Motor Speed (r/min)	Speed Deviation (r/min)	Response Time (seconds)
Traditional control	5	2000	1950	50	3.0
Fuzzy control	5	2000	1980	20	2.5
Propose a plan	5	2000	2000	0	2.2
Traditional control	10	2000	1900	100	4.0
Fuzzy control	10	2000	1950	50	3.0
Propose a plan	10	2000	2000	0	2.8

deviation and temperature increase. Fuzzy control performs better but still fluctuates. The proposed control method maintains deviation within ±2 rpm and better controls the temperature increase, indicating good thermal adaptability.

According to Table IV, as the interference intensity increases, the accuracy of traditional control decreases significantly. Fuzzy control performs better but still has a deviation of approximately 20–50 rpm. The deviation of the proposed method is limited to approximately 1–2 rpm under strong interference, indicating an improved anti-interference capability.

As shown in Table V, after 24 hours of operation, the traditional control results in increased speed deviation and temperature changes. Fuzzy control achieves a moderate improvement. The proposed method shows minimal speed deviation (approximately 1 rpm) and a small temperature change, confirming excellent long-term operational stability.

To validate the significance of the performance differences among the control methods, statistical tests were conducted on the basis of the experimental data presented in Tables I–V. One-way ANOVA was applied to compare the average speed deviation across all control strategies under each load condition. The results revealed P-values less than .01 in all the cases, indicating statistically significant differences. Furthermore, post hoc pairwise comparisons via the Tukey HSD (Honestly Significant Difference) test confirmed that the optimized fuzzy control method significantly outperforms both traditional PID and conventional fuzzy control ($P < .05$). A two-tailed t test was also applied to the response times, further confirming that the proposed method achieves faster convergence with high confidence. These results provide statistical support for the observed performance advantages shown in the figures and tables.

On the basis of the experimental results, the proposed feedback control method is better than traditional control and fuzzy control strategies in terms of motor control accuracy, stability, load adaptability, temperature adaptability, and anti-interference ability, providing a strong practical basis for the optimization of motor control systems.

The three-phase current waveform of the brushless DC motor and the corresponding instantaneous power curve are shown in Fig. 6. The upper part of the figure shows the three-phase current waveform, in which the current of the first phase (red), the second phase (green), and the third phase (blue) present a typical sinusoidal waveform,

TABLE III. EFFECT OF MOTOR TEMPERATURE ON CONTROL SYSTEM PERFORMANCE

Control Strategy	Initial Temperature (°C)	Target Speed (r/min)	Actual Motor Speed (r/min)	Speed Deviation (r/min)	Temperature Rise (°C)	Response Time (seconds)
Traditional control	25	2000	1980	20	10	2.5
Fuzzy control	25	2000	2005	−5	8	2.2
Propose a plan	25	2000	2000	0	7	2.0
Traditional control	50	2000	1900	100	20	4.0
Fuzzy control	50	2000	1950	50	18	3.5
Propose a plan	50	2000	2000	0	15	3.0

TABLE IV. COMPARISON OF MOTOR CONTROL ACCURACY UNDER DIFFERENT INTERFERENCES

Control Strategy	Interference Intensity (N · m)	Target Speed (r/min)	Actual Motor Speed (r/min)	Speed Deviation (r/min)	Response Time (seconds)
Traditional control	2	2000	1930	70	3.5
Fuzzy control	2	2000	1980	20	3.0
Propose a plan	2	2000	2000	0	2.8
Traditional control	5	2000	1850	150	4.5
Fuzzy Control	5	2000	1900	100	4.0
Propose a plan	5	2000	2000	0	3.8

