Induction motor drive control and estimation is a wide subject. The market for variable speed drives has grown dramatically in the last few years. Manufacturers have recognized the importance of not only managing the speed or torque range, but also reducing power consumption. This necessitates the development of new control algorithms and schemes to include these solutions. Indeed, the speed estimate must be employed in one or more regions of the control scheme, depending on the control objective. This concept, as well as the most common speed estimation methodologies, is investigated.

Currently, many tools can be used for the evaluation of the rotor speed without a speed sensor. By modern signal processing methods, it is possible to implement an estimation scheme with the possibility of monitoring currents and voltages. Therefore, in this paper, the concept of currents, speed and fluxes estimation based on the extended Kalman filter is proposed. By monitoring the ratio of the theoretical residual to the actual residual, the measured noise covariance matrix is recursively corrected online to make it gradually approach the real noise level. So that the filter performs the optimal estimation, improves the accuracy of the speed estimation. The effect of the load change on the currents, fluxes and speed estimation was also studied. Simulation and experimental results show that the proposed improved adaptive extended Kalman estimator has a strong ability to suppress random measurement noise. The experimental and simulation results prove the accuracy of the proposed scheme towards the state estimation of an induction motor at different load levels. It can accurately estimate the speed of the motor and has a good anti-error ability to meet the actual needs of the project.

Keywords: induction motor, extended Kalman filter, speed estimation, rotor flux estimation, sensorless drive

EXPERIMENTAL EVALUATION FOR FLUXES, CURRENTS AND SPEED ESTIMATION OF INDUCTION MOTOR

Najimaldin M. Abbas
Corresponding author
Assistant Professor*
E-mail: dralbyati@uokirkuk.edu.iq
Ali Merwan Shakor
Assistant Lecturer*
*Department of Electrical Engineering
College of Engineering
University of Kirkuk
Baghdad str., Kirkuk, Iraq, 36001

1. Introduction

In the field of modern motor control, induction motor vector control technology has been widely used due to its excellent control performance [1]. However, because the use of the speed sensor destroys the advantages of the induction motor's simple structure, reliability, low cost and convenient maintenance, it also limits its application range and reduces the robustness of the system. Therefore, speed sensorless control has not only become an important research direction of modern AC drive control technology, but also a key technology for studying high-performance general-purpose inverters [2].

Sensorless vector control has gotten a lot of press recently. The removal of the speed sensor decreases the drive's hardware complexity, size, and cost while also increasing its reliability. A high-performance four-quadrant drive that can generate controlled torque over the whole speed range is required. While the problem has been overcome for medium and high speeds, reliable operation and good performance at low speeds have yet to be accomplished [3].

With the rapid development of high-performance digital signal processors, various speed estimation methods emerge endlessly, such as direct calculation method, state equation synthesis method, model reference adaptive method [4], sliding mode observer method [5], adaptive full-order observer method [6], high-frequency signal injection method [7] and extended Kalman filter (EKF) method [8–11], etc. The speed sensorless technology has high requirements for

measurement parameters. The main problems are poor dynamic characteristics, limited adjustment capabilities, susceptibility to external environmental interference, and jitter in the speed estimation scheme. Furthermore, it can decrease the cost and size of the electric drive system by eliminating sensors and subsequently improving system reliability.

2. Literature review and problem statement

In recent years, many researchers have used a lot of research works on the application of EKF in induction motor speed sensorless vector control systems. In [7], an EKF-based parameter estimator is used to estimate the rotor inductance and mutual inductance. The results show that combining the estimation method proposed in this paper with other kinds of induction motor control methods provides better control results. In [9], the EKF method was used to estimate the speed and flux linkage in the direct torque control of induction motors. The experimental results indicate that the EKF approach has a broader velocity range and better output estimation. In [11], a third-order EKF algorithm was studied that only estimates the flux linkage and speed. It not only obtains the same estimation performance as the traditional EKF method, but also significantly reduces the amount of calculation. Research shows that the measurement data includes noise in the control mechanism of the induction

motor nonlinear dynamic system, and the statistical characteristics of the measurement noise change with the actual working environment, so the fixed noise prior model in EKF does not represent the true noise of the actual system operation. In addition, the extended Kalman observer is not affected by voltage DC offset, can effectively suppress noise, and has good low-speed performance. It is sensitive to changes in motor parameters, especially changes in resistance, and has been widely used in motor control [12].

To improve the performance of a sensorless vector controller, model reference adaptive control (MRAC) is proposed in [13]. State variables such as rotor flux and back EMF are estimated in a reference model using MRAC methods.

Due to the complex structure of induction motors and the unsatisfactory direct control effects, many control strategies have emerged [14]. In [15], adaptive control is the most used vector control and direct torque control ideas have improved the control performance of the motor [16]. At the same time, vector control requires vector transformation according to the magnetic pole position to achieve magnetic field orientation [17]. Therefore, the accuracy of the magnetic pole position directly affects the performance of the system [18]. However, the traditional direct torque control has an integral link, and the initial value of the integral, the position error and the change of the stator resistance will affect the accuracy of the flux linkage calculation. In addition, direct torque control also has the problems of DC bias in current measurement and inconstant inverter switching frequency [19]. In [20], an effective observer is shown to be used to estimate fluxes at external loads. It has a solid foundation for overcoming the constraint imposed by the coupling of the control and parameter estimation processes.

At present, the control technology of an asynchronous motor has been relatively mature. Traditional direct torque and vector control have enhanced the motor's control performance. However, in conventional control strategies, the installation of sensors, measurement accuracy and errors will reduce the reliability of the control system. The sensorless measurement technology proposed to solve the above problems has become a research hotspot in recent years. Among them, the Kalman-based estimation method has attracted much attention for its good dynamics and robustness.

3. The aim and objectives of the study

The aim of the presented study is to use a new scheme based on EKF to estimate the current, flux and speed of an induction motor.

