

Article

Model-Free Current Controller for PMSM Based on Super-Twisting Sliding Mode Observer

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Abstract

This paper proposes a super-twisting sliding mode observer-based model-free current controller (ST-MFCC) for permanent-magnet synchronous motor (PMSM). First, the mathematical model of the PMSM is established, and the model dependence of the deadbeat predictive current controller which serves as the foundation for the proposed ST-MFCC is analyzed, along with the stability impact of parameter variations on deadbeat predictive current control. Subsequently, the ST-MFCC is designed based on an ultralocal model and the super-twisting algorithm, eliminating dependence on the current model. Additionally, an adaptive method for tuning the key coefficients of the ultralocal model is introduced, enabling controller parameters to be rapidly optimized when deviations from actual system parameters occur. This approach reduces dependency on inductance parameters and aims to achieve high-performance PMSM current control with deadbeat characteristics. Finally, the effectiveness of the ST-MFCC is verified on a 400 W experimental platform.

Keywords: permanent magnet synchronous motor; super twisting sliding mode observer; model free current controller



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1. Introduction

Permanent-magnet synchronous motors are widely used in electric vehicles, unmanned delivery vehicles, and deep-sea robots due to their high power density, high torque density, and high efficiency [1,2]. Based on the arrangement of internal permanent magnets, they can be mainly classified into two types: surface-mounted and interior-mounted [3].

As a classic motor controller structure, the speed-current double closed-loop control is built upon the control performance of the current loop. Typical current controllers include PI regulators, sliding mode controllers, model predictive control and deadbeat controllers [4–9]. Among these, the PI controller has a simple structure but its dynamic performance is limited due to coupling effects. The sliding mode controller exhibits strong robustness, but its sliding mode characteristics tend to cause chattering problems and its dynamic performance is difficult to improve. Model predictive control can conveniently incorporate various nonlinear factors and achieve a fast dynamic response. However, it suffers from pulsations, high computational load, unfixed switching frequency, torque ripple, and parameter sensitivity [8]. To address this issue, some studies have proposed a method combining SVPWM with a torque error cost function. However, due to the inclusion of two additional non-zero vectors, the computational load increases significantly [10]. Furthermore, to improve control performance under parameter errors, a scheme that incorporates the prediction error from the previous time step into the controller has been

introduced. Although this method can reduce torque ripple, its suppression effectiveness is limited, and the dynamic performance has not been analyzed or considered [11].

As for the deadbeat predictive controller, it is more favored by researchers and employed in this paper due to its simple structure, high feasibility, and excellent dynamic performance [12]. The implementation process is as follows: First, the stator currents in the dq-axis are obtained through current sampling and transformation. Then, based on the discretized predictive current model, the optimal voltage vector is derived by combining the current reference values and sampled values. Finally, SVPWM is used to convert this into a PWM waveform, which enables the inverter to drive the motor, thereby achieving deadbeat current control. However, as mentioned above, since the design of the deadbeat predictive controller relies on the motor model and parameters, its steady-state accuracy, dynamic performance, and stability are all limited by the accuracy of the model and parameters. Parameter mismatches can degrade controller performance. To reduce parameter dependence, the literature [13] proposes an Extended State Observer (ESO) to estimate and compensate for total disturbances caused by parameter mismatches, and predicts the next-sample current value through the observer to enhance the controller's dynamic performance.

Similar methods include the Luenberger observer [14] and the sliding mode observer [15]. Although these methods can reduce parameter dependence, they still require motor models and parameters, they have limited tolerance for model and parameter mismatches, and their robustness remains insufficient.

In order to reduce the dependency of motor control performance on parameters, model-free control methods have gradually attracted the attention of scholars. A typical example is the adaptive model-free control strategy proposed in [16]. However, this paper primarily focuses on model-free control of the mechanical parameters, with limited discussion on the current loop. In terms of the current loop, ref. [17] proposes a model-free control strategy based on deep learning theory. By leveraging deep learning, the method effectively estimates and compensates for model errors, thereby enhancing the stability of the current loop. However, this approach suffers from high computational complexity. To further reduce the dependency on current loop parameters and computational complexity, refs. [18,19] designed current controllers based on the ultralocal model [20]. The ultralocal model uses a general differential equation to replace the motor model, which can effectively reduce the controller's dependence on the model. It is worth mentioning that the ultralocal model has also been applied to islanded AC microgrids, where it is used to model LC filters for enhancing the robustness of grid frequency and voltage [21].

