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Reliable Dissipative Interval Type-2 Fuzzy Control for Nonlinear Systems with Stochastic Incomplete Communication Route and Actuator Failure

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Abstract This paper investigates the dissipative interval type-2 (IT2) fuzzy control issue for a group of uncertain nonlinear systems subject to randomly occurring sensor saturation and quantization. By utilizing the both lower and upper membership functions with relevant tradeoff moduli, uncertainties, which exist in the considered systems, can be captured effectively. During the design of the IT2 fuzzy controller, we take the actuator failure into consideration. Considering the randomities for the occurrences of sensor saturation and quantization, two separate Bernoulli stochastic distributed courses are utilized to construct the corresponding complicated transmission route. In term of Lyapunov stability theory, sufficient criteria to design dissipative IT2 fuzzy controller are presented to assure the stochastic stability with strict dissipativity

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of resulting closed-loop systems. Finally, illustrative example verifies the effectiveness and merits of the control strategy proposed in this paper.

Keywords Random incomplete transmission, interval type-2 (IT2) fuzzy control, sensor saturation, quantization, actuator failure, dissipativity.

1 Introduction

In modern industries, numerous plants are nonlinear [1–5] and cannot handle by the existing linear control methods [6,7]. In order to tackle such an intractable issue, abundant intelligent control strategies have been developed such as Takagi-Sugeno (T-S) fuzzy control [8,9], neural network [10,11], sliding mode control [12] and adaptive control [13–17]. Among these control approaches, T-S fuzzy control can tackle the nonlinearities effectively and has been utilized in many significant results. Considering the packet loss and actuator failure, a reliable event-triggered fuzzy controller was designed for nonlinear networked systems by T-S fuzzy model [8]. In [18], the authors investigated the robust $\mathcal{H}_\infty$ control problem of a category of nonlinear plants by using the T-S fuzzy model. A T-S fuzzy filter was designed in [19] for Markovian jump systems, where the faults could be detected effectively with the proposed filter design method. Considering the variation of the numbers of people in vehicles, Li *et al.* in [20] utilized T-S fuzzy approach to describe such phenomenon for uncertain suspension systems, and proposed a fuzzy control policy to enhance driving comfort.

Nevertheless, uncertainties often exist in plants, hence, traditional type-1 T-S fuzzy method [8,21] whose membership functions are determined lose the ability to handle uncertain membership grades. To this end, a novel

interval type-2 (IT2) T-S fuzzy model was proposed by H.K. Lam to handle uncertainties [22] and membership-function-dependent analysis subject to imperfect premise matching [23] was proposed in [24] to approach control synthesis and stability analysis issues, then, it has attracted considerable research interests [25, 26]. Using lower and upper membership functions with relevant tradeoff coefficients, uncertainties can be captured effectively. To name a few, according to the IT2 T-S fuzzy method, the finite-time stabilization problem of interconnected plants was studied in [27]. For the data missing case, a fuzzy controller which based on IT2 T-S fuzzy method was designed to stabilize networked systems. The authors in [28] designed a new IT2 fuzzy detector for T-S fuzzy systems, in which the problems of finite communication space and sensor failure were addressed simultaneously. A reliable fuzzy filter design approach based on IT2 T-S fuzzy model was presented for nonlinear plants to ensure the asymptotic stability and dissipative performance of resulting plants with sensor failure [25]. It is worth mentioning that membership-function-dependent analysis play an important role in dealing with the imperfect premise matching issue in IT2 fuzzy model based control. Readers could refer to [29] for a comprehensive review of membership-function-dependent analysis techniques.

Dissipative performance has been analyzed in many results since the dissipativity theory generalizes many basic theories, see [25, 30] and references therein. A reliable dissipative filter was designed for time-delay systems in [30]. However, the above works [25, 30] failed to cope with the failure which is generated by actuators. How to design a reliable dissipative IT2 fuzzy controller to withstand failure while guaranteeing the stability of considered systems still deserves a deep exploration.

Saturation is a troublesome obstacle for plants in acquiring a high performance. It often exists in any sensors, actuators and even certain plant components. Saturation produces nonlinear features which can severely limit the control scheme. Such a factor not only influences the performance of systems, but also results in unpredictable oscillatory behaviour and even instability. Therefore, the control issue for plants in context of sensor/actuator saturation has attracted much attentions of a large number of scholars [31–34]. Pan *et al.* in [31] focused on the event-driven FD issue for a category of IT2 fuzzy networked control systems with nonlinear perturbations. In [32], a robust $\mathcal{H}_\infty$ filter was designed for Markovian jump systems to against sensor saturation and stochastic nonlinearities. In [33], a synthesis control strategy was proposed for suspension system with actuator saturation, input delay and parameter uncertainties, by researching the characters of actuator

saturation, the existence criteria of desired controller were obtained. On the other hand, the quantized control, as an effective technique in decreasing transmission burden, can be found in many existing results [35–37]. Based on state quantized and sampled-data control, the stabilization issue was investigated in [35] for T-S fuzzy systems. It is noteworthy that in literatures [31–33, 35], the saturation and quantization problems they considered were all assumed to always happen. Actually, in complicated transmission environment, the saturation and quantization themselves may be subjected to stochastic abrupt changes. In other words, they occur in a probabilistic manner and change randomly. This phenomenon, namely, stochastically occurring sensor saturation and quantization, has been widely neglected in this area. However, there were few works that placed stochastically occurring quantization and sensor saturation with a unified structure for IT2 T-S fuzzy plants. Meanwhile, it is unavoidable for an actuator to generate failure due to the long-term operation and age of enginery in the industrial systems, which motivate our present study.

Inspired by the above discussions, this paper develops the reliable dissipative IT2 fuzzy control problem for a family of nonlinear systems with actuator failure and stochastic incomplete communication route. The main innovations of this paper are organized as follows:

1. The uncertainties, which exist in considered systems, are addressed via employing upper and lower membership functions. Besides, considering the actuator failure, which always obstructs the stabilization of systems, a corresponding model is established.
2. By utilizing two independent Bernoulli stochastic distribution processes, a new data transmission pattern is built. Compared with the existing literature [8, 25], the randomly occurring sensor saturation and quantization can be depicted and solved effectively through the established transmission pattern and designed controller, respectively.
3. In order to guarantee the stochastic stability while ensure the strictly dissipative performance for the system (2), sufficient conditions are given in this paper. Moreover, the method of how to acquire dissipative IT2 fuzzy controller gains is also given.

The structure of this paper is shown below. Problem formulation is offered in Section II. The main results are furnished in Section III. Illustrative examples are supplied in Section IV. At last, we conclude this paper in Section V.

Notations: The sign “ $\star$ ” denotes a symmetric term. The superscript “ T ” represents matrix transposition. “ E ” means the mathematical expectation oper-

ator. Matrices without any detailed explanation, are presumed to equip with suitable dimensions.

2 Problem Formulation

For the sake of presenting the proposed control algorithm intuitively, in this section, the preliminaries, comprise modeling nonlinear plants via IT2 T-S fuzzy model, depicting complex signal transmission route, establishing actuator failure model and designing reliable fuzzy controller, are given.

