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Low Speed Estimation in Sensorless Direct Torque Controlled Induction Motor Drive Using Extended Kalman Filter

Mini R[1], Saranya C[2], B. Hariram Satheesh[3], Dinesh M. N[4]
[1]VTU Research scholar, Faculty of Amrita Vishwa Vidyapeetham University, India
[2]Amrita Vishwa Vidyapeetham University, India
[3]ABB GISL, Bangalore, India
[4]R V College of Engineering, Bangalore, India

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ABSTRACT

Sensorless Direct Torque Control (DTC) is a powerful control scheme for high performance control of induction motor (IM) drives, which provides very quick dynamic response with simple structure and a decoupled control of torque and flux. The performance of the DTC drive greatly depends on the accuracy of the estimated flux components, torque and speed, using monitored stator voltages and currents. Low speed estimation is a great challenge because of the presence of transient offset, drift and domination of ohmic voltage drop.Extended Kalman filter (EKF) is a non linear adaptive filter which performs the process of finding the best estimate from the noisy data based on state space technique and recursive algorithm.This paper mainly focuses on the accurate estimation of speed ranging from very low speed to rated speed using the equation of motion. A new state space model of the IM is developed for estimation in EKF, with load torque as an input variable and not as an estimated quantity which is the case in most previous studies.The developed algorithm is validated using MATLAB-Simulink platform for speeds ranging from low speed to rated speed at rated torque and at various torque conditions. An exhaustive analysis is carried out to validate the performance of DTC Induction motor drive especially at the low speeds. The results are promising for accurate estimation of speed ranging from low speed to rated speed using EKF.

Corresponding Author:

Mini R,
Departement of Electrical and Electronics Engineering,
Amrita Vishwa Vidyapeetham, Bangalore Campus,
Carmalram, Off Sarjapur Road, Bangalore-560035, Karnataka, India.
Email: mini_sujith@blr.amrita.edu, minir_sujithr@yahoo.com

1. INTRODUCTION

Developments in power electronics in the last decades resulted in an unprecedented growth of adjustable speed drives. Induction Machines (IM) are widely used in most of these drives, because they are relatively cheap and rugged machines and their construction is realized without commutators. But induction motor control is complex due to rotating stator field and also the rotor current cannot be measured directly. In vector control schemes, the rotor flux and the torque producing stator current are controlled independently, hence faster torque and speed control can be achieved[1],[2].

Sensorless Direct Torque Control (DTC) is a powerful vector control scheme which gives instantaneous torque and flux control using optimum inverter output voltage vectors to obtain sharp torque response with greater efficiency [3]-[5]. Selection of inverter voltage vector using Space Vector Modulation (SVM) has the advantage of reducing the fluctuations in torque, flux and speed [6]. Stator voltages and currents at the motor terminals are used to extract the rotor speed by estimating the magnitude and spatial position of the revolving magnetic flux in the stator or in the rotor [7]. Sensorless DTC needs a great knowledge of the dynamic properties of the induction motor for the estimation of speed, flux and torque [8],[9],[10]. Various estimation techniques like open loop estimators, closed loop estimators or observers and adaptive models are used in high performance drives [11],[12]. The main difference of closed loop estimator from open loop estimator is the inclusion of estimation error correction term to adjust the response of the estimator. Open loop estimators are not using this correction term but closed loop estimators are using this correction term and hence they are called as observers. The estimators or observers used vary in terms of accuracy, robustness and sensitivity against model parameter variations. The speed sensorless control gives good performance in the higher ranges of speed but performance deteriorates at low speed including zero speed. The poor performance of estimators at low speeds is mainly due to the variation in measured motor voltage and current due to the domination of dc offset of electronic components involved, variation in machine parameters due to the change in winding temperature, drift problems associated with direct integration and noise in the low speed range [7],[13].

In this paper a closed loop (observer) type estimation technique is sought to investigate and come up with a reliable solution for the low speed estimation issues in high performance induction motor drive. Kalman filter takes a stochastic approach to this problem, while other observers are deterministic [14],[15]. It is called stochastic because of the fact that it takes into account the noise in the system, falsity in measurements as well as the uncertainty in estimation during its filtering process, to give an optimal estimate of the state. Kalman filter uses the state space model of the system which gives an insight into internal/non measurable variables which are to be estimated. State space representation of IM with current, flux and speed as state variables involve nonlinear differential equations; hence an extended version of the Kalman filter known as Extended Kalman Filter (EKF) applicable to nonlinear systems is used as estimator in IM drives. After exhaustive literature survey, EKF is chosen to investigate for mitigating the low speed estimation issues in DTC Induction Motor Drives [16]-[21].