Among them, [18], combined with the ultralocal model, adopts an algebraic method to observe unmodeled disturbances in the model. This method involves a complex disturbance estimation process, and its accuracy is severely affected by sampling frequency and sampling precision, resulting in poor anti-interference performance for sampling. In addition, ref. [19] designed a sliding mode observer (SMO) to observe disturbances.

The sliding mode observer can reduce dependence on sampling and exhibits stronger robustness. Similar applications are commonly found in power systems; for instance, ref. [22] employs a sliding mode observer to enhance grid stability. However, due to the existence of the sliding mode surface, the system inevitably experiences chattering, thereby limiting its performance.

Moreover, the coefficient tuning of the above model-free current controllers, whether using the algebraic method or the sliding mode observer method, directly uses inductance parameters, which to some extent increases the dependence on motor parameters.

To this end, this paper proposes a model-free current controller for PMSMs, with the main contributions as follows:

1. An ultralocal model is adopted to replace the traditional motor model, enabling model-free deadbeat control without relying on the motor model;
2. An observer based on the super-twisting sliding mode algorithm is designed to estimate disturbances and predict currents, thereby enhancing the dynamic performance of current control and improving robustness to variations in electromagnetic parameters;
3. A coefficient-adaptive method based on deadbeat current tracking is proposed to ensure rapid optimization when controller coefficients deviate from actual parameters, thereby eliminating dependence on inductance parameters.

2. Modeling of the PMSM

The voltage model of the PMSM under the dq -axis can be represented as:

$$\begin{aligned} u_d &= R_m i_d - L_m \omega i_q + L_m p i_d \\ u_q &= R_m i_q + L_m \omega i_d + L_m p i_q + \psi_m \omega_e \end{aligned} \quad (1)$$

where u and i are the voltage and current, the subscript dq indicates the dq -axis, ω_m is the mechanical angular speed, L_m , R , and ψ_m are the inductance, stator resistance, and permanent-magnet flux linkage, the subscript m indicates the actual motor parameter, and p indicates a differential operator.

Consistent with conventional control methods, this paper also employs SVPWM to generate the duty cycle. However, due to the limitations of the digital signal processor, the update of the duty cycle causes a one-period delay in sampling and calculation, as shown in Figure 1, which illustrates the timing diagram of sampling, calculation, and PWM loading; therefore, the dq -axis current differential equations of the PMSM can be derived by the Euler method $s = (z - 1)/T_s$ as:

$$\begin{aligned} i_d(k+1) &= \left(1 - \frac{R_m T_s}{L_m}\right) i_d(k) + \omega_e T_s i_q(k) + \frac{T_s}{L_m} u_d(k-1) \\ i_q(k+1) &= \left(1 - \frac{R_m T_s}{L_m}\right) i_q(k) - \omega_e T_s i_d(k) + \frac{T_s}{L_m} u_q(k-1) - \frac{T_s \omega_e \psi_m}{L_m} \end{aligned} \quad (2)$$

where k represents the control time step and T_s represents the control period.

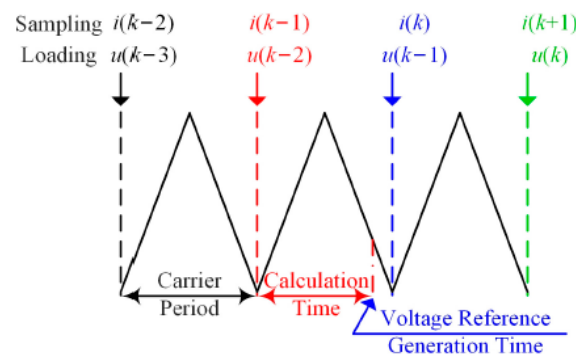


Figure 1. The timing diagram of sampling, calculation, and PWM loading.

3. Traditional Deadbeat Predictive Current Controller

In the conventional deadbeat predictive current control, to compensate for the delay caused by the digital control system, the current value at time step $k + 1$ is typically predicted based on (2) as:

$$\begin{aligned} i_d(k+1) &= \left(1 - \frac{R_c T_s}{L_c}\right) i_d(k) + \omega_e T_s i_q(k) + \frac{T_s}{L_c} u_d(k-1) \\ i_q(k+1) &= \left(1 - \frac{R_c T_s}{L_c}\right) i_q(k) - \omega_e T_s i_d(k) + \frac{T_s}{L_c} u_q(k-1) - \frac{T_s \omega_e \psi_c}{L_c} \end{aligned} \quad (3)$$

where the subscript c represents the parameter used in the current controller.

