THE ANNALS OF "DUNAREA DE JOS" UNIVERSITY OF GALATI
FASCICLE III, 2002 ISSN 1221-454X
ELECTROTECHNICS, ELECTRONICS, AUTOMATIC CONTROL, INFORMATICS

SPEED AND ROTOR FLUX ESTIMATION IN SPEED SENSORLESS CONTROL OF INDUCTION MOTOR

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Abstract: The paper compares the performances of several adaptive rotor flux and speed estimation methods used in speed sensorless vector control of induction motor. First, a short review of Luenberger, Gopinath, MRAS, Torque Error MRAS and Kalman Filter estimation methods is presented. Then, the vector control drive using each estimation principle is simulated, using the real-time simulation techniques. The simulation results are compared and discussed by means of stability, sensitivity to parameter variation and operation in the low speed region, taking also into account the impossibility to estimate without any error both speed and rotor resistance, when the rotor equations are used as reference or adjustable model in estimation.

Keywords: Flux, speed and rotor resistance estimation, vector control, low speed region.

1. INTRODUCTION

Speed and flux observers for sensorless induction motor drives form a huge research topic. There are many estimation techniques already reported, but few comparative studies [Holtz, 1993, Has et al, 1994, Ohyama et al, 19999]. In [Holtz, 1993] a summary of claimed performance is presented and in [Has et al, 1994] a comparison between EKF, Luenberger and MRAS estimation principle is studied comparatively, insisting only on speed estimation. It has also to be mentioned the study presented in [SongWongWanich, 1993] where a unified viewpoint for the topologies of all vector controllers is presented. The experience in the field of vector-controlled drives proved that rotor flux estimation is most important in the speed estimation process especially when sensitivity to parameter variation is taken also into consideration. The study has been performed using a direct field-oriented drive system, considering the most adequate combination between the flux and speed estimation techniques.

Real-time simulation was performed in order to analyze the performances of the estimation techniques, taking into consideration the rotor resistance variation and the operation in the low speed region.

In [Tamai et al., 1987] a very important observation has been pointed out, which, we think, has not been enough taken into consideration yet. It is proved that using the direct field orientation method and the rotor equation for flux, speed and parameter estimation, the estimation error cannot be avoided under any circumstances, independent on the estimation principle considered. As it is already well known, all the adaptive methods including those studied in the present paper are based on this equation. Consequently, we consider that it is much better to use simple estimation algorithms and moreover, rough parameter estimation, with good results in applications dedicated to the induction motor.

This paper was recommended for publication by Ion BIVOL

2. THE SENSORLESS DRIVE SYSTEM

In Figure 1 the structure of the vector-controlled drive used in testing the performances of the flux and speed methods is presented. The following methods have been considered:

1). The Luenberger nonlinear flux observer together with a speed adaptation method based on a torque error MRAS, reported by Kubota [Kubota et al, 1990];

2). The reduced order flux observer (Gopinath) and the MRAS speed estimator, reported by Schauder [Schauder, 1992] ;

3). The Reduced Order Kalman Filter .

2.1. The Luenberger Observer

The general equation of Luenberger observer for a linear system is:

$$[\dot{x}] = [A]\,[x] + [B]\,[u] + [G]\,[\hat{i}_s - i_s] \quad (1)$$

where

$$\hat{x} = \begin{bmatrix} \hat{i}_{sd} \\ \hat{i}_{sq} \\ \hat{\psi}_{rd} \\ \hat{\psi}_{rq} \end{bmatrix}, \qquad u = \begin{bmatrix} u_{sd} \\ u_{sq} \end{bmatrix}, \qquad y = \begin{bmatrix} i_{sd} \\ i_{sq} \end{bmatrix} \qquad (2)$$

Here A is the motor parameter matrix, B is the input matrix and Y is the output one. The gain matrix G is chosen by means of stability criteria. The most usual way to tune up the Luenberger gain is to choose the poles of the observer proportional to the motor ones, thus assuring the stability. Because the matrix A depends on the rotor speed, it has to be computed real time, at each sampling time.

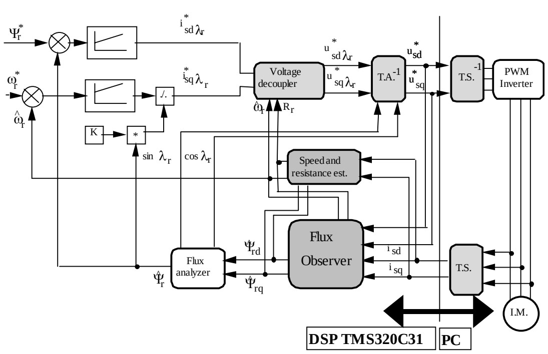

Fig1.The field-oriented induction motor drive system.

