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A Robust EKF Based Speed Estimator and Fuzzy Optimization Technique for Sensorless Induction Motor Drives

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ABSTRACT

The speed estimation technique of induction machines has become a non-trivial task. For estimating the speed of an induction motor precisely and accurately an optimum state estimator is necessary. This paper deals with the performance analysis of induction motor drives using a recursive, optimum state estimator. This technique uses a full order state space Extended Kalman Filter (EKF) model where the rotor flux, rotor speed and stator currents are estimated. A major challenge with induction motor occurs at very low and at near zero speed. In such cases, information about the rotor parameters with respect to stator side become unobservable while using the synchronously rotating reference frame. To overcome this lost coupling effect, EKF observer linearizes the non-linear parameter in every sampling period and estimates the states and machine parameters simultaneously. The proposed algorithm is tuned to obtain least error in estimated speed. Any error found is further optimized using a non-linear fuzzy controller to obtain improved performance of the drive.

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1. INTRODUCTION

Induction machines are more rugged, compact, cheap and reliable when compared to other machines. Vector controlled induction motor drives out performs other drives because of high transient capability, increased speed range and lower rotor inertia. Sensorless control methods are making excellent in the most recent years because of their low cost and greater reliability without mounting problems [1]. Speed estimation methods are being used that avoid the speed measurement setup thereby reducing the hardware complexity and maintenance requirements. There are several speed estimation techniques discussed in the literature that are used to estimate the speed using different machine parameters.

A recent effort on the research front is on sensorless speed estimation that has been done from the measurement of stator voltages, phase currents and frequency using several techniques and algorithms. Techniques for obtaining speed information of an induction motor are based on slip frequency calculation [2], Model Reference Adaptive System (MRAS) [3] is an Adaptive Observer (AO) [4], where the same parameter is calculated by using an independent variable that is to be estimated and the other is an dependent variable. Comprehensive reports on sensorless drives obtained through model based estimation failed to assure permanent stability of the drive [5]-[8]. Moreover, the electrical drives are quite sensitive for changes occurring in equivalent circuit parameters of the motor. These errors in parameter changes degrade the speed holding characteristics of the drive. Many other closed loop methods for speed estimation such as rotor flux derivative [9]-[10], stator voltages [11], modified stator model [12], full order observer [13]-[14], reduced order observer [15]-[16], Kalman Filter observer [17], sliding mode observer [18]-[20]. Few sensorless method don't rely on voltage and current measurement. They include artificial intelligence techniques based on neural networks [21]-[22] against variation in parameters. There are various online Speed estimation techniques such as Speed adaptive flux observer [23]. In signal based method the signals are injected on the motor. This has adverse effects on the dynamics that require additional hardware component for signal injection. Parameter estimation consists of Luenberg observer and adaptive observers.

For lower order machine parameters the estimation technique using MRAS was considered as the most simplest and convenient method. Estimating parameters is a difficult task, especially, when the systems are large. Estimating large number of parameters becomes computationally expensive and the model based approach can no longer be adopted for speed estimation especialy in high performance drives. This has led to the development of new techniques in order to identify the parameters that affect the dynamic performance of the machine. The EKF is a stochastic state observer. The function of this observer is to linearize the nonlinear parameter in every sampling period. The EKF has the ability to estimate the states and machine parameters simultaneously in a dynamic process. This is useful for both control and diagnosis of the process [24]. Analysis on observability on 6^{th} order discrete time model based on 6^{th} order discrete time Extended Kalman Filter discusses the convergence of speed during transient conditions [25].

The EKF is a suboptimal control approach where fast parameter estimation is a non-trivial task and the parameters evolve with time as in real time applications. Recently, fuzzy logic based techniques have gained a wide attention in control applications. In high performance drive applications a desirable control in both transient and steady state conditions have to be provided even when the parameters and the load of the motor are varying. Hence, the control strategy developed for high performance drives must be adaptive and robust. The neural network based vector control has been able to produce better results but requires rigorous offline training process [26]. The fuzzy logic control technique has been an active research topic in automation and control engineering and has been applied to electric drives to deal with the nonlinearities and uncertainties of the control system [27].

