Speed Estimation Schemes for Sensorless Vector Control of Induction Motor Drive

R. Gunabalan and V. Subbiah

Abstract

This paper describes the speed estimators for sensorless vector control of induction motor drive. Speed and rotor fluxes of the induction motor are estimated by adaptive rotor flux observer, natural observer with load torque adaptation and Extended Kalman Filter (EKF). The performance parameters speed and rotor fluxes are estimated from the measured terminal voltages and currents. Fourth order induction motor model is used in natural observer and adaptive rotor flux observer and speed is considered as a parameter. In EKF algorithm, fifth order model is used and speed is considered as a parameter and state. Direct filed oriented control is used in all the estimators. The speed of an induction motor is estimated by MATLAB simulation under different speed and load conditions. The estimated parameters along with speed are used for closed loop control.

Index Terms – adaptive observer, natural observer, Sensorless control

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1. Introduction

IIn controlling DC and AC machine drives speed transducers such as tacho-generators, resolvers or digital encoders are used to obtain speed information. They are usually expensive. In defective and aggressive environments, the speed sensor might be the weakest part of the system. These degrade the system's reliability. This has led to a speed-sensorless vector control. In sensorless vector control, speed is estimated by an estimator. In general, an estimator is defined as a dynamic system whose state variables are estimates of the system of interest. Nowadays, a number of adaptive observer design techniques are available for control systems. A limited number of adaptive observer design techniques have been successfully applied to speed-sensorless induction motor control. The speed dependent model uses the estimated speed and the output error between the models to drive the estimated speed toward the actual speed using speed torque adaptation. Kubota's adaptive observer [1]–[5] uses the fourth order model of the induction motor considering only the electrical variables as states and the speed as a parameter to be adapted. Speed is considered as a parameter and state in EKF algorithm [6]-[10].

2. Observers

A lot of speed observer systems are presented in the literature. Most popular methods are based on Luenberger theory, Kalman filters and neural observers [11], [12]. Good results can be obtained with all mentioned observers, but Luenberger algorithms can be simplified, so it can be more useful for industrial applications. Kubota's adaptive observer for multiple parallel connected induction motor drive system is presented in [3], [4]. Average and differential current flowing through the induction motors are considered to make the system stable under unbalanced load conditions. Adaptive scheme is used to estimate the rotor speed combined with state model. In the general observer approaches, the proper observer pole or gain selection which gives reasonable estimation both in the steady state and transient state is very difficult and a tedious task. The structure of Luenberger observer is shown in Fig. 1.

The state space representation of the system is as follows:

$$\frac{dX}{dt} = AX + BU \quad (1)$$

$$Y = CX \quad (2)$$

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

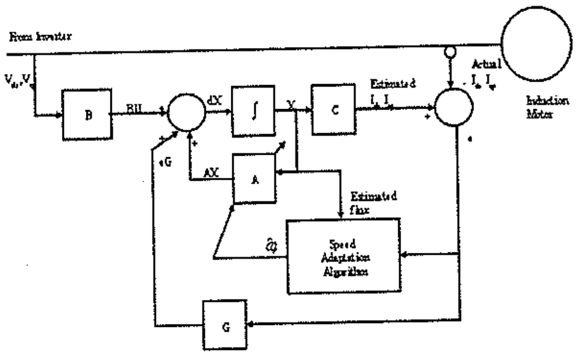

Figure 1 : Block diagram of Luenberger observer

$$A = \begin{bmatrix} \frac{-1}{T_s} & 0 & \frac{L_m}{L'_s L_r \tau_r} & \frac{\omega_r L_m}{L'_s L_r} \\ 0 & \frac{-1}{T_s} & \frac{-\omega_r L_m}{L'_s L_r} & \frac{L_m}{L'_s L_r \tau_r} \\ \frac{L_m}{\tau_r} & 0 & \frac{-1}{\tau_r} & -\omega_r \\ 0 & \frac{L_m}{\tau_r} & \omega_r & \frac{-1}{\tau_r} \end{bmatrix}$$

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

where,

$$\frac{1}{T_s} = \frac{R_s + R_r (L_m / L_r)^2}{L'_s}$$

$$L'_s = \sigma L_s$$

$$X = \begin{bmatrix} i^s_{ds} & i^s_{qs} & \phi^s_{dr} & \phi^s_{qr} \end{bmatrix}^T$$

$$Y = \begin{bmatrix} i^s_{ds} & i^s_{qs} \end{bmatrix}^T = i_s$$

$$U = \begin{bmatrix} v^s_{ds} & v^s_{qs} \end{bmatrix}^T$$

R_s, R_r -stator and rotor resistance respectively (ohm)

L_s, L_r -stator and rotor self inductance respectively (H)

L_m -mutual inductance (H)

$\sigma = 1 - \frac{L_m^2}{L_s L_r}$ -leakage coefficient

τ_r -rotor time constant $= \frac{L_r}{R_r}$

ω_r -motor angular velocity (rad/s)

The full order state observer which estimates the stator current and the rotor flux is given by the following state equations:

equations:

$$\dot{\hat{X}} = \hat{A}\hat{X} + BV_s + G(\hat{i}_s - i_s) \quad (3)$$

where the cap '^' represents the estimated values.

