SPEED SENSORLESS INDIRECT FIELD ORIENTED CONTROL OF INDUCTION MOTOR USING AN EXTENDED KALMAN FILTER

A. BENNASSAR, A. ABBOU, M. AKHERRAZ
Mohammedia School of Engineers, Street Ibn Sina B.P 767 Agdal Rabat, Morocco.
Department of Electrical Engineering, Laboratory of Electrotechnic and Power Electronics
ab.bennassar@gmail.com, abbou@emi.ac.ma, akherraz@emi.ac.ma

Abstract: *This paper presents the performance of the extended Kalman filter (EKF) for speed sensorless indirect field oriented control (IFOC) of a squirrel cage induction motor (IM) supplied by a pulse width modulated (PWM) voltage-source inverter. The rotor speed of the induction motor is estimated, according to this method, using the direct measurements of the stator voltages and currents without the speed sensor. The regulator of speed used is an IP type. Simulation results are illustrated and demonstrate the good performance and robustness of the extended Kalman filter observer to estimate the high and low speeds.*

Key-words: *EKF, IFOC, IM, PWM voltage-source inverter, Observer, Speed Sensorless.*

1. Introduction

Because of the highly non-linear dynamic structure of the induction motor drives, a vector control method has been widely used for high performance applications and has become the standard in various industries. Furthermore, the strategy of the indirect field oriented control is the most technique used in induction motor control. This technique was introduced by Blaschke and Leonard and employs a direct estimation, by using sensors, of slip frequency obtained from the induction parameters, and adding to the shaft speed to determine the angular frequency.

Since three decades, great efforts have been made to increase the mechanical robustness and reliability of the induction motor, and to reduce costs and hardware complexity. Thus it is necessary to eliminate the speed sensor. Most methods are basically on the extended Kalman filter for the design of sensorless control schemes of the IM. This stochastic observer estimates simultaneously the states and the parameters of a dynamic process of the induction motor drive by measuring the stator voltages and currents. In this paper, we present the design of a high performance sensorless IM indirect field oriented control. The non-linear observer (EKF) is developed to estimate the rotor speed. Simulation results are illustrated to highlight the robustness and the performance of the proposed control scheme in high and low speeds and against load torque variations.

2. Dynamic model of induction motor

A dynamic model of the induction motor in stationary reference frame fixed to the stator can be expressed, by choosing stator currents and rotor fluxes as state variables and stator voltages as input variables, in the form of the state equation as shown below:

$$\dot{x} = A.x + B.u \quad (1)$$

$$y = C.x \quad (2)$$

Where:

$$x = \left[i_{s\alpha} \;\; i_{s\beta} \;\; \varphi_{r\alpha} \;\; \varphi_{r\beta} \right]^T \; ; \quad u = \left[u_{s\alpha} \;\; u_{s\beta} \right]^T ; \quad y = \left[i_{s\alpha} \;\; i_{s\beta} \right]^T$$

$$A = \begin{bmatrix} -\left(\frac{1}{\sigma T_s} + \frac{1-\sigma}{\sigma T_r}\right) & 0 & \frac{1-\sigma}{\sigma L_m T_r} & \frac{1-\sigma}{\sigma L_m}\omega \\ 0 & -\left(\frac{1}{\sigma T_s} + \frac{1-\sigma}{\sigma T_r}\right) & -\frac{1-\sigma}{\sigma L_m}\omega & \frac{1-\sigma}{\sigma L_m T_r} \\ \frac{L_m}{T_r} & 0 & -\frac{1}{T_r} & -\omega \\ 0 & \frac{L_m}{T_r} & \omega & -\frac{1}{T_r} \end{bmatrix}$$

$$B = \begin{bmatrix} \frac{1}{\sigma L_s} & 0 \\ 0 & \frac{1}{\sigma L_s} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \quad ; \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

With:

$$\sigma = 1 - \frac{L_m^2}{L_s L_r} \quad ; \quad T_s = \frac{L_s}{R_s} \quad ; \quad T_r = \frac{L_r}{R_r}$$

