

Indirect Vector Control of Induction Motor with on Line Rotor Resistance Identification

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Abstract: Vector Control (VC) has been accepted as one of the most effective methods for the control of induction motor drives. The decoupling of flux and the electromagnetic torque obtained by Indirect Field Oriented Control (IFOC) depends on the precision of slip calculation; which depends strongly to rotor resistance value. However, rotor resistance varies with temperature, frequency. In this paper, the authors present a Matlab-Simulink based simulation of a high performance induction motor indirect field oriented control which is robust against rotor resistance variations. These variations are tracked using the Extended Kalman Filter (EKF) algorithm. The on line estimated rotor resistance actual value is fed forward to the slip speed calculation module to obtain robust control performance with the proposed indirect field-oriented control scheme.

Key words: Induction motor, IFOC, EKF, identification, resistance

INTRODUCTION

Direct and indirect vector control methods for the speed and torque control of Induction Motors (IM) have found intensive application through the last two decades. These methods can provide at least the same performance from an inverter-driven induction machine as is obtainable from a separately excited dc machine^[1]. The direct control (DFOC) of IM necessitates accurate information on the rotor speed, as well as rotor flux as referred to the stator stationary frame.

On the other hand, indirect control (IFOC) of IM, in addition to the rotor speed, accurate knowledge of the slip frequency (calculated as a function of the IM parameters) is required. However, the IFOC depends strongly on the motor parameters; particularly the rotor time constant which may vary considerably over the operational range of the motor due to changes in rotor resistance with temperature, frequency^[2]. If the rotor resistance value used in the IFOC mechanism is not correct, the efficiency of motor drive will be decreased due to the reduction of the torque generator capabilities and/or to over-excitation or the under-excitation machine state^[3-5].

Therefore, variation in motor parameters, particularly rotor resistance, should be tracked as they occur. One method of on line tracking using parameters estimation techniques is described in this study.

The particular estimation technique discussed here employs an extended Kalman filter algorithm. The algorithm involves the estimation of the rotor resistance,

rotor flux and the stator currents (referred to the stator stationary frame), which are also measured as output. The decoupling control of torque and flux in the IFOC method is guaranteed by the on line estimated rotor resistance. Good results are obtained through the performed simulations.

Mathematical model of the IM: The dynamic model for induction machine developed in stationary reference frame (α, β) is as following:

$$\begin{aligned} X(k+1) &= \Phi X(k) + BU(k) \\ Y(k) &= CX(k) \end{aligned} \quad (1)$$

Where:

$X(k) = [i_{s\alpha}(k) \ i_{s\beta}(k) \ \psi_{r\alpha}(k) \ \psi_{r\beta}(k)]^T$: the state vector.

$U(k) = [v_{s\alpha}(k) \ v_{s\beta}(k)]^T$: the input vector

$Y = [i_{s\alpha}(k) \ i_{s\beta}(k)]^T$: the output vector

$$\Phi = \begin{bmatrix} 1 - T_s \gamma & 0 & T_s \frac{K_1}{T_r} & T_s p K_1 \Omega \\ 0 & 1 - T_s \gamma & -T_s p K_1 \Omega & T_s \frac{K_1}{T_r} \\ T_s \frac{L_m}{T_r} & 0 & 1 - T_s \frac{1}{T_r} & -T_s p \Omega \\ 0 & T_s \frac{L_m}{T_r} & T_s p \Omega & 1 - T_s \frac{1}{T_r} \end{bmatrix}$$

$$B = \frac{T_s}{\sigma L_s} \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}^T$$

$$\sigma = 1 - \frac{L_m^2}{L_s L_r}, \gamma = \frac{R_s}{\sigma L_s} + \frac{R_r L_m^2}{\sigma L_s L_r^2}, K_1 = \frac{L_m}{\sigma L_s L_r}, T_r = \frac{L_r}{R_r}$$

