EKF BASED SPEED SENSORLESS DIRECT TORQUE CONTROL SYSTEM FOR IMs

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ABSTRACT

In this study, it is aimed to design a speed sensorless DTC system for induction motors (IMs). All the states required for DTC system in addition to the load torque are estimated using an Extended Kalman Filter (EKF). Simulation results demonstrate a good performance and robustness.

I. INTRODUCTION

High efficiency control and estimation techniques related to induction motors(IM's) have been finding more and more application fields with Blaschke's well-known field-oriented control(FOC) established in 1971. There has been an intensive amount of work to improve the dynamic response and reduce the complexity of FOC methods. One such method is the Direct Torque Control(DTC) method developed by Takahashi in 1984[1] and has been getting increased attention due to the improved dynamic performance and simplified control strategy that it offers with respect to the FOC methods.

The DTC method involves the direct choice of the appropriate/optimum switching modes, in order to keep the flux and torque errors within a prefixed band limit. The errors are defined as the difference between the reference and the measured/estimated values of flux and torque. Unlike FOC methods, DTC techniques require the utilization of hysterisis band controllers instead of flux and torque controllers. To replace the coordinate transformations and PWM signal generators of FOC, DTC uses look-up tables to carry out the switching procedure based on the inverter states. However, both methods require the accurate knowledge of the amplitude of the controlled flux and angular position (with respect to the stationary stator axis) in addition to the angular velocity for velocity control applications.

As it is well known, speed sensors like tachometers or incremental encoders increase the size and cost of systems unnecessarily. Similar problems arise with the addition of search coils or Hall effect sensors to the motor for the measurement of flux, hindering functionality in terms of implementation. Thus, to improve the overall system performance, state estimators or observers are usually more preferrable than physical measurements.

However, the 5^{th} order and nonlinear structure of the IM model[3], in addition to the sensivity of the system parameters to temperature[4] and frequency[5] makes the design of observers for IM's a challenge.

In DTC, the flux is conventionally obtained from the stator voltage model, using the measured stator voltages and currents. This method, utilizing open-loop pure integration suffers from increased noise on voltage and current and quantization errors in the digital system, in addition to the offset, gain and conversions factors in the low speed operation range[6], even with the correct knowledge of the stator resistance. Moreover, it will require the rotor angular velocity for velocity control applications. Among the current studies conducting simultaneous flux and velocity estimation for DTC, in [7] a robust performance to 50% variations in the stator resistance has been obtained with a sliding mode approach, while the adaptive flux observer in [8] and the Extended Luenberger Observer in [9] demonstrate robustness to step shaped load torque variations. There are also Extended Kalman Filter applications in the literature , taking a stochastic approach for the solution of the problem.

Unlike the other methods, model uncertainties and nonlinearities inherent to IM's are well-suited to the stochastic nature of EKF's[10] With this method, it is possible to make the on-line estimation of states while simultaneously performing identification of parameters in a relatively short time interval [11-13], also taking system/process and measurement noises directly into. This is the reason why EKF has found wide application in the sensorless control of IM's, in spite of its computational complexity. In the EKF based previous DTC studies, [14] estimates the stator flux components and velocity under the assumption of known load, while in [15], the velocity is estimated as a constant parameter. In spite of an improved performance in the steady-state, this approach has given rise to a significant observer error in the velocity during the transient state.

The major contribution of this study is the development of an EKF based speed sensorless DTC system that achieves robustness to load torques that are step-like or varying linearly with the rotor velocity. The developed EKF algorithm involves the estimation of stator flux, angular velocity and load torque in addition to the stator currents (referred to the stator stationary frame), which are also measured as output. With the square shaped voltage obtained by switching the inverter on and off, there has been no need for the addition of white noise to the measured states; thus, a more realistic approach has been taken to the solution of the problem. The performance of the control system with the proposed EKF algorithm has been demonstrated with simulations.

