Neurocomputing 153 (2015) 159–163

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Adaptive controller design-based neural networks for output constraint continuous stirred tank reactor

Dong-Juan Li [a], Da-Peng Li [b,*]

[a] School of Chemical and Environmental Engineering, Liaoning University of Technology, Jinzhou, Liaoning 121001, China
[b] School of Electrical Engineering, Liaoning University of Technology, Jinzhou, Liaoning 121001, China

ARTICLE INFO

Article history:
Received 19 September 2014
Received in revised form
14 November 2014
Accepted 23 November 2014
Communicated by H. Zhang
Available online 29 November 2014

Keywords:
Continuous stirred tank reactor
Adaptive control
The neural networks
Barrier Lyapunov function

ABSTRACT

For a class of continuous stirred tank reactor with output constraint and uncertainties, an adaptive control approach is proposed based on the approximation property of the neural networks. The considered systems can be viewed as a class of pure-feedback systems. At present, the control approach for the systems with output constraint is restricted to strict-feedback systems. No effective control approach is obtained for a general class of pure-feedback systems. In order to control this class of systems, the systems are decomposed by using the mean value theory, the unknown functions are approximated by using the neural networks, and Barrier Lyapunov function is introduced. Finally, it is proven that all the signals in the closed-loop system are bounded and the system output is not violated by using Lyapunov stability analysis method. A simulation example is given to verify the effectiveness of the proposed approach.

1. Introduction

Based on the approximation property of the fuzzy logic systems and the neural networks [1–5], the stability and control problems of the real systems had been addressed in [6–15]. Specifically, the adaptive control of uncertain nonlinear systems has attracted much attention and some significant works were obtained for nonlinear systems with completely unknown functions. In [16], Chen et al. designed an adaptive output feedback neural control for nonlinear SISO systems with time-delay to ensure the stability of the closed-loop system. The design idea of the method of [16] is extended to control nonlinear interconnected large-scale systems in [17]. Based on the small-gain theory, an adaptive fuzzy output feedback control was given in [18] for a class of nonlinear SISO systems with unmodelled dynamics. In [19], a robust adaptive neural network control algorithm was developed for uncertain nonlinear systems with unknown gain function and control direction. By combining the dynamic surface control method and the backstepping method, the complexity of the controller is reduced. Subsequently, some significant works are made in [20–35] for different classes of nonlinear systems by using the adaptive fuzzy or neural control. The above several methods in [20–29] were proposed for nonlinear affine systems. In [30–35], several adaptive control methods were proposed to stabilize the uncertain nonlinear nonaffine systems.

At present, the adaptive control for continuous stirred tank reactor (CSTR) based on the fuzzy logic systems and the neural networks have obtained many interests. Based on the approximation properties of the multi-step neural networks, an adaptive tracking control method was studied in [36] to be applied in CSTR. In [37], Zhang et al. provided an adaptive fuzzy sliding control to a general class of nonlinear systems and this method is used to control CSTR. In [38], a very effective and easy way is used to implement multiple model control. The simulation results showed that the fuzzy multiple model control can make a good tracking performance. In [39,40], two adaptive fuzzy control approaches were proposed for CSTR and the experiment results were given for validating the effectiveness. For SISO and MIMO CSTR with dead-zone, two adaptive neural network control approaches were presented in [41,42].

A common restriction in the above approaches is that output constraint problem is not considered. To this end, two adaptive controls were studied in [43,44] for nonlinear systems with output constraint by using Barrier Lyapunov function and the output constraint is not violated. In [45], an adaptive neural output feedback control algorithm was proposed for a class of nonlinear systems with output constraint and unknown function to ensure that the closed-loop system is uniformly bounded and the simulation example is given to verify the feasibility of the proposed method. The results in [42,45] can be only to control a class of strict-feedback systems. As

* Corresponding author. Tel: +864164199647.
E-mail addresses: ldjuan@126.com (D.-J. Li), 502433925@qq.com (D.-P. Li).

http://dx.doi.org/10.1016/j.neucom.2014.11.041
0925-2312/© 2014 Elsevier B.V. All rights reserved.

stated in [30], it is known that the pure-feedback systems are more general than strict-feedback ones.

In this paper, an adaptive neural network control problem is solved for a class of CSTR with unknown functions. The neural networks are used to approximate unknown function of systems. The considered reactor can be viewed as a class of nonlinear pure-feedback systems with output constraint.

The main contributions are as follows:

(1) At present, no effective adaptive control method is studied to control nonlinear pure-feedback systems with output constraint.
(2) To control this class of systems, the novel Barrier Lyapunov function is chosen and the mean-value theorem is correctly used to decompose the systems.

Based on the decomposed systems, a stable controller is designed. Using Lyapunov stability, it is proven that all the signals in the closed-loop system are bounded and the output constraint is not violated. A simulation example is illustrated to validate the feasibility of the approach.

2. System description

Consider the following model of continuous stirred tank reactors

$$\begin{cases} V\frac{dC_A}{dt'} = (C_{AF} - C_A)F - VK_0 \exp(E_a/RT)C_A \\ V\rho C_P\frac{dT}{dt'} = F\rho C_P(T_F - T) - hA(T - T_c) \\ -(\Delta H)VK_0 \times \exp(-\frac{E_a}{RT})C_A \end{cases} \tag{1}$$

where the meanings of some notations are listed in the following Table 1.

