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NEURAL NETWORK-BASED ADAPTIVE COMMAND FILTERED CONTROL FOR INDUCTION MOTORS

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Abstract. *This paper developed an adaptive neural networks (NNs) command filtered control approach to speed regulation for induction motors. First, neural networks are used to approximate unknown nonlinear functions and the adaptive command filtered backstepping is employed to construct controllers. Next, the proposed control method can overcome the problems of "nonlinear systems with parameter uncertainties" and "explosion of complexity" inherent in the traditional backstepping design and the adaptive neural controllers guarantee the tracking error can converge to a small neighborhood of the origin. Then, simulation results illustrate the effectiveness of the proposed approach.*
Keywords: Induction motor, Neural networks, Command filtered control, Backstepping

1. **Introduction.** In the past decades, induction motors (IMs) have been widely used in industrial applications because of their simple and robust construction, low cost, high reliability and ruggedness. However, the control of IMs is complex due to its highly nonlinear, multivariable dynamic model. Hence, many control techniques have been developed to control IMs, such as sliding mode control [1], backstepping control [2] and other control methods [3]. Backstepping control is considered to be a powerful tool for the design of controllers for nonlinear systems. However, there are some drawbacks in backstepping approach. One problem is that certain functions must be linear in the unknown system parameters. Another limitation is the "explosion of complexity" caused by the repeated differentiations of virtual input. Theoretically, the calculation of virtual control derivation is simple, but it can be quite tedious and complicated in practical applications when n is larger than three because the desired controller u will include the derivation of α_n, which requires the second derivation of α_{n-1} and so on. To overcome these problems, a command filtered backstepping technique is proposed to approximate the derivative of the virtual control by utilizing the output of a command filter at each step of the adaptive backstepping approach [4, 5]. In addition, NN approximation method has been used in many applications, mainly by its inherent capability of modeling and controlling highly uncertain, nonlinear, and complex systems [6, 7]. Therefore, NNs can be employed to control the systems which are too complex to have a precise mathematical model.

Motivated by the above observations, NN approximation-based command filtered adaptive backstepping control is proposed for the IMs system in this paper. The benefits of the presented approach include. (1) The command filtered control technique is proposed to overcome the problem of "explosion of complexity". (2) NNs are used to approximate the unknown nonlinear functions to solve the problem of the unknown system parameters. It is shown that the proposed approach can guarantee that 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 IM drive system. The command filtered neural adaptive backstepping control is designed in Section 3. In Section 4, the simulation results are given. Finally, some conclusions are presented.

2. **Mathematical Model of the IM Drive System.** Induction motor's dynamic mathematical model can be described in the well known (d-q) frame as follows [8]:

$$\begin{cases} \frac{d\omega}{dt} = \frac{n_pL_m}{L_rJ}\psi_d i_q - \frac{T_L}{J}, \\ \frac{di_q}{dt} = -\frac{L_m^2R_r+L_r^2R_s}{\sigma L_sL_r^2}i_q - \frac{L_mn_p}{\sigma L_sL_r}\omega\psi_d - n_p\omega i_d - \frac{L_mR_r}{L_r}\frac{i_qi_d}{\psi_d} + \frac{1}{\sigma L_s}u_q, \\ \frac{d\psi_d}{dt} = -\frac{R_r}{L_r}\psi_d + \frac{L_mR_r}{L_r}i_d, \\ \frac{di_d}{dt} = -\frac{L_m^2R_r+L_r^2R_s}{\sigma L_sL_r^2}i_d + \frac{L_mR_r}{\sigma L_sL_r^2}\psi_d + n_p\omega i_q + \frac{L_mR_r}{L_r}\frac{i_q^2}{\psi_d} + \frac{1}{\sigma L_s}u_d, \end{cases} \tag{1}$$

