Backstepping Control of Permanent Magnet Synchronous Motor: A Parallel Control Approach

Jingwei Lu, Qinglai Wei, and Xiang Cheng

***Abstract*—This paper uses parallel control to investigate the problem of tracking control of permanent magnet synchronous motors (PMSMs). First, an augmented PMSM system is designed to introduce the control input into the feedback system, and then achieve parallel control. Second, based on the backstepping control technique, the detailed steps of the derivation of the parallel controller are provided. The stability analysis shows that the tracking error of the PMSM system asymptotically converges to zero. Finally, the proposed parallel controller is validated in simulations, where the time-invariant reference signal and time-varying reference signal are considered, showing that the proposed parallel controller effectively enables the PMSM to track different reference signals.**

***Index Terms*—Backstepping control, parallel controller, permanent magnet synchronous motors, tracking control**

I. Introduction

Parallel control is a powerful control approach [1], which has obtained considerable fruits in many fields, including classical control [2, 3], intelligent control [4], and practical applications [5–7]. Parallel control is established on the ACP methodology, i.e., artificial systems, computational experiments, and parallel execution [1, 8]. In parallel control, artificial systems are constructed in accordance with original systems to form parallel systems, which induces massive artificial data from small real-world data, thus providing more useful samples for training with low cost. Recently, Wang et al. further proposed a new type of dynamic parallel controller that incorporates the control input into the feedback system [9], formulating a dynamic control law. Nowadays, this new parallel control method has shown the potential to improve control performance for dealing with complex systems [10, 11]. Parallel control constructs dynamic parallel controller by incorporating the control input into the feedback system, which makes it in line with dynamic feedback control [12]. Besides parallel control, backstepping control is effective in controlling cascaded systems, and related research has attracted much attention from scholars [13, 14].

Permanent magnet synchronous motor (PMSM) is a kind of brush-less motor which utilizes permanent magnets to provide excitation instead of field coils. This simplified structure brings smaller volume, lower noise, larger torque-current ratio, and convenient manufacturing, therefore it has attracted special attention. In recent years, PMSMs have been widely used in industrial servo, electric vehicles, new energy power generation, and robotic fields. Despite these advantages, the derivation of high-performance controllers for PMSMs is a challenging issue. The mathematical model of PMSMs has the characteristics of multi-variable, nonlinear, and strong coupling. Although proportional-integral (PI) control is still the mainstream method of motor control in industrial servo, it has limitations in practical application scenarios with parameter perturbation, model uncertainty, and disturbances. To achieve high-performance control of PMSMs, sliding mode control [15], adaptive fuzzy control [16], active disturbance rejection control [17], and model predictive control [18] have been adopted.

As mentioned earlier, the tracking control performance is one of the key factors in applying PMSMs. To further improve the tracking control performance of PMSMs, we introduce a parallel controller for tracking control of PMSM based on the backstepping control technique. The main contributions are as follows:

(1) Different from the existing static state feedback controllers for PMSMs [15–18], a new dynamic tracking controller is developed for PMSMs by introducing the control input into the feedback system.

(2) In the derivation of the parallel controller, an augmented PMSM system is formulated according to the original PMSM system. Then, we can construct the parallel controller using the backstepping control technique.

(3) The simulation study, including tracking control of the time-invariant reference signal and time-varying reference signal, demonstrates the effectiveness of the proposed parallel controller in multiple tracking control scenarios.

This paper is arranged as follows. Section II presents a brief description of PMSM and formulates the tracking control target for PMSMs. Section III introduces a parallel controller for PMSMs based on the backstepping control technique with theoretical analysis. Section IV conducts a numerical study for tracking control of PMSM, including tracking time-invariant reference speed signal and time-varying reference speed signal. Section V gives the conclusion of this paper.

Manuscript received: 22 May 2024; revised: 22 July 2024; accepted: 25 August 2024. *(Corresponding author: Jingwei Lu.)*

Citation: J. Lu, Q. Wei, and X. Cheng, Backstepping control of permanent magnet synchronous motor: A parallel control approach, *IJICS*, 2024, 29(3), 141–146.

Jingwei Lu is with Department of Industrial Engineering, Tsinghua University, Beijing 100084, China (e-mail: lujingweihh@gmail.com).

Qinglai Wei and Xiang Cheng are with State Key Laboratory of Multimodal Artificial Intelligence Systems, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China (e-mail: qinglai.wei@ia.ac.cn; xiang.cheng@ia.ac.cn).

Qinglai Wei is also with Institute of Systems Engineering, Macau University of Science and Technology, Macao 999078, China.

Digital Object Identifier 10.62678/IJICS202409.10138

II. Problem Statement

In this section, the PMSM system and the parallel control based tracking target are introduced briefly.

