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On-line parameter estimator of an induction motor at standstill

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Abstract

This paper describes an automatic identification procedure for an induction motor. The transfer function of the motor at standstill is used to obtain a linear parametric model. An on-line parameter estimator is then derived from this model. In the implementation of the proposed estimator, a PI current controller is constructed to stabilize the current signal and to prevent the flux from saturation. An experiment with an input that is persistently exciting verifies the theory of the proposed estimator and demonstrates its usefulness in industry applications.

Keywords: Induction motor; Parameter identification; Gradient estimator; Current controller; Persistent excitation

1. Introduction

Recently, many researchers have developed high performance AC drives for the induction motor (IM) in accordance with critical industrial demands. With such a drive, a fast dynamic response of induction machine can be achieved by the field-oriented control (FOC) (Vas, 1996). The FOC techniques demand a good motor parameter knowledge to find an effective decoupling between motor torque and motor flux actuating signals (Belini, Figalli, & Cava, 1985). Only when this decoupling is guaranteed, the FOC techniques can be applied for critical demands.

The classical procedures to identify the electrical motor parameters are no-load and/or locked rotor tests. However, they are not automatic estimation, which is nowadays the main demand for a standard AC drive (Vas, 1993). The automatic measurement procedure must be simple, user friendly, and the accuracy on measured parameters comparable to that obtained from classical test procedures; and not need mechanical-locking of the shaft or load-disconnecting (Aiello, Cataliotti, & Nuccio, 2002). Thus, a practical inverter system containing a parameter identification scheme has been a trend in drive technology as long as it allows the automatic set-up of the control system (self-commissioning) (Khambadkone & Holtz, 1991).

The most popular methods for automatically identifying the parameters of an IM are to force the motor to be at standstill, i.e., to give two of three phases the same voltage so that only a single phase is excited. There is no net torque acting on the rotor and the rotor speed is then zero when the motor is at standstill.

Many researchers have dealt with the identification of the IM parameters while the motor is at standstill. Willis, Brook, and Edmonds (1989) proposed a model fitting method using frequency-response data. The maximum likelihood method was used by Moon and Keykani (1994) and Karayaka, Marwali, and Keyhani (1997). This method requires several steps in the estimating process. On the other hand, the current-loop tests proposed by Rasmussen, Knudsen, and Tonnes (1996) also divide the process into three steps. The above methods still do not meet the automation requirement. An attractive way is to develop the estimation method from the transfer function of the IM model at standstill. The continuous transfer function or the discrete transfer function of an IM at standstill has been utilized. Peixoto and Seixas (2000) developed a recursive least (RLS) estimating method from the continuous transfer function, while Michalik and Devices (1998) and Barrero, Perez, Millan, and Franquelo (1999) derived a RLS

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method from the discrete transfer function. The continuous transfer function was also used by Couto and Aguiar (1998) to develop a step-response model fitting method. A more moderate estimating method was proposed by Buja, Menis, and Valla (2000). They presented a method based on the model reference adaptive system (MRAS). This method is derived from state-space equations of the IM model. Although it is an on-line method, the knowledge of the torque constant is required in advance.

In this paper an on-line estimator to determine stator resistor, rotor resistor, stator inductance, and mutual inductance is proposed, which also requires the transfer function of the motor at standstill. This is an analytic method that ensures the convergence of the identification procedure. Actually, the theory of the proposed estimator is a basis for adaptive control. Thus, the estimator is easily implemented on a FOC control system of AC drives. A persistently exciting input signal required by the estimator is also suggested. Furthermore, a feedback current control loop is added in the implementation of the estimator and then the persistently exciting voltage signal is generated by the feedback current control loop to constrain the current under rated value. The verification is performed by a V/F speed control of the IM. Two curves of measured and computed current are presented to validate the correctness of the estimated parameters.

This paper is organized as follows. Section 2 reviews the model of the induction motor at standstill. The on-line parameter estimator is derived in Section 3. Section 4 addresses the experimentation. Finally, Section 5 draws conclusions.

