# A COMPARATIVE ANALYSIS OF MRAS BASED AND EXTENDED KALMAN FILTER BASED SENSORLESS VECTOR CONTROL OF INDUCTION MOTOR DRIVES.

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**Abstract**

In recent years, sensorless control scheme for AC drives has been one of the most popular research topics in the area. For direct control of AC motor s, information about its rotational speed or rotational position is crucial and in general shaft mounted tacho-generators and resolvers are used to measure them. The elimination of those transducers has long been an attractive prospect, since the shaft transducers and associated signal wiring are a significant source of failure, additional cost and additional weight. Numerous approaches have been proposed to estimate the rotor velocity and/or position from the machine terminal properties, such as the stator voltage or current. The operation of speed controlled AC drives without mechanical speed sensor or position sensors requires the estimation of internal state variable of the machine. The objective of this paper is to present implementation of a sensorless vector control for a three phase induction motor using Model Referencing Adaptive System and Extended Kalman Filter; compare the results of both the methods.

**Keywords:** Vector Control, Sensorless Control, Model Referencing Adaptive System, Extended Kalman Filter, State Vector, Indirect stator field orientation, Induction motor drives, Rotor speed estimation

## I. INTRODUCTION

Sensorless control schemes using motor terminal voltages and currents, works very well at high speeds of operation, with the assumption that stator drops are negligible**.** Several speed estimation techniques are available for sensorless vector control of three phase induction motor drives. The speed can be calculated by Model Referencing Adaptive System (MRAS), where the output of a reference model is compared with the output of an adjustable or adaptive model until the errors between the two models is zero. MRAS based estimators are preferred because of their simplicity, ease of implementation and stability.

The biggest problem of MRAS based approach is that it does not work at zero and low speed due to parameter variation at low speed, which are generally considered to be constant. It has been mathematically proven that the induction motor model becomes unobservable at zero speed operation. For better results we need an observer or a filter. The Kalman filter has a good dynamic behaviour, disturbance resistance, and it can work even in a standstill position. Implementing a filter is a very complex problem, and it requires the model of the AC motor to be calculated in real time. Also, the Filter equations must be calculated, which normally means many matrix multiplications and one matrix inversion. Nevertheless, these requirements can be fulfilled by a processor with high calculation performance. The Extended Kalman Filter (EKF) is a full order stochastic observer for the recursive optimum state estimation of a nonlinear dynamic system in real time by using signals that are corrupted by noise. The EKF algorithm uses the full machine dynamic model, where the speed $\omega_r$ is considered a parameter as well as a state. In this paper the results obtained in Model Referencing Adaptive Control (MRAC) and EKF estimation are presented and are compared.

## II. Machine Model For MRAC.

The basic block diagram of MRAS speed estimation is shown in Fig 1. The output of a reference model is compared with the output of an adjustable or adaptive model until the errors between the two models vanish to zero. The voltage model's stator side equations are defined as a *Reference Model.* The reference model receives the machine stator voltage and current signals and calculates the rotor flux vector signals. The current model flux equations are defined as an adaptive model in fig 1. This model calculates fluxes from the input stator currents only if the speed signal $\omega_r$ is known. This approach makes use of redundancy of two machine model of different structure that estimates the state variables. Both models are referred to a stationary reference frame (Stanley Model)[10] in which time varying inductance in the voltage equations of an induction machine due to electric circuits in relative motion can be eliminated by transforming the rotor variables associated with fictitious stationary windings. The rotor variables are transformed to a stationary reference frame fixed on the stator.