To achieve this aim, the following objectives were set:
– to perform a simulation study to support and evaluate the proposed methodology;
– to study the experimental evaluation for the effect of the load change on the currents, fluxes and speed estimation.

4. Materials and methods

In order to use the state estimation for a three-phase induction motor, the discrete model must be obtained. The conversion is done by Euler transformations. The discrete model of the induction motor is shown in the following equation [1, 15].

$$
\begin{bmatrix}
I_{s\alpha}(k+1) \\
I_{s\beta}(k+1) \\
\varphi_{r\alpha}(k+1) \\
\varphi_{r\beta}(k+1) \\
\omega_r(k+1)
\end{bmatrix}
=
$$

$$
=
\begin{bmatrix}
a_1 - a_2 \dfrac{1}{t_r(k)} I_{s\alpha}(k) + a_3 \dfrac{1}{t_r(k)} \varphi_{r\alpha}(k) + \\
+ a_3 \varphi_{r\beta}(k)\omega_r(k) + a_s V_{s\alpha}(k) \\[4pt]
a_1 - a_2 \dfrac{1}{t_r(k)} I_{s\beta}(k) + a_3 \dfrac{1}{t_r(k)} \varphi_{r\beta}(k) + \\
+ a_3 \varphi_{r\alpha}(k)\omega_r(k) + a_s V_{s\beta}(k) \\[4pt]
a_3 \dfrac{1}{t_r(k)} I_{s\alpha}(k) + \left(1 - \dfrac{\Delta t}{t_r(k)}\right)\varphi_{r\alpha}(k) - \\
- \Delta t\,\omega_r(k)\varphi_{r\beta}(k) \\[4pt]
a_3 \dfrac{1}{t_r(k)} I_{s\beta}(k) + \left(1 - \dfrac{\Delta t}{t_r(k)}\right)\varphi_{r\beta}(k) - \\
- \Delta t\,\omega_r(k)\varphi_{r\alpha}(k) \\[4pt]
a_6 \begin{Bmatrix} I_{s\beta}(k)\varphi_{r\alpha}(k) - \\ -I_{s\alpha}(k)\varphi_{r\beta}(k) \end{Bmatrix} + a_6 \omega_r(j)
\end{bmatrix},
\qquad (1)
$$

where $I_{s\alpha}$ – stator current in α stationary reference frame, A; $I_{s\beta}$ – stator current in β stationary reference frame, A; I_s, I_r – stator and rotor currents, A; $\phi_{r\alpha}$, $\phi_{r\beta}$ – rotor alpha-beta fluxes, Wb; $V_{s\alpha}$ – stator voltage in α stationary reference frame, V; $V_{s\beta}$ – stator voltage in β stationary reference frame, V; R_s, R_r – resistance of stator and rotor windings, Ω; L_s, L_r – stator and rotor self-inductance, H; G, u – input matrix, known input; w – system noise vector; v – measurement noise vector; H – output matrix; L_m – mutual inductance, H; ω_r – rotor angular speed, rad/s; t_r – rotor time constant, s.

$$a_1 = 1 - a_0 R_s L_r \Delta t,$$

$$a_2 = a_0 L_m^2 \Delta t,$$

$$a_3 = a_0 L_m \Delta t,$$

$$a_4 = a_0 L_m$$

$$a_5 = a_0 L_r \Delta t,$$

$$a_6 = \frac{3 p^2 L_m \Delta t}{2 J L_r},$$

$$a_7 = \left\{ 1 - \frac{F \Delta t}{J} - \frac{p \Delta t\, T_{\max}}{J w_{r.\max}} \right\},$$

$$a_0 = \frac{1}{\left(L_s L_r - L_m^2 \right)}.$$

From the above equations, Δt represents the length of the sampling interval.

4. 1. Linear Kalman filter method

In practical problems, people often only get a series of actual measurement values with errors. In order to get the ideal result, it is necessary to eliminate the interference of the error, separate the estimated value of the required physical parameter, and minimize the error of the estimated value. This is the basic idea of filtering. Mathematically speaking, filtering is a statistical estimation method. The best estimate of the required physical parameters can be obtained by processing a series of actual measurement data with errors. The traditional Kalman filter assumes that the estimated process or the relationship between the observed variable and the process is linear, and uses a linear stochastic difference equation to describe the state variable of the discrete-time process.

The Kalman filter induction motor speed estimation method is the application of the linear Kalman filter method in nonlinearity. The main idea is to regard the motor motion equation as a state equation, and the motor load torque as the extended state of the system. According to the voltage and current values measured on the stator side (including measurement errors), the Kalman filter estimates the motor rotor flux, speed and other information. When the system is close to linear but not absolutely linear, the Kalman filter can effectively solve the nonlinear problem through a series of approximate calculations and give a better state estimation. At present, the Kalman filter has been widely used in motor parameter estimation, and has achieved good results [2–8]. EKF is a random observer based on the principle of minimum square error and with feedback correction link applied to nonlinear systems. EKF has attracted widespread attention from scholars from all over the world, and has been applied to the speed estimation of sensorless vector control. This method provides an iterative non-linear estimation algorithm, which avoids the differential operation, can estimate the system state online, and realize the real-time control of the system. EKF is suitable for high-performance servo drive systems. It can operate at a wide variety of speeds and even complete the calculation of speed at very low speeds. It can also estimate related states and certain parameters, which is not available in other speed estimation algorithms. The statistical nature of its algorithm enables EKF to overcome the shortcomings of the uncertainty and non-linearity of the asynchronous motor model, and the estimation performance is superior, so it has become the focus of research on speed estimation.

4. 2. Proposed model

In a traditional EKF filter, the choice of noise covariance matrix R is determined empirically, and it is a constant matrix during the entire iteration. However, when the motor is running, the largest variable and the strongest randomness is the measurement noise statistics characteristics, and difficult to accurately obtain.

