

Received February 23, 2020, accepted March 9, 2020, date of publication March 13, 2020, date of current version March 31, 2020. Digital Object Identifier 10.1109/ACCESS.2020.2980566

Two-Mode-Dependent Controller Design for Networked Markov System With Time-Delay in Both S/C Link and C/A Link

YANFENG WANG¹, PING HE^{2,3,4}, HENG LI³, XIAOYUE SUN¹, WEI WEI^{®5}, (Senior Member, IEEE), HAOYANG MI^{®6}, AND YANGMIN LI¹⁰⁷, (Senior Member, IEEE)

¹School of Engineering, Huzhou University, Huzhou 313000, China
²School of Intelligent Systems Science and Engineering (Institute of Physical Internet), Jinan University, Zhuhai 519070, China

³Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong

⁴Artificial Intelligence Key Laboratory of Sichuan Province, Sichuan University of Science & Engineering, Yibin 644004, China

⁵School of Computer Science and Engineering, Xi'an University of Technology, Xi'an 710048, China

⁶National Engineering Research Center for Advanced Polymer Processing Technology, Zhengzhou University, Zhengzhou 450000, China

⁷Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong

Corresponding author: Ping He (pinghecn@qq.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 11705122, Grant 61902268, Grant 61573136, and Grant 61603133, in part by the Fundamental Research Funds for the Central Universities, Jinan University, under Grant 12819026, in part by the Hong Kong Research Grants Council under Grant BRE/PolyU 152099/18E and Grant PolyU 15204719/18E, in part by the Natural Science Foundation of The Hong Kong Polytechnic University under Grant G-YW3X, in part by the Zhejiang Natural Science Foundation of China under Grant Y19F030001, in part by the Huzhou Public Welfare Application Research Project under Grant 2019GZ02, in part by the Sichuan Science and Technology Program under Grant 2019YFSY0045, Grant 2018GZDZX0046, Grant 2018JY0197, and Grant 20GJHZ0138, in part by the Guangxi Natural Science Foundation of China under Grant 2018GXNSFAA138092, in part by the Key Research and Development Program of Shaanxi Province under Grant 2018ZDXM-GY-036, in part by the Open Foundation of Artificial Intelligence Key Laboratory of Sichuan Province under Grant 2018RZJ01, in part by the Nature Science Foundation of Sichuan University of Science and Engineering under Grant 2017RCL52, in part by the Zigong Science and Technology Program of China under Grant 2019YYJC03 and Grant 2019YYJC15, in part by the Shaanxi Key Laboratory of Intelligent Processing for Big Energy Data under Grant IPBED7, and in part by the Zhejiang Province Key Laboratory of Smart Management and Application of Modern Agricultural Resources under Grant 2020E10017.

ABSTRACT The two-mode-dependent controller design problem for networked Markov system with timedelay in both S/C link and C/A link is investigated in this paper. Two independent Markov chains are used to describe the time-delay in S/C link and C/A link. A two-mode-dependent state feedback controller is proposed that depends on both the S/C time-delay and the mode of the Markov controlled plant. The sufficient conditions on the stochastic stability of the closed-loop system are established. The design method of the controller is also proposed on condition that the transition probability matrices of S/C time-delay and mode of the controlled plant are completely known and partly unknown respectively. A numerical example is exploited to illustrate the effectiveness and superiority of the proposed method.

INDEX TERMS Markov jump system, stochastic stability, two-mode-dependent, closed-loop system, stabilization.

I. INTRODUCTION

Networked control system (NCS) has gained great attentions during the past decades and it is applied widely in realtime industrial control, environmental monitoring, military, telemedicine and other fields [1]–[4]. The stability analysis and controller design for NCS with time-delay and data packet dropout has become a hot research filed on account of its essential impact on modern control theory, and a great many literatures have been reported [5]-[7].

The associate editor coordinating the review of this manuscript and approving it for publication was Hao Shen $^{\square}$.

One of the focuses of research for NCS is the time-delay, which may degrade the performance of the system or even cause instability [8], [9]. How to explicitly incorporate the time-delay into the controller design is the object of the related research. Modeling the time-delay as a random sequence of Bernoulli distribution is one of the common methods in research of NCS. However this method can only deal with one-step time-delay [10], [11]. The time-delay was modeled as a random sequence of Bernoulli distribution, and the robust \mathcal{H}_{∞} filtering problem for NCS with both random time-delay and packet dropout was researched. The sufficient condition on making the filtering error system

exponentially stable was given [10]. The optimal linear estimation problem of NCS with random time-delay and packet dropout was researched. Two random variables that satisfied Bernoulli distribution were used to describe the one-step random time-delay and multiple packet loss that may exist in network data transmission. The optimal linear state filter, predictor and smoother under linear minimum variance were proposed [11].

Another method to deal with the time-delay is to model the time-delay as a Markov chain. The Markov chain can not only describe the dependency between the current timedelay and the previous time-delay, but also include packet dropout, and it is an effective method to describe the timedelay in NCS [12]-[16]. A time-delay compensation control scheme was proposed, in which the random time-delay was modeled as a Markov chain, thus the closed-loop system was modeled as a Markovian jump linear system (MJLS). To perform the stability analysis, a new necessary and sufficient condition was established [12]. The time-delay τ_k from sensor to controller (S/C) and the time-delay γ_k from controller to actuator (C/A) were modeled as two Markov chains. An asymptotic mean-square stability criterion was established to compensate for the random time-delay and packet losses in both S/C link and C/A link [13]. The state feedback control problem for a class of nonlinear NCS with S/C time-delay τ_k was researched. The state augmentation method was used to obtain the model of the closed-loop system based on that τ_k was modeled as a Markov chain. The sufficient conditions on stochastic stability of the closedloop system were given [14]. Considering the S/C time-delay τ_k and C/A time-delay γ_k , based on the free weight matrix method, the sufficient conditions on the stochastic stability of closed-loop systems under \mathcal{H}_{∞} performance constraints were obtained. The design method of mode-dependent \mathcal{H}_{∞} state feedback controller was given [15]. Both the S/C time-delay and C/A time-delay were modeled as Markov processes, and the resulting closed-loop system was modeled as a MJLS. A state feedback controller that made the closed-loop system stochastically stable was designed, which could be solved by the proposed algorithm [16].

