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Nonfragile Observer-Based Control for Markovian Jump Systems Subject to Asynchronous Modes

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***Abstract*—In this paper, the problem of resilient observer-based robust control is considered for discrete-time Markov jump systems subject to asynchronous models and extended dissipativity. The model uncertainty is in the interval type, which has an ability to describe parameter fluctuating phenomenon more accurately than using the norm-bounded uncertainty. A hidden Markov chain is employed to depict the mismatch between the original system and the observer-based controller. Conditions are provided to ensure the stability of the resulting closed-loop system with a desired dissipation performance regardless of the uncertainties. An example is presented to illustrate the effectiveness and potential of the proposed new design techniques.**

***Index Terms*—Extended dissipativity, hidden Markov model, nonfragile control, observer-based controller.**

I. Introduction

RECENTLY, a great deal of attention has been received to investigate the Markov jump systems owing to its powerful ability to model the practical engineering system characterized with sudden changes and its widely applications, including circuit systems, mathematical finance, robotics, and so on. An extensive amount of work has been reported on Markov jump systems [1]–[7]. For example, [1] was devoted to designing a state estimator and discussing the extended dissipative state estimation problem for Markov jump neural networks in the presence of unreliable communication links. Reference [2] was devoted to designing a nonlinear robust controller and addressing the problem for a single-master multi-slave teleoperation systems in the presence of semi-Markovian jump stochastic interval time-varying delayed communication network. In [5], a robust state feedback control approach is introduced for stability and stabilization analysis of Markov jump systems with norm-bounded time-varying uncertainties.

It is worth pointing out that all of the above-mentioned work assumes that the to-be-designed controller/filter/state estimator has full knowledge of mode information of original systems at any time. Unfortunately, due to the network-induced phenomena, including delays [8], packet loss [9], and cyber-attack [10]–[12], this assumption is generally not practical useful in practice which places a restriction on the application and popularization of mode-dependent method. A practical way has been proposed in [13] where a nonhomogeneous Markov chain is employed to describe clearly the partially known relationship between system mode and filter mode. However, this approach is complicated to implement and needs an additional assumption on nonhomogeneous Markov chain. Very recently, hidden Markov model is employed to relax these assumptions. Since hidden Markov model was first brought up in [14], some relevant research achievements have emerged in recent years, covering the filtering problem for fuzzy systems with nonuniform sampling [15], the control problem for two-dimensional Markov jump systems [16] and the fault detection problem for fuzzy Markov jump systems with network data losses [17], to name a few. There still exist many open problems to be addressed on hidden Markov model.

Many literatures [18]–[20] reported that small parameter perturbation exists extensively in design of controllers and has a great impact on the control performance. Usually, parameter uncertainty can be divided into two cases. The first case is norm-bounded type of uncertainties which is relatively easy to analyze [5], [13], [21], [22]. The second case is the interval type of uncertainties of which the structure is more informative [23]–[25]. However, the former type of uncertainty cannot accurately characterize the uncertain phenomenon caused by the finite word length (FWL) effects which may destabilize control systems. It is generally known that FWL effects are inevitable in the digital control systems. The above observation and analysis lead us to conduct the work in this paper.

This paper focuses on the problem of nonfragile observer-based control of Markovian jump systems, taking into account

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asynchronous modes and extended dissipativity. To overcome the immeasurability of some system states, dynamic observers are designed to estimate unmeasurable states before proceeding to controller design. Then, with the aid of the singular-value decomposition, we can loosen the coupling between slack matrix and observer/controller gains. Finally, new sufficient conditions satisfying linear constraint are derived which can guarantee the stability of the closed-loop system and achieve a prescribed extended dissipation performance. The novelty and innovation from this paper are highlighted as follows.

1) An asynchronous observer-based controller via applying the hidden Markov model is introduced. In contrast with piecewise homogeneous Markov model, the design procedure of asynchronous controller can not only simplify the theoretical derivation but also reduce the conservatism due to the introduction of free matrix $\mathcal{P}_{\mu\nu}$.
2) In order to overcome the unfavorable effect caused by FWL, the interval type of uncertainty is introduced to characterize the uncertain phenomenon in observer-based controller.
3) We provide an unified framework for Markov jump systems, which can be directly applied to solve many control synthesis issues, including H_∞ control, l_2–l_∞ control, and dissipative control.

Notation: $\mathbb{R}^n$ denotes the n-dimensional Euclidean space. The notation $P > 0$ (≥ 0) means that P is real symmetric and positive definite (positive semidefinite). I and 0 represent the identity matrix and the zero matrix with appropriate dimensions, respectively. The superscript "T" represents the transpose. Moreover, in symmetric block matrices, "$*$" denotes the term that is induced by symmetry, and diag$\{\cdots\}$ stands for a block-diagonal matrix. Besides, $\mathcal{E}\{x\}$ and $\mathcal{E}\{x|y\}$ will, respectively, mean expectation of x and expectation of x condition on y. $\Pr\{\cdot\}$ stands for the probability.

II. Definitions and Preliminary Results

Let system parameter $\{s_k, k \geq 0\}$ represent a discrete-time Markov chain taking values in a finite state space $\mathcal{M}_s = \{1, 2, \ldots, m_s\}$ with the mode transition probability matrix $\Pi = \{\pi_{\mu\mu_+}\}$. For any $\mu, \mu_+ \in \mathcal{M}_s$, one has $\pi_{\mu\mu_+} = \Pr\{s_{k+1} = \mu_+ | s_k = \mu\}$, where $0 \leq \pi_{\mu\mu_+} \leq 1$ and $\sum_{\mu_+=1}^{m_s} \pi_{\mu\mu_+} = 1$.

The controller parameter $\{c_k, k \geq 0\}$ represents a discrete-time hidden Markov chain taking values in a finite state space $\mathcal{M}_c = \{1, 2, \ldots, m_c\}$ with conditional probability matrix $\Xi = \{\Xi_{\mu\nu}\}$. For any $\mu \in \mathcal{M}_s, \nu \in \mathcal{M}_c$, one has $\Xi_{\mu\nu} = \Pr\{c_k = \nu | s_k = \mu\}$, where $0 \leq \Xi_{\mu\nu} \leq 1$ and $\sum_{\nu=1}^{m_c} \Xi_{\mu\nu} = 1$.

For brevity, in the following, we denote s_k, s_{k+1}, and c_k as μ, μ_+, and ν, respectively. Then, the considered discrete-time Markov jump systems are given as follows:

$$\begin{cases} x(k+1) = A_\mu x(k) + B_\mu u(k) + D_\mu \omega(k) \\ y(k) = C_\mu x(k) \\ z(k) = E_\mu x(k) \end{cases} \tag{1}$$

where $x(k) \in \mathbb{R}^{n_x}$, $y(k) \in \mathbb{R}^{n_y}$, and $z(k) \in \mathbb{R}^{n_z}$ stand for the system state vector, the measured output, and the controlled output of Markov jump systems, respectively. $\omega(k) \in \mathbb{R}^{n_\omega}$ is the external disturbance signal belonging to $l_2[0, \infty)$. The system matrices A_μ, B_μ, C_μ, D_μ, and E_μ are preknown real matrices with appropriate dimensions.