II. EXTENDED MATHEMATICAL MODEL OF THE IM

The extended discrete model of IM in stator stationary axis can be given as follows:

$$\underline{x}_e(k+1) = \underline{f}_e(\underline{x}_e(k), \underline{u}_e(k)) + \underline{w}_1(k)$$
$$= \underline{A}_e(\underline{x}_e(k))\underline{x}_e(k) + \underline{B}_e \underline{u}_e(k) + \underline{w}_1(k) \quad (1)$$
$$\underline{y}(k) = \underline{h}_e(\underline{x}_e(k)) + \underline{w}_2(k) \text{ (measurement equation)}$$
$$= \underline{H}_e \underline{x}_e(k) + \underline{w}_2(k) \quad (2)$$

$$\underline{A}_e = \begin{bmatrix} 1-a_2-a_4 & -a_5\omega_m(k) & a_3 & a_6\omega_m(k) & 0 & 0 \\ a_5\omega_m(k) & 1-a_2-a_4 & -a_6\omega_m(k) & a_3 & 0 & 0 \\ -a_7 & 0 & 1 & 0 & 0 & 0 \\ 0 & -a_7 & 0 & 1 & 0 & 0 \\ -a_8\psi_{s\beta}(k) & a_8\psi_{s\alpha}(k) & 0 & 0 & 1-a_{10} & -a_9 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\underline{B}_e = \begin{bmatrix} a_1 & 0 & T & 0 & 0 & 0 \\ 0 & a_1 & 0 & T & 0 & 0 \end{bmatrix}^T, \quad \underline{H}_e = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\underline{x}_e(k) = \begin{bmatrix} i_{s\alpha}(k) & i_{s\beta}(k) & \psi_{s\alpha}(k) & \psi_{s\beta}(k) & \omega_m(k) & t_L(k) \end{bmatrix}^T$$

$$\underline{u}_e(k) = \begin{bmatrix} v_{s\alpha}(k) & v_{s\beta}(k) \end{bmatrix}^T$$

$a_1 = T/\left(L_s - L_m^2/L_r^{'}\right)$, $a_2 = R_s a_1$, $a_3 = R_r^{'} a_1 / L_r^{'}$, $a_4 = a_3 L_s$, $a_5 = p_p T$, $a_6 = p_p a_1$, $a_7 = R_s T$, $a_8 = 1.5 p_p T / J_L$, $a_9 = T / J_L$, $a_{10} = B_L a_9$

where $\underline{f}_e$: nonlinear function vector of the states. $\underline{x}_e$: extended state vector. $\underline{A}_e$: system matrix. $\underline{u}_e$: control input vector. $\underline{B}_e$: input matrix. $\underline{h}_e$: function vector of the outputs $\underline{H}_e$ measurement matrix. $\underline{w}_1$, $\underline{w}_2$: process and measurement noise, respectively. p_p: number of pole pairs. L_s, R_s: stator inductance and resistance, respectively. $L_r^{'}$, $R_r^{'}$: rotor inductance and resistance, referred to the stator side, respectively. $v_{s\alpha}$, $v_{s\beta}$: stator stationary axis components of stator voltages. $\psi_{s\alpha}$ $\psi_{s\beta}$: stator stationary axis components of stator flux. $i_{s\alpha}$, $i_{s\beta}$: stator stationary axis components of stator currents. ω_m: angular velocity. t_L: load torque. T: sampling time.

III. DEVELOPMENT OF THE EKF ALGORITHM

The Kalman filter is a well-known recursive algorithm that takes the stochastic state space model of the system together with measured outputs to achieve the optimal estimation of states [16] in multi-input, multi-output systems. The filter takes system and measurement noises into account in the form of white noise. The optimality of the state estimation is achieved with the minimization of the mean estimation error. In this study, EKF, which is a form of Kalman filter that could be used for nonlinear systems is used for the estimation $i_{s\alpha}$, $i_{s\beta}$, $\psi_{s\alpha}$, $\psi_{s\beta}$, ω_m and t_L.

