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Simplified Model Predictive Current Control for PMSM Drives Based on Bayesian Inference

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Abstract

In order to solve the problem of the dependence of the traditional model predictive current control method on motor parameters, this paper proposes a simplified model predictive current control method based on Bayesian inference, which makes the predictive model structure simpler by reducing the motor parameters in the predictive model. Firstly, the *d*-*q*-axis current prediction model is simplified and the *q*-axis current prediction model is incrementally processed to eliminate the influence of the magnetic chain parameters, so that the *d*-*q*-axis current prediction model contains only the unique motor parameter - inductance. Then, Bayesian inference is used to identify the parameters of the inductor, and the likelihood function is established with the *d*-axis current error as the criterion, and the posterior distribution of the inductor is sampled by the Metropolis-Hastings sampling algorithm, and the inductor sample is selected to be accepted or rejected based on the likelihood of the inductor samples, which generates a randomized sequence of inductor samples. After the sample burn-in period, the inductor sample sequence can converge and form a Markov chain with a smooth distribution, and the expectation value of the inductor parameters in Bayesian inference can be calculated by intercepting the valid inductor samples in the smooth distribution, which completes the accurate identification of the inductor parameters. Simulation results show that the control method proposed in this paper significantly reduces the dependence of the prediction model on the motor parameters, effectively improves the robustness of the whole control system, and achieves good control results.

1 Introduction

In today's society, permanent magnet synchronous motor (PMSM) is widely used in various fields due to their high efficiency, low power consumption, and fast response time. With the progress of PMSM technology, the corresponding control theory is also developing. Early control algorithms applied to PMSMs were mainly based on proportional integral control (PI) [1], but because of its use as a linear current control method, there are some limitations in the control of nonlinear PMSM systems. With the development of vector control theory, field-oriented control (FOC) [2] is widely used in various applications requiring high dynamic performance and high efficiency because it can realize more accurate and efficient control of PMSM. On the basis of vector control, direct torque control (DTC) [3] has been proposed by scholars, which has a faster response speed and a simpler control structure than FOC. With the development of microelectronics technology, advanced Model Predictive Control (MPC) [4] has been proposed, and MPC as an advanced control strategy based on the optimal control theory has been applied to the control of PMSMs. The MPC strategy is able to deal with the nonlinear and time-varying systems effectively, and has achieved remarkable results in the control of high-performance motors.

In PMSM control methods, model predictive control (MPC) can be categorized into model predictive current control (MPCC) [5], model predictive torque control (MPTC) [6], and model predictive voltage control (MPVC) [7] depending on the control variables. For the MPC strategy, when the temperature of the permanent magnet of the PMSM is too high or the magnetic field reaches saturation, the motor parameters will be mismatched, and this mismatched motor parameters will lead to an inaccurate prediction model, which will affect the control effect of the motor [8]. Therefore, it is important to reduce the dependence of the prediction model on the motor parameters. Literature [9] introduces a parameter-free PMSM model predictive current control, which does not require motor parameters and uses the prediction current error, sampling and storage information to achieve current prediction. In [10], a simple robust model predictive current control strategy is proposed, where an integral controller is designed to extract the exact inductor parameters based on the current error, and the exact inductor parameters are used to replace the magnetic chain parameters. Literature [11] proposed an improved model predictive current control method based on the incremental model by introducing an incremental predictive model to eliminate the magnetic chains of permanent magnets in the current prediction model, and an inductance perturbation controller including an inductance perturbation observer and an inductance extraction algorithm is used to update the accurate inductance information of the whole control system in real time. Literature [12] and [13] proposed a low parameter-sensitive MPVC method

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based on an incremental prediction model, and a novel controller was designed to eliminate the undesirable effects of inductance mismatch. All the above control methods effectively reduce the sensitivity of motor parameters, but the process of constructing controllers and observers is complicated.

