On-Line Stator and Rotor Resistance Estimation for Induction Motors

Riccardo Marino, Sergei Peresada, and Patrizio Tomei

***Abstract*—A ninth-order estimation algorithm is designed which provides on-line exponentially convergent estimates of both rotor and stator resistance for induction motors, when persistency of excitation conditions are satisfied and the stator currents integrals are bounded, on the basis of rotor speed, stator voltages, and stator currents measurements. Rotor flux is also asymptotically recovered. Experimental tests are reported which show that: persistency of excitation and boundedness of stator currents integrals hold in typical operating conditions; both resistance estimates converge exponentially to true values; the algorithm is implementable on-line by currently available digital signal processors; and the algorithm is robust with respect to modeling inaccuracies. The proposed estimation scheme is intended to improve performance and efficiency of currently available induction motor control algorithms.**

***Index Terms*—AC motors, adaptive observers, flux observers, induction motors, parameter estimation.**

I. Introduction

It is well documented in the literature (see [1]–[10]) that the knowledge of rotor resistance (R_r), a parameter which largely varies during operation, is crucial in the design of high-performance induction motor control algorithms when flux measurements are not available. In fact, flux observers [2], [11]–[13] require the exact knowledge of rotor resistance, while both indirect (observer-less) and direct (observer-based) field oriented controls do not achieve field orientation when rotor resistance is not exactly known, so that performance and power efficiency degrade.

Rotor resistance may vary up to 100% due to rotor heating and can hardly be recovered using thermal models and temperature sensors. This motivated, starting with [14], several contributions [15]–[20], [4], [5], [21]–[23] on rotor resistance estimation. As discussed in [24], most contributions are based on simplifying assumptions such as linear approximations, restricted operating conditions including quasi steady-state operations and rotor speed different than zero. Least squares identification techniques are proposed in [25] for the estimation of all parameters (both mechanical and electrical) of an induction motor with slowly varying rotor speed. Recently, two rotor resistance estimation algorithms (an eleventh-order one in [24] and a seventh-order one in [10]) were designed on the basis of the standard nonlinear model and experimentally tested; they provide exponentially convergent on-line estimates in physical operating conditions (including zero speed), on the basis of rotor speed, stator voltages, and stator currents measurements. In [10] the estimation algorithm was used to update (not in closed loop) an observer-based controller for current-fed machines; in [26] a controller for a full-order model which is adaptive with respect to rotor resistance and does not employ any flux observer is directly designed (it is continuously updated in closed loop). Experiments reported in [10] clearly indicate that performance and power efficiency are significantly improved when rotor resistance estimates are used.

With the exception of [14], where stator current derivatives are assumed to be available, rotor resistance estimation schemes require the knowledge of stator resistance (R_s) which may also vary up to 50% during motor operation. In [10] and [24] the influence of stator resistance errors on rotor resistance estimation errors was investigated: the smaller the rotor speed and the ratio R_r/R_s are, the larger the influence results. Actually, as shown in [10], [18], and [24], in worst cases a stator resistance error may cause a rotor resistance estimation error of the same magnitude. Indirect stator resistance estimates may be obtained on the basis of stator temperature measurements and thermal models which are to be developed for each motor: this approach is, therefore, limited to expensive applications. Under the assumption that rotor flux linkages are measured as well, speed tracking controls which are adaptive with respect to stator and rotor resistance are given in [27] while in [28] a torque regulating control which is adaptive with respect to all electrical parameters (resistances and inductances) is obtained. A main goal of current research on induction motor control is to obtain the same results without flux measurements. Some work along this direction has been recently presented in [29]: a control algorithm which does not require rotor flux measurements and is adaptive with respect to the parameters of both the stator electrical circuit and of the mechanical subsystem is proposed. A different approach is proposed in [30] where an output feedback high-gain control is given which achieves local stability and guarantees arbitrarily small speed tracking error, in the presence of uncertainties in rotor/stator resistances and time-varying load torque.

In this paper we address the problem of simultaneous on-line estimation of stator and rotor resistances, on the basis of measurements of rotor speed, stator currents and voltages. This problem may be viewed as an intermediate step toward the design of control algorithms when both resistances are uncertain. The first contribution on this subject was given in [31] where a sixth-order estimation algorithm is proposed and tested

Manuscript received March 24, 1998; revised November 23, 1998. Recommended by Associate Editor, D. Dawson. This work was supported in part by MURST.

R. Marino and P. Tomei are with the Department of Electrical Engineering, University of Rome “Tor Vergata,” Via di Tor Vergata, 00133 Rome, Italy (e-mail: tomei@ein.uniroma2.it).

S. Peresada is with the Department of Electrical Engineering, Kiev Polytechnical Institute, Kiev 252056 Ukraine.

Publisher Item Identifier S 1063-6536(00)03199-7.

by simulations, which show convergence of both stator and rotor resistance estimates when the electromechanical torque is piece-wise constant: the stability analysis is performed under simplifying assumptions while parameter convergence is not investigated. The contribution of this paper is to design (in Section II) a novel ninth-order estimation algorithm which contains both rotor flux and stator current estimates: the design goal is to force stator current estimation errors to tend asymptotically to zero for any initial condition. It is shown that, under persistency of excitation conditions, stator and rotor resistance estimates tend exponentially to the true values for any unknown value of stator and rotor resistance, provided that the time integrals of the stator currents are bounded. Simpler persistency of excitation conditions are obtained when rotor speed is constant (including zero speed). It is also shown that in particular operating conditions for unloaded motors (constant speed and constant flux modulus), rotor resistance is not identifiable while stator resistance may be independently estimated by a simple third-order estimator. Experimental tests are finally reported in Section III which show exponentially converging estimates of both resistances in typical operating conditions in spite of current and voltage sensors noise; quantization effects on measured signals (the sampling time is 0.5 ms while the optical encoder has 2000 lines per revolution); discretization of the estimation algorithm by an improved Euler integration method; inaccuracies on motor inductance parameters; modeling assumptions such as unsaturated machine. The identification algorithm is implementable on-line by currently available digital signal processors.

II. Stator and Rotor Resistance Estimation Algorithm

Assuming linear magnetic circuits and neglecting any mechanical friction, the dynamical model of an induction motor in a fixed reference frame attached to the stator (see [8], [32], and [33]) is given by

$$\begin{aligned}
\frac{d\omega}{dt} &= \mu(\psi_a i_b - \psi_b i_a) - \frac{T_L}{J}\\
\frac{di_a}{dt} &= -(R_{sN}+\theta_s)\frac{1}{\sigma}\, i_a + \frac{1}{\sigma}\, u_a + (R_{rN}+\theta_r)\frac{\beta}{L_r}\,\psi_a\\
&\quad + \beta\omega\psi_b - (R_{rN}+\theta_r)\frac{\beta M}{L_r}\, i_a\\
\frac{di_b}{dt} &= -(R_{sN}+\theta_s)\frac{1}{\sigma}\, i_b + \frac{1}{\sigma}\, u_b + (R_{rN}+\theta_r)\frac{\beta}{L_r}\,\psi_b\\
&\quad - \beta\omega\psi_a - (R_{rN}+\theta_r)\frac{\beta M}{L_r}\, i_b\\
\frac{d\psi_a}{dt} &= -(R_{rN}+\theta_r)\frac{1}{L_r}\,\psi_a - \omega\psi_b + (R_{rN}+\theta_r)\frac{M}{L_r}\, i_a\\
\frac{d\psi_b}{dt} &= -(R_{rN}+\theta_r)\frac{1}{L_r}\,\psi_b + \omega\psi_a + (R_{rN}+\theta_r)\frac{M}{L_r}\, i_b
\end{aligned} \tag{1}$$

in which i_a, i_b, ψ_a, ψ_b, u_a, and u_b denote stator currents, rotor flux linkages, and stator voltages, ω is the rotor speed, T_L is the load torque, J is the total motor and load inertia, $R_s = R_{sN} + \theta_s$, and $R_r = R_{rN} + \theta_r$ are stator and rotor winding resistances with θ_s and θ_r denoting the variations from the nominal values R_{sN} and R_{rN}, L_s, and L_r are the inductances of the stator and rotor circuits while M is the stator-rotor mutual inductance. We assume that θ_s and θ_r are constant during the estimation process. The number of pole pairs is assumed to be one. To simplify notations we use in (1) the parameters $\sigma = L_s(1 - M^2/(L_sL_r))$, $\beta = M/(\sigma L_r)$ and $\mu = M/(JL_r)$. We assume that the motor operates so that: $i_a(t)$, $i_b(t)$, $\int_0^t i_a(\tau)\,d\tau$, $\int_0^t i_b(\tau)\,d\tau$, $\psi_a(t)$, $\psi_b(t)$, $\omega(t)$, $u_a(t)$, $u_b(t)$ are bounded for every $t > 0$. Note that the time integrals of stator currents are assumed to be bounded: this assumption is satisfied, for instance, when the motor is operating at constant speed ω, constant rotor flux modulus $|\Psi|$ and is subject to a nonzero constant load torque T_L. In this case, we have

$$\begin{bmatrix} i_a \\ i_b \end{bmatrix} = \begin{bmatrix} \cos\rho(t) & -\sin\rho(t) \\ \sin\rho(t) & \cos\rho(t) \end{bmatrix} \begin{bmatrix} \dfrac{|\Psi|}{M} \\ \dfrac{T_L}{\mu J|\Psi|} \end{bmatrix}$$

$$\rho(t) = \rho(t_0) + \left(\omega + \frac{R_r M T_L}{L_r \mu J |\Psi|^2}\right)(t - t_0)$$

and the stator currents integrals are sinusoidal.