A. Permanent Magnet Synchronous Motor

PMSMs are widely deployed in driving devices in order to achieve higher operating efficiency and better speed regulation performance. In terms of the control of PMSMs, field-oriented control (FOC), proposed in 1972 [19], is a widely used vector control strategy. In FOC, the rotor phase is transferred to a two-phase α-β system by Clark transform, and then rotated to d-q coordinate system by Park transform. Assuming that the PMSM is with smooth air gap (the stator self-inductance values in quadrature axis and direct axis are equal), the system dynamics of the PMSM can be described by

$$\begin{cases} \dfrac{\mathrm{d}\omega_{\mathrm{m}}}{\mathrm{d}t} = -\dfrac{B}{J}\omega_{\mathrm{m}} + \dfrac{3p\psi_{\mathrm{f}}}{2J}i_q - \dfrac{T_{\mathrm{L}}}{J}, \\ \dfrac{\mathrm{d}i_d}{\mathrm{d}t} = -\dfrac{R}{L}i_d + p\omega_{\mathrm{m}}i_q + \dfrac{1}{L}u_d, \\ \dfrac{\mathrm{d}i_q}{\mathrm{d}t} = -\dfrac{p\psi_{\mathrm{f}}}{L}\omega_{\mathrm{m}} - p\omega_{\mathrm{m}}i_d - \dfrac{R}{L}i_q + \dfrac{1}{L}u_q \end{cases} \tag{1}$$

where state ω_{m} is mechanical rotor speed, B is the viscous friction coefficient, p is the number of pole pairs, R is the stator resistance, states i_d and i_q are the d-axis and q-axis currents, control inputs u_d and u_q are the d-axis and q-axis voltages, L is the inductance, ψ_{f} is armature flux linkage due to rotor magnets, J is the moment of inertia, and T_{L} is the load torque, respectively.

In classical FOC problems, to maintain the maximum torque with a given stator current, it is common to set the ideal current i_d value to $i_d^* = 0$, that is, the problem of $i_d = 0$. This makes the flux constant help to decouple and simplify the PMSM dynamics, which is also employed in this paper.

B. Parallel Control Based Tracking Control Target for PMSM

Based on the PMSM system in Eq. (1), this section presents the tracking control target of PMSM using parallel control.

In the beginning, we give a brief introduction to parallel control. Consider a dynamical system

$$\dot{x} = \frac{\mathrm{d}x}{\mathrm{d}t} = f(x,u) \tag{2}$$

where $x \in \mathbb{R}^n$ is the state, $u \in \mathbb{R}^m$ is the control, and $f(x,u)$ is the system dynamics, respectively. Clearly, the PMSM system in Eq. (1) is an instance of the dynamical system in Eq. (2) by letting $x = [\omega_{\mathrm{m}}, i_d, i_q]^{\mathrm{T}} \in \mathbb{R}^3$ and $u = [u_d, u_q]^{\mathrm{T}} \in \mathbb{R}^2$. In general, a commonly used state feedback controller can be formulated as follows

$$u = k(x) \tag{3}$$

where $k(x)$ is a control law to be designed.

Parallel control is different from the control law in Eq. (3), and it seeks to obtain a dynamic parallel controller

$$\dot{u} = \mathcal{K}(x,u) \tag{4}$$

with $\mathcal{K}(x,u)$ being dynamic control law by introducing the control input into the feedback system. Therefore, the basic framework of parallel control is shown in Fig. 1.

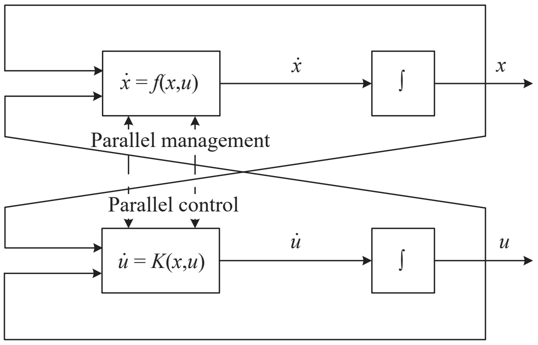

Figure 1 Framework of parallel control.

In the tracking control problem of PMSMs, the reference signal is necessary

$$\dot{r} = f(r, u_r) \tag{5}$$

where r is the desired signal of the states, and u_r is the desired signal of the control inputs. Sometimes, tracking signals can be further simplified, that is, simply give a desired signal of mechanical rotor speed ω_r.

Therefore, the tracking control target of PMSM using parallel control is to derive the dynamical parallel controller in Eq. (4), allowing the PMSM system in Eq. (1) to track the reference signal $\dot{r} = f(r, u_r)$ or ω_r.