2. Model of an induction motor at standstill

The mathematical model of an induction motor in a stator-fixed frame (α, β) can be described by five nonlinear differential equations with four electrical variables [stator currents $(i_{\alpha s}, i_{\beta s})$ and rotor fluxes $(\varphi_{\alpha r}, \varphi_{\beta r})$], a mechanical variable [rotor speed (ω)], and two control variables [stator voltages $(u_{\alpha s}, u_{\beta s})$] (Vas, 1996; Novotny & Lipo, 1996) as follows:

$$\dot{\varphi}_{\alpha r} = \frac{L_m}{\tau_r} i_{\alpha s} - \frac{1}{\tau_r}\varphi_{\alpha r} - p\omega\varphi_{\beta r}, \tag{1}$$

$$\dot{\varphi}_{\beta r} = \frac{L_m}{\tau_r} i_{\beta s} - \frac{1}{\tau_r}\varphi_{\beta r} + p\omega\varphi_{\alpha r}, \tag{2}$$

$$\dot{i}_{\alpha s} = -\gamma i_{\alpha s} + \frac{K}{\tau_r}\varphi_{\alpha r} + pK\omega\varphi_{\beta r} + \alpha_s u_{\alpha s}, \tag{3}$$

$$\dot{i}_{\beta s} = -\gamma i_{\beta s} + \frac{K}{\tau_r}\varphi_{\beta r} - pK\omega\varphi_{\alpha r} + \alpha_s u_{\beta s}, \tag{4}$$

$$\dot{\omega} = -\frac{B}{J}\omega + \frac{T_e}{J} - \frac{T_L}{J}, \tag{5}$$

where R_s and R_r are the stator and rotor resistance, L_s, L_r, and L_m are the stator, rotor, and mutual inductance, B and J are the friction coefficient and the moment of inertia of the motor, p is the number of pole-pairs. Furthermore, $\tau_r = L_r/R_r$ is the rotor time constant and the parameters used in (1)–(5) are defined as $\sigma \equiv 1 - L_m^2/(L_s L_r)$, $K \equiv L_m/(\sigma L_s L_r)$, $\alpha_s \equiv 1/(\sigma L_s)$, and $\gamma \equiv R_s/(\sigma L_s) + R_r L_m^2/(\sigma L_s L_r^2)$.

Now, consider the IM at standstill, i.e., the IM is controlled to produce zero torque, so that the motor is at standstill with $\omega = 0$. This can be achieved by magnetizing the IM in the β-axis. Under such a circumstance, $u_{\alpha s}$, $i_{\alpha s}$, and $\varphi_{\alpha s}$ are all zero. This can be seen by substituting $p\omega\varphi_{\beta r}$ in terms of $\dot{\varphi}_{\alpha r}, i_{\alpha s}$, and $\varphi_{\alpha r}$, obtained from (1), into (3) and letting $u_{\alpha s} = 0$, which implies $i_{\alpha s} = \varphi_{\alpha s} = 0$. Thus, it follows from (1)–(4) that the model of an IM at standstill consists of only the state space equations along the β-axis:

$$\dot{\varphi}_{\beta r} = -\frac{1}{\tau_r}\varphi_{\beta r} + \frac{L_m}{\tau_r} i_{\beta s}, \tag{6}$$

$$\dot{i}_{\beta s} = -\gamma i_{\beta s} + \frac{K}{\tau_r}\varphi_{\beta r} + \alpha_s u_{\beta s}. \tag{7}$$

Taking Laplace transforms of both sides of (6) and (7) and then substituting the result of (6) into that of (7), the transfer function of the present system is obtained as follows:

$$\frac{i_{\beta s}}{u_{\beta s}} = \frac{b_1 s + b_0}{s^2 + a_1 s + a_0}, \tag{8}$$

where

$$a_1 = (R_s L_r + R_r L_s)/(\sigma L_s L_r),$$

$$a_0 = R_s R_r/(\sigma L_r L_s),$$

$$b_1 = 1/(\sigma L_s),$$

$$b_0 = R_r/(\sigma L_r L_s). \tag{9}$$

These four parameters will be identified by an on-line parameter estimator described in the next section. Although (8) is reported in the earlier works (Barrero et al., 1999; Peixoto & Seixas, 2000; Couto & Aguiar, 1998), this paper develops an on-line estimator, which is different from the estimating methods in these earlier works.

