T–S Fuzzy Model-Based Robust Stabilization for Networked Control Systems With Probabilistic Sensor and Actuator Failure

Engang Tian, Dong Yue, *Senior Member, IEEE*, Tai Cheng Yang, Zhou Gu, and Guoping Lu

***Abstract*—The system studied in this paper has four main features: 1) It is a networked controlled system (NCS), and therefore, the signal transfer is subject to random delay and/or loss; 2) it is a nonlinear system approximated by a Takegi–Sugeno (T–S) fuzzy model; 3) its multisensors and multiactuators are subject to various possible faults/failures; and 4) there are uncertainties in the plant model parameters. A comprehensive model is first developed in this paper to cover these features for a class of NCS nonlinear systems. This model has removed some limitations of similar models in the published literature. Then, the Lyapunov functional and the linear matrix inequality (LMI) are applied to develop two new stability conditions (Theorems 1 and 2). These conditions and an algorithm are used to design a controller to achieve robust mean square stability of the system. Finally, two examples are used to demonstrate the application of the modeling and the controller design method developed.**

***Index Terms*—Networked control systems (NCS), probabilistic failure, robust mean square stability (RMSS), Takegi–Sugeno (T–S) fuzzy model.**

I. Introduction

Many infrastructure, manufacture, service, and military systems of present-day society can naturally be described as networks of a large number of simple interacting units. Shared communication networks are increasingly being used to support the information exchange in distributed control systems. Therefore, networked control systems (NCSs) have become an active research area in recent years [5], [16], [18], [22], [24], [30], [31], [33] . They differ from traditional control systems in that the connections of their components are via shared communication networks instead of point-to-point wiring. This is mainly motivated by practical considerations, such as modularity, low cost, easier maintenance, etc. However, the introduction of communication networks in control systems complicates the system modeling, analysis, and controller design. Network-induced random time delay, packet loss, and possible packet out-of-order are major issues in front of any NCS designer. Up to very recently, these issues were only topics of many NCS studies [2], [7], [22]. It is known that these issues present some significant challenges to designers. Furthermore, some research also takes into account uncertainties in the plant model [7], [22], [26], [29]. All the aforementioned NCS fundamental issues are addressed in the model presented in this paper.

Naturally, most existing NCS studies are concentrated on linear systems. Nonlinear system analysis and design is difficult by its own nature—there are still many open challenges even under the traditional structure [14], [15]. There are currently only a few publications that study NCS for some forms of nonlinear systems [12], [19]. However, in recent years, there has been some NCS research on the plant being modeled as a nonlinear Takegi–Sugeno (T–S) fuzzy system [8], [10], [27], [28]. The plant considered in this paper, broadly speaking, is also such a model. However, the overall system modeling and controller design studied, as outlined in the following, is different from those published in the literature.

Within the general framework as described earlier, we also address the issue of possible fault/failure of sensors and actuators in an NCS environment. Fault-tolerant control is a great concern in many applications. In distributed industrial and military NCSs, sensors and actuators can be in a hostile environment and subject to fault, failure, and malfunction. One of the main focuses of this paper is to address this problem. In particular, the fault/failure model proposed is more general and is different from those published in the NCS literature [7], [22], [26], [29]. A set of different stochastic variables are proposed in this paper to specify the fault/failure status of every sensor/actuator, such as complete failure, partial failure, complete normal, and measurement distortion. The stochastic variables proposed are in a general statistics form and these enable various random events of fault/failure to be modeled. Including these stochastic variables in the system model, a new kind of stochastic nonlinear NCS model is established. Some existing models are special cases of this general model presented. The details of the model are given in Section II.

The model outlined earlier has removed some limitations of some existing work. Noticeably, some NCS plus T–S fuzzy models do not take into account possible fault/failure of sensors and actuators [8], [10], [27], [28]. When possible failure is considered, some only consider sensor failure but assume that there

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E. Tian is with the School of Electrical and Automation Engineering, Nanjing Normal University, Nanjing 210042, China (e-mail: teg@njnu.edu.cn).

D. Yue (corresponding author) is with the Department of Control Science and Engineering, Huazhong University of Science and Technology, Wuhan 430074, Hubei, China (e-mail: medongy@vip.163.com).

T. C. Yang is with the Department of Engineering and Design, University of Sussex, Brighton BN1 9QT, U.K. (e-mail: t.c.yang@sussex.ac.uk).

Z. Gu is with the College of Power Engineering, Nanjing Normal University, Nanjing, Jiangsu 210042, China (e-mail: guzhou@njnu.edu.cn).

G. Lu is with the College of Electrical Engineering, Nantong University, Jiangsu 226007, China (e-mail: lu.gp@ntu.edu.cn).

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is no actuator failure [3], [4], [6]; some only consider two states of the sensors/actuators: normal and complete failure [4], [6], [21], [23], [25] without considering possible malfunction and measurement distortion; some assume that the failure statistics is the same for the all sensors and actuators in a system [4], [21], [23], [25]. In fact, the limitations of each work quoted here are on more than one aspect. For example, in [21] and [23], it only considers sensor failure and two conditions: normal and complete failure. It also assumes that the failure statistics is the same for the all sensors.

One of the two main contributions of this paper is to develop a comprehensive model for the study of a class of nonlinear NCS systems, taking into account various possible failures of sensors and actuators and their specific statistic characteristics. This is presented in Section II. Another main contribution is the controller design for the robust stabilization of such a system. This is presented in Section III. Section IV uses two examples to show the modeling and controller design methods developed, and the paper is concluded in Section V.

The two theorems developed in this paper on the robust mean square stability (RMSS) are based on the Lyapunov functional and the linear matrix inequality (LMI) method. Apart from some nontrivial mathematical formulations and manipulations—which may be also useful for some further theoretical work or other applications—there is no fundamental contribution in applying these two commonly used tools in this paper. However, in order to have a workable design method based on these two newly proved theorems, an algorithm is developed. It is also interesting to note that the solvability of the stability conditions derived depends not only on the upper bound of the delay due to networked communications but on the failure rates of the sensors or actuators as well. These details are shown in Section III.