According to the optimal filtering theory, monitoring residuals can determine whether the filter is working in an optimal state. The residual is actually the difference between the real measured value and the estimated value in the filter model. The residual sequence of EKF is

$$r_k = Y_k - H_k \hat{X}_{k|k-1}. \tag{2}$$

Define the actual variance c_r of the residuals as

$$c_r = \frac{1}{M} \sum_{i=i_o}^{k} r_i r_i^T, \tag{3}$$

where c_r is the average of the variance of the latest M residual vectors; $i_0=kM+1$; M is selected by experience according to the specific situation, and it mainly plays a smoothing role.

When the Kalman filter is the optimal filter, the residual sequence is 0-mean Gaussian white noise sequence, and the theoretical value of the residual variance is defined

$$p_r = H_k \left(F_{k,k-1} P_{k-1} F_{k,k-1}^T + Q \right) H_k^T + R_{k-1}. \tag{4}$$

If the measured noise model is accurate enough, the actual value of the residual error should be approximately equal to the theoretical value, that is

$$c_r \approx p_r. \tag{5}$$

The EKF equations are:

$$x(k+1/k) = f(x(k), u(k)), \tag{6}$$

$$\Phi(k) = \frac{\partial}{\partial X} f\left(x\left(\frac{k}{k}\right) \cdot u(k) \right)\bigg|_{x(k)-x\left(\frac{k}{k}\right)}, \tag{7}$$

$$P(k+1/k) = \Phi(k) P(k/k) \Phi^T(k) + Q(k), \tag{8}$$

$$x\left(k+\frac{1}{k}\right) = x\left(k+\frac{1}{k}\right) + $$
$$+ K(k+1)\left[y(k+1) - H(k+1) x\left(k+\frac{1}{k}\right) \right], \tag{9}$$

$$K(k+1) = P\left(k+\frac{1}{k}\right) H^T(k) \left[\begin{matrix} R(k) + H(k+1) \times \\ \times P\left(k+\frac{1}{k}\right) H^T(k+1) \end{matrix} \right]^{-1}, \tag{10}$$

$$P\left(k+\frac{1}{k}\right) = \left[I - K(k+1) H(k+1) \right] P\left(k+\frac{1}{k}\right), \tag{11}$$

$$x\left(\frac{0}{0}\right) = x_0; \quad P\left(\frac{0}{0}\right) = P_0. \tag{12}$$

In general, it is possible for the estimates to diverge due to the linear approximation of the EKF in which eq.(13) can be

$$P(k+1/k) = \left[I - K(k) H(k+1) P(k+1/k) \right] \times $$
$$\times \left[I - K(k) H(k+1) \right]^{(-1)} + K(k+1) R(k+1) K^T(k+1),$$

where σ – coefficient of dispersion; Q – process noise covariance matrix; R – measurement covariance matrix; P – state covariance matrix; K – Kalman gain; X – state matrix; Y – measurement of state; Δt – sampling time; F – system matrix; δ_{kj} – Kronecker delta; X_a, X_b – active group of states, passive group of states; P_{aa}, P_{bb} – state covariance matrix of X_a, state covariance matrix of X_b.

In order to apply the extended Kalman filter on an induction motor, we have to define the state transition equations of the induction motor as follows [19].

$$Y(k) = h(x(k), k) + V(k), \tag{13}$$

$$X(k+1) = f(x(k), U(k), k) + W(k), \tag{14}$$

where k, $U(k)$, $Y(k)$ are the state vector, the stator voltage space vector and the output vector.

$$X(k)=[[I_{s\alpha}(k)I_{s\beta}(k)\varphi_{r\alpha}(k)\varphi_{r\beta}(k)\omega_r(k)]]^T, \quad (15)$$

$$U(k)=[[V_{s\alpha}(k)V_{s\beta}(k)]]^T, \quad (16)$$

$$Y(k)=[[I_{s\alpha}(k)I_{s\beta}(k)]]^T, \quad (17)$$

where $W(k)$ and $V(k)$ represent the measurement weight and voltage vectors, respectively.

$$F=\vdash\partial/\partial Xf(X(k),U(k))\dashv|\_(X(k)), \quad (18)$$

$$G=\vdash\partial/\partial Uf(X(k),U(k))\dashv|\_(X(k),U(k)), \quad (19)$$

where F is the Jacobian matrix of the plant due to states and G is the Jacobian matrix of the plant due to inputs.

5. Results of research for fluxes, currents and speed estimation of an induction motor based on EKF

The proposed algorithm has been verified through many experimental and simulation results using MATLAB software.

5. 1. Estimation results of the flux, current and speed of an induction motor

In order to apply the proposed method for estimating the flux, current and speed of an induction motor, the values shown in Table 1 have been relied upon. The proposed scheme was tested on a three-phase induction motor with the parameter values shown in Table 1.

The first simulation results present the estimated and actual speed of the rotor of an induction motor at full load as shown in Fig. 1.

Fig. 1 shows that there is a significant similarity between the actual speed and the estimated speed and the error percentage (Er) does not exceed 0.03 % in the steady state as shown in Fig. 2. Where

