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Barrier Lyapunov Functions-Based Adaptive Neural Control for Permanent Magnet Synchronous Motors With Full-State Constraints

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ABSTRACT Considering the requirement of high accuracy and nonlinear problems in drive systems, a novel adaptive position tracking control approach based on neural networks is presented for permanent magnet synchronous motors with full-state constraints. The neural networks technique is employed to approximate the unknown nonlinear functions. Then, the barrier Lyapunov functions are used to restrict the state variables within a bounded compact set to improve the property of system. The proposed adaptive neural network controllers can guarantee that all closed-loop variables are bounded, and the full state variables do not exceed their constraint spaces. Simulation results show the effectiveness and the potentials of the theoretic results obtained.

INDEX TERMS Adaptive neural control, permanent magnet synchronous motors, full-state constraints, barrier Lyapunov functions.

I. INTRODUCTION

Recently, permanent magnet synchronous motors (PMSMs) have attracted more and more attentions owing to their simple and robust construction, high power density and ruggedness over other kinds of motors. Nevertheless, the dynamic model of PMSMs is high nonlinear, strong coupling and multivariable. Besides, PMSMs are easily influenced by parameter variations and external load disturbances. Therefore, it is necessary to find optimal and efficient controllers for PMSMs, which will be filled with many challenges. A lot of work has been done to solve the nonlinear problem of PMSMs. Then many advanced nonlinear control methods have been proposed and applied to control PMSMs for a higher performance, such as fuzzy logic control [1]–[3], sliding mode control [4]–[6], dynamic surface control [7], [8], backstepping [9]–[11], Hamiltonian control [12], and other control methods [13], [14].

In the above control methods, the backstepping approach has shown its superiority in designing controllers for uncertain systems, especially when the disturbances or uncertainties do not satisfy the matching conditions. At present, the backstepping method has been successfully applied in the control system of PMSMs [15]–[17]. But, the state constraints are ignored on the aforementioned control methods of PMSMs. The state variables such as rotor angular velocity, currents, should be constrained by the inherent properties of the PMSMs. The mathematical model of PMSMs is nonlinear, including the nonlinear coupling of speed and current. So it can't guarantee that the state variables are always within the desired set only under the control quantity. For example, the excessive voltage and current affect the security of the system. Therefore, it is necessary to consider the full-state constraints [18]–[21] in the control of PMSMs. To ameliorate the traditional widely used Lyapunov theorem and satisfy the constraint conditions of the PMSMs system, some researchers proposed a new kind of Lyapunov function named barrier Lyapunov function (BLF) [22]–[27] to restrict the state interval. When the constraint signal tends to expected conditions, the value of Lyapunov function will tend to infinity. The constraint variables can be guaranteed in the given range by BLFs. To the best of our knowledge, there are no researches on the permanent magnet synchronous motor (PMSM) with full-state constraints, which motivates us for this study.

In addition, many adaptive control methods are proposed in [28]–[31] to solve the uncertain nonlinear functions, such as the methods based on neural networks (NNs) [32]–[34] or fuzzy logic systems (FLS) [35]–[38], which are introduced to dispose of the nonlinear systems with parametric uncertainty. The uncertain information can be approximated by NNs, which can be employed to control ill-defined or complex systems. So, the radial basis function (RBF) NNs are widely used to approximate the uncertain nonlinearities [39]–[45].

According to the above researches, an adaptive neural control based on the barrier Lyapunov functions (BLFs) is proposed for PMSMs drive system. Compared with the extant accomplishments, the superiorities of the proposed control can be summarized as follows:

1) In our work, RBF NNs are applied to approximate unknown nonlinear functions and the BLFs are employed in PMSMs and the full state variables of PMSMs are restricted in a bounded compact set in order to improve the property of the system;

2) Compared with the adaptive backstepping control in [36] with four adaptive laws, only one adaptive law is needed for the proposed approach, which will reduce the online computation burden and make it more suitable for practical applications.

The rest of the paper is organized as follows. Section 2 describes dynamic mathematical model of PMSMs. Adaptive neural network controllers are designed for the PMSMs drive system with full-state constraints in Section 3. Section 4 testifies the stability of this method. In Section 5, simulation results are given to demonstrate the effectiveness of the proposed scheme. Ultimately, some conclusions are presented in Section 6.