II. Modeling

Consider a discrete nonlinear system represented by a T–S fuzzy model

Plant rule i: IF $\theta_1(k)$ is $F_{i1}, \ldots, \theta_r(k)$ is F_{ir}, THEN

$$x(k+1) = (A_i + \Delta A_i(k))\, x(k) + B_i u(k)$$

where A_i and B_i are matrices with appropriate dimensions. $x(t) \in \mathbb{R}^n$ and $u(t) \in \mathbb{R}^m$ are the state vector and control vector, respectively. $i \in \{1, 2, \ldots, r\} \triangleq \mathbb{S}$, and r is the number of IF–THEN rules. $\Delta A_i(k)$ are unknown matrices of appropriate dimensions satisfying

$$\Delta A_i(k) = H_i F_i(k) E_{1i} \tag{1}$$

where H_i and $E_{1i} (i \in \mathbb{S})$ are known constant matrices of appropriate dimensions, and $F_i(k)$ is an unknown matrix function with Lebesgue measurable elements satisfying

$$F_i^T(k) F_i(k) \leq I.$$

Applying center-average defuzzifier, product interference, and singleton fuzzifier, the T–S fuzzy system can be inferred as follows:

$$x(k+1) = \sum_{i=1}^{r} \mu_i \left((A_i + \Delta A_i(k))\, x(k) + B_i u(k) \right) \tag{2}$$

and

$$\mu_i(\theta(k)) = \frac{\omega_i(\theta(k))}{\sum_{i=1}^{r} \omega_i(\theta(k))}, \qquad \omega_i\left(\theta(k)\right) = \prod_{j=1}^{g} W_j^i(\theta_j(k))$$

$W_j^i(\theta_j(k))$ is the grade membership of $\theta_j(k)$ in W_j^i, and $\mu_i(\theta(k))$ satisfies

$$\mu_i(\theta(k)) \geq 0, \quad \sum_{i=1}^{r} \mu_i(\theta(k)) = 1.$$

For notational simplicity, we use μ_i to represent $\mu_i(\theta(k))$.

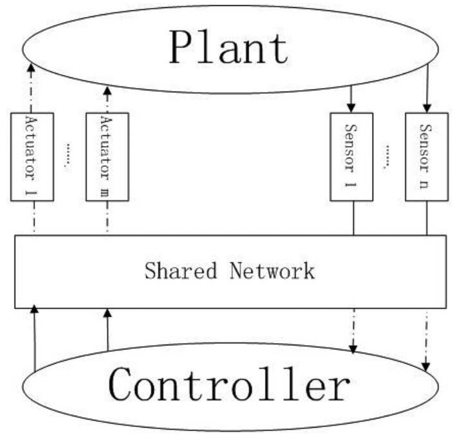

Fig. 1. Structure of a nonlinear NCS.

For the system studied in this paper and shown in Fig. 1, we assume that 1) sensors are clock-driven and that the controller and actuators are even-driven and 2) that each data packet in networked communication is time-stamped. Time stamps are used to obtain the information about the time delay and packet loss at the actuator nodes.

Given these assumptions, for $k \in [\tau_k + i_k, \tau_{k+1} + i_{k+1} - 1]$, the controller u_k can be designed in a form of

Control rule i: IF $\theta_1(k)$ is $F_{i1}, \ldots, \theta_r(k)$ is F_{ir}

THEN $u(k) = K_i x(i_k)$

where $K_i \; (i \in \mathbb{S})$ is the fuzzy control feedback gain to be determined. τ_k is the network-induced delay, and i_k is the kth sampling instant at the sensor. $\{i_1, i_2, i_3, \ldots\}$ is a subset of $\{1, 2, 3, \ldots\}$, which contains the information of packet loss and packet out-of-order. If $\{i_1, i_2, i_3, \ldots\} = \{1, 2, 3, \ldots\}$, $i_{k+1} = i_k + 1$, it means no packet loss. If $i_{k+1} - i_k = n (\geq 2)$, it means that $n - 1$ continuous packets are lost.

Let us define $d_k = k - i_k$, this leads to

$$\tau_k \leq d_k \leq \tau_{k+1} + (i_{k+1} - i_k - 1).$$

Applying the parallel distributed compensation (PDC) method, the inferred fuzzy controller is given by

$$u(k) = \sum_{j=1}^{r} \mu_j^k K_j x(k - d_k) \tag{3}$$

where μ_j^k contains the delay information in both forward and backward channels. Combining (2) and (3), for $k \in [\tau_k + i_k, \tau_{k+1} + i_{k+1} - 1]$, the closed-loop nonlinear NCS becomes

$$\begin{aligned} x(k+1) &= \sum_{i=1}^{r}\sum_{j=1}^{r} \mu_i \mu_j^k \left[(A_i + \Delta A_i(k))\, x(k) \right. \\ &\quad \left. + B_i K_j x(k - d_k) \right] \\ x(k) &= \phi_k, k = -d_M, \quad -d_M - 1, \ldots, -1, 0 \end{aligned} \tag{4}$$

where ϕ_k is the initial condition of $x(k)$, and d_M is the upper bound of d_k.

Remark 1: The systems studied in [10], [27], [28], and [32] also use the model of (4). However, their studies do not include the dynamics associated with possible sensor/actuator failure.

In this paper, different from those in [4], [6], and [23], the failure of sensors or actuators has each individually specified probabilistic distribution. Its value is in an interval $[0, \theta_l]$ $(l = 1, 2, \theta_l \geq 1)$.

Taking into account the possible failures, for $k \in [\tau_k + i_k, \tau_{k+1} + i_{k+1} - 1]$, the controller is as follows:

$$u(k) = \sum_{j=1}^{r} \mu_j^k \Pi_2 K_j \Pi_1 x(k - d_k) \tag{5}$$

where $\Pi_1 = \text{diag}\{\pi_{11}, \pi_{12}, \ldots, \pi_{1n}\}$ and $\pi_{1i} (i = 1, 2, \ldots, n)$ are n uncorrelated random variables taking values on the interval $[0, \theta_{1i}]$, where $\theta_{1i} \geq 1$. The expectation and variance of $\pi_{1i} (i = 1, 2, \ldots, m)$ are α_i and $\breve{\alpha}_i^2$, respectively. $\Pi_2 = \text{diag}\{\pi_{21}, \pi_{22}, \ldots, \pi_{2m}\}$ with $\pi_{2i} (i = 1, 2, \ldots, m)$ being m uncorrelated random variables taking values on the interval $[0, \theta_{2j}]$, where $\theta_{2i} \geq 1$. The expectation and variance of $\pi_{2i} (i = 1, 2, \ldots, m)$ are β_i and $\breve{\beta}_i^2$, respectively.

Remark 2: It is assumed that the earlier detailed probabilistic distribution data is known to the designer. If not, then some procedures given in the Appendix can be used to obtain the required data.