A. Rotor Resistance Identifiability

If the motor operates so that in a time interval $\psi_a(t) = Mi_a(t)$, $\psi_b(t) = Mi_b(t)$, $T_L = 0$, the model (1) becomes

$$\begin{aligned}
\frac{di_a}{dt} &= -(R_{sN}+\theta_s)\frac{1}{\sigma}\, i_a + \frac{1}{\sigma}\, u_a + \beta\omega\psi_b\\
\frac{di_b}{dt} &= -(R_{sN}+\theta_s)\frac{1}{\sigma}\, i_b + \frac{1}{\sigma}\, u_b - \beta\omega\psi_a\\
\frac{d\psi_a}{dt} &= -\omega\psi_b\\
\frac{d\psi_b}{dt} &= \omega\psi_a\\
\frac{d\omega}{dt} &= 0
\end{aligned} \tag{2}$$

and does not depend on R_r, that is R_r can not be identified: this physically happens for instance when both speed and flux modulus are kept constant with $T_L = 0$. In this case θ_s may be independently estimated by the algorithm

$$\begin{aligned}
\frac{d\hat{i}_a}{dt} &= -(R_{sN}+\hat\theta_s)\frac{1}{\sigma}\, i_a + \frac{1}{\sigma}\, u_a + \beta\omega M i_b + k\tilde{i}_a\\
\frac{d\hat{i}_b}{dt} &= -(R_{sN}+\hat\theta_s)\frac{1}{\sigma}\, i_b + \frac{1}{\sigma}\, u_b - \beta\omega M i_a + k\tilde{i}_b\\
\frac{d\hat\theta_s}{dt} &= -\frac{\gamma}{\sigma}(i_a\tilde{i}_a + i_b\tilde{i}_b)
\end{aligned} \tag{3}$$

with $k > 0$, $\gamma > 0$, $\tilde{i}_a = i_a - \hat{i}_a$, $\tilde{i}_b = i_b - \hat{i}_b$ and $\hat\theta_s$ denoting the estimate of θ_s. The error dynamics become ($\tilde\theta_s = \theta_s - \hat\theta_s$)

$$\begin{aligned}
\frac{d\tilde{i}_a}{dt} &= -k\tilde{i}_a - \frac{1}{\sigma}\,\tilde\theta_s i_a\\
\frac{d\tilde{i}_b}{dt} &= -k\tilde{i}_b - \frac{1}{\sigma}\,\tilde\theta_s i_b\\
\frac{d\tilde\theta_s}{dt} &= \frac{\gamma}{\sigma}(i_a\tilde{i}_a + i_b\tilde{i}_b).
\end{aligned} \tag{4}$$

Using the Lyapunov function

$$V = \frac{1}{2}(\tilde{i}_a^2 + \tilde{i}_b^2) + \frac{1}{2\gamma}\,\tilde\theta_s^2$$

we obtain $\dot V = -k(\tilde{i}_a^2 + \tilde{i}_b^2)$. Then, since the currents and their time derivatives are bounded, Barbalat's Lemma (see [34]) can be applied to show that both $(\tilde{i}_a,\, \tilde{i}_b)$ and $(\dot{\tilde{i}}_a,\, \dot{\tilde{i}}_b)$ tend asymptotically to zero, which implies that also $\tilde\theta_s(t)$ tend to zero, provided that $i_a(t)$ and $i_b(t)$ do not tend simultaneously to zero as time goes to infinity.

B. Estimator Design

Assuming that there is no time interval in which $\psi_a(t) = Mi_a(t)$, $\psi_b(t) = Mi_b(t)$, we intend to design, on the basis of measured signals ($\omega, i_a, i_b, u_a, u_b$), a dynamical system (a stator-rotor resistance estimator) which asymptotically provides under suitable conditions, the values of R_r and R_s (or equivalently θ_r and θ_s). Our design is based on the last four equations in (1) and will be, therefore, limited by the underlying assumptions of linear magnetic circuits. We start the design from a modified version of the well-known full-order flux observer (see [13])

$$\begin{aligned}
\frac{d\hat{i}_a}{dt} =& -\left(\frac{R_{sN}}{\sigma} + R_{rN}\beta\frac{M}{L_r}\right) i_a + \frac{u_a}{\sigma} + v_a + k_1(i_a - \hat{i}_a)\\
&+ \beta\left(\frac{R_{rN}}{L_r}\hat{\psi}_a + \omega\hat{\psi}_b\right) + \hat{\theta}_r\frac{\beta}{L_r}(\hat{\psi}_a - Mi_a)\\
\frac{d\hat{i}_b}{dt} =& -\left(\frac{R_{sN}}{\sigma} + R_{rN}\beta\frac{M}{L_r}\right) i_b + \frac{u_b}{\sigma} + v_b + k_1(i_b - \hat{i}_b)\\
&+ \beta\left(\frac{R_{rN}}{L_r}\hat{\psi}_b - \omega\hat{\psi}_a\right) + \hat{\theta}_r\frac{\beta}{L_r}(\hat{\psi}_b - Mi_b)\\
\frac{d\hat{\psi}_a}{dt} =& -\frac{R_{rN}}{L_r}\hat{\psi}_a - \omega\hat{\psi}_b + R_{rN}\frac{M}{L_r}i_a - \frac{1}{\beta}v_a\\
&- \frac{k_2}{\beta}(i_a - \hat{i}_a) - \frac{\hat{\theta}_r}{L_r}(\hat{\psi}_a - Mi_a)\\
\frac{d\hat{\psi}_b}{dt} =& -\frac{R_{rN}}{L_r}\hat{\psi}_b + \omega\hat{\psi}_a + R_{rN}\frac{M}{L_r}i_b - \frac{1}{\beta}v_b\\
&- \frac{k_2}{\beta}(i_b - \hat{i}_b) - \frac{\hat{\theta}_r}{L_r}(\hat{\psi}_b - Mi_b)
\end{aligned} \tag{5}$$

in which (v_a, v_b) are additional signals yet to be designed; $\hat{i}_a$, $\hat{i}_b$, $\hat{\psi}_a$, $\hat{\psi}_b$ are estimates of i_a, i_b, ψ_a, ψ_b; k_1 and k_2 are design parameters with $k_1 > 0$. Note that $\hat{\theta}_r$, the estimate of θ_r, is incorporated in (5) while only the nominal value R_{sN} is used in (5). Let us introduce the error variables $\tilde{i}_a = i_a - \hat{i}_a$, $\tilde{i}_b = i_b - \hat{i}_b$, $\tilde{\psi}_a = \psi_a - \hat{\psi}_a$, $\tilde{\psi}_b = \psi_b - \hat{\psi}_b$, $\tilde{\theta}_r = \theta_r - \hat{\theta}_r$, so that from (1) and (5) we may compute the error dynamics

$$\begin{aligned}
\frac{d\tilde{i}_a}{dt} =& -k_1\tilde{i}_a + \frac{R_{rN}}{L_r}\beta\tilde{\psi}_a + \beta\omega\tilde{\psi}_b + \tilde{\theta}_r\frac{\beta}{L_r}(\hat{\psi}_a - Mi_a)\\
&- \frac{\theta_s}{\sigma}i_a - v_a\\
\frac{d\tilde{i}_b}{dt} =& -k_1\tilde{i}_b + \frac{R_{rN}}{L_r}\beta\tilde{\psi}_b - \beta\omega\tilde{\psi}_a + \tilde{\theta}_r\frac{\beta}{L_r}(\hat{\psi}_b - Mi_b)\\
&- \frac{\theta_s}{\sigma}i_b - v_b\\
\frac{d\tilde{\psi}_a}{dt} =& -\frac{R_{rN}}{L_r}\tilde{\psi}_a - \omega\tilde{\psi}_b + \frac{k_2}{\beta}\tilde{i}_a - \frac{\tilde{\theta}_r}{L_r}(\hat{\psi}_a - Mi_a) + \frac{v_a}{\beta}\\
\frac{d\tilde{\psi}_b}{dt} =& -\frac{R_{rN}}{L_r}\tilde{\psi}_b + \omega\tilde{\psi}_a + \frac{k_2}{\beta}\tilde{i}_b - \frac{\tilde{\theta}_r}{L_r}(\hat{\psi}_b - Mi_b) + \frac{v_b}{\beta}.
\end{aligned} \tag{6}$$