3. Principle of the indirect field oriented control

The main objective of the vector control of IM is to independently control the torque and the flux. The d-axis is aligned with the rotor flux space vector *[10]*. In this case, the electromagnetic torque can be expressed as:

$$Te = p\frac{L_m}{L_r}\varphi_r i_{sq} \tag{3}$$

The rotor flux and the torque are controlled by i_{sd}^* and i_{sq}^* respectively. The reference value of the rotor flux φ_r^* when it is divided by the magnetizing inductance, the direct-axis stator current reference i_{sd}* is obtained:

$$i_{sd}^* = \frac{\varphi_r^*}{L_m} \tag{4}$$

The quadrature-axis stator current i_{sq}^* is proportional to the reference torque T_e^*:

$$i_{sq}^* = \frac{1}{p}\frac{L_r}{L_m}\frac{T_e}{\varphi_r^*} \tag{5}$$

The angular slip frequency of the rotor flux ω_{sl} is calculated from the reference values isd^* and isq^*:

$$\omega_{sl} = \frac{1}{T_r}\frac{i_{sq}^*}{i_{sd}^*} \tag{6}$$

The angular speed of the rotor flux ω_s is equal to the sum of the angular rotor speed and the angular slip frequency of the rotor flux:

$$\omega_s = \omega_{sl} + p\Omega \tag{7}$$

Where p is the pole-pair.

Fig. 1 shows a block diagram of the indirect field oriented control system (IFOC) for a sensorless induction motor.

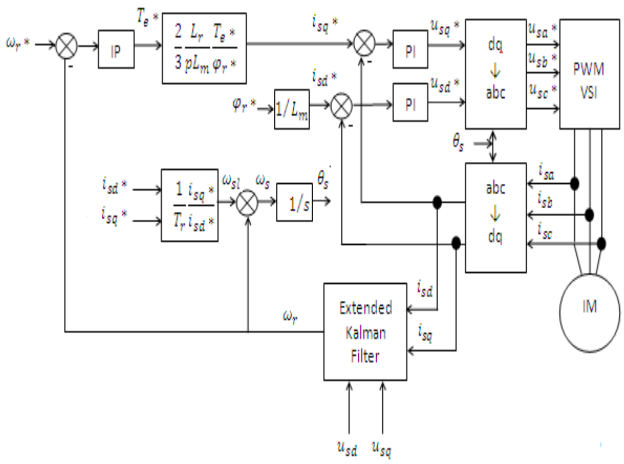

Fig. 1. Block diagram of sensorless indirect field oriented control for induction motor drives.

4. Extended Kalman filter algorithm for rotor speed estimation

An extended Kalman filter is a stochastic observer used for state and parameters estimation of a non-linear dynamic system in real time disturbed by random noise.

The filter estimation is obtained from the predicted values of the states and this is corrected recursively by using a correction term, which is the product of the Kalman gain and the deviation of the estimated measurement output vector and the actual output vector. The Kalman gain is chosen to result in the best possible estimated states *[5]*.

4.1 Selection of the time-domain motor model

The dimension of the state vector is increased by adding an angular speed of rotor, in this case, the angular speed of the rotor is considered as a state variable and the state vector becomes:

$$x = \begin{bmatrix} i_{s\alpha} & i_{s\beta} & \varphi_{r\alpha} & \varphi_{r\beta} & \omega \end{bmatrix}^T \tag{8}$$

The time-domain motor model is given as:

$$\dot{x} = f(x, u) \tag{9}$$

$$y = h(x) \tag{10}$$

Where:

$$f(x,u)=\begin{bmatrix} -\left(\frac{1}{\sigma T_s}+\frac{1-\sigma}{\sigma T_r}\right)i_{s\alpha}+\frac{1-\sigma}{\sigma L_m T_r}\varphi_{r\alpha}+\frac{1-\sigma}{\sigma L_m}\omega\varphi_{r\beta}+\frac{1}{\sigma L_s}u_{s\alpha} \\ -\left(\frac{1}{\sigma T_s}+\frac{1-\sigma}{\sigma T_r}\right)i_{s\beta}-\frac{1-\sigma}{\sigma L_m}\omega\varphi_{r\alpha}+\frac{1-\sigma}{\sigma L_m T_r}\varphi_{r\beta}+\frac{1}{\sigma L_s}u_{s\beta} \\ \frac{L_m}{T_r}i_{s\alpha}-\frac{1}{T_r}\varphi_{r\alpha}-\omega\varphi_{r\beta} \\ \frac{L_m}{T_r}i_{s\alpha}+\omega\varphi_{r\alpha}-\frac{1}{T_r}\varphi_{r\beta} \\ \omega \end{bmatrix}$$

