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REDUCED-ORDER OBSERVER AND COMMAND FILTER-BASED ADAPTIVE FUZZY CONTROL FOR INDUCTION MOTORS

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Abstract. *In this paper, reduced-order observer and command filter-based adaptive fuzzy control is proposed for induction motors with parametric uncertainties and external load disturbance. First, a reduced-order observer is used to estimate its angle speed. Next, fuzzy logic systems are used to approximate unknown nonlinear functions. In addition, command filtered backstepping control is designed to overcome the problem of "explosion of complexity" inherent in the traditional backstepping design and the adaptive backstepping technique is employed to construct controllers. The adaptive fuzzy controllers guarantee the tracking error can converge to a small neighborhood of the origin. Finally, simulation results illustrate the effectiveness of the proposed approach.*
Keywords: Induction motor, Fuzzy control, Reduced-order observer, Command filter

1. **Introduction.** In the past decades, induction motors (IMs) have been widely used in industrial applications because of their simple and robust construction, high operating efficiency and ruggedness. However, the drive system is highly nonlinear, strong coupling, multivariable, and it is influenced by some uncertainties easily, such as parameter variations and external load disturbances. Hence, there are many challenges to control IMs efficiently. In recent years, many control techniques have been developed to control IMs and have made some tremendous progress, such as sliding mode control [1], Hamiltonian control [2, 3], backstepping control [4] and other control methods [5, 6, 7, 8, 9]. The backstepping control is considered to be one of the popular techniques for controlling the nonlinear systems with the linear parametric uncertainty. However, when the virtual control is differentiated repeatedly, the problem of "explosion of complexity" inherent in the traditional backstepping approach arises. And the applications of the above control methods for the IMs drive system require the information of systematic state variables which are measured by the various sensors directly. For example, the motor speed is needed so that the control system requires an actual speed signal provided by shaft sensors for closing the speed loop. However, the application of shaft sensors will induce several drawbacks such as high drive cost, large machine size, low reliability and noise immunity as well as performance degradation owing to vibration or humidity.

To solve the above problems, reduced-order observer and command filter-based adaptive fuzzy control is proposed for IMs drive systems in the paper. During the controller design, fuzzy logic system is used to approximate the unknown nonlinear functions. By designing reduced-order observer, the proposed method does not require measuring the value of the speed signal, which will reduce hardware complexity and increase reliability for the IMs. Also, command filtered backstepping technique is proposed to overcome the problem of "explosion of complexity". The proposed adaptive fuzzy controllers guarantee the tracking error can converge to a small range of the origin and all the closed-loop signals are bounded. Simulation results illustrate the effectiveness of the proposed approach.

The rest of the paper is organized as follows. Section 2 describes the mathematical model of IMs drive system. The reduced-order observer and command filtered fuzzy adaptive backstepping controller is designed in Section 3 and Section 4. In Section 5, the simulation results are given. Finally, some conclusions are presented in Section 6.

2. **Mathematical Model of the IMs Drive System.** Induction motor's dynamic mathematical model can be described in the well known (d-q) frame as follows:

$$\begin{cases} \dfrac{d\omega}{dt} = \dfrac{n_p L_m}{L_r J}\psi_d i_q - \dfrac{T_L}{J}, \\ \dfrac{di_q}{dt} = -\dfrac{L_m^2 R_r + L_r^2 R_s}{\sigma L_s L_r^2} i_q - \dfrac{L_m n_p}{\sigma L_s L_r}\omega\psi_d - n_p\omega i_d - \dfrac{L_m R_r}{L_r}\dfrac{i_q i_d}{\psi_d} + \dfrac{1}{\sigma L_s}u_q, \\ \dfrac{d\psi_d}{dt} = -\dfrac{R_r}{L_r}\psi_d + \dfrac{L_m R_r}{L_r} i_d, \\ \dfrac{di_d}{dt} = -\dfrac{L_m^2 R_r + L_r^2 R_s}{\sigma L_s L_r^2} i_d + \dfrac{L_m R_r}{\sigma L_s L_r^2}\psi_d + n_p\omega i_q + \dfrac{L_m R_r}{L_r}\dfrac{i_q^2}{\psi_d} + \dfrac{1}{\sigma L_s}u_d, \\ \dfrac{d\Theta}{dt} = \omega, \end{cases}$$