Our goal is to design v_a, v_b, and the updating dynamics for $\hat{\theta}_s$ and $\hat{\theta}_r$ so that $\tilde{i}_a$ and $\tilde{i}_b$ tend asymptotically to zero. To this purpose, let us introduce the new variables

$$\begin{aligned}
z_a &= \tilde{i}_a + \beta\tilde{\psi}_a + \frac{\theta_s}{\sigma}\xi_a\\
z_b &= \tilde{i}_b + \beta\tilde{\psi}_b + \frac{\theta_s}{\sigma}\xi_b
\end{aligned} \tag{7}$$

which depend on the unknown parameter θ_s and on

$$\begin{aligned}
\xi_a &= \int_0^t i_a(\tau)\,d\tau\\
\xi_b &= \int_0^t i_b(\tau)\,d\tau
\end{aligned} \tag{8}$$

which are assumed to be bounded. From (6)–(8), we obtain

$$\begin{aligned}
\frac{d\tilde{i}_a}{dt} =& -\left(k_1 + \frac{R_{rN}}{L_r}\right)\tilde{i}_a - \omega\tilde{i}_b + \frac{R_{rN}}{L_r}z_a + \omega z_b - \frac{\theta_s}{\sigma}i_a\\
&+ \tilde{\theta}_r\frac{\beta}{L_r}(\hat{\psi}_a - Mi_a) - \frac{R_{rN}}{L_r\sigma}\theta_s\xi_a - \omega\frac{\theta_s}{\sigma}\xi_b - v_a\\
\frac{d\tilde{i}_b}{dt} =& -\left(k_1 + \frac{R_{rN}}{L_r}\right)\tilde{i}_b + \omega\tilde{i}_a + \frac{R_{rN}}{L_r}z_b - \omega z_a - \frac{\theta_s}{\sigma}i_b\\
&+ \tilde{\theta}_r\frac{\beta}{L_r}(\hat{\psi}_b - Mi_b) - \frac{R_{rN}}{L_r\sigma}\theta_s\xi_b + \omega\frac{\theta_s}{\sigma}\xi_a - v_b\\
\frac{dz_a}{dt} =& -(k_1 - k_2)\tilde{i}_a\\
\frac{dz_b}{dt} =& -(k_1 - k_2)\tilde{i}_b
\end{aligned} \tag{9}$$

in which the dynamics of the unknown variables (z_a, z_b) are known with unknown initial conditions. This is an advantage with respect to (6) in which the dynamics of the unknown variables $(\tilde{\psi}_a, \tilde{\psi}_b)$ are not known. This justifies the introduction of the variables (z_a, z_b). Now, we define v_a and v_b in order to partially compensate some of the terms in the right-hand side of the first two equations in (9)

$$\begin{aligned}
v_a &= \omega\hat{z}_b - \frac{\hat{\theta}_s}{\sigma}i_a - \hat{\theta}\xi_a - \frac{\hat{\theta}_s}{\sigma}\omega\xi_b\\
v_b &= -\omega\hat{z}_a - \frac{\hat{\theta}_s}{\sigma}i_b - \hat{\theta}\xi_b + \frac{\hat{\theta}_s}{\sigma}\omega\xi_a
\end{aligned} \tag{10}$$

with $\hat{\theta}_s$ and $\hat{\theta}$ being the estimates of the unknown constants θ_s and $\theta = R_{rN}\theta_s/L_r\sigma$ and $\hat{z}_a$, $\hat{z}_b$ being the estimates of the unknown variables z_a, z_b; let $\tilde{\theta}_s = \theta_s - \hat{\theta}_s$, $\tilde{\theta} = \theta - \hat{\theta}$, $\tilde{z}_a = z_a - \hat{z}_a$, $\tilde{z}_b = z_b - \hat{z}_b$ be the corresponding errors. Substituting (10) in (9), the error dynamics become

$$\begin{aligned}
\frac{d\tilde{i}_a}{dt} =& -\left(k_1 + \frac{R_{rN}}{L_r}\right)\tilde{i}_a - \omega\tilde{i}_b + \frac{R_{rN}}{L_r}z_a + \omega\tilde{z}_b\\
&+ \tilde{\theta}_r\frac{\beta}{L_r}(\hat{\psi}_a - Mi_a) - \frac{\tilde{\theta}_s}{\sigma}(i_a + \omega\xi_b) - \tilde{\theta}\xi_a\\
\frac{d\tilde{i}_b}{dt} =& -\left(k_1 + \frac{R_{rN}}{L_r}\right)\tilde{i}_b + \omega\tilde{i}_a + \frac{R_{rN}}{L_r}z_b - \omega\tilde{z}_a\\
&+ \tilde{\theta}_r\frac{\beta}{L_r}(\hat{\psi}_b - Mi_b) - \frac{\tilde{\theta}_s}{\sigma}(i_b - \omega\xi_a) - \tilde{\theta}\xi_b\\
\frac{dz_a}{dt} =& -(k_1 - k_2)\tilde{i}_a\\
\frac{dz_b}{dt} =& -(k_1 - k_2)\tilde{i}_b.
\end{aligned} \tag{11}$$

To design updating dynamics for the estimates $\hat{\theta}_r$, $\hat{\theta}_s$, $\hat{\theta}$ of the unknown parameters θ_r, θ_s, θ and for the estimates $\hat{z}_a$, $\hat{z}_b$ of the unknown variables z_a, z_b which will complete the identification algorithm, we consider the function (γ_i, $1 \le i \le 5$ are positive design parameters and $\gamma_1 = k_1 - k_2$)

$$V = \frac{1}{2}\left[\tilde{i}_a^2 + \tilde{i}_b^2 + \frac{R_{rN}}{L_r\gamma_1}(z_a^2 + z_b^2) + \frac{1}{\gamma_2}(\tilde{z}_a^2 + \tilde{z}_b^2) + \frac{1}{\gamma_3}\tilde{\theta}_s^2 + \frac{1}{\gamma_4}\tilde{\theta}_r^2 + \frac{1}{\gamma_5}\tilde{\theta}^2\right]. \tag{12}$$

Its time derivative along the solutions of (11) is given by

$$\begin{aligned}\dot{V} =& -\left(k_1 + \frac{R_{rN}}{L_r}\right)(\tilde{i}_a^2 + \tilde{i}_b^2) + \tilde{i}_a\omega\tilde{z}_b - \tilde{i}_b\omega\tilde{z}_a \\ &- \frac{\tilde{\theta}_s}{\sigma}[\tilde{i}_a(i_a + \omega\xi_b) + \tilde{i}_b(i_b - \omega\xi_a)] \\ &+ \tilde{\theta}_r\frac{\beta}{L_r}[\tilde{i}_a(\hat{\psi}_a - Mi_a) + \tilde{i}_b(\hat{\psi}_b - Mi_b)] \\ &- \tilde{\theta}(\tilde{i}_a\xi_a + \tilde{i}_b\xi_b) + \frac{1}{\gamma_2}(\tilde{z}_a\dot{\tilde{z}}_a + \tilde{z}_b\dot{\tilde{z}}_b) + \frac{1}{\gamma_3}\tilde{\theta}_s\dot{\tilde{\theta}}_s \\ &+ \frac{1}{\gamma_4}\tilde{\theta}_r\dot{\tilde{\theta}}_r + \frac{1}{\gamma_5}\tilde{\theta}\dot{\tilde{\theta}}.\end{aligned} \tag{13}$$

From (13), we choose the dynamics of $\hat{z}_a$, $\hat{z}_b$, $\hat{\theta}_s$, $\hat{\theta}_r$, and $\hat{\theta}$ as follows:

$$\begin{aligned}\dot{\tilde{z}}_a &= \dot{z}_a - \dot{\hat{z}}_a = \gamma_2\omega\tilde{i}_b \\ \dot{\tilde{z}}_b &= \dot{z}_b - \dot{\hat{z}}_b = -\gamma_2\omega\tilde{i}_a \\ \dot{\tilde{\theta}}_s &= -\dot{\hat{\theta}}_s = \frac{\gamma_3}{\sigma}[\tilde{i}_a(i_a + \omega\xi_b) + \tilde{i}_b(i_b - \omega\xi_a)] \\ \dot{\tilde{\theta}}_r &= -\dot{\hat{\theta}}_r = -\gamma_4\frac{\beta}{L_r}[\tilde{i}_a(\hat{\psi}_a - Mi_a) + \tilde{i}_b(\hat{\psi}_b - Mi_b)] \\ \dot{\tilde{\theta}} &= -\dot{\hat{\theta}} = \gamma_5(\tilde{i}_a\xi_a + \tilde{i}_b\xi_b)\end{aligned} \tag{14}$$

so that we obtain

$$\dot{V} = -\left(k_1 + \frac{R_{rN}}{L_r}\right)(\tilde{i}_a^2 + \tilde{i}_b^2). \tag{15}$$