The poles of the observer are made proportional to the poles of the induction motor. Then the gain matrix G is calculated as follows:

$$G = \begin{bmatrix} g_1 & g_2 & g_3 & g_4 \\ -g_2 & g_1 & -g_4 & g_3 \end{bmatrix}^T \quad (4)$$

where

$g_1 = (k-1)(-a_{r11}-a_{r22})$

$g_2 = (k-1)(-a_{i22})$

$g_3 = (k^2-1)(c\, a_{r11}-a_{r21}) + c\,(k-1)(-a_{r11}-a_{r22})$

$g_4 = c\,(k-1)(-a_{i22})$

k is the proportional constant and the value of k chosen is 0.5.

The following proportional-integral adaptive scheme is used practically in order to improve the response of the speed estimation:

$$\hat{\omega}_r = K_P(e_{ids}\hat{\varphi}_{qr} - e_{iqs}\hat{\varphi}_{dr}) + K_I \int (e_{ids}\hat{\varphi}_{qr} - e_{iqs}\hat{\varphi}_{dr})dt \quad (5)$$

Natural observer proposed in [13] is applied to both DC servo and induction motor. It has the natural characteristics of the actual motor under the same conditions of load torque and input voltage. Its convergence will be as fast as that of the motor in reaching its steady state, which is fast enough for most applications. Torque is also estimated along with speed without any feedback. To estimate the rotor speed of an induction machine using natural observer, various machine models have been used. Generally the model is expressed in stator flux oriented reference frame. The motor model proposed in [13] is fifth order model. In this work, fourth order model is used similar to Kubota's adaptive observer [2] – [3]

The natural observer, shown in Fig. 2 for the system described by (1) and (2) is in exactly the same form as the actual system model and has no external feedback i.e. no gain matrix.

The natural observer which estimates the stator current and the rotor flux is written by the following equations:

$$\frac{d\hat{X}}{dt} = \hat{A}\hat{X} + BU \quad (5)$$

$$Y = CX \quad (6)$$

The estimated quantities are denoted by "^".

Load torque is estimated using the active power error as the correction term and is kept within two particular limits to avoid unstable oscillations.

$$\hat{T}_L = K_D\, \dot{e}_P + K_P e_P + K_I \int e_P dt \ \text{limiting} \quad (7)$$

$$\hat{T}_L \in (T_{min}, T_{max}) \quad (8)$$

where

$$e_P = \hat{P} - P = v_{ds}(\hat{i}_{ds} - i_{ds}) + v_{qs}(\hat{i}_{qs} - i_{qs})$$

where "..." denotes all of the other terms not including $\hat{\omega}_r$. These terms are disregarded because $\hat{T}_L$ appears only in the derivative of $\hat{\omega}_r$.

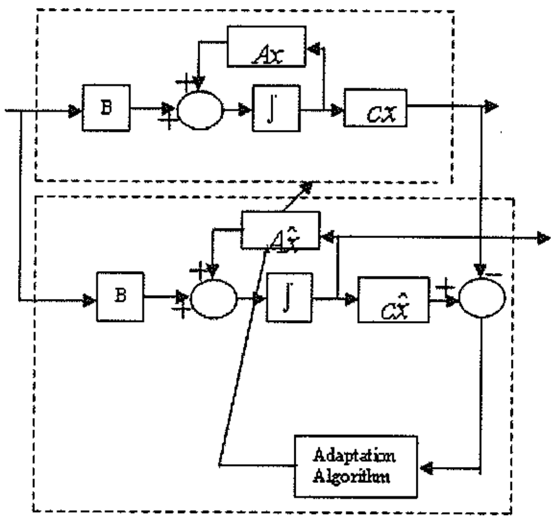

Figure 2 : Block diagram of a natural observer with adaptation

The speed estimation technique in [1] - [4] always needs some correction term in order to follow speed changes. This results in the estimations always lagging the actual values. In natural observer [13], the speed estimation follows the speed changes simultaneously. A new scheme based on current estimation without flux and speed estimations are shown in [14]. The input variables are stator voltages and the output variables are stator current and rotor speed.

3. Extended Kalman Filter

A Kalman filter is simply an optimal recursive data processing algorithm. It processes all available measurements, regardless of their precision, to estimate the current value of all the variables of interest, with the use of (1) knowledge of the system and measurement device dynamics, (2) the statistical description of the system noises, measurement errors and uncertainty in the dynamics models and (3) any available information about initial conditions of the variables of interest. The basic Kalman filter is only applicable to linear stochastic systems, and for non-linear systems the Extended Kalman Filter (EKF) can be used, which can provide estimates of the states of a system or of both the states and parameters.

