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Design & Analysis of Advanced Adaptive Neuro Fuzzy Interface systems for Nonlinear Networked Control Systems

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Abstract—*This paper studies the problem of adaptive fuzzy control for a category of single-input single-output nonlinear networked control systems with network-induced delay and data loss based on adaptive backstepping control approach. Fuzzy logic systems are used to approximate the unknown nonlinear characteristics existing in the system, while Pade approximation is introduced to handle network-induced delay. Data loss occurs intermittently and stochastically in the data transmitting process,which is regarded as the delay in the controller design. In the framework of adaptive fuzzy back stepping technique, a novel state-feedback adaptive controller is constructed to ensure all signals in the resulting closed-loop system to be bounded and the state variables can be regulated to the origin. Finally, two examples are given to show the validity of the proposed results.*

Index Terms—Adaptive fuzzy control, networked control systems (NCSs), network-induced delay.

I. INTRODUCTION

NONLINEAR characteristics often occur in modernindustries. Some advanced control methods have been provided to cope with nonlinear systems [1]–[5]. Via using adaptive control scheme, the authors in [6]–[8] studied the problem of adaptive control for a class of nonlinear systems. A category of nonlinear systems were investigated through using fuzzy control in [9]–[14]. Sliding mode control was employed to stabilize nonlinear systems in [15]–[18]. Different from the above strategies, combining frequency-domain analysis and volterra-series-expansion-based control, Jing [19] studied the problem of nonlinear analysis and design. Manuscript received August 31, 2016; revised December 19, 2016; accepted February 19, 2017. This work was supported in part by the National Natural Science Foundation of China under Grant 61525303, Grant 61503099, Grant 61622302, and Grant 61573070, in part by the China Postdoctoral With these advantages, NCSs have been widely applied to industrial processes. Though NCSs boost the improvement of industrial processes, researchers and engineers have to face some challenges caused by communication networks, such as data packet dropouts, network-induced delay, and quantization. To overcome these obligations, considerable attention has been paid [21], [22].

For random data loss, Bernoulli stochastic distribution process and Markov chain were introduced to describe such a phenomenon in [23]. As an modification, Qiu*et al.* [24] proposed

novel approaches to describe imperfect communication links, and designed corresponding controllers to stabilize the NCSs. To address random delay, Liu *et al.* [25] transformed the linear

NCSs into a Markovian jump linear system, and then studied the stabilization problem. As to systems with data quantization, an event-triggered control strategy was developed in [26].

In a uniformed framework, data loss, network-induced delay, and quantization were taken into

consideration simultaneously in [27]. The existing results on linear NCSs cannot be applied to
nonlinear ones directly due to complex nonlinearities. Some of the above advanced control methods have been applied to modeling, analysis, and synthesis for nonlinear NCSs. For example, based on fuzzy Takagi–Sugeno (T–S) model, a statefeedbackcontrol strategy was proposed for nonlinear NCSs in presence of data loss and network-induced delay, and applied to a flexible-joint robot system in [28]. To address the unmeasurable states problem, Qiu*et al.* [29] provided a piecewiseoutput-based control scheme for NCSs in the framework offuzzy T–S model. In addition, considerable remarkable nonlinear NCSs results based on fuzzy T–S model have been published in literature, including filter [30], fault detection and isolation [31], fault-tolerant control [32], and model predictive control [33]. It should be noticed that existing schemes in the framework of T–S fuzzy model involve computing a group of linear matrix inequalities, which may lead to complex computation.

In addition to the computational complexity, the coupling variables is also an obstacle to obtain the sufficient conditions to synthesize systems. Combining adaptivecontrol with sliding mode control approaches, a novel adaptivesliding mode controller was designed for single-input single-output (SISO) nonlinear NCSs in [34]. The control strategy in [34] can be implemented easily due to its simple and structural steps, in which only some adaptive parameters and the designed controller require computing. Despite some improvements have been achieved in [34], the proposed control algorithm is limited to a category of simple strict-feedback systems, which do not comprise mismatched unknown uncertain nonlinear functions. As a structured control method, backstepping approach can be utilized to tackle mismatched uncertain items through designing a virtual control signal stepby-step, which has received considerable attention [35]–[37].

An output-based adaptive fuzzy control method was provided for multi-input and multi-output systems in [38]. Considering input constraints in discrete nonlinear systems, an observerbased adaptive fuzzy control scheme was developed . To address the problem of fault-tolerant control, Tong *et al.* combined adaptive backstepping with fuzzy logic systems (FLSs), and proposed a novel fault-tolerant controller for large-scale nonlinear systems in the strict-feedback form. However, the adaptive backstepping control problem for nonlinear NCSs has not been adequately researched yet, and this is the motivation for this paper.The adaptive fuzzy control problem for a category of SISO nonlinear NCSs in presence of network-induced delay and data loss is investigated through employing adaptive backsteppingcontrol technique. FLSs are employed to recognize unknown nonlinear characteristics in the system. The main contributions of this paper can be summarized as follows.

1) The adaptive backstepping control approach is utilized to account for the controller design for NCSs, and only some adaptive parameters, designed virtual control signals and controller need computing. Compared with existing results involving linear matrix inequalities, the computational complexity can be decreased to some degree.

2) Both random data loss and network-induced delay aretaken into consideration, therein Pade approximation is introduced to handle network-induced delay. In order to overcome the difficulty resulting from delay, a novel change of coordinates method is inspired by recalling the scheme concerning input saturation. Finally, illustrative examples are presented to demonstrate the validity and the applicability of the proposed method. The remaining paper is organized as follows. Section II provides problem formulation. The process of adaptive controller design is

presented in Section III. Section IV provides the simulation results and Section V concludes this paper.

II. PROBLEM FORMULATION

Some main preliminaries are provided in this section. First, we describe the considered nonlinear NCSs, which are transformed from traditional systems due to the use of communication

networks. Pade approximation method is followed to demonstrate how to separate network-induced delay from controller. At the end of this section, a clear description for FLSs is given.

