COMPUTER SIMULATION OF REAL TIME IDENTIFICATION FOR INDUCTION MOTOR DRIVES

by
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Abstract. The paper was meant to be an unitary approach to state and parameter identification in induction motor drives. The main methods for rotor flux, mechanical parameters and load torque estimation were compared and classified. In the area of state and parameter simultaneous identification a general adaptation mechanism, valid for all the solutions based on a reference model, was introduced. Four of the most used solutions for sensorless drives were discussed and compared.
There are two general approaches to state and parameter identification in induction motor drives: the Kalman filter, and the linear state observer (Luenberger) plus an adaptation mechanism. For each problem there are also some particular solutions, based not on a general theory, but on solving various specific equation.
Theoretical analyze, numerous simulations and experiments show in every case the superiority of general solutions on those called 'particular'. From these two general solutions, the one based on a linear state observer was chosen, because it is much simpler and demands a considerably smaller computation time than a Kalman filter, while their performance is very close. This observer is completed by an adaptation mechanism (for electrical parameters identification) and possible by a least square algorithm (for mechanical parameters identification). This solution was improved (in simplicity, reliability and computation time reduction) for an industrial implementation.
Keywords. Sensorless drives, Kalman filter, linear state observer.

1. Induction Motor Model for Real Time Identification.

It is the simplified motor model, used in the control of any FOC drive. In stator reference frame its equations are:

$$\frac{d}{dt}\begin{bmatrix} i_{qs} \\ i_{ds} \\ \lambda_{qr} \\ \lambda_{dr} \end{bmatrix} = \begin{bmatrix} -\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma \tau_r}\right) & 0 & \frac{L_m}{\sigma L_s L_r \tau_r} & -\frac{L_m}{\sigma L_s L_r}\omega_r \\ 0 & -\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma \tau_r}\right) & \frac{L_m}{\sigma L_s L_r}\omega_r & \frac{L_m}{\sigma L_s L_r \tau_r} \\ \frac{L_m}{\tau_r} & 0 & -\frac{1}{\tau_r} & \omega_r \\ 0 & \frac{L_m}{\tau_r} & -\omega_r & -\frac{1}{\tau_r} \end{bmatrix} \begin{bmatrix} i_{qs} \\ i_{ds} \\ \lambda_{qr} \\ \lambda_{dr} \end{bmatrix} + \begin{bmatrix} \frac{1}{\sigma L_s} & 0 \\ 0 & \frac{1}{\sigma L_s} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_{qs} \\ v_{ds} \end{bmatrix}$$

$$J\frac{d\omega}{dt} = T_e - T_l$$

$$T_e = \frac{3}{2}p\frac{L_m}{L_r}(\lambda_{dr} i_{qs} - \lambda_{qr} i_{ds})$$

Rotor flux identification is determinant for the performance of any DFOC system, no matter how complex this is. That is why it is the first discussed. Moreover, the results obtained in this part are very important for understanding and comparing different solutions of state and parameter simultaneous identification problem.

2. Linear State Observers (Luenberger Observers).

They are given by the general state estimation theory. A full continuos or discrete observer is given by:

$$\hat{x}' = A\hat{x} + Bu + L(y - C\hat{x})$$

where the gain matrix $\boldsymbol{L}$ controls the observer pole placement, as it is demanded by stability, dynamics, noise sensitivity conditions. As for the induction motor the $\boldsymbol{A}$ matrix has variable parameters, $\boldsymbol{L}$ has to assure these conditions for any parameters value. Usually this is done trough some relations assuring a proportionality of matrix $\boldsymbol{A}$ and observer poles. Each sampling time the matrix gain for the continuos time observer is thus computed, and then its discrete equivalent is obtained.