In all the aforementioned references, the controlled plant was described by the deterministic model which was linear or certainty kind of nonlinear system. However, the deterministic model cannot be used to represent the behavior of many actual systems, because the phenomena embodied by these systems are not specific, and their structures and parameters have characteristics of random changes. These random changed are often caused by system jumps, such as random failures and repairs of system components, changes in internal interconnected systems, sudden changes in the environment. In this regard, Markov controlled plant exists widely in communication, power systems, and aircraft control systems [17]-[19]. Therefore, the design and research of NCS controller based on Markov controlled plant has important theoretical and practical significance.



FIGURE 1. Structure of networked Markov system with time-delay.

Some literatures for Markov controlled plant based NCS have been reported [20], [21]. The event-triggered \mathcal{H}_{∞} control problem for networked Markov jump system subject to repeated scalar nonlinearities was researched. An eventtriggered transmission scheme was adopted and an event generator was presented between the controller and the sensor [20]. The stabilization problem for a kind of networked Markovian jump systems with random time-delay was researched. The closed-loop system model was established through the state augmentation technique and the necessary and sufficient conditions on the stochastic stability were derived [21]. However, the controller in [20] and [21] was designed without the consideration of the system mode or even independent of the time-delay. To the best of the authors' knowledge, involving time-delay and system mode to design the state feedback controller has not been researched, which motivate this investigation. The main contributions of this paper can be exhibited in the following two aspects:

- 1) Through the analysis of time-delay and system mode information, a two-mode-dependent state feedback controller that simultaneously depends on both τ_k and $\delta_{k-\tau_k}$ is proposed for the networked Markov system.
- By constructing proper Lyapunov-Krasovskii functional, the design method of state feedback controller gain matrix is derived on condition that the transition probabilities are completely available and partly unavailable, respectively.

The rest content of the paper is organized as follows. In Section II, the available time-delay and system mode information is analyzed and a two-mode-dependent controller is proposed. The sufficient conditions on the stochastic stability of the closed-loop system are presented first and the equivalent conditions with constrains are derived in section III. In Section IV, a simulation example is given to illustrate the effectiveness of the proposed controller. The conclusions are addressed in Section V.

II. PROBLEM FORMULATION AND PRELIMINARIES

The structure of the NCS with random time-delay considered in this paper is shown in Figure 1, where the controlled plant is a MJLS and the state equation of which is as follows:

$$x_{k+1} = A_{\delta_k} x_k + B_{\delta_k} u_k \tag{1}$$

where x_k is the system state vector, u_k is the control input vector, A_{δ_k} and B_{δ_k} are known real constant matrices with appropriate dimensions. δ_k takes value from the set $\mathcal{W} =$ $\{1, \dots, D\}$, and the transition probability matrix of δ_k is $\Theta =$ $[\rho_{pq}]$, where ρ_{pq} is defined as $\rho_{pq} = \Pr\{\delta_{k+1} = q | \delta_k = p\}$, $\sum_{q=1}^{D} \rho_{pq} = 1, \rho_{pq} \ge 0, p, q \in \mathcal{W}$.

 τ_k and γ_k stands for the time-delay in S/C link and the timedelay in C/A link and takes value from the finite set $\mathcal{M} = \{0, \dots, \tau\}, \ \mathcal{N} = \{0, \dots, \gamma\}$, respectively. The transition probability matrix of τ_k and γ_k is $\Xi = [\omega_{ij}]$ and $\Pi = [\pi_{rs}]$, respectively, where ω_{ij} and π_{rs} is defined as $\omega_{ij} = \Pr\{\tau_{k+1} = j | \tau_k = i\}, \ \pi_{rs} = \Pr\{\gamma_{k+1} = s | \gamma_k = r\}$, respectively, where $\sum_{j=0}^{\tau} \omega_{ij} = 1, \ \sum_{s=0}^{\gamma} \pi_{rs} = 1, \ \omega_{ij} \ge 0, \ \pi_{rs} \ge 0, \ i, j \in \mathcal{M}, r, s \in \mathcal{N}.$

On one hand, due to the existence of S/C time-delay τ_k , the system state obtained at the controller node at time instant *k* is as follows:

$$\tilde{x}_k = x_{k-\tau_k} \tag{2}$$

On the other hand, at time instant k, the information of the S/C time-delay τ_k and the system mode $\delta_{k-\tau_k}$ is available to the controller node. Hence, the state feedback controller that depends both τ_k and $\delta_{k-\tau_k}$ can be designed as follows:

$$\tilde{u}_k = K_{\tau_k, \delta_{k-\tau_k}} x_{k-\tau_k} \tag{3}$$

Apparently, the controller in (3) is two-mode-dependent.

Due to the existence of C/A time-delay γ_k , the control input acting on the controlled plant at time instant *k* is as follows:

$$u_k = \tilde{u}_{k-\gamma_k} \tag{4}$$

The state equation of the closed-loop system can be obtained from (1)-(4):

$$x_{k+1} = A_{\delta_k} x_k + B_{\delta_k} K_{\tau_k, \delta_{k-\tau_k}} x_{k-\tau_k-\gamma_k}$$
(5)

Remark 1: By applying the two-mode-dependent controller in (3), the resulting closed-loop system (5) is not a standard MJLS, due to the fact that the closed-loop system depends on δ_k , τ_k , $\delta_{k-\tau_k}$ and $\tau_k + \gamma_k$. Furthermore, $\delta_{k-\tau_k}$ is related with both δ_k and τ_k , which makes the system stability analysis and controller design more complex.

The objective of this paper is to design the two-modedependent controller in (3) to guarantee the stochastic stability of the closed-loop system (5).