A. System Description

The SISO nonlinear system considered in this paper is as follows:

$$\begin{aligned} \dot{x}_i &= x_{i+1} + f_i(\bar{x}_i) + \delta_i(x,t), \quad i = 1,2,\ldots,n-1 \\ \dot{x}_n &= u(t) + f_n(\bar{x}_n) + \delta_n(x,t) \\ y &= x_1 \end{aligned} \tag{1}$$

where$x = \bar{x}_n = [x1, x2, \ldots, xn]^T \in R^n$ and $y \in R$ stand for state and output, respectively. $\bar{x}_i = [x1, x2, \ldots, x_i]^T$, $f_i(\bar{x}_i)$ stands for unknown nonlinear function. $f_i(0, 0, \ldots, 0) = 0$. $\delta_i(x, t)$ denotes the bounded disturbance and satisfies $|\delta_i(x, t)| \le D_i$. System in (1) stands for a class of traditional nonlinear SISO strict-feedback systems. Due to the insertion of the communication network, network-induced delay needs to be considered. In this paper, the input delay isconsidered and the followingform is introduced for NCSs:

$$\begin{aligned} \dot{x}_i &= x_{i+1} + f_i(\bar{x}_i) + \delta_i(x,t), \quad i = 1,2,\ldots,n-1 \\ \dot{x}_n &= u(t-\tau) + f_n(\bar{x}_n) + \delta_n(x,t) \\ y &= x_1 \end{aligned} \tag{2}$$

whereτ stands for network-induced delay. In order to handle delay, Pade approximation technique is introduced as follows:

$$\mathcal{L}\{u(t-\tau)\} = e^{(-\tau s)}\mathcal{L}\{u(t)\} = \frac{e^{\left(\frac{-\tau s}{2}\right)}}{e^{\left(\frac{\tau s}{2}\right)}}\mathcal{L}\{u(t)\} \approx \frac{1-\frac{\tau s}{2}}{1+\frac{\tau s}{2}}\mathcal{L}\{u(t)\}$$

where$L\{u(t)\}$ means the Laplace transform of $u(t)$. $s$is the Laplace variable. Then, the following variable x_{n+1} is defined:

$$\frac{1-\frac{\tau s}{2}}{1+\frac{\tau s}{2}}\mathcal{L}\{u(t)\} = \mathcal{L}\{x_{n+1}(t)\} - \mathcal{L}\{u(t)\}.$$

According to Z transform, we can get

$$u - \frac{\tau\dot{u}}{2} = x_{n+1} + \frac{\tau\dot{x}_{n+1}}{2} - u - \frac{\tau\dot{u}}{2}$$

which yields

$$\dot{x}_{n+1} = -\bar{\tau}x_{n+1} + 2\bar{\tau}u$$

where $\bar{\tau} = (2/\tau)$.

Then, system (2) is described as

$$\begin{aligned} \dot{x}_i &= x_{i+1} + f_i(\bar{x}_i) + \delta_i(x,t) \\ \dot{x}_n &= (x_{n+1} - u(t)) + f_n(x) + \delta_n(x,t) \\ \dot{x}_{n+1} &= -\bar{\tau}x_{n+1} + 2\bar{\tau}u \\ y &= x_1. \end{aligned} \tag{3}$$

B. Fuzzy Logic Systems

The nonlinear terms existing in the system are approximated via using FLSs, which are described as follows.

Fuzzy Rule j: IF $x1$ is M_j1, and $x2$ is M_j2 and, . . . , and $x_n$is M_jn, THEN

yis Nj, j = 1,2, . . .,^

where$x = [x1, x2, \ldots, xn]^T$ is the system input, y stands for the system output. M_jl, N_j, $uM_jl(x_l)$ and $uN_j(y)$ are the fuzzysets and membership functions, respectively. _ represents the number of fuzzy rules.Then, the fuzzy dynamics system is as follows:

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$$y(x) = \frac{\sum_{j=1}^{\Lambda} \tilde{y}_j \prod_{l=1}^{n} u_{M_{jl}}(x_l)}{\sum_{j=1}^{\Lambda} \prod_{l=1}^{n} u_{M_{jl}}(x_l)} \quad (4)$$

where˜yj= maxy∈RuNj(y). The membership functions are defined as

$$\phi_j(x) = \frac{\prod_{l=1}^{n} u_{M_{jl}}(x_l)}{\sum_{j=1}^{\Lambda} \prod_{l=1}^{n} u_{M_{jl}}(x_l)}.$$

Define $\chi = [\tilde{y}_1, \tilde{y}_2, \ldots, \tilde{y}_\Lambda]^T = [\chi_1, \chi_2, \ldots, \chi_\Lambda]^T$ and $\phi(x) = [\phi_1(x), \phi_2(x), \ldots, \phi_\Lambda(x)]^T$. Then, the system in (4) is rewritten as

$$y(x) = \chi^T \phi(x). \quad (5)$$

Lemma 1 [42]: For any smooth function *f (x)* defined on the compact set _, there exists a sufficient small scalar ε >0such that the following inequality holds:

$$\sup_{x\in\Omega} \left| f(x) - \chi^T \phi(x) \right| \le \varepsilon$$

whereε is the estimation error.

III. ADAPTIVE CONTROL DESIGN

The main results are provided in this section. Before deriving immediate control signals, adaptive laws, and the desired controller, the change of coordinates should be considered as follows:

$$e_1 = x_1$$
$$e_i = x_i - \alpha_{i-1}, \quad i = 2, 3, \ldots, n-1$$
$$e_n = x_n - \alpha_{n-1} + \frac{1}{\bar{\tau}} x_{n+1}$$

whereαi *(i* = 1, 2, . . . , *n* − 1*)* will be given in the following part.

Remark 5: It can be seen from the above change of coordinates, *en* is different from the definition of existing control systems. In order to eliminate the variable *xn*+1, we introduce the item *(1/* ¯ *τ)xn*+1 in the last step, which is similar to the design of coping with input saturation. The first immediate control signal $\alpha 1$ as well as the adaptive law$\theta 1$ are as follows:

$$\alpha_1 = -k_1 e_1 - \frac{e_1 \hat{\theta}_1 \phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} - \frac{e_1}{2} \quad (6)$$

$$\dot{\hat{\theta}}_1 = \frac{\eta_1 e_1^2 \phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} - \sigma_1 \hat{\theta}_1 \quad (7)$$

where*ki*>0*, ρi*>0*, ηi*>0, and *σi*>0 are constants to be designed. ˆ *θi*is the estimation of *θi*and ˆ *θi*= *θi*− ˜ *θi*. The following desired controller *u* and the adaptive law *θn*are designed:

$$u = -k_n e_n - \frac{e_n \hat{\theta}_n \phi_n^T(x)\phi_n(x)}{2\rho_n^2} - \frac{e_n}{2} \quad (10)$$

$$\dot{\hat{\theta}}_n = \frac{\eta_n e_n^2 \phi_n^T(x)\phi_n(x)}{2\rho_n^2} - \sigma_n \hat{\theta}_n \quad (11)$$

where*kn*>0*, ρn*>0*, ηn*>0, and *σn*>0 are constants to be determined. ˆ *θn*represents the estimation of *θn*and ˆ *θn*= *θn*−˜ *θn*. Based on the aforementioned design concluding equationsin (6)–(10), the variables in system (2) can be ensured to bebounded, and can be also driven to the origin. In the followingpart, the detailed proof will be provided.

