Front. Electr. Electron. Eng. 2012, 7(3): 347–355
DOI 10.1007/s11460-012-0206-y

RESEARCH ARTICLE

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Learning fuzzy controller and extended Kalman filter for sensorless induction motor robust against resistance variation

Abstract This paper presents a new sensorless vector controlled induction motor drive robust against rotor resistance variation. Indeed, the speed and rotor resistance are estimated using extended Kalman filter (EKF). Then, we introduce a new fuzzy logic speed controller based on learning by minimizing cost function. This strategy is based on a topology control self-organized and an algorithm for modifying the knowledge base of fuzzy corrector. The learning mechanism addresses the consequences of corrector rules, which are modified according to the comparison between the current speed of machine and an output signal or a desired trajectory. Thus, fuzzy associative memory is constructed to meet the criteria imposed in problems either control or pursuit. The consequent algorithm updating consists of a regulator mechanism allowing a fast and robust learning without unnecessarily compromising the control signal and steady-state performance. The performance of this new strategy is satisfactory, even in the presence of noise or when there are variations in the parameters of induction motor drive.

Keywords extended Kalman filter, induction motor, learning fuzzy control, rotor resistance, sensorless control

1 Introduction

The induction motor is the machine that most used in industry. It is more robust, reliable, efficient, and low cost compared to other machines for similar applications [1]. However, when the engine is controlled by the indirect method for rotor flux oriented [2], it is exposed to stresses that can potentially affect its performance. In other words, the linear control of torque, which achieved through effective unbundling of the machine, is no longer valid when the rotor resistance changes [3]. The latter obtained by identification tests is highly dependent on the temperature of rotor circuit. During operation of the machine, the temperature increases because of the different types of losses, which causes the variation of rotor resistance and hence the loss of decoupling. This phenomenon affects both the performance of speed control and efficiency of the induction motor [3–5].

The robustness of induction motor is also altered, by indirect field oriented control, since it requires the location of a speed sensor to satisfy the decoupling process. The speed sensor is involved in the increased cost of installation and the degree of redundancy failure. Therefore, its removal and use of speed estimators can significantly improve the robustness of the drive and lowers its cost [5].

To overcome these problems, an estimator of speed and rotor resistance based on the algorithm of the extended Kalman filter (EKF) with a learning fuzzy proportional-integral (PI) controller has been established.

The Kalman filter is an optimal recursive data processing algorithm for linear systems [6–8]. It is optimal in that it incorporates all the information that is provided to it, regardless of their precision, to estimate the current value of the state. The latter is obtained by combining a prediction of the state, computed from history based on a given model, and the current weighted measurement data in such a way that the error is minimized statistically (minimizing the covariance of the state) [8,9]. The Kalman filter is recursive in the sense that although it incorporates the history into the present, it does not require all previous data to be kept in storage and reprocessed at every iteration.

Received March 5, 2012; accepted July 23, 2012

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The setting of fuzzy logic with its nonlinear structure presented good performance and robustness in the control of induction motor. This is a new technique addressing the digital control of processes and decision making. Fuzzy logic based on fuzzy set theory developed by Zadeh [10]. Besides, a mathematical formalism developed strong interest in fuzzy logic control is the fact that the theory of fuzzy sets can handle and reasoning using variables that incorporate the notion of imprecision, uncertainty assessments or subjective quantifications language, which allows the controller to be fuzzy designed to replace a skilled human operator [11,12]. The fuzzy logic controllers (FLCs) can be considered as nonlinear PI where their parameters are determined in real time using the error and its derivative. The disadvantage of FLC is that they need a lot of information to compensate for nonlinearity when the parameters change, more if the number of inputs of FLC increases the size of the basic rules increases. To overcome the disadvantages, a learning method by modifying the consequences of fuzzy correction has been proposed. This strategy is based on a topology control self-organized and an algorithm for modifying the knowledge base of fuzzy corrector. The learning mechanism addresses the consequences of corrector rules, which are modified according to the comparison between the current speed of machine and an output signal or a desired trajectory. Thus, fuzzy associative memory is constructed to meet the criteria imposed in problems either control or pursuit. The consequent algorithm updating consists of a regulator mechanism allowing a fast and robust learning without unnecessarily compromising the control signal and steady-state performance.

This paper is organized as follows: The principle of indirect field oriented control is presented in the second part; an estimator of speed and rotor resistance based on EKF algorithm is developed in the third section; the design of a learning fuzzy speed controller is performed in section four; the fifth part is devoted to illustrate the simulation performance of this control strategy; and a conclusion and reference list at the end.

