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APPLIACATION OF THE KALMAN FILTER IN CONTROL SYSTEMS OF POWER ELECTRONICS

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ABSTRACT

Kalman filter can deal with measurement and modelling inaccuracies and, also, can be used for the join state estimation.Higher accuracy of the parameters estimation of a control object can increase the power efficiency of control systems in inverter-fed drives. This paper introduces the improved extended Kalman Filter (EKF) for the real-time speed estimation of an induction motor (IM) in the sensorless control system of inverter-fed drive.

Key words: power electronics, inverter-fed drive, extended Kalman Filter, sensorless vector control system, microcontroller.

INTRODUCTION

The purpose of the inverter control system in the electrical drive is to maintain the maximum electromagnetic torque. One uses speed estimators, when speed or position sensors are not applicable due to rough environment conditions. This paper describes a sensorless vector control system of an inverter-fed drive using the improved EKF.

Proposed structure of the sensorless inverter-fed drive

The estimation produced by the EKF is depended on the accuracy of its mathematical model. The flux estimator is necessary to determine the position of rotor flux-linkage in classic vector control system of an induction motor.

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In this paper it is suggested to take into account the estimation of the rotor flux-linkages, obtained by the rotor flux estimator, in the mathematical model of the EKF to improve rotor speed estimation [1][2][3].

The structure of the proposed sensorless vector control system is shown in Fig. 1.

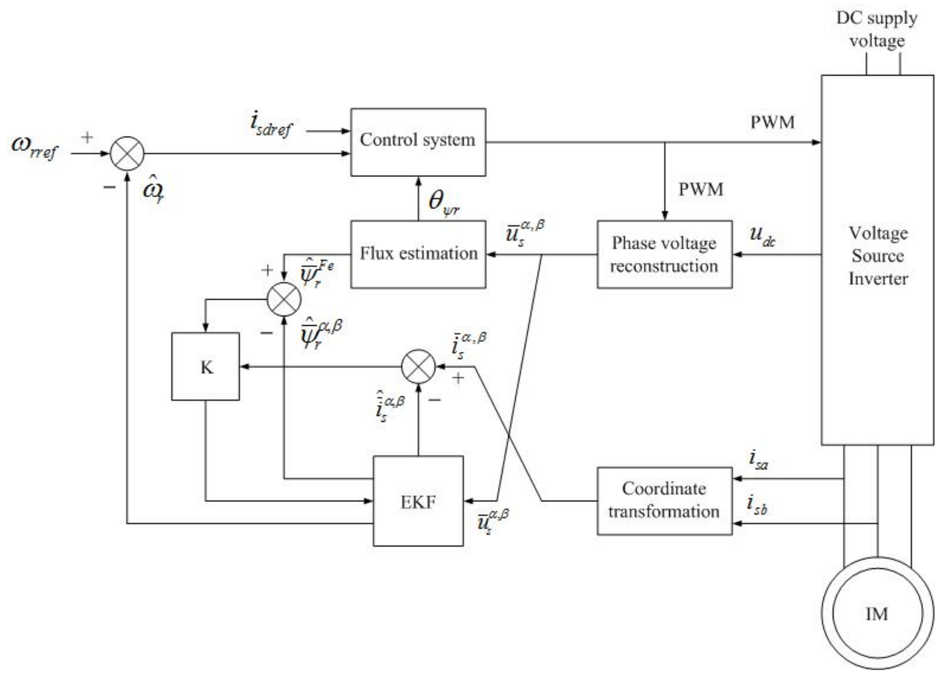

Fig.1. Sensorless vector control system of an induction motor

It is reasonable to use the mathematical model of the induction machine expressed in the stationary reference frame in our application [4]. Structure of the proposed EKF is based on the well-known structure of the EKF [5] shown in Fig. 2.