Theorem 1: Under the immediate control signals *αi* (6) as well as (8), the adaptive law˙ˆ*θi*(7), (9) as well as (11) andthe desired controller *u* (10), the variables of system (2) can be ensured to be bounded and system state variables can be driven to the origin.

Proof: The proof is divided into the following *n* steps.

Step 1: The derivative of *e*1 can be calculated as follows:

$$\dot{e}_1 = \dot{x}_1 = x_2 + f_1(x_1) + \delta_1(x, t).$$

The following Lyapunov function is defined:

$$V_1 = \frac{1}{2}e_1^2 + \frac{1}{2\eta_1}\tilde{\theta}_1^2. \quad (12)$$

The derivative of $V1$ can be computed as

$$\dot{V}_1 = e_1\dot{e}_1 - \frac{1}{\eta_1}\tilde{\theta}_1\dot{\hat{\theta}}_1$$
$$= e_1(x_2 + f_1(x_1) + \delta_1(x,t)) - \frac{1}{\eta_1}\tilde{\theta}_1\dot{\hat{\theta}}_1. \quad (13)$$

According to Young's inequality, one can obtain

$$e_1\delta_1(x,t) \le \frac{e_1^2 D_1^2}{2a_1^2} + \frac{a_1^2}{2}. \quad (14)$$

Substituting (14) into (13), we can get

$$\dot{V}_1 \le e_1\left(x_2 + f_1(x_1) + \frac{e_1 D_1^2}{2a_1^2}\right) + \frac{a_1^2}{2} - \frac{1}{\eta_1}\tilde{\theta}_1\dot{\hat{\theta}}_1. \quad (15)$$

Define $\bar{f}1(x1) = f1(x1) + (e1D21/2a21)$. According to Lemma 1, we can obtain $\bar{f}1(x1) = \chi T1\ \varphi1(x1) + \varepsilon1(x1)$where$|\varepsilon1(x1)| \le \varepsilon1$ with $\varepsilon1$ being a known scalar.

$$\dot{V}_1 \le e_1\left(x_2 + \chi_1^T\phi_1(x_1) + \varepsilon_1\right) + \frac{a_1^2}{2} - \frac{1}{\eta_1}\tilde{\theta}_1\dot{\hat{\theta}}_1. \quad (16)$$

By using Young's inequality, we can have

$$e_1\chi_1^T\phi_1(x_1) \le \frac{e_1^2\|\chi_1\|^2\phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} + \frac{\rho_1^2}{2} \quad (17)$$

$$e_1\varepsilon_1 \le \frac{e_1^2}{2} + \frac{\varepsilon_1^2}{2}. \quad (18)$$

Substituting (17) and (18) into (16), we can get

$$\dot{V}_1 \le e_1\left(\frac{e_1\|\chi_1\|^2\phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} + \frac{e_1}{2} + x_2\right) + \frac{\rho_1^2 + \varepsilon_1^2 + a_1^2}{2} - \frac{1}{\eta_1}\tilde{\theta}_1\dot{\hat{\theta}}_1.$$

Defining $\theta_1 = \|\chi_1\|^2$, we have

$$\dot{V}_1 \le e_1\left(\frac{e_1\theta_1\phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} + \frac{e_1}{2} + x_2\right) + \frac{\rho_1^2 + \varepsilon_1^2 + a_1^2}{2} - \frac{1}{\eta_1}\tilde{\theta}_1\dot{\hat{\theta}}_1. \quad (19)$$

In order to stabilize the first order subsystem, choose the following virtual control signal:

$$\alpha_1 = -k_1e_1 - \frac{e_1\hat{\theta}_1\phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} - \frac{e_1}{2}.$$

Substituting virtual control signal $\alpha1$ into (19), we can get

$$\dot{V}_1 \le -k_1e_1^2 + \frac{e_1^2\tilde{\theta}_1\phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} + e_1e_2 + \frac{\rho_1^2 + \varepsilon_1^2 + a_1^2}{2} - \frac{1}{\eta_1}\tilde{\theta}_1\dot{\hat{\theta}}_1$$
$$= -k_1e_1^2 + \frac{\tilde{\theta}_1}{\eta_1}\left(\frac{\eta_1e_1^2\phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} - \dot{\hat{\theta}}_1\right) + e_1e_2 + \frac{\rho_1^2 + \varepsilon_1^2 + a_1^2}{2}.$$

Step 2: The derivative of $e2$ can be obtained as follows:

$$\dot{e}_2 = \dot{x}_2 - \dot{\alpha}_1$$
$$= x_3 + f_2(\bar{x}_2) + \delta_2(x,t) - \dot{\alpha}_1.$$

The Lyapunov function is defined as follows:

$$V_2 = V_1 + \frac{1}{2}e_2^2 + \frac{1}{2\eta_2}\tilde{\theta}_2^2. \quad (20)$$

The derivative of $V2$ can be computed as

$$\dot{V}_2 = \dot{V}_1 + e_2\dot{e}_2 - \frac{1}{\eta_2}\tilde{\theta}_2\dot{\hat{\theta}}_2$$
$$\le -k_1e_1^2 + e_2(x_3 + f_2(\bar{x}_2) + \delta_2(x,t) - \dot{\alpha}_1 + e_1) - \frac{1}{\eta_2}\tilde{\theta}_2\dot{\hat{\theta}}_2 + \frac{\rho_1^2 + \varepsilon_1^2 + a_1^2}{2} + \frac{\tilde{\theta}_1}{\eta_1}\left(\frac{\eta_1e_1^2\phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} - \dot{\hat{\theta}}_1\right). \quad (21)$$