In addition, the method of online parameter identification can also significantly reduce the dependence of the prediction model on the motor parameters. Literature [14] presents an extended Kalman filter-based permanent magnet chain identification method for built-in PMSM, which employs a rotor chain vector control strategy based on a model-referenced adaptive system to achieve online permanent magnet chain identification for IPMSM. Literature [15] presents a robust incremental magnetic chain estimation method based on Bayesian learning for PMSM drives, which is based on a Bayesian learning strategy with hierarchical noise model for PMSM nonlinear magnetic chain estimation. Although these parameter identification methods mentioned above can accurately identify the dynamic parameters, the calculation process is cumbersome.

To address the above problems, a simplified model predictive current control method based on Bayesian inference is proposed in this paper, which is organized as follows: Firstly, the system topology and conceptual method are given in Section 2 Then, the incremental model predictive current control method based on Bayesian inference proposed in this paper is highlighted in Section 3. The basic principles of the simplified *d*-*q*-axis current prediction model and the identification process of the inductor parameters are described in detail therein. Section 4 carries out simulation experiments to validate the control method proposed in this paper, and compares and analyzes the total harmonic distortion (THD) of the proposed control method with that of the traditional model predictive current control (T-MPCC) method, and gives the parameter identification process of the inductor parameters under rated load torque and different speed conditions. Finally, Section 5 summarizes and analyzes the whole paper.

2 System Topology and Conceptual Method

2.1 SPMSM Control System Topology

A sketch of the SPMSM drive control system containing a two-level three-phase voltage source inverter(2L-VSI) is shown in Fig. 1:

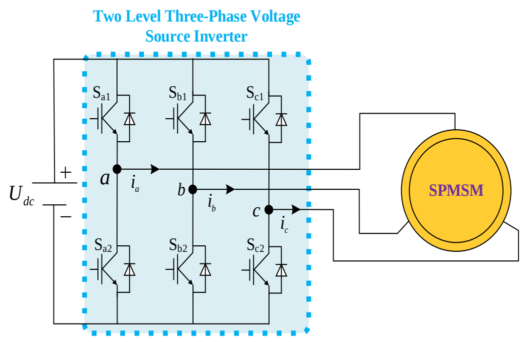

Fig. 1. Topology of 2L-VSI and SPMSM

The mathematical model of the *d*-*q* axis voltage of a SPMSM is as follows:

$$\begin{cases} u_d = Ri_d + L\cdot(\dfrac{di_d}{dt} - \omega_e i_q) \\ u_q = Ri_q + L\cdot(\dfrac{di_q}{dt} + \omega_e i_d) + \omega_e \psi_f \end{cases} \tag{1}$$

where u_d and u_q denote the voltage in the *d*-axis and *q*-axis, respectively; i_d and i_q denote the current in the *d*-axis and *q*-axis, respectively; ω_e is the electrical angular velocity; *R* is the stator resistance; ψ_f is the magnetic chain of permanent magnets; and L is the inductance of SPMSM.

2.2 Traditional Model Predictive Current Control Method

The control block diagram of the T-MPCC method is shown in Fig. 2, which consists of three main parts: one-beat delay compensation, current prediction model, and value function.

From the *d*-*q*-axis voltage mathematical model, the forward Euler discretization equation is used to predict the *d*-*q*-axis current at the next moment, and the specific current prediction equation is shown below:

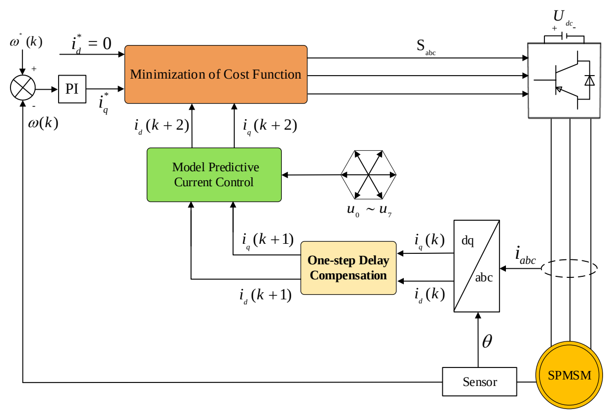

Fig. 2. T-MPCC method control block diagram

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$$\begin{cases} i_d^p(k+1) = \left(1-\frac{T_sR}{L}\right)\cdot i_d(k) + \frac{T_s}{L}\cdot u_d(k) + T_s\omega_e i_q(k) \\ i_q^p(k+1) = \left(1-\frac{T_sR}{L}\right)\cdot i_q(k) - T_s\omega_e i_d(k) + \frac{T_s}{L}\cdot[u_q(k) + \omega_e\psi_f] \end{cases} \tag{2}$$

where T_s is the control period of the system.

