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NEURAL NETWORK-BASED ADAPTIVE TRACKING CONTROL FOR PERMANENT MAGNET SYNCHRONOUS MOTORS WITH IRON LOSS

Wei Li, Yumei Ma, Jinpeng Yu, Xiaoling Wang and Lichao Liu

College of Automation Engineering
Qingdao University
No. 308, Ningxia Road, Qingdao 266071, P. R. China
yjp1109@hotmail.com

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Abstract. *This paper focuses on the problem of neural networks (NNs)-based adaptive backstepping control for permanent magnet synchronous motors (PMSMs) with iron loss. Based on backstepping technique, an adaptive neural network control method is proposed by using neural network systems to approximate unknown nonlinearities of permanent magnet synchronous motor drive system with uncertainty parameters and load torque disturbance. The proposed adaptive neural network controllers guarantee that the tracking error converges to a small neighborhood of the origin. Finally, the simulation results illustrate the effectiveness of the proposed control scheme.*
Keywords: Permanent magnet synchronous motor, Iron loss, Adaptive control, Neural networks, Backstepping, Nonlinear system

1. **Introduction.** Permanent magnet synchronous motors (PMSMs) have been widely used in many industrial control fields due to its high power density, high reliability and long life over other kinds of motors. However, it is still a challenging problem to control PMSM to get the perfect dynamic performance because its dynamic model is usually multivariable, coupled and highly nonlinear. Especially, during the actual production process, the iron loss [1] varies with both synchronous frequency and magnetic flux of the PMSMs, and neglecting the iron loss can lead to serious error. Therefore, the main disadvantage of the motor drive system is that PMSMs need more complex controllers for high performance industrial applications, and taking iron loss into account has an important effect on improving the position tracking performance of the PMSMs. The control strategies based on recent modern control theories such as backstepping control [2], sliding mode control [3] and other control methods [4] are put forward to meet high performance application requirements of industrial applications. The backstepping-based adaptive control technique has become one of the most popular nonlinear control approaches because of its ability to clear up the influence of the uncertain parameters. The most appealing point of it is to use the virtual control variable to make the original high order system simple. Thus, the final control outputs can be derived systematically through the suitable Lyapunov functions. Neural network (NN) approximation [5] method has attracted great attention in PMSM drive system with iron loss because of its inherent capability for modeling and controlling highly uncertain, nonlinear and complex systems.

This paper is based on the dynamic mathematical model of PMSM with iron loss and designs adaptive NN controllers to realize the position tracking control. NN systems are employed to approximate the nonlinearities. And the adaptive technique and backstepping are used to construct NN controllers. The simulation results show that the adaptive NN control guarantees that PMSMs servo drives have a good tracking performance [6] even with the unknown parameters and load disturbances.

The model of PMSM drive system with iron loss is described in Section 2. Then the controller design of PMSM system with iron loss is developed in Section 3. And its stability is analyzed in Section 4. The simulation results of the PMSM position control system are given in Section 5. Finally, Section 6 draws some conclusions.

2. **Modeling of PMSM Drive System.** The mathematical model of PMSM drive system with iron loss can be described in the well-known (d-q) frame as follows [7]:

$$\begin{cases} \frac{d\Theta}{dt} = \omega,\ \frac{d\omega}{dt} = \frac{n_p\lambda_{PM}}{J}i_{oq} + \frac{n_p(L_{md}-L_{mq})i_{oq}i_{od}}{J} - \frac{T_L}{J} \\ \frac{di_{oq}}{dt} = \frac{R_c}{L_{mq}}i_q - \frac{R_c}{L_{mq}}i_{oq} - \frac{n_pL_d}{L_{mq}}\omega i_{od} - \frac{n_p\lambda_{PM}}{L_{mq}}\omega,\ \frac{di_{od}}{dt} = \frac{R_c}{L_{md}}i_d - \frac{R_c}{L_{md}}i_{od} + \frac{n_pL_q}{L_{md}}\omega i_{oq} \\ \frac{di_q}{dt} = -\frac{R_1}{L_{lq}}i_q + \frac{R_c}{L_{lq}}i_{oq} + \frac{1}{L_{lq}}u_q,\ \frac{di_d}{dt} = -\frac{R_1}{L_{ld}}i_d + \frac{R_c}{L_{ld}}i_{od} + \frac{1}{L_{ld}}u_d \end{cases} \tag{1}$$