- $i_{s\alpha}, i_{s\beta}$ = α -axis β -axis stator current
- $\Psi_{r\alpha}, \Psi_{r\beta}$ = α -axis β -axis rotor flux
- $v_{s\alpha}, v_{s\beta}$ = α -axis β -axis stator voltage
- Ω = mechanical rotor speed
- L_s = stator self inductance per phase
- L_m = magnetising inductance per phase
- R_s = stator phase resistance
- R_r = rotor phase resistance
- P = number of pole pairs
- σ = total leakage factor
- T_s = sampling interval

The EKF can be used for combined state and parameters estimation by treating selected parameters as extra states and forming an augmented state vector. Since R_r is the parameter to be estimated, R_r is augmented into $(X)k$ and $(X)k$ becomes:

$$X(k) = [i_{s\alpha}(k) \ i_{s\beta}(k) \ \Psi_{r\alpha}(k) \ \Psi_{r\beta}(k) \ R_r(k)]^T \quad (2)$$

$$= [x_1(k) \ x_2(k) \ x_3(k) \ x_4(k) \ x_5(k)]^T$$

Considering the inherent stochastic characteristic of PWM, treating the fundamental as the deterministic input $U(k)$ and all the higher order harmonics as white Gaussian noise $w(k)$ and considering the measurement noise $v(k)$, the dynamic behavior of three- phase can be modeled as:

$$X(k+1) = f(X(k), U(k)) + w(k) \quad (3)$$

$$Y(k) = h(X(k)) + v(k)$$

where:

$$f(X(k), U(k)) =$$

$$\begin{bmatrix} (1 - T_s(\gamma_1 + \gamma_2 x_5))x_1 + T_s \frac{K_1}{L_r} x_5 x_3 + T_s p K_1 \Omega x_4 + \frac{T_s}{\sigma L_s} v_{s\alpha} \\ (1 - T_s(\gamma_1 + \gamma_2 x_5))x_2 - T_s p K_1 \Omega x_3 + T_s \frac{K_1}{L_r} x_5 x_4 + \frac{T_s}{\sigma L_s} v_{s\beta} \\ T_s \frac{L_m}{L_r} x_5 x_1 + (1 - \frac{T_s}{L_r} x_5 x_3) - T_s p \Omega x_4 \\ T_s \frac{L_m}{L_r} x_5 x_2 + T_s p \Omega x_3 (1 - \frac{T_s}{L_r} x_5 x_4) \\ x_5 \end{bmatrix}$$

et:

$$h(X(k)) = [i_{s\alpha}(k) \ i_{s\beta}(k)]^T \quad (5)$$

$$\gamma_1 = \frac{R_s}{\sigma L_s}, \quad \gamma_2 = \frac{L_m^2}{\sigma L_s L_r^2}$$

w, v : Are assumed to be stationary, white and Gaussian noise and their expectation values are zero, the covariance matrices Q and R of these noises are defined as:

$$Q = \text{cov}(w) = E(ww')$$

$$R = \text{cov}(v) = E(vv')$$

Where $E(\cdot)$ denotes the expected values.

Design of EKF observer for the estimation of rotor resistance:

To use the Kalman Filter (KF) with nonlinear plant models, such as Eq. 3, the model must be linearized about a nominal state trajectory to produce a linear perturbation model. The standard KF is then used to estimate the perturbation states. The EKF estimator can be summarized as follows^[6]:

Step 1: Prediction

- Prediction of the state vector

$$\tilde{X}(k+1/k) = f(\tilde{X}(k/k), U(k)) \quad (6)$$

- Prediction covariance computation

$$P(k+1/k) = F(k)P(k)F(k)^T + Q \quad (7)$$

where:

$$F(k) = \left. \frac{\partial f(X(k), U(k))}{\partial X^T(k)} \right|_{x(k)=\tilde{x}(k/k)} \quad (8)$$

