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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 prediction current control method on motor parameters, this paper proposes a simplified model prediction current control method based on Bayesian inference, which makes the prediction model structure simpler by reducing the motor parameters in the prediction model. Firstly, the *d*-axis current prediction model is simplified and the *q*-axis current prediction model is incrementally processed to eliminate the influence of the magnetic chain parameter, so that the *dq*-axis current prediction model contains only the only motor parameter, the inductance. The inductor parameters are then accurately identified using Bayesian inference and Metropolis-Hastings sampling algorithm. 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.

I. The Simplified MPCC Method Based on Bayesian Inference

A. Simplification of d-q axis Current Prediction Model

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

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

The T*R/L value of the *dq*-axis current prediction model in Equation 1 is much less than 1, so the neglect of the T*R/L term has no effect on the control effect. In addition, since the magnetic chain parameter is only included in the *q*-axis current prediction model, an incremental current prediction model is introduced in this paper in order to eliminate the influence of the magnetic chain parameter on the prediction model. The model is based on the predicted currents at two different moments, and the difference between the two is made to eliminate the magnetic chain, so as to obtain the incremental current prediction equation. The simplified *dq*-axis current prediction model is shown in Equation 2:

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

B. Inductance Parameter Identification

In this paper, the difference between the actual sampling current and the predicted current in the *d*-axis at moment *k* is used as the observation data and criterion, and the expression of the actual predicted current error in the *d*-axis is given in Eq. 3.

$$E_d(k)=i_{ds}(k)-i_d(k) \tag{3}$$

In Bayesian inference, the prior distribution of the target inductance adopts normal distribution. In addition, the likelihood function of the target inductance is established according to the *d*-axis current error, and the corresponding target posterior distribution can be calculated by applying the Bayesian inference formula. In order to ensure the numerical stability and simplify the calculation, it is necessary to logarithmically transform the target inductance prior distribution, the likelihood function and the posterior distribution, and the results are respectively:

$$\begin{cases} P(L)=-\dfrac{1}{2}\ln(2\pi\sigma_l{}^2)-\dfrac{(L-L_\mu)^2}{2\sigma_l{}^2} \\ P(E_d\mid L)=-\dfrac{1}{2}\ln(2\pi\sigma_s{}^2)-\dfrac{(E_d-E_{d_\mu})^2}{2\sigma_s{}^2} \\ P(L\mid E_d)=-\ln(2\pi\sigma_l\sigma_s)-\dfrac{(L-L_\mu)^2}{2\sigma_l{}^2}-\dfrac{(E_d-E_{d_\mu})^2}{2\sigma_s{}^2} \end{cases} \tag{4}$$

The posterior distribution of the target inductance is sampled by the Metropolis-Hastings sampling algorithm, and a random perturbation is added to the initial inductance L using the symmetric proposed distribution to generate simulated candidate inductances:

$$L_m=L+\lambda\cdot\varepsilon \tag{5}$$

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

$$E_{dm}(k)=i_{dm}(k)-i_d(k) \tag{6}$$

The expression for the probability density of the posterior distribution after taking the logarithm can be calculated from the simulated candidate inductance as Equation 7:

$$P(L_m\mid E_{dm})=-\ln(2\pi\sigma_{l_m}\sigma_{s_m})-\frac{(L_m-L_{\mu_m})^2}{2\sigma_{l_m}{}^2}-\frac{(E_{dm}-E_{d_{\mu m}})^2}{2\sigma_{s_m}{}^2} \tag{7}$$

Acceptance or rejection of the simulated candidate inductive samples is sampled based on their likelihood to be accepted at an acceptance rate:

$$\alpha_{L_m}=\min\left\{1,e^{[P(L_m|E_{d_m})-P(L|E_d)]}\right\} \tag{8}$$

The acceptance rate is compared with a random number generated from 0 to 1. If the random number is less than the acceptance rate, the analogue candidate inductor is accepted, and vice versa, the sample is rejected, keeping the last sampled inductor unchanged. The identification of inductors for the current cycle is done by taking the expected mean value of all inductor samples in a control cycle.

$$L=\frac{1}{N}\sum_{i=1}^{N}L_i \tag{9}$$

The control framework of proposed BH-MPCC method with one-step delay compensation is shown in Fig. 1.