The main objective of the proposed strategy is to design a robust speed estimator and optimization mechanism using an adaptive fuzzy logic controller. The EKF not only estimates the speed, it also monitors and tracks the parameter variations. The discretized model of IM is used for this purpose to track the changes in parameters over time and respective control and monitoring process is carried out. Further work aims in sensorless speed control using Fuzzy based speed – regulator. The work proposed presents an improvised speed regulation performance under transient and steady state uncertainties caused by variations in load torque and speed reversals.

2. DISCRETIZED STATE MODEL OF INDUCTION MOTOR

A dynamic electrical model for a three-phase induction motor has four state variables, namely, the stator currents in the direct and quadrature axis (i_{ds}, i_{qs}) and the rotor fluxes (Φ_{dr}, Φ_{qr}). An extended induction motor model results, if the rotor speed is included as an additional state variable. The discretized extended model is as obtained from equations (1) to (4).

$$X(t_{k+1}) = A\,\widehat{X}(t_k) + B\,U(t_k) \quad (1)$$

$$Y(t_k) = C\,X(t_k) \quad (2)$$

where,

$$\widehat{X}(t_k) = \left[i_{ds}^{s}(t_k) \;\; i_{qs}^{s}(t_k) \;\; \phi_{dr}^{s}(t_k) \;\; \phi_{qr}^{s}(t_k) \;\; \omega_r(t_k) \right]^T \quad (3)$$

$$Y(t_k) = \left[i_{ds}^{s}(t_k) \quad i_{qs}^{s}(t_k) \right]^T \quad (4)$$

$$U(t_k) = \left[v_{ds}^{s}(t_k) \quad v_{qs}^{s}(t_k) \right]^T \quad (5)$$

where,

$$A = \begin{bmatrix} 1-\frac{T}{T_s^*} & 0 & \frac{TL_m}{L_s^{'}L_r\tau_r} & \frac{\omega_r TL_m}{L_s^{'}L_r} & 0 \\ 0 & 1-\frac{T}{T_s^*} & \frac{-\omega_r TL_m}{L_s^{'}L_r} & \frac{TL_m}{L_s^{'}L_r\tau_r} & 0 \\ \frac{TL_m}{L_s^{'}L_r\tau_r} & 0 & 1-\frac{T}{T_s^*} & -\omega_r T & 0 \\ 0 & \frac{TL_m}{\tau_r} & \omega_r T & 1-\frac{T}{T_s^*} & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

$$B = \begin{bmatrix} \frac{T}{L_s^{'}} & 0 \\ 0 & \frac{T}{L_s^{'}} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{7}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \tag{8}$$

But, for an IM, the values of R_r, R_s, L_r, L_s, L_m *and* ω_r are constant. Hence the state matrix, input matrix and output matrix will be constant matrices.

3. PARAMETER ESTIMATION USING EXTENDED KALMAN FILTER

The EKF is a recursive algorithm that uses series of measurements observed over time and produces estimates of unknown variables that tends to be more precise than those based on a single measurement alone. The conventional controller assumes the model to be linear [26]-[27].