$$F(k) = \begin{bmatrix} 1 - T_s(\gamma_1 + \gamma_2 x_5) & 0 & T_s \frac{K_1}{L_r} x_5 & T_s p K_1 \Omega \\ 0 & 1 - T_s(\gamma_1 + \gamma_2 x_5) & -T_s p K_1 \Omega & T_s \frac{K_1}{L_r} x_5 \\ T_s \frac{L_m}{L_r} x_5 & 0 & 1 - \frac{T_s}{L_r} x_5 & T_s p \Omega \\ 0 & T_s \frac{L_m}{L_r} x_5 & T_s p \Omega & 1 - T_s \frac{1}{L_r} x_5 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Eq. continue

$$\begin{bmatrix} T_s(\frac{K_1}{L_f}x_3 - \gamma_2x_1) \\ T_s(\frac{K_1}{L_f}x_4 - \gamma_2x_2) \\ T_s(\frac{L_m}{L_r}x_1 - \frac{T_s}{L_r}x_3) \\ T_s(\frac{L_m}{L_r}x_2 - \frac{T_s}{L_r}x_4) \\ 1 \end{bmatrix}$$

Step 2: Filtering: The second step (Filtering) corrects the predicted state estimate and its covariance matrix through a feedback correction scheme that makes use of the actual measured quantities; this is realized by the following recursive relations:

- Kalman gain computation

$$\begin{aligned} K(k+1) &= P(k+1/k)H(k)^T \\ &(H(k)P(k+1/k)H(k)^T + R)^{-1} \end{aligned} \quad (9)$$

- State vector estimation (filtering)

$$\tilde{X}(k+1/k+1) = X(k+1/k) + K(k+1)(Y(k+1) - HX(k+1/k)) \quad (10)$$

- Estimation covariance computation

$$P(k+1/k+1) = P(k+1/k) - K(k+1)H(k)P(k+1/k) \quad (11)$$

where:

$$H(k) = \frac{\partial h(X(k))}{\partial X(k)} \Big|_{X(k)=\tilde{X}(k)} \quad (12)$$

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

The critical step in the EKF is the search for the best covariance matrices Q and R have to be set-up based on the stochastic properties of the corresponding noise. The noise covariance R accounts for the measurement noise introduced by the current sensors and quantization errors of the A/D converters.

Increasing R indicates stronger disturbance of the current. The noise is weighted less by the filter, causing also a slower transient performance of system. The noise covariance Q reflects the system model inaccuracy, the

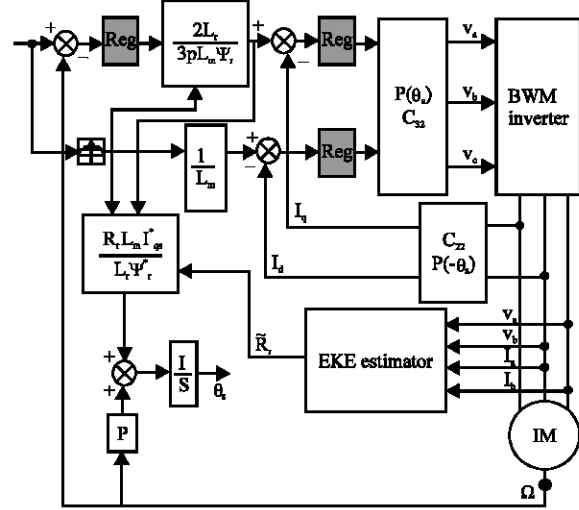


Fig. 1: Indirect field-oriented motor drive with EKF rotor estimator

errors of the parameters and the noise introduced by the voltage estimation^[7]. Q has to be increased at stronger noise driving the system, entailing a more heavily weighting of the measured current and a faster transient performance. An initial matrix P₀ represents the matrix of the covariance in knowledge of the initial condition.

Varying P₀ affects neither the transient performance nor the steady state condition of the system. In this study, the value of these elements is tuned “manually”, by running several simulations. This is maybe one of the major drawbacks of the Kalman filter.

