Research Article

Adaptive Neural Control and Modeling for Continuous Stirred Tank Reactor with Delays and Full State Constraints

Dongjuan Li,¹ Dongxing Wang,¹ and Ying Gao ²

¹School of Chemical and Environmental Engineering, Liaoning University of Technology, Jinzhou 121001, Liaoning, China

²School of Mathematics and Computational Sciences, Tangshan Normal University, Tangshan 63000, Hebei, China

Correspondence should be addressed to Ying Gao; gaoying956573@163.com

Received 21 March 2021; Revised 18 August 2021; Accepted 13 September 2021; Published 7 October 2021

Academic Editor: Dan Selişteanu

Copyright © 2021 Dongjuan Li et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In this paper, an adaptive neural network control method is described to stabilize a continuous stirred tank reactor (CSTR) subject to unknown time-varying delays and full state constraints. The unknown time delay and state constraints problem of the concentration in the reactor seriously affect the input-output ratio and stability of the entire system. Therefore, the design difficulty of this control scheme is how to debar the effect of time delay in CSTR systems. To deal with time-varying delays, Lyapunov–Krasovskii functionals (LKFs) are utilized in the adaptive controller design. The convergence of the tracking error to a small compact set without violating the constraints can be identified by the time-varying logarithm barrier Lyapunov function (LBLEF). Finally, the simulation results on CSTR are shown to reveal the validity of the developed control strategy.

1. Introduction

To eliminate the effect of nonlinearities and uncertainties appearing in nonlinear systems, the fuzzy logic systems (FLSs) and neural networks (NNs) [1, 2] are useful tools, which avoid the requirement that nonlinearities must be known or can be linearly parameterized. Therefore, adaptive neural or fuzzy control methods are usually applied for the nonlinear single-input-single-output (SISO) systems in [3–8] and multi-input-multi-output (MIMO) systems in [9–12]. In recent years, more and more scholars have paid attention to the practical field. By employing neural networks or fuzzy logic systems, many stable control strategies for CSTR (a common chemical engineering reactor, usually with multiple reactors connected to each other for material conversion) have been caused widespread concern in [13–19] currently. A robust adaptive control method for the nonlinear CSTR system was proposed to ensure that the entire system remains stable in [20]. A novel controller design method was reported in [21] for a CSTR system. In practical CSTR systems, the concentration or temperature must be considered and controlled within certain limits to ensure the stability and safety of the system [22]. Hence, it is

meaningful to consider the constraint problem in CSTRs. It is noteworthy that these above methods neglect the constraint limitations of operating spaces and safety specifications on system states.

Constraints could be seen everywhere in practical systems, for instance, car suspension [23, 24], motor servo systems [25, 26], mobile manipulators [27], and chemical systems [28]; the violation of constraints is a main source of reducing control quality and even causing instability. Logarithm barrier Lyapunov functions were first proposed for constant output constraints in [29] to ensure that system output stays within the prescribed barrier functions. Afterwards, several constraint control methods, such as Logarithm-BLFs, Tangent-BLFs, and Integral-BLFs, were presented for output constraint in [30] and full state constraints in [31–34]. In recent years, novel state-dependent nonlinear-transformation-based state-constrained control schemes have been developed, see, for example, [31, 32]. The new solution that completely removes the feasibility conditions for virtual controllers is first proposed in [31] by constructing a nonlinear state-dependent function. Besides, the authors in [32] propose a unified barrier function upon the constrained states, with which the original constrained

nonlinear system is transformed into an equivalent “non-constrained” system. From a practical point of view, comparing with constant constraint, the time-varying constraint is more general. Hence, based on time-varying BLFs, some novel adaptive constraint controllers were designed, such as nonlinear strict-feedback systems and robotic manipulator with time-varying output constraint in [35, 36] and active suspension systems and nonlinear input saturated systems with time-varying state constraints in [37]. However, a major obstacle was that these control methods were proposed for delay-free systems.

The time-delay control problem always attracts the attention of the researchers. Some relative strategies were developed for the treatment of several categories of nonlinear time delayed systems. Some new impulsive delay control methods were proposed for nonlinear impulsive delay differential systems in [38–40], and in order to achieve the system stability, the change rates of states and impulses were imposed. Employing appropriate LKFs, the robust adaptive backstepping control strategies in [41–43] were reported for nonlinear strict-feedback systems to debar time delays. Afterwards, based on [41–43], some adaptive NN and fuzzy controllers in [44–47] were further constructed to debar the effect of unknown time-varying delays appearing in several classes of nonlinear systems. In practical application, it must take times to transfer materials from one reactor to the next in the CSTR system, which creates time delay. In [48, 49], two adaptive state feedback controllers were designed for the CSTR system with unknown time delays.

According to the above discussion, this study develops an adaptive NN control strategy for CSTRs with both time-varying delays and full time-varying state constraints. As the best of our knowledge, there are only few results solving the

stability problem of such CSTRs in the existing literatures. The primary contributions are as follows:

- (1) Under the adaptive control framework, the problem of time-varying delays and time-varying full state constraints is considered for CSTRs simultaneously, which is more in line with the needs of engineering systems. By using the time-varying barrier Lyapunov functions, all the states never violate the prescribed time-varying ranges.
- (2) It is inevitable that there will be time delays in the transfer of substances in the reactor, resulting in the corresponding delay of the reaction time in the next stage. The time delayed functions are decomposed into a number of positive continuous functions based on the separation technique. With the help of the Lyapunov–Krasovskii functionals, these positive continuous functions with delayed states are eliminated.

Finally, the construct integrity of the closed-loop nonlinear system is obtained by Lyapunov theory and the effectiveness of the proposed control scheme is proved by giving the simulation results.

The paper is divided into the following parts. Certain preliminaries are assumed during Section 2. Then, the adaptive NN control and stability analysis which are designed by backstepping technique are recommended during Section 3. Section 4 demonstrates certain experimental results. In Section 5, the conclusion is presented.

2. Preliminaries and Problem Formulation

We discuss the CSTR systems with two reactors A and B , as shown in Figure 1 [45]:

$$\begin{cases} \dot{C}_A = -\eta_A C_A - \frac{H_A(C_A, C_A(t - \tau_A))}{\theta_A} + \frac{(1 - R_B)C_B}{D_A} + \xi_A(t, C_A(t - \tau_A)), \\ \dot{C}_B = -\eta_B C_B - \frac{H_B(C_B, C_B(t - \tau_B))}{\theta_B} + \frac{R_A C_A(t - \tau_A)}{D_B} + \frac{R_B C_B(t - \tau_B)}{D_B} + \frac{Fu(t)}{D_B + \xi_B(t, C_B(t - \tau_B))}, \end{cases} \quad (1)$$

where R_i denotes the recycle flow rate, θ_i is the reactor residence time, η_i stands for the reaction constant, F is the feed rate, D_i is the reactor volume, H_i is the nonlinear function representing the complex behavior of the systems, ξ_i is nonlinear function for describing the system uncertainties and external disturbances, C_i denotes the reactor i concentration, and τ_i denotes time-varying delay, $i = A, B$.