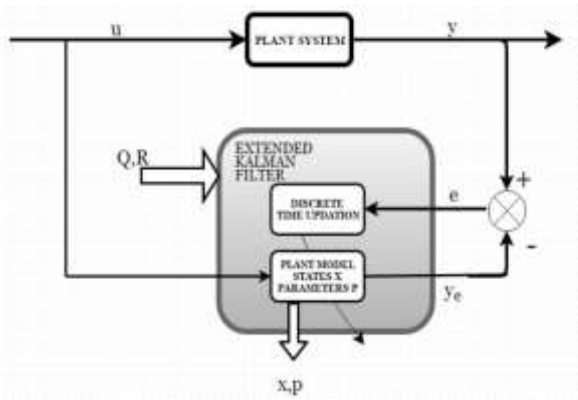

Figure 1. Model of EKF

The algorithm is based on Taylor's expansion of non-linear functions. It is intuitive and computationally efficient. Accurate parameter estimation becomes essential for any model based simulation, Control and optimization. The EKF uses the discretized mathematical model of the machine, the stator currents and rotor fluxes for speed estimation. The model of EKF observer used for parameter estimation is depicted in Figure 1. The system consists of a plant whose parameters are to be estimated. The state is defined by x and the covariance matrix is obtained as p. For various working conditions of the machine, the parameters of x and p are updated. The state is propagated from t^{k-1} to t^k using model equations. Covariance matrix is propagated using tangent linear operator and its adjoint.

Figure 1 represents the continuous time model with parameters augmented states as:

$$\dot{x} = f(x, u, p) \tag{9}$$

$$\dot{p} = 0 \tag{10}$$

$$y_e = h(x, u\ , p) \tag{11}$$

The discrete time updates of states and parameters at time t_k are taken as:

$$\dot{\hat{X}} = f(X) \tag{12}$$

$$\dot{P} = \frac{\partial f}{\partial x}\ (\widehat{X\,(t_k})) P + P \frac{\partial f^{|}}{\partial x}\ (\widehat{X\,(t_k})) + Q \tag{13}$$

The error estimation is obtained from

$$e(t_{k+1}) = y(t_{k+1}) - h(\widehat{X}\,(t_{k+1})) \tag{14}$$

Estimation error covariance matrix is given by,

$$A(t_{k+1}) = R + \frac{\partial h}{\partial x}\ (\widehat{X\,(\overline{t_{k+1}})}) P(t_{k+1}) \frac{\partial h^{|}}{\partial x}\ (\widehat{X\,(\overline{t_{k+1}})}) \tag{15}$$

The gain of the Kalman filter is calculated as:

$$k(t_{k+1}) = P(\overline{t_{k+1}}) \frac{\partial h^{|}}{\partial x}\ (\widehat{X\,(\overline{t_{k+1}})})\ /\ A(t_{k+1}) \tag{16}$$

The final Updation in parameters is obtained from:

$$\widehat{X\,(t_{k+1}}) =\ \widehat{X\,(\overline{t_{k+1}})} + k(t_{k+1}) e(t_{k+1}) \tag{17}$$

$$P(t_{k+1}) = P(\overline{t_{k+1}}) - k(t_{k+1})\ A(t_{k+1}) k^{|}(t_{k+1}) \tag{18}$$

In the methodology proposed, the estimator is developed with the measured direct and quadrature axes stator current, direct and quadrature axes stator flux and the reference speed to be used as state variables to estimate the rotor speed. In this paper, the sensitivity to motor parameter with respect to the EKF estimates is analyzed using *MatLab/Simulink*. The simulation results are presented for the sensorless drive system under different operating conditions.

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

Step 1: Prediction of the state vector:

The state vector is predicted at the sampling interval (t_{k+1}). It is obtained from the input vector *U* (*k*) and state vector $\hat{X}(t_k)$.

$$X^{*}(t_{k+1}) = A\hat{X}(t_k) + B\ U(t_k) \tag{19}$$

The values of matrices A, B, $\hat{X}(t_k)$ and $U(t_k)$ are obtained from equations (3), (5), (6) & (7) respectively.