II. PROBLEM FORMULATION AND PRELIMINARIES

The dynamic mathematical model of PMSM [16] is described in the well-known $(d-q)$ frame as:

$$\begin{cases} \dfrac{d\theta}{dt} = \omega, \\ J\dfrac{dw}{dt} = \dfrac{3}{2}n_p[(L_d - L_q)i_d i_q + \Phi i_q] - B\omega - T_L, \\ L_q\dfrac{di_q}{dt} = -R_s i_q - n_p\omega L_d i_d - n_p\omega\Phi + u_q, \\ L_d\dfrac{di_d}{dt} = -R_s i_d + n_p\omega L_q i_q + u_d \end{cases} \tag{1}$$

where i_d and i_q stand for the $d-q$ axis currents, u_d and u_q are the $d-q$ axis voltages for the system control inputs, θ, ω, J, T_L, B, n_p, Φ and R_s represent the rotor position, rotor angular velocity, rotor moment of inertia, load torque, viscous friction coefficient, pole pair, flux linkage and stator resistance, L_d and L_q are the $d-q$ axis inductance, respectively.

For simplicity, the following symbols are represented as:

$$x_1 = \theta, \quad x_2 = \omega, \; x_3 = i_q, \; x_4 = i_d, \; a_1 = \frac{3n_p\Phi}{2},$$
$$a_2 = \frac{3n_p(L_d - L_q)}{2}, \quad b_1 = -\frac{R_s}{L_q}, \; b_2 = -\frac{n_p L_d}{L_q},$$
$$b_3 = -\frac{n_p\Phi}{L_q}, \quad b_4 = \frac{1}{L_q}, \; c_1 = -\frac{R_s}{L_d},$$

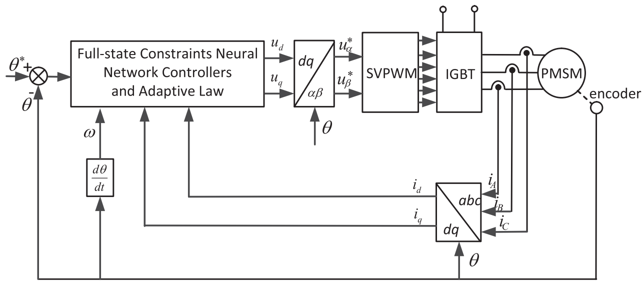

FIGURE 1. Adaptive neural control system block diagram for PMSM.

$$c_2 = \frac{n_p L_q}{L_d}, \quad c_3 = \frac{1}{L_d}. \tag{2}$$

Using the above symbols, the mathematical model of PMSM driver system can be rewritten as:

$$\begin{aligned} \dot{x}_1 &= x_2, \\ \dot{x}_2 &= \frac{a_1}{J}x_3 + \frac{a_2}{J}x_3x_4 - \frac{B}{J}x_2 - \frac{T_L}{J}, \\ \dot{x}_3 &= b_1x_3 + b_2x_2x_4 + b_3x_2 + b_4u_q, \\ \dot{x}_4 &= c_1x_4 + c_2x_2x_3 + c_3u_d. \end{aligned} \tag{3}$$

The control orientation is to devise adaptive NNs controllers such that the reference signal x_d is tracked well by the state variable x_1. Besides, all the states are constrained in the compact sets, and x_i is required to satisfy that $|x_i| < k_{c_i}$ where $k_{c_i} > 0$ is a constant.

The adaptive neural control system structure for PMSM is illustrated in Fig.1. The RBF NNs are employed to approximate the continuous function $\varphi(z) : R^q \rightarrow R$ as $\hat{\varphi}(z) = W^{*T}S(Z)$ where $Z \in \Omega_Z \subset R^q$ is the input variable of the NNs and q is the input dimension, $W^* = \left[\Phi_1^*, \ldots, \Phi_l^*\right]^T$, is the weight vector with l being the NNs node number. The definition of NN and parameters are shown in [45]. From [45], we know $||W_i(S_i(k))||^2 \leq l_i$, $(i = 1, \cdots, n)$.

Assumption 1: There exist positive constants A_0, A_1, A_2, A_3 such that x_d and its derivatives satisfy $|x_d| \leq A_0 < k_{c_1}$ and $\left|x_d^{(i)}\right| \leq A_i$.

III. ADAPTIVE NEURAL CONTROLLERS DESIGN WITH FULL-STATE CONSTRAINTS

In this section, adaptive neural controllers are designed for the PMSM drive system with full-state constraints. The tracking error variable is defined as $z_1 = x_1 - x_d$ with the reference signal x_d and the variables $z_2 = x_2 - \alpha_1$, $z_3 = x_3 - \alpha_2$, $z_4 = x_4$ with α_i being a virtual controller.

Define a compact set $\Omega_z := \{|z_i| < k_{b_i}, i = 1, ..., 4\}$, which k_{b_i} will be specified later.