The control objective is to develop an adaptive neural controller to ensure that the concentrations C_A and C_B of the producing reactors A and B never overstep the correspondent barrier functions, and the boundedness of all signals in the CSTR systems are obtained.

Remark 1. Comparing with the CSRT systems with only constant time delays in [44, 45], the considered systems in this paper with unknown time-varying delays are more important and general. In addition, to improve the control performance and system stability, full time-varying state constraints’ problem is also considered in the design process. Hence, the developed control approach is more responsive to actual engineering needs.

When $\xi_A = 0$ and $\xi_B = 0$, the entire CSTR system achieves dynamic equilibrium; assume $H_A = C_A + C_A(t - \tau_1)$ and $H_B = C_B^2(t)$. We can get that the equilibrium points C_A^* and C_B^* satisfy

FIGURE 1: Continuously stirred tank reactor (CSTR) system.

$$\begin{cases} \left(\frac{2}{\theta_A} + \eta_A \right) C_A^* = \frac{1 - R_B}{D_A} C_B^*, \\ \eta_B C_B^* + \frac{1}{\theta_B} C_B^{*2} = \frac{R_A}{D_B} C_A^* + \frac{R_B}{D_B} C_B^*. \end{cases} \quad (2)$$

Letting $x_1 = C_A(t) - C_A^*$ and $x_2 = C_B(t) - C_B^*$, the constraints of $x_i, i = 1, 2$, can be regarded as the constraints of the concentrations C_A and C_B ; we can further have

$$\begin{cases} \dot{x}_1 = -\eta_A x_1 - \frac{x_1}{\theta_A} - \frac{x_1(t - \tau_1)}{\theta_A} + x_2 \frac{(1 - R_B)}{D_A} + \xi_A(t, C_A(t - \tau_1)), \\ \dot{x}_2 = -\eta_B x_2 - \frac{x_2^2(t)}{\theta_B} + \frac{R_A x_1(t - \tau_1)}{D_B} - \frac{2C_B^* x_2(t)}{\theta_B} + \frac{R_B x_2(t - \tau_2)}{D_B} + \frac{Fu(t)}{D_B} + \xi_B(t, C_B(t - \tau_2)). \end{cases} \quad (3)$$

Let $\varphi_1 = (1 - R_B)/D_A$ and $\varphi_2 = F/D_B$:

$$\begin{aligned} g_1(x_1(t)) &= -\eta_A x_1 - \frac{x_1}{\theta_A}, \\ g_2(x_2(t)) &= -\eta_B x_2 - \frac{x_2^2(t)}{\theta_B} - \frac{2C_B^* x_2(t)}{\theta_B}, \\ \bar{\xi}_A(t, x_1(t - \tau_1)) &= \xi_A(t, C_A(t - \tau_1)), \\ \bar{\xi}_B(t, x_2(t - \tau_1)) &= \xi_B(t, C_B(t - \tau_1)), \\ h_1(x_{1,\tau(t)}) &= -\frac{x_1(t - \tau_1)}{\theta_A} + \bar{\xi}_A(t, x_1(t - \tau_1)), \\ h_2(\bar{x}_{2,\tau(t)}) &= \frac{R_A x_1(t - \tau_1)}{D_B} + \bar{\xi}_B(t, x_2(t - \tau_1)) + \frac{R_B x_2(t - \tau_2)}{D_B}. \end{aligned} \quad (4)$$

For brevity, thus, (3) can be rewritten as

$$\begin{cases} \dot{x}_1 = \varphi_1 x_2(t) + g_1(x_1(t)) + h_1(x_{1,\tau(t)}), \\ \dot{x}_2 = \varphi_2 u(t) + g_2(x_2(t)) + h_2(\bar{x}_{2,\tau(t)}), \\ y(t) = x_1(t), \end{cases} \quad (5)$$

where $x_i, i = 1, 2$, are the state variables, $u \in \mathbb{R}$ and $y(t)$ are control input and output, respectively, $\bar{x}_2 = [x_1, x_2]^T$, $g_i(\cdot)$ and $h_i(\cdot)$ are known and unknown smooth nonlinear functions, respectively, and $g_i(0) = h_i(0) = 0$, $\varphi_i(t)$ is the continuous function, and $\tau_i(t)$ is the unknown time-varying time delay satisfying $\tau_i(t) \leq \tau_{\max}$ and $\dot{\tau}_i(t) \leq \bar{\tau} \leq 1$, with $\bar{\tau}$ and $\tau_{\max}$ being two known constants. Here, $|x_i| \leq k_{c_i}(t)$, $i = 1, 2$, with $k_{c_i}(t)$ are known functions.

A continuous function $f(z)$ can be approximated by the radial basis function neural networks (RBFNN) as

$$f(z) = W^T I(z), \quad (6)$$

where $W = [W_1, W_2, \dots, W_k]^T \in \mathbb{R}^k$ denote the adjustable weight vector, k expresses the number of neuron, and $I(z) = [I_1(z), I_2(z), \dots, I_k(z)]^T$ signify the basis function vector. There is a smooth vector function $f(z) \in \mathbb{R}$ and ideal weights W^* ; hence, the smooth function $f(z)$ can be approximated by the RBFNN as follows:

$$f(z) = W^{*T} I(z) + \vartheta(z), \quad \forall z \in \Omega \in \mathbb{R}^q. \quad (7)$$

We choose W^* as follows:

$$W^* \triangleq \arg \min \{ \sup \|f(z) - W^T I(z)\| \}, \quad (8)$$

in which the error $\vartheta(z)$ fulfills $|\vartheta(z)| \leq \varepsilon$ within $\varepsilon > 0$. During the thesis, undermentioned Gaussian basis function $I_i(z)$ will be employed:

$$I_i(z) = \exp \left[-\frac{(z - \iota_i)^T (z - \iota_i)}{w_i^2} \right], \quad (9)$$

where $\iota_i = [\iota_{i1}, \iota_{i2}, \dots, \iota_{iq}]^T$ depicts the center of the receptive field and w_i represents the width of the Gaussian function within, $i = 1, 2, \dots, k$.

Assumption 1 (see [35]). There exist positive constants $K_i^{(j)}$, $i = 1, 2$ and $j = 0, 1, 2$, such that, for $t > 0$, the functions $k_{c_i}(t)$ and the j th time derivative satisfy $|k_{c_i}(t)| \leq K_i^{(0)}$ and $|\dot{k}_{c_i}^{(j)}(t)| \leq K_i^{(j)}$.

Assumption 2. The smooth functions $h_i, i = 1, 2$, satisfy

$$h_i^2(x_i(t - \tau_i(t))) \leq z_1^2(t - \tau_i(t)) a_1^2(\bar{z}_1(t - \tau_i(t))), \quad (10)$$

where $a_1(\cdot)$ is a positive smooth function.

Assumption 3 (see [32]). There exist a positive function $Y_0(t): \mathbb{R}_+ \rightarrow \mathbb{R}_+$ and the constants $Y_i > 0, i = 1, 2$, so that the desired trajectory y_d and its time derivatives satisfy $|y_d(t)| \leq Y_0(t)$ and $|y_d^{(i)}(t)| \leq Y_i$.