Principle of vector control: The block diagram of the indirect field-oriented induction motor drive system combined with EKF estimator is shown in the Fig. 1.

The outputs of a PWM voltage source inverter are used as the control inputs for the EKF. These signals contain components at high frequencies, which are used as the required noise by the Kalman filter. Thus, no additional external signals are then needed

The field-oriented induction motor drive shown in Fig. 1, can be reasonably represented by the control system block shown in Fig. 2, in which G_c(s) is an IP speed controller and:

$$T_e = K_t i_{qs}^* \quad (13)$$

$$K_t = \frac{3pL_m^2}{2L_r} i_{ds}^* \quad (14)$$

$$H(s) = \frac{1}{Js + B} \quad (15)$$

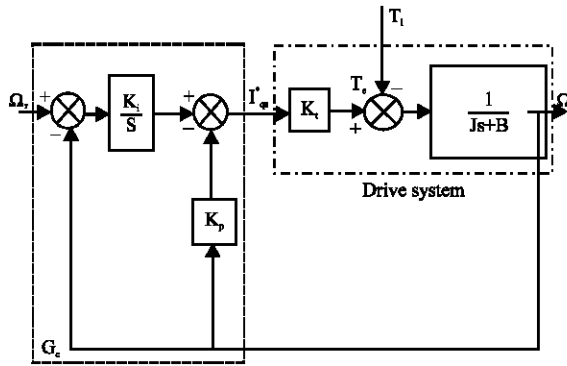


Fig. 2: Indirect field-oriented motor drive with EKF rotor resistance estimator showing the control system block diagram

From Eq. 13 to 14 and after some steps of calculation, one can find the parameters integral and proportional of the IP controller as^[1]:

$$\begin{cases} K_i = \frac{J\omega_n^2}{K_t} \\ K_p = \frac{(2J\omega_n - B)}{K_t} \end{cases} \quad (16)$$

where:

- i_{qs}^* = torque current command generated from the speed controller.
- i_{ds}^* = flux current command,
- J = total mechanical inertia constant,
- B = total damping constant,
- ω_n = natural frequency.

The unit vector $(\cos\theta_e + j\sin\theta_e)$ used in the coordinate translator is generated by using the measured angular velocity ω and the following estimated slip angular velocity ω_{sl} :

$$\omega_{sl} = \frac{R_r i_{qs}^*}{L_r i_{ds}^*} = \frac{R_r L_m i_{qs}^*}{L_r \Psi_r^*} \quad (17)$$

Since R_r is sensitive for different operating conditions, the estimated \hat{R}_r from the EKF estimator will be used in (17).

Remark: As shown in Eq. 16, the parameters K_i and K_p of the IP controller depend on the rotor inertia and damping constants value, For obtaining more accuracy

and robust control performance, the on-line tuning IP controller with feed forward of the rotor inertia and damping constants is more preferred. This technique is discussed in^[1].

SIMULATION RESULTS

Simulations using Matlab-Simulink software package have been carried out to verify the effectiveness of the proposed IM indirect field oriented control.

The induction motor used for the simulation studies has the following parameters:

Type: tree-phase, 0.75kW.220 380V⁻¹, squirrel-cage induction motor.

- $R_s = 10\Omega$; $R_r = 6.3\Omega$; $L_s = 0.6560H$; $L_r = 0.6530H$;
- $L_m = 0.613H$; $J = 0.02Kg.m^2$; $B = 0Nm.s rad^{-1}$;
- $p = 2$; $T_l = 5Nm$; $\Omega = 146Rad s^{-1}$.

These parameters are in the nominal condition.

The results are shown in Fig. 3 to 5. Fig. 3 shows the tracking of the rotor resistance variations and the estimation error, when the rotor resistance value of the IM is changed abruptly: stepped-up by 50% of its initial value in 1s and by 100% of its initial value in 2s. This result demonstrates that even if the rotor resistance changes abruptly, the EKF still gives a good estimation of this parameter. Where, $(R_r\text{-real})$ represent the real motor resistance and $est-R_r$ the estimated rotor resistance by EKF.