In real motor control systems, due to hardware and other factors, the control system will have computational delays, so one-step delay compensation is required. After the introduction of one beat delay compensation, the current prediction model is updated as:

$$\begin{cases} i_d^p(k+2) = \left(1-\frac{T_sR}{L}\right)\cdot i_d^p(k+1) \\ \qquad +T_s\omega_e i_q^p(k+1) + \frac{T_s}{L}\cdot u_d(k+1) \\ i_q^p(k+2) = \left(1-\frac{T_sR}{L}\right)\cdot i_q^p(k+1) \\ \qquad -T_s\omega_e i_d^p(k+1) + \frac{T_s}{L}\cdot[u_q(k+1) + \omega_e\psi_f] \end{cases} \tag{3}$$

By bringing the eight fundamental voltage vectors generated by the 2L-VSI into the prediction equation, eight predicted currents at *k*+1 moments can be obtained, which are brought into the value function to select the optimal voltage vectors and act on the motor through the inverter. The value function can be expressed as:

$$C = \left|i_d^* - i_d^p(k+2)\right| + \left|i_q^* - i_q^p(k+2)\right| \tag{4}$$

where and represent the given values of the *d*-axis and *q*-axis currents, the given current is zero, and is the output of the rotating speed ring.

2.3 Bayesian Inference Concept

Bayesian inference is an important method of statistical inference based on Bayes' theorem, which updates the posterior probability of an event by means of a prior probability and likelihood function. In the philosophy of decision making, Bayesian inference is closely related to the Bayesian view of probability, which centers around the idea of probabilistic inference, which allows us to probabilistically quantify the degree of belief or certainty about various hypotheses, models, or parameters. The Bayesian inference formula is as follows:

$$P(\theta \mid Data) = \frac{P(Data \mid \theta)\cdot P(\theta)}{P(Data)} \tag{5}$$

where $P(\theta)$ is the prior distribution, which refers to the initial belief or a priori knowledge of the hypothesis, model, or parameter prior to observing any sampled data; it is a subjective belief; $P(Data \mid \theta)$ is the likelihood function, which quantifies the consistency of the sampled data with each of the hypotheses, models, or parameters considered as a measure of the probability that the data will be sampled with the given assumptions; and $P(\theta \mid Data)$ is the posterior distribution, which refers to the distribution of the hypotheses, models, or parameters after considering the new sampled data after the hypotheses, models, or parameters are distribution of parameters after updating. It is determined by Bayes' rule, combines the prior distribution and the likelihood function, and is the core of Bayesian inference. $P(Data)$ is the evidence, the probability of observing the data under all possible values of the hypothesis, model, or parameters. It acts as a normalizing constant in Bayes' theorem to ensure that the posterior distribution probabilities sum to 1. The formula is as follows:

$$P(Data) = \int P(\theta \mid Data)\cdot P(\theta)\, d\theta \tag{6}$$

It is worth noting that in Bayesian inference, emphasis is usually placed on the values of the parameters, and the evidence is independent of the values of the parameters and computed as a normalized constant. When the only concern is when the peak of the posterior distribution occurs, rather than whether it is normalized or not, the evidence can be ignored and the Bayesian inference formula can be simplified, as evidenced by the acceptance or rejection of simulation candidates in the Metropolis-Hastings algorithm. The simplified Bayesian inference formula is as follows:

$$P(\theta \mid Data) \propto P(Data \mid \theta)\cdot P(\theta) \tag{7}$$

In the Bayesian inference method, in order to avoid complex numerical integration operations and make the Bayesian updating process more efficient and convenient, the posterior distribution should be guaranteed to be conjugate with the prior distribution. Based on the existing knowledge and historical data, this paper chooses normal distribution as the prior distribution and likelihood function. The probability density expression of the normal distribution is:

$$P(\theta \mid Data) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(\theta-\theta_\mu)^2}{2\sigma^2}} \tag{8}$$

where θ_μ is the mean of parameter θ and σ is the variance of parameter θ.