Remark 2. Assumption 1 shows that the function and the j th time derivative less than or equal to positive constants. Assumptions 1–3 are used to prove the stability of the system; all the signals in the closed-loop system are bounded.

Lemma 1 (see [23]). For all $|\varsigma| < 1$, such that the following inequality holds:

$$\log \frac{1}{1 - \varsigma^2} \leq \frac{\varsigma^2}{1 - \varsigma^2}. \quad (11)$$

3. The Controller Design and Stability Analysis

An adaptive NN control approach will be investigated in this section. It is used to solve the control problem of time delays and state constraints. The time variable t is omitted except for delay terms to improve the readability of this paper.

Step 1: define the error $z_1 = x_1$ and a compact set $\Omega_z = \{|z_i| < k_{b_i}, i = 1, 2\}$ with $k_{b_i}, i = 1, 2$, are known positive constants, and we have

$$\dot{z}_1 = \dot{x}_1 = \varphi_1 x_2 + g_1(x_1) + h_1(x_{1,\tau(t)}). \quad (12)$$

Consider the time-varying BLF candidate:

$$V_{D1} = \frac{1}{2} \log \frac{k_{b_1}^2}{k_{b_1}^2 - z_1^2} + \frac{1}{2} \tilde{W}_1^T \Gamma_1^{-1} \tilde{W}_1, \quad (13)$$

where Γ_1 is a positive constant matrix satisfying $\Gamma_1 = \Gamma_1^{-1} > 0$, $\tilde{W}_1 = \hat{W}_1 - W_1^*$ represents the estimate error, and $\hat{W}_1$ is the estimation weight of the optimal weight W_1^* . We define

$$\psi_{b_i} = \frac{z_i}{k_{b_i}}, \quad (14)$$

$$\mu_i = \frac{1}{(k_{b_i}^2 - z_i^2)}, \quad i = 1, 2.$$

Combining (13) and (14), one can obtain

$$\dot{V}_{D1} = \frac{\psi_{b_1}}{k_{b_1}(1 - \psi_{b_1}^2)} \dot{z}_1 - \frac{\dot{k}_{b_1} \psi_{b_1}^2}{k_{b_1}(1 - \psi_{b_1}^2)} + \tilde{W}_1^T \Gamma_1^{-1} \dot{\tilde{W}}_1. \quad (15)$$

Based on (12) and (15), we obtain

$$\begin{aligned} \dot{V}_{D1} = & \frac{\psi_{b_1}}{k_{b_1}(1 - \psi_{b_1}^2)} (\varphi_1 x_2 + g_1(x_1)) + \tilde{W}_1^T \Gamma_1^{-1} \dot{\tilde{W}}_1 \\ & + \frac{\psi_{b_1}}{k_{b_1}(1 - \psi_{b_1}^2)} h_1(x_{1,\tau(t)}) - \frac{\dot{k}_{b_1} \psi_{b_1}^2}{k_{b_1}(1 - \psi_{b_1}^2)}. \end{aligned} \quad (16)$$

Using Young's inequality, one has

$$\begin{aligned} \frac{\psi_{b_1}}{k_{b_1}(1-\psi_{b_1}^2)} h_1(x_{1,\tau(t)}) &\leq \frac{\exp(\tau_{\max})}{2c} \left(\frac{\psi_{b_1}}{k_{b_1}(1-\psi_{b_1}^2)} \right)^2 \\ &+ \frac{c \exp(-\tau_{\max})}{2} h_1^2(x_{1,\tau(t)}), \end{aligned} \quad (17)$$

where $c = 1 - \bar{d}$.

Define the unknown function $G_1(Z_1)$ as

$$G_1(Z_1) = g_1(x_1) + \frac{1}{\mu_1} H_1 + \frac{\exp(\tau_{\max})}{2c} z_1 \mu_1, \quad (18)$$

where $H_1 = z_1 a_1^2(z_1) + z_1(\psi_{211}(z_1) + \psi_{212}(z_1))/2$ with $a_1(\cdot)$, $\psi_{211}(\cdot)$, and $\psi_{212}(\cdot)$ being continuous smooth functions and defined later.

By substituting (17) and (18) into (16), meanwhile, $x_2 = z_2 + \alpha_1$, we can get the following inequality:

$$\begin{aligned} \dot{V}_{D1} &\leq \mu_1 z_1 \left[G_1(Z_1) + \varphi_1(z_2 + \alpha_1) - \frac{\dot{k}_{b_1}}{k_{b_1}} z_1 \right] - z_1 H_1 \\ &+ \tilde{W}_1^T \Gamma_1^{-1} \dot{\tilde{W}}_1 + \frac{c \exp(-\tau_{\max})}{2} h_1^2(x_{1,\tau(t)}). \end{aligned} \quad (19)$$

By using the NN approximation property, the continuous function $G_1(Z_1)$ can be approximated as

$$G_1(Z_1) = W_1^{*T} I_1(Z_1) + \vartheta_1(Z_1), \quad (20)$$

where $I_1(Z_1) \in R$ indicates the Gaussian basis function and $\vartheta_1(Z_1)$ indicates inherent approximation error of the NNs satisfying $|\vartheta_1(Z_1)| \leq \bar{\vartheta}_1$ with $\bar{\vartheta}_1$ being a positive constant; $Z_1 = x_1$.

The middle controller and the adaptive law are designed as

$$\alpha_1 = \frac{1}{\varphi_1} \left(-k_1 z_1 - K_1 z_1 - \tilde{W}_1^T I_1(Z_1) - \frac{1}{2\gamma_1} \mu_1 z_1 - \frac{1}{2} \varphi_1 z_1 \right), \quad (21)$$

$$\dot{\tilde{W}}_1 = \Gamma_1 [\mu_1 z_1 I_1(Z_1) - \sigma_1 \tilde{W}_1], \quad (22)$$

where k_1 , γ_1 , and σ_1 are the positive constants. Denote $K_i = \sup \sqrt{(\dot{k}_{b_i}/k_{b_i})^2} + \varepsilon_i$ with $\varepsilon_i > 0$ being a small constant.