As analyzed above, k -th interval sampling currents are induced by $(k - 1)$ -th reference voltages; hence, $(k + 1)$ -th predictive currents are always used to calculate reference voltages at the k -th interval to realize the current control as:

$$\begin{aligned} u_d(k) &= \frac{L_c}{T_s} i_d(k+2) - \omega_e L_c i_q(k+1) - \left(\frac{L_c}{T_s} - R_m\right) i_d(k+1) \\ u_q(k) &= \frac{L_c}{T_s} i_q(k+2) + \omega_e L_c i_d(k+1) - \left(\frac{L_c}{T_s} - R_m\right) i_q(k+1) + \omega_e \psi_c \end{aligned} \quad (4)$$

where the current at time $k + 2$ is replaced by the reference current, i.e., $i_{dq}(k + 2) = i_{dq}(\text{ref})$. However, the traditional deadbeat predictive current controller relies too much on the motor model and motor parameters, resulting in its dynamic and steady-state performance as well as its stability being dependent on the accuracy of the model and parameters. To illustrate this situation more precisely, the current closed-loop transfer function considering parameter adaptation is given as follows:

$$\begin{aligned} i_{dq} &= \frac{\frac{L_c}{L_m}}{z^2 + \frac{L_c}{L_m}(1 - j\omega_e T_s)^2 - (1 - j\omega_e T_s)^2} i_{dq}(\text{ref}) \\ &\quad + \frac{\left(z^{-1} \frac{T_s}{L_m} \omega_e^2 T_s + j \frac{2\omega_e T_s}{L_m}\right)}{z^2 + \frac{L_c}{L_m}(1 - j\omega_e T_s)^2 - (1 - j\omega_e T_s)^2} (\psi_c - \psi_m) \end{aligned} \quad (5)$$

Further, based on (5), and taking the inductance parameter, which has the most significant impact on the system, as an example, the pole distribution diagrams under different parameter errors are presented in Figure 2. It can be observed from the figure that

- When the controller inductance parameter is smaller than the actual inductance, the closed-loop poles deviate from the origin, resulting in a stable system but with degraded dynamic performance;
- When the controller inductance parameter is larger than the actual inductance, as the rotational speed increases, the closed-loop poles move closer to the boundary, leading to deteriorating stability;
- When the inductance parameter error exceeds twice the actual value, the system becomes unstable.

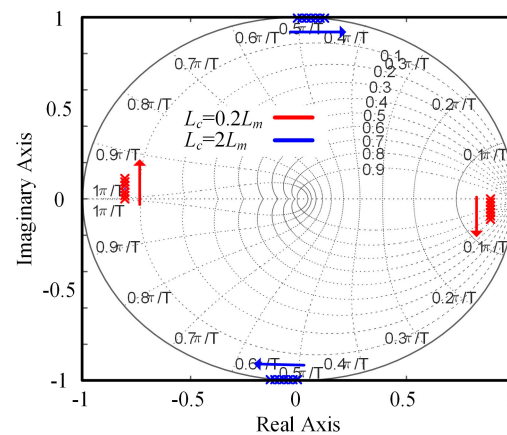


Figure 2. Pole distribution diagrams under different parameter errors.

4. Proposed ST-MFCC

To address the aforementioned issues, this paper proposes a model-free current control strategy that combines an ultralocal model with a super-twisting sliding mode observer. This approach eliminates reliance on the PMSM voltage model while reducing the computational burden associated with unmodeled disturbance observation and enhancing

both robustness and accuracy. Furthermore, a model coefficient adaptation strategy is incorporated to further improve robustness against PMSM parameter variations.

4.1. MFCC

To shape the unknown ‘complex’ mathematical model, an ultralocal model is proposed as [18]:

$$p^v y = F + \alpha_m u \quad (6)$$

where v is the order of the model, α_m is the model gain, and F denotes the total perturbation. According to the ultralocal model shown above, the current differential equations of the PMSM are derived as:

$$\begin{aligned} i_d(k+1) &= i_d(k) + T_s F_d(k) + \alpha_m T_s u_d(k-1) \\ i_q(k+1) &= i_q(k) + T_s F_q(k) + \alpha_m T_s u_q(k-1) \end{aligned} \quad (7)$$

This shows that the initiation of the model gain α_m can be selected as L_m^{-1} , and $F_d(k) = -R_m L_m^{-1} i_d(k) + \omega_e i_q(k)$, $F_q(k) = -R_m L_m^{-1} i_q(k) - \omega_e i_d(k) - L_m^{-1} \omega_e \psi_m$. Likewise, by considering the digital signal processor delay, the MFCC based on the ultralocal model can be deduced as:

$$\begin{aligned} u_d(k) &= (\alpha_m T_s)^{-1} [i_d(\text{ref}) - i_d(k+1)] - \alpha_m^{-1} F_d(k+1) \\ u_q(k) &= (\alpha_m T_s)^{-1} [i_q(\text{ref}) - i_q(k+1)] - \alpha_m^{-1} F_q(k+1) \end{aligned} \quad (8)$$