For control systems, there are generally three types of controllers, including the static output feedback controllers [26], dynamic output feedback controllers [10], and observer-based output feedback controllers [12], [27]–[29]. In consideration of the unavailability of some system states, it is necessary to construct a state observer before designing the controller. This paper adopts the following full-order and mode-dependent state observer for Markov jump systems (1):

$$\begin{cases} \hat{x}(k+1) = A_\mu \hat{x}(k) + B_\mu u(k) \\ \quad + \big(H_\mu + \Delta H_\mu\big)\big(y(k) - \hat{y}(k)\big) \\ \hat{y}(k) = C_\mu \hat{x}(k) \end{cases} \tag{2}$$

where $\hat{x}(k) \in \mathbb{R}^{n_x}$ and $\hat{z}(k) \in \mathbb{R}^{n_z}$ denote the observer state vector and the observer output vector, respectively. H_μ represents the observer gain to be determined later.

Remark 1: With the scale expansion of the controlled systems, it is quite uneconomic to reconstruct all the system states rather than some unmeasurable state variables. This motivates us to consider the reduced-order observers [30] and functional observers [31], [32] in our future work.

In a real application, it is nearly impossible for controller to acquire the system mode all the time. Motivated by the controller design approach in [12] and [23], in this paper, the following asynchronous observer-based controller is constructed:

$$u(k) = (K_\nu + \Delta K_\nu)\hat{x}(k) \tag{3}$$

where $K_\nu \in \mathbb{R}^{n_u \times n_x}$ are the gains of the observer-based controller which will be determined in the next section. The stochastic variable $\nu \in \mathcal{M}_c$ is used to describe asynchronization between the underlying system and the observer-based controller.

The uncertain terms in (2) and (3) (i.e., ΔH_μ and ΔK_ν) denote the interval type of uncertainty and satisfy the following forms:

$$\Delta H_\mu = \left[\delta_{\rho\varrho}^{H\mu}\right]_{n_x \times n_y}, \quad \Delta K_\nu = \left[\delta_{\rho\varrho}^{K\nu}\right]_{n_u \times n_x} \tag{4}$$

where $|\delta_{\rho\varrho}^{H\mu}| \leq \delta$ and $|\delta_{\rho\varrho}^{K\nu}| \leq \delta$.

To ease the later derivation, define j-dimensional column vector $\mathbf{1}_{i|j} \triangleq [\underbrace{0 \ \ldots \ 0}_{i-1} \ 1 \ 0 \ \ldots \ 0]^{\mathrm{T}}$ with $1 \leq i \leq j$. Then we can obtain an equivalent form of (4)

$$\Delta H_\mu = \sum_{\rho=1}^{n_x} \sum_{\varrho=1}^{n_y} \delta_{\rho\varrho}^{H\mu} \mathbf{1}_{\rho|n_x} \mathbf{1}_{\varrho|n_y}^{\mathrm{T}}$$

$$\Delta K_\nu = \sum_{\rho=1}^{n_u} \sum_{\varrho=1}^{n_x} \delta_{\rho\varrho}^{K\nu} \mathbf{1}_{\rho|n_u} \mathbf{1}_{\varrho|n_x}^{\mathrm{T}}.$$

Remark 2: In many existing papers, state observer and controller can achieve a perfect implementation. However, in many practical engineering, the small parameter perturbations may occur owing to a variety of reasons, including numerical roundoff errors, FWL, programming errors, etc. [13], [21]. These parameter fluctuations of observer/controller, though

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small, have vast effects on system performance and even may cause instability. To avoid this, it is necessary to design a nonfragile observer-based controller which is insensitive to parameter variations.

Remark 3: The norm-bounded method is widely used for characterizing the phenomenon of parameter uncertainty. However, owing to the FWL effects, the norm-bounded type of uncertainty has a limited accuracy [24]. To overcome this drawback, we introduce the interval type of uncertainty in this paper.

Remark 4: Motivated by works in [16], we consider mode-dependent state observer and asynchronous controller. In fact, not only controller but also observer has great difficulty obtaining the accurate system mode timely. It is worth mentioning that two hidden Markov models lead to substantial difficulties in the subsequent analysis and design. Introducing another hidden Markov chain to characterize the asynchronous phenomenon between the original system and state observer is beyond the scope of this paper and will be left as our future work.

Let $\mathbf{X}(k) = \left[x^{\mathrm{T}}(k) - \hat{x}^{\mathrm{T}}(k) \;\; x^{\mathrm{T}}(k)\right]^{\mathrm{T}}$, $\tilde{z}(k) = z(k) - \hat{z}(k)$. Then, from (1)–(3), the closed-loop system can be obtained as the following compact form:

$$\begin{cases} \mathbf{X}(k+1) = \mathbf{A}_{\mu\nu}\mathbf{X}(k) + \mathbf{D}_{\mu}\omega(k) \\ z(k) = \mathbf{E}_{\mu}\mathbf{X}(k) \end{cases} \tag{5}$$

where $\mathbf{D}_{\mu} = \left[D_{\mu}^{\mathrm{T}} \;\; D_{\mu}^{\mathrm{T}}\right]^{\mathrm{T}}$, $\mathbf{E}_{\mu} = \left[0 \;\; E_{\mu}\right]$, and

$$\mathbf{A}_{\mu\nu} = \begin{bmatrix} A_{\mu} - \left(H_{\mu} + \Delta H_{\mu}\right)C_{\mu} & 0 \\ -B_{\mu}(K_{\nu} + \Delta K_{\nu}) & A_{\mu} + B_{\mu}(K_{\nu} + \Delta K_{\nu}) \end{bmatrix}.$$

The following definitions provide theoretical basis in the sequel.

Definition 1 [33]: For any initial system mode s_0 and controller mode c_0, the closed-loop system (5) is said to be stochastically stable if for every initial state $\mathbf{X}(0)$, there exists an observer-based controller (3), such that

$$\mathcal{E}\left\{\sum_{k=0}^{\infty} \mathbf{X}^{\mathrm{T}}(k)\mathbf{X}(k) \;\middle|\mathbf{X}(0), s_0, c_0\right\} < \infty \tag{6}$$

without external disturbance (i.e., $\omega(k) \equiv 0$).

Assume that matrices $\mathcal{R}_1 = \mathcal{R}_1^{\mathrm{T}} = -(\mathcal{R}_1^{+})^2 \leq 0$, $\mathcal{R}_1^{+} \geq 0$, and $\mathcal{R}_3 = \mathcal{R}_3^{\mathrm{T}} > 0$. Define the supply rate $r(z(k), \omega(k)) = z^{\mathrm{T}}(k)\mathcal{R}_1 z(k) + 2z^{\mathrm{T}}(k)\mathcal{R}_2\omega(k) + \omega^{\mathrm{T}}(k)\mathcal{R}_3\omega(k)$. Then, we give the definition of extended dissipativity.

Definition 2 [34]: Given matrices $\mathcal{R}_4^{+} \geq 0$ and $\mathcal{R}_4 = \mathcal{R}_4^{\mathrm{T}} = (\mathcal{R}_4^{+})^2 \geq 0$, under assumptions of $(\|\mathcal{R}_1\| + \|\mathcal{R}_2\|) \cdot \|\mathcal{R}_4\| = 0$, if for any $T > 0$, under the zero-initial condition, the inequality shown below holds

$$\sum_{k=0}^{\mathrm{T}} \mathcal{E}\{r(z(k), \omega(k))\} \geq \sup_{0 \leq k \leq T} \mathcal{E}\left\{z^{\mathrm{T}}(k)\mathcal{R}_4 z(k)\right\} \tag{7}$$

then the resultant closed-loop system (5) is said to be extended dissipative.

In the closed-loop system, we will design an observer-based controller to make sure that the closed-loop systems (5) are stochastically stable in the case of $\omega(k) = 0$ and achieve a prescribed extended dissipativity performance index.

To proceed further, the following lemmas will be needed to be introduced.