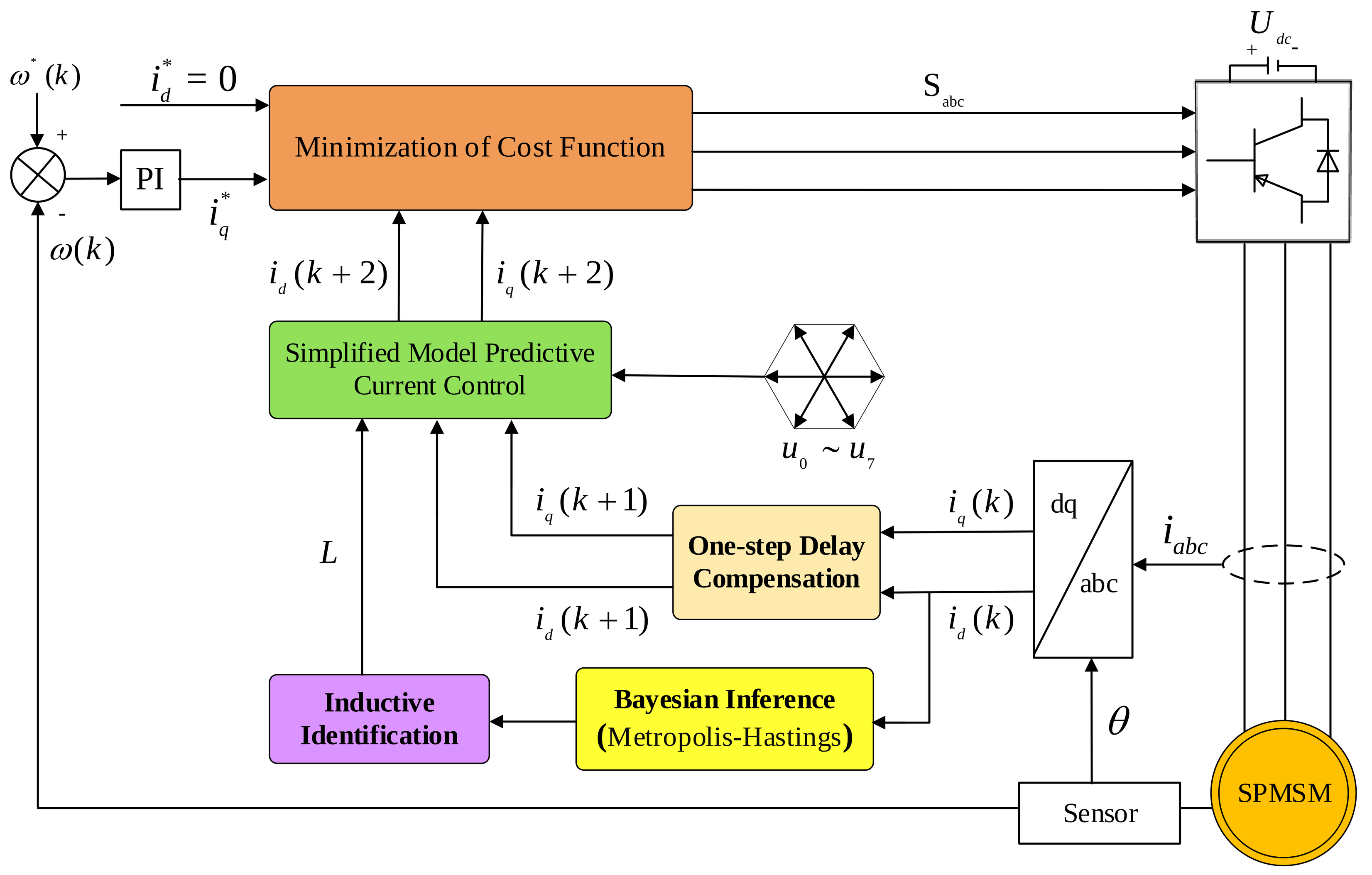

Fig. 1. Control block diagram of the BH-MPCC method

II. Simulation Results

In order to verify the effectiveness of the proposed method, simulation experiments are carried out on MATLAB/Simulink. The control frequency in the simulation experiment is 10kHz.

