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A Virtual-Vector Based Model-Free Predictive Current Control for PMSM Drives with Adaptive Control Gain

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Abstract

Model predictive current control (MPCC), owing to its straightforward design and convenient multi-objective optimization, has been widely adopted in applications demanding high dynamic performance. However, the conventional MPCC suffers from poor current steady-state performance and severe parameter dependence. To address these issues, this paper proposes a virtual-vector based model-free predictive current control (MFPPC) scheme for permanent magnet synchronous machine (PMSM) drives with adaptive control-gain. The proposed approach is developed based on the ultra-local model (ULM) concept to simplify the control structure and enhance robustness. The disturbance is observed by a linear extended state observer (LESO) and the effect of control-gain deviation on disturbance observation is analyzed. In addition, a control gain adaptive method is introduced to weaken the high-frequency components of the integrated disturbance, which can further improve the performance of observer. Furthermore, the virtual-vector control set is built where symmetrical vector sequences are included to reduce torque ripple. An improved optimization strategy is also developed that reduces computation and improves steady-state performance. Comprehensive experimental results confirm the effectiveness and superiority of the proposed method in terms of steady-state performance, robustness, and computational burden.

Keywords: permanent magnet synchronous machine; virtual-vector; model-free predictive current control; control gain



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1. Introduction

Over the past decade, permanent magnet synchronous motors (PMSMs) have emerged as a dominant solution in electric transportation, e.g., electrical vehicles (EVs), owing to their wide speed range, high torque and power density, and superior energy efficiency [1]. Conventional control strategies for PMSM drives are primarily categorized into vector control (VC) and direct torque control (DTC) [2]. While VC offers satisfactory steady-state performance, it typically requires careful tuning of proportional–integral (PI) regulators and often exhibits limited transient dynamics. In contrast, DTC features a concise control structure and enables rapid torque response; however, its reliance on predefined switching tables leads to variable switching frequency and deteriorated performance under varying operating conditions [3,4].

In recent years, model predictive control (MPC) has attracted considerable attention as a competitive alternative, owing to its straightforward control concept, rapid transient

response, and inherent capability to manage multivariable systems [5]. Relative to VC, MPC enables substantially faster dynamic performance [6], while offering more accurate voltage-vector selection than DTC [7]. Based on the target variables, MPC strategies are generally classified into predictive current control (MPCC) [8] and predictive torque control (MPTC) [7]. In the standard finite-control-set MPC framework, a single active voltage vector is selected and applied per sampling period, which often leads to pronounced current ripple and hence current harmonics.

To address the aforementioned limitations, several effective strategies have been proposed, including the duty ratio optimization [9] and control set expansion, both of which rely on modulation-like multi-vector synthesis techniques. In duty-ratio-optimized MPCC, multiple voltage vectors are selected and their duty cycles are optimally allocated [10,11], so that the synthesized vector approximates the reference voltage vector. The most typical combination of applied vectors is the vector sequence with nonzero vectors and zero vectors [12]. However, this type of scheme requires solving the duty cycle of multiple vectors online, which will significantly increase the computational complexity. From the perspective of the control structure, this scheme can be regarded as optimizing the post-processing stage, which to some extent reduces the flexibility of implementation. Rather, in MPCC based on control set expansion, virtual voltage vectors can be constructed to enlarge the spatial domain of the control set and to reduce the current ripples [13,14]. Although this scheme ensures the simplicity of the algorithm structure, the enumeration optimization scheme will multiply the number of current prediction cycles, resulting in extremely high computational costs and raising the requirements of the processors for executing the related programs [15].

In addition, limited by the characteristic of model-based design, the main deficiency of FCS-MPCC is that its control performance depends on the accuracy of the mathematical modeling of the object under control [16]. However, the mathematical model of the controlled system is often structurally complex and depends on multiple physical parameters, such as inductance, flux linkage, and resistance, which results in a high computational burden for the control algorithm [17]. These parameters are not constant; instead, they can be strongly influenced by operating conditions and environmental factors. The parameter mismatches would affect the accuracy of current prediction, reduce the dynamic and steady-state performance, and even lead to system instability. As a solution, existing studies, based on the concept of the ultra-local model (ULM), regard the input-independent terms in the model as a lumped disturbance and propose a finite-control-set model-free predictive current control (FCS-MFPCC) [18].

The lumped disturbance is commonly estimated by using observers, such as sliding-mode observers (SMO) and extended state observers (ESO). An ESO-based MFPCC was proposed in [19], which effectively reduces the reliance on accurate plant models but raises new issues, i.e., tuning the observer bandwidth and assigning non-physical gains. With appropriate parameter design, the generalized disturbance can be estimated accurately, enabling satisfactory performance. Because ULM is more concise in form, it is conducive to simplifying the complexity of the algorithm. Nevertheless, the design of the control-gain term in ULM still depends on machine inertial parameters (e.g., stator inductance), and the observer cannot fully compensate for the high-frequency disturbances caused by parameter deviations [20], which limits the universality of this method.

In general, the existing MFPCC does not consider the accuracy of control gains in ULM. Meanwhile, the limited control set and the substantial optimization burden significantly constrain the industrial applicability of MFPCC. Therefore, this paper proposes a virtual-vector based MFPCC scheme to ensure better steady-state performance without any motor parameters.

The main contributions of this paper are two-fold:

- (1) An ULM-based MFPCC scheme is developed, where the control gain does not rely on any prior knowledge of machine parameters. Instead, a simple generalized estimation strategy is designed to estimate both control gain and lumped disturbance term of the ULM by current data only, thereby completely eliminating the dependence on motor parameters.
- (2) A virtual-vector control set is constructed based on a symmetrical pulse pattern, which enhances the steady-state performance of the system. In addition, an improved optimization strategy is introduced to reduce the computational burden.

The remainder of this paper is organized as follows. Section 2 introduces the conventional FCS-MPCC of PMSM. Section 3 presents the proposed virtual-vector based MFPCC scheme. Section 4 provides both steady-state and dynamic experimental results, and Section 5 concludes the paper.

2. Traditional FCS-MPCC of PMSM

2.1. Model of PMSM Drive System

Figure 1a shows the topology of a PMSM drive, where the inverter is under control to drive the machine. For the convenience of controller design, the mathematical model is generally established in the dq coordinate, according to the equivalent circuits as given in Figure 1b, written as

$$\begin{cases} u_d = L_d \frac{di_d}{dt} + R_s i_d - \omega_e L_q i_q \\ u_q = L_q \frac{di_q}{dt} + R_s i_q + \omega_e [L_d i_d + \Psi_{PM}(i_d)] \end{cases} \quad (1)$$

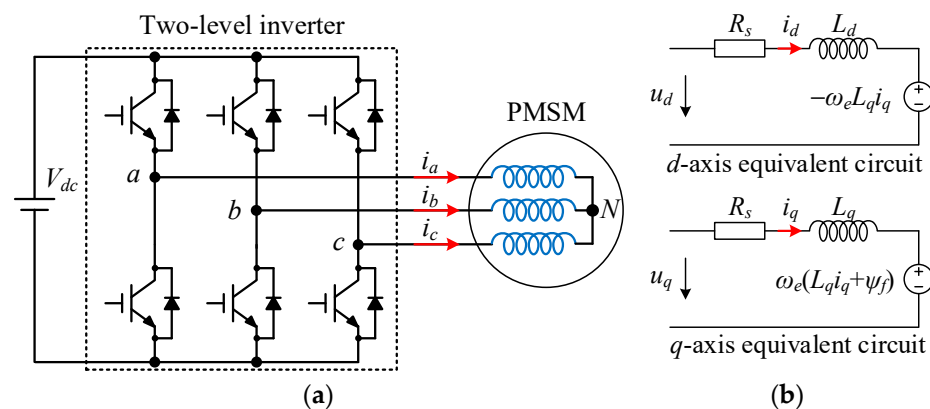


Figure 1. Configuration of a PMSM drive, (a) topology and (b) dq-axis equivalent circuits.

Therefore, the following state space equation can be obtained, as

$$\dot{x} = Ax + Bu + C \quad (2)$$

with

$$x = \begin{bmatrix} i_d & i_q \end{bmatrix}^T, u = \begin{bmatrix} u_d & u_q \end{bmatrix}^T \quad (3)$$

$$A = \begin{bmatrix} -\frac{R_s}{L_d} & \frac{\omega_e L_q}{L_d} \\ -\frac{\omega_e L_d}{L_q} & -\frac{R_s}{L_q} \end{bmatrix}, B = \begin{bmatrix} \frac{1}{L_d} & 0 \\ 0 & \frac{1}{L_q} \end{bmatrix}, C = \begin{bmatrix} 0 \\ -\frac{\omega_e \Psi_f}{L_q} \end{bmatrix} \quad (4)$$

where u , i , and L are the voltage, current, and inductance, respectively. The subscript d and q represent the information of d -axis and q -axis, respectively. R_s denotes the stator resistance. Ψ_f and ω_e are the permanent magnet flux and electrical rotor speed.

