

Direct Torque Control of Saturated Induction Machine with and without speed sensor

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Abstract. In this paper, a modified KALMAN filter is proposed to estimate speed. At first, the influence of the magnetic saturation is taken into account in the modelling. In the second part, the direct torque control (DTC) is elaborated; the control of the speed loop is ensured by an IP controller, the flux and the torque are estimated from source voltages and measured currents. The last part of this work is devoted to the operating system without mechanical sensor, using a KALMAN filter as a speed observer. Simulation results are presented to verify the effectiveness of the proposed approach.

Keywords: DTC, Sensors, KALMAN filter, induction machine, saturated model, speed observer.

1. Introduction

To study the control of any system, one of the most important parts is the system modelling. The induction machine is not a simple system, because of numerous complicated phenomena which affect its operation, such as saturation, eddy currents, skin effect etc... However, firstly these phenomena will not be taken into account; this allows obtaining simple equations which reflect accurately the machine operation [1].

2. Modeling of the induction motor

The application of Concordia transformation to the rotor and stator windings results on the following equations of the induction machine in the d-q reference frame [1, 3]:

$$\underline{V}_s = R_s \underline{I}_s + \frac{d\underline{\Phi}_s}{dt} + j\omega_s \underline{\Phi}_s \quad (1)$$

$$\underline{V}_r = R_r \underline{I}_r + \frac{d\underline{\Phi}_r}{dt} + j\omega_{sl} \underline{\Phi}_r \quad (2)$$

$$\underline{\Phi}_s = L_{\sigma s} \underline{I}_s + \underline{\Phi}_m \quad , \quad \underline{\Phi}_m = L_m \underline{I}_m \quad (3)$$

$$\underline{\Phi}_r = L_{\sigma r} \underline{I}_r + \underline{\Phi}_m \quad , \quad \underline{I}_m = \underline{I}_s + \underline{I}_r \quad (4)$$

$$T_{em} = P(\Phi_{ds} I_{qs} - \Phi_{qs} I_{ds}) \quad (5)$$

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- R_s , R_r stator and rotor resistances;
- $L_{\sigma s}$, $L_{\sigma r}$ stator and rotor leakage inductances;
- L_m mutual inductance;
- $\underline{\Phi}_s$, $\underline{\Phi}_r$ stator and rotor flux vectors;
- \underline{V}_s , \underline{V}_r stator and rotor voltage vectors;
- \underline{I}_s , \underline{I}_r stator and rotor currents vectors;
- $\underline{\Phi}_m$, \underline{I}_m magnetizing flux and current vectors;
- ω_s , ω_{sl} synchronous and slip angular speeds;
- T_{em} electromagnetic torque.

method and can be presented by the following matrix form as [3, 4]:

$$[V] = [L][\dot{I}] + [R][I] \quad (6) \quad [V] = [V_{ds}, V_{qs}, 0, 0]^T \quad [I] = [I_{ds}, I_{qs}, I_{dr}, I_{qr}]^T$$

$$[L] = \begin{bmatrix} L_{\sigma s} + M_d & M_{dq} & M_d & M_{dq} \\ M_{dq} & L_{\sigma s} + M_q & M_{dq} & M_q \\ M_d & M_{dq} & L_{\sigma r} + M_d & M_{dq} \\ M_{dq} & M_q & M_{dq} & L_{\sigma r} + M_q \end{bmatrix}$$

$$[R] = \begin{bmatrix} R_s & -\omega_s L_s & 0 & -\omega_s L_m \\ \omega_s L_s & R_s & \omega_s L_m & 0 \\ 0 & -\omega_{sl} L_m & R_r & -\omega_{sl} L_r \\ \omega_{sl} L_m & 0 & \omega_{sl} L_r & R_r \end{bmatrix}$$

$M_d = L_{m dy} \cos^2 \alpha + L_m \sin^2 \alpha$: Mutual inductance of the axis d

$M_q = L_m \cos^2 \alpha + L_{m dy} \sin^2 \alpha$: Mutual inductance of the axis q

$M_{dq} = (L_{m dy} - L_m) \cos \alpha \sin \alpha$: Term explaining the cross effect between the axis in quadrate

M_{dy} and L_m are the dynamic and the static mutual inductance's, respectively. α is the angle between the d axis and the magnetizing current I_m .

