

Article

Online Parameter Identification of PMSM for Hybrid Locomotive Based on FFRLS

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Abstract

Permanent magnet synchronous motors (PMSMs) used in hybrid shunting locomotive traction systems operate under complex conditions, and their electrical parameters may vary with temperature rise, load disturbance and magnetic saturation. To improve online parameter tracking under such conditions, this paper investigates a forgetting-factor recursive least squares (FFRLS)-based identification method for stator resistance, stator inductance and permanent magnet flux linkage. The main contribution lies in the traction-oriented formulation of the identification model, DSP28335-based real-time implementation, and simulation/experimental validation of three-parameter online tracking. Simulation results show that the proposed method can track the three key parameters under selected perturbation conditions. The experimental results provide algorithm-level evidence for the real-time implementation and three-parameter tracking capability of the proposed method on a scaled-down PMSM platform, thereby establishing a basis for subsequent full-scale validation and studies on traction-control robustness and energy-efficiency optimization.

Keywords: hybrid shunting locomotive; online parameter identification; permanent magnet synchronous motor; recursive least squares with forgetting factors

1. Introduction

The Permanent magnet synchronous motor (PMSM) is a kind of synchronous motor that uses permanent magnets to establish the excitation magnetic field. It has the characteristics of a simple structure, high power density and high reliability [1,2], and has been widely used in the traction system of rail transit. The traction motors of hybrid shunting locomotives usually have a higher rated power and operate for long periods under low-speed, high-torque and frequent start–stop conditions, which places higher demands on the robustness and stability of the control system [3]. Nowadays, most PMSM non-inductive algorithms are highly dependent on motor parameters. However, in actual locomotive traction applications, inaccurate acquisition of motor parameters will directly lead to a decline in the performance of the motor drive system, thereby affecting the operational efficiency and energy consumption level of the locomotive. Therefore, in order to ensure the traction performance and control effect of hybrid shunting locomotives under complex working conditions, it is necessary to identify the key parameters of PMSMs.

At present, the parameter identification methods of PMSMs are mainly divided into two categories: offline parameter identification and online parameter identification.

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Among these, offline parameter identification refers to the method of estimating the motor parameters based on the motor model by collecting the output signal given the input signal when testing the motor on a bench. Online identification involves the real-time collection of signals such as voltage and current during the actual operation of the motor, and parameter estimation through control algorithms. Due to the fact that the parameters of PMSM change dynamically with factors such as temperature and electromagnetic saturation during actual operation, relying solely on offline identification is insufficient to ensure control accuracy. Therefore, online parameter identification has become an important way to guarantee the traction performance of hybrid locomotives.

The PMSM parameters that commonly need online identification include stator resistance, stator inductance and permanent magnet flux linkage. Existing online identification methods mainly include the model reference adaptive system (MRAS) [4–7], conventional least squares (LS) [8–11], recursive least squares (RLS) [12,13], FFRLS, extended Kalman filter (EKF) [14], adaptive observers, signal-injection methods and data-driven algorithms [15–17]. These methods differ in online tracking ability, computational burden, sensitivity to model mismatch and suitability for traction PMSM controllers. Compared with batch LS, FFRLS avoids repeated matrix inversion over all historical samples. Compared with conventional RLS, the forgetting factor improves tracking of slowly time-varying parameters. Compared with EKF and data-driven methods, FFRLS has lower computational and tuning burden, which is beneficial for DSP implementation [18,19]. A method-level comparison is summarized in Table 1.

Table 1. Comparison of representative PMSM parameter-identification methods.

Method	Advantages	Limitations	Applicability to Traction PMSM
Conventional LS	Simple structure and easy implementation	Requires batch data and cannot update recursively	Useful offline baseline; less suitable for online tracking
Conventional RLS	Low computation and easy embedded implementation	Tracking of time-varying parameters is slow	Important baseline; equivalent to $\alpha=1$ in FFRLS
FFRLS	Better tracking of slowly varying parameters	Small forgetting factor may amplify noise	Suitable for real-time DSP-based PMSM identification
EKF	Handles nonlinear models and noise	Higher computation and covariance tuning burden	Feasible but less attractive for low-cost DSP implementation
MRAS/adaptive observer	Combines state and parameter estimation	Sensitive to model mismatch and gain tuning	Useful for sensorless control; application-dependent tuning
Signal injection	Improves low-speed observability	May introduce torque ripple and noise	Useful in specific regimes; less suitable for continuous traction
Data-driven method	Models nonlinearities from data	Requires representative training data	Promising, but validation burden is high

Therefore, the main contribution of this paper is clarified as follows: (1) a traction-oriented FFRLS identification model is organized for online tracking of stator resistance, equivalent stator inductance and permanent magnet flux linkage under the operating background of a hybrid shunting locomotive; (2) the exact scalar regressors used for the three identified parameters, the forgetting factor, initial covariance matrix, sampling time and preprocessing strategy are specified to improve reproducibility; (3) a DSP28335-based 7.5 kW PMSM platform is used to provide algorithm-level experimental validation of the real-time implementation and online tracking of the three parameters under a scaled-down PMSM vector-control structure.

2. The Mathematical Model of PMSM

This study focuses on the traction system of a hybrid shunting locomotive modified from the GK1-type locomotive, with the PMSM taken as the research object. The identification model is established in the two-phase rotating dq reference frame. To make the estimator suitable for embedded online implementation, an equivalent non-salient PMSM model is adopted, in which the d-axis and q-axis inductances are represented by a single equivalent stator inductance. Magnetic saturation, iron loss, cross-saturation and inverter nonlinearities are not explicitly included in the regression model, but are treated as sources of modeling and experimental uncertainty. These assumptions reduce the computational burden of the online estimator, while they may also increase steady-state identification errors. Based on these assumptions, the PMSM voltage equations are expressed as follows:

$$\begin{cases} u_d = Ri_d + L \frac{di_d}{dt} - \omega_e Li_q \\ u_q = Ri_q + L \frac{di_q}{dt} + \omega_e (Li_d + \psi_f) \end{cases}, \quad (1)$$

where R is the stator resistance of the PMSM; L is the stator inductance; ψ_f is the permanent magnet flux linkage; ω_e is the electric angular velocity; u_d and u_q are the dq axial components of the stator voltage; and i_d and i_q are the dq axial components of the stator current.

For experimental verification, a 7.5 kW PMSM test platform is used to evaluate the real-time implementation of the proposed identification algorithm. The platform adopts the same vector-control framework and dq-axis modeling basis as the locomotive traction application, and its rated speed is close to the equivalent rated speed of the traction PMSM. Therefore, it is suitable for verifying the embedded implementation process and the parameter-tracking behavior of the algorithm. However, the reduction in rated power and torque does not guarantee full electromagnetic, thermal or mechanical similarity with the 300 kW traction PMSM. In particular, thermal time constants, saturation characteristics, cooling conditions and long-duration load profiles may differ significantly between the laboratory platform and the full-scale traction motor. Therefore, the experimental results constitute algorithm-level validation on a scaled-down platform rather than full-scale validation of the 300 kW traction PMSM. The relevant parameters are shown in Table 2.

Table 2. Parameter comparison between the experimental PMSM and the locomotive traction PMSM.