where $\sigma = 1 - \frac{L_m^2}{L_sL_r}$. ω, L_m, n_p, J, T_L and ψ_d denote 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: $x_1 = \omega$, $x_2 = i_q$, $x_3 = \psi_d$, $x_4 = i_d$, $a_1 = \frac{n_pL_m}{L_r}$, $b_1 = -\frac{L_m^2R_r+L_r^2R_s}{\sigma L_sL_r^2}$, $b_2 = -\frac{n_pL_m}{\sigma L_sL_r}$, $b_3 = n_p$, $b_4 = \frac{L_mR_r}{L_r}$, $b_5 = \frac{1}{\sigma L_s}$, $c_1 = -\frac{R_r}{L_r}$, $d_2 = \frac{L_mR_r}{\sigma L_sL_r^2}$. By using these notations, the dynamic model of IM driver system can be described by the following differential equations:

$$\begin{cases} \dot{x}_1 = \frac{a_1}{J}x_2x_3 - \frac{T_L}{J}, \\ \dot{x}_2 = b_1x_2 + b_2x_1x_3 - b_3x_1x_4 - b_4\frac{x_2x_4}{x_3} + b_5u_q, \\ \dot{x}_3 = c_1x_3 + b_4x_4, \\ \dot{x}_4 = b_1x_4 + d_2x_3 + b_3x_1x_2 + b_4\frac{x_2^2}{x_3} + b_5u_d. \end{cases} \tag{2}$$

In this paper, the radial basis function (RBF) neural network will be used to approximate the unknown continuous function $\varphi(z) : R^q \to R$ as $\hat{\varphi}(z) = \phi^{*T}P(z)$ where $z \in \Omega_z \subset R^q$ is the input vector with q being the neural network input dimension, $\phi^* = [\phi_1^*, \ldots, \phi_n^*]^T \in R^n$ is the weight vector, $P(z) = [p_1(z), \ldots, p_n(z)]^T \in R^n$ is the basis function vector with $n > 1$ being the neural network node number, and $p_i(z)$ are chosen as the commonly used Gaussian function in the following form: $p_i(z) = \exp\left[\frac{-(z-\nu_i)^T(z-\nu_i)}{q_i^2}\right]$, $i = 1, 2, \ldots, n$ where $\nu_i = [\nu_{i1}, \ldots, \nu_{iq}]^T$ is the center of the receptive field and q_i is the width of the Gaussian function. It has been proved in [9] that, for given scalar $\varepsilon > 0$, by choosing sufficiently large l, the RBF neural network can approximate any continuous function over a compact set $\Omega_z \in R^q$ to arbitrary accuracy as $\varphi(z) = \phi^TP(z) + \delta(z)$ $\forall z \in \Omega_z \subset R^q$ where $\delta(z)$ is the approximation error, satisfying $|\delta(z)| \le \varepsilon$ and ϕ is an unknown ideal constant weight vector, which is an artificial quantity required for analytical purpose. Typically, ϕ is chosen as the value of ϕ^* that minimizes $|\delta(z)|$ for all $z \in \Omega_z$.

Lemma 2.1. *The command filter is defined as*

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

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 $|\varphi_1 - \alpha_1| \le \mu$, $|\dot{\varphi}_1|$, $|\ddot{\varphi}_1|$ and $|\dddot{\varphi}_1|$ are bounded.

3. **Adaptive Neural Command Filtered Control for IMs.** In this section, we will present an adaptive neural command filtered control for IMs via 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 $V_1 = \frac{J}{2}z_1^2$, and the time derivative of V_1 is computed by $\dot{V}_1 = Jz_1\dot{z}_1 = z_1(a_1x_2x_3 - T_L - J\dot{x}_{1d})$.

In this paper, due to the parameter T_L being bounded in practice system, we assume the T_L is unknown but its upper bound is $d > 0$. Namely, $0 \le T_L \le d$. Obviously, $-z_1T_L \le \frac{1}{2\varepsilon_5^2}z_1^2 + \frac{1}{2}\varepsilon_5^2 d^2$, where ε_5 is an arbitrary small positive constant. Then we can get

$$\dot{V}_1 \le \frac{1}{2}\varepsilon_5^2 d^2 + z_1\left(x_2 - J\dot{x}_{1d} + f_1\right) \tag{3}$$

where $f_1(Z) = a_1x_2x_3 + \frac{1}{2\varepsilon_5^2}z_1 - x_2$, $Z = [x_1, x_2, x_3, x_4, x_{1d}, \dot{x}_{1d}]$. According to the RBF neural network approximation property, for given $\varepsilon_1 > 0$, there exists a RBF NN $\phi_1^T P_1(Z)$ such that $f_1(Z) = \phi_1^T P_1(Z) + \delta_1(Z)$, where $\delta_1(Z)$ is the approximation error and satisfies $|\delta_1| \le \varepsilon_1$. Consequently, a straightforward calculation produces the following inequality.