At this point the design is complete: from (5), (9), (10), and (14), the stator and rotor resistance estimation algorithm is given by a ninth-order nonlinear dynamical system:

$$\begin{aligned}\dot{\hat{\theta}}_s =& -\frac{\gamma_3}{\sigma}[\tilde{i}_a(i_a + \omega\xi_b) + \tilde{i}_b(i_b - \omega\xi_a)] \\ \dot{\hat{\theta}}_r =& \gamma_4\frac{\beta}{L_r}[\tilde{i}_a(\hat{\psi}_a - Mi_a) + \tilde{i}_b(\hat{\psi}_b - Mi_b)] \\ \dot{\hat{\theta}} =& -\gamma_5(\tilde{i}_a\xi_a + \tilde{i}_b\xi_b) \\ \dot{\hat{i}}_a =& -\left(\frac{R_{sN}}{\sigma} + R_{rN}\beta\frac{M}{L_r}\right)i_a + \beta\left(\frac{R_{rN}}{L_r}\hat{\psi}_a + \omega\hat{\psi}_b\right) \\ &+ \frac{1}{\sigma}u_a + k_1\tilde{i}_a + \hat{\theta}_r\frac{\beta}{L_r}(\hat{\psi}_a - Mi_a) + v_a \\ \dot{\hat{i}}_b =& -\left(\frac{R_{sN}}{\sigma} + R_{rN}\beta\frac{M}{L_r}\right)i_b + \beta\left(\frac{R_{rN}}{L_r}\hat{\psi}_b - \omega\hat{\psi}_a\right) \\ &+ \frac{1}{\sigma}u_b + k_1\tilde{i}_b + \hat{\theta}_r\frac{\beta}{L_r}(\hat{\psi}_b - Mi_b) + v_b \\ \dot{\hat{\psi}}_a =& -\frac{R_{rN}}{L_r}\hat{\psi}_a - \omega\hat{\psi}_b + R_{rN}\frac{M}{L_r}i_a - \frac{k_2}{\beta}\tilde{i}_a \\ &- \frac{\hat{\theta}_r}{L_r}(\hat{\psi}_a - Mi_a) - \frac{1}{\beta}v_a \\ \dot{\hat{\psi}}_b =& -\frac{R_{rN}}{L_r}\hat{\psi}_b + \omega\hat{\psi}_a + R_{rN}\frac{M}{L_r}i_b - \frac{k_2}{\beta}\tilde{i}_b \\ &- \frac{\hat{\theta}_r}{L_r}(\hat{\psi}_b - Mi_b) - \frac{1}{\beta}v_b \\ \dot{\hat{z}}_a =& -\gamma_1\tilde{i}_a - \gamma_2\omega\tilde{i}_b \\ \dot{\hat{z}}_b =& -\gamma_1\tilde{i}_b + \gamma_2\omega\tilde{i}_a \\ v_a =& \omega\hat{z}_b - \frac{\hat{\theta}_s}{\sigma}i_a - \hat{\theta}\xi_a - \frac{\hat{\theta}_s}{\sigma}\omega\xi_b \\ v_b =& -\omega\hat{z}_a - \frac{\hat{\theta}_s}{\sigma}i_b - \hat{\theta}\xi_b + \frac{\hat{\theta}_s}{\sigma}\omega\xi_a.\end{aligned} \tag{16}$$

It contains six design parameters: k_1, k_2, γ_2, γ_3, γ_4, γ_5 (recall that $\gamma_1 = k_1 - k_2$) and depends on motor inductances L_r, L_s, M, and nominal values of both resistances R_{rN}, R_{sN}; its inputs are ω, u_a, u_b, i_a, i_b, and their time integrals $\xi_a = \int_0^t i_a(\tau)\,d\tau$, $\xi_b = \int_0^t i_b(\tau)\,d\tau$; its outputs are the estimates $\hat{\theta}_s$ and $\hat{\theta}_r$.

C. Stability Analysis

From (12) and (15) it follows that $\tilde{i}_a$, $\tilde{i}_b$, z_a, z_b, $\tilde{z}_a$, $\tilde{z}_b$, $\tilde{\theta}_s$, $\tilde{\theta}_r$, and $\tilde{\theta}$ are bounded. From (7), since $\psi_a(t)$, $\psi_b(t)$, and $\xi_a(t)$, $\xi_b(t)$ defined in (8) are bounded by assumption, it follows that $\tilde{\psi}_a$, $\tilde{\psi}_b$ are bounded and therefore $\hat{\psi}_a$, $\hat{\psi}_b$ are bounded as well. The current error dynamics may be rewritten in matrix form as

$$\frac{d\tilde{i}}{dt} = \Lambda(t)\tilde{i} + W^T(t)\tilde{p} \tag{17}$$

with (17a), shown at the bottom of the next page, while the last two equations in (11) and (14) may be rewritten as

$$\dot{\tilde{p}} = -\Gamma W(t)\tilde{i} \tag{18}$$

with Γ a constant diagonal positive definite matrix

$$\Gamma = \mathrm{diag}[\gamma_1 L_r/R_{rN},\ \gamma_1 L_r/R_{rN},\ \gamma_2,\ \gamma_3,\ \gamma_4,\ \gamma_5].$$

From (17) it follows that $\dot{\tilde{i}}$ is bounded. On the other hand, from (15) we have

$$\begin{aligned}\int_0^t \dot{V}(\tau)\,d\tau &= -\left(k_1 + \frac{R_{rN}}{L_r}\right)\int_0^t [\tilde{i}_a^2(\tau) + \tilde{i}_b^2(\tau)]\,d\tau \\ &= V(t) - V(0)\end{aligned}$$

which implies that $\lim_{t\to\infty}\int_0^t [\tilde{i}_a^2(\tau) + \tilde{i}_b^2(\tau)]\,d\tau < \infty$, since $V(t)$ has been shown to be bounded. From Barbalat's Lemma it follows that (see [34])

$$\lim_{t\to\infty}\tilde{i}_a(t) = 0, \qquad \lim_{t\to\infty}\tilde{i}_b(t) = 0. \tag{19}$$

Since from (1) di_a/dt, di_b/dt, and $d\omega/dt$ are bounded, from (17) and (18) $d^2\tilde{i}_a/dt^2$, $d^2\tilde{i}_b/dt^2$ are bounded as well and applying again Barbalat's Lemma we conclude that

$$\lim_{t\to\infty}\frac{d\tilde{i}_a}{dt} = 0, \qquad \lim_{t\to\infty}\frac{d\tilde{i}_b}{dt} = 0 \tag{20}$$

which from (17) imply that

$$\lim_{t\to\infty} W^T(t)\tilde{p}(t) = 0 \tag{21}$$

which represents an asymptotic constraint for $\tilde{p}$. Moreover, if the matrix

$$\int_t^{t+T} W(\tau)W^T(\tau)\,d\tau \ge cI > 0 \tag{22}$$

for some $T > 0$, $c > 0$ and for every $t \ge 0$, the system (17), (18) is persistently excited and $(\tilde{\imath}, \tilde{p})$ tend exponentially to zero (see [34]).

Remark II.1: Even if z_a, z_b, $\tilde{\imath}_a$, and $\tilde{\imath}_b$ tend exponentially to zero [for instance when persistency of excitation condition (22) is satisfied], from (7) we have

$$\lim_{t\to\infty}\left(\beta\tilde{\psi}_a(t) + \frac{\theta_s}{\sigma}\,\xi_a(t)\right) = 0$$
$$\lim_{t\to\infty}\left(\beta\tilde{\psi}_b(t) + \frac{\theta_s}{\sigma}\,\xi_b(t)\right) = 0$$

and therefore the flux estimates $(\hat{\psi}_a(t), \hat{\psi}_b(t))$ may not converge to the true flux $(\psi_a(t), \psi_b(t))$ since in general ξ_a and ξ_b do not converge to zero. Nevertheless, in this case the estimates of the fluxes may be recovered by observing that

$$\lim_{t\to\infty}\left[\beta(\hat{\psi}_a(t) - \psi_a(t)) + \frac{\hat{\theta}_s(t)}{\sigma}\,\xi_a(t)\right] = 0$$
$$\lim_{t\to\infty}\left[\beta(\hat{\psi}_b(t) - \psi_b(t)) + \frac{\hat{\theta}_s(t)}{\sigma}\,\xi_b(t)\right] = 0$$

which allow us to obtain asymptotically the flux vector $(\psi_a(t), \psi_b(t))$ as a function of the known variables $\hat{\psi}_a$, $\hat{\psi}_b$, $\hat{\theta}_s$, ξ_a, and ξ_b.