3. On-line parameter estimator

To derive an on-line parameter estimator, the transfer function (8) should be transformed to a linear parametric model. Since the system is second-order, it needs a second-order filter for the transformation. It is, however, desirable to make the order of the resulting linear parametric model as low as possible. This motivates us to use the filter of $\Lambda(s)=(s+h_1)(s+h_0)$. Let $z\equiv s^2 i_{\beta s}/\Lambda(s)$. It then follows from (8) that

$$z=[-a_1\ \ -a_0\ \ b_1\ \ b_0]\begin{bmatrix} si_{\beta s}/\Lambda(s)\\ i_{\beta s}/\Lambda(s)\\ su_{\beta s}/\Lambda(s)\\ u_{\beta s}/\Lambda(s)\end{bmatrix}. \tag{10}$$

According to the definition of z, it is apparent that

$$\begin{aligned} i_{\beta s} &= z+\frac{(h_1+h_0)s+h_1h_0}{\Lambda(s)}i_{\beta s},\\ &= \frac{(h_1+h_0-a_1)s+(h_1h_0-a_0)}{\Lambda(s)}i_{\beta s}+\frac{b_1s+b_0}{\Lambda(s)}u_{\beta s}, \end{aligned} \tag{11}$$

which leads to the linear parametric model by the method of partial fractions as follows:

$$i_{\beta s}=\boldsymbol{\theta}^{*\mathrm{T}}\mathbf{w}, \tag{12}$$

where

$$\boldsymbol{\theta}^*=\begin{bmatrix} c_1\\ c_2\\ c_3\\ c_4\end{bmatrix}=\begin{bmatrix} \dfrac{b_0-b_1h_1}{h_0-h_1}\\ \dfrac{b_1h_0-b_0}{h_0-h_1}\\ \dfrac{-a_0+a_1h_1-h_1^2}{h_0-h_1}\\ \dfrac{a_0-a_1h_0+h_0^2}{h_0-h_1}\end{bmatrix},$$

$$\mathbf{w}=\begin{bmatrix} w_1\\ w_2\\ w_3\\ w_4\end{bmatrix}=\begin{bmatrix} \dfrac{1}{s+h_1}u_{\beta s}\\ \dfrac{1}{s+h_0}u_{\beta s}\\ \dfrac{1}{s+h_1}i_{\beta s}\\ \dfrac{1}{s+h_0}i_{\beta s}\end{bmatrix}. \tag{13}$$

Note $\boldsymbol{\theta}^*$ is the vector of the parameters to be estimated and $\mathbf{w}$ is the vector of measured signals. The measured signals in (13) is only first-order, instead of second-order. This is because a factored second-order filter $\Lambda(s)$ is assigned in advance.

Let the estimate of $i_{\beta s}$ be $\hat{i}_{\beta s}$:

$$\hat{i}_{\beta s}=\hat{\boldsymbol{\theta}}^{\mathrm{T}}\mathbf{w}, \tag{14}$$

where $\hat{\boldsymbol{\theta}}$ is the estimate of $\boldsymbol{\theta}^*$. Moreover, define a normalized estimation error as

$$\varepsilon=\frac{i_{\beta s}-\hat{i}_{\beta s}}{m^2}, \tag{15}$$

where $m^2=1+n_s^2$ with $n_s^2=\alpha\mathbf{w}^{\mathrm{T}}\mathbf{w}$ and $\alpha>0$. The purpose of m is to make $\mathbf{w}/m$ bounded. A quadratic cost function is further define as

$$J(\hat{\boldsymbol{\theta}})=\frac{\varepsilon^2m^2}{2}=\frac{(i_{\beta s}-\hat{\boldsymbol{\theta}}^{\mathrm{T}}\mathbf{w})^2}{2m^2}. \tag{16}$$

The gradient method to minimize $J(\hat{\boldsymbol{\theta}})$ is the trajectory of

$$\dot{\hat{\boldsymbol{\theta}}}=-\Gamma\nabla J(\hat{\boldsymbol{\theta}})=\Gamma\varepsilon\mathbf{w}, \tag{17}$$

where Γ is a diagonal matrix with positive diagonal entries. Eq. (17) is then used as the gradient on-line parameter estimator for (12).