$$z_1 f_1(Z) = z_1\left(\phi_1^T P_1(Z) + \delta_1(Z)\right) \le \frac{1}{2l_1^2}z_1^2\left\|\phi_1\right\|^2 P_1^T(Z)P_1(Z) + \frac{1}{2}l_1^2 + \frac{1}{2}z_1^2 + \frac{1}{2}\varepsilon_1^2 \tag{4}$$

Construct the virtual control law α_1 as $\alpha_1 = -k_1z_1 - \frac{1}{2}z_1 - \frac{1}{2l_1^2}z_1\hat{\theta}P_1^TP_1 + \hat{J}\dot{x}_{1d}$, with $k_1 > 0$ being a constant and $\hat{\theta}$ is the estimation of the unknown constant θ which will be specified later. Let α_1 pass through the command filter to obtain $x_{1,c}$. And we have $z_2 = x_2 - x_{1,c}$. Substituting (4) into (3), we can obtain

$$\begin{aligned}\dot{V}_1 \le\ & -k_1z_1^2 + \frac{1}{2}\varepsilon_5^2 d^2 + z_1(x_{1,c} - \alpha_1) + \frac{1}{2}l_1^2 + \frac{1}{2}\varepsilon_1^2 \\ & + \frac{1}{2l_1^2}z_1^2\left(\left\|\phi_1\right\|^2 - \hat{\theta}\right)P_1^TP_1 + z_1z_2 + z_1\left(\hat{J} - J\right)\dot{x}_{1d}\end{aligned} \tag{5}$$

Step 2: Differentiating z_2 gives $\dot{z}_2 = \dot{x}_2 - \dot{x}_{1,c} = b_1x_2 + b_2x_1x_3 - b_3x_1x_4 - b_4\frac{x_2x_4}{x_3} + b_5u_q - \dot{x}_{1,c}$. Now choose the Lyapunov function candidate as $V_2 = V_1 + \frac{1}{2}z_2^2$. Obviously, the time derivative of V_2 is given by

$$\begin{aligned}\dot{V}_2 \le\ & -k_1z_1^2 + \frac{1}{2}\varepsilon_5^2 d^2 + z_1(x_{1,c} - \alpha_1) + \frac{1}{2l_1^2}z_1^2\left(\left\|\phi_1\right\|^2 - \hat{\theta}\right)P_1^TP_1 \\ & + \frac{1}{2}l_1^2 + \frac{1}{2}\varepsilon_1^2 + z_1z_2 + z_1\left(\hat{J} - J\right)\dot{x}_{1d} + z_2(f_2 + b_5u_q - \dot{x}_{1,c})\end{aligned} \tag{6}$$

where $f_2(Z) = b_1x_2 + b_2x_1x_3 - b_3x_1x_4 - b_4\frac{x_2x_4}{x_3} = \phi_2^TP_2(Z) + \delta_2(Z)$. Similarly, for given $\varepsilon_2 > 0$, we can get

$$z_2 f_2(Z) \le \frac{1}{2l_2^2}z_2^2\left\|\phi_2\right\|^2 P_2^T(Z)P_2(Z) + \frac{1}{2}l_2^2 + \frac{1}{2}z_2^2 + \frac{1}{2}\varepsilon_2^2 \tag{7}$$

The control law u_q is designed as

$$u_q = \frac{1}{b_5}\left(-k_2z_2 - \frac{1}{2}z_2 - z_1 + \dot{x}_{1,c} - \frac{1}{2l_2^2}z_2\hat{\theta}P_2^TP_2\right) \tag{8}$$