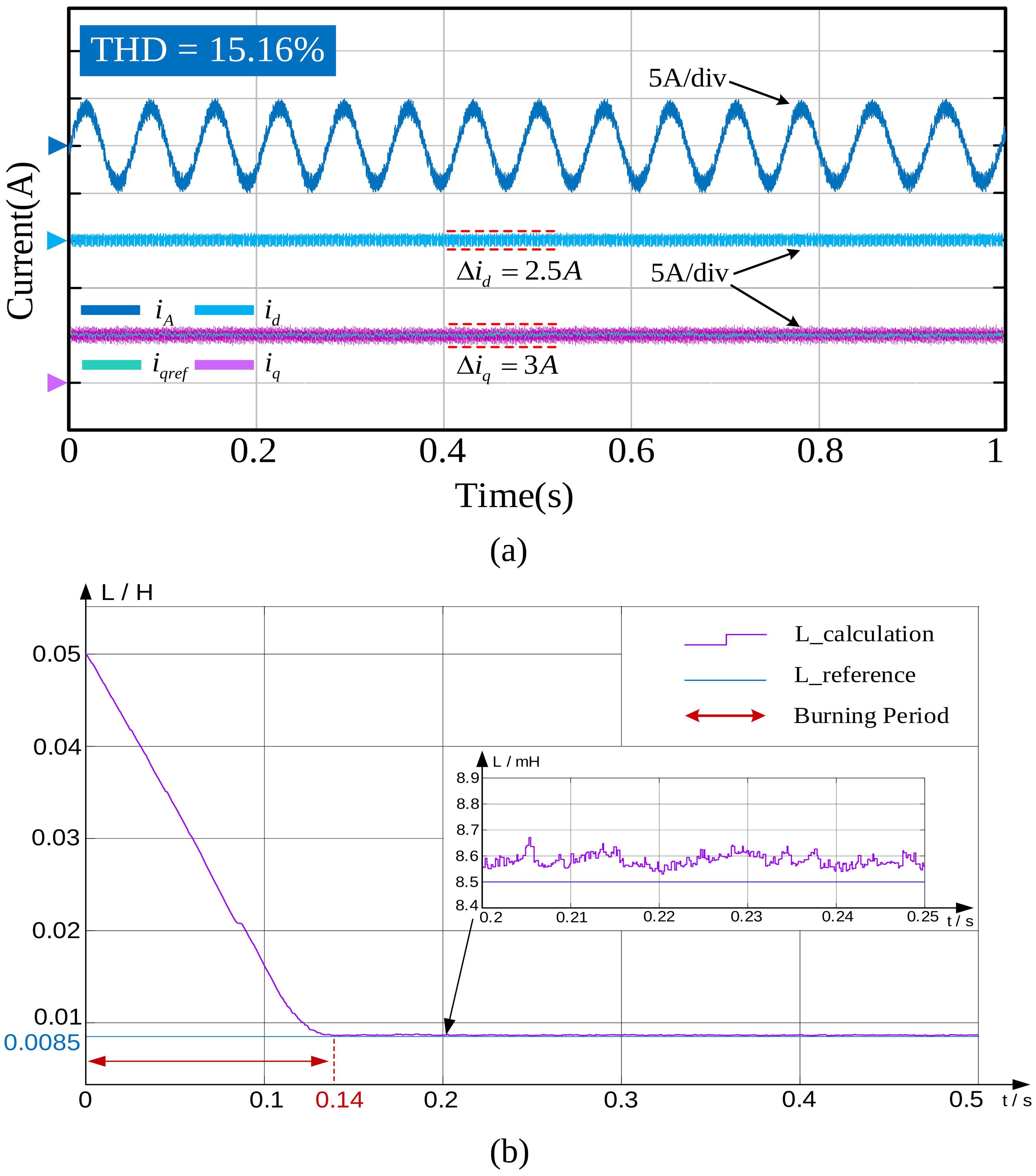

Fig. 3. Simulation results at rated load 5N and speed of 500 r/min: (a) Simulation results of BH-MPCC method; (b) Inductance parameter identification process.