4.2. Super-Twisting Sliding Mode Observer

According to (8), the implementation of the MFCC relies on the prediction accuracy of i_{dq} and F_{dq} at the $(k+1)$ -th interval. Furthermore, considering the robustness of the SMO and the problem of traditional sliding mode chattering, the SMO based on the super-twisting algorithm (STA) is designed to predict $i_{dq}(k+1)$ and $F_{dq}(k+1)$ to realize model-free current control, in which the STA is proposed by Levant [23] and its basic form is

$$\begin{aligned} p x_1 &= -k_1 |x_1|^{0.5} \text{sign}(x_1) + x_2 + \rho_1(x, t) \\ p x_2 &= -k_2 \text{sign}(x_1) + \rho_2(x, t) \end{aligned} \quad (9)$$

where x_i denote state variables, k_i are the coefficients, ρ_i are perturbation terms, and sign is the sign function. Moreover, Moreno et al. in [24] proved that the observer (9) is stable when its perturbation terms are globally bounded by $|\rho_1| \leq \delta_1 |x_1|^{0.5}$, $\rho_2 = \delta_1(\delta_1, \delta_2 \in \mathbb{R}_+)$, and its sliding mode coefficients satisfy the conditions

$$k_1 > 2\delta_1, k_2 > k_1 \frac{5\delta_1 k_1 + 6\delta_2 + 4(\delta_1 + k_1^{-1}\delta_1)^2}{2(k_1 - 2\delta_1)} \quad (10)$$

Following (9), the observer for predicting perturbances and currents based on STA is designed as:

$$\begin{aligned} p i_{dq}^{pre} &= \alpha_m u_{dq} + k_1 |i_{dq}^{err}|^{0.5} \text{sign}(i_{dq}^{err}) + F_{dq}^{pre} \\ p F_{dq}^{pre} &= k_2 \text{sign}(i_{dq}^{err}) \end{aligned} \quad (11)$$

Before deducing the error differential equation, the ultralocal model (7) is represented and the differential equation of disturbance F_{dq} is added

$$\begin{aligned} p i_{dq} &= F_{dq} + \alpha u_{dq} \\ p F_{dq} &= f_{dq} \end{aligned} \quad (12)$$

Then, according to the observer (11) and ultralocal model (12), the error differential equation is

$$\begin{aligned} p i_{dq}^{err} &= -k_1 |i_{dq}^{err}|^{0.5} \text{sign}(i_{dq}^{err}) + F_{dq}^{err} \\ p F_{dq}^{err} &= f_{dq} - k_2 \text{sign}(i_{dq}^{err}) \end{aligned} \quad (13)$$

When the error in (13) converges to zero, the discrete $(k + 1)$ -th prediction values of currents and disturbances are:

$$\begin{aligned} i_{dq}^{pre}(k + 1) &= i_{dq}^{pre}(k) + \alpha_m T_s u_{dq}(k - 1) \\ &\quad + T_s k_1 |i_{dq}^{err}(k)|^{0.5} \text{sign}(i_{dq}^{err}(k)) + T_s F_{dq}^{err}(k + 1) \\ F_{dq}^{pre}(k + 1) &= F_{dq}^{err}(k) + T_s k_2 \text{sign}(i_{dq}^{err}) \end{aligned} \quad (14)$$

Then, the model-free deadbeat controller is designed as:

$$u_{dq}(k) = (\alpha_m T_s)^{-1} [i_{dq}(\text{ref}) - i_{dq}^{pre}(k + 1) - \alpha_m^{-1} F_{dq}^{pre}(k + 1)] \quad (15)$$

Stability Proof: From (11), it can be seen that $\rho_1(x, t) = 0$, $\rho_2(x, t) = f_{dq}$, large enough δ_1 and δ_2 can be easily selected to satisfy boundary condition, and finally k_1 and k_2 can be set from (10). In addition, as mentioned above, α_m is essentially the reciprocal of inductance. To eliminate the reliance of the current controller on motor parameters, the adaptive algorithm based on the deadbeat characteristic in [3] is used.

4.3. Adaption of the Coefficient

As mentioned above, the key coefficient of the designed model-free controller is essentially the inverse of the inductance, so it still depends on the PMSM parameters to some extent. To address this issue, this paper proposes a parameter adaptation strategy that combines the deadbeat characteristic shown in Table 1 with a bang-bang controller. This strategy ensures the deadbeat control of the current loop, meaning that the current at time step $k + 2$ tracks the reference value set at time step k .