where $\sigma = 1 - \frac{L_m^2}{L_s L_r}$. Θ, ω, L_m, n_p, J, T_L and ψ_d denote the rotor angle, the rotor angular velocity, mutual inductance, pole pairs, inertia, load torque and rotor flux linkage, respectively. i_d and i_q stand for the d-q axis currents. u_d and u_q are the d-q axis voltages. R_s and L_s mean the resistance, inductance of the stator. R_r and L_r denote the resistance, inductance of the rotor. For simplicity, the following notations are introduced: $x_1 = \Theta$, $x_2 = \omega$, $x_3 = i_q$, $x_4 = \psi_d$, $x_5 = i_d$, $a_1 = \frac{n_p L_m}{L_r}$, $b_1 = -\frac{L_m^2 R_r + L_r^2 R_s}{\sigma L_s L_r^2}$, $b_2 = -\frac{n_p L_m}{\sigma L_s L_r}$, $b_3 = n_p$, $b_4 = \frac{L_m R_r}{L_r}$, $b_5 = \frac{1}{\sigma L_s}$, $c_1 = -\frac{R_r}{L_r}$, $d_2 = \frac{L_m R_r}{\sigma L_s L_r^2}$. By using these notations, the dynamic model of IMs driver system can be described by the following differential equations:

$$\begin{cases} \dot{x}_1 = x_2, \\ \dot{x}_2 = \dfrac{a_1}{J}x_3 x_4 - \frac{T_L}{J}, \\ \dot{x}_3 = b_1 x_3 + b_2 x_2 x_4 - b_3 x_2 x_5 - b_4\dfrac{x_3 x_5}{x_4} + b_5 u_q, \\ \dot{x}_4 = c_1 x_4 + b_4 x_5, \\ \dot{x}_5 = b_1 x_5 + d_2 x_4 + b_3 x_2 x_3 + b_4\dfrac{x_3^2}{x_4} + b_5 u_d. \end{cases} \tag{1}$$

Lemma 2.1. *Let $f(x)$ be a continuous function defined on a compact set Ω. Then for any scalar $\varepsilon > 0$, there exists a fuzzy logic system $W^T S(x)$ such that $\sup_{x\in\Omega}\left|f(x) - W^T S(x)\right| \le \varepsilon$, where $W = [W_1, \ldots, W_N]^T$ is the ideal constant weight vector, and $S(x) = [p_1(x), p_2(x), \ldots, p_N(x)]^T / \sum_{i=1}^N p_i(x)$ is the basis function vector.*

Lemma 2.2. *The command filter is defined as*

$$\begin{aligned} \dot{\varphi}_1 &= \omega_n \varphi_2 \\ \dot{\varphi}_2 &= -2\zeta\omega_n\varphi_2 - \omega_n(\varphi_1 - \alpha_1) \end{aligned} \tag{2}$$

If the input signal α_1 satisfies $|\dot{\alpha}_1| \le \rho_1$ and $|\ddot{\alpha}_1| \le \rho_2$ for all $t \ge 0$, where ρ_1 and ρ_2 are positive constants and $\varphi_1(0) = \alpha_1(0)$, $\varphi_2(0) = 0$, then for any $\mu > 0$, there exist $\omega_n > 0$ and $\zeta \in (0, 1]$, such that $|\varphi_1 - \alpha_1| \le \mu$, and $|\dot{\varphi}_1|$, $|\ddot{\varphi}_1|$ and $|\dddot{\varphi}_1|$ are bounded.

