

## OPTIMIZING THE HIGH-SPEED REGULATION PERFORMANCE OF PERMANENT MAGNET SYNCHRONOUS MOTORS WITH HYSTERESIS CURRENT CONTROL USING DE-PSO ALGORITHM

XIA LIU<sup>1,\*</sup> AND GANG BAI<sup>2</sup>

<sup>1</sup>School of Mechanical and Material Engineering  
Xi'an University

No. 1, Keji 6th Road, Yanta District, Xi'an 710065, P. R. China

\*Corresponding author: liuxia@xawl.edu.cn

<sup>2</sup>Xi'an Locomotive Repair Depot

No. 301, Fangwei Road, Baqiao District, Xi'an 710000, P. R. China

gangbai2021@163.com

Received September 2025; revised January 2026

**ABSTRACT.** *During high-speed operation of a permanent magnet synchronous motor, hysteresis current control can amplify dead zone and delay effects, leading to current mismatch and reduced robustness. This paper addresses this issue by applying the Differential Evolution-Particle Swarm Optimization (DE-PSO) algorithm. First, a coupled PMSM (Permanent Magnet Synchronous Motor) model is established that considers dead zone effects, sampling, and computational delays, and the delay and dead zone compensation parameters are parameterized as optimization vectors. A DE-PSO hybrid algorithm is then applied, leveraging differential evolution to enhance global search capabilities and particle swarm optimization to improve convergence efficiency, achieving a multi-objective collaborative optimization of the hysteresis bandwidth, delay compensation factor, and dead zone correction coefficient. Finally, an online adaptive framework based on real-time current feedback is constructed, and a lightweight DE-PSO algorithm is used to update the compensation parameters to achieve dynamic update and robust control of parameters under high-speed operation. Experiments show that after optimization, the amplitude of current harmonics is reduced; the torque ripple rate is reduced from 10% (maximum speed) to 4.2%; the speed fluctuation is reduced from 3.0% to 1.1%; the overshoot under 50% rated torque step disturbance is reduced from 12% to 3%; the recovery time is stabilized at 50-72 ms. This shows that the system is effective in reducing torque fluctuations, improving dynamic performance and temperature robustness.*

**Keywords:** High-speed PMSM control, Hysteresis current control, Differential evolution-particle swarm optimization, Delay and dead zone compensation, Online adaptive optimization

**1. Introduction.** Permanent Magnet Synchronous Motors (PMSMs) are widely used in new energy vehicle drive systems, high-speed CNC machine tool servos, and aerospace electric propulsion units due to their high power density, outstanding efficiency, and excellent dynamic performance [1,2]. As modern industrial equipment and vehicles develop towards higher speeds and higher performance, the control strategies of motor drive systems are receiving increasing attention. In motor speed control, hysteresis current control has become an important method for motor current control due to its advantages such as simple structure, fast response speed, and easy implementation [3,4]. However, when the motor enters high-speed operation, the hysteresis current control method has significant

shortcomings. Due to the switching dead zone of the inverter in actual operation, there is a delay in current sampling, and there is a delay in controller operation and PWM (Pulse Width Modulation) update, resulting in an error between the control signal and the actual current [5,6]. These non-ideal effects have limited impact under low-speed operating conditions, but are significantly amplified under high-speed operation, causing the deviation between the current command and the actual current to increase, ultimately manifesting as current waveform distortion, a significant increase in torque pulsation, and a decrease in control stability [7,8].

Traditional hysteresis band design fails to account for these non-ideal factors during modeling, and can only achieve good speed regulation performance under idealized conditions. As motor speed increases, hysteresis current control exhibits significant performance degradation in terms of current loop bandwidth, voltage margin, and PWM switching frequency. This degradation makes it difficult for high-speed motor systems to maintain stable and efficient operation, hindering the performance of high-speed servo systems and new energy vehicle drives. Therefore, how to effectively suppress the adverse effects of dead zone effects and delays under high-speed operating conditions and improve the robustness and speed regulation performance of hysteresis current control has become a key research issue.

In the field of high-speed permanent magnet synchronous motor control, existing research focuses on in-depth exploration of multi-mode modulation strategies. Dai et al. [9] proposed a mode conversion mechanism for synchronous optimal modulation for high-speed working conditions, and coped with the challenges of wide speed range operation by dynamically adjusting the modulation strategy; Wang et al. [10] innovatively developed a harmonic injection method for equivalent resonant control to effectively suppress the speed ripple problem of PMSM. For system reliability, Li et al. [11] constructed a current sensor fault-tolerant control framework for five-phase PMSM based on the third harmonic space, significantly enhancing the fault response capability of the drive system. In the direction of motor modeling and loss analysis, Ba et al. [12] established a generalized per-phase equivalent circuit model including iron loss prediction, providing a theoretical basis for high-speed motor efficiency optimization; Usama and Kim [13] improved the speed control accuracy of PMSM through nonlinear current control strategy. For torque pulsation suppression, Shao et al. [14] proposed a torque pulsation suppression method based on nonlinear current control. Using multi-virtual voltage vector technology, the torque pulsation in a dual three-phase PMSM was suppressed from 9.2% to 4.7%. Aboelhassan et al. [15] developed a discontinuous modulation model predictive control strategy for low-inductance high-speed motors. In terms of the application of advanced control algorithms, Sangar et al. [16] applied ANFIS to improving predictive current control in the PMSM drive system of electric vehicles, reducing torque ripple from 11.5% to 6.8% under rated load conditions at 3000 rpm. Although some studies have attempted to use PSO or DE for PMSM control parameter tuning, most of these works focus on a single objective (such as minimizing speed error) or offline tuning of PI parameters, without considering the coupling effect of dead zone, sampling delay and PWM delay at high speeds [17,18]. More importantly, their optimization variables are usually limited to controller gain, rather than directly co-tuning physical mechanism parameters such as hysteresis bandwidth, dead zone correction coefficient and delay compensation factor [19,20]. At present, hysteresis control of high-speed permanent magnet synchronous motors faces severe challenges when running at high speeds: the amplification effect of dead zone and system delay leads to increased distortion of current waveform [21,22], and the mainstream solutions in the industry are difficult to maintain control accuracy in the ultra-high speed domain. Although existing intelligent optimization algorithms have made

some breakthroughs in low-speed conditions, their single-objective optimization mechanism generally has inherent limitations such as low convergence efficiency and insufficient robustness when facing multi-parameter coupling in the high-speed weak magnetic field region [23]. Therefore, it is urgent to develop a new hybrid architecture that takes account of both global search and dynamic response. This paper, for the first time, unifies the parameterization of three types of non-ideal effects into optimization vectors and constructs a collaborative optimization framework with current tracking accuracy, torque ripple and switching frequency stability as multiple objectives. Through the DE-PSO hybrid architecture, a balance between global exploration and fast convergence is achieved, thereby achieving simultaneous improvement of robustness and dynamic performance in the high-speed weak magnetic field region.

In recent years, intelligent optimization algorithms have been increasingly used in the field of motor control. Soundirarajan and Srinivasan [24] first applied the ant lion optimization algorithm into the field of PMSM speed control, and improved the speed regulation performance through PID (Proportional-Integral-Derivative) parameter self-tuning; Feng et al. [25] combined the hybrid optimization algorithm to realize the variable flux direct torque control of the switched reluctance motor, significantly reducing the torque pulsation. The particle swarm optimization algorithm is widely used in motor parameter optimization due to its fast convergence speed, but its global search capability is insufficient, and it is easy to fall into local extreme values, resulting in unstable optimization results. The differential evolution algorithm has advantages in global search and escaping local extreme values, but it is slow in convergence speed. When the two algorithms are combined to form a hybrid optimization structure, it can achieve a balance between global search and fast convergence, and therefore shows good potential in complex multi-parameter optimization problems. In the high-speed operation scenario of a permanent magnet synchronous motor, the key parameters of hysteresis current control include hysteresis bandwidth, delay compensation factor, and dead zone correction coefficient. These parameters are coupled and significantly affected by operating conditions [26,27], making this a typical multi-objective complex optimization problem. Some studies have attempted to use particle swarm optimization or differential evolution alone for motor PI parameter tuning, achieving some improvement, but the optimization capabilities are insufficient in the high-speed field weakening region and when delay effects are significant [28,29]. Therefore, combining differential evolution with particle swarm optimization for robust optimization of hysteresis current control parameters is expected to address the problems of premature convergence, insufficient global performance, and poor adaptability found in traditional research.

Based on these issues, this paper proposes a hybrid optimization strategy based on DE-PSO, with the goal of improving the high-speed speed regulation performance of permanent magnet synchronous motors. This study first establishes an electrical and mechanical coupling model of a permanent magnet synchronous motor that takes account of dead zone effects, sampling delay, and computational delay, revealing the error bounds and frequency imbalance characteristics of hysteresis current control under high-speed operation. Subsequently, the delay compensation factor, dead zone correction parameter, and hysteresis bandwidth are used as optimization variables to construct a non-ideal control model under high-speed operation. By applying a hybrid differential evolution-particle swarm optimization algorithm, the global search capabilities of differential evolution and the rapid convergence characteristics of particle swarm optimization are utilized to achieve multi-objective collaborative optimization. To ensure the effectiveness of this method in practical applications, this paper further designs an online adaptive optimization mechanism based on real-time current feedback, allowing the compensation parameters to be

dynamically updated under different operating conditions, thereby enhancing the robustness of the control.