$$h(x)=\left[i_{s\alpha}\;\; i_{s\beta}\right]^T$$

4.2 Discretization of the induction motor

The time-discrete state space model of the induction motor can be obtained from eqns (1, 2) as follow:

$$x_{k+1}=f\left(x_k,u_k\right)=A_k x_k+B_k u_k \quad (11)$$

$$y_k=h\left(x_k\right)=C_k x_k \quad (12)$$

A_k, B_k and C_k are the discretized system matrix, input matrix and output matrix respectively:

$$A_k=I+AT_s \quad ; \quad B_k=BT_s \quad ; \quad C_k=C$$

Where:

$$A_k=\begin{bmatrix} 1-T_s\left(\frac{1}{\sigma T_s}+\frac{1-\sigma}{\sigma T_r}\right) & 0 & T_s\frac{1-\sigma}{\sigma L_m T_r} & T_s\frac{1-\sigma}{\sigma L_m}\omega & 0 \\ 0 & 1-T_s\left(\frac{1}{\sigma T_s}+\frac{1-\sigma}{\sigma T_r}\right) & -T_s\frac{1-\sigma}{\sigma L_m}\omega & T_s\frac{1-\sigma}{\sigma L_m T_r} & 0 \\ T_s\frac{L_m}{T_r} & 0 & 1-T_s\frac{1}{T_r} & -T_s\omega & 0 \\ 0 & T_s\frac{L_m}{T_r} & T_s\omega & 1-T_s\frac{1}{T_r} & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$B_k=\begin{bmatrix} \frac{T_s}{\sigma L_s} & 0 \\ 0 & \frac{T_s}{\sigma L_s} \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

T_s denotes the sampling time and I is an identity matrix.

The state vector is disturbed by system noise vector v, and the measurement vector is disturbed by the measurement noise vector w:

$$x_{k+1}=f\left(x_k,u_k\right)+w_k \quad (13)$$

$$y_k=h\left(x_k\right)+v_k \quad (14)$$

Where the system noise vector and the measurement noise vector are a zero-mean, white Gaussian noise, independent of the initial state vector and their covariance matrices are Q and R respectively. These covariance matrices are defined as:

$$Q=\mathrm{cov}(w)=E\left\{ww^T\right\} \quad ; \quad R=\mathrm{cov}(v)=E\left\{vv^T\right\}$$

4.3 Determination of the noise and state covariance matrices Q, R and P

A critical part of the design of the EKF is to use correct initial values for the various covariance matrices, Q, R, and P. These have important effects on the filter stability and convergence time. To obtain the best estimate value of the speed, it is important to use accurate initial values for the covariance matrices of the system noise, measurement noise and the state noise Q, R and P respectively *[5]*. These matrices are assumed as diagonal covariance matrices.

4.4 Implementation of the discretized EKF algorithm

The extended Kalman filter algorithm is a recursive state estimator and is based on two main stages, a prediction stage and a filtering stage:

Prediction: During this stage, the next predicted values of the states $\hat{x}(k+1)$ and the predicted state covariance matrix P are obtained.

Filtering: During this stage, the filtered states x are obtained from the predicted estimates by adding a correction term $K(y-\hat{y})$ to the predicted value $\hat{x}$.