Substituting (7) and (8) into (6), we can obtain

$$\begin{aligned}\dot{V}_2 \le\ & -k_1z_1^2 - k_2z_2^2 + \frac{1}{2}\varepsilon_5^2 d^2 + z_1(x_{1,c} - \alpha_1) + \frac{1}{2}l_1^2 + \frac{1}{2}l_2^2 + \frac{1}{2}\varepsilon_1^2 + \frac{1}{2}\varepsilon_2^2 \\ & + \frac{1}{2l_1^2}z_1^2\left(\left\|\phi_1\right\|^2 - \hat{\theta}\right)P_1^TP_1 + \frac{1}{2l_2^2}z_2^2\left(\left\|\phi_2\right\|^2 - \hat{\theta}\right)P_2^TP_2 + z_1\left(\hat{J} - J\right)\dot{x}_{1d}\end{aligned} \tag{9}$$

Step 3: For the reference signal x_{3d}, define the tracking error variable as $z_3 = x_3 - x_{3d}$. From the third differential equation of (2), one has $\dot{z}_3 = \dot{x}_3 - \dot{x}_{3d}$. 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

$$\begin{aligned}\dot{V}_3 \leq & -k_1 z_1^2 - k_2 z_2^2 + z_1(x_{1,c} - \alpha_1) + \frac{1}{2}l_1^2 + \frac{1}{2}l_2^2 + \frac{1}{2}\varepsilon_1^2 + \frac{1}{2}\varepsilon_2^2 + z_1\left(\hat{J} - J\right)\dot{x}_{1d} \\ & + \frac{1}{2l_1^2}z_1^2\left(\|\phi_1\|^2 - \hat{\theta}\right)P_1^T P_1 + \frac{1}{2l_2^2}z_2^2\left(\|\phi_2\|^2 - \hat{\theta}\right)P_2^T P_2 \\ & + z_3(c_1 x_3 + b_4 x_4 - \dot{x}_{3d}) + \frac{1}{2}\varepsilon_5^2 d^2\end{aligned} \tag{10}$$

Construct the virtual control law α_2 as

$$\alpha_2 = \frac{1}{b_4}(-k_3 z_3 + \dot{x}_{3d} - c_1 x_3) \tag{11}$$

Similarly, let α_2 pass through the command filter to obtain $x_{2,c}$. In addition, defining $z_4 = x_4 - x_{2,c}$ and substituting (11) into (10) result in

$$\dot{V}_3 \leq \dot{V}_2 - k_3 z_3^2 + b_4 z_3 z_4 + b_4 z_3(x_{2,c} - \alpha_2) \tag{12}$$

Step 4: At this step, we will construct the control law u_d. Define $z_4 = x_4 - x_{2,c}$ and choose $V_4 = V_3 + \frac{1}{2}z_4^2$. Then, we have $\dot{V}_4 = \dot{V}_3 + z_4(f_4 + b_5 u_d)$, where $f_4(Z) = b_1 x_4 + d_2 x_3 + b_3 x_1 x_2 + b_4 \frac{x_2^2}{x_3} = \phi_4^T P_4(Z) + \delta_4(Z)$. Similarly,

$$z_4 f_4(Z) \leq \frac{1}{2l_4^2}z_4^2\|\phi_4\|^2 P_4^T(Z)P_4(Z) + \frac{1}{2}l_4^2 + \frac{1}{2}z_4^2 + \frac{1}{2}\varepsilon_4^2 \tag{13}$$

We design u_d as

$$u_d = \frac{1}{b_5}\left(-k_4 z_4 - \frac{1}{2}z_4 - b_4 z_3 + \dot{x}_{2,c} - \frac{1}{2l_4^2}z_4\hat{\theta}P_4^T P_4\right) \tag{14}$$