The input variable $u = [u_d \ u_q]^T$ is controlled by the inverter switching state and can be calculated by

$$\begin{bmatrix} u_d \\ u_q \end{bmatrix} = T_{abc/dq} \begin{bmatrix} u_{aN} \\ u_{bN} \\ u_{cN} \end{bmatrix} = T_{abc/dq} \cdot \frac{V_{dc}}{3} \begin{bmatrix} 2S_a - S_b - S_c \\ 2S_b - S_a - S_c \\ 2S_c - S_a - S_b \end{bmatrix} \quad (5)$$

where U_{dc} denotes the DC bus voltage. u_{kN} ($k = a, b, c$) is the voltage of the three-phase bridge-arm midpoint with respect to the winding neutral point. S_k is the switching status of the three-phase bridge arm, as shown in Figure 1a. $S_k = 1$ indicates that the upper switch of phase k is turned on. Meanwhile, $T_{abc/dq}$ represents the Park transformation, as

$$T_{abc/dq} = \frac{2}{3} \begin{bmatrix} \cos \theta_e & \cos(\theta_e - 2\pi/3) & \cos(\theta_e + 2\pi/3) \\ -\sin \theta_e & -\sin(\theta_e - 2\pi/3) & -\sin(\theta_e + 2\pi/3) \end{bmatrix} \quad (6)$$

where θ_e is the electrical angle of the rotor.

On the other hand, a three-phase two-level inverter has eight switching states, each corresponding to a specific voltage vector, as illustrated in Figure 2. The six nonzero voltage vectors ($V_1 \sim V_6$) form a regular hexagon, while the two zero vectors (V_0 and V_7) are located at the origin. The lines connecting the nonzero vector vertices to the origin partition the plane into six sectors, denoted as Sectors I–VI.

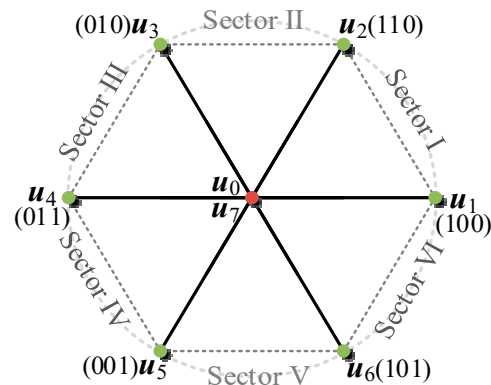


Figure 2. Voltage vectors of three-phase two-level inverters.

2.2. Traditional FCS-MPCC

Traditional FCS-MPCC includes three elements, namely the prediction model, cost function and optimization strategy.

- (1) By applying the forward Euler discretization, the stator currents at the $(k + 1)$ th instant can be predicted as

$$x^p(k + 1) = (1 + T_s A)x(k) + T_s [Bu(k) + C] \quad (7)$$

1. where (k) and $(k + 1)$ denote information of the k th and $(k + 1)$ th sampling periods, respectively. T_s is the control period. The error due to such a first-order discretization method is analyzed in the Appendix A. With the consideration of digital delay, the subsequent current of $(k + 2)$ th sampling periods can then be predicted as

$$x^p(k + 2) = (1 + T_s A)x(k + 1) + T_s [Bu(k + 1) + C] \quad (8)$$

where $(k + 2)$ denotes information of the $(k + 2)$ th sampling periods.

- (2) A cost function is constructed to quantitatively evaluate the effect of input state variables, which can be defined using the 2-norm of the deviation between the references and predicted state values. The cost function is termed as $g(V_i)$, as follows

$$g(V_i) = \|x^* - x^p(k+2|V_i)\|_2^2 \quad (9)$$

where $x^* = [i_d^* \ i_q^*]^T$ refers to the state reference.

- (3) The enumeration method is commonly employed as the optimization strategy, in which the predicted current and the corresponding cost function value are computed for every possible input state. The optimal voltage vector is then selected as the one that yields the minimum cost function value, like

$$V_{opt} = \arg \min_{V_i \in v} g(V_i) \quad (10)$$

where V_{opt} is the optimal applied voltage vector. $v = \{V_0, V_1, \dots, V_7\}$ and represents the control set composed of voltage vectors as shown in Figure 1.

3. Proposed FCS-MFPCC

3.1. MFPCC Based on Ultra-Local Model

Compared with the original mathematical model, ULM removes the precise model parameters so that the modeling process is greatly simplified and the complexity of controller design is reduced. In detail, ULM is constructed based on the input and output of the system, and contains several uncertainties. Based on Equation (2), the ULM of PMSM is constructed as

$$\dot{x} = F + \alpha u \quad (11)$$

where $F = [F_d \ F_q]^T$ denotes the integrated disturbance. α is the control-gain matrix.

Accordingly, the prediction model based on ULM is

$$x^p(k+2) = x(k+1) + T_s[\alpha u(k+1) + F] \quad (12)$$

3.2. Estimation of Disturbance F

To achieve the accurate prediction of future states, it is essential to estimate the disturbance in the model. A linear extended state observer (LESO) is designed to estimate the integrated disturbance F , which is built as

$$\begin{cases} e_{rr} = z_1 - x \\ \dot{z}_1 = z_2 + \alpha u - \beta_1 e_{rr} \\ \dot{z}_2 = -\beta_2 e_{rr} \end{cases} \quad (13)$$

where e_{rr} is the error between the estimated value and the actual value of the state variable. z_1 and z_2 are the estimated values of the state variable x and the integrated disturbance F , respectively. β_1 and β_2 are the error feedback coefficient.

The details of deriving the transfer function are given in Appendix B. The transfer function of the integrated disturbance observed values relative to the actual values is

$$\frac{\hat{F}(s)}{F(s)} = \frac{\beta_2}{s^2 + \beta_1 s + \beta_2} \quad (14)$$

Configure the poles on the negative real axis, that is

$$s^2 + \beta_1 s + \beta_2 = (s + \omega_0)^2 \quad (15)$$

where ω_0 denotes the bandwidth of the observer, and its selection should take into account the trade-off between the steady-state performance of the observer and its noise resistance capability. Numerically, it must be less than the reciprocal of the sampling period. The feedback coefficients β_1 and β_2 can be designed as

$$\begin{cases} \beta_1 = 2\omega_0 \\ \beta_2 = \omega_0^2 \end{cases} \quad (16)$$

Obviously, the bandwidth affects the accuracy of disturbance observation by LESO. The amplitude-frequency gain and phase-frequency gain curves of LESO under different bandwidths can be plotted by Equation (14), as exhibited in Figure 2. It can be observed that the LESO exhibits the characteristic behavior of a second-order low-pass filter in disturbance estimation, with its cutoff frequency determined by the observer bandwidth. This implies that high-frequency disturbances cannot be effectively addressed by the LESO. Increasing the bandwidth enhances the observer's high-frequency gain but simultaneously amplifies measurement noise. Therefore, an appropriate trade-off between estimation accuracy and noise sensitivity is required when selecting the bandwidth ω_0 .

For PMSM drive systems, integrated disturbances should simultaneously include steady-state disturbances, dynamic disturbances caused by control-gain deviations, and unknown disturbances, as

$$F = \underbrace{Ax + C}_{F_s} + \underbrace{(\alpha_c - \alpha_0)u}_{F_d} + d \quad (17)$$

$:= \Delta\alpha$

where α_c and α_0 represent the actual and initial control-gains, respectively. $\Delta\alpha$ is defined as the control-gain deviation. F_s and F_d are steady-state disturbances and dynamic disturbances, respectively. d is the bounded disturbances brought about by the unmodeled and unknown term. In contrast, the dynamic disturbance mainly arises from control-gain deviations and variations in the input states. Although the gain deviation itself manifests as a dc offset, variations in the input states generate high-frequency disturbances; for example, the wideband harmonic voltages caused by inverter nonlinearities, dead-time effects, and modulation algorithms. As shown in Figure 3, LESO has difficulty dealing with the high-frequency components in dynamic disturbances. Nevertheless, if the control gain deviation can be suppressed, the dynamic disturbances can be weakened comprehensively, thereby enhancing the overall control performance.