## 2. Optimization Design of High-Speed Regulation of Permanent Magnet Synchronous Motor.

### 2.1. Mathematical modeling of permanent magnet synchronous motor.

*2.1.1. Establishment of electrical model.* When constructing the mathematical model of the motor, the voltage equation of the abc coordinate system of the three-phase permanent magnet synchronous motor is converted into the  $dq$  coordinate system through Clarke and Park transformation to facilitate the subsequent control law design. To accurately reflect the errors caused by dead zone and delay during high-speed operation, correction terms for inverter dead zone voltage drop, sampling delay, and calculation delay are applied in the modeling process. The voltage equation of the motor in the  $dq$  coordinate system is

$$\begin{cases} u_d = R_s i_d + L_d \frac{di_d}{dt} - \omega_e L_q i_q + u_{d,err} \\ u_q = R_s i_q + L_q \frac{di_q}{dt} + \omega_e L_d i_d + \omega_e \psi_f + u_{q,err} \end{cases} \quad (1)$$

$R_s$  is the stator resistance;  $L_d$  and  $L_q$  are the  $d$ -axis and  $q$ -axis inductances, respectively;  $\psi_f$  is the permanent magnet flux;  $\omega_e$  is the electrical angular speed. The error terms  $u_{d,err}$ ,  $u_{q,err}$  correspond to the compensation voltage applied by the dead zone voltage drop and delay correction, respectively. The inverter dead zone voltage drop adopts an equivalent voltage model, which is defined as

$$u_{dead} = \frac{2V_{dc}t_{dead}f_s}{\pi} \quad (2)$$

$V_{dc}$  is the DC (Direct Current) bus voltage;  $t_{dead}$  is the dead zone time;  $f_s$  is the switching frequency. Under high-speed conditions, the voltage drop is related to the current direction and needs to be corrected according to the current sign. The sampling delay is modeled as a time-delayed first-order hold of the current detection value, and its equivalent transfer function is

$$G_{delay}(s) = e^{-T_s s} \quad (3)$$

$T_s$  is the sampling period. The calculation delay and PWM update delay are uniformly treated as a one-cycle delay in the model and converted into a differential equation through discretization. In this way, the electrical model not only reflects the electromagnetic coupling characteristics under ideal conditions, but also includes the non-ideal factors in the actual inverter and sampling link.

*2.1.2. Mechanical model establishment.* To reflect the torque fluctuation and inertia effect under high-speed operation, the mechanical motion equation is established, as shown in Equation (4):

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

$J$  is the moment of inertia, which is set to  $0.0025 \text{ kg}\cdot\text{m}^2$  based on the typical parameters of a 5 kW high-speed permanent magnet synchronous motor;  $B$  is the viscous friction coefficient, which is set to  $0.001 \text{ N}\cdot\text{m}\cdot\text{s}/\text{rad}$ ;  $\omega_m$  is the mechanical angular speed;  $T_L$  is the load torque. The electromagnetic torque is obtained from the coupling relationship between current and flux linkage, as shown in Equation (5):

$$T_e = \frac{3}{2}p[\psi_f i_q + (L_d - L_q)i_d i_q] \quad (5)$$

$p$  is the number of pole pairs, and 2 pole pairs are selected in this study. Under high-speed field-weakening conditions, the  $q$ -axis current component plays a dominant role in electromagnetic torque. Therefore, subsequent optimization requires a focus on the accuracy and stability of  $i_q$  current control. The mechanical model, coupled with the electrical model, forms a complete PMSM state equation, providing constraints for subsequent robust optimization and control strategy verification.

Figure 1 illustrates the electrical and mechanical characteristics of a permanent magnet synchronous motor during high-speed operation. In Figure 1(a), the horizontal axis represents time (ms), and the vertical axis represents current (A). The blue curve represents the  $d$ -axis current  $i_d$ , and the red curve represents the  $q$ -axis current  $i_q$ . During high-speed operation, the current rapidly decays with time and exhibits high-frequency oscillations. The maximum  $q$ -axis current is approximately 15 A, and the  $d$ -axis current is approximately 8 A, demonstrating the dynamic response of the motor current. Figure 1(b) shows time (s) on the horizontal axis, speed (rpm) on the left vertical axis, and electromagnetic torque (Nm) on the right vertical axis. The blue curve represents the mechanical speed, and the red curve represents the electromagnetic torque. Initially, the motor speed rapidly increases to approximately 8000 rpm, while the electromagnetic torque slowly decays from an initial 8 Nm to approximately 0.25 Nm, exhibiting periodic, slight fluctuations. This reflects the mechanical inertia and electromagnetic characteristic response during high-speed starting.

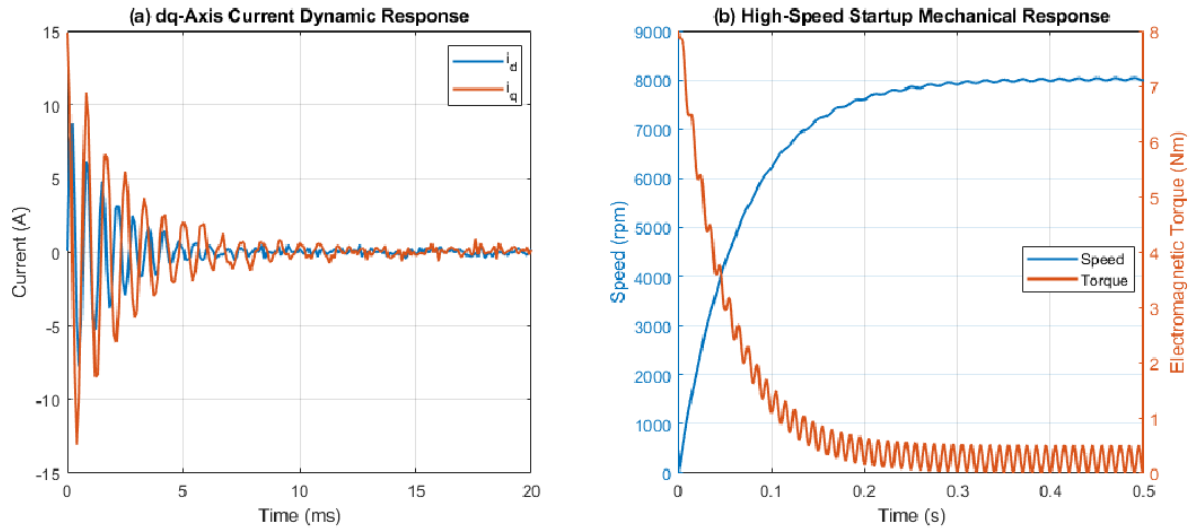


FIGURE 1. (color online) Electrical model dynamic response and high-speed mechanical characteristics: (a)  $dq$  axis current dynamic response, and (b) high-speed starting mechanical response

**2.1.3. Modeling and constraint application of non-ideal factors.** To solve the mismatch problem of HCC (Hysteresis Current Control) under high-speed conditions due to the influence of delay and dead zone amplification, the non-ideal factors are parameterized and embedded in the motor mathematical model. Specifically, they include 1) dead zone compensation factor  $\alpha_{dead}$ : used to correct the equivalent dead zone voltage drop of the inverter, with a range of 0.8-1.2, and used to adaptively adjust the compensation amplitude; 2) sampling delay correction factor  $\alpha_{samp}$ : used to adjust the deviation between the sampled value and the actual value, defined as the ratio of the delay time to the sampling period, with a range of 0.9-1.1; 3) calculation delay correction factor  $\alpha_{calc}$ : used to correct

the lag caused by the PWM update delay, with an adjustment range of  $\pm 10\%$  of the calculation period.

The above correction parameters together form the optimization vector  $\theta = [\alpha_{dead}, \alpha_{smp}, \alpha_{calc}]$ , which is added to the state equation in the model in the form of compensation voltage and delay factor. In this way, the established mathematical model can truly describe the error accumulation caused by non-ideal effects in hysteresis current control during high-speed operation, and provide direct constraints for the optimization of the DE-PSO algorithm.

To ensure consistency with the actual digital controller structure, the electrical and mechanical models are discretized, with a sampling period of 100  $\mu\text{s}$ , corresponding to a switching frequency of 10 kHz. In Matlab, the state equation is discretized into differential form; sampling delays are handled using a zero-order hold method; calculation and PWM update delays are simulated using a single-cycle delay module.

## 2.2. Description of hysteresis current control characteristics.

**2.2.1. Derivation of current error boundary.** Under high-speed operation conditions, the error boundary of the hysteresis current controller directly determines the current tracking accuracy and switching frequency fluctuation characteristics. To establish the error boundary model, the current error in the  $dq$  coordinate system is defined as  $\Delta i_d = i_d^* - i_d$  and  $\Delta i_q = i_q^* - i_q$ . In hysteresis current control, the switching state is determined by whether the error current exceeds the limit, so the dynamic equation of the error current needs to be derived. Substituting the electrical model obtained in the previous section and considering the hysteresis bandwidth  $h$ , the boundary conditions of the error current are

$$\frac{d\Delta i_d}{dt} = \frac{1}{L_d} (u_d - R_s i_d + \omega_e L_q i_q - u_{d,err}) - \frac{di_d^*}{dt} \quad (6)$$

$$\frac{d\Delta i_q}{dt} = \frac{1}{L_q} (u_q - R_s i_q - \omega_e L_d i_d - \omega_e \psi_f - u_{q,err}) - \frac{di_q^*}{dt} \quad (7)$$

The compensation voltages  $u_{d,err}$  and  $u_{q,err}$  include corrections for dead zone and delay effects. It can be seen that the boundary of the error current is not symmetrically distributed, but changes dynamically with the speed, load current, and delay correction parameters. By setting the hysteresis bandwidth to  $h = 0.5$  A through the numerical integration method, the asymmetric boundary curve of the error current as the speed increases can be obtained, thereby establishing mathematical constraints for the subsequent compensation parameter optimization.

**2.2.2. Modeling of unconstant switching frequency.** The inherent characteristics of hysteresis current control cause the switching frequency to be non-constant with the current error. This phenomenon is amplified by delay and dead zone during high-speed operation. To accurately describe this characteristic, the current error boundary is combined with the voltage vector switching process to establish an analytical expression for the switching frequency. The switching frequency is approximately as follows:

$$f_{sw} \approx \frac{V_{dc}}{8hL_{eq}} \left( 1 - \frac{\Delta u_{err}}{V_{dc}} \right) \quad (8)$$

$L_{eq}$  is the equivalent inductance, and  $\Delta u_{err}$  is the equivalent voltage deviation applied by delay and dead zone. According to the model derivation, the fluctuation range of the switching frequency is inversely proportional to the hysteresis bandwidth  $h$  and is directly related to the delay correction factor and the dead zone compensation factor. It can be seen that parameter optimization is required to suppress frequency instability in the

high-speed area. To this end, the switching frequency function is included as part of the optimization target in the modeling to ensure that the frequency fluctuation is controlled within a certain range. The switching frequency estimation Formula (8) is derived based on the simplified assumptions of ideal voltage source, linear current rise/fall slope, and neglect of phase coupling. It is mainly used to qualitatively analyze the influence trend of dead zone and delay on switching frequency fluctuation. Its effectiveness has been verified by the experimental results of switching frequency distribution and standard deviation changes at different speeds.

