Induction Motor Drive's Parameters Identification Using Extended Kalman Filter Algorithms

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Abstract: - This paper presents a detailed study of the extended Kalman filter (EKF) for estimating the rotor resistance and rotor speed of an induction motor drive. The overall structure of the EKF is reviewed and the various system vectors and matrices are defined. By including the rotor resistance and rotor speed as a state variables, the EKF equations are established from a discrete two-axis model of the three-phase induction motor. The investigations show that the EKF is capable of estimating the rotor resistance and capable of tracking the actual rotor speed provided that the elements of the covariance matrices are properly selected. Moreover, the performance of the EKF is satisfactory even in the presence of noise or when there are variations in the induction machine parameters.

Key-Words: - extended Kalman filter**,** parameters estimation, induction motor

1 Introduction

In IFOC, imperfect knowledge of the rotor resistance degrades the steady-state and transient responses of the drive because the decoupling between torque and rotor flux is lost [1]. Then, on-line estimation of the rotor resistance is needed. Many methods for such estimation have been proposed. Many of them have limitations for practical use, mainly at low load level because of the low rotor currents. Generally, the lower load limit for good rotor-resistance estimation is around 30% of nominal load [2],[3]. Some efficient techniques for low load level use algorithms which require knowledge of the stator resistance, but they are sensitive to temperature drift [4], [5]. Other strategies simultaneously estimate rotor flux and parameters using observers. A first set of flux estimators is based on the deterministic observer's theory. The observer structure and its gains allow a reduction in the sensitivity to rotor-resistance variations [6], [7], [8]. However, the error dynamic contains a driving term which is associated with the uncertainty on the stator resistance, and causes steady-state error. A second set of observers is based on the extended Kalman filter (EKF) theory [9], [10] and adaptive approach [11], [12], but they are also sensitive to the stator resistance uncertainties. Another problem is the use of a mechanical sensor. It reduces the robustness of the drive and, together with the cost of the hardware, cause additional expense. This has led to a speed sensorless vector control [13]. The observer theory has been also applied to the design of the extended Luenberger observer for speed estimation. However, these schemes are very sensitive to stator-resistance variations, and the choice of the observer gains becomes a difficult problem [14], [15]. The EKF algorithm has already been used for the rotor speed estimation. This algorithm is very complex and has high computational requirements due to the use of a high-order model of the motor. Also, the adaptive approach was developed for the sensorless vector-controlled induction motor [16].

In this paper, an effective approach is proposed for parameter estimation, rotor resistance, and speed sensorless control using the EKF technique. For this, an EKF is expressed in a frame rotating synchronously with the stator current vector with the use of a reduced dynamic motor model to economize the computational requirements of the EKF. This algorithm is optimized to reduce the computational complexity. The investigations show that the EKF is capable of tracking the actual rotor resistance and speed provided that the elements of the covariance matrices are properly selected. Moreover, the performance of the EKF is satisfactory even in the presence of noise or when there are variations in the induction machine parameters. Computer simulations tests of the transient and steady-state performances are presented to highlight the effectiveness of the proposed methods.

List of Symbols

R_s , R_r	stator and rotor resistances [Ω]
i_{ds} , i_{qs}	direct and quadrature stator currents [A]
i_{dr} , i_{qr}	direct and quadrature rotor currents [A]
v_{ds} , v_{qs}	direct and quadrature stator voltages [V]
v_{dr} , v_{qr}	direct and quadrature rotor voltages [V]
L_s , L_r, L_m	stator, rotor and mutual inductance [H]
λ_{ds}, λ_{qs}	direct and quadrature stator fluxes [Wb]
λ_{dr}, λ_{qr}	direct and quadrature rotor fluxes [Wb]
T_{em}	electromagnetic torque [N.m]
ω_r, ω_e, ω_{sl}	rotor, synchronous and slip frequency [rad/s]
τ_r	rotor time constant (=L_r/R_r) [s]
J	inertia moment [Kg.m^2]
σ	leakage coefficient
t_s	sampling period [s]
n_p	number of pole pairs
A_n, B_n, C_n	input and output matrices of discrete system
G	weighting matrix of noise
F	matrix of state prediction
H	matrix of output prediction
K	Kalman filter gain
P	error covariance matrix
Q	covariance matrix of system noise
R	covariance matrix of measurement noise
u_k	control function, vector
v_k	noise matrix of output model
w_k	noise matrix of state model
x_k	system state
y_k	system output
CRPWM	current-regulated pulse width modulation