2.1 Modeling for Nonlinear Plants via IT2 T-S Fuzzy Approach

According to IT2 T-S fuzzy model, a class of discrete-time systems are shown as the following form,

Plant Rule i : IF $\theta_1(\sigma(k))$ is $\mathcal{L}_{i1}$, and $\theta_2(\sigma(k))$ is $\mathcal{L}_{i2}$, and $\dots$, and $\theta_\tau(\sigma(k))$ is $\mathcal{L}_{i\tau}$, **THEN**

$$\begin{cases} x(k+1) = \mathcal{A}_i x(k) + \mathcal{B}_i u(k) + \mathcal{B}_{1i} w(k), \\ z(k) = \mathcal{C}_i x(k) + \mathcal{D}_i u(k), \end{cases} \quad (1)$$

where $\mathcal{L}_{ij}$ is the fuzzy set, $\theta(\sigma(k)) = [\theta_1(\sigma(k)), \theta_2(\sigma(k)), \dots, \theta_\tau(\sigma(k))]^T$ denotes the premise variable, τ means that the amount of the fuzzy sets. $x(k) \in \mathbb{R}^n$ represents the state vector, $u(k) \in \mathbb{R}^l$ is the input vector, $w(k) \in \mathbb{R}^m$ refers to the external disturbance which belongs to $\ell_2[0, \infty)$. $z(k) \in \mathbb{R}^p$ is the controlled output. $\mathcal{A}_i, \mathcal{B}_i, \mathcal{B}_{1i}, \mathcal{C}_i$ and $\mathcal{D}_i$ are known matrices with appropriate dimensions. $i = 1, \dots, r$, and r is the number of fuzzy rules. The interval sets which represent the triggering strength of the i -th rule are shown below

$$\mathcal{W}_i(\sigma(k)) = [\underline{m}_i(\sigma(k)), \bar{m}_i(\sigma(k))],$$

where

$$\underline{m}_i(\sigma(k)) = \prod_{p=1}^{\tau} \underline{u}_{\mathcal{L}_{ip}}(\theta_p(\sigma(k))) \geq 0,$$

$$\bar{m}_i(\sigma(k)) = \prod_{p=1}^{\tau} \bar{u}_{\mathcal{L}_{ip}}(\theta_p(\sigma(k))) \geq 0,$$

$$\bar{u}_{\mathcal{L}_{ip}}(\theta_p(\sigma(k))) \geq \underline{u}_{\mathcal{L}_{ip}}(\theta_p(\sigma(k))) \geq 0,$$

$$\bar{m}_i(\sigma(k)) \geq \underline{m}_i(\sigma(k)) \geq 0,$$

$\underline{u}_{\mathcal{L}_{ip}}(\theta_p(\sigma(k)))$, $\bar{u}_{\mathcal{L}_{ip}}(\theta_p(\sigma(k)))$, $\underline{m}_i(\sigma(k))$ and $\bar{m}_i(\sigma(k))$ present lower membership function, upper membership function, lower and upper grades of memberships, respectively.

Whereafter, the system (1) is inferred below

$$\begin{cases} x(k+1) = \sum_{i=1}^r m_i(\sigma(k)) [\mathcal{A}_i x(k) + \mathcal{B}_i u(k) + \mathcal{B}_{1i} w(k)], \\ z(k) = \sum_{i=1}^r m_i(\sigma(k)) [\mathcal{C}_i x(k) + \mathcal{D}_i u(k)], \end{cases} \quad (2)$$

where

$$m_i(\sigma(k)) = \frac{\underline{\alpha}_i(\sigma(k)) \underline{m}_i(\sigma(k)) + \bar{\alpha}_i(\sigma(k)) \bar{m}_i(\sigma(k))}{\sum_{d=1}^r [\underline{\alpha}_d(\sigma(k)) \underline{m}_d(\sigma(k)) + \bar{\alpha}_d(\sigma(k)) \bar{m}_d(\sigma(k))]},$$

$$m_i(\sigma(k)) \geq 0,$$

$$0 \leq \underline{\alpha}_i(\sigma(k)) \leq 1, 0 \leq \bar{\alpha}_i(\sigma(k)) \leq 1,$$

$$\sum_{i=1}^r m_i(\sigma(k)) = 1, \underline{\alpha}_i(\sigma(k)) + \bar{\alpha}_i(\sigma(k)) = 1,$$

with $m_i(\sigma(k))$ being the grade of membership, $\underline{\alpha}_i(\sigma(k))$ and $\bar{\alpha}_i(\sigma(k))$ stand for tradeoff coefficients.

2.2 Sensor Saturation

Due to the limitation of bandwidth in transmission route, the phenomenon of sensor saturation often occurs. The sensor saturation is depicted by the function $\phi(\cdot) : \mathbb{R}^n \rightarrow \mathbb{R}^n$ satisfying $\phi(\cdot) \in [K_1, K_2]$. For some given diagonal matrices $K_1 \geq 0, K_2 \geq 0$ with $K_1 \geq K_2$, $\phi(\cdot)$ satisfies the following sector condition:

$$(\phi(x(k)) - K_1(x(k))) (\phi(x(k)) - K_2(x(k))) \leq 0, \forall x(k) \in \mathbb{R}^n.$$

The function $\phi(x(k))$ is decomposed as [38] and shown as follows

$$\phi(x(k)) = \phi_s(x(k)) + K_1 x(k), \quad (3)$$

where $\phi_s(x(k))$ satisfies the following set:

$$\Phi_s = \{\phi_s : \phi_s(x(k))^T (\phi_s(x(k)) - K_1 x(k)) \leq 0\}.$$

2.3 Measurement Quantization

The logarithmical quantizer which is the same as [39] is adopted in this study, the model is shown as

$$\tilde{x}(k) = U(x(k)) = [U_1(x_1(k)) \ U_2(x_2(k)) \ \dots \ U_n(x_n(k))]^T,$$

where $\tilde{x}(k) \in \mathbb{R}^n$ is the signal to be quantized. $U(x(k))$ is the type of quantizer. The quantized level of each $U_m(x_m(k))$ ($1 \leq m \leq n$) is described by

$$q_m = \{\pm \mathcal{X}_f^{(m)}, \pm \mathcal{X}_f^{(m)} = k_m^f \mathcal{X}_0^{(m)}, f = 0, \pm 1, \pm 2, \dots\} \cup \{0\},$$

with $0 < k_m < 1, \mathcal{X}_0^{(m)} > 0$.

The total parts to the level of quantization are depicted via the quantizer by means of relative each of the quantization level to a segment, $U_j(\cdot)$ is demoted as

$$U_m(x_m(k)) = \begin{cases} \mathcal{X}_f^{(m)}, & \frac{1}{1+\varepsilon_m} \mathcal{X}_f^{(m)} < x_m(k) \leq \frac{1}{1-\varepsilon_m} \mathcal{X}_f^{(m)}, \\ 0, & x_m(k) = 0, \\ -U_m(-x_m(k)), & x_m(k) < 0, \end{cases} \text{ where}$$

where $\varepsilon_m = \frac{1-k_m}{1+k_m}$.

By using the sector-bound approach which is provided in [40], we can obtain the quantization error as

$$\tilde{x}(k) = (\mathcal{I} + \Delta(k))x(k), \quad (4)$$

where $\Delta(k) = \text{diag}\{\Delta_1(k), \dots, \Delta_n(k)\}$, $|\Delta_m(x_m(k))| < \varepsilon_m$, $m = 1, \dots, n$.