The EKF is a recursive filter which can be applied to a non-linear, time-varying stochastic system. The EKF uses the partial derivatives of the measurement with respect to the state variables in generating the measurement transformation matrix. In electric drives, the purpose of the Kalman filter is to obtain the unmeasurable states (e.g. rotor speed) by using the measured states and also the statistics of the noise and measurements. In general, the computational inaccuracies, modeling errors and errors in the measurements are considered by means of noise inputs. A critical part of the design is to use correct initial values for the covariance matrices. The main design steps for a speed-sensorless induction motor drive implementation using the discretized EKF algorithm are as follows:

1. Selection of the time domain induction machine model.
2. Discretization of the induction machine model.
3. Determination of the noise and state covariance matrices Q, R and P.
4. Implementation of the discretized EKF algorithm; tuning.

In recent years, the EKF algorithm has been used for the parameter estimation of induction motor. The structure of the EKF is shown in Fig. 3.

In EKF, the rotor speed is considered as a state variable and parameter. This makes the system matrix A nonlinear i.e. $A = A(X)$.

$$X = \begin{bmatrix} i_{ds}^{s} & i_{qs}^{s} & \phi_{dr}^{s} & \phi_{qr}^{s} & \omega_r \end{bmatrix}^T$$

$$Y = \begin{bmatrix} i_{ds}^{s} & i_{qs}^{s} \end{bmatrix}^T = i_s$$

$$U = \begin{bmatrix} v_{ds}^{s} & v_{qs}^{s} \end{bmatrix}^T$$

$$A = \begin{bmatrix} \frac{-1}{T_s^{*}} & 0 & \frac{L_m}{L_s' L_r \tau_r} & \frac{\omega_r L_m}{L_s' L_r} & 0 \\ 0 & \frac{-1}{T_s^{*}} & \frac{-\omega_r L_m}{L_s' L_r} & \frac{L_m}{L_s' L_r \tau_r} & 0 \\ \frac{L_m}{\tau_r} & 0 & \frac{-1}{\tau_r} & -\omega_r & 0 \\ 0 & \frac{L_m}{\tau_r} & \omega_r & \frac{-1}{\tau_r} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

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

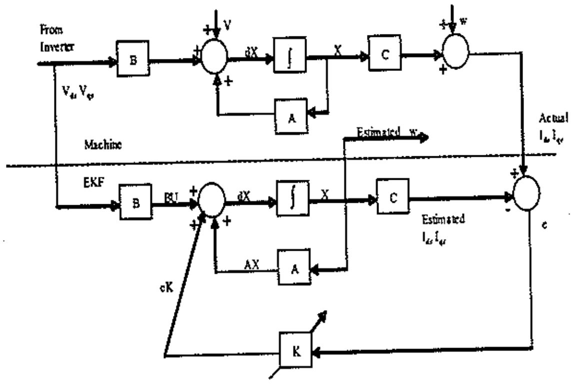

Figure.3 : Structure of EKF

B. Discretized Induction Machine Model

For digital implementation of the EKF, the discretized machine equations are required. These can be obtained from (1) and (2).

$$X(k+1) = A_d X(k) + B_d U(k) \quad (9)$$

$$Y(k) = C_d X(k) \quad (10)$$

$$A_d = \begin{bmatrix} 1-\frac{T}{T_s^*} & 0 & \frac{TL_m}{L_s' L_r \tau_r} & \frac{\omega_r TL_m}{L_s' L_r} & 0 \\ 0 & 1-\frac{T}{T_s^*} & \frac{-\omega_r TL_m}{L_s' L_r} & \frac{TL_m}{L_s' L_r \tau_r} & 0 \\ \frac{TL_m}{\tau_r} & 0 & 1-\frac{T}{\tau_r} & -T\omega_r & 0 \\ 0 & \frac{TL_m}{\tau_r} & T\omega_r & 1-\frac{T}{\tau_r} & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$B_d = \begin{bmatrix} \frac{T}{L_s'} & 0 \\ 0 & \frac{T}{L_s'} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \quad C_d = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

To achieve adequate accuracy, the sampling time should be appreciably smaller than the characteristic time constants of the machine. The final choice for the sampling time should be based on obtaining adequate execution time of the full EKF algorithm and also satisfactory accuracy and stability.

The system noise is represented by $v(k)$ (v-noise vector of the states) which is assumed to be zero-mean and white Gaussian noise. It is independent of $X(k)$ and its covariance matrix is Q and the system model becomes

$$X(k+1) = A_d X(k) + B_d U(k) + v(k) \quad (11)$$

The measurement noise is represented by $w(k)$ which is assumed to be zero-mean and white Gaussian noise. It is independent of $X(k)$ and $V(k)$ and its covariance matrix is P and the output equation becomes

$$Y(k) = CX(k) + w(k) \quad (12)$$

C. Determination of the Noise and State Covariance Matrices Q, R and P

The purpose of the Kalman filter is to obtain the unmeasurable states (e.g. rotor speed) by using the measured states and also the statistics of the noise and measurements. In general, the computational inaccuracies, modeling errors and errors in the measurements are considered by means of noise inputs. A critical part of the design is to use correct initial values for the covariance matrices.