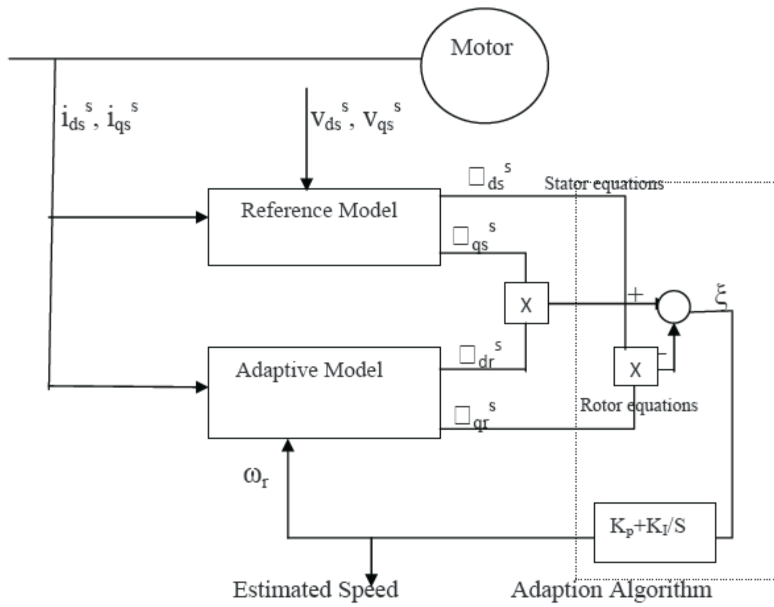


Fig. 1. Basic Block Diagram of MRAS speed estimation

**Reference Model**

The stator voltage is given by

$$V_s = R_s i_{ds} + p\Psi_{ds}^s$$

And by applying KVL to stator side, the stator voltage is given by

$$V_s = R_s i_{ds} + L_{ls} p i_{ds} + p\Psi_{dm}$$

$$\Psi_{dr} = L_r i_{dr} + L_m i_{ds}$$

$$\Psi_{dr} = \frac{L_r}{L_m}\Psi_{dm} - L_{lr} i_{ds}$$

$$\Psi_{dm} = \frac{L_m \Psi_{dr} + L_{lr} L_m i_{ds}}{L_r}$$

$$V_{ds} = \frac{L_m}{L_r}\frac{d}{dt}\Psi_{\mathrm{dr}} + (R_s + \sigma S L_s) i_{ds}$$

Where

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

$$L_{ls} = L_s - L_m$$

And

$$L_{lr} = L_r - L_m$$

The stationary frame equations for reference model are given by

$$\frac{d}{dt}\Psi_{dr}^{s} = \frac{L_r}{L_m}[\,V_{ds}^{s} - (R_s + \sigma S L_s) i_{ds}^{s}\,]$$

And

$$\frac{d}{dt}\Psi_{qr}^{s} = \frac{L_r}{L_m}[\,V_{qs}^{s} - (R_s + \sigma S L_s) i_{qs}^{s}\,]$$

**Adaptive Model**

The rotor circuit equations are given by

$$R_r i_{dr} + \omega_r \Psi_{qr} + p\Psi_{dr} = 0$$

$$R_r i_{qr} - \omega_r \Psi_{dr} + p\Psi_{qr} = 0$$

The stationary frame equations for adaptive model are given by

$$\frac{d}{dt}\Psi_{dr}^{s} = \frac{L_m}{T_r} i_{ds}^{s} - \omega_r \Psi_{qr}^{s} - \frac{1}{T_r}\Psi_{dr}^{s}$$

And

$$\frac{d}{dt}\Psi_{qr}^{s} = \frac{L_m}{T_r} i_{qs}^{s} + \omega_r \Psi_{dr}^{s} - \frac{1}{T_r}\Psi_{qr}^{s}$$

Where

$$T_r = \frac{L_r}{R_r}$$

## III. MACHINE MODEL FOR EXTENDED KALMAN FILTER METHOD.

The block diagram for Extended Kalman Filter for speed estimation is shown in Fig.2, where the machine model is indicated on the top. The EKF algorithm uses the full machine dynamic model. The augmented machine model is given by

