



# Robust $\mathcal{H}_\infty$ Fuzzy Control Design for Time Delay Nonlinear Markovian Jump Systems: An LMI Approach

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**Abstract:** This paper considers the problem of designing a robust  $\mathcal{H}_\infty$  fuzzy state-feedback controller for a class of time delay nonlinear Markovian jump systems. The proposed controller guarantees the  $\mathcal{L}_2$ -gain of the mapping from the exogenous input noise to the regulated output to be less than some prescribed value. Solutions to the problem are provided in terms of linear matrix inequalities. To illustrate the effectiveness of the design developed in this paper, a numerical example is also provided.

**Keywords:**  $\mathcal{H}_\infty$  fuzzy control; Takagi–Sugeno (TS) fuzzy model; linear matrix inequalities (LMIs); Markovian jump parameters; time-varying delay.

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## 1 Introduction

Markovian jump systems are also called hybrid systems, that is, the state space of a system contains both continuous (differential equation) and discrete states (Markov process). The Markovian jump system has been widely used to describe a physical system that changes abruptly from one mode to another mode. These abrupt changes may be caused by environmental disturbances, component and interconnection failures, parameters shifting, tracking, and fast variations in the operating point of the system. Over the past few decades, the Markovian jump system has been extensively studied by many researchers (see [1–7]).

It is a well known fact that engineering processes frequently contain time delays. Stability and control synthesis for time delay systems have been one of the most significant

issues in control engineering applications. Linear systems with Markovian jumps and time delays have been addressed by a number of researchers (see, for example, [9–11]). In [11], the delay-dependent robust stability and the  $\mathcal{H}_\infty$  control of time delay linear Markovian jump systems have been investigated. Although many researchers have studied the control design for time delay linear Markovian jump systems for many years, the control design for time delay nonlinear Markovian jump systems remains as an open area.

In the past two decades, the  $\mathcal{H}_\infty$  control design for a class of nonlinear systems described by a Takagi-Sugeno (TS) fuzzy model has been studied by a number of researchers (see [12–25]). In this TS fuzzy model, local dynamics in different state space regions are represented by local linear systems. The overall model of the system is obtained by “blending” of these linear models through nonlinear membership functions. In other words, a TS fuzzy model is essentially a multi-model approach in which simple sub-models are combined to represent the global behavior of the system. Recently, the design of fuzzy  $\mathcal{H}_\infty$  control for a class of nonlinear systems without delays has been significantly considered and many results have been reported (e.g., [12–14]). Furthermore, there have been also some attempts in [18–23] in which robust fuzzy control analysis and synthesis for nonlinear time-delay systems have been examined. To the best of our knowledge, the global robust  $\mathcal{H}_\infty$  fuzzy state-feedback control problem for a class of uncertain nonlinear Markovian jump systems with time-varying delay via an LMI approach has not yet been considered in the literature.

The main contribution of this paper is to design an  $\mathcal{H}_\infty$  fuzzy state-feedback controller for a class of time delay nonlinear Markovian jump systems described by a Takagi-Sugeno (TS) fuzzy model. Based on an LMI approach, we develop a state-feedback controller that guarantees the  $\mathcal{L}_2$ -gain of the mapping from the exogenous input noise to the regulated output to be less than a prescribed value. The solutions are given in terms of a family of linear matrix inequalities.

This paper is organized as follows. In Section 2, system description and definition are presented. In Section 3, based on an LMI approach we develop a technique for designing a robust  $\mathcal{H}_\infty$  fuzzy state-feedback controller that guarantees the  $\mathcal{L}_2$ -gain of the mapping from the exogenous input noise to the regulated output to be less than a prescribed value. The validity of this approach is demonstrated by an example from the literature in Section 4. Finally in Section 5, the conclusion is given.

## 2 System Description and Definition

The class of time delay uncertain nonlinear Markovian jump system under consideration is described by the following TS fuzzy models:

Plant Rule  $i$ : If  $\nu_1(t)$  is  $M_{i1}$  and  $\dots$  and  $\nu_\vartheta(t)$  is  $M_{i\vartheta}$  then

$$\begin{aligned} \dot{x}(t) &= [A_i(\eta(t)) + \Delta A_i(\eta(t))]x(t) + A_{d_i}(\eta(t))x(t - \tau(t)) \\ &\quad + B_{1_i}(\eta(t))w(t) + [B_{2_i}(\eta(t)) + \Delta B_{2_i}(\eta(t))]u(t), \quad x(0) = 0, \\ z(t) &= [C_{1_i}(\eta(t)) + \Delta C_{1_i}(\eta(t))]x(t) + [D_{12_i}(\eta(t)) + \Delta D_{12_i}(\eta(t))]u(t) \\ x(t) &= \psi(t), \quad t \in [-\tau, 0], \quad \tau(t) \leq \tau \end{aligned} \tag{2.1}$$

where  $M_{iq}$  ( $j = 1, 2, \dots, \vartheta$ ) is fuzzy sets  $q$  for rule  $i$ ,  $\nu_i(t)$  are the premise variables,  $x(t) \in R^n$  is the state vector,  $u(t) \in R^m$  is the input,  $w(t) \in R^p$  is the disturbance

which belongs to  $\mathcal{L}_2[0, \infty)$ ,  $z(t) \in R^s$  is the controlled output, the matrices  $A_i(\eta(t))$ ,  $A_{d_i}(\eta(t))$ ,  $B_{1_i}(\eta(t))$ ,  $B_{2_i}(\eta(t))$ ,  $C_{1_i}(\eta(t))$  and  $D_{12_i}(\eta(t))$  are of appropriate dimensions,  $r$  is the number of IF-THEN rules,  $\tau(t)$  is the bounded time-varying delay in the state with the following assumption

$$0 \leq \tau(t) \leq \tau \quad \text{and} \quad \dot{\tau}(t) \leq \beta < 1$$

and  $\psi(t)$  is a vector-valued initial continuous function defined on the interval  $[-\tau, 0]$ .  $\{\eta(t)\}$ ,  $t \geq 0$  is a continuous-time discrete-state homogenous Markov process taking values on a finite set  $\mathcal{S} = \{1, 2, \dots, s\}$  with transition probability matrix  $Pr = \{P_{ik}(t)\}$  given by

$$\begin{aligned} P_{ik}(t) &= Pr(\eta(t + \Delta) = k \mid \eta(t) = i) \\ &= \begin{cases} \lambda_{ik}\Delta + O(\Delta) & \text{if } i \neq k, \\ 1 + \lambda_{ii}\Delta + O(\Delta) & \text{if } i = k, \end{cases} \end{aligned} \tag{2.2}$$

and  $\sum_{k=1}^s P_{ik}(t) = 1$ , where  $\Delta > 0$ ;  $\lim_{\Delta \rightarrow 0} \frac{O(\Delta)}{\Delta} = 0$ ;  $\lambda_{ik} \geq 0$ ,  $i \neq k$  is the transition rate from mode  $i$  to mode  $k$ ;  $\lambda_{ii} = -\sum_{k=1, k \neq i}^s \lambda_{ik}$ ,  $i, k \in \mathcal{S}$  gives the infinitesimal generator of the Markov process  $\{\eta(t), t \geq 0\}$ .

