Flux and Parameters Identification of Vector-Controlled Induction Motor in the Rotor Reference Frame

Vicente Leite
Instituto Politécnico de Bragança
Escola Superior de Tecnologia e de Gestão
Campus de Sta. Apolónia - Apartado 134
5301-857 Bragança, Portugal
avtl@ipb.pt

Rui Araújo
Universidade do Porto
Faculdade de Engenharia
Rua Dr. Roberto Frias s/n
4200-465 Porto, Portugal
raraujo@fe.up.pt

Diamantino Freitas
Universidade do Porto
Faculdade de Engenharia
Rua Dr. Roberto Frias s/n
4200-465 Porto, Portugal
dfreitas@fe.up.pt

Abstract: This paper presents a new approach for the simultaneous identification of rotor flux components in the rotor reference frame and electrical parameters of a vector controlled induction motor, for real-time implementations, using an extended Kalman filter (EKF) and a reduced order model structure for lower computational effort. The proposed new method requires the measurement of motor speed, stator voltages and currents signals. Using a motor model structure with four electrical parameters, the estimation of flux space phasor and rotor parameters is presented. The estimation is subsequently further extended to include the motor stator parameters and the results are analyzed as well as robustness. Simulated and experimental studies highlight the improvements brought by this new approach, mainly, a simple and reduced state equation, the introduced scalar output equation and lower computational cadency, by using lower sampling frequencies in the proposed rotor reference frame.

1 Introduction

During the last decades we have witnessed the development of high performance control methods of the induction motor. Most of them require the knowledge of the electrical parameters of the motor model, which can vary significantly during the normal operation because of well-known physical phenomena. Thus, uncertainties and parameter variations can deteriorate control performance. The effects of parameter sensitivities on the performance in vector control schemes and the possibility of identification of the changes in motor parameters while the drive is in its normal operation have been given in [1]. Therefore, it is necessary to estimate and track the parameters values in real-time operation. A variety of algorithms for parameter identification based on the least squares method, observer theory, and so forth, has been proposed in the relevant scientific literature. Among them, the Kalman filter-based algorithms have been demonstrated to be the best for processing noisy discrete measurements while obtaining accurate estimates [2]-[8]. The extended Kalman filter is a recursive, optimal, real-time data processing algorithm for nonlinear systems for both state and parameters estimation [9] of a dynamic system in a noisy environment. The fundamental components either of the PWM voltages or currents generated by an inverter are considered as deterministic inputs or outputs depending on the model structure, and the wideband harmonic components are included in the noise vectors of the state space model structure as suggested in [10]. A lot of work has already been developed on this subject. Many cases are treating single parameter identification, namely rotor time constant or rotor resistance, with rotor flux estimation for indirect vector control purposes. Two approaches are commonly used: full order models [2], [6], [8] or reduced order models motivated by a reduced computational effort [3], [7] and [8]. In both types the stator reference frame is used. Two of them, [4] and [7], are related to the identification of all the parameters in the rotor and stator reference frame, respectively.

In this paper the authors present a new approach for rotor flux components and physical parameters estimation algorithms which are based on a reduced order state space model with a single (scalar) output equation in the rotor reference frame, using an EKF technique.

2. Induction motor model

The well-known and established *dq* dynamic model of the induction motor, in a general reference frame, is represented by its stator and rotor space phasors voltage equations and stator and rotor flux expressed in terms of stator and rotor currents space phasors, like in [10]. Considering the squirrel-cage induction motor equations, in the rotor reference frame, and eliminating stator flux and rotor currents space phasors followed by some algebraic manipulations one can obtain:

$$\begin{bmatrix} \dot{i}_{sd}^r \\ \dot{i}_{sq}^r \\ \dot{\psi}_{rd}^r \\ \dot{\psi}_{rq}^r \end{bmatrix} = \begin{bmatrix} -a_1 & \omega & a_2 & \omega a_3 \\ -\omega & -a_1 & -\omega a_3 & a_2 \\ a_4 & 0 & -a_5 & 0 \\ 0 & a_4 & 0 & -a_5 \end{bmatrix} \begin{bmatrix} i_{sd}^r \\ i_{sq}^r \\ \psi_{rd}^r \\ \psi_{rq}^r \end{bmatrix} + \begin{bmatrix} a_3 & 0 \\ 0 & a_3 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u_{sd}^r \\ u_{sq}^r \end{bmatrix} \quad (1)$$