2 Design of Extended Kalman Filter

The Kalman filter is an optimal recursive data processing algorithm for linear systems. It is optimal in that it incorporates all the information that is provided to it, regardless of their precision, to estimate the current value of the state. The latter is obtained by combining a prediction of the state, computed from history based on a given model, and the current weighted measurement data in such a way that the error is minimized statistically (minimizing the covariance of the state) [17]. The EKF is recursive in the sense that although it incorporates the history into the present, it does not require all previous data to be kept in storage and reprocessed at every iteration [18].

The dynamics of the discrete-time system to which the EKF will be applied is modeled in the form:

$$x_{k+1} = f\,(x_k, u_k) + G_k w_k\,, \tag{1}$$

$$y_k = h(x_k, u_k) + v_k\,, \tag{2}$$

where $x_k \in R^n$ is the system state vector at time step k, $y_k \in R^m$ is the measurement vector, $f(.) \in R^{n\times n}$ is the state transition matrix, $G_k \in R^{n\times r}$ and $h(.) \in R^{m\times n}$ are discrete-time matrix functions, and $w_k \in R^r$ and $v_k \in R^m$ are Gaussian white-noise sequences satisfying.

$$\mathrm{E}\{w_k\} = 0, \qquad \mathrm{E}\{w_k w_l^T\} = Q_k \delta_{kl}\,, \tag{3}$$

$$\mathrm{E}\{v_k\} = 0, \qquad \mathrm{E}\{v_k v_l^T\} = R_k \delta_{kl}\,, \tag{4}$$

where $Q_k \in R^{r\times r}$ and $R_k \in R^{m\times m}$ are symmetric positive definite covariance matrices, and δ_{kl} is the discrete Dirac function satisfying:

$$\delta_{kl} = \begin{cases} 1, & k = l, \\ 0, & k \neq l. \end{cases}, \tag{5}$$

After initialization, the EKF proceeds recursively in two steps: a prediction step using the process model of the system dynamics; and a measurement update step that adjusts the predicted states based on the measured outputs and relative magnitudes of the disturbance and measurement noise covariance's [19].

In the pose estimation system, the prediction step, at time step k, uses the previous estimate to predict the system states using the process model:

$$\hat{x}_{k|k-1} = F(\hat{x}_{k-1|k-1}, u_k, 0), \tag{6}$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^{\mathrm{T}} + Q_k\,, \tag{7}$$

where k/k denotes a prediction at time k based on data up to time k. Similarly, $(k+1)/k$ denotes a prediction at time $k+1$ based on data up to time k. Q_k is the disturbance noise covariance at the k^{th} time step; F_k is the linearization, through Taylor series expansion, of the process model:

$$F_k = \frac{\partial f}{\partial x}\Big|_{\hat{x}_{k-1|k-1}}\,, \tag{8}$$

and F_k^{T} is the matrix transpose of F_k.

Similarly, the measurement model is linearized about the current state estimate, resulting in the measurement Jacobian, H_k,

$$H_k = \frac{\partial h}{\partial x}\Big|_{\hat{x}_{k|k-1}}\,, \tag{9}$$

The Kalman gain, K is calculated using this linearized model, the previous estimate covariance, and the measurement noise covariance, R_k,

$$K_k = P_{k|k-1} H_k^{\mathrm{T}} \left[H_k P_{k|k-1} H_k^{\mathrm{T}} + R_k \right]^{-1}, \quad (10)$$

Finally, the estimates and estimate covariance are updated using this gain and the innovation of the measurements, the difference between the measured and predicted outputs,

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left[y_k - h(\hat{x}_{k|k-1}) \right], \quad (11)$$

$$P_{k|k} = \left[I - K_k H_k \right] P_{k|k-1}, \quad (12)$$

The block diagram of the EKF estimator is shown in Fig.1.