This paper mainly aims at accurate low speed estimation under various load conditions ranging from no load to full load. Literature survey shows that the speed is estimated in EKF by considering the rate of change of speed as negligible [1]. This corresponds to infinite inertia of the machine which is not practically realizable.Since the speed cannot be normally treated as a constant [2], an alternative and more efficient approach for speed estimation is mentioned in literatures using the equation of motion which relates the speed to load torque and electromagnetic torque.The study in [22] also uses the equation of motion, but considers load torque required for speed estimation as a constant. This approach offers good performance during the high speed operation of the drive, but the response is comparatively sluggish at low speeds especially when they are subjected to high loads. The main contribution in this paper is the validation of a new approach for the estimation of speed where the load profile is given as an input to the EKF estimator. EKF uses this load torque input for estimating speed using the equation of motion. This method has the benefit of providing fast response and high estimation accuracy under all load conditions over a wide range of speed from rated to low speed including zero speed. Simulation is carried out in MATLAB-SIMULINK platform to validate the effectiveness of modified EKF for low speed estimation at various load torque conditions.

2. SENSORLESS DTC CONTROL

Figure 1 shows the DTC structure using EKF. DTC scheme offers direct control of the electromagnetic torque and stator flux linkage of the motor through optimum inverter voltage vector selection using SVM**.**

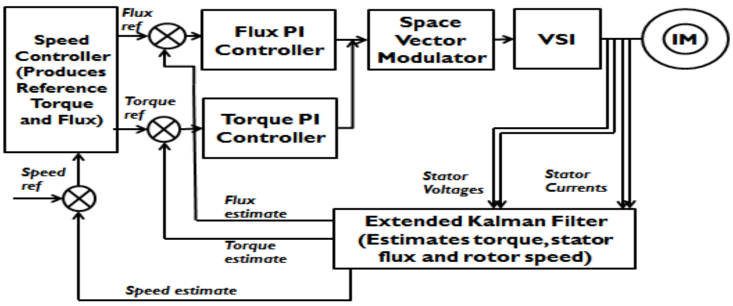


Figure 1. Structure of DTC using EKF

The choice of the voltage vector is decided by the command signals from the torque and flux PI controllers. The reference and actual values of flux and torque required for the PI controllers are generated by the speed controller and EKF estimator respectively. EKF uses the monitored stator voltages and stator current to estimate the actual flux and torque. The speed controller needs actual speed of the motor and the reference speed for generating flux and torque reference values. The actual rotor speed for the speed controller is obtained from EKF estimator using the equation of motion.

3. STATE SPACE MODEL OF INDUCTION MOTOR

The two axis state space model of three phase induction motor in stationary reference frame consists of stator currents and rotor flux linkages as the state variables. The rotor speed signal is required for the estimation of stator currents and rotor flux linkages and also for the generation of reference torque and flux by the speed controller.In EKF, the rotor speed is augmented as the fifth state variable and is estimated using the equation of motion. Load torque required in the equation of motion is fed in the form of load profile. Based on these derivations, the mathematical representation of the induction machine involving the five state variables is expressed below.

$$\frac{d}{dt}\begin{bmatrix} i_{ds} \\ i_{qs} \\ \psi_{dr} \\ \psi_{qr} \\ \omega_r \end{bmatrix} = \begin{bmatrix} -\left(\frac{R_s}{L_s'} + \frac{R_r' L_m^2}{L_s'(L_r')^2}\right) & 0 & \frac{L_m}{L_s' L_r' T_r} & \frac{\omega_r L_m}{L_s' L_r'} & 0 \\ 0 & -\left(\frac{R_s}{L_s'} + \frac{R_r' L_m^2}{L_s'(L_r')^2}\right) & -\frac{\omega_r L_m}{L_s' L_r'} & \frac{L_m}{L_s' L_r' T_r} & 0 \\ \frac{L_m}{T_r} & 0 & -\frac{1}{T_r} & -\omega_r & 0 \\ 0 & \frac{L_m}{T_r} & \omega_r & -\frac{1}{T_r} & 0 \\ -\frac{P}{2J} * \frac{3}{2} * \frac{P}{2} * \psi_{qr} & \frac{P}{2J} * \frac{3}{2} * \frac{P}{2} * \psi_{dr} & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \\ \psi_{dr} \\ \psi_{qr} \\ \omega_r \end{bmatrix}$$

$$+ \begin{bmatrix} \frac{1}{L_\sigma} & 0 & 0 \\ 0 & \frac{1}{L_\sigma} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -\frac{P}{2J} \end{bmatrix} \begin{bmatrix} V_{ds} \\ V_{qs} \\ T_l \end{bmatrix} \qquad (1)$$

$$\begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \\ \psi_{dr} \\ \psi_{qr} \\ \omega_r \end{bmatrix} \qquad (2)$$

The model of the induction machine given by (1) and (2) are in the state space form as given below

$$\frac{dx}{dt} = Ax + Bu \qquad (3)$$

$$y = Cx \qquad (4)$$

where x is the state vector, u is the input vector, y is the output vector, A is the system matrix,B is the input matrix and C is the output matrix.