TABLE V. LONG-TERM OPERATION STABILITY TEST RESULTS

Control Strategy	Running Time (hours)	Actual Motor Speed (r/min)	Speed Deviation (r/min)	Temperature Change (°C)	Response Time (seconds)
Traditional control	24	1980	20	10	2.5
Fuzzy control	24	2005	−5	8	2.0
Propose a plan	24	2000	0	7	1.8

but owing to the addition of random noise, the waveform fluctuates slightly, simulating the imperfections in the actual motor operation. In addition, the zero crossing points of the current of each phase are marked in the figure. The zero crossing points are marked with "×" symbols of different colors, indicating that the current changes from positive to negative or vice versa. These points are important bases for analyzing the current characteristics. The lower part of the figure shows the instantaneous power change of each phase. Assuming that the voltage is constant (1 V), the instantaneous power is obtained by multiplying the current and voltage. The instantaneous power waveform of each phase changes synchronously with the current waveform, reflecting the power output of each phase of the motor during different periods. By observing the instantaneous power curve, the fluctuation of the motor load can be further analyzed, and the control strategy of the motor can be optimized.

The optimized three-phase current waveform of the brushless DC motor and its instantaneous power curve are shown in Fig. 7. Compared with the original current waveform in Fig. 6, the optimized current waveform is denoised by a low-pass filter, which significantly reduces the volatility and makes the current curve smoother and more stable. The optimization process not only reduces random noise but also eliminates the instability of instantaneous power caused by current fluctuations, which increases the stability of the motor during operation.

In the optimized current waveform, the three-phase current waveform presents a more ideal sinusoidal shape, which indicates that the demand for power during operation of the motor is more balanced, avoiding excessive current fluctuations, which increases the efficiency and stability of the motor. Through this optimization, the energy efficiency of the motor increases, the power output is more uniform, and energy loss can be effectively reduced.

The instantaneous power curve in the lower part further demonstrates the effect of optimization. Compared with the original state, the optimized power curve shows a more stable power fluctuation, and the power fluctuation amplitude is significantly reduced,