Based on Young's inequality, we obtain

$$e_2\delta_2(x,t) \le \frac{e_2^2D_2^2}{2a_2^2} + \frac{a_2^2}{2}. \quad (22)$$

Substituting (22) into (21), we can get

$$\dot{V}_2 \le -k_1 e_1^2 + e_2\left(x_3 + f_2(\bar{x}_2) + \frac{e_2 D_2^2}{2a_2^2} - \dot{\alpha}_1 + e_1\right) - \frac{1}{\eta_2}\tilde{\theta}_2\dot{\hat{\theta}}_2 + \frac{\tilde{\theta}_1}{\eta_1}\left(\frac{\eta_1 e_1^2 \phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} - \dot{\hat{\theta}}_1\right) + \frac{a_2^2}{2} + \frac{\rho_1^2 + \varepsilon_1^2 + a_1^2}{2}. \quad (23)$$

Define ¯ $f2(¯x2) = f2(¯x2) + (e2D22 /2a22)−\ \dot{}\alpha1 + e1$.
According to Lemma 1, we can obtain

$$\bar{f}_2(\bar{x}_2) = \chi_2^T \phi_2(\bar{x}_2) + \varepsilon_2(\bar{x}_2)$$

where$|\varepsilon2(¯x2)| \le \varepsilon2$ with $\varepsilon2$ being a known scalar.
Then, inequality (23) can be rewritten as

$$\dot{V}_2 \le -k_1 e_1^2 + e_2(x_3 + \chi_2^T \phi_2(\bar{x}_2) + \varepsilon_2) - \frac{1}{\eta_2}\tilde{\theta}_2\dot{\hat{\theta}}_2 + \frac{\tilde{\theta}_1}{\eta_1}\left(\frac{\eta_1 e_1^2 \phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} - \dot{\hat{\theta}}_1\right) + \frac{a_2^2}{2} + \frac{\rho_1^2 + \varepsilon_1^2 + a_1^2}{2}. \quad (24)$$

Based on Young's inequality, we can have

$$e_2 \chi_2^T \phi_2(\bar{x}_2) \le \frac{e_2^2 \|\chi_2\|^2 \phi_2^T(\bar{x}_2)\phi_2(\bar{x}_2)}{2\rho_2^2} + \frac{\rho_2^2}{2} \quad (25)$$

$$e_2 \varepsilon_2 \le \frac{e_2^2}{2} + \frac{\varepsilon_2^2}{2}. \quad (26)$$

Substituting (25) and (26) into (24), we can get

$$\dot{V}_2 \le -k_1 e_1^2 + e_2\left(\frac{e_2 \|\chi_2\|^2 \phi_2^T(\bar{x}_2)\phi_2(\bar{x}_2)}{2\rho_2^2} + \frac{e_2}{2} + x_3\right) + \frac{\tilde{\theta}_1}{\eta_1}\left(\frac{\eta_1 e_1^2 \phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} - \dot{\hat{\theta}}_1\right) - \frac{1}{\eta_2}\tilde{\theta}_2\dot{\hat{\theta}}_2 + \sum_{l=1}^{2}\frac{\rho_l^2 + \varepsilon_l^2 + a_l^2}{2}.$$

Defining $\theta2 = \_\chi2\_2$, we have

$$\dot{V}_2 \le -k_1 e_1^2 + e_2\left(\frac{e_2 \theta_2 \phi_2^T(\bar{x}_2)\phi_2(\bar{x}_2)}{2\rho_2^2} + \frac{e_2}{2} + x_3\right) - \frac{1}{\eta_2}\tilde{\theta}_2\dot{\hat{\theta}}_2 + \frac{\tilde{\theta}_1}{\eta_1}\left(\frac{\eta_1 e_1^2 \phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} - \dot{\hat{\theta}}_1\right) + \sum_{l=1}^{2}\frac{\rho_l^2 + \varepsilon_l^2 + a_l^2}{2}. \quad (27)$$

In order to stabilize the second order subsystem, choose the following virtual control signal:

$$\alpha_2 = -k_2 e_2 - \frac{e_2 \hat{\theta}_2 \phi_2^T(\bar{x}_2)\phi_2(\bar{x}_2)}{2\rho_2^2} - \frac{e_2}{2}.$$

Substituting virtual control signal $\alpha2$ into (27), we can get

$$\begin{aligned}\dot{V}_2 &\le -\sum_{l=1}^{2} k_l e_l^2 + \frac{e_2^2 \tilde{\theta}_2 \phi_2^T(\bar{x}_2)\phi_2(\bar{x}_2)}{2\rho_2^2} + e_2 e_3 - \frac{1}{\eta_2}\tilde{\theta}_2\dot{\hat{\theta}}_2 + \frac{\tilde{\theta}_1}{\eta_1}\left(\frac{\eta_1 e_1^2 \phi_1^T(x_1)\phi_1(x_1)}{2\rho_1^2} - \dot{\hat{\theta}}_1\right) + \sum_{l=1}^{2}\frac{\rho_l^2 + \varepsilon_l^2 + a_l^2}{2} \\ &= -\sum_{l=1}^{2} k_l e_l^2 + \sum_{l=1}^{2}\frac{\tilde{\theta}_l}{\eta_l}\left(\frac{\eta_l e_l^2 \phi_l^T(\bar{x}_l)\phi_l(\bar{x}_l)}{2\rho_l^2} - \dot{\hat{\theta}}_l\right) + e_2 e_3 + \sum_{l=1}^{2}\frac{\rho_l^2 + \varepsilon_l^2 + a_l^2}{2}.\end{aligned}$$