In case of using Luenberger observer for rotor flux estimation, speed could be estimated from the error between the estimated stator current and the real one, with the following expression [Has et al, 1994]:

$$\hat{\omega}_r = K_P\left(\varepsilon_{isd}\,\hat{\psi}_{rq} - \varepsilon_{isq}\,\hat{\psi}_{rd}\right) + $$
$$+ K_I \int_0^T \left(\varepsilon_{isd}\,\hat{\psi}_{rq} - \varepsilon_{isq}\,\hat{\psi}_{rd}\right)dt \qquad (3)$$

where

$$\varepsilon_{ids} = i_{sd} - \hat{i}_{sd} \qquad (4)$$
$$\varepsilon_{iqs} = i_{sq} - \hat{i}_{sq}$$

The flux and speed estimation principle using Luenberger and torque error MRAS is presented in Figure 2.

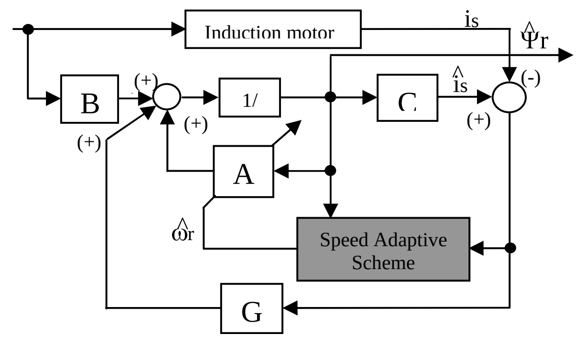

Fig 2. The rotor flux and speed estimation principle.

2.2. The Robust Adaptive Flux Observer

The observer has been designed as a combination of a flux simulator and a predictive error correction feedback:

$$\hat{\dot{\psi}}_r = (a_{22} - ga_{12})\hat{\psi}_r + (a_{21} - ga_{11})i_s - gb_1 u_s + g\dot{i}_s \qquad (5)$$

where g is the observer gain. The gain coefficients g_d and g_q are deduced by choosing the observer poles on the negative real axis of the complex plan (x=-α, y =β=0) each sampling time, with the following relations:

$$g_a = \left(\frac{\frac{R_r}{L_r}\alpha + \omega_r \beta}{\left(\frac{R_r}{L_r}\right)^2 + \omega_r^2} - 1 \right) \frac{\sigma L_s L_r}{M}, \quad g_b = \frac{\omega_r \alpha - \frac{R_r}{L_r}\beta}{\left(\frac{R_r}{L_r}\right)^2 + \omega_r^2} \frac{\sigma L_s L_r}{M} \qquad (6)$$

where

$$\beta = 0, \;\; \alpha = k\sqrt{\left(\frac{R_r}{L_r}\right)^2 + \omega_r^2} \;\; (k > 0) \qquad (7)$$

The principle of rotor flux estimation using the reduced order observer is shown in Figure 3.

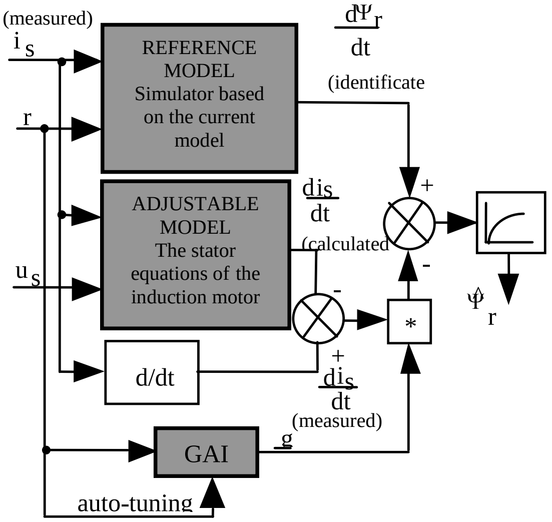

Fig. 3. The principle of the rotor flux estimation.