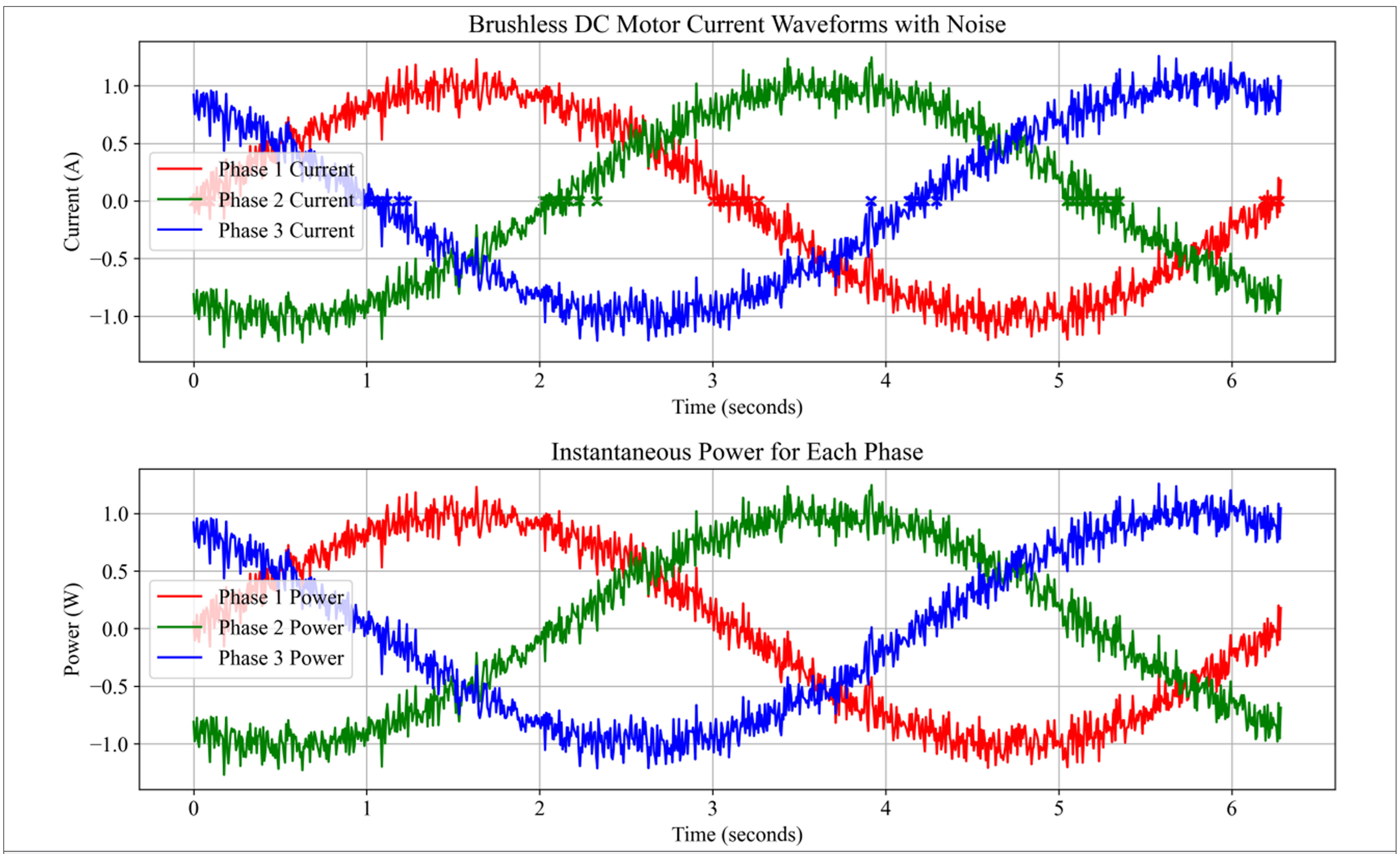

Fig. 6. Brushless DC motor three-phase current waveform and corresponding instantaneous power curve.