2.4 Random Incomplete Communication Route

Consider the complexities of transmission environment, sensor saturation and quantization often occur in a stochastic way. Thus, we establish an innovative signal communication model shown below

$$\tilde{x}(k) = \alpha(k)\phi(x(k)) + (1 - \alpha(k))\beta(k)\tilde{x}(k). \quad (5)$$

In the above model, the random variables $\alpha(k)$ and $\beta(k)$ meet the following conditions:

$$\begin{aligned} \text{Prob}\{\alpha(k) = 1\} &= \bar{\alpha}, \text{Prob}\{\alpha(k) = 0\} = 1 - \bar{\alpha}, \\ \text{Prob}\{\beta(k) = 1\} &= \bar{\beta}, \text{Prob}\{\beta(k) = 0\} = 1 - \bar{\beta}. \end{aligned}$$

Remark 1 In actual applications, sensor saturation and quantization are two crucial factors that inevitably occur during data transmission on account of the limit bandwidth. The two situations mentioned above can be described via a unified structure by the newly designed model (5). More concretely,

1. if $\alpha(k) = 1 \Rightarrow$ The data only suffers from saturation.
2. if $\alpha(k) = 0, \beta(k) = 1 \Rightarrow$ The data undergoes quantization.
3. if $\alpha(k) = 0, \beta(k) = 0 \Rightarrow$ The data is lost totally.

2.5 IT2 T-S Fuzzy State-Feedback Controller

The fuzzy controller is designed as the following form:

Controller Rule j : IF $\delta_1(\sigma(k))$ is $\mathcal{V}_{j1}$, and $\delta_2(\sigma(k))$ is $\mathcal{V}_{j2}$, and ..., and $\delta_u(\sigma(k))$ is $\mathcal{V}_{ju}$, **THEN**

$$u(k) = \mathcal{K}_j \tilde{x}(k),$$

where $\mathcal{K}_j$ ($j = 1, \dots, r$) denote the controller gains. The interval sets shown below are utilized to depict the j -th rule's triggering intensity:

$$\Omega_j(\sigma(k)) = [\underline{w}_j(\sigma(k)), \bar{w}_j(\sigma(k))],$$

$$\underline{w}_j(\sigma(k)) = \prod_{q=1}^u \underline{u}_{\mathcal{V}_{jq}}(\delta_q(\sigma(k))) \geq 0,$$

$$\bar{w}_j(\sigma(k)) = \prod_{q=1}^u \bar{u}_{\mathcal{V}_{jq}}(\delta_q(\sigma(k))) \geq 0,$$

$$\bar{u}_{\mathcal{V}_{jq}}(\delta_q(\sigma(k))) \geq \underline{u}_{\mathcal{V}_{jq}}(\delta_q(\sigma(k))) \geq 0,$$

$$\bar{w}_j(\sigma(k)) \geq \underline{w}_j(\sigma(k)) \geq 0,$$

$\underline{u}_{\mathcal{V}_{jq}}(\delta_q(\sigma(k)))$, $\bar{u}_{\mathcal{V}_{jq}}(\delta_q(\sigma(k)))$, $\underline{w}_j(\sigma(k))$ and $\bar{w}_j(\sigma(k))$ denote lower membership function, upper membership function, lower grade of membership and upper grade of membership, respectively. Modeling overall controller as the following form

$$u(k) = \sum_{j=1}^r w_j(\sigma(k)) \mathcal{K}_j \tilde{x}(k), \quad (6)$$

where

$$w_j(\sigma(k)) = \frac{\underline{b}_j(\sigma(k))\underline{w}_j(\sigma(k)) + \bar{b}_j(\sigma(k))\bar{w}_j(\sigma(k))}{\sum_{l=1}^r [\underline{b}_l(\sigma(k))\underline{w}_l(\sigma(k)) + \bar{b}_l(\sigma(k))\bar{w}_l(\sigma(k))]},$$

$$w_j(\sigma(k)) \geq 0,$$

$$0 \leq \underline{b}_j(\sigma(k)) \leq 1, \quad 0 \leq \bar{b}_j(\sigma(k)) \leq 1,$$

$$\sum_{i=1}^r w_j(\sigma(k)) = 1, \quad \underline{b}_j(\sigma(k)) + \bar{b}_j(\sigma(k)) = 1,$$

in which $w_j(\sigma(k))$ is the grade of membership, the trade-off coefficients are represented by $\underline{b}_j(\sigma(k))$ and $\bar{b}_j(\sigma(k))$.

In what follows, we define $m_i \triangleq m_i(\sigma(k))$, $w_j \triangleq w_j(\sigma(k))$ for simplicity.

Remark 2 The membership functions of controller (6) are not the same as the fuzzy plant (2) due to the utilization of IT2 T-S fuzzy model, which lead to imperfect premise matching [29]. Compared with the traditional type-1 T-S fuzzy model [21], the imperfect preface premise is not only improving the flexibility of designing fuzzy controller, but also reducing the calculation burden.

2.6 Actuator Failure Model

The following model is used to describe the phenomenon of actuator failure:

$$u_f(k) = \Phi u(k), \quad (7)$$

where Φ stands for a known parameter which belongs to interval $[0, 1]$.

Remark 3 According to the model (7), we can obtain that the actuator has two cases:

- 1) $\Phi = 1 \Rightarrow$ it means that the actuator is working in normal condition.
- 2) $\Phi \in [0, 1) \Rightarrow$ the actuator has local failure.

Combining (2), (3), (4)-(7), it yields the following closed-loop system

$$\begin{cases} x(k+1) = \sum_{i=1}^r \sum_{j=1}^r m_i w_j [\bar{A}_{ij} x(k) + \bar{\alpha} \mathcal{B}_i \Phi \mathcal{K}_j \phi(x(k)) \\ \quad + (\alpha(k) - \bar{\alpha}) \mathcal{B}_i \Phi \mathcal{K}_j K_1 x(k) + \mathcal{B}_{1i} w(k) \\ \quad + (\alpha(k) - \bar{\alpha}) \mathcal{B}_i \Phi \mathcal{K}_j \phi(x(k)) + ((1 - \alpha(k))\beta(k) - (1 - \bar{\alpha})\bar{\beta}) \mathcal{B}_i \Phi \mathcal{K}_j (\mathcal{I} \\ \quad + \Delta(k)) x(k)], \\ z(k) = \sum_{i=1}^r \sum_{j=1}^r m_i w_j [\bar{C}_{ij} x(k) + \bar{\alpha} \mathcal{D}_i \Phi \mathcal{K}_j \phi(x(k)) \\ \quad + (\alpha(k) - \bar{\alpha}) \mathcal{D}_i \Phi \mathcal{K}_j K_1 x(k) + (\alpha(k) - \bar{\alpha}) \mathcal{D}_i \Phi \mathcal{K}_j \phi(x(k)) + ((1 - \alpha(k))\beta(k) \\ \quad - (1 - \bar{\alpha})\bar{\beta}) \mathcal{D}_i \Phi \mathcal{K}_j (\mathcal{I} + \Delta(k)) x(k)], \end{cases} \quad (8)$$

where

$$\begin{aligned} \bar{A}_{ij} &= \mathcal{A}_i + \bar{\alpha} \mathcal{B}_i \Phi \mathcal{K}_j K_1 + (1 - \bar{\alpha}) \bar{\beta} \mathcal{B}_i \Phi \mathcal{K}_j (\mathcal{I} + \Delta(k)), \\ \bar{C}_{ij} &= \mathcal{C}_i + \bar{\alpha} \mathcal{D}_i \Phi \mathcal{K}_j K_1 + (1 - \bar{\alpha}) \bar{\beta} \mathcal{D}_i \Phi \mathcal{K}_j (\mathcal{I} + \Delta(k)). \end{aligned}$$

It is effortless to get that

$$\begin{aligned} E\{(\alpha(t) - \bar{\alpha})^2\} &= \bar{\alpha}(1 - \bar{\alpha}), \\ E\{(1 - \alpha(t))\beta(t) - (1 - \bar{\alpha})\bar{\beta}\} &= (1 - \bar{\alpha})\bar{\beta} \\ &\quad - (1 - \bar{\alpha})^2 \bar{\beta}^2. \end{aligned}$$