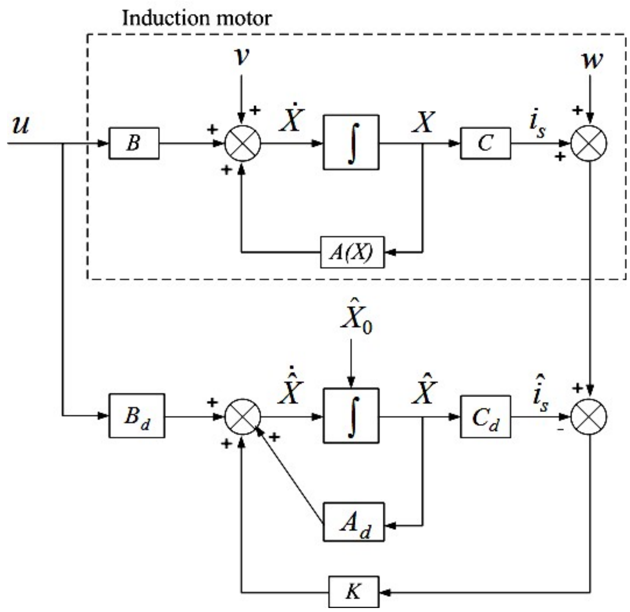

Fig.2. Structure of the EKF

In Fig.2 $x = \begin{bmatrix} i_{s\alpha} & i_{s\beta} & \psi_{r\alpha} & \psi_{r\beta} & \omega_r \end{bmatrix}^T$ is the system state vector, x_0 is starting value of the state vector, $\hat{x}$ is estimation of the state vector, $u = \begin{bmatrix} u_{s\alpha} & u_{s\beta} \end{bmatrix}^T$ is the system input, v and w are zero-mean white Gaussian noises with covariance Q and R, A_d – discrete system matrix, B_d – discrete input matrix, C_d – discrete output matrix. Matrices A_d, B_d and C_d are given here:

$$A_d = \begin{bmatrix} 1-\frac{T}{T_s'^*} & 0 & \frac{TL_m}{L_s' L_r T_r} & \frac{T\omega_r L_m}{L_s' L_r} & \frac{T\psi_{r\beta} L_m}{L_s' L_r} \\ 0 & 1-\frac{T}{T_s'^*} & \frac{-T\omega_r L_m}{L_s' L_r} & \frac{TL_m}{L_s' L_r T_r} & \frac{-T\psi_{r\alpha} L_m}{L_s' L_r} \\ \frac{TL_m}{T_r} & 0 & 1-\frac{T}{T_r} & -T\omega_r & -T\psi_{r\beta} \\ 0 & \frac{TL_m}{T_r} & T\omega_r & 1-\frac{T}{T_r} & T\psi_{r\alpha} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} B_d = \begin{bmatrix} T / L_s' & 0 \\ 0 & T / L_s' \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} C_d = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix},$$

and $L_s' = \sigma L_s$ – transient stator inductance, where $\sigma = 1 - L^2{}_m / (L_s L_r)$ – leakage coefficient, L_s – stator inductance; L_m – magnetizing inductance; $L_r = L_{lr} + L_m$ – rotor inductance, where L_{lr} – rotor leakage inductance; $T_r = L_r / R_r$ – rotor time constant; $\omega_r = \omega_m p$ – electrical angular rotor speed, where ω_m – mechanical angular rotor speed, p – number of pole-pairs; $T_s'^* = L_s' / (R_s + R_r (L_m / L_r)^2)$ – parameter, where R_s – stator resistance, R_r – rotor resistance; $i_{s\alpha}$ and $i_{s\beta}$ –stator currents in the stationary reference frame, $u_{s\alpha}$ and $u_{s\beta}$ – linear stator voltages in the stationary reference frame, $\psi_{r\alpha}$ and $\psi_{r\beta}$ – rotor flux-linkages in the stationary reference frame.

Implementation of the improved EKF

The EKF algorithm contains two stages: extrapolation – equations (1)-(2), and correction – equations (3)-(5). Extrapolation of the state vector is based on the discretized equation of the induction motor. It is suggested to modify the state vector estimation $\hat{\bar{x}}(t_k)$ in equation (4) by the additional introduction of the rotor flux-linkage estimation $\hat{\bar{\psi}}_r^{Fe}(t_k)$. Thus, the improved EKF uses the measured stator currents and the estimation of the rotor flux-linkage to calculate the state vector:

$$\hat{\bar{x}}(t_{k+1|k}) = f(\hat{\bar{x}}(t_k), \bar{u}_s^{\alpha,\beta}(t_k)) =$$