In order to ensure numerical stability and simplify the calculation, as well as to avoid the numerical underflow that may be caused by the multiplication of small probabilities, so that the calculation process is more accurate, this paper carries out a logarithmic transformation of the probability density function of the normal

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distribution, turning multiplication into addition. The expression for the probability density of the normal distribution after taking the logarithm is:

$$P(\theta \mid Data) = -\frac{1}{2}\ln(2\pi\sigma^2) - \frac{(\theta-\theta_\mu)^2}{2\sigma^2} \tag{9}$$

3 Simplified MPCC Method Based on Bayesian Inference

A simplified MPCC method based on Bayesian inference (BH-MPCC) proposed in this paper simplifies the *d*-axis current prediction equation, ignores the influence of resistance mismatch on the control effect, and incrementally treats the *q*-axis current prediction equation to eliminate the influence of the magnetic chain parameters. Using the *d*-axis current error as a criterion, Bayesian inference is introduced into the simplified current prediction model, and the Metropolis-Hastings sampling algorithm is used to identify the inductance parameters, which are then brought into the simplified current prediction model to predict the current value of the next cycle, and the optimal inverter switching combination is selected to act on the SPMSM motor through the cost function. The control block diagram of the BH-MPCC method is shown below:

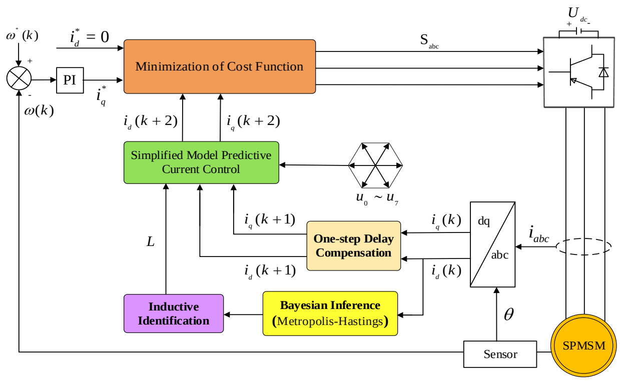

Fig. 3. Control block diagram of BH-MPCC method

3.1 Simplification of *d-q* axis Current Prediction Model

Since the value of T*R/L for the *d*-axis current prediction model in Eq. 2 is much less than 1, and the effect on the control effect when the resistance parameter is mismatched is very small, the *d*-axis current prediction equation can be simplified to Eq. 10 by ignoring the T*R/L term:

$$i_d(k+1) = i_d(k) + T_s\omega_e i_q(k) + \frac{T_s}{L}\cdot u_d(k-1) \tag{10}$$

From Eq. 2, it can be seen that the magnetic chain parameter is only included in the *q*-axis current, and in order to eliminate the influence of the magnetic chain parameter on the prediction model, an incremental current prediction model is introduced in this paper. The model predicts the current based on two different moments and makes a difference between the predicted currents of the two different moments to eliminate the magnetic chain, thus obtaining the incremental current prediction equation. At moment *k*, the *q*-axis current prediction equation is given by Eq. 11:

$$\begin{aligned} i_q(k) = {} & \left(1-\frac{T_s R}{L}\right)\cdot i_q(k-1) - T_s\omega_e i_d(k-1) \\ & + \frac{T_s}{L}\cdot[u_q(k-1)+\omega_e\psi_f] \end{aligned} \tag{11}$$

The *q*-axis incremental current prediction model for the *q*-axis can be obtained as Eq. 12 by subtracting Eq. 11 from the *q*-axis current equation in Eq. 2:

$$\begin{aligned} i_q(k+1) = {} & \left(2-\frac{T_s R}{L}\right)\cdot i_q(k) - \left(1-\frac{T_s R}{L}\right)\cdot i_q(k-1) \\ & + \frac{T_s}{L}\cdot[u_q(k)-u_q(k-1)] - T_s\omega_e[i_d(k)-i_d(k-1)] \end{aligned} \tag{12}$$