According to (20)–(22), (19) becomes

$$\begin{aligned} \dot{V}_{D1} &\leq \mu_1 z_1 \left[-k_1 z_1 - \frac{1}{2\gamma_1} \mu_1 z_1 + \varphi_1 z_2 - \frac{1}{2} \varphi_1 z_1 + \vartheta_1(Z_1) \right] - z_1 H_1 \\ &+ \frac{c \exp(-\tau_{\max})}{2} h_1^2(x_{1,\tau(t)}) - \sigma_1 \tilde{W}_1^T \tilde{W}_1. \end{aligned} \quad (23)$$

By employing Young's inequality, we can obtain

$$\mu_1 z_1 \vartheta_1(Z_1) \leq \frac{1}{2\gamma_1} \mu_1^2 z_1^2 + \frac{\gamma_1 \bar{\vartheta}_1^2}{2}, \quad (24)$$

$$\mu_1 \varphi_1 z_1 z_2 \leq \mu_1 \varphi_1 \frac{1}{2} (z_1^2 + z_2^2). \quad (25)$$

Based on (24) and (25), (23) can be written as

$$\begin{aligned} \dot{V}_{D1} &\leq \frac{1}{2} \mu_1 \varphi_1 z_2^2 - k_1 \mu_1 z_1^2 + \frac{\gamma_1 \bar{\vartheta}_1^2}{2} \\ &- \sigma_1 \tilde{W}_1^T \tilde{W}_1 + \frac{c \exp(-\tau_{\max})}{2} h_1^2(x_{1,\tau(t)}) - z_1 H_1. \end{aligned} \quad (26)$$

Step 2 : since $z_2 = x_2 - \alpha_1$, its time derivative is given as follows:

$$\dot{z}_2 = \dot{x}_2 - \dot{\alpha}_1 = \varphi_2 u + g_2(\bar{x}_2) + h_2(\bar{x}_{2,\tau(t)}) - \dot{\alpha}_1, \quad (27)$$

where

$$\begin{aligned} \dot{\alpha}_1 = & \frac{\partial \alpha_1}{\partial x_1} [\varphi_1 x_2 + g_1(x_1) + h_1(x_{1,\tau(t)})] \\ & + \frac{\partial \alpha_1}{\partial \hat{W}_1} \dot{\hat{W}}_1 + \sum_{i=0}^1 \frac{\partial \alpha_1}{\partial k_{b_1}^2} k_{b_1}^{(i+1)}. \end{aligned} \quad (28)$$

The BLF candidate is given as

$$V_{D2} = V_{D1} + \frac{1}{2} \log \frac{k_{b_2}^2}{k_{b_2}^2 - z_2^2} + \frac{1}{2} \tilde{W}_2^T \Gamma_2^{-1} \tilde{W}_2, \quad (29)$$

where $\Gamma_2 = \Gamma_2^{-1} > 0$ is a constant matrix and $\tilde{W}_2 = \hat{W}_2 - W_2^*$ denotes the estimate error with $\hat{W}_2$ being the estimation weight of W_2^* .

Based on (27), differentiating V_{D2} , one obtains

$$\begin{aligned} \dot{V}_{D2} = & \dot{V}_{D1} + \frac{\psi_{b_2}}{k_{b_2}(1 - \psi_{b_2}^2)} [\varphi_2 u + g_2(\bar{x}_2) \\ & + h_2(\bar{x}_{2,\tau(t)}) - \frac{\partial \alpha_1}{\partial x_1} \varphi_1 x_2 - \frac{\partial \alpha_1}{\partial x_1} g_1(x_1) \\ & - \frac{\partial \alpha_1}{\partial x_1} h_1(x_{1,\tau(t)}) - \frac{\partial \alpha_1}{\partial \hat{W}_1} \dot{\hat{W}}_1 - \sum_{i=0}^1 \frac{\partial \alpha_1}{\partial k_{b_1}^2} k_{b_1}^{(i+1)}] - \frac{k_{b_2} \psi_{b_2}^2}{k_{b_2}(1 - \psi_{b_2}^2)} + \tilde{W}_2^T \Gamma_2^{-1} \dot{\tilde{W}}_2. \end{aligned} \quad (30)$$

By using Young's inequality, it has

$$\begin{aligned} \frac{\psi_{b_2}}{k_{b_2}(1 - \psi_{b_2}^2)} h_2(\bar{x}_{2,\tau(t)}) \leq & \frac{\exp(\tau_{\max})}{2c} \left(\frac{\psi_{b_2}}{k_{b_2}(1 - \psi_{b_2}^2)} \right)^2 \\ & + \frac{c \exp(-\tau_{\max})}{2} h_2^2(\bar{x}_{2,\tau(t)}), \end{aligned} \quad (31)$$

$$\begin{aligned} -\frac{\psi_{b_2}}{k_{b_2}(1 - \psi_{b_2}^2)} \frac{\partial \alpha_1}{\partial x_1} h_1(x_{1,\tau(t)}) \leq & \frac{\exp(\tau_{\max})}{2c} \left(\frac{\psi_{b_2}}{k_{b_2}(1 - \psi_{b_2}^2)} \frac{\partial \alpha_1}{\partial x_1} \right)^2 \\ & + \frac{c \exp(-\tau_{\max})}{2} h_1^2(x_{1,\tau(t)}). \end{aligned} \quad (32)$$

The unknown function $G_2(Z_2)$ is concluded as

$$\begin{aligned} G_2(Z_2) = & g_2(\bar{x}_2) - \frac{\partial \alpha_1}{\partial x_1} [g_1(x_1) + \varphi_1 x_2] \\ & - \frac{\partial \alpha_1}{\partial \hat{W}_1} \dot{\hat{W}}_1 - \sum_{i=0}^1 \frac{\partial \alpha_1}{\partial k_{b_1}^2} k_{b_1}^{(i+1)} + \frac{1}{\mu_2} H_2 + \exp(\tau_{\max}) \frac{\mu_2 z_2}{2c} \left[1 + \left(\frac{\partial \alpha_1}{\partial x_1} \right)^2 \right], \end{aligned} \quad (33)$$

where $H_2 = z_2 q_2^2(z_2)/2$ with $q_2(\cdot)$ being a continuous and smooth function.

By using the NNs, the continuous unknown function $G_2(Z_2)$ is approximated as

$$G_2(Z_2) = W_2^{*T} I_2(Z_2) + \vartheta_2(Z_2), \quad (34)$$

where $Z_2 = [x_1, x_2, \hat{W}_1^T]^T$, $I_2(Z_2) \in \mathbb{R}$ indicates the Gaussian basis function, and $\vartheta_2(Z_2)$ indicates inherent approximation error of the NNs satisfying $|\vartheta_2(Z_2)| \leq \bar{\vartheta}_2$ with $\bar{\vartheta}_2$ being a positive constant.

The virtual controller and the adaptive law are given as

$$u = \frac{1}{\varphi_2} \left(-k_2 z_2 - K_2 z_2 - \hat{W}_2^T I_2(Z_2) - \frac{\gamma_2}{2} \mu_2 z_2 - \frac{\mu_1 \varphi_1 z_2}{2\mu_2} \right), \quad (35)$$

$$\dot{\hat{W}}_2 = \Gamma_2 [\mu_2 z_2 I_2(Z_2) - \sigma_2 \hat{W}_2], \quad (36)$$

where k_2 , γ_2 , and σ_2 are the positive constants.