Remark II.2: If the motor speed is constant (including zero speed), a simpler persistency of excitation condition may be obtained. In fact, assume that $\omega(t)$ is constant and define

$$z_1 = \frac{R_{rN}}{L_r}\,z_a + \omega\tilde{z}_b$$
$$z_2 = \frac{R_{rN}}{L_r}\,z_b - \omega\tilde{z}_a$$

so that from (11) and (14) we have

$$\begin{aligned}
\dot{\tilde{\imath}}_a &= -\left(k_1 + \frac{R_{rN}}{L_r}\right)\tilde{\imath}_a - \omega\tilde{\imath}_b + z_1\\
&\quad + \tilde{\theta}_r\,\frac{\beta}{L_r}(\hat{\psi}_a - Mi_a) - \frac{\tilde{\theta}_s}{\sigma}(i_a + \omega\xi_b) - \tilde{\theta}\xi_a\\
\dot{\tilde{\imath}}_b &= -\left(k_1 + \frac{R_{rN}}{L_r}\right)\tilde{\imath}_b + \omega\tilde{\imath}_a + z_2\\
&\quad + \tilde{\theta}_r\,\frac{\beta}{L_r}(\hat{\psi}_b - Mi_b) - \frac{\tilde{\theta}_s}{\sigma}(i_b - \omega\xi_a) - \tilde{\theta}\xi_b\\
\dot{z}_1 &= \frac{R_{rN}}{L_r}\,\dot{z}_a + \omega\dot{\tilde{z}}_b = -\frac{R_{rN}}{L_r}(k_1 - k_2)\tilde{\imath}_a - \gamma_2\omega^2\tilde{\imath}_a\\
\dot{z}_2 &= \frac{R_{rN}}{L_r}\,\dot{z}_b - \omega\dot{\tilde{z}}_a = -\frac{R_{rN}}{L_r}(k_1 - k_2)\tilde{\imath}_b - \gamma_2\omega^2\tilde{\imath}_b\\
\dot{\tilde{\theta}}_s &= \frac{\gamma_3}{\sigma}[\tilde{\imath}_a(i_a + \omega\xi_b) + \tilde{\imath}_b(i_b - \omega\xi_a)]\\
\dot{\tilde{\theta}}_r &= -\gamma_4\,\frac{\beta}{L_r}[\tilde{\imath}_a(\hat{\psi}_a - Mi_a) + \tilde{\imath}_b(\hat{\psi}_b - Mi_b)]\\
\dot{\tilde{\theta}} &= \gamma_5(\tilde{\imath}_a\xi_a + \tilde{\imath}_b\xi_b)
\end{aligned}$$

which may be rewritten as

$$\frac{d\tilde{\imath}}{dt} = \Lambda\tilde{\imath} + W_c^T(t)\tilde{p}_c$$
$$\frac{d\tilde{p}_c}{dt} = -\Gamma_c W_c(t)\tilde{\imath}$$

with $p_c = [z_1,\, z_2,\, \tilde{\theta}_s,\, \tilde{\theta}_r,\, \tilde{\theta}]^T$ and

$$W_c^T = \begin{bmatrix} 1 & 0 & -\dfrac{1}{\sigma}(i_a + \omega\xi_b) & \dfrac{\beta}{L_r}(\hat{\psi}_a - Mi_a) & -\xi_a\\ 0 & 1 & -\dfrac{1}{\sigma}(i_b - \omega\xi_a) & \dfrac{\beta}{L_r}(\hat{\psi}_b - Mi_b) & -\xi_b \end{bmatrix}$$

$$\Gamma_c = \mathrm{diag}\left[\frac{R_{rN}}{L_r}(k_1 - k_2) + \gamma_2\omega^2,\ \frac{R_{rN}}{L_r}(k_1 - k_2) + \gamma_2\omega^2,\ \gamma_3,\ \gamma_4,\ \gamma_5\right].$$

The persistency of excitation condition becomes in this case

$$\int_t^{t+T} W_c(\tau)W_c^T(\tau)\,d\tau \ge cI > 0 \tag{23}$$

for some $T > 0$, $c > 0$, and every $t \ge 0$. □

III. Experimental Results

The experimental setup is illustrated by the block diagram in Fig. 1. A 0.6-kW induction motor (OEMER 7-80/C), whose data are reported in the Appendix, is supplied by a power inverter with symmetrical PWM and switching frequency of 15 kHz. A current controlled dc motor provides the required time-varying load torque. The motor speed is measured by an optical incremental encoder with 2000 lines per revolution. The stator phase currents and voltages are measured by Hall-type sensors. All measured electrical signals are properly filtered by low-pass second-order filters with cutoff frequency of 2.6 kHz and converted by 12-bit A/D converters with 25-μs conversion time. A 32-bit DSP

$$\Lambda(t) = \begin{bmatrix} -k_1 - \dfrac{R_{rN}}{L_r} & -\omega\\ \omega & -k_1 - \dfrac{R_{rN}}{L_r} \end{bmatrix}$$

$$W^T(t) = \begin{bmatrix} \dfrac{R_{rN}}{L_r} & 0 & 0 & \omega & -\dfrac{i_a + \omega\xi_b}{\sigma} & \dfrac{\beta}{L_r}(\hat{\psi}_a - Mi_a) & -\xi_a\\ 0 & \dfrac{R_{rN}}{L_r} & -\omega & 0 & -\dfrac{i_b - \omega\xi_a}{\sigma} & \dfrac{\beta}{L_r}(\hat{\psi}_b - Mi_b) & -\xi_b \end{bmatrix}$$

$$\tilde{\imath} = [\,\tilde{\imath}_a \quad \tilde{\imath}_b\,]$$
$$\tilde{p} = [\,z_a \quad z_b \quad \tilde{z}_a \quad \tilde{z}_b \quad \tilde{\theta}_s \quad \tilde{\theta}_r \quad \tilde{\theta}\,]. \tag{17a}$$

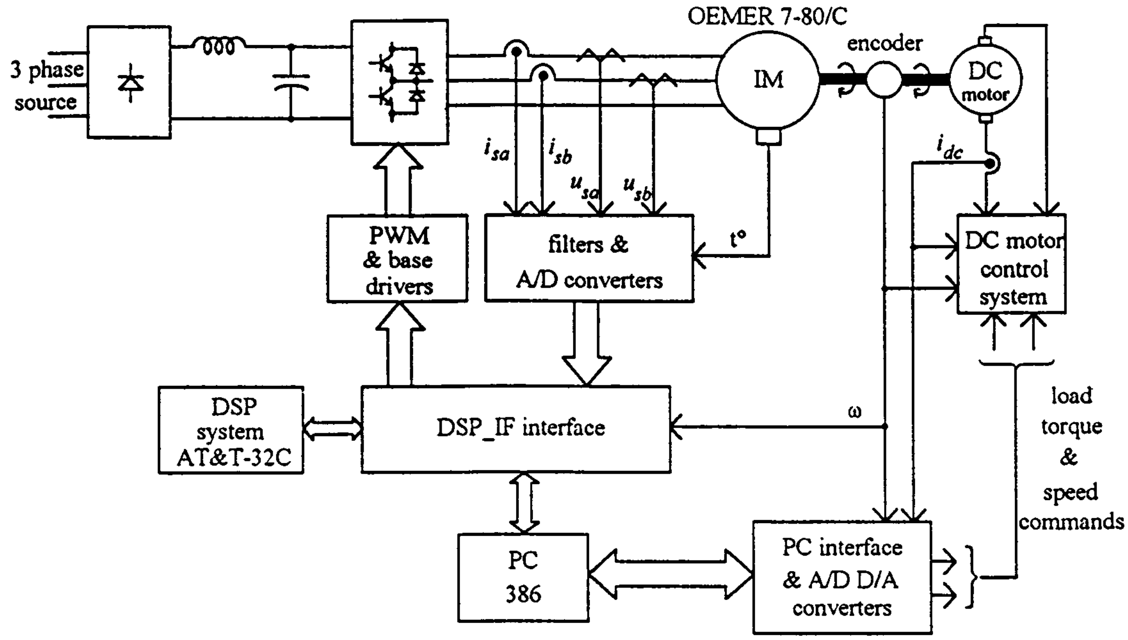

Fig. 1. Block diagram of the experimental setup.