III. Backstepping Control of Pmsm Using Parallel Control

This section introduces parallel control based backstepping control of PMSM in detail, including an augmented PMSM system and the detailed steps of the derivation of our parallel controller.

A. Augmented PMSM System

To derive the dynamical parallel controller in Eq. (4), this section presents the formulation of the augmented PMSM system. Inspired by our pevious work [2], we define the following virtual control inputs

$$\begin{cases} v_d = \dfrac{\mathrm{d}u_d}{\mathrm{d}t}, \\ v_q = \dfrac{\mathrm{d}u_q}{\mathrm{d}t} \end{cases} \tag{6}$$

Subsequently, the following augmented PMSM system can be obtained

$$\begin{cases} \dfrac{\mathrm{d}\omega_{\mathrm{m}}}{\mathrm{d}t} = -\dfrac{B}{J}\omega_{\mathrm{m}} + \dfrac{3p\psi_{\mathrm{f}}}{2J}i_q - \dfrac{T_{\mathrm{L}}}{J}, \\ \dfrac{\mathrm{d}i_d}{\mathrm{d}t} = -\dfrac{R}{L}i_d + p\omega_{\mathrm{m}}i_q + \dfrac{1}{L}u_d, \\ \dfrac{\mathrm{d}i_q}{\mathrm{d}t} = -\dfrac{p\psi_{\mathrm{f}}}{L}\omega_{\mathrm{m}} - p\omega_{\mathrm{m}}i_d - \dfrac{R}{L}i_q + \dfrac{1}{L}u_q, \\ \dfrac{\mathrm{d}u_d}{\mathrm{d}t} = v_d, \\ \dfrac{\mathrm{d}u_q}{\mathrm{d}t} = v_q \end{cases} \tag{7}$$

This concludes the formulation of the augmented PMSM system. Now, we seek to obtain the following controller

$$\begin{cases} v_d = \pi_d(\omega_\mathrm{m}, i_d, i_q, u_d, u_q), \\ v_q = \pi_q(\omega_\mathrm{m}, i_d, i_q, u_d, u_q) \end{cases} \tag{8}$$

with $\pi_d(\cdot)$ and $\pi_q(\cdot)$ being dynamic control laws to achieve the tracking control of the PMSM system in Eq. (1).

Remark 1 Based on the augmented PMSM system in Eq. (7), we transform the control inputs u_d and u_q of the original PMSM system in Eq. (1) into states of the augmented PMSM system. At the same time, the new control inputs of the augmented PMSM system are v_d and v_q. At this point, it is possible to design a parallel controller for the original PMSM system based on the existing state feedback approaches.

Remark 2 From the state feedback control perspective, in the parallel controller in Eq. (4), the control input u is considered as the state, which is different from the pure state feedback controller in Eq. (3). As a consequence, the control function $\mathcal{K}(\cdot)$ is the memory function of x, which is in accordance with dynamic feedback control. Besides, to achieve the parallel controller, the augmented PMSM system introduces virtual control inputs v_d and v_q (derivatives of real control inputs u_d and u_q), which is the major difference between the original PMSM system and the augmented PMSM system. Since the control inputs are introduced into the state, the initial control inputs under the parallel controller can be set arbitrarily, which is impossible with pure state feedback control. This feature is important for systems where the control inputs cannot be changed quickly (e.g., mechanical systems with large inertia).

B. Design and Analysis for Parallel Controller

Noting that the reference signal in Eq. (4) is commonly used in optimal control to formulate the performance index, we adopt ω_r as the reference signal in this paper. Based on the augmented PMSM system, we develop a parallel controller using the backstepping technique in this section. First, the following tracking error is defined

$$e_\omega = \omega_\mathrm{m} - \omega_r \tag{9}$$

Choose the following Lyapunov function

$$V_\omega = \frac{1}{2}e_\omega^2 \tag{10}$$

Taking derivative along time yields

$$\begin{aligned} \dot{V}_\omega &= e_\omega \dot{e}_\omega = \\ & e_\omega(\dot{\omega}_\mathrm{m} - \dot{\omega}_r) = \\ & e_\omega\left(-\frac{B}{J}\omega_\mathrm{m} + \frac{3p\psi_\mathrm{f}}{2J}i_q - \frac{T_\mathrm{L}}{J} - \dot{\omega}_r\right) \end{aligned} \tag{11}$$

By choosing

$$i_q = i_q^* = \frac{2J}{3p\psi_\mathrm{f}}\left(\frac{B}{J}\omega_\mathrm{m} + \frac{T_\mathrm{L}}{J} + \dot{\omega}_r - k_\omega e_\omega\right) \tag{12}$$

with $k_\omega > 0$, we can obtain $\dot{V}_\omega < 0$. The desired current in d-axis is chosen as $i_d = i_d^* = 0$.