2.7 Dissipativity Theory

Definition 1 [25]: For the given matrix $\mathcal{Q} < 0 \in \mathbb{R}^{p \times p}$, symmetric matrices $\mathcal{R} \in \mathbb{R}^{m \times m}$ and $\mathcal{S} \in \mathbb{R}^{p \times m}$, the closed-loop system in (8) satisfies the strictly dissipative performance provided that for some real functions $\phi(\cdot)$ with $\phi(0) = 0$, the following condition can be guaranteed:

$$\sum_{k=0}^T \begin{bmatrix} z(k) \\ w(k) \end{bmatrix}^T \begin{bmatrix} \mathcal{Q} & \mathcal{S} \\ \star & \mathcal{R} \end{bmatrix} \begin{bmatrix} z(k) \\ w(k) \end{bmatrix} + \phi(\eta(0)) \geq 0.$$

Assume that there exists a scalar $\delta > 0$ which satisfies the following form

$$\begin{aligned} \sum_{k=0}^T \begin{bmatrix} z(k) \\ w(k) \end{bmatrix}^T \begin{bmatrix} \mathcal{Q} & \mathcal{S} \\ \star & \mathcal{R} \end{bmatrix} \begin{bmatrix} z(k) \\ w(k) \end{bmatrix} + \phi(\eta(0)) \\ \geq \delta \sum_{k=0}^T w^T(k) w(k) \geq 0, \end{aligned}$$

then, the system in (8) satisfies the strictly dissipative performance.

Lemma 1 [39]: Giving the proper matrices Σ_1, Σ_2 and Σ_3 with $\Sigma_1 = \Sigma_1^T$, if there exists a constant ε so that

$$\Sigma_1 + \varepsilon^{-1} \Sigma_3 \Sigma_3^T + \varepsilon \Sigma_2^T \Sigma_2 < 0$$

holds, then, the expression

$$\Sigma_1 + \Sigma_3 \Delta(k) \Sigma_2 + \Sigma_2^T \Delta^T(k) \Sigma_3^T < 0$$

is guaranteed for all $\Delta(k)$ that satisfy $\Delta(k)^T \Delta(k) \leq \mathcal{I}$.

3 Main Results

3.1 Strict Dissipativity Analysis

The existence criteria of stochastic stability as well as strictly dissipative performance for the resulting closed-loop system is provided in this subsection.

Theorem 1 For the given controller gains $\mathcal{K}_j$ ($j = 1, \dots, r$), matrices $0 > \mathcal{Q} \in \mathbb{R}^{p \times p}$, $\mathcal{R} \in \mathbb{R}^{m \times m}$, $\mathcal{S} \in \mathbb{R}^{p \times m}$ and scalars $\bar{\alpha}, \bar{\beta}, \delta > 0$, in the context of $w_j - \varphi_j m_j > 0$ ($\varphi_j > 0$), the closed-loop system in (8) is stochastically stable and satisfy the strictly dissipative performance if there exists a positive definite matrix $0 < \mathcal{P} \in \mathbb{R}^{n \times n}$, for $i, j = 1, 2, \dots, r$, the conditions shown below hold:

$$\varphi_i \bar{\mathcal{Q}}_{ii} - \varphi_i \Lambda + \Lambda < 0, \quad (9)$$

$$\varphi_j \bar{\mathcal{Q}}_{ij} - \varphi_j \Lambda + \varphi_i \bar{\mathcal{Q}}_{ji} - \varphi_i \Lambda + 2\Lambda < 0, \quad (10)$$

$$\bar{\mathcal{Q}}_{ij} - \Lambda < 0, \quad (11)$$

where

$$\bar{\mathcal{Q}}_{ij} = \mathcal{Q}_{ij} + \Pi,$$

$$\mathcal{Q}_{ij} = \begin{bmatrix} \hat{\mathcal{Q}}_{ij} & \Xi \\ \star & \mathcal{B}_{1i}^T \mathcal{P} \mathcal{B}_{1i} \end{bmatrix}, \quad \hat{\mathcal{Q}}_{ij} = \begin{bmatrix} \varpi & v \\ \star & \mu \end{bmatrix},$$

$$\Xi = \begin{bmatrix} \bar{\mathcal{A}}_{ij}^T \mathcal{P} \mathcal{B}_{1i} \\ \bar{\alpha} \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T \mathcal{P} \mathcal{B}_{1i} \end{bmatrix}, \quad \Pi = \begin{bmatrix} \vartheta & \varsigma \\ \star & -\mathcal{R} + \delta \mathcal{I} \end{bmatrix},$$

$$\varpi = \bar{\mathcal{A}}_{ij}^T \mathcal{P} \bar{\mathcal{A}}_{ij} - \mathcal{P} + f_1^2 K_1^T \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T \mathcal{P} \mathcal{B}_i \Phi \mathcal{K}_j K_1$$

$$+ f_2^2 (\mathcal{I} + \Delta(k))^T \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T \mathcal{P} \mathcal{B}_i \Phi \mathcal{K}_j (\mathcal{I} + \Delta(k)),$$

$$v = \bar{\alpha} \bar{\mathcal{A}}_{ij}^T \mathcal{P} \mathcal{B}_i \Phi \mathcal{K}_j + f_1^2 K_1^T \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T \mathcal{P} \mathcal{B}_i \Phi \mathcal{K}_j + K^T,$$

$$\mu = \bar{\alpha}^2 \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T \mathcal{P} \mathcal{B}_i \Phi \mathcal{K}_j + f_1^2 \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T \mathcal{P} \mathcal{B}_i \Phi \mathcal{K}_j - 2\mathcal{I},$$

$$\begin{aligned} \vartheta &= \begin{bmatrix} \vartheta_1 & \vartheta_2 \\ \star & \vartheta_3 \end{bmatrix}, \varsigma = \begin{bmatrix} -\bar{C}_{ij}^T \mathcal{S} \\ -\bar{\alpha} \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{S} \end{bmatrix}, \\ \vartheta_1 &= -\bar{C}_{ij}^T \mathcal{Q} \bar{C}_{ij}^T - f_1^2 K_1^T \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{Q} \mathcal{D}_i \Phi \mathcal{K}_j K_1 \\ &\quad - f_2^2 (\mathcal{I} + \Delta(k))^T \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{Q} \mathcal{D}_i \Phi \mathcal{K}_j (\mathcal{I} + \Delta(k)), \\ \vartheta_2 &= -\bar{\alpha} \bar{C}_{ij}^T \mathcal{Q} \mathcal{D}_i \Phi \mathcal{K}_j - f_1^2 K_1^T \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{Q} \mathcal{D}_i \Phi \mathcal{K}_j, \\ \vartheta_3 &= -\bar{\alpha}^2 \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{Q} \mathcal{D}_i \Phi \mathcal{K}_j - f_1^2 \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{Q} \mathcal{D}_i \Phi \mathcal{K}_j, \\ f_1 &= \sqrt{\bar{\alpha}(1-\bar{\alpha})}, \quad f_2 = \sqrt{(1-\bar{\alpha})\bar{\beta} - (1-\bar{\alpha})^2 \bar{\beta}^2}. \end{aligned}$$

Proof The Lyapunov function of the system (8) is selected below

$$\mathcal{V}(k) = x^T(k) \mathcal{P} x(k),$$

with $\mathcal{P} > 0$ being positive definite matrix to be calculated.