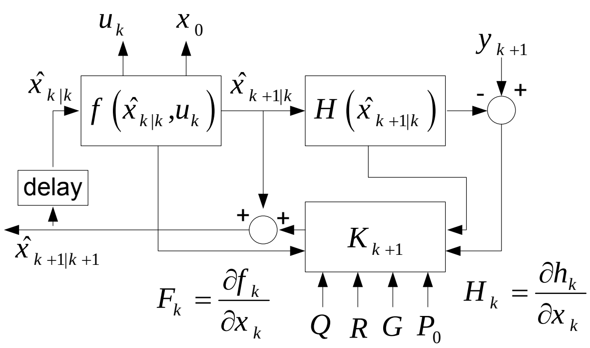

Fig.1 EKF bloc diagram

The state and output equations of the reduced order model of the induction motor established in stationary stator reference frame d-q can be written as:

$$f(x_k, u_k) = A_k x_k + B_k u_k, \quad (13)$$

$$h(x_k) = C_k x_k, \quad (14)$$

$$\begin{cases} x_{k+1} = \begin{bmatrix} \lambda_{dr} \\ \lambda_{qr} \\ \omega_r \\ R_r \end{bmatrix}_{k+1} = A_k \begin{bmatrix} \lambda_{dr} \\ \lambda_{qr} \\ \omega_r \\ R_r \end{bmatrix}_k + B_k \begin{bmatrix} i_{ds} \\ i_{qs} \\ T_{em} \end{bmatrix}_k, \\ y_k = \begin{bmatrix} v_{ds} - R_s i_{ds} - \sigma L_s \varepsilon i_{ds} \\ v_{qs} - R_s i_{qs} - \sigma L_s \varepsilon i_{qs} \end{bmatrix}_k = C_k \begin{bmatrix} \lambda_{dr} \\ \lambda_{qr} \\ \omega_r \\ R_r \end{bmatrix}_k, \end{cases} \quad (15)$$

where

$$A_k = \begin{bmatrix} 1 - \frac{R_r}{L_r} t_s & -\omega_r t_s & 0 & 0 \\ \omega_r t_s & 1 - \frac{R_r}{L_r} t_s & 0 & 0 \\ 0 & 0 & 1 - \frac{\upsilon_s}{J} t_s & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}_k, \quad (16)$$

$$B_k = \begin{bmatrix} \frac{L_m R_r}{L_r} t_s & 0 & 0 \\ 0 & \frac{L_m R_r}{L_r} t_s & 0 \\ 0 & 0 & \frac{1}{J} t_s \\ 0 & 0 & 0 \end{bmatrix}_k, \quad (17)$$

$$C_k = \begin{bmatrix} -\frac{R_r L_m}{L_r^2} & -\frac{\omega_r L_m}{L_r} & 0 & \frac{L_m^2}{L_r^2} i_{ds} \\ \frac{\omega_r L_m}{L_r} & -\frac{R_r L_m}{L_r^2} & 0 & \frac{L_m^2}{L_r^2} i_{qs} \end{bmatrix}_k, \quad (18)$$

$$\varepsilon i_{ds_k} = \frac{i_{ds_k} - i_{ds_{k-1}}}{t_s}, \quad (19)$$

$$\varepsilon i_{qs_k} = \frac{i_{qs_k} - i_{qs_{k-1}}}{t_s}, \quad (20)$$

where A_K, B_k, C_k are input and output matrices of discrete system, υ_s is viscous friction load, $\sigma = 1 - \frac{L_m^2}{L_s L_r}$ is leakage coefficient, and t_s is sampling period.

The matrices f, h, $\partial f/\partial x$, $\partial h/\partial x$ are obtained as follows:

$$f_k = \begin{bmatrix} \left(1 - \frac{R_r}{L_r} t_s\right) \lambda_{dr} - \omega_r t_s \lambda_{qr} + \frac{L_m R_r}{L_r} t_s i_{ds} \\ \omega_r t_s \lambda_{dr} + \left(1 - \frac{R_r}{L_r} t_s\right) \lambda_{qr} + \frac{L_m R_r}{L_r} t_s i_{qs} \\ \left(1 - \frac{\upsilon_s}{J} t_s\right) \omega_r + \frac{T_{em}}{J} t_s \\ R_r \end{bmatrix}_k, \quad (21)$$

$$h_k = \begin{bmatrix} -\dfrac{R_r L_m}{L_r^2}\lambda_{dr} - \dfrac{L_m \omega_r}{L_r}\lambda_{qr} + \dfrac{L_m^2 R_r}{L_r^2} i_{ds} \\ \dfrac{L_m \omega_r}{L_r}\lambda_{dr} - \dfrac{R_r L_m}{L_r^2}\lambda_{qr} + \dfrac{L_m^2 R_r}{L_r^2} i_{qs} \end{bmatrix}_k , \quad (22)$$