Item	Experimental PMSM	Hybrid Locomotive PMSM
motor type/specification	TZQ180-7.5-72B01-X	Equivalent 300 kW locomotive traction PMSM
rated DC voltage	72 V	720 V
rated power	7.5 kW	300 kW
power scaling ratio	1	40
rated torque	23.8 N·m	952 N·m
torque scaling ratio	1	40
equivalent rated speed	≈3000 r/min	≈3000 r/min

3. Online Parameter Identification Based on FFRLS

3.1. Overview of FFRLS

RLS evolved from the least squares method. Its fundamental principle is to minimize the sum of the squares of the errors between the estimated value and the actual value, thereby achieving a state where the estimated value is closest to the actual value. The least squares method is easy to implement. However, as the sampling data keeps increasing, it will lead to a sudden increase in the amount of computation. To address this issue, relevant researchers have improved and proposed RLS. Here, a linear system is assumed to be

$$y = \varphi_1 \theta_1 + \varphi_2 \theta_2 + \cdots + \varphi_n \theta_n + e, \quad (2)$$

where $\theta = [\theta_1 \ \theta_2 \ \cdots \ \theta_n]^T$ is the parameter to be identified; e is the measurement of the noise signal; y is the input; and $\Phi = [\varphi_1 \ \varphi_2 \ \cdots \ \varphi_n]$ is the output. In order to obtain the optimal estimate $\hat{\theta}$ satisfying (2), the number of measured data $m \geq n$, and $\hat{\theta}$ should minimize $\sum \|y(m) - \Phi(m)\hat{\theta}\|^2$. The error vector is defined as

$$\varepsilon = Y - \Phi \hat{\theta}, \quad (3)$$

where $\varepsilon = [\varepsilon(1) \ \varepsilon(2) \ \cdots \ \varepsilon(m)]^T$; $Y = [y(1) \ y(2) \ \cdots \ y(m)]^T$; $\Phi = [\varphi_1(1) \cdots \varphi_n(1) \ \varphi_1(2) \cdots \varphi_n(2) \ \cdots \ \varphi_1(m) \cdots \varphi_n(m)]^T$; and $\hat{\theta} = [\hat{\theta}_1 \ \hat{\theta}_2 \ \cdots \ \hat{\theta}_n]^T$. The selection of criterion functions is as follows:

$$J = \sum_{i=1}^m \varepsilon_i^2 = \varepsilon^T \varepsilon, \quad (4)$$

By substituting (3) into (4), we get

$$J = (Y - \Phi \hat{\theta})^T (Y - \Phi \hat{\theta}) = Y^T Y - \hat{\theta}^T \Phi^T Y - Y^T \Phi \hat{\theta} + \hat{\theta}^T \Phi^T \Phi \hat{\theta}, \quad (5)$$

Differentiating J from $\hat{\theta}$ results in 0:

$$\left. \frac{\partial J}{\partial \hat{\theta}} \right|_{\hat{\theta}=\hat{\theta}} = -2\Phi^T Y + 2\Phi^T \Phi \hat{\theta} = 0, \quad (6)$$

The best estimate of the parameters to be identified is obtained by

$$\hat{\theta}(m) = (\Phi^T \Phi)^{-1} \Phi^T Y, \quad (7)$$

Since (7) requires matrix inversion operation and occupies operation resources, the recursive calculation method can be improved. The following matrix is defined:

$$P(m) = (\Phi^T \Phi)^{-1}, \quad (8)$$

Expanding, we get

$$P(m) = [P^{-1}(m-1) + \Phi^T(m)\Phi(m)]^{-1}, \quad (9)$$

The inversion formula is expressed as

$$(A + BCD)^{-1} = A^{-1} - A^{-1}B(C^{-1} + DA^{-1}B)^{-1}DA^{-1}, \quad (10)$$

According to (10), we can convert (9) to

$$P(m) = P(m-1) - \frac{P(m-1)\Phi^T(m)\Phi(m)P(m-1)}{1 + \Phi(m)P(m-1)\Phi^T(m)}, \quad (11)$$

By substituting (11) into (7), we get

$$\hat{\theta}(m) = \hat{\theta}(m-1) + P(m)\Phi^T(m)[y(m) - \Phi(m)\hat{\theta}(m-1)], \quad (12)$$

At this point, the relevant calculation formula of RLS is obtained:

$$\begin{cases} \hat{\boldsymbol{\theta}}(m) = \hat{\boldsymbol{\theta}}(m-1) + \mathbf{K}(m) [y(m) - \boldsymbol{\phi}(m) \hat{\boldsymbol{\theta}}(m-1)] \\ \mathbf{K}(m) = \frac{\mathbf{P}(m-1) \boldsymbol{\phi}^T(m)}{1 + \boldsymbol{\phi}(m) \mathbf{P}(m-1) \boldsymbol{\phi}^T(m)} \\ \mathbf{P}(m) = [\mathbf{I} - \mathbf{K}(m) \boldsymbol{\phi}(m)] \mathbf{P}(m-1) \end{cases} \quad (13)$$

For conventional RLS, all historical samples are assigned the same weight in the accumulated squared-error criterion. After introducing the forgetting factor α , the cost function is changed into an exponentially weighted least-squares criterion:

$$J = \sum_{i=1}^m \alpha^{m-i} [y(i) - \boldsymbol{\phi}(i) \boldsymbol{\theta}]^2, 0 < \alpha \leq 1, \quad (14)$$

When $\alpha = 1$, all historical samples have the same weight, and the above expression becomes the conventional RLS criterion. When $\alpha < 1$, the weight of the i -th historical sample is α^{m-i} . Therefore, the newest sample has the weight $\alpha^0 = 1$, while older samples have the weights α , α^2 , α^3 , and so on. Since $0 < \alpha < 1$, the influence of older samples gradually decreases. Therefore, the estimator depends more strongly on recent data than conventional RLS.

The same weighting mechanism also explains the cost of using the forgetting factor. A smaller α means that historical data are forgotten faster, so the estimator has a shorter effective memory. This improves tracking speed, but weakens the averaging effect on measurement noise. As a result, a smaller α may increase steady-state fluctuation and reduce numerical robustness. Therefore, FFRLS does not always outperform conventional RLS. When the identified parameters are nearly constant and measurement noise is dominant, conventional RLS, corresponding to $\alpha = 1$, can provide smoother and more stable estimates. For this reason, conventional RLS remains an important baseline for parameter identification. To evaluate the sensitivity of the estimator to the forgetting factor, simulations were conducted with α varying from 0.95 to 1.00, while the motor parameters, operating condition, sampling period, initial covariance matrix and measurement-noise setting were kept unchanged. The results of the sensitivity analysis of the forgetting factor and the comparison with conventional RLS are presented in Table 3.

Table 3. Sensitivity analysis of the forgetting factor and comparison with conventional RLS.

Forgetting Factor	Convergence Time	Steady-State Error	Noise Fluctuation STD
0.95	0.18 s	7.8%	3.6%
0.96	0.21 s	6.8%	3.0%
0.97	0.24 s	6.1%	2.4%
0.98	0.31 s	5.6%	1.6%
0.99	0.46 s	5.3%	0.9%
1.00	0.72 s	6.9%	0.5%

The sensitivity analysis indicates that decreasing α improves convergence speed because recent samples receive larger weights, but it also increases noise-induced fluctuation. The case $\alpha = 1.00$ corresponds to conventional RLS without exponential forgetting and therefore provides a direct baseline under the same tested condition. Compared with conventional RLS, the selected FFRLS setting with $\alpha = 0.98$ reduces the convergence time from 0.72 s to 0.31 s and decreases the steady-state error from 6.9% to 5.6%, although the noise-fluctuation standard deviation increases from 0.5% to 1.6%. It should also be noted that, despite producing the smallest noise fluctuation, conventional RLS retains all historical data and consequently responds more slowly to parameter variations. This weaker

tracking capability explains why $\alpha = 1.00$ produces a higher steady-state error than $\alpha = 0.99$ under the tested time-varying condition. These results demonstrate that the forgetting factor improves parameter-variation tracking at the cost of increased noise sensitivity. Therefore, $\alpha = 0.98$ is selected as a balanced compromise among convergence speed, steady-state accuracy and noise robustness.