The notion of stochastic stability is introduced as follows:

Definition 1 [22]: The closed-loop system (5) is stochastically stable if for every initial state x_0 and initial mode $\tau_0 \in \mathcal{M}, \, \delta_{-\tau_0} \in \mathcal{W}$, there exists a positive-definite matrix R > 0 such that $E\left\{\sum_{k=0}^{\infty} ||x_k||^2 |x_0, \tau_0, \delta_{-\tau_0}\right\} < x_0^T R x_0$ holds. Before the main results are given, two related lemmas are introduced as follows:

Lemma 1 [23]: If the transition probability matrix from δ_k to δ_{k+1} is Θ , then the transition probability matrix from

 $\delta_{k-\tau_k}$ to $\delta_{k+1-\tau_{k+1}}$ is $\Theta^{1+\tau_k-\tau_{k+1}}$, which is still a transition probability matrix.

Lemma 2 [24]:
$$(\theta - \theta_0 + 1) \sum_{\rho=\theta_0}^{\theta} \upsilon_{\rho}^T X \upsilon_{\rho} \geq \sum_{\rho=\theta_0}^{\theta} \upsilon_{\rho}^T X$$

 $\sum_{\rho=\theta_0} \upsilon_{\rho} \text{ holds for any positive-definite matrix } X > 0 \text{ and}$ arbitrary vector υ , where θ and θ_0 two scalars which satisfies $\theta \ge \theta_0 \ge 1$.

Remark 2: If an embedded processor is placed at the actuator node, by comparing the current time with the time-stamp of the control input received by the embedded processor, the C/A time-delay γ_k can be calculated, and the information of $\gamma_{k-\tau_k}$ at time instant *k* would be available to the controller node. Further, the controller $\tilde{u}_k = K_{\tau_k,\gamma_{k-\tau_k},\delta_{k-\tau_k}} x_{k-\tau_k}$ which simultaneously depends on τ_k , $\delta_{k-\tau_k}$ and $\gamma_{k-\tau_k}$ can be designed. However, this will increase the system cost and make the system structure more complicated.

III. MAIN RESULTS

In this section, the sufficient conditions on the stochastic stability for the closed-loop systems (5) will be presented and the equivalent conditions of linear matrix inequalities (LMIs) with nonconvex constraints will be derived.

Theorem 1: Under the state feedback control law (3), the resulting closed-loop system (5) is stochastically stable if there exist positive-definite matrices $P_{i,r} > 0$, $P_{j,q} > 0$, $S_1 > 0$, $S_2 > 0$, Z > 0 and matrix $K_{i,r}$ such that the following matrix inequality

$$\Lambda = \begin{bmatrix} \Lambda_{11} & * & * \\ \Lambda_{21} & \Lambda_{22} & * \\ 0 & Z & -S_2 - Z \end{bmatrix} < 0, \tag{6}$$

where

$$\begin{split} \Lambda_{11} &= A_{\delta_{k}}^{T} \tilde{P}_{j,q} A_{\delta_{k}} + (\tau + \gamma)^{2} (A_{\delta_{k}} - I)^{T} Z (A_{\delta_{k}} - I) \\ &+ (\tau + \gamma + 1) S_{1} + S_{2} - Z - P_{i,p}, \\ \Lambda_{21} &= A_{\delta_{k}}^{T} \tilde{P}_{j,q} B_{\delta_{k}} K_{i,p} + (\tau + \gamma)^{2} (A_{\delta_{k}} - I)^{T} Z B_{\delta_{k}} K_{i,p} \\ &+ Z, \\ \Lambda_{22} &= (B_{\delta_{k}} K_{i,p})^{T} \tilde{P}_{j,q} B_{\delta_{k}} K_{i,p} - 2Z - S_{1} \\ &+ (\tau + \gamma)^{2} (B_{\delta_{k}} K_{i,p})^{T} Z B_{\delta_{k}} K_{i,p}, \\ \tilde{P}_{j,q} &= \sum_{j=0}^{\tau} \sum_{q=1}^{D} \omega_{jj} \Theta_{pq}^{i-j+1} P_{j,q}, \end{split}$$

holds for all $i, j \in \mathcal{M}, p, q \in \mathcal{W}$.

Proof: For the closed-loop system (5), construct the following Lyapunov-Krasovskii functional:

$$V(x_k, \tau_k, \delta_{k-\tau_k}) = \sum_{l=1}^4 V_l(x_k, \tau_k, \delta_{k-\tau_k}) \stackrel{\Delta}{=} x_k^T \Omega_{\tau_k, \delta_{k-\tau_k}} x_k,$$

where

$$V_1(x_k, \tau_k, \delta_{k-\tau_k}) = x_k^T P_{\tau_k, \delta_{k-\tau_k}} x_k,$$

$$V_{2}(x_{k}, \tau_{k}, \delta_{k-\tau_{k}}) = \sum_{n=-\tau-\gamma+1}^{0} \sum_{m=k+n}^{k-1} x_{m}^{T} S_{1} x_{m}$$
$$+ \sum_{l=k-\tau_{k}-\gamma_{k}}^{k-1} x_{l}^{T} S_{1} x_{l},$$
$$V_{3}(x_{k}, \tau_{k}, \delta_{k-\tau_{k}}) = \sum_{l=k-\tau-\gamma}^{k-1} x_{l}^{T} S_{2} x_{l},$$
$$V_{4}(\chi_{k}, \tau_{k}, \delta_{k-\tau_{k}}) = \sum_{n=-\tau-\gamma+1}^{0} \sum_{m=k+n}^{k-1} (\tau + \gamma) \chi_{m}^{T} Z \chi_{m}$$
$$\chi_{m} = x_{m+1} - x_{m}.$$

It is noted that $\Omega_{\tau_k,\delta_{k-\tau_k}} > 0$.

$$E \{ \Delta V_1 \} = E \left\{ x_{k+1}^T P_{\tau_{k+1}, \delta_{k+1} - \tau_{k+1}} x_{k+1} | \tau_k = i, \ \delta_{k-\tau_k} = p \right\} - x_k^T P_{\tau_k, \delta_{k-\tau_k}} x_k.$$