It is shown in the book of Ioannou and Sun (1996) that if $\mathbf{w}$ is bounded and PE (persistently exciting), then $\hat{\boldsymbol{\theta}}$ converges exponentially to $\boldsymbol{\theta}^*$. Since the filter Λ is a stable transfer function, $\mathbf{w}$ is bounded if $u_{\beta s}$ and $i_{\beta s}$ are bounded. $u_{\beta s}$ is the input signal and is given by the user, while $i_{\beta s}$ is the output of a physical system whose response to a finite input is still finite. Thus, the bound of $\mathbf{w}$ is always satisfied.

The PE property of $\mathbf{w}$ can be related to the sufficient richness of $u_{\beta s}$ (Sastry & Bodson, 1989). A simple result is that $\mathbf{w}\in\Re^4$ is PE if and only if $u_{\beta s}$ is sufficiently rich of order 4. According to the definition, the signal $u_{\beta s}$ is sufficiently rich of order $n=4$ if it consists of at least $n/2=2$ distinct frequencies. It is then not difficult to construct the input signal so that $\mathbf{w}$ is PE.

The above proposed on-line estimator is used to obtain a convergent value of $\hat{\boldsymbol{\theta}}$. The next step is to calculate the coefficients of (8) from the values of the estimate $\hat{\boldsymbol{\theta}}$ by

$$\begin{aligned} \hat{a}_1 &= h_1+h_0-\hat{c}_3-\hat{c}_4,\\ \hat{a}_0 &= h_1h_0-h_1\hat{c}_4-h_0\hat{c}_3,\\ \hat{b}_1 &= \hat{c}_1+\hat{c}_2,\\ \hat{b}_0 &= h_0\hat{c}_1+h_1\hat{c}_2, \end{aligned} \tag{18}$$

which follows from (13), where $\hat{c}_i$ are the entries of $\hat{\boldsymbol{\theta}}^*$. The inverse relation of (9) allows us to obtain the parameter estimates as

$$\begin{aligned} \hat{R}_s &= \hat{a}_0/\hat{b}_0,\\ \hat{R}_r &= \hat{a}_1/\hat{b}_1-\hat{R}_s,\\ \hat{L}_s &= \hat{L}_r=\hat{R}_r\hat{b}_1/\hat{b}_0,\\ \hat{L}_m &= \sqrt{\hat{L}_s^2-\hat{L}_s/\hat{b}_1}. \end{aligned} \tag{19}$$

Alternatively, (18) and (19) are combined to directly calculate out the parameter estimates as follows:

$$\hat{R}_s=(h_1h_0-h_0\hat{c}_3-h_1\hat{c}_4)/(h_0\hat{c}_1+h_1\hat{c}_2), \tag{20}$$

$$\hat{R}_r=(h_1-h_0-\hat{c}_3-\hat{c}_4)/(\hat{c}_1+\hat{c}_2)-\hat{R}_s, \tag{21}$$

$$\hat{L}_s=\hat{L}_r=\hat{R}_r(\hat{c}_1+\hat{c}_2)/(h_0\hat{c}_1+h_1\hat{c}_2), \tag{22}$$

$$\hat{L}_m = \sqrt{\hat{L}_s^2 - \hat{L}_s/(\hat{c}_1 + \hat{c}_2)}. \quad (23)$$

4. Experimentation

The experimental system is a PC-based control system. A servo control card on the ISA bus of the PC provides eight A/D converters, four D/A converters, and an encoder counter. The ramp comparison modulation circuit is used to generate the PWM for driving the IGBT module inverter. The sampling time for the adaptive identification is 0.3 ms. The induction motor in the experimental system is a 4-pole, 5 HP, and 220 V with the rated current 14 A, rated speed 1700 rpm, and rated torque 19.5 Nm.