where: Θ, ω, n_p, J, T_L denote the rotor position, rotor angular velocity, pole pair, rotor moment of inertia and load torque. i_d and i_q stand for the d-q axis currents. u_d and u_q are the d-q axis voltages. L_d and L_q are the stator inductors. L_{ld} and L_{lq} are the leakage inductance. L_{md} and L_{mq} are the magnetic inductance. R_1 and R_c are the stator resistance and iron loss resistance. λ_{PM} is the excitation flux.

For simplicity, the following notations are introduced:

$$\begin{cases} x_1 = \Theta,\ x_2 = \omega,\ x_3 = i_{oq},\ x_4 = i_q,\ x_5 = i_{od},\ x_6 = i_d, \\ a_1 = n_p\lambda_{PM},\ a_2 = n_p(L_{md} - L_{mq}),\ b_1 = R_c/L_{mq},\ b_2 = n_pL_d/L_{mq}, \\ b_3 = -n_p\lambda_{PM}/L_{mq},\ b_4 = -R_1/L_{lq},\ b_5 = R_c/L_{lq},\ c_1 = 1/L_{lq} \end{cases} \tag{2}$$

By using these notations, the dynamic model can be described as follows:

$$\begin{cases} \dot{x}_1 = x_2,\ \dot{x}_2 = (a_1x_3 + a_2x_3x_5 - T_L)/J,\ \dot{x}_3 = b_1x_4 - b_1x_3 + b_2x_2x_5 + b_3x_2, \\ \dot{x}_4 = b_4x_4 + b_5x_3 + c_1u_q,\ \dot{x}_5 = b_1x_6 - b_1x_5 - b_2x_2x_3,\ \dot{x}_6 = b_4x_6 + b_5x_5 + c_1u_d \end{cases} \tag{3}$$

In this paper, the radial basis function RBF NN [8] will be used to approximate the unknown continuous function $\phi(z) : R^q \to R$ as $\hat{\varphi}(z) = \phi^{*T}P(z)$, where $z \in \Omega_z \subset R^q$ is the input vector with q being NN input dimension, $\phi^* = [\varphi_1^*, \ldots, \varphi_n^*]^T \in R^n$ is the weight vector with $n > 1$ being the NN node number, and $P(z) = [p_1(z), \ldots, p_n(z)]^T \in R^n$ is the basis function vector with $p_i(z)$ chosen as the commonly used Gaussian function in the following form: $p_i(z) = \exp\left[-(z-\nu_i)^T(z-\nu_i)/q_i^2\right]$, $i = 1, 2, \ldots, n$, 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 shown that, for a given scalar $\varepsilon > 0$, by choosing sufficiently large l, the RBF NN can approximate any continuous function over a compact set $\Omega_z \in R^q$ to an 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 $|\delta(z) \leq \varepsilon|$ 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 $z \in \Omega_z$, $\varphi := \arg\min_{\varphi* \in R^n}\left\{\sup_{z\in\Omega_z}|\phi(z) - \varphi^{*T}P(z)|\right\}$.

3. **Adaptive Neural Network Controllers Design with Backstepping Technique.** In this section, we will design controllers for the PMSMs based on backstepping.

Step 1: For the reference signal x_d, define the tracking error variable as $z_1 = x_1 - x_d$. From Equation (1), choose a Lyapunov function candidate as $V_1 = z_1^2/2$, and the time derivative of V_1 is computed by $\dot{V}_1 = z_1\dot{z}_1 = z_1(x_2 - \dot{x}_d)$. Construct $\alpha_1 = -k_1z_1 + \dot{x}_d$, with $k_i > 0$ ($i = 1, 2, 3, 4, 5, 6$) being design parameters and $z_2 = x_2 - \alpha_1$. Then, $\dot{V}_1$ can be written as $\dot{V}_1 = -k_1z_1^2 + z_1z_2$.

