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Adaptive neural network control for a two continuously stirred tank reactor with output constraints

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ABSTRACT

An adaptive control scheme is studied for a class of continuous stirred tank reactors (CSTR). The considered reactors can be viewed as a class of MIMO systems with unknown functions and interconnections as well as the output constraints. These properties of the reactors will lead to a completed task for designing a stable control algorithm. To this end, several unknown functions are approximated based on the neural approximation, a novel recursive design method is used to remove the interconnection term, and Barrier Lyapunov function is introduced to avoid the violation of the output constraints. The stability of the proposed scheme is proved based on the Lyapunov analysis method. A simulation example for continuous stirred tank reactor is illustrated to verify the validity of the algorithm.

1. Introduction

Recently, the stability of uncertain systems has received much interest because a great deal of practical systems can be represented as uncertain systems. The control problem of uncertain systems becomes especially importance. Large numbers of design strategies with system modeling function approximation and big Data etc. were studied in [1–16]. Specifically, it has received outstanding achievement in the area of adaptive control based on the neural or fuzzy approximation [17,18]. Much advancement has been made for uncertain nonlinear systems. For example, some scholars proposed a series of adaptive neural network controls for nonlinear dynamics systems in the strict-feedback systems [19,20], the pure-feedback systems [21,22], MIMO block-triangular systems [23–25], and pure-feedback discrete-time systems [26–28]. Subsequently, multifarious adaptive neural control approaches were provided for different classes of nonlinear dynamic systems [29–36]. In addition, adaptive output feedback controller design was studied in [37–47] for nonlinear systems with unmeasured states. However, the approaches do not consider the constraint problem. When the output constraint appears in the systems, these approaches are difficult to ensure the stability. To this end, the output constraint control approach-based adaptive technique was designed in [48] for nonlinear parametric systems with the output constraint. In [49], the full state constraint was considered in the plant and an adaptive control technique was proposed to control a class of nonlinear systems in parametric output canonical form. In [50], an adaptive output feedback control was studied for nonlinear systems with output constraint.

In real world, it is very significant for applying the theorem method to practical systems. In [51], an adaptive fuzzy control was developed to solve dynamic balance and motion for wheeled inverted pendulums with parametric and functional uncertainties and a systematic adaptation online mechanism is given to approximate the unknown parts. An adaptive neural approximation control was proposed in [52] for multiple mobile manipulators with considering time delays and input dead-zone. By designing a model reference neural control strategy with linear matrix inequalities and adaptive techniques, the control approach can guarantee that the tracking errors converge to zero whereas the coordination internal force errors remain bounded. In recent years, a much more attention has been allured for solving the control problems of continuous stirred tank reactors.

In [53], an adaptive multilayer neural tracking control was designed for a class of general nonlinear systems and it is to establish an ideal of implicit feedback linearization control. A temperature controller based on adaptive fuzzy and feedback linearization was developed in [54] for a class of continuous stirred tank reactors. It can achieve that H^{∞} tracking control performance with a prescribed attenuation level and the effectiveness of the controller can been validated by applying this approach to a benchmark chemical reactor. In [55], the control problem of continuous stirred tank reactors with dead-zone input was first studied and an adaptive compensate controller was provided to avoid the effect of dead-zone input. For a two continuous stirred tank reactor, the problem of almost disturbance

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decoupling was solved in [56]. Based on this result, the neural network-based control for a two continuous stirred tank reactor with dead-zone input was studied in [57] and a novel recursive method was constructed to remove the interconnection term and the effect of dead-zone input. These approaches are not to consider the constraint problem. When there are the constraints in the practical systems, it must to ensure that the constraints are not violated. In [58], an output constraint controller was designed for continuous stirred tank reactor. However, these approaches can only stabilize simple SISO systems and it is very difficult to control a two continuous stirred tank reactor.

Based on the above presentations, this paper will try to solve the adaptive control problem for a two continuous stirred tank reactor with the output constraints. This reactor can be viewed as a class of MIMO systems and contain the interconnections. In [48–50], the constraint is considered in simple SISO systems and they are not used to control MIMO. Thus, compared with the previous works, the approach in this paper can be applied to a general class of systems. In addition, the unknown interconnections are included in the considered reactor and it will lead to the difficulty in the design. To design a stability controller, the neural networks are used to approximate the unknown functions and the adaptive compensatory terms are given to compensate for the unknown parameters of approximator. Based on Barrier Lyapunov function, it is proved that the control approach can guarantee the stability of the closed-loop system and the output constraint is not violated. The effectiveness of the proposed approach can be verified by a simulation example.