2 Indirect vector control

In field orientation concept of induction motor, the goal is to obtain an electromagnetic torque proportional to the quadrature component of stator current i_{sq} (at constant flux) and can control the flux by acting on the direct component of this current i_{sd}. This can be accomplished by choosing ω_e to be the instantaneous speed of Ψ_r and locking the phase of the reference system such that the rotor flux is entirely in the d-axis (flux axis), resulting in the mathematical constraint:

$$\Psi_r = \Psi_{rd}. \tag{1}$$

The rotor dynamics are given by the following equations:

$$\frac{\mathrm{d}\Psi_r}{\mathrm{d}t} = \frac{L_m}{\tau_r} i_{sd} - \frac{1}{\tau_r}\Psi_r, \tag{2}$$

$$\frac{\mathrm{d}\omega_r}{\mathrm{d}t} = \frac{3p^2 L_m}{2JL_r}\Psi_r i_{sq} - \frac{F}{J}\omega_r - \frac{p}{J}\Gamma_l, \tag{3}$$

$$\Gamma_{em} = \frac{3pL_m\Psi_r}{2L_r} i_{sq}, \tag{4}$$

$$\rho = \int \omega_e \mathrm{d}t = \int \left(\omega_r + \frac{R_r L_m i_{sq}}{L_r \Psi_r}\right)\mathrm{d}t. \tag{5}$$

The rotor flux magnitude is related to the direct axis stator current by a first-order differential equation; thus, it can be controlled by controlling the direct axis stator current. Under steady-state operation rotor flux is constant, so Eq. (2) becomes:

$$\Psi_r = L_m i_{sd}. \tag{6}$$

Indirect vector control can be implemented using the following equations:

$$i_{sd}^* = \frac{\Psi_r^*}{L_m}, \tag{7}$$

$$i_{sq}^* = \frac{2L_r\Gamma_{em}^*}{3pL_m\Psi_r^*}, \tag{8}$$

$$\omega_{sl}^* = \frac{R_r L_m i_{sq}^*}{L_r \Psi_r^*}, \tag{9}$$

$$\rho^* = \int \omega_e^* \mathrm{d}t = \int (\omega_r + \omega_{sl}^*)\mathrm{d}t, \tag{10}$$

where

v_{sd}, v_{sq}: stator voltages in d-q axes [V];
i_{sd}, i_{sq}: stator currents in d-q axes [A];
i_{rd}, i_{rq}: rotor currents in d-q axes [A];
Ψ_{rd}, Ψ_{rq}: rotor flux components in d-q axes [Wb];
R_s, R_r: stator and rotor resistances [Ω];
L_m, L_s, L_r: mutual, stator, and rotor inductances [H];
ω_e, ω_r, ω_{sl}: synchronous, rotor, and slip frequencies [rad/s];
Γ_{em}, Γ_l: electromagnetic torque, mechanical loads [N·m];
F: damping coefficient [N·m·s];
ρ: angle of rotor flux [rad];
τ_r: rotor time constant [s];
J: inertia moment [kg·m²];
p: motor poles number;
*: reference symbol.

3 Extended Kalman filter algorithm

The EKF has become the standard state estimation scheme for nonlinear systems. The EKF is based upon the linearized dynamics of the system that it estimates. It has the advantage that it is computationally inexpensive and fairly robust with respect to model errors. However, the disadvantage is that when used for severely nonlinear systems (the EKF being a linearized technique), the EKF may perform poorly since the nonlinearities are not fully accounted for. Large initial estimation errors may also cause the EKF to diverge since its inherent stability is only guaranteed locally [7–9].

Consider the discrete dynamical system:

$$\begin{cases} x_k = f(x_{k-1}, u_k) + \eta_k, \\ y_k = h(x_k) + v_k, \end{cases} \tag{11}$$

where $x_k \in R^n$ is the state vector at time step k, $y_k \in R^m$ is the measurement vector, $f(x)$: $R^n \rightarrow R^n$ is the process model, $g(x)$: $R^n \rightarrow R^m$ is the measurement model, and $\eta_k \in R^r$ and $v_k \in R^m$ are Gaussian white noise sequences satisfying:

$$\begin{cases} \mathrm{E}\{\eta_k\} = 0, \quad \mathrm{E}\{\eta_k \eta_l^{\mathrm{T}}\} = Q_k \delta_{kl}, \\ \mathrm{E}\{v_k\} = 0, \quad \mathrm{E}\{v_k v_l^{\mathrm{T}}\} = R_k \delta_{kl}, \end{cases} \tag{12}$$

where $Q_k \in R^{r \times r}$ and $R_k \in R^{m \times n}$ are symmetric positive definite covariance matrices, and δ_{kl} is the discrete Dirac function satisfying:

$$\delta_{kl} = \begin{cases} 1, & k = l, \\ 0, & k \neq l. \end{cases} \tag{13}$$

After initialization, the EKF proceeds recursively in two steps: a prediction step using the process model of the system dynamics; and a measurement update step that adjusts the predicted states based on the measured outputs and relative magnitudes of the disturbance and measurement noise covariance's [13].

In the pose estimation system, the prediction step, at time step k, uses the previous estimate to predict the system states using the process model:

$$\hat{x}_{k|k-1} = F\left(\hat{x}_{k-1|k-1}, u_k, 0\right), \tag{14}$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^{\mathrm{T}} + Q_k, \tag{15}$$

where Q_k is the disturbance noise covariance at the kth time step; F_k is the linearization, through Taylor series expansion, of the process model:

$$F_k = \frac{\partial f}{\partial x}\Big|_{\hat{x}_{k-1|k-1}}, \tag{16}$$

and F_k^{T} is the matrix transpose of F_k.