The selection of FFRLS for J is as follows:

$$J(m) = \alpha J(m-1) + [y(m) - \Phi(m)\hat{\theta}(m-1)]^2, \quad (15)$$

At this point, the relevant calculation formula of FFRLS is obtained:

$$\begin{cases} \hat{\theta}(m) = \hat{\theta}(m-1) + \mathbf{K}(m)[y(m) - \Phi(m)\hat{\theta}(m-1)] \\ \mathbf{K}(m) = \frac{\mathbf{P}(m-1)\Phi^T(m)}{\alpha + \Phi(m)\mathbf{P}(m-1)\Phi^T(m)} \\ \mathbf{P}(m) = \frac{1}{\alpha}[\mathbf{I} - \mathbf{K}(m)\Phi(m)]\mathbf{P}(m-1) \end{cases}, \quad (16)$$

Before performing FFRLS, the initial values of $\hat{\theta}$, $\mathbf{P}$, $\hat{\theta}(0)$ and $\mathbf{P}(0)$ are also determined, usually so that

$$\begin{cases} \hat{\theta}(0) = 0 \\ \mathbf{P}(0) = c\mathbf{I} \end{cases}, \quad c > 0, \quad (17)$$

where the value of c ranges from 104 to 1010.

In the experiment, the initial conditions are set as $\hat{\theta}(0) = 0$ and $\mathbf{P}(0) = c\mathbf{I}$ with $c = 10^6$. The forgetting factor is $\alpha = 0.98$, and the sampling period is 200 μs , corresponding to the 5 kHz PWM switching and current-loop sampling frequency of the DSP28335 platform. The FFRLS routine uses the controller-processed dq-axis currents, reconstructed dq-axis voltages and encoder-based speed signal as input variables. The controller interface includes signal-conditioning parameters for the sine/cosine magnetic encoder and the current/speed loops; therefore, the estimator uses the same preprocessed signals as the vector-control system. Rotor position and speed are obtained from the sine/cosine magnetic encoder, and the estimator is embedded into the existing vector-control loop. Since each regression model is scalar, the online computation mainly consists of gain calculation, parameter updating and covariance updating, which is suitable for real-time execution on the DSP28335 controller.

For reproducibility, each estimator is expressed in the scalar regression form $y(m) = \Phi(m)\theta$. The discrete output $y(m)$ and regressor $\Phi(m)$ used for stator resistance, stator inductance and permanent-magnet flux linkage are given in Equations (19), (20) and (21), respectively. In the implementation, the resistance estimator is constructed from the q-axis voltage residual, the inductance estimator from the d-axis voltage residual, and the flux-linkage estimator from the q-axis back-EMF residual. Current-difference terms are calculated from the preprocessed current samples. This scalar implementation reduces computational burden compared with a full vector estimator, while allowing the three parameters to be updated online.

PMSM is based on FFRLS online parameter identification, and its theoretical implementation steps are shown in Figure 1:

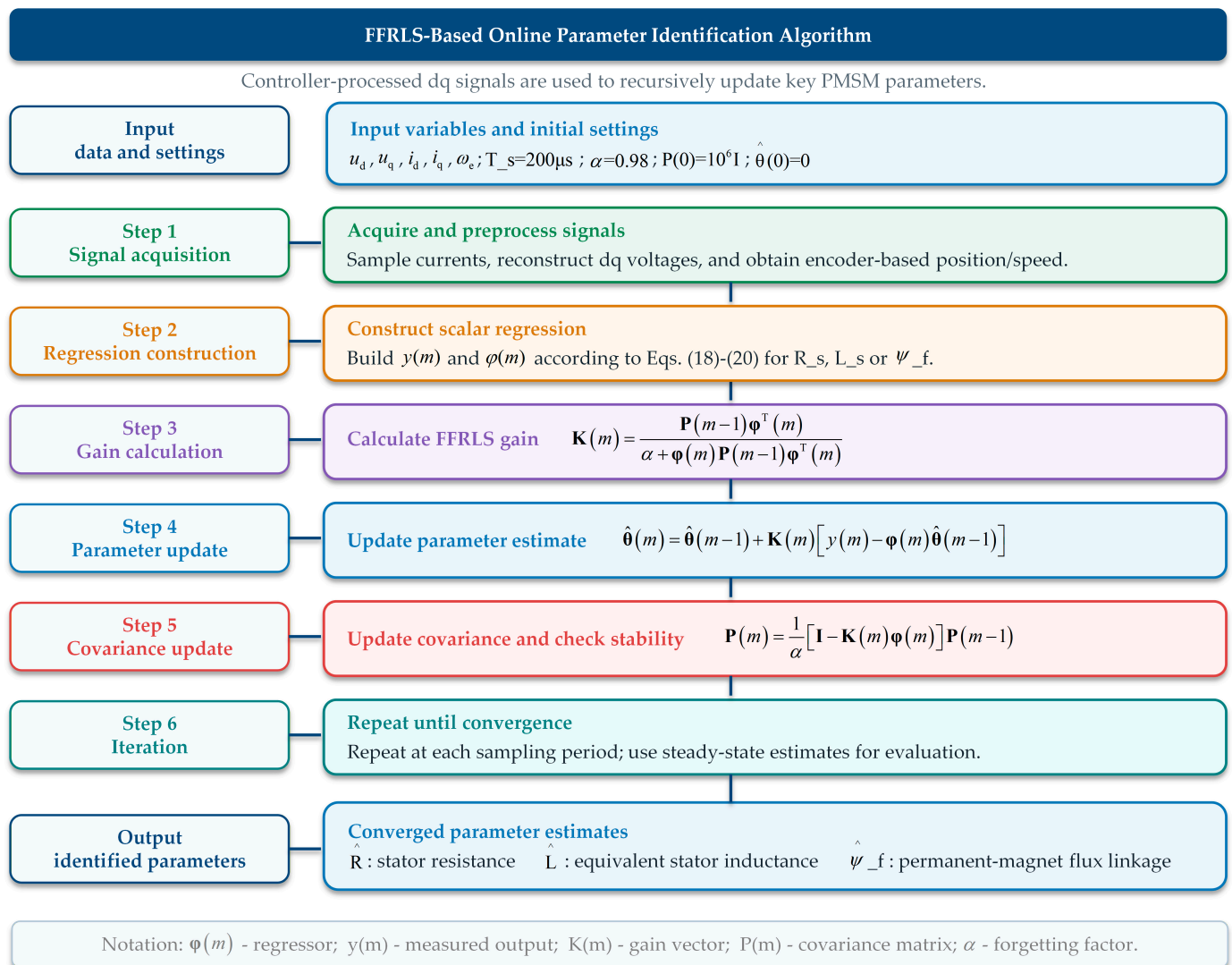


Figure 1. Flowchart of the FFRLS-based online parameter-identification algorithm.