$$= \begin{Vmatrix} (1-T/K_s)\hat{i}_{s\alpha}(t_k) + TL_m/(L_s'L_rT_r)\hat{\psi}_{r\alpha}(t_k) + TL_m/(L_s'L_r)\hat{\omega}_r(t_k)\hat{\psi}_{r\beta}(t_k) + (T/L_s')u_{s\alpha}(t_k) \\ (1-T/K_s)\hat{i}_{s\beta}(t_k) - TL_m/(L_s'L_r)\hat{\omega}_r(t_k)\hat{\psi}_{r\alpha}(t_k) + TL_m/(L_s'L_rT_r)\hat{\psi}_{r\beta}(t_k) + (T/L_s')u_{s\beta}(t_k) \\ (TL_m/T_r)\hat{i}_{s\alpha}(t_k) + (1-T/T_r)\hat{\psi}_{r\alpha}(t_k) - T\hat{\omega}_r(t_k)\hat{\psi}_{r\beta}(t_k) \\ (TL_m/T_r)\hat{i}_{s\beta}(t_k) + (1-T/T_r)\hat{\psi}_{r\beta}(t_k) + T\hat{\omega}_r(t_k)\hat{\psi}_{r\alpha}(t_k) \\ \hat{\omega}_r(t_k) \end{Vmatrix} \quad (1)$$

$$P(t_{k+1|k}) = F(\hat{\bar{x}}(t_k))P(t_k)F^T(\hat{\bar{x}}(t_k)) + Q \quad (2)$$

$$K(t_k) = P(t_{k+1|k})H^T(\hat{\bar{x}}(t_{k+1|k}))\left\| H(\hat{\bar{x}}(t_{k+1|k}))P(t_{t_{k+1|k}})H^T(\hat{\bar{x}}(t_{k+1|k})) + R \right\|^{-1} \quad (3)$$

$$\hat{\bar{x}}(t_k) = \begin{Vmatrix} \hat{i}_{s\alpha}(t_k) \\ \hat{i}_{s\beta}(t_k) \\ \hat{\psi}_{r\alpha}(t_k) \\ \hat{\psi}_{r\beta}(t_k) \\ \hat{\omega}_r(t_k) \end{Vmatrix} = \begin{Vmatrix} \hat{i}_{s\alpha}(t_{k+1|k}) \\ \hat{i}_{s\beta}(t_{k+1|k}) \\ \hat{\psi}_{r\alpha}(t_{k+1|k}) \\ \hat{\psi}_{r\beta}(t_{k+1|k}) \\ \hat{\omega}_r(t_{k+1|k}) \end{Vmatrix} + K(t_k)\left[\begin{Vmatrix} i_{s\alpha}(t_k) \\ i_{s\beta}(t_k) \\ \hat{\psi}_{r\alpha}^{Fe}(t_k) \\ \hat{\psi}_{r\beta}^{Fe}(t_k) \end{Vmatrix} - \begin{Vmatrix} \hat{i}_{s\alpha}(t_{k+1|k}) \\ \hat{i}_{s\beta}(t_{k+1|k}) \\ \hat{\psi}_{r\alpha}(t_{k+1|k}) \\ \hat{\psi}_{r\beta}(t_{k+1|k}) \end{Vmatrix} \right] \quad (4)$$

$$P(t_k) = P(t_{_{k+1|k}}) - K(t_k)H(\hat{\bar{x}}(t_{k+1|k}))P(t_{_{k+1|k}}) \quad (5)$$

$$H(\hat{\bar{x}}(t_{k+1|k})) = \left. \frac{\partial h(x)}{\partial x} \right|_{x=\hat{\bar{x}}(t_{k+1|k})} \quad (6)$$

$$F(\hat{\bar{x}}(t_k)) = \left. \frac{\partial f(x, \bar{u}_s^{\alpha,\beta}(t_k))}{\partial x} \right|_{x=\hat{\bar{x}}(t_k)}, \quad (7)$$

