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Keywords

PMSM, multiple models, simulation, parameter identification, RLS

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Novel Method to Identify PMSM Parameters Based on Multiple Linear Regressive Models

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基于多元线性回归模型的永磁同步电机参数辨识的新方法

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摘要： *根据推导出的简单和实用的永磁同步电机(PMSM)多元线性回归辨识模型，提出了一种新的耦合带遗忘因子的递归最小二乘(C-FF-RLS)永磁同步电机参数辨识算法，与传统的多变量带遗忘因子递归最小二乘算法 M-FF-RLS 相比，因为 C-FF-RLS 算法在增益矩阵中避免了矩阵求逆运算，所以 C-FF-RLS 算法具有较高的计算效率和快速的收敛速度。*所提出的辨识算法被应用于一个永磁同步电机的仿真系统。在仿真系统中，C-FF-RLS 算法获得的辨识结果与 M-FF-RLS 算法得到的永磁同步电机参数进行了比较。比较表明，C-FF-RLS 算法优于 M-FF-RLS 算法在辨识永磁同步电机参数时。

关键词： 永磁同步电机；多模型；仿真；参数辨识；RLS

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Introduction

Permanent magnet synchronous motors (PMSMs) are successfully used in many industrial applications, because of their unique advantages, such as high efficiency, high capacity, reliable operation and wide constant power speed range [1-2]. The high-performance control of PMSM typically relies some flux-oriented control such as direct torque control[3] or field-oriented control[4]. The flux-

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oriented control of PMSM is derived based on PMSM model[5]. Therefore, the PMSM parameters are necessary for achieving high-performance control; but the parameters of PMSM change with temperature, magnetic saturation and frequency[6]. In these cases, the online oparameter identification of PMSM is needed in the control process.

Several algorithms for the parameters identification of PMSM were proposed: the extended Kalman filter (EKF)[7], the model reference adaptive system[8], and artificial intelligence algorithms (neural networks, particle swarm algorithms, genetic algorithms, etc.)[9]. These identification algorithms can obtain the identification results with high accuracy. However, they have a huge computational burden owing to large number of calculation in the process of operation, especially in the multi-variable system identification. Therefore, these identification algorithms are not suitable for the online parameter identification of PMSM.

The recursive least squares (RLS) identification algorithm is the simple and commonly used online parameter identification algorithms. Various type of RLS algorithms were proposed to identify the parameters of PMSM[10-12]. In [10], Wang presented a novel windowed least algorithm to identify the PMSM parameters with fixed value and with time-varying characteristic. Xu et al. applied a novel residual based extended least squares identification algorithm to identify PMSM based on the dual-rate mathematical model of PMSM[11]. In [12], the phase resistances were identified by the recursive least squares in the rotating reference frame in online. Appling the identification resistances, torque ripple reduction was achieved by a compensation scheme in the stationary reference frame.

The objective of this paper is to online identify the parameters of a PMSM. We propose a new coupled recursive least squares (C-FF-RLS) algorithm with a forgetting factor for online parameter identification of a PMSM, based on the multiple linear identification models of PMSM. Due to avoiding the matrix inversion operation in the gain matrix, the proposed C-FF-RLS algorithm has a smaller computational burden and a faster convergence speed than the traditional multivariable recursive least squares (M-FF-RLS) algorithm with a forgetting factor. The simulation results show that the proposed algorithm is simple in principle, with less computational burden, excellent accuracy and fast convergence. The proposed identification method can be further combined with the predictive control theory or the model reference adaptive system (MRAS) schemes to improve the performance of PMSM control[13].

The multiple linear regression models of PMSM and the identification algorithm used in this paper are presented in Sections 2 and 3, respectively. The input-output data from a simulated control system of a PMSM used for the parameter identification of PMSM is presented in Section 4 and the test results of the proposed identification algorithm is described. Section 5 gives concluding remarks.

1 The multiple linear regression models of PMSM

With reference to the rotating dp reference frame, the commonly used continuous-time electrical equations of the PMSM can be expressed as [14].

$$\begin{cases} u_d = R_s i_d + L_d \dfrac{di_d}{dt} - L_q \omega_e i_q \\ u_q = R_s i_q + L_q \dfrac{di_q}{dt} + L_d \omega_e i_d + \omega_e \psi_f \end{cases}, \quad (1)$$

where R_s is the stator resistance, L_d and L_q are the $d-$ and $q-$ axis inductances, respectively,

ω_e is the electrical rotational speed, ψ_f is the flux linkage established by the permanent magnet and u_d, u_q, i_d, i_q are the $d-$ and $q-$axis component of instant voltage, current.

Refering to [15], the discrete differential $\frac{di_d}{dt}$ and $\frac{di_q}{dt}$ are as follows:

$$\begin{cases} \frac{di_d}{dt} = \frac{i_d(k)-i_d(k-1)}{T_s} \\ \frac{di_q}{dt} = \frac{i_q(k)-i_q(k-1)}{T_s} \end{cases}, \tag{2}$$

where T_s is a sample period.