3.2. Online Identification of Stator Resistance Based on FFRLS

The stator resistance of the locomotive varies significantly with temperature under the long-term high-current operation condition. Therefore, its online identification is particularly crucial for ensuring the accuracy and efficiency of torque output. Combining Equation (1) and rewriting,

$$\begin{cases} u_d = Ri_d + L \frac{di_d}{dt} - \hat{\omega}_e Li_q \\ u_q = Ri_q + L \frac{di_q}{dt} + \hat{\omega}_e (Li_d + \psi_f) \end{cases} \quad (18)$$

where $\hat{\omega}_e$ is the estimated value of the electrical angular velocity. According to (18), when R is the identification parameter of the PMSM, the R identification model based on FFRLS can be obtained through discretization processing:

$$\begin{cases} \theta = R \\ y(m) = u_q(m) - L \frac{i_q(m) - i_q(m-1)}{T_s} - \hat{\omega}_e Li_d(m) - \hat{\omega}_e \psi_f \\ \varphi(m) = i_q(m) \end{cases} \quad (19)$$

3.3. Online Identification of Stator Inductance Based on FFRLS

According to (18), the stator inductance identification model based on FFRLS can be obtained similarly. Compared with stator resistance, inductance estimation is more sensitive to voltage reconstruction error, current derivative information, magnetic saturation and current excitation level.

The reliability of the inductance estimate is closely related to the persistence of excitation of the corresponding regression signal. Unlike resistance identification, which benefits from the current information under load variation, and flux-linkage identification, which benefits from the speed-dependent back-EMF term, inductance identification depends strongly on current variation and current-difference terms. During no-load start-up or near-steady-current operation, the inductance-related regressor contains limited dynamic information and therefore provides relatively weak excitation. Under such conditions, voltage reconstruction errors and current-sampling noise account for a larger proportion of the regression output, leading to reduced observability and a larger inductance-estimation deviation.

$$\begin{cases} \theta = L \\ y(m) = u_d(m) - Ri_d(m) - \hat{L} \frac{i_d(m) - i_d(m-1)}{T_s} \\ \varphi(m) = -\hat{\omega}_e i_q(m) \end{cases}, \quad (20)$$

3.4. Online Identification of Permanent Magnet Flux Linkage Based on FFRLS

Long-term operation of locomotive motors can cause the permanent magnet flux chains to be affected by temperature and demagnetization effects, so real-time tracking is necessary. According to (18), the ψ_f identification model based on FFRLS can be obtained similarly:

$$\begin{cases} \theta = \psi_f \\ y(m) = u_q(m) - Ri_q(m) - L \frac{i_q(m) - i_q(m-1)}{T_s} - \hat{\omega}_e Li_d(m) \\ \varphi(m) = \hat{\omega}_e \end{cases}, \quad (21)$$

When stator resistance, stator inductance and permanent magnet flux linkage are updated online, parameter coupling and observability limitations should be considered. Reliable convergence requires sufficient excitation in the measured voltage, current and speed signals. Under low-speed, constant-load or near-steady-current operation, the regression information becomes weak, and the inductance estimate is more susceptible to current noise, voltage reconstruction error and magnetic saturation. Therefore, the simulation and experimental results are interpreted with these coupling and observability limitations in mind.

4. Simulation Implementation

In order to verify the identification effect of FFRLS under PMSM vector-control conditions, this chapter builds the simulation model shown in Figure 2 in MATLAB according to (18)–(20).

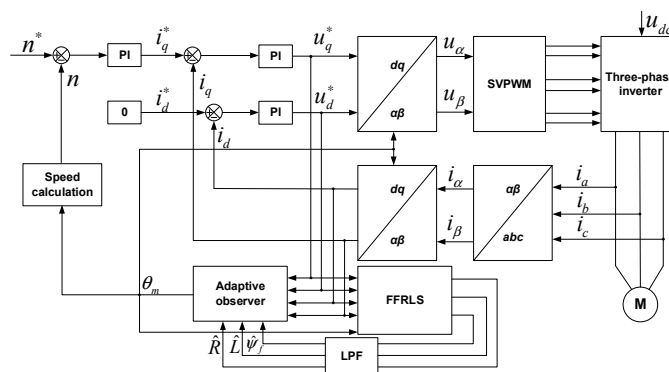


Figure 2. Schematic diagram of PMSM online parameter recognition.

The reference speed is set to 1500 r/min, which corresponds to 50% of the rated speed. This medium-speed operating point provides a stable operating region for observing estimator convergence while avoiding low-speed weak back-EMF effects and high-speed field-weakening or voltage-limitation effects. The identification accuracy of FFRLS is simulated and analyzed according to stator resistance perturbation, stator inductance perturbation and permanent magnet flux linkage perturbation. The forgetting factor is $\alpha = 0.98$, and the specific parameters are shown in Table 4.

Table 4. Simulation parameters for PMSM control system.

Parameter	Parameter Definition	Parameter Value
u_{dc}	DC bus voltage	72 V
P_N	rated power	7.5 kW
T_L	rated torque	23.8 N·m
R	stator resistance	0.009 Ω
L	stator inductance	0.065 mH
ψ_f	Permanent magnet flux linkage	0.05 Wb

4.1. Stator Resistance Perturbation Condition

The simulation conditions are as follows: reference speed, 1500 r/min; no-load start. The stator resistance was stepped from 0.3 s to 120% of the original value to simulate the working condition where the stator resistance changes due to temperature rise during the long-term traction operation of the locomotive.

The simulation results are shown in Figure 3. Before the resistance step, the estimated values converge close to the nominal values. After the resistance step, the estimated resistance responds and finally converges to 0.0118 Ω . Compared with the actual value of 0.0108 Ω , the steady-state error is approximately 9.3%. The estimated inductance and flux linkage remain nearly unchanged, indicating limited coupling from the resistance perturbation under this simulated condition.