Step 2: Covariance estimation of prediction:

The covariance matrix is calculated from equation 9:

$$P^{*}(t_{k+1}) = \frac{\partial}{\partial x}[A\ X + B\ U] P(t_k) \left[\frac{\partial}{\partial x}[A\ X + B\ U]\right]^{T} + Q \tag{20}$$

The covariance matrix has the order of 5x5. The terms in Eqn. (20) can be represented by a gradient matrix *f* as: Where, *f* is the gradient matrix.

$$\frac{\partial}{\partial x}[A\ X + B\ U] = f(t_{k+1}) \tag{21}$$

where, $X=X^{*}(t_{k+1})$

Step 3: Computing the Kalman filter gain:

The gain matrix of the Kalman filter consists of 2 rows and 5 columns. The gain K is calculated as:

$$K(t_{k+1}) = P^*(t_{k+1}) * \left[\frac{\partial}{\partial x}[CX]\right]^T * \left[\frac{\partial}{\partial x}[CX]P^*(t_{k+1})\right] * \left[\left[\frac{\partial}{\partial x}[CX]\right]^T + R\right]^{-1} \quad (22)$$

Here the parameter $C\ X$ is defined as another gradient matrix as:

$$\frac{\partial}{\partial x}[C\ X] = h(t_{k+1}) \quad (23)$$

where, X=$X^*(t_{k+1})$
Step 4: Estimation of state vector:

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

$$\hat{Y}(t_{k+1}) = C\ X^*(t_{k+1}) \quad (24)$$

$$\hat{X}(t_{k+1}) = X^*(t_{k+1}) + K(t_{k+1})[Y(t_{k+1}) - \hat{Y}(t_{k+1})] \quad (25)$$

Step 5: Error covariance matrix:

The error covariance matrix is obtained from

$$\hat{P}(t_{k+1}) = P^*(t_{k+1}) - K(t_{k+1}) \left[\frac{\partial}{\partial x}[CX]\right] P^*(t_{k+1}) \quad (26)$$

Step 6: Parameter Updation:

Substitute the value for k as:

$$k = (t_{k+1}), X(t_k) = X(t_{k-1}), P(t_k k) = P(t_{k-1}) \quad (27)$$

The algorithm is updated with the above values and an iterative modification of the covariance matrix is developed to obtain the most accurate estimation of the states. A faster transient response is obtained through proper tuning of the matrices Q & R. The algorithm described above can be used for the speed estimation of induction motor under both steady state and transient conditions. The estimated speed is compared with the actual speed and the error is given to the PI-Fuzzy controller which produces the required torque reference. From the estimated speed and the torque reference, the direct and quadrature axes reference currents are calculated and fed to the EKF estimator, giving an output of the estimated speed of the motor. The control and monitoring of the speed under no load and loaded conditions is obtained from an adaptive fuzzy logic controller. The proposed fuzzy controller acts as a speed regulator and regulates the speed to the required value depending upon the application.

4. ADAPTIVE FUZZY SPEED REGULATOR

Although the EKF algorithm is developed to produce least estimation errors, a need for optimizing the entire control system prevails. Hence, a fuzzy based speed regulator is developed as indicated in Figure 2. The inputs to the fuzzy logic controller are chosen as the speed error ‘e (k)’ and change in error ‘ce (k)’ at a sampling time t_s. Both the input variables are calculated at every sampling interval. The Mamadani principle consisting of triangular membership function is selected. The set of fuzzy rules required to diminish the error obtained in speed variations is quoted in Table 1. The linguistic variables in Table I indicate the fuzzy rules represented in the Fuzzy Associative Memory (FAM). Fuzzy control rule is regarded as the core of the whole fuzzy control. The proposed fuzzy control rules are based on the step response of conventional PI regulator, together with the characteristics of the vector control of induction motor. Here, E and CE represent the fuzzified values of error and its rate of change.

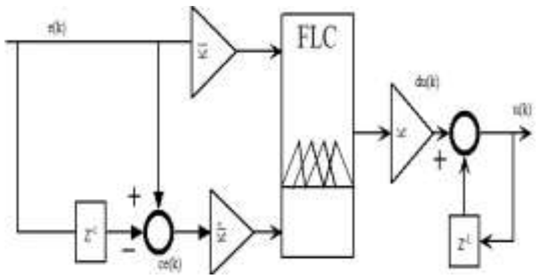

Figure 2. Basic Structure of Fuzzy speed regulator

According to the different speed error e (k) and its rate of change, the principles about the self-adjustment of K_P and K_I are listed as follows:

a. When e(k) takes a relatively big number, a big number should also be assigned to K_P in order to accelerate the system speed response, but K_I must take a quite small number or even zero in order to prevent integral saturation and distinct speed overshooting.
b. When e (k) takes a moderate number, K_P must take a relatively small number and K_I must take a moderate one, in order to decrease the overshooting and ensure the swift speed response.
c. When e (k) takes a relatively small number, the system usually runs in steady state, thus a moderate K_P and a big K_I, should be assigned to decrease static error and ensure the stability of the system.

According to the different speed error e (k) and its rate of change, fuzzy control rules of K_P and K_I at different states can be acquired as shown in Table 1.

Table 1. FAM of FLC as a Fuzzy Speed regulator

CE/E	NB	NM	NS	ZE	PS	PM	PB
NB	NVB	NVB	NVB	NB	NM	NS	ZE
NM	NVB	NVB	NB	NM	NS	ZE	PS
NS	NVB	NB	NM	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PM	PB	PVB
PM	NS	ZE	PS	PM	PB	PVB	PVB
PB	ZE	PS	PM	PB	PVB	PVB	PVB

5. SIMULATION ANALYSIS AND RESULTS

5.1. No Load Condition

The sensorless control of induction motor using EKF is simulated on MatLab/Simulink platform to study the various aspects of the speed estimator and adaptive fuzzy regulator. Figure 3 shows the speed response obtained using EKF under no-load condition for a reference speed of 500 rpm. The simulation result shows that the actual speed almost exactly follows the reference speed.

Figure 3. EKF speed estimation (ω_{ref} = [0 500] rpm, with the Time interval of t= [0 1] s and under no-load)

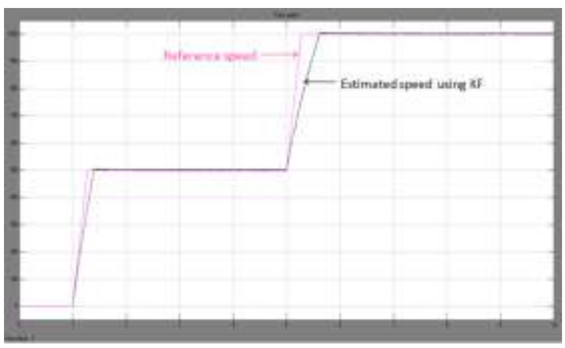

Figure 4. EKF speed estimation (ω_{ref} = [0 500 1000] rpm, with the time interval of t = [0 1 5] s and under no-load)

Also for a step change in the reference speed at 500 rpm and 1000 rpm, the response obtained from KF follows nearly the same response as the reference. This is illustrated in Figure 4. Another significant contribution of the developed fuzzy speed regulator is the reduction in ripple in the electromagnetic torque. As vector control schemes are said to produce large ripple, the reduction in torque ripple can be achieved to a greater extent using a robust fuzzy adaptive control as depicted in Figure 5. Figure 6 shows the response of the speed control obtained using EKF during speed changes over different ranges under no-load.