From Lemma 1, one can obtain that the transition probability matrix from $\delta_{k-\tau_k}$ to $\delta_{k+1-\tau_{k+1}}$ is Θ^{i-j+1} , and the transition probability from $\delta_{k-\tau_k}$ to $\delta_{k+1-\tau_{k+1}}$ under the transition probability matrix Θ^{i-j+1} is denoted as Θ_{pq}^{i-j+1} . Hence, one has:

$$E \left\{ x_{k+1}^{T} P_{\tau_{k+1},\delta_{k+1}-\tau_{k+1}} x_{k+1} | \tau_{k} = i, \ \delta_{k-\tau_{k}} = p \right\}$$

$$-x_{k}^{T} P_{\tau_{k},\delta_{k-\tau_{k}}} x_{k}$$

$$= E \left\{ \left(A_{\delta_{k}} x_{k} + B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}} \right)^{T} \right\} \sum_{j=0}^{\tau} \sum_{q=1}^{D} \omega_{ij} \Theta_{pq}^{i-j+1}$$

$$P_{j,q} \left(A_{\delta_{k}} x_{k} + B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}} \right) - x_{k}^{T} P_{i,p} x_{k}$$

$$= x_{k}^{T} A_{\delta_{k}}^{T} \tilde{P}_{j,q} A_{\delta_{k}} x_{k} + x_{k}^{T} A_{\delta_{k}}^{T} \tilde{P}_{j,q} B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}}$$

$$+ x_{k-\tau_{k}-\gamma_{k}}^{T} \left(B_{\delta_{k}} K_{i,p} \right)^{T} \tilde{P}_{j,q} A_{\delta_{k}} x_{k} - x_{k}^{T} P_{i,p} x_{k}.$$

$$(7)$$

$$E \left\{ \Delta V_{2} \right\}$$

$$= (\tau + \gamma) x_k^T S_1 x_k - \sum_{l=k+1-\tau-\gamma}^k x_l^T S_1 x_l + x_k^T S_1 x_k$$

$$- x_{k-\tau_k-\gamma_k}^T S_1 x_{k-\tau_k-\gamma_k} + \sum_{l=k+1-\tau_{k+1}-\gamma_{k+1}}^{k-1} x_l^T S_1 x_l$$

$$- \sum_{l=k+1-\tau_k-\gamma_k}^{k-1} x_l^T S_1 x_l$$

$$= (\tau + \gamma) x_k^T S_1 x_k - \sum_{l=k+1-\tau-\gamma}^k x_l^T S_1 x_l + x_k^T S_1 x_k$$

$$- x_{k-\tau_k-\gamma_k}^T S_1 x_{k-\tau_k-\gamma_k} + \sum_{l=k+1-\tau_k-\gamma_k}^{k-1} x_l^T S_1 x_l$$

$$+ \sum_{l=k+1-\tau_{k+1}-\gamma_{k+1}}^{k-\tau_k-\gamma_k} x_l^T S_1 x_l - \sum_{l=k+1-\tau_k-\gamma_k}^{k-1} x_l^T S_1 x_l$$

$$\leq (\tau + \gamma) x_{k}^{T} S_{1} x_{k} - \sum_{l=k+1-\tau-\gamma}^{k} x_{l}^{T} S_{1} x_{l} + x_{k}^{T} S_{1} x_{k} \\ - x_{k-\tau_{k}-\gamma_{k}}^{T} S_{1} x_{k-\tau_{k}-\gamma_{k}} + \sum_{l=k+1-\tau_{k}-\gamma_{k}}^{k-1} x_{l}^{T} S_{1} x_{l} \\ + \sum_{l=k+1-\tau-\gamma}^{k} x_{l}^{T} S_{1} x_{l} - \sum_{l=k+1-\tau_{k}-\gamma_{k}}^{k-1} x_{l}^{T} S_{1} x_{l} \\ = (\tau + \gamma) x_{k}^{T} S_{1} x_{k} + x_{k}^{T} S_{1} x_{k} - x_{k-\tau_{k}-\gamma_{k}}^{T} S_{1} x_{l-\tau_{k}-\gamma_{k}}.$$
(8)
$$E\{\Delta V_{3}\} = x_{k}^{T} S_{2} x_{k} - x_{k-\tau-\gamma}^{T} S_{2} x_{k-\tau-\gamma}.$$
(9)
$$E\{\Delta V_{4}\} \\ = E\left\{(\tau + \gamma)^{2} ((A_{\delta_{k}} - l) x_{k} + B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}})^{T} Z((A_{\delta_{k}} - l) x_{k} + B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}})^{T} Z(A_{\delta_{k}} - l) x_{k} + (\tau + \gamma)^{2} x_{k}^{T} (A_{\delta_{k}} - l)^{T} Z B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}}} + (\tau + \gamma)^{2} x_{k-\tau_{k}-\gamma_{k}}^{T} (B_{\delta_{k}} K_{i,p})^{T} Z (A_{\delta_{k}} - l) x_{k} + (\tau + \gamma)^{2} x_{k-\tau_{k}-\gamma_{k}}^{T} (B_{\delta_{k}} K_{i,p})^{T} Z B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}} + (\tau + \gamma)^{2} x_{k}^{T} (A_{\delta_{k}} - l)^{T} Z B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}} + (\tau + \gamma)^{2} x_{k}^{T} (A_{\delta_{k}} - l)^{T} Z B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}} + (\tau + \gamma)^{2} x_{k-\tau_{k}-\gamma_{k}}^{T} (B_{\delta_{k}} K_{i,p})^{T} Z A_{\delta_{k}} - l) x_{k} + (\tau + \gamma)^{2} x_{k-\tau_{k}-\gamma_{k}}^{T} (B_{\delta_{k}} K_{i,p})^{T} Z B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}} + (\tau + \gamma)^{2} x_{k-\tau_{k}-\gamma_{k}}^{T} (B_{\delta_{k}} K_{i,p})^{T} Z B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}} + (\tau + \gamma)^{2} x_{k-\tau_{k}-\gamma_{k}}^{T} (B_{\delta_{k}} K_{i,p})^{T} Z B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}} + (\tau + \gamma)^{2} x_{k-\tau_{k}-\gamma_{k}}^{T} (B_{\delta_{k}} K_{i,p})^{T} Z B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}} + (\tau + \gamma)^{2} x_{k-\tau_{k}-\gamma_{k}}^{T} (B_{\delta_{k}} K_{i,p})^{T} Z B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}} + (\tau + \gamma)^{2} x_{k-\tau_{k}-\gamma_{k}}^{T} (B_{\delta_{k}} K_{i,p})^{T} Z B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}} + (\tau$$