The elements of Q and R depend on the number of state variables [2], [4]. The system noise matrix Q is a five-by-five matrix and the measurement noise matrix R is a two-by-two matrix. This should require the knowledge of 29 elements. However, by assuming that the noise signals are not correlated (no relation between the covariance noise matrices), both Q and R are diagonal and only 5 elements must be known in Q and 2 elements in R.

Generally, the parameters in the direct and quadrature axes are same. This implies that the first two elements in the diagonal of Q are equal ($q_{11} = q_{22}$) and the third and fourth elements are also equal. So Q= diag ($q_{11}, q_{11}, q_{33}, q_{33}, q_{55}$) contains only 3 elements. Similarly, the two diagonal elements in R are equal ($r_{11} = r_{22} = r$), thus R=diag(r, r). It follows that in total only 4 noise covariance elements must be known.

$$Q = \begin{bmatrix} q_{11} & 0 & 0 & 0 & 0 \\ 0 & q_{11} & 0 & 0 & 0 \\ 0 & 0 & q_{33} & 0 & 0 \\ 0 & 0 & 0 & q_{33} & 0 \\ 0 & 0 & 0 & 0 & q_{55} \end{bmatrix} \quad R = \begin{bmatrix} r & 0 \\ 0 & r \end{bmatrix}$$

D. Implementation of the Discretized EKF Algorithm

The state estimates are obtained by the EKF algorithm in the following steps:

Step1. Initialization of the state vector and covariance matrices

Starting values of the state vector $X_o = X(t_o)$, the noise covariance matrices $Q_o(5\times 5)$ and $R_o(2\times 2)$ are set together with the starting value of the state covariance matrix $P_o(5\times 5)$. The starting value of the state covariance matrix can be considered as a diagonal matrix where all the elements are equal. The initial values of the covariance matrices reflect the degree of knowledge of the initial states.

Step2: Prediction of the state vector

Prediction of the state vector at the sampling instant $(k+1)$ is obtained from the input $U(k)$ and the state vector $\hat{X}(k)$.

$$X^*(k+1) = A_d\hat{X}(k) + B_dU(k) \qquad (13)$$

where,

$$\hat{X} = \left[\hat{i}_{ds}(k) \quad \hat{i}_{qs}(k) \quad \hat{\phi}_{dr}(k) \quad \hat{\phi}_{qr}(k) \quad \hat{\omega}_r(k)\right]^T$$

$$U(k) = \left[V_{ds}(k) \quad V_{qs}(k) \quad 0 \quad 0 \quad 0\right]^T$$

Step3: Covariance estimation of prediction

The covariance matrix of prediction is estimated as

$$P^*(k+1) = f(k+1)\hat{P}(k)f^T(k+1) + Q \qquad (14)$$

where, f is the gradient matrix.

$$f(k+1) = \partial/\partial x\left[A_dX + B_dU\right]_{x=\hat{x}(k+1)} \qquad (15)$$

$$f(k+1) = \begin{bmatrix} 1-\frac{T}{T_s^*} & 0 & \frac{TL_m}{L_s^{'}L_r\tau_r} & \frac{\omega_r TL_m}{L_s^{'}L_r} & \frac{TL_m}{L_s^{'}L_r}\phi_{qr} \\ 0 & 1-\frac{T}{T_s^*} & \frac{-\omega_r TL_m}{L_s^{'}L_r} & \frac{TL_m}{L_s^{'}L_r\tau_r} & \frac{-TL_m}{L_s^{'}L_r}\phi_{dr} \\ \frac{TL_m}{\tau_r} & 0 & 1-\frac{T}{\tau_r} & -T\omega_r & T\phi_{qr} \\ 0 & \frac{TL_m}{\tau_r} & T\omega_r & 1-\frac{T}{\tau_r} & T\phi_{dr} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

where,

$$\omega_r = \hat{\omega}_r(k+1) \qquad \phi_{dr} = \hat{\phi}_{qr}(k+1) \qquad \phi_{qr} = \hat{\phi}_{qr}(k+1)$$

In $f(k+1)$, 17 elements are constants and remaining 8 elements are variables. In a practical DSP application it is useful to compute first $f(k+1)$, since it contains the constant required in $X^*(k+1)$. This leads to reduced memory requirements and reduced computational time.