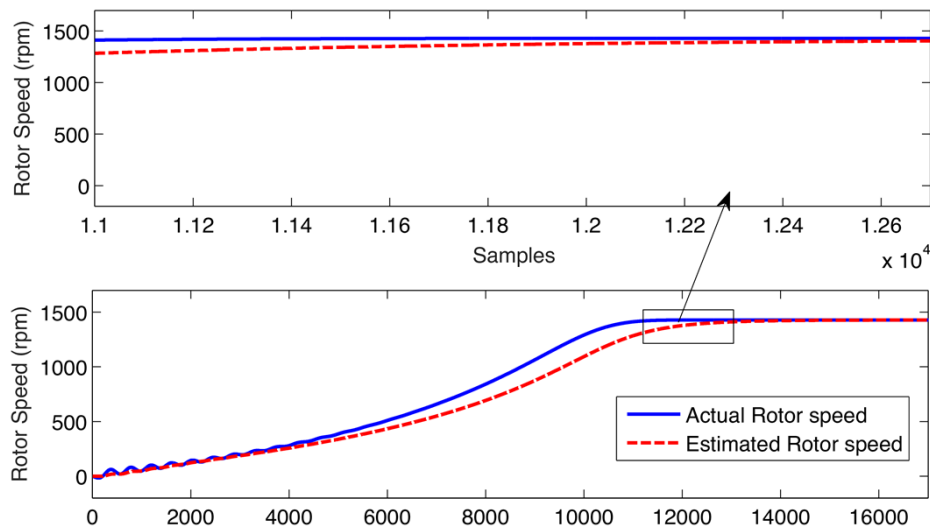$$Er = \frac{\text{Actual value} - \text{Estimated value}}{\text{Actual value}} *100 \text{ %.}$$

Table 1

Parameters of induction motor

Parameter	Value
P_{rated}	1.12 kW
V_N	380 V
I_N	2.7 A
F_N	50 Hz
T_l	7.5 N·m
J	0.02 kg·m²
n_N	1415 r/min
R_s	5.275 Ω
R_r	5.075 Ω
L_m	0.425 H
L_s	0.425 H
L_r	0.485 H
σL_s	0.05 H
P (pole pair)	2
Δt (sec)	$50*10^{-6}$

As it can be observed from Fig. 3, 4, the values of estimated and actual rotor flux at full load are very similar and the error percentage is less than 0.1 % in the steady state.

Fig. 5, 6 depict the stator alpha and beta currents at full load, respectively. It can be seen that the estimated and actual values are identical and the error percentages in both cases are around 0.1 % in the steady state.

The electromechanical torque and load torque are presented in Fig. 7. The electromagnetic torque is capable of generating a full load torque of 7.5 N·m in the steady state.

Estimates of the five states of the induction motor were also studied when changing the motor load. Fig. 8 shows the change in the motor load, where at first the load torque at a rated value of 7.5 N·m is applied, then the load was gradually reduced to 50 % (3.75 N·m), then to 25 % (1.875 N·m), then to the no-load case and finally back to the full load condition.

Fig. 9 shows that the electromagnetic torque represented by a dashed line is able to supply the motor with the required torque at different loads and the transit period is very little approx 0.1 seconds at each load change.
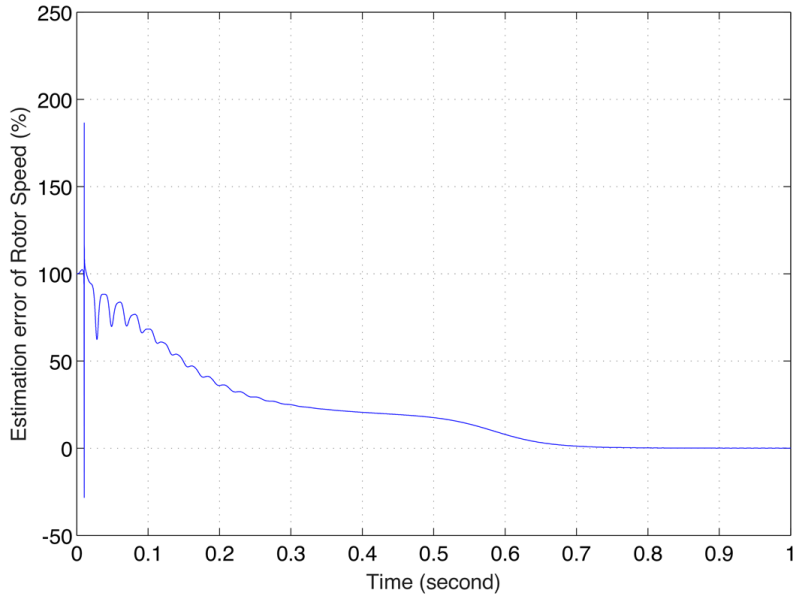

Fig. 1. Estimated and actual rotor speed

Fig. 2. Error percentage of the estimated speed of the induction motor at full load
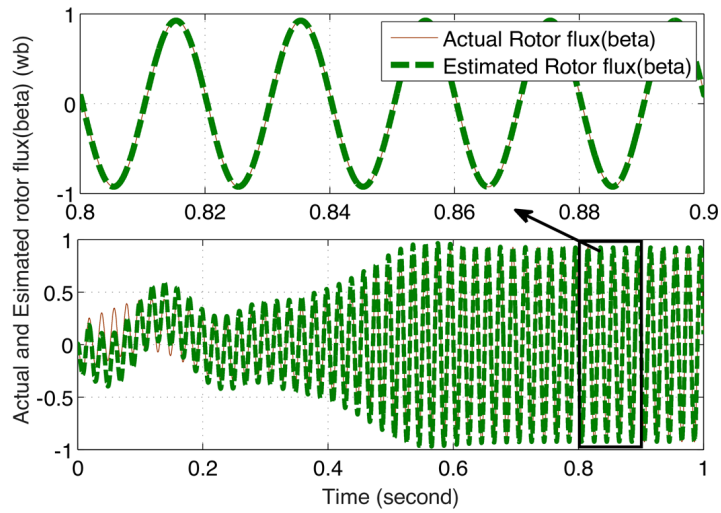

