# Chapter - 10
# Controlling of Flux and Torque Vector Controlled Induction Motor using Extended Kalman Filter


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**Abstract**

The most popular industrial machines are three-phase induction motors since they are significantly less expensive and durable because they don't have a commutator. The majority of activities in businesses, agriculture, commercial complexes, etc. are propelled by them. The flux axis and the armature axis are, however, always in quadrature in the separately excited DC machines due to the inclusion of a commutator. As a result, there is always an inherent decoupling between the main flux and the armature flux, also known as vector or decoupled control, which allows for flexible operation and, as a result, accurate control. The stator current must satisfy the induction motor's torque and flux requirements because it is singly supplied.

The basic foundation needed for vector control of induction motor (IM) is decoupling of stator currents into flux and torque components along the rotor flux axis. For this information, the instantaneous rotor position is necessary. Depending on the methods employed for finding rotor position, vector control is two types. Direct vector control (DVC) and indirect vector control (IVC). In direct vector control, the rotor position is sensed by Hall Effect sensors introduced in the stator. The basic drawback is that it introduces harmonics in the output voltage and results in cost and size. In Sensorless vector control (SVC), the rotor position is estimated using mathematical analysis and a dynamic machine model, which eliminates speed sensors, encoder, and motor shaft extension and hence reduces cost and ruggedness. The basic methods employed for detecting rotor position by sensorless control involve Conventional methods like the Extended Kalman filter method.

**Keywords:** Kalman filter, sensorless control, induction motor, flux, torque speed

## 1. Introduction

The thyristor controlled rectifiers are playing a great role in DC drives, because of their excellent performance characteristics like torque-speed and effective-flux control [8]. However, the variable speed induction motor drives (IMD) are great importance in the area of research and the related industry applications. This technology has been used because of its applications in inverter with pulse width modulation (PWM) schemes, which generate a poly-phase supply of a known frequency [8].

Induction motors (IM) have notable advantages like excellent self-starting capability, high efficiency, very simple and rugged structure, high torque-to-weight ratio, low cost, absence of the commutator and small inertia [8]. But in most industrial applications, it is required to get a tremendous response for torque, speed or position control, similar to DC motors. Besides, it has its own disadvantages, i.e., nonlinear, complex, multivariable mathematical model and not capable of variable speed operations [15, 16]. The above disadvantages are addressed by using elegant motor controllers and variable controllers, i.e., Scalar as well Vector drive or Field-Orientation Control (FOC) [1, 3].

The block diagram of SVCIM, shown in Figure.1, gives the estimation of speed by the EKF method.

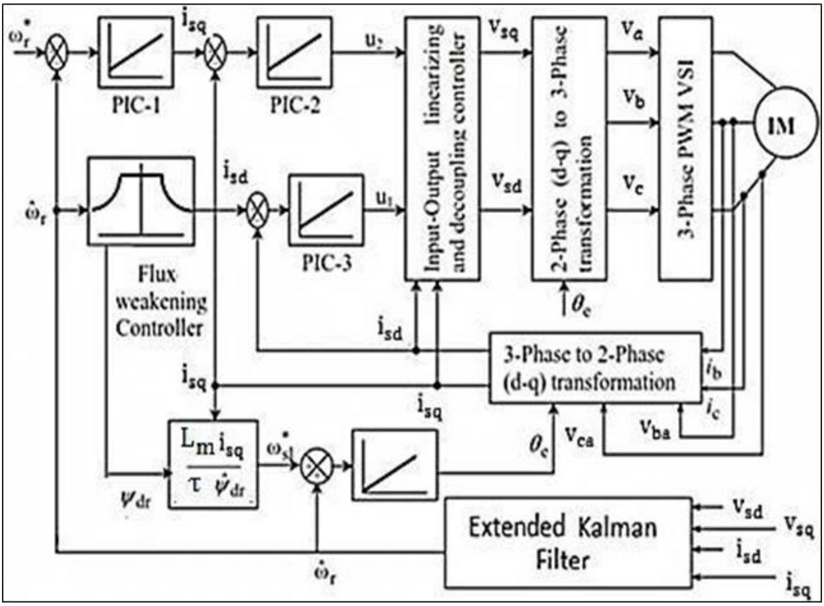


**Fig 1:** Block diagram of speed estimation of SVCIM by EKF Method

## 2. Extended kalman filter method

The block diagram of SVCIM, shown in Figure. 1, gives the estimationof speed by the EKF method.