Lemma 1 [24]: Let Ω, Ω_1, and Ω_2 be any known matrices with appropriate dimensions. Denote the following two κ-dimensional diagonal matrices:

$$\Lambda_1 = \mathrm{diag}\{\Lambda_{11}, \ldots, \Lambda_{1\kappa}\}, \quad \Lambda_2 = \mathrm{diag}\{\Lambda_{21}, \ldots, \Lambda_{2\kappa}\}$$
$$\Lambda_{1i} \in [-\delta, \delta], \quad \Lambda_{2i} \in \{-\delta, \delta\} \;\; \forall i \in \{1, 2, \ldots, \kappa\}.$$

Then the following inequality

$$\Omega + \Omega_1\Lambda_1\Omega_2 + (\Omega_1\Lambda_1\Omega_2)^{\mathrm{T}} < 0 \tag{8}$$

holds if and only if there exists a 2κ-dimensional symmetric matrix Ψ satisfies

$$\begin{bmatrix} \Omega & \Omega_1 \\ \Omega_1^{\mathrm{T}} & 0 \end{bmatrix} + \begin{bmatrix} \Omega_2 & 0 \\ 0 & I \end{bmatrix}^{\mathrm{T}} \Psi \begin{bmatrix} \Omega_2 & 0 \\ 0 & I \end{bmatrix} < 0 \tag{9}$$

$$\begin{bmatrix} I \\ \Lambda_2 \end{bmatrix}^{\mathrm{T}} \Psi \begin{bmatrix} I \\ \Lambda_2 \end{bmatrix} \geq 0, \quad \text{for any } \Lambda_2. \tag{10}$$

Remark 5: In order to ensure that condition (9) is linear matrix inequality, Ω_2 in Lemma 1 must be matrix without variables. In some cases, where Ω_1 is constant matrix and Ω_2 has some unknown quantities, (9) can be transformed into

$$\begin{bmatrix} \Omega & \Omega_2^{\mathrm{T}} \\ \Omega_2 & 0 \end{bmatrix} + \begin{bmatrix} \Omega_1^{\mathrm{T}} & 0 \\ 0 & I \end{bmatrix}^{\mathrm{T}} \Psi \begin{bmatrix} \Omega_1^{\mathrm{T}} & 0 \\ 0 & I \end{bmatrix} < 0. \tag{11}$$

Note that uncertain terms must be preprocessed before applying Lemma 1. Denote $\otimes$ as the Kronecker product and define $1_k = [\underbrace{1 \;\ldots\; 1}_{k}]$. We then introduce the following lemma.

Lemma 2 [25]: For any matrix R, one has

$$\begin{aligned} \Theta^{uk} &\triangleq \begin{bmatrix} 0 & 0 & 0 & -\Delta H_{\mu}C_{\mu}R & 0 & 0 \\ 0 & 0 & 0 & -B_{\mu}\Delta K_{\nu}R & B_{\mu}\Delta K_{\nu}R & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \\ &= \mathbf{U}^{v}\delta^{HK}\mathbf{U}^{h} \end{aligned} \tag{12}$$

where ΔH_{μ}, ΔK_{ν}, B_{μ}, and C_{μ} are defined in (1) and (4)

$$\mathbf{U}^{v} = \begin{bmatrix} \mathbf{U}_{\mu}^{v} & \mathbf{U}_{\nu}^{v} \end{bmatrix}, \; \mathbf{U}^{h} = \begin{bmatrix} \mathbf{U}_{\mu}^{h} \\ \mathbf{U}_{\nu}^{h} \end{bmatrix}, \; \delta^{HK} = \begin{bmatrix} \delta^{H\mu} & 0 \\ 0 & \delta^{K\nu} \end{bmatrix}$$

$$U_{\mu\rho}^{v} = \begin{bmatrix} \left(\mathbf{1}_{\rho|n_x}\right)^{\mathrm{T}} & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^{\mathrm{T}}$$
$$U_{\mu\varrho}^{h} = \begin{bmatrix} 0 & 0 & 0 & -\mathbf{1}_{\varrho|n_y}^{\mathrm{T}}C_{\mu}R & 0 & 0 \end{bmatrix}$$
$$\mathbf{U}_{\mu}^{v} = \begin{bmatrix} 1_{n_y} \otimes U_{\mu 1}^{v} & 1_{n_y} \otimes U_{\mu 2}^{v} & \ldots & 1_{n_y} \otimes U_{\mu n_x}^{v} \end{bmatrix}$$
$$\mathbf{U}_{\mu}^{h} = 1_{n_x}^{\mathrm{T}} \otimes \begin{bmatrix} U_{\mu 1}^{hT} & U_{\mu 2}^{hT} & \ldots & U_{\mu n_y}^{hT} \end{bmatrix}^{\mathrm{T}}$$
$$\begin{aligned} \delta^{H\mu} = \mathrm{diag}\Big\{&\delta_{11}^{H\mu}, \delta_{12}^{H\mu}, \ldots, \delta_{1n_y}^{H\mu}, \ldots, \delta_{k1}^{H\mu}, \delta_{k2}^{H\mu}, \ldots, \delta_{kn_y}^{H\mu}, \\ &\ldots, \delta_{n_x 1}^{H\mu}, \delta_{n_x 2}^{H\mu}, \ldots, \delta_{n_x n_y}^{H\mu}\Big\} \end{aligned}$$
$$U_{\nu\rho}^{v} = \begin{bmatrix} 0 & \left(B_{\mu}\mathbf{1}_{\rho|n_u}\right)^{\mathrm{T}} & 0 & 0 & 0 & 0 \end{bmatrix}^{\mathrm{T}}$$
$$U_{\nu\varrho}^{h} = \begin{bmatrix} 0 & 0 & 0 & -\mathbf{1}_{\varrho|n_x}^{\mathrm{T}}R & \mathbf{1}_{\varrho|n_x}^{\mathrm{T}}R & 0 \end{bmatrix}$$

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$$\mathbf{U}_\nu^v = \begin{bmatrix} 1_{n_x} \otimes U_{\nu 1}^v & 1_{n_x} \otimes U_{\nu 2}^v & \dots & 1_{n_x} \otimes U_{\nu n_u}^v \end{bmatrix}$$
$$\mathbf{U}_\nu^h = 1_{n_u}^{\mathrm{T}} \otimes \begin{bmatrix} U_{\mu 1}^{hT} & U_{\mu 2}^{hT} & \dots & U_{\mu n_x}^{hT} \end{bmatrix}^{\mathrm{T}}$$
$$\delta^{K\nu} = \mathrm{diag}\{\delta_{11}^{K\nu}, \delta_{12}^{K\nu}, \dots, \delta_{1n_x}^{K\nu}, \dots, \delta_{k1}^{K\nu}, \delta_{k2}^{K\nu}, \dots, \delta_{kn_x}^{K\nu}, \dots, \delta_{n_u 1}^{K\nu}, \delta_{n_u 2}^{K\nu}, \dots, \delta_{n_u n_x}^{K\nu}\}.$$

III. MAIN RESULTS

The nonfragile controller will be figured out for Markov jump systems subject to asynchronous modes and extended dissipativity (1) in this section. We can see, the proposed controller design method can make sure that the closed-loop Markov jump systems are stochastically stable despite interval gain uncertainty. Furthermore, the way of computing the controller gains will be given in Theorems 2 and 3.