The following variables are introduced

$$\begin{cases} x_1 = \frac{C_{AF} - C_A}{C_{AF}}, \quad x_2 = \frac{T - T_F}{T_F}, \quad \varphi = \frac{E_a}{RT_F}, \\ t = t'\frac{F}{V}, \quad \delta = \frac{hA}{F\rho C_P}, \quad D_a = \frac{K_0 V e^{-\varphi}}{F}, \\ B = \frac{(-\Delta H)\varphi C_{AF}}{\rho C_P T_F}, \quad u = \frac{T_c - T_F}{T_F}\varphi \end{cases}$$

Then, Eq. (1) can be expressed as

$$\begin{cases} \dot{x}_1 = -x_1 + D_a(1 - x_1)\exp[x_2/(1 + (x_2/\varphi))] \\ \dot{x}_2 = -x_2(1+\delta) + BD_a(1 - x_1) \\ \qquad \times \exp[x_2/(1 + (x_2/\varphi))] + \delta u(t) \\ y = x_1 \end{cases} \tag{2}$$

where x_1 and x_2 denote the dimensionless reactant concentration and mixture temperature, respectively; u is the dimensionless coolant flow rate; control target of process is to use the coolant flow rate u control reactant temperature x_2; the physical parameters δ, φ, B and D_a denote the heat transfer coefficient, the activated energy, heat of reaction, and Damokhler number, respectively; $y = x_1$ is the output of system, be constrained in the compact set $|x_1| \le k_{c_1}$, where k_{c_1} is a number of normal.

Define

$$f_1(x_1, x_2) = -x_1 + D_a(1 - x_1)\exp[x_2/(1 + x_2/\varphi)]$$

$$f_2(x_1, x_2) = -x_2(1+\delta) + BD_a(1 - x_1)\exp[x_2/(1 + x_2/\varphi)]$$

Then, we can rewrite (2) as

$$\begin{cases} \dot{x}_1 = f_1(x_1, x_2) \\ \dot{x}_2 = f_2(x_1, x_2) + \delta u(t) \\ y = x_1 \end{cases} \tag{3}$$

In this paper, the our goal is to construct an adaptive NN scheme such that $y = x_1$ follows the reference signal $y_d(t)$ to a small set and all the signals in the closed-loop are retained to be bounded and the output constraint is not violated.

Remark 1. In (3), $f_1(x_1, x_2)$ is a nonaffine function of x_2. According to this characteristic, it is known that these systems can be seen as a class of nonlinear pure feedback system [30].

Remark 2. In [42,45], several kinds of adaptive control methods are designed to avoid the output constraints of the systems. However, these methods are proposed for strict-feedback systems and difficult to be applied in more complex pure feedback systems. Therefore, in this paper, an adaptive neural network control method is proposed to guarantee that the system output constraints are not violated for more complex nonlinear pure-feedback systems.

For the system (3), the assumptions and lemma are given as follows.

Assumption 1. There exist the constants $\overline{a} > \underline{a} > 0$ such that $\underline{a} \le \partial f_1(x_1, x_2)/\partial x_2 \le \overline{a}$.

Assumption 2. There exist the constants $\overline{\delta} > \underline{\delta} > 0$ such that $\underline{\delta} \le \delta \le \overline{\delta}$.

Assumption 3. For $k_{c_1} > 0$, there exist the constants $0 < A_0 \le k_{c_1}$ and A_1 such that $|y_d(t)| \le A_0$ and $|\dot{y}_d(t)| \le A_1$.

Lemma 1. *[36] $f(x, u)$ is assumed to be continuously differentiable and exists positive definite constant d such that $\partial f(x, u)/\partial u > d > 0$. Then, there exists a continuously function $u^* = u(x)$ such that $f(x, u^*) = 0$.*

Lemma 2. *[45] For any positive constant k_{b_1}, for all of e_1, there exists $|e_1| < k_{b_1}$ such that $\log \frac{k_{b_1}^2}{k_{b_1}^2 - e_1^2} < \frac{e_1^2}{k_{b_1}^2 - e_1^2}$.*

In the following, we will be briefly to introduce the approximation ability of the neural networks.

The approximation ability of neural networks has a unique advantage for pattern recognition, function approximation, etc. Nonlinear function $f(y): R \to R$ is approximated by the following RBF neural networks

$$f(y) = \eta^T \varsigma(y) + \varepsilon(y)$$

which, $\varsigma(y) = [\varsigma_1(y), \dots, \varsigma_N(y)]^T : \Omega \to R^N$ is smoothly known vector function, $N > 1$ indicate neural network nodes. $\varepsilon(y)$ indicates inherent error approximation of neural networks. $\varsigma_i(y), 1 \le i \le N$ is expressed by Gaussian function as follows:

$$\varsigma_i(y) = \exp\left[-\frac{(y - \upsilon_i)^2}{\tau^2}\right] \ge 0, \upsilon_i \in \Omega$$

Table 1
Parameters of the CSTR system.

Symbol	Physical significance
C_A	Concentration of component A
F	Feed velocity
C_{AF}	Input concentration of component A
F_c	Feed velocity of cooling water
K_0	Pre-exponential factor
R	Gas constant
E_a	Activation energy
ρ	Liquid densities
T_F	Feed temperature
V	Volume of tank
T	Reaction temperature
$-\Delta H$	Heat of reaction
h	Heat transfer area
C_P	Heat capacities
T_c	Inlet coolant temperature
F_c	Feed velocity of inlet coolant