3. **Reduced-Order Observer Design for IMs.** In this section, we will design fuzzy reduced-oder observer to estimate the states of IMs. So the observer can be designed as:

$$\begin{cases} \dot{\hat{x}}_1 = \hat{x}_2 + c_1(y - \hat{x}_1) \\ \dot{\hat{x}}_2 = \hat{\theta}_2^T \phi(z) + c_2(y - \hat{x}_1) + x_3 \\ \hat{y} = \hat{x}_1 \end{cases} \tag{3}$$

From Equation (1), we can obtain $\dot{x}_2 = f_2(Z) + x_3$, where $f_2(Z) = \frac{a_1}{J} x_3 x_4 - \frac{T_L}{J}$, $Z = [\ \hat{x}_1 \ \ \hat{x}_2 \ \ x_3 \ \ x_4 \ \ x_5\ ]$. Choose universal approximation theorem to approximate the nonlinear function $f_2(Z)$; according to the fuzzy logic system $\theta_2^{*T}\phi(Z)$, we can also obtain $f_2(Z) = \theta_2^{*T}\phi(Z) + \varepsilon_2$, where ε_2 is the approximation error and satisfies $\varepsilon_2 \leq |\delta_2|$. We can conclude that $\dot{x}_2 = \theta_2^{*T}\phi(Z) + \varepsilon_2 + x_3$. Let $e = x - \hat{x}$ be the observer error, and then the observer error of system is $\dot{e} = Ae + \varepsilon + \tilde{\omega}$, where $\varepsilon = \left[\ 0, \varepsilon_2\ \right]^T$, $A = \begin{bmatrix} -c_1 & 1 \\ -c_2 & 0 \end{bmatrix}$, $\tilde{\omega} = \left[\ 0, \tilde{\theta}_2^T \phi(Z)\ \right]^T$. Let $\tilde{\theta}_i = \theta_i^* - \hat{\theta}_i$ $(i = 1, 2)$. Supposing there exists a matrix $Q^T = Q > 0$, there also exists a positive definite matrix $P^T = P > 0$, which satisfies $A^T P + PA = -Q$. Choosing Lyapunov function candidate as $V_0 = e^T Pe$, then $\dot{V}_o = \dot{e}^T Pe + e^T P\dot{e} = -eQ^T e + 2e^T P(\varepsilon + \tilde{\omega})$. By using Young's inequality, we can obtain that $2e^T P\varepsilon \leq \|e\|^2 + \|P\|^2 \delta_2^2, 2e^T P\tilde{\omega} \leq \|e\|^2 + \|P\|^2 \tilde{\theta}_2^T \tilde{\theta}_2$. Substituting it into $\dot{V}_o$, we can conclude that

$$\dot{V}_o \leq -eQ^T e + 2\|e\|^2 + \|P\|^2 \delta_2^2 + \|P\|^2 \tilde{\theta}_2^T \tilde{\theta}_2 \tag{4}$$

4. **Adaptive Fuzzy Command Filtered Control.** In this section, we will design a controller for the IMs based on backstepping.

Step 1: For the reference signal x_{1d}, define the tracking error variable as $z_1 = x_1 - x_{1d}$. Consider Lyapunov function candidate as $V_1 = V_0 + \frac{1}{2}z_1^2$, and the time derivative of V_1 is computed by $\dot{V}_1 = \dot{V}_0 + z_1(z_2 + (x_{1,c} - \alpha_1) + \alpha_1 + e_2 - \dot{x}_{1d})$. By using Young's inequality, we can get the following inequality: $z_1 e_2 \leq \frac{1}{2}\|e\|^2 + \frac{1}{2}z_1^2$. Design the virtual control function $\alpha_1 = -\frac{1}{2} + \dot{x}_{1d} - k_1 z_1$, and then we can obtain

$$\dot{V}_1 \leq \dot{V}_0 + \frac{1}{2}\|e\|^2 - k_1 z_1^2 - z_1 z_2 + z_1(x_{1,c} - \alpha_1) \tag{5}$$

Step 2: Define the tracking error variable as $z_2 = \hat{x}_2 - x_{1,c}$. Consider Lyapunov function candidate as $V_2 = V_1 + \frac{1}{2}z_2^2 + \frac{1}{2r_1}\tilde{\theta}_2^T\tilde{\theta}_2$, where $r_1 > 0$. Obviously, the time derivative of V_2 is given by

$$\begin{aligned} \dot{V}_2 \leq \dot{V}_0 &+ \frac{1}{2}\|e\|^2 - k_1 z_1^2 - z_1 z_2 + z_1(x_{1,c} - \alpha_1) + z_2\Big[z_3 + (x_{2,c} - \alpha_2) \\ &+\alpha_2 + \hat{\theta}_2^T\phi(Z) - \tilde{\theta}_2^T\phi(Z) + c_2 e_1 - \dot{x}_{1,c}\Big] - \frac{\tilde{\theta}_2^T}{r_1}\left(r_1 z_2 \phi(Z) - \dot{\hat{\theta}}_2\right) \end{aligned} \tag{6}$$