Theorem 1: Consider the discrete-time closed-loop systems (5). For given matrices $\mathcal{R}_1^+ \geq 0$, $\mathcal{R}_4^+ \geq 0$ and uncertain parameter $\delta > 0$, if for any $\mu \in \mathcal{M}_s$, $\nu \in \mathcal{M}_c$, there exist matrices $P_{1\mu} > 0$, $P_{2\mu} > 0$, $\mathcal{P}_{1\mu\nu} > 0$, $\mathcal{P}_{2\mu\nu} > 0$, H_μ, and K_ν satisfying the following conditions:

$$\sum_{\nu=1}^{m_c} \Xi_{\mu\nu}\mathcal{P}_{\mu\nu} < P_\mu \tag{13}$$

$$\begin{bmatrix} -\bar{P}_\mu^{-1} & 0 & \mathbf{A}_{\mu\nu} & \mathbf{D}_\mu \\ * & -I & \mathcal{R}_1^+\mathbf{E}_\mu & 0 \\ * & * & -\mathcal{P}_{\mu\nu} & -\mathbf{E}_\mu^{\mathrm{T}}\mathcal{R}_2 \\ * & * & * & -\mathcal{R}_3 \end{bmatrix} < 0 \tag{14}$$

$$\begin{bmatrix} -I & \mathcal{R}_4^+\mathbf{E}_\mu \\ * & -P_\mu \end{bmatrix} < 0 \tag{15}$$

where $\bar{P}_\mu = \mathrm{diag}\{\bar{P}_{1\mu}, \bar{P}_{2\mu}\} = \sum_{\mu_+=1}^{m_s} \pi_{\mu\mu_+}\mathrm{diag}\{P_{1\mu}, P_{2\mu}\}$ and $\mathcal{P}_{\mu\nu} = \mathrm{diag}\{\mathcal{P}_{1\mu\nu}, \mathcal{P}_{2\mu\nu}\}$. Then, the closed-loop Markov jump systems are stochastically stable and a predefined extended dissipativity performance index.

Proof: Consider the following mode-dependent Lyapunov function inspired by the work [14]:

$$V(\mathbf{X}(k), \mu) = \mathbf{X}^{\mathrm{T}}(k)P_\mu\mathbf{X}(k) \tag{16}$$

where $P_\mu = \mathrm{diag}\{P_{1\mu}, P_{2\mu}\}$.

Define $\mathbf{X}_\omega(k) = [\mathbf{X}^{\mathrm{T}}(k) \;\; \omega^{\mathrm{T}}(k)]^{\mathrm{T}}$, then it can be concluded that

$$\begin{aligned} &\Delta V(\mathbf{X}(k), \mu) \\ &= \mathcal{E}\{\mathbf{X}^{\mathrm{T}}(k+1)\bar{P}_\mu\mathbf{X}(k+1)\} - \mathbf{X}^{\mathrm{T}}(k)P_\mu\mathbf{X}(k) \\ &= \mathcal{E}\left\{\mathbf{X}_\omega^{\mathrm{T}}(k)\begin{bmatrix} \mathbf{A}_{\mu\nu}^{\mathrm{T}} \\ \mathbf{D}_\mu^{\mathrm{T}} \end{bmatrix}\bar{P}_\mu\begin{bmatrix} \mathbf{A}_{\mu\nu}^{\mathrm{T}} \\ \mathbf{D}_\mu^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}\mathbf{X}_\omega(k)\right\} - \mathbf{X}^{\mathrm{T}}(k)P_\mu\mathbf{X}(k) \\ &= \sum_{\nu=1}^{m_c} \Xi_{\mu\nu}\mathbf{X}_\omega^{\mathrm{T}}(k)\begin{bmatrix} \mathbf{A}_{\mu\nu}^{\mathrm{T}} \\ \mathbf{D}_\mu^{\mathrm{T}} \end{bmatrix}\bar{P}_\mu\begin{bmatrix} \mathbf{A}_{\mu\nu}^{\mathrm{T}} \\ \mathbf{D}_\mu^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}\mathbf{X}_\omega(k) \\ &\quad - \mathbf{X}^{\mathrm{T}}(k)P_\mu\mathbf{X}(k). \end{aligned} \tag{17}$$

Next, to prove the extended dissipativity of closed-loop systems, we rewrite the supply rate $r(z(k), \omega(k))$ as follows:

$$\begin{aligned} &r(z(k), \omega(k)) \\ &= z^{\mathrm{T}}(k)\mathcal{R}_1z(k) + 2z^{\mathrm{T}}(k)\mathcal{R}_2\omega(k) + \omega^{\mathrm{T}}(k)\mathcal{R}_3\omega(k) \\ &= \mathbf{X}_\omega^{\mathrm{T}}(k)\begin{bmatrix} \mathbf{E}_\mu^{\mathrm{T}}\mathcal{R}_1\mathbf{E}_\mu & -\mathbf{E}_\mu^{\mathrm{T}}\mathcal{R}_2 \\ * & -\mathcal{R}_3 \end{bmatrix}\mathbf{X}_\omega(k). \end{aligned} \tag{18}$$

Combining conditions (13), (17), and (18), one immediately obtains

$$\begin{aligned} &\mathcal{E}\left\{V(\mathbf{X}(T+1), \mu_+) - V(\mathbf{X}(0), s_0) - \sum_{k=0}^{\mathrm{T}} r(z(k), \omega(k))\right\} \\ &= \sum_{k=0}^{\mathrm{T}} \mathcal{E}\{\Delta V(\mathbf{X}(k), \mu) - r(z(k), \omega(k))\} \\ &\leq \sum_{k=0}^{\mathrm{T}}\sum_{\nu=1}^{m_c} \Xi_{\mu\nu}\mathbf{X}_\omega^{\mathrm{T}}(k)\left\{\begin{bmatrix} \mathbf{A}_{\mu\nu}^{\mathrm{T}} \\ \mathbf{D}_\mu^{\mathrm{T}} \end{bmatrix}\bar{P}_\mu\begin{bmatrix} \mathbf{A}_{\mu\nu}^{\mathrm{T}} \\ \mathbf{D}_\mu^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}} \right. \\ &\quad \left. - \begin{bmatrix} \mathbf{E}_\mu^{\mathrm{T}}\mathcal{R}_1\mathbf{E}_\mu + \mathcal{P}_{\mu\nu} & \mathbf{E}_\mu^{\mathrm{T}}\mathcal{R}_2 \\ * & \mathcal{R}_3 \end{bmatrix}\right\}\mathbf{X}_\omega(k) \end{aligned} \tag{19}$$

in which the inequality holds due to condition (13). We next investigate the stochastic stability condition. Under the case of $\omega(k) = 0$, in light of condition (13), the preceding inequality (17) reduces to

$$\begin{aligned} &\Delta V(\mathbf{X}(k), \mu) \\ &= \sum_{\nu=1}^{m_c} \Xi_{\mu\nu}\mathbf{X}^{\mathrm{T}}(k)\mathbf{A}_{\mu\nu}^{\mathrm{T}}\bar{P}_\mu\mathbf{A}_{\mu\nu}^{\mathrm{T}}\mathbf{X}(k) - \mathbf{X}^{\mathrm{T}}(k)P_\mu\mathbf{X}(k) \\ &\leq \sum_{\nu=1}^{m_c} \Xi_{\mu\nu}\mathbf{X}^{\mathrm{T}}(k)\{\mathbf{A}_{\mu\nu}^{\mathrm{T}}\bar{P}_\mu\mathbf{A}_{\mu\nu}^{\mathrm{T}}\mathbf{X}(k) - \mathcal{P}_{\mu\nu}\}\mathbf{X}(k). \end{aligned} \tag{20}$$

Following the similar lines of [25], we can readily obtain that the closed-loop systems are stochastically stable.