By using Young's inequality, it has

$$\mu_2 z_2 \vartheta_2(Z_2) \leq \frac{\gamma_2}{2} \mu_2^2 z_2^2 + \frac{1}{2\gamma_2} \bar{\vartheta}_2^2. \quad (37)$$

Along with (31)–(37), we obtain

$$\begin{aligned} \dot{V}_{D2} \leq & \dot{V}_{D1} - \frac{1}{2} \mu_1 \varphi_1 z_2^2 - k_2 \mu_2 z_2^2 + \frac{1}{2\gamma_2} \bar{\vartheta}_2^2 - \sigma_2 \tilde{W}_2^T \hat{W}_2 \\ & - z_2 H_2 + \sum_{i=1}^2 \frac{c \exp(-\tau_{\max})}{2} h_i^2(\bar{x}_{i,\tau(t)}). \end{aligned} \quad (38)$$

In Step 1, we can obtain

$$\begin{aligned} \dot{V}_{D1} \leq & -k_1 \mu_1 z_1^2 + \frac{1}{2} \mu_1 \varphi_1 z_2^2 - z_1 H_1 + \frac{1}{2\gamma_1} \bar{\vartheta}_1^2 \\ & - \sigma_1 \tilde{W}_1^T \hat{W}_1 + \frac{c \exp(-\tau_{\max})}{2} h_1^2(x_{1,\tau(t)}). \end{aligned} \quad (39)$$

Hence, (38) becomes

$$\begin{aligned} \dot{V}_{D2} \leq & - \sum_{i=1}^2 k_i \mu_i z_i^2 - \sum_{i=1}^2 z_i H_i + \sum_{i=1}^2 \frac{1}{2\gamma_i} \bar{\vartheta}_i^2 - \sum_{i=1}^2 \sigma_i \tilde{W}_i^T \hat{W}_i \\ & + c \exp(-\tau_{\max}) \left(h_1^2(x_{1,\tau(t)}) + \frac{1}{2} h_2^2(\bar{x}_{2,\tau(t)}) \right). \end{aligned} \quad (40)$$

Based on Assumption 1 in [45], the delay term in (40) becomes

$$h_i^2(\bar{x}_{i,\tau(t)}) \leq \bar{q}_i(z_i(t - \tau_i(t))) + \sum_{j=1}^{i-1} \sum_{l=1}^i \bar{\psi}_{ijl}(z_j(t - \tau_l(t))), \quad (41)$$

where $\bar{q}_i$ and $\bar{\psi}_{ijl}$ represent positive definite and sufficiently smooth known functions with $\bar{q}_i(x) = x^2 q_i(x)$ and $\bar{\psi}_{mjl}(x) = x^2 \psi_{mjl}(x)$ with $q_i(x)$ and $\psi_{mjl}(x)$ being continuous and smooth functions.

Noting the term $\sigma_i \tilde{W}_i^T \hat{W}_i$, the following inequality can be obtained:

$$-\sigma_i \tilde{W}_i^T \hat{W}_i = -\sigma_i \tilde{W}_i^T (\tilde{W}_i + W_i^*) \leq -\frac{1}{2} \sigma_i \|\tilde{W}_i\|^2 + \frac{1}{2} \sigma_i \|W_i^*\|^2. \quad (42)$$

Thus, (40) can be rewritten as

$$\begin{aligned} \dot{V}_{D2} \leq & - \sum_{i=1}^2 k_i \mu_i z_i^2 - \sum_{i=1}^2 z_i H_i + \sum_{i=1}^2 \frac{1}{2\gamma_i} \bar{\vartheta}_i^2 \\ & + \frac{c \exp(-\tau_{\max})}{2} (2z_1^2(t - \tau_1(t)) q_1(z_1(t - \tau_1(t))) \\ & + z_2^2(t - \tau_2(t)) q_2(z_2(t - \tau_2(t))) + \frac{1}{2} \sum_i \sigma_i \|W_i^*\|^2 \\ & + z_1^2(t - \tau_1(t)) \psi_{211}(z_1(t - \tau_1(t))) - \frac{1}{2} \sum_i \sigma_i \|\tilde{W}_i\|^2 \\ & + z_1^2(t - \tau_2(t)) \psi_{212}(z_1(t - \tau_2(t))))). \end{aligned} \quad (43)$$

Choose the Lyapunov function candidate as

$$V = V_{D2} + V_L, \quad (44)$$

in which, LKF V_L is considered as

$$\begin{aligned} V_L = & \frac{1}{2} \sum_{m=1}^2 \int_{t-\tau_m(t)}^t (3-m) \exp(s-t) z_m^2(s) q_m(z_m(s)) ds \\ & + \frac{1}{2} \sum_{m=1}^2 \sum_{j=1}^{m-1} \sum_{l=1}^m \int_{t-\tau_l(t)}^t \exp(s-t) z_j^2(s) \psi_{mjl}(z_j(s)) ds. \end{aligned} \quad (45)$$

The time derivative of V_L is given as

$$\begin{aligned} \dot{V}_L = & \frac{1}{2} \sum_{m=1}^2 (3-m) z_m^2 q_m(z_m) + \frac{1}{2} \sum_{m=1}^2 \sum_{j=1}^{m-1} \sum_{l=1}^m z_j^2 \psi_{mjl}(z_j) - V_L \\ & - \sum_{m=1}^2 \frac{c(3-m)}{2} \exp(-\tau_m(t)) z_m^2(t - \tau_m(t)) q_m(z_m(t - \tau_m(t))) \\ & - \frac{c}{2} \sum_{m=1}^2 \sum_{j=1}^{m-1} \sum_{l=1}^m \exp(-\tau_l(t)) z_j^2(t - \tau_l(t)) \psi_{mjl}(z_j(t - \tau_l(t))). \end{aligned} \quad (46)$$

Noting $\tau_i \leq \tau_{\max}$, according to (43) and (46), the time derivative of V can be obtained as

$$\begin{aligned} \dot{V} \leq & -\sum_{i=1}^2 k_i \mu_i z_i^2 + \sum_{i=1}^2 \frac{1}{2\gamma_i} \bar{\vartheta}_i^2 - \frac{1}{2} \sum_i \sigma_i \|\tilde{W}_i\|^2 \\ & + \frac{1}{2} \sum_i \sigma_i \|W_i^*\|^2 + \Lambda_1 + \Lambda_2 + \Lambda_3 - V_L, \end{aligned} \quad (47)$$

$$\begin{aligned} \Lambda_1 = & \frac{c \exp(-\tau_{\max})}{2} (2z_1^2(t - \tau_1(t))q_1(z_1(t - \tau_1(t))) \\ & + z_2^2(t - \tau_2(t))q_2(z_2(t - \tau_2(t)))) - \frac{c \exp(-\tau_{\max})}{2} \\ & \times \sum_{m=1}^2 (3-m)z_m^2(t - \tau_m(t))q_m(z_m(t - \tau_m(t))) = 0, \\ \Lambda_2 = & \frac{c \exp(-\tau_{\max})}{2} (z_1^2(t - \tau_1(t))\psi_{211}(z_1(t - \tau_1(t))) \\ & + z_1^2(t - \tau_2(t))\psi_{212}(z_1(t - \tau_2(t)))) - \frac{c \exp(-\tau_{\max})}{2} \\ & \times \sum_{m=1}^2 \sum_{j=1}^{m-1} \sum_{l=1}^m z_j^2(t - \tau_l(t))\psi_{mjl}(z_j(t - \tau_l(t))) = 0, \\ \Lambda_3 = & \frac{1}{2} \sum_{m=1}^2 (3-m)z_m^2 q_m(z_m) + \frac{1}{2} \sum_{m=1}^2 \sum_{j=1}^{m-1} \sum_{l=1}^m z_j^2 \psi_{mjl}(z_j) - \sum_{i=1}^2 z_i H_i = 0. \end{aligned} \quad (48)$$