Similar to the steps 1 and 2, one can obtain

$$\begin{aligned}\bar{V}_i &\le -\sum_{l=1}^{i-1} k_l e_l^2 + \sum_{l=1}^{i-1}\frac{\rho_l^2 + \varepsilon_l^2 + a_l^2}{2} + \sum_{l=1}^{i-1}\frac{\tilde{\theta}_l}{\eta_l}\left(\frac{\eta_l e_l^2 \phi_l^T(\bar{x}_l)\phi_l(\bar{x}_l)}{2\rho_l^2} - \dot{\hat{\theta}}_l\right) - \frac{1}{\eta_i}\tilde{\theta}_i\dot{\hat{\theta}}_i \\ &\quad + e_i(x_{i+1} + f_i(\bar{x}_i) + \delta_i(x,t) - \dot{\alpha}_{i-1} + e_{i-1}) \\ &\le -\sum_{l=1}^{i-1} k_l e_l^2 + \sum_{l=1}^{i}\frac{\rho_l^2 + \varepsilon_l^2 + a_l^2}{2} + e_i e_{i+1} + \sum_{l=1}^{i}\frac{\tilde{\theta}_l}{\eta_l}\left(\frac{\eta_l e_l^2 \phi_l^T(\bar{x}_l)\phi_l(\bar{x}_l)}{2\rho_l^2} - \dot{\hat{\theta}}_l\right) \\ &\quad + e_i\left(\frac{e_i \hat{\theta}_i \phi_i^T(\bar{x}_i)\phi_i(\bar{x}_i)}{2\rho_i^2} + \frac{e_i}{2} + \alpha_i\right) \quad (28)\end{aligned}$$

where$\theta i = _\chi i_2$. Following the virtual control signal αi defined in (8), (28)can be computed as

$$\dot{V}_i \le -\sum_{l=1}^{i} k_l e_l^2 + \sum_{l=1}^{i}\frac{\tilde{\theta}_l}{\eta_l}\left(\frac{\eta_l e_l^2 \phi_l^T(\bar{x}_l)\phi_l(\bar{x}_l)}{2\rho_l^2} - \dot{\hat{\theta}}_l\right) + e_i e_{i+1} + \sum_{l=1}^{i}\frac{\rho_l^2 + \varepsilon_l^2 + a_l^2}{2}.$$

Step n: The derivative of *en* is calculated as follows:

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$$\begin{aligned}\dot{e}_n &= \dot{x}_n - \dot{\alpha}_{n-1} + \frac{1}{\bar{\tau}}\dot{x}_{n+1} \\ &= x_{n+1} - u + f_n(x) + \delta_n(x,t) \\ &\quad - \dot{\alpha}_{i-1} + \frac{1}{\bar{\tau}}(-\bar{\tau}x_{n+1} + 2\bar{\tau}u) \\ &= u + f_n(x) + \delta_n(x,t) - \dot{\alpha}_{i-1}.\end{aligned}$$

Similarly, we can obtain

$$\begin{aligned}\dot{V}_n &= \dot{V}_{n-1} + e_n\dot{e}_n - \frac{1}{\eta_n}\tilde{\theta}_n\dot{\hat{\theta}}_n \\ &\le -\sum_{l=1}^{n} k_l e_l^2 + \sum_{l=1}^{n}\frac{\tilde{\theta}_l}{\eta_l}\left(\frac{\eta_l e_l^2 \phi_l^T(\bar{x}_l)\phi_l(\bar{x}_l)}{2\rho_l^2} - \dot{\hat{\theta}}_l\right) \\ &\quad + \sum_{l=1}^{n}\frac{\rho_l^2 + \varepsilon_l^2 + a_l^2}{2}.\end{aligned} \quad (29)$$

Submitting predefined adaptive laws ˙ˆ*θi*(*i* = 1, 2 . . . *n*)into (29) yields

$$\dot{V}_n \le -\sum_{l=1}^{n} k_l e_l^2 + \sum_{l=1}^{n}\frac{\sigma_l\tilde{\theta}_l\hat{\theta}_l}{\eta_l} + \sum_{l=1}^{n}\frac{\rho_l^2 + \varepsilon_l^2 + a_l^2}{2}.$$

According to Young's inequality and $\hat{\theta}_l = \theta_l - \tilde{\theta}_l$, one can obtain

$$\tilde{\theta}_l\hat{\theta}_l = \tilde{\theta}_l(\theta_l - \tilde{\theta}_l) \le \frac{1}{2}\theta_l^2 - \frac{1}{2}\tilde{\theta}_l^2.$$

Then, we can obtain

$$\dot{V}_n \le -\sum_{l=1}^{n}\left(k_l e_l^2 + \frac{\sigma_l}{2\eta_l}\tilde{\theta}_l^2\right) + \sum_{l=1}^{n}\left(\frac{\rho_l^2 + \varepsilon_l^2 + a_l^2}{2} + \frac{\sigma_l\theta_l^2}{2\eta_l}\right)$$

which yields

$$\dot{V}_n \le -a_0 V_n + b_0 \quad (30)$$

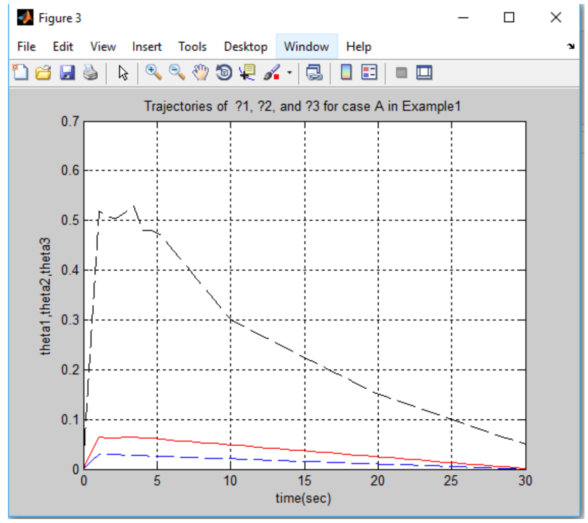
where

$$\begin{aligned}a_0 &= \min\{2k_l, \sigma_l\} \\ b_0 &= \sum_{l=1}^{n}\left(\frac{\rho_l^2 + \varepsilon_l^2 + a_l^2}{2} + \frac{\sigma_l\theta_l^2}{2\eta_l}\right).\end{aligned}$$

Through regulating the parameters in *a*0 and *b*0, the desired performance can be guaranteed. However, due to the existence of unknown parameters *θl*, it is impossible to eliminate the negative effect of those unknown parameters absolutely. By designing approximate parameters, the stability of the resulting closed-loop system can be guaranteed. This completes the proof.

IV. SIMULATION RESULTS

Two examples are presented to illustrate the validity of the control scheme proposed in this paper. First, a numerical one is given.