Whereafter, calculating the difference of $\mathcal{V}(k)$ as follows

$$\begin{aligned} \Delta \mathcal{V}(k) &= E\{\mathcal{V}(k+1)\} - \mathcal{V}(k), \\ &\leq E \left\{ \sum_{i=1}^r \sum_{j=1}^r m_i w_j [\bar{\mathcal{A}}_{ij} x(k) + \bar{\alpha} \mathcal{B}_i \Phi \mathcal{K}_j \phi(x(k)) \right. \\ &\quad + (\alpha(k) - \bar{\alpha}) \mathcal{B}_i \Phi \mathcal{K}_j K_1 x(k) + \mathcal{B}_{1i} w(k) \\ &\quad + (\alpha(k) - \bar{\alpha}) \mathcal{B}_i \Phi \mathcal{K}_j \phi(x(k)) + ((1 - \alpha(k)) \\ &\quad \times \beta(k) - (1 - \bar{\alpha}) \bar{\beta}) \mathcal{B}_i \Phi \mathcal{K}_j (\mathcal{I} + \Delta(k)) \\ &\quad \times x(k)]^T \mathcal{P} [\bar{\mathcal{A}}_{ij} x(k) + \bar{\alpha} \mathcal{B}_i \Phi \mathcal{K}_j \phi(x(k)) \\ &\quad + (\alpha(k) - \bar{\alpha}) \mathcal{B}_i \Phi \mathcal{K}_j K_1 x(k) + \mathcal{B}_{1i} w(k) \\ &\quad + (\alpha(k) - \bar{\alpha}) \mathcal{B}_i \Phi \mathcal{K}_j \phi(x(k)) + ((1 - \alpha(k)) \\ &\quad \times \beta(k) - (1 - \bar{\alpha}) \bar{\beta}) \mathcal{B}_i \Phi \mathcal{K}_j (\mathcal{I} + \Delta(k)) x(k)] \} \\ &\quad - x(k)^T \mathcal{P} x(k) - 2\phi^T(x(k))(\phi(x(k)) - Kx(k)), \\ &= E \left\{ \sum_{i=1}^r \sum_{j=1}^r m_i w_j \bar{\xi}^T(k) \mathcal{Q}_{ij} \bar{\xi}(k) \right\}, \end{aligned} \quad (12)$$

where $\bar{\xi}^T(k) = [x^T(k) \ \phi_s^T(k) \ w^T(k)]$.

For the sake of decreasing the conservatism, the following slack matrix [24] is introduced:

$$\sum_{i=1}^r \sum_{j=1}^r m_i (m_j - w_j) \Lambda = 0. \quad (13)$$

Combining (12) and (13), one has

$$\begin{aligned} \Delta \mathcal{V}(k) &\leq E \left\{ \sum_{i=1}^r \sum_{j=1}^r m_i w_j \bar{\xi}^T(k) \mathcal{Q}_{ij} \bar{\xi}(k) + \sum_{i=1}^r \sum_{j=1}^r \right. \\ &\quad + \Lambda) \bar{\xi}(k) + \sum_{i=1}^r \sum_{j=1}^r m_i (w_j - \varphi_j m_j) \\ &\quad \times \bar{\xi}^T(k) (\mathcal{Q}_{ij} - \Lambda) \bar{\xi}(k) \} \\ &= E \left\{ \sum_{i=1}^r m_i^2 \bar{\xi}^T(k) (\varphi_i \mathcal{Q}_{ii} - \varphi_i \Lambda + \Lambda) \bar{\xi}(k) \right. \end{aligned}$$

$$\begin{aligned} &+ \sum_{i=1}^{r-1} \sum_{i < j}^r m_i w_j \bar{\xi}^T(k) (\varphi_j \mathcal{Q}_{ij} - \varphi_j \Lambda \\ &+ \varphi_i \mathcal{Q}_{ji} - \varphi_i \Lambda + 2\Lambda) \bar{\xi}(k) + \sum_{i=1}^r \sum_{j=1}^r \\ &\times m_i (w_j - \varphi_j m_j) \bar{\xi}^T(k) (\mathcal{Q}_{ij} - \Lambda) \bar{\xi}(k) \}. \end{aligned}$$

By means of the Schur complement, if $w(k) = 0$, from (9)-(11), one has $\epsilon < 0$, where

$$\begin{aligned} \epsilon &= E \left\{ \sum_{i=1}^r m_i^2 \bar{\xi}^T(k) (\varphi_i \hat{\mathcal{Q}}_{ii} - \varphi_i \Lambda_1 + \Lambda_1) \bar{\xi}(k) \right. \\ &+ \sum_{i=1}^{r-1} \sum_{i < j}^r m_i w_j \bar{\xi}^T(k) (\varphi_j \hat{\mathcal{Q}}_{ij} - \varphi_j \Lambda_1 + \varphi_i \hat{\mathcal{Q}}_{ji} \\ &- \varphi_i \Lambda_1 + 2\Lambda_1) \bar{\xi}(k) + \sum_{i=1}^r \sum_{j=1}^r m_i (w_j - \varphi_j m_j) \\ &\times \bar{\xi}^T(k) (\hat{\mathcal{Q}}_{ij} - \Lambda_1) \bar{\xi}(k) \}, \end{aligned}$$

with Λ_1 being the top left part of Λ . Accordingly, the system in (8) is stochastically stable. Define

$$\begin{aligned} \mathcal{J}(T) &= E \left\{ \sum_{k=0}^T \begin{bmatrix} z(k) \\ w(k) \end{bmatrix}^T \begin{bmatrix} \mathcal{Q} & \mathcal{S} \\ \star & \mathcal{R} \end{bmatrix} \begin{bmatrix} z(k) \\ w(k) \end{bmatrix} \right. \\ &\quad \left. - \delta \sum_{k=0}^T w^T(k) w(k) \right\}. \end{aligned}$$

In the case of zero initial condition, for any nonzero $w(k)$, it is found that

$$\begin{aligned} &\mathcal{V}(T+1) - \mathcal{V}(0) - \mathcal{J}(T) \\ &= E \left\{ \sum_{k=0}^T \{ \Delta \mathcal{V}(k) - z^T(k) \mathcal{Q} z(k) - 2z^T(k) \mathcal{S} w(k) \right. \\ &\quad \left. - w^T(k) (\mathcal{R} - \delta \mathcal{I}) w(k) \} \right\}, \\ &\leq E \left\{ \sum_{k=0}^T \left\{ \sum_{i=1}^r m_i^2 \bar{\xi}^T(k) (\varphi_i \bar{\mathcal{Q}}_{ii} - \varphi_i \Lambda + \Lambda) \bar{\xi}(k) \right. \right. \\ &\quad + \sum_{i=1}^{r-1} \sum_{i < j}^r m_i w_j \bar{\xi}^T(k) (\varphi_j \bar{\mathcal{Q}}_{ij} - \varphi_j \Lambda + \varphi_i \bar{\mathcal{Q}}_{ji} \\ &\quad - \varphi_i \Lambda + 2\Lambda) \bar{\xi}(k) + \sum_{i=1}^r \sum_{j=1}^r m_i (w_j - \varphi_j m_j) \bar{\xi}^T(k) \\ &\quad \left. \left. \times (\bar{\mathcal{Q}}_{ij} - \Lambda) \bar{\xi}(k) \right\} \right\}. \end{aligned}$$

According to (9)-(11) and $\mathcal{V}(T) > 0$, we know that $\mathcal{J}(T) \geq 0$, which means that the system (8) satisfies the strictly dissipative performance.

Remark 4 In this paper, the slack matrix is adopted to handle the problem of mismatched membership functions which cannot be solved by the existing results [8, 21, 41]. In order to improve the flexibility of the

controller, an IT2 fuzzy model was adopted in [25], and the sensor saturation was also considered in [25]. However, quantization and actuator failure which are put in a unified framework are both considered in this paper except sensor saturation.

3.2 Controller Design

The way of a reliable fuzzy controller design in the form of (6) is provided in this subsection.