where $\hat{\bar{x}}(t_{k+1|k})$ means that it is a predicted value at the t_{k+1} instant and it is calculated on the measurements up to the t_k instant; $\hat{\bar{x}}(t_k)=\left\|\hat{i}_{s\alpha}(t_k)\ \ \hat{i}_{s\beta}(t_k)\ \ \hat{\psi}_{r\alpha}(t_k)\ \ \hat{\psi}_{r\beta}(t_k)\ \ \hat{\omega}_r(t_k)\right\|^T$ – corrected state vector estimation; $\hat{\bar{x}}(t_{k+1|k})=\left\|\hat{i}_{s\alpha}(t_{k+1|k})\ \ \hat{i}_{s\beta}(t_{k+1|k})\ \ \hat{\psi}_{r\alpha}(t_{k+1|k})\ \ \hat{\psi}_{r\beta}(t_{k+1|k})\ \ \hat{\omega}_r(t_{k+1|k})\right\|^T$ – extrapolation of the state vector; $P(t_{k+1|k})$ – covariance matrix of extrapolation error, $P(t_k)$ – covariance matrix of estimation error, $F(\hat{\bar{x}}(t_k))$ – gradient matrix, Q – covariance matrix of the system noise, R – covariance matrix of the measurement noise, $K(t_k)$ – the EKF gain matrix, $H(\hat{\bar{x}}(t_{k+1|k}))$ – sensitivity matrix, $h(\hat{\bar{x}}(t_{k+1|k}))=\left\|\hat{i}_{s\alpha}(t_{k+1|k})\ \ \hat{i}_{s\beta}(t_{k+1|k})\ \ \hat{\psi}_{r\alpha}(t_{k+1|k})\ \ \hat{\psi}_{r\beta}(t_{k+1|k})\right\|^T$ – the result of multiplying the output matrix by the state vector $\hat{\bar{x}}(t_{k+1|k})$; $f(\hat{\bar{x}}(t_k),\bar{u}_s^{\alpha,\beta}(t_k))$ – the amount of the state matrix, multiplied by the state vector $\hat{\bar{x}}(t_k)$, and entry matrix, multiplied by the control input vector $\bar{u}_s^{\alpha,\beta}(t_k)$; $\hat{\bar{\psi}}_r^{Fe}(t_k)=\left\|\hat{\psi}_{r\alpha}^{Fe}(t_k)\ \ \hat{\psi}_{r\beta}^{Fe}(t_k)\right\|^T$ – estimation of the rotor flux-linkages in the stationary reference frame obtained using rotor flux estimator; $T=(t_k-t_{k-1})\leq 500\ \mu s$ – sampling time. Due to the modification of the filtering algorithm, the matrix size of R needs to be increased to 4×4, and the sensitivity matrix $H(\hat{\bar{x}}(t_{k+1|k}))$ must be augmented by two rows and have a size of 4×5.

Estimation of the rotor speed $\hat{\omega}_r(t_k)$ required for the sensorless vector control system is calculated according to the equation (4). Extrapolation of the rotor speed $\hat{\omega}_r(t_{k+1|k})$ in equation (1) is performed using the estimation of rotor speed obtained in the previous step of the calculation.

Calculation of the gain matrix $K(t_k)$ requires the computation of the inverse matrix $\left\|H(\hat{\bar{x}}(t_{k+1|k}))P(t_{t_{k+1|k}})H^T(\hat{\bar{x}}(t_{k+1|k}))+R\right\|^{-1}$. Since the sensitivity matrix is equal to $H(\hat{\bar{x}}(t_{k+1|k}))=\begin{Vmatrix}1&0&0&0&0\\0&1&0&0&0\\0&0&1&0&0\\0&0&0&1&0\end{Vmatrix}$ and the dimension of the matrix $\left\|H(\hat{\bar{x}}(t_{k+1|k}))P(t_{t_{k+1|k}})H^T(\hat{\bar{x}}(t_{k+1|k}))+R\right\|$ is 4×4, to calculate the inverse matrix it is sufficient to use a part of the matrix $H(\hat{\bar{x}}(t_{k+1|k}))$, which is an identity matrix. Therefore, to calculate the inverse matrix it is possible to use the solution of the system of linear algebraic equations. Perform the multiplication of the left and right side of equation (3)by $H(\hat{\hat{x}}(t_{k+1|k}))$ in order to obtain the required system:

$$K(t_k)H(\hat{\hat{x}}(t_{k+1|k})) = P(t_{k+1|k})H^T(\hat{\hat{x}}(t_{k+1|k}))\cdot \cdot\left\|H(\hat{\hat{x}}(t_{k+1|k}))P(t_{t_{k+1|k}})H^T(\hat{\hat{x}}(t_{k+1|k})) + R\right\|^{-1}\cdot . \cdot H(\hat{\hat{x}}(t_{k+1|k})) \quad (8)$$