Now, we proceed with proving the extended dissipativity of closed-loop systems. Under the zero-initial condition, it is evident that $V(\mathbf{X}(0), s_0) = 0$. Based on the Schur complement, applying condition (14) into (19) indicates

$$\mathcal{E}\{V(\mathbf{X}(T+1), \mu_+)\} - \sum_{k=0}^{\mathrm{T}} \mathcal{E}\{r(z(k), \omega(k))\} \leq 0. \tag{21}$$

On the other hand, applying the Schur complement to (15), it yields

$$\begin{aligned} z^{\mathrm{T}}(k)\mathcal{R}_4z(k) &= \sum_{\nu=1}^{m_c} \Xi_{\mu\nu}\mathbf{X}^{\mathrm{T}}(k)\mathbf{E}_\mu^{\mathrm{T}}\mathcal{R}_4\mathbf{E}_\mu\mathbf{X}(k) \\ &< \sum_{\nu=1}^{m_c} \Xi_{\mu\nu}\mathbf{X}^{\mathrm{T}}(k)P_\mu\mathbf{X}(k) \\ &= \sum_{\nu=1}^{m_c} \Xi_{\mu\nu}V(\mathbf{X}(k), \mu). \end{aligned} \tag{22}$$

Recalling the inequality (21), it can be directly concluded that $z^{\mathrm{T}}(k)\mathcal{R}_4z(k) < \sum_{i=0}^{k-1} \mathcal{E}\{r(z(k), \omega(k))\}$.

According to the work in [1] and [25], extended dissipativity of the closed-loop systems can be guaranteed in a similar way. ■

Due to the existence of multivariable coupling and uncertain terms, controller designs cannot be achieved by using the classic linear matrix inequality optimization techniques. For multivariable coupling, with the aid of the singular-value decomposition, we can loosen the coupling between slack matrix and observer/controller gains in Theorem 2. For uncertain terms, the method in [23, Th. 5] is unrealistic owing to

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enormous computation. To overcome this difficulty, we introduce Lemmas 1 and 2 to derive the gain matrices of the observer and controller in Theorem 3.

Assumption 1: For the output matrices C_μ, we assume

$$\mathrm{Rank}(C_\mu) = n_y, \quad C_\mu = C \quad \forall \mu \in \mathcal{M}_s. \tag{23}$$

Formally, the singular-value decomposition of the output matrices C is a factorization of the form $C = \mathcal{C}_1[\mathcal{C}_2\ 0]\mathcal{C}_3^{\mathrm{T}}$ where $\mathcal{C}_1 \in \mathbb{R}^{n_y \times n_y}$, $\mathcal{C}_2 \in \mathbb{R}^{n_y \times n_y}$, $\mathcal{C}_3 \in \mathbb{R}^{n_x \times n_x}$, $\mathcal{C}_1\mathcal{C}_1^{\mathrm{T}} = I$, and $\mathcal{C}_3\mathcal{C}_3^{\mathrm{T}} = I$.

Theorem 2: Consider the discrete-time closed-loop systems (5). Under Assumption 1, for given matrices $\mathcal{R}_1^+ \geq 0$, $\mathcal{R}_4^+ \geq 0$ and uncertain parameter $\delta > 0$, if for any $\mu \in \mathcal{M}_s$, $\nu \in \mathcal{M}_c$, there exist matrices $\tilde{P}_{1\mu} > 0$, $\tilde{P}_{2\mu} > 0$, $\tilde{\mathcal{P}}_{1\mu\nu} > 0$, $\tilde{\mathcal{P}}_{2\mu\nu} > 0$, R_1, R_2, R_3, H_μ, and K_ν satisfying the following conditions:

$$\sum_{\nu=1}^{m_c} \Xi_{\mu\nu}\tilde{\mathcal{P}}_{\mu\nu} < \tilde{P}_\mu \tag{24}$$

$$\Theta \triangleq \begin{bmatrix} \tilde{P}_\mu - \tilde{R}^{\mathrm{T}} - \tilde{R} & 0 & \tilde{\mathbf{A}}_{\mu\nu} & \mathbf{D}_\mu \\ * & -I & \mathcal{R}_1^+\tilde{\mathbf{E}}_\mu & 0 \\ * & * & -\tilde{\mathcal{P}}_{\mu\nu} & -\tilde{\mathbf{E}}_\mu^{\mathrm{T}}\mathcal{R}_2 \\ * & * & * & -\mathcal{R}_3 \end{bmatrix} < 0 \tag{25}$$

$$\begin{bmatrix} -I & \mathcal{R}_4^+\tilde{\mathbf{E}}_\mu \\ * & -\tilde{P}_\mu \end{bmatrix} < 0 \tag{26}$$

in which $\tilde{R} = \mathrm{diag}\{R, R\}$, $\tilde{P}_\mu = \mathrm{diag}\{\tilde{P}_{1\mu}, \tilde{P}_{2\mu}\}$, $\tilde{\mathcal{P}}_{\mu\nu} = \mathrm{diag}\{\tilde{\mathcal{P}}_{1\mu\nu}, \tilde{\mathcal{P}}_{2\mu\nu}\}$, $\tilde{\mathbf{E}}_\mu = [0\ E_\mu]R$, and

$$\tilde{\mathbf{A}}_{\mu\nu} = \begin{bmatrix} A_\mu R - H_\mu[R_1\ 0]\mathcal{C}_3^{\mathrm{T}} - \Delta H_\mu C_\mu R & 0 \\ -B_\mu(K_\nu R + \Delta K_\nu R) & A_\mu + B_\mu(K_\nu + \Delta K_\nu)R \end{bmatrix}$$

$$R = \mathcal{C}_3\begin{bmatrix} \mathcal{C}_2^{-1}\mathcal{C}_1^{\mathrm{T}}R_1 & 0 \\ R_2 & R_3 \end{bmatrix}\mathcal{C}_3^{\mathrm{T}}.$$

Then, a resilient controller can be designed to guarantee the stochastic stability and prescribed extended dissipativity performance of the closed-loop systems.

Proof: According to Assumption 1 and the definition of R, one immediately obtains

$$\begin{aligned} H_\mu CR &= H_\mu\mathcal{C}_1[\mathcal{C}_2\ 0]\mathcal{C}_3^{\mathrm{T}}\mathcal{C}_3\begin{bmatrix} \mathcal{C}_2^{-1}\mathcal{C}_1^{\mathrm{T}}R_1 & 0 \\ R_2 & R_3 \end{bmatrix}\mathcal{C}_3^{\mathrm{T}} \\ &= H_\mu[R_1\quad 0]\mathcal{C}_3^{\mathrm{T}}. \end{aligned} \tag{27}$$

On the other hand, as we know, $(R-\bar{P}_\mu^{-1})^{\mathrm{T}}\bar{P}_\mu(R-\bar{P}_\mu^{-1}) \geq 0$ which is equivalent to $R^{\mathrm{T}}\bar{P}_\mu R - R^{\mathrm{T}} - R \geq -\bar{P}_\mu^{-1}$.