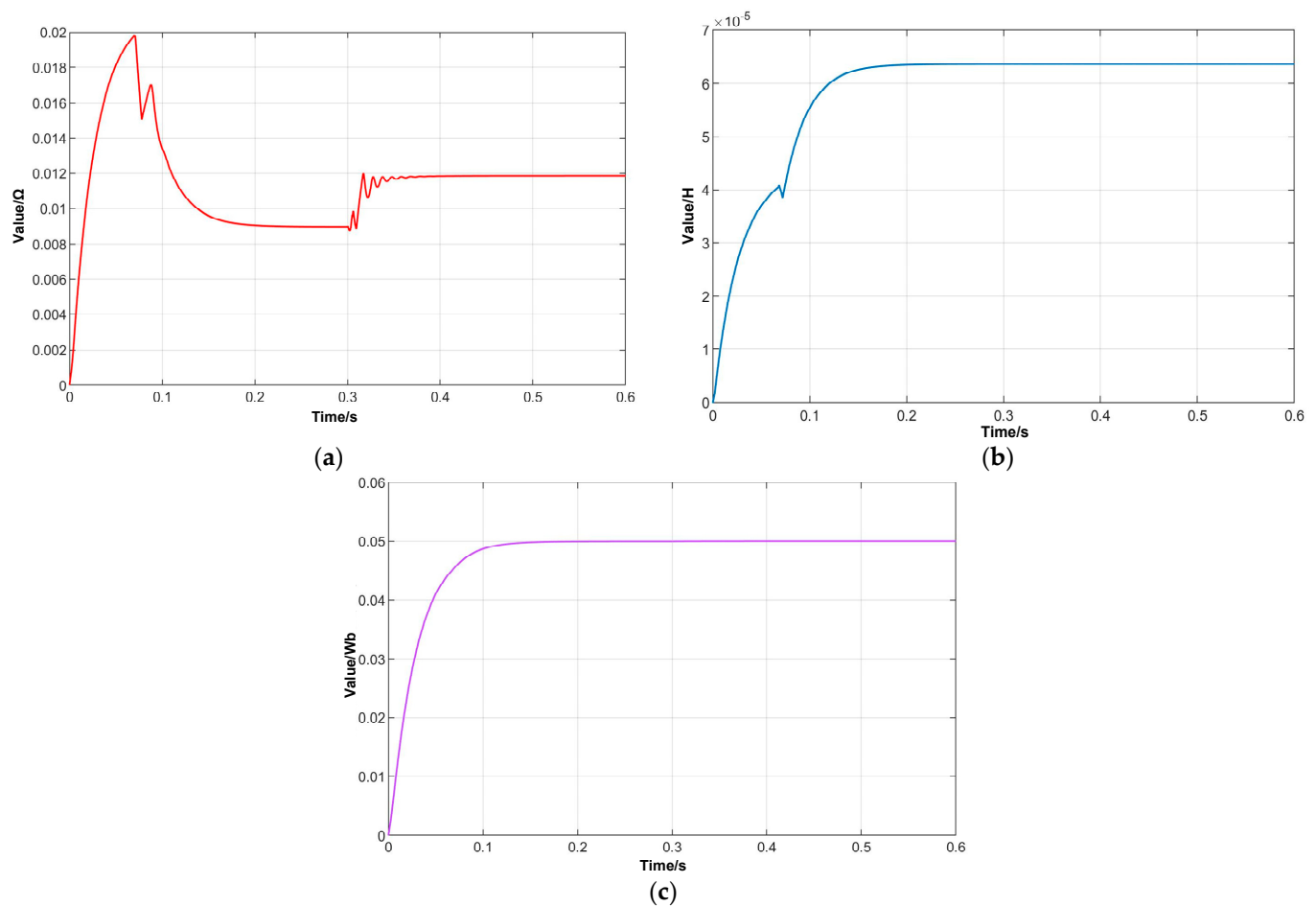


Figure 3. (a) Estimated stator resistance; (b) estimated stator inductance; (c) estimated flux linkage of permanent magnet.

4.2. Stator Inductance Perturbation Condition

The simulation conditions are as follows: reference speed, 1500 r/min; no-load start. The stator inductance was stepped from 0.3 s to 80% of the original value to simulate the nonlinear variation in the inductance of the traction motor under different loads and weak magnetic operation intervals.

The simulation results are shown in Figure 4. Before the inductance step, the estimated values converge close to the nominal values. After the inductance step, the estimated inductance changes from the nominal level and finally converges to about 0.062 mH. Compared with the actual stepped value of 0.052 mH, the steady-state error is approximately 19.2%. This indicates that inductance estimation is less accurate than resistance and flux-linkage estimation under the present excitation condition. This result is consistent with the persistence-of-excitation analysis in Section 3.3, because the near-steady-current operating condition provides less dynamic information for the inductance-related regressor.

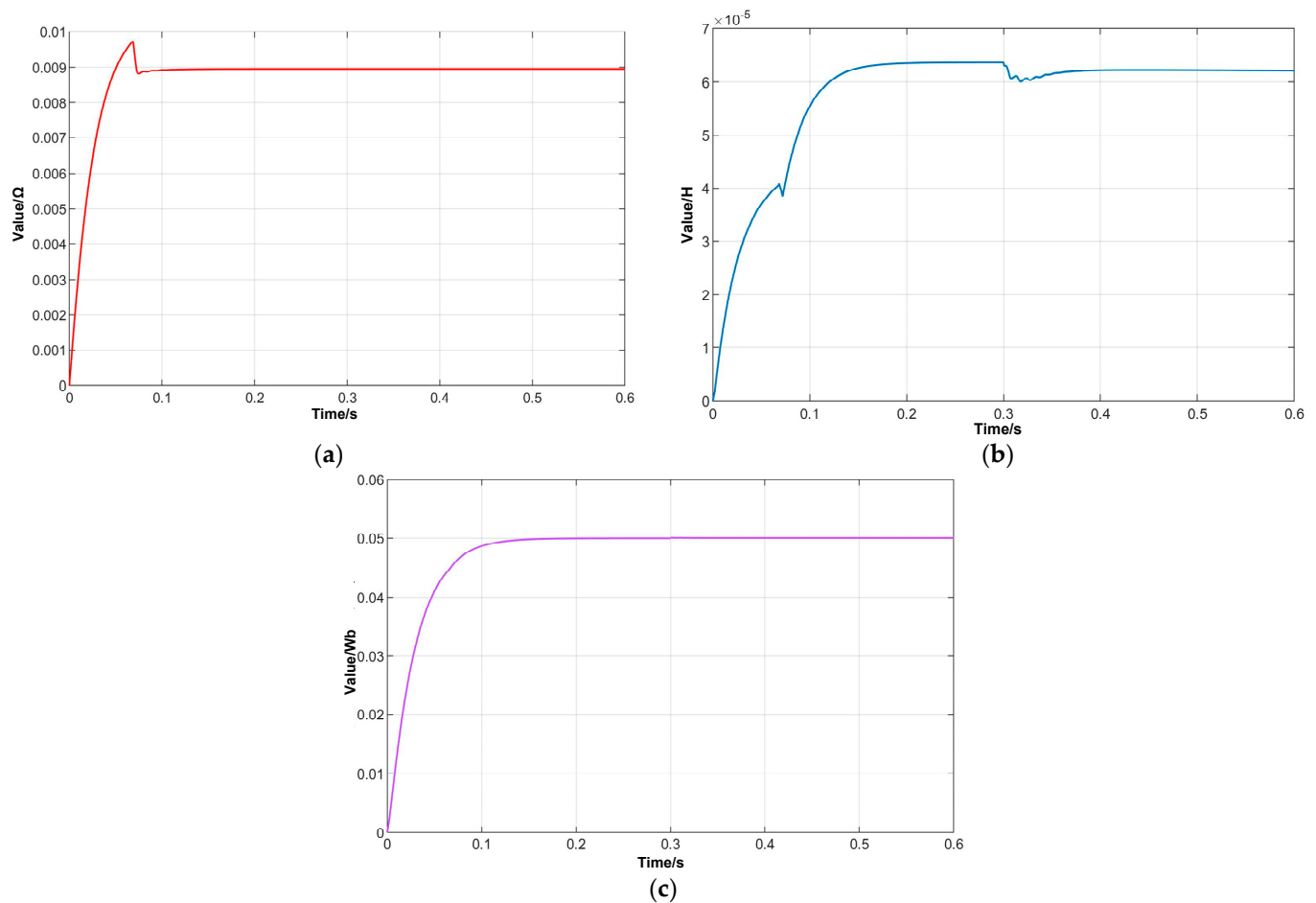


Figure 4. (a) Estimated stator resistance; (b) estimated stator inductance; (c) estimated flux linkage of permanent magnet.

4.3. Permanent Magnet Flux Linkage Perturbation Condition

The simulation conditions are as follows: reference speed, 1500 r/min; no-load start. The flux link of the permanent magnet was jumped to 80% of the original value in 0.3 s to simulate the flux link attenuation condition of the locomotive traction motor due to temperature rise or partial demagnetization during long-term operation.

The simulation results are shown in Figure 5. Before the flux-linkage step, the estimated values converge close to the nominal values. After the permanent magnet flux linkage is stepped to 80% of the original value, the estimated value responds quickly and eventually converges to 0.0401 Wb. Compared with the actual value of 0.0400 Wb, the steady-state error is approximately 0.2%. The resistance and inductance estimates remain almost unchanged, showing small coupling from the flux-linkage perturbation in this simulation.