$$F_k = \begin{bmatrix} 1-\dfrac{R_r}{L_r}t_s & -\omega_r t_s & -\lambda_{qr} t_s & \dfrac{\left(L_m i_{ds} - \lambda_{dr}\right)t_s}{L_r} \\ \omega_r t_s & 1-\dfrac{R_r}{L_r}t_s & \lambda_{dr} t_s & \dfrac{\left(L_m i_{qs} - \lambda_{qr}\right)t_s}{L_r} \\ 0 & 0 & 1-\dfrac{\upsilon_s}{J}t_s & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}_k , \quad (23)$$

$$H_k = \begin{bmatrix} -\dfrac{R_r L_m}{L_r^2} & -\dfrac{L_m \omega_r}{L_r} & -\dfrac{L_m \lambda_{qr}}{L_r} & \dfrac{\left(L_m i_{ds} - \lambda_{dr}\right)L_m}{L_r^2} \\ \dfrac{L_m \omega_r}{L_r} & -\dfrac{R_r L_m}{L_r^2} & \dfrac{L_m \lambda_{dr}}{L_r} & \dfrac{\left(L_m i_{qs} - \lambda_{qr}\right)L_m}{L_r^2} \end{bmatrix}_k , \quad (24)$$

The combination of rotor speed and rotor resistance used the EKF algorithm illustrated by the flowchart of Fig.2.

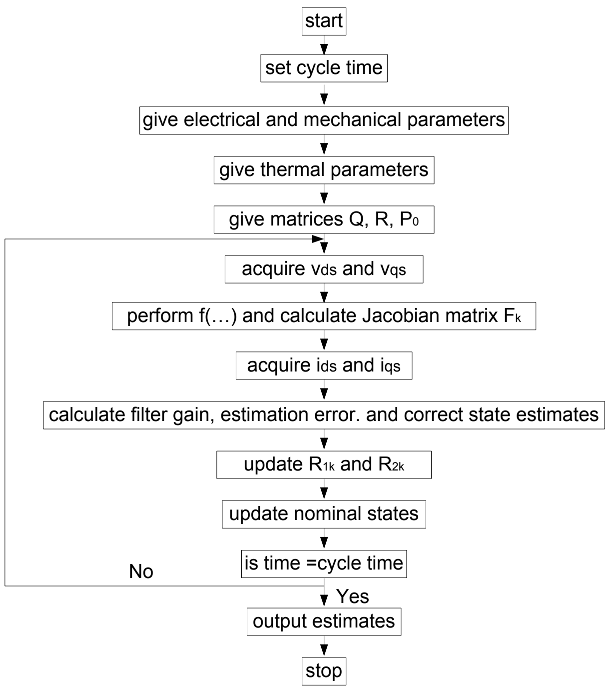

Fig.2 Flowchart of EKF algorithm used for combination of rotor speed and rotor resistance estimation in induction motor

A critical point during the design of the EKF is the choice of the elements of the covariance matrices P_0, Q and R, which affect the performance and the convergence as well. Diagonal initial state covariance matrix P_0 represents variances or mean squared errors in the knowledge of the initial conditions. Varying P_0 yields different amplitude of the transient, while both transient duration and steady state conditions will be unaffected [20]. The matrix Q gives the statistical description of the drive model. The increasing Q would indicate the presence of either heavy system noise or increased parameter uncertainty. An increment of the elements of Q will likewise increase the EKF gain, resulting in a faster filter dynamic. On the other hand, matrix R is related to measurement noise. The increasing the values of the elements of R will mean that the measurements are affected by noise and thus they are of little confidence.

Accordingly the filter gain K will decrease, yielding poorer transient response.

It is a common practice to assume the covariance matrices Q, R and P_0 to be diagonal, for the lack of sufficient statistical information to evaluate their off-diagonal terms [21], [22]. On the other hand, practice has revealed that even starting with non-zero off-diagonal values; at steady state off-diagonal terms remains several times smaller than the corresponding diagonal terms.

It can be realized that both Q and R depend on the drive parameters, the sampling time, the measurements amplitude and some other secondary factors.

The advantage of the proposed method is that the appropriate design and tuning of Q and R made for an IM drive works well for any other drive with similar sampling time. It's also been experienced that the EKF behavior is not influenced by different SVM technique.