$$\frac{dX}{dt} = AX + BV_s \qquad (1)$$

$$Y = CX$$

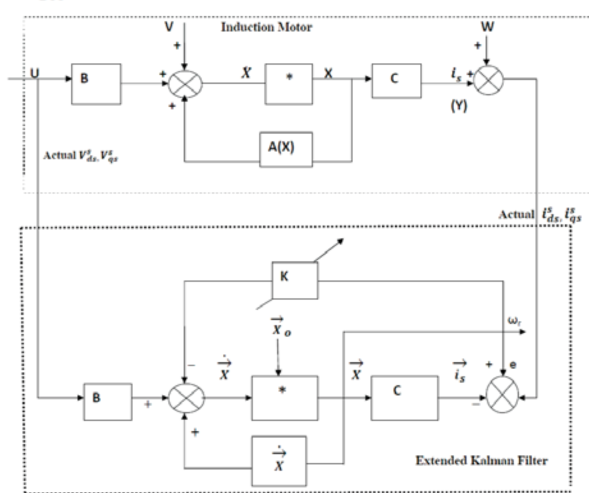


Fig. 2. Extended Kalman Filter For Speed Estimation

Where
$$A = \begin{bmatrix} \frac{-(L_m^2 R_r + L_r^2 R_s)}{\sigma L_s L_r^2} & 0 & \frac{L_m R_r}{\sigma L_s L_r^2} & \frac{L_m \omega_r}{\sigma L_s L_r} & 0 \\ 0 & \frac{-(L_m^2 R_r + L_r^2 R_s)}{\sigma L_s L_r^2} & \frac{-L_m \omega_r}{\sigma L_s L_r} & \frac{L_m R_r}{\sigma L_s L_r^2} & 0 \\ \frac{L_m R_r}{L_r} & 0 & \frac{-R_r}{L_r} & -\omega_r & 0 \\ 0 & \frac{L_m R_r}{L_r} & \omega_r & \frac{-R_r}{L_r} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

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

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

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

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

And $V_s = \begin{bmatrix} v_{ds}^s & v_{qs}^s \end{bmatrix}^T$ is the input vector.

Equation (1) is of the fifth order, where $\omega_r$ is a state as well as a parameter. If speed variation is negligible, then $\frac{d\omega_r}{dt} = 0$ . This is a valid consideration if the computational sampling time is small or load inertia is high. With $\omega_r$ as a constant parameter, the machine model used in the EKF is linear.

## IV. SIMULATION RESULTS

The simulation results for MRAC and EKF based sensorless vector control of a three phase induction motor are as given below.

Simulink Root Block Diagram Of Sensorless Control Of Induction Motor Using MRAS and EKF are given in Fig 3.and Fig.4 respectively. The simulation results for various case studies are shown from Fig. 5 to Fig.8