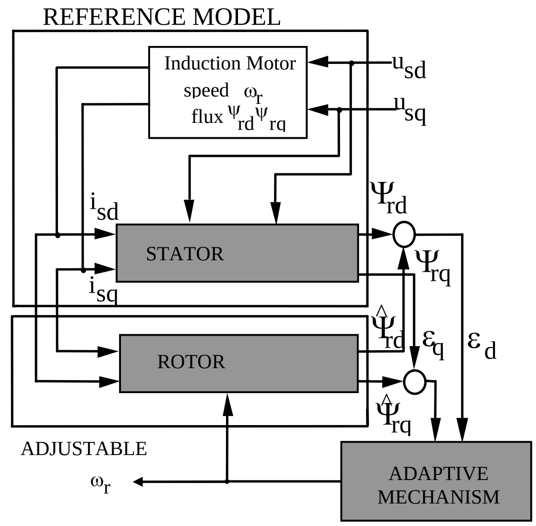

Fig.4. The structure of the MRAS speed estimation block.

2.3. The Model Reference Adaptive System (MRAS)

Figure 4 illustrates the way of calculation the rotor speed by means of MRAS techniques. Two independent observers are used in order to estimate the rotor flux, one based on equation (8) (which does not involve ωr) and the other on equation (9), as follows:

$$\begin{bmatrix}\dot{\psi}_{rd}\\ \dot{\psi}_{rq}\end{bmatrix}=\frac{L_r}{L_m}\begin{bmatrix}u_{sd}\\ u_{sq}\end{bmatrix}-\begin{bmatrix}R_s+\sigma L_s & 0\\ 0 & R_s+\sigma L_s\end{bmatrix}\begin{bmatrix}\dot{i}_{sd}\\ \dot{i}_{sq}\end{bmatrix} \tag{8}$$

$$\begin{bmatrix}\dot{\psi}_{rd}\\ \dot{\psi}_{rq}\end{bmatrix}=\begin{bmatrix}-\frac{R_r}{L_r} & -\omega_r\\ \omega_r & -\frac{R_r}{L_r}\end{bmatrix}\begin{bmatrix}\psi_{rd}\\ \psi_{rq}\end{bmatrix}+\frac{L_m R_r}{L_r}\begin{bmatrix}i_{sd}\\ i_{sq}\end{bmatrix} \tag{9}$$

The error between the states of the two models is used then to drive an adaptation mechanism, in order to generate the estimated rotor speed. The state error equations describe in this case a nonlinear feedback system, for which hyperstability is assured when Popov criterion is satisfied for the nonlinear feedback. In this case the estimated rotor speed has the following structure:

$$\hat{\omega}_r=\phi_2+\int_0^t \phi_1 dt=K_1\varepsilon+\int_0^t K_2\varepsilon dt \tag{10}$$

where Popov's inequality is satisfied for the following functions:

$$\phi_1=K_2(\varepsilon_q\hat{\psi}_{rd}-\varepsilon_d\hat{\psi}_{rq})=K_2(\psi_{rq}\hat{\psi}_{rd}-\psi_{rd}\hat{\psi}_{rq})=K_2\varepsilon \quad (11)$$
$$\phi_2=K_1(\varepsilon_q\hat{\psi}_{rd}-\varepsilon_d\hat{\psi}_{rq})=K_1(\psi_{rq}\hat{\psi}_{rd}-\psi_{rd}\hat{\psi}_{rq})=K_1\varepsilon$$

2.3. The Kalman Filter

The Kalman Filter is described by the following equations:

$$\hat{x}\left(\frac{k+1}{k}\right)=F(k)\cdot\hat{x}\left(\frac{k}{k}\right)+G(k)\cdot u(k)$$

$$P\left(\frac{k+1}{k}\right)=F(k)\cdot P\left(\frac{k}{k}\right)\cdot G(k)^T+Q \tag{12}$$

$$\hat{x}\left(\frac{k+1}{k+1}\right)=\hat{x}\left(\frac{k+1}{k}\right)+K(k+1)\cdot\left[y(k+1)-H(k+1)\cdot\hat{x}\left(\frac{k+1}{k}\right)\right]$$

$$K(k+1)=P\left(\frac{k+1}{k}\right)\cdot H(k+1)^T\cdot\left[H(k)\cdot P\left(\frac{k+1}{k}\right)\cdot H(k)^T+R\right]^{-1}$$

$$P\left(\frac{k+1}{k+1}\right)=P\left(\frac{k+1}{k}\right)-K(k+1)\cdot H(k+1)\cdot P\left(\frac{k+1}{k}\right)$$

where R and Q are the measurement and system noise covariance matrices, which rather depend on noise shape and magnitude. Moreover, there is no analytical method to tune up these matrices. Taking also into account the complexity of the algorithm, as well as the aspects shown above, we consider that Kalman filter for estimation in vector control of induction motor still is not the best choice.

