

**STATES AND PARAMETERS ESTIMATION OF THE
ASYNCHRONOUS MACHINE BY USING THE OPTIMAL
OBSERVERS
PART I – ESTIMATION OF THE FLUX COMPONENTS BY
USING A LUENBERGER OBSERVER**

MIHAI PUIU-BERIZINTU, PETRU GABRIEL PUIU

University of Bacau, ROMANIA,

Abstract. This paper discusses the asynchronous machine flux estimation by using a complete order estimator (Luenberger estimator). There is presented the structure of this optimal observer type and the numerical implementations algorithm. It is performed the time-discrete state-space model of the asynchronous machine and the algorithm for the numerical implementations of the Luenberger state estimator. The estimator of the rotor and stator flux is simulated using the MATLAB\SIMULINK files. Finally, the conclusions of this estimator study are presented.

Keywords: asynchronous machine, state estimator, Luenberger observer.

1. INTRODUCTION

The optimal control of the asynchronous machine used either motor drive or generator in the particular case of wind power stations or low power hydro-electric power stations, requires a higher precision knowledge of the variable quantities and parameters with the operating conditions. The modern systems of the asynchronous machine with static power converters conceived on the field-orientation control principle, using the mathematical model of the machine what contains a few quantities that continuously varying with the speed and with the magnetic and thermal level strains. The optimal control with dynamic and energetic higher performance of this type systems, requires an accurately real time values determination of the variables quantities that contained in the machine model, thing that can not easy realised by the direct measurement. The systems with the field-orientated controls, use the machine model in a reference frame orientated by one from those tree components of the magnetic flux: stator flux, rotor flux or air-gap flux. In this case importantly is to know with precision and in real time as well as of value as of components flux positions. The direct measurement of the magnetic flux is generally difficult and it supposes the intervention in the machines construction for the sensor settlement (e.g. measurement coils, Hall sensors), that's not always possible and that can affect the reliability of the machine. The indirect calculus of the flux is preferred and it is based on some measurable quantities such as: tensions, currents, speed. As the machine model is non-linear, to determine with high precision the variable quantities like the magnetic flux, it imposes the use of some optimal closed loop estimator like the Luenberger state estimator is.

2. THE CLOSED LOOP STATE ESTIMATOR

The fundamental problem of a state estimator or observer is to determine, for a given system, a state variables set, generally non-directly measurable on the base of the input and output measurable variables.

It considers the linear system, input and output mono-variable, described by state-variable equations as follows:

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{A}\mathbf{x} + \mathbf{B}u \\ y &= \mathbf{C}\mathbf{x}\end{aligned}\quad (1)$$

The closed loop state estimator determines the components of the state vector $\hat{\mathbf{x}}$ on the base of the input command u and performs this continuous correction on the base of the principle that the estimated state $\hat{\mathbf{x}}$ coincides with the real one $\mathbf{x}$ when the error between the real exit y and the estimated one $\hat{y}$ is cancelled. This way, the used model for the states estimator is corrected on the base of the error between the real system output and the model output calculated on the base of the estimated state. The structure of a closed loop estimator, is shown in figure 1. Through the weight matrix L it is controlled the estimated state convergence to real state of the controlled process.

The estimator can be designed for the reconstruction of the whole state vector that completely characterizes the controlled system dynamics, named in this case, complete estimator, or for the estimation of some state variables that can't be directly determined from the measured quantities, named reduced order estimator. In the case of some high values of the measure noise, the complete estimator assures a high precision as to the reduced order estimator.

On the base of the continuous model of the linear system described by the equations (1) and by the bloc diagram in figure 1, it is deduced from

$$\begin{aligned}\dot{\hat{\mathbf{x}}} &= \mathbf{A}\hat{\mathbf{x}} + \mathbf{B}u + L(y - \hat{y}) \\ \hat{y} &= \mathbf{C}\hat{\mathbf{x}}\end{aligned}$$

(2)