Theorem 2 *Giving the matrices $0 > \mathcal{Q} \in \mathbb{R}^{p \times p}$, $\mathcal{R} \in \mathbb{R}^{m \times m}$, $\mathcal{S} \in \mathbb{R}^{p \times m}$ and scalars $\bar{\alpha}$, $\bar{\beta}$, $\delta > 0$, in the context of $w_j - \varphi_j m_j > 0$ ($\varphi_j > 0$), the closed-loop system in (8) is stochastically stable as well as satisfy strictly dissipative performance provided that there exist positive definite matrix $0 < \mathcal{P} \in \mathbb{R}^{n \times n}$, controller gains $\mathcal{K}_j$ ($j = 1, \dots, r$) and scalar $\varepsilon > 0$, for $i, j = 1, 2, \dots, r$, the conditions shown below hold:*

$$\begin{bmatrix} \Theta_{ii} & \Omega_{ii} \\ \star & \Upsilon_{ii} \end{bmatrix} < 0, \quad (14)$$

$$\begin{bmatrix} F_{ij} & \Omega_{ij} \\ \star & \Psi_{ij} \end{bmatrix} < 0, \quad (15)$$

$$\begin{bmatrix} \Theta_{ij} & \Omega_{ij} \\ \star & \Upsilon_{ij} \end{bmatrix} + \begin{bmatrix} \Theta_{ji} & \Omega_{ji} \\ \star & \Upsilon_{ji} \end{bmatrix} < 0, \quad (16)$$

$$\mathcal{P}\mathcal{X} = \mathcal{I}, \quad (17)$$

where

$$\Theta_{ij} = \begin{bmatrix} \eta & \varrho \\ \star & \varkappa \end{bmatrix}, \quad \eta = \begin{bmatrix} \eta_1 & \eta_2 & \eta_3 \\ \star & \eta_4 & \eta_5 \\ \star & \star & \eta_6 \end{bmatrix}, \quad \Omega_{ij} = \begin{bmatrix} \kappa & \ell \\ 0 & \pi \end{bmatrix},$$

$$\Upsilon_{ij} = \begin{bmatrix} r & \tau \\ \star & \iota \end{bmatrix}, \quad F_{ij} = \begin{bmatrix} d & \varrho \\ \star & e \end{bmatrix}, \quad \Psi_{ij} = \begin{bmatrix} g & \tau \\ \star & \iota \end{bmatrix},$$

$$\varrho = \begin{bmatrix} \varrho_1 & \varrho_2 & \varrho_3 \\ \varrho_4 & \varrho_5 & \varrho_6 \\ \varrho_7 & 0 & 0 \end{bmatrix},$$

$$\varkappa = \text{diag}\{-\varphi_j^{-1}\mathcal{X}, \varphi_j^{-1}\mathcal{Q}^{-1}, -\varphi_j^{-1}\mathcal{X}\},$$

$$\eta_1 = -\varphi_j\mathcal{P} - \varphi_j\Lambda_{11} + \Lambda_{11},$$

$$\eta_2 = \varphi_j K^T - \varphi_j\Lambda_{12} + \Lambda_{12},$$

$$\eta_3 = -\mathcal{C}_i^T \mathcal{S} - \bar{\alpha} K_1^T \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{S} - (1 - \bar{\alpha})\bar{\beta} \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{S} - \varphi_j \Lambda_{13} + \Lambda_{13},$$

$$\eta_4 = -2\varphi_j \mathcal{I} - \varphi_j \Lambda_{22} + \Lambda_{22},$$

$$\eta_5 = -\bar{\alpha} \varphi_j \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{S} - \varphi_j \Lambda_{23} + \Lambda_{23},$$

$$\eta_6 = -\varphi_j(\mathcal{R} - \delta \mathcal{I}) - \varphi_j \Lambda_{33} + \Lambda_{33},$$

$$\varrho_1 = \mathcal{A}_i^T + \bar{\alpha} K_1^T \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T + (1 - \bar{\alpha})\bar{\beta} \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T,$$

$$\varrho_2 = \mathcal{C}_i^T + \bar{\alpha} K_1^T \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T + (1 - \bar{\alpha})\bar{\beta} \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T,$$

$$\varrho_3 = f_1 K_1^T \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T, \quad \varrho_4 = \bar{\alpha} \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T,$$

$$\varrho_5 = \bar{\alpha} \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T, \quad \varrho_6 = f_1 \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T, \quad \varrho_7 = \mathcal{B}_{1i}^T,$$

$$d = \begin{bmatrix} d_1 & d_2 \\ \star & d_3 \end{bmatrix}, \quad d_1 = \begin{bmatrix} -\mathcal{P} - \Lambda_{11} & K^T - \Lambda_{12} \\ \star & -2\mathcal{I} - \Lambda_{22} \end{bmatrix},$$

$$d_2 = \begin{bmatrix} -\mathcal{C}_i^T \mathcal{S} - \bar{\alpha} K_1^T \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{S} - (1 - \bar{\alpha})\bar{\beta} \\ \times \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{S} \Lambda_{13} \\ -\bar{\alpha} \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{S} - \Lambda_{23} \end{bmatrix},$$

$$d_3 = -\mathcal{R} + \delta \mathcal{I} - \Lambda_{33}, \quad g = \text{diag}\{\mathcal{Q}^{-1}, -\mathcal{X}, \mathcal{Q}^{-1}\},$$

$$e = \text{diag}\{-\mathcal{X}, \mathcal{Q}^{-1}, -\mathcal{X}\},$$

$$r = \text{diag}\{\varphi_j^{-1}\mathcal{Q}^{-1}, -\varphi_j^{-1}\mathcal{X}, \varphi_j^{-1}\mathcal{Q}^{-1}\},$$

$$\kappa = \begin{bmatrix} f_1 K_1^T \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T & f_2 \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T & f_2 \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \\ f_1 \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix},$$

$$\ell = \begin{bmatrix} (1 - \bar{\alpha})\bar{\beta} \varepsilon \mathcal{I} & 0 \\ 0 & 0 \\ 0 & -\mathcal{S}^T \mathcal{D}_i \Phi \mathcal{K}_j \end{bmatrix},$$

$$\pi = \begin{bmatrix} 0 & \mathcal{B}_i \Phi \mathcal{K}_j \\ 0 & \mathcal{D}_i \Phi \mathcal{K}_j \\ 0 & 0 \end{bmatrix}, \quad \tau = \begin{bmatrix} 0 & 0 \\ 0 & \frac{f_2}{(1 - \bar{\alpha})\bar{\beta}} \mathcal{B}_i \Phi \mathcal{K}_j \\ 0 & \frac{f_2}{(1 - \bar{\alpha})\bar{\beta}} \mathcal{D}_i \Phi \mathcal{K}_j \end{bmatrix},$$

$$\iota = \begin{bmatrix} -\varepsilon \mathcal{I} & 0 \\ \star & -\varepsilon \mathcal{I} \end{bmatrix}.$$