3. Kalman Filter.

It is a state observer with the same structure but having a gain matrix denoted ***K***, computed each step, so that a quadratic performance criterion is minimized. This criterion is constructed according to covariance matrices of input and measurement noise. For the system:

$$x(k+1) = A(k)x(k) + B(k)u(k) + G(k)w(k)$$
$$y(k) = Cx(k) + v(k)$$

if we denote covariance matrices of ***w*** and ***v*** with ***Q*** and respectively ***R***, the Kalman Filter is:

$$P_{k,k-1} = A_{k-1}P_{k-1,k-1}A_{k-1}^T + G_{k-1}Q_{k-1}G_{k-1}^T$$
$$K_k = P_{k,k-1}C^T(CP_{k,k-1}C^T + R_k)^{-1}$$
$$P_{k,k} = (I - K_kC)P_{k,k-1}$$
$$\hat{x}_{k,k-1} = A_{k-1}\hat{x}_{k-1,k-1} + Bu_{k-1}$$
$$\hat{x}_{k,k} = \hat{x}_{k,k-1} + K_k(y_k - C\hat{x}_{k,k-1})$$

where simple subscripts show the time moment, while the doubles are to be read like this: *k*,*k*-1: computed at *k* moment, based on information at *k*-1 moment.

Obviously it is the most complex of all the state estimation algorithms and it demands the greatest computation time (including a matrix inverse operation).

4. Simulation Testing of Induction Motor Rotor Flux Observers.

For evaluating their performance, observers described have been simulated in various operating conditions. In all cases the drive was controlled by the analog system, while the digital observers were working in open loop.

The following situations have been considered:

- operation under “normal” conditions: machine parameters are identical to those used in the algorithms, and voltage, current and speed measurement is not affected by noise. However the measured voltage is according to real PWM and filter characteristics. Machine started and operated at three reference speed levels: small (30 rpm, i.e. a stator frequency of 1 Hz), medium (990 rpm, i.e. a stator frequency of 33 Hz) and high (2010 rpm, i.e. a stator frequency of 67 Hz);
- motor rotor resistance is different to that used by algorithms. Rotor resistance is assumed 40% higher than the rated value, used by flux observers;

- measurement white noise of about 10% the rated current, voltage and speed. Noise covariance matrices are known.

Simulation has been made, in various operating conditions, for DFOC schemes based on both Luenberger and VIω observers. Systems in which rotor flux is estimated by a Luenberger observer have been found superior, especially in what regards the low operation. Fig.1 and 2 presents the results for a starting and a reversal process.