Finally, we define

$$\begin{cases} \tilde{P}_{1\mu} = R^{\mathrm{T}}\bar{P}_{1\mu}R, & \tilde{P}_{2\mu} = R^{\mathrm{T}}\bar{P}_{2\mu}R \\ \tilde{\mathcal{P}}_{1\mu\nu} = R^{\mathrm{T}}\mathcal{P}_{1\mu\nu}R, & \tilde{\mathcal{P}}_{2\mu\nu} = R^{\mathrm{T}}\mathcal{P}_{2\mu\nu}R. \end{cases} \tag{28}$$

Combining conditions from (27) to (28), performing a congruence transformation to conditions (24)–(26) with $\tilde{R}^{-T}$, $\mathrm{diag}\{I, I, \tilde{R}^{-T}, I\}$, and $\mathrm{diag}\{I, \tilde{R}^{-T}\}$, one immediately obtains inequalities (13)–(15), respectively. This completes the proof of Theorem 2. ■

Theorem 3: Consider the discrete-time closed-loop systems (5). Under Assumption 1, for given matrices $\mathcal{R}_1^+ \geq 0$, $\mathcal{R}_4^+ \geq 0$ and uncertain parameter $\delta > 0$, if for any $\mu \in \mathcal{M}_s$, $\nu \in \mathcal{M}_c$, there exist symmetric matrices $\tilde{P}_{1\mu} > 0$, $\tilde{P}_{2\mu} > 0$, $\tilde{\mathcal{P}}_{1\mu\nu} > 0$, $\tilde{\mathcal{P}}_{2\mu\nu} > 0$, Ψ and matrices R_1, R_2, R_3, $\tilde{H}_\mu$, and $\tilde{K}_\nu$ such that inequalities (24) and (26) hold

$$\begin{bmatrix} \Theta^{kn} & \mathbf{U}^{hT} \\ \mathbf{U}^h & 0 \end{bmatrix} + \begin{bmatrix} \mathbf{U}^{vT} & 0 \\ 0 & I \end{bmatrix}^{\mathrm{T}} \Psi \begin{bmatrix} \mathbf{U}^{vT} & 0 \\ 0 & I \end{bmatrix} < 0 \tag{29}$$

$$\begin{bmatrix} I \\ \delta^{HK} \end{bmatrix}^{\mathrm{T}} \Psi \begin{bmatrix} I \\ \delta^{HK} \end{bmatrix} \geq 0, \quad \text{for any } \delta^{HK} \in \Lambda_2 \tag{30}$$

where Ψ and Λ_2 are defined in Lemma 1, and

$$\Theta^{kn} \triangleq \begin{bmatrix} \tilde{P}_\mu - \tilde{R}^{\mathrm{T}} - \tilde{R} & 0 & \tilde{\mathbf{A}}_{\mu\nu}^{kn} & \mathbf{D}_\mu \\ * & -I & \mathcal{R}_1^+\tilde{\mathbf{E}}_\mu & 0 \\ * & * & -\tilde{\mathcal{P}}_{\mu\nu} & -\tilde{\mathbf{E}}_\mu^{\mathrm{T}}\mathcal{R}_2 \\ * & * & * & -\mathcal{R}_3 \end{bmatrix}$$

$$\tilde{\mathbf{A}}_{\mu\nu}^{kn} = \begin{bmatrix} A_\mu R - [\tilde{H}_\mu\ 0]\mathcal{C}_3^{\mathrm{T}} & 0 \\ -B_\mu\tilde{K}_\nu & A_\mu + B_\mu\tilde{K}_\nu \end{bmatrix}.$$

Then, there exists a state observer and an observer-based controller such that the closed-loop Markov jump systems are stochastically stable and extended dissipative. Meanwhile, the gain matrices of state observer and observer-based controller are given by

$$H_\mu = \tilde{H}_\mu R_1^{-1}, \quad K_\nu = \tilde{K}_\nu R^{-1}. \tag{31}$$

Proof: Recalling Lemmas 1 and 2, it can directly result from (29) and (30) that

$$\begin{aligned} \Theta &= \Theta^{kn} + \mathbf{U}^v\delta^{HK}\mathbf{U}^h + \left(\mathbf{U}^v\delta^{HK}\mathbf{U}^h\right)^{\mathrm{T}} \\ &= \Theta^{kn} + \Theta^{uk} + \left(\Theta^{uk}\right)^{\mathrm{T}}. \end{aligned} \tag{32}$$

By combining condition (31) with (32), it yields that inequality (25) holds. Then, the proof is completed. ■

IV. Numerical Example

In this section, the correctness and validity of observer-based controller design technique are validated with the dc motor device. Consider discrete-time Markov jump systems (1) with the following parameters:

$$A_1 = \begin{bmatrix} 1.1 & 0 \\ 0.2 & 0.8 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 0.9 & 0.1 \\ 0 & 1 \end{bmatrix}$$

$$B_1 = \begin{bmatrix} 0.2 \\ 0.5 \end{bmatrix}, \quad B_2 = \begin{bmatrix} 0.3 \\ 0.2 \end{bmatrix}, \quad D_1 = \begin{bmatrix} 0.2 \\ 0.2 \end{bmatrix}, \quad D_2 = \begin{bmatrix} 0.4 \\ 0.4 \end{bmatrix}$$

$$C_1 = C_2 = \begin{bmatrix} 1 & 1 \\ 1 & 0.2 \end{bmatrix}, \quad E_1 = E_2 = \begin{bmatrix} 0.7 & 1 \end{bmatrix}.$$

Remark 6: The number of conditions in terms of linear matrix inequalities in (30) exhibits an exponential increase with the vertices of all uncertain parameters $(n_x \times n_y + n_x \times n_u)$. Therefore, it is easy to see that for a high-dimensional systems, the gain matrices of state observer and observer-based controller almost cannot be solved due to the finite computation ability.

The transition probabilities matrix of Markov chain s_k and c_k are selected as follows:

$$\Pi = \begin{bmatrix} 0.6 & 0.4 \\ 0.2 & 0.8 \end{bmatrix}, \quad \Xi = \begin{bmatrix} 0.7 & 0.3 \\ 0 & 1 \end{bmatrix}.$$

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TABLE I
COMPARISON OF $\beta_{\min}$ AND $\gamma_{\max}$ UNDER DIFFERENT LEVELS OF UNCERTAINTY δ

	$\delta=0$	$\delta=0.1$	$\delta=0.2$
minimum l_2-l_∞ performance indices $\beta_{\min}$	0.0972	0.2092	0.3370
maximum dissipative performance indices $\gamma_{\max}$	3.3828	3.2696	3.0233

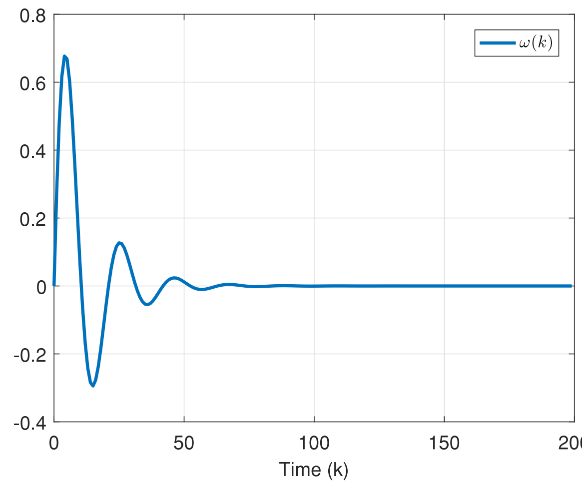

Fig. 1. Response curves of the exogenous disturbance input.