Proof According to (17), we know that $\mathcal{X} = \mathcal{P}^{-1}$, thus, (14)-(16) are transformed into

$$\begin{bmatrix} \hat{\Theta}_{ii} & \Omega_{ii} \\ \star & \hat{\Upsilon}_{ii} \end{bmatrix} < 0, \quad (18)$$

$$\begin{bmatrix} \hat{F}_{ij} & \Omega_{ij} \\ \star & \hat{\Psi}_{ij} \end{bmatrix} < 0, \quad (19)$$

$$\begin{bmatrix} \hat{\Theta}_{ij} & \Omega_{ij} \\ \star & \hat{\Upsilon}_{ij} \end{bmatrix} + \begin{bmatrix} \hat{\Theta}_{ji} & \Omega_{ji} \\ \star & \hat{\Upsilon}_{ji} \end{bmatrix} < 0, \quad (20)$$

where

$$\hat{\Theta}_{ij} = \begin{bmatrix} \eta & \varrho \\ \star & \bar{\varkappa} \end{bmatrix}, \quad \hat{\Upsilon}_{ij} = \begin{bmatrix} \bar{r} & \tau \\ \star & \iota \end{bmatrix},$$

$$\hat{F}_{ij} = \begin{bmatrix} d & \varrho \\ \star & \bar{e} \end{bmatrix}, \quad \hat{\Psi}_{ij} = \begin{bmatrix} \bar{g} & \tau \\ \star & \iota \end{bmatrix},$$

$$\bar{\varkappa} = \text{diag}\{-\varphi_j \mathcal{P}^{-1}, \varphi_j^{-1} \mathcal{Q}^{-1}, -\varphi_j^{-1} \mathcal{P}^{-1}\},$$

$$\bar{r} = \text{diag}\{\varphi_j^{-1} \mathcal{Q}^{-1}, -\varphi_j^{-1} \mathcal{P}^{-1}, \varphi_j^{-1} \mathcal{Q}^{-1}\},$$

$$\bar{e} = \text{diag}\{-\mathcal{P}^{-1}, \mathcal{Q}^{-1}, -\mathcal{P}^{-1}\},$$

$$\bar{g} = \text{diag}\{\mathcal{Q}^{-1}, -\mathcal{P}^{-1}, \mathcal{Q}^{-1}\}.$$

Pre- and post- multiplying $\text{diag}\{\mathcal{I}, \mathcal{I}, \mathcal{I}, \mathcal{I}, \mathcal{I}, \mathcal{I}, \mathcal{I}, \mathcal{I}, \mathcal{I}, \varepsilon^{-1}, \mathcal{I}\}$ and its transposition to (18)-(20), respective-

ly and by using Lemma 1, (18)-(20) are changed into

$$\begin{bmatrix} \bar{\Theta}_{ii} & \bar{\Omega}_{ii} \\ \star & \bar{\Upsilon}_{ii} \end{bmatrix} < 0, \quad (21)$$

$$\begin{bmatrix} \bar{F}_{ij} & \bar{\Omega}_{ij} \\ \star & \bar{\Psi} \end{bmatrix} < 0, \quad (22)$$

$$\begin{bmatrix} \bar{\Theta}_{ij} & \bar{\Omega}_{ij} \\ \star & \bar{\Upsilon}_{ij} \end{bmatrix} + \begin{bmatrix} \bar{\Theta}_{ji} & \bar{\Omega}_{ji} \\ \star & \bar{\Upsilon}_{ji} \end{bmatrix} < 0, \quad (23)$$

where

$$\begin{aligned} \bar{\Theta}_{ij} &= \begin{bmatrix} \bar{\eta} & \bar{\rho} \\ \star & \bar{\kappa} \end{bmatrix}, \quad \bar{\eta} = \begin{bmatrix} \eta_1 & \eta_2 & \bar{\eta}_3 \\ \star & \eta_4 & \eta_5 \\ \star & \star & \eta_6 \end{bmatrix}, \\ \bar{\rho} &= \begin{bmatrix} \bar{\mathcal{A}}_{ij}^T & \bar{\mathcal{C}}_{ij}^T & f_1 K_1^T \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T \\ \bar{\alpha} \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T & \bar{\alpha} \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T & f_1 \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T \\ \mathcal{B}_{1i}^T & 0 & 0 \end{bmatrix}, \\ \bar{\eta}_3 &= -\varphi_j \mathcal{C}_{ij}^T \mathcal{S} - \varphi_j \Lambda_{13} + \Lambda_{13}, \\ \bar{\Omega}_{ij} &= \begin{bmatrix} \bar{\kappa} \\ 0 \end{bmatrix}, \quad \bar{\Upsilon}_{ij} = \bar{r}, \quad \bar{\kappa} = \begin{bmatrix} \bar{\kappa}_1 & \bar{\kappa}_2 & \bar{\kappa}_3 \\ \bar{\kappa}_4 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \\ \bar{\kappa}_1 &= f_1 K_1^T \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T, \quad \bar{\kappa}_2 = f_2 (\mathcal{I} + \Delta(k))^T \mathcal{K}_j^T \Phi^T \mathcal{B}_i^T, \\ \bar{\kappa}_3 &= f_2 (\mathcal{I} + \Delta(k))^T \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T, \quad \bar{\kappa}_4 = f_1 \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T, \\ \bar{F}_{ij} &= \begin{bmatrix} \bar{d} & \bar{\rho} \\ \star & \bar{e} \end{bmatrix}, \quad \bar{\Psi} = \bar{g}, \quad \bar{d} = \begin{bmatrix} \bar{d}_1 & \bar{d}_2 \\ \star & \bar{d}_3 \end{bmatrix}, \\ \bar{d}_1 &= \begin{bmatrix} -\mathcal{P} - \Lambda_{11} & K^T - \Lambda_{12} \\ \star & -2\mathcal{I} - \Lambda_{22} \end{bmatrix}, \\ \bar{d}_2 &= \begin{bmatrix} -\mathcal{C}_{ij}^T \mathcal{S} - \Lambda_{13} \\ -\bar{\alpha} \mathcal{K}_j^T \Phi^T \mathcal{D}_i^T \mathcal{S} - \Lambda_{23} \end{bmatrix}, \quad \bar{d}_3 = -\mathcal{R} + \delta \mathcal{I} - \Lambda_{33}. \end{aligned}$$

Conditions (9)-(11) are derived from (21)-(23) by utilizing Schur complement.

The cone complementarity linearization algorithm is adopted to deal with bilinear terms exist in Theorem 2.

Procedure 1: Presetting $(\mathcal{P}^{(0)}, \mathcal{X}^{(0)}, \mathcal{K}_j^{(0)})$, such that (14)-(16) and

$$\begin{bmatrix} \mathcal{P} & \mathcal{I} \\ \mathcal{I} & \mathcal{X} \end{bmatrix} \geq 0. \quad (24)$$

hold. Setting $t = 0$.

Procedure 2: Solving the following optimal problem:

$$\min \text{tr} \left(\mathcal{P} \mathcal{X}^{(t)} + \mathcal{P}^{(t)} \mathcal{X} \right),$$

subjected to (14)-(16) and (24).

Procedure 3: Replacing the gained results $(\mathcal{P}, \mathcal{X}, \mathcal{K}_j)$ into (9)-(11). If (9)-(11) satisfy the following inequality

$$|\text{tr}(\mathcal{P} \mathcal{X}) - rn| < \zeta,$$

for constant $\zeta > 0$, then, $(\mathcal{P}, \mathcal{X}, \mathcal{K}_j)$ can be deemed as a set of feasible solution, output these parameters and exit iteration.

Procedure 4: If $\mathcal{G} > \mathcal{T}$, where $\mathcal{G}$ denotes the iteration time and $\mathcal{T}$ means the maximum allowable iteration time. EXIT.

Procedure 5: Setting $t = t+1$ and $(\mathcal{P}^{(t)}, \mathcal{X}^{(t)}, \mathcal{K}_j^{(t)}) = (\mathcal{P}, \mathcal{X}, \mathcal{K}_j)$, then, go back to *Procedure 2*.

4 Illustrative Examples

An example is provided to testify the effectiveness of the control strategy proposed in this paper.