Step 2: Differentiating z_2 gives $\dot{z}_2 = (a_1x_3 + a_2x_3x_5 - T_L)/J - \dot{\alpha}_1$. Choose the Lyapunov function candidate as $V_2 = V_1 + Jz_2^2/2$.

Remark 3.1. *In this paper, due to the parameters T_L being bounded in practice system, assuming its upper bound is $d > 0$, which is an unknown constant, namely, $0 \le T_L \le d$. Obviously, $-z_2 T_L \le \frac{1}{2\varepsilon_1^2} z_2^2 + \frac{1}{2}\varepsilon_1^2 d^2$, where ε_1 is an arbitrary small positive constant.*

Then, the time derivative of V_2 satisfies $\dot{V}_2 = -k_1 z_1^2 + z_2(a_1 x_3 + f_2) + 1/2\varepsilon_1^2 d^2$, where $f_2(Z) = z_1 + a_2 x_3 x_5 - J\dot{\alpha}_1 + z_2/2\varepsilon_1^2$ and $Z = [x_1, x_2, x_3, x_4, x_5, x_6, x_d, \dot{x}_d]$. According to the RBF NN approximation property, for given $\varepsilon_2 > 0$, there exists an RBF NN $\phi_2^T P_2(Z)$ such that $f_2(Z) = \phi_2^T P_2(Z) + \delta_2(Z)$, where $\delta_2(Z)$ is the approximation error satisfying $|\delta_2| \le \varepsilon_2$. Then, we can get $z_2 f_2 \le z_2^2 \|\phi_2\|^2 P_2^T P_2 / 2l_2^2 + (l_2^2 + z_2^2 + \varepsilon_2^2)/2$.

Construct $\alpha_2 = \left(-k_2 z_2 - \frac{1}{2} z_2 - \frac{1}{2l_2^2} z_2 \hat{\theta} P_2^T P_2\right)/a_1$, where $\hat{\theta}$ is the estimation of the unknown constant θ which will be specified later and define $z_3 = x_3 - \alpha_2$, with l_i $(i = 2, 3, 4, 6)$ being positive constants.

$$\dot{V}_2 \le -\sum_{i=1}^{2} k_i z_i^2 + a_1 z_2 z_3 + \frac{1}{2l_2^2} z_2^2 \left(\|\phi_2\|^2 - \hat{\theta}\right) P_2^T P_2 + \frac{1}{2}\left(l_2^2 + \varepsilon_2^2 + \varepsilon_1^2 d^2\right) \tag{4}$$

Step 3: Differentiating z_3 obtains $\dot{z}_3 = b_1 x_4 - b_1 x_3 + b_2 x_2 x_5 + b_3 x_2 - \dot{\alpha}_2$. Choosing the Lyapunov function candidate as $V_3 = V_2 + z_3^2/2$, the time derivative of V_3 is given by

$$\dot{V}_3 \le -\sum_{i=1}^{2} k_i z_i^2 + \frac{1}{2l_2^2} z_2^2 \left(\|\phi_2\|^2 - \hat{\theta}\right) P_2^T P_2 + \frac{1}{2}\left(l_2^2 + \varepsilon_2^2 + \varepsilon_1^2 d^2\right) + z_3(b_1 x_4 + f_3) \tag{5}$$

where $f_3(Z) = a_1 z_2 - b_1 x_3 + b_2 x_2 x_5 + b_3 x_2 - \dot{\alpha}_2 = \phi_3^T P_3(Z) + \delta_3(Z)$. Similarly, for given $|\delta_3| \le \varepsilon_3$, $\varepsilon_3 > 0$, we can obtain $z_3 f_3 \le z_3^2 \|\phi_3\|^2 P_3^T P_3 / 2l_3^2 + (l_3^2 + z_3^2 + \varepsilon_3^2)/2$. Then, construct $\alpha_3 = \left(-k_3 z_3 - \frac{1}{2} z_3 - \frac{1}{2l_3^2} z_3 \hat{\theta} P_3^T P_3\right)/b_1$. By using α_3, with $z_4 = x_4 - \alpha_3$, it can be obtained that