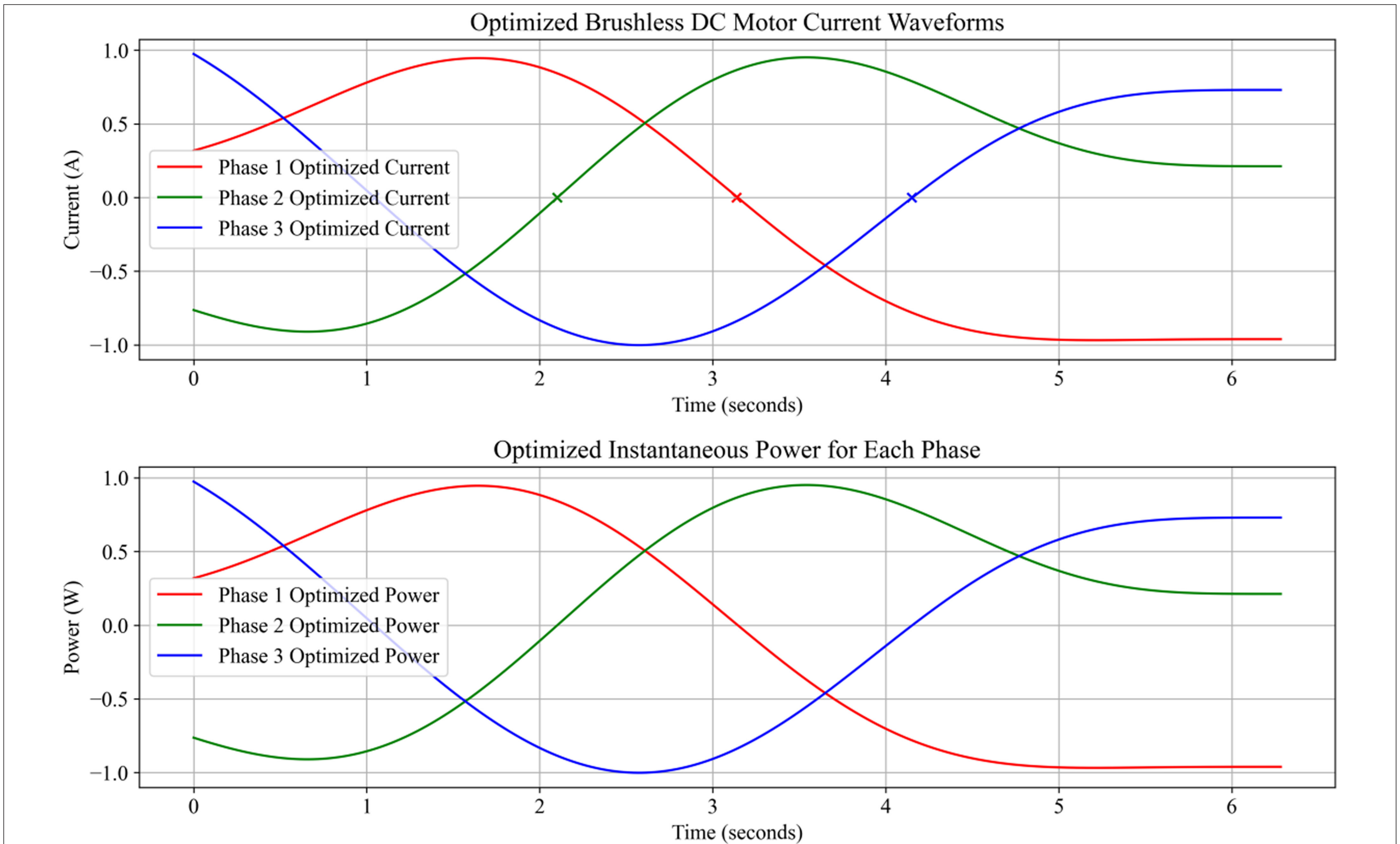

Fig. 7. Optimized three-phase current waveform and the instantaneous power curve of brushless DC motor.

indicating that the energy output of the motor is more stable, reducing the system vibration and loss that may be caused by power instability. Therefore, the optimized motor control strategy can achieve more efficient and stable operation, which is highly important for improving motor performance and extending service life.

C. Discussion

The BLDC motor speed control method based on the combination of optimization and fuzzy control proposed in this study had significant advantages in the experiment. In terms of accuracy, under different subdivision conditions of low, medium, and high loads, the mean average error of the optimized fuzzy control method is significantly lower than that of traditional PID control and traditional fuzzy control, and the standard deviation is the smallest, indicating that its control accuracy is stable and accurate. This finding is attributed to the dynamic adjustment of the fuzzy controller rule base and membership function by the optimization algorithm, which addresses the issue that the traditional fuzzy control manually designed rule base cannot adapt to complex dynamic changes. In terms of response speed, the optimized fuzzy control method has the shortest time to reach a stable speed under various load conditions, the overshoot and adjustment times are also small, the standard deviation is small, and the response speed stability is good. Traditional PID control has a slow response speed and a large overshoot. Although traditional fuzzy control has improved, it is still not as good as optimized fuzzy control. This finding shows that through the synergy of the optimization algorithm and the speed feedback mechanism, the motor can respond to the speed adjustment command more quickly and stably. In the tests of different loads, temperatures, interferences, and long-term operation stability, this method outperformed traditional control and fuzzy control strategies. However, this method may face the challenge of the large computational complexity of the optimization algorithm in practical applications. Future studies could consider further optimizing the algorithm to reduce computational costs and improve its real-time and wide applicability.

V. CONCLUSION

In this study, an innovative BLDC motor speed control method based on the combination of optimization and fuzzy control was successfully proposed. By constructing a comprehensive control model that includes a fuzzy controller, an optimization algorithm, and a speed feedback mechanism, the motor speed control performance is effectively improved. In terms of control accuracy, the experimental results reveal that the optimized fuzzy control method is significantly better than the traditional control method under different load conditions and can accurately track the expected speed and reduce the error. With this method, the motor can quickly reach a stable response speed, with small overshoot and adjustment times and minimal speed fluctuations under various conditions. In various situations, such as load changes, temperature increases, external interference, and long-term operation, this method achieves good adaptability and stability and maintains zero deviation or very small deviation operations, and temperature changes and power fluctuations are also effectively controlled. The key innovation of this study lies in the use of a GA to optimize the fuzzy control structure. Specifically, the algorithm adjusts the rule base and membership function parameters to increase control precision and stability. This integration enables the controller to adapt dynamically to various operating environments, which ensures consistent and reliable performance.