Step 1: Choose a barrier Lyapunov function

$$V_1 = \frac{1}{2}\log\left(\frac{k_{b_1}^2}{k_{b_1}^2 - z_1^2}\right) \tag{4}$$

where k_{b_1} is a positive constant, $k_{b_1} = k_{c_1} - A_0$. The time derivative of V_1 is computed by

$$\dot{V}_1 = K_{z_1}\dot{z}_1 = K_{z_1}(z_2 + \alpha_1 - \dot{x}_d) \tag{5}$$

where $K_{z_1} = z_1/(k_{b_1}^2 - z_1^2)$ and $K_{z_i} = z_i/(k_{b_i}^2 - z_i^2)(i = 2, 3, 4)$ will be applied in the following process. The virtual controller is constructed as $\alpha_1 = -k_1 z_1 + \dot{x}_d$, then

$$\dot{V}_1 = -k_1 K_{z_1} z_1 + K_{z_1} z_2. \tag{6}$$

Step 2: Choose the barrier Lyapunov function as

$$V_2 = V_1 + \frac{J}{2} \log(\frac{k_{b_2}^2}{k_{b_2}^2 - z_2^2}). \tag{7}$$

Obviously, $\dot{V}_2$ can be calculated by

$$\begin{aligned}\dot{V}_2 &= \dot{V}_1 + JK_{z_2}\dot{z}_2 = -k_1 K_{z_1} z_1 + K_{z_1} z_2 \\ &+ K_{z_2}(a_1 x_3 + a_2 x_3 x_4 - Bx_2 - T_L - J\dot{\alpha}_1).\end{aligned} \tag{8}$$

Remark 1: In the practical system, T_L is unknown but its bound is $|T_L| \le d$. Furthermore, $-K_{z_2} T_L \le \frac{1}{2\varepsilon_1^2} K_{z_2}^2 + \frac{1}{2}\varepsilon_1^2 d^2$ with ε_1 being an arbitrary small positive constant.

Then, $\dot{V}_2$ can be written as

$$\dot{V}_2 = -k_1 K_{z_1} z_1 + K_{z_2}(a_1(z_3 + \alpha_2) + f_2(Z_2)) + \frac{1}{2}\varepsilon_1^2 d^2 \tag{9}$$

where $f_2(Z_2) = a_2 x_3 x_4 - Bx_2 - J\dot{\alpha}_1 + (k_{b_2}^2 - z_2^2)K_{z_1} + K_{z_2}/2\varepsilon_1^2$, $Z_2 = [x_1, x_2, x_3, x_4, x_d, \dot{x}_d, \ddot{x}_d]$. By using the RBF NNs, for any $\varepsilon_2 > 0$, there exists a RBF NN $W_2^T S_2(Z_2)$ such that $f_2(Z_2) = W_2^T S_2(Z_2) + \delta_2(Z_2)$ where $\delta_2(Z_2)$ is the approximation error satisfying $|\delta_2(Z_2)| \le \varepsilon_2$.

$$\begin{aligned}K_{z_2} f_2(Z_2) &= K_{z_2}(W_2^T S_2 + \delta_2) \\ &\le \frac{\|W_2\|^2 K_{z_2}^2 S_2^T S_2}{2l_2^2} + \frac{l_2^2}{2} + \frac{K_{z_2}^2}{2} + \frac{\varepsilon_2^2}{2}.\end{aligned} \tag{10}$$

Construct the virtual controller α_2 as follows

$$\alpha_2 = -\frac{1}{a_1}(k_2 z_2 + \frac{1}{2}K_{z_2} + \frac{K_{z_2}\hat{\theta} S_2^T S_2}{2l_2^2}) \tag{11}$$

where $\hat{\theta}$ is the estimation of θ and θ will be given later.

Substituting (10), (11) into (9) yields

$$\begin{aligned}\dot{V}_2 &\le -k_1 K_{z_1} z_1 - k_2 K_{z_2} z_2 + K_{z_2} a_1 z_3 + \frac{1}{2}\varepsilon_1^2 d^2 \\ &+ \frac{(\|W_2\|^2 - \hat{\theta})K_{z_2}^2 S_2^T S_2}{2l_2^2} + \frac{l_2^2}{2} + \frac{\varepsilon_2^2}{2}.\end{aligned} \tag{12}$$

Step 3: The barrier Lyapunov function V_3 is defined as

$$V_3 = V_2 + \frac{1}{2} \log(\frac{k_{b_3}^2}{k_{b_3}^2 - z_3^2}). \tag{13}$$

Then, $\dot{V}_3$ can be computed as

$$\begin{aligned}\dot{V}_3 &\le -\sum_{i=1}^{2} k_i K_{z_i} z_i + K_{z_3}(f_3(Z_3) + b_4 u_q) + \frac{1}{2}\varepsilon_1^2 d^2 \\ &+ \frac{(\|W_2\|^2 - \hat{\theta})K_{z_2}^2 S_2^T S_2}{2l_2^2} + \frac{l_2^2}{2} + \frac{\varepsilon_2^2}{2}\end{aligned} \tag{14}$$

where $f_3(Z_3) = b_1 x_3 + b_2 x_2 x_4 + b_3 x_2 + a_1 K_{z_2}(k_{b_3}^2 - z_3^2) - \dot{\alpha}_2$, $Z_3 = [x_1, x_2, x_3, x_4, x_d, \dot{x}_d, \ddot{x}_d, \dddot{x}_d]$. Similarly, there exists a RBF NN $W_3^T S_3(Z_3)$ such that $f_3(Z_3) = W_3^T S_3(Z_3) + \delta_3(Z_3)$ where $\delta_3(Z_3)$ is the approximation error satisfying $|\delta_3(Z_3)| \le \varepsilon_3$.