The matrices  $\Delta A_i(\eta(t))$ ,  $\Delta B_{2_i}(\eta(t))$ ,  $\Delta C_{1_i}(\eta(t))$  and  $\Delta D_{12_i}(\eta(t))$  represent the uncertainties in the system and satisfy the following assumption.

**Assumption 2.1** Following equalities take place

$$\begin{aligned} \Delta A_i(\eta(t)) &= E_{1_i}(\eta(t))F(x(t), \eta(t), t)H_{1_i}(\eta(t)), \\ \Delta B_{2_i}(\eta(t)) &= E_{2_i}(\eta(t))F(x(t), \eta(t), t)H_{2_i}(\eta(t)), \\ \Delta C_{1_i}(\eta(t)) &= E_{3_i}(\eta(t))F(x(t), \eta(t), t)H_{3_i}(\eta(t)), \\ \Delta D_{12_i}(\eta(t)) &= E_{4_i}(\eta(t))F(x(t), \eta(t), t)H_{4_i}(\eta(t)), \end{aligned}$$

where  $E_{j_i}(\eta(t))$  and  $H_{j_i}(\eta(t))$ ,  $j = 1, 2, \dots, 4$ , are known matrix functions which characterize the structure of the uncertainties. Furthermore, the following inequality holds:

$$\|F(x(t), \eta(t), t)\| \leq \rho(\eta(t)) \tag{2.3}$$

for any known positive constant  $\rho(\eta(t))$ .

Let

$$\varpi_i(\nu(t)) = \prod_{q=1}^n M_{iq}(\nu_q(t)), \quad \text{and} \quad \mu_i(\nu(t)) = \frac{\varpi_i(\nu(t))}{\sum_{i=1}^r \varpi_i(\nu(t))},$$

where  $M_{iq}(\nu_q(t))$  is the grade of membership of  $\nu_q(t)$  in  $M_{iq}$ . It is assumed in this paper that

$$\varpi_i(\nu(t)) \geq 0, \quad i = 1, 2, \dots, n, \quad \text{and} \quad \sum_{i=1}^r \varpi_i(\nu(t)) > 0,$$

where  $r$  are the number of local plant rules, for all  $t$ . Therefore,

$$\mu_i(\nu(t)) \geq 0, \quad i = 1, 2, \dots, n, \quad \text{and} \quad \sum_{i=1}^r \mu_i(\nu(t)) = 1$$

for all  $t$ . For the convenience of notations, let  $\varpi_i = \varpi_i(\nu(t))$ ,  $\mu_i = \mu_i(\nu(t))$ ,  $\eta = \eta(t)$  and any matrix  $N(\mu, \eta(t) = \nu) = N(\mu, \nu)$ .

The resulting fuzzy system model is inferred as the weighted average of the local models of the form

$$\begin{aligned} \dot{x}(t) &= [A(\mu, \nu) + \Delta A(\mu, \nu)]x(t) + A_d(\mu, \nu)x(t - \tau(t)) \\ &\quad + B_1(\mu, \nu)w(t) + [B_2(\mu, \nu) + \Delta B_2(\mu, \nu)]u(t), \quad x(0) = 0, \\ z(t) &= [C_1(\mu, \nu) + \Delta C_1(\mu, \nu)]x(t) + [D_{12}(\mu, \nu) + \Delta D_{12}(\mu, \nu)]u(t), \end{aligned} \tag{2.4}$$

where

$$\begin{aligned} A(\mu, \nu) &= \sum_{i=1}^r \mu_i A_i(\nu), & A_d(\mu, \nu) &= \sum_{i=1}^r \mu_i A_{d_i}(\nu), & B_1(\mu, \nu) &= \sum_{i=1}^r \mu_i B_{1_i}(\nu), \\ B_2(\mu, \nu) &= \sum_{i=1}^r \mu_i B_{2_i}(\nu), & C_1(\mu, \nu) &= \sum_{i=1}^r \mu_i C_{1_i}(\nu), & D_{12}(\mu, \nu) &= \sum_{i=1}^r \mu_i D_{12_i}(\nu), \\ \Delta A(\mu, \nu) &= \sum_{i=1}^r \mu_i \Delta A_i(\nu) = E_1(\mu, \nu)F(x(t), \nu, t)H_1(\mu, \nu), \\ \Delta B_2(\mu, \nu) &= \sum_{i=1}^r \mu_i \Delta B_{2_i}(\nu) = E_2(\mu, \nu)F(x(t), \nu, t)H_2(\mu, \nu), \\ \Delta C_1(\mu, \nu) &= \sum_{i=1}^r \mu_i \Delta C_{1_i}(\nu) = E_3(\mu, \nu)F(x(t), \nu, t)H_3(\mu, \nu), \\ \Delta D_{12}(\mu, \nu) &= \sum_{i=1}^r \mu_i \Delta D_{12_i}(\nu) = E_4(\mu, \nu)F(x(t), \nu, t)H_4(\mu, \nu) \end{aligned}$$

with

$$\begin{aligned} E_1(\mu, \nu) &= \sum_{i=1}^r \mu_i E_{1_i}(\nu), & E_2(\mu, \nu) &= \sum_{i=1}^r \mu_i E_{2_i}(\nu), & E_3(\mu, \nu) &= \sum_{i=1}^r \mu_i E_{3_i}(\nu), \\ E_4(\mu, \nu) &= \sum_{i=1}^r \mu_i E_{4_i}(\nu), & H_1(\mu, \nu) &= \sum_{i=1}^r \mu_i H_{1_i}(\nu), & H_2(\mu, \nu) &= \sum_{i=1}^r \mu_i H_{2_i}(\nu), \\ H_3(\mu, \nu) &= \sum_{i=1}^r \mu_i H_{3_i}(\nu), & H_4(\mu, \nu) &= \sum_{i=1}^r \mu_i H_{4_i}(\nu). \end{aligned}$$

**Definition 2.1** Suppose  $\gamma$  is a given positive real number. A system of the form (2.4) is said to have  $\mathcal{L}_2[0, T_f]$  gain less than or equal to  $\gamma$  if

$$E \left[ \int_0^{T_f} \{z^T(t)z(t) - \gamma w^T(t)w(t)\} dt \right] < 0, \tag{2.5}$$

where  $E[\cdot]$  denotes as the expectation operator.

In this paper, we consider the following  $\mathcal{H}_\infty$  fuzzy state-feedback which is inferred as the weighted average of the local models of the form:

$$u(t) = K(\mu, \nu)x(t), \tag{2.6}$$

where  $K(\mu, \nu) = \sum_{j=1}^r \mu_j K_j(\nu)$ . Before ending this section, we describe the problem under our study as follows.

**Problem Formulation** Given the system (2.4), design an  $\mathcal{H}_\infty$  fuzzy state-feedback controller of the form (2.6) such that the  $\mathcal{L}_2$  gain  $\gamma$ -performance (2.5) is guaranteed.