2. System description and preliminaries

A two continuously stirred tank reactor process is given in [55,56], which is shown in Fig. 1.

An irreversible, exothermic reaction, $1 \rightarrow 2$, occurs in two reactors. Cooling water is added to the cooling jackets around both reactors at flow rates q_{j1} and q_{j2}, and at temperatures T_{j1} and T_{j2}, respectively. Assume that the volume of the cooling jackets is $V_{j1}=V_{j2}=V_j$; the volume of the reactor is $V_1=V_2=V$; and the flow of reactants are $q_0=q_2=q$ and $q_1=q+q_R$. The process is described by the following differential equations

$$\begin{cases} \frac{dC_{A1}}{dt}=\frac{q_0}{V}C_{A0}-\frac{q+q_R}{V}C_{A1}+\frac{q_R}{V}C_{A2}-\alpha C_{A1}e^{-(E_a/RT_1)} \\ \frac{dC_{A2}}{dt}=\frac{q+q_R}{V}C_{A1}-\frac{q+q_R}{V}C_{A2}-\alpha C_{A2}e^{-(E_a/RT_2)} \end{cases} \quad (1)$$

$$\begin{cases} \frac{dT_1}{dt}=\frac{q_0}{V}T_0-\frac{q+q_R}{V}T_1+\frac{q_R}{V}T_2 \\ -\frac{\alpha\lambda}{\rho c_p}C_{A1}e^{-(E_a/RT_1)}-\frac{UA}{\rho c_p V}(T_1-T_{j1}) \\ \frac{dT_2}{dt}=\frac{q_0}{V}T_1-\frac{q+q_R}{V}T_2-\frac{\alpha\lambda}{\rho c_p}C_{A2}e^{-(E_a/RT_2)} \\ -\frac{UA}{\rho c_p V}(T_2-T_{j2}) \end{cases} \quad (2)$$

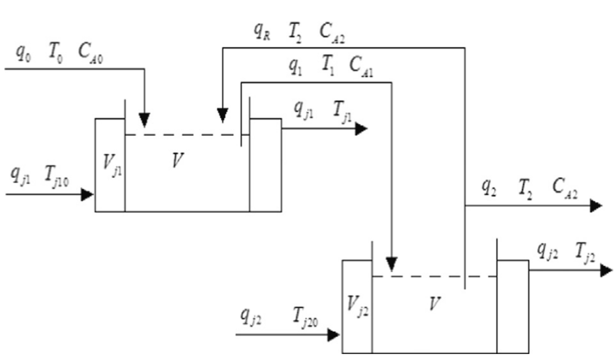

Fig. 1. Two continuous stirred tank reactor.

$$\begin{cases} \frac{dT_{j1}}{dt}=\frac{q_{j1}}{V_j}(T_{j10}-T_{j1})-\frac{UA}{\rho_j c_j V_j}(T_1-T_{j1}) \\ \frac{dT_{j2}}{dt}=\frac{q_{j2}}{V_j}(T_{j20}-T_{j2})-\frac{UA}{\rho_j c_j V_j}(T_2-T_{j2}) \end{cases} \quad (3)$$

Let $x_{11}=C_{A2}-C_{A2}^d$, $x_{12}=f_2$, $x_{21}=T_2-T_2^d$, $x_{22}=T_{j2}-T_{j2}^d$, $x_{31}=T_1-T_1^d$, and $x_{32}=T_{j1}-T_{j1}^d$. Then, the systems (1)–(3) can be changed to

$$\begin{cases} \dot{x}_{11}=g_{11}x_{12}, \dot{x}_{12}=g_{12}u_1, y_1=x_{11} \\ \dot{x}_{21}=g_{21}x_{22}+\phi_{21}+\Phi x_{31}, \dot{x}_{22}=g_{22}u_2+\phi_{22}, y_2=x_{21} \\ \dot{x}_{31}=g_{31}x_{32}+\phi_{31}+\Psi\omega, \dot{x}_{32}=g_{32}u_3+\phi_{32}, y_3=x_{31} \end{cases} \quad (4)$$

where

$$g_{11}=1, g_{12}=1;\ g_{21}=\frac{UA}{\rho c_p V},\ g_{22}=\frac{q_{j2}}{V_j},\ g_{31}=\frac{UA}{\rho c_p V}$$