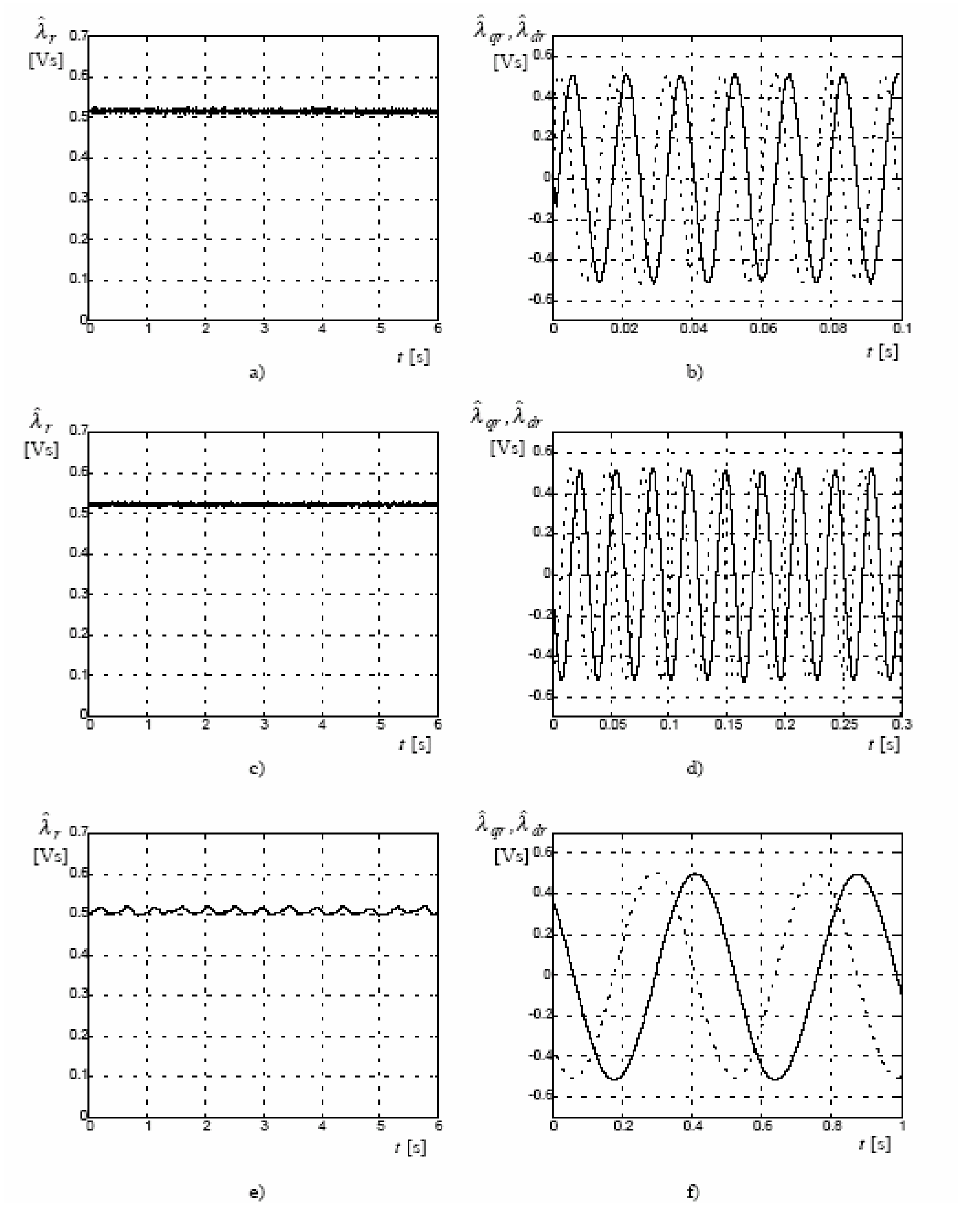

Fig. 1. Estimated rotor flux magnitude and components on stator 'q' and 'd' (dotted) axis. Luenberger observer, in off-line operation, 0.2 ms sampling time - experimental results.
a), b) motor speed of 2010 rpm; c), d) motor speed of 990 rpm; e), f) motor speed of 60 rpm;