Here the speed is estimated by Extended Kalman filter and from the estimated speed, the flux proportional to the speed required for saturation is the estimated value of flux. The EKF is a full order stochastic observer for the recursive optimum state estimation of a nonlinear dynamical system in real-time by using signals that are corrupted by noise. The noise sources in EKF take into account measurement and modeling inaccuracies. The block diagram of the EKF in Figure. 2 estimates speed, the machine model of the same indicated on the top. The EKF algorithm uses the full machine dynamic model where $\omega_r$ is considered as a parameter as well as a state [4].

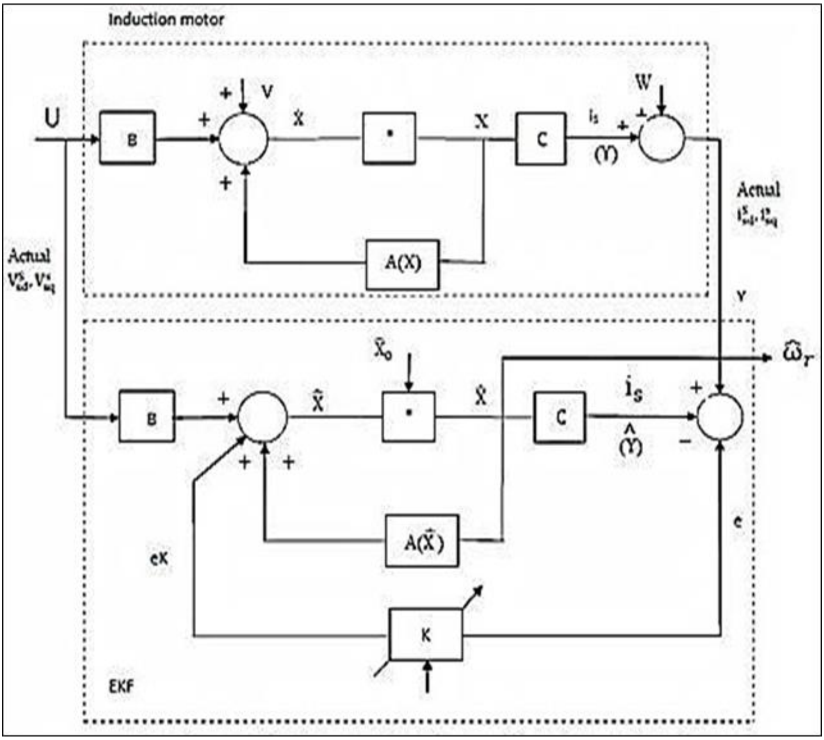


**Fig 2:** Extended kalman filter for the estimation of speed

The EKF modeling to estimate the speed of SVCIM is done considering the following notations:

Where: x is the state vector

A = System matrix

B = Input matrix

The speed obtained by the extended Kalman filter is the estimated speed for the Control of IM. The implementation of the discretized EKF algorithm is as follows:

1) Selecting an induction motor model in the time domain.
2) Discretization of the machine model.
3) Calculating the noise and state covariance matrices Q, R and P.
4) Implementation of the discretized EKF algorithm.
5) Tuning of the covariance matrices.

## 3. Time domain induction machine model

The modelling of the induction motor is in a stator flux oriented reference frame to estimate the rotor speed using EKF. In EKF, the rotor speed is a state variable and parameter. For the induction motor control in the above mode, the modelling is required in the state-space analysis [18].