By using Young's inequality, we can get the following inequalitie: $-z_2\tilde{\theta}_2^T\phi(Z) \leq \frac{1}{2}z_2^2 + \frac{1}{2}\tilde{\theta}_2^T\tilde{\theta}_2$. Design the virtual control functions α_2 and the adaptive law as:

$\alpha_2 = -k_2 z_2 - \frac{1}{2}z_2 - z_1 + \dot{x}_{1,c} - \tilde{\theta}_2^T\phi(Z)$,

$\dot{\hat{\theta}}_2 = r_1 z_2 \phi(Z) - m_1\hat{\theta}_2$. Substituting it into (6), we can obtain:

$$\dot{V}_2 \leq \dot{V}_0 + \frac{1}{2}\|e\|^2 - \sum_{i=1}^{2} k_i z_i^2 + z_1(x_{1,c} - \alpha_1) + z_2(x_{2,c} - \alpha_2) + z_2 z_3 + \frac{1}{2}\tilde{\theta}_2^T\tilde{\theta}_2 + \frac{m_1}{r_1}\tilde{\theta}_2^T\hat{\theta}_2 \tag{7}$$

Step 3: At this step, we will construct the control law u_q. Define the tracking error variable as $z_3 = x_3 - x_{2,c}$. Choose the Lyapunov candidate function as $V_3 = V_2 + \frac{1}{2}z_3^2$. Then the time derivative of V_3 is given by $\dot{V}_3 \leq \dot{V}_2 + z_3(f_3(Z) + b_5 u_q - \dot{x}_{2,c})$, where

$f_3(Z) = b_1x_3 + b_2x_2x_4 - b_3x_2x_5 - b_4\frac{x_3x_5}{x_4} = W_3^TS_3(Z) + \delta_3(Z)$. By using fuzzy logic system, we can obtain $z_3f_3 \le \frac{1}{2l_3^2}z_3^2\|W_3\|^2S_3^TS_3 + \frac{1}{2}l_3^2 + \frac{1}{2}z_3^2 + \frac{1}{2}\varepsilon_3^2$. Choose the real control law u_q as

$$u_q = \frac{1}{b_5}\left(-k_3z_3 - \frac{1}{2}z_3 - z_2 + \dot{x}_{2,c} - \frac{1}{2l_3^2}z_3\hat{W}S_3^TS_3\right) \tag{8}$$

Substituting (8) into (7), we can obtain

$$\begin{aligned}\dot{V}_3 \le{} & \dot{V}_0 + \frac{1}{2}\|e\|^2 - \sum_{i=1}^{3}k_iz_i^2 + z_1(x_{1,c} - \alpha_1) + z_2(x_{2,c} - \alpha_2) + \frac{1}{2}\tilde{\theta}_2^T\tilde{\theta}_2\\ & + \frac{m_1}{r_1}\tilde{\theta}_2^T\hat{\theta}_2 + \frac{1}{2l_3^2}z_3^2\left(\|W_3\|^2 - \hat{W}\right)S_3^TS_3 + \frac{1}{2}l_3^2 + \frac{1}{2}\varepsilon_3^2\end{aligned} \tag{9}$$

Step 4: Define $z_4 = x_4 - x_{4d}$ and choose the Lyapunov candidate function as $V_4 = V_3 + \frac{1}{2}z_4^2$. Design the virtual control function $\alpha_3 = \frac{1}{b_4}(-k_4z_4 + \dot{x}_{4d} - c_1x_4)$ and substitute it into $\dot{V}_4$, and we can obtain

$$\begin{aligned}\dot{V}_4 \le{} & \dot{V}_0 + \frac{1}{2}\|e\|^2 - \sum_{i=1}^{4}k_iz_i^2 + z_1(x_{1,c} - \alpha_1) + z_2(x_{2,c} - \alpha_2) + b_4z_4(x_{3,c} - \alpha_3) + \frac{1}{2}\tilde{\theta}_2^T\tilde{\theta}_2\\ & + \frac{m_1}{r_1}\tilde{\theta}_2^T\hat{\theta}_2 + \frac{1}{2l_3^2}z_3^2\left(\|W_3\|^2 - \hat{W}\right)S_3^TS_3 + \frac{1}{2}l_3^2 + \frac{1}{2}\varepsilon_3^2 + b_4z_4x_5\end{aligned} \tag{10}$$