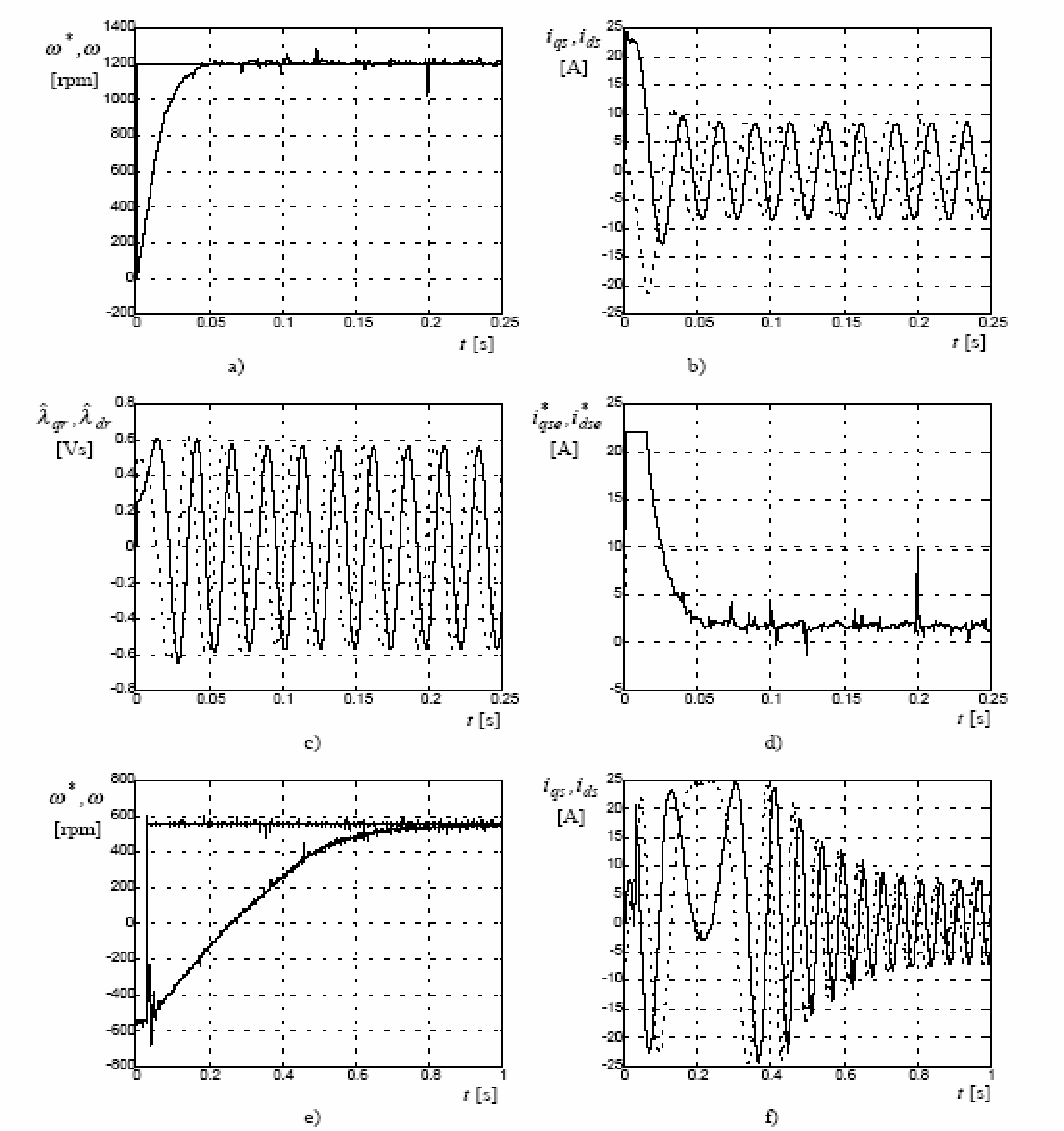

Fig.2. Starting and reversal process for a DFOC system based on a Luenberger flux observer. The sampling time is 0.2 ms - experimental results.
a) reference and measured speed, starting process; b) stator current components on stator ‘q’ and ‘d’(dotted) axis; c) estimated rotor flux components on stator ‘q’ and ‘d’(dotted) axis; d) stator reference currents, in rotor flux frame - flux controlling current is dotted; e) reference and measured speed, reversal process; f) stator current components on stator ‘q’ and ‘d’(dotted) axis.

5. Rotor Flux and Speed Simultaneous Identification. Sensorless drives.

Respecting the most utilized terminology, the solutions are given by:

• methods based on an adaptation mechanism:

- ELO - (Extended Luenberger Observer) - the reference model is the induction motor, while the adjustable one is a Luenberger state observer;
- EKF - (Extended Kalman Filter);

ELO Method

The adaptation mechanism is obtained from the general one, using the particular expression of each variable, that is:

$$e_y = \begin{bmatrix} i_{qs} - \hat{i}_{qs} \\ i_{ds} - \hat{i}_{ds} \\ 0 \\ 0 \end{bmatrix}; \qquad \hat{x} = \begin{bmatrix} \hat{i}_{qs} \\ \hat{i}_{ds} \\ \hat{\lambda}_{qr} \\ \hat{\lambda}_{dr} \end{bmatrix}; \qquad A_{\omega r} = \frac{1}{\omega_R - \tilde{\omega}_r}\left(A - \tilde{A}\right) = \begin{bmatrix} 0 & 0 & 0 & -\frac{L_m}{L_r L_s \sigma} \\ 0 & 0 & \frac{L_m}{L_r L_s \sigma} & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -1 & 0 \end{bmatrix}$$