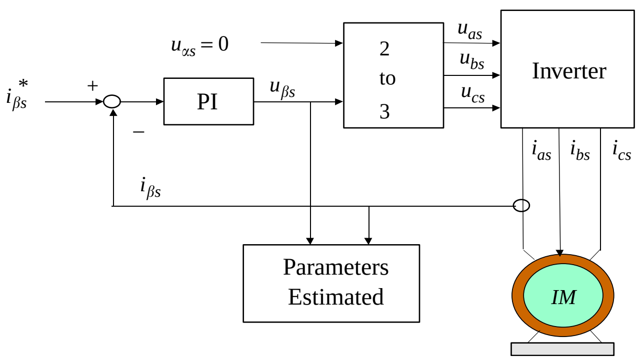

Fig. 1. Block diagram of the identifying implement of an induction motor at standstill.

The proposed on-line parameter estimator is implemented on a current-controlled PWM inverter, which is shown in Fig. 1. The advantages of the current-controlled loop are that it is easy to implement and can alleviate the saturation of the magnetic flux. In the experiment, the input of voltage $v_{\alpha s}$ is always set to be zero, whereas $v_{\beta s}$ is generated by a PI controller as follows:

$$u_{\beta s} = (k_p + k_i/s)(i_{\beta s}^* - i_{\beta s}), \quad (24)$$

where k_p and k_i are the regulator gains. The feedback signal $i_{\beta s}$ is the measured current by a Hall sensor. The dead-time compensator presented in (Aiello et al., 2002) is also utilized in this experimental system in order to reduce the effects of the inverter dead-time. The proposed on-line parameter estimator is implemented by a numerical algorithm. The transfer function (12) of the motor at standstill is just used to derive the gradient

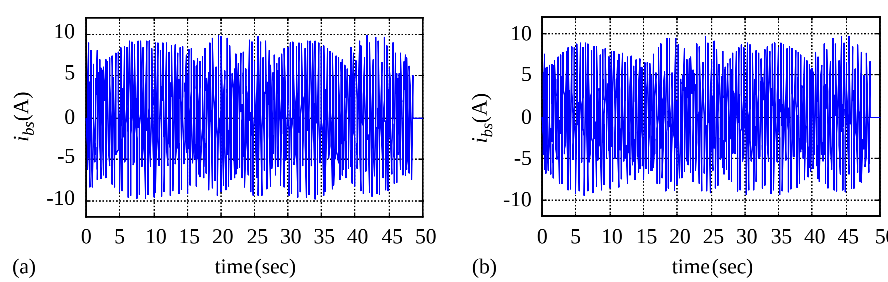

Fig. 2. Input signals of the estimation implementation: (a) measured current; (b) estimated current.