3. REAL-TIME SIMULATION

In order to compare as fairly as possible the estimation techniques considered in the paper, the following conditions have been provided:

1. Same load conditions;
2. Same rotor resistance variation (ΔRr=100%);
3. The most advantageous combination of flux and speed estimation techniques.

The vector control structure used in real-time simulation is presented in Figure 1 and it's implementation in Figure 5. Here, the control algorithm has been implemented on the TMS320C31

DSP and the model of the drive (motor and load) on the PC computer. This is the closest structure to the real one, but which allow the comparison between the real rotor flux computed by the PC and the estimated one performed by the DSP and the consideration of the rotor resistance variation on the rotor flux estimation. A 500μs sample time has been considered.

4. THE COMPARATIVE STUDY OF THE ESTIMATION METHODS

The real-time simulation results have been used in challenging the performances of the flux observers and speed estimation devices. Rotor flux estimation has been considered individually, because its influence on speed estimation, when rotor resistance variation is considered. In all simulations a 100% rotor resistance variation (from 1.47Ω to 3Ω) has been considered.

4.1. The Rotor Flux Estimation

The simulation results obtained using the Luenberger and Gopinath flux observers are presented in Figure 6. The following conclusions would be pointed out:

Steady State Error and Parameter Sensitivity. In case of Gopinath Observer (Reduced Order Robust Adaptive Observer) practically there is no steady error, even if the rotor resistance variation is greater than 100%. Good results have been reported at 250% rotor resistance variation, due to the poles allocation strategy which is performed taking into account the robustness to parameter variation principles [Hori, 1990].

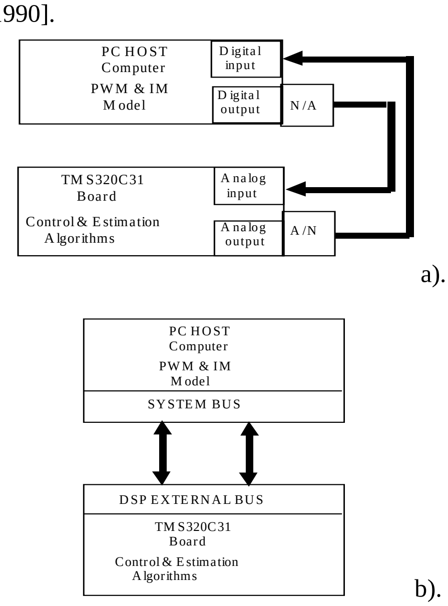

Fig.5. The structure of the bi-processor real-time simulation system.

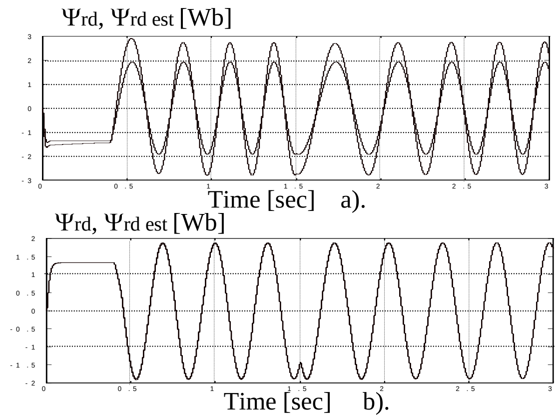

Fig.6. The simulation results for flux estimation algorithms using: a). Luenberger Observer; b). Gopinath Observer.

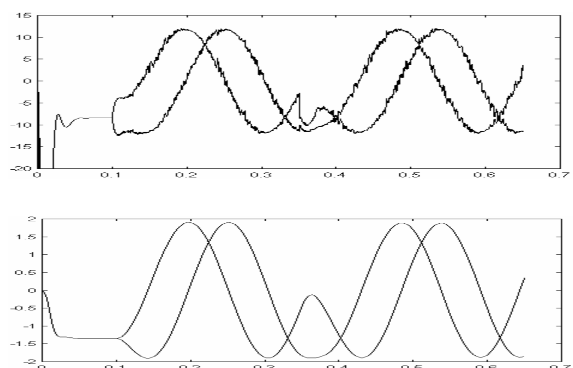

Fig. 7. The measured and the estimated rotor flux components using the Kalman Filter with an input and system noise of -14dB.