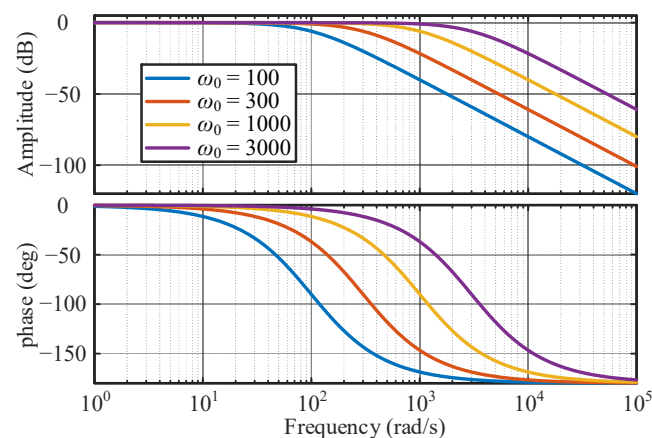


Figure 3. Amplitude-frequency and phase-frequency gain curves of LESO under different bandwidths.

3.3. Adaptive Method of Control Gain

In general, the controller gain is regarded as a non-physical tuning parameter, which is typically adjusted through trial and error method to achieve the optimal operating condition of the system. However, in the current prediction model, the proportional factor acts on the voltage vector and jointly interacts with the lumped disturbance term to estimate the current variation. When the selected controller gain deviates from its optimal value, the product of the factor error and the voltage vector introduces a periodic voltage disturbance. Moreover, in the designed LESO, the proportional factor, treated as a known quantity, directly influences the estimation of the lumped disturbance term. Consequently, any mismatch in the controller gain leads to an estimation error of the current variation, thereby degrading the accuracy of current prediction and deteriorating the reference current tracking performance.

To this end, a current-increment-based identification method is introduced. For the $(k - 1)$ th sampling instant, the current difference can be written as

$$\Delta \mathbf{x}(k - 1) = \mathbf{x}(k) - \mathbf{x}(k - 1) = \alpha(k - 1)\mathbf{u}(k - 1) + \mathbf{F}(k - 1) \quad (18)$$

Comparing the original model as in Equation (2) and the ULM as in Equation (11), it can be seen that the control gain α is theoretically equal to $\mathbf{B}$ (in relation to dq -axis inductance values), while the disturbance $\mathbf{F}$ should be equal to $\mathbf{A}\mathbf{x} + \mathbf{C}$ (in relation to machine parameters and dq -axis currents). For PMSM drives, the parameters and currents vary slowly with respect to the very high sampling frequency, and hence the control gain α and the disturbance $\mathbf{F}$ are slow-varying terms. So, it is reasonable to assume that

$$\begin{cases} \alpha(k - 1) \approx \alpha(k - 2) \\ \mathbf{F}(k - 1) \approx \mathbf{F}(k - 2) \end{cases} \quad (19)$$

Subtracting two consecutive current increments yields an estimation of the control gain, as

$$\hat{\alpha}(k) = \frac{\Delta \mathbf{x}(k - 1) - \Delta \mathbf{x}(k - 2)}{\mathbf{u}(k - 1) - \mathbf{u}(k - 2)} \quad (20)$$

As $\Delta \mathbf{u}(k - 1) = \mathbf{u}(k - 1) - \mathbf{u}(k - 2)$, is at the position of denominator, $\Delta \mathbf{u}(k - 1)$ cannot be zero. In other words, $\mathbf{u}(k - 1)$ must be different to $\mathbf{u}(k - 2)$; otherwise, the calculation is not feasible. To address this issue, the identification method is further improved as

$$\hat{\alpha}(k) = \frac{\Delta \mathbf{x}(k - 1) - \Delta \mathbf{x}(k - 2) + k_1 \text{sign}[\Delta \mathbf{u}(k - 1)]\hat{\alpha}(k - 1)}{\Delta \mathbf{u}(k - 1) + k_1 \text{sign}[\Delta \mathbf{u}(k - 1)]} \quad (21)$$

where $\hat{\alpha}(k - 1)$ is the previous estimate, $k_1 > 0$ is a tuning parameter. For explanation, Equation (21) can be further written as

$$\hat{\alpha}_c(k) = (1 - \gamma) \frac{\Delta \mathbf{x}(k - 1) - \Delta \mathbf{x}(k - 2)}{\Delta \mathbf{u}(k - 1)} + \gamma \hat{\alpha}(k - 1) \quad (22)$$

with

$$\gamma = \frac{k_1 \text{sign}[\Delta \mathbf{u}(k - 1)]}{\Delta \mathbf{u}(k - 1) + k_1 \text{sign}[\Delta \mathbf{u}(k - 1)]} \quad (23)$$

Note that the coefficient γ is equal to 1 when $\Delta \mathbf{u}(k - 1) = 0$, the estimation of α holds as its previous result. Therefore, we have

$$\hat{\alpha}_c(k) = \begin{cases} (1 - \gamma)\hat{\alpha}(k) + \gamma\hat{\alpha}(k - 1), & \text{when } \Delta \mathbf{u}(k - 1) \neq 0 \\ \hat{\alpha}(k - 1), & \text{when } \Delta \mathbf{u}(k - 1) = 0 \end{cases} \quad (24)$$

By introducing the adaptive coefficient, the issue of infeasible calculation is addressed. As a consequence, there no constraint placed on the control actions. In summary, this formulation adaptively adjusts the weighting between the instantaneous estimate and its historical value, thereby improving robustness against small or zero voltage differences.

3.4. Virtual-Vector Control Set and Optimization Strategy

When a voltage-source inverter applies space voltage vectors to machine, the temporal structure of the switching sequence directly determines the spectral characteristics of the phase voltage, which in turn influences the distribution of stator current harmonics and the resulting torque ripple.

In ref. [21], the candidate virtual vectors are constructed based on an asymmetric sequence, in which only one voltage-vector transition occurs within each switching period. Consequently, the resulting phase-voltage waveform exhibits a pronounced temporal asymmetry. According to the Fourier expansion, such an asymmetric PWM structure introduces noticeable low-order and even-order harmonic components. The corresponding voltage spectrum can be expressed as

$$u(t) = V_{dc} \sum_{k=1}^{\infty} [a(k) \cos(k\omega_s t) + b(k) \sin(k\omega_s t)] \quad (25)$$

where V_{dc} denotes the dc-link voltage and ω_s is the switching angular frequency. The coefficients a_k and b_k represent the cosine and sine components of the k -th harmonic, respectively, and their values depend on the temporal structure of the PWM waveform. The index k denotes the harmonic order, corresponding to a harmonic frequency of $k\omega_s$.

When the waveform lacks temporal symmetry, both a_k and b_k contain even-order and low-frequency components. Because the stator inductance presents relatively low impedance to these low-frequency harmonics, the voltage components are directly transferred into the phase current, thereby leading to a significant increase in the current THD. Moreover, the effective duty-cycle shift introduced by the asymmetric switching pattern generates sideband frequencies near the fundamental frequency, further increasing the electromagnetic noise accordingly [12].

In addition, an asymmetric switching pattern can cause severe torque ripples. As observed in Figure 4a, only a single voltage-vector transition occurs within each switching period, resulting in a torque trajectory composed of two unequal slopes. Because the rising and falling torque intervals are not temporally balanced, the positive and negative torque deviations fail to cancel each other within one switching cycle. This asymmetry introduces a nonzero residual torque error at the end of each period, leading to a larger root-mean-square error (RMSE) and potentially causing additional acoustic noise and mechanical stress. In contrast, the symmetric sequence shown in Figure 4b applies two voltage vectors in a temporally mirrored manner. In this case, the torque increases and decreases with slopes S_1 and S_0 over two strictly symmetric sub-intervals. Such a mirrored structure ensures that the positive and negative torque deviations cancel exactly within a switching period, thereby preventing torque bias and eliminating residual error accumulation. As a result, the symmetric sequence minimizes the integral torque-error energy over the switching cycle and achieves significantly lower torque ripple compared with the asymmetric pattern in Figure 4a.