Step 5: At this step, we will construct the control law u_d. Define $z_5 = x_5 - x_{3,c}$ and choose the Lyapunov candidate function as $V_5 = V_4 + \frac{1}{2}z_5^2$. Then the time derivative of V_5 is given by $\dot{V}_5 = \dot{V}_4 + z_5(f_5 + b_5u_d - \dot{x}_{3,c})$, where $f_5(Z) = b_1x_5 + d_2x_4 + b_3x_2x_3 + b_4\frac{x_3^2}{x_4} = W_5^TS_5(Z) + \delta_5(Z)$. By using the fuzzy logic system, we can obtain $z_5f_5 \le \frac{1}{2l_5^2}z_5^2\|W_5\|^2S_5^TS_5 + \frac{1}{2}l_5^2 + \frac{1}{2}z_5^2 + \frac{1}{2}\varepsilon_5^2$. Substituting it into $\dot{V}_5$, we can obtain

$$\begin{aligned}\dot{V}_5 \le{} & \dot{V}_0 + \frac{1}{2}\|e\|^2 - \sum_{i=1}^{4}k_iz_i^2 + z_1(x_{1,c} - \alpha_1) + z_2(x_{2,c} - \alpha_2) + z_3(x_{3,c} - \alpha_3) + \frac{1}{2}\tilde{\theta}_2^T\tilde{\theta}_2\\ & + \frac{m_1}{r_1}\tilde{\theta}_2^T\hat{\theta}_2 + \frac{1}{2l_3^2}z_3^2\left(\|W_3\|^2 - \hat{W}\right)S_3^TS_3 + \frac{1}{2}l_3^2 + \frac{1}{2}\varepsilon_3^2 + b_4z_4z_5\\ & + z_5\left(\frac{1}{2}z_5 + b_5u_d - \dot{x}_{3,c}\right) + \frac{1}{2l_5^2}z_5^2\|W_5\|^2S_5^TS_5 + \frac{1}{2}l_5^2 + \frac{1}{2}\varepsilon_5^2\end{aligned} \tag{11}$$

Choose the real control law u_d as

$$u_d = \frac{1}{b_5}\left(-k_5z_5 - \frac{1}{2}z_5 - b_4z_4 + \dot{x}_{3,c} - \frac{1}{2l_5^2}z_5\hat{W}S_5^TS_5\right) \tag{12}$$

Design $W = \max\{||W_3||^2, ||W_5||^2\}$, $\tilde{W} = W - \hat{W}$. Then we choose the Lyapunov function as $V = V_5 + \frac{1}{2r_2}\tilde{\theta}^T\tilde{\theta}$, where $r_2 > 0$. And the time derivative of V is given by

$$\begin{aligned}\dot{V} \le{} & \dot{V}_0 + \frac{1}{2}\|e\|^2 + \frac{1}{2}\tilde{\theta}_2^T\tilde{\theta}_2 + \frac{m_1}{r_1}\tilde{\theta}_2^T\hat{\theta}_2 - \sum_{i=1}^{5}k_iz_i^2 + z_1(x_{1,c} - \alpha_1)\\ & + z_2(x_{2,c} - \alpha_2) + b_4z_4(x_{3,c} - \alpha_3) + \frac{1}{2}l_3^2 + \frac{1}{2}\varepsilon_3^2 + \frac{1}{2}l_5^2 + \frac{1}{2}\varepsilon_5^2\\ & + \frac{1}{r_2}\tilde{W}\left(\dot{\hat{W}} - \frac{r_2}{2l_3^2}z_3^2S_3^TS_3 - \frac{r_2}{2l_5^2}z_5^2S_5^TS_5\right)\end{aligned} \tag{13}$$

Choose the adaptive law as $\dot{\hat{W}} = \frac{r_2}{2l_3^2}z_3^2S_3^TS_3 + \frac{r_2}{2l_5^2}z_5^2S_5^TS_5 - m_2\hat{W}$, where m_i for $i = 1, 2$ and l_i for $i = 3, 5$ are positive constants.