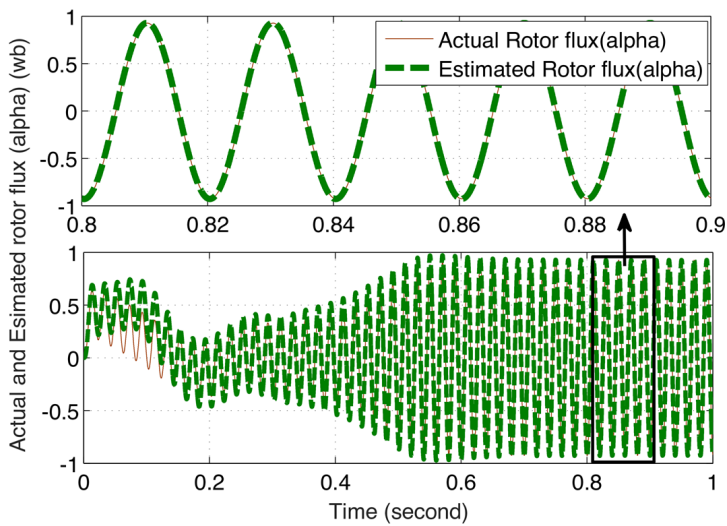Fig. 3. Estimated and actual rotor flux beta

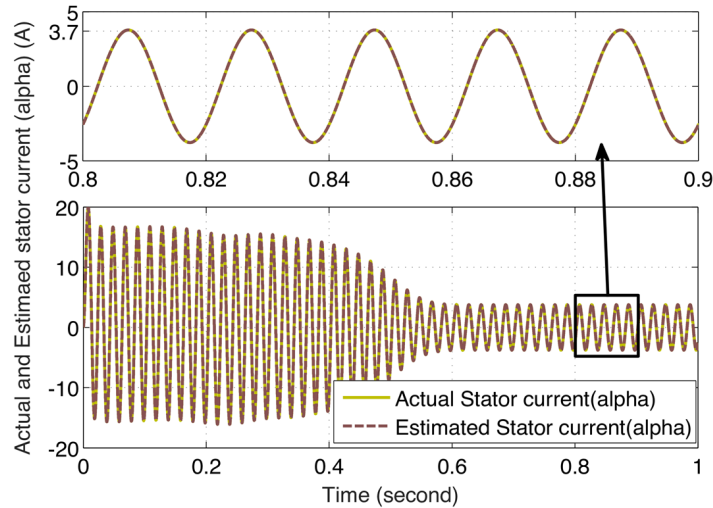Fig. 4. Estimated and actual rotor flux alpha

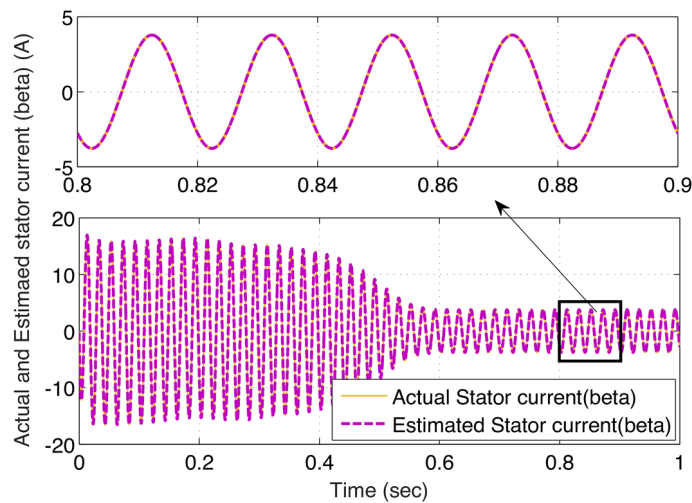Fig. 5. Estimated and actual rotor current alpha
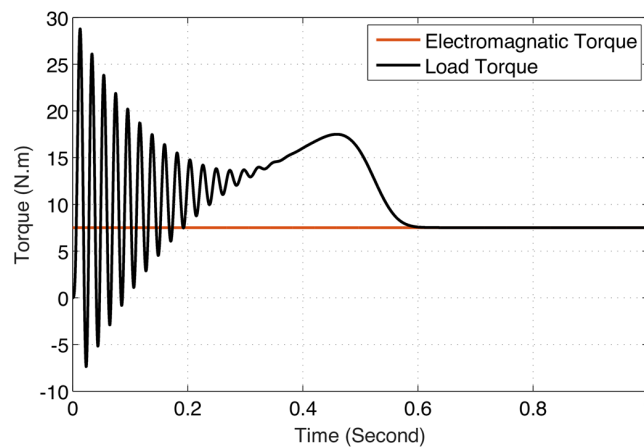

Fig. 6. Estimated and actual rotor current beta

Fig. 7. Electromechanical and load torque of induction motor

There is an identity between the actual rotor speed and the estimated speed as shown in Fig. 10 at different loads with a very small error percentage that does not exceed 0.07 % caused by the system noise and measurement. The speeds reached 1485 rpm in the no-load case (the period 8–10 sec) of the induction motor because of the rotation losses and friction. The rotor speed is inversely proportional to the load on the induction

motor while the motor speed is 1410 rpm at full load, 1468 rpm and 1450 rpm at 25 % and 50 % of full load, respectively.