Table 1. Table of current values at the first two steps of the current step response.

$(k + n)\text{th}, n =$	0	1	2
$i_d(\text{ref})$	i_d^*	0	0
$i_d(k)$	0	0	$(\alpha_m / \alpha_c) i_d^*$

To implement this parameter adaptation, an analysis of the current values during deadbeat control is first conducted. The following table presents the key variable values at several adjacent time steps in the deadbeat predictive current controller.

As can be observed from the table, when deadbeat current control is adopted, the sampled current value at time step $k + 2$ is related to the accuracy of the key coefficient α , and is positively correlated with the error between the controller parameter α_c and the actual parameter α_m . Specifically

- When α_c is greater than α_m , the sampled current at $k + 2$ exceeds the reference value at k , resulting in overshoot;
- When α_c is less than α_m , the sampled current at $k + 2$ is less than the reference value at k , preventing fast tracking;
- When and only when α_c equals α_m , the sampled current at $k + 2$ equals the reference value at k , achieving deadbeat current control.

Therefore, a parameter adaptation rule is proposed by combining this deadbeat characteristic with a bang-bang controller as follows:

$$\alpha_c = k_\alpha \text{sign}[i_d(\text{ref}) - i_d(k+2)] \quad (16)$$

where k_α is the coefficient of the α adaptive adaptation strategy. Thus, the proposed ST-MFCC can achieve deadbeat predictive current control under arbitrary operating conditions, featuring advantages of model independence, parameter independence, strong robustness, and fast dynamic performance.

To facilitate a better understanding of the application of the proposed method in this paper, a control block diagram is provided in Figure 3. It primarily consists of a controller, prediction module, adaptive module, and the plant. The control procedure is as follows: First, the three-phase currents of the motor are sampled and transformed into dq-axis-sampled currents via the Park transform. Subsequently, based on the injected auxiliary current signal in the d-axis and the sampled signals, the coefficient α_c is adaptively updated according to (16). Then, the observer, as given in (14), is utilized to predict the current and unmodeled disturbances for the next time step. Finally, the controller computes the optimal voltage vector for the current period, which is converted via SVPWM into chopped signals to drive the inverter, thereby supplying power to the motor and completing the motor control process.

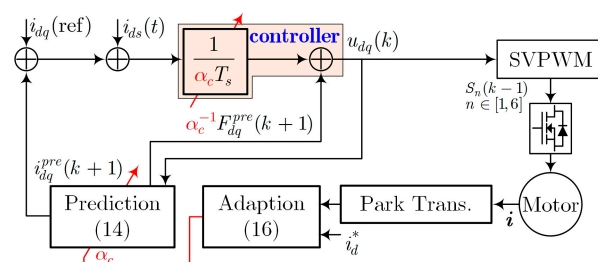


Figure 3. Control diagram of the proposed method.

It is worth mentioning that the method proposed in this paper also has certain limitations. Its parameter adaptation process relies on (16), and to obtain sufficient information for parameter adaptation, a continuous signal needs to be injected into the d-axis, which will cause slight additional losses. However, the amplitude of the auxiliary signal injected into the d-axis is extremely small, only 0.1 A. Moreover, considering that the d-axis does not produce torque pulsations, injecting such a minimal signal into the d-axis does not affect motor performance, while significantly enhancing the robustness of the current loop against parametric variations.

5. Experimental Results

5.1. Introduction to the Experimental Platform

An experimental study is carried out to assess the proposed algorithm, using the test bench illustrated in Figure 4, and the main parameters of the platform are shown in Table 2. This setup comprises two main components: the motor system and the control unit. The motor system features two 400 W permanent-magnet synchronous motors. The test motor is a commercial motor, adopting a surface-mounted PMSM structure with four pole pairs. Since it is a commercial motor and its internal structure cannot be obtained, a typical surface-mounted PMSM structure with four pole pairs is provided here, as shown in Figure 4c. Additionally, its stator resistance is 1.6 Ω , inductance is 9 mH, and flux linkage is 0.006 Wb. Moreover, A YASKAWA Sigma-7 motor from Yaskawa Electric Corporation,

Kitakyushu, Japan, serves as the load motor, responsible for speed regulation during the current loop performance evaluation.