**2.2.3. Functions affecting the stability of delay and dead zone.** Under high-speed conditions, delay and dead zone not only cause voltage vector distortion, but also affect the stability of the current loop. To quantify this effect, a stability function is applied into the error current dynamic equation, as shown in Equation (9):

$$S(\omega_e) = \frac{\partial \Delta i}{\partial u_{err}} = \frac{1}{L_{eq}} \cdot \frac{e^{-\alpha_{delay} T_s \omega_e}}{1 + \alpha_{dead}} \quad (9)$$

$\alpha_{delay}$  is the delay correction factor;  $\alpha_{dead}$  is the dead zone compensation factor;  $T_s$  is the sampling period. This function shows that as the electrical angular speed  $\omega_e$  increases, the exponential decay characteristics of the delay term multiply the sensitivity of the current loop to the compensation error, resulting in system instability at high speeds. By linearizing the function, the robust stability margin is defined as

$$M_r = \frac{1}{\sup_{\omega_e} |S(\omega_e)|} \quad (10)$$

When  $M_r < 0.2$ , the current loop has a high oscillation risk. Based on this stability index, the delay and dead zone compensation factors can be directly linked to the robust margin in the subsequent DE-PSO optimization to avoid the excessive amplification effect of the compensation factor in the high-speed area.

To be consistent with the digital control system, the error current boundary equation and the stability function are discretized. The sampling period is set to  $T_s = 100 \mu s$ , and the forward Euler method is used to discretize the error differential equation. The discrete form of the current error update equation is obtained as shown in Equation (11):

$$\Delta i_{k+1} = \Delta i_k + \frac{T_s}{L_{eq}} (u_k - R_s i_k - u_{err,k}) \quad (11)$$

This form facilitates real-time simulation in Matlab/Simulink and allows direct embedding on FPGA (Field-Programmable Gate Array) control platforms. By gradually adjusting the dead zone compensation factor and delay correction factor in the simulation platform, the current error boundary and switching frequency fluctuation curves under different parameter combinations can be obtained. The above results are used as the fitness function input of the DE-PSO algorithm to achieve the joint optimization of the compensation parameters and loop bandwidth.

Figure 2 shows the dynamic characteristics of motor current error and its stability as a function of electrical angular speed and delay factor under Hysteretic Current Control (HCC). In Figure 2(a), the horizontal axis represents time (seconds), and the vertical axis represents current error  $\Delta i$  (A). Simulations show that the current error fluctuates within the  $\pm 0.5$  A hysteresis bandwidth, with slight offsets due to control delay and disturbances, reflecting the non-ideal nature of current tracking in actual HCC. In Figure 2(b), the horizontal axis represents electrical angular speed  $\omega_e$  (rad/s), and the vertical axis represents the delay correction factor  $\alpha_{delay}$ . The color or height of the vertical axis

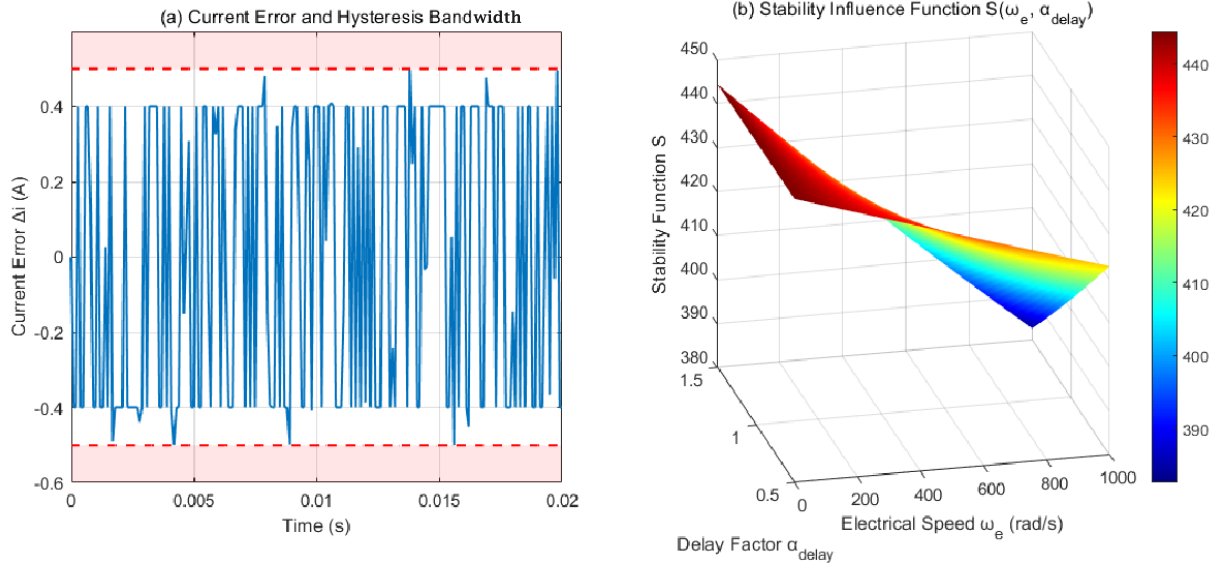


FIGURE 2. (color online) Analysis of hysteretic current control characteristics: (a) Current error and hysteresis bandwidth, and (b) stability influence function

represents the stability function  $S$ , showing that system stability exponentially decays with increasing speed or varying delay factors. This indicates that high speeds or excessive control delays can reduce the current stability of hysteretic control.

### 2.3. Parameterized modeling of delay and dead zone.

**2.3.1. Modeling and discretization of delay factors.** In high-speed permanent magnet synchronous motor systems, sampling delay and PWM update delay significantly impact the current control process. To establish a unified model suitable for optimization, this study discretizes the delay factors. Sampling delay typically occurs in the process of current sensing and digital signal processing. On DSP (Digital Signal Processor) and FPGA control platforms, its time scale ranges from 5 to 20  $\mu\text{s}$ . PWM update delay arises from the delay between the modulation signal and the actual triggering of the power device, with typical values ranging from 1 to 10  $\mu\text{s}$ . To incorporate these delays into the control loop model, this paper uniformly expresses the delays as integer multiples of the control sampling period. Taking the sampling period  $T_s = 100 \mu\text{s}$  as an example, the sampling delay can be discretized as  $n_s T_s$ , where  $n_s$  is the number of sampling periods corresponding to the delay. The PWM update delay is represented by  $n_d T_s$ , with  $n_d$  being the number of sampling periods corresponding to the update delay. This approach simplifies the delay factors into integer parameters to be estimated, allowing them to be directly incorporated into the optimization parameter vector. This step avoids the complex effects of continuous time delays on numerical calculations and ensures computability of parameter modeling under high-speed operating conditions.

To further improve modeling accuracy, this study linearizes the current prediction error caused by delay. The current mismatch caused by delay is converted into a hysteresis effect of the input voltage, which is expressed as a one-step or multi-step delay term in the discrete control equation. In this way, sampling delay and PWM update delay are mapped into linear offsets of the current prediction error, which then form constraints in the optimization objective function.

**2.3.2. Dead zone effect parameterization and compensation vector construction.** The inverter's dead zone effect is significantly amplified under high-speed operation, leading to increased current distortion and torque ripple. Therefore, parameterized modeling is necessary. The dead zone time is typically determined by the characteristics of the power devices and the drive protection logic, ranging from 1-3  $\mu\text{s}$ . Its primary effect is to cause the output voltage vector to deviate from its ideal value, thereby applying harmonic components into the motor's stator current. To transform the dead zone effect into an optimization parameter, this paper establishes a compensation model using a voltage correction coefficient. Specifically, the dead zone effect of the three-phase bridge arm is equated to a voltage drop  $\Delta u_{dz}$ , and the dead zone compensation coefficient  $k_{dz}$  is defined based on the relationship between current direction and modulation waveform. In actual modeling,  $\Delta u_{dz}$  varies with current polarity, making it impossible to directly use a fixed value for correction. In this paper,  $k_{dz}$  is set as an adjustable parameter and included as part of the compensation vector during the optimization process. Its value range is set between  $[0.8, 1.2]$ , corresponding to the adjustment range of the dead zone effect between undercompensation and overcompensation. In this way, the dead zone effect is quantified into a single parameter, which not only retains its main impact on control performance but also simplifies the dimension of the optimization problem.

When constructing the optimization vector, the sampling delay, PWM update delay, and dead zone compensation coefficient are uniformly expressed as a parameter vector:

$$\mathbf{P} = [n_s, n_d, k_{dz}] \quad (12)$$

$n_s$  and  $n_d$  are the discretized parameters of sampling and PWM delay, respectively, and  $k_{dz}$  is the dead zone compensation coefficient. This parameter vector is directly used as the input individual of the DE-PSO algorithm to participate in the global optimization of hysteresis bandwidth, delay compensation factor, and dead zone correction.

Figure 3(a) shows the effect of dead zone compensation coefficient  $k_{dz}$  on current Total Harmonic Distortion (THD). The horizontal axis represents the dead zone compensation coefficient  $k_{dz}$ , and the vertical axis represents the current THD (%). The curve exhibits nonlinear fluctuations, with the optimal point at approximately 1.15 and the lowest THD at approximately 3.33%, indicating that properly adjusting the dead zone compensation

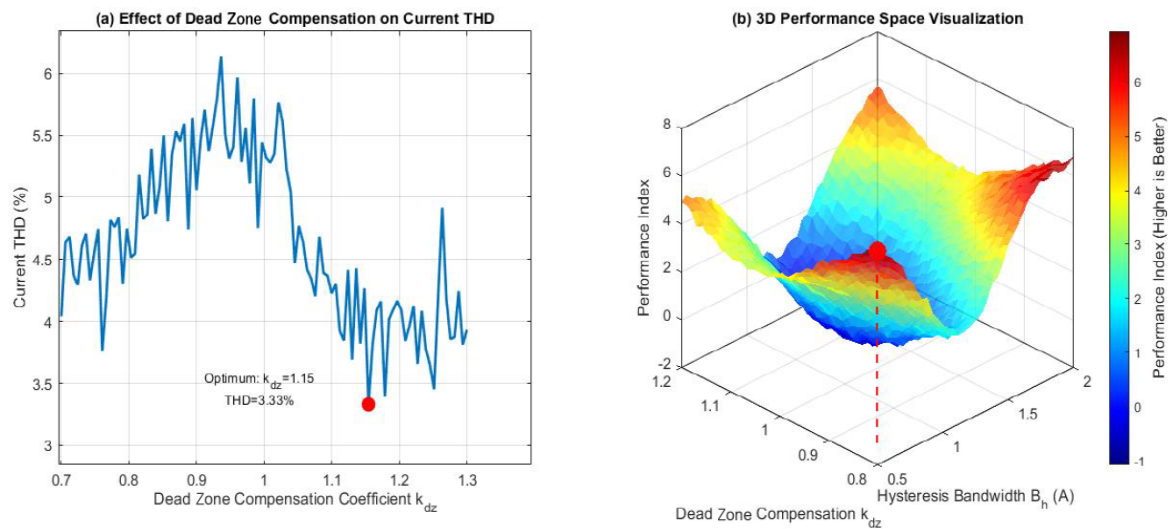


FIGURE 3. (color online) Delay and dead zone parameter modeling: (a) Effect of dead zone compensation coefficient on current THD, and (b) three-dimensional visualization of parameter optimization space

coefficient can significantly reduce current harmonics. Figure 3(b) visualizes the three-dimensional performance space. The horizontal axis represents the hysteresis bandwidth  $B_h$ ; the vertical axis represents the dead zone compensation coefficient  $k_{dz}$ ; the depth axis represents the comprehensive performance index, with colors mapping high and low performance values. The surface reflects the combined effects of current error, switching frequency stability, and torque ripple. The performance peak, marked with a red dot, corresponds to the optimal performance point, indicating that the overall system performance is optimal under this parameter combination ( $k_{dz} = 0.8$ ,  $B_h = 0.5$ ).