Similarly, the measurement model is linearized about the current state estimate, resulting in the measurement Jacobian, H_k,

$$H_k = \frac{\partial h}{\partial x}\Big|_{\hat{x}_{k|k-1}}. \tag{17}$$

The Kalman gain, K_k, is calculated using this linearized model, the previous estimate covariance, and the measurement noise covariance, R_k,

$$K_k = P_{k|k-1} H_k^{\mathrm{T}} [H_k P_{k|k-1} H_k^{\mathrm{T}} + R_k]^{-1}. \tag{18}$$

Finally, the estimates and estimate covariance are updated using this gain and the innovation of the measurements — the difference between the measured and predicted outputs,

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left[y_k - h\left(\hat{x}_{k|k-1}\right)\right], \tag{19}$$

$$P_{k|k} = [I - K_k H_k] P_{k|k-1}. \tag{20}$$

The state and output equations of the reduced order model of the induction motor established in stationary stator reference frame d-q can be written as

$$f(x_{k-1}, u_k) = A_k x_k + B_k u_k, \tag{21}$$

$$h(x_k) = C_k x_k, \tag{22}$$

$$\begin{cases} x_{k+1} = \begin{bmatrix} \Psi_{rd} \\ \Psi_{rq} \\ \omega_r \\ R_r \end{bmatrix}_{k+1} = A_k \begin{bmatrix} \Psi_{rd} \\ \Psi_{rq} \\ \omega_r \\ R_r \end{bmatrix}_k + B_k \begin{bmatrix} i_{sd} \\ i_{sq} \\ \Gamma_{em} \end{bmatrix}_k, \\ y_k = \begin{bmatrix} v_{sd} - R_s i_{sd} - \sigma L_s \varepsilon i_{sd} \\ v_{sq} - R_s i_{sq} - \sigma L_s \varepsilon i_{sq} \end{bmatrix}_k = C_k \begin{bmatrix} \Psi_{rd} \\ \Psi_{rq} \\ \omega_r \\ R_r \end{bmatrix}_k, \end{cases} \tag{23}$$

where

$$A_k = \begin{bmatrix} 1 - \frac{R_r}{L_r} t_s & -\omega_r t_s & 0 & 0 \\ \omega_r t_s & 1 - \frac{R_r}{L_r} t_s & 0 & 0 \\ 0 & 0 & 1 - \frac{\lambda}{J} t_s & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}_k,$$

$$B_k = \begin{bmatrix} \frac{L_m R_r}{L_r} t_s & 0 & 0 \\ 0 & \frac{L_m R_r}{L_r} t_s & 0 \\ 0 & 0 & \frac{1}{J} t_s \\ 0 & 0 & 0 \end{bmatrix}_k,$$

$$C_k = \begin{bmatrix} -\frac{R_r L_m}{L_r^2} & -\frac{\omega_r L_m}{L_r} & 0 & \frac{L_m^2}{L_r^2} i_{sd} \\ \frac{\omega_r L_m}{L_r} & -\frac{R_r L_m}{L_r^2} & 0 & \frac{L_m^2}{L_r^2} i_{sq} \end{bmatrix}_k,$$

$$\varepsilon i_{sd_k} = \frac{i_{sd_k} - i_{sd_{k-1}}}{t_s},$$

$$\varepsilon i_{sq_k} = \frac{i_{sq_k} - i_{sq_{k-1}}}{t_s}, \tag{24}$$

where A_K, B_k, C_k are input and output matrices of discrete system, λ is viscous friction load, σ is leakage coefficient, and t_s is sampling period.

The matrices f_k, h_k, F_k, H_k are obtained as follows:

$$f_k = \begin{bmatrix} \left(1 - \frac{R_r}{L_r} t_s\right) \Psi_{rd} - \omega_r t_s \Psi_{rq} + \frac{L_m R_r}{L_r} t_s i_{sd} \\ \omega_r t_s \Psi_{rd} + \left(1 - \frac{R_r}{L_r} t_s\right) \Psi_{rq} + \frac{L_m R_r}{L_r} t_s i_{sq} \\ \left(1 - \frac{\lambda}{J} t_s\right) \omega_r + \frac{\Gamma_{em}}{J} t_s \\ R_r \end{bmatrix}_k,$$

$$h_k = \begin{bmatrix} -\frac{R_r L_m}{L_r^2} \Psi_{rd} - \frac{L_m \omega_r}{L_r} \Psi_{rq} + \frac{L_m^2 R_r}{L_r^2} i_{sd} \\ \frac{L_m \omega_r}{L_r} \Psi_{rd} - \frac{R_r L_m}{L_r^2} \Psi_{rq} + \frac{L_m^2 R_r}{L_r^2} i_{sq} \end{bmatrix}_k,$$