So, $\dot{V}$ further becomes

$$\begin{aligned} \dot{V} \leq & -\sum_{i=1}^2 k_i \mu_i z_i^2 - \frac{1}{2} \sum_i \sigma_i \|\tilde{W}_i\|^2 \\ & + \frac{1}{2} \sum_i \sigma_i \|W_i^*\|^2 + \sum_{i=1}^2 \frac{1}{2\gamma_i} \bar{\vartheta}_i^2 - V_L. \end{aligned} \quad (49)$$

With the help of Lemma 1, we have

$$-\sum_{i=1}^2 k_i \mu_i z_i^2 \leq -\sum_{i=1}^2 \log \frac{k_i k_{bi}^2}{k_{bi}^2 - z_i^2}. \quad (50)$$

Then, (49) is further shown as

$$\begin{aligned} \dot{V} \leq & -\sum_{i=1}^2 \log \frac{k_i k_{bi}^2}{k_{bi}^2 - z_i^2} + \sum_{i=1}^2 \frac{1}{2\gamma_i} \bar{\vartheta}_i^2 \\ & - \frac{1}{2} \sum_i \sigma_i \|\tilde{W}_i\|^2 + \frac{1}{2} \sum_i \sigma_i \|W_i^*\|^2 - V_L. \end{aligned} \quad (51)$$

According to (13), (29), (44), and (45), one has

where

$$\begin{aligned} V = & \frac{1}{2} \sum_{i=1}^2 \log \frac{k_{bi}^2}{k_{bi}^2 - z_i^2} + \frac{1}{2} \sum_{i=1}^2 \tilde{W}_i^T \Gamma_i^{-1} \tilde{W}_i \\ & + \frac{1}{2} \sum_{m=1}^2 \int_{t-\tau_m(t)}^t (3-m) \exp(s-t) z_m^2(s) a_m(z_m(s)) ds \\ & + \frac{1}{2} \sum_{m=1}^2 \sum_{j=1}^{m-1} \sum_{l=1}^m \int_{t-\tau_l(t)}^t \exp(s-t) z_j^2(s) \psi_{mjl}(z_j(s)) ds. \end{aligned} \quad (52)$$

Based on (51) and (52), the following inequality holds:

$$\dot{V} \leq -pV + q, \quad (53)$$

where $p = \min\{2k_i, \sigma_i \lambda_{\min}(\Gamma_i), 1, i = 1, 2\}$,

$$q = \frac{1}{2} \sum_{i=1}^2 \sigma_i \|W_i^*\|^2 + \sum_{i=1}^2 \frac{1}{2\gamma_i} \bar{\vartheta}_i^2. \quad (54)$$

Theorem 1. Consider the CSTR systems (1); if Assumptions 1–3 hold, the proposed virtual controller (21), the actual controller (35), and the adaptation laws (22) and (36) are utilized to ensure the boundedness of closed-loop system

signals, and all the system states remain within the corresponding constraint set.

Proof. According to (53), one can obtain

$$V(t) \leq \left(V(0) - \frac{q}{p} \right) e^{-pt} + \frac{q}{p} \leq V(0) + \frac{q}{p}. \quad (55)$$

From (13), we can get that every term is positive, so, the following term satisfies

$$\frac{1}{2} \log \frac{1}{1 - \psi_i^2} \leq V(t) \leq V(0) e^{-pt} + \frac{q}{p}, \quad (56)$$

$$\frac{1}{2} \tilde{W}_i^T \Gamma_i^{-1} \tilde{W}_i \leq V(0) e^{-pt} + \frac{q}{p}. \quad (57)$$

From (56) and (57), the error signal is bounded:

$$-\Delta_i \leq z_i(t) \leq \Delta_i, \quad (58)$$

where $\Delta_i = k_{b_i}(t) (1 - e^{-2(V(0)e^{-pt} - 2q/p)^{1/2}})$.

The adaptation laws can be obtained:

$$\|\tilde{W}_i\| \leq \sqrt{2\lambda_{\max}(\Gamma_i)} \left((V(0))e^{-pt} + \frac{q}{p} \right). \quad (59)$$

Then, according to Assumptions 1–3, it is known that $|k_{b_i}(t)| \leq Y_1 + K_1^{(1)}$ and $y_d(t) - \Delta_1 \leq x_1(t) \leq y_d(t) + \Delta_1$, so we can obtain $-k_{c_1}(t) \leq x_1(t) \leq k_{c_1}(t)$. Due to the definition of α_1 , meanwhile, the boundedness of y_d , $k_{b_1}(t)$, $\dot{k}_{b_1}(t)$, and x_1 ; it is easy to obtain α_1 is bounded and $x_2 = z_2 + \alpha_1$ is bounded. From the definition in (35), it can be obtained that the controller u is bounded by the same way. Therefore, all the signals in the closed-loop system are bounded. The proof completes. $\square$

Remark 3. CSTRs' system is a complex and nonlinear system. It has time-varying delayed states. This paper adopts the mechanism modeling method; according to the kinetic equation, by conservation of mass and conservation of energy, the nonlinear model equation is derived. The Lyapunov–Krasovskii functional is used to eliminate these continuous functions with the delayed state in this paper so that the CSTRs system with the delayed state is stable.

In the case of cascade reaction between two reaction reactors, there will be time delays in the transfer of substances in the reactor, which has a strong delay characteristic. At the same time, the CSTR system is nonlinear. In the reaction process, the reactant concentration and other parameters are easy to fluctuate with time-varying, and the temperature in the chemical reaction system must be controlled within a certain safety limit since its data are constrained. Therefore, the time delay and state constraints of the CSTR system should be considered when designing the controller.

4. Simulation Example

In this part, the simulation example is shown to demonstrate the effectiveness of the presented method for CSTR systems

FIGURE 2: Responses of x_1 and its constrained functions.

FIGURE 3: Response of system state x_2 and its constrained functions.

(1) with both time-varying full state constraints and time-varying delays.