Based on the simulation results, the FFRLS estimator can effectively track stator resistance and permanent magnet flux linkage under the selected perturbation conditions. In contrast, the inductance identification case exhibits a larger steady-state error, indicating that the inductance estimate is more sensitive to excitation conditions, voltage/current measurement errors and simplified modeling assumptions. The resistance and flux-linkage perturbation cases show limited cross-coupling among the identified parameters, whereas the inductance estimate is more strongly constrained by excitation and observability conditions.

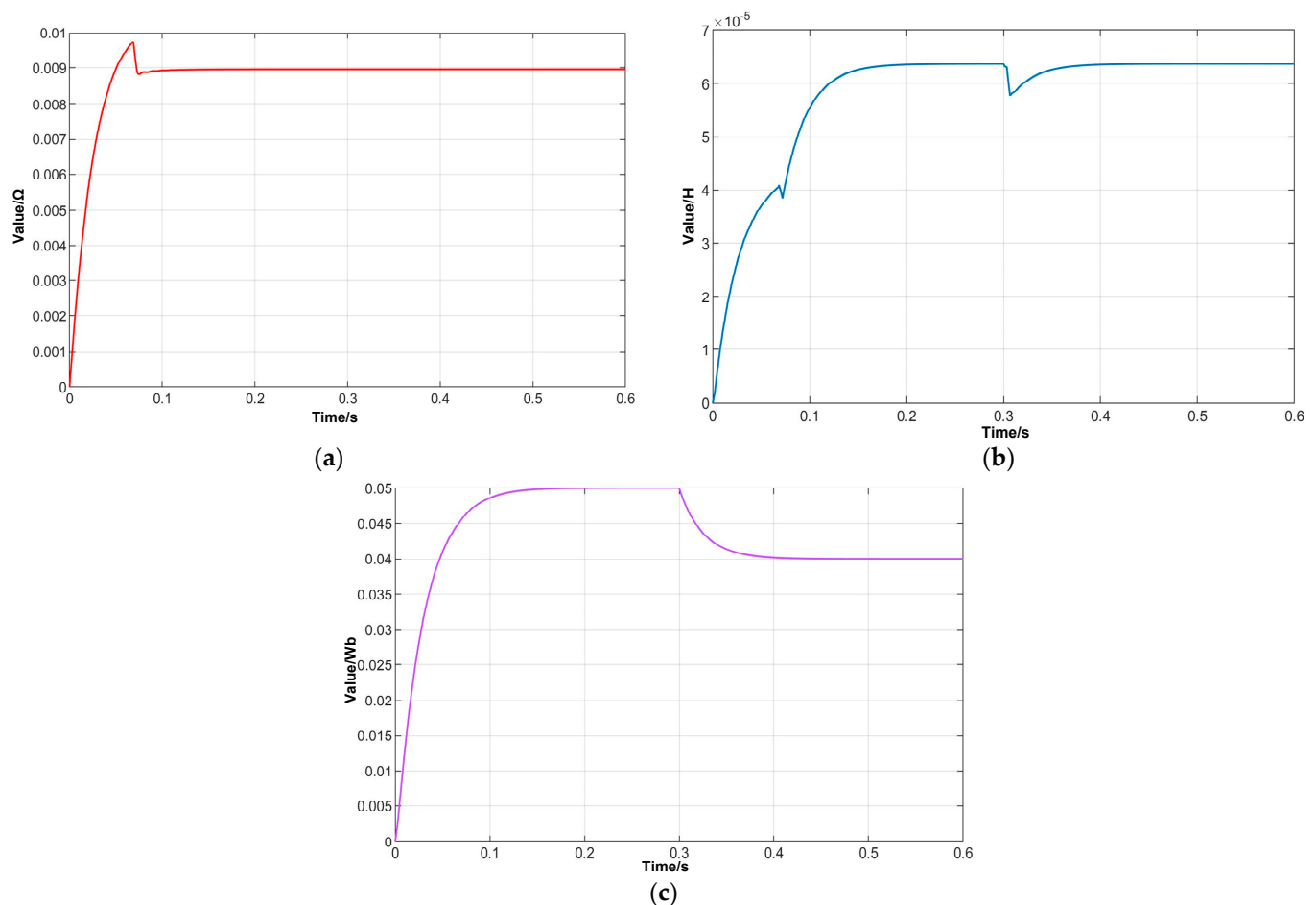


Figure 5. (a) Estimated stator resistance; (b) estimated stator inductance; (c) estimated flux linkage of permanent magnet.

5. Experimental Verification

As shown in Figure 6, the recognition effect of FFRLS was experimentally validated on the PMSM platform, which uses TMS320F28335 as the system control core. The experimental platform mainly includes a 72 V power supply–battery simulation power supply, DSP28335(Dallas, TX, USA) control board and driver board, laptop setup, data transmission simulator and CAN card, oscilloscope, TZQ180-7.5-72B01-X PMSM (Lianyungang, China.), sine/cosine magnetic encoder, coaxial magnetic powder brake, and load controller. The nameplate parameters of the experimental motor are shown in Table 5.

The 7.5 kW platform is not intended to fully reproduce the electromagnetic, thermal or dynamic behavior of the 300 kW traction PMSM. Instead, it is used to verify the real-time implementation feasibility and parameter-tracking behavior of the proposed identification algorithm under a PMSM traction-control structure.

The DSP implementation is organized using interrupt service routines. In the PWM interrupt, the controller performs ADC sampling, signal conditioning, three-phase current calculation, rotor electrical angle and speed calculation, Clarke/Park transformation, current-loop PI control, inverse Park transformation and SVPWM generation. The PWM interrupt frequency is 5 kHz, corresponding to a sampling period of 200 μ s. To reduce the computational burden, the speed-loop PI controller is updated every 10 PWM interrupt cycles, giving a speed-loop update period of 2 ms. The FFRLS estimator uses the controller-preprocessed dq-axis currents, reconstructed dq-axis voltages and encoder-based speed signals as input data.

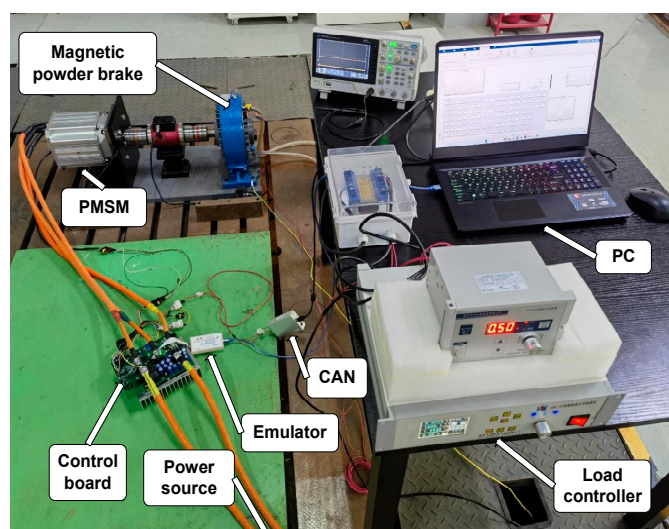


Figure 6. Experimental platform of PMSM.

Table 5. The nameplate parameters of the experimental motor.