As can be seen in the Fig.1, in steady state, the difference is clear between the saturated model and the linear model. The instantaneous torque is maximal at starting, after that it is stabilized to compensate the losses at no-load. From Fig.1, we can observe that there is a difference between the torque of saturated model compared to linear model, which explains the slower transient of the speed with this model compared to the linear model.

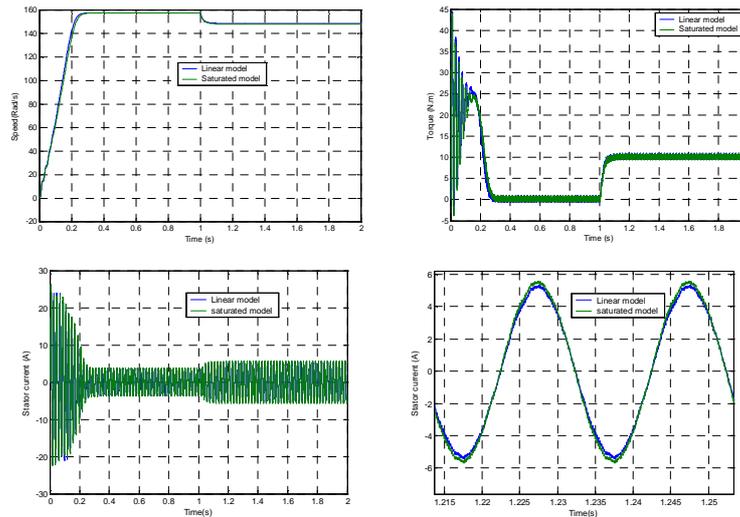


Fig.1. Start up following by a load application of an induction motor: linear model (blue curve), saturated model (green curve).

3. Direct torque control (DTC)

Direct Torque Control (DTC) of an induction machine is based on adequate voltage source inverter. In a stator reference frame, the instantaneous values of stator flux and electromagnetic torque are estimated from the stator magnitudes. Using hysteresis comparators, the flux and the torque are controlled directly and independently with an appropriate selection of voltage vector imposed by the inverter. The inverter provides eight voltage vectors.

These vectors are chosen from a switching table based on errors of flux and torque and the stator flux vector position (Tab.1). Application of a stator voltage vectors which makes possible to decrease or to increase the stator flux and the electromagnetic torque in the same time

Tab.1 Switching table using hysteresis comparators of torque and flux

N		1	2	3	4	5	6
$\Delta\phi_s$	ΔC_{em}						
1	1	V ₂	V ₃	V ₄	V ₅	V ₆	V ₁
	0	V ₇	V ₀	V ₇	V ₀	V ₇	V ₀
	-1	V ₆	V ₁	V ₂	V ₃	V ₄	V ₅
0	1	V ₃	V ₄	V ₅	V ₆	V ₁	V ₂
	0	V ₀	V ₇	V ₀	V ₇	V ₀	V ₇
	-1	V ₅	V ₆	V ₁	V ₂	V ₃	V ₄

The bloc diagram of the DTC is shown in Fig.2.

4. DTC Without speed sensor by EKF

The machine speed is obtained through a mechanical speed sensor. However, this sensor requires a place for its installation and leads to difficulties in its mounting; it is sensitive to noise and vibration. Several strategies have been proposed in the literature to eliminate this mechanical sensor. Among these strategies, there is the estimation by the extended Kalman filter (EKF). The Kalman filter is an observer for nonlinear closed-loop whose gain matrix is variable. At each calculation step, the Kalman filter predicts the new values of state variables of the induction machine (current, flux and speed). This prediction is made by minimizing the noise effects and modelling errors of the parameters or the state variables. The noises are supposed to be white, Gaussian and not correlated with the estimated states [5]. The extended Kalman filter

as any other observer is based on the system model. The output equation is:

$$\frac{d}{dt} \begin{bmatrix} I_{\alpha s} \\ I_{\beta s} \\ \phi_{\alpha s} \\ \phi_{\beta s} \\ \Omega \end{bmatrix} = \frac{1}{\sigma L_s} \begin{bmatrix} -(R_s + \frac{L_s}{T_r}) & -\omega \sigma L_s & \frac{1}{T_r} & \omega r & 0 \\ \omega \sigma L_s & -(R_s + \frac{L_s}{T_r}) & -\omega r & \frac{1}{T_r} & 0 \\ -\sigma L_s R_s & 0 & 0 & 0 & 0 \\ 0 & -\sigma L_s R_s & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} I_{\alpha s} \\ I_{\beta s} \\ \phi_{\alpha s} \\ \phi_{\beta s} \\ \Omega \end{bmatrix} + \begin{bmatrix} \frac{1}{\sigma L_s} & 0 \\ 0 & \frac{1}{\sigma L_s} \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u_{\alpha s} \\ u_{\beta s} \end{bmatrix}$$