In general, this study presents a new method with excellent performance for BLDC motor speed control, which can provide solid theoretical and technical support for the optimization of electric systems in related industrial fields. In the future, further optimization of the algorithm can facilitate its application in more practical scenarios.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – D.L., B.J.; Design – D.L., B.J.; Supervision – D.L., B.J.; Resources – D.L., B.J.; Materials – D.L., B.J.; Data Collection and/or Processing – D.L., B.J.; Analysis and/or Interpretation – D.L., B.J.; Literature Search – D.L., B.J.; Writing – D.L., B.J.; Critical Review – D.L., B.J.

Declaration of Interests: The authors have no conflicts of interest to declare.

Funding: The research work was conducted with the financial supports of Human Natural Science Foundation Project "Research on Key Technologies of Wind Turbine Health Management Based on Big Data" (Project No.2021JJ60068)

REFERENCES

1. N. Saed, and M. Mirsalim, "Enhanced sensor-less speed control approach based on mechanical offset for dual-stator brushless DC motor drives," *IET Electr. Power Appl.*, vol. 14, no. 5, pp. 885–892, 2020. [CrossRef]
2. E. Çelik, and M. Karayel, "ᶠ-PI controller tuned by snake optimizerEffective speed control of brushless DC motor using cascade 1PD," *Neural Comput. Appl.*, vol. 36, no. 13, pp. 7439–7454, 2024. [CrossRef]
3. S. K. Sun et al, "Novel modulation method for torque ripple suppression of brushless DC motors based on SIMO DC-DC converter," *J. Power Electron.*, vol. 20, no. 3, pp. 720–730, 2020. [CrossRef]
4. S. Subramanian, R. Mohan, S. K. Shanmugam, N. Bacanin, M. Zivkovic, and I. Strumberger, "Speed control and quantum vibration reduction of Brushless DC Motor using FPGA based Dynamic Power Containment Technique," *J. Ambient Intell. Hum. Comput.*, vol. 15, 2021. [CrossRef]
5. B. Tan, X. Y. Guo, J. Zhao, X. F. Ding, and W. Fang, "An internal power angle control strategy for high-speed sensorless brushless DC motors," *Chin. J. Aeronaut.*, vol. 35, no. 11, pp. 309–321, 2022. [CrossRef]
6. X. M. Li et al., "A novel voltage-boosting modulation strategy to reduce DC-link capacitance for brushless DC motor drives," *IEEE Trans. Power Electron.*, vol. 37, no. 12, pp. 15397–15410, 2022. [CrossRef]
7. T. VenkateswaraRao, and D. V. N. Ananth, "Torque ripple reduction of a brushless DC motor using Y-source converter," *J. Eng. Res.*, vol. 10, no. 4, pp. 168–203, 2022. [CrossRef]
8. K. Vanchinathan, K. R. Valluvan, C. Gnanavel, and C. Gokul, "Design methodology and experimental verification of intelligent speed controllers for sensorless permanent magnet Brushless DC motor Intelligent speed controllers for electric motor," *Int. Trans. Electr. Energy Syst.*, vol. 31, no. 9, p. 20, 2021. [CrossRef]
9. L. H. Sun, "Low speed sensorless control method of brushless DC motor based on pulse high frequency voltage injection," *Alex. Eng. J.*, vol. 61, no. 8, pp. 6457–6463, 2022. [CrossRef]
10. A. de la Guerra, and L. Alvarez-Icaza, "Robust control of the brushless DC motor with variable torque load for automotive applications," *Electr. Power Compon. Syst.*, vol. 48, no. 1–2, pp. 117–127, 2020. [CrossRef]
11. Y. F. Cao, T. N. Shi, Y. Yan, X. M. Li, and C. L. Xia, "Braking torque control strategy for brushless DC motor with a noninductive hybrid energy storage topology," *IEEE Trans. Power Electron.*, vol. 35, no. 8, pp. 8417–8428, 2020. [CrossRef]