$$F_k = \begin{bmatrix} 1 - \frac{R_r}{L_r} t_s & -\omega_r t_s & -\Psi_{rq} t_s & \frac{(L_m i_{sd} - \Psi_{rd}) t_s}{L_r} \\ \omega_r t_s & 1 - \frac{R_r}{L_r} t_s & \Psi_{rd} t_s & \frac{(L_m i_{sq} - \Psi_{rq}) t_s}{L_r} \\ 0 & 0 & 1 - \frac{\lambda}{J} t_s & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}_k,$$

$$H_k = \begin{bmatrix} -\frac{R_r L_m}{L_r^2} & -\frac{L_m \omega_r}{L_r} & -\frac{L_m \Psi_{rq}}{L_r} & \frac{(L_m i_{sd} - \Psi_{rd}) L_m}{L_r^2} \\ \frac{L_m \omega_r}{L_r} & -\frac{R_r L_m}{L_r^2} & \frac{L_m \Psi_{rd}}{L_r} & \frac{(L_m i_{sq} - \Psi_{rq}) L_m}{L_r^2} \end{bmatrix}_k.$$

The covariance matrix of system and measurement noise constitutes the control parameters of Kalman filter. The initial choice of these matrices is very crucial for the proper functioning and for filter convergence. For our application, they are chosen diagonal and stationary.

The matrix elements R quantify the noise on measurements. The increase implies that measures are subject to more noise corruption. The increase of matrix R affects the transient performance of filter and its decrease may lead to unstable estimates.

The elements of matrix Q quantify the model precision (uncertainties on filter prediction). Increasing these elements means either most important noise in system either greater uncertainty on model. Larger values may lead to unstable estimation, by cons too small values do not allow the filter to follow the states variations and parameters to be estimated.

4 Fuzzy learning speed controller by minimizing cost function

4.1 Fuzzy speed controller

Mamdani's fuzzy inference method [14] is the most commonly seen fuzzy methodology. The control law is described by a knowledge-based system which consists of IF-THEN rules with vague predicates and a fuzzy inference system (FIS). The rule base of IF-THEN statements describes the relationship between the inputs and the outputs of the controller. The control action is brought about by an incremental change in the controllers output (see Fig. 1). The most significant variables of the inputs of the fuzzy speed controller have been selected as the speed error e and its change Δe, the output of this controller is Γ_{em}^*. The equations of input/output controller written at time k are:

$$e(k) = \omega_r^*(k) - \omega_r(k), \tag{25}$$

$$\Delta e(k) = e(k) - e(k-1), \tag{26}$$

$$\Gamma_{em}^*(k) = \Gamma_{em}^*(k-1) + \Delta\Gamma_{em}^*(k). \tag{27}$$

The fuzzy sets are characterized by standard designations: NB (negative big), NM (negative medium), NS (negative small), AZ (approximate zero), PS (positive small), PM (positive medium), and PB (positive big).

Fuzzy distribution is symmetric and non-equidistant in our choice. We have chosen also in our application the singleton-shaped membership function.

The input and output gains are introduced [15]:

$$G_e = \frac{e_G(k)}{e(k)},$$

$$G_{\Delta e} = \frac{\Delta e_G(k)}{\Delta e(k)}, \tag{28}$$

$$G_{\Delta\Gamma} = \frac{\Delta\Gamma_{em}^*(k)}{\Delta\Gamma_G(k)},$$

with

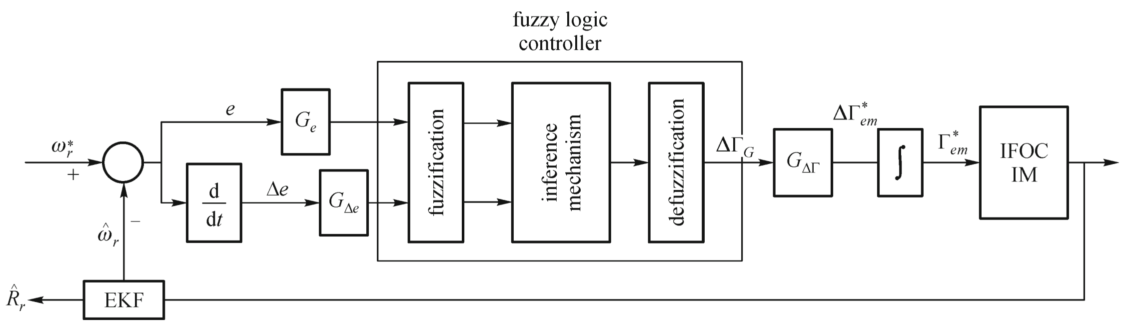

Fig. 1 Basic structure of fuzzy logic speed controller for indirect field oriented control

G_e, $G_{\Delta e}$, $G_{\Delta\Gamma}$: normalized and denormalized factors;
e_G, Δe_G, $\Delta\Gamma_G$: normalized and denormalized error vectors.