By Lemma 2, one has:

$$E \{\Delta V_{4}\}$$

$$\leq (\tau + \gamma)^{2} x_{k}^{T} (A_{\delta_{k}} - I)^{T} Z (A_{\delta_{k}} - I) x_{k}$$

$$+ (\tau + \gamma)^{2} x_{k}^{T} (A_{\delta_{k}} - I)^{T} Z B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}}$$

$$+ (\tau + \gamma)^{2} x_{k-\tau_{k}-\gamma_{k}}^{T} (B_{\delta_{k}} K_{i,p})^{T} Z (A_{\delta_{k}} - I) x_{k}$$

$$+ (\tau + \gamma)^{2} x_{k-\tau_{k}-\gamma_{k}}^{T} (B_{\delta_{k}} K_{i,p})^{T} Z B_{\delta_{k}} K_{i,p} x_{k-\tau_{k}-\gamma_{k}}$$

$$- [x_{k} - x_{k-\tau_{k}-\gamma_{k}}]^{T} Z [x_{k} - x_{k-\tau_{k}-\gamma_{k}}]$$

$$- [x_{k-\tau_{k}-\gamma_{k}} - x_{k-\tau-\gamma}]^{T} Z [x_{k-\tau_{k}-\gamma_{k}} - x_{k-\tau-\gamma}]. \quad (10)$$

From (7)-(10), one can obtain:

$$E\left\{\Delta V\left(x_{k},\tau_{k},\delta_{k-\tau_{k}}\right)\right\} \leq \xi_{k}^{T}\Lambda\xi_{k},$$
(11)

where $\xi_k^T = \begin{bmatrix} x_k^T & x_{k-\tau_k-\gamma_k}^T & x_{x_{k-\tau-\gamma}}^T \end{bmatrix}$. Hence, if $\Lambda < 0$, one has

$$E\left\{\sum_{k=0}^{T} \|x_{k}\|^{2}\right\} \leq -\lambda_{\min}(-\Lambda)\xi_{k}^{T}\xi_{k}$$
$$\leq -\lambda_{\min}(-\Lambda)x_{k}^{T}x_{k}$$
$$= -\lambda_{\min}(-\Lambda)\|x_{k}\|^{2}.$$
(12)

For any positive integer $T \ge 1$, the follows holds:

$$E\left\{\sum_{k=0}^{T} \|x_{k}\|^{2}\right\}$$

$$\leq \frac{1}{\lambda_{\min}(-\Lambda)} \left(E\left\{V\left(x_{0}, \tau_{0}, \delta_{-\tau_{0}}\right)\right\}\right)$$

$$-E\left\{V\left(x_{T+1}, \tau_{T+1}, \delta_{T+1-\tau_{T+1}}\right)\right\}$$

$$\leq \frac{1}{\lambda_{\min}(-\Lambda)}E\left\{V\left(x_{0}, \tau_{0}, \delta_{-\tau_{0}}\right)\right\}$$

$$= \frac{1}{\lambda_{\min}(-\Lambda)}x_{k}^{T}\Omega_{\tau_{0},\delta_{-\tau_{0}}}x_{k}.$$
(13)

From the Definition 1, the closed-loop system (5) is stochastically stable, which completes the proof. \Box

Theorem 1 presents the sufficient conditions on the existence of the state feedback controller. To get a feasible solution for controller gain matrix $K_{\tau_k,\delta_{k-\tau_k}}$, the equivalent LMIs conditions with nonconvex constraints will be given in Theorem 2.

Theorem 2: There exists a controller (3) such that the closed-loop system (5) is stochastically stable if there exist positive-definite matrices $P_{i,p} > 0$, $L_{j,q} > 0$, $S_1 > 0$, $S_2 > 0$, Z > 0, Y > 0 and matrix $K_{i,r}$ such that

$$\begin{vmatrix} \Sigma_{11} & * & * \\ \Sigma_{21} & -Y & * \\ \Sigma_{31} & 0 & \Sigma_{33} \end{vmatrix} < 0, \tag{14}$$

$$P_{j,q}L_{j,q} = I, \quad ZY = I,$$
 (15)

where

$$\begin{split} \Sigma_{11} = \begin{bmatrix} \tilde{\Sigma}_{11} & * & * \\ Z & S_1 - 2Z & * \\ 0 & Z & S_2 - Z \end{bmatrix}, \\ \tilde{\Sigma}_{11} = (\tau + \gamma + 1) S_1 + S_2 - Z - P_{i,p}, \\ \Sigma_{21} = (\tau + \gamma) \begin{bmatrix} A_{\delta_k} - I & B_{\delta_k} K_{i,p} & 0 \end{bmatrix}, \\ \Sigma_{31}^T = \begin{bmatrix} \sqrt{\lambda_{i1} \Theta_{p1}^{i-j+1}} \vartheta^T \cdots \sqrt{\lambda_{i\tau} \Theta_{pD}^{i-j+1}} \vartheta^T \end{bmatrix}, \\ \vartheta = \begin{bmatrix} A_{\delta_k} & B_{\delta_k} K_{i,p} & 0 \end{bmatrix}, \\ \Sigma_{33} = \text{Diag} \{ L_{01}, \cdots, L_{\tau D} \}, \end{split}$$

hold for all $i, j \in \mathcal{M}, p, q \in \mathcal{W}$.

Proof: Letting $Y = Z^{-1}$, $L_{j,q} = P_{j,q}^{-1}$, $j \in \mathcal{M}$, $q \in \mathcal{W}$ and by applying the Schur complement, the proof can be readily completed.