$$\begin{aligned}K_{z_3} f_3(Z_3) &= K_{z_3}(W_3^T S_3 + \delta_3) \\ &\le \frac{\|W_3\|^2 K_{z_3}^2 S_3^T S_3}{2l_3^2} + \frac{l_3^2}{2} + \frac{K_{z_3}^2}{2} + \frac{\varepsilon_3^2}{2}.\end{aligned} \tag{15}$$

At this present stage, construct the control law u_q as

$$u_q = -\frac{1}{b_4}(k_3 z_3 + \frac{1}{2}K_{z_3} + \frac{K_{z_3}\hat{\theta} S_3^T S_3}{2l_3^2}). \tag{16}$$

Furthermore, employing (15) and (16), (14) becomes

$$\begin{aligned}\dot{V}_3 &\le -\sum_{i=1}^{3} k_i K_{z_i} z_i + \frac{(\|W_2\|^2 - \hat{\theta})K_{z_2}^2 S_2^T S_2}{2l_2^2} \\ &+ \frac{(\|W_3\|^2 - \hat{\theta})K_{z_3}^2 S_3^T S_3}{2l_3^2} + \frac{l_2^2}{2} + \frac{\varepsilon_2^2}{2} \\ &+ \frac{l_3^2}{2} + \frac{\varepsilon_3^2}{2} + \frac{1}{2}\varepsilon_1^2 d^2.\end{aligned} \tag{17}$$

Step 4: Choose the following barrier Lyapunov function as

$$V_4 = V_3 + \frac{1}{2} \log(\frac{k_{b_4}^2}{k_{b_4}^2 - z_4^2}). \tag{18}$$

Afterwards, it is easy to obtain

$$\begin{aligned}\dot{V}_4 &\le -\sum_{i=1}^{3} k_i K_{z_i} z_i + \frac{(\|W_2\|^2 - \hat{\theta})K_{z_2}^2 S_2^T S_2}{2l_2^2} \\ &+ \frac{(\|W_3\|^2 - \hat{\theta})K_{z_3}^2 S_3^T S_3}{2l_3^2} + K_{z_4}(f_4(Z_4) + c_3 u_d) \\ &+ \frac{l_2^2}{2} + \frac{\varepsilon_2^2}{2} + \frac{l_3^2}{2} + \frac{\varepsilon_3^2}{2} + \frac{1}{2}\varepsilon_1^2 d^2\end{aligned} \tag{19}$$

where $f_4(Z_4) = c_1 x_4 + c_2 x_2 x_3$, $Z_4 = [x_2, x_3, x_4]$. Similarly, there exists a RBF NN $W_4^T S_4(Z_4)$ such that $f_4(Z_4) = W_4^T S_4(Z_4) + \delta_4(Z_4)$ where $\delta_4(Z_4)$ is the approximation error contenting $|\delta_4(Z_4)| \le \varepsilon_4$.

$$\begin{aligned}K_{z_4} f_4(Z_4) &= K_{z_4}(W_4^T S_4 + \delta_4) \\ &\le \frac{\|W_4\|^2 K_{z_4}^2 S_4^T S_4}{2l_4^2} + \frac{l_4^2}{2} + \frac{K_{z_4}^2}{2} + \frac{\varepsilon_4^2}{2}.\end{aligned} \tag{20}$$

Construct the control law u_d as

$$u_d = -\frac{1}{c_3}(k_4 z_4 + \frac{1}{2}K_{z_4} + \frac{K_{z_4}\hat{\theta} S_4^T S_4}{2l_4^2}) \tag{21}$$

and define $\theta = \max\left\{\|W_2\|^2, \|W_3\|^2, \|W_4\|^2\right\}$.