Fig. 11 presents the actual current beta and the estimated current beta at variable loads of the induction motor. It can be seen that the estimated and actual values are identical and the error percentage does not exceed 0.01 % in the steady state.
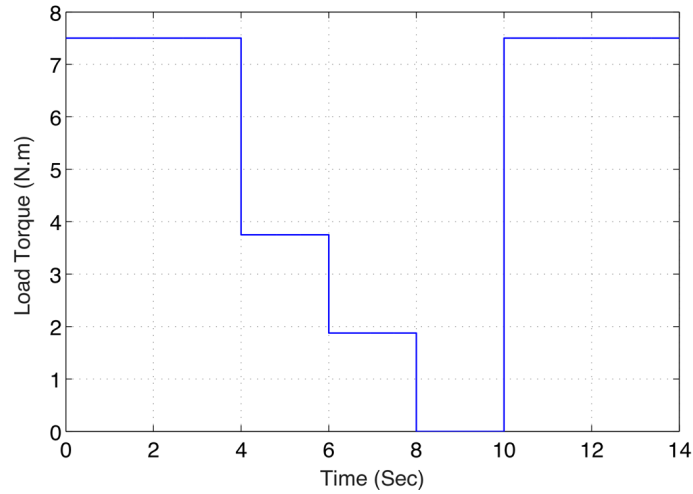
Fig. 8. Change in the load torques applied to the induction motor
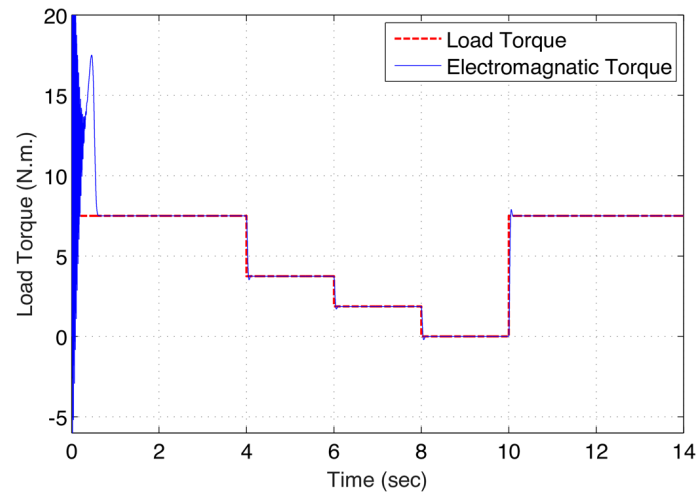

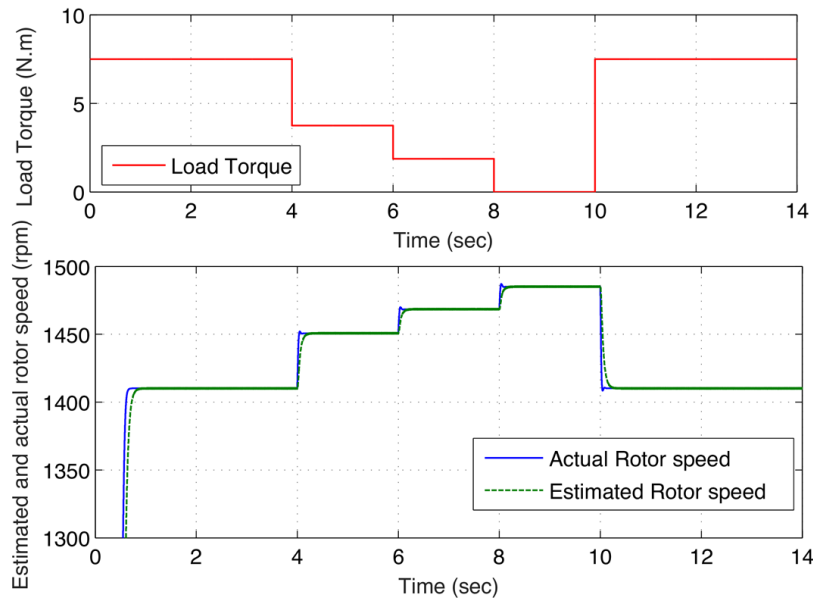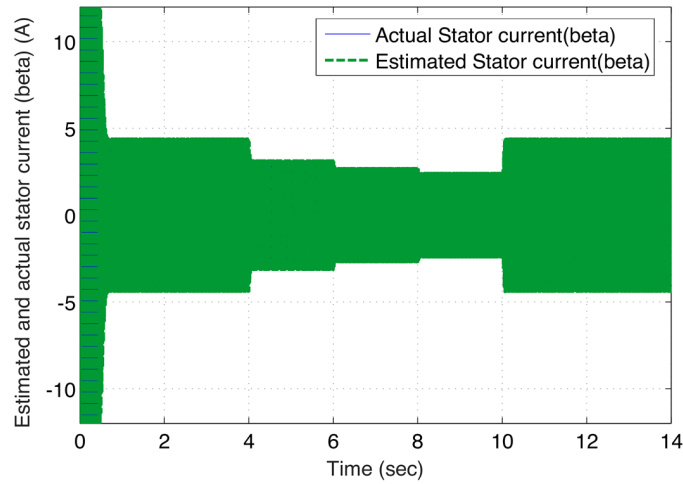Fig. 9. Electromagnetic torque and variable load torque applied to the motor

Fig. 10. Actual and estimated rotor speed at variable motor loads

Fig. 12 depicts the actual and estimated flux beta at variable loads of the induction motor. It can be seen that the estimated and actual values are identical and the error percentage does not exceed 0.1 % in the steady state.

Fig. 11. Actual current beta and estimated current beta at variable loads of the induction motor
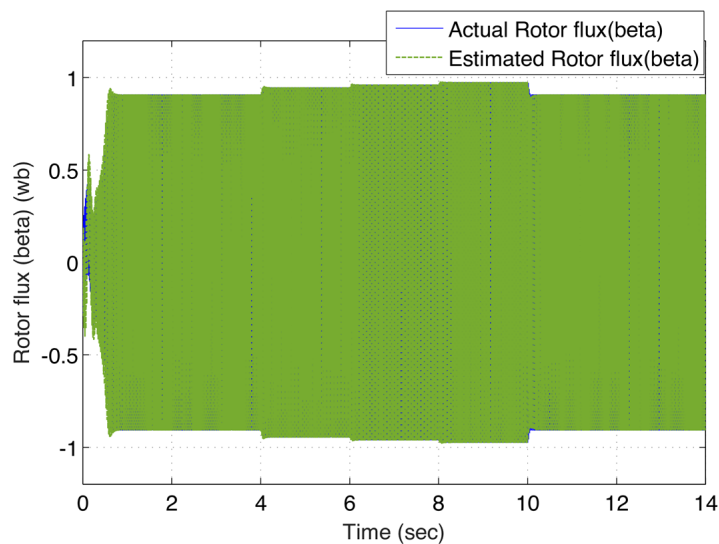

Fig. 12. Actual flux beta and estimated flux beta at variable motor loads

Fig. 10–12 show the significance of the proposed method for estimating the states of the induction motor, especially at light loads and no-load conditions. It is very obvious that EKF successfully estimates the speed, current and flux of the induction motor in each period of load change.