Perform LU-decomposition of the matrix $\left\|H(\hat{\hat{x}}(t_{k+1|k}))P(t_{t_{k+1|k}})H^T(\hat{\hat{x}}(t_{k+1|k})) + R\right\|$ using Crout's method, because this algorithm gives less round-off error compared to other methods. Also, it can save memory, because it writes result in place of the origin matrix without writing intermediate data.

The required system of linear algebraic equations is:

$$LU\cdot\left\|H(\hat{\hat{x}}(t_{k+1|k}))P(t_{t_{k+1|k}})H^T(\hat{\hat{x}}(t_{k+1|k})) + R\right\|^{-1}H(\hat{\hat{x}}(t_{k+1|k})) = H(\hat{\hat{x}}(t_{k+1|k})). \quad (9)$$

Denoting as unknown X:

$$X = \left\|H(\hat{\hat{x}}(t_{k+1|k}))P(t_{t_{k+1|k}})H^T(\hat{\hat{x}}(t_{k+1|k})) + R\right\|^{-1}H(\hat{\hat{x}}(t_{k+1|k})), \quad (10)$$

we can find, that

$$LUX = H(\hat{\hat{x}}(t_{k+1|k})). \quad (11)$$

Performing a direct substitution $LB = H(\hat{\hat{x}}(t_{k+1|k}))$, and then backward substitution $UX = B$ we can calculate X.

To obtain the gain matrix $K(t_k)$ in equation (8) it is sufficient to write down the first four column in the product $P(t_{k+1|k})H^T(\hat{\hat{x}}(t_{k+1|k}))X$, because:

$$K(t_k)H(\hat{\hat{x}}(t_{k+1|k})) = P(t_{k+1|k})H^T(\hat{\hat{x}}(t_{k+1|k}))X = = P(t_{k+1|k})H^T(\hat{\hat{x}}(t_{k+1|k}))\left\|H(\hat{\hat{x}}(t_{k+1|k}))P(t_{k+1|k})H^T(\hat{\hat{x}}(t_{k+1|k})) + R)\right\|^{-1}H(\hat{\hat{x}}(t_{k+1|k})). \quad (12)$$

Estimation results

The proposed sensorless vector control system with the improved EKF was implemented in MATLAB Simulink.

In Fig. 3 the speed of the IM is maintained by the vector control system at ω_{rref} = 120 rad/sec. At t = 2 sec a load bounce of 100 Nm is applied to the motor. Fig. 3 shows the speed ω_r obtained from the IM model and the estimated speed $\hat{\omega}_r$ produced by the suggested observer.

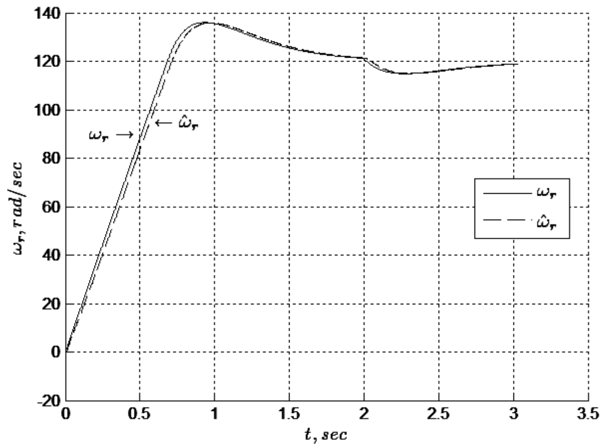

Fig.3. IM angular rotor speed and estimated rotor speed

CONCLUSION

This paper has introduced the implementation of the improved EKF for a sensorless vector control system of an inverter-fed drive. The proposed algorithm was modelled in MATLAB Simulink.

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