Suppose, thus, a general fuzzy controller with n inputs (x_1, x_2, ..., x_n) and output u. For the weighted average defuzzification technique, the controller output is calculated by [16,17]

$$u^* = \frac{\sum_{i_1=1}^{N_1} \cdots \sum_{i_n=1}^{N_n} \mu_{i_1}(x_1^*) \cdots \mu_{i_n}(x_n^*) c_{i_1} \cdots c_{i_n}}{\sum_{i_1=1}^{N_1} \cdots \sum_{i_n=1}^{N_n} \mu_{i_1}(x_1^*) \cdots \mu_{i_n}(x_n^*)}, \tag{29}$$

where N_j represents the number of fuzzy sets on universe of discourse of variable x_j. The product of membership functions for each combination sets designates the degree of activation of each rule $R^{(i)}$. The elements $c_{i_1},\ldots,c_{i_n}$ represent the values singleton consequents. By adopting a system of rules (Table 1), Eq. (29) can be simplified as follows:

$$u^* = \frac{\sum_{i=1}^{N} \mu_i c_i}{\sum_{i=1}^{N} \mu_i}, \; u = K_u u^*, \tag{30}$$

where $N = N_1 \times \cdots \times N_n$ is the number of rules and μ_i is the degree of activation of the rule $R^{(i)}$.

Table 1 Fuzzy linguistic rule table

$\Delta\Gamma$		e						
		NB	NM	NS	AZ	PS	PM	PB
	NB	NB	NB	NB	NB	NM	NS	AZ
	NM	NB	NB	NB	NM	NS	AZ	PS
	NS	NB	NB	NM	NS	AZ	PS	PM
Δe	AZ	NB	NM	NS	AZ	PS	PM	PB
	PS	NM	NS	AZ	PS	PM	PB	PB
	PM	NS	AZ	PS	PM	PB	PB	PB
	PB	AZ	PS	PM	PB	PB	PB	PB

In pursuit of speed reference of rotor induction motor, it is necessary to calculate the digital version of system equation. The continuous transfer function that describes the ratio between speed and quadrature current reference is given by

$$\omega_r = \left(\frac{K}{F}\right) \frac{\frac{F}{J}}{p + \frac{F}{J}} \Gamma_{em}^*. \tag{31}$$

The sampling of above relation with a zero-order hold [18] is as follows:

$$\omega_r(k) = \left(\frac{K}{F}\right) \frac{1 - e^{-\frac{F}{J}t_s}}{z - e^{-\frac{F}{J}t_s}} \Gamma_{em}^*(k). \tag{32}$$

We deduce the difference equation below:

$$\omega_r(k+1) = A\omega_r(k) + B\Gamma_{em}^*(k-1) + B\Delta\Gamma_{em}^*(k), \tag{33}$$

where $A = e^{\frac{F}{J}t_s}$, $B = \dfrac{K(1-A)}{F}$, and $\Delta\Gamma_{em}^*(k) = K_{\Delta u}\Delta u^*$.

Considering the last equation, the reference current variation affects the speed in period t_s before.

4.2 Learning by minimizing cost function

The objective is to minimize a cost function capable of "measuring" the performance of system:

$$f_{obj}(k+p) = \chi_e \frac{e^2(k+p)}{2} + \chi_{\Delta e} \frac{\Delta e^2(k+p)}{2}, \; \chi_e, \chi_{\Delta e} \succ 0. \tag{34}$$

The parameters updating is carried out according to the expression:

$$c_i(k)_{new} = c_i(k)_{old} + \Delta c_i(k). \tag{35}$$

In the learning process, a certain delay is considered, so that the control signal $\Delta\Gamma_{em}^*$ will have a dominant effect that after the next p calculation steps, where $p \geqslant n$. According to the gradient method, consequent variations will be defined as

$$\Delta c_i(k) \propto -\frac{\partial f_{obj}(k+p)}{\partial c_i(k)} = -\frac{\partial f_{obj}(k+p)}{\partial \Delta\Gamma^*_{em}(k)}\frac{\partial \Delta\Gamma^*_{em}(k)}{\partial c_i(k)}. \tag{36}$$

Using Eqs. (33), (34) and (36), we obtain

$$\frac{\partial f_{bj}(k+p)}{\partial \Delta\Gamma^*_{em}(k)} = -\chi_e e(k+p)\frac{\partial \omega_r(k+p)}{\partial \Delta\Gamma^*_{em}(k)} -\chi_{\Delta e}\Delta e(k+p)\frac{\partial\left(\omega_r(k+p)-\omega_r(k+p-1)\right)}{\partial \Delta\Gamma^*_{em}(k)}. \tag{37}$$

However, after Eq. (30),

$$\frac{\partial \Delta\Gamma^*_{em}(k)}{\partial c_i(k)} = K_{\Delta u}\frac{\mu_i}{\sum\limits_{l=1}^{N}\mu_i}. \tag{38}$$