Where:

$$a_1 = \frac{R_s}{L_s^{'}} + \frac{L_M}{L_s^{'}\tau_r} \quad a_2 = \frac{1}{L_s^{'}\tau_r} \quad a_3 = \frac{1}{L_s^{'}} \quad a_4 = \frac{L_M}{\tau_r} \quad a_5 = \frac{1}{\tau_r}$$

$$\psi_{rd}^r(t) = \frac{L_m}{L_r}\phi_{rd}^r \quad \psi_{rq}^r(t) = \frac{L_m}{L_r}\phi_{rq}^r \quad \tau_r = \frac{L_r}{R_r} \quad L_s^{'} = L_s - \frac{L_m^2}{L_r} \quad L_M = \frac{L_m^2}{L_r}$$

A discrete-time state-space model can be obtained by assuming that the series expansion of the matrix exponential function is performed and only the first terms are considered as defined in [11]:

$$\begin{bmatrix} i_{sd}^r(k+1) \\ i_{sq}^r(k+1) \\ \psi_{rd}^r(k+1) \\ \psi_{rq}^r(k+1) \end{bmatrix} = \begin{bmatrix} 1-a_1T_s & \omega T_s & a_2T_s & \omega a_3T_s \\ -\omega T_s & 1-a_1T_s & -\omega a_3T_s & a_2T_s \\ a_4T_s & 0 & 1-a_5T_s & 0 \\ 0 & a_4T_s & 0 & 1-a_5T_s \end{bmatrix} \begin{bmatrix} i_{sd}^r(k) \\ i_{sq}^r(k) \\ \psi_{rd}^r(k) \\ \psi_{rq}^r(k) \end{bmatrix} +$$

$$+\begin{bmatrix} a_3T_s & 0 \\ 0 & a_3T_s \\ 0 & 0 \\ 0 & 0 \end{bmatrix}\begin{bmatrix} u_{sd}^r(k) \\ u_{sq}^r(k) \end{bmatrix} \quad (2)$$

where T_s is the sampling period. This, together with an output equation, usually $\left[i_{sd}(k) \quad i_{sq}(k)\right]^T$, composes a so-denominated full-order state-space model. It is clear that the stator quantities in the above state equation can be measured directly. Therefore, one can reduce this state equation, by considering only the flux components in the state vector, as follows:

$$\begin{bmatrix} \psi_{rd}^r(k+1) \\ \psi_{rq}^r(k+1) \end{bmatrix} = \begin{bmatrix} 1-\frac{T_s}{\tau_r} & 0 \\ 0 & 1-\frac{T_s}{\tau_r} \end{bmatrix}\begin{bmatrix} \psi_{rd}^r(k) \\ \psi_{rq}^r(k) \end{bmatrix} +$$

$$+\begin{bmatrix} \frac{L_M T_s}{\tau_r} & 0 \\ 0 & \frac{L_M T_s}{\tau_r} \end{bmatrix}\begin{bmatrix} i_{sd}^r(k) \\ i_{sq}^r(k) \end{bmatrix} \quad (3)$$

And the output equation can be set as follows:

$$\begin{bmatrix} u_{sd}^r(k) \\ u_{sq}^r(k) \end{bmatrix} = \begin{bmatrix} -a_5 & -\omega \\ \omega & -a_5 \end{bmatrix}\begin{bmatrix} \psi_{rd}^r(k) \\ \psi_{rq}^r(k) \end{bmatrix} + \begin{bmatrix} b_1 & -\omega L_s^{'} \\ \omega L_s^{'} & b_1 \end{bmatrix}\begin{bmatrix} i_{sd}^r(k) \\ i_{sq}^r(k) \end{bmatrix} +$$

$$+\begin{bmatrix} \frac{L_s^{'}}{T_s} & 0 \\ 0 & \frac{L_s^{'}}{T_s} \end{bmatrix}\begin{bmatrix} i_{sd}^r(k+1) \\ i_{sq}^r(k+1) \end{bmatrix} \quad (4)$$

Where $b_1 = -\frac{L_s^{'}}{T_s} + R_s + \frac{L_M}{\tau_r}$

This is usually classified as a reduced-order model. It is important to notice here that both equations in the above output equation have the same structure with the same states (parameters) and the same signals (voltages and currents components) but shifted in time. Therefore, they contain the same information for identification purposes. So we will use only one of them, for instance, the first one and the new output equation becomes:

$$u_{sd}^r(k) = -\frac{1}{\tau_r}\psi_{rd}^r(k) - \omega(k)\psi_{rq}^r(k) + \left(R_s + \frac{L_M}{\tau_r}\right)i_{sd}^r(k) +$$

$$+ L_s^{'}\left(\frac{i_{sd}^r(k+1) - i_{sd}^r(k)}{T_s} - \omega(k)i_{sq}^r(k)\right) \quad (5)$$

It is worth noting that, to the authors' knowledge, this is the first time that such simplification is performed and transforms the initial model in a single and therefore scalar output model structure.