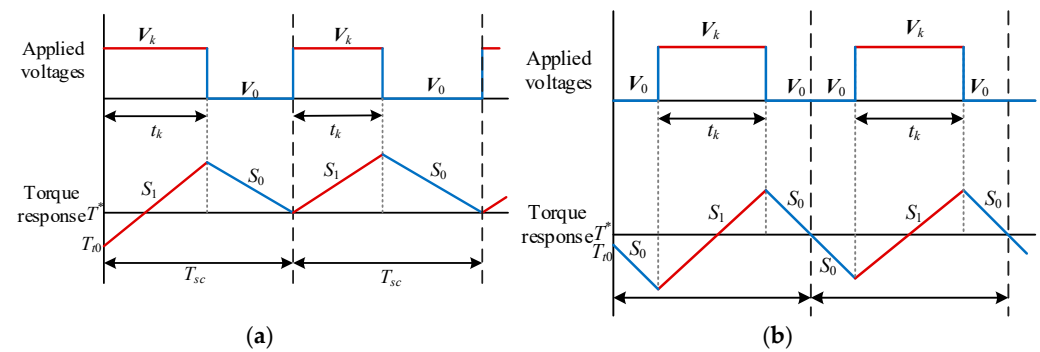


Figure 4. Applied voltages and torque responses of different vector sequence. (a) unsymmetrical sequence. (b) symmetrical sequence.

To improve the steady-state performance, symmetric voltage-vector sequences are considered by constructing the virtual vectors, as illustrated in Figure 5a. The resulting virtual vectors can be classified into two groups. The first group consists of 12 virtual vectors synthesized from symmetric sequences formed by two adjacent active vectors. For example, $V_{010} = 1/4V_0 + 1/2V_1 + 1/4V_0$, as shown in Figure 5b. The second group contains six virtual vectors synthesized from three voltage vectors within the same sector; for instance, $V_{012} = 1/3V_0 + 1/3V_1 + 1/3V_2$, as illustrated in Figure 5c. In addition, this construction uniformly partitions each sector into three sub-sectors, as shown in Figure 5c.

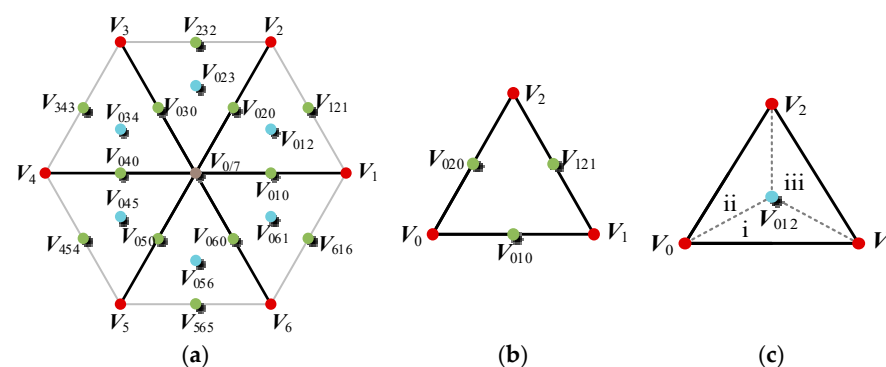


Figure 5. Method of expanding the control set. (a) The extended control set method. (b) The first group of virtual vectors. (c) The second group of virtual vectors.

The conventional enumeration method is computationally inefficient; for the proposed expanded control set, it requires 25 repetitions of current prediction and cost-function evaluation, which inevitably imposes a substantial computational burden. Building upon the expanded control set shown in Figure 5a, an improved searching strategy is further developed in this work. The proposed strategy requires only seven current predictions and cost-function evaluations, thereby significantly enhancing the computational efficiency.

To explain the principle of the proposed searching strategy, a reference voltage vector V_{ref} is defined and its associated cost function value is zero, corresponding to zero current tracking error, as

$$g(V_{ref}) = \|x^* - x^p(k+2|V_{ref})\|_2^2 = 0 \quad (26)$$

According to ref. [18], the essence of FCS-MPC is to identify the voltage vector that is spatially closest to V_{ref} . Taking the case where V_{ref} lies in Sector I and Sub-sector i, with the optimal vector being V_{012} , the implementation procedure of the proposed search strategy is illustrated in Figure 6 and described in the following three steps:

- (1) Sector identification: As described in ref. [18], the sector in which the reference voltage vector resides can be determined by comparing the cost-function values associated with the three voltage vectors V_1 , V_3 and V_5 . The procedure is summarized in Table 1, and this step requires three cost-function evaluations.
- (2) Sub-control-set identification: This step further determines the sub-sector in which the reference voltage vector lies, as well as the corresponding sub-control set. For the case illustrated in Figure 6, the cost-function values of V_0 and V_2 are additionally evaluated and compared with $g(V_1)$. The ranking of these three cost-function values determines both the sub-sector and the sub-control set, as summarized in Table 2. This step requires two cost-function evaluations.
- (3) Selection of optimal voltage vector: The optimal voltage vector is then selected from the sub-control set $\{V_0, V_1, V_{010}, V_{012}\}$. This step requires two additional cost-function evaluations. Finally, the optimal voltage vector can be expressed as

$$V_{opt} = \arg \min_{V_i \in v_{sub}} g(V_i) \quad (27)$$

Table 1. Sector determination.

Cost Function Sorting	Sector
$g(V_1) < g(V_3) < g(V_5)$	I
$g(V_3) < g(V_1) < g(V_5)$	II
$g(V_3) < g(V_5) < g(V_1)$	III
$g(V_5) < g(V_3) < g(V_1)$	IV
$g(V_5) < g(V_1) < g(V_3)$	V
$g(V_1) < g(V_5) < g(V_3)$	VI

Table 2. Determinations of sub-sector and sub-control set.

Cost Function Sorting	Sub-Sector	Sub-Control Set v_{sub}
$g(V_2) > g(V_1)$ and $g(V_2) > g(V_0)$	i	$\{V_0, V_1, V_{010}, V_{012}\}$
$g(V_1) > g(V_0)$ and $g(V_1) > g(V_2)$	ii	$\{V_0, V_2, V_{020}, V_{012}\}$
$g(V_0) > g(V_1)$ and $g(V_0) > g(V_2)$	iii	$\{V_1, V_2, V_{121}, V_{012}\}$

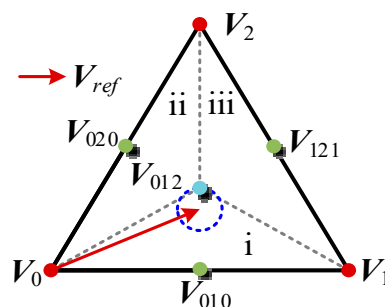


Figure 6. Case of that referenced voltage vector locates at Sector I, sub-sector i. The blue dashed circle is intended to highlight that V_{ref} is nearest to V_{012} .

It should be noted that, except for the four vectors V_0 , V_1 , V_3 and V_5 , the state predictions corresponding to all other voltage vectors can be directly computed using the vector-synthesis rules, which effectively reduces the computational burden of the algorithm. For example, $x^p(k+2|V_2) = 1/2[x^p(k+2|V_1) + x^p(k+2|V_3)]$, $x^p(k+2|V_{010}) = 1/2[x^p(k+2|V_0) + x^p(k+2|V_1)]$, $x^p(k+2|V_{012}) = 1/3[x^p(k+2|V_0) + x^p(k+2|V_1) + x^p(k+2|V_2)]$.

3.5. Implementation Process of the Proposed MFPCC

The control diagram of the proposed MFPCC strategy is described in Figure 7. First, a PI controller is employed in the speed outer loop to generate the i_q^* , while the i_d^* is set to zero. Second, the control gain α is estimated and updated using the proposed gain-adaptation method, and the integrated disturbance F is observed by the LESO. Then, based on the predictive model, the state predictions and corresponding cost-function values associated with the four voltage vectors V_0 , V_1 , V_3 , and V_5 are computed. On this basis, the optimal voltage vector V_{opt} is determined from the expanded control set using the proposed search strategy. Finally, the inverter is driven according to the switching state of the selected optimal vector. The overall implementation procedure of the proposed method is illustrated in Figure 8.