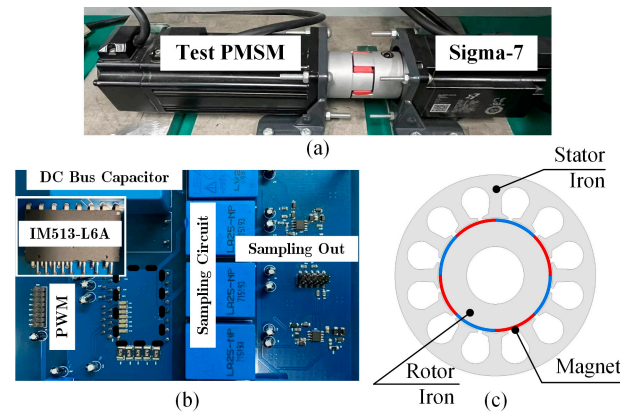


Figure 4. PMSM experimental platform. (a) Motor system. (b) Control unit. (c) Structure.

Table 2. Main parameters of the PMSM platform.

Stator Resistance R_m	Inductance L_m	Sampling Frequency
1.6 Ω	9 mH	10 k
Permanent Magnet Flux ψ_m	Pole Pairs p_n	Control Frequency
0.006 Wb	4	10 k

The control unit integrates both drive and sensing circuitry. The power stage utilizes an Infineon IM513-L6A intelligent power module from Infineon Technologies AG, Neubiberg, Germany configured in a conventional two-level voltage source inverter topology. Voltage and current measurements are acquired using LV25-P and LA25-NP sensors, respectively. The control algorithm runs on a TMS320F28335 microcontroller with a PWM switching frequency of 10 kHz.

5.2. Experimental Comparison

To verify the convergence, dynamic, and robust performance of the proposed ST-MFCC, this paper presents experimental results of step responses comparing the traditional DPCC, SMO-DPCC, and ST-MFCC under various parameter conditions. Figures 5–10 illustrate the coefficient convergence, the step response comparisons without parameter error, the step response comparisons with parameter error, and the step response comparisons under step changes in parameters, respectively.

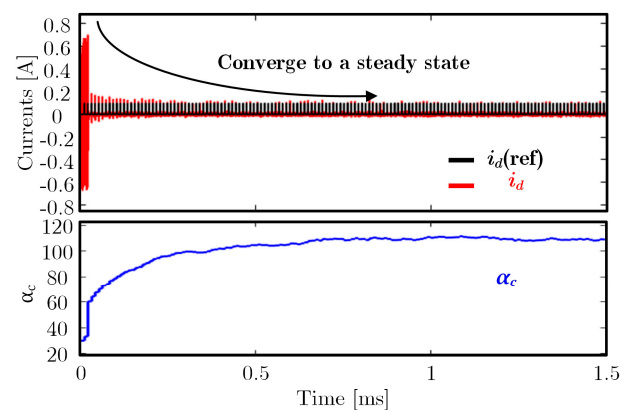


Figure 5. Experimental verification of the coefficient adaptation algorithm.

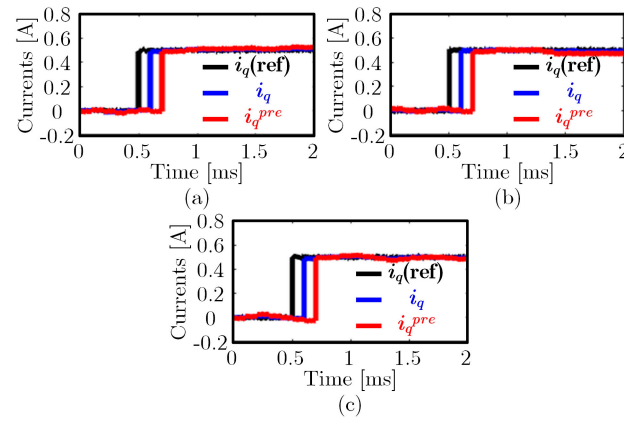


Figure 6. Experimental results comparing the three methods under accurate parameters: (a) DPCC, (b) SMO-DPCC, and (c) ST-MFCC.

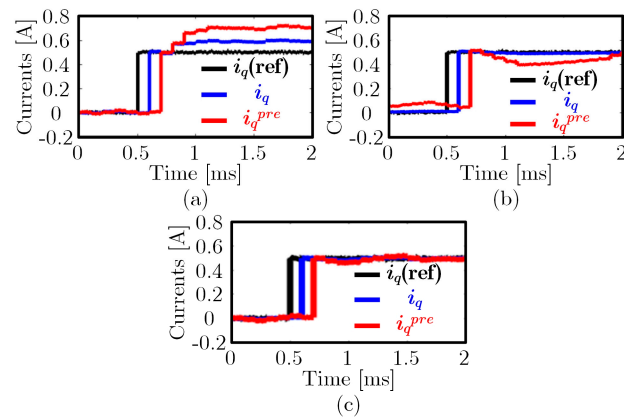


Figure 7. Experimental results comparing the three methods under $R_c = 10R_m$: (a) DPCC, (b) SMO-DPCC, and (c) ST-MFCC.