We can easily identify in the last term of the above equation, the first derivative of the d component stator current which corresponds to the Euler formula. Instead, the following better approximation to the first derivative, will be used, based only on past values:

$$\left.\frac{di_{sd}^r}{dt}\right|_{t=t_k} = \frac{1}{2T_s}\left[3i_{sd}^r(k) - 4i_{sd}^r(k-1) + i_{sd}^r(k-2)\right] \quad (6)$$

3. Extended Kalman Filter (*EKF*)

The *EKF* is used here to estimate the rotor flux dq components and physical parameters of the induction motor, modeled as above. The *EKF* can be used for both state and parameter estimation by treating the above physical induction motor parameters as additional states and forming an augmented state vector. As a result, even if the original state space model is linear, the augmented one is nonlinear because of inter-multiplication of states. The *EKF* deals directly with this nonlinear augmented model.

Here the application of the *EKF* to the simultaneous estimation of rotor flux together with induction motor parameters produces a $(2+n_\theta)$-order extended state-space model with the following state vector:

$$x_e(k) = \left[x_{e1}(k) \ \cdots \ x_{e6}(k)\right]^T = \left[x_1(k) \quad x_2(k) \quad \theta_1(k) \ \cdots \ \theta_4(k)\right]^T =$$

$$= \left[\psi_{rd}(k) \quad \psi_{rq}(k) \quad \theta(k)\right]^T \quad (7)$$

The subscript e denotes the extended or augmented state vector. For the estimation of n_θ parameters, n_θ extra equations are obtained by assuming a random walk to their adaptation:

$$\theta_j(k+1) = \theta_j(k) + r_{\theta j}(k) \quad (8)$$

Consider the stochastic discrete-time nonlinear state-space model [9]:

$$x_e(k+1) = f\left(x(k), u(k), \theta(k)\right) + r_{se}(k) \quad (9)$$

$$y(k) = h\left(x(k), \theta(k)\right) + r_m(k) \quad (10)$$

$$x_e(0) = x_e\left(x(0), \theta(0)\right) \quad (11)$$

It is usually assumed that the process noise $r_{se}(k)$ and measurement noise $r_m(k)$ are white, zero-mean Gaussian and independent sequences.

The associated *EKF* algorithm is given as follows.

1. Determination of the initial conditions.

Prediction process:

2. $$\hat{x}_e(k+1\mid k) = \begin{bmatrix} f\left(\hat{x}(k\mid k), u(k), \hat{\theta}(k\mid k)\right) \\ \theta(k) \end{bmatrix} + \begin{bmatrix} r_s(k) \\ r_\theta(k) \end{bmatrix} =$$

$$= f_e\left(\hat{x}_e(k\mid k), u(k)\right) + r_{se}(k) \quad (12)$$

3. $$F(k) = \left.\frac{\partial f_e\left(x_e(k), u(k)\right)}{\partial x_e^T(k)}\right|_{x_e(k)=\hat{x}_e(k|k)} =$$

$$= \left.\begin{bmatrix} \frac{\partial f_e\left(x(k), u(k), \theta(k)\right)}{\partial x^T(k)} & \frac{\partial f_e\left(x(k), u(k), \theta(k)\right)}{\partial \theta^T(k)} \\ 0 & I \end{bmatrix}\right|_{\hat{x}_e(k|k)} =$$

$$= \begin{bmatrix} A_d\left(\hat{\theta}(k)\right) & \begin{bmatrix} E_{11} & \cdots & E_{1n_\theta} \\ \vdots & & \vdots \\ E_{n_f 1} & \cdots & E_{n_f n_\theta} \end{bmatrix} \\ 0 & I \end{bmatrix}, \text{ where } E_{ij} = \left.\frac{\partial f_{e_{if}}(\cdot)}{\partial \theta_j}\right|_{\hat{x}_e(k|k)} \quad (13)$$

4. $$\hat{P}(k+1\mid k) = F(k)\hat{P}(k\mid k)F^T(k) + R_s \quad (14)$$

Correction process:

5. $$H(k) = \left.\frac{\partial h_e\left(x_e(k)\right)}{\partial x_e^T(k)}\right|_{\hat{x}_e(k+1|k)} =$$

$$= \left.\begin{bmatrix} \frac{\partial h\left(x(k), \theta(k)\right)}{\partial x^T(k)} & \frac{\partial h\left(x(k), \theta(k)\right)}{\partial \theta^T(k)} \end{bmatrix}\right|_{\hat{x}_e(k+1|k)} \quad (15)$$

6. $$K(k+1) == \hat{P}(k+1\mid k)H^T(k)\left[H(k)\hat{P}(k+1\mid k)H^T(k) + R_m\right]^{-1} \quad (16)$$

7. $$\hat{y}(k+1) = h\left(\hat{x}_e(k+1\mid k), k\right) \quad (17)$$

8. $$\hat{x}_e(k+1\mid k+1) = \hat{x}_e(k+1\mid k) + K(k+1)\left[y(k+1) - \hat{y}(k+1)\right] \quad (18)$$

9. $$\hat{P}(k+1\mid k+1) = \left[I - K(k+1)H(k)\right]\hat{P}(k+1\mid k) \quad (19)$$

10. Go to step 2

The following sections will present the results and analysis of robustness of identifying rotor flux components plus two, three or four physical parameters of the three-phase squirrel cage induction motor per phase equivalent circuit as presented in [10], in the rotor reference frame.