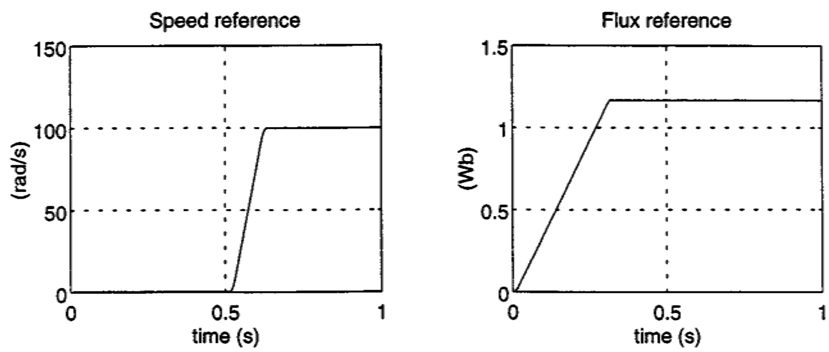

Fig. 2. Speed and flux reference trajectories.

(AT&T-32c) performs data acquisition and implements the identification algorithm (16) with sampling time 0.5 ms, using the improved Euler integration algorithm. During all experiments the induction motor has been controlled by an output feedback controller, whose detailed description is given in [10]. The identification of the nominal motor parameters, the validation of the model, the real and computed static torque-speed characteristics and transients during start-up are presented in [24]. The experiments are intended to test the performance of the identification algorithm in the presence of sensor noise, inverter voltage distortion, quantization effect, and modeling inaccuracies.

The stator-rotor resistance identification algorithm (16) has been tested in the following operating conditions: the unloaded motor is required to reach the rated speed in 140 ms, starting from 0.5 s; an initial time interval, from zero to 0.31 s, is needed to drive the motor flux to the rated value (1.16 Wb); after start-up, at $t = 0.75$ s, a step load torque, equal to the rated value, is applied. Both speed and flux reference signals (reported in Fig. 2) are twice time differentiable. The transient behavior of the motor speed and flux, as well as direct and quadrature currents are shown in Fig. 3. Although the original measurements were phase motor currents, the pictures show two-phase equivalent stator currents, in a synchronously rotating frame. The estimated rotor flux modulus, also presented in Fig. 3, is obtained by a flux observer with the correct value of rotor resistance. The dynamic behavior of the identification scheme (16) whose tuning parameters were set to $\gamma_1 = 5.0$, $\gamma_2 = 0.01$, $\gamma_3 = 0.2$, $\gamma_4 = 0.8$, $\gamma_5 = 1.0$, $k_2 = 95.0$ and whose initial conditions for all state variables (excepting $\hat{\theta}_s$ and $\hat{\theta}_r$) are set to zero, is illustrated in Figs. 4–8. Figs. 4 and 5 report the results in the cases in which the initial estimates are $\hat{\theta}_s(0) = -0.8R_{sN}$, $\hat{\theta}_r(0) = -0.5R_{rN}$ and $\hat{\theta}_s(0) = 0.8R_{sN}$, $\hat{\theta}_r(0) = 0.8R_{rN}$, respectively, with $R_{sN} = 5.3\ \Omega$ and $R_{rN} = 3.3\ \Omega$. In both cases the estimated values of the resistances converge to the

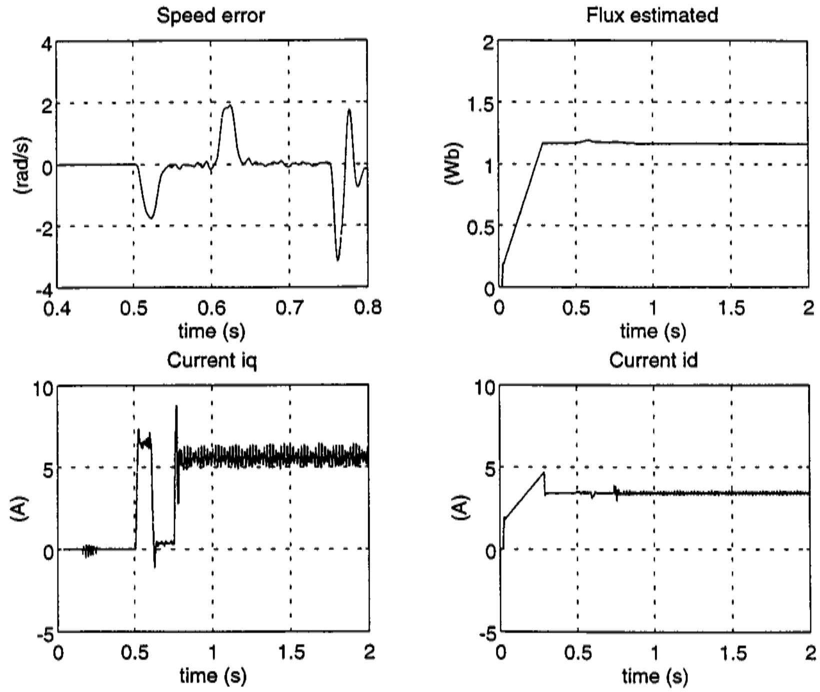

Fig. 3. Transient behavior of the induction motor drive.

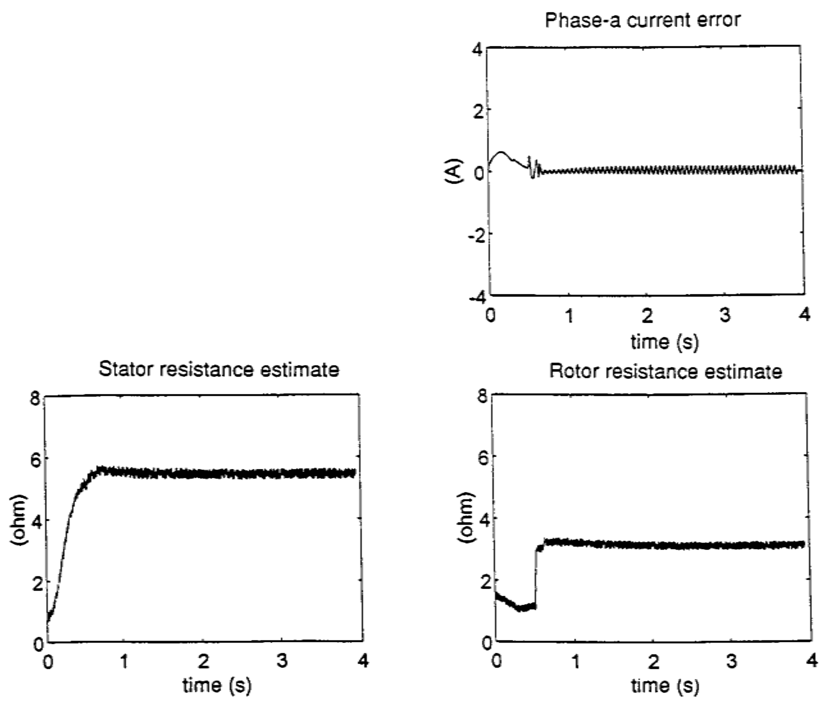

Fig. 4. Stator and rotor resistance estimates with -80 and -50% initial errors, respectively.

true values within 3 s. Note that R_r is not identifiable in the time interval [0, 0.5] s. The steady-state parameter estimation errors are not equal to zero due to sensor noise, quantization and discretization effects, inaccuracies on nominal inductances. The results depicted in Figs. 6 and 7 have been obtained starting from $\hat{\theta}_s(0) = 0.8R_{sN}$, $\hat{\theta}_r(0) = -0.8R_{rN}$ and $\hat{\theta}_s(0) = -0.8R_{sN}$, $\hat{\theta}_r(0) = 0.5R_{rN}$. Finally, Fig. 8 illustrates the behavior of the identification scheme when the initial estimates of θ_s and θ_r are set to the corresponding true values. Exponential convergence of the stator and rotor resistance estimates may be observed from these figures for any combination of initial conditions, while persistency of excitation conditions are always satisfied.