### 3 Main Result

First, let us consider the closed-loop state space form of the fuzzy system model (2.4) with the controller (2.6) which is given by

$$\begin{aligned} \dot{x}(t) &= [A(\mu, \nu) + B_2(\mu, \nu)K(\mu, \nu)]x(t) + A_d(\mu, \nu)x(t - \tau(t)) \\ &\quad + [\Delta A(\mu, \nu) + \Delta B_2(\mu, \nu)K(\mu, \nu)]x(t) + B_1(\mu, \nu)w(t), \quad x(0) = 0, \end{aligned} \tag{3.1}$$

or in a more compact form

$$\begin{aligned} \dot{x}(t) &= [A(\mu, \nu) + B_2(\mu, \nu)K(\mu, \nu)]x(t) + A_d(\mu, \nu)x(t - \tau(t)) + \tilde{B}_1(\mu, \nu)\tilde{w}(t), \\ x(0) &= 0, \end{aligned} \tag{3.2}$$

where

$$\begin{aligned} \tilde{B}_1(\mu, \nu) &= [E_1(\mu, \nu) \quad E_2(\mu, \nu) \quad B_1(\mu, \nu) \quad 0 \quad 0], \\ \tilde{w}(t) &= \begin{bmatrix} F(x(t), \nu, t)H_1(\mu, \nu)x(t) \\ F(x(t), \nu, t)H_2(\mu, \nu)K(\mu, \nu)x(t) \\ w(t) \\ F(x(t), \nu, t)H_3(\mu, \nu)x(t) \\ F(x(t), \nu, t)H_4(\mu, \nu)K(\mu, \nu)x(t) \end{bmatrix}. \end{aligned} \tag{3.3}$$

To provide LMI-based solutions to the problem of designing a robust  $\mathcal{H}_\infty$  controller that guarantees the  $\mathcal{L}_2$ -gain of the mapping from the exogenous input noise to the regulated output to be less than some prescribed value for a class of time delay uncertainty nonlinear Markovian jump systems, the following theorem is given.

**Theorem 3.1** *Given the system (2.4), the inequality (2.5) holds if there exist a prescribed  $\mathcal{H}_\infty$  performance  $\gamma > 0$ , positive definite symmetric matrices  $P(\nu)$  and  $W(\nu)$  for  $\nu = 1, 2, \dots, s$ , such that the following conditions hold:*

$$\Omega_{ii}(\nu) < 0, \quad i = 1, 2, \dots, r, \tag{3.5}$$

$$\Omega_{ij}(\nu) + \Omega_{ji}(\nu) < 0, \quad i < j \leq r, \tag{3.6}$$

where

$$\Omega_{ij}(\nu) = \begin{pmatrix} \Psi_{ij}(\nu) & (*)^T & (*)^T & (*)^T & (*)^T & (*)^T & (*)^T \\ B_{ij}(\nu) & -\mathcal{M} + \tilde{E}_i^T(\nu)\tilde{E}_j(\nu) & (*)^T & (*)^T & (*)^T & (*)^T & (*)^T \\ W(\nu)A_{d_i}(\nu) & 0 & -(1-\beta)W(\nu) & (*)^T & (*)^T & (*)^T & (*)^T \\ P(\nu) & 0 & 0 & -W(\nu) & (*)^T & (*)^T & (*)^T \\ \Gamma_{ij}(\nu) & 0 & 0 & 0 & -I & (*)^T & (*)^T \\ \Upsilon_{ij}(\nu) & 0 & 0 & 0 & 0 & -I & (*)^T \\ \mathcal{Z}^T(\nu) & 0 & 0 & 0 & 0 & 0 & -\mathcal{P}(\nu) \end{pmatrix}, \tag{3.7}$$

$$\Psi_{ij}(\iota) = A_i(\iota)P(\iota) + P(\iota)A_i^T(\iota) + B_{2_i}(\iota)Y_j(\iota) + Y_j^T(\iota)B_{2_i}^T(\iota) + \lambda_{\iota}P(\iota), \quad (3.8)$$

$$\mathcal{B}_{ij}(\iota) = \tilde{B}_{1_i}^T(\iota) + \tilde{E}_i^T(\iota)C_{1_i}(\iota)P(\iota) + \tilde{E}_i^T(\iota)D_{12_i}(\iota)Y_j(\iota), \quad (3.9)$$

$$\Gamma_{ij}(\iota) = C_{1_i}(\iota)P(\iota) + D_{12_i}(\iota)Y_j(\iota), \quad (3.10)$$

$$\Upsilon_{ij}(\iota) = \tilde{C}_i(\iota)P(\iota) + \tilde{D}_i(\iota)Y_j(\iota), \quad (3.11)$$

$$\mathcal{M} = \text{diag}\{I, I, \gamma I, I, I\}, \quad (3.12)$$

$$\mathcal{Z}(\iota) = \left( \sqrt{\lambda_{\iota_1}}P(\iota) \dots \sqrt{\lambda_{\iota_{(\iota-1)}}}P(\iota) \sqrt{\lambda_{\iota_{(\iota+1)}}}P(\iota) \dots \sqrt{\lambda_{\iota_s}}P(\iota) \right), \quad (3.13)$$

$$\mathcal{P}(\iota) = \text{diag}\{P(1), \dots, P(\iota-1), P(\iota+1), \dots, P(s)\}, \quad (3.14)$$

with

$$\tilde{B}_{1_i}(\iota) = [E_{1_i}(\iota) \quad E_{2_i}(\iota) \quad B_{1_i}(\iota) \quad 0 \quad 0], \quad (3.15)$$

$$\tilde{C}_i(\iota) = [\rho(\iota)H_{1_i}^T(\iota) \quad \rho(\iota)H_{3_i}^T(\iota) \quad 0 \quad 0]^T, \quad (3.16)$$

$$\tilde{D}_i(\iota) = [0 \quad 0 \quad \rho(\iota)H_{2_i}^T(\iota) \quad \rho(\iota)H_{4_i}^T(\iota)]^T, \quad (3.17)$$

$$\tilde{E}_i(\iota) = [0 \quad 0 \quad 0 \quad E_{3_i}(\iota) \quad E_{4_i}(\iota)]. \quad (3.18)$$

Furthermore, a suitable choice of the fuzzy controller is

$$u(t) = \sum_{j=1}^r \mu_j K_j(\iota) x(t) \quad (3.19)$$

where

$$K_j(\iota) = Y_j(\iota)(P(\iota))^{-1}. \quad (3.20)$$

*Proof* Consider a Lyapunov-Krasovskii functional candidate as follows:

$$V(x(t), \iota) = x^T(t)Q(\iota)x(t) + \int_{t-\tau(t)}^t x^T(v)G(\iota)x(v)dv, \quad \forall \iota \in \mathcal{S}, \quad (3.21)$$

where  $Q(\iota) > 0$  and  $G(\iota) > 0$ . Now let us consider the weak infinitesimal operator  $\tilde{\Delta}$  of the joint process  $\{(x(t), \iota), t \geq 0\}$ , which is the stochastic analog of the deterministic derivative [28].  $\{(x(t), \iota), t \geq 0\}$  is a Markov process with infinitesimal operator given by [3]

$$\begin{aligned} \tilde{\Delta}V(x(t), \iota) &= x^T(t)[Q(\iota)(A(\mu, \iota) + B_2(\mu, \iota)K(\mu, \iota)) + (A(\mu, \iota) + B_2(\mu, \iota)K(\mu, \iota))^T Q(\iota) \\ &\quad + G(\iota)]x(t) + x^T(t)Q(\iota)\tilde{B}_1(\mu, \iota)\tilde{w}(t) + \tilde{w}^T(t)\tilde{B}_1^T(\mu, \iota)Q(\iota)x(t) \\ &\quad + x^T(t) \sum_{k=1}^s \lambda_{\iota k} Q(k)x(t) - (1 - \dot{\tau})x^T(t - \tau(t))G(\iota)x(t - \tau(t)) \\ &\quad + x^T(t)Q(\iota)A_d(\mu, \iota)x(t - \tau(t)) + x^T(t - \tau(t))A_d^T(\mu, \iota)Q(\iota)x(t). \end{aligned} \quad (3.22)$$