Example 1 For the sake of testifying the algorithm which we proposed, the mass-spring-damping plant displayed in Fig. 1 is employed. According to relevant physical formulas, the following equation is derived

$$F_f + F_s + m\ddot{x} = u(t),$$

in which m , F_f , F_s and $u(t)$ have similar meanings in [8]. It is omitted here. F_f is expressed by $F_f = c\dot{x}$ ($c > 0$), and the spring elasticity is derived by the equation $F_s = k(1+b^2x^2)x$, in which k and b are known constants. Accordingly, the above equation can be rewritten as

$$m\ddot{x} + c\dot{x} + kx + kb^2x^3 = u(t),$$

where x denotes the distance of wedge movement.

Fig. 1 Mass-Spring-Damping system

Define $x(t) = \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} = \begin{bmatrix} x \\ \dot{x} \end{bmatrix}$, assume that $x_1(t) \in [-2, 2]$, letting $\hat{f} = \frac{-k-kb^2x_1^2(t)}{m}$, giving the scalars $k = 6N/m$, $c = 0.6N \cdot m/s$, $b = 0.1m^{-1}$. Suppose that $k \in [3, 6]$, according to the calculation, we can obtain that $\hat{f}_{\min} = -5.2$ ($k = 6, x_1^2(t) = 4$) and $\hat{f}_{\max} = -2.5$ ($k = 3, x_1^2(t) = 0$).

Table 1 and Table 2 list the lower and upper membership functions of system and controller, respectively.

Fig. 2 The locations of signal transmission with dissipativity

Fig. 3 Control input with dissipativity

Fig. 4 Responses of closed-loop system with dissipativity

According to T-S fuzzy modeling method, one can get

$$\mathcal{A}_1 = \begin{bmatrix} 0 & 1 \\ \hat{f}_{\min} - \frac{c}{m} & 0 \end{bmatrix}, \mathcal{B}_1 = \begin{bmatrix} 0 \\ \frac{1}{m} \end{bmatrix},$$

$$\mathcal{A}_2 = \begin{bmatrix} 0 & 1 \\ \hat{f}_{\max} - \frac{c}{m} & 0 \end{bmatrix}, \mathcal{B}_2 = \begin{bmatrix} 0 \\ \frac{1}{m} \end{bmatrix}.$$

The weighting coefficients are given as follows

$$\underline{\alpha}_i(\sigma(k)) = x_1^2(k)/4, \bar{\alpha}_i(\sigma(k)) = 1 - \underline{\alpha}_i(\sigma(k)),$$

$$\underline{b}_j(\sigma(k)) = 0.5, \bar{b}_j(\sigma(k)) = 0.5.$$

Fig. 5 Responses of open-loop system with dissipativity

Table 1 The lower and upper membership functions of system

Lower membership functions	Upper membership functions
$\underline{u}_{\mathcal{L}11}(x_1) = \frac{\hat{f}_{\max} - \hat{f}}{\hat{f}_{\max} - \hat{f}_{\min}}, k = 3$	$\bar{u}_{\mathcal{L}11}(x_1) = \frac{\hat{f}_{\max} - \hat{f}}{\hat{f}_{\max} - \hat{f}_{\min}}, k = 6$
$\underline{u}_{\mathcal{L}12}(x_1) = \frac{\hat{f} - \hat{f}_{\min}}{\hat{f}_{\max} - \hat{f}_{\min}}, k = 6$	$\bar{u}_{\mathcal{L}12}(x_1) = \frac{\hat{f} - \hat{f}_{\min}}{\hat{f}_{\max} - \hat{f}_{\min}}, k = 3$

Table 2 The lower and upper membership functions of controller

Lower membership functions	Upper membership functions
$\underline{u}_{\mathcal{N}11}(x_1) = 0.3 \times e^{-x_1^2}$	$\bar{u}_{\mathcal{N}11}(x_1) = \underline{u}_{\mathcal{N}11}(x_1)$
$\underline{u}_{\mathcal{N}12}(x_1) = 1 - \underline{u}_{\mathcal{N}11}(x_1)$	$\bar{u}_{\mathcal{N}12}(x_1) = \underline{u}_{\mathcal{N}12}(x_1)$

The sampling period is defined as $T = 0.9s$, which yields the following discrete matrices:

$$\mathcal{A}_1 = \begin{bmatrix} -0.2825 & 0.3142 \\ -1.6340 & -0.4396 \end{bmatrix}, \mathcal{B}_1 = \begin{bmatrix} 0.2055 \\ 0.2619 \end{bmatrix},$$

$$\mathcal{A}_2 = \begin{bmatrix} 0.2578 & 0.5045 \\ -1.2611 & 0.0056 \end{bmatrix}, \mathcal{B}_2 = \begin{bmatrix} 0.2474 \\ 0.4204 \end{bmatrix}.$$

Define the remaining matrices as

$$\mathcal{B}_{11} = \begin{bmatrix} 0.2019 \\ 0.1987 \end{bmatrix}, \mathcal{B}_{12} = \begin{bmatrix} 0.4988 \\ 0.3012 \end{bmatrix},$$

$$\mathcal{C}_1 = [0.1934 \ 0], \mathcal{C}_2 = [0.3058 \ 0],$$

$$\mathcal{D}_1 = -0.5001, \mathcal{D}_2 = -0.3997.$$

Giving the external disturbance as

$$w(k) = \begin{cases} \frac{1}{1+k}, & 10 < k < 30, \\ -0.1 \sin(k), & 40 < k < 70, \\ 0, & \text{else.} \end{cases}$$

Define $K_1 = \text{diag}\{0.3, 0.3\}$, $K_2 = \text{diag}\{1.2, 1.2\}$ and $\Phi = 0.8$. Selecting $\mathcal{Q} = -2.2$, $\mathcal{S} = 1.2$, $\mathcal{R} = 2$, $\bar{\alpha} = 0.6$, $\bar{\beta} = 0.6$, $\varphi_1 = 0.9$, $\varphi_2 = 0.7$ and $\delta = 0.7$. The initial state is given as $x(0) = [0.9 \ -1.3]^T$, and the controller

initial state is the same as system state. Through calculating conditions (14)-(16), the controller gains are obtained as:

$$\mathcal{K}_1 = [0.8830 \ -0.2756], \mathcal{K}_2 = [0.6371 \ -0.6463].$$

Simulation results are shown in Figs. 2-5. The signal transmission is described in Fig. 2, in which the saturated data is labeled by “-1”, the missing data is marked by “0” and the quantized data is represented by “1”. Fig. 3 plots the control force which tends to zero eventually. Fig. 4 present the states responses of the closed-loop system, and Fig. 5 means the states responses of open-loop system. According to Fig. 3 and Fig. 4, we can obtain that the system ultimately tends to be stable. From Figs. 4 and 5, it is observed that the convergence rate of closed-loop system is faster than uncontrolled one. Therefore, the effectiveness of the fuzzy controller which we designed is verified.

5 Conclusion

The dissipative IT2 fuzzy control problem for a class of uncertain nonlinear systems has been developed in this paper. By IT2 T-S fuzzy model, the flexibility of designing controller has been improved while reducing the computation burden. By utilizing two independent Bernoulli stochastic distribution processes, an innovative model has been built to against sensor saturation and quantization. An actuator failure model has been introduced for describing complicated phenomenon occurred in practical applications. Sufficient criteria for designing dissipative fuzzy controller have been given to ensure stochastic stability for the resulting closed-loop plant. The feasibility of the presented algorithm has been verified by a demonstrative simulation. In our future work, it will be an interesting and challenging issue to apply the method proposed in this paper to the neural network in [42–44], containment control in [45, 46], sliding mode control in [47], and adaptive fuzzy control in [48, 49].

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