Then, consider the current tracking errors of d-q system and take the following Lyapunov function into consideration

$$V_\mathrm{c} = \frac{1}{2}e_\omega^2 + \frac{1}{2}e_{i,d}^2 + \frac{1}{2}e_{i,q}^2 \tag{13}$$

where $e_{i,d} = i_d - i_d^*$ and $e_{i,q} = i_q - i_q^*$. Taking derivative along time yields

$$\begin{aligned} \dot{V}_\mathrm{c} &= e_\omega\dot{e}_\omega + e_{i,d}\dot{e}_{i,d} + e_{i,q}\dot{e}_{i,q} = \\ & e_\omega\left(-\frac{B}{J}\omega_\mathrm{m} + \frac{3p\psi_\mathrm{f}}{2J}\left(e_{i,q} + i_q^*\right) - \frac{T_\mathrm{L}}{J} - \dot{\omega}_r\right) + \\ & e_{i,d}\left(-\frac{R}{L}i_d + p\omega_\mathrm{m}i_q + \frac{1}{L}u_d\right) + \\ & e_{i,q}\left(-\frac{p\psi_\mathrm{f}}{L}\omega_\mathrm{m} - p\omega_\mathrm{m}i_d - \frac{R}{L}i_q + \frac{1}{L}u_q - \dot{i}_q^*\right) = \\ & -k_\omega e_\omega^2 + \frac{3p\psi_\mathrm{f}}{2J}e_\omega e_{i,q} + \\ & e_{i,d}\left(-\frac{R}{L}i_d + p\omega_\mathrm{m}i_q + \frac{1}{L}u_d\right) + \\ & e_{i,q}\left(-\frac{p\psi_\mathrm{f}}{L}\omega_\mathrm{m} - p\omega_\mathrm{m}i_d - \frac{R}{L}i_q + \frac{1}{L}u_q - \dot{i}_q^*\right) \end{aligned} \tag{14}$$

We choose

$$u_d = u_d^* = L\left(\frac{R}{L}i_d - p\omega_\mathrm{m}i_q - k_{i,d}e_{i,d}\right) \tag{15}$$

and

$$\begin{aligned} u_q &= u_q^* = \\ & L\left(\frac{p\psi_\mathrm{f}}{L}\omega_\mathrm{m} + p\omega_\mathrm{m}i_d + \frac{R}{L}i_q + \dot{i}_q^* - k_{i,q}e_{i,q} - \frac{3p\psi_\mathrm{f}}{2J}e_\omega\right) \end{aligned} \tag{16}$$

with $k_{i,d} > 0$ and $k_{i,q} > 0$, and then we can obtain $\dot{V}_\mathrm{c} < 0$.

Similar to Eq. (13), consider the following Lyapunov function

$$V_\mathrm{p} = \frac{1}{2}e_\omega^2 + \frac{1}{2}e_{i,d}^2 + \frac{1}{2}e_{i,q}^2 + \frac{1}{2}e_{u,d}^2 + \frac{1}{2}e_{u,q}^2 \tag{17}$$

where $e_{u,d} = u_d - u_d^*$ and $e_{u,q} = u_q - u_q^*$.

Taking derivative along time, we have

$$\begin{aligned} \dot{V}_\mathrm{p} &= e_\omega\dot{e}_\omega + e_{i,d}\dot{e}_{i,d} + e_{i,q}\dot{e}_{i,q} + e_{u,d}\dot{e}_{u,d} + e_{u,q}\dot{e}_{u,q} = \\ & -k_\omega e_\omega^2 - k_{i,d}e_{i,d}^2 - k_{i,q}e_{i,q}^2 + \frac{1}{L}e_{i,d}e_{u,d} + \frac{1}{L}e_{i,q}e_{u,q} + \\ & e_{u,d}\left(v_d - \dot{u}_d^*\right) + e_{u,q}\left(v_q - \dot{u}_q^*\right) \end{aligned} \tag{18}$$

Similarly, by taking

$$v_d = -\frac{1}{L}e_{i,d} - k_{u,d}e_{u,d} + \dot{u}_d^* \tag{19}$$

and

$$v_q = -\frac{1}{L}e_{i,q} - k_{u,q}e_{u,q} + \dot{u}_q^* \tag{20}$$

with $k_{u,d} > 0$ and $k_{u,q} > 0$, we can obtain

$$\dot{V}_\mathrm{p} = -k_\omega e_\omega^2 - k_{i,d}e_{i,d}^2 - k_{i,q}e_{i,q}^2 - k_{u,d}e_{u,d}^2 - k_{u,q}e_{u,q}^2 < 0 \tag{21}$$

Therefore, we can obtain that the augmented PMSM system in Eq. (7) is asymptotically stable. Consequently, according to Lemma 1 in Ref. [2], the closed-loop form of the PMSM system in Eq. (1) is asymptotically stable under parallel controllers in Eqs. (19) and (20).