EKF involves the linearization of Eq.(1) and (2) around the states, $\hat{\underline{x}}_e(k)$ and inputs ($\hat{\underline{u}}_e(k)$) of the previous step, using

$$\underline{F}_e(k) = \left.\frac{\partial \underline{f}_e(\underline{x}_e(k), \underline{u}_e(k))}{\partial \underline{x}_e(k)}\right|_{\hat{\underline{x}}_e(k), \hat{\underline{u}}_e(k)} \quad (3)$$

$$\underline{F}_u(k) = \left.\frac{\partial \underline{f}_e(\underline{x}_e(k), \underline{u}_e(k))}{\partial u_e(k)}\right|_{\hat{\underline{x}}_e(k), \hat{\underline{u}}_e(k)} \quad (4)$$

The EKF algorithm is thus obtained with the following recursive equations;

$$\underline{N}(k+1) = \underline{F}_e(k)\underline{P}(k)\underline{F}_e(k)^T + \underline{F}_u(k)\underline{D}_u\underline{F}_u(k)^T + \underline{Q}$$
$$\underline{P}(k+1) = \underline{N}(k+1) - \underline{N}(k+1)\underline{H}^T\left(\underline{D}_\xi + \underline{H}\underline{N}(k+1)\underline{H}^T\right)^{-1}\underline{H}\underline{N}(k+1)$$
$$\hat{\underline{x}}_e(k+1) = \hat{\underline{f}}_e(\underline{x}_e(k), \hat{\underline{u}}_e(k)) + \underline{P}(k+1)\underline{H}^T\underline{D}_\xi^{-1}\left(\underline{Z}(k) - \underline{H}\hat{\underline{x}}_e(k)\right) \quad (5)$$

Here, $\underline{Q}$: covariance matrix of the model error (noise). $\underline{D}_\xi$: covariance matrix of measurement noise. $\underline{D}_u$: covariance matrix of control input. $\underline{P}(k+1/k)$, $\underline{N}(k+1/k)$: covariance matrix of state estimation error and extrapolation error, respectively

IV SPEED SENSORLESS DTC SYSTEM

Fig. 1 demonstrates the speed sensorles DTC system. Here, $\hat{\theta}_{rf}$ stands for the position of the flux with reference to the stationary axis. The velocity controller given in the diagram is a conventional PID controller. The development of the sector selector and the switching table is based on Takahashi's study presented in[1].

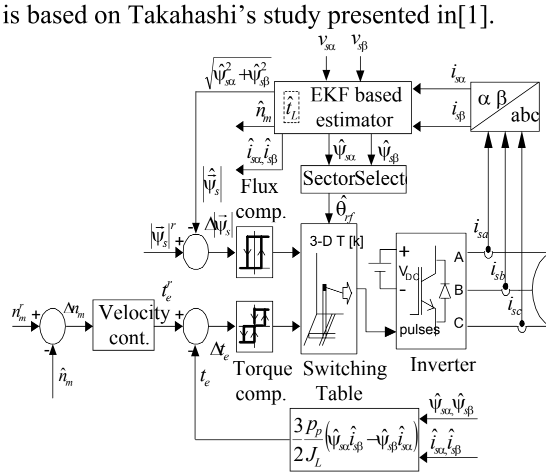


Fig. 1 The speed sensorless DTC system.

V. SIMULATION RESULTS AND OBSERVATIONS

To test the performance of the estimation method, simulations were performed on an IM with the following rated parameters;

$R_s = 2.283\,\Omega$, $R_r^{'} = 2.133\,\Omega$, $L_s = 0.23\,\mathrm{H}$, $L_r^{'} = 0.23\,\mathrm{H}$, $L_m = 0.22\,\mathrm{H}$, $p_p = 2$, $t_L = 20\,\mathrm{Nm}$, $J_L = 0.005\,\mathrm{kg.m}^2$, $B_L = 0.01\,\mathrm{Nm/(rad/s)}$

System covariance matrix

$$\underline{Q} = \begin{bmatrix} 10^{-6} & & & & & \\ & 10^{-6} & & & & \\ & & 10^{-6} & & & \\ & & & 10^{-6} & & \\ & & & & 10^{-5} & \\ & & & & & 10^{-5} \end{bmatrix}, \text{variances } \underline{D}_{\xi} = \begin{bmatrix} 10^{-6} & \\ & 10^{-6} \end{bmatrix},$$

$\underline{D}_u = \begin{bmatrix} 10^{-5} & \\ & 10^{-5} \end{bmatrix}$ and sampling time $T = 100\,\mu\mathrm{s}$.