Simplifying Eq. 12, taking the same way as simplifying the *d*-axis current prediction model and ignoring the T*R/L term, the *q*-axis incremental simplified current prediction model can be obtained as Eq. 13:

$$\begin{aligned} i_q(k+1) = {} & 2\cdot i_q(k) - i_q(k-1) - T_s\omega_e[i_d(k)-i_d(k-1)] \\ & + \frac{T_s}{L}\cdot[u_q(k)-u_q(k-1)] \end{aligned} \tag{13}$$

Therefore, the simplified equation of the *d-q* axis current prediction model is Eq. 14:

$$\begin{cases} i_d(k+1) = i_d(k) + T_s\omega_e i_q(k) + \frac{T_s}{L}\cdot u_d(k-1) \\ i_q(k+1) = 2\cdot i_q(k) - i_q(k-1) - T_s\omega_e[i_d(k)-i_d(k-1)] \\ \qquad + \frac{T_s}{L}\cdot[u_q(k)-u_q(k-1)] \end{cases} \tag{14}$$

3.2 Inductance Parameter Identification

In Bayesian inference, based on the available prior knowledge, the prior distribution of the target inductance is normally distributed, and the expression for the probability density of the prior distribution after taking the logarithm is Eq. 15 :

$$P(L) = -\frac{1}{2}\ln(2\pi\sigma_l^2) - \frac{(L-L_\mu)^2}{2\sigma_l^2} \tag{15}$$

where L is the target inductance, σ_l is the variance of the a priori distribution of the target inductance, which is taken as 0.085 in this paper; L_μ is the mean of the a

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priori distribution of the target inductance, which is assumed to be 0.02 based on the a priori knowledge.

The difference between the actual sampled current and the predicted current of the *d*-axis at moment k is used as the observation data and criterion, and the expression of the actual predicted current error of the *d*-axis is Eq. 16:

$$E_d(k) = i_{ds}(k) - i_d(k) \tag{16}$$

where $i_d(k)$ denotes the predicted current in the *d*-axis at moment k and $i_{ds}(k)$ denotes the actual sampled current in the *d*-axis at moment k.

Based on the *d*-axis current error a likelihood function for the target inductance can be established as a means of correcting for the assumed target prior distribution, and the likelihood function is expressed as Eq. 17:

$$P(E_d \mid L) = -\frac{1}{2}\ln(2\pi\sigma_s{}^2) - \frac{(E_d - E_{d_\mu})^2}{2\sigma_s{}^2} \tag{17}$$

where σ_s is the variance of the likelihood function of the target inductance; E_{d_μ} is the mean value of the prediction current error in the *d*-axis, which in the ideal case is 0, indicating that the desired target inductance is equal to the actual parameters of the motor.

According to the prior distribution and likelihood function of the target inductance, the corresponding posterior distribution can be calculated by applying the simplified Bayesian inference formula with the following expression:

$$P(L \mid E_d) = -\ln(2\pi\sigma_l\sigma_s) - \frac{(L - L_\mu)^2}{2\sigma_l{}^2} - \frac{(E_d - E_{d_\mu})^2}{2\sigma_s{}^2} \tag{18}$$

After determining the posterior distribution of the target inductor, the posterior distribution of the target inductor needs to be sampled by the Metropolis-Hastings sampling algorithm. Assuming that the initial value of *L* for sampling is 0.05H, a simulated candidate inductor is generated by adding a random perturbation to the inductor *L* using the symmetric proposed distribution with the following equation:

$$L_m = L + \lambda \cdot \varepsilon \tag{19}$$

where L_m is the simulated candidate inductance, λ is the perturbation step size, and ε is the randomly generated perturbation value for the symmetric proposal distribution.

The expression for the probability density of the prior distribution of the simulated candidate inductance after taking logarithms is Eq. 20:

$$P(L_m) = -\frac{1}{2}\ln(2\pi\sigma_{l_m}{}^2) - \frac{(L_m - L_{\mu_m})^2}{2\sigma_{l_m}{}^2} \tag{20}$$

where σ_{l_m} is the variance of the a priori distribution of the simulated candidate inductors and L_{μ_m} is the mean of the a priori distribution of the simulated candidate inductors, which is assumed to be 0.02 based on a priori knowledge.