IV. Conclusions

We presented in Section II a ninth-order nonlinear algorithm for on-line estimation of both rotor and stator resistances on the

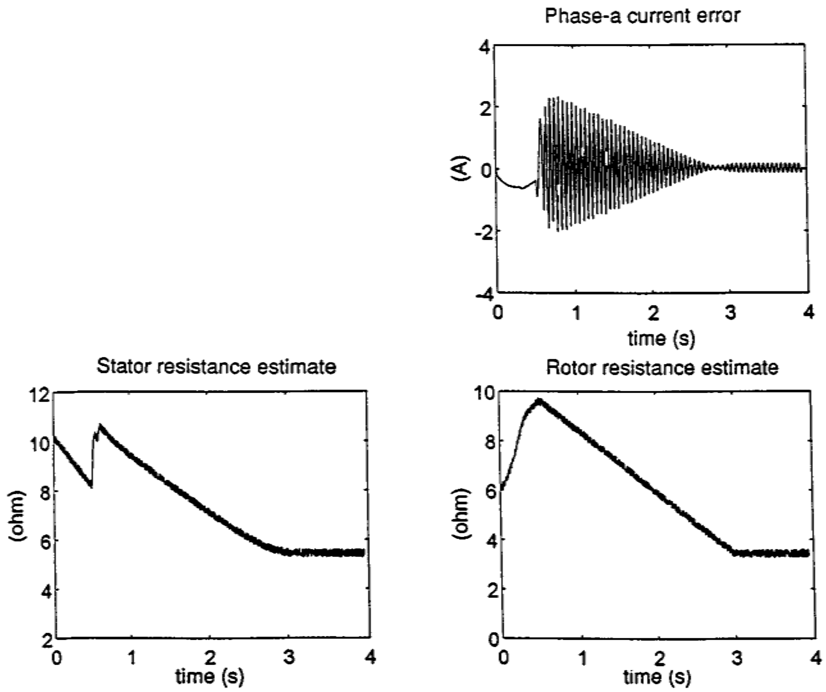

Fig. 5. Stator and rotor resistance estimates with +80% initial errors.

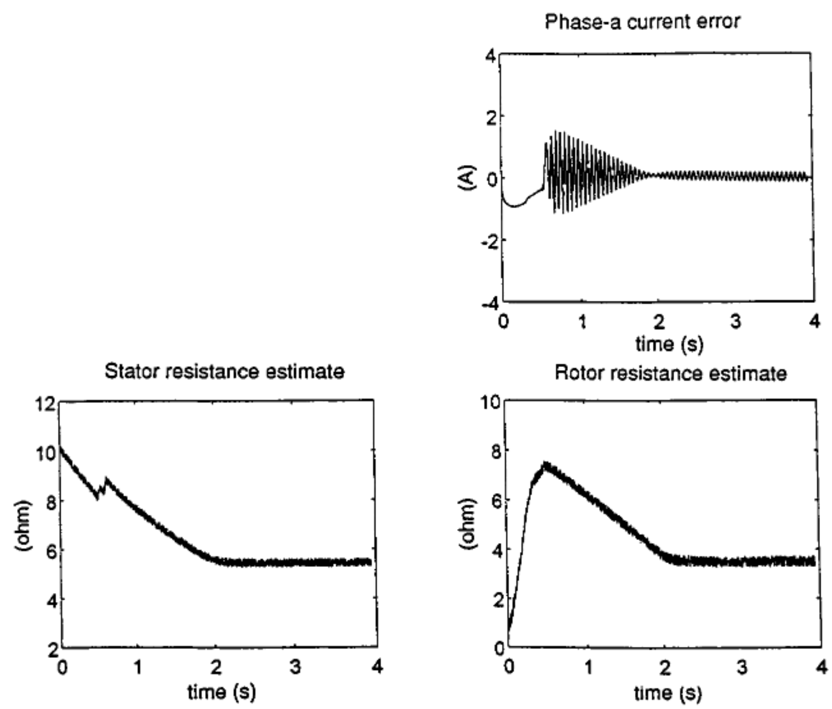

Fig. 6. Stator and rotor resistance estimates with $+80$ and -80% initial errors, respectively.

basis of rotor speed, stator currents, and stator voltages measurements. We show that all signals are bounded and that, under persistency of excitation (22) [or (23) when speed is constant], rotor and stator resistance estimates converge exponentially to their true values, provided that the stator currents time integrals are bounded: rotor flux may also be asymptotically recovered as explained in Remark II.1. The experiments reported in Section III show a quick convergence of resistance estimates for different initial conditions, during typical motor operations; they also show the robustness of the estimation algorithm with respect to sensor noise, quantization and discretization effects, and modeling inaccuracies. The proposed estimator may be implemented on-line to improve power efficiency and performance of currently available induction motor controllers.

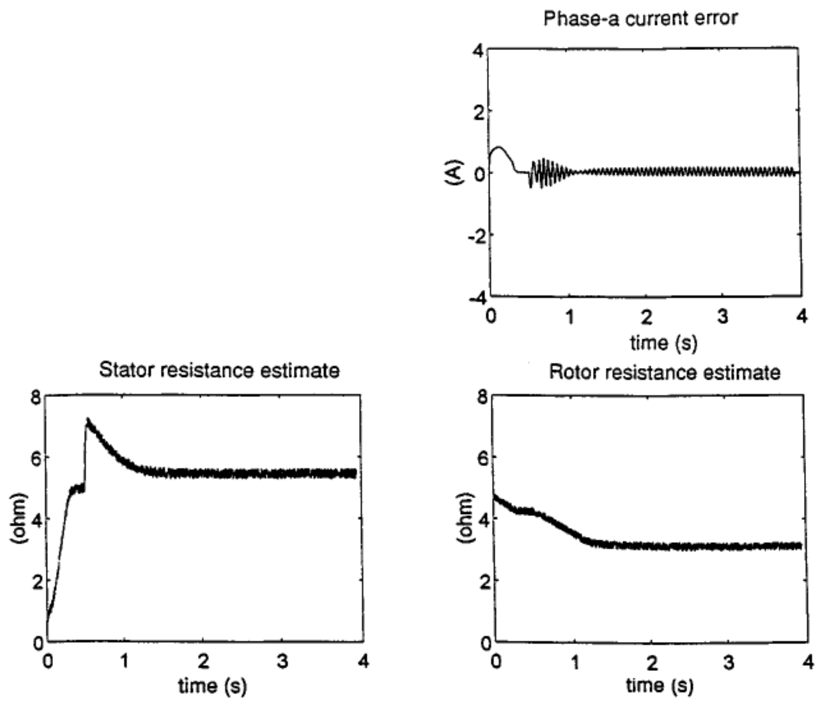

Fig. 7. Stator and rotor resistance estimates with −80 and +50% initial errors, respectively.

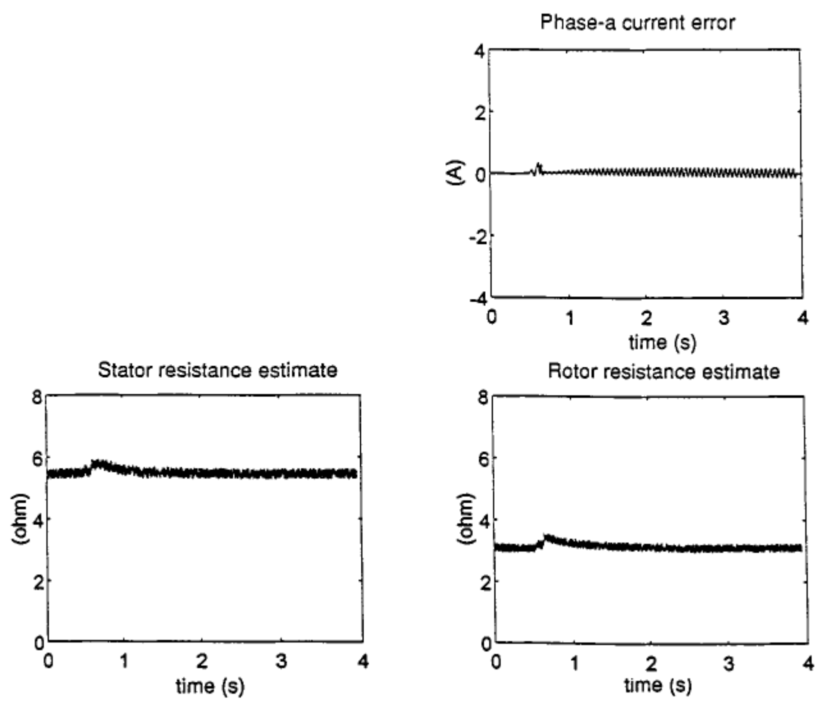

Fig. 8. Stator and rotor resistance estimates with zero initial errors.

APPENDIX
INDUCTION MOTOR DATA

600 W	Rated power.
1000 r/min	Rated speed.
5.8 Nm	Rated torque.
16.7 Hz	Rated frequency.
2 A	Excitation current.
4 A	Rated current.
$R_{sN} = 5.3\ \Omega$	Stator resistance.
$R_{rN} = 3.3\ \Omega$	Rotor resistance.
$M_N = 0.34$ H	Mutual inductance.
$L_{rN} = 0.375$ H	Rotor inductance.
$L_{sN} = 0.365$ H	Stator inductance.
$J = 0.0075$ kg m^2	Motor-load inertia.

REFERENCES

[1] W. Leonhard, "Microcomputer control of high dynamic performance ac-drives—A survey," *Automatica*, vol. 22, pp. 1–19, 1986.

[2] Y. Hori, V. Cotter, and Y. Kaya, "A novel induction machine flux observer and its application to a high performance ac drive system," in *10th IFAC World Congr.*, Munich, Germany, 1987, pp. 363–368.