The simulations tests on a motor drive can derive appropriate ranges of normalized elements of the covariance matrices.

In the simulation, the error covariance matrix P, the noise covariance matrices R, Q, and noise weight matrix G of the EKF are assumed as:

$$P_0 = \begin{bmatrix} 2.3 & 0 & 0 & 0 \\ 0 & 2.3 & 0 & 0 \\ 0 & 0 & 2.3 & 0 \\ 0 & 0 & 0 & 2.3 \end{bmatrix}, \quad (25)$$

$$R = \begin{bmatrix} 10^{-3} & 0 \\ 0 & 10^{3} \end{bmatrix}, \quad (26)$$

$$G = \begin{bmatrix} \lambda & 0 & 0 & 0 \\ 0 & \lambda & 0 & 0 \\ 0 & 0 & \lambda & 0 \\ 0 & 0 & 0 & \sigma \end{bmatrix}, \qquad (27)$$

$$Q = \begin{bmatrix} \alpha & 0 & 0 & 0 \\ 0 & \alpha & 0 & 0 \\ 0 & 0 & \alpha & 0 \\ 0 & 0 & 0 & \beta \end{bmatrix}, \qquad (28)$$

The values of λ, ρ, α and β in matrices G and Q are usually determined using a trial-and-error process. For comparison purposes, the performance of the EKF with different compositions of G and Q is evaluated by the mean-squared error between the estimated rotor resistance - rotor speed and the actual rotor resistance - rotor speed. Simulation is carried out in order to verify the performance of the rotor resistance and speed estimation algorithm in addition to verifying the response of drive system. The block diagram of indirect vector controlled induction motor drive system incorporating the estimation algorithm using EKF is shown in Fig.3.

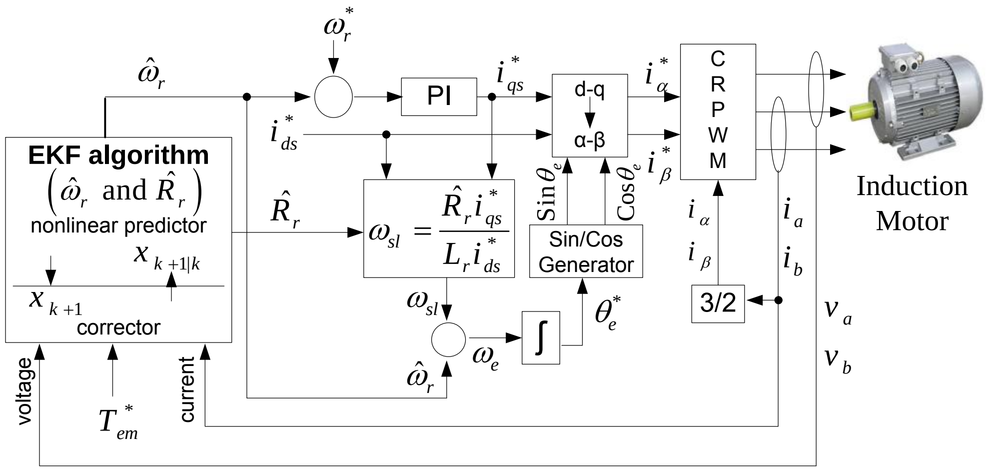

Fig.3 Indirect field oriented induction motor drive with EKF rotor resistance and speed estimator

Table 1 shows typical EKF performance obtained by a trial-and-error method. It is found that poor rotor resistance - rotor speed estimation performance results when the parameters λ, ρ, α and β are equal (Cases 1–3). By selecting larger values of β and ρ relative to α and λ, the EKF performance is improved (Case 4). Very good rotor resistance - rotor speed estimation performance is obtained with the matrix Q=Diag[$1.2.10^{-5}$, $1.2.10^{-5}$, $1.2.10^{-5}$, $1.2.10^{-3}$] and G=Diag[$1.2.10^{-5}$, $1.2.10^{-5}$, $1.2.10^{-5}$, $1.2.10^{-3}$] (Case 5). Fig.4 and Fig.5 shows the estimated rotor resistance and rotor speed of the EKF for Cases 1, 2, 3, and 5 respectively. The results are consistent with the observation made with reference to Table 1.