The prediction current error expression for the *d*-axis when using the simulated candidate inductance for prediction is:

$$E_{dm}(k) = i_{dm}(k) - i_d(k) \tag{21}$$

where $i_{dm}(k)$ denotes the predicted current at moment k using the simulated candidate inductance for prediction. The expression of the likelihood function established using the simulated candidate inductance is:

$$P(E_{dm} \mid L_m) = -\frac{1}{2}\ln(2\pi\sigma_{s_m}{}^2) - \frac{(E_{dm} - E_{d_{\mu_m}})^2}{2\sigma_{s_m}{}^2} \tag{22}$$

where σ_{s_m} is the variance of the likelihood function of the simulated candidate inductance, and $E_{d_{\mu_m}}$ is the mean value of the *d*-axis current error when the simulated candidate inductance is used for prediction.

The expression for the probability density of the posterior distribution when simulated candidate inductances are used for prediction is:

$$P(L_m \mid E_{dm}) = -\ln(2\pi\sigma_{l_m}\sigma_{s_m}) - \frac{(L_m - L_{\mu_m})^2}{2\sigma_{l_m}{}^2} - \frac{(E_{dm} - E_{d_{\mu_m}})^2}{2\sigma_{s_m}{}^2} \tag{23}$$

After random wandering using the symmetric proposal distribution, the generated simulated candidate inductors need to be accepted or rejected for sampling depending on their sample likelihood, which can be accomplished by the following two steps:

In the first step, the acceptance probability of the simulated candidate inductor is determined:

$$\alpha_{L_m} = \min\left\{1, e^{[P(L_m \mid E_{d_m}) - P(L \mid E_d)]}\right\} \tag{24}$$

In the second step, a random number u ~ Uniform(0,1) is generated and a decision is made on whether to accept the simulated candidate inductance L_m, and if $u < \alpha_{L_m}$, the simulated candidate inductance is closer to the actual inductance of the motor, and the choice is made to accept the sampling, let $L_i = L_m$. Conversely, the sampling is rejected, keeping the target

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inductance unchanged, let $L_i = L$. Where, i = 1 ... .N, N is the number of sampling times.

In a control cycle, according to the actual hardware conditions to choose the number of samples of the target posterior distribution, this simulation experiment sampling 100 times, all the samples sampled to find the average value, as the iterative inductance of this control cycle.

$$L = \frac{1}{N}\sum_{i=1}^{N} L_i \tag{25}$$

The next control cycle uses this iterative inductance as the initial value for sampling the posterior distribution of the inductance for the next iteration, and after the sample burn-in period, a converged sequence of iterative inductance samples can be obtained, which is a Markov chain with a smooth distribution, and whose smooth distribution has an effective sample mean that is the desired expected value of the inductance.

4 Simulation Results

To verify the effectiveness of the proposed method, simulation experiment is carried out on MATLAB/Simulink in this paper. The parameter details of SPMSM are given in TABLE I and the control frequency in the simulation experiment is 10 kHz.

TABLE I

Symbol	Value	Symbol	Value
U_{dc} (V)	310	J (kg.m2)	0.00046
R_s (Ω)	3.18	T_N (N·m)	5
L (mH)	8.5	n_N (r/min)	2000
ψ_f (Wb)	0.325	p	2
P_n(kW)	1.25	I_N (A)	5

In order to have a clearer view of the steady state performance of the proposed control method (BH-MPCC), this paper compares it with the T-MPCC method, and the THD of the two control methods is shown in Fig. 4.