Step4: Kalman filter gain computation

For induction motor applications, the Kalman gain matrix contains 2 columns and 5 rows.

$$K(k+1) = P^*(k+1)h^T(k+1)[h(k+1)P^*(k+1)h^T(k+1)+R]^{-1} \qquad (16)$$

$h(k+1)$ is a gradient matrix, defined as

$$h(k+1) = \partial/\partial x\left[C_dX\right]_{x=x^*(k+1)} \qquad (17)$$

$$h(k+1) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

Step5: State vector estimation

The state vector estimation (corrected state vector estimation, filtering) at time $(k+1)$ is performed as follows:

$$\hat{X}(k+1) = X^*(k+1) + K(k+1)[Y(k+1) - \hat{Y}(k+1)] \qquad (18)$$

$$\hat{Y}(k+1) = C_dX^*(k+1) \qquad (19)$$

Step6: Covariance matrix of estimation error

The error covariance matrix is obtained from

$$\hat{P}(k+1) = P^*(k+1) - K(k+1)h(k+1)P^*(k+1) \qquad (20)$$

Step7: Updation

Put $k = k+1$, $X(k) = X(k-1)$, $P(k) = P(k-1)$ and go to step 2.

The EKF described above can be used to estimate the speed of an induction motor under both steady state and transient conditions.

E. Tuning of the Covariance Matrices

The tuning of the EKF involves an iterative modification of the covariance in order to yield the best estimates of the states [6]. Changing the covariance matrices Q and R affects both the transient and steady state operation of the filter. Increasing Q corresponds to stronger system noises or larger uncertainty in the machine model used. If the covariance R is increased, this corresponds to the fact that the measurements of the currents are subjected to a stronger noise and should be weighted less by the filter. Thus the filter gain matrix elements will decrease and this results in slower transient performance. The initial values of Q and R are selected randomly and tuned accordingly.

A reduced-order EKF-based estimator is presented to estimate the rotor flux in [5]. Speed of the induction motor is not estimated in this paper. The estimator uses the mathematical model of the rotor circuit to perform the function of prediction of the rotor flux components. Moreover the estimator includes a third equation to predict the inverse rotor time constant. Reducing the order of the mathematical model simplifies the computational problems and makes it technologically feasible to implement Kalman filters in real time with DSP processors.

DC link voltage is used to estimate the speed of the induction motor along with the measured stator currents in [6]. The execution time of the EKF algorithm itself is about 150μs and the EKF is updated every 200μs. Within this time span the rotor speed is regarded as almost constant. The speed estimation method is implemented by TMS320C30 DSP chip. The compensation of the parameter variation with the increase of temperature is not studied.

To optimize the covariance and weight matrices of EKF, little attempt has been made in [7] using genetic algorithm. Speed is estimated from the measured terminal voltage instead of DC link voltage. EKF based sensorless estimation algorithms for the stator and rotor oriented models of induction motor is developed in [8]. This algorithm is aiming minimum estimation error in both transient and steady state over a wide speed range including very low and zero speed estimation.

A major challenge at very low and zero speed is the lost coupling effect from the rotor to the stator. So as a solution, load torque and rotor speed are simultaneously estimated, with the velocity taken into consideration via the equation of motion and not as a constant parameter. The advantage is that it does not require change of algorithm or adjustment of gain or parameters for convergence at steady state. Closed loop operation is not discussed in that paper.

Temperature and frequency- dependent variations of the rotor (R_r') and stator (R_s) resistances are estimated accurately along with load torque, flux and speed in transient and steady state [9]. Two EKF algorithms are executed consecutively at every time step when compared with single EKF which estimate R_s or (R_r') only.

In EKF algorithm [5]-[9] and [15], manual tuning of covariance matrices using 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. In the past, the implementation of Kalman filter for the motor drive system is difficult due to the large computation time. But, recent advances in computer technology including high-speed digital signal processor make the digital implementation of Kalman filter feasible without heavy computation burden in the motor drive system.

4. Simulation Results

Table I shows the rating of the induction motor used for simulation. Direct oriented field sensorless control scheme is used because it is less sensitive to parameter variation. Simulations are carried out under different load and speed conditions.

TABLE I

Rating and Parameters of Induction Motor

Motor Rating	
Output	3.7 kW
Poles	4
Voltage	160 V
Current	20 A
Motor Speed	1500 rpm
R_s	0.3831 ohm
R_r	0.2367 ohm
L_s	33.34 mH
L_r	33.34 mH
L_m	32.11 mH

Case (i) Luenberger observer method

Speed is estimated from the measured terminal voltages and currents using Luenberger observer. Proportional and integral gain constants used for Luenberger observer are 0.8 and 1200 respectively. The estimated speed and actual speed response are shown in Fig. 4 for a step change in speed and load. At first, the speed is set at 400 rpm and at t = 1.5s, speed command changes from 400 rpm to 600 rpm and motor runs at no load condition. At t=3s, a load of 5 Nm is applied to the motor at a speed of 600 rpm. The torque response and the torque reference current (i_{qs}) are depicted in Fig. 5. The difference between the actual speed and the estimated speed is shown in Fig. 6 and is almost zero value under steady state.