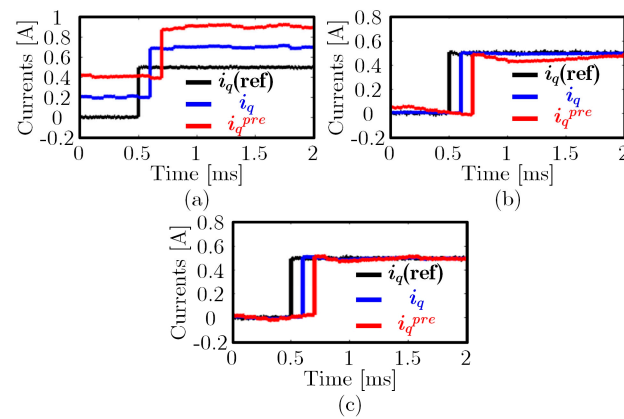


Figure 8. Experimental results comparing the three methods under $\psi_c = 10\psi_m$: (a) DPCC, (b) SMO-DPCC, and (c) ST-MFCC.

Figure 5 illustrates the parameter adaptation process of the proposed ST-MFCC algorithm during the start-up phase, where the initial parameter value is set to 30. It can be observed that at the initial start-up stage, since the set controller inductance value is nearly 4 times larger than the actual value, the system exhibits severe oscillations, which can also be concluded from the current waveforms. However, as the parameter adaptation algorithm based on deadbeat characteristics converges, the controller inductance value gradually approaches the actual value, and the oscillation phenomenon during the cur-

rent step process gradually diminishes. Eventually, when the coefficient converges to the deadbeat value, the current achieves optimal control performance.

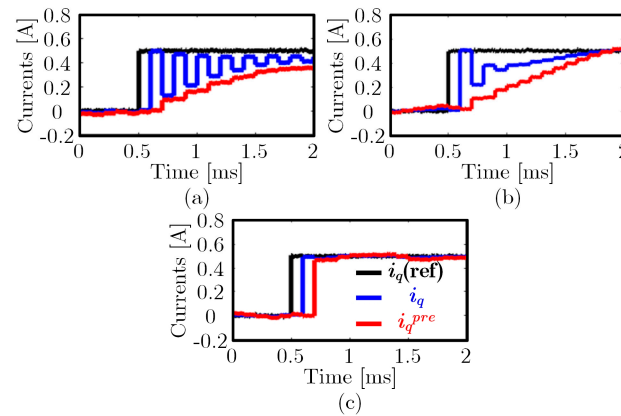


Figure 9. Experimental results comparing the three methods under $L_c = 0.2L_m$: (a) DPCC, (b) SMO-DPCC, and (c) ST-MFCC.

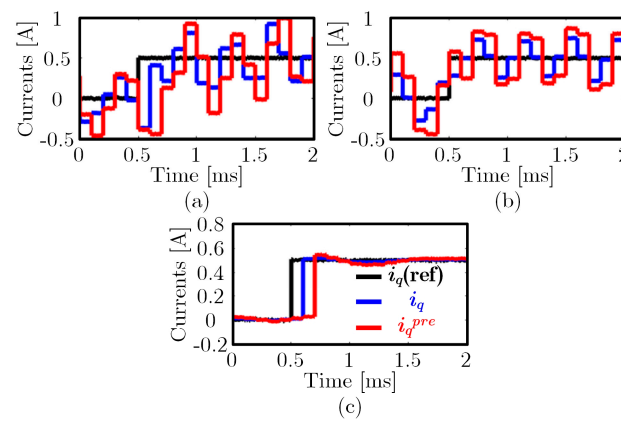


Figure 10. Experimental results comparing the three methods under $L_c = 3L_m$: (a) DPCC, (b) SMO-DPCC, and (c) ST-MFCC.

Figure 6 presents the experimental comparison results under the condition of no parameter mismatch, showing the waveforms of q -axis reference current, predicted current, and sampled current. In the absence of parameter errors, all three algorithms exhibit high dynamic response capability and steady-state accuracy. Moreover, compared with MFCC, SMO-DPCC has obvious chattering. However, the proposed ST-MFCC, which adopts a high-order sliding mode observer, can effectively suppress the chattering problem, resulting in smaller chattering in the q -axis current. In general, the three algorithms show little difference when there is no parameter error, and all possess good current control performance.