Combining Eq. (1) with Eq. (2), we can obtain the following discrete identification model of PMSM:

$$\begin{bmatrix} u_d(k) \\ u_q(k)-\omega_e(k)\psi_f \end{bmatrix} = \begin{bmatrix} i_d(k) & -\omega_e(k)i_q(k) & \frac{i_d(k)-i_d(k-1)}{T_s} \\ i_q(k) & \frac{i_q(k)-i_q(k-1)}{T_s} & \omega_e(k)i_d(k) \end{bmatrix} \begin{bmatrix} R_s \\ L_d \\ L_q \end{bmatrix}. \tag{3}$$

Define the output vector $\mathbf{y}(k)$, the information matrix $\mathbf{\Phi}^{\mathrm{T}}(k)$ and the parameter vector θ as

$$\mathbf{y}(k) := \begin{bmatrix} y_1(k) \\ y_2(k) \end{bmatrix} = \begin{bmatrix} u_d(k) \\ u_q(k)-\omega_e(k)\psi_f \end{bmatrix}, \tag{4}$$

$$\mathbf{\Phi}^{\mathrm{T}}(k) := \begin{bmatrix} \Phi_1^{\mathrm{T}}(k) \\ \Phi_2^{\mathrm{T}}(k) \end{bmatrix} = \begin{bmatrix} i_d(k) & -\omega_e(k)i_q(k) & \frac{i_d(k)-i_d(k-1)}{T_s} \\ i_q(k) & \frac{i_q(k)-i_q(k-1)}{T_s} & \omega_e(k)i_d(k) \end{bmatrix}, \tag{5}$$

$$\theta := [R_s \ \ L_d \ \ L_q]^{\mathrm{T}}.$$

Taking into account disturbances in a physical PMSM and introducing a noise vector $\mathbf{v}(k) = [v_1(k),\ v_2(k)]^{\mathrm{T}} \in \mathbb{R}^2$ into Eq. (3), then Eq. (3) can be rewritten as

$$\mathbf{y}(k) = \mathbf{\Phi}^{\mathrm{T}}(k)\theta + \mathbf{v}(k), \tag{6}$$

which is called the multiple linear regression identification models [16].

In the following, we will study the parameter identification of PMSM based on the multiple linear regression models.

2 The PMSM parameters identification using the C-FF-RLS algorithm

In this section, we present a C-FF-RLS algorithm for the multiple linear regression model of PMSM (see Eq. (6)), based on the famous recursive least squares algorithm and the coupling identification theory[16]. As a comparison, the following also derives an M-FF-RLS algorithm for the parameters identification of PMSM.

2.1 The M-FF-RLS algorithm for the parameters identification of PMSM

In Eq. (6), define and minimize the following criterion function

$$J_1(\theta) := \sum_{i=1}^{k} \lambda^{k-i} \left\| \mathbf{y}(i) - \mathbf{\Phi}^{\mathrm{T}}(i)\theta \right\|^2$$

and obtain the M-FF-RLS algorithm for the parameters identification of PMSM θ

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \mathbf{L}(k)[\mathbf{y}(k) - \mathbf{\Phi}^{\mathrm{T}}(k)\hat{\theta}(k-1)], \tag{7}$$

$$\mathbf{L}(k) = \mathbf{P}(k-1)\mathbf{\Phi}(k)[\lambda \mathbf{I}_2 + \mathbf{\Phi}^{\mathrm{T}}(k)\mathbf{P}(k-1)\mathbf{\Phi}(k)]^{-1}, \tag{8}$$

$$\mathbf{P}(k) = \frac{1}{\lambda}(\mathbf{P}(k-1) - \mathbf{L}(k)\mathbf{\Phi}^{\mathrm{T}}(k)\mathbf{P}(k-1)),\ \ \mathbf{P}(0) = p_0\mathbf{I}_3, \tag{9}$$

where $\mathbf{P}(k) \in \mathbb{R}^{3\times3}$ is the covariance matrix, $\mathbf{L}(k) \in \mathbb{R}^{3\times2}$ is the gain matrix, $\hat{\theta}(k)$ represents the identified PMSM parameters at kth iteration step, $0 < \lambda \leqslant 1$ stands for the forgetting factor and p_0 represents a large positive number, e.g., $p_0 = 10^6$. Notice that the output vector $\mathbf{y}(k)$ and the information matrix $\mathbf{\Phi}^{\mathrm{T}}(k)$ are composed of measurable electricity. Thus, the PMSM parameters

$\hat{\theta}(k)$ can be directly obtained by the M-FF-RLS algorithm.