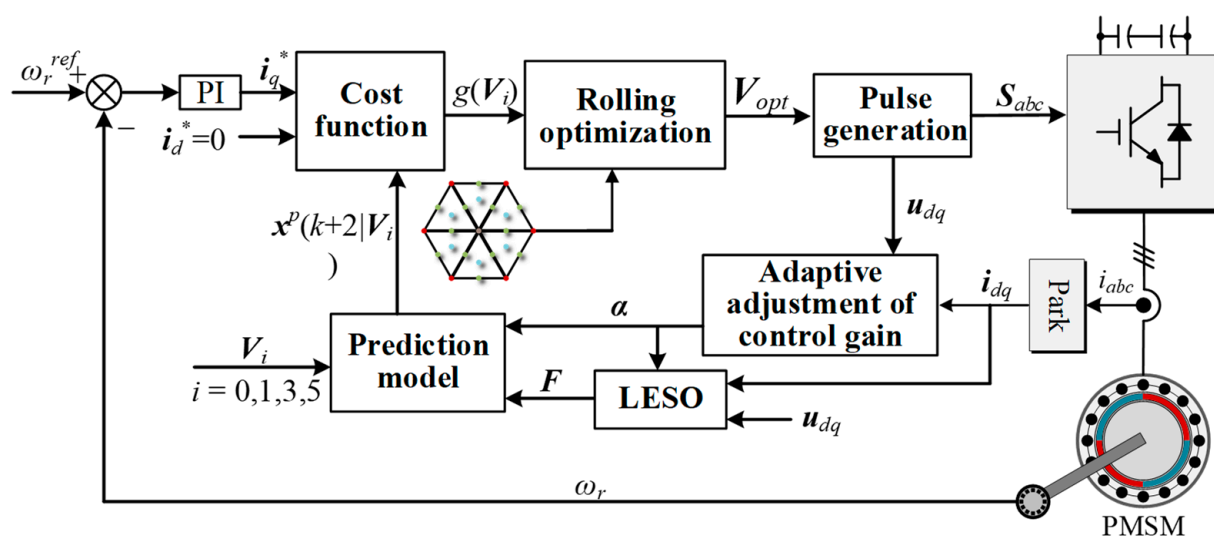


Figure 7. Control diagram of the proposed method.

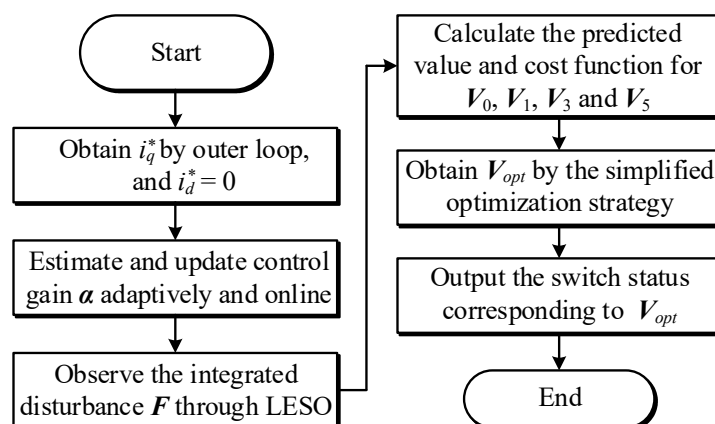


Figure 8. Implementation flowchart of the proposed method.

4. Experimental Verification

4.1. Overview of Experiments

The proposed method is verified on the experimental test rig shown in Figure 9. The main parameters of the tested PMSM are listed in Table 3. The digital controller is TMS320F28335 (from Texas Instruments, Dallas, TX, USA), and both the sampling frequency and control frequency of the control algorithm are 25 kHz. To validate the effectiveness and superiority of the proposed FCS-MFPCC method, experimental comparisons are conducted among the conventional FCS-MFPCC (MFPCC-I), the FCS-MFPCC employing the proposed

expanded control set with an enumeration-based search strategy (MFPCC-II), and the fully proposed method (MFPCC-III). A summary of the results is provided in Table 4. All three algorithms use the same LESO, with the observer bandwidth parameter ω_0 uniformly set to 1500. In addition, in the experiments, the proportional and integral gains of the PI controller in the speed outer loop are set to 0.25 and 8, respectively.

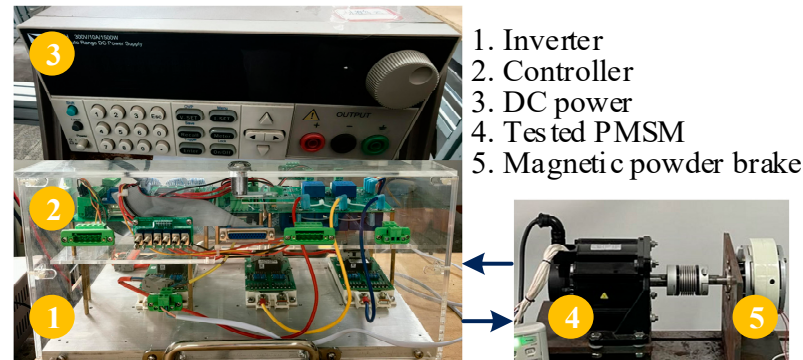


Figure 9. Experimental test rig.

Table 3. Main parameters of the PMSM under test.

Symbol	Quantity	Value
P_N	Rated power	1.5 kW
V_{dc}	DC-link voltage	300 V
n_p	Pole pairs	4
I_N	Rated current	15 A
R_s	Stator resistance	0.559 Ω
L_d	d -axis inductance	4.35 mH
L_q	q -axis inductance	4.35 mH
Ψ_f	PM flux	0.2748 Wb
n_N	Rated speed	600 rpm

Table 4. Details of three tested methods.

Method	Control Set	Optimization	Control Gain
MFPCC-I	Initial control set (Figure 1)	Enumeration	Fixed
MFPCC-II	Virtual-Vector Control Set (Figure 4)	Enumeration	Fixed
MFPCC-III	Virtual-Vector Control Set (Figure 4)	Simplified strategy	Adaptive

4.2. Estimation Results of Control Gain

First, the effectiveness of the proposed adaptive control-gain adjustment algorithm is validated under the operating condition of 600 rpm and a load torque of 12 N·m. As shown in Figure 10, although the estimated gain exhibits noticeable fluctuations, it converges accurately to the theoretical value (i.e., α_{dq}^* that can be calculated the reciprocal of the inductance), thereby ensuring the robustness of the proposed control method against variations in the physical parameters.

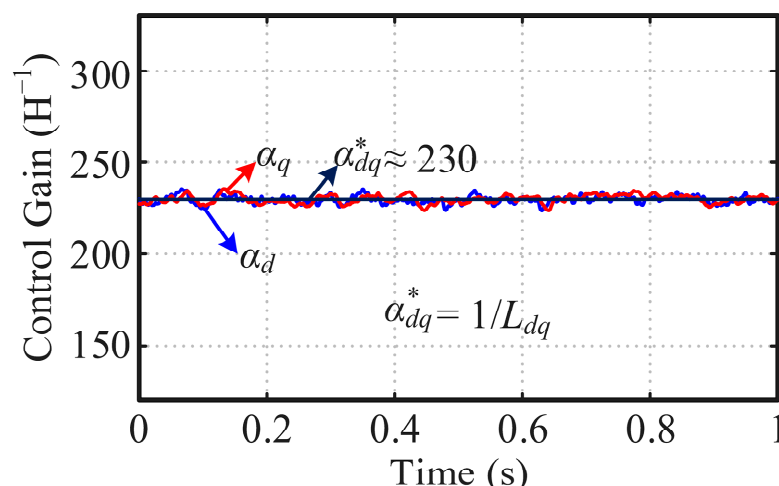


Figure 10. Experiment result of control-gain observation.

In order to further verify the robustness of the proposed method, the estimation performance during start-up stage (from 0 rpm to 600 rpm) is evaluated under different initial values of control gains. The initial values of 10, 100 and 1000 are tested, which is to simulate the case where the motor inductances are completely unknown. The results are given in Figure 11. As seen, under all conditions, the estimated control gains can rapidly converge to the desired values. The results can verify that the proposed method is applicable to a PMSM without any prior knowledge of parameters.

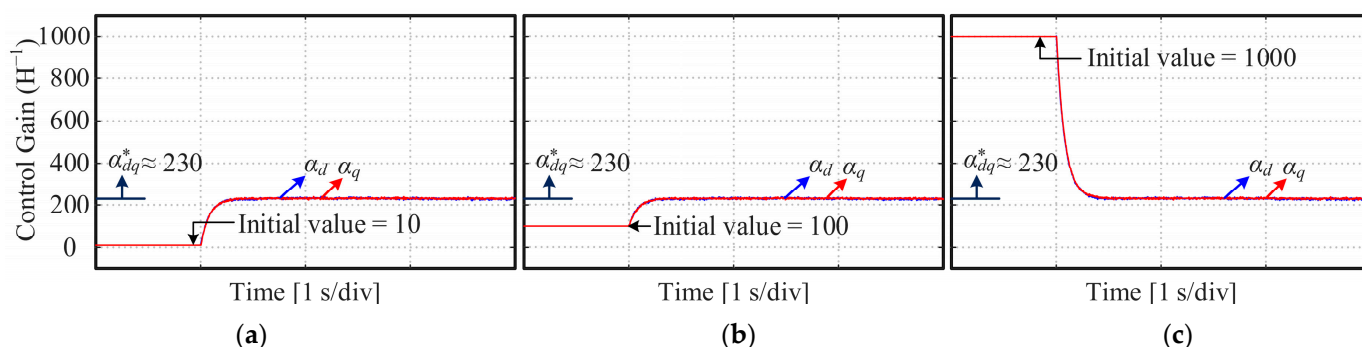


Figure 11. Experiment result of control-gain observation under different initial values. (a) The initial value is 10. (b) The initial value is 100. (c) The initial value is 1000.