That means (K >0 is an arbitrary constant):

$$\hat{\omega}_r = \tilde{\omega}_r = K\int e_y^T A_{\omega r} \hat{x} dt = K\int \begin{bmatrix} e_{iqs} & e_{ids} & 0 & 0 \end{bmatrix} \begin{bmatrix} -\frac{L_m}{L_r L_s \sigma} \hat{\lambda}_{dr} \\ \frac{L_m}{L_r L_s \sigma} \hat{\lambda}_{qr} \\ \hat{\lambda}_{dr} \\ -\hat{\lambda}_{qr} \end{bmatrix} dt = K\int \left[-e_{iqs} \hat{\lambda}_{dr} + e_{ids} \hat{\lambda}_{qr} \right] dt$$

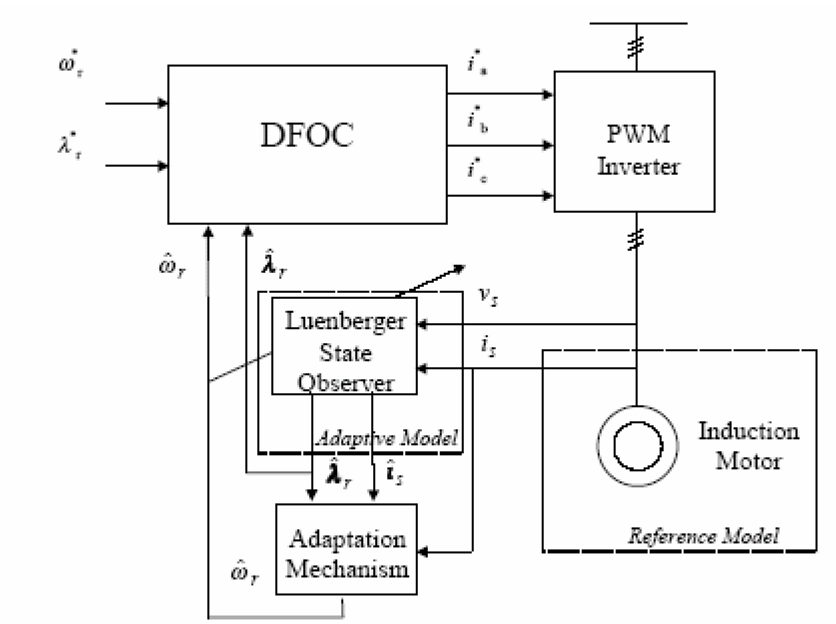

Fig.3. Structure of a sensorless DFOC, based on ELO speed estimation method.

EKF Method

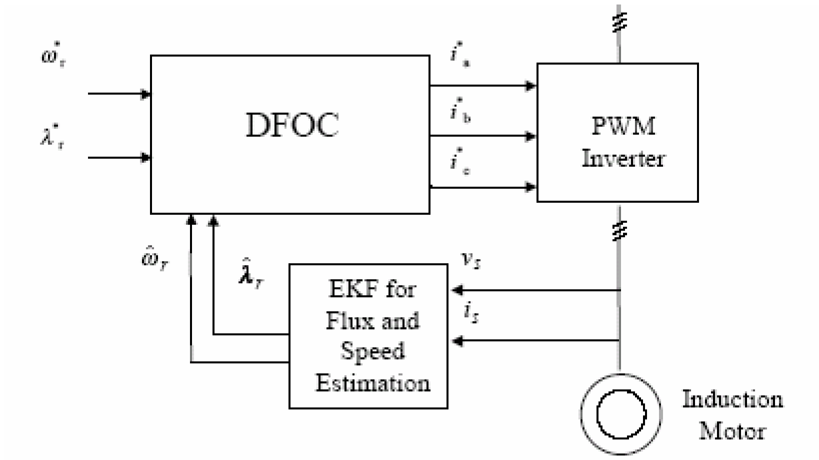

Fig. 4. Structure of a sensorless DFOC, based on EKF speed estimation method.

ELO and EKF schemes are clearly the best. These two schemes are different especially on what regards method complexity and computation time, ELO being superior. In this way is repeated the conclusion given by the comparison of Luenberger and Kalman flux observers. Again, and practically from the same reason, the solution based on Luenberger observer is preferred.