IV. Numerical Study

This section conducts a numerical study for tracking control of the PMSM system in Eq. (1) under our parallel controller to demonstrate the effectiveness of the parallel controller, including tracking a time-invariant reference speed signal and a time-varying reference speed signal. In the numerical study, the parameters of the PMSM system in Eq. (1) are shown in Table 1.

Table 1 PMSM parameter.

Parameter	Value
R	2.46 Ω
L	6.35×10^{-3} H
ψ_f	0.175 V·s
p	4
J	1.02×10^{-3} kg·m^2
B	1×10^{-4}
T_L	0 N·m

Case I: Time-invariant reference speed signal. In this case, the reference speed signal is chosen as ω_r = 1000 r/min. The control parameters are $k_\omega = 500$, $k_{i,d} = 1000$, $k_{i,q} = 10$, $k_{u,d} = 1\times10^6$, and $k_{u,q} = 1\times10^6$. The control constraints are $|u_d| \leqslant u_{\max}$ and $|u_q| \leqslant u_{\max}$, where $u_{\max} = 100$. Then, by implementing the proposed parallel controller, the results under the proposed parallel controller are shown in Figs. 2–6, where Figs. 2–4 display the trajectories of the states of PMSM, i.e., ω_m, i_d, and i_q, and Figs. 5 and 6 present the trajectories of the control inputs u_d and u_q. It can be seen from Figs. 2–6 that our parallel controller effectively enables the PMSM in Eq. (1) to track the reference signal ω_r = 1000 r/min.

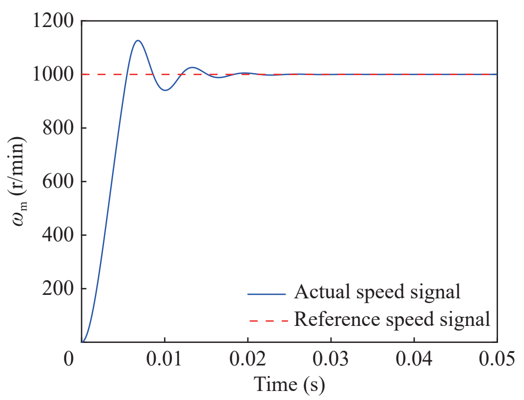

Figure 2 Mechanical rotor speed ω_m of case I.

Case II: Time-varying reference speed signal. In this case, a time-varying reference signal is adopted to test the proposed parallel controller. The reference speed signal is chosen as follows

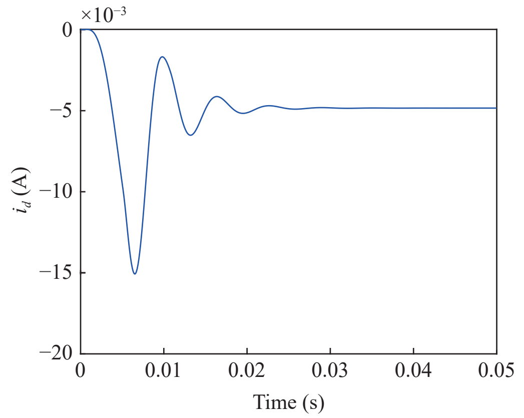

Figure 3 i_d of case I.

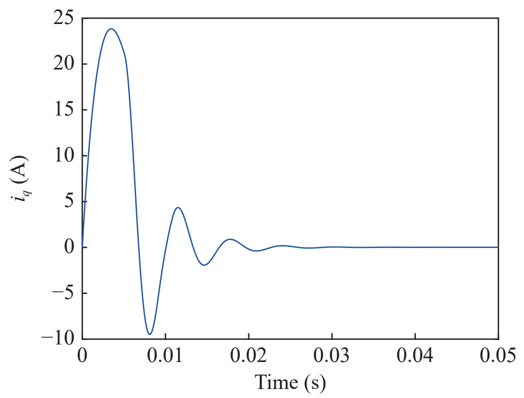

Figure 4 i_q of case I.