The state estimates are obtained in the following steps:

- Initialization of the state vector and covariance matrices.
- Prediction of the state vector

$$\hat{x}_{k+1|k}=f\left(x_{k|k},u_k\right) \quad (15)$$

- Prediction covariance computation

$$P_{k+1|k} = F_k P_{k|k} F_k^T + Q \qquad (16)$$

Where $$F_k = \left. \frac{\partial f\left(x_{k|k}, u_k\right)}{x_k} \right|_{x_k = \hat{x}_{k|k}} \qquad (17)$$

$$F_k = \begin{bmatrix} 1 - T_s\left(\frac{1}{\sigma T_s} + \frac{1-\sigma}{\sigma T_r}\right) & 0 & T_s \frac{1-\sigma}{\sigma L_m T_r} & T_s \frac{1-\sigma}{\sigma L_m}\omega & T_s \frac{1-\sigma}{\sigma L_m}\varphi_{r\beta} \\ 0 & 1 - T_s\left(\frac{1}{\sigma T_s} + \frac{1-\sigma}{\sigma T_r}\right) & -T_s \frac{1-\sigma}{\sigma L_m}\omega & T_s \frac{1-\sigma}{\sigma L_m T_r} & -T_s \frac{1-\sigma}{\sigma L_m}\varphi_{r\alpha} \\ T_s \frac{L_m}{T_r} & 0 & 1 - T_s \frac{1}{T_r} & -T_s\omega & -T_s\varphi_{r\beta} \\ 0 & T_s \frac{L_m}{T_r} & T_s\omega & 1 - T_s \frac{1}{T_r} & T_s\varphi_{r\alpha} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

- Kalman gain computation

$$K_{k+1} = P_{k+1|k} H_k^T \left[H_k P_{k+1|k} H_k^T + R \right]^{-1} \qquad (18)$$

Where $$H_k = \left. \frac{\partial h(x_k)}{x_k} \right|_{x_k = \hat{x}_{k|k}} \qquad (19)$$

$$H_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

- State vector estimation

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1}\left(y_{k+1} - H_k \hat{x}_{k+1|k}\right) \qquad (20)$$

- Covariance matrix of estimation error

$$P_{k+1|k+1} = P_{k+1|k} - K_{k+1} H_k P_{k+1|k} \qquad (21)$$

Where ^ denotes the estimation value.

5. Simulation results

The simulations are done for the speed estimation of induction motor by indirect field oriented control method with extended Kalman using the MATLAB/Simulink software. Classical Proportional-Integral controllers are used for speed and stator current loops. The IM parameters used in simulation are given in table 1. The performances of the observer are analyzed according to the simulation of the following transients:

a. Inversion of the speed

To test the robustness of the sensorless control, we applied a changing of the speed reference from 100 rad/s and -100 rad/s. Fig.2 presents the actual, estimated speed, and estimation error. Fig.3 presents the real rotor flux, estimated rotor flux and the estimation error.

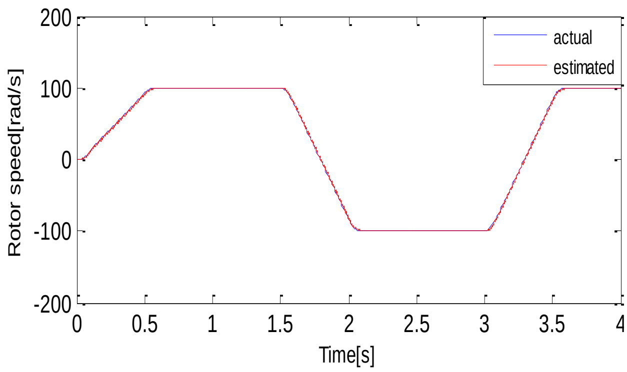

Fig. 2. Actual and estimated speed.

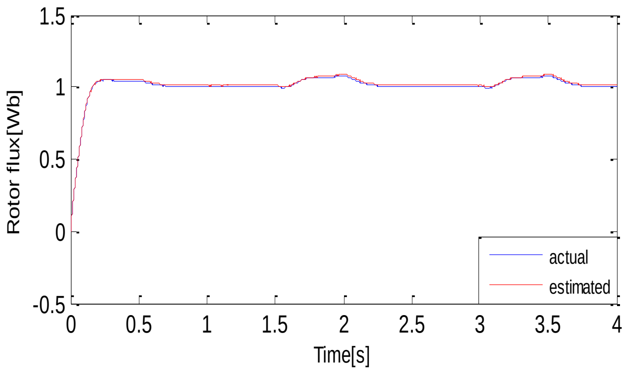

Fig. 3. Actual and estimated flux.

b. Operation at low speed

To test the good working of the EKF, the simulation was established in low speed. Fig.4 illustrates the process of speed estimation with a speed reference between 5 rad/s and -5 rad/s.