Dynamic Behavior. Both observers are stable because in both cases the pole allocation is performed by means of stability. However, higher performances could be achieved using Gopinath Observers when the gain is chosen by imposing the poles to move on a parabola situated in the negative half of the complex plan.

4.2. The Speed Estimation

The performances of MRAS and torque error MRAS speed estimation devices have been tested in the following regimes:
-start to 30rad/sec and reversal to –30rad/sec with 100% resistant torque and ΔRr =100% (Figure 8a. and Figure 9a);
-start to 40 rad/sec and chance of speed to –40rad/sec in steps of 10 rad/sec and ΔRr =100% (Figure 8b. and Figure 9b);
-start at 190 rpm and decrease to 9 rpm with 100% load and ΔRr =100% (Figure 8c. and Figure 9c).
The real time simulation results are presented in Figure 8 for torque error MRAS estimator and in

Figure 9 for MRAS estimator. In each figure, the reference speed, the estimated and the real one are presented. Conclusions have been formulated related to steady state error and parameter sensitivity, stability and dynamic behavior, and operation in the load speed region.

Steady State Error. Tests have been made on normal load conditions, when highest steady state errors appear. However, in both cases in the nominal speed region this error in acceptable, but it raises in the low speed region. The error is greater in torque error MRAS than in MRAS, as Figures 8c and 9c show, because of the better behavior of the Gopinath Observer at rotor resistance variation.

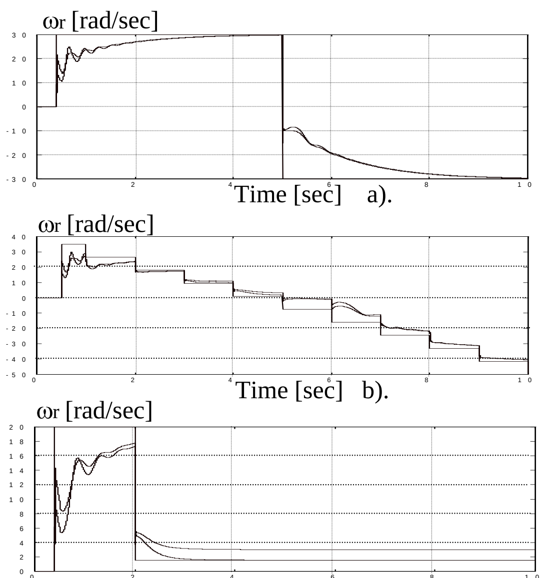

Fig.8. The simulation results for the torque error MRAS estimation method

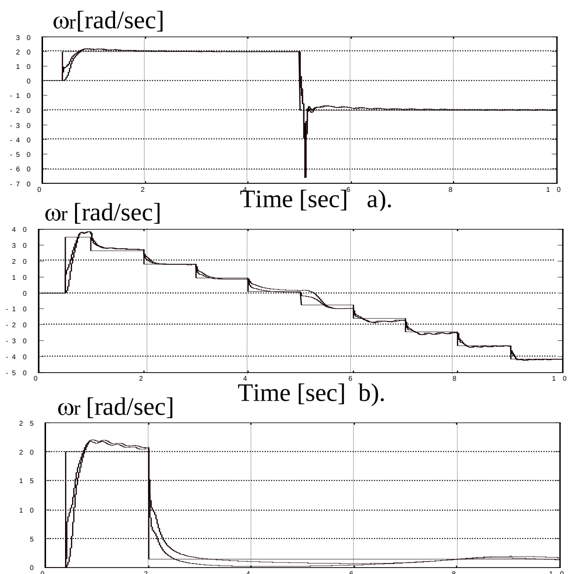

Fig.9. The simulation results for the MRAS estimation method.

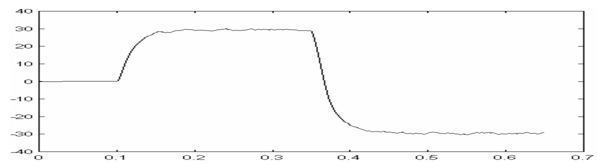

Fig. 10. The rotor speed using Kalman Filter with an input and system noise of -14dB.