Parameter	Value
rated DC voltage	72 V
rated power	7.5 kW
peak power	15 kW
rated torque	23.8 N·m
peak torque	90 N·m
maximum speed	5200 r/min
number of phases	3
degrees of protection	IP66
duty type	S9
insulation class	Class H
cooling method	Natural air cooling

The control software adopts a modular structure, in which the FFRLS identification module is encapsulated as an independent function and invoked once within each PWM interrupt. The CAN communication frequency is set to 1 kHz, and the host-computer software is used for real-time monitoring and data export. Because the identification function requires the real-time voltage, current and speed signals generated by the motor-control program, its execution time cannot be measured independently of the complete control interrupt. Therefore, the incremental computational cost of the FFRLS module was evaluated using a differential measurement method.

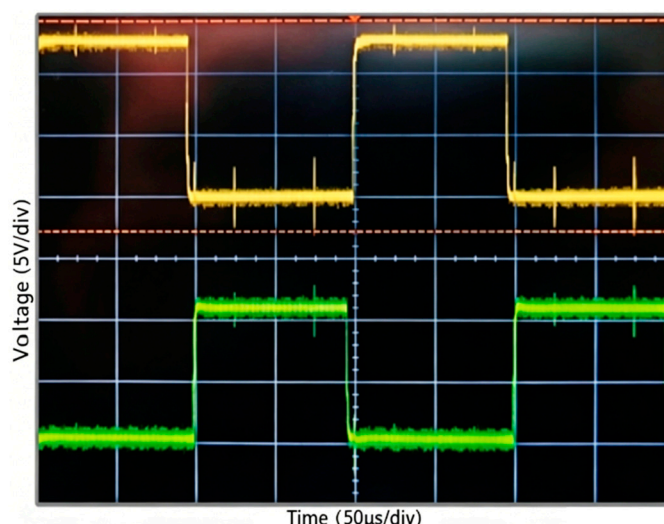
Two control-program configurations were tested while the motor was operating under the same condition. The first configuration contained the baseline motor-control program without the parameter-identification function, whereas the second configuration incorporated the FFRLS identification function into the same control program. All other control functions and interrupt settings were kept unchanged. The execution time of the complete PWM interrupt was measured for both configurations using the CLOCK function in Code Composer Studio (CCS) (Dallas, TX, USA.). The corresponding measurement results are summarized in Table 6.

Table 6. Measured PWM-interrupt execution time with and without the FFRLS identification module.

Parameter	Average CLOCK Count	Execution Time	Occupation of 200 μ s Control Period
Baseline motor-control program without FFRLS	7055.7 cycles	47.04 μ s	23.52%
Motor-control program incorporating FFRLS	10421 cycles	69.47 μ s	34.74%
Incremental overhead attributable to FFRLS	3365.3 cycles	22.44 μ s	11.22%
Remaining timing margin with FFRLS	—	130.53 μ s	65.26%

At the DSP28335 clock frequency of 150 MHz, the average execution time of the complete PWM interrupt was 47.04 μ s for the baseline motor-control program and 69.47 μ s after the FFRLS identification module was incorporated. The difference between the two measurements indicates that the incremental execution time attributable to the FFRLS module is approximately 22.44 μ s, corresponding to 11.22% of the 200 μ s control period. With the identification module enabled, the complete PWM interrupt occupies 34.74% of the control period and leaves a timing margin of approximately 130.53 μ s. Therefore, the FFRLS identification calculation can be completed within one 5 kHz PWM interrupt cycle, confirming the real-time implementation feasibility of the proposed method on the DSP28335 platform.

Before testing the motor control algorithm, the drive circuit in the DSP28335 control board is first verified. A test program outputs a 50% fixed-duty-cycle PWM signal without connecting the motor on the drive side. The test points are selected at the upper- and lower-switch drive-signal pins of one phase bridge arm. Figure 7 is used only to confirm the correctness of the gate-drive timing, complementary PWM relationship, switching period and dead time.

**Figure 7.** Driving waveform diagram of upper and lower pipe of single-phase bridge arm(upper switch (yellow) and lower switch (green)).

The yellow and green waveforms represent the upper- and lower-switch gate-drive signals, respectively. They exhibit the expected complementary relationship at a switching frequency of 5 kHz. At this point, the oscilloscope displays the PWM waveforms of a certain phase bridge arm driving the upper and lower tubes to turn on and off. It can be seen that this pair of PWM waveforms complement each other and meet the setting of a duty cycle of 50%. The PWM period is 200 μ s, which can meet the setting of a switching frequency of 5 kHz. The dead time is also reflected during

the MOSFET's action switching and can meet the setting of 4 μ s. Similarly, the driving functions of the other two-phase bridge arms can also be verified.

The experimental test is conducted at a reference speed of 1500 r/min. The motor starts under the no-load condition, and the magnetic powder brake is then used to provide the load during the identification test. The control sampling frequency is 5 kHz, the CAN recording frequency is 1 kHz, and the estimator sampling period is $T_s = 200 \mu$ s. The forgetting factor is set to $\alpha = 0.98$, and the initial covariance matrix is $\mathbf{P}(0) = 10^6 \mathbf{I}$. According to the controller torque-limit schedule, the maximum torque command at 1500 r/min is 70 N·m; therefore, the bench load is kept within the allowable motor/controller protection range. The motor parameters are not physically changed during the experiment. Instead, the online estimates are evaluated during start-up, speed regulation and brake-load operation, and the steady-state identified values are compared with the measured nominal parameter values.

The experimental identification results are shown in Figure 8, and the corresponding quantitative results are summarized in Table 7. The estimated stator resistance converges to 0.0095 Ω at approximately 9 s, corresponding to a steady-state error of 5.6% relative to the measured value of 0.0090 Ω . The transient value near 0.027 Ω appears during the initial covariance adjustment stage. The estimated stator inductance converges to 0.056 mH at approximately 7.8 s, with a steady-state error of 13.8% relative to the measured value of 0.065 mH. The estimated permanent magnet flux linkage converges to 0.044 Wb at approximately 4.4 s, corresponding to a steady-state error of 12.0% relative to the measured value of 0.050 Wb. The achieved accuracy should be assessed according to the intended function of the online estimator. The stator-resistance error of 5.6% demonstrates relatively reliable resistance tracking and supports online updating of the resistance-related motor model. The inductance and permanent-magnet flux-linkage errors of 13.8% and 12.0%, respectively, are comparatively larger and may limit the direct use of the identified values as stand-alone parameters for demanding functions such as precision torque calculation, efficiency optimization and field-weakening control. Nevertheless, the stable convergence of all three estimates demonstrates that the proposed FFRLS estimator can simultaneously track the principal electrical parameters in real time on the DSP28335-based PMSM platform. Therefore, the achieved accuracy is considered sufficient for algorithm-level feasibility verification, parameter-variation tracking and online model adaptation under the tested condition, while further accuracy improvement and full-scale validation are required before the estimates are used as the sole basis for high-precision control of a full-scale traction PMSM.

The experimental errors are larger than those observed in the idealized simulation because the practical platform includes sensor noise, inverter dead time, voltage reconstruction error, temperature variation, mechanical disturbance, magnetic saturation and unmodeled iron-loss effects [20]. In the present implementation, the dq-axis voltages used by the estimator are reconstructed from the inverter command voltages rather than directly measured at the motor terminals. Consequently, dead time, semiconductor voltage drops and switching nonlinearities introduce deviations between the reconstructed voltages and the actual stator-terminal voltages. These deviations directly enter the regression equations and are particularly influential for inductance identification because the inductance-related voltage component is relatively small and strongly dependent on current variation. No dedicated inverter dead-time or voltage-drop compensation was implemented in the present experiment. Therefore, inverter nonlinearity, together with weak excitation and simplified modeling assumptions, is considered an important contributor to the comparatively large inductance error. Future work will incorporate inverter-voltage compensation or direct terminal-voltage measurement to improve identification accuracy.