The M-FF-RLS algorithm (see Eqs. (7) - (9)) has a heavy computational burden, mainly because the matrix inversion $[\lambda\mathbf{I}_2+\mathbf{\Phi}(k)\mathbf{P}(k-1)\mathbf{\Phi}^{\mathrm{T}}(k)]^{-1}\in\mathbb{R}^{2\times 2}$ is calculated at each iteration step. In order to eliminate the disadvantages of the M-FF-RLS algorithm, the C-FF-RLS algorithm is presented to identify the PMSM parameters.

2.2. The C-FF-RLS algorithm for the parameters identification of PMSM

Combining Eq. (4) and Eq. (5), Eq. (6) can be written as two identification subsystems

$$y_j(k)=\Phi_j{}^{\mathrm{T}}(k)\theta+v_j(k),\quad j=1,2. \tag{10}$$

In Eq. (10), define and minimize the following cost function

$$J_{j+1}(\theta):=\sum_{i=1}^{t}\alpha_j{}^{t-i}\left\|y_j(i)-\Phi_j^{\mathrm{T}}(i)\theta\right\|^2,\quad j=1,2,$$

and gives the following subsystem FF-RLS (S-FF-RLS) algorithm of identifying the PMSM parameters θ,

$$\hat{\theta}(k)=\hat{\theta}(k-1)+ L_j(k)[y_j(k)-\Phi_j^{\mathrm{T}}(k)\hat{\theta}(k-1)], \tag{11}$$

$$L_j(k)=P_j(k-1)\Phi_j(k)[\alpha_j+ \Phi_j^{\mathrm{T}}(k)P_j(k-1)\Phi(k)]^{-1}, \tag{12}$$

$$P_j(k)=\frac{1}{\alpha_j}(P_j(k-1)-L_j(k)\Phi_j^{\mathrm{T}}(k)P_j(k-1)),\quad P(0)=p_0\mathbf{I}_3,\quad j=1,2, \tag{13}$$

where $P_j(k)\in\mathbb{R}^{3\times 3}$ is the covariance matrix of subsystem j, $0<\alpha_j\leqslant 1, j=1,2$ is the forgetting factor of each subsystems, respectively and the output vectors $y_j(k)$ and the information vectors $\Phi_j^{\mathrm{T}}(k),\ j=1,2$ of subsystem j see Eq. (4) and (5). Obviously, the parameters identification of PMSM $\hat{\theta}(k)$ of two subsystems (see Eqs. (11) - (13)) are independent. In order to show a clear, we use $\hat{\theta}_j(k)$ instead of $\hat{\theta}(k)$ in subsystem j and then the S-FF-RLS algorithm (see Eqs. (11) - (13)) can be rewritten as [17].

$$\hat{\theta}_j(k)=\hat{\theta}_j(k-1)+ L_j(k)[y_j(k)-\Phi_j^{\mathrm{T}}(k)\hat{\theta}_j(k-1)], \tag{14}$$

$$L_j(k)=P_j(k-1)\Phi_j(k)[\alpha_j+ \Phi_j^{\mathrm{T}}(k)P_j(k-1)\Phi_j(k)]^{-1}, \tag{15}$$

$$P_j(k)=\frac{1}{\alpha_j}(P_j(k-1)-L_j(k)\Phi_j^{\mathrm{T}}(k)P_j(k-1)),\quad P(0)=p_0\mathbf{I}_3,\quad j=1,2. \tag{16}$$

For recursive identification algorithms, it is desired that the parameters identification generally approach their real values with the information data length k increasing. That is, the $\hat{\theta}_j(k-1)$ can be replaced with $\hat{\theta}_{j-1}(k)$ [18]. Refering to the coupled identification theory in [19], replacing $\hat{\theta}_j(k-1)$ on the right side of Eq. (14) with $\hat{\theta}_{j-1}(k)$ for $j=2$ and replacing $\hat{\theta}_1(k-1)$ on the right side of Eq. (14) with $\hat{\theta}_j(k-1)$, the C-FF-RLS algorithm for the PMSM parameters identification $\hat{\theta}(k)$ can be expressed as

$$\hat{\theta}_2(k)=\hat{\theta}_1(k)+L_2(k)[y_2(k)-\Phi_2^{\mathrm{T}}(k)\hat{\theta}_1(k)], \tag{17}$$

$$L_2(k)=P_1(k)\Phi_2(k)[\alpha_2+\Phi_2^{\mathrm{T}}(k)P_1(k)\Phi_2(k)]^{-1}, \tag{18}$$

$$P_2(k)=\frac{1}{\alpha_2}(P_1(k)-L_2(k)\Phi_2^{\mathrm{T}}(k)P_1(k)), \tag{19}$$

$$\hat{\theta}_1(k)=\hat{\theta}_2(k-1)+ L_1(k)[y_1(k)-\Phi_1^{\mathrm{T}}(k)\hat{\theta}_2(k-1)], \tag{20}$$

$$L_1(k)=P_2(k-1)\Phi_1(k) [\alpha_1+\Phi_1^{\mathrm{T}}(k)P_2(k-1)\Phi_1(k)]^{-1}, \tag{21}$$

$$P_1(k)=\frac{1}{\alpha_1}(P_2(k-1)-L_1(k)\Phi_1^{\mathrm{T}}(k)P_2(k-1)),\quad P_2(0)=p_0\mathbf{I}_3. \tag{22}$$