Using the fact that for any vectors  $x(t)$  and  $x(t - \tau(t))$

$$\begin{aligned} & x^T(t)Q(\nu)A_d(\mu, \nu)x(t - \tau(t)) + x^T(t - \tau(t))A_d^T(\mu, \nu)Q(\nu)x(t) \\ & \leq \frac{1}{(1 - \beta)}x^T(t)Q(\nu)A_d(\mu, \nu)G^{-1}(\nu)A_d^T(\mu, \nu)Q(\nu)x(t) \\ & \quad + (1 - \beta)x^T(t - \tau(t))G(\nu)x(t - \tau(t)), \end{aligned}$$

(3.22) becomes

$$\begin{aligned} \tilde{\Delta}V(x(t), \nu) & \leq x^T(t) \left[ Q(\nu)(A(\mu, \nu) + B_2(\mu, \nu)K(\mu, \nu)) + (A(\mu, \nu) + B_2(\mu, \nu)K(\mu, \nu))^T Q(\nu) \right. \\ & \quad \left. + \frac{1}{(1 - \beta)}Q(\nu)A_d(\mu, \nu)G^{-1}(\nu)A_d^T(\mu, \nu)Q(\nu) + G(\nu) + \sum_{k=1}^s \lambda_{\nu k}Q(k) \right] x(t) \\ & \quad + x^T(t)Q(\nu)\tilde{B}_1(\mu, \nu)\tilde{w}(t) + \tilde{w}^T(t)\tilde{B}_1^T(\mu, \nu)Q(\nu)x(t). \end{aligned} \tag{3.23}$$

Adding and subtracting  $-z^T(t)z(t) + \tilde{w}^T(t)\mathcal{M}\tilde{w}(t)$  to and from (3.23), we get

$$\begin{aligned} \tilde{\Delta}V(x(t), \nu) & \leq -z^T(t)z(t) + \tilde{w}^T(t)\mathcal{M}\tilde{w}(t) + z^T(t)z(t) + \begin{bmatrix} x(t) \\ \tilde{w}(t) \end{bmatrix}^T \\ & \quad \times \begin{bmatrix} [A(\mu, \nu) + B_2(\mu, \nu)K(\mu, \nu)]^T Q(\nu) \\ + Q(\nu)[A(\mu, \nu) + B_2(\mu, \nu)K(\mu, \nu)] \\ + \sum_{k=1}^s \lambda_{\nu k}Q(k) + G(\nu) \\ + \frac{1}{(1 - \beta)}Q(\nu)A_d(\mu, \nu)G^{-1}(\nu)A_d^T(\mu, \nu)Q(\nu) \\ \tilde{B}_1^T(\mu, \nu)Q(\nu) \end{bmatrix} \begin{matrix} (*)^T \\ \\ \\ \\ -\mathcal{M} \end{matrix} \begin{bmatrix} x(t) \\ \tilde{w}(t) \end{bmatrix}, \end{aligned} \tag{3.24}$$

where  $\mathcal{M} = \text{diag}\{I, I, \gamma I, I, I\}$ .

Now let us consider the following terms

$$\begin{aligned} \tilde{w}^T(t)\mathcal{M}\tilde{w}(t) & = \begin{bmatrix} F(x(t), \nu, t)H_1(\mu, \nu)x(t) \\ F(x(t), \nu, t)H_2(\mu, \nu)K(\mu, \nu)x(t) \\ w(t) \\ F(x(t), \nu, t)H_3(\mu, \nu)x(t) \\ F(x(t), \nu, t)H_4(\mu, \nu)K(\mu, \nu)x(t) \end{bmatrix}^T \mathcal{M} \begin{bmatrix} F(x(t), \nu, t)H_1(\mu, \nu)x(t) \\ F(x(t), \nu, t)H_2(\mu, \nu)K(\mu, \nu)x(t) \\ w(t) \\ F(x(t), \nu, t)H_3(\mu, \nu)x(t) \\ F(x(t), \nu, t)H_4(\mu, \nu)K(\mu, \nu)x(t) \end{bmatrix} \\ & \leq \rho^2(\nu)x^T(t)\{H_1^T(\mu, \nu)H_1(\mu, \nu) + K^T(\mu, \nu)H_2^T(\mu, \nu)H_2(\mu, \nu)K(\mu, \nu) \\ & \quad + H_3^T(\mu, \nu)H_3(\mu, \nu) + K^T(\mu, \nu)H_4^T(\mu, \nu)H_4(\mu, \nu)K(\mu, \nu)\}x(t) + \gamma w^T(t)w(t) \end{aligned} \tag{3.25}$$

and

$$\begin{aligned} z^T(t)z(t) & = x^T(t)[C_1(\mu, \nu) + E_3(\mu, \nu)F(x(t), \nu, t)H_3(\mu, \nu) + D_{12}(\mu, \nu)K(\mu, \nu) \\ & \quad + E_4(\mu, \nu)F(x(t), \nu, t)H_4(\mu, \nu)K(\mu, \nu)]^T [C_1(\mu, \nu) + E_3(\mu, \nu)F(x(t), \nu, t)H_3(\mu, \nu) \\ & \quad + D_{12}(\mu, \nu)K(\mu, \nu) + E_4(\mu, \nu)F(x(t), \nu, t)H_4(\mu, \nu)K(\mu, \nu)]x(t) \\ & = \begin{bmatrix} x(t) \\ \tilde{w}(t) \end{bmatrix}^T \begin{bmatrix} [C_1(\mu, \nu) + D_{12}(\mu, \nu)K(\mu, \nu)]^T \times \\ [C_1(\mu, \nu) + D_{12}(\mu, \nu)K(\mu, \nu)] \\ \tilde{E}^T(\mu, \nu)[C_1(\mu, \nu) + D_{12}(\mu, \nu)K(\mu, \nu)] \\ \tilde{E}^T(\mu, \nu)\tilde{E}(\mu, \nu) \end{bmatrix} \begin{matrix} (*)^T \\ \\ \\ \end{matrix} \begin{bmatrix} x(t) \\ \tilde{w}(t) \end{bmatrix}, \end{aligned} \tag{3.26}$$

where

$$\tilde{E}(\mu, \nu) = [0 \quad 0 \quad 0 \quad E_3(\mu, \nu) \quad E_4(\mu, \nu)].$$