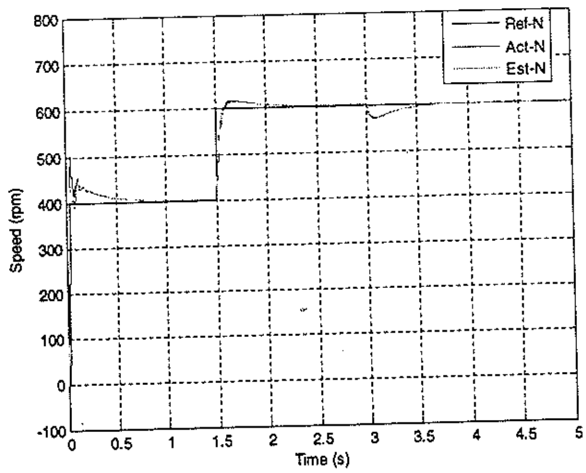

Fig.ure 4 : Speed response

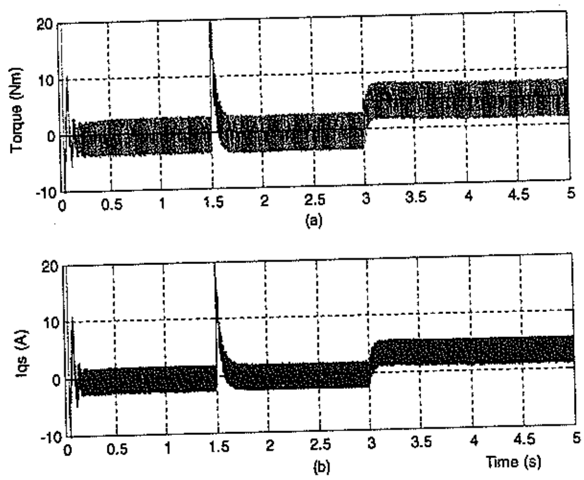

Figure 5 : Torque and current response (a) Torque (b) iqs

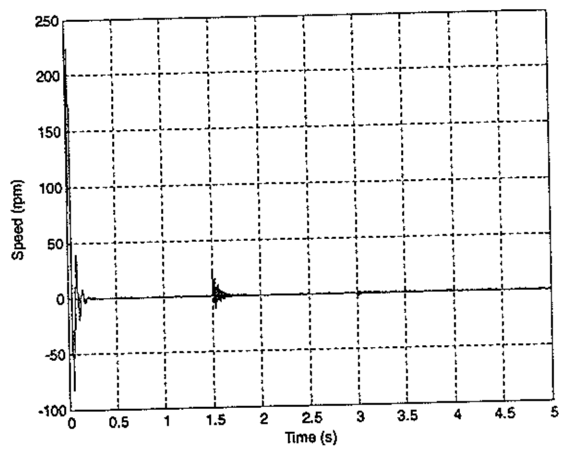

Fig 6 : Error in estimated speed

Case (ii) Natural observer method

Natural observer algorithm is explained clearly in [13]. Fourth order induction motor model is used similar to Luenberger observer but the model used in [13] is fifth order. The torque adaptation gains used in natural observer are $K_P = 0.005$, $K_I = 0.2$ and $K_D = 0$. Load torque is limited between 80Nm to -80 Nm for estimators. Fig. 7 depicts the speed response of a natural observer for a step change in speed and load. It estimates the load torque along with speed. Initially, the speed is set at 400 rpm at no load condition and at t = 1.5s, speed command changes from 400 rpm to 600 rpm. It is observed that the estimated speed follows the actual speed. At t = 3s, a load of 5 Nm is applied the motor and speed is maintained at 600 rpm. The estimated torque by load torque adaptation is shown in Fig. 8.