5. 2. Experimental results

The EKF method has been experimentally evaluated for a squirrel cage induction motor. The motor rating is 380 V, 4 pole, 50 Hz, 1410 rpm, and 1.1 kW as shown in Table 1. The experimental study was carried out at full load conditions. In the beginning, the three-phase voltages and three-phase currents were converted to alpha-beta components by Clark's transformations. The process started with using alpha-beta data that were entered into the EKF, which in turn works to estimate the five states of the induction motor.

Fig. 13 presents the experimental results of the estimated rotor speed of an induction motor at full load. The rated speed is 1410 rpm, and the estimated error percentage is 0.5 % in the steady state. However, they vary a bit from the actual speed, and this could be the re-

sult of motor parameters that are not optimum and temperature changes.

Fig. 14, 15 present the experimental estimated alpha and beta currents components, respectively, at full load. It is also depicted that the peak value of the current is 3.5 A.
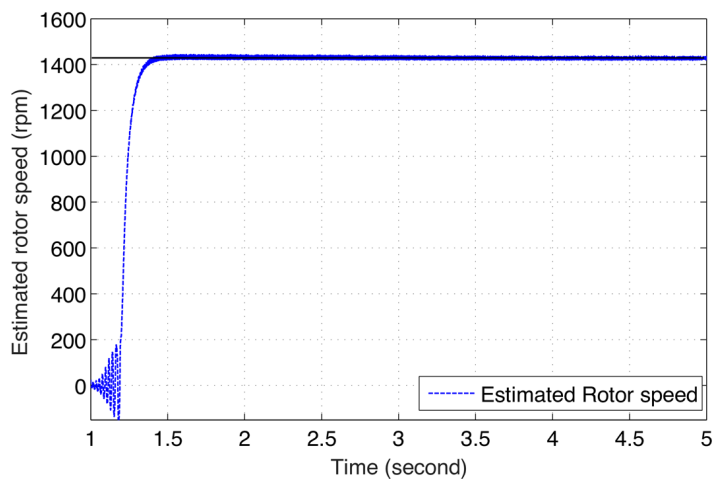

Fig. 13. Estimated and actual rotor speed experimentally

Furthermore, Fig. 16, 17 present the experimental estimated alpha and beta flux components, respectively, at full load. It is also depicted that the peak value of the current is 0.92 W.
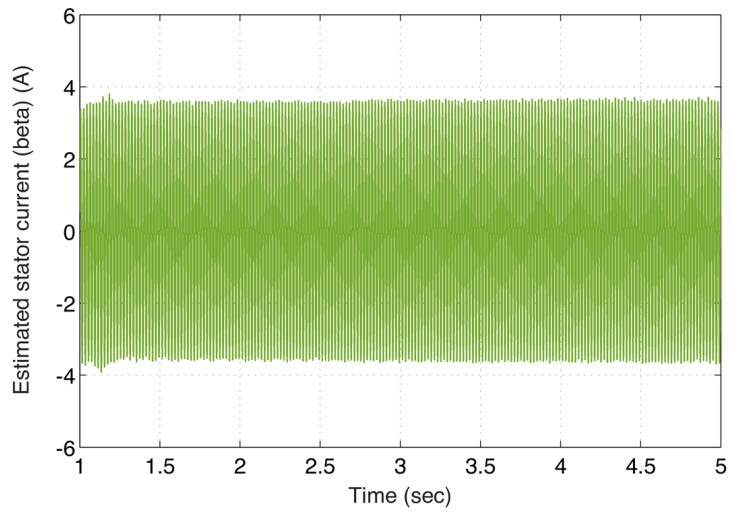

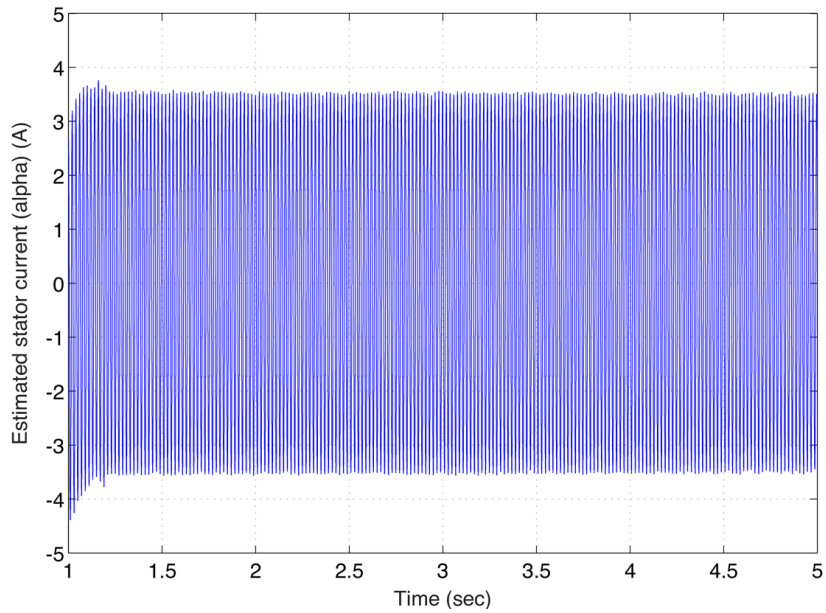Fig. 14. Estimated flux beta components experimentally