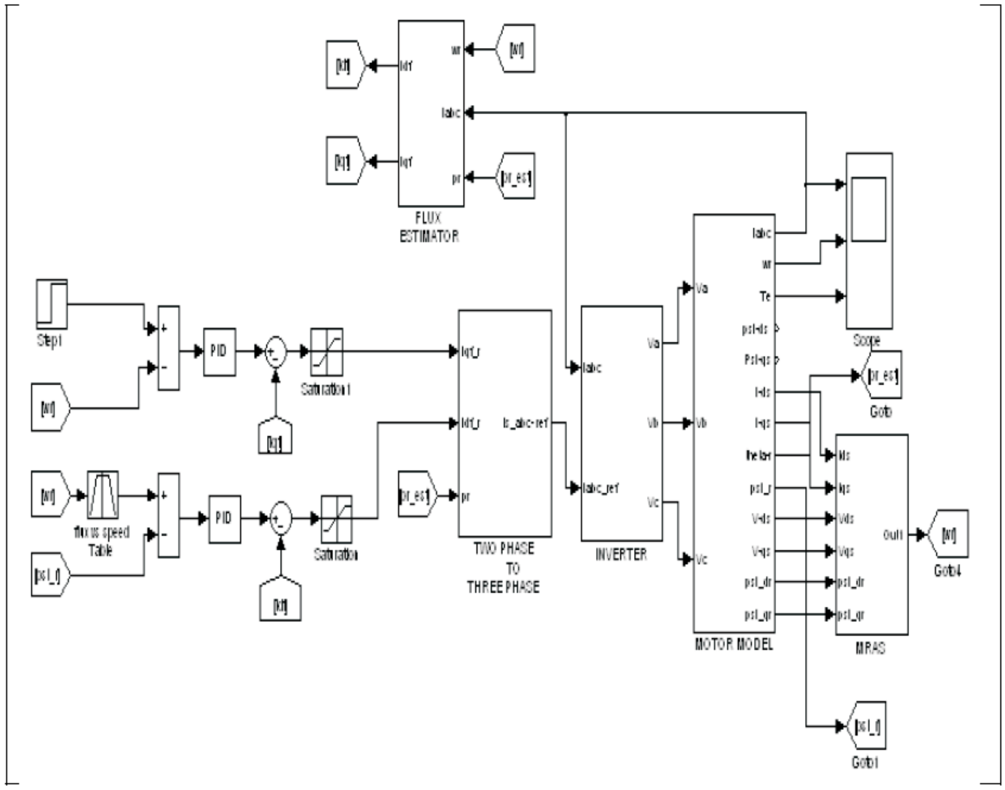


Fig.3 Simulink Root Block Diagram of Sensorless Control of Induction Motor Using MRAS

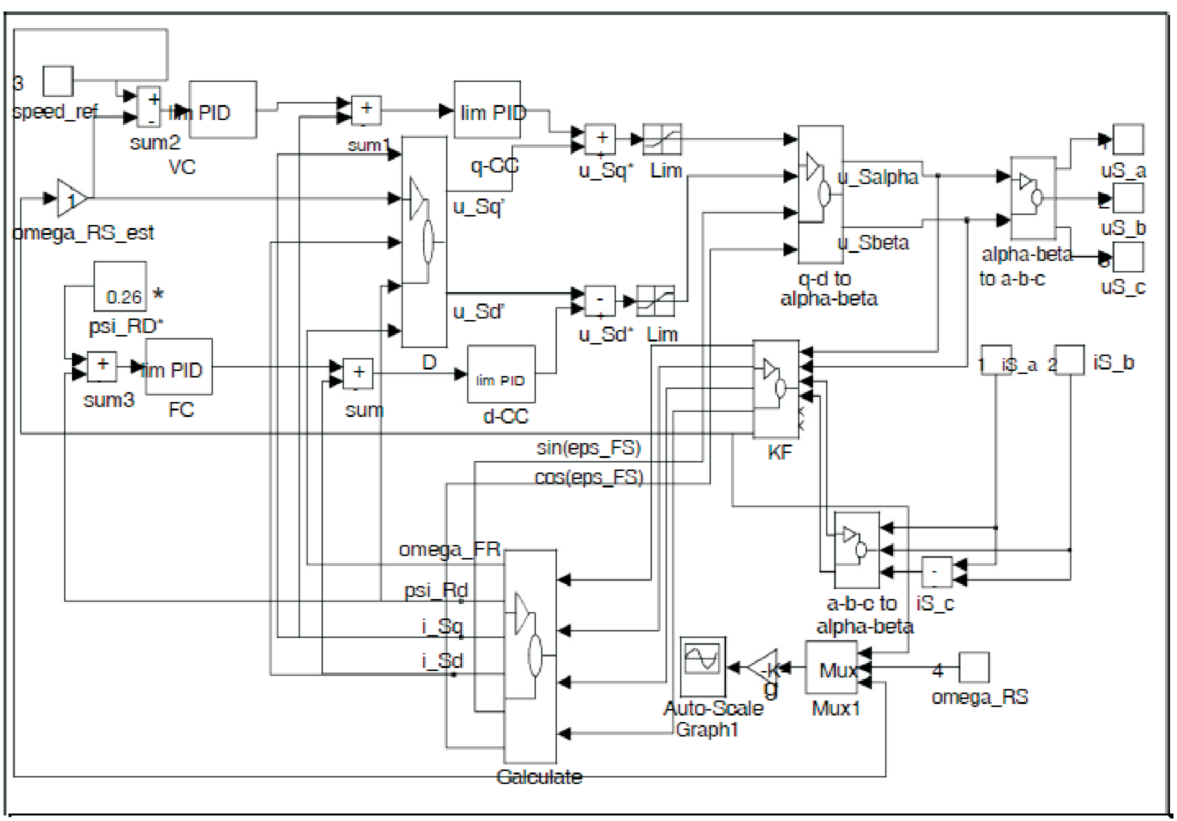


Fig.4 Simulink Root Block Diagram of Sensorless Control of Induction Motor Using EKF

**Case Studies**

**Case 1: Speed reversal command**

Speed reversal command is applied at t = 0.1s and 2.2 s.