$$\dot{V}_3 \le -\sum_{i=1}^{3} k_i z_i^2 + b_1 z_3 z_4 + \sum_{i=2}^{3} \frac{1}{2l_i^2} z_i^2 \left(\|\phi_i\|^2 - \hat{\theta}\right) P_i^T P_i + \sum_{i=2}^{3} \frac{1}{2}\left(l_i^2 + \varepsilon_i^2\right) + \frac{1}{2}\varepsilon_1^2 d^2 \tag{6}$$

Step 4: Differentiating z_4 obtains $\dot{z}_4 = b_4 x_4 + b_5 x_3 + c_1 u_q - \dot{\alpha}_3$. At this step, we will construct the control law u_q. Choosing $V_4 = V_3 + z_4^2/2$, then V_4 is computed by

$$\dot{V}_4 = \dot{V}_3 + z_4 \dot{z}_4 = \dot{V}_3 + z_4(f_4 + c_1 u_q) \tag{7}$$

where $f_4(Z) = c_1 x_4 + c_2 x_2 x_3 = \phi_4^T P_4(Z) + \delta_4(Z)$. For given $|\delta_4| \le \varepsilon_4$, $\varepsilon_4 > 0$, we can get

$$z_4 f_4 \le z_4^2 \|\phi_4\|^2 P_4^T P_4 / 2l_4^2 + \left(l_4^2 + z_4^2 + \varepsilon_4^2\right)/2 \tag{8}$$

Construct the control law u_q as

$$u_q = \frac{1}{c_1}\left(-k_4 z_4 - \frac{1}{2} z_4 - \frac{1}{2l_4^2} z_4 \hat{\theta} P_4^T P_4\right) \tag{9}$$

Furthermore, by using (9), it can be verified easily that

$$\dot{V}_4 \le -\sum_{i=1}^{4} k_i z_i^2 + \sum_{i=2,3,4} \frac{1}{2l_i^2} z_i^2 \left(\|\phi_i\|^2 - \hat{\theta}\right) P_i^T P_i + \sum_{i=2,3,4} \frac{1}{2}\left(l_i^2 + \varepsilon_i^2\right) + \frac{1}{2}\varepsilon_1^2 d^2 \tag{10}$$

Step 5: Define the tracking error variable as $z_5 = x_5$, so $\dot{z}_5 = \dot{x}_5$. Then, define $\dot{z}_6 = \dot{x}_6 - \alpha_4$. Choose the Lyapunov function candidate as $V_5 = V_4 + z_5^2/2$. Differentiate V_5, and construct $\alpha_4 = (-k_5 z_5 + b_1 x_5 + b_2 x_2 x_3)/b_1$. By using α_4, $\dot{V}_5$ can be expressed as

$$\dot{V}_5 \le -\sum_{i=1}^{5} k_i z_i^2 + \sum_{i=2,3,4} \frac{1}{2l_i^2} z_i^2 \left(\|\phi_i\|^2 - \hat{\theta}\right) P_i^T P_i + \sum_{i=2,3,4} \frac{1}{2}\left(l_i^2 + \varepsilon_i^2\right) + \frac{1}{2}\varepsilon_1^2 d^2 + b_1 z_5 z_6 \tag{11}$$