The stochastic variables $\pi_{1i} (i = 1, 2, \ldots, n)$ and $\pi_{2j} (j = 1, 2, \ldots, m)$ given earlier are used to model fault/failure including measurement distortions and the network-induced delay or packet loss. At time k, 1) when $\pi_{1i} = 0$(or $\pi_{2j} = 0$), it means complete failure of the ith sensor (or jth actuator) or packet loss during the transmission from a sensor to the controller (or from the controller to an actuator); 2) when $\pi_{1i} = 1$(or $\pi_{2j} = 1$) and $\breve{\alpha}_i^2 = 0$(or $\breve{\beta}_j^2 = 0$), the ith sensor (or jth actuator) is in a good work condition; 3) when $\pi_{1i} \in (0, 1)$ (or $\pi_{2j} \in (0, 1)$), it means partial failure of the ith sensor (or jth actuator) or measurements distortion, i.e., the signal used in the controller or an actuator is smaller than its true value; and 4) when $\pi_{1i} \in (1, \theta_{1i})$ (or $\pi_{2j} \in (1, \theta_{2j})$), it means that the signal used is larger than its true value.

Remark 3: There are some limitations of the failure models used in the existing literature: 1) In [6], [20], and [21], the failure models used can only deal with either complete normal or complete failure; and 2) in [4], there is a partial-failure model, but in [6], [20], and [21], the failure models for all sensors (actuators) are the same. It can be seen that the models used in these references can be considered as special cases of the general failure model proposed in this paper.

Substituting (5) into (4), for $k \in [\tau_k + i_k, \tau_{k+1} + i_{k+1} - 1]$, the system with probabilistic sensor and actuator failures can be modeled in a form of

$$\begin{aligned} x(k+1) &= \sum_{i=1}^{r}\sum_{j=1}^{r} \mu_i \mu_j^k \left[(A_i + \Delta A_i(k))\, x(k) \right. \\ &\quad \left. + B_i \Pi_2 K_j \Pi_1 x(k - d_k) \right] \\ x(k) &= \phi_k, k = -d_M, -d_M - 1, \ldots, -1, 0. \end{aligned} \tag{6}$$

One of the main purposes of this paper is to design a feedback gain K_j to guarantee the RMSS of system (6) with probabilistic failures of sensors and actuators.

III. Stability Conditions and Controller Design

From the definitions of Π_1 and Π_2, it leads to $\mathcal{E}\{\Pi_1\} = \text{diag}\{\alpha_1, \ldots, \alpha_n\} \stackrel{\triangle}{=} \bar{\Pi}_1 = \sum_{i=1}^{n} \alpha_i \Theta_1^i, \mathcal{E}\{\Pi_2\} = \text{diag}\{\beta_1, \ldots, \beta_m\} \stackrel{\triangle}{=} \bar{\Pi}_2 = \sum_{i=1}^{m} \beta_i \Theta_2^i$, and $\mathcal{E}\{\Pi_1 - \bar{\Pi}_1\} = \text{diag}\{0, \ldots, 0\}, \mathcal{E}\{\Pi_2 - \bar{\Pi}_2\} = \text{diag}\{0, \ldots, 0\}$, where

$$\Theta_1^i = \text{diag}\{\underbrace{0, \ldots, 0}_{i-1}, 1, \underbrace{0, \ldots, 0}_{n-i}\}$$

$$\Theta_2^j = \text{diag}\{\underbrace{0, \ldots, 0}_{j-1}, 1, \underbrace{0, \ldots, 0}_{m-j}\}.$$

For simplicity, we assume that $\Delta A_i(k) = 0$ and denote $\hat{\Pi}_1 = \Pi_1 - \bar{\Pi}_1$ and $\hat{\Pi}_2 = \Pi_2 - \bar{\Pi}_2$; therefore, (6) becomes

$$\begin{aligned} x(k+1) &= \sum_{i=1}^{r}\sum_{j=1}^{r} \mu_i \mu_j^k \left\{ A(i,j)\zeta(k) + B(i,j) x(k - d_k) \right\} \\ & k \in [\tau_k + i_k, \tau_{k+1} + i_{k+1} - 1] \end{aligned} \tag{7}$$

where

$$\begin{aligned} \zeta^T(k) &= \begin{bmatrix} x^T(k) & x^T(k - d_k) & x^T(k - d_M) \end{bmatrix} \\ A(i,j) &= \begin{bmatrix} A_i & B_i \bar{\Pi}_2 K_j \bar{\Pi}_1 & 0 \end{bmatrix} \\ B(i,j) &= B_i \hat{\Pi}_2 K_j \bar{\Pi}_1 + B_i \bar{\Pi}_2 K_j \hat{\Pi}_1 + B_i \hat{\Pi}_2 K_j \hat{\Pi}_1. \end{aligned} \tag{8}$$

Before the main results, the definition of RMSS is given as follows.

System (6) is said to be RMSS, if there exists a scalar $c > 0$ such that

$$\mathcal{E}\left\{ \sum_{k=0}^{\infty} \|x(k)\|^2 \right\} \leq c\mathcal{E}\left\{ \|\phi_k\| \right\}^2. \tag{9}$$

The following lemmas are necessary in the proof of the main theorems.

Lemma 1: [9] For matrix $W \in \mathbb{R}^{n\times n}$, $W = W^T > 0$, a constant $d > 0$ and a vector function $x(k) \in \mathbb{R}^n$, $y(k) = x(k+1) - x(k)$ such that the following integration is well defined, it holds that

$$-d\sum_{i=k-d}^{k-1} y^T(i)Wy(i) \le \begin{bmatrix} x(k) \\ x(k-d)\end{bmatrix}^T \begin{bmatrix} -W & W \\ W & -W\end{bmatrix}\begin{bmatrix} x(k) \\ x(k-d)\end{bmatrix}. \quad (10)$$

Lemma 2: For matrix $W \in \mathbb{R}^{n\times n}$, $W = W^T > 0$, a function d_k satisfying $0 \le d_k \le d_M$ and a vector function $x(k) \in \mathbb{R}^n$, $y(k) = x(k+1) - x(k)$ such that the following integration is well defined, it holds that

$$-d_M\sum_{i=k-d_M}^{k-1} y^T(i)Wy(i) \le \eta^T(k)\begin{bmatrix} -W & W & 0 \\ W & -2W & W \\ 0 & W & -W\end{bmatrix}\eta(k) \quad (11)$$

where $\eta^T(k) = [\,x^T(k) \quad x^T(k-d_k) \quad x^T(k-d_M)\,]$.

Proof: Note that

$$\begin{aligned} -d_M\sum_{i=k-d_M}^{k-1} y^T(i)Wy(i) &\le -d_k\sum_{i=k-d_k}^{k-1} y^T(i)Wy(i) \\ &\quad -(d_M-d_k)\sum_{i=k-d_M}^{k-d_k-1} y^T(i)Wy(i) \end{aligned} \quad (12)$$

applying Lemma 1 to (12), it leads to (11).