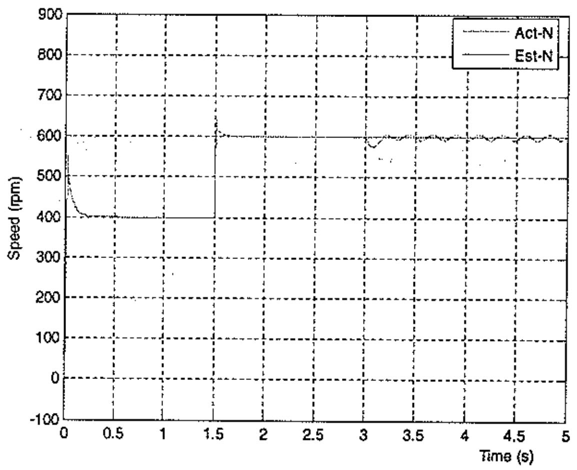

Figure. 7 Speed response by natural observer

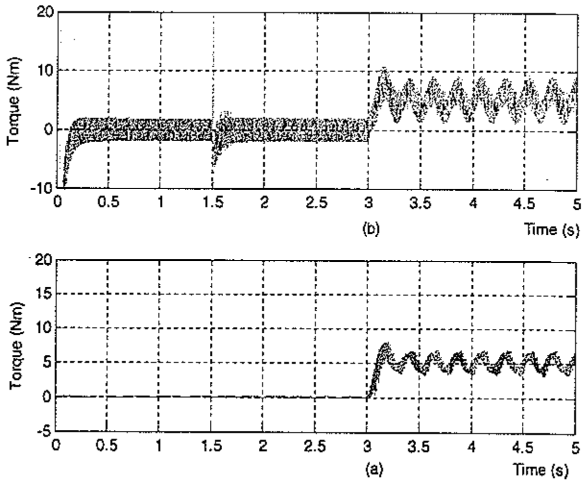

Fig. 8 Torque response by natural observer (a) Actual torque (b)Estimated torque

Case (iii) EKF Algorithm

Speed reversal test is conducted in EKF. The speed and i_{ds} responses are shown in Fig. 9. The motor speed command is set at 1000 rpm. The induction motor runs at no load and at t = 5s, speed is reversed to -1000 rpm and the estimated speed follows the actual speed. The error between the estimated speed and the actual speed depends on the elements of the covariance matrices. Actual speed refers the speed derived from the model. The torque response and the corresponding torque reference current are shown in Fig. 10.

Step change in load test is also carried out by simulation. The speed of the motor is maintained constant at 1000rpm. At t = 0, the load torque is zero and at t = 2.5s, a sudden load of 10 Nm is applied to the motor. The speed response and the torque response are shown in Fig. 11 and Fig. 12.

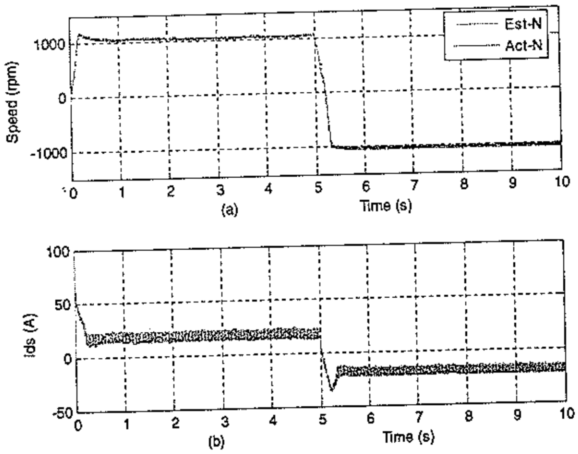

Figure 9 Speed Reversal test by EKF

(a) Speed response (b) i_{ds}

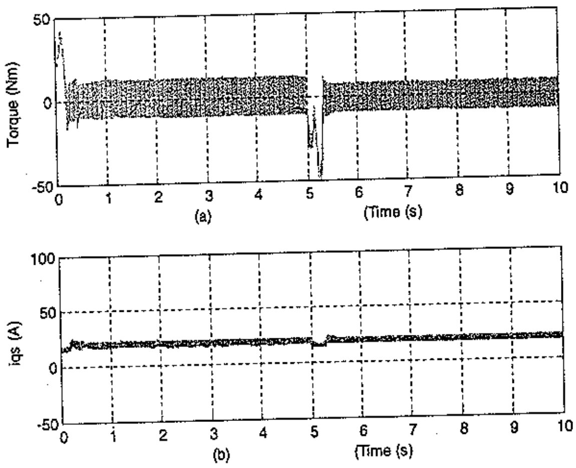

Figure 10 Torque Response by EKF

(a) Torque response (b) i_{qs}

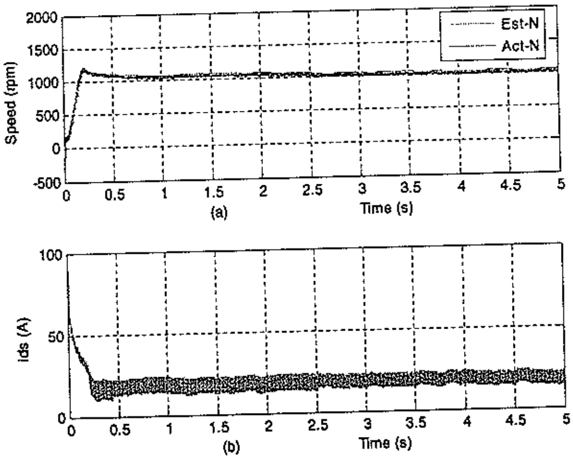

Figure 11 Step torque response by EKF

(a) Speed response (b) i_{ds}

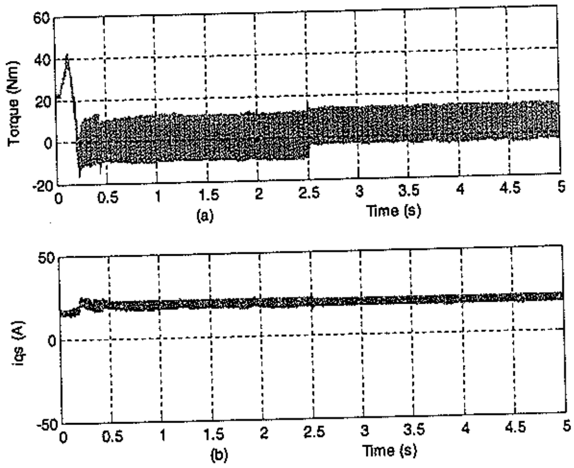

Fig. 12 Torque Response by EKF

(a) Torque response (b) i_{qs}

TABLE II
Performance Comparison

Parameters	Luenberger Observer	Natural Observer	Extended Kalman Filter
Machine Model	Fourth Order induction motor model	Fourth or fifth order induction motor model	Fifth order induction motor model
Speed	Considered as a parameter	Considered as a parameter	Considered as a parameter and state
Steady state error	Less	Around zero	Depends upon the noise covariance matrices
Algorithm	Simple	Simple	Computationally Complex
Correction term (feedback)	Required (by observer gain G)	Not required	Required (by Kalman gain K)