4. Simulation Results

The above-proposed algorithm has been developed in the *Matlab* with *Simulink* environment and tested under a vector control scheme. The rotor-referred stator voltages, stator currents and angular speed are sampled at 2,5ksamples/sec. Elliptic low-pass pre-filters of fifth order with a 500Hz cutoff frequency have been used. These simulation conditions were chosen to be the same as the experimental ones [12].

A trial of simulations shows that it must be born in mind that several important and difficult aspects arise when trying to estimate simultaneously rotor flux and all induction motor parameters with a reduced order model. On one hand the noise covariance matrices must be correctly set, the state-vector and error covariance matrix initialized, the state vector properly scaled, and on the other hand, the signals must be persistent and the model structure identifiable.

All induction motor state-space model structures with state vector including fluxes or currents and direct or modified physical parameters of the machine, will have significant different sizes of state variables. When the model structure contains parameters with different orders of magnitude, it is mandatory to scale the variables so that the parameters are all roughly the same magnitude. On the contrary, if we do not scale the state vector states (in this case), significant estimation errors occur for small size variables and some numerical difficulties may arrise. To overcome this problem, the following scaled state vector has been selected:

$$x = \begin{bmatrix} \psi_{rd} & \psi_{rq} & 0.5\times\frac{1}{\tau_r} & 100\times L_s' & 10\times L_M & R_s \end{bmatrix}^T \qquad (20)$$

As a result, the diagonal initial values of the state covariance matrix and the diagonal elements of the noise covariance matrices will approximately have the same values and the same conclusion is applicable to the initial values of the state variables.

The EKF has been started with the following initial conditions:

$$\begin{cases} x(0) = \begin{bmatrix} 0.01 & 0.01 & 0.2 & 0.2 & 0.2 & 0.2 \end{bmatrix}^T \\ P(0) = diag\begin{bmatrix} 1e-5 & 1e-5 & 1e-4 & 1e-4 & 1e-4 & 1e-4 \end{bmatrix} \\ R_m = 0.01 \end{cases} \qquad (21)$$

It should be noticed that the measurement matrix R_m is no more a matrix but a scalar value because the system output becomes a scalar equation instead of a matrix one.

As to the initialization of the noise system matrix, the same improvements were also introduced. To get a good trade-off between starting period of parameters convergence and tracking of time-varying parameters, the filter dynamics (and in the sequel the noise covariance matrices R_m and R_s) should be properly tuned during these two phases. It is known that the larger the ith diagonal entry of R_s is, the more quickly the filter will modify the estimate of the ith component (flux or parameter) of the state vector in the light of the measurements. In other words, the larger the correction gain is, for any given R_m, the more jittery the behaviour of the filter will be, and more drastically the state estimate will be modified to take new measurements into account. This behaviour expresses a lack of confidence in the predicted state estimate. Conversely, for any given R_s, the larger of covariance of measurement noise R_m is, the smaller the correction gain will be and the less the new measurements will be taken into account to update the state estimate. This expresses a lack of confidence in the new measurements. So, it is possible to get a satisfactory compromise between the state update dynamics when starting the algorithm in which the state variables are far away of their real values, and the dynamics for tracking the time-variant states after that transient period. In this work, a simple approach was created to do this, by using an exponential function to control each ith diagonal element corresponding to parameters, as follows:

$$R_s(k) = diag\begin{bmatrix} 1e-8 & 1e-8 & f(k) & f(k) & f(k) & f(k) \end{bmatrix} \qquad (22)$$

where:

$$f(k) = 1e-7\times\left(\exp(-2kT_s) + 0.1\right) \qquad (23)$$

The introduction of this new exponential control caused a significant decrease of convergence time as well as better long-term stability of the estimated values, without significant bias. The following figures show the results of the robustness study of three algorithms for flux estimation in all of them extended to rotor parameters τ_r and L_M estimation in the first one, to τ_r, L_M and L_s' estimation in the second one and, finally, extended to all four parameters in the last one. Studies of characteristics of EKF in estimating the rotor resistance and magnetizing inductance in the synchronous reference frame were made in [5].