As the C-FF-RLS algorithm in Eqs. (17) - (22) shown, the parameter identification $\hat{\theta}_1(k)$ of subsystem 1 is equal to the identification $\hat{\theta}_2(k-1)$ of subsystem 2 at the $(k-1)$th iteration step plus the modified term $L_1(k)[y_1(k)-\Phi_1^{\mathrm{T}}(k)\hat{\theta}_2(k-1)]$ in Eq. (20); and the $P_1(k)$ of subsystem 1 at the kth iteration step is calculated through the $P_2(k-1)$ of subsystem 2 at the $(k-1)$th iteration step in Eq. (22); the $L_1(k)$ of subsystem 1 can be computed by Eq. (21). Similarly, the parameter identification $\hat{\theta}_2(k)$ of subsystem 2 is equal to the identification $\hat{\theta}_1(k)$ of subsystem 1 plus the modified term $L_2(k)[y_2(k)-\Phi_2^{\mathrm{T}}(k)\hat{\theta}_1(k)]$ in Eq. (17); the $P_2(k)$ of subsystem 2 is calculated through the $P_1(k)$ of subsystem 1 in Eq. (19) and the $L_2(k)$ of subsystem 2 can be computed by Eq. (18). Finally, the parameter identification $\hat{\theta}_2(k)$ of subsystem 2 is used as the parameters identification of PMSM $\hat{\theta}(k)$ and that is $\hat{\theta}(k)=\hat{\theta}_2(k)$.

One of the important indicators of a parameter identification algorithm is algorithm complexity. The M-FF-RLS algorithm (see Eqs. (7) – (9)) involves the matrix inversion computations at each iteration step. The proposed C-FF-RLS algorithm (see Eqs. (17) – (22)) is less complex and easier to implement than the M-FF-RLS algorithm. The execution time of the proposed C-FF-RLS algorithm (using in the PMSM parameters identification—see Section 4) is $30\mu s$ at each iteration step, while the M-FF-RLS algorithm takes $41\mu s$.

The steps of computing the PMSM parameters $\hat{\theta}_j(k),\ j=1,2$ by the C-FF-RLS algorithm are listed in the following:

Step 1: Let $k=1$, set the initial values $P_2(0)=p_0\mathbf{I}_3$, $\hat{\theta}_2(0)=\mathbf{1}_3/p_0$, $p_0=10^6$.

Step 2: Collect the measurement data $u_d(k),\ u_q(k),\ \ i_d(k),\ i_q(k),\ \omega_e(k)$ and construct out-put vectors $\mathbf{y}(k)$ and $\mathbf{\Phi}^{\mathrm{T}}(k)$ by Eq. (4) and Eq. (5),respectively. Let $y_j(k)$ be the jth row of $\mathbf{y}(k)$ and let $\Phi_j^{\mathrm{T}}(k)$ be the jth row of $\mathbf{\Phi}^{\mathrm{T}}(k)$.

Step 3: Compute the gain vector $L_1(k)$ by Eq. (21) and covariance matrix $P_1(k)$ by Eq. (22) and update the identification $\hat{\theta}_1(k)$ by Eq. (20).

Step 4: Compute the gain vector $L_2(k)$ by Eq. (18) and covariance matrix $P_2(k)$ by Eq. (19) and update the identification $\hat{\theta}_2(k)$ by Eq. (17).

Step 5: Let $k=k+1$ and go to Step 2.

3 Simulation and analysis

In order to show the advantage and the efficiency of the proposed C-FF-RLS algorithm, the C-FF-RLS algorithm and the M-FF-RLS algorithm are respectively applied to identify the parameters of a PMSM in a simulation system.

3.1 Construction of the PMSM simulation platform

The PMSM simulation system, which is designed to obtain the identification data, is established by Matlab/Simulink, shown as Fig. 1. In the simulation, the PMSM is applied to vector control drive system with cascaded PI controllers which are widely used in industrial motor drive system. The simulation step is set to fixed step form and the step time is selected to be 0.0001 second. Because of the five groups of signals $i_d,\ i_q,\ u_d,\ u_q,\ \omega_e$ containing higher harmonic and noise, we choose third-order Butterworth filters to filter the acquisition signals. Due to the carrier frequency of the PWM Generator is set $1\,\mathrm{kHz}$, cut-off frequency of each Butterworth filter is set to $750\,\mathrm{Hz}$. The analog-to-digital (A/D) converters sampling period is 0.0001 second. The electrical and mechanical parameters used in the simulation are listed in Table 1.