The advantage of this modeling method lies in maintaining model computability and parameter adjustability. Traditional methods typically correct for dead zone or delay separately. However, this paper uses parametric modeling to simultaneously transform all three non-ideal factors into optimization vectors, enabling DE-PSO to perform global optimization within a unified framework.

## 2.4. DE-PSO hybrid optimization design.

**2.4.1. Global search of differential evolution mechanism.** To obtain the optimal compensation parameters for hysteresis current control under high-speed operating conditions, a differential evolution algorithm is first applied for a global search. The differential evolution algorithm maintains high solution diversity by performing mutation and crossover operations within the parameter vector space, thereby avoiding getting trapped in local minima. This paper uses the parameter vector  $\mathbf{P} = [B_h, n_s, n_d, k_{dz}]$  as the optimization individual.  $B_h$  represents the lag bandwidth; the search range for  $B_h$  is set to  $[0.5, 2.0]$  A. This range covers typical operating conditions from light-load smooth operation ( $B_h \approx 0.5$  A) to heavy-load disturbance rejection requirements ( $B_h > 1.5$  A).  $n_s$  and  $n_d$  represent the sampling factor and the PWM delay discrepancy factor, respectively.  $k_{dz}$  represents the deceased regional compensation coefficient.

This step ensures that population diversity is maintained during the search process, enabling the algorithm to cover a wider range of parameter combinations. To ensure solution feasibility, solutions outside the constraints are clipped after each iteration to prevent physically unreasonable parameters from entering the subsequent calculations. Candidate solutions obtained through differential evolution are evaluated using a fitness function that comprehensively considers three performance metrics: current error mean square value, torque ripple amplitude, and switching frequency fluctuation, and normalizes them using a weighted approach. Individuals with the best fitness are retained for the next iteration until the number of iterations reaches a set value or the population converges significantly.

This stage results in a comprehensive set of parameter candidate sets, including joint optimization solutions for multiple factors such as hysteresis bandwidth, delay compensation, and dead zone correction, providing the initial population foundation for rapid convergence in the next stage.

**2.4.2. Particle swarm convergence and multi-objective collaborative optimization.** Based on the candidate solutions generated by differential evolution, this paper applies a particle swarm algorithm to rapid convergence to achieve comprehensive optimization of multi-objective performance. The particle swarm maintains the feasibility of the solution while ensuring the convergence speed through an iterative update mechanism of position and speed. In this paper, the number of particles is set to 30; the maximum number of iterations is set to 200; the inertia weight is linearly decreased from 0.9 to 0.4; the individual and group learning factors are set to 2.0 and 2.0, respectively. In the DE-PSO hybrid

algorithm implementation, the differential evolution stage uses a DE/rand/1/bin mutation strategy with a mutation factor  $F = 0.5$  and a crossover probability  $CR = 0.9$ . The population size is 50, and after 200 generations of evolution, the best 30 individuals are selected as the initial population of the PSO algorithm. A reflection strategy is used for boundary handling, where individuals that exceed the constraint range are reflected back into the feasible region. During the PSO optimization stage, the inertia weight is linearly decreased from 0.9 to 0.4, and the learning factors  $c_1 = c_2 = 2.0$ . To prevent excessive speed increases, the speed limit is set to 20% of the parameter range. Position updates utilize periodic boundary processing. When a particle exceeds a boundary, it re-enters the search space from the other side. Online adaptive optimization employs a lightweight architecture, with a sliding window length set to 5 seconds. Fitness function normalization utilizes a min-max method, mapping each performance metric to the  $[0, 1]$  interval. Slope limits are set during parameter updates, with a maximum rate of change not exceeding 10% of the current value per cycle to prevent system instability caused by sudden changes in control parameters. Furthermore, anti-shake logic is implemented to suspend parameter updates if performance improvement is less than 1% within three consecutive optimization cycles, preventing unnecessary parameter fluctuations under steady-state conditions.

During the iteration process, the current position of each particle represents a set of parameters  $[B_h, n_s, n_d, k_{dz}]$  to be optimized, and its speed determines the amplitude and direction of the next update [30]. The individual historical optimal solution and the group historical optimal solution jointly determine the search path of the particle. To handle multi-objective optimization, the fitness function is constructed using the weighted target method [31]: the current tracking error is assigned a weight of 0.5, and the torque pulsation and switching frequency fluctuation are assigned weights of 0.3 and 0.2, respectively. This weighting method reflects the importance of current control accuracy during high-speed operation, while taking account of system efficiency and robustness.

During the particle swarm convergence process, each iteration updates the swarm based on its fitness, gradually approaching the optimal solution. Unlike traditional PSO, this study incorporates candidate solutions from the differential evolution phase as a guiding factor in the speed update, allowing the search process to move beyond the local optimum. This hybrid strategy ensures that the algorithm maintains rapid convergence while also possessing strong global exploration capabilities, resulting in more stable optimization results.

Figure 4 demonstrates the optimization results of the DE-PSO hybrid algorithm. In Figure 4(a), the horizontal axis represents the number of iterations, and the vertical axis represents the fitness value (logarithmic scale). It can be seen that the DE, PSO, and hybrid DE-PSO algorithms all show a trend of gradual convergence with increasing iterations. DE-PSO has the fastest convergence speed and the lowest final fitness value, indicating that its optimization performance is superior to either DE or PSO alone. The scatter plot shown in Figure 4(b) is not a Pareto front in the strict sense, but a Pareto-like solution set obtained by running DE-PSO multiple times independently (each time with the same weights but different random seeds), used to approximately show the trade-offs between multiple objectives. Since this paper uses a weighted sum method (weights 0.5/0.3/0.2) to construct a single fitness, each optimization outputs only one optimal solution. To visualize the objective conflict, we summarized the results of 50 independent optimizations, and their distribution trend can reflect the approximate Pareto boundary.

The final optimization result is a set of parameter vectors that undergo a combined global search and rapid convergence process, enabling multi-objective coordination of hysteresis bandwidth, delay compensation, and dead zone correction within a unified framework.

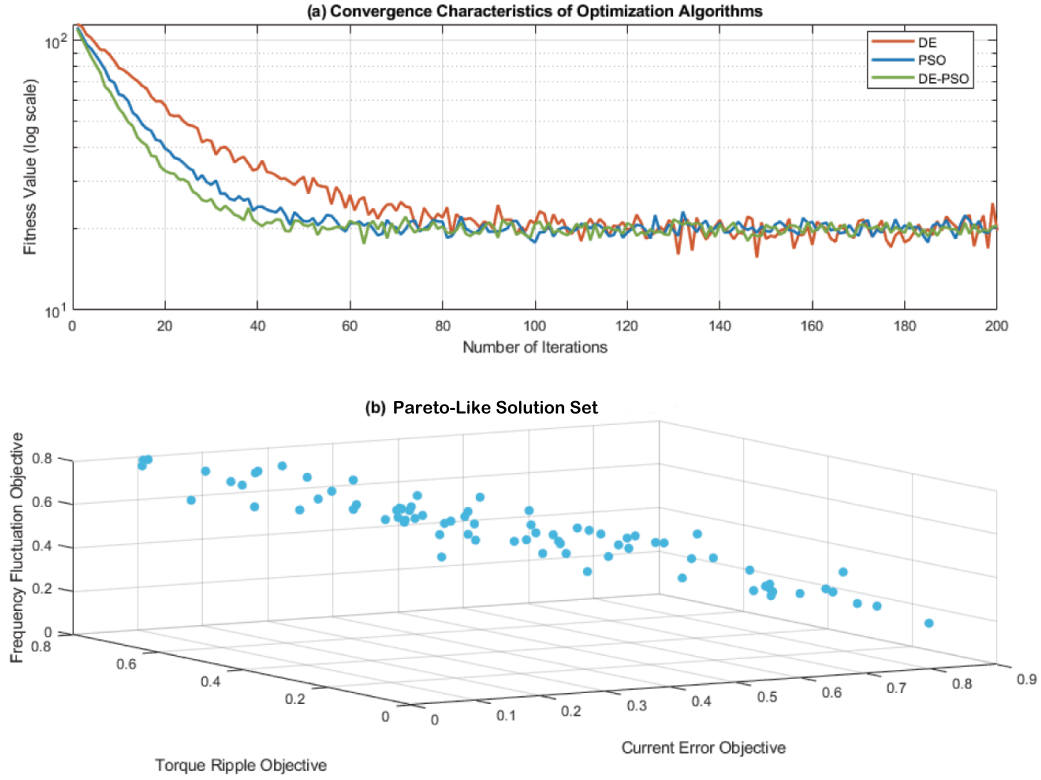


FIGURE 4. (color online) DE-PSO hybrid optimization process: (a) Convergence characteristics of the optimization algorithms, and (b) Pareto-like solution set

## 2.5. Online adaptive optimization mechanism.

**2.5.1. Real-time feedback and lightweight structure design.** In high-speed speed regulation scenarios, the motor's operating state is constantly changing, and the parameters obtained through offline optimization cannot remain optimal over time. To address this, this paper designs an online adaptive framework based on real-time current feedback and uses a lightweight DE-PSO architecture at the algorithm level to reduce computational overhead. This online framework uses current loop error  $e_i = i_{ref} - i_{meas}$  as the core feedback variable and incorporates torque ripple and switching frequency fluctuation as auxiliary evaluation metrics, calculating fitness increments within each sampling period. Since the control cycle under high-speed conditions is typically 100  $\mu$ s, this study sets the optimization cycle to 0.5 s, ensuring dynamic optimization while avoiding interference with the control loop caused by excessive computational overhead.