Fig. 3 shows the simulation experimental results of the BH-MPCC method at rated load torque and 500 r/min. Fig. 4 shows the simulation experimental results of the BH-MPCC method at rated load torque and 1500 r/min. In the simulation experiments, the initial value of the inductance iteration is set to 0.05 H, which converges to the actual inductance parameter of the motor after a sample burn-in period of 0.0085 H. From the simulation results, it can be seen that the error between the inductance identification results and the actual values is very small.

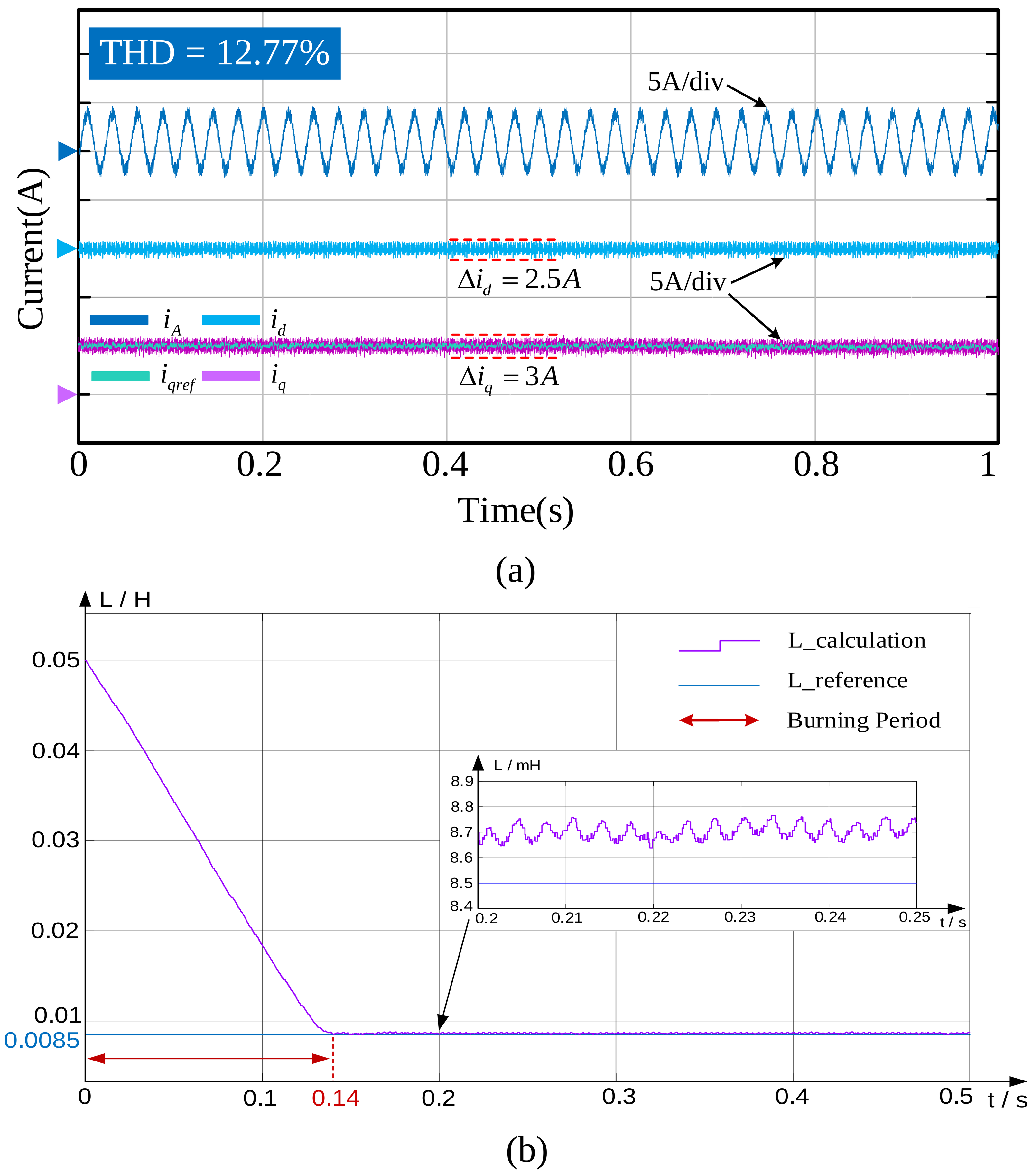

Fig. 4. Simulation results at rated load 5N and speed of 1500 r/min: (a) Simulation results of BH-MPCC method; (b) Inductance parameter identification process.