The system corresponding to the complete estimator is of the same order with the controlled physical system, and its output is the estimated state $\hat{\mathbf{x}}$ of the real dynamic system. The estimator can be implemented by using analog or digital circuits. The time-discrete model of the estimator is determined on the base of the time-discrete model of the controlled physical process, generally obtained through the continuous model characterized by the eq (1). Thus, by applying the forward differences method, the process time-discrete model results as follows:

$$\begin{aligned}\mathbf{x}(k+1) &= \mathbf{F} \cdot \mathbf{x}(k) + \mathbf{G} \cdot u(k) \\ y(k) &= \mathbf{H} \cdot \mathbf{x}(k)\end{aligned}\quad (3)$$

in which the matrix $\mathbf{F}$, $\mathbf{G}$ and $\mathbf{H}$ could be thus estimated as

$$\mathbf{F} = e^{\mathbf{A}T_e} \approx \mathbf{I} + \mathbf{A} \cdot T_e; \quad \mathbf{G} \approx \mathbf{B} \cdot T_e; \quad \mathbf{H} = \mathbf{C} \quad (4)$$

where T_e is the sampling time.

The estimator can be digital implemented in more many ways [3]. It is taken here into account only the estimator with prediction in which the estimated state $\hat{\mathbf{x}}(k+1)$ is obtained through the correction of the predicted state $\tilde{\mathbf{x}}(k+1)$ on the base of the performed estimation at the current time step k , the estimator equation being

$$\begin{aligned}\hat{\mathbf{x}}(k+1) &= \tilde{\mathbf{x}}(k+1) + L \cdot [y(k) - \hat{y}(k)] \\ \tilde{\mathbf{x}}(k+1) &= \mathbf{F} \cdot \hat{\mathbf{x}}(k) + \mathbf{G} \cdot u(k) \\ \hat{y}(k) &= \mathbf{H} \cdot \hat{\mathbf{x}}(k)\end{aligned}\quad (5)$$

After a simple calculus, the estimator equations can have the following form:

$$\begin{aligned}\hat{\mathbf{x}}(k+1) &= \mathbf{F} \cdot \hat{\mathbf{x}}(k) + \mathbf{G} \cdot u(k) + L \cdot [y(k) - \hat{y}(k)] \\ \hat{y}(k) &= \mathbf{H} \cdot \hat{\mathbf{x}}(k)\end{aligned}\quad (6)$$

to which corresponds the block diagram presented in figure 2.

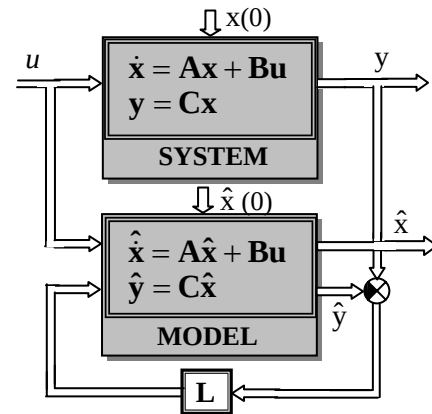


Fig. 1.

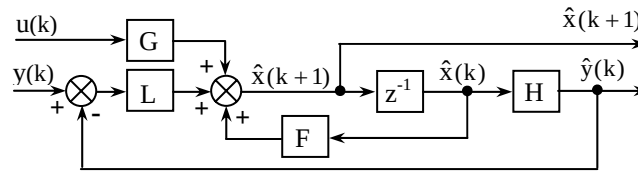


Fig. 2.

It is obviously that the estimation is correct if the estimated state $\hat{x}(t)$ coincides with the real state $x(t)$ of the process, and if the estimation error

$$e(t) = x(t) - \hat{x}(t) \quad (7)$$

is very low, in its limit: $\lim_{t \rightarrow \infty} e(t) = 0$.

In the discrete form, the estimation error at the time step k is

$$e(k) = x(k) - \hat{x}(k) \quad (8)$$

and from the relations (5) and (6), the error equation for the estimator with prediction results:

$$e(k+1) = (F - LC) \cdot e(k). \quad (9)$$

By transposing the matrix in this equation it obtains a similar structure with that of a controller

$$e(k+1) = (F^t - C^t \cdot L^t) \cdot e(k) \quad (10)$$

where the superscript 't' represents the transpose of the matrix.