Proof: By using $|x_{i,c}-\alpha_i|\leq\mu$ and Young's inequalities, we can get

$$z_1(x_{1,c}-\alpha_1)\leq z_1^2+\frac{1}{4}\mu^2,\quad z_2(x_{2,c}-\alpha_1)\leq z_2^2+\frac{1}{4}\mu^2,\quad b_4z_4(x_{3,c}-\alpha_3)\leq z_4^2+\frac{b_4^2}{4}\mu^2 \tag{14}$$

$$\frac{m_1}{r_1}\tilde{\theta}_2^T\left(\theta_2^*-\tilde{\theta}_2\right)\leq-\frac{m_1}{2r_1}\tilde{\theta}_2^T\tilde{\theta}_2+\frac{m_1}{2r_1}\theta_2^{*T}\theta_2^*,\quad -\tilde{W}\hat{W}\leq-\frac{1}{2}\tilde{W}^T\tilde{W}+\frac{1}{2}W^TW \tag{15}$$

To address the stability analysis of closed-loop system, substituting the adaptive law $\dot{\hat{W}}$, (14) and (15) into (13), we can obtain

$$\begin{aligned}\dot{V}\leq{}& r_3\|e\|^2-(k_1-1)z_1^2-(k_2-1)z_2^2-k_3z_3^2-(k_4-1)z_4^2-k_5z_5^2\\ &-\tilde{\theta}_2^T\tilde{\theta}_2\left(\frac{m_1}{2r_1}-\|P\|^2-\frac{1}{2}\right)-\tilde{W}^T\tilde{W}\frac{m_2}{2r_2}+\|P\|^2\delta_2^2+\frac{m_1}{2r_1}\theta_2^{*T}\theta_2^*\\ &+\frac{m_2}{2r_2}W^TW+\frac{1}{2}l_3^2+\frac{1}{2}\varepsilon_3^2+\frac{1}{2}l_5^2+\frac{1}{2}\varepsilon_5^2+\frac{1}{4}\mu^2\left(2+b_4^2\right)\leq-aV+b\end{aligned} \tag{16}$$

where $a=\min\left\{\frac{-2\lambda_{\min}(Q)-5}{\lambda_{\max}(P)},\ 2(k_1-1),\ 2(k_2-1),\ 2k_3,\ 2(k_4-1),\ 2k_5,\ 2r_1\left(\frac{m_1}{r_1}-\|P\|^2-\frac{1}{2}\right),\right.$ $\left.2r_2\frac{m_2}{2r_2}\right\}$, $b=\|P\|^2\delta_2^2+\frac{m_1}{2r_1}\theta_2^{*T}\theta_2^*+\frac{m_2}{2r_2}\theta^T\theta+\frac{1}{2}l_3^2+\frac{1}{2}\varepsilon_3^2+\frac{1}{2}l_5^2+\frac{1}{2}\varepsilon_5^2+\frac{1}{4}\mu^2\left(2+b_4^2\right)$.

Then, (16) implies that

$$V(t)\leq\left(V(t_0)-\frac{b}{a}\right)e^{-a(t-t_0)}+\frac{b}{a}\leq V(t_0)+\frac{b}{a},\quad\forall t\geq t_0 \tag{17}$$

where z_i $(i=1,\ldots,5)$, and $\tilde{W}$ belong to the compact set $\tilde{W}=\left\{\left(z_i,\tilde{W}\right)|V\leq V(t_0)+\frac{b}{a},\ \forall t\geq t_0\right\}$. Namely, all the signals in the closed-loop system are bounded. Especially, from (17) we can get $\lim_{t\to\infty}z_1^2\leq\frac{2b}{a}$. By the definitions of a and b, we can set r_i large enough to get a smaller tracking error, with l_i and ε_i small enough after giving the the parameters k_i and m_i.