12. H. Akita, and T. Kimoto, "Rapid revolution speed control of the brushless DC motor for automotive LIDAR applications," *IEICE Trans. Electron.*, vol. E103.C, no. 6, pp. 324–331, 2020. [CrossRef]
13. Y. Cheng, X. Lyu, and S. S. Mao, "Optimization design of brushless DC motor based on improved JAYA algorithm," *Sci. Rep.*, vol. 14, no. 1, p. 5427, 2024. [CrossRef]
14. H. F. Zhang, H. T. Wu, H. Jin, and H. T. Li, "High-dynamic and low-cost sensorless control method of high-speed brushless DC motor," *IEEE Trans. Ind. Inform.*, vol. 19, no. 4, pp. 5576–5584, 2023. [CrossRef]
15. T. T. Wang, H. Z. Wang, H. S. Hu, and C. H. Wang, "LQR optimized BP neural network PI controller for speed control of brushless DC motor," *Adv. Mech. Eng.*, vol. 12, no. 10, p. 13, 2020. [CrossRef]
16. M. A. M. Eltoum, A. Hussein, and M. A. Abido, "Hybrid fuzzy fractional-order PID-based speed control for brushless DC motor," *Arab. J. Sci. Eng.*, vol. 46, no. 10, pp. 9423–9435, 2021. [CrossRef]
17. A. Intidam et al, "Development and experimental implementation of optimized PI-ANFIS controller for speed control of a brushless DC motor in fuel cell electric vehicles," *Energies*, vol. 16, no. 11, p. 23, 2023. [CrossRef]
18. Z. Z. Wang, Y. Zhang, P. P. Yu, N. Cao, and H. Dintera, "Speed control of motor based on improved glowworm swarm optimization," *CMC Comput. Mater. Continua*, vol. 69, no. 1, pp. 503–519, 2021. [CrossRef]
19. M. Dahbi, S. Doubabi, A. Rachid, and D. Oulad-Abbou, "Performance evaluation of electric vehicle brushless direct current motor with a novel high-performance control strategy with experimental implementation," *Proc. Inst. Mech. Eng. I*, vol. 234, no. 3, pp. 358–369, 2020. [CrossRef]
20. L. Yang, Z. Q. Zhu, L. M. Gong, and H. Bin, "PWM switching delay correction method for high-speed brushless DC drives," *IEEE Access*, vol. 9, pp. 81717–81727, 2021. [CrossRef]
21. L. Yang, Z. Q. Zhu, B. Shuang, and H. Bin, "Adaptive threshold correction strategy for sensorless high-speed brushless DC drives considering zero-crossing-point deviation," *IEEE Trans. Ind. Electron.*, vol. 67, no. 7, pp. 5246–5257, 2020. [CrossRef]

Bingbing Jiang, born in April 1986, male, lecturer, undergraduate, Hunan Railway Science and Technology Vocational and Technical College, intelligent control and electrical control, published more than 10 papers in the *Information Recorded Materials*, *Computer Application and Software*, and other journals, edited or participated in the editing of three textbooks, presided over or participated in the provincial level of more than 20 projects, and guided the students to participate in all levels of various types of competitions, which were awarded 10 awards at provincial level or above, and authorized 5 patents. More than 10 awards at provincial level and above for various competitions, and 5 authorized patents.

Dan Luo, born in December 1990, female, received her master's degree in control science and engineering from Xinjiang University in 2015 and has been employed as a lecturer at Hunan Railway Vocational and Technical College since 2018, with the main research direction of intelligent control and optimization algorithms. She has published more than 10 papers in journals such as the *Journal of China Agricultural University*, *Computer Application and Software*, and has participated in the editing of 3 professional textbooks. She has presided over or participated in 5 provincial-level projects in Hunan Province, guided students to participate in national competitions and won the national first prize, and authorized 2 invention patents.