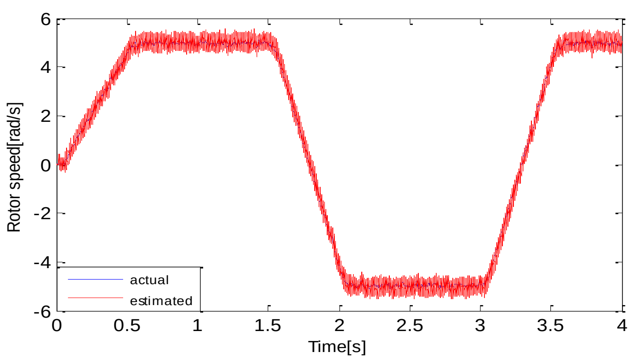

Fig. 4. Actual and estimated speed.

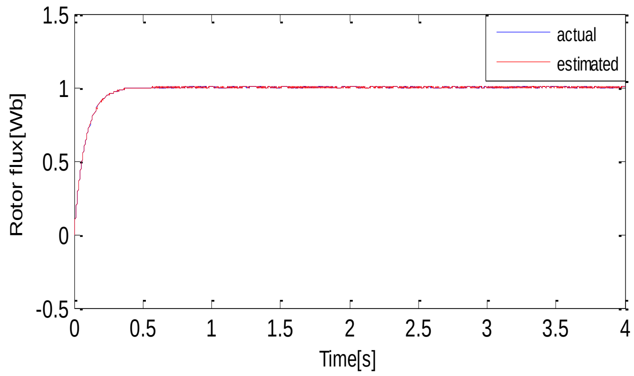

Fig. 5. Actual and estimated speed.

c. Variation of the load torque

To test the performance at high speed a load torque equal to 20 N.m is applied between 1s and 2.5s.

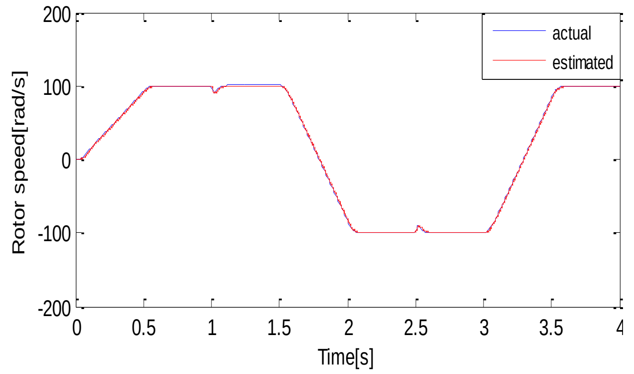

Fig. 6. Actual and estimated speed.

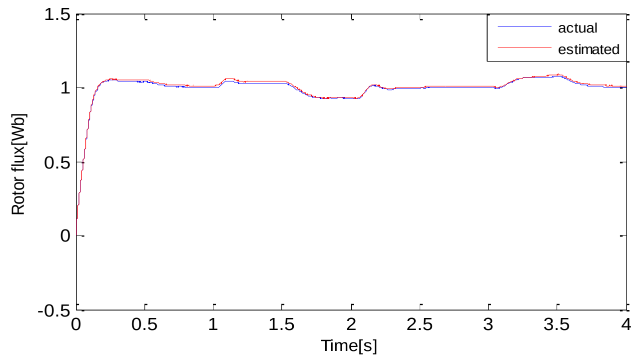

Fig. 7. Actual and estimated flux.

6. Conclusion

In this paper, an extended Kalman filter approach for indirect field oriented control of the induction motor drive has been proposed and tested. In this proposed scheme, the estimate of rotor speed is obtained from the directly measurable stator currents and voltages. Simulation results show good performance and robustness of the sensorless vector control at high and low speeds. In addition, the simulation results show the robustness of the proposed algorithm against measurement noises and load torque variations. Finally, an IP regulator has been used in the speed control of an IFOC.