According to the considered CSTR systems, system states x_1 and x_2 are constrained by $-k_{c_1}(t) \leq x_1(t) \leq k_{c_1}(t)$ and $-k_{c_2}(t) \leq x_2(t) \leq k_{c_2}(t)$ with $k_{c_1}(t) = 0.4e^{-2t} + 0.005$ and $k_{c_2}(t) = 2e^{-2t} + 0.05$. The equilibrium points are $C_A^* = 14/9$ and $C_B^* = 7/3$. The system parameters are chosen as $\eta_A = \eta_B = 0.5$, $\theta_A = \theta_B = 2$, $R_A = R_B = 0.5$, $D_A = D_B = 0.5$, $F = 0.5$, $\xi_A(t, C_A(t - \tau_1(t))) = 0.5 \sin(t)x_1(t - \tau_1(t))$, and $\xi_B(t, C_B(t - \tau_2(t))) = 0.5 \times \exp(0.01x_2(t - \tau_2(t)))\cos(t) \times x_2^2(t - \tau_2(t))$ with time-varying delays $\tau_1(t) = 0.25 - 0.2 \sin(0.5t)\cos(2t)$ and $\tau_2(t) = 0.55 - 0.5 \sin(0.5t)$. The initial conditions are selected as $x_1(0) = 0.1$, $x_2(0) = 0$, $\tilde{W}_1 = \tilde{W}_2 = 0$, $\Gamma_1 = 0.4\text{diag}(\text{ones}(1, 30))$, and $\Gamma_2 = 0.2\text{diag}(\text{ones}(1, 30))$. The design parameters are selected as $k_1 = 1.1$, $k_2 = 12$, $\gamma_1 = 0.5$, $\gamma_2 = 2$, and $\varepsilon_1 = \varepsilon_2 = 0.01$.

The simulation results are shown as Figures 2–5 to certify the effectiveness of the presented control method. Figure 2

FIGURE 4: Responses of adaptation parameters $\|\hat{W}_1\|$ and $\|\hat{W}_2\|$.

FIGURE 5: Response of control input u .

illustrates the responses of system state x_1 and the corresponding constrained functions. In Figure 3, it obtains the trajectories of x_2 and its constrained functions. It is worth stressing that system states x_1 and x_2 always stay within the prescribed compact set in Figures 2 and 3. From Figures 4 and 5, the boundedness of control input and adaptation laws are obtained.

5. Conclusion

The time delays and constraints are often occurring in the chemical reactor system, which also are main limitation factors of system performance severely. This paper has studied the tracking problem of the continuous stirred tank reactor containing the time-varying delays and full state constraints simultaneously. By constructing appropriate LKFs and LBLF, the effects of unknown time-varying delays were eliminated and the time-varying full states are never

violated. By employing the proposed control method, we can make the conclusion that the tracking error can converge into a small set of zero and ensure all the signals in the system are bounded. The simulation results are proved to the rationality and effectiveness of the scheme. The future research directions should focus on the integral BLF-based finite-time adaptive control for a CSTR system.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China, under Grants 61603164, 61803189, and 62025303, and the Project of Education Department of Liaoning Province, under Grant JYL202015406.

References

- [1] C. L. P. Chen and Y. H. Pao, "An integration of neural network and rule-based systems for design and planning of mechanical assemblies," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 5, pp. 1359–1371, 1993.
- [2] P. Ping Guo, C. L. P. Chen, and M. R. Lyu, "Cluster number selection for a small set of samples using the Bayesian Ying-Yang model," *IEEE Transactions on Neural Networks*, vol. 13, no. 3, pp. 757–763, 2002.
- [3] J. Wang, Z. Liu, Y. Zhang, and C. L. P. Chen, "Neural adaptive event-triggered control for nonlinear uncertain stochastic systems with unknown hysteresis," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 11, pp. 3300–3312, 2019.
- [4] B. Niu, P. Duan, J. Li, and X. Li, "Adaptive neural tracking control scheme of switched stochastic nonlinear pure-feedback nonlower triangular systems," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 2, pp. 975–986, 2021.
- [5] S. Tong, X. Min, and Y. Li, "Observer-based adaptive fuzzy tracking control for strict-feedback nonlinear systems with unknown control gain functions," *IEEE Transactions on Cybernetics*, vol. 50, no. 9, pp. 3903–3913, 2020.
- [6] G. Lin, H. Li, H. Ma, D. Yao, and R. Lu, "Human-in-the-loop consensus control for nonlinear multi-agent systems with actuator faults," *IEEE/CAA Journal of Automatica Sinica*, pp. 1–12, 2020, to be published.
- [7] H. Ma, H. Y. Li, R. Q. Lu, and T. W. Huang, "Adaptive event-triggered control for a class of nonlinear systems with periodic disturbances," *Science China Information Sciences*, vol. 63, no. 5, pp. 1–15, 2020.
- [8] L. Wang and C. L. P. Chen, "Reduced-order observer-based dynamic event-triggered adaptive NN control for stochastic nonlinear systems subject to unknown input saturation," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 4, pp. 1678–1690, 2021, to be published.