Theorem 1: For constant d_M, system (7) is mean square stability (MSS) if there exist matrices $P > 0$, $Q > 0$, $R > 0$, and K_j with appropriate dimensions such that the following conditions hold:

$$\Xi^{ij} + \Xi^{ji} < 0, \qquad i \le j \in \mathbb{S} \quad (13)$$

where

$$\Xi^{ij} = \begin{bmatrix} \Xi_{11} & * & * \\ \Xi_{21}^{ij} & \Xi_{22} & * \\ \Xi_{31}^{ij} & 0 & \Xi_{33}\end{bmatrix}$$

$$\Xi_{11} = \begin{bmatrix} -P-R+Q & * & * \\ R & -2R & * \\ 0 & R & -R-Q\end{bmatrix}$$

$$\Xi_{22} = \mathrm{diag}\{-P^{-1}, -R^{-1}\}$$

$$\Xi_{33} = \mathrm{diag}\{-P^{-1},\ldots,-P^{-1},-R^{-1},\ldots,-R^{-1}\}$$

$$\Xi_{21}^{ij} = \begin{bmatrix} A(i,j) \\ d_M\bar{A}(i,j)\end{bmatrix}, \quad \Xi_{31}^{ij} = \begin{bmatrix} \Sigma \\ d_M\Sigma\end{bmatrix}$$

$$\begin{aligned} \bar{A}(i,j) &= [\,A_i - I \quad B_i\bar{\Pi}_2K_j\bar{\Pi}_1 \quad 0\,] \\ \Sigma^T &= [\,\chi_1^T \quad \chi_2^T \quad \ldots \quad \chi_n^T\,] \\ \chi_l^T &= [\,\mathcal{B}_{1l}^T \quad \mathcal{B}_{2l}^T \quad \ldots \quad \mathcal{B}_{ml}^T\,] \\ \mathcal{B}_{ls} &= [\,0 \quad \sqrt{v_{ls}}B_i\Theta_2^sK_j\Theta_1^l \quad 0\,] \\ v_{ls} &= \breve{\alpha}_l^2\beta_s^2 + \alpha_l^2\breve{\beta}_s^2 + \breve{\alpha}_l^2\breve{\beta}_s^2, \quad l=1,\ldots,n, s=1,\ldots,m. \end{aligned}$$

Proof: Define

$$y(k) = x(k+1) - x(k).$$

Choose a Lyapunov–Krasovskii functional candidate

$$\begin{aligned} V(k+1) &= x^T(k)Px(k) + \sum_{i=k-d_M}^{k-1} x^T(i)Qx(i) \\ &\quad + d_M\sum_{i=1}^{d_M}\sum_{j=k-i}^{k-1} y^T(j)Ry(j) \end{aligned} \quad (14)$$

take the forward difference of (14), and then evaluate its expectation

$$\begin{aligned} &\mathcal{E}\{\Delta V(k)\} \\ &= \mathcal{E}\left\{\sum_{i=1}^{r}\sum_{j=1}^{r}\mu_i\mu_j^k\left\{\zeta^T(k)A^T(i,j)PA(i,j)\zeta(k)\right.\right. \\ &\quad + x^T(k-d_k)B^T(i,j)PB(i,j)x(k-d_k) \\ &\quad + x(k)(Q-P)x(k) - x^T(k-d_M)Qx(k-d_M) \\ &\quad \left.\left. + d_M^2y^T(k)Ry(k) - d_M\sum_{i=k-d_M}^{k-1} y^T(i)Ry(i)\right\}\right\}. \end{aligned} \quad (15)$$

Recalling the definition of $B(i,j)$ and noting that $\mathcal{E}\{\hat{\Pi}_1\} = \mathrm{diag}\{0,\ldots 0\}, \mathcal{E}\{\hat{\Pi}_2\} = \mathrm{diag}\{0,\ldots 0\}$

$$\begin{aligned} &\mathcal{E}\{B^T(i,j)PB(i,j)\} \\ &= \mathcal{E}\{(B_i\hat{\Pi}_2K_j\bar{\Pi}_1 + B_i\bar{\Pi}_2K_j\hat{\Pi}_1 + B_i\hat{\Pi}_2K_j\hat{\Pi}_1)^T \\ &\quad \cdot P(B_i\hat{\Pi}_2K_j\bar{\Pi}_1 + B_i\bar{\Pi}_2K_j\hat{\Pi}_1 + B_i\hat{\Pi}_2K_j\hat{\Pi}_1)\} \\ &= \mathcal{E}\{(B_i\hat{\Pi}_2K_j\bar{\Pi}_1)^TP(B_i\hat{\Pi}_2K_j\bar{\Pi}_1)\} \\ &\quad + \mathcal{E}\{(B_i\bar{\Pi}_2K_j\hat{\Pi}_1)^TP(B_i\bar{\Pi}_2K_j\hat{\Pi}_1)\} \\ &\quad + \mathcal{E}\{(B_i\hat{\Pi}_2K_j\hat{\Pi}_1)^TP(B_i\hat{\Pi}_2K_j\hat{\Pi}_1)\} \end{aligned} \quad (16)$$

and the property of Π_1 and Π_2, then from (16)

$$\begin{aligned} &\mathcal{E}\{(B_i\hat{\Pi}_2K_j\bar{\Pi}_1)^TP(B_i\hat{\Pi}_2K_j\bar{\Pi}_1)\} \\ &= \mathcal{E}\left\{\sum_{l=1}^{n}\sum_{s=1}^{m}\alpha_l^2\breve{\beta}_s^2\left(B_i\Theta_2^sK_j\Theta_1^l\right)^TP\left(B_i\Theta_2^sK_j\Theta_1^l\right)\right\} \end{aligned} \quad (17)$$

$$\begin{aligned} &\mathcal{E}\{(B_i\bar{\Pi}_2K_j\hat{\Pi}_1)^TP(B_i\bar{\Pi}_2K_j\hat{\Pi}_1)\} \\ &= \mathcal{E}\left\{\sum_{l=1}^{n}\sum_{s=1}^{m}\breve{\alpha}_l^2\beta_s^2\left(B_i\Theta_2^sK_j\Theta_1^l\right)^TP\left(B_i\Theta_2^sK_j\Theta_1^l\right)\right\} \end{aligned} \quad (18)$$

$$\mathcal{E}\{(B_i\hat{\Pi}_2K_j\hat{\Pi}_1)^T P(B_i\hat{\Pi}_2K_j\hat{\Pi}_1)\}$$
$$= \mathcal{E}\left\{\sum_{l=1}^{n}\sum_{s=1}^{m}\breve{\alpha}_l^2\breve{\beta}_s^2\left(B_i\Theta_2^sK_j\Theta_1^l\right)^T P\left(B_i\Theta_2^sK_j\Theta_1^l\right)\right\}. \tag{19}$$