The electromagnetic torque developed by the motor is estimated in EKF using stator currents and rotor flux linkages as given in (5).

$$Te = \frac{3}{2}\frac{P}{2}\frac{L_m}{L_r'}\left(\psi_{dr}\, i_{qs} - \psi_{qr}\, i_{ds}\right) \qquad (5)$$

The terms in equations (1), (2) and (5) are defined as, i_{ds} and i_{qs}: direct and quadrature components of stator currents in stationary reference frame. ψ_{dr} and ψ_{qr}: direct and quadrature components of rotor flux linkages in stationary reference frame. ω_r: rotor speed. V_{ds} and V_{qs}: direct and quadrature components of stator voltages in stationary reference frame. T_l : load torque. R_s and L_s :stator resistance and inductance respectively. R_r' and L_r': rotor resistance and inductance referred to stator side,respectively. L_m: magnetizing inductance. $L_s' = L_s - (L_m^2/L_r')$: transient inductance. $T_r = L_r' / R_r'$ rotor time constant. P: number of poles. J: moment of inertia.

According to this approach, the load torque profile data needs to be given to the EKF estimator for the estimation of rotor speed. To incorporate this load profile input in the mathematical model, load torque is considered as the third element in the input matrix in addition to stator voltages. Electromagnetic torque of the motor is estimated by EKF using the values of stator currents and rotor flux linkages. Unlike the study in [18], this paper does not consider load torque as an estimated quantity in EKF thereby reducing the order of the filter to five and hence reducing the burden of computation but it limits the applications.

4. DEVELOPMENT OF EKF ALGORITHM

The EKF is an optimum estimator because of its stochastic and recursive nature and it can be used for joint state and parameter estimation of a non-linear dynamic system. The algorithm processes the state variables by taking into account the noisy environment of the system. The statistics of the noise are incorporated in the algorithm using the matrices P, Q, Ru and Re which are the covariance matrices of the state variables, system noise, voltage measurement noise and current measurement noise respectively. These matrices take into account the noises and errors in measurement and inaccuracies due to computational modeling errors.The two main stages of the algorithm are the prediction stage and the estimation stage. In prediction stage, the values of state variables are predicted using the discretized state space model of IM containing their estimated values at the previous instant. Estimation is then done by adding the weighted difference between the measured and predicted output signals to the predicted values.

For use of the algorithm with a digital processor, the state space model of the machine given in (1) and (2) has to be discretized with a sampling time T which can be expressed as shown below.

$$\begin{bmatrix} i_{ds}(k+1) \\ i_{qs}(k+1) \\ \psi_{dr}(k+1) \\ \psi_{qr}(k+1) \\ \omega_r(k+1) \end{bmatrix} = \begin{bmatrix} 1-(\frac{R_s}{L_s'}+\frac{R_r' L_m^2}{L_s'(L_r')^2})T & 0 & \frac{L_m T}{L_s' L_r' T_r} & \frac{\omega_r L_m T}{L_s' L_r'} & 0 \\ 0 & 1-(\frac{R_s}{L_s'}+\frac{R_r' L_m^2}{L_s'(L_r')^2})T & -\frac{\omega_r L_m T}{L_s' L_r'} & \frac{L_m T}{L_s' L_r' T_r} & 0 \\ \frac{L_m T}{T_r} & 0 & -\frac{T}{T_r} & -T\omega_r & 0 \\ 0 & \frac{L_m T}{T_r} & T\omega_r & -\frac{T}{T_r} & 0 \\ -\frac{P}{2J}*\frac{3}{2}*\frac{P}{2}*\psi_{qr}*T & \frac{P}{2J}*\frac{3}{2}*\frac{P}{2}*\psi_{dr}*T & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{ds}(k) \\ i_{qs}(k) \\ \psi_{dr}(k) \\ \psi_{qr}(k) \\ \omega_r(k) \end{bmatrix}$$

$$+ \begin{bmatrix} \frac{T}{L_s'} & 0 & 0 \\ 0 & \frac{T}{L_s'} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -\frac{P}{2J}T \end{bmatrix} \begin{bmatrix} V_{ds}(k) \\ V_{qs}(k) \\ T_l(k) \end{bmatrix} \tag{6}$$

$$\begin{bmatrix} i_{ds}(k) \\ i_{qs}(k) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{ds}(k) \\ i_{qs}(k) \\ \psi_{dr}(k) \\ \psi_{qr}(k) \\ \omega_r(k) \end{bmatrix} \tag{7}$$

The discretized model given in (6) and (7) can be expressed in a form mentioned below.

$$(k+1) = A_d\, x(k) + B_d\, u(k) \tag{8}$$

$$y(k) = C_d\ x(k) \quad (9)$$

The steps in the EKF algorithm to obtain the state estimates are described below.

Step1. Prediction of the state vector using previous estimated values and measured stator voltages

The predicted value of states at (k+1)[th] instant $x^*(k+1)$ is obtained using the following equation

$$x^*(k+1) = A_d\ \hat{x}(k) + B_d\ u(k) \quad (10)$$

where $\hat{x}$ (k) is the estimated value of states at previous sampling time ;u(k) is the input vector;

The discretized model of the machine given in (6) and (7) is used for predicting the values of the state variables.