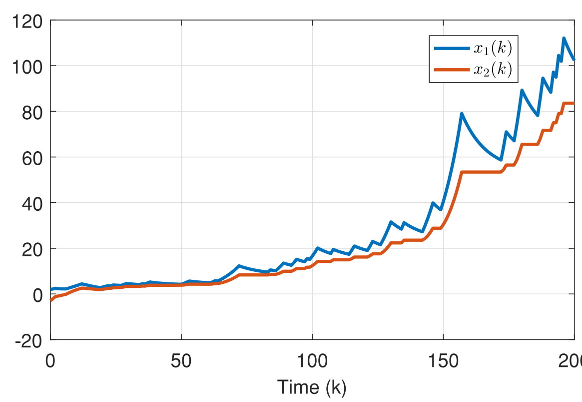

Fig. 2. Response curves of the open-loop system states.

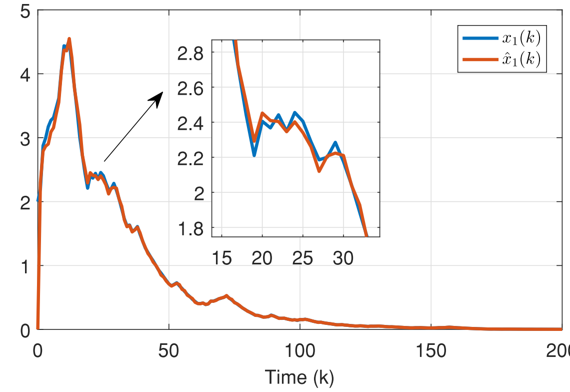

Fig. 3. Closed-loop system state $x_1(k)$ and its estimation.

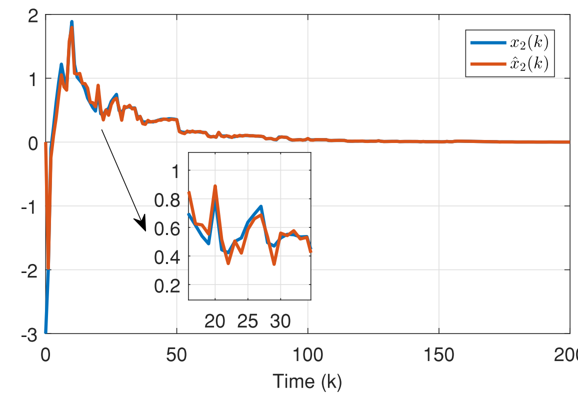

Fig. 4. Closed-loop system state $x_2(k)$ and its estimation.

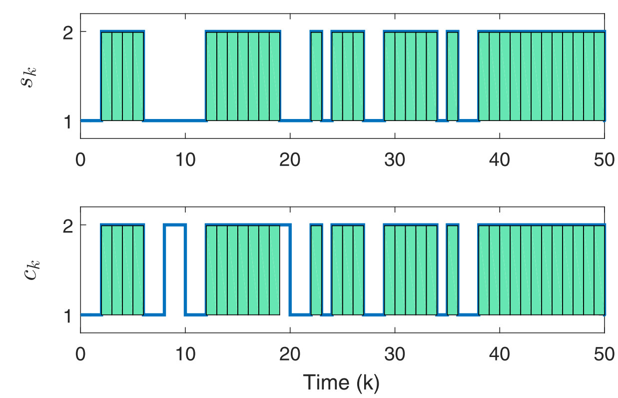

Fig. 5. Modes of system and controller.

We compare the minimum l_2–l_∞ performance indices $\beta_{\min}$ ($G_1=G_2=0$, $G_3=\beta^2 I$, and $G_4=I$) and the maximum dissipative performance indices $\gamma_{\max}$ ($G_1=-0.25$, $G_2=0.5$, $G_3=4-\gamma$, and $G_4=0$) under different levels of uncertainty. From Table I, more uncertainty in controller and observer leads to a more conservative performance.

Setting uncertain parameter $\delta=0.1$, dissipative coefficients $G_1=-0.25$, $G_2=0.5$, $G_3=4$, and $G_4=0$, and solving a group of inequalities in Theorem 3, one can obtain optimal performance index 3.2696 and following the gain matrices of state observer and observer-based controller:

$$K_1=\begin{bmatrix}-0.1784 & -1.1548\end{bmatrix},\ K_2=\begin{bmatrix}0.1728 & -0.8127\end{bmatrix}$$

$$H_1=\begin{bmatrix}-0.0169 & 1.1109\\ 0.7835 & -0.5895\end{bmatrix},\ H_2=\begin{bmatrix}0.1731 & 0.7818\\ 1.0651 & -1.0007\end{bmatrix}.$$

The exogenous disturbance signal and initial conditions taken as $\omega(k)=e^{-0.08k}\sin(0.3k)$ and $x(0)=[2\ \ -3]^{\mathrm{T}}$, respectively. The simulation results are shown in Figs. 1–5. Fig. 1 depicts the exogenous disturbance input. Fig. 2 plots the response curves of the open-loop system states which are divergent. Figs. 3 and 4 describe the estimates of the closed-loop system states. Fig. 5 plots the system modes and controller modes. It can be observed from Fig. 5 that the controller mode $c_k\equiv 2$ at any time, as long as $s_k=2$ (i.e., the green histograms in the upper and lower subfigure are the same).

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V. Conclusion

The work presented in this paper focused on a design method of the nonfragile controller for discrete-time Markov jump systems subject to asynchronous modes and extended dissipativity. Sufficient conditions are derived to design a control such that the resultant closed-loop system is stability with a desired performance. Note that the above-mentioned result is obtained under the condition that the mode transition probability is completely known. However, in practice, due to various reasons, such as difficult to have accurate system model, sensor error or failure, parameter and environmental change, etc., it is almost impossible to obtain an exact model to describe the practical system. Considering the problem studied in this paper with partially know transition probability matrix will be one of our future focuses.

References

[1] H. Shen, Y. Zhu, L. Zhang, and J. H. Park, "Extended dissipative state estimation for Markov jump neural networks with unreliable links," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 28, no. 2, pp. 346–358, Feb. 2017.

[2] R. Baranitha, R. Mohajerpoor, and R. Rakkiyappan, "Bilateral teleoperation of single-master multislave systems with semi-Markovian jump stochastic interval time-varying delayed communication channels," *IEEE Trans. Cybern.*, to be published. doi: 10.1109/TCYB.2018.2876520.

[3] Y. Xu, J.-G. Dong, R. Lu, and L. Xie, "Stability of continuous-time positive switched linear systems: A weak common copositive Lyapunov functions approach," *Automatica*, vol. 97, pp. 278–285, Nov. 2018.

[4] M. Zhang, P. Shi, L. Ma, J. Cai, and H. Su, "Quantized feedback control of fuzzy Markov jump systems," *IEEE Trans. Cybern.*, vol. 49, no. 9, pp. 3375–3384, Sep. 2019. doi: 10.1109/TCYB.2018.2842434.

[5] H. R. Karimi, "Robust delay-dependent H_∞ control of uncertain time-delay systems with mixed neutral, discrete, and distributed time-delays and Markovian switching parameters," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 58, no. 8, pp. 1910–1923, Aug. 2011.

[6] M. Zhang, P. Shi, L. Ma, J. Cai, and H. Su, "Network-based fuzzy control for nonlinear Markov jump systems subject to quantization and dropout compensation," *Fuzzy Sets Syst.*, vol. 371, pp. 96–109, Sep. 2019. doi: 10.1016/j.fss.2018.09.007.

[7] D. Yao, R. Lu, Y. Xu, and L. Wang, "Robust H_∞ filtering for Markov jump systems with mode-dependent quantized output and partly unknown transition probabilities," *Signal Process.*, vol. 137, pp. 328–338, Aug. 2017.

[8] J. Tao, R. Lu, P. Shi, H. Su, and Z.-G. Wu, "Dissipativity-based reliable control for fuzzy Markov jump systems with actuator faults," *IEEE Trans. Cybern.*, vol. 47, no. 9, pp. 2377–2388, Sep. 2017.