Combining (17)–(19)

$$\mathcal{E}\left\{x^T(k-d_k)B^T(i,j)PB(i,j)x(k-d_k)\right\}$$
$$= \mathcal{E}\left\{\sum_{l=1}^{n}\sum_{s=1}^{m}v_{ls}x^T(k-d_k)\left(B_i\Theta_2^sK_j\Theta_1^l\right)^T \cdot P\left(B_i\Theta_2^sK_j\Theta_1^l\right)x(k-d_k)\right\}$$
$$= \mathcal{E}\left\{\sum_{l=1}^{n}\sum_{s=1}^{m}\zeta^T(k)\mathcal{B}_{ls}^TP\mathcal{B}_{ls}\zeta(k)\right\} \tag{20}$$

where v_{ls} and $\mathcal{B}_{ls}$ are defined in (13). Similarly

$$\mathcal{E}\left\{y^T(k)Ry(k)\right\} = \mathcal{E}\left\{\sum_{i=1}^{r}\sum_{j=1}^{r}\mu_i\mu_j^k\left\{\zeta^T(k)\Upsilon\zeta(k)\right\}\right\} \tag{21}$$

where

$$\Upsilon = \left[\bar{A}^T(i,j)R\bar{A}(i,j) + \sum_{l=1}^{n}\sum_{s=1}^{m}\mathcal{B}_{ls}^TR\mathcal{B}_{ls}\right]$$
$$\bar{A}(i,j) = [\,A_i - I \quad B_i\bar{\Pi}_2K_j\bar{\Pi}_1 \quad 0\,].$$

Applying Lemma 2 for

$$-d_M\sum_{i=k-d_M}^{k-1}y^T(i)Ry(i) \le \eta^T(k)\begin{bmatrix}-R & R & 0\\ R & -2R & R\\ 0 & R & -R\end{bmatrix}\eta(k) \tag{22}$$

and substituting (20)–(22) into (15)

$$\mathcal{E}\{\Delta V(k)\} \le \mathcal{E}\left\{\sum_{i=1}^{r}\sum_{j=1}^{r}\mu_i\mu_j^k\left[\zeta^T(k)\Psi(i,j,l,s)\zeta(k)\right]\right\}$$
$$= \mathcal{E}\left\{\sum_{i=1}^{r}\sum_{i\le j}\mu_i\mu_j^k\left[\zeta^T(k)\bar{\Psi}(i,j,l,s)\zeta(k)\right]\right\}$$
$$\bar{\Psi}(i,j,l,s) = \Psi(i,j,l,s) + \Psi(j,i,l,s) \tag{23}$$

where $\Psi(i,j,l,s) = \Xi_{11} + A^T(i,j)PA(i,j) + d_M^2\bar{A}^T(i,j)R\bar{A}(i,j) + \sum_{l=1}^{n}\sum_{s=1}^{m}(\mathcal{B}_{ls}^TP\mathcal{B}_{ls} + d_M^2\mathcal{B}_{ls}^TR\mathcal{B}_{ls})$. Recalling (13) and using Schur complement, there exists constant $\lambda > 0$ such that

$$\mathcal{E}\{\Delta V_k\} \le -\lambda\mathcal{E}\left\{\zeta^T(k)\zeta(k)\right\} \le -\lambda\mathcal{E}\left\{x^T(k)x(k)\right\}. \tag{24}$$

Since $\cup_{k=1}^{\infty}[\tau_k + i_k, \tau_{k+1} + i_{k+1} - 1] = [0,\infty)$, from (24)

$$\mathcal{E}\left\{\sum_{k=0}^{\infty}x^T(k)x(k)\right\} \le \frac{1}{\lambda}\mathcal{E}\{V(0)\} \tag{25}$$

and from the construction of $V(k)$, there exists a constant c such that

$$\mathcal{E}\{V(0)\} \le \lambda c\mathcal{E}\left\{\phi_k^T\phi_k\right\}. \tag{26}$$

Based on the definition of the RMSS, the proof is completed. ■

Remark 4: From this proof, one can see that the solvability of the stability conditions derived depends not only on the upper bound of the delay τ_M, due to networked communications but to the failure rates of the sensors or actuators $\bar{\Pi}_i, i = 1, 2$ as well.

Applying a similar approach for parameter uncertainties [17] and base on Theorem 1, it leads to the following.

Theorem 2: For a given constant d_M, system (6) is RMSS if there exist matrices $P > 0$, $Q > 0$, $R > 0$, and K_j with appropriate dimensions such that the following conditions hold:

$$\bar{\Xi}^{ij} + \bar{\Xi}^{ji} < 0, \qquad i \le j \in \mathbb{S} \tag{27}$$

where

$$\bar{\Xi}^{ij} = \begin{bmatrix}\Xi_{11} & * & * & *\\ \Xi_{21}^{ij} & \Xi_{22} & * & *\\ \Xi_{31}^{ij} & 0 & \Xi_{33} & *\\ \Xi_{41}^{i} & \Xi_{43}^{i} & 0 & \Xi_{44}^{i}\end{bmatrix}$$

where $\Xi_{11}, \Xi_{21}^{ij}, \Xi_{31}^{ij}, \Xi_{22}$, and Ξ_{33} are defined in (13), and

$$\Xi_{41}^i = \begin{bmatrix}0 & 0 & 0\\ \varepsilon_iE_{1i} & 0 & 0\end{bmatrix}, \Pi_{43}^i = \begin{bmatrix}H_i^T & d_MH_i^T\\ 0 & 0\end{bmatrix}$$
$$\Pi_{44}^i = \text{diag}\{-\varepsilon_iI, -\varepsilon_iI\}.$$

The next task is to design a controller, i.e., to find feedback gain K_j, based on these two new theorems. In the existing literature, for example, in [1], [13], and [27], the design algorithm is based on pre- and postmultiplying the stability conditions with $\text{diag}\{P^{-1},\ldots,P^{-1}\}$ and defining some new parameters $X = P^{-1}, \tilde{Q} = XQX$, and $Y = KX$. This first leads to some inequalities, which are not strict LMIs due to the existence of $XR^{-1}X$. Then, in the second step, this is reformulated into a sequence of optimizations subject to some LMI constrains. However, this approach cannot be applied here. If one pre- and postmultiplies $B_i\bar{\Pi}_2K_j\bar{\Pi}_1$ with X, the result $XB_i\bar{\Pi}_2K_j\bar{\Pi}_1X$ is a nonlinear variable. In the second step of reformulation, the resultant constrains are no longer LMIs and cannot be solved by the aforementioned algorithm used in [1], [13], and [27]. Therefore, the following algorithm is proposed in this paper.

Define new variables $\bar{P} = P^{-1}$ and $\bar{R} = R^{-1}$, and replace them in (13) and (27), respectively. These new inequalities are denoted as (13)' and (27)', respectively.

Given constants d_M and c, where c denotes the maximum number of iterations, the algorithm for the controller design based on Theorem 1 (or Theorem 2) is given as follows.