Substituting (3.25) and (3.26) into (3.24), we have

$$\tilde{\Delta}V(x(t), \nu) \leq -z^T(t)z(t) + \gamma w^T(t)w(t) + \begin{bmatrix} x(t) \\ \tilde{w}(t) \end{bmatrix}^T \Phi(\mu, \nu) \begin{bmatrix} x(t) \\ \tilde{w}(t) \end{bmatrix}, \quad (3.27)$$

where

$$\Phi(\mu, \nu) = \begin{bmatrix} [A(\mu, \nu) + B_2(\mu, \nu)K(\mu, \nu)]^T Q(\nu) \\ + Q(\nu)[A(\mu, \nu) + B_2(\mu, \nu)K(\mu, \nu)] \\ + [C_1(\mu, \nu) + D_{12}(\mu, \nu)K(\mu, \nu)]^T \\ \times [C_1(\mu, \nu) + D_{12}(\mu, \nu)K(\mu, \nu)] \\ + [\tilde{C}(\mu, \nu) + \tilde{D}(\mu, \nu)K(\mu, \nu)]^T \\ \times [\tilde{C}(\mu, \nu) + \tilde{D}(\mu, \nu)K(\mu, \nu)] \\ + \sum_{k=1}^s \lambda_{ik} Q(k) + G(\nu) \\ + \frac{1}{(1-\beta)} Q(\nu) A_d(\mu, \nu) G^{-1}(\nu) A_d^T(\mu, \nu) Q(\nu) \\ \tilde{B}_1^T(\mu, \nu) Q(\nu) + \\ \tilde{E}^T(\mu, \nu) [C_1(\mu, \nu) + D_{12}(\mu, \nu)K(\mu, \nu)] \end{bmatrix} \quad (*)^T \quad (3.28)$$

with

$$\begin{aligned} \tilde{C}(\mu, \nu) &= [\rho(\nu)H_1^T(\mu, \nu) \quad \rho(\nu)H_3^T(\mu, \nu) \quad 0 \quad 0]^T, \\ \tilde{D}(\mu, \nu) &= [0 \quad 0 \quad \rho(\nu)H_2^T(\mu, \nu) \quad \rho(\nu)H_4^T(\mu, \nu)]^T. \end{aligned}$$

Using the fact

$$\sum_{i=1}^r \sum_{j=1}^r \sum_{m=1}^r \sum_{n=1}^r \mu_i \mu_j \mu_m \mu_n M_{ij}^T(\nu) N_{mn}(\nu) \leq \frac{1}{2} \sum_{i=1}^r \sum_{j=1}^r \mu_i \mu_j [M_{ij}^T(\nu) M_{ij}(\nu) + N_{ij}(\nu) N_{ij}^T(\nu)],$$

we can rewrite (3.27) as follows:

$$\begin{aligned} \tilde{\Delta}V(x(t), \nu) &\leq -z^T(t)z(t) + \gamma w^T(t)w(t) + \sum_{i=1}^r \sum_{j=1}^r \mu_i \mu_j \begin{bmatrix} x(t) \\ \tilde{w}(t) \end{bmatrix}^T \Phi_{ij}(\nu) \begin{bmatrix} x(t) \\ \tilde{w}(t) \end{bmatrix} \\ &= -z^T(t)z(t) + \gamma w^T(t)w(t) + \sum_{i=1}^r \mu_i^2 \begin{bmatrix} x(t) \\ \tilde{w}(t) \end{bmatrix}^T \Phi_{ii}(\nu) \begin{bmatrix} x(t) \\ \tilde{w}(t) \end{bmatrix} \\ &\quad + \sum_{i=1}^r \sum_{i < j}^r \mu_i \mu_j \begin{bmatrix} x(t) \\ \tilde{w}(t) \end{bmatrix}^T (\Phi_{ij}(\nu) + \Phi_{ji}(\nu)) \begin{bmatrix} x(t) \\ \tilde{w}(t) \end{bmatrix}, \end{aligned} \quad (3.29)$$



where

$$\Phi_{ij}(\iota) = \begin{bmatrix} [A_i(\iota) + B_{2_i}(\iota)K_j(\iota)]^T Q(\iota) \\ + Q(\iota)[A_i(\iota) + B_{2_i}(\iota)K_j(\iota)] \\ + [C_{1_i}(\iota) + D_{12_i}(\iota)K_j(\iota)]^T \\ \times [C_{1_i}(\iota) + D_{12_i}(\iota)K_j(\iota)] \\ + [\tilde{C}_i(\iota) + \tilde{D}_i(\iota)K_j(\iota)]^T \\ \times [\tilde{C}_i(\iota) + \tilde{D}_i(\iota)K_j(\iota)] \\ + \sum_{k=1}^s \lambda_{ik} Q(k) + G(\iota) \\ + \frac{1}{(1-\beta)} Q(\iota) A_{d_i}(\iota) G^{-1}(\iota) A_{d_i}^T(\iota) Q(\iota) \\ \tilde{B}_{1_i}^T(\iota) Q(\iota) + \tilde{E}_i^T(\iota) [C_{1_i}(\iota) + D_{12_i}(\iota)K_j(\iota)] \quad -\mathcal{M} + \tilde{E}_i^T(\iota) \tilde{E}_j(\iota) \end{bmatrix} \quad (*)^T \tag{3.30}$$

Using (3.20) and pre and post multiplying (3.30) by

$$\Xi(\iota) = \begin{bmatrix} P(\iota) & 0 \\ 0 & I \end{bmatrix},$$

we obtain

$$\Xi(\iota) \Phi_{ij}(\iota) \Xi(\iota) = \begin{bmatrix} P(\iota) A_i^T(\iota) + Y_j^T(\iota) B_{2_i}^T(\iota) \\ + A_i(\iota) P(\iota) + B_{2_i}(\iota) Y_j(\iota) \\ + [C_{1_i}(\iota) P(\iota) + D_{12_i}(\iota) Y_j(\iota)]^T \\ \times [C_{1_i}(\iota) P(\iota) + D_{12_i}(\iota) Y_j(\iota)] \\ + [\tilde{C}_i(\iota) P(\iota) + \tilde{D}_i(\iota) Y_j(\iota)]^T \\ \times [\tilde{C}_i(\iota) P(\iota) + \tilde{D}_i(\iota) Y_j(\iota)] \\ + \sum_{k=1}^s \lambda_{ik} P(\iota) P^{-1}(k) P(\iota) \\ + P(\iota) G(\iota) P(\iota) + \frac{1}{(1-\beta)} A_{d_i}(\iota) G^{-1}(\iota) A_{d_i}^T(\iota) \\ \tilde{B}_{1_i}^T(\iota) + \tilde{E}_i^T(\iota) C_{1_i}(\iota) P(\iota) + \tilde{E}_i^T(\iota) D_{12_i}(\iota) Y_j(\iota) \quad -\mathcal{M} + \tilde{E}_i^T(\iota) \tilde{E}_j(\iota) \end{bmatrix} \quad (*)^T \tag{3.31}$$

Note that (3.31) is the Schur complement of  $\Omega_{ij}(\iota)$  defined in (3.7). Using (3.5), (3.6) and (3.31), we learn that

$$\Phi_{ii}(\iota) < 0, \tag{3.32}$$

$$\Phi_{ij}(\iota) + \Phi_{ji}(\iota) < 0. \tag{3.33}$$

Following from (3.29), (3.32) and (3.33), we know that

$$\tilde{\Delta} V(x(t), \iota) < -z^T(t) z(t) + \gamma w^T(t) w(t). \tag{3.34}$$

Applying the operator  $E \left[ \int_0^{T_f} (\cdot) dt \right]$  on both sides of (3.34), we obtain

$$E \left[ \int_0^{T_f} \tilde{\Delta} V(x(t), \iota) dt \right] < E \left[ \int_0^{T_f} (-z^T(t) z(t) + \gamma w^T(t) w(t)) dt \right]. \tag{3.35}$$

From the Dynkin's formula [29], it follows that

$$E \left[ \int_0^{T_f} \tilde{\Delta} V(x(t), \iota) dt \right] = E[V(x(T_f), \iota(T_f))] - E[V(x(0), \iota(0))]. \quad (3.36)$$

Substitute (3.36) into (3.35) yields

$$0 < E \left[ \int_0^{T_f} (-z^T(t)z(t) + \gamma w^T(t)w(t)) dt \right] - E[V(x(T_f), \iota(T_f))] + E[V(x(0), \iota(0))].$$

Using (3.34) and the fact that  $V(x(0) = 0, \iota(0)) = 0$  and  $V(x(T_f), \iota(T_f)) > 0$ , we have

$$E \left[ \int_0^{T_f} \{ z^T(t)z(t) - \gamma w^T(t)w(t) \} dt \right] < 0. \quad (3.37)$$

Hence, the inequality (2.5) holds. This completes the proof of Theorem 3.1.