Figures 1 to 5 show the errors, in percentage, of the estimated parameters with respect to the parameters assumed as known and with respect to the angular velocity. Figures 1 and 2 show that the maximum error in the rotor parameters estimates is about 10%, when stator parameters vary from -50% to 50% of their real values.

The figure 4 corresponds to the simultaneous estimation of rotor fluxes and rotor parameters as well as estimation of L_s'. In this case the estimation of rotor parameters is robust enough with respect to errors in stator resistance, but the error in estimated value of L_s' is larger than 10% when the error in R_s is more than 40%.

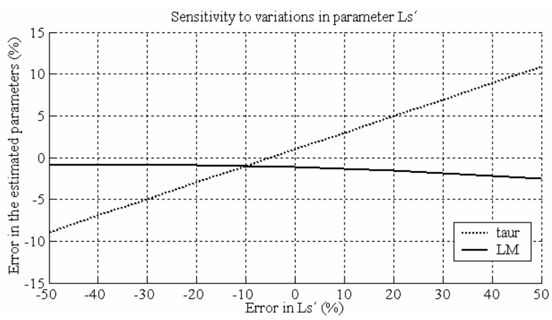

Fig. 1: Sensitivity of τ_r and L_M to variations in parameter L_s'.

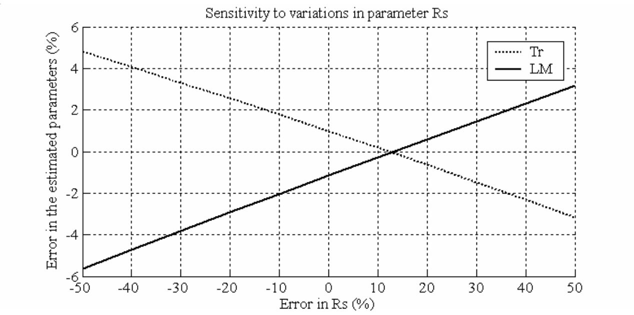

Fig. 2: Sensitivity of τ_r and L_M to variations in parameter R_s.

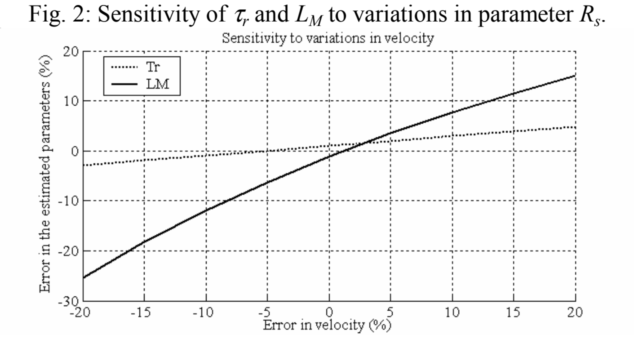

Fig. 3: Sensitivity of τ_r and L_M to variations in velocity ω.

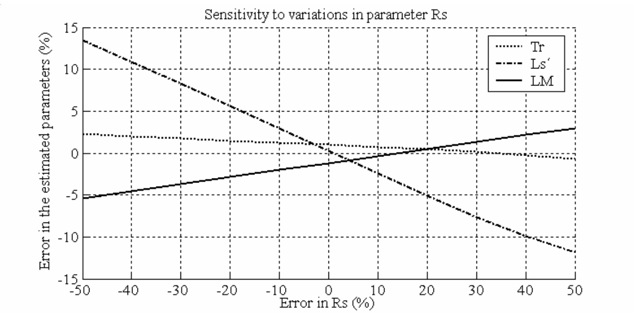

Fig. 4: Sensitivity of τ_r, L_s' and L_M to variations in parameter R_s.

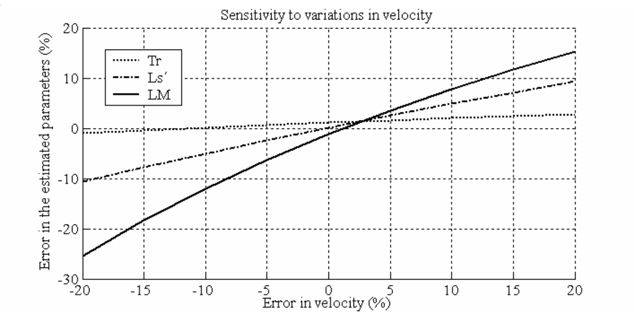

Fig. 5: Sensitivity of τ_r, L_s' and L_M to variations in velocity ω.

Figures 3 and 5 show that, for errors less than 10% in the estimated parameters, the error in the angular velocity should be less than 10%.

The simulation results, demonstrate that the simultaneous identification of rotor fluxes and rotor parameters is feasible with good enough robustness with respect to errors in stator parameters and angular velocity, but precise knowledge and time update of stator parameters is also convenient.