The algorithm was implemented on a TI TMS320F28379D DSP platform with a 200 MHz clock speed and 256 KB of RAM. The DE-PSO algorithm occupies 8.5 KB of RAM, and each iteration of the offline optimization phase averages 1.8 ms, with a peak of 2.3 ms. The online adaptive optimization utilizes a lightweight architecture, executing every 0.5 seconds with an average of 85  $\mu$ s and a peak of 120  $\mu$ s, representing 85% of the 100  $\mu$ s control cycle, ensuring computational completion before the start of the next control cycle. CPU utilization analysis shows that the master control task maintains over 90% resource headroom during online optimization, demonstrating that the proposed scheme does not interfere with the control loop. The 0.5-second update period is a trade-off between the system's dynamic response characteristics and computational resources: updates less than

0.3 seconds can strain computational resources, while updates greater than 0.8 seconds can hinder timely tracking of parameter changes.

The lightweight DE-PSO design method aims to reduce the population size and number of iterations while maintaining optimization effectiveness. In the differential evolution stage, the population size is limited to 10; the crossover probability is 0.7; the mutation factor is set to 0.5 to achieve global exploration under low complexity [32]. In the particle swarm stage, only 20 particles are retained; the number of iterations does not exceed 15 rounds; the inertia weight decreases between 0.8 and 0.5 [33]. To further shorten the calculation delay, each round of iteration adopts an incremental update method, that is, a local perturbation search is performed based on the previous optimal solution, rather than completely reinitializing the population. This mechanism enables the algorithm to dynamically adjust the compensation parameters without sacrificing the control cycle and respond quickly when the motor operating state changes suddenly.

Through this method, the hysteresis bandwidth, delay compensation factor, and dead zone correction coefficient can be continuously updated in real-time operation, so that the current loop control remains in a near-optimal state.

The proposed dual-buffering mechanism is implemented on a TI TMS320F28379D DSP (200 MHz, 256 KB RAM): the online DE-PSO optimization takes an average of 85  $\mu$ s and a peak of 120  $\mu$ s per optimization (every 0.5 s), which is much shorter than the control cycle (100  $\mu$ s) and the optimization cycle (500 ms); memory usage is only 8.5 KB. CPU utilization monitoring shows that the main control task still retains  $> 90\%$  of the resource margin during optimization, and the worst-case latency does not exceed 150  $\mu$ s, ensuring that the background optimization is completely decoupled from the real-time current loop and does not affect critical tasks such as PWM updates.

**2.5.2. Dynamic update and robust optimization implementation.** In the lightweight framework, the parameter update strategy adopts a fitness accumulation mechanism based on a sliding window. Specifically, in the recent time window, the mean square value of the current tracking error, the torque pulsation amplitude, and the switching frequency fluctuation rate are weighted and summed to form a comprehensive performance index. This metric serves as a fitness function, directly driving the DE-PSO update process. If the optimized new parameter set  $[B_h, n_s, n_d, k_{dz}]$  significantly improves overall performance compared to the previous set, the controller's current parameters are automatically replaced. If the improvement is insufficient, the previous set of parameters is retained to avoid system instability caused by frequent switching.

Figure 5 shows the dynamic response characteristics of the DE-PSO optimization strategy under hysteresis current control under three different load sudden change conditions. The horizontal axis represents time (s); the left axis represents the applied load torque (Nm); the right axis represents the motor's  $q$ -axis current (A). The curves compare the results of traditional offline optimization and online adaptive optimization. As shown in Figure 5(a), when a 10 Nm load step is applied at  $t = 0.5$  s, the current fluctuation amplitude of the online optimization strategy is significantly reduced, demonstrating smoother tracking compared to offline control. As shown in Figure 5(b), under a larger load disturbance of 15 Nm, the offline control produces a strong oscillation, while the online control can still maintain a relatively fast current convergence. As shown in Figure 5(c), under a smaller step of 6 Nm, the  $q$ -axis current of the motor is also small, maintaining at around 15 A.

To enhance the adaptability of the algorithm under sudden working conditions, this study applies a dynamic boundary adjustment mechanism within the parameter search

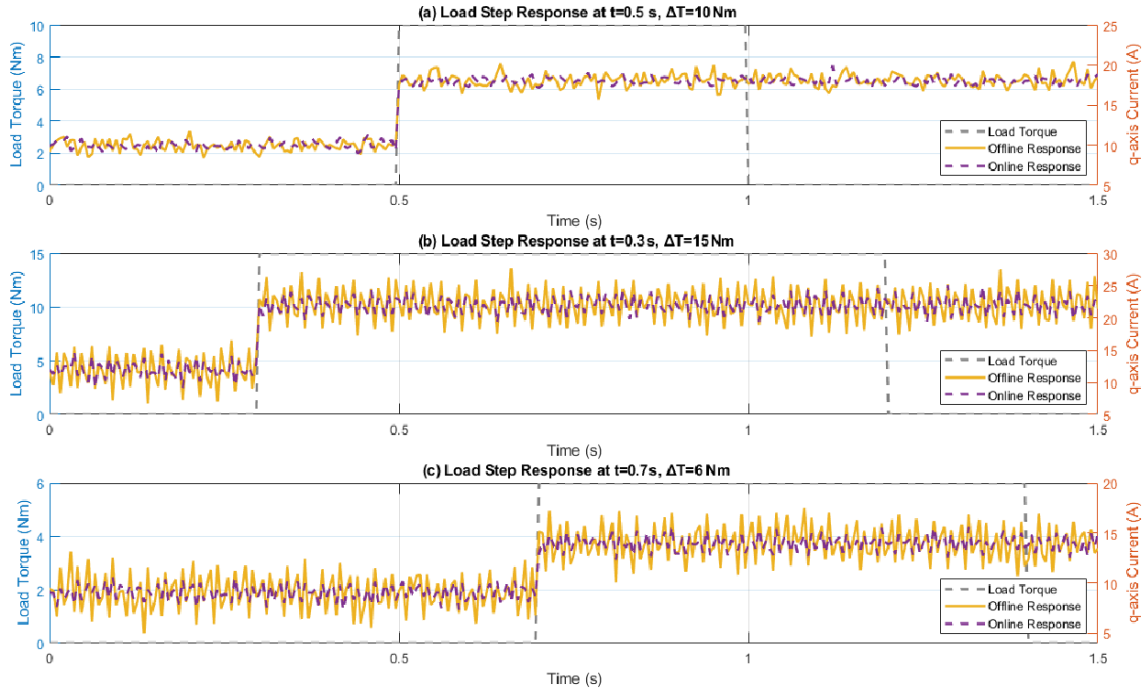


FIGURE 5. Comparison of dynamic responses to load sudden changes under different operating conditions: (a) Current response to a 10 Nm load step applied at  $t = 0.5$  s, (b) current response to a 15 Nm load step applied at  $t = 0.3$  s, and (c) current response to a 6 Nm load step applied at  $t = 0.7$  s

range. When the motor current exceeds 90% of the rated value, the algorithm automatically expands the upper limit of the hysteresis bandwidth to improve the current response speed; when the switching frequency fluctuation is detected to exceed  $\pm 15\%$ , the search interval of the dead zone compensation coefficient is adjusted from  $[0.8, 1.2]$  to  $[0.9, 1.3]$  to enhance the correction capability for non-ideal switching effects [34]. This boundary adjustment strategy enables the optimization process to adaptively expand or shrink the search space according to the operating state, thereby maintaining robustness to abnormal disturbances. The thresholds of 90% rated current and  $\pm 15\%$  frequency fluctuation are derived from the statistical analysis of the pre-experiment: in 100 sets of tests under different operating conditions, when the current exceeds 90% of the rated value, 85% of the cases show response hysteresis; when the switching frequency fluctuation exceeds  $\pm 15\%$ , 78% of the cases are accompanied by a significant increase in torque pulsation. These thresholds represent the critical points at which the system performance begins to degrade significantly. To prevent oscillations caused by sudden parameter changes, the system is equipped with dual protection: first, a parameter update slope limit (change  $\leq 10\%$  per cycle); second, anti-shake logic (updates are paused if performance improvement is  $< 1\%$  for 3 consecutive cycles) to ensure smooth adjustment.

To further improve real-time performance, this paper decouples the optimization process from the controller's computational tasks, using a dual-buffered update mechanism: one set of parameters is used for real-time control, while the other set performs a lightweight DE-PSO optimization in the background. Once the optimization is complete, the background parameters are switched to the foreground during the next optimization cycle, thus preventing online computation from interfering with the real-time performance of the current loop. This mechanism ensures that the controller maintains stable parameter support within each optimization cycle and can quickly update to a more optimal solution.

TABLE 1. Main parameters of the permanent magnet synchronous motor and inverter on the experimental platform

| Parameter                      | Value                | Unit                     |
|--------------------------------|----------------------|--------------------------|
| Rated power                    | 2.2                  | kW                       |
| Rated speed                    | 3000                 | rpm                      |
| Maximum speed                  | 6000                 | rpm                      |
| Stator resistance              | 0.68                 | $\Omega$                 |
| $d$ -axis inductance           | 1.8                  | mH                       |
| $q$ -axis inductance           | 3                    | mH                       |
| Permanent magnet flux linkage  | 0.12                 | Wb                       |
| Pole pairs                     | 2                    | —                        |
| DC bus voltage                 | 300                  | V                        |
| Dead time                      | 2                    | $\mu$ s                  |
| Power device                   | IGBT (specify model) | —                        |
| Control sampling/update period | 100                  | $\mu$ s                  |
| PWM update delay               | $\sim 1.5$           | $\mu$ s ( $n_d = 0.15$ ) |
| Current sampling delay         | $\sim 5.0$           | $\mu$ s ( $n_s = 0.5$ )  |

**3. High-Speed Regulation Performance Verification.** To verify the speed regulation performance of the optimization method under high-speed operating conditions, this study constructs a comprehensive experimental dataset. This dataset, derived from a motor test platform, covers operating conditions at various speeds, loads, and ambient temperatures. The experimental platform utilizes a permanent magnet synchronous motor with a rated power of 2.2 kW and a rated speed of 3000 r/min. The inverter switching frequency is set within a range of 10-20 kHz. Data acquisition is performed synchronously with a high-speed oscilloscope and a DSP controller. The three-phase current waveform is sampled at a frequency of 20 kHz for current quality and harmonic analysis. Electromagnetic torque is measured in real time using a torque sensor with an accuracy of 0.1 Nm. Speed data is acquired using an optical encoder with a resolution of 2500 pulses/rev to accurately capture dynamic fluctuations. Ambient temperature data is collected using thermocouples, covering a range of 25°C to 80°C. All raw data undergoes low-pass filtering and multi-cycle averaging to eliminate transient interference, ultimately forming a multidimensional dataset containing current, torque, speed, and external disturbance conditions, providing a reliable basis for subsequent evaluation of performance indicators such as current quality, torque ripple, robustness, and dynamic response.