Example 1: Consider the following third-order system:

$$\begin{aligned}\dot{x}_1 &= x_2 + f_1(x_1) + \delta_1(x,t) \\ \dot{x}_2 &= x_3 + f_2(\bar{x}_2) + \delta_2(x,t) \\ \dot{x}_3 &= u(t-\tau) + f_3(\bar{x}_3) + \delta_3(x,t) \\ y &= x_1\end{aligned}$$

Where

$$\begin{aligned}f_1(x_1) &= -0.1\sin(x_1) \\ f_2(\bar{x}_2) &= 0.01\cos(x_1x_2) \\ f_3(\bar{x}_3) &= -0.01e^{-x_3^2}\sin(x_1)\cos(x_2) \\ \delta_1(x,t) &= \delta_2(x,t) = \delta_3(x,t) = 0.01\sin(x_1x_2x_3)\cos(t).\end{aligned}$$

In order to approximate the nonlinear terms in the system, the following membership functions are provided:

$$u_{M_{ji}}(x_i) = e^{-\frac{(x_i - 2 + 0.5j)^2}{8}}, \quad j = 1, 2, \ldots, 7.$$

The parameters are defined as *k*1 = 1.1, *k*2= 3, *k*3 = 1.5*, σ*1 = *σ*2 = *σ*3 = 0.1*, η*1 = *η*2 = *η*3 = 1, and *ρ*1 = *ρ*2 =*ρ*3 = 2. The initial condition is *x*1 = 0.5, *x*2 = 0.5, *x*3 = 0.5 *x*4 = 0, ˆ *θ*1 = 0, ˆ *θ*2 = 0, and ˆ *θ*3 = 0. Next, network-induced delay and stochastic data loss will be considered in different cases.

Case A—Constant delay: Assuming the network-induced delay to be a constant, that is, *τ* = 0.006, simulation results are provided in Figs. 1–4, where Fig. 1 plots the trajectories of system states *x*1, *x*2, and *x*3, Fig. 2 plots the trajectory of introduced variable $x4$, Fig. 3 plots the response of the input u, and the responses of adaptive laws are plotted in Fig. 4.

Case B—Constant Delay With Data Loss: To address the robustness of the proposed control scheme, the stochastic data loss is considered. Assume that the data loss satisfies the following data model:

$$x_u(t) = \bar{\alpha}x(t) + (1 - \bar{\alpha})x(t - 1)$$

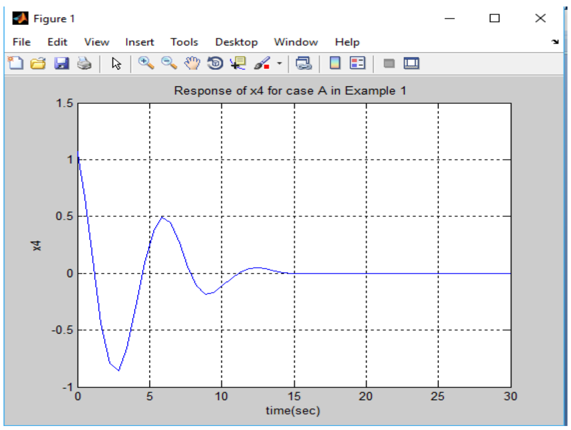


Fig. 2. Response of $x4$ for case A in Example 1.

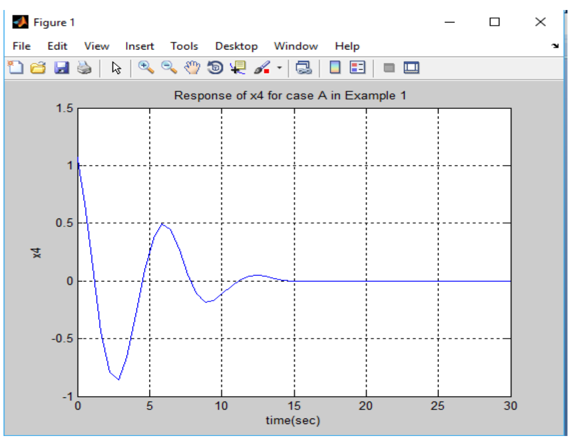


Fig. 3. Trajectory of input u for case A in Example 1.

Fig. 4. Trajectories of ˆ $\theta 1$, ˆ $\theta 2$, and ˆ $\theta 3$ for case A in Example 1.

rand≤ Ploss, in which rand is a random function describing the stochastic data loss and 0 <Ploss<1 is the data-loss probability. Here, we define Ploss= 0.8. Other conditions keepthe same with the above simulation. Figs. 5–8 plot the trajectories of system states, trajectory of variable $x4$, response ofcontrol input, and responses of adaptive parameters, respectively. Through comparing Figs. 1 and 5, we can learn that even data loss has some negative effect on the system stability,our proposed control scheme can still maintain the desired performance.

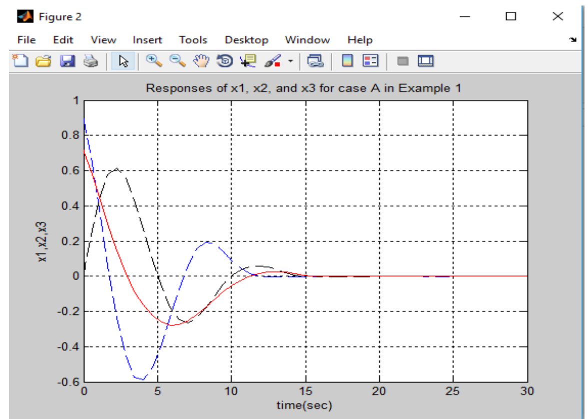


Fig. 5.Trajectories of $x1$, $x2$, and $x3$ for case B in Example 1.

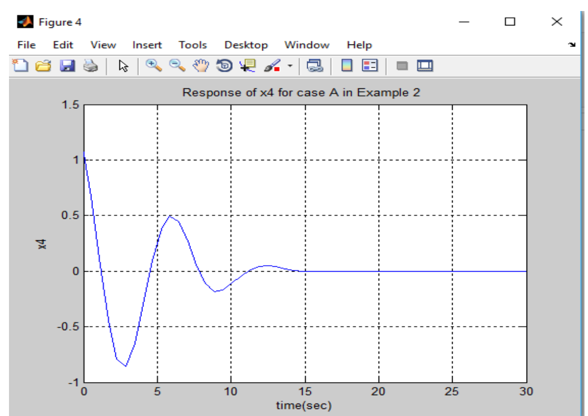


Fig. 6.Trajectory of $x4$ for case B in Example 1.