Step2. Estimation of covariance matrix of prediction

The covariance matrix of prediction is predicted as

$$P^*(k+1) = Fe(k+1)\ \hat{P}(k)\ Fe(k+1)^T + Fu(k+1)\ Ru\ Fu(k+1)^T + Q \quad (11)$$

where Q represents the covariance of the system level noise; Ru represents the covariance of stator voltage measurement noise; P represents the covariance of estimated state vector $\hat{x}$.The gradient matrix of the states and inputs are given below.

$$Fe(k+1) = \frac{\partial}{\partial x}(A_d\ x + B_d\ u)\ \Big|\ x = \hat{x}(k) \quad (12)$$

$$Fu(k+1) = \frac{\partial}{\partial u}(A_d x + B_d\ u)\ \Big|\ u = u(k) \quad (13)$$

Step 3. Kalman filter gain computation and updation of covariance matrix

Kalman gain $K(k+1)$ is computed using the equation given below

$$K(k+1) = P^*(k+1)\ He(k+1)^T\ [He(k+1)\ P^*(k+1)\ He(k+1)^T + Re]^{-1} \quad (14)$$

where Re represents the covariance of stator current measurement noise ;$He(k+1)$ represents the variations in predicted stator currents due to uncertainty in previous estimated values.

$$He(k+1) = \frac{\partial}{\partial x}(C_d\ x)\ \Big|\ x = x^*(k+1) \quad (15)$$

State vector covariance matrix P is estimated using the Kalman gain as given below

$$\hat{P}(k+1) = P^*(k+1) - K(k+1)He(k+1)\ P^*(k+1) \quad (16)$$

Step 4. Estimation of state vector

The estimated values of state vector at k+1[th] instant is obtained by summing up the predicted values of the states with a correction term to minimize the covariance of the state variables.The correction term is the weighted difference between the measured output vector $y(k)$ and predicted output vector $\hat{y}(k)$.

$$\hat{x}(k+1) = x^*(k+1) + \hat{P}(k+1)\ He(k+1)^T\ Re^{-1}\ [y(k) - \hat{y}(k)] \quad (17)$$

where $y(k)$ represents the measured stator currents; $\hat{y}(k)$ represents the estimated stator currents at previous instant which is calculated using as $\hat{y}(k) = C_d\ x\ \big|\ x = x^*(k+1)$

Figure 2 shows the block wise representation of the estimation procedure in EKF. The estimated values of the states at previous instant and the stator voltages are used for predicting the values of the state variables at the present instant. The predicted stator currents and the measured stator currents are then compared to calculate the variation of predicted values from the actual values. This error is tuned using a correction factor to obtain an accurate estimate of the states, which is the characteristic of Kalman filter. The corrected error is then summed up with the predicted values for estimating the values of the state variables.

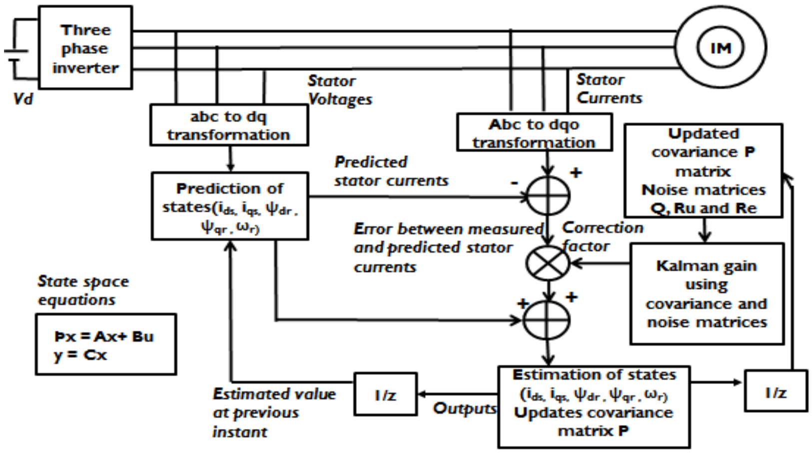


Figure 2. Block diagram representation of estimation procedure in EKF

5. RESULTS AND ANALYSIS

Simulation of the DTC drive using 20 hp motor is carried out in Matlab Simulink to evaluate the effectiveness of the proposed EKF algorithm. The parameters of the motor are listed in the Table 1.

Table 1. Machine parameters

Power(kw)	15	R_s (ohm)	0.2147
Frequency(Hz)	50	R_r' (ohm)	0.2205
J(kg/m2)	0.102	L_{ls}(H)	0.000991
B(Nm/rad/s)	0.009541	L_{lr}'(H)	0.000991
P	2	L_m(H)	0.06419
Voltage(v)	400	N_m(rpm)	1460
Current(A)	36	T_l(Nm)	98

P, Q, Ru and Re matrices are initialized as diagonal matrices to obtain optimum performance at steady state and transient state. The values of these matrices used in the simulation are given below.