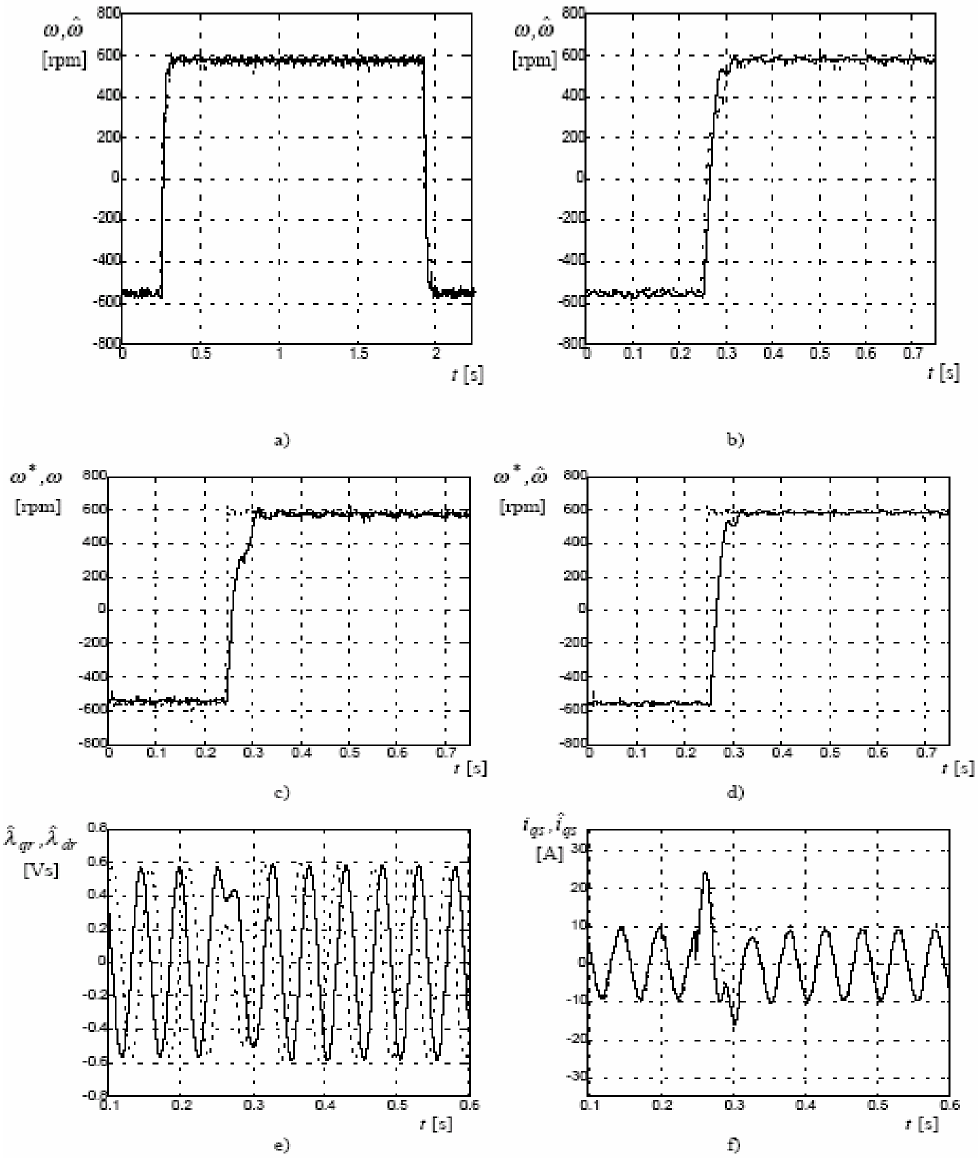

Fig. 5. Simulation results for an ELO sensorless drive.
a) measured (dotted) and estimated speed; b) same, zoom on time; c) measured and reference (dotted) speed; d) estimated and reference (dotted) speed; e) estimated rotor flux on stationary 'd' (dotted) and 'q' axis; f) measured (dotted) and estimated stator current on stationary 'q' axis;