$$\begin{bmatrix} I_{\alpha s} \\ I_{\beta s} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} I_{\alpha s} & I_{\beta s} & \phi_{\alpha s} & \phi_{\beta s} & \Omega \end{bmatrix}^T \quad (7)$$

The equivalent discrete filter is necessary for the implementation of the EKF in real time. It is assumed that the control input U(kT) is constant between the actual sampling instant [kT] and the previous sampling instant [(k + 1)T]. Thus, the discrete model of the machine in extended form becomes:

$$\begin{bmatrix} I_{\alpha s}(k+1) \\ I_{\beta s}(k+1) \\ \phi_{\alpha s}(k+1) \\ \phi_{\beta s}(k+1) \\ \Omega(k+1) \end{bmatrix} = \begin{bmatrix} (1+a_1T) & a_2p\Omega T & a_3T & a_4p\Omega T & 0 \\ -a_2p\Omega T & (1+a_1T) & -a_4p\Omega T & a_3T & 0 \\ a_5T & 0 & 1 & 0 & 0 \\ 0 & a_5T & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} I_{\alpha s}(k) \\ I_{\beta s}(k) \\ \phi_{\alpha s}(k) \\ \phi_{\beta s}(k) \\ \Omega(k) \end{bmatrix} + T \begin{bmatrix} \frac{1}{\sigma L_s} & 0 & 1 & 0 & 0 \\ 0 & \frac{1}{\sigma L_s} & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} u_{\alpha s}(k) \\ u_{\beta s}(k) \end{bmatrix} \quad (13)$$

$$\begin{bmatrix} I_{\alpha s}(k+1) \\ I_{\beta s}(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} I_{\alpha s}(k) & I_{\beta s}(k) & \phi_{\alpha s}(k) & \phi_{\beta s}(k) & \Omega(k) \end{bmatrix}^T \quad a_1 = -\frac{T_r R_s + L_s}{\sigma L_s T_r} \quad a_2 = -1 \quad a_3 = \frac{1}{\sigma L_s T_r} \quad a_4 = \frac{1}{\sigma L_s} \quad a_5 = -R_s$$

It is assumed that the matrix of the state vector P and the matrices Q & R of the measurement noise are diagonal.

There are two steps to implement the EKF algorithm, the first is the prediction, the second is the correction, and these two steps are introduced by an initialization of state vector X_0 and the covariance matrix P_0 , Q_0 and R_0 .

The first estimation of the state vector at time $(k+1)$ is:

$$\hat{X}(k+1) = f[\hat{X}(k/k), U(k), k] \quad (9)$$

Thus, this measure state allows the prediction of the output:

$$\hat{Y}(k+1/k) = C\hat{X}(k+1/k) \quad (10)$$

The prediction covariance matrix of the filter is given by the following formula:

$$P(k+1/k) = A(k)P(k/k)A^T(k) + Q \quad (11)$$

Then:

$$A(k) = \begin{bmatrix} (1+a_1T) & a_2\Omega(k)T & a_3T & a_4\Omega(k)T & (a_2I_{\beta s}(k)+a_4\phi_s(k))T \\ -a_2\Omega(k)T & (1+a_1T) & -a_4\Omega(k)T & a_3T & -(a_2I_{\alpha s}(k)+a_4\phi_s(k))T \\ a_5T & 0 & 0 & 0 & 0 \\ 0 & a_5T & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Finally, the new value of the estimated state vector at time $(k+1)$ is given by:

$$\hat{X}(k+1/k+1) = \hat{X}(k+1/k) + K(k+1)[Y(k+1) - \hat{Y}(k+1/k)] \quad (12)$$

The calculation of the error covariance is as follows:

$$P(k+1/k+1) = \{I - K(k+1)C\}P(k+1/k) \quad (13)$$

Therefore, in the DTC without mechanical sensor, the estimated speed is used only for the control. The Kalman filter also estimates the electromagnetic torque and the components, the magnitude and the sector of stator flux. This allows the complete elimination of the two estimators of torque and flux presented previously. Thus, Only the KALMAN filter which gives all the estimated quantities that the DTC needs. Fig.4 illustrates the scheme of this control.