Thus, Eq. (36) becomes

$$\Delta c_i(k) \propto \left[\chi_e e(k+p)\frac{\partial \omega_r(k+p)}{\partial \Delta\Gamma^*_{em}(k)} +\chi_{\Delta e}\Delta e(k+p)\frac{\partial\left(\omega_r(k+p)-\omega_r(k+p-1)\right)}{\partial \Delta\Gamma^*_{em}(k)}\right] \cdot K_{\Delta u}\frac{\mu_i}{\sum\limits_{l=1}^{N}\mu_l}. \tag{39}$$

The partial derivatives in Eq. (39) can be expressed by positive constants, provided they are positive at least not from the future p steps. The delay of learning p is a project parameter, determined by taking into account the process order and possible unstable zeros. In this way, the partial derivatives will be included in the learning gains, and the approximation of Eq. (39) is written as

$$\Delta c_i(k) = \left(\eta_e e(k+p) + \eta_{\Delta e}\Delta e(k+p)\right)K_{\Delta u}\frac{\mu_i}{\sum\limits_{l=1}^{N}\mu_l}. \tag{40}$$

5 Simulation results

Induction motor parameters:

$$P_n = 3\text{kW},$$
$$V_n = 230\text{V},$$
$$R_s = 2.89\Omega,$$
$$R_r = 2.39\Omega,$$
$$L_s = 0.225\text{H},$$
$$L_r = 0.220\text{H},$$
$$L_m = 0.214\text{H},$$
$$J = 0.2\text{kg}\cdot\text{m}^2,$$
$$P = 2.$$

Simulation is carried out in order to verify the performance of the speed and rotor resistance estimation algorithm in addition to verifying the response of drive system. The block diagram of indirect vector controlled induction motor drive system incorporating the estimation algorithm using EKF and learning fuzzy speed is shown in Fig. 2. The figures below (Figs. 3 and 4) show the estimation results of speed and rotor resistance using EKF with and without learning fuzzy logic controllers.

First, acceleration and reversal of the drive are carried out in order to observe the performance of estimator during the operation. The machine is accelerated at 0.04 s to a command speed of 100 rad/s; and then, it is reversed at

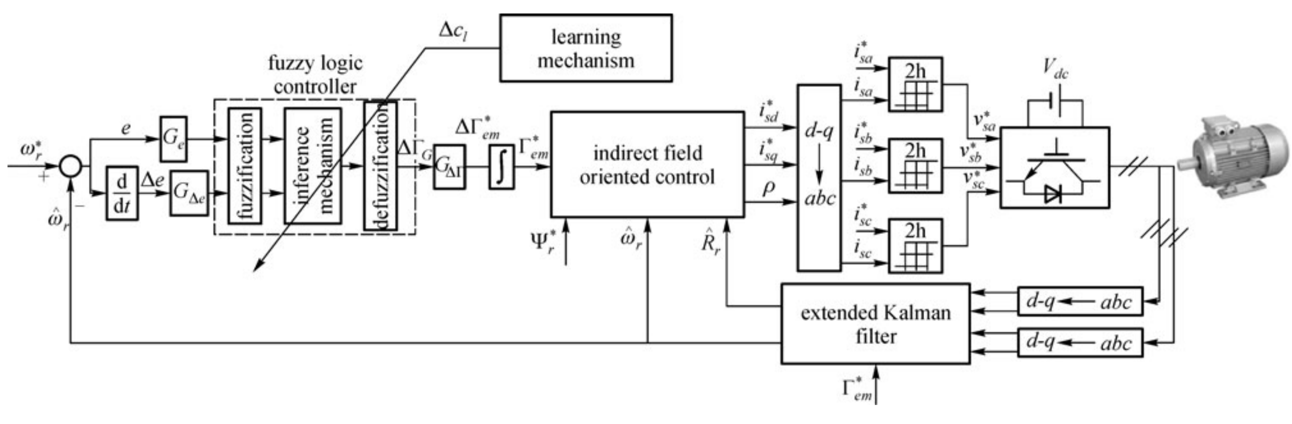

Fig. 2 Block diagram of new proposed strategy

1.5 s. The rotor resistance is changed abruptly during steady-state operation of the drive. Its value is increased from the nominal value of 2.39 Ω to 5 Ω at 0.5 s; and then, decreased to original value at 1 s. The resistance is increased again to 5 Ω at 2 s; and then, decreased to its nominal value at 2.5 s (see Fig. 3).

Next, the speed is increased in steps with sudden changes in rotor resistance. The machine is accelerated to 100 rad/s at t = 0.04 s; then, the speed is increased in steps to 200 rad/s at 1 s; and finally, to 300 rad/s at 2 s. The rotor resistance is varied with sudden changes in its value in order to observe the performance of the estimator at these speeds. The rotor resistance is increased from its nominal value of 2.39 Ω to 5 Ω at 0.5 s; and then, brought down to nominal value at 1.5 s. It is increased again to 5 Ω at 2.5 s. The estimation results and response of the sensorless drive are shown in Fig. 4.