P = diag {30 30 30 30 30}
Q = diag {3.4e-12 2e-12 3.2e-12 5.3e-12 7.6e-14}
Ru = diag {1e-2 1e-2}
Re = diag {4.6e-7 4.6e-7}

5.1. Speed estimation using EKF considering load torque as a constant.

Analysis is carried out to investigate the efficiency of an existing speed estimation method in which the load torque required for speed computation is estimated in EKF by treating it as a constant. Simulations are performed at different speeds with varying load conditions and the time taken to reach the steady state is monitored for all the scenarios. The speed estimated by EKF follows the reference value in few milliseconds. But the time taken by the motor to ramp up to the set speed is relatively very large which brings the delay in attaining the steady state. The observations are listed in Table 2.

Table 2. Time taken for the drive to reach the steady state at various speeds and load conditions

Speed(rpm)	At 5% load(5 Nm)	At 25% load(24.5 Nm)	At 50% load(49 Nm)	At full load(98 Nm)
1460	0.9 s	1.3 s	1.65 s	2.6 s
1000	1.02 s	1.45 s	2.08 s	3.2 s
750	1.04 s	1.63 s	2.27 s	4.4 s
500	1.19 s	2.1 s	2.7 s	5.5 s
100	3.58 s	9 s	11 s	15 s

The data shows variation in settling time with change in operating speeds and load conditions. For the same operating speed, the time taken to reach the steady state is found to increase with increase in load.The settling time is also observed to increase with the reduction in speed even if the load applied to the motor is maintained equal in all scenarios. For speeds below 100 rpm, the response is very sluggish and the performance further deteriorates when the drive is exposed to frequent load variations. This method ensures fairly better convergence at high speeds, but the low speed performance is acceptable only if the drive is subjected to very light loads less than 5% of rated torque. Since motivation behind the work is low speed estimation under all load conditons, a new approach is adopted where the load profile of the application is used for speed estimation in EKF.

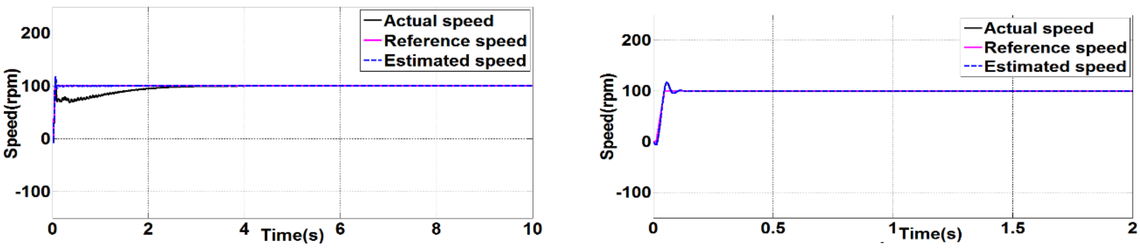
5.2. New speed estimation method using EKF with load torque profile given as an input.

According to this approach, the load profile of the application is provided as an input to EKF which is used for the estimation of speed. This method provides quick response, accurate speed and torque estimation over the entire speed range including very low speeds under all load conditions thereby overcoming the shortcomings of the previous method. The convergence time taken by the DTC drive for different scenarios using this approach is tabulated in Table 3.

Table 3. Time taken for the drive to reach the steady state at various speeds and load conditions

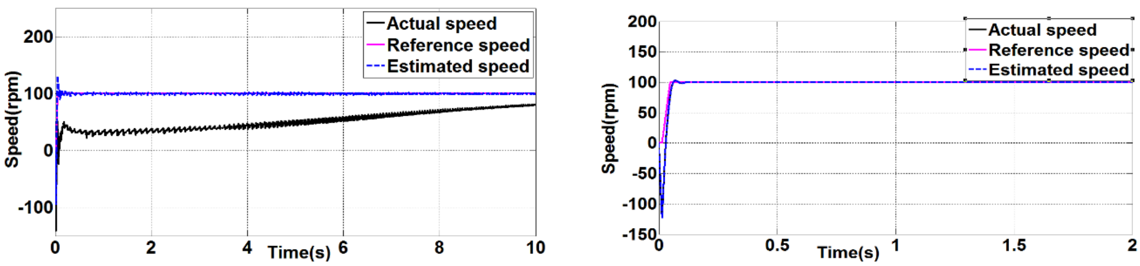
Speed(rpm)	At 5% load(5 Nm)	At 25% load(24.5 Nm)	At 50% load(49 Nm)	At full load(98 Nm)
1460	0.53 s	0.53 s	0.53 s	0.54 s
1000	0.38 s	0.38 s	0.38 s	0.38 s
500	0.22 s	0.21 s	0.212 s	0.213 s
100	0.133 s	0.12 s	0.113 s	0.11 s
10	0.11 s	0.12 s	0.125 s	0.1 s
7	0.145 s	0.122 s	0.115 s	0.09 s
5	0.123 s	0.11 s	0.12 s	0.096 s
3	0.122 s	0.126 s	0.127 s	0.11 s
2	0.12 s	0.129 s	0.126 s	0.092 s
1	0.13 s	0.1304 s	0.12 s	0.139 s

The data shown in Table 3 indicate significant reduction in response time compared to the previous method for all the operating conditions. The settling time remains almost constant for a particular operating speed regardless of the change in load. The low speed performance is also extremely adequate under all values of applied load which is an important achievement using this method. In order to provide an illustrative comparison, the traces of speed obtained using both the approaches are shown in Figure 3 and Figure 4 for drive operation at 100 rpm.