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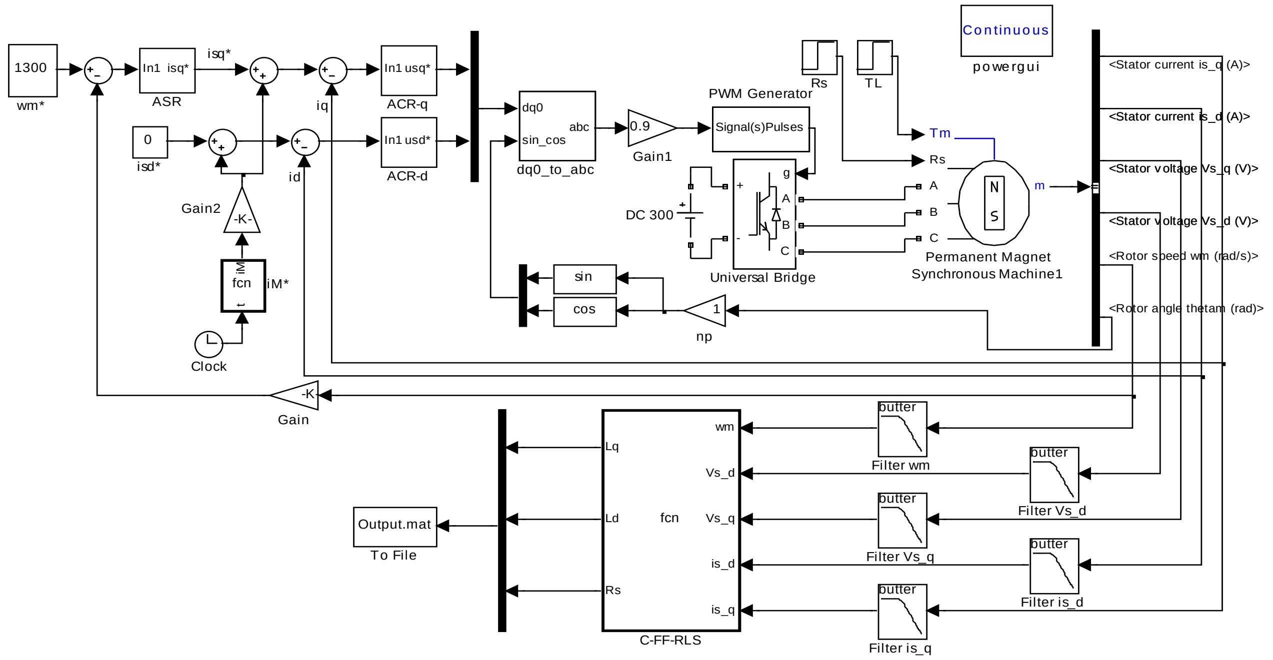

Fig. 1 PMSM simulation system on Matlab/Simulink

Table 1 Simulation parameters of the PMSM

Parameter	Value
Rated power /W	1 800
Rated current / A	10
Rated phase voltage /V	220
Rated speed /($r\cdot \text{min}^{-1}$)	1 400
Rated Torque /(N·m)	5
Maximum speed /($r\cdot \text{min}^{-1}$)	1 500
Stator resistance R_s / Ω	2.875
d – axis inductance / H	0.008 5
q – axis inductance / H	0.008 5
Permanent magnet flux linkage /Wb	0.175
Shaft and load inertia /(kg·m^2)	0.008
Number of pole pairs p	1

M-sequence signals are the pseudorandom sequence signals, which are often used in systems identification [14-15]. The injection signals i_M^* are produced by thirteen shift registers in the simulation and the length of i_M^* is 8191 [20]. The current size of M-sequence signals are rated current of 5%~6%. The injection signals i_M^* are loaded into $d-$ and $q-$ axis current references when the PMSM parameters are identified. Of course, the i_M^* is not necessary to inject the each current references when the PMSM parameters need not be identified. The speed and two currents controllers consist of the conventional proportional-integral (PI) controllers and the parameters of three PI controllers are set to the appropriate values according to the control demand, respectively.

In order to simulate the time-varying characteristic of the stator resistance $R_s(t)$, we modify the PMSM simulation model in Matlab/Simulink, refering to [21]. Therefore, the stator resistance $R_s(t)$ can be changed flexibly in the simulation.

3.2 PMSM parameters identification

3.2.1 Constant parameters identification

In the simulation, the reference speed is fixed at $1300 r/\text{min}$, i.e., $\omega^* = 1300 r/\text{min}$, the load-torque is set to $3\text{N}\cdot\text{m}$, i.e., $T_L = 3\text{N}\cdot\text{m}$, and the PMSM parameters are set to fixed values, i.e., $\theta = [R_s \quad L_d \quad L_q]^{\text{T}} = [2.875 \quad 0.0085 \quad 0.0085]^{\text{T}}$.