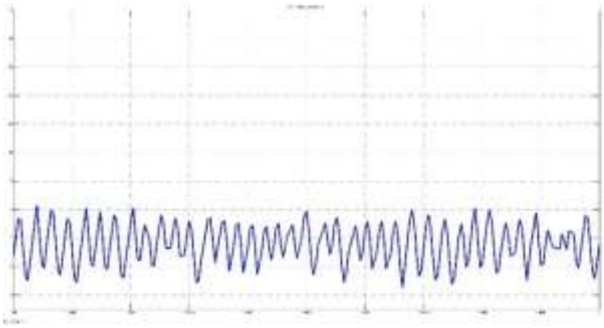

Figure 5. Electromagnetic torque

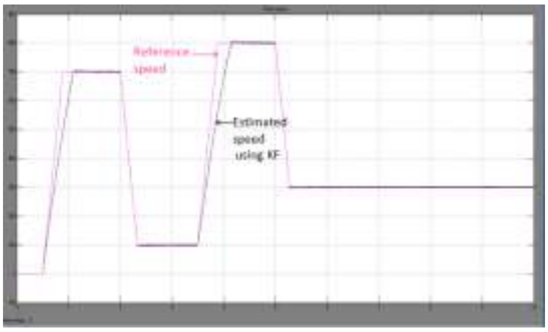

Figure 6. EKF speed estimation (ω_{ref} = [0 700 100 800 200] rpm, with the time interval of t = [0 0.5 2 3.5 5] s and under no-load)

5.2. Performance Analysis under load changes (transient-condition)

Simulation studies have been performed for load changes and various speed ranges. The simulation results shows the use of the full order observer working efficiently even during load changes and speed change conditions. With a reference speed of 500rpm and a load of 3 N-m, the output obtained from EKF is exactly similar to that obtained for no-load condition, as in Figure 7. Under this condition, the EKF estimator gives the response almost nearer to the reference speed, proving the efficiency of the algorithm.

Figure 8 presents the response obtained by the estimation algorithm and the fuzzy controller for a change in speed in the range [0 700 100 800 200] rpm under the load conditions of [0 0.7 0.1 0.8 0.2] N-m applied at the time interval of [0 0.5 2 3.5 5] s. Even during Speed changes, it is seen that the machine remains stable and yields constant output over wide range of speed variations.

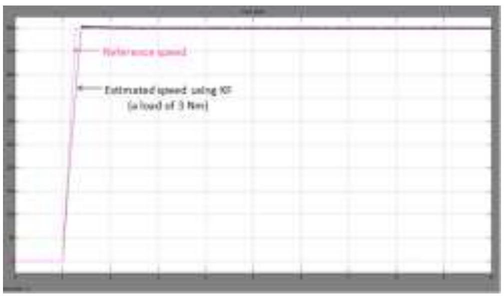

Figure 7. EKF speed estimation (ω_{ref} = [0 500] rpm, with the Time Interval of t = [0 1] s and under a load of 3 N-m)

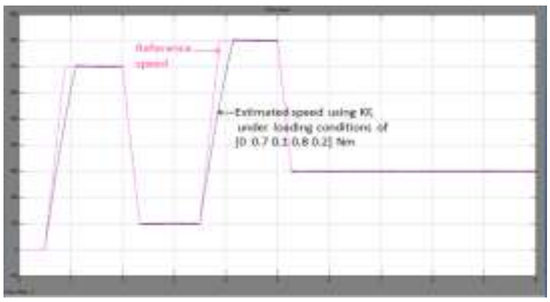

Figure 8. EKF speed estimation (ω_{ref} = [0 700 100 800 200] rpm, With the Load changes of [0 0.7 0.1 0.8 0.2] N-m and in the time interval of t = [0 0.5 2 3.5 5] s)

6. CONCLUSIONS

The algorithm proposed is less sensitive to drift and saturation. This makes the estimation at or near zero speed quite accurate. For real time applications, the induction motor model is discretised. The performance of EKF is examined through several simulation studies. The EKF helps in estimating the non-observable system states and parameters. This method proves to be a robust technique wen compared to conventional model based approaches. The optimum value of speed is obtained by a non-linear fuzzy controller. With significant uncertainties in load & other parameters, the EKF provides better state estimation. Also, decrease in the computational complexity and improvements in hard tuning of co-variance matrices have been achieved. The tuning of the algorithm is simpler compared to other EKF techniques due to the lower dimension of the state vector. The estimation algorithm is in the form of a probability density function and all the process such as monitoring, tracking and model parameter tuning is achieved proving the efficacy of the proposed algorithm. Also, the Fuzzy speed- regulator tends to provide satisfactory high dynamic and static performances. The approach has shown a great improvement in computational efficiency over other parameter estimation methods.

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