(a) (b)

Figure 3. Traces of speeds using (a) existing and (b) proposed methods at 100 rpm under a load of 5 Nm

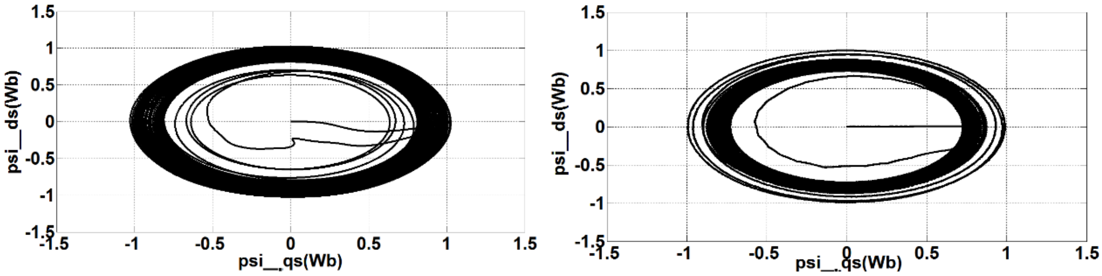


(a) (b)

Figure 4. Traces of speeds using (a) existing and (b) proposed methods at 100 rpm under full load of 98 Nm

Figure 3(a) and Figure 4(a) shows the traces of speed obtained using the existing speed estimation method with the drive set to run at 100 rpm with a load of 5 Nm and 98 Nm respectively. The time taken for the motor to attain the reference speed is 3.58 s in the first case and is more than 10 s in the second case, which conveys an increase in settling time with increase in load. Figure 3(b) and Figure 4(b) shows the traces of speed for the same scenario using the proposed method. The settling time is comparatively very less of the order 0.12 s irrespective of the change in applied load. The plots reveal that the proposed method of providing load profile input for estimation has a key advantage of rapid steady state convergence with very high precision in estimation.

Figure 5 shows the trajectory of stator flux obtained by plotting the direct axes stator flux against the quadrature axes stator flux using both the speed estimation methods. Figure 5(b) shows the improvement in the stator flux trajectory of IM drive using modified EKF for speed estimation.



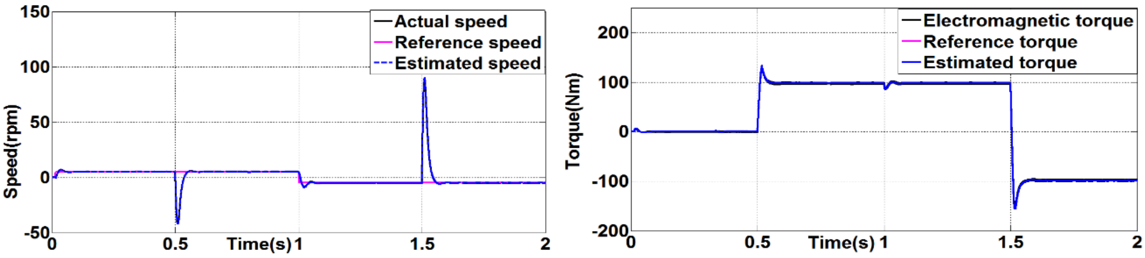
(a) (b)

Figure 5. Stator flux trajectory using (a)existing and (b)proposed methods at 1460 rpm with full load

In order to validate the effectiveness of the proposed algorithm during steady state and transient operations, the condition of speed and torque reversal are tested for all values of speed with full load. The accuracy of estimation is found to be very high under all conditions. The traces of speed and torque depicting this situation are shown in Figure 6 for drive operation at 5 rpm .The profile of reference speed and applied load at which drive is operated is given in Table 4.

Table 4. Profile of reference speed and applied load

Time(s)	0	1	Time(s)	0	0.5	1.5
Speed(rpm)	5	-5	Torque(Nm)	0	98	-98



(a) (b)

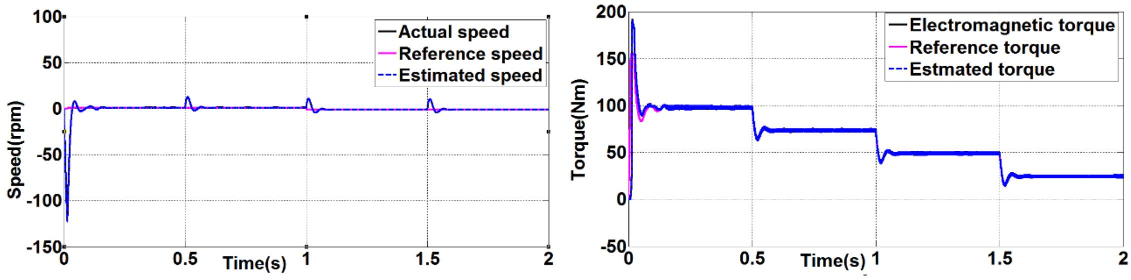
Figure 6. Traces of (a) speeds and (b) torques in DTC-SVM at 5 rpm under full load

Figure 6 shows that the values of speed and torque estimated by EKF is very close to the actual values and the drive is found to run at reference speed and torque. This shows the ability of EKF to provide accurate estimation at very low speeds when exposed to frequent reversals of speed and torque.