The bandwidth (b_ψ) of the flux comparator is 0.02, while that of the torque comparator (b_{t_e}) is 0.01. The simulations are performed for 12 different scenarios for the IM motor. Fig.2 depicts the stator flux. Fig. 3(a), (b), (c), (d) (e) and (f) depict the variations of $n_m^r \,\&\, \hat{n}_m$, $n_m - \hat{n}_m$, $|\psi_s|^r \,\&\, |\hat{\psi}_s|$, $|\psi_s| - |\hat{\psi}_s|$, $t_L \,\&\, \hat{t}_L$ and $t_L - \hat{t}_L$, respectively. The $e_{(.)}$ error signals illustrate the deviation between the actual and the estimated parameter or state.

Analysing the simulation results, the following observations are made:

-With initial values taken as zero, it has been demonstrated that the EKF based estimation and control perform quite well even in spite of instantaneous variations in the load and velocity.

-Another advantage of the developed scheme is the ability to account for various other constant uncertainties (the viscous friction, in this case), within the estimated constant load value. e_{t_L} should be expected to be equal to $-B_L\omega_m$, and as can be seen in the second time interval (1-2 s) of Fig. 3(f),

$$\begin{aligned} \omega_m(\infty) &= 2\pi 1500/60 = 157.0796[\mathrm{rad/s}] \\ e_{tL} &\overset{!}{=} -B_L\omega_m(\infty) \\ -1.5708 &\overset{!}{=} -0.01 \times 157.0796 \\ -1.5708[\mathrm{Nm}] &\cong -1.570796[\mathrm{Nm}] \end{aligned} \tag{6}$$

-The deviations detected in Fig.2 are caused by the instantaneous reversal of the load torque at the zero crossings of the velocity, as can be seen in Fig.3. However, it is important to note that the control system demonstrates a good performance even under those variations.

-Between 9-10 sec. in Fig.3(b), the velocity is varied instantaneously from 10 to 1500rpm, with an additional linear variation in the torque from 0 to 20[Nm]. The error band decreases with reduced rates of variation.

In summary, the speed sensorless DTC system has demonstrated a good performance for the IM, in the whole velocity range, in spite of step-like and linear variations of the load torque with the angular velocity.

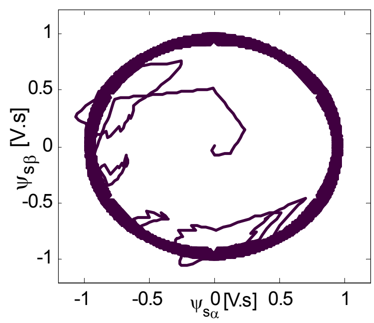
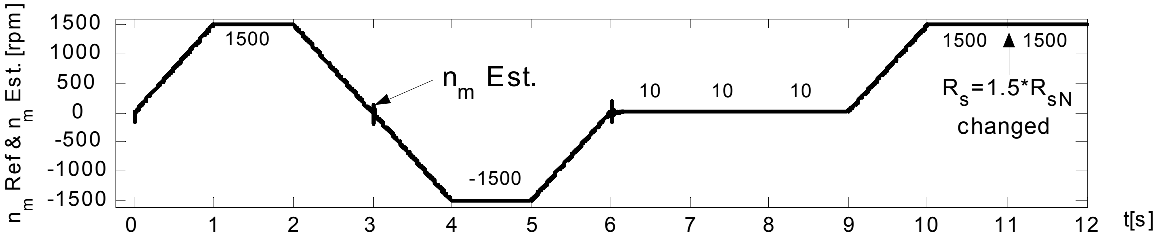


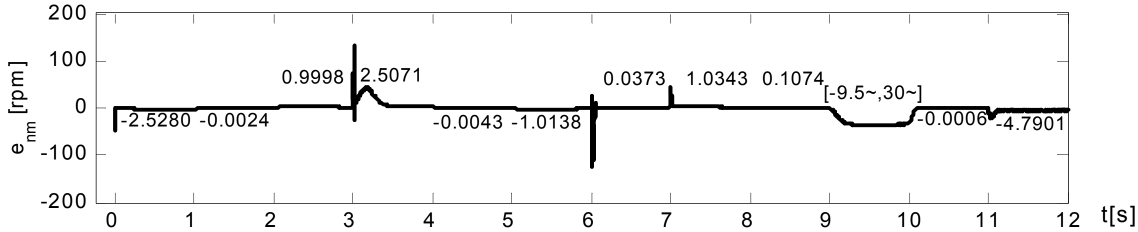
Fig.2 Trajectory of $\hat{\psi}_{s\alpha}$ and $\hat{\psi}_{s\beta}$