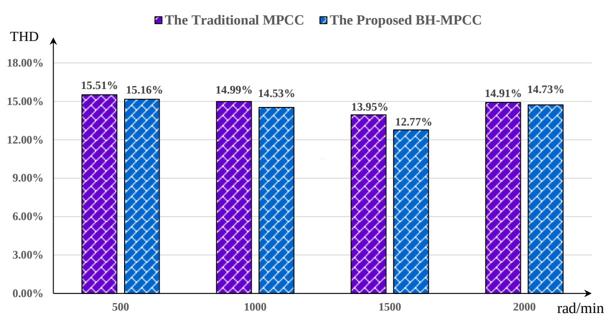
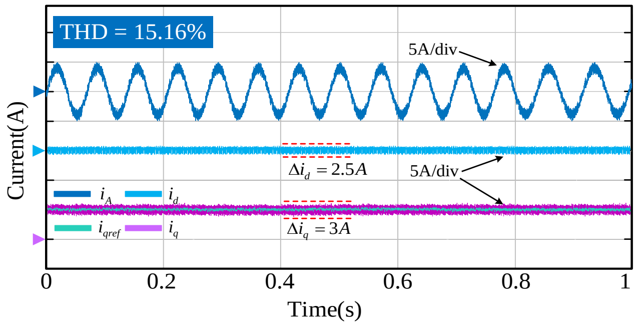
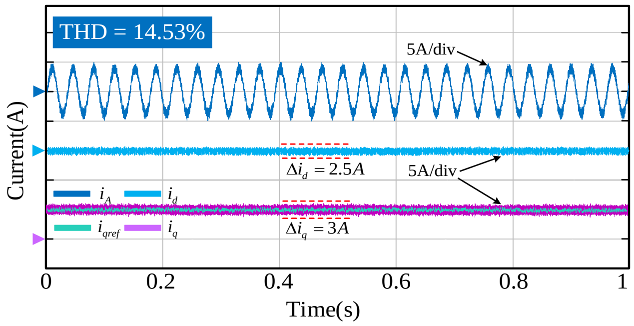


Fig. 4. THD of phase current for T-MPCC method and BH-MPCC method

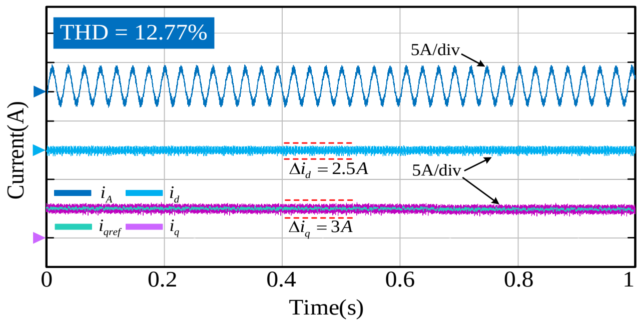
Fig. 5 shows the experimental results of the simulation of the BH-MPCC method at rated load torque with different speed conditions.



(a)



(b)



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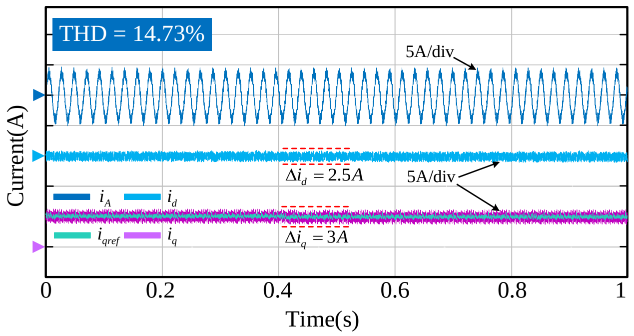

(d)

Fig. 5. Simulation results of BH-MPCC method: (a) at 500rpm and 5N.m rated load torque (b) at 1000rpm and 5N.m rated load torque (c) at 1500rpm and 5N.m rated load torque (d) at 2000rpm and 5N.m rated load torque.