In order to demonstrate the effectiveness and advantages of the proposed design methodology, an illustrative example is given in next section.

#### 4 An Illustrative Example

Consider an uncertain nonlinear system which is governed by the following state equation [21]

$$\begin{aligned} \dot{x}_1(t) &= -0.1c(t)x_1^3(t) - \alpha(\eta(t))x_1(t - \tau(t)) - 0.02x_2(t) - 0.67x_2^3(t) \\ &\quad - 0.1x_2^3(t - \tau(t)) - 0.005x_2(t - \tau(t)) + u(t) + 0.1w_1(t), \\ \dot{x}_2(t) &= x_1(t) + 0.1w_2(t), \\ z(t) &= \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix}, \end{aligned} \quad (4.1)$$

where  $x_1(t)$  and  $x_2(t)$  are the state vectors,  $u(t)$  is the control input,  $w_1(t)$  and  $w_2(t)$  are the disturbance input,  $z(t)$  is the regulated output,  $\eta(t)$  is the discrete state of the Markov process,  $\tau(t) = 4 + 0.5 \cos(0.9t)$  and  $c(t)$  is the uncertain term, that is,  $c(t) \in [0 \ 2.25]$ . It is assumed that

$$x_1(t) \in [-1.5 \ 1.5] \quad \text{and} \quad x_2(t) \in [-1.5 \ 1.5].$$

Using the same procedure as in [14], the nonlinear term can be represented as

$$\begin{aligned} -0.67x_2^3(t) &= M_1 \cdot 0 \cdot x_2(t) - (1 - M_1) \cdot 1.5075x_2(t), \\ -0.1x_2^3(t - \tau(t)) &= M_1 \cdot 0 \cdot x_2(t - \tau(t)) - (1 - M_1) \cdot 0.225x_2(t - \tau(t)). \end{aligned}$$

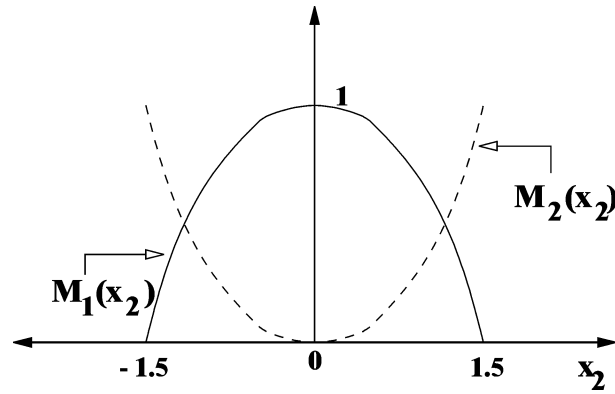


Figure 4.1. Membership functions for two fuzzy set.

Solving the above equations,  $M_1$  is obtained as follows:

$$M_1(x_2(t)) = 1 - \frac{x_2^2(t)}{2.25},$$

$$M_2(x_2(t)) = 1 - M_1(x_2(t)) = \frac{x_2^2(t)}{2.25}.$$

Note that  $M_1(x_2(t))$  and  $M_2(x_2(t))$  can be interpreted as the membership functions of fuzzy set.

Using these two fuzzy set, the uncertain nonlinear Markovian jump system with time-varying delay can be represented by the following TS fuzzy model:

*Plant Rule 1:* If  $x_2(t)$  is  $M_1(x_2(t))$  then

$$\begin{aligned} \dot{x}(t) &= [A_1(\iota) + \Delta A_1(\iota)]x(t) + A_{d_1}(\iota)x(t - \tau(t)) + B_1(\iota)w(t) + B_2(\iota)u(t), \quad x(0) = 0, \\ z(t) &= C_1(\iota)x(t), \end{aligned}$$

*Plant Rule 2:* If  $x_2(t)$  is  $M_2(x_2(t))$  then

$$\begin{aligned} \dot{x}(t) &= [A_2(\iota) + \Delta A_2(\iota)]x(t) + A_{d_2}(\iota)x(t - \tau(t)) + B_1(\iota)w(t) + B_2(\iota)u(t), \quad x(0) = 0, \\ z(t) &= C_1(\iota)x(t), \end{aligned}$$

where

$$\begin{aligned} A_1(\iota) &= \begin{bmatrix} -0.1125 & -0.02 \\ 1 & 0 \end{bmatrix}, & A_2(\iota) &= \begin{bmatrix} -0.1125 & -1.5275 \\ 1 & 0 \end{bmatrix}, \\ A_{d_1}(\iota) &= \begin{bmatrix} -\alpha(\iota) & -0.005 \\ 0 & 0 \end{bmatrix}, & A_{d_2}(\iota) &= \begin{bmatrix} -\alpha(\iota) & -0.23 \\ 0 & 0 \end{bmatrix}, \\ B_1(\iota) &= \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix}, & B_2(\iota) &= \begin{bmatrix} 1 \\ 0 \end{bmatrix}, & C_1(\iota) &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \\ \Delta A_1(\iota) &= E_{1_1}(\iota)F(x(t), \iota, t)H_{1_1}(\iota), & \Delta A_2(\iota) &= E_{1_2}(\iota)F(x(t), \iota, t)H_{1_2}(\iota), \end{aligned}$$

$$x(t) = [x_1^T(t) \quad x_2^T(t)]^T \quad \text{and} \quad w(t) = [w_1^T(t) \quad w_2^T(t)]^T.$$

Assuming  $\|F(x(t), i, t)\| \leq \rho(i) = 1$  and letting

$$E_{1_1}(i) = E_{1_2}(i) = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix},$$

we have

$$H_{1_1}(i) = H_{1_2}(i) = \begin{bmatrix} -1.1250 & 0 \\ 0 & 0 \end{bmatrix}.$$

Assume that the system is a three modes Markov process as shown in Table 4.1.