It results from here that, to determine the weigh matrix L is an allocation problem to obtain the desired dynamic performances for the system characterized by eqn (10). For the zero convergence of the estimation error it is necessary that $\lim_{k \rightarrow \infty} \hat{x}(k) = x(k)$ and the system formed by the estimator to be asymptotic stable. For this, the characteristic equation of the estimator

$$\det[z \cdot I - F + L \cdot C] = 0 \quad (11)$$

needs to have the roots situated inside the unitary radius circle $|z_j| < 1$.

The L matrix is determined by imposing the characteristic equation roots, and the estimator poles too, to obtain the desired dynamic. It states that the response time of the estimator has to be at least two times larger than the response time of the regulator with the state estimator.

3. ALGORITHM OF THE FLUX ESTIMATOR

In order to perform a state estimator of complete order for the stator and rotor fluxes estimation of the asynchronous machine, there uses the flux model with the state-variable equations of the machine in a stationary reference frame d-q [4]:

$$\begin{aligned} \frac{d\psi_{1d}}{dt} &= \frac{1}{\sigma T_1} \psi_{1d} + \frac{1}{\sigma T_1} \frac{x_m}{x_2} \psi_{2d} + \omega_1 u_{1d} \\ \frac{d\psi_{1q}}{dt} &= \frac{1}{\sigma T_1} \psi_{1q} + \frac{1}{\sigma T_1} \frac{x_m}{x_2} \psi_{2q} + \omega_1 u_{1q} \\ \frac{d\psi_{2d}}{dt} &= \frac{1}{\sigma T_2} \frac{x_m}{x_1} \psi_{1d} - \frac{1}{\sigma T_2} \psi_{2d} - \omega_1 \psi_{2q} \\ \frac{d\psi_{2q}}{dt} &= \frac{1}{\sigma T_2} \frac{x_m}{x_1} \psi_{1d} - \frac{1}{\sigma T_2} \psi_{2d} + \omega_1 \psi_{2q} \end{aligned} \quad (12)$$

The equations (12) have been done in rated quantities and there have been used the notations:

- $T_1 = \frac{x_1}{\omega_1 r_1} = \frac{L_1}{R_1}$ – the stator time constant, L_1 and R_1 being the phase self inductance and the phase resistance of the stator winding;
- $T_2 = \frac{x_2}{\omega_1 r_2} = \frac{L_2}{R_2}$ – the rotor time constant, L_2 and R_2 being the phase self inductance and the phase resistance of the rotor winding;
- $\sigma = 1 - \frac{x_m}{x_1 x_2}$ – the total dispersion coefficient, x_1 , x_2 and x_m being, respectively, the stator, rotor and magnetizing rated reactance.

If there take as the command quantities the components u_{1d} and u_{1q} of the stator voltages and as output (measured) quantities the components i_{1d} and i_{1q} of the stator current, the complete model input-state-output of the asynchronous machine used for the flux estimation, takes the following form:

$$\frac{d}{dt} \begin{bmatrix} \psi_{1d} \\ \psi_{1q} \\ \psi_{2d} \\ \psi_{2q} \end{bmatrix} = \begin{bmatrix} -\frac{1}{\sigma T_1} & 0 & \frac{1}{\sigma T_1} \frac{x_m}{x_2} & 0 \\ 0 & -\frac{1}{\sigma T_1} & 0 & \frac{1}{\sigma T_1} \frac{x_m}{x_2} \\ \frac{1}{\sigma T_2} \frac{x_m}{x_1} & 0 & -\frac{1}{\sigma T_2} & 0 \\ 0 & \frac{1}{\sigma T_2} \frac{x_m}{x_1} & 0 & -\frac{1}{\sigma T_2} \end{bmatrix} \cdot \begin{bmatrix} \psi_{1d} \\ \psi_{1q} \\ \psi_{2d} \\ \psi_{2q} \end{bmatrix} + \begin{bmatrix} \omega_1 & 0 \\ 0 & \omega_1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} u_{1d} \\ u_{1q} \end{bmatrix} \quad (13)$$

$$\begin{bmatrix} i_{1d} \\ i_{1q} \end{bmatrix} = \begin{bmatrix} \frac{1}{\sigma x_1} & 0 & -\frac{x_m}{\sigma x_1 x_2} & 0 \\ 0 & \frac{1}{\sigma x_1} & 0 & -\frac{x_m}{\sigma x_1 x_2} \end{bmatrix} \cdot \begin{bmatrix} \psi_{1d} \\ \psi_{1q} \\ \psi_{2d} \\ \psi_{2q} \end{bmatrix}$$