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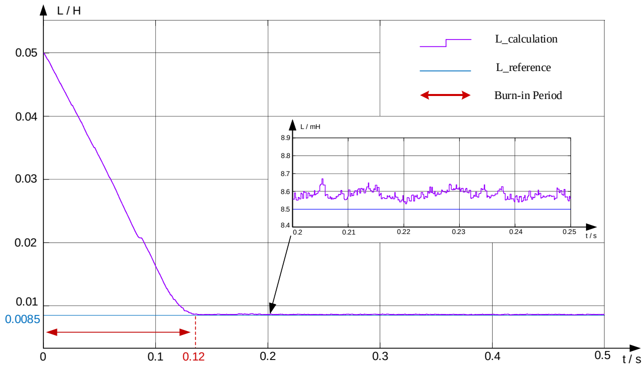
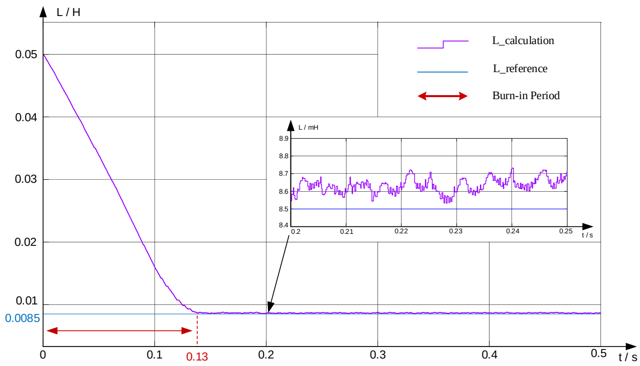
Figure 6 gives the parameter identification process of inductance parameter under rated load torque and different rotational speeds. the initial value of inductance iteration is set to be 0.05H in the simulation experiments, and it converges to the actual inductance parameter of the motor, 0.0085H, after the sample burn-in period. From the simulation results, it can be seen that the error between the inductor identification results and the actual values is very small.



(a)



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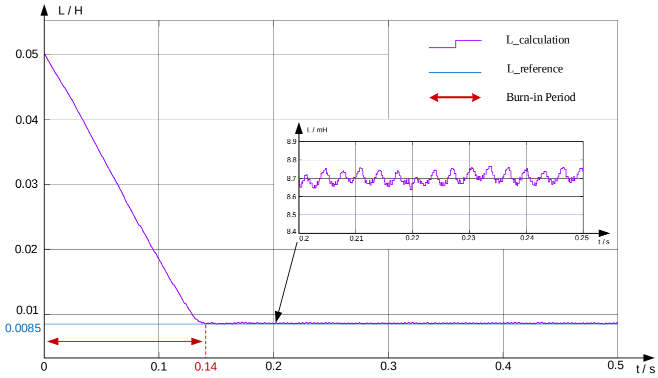

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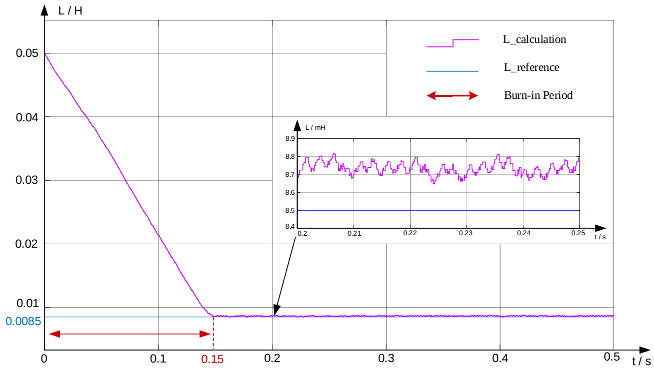

(d)

Fig. 6. Inductive identification process of BH-MPCC method: (a) at 500rpm and 5N.m rated load torque (b) at 1000rpm and 5N.m rated load torque (c) at 1500rpm and 5N.m rated load torque (d) at 2000rpm and 5N.m rated load torque.

5 Conclusion

The main contributions of the BH-MPCC method proposed in this paper are as follows:

(1) A new MPCC method is proposed to realize the accurate control of SPMSM without knowing the motor parameters.

(2) The dependence of the T-MPCC method on motor parameters is effectively reduced, and satisfactory control results are achieved.

(3) By simplifying the *d*-*q*-axis current prediction model, the prediction model of the BH-MPCC method contains only the inductance parameter, and does not need to take into account the effects of resistance and magnetic chain. When a parameter mismatch occurs in the motor, the current prediction model uses only the accurately recognized inductance parameters for prediction, which makes the robustness of the control system significantly improved.

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