By means of simulation tests we have concluded that the EKF algorithm can be extended to stator parameters estimation but its robustness presents some difficulties, as we will refer in the next section.

5. Experimental Results

For simulation and experimental purposes a 3kW squirrel-cage induction motor was used with the following nominal rated parameters: 400V, 6.6A, 1430 rpm, 50Hz and 2 pole pairs. The following electrical parameters were obtained by classical methods: stator resistance 2.9Ω, rotor resistance 1.7Ω, stator and rotor inductances 240.3mH and magnetising inductance 230mH.

The voltage, current and speed signals are available in the range of ±10V in both rotor and stator reference frames by using the AD2S100 analogue vector processor. The hardware [12] provides an adjustable cutoff frequency by means of an accurate analogue elliptic low-pass filter, *MAX7411*, to avoid aliasing errors. Data was collected by using the 16 bits *National Instruments PCI-6035E* data acquisition card and the module *SC-2040* with 8 S/H for simultaneous acquisition, at a sampling rate of 2.5kHz. The EKF algorithms were developed in *MATLAB* language and calculations were made off-line.

Errors in the 12 bits resolution mechanical angle, obtained from an incremental encoder followed by a counter, were simulated. The signals in the stator reference frame are converted to the rotor frame at the rate of the least significant bit. Residuals errors do not affect rotor parameters estimates but further software low-pass filtering is required to avoid divergence of stator parameters estimates. In [13] an interesting work is shown with respect to error in the rotor flux angular position due to finite resolution of different sensors, and the influence of different problems as a result of numerical processing data by the computer on the system performances.

The EKF algorithms initialization considerations presented in the above section should also be applicable here. The identification test run consists of a start-up with load torque set to 11Nm, that is to say, about half rated load.

The induction machine is controlled by the *ABB* industrial frequency converter *ACS-601-0006-3* and therefore the vector control scheme developed in *MATALAB* and the one implemented by *ABB* do not coincide. Therefore also here some sensitivity tests were made relatively to sensitivity of rotor only parameter estimation or all, rotor and stator, parameter estimation. Figures 6 and 7 show the variation on estimated scaled τ_r and L_M parameters with respect to uncertainty in stator parameters.

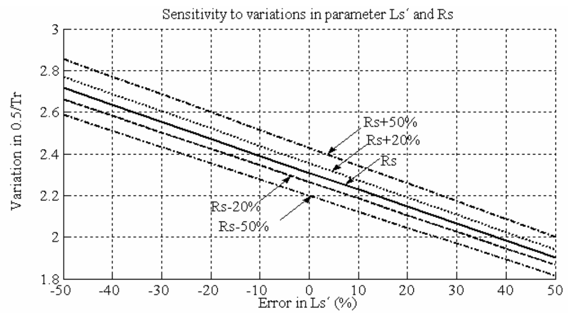

Fig. 6: Sensitivity of τ_r to variations in R_s and L_s'.

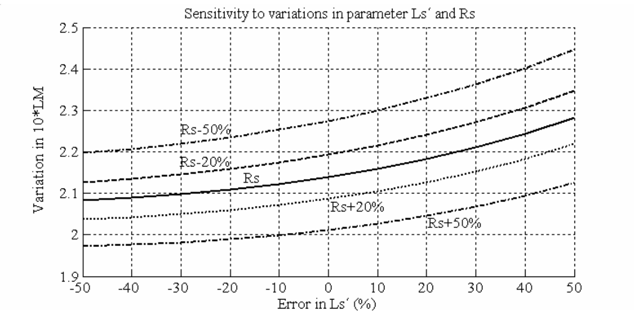

Fig. 7: Sensitivity of L_M to variations in R_s and L_s'.

From figures 6 and 7 we can see that the variation in the estimated scaled values of τ_r and L_M parameters with respect to uncertainty in stator parameters is, in the worst case, about 35% and 23%, respectively.

The following figures (8 to 12) show the dynamic behaviour of the algorithm when all parameters and rotor flux components are estimated.

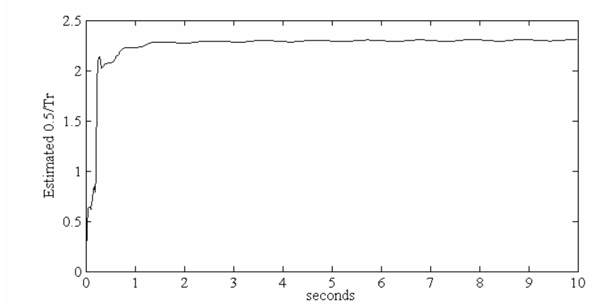

Fig. 8: Estimated τ_r ($0.5/\tau_r$).