Note that this R_r estimate is, as shown in Fig. 1, fed forward to the slip speed calculation module to obtain robust indirect field orientation control performance. Thus, the following observations can take:

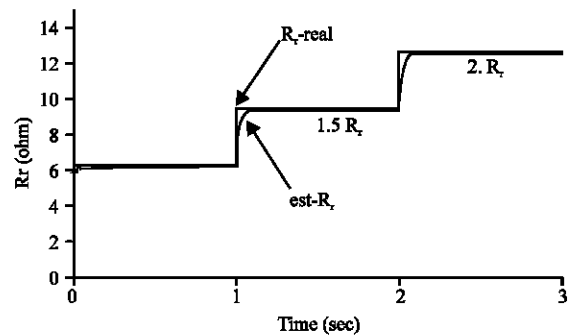


Fig. 3: Tracking of rotor resistance variation by EKF
 From $t = 1s$ to $t = 2s$: $R_r\text{-real} = 1.5 R_r$
 From $t = 2s$ to $t = 3s$: $R_r\text{-real} = 2 R_r$

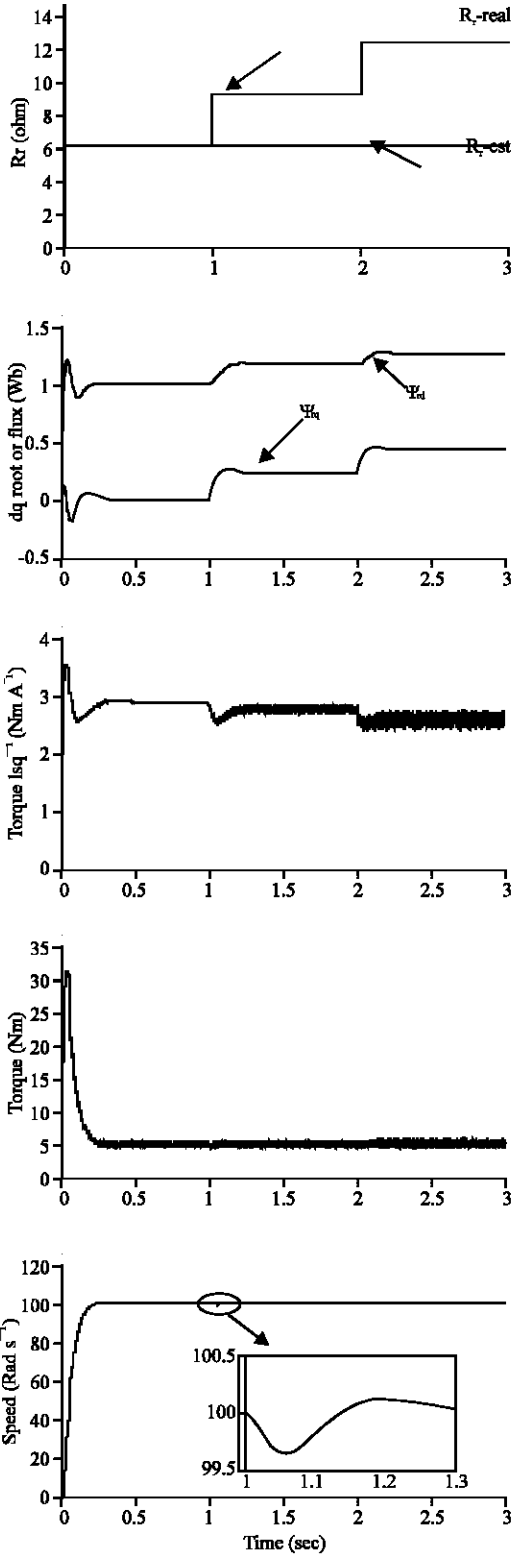


Fig. 4: IFOC performance without R_r adaptation in slip speed calculation

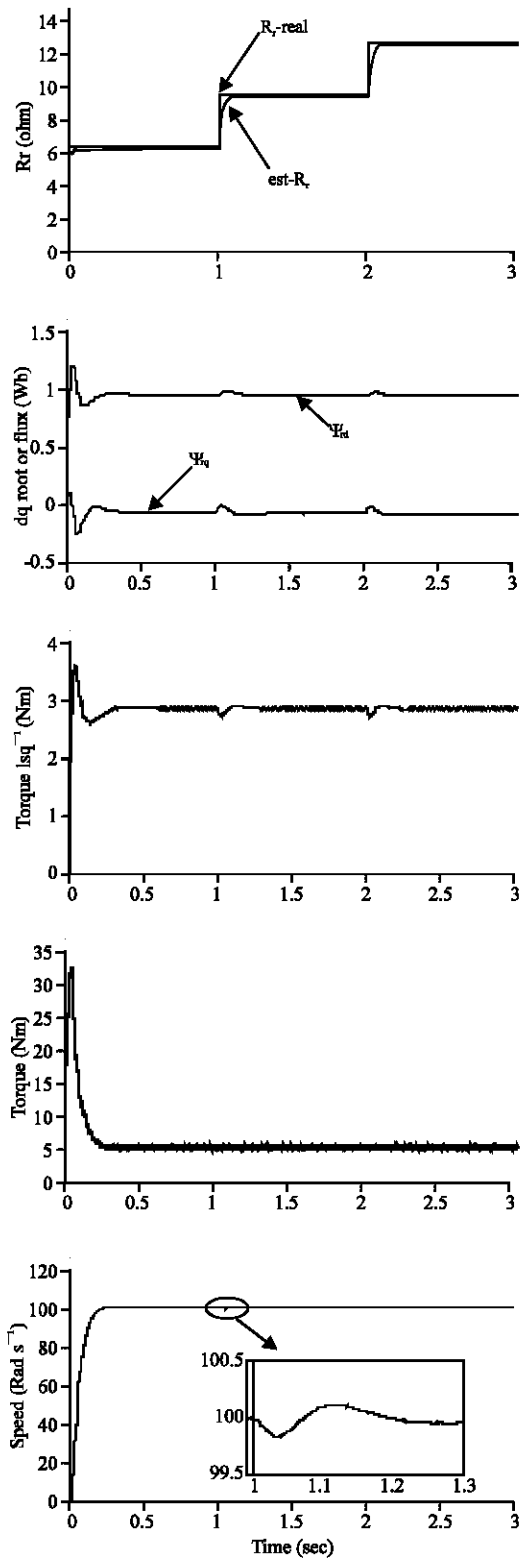


Fig. 5: IFOC performance with R_r adaptation in slip speed calculation

IFOC without R_r adaptation: Figure 4 shows the performance of the IFOC without R_r adaptation, in this case, R_{r_est} is the value of R_r used for slip speed calculation. where, one can observe the poor performances of the IFOC due to the variation of the rotor resistance, this variation causes the loss of the decouple control of torque and flux, where result a steady state error and oscillations in the flux and torque, the vector control becomes nonlinear technique. So, we must use the on-line adaptation of R_r in the slip speed calculation block.

IFOC with R_r adaptation: The robustness of the proposed IFOC with on-line rotor resistance estimation is demonstrated in Fig. 5. The rotor resistance value is stepped- up twice (at $t = 1$ and $t = 2$) by 50% of its initial values. The results shows that the decouple control of torque and flux is preserved and guaranteed by the on-line feed forward of the rotor resistance estimated value in the slip speed calculation.

CONCLUSION

Changes in the rotor resistance have an important effect on the performance of induction indirect field oriented control drive systems. The application of the extended Kalman filter to the rotor resistance estimation is successfully implemented. The on line estimation of this parameter is used in the slip speed calculation module to obtain robust control performance with the proposed indirect field oriented control scheme.

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