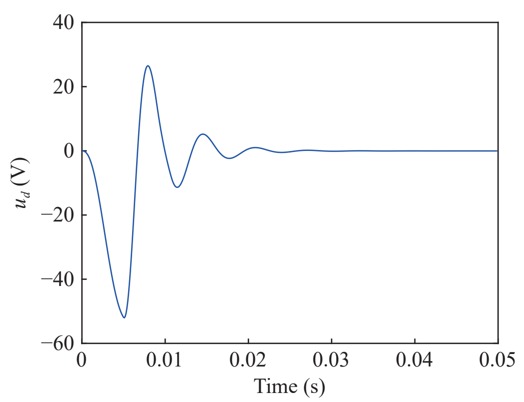

Figure 5 u_d of case I.

$$\omega_r = \begin{cases} 20{,}000t \text{ r/min}, & t \in [0.00, 0.05); \\ 1000 \quad \text{r/min}, & t \in [0.05, 1.00] \end{cases} \tag{22}$$

The selection of control parameters is the same as in case I. Similar to case I, after implementing the proposed parallel controller, the results under the proposed parallel controller are shown in Figs. 7–11, where Figs. 7–9 present the trajectories of the states of PMSM, namely, ω_m, i_d, and i_q, and Figs. 10 and 11 give the trajectories of the control inputs u_d and u_q. Based on the control results, we can obtain that the proposed parallel controller is effective in a more complex tracking and control task, that is, tracking control of the time-varying reference signal in Eq. (22).

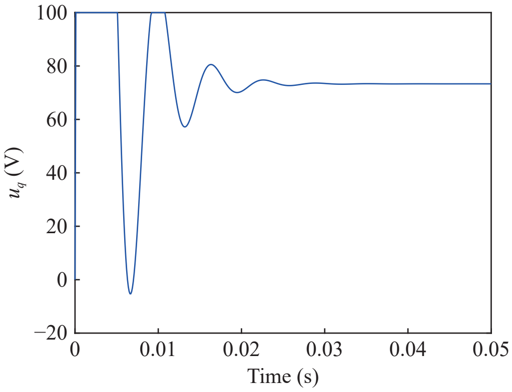

Figure 6 u_q of case I.

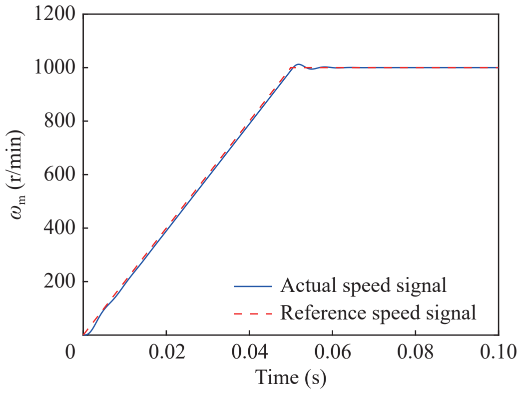

Figure 7 Mechanical rotor speed ω_{m} of case II.

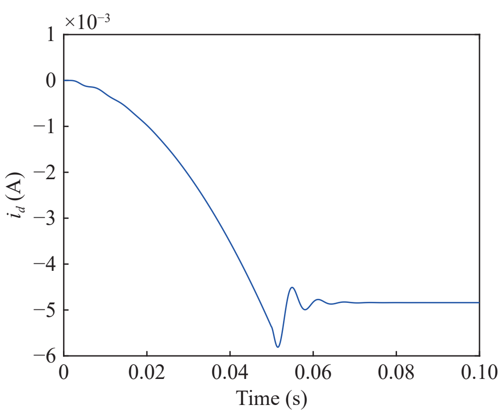

Figure 8 i_d of case II.

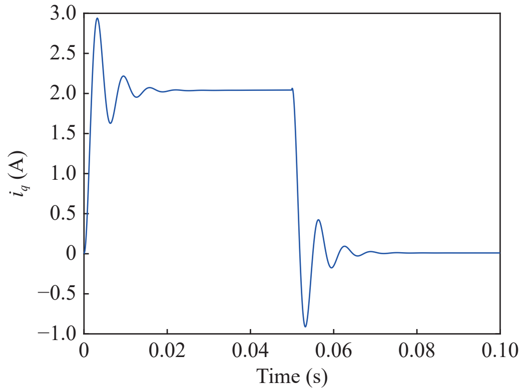

Figure 9 i_q of case II.

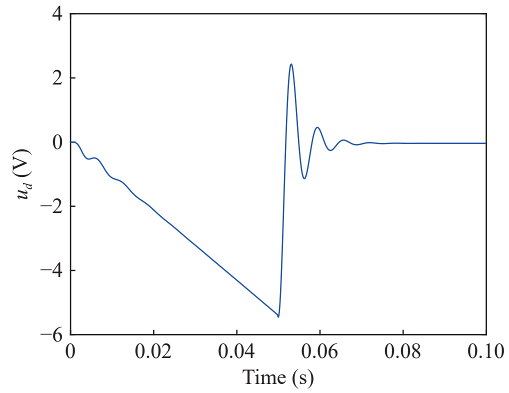

Figure 10 u_d of case II.