By comparison these equations with eqns (1) of the general model, the matrix A, B, and C are obviously. To obtain the discrete-time model described by the eqns (3) there are used the approximation relations (4). Thus, it results the discrete-time model of the asynchronous machine as follow:

$$\frac{d}{dt} \begin{bmatrix} \psi_{1d} \\ \psi_{1q} \\ \psi_{2d} \\ \psi_{2q} \end{bmatrix}_{k+1} = \begin{bmatrix} 1 - \frac{T_e}{\sigma T_1} & 0 & \frac{T_e}{\sigma T_1} \frac{x_m}{x_2} & 0 \\ 0 & 1 - \frac{T_e}{\sigma T_1} & 0 & \frac{T_e}{\sigma T_1} \frac{x_m}{x_2} \\ \frac{T_e}{\sigma} \frac{x_m}{x_1} d_2 & 0 & 1 - \frac{1}{\sigma} d_2 & -\omega_1 T_e v \\ 0 & \frac{T_e}{\sigma} \frac{x_m}{x_1} d_2 & \omega_1 T_e v & 1 - \frac{1}{\sigma} d_2 \end{bmatrix}_k \cdot \begin{bmatrix} \psi_{1d} \\ \psi_{1q} \\ \psi_{2d} \\ \psi_{2q} \end{bmatrix}_k + \begin{bmatrix} \omega_1 & 0 \\ 0 & \omega_1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} u_{1d} \\ u_{1q} \end{bmatrix}_k \quad (14)$$

$$\begin{bmatrix} i_{1d} \\ i_{1q} \end{bmatrix}_k = \begin{bmatrix} \frac{1}{\sigma x_1} & 0 & -\frac{x_m}{\sigma x_1 x_2} & 0 \\ 0 & \frac{1}{\sigma x_1} & 0 & -\frac{x_m}{\sigma x_1 x_2} \end{bmatrix} \cdot \begin{bmatrix} \psi_{1d} \\ \psi_{1q} \\ \psi_{2d} \\ \psi_{2q} \end{bmatrix}_k$$

where it wrote down with $d_2 = 1/T_2$ and with v the rotor rated speed.

Considering the complete order estimator with prediction, the block diagram of the flux observer at the asynchronous machine is presented in figure 3.

The F_k matrix has to be updated at every sample step, to take into account the rotor speed variations. The L_k weight matrix for the discrete systems of the estimator is determined so that its poles have some imposed values, inside the unitary radius circle. As it depends on the F_k matrix value which is on-line actualised, it results that the L_k matrix too has to be recalculated in accordance with the new F_k value at every sample step. So, because the linear systems whose state is estimated is with variable parameters, the gain matrix L of the estimator can't be once calculated, at the beginning of the algorithms and there constantly maintained, like in the invariant systems case, but it calculates at every sampling step.

A solution for the on-line calculus of the L_k - matrix is the use of some relations that assure the proportionality between the machine poles and those of the estimator. These relations deduce in the continuous system case, getting the L matrix, from which, by time-discrete conversion, results the L_k matrix. By assuring the poles proportionality, the estimator stability is assured, the machine model being stable regardless of the rotor speed. It is obviously that the proportionality won't maintain and after time-discrete conversion, but the stability will surely maintain. Considering the L matrix of the follow form

$$L = \begin{bmatrix} l_1 & -l_2 \\ l_2 & l_1 \\ l_3 & -l_4 \\ l_4 & l_3 \end{bmatrix} \quad (15)$$

its terms can be calculated with the relations [4]:

$$\begin{aligned} l_1 &= (g-1) \cdot (a_{11} + a_{33}); \quad l_2 = (g-1) \cdot a_{34}; \\ l_3 &= (g^2 - 1) \cdot (ca_{11} + a_{33}) - c(g-1) \cdot (a_{11} + a_{33}); \\ l_4 &= -c(g-1) \cdot a_{34} \end{aligned} \quad (16)$$

in which a_{ij} are the corresponding terms of the A matrix, g is the proportionality coefficient between the estimator poles and those of the machine and with c wrote down the ratio $\sigma x_1 x_2 / x_m$. This systems dynamics (and that of the estimator with dominant poles) is very different when the rotor speed variations. But through the matrix time-discrete conversion the proper values variations is in lower limits than for the time-continuous system.