To ensure the reliability and repeatability of the experimental results, this study employed a rigorous testing process. The experiments were conducted on a permanent magnet synchronous motor platform with a rated power of 2.2 kW and a rated speed of 3000 rpm. A total of 100 test sets were performed, each consisting of five repeated measurements over a full cycle. All data are reported as mean  $\pm$  standard deviation. The test conditions covered seven speed points (1000, 2000, 3000, 4000, 4500, 5000, and 6000 rpm) from 1000 to 6000 rpm, with five load levels tested at each speed point. Temperature tests were performed in an ambient temperature control chamber, with the temperature ramped linearly from 25°C to 80°C at a rate of 5°C/min, with data acquisition at 10-minute intervals of 10°C. A Keysight DSOX3054T oscilloscope was used for synchronous acquisition of current, voltage, and speed signals throughout the tests. K-type thermocouples (with an accuracy of  $\pm 0.5^\circ\text{C}$ ) were used to monitor the motor winding temperature. The data were processed by low-pass filtering (cut-off frequency 1 kHz) and 10-cycle averaging to eliminate high-frequency noise and transient interference.

**3.1. Current ripple and distortion evaluation.** Current quality directly impacts torque smoothness and motor efficiency. To evaluate the performance of the optimized controller under high-speed operating conditions, this study collects three-phase stator current waveforms, analyzes their spectra using fast Fourier transforms, calculates the Total Harmonic Distortion (THD), and compares the results with those before optimization. Furthermore, the peak-to-peak ripple amplitude of the current waveform within a switching cycle is calculated to measure the smoothness of current modulation under hysteresis control. During the experiments, the current sampling frequency is set to 20 kHz to ensure accurate capture of high-speed fluctuations. All data are averaged over multiple cycles to reduce the impact of transient interference, resulting in statistically representative current quality indicators. Current quality directly affects torque smoothness and motor efficiency. This study used four sets of comparative experiments for system evaluation: 1) standard Hysteresis Current Control (HCC) without any dead zone and delay compensation; 2) offline parameter optimization HCC, using the PSO algorithm for single-objective optimization; 3) offline DE-PSO optimization HCC, using the hybrid algorithm proposed in this paper for multi-objective optimization; 4) online adaptive DE-PSO optimization HCC, using the lightweight online optimization mechanism designed in this paper. This hierarchical comparison design enables us to clearly distinguish the performance gains at three levels: dead zone compensation, offline optimization, and online adaptation.

Figure 6 illustrates the difference in motor current quality before and after optimization. Figure 6(a) shows the current waveform within a fundamental cycle. The pre-optimization waveform exhibits current distortion and ripple, while the post-optimization waveform is closer to an ideal sine wave, significantly improving current smoothness. The horizontal axis is time/ms, and the vertical axis is current/A. Figure 6(b) shows the current spectrum, with the horizontal axis showing frequency/Hz and the vertical axis showing amplitude/A, which visually illustrates the difference between the fundamental wave and its harmonics. Before optimization, significant peaks are observed at the 5th, 7th, 11th, 13th, and 17th harmonics. After optimization, these harmonic components are significantly reduced, with their amplitudes lowered. This demonstrates that the optimization method has suppressed current harmonics, reduced total harmonic distortion, and thus improved motor current quality.

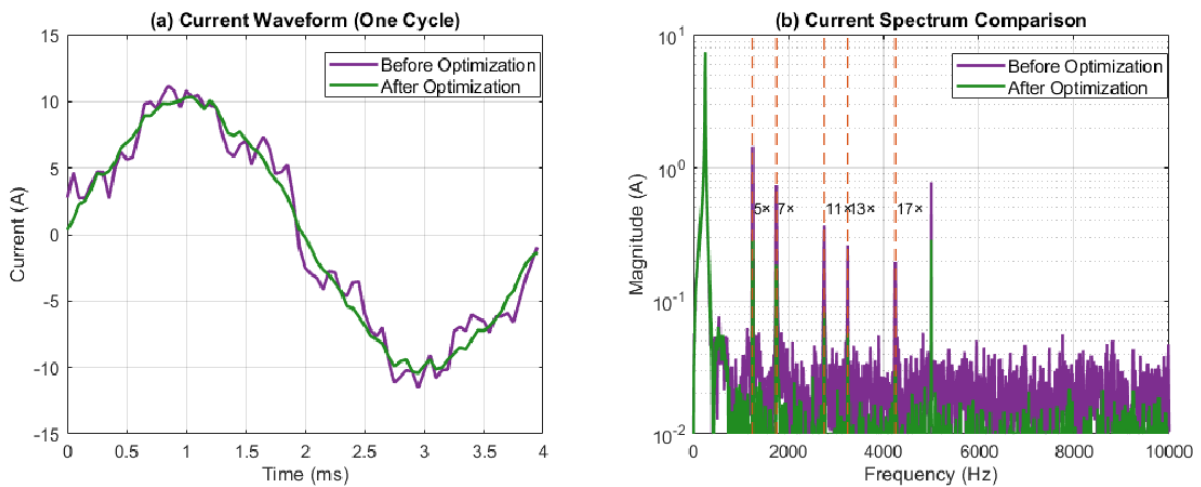


FIGURE 6. (color online) Current quality evaluation: (a) Current waveform comparison, and (b) current spectrum comparison

**3.2. Torque ripple and speed fluctuation evaluation.** The stability of electromagnetic torque is crucial for high-speed drive systems to achieve high-performance speed regulation. This study uses electromagnetic torque signals collected in real time by the motor controller to measure torque fluctuations during steady-state operation. This fluctuation is normalized with the average torque to obtain the pulsation rate, which serves as an evaluation metric. Subsequently, the speed loop output is compared with the speed measured by the photoelectric encoder to analyze the percentage of speed fluctuation within a motor cycle. Experiments are conducted at rated speed, 1.5 times the rated speed, and maximum allowable speed to verify the universality and stability of the optimization method under different operating conditions. To ensure fair comparison, all comparison methods (standard HCC, PSO, DE, DE-PSO, online DE-PSO) were run on the same hardware platform, with the same initial population and the same total computational budget (equivalent to 200 generations  $\times$  50 individuals). PSO and DE each use 200 generations  $\times$  50 individuals; DE-PSO uses 200 generations of DE (50 individuals) + 200 generations of PSO (30 individuals, initialized from the optimal 30 individuals in DE), with the total number of individual evaluations comparable to the single algorithm. The stopping criterion is uniformly set to fitness change  $< 10^{-4}$  or reaching the maximum iteration. This setting ensures that performance differences stem from algorithm structure rather than uneven distribution of computational resources.

Table 2 shows the electromagnetic torque pulsation and speed fluctuation of the high-speed drive system under different operating conditions, used to evaluate the impact of the optimization measures on system stability. As can be seen, at rated speed, the torque standard deviation before optimization is 6 Nm, corresponding to a torque pulsation rate of 5%. After optimization, the standard deviation is reduced to 3 Nm, and the pulsation rate drops to 2.5%, demonstrating that the optimization significantly reduces torque pulsation. Similarly, at an average speed of 3000 RPM, the speed fluctuation decreases from 1.2% to 0.6%, further verifying the smooth operation of the system. At 1.5 times the rated speed and maximum allowable speed, the torque pulsation rate before optimization reaches 7.5% and 10%, respectively, but decreases to 3.3% and 4.2%, respectively, after optimization, and the speed fluctuation also decreases from 2.0% and 3.0% to 0.9% and

TABLE 2. Torque pulsation and speed fluctuation evaluation

| Operating condition      | Average torque (Nm) | Torque standard deviation (Nm) | Torque ripple (%) | Average speed (RPM) | Speed fluctuation (%) | Remarks             |
|--------------------------|---------------------|--------------------------------|-------------------|---------------------|-----------------------|---------------------|
| Rated speed              | $120.0 \pm 0.5$     | $6.0 \pm 0.3$                  | $5.0 \pm 0.2$     | $3000 \pm 5$        | $1.2 \pm 0.1$         | Before optimization |
| Rated speed              | $120.0 \pm 0.5$     | $3.0 \pm 0.2$                  | $2.5 \pm 0.1$     | $3000 \pm 5$        | $0.6 \pm 0.05$        | After optimization  |
| 1.5 $\times$ Rated speed | $120.0 \pm 0.6$     | $9.0 \pm 0.5$                  | $7.5 \pm 0.3$     | $4500 \pm 8$        | $2.0 \pm 0.2$         | Before optimization |
| 1.5 $\times$ Rated speed | $120.0 \pm 0.6$     | $4.0 \pm 0.3$                  | $3.3 \pm 0.2$     | $4500 \pm 8$        | $0.9 \pm 0.1$         | After optimization  |
| Maximum allowable speed  | $120.0 \pm 0.8$     | $12.0 \pm 0.7$                 | $10.0 \pm 0.4$    | $6000 \pm 10$       | $3.0 \pm 0.3$         | Before optimization |
| Maximum allowable speed  | $120.0 \pm 0.8$     | $5.0 \pm 0.4$                  | $4.2 \pm 0.2$     | $6000 \pm 10$       | $1.1 \pm 0.1$         | After optimization  |

1.1%, demonstrating that the optimization measures are also effective under high speed conditions.