1) Find a feasible solution $\{P, \bar{P}, R, \bar{R}\}$ to LMIs [13]' [or (27)'] and

$$\begin{bmatrix}P & I\\ I & \bar{P}\end{bmatrix} \ge 0, \quad \begin{bmatrix}R & I\\ I & \bar{R}\end{bmatrix} \ge 0. \tag{28}$$

If there is no feasible solution, EXIT. Else, set $k = 0$.

2) Solve the minimization problem

$$\min \text{ tr}\left(P_k\bar{P} + \bar{P}_k P + R_k\bar{R} + \bar{R}_k R\right)$$
$$\text{subject to LMIs (13)' [or (27)'] and (28).} \quad (29)$$

3) If (30), shown below, is satisfied for a sufficient small scalar $\varepsilon > 0$, the feedback gain K_j is obtained; otherwise, set $k = k + 1$. If $k < c$, go to Step 2); otherwise, EXIT (no feasible solution is found).

$$\left|tr(P_k\bar{P} + \bar{P}_k P + R_k\bar{R} + \bar{R}_k R) - 4n\right| < \varepsilon. \quad (30)$$

IV. Examples

To illustrate applications of the proposed design method, two examples are presented in this section.

Example 1: Consider a nonlinear mass-spring-damper mechanical system [11]

$$M\ddot{y}(t) + g(y(t), \dot{y}(t)) + f(y(t)) = \phi(\dot{y}(t))u(t)$$

where M is the mass, $u(t)$ is the force, $f(y(t)), g(y(t), \dot{y}(t))$, and $\phi(\dot{y}(t))$ are the nonlinear or uncertain terms with respect to the spring, the damper, and the input, respectively. Assume that $g(y(t), \dot{y}(t)) = c_1 y(t) + c_2\dot{y}(t)$, $f(y(t)) = c(t)y(t)$, and $\phi(\dot{y}(t)) = 1 + c_5\dot{y}^3(t)$, where $c(t)$ is the uncertain term within the sector $[c_3, c_4]$ and $M = 1.0, c_1 = 0, c_2 = 1, c_3 = 0.5, c_4 = 1.81$, and $c_5 = 0.13$. Similar to [11], choose state variable $x(t) = [\dot{y}\ y]^T$, then the A and B matrices in the model of (6) are as follows:

$$A_1 = \begin{bmatrix} -1.0 & -1.155 \\ 1 & 0 \end{bmatrix}, \quad B_1 = \begin{bmatrix} 1.4387 \\ 0 \end{bmatrix}$$
$$A_2 = \begin{bmatrix} -1.0 & -1.155 \\ 1 & 0 \end{bmatrix}, \quad B_2 = \begin{bmatrix} 0.1217 \\ 0.0023 \end{bmatrix}.$$

The aforementioned continuous-time system is discretized with a zero-order hold and a sampling period T = 0.2 s. The discrete-time version of A and B matrices are as follows:

$$A_1 = \begin{bmatrix} 0.7986 & -0.2078 \\ 0.1799 & 0.9784 \end{bmatrix}, \quad B_1 = \begin{bmatrix} 0.3119 \\ 0.0058 \end{bmatrix}$$
$$A_2 = \begin{bmatrix} 0.7986 & -0.2078 \\ 0.1799 & 0.9784 \end{bmatrix}, \quad B_2 = \begin{bmatrix} 0.5613 \\ 0 \end{bmatrix}.$$

The parameter uncertainties are as follows:

$$H_1 = H_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad E_{11} = \begin{bmatrix} 0.05 & 0 \\ 0 & 0.07 \end{bmatrix}$$
$$E_{12} = \begin{bmatrix} 0.07 & 0 \\ 0 & 0.05 \end{bmatrix}.$$

For $d_M = 4$, $\mathcal{E}\{\Pi_1\} = \text{diag}\{0.8, 1.1\}$, $\breve{\alpha}_1 = \breve{\alpha}_2 = 0.1$, applying the proposed algorithm, the feedback gain can be obtained as follows:

$$K_1 = [-0.0054 \quad -0.0219], \qquad K_2 = [-0.0169 \quad 0.0014].$$

Choosing a membership function as $\mu_1(\dot{y}) = \sin^2(\dot{y})$, $\mu_2(\dot{y}) = 1 - \mu_1(\dot{y})$, and an initial function $\phi(k) = [1 \quad -1]^T$, the state responses of $x(k)$ are plotted in Fig. 2. It shows that the designed controller indeed stabilizes the system. The stochastic variables π_{11} and π_{12} in this simulation are plotted in Fig. 3.

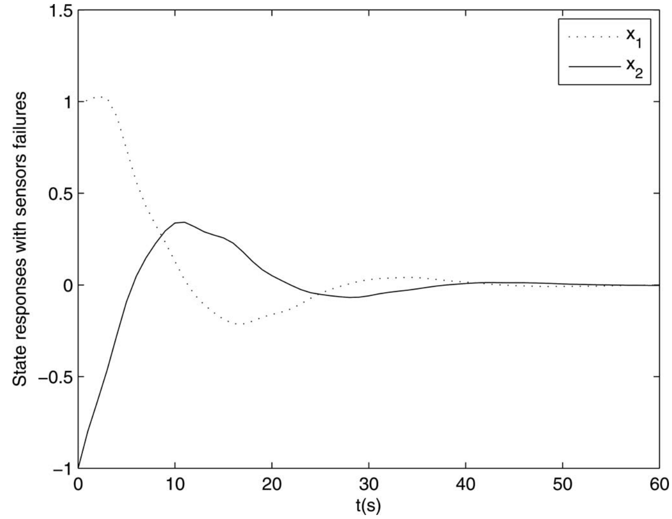

Fig. 2. State responses of the system with unreliable sensors having different failure rates.

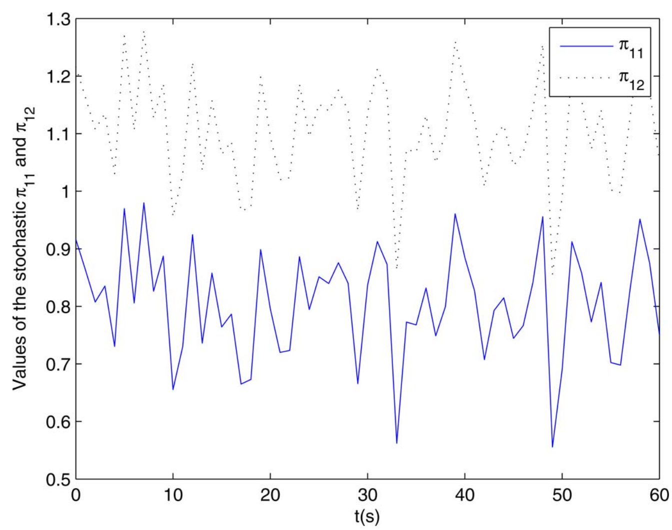

Fig. 3. Values of the stochastic variables π_{11} and π_{12}.