[9] M. Zhang, P. Shi, Z. Liu, L. Ma, and H. Su, "H_∞ filtering for discrete-time switched fuzzy systems with randomly occurring time-varying delay and packet dropouts," *Signal Process.*, vol. 143, pp. 320–327, Feb. 2018.

[10] D. Ding, Z. Wang, Q.-L. Han, and G. Wei, "Security control for discrete-time stochastic nonlinear systems subject to deception attacks," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 5, pp. 779–789, May 2018.

[11] Y. Xu, J. Y. Li, R. Lu, C. Liu, and Y. Wu, "Finite-horizon $l_2 - l_\infty$ synchronization for time-varying Markovian jump neural networks under mixed-type attacks: Observer-based case," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 6, pp. 1695–1704, Jun. 2019. doi: 10.1109/TNNLS.2018.2873163.

[12] D. Ding, Z. Wang, D. W. C. Ho, and G. Wei, "Observer-based event-triggering consensus control for multiagent systems with lossy sensors and cyber-attacks," *IEEE Trans. Cybern.*, vol. 47, no. 8, pp. 1936–1947, Aug. 2017.

[13] L. Zhang, Y. Zhu, P. Shi, and Y. Zhao, "Resilient asynchronous H_∞ filtering for Markov jump neural networks with unideal measurements and multiplicative noises," *IEEE Trans. Cybern.*, vol. 45, no. 12, pp. 2840–2852, Dec. 2015.

[14] Z.-G. Wu, P. Shi, Z. Shu, H. Su, and R. Lu, "Passivity-based asynchronous control for Markov jump systems," *IEEE Trans. Autom. Control*, vol. 62, no. 4, pp. 2020–2025, Apr. 2017.

[15] J. Tao, R. Lu, H. Su, and Z.-G. Wu, "Filtering of T–S fuzzy systems with nonuniform sampling," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 12, pp. 2442–2450, Dec. 2018.

[16] V. H. Le and H. Trinh, "Observer-based control of 2-D Markov jump systems," *IEEE Trans. Circuits Syst. II, Exp. Briefs*, vol. 64, no. 11, pp. 1322–1326, Nov. 2017.

[17] S. Dong, Z.-G. Wu, P. Shi, H. R. Karimi, and H. Su, "Networked fault detection for Markov jump nonlinear systems," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 6, pp. 3368–3378, Dec. 2018. doi: 10.1109/TFUZZ.2018.2826467.

[18] Z. Chen, Z. Li, and C. L. P. Chen, "Adaptive neural control of uncertain MIMO nonlinear systems with state and input constraints," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 28, no. 6, pp. 1318–1330, Jun. 2017.

[19] S. Sui, S. Tong, and C. L. P. Chen, "Finite-time filter decentralized control for nonstrict-feedback nonlinear large-scale systems," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 6, pp. 3289–3300, Dec. 2018. doi: 10.1109/TFUZZ.2018.2821629.

[20] L. Zhang, Z. Ning, and Z. Wang, "Distributed filtering for fuzzy time-delay systems with packet dropouts and redundant channels," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 46, no. 4, pp. 559–572, Apr. 2016.

[21] R. Lu, J. Tao, P. Shi, H. Su, Z.-G. Wu, and Y. Xu, "Dissipativity-based resilient filtering of periodic Markovian jump neural networks with quantized measurements," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 5, pp. 1888–1899, May 2018.

[22] J.-Y. Li, B. Zhang, R. Lu, and Y. Xu, "Robust distributed H_∞ state estimation for stochastic periodic systems over constraint sensor networks," *IEEE Trans. Neural Netw. Learn. Syst.*, to be published, doi: 10.1109/TSMC.2018.2837047.

[23] W.-W. Che, H. Su, P. Shi, and Z.-G. Wu, "Nonfragile and nonsynchronous synthesis of reachable set for bernoulli switched systems," *IEEE Trans. Syst., Man, Cybern., Syst.*, to be published. doi: 10.1109/TSMC.2017.2773480.

[24] G.-H. Yang and W.-W. Che, "Non-fragile H_∞ filter design for linear continuous-time systems," *Automatica*, vol. 44, no. 11, pp. 2849–2856, Nov. 2008.

[25] J. Tao, Z.-G. Wu, H. Su, Y. Wu, and D. Zhang, "Asynchronous and resilient filtering for Markovian jump neural networks subject to extended dissipativity," *IEEE Trans. Cybern.*, vol. 49, no. 7, pp. 2504–2513, Jul. 2019.

[26] J. Tao, R. Lu, Z.-G. Wu, and Y. Wu, "Reliable control against sensor failures for Markov jump systems with unideal measurements," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 2, pp. 308–316, Feb. 2019.

[27] A. Kanchanaharuthai and E. Mujjalinvimut, "Nonlinear disturbance observer-based backstepping control for a dual excitation and steam-valving system of synchronous generators with external disturbances," *Int. J. Innov. Comput. Inf. Control*, vol. 14, no. 1, pp. 111–126, 2018.

[28] M. Zhang, C. Shen, and Z.-G. Wu, "Asynchronous observer-based control for exponential stabilization of Markov jump systems," *IEEE Trans. Circuits Syst. II, Exp. Briefs*, to be published.

[29] D. Yao, B. Zhang, P. Li, and H. Li, "Event-triggered sliding mode control of discrete-time Markov jump systems," *IEEE Trans. Syst., Man, Cybern., Syst.*, to be published. doi: 10.1109/TSMC.2018.2836390.

[30] Y. Xu, R. Lu, H. Peng, and J. Chen, "Passive filter design for periodic stochastic systems with quantized measurements and randomly occurring nonlinearities," *J. Frankl. Inst.*, vol. 353, no. 1, pp. 144–159, 2016.

[31] R. Mohajerpoor, H. Abdi, and S. Nahavandi, "A new algorithm to design minimal multi-functional observers for linear systems," *Asian J. Control*, vol. 18, no. 3, pp. 842–857, 2016.

[32] R. Mohajerpoor, H. Abdi, and S. Nahavandi, "Minimal unknown-input functional observers for multi-input multi-output LTI systems," *J. Process Control*, vol. 35, pp. 143–153, Nov. 2015.

[33] H. Zhang, Y. Shi, and J. Wang, "On energy-to-peak filtering for nonuniformly sampled nonlinear systems: A Markovian jump system approach," *IEEE Trans. Fuzzy Syst.*, vol. 22, no. 1, pp. 212–222, Feb. 2014.

[34] X.-Z. Dong, "Robust strictly dissipative control for discrete singular systems," *IET Control Theory Appl.*, vol. 1, no. 4, pp. 1060–1067, Jul. 2007.

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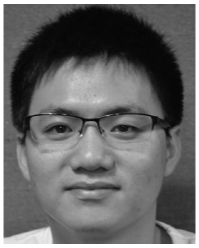

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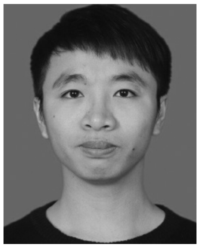

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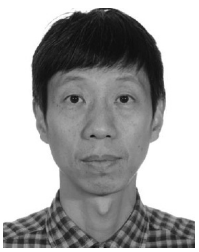

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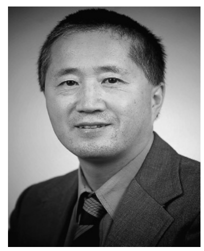

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