The conditions stated in Theorem 2 are in fact a set of LMIs with some matrix inverse constraints. Although they are nonconvex, which bring difficulties in using the existing convex optimization tool to solve them, one can use the cone complementary linearization (CCL) algorithm to transform this problem into the nonlinear minimization problem with LMI constraints as follows:

$$\operatorname{Min} \operatorname{tr}\left(\sum_{j=0}^{\tau} \sum_{q=1}^{D} P_{j,q} L_{j,q} + ZY\right) \text{ s.t. (14), (16) and (17).}$$
$$\begin{bmatrix} P_{j,q} & I \\ I & L_{j,q} \end{bmatrix} > 0, \quad j \in \mathcal{M}, \ q \in \mathcal{W}, \qquad (16)$$
$$\begin{bmatrix} Z & I \\ I & Y \end{bmatrix} > 0. \qquad (17)$$

Further, the procedure for solving the state feedback controller gain matrix $K_{i,p}$ is exhibited in Algorithm 1.

The state feedback controller gain matrix $K_{i,p}$ is derived in Theorem 2 on condition that all elements in Ξ and Θ^{i-j+1} are completely known. However, it is usually difficult to obtain the full transition probabilities, and the controller gain matrix $K_{i,p}$ will be derived on Theorem 3 on condition that there are some unknown elements in Ξ and Θ^{i-j+1} .

For notational clarity, $\forall j \in \mathcal{M}$, let $\mathcal{M} = \mathcal{M}_k^i + \mathcal{M}_{uk}^i$ with $\mathcal{M}_k^i = \{j : \omega_{ij} \text{ is known}\}, \mathcal{M}_{uk}^i = \{j : \omega_{ij} \text{ is unknown}\}$. If \mathcal{M}_k^i is not empty, it can be further described as $\mathcal{M}_k^i = \{\mathcal{M}_{k_1^i}, \mathcal{M}_{k_2^i}, \cdots, \mathcal{M}_{k_a^i}\}$, where $\mathcal{M}_{k_a^i}$ represents the column index of the *a* th known transition probability in the *i*th row of Ξ . \mathcal{M}_{uk}^i can be described as $\mathcal{M}_{uk}^i = \{\mathcal{M}_{\bar{k}_1^i}, \mathcal{M}_{\bar{k}_2^i}, \cdots, \mathcal{M}_{\bar{k}_{u-a}^i}\}$, where $\mathcal{M}_{\bar{k}_{\tau-a}^i}$ represents the column index of the $(\tau - a)$ th unknown transition probability in the *i*th row of Ξ .

Similarly, $\forall q \in \mathcal{W}$, let $\mathcal{W} = \mathcal{W}_k^p + \mathcal{W}_{uk}^p$ with $\mathcal{W}_k^p = \{q : \omega_{pq} \text{ is known}\}, \mathcal{W}_{uk}^p = \{q : \omega_{pq} \text{ is unknown}\}.$ If \mathcal{W}_k^p is not empty, it can be further described as $\mathcal{W}_k^p = \{\mathcal{W}_{k_1^p}, \mathcal{W}_{k_2^p}, \cdots, \mathcal{W}_{k_b^p}\}$, where $\mathcal{W}_{k_b^p}$ represents the column index of the *b*th known transition probability in the *p*th row of matrix Θ^{i-j+1} . \mathcal{W}_{uk}^p can be described as $\mathcal{W}_{uk}^p = \{\mathcal{W}_{\bar{k}_1^p}, \mathcal{W}_{\bar{k}_2^p}, \cdots, \mathcal{W}_{\bar{k}_{D-b}^p}\}$, where $\mathcal{W}_{\bar{k}_{D-b}^p}$ represents the column index of the (D-b) th unknown transition probability in the *p*th row of matrix Θ^{i-j+1} .

Theorem 3: If there exist positive-definite matrix $P_{i,p} > 0$, $L_{j,q} > 0$, $S_1 > 0$, $S_2 > 0$, Z > 0, Y > 0 and matrix $K_{i,r}$ satisfying

$$\begin{bmatrix} \tilde{\omega} \sum_{q \in \mathcal{W}_{k}^{p}} \Theta_{pq}^{i-j+1} \Sigma_{11} & * & * \\ \tilde{\omega} \sum_{q \in \mathcal{W}_{k}^{p}} \Theta_{pq}^{i-j+1} \Sigma_{21} - \tilde{\omega} \sum_{q \in \mathcal{W}_{k}^{p}} \Theta_{pq}^{i-j+1} Y & * \\ \Upsilon_{\mathcal{M}_{k}^{i}, \mathcal{W}_{k}^{p}} & 0 & \Sigma_{\mathcal{M}_{k}^{i}, \mathcal{W}_{k}^{p}} \end{bmatrix} < 0,$$

$$\begin{bmatrix} \sum_{q \in \mathcal{W}_{k}^{p}} \Theta_{pq}^{i-j+1} \Sigma_{11} & * & * \\ \sum_{q \in \mathcal{W}_{k}^{p}} \Theta_{pq}^{i-j+1} \Sigma_{21} & - \sum_{q \in \mathcal{W}_{k}^{p}} \Theta_{pq}^{i-j+1} Y & * \\ \Upsilon_{\mathcal{M}_{uk}^{i}, \mathcal{W}_{k}^{p}} & 0 & \Sigma_{\mathcal{M}_{uk}^{i}, \mathcal{W}_{k}^{p}} \end{bmatrix} < 0,$$

Algorithm 1 Procedure for Solving the Controller Gain Matrix $K_{i,p}$

1: Set the maximum number of iterations R_{\max} 2: Find a set of feasible solution $(P_{j,q}^0, L_{j,q}^0, S_1^0, S_2^0, Z^0, Y^0, K_{i,p}^0)$ satisfying (14), (16) and (17), and let k = 03: Solve the following optimization problem for variables: $\operatorname{Min} \operatorname{tr} \left(\sum_{j=0}^{\tau} \sum_{q=1}^{D} P_{j,q} L_{j,q} + ZY \right), \text{ s.t. (14), (16) and (17)} \\
4: \operatorname{Set} \left(P_{j,q}^{k} = P_{j,q}, L_{j,q}^{k} = L_{j,q}, S_{1}^{k} = S_{1}, S_{2}^{k} = S_{2}, Z^{k} = Z, Y^{k} = Y, K_{i,p}^{k} = K_{i,p} \right) \\
5: \text{ while number of iterations } < R_{\max} \text{ do}$