Step 6: At this step, we will construct the control law u_d. To this end, choose the Lyapunov function candidate as $V_6 = V_5 + z_6^2/2$. Then the derivative of V_6 is given by

$$\dot{V}_6 \leq -\sum_{i=1}^{5} k_i z_i^2 + \sum_{i=2,3,4} \frac{1}{2l_i^2} z_i^2 \left(\|\phi_i\|^2 - \hat{\theta}\right) P_i^T P_i + \sum_{i=2,3,4} \frac{1}{2}\left(l_i^2 + \varepsilon_i^2\right) + \frac{1}{2}\varepsilon_1^2 d^2 + z_6(f_6 + c_1 u_d)$$

where $f_6(Z) = b_1 z_5 + b_4 x_6 + b_5 x_5 - \dot{\alpha}_4$. Similarly, for given $|\delta_6| \leq \varepsilon_6$, $\varepsilon_6 > 0$, we can get

$$z_6 f_6(Z) \leq z_6^2 \|\phi_6\|^2 P_6^T P_6/2l_6^2 + \left(l_6^2 + z_6^2 + \varepsilon_6^2\right)/2 \tag{12}$$

Now, construct the control law u_d as

$$u_d = \frac{1}{c_1}\left(-k_6 z_6 - \frac{1}{2} z_6 - \frac{1}{2l_6^2} z_6 \hat{\theta} P_6^T P_6\right) \tag{13}$$

Define $\theta = \max\left\{\|\phi_2\|^2, \|\phi_3\|^2, \|\phi_4\|^2, \|\phi_6\|^2\right\}$. By using (13), it can be verified easily that

$$\dot{V}_6 \leq -\sum_{i=1}^{6} k_i z_i^2 + \sum_{i=2,3,4,6} \frac{1}{2l_i^2} z_i^2 \left(\theta - \hat{\theta}\right) P_i^T P_i + \sum_{i=2,3,4,6} \frac{1}{2}\left(l_i^2 + \varepsilon_i^2\right) + \frac{1}{2}\varepsilon_1^2 d^2 \tag{14}$$

Introduce variable as $\tilde{\theta} = \hat{\theta} - \theta$, and choose the Lyapunov function candidate as $V = V_6 + \tilde{\theta}^2/2r_1$, where r_1 and m_1 are positive constants. By differentiating V, one has

$$\dot{V} \leq -\sum_{i=1}^{6} k_i z_i^2 + \sum_{i=2,3,4,6} \frac{1}{2}\left(l_i^2 + \varepsilon_i^2\right) + \frac{1}{2}\varepsilon_1^2 d^2 + \frac{1}{r_1}\tilde{\theta}\left[-\sum_{i=2,3,4,6} \frac{r_1}{2l_i^2} z_i^2 P_i^T P_i + \dot{\hat{\theta}}\right] \tag{15}$$

The corresponding adaptive law is chosen as $\dot{\hat{\theta}} = \sum_{i=2,3,4,6} \frac{r_1}{2l_i^2} z_i^2 P_i^T P_i - m_1 \hat{\theta}$.

4. Stability Analysis of PMSM Position Control.

Lyapunov stability theorem is used to analyze stability of PMSM position system in this paper. Substituting $\dot{\hat{\theta}}$ into $\dot{V}$, and for the term $-\tilde{\theta}\hat{\theta}$, one has $-\tilde{\theta}\hat{\theta} \leq -0.5\tilde{\theta}^2 + 0.5\theta^2$. Consequently, by using this inequality, $\dot{V}$ can be rewritten in the following form

$$\dot{V} \leq -\sum_{i=1}^{6} k_i z_i^2 + \sum_{i=2,3,4,6} \frac{1}{2}\left(l_i^2 + \varepsilon_i^2\right) + \frac{1}{2}\varepsilon_1^2 d^2 + \frac{m_1}{2r_1}\tilde{\theta}^2 - \frac{m_1}{2r_1}\theta^2 \leq -aV + b \tag{16}$$

where $a = \min\{2k_1, 2k_2/J, 2k_3, 2k_4, 2k_5, 2k_6, m_1\}$, $b = \sum_{i=2,3,4,6} \frac{1}{2}\left(l_i^2 + \varepsilon_i^2\right) + \frac{\varepsilon_1^2 d^2}{2} + \frac{m_1 \theta^2}{2r_1}$.

Then, (16) implies that $V(t) \leq (V(t_0) - b/a)e^{-a(t-t_0)} + b/a \leq V(t_0) + b/a, \forall t \geq t_0$.