Applying the proposed C-FF-RLS algorithm and the M-FF-RLS algorithm to identify the PMSM parameters, the identification results are shown in Table 2 and Fig. 2. It can be seen that parameters identified by the C-FF-RLS algorithm are close to the real value and it is found that there is some relatively serious ripple in the results of parameter identification produced by the M-FF-RLS algorithm, in Fig. 2. Further, comparing Figs. 2(a), 2(b) and 2(c), it is obvious that the C-FF-RLS algorithm has better performance on the rate of convergence.

Table 2 The PMSM parameters identification obtained from the M-FF-RLS and the C-FF-RLS algorithms

Algorithms	t	$\hat{R}_s$	$\hat{L}_d$	$\hat{L}_q$
M-FF-RLS	100	2.85509	0.00854	0.00767
	500	2.86448	0.00849	0.00851
	1000	2.87508	0.00851	0.00856
	3000	2.86262	0.00847	0.00855
	5000	2.86967	0.00849	0.00865
C-FF-RLS	100	2.85241	0.00856	0.00759
	500	2.86712	0.00849	0.00855
	1000	2.87411	0.00850	0.00856
	3000	2.87220	0.00848	0.00856
	5000	2.87487	0.00849	0.00854
Real values		2.875	0.0085	0.0085

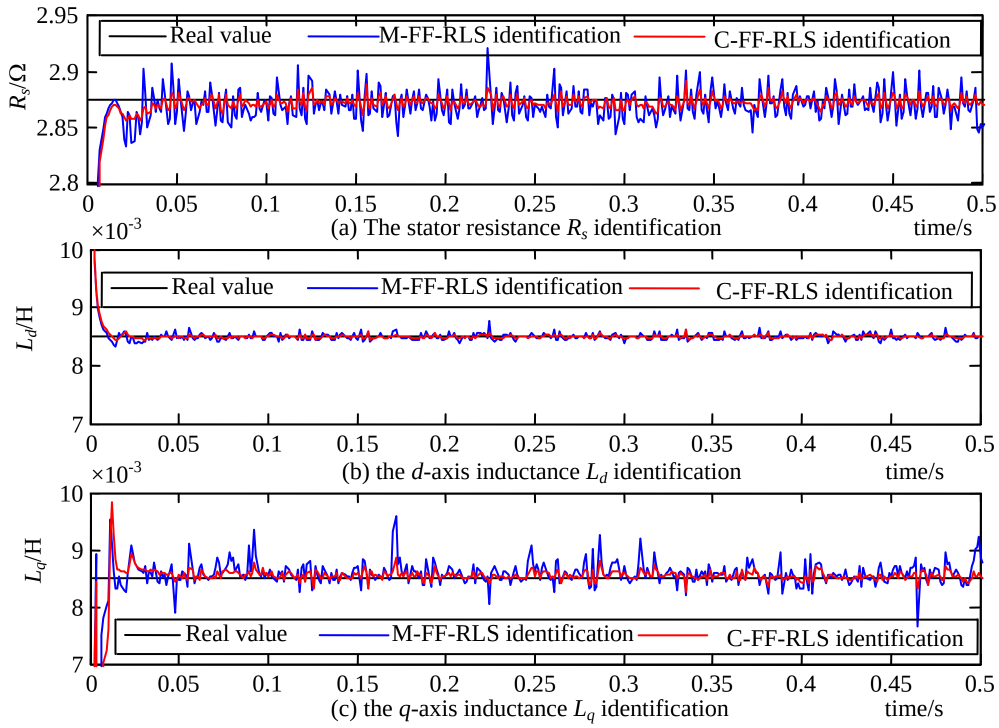

Fig. 2 The PMSM parameters identification under constant parameters

Fig. 3 presents a detail of comparison between the measured and the simulated $d-$ and $q-$axis voltages under constant parameters condition. Fig. 3(a) presents the comparison between the measured and the simulated $d-$axis voltage when the PMSM parameters are identified by the C-FF-RLS algorithm and the M-FF-RLS algorithm, respectively, while in Fig. 3(b) is presented the comparison between the measured and the simulated $q-$axis voltage when the PMSM parameters are identified by two above algorithms. From the Figs. 3(a) and 3(b), it can be seen that the simulated (C-FF-RLS-Parameters) voltages ($\hat{u}_d(t)$, $\hat{u}_q(t)$) match with the measured voltages ($u_d(t)$, $u_q(t)$) more satisfactorily than the simulated (M-FF-RLS - Parameters) voltages. It is evidenced that the C-FF-RLS algorithm performs better on rate of convergence and accuracy than the M-FF-RLS algorithm.