Furthermore, putting (20) and (21) into (19), it can obviously get that

$$\begin{aligned}\dot{V}_4 &\le -\sum_{i=1}^{4} k_i K_{z_i} z_i + \sum_{i=2}^{4}\left(\frac{l_i^2}{2} + \frac{\varepsilon_i^2}{2}\right) \\ &+ \sum_{i=2}^{4} \frac{(\theta - \hat{\theta})K_{z_i}^2 S_i^T S_i}{2l_i^2} + \frac{1}{2}\varepsilon_1^2 d^2.\end{aligned} \tag{22}$$

Step 5: Introduce variable θ as $\tilde{\theta} = \hat{\theta} - \theta$. Define a barrier Lyapunov function

$$V = V_4 + \frac{1}{2r}\tilde{\theta}^2. \tag{23}$$

Thus, differentiating V yields

$$\begin{aligned}\dot{V} \leq & -\sum_{i=1}^{4} k_i K_{z_i} z_i + \sum_{i=2}^{4}\left(\frac{l_i^2}{2} + \frac{\varepsilon_i^2}{2}\right) + \frac{1}{2}\varepsilon_1^2 d^2 \\ & + \frac{1}{r}\tilde{\theta}\left(-\sum_{i=2}^{4}\frac{rK_{z_i}^2 S_i^T S_i}{2l_i^2} + \dot{\hat{\theta}}\right).\end{aligned} \tag{24}$$

Based on (24), the corresponding adaptive law can be chosen as below

$$\dot{\hat{\theta}} = \sum_{i=2}^{4}\frac{rK_{z_i}^2 S_i^T S_i}{2l_i^2} - m\hat{\theta} \tag{25}$$

where r, m, l_2, l_3, and l_4 are positive constants.

Remark 2: Compared with the four adaptive laws (34), (35), (36) and (37) for the adaptive backstepping control in [36] which list in Appendix, it can be seen that the proposed approach of this paper only needs one adaptive law and less design parameters, which will make it more suitable for practical applications.

Theorem 1: Suppose system (1) meet Assumption 1 and consider the reference signals x_d. Then, under the virtual controllers α_1, α_2 and the adaptive neural controllers u_q, u_d, all closed-loop variables are bounded, and the full state variables don't exceed their constraint spaces.

IV. STABILITY ANALYSIS

In order to prove that all the signals are bounded in the system, using (25), (24) becomes

$$\dot{V} \leq -\sum_{i=1}^{4} k_i K_{z_i} z_i + \sum_{i=2}^{4}\left(\frac{l_i^2}{2} + \frac{\varepsilon_i^2}{2}\right) + \frac{1}{2}\varepsilon_1^2 d^2 - \frac{m\tilde{\theta}\hat{\theta}}{r}. \tag{26}$$

In [22], it has been proved that $\log k_{b_i}^2/(k_{b_i}^2 - z_i^2) < z_i^2/(k_{b_i}^2 - z_i^2)$ in the set $|z_i| < k_{b_i}$. Based on the research and utilizing $-\tilde{\theta}\hat{\theta} \leq -\frac{\tilde{\theta}^2}{2} + \frac{\theta^2}{2}$, we have

$$\begin{aligned}\dot{V} \leq & -\sum_{i=1}^{4} k_i \log\left(\frac{k_{b_i}^2}{k_{b_i}^2 - z_i^2}\right) + \sum_{i=2}^{4}\left(\frac{l_i^2}{2} + \frac{\varepsilon_i^2}{2}\right) \\ & - \frac{m\tilde{\theta}^2}{2r} + \frac{m\theta^2}{2r} + \frac{1}{2}\varepsilon_1^2 d^2 \\ \leq & -aV + b\end{aligned} \tag{27}$$

where $a = \min\left\{2k_1, \frac{2k_2}{J}, 2k_3, 2k_4, m\right\}$, $b = \sum_{i=2}^{4}\left(\frac{l_i^2}{2} + \frac{\varepsilon_i^2}{2}\right) + \frac{1}{2}\varepsilon_1^2 d^2 + \frac{m\theta^2}{2r}$. According to (27), it can be concluded that $\log k_{b_i}^2/(k_{b_i}^2 - z_i^2)$ and $\tilde{\theta}$ are in constrain intervals.

Multiplying both sides by e^{at}, (27) is rewritten as $d(V(t)e^{at})/dt \leq be^{at}$ and integrating it over $[0, t]$, (27) becomes

$$V(t) \leq \left(V(0) - \frac{b}{a}\right)e^{-at} + \frac{b}{a} \leq V(0) + \frac{b}{a}. \tag{28}$$

By $\tilde{\theta} = \hat{\theta} - \theta$, we know that $\hat{\theta}$ is bounded. Since $z_1 = x_1 - x_d$ and $x_d \leq Y_0$, $|x_1| < k_{b_1} + Y_0 \leq k_{c_1}$. Because z_1, $\dot{x}_d$ are bounded, α_1 is bounded with $|\alpha_1| \leq \bar{\alpha}_1$. Then, according to $z_2 = x_2 - \alpha_1$, it follows that $|x_2| < \bar{\alpha}_1 + k_{b_2} < k_{c_2}$. Then we can get $|x_3| < k_{c_3}$ and $|x_4| < k_{c_4}$. It can be known from the definitions of u_q, u_d in (16) and (21) that u_q is a function of z_3 and $\hat{\theta}$, u_d is a function of z_4 and $\hat{\theta}$. Then u_q, u_d are bounded. Therefore, all the signals of the closed-loop system u_q, u_d, x_i and $\hat{\theta}$ are bounded and constraint conditions of the states are satisfied.