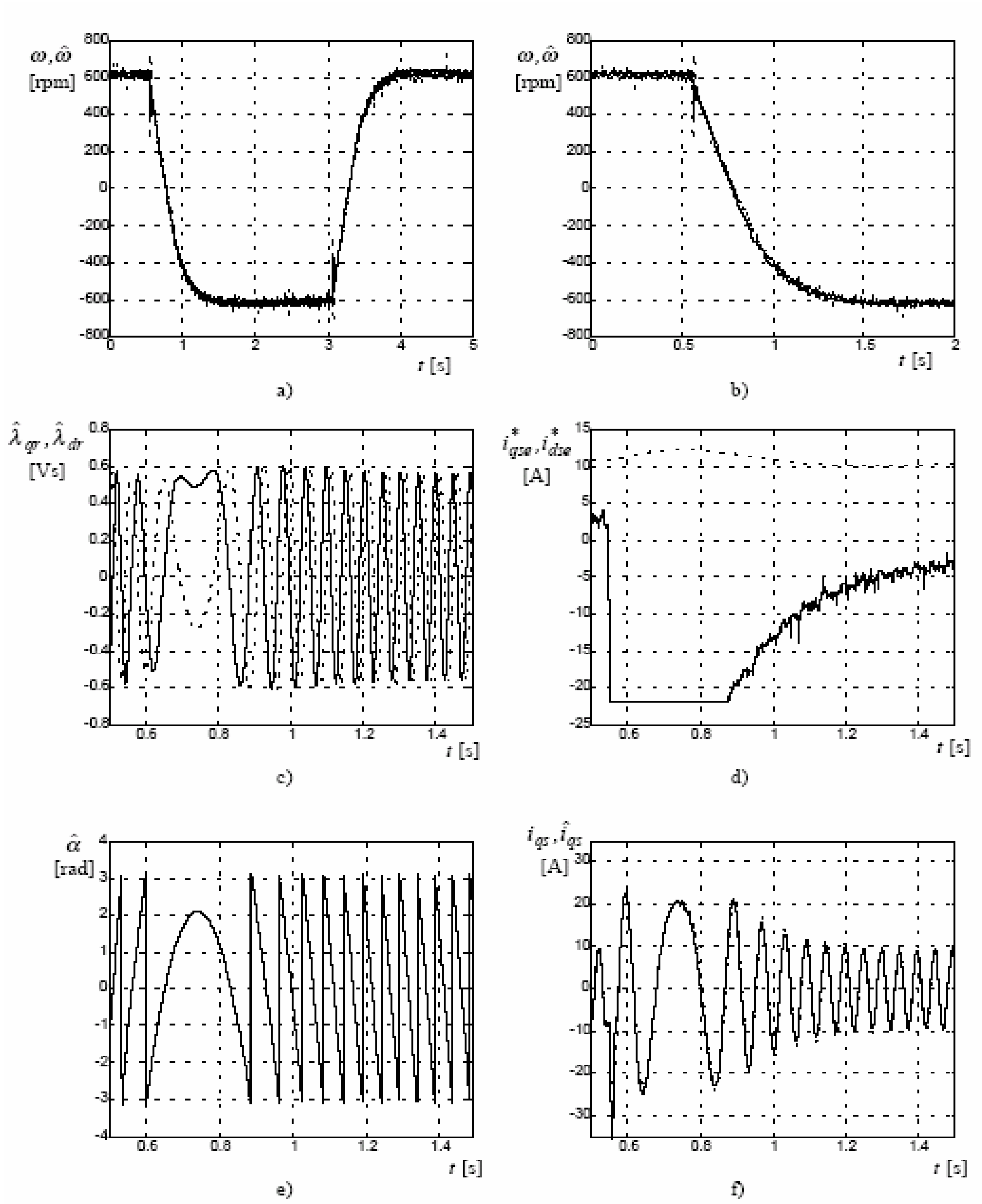

Fig. 6. Simulation results for an EKF sensorless drive.
a) measured (dotted) and estimated speed; b) same, zoom on time;
c) estimated rotor flux on stationary 'd' (dotted) and 'q' axis; d) reference stator currents on synchronous frame: flux current dotted; e) rotor flux angle;

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