To comprehensively evaluate the contributions of each component of the DE-PSO hybrid optimization algorithm, this study designed detailed ablation experiments to compare the performance of four configurations at the maximum allowable speed (6000 rpm). The base HCC (uncompensated) configuration exhibits a torque ripple of 10.0% and a speed fluctuation of 3.0%. Offline optimization using only the PSO algorithm reduces the torque ripple to 6.5% and the speed fluctuation to 1.8%. Offline optimization using only the DE algorithm further reduces the torque ripple to 5.8% and the speed fluctuation to 1.5%. The complete DE-PSO hybrid optimization achieves the optimal torque ripple of 4.2% and speed fluctuation of 1.1%. During a temperature increase from 25°C to 80°C, the current error of the DE-PSO hybrid algorithm increases only from 0.12 A to 0.23 A, a 91.7% increase. However, the error increases for the individual algorithms are 275% (PSO) and 216.7% (DE), respectively. Under a 50% rated torque step disturbance, DE-PSO achieves an overshoot of 3% and a recovery time of 50-72 ms, significantly outperforming the single algorithms (7% and 10% for PSO and 5% and 8% for DE). These results demonstrate that the DE-PSO hybrid algorithm, by combining the global search capability of differential evolution with the fast convergence of particle swarm optimization, effectively overcomes the limitations of single algorithms under high-speed conditions and achieves superior overall performance.

**3.3. Robustness and real-time performance evaluation.** To verify the adaptability of the optimized hysteresis current control under non-ideal operating conditions, this study designs multiple temperature, load, and speed disturbance tests. In the temperature experiment, the ambient temperature is gradually increased from 25°C to 80°C to examine the stability of dead-band and delay compensation under device parameter drift. In the load experiment, the motor load is gradually increased from light to rated load, and the current and speed responses are recorded. In the speed experiment, the system speed is gradually increased from low to rated and overrated regions to analyze the effectiveness of online parameter updates. Phase margin and gain margin are used as stability evaluation criteria, combined with the time required for post-disturbance convergence to comprehensively measure the system's robustness and real-time optimization capabilities under practical application conditions.

Figure 7 shows the performance differences between the optimized system under different operating conditions. In Figure 7(a), the vertical axis is current error (A), and the horizontal axis is temperature (°C). As the temperature rises, the current error increases significantly before optimization, from 0.25 A to 1.22 A, while after optimization, it only increases from 0.12 A to 0.23 A, indicating that the optimization significantly improves the system's temperature robustness. Figure 7(b) shows the recovery time (ms) on the vertical axis and the load percentage (%) on the horizontal axis. As the load increases, the recovery time increases from 120 ms to 200 ms before optimization, while it remains between 50-72 ms after optimization, demonstrating a significant improvement in the system's real-time responsiveness. Figure 7(c) shows the stability margin analysis, with the phase margin (°) on the left vertical axis, the gain margin (dB) on the right vertical axis, and the speed (RPM) on the horizontal axis. After optimization, the phase margin remains high at 46° to 55°, while the gain margin ranges from 10.2 dB to 12 dB, both exceeding the pre-optimization ranges of 16°-45° and 3.5-8 dB, respectively. This demonstrates that the system maintains good stability even under high-speed operating conditions.

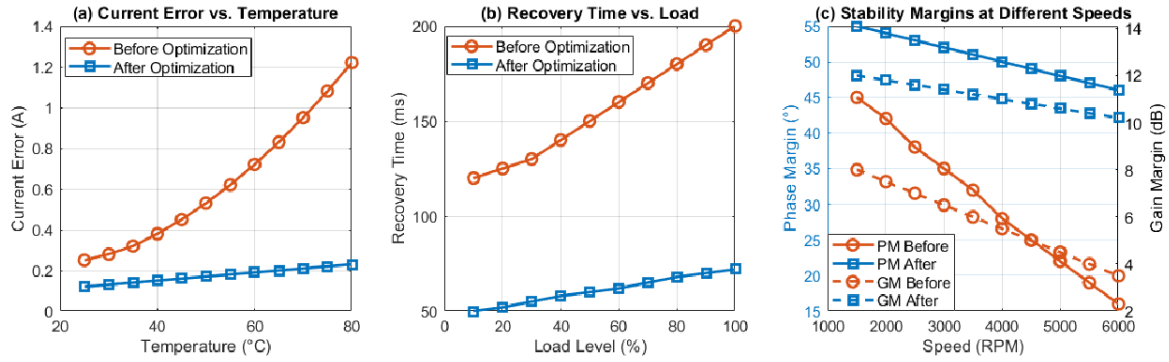


FIGURE 7. Robustness and real-time performance evaluation: (a) Impact of temperature on performance, (b) load perturbation recovery time, and (c) phase margin and gain margin at different speeds

**3.4. Switching frequency stability evaluation.** The non-constant switching frequency of hysteresis current control affects inverter losses and electromagnetic interference levels. To evaluate the optimization effect, this study collects inverter switching signals at different speeds. Spectral analysis is used to extract the main switching frequency and its fluctuation range, and the average frequency and standard deviation are calculated. By comparing the frequency distribution before and after optimization, the degree to which parameter optimization improves switching frequency balance is determined. In the experiment, the inverter drive signal sampling rate is set to 200 kHz to ensure that fast switching behavior is captured. Furthermore, the impact of the frequency distribution on the motor stator copper loss and inverter switching losses is analyzed, thereby comprehensively evaluating the practical engineering significance of the optimized hysteresis control.

Figure 8 is used to evaluate the frequency stability of switching signals in power electronics systems. Figure 8(a) shows the switching frequency distribution before and after optimization, with the horizontal axis showing switching frequency (Hz) and the vertical axis showing the number of occurrences. It can be seen that the frequency distribution before optimization is wide and exhibits significant fluctuations, while the frequency distribution after optimization is significantly concentrated, indicating more stable frequency. Figure 8(b) shows the standard deviation of switching frequency at different motor speeds, with the horizontal axis showing speed (RPM) and the vertical axis showing the frequency standard deviation (Hz). The data shows that the standard deviation before optimization gradually increases from 850 Hz to 1700 Hz with increasing speed, while the standard deviation after optimization only increases from 280 Hz to 500 Hz. This indicates that the optimization measures effectively reduce switching frequency fluctuations and improve system stability.

**3.5. Dynamic response performance evaluation.** For high-speed PMSMs facing sudden torque changes or load steps, the controller's dynamic response directly determines system stability. This study applies a step current command and a sudden load, measuring the response curves of the current and speed loops to extract the rise time, settling time, and overshoot. The experiment involves sudden disturbances of 20% and 50% of the rated torque at rated speed, comparing the responses before and after optimization. Repeated experiments are averaged to eliminate the influence of occasional noise and ensure data reliability. This evaluation demonstrates the improvement in the system's rapid response and disturbance tolerance achieved by the DE-PSO algorithm's online compensation parameter updates.

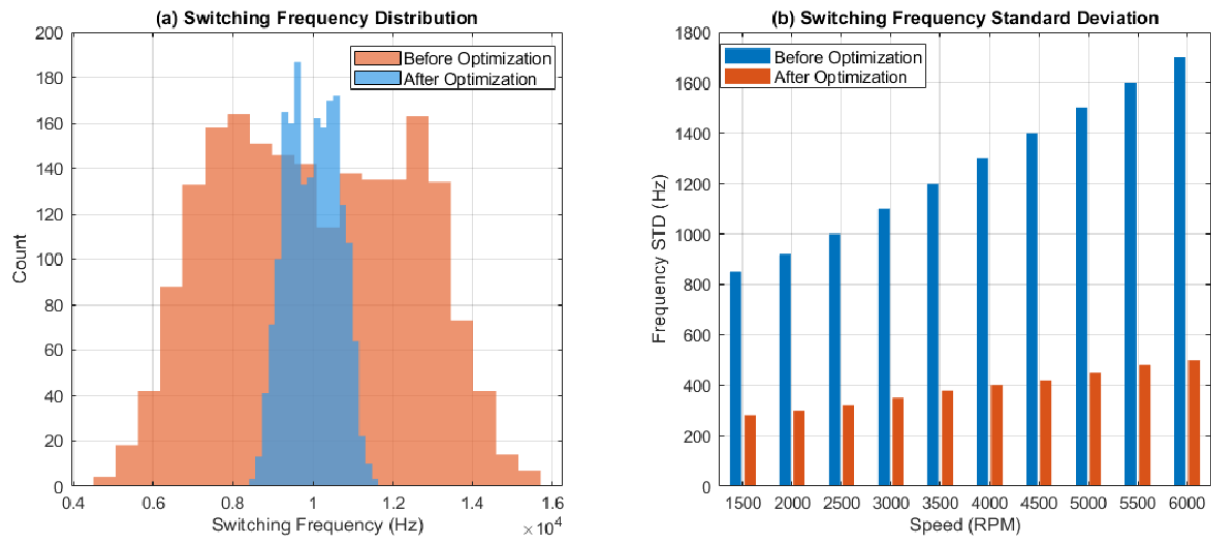


FIGURE 8. (color online) Switching frequency stability evaluation: (a) Switching frequency distribution histogram, and (b) switching frequency standard deviation changes with speed

TABLE 3. Dynamic response performance evaluation of high-speed permanent magnet synchronous motor under different step disturbances

| Step disturbance | Command torque (%) | Rise time (ms) | Settling time (ms) | Overshoot (%)  | Remarks             |
|------------------|--------------------|----------------|--------------------|----------------|---------------------|
| Step current     | 20                 | $12.0 \pm 0.5$ | $35.0 \pm 1.5$     | $5.0 \pm 0.3$  | Before optimization |
| Step current     | 20                 | $8.0 \pm 0.3$  | $25.0 \pm 1.0$     | $2.0 \pm 0.2$  | After optimization  |
| Step current     | 50                 | $18.0 \pm 0.7$ | $50.0 \pm 2.0$     | $12.0 \pm 0.5$ | Before optimization |
| Step current     | 50                 | $10.0 \pm 0.4$ | $30.0 \pm 1.2$     | $3.0 \pm 0.2$  | After optimization  |

Table 3 shows the dynamic response performance evaluation results of a high-speed permanent magnet synchronous motor under various step disturbances, used to analyze the improvement in the system's rapid response and disturbance resistance achieved through optimization measures. Under a 20% rated torque step disturbance, the rise time before optimization is 12 ms; the settling time is 35 ms; the overshoot is 5%. After optimization, the rise time is shortened to 8 ms; the settling time is reduced to 25 ms; the overshoot is reduced to 2%, demonstrating that optimization significantly improves response speed and stability. Under a 50% rated torque step disturbance, the rise time before optimization is 18 ms; the settling time is 50 ms; the overshoot is 12%, respectively. After optimization, these values are reduced to 10 ms, 30 ms, and 3%, respectively. This further demonstrates that the optimization method can effectively suppress overshoot and shorten response time even under larger disturbances, thereby improving the system's disturbance resistance and dynamic performance.