Owing to (28), it can be obtained

$$\log k_{b_1}^2/(k_{b_1}^2 - z_1^2) \leq 2\left(V(0) - \frac{b}{a}\right)e^{-at} + 2b/a. \tag{29}$$

By taking exponentials on both sides of above inequality, we have $k_{b_1}^2/(k_{b_1}^2 - z_1^2) \leq e^{2\left(V(0)-\frac{b}{a}\right)e^{-at}+2b/a}$. Then, it can be obtained $|z_1| \leq \sqrt{1 - e^{-2\left(V(0)-\frac{b}{a}\right)e^{-at}+2b/a}}$. If $V(0) = b/a$, then it holds $|z_1| \leq \sqrt{1 - e^{-2b/a}}$. If $V(0) \neq b/a$, it can be concluded that given any $\sqrt{1 - e^{-2\left(V(0)-\frac{b}{a}\right)e^{-at}+2b/a}} > \sqrt{1 - e^{-2b/a}}$, there exists T such that for any $t > T$, it has $|z_1| \leq \sqrt{1 - e^{-2\left(V(0)-\frac{b}{a}\right)e^{-at}+2b/a}}$. As $t \to \infty$, $|z_1| \leq \sqrt{1 - e^{-2b/a}}$. The z_1 can be made arbitrarily small by selecting the design parameters appropriately.

V. SIMULATION RESULTS

In order to prove the effectiveness of the control method proposed in this paper, a simulation of adaptive NNs control is provided and the parameters of PMSM [36] are chosen as:

$$\begin{aligned}& J = 0.003798\text{Kg}\cdot\text{m}^2, \quad B = 0.001158\text{N}\cdot\ \text{m/(rad/s)}, \\ & \Phi = 0.1245\text{Wb}, \quad L_d = 0.00285\text{H}, \ L_q = 0.00315\text{H}, \\ & n_p = 3, \quad R_s = 0.68\Omega.\end{aligned}$$

Take the T_L as:

$$T_L = \begin{cases} 1, 0 \leq t < 2.5, \\ 1.5, t \geq 2.5 \end{cases}$$

and $x_1(0) = 0.2$, $x_2(0) = x_3(0) = x_4(0) = 0$ are defined as the initial condition for the PMSM in the simulation. The reference signal is selected as $x_d = \sin(5t)$.

(a). Simulation for the adaptive NNs controllers with full-state constraints. Considering the system efficiency and control performance, we select the the design parameters as $k_1 = 20$, $k_2 = 30$, $k_3 = 200$, $k_4 = 40$, $r = 0.01$, $m = 0.2$, $l_2 = l_3 = l_4 = 0.5$. Besides, the NNs $W_2^T S_2(Z_2)$, $W_3^T S_3(Z_3)$ and $W_4^T S_4(Z_4)$ contain nine nodes with centers spaced in the interval $[-8, 8]$ and widths being equal to 2.

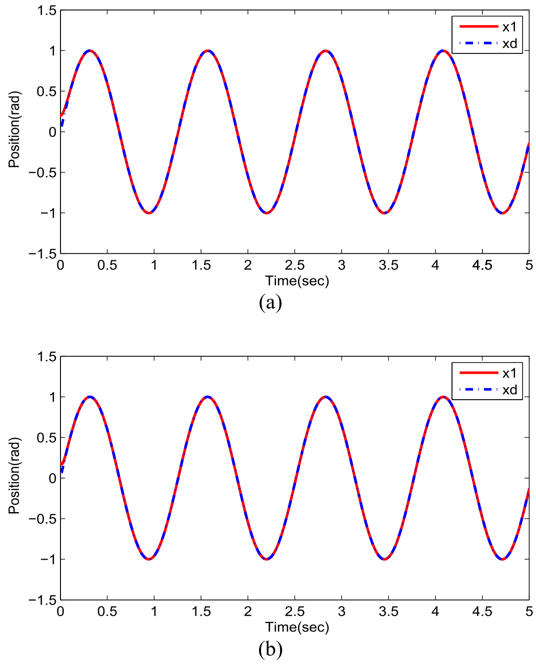

FIGURE 2. (a) x_1 and x_d with full-state constraints. (b) x_1 and x_d without full-state constraints.