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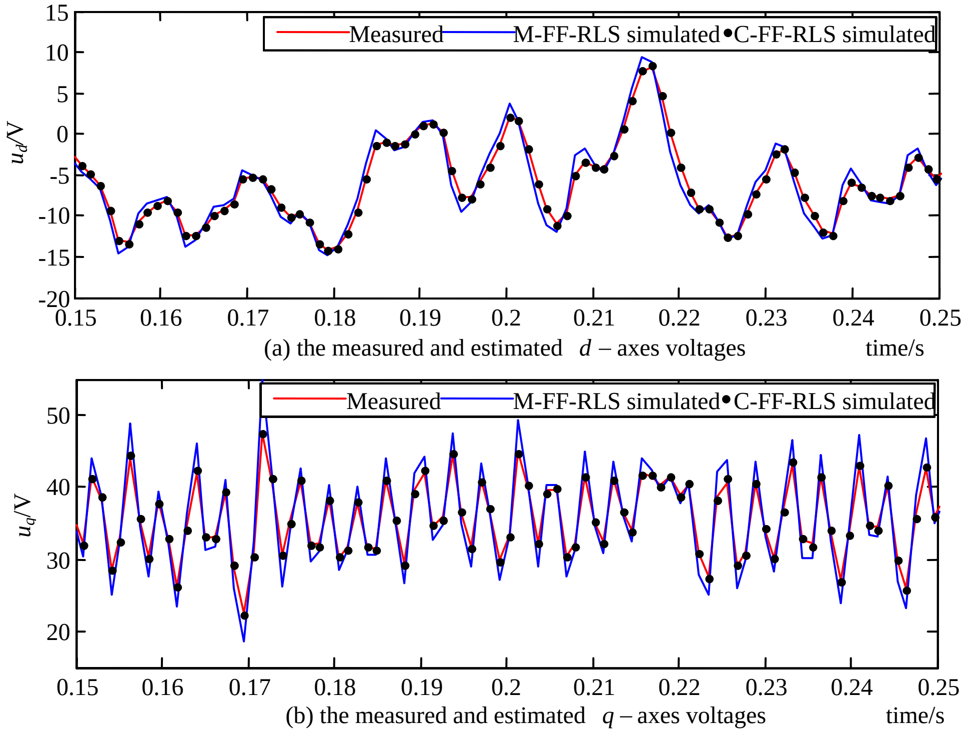

(a) the measured and estimated $d-$axes voltages

(b) the measured and estimated $q-$axes voltages

Fig.3 Simulation results under constant parameters

3.2.2 Time-varying parameter identification

Simulation conditions are similar to those of the section 4.2.1 and in the simulation the stator resistance R_s of the PMSM changes with time, i.e., $\theta=[R_s(t)\ L_d\ L_q]^{\mathrm{T}}=[R_s(t)\ 0.0085\ 0.0085]^{\mathrm{T}}$, where $R_s(t)=2.87+2\sin(2t),\ 0<t$. In the two identification algorithms, the corresponding forgetting factors are set to $\alpha_1=0.991$, $\alpha_2=0.988$ and $\lambda=0.995$. Comparison of the PMSM time-varying parameters identification obtained by the two identification algorithms are shown in Fig. 4. Fig. 4(a) shows the stator resistance $R_s(t)$ identification results. It can be see that the C-FF-RLS algorithm has the faster tracking change in the stator resistance $R_s(t)$ and smaller error than the M-FF-RLS algorithm. The identification results of the $d-$and $q-$axis inductance, (L_d, L_q) are shown in Figs. 4(b) and 4(c), respectively. It is found that there are some relatively large ripple in the $d-$and $q-$axis inductance identification value produced by the M-FF-RLS algorithm. In contrast, the identification effect of the C-FF-RLS algorithm is good.

Fig. 5 presents a comparison between the measured and the simulated $d-$ and $q-$ axis voltages under change in stator resistance condition. In Fig. 5(a) is shown the measured $d-$ axis voltage and the simulated $d-$ axis voltage using parameters identified by the C-FF-RLS algorithm and the M-FF-RLS algorithm in the PMSM, while in Fig. 5 (b) is shown the measured $q-$axis voltage and, the simulated $q-$ axis voltage using parameters identified by two above algorithms. From Figs 5(a) and 5(b), it is confirmed that the simulated $d-$and $q-$axis voltages with the C-FF-RLS parameters are better than the simulated voltages with the M-FF-RLS parameters, in comparison with the measured $d-$and $q-$axis voltages. It can be seen that the proposed algorithm is very successful in identifying the time-varying parameters of PMSM.