Design $\theta = \max\{||\phi_1||^2, ||\phi_2||^2, ||\phi_4||^2\}, \tilde{\theta} = \hat{\theta} - \theta, \tilde{J} = \hat{J} - J$. Furthermore, it can be verified easily that

$$\begin{aligned}\dot{V}_4 \leq & -\sum_{i=1}^{4} k_i z_i^2 + z_1(x_{1,c} - \alpha_1) + b_4 z_3(x_{2,c} - \alpha_2) + \frac{1}{2}l_1^2 + \frac{1}{2}\varepsilon_1^2 + \frac{1}{2}l_2^2 + \frac{1}{2}\varepsilon_2^2 \\ & + \frac{1}{2}l_4^2 + \frac{1}{2}\varepsilon_4^2 + \frac{1}{2}\varepsilon_5^2 d^2 - \frac{1}{2l_1^2}z_1^2\tilde{\theta}P_1^T P_1 - \frac{1}{2l_2^2}z_2^2\tilde{\theta}P_2^T P_2 - \frac{1}{2l_4^2}z_4^2\tilde{\theta}P_4^T P_4 + z_1\tilde{J}\dot{x}_{1d}\end{aligned} \tag{15}$$

Then we choose the Lyapunov function as $V = V_4 + \frac{1}{2r_1}\tilde{\theta}^2 + \frac{1}{2r_2}\tilde{J}^2$. And the time derivative of V is given by

$$\begin{aligned}\dot{V} \leq & -\sum_{i=1}^{4} k_i z_i^2 + z_1(x_{1,c} - \alpha_1) + b_4 z_3(x_{2,c} - \alpha_2) + \frac{1}{2}l_1^2 + \frac{1}{2}\varepsilon_1^2 + \frac{1}{2}l_2^2 \\ & + \frac{1}{2}\varepsilon_4^2 + \frac{1}{2}\varepsilon_5^2 d^2 + \frac{1}{2}\varepsilon_2^2 + \frac{1}{2}l_4^2 + \frac{\tilde{J}}{r_2}\left(r_2 z_1 \dot{x}_{1d} + \dot{\hat{J}}\right) \\ & + \frac{1}{r_1}\tilde{\theta}\left(\dot{\hat{\theta}} - \frac{r_1}{2l_1^2}z_1^2 P_1^T P_1 - \frac{r_1}{2l_2^2}z_2^2 P_2^T P_2 - \frac{r_1}{2l_4^2}z_4^2 P_4^T P_4\right)\end{aligned} \tag{16}$$

We choose the adaptive law as

$$\dot{\hat{\theta}} = \frac{r_1}{2l_1^2}z_1^2 P_1^T P_1 + \frac{r_1}{2l_2^2}z_2^2 P_2^T P_2 + \frac{r_1}{2l_4^2}z_4^2 P_4^T P_4 - m_1\hat{\theta}, \quad \dot{\hat{J}} = -r_2 z_1 \dot{x}_{1d} - m_2\hat{J} \tag{17}$$

where m_1, m_2 and l_i for $i = 1, 2, 4$ are positive constants.

Proof: To address the stability analysis of the resulting closed-loop system, substituting (17) into (16), we have

$$\dot{V} \leq -\sum_{i=1}^{4} k_i z_i^2 + \frac{1}{2}l_1^2 + \frac{1}{2}\varepsilon_1^2 + \frac{1}{2}l_2^2 + \frac{1}{2}\varepsilon_2^2 + \frac{1}{2}l_4^2 + \frac{1}{2}\varepsilon_4^2 + \frac{1}{2}\varepsilon_5^2 d^2 \tag{18}$$
$$-\frac{m_1\tilde{\theta}\hat{\theta}}{r_1} - \frac{m_2\tilde{J}\hat{J}}{r_2} + z_1(x_{1,c} - \alpha_1) + b_4 z_3(x_{2,c} - \alpha_2)$$