Figures 3(b) and 4(b) show that a good operation of the

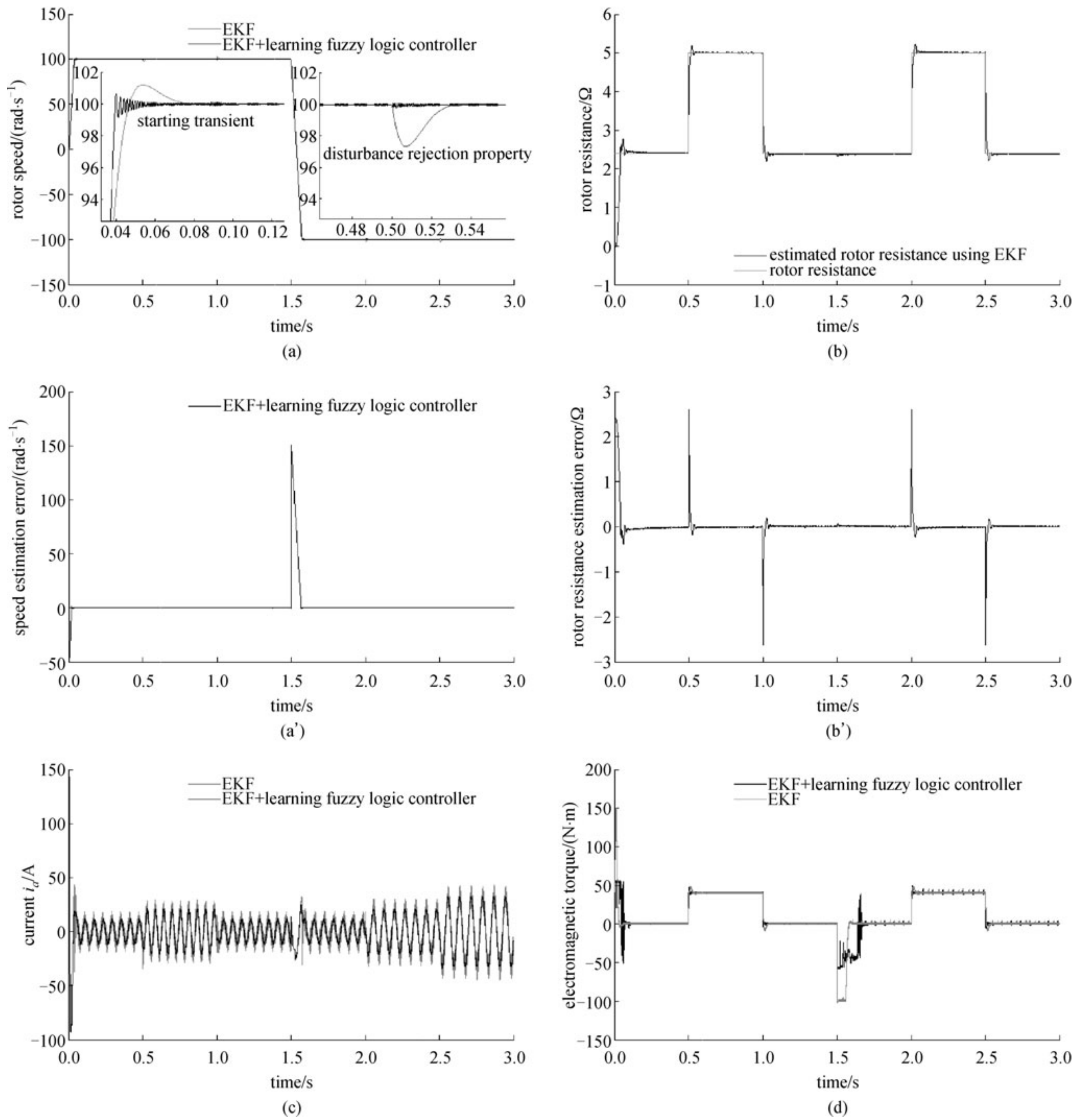

Fig. 3 EKF compared to EKF with learning fuzzy logic controller. (a) Rotor speed estimation reversal; (a') rotor speed estimation error; (b) rotor resistance estimation; (b') rotor resistance estimation error; (c) single-phase current i_a; (d) electromagnetic torque