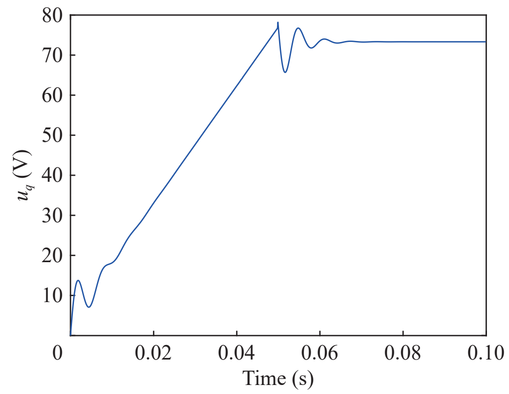

Figure 11 u_q of case II.

V. Conclusion

In this paper, a novel parallel controller was designed for PMSMs via the backstepping control technique. First, an augmented PMSM system was introduced. Second, the detailed steps of obtaining the parallel controller were given via the backstepping control technique, and the stability analysis was provided. It was shown that the closed-loop PMSM system is asymptotically stable under the tracking control scenarios. Finally, we verified the proposed parallel controller under both time-invariant reference signals and time-varying reference signals. The simulation results demonstrated that the proposed parallel controller effectively enables PMSM to track the given reference signals. Based on the framework of parallel control, the following topics will be studied in the future. First, study parallel controllers for cases with the time-varying load torque T_{L}. Second, investigate parallel controllers in the case of the unknown PMSM model. Third, conduct the experimental verification for the parallel controller and provide a comparative study of parallel and non-parallel controllers.

ACKNOWLEDGMENT

This work was supported by the Postdoctoral Fellowship Program of CPSF (No. GZC20240839).

REFERENCES

[1] F.-Y. Wang, Parallel system methods for management and control of complex systems, *Control Decis*., 2004, 19(5), 485–489, (in Chinese).

[2] J. Lu, Q. Wei, and F.-Y. Wang, Parallel control for optimal tracking via adaptive dynamic programming, *IEEE/CAA J. Autom. Sin*., 2020, 7(6), 1662–1674.

[3] Q. Wei, H. Li, and F.-Y. Wang, Parallel control for continuous-time linear systems: A case study, *IEEE/CAA J. Autom. Sin*., 2020, 7(4), 919–928.

[4] J. Lu, L. Han, Q. Wei, X. Wang, X. Dai, and F.-Y. Wang, Event-triggered deep reinforcement learning using parallel control: A case study in autonomous driving, *IEEE Trans. Intell. Veh*., 2023, 8(4), 2821–2831.

[5] J. Lu, L. Li, and F.-Y. Wang, Event-triggered parallel control using deep reinforcement learning with application to comfortable autonomous driving, *IEEE Trans. Intell. Veh*., 2024, 9(3), 4470–4479.

[6] K. Xia, X. Li, K. Li, Y. Zou, and Z. Zuo, Cooperative tracking of quadrotor UAVs using parallel optimal learning control, *IEEE Trans. Autom. Sci. Eng*., to be published.

[7] J. Xu, F. Xia, N. Gu, Y. Li, B. Han, M. Fu, and Z. Peng, Parallel path following of under-actuated cyber-physical autonomous surface vehicles based on meta-learning extended state observer, *IEEE Trans. Veh. Technol*., 2024, 73(11), 16041–16050.

[8] Q. Wei, L. Wang, J. Lu, and F.-Y. Wang, Discrete-time self-learning parallel control, *IEEE Trans. Syst. Man Cybern. Syst*., 2022, 52(1), 192–204.

[9] F.-Y. Wang, J. Zhang, X. Zheng, X. Wang, Y. Yuan, X. Dai, J. Zhang, and L. Yang, Where does AlphaGo go: From church-Turing thesis to AlphaGo thesis and beyond, *IEEE/CAA J. Autom. Sin*., 2016, 3(2), 113–120.

[10] J. Lu, Q. Wei, T. Zhou, Z. Wang, and F.-Y. Wang, Event-triggered near-optimal control for unknown discrete-time nonlinear systems using parallel control, *IEEE Trans. Cybern*., 2023, 53(3), 1890–1904.

[11] S. Jiao, Q. Wei, and F.-Y. Wang, A novel parallel control method for optimal consensus of nonlinear multiagent systems, *IEEE Trans. Cybern*., 2024, 54(10), 5912–5925.

[12] H. K. Khalil, *Nonlinear Systems*, *3rd ed*. Upper Saddle River, NJ, USA: Prentice Hall, 2002.

[13] X. Yu and Y. Lin, Adaptive backstepping quantized control for a class of nonlinear systems, *IEEE Trans. Automat. Control*, 2017, 62(2), 981–985.