4.3. Steady-State Performance

Second, the steady-state performance of the three FCS-MFPCC methods is compared under the operating condition of 600 rpm and a load torque of 12 N·m. The experimental results of MFPCC-I and MFPCC-II under different control-gain values (100, 200, and 300) are shown in Figures 12 and 13. It is observed that, owing to the use of the observer, variations in the control gain do not introduce steady-state tracking errors. This indicates that the conventional FCS-MFPCC achieves zero steady-state error over a wide range of control gains, thereby enhancing the robustness of the system. However, changes in the control gain substantially affect the dq -axis current ripple and the total harmonic distortion (THD) of the phase current. In particular, for MFPCC-II, when the control gain is set to 100, the dq -axis current ripple exceeds 4 A and the phase-current THD reaches 12.98%.

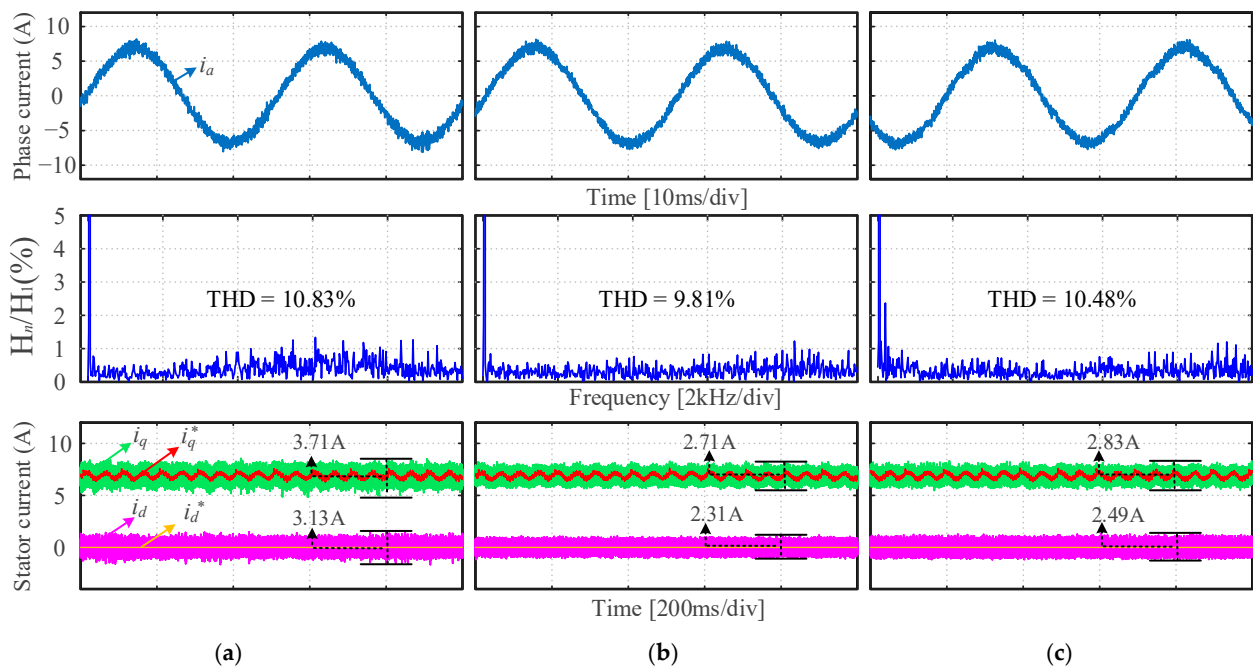


Figure 12. Steady-state experiment results of MFPCC-I. (a) $\alpha_{dq} = 100$. (b) $\alpha_{dq} = 200$. (c) $\alpha_{dq} = 300$.

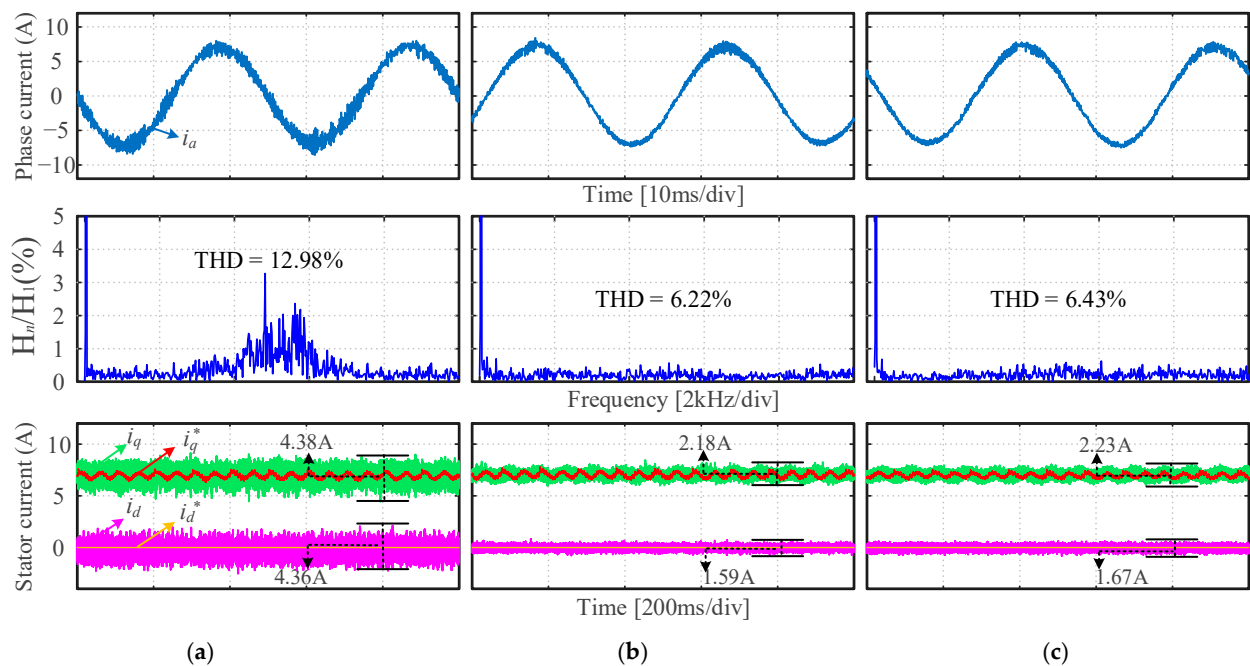


Figure 13. Steady-state experiment results of MFPCC-II. (a) $\alpha_{dq} = 100$. (b) $\alpha_{dq} = 200$. (c) $\alpha_{dq} = 300$.

The steady-state experimental results of MFPCC-III are shown in Figure 14. It can be observed that the proposed method delivers significantly better steady-state performance than MFPCC-I, exhibiting more sinusoidal phase currents, lower THD (approximately 6.07%), and smaller dq -axis current ripple. Moreover, although both approaches employ an expanded control set, the proposed method also achieves slightly better steady-state performance than MFPCC-II, which is attributed to the adaptive adjustment of the control gain.

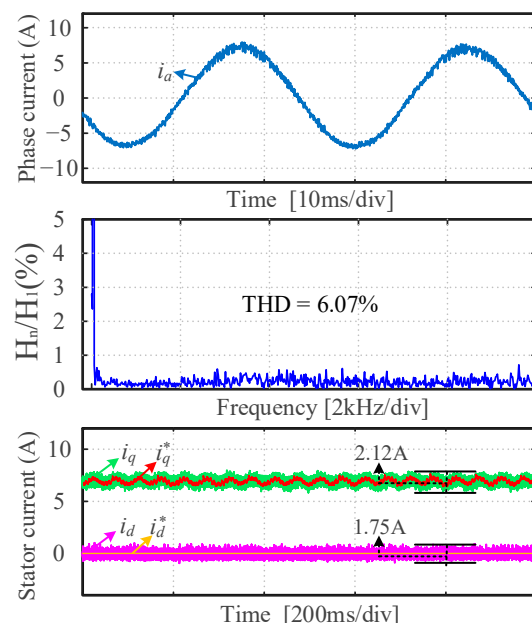


Figure 14. Steady-state experiment results of MFPCC-III.

Figure 15 provides a detailed comparison of the steady-state performance indices of the three algorithms, including the dq -axis current ripple and the dq -axis root-mean-square error (RMSE). These results clearly demonstrate that the proposed method offers substantial advantages over the conventional FCS-MFPCC in terms of parameter robustness and steady-state performance.