$$g_{32}=\frac{q_{j1}}{V_j}, \Psi=\frac{q_0}{V},\ \Phi=\frac{q+q_R}{V},\ \omega=T_0-T_0^d$$

$$u_1=\frac{(q+q_R)q_0}{V^2}C_{A0}-f_4,\ u_2=T_{j20}-T_{j20}^d,\ u_3=T_{j10}-T_{j10}^d$$

$$C_{A1}=\frac{V}{q+q_R}\Big[x_{12}+\frac{q+q_R}{V}\left(x_{11}+C_{A2}^d\right) +\alpha\left(x_{11}+C_{A2}^d\right)e^{-\left(E_a/R\left(x_{21}+T_2^d\right)\right)}\Big]$$

$$\phi_{21}=\frac{q+q_R}{V}T_1^d-\frac{q+q_R}{V}\left(x_{21}+T_2^d\right)-\frac{\alpha\lambda}{\rho c_p}\left(x_{11}+C_{A2}^d\right) \times e^{-\left(E_a/R\left(x_{21}+T_2^d\right)\right)}-\frac{UA}{\rho c_p V}\left(x_{21}+T_2^d-T_{j2}^d\right)$$

$$\phi_{22}=\frac{q_{j2}}{V}\left(T_{j20}^d-x_{22}-T_{j2}^d\right)+\frac{UA}{\rho_j c_j V_j}\left(x_{21}+T_2^d-x_{22}-T_{j2}^d\right)$$

$$\phi_{31}=\frac{q_0}{V}T_0^d-\frac{q+q_R}{V}\left(x_{31}+T_1^d\right)-\frac{\alpha\lambda}{\rho c_p}C_{A1}e^{-\left(E_a/R\left(x_{31}+T_1^d\right)\right)} -\frac{q_R}{V}\left(x_{21}+T_2^d\right)-\frac{UA}{\rho c_p V}\left(x_{31}+T_1^d-T_{j1}^d\right)$$

$$\phi_{32}=\frac{q_{j1}}{V_j}\left(T_{j10}^d-x_{32}-T_{j1}^d\right)+\frac{UA}{\rho_j c_j V_j}\left(x_{31}+T_1^d-x_{32}-T_{j1}^d\right)$$

$$f_1=\frac{q+q_R}{V}C_{A1}+\frac{q_R}{V}C_{A2}-\alpha C_{A1}e^{-(E_a/RT_1)}$$

$$f_2=\frac{q+q_R}{V}C_{A1}-\frac{q_R}{V}C_{A2}-\alpha C_{A2}e^{-(E_a/RT_2)}$$

$$f_3=\frac{q+q_R}{V}T_1-\frac{q_R}{V}T_2-\frac{\alpha\lambda}{\rho c_p}C_{A2}e^{-(E_a/RT_2)}-\frac{UA}{\rho c_p V}(T_2-T_{j2})$$

$$f_4=\frac{q+q_R}{V}f_1-\left(\frac{q+q_R}{V}+\alpha e^{-(E_a/RT_2)}\right)f_2 -\alpha\frac{E_a}{RT_2^2}C_{A2}e^{-(E_a/RT_2)}f_3$$

In the system (4), the output variables $y_i, i=1,2,3$ are constrained in the compact sets $\Omega_i=\{y_i||y_i|\le k_{c_i}\}$ where k_{c_i} is a constant.

The control objective is to design an adaptive NN controller for the system (4) such that all the signals in the closed-loop system are bounded and the constraint of the system output is not violated.

Because the system (4) contains the unknown functions, they can be used in the controller. Due to the approximation property of the neural networks, they have been used in the control problem and modeling of the nonlinear systems. The approximation property of the neural networks can be founded in [4]. Using the neural networks, unknown functions $f(y): R \rightarrow R$ can be expressed as

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

where η^* is the optimal weight vector, $\varsigma(y)=[\varsigma_1(y),\cdots,\varsigma_N(y)]^T$ are fuzzy basis function vector and $\varepsilon(y)$ is the approximation error.

Assumption 1. [17] η^* and $\varepsilon(y)$ are bounded, i.e., $\|\eta^*\|\le\overline{\eta}$ and $|\varepsilon(X)|\le\varepsilon^*$.

Remark 1. In [48–50,58], several adaptive control schemes were designed for uncertain nonlinear systems to avoid the output