The proper values of the time-discrete matrix, when the rotation speed is very low, go to the unitary mod. Because of this, the cumulated calculus errors can determine the stability limit surpassing where the machine states are estimated in conformity with Luenberger estimator algorithm in numerical form.

The algorithm of the current state estimation of the asynchronous machine with a linear state-estimator of complete order can be resumed as following:

- step 1 - the model A matrix is bringing up-to-date in conformity with the new values of the rotor speed;
- step 2 - the L matrix coefficients calculates in conformity with the new elements of the A matrix;
- step 3 - time-discrete conversion of the A and B matrix, getting the G_k and F_k matrix;
- step 4 - the L_k matrix calculates for the discrete model;
- step 5 - the new estimated state is calculated.

The Luenberger observer algorithm presented above was executed through Matlab/Simulink "S-function" type, conceived for the numerical simulation of the dynamic process regarding the estimation of the magnetic flux at the asynchronous machine. The components estimation of the rotor and stator fluxes is realized in a stationary

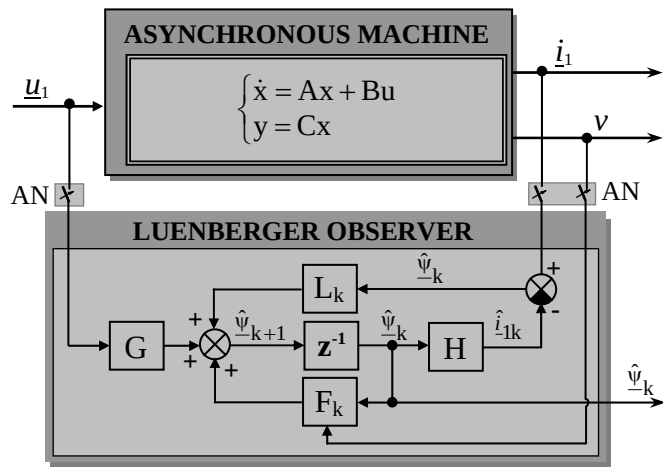


Fig. 3.

reference frame. The estimator uses as input quantities the components of the space phasors of the stator voltages $\underline{u}_s$, of the stator current $\underline{i}_s$, and the rated speed v , giving at the output the state-variables: the stator and rotor flux components. The overall diagram of the MATLAB/SIMULINK simulation are shown in figure 4.

For to study the estimator behaviour to the different speed values it is done the scalar control method (constant volt per hertz control method) of the asynchronous motor speed. The model used for the asynchronous machine allows the changes, during the simulation, of the stator and rotor resistance, of the reversal time constants of the stator and rotor, $1/T_1$ and $1/T_2$, as one can see in the overall diagram shown in figure 4.