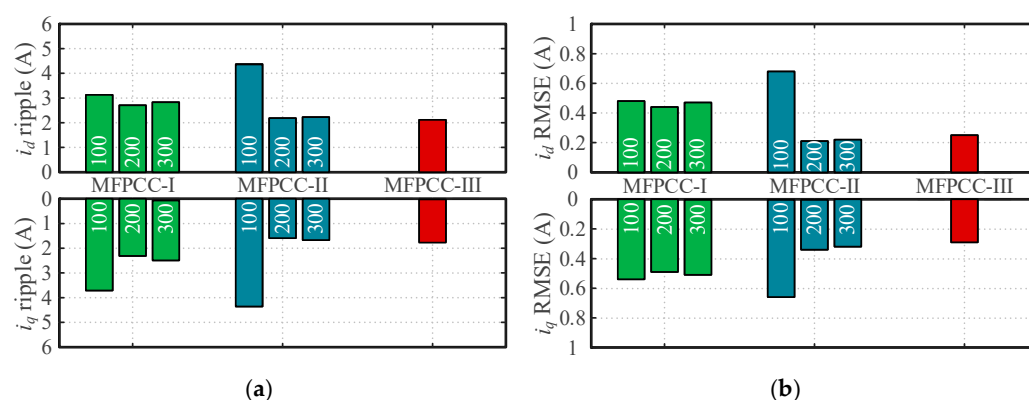


Figure 15. Comparison on steady-state performance of three methods. (a) dq -axis current ripples, (b) dq -axis RMSE.

4.4. Dynamic Performance

Next, the dynamic performance of the three methods is compared, and the corresponding experimental results are presented in Figures 16 and 17. In this set of experiments, the control gains of MFPCC-I and MFPCC-II are both set to 200. Figure 16 illustrates the results under a 12 N·m load torque when the speed reference (namely n^*) steps from 600 r/min to 300 r/min. All three methods achieve a rapid speed response, with settling times of approximately 0.33 s, 0.34 s, and 0.32 s, respectively, and an overshoot of only around 50 r/min. Figure 17 shows the results for a 600 rpm operating condition when the load torque undergoes a step change from 12 N·m to 6 N·m. As observed, the three methods handle the load disturbance effectively, with speed overshoots of roughly 50 r/min and settling times of about 0.24 s, 0.24 s, and 0.25 s, respectively. These observations confirm

that the proposed method exhibits dynamic performance nearly identical to that of the conventional FCS-MFPC.

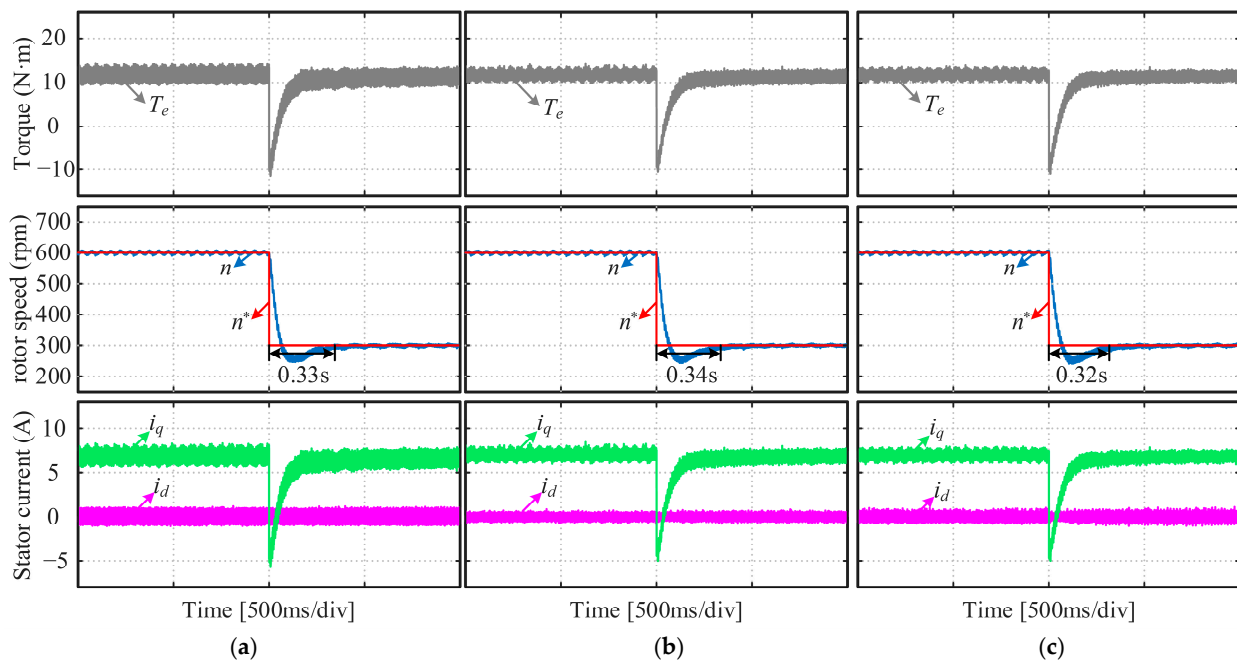


Figure 16. Experimental results under variable speed conditions. (a) MFPCC-I. (b) MFPCC-II. (c) MFPCC-III.

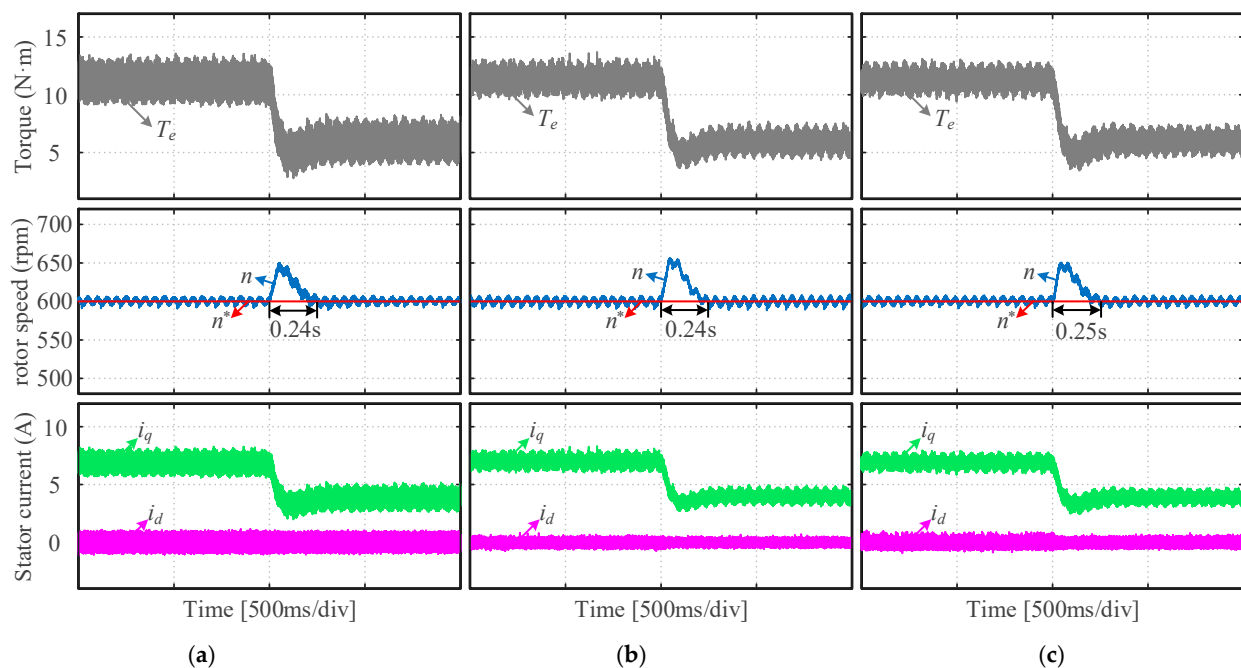


Figure 17. Experimental results under variable load torque conditions. (a) MFPCC-I. (b) MFPCC-II. (c) MFPCC-III.

4.5. Computational Burden

Finally, the computational time of the three methods is evaluated by measuring the number of clock cycles required for executing each code segment. The results are summarized in Table 5, and the execution time distribution of the main computational components is given in Figure 18, including sampling and initialization, disturbance estimation, speed control, gain estimation, and optimization. From the results, it can be observed that the

main difference in computational complexity among the three methods lies in the optimization stage, which spends about 11.37 μs , 30.9 μs and 13.94 μs in three methods, respectively. In particular, compared to MFPCC-II, the execution time of optimization in MFPCC-III is reduced by 55% approximately, verifying that the proposed searching strategy is highly computation-efficient. Meanwhile, compared to MFPCC-I, the total execution time of MFPCC-III increases by only 4.46 μs , while the control performance is improved to a large extent.