The simulation compares the total harmonic distortion（THD）of phase currents between the conventional MPCC method and the BH-MPCC method at 500r/min to 2000r/min with a rated load of 5N.m. The results are shown in Fig. 5:

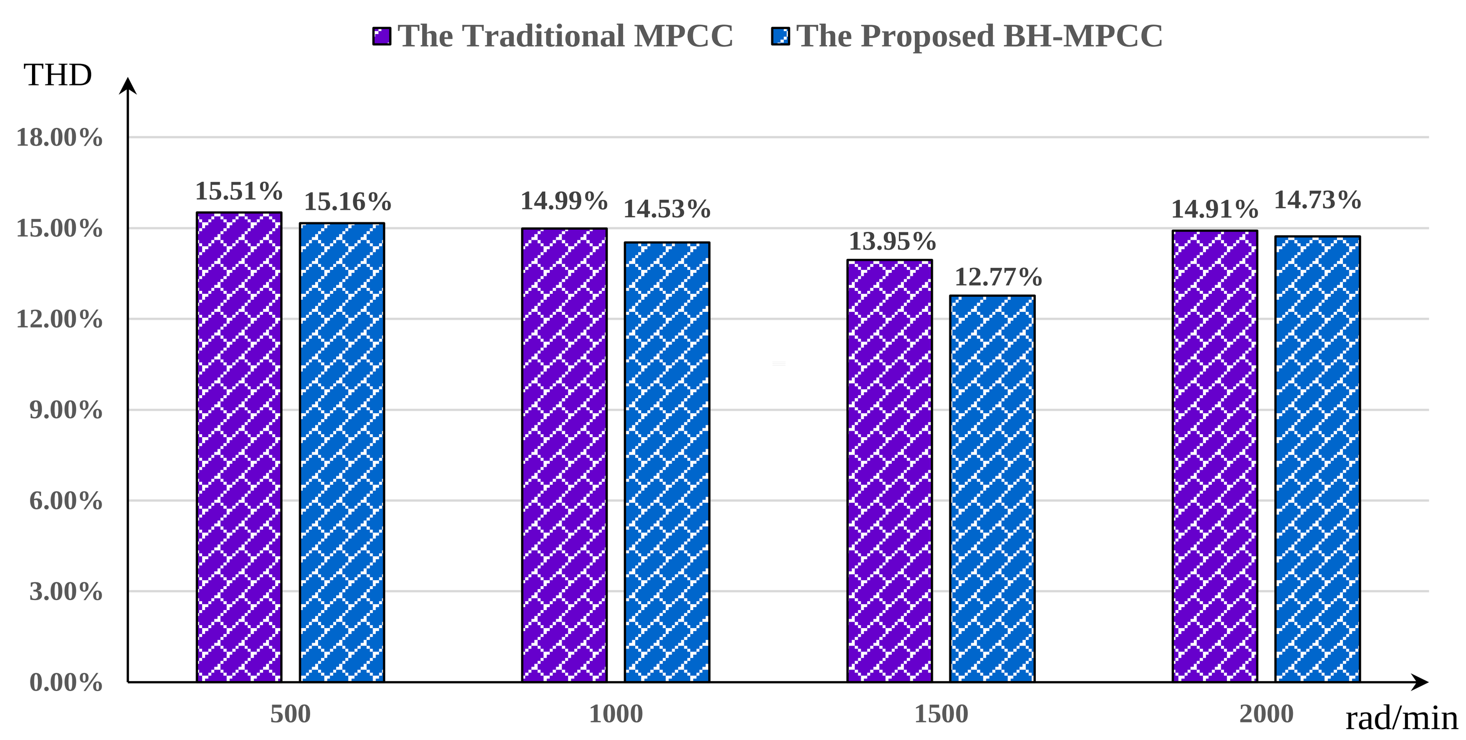

Fig. 5. Histogram of total harmonic distortion of phase current for conventional MPCC method and proposed BH-MPCC method

III. 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 *dq*-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.