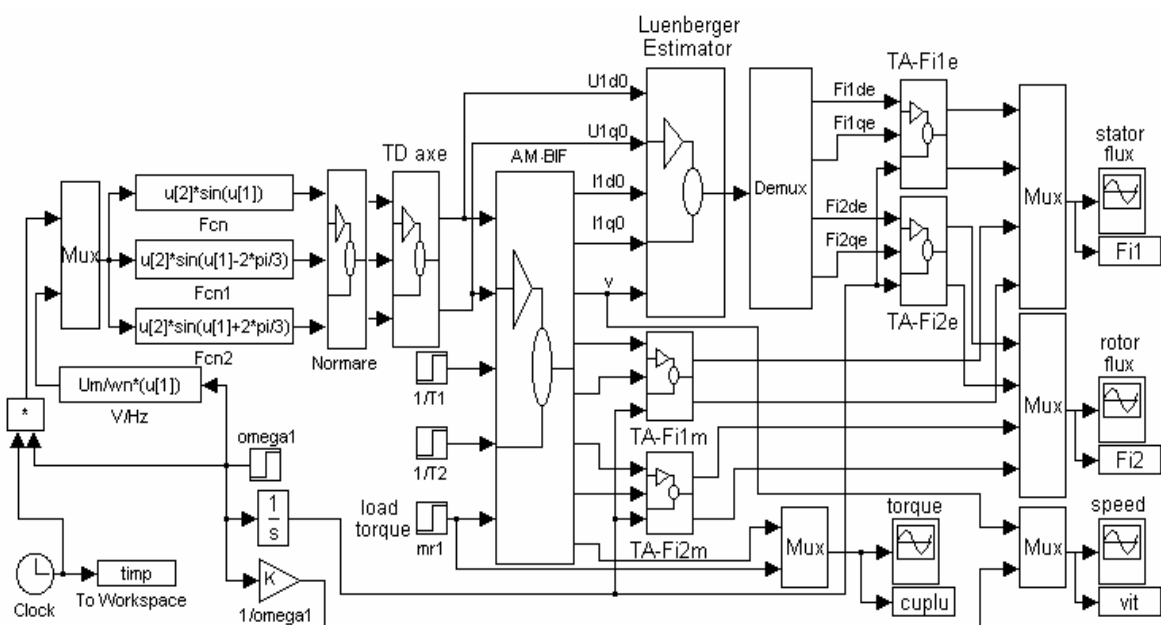


Fig. 4. Overall diagram of the MATLAB\SIMULINK simulation.

The simulation program was performed after the following stages:

- 1) the no load start of the asynchronous machine at the $V/Hz = \text{const}$ with reference speed at nominal value (rated speed $v = 1$);
- 2) at the instant $t = 0,4$ sec a nominal value of the load torque it is applied;
- 3) at the instant $t = 0,5$ sec it was increased the stator resistance at 1,25 of nominal value R_{1n} ;
- 4) at the instant $t = 0,7$ sec it was increased the rotor resistance at 1,5 of nominal value R_{2n} ;
- 5) at the instant $t = 0,8$ sec the load torque was reduced at half ;
- 6) at the instant $t = 0,9$ sec the stator and rotor resistance were reduced, $R_1 = 0,75 R_{1n}$, and $R_2 = 0,5R_{2n}$;
- 7) at the instant $t = 1$ sec the reference speed was reduced at half ($v^*=0,5$);
- 8) at the instant $t = 1,2$ sec the load torque was cancelled and the stator and rotor resistances were brought at their nominal values;
- 9) at the instant $t = 1,3$ sec the reference speed was reduced at the value $v^* = 0,2$.

4. THE SIMULATION RESULTS. CONCLUSIONS.

By the simulation program it was followed the analyse of the estimation precision and of the dynamic stability of the estimator at the variations of the speed, of the load torque and of the asynchronous machine parameters (the rotor and stator resistances). The obtained results, shown in figure 5, correspond to a proportionality factor $g = 98$ between the poles of the time-continuous systems of the estimator and the poles of the asynchronous motor. The simulation was performed at a sampling frequency of 2 kHz.

The study done by simulation proved a great influence of the g proportionality factor over the estimator precision and stability. As the simulation results presented in figure 5 show, it is proved that there are some values of the proportionality factor for whom the estimator stability is assured at the speed changes.