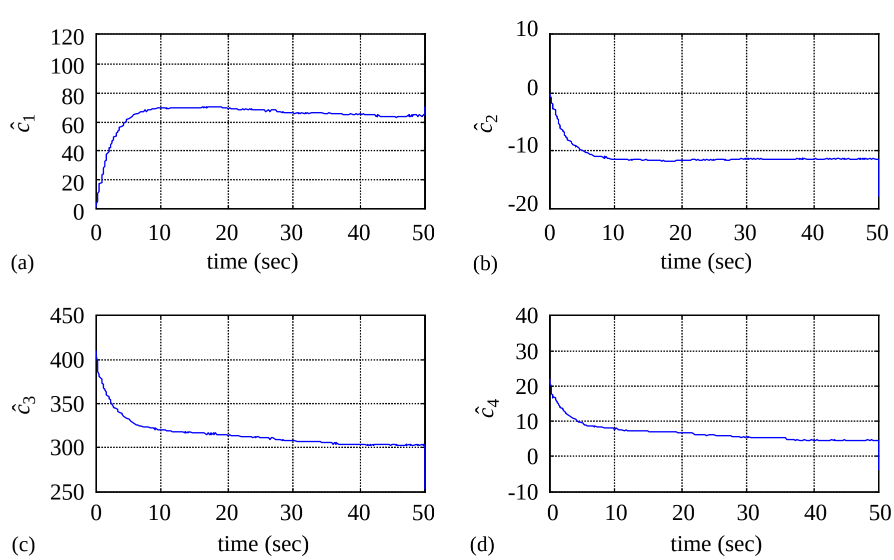

Fig. 3. Identification procedure of the estimated parameters: (a) $\hat{c}_1$; (b) $\hat{c}_2$; (c) $\hat{c}_3$; (d) $\hat{c}_4$.

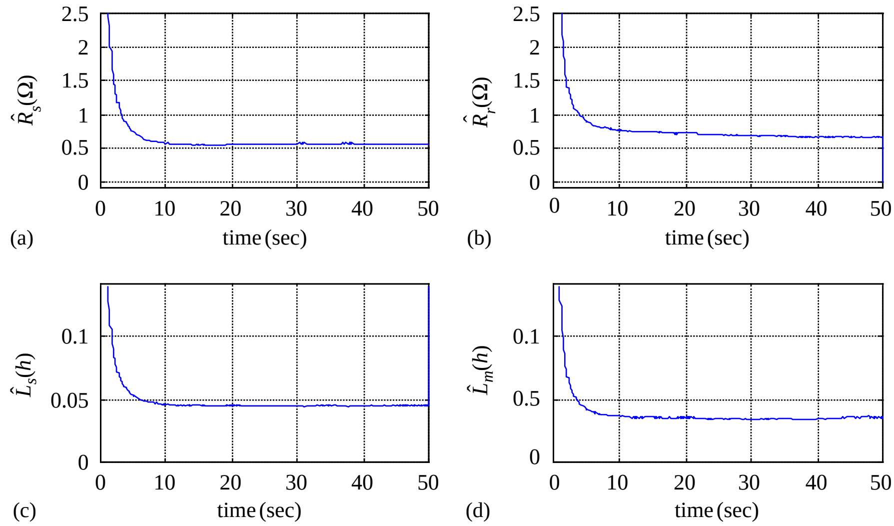

Fig. 4. Identification procedure of the IM parameters: (a) $\hat{R}_s$; (b) $\hat{R}_r$; (c) $\hat{L}_s$; (d) $\hat{L}_m$.

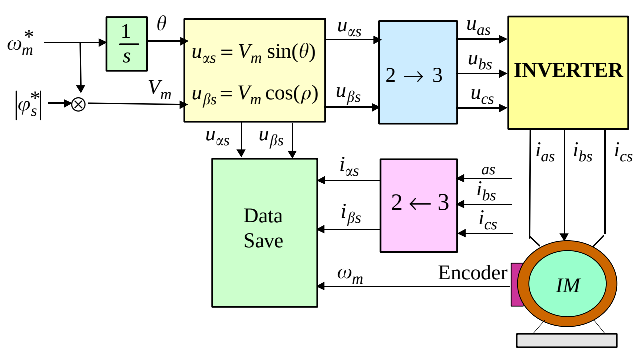

Fig. 5. Block diagram of the validate structure of V/F speed control.

on-line parameter estimator (17), which uses $\mathbf{w}$ in (13). Eq. (13) is actually implemented by a differential equation, e.g., $\dot{w}_1 + h_1 w_1 = u_{\beta s}$. In the PC-based experiment system, all differential equations are solved by the well known 3-step Adam–Bashforth numerical method.

The input current command is $i_{\beta s}^* = 3\sin(12t) + 4\sin(25t) + 6\sin(70t)$, which consists of three distinct frequencies and can make $u_{\beta s}$ also consist of three distinct frequencies so that the signal $\mathbf{w}$ is PE. The parameters of the filter in the parameter estimator are $h_0 = 40$ and $h_1 = 160$, while the PI controller has the gains of $k_p = 1.6$ and $k_i = 116$.