5. **Simulation Results.** In order to illustrate the effectiveness of the proposed results, the simulation is run for the induction motors with the parameters: $J=0.0586\text{Kgm}^2$, $R_s=0.1\Omega$, $R_r=0.15\Omega$, $L_s=L_r=0.0699\text{H}$, $L_m=0.068\text{H}$, $n_p=1$. The simulation is carried out under the zero initial condition. The reference signals are taken as $x_{1d}=0.5\sin(t)+0.5\sin(0.5t)$ and $x_{4d}=1$. The load parameter is chosen as $T_L=\begin{cases}0.5, & 0\leq t\leq 5,\\ 1.0, & t\geq 5.\end{cases}$

The fuzzy membership functions are $\mu_{F_i^l}=\exp\left[-(x+l)^2/2\right]$, $l=N$, $l\in[-5,5]$. The control parameters are chosen as: $k_1=200$, $k_2=80$, $k_3=300$, $k_4=k_5=100$, $r_1=r_2=0.1$, $m_1=m_2=0.05$, $l_3=l_5=0.5$, $\zeta=0.5$, $\omega_n=5000$.

Choose observer gain vector $C=[10,100]$ so that the matrix A is a strict Hurwitz matrix. Specify positive definite matrix $Q=\text{diag}\{1,1\}$, such that $-2\lambda_{\min}(Q)-5>0$, and we can get $P=\begin{bmatrix}5.05 & -0.5\\ -0.5 & 1.005\end{bmatrix}$.

Figure 1 shows the reference signal x_1 and x_{1d} and Figure 2 shows the reference signal x_1 and $\hat{x}_1$. It can be observed from Figure 1 and Figure 2 that the system output can track the given reference signals well. Figure 3 displays the reference signal x_2 and $\hat{x}_2$ and Figure 4 shows the trajectories of tracking error e. Figure 5 and Figure 6 show the trajectories of u_q and u_d. From the above simulation results, it is clearly shown that the proposed control method can track the reference signal quite well even under parameter uncertainties and load torque disturbance.