[3] Y. Hori and T. Umeno, "Flux observer-based field orientation FOFO controller for high performance torque control," in *IPEC*, Tokyo, Japan, 1990, pp. 1219–1226.

[4] D. I. Kim, I. J. Ha, and M. S. Ko, "Control of induction motors via feedback linearization with input–output decoupling," *Int. J. Contr.*, vol. 51, pp. 863–883, 1990.

[5] J. Holtz and T. Thimm, "Identification of the machine parameters in a vector-controlled induction motor drive," *IEEE Trans. Ind. Applicat.*, vol. 27, pp. 1111–1118, 1991.

[6] R. Marino and P. Valigi, "Nonlinear control of induction motors: A simulation study," in *European Contr. Conf.*, Grenoble, France, 1991, pp. 1057–1062.

[7] X. Roboam, C. Andrieux, B. de Fornel, and J. Hapiot, "Rotor flux observation and control in squirrel-cage induction motor: Reliability with respect to parameters variations," *Proc. Inst. Elect. Eng.*, pt. D, vol. 139, pp. 363–370, 1992.

[8] R. Marino, S. Peresada, and P. Valigi, "Adaptive input–output linearizing control of induction motors," *IEEE Trans. Automat. Contr.*, vol. 38, pp. 208–221, 1993.

[9] W. Leonhard, *Control of Electrical Drives*, 2nd ed. Berlin, Germany: Springer-Verlag, 1996.

[10] R. Marino, S. Peresada, and P. Tomei, "Output feedback control of current-fed induction motors with unknown rotor resistance," *IEEE Trans. Contr. Syst. Technol.*, vol. 4, pp. 336–347, 1996.

[11] Y. Dote, "Stabilization of controlled current induction motor drive system via new nonlinear state observers," *IEEE Trans. Ind. Electron.*, vol. 27, pp. 77–81, 1980.

[12] A. Bellini, G. Figalli, and G. Ulivi, "Analysis and design of a microcomputer-based observer for an induction machine," *Automatica*, vol. 24, pp. 549–555, 1988.

[13] G. C. Verghese and S. R. Sanders, "Observers for flux estimation in induction machines," *IEEE Trans. Ind. Electron.*, vol. 35, pp. 85–94, 1988.

[14] L. J. Garces, "Parameter adaptation for the speed-controlled static AC drive with a squirrel-cage induction motor," *IEEE Trans. Ind. Applicat.*, vol. 16, pp. 173–178, 1980.

[15] R. Gabriel and W. Leonhard, "Microprocessor control of induction motor," in *Power Electron. Conf. IPEC*, Orlando, FL, 1982, pp. 385–396.

[16] W. Schumaker and W. Leonhard, "AC-servo drive with microprocessor control," in *Power Electron. Conf. IPEC*, Tokyo, Japan, 1983, pp. 1465–1476.

[17] T. Matsuo and T. A. Lipo, "A rotor parameter identification scheme for vector controlled induction motor drives," *IEEE Trans. Ind. Applicat.*, vol. 21, pp. 624–632, 1985.

[18] L. C. Zai and T. A. Lipo, "An extended Kalman filter approach in rotor time constant measurement in PWM induction motor drives," in *IEEE Ind. Applicat. Soc. Annu. Meet.*, Atlanta, GA, 1987, pp. 177–183.

[19] R. D. Lorenz and D. B. Lawson, "A simplified approach to continuous, on-line tuning of field oriented induction machine drives," in *IEEE Ind. Applicat. Soc. Annu. Meet.*, Pittsburgh, PA, 1988, pp. 444–449.

[20] S. K. Sul, "A novel technique of rotor resistance estimation considering variation of mutual inductance," *IEEE Trans. Ind. Applicat.*, vol. 25, pp. 578–587, 1989.

[21] C. C. Chang and H. Wang, "An efficient method for rotor resistance identification for high-performance induction motor vector control," *IEEE Trans. Ind. Electron.*, vol. 37, pp. 477–482, 1990.

[22] D. Atkinson, P. Acarnley, and J. Finch, "Observers for induction motor state and parameter estimation," *IEEE Trans. Ind. Applicat.*, vol. 27, pp. 1119–1127, 1991.

[23] D. I. Kim, I. J. Ha, and M. S. Ko, "Control of induction motors for both high dynamic performance and high power efficiency," *Proc. Inst. Elect. Eng.*, pt. D, vol. 139, pp. 363–370, 1992.

[24] R. Marino, S. Peresada, and P. Tomei, "Exponentially convergent rotor resistance estimation for induction motors," *IEEE Trans. Ind. Electron.*, vol. 42, pp. 508–515, 1995.

[25] J. Stephan, M. Bodson, and J. Chiasson, "Real-time estimation of the parameters and fluxes of induction motors," *IEEE Trans. Ind. Applicat.*, vol. 30, pp. 746–759, 1994.

[26] R. Marino, S. Peresada, and P. Tomei, "Global adaptive output feedback control of induction motors with uncertain rotor resistance," in *IEEE 35th Conf. Decision Contr.*, Kobe, Japan, 1996, pp. 4701–4706.

[27] T. von Raumer, J. M. Dion, and L. Dugard, "Adaptive nonlinear speed control of induction motors," *Int. J. Adaptive Contr. Signal Processing*, vol. 7, pp. 435–455, 1993.

[28] A. D. Ndoudi-Likoho, S. I. Seleme, and C. Canudas-de-Wit, "Full adaptive control of induction motor drives," in *Europ. Contr. Conf.*, Groningen, The Netherlands, 1993, pp. 597–602.

[29] P. Vedagarbha, D. Dawson, W. Rhodes, and T. Burg, "Nonlinear control of induction motors: The observed field oriented control scheme," in *IEEE 35th Conf. Decision Contr.*, Kobe, Japan, 1996, pp. 4707–4712.

[30] H. K. Khalil and E. Strangas, "Robust speed control of induction motors using position and current measurements," *IEEE Trans. Automat. Contr.*, vol. 41, pp. 1216–1220, 1996.

[31] H. Kubota and K. Matsuse, "Adaptive flux observer of induction motor and its stability," *Elect. Eng. Japan*, vol. 111, pp. 97–104, 1991.

[32] A. E. Fitzgerald, C. Kingsly, and S. D. Umans, *Electric Machinery*. New York: McGraw-Hill, 1983.

[33] P. C. Krause, *Analysis of Electric Machinery*. New York: McGraw-Hill, 1986.

[34] R. Marino and P. Tomei, *Nonlinear Control Design—Geometric, Adaptive and Robust*. Englewood Cliffs, NJ: Prentice-Hall, 1995.

Riccardo Marino was born in Ferrara, Italy, in 1956. He received the Laurea degree in nuclear engineering and the M.S. degree in systems engineering from the University of Rome "La Sapienza" in 1979 and 1981, respectively, and the D.Sc. degree in system science and mathematics from Washington University, St. Louis, MO, in 1982.

Since 1984, he has been with the Department of Electronic Engineering at the University of Rome "Tor Vergata" where he is currently a Professor of systems theory. He is coauthor of *Nonlinear Control Design* (Engelwood Cliffs, NJ: Prentice-Hall, 1995). His research interests include theory and applications of nonlinear control.

Sergei Peresada was born in Donetsk, Ukraine, on January 14, 1952. He received the Diploma of electrical engineer degree from Donetsk Polytechnical Institute in 1974, and the Candidate of Sciences degree in electrical engineering from the Kiev Polytechnical Institute, Kiev, Ukraine, in 1983.

From 1974 to 1977, he was a Research Engineer in the Department of Electrical Engineering, Donetsk Polytechnical Institute. Since 1977, he has been with the Department of Electrical Engineering, Kiev Polytechnical Institute, where he is currently an Associate Professor. From 1985 to 1986, he was a Visiting Professor in the Department of Electrical and Computer Engineering, University of Illinois at Urbana, Champaign. His research interests include applications of modern control theory (nonlinear control, adaptation, VSS control) in electromechanical systems, model development, and control of electrical drives and internal combustion engines.

Patrizio Tomei was born in Rome, Italy, on June 21, 1954. He received the "dottore" degree in electronic engineering in 1980, and the "dottore di ricerca" degree in 1987, both from the University of Rome "La Sapienza."

From 1980 to 1984, he was in industry working on the implementation of real-time process controls. From 1984 to 1992, he was a Research Assistant at the University of Rome "Tor Vergata." From 1992 to 1994, he was an Associate Professor of "system theory" at the University of Perugia. He is currently an Associate Professor of "adaptive systems" at the University of Rome "Tor Vergata." He is coauthor of the book *Nonlinear Control Design* (Englewood Cliffs, NJ: Prentice-Hall, 1995). His research interests include adaptive control, nonlinear control, robotics, and control of electrical machines.