Appendix

P_r = 3 KW	U_r = 220 V	f = 50 Hz
p = 2	R_s = 2.2 Ω	R_r = 2.68 Ω
L_s = 229 H	L_r = 229 H	L_m = 217 H
J = 0.047 Kg.m²	f_v = 0.004 Kg.m²/s	W_r = 1440 rpm

Table 1. Induction motor parameters

References

[1] J. –P. Caron et J. –P. Hautier, "*Modélisation et commande de la machine asynchrone*", Editions Technip, Paris, 1995.

[2] K. Young-Real, S. Seung-Ki, and P. Min-Ho, "*Speed sensorless vector control of induction motor using extended Kalman filter*", IEEE Transactions on Industry Applications, vol. 30, pp. 1225-1233, 1994.

[3] K. L. Shi, T. F. Chan, Y. K. Wong, and S. L. Ho, "*Speed estimation of an induction motor drive using an optimized extended Kalman filter*", IEEE Transactions on Industrial Electronics, vol. 49, pp. 124-133, 2002.

[4] M. Barut, M. Gokasan, and O. S. Bogosyan, "*An extended Kalman filter based sensorless direct vector control of induction motor*", in IECON vol.1, pp. 318-322, 2003.

[5] Vas Peter. "*Sensorless Vector and Direct Torque Control*", Oxford University Press, inc. 1998.

[6] K. Yahia, S.E. Zouzou, F. Benchabane and D. Taibi, "*Comparative study of an adaptive Luenberger observer and extended Kalman filter for a sensorless direct vector control of induction motor*", vol. 50, pp. 99-107, 2009.

[7] C.B. Jacobina, J. Bione de M. Fl., F. Salvadori, A.M.N. Lima, and L.A.S. Ribeiro. "*A simple indirect field oriented control of induction machines without speed measurement*", In Conf. Rec. IAS'97, pages 1809-1813, Roma - Italy, October 2000. IEEE - Industry Application Society.

[8] Fang-Zheng Peng and Tadashi Fukao. "*Robust speed identification for speed-sensorless vector control of induction motors*", IEEE Trans. Indust. Appl., 30(5):1234–1240, Sep/Oct 1994.

[9] S. Peresada, A. Tilli, and A. Tonielli. "*Indirect field oriented control of induction motor: new design leads to improved performance and efficiency*", Conf. Rec. IEEEIECON, 3:1609–1614, 1998

[10] Sellami Said, Belkacem Sebti and Naceri Farid. "*Performance analysis of field oriented control and direct torque control for sensorless induction motor drives*", Mediterranean conference on control & automation, p. 215-212, 2007.

[11] M. Messaoudi, L. Sbita and M. N. Abdelkrim. "*A robust nonlinear observer for states and parameters estimation and on-line adaptation of rotor time constant in sensorless induction motor drives*", International Journal of Physical Sciences Vol. 2 (8), pp. 217-225, August, 2007.

[12] L. Salvatore, S. Stasi, and L. Tarchioni, "*A new EKF-based algorithm for flux estimation in induction machines*", IEEE Transactions on Industrial Electronics, vol. 40, pp. 496-504, 1993.

[13] J. W. Finch, D. J. Atkinson, and P. P. Acarnley, "*Full-order estimator for induction motor states and parameters*", in IEE Proceedings- Electric Power Applications, 1998, pp. 169-179.

[14] A. Abbou, Y. Sayouti, H. Mahmoudi and M. Akherraz, "*dSPACE Direct Torque Control Implementation for Induction Motor Drive*", Proceedings in the 18th IEEE Mediterranean Conference on control and Automation, Congress Palace, Marrakech, Morocco, June 23-25, pp. 1121-1126, 2010.

[15] A. Abbou, Y. Sayouti, H. Mahmoudi and M. Akherraz , "*Recent Patents on Induction Motor and DTFC based Fuzzy Logic*", Recent Patents on Electrical Engineering (JEEG), Volume 1, N°3, pp. 244-252, 2008.