**Table 4.1** Modes of the Markov process.

Mode $i$	$\alpha(i)$
1	0.0120
2	0.0125
3	0.0130

The transition probability matrix that relates the three modes is given as follows:

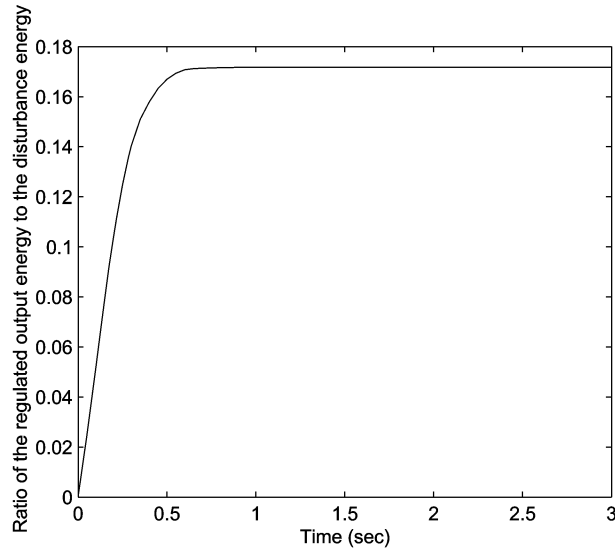
$$P_{ik} = \begin{bmatrix} 0.67 & 0.17 & 0.16 \\ 0.30 & 0.47 & 0.23 \\ 0.26 & 0.10 & 0.64 \end{bmatrix}.$$

Using the LMI optimization algorithm and Theorem 3.1 with  $\beta = 0.6$ , we obtain  $\gamma = 0.1680$

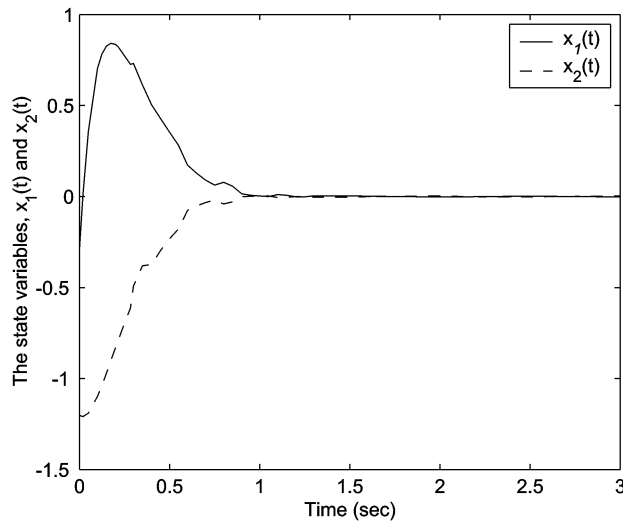
$$\begin{aligned} P(1) &= \begin{bmatrix} 2.4912 & -0.2673 \\ -0.2673 & 0.0718 \end{bmatrix}, & W(1) &= \begin{bmatrix} 1.1072 & -0.1535 \\ -0.1535 & 16.1836 \end{bmatrix}, \\ Y_1(1) &= [-16.9067 \quad -0.1051], & Y_2(1) &= [-17.2552 \quad -0.0235], \\ K_1(1) &= [-11.5635 \quad -44.5276], & K_2(1) &= [-11.5934 \quad -43.5022], \\ P(2) &= \begin{bmatrix} 2.3815 & -0.2881 \\ -0.2881 & 0.0841 \end{bmatrix}, & W(2) &= \begin{bmatrix} 1.1489 & -0.1931 \\ -0.1931 & 16.4120 \end{bmatrix}, \\ Y_1(2) &= [-15.9725 \quad 0.0589], & Y_2(2) &= [-16.3401 \quad 0.1485], \\ K_1(2) &= [-11.3092 \quad -38.0433], & K_2(2) &= [-11.3526 \quad -37.1260], \\ P(3) &= \begin{bmatrix} 2.4793 & -0.2638 \\ -0.2638 & 0.0857 \end{bmatrix}, & W(3) &= \begin{bmatrix} 0.9718 & -0.1883 \\ -0.1883 & 15.8428 \end{bmatrix}, \\ Y_1(3) &= [-17.0602 \quad -0.0867], & Y_2(3) &= [-17.4006 \quad 0.0530], \\ K_1(3) &= [-10.3932 \quad -33.0111], & K_2(3) &= [-10.3394 \quad -31.2150]. \end{aligned}$$

The resulting fuzzy controller is

$$u(t) = \sum_{j=1}^2 \mu_j K_j(i)x(t) \tag{4.2}$$



**Figure 4.2.** The result of the changing between modes during the simulation with the initial mode at Mode 2.

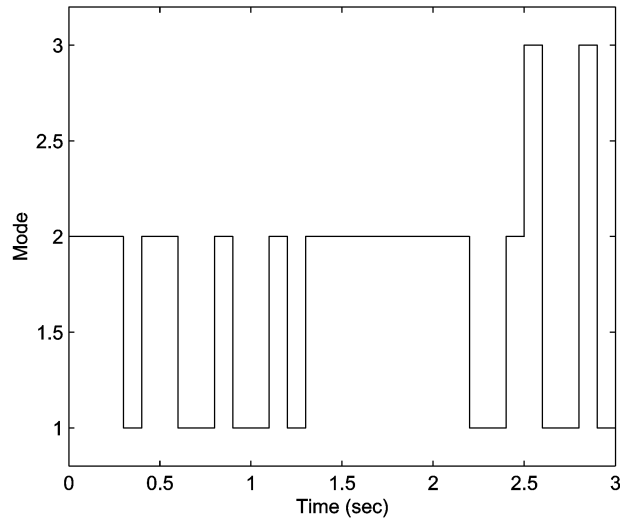


**Figure 4.3.** The histories of the state variables,  $x_1(t)$  and  $x_2(t)$ .

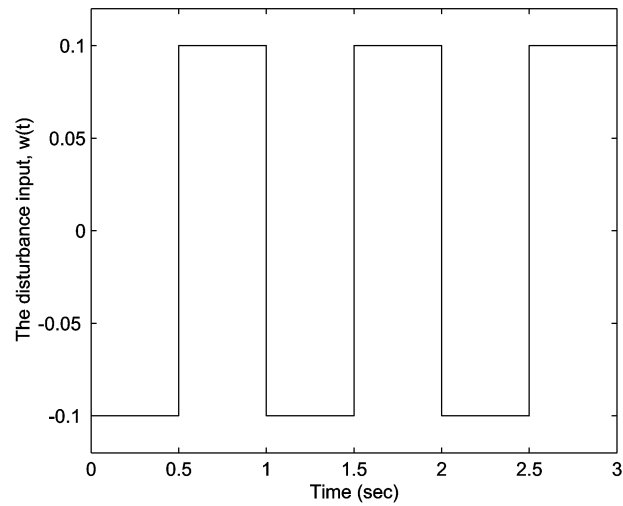
where

$$\mu_1 = M_1(x_2(t)) \quad \text{and} \quad \mu_2 = M_2(x_2(t)).$$

*Remark 4.1* Figure 4.2 shows the changing between modes with the initial mode at Mode 2. The histories of the state variables,  $x_1(t)$  and  $x_2(t)$  are given in Figure 4.3. The disturbance input signal,  $w(t)$ , which was used during simulation is given in Figure 4.4. The ratio of the regulated output energy to the disturbance input noise energy obtained by using the  $\mathcal{H}_\infty$  fuzzy controller (4.2) is depicted in Figure 4.5. After 3 seconds, the ratio



**Figure 4.4.** The disturbance input noise,  $w(t)$ .



**Figure 4.5.** The ratio of the regulated output energy to the disturbance noise energy,  $\left( \int_0^{T_f} z^T(t)z(t) dt / \int_0^{T_f} w^T(t)w(t) dt \right)$ .

of the regulated output energy to the disturbance input noise energy tends to a constant value which is about 0.1680. From Figure 4.5, we can conclude that the inequality (2.5) is guaranteed by the fuzzy controller (4.2).