- [9] M. Chen, W. Chen, and Q. Wu, "Adaptive fuzzy tracking control for a class of uncertain MIMO nonlinear systems using disturbance observer," *Science China Information Sciences*, vol. 57, no. 1, pp. 1–13, 2014.
- [10] H. Liang, X. Guo, Y. Pan, and T. Huang, "event-triggered fuzzy bipartite tracking control for network systems based on distributed reduced-order observers," *IEEE Transactions on Fuzzy Systems*, vol. 29, no. 6, pp. 1601–1614, 2021.
- [11] H. Liang, G. Liu, H. Zhang, and T. Huang, "Neural-network-based event-triggered adaptive control of nonaffine nonlinear multiagent systems with dynamic uncertainties," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 5, pp. 2239–2250, 2021.
- [12] R. Shahnazi, "Cooperative neuro adaptive control of leader following uncertain multi-agent systems with unknown hysteresis and dead-zone," *Journal of Systems Science and Complexity*, vol. 33, no. 2, pp. 312–332, 2020.
- [13] M. Nikravesh, A. E. Farrell, and T. G. Stanford, "Control of nonisothermal CSTR with time varying parameters via dynamic neural network control (DNNC)," *Chemical Engineering Journal*, vol. 76, no. 1, pp. 1–16, 2000.
- [14] T. D. Knapp, H. M. Budman, and G. Broderick, "Adaptive control of a CSTR with a neural network model," *Journal of Process Control*, vol. 11, no. 1, pp. 53–68, 2001.
- [15] R. Gao, A. O'dwyer, and E. Coyle, "A nonlinear PID controller for CSTR using local model networks," in *Proceedings of the 4th IEEE World Congress on Intelligent Control and Automation*, vol. 4, pp. 3278–3282, Shanghai, China, June 2002.
- [16] J. Lei, G. He, and J. P. Jiang, "The state estimation of the CSTR system based on a recurrent neural network trained by HGAs," *Proceedings of International Conference on Neural Networks (ICNN'97)*, vol. 2, pp. 779–782, 1997.
- [17] T. Zhang and M. Guay, "Adaptive control of uncertain continuously stirred tank reactors with unknown actuator nonlinearities," *ISA Transactions*, vol. 44, no. 1, pp. 55–68, 2005.
- [18] S. S. Ge, C. C. Hang, and T. Zhang, "Nonlinear adaptive control using neural networks and its application to CSTR systems," *Journal of Process Control*, vol. 9, no. 4, pp. 313–323, 1999.
- [19] H. G. Lilong Cai and L. L. Cai, "Nonlinear adaptive control using the Fourier integral and its application to CSTR systems," *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)*, vol. 32, no. 3, pp. 367–372, 2002.
- [20] B. Zhang and Z. Mao, "Robust adaptive control of Hammerstein nonlinear systems and its application to typical CSTR problems," *International Journal of Adaptive Control and Signal Processing*, vol. 31, no. 2, pp. 163–190, 2017.
- [21] G.-B. So and G.-G. Jin, "Fuzzy-based nonlinear PID controller and its application to CSTR," *Korean Journal of Chemical Engineering*, vol. 35, no. 4, pp. 819–825, 2018.
- [22] D.-J. Li, "Neural network control for a class of continuous stirred tank reactor process with dead-zone input," *Neurocomputing*, vol. 131, pp. 453–459, 2014.
- [23] W. Qin, W. B. Shangguan, and H. Yin, "Constraint-following control design for active suspension systems," *Mechanical Systems and Signal Processing*, vol. 154, Article ID 107578, 2021.
- [24] L. Liu, X. S. Li, Y. J. Liu, and S. C. Tong, "Neural network based adaptive event trigger control for a class of electromagnetic suspension systems," *Control Engineering Practice*, vol. 106, Article ID 104675, 2021.
- [25] Q. Chen, L. Yu, and Y. Nan, "Finite-time tracking control for motor servo systems with unknown dead-zones," *Journal of Systems Science and Complexity*, vol. 26, no. 6, pp. 940–956, 2013.
- [26] Y. He, J. Wang, and R. Hao, "Adaptive robust dead-zone compensation control of electro-hydraulic servo systems with load disturbance rejection," *Journal of Systems Science and Complexity*, vol. 28, no. 2, pp. 341–359, 2015.
- [27] W. Sun, J. Xia, and Y. Wu, "Adaptive tracking control for mobile manipulators with stochastic disturbances," *Journal of Systems Science and Complexity*, vol. 32, no. 5, pp. 1393–1403, 2019.
- [28] D.-J. Li and D.-P. Li, "Adaptive controller design-based neural networks for output constraint continuous stirred tank reactor," *Neurocomputing*, vol. 153, pp. 159–163, 2015.
- [29] K. P. Tee, S. S. Ge, and E. H. Tay, "Barrier Lyapunov functions for the control of output-constrained nonlinear systems," *Automatica*, vol. 45, no. 4, pp. 918–927, 2009.
- [30] C. C. Chen and Z. Y. Sun, "Output feedback finite-time stabilization for high-order planar systems with an output constraint," *Automatica*, vol. 114, Article ID 108843, 2020.
- [31] K. Zhao and Y. Song, "Removing the feasibility conditions imposed on tracking control designs for state-constrained strict-feedback systems," *IEEE Transactions on Automatic Control*, vol. 64, no. 3, pp. 1265–1272, 2019.
- [32] K. Zhao, Y. Song, and C. L. P. Chen, "Control of nonlinear systems under dynamic constraints: a unified barrier function-based approach," *Automatica*, vol. 119, Article ID 109102, 2021.
- [33] Y.-J. Liu, W. Zhao, L. Liu, D. Li, S. Tong, and C. L. P. Chen, "Adaptive neural network control for a class of nonlinear systems with function constraints on states," *IEEE Transactions on Neural Networks and Learning Systems*, pp. 1–10, in press, 2021.
- [34] L. Liu, Y.-J. Liu, A. Chen, S. Tong, and C. L. P. Chen, "Integral Barrier Lyapunov function-based adaptive control for switched nonlinear systems," *Science China Information Sciences*, vol. 63, no. 3, Article ID 132203, 2020.
- [35] K. P. Tee, B. Ren, and S. S. Ge, "Control of nonlinear systems with time-varying output constraints," *Automatica*, vol. 47, no. 11, pp. 2511–2516, 2011.
- [36] W. He, H. Huang, and S. S. Ge, "Adaptive neural network control of a robotic manipulator with time-varying output constraints," *IEEE Transactions on Cybernetics*, vol. 47, no. 10, pp. 3136–3147, 2017.
- [37] L. Wang, C. L. P. Chen, and H. Li, "Event-triggered adaptive control of saturated nonlinear systems with time-varying partial state constraints," *IEEE Transactions on Cybernetics*, vol. 50, no. 4, pp. 1485–1497, 2020.
- [38] L. Qiu, L. Guo, and J. Liu, "Mean square average generalized consensus of multi-agent systems under time-delays and stochastic disturbances," *Journal of Systems Science and Complexity*, vol. 32, no. 2, pp. 588–599, 2019.
- [39] X. Li and J. Wu, "Stability of nonlinear differential systems with state-dependent delayed impulses," *Automatica*, vol. 64, pp. 63–69, 2016.
- [40] X. Li and J. Cao, "An impulsive delay inequality involving unbounded time-varying delay and applications," *IEEE Transactions on Automatic Control*, vol. 62, no. 7, pp. 3618–3625, 2017.
- [41] S. S. Ge, F. Hong, and T. H. Lee, "Robust adaptive control of nonlinear systems with unknown time delays," *Automatica*, vol. 41, no. 7, pp. 1181–1190, 2005.
- [42] M. Wang, B. Chen, X. Liu, and P. Shi, "Adaptive fuzzy tracking control for a class of perturbed strict-feedback nonlinear time-delay systems," *Fuzzy Sets and Systems*, vol. 159, no. 8, pp. 949–967, 2008.

- [43] D.-P. Li and D.-J. Li, "Adaptive neural tracking control for nonlinear time-delay systems with full state constraints," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 7, pp. 1590–1601, 2017.
- [44] B. Ren, S. S. Ge, T. H. Lee, and C. Y. Su, "Adaptive neural control for a class of nonlinear systems with uncertain hysteresis inputs and time-varying state delays," *IEEE Transactions on Neural Networks*, vol. 20, no. 7, pp. 1148–1164, 2009.
- [45] D.-P. Li, D.-J. Li, Y.-J. Liu, S. Tong, and C. L. P. Chen, "Approximation-based adaptive neural tracking control of nonlinear MIMO unknown time-varying delay systems with full state constraints," *IEEE Transactions on Cybernetics*, vol. 47, no. 10, pp. 3100–3109, 2017.
- [46] T. P. Zhang and S. S. Ge, "Adaptive neural control of MIMO nonlinear state time-varying delay systems with unknown dead-zones and gain signs," *Automatica*, vol. 43, no. 6, pp. 1021–1033, 2007.
- [47] Y. Li, X. Min, and S. Tong, "Observer-based fuzzy adaptive inverse optimal output feedback control for uncertain nonlinear systems," *IEEE Transactions on Fuzzy Systems*, vol. 29, no. 6, pp. 1484–1495, 2021.
- [48] X. Zhang and Y. Lin, "Adaptive control of nonlinear time-delay systems with application to a two-stage chemical reactor," *IEEE Transactions on Automatic Control*, vol. 60, no. 4, pp. 1074–1079, 2015.
- [49] C. C. Hua, P. X. Liu, and X. P. Guan, "Backstepping control for nonlinear systems with time delays and applications to chemical reactor systems," *IEEE Transactions on Industrial Electronics*, vol. 56, no. 9, pp. 3723–3732, 2009.