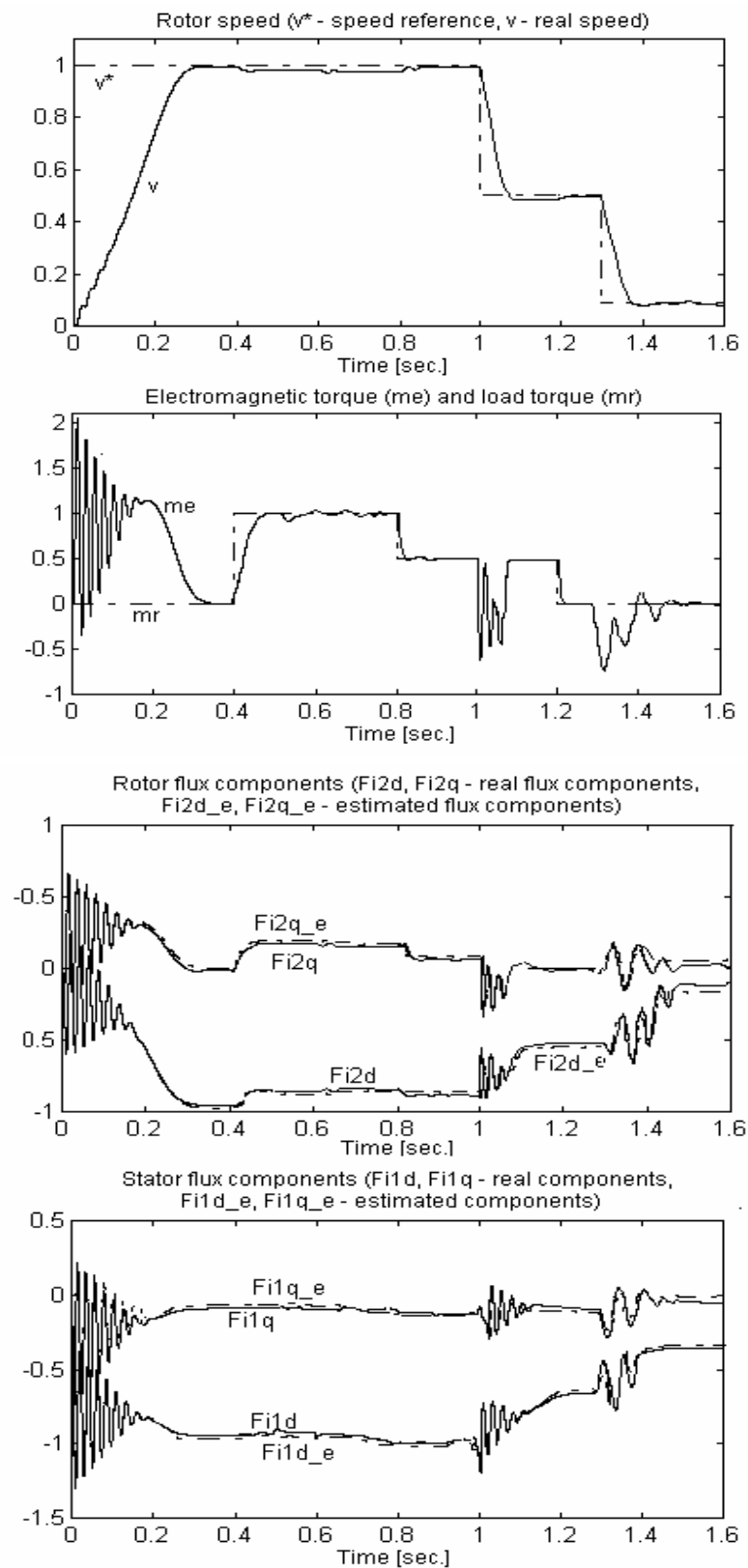


Fig. 5. Simulation results.

What is all-important, is that the estimation dynamics and precision are very little affected by the variable

parameters change of the machine, if the proportionality factor between the estimator poles and machine ones is correct. The value of this proportionality factor is difficult to establish by calculus, taking into account the speed and machine variation parameters. The only practical possibility is its determination by simulation, followed by an eventually adjustment done by experimental tests.

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The simulation results prove that the evaluation precision decrease in the same time with the speed decrease. More, the evaluator stability can be easily loaded at high values or at low values of the speed, at little changes regarding the proportionality factor and the sampling frequency. To choose this proportionality factor, it imposes the acceptance of a compromise for the evaluation precision and for the evaluation dynamics to assure the stability on the entire adjustment range.

In the real, practical, situations a great influence over the evaluator precision and dynamics can have the measurement and system noises due to the out of precision measurements and variations of the machine parameters. The precise measurement of the tension and of the current regarding the PWM invertors is difficult, imposing the acceptance of some filters that bring supplementary delays and errors at the inverter commutation frequency changes.

Appendix. Parameters of the asynchronous machine used for flux estimator simulation:

Rated power = 2,2 KW
Rated speed = 2800 r/min;
Number of poles pair = 1;
Stator resistance = 8,5 Ω ;
Rotor resistance related to stator = 7,8 Ω ;
Total stator inductance = 852 mH;
Total rotor inductance related to stator = 852 mH;
Magnetizing inductance = 815 mH.

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