- **if** (14), (15) is satisfied **then** 6:
- 7: break
- 8: else
- 9: k = k + 1, go to step 3.
- 10: end if

Γ

11: end while

$$j \in \mathcal{M}_{uk}^{\iota}, \tag{19}$$
$$\tilde{\omega} \Sigma_{11} * * \rceil$$

$$\begin{bmatrix} \tilde{\omega}\Sigma_{21} & -\tilde{\omega}Y & * \\ \Upsilon_{\mathcal{M}_{k}^{i},\mathcal{W}_{uk}^{p}} & 0 & \Sigma_{\mathcal{M}_{k}^{i},\mathcal{W}_{uk}^{p}} \end{bmatrix} < 0, \quad q \in \mathcal{W}_{uk}^{p}, \quad (20)$$
$$\begin{bmatrix} \Sigma_{11} & * & * \\ \Sigma_{21} & -Y & * \\ \Upsilon_{\mathcal{M}_{uk}^{i},\mathcal{W}_{uk}^{p}} & 0 & \Sigma_{\mathcal{M}_{uk}^{i},\mathcal{W}_{uk}^{p}} \end{bmatrix} < 0, \quad j \in \mathcal{M}_{uk}^{i}, \quad q \in \mathcal{W}_{uk}^{p},$$

$$P_{i,a}L_{i,a} = I, ZY = I, \tag{21}$$

where

$$\begin{split} \Upsilon^{T}_{\mathcal{M}_{k}^{i},\mathcal{W}_{k}^{p}} &= \left[\sqrt{\lambda_{i1} \Theta_{p1}^{i-j+1}} \vartheta^{T} \cdots \sqrt{\lambda_{ia} \Theta_{pb}^{i-j+1}} \vartheta^{T} \right], \\ \Sigma_{\mathcal{M}_{k}^{i},\mathcal{W}_{k}^{p}} &= \mathrm{Diag} \{ -L_{\mathcal{M}_{k_{1}^{i}},\mathcal{W}_{k_{1}^{p}}}, \dots, -L_{\mathcal{M}_{k_{a}^{i}},\mathcal{W}_{k_{b}^{p}}} \}, \\ \Upsilon^{T}_{\mathcal{M}_{uk}^{i},\mathcal{W}_{k}^{p}} &= \left[\sqrt{\Theta_{p1}^{i-j+1}} \vartheta^{T} \cdots \sqrt{\Theta_{pb}^{i-j+1}} \vartheta^{T} \right], \\ \Sigma_{\mathcal{M}_{uk}^{i},\mathcal{W}_{k}^{p}} &= \mathrm{Diag} \{ -L_{j,\mathcal{W}_{k_{1}^{p}}}, \dots, -L_{j,\mathcal{W}_{k_{b}^{p}}} \}, \\ \Upsilon^{T}_{\mathcal{M}_{k}^{i},\mathcal{W}_{uk}^{p}} &= \left[\sqrt{\lambda_{i1}} \vartheta^{T} \cdots \sqrt{\lambda_{ia}} \vartheta^{T} \right], \\ \Sigma_{\mathcal{M}_{k}^{i},\mathcal{W}_{uk}^{p}} &= \mathrm{Diag} \{ -L_{\mathcal{M}_{k_{1}^{i}},q}, \dots, -L_{\mathcal{M}_{k_{a}^{i}},q} \}, \\ \Upsilon^{T}_{\mathcal{M}_{uk}^{i},\mathcal{W}_{uk}^{p}} &= \left[\vartheta^{T} \cdots \vartheta^{T} \right], \\ \tilde{\omega} &= \sum_{j \in \mathcal{M}_{k}^{i}} \omega_{ij}, \end{split}$$

for all $i, j \in \mathcal{M}, p, q \in \mathcal{W}$, the closed-loop system (5) under the controller (3) is stochastically stable. *Proof:* By the Schur complement, $\Lambda < 0$ is equivalent to

$$\begin{bmatrix} \Sigma_{11} * \\ \Sigma_{21} - Y \end{bmatrix} + \begin{bmatrix} \vartheta \\ 0 \end{bmatrix}^T \tilde{P}_{j,q} \left[\vartheta \, 0 \right] < 0, \tag{23}$$

which can be written as

$$\left(\sum_{j\in\mathcal{M}_{k}^{i}}\sum_{q\in\mathcal{W}_{k}^{p}}\omega_{ij}\Theta_{pq}^{i-j+1}+\sum_{j\in\mathcal{M}_{uk}^{i}}\sum_{q\in\mathcal{W}_{k}^{p}}\omega_{ij}\Theta_{pq}^{i-j+1}\right)$$
$$+\sum_{j\in\mathcal{M}_{k}^{i}}\sum_{q\in\mathcal{W}_{uk}^{p}}\omega_{ij}\Theta_{pq}^{i-j+1}+\sum_{j\in\mathcal{M}_{uk}^{i}}\sum_{q\in\mathcal{W}_{uk}^{p}}\omega_{ij}\Theta_{pq}^{i-j+1}\right)$$

$$\begin{split} & \left(\begin{bmatrix} \Sigma_{11} & * \\ \Sigma_{21} - Y \end{bmatrix} + \begin{bmatrix} \vartheta \\ 0 \end{bmatrix}^T \tilde{P}_{j,q} \begin{bmatrix} \vartheta & 0 \end{bmatrix} \right) \\ = & \tilde{\omega} \sum_{q \in \mathcal{W}_k^p} \Theta_{pq}^{i-j+1} \left(\begin{bmatrix} \Sigma_{11} & * \\ \Sigma_{21} - Y \end{bmatrix} + \begin{bmatrix} \vartheta \\ 0 \end{bmatrix}^T \tilde{P}_{j,q} \begin{bmatrix} \vartheta & 0 \end{bmatrix} \right) \\ & + \bar{\omega} \left(\sum_{q \in \mathcal{W}_k^p} \Theta_{pq}^{i-j+1} \left(\begin{bmatrix} \Sigma_{11} & * \\ \Sigma_{21} - Y \end{bmatrix} + \begin{bmatrix} \vartheta \\ 0 \end{bmatrix}^T \tilde{P}_{j,q} \begin{bmatrix} \vartheta & 0 \end{bmatrix} \right) \right) \\ & + \sum_{q \in \mathcal{W}_{uk}^p} \Theta_{pq}^{i-j+1} \left(\tilde{\omega} \left(\begin{bmatrix} \Sigma_{11} & * \\ \Sigma_{21} - Y \end{bmatrix} + \begin{bmatrix} \vartheta \\ 0 \end{bmatrix}^T \tilde{P}_{j,q} \begin{bmatrix} \vartheta & 0 \end{bmatrix} \right) \right) \\ & + \bar{\omega} \sum_{q \in \mathcal{W}_{uk}^p} \Theta_{pq}^{i-j+1} \left(\begin{bmatrix} \Sigma_{11} & * \\ \Sigma_{21} - Y \end{bmatrix} + \begin{bmatrix} \vartheta \\ 0 \end{bmatrix}^T \tilde{P}_{j,q} \begin{bmatrix} \vartheta & 0 \end{bmatrix} \right), \end{split}$$

