A REAL-TIME ESTIMATOR OF ELECTRICAL PARAMETERS FOR VECTOR CONTROLLED INDUCTION MOTOR USING A REDUCED ORDER EXTENDED KALMAN FILTER

Vicente Leite [1], *Rui Araújo* [2], *Diamantino Freitas* [3]

[1]ESCOLA SUPERIOR DE TECNOLOGIA E GESTÃO DO INSTITUTO POLITÉCNICO DE BRAGANÇA
Campus de Santa Apolónia, Apartado 134, 5301-857 Bragança, Portugal
[2, 3]FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO
Rua Dr. Roberto Frias s/n, 4200-465 Porto, Portugal
[1]avtl@ipb.pt, Tel: + 351-273-303158, Fax: +351-273-313051; [2]raraujo@fe.up.pt, Tel: +351-22-5081808, Fax: +351-22-5081443; [3]dfreitas@fe.up.pt, Tel: +351-22-5081837, Fax: +351-22-5081443

Abstract – This paper presents an application of the extended Kalman filter (EKF) to the simultaneous on-line estimation of the rotor flux components and electrical parameters of a vector controlled induction motor. A time-discrete reduced order model structure is deduced and presents a simple and reduced state equation and a scalar output equation. This, combined with the use of the rotor reference frame, offers many advantages for real-time identification, compared with full order models, because it reduces the computational cost of the EKF.

Keywords – Induction motors, estimation techniques, variable speed drives, adaptive control.

Summary – A different strategy is proposed for discretization of a reduced order state space model structure of the induction motor with a scalar output equation instead of a matrix one, which results as follows:

$$\begin{cases} \begin{bmatrix} \psi^r_{rd}(k+1) \\ \psi^r_{rq}(k+1) \end{bmatrix} = \begin{bmatrix} 1-T_s\tau_r^{-1} & 0 \\ 0 & 1-T_s\tau_r^{-1} \end{bmatrix} \begin{bmatrix} \psi^r_{rd}(k) \\ \psi^r_{rq}(k) \end{bmatrix} + \begin{bmatrix} T_s L_M \tau_r^{-1} & 0 \\ 0 & T_s L_M \tau_r^{-1} \end{bmatrix} \begin{bmatrix} i^r_{sd}(k) \\ i^r_{sq}(k) \end{bmatrix} \\ u^r_{sd}(k) = -\tau_r^{-1}\psi^r_{rd}(k) - \omega(k)\psi^r_{rq}(k) + a i^r_{sd}(k) + L'_s\left(\frac{1}{2T_s}\left(3i^r_{sd}(k) - 4i^r_{sd}(k-1) + i^r_{sd}(k-2)\right) - \omega(k) i^r_{sq}(k)\right) \end{cases}$$

This state-space time-discrete model in the rotor reference frame with the EKF algorithm is used for identification of the state vector, based on measured rotor speed and dq components of stator voltages and currents. The state vector x is composed by the following states: rotor flux dq components and electrical parameters of the induction motor which are scaled as follows:

$$x = \begin{bmatrix} \psi_{rd} & \psi_{rq} & 0.2\times\tau_r^{-1} & 50\times L'_s & 5\times L_M & 0.5\cdot R_s \end{bmatrix}^T$$

Simulation tests with start-up transients and steady state operation showed that, on the one hand, the rotor parameters have a good convergence behavior and, on the other, the stator parameters require a longer transient. A series of initial square pulses in the motor speed reference is proposed to improve the speed and the asymptotic behavior of the stator parameters mainly the stator resistance. The robustness of the algorithm initialization and convergence performance is presented. The rotor reference frame is very useful since the signals' frequency bandwith is lower than in the stator reference frame and therefore, the sampling period can be made longer. This, together with the reduced order model, allows cutting down on the computational effort, which is one main drawback of the EKF. The sampling frequency can be as low as 1 kHz while in the stator reference frame it is usually in the range of 5 to 10 kHz. A diagonal process noise covariance matrix, weighted by exponential functions, is used to raise the speed of convergence of the state estimates when the algorithm starts, by improving the filter dynamics by means of high values of the covariance matrix diagonal elements. These values decrease exponentially with time to the steady state values to guarantee filter stability and parameters tracking. This covariance matrix has the following form:

$$\begin{cases} R_s(k) = diag\begin{bmatrix} 1e-8 & 1e-8 & g_1(k) & g_2(k) & g_3(k) & g_4(k) \end{bmatrix} \\ g_{1,2,3}(k) = 1e-8\times\left(\exp(-0.8kT_s)+0.01\right) \quad \text{and} \quad g_4(k) = 1e-7\times\left(\exp(-0.8kT_s)+0.01\right) \end{cases}$$

Simulation and experimental studies presented in this paper highlight the improvements brought by this new approach based on an extended Kalman filtering technique under real operation conditions.