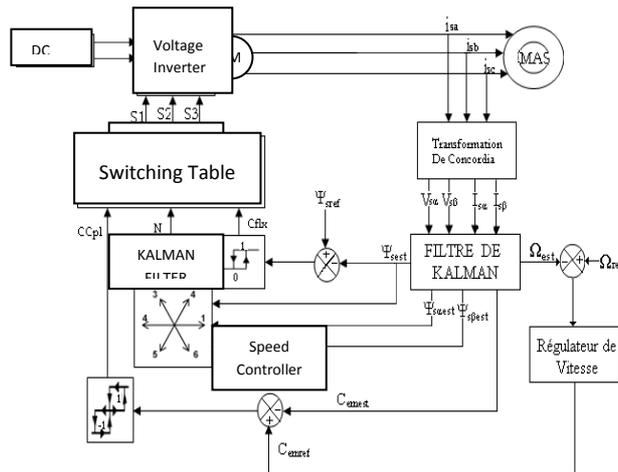


Fig.4. General structure of the direct torque control without mechanical sensor by the use of the extended KALMAN filter

The simulation results of the DTC without mechanical sensor control is shown in the Figures 5 and 6. The insertion of the Kalman filter in the DTC, gives good performance, the estimated quantities follow perfectly the reference quantities with a slight error of estimation in transients. The System behaviour is good even in the presence of magnetic saturation; however, the mutual inductance value adaptation is introduced inside the EKF algorithm.

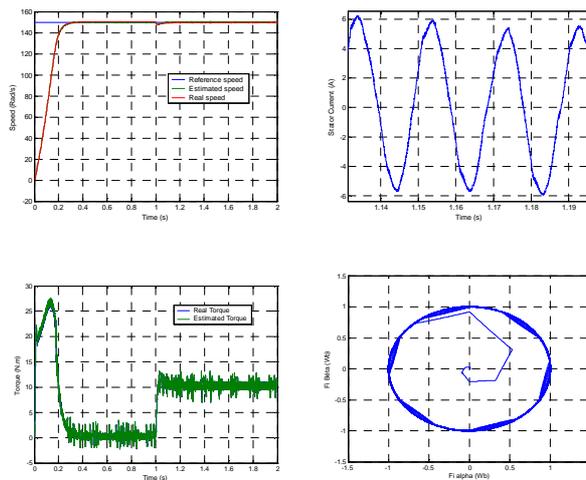


Fig.5. without speed sensor DTC by EKF applied to the linear model

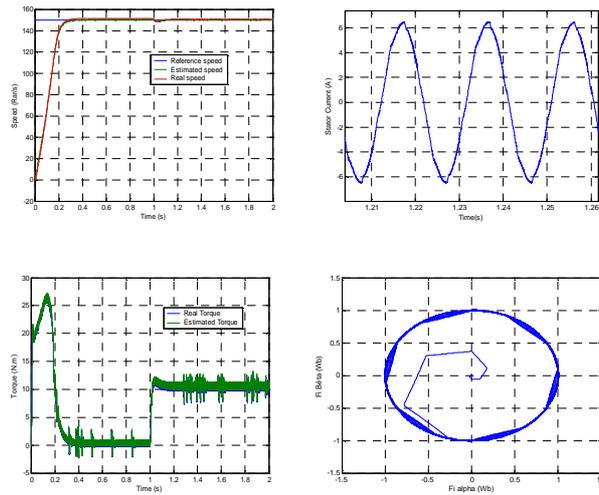


Fig.6. without speed sensor DTC by EKF applied to the saturated model

5. Conclusion

This paper presents an approach for the induction machine modeling including magnetic saturation. The saturated model is more accurate than the simplified model in every facet of the prediction of machine performance.

The main basic concepts of direct torque control DTC are presented. This control can be performed by using a suitable choice of inverter voltage vectors. Simulation results show the robustness and the advantages of this control, such as the no need of the magnetic saturation compensation.

The application of the Extended KALMAN Filter (EKF) for the direct torque control (DTC) without speed sensor gives an excellent performance; the machine electrical quantities are perfectly estimated. The results obtained show the need for the adaptation of the mutual value function of the saturation level inside Kalman filter algorithm.

6. References

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