Table 1. Effects of the covariance matrices G and Q on the mean squared error of estimated rotor resistance - rotor speed

		Rotor resistance estimation	Rotor speed estimation	
case	Covariance matrices G and Q	$\varepsilon = \frac{1}{n}\sum_{i=1}^{n}\left(act_i - est_i\right)^2$	$\varepsilon = \frac{1}{n}\sum_{i=1}^{n}\left(act_i - est_i\right)^2$	Estimation results
1	$\lambda=\rho=\alpha=\beta=1.2.10^{-3}$	126.1558	167.0661	poor
2	$\lambda=\rho=\alpha=\beta=1.2.10^{-4}$	273.9267	290.4005	poor
3	$\lambda=\rho=\alpha=\beta=1.2.10^{-5}$	391.4082	413.3117	poor
4	$\lambda=\alpha=\beta=1.2.10^{-4}$ and $\rho=1.2.10^{-3}$	1.3648	1.7448	good
5	$\lambda=\alpha=1.2.10^{-5}$ and $\rho=\beta=1.2.10^{-3}$	0.9701	0.4057	very good

act: actual rotor resistance –speed;
est: estimated rotor resistance –speed;
n: number of data samples (=30000);
ε: mean squared error of estimated rotor resistance –speed.

Manual tuning of the EKF using the trial-and-error method is simple to carry out, but the process is very time consuming and satisfactory performance can only be obtained with great effort from an experienced operator. As the distribution of noise is usually unknown, it is not possible to deduce a generic relationship between the values of the matrix elements and the EKF performance for fine tuning of the matrices to yield the best speed estimation results.

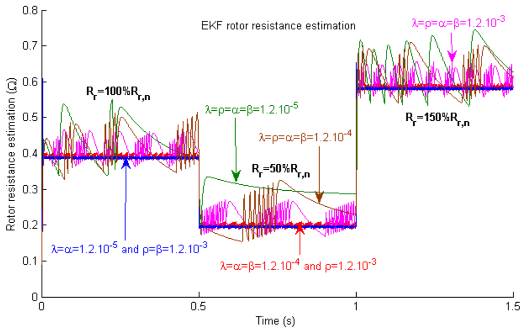

Fig.4 Estimated rotor resistance with various covariance matrices

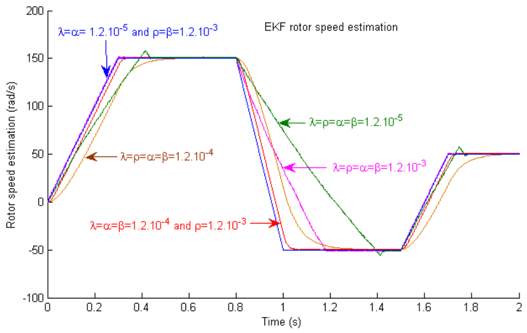

Fig.5 Estimated rotor speed with various covariance matrices

Acceleration and reversal of the drive are carried out in order to observe the performance of estimator during the operation. The machine is accelerated at 0.04 s to a command speed of 100 rad/s; and then, it is reversed at 1.5 s (see Fig.7). The rotor resistance is changed abruptly during steady-state operation of the drive. Its value is increased from the nominal value of 0.3858 Ω to 150%$R_{r,n}$ at 0.5 s; and then, decreased to 50%$R_{r,n}$ at 1 s. The resistance is increased again to 125%$R_{r,n}$ at 2 s; and then, decreased to its nominal value at 2.5 s (see Fig.6).