The experimental results are reported in Figs. 2–4. The history of the measured current and the estimated current are shown Fig. 2. They match very well. It can be seen from Fig. 3 that the estimates $\hat{c}_i$ converge to some values. The steady-state values are recorded as $\hat{c}_1 = 66$, $\hat{c}_2 = -12.5$, $\hat{c}_3 = 305$, and $\hat{c}_4 = 5.4$. Then, using (23) to obtain the parameter estimates are $\hat{R}_s = 0.56\ \Omega$, $\hat{R}_r = 0.78\ \Omega$, $\hat{L}_s = \hat{L}_r = 0.046$ H, $\hat{L}_m = 0.039$ H. Besides, the estimate histories of the electrical parameters are also depicted in Fig. 4.

To verify the correctness of the estimated values, a simple V/F speed control of the IM is conducted (see

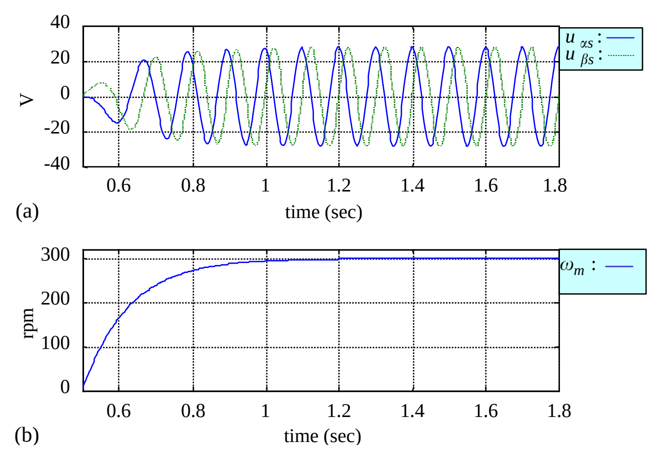

Fig. 6. The signals of experiment: (a) voltage command; (b) output speed.

Fig. 5). For the speed command of 300 rpm, the generated voltages by the controller and the speed response are shown in Fig. 6(a) and (b). The values are substituted into the IM mode (1)–(4) with the estimated values for the parameters to calculate out $\hat{i}_\alpha$ and $\hat{i}_\beta$. In the V/F speed control experiment, the currents are also measured using three Hall sensors. The measured currents and the computed currents are all shown in Fig. 7. It is apparent that these two kinds of curves match very well, especially after the transient stage. It is then evident that the estimated parameter values are acceptable.

5. Conclusions

An on-line parameter estimator for an IM is proposed in this paper. This estimator is a gradient normalization method, which is based on the system transfer function of the motor at standstill. One of the features of this

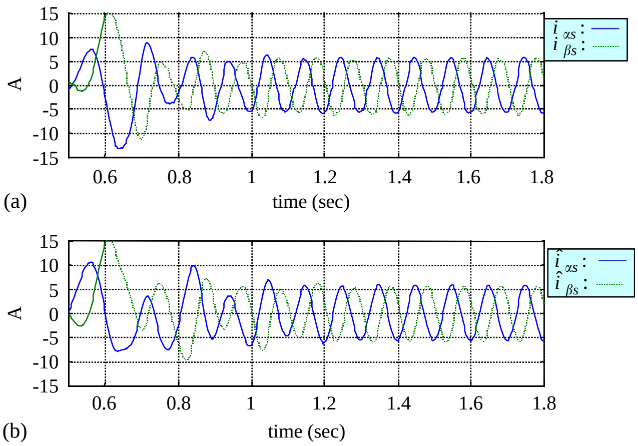

Fig. 7. Currents compare of experiment and model: (a) measured current; (b) computed current.

approach is that the order in the linear parametric model is at most first-order, although the system is second-order. Another salient feature is the current control loop in the implementation of the estimator, which can prevent the flux from saturation, an undesirable situation in the identification. The proposed method is easy to implement. The input signal requires only a current command that consists of at least two distinct frequencies, so that the signals in the estimator are persistently exciting (PE). An experiment reported in Section 3 verifies the theory and demonstrates the usefulness of the proposed estimator.

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