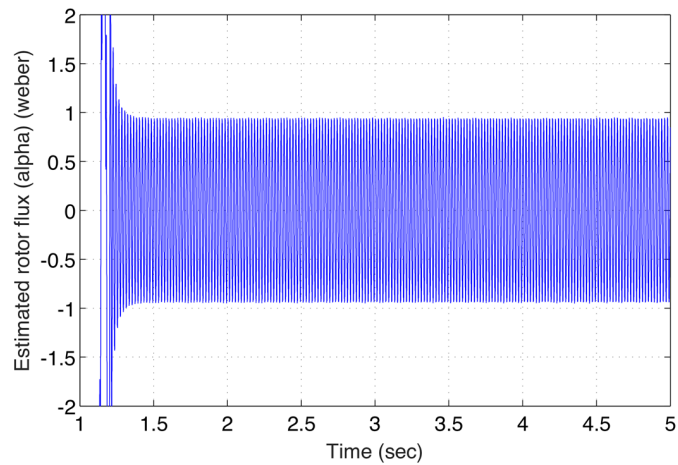Fig. 15. Estimated current alpha components experimentally

Fig. 16. Estimated flux alpha components experimentally

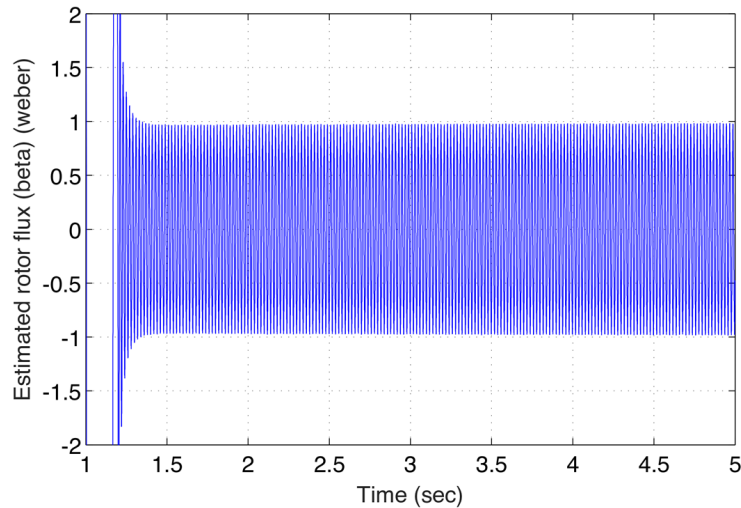Fig. 18 shows the estimated torque under full load experimentally.

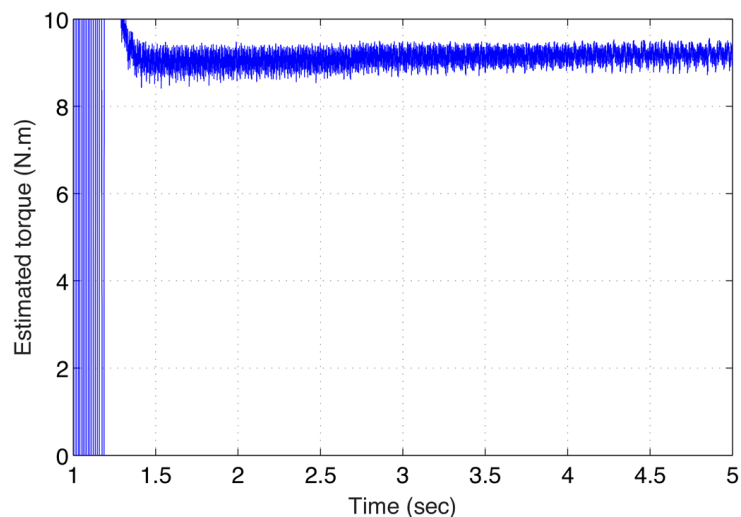Fig. 17. Estimated flux beta components experimentally

Fig. 18. Estimated motor torque experimentally

It can be seen from Fig. 18 that the estimated values have fluctuations due to the change of the motor temperatures and other varying factors where the error percentage of the estimation value is 6 % in the steady state.

6. Discussion of the estimation and experimental results

To implement the proposed method for the state estimation of an induction motor, experimental and simulation studies are presented based on EKF by using Matlab/Simulink. The results demonstrate that the proposed method is highly promising, and the estimated values are essentially accurate. Furthermore, the simulation results show that the EKF is an effective method. Except in the transient area, where the inaccuracy is fairly minor, as illustrated in Fig. 2, the anticipated speed is nearly identical to the actual one. The greatest percentage of this error is 0.15 % in the steady state due to the IM model and system noise as illustrated in Fig. 11.

In the variable speed zone of operation, state estimation significantly increases the performance of the rotor flux-based model reference adaptive system. To estimate the rotor speed, the technique employs a Kalman filter as a rotor flux observer adaptation mechanism. Only the stator voltages and currents must be measured for state estimation.

The results show an acceptable superposition between speed values, however, it is clear from Fig. 10 that the proposed method has better estimation and more precise accuracy between speed values than the results in [14]. All these remarks can be confirmed from the estimation errors shown in Fig. 2. Furthermore, one of the limitations of the proposed method is that in the sensorless vector control mode, this estimator may not be able to give flux information for motor initiation.

7. Conclusions

1. The proposed structure has been presented to improve the performance of the EKF. Indeed, to estimate the rotor flux and speed of an induction motor, the rotor flux observer and speed observer were described. For input signals, the EKF observer simply needs the stator voltages and currents of an induction motor. Following the rotor flux and speed from the induction motor model, the KF observer is successfully employed to estimate the rotor flux and speed of the induction motor. The simulation results show that the EKF observer can accurately predict rotor flux and speed. The current estimation Er value was 0.001, whereas the flux estimation Er value was less than 0.1 % and the Er value was less than 0.07 % for speed estimation.

2. The results show that the traditional observer methods show sensitivity and errors in different speed tests, while the EKF has kept its good accuracy and response. Furthermore, the validation study for the proposed method showed the effectiveness of the EKF and good accuracy for all estimated values.

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