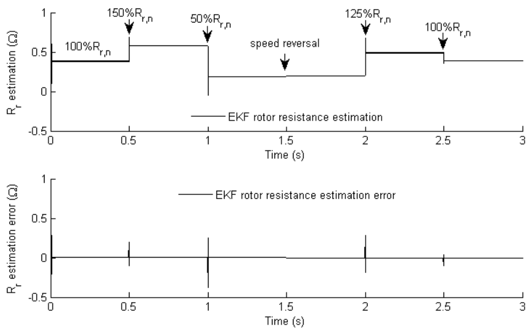

Fig.6 EKF rotor resistance estimation

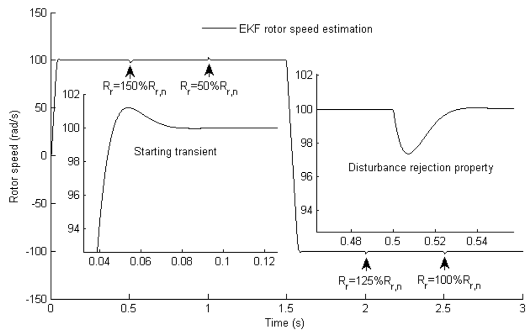

Fig.7 EKF rotor speed estimation

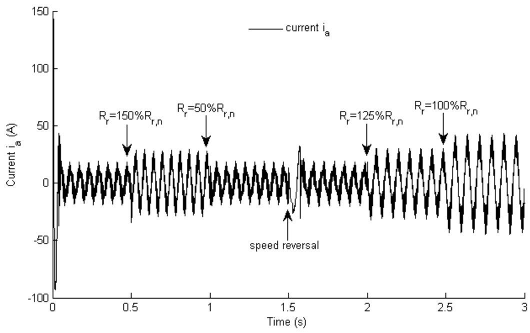

Fig.8 Current i_a

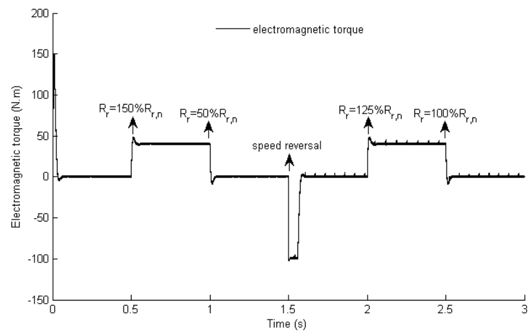

Fig.9 Electromagnetic torque

Table 2 EKF rotor speed results summary

Rotor speed	rise time/s	overshoot/%	settling time/%	steady-state error/%
EKF	0.03	2.9	0.08	0.7

Figure 6 show that a good operation of the estimator does not depend on, in addition, the initial value of R_r that is chosen in the algorithm. This is very important since in reality we do not know the exact value of the resistance when the estimation algorithm starts. The convergence of this method is thus confirmed. In reality, the actual rotor resistance varies much more slowly, this means that the estimated rotor resistance can track even better the actual rotor resistance.

We can confirm that the estimated rotor resistance allows us to obtain an optimal vector control where there is a perfect decoupling between torque and flux. The report torque/current (T_{em}/i_{sq}) is then maintained its maximum value corresponding to a given load.

The speed estimation response using EKF controller shows that the drive can follow the low command speed very quickly and smoothly without overshoot, no steady-state error and rapid rejection of disturbances, with a low dropout speed (Fig.7 and Table 2). The current responses are sinusoidal and balanced, and its distortion is small (Fig.8). The torque ripple is reduced and its dynamic is enhanced by the new control method (Fig.9) well as the decoupling between the flux and torque is verified.

The question of sensitivity of the control system to variations in parameters of induction machine has been analyzed. We have focused our attention on the influence of rotor resistance because it varies most a function of temperature among the parameters of induction machine.

3 Conclusions

The estimation results have shown the ability of the EKF to combine speed and rotor resistance estimation in the indirect field-oriented control of an induction machine. The effects of the covariance matrices of the EKF are investigated and a guideline for selecting the covariance matrices is proposed. Moreover, this model has been expressed in a frame rotating synchronously with the stator-current vector in order to deal with constant quantities in steady-state, and avoid lag errors. The performance of this strategy is satisfactory even in the presence of noise, at low speeds, or when there has variations in the parameters of the induction machine. Good estimation accuracy for the rotor resistance and the rotor speed was obtained, and the response of the sensorless indirect vector controlled drive was found to be satisfactory.

References:

[1] K. B. Nordin, D. W. Novotny, D. S. Zinger, Influence of motor parameter deviations in feedforward field orientation drive systems, *IEEE Transactions on Industry Applications*, Vol. IA-21, No. 4, 1985, pp. 1009-1015

[2] R. Marino, S. Peresada, P. Tomei, Exponentially convergent rotor resistance estimation for induction motors, *IEEE Transactions on Industrial Electronics*, Vol. 42, No. 5, 1995, pp. 508-515

[3] G. Kenné, T. Ahmed-Ali, F. Lamnabhi-Lagarrigue, A. Arzandé, V. J. Claude, An improved rotor resistance estimator for induction motors adaptive control, *Electric Power Systems Research*, Vol. 81, No. 4, 2011, pp. 930-941