VI. CONCLUSION

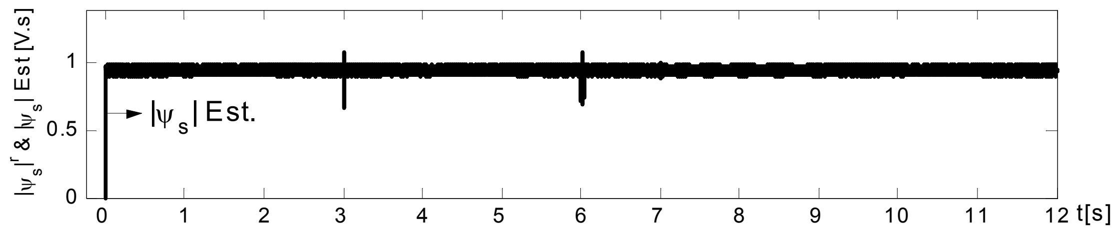
In this study, a speed sensorless DTC system has been designed, particularly to achieve robustness against a step-like and linear variations of the load torque with the angular velocity. All the states and the load torque required by developed control algorithm have been estimated by EKF. The speed sensorles DTC system has demonstrated a good performance even under instantaneous variations of load and velocity.



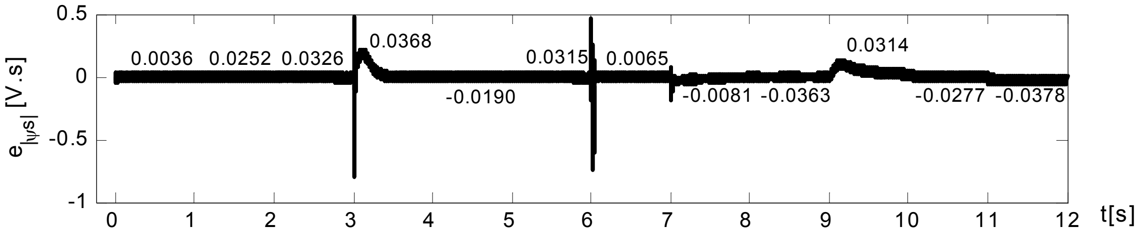
(a) Variation of the n_m^r and $\hat{n}_m$



(b) Variation of the estimation error of n_m, e_{n_m}

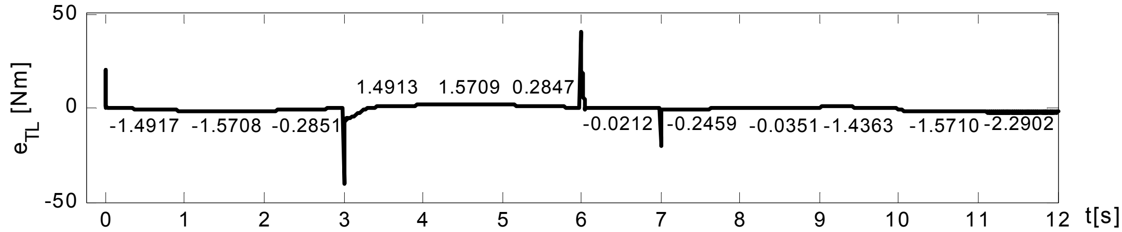


(c) Variation of the $|\psi_s|^r$ and $|\hat{\psi}_s|$



(d) Variation of the estimation error of $|\psi_s|$, $e_{|\psi_s|}$

(e) Variation of the t_L and $\hat{t}_L$



(f) Variation of the estimation error of t_L, e_{t_L}

Fig. 3 Simulation results of the EKF based estimator and the speed sensorles DTC system.

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