To test the response of the drive under varying load torque conditions, the drive is set to run at full load, 3/4th load, 1/2th load and 1/4th load and the speed and torque estimation is found to be satisfactory for the entire speed range. The waveforms illustrating this condition are shown in Figure 7 for the operation of drive at 1 rpm. DTC drive is set to work at the reference speed and the load torque as given in Table 5.

Table 5. Profile of reference speed and applied load

Time(s)	0	Time(s)	0	0.5	1	1.5
Speed(rpm)	1	Torque(Nm)	98	73.5	49	24.5



(a) (b)

Figure 7. Traces of (a) speeds and (b) torques in DTC-SVM at 1 rpm under varying load conditions

Figure 7 confirms that the speed and torque estimation is extremely effective at very low speeds with varying load conditions.

To further substantiate the significance of the new speed estimation approach especially at very low speeds, various performance parameters are evaluated during the steady state operation of DTC drive. The factors that are assessed constitute speed estimation error, actual speed error and percentage ripple in speed as well as torque. Speed estimation error is calculated as the percentage difference between the actual and estimated speed which is a measure of proximity between real and estimated values. Actual speed error is considered as the percentage difference between the reference and actual speed and it specifies how much the actual drive characteristics are aligned with required settings. The results are found to remain within satisfactory limit for a wide range of speeds. The parameters are represented graphically to show their variations over the entire speed range under full load condition.

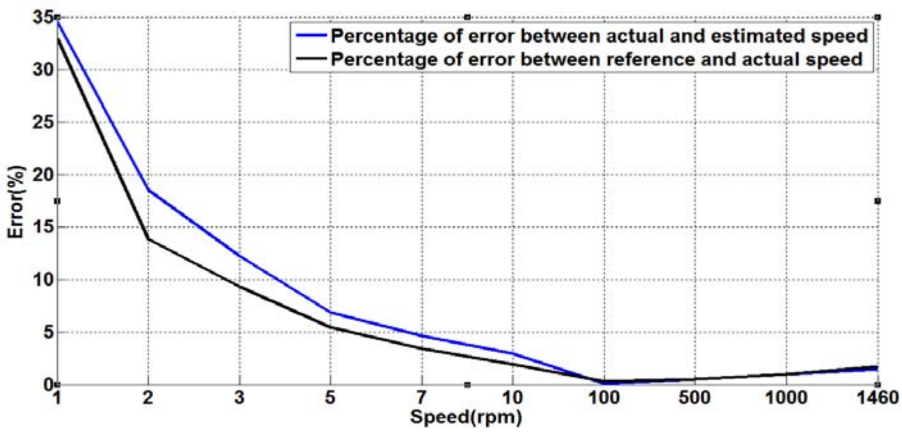


Figure 8. Trace of variation of speed estimation error and actual speed error with speed

Figure 8 shows the variations of speed estimation error and actual speed error for various speeds. The speed estimation error is less than 10% for all the speeds ranging from 5 rpm to the rated speed, but is slightly higher for speeds below 5 rpm. Similarly, the actual speed error is within 10% limit for speeds from 3rpm to 1460 rpm. Below 3 rpm, the actual speed error is found to be increasing. Hence this method of estimation is suitable for a wide range of speed especially for low speeds above 5 rpm.

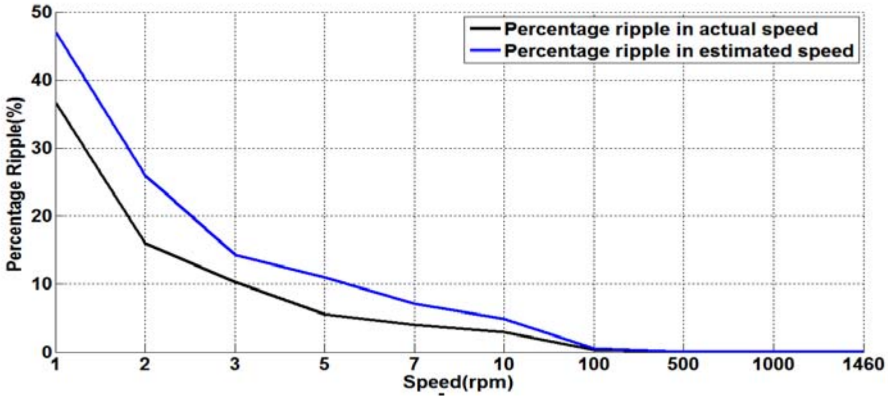


Figure 9. Trace of variation of percentage ripple in actual and estimated speed for various speeds

Figure 9 shows the percentage ripple in actual and estimated speed starting from very low speed upto the rated value. Percentage of ripple in actual speed and estimated speed is within 10% for all the speeds starting from 5 rpm. This appreciates the performance of EKF estimator at very low speeds. At higher speeds also, the speed ripple is very minimal. This shows that the new speed estimation scheme using EKF maintains the speed ripple within narrow tolerance band.