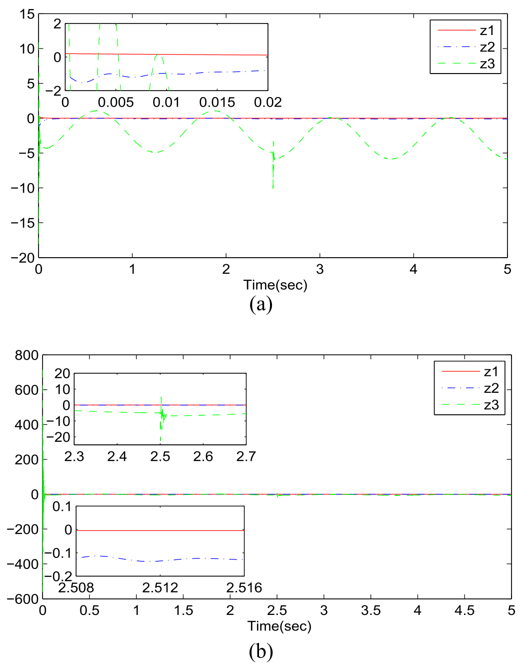

FIGURE 3. (a) The errors with full-state constraints. (b) The errors without full-state constraints.

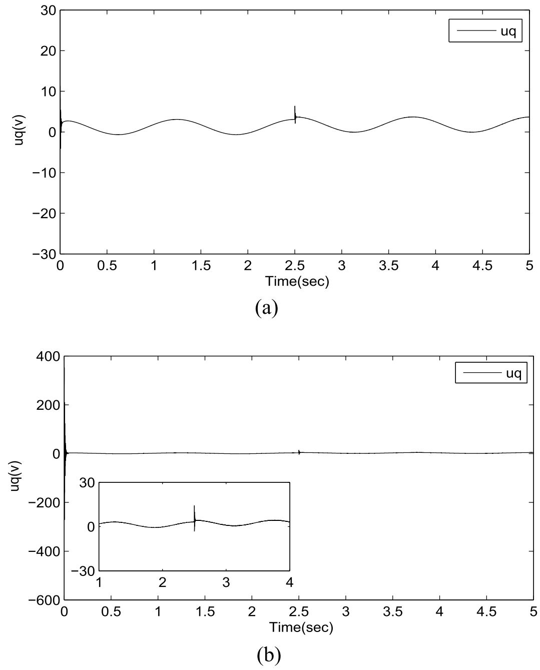

FIGURE 4. (a) u_q with full-state constraints. (b) u_q without full-state constraints.

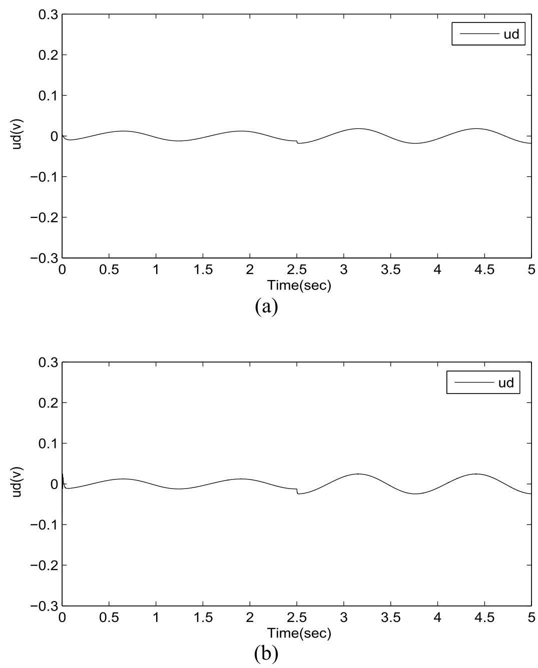

FIGURE 5. (a) u_d with full-state constraints. (b) u_d without full-state constraints.

All the states are restricted in $|x_1| < 2.5$, $|x_2| < 50$, $|x_3| < 25$, $|x_4| < 25$. Given the state constraints and initial states and using the MATLAB to perform the feasibility check, we obtain the optimal design parameters $k_{b_1} = k_{c_1} - A_0 = 1.5$. $k_{b_2} = 20$, $k_{b_3} = 20$, $k_{b_4} = 25$.

(b). Simulation for the backstepping control method without full-state constraints. The design parameters are selected as $k_1 = 20$, $k_2 = 30$, $k_3 = 200$, $k_4 = 40$, $r_1 = r_2 = r_3 = 0.01$, $m_1 = m_2 = m_3 = 0.2$, $l_3 = l_4 = 0.5$.