Reference Speed=2000RPM

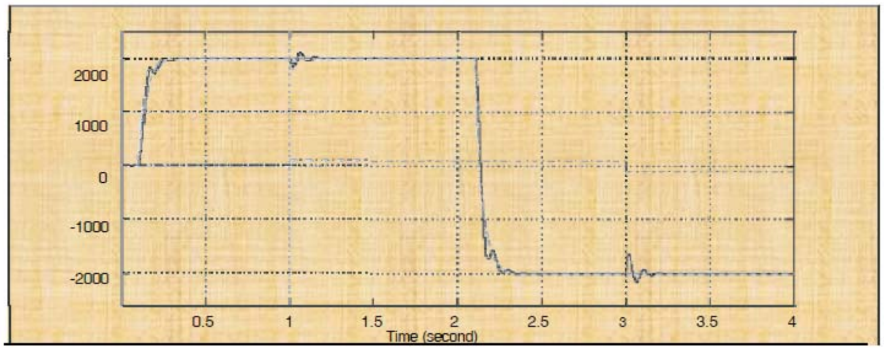


Fig. 5 Speed Reversal with MRAC

The figure shows the speed reference, Actual speed and the load torque

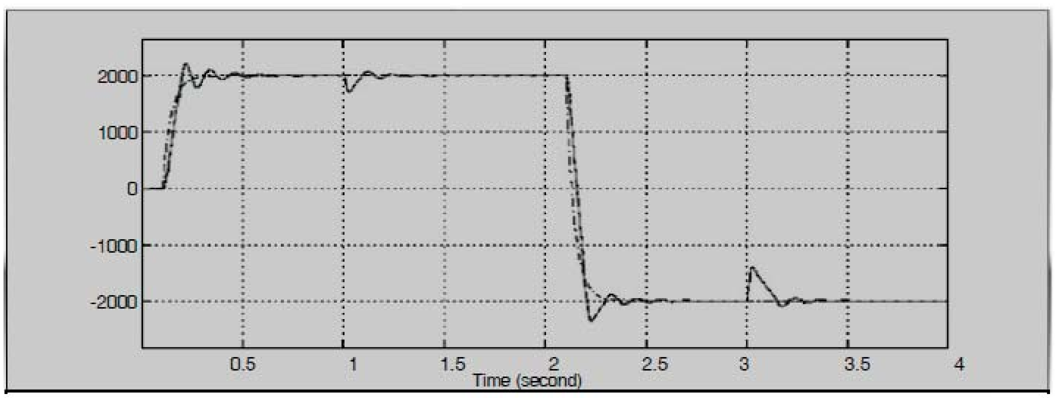


Fig. 6 Speed Reversal with EKF

The figure shows the speed reference, estimated speed and the actual speed.