From $|x_{i,c} - \alpha_i| < \mu$ and using the Young's inequalities, we can get $z_1(x_{1,c} - \alpha_1) \leq z_1^2 + \frac{1}{4}\mu^2$, $b_4 z_3(x_{2,c} - \alpha_2) \leq \frac{b_4^2}{4}\mu^2 + z_3^2$, $-\tilde{\theta}\hat{\theta} \leq -\frac{\tilde{\theta}^2}{2} + \frac{\theta^2}{2}$, $-\tilde{J}\hat{J} \leq -\frac{\tilde{J}^2}{2} + \frac{J^2}{2}$, and (18) can be rewritten in the following inequality

$$\begin{aligned}\dot{V} &\leq -(k_1 - 1)z_1^2 - k_2 z_2^2 - (k_3 - 1)z_3^2 - k_4 z_4^2 - \frac{m_1\tilde{\theta}^2}{2r_1} - \frac{m_2\tilde{J}^2}{2r_2} + \frac{1}{2}\varepsilon_5^2 d^2 \\ &\quad + \frac{m_1\theta^2}{2r_1} + \frac{m_2 J^2}{2r_2} + \frac{1}{2}l_1^2 + \frac{1}{2}\varepsilon_1^2 + \frac{1}{2}l_2^2 + \frac{1}{2}\varepsilon_2^2 + \frac{1}{2}l_4^2 + \frac{1}{2}\varepsilon_4^2 + \frac{1}{4}\mu^2\left(1 + b_4^2\right) \\ &\leq -aV + b\end{aligned} \tag{19}$$

where $a = \min\{2(k_1 - 1)/J, 2k_2, 2(k_3 - 1), 2k_4, m_1, m_2\}$ and $b = \frac{1}{2}l_1^2 + \frac{1}{2}\varepsilon_1^2 + \frac{1}{2}l_2^2 + \frac{1}{2}\varepsilon_2^2 + \frac{1}{2}l_4^2 + \frac{1}{2}\varepsilon_4^2 + \frac{1}{2}\varepsilon_5^2 d^2 + \frac{m_1\theta^2}{2r_1} + \frac{m_2 J^2}{2r_2} + \frac{1}{4}\mu^2\left(1 + b_4^2\right)$. Then, (19) implies that

$$V(t) \leq \left(V(t_0) - \frac{b}{a}\right)e^{-a(t-t_0)} + \frac{b}{a} \leq V(t_0) + \frac{b}{a}, \quad \forall t \geq t_0 \tag{20}$$

All z_i $(i = 1, 2, 3, 4)$, $\tilde{J}$ and $\tilde{\theta}$ belong to the compact set

$$\Omega = \left\{\left(z_i, \tilde{J}, \tilde{\theta}\right) \middle| V \leq V(t_0) + \frac{b}{a}, \forall t \geq t_0\right\}$$

Namely, all the signals in the closed-loop system are bounded. Especially, from (20) we can get $\lim_{t\to\infty} z_1^2 \leq \frac{2b}{a}$. By the definitions of a and b, it is proved that to get a small tracking error we can take r_i large but l_i and ε_i small enough after giving the parameters k_i and m_i.

4. **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 $x_{1d} = \begin{cases} 80, & 0 \leq t \leq 8, \\ 85, & t \geq 8 \end{cases}$ and $x_{3d} = 1$. T_L is chosen as $T_L = \begin{cases} 0.5, & 0 \leq t \leq 5, \\ 1.0, & t \geq 5. \end{cases}$

The RBF NNs are chosen in the following way. The NNs $\phi_1^T P_1(Z)$, $\phi_2^T P_2(Z)$ and $\phi_4^T P_4(Z)$ contain eleven nodes with centers spaced evenly in the interval $[-9, 9]$ and widths being equal to 2, respectively. The proposed adaptive neural controllers are used to control the induction motor. The control parameters are chosen as: $k_1 = 20$, $k_2 = 36$, $k_3 = 12$, $k_4 = 16$, $r_1 = r_2 = 0.1$, $m_1 = m_2 = 0.2$, $l_1 = l_2 = l_4 = 0.01$, $\zeta = 0.5$, $\omega_n = 5000$.