[4] D. J. Atkinson, J. W. Finch, P. P. Acarnley, Estimation of rotor resistance in induction motors, *IEE Proceedings: Electric Power Applications*, Vol. 143, No. 1, 1996, pp. 87-94

[5] H. –J. Shieh, K. –K. Shyu, F. –J. Lin, Adaptive estimation of rotor time constant for indirect field-oriented induction motor drive, *IEE Proceedings: Electric Power Applications*, Vol. 145, No. 2, 1998, pp. 111-118

[6] H. Chehimi, S. S. Hadj, F. A. Msahli, predictive controller for induction motors using an unknown input observer for online rotor resistance estimation and an update technique for load torque, *Journal of Control Theory and Applications*, Vol. 11, No. 3, 2013, pp. 367-375

[7] P. M. de la Barrera, G. R. Bossio, J. A. Solsona, G. O. García, On-line iron loss resistance identification by a state observer for rotor-flux-oriented control of induction motor, *Energy Conversion and Management*, Vol. 49, No. 10, 2008, pp. 2742-2747

[8] F. Lin, C. Zhang, W. Song, S. Chen, A robust rotor flux observer of induction motor with unknown rotor and stator resistance, *IECON Proceedings (Industrial Electronics Conference)1*, 2003, pp. 738-741

[9] Glielmo L, Marino P, Setola R, Vasca F. Reduced order extended Kalman filter for estimation of induction motor rotor resistance. Proceedings of the IEEE Conference on Decision and Control 2, 1993: 1222-1223

[10] B. Jayanand, V. Subrahmanyam, Parameter insensitive vector control of a current-fed induction motor using extended Kalman filter, *International Journal of Power and Energy Systems*, Vol. 18, No. 2, 1998, pp. 124-129

[11] R. Marino, S. Peresada, P. Tomei, Adaptive observer-based control of induction motors with unknown rotor resistance, *International Journal of Adaptive Control and Signal Processing*, Vol. 10, No. 4-5, 1996, pp. 345-363

[12] A. Dell'Aquila, F. Cupertino, L. Salvatore, S. Stasi, Kalman filter estimators applied to robust control of induction motor drives, *IECON Proceedings (Industrial Electronics Conference) 4*, 1998, pp. 2257-2262

[13] W. Leonhard, *Control of Electrical Drives*, Springer-Verlag Berlin Heidelberg New York, 3rd edition, 2001

[14] T. Du, M. A. Brdys, Implementation of extended Luenberger observers for joint state and parameter estimation of PWM induction motor drive, *IEE Conference Publication*, Vol. 4, No. 377, 1993, pp. 439-444

[15] T. Du, P. Vas, F. Stronach, Design and application of extended observers for joint state and parameter estimation in high-performance AC drives, *IEE Proceedings: Electric Power Applications*, Vol. 142, No. 2, 1995, pp. 71-78

[16] F. Alonge, F. D'Ippolito, A. Sferlazza, Sensorless control of induction-motor drive based on robust kalman filter and adaptive speed estimation, *IEEE Transactions on Industrial Electronics*, Vol. 61, No. 3, 2014, art. no. 6494615, pp. 1444-1453

[17] P. G. Bruce, *Advanced Kalman Filtering, Least-Squares and Modeling: A Practical Handbook*, Wiley-Blackwell, 2011

[18] C. K. Chui, G. Chen, *Kalman Filtering: with Real-Time Applications*, Springer Series in Information Sciences, 4th edition, 2009

[19] M. Hoshiya, E. Saito, Structural identification by extended kalman filter, *Journal of Engineering Mechanics*, Vol. 110, No. 12, 1984, pp. 1757-1772

[20] T.L. Song, J. L. Speyer, The modified gain extended Kalman filter and parameter identification in linear systems, *Automatica*, Vol. 22, No. 1, 1986, pp. 59-75

[21] E. G. Klimova, Simplified models of computation of the covariance matrices in the Kalman filter algorithm, *Russian Meteorology and Hydrology*, No. 6, 2000, pp. 12-18

[22] Z. –L. Deng, Y. Gao, Information fusion in Kalman filter weighted by diagonal matrices, *Kongzhi Lilun Yu Yingyong/Control Theory and Applications*, Vol. 22, No. 6, 2005, pp. 870-874