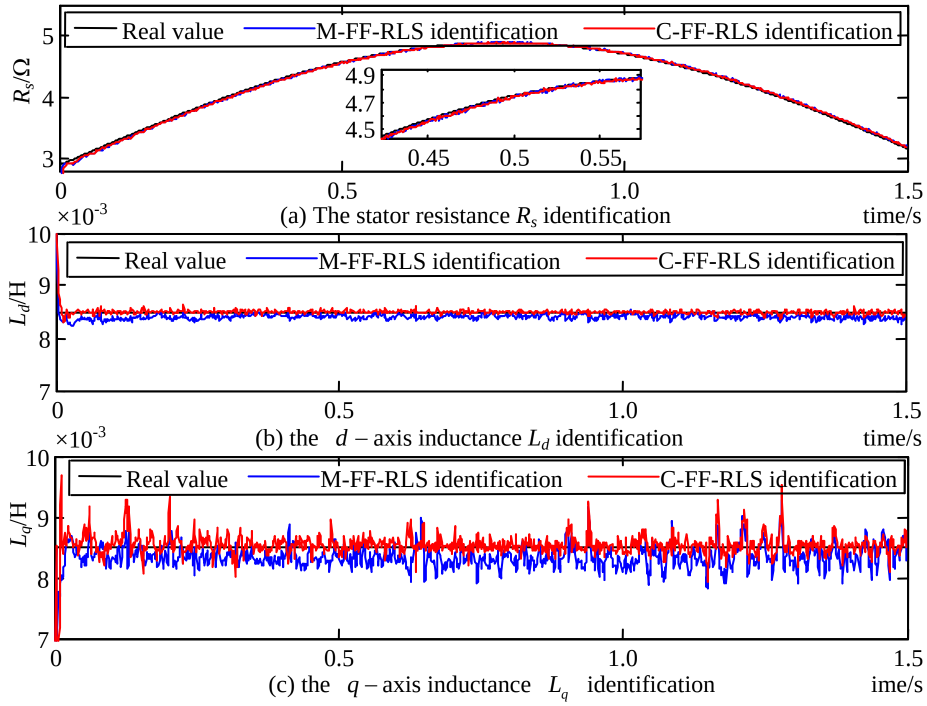

Fig. 4　The PMSM parameters identification under change in stator resistance

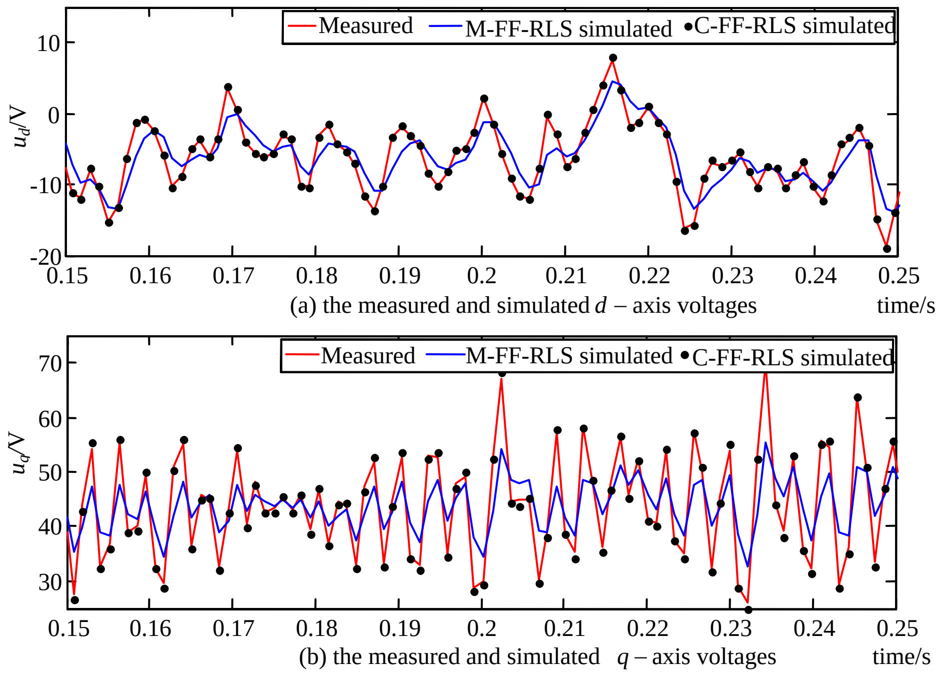

Fig. 5　Simulation results under change in stator resistance

4　Conclusions

In this paper, a C-FF-RLS identification algorithm for the online parameters of the PMSM is described based on the multiple linear regressive models. The C-FF-RLS identification algorithm has a higher computational efficiency and a faster convergence speed than the traditional M-FF-RLS algorithm. The two identification algorithms have been tested on a PMSM simulation system in Matlab/Simulink. Simulation results indicate that the C-FF-RLS identification algorithm can be used more successfully for the identification of the constant and time-varying parameters of PMSM than the M-FF-RLS algorithm.

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