Table 5. Comparison on computational burden.

Method	Number of Candidate Vectors	Execution Time
MFPCC-I	7	19.12 μs
MFPCC-II	25	38.65 μs
MFPCC-III	25	23.58 μs

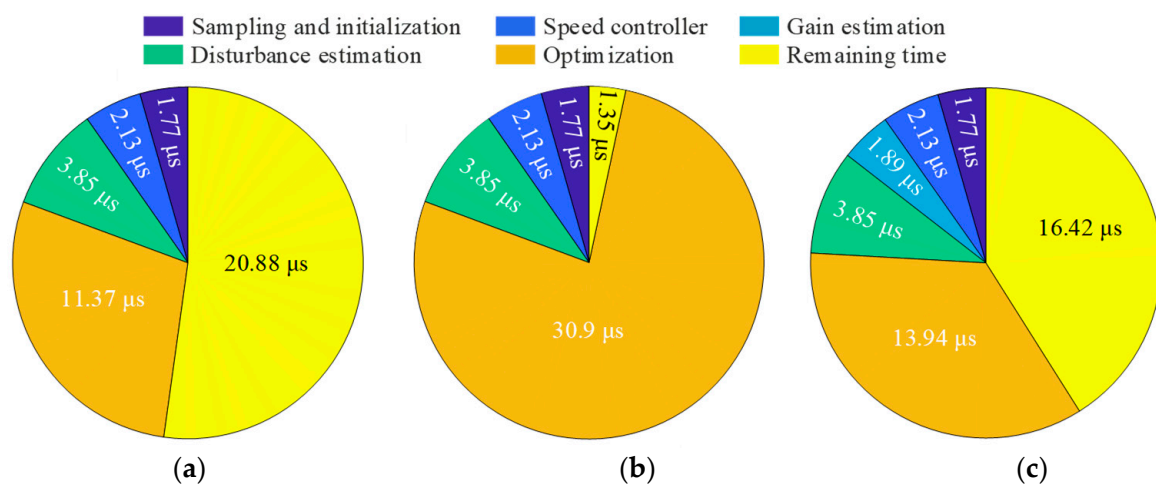


Figure 18. Summary and comparison on execution time of three methods. (a) MFPCC-I. (b) MFPCC-II. (c) MFPCC-III.

5. Conclusions

To enhance the steady-state performance and robustness of PMSM drive systems, this paper proposes an FCS-MFPCC method incorporating adaptive control-gain adjustment. On the one hand, an adaptive control-gain update strategy is introduced to improve disturbance-observation capability by attenuating the high-frequency components contained in the integrated disturbance. On the other hand, the control set is expanded to improve steady-state performance, and an improved search strategy is developed to reduce the computational burden of the algorithm. The experimental results fully verify the effectiveness and superiority of the proposed method, leading to the following conclusions:

- (1) In conventional FCS-MFPCC, variations in the control gain significantly affect the accuracy of current control but do not cause steady-state error. By online estimation of the control gain, the proposed method effectively resolves this issue, substantially improving steady-state performance and current-control accuracy. The proposed method yields noticeably lower dqdq-axis current ripple, reduced RMSE, and decreased phase-current THD. In particular, the phase-current THD is reduced from 9.81% to 6.07%, demonstrating a marked improvement over the conventional FCS-MFPCC.
- (2) The proposed method exhibits dynamic behavior comparable to that of the conventional FCS-MFPCC under speed and load transients. The speed overshoot and

transient response time remain nearly identical, indicating that the proposed approach maintains excellent dynamic performance.

- (3) Compared with the FCS-MFPCC using the original control set (19.12 μs), the expanded control set doubles the computation time (38.65 μs). In contrast, by adopting the improved search strategy, the proposed method significantly enhances algorithmic efficiency, requiring only 23.58 μs in computation time.

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Appendix A. Analyses on Error Due to Forward Euler Discretization Method

With a short sampling period, the forward Euler discretization method is most commonly adopted to obtain the prediction model for machine drive and power electronic systems. The exact discretized model should be expressed as

$$\mathbf{x}(k+1) = e^{AT_s} \mathbf{x}(k) + \int_0^{T_s} e^{A(T_s-\tau)} [\mathbf{B}\mathbf{u}(k) + \mathbf{C}] d\tau \quad (\text{A1})$$

Regarding the term e^{AT_s} , the Taylor expansion is

$$e^{AT_s} = \mathbf{I} + AT_s + \frac{1}{2}A^2T_s^2 + O(T_s^3) \quad (\text{A2})$$

Therefore, the error introduced by the first-order approximation is

$$\mathbf{E} = \frac{1}{2}A^2T_s^2 + O(T_s^3) \quad (\text{A3})$$

which is of second order with respect to the sampling period T_s . Taking the matrix norm, the error satisfies

$$\|\mathbf{E}\| \leq \frac{1}{2}\|\mathbf{A}\|^2T_s^2e^{\|\mathbf{A}\|T_s} \quad (\text{A4})$$

Considering the parameters of the machine under test ($L_d = L_q = 0.00435$ H, $R_s = 0.559$ Ω , $\omega_e = 80\pi$ rad/s, $T_s = 0.00004$ s), the value of $\rho(\mathbf{A})T_s$ is approximately 0.0113 (<1). Hence, the second-order term is much smaller than the first-order term. The ratio between the second-order error term and the first-order term is

$$\frac{\|\mathbf{E}\|}{\|\mathbf{A}T_s\|} \approx \frac{1}{2}\rho(\mathbf{A})T_s = 0.00565 \quad (\text{A5})$$

This indicates that the error due to first-order approximation is negligible. As a result, the prediction model can be approximately expressed as

$$\mathbf{x}^p(k+1) = (1 + T_s\mathbf{A})\mathbf{x}(k) + T_s[\mathbf{B}\mathbf{u}(k) + \mathbf{C}] \quad (\text{A6})$$

where $x^p(k+1)$ denotes the predicted state.

Moreover, as the variables in the prediction model update at each sampling period, the accumulative error due to approximation does not exist in real-time digital systems. In other words, the approximation error only affects the one-step prediction used to compute the control action $u(k)$.

Appendix B. Derivation of Transfer Function for LESO

Defining the estimation errors

$$e_1 \triangleq z_1 - x, \quad e_2 \triangleq z_2 - F \quad (A7)$$

Taking the derivatives of Equation (A7), one can obtain

$$\begin{aligned} \dot{e}_1 &= \dot{z}_1 - \dot{x} = (z_2 + \alpha u - \beta_1 e_{rr}) - (F + \alpha u) \\ &= (z_2 - F) - \beta_1 e_1 = -\beta_1 e_1 + e_2 \end{aligned} \quad (A8)$$

and

$$\dot{e}_2 = \dot{z}_2 - \dot{F} = -\beta_2 e_1 - \dot{F} \quad (A9)$$

The error system is

$$\begin{cases} \dot{e}_1 = -\beta_1 e_1 + e_2 \\ \dot{e}_2 = -\beta_2 e_1 - \dot{F} \end{cases} \quad (A10)$$

Taking Laplace transforms, from Equation (A8), we have

$$\begin{aligned} sE_1(s) &= -\beta_1 E_1(s) + E_2(s) \\ \Rightarrow E_2(s) &= (s + \beta_1) E_1(s) \end{aligned} \quad (A11)$$

From Equation (A9), it has

$$sE_2(s) = -\beta_2 E_1(s) - sF(s) \quad (A12)$$

Substituting Equations (A11) and (A12), it gives

$$\begin{aligned} s(s + \beta_1)E_1(s) &= -\beta_2 E_1(s) - sF(s) \\ \Rightarrow E_1(s) &= -\frac{s}{s^2 + \beta_1 s + \beta_2} F(s) \end{aligned} \quad (A13)$$

Then,

$$E_2(s) = -\frac{s(s + \beta_1)}{s^2 + \beta_1 s + \beta_2} F(s) \quad (A14)$$

As $e_2 = z_2 - F$, we have

$$\hat{F}(s) = \left(1 - \frac{s(s + \beta_1)}{s^2 + \beta_1 s + \beta_2}\right) F(s) = \frac{\beta_2}{s^2 + \beta_1 s + \beta_2} F(s) \quad (A15)$$

As a consequence, the transfer function in Equation (14) can be obtained.

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