All z_i $(i=1,\ldots,6)$, $\tilde{\theta}$ belong to the compact set $\Omega = \left\{\left(z_i, \tilde{\theta}\right) | V \leq V(t_0) + b/a, \forall t \geq t_0\right\}$.

Namely, all the signals in the closed-loop system are bounded. From $V(t)$, we have $\lim_{t\to\infty} z_1^2 \leq 2b/a$. By the definitions of a and b, we can set r_1 large enough to get a small tracking error, with l_i and ε_i small enough after giving the parameters k_i and m_1.

5. Simulation Results.

In order to illustrate the effectiveness of the proposed results, the simulations are performed to evaluate the performance of closed-loop system by using Matlab/Simulink. The motor parameters of the PMSMs with iron loss are: $J = 0.002\text{Kgm}^2$, $R = 2.21\Omega$, $R_c = 200\Omega$, $Vpm = 0.0844$, $L_{ld} = 0.00977\text{H}$, $L_{lq} = 0.00177\text{H}$, $L_{mq} = 0.008\text{H}$, $L_{md} = 0.007\text{H}$, $n_p = 3$. The RBF NN is chosen in the following way. Then, adaptive neural network controllers are used to control the PMSMs. The control parameters are chosen as follows: $k_1 = 300$, $k_2 = 160$, $k_3 = 200$, $k_4 = 200$, $k_5 = 400$, $k_6 = 400$, $r_1 = 0.05$, $m_1 = 0.005$, $l_2 = l_3 = l_4 = l_6 = 2.5$. The simulation is carried out under the zero initial condition for the PMSMs. Give the signals: $x_d = 0.5 * \sin(4 * t) + 0.3 * \sin(2 * t)$, $T_L = 1.5N \cdot m$, $0 \leq t \leq 1$; $T_L = 3N \cdot m$, $t \geq 1$.

Figure 1 shows the reference signals x_1 and x_d. Figure 2 shows the error curve. It can be observed from Figure 1 and Figure 2 that x_1 and x_d are mostly overlapped from the very beginning of the simulation, so the system can track the given reference signal