Further experimental comparisons are conducted which are illustrated in Figure 7 under parameter mismatch conditions, starting with the case where the controller resistance parameter is set to ten times its actual value. The results indicate that the conventional DPCC exhibits a significant DC offset due to the large resistance error, whereas the SMO-DPCC can compensate for the effects caused by the resistance mismatch through its sliding mode observer, albeit at the cost of some dynamic performance. In contrast, the proposed ST-MFCC, being model-independent, remains unaffected by resistance variations in the model and thus maintains excellent step response performance.

Similarly, the experimental results for the case where the controller flux linkage parameter is set to ten times the actual value are presented in Figure 8. Since both resistance and

flux linkage have similar effects on the current loop, both can cause DC offset issues. Consequently, the experimental results shown in Figure 8 are similar to those in Figure 7, with the proposed ST-MFCC continuing to demonstrate the best control performance among the three methods.

Further experiments are conducted to verify the effects of inductance parameter errors, which have the most significant impact on the current loop. Figure 9 presents the experimental results when the controller inductance is set to 0.2 times the actual value. As shown in the figure, while the conventional DPCC avoids instability despite the underestimated inductance value, its dynamic performance deteriorates sharply. The SMO-DPCC faces the same issue due to its lack of coefficient adaptation capability. In contrast, the proposed ST-MFCC, through its coefficient adaptation mechanism, can adjust the controller parameters from initial values lower than the actual parameters to the correct values, ensuring deadbeat current tracking and achieving the best current control performance among the three methods.

The periodic delay between the given, predicted, and actual values shown in Figures 7–9 is caused by the PWM loading delay mentioned in Figure 1. The DPCC method adopted in this paper has reduced the delay between the actual and predicted values to the theoretical minimum of two cycles through prediction. As shown, when there are errors in the resistance and flux linkage parameters, traditional DPCC exhibits a DC bias due to parameter errors, a conclusion that can be verified in (5). However, when there are errors in the inductance parameters, traditional DPCC does not exhibit a DC bias but only experiences a reduction in dynamic performance, eventually converging to the given value. This point can also be explained by the pole trajectory shown in Figure 2.

Additionally, the experimental results with the controller inductance parameter set to three times the actual value are presented in Figure 10. As shown in the figure, the conventional DPCC system becomes unstable due to the excessive inductance parameter error, resulting in severe oscillations in the current waveform. While the SMO-DPCC inherently possesses a certain degree of robustness, it fails to fully compensate for the disturbance factors caused by parameters under the given operating condition with excessive inductance error, thus also exhibiting significant oscillations in its current response waveform. In contrast, the ST-MFCC proposed in this paper, with its excellent parameter adaptation capability, can maintain stability even under the condition of threefold inductance error.

Finally, to provide a clearer comparison of the performance of the three algorithms, a quantitative performance comparison table is presented as shown in Table 3, evaluating their step response performance under different parameter errors. When no parameter errors exist, the performance of all three algorithms is similar, and each can achieve deadbeat current control. When there is a 10 times error in the resistance and flux linkage parameters, the conventional DPCC fails to achieve deadbeat control due to the presence of DC bias, while both the SMO-DPCC and ST-MFCC still maintain deadbeat control performance. When the controller inductance is set to 0.2 times the actual inductance, the dynamic response of the conventional DPCC deteriorates significantly, requiring over 15 control cycles to settle. The SMO-DPCC also needs nearly 15 cycles to track the reference, whereas the proposed ST-MFCC can track the reference within just 2 cycles. When the controller inductance is set to 3 times the actual inductance, both the conventional DPCC and SMO-DPCC become unstable. In contrast, the proposed algorithm remains stable and continues to achieve deadbeat current control, demonstrating its effectiveness.

Table 3. Comparison of three methods.

	Parameter	DPCC	SMO-DPCC	ST-MFCC
Step Time	accurate	2	2	2
	$R_c = 10R_m$	DC Bias	2	2
	$\psi_c = 10\psi_m$	DC Bias	2	2
	$L_c = 0.2L_m$	>15	15	2
	$L_c = 3L_m$	Unstable	Unstable	2

6. Conclusions

This paper proposes an ST-MFCC for PMSM based on a super-twisting sliding mode observer. By combining an ultralocal model with a coefficient adaptation mechanism, the proposed controller effectively addresses the high parameter sensitivity issue of traditional deadbeat predictive current control. Experimental results on a 400 W platform demonstrate that, compared with conventional DPCC and SMO-DPCC, the ST-MFCC exhibits superior dynamic response, enhanced robustness, and better steady-state performance under conditions such as parameter mismatch and step changes, verifying its effectiveness and practicality.

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