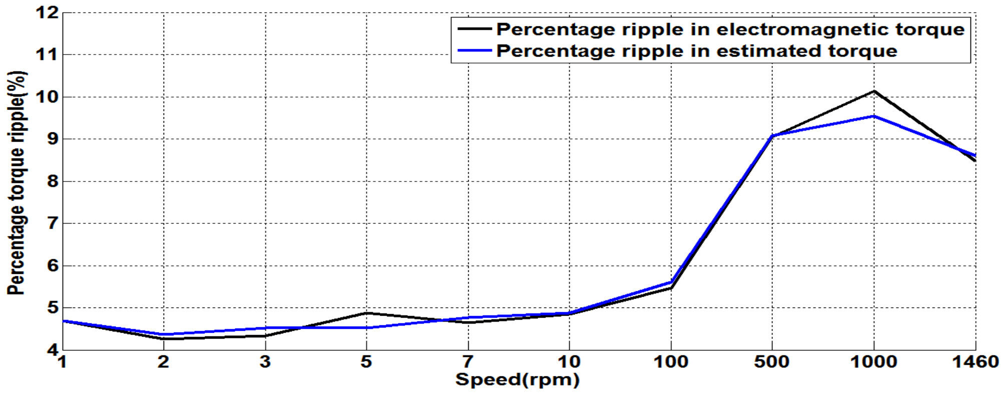


Figure 10. Trace of variation of percentage ripple in actual and estimated torque for various speeds

Figure 10 shows the percentage ripple in electromagnetic torque and estimated torque for a wide range of speeds at full load condition. The ripples in actual and estimated torques are very less and are within 6% for all the low speeds upto 100 rpm. For speeds above 100 rpm, the maximum percentage of ripple is 10%.

The graphical representations suggest that the EKF estimation holds good for all the speeds ranging from very low speed of 5 rpm to the rated speed with speed estimation error and actual speed error maintained within 10% and speed and torque ripple limited within 10%.

6. CONCLUSION

In this paper, a new mathematical model is developed for speed estimation using EKF inorder to improve the performance of DTC IM drive at low speeds. Speed is estimated using the equation of motion and the load torque required for speed estimation is fed to EKF in the form of load profile data. Since load torque is not an estimated quantity in EKF, the order of the filter is reduced thereby lowering the burden on computation. Also, this method has fast convergence when compared to the speed estimation in EKF considering load torque as a constant.

Simulation is carried out for wide range of speed at varying load conditions with reversals in speed and torque.The results proves the effectiveness of the new approach using EKF in speed and torque estimation at various speeds under varying torque conditions. A rigorous analysis is done in terms of speed estimation error, actual speed error and ripples in actual and estimated values of speed as well as torque from very low speeds to the rated speed.The work is mainly focused on low speeds and the statistics of anlaysis shows that this technique gives promising results during low speed operation.The maximum percentage error in these parameters are less than 10% for the speeds ranging from 5 rpm to the rated speed. For speeds between 1 rpm and 5 rpm, the errors are limited within 18%.But for very low speeds less than 1 rpm, percentage error in these paramaters are close to 40%. Further research is planned to improvise the performance of the DTC drive at very low speeds using existing variables of the system for speed estimation.

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BIOGRAPHIES OF AUTHORS

Mini R obtained her B.Tech. Degree in Electrical Engineering from Kerala university and M.Tech in Power Electronics from Visvewaraye Technological University (VTU). She is currently pursuing her Ph.D. in VTU on Electric Drives and Controlsl. With 9 years of industial experience, she has been with the Amrita School of Engineering, Bangalore Campus, Amrita Vishwa Vidyapeetham (University), India since 2002. She is currently Assistant Professor (Selection Grade) of the Department of Electrical Engineering.

Saranya C obtained her B. Tech in Electrical and Electronics Engineering from Calicut University, Kerala, India. Currently she is doing her M.Tech in Power Electronics at Amrita School of Engineering, Bengaluru campus, Amrita Vishwa Vidyapeetham (University). She as five years of Industrial Experience.

B. Hariram Satheesh obtained his B.E. in Electrical and Electronics Engineering from Manonmanium Sundaravar University, M.Tech in Industrial Drives from Mysore University and Ph.D. from Anna University. He has 12 years of experience in accademics and 8 years of Industrial experience. He is currently working as Principal Scientist in ABB and has several publications.

Dinesh M.N obtained his B.E in Electrical Engineering and M.E in Power Systems from Bangalore University and Ph.D.from Visvewaraye Technological University (VTU). He has 25 years of teaching experience. He has several publications and his research interests are Power Electronics, Control Systems, High voltage insulators, Electric Drives.