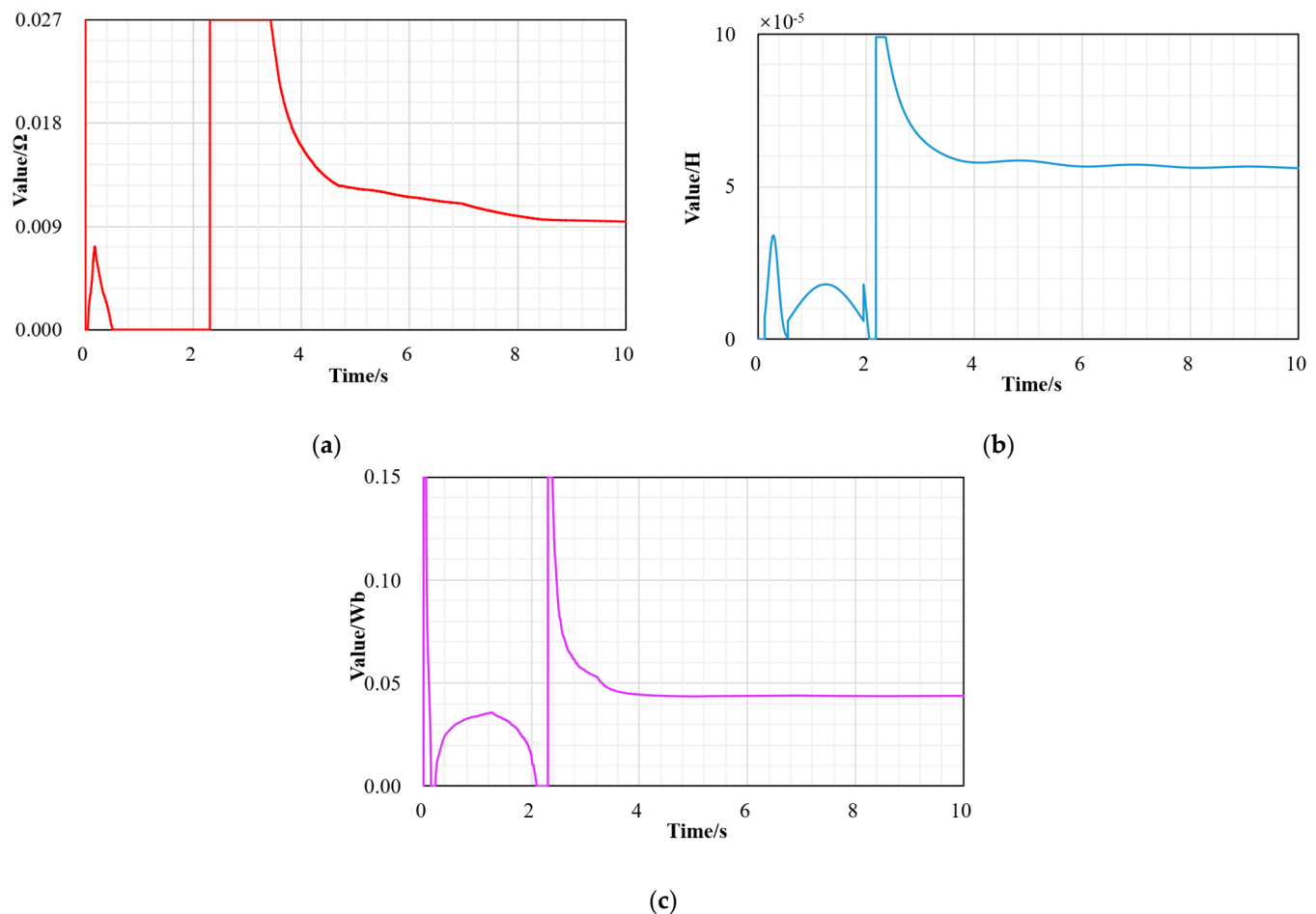


Figure 8. (a) Estimated stator resistance; (b) estimated stator inductance; (c) estimated flux linkage of permanent magnet.

Table 7. Quantitative summary of experimental identification results.

Parameter	Actual Value	Estimated Steady-State Value	Convergence Time	Relative Error
Stator resistance	0.0090 Ω	0.0095 Ω	9.0 s	5.6%
Stator inductance	0.065 mH	0.056 mH	7.8 s	13.8%
Permanent magnet flux linkage	0.050 Wb	0.044 Wb	4.4 s	12.0%

The 7.5 kW laboratory platform and the 300 kW locomotive traction PMSM are not exactly the same in terms of electromagnetic, thermal, and mechanical characteristics. Nevertheless, they share the same PMSM vector-control principle, dq-axis voltage-equation form, and FFRLS-based parameter-identification framework, which supports algorithm-level validation on the scaled-down laboratory platform. Therefore, the experimental results should be interpreted as algorithm-level validation of the real-time FFRLS implementation and parameter-tracking behavior on a scaled-down PMSM platform, rather than as full-scale validation of the 300 kW traction motor. Further validation on a high-power traction platform remains necessary.

6. Conclusions

This paper investigates an online PMSM parameter-identification method based on forgetting-factor recursive least squares (FFRLS) for the traction-control application of hybrid shunting locomotives. Since FFRLS is a mature recursive identification method, the contribution of this study lies in its traction-oriented model formulation, explicit scalar regression construction, DSP28335-based real-time implementation, and simulation/experimental validation for three key PMSM parameters. The identification model is established under simplified PMSM assumptions, and the effects of magnetic saturation, parameter coupling and weak observability are discussed.

Simulation results show that the proposed method can track stator resistance, stator inductance and permanent magnet flux linkage under the selected perturbation conditions, but the identification accuracy differs among the three parameters. The resistance and flux-linkage estimates show relatively good tracking performance, while the inductance estimate exhibits a larger steady-state error because it is more sensitive to excitation conditions, voltage/current measurement errors and modeling uncertainty. Experimental results on the 7.5 kW DSP28335-based PMSM platform further verify online identification of all three parameters. The estimated stator resistance, stator inductance and permanent magnet flux linkage converge to 0.0095 Ω , 0.056 mH and 0.044 Wb, respectively, with relative errors of 5.6%, 13.8% and 12.0%. These results indicate that the proposed method provides the highest accuracy for stator resistance, moderate accuracy for permanent magnet flux linkage, and lower accuracy for stator inductance under the tested condition.

Compared with offline parameter measurement, the FFRLS-based method can update parameters during motor operation. Compared with conventional RLS, the forgetting factor increases the weight of recent data and improves the tracking ability for slowly varying parameters, while introducing a trade-off between tracking speed and noise robustness. The scaled-down experimental platform provides algorithm-level validation of the real-time implementation feasibility and parameter-tracking behavior of the proposed method under a PMSM vector-control structure. Future work will focus on full-scale traction validation, direct winding-temperature measurement, and closed-loop evaluation of torque accuracy, control robustness and energy-efficiency improvement.

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Abbreviations

The following abbreviations are used in this manuscript:

PMSM	Permanent Magnet Synchronous Motor
FFRLS	Forgetting-Factor Recursive Least Squares
DSP	Digital Signal Processor

MRAS	Model Reference Adaptive System
LS	Least Squares
RLS	Recursive Least Squares
EKF	Extended Kalman Filter
CAN	Controller Area Network
ADC	Analog-to-Digital Converter
SVPWM	Space Vector Pulse Width Modulation
CCS	Code Composer Studio

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