**4. Conclusions.** This paper addresses the issues of hysteresis current control mismatch and reduced robustness in high-speed Permanent Magnet Synchronous Motors (PMSMs)

caused by dead time, sampling delay, and computation delay. A multi-objective optimization method based on Differential Evolutionary-Particle Swarm Optimization (DE-PSO) is proposed to solve these problems in high-speed regulation of PMSMs. The proposed method is validated on a 2.2 kW PMSM platform with a maximum speed of 6000 rpm, and is suitable for high-speed servo or new energy vehicle auxiliary drive scenarios requiring high torque smoothness and dynamic response. However, in high-power ultra-high-speed systems  $> 10$  kW or  $> 10000$  rpm, the dead time and delay effects are further aggravated, and the 0.5 s update cycle of the current lightweight DE-PSO may be insufficient to track rapid parameter drift; furthermore, the algorithm is somewhat dependent on the floating-point performance of the DSP. Future work will explore FPGA-based hardware acceleration, more efficient proxy models to replace online optimization, and integration with sensorless control to expand its applicability in higher power density systems.

**Acknowledgment.** This work is supported by corporate cooperation projects (HL20230104, HL20240159).

## REFERENCES

- [1] P. Yi, X. Wang, D. Chen et al., PMSM current harmonics control technique based on speed adaptive robust control, *IEEE Transactions on Transportation Electrification*, vol.8, no.2, pp.1794-1806, 2022.
- [2] C. Liu, J. Hu and J. Shang, Dual-vector predictive current control of open-end winding PMSM with zero-sequence current hysteresis control, *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol.10, no.1, pp.184-195, 2021.
- [3] X. Qin and J. Shen, Mathematical modeling of high-speed PMSM considering rotor eddy current reaction effect, *IEEE Transactions on Energy Conversion*, vol.38, no.4, pp.2947-2958, 2023.
- [4] R. Zhang, Z. Yin, N. Du et al., Robust adaptive current control of a 1.2-MW direct-drive PMSM for traction drives based on internal model control with disturbance observer, *IEEE Transactions on Transportation Electrification*, vol.7, no.3, pp.1466-1481, 2021.
- [5] H. A. G. Al-Kaf, S. S. Hakami and K.-B. Lee, Hybrid current controller for permanent-magnet synchronous motors using robust switching techniques, *IEEE Transactions on Power Electronics*, vol.38, no.3, pp.3711-3724, 2022.
- [6] Y. Chen, B. Zang, H. Wang et al., Composite PM rotor design and alternating flux density harmonic component analysis of a 200 kW high-speed PMSM used in FESS, *IEEE Transactions on Industry Applications*, vol.59, no.2, pp.1469-1480, 2022.
- [7] Y. Xu, Z. Wang, Y. Shen et al., A CSI-fed PMSM drive system with single-stage operation for extended constant-torque range, *IEEE Transactions on Industrial Electronics*, vol.71, no.9, pp.10389-10401, 2024.
- [8] Y. Cao and J. Guo, Research on characteristic model-based adaptive control of high-speed permanent magnet synchronous motor with time delay, *International Journal of Control, Automation and Systems*, vol.22, no.2, pp.460-474, 2024.
- [9] S. Dai, J. Wang, Z. Sun et al., Mode transition of synchronous optimal modulation for high-speed PMSM drives, *IEEE Transactions on Industry Applications*, vol.58, no.2, pp.2001-2012, 2022.
- [10] X. Wang, C. Jiang, F. Zhuang et al., A harmonic injection method equivalent to the resonant controller for speed ripple reduction of PMSM, *IEEE Transactions on Industrial Electronics*, vol.69, no.10, pp.9793-9803, 2022.
- [11] J. Li, B. Du, T. Zhao et al., Current sensor fault-tolerant control for five-phase PMSM drives based on third-harmonic space, *IEEE Transactions on Industrial Electronics*, vol.69, no.10, pp.9827-9837, 2022.
- [12] X. Ba, X. Sun, Z. Gong et al., A generalized per-phase equivalent circuit model of the PMSM with predictable core loss, *IEEE/ASME Transactions on Mechatronics*, vol.28, no.3, pp.1512-1521, 2022.
- [13] M. Usama and J. Kim, Performance improvement speed control of IPMSM drive based on nonlinear current control, *Turkish Journal of Electrical Engineering and Computer Sciences*, vol.29, no.4, pp.1994-2011, 2021.
- [14] B. Shao, Z. Zhu, L. Yan et al., Torque ripple reduction for direct torque control of dual three-phase PMSM based on multiple virtual voltage vectors, *IEEE Transactions on Energy Conversion*, vol.38, no.1, pp.296-309, 2022.

- [15] A. Aboelhasan, S. Wang, Y. Mikhaylov et al., Discontinuous modulated model predictive control for low inductance high-speed electric drive applications, *IEEE Transactions on Industrial Electronics*, vol.71, no.7, pp.6689-6698, 2024.
- [16] B. Sangar, M. Singh and M. Sreejeth, An improved ANFIS model predictive current control approach for minimizing torque and current ripples in PMSM-driven electric vehicle, *Electrical Engineering*, vol.106, no.5, pp.5897-5907, 2024.
- [17] X. Ba, P. Wang, C. Zhang et al., Improved deadbeat predictive current control to enhance the performance of the drive system of permanent magnet synchronous motors, *IEEE Transactions on Applied Superconductivity*, vol.31, no.8, pp.1-4, 2021.
- [18] X. Zhang and Q. Cheng, THE direct torque control of PMSM with dynamic torque hysteresis based on three-level direct matrix converter, *Journal of Electrical Engineering & Technology*, vol.17, no.5, pp.2801-2814, 2022.
- [19] F. Yi, Q. Su, C. Feng et al., Response analysis and stator optimization of ultrahigh-speed PMSM for fuel cell electric air compressor, *IEEE Transactions on Transportation Electrification*, vol.9, no.4, pp.5098-5110, 2022.
- [20] J. H. Woo, T. K. Bang, H. K. Lee et al., Electromagnetic characteristic analysis of high-speed motors with rare-earth and ferrite permanent magnets considering current harmonics, *IEEE Transactions on Magnetics*, vol.57, no.2, pp.1-5, 2020.
- [21] X. Sun, Z. Su, G. Lei et al., Robust predictive cascaded speed and current control for PMSM drives considering parameter variations, *IEEE Transactions on Industrial Electronics*, vol.71, no.9, pp.10235-10245, 2024.
- [22] Y. Liang, D. Liang, S. Jia et al., Compound current controller based on SiC/Si hybrid converter for current harmonics suppression of high-speed PMSMs, *IEEE Transactions on Industry Applications*, vol.59, no.6, pp.6852-6867, 2023.
- [23] M. Mamdouh and M. A. Abido, Current gradient based modified hysteresis controller for asymmetrical six-phase induction motor, *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol.12, no.5, pp.5164-5175, 2024.
- [24] N. Soundirarajan and K. Srinivasan, Performance evaluation of ant lion optimizer-based PID controller for speed control of PMSM, *Journal of Testing and Evaluation*, vol.49, no.2, pp.1104-1118, 2021.
- [25] L. Feng, X. Sun, X. Tian et al., Direct torque control with variable flux for an SRM based on hybrid optimization algorithm, *IEEE Transactions on Power Electronics*, vol.37, no.6, pp.6688-6697, 2022.
- [26] W. Zhang, H. Fan, K. Yao et al., Research on efficiency optimization control strategy of axial field flux-switching permanent magnet motor, *IEEE Transactions on Industry Applications*, vol.60, no.4, pp.6209-6221, 2024.
- [27] A. Ramaveerapathiran, R. Muniraj, T. Jarin et al., Evaluation of a robust PID dead-time compensation controller based on the evolutionary computation method, *Automatika*, vol.66, no.4, pp.32-46, 2025.
- [28] Y. Zhang, M. Zhou, C. Zhang et al., Identification of PMSM parameters with time-error compensated based on contractile factor antipredator PSO, *IEEE Transactions on Transportation Electrification*, vol.10, no.2, pp.4006-4017, 2023.
- [29] W. Feng, W. Zhang and S. Huang, A novel parameter estimation method for PMSM by using chaotic particle swarm optimization with dynamic self-optimization, *IEEE Transactions on Vehicular Technology*, vol.72, no.7, pp.8424-8432, 2023.
- [30] K. Zhang, L. Qing, G. Liu et al., Sensorless fuzzy control algorithm for permanent magnet synchronous motor based on particle swarm optimization parameter identification and harmonic extraction, *Journal of Electromagnetic Waves and Applications*, vol.38, no.8, pp.877-897, 2024.
- [31] M. Maheedhar and T. Deepa, A behavioral study of different controllers and algorithms in real-time applications, *IETE Journal of Research*, vol.70, no.2, pp.1657-1681, 2024.
- [32] D. T. Nguyen, J. R. Ho, P. C. Tung et al., A hybrid PSO-GWO fuzzy logic controller with a new fuzzy tuner, *International Journal of Fuzzy Systems*, vol.24, no.3, pp.1586-1604, 2022.
- [33] T. George and V. Ganesan, Optimal tuning of PID controller in time delay system: A review on various optimization techniques, *Chemical Product and Process Modeling*, vol.17, no.1, pp.1-28, 2022.
- [34] S. H. Ashraf Talesh, N. Nariman-Zadeh and A. Jamali, Multi-objective parametric design of PI/PID controllers via multi-level game-theoretic optimization for systems with time delay, *Transactions of the Institute of Measurement and Control*, vol.44, no.13, pp.2532-2544, 2022.

## Author Biography



**Xia Liu** received the Master's degree from Southwest Jiaotong University, China, in 2005. Now, she works in School of Mechanical and Material Engineering, Xi'an University, China. Her research interests include computational intelligent algorithm and motor speed control.



**Gang Bai** received the Bachelor's degree from Lanzhou Jiaotong University, China, in 2007. Now, he works in Xi'an Locomotive Repair Depot. His research interests include motor fault diagnosis and control.