Example 2: Consider a nonlinear system, whose dynamics is approximated by (7) with following A and B matrices:

$$A_1 = \begin{bmatrix} 0.3996 & 0.0003 & 0.0002 & -0.0037 \\ 0.3005 & 0.4900 & -0.0002 & -0.0406 \\ 0.0010 & 0.0037 & 0.8453 & -0.5644 \\ 0 & 0 & 0.0101 & -0.5644 \end{bmatrix}$$
$$A_2 = \begin{bmatrix} 0.8729 & 0.0 & -0.0013 & -0.0020 \\ 0 & -0.2300 & -0.0002 & 0.0146 \\ 0.0010 & 0.0037 & 0.5300 & 0.0832 \\ 0.2742 & 0 & 0.0101 & 0.8356 \end{bmatrix}$$

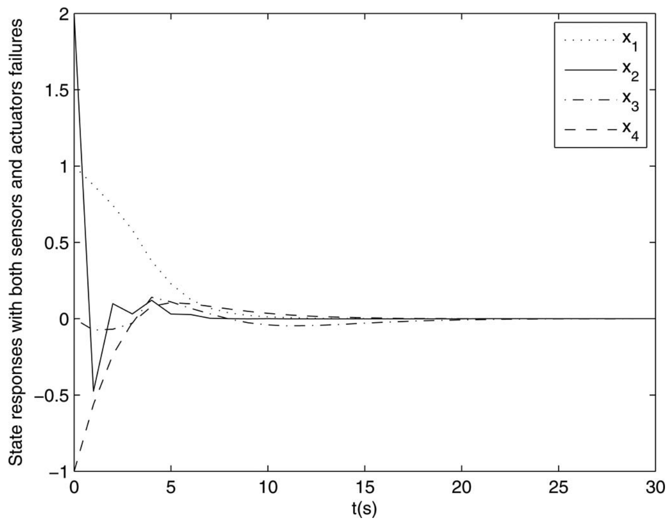

Fig. 4. State responses for NNCS with unreliable sensors and actuators with different failure rate.

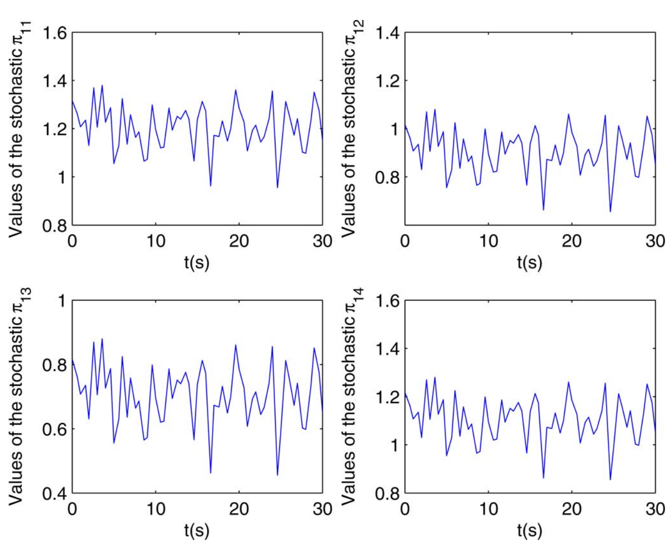

Fig. 5. Values of the stochastic variables $\pi_{1i}, i = 1, 2, 3, 4$.

$$B_1 = \begin{bmatrix} 0.0044 & 0.0019 \\ 0.0356 & -0.0759 \\ -0.0484 & 0.0405 \\ -0.0003 & 0.0003 \end{bmatrix} \quad B_2 = \begin{bmatrix} 0 & -0.0001 \\ -0.0003 & 0.0004 \\ -0.0075 & 0.0049 \\ 0 & -0.0001 \end{bmatrix}. \tag{31}$$

For $d_M = 3$, $\mathcal{E}\{\Pi_1\} = \text{diag}\{1.2, 0.9, 0.7, 1.1\}$, $\mathcal{E}\{\Pi_2\} = \text{diag}\{1.0, 0.8\}, \breve{\alpha}_i = 0.1(i = 1, 2, 3, 4)$, $\breve{\beta}_1 = 0, \breve{\beta}_2 = 0.1$, applying the proposed algorithm, the feedback gains obtained are as follows:

$$K_1 = \begin{bmatrix} -0.1045 & 0.9322 & 0.2444 & -0.9581 \\ -0.3428 & 1.6165 & -0.3070 & -1.0380 \end{bmatrix}$$

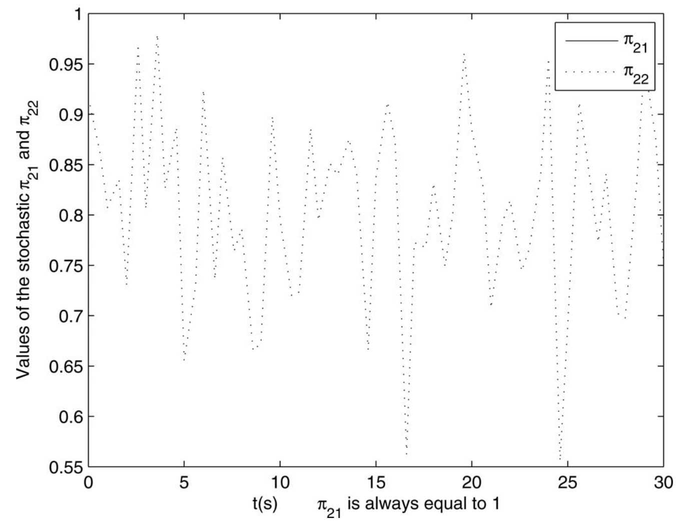

Fig. 6. Values of the stochastic variables $\pi_{2i}, i = 1, 2$.

$$K_2 = \begin{bmatrix} 0.8165 & -8.7631 & 5.2214 & 7.1656 \\ 3.6738 & -9.0581 & 3.4036 & 5.6680 \end{bmatrix}.$$

For a membership function $\mu_1(x_1) = \sin^2(x_1), \mu_2(x_1) = 1 - \mu_1(x_1)$, and an initial function $\phi(k) = \begin{bmatrix} 1 & 2 & 0 & -1 \end{bmatrix}^T$, the state responses of $x(k)$ are plotted in Fig. 4. It shows that the closed-loop system is stable. The stochastic variables $\pi_{1i}(i = 1, 2, 3, 4)$ and $\pi_{2i}(i = 1, 2)$ in this simulation are plotted in Figs. 5 and 6, respectively.