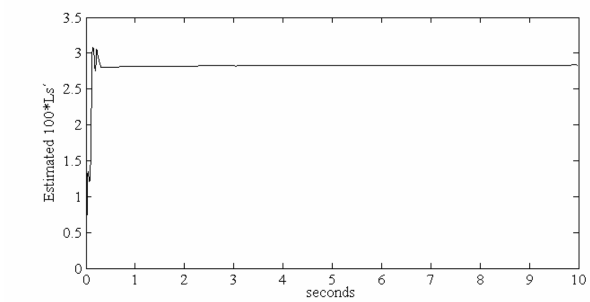

Fig. 9: Estimated L_s' ($100L_s$').

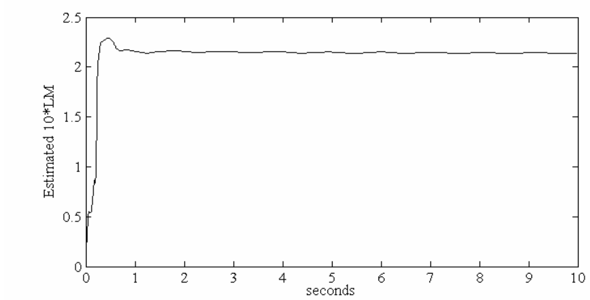

Fig. 10: Estimated L_M ($10L_M$).

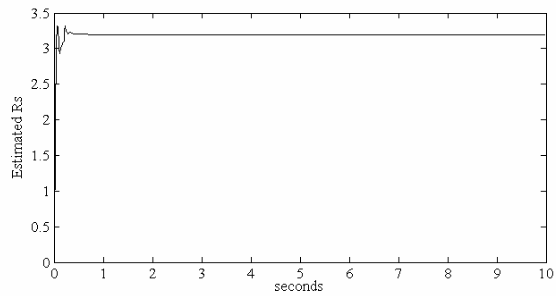

Fig. 11: Estimated R_s.

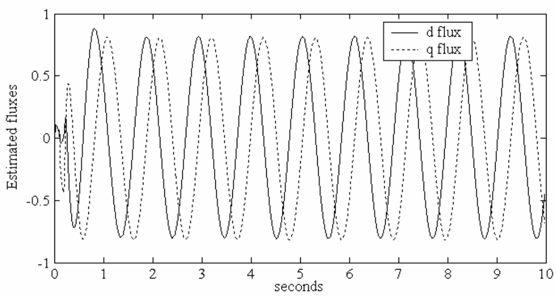

Fig. 12: Estimated flux *dp* components.

Estimated values of the electrical parameters are obtained by averaging the last 10 iterations. The results are:

$$\hat{x}_3 = 0.5/\hat{\tau}_r = 2.30, \quad \hat{x}_4 = 100\times \hat{L}_s' = 2.83,$$

$$\hat{x}_5 = 10\times L_M = 2.14, \quad \hat{x}_6 = \hat{R}_s = 3.19$$

To conclude the identification process it was necessary to validate the identified model through some validation test to evaluate the performance of the EKF algorithm. The validation test was based on the simulation of a modified induction motor model, with the estimated parameters, by injection of the measured voltages and angular velocity and subsequent comparison of simulated and measured stator current *dq* components.

The results are shown in figures 13 and 14 and as can seen the simulated and experimental currents are very similar (practically equal). So the EKF algorithm for full parameters and fluxes estimation is capable of fitting adequately this input-output data set with this identified model.

Simulation and experimental tests have shown that some care must be taken to avoid erroneous convergence of stator resistance.

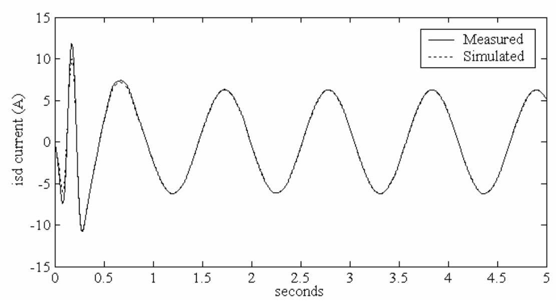

Fig. 13: *d* components of measured and estimated currents.

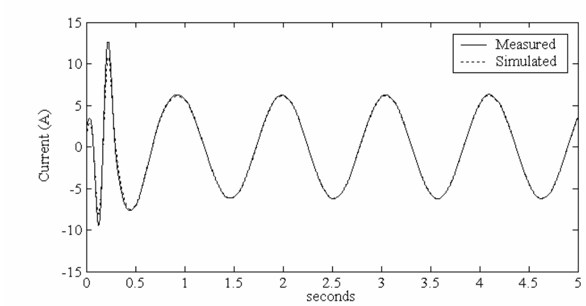

Fig. 14: *q* components of measured and estimated currents.