Example 2: To further illustrate the effectiveness of the proposed method, a one-link manipulator with the inclusion of motor dynamics shown in Fig. 9 is used. It is governed via the following dynamic equation:

$$\mathcal{D}\ddot{q} + \mathcal{B}\dot{q} + \mathcal{N}\sin(q) = \vartheta$$
$$\mathcal{M}\dot{\vartheta} + \mathcal{H}\vartheta = u - \mathcal{L}\dot{q}$$

where $\ddot{q}$, $\dot{q}$, and q stand for the link acceleration, velocity, and position, respectively. ϑ means the torque caused by the electrical subsystem, u represents the input. D = 1 kg m2,B = 1 Nm s/rad, H = 1 _, M= 0.1H, and L = 0.2 Nm/A is the mechanical inertia, coefficient of viscous friction at

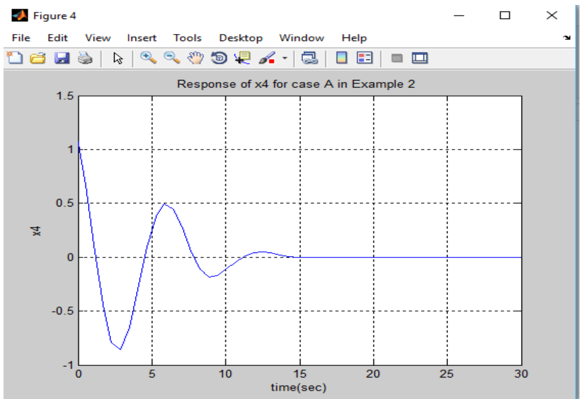


Fig. 7.Trajectory of input u for case B in Example 1.

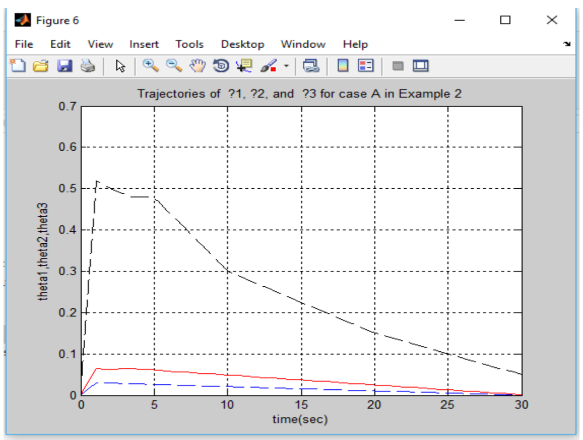


Fig. 8.Trajectories of $\hat{\theta}1$, $\hat{\theta}2$, and $\hat{\theta}3$ for case B in Example 1.

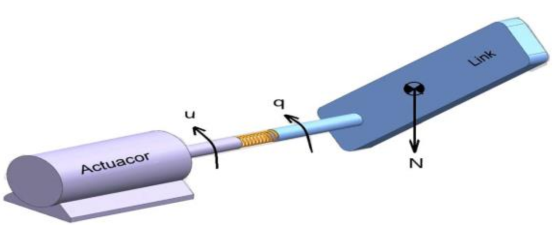


Fig. 9. One-link manipulator

the joint, armature resistance, armature inductance, and back electromotive force coefficient, respectively. Defining $x1 = q$, $x2 = \dot{q}$, and $x3 = \vartheta$ and considering network-induced delay and external disturbance, we can rewrite the above system as follows:

$$\dot{x}_1 = x_2 + \delta_1(x, t)$$
$$\dot{x}_2 = x_3 + f_2(\bar{x}_2) + \delta_2(x, t)$$
$$\dot{x}_3 = 10u(t - \tau) + f_3(\bar{x}_3) + \delta_3(x, t)$$

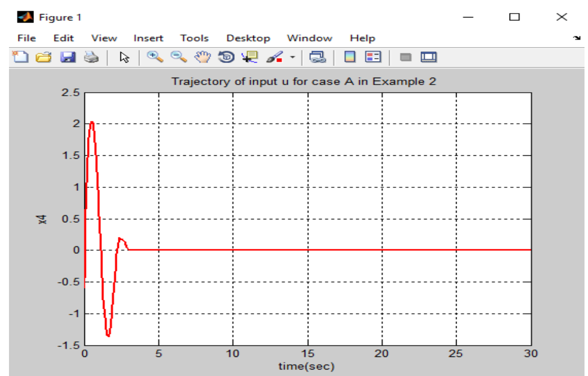


Fig. 10. Trajectories of $x1$, $x2$, and $x3$ for case A in Example 2.

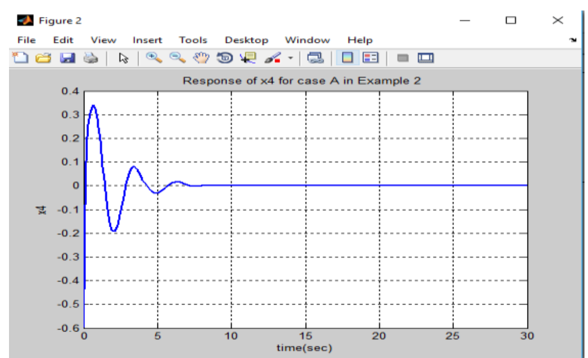


Fig. 11. Trajectory of $x4$ for case A in Example 2.

Where $f2(\bar{x}2) = -x2 - 10\sin(x1)f3(\bar{x}3) = -2x2 - 10x3$ $\delta1(x, t) = \delta2(x, t) = \delta3(x, t) = 0.01\sin(x1x2x3)\cos(t)$.To validate the effectiveness of the proposed scheme, parameters to be designed are defined as $k1 = 3.5$, $k2= 2.2$, $k3 = 1$, $\sigma1 = \sigma2 = \sigma3 = 0.1$, $\eta1 = \eta2 = \eta3 = 1$, and$\rho1 = \rho2 = \rho3 = 2$. The initial condition is $x1 = 0.5$, $x2 = 0.8$, $x3 = 0.6$, $x4 = 0$, $\hat{\theta}1 = 0$, $\hat{\theta}2 = 0$, and $\hat{\theta}3 = 0$. Membership functions are defined as those in Example 1.