[14] J. Deutscher and S. Kerschbaum, Backstepping control of coupled linear parabolic PIDEs with spatially varying coefficients, *IEEE Trans. Automat. Control*, 2018, 63(12), 4218–4233.

[15] X. Zhang, L. Sun, K. Zhao, and L. Sun, Nonlinear speed control for PMSM system using sliding-mode control and disturbance compensation techniques, *IEEE Trans. Power Electron*., 2013, 28(3), 1358–1365.

[16] S. Barkat, A. Tlemçani, and H. Nouri, Noninteracting adaptive control of PMSM using interval type-2 fuzzy logic systems, *IEEE Trans. Fuzzy Syst*., 2011, 19(5), 925–936.

[17] H. Sira-Ramírez, J. Linares-Flores, C. García-Rodríguez, and M. A. Contreras-Ordaz, On the control of the permanent magnet synchronous motor: An active disturbance rejection control approach, *IEEE Trans. Control Syst. Technol*., 2014, 22(5), 2056–2063.

[18] M. Preindl and S. Bolognani, Model predictive direct speed control with finite control set of PMSM drive systems, *IEEE Trans. Power Electron*., 2013, 28(2), 1007–1015.

[19] F. Blaschke, The principle of field orientation as applied to the new TRANSVECTOR closed loop control system for rotating field machines, *Siemens Rev*., 1972, 34(5), 217–220.

Jingwei Lu received the PhD degree in computer application technology from University of Chinese Academy of Sciences, Beijing, China, in 2022. He is currently a postdoctoral research fellow at Department of Industrial Engineering, Tsinghua University, Beijing, China. He has authored or coauthored over 30 journal and conference papers. He was the guest editor of the *IEEE Journal of Radio Frequency Identification* and served as a peer reviewer for the *IEEE Transactions on Cybernetics*, *IEEE Transactions on Industrial Electronics*, *IEEE Transactions on Intelligent Vehicles*, etc. He is also a recipient of the Shuimu Tsinghua Scholar Program. His research interests include optimal control, adaptive dynamic programming, deep reinforcement learning, and autonomous driving.

Qinglai Wei received the BS degree in automation and the PhD degree in control theory and control engineering from Northeastern University, Shenyang, China, in 2002 and 2009, respectively. From 2009 to 2011, he was a postdoctoral fellow at State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing, China. He is currently a professor at Institute of Automation, Chinese Academy of Sciences, China. He has authored 4 books and published over 80 international journal articles. He was a recipient of the IEEE/CAA Journal of Automatica Sinica Best Paper Award, the IEEE System, Man, and Cybernetics Society Andrew P. Sage Best Transactions Paper Award, the IEEE Transactions on Neural Networks and Learning Systems Outstanding Paper Award, the Outstanding Paper Award of Acta Automatica Sinica, and the Zhang Siying Outstanding Paper Award of the Chinese Control and Decision Conference. He was also a recipient of the Shuang-Chuang Talents in Jiangsu Province, China, and the Young Researcher Award of Asia-Pacific Neural Network Society. He has been the vice president of the IEEE Computational Intelligence Society's Beijing Chapter, since 2022. He was the general co-chair of the 2019 Symposium of Parallel Intelligence, the invited session chair of the IEEE 8th Data Driven Control and Learning Systems Conference, the special sessions chair of the 25th International Conference on Neural Information Processing, the program co-chair of the 24th International Conference on Neural Information Processing, and the registration chair of the 12th World Congress on Intelligent Control and Automation and the 2014 IEEE World Congress on Computational Intelligence. He was a guest editor of several international journals. He is the associate editor-in-chief/deputy editor-in-chief of *IEEE/CAA Journal of Automatica Sinica*, *Neurocomputing*, and *Acta Automatica Sinica*. He is also an associate editor of *IEEE Transactions on Neural Networks and Learning Systems*, *IEEE Transactions on Automation Science and Engineering*, *IEEE Transactions on Consumer Electronics*, *IEEE Transactions on Cognitive and Developmental Systems*, and *IEEE Transactions on Systems, Man, and Cybernetics: Systems*. His research interests include adaptive dynamic programming, neural network based control, optimal control, nonlinear systems, and their industrial applications.

Xiang Cheng received the BS degree in electrical engineering and the MS degree in control science and engineering from China University of Mining and Technology, Xuzhou, China, in 2016 and 2019, respectively. He is currently pursuing the PhD degree in pattern recognition and intelligent system at School of Artificial Intelligence, University of Chinese Academy of Sciences, China and State Key Laboratory of Multimodal Artificial Intelligence Systems, Institute of Automation, Chinese Academy of Sciences, China. He is also an engineer at Institute of Automation, Chinese Academy of Sciences, China. His research interests include adaptive dynamic programming, reinforcement learning, and modeling and optimization of complex industrial processes.