## 5 Conclusion

In this paper, we have developed a technique for designing a robust  $\mathcal{H}_\infty$  fuzzy state-feedback controller for a class of time delay nonlinear Markovian jump systems that

guarantees the  $\mathcal{L}_2$ -gain of the mapping from the exogenous input noise to the regulated output to be less than some prescribed value. In addition, solutions to the problem are given in terms of linear matrix inequalities which make them more useful. Finally, an illustrative example is provided to demonstrate the effectiveness and advantages of the proposed design methodology.

## References

- [1] Feng, X., Loparo, K.A., Ji, Y. and Chizeck, H.J. Stochastic stability properties of jump linear system. *IEEE Trans. Automat. Contr.* **37** (1992) 38–53.
- [2] Ji, Y. and Chizeck, H.J. Controllability, stabilizability, and continuous-time Markovian jump linear quadratic control. *IEEE Trans. Automat. Contr.* **35** (1990) 777–788.
- [3] Souza, C.E. de and Fragoso, M.D.  $\mathcal{H}_\infty$  control for linear systems with Markovian jumping parameters. *Control-Theory and Advanced Tech.* **9** (1993) 457–466.
- [4] Boukas, E.K. and Liu, Z.K. Suboptimal design of regulators for jump linear system with time-multiplied quadratic cost. *IEEE Trans. Automat. Contr.* **46** (2001) 944–949.
- [5] Boukas, E.K. and Yang, H. Exponential stabilizability of stochastic systems with Markovian jump parameters. *Automatica* **35** (1999) 1437–1441.
- [6] Rami, M.A. and Ghaoui, L.Ei.  $\mathcal{H}_\infty$  state-feedback control of jump linear systems. In: *Proc. Conf. Decision and Contr.*, 1995, P.951–952.
- [7] Shi, P. and Boukas, E.K.  $\mathcal{H}_\infty$  control for Markovian jumping linear system with parametric uncertainty. *J. of Opt. Theory and Appl.* **95** (1997) 75–99.
- [8] Dragan, V., Shi, P. and Boukas, E.K. Control of singularly perturbed system with Markovian jump parameters: An  $\mathcal{H}_\infty$  approach. *Automatica* **35** (1999) 1369–1378.
- [9] Cao, Y.Y. and Sun, Y.X. Robust stabilization of uncertain systems with time-varying multi-state-delay. *IEEE Trans. Automat. Contr.* **43** (1998) 1484–1488.
- [10] Benjelloun, K., Boukas, E.K. and Costa, O.L.V.  $\mathcal{H}_\infty$  control for linear time delay with Markovian jumping parameters. *J. of Opt. Theory and Appl.* **105** (1997) 73–95.
- [11] Boukas, E.K. and Liu, Z.K. Robust stability and stabilizability of Markov jump linear uncertain systems with mode-dependent time delays. *J. Optimization Theory Appl.* **109**(3) (2001) 587–600.
- [12] Han, Z.X. and Feng, G. State-feedback  $\mathcal{H}^\infty$  controller design of fuzzy dynamic system using LMI techniques. In: *Fuzzy-IEEE'98*, 1998, P.538–544.
- [13] Chen, B.S., Tseng, C.S. and He, Y.Y. Mixed  $\mathcal{H}_2/\mathcal{H}_\infty$  fuzzy output feedback control design for nonlinear dynamic systems: An LMI approach. *IEEE Trans. Fuzzy Syst.* **8** (2000) 249–265.
- [14] Tanaka, K., Ikeda, T. and Wang, H.O. Robust stabilization of a class of uncertain nonlinear systems via fuzzy control: Quadratic stability,  $\mathcal{H}_\infty$  control theory, and linear matrix inequality. *IEEE Trans. Fuzzy Syst.* **4** (1996) 1–13.
- [15] Tanaka, K., Iwasaki, M. and Wang, H.O. Switching control of an R/C hovercraft: Stabilization and smooth switching. *IEEE Trans. Syst. Man and Cybern.* **31** (2001) 1–13.
- [16] Wang, H.O., Tanaka, K. and Griffin, M.F. An approach to fuzzy control of nonlinear systems: Stability and design issues. *IEEE Trans. Fuzzy Syst.* **4**(1) (1996) 14–23.
- [17] Nguang, S.K. and Shi, P.  $\mathcal{H}_\infty$  fuzzy output feedback control design for nonlinear systems: An LMI approach. In: *Proc. IEEE Conf. Decision and Contr.*, 2001, P.4352–4357.
- [18] Cao, Y.Y. and Frank, P.M. Stability analysis and synthesis of nonlinear time-delay systems via linear Takagi-Sugeno fuzzy models. *Fuzzy Sets Syst.* **124** (2001) 213–229.
- [19] Wang, W.J. and Lin, W.W. State feedback stabilization for T-S fuzzy time delay systems. In: *Proc. IEEE Conf. Fuzzy Syst.*, 2000, P.561–565.
- [20] Yoneyama, J. Robust control analysis and synthesis for uncertain fuzzy systems with time-delay. In: *Proc. IEEE Conf. Fuzzy Syst.*, 2000, P.396–401.

- [21] Lee, K.R., Kim, J.H., Jeung, E.T. and Park, H.B. Output feedback robust  $\mathcal{H}_\infty$  control of uncertain fuzzy dynamic systems with time-varying delay. *IEEE Trans. Fuzzy Syst.* **8** (2000) 657–664.
- [22] Wang, R.J., Lin, W.W. and Wang, W.J. Stabilizability of linear quadratic state feedback for uncertain fuzzy time-delay systems. *IEEE Trans. Syst., Man, Cybern. Part B* **34** (2004) 1–4.
- [23] Nguang, S.K. and Shi, P. Stabilisation of a class of nonlinear time-delay systems using fuzzy models. In: *Proc. IEEE Conf. Decision and Contr.*, 2000, P.4415–4419.
- [24] Assawinchaichote, W. and Nguang, S.K. Fuzzy control design for singularly perturbed nonlinear systems: An LMI approach. In: *ICAIET*, Malaysia, 2002, P.146–151.
- [25] Assawinchaichote, W. and Nguang, S.K. Fuzzy observer-based controller design for singularly perturbed nonlinear systems: An LMI approach. In: *Proc. IEEE Conf. Decision and Contr.*, Las Vegas, USA, 2002, P.2165–2170.
- [26] Nguang, S.K. and Assawinchaichote, W.  $\mathcal{H}_\infty$  filtering for fuzzy dynamic systems with pole placement. *IEEE Trans. Circuits Syst. I* **50** (2003) 1503–1508.
- [27] Assawinchaichote, W. and Nguang, S.K.  $\mathcal{H}_\infty$  fuzzy control design for nonlinear singularly perturbed systems with pole placement constraints: An LMI approach. *IEEE Trans. Syst., Man, Cybern. Part B* **34** (2004) 579–588.
- [28] Kushner, H.J. *Stochastic Stability and Control*. Academic Press, New York, 1967.
- [29] Dynkin, E.B. *Markov Processes*. Springer-Verlag, Berlin, 1965.
- [30] Chua, L.O., Komuro, M. and Matsumoto, T. The double scroll family: I and II. *IEEE Trans. Circuits Syst.* **33** (1986) 1072–1118.
- [31] Wang, H.O., Tanaka, K. and Ikeda, T. Fuzzy modeling and control of chaotic systems. In: *ISCAS'96*, 1996, P.209–212.