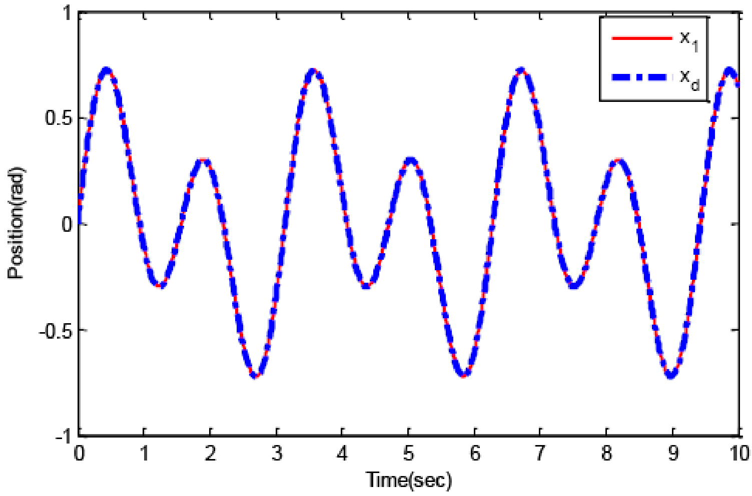

Figure 1. Position curve

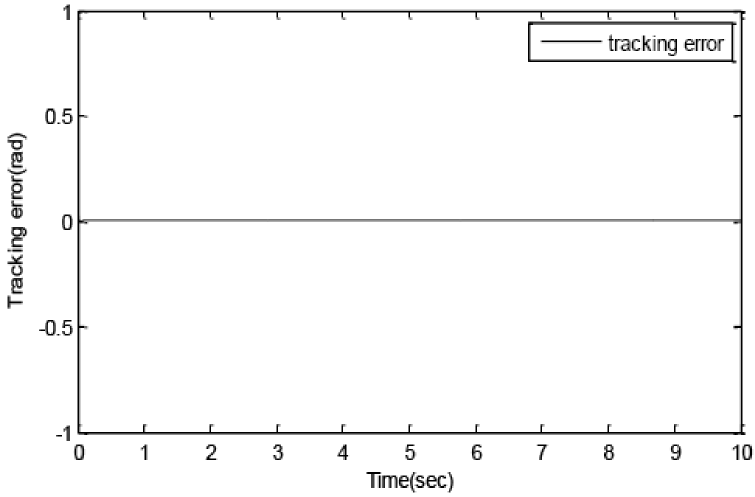

Figure 2. Error curve

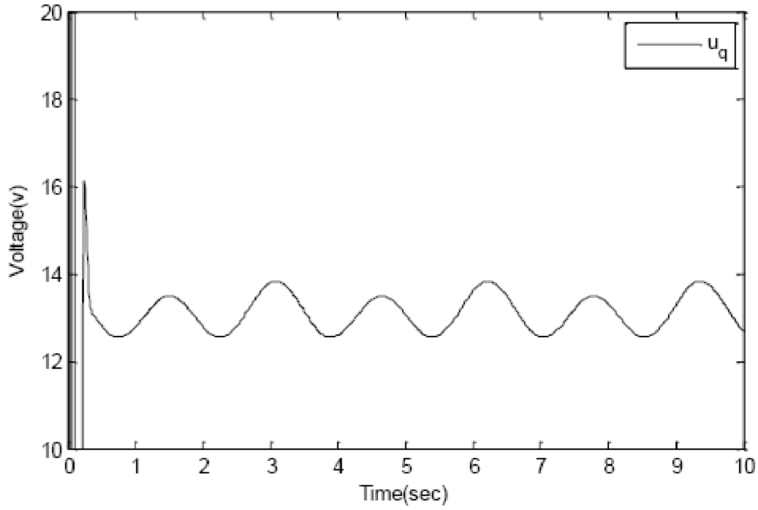

Figure 3. Voltage u_q curve

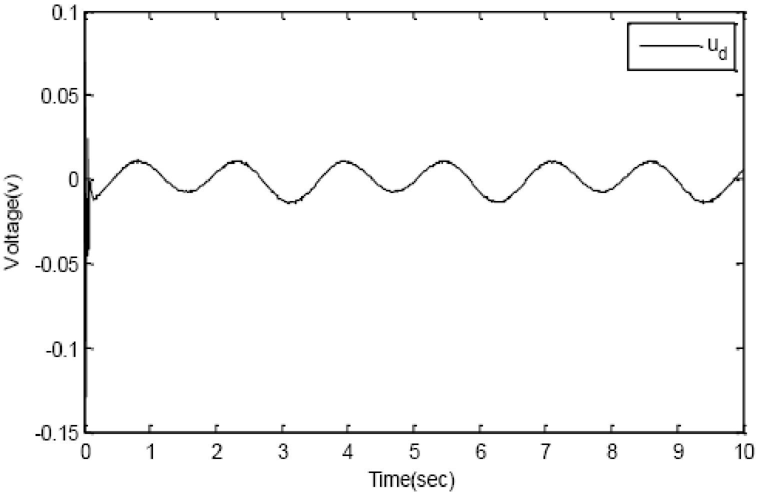

FIGURE 4. Voltage u_d curve

quickly and accurately. Figure 3 and Figure 4 show the trajectories of u_q and u_d. It can be seen that the controllers are bounded. From the above simulation results, it is clearly seen that the proposed controllers can track the reference signal quite well even under parameter uncertainties and load torque disturbance.

6. **Conclusions.** Based on backstepping technique, an adaptive NN control method is designed to control PMSMs with iron loss. The proposed controllers are able to overcome the problem of "explosion of complexity" inherent in the traditional backstepping design. And the designed controllers guarantee that the system can track the given desired signals quickly and accurately. Simulation results testify its effectiveness in the PMSM drive system with iron loss. In the future work, we will focus on the practical application of the proposed control algorithm.

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