V. Conclusion

This paper investigates reliable control of a class of nonlinear NCSs via T–S fuzzy model with probabilistic sensor and actuator faults/failures, measurement distortion, time-varying delay, packet loss, and norm-bounded parameter uncertainties. A new model is developed in this paper. This model has removed some limitations of similar models in the published literature. The Lyapunov functional and the LMI are applied to develop two sufficient stability conditions. These conditions and the proposed algorithm are used to design a controller to achieve RMSS of the system.

Appendix

In this paper, the expectation and variance of each stochastic variable (π_{1i} and $\pi_{2j}, i = 1, .., n, j = 1, .., m$) are supposed to be known *a priori*. In fact, these can be measured by the following method.

1) If the probabilistic density function of π_{1i} is known, the expectation and variance of π_{1i} can be calculated easily.

2) Otherwise, these can be obtained as follows. Placing a counter before the controller to measure the fault condition of the ith sensor, then dividing the variable range $\left[0, \pi_{1i}^M\right]$ into l equal intervals (l is large enough to ensure that each interval is sufficiently small), the probability of π_{1i} falling into each interval $\left[i(\pi_{1i}^M/l), (i+1)\left(\pi_{1i}^M/l\right)\right)$ can be obtained, which is denoted as $\varepsilon_i = P\left\{\pi_{1i} \in \left[i(\pi_{1i}^M/l), (i+1)\left(\pi_{1i}^M/l\right)\right)\right\}$. Since

l is large, the probabilistic density function can be approximated by

$$p_{1i} = \begin{cases} \varepsilon_1, & \pi_{1i} = \dfrac{\pi_{1i}^M}{2l} \\ \cdots & \cdots \\ \varepsilon_i, & \pi_{1i} = i\dfrac{\pi_{1i}^M}{l} + \dfrac{\pi_{1i}^M}{2l} \\ \cdots & \cdots \\ \varepsilon_l, & \pi_{1i} = \pi_{1i}^M - \dfrac{\pi_{1i}^M}{2l}. \end{cases}$$

The expectation of π_{1i} can be obtained as $\hat{\alpha}_i = \sum_{i=1}^{l} \varepsilon_i (i(\pi_{1i}^M/l) + (\pi_{1i}^M/2l))$, and the variance can also be obtained. The expectation and variance of π_{2j} can be obtained similarly.

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Engang Tian was born in Shandong Province, China, in 1980. He received the B.S. degree from Shandong Normal University, Jinan, China, the M.S. degree from Nanjing Normal University, Nanjing, China, and the Ph.D. degree from Donghua University, Shanghai, China, in 2002, 2005, and 2008, respectively.

Since 2008, he has been with the School of Electrical and Automation Engineering, Nanjing Normal University. From February 2010 to May 2010, he was a Visiting Scholar with Northumbria University, Newcastle, U.K. His current research interests include networked control systems, Takegi–Sugeno (T–S) fuzzy systems, and time-delay systems.

Dong Yue (SM'08) was born in China, in 1964. He received the B.S. degree from the Guilin Institute of Electrical Engineering, Guilin, China, in 1985, the M.S. degree from Anhui University, Hefei, China, in 1991, and the Ph.D. degree from the South China University of Technology, Guangzhou, China, in 1995.

From 1995 to 1997, he was a Postdoctoral Research Fellow with the China University of Mining and Technology, Beijing, China, where he was appointed as an Associate Professor in 1997 and a Professor in 2000. From June 1999 to September 1999, he was a Research Associate with the City University of Hong Kong, Kowloon, Hong Kong. From August 2000 to August 2001, he was with Pohang University of Science and Technology, Pohang, Korea, as a Senior Scientist. From June 2002 to September 2002, he was a Research Associate with The University of Hong Kong. From August 2003 to October 2003, he was a Visiting Professor with Central Queensland University, Rockhampton, Qld., Australia. From March 2004 to March 2005, he was a Research Fellow with the Central Queensland University. From January 2007 to February 2007, supported by the Royal Society of the U.K., he was a Visiting Professor with Brunel University, Uxbridge, U.K. Since 1997, he has been a Leader of some institutes, such as the Institute of Computer Integrated Manufacturing Systems (CIMS) and Robots, the China University of Mining and Technology, and the Institute of Information and Control Engineering, Nanjing Normal University, Nanjing, China. He has also been responsible for 11 foundations supported by the Chinese government or other countries. He is currently a TePin Professor with the Department of Control Science and Engineering, Huazhong University of Science and Technology, Wuhan, China. As a Coeditor, he edited a special issue for the *International Journal of Computer Mathematics* in 2007. He is currently an Associate Editor of the *International Journal of Systems Science*, the *Journal of Mathematical Control Science and Applications*, and the *International Journal of Systems, Control and Communications*. He has authored or coauthored more than 100 papers in international journals, domestic journals, and international conferences. His research interests include the analysis and synthesis of networked control systems, time-delay systems, robust control design, and CIMS applications.

Dr. Yue is an Associate Editor of the IEEE Control Systems Society Conference Editorial Board. He is currently a Reviewer for more than 20 international journals or conferences, such as the IEEE TRANSACTIONS ON AUTOMATIC CONTROL, *Automatica*, the IEEE TRANSACTIONS ON SIGNAL PROCESSING, etc. He was also the recipient of several awards from the Chinese government.

Tai Cheng Yang received the M.Sc. degree in control engineering from Shanghai Tongji University, Shanghai, China, in 1981 and the Ph.D. degree in control engineering from the University of Manchester Institute of Science and Technology, Manchester, U.K., in 1987.

He is currently a Reader with the Department of Engineering and Design, University of Sussex, Brighton, U.K. He has authored or coauthored more than 141 publications, including 57 journal papers. His research interests include networked control systems, wind power and power system control, and control applications.

Zhou Gu received the B.S. degree from North China Electric Power University, Beijing, China, in 1996 and the M.S. and Ph.D. degrees from Nanjing University of Aeronautics and Astronautics, Nanjing, China, in 2007 and 2010, respectively.

Since 1999, he has been with the School of Power engineering, Nanjing Normal University. His current research interests include networked control systems, Takegi–Sugeno (T–S) fuzzy systems, and time-delay systems.

Guoping Lu received the B.S. degree from the Department of Applied Mathematics, Chengdu University of Science and Technology, Chengdu, China, in 1984 and the M.S. and Ph.D. degrees from the Department of Mathematics, East China Normal University, Shanghai, China, in 1989 and 1998, respectively.

He is currently a Professor with the College of Electrical Engineering, Nantong University, Jiangsu, China. His research interests include nonlinear signal processing, robust control, and networked control.