Indeed slightly different estimated values of this parameter can occur when different values of the respective diagonal element of the state covariance matrix are selected, what does not happen with the other parameters.

With the model structure adopted in this work it is very simple and not fastidious to implement a second order discrete-time model of the state-space induction motor model. Simulation and experimental tests have shown that first and second approximations of the discrete state equation (3) give approximately the same results provided that in the output equation (5) an adequate choice for the first derivative of stator current *d* component is adopted, like the one defined by equation (6). The expression used in equation (5) for the first derivative gave bad estimated results.

The results of this identification procedure show that the estimation robustness of rotor fluxes and rotor parameters is improved provided that we have good enough information about stator parameters. If this is not true it is possible and convenient to extend de estimation algorithm to L_s' or even to both stator parameters L_s' and R_s with some loss of robustness with respect to model validity domain, that is to say, relative to dynamics of signals, load torque and speed range.

6. Conclusions

In this paper the application of some algorithms based on EKF is proposed to rotor flux and electrical parameters estimation of an induction motor. A new approach is presented to the reduced order model with four electrical parameters and a single (scalar) output equation. The rotor reference frame is selected in which the state equation results more simple and low sampling frequencies are possible since the signals' frequency range is lower than in the stator reference frame. The EKF is applied to simultaneous estimation of flux and two, three or four parameters and its robustness is analyzed by simulated and experimental results. Experimental results show that the algorithm described in this paper is also adequate for on-line estimation of physical induction motor parameters and is not restricted to steady state operation being capable to operate in transient conditions. As the EKF can deal with time-varying linear plant model structures, the rotor flux and the parameters can be estimated while the rotor speed is varying and tracking of parameters can be done.

Therefore, these approaches are useful for auto-tuning and adaptive direct field-oriented induction motor control.

7. References

[1] Krishnan R., Bharadwaj A. S., "A Review of Parameter Sensitivity and Adaptation in Indirect Vector Controlled Induction Motor Drive Systems", *IEEE Trans. on Power Elect*r., Vol. 6, No. 4, pp. 695-703, October 1991.

[2] Finch J. W., Atkinson D. J., Acarnley P. P., "Full-Order Estimator for Induction Motor States and Parameters", *IEE Electr. Power Appl.*, Vol. 145, No. 3, pp. 169-179, May 1998.

[3] Aquilla A. D., Cupertino F., Salvatore L., Stasi S., "Kalman Filter Estimators Applied to Robust Control of Induction Motor Drives", in *Proc. IECON'98*, Aachen, Germany, 1998, pp. 2257-2262.

[4] Loron L., Laliberté G., "Application of the Extended Kalman Filter to Parameters Estimation of Induction Motors", in *Proc. EPE*, Brighton, 1993 pp. 85-90.

[5] Pena R. S., Asher G. M., "Parameter Sensitivity Studies for Motor Parameter Identification Using Extended Kalman Filter", in *Proc. EPE*, Brighton, 1993 pp. 306-311.

[6] Lin F.-J., "Robust Speed-Controlled Induction-Motor Drive Using EKF and RLS Estimators", *IEE Proc.-Electr. Power Appl.*, Vol. 143, No. 3, pp. 186-192, May 1996.

[7] Aquilla A. D., Papa S., Salvatore L., Stasi S., "A Delayed Kalman Filter for On-Line Estimation of Induction Motor Parameters and Rotor Flux Space Vector Position", in *Proc. MELECON'96*, 1996, pp. 269-273.

[8] Atkinson D. J., Acarnley P. P., Finch J. W., "Observers for Induction Motor State and Parameter Estimation", *IEEE Trans. on IA*, Vol. 27, No. 6, pp. 1119-1127, November/December 1991.

[9] Walker É., Pronzato L., *Identification of Parametric Models from Experimental Data*. Masson, 1997.

[10] Vas P., *Parameter Estimation, Condition Monitoring, and Diagnosis of Electrical Machines*. Oxford Science Publications, 1993.

[11] Astrom, K. J., Wittenmark, B., *Computer Controlled Systems: Theory and Design*. Prentice-Hall, 1997.

[12] Leite V., Teixeira H., Araújo R., Freitas D., "Sistema Electrónico de Condicionamento e Processamento, em Tempo Real, das Tensões e Correntes do Motor de Indução Trifásico Alimentado por Conversores de Frequência", in *Proc. 7as Jornadas Hispano-Lusas de Ingeniería Eléctrica*, Madrid, Spain, July, 2001, Vol. IV, pp. 111-116.

[13] Jelassi K., Fornel D. B., Pietrzak-David M., "Influence of Quantization Effects and Parameters Deviations on the Performance of a Field Oriented Asynchronous Drive", *Electric Machines and Power Systems*., 21, pp. 85-102, 1993.