The augmented machine model is given by:

For attaining acceptable accuracy, the sampling time should be appreciably shorter than the characteristic time constant of the machine; the final choice of sampling time should enable adequate execution time of the full EKF algorithm and satisfactory accuracy and stability. The sampling time for simulation analysis is 0.001 seconds.

Here v (k) (v-noise vector of the state, which is assumed to be zero mean and white Gaussian noise) represents system noise. It is independent of X (k) and if its covariance matrix is Q, then the system model becomes

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

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 if its covariance matrix is P, then the output becomes $Y(k) = C_d X(k) + w(k)$

## 4. To find the noise and state covariance matrices

The Kalman filter plays a vital role in obtaining the immeasurable states by using the measured states and statistics involved in noise and measurements. A critical design lies in the correct initial values of covariance matrices Q and R. The size of the covariance matrix Q and R depend on no of state vector and output vector, here Q is a 5x5 matrix, and R is a 2x2 matrix.

The number of state variables depends on elements of Q and R. The system noise matrix Q is a five by five matrix, and the measured noise matrix R is a two by two matrix. The assumption is that the noise signals are not correlated. Now both Q and R get reduced to diagonal matrices with 5 elements and 2 elements, respectively. Since the parameters in the direct and quadrature axes are the same, the first two elements in the diagonal matrices of Q are equal, and the third and fourth elements are also equal. So Q = diagonal ($q_{11}$, $q_{11}$, $q_{33}$, $q_{33}$, $q_{55}$) contain only 3 elements and two diagonal elements in R are equal ($r_{11}=r_{22}=r$), hence R = diagonal (r, r). It follows that only 4 noise covariant elements must be known.

## 5. Tuning of the covariance matrix

The tuning of the EKF involves an iterative modification of the covariance matrix, which gives the best estimates of the states. Changing the covariance matrices Q and R affect both the transient and steady-state operation of the EKF. Increasing Q corresponds to more substantial system noises or enormous uncertainty in the machine model and increasing covariance R corresponds to the fact that measurement of the currents are subjected to more substantial noise and should be weighed less by the filter.

The initialization of matrices Q and R is by hit and trial method and tuned accordingly. From experience, the value of $Q_{55}$ is chosen higher than the remaining elements in the Q matrix, and the values of R matrix elements are higher than Q matrix elements [17].

## 6. Results

The convergence criteria and precision value of flux and speed lie in the convergence of the covariance error matrix, which gives the estimated value of flux and speed for the machine. The performance of the motor in terms of speed and flux along with other parameters like speed error, flux error, and torque are analysed. The performance of speed and torque in terms of peak overshoot and peak time is found numerically and tabulated. The peak overshoot ($M_p$) is the peak value attained by the curve during simulation time and peak time ($t_p$) is a time where magnitude reaches a peak value. Table. 1 gives the ratings of the induction motor considered.

**Table 1:** Ratings and parameters of induction motors

| 3Φ-Induction motor Specifications | |
|---|---|
| **Parameter** | **Value** |
| Input voltage (AC) | 220V(Rms), 50Hz |
| Rated Power and current | 0.75 kW, 3A |
| Base speed | 1440 rpm |
| Stator and rotor resistances ($R_S$, $R_r$) | 6.37Ω,4.3Ω |
| Stator and rotor self-inductances ($L_S$, $L_r$) | 0.26H |
| Mutual inductance between stator and rotor ($L_m$) | 0.24H |
| Moment of Inertia of motor and load (J) | 0.0088 $Kg \cdot m^2$ |
| Viscous friction coefficient (β) | 0.003N·m·s/rad |

The performance curves for estimated speed, speed error, estimated torque, reference flux, estimated flux, and flux error is as follows:

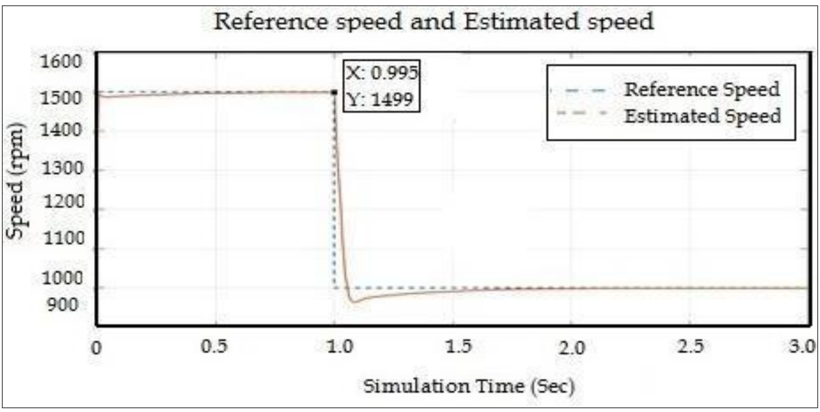


**Fig 3:** Plot showing the estimated and reference speeds for the EKF controller

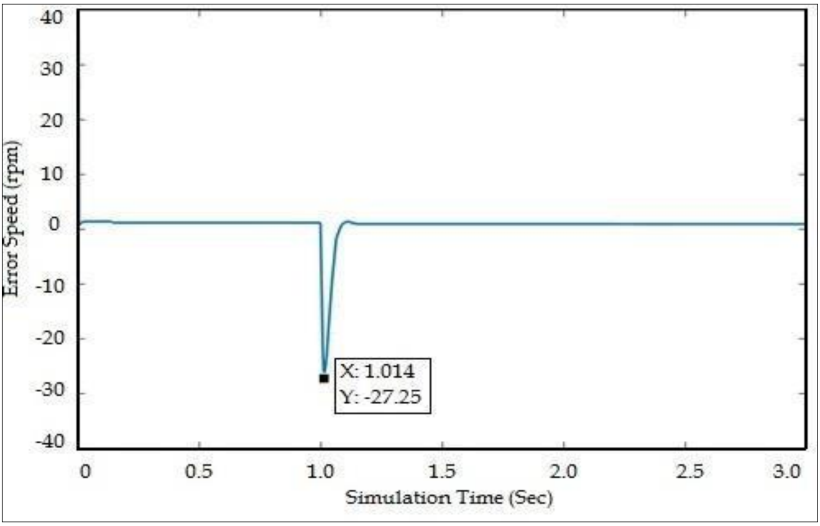


**Fig 4:** Plot showing speed error and time using the EKF controller

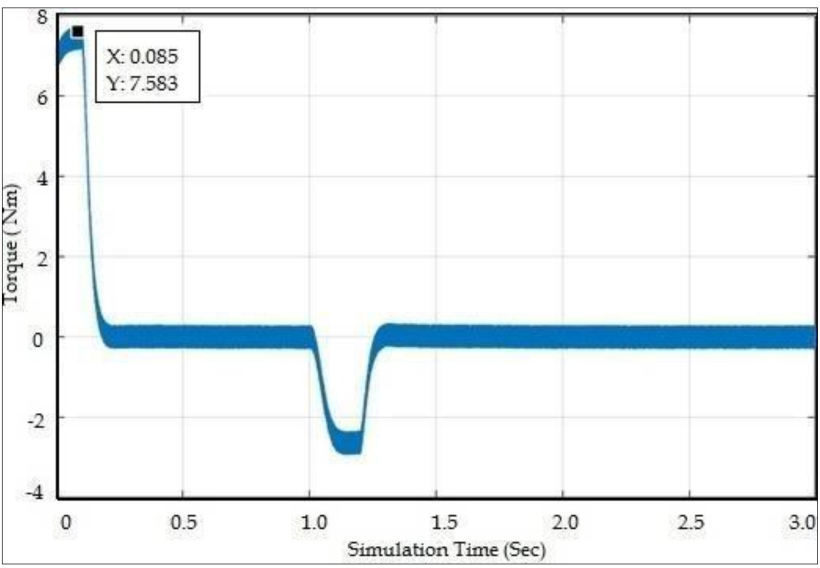


**Fig 5:** Plot showing actual torque using the EKF controller

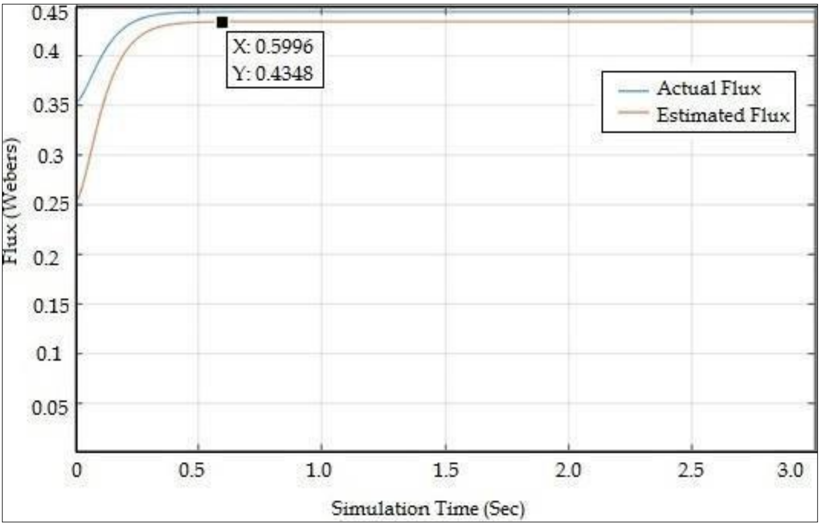


**Fig 6:** Plot showing actual flux and estimated flux Vs. Time by EKF controller

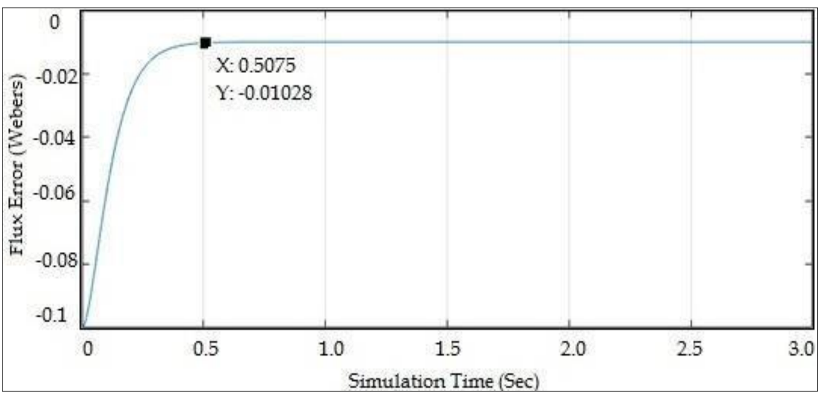


**Fig 7:** Plot showing Flux error using the EKF controller

From the above Figures. 3 to 7 for estimated speed, reference speed, speed error, estimated torque reference flux, estimated flux, and flux error for EKF controlled SVCIM, the following is analysis drawn: the estimated speed is less than reference by 0.2%, and the settling time is 716 milliseconds. The estimated torque reaches a peak value of 7.736 seconds in a peak time of 94 milliseconds. The estimated flux is 0.434 Weber's and reaches a peak value in 2.36 seconds. Table.3.2gives the response for speed and torque in terms of peak overshoot ($M_p$) and peak time ($t_p$) for EKF controlled SVCIM.

**Table 2:** Response for speed and torque in terms of peak overshoot (Mp) and peak time (tp) for EKF controlled SVCIM

| Parameter | Peak overshoot (Mp) (RPM) | Peak time (tp) (Seconds) |
|---|---|---|
| Speed (RPM) | 1491 | 0.716 |
| Speed error | 1.430 | 2.221 |
| Torque (N-m) | 7.736 | 0.094 |

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