By using the presented control approach, it can be seen that the results of simulations are given Figs.2-6, where Fig.2(a)-Fig.6(a) reveal the control method proposed in this paper and Fig.2(b)-Fig.6(b) display the backstepping control method without full-state constraints. Fig.2 shows the

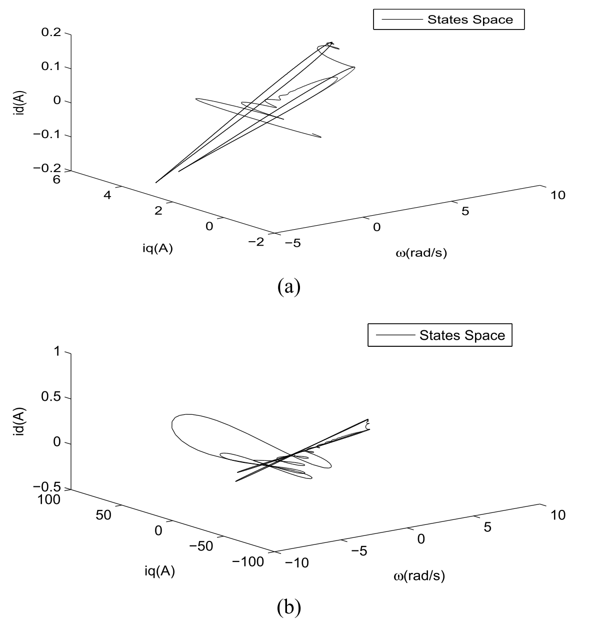

FIGURE 6. (a) The space of i_d, i_q and ω with full-state constraints. (b) The space of i_d, i_q and ω without full-state constraints.

trajectories of x_1, x_d, and these Figs show that the desired reference signals can be tracked well by the system output. Fig.3 is the errors of z_1, z_2, z_3, and it can be observed that Fig.2(a) can make the errors in a smaller range. Fig.4-Fig.5 represent the simulation results of u_q and u_d, where the control voltage of Fig.4(b) is larger than normal value in tracking process. Fig.6 reflects the state parameters of x_2, x_3, x_4. From the simulation, we know that the controllers have better robustness to resistance load disturbances and parameter changes.

Remark 3: From the simulations, it can be clearly seen that both two kinds of methods can gain good control effects. Compared the above two sets of simulation results, it is easily observed that i_q of Fig.6(b) is changing in the range of -100 to 100, exceeding the reasonable range of the current. In contrast, i_q of Fig.6(a) is varying in the range of -2 to 6, which mean that the proposed method in this paper is more suitable for practical engineering.

VI. CONCLUSION

An adaptive neural control approach based on the BLFs has been addressed to improve the property for PMSMs. The NNs are exploited to approximate the unknown nonlinear functions. In addition, the state variables are restrained in a bounded compact set. The raised adaptive neural control method has resolved the problem of the constrained state variables, meanwhile, the desired reference signal can be tracked well by the system output even with the existence of the parameter uncertainties and load torque disturbance. Besides, the online computation burden is reduced. The effectiveness and robustness are proved by the simulation results of the proposed control approach. The proposed scheme can be applied not only in PMSMs but also for a class of nonlinear systems. The future research will combine this method with command filtering and consider the problem of PMSMs with iron loss.

APPENDIX

The adaptive fuzzy control laws and adaptive laws in [36] are listed as:

$$a_1 = -k_1 z_1 + \dot{x}_d, \tag{30}$$

$$\alpha_2 = \frac{1}{a_1}(-k_2 z_2 - z_1 + \hat{B} x_2 + \hat{T}_L + \hat{J}\dot{a}_1), \tag{31}$$

$$u_q = \frac{1}{b_4}(-k_3 z_3 - \frac{1}{2} z_3 - \frac{z_3 \hat{\theta} S_3^T S_3}{2 l_3^2}), \tag{32}$$

$$u_d = \frac{1}{c_3}(-k_4 z_4 - \frac{1}{2} z_4 - \frac{z_4 \hat{\theta} S_4^T S_4}{2 l_4^2}), \tag{33}$$

$$\dot{\hat{T}}_L = -r_1 z_2 - m_1 \hat{T}_L, \tag{34}$$

$$\dot{\hat{B}} = -r_2 z_2 x_2 - m_2 \hat{B}, \tag{35}$$

$$\dot{\hat{J}} = -r_3 z_2 \dot{a}_1 - m_3 \hat{J}, \tag{36}$$

$$\dot{\hat{\theta}} = \sum_{i=2}^{4} \frac{r_4}{2 l_i^2} z_i^2 S_i^T S_i - m_4 \hat{\theta}. \tag{37}$$

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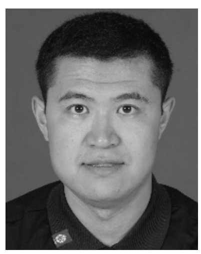

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