Case A—Time-Varying Delay: In this example, the networkinduceddelay is defined as a time-varying random one, i.e., τ = rand and $\tau \in$[0.005, 0.007]. Simulation results

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are shown in Figs. 10–13, from which we can conclude that the stability of the system are guaranteed.

Case B—Time-Varying Delay With Data Loss: To further demonstrate the effectiveness and robustness of the proposed adaptive control scheme, data loss model used in Example 1 is adopted. Figs. 14–17 provide the simulation resultsfor the time-varying delay and data loss case. From the above figures, we know that the proposed control strategy is

effective.

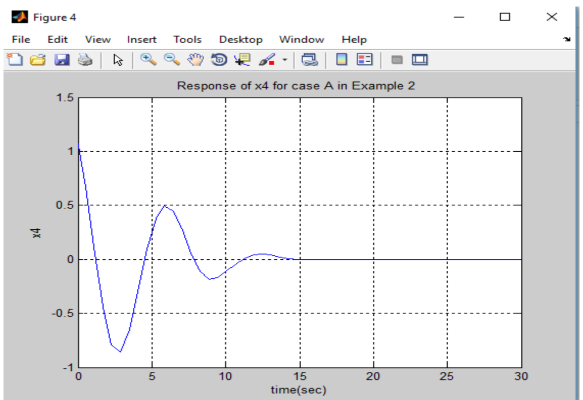

Fig. 12. Trajectory of input *u* for case A in Example2.

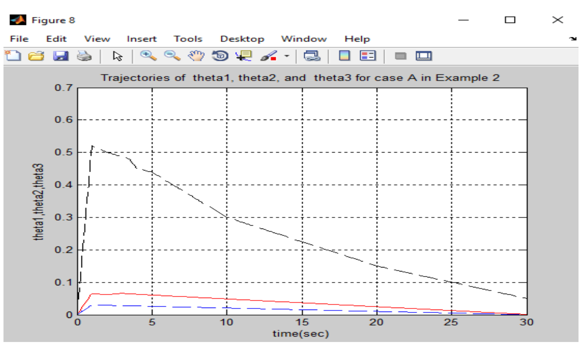

Fig. 13. Trajectories of $\hat{\theta}1$, $\hat{\theta}2$, and $\hat{\theta}3$ for case A in Example 2.

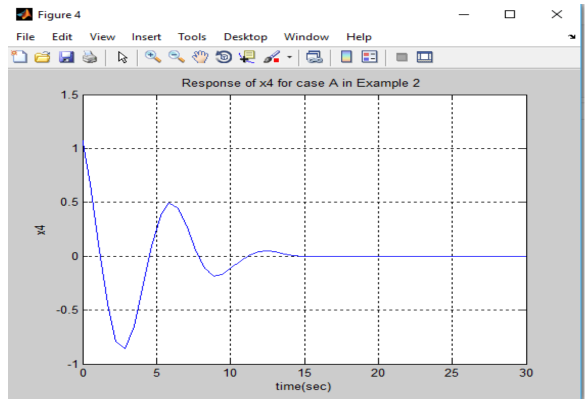

Fig. 14. Trajectory of input *u* for case B in Example2

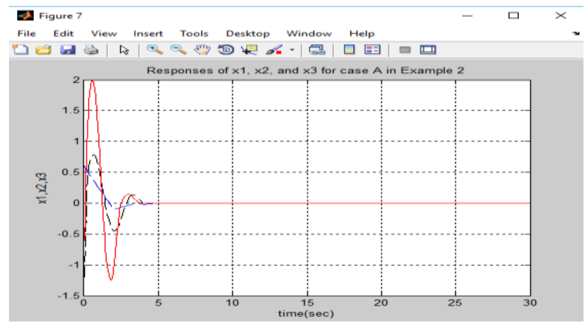

Fig. 15.Trajectory of *x*4 for case B in Example 2.

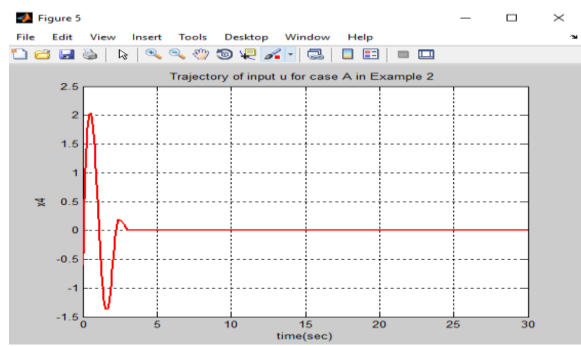

Fig. 16. Trajectory of input *u* for case B in Example 2

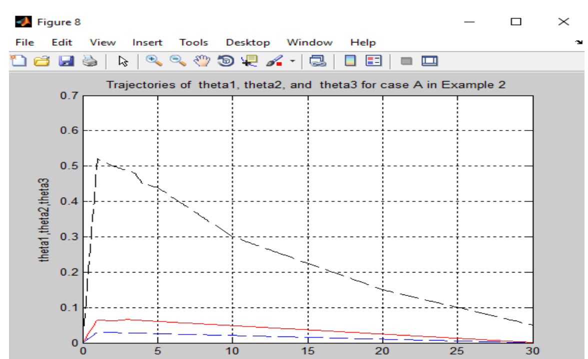

Fig. 17.Trajectories of $\hat{\theta}1$, $\hat{\theta}2$, and $\hat{\theta}3$ for case B in Example 2.

Remark 8:Despite data loss is not considered in the mathematical process, simulation results demonstrate that theproposed control strategy is robust to the stochastic data loss phenomenon.

V. CONCLUSION

In this paper, the problem of adaptive fuzzy control for a class of SISO nonlinear NCSs has been studied in the framework of adaptivebackstepping control approach. Network-induced delay and data loss have been considered simultaneously. By using FLSs, unknown nonlinear functions in the system have been approximated to realize the controller design. With Pade approximation, network-induced delay was separated from the control input signal, and a novel change of coordinates in the last step was constructed to eliminate the effect of $xn+1$. Moreover, an adaptive fuzzy controller was developed to ensure all signals of the resulting closedloopsystem are bounded and state variables can be driven to the origin. In addition, the impact of stochastic data loss has been demonstrated in simulation results, showing the robustness of the proposed control scheme. Finally, two examples have been presented to validate the effectiveness of the control methodology proposed in this paper.

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