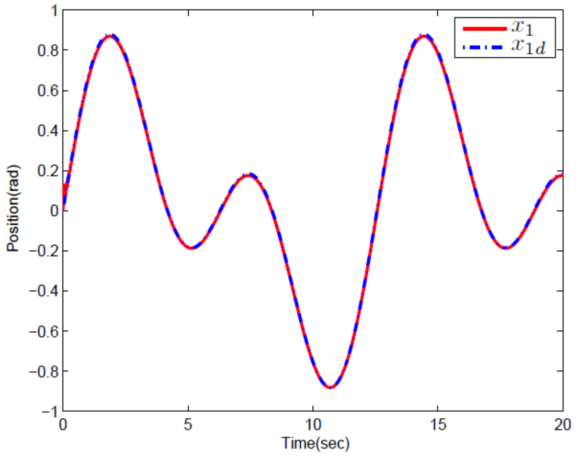

FIGURE 1. x_1 and x_{1d}

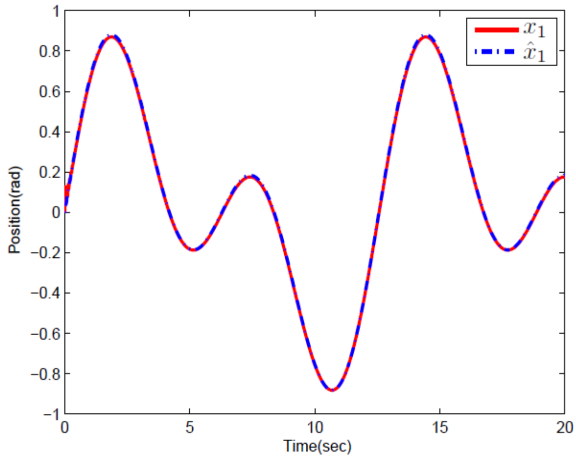

FIGURE 2. x_1 and $\hat{x}_1$

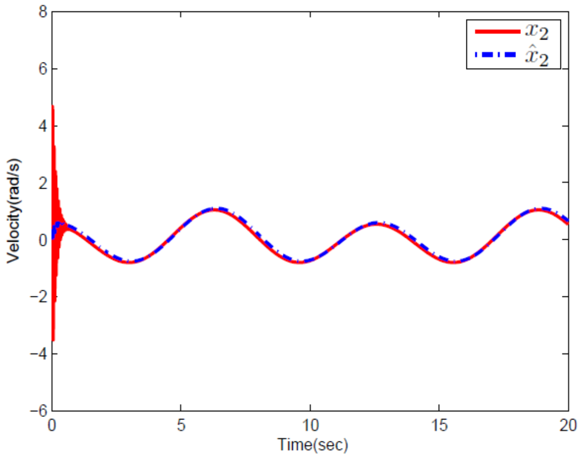

FIGURE 3. x_2 and $\hat{x}_2$

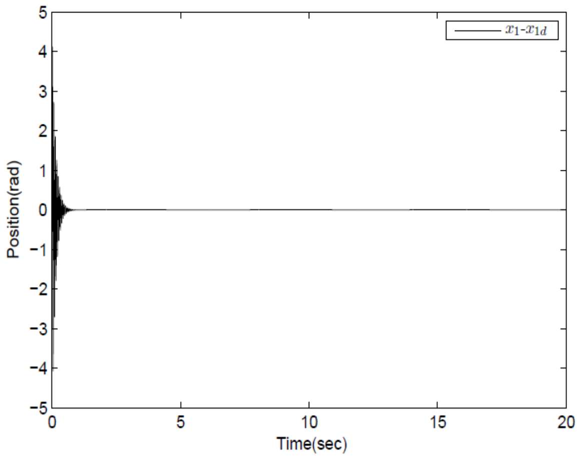

FIGURE 4. The tracking error

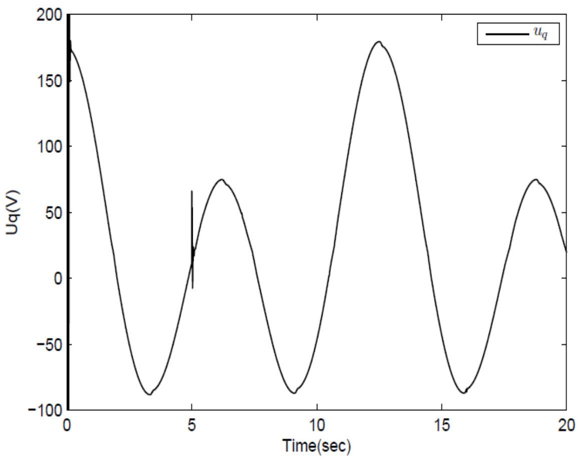

FIGURE 5. The control law u_q

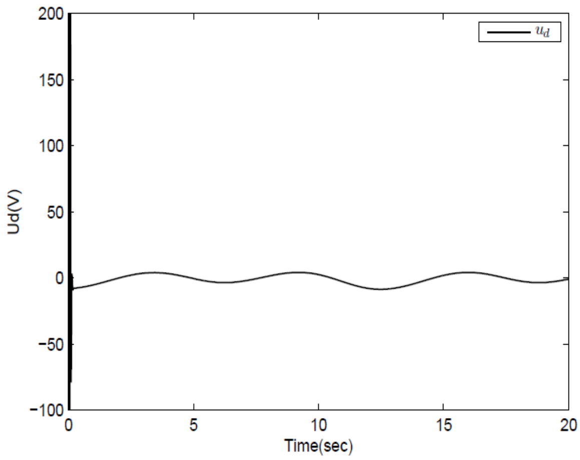

FIGURE 6. The control law u_d

6. **Conclusion.** Reduced-order observer and command filter-based adaptive fuzzy control for induction motors approach has been proposed in this paper. Reduced-order observer is designed to estimate the angle speed of induction motors and command filter can overcome the problem of "explosion of complexity". The designed controllers guarantee the position tracking error can converge to a small neighborhood of the origin. Simulation

results testify its effectiveness in the IMs drive system. In the future work, we will focus on the practical application of the proposed control algorithm.

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