Figure 1 displays the reference signal x_1 and x_{1d} and Figure 2 shows the reference signal x_3 and x_{3d}. It can be observed from Figure 1 and Figure 2 that the system output can track the given reference signals well. Figure 3 and Figure 4 show the trajectories of u_q and u_d. It can be seen that the controllers are bounded into a certain area. We can see a load torque disturbance appeared at $t = 5s$ from Figure 3. However, 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.

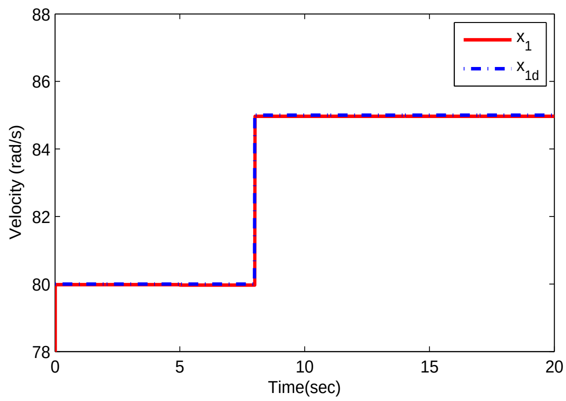

FIGURE 1. Trajectories of x_1 and x_{1d}

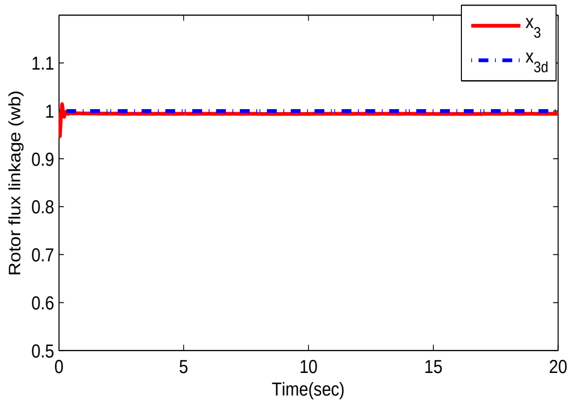

FIGURE 2. Trajectories of x_3 and x_{3d}

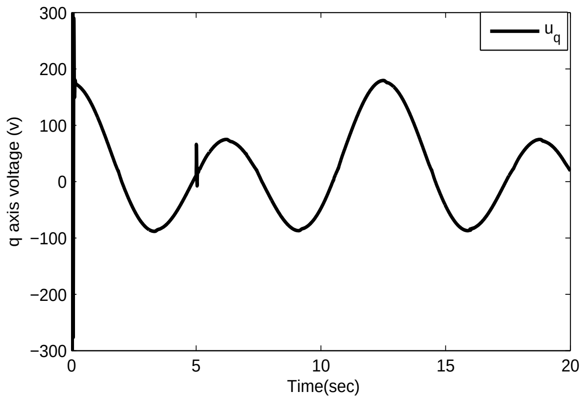

FIGURE 3. Trajectory of the control law u_q

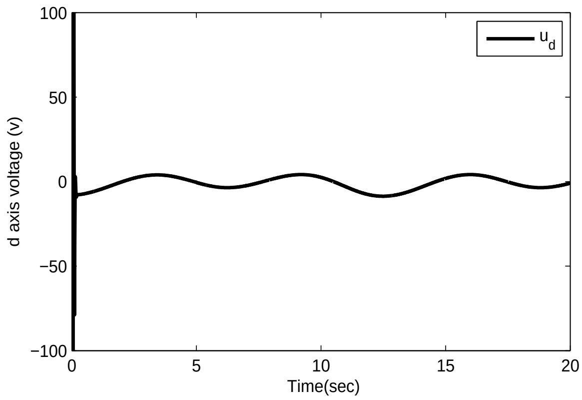

FIGURE 4. Trajectory of the control law u_d

5. **Conclusion.** Neural network-based adaptive command filtered backstepping approach has been presented for induction motors in this paper. This method can overcome the problem of "explosion of complexity" inherent in the traditional backstepping design. The designed controllers guarantee the speed tracking error can converge to a small neighborhood of the origin. Simulation results testify its effectiveness in the IM drive system. In the future work, we will focus on the practical application of the proposed control algorithm.

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