where $\bar{\omega} = \sum_{j \in \mathcal{M}_{uk}^i} \omega_{ij}$. Appling Schur complement again, one can get:

$$\sum_{j \in \mathcal{M}_{k}^{i}} \sum_{q \in \mathcal{W}_{k}^{p}} \omega_{ij} \Theta_{pq}^{i-j+1} \left(\begin{bmatrix} \Sigma_{11} & * \\ \Sigma_{21} - Y \end{bmatrix} + \begin{bmatrix} \vartheta \\ 0 \end{bmatrix}^{T} \tilde{P}_{j,q} \begin{bmatrix} \vartheta & 0 \end{bmatrix} \right) < 0 \quad (24)$$

is equivalent to (18).

Therefore, if (18) holds, then (24) holds. Because $\omega_{ii} \ge 0$, $\pi_{rs} \geq 0$, if (18)-(22) hold, then $\Lambda < 0$ holds, that is, the closed-loop system (5) is stochastically stable. This completes the proof.

Remark 3: If there are some unknown elements in matrix Θ , then matrix Θ^{i-j+1} has more unknown elements than Θ , for example, if $\Theta = \begin{bmatrix} ? & ? \\ 0.5 & 0.5 \end{bmatrix}$, then all the elements are unknown in Θ^2 . In this case, only (20)-(22) should be satisfied to guarantee the stochastic stability of the closedloop system (5).

Remark 4: Similar to Theorem 2, (18)-(22) in Theorem 3 can also be solved by the CCL algorithm, the detail procedure is omitted here.



FIGURE 2. The boost converter.

IV. NUMERICAL EXAMPLE

To illustrate the effectiveness of the proposed method, the results in this paper are applied to the pulse-widthmodulation (PWM)-driven boost converter as shown in Figure 2, where the switch s(t) is controlled by a PWM device, *R* is the resistance, *L* is the inductance, *C* is the capacitance, and $e_s(t)$ is the power source [25]. The converter is used to transform the source voltage into a higher voltage. With different closed positions of the s(t), the state space equation of the converter is also different, which can be modeled as a typical Markov jump system. The state space model of the converter is as follows:

where

$$\begin{bmatrix} 0.94 & 0.1 & 0.06 \\ 0.2 & 0.05 & 0.2 \end{bmatrix}$$
 D $\begin{bmatrix} -0.3 \\ 0.2 \end{bmatrix}$

 $x_{k+1} = A_{\delta_k} x_k + B_{\delta_k} u_k, \, \delta_k \in \{1, 2\},\$

$$A_{1} = \begin{bmatrix} -0.5 & 0.95 & -0.3 \\ -0.25 & -0.06 & 0.63 \end{bmatrix}, B_{1} = \begin{bmatrix} 0.2 \\ 0.1 \end{bmatrix}, A_{2} = \begin{bmatrix} 0.93 & 0.08 & 0.07 \\ -0.14 & 0.66 & -0.2 \\ -0.16 & -0.4 & 0.66 \end{bmatrix}, B_{2} = \begin{bmatrix} -1.4 \\ 0.3 \\ 0.2 \end{bmatrix}.$$

The transition probability matrix between the two subsystems is $\Theta = \begin{bmatrix} 0.8 & 0.2 \\ 0.3 & 0.7 \end{bmatrix}$. Assume S/C time-delay $\tau_k \in \mathcal{M} = \{0, 1\}$ and C/A time-delay $\gamma_k \in \mathcal{N} = \{0, 1\}$. The transition probability matrix of τ_k and γ_k is as follows, respectively:

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

According to Theorem 2, the mode-dependent controller gain matrix is obtained as follows:

$$\begin{split} K_{01} &= \begin{bmatrix} 0.2422 & -0.1052 & -0.0149 \end{bmatrix}, \\ K_{11} &= \begin{bmatrix} 0.2586 & -0.1055 & -0.0253 \end{bmatrix}, \\ K_{02} &= \begin{bmatrix} 0.0958 & 0.0166 & -0.0157 \end{bmatrix}, \\ K_{12} &= \begin{bmatrix} 0.0959 & 0.0155 & -0.0307 \end{bmatrix}. \end{split}$$

By the traditional Lyapunov-Krasovskii method, the modeindependent controller gain matrix can be obtained: K = [0.1191 -0.0025 -0.0265]. The system mode δ_k , the time-delay τ_k and the time-delay γ_k is shown in Figure 3, Figure 4 and Figure 5, respectively. Assuming the initial state of the system $x_0^T = [1 -0.5 \ 0.5]$, Figure 6, Figure 7 and Figure 8 illustrate the state response of the closed-loop



FIGURE 3. The system mode δ_k .



FIGURE 4. The S/C time-delay τ_k .



FIGURE 5. The C/A time-delay γ_k .

system (5) using the mode-dependent controller proposed in this paper and the mode-independent controller.

From Figure 6, Figure 7 and Figure 8, it can be seen that the proposed two-mode-dependent controller outperforms the mode-independent one.

Assuming that all the elements in Θ and Ξ are completely unknown, the mode-dependent controller gain matrix can also be obtained by Theorem 3 as follows:

$$\begin{split} & K