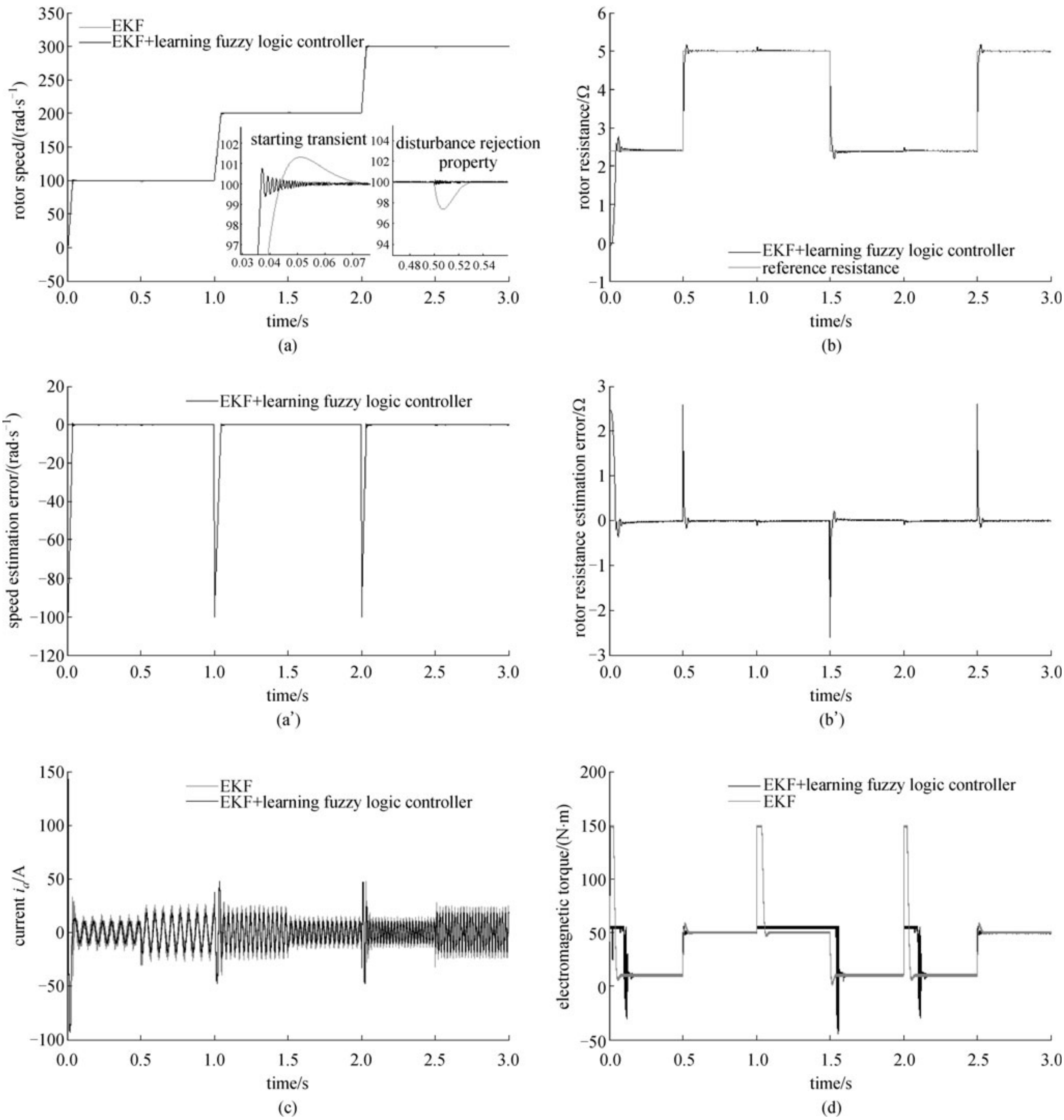

Fig. 4 EKF compared to EKF with learning fuzzy logic controller. (a) Rotor speed estimation acceleration; (a’) rotor speed estimation error; (b) rotor resistance estimation; (b’) rotor resistance estimation error; (c) single-phase current i_a; (d) electromagnetic torque

estimator does not depend on, in addition, the initial value of R_r that is chosen in the algorithm. This is very important since in reality we do not know the exact value of the resistance when the estimation algorithm starts. The convergence of this method is thus confirmed. In reality, the actual rotor resistance varies much more slowly, this means that the estimated rotor resistance can track even better the actual rotor resistance.

We can confirm that the estimated rotor resistance allows us to obtain an optimal vector control where there is a perfect decoupling between torque and flux. The report torque/current (Γ_{em}/i_{sq}) is then maintained its maximum value corresponding to a given load.

The speed estimation response using EKF with learning fuzzy logic controller shows that the drive can follow the low command speed very quickly and smoothly without

Table 2 Summary of results (LFLC: learning fuzzy logic controller)

	rise time/s	overshoot/%	settling time/%	steady-state error/%
EKF	0.03	2.9	0.08	0.7
EKF-LFLC	0.02	0.05	0.001	0.4

overshoot, no steady-state error and rapid rejection of disturbances, with a low dropout speed (Figs. 3(a), 4(a) and Table 2). The current responses are sinusoidal and balanced, and its distortion is small compared with that obtained by EKF alone (Figs. 3(c) and 4(c)). The torque ripple is reduced and its dynamic is enhanced by the new control method (Figs. 3(d) and 4(d)) well as the decoupling between the flux and torque is verified.

The question of sensitivity of the control system to variations in parameters of induction machine has been analyzed. We have focused our attention on the influence of rotor resistance because it varies most a function of temperature among the parameters of induction machine.

6 Conclusions

A new sensorless indirect vector that is controlled by using learning fuzzy logic controller and EKF has been developed. The performance of this strategy is satisfactory even in the presence of noise, or when there has variations in the parameters of the induction machine. Good estimation accuracy was obtained, and the response of the sensorless indirect vector controlled drive was found to be satisfactory.

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