**Conclusion:** The response of MRAC is better than the EKF response.

**Case 2: Step change in load**

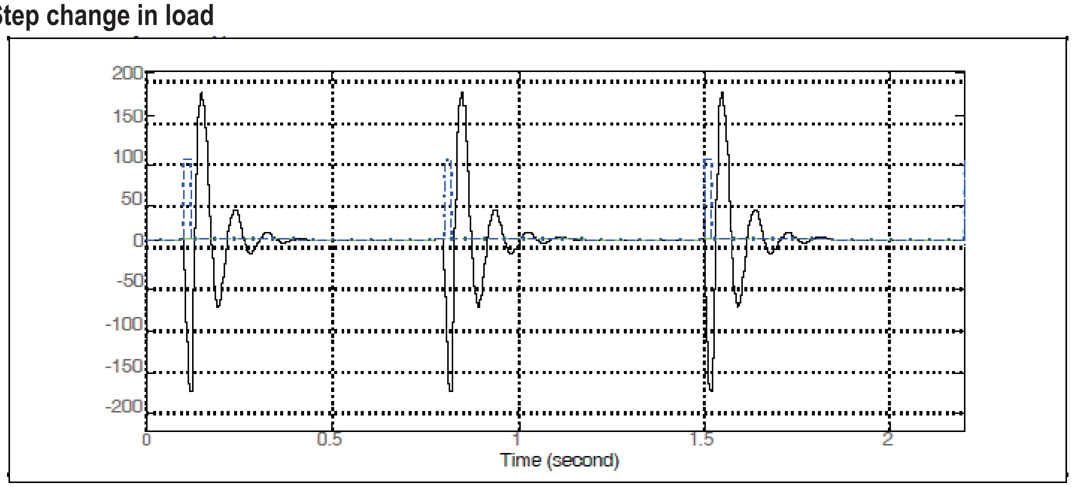


Fig. 7. Applying Load with MRAS

The figure shows speed, torque and speed reference

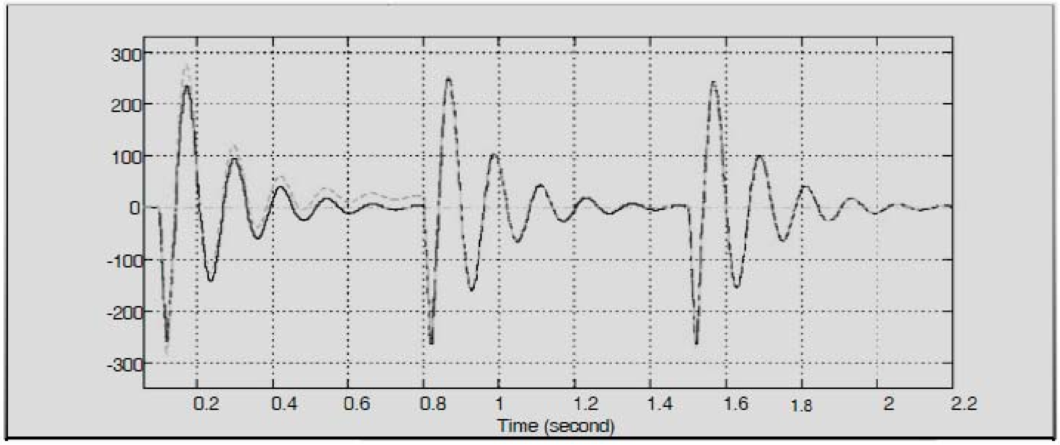


Fig. 8 Applying Load with EFK

**Conclusion:** EKF shows a stable behaviour after a certain time has passed for settling. The torque disturbances are reduced compared to MRAC.

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## NOMENCLATURE

$i_{ds}^{s}$ $d^s$ –axis stator current

$i_{qs}^{s}$ $q^s$ –axis stator current

$v_{ds}^{s}$ $d^s$ –axis stator voltage

$v_{qs}^{s}$ $q^s$ –axis stator voltage

$\Psi_{ds}^{s}$ $d^s$ –axis stator flux linkage

$\Psi_{qs}^{s}$ $q^s$ –axis stator flux linkage

$\Psi_{dr}^{s}$ $d^s$ –axis rotor flux linkage

$\Psi_{qr}^{s}$ $q^s$ –axis rotor flux linkage

$\Psi_{dm}$ Airgap Flux Linkage

$\omega_r$ Rotor Electrical Speed

$L_s$ Stator Inductance

$L_r$ Rotor Inductance

$L_m$ Magnetizing Inductance

$L_{ls}$ Stator Leakage Inductance

$L_{lr}$ Rotor Leakage Inductance

$R_s$ Stator Resistance

$R_r$ Rotor Resistance

Differential Operator

Peak Value of a Sinusoidal Phasor.

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