5. Conclusion

This paper has presented the overview of three different speed estimation schemes and simulation results are presented. In Luenberger observer, speed and rotor fluxes of the induction motor are estimated based on adaptive control theory. The natural observer design technique is very simple in structure. Natural observer estimates torque along with speed. The convergence is achieved using parameter adaptation; the convergence problems of the adaptation algorithm and observer are simplified. Also, since the feedback signal is used only in the adaptation scheme, the measurement noise is filtered by the adaptation scheme. EKF considers the modeling inaccuracies and measurement errors and thereby improves the performance of the induction motor drive. EKF is computationally more complex than other estimators. The error in the estimated speed depends on the initial values of system and measurement noise covariance matrices.

References

[1] H. Kubota and K. Matsuse, "Speed sensorless field-oriented control of induction motor with rotor resistance adaptation," *IEEE Transactions on Industrial Applications.*, vol. 30, pp. 1219–1224, Sept. /Oct. 1994.

[2] H. Kubota, K. Matsuse, and T. Nakano, " New adaptive flux observer of induction motor for wide speed range motor drives," in Proc.*IEEE IECON'90*, vol.2, pp.921-926, 1990.

[3] K. Matsuse, Y. Kouno,H. Kawai and J. Oikawa, " Characteristics of speed sensor-less vector controlled dual induction motor drive connected in parallel fed by a single Inverter", *IEEE Transactions on Industrial Applications.*, vol. 40, pp. 153-161, Jan./Feb. 2004.

[4] K. Matsuse, Y. Kouno, H. Kawai and S. Yokomizo, "A speed-sensor-less vector control method of parallel-connected dual induction motor fed by a single inverter", *IEEE Transactions on Industrial Applications.*, vol. 38, pp. 1566–1571, Nov./Dec. 2002.

[5] H. Kubota, K. Matsuse, and T. Nakano, "DSP-based speed adaptive flux observer of induction motor", *IEEE Transactions on industry applications*, vol. 29, no. 2, pp.344-348, March / April 1993.

[6] Luigi Salvatore, Silvio Stasi, and Lea Tarchioni, "A new EKF-based algorithm for flux estimation in induction machines", *IEEE Transactions on Industrial Electronics*, vol.40, no.5, pp.496-504, October 1993.

[7] Young-Real Kim, Seung-Ki Sul and Min-Ho Park, "Speed sensorless vector control of induction motor using Extended Kalman Filter", *IEEE Transactions on industry applications*, vol. 30, no. 5, pp.1225-1233, September / October 1994.

[8] 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, Feb. 2002.

[9] Murat Barut, Seta Bogosyan and Metin Gokasan, "Speed-sensorless estimation for induction motors using Extended Kalman Filters", *IEEE Transactions on. Industrial Electronics*, vol. 54, no.1, pp. 272-280, Feb. 2007.

[10] Murat Barut, Seta Bogosyan and Metin Gokasan, "Experimental evaluation of braided EKF for sensorless control of induction motors", *IEEE Transactions on Industrial Electronics*, vol. 55, no.2, pp. 620-632, Feb. 2008.

[11] T. Orlowska-Kowalska and K. Szabat, "Control of the drive system with stiff and elastic couplings using adaptive neuro-fuzzy approach," *IEEE Transactions on Industrial Electronics*, vol. 54, no. 1, pp. 228–240, Feb. 2007.

[12] T. Orlowska-Kowalska and K. Szabat, "Neural-network application for mechanical variables estimation of a two-mass drive system," *IEEE Trans.Industrial Electronics*, vol. 54, no. 3, pp. 1352–1364, Jun. 2007.

[13] Sidney R. Bowes, Ata Sevinc and Derrick Holliday, " New natural observer applied to speed sensorless DC servo and induction motors,", *IEEE Transactions on Industrial Applications.*, vol. 51, no.5, pp. 1025–1032, Oct. 2004.

[14] Young Ahn Kwon and Sung Hwan Kim, "A new scheme for speed-sensorless control of induction motor", *IEEE Transactions on Industrial Electronics*, vol. 51, no.3, pp. 545–550, June 2004.

Heui-Wook Kim and Seung-Ki Sul, "A New motor Speed Estimator Using Kalman Filter in Low-Speed range", *IEEE Transactions on Industry Applications*, vol. 43, no. 4, pp.498-504, August 1996.

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