Dynamic behavior and stability. There have been already reported good research in connection with the stability of the considered adaptive estimators in [9]. In concordance with his study, the MRAS estimator fails in speed reversal in regenerative regime, while the torque error MRAS working in the same conditions recovered in a short time. The second observation has been confirmed by our study too, as it can be seen in Figure 8b. In case of MRAS estimator failure has been avoided by using the Gopinath flux observer which is more robust even in the low speed region. The behavior of the MRAS estimator is illustrated in Figure 9b.

Low speed operation. In both cases in low speed region speed estimation error is considerable, higher in case of torque error MRAS as Figure 8c. and 9c. show. Speed estimation fails at zero speed because pole 1 and zero 1 move into the unstable zone. The unstable region enlarges when the load torque rotor resistance variation increases.

We think that it is important to emphasis the role of the flux estimation in the whole estimation process. When the flux observer is robust to the parameter variation (as in the case or Gopinath Observer), the parameter estimation partially looses its importance. With other words, *ACCURACY OF FLUX ESTIAMTION IS MUCH MORE IMPORTANT THAN PARAMETER ESTIMATION, the more so estimation errors couldn't be avoided anyway.* In order to illustrate the former affirmations, a very simple estimation method for estimating both speed and rotor resistance estimation has been considered [Pana et al, 2000]. The real-time simulation results are presented in Figure 11, using the same conditions as for the torque error MRAS and MRAS estimators. Here rotor resistance has been estimated, but has not been used at all in the vector control.

6. CONCLUSIONS

The paper studies comparatively the most used methods for flux estimation as well as the most popular speed estimators. The variation of the rotor resistance should be always taken into consideration when the flux and speed estimators are challenged. The Gopinath flux Observer gives the best results, even when the rotor resistance variation is about 250%.

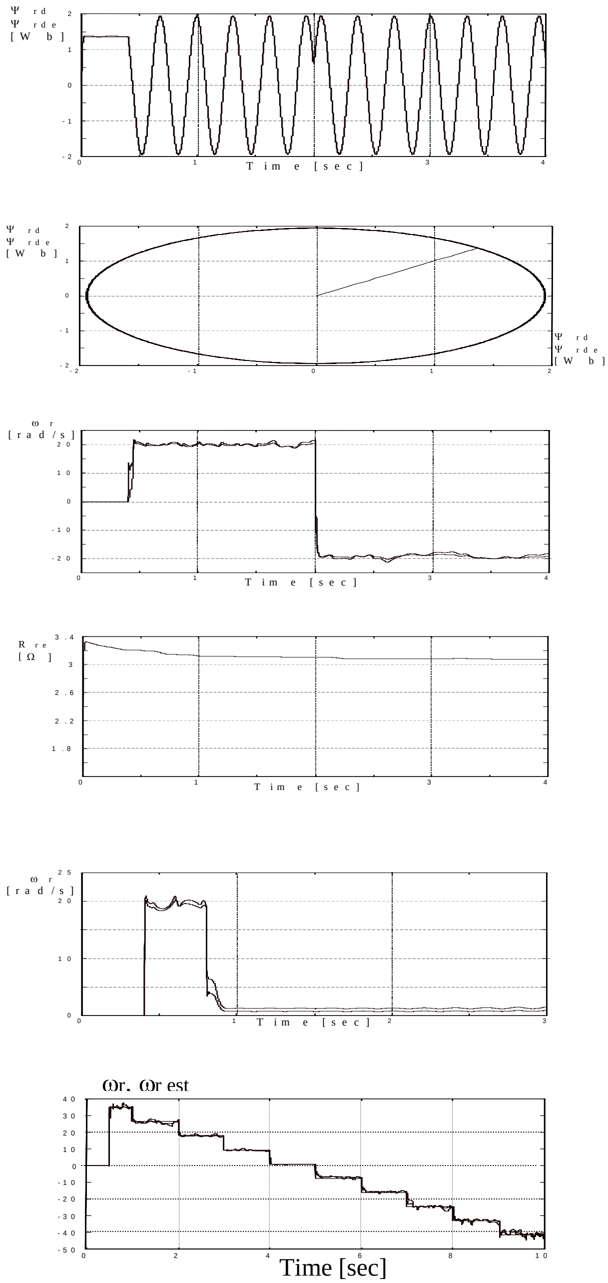

Fig.11. Real-time simulation results using the model of the induction motor together with statistical algorithm.

Using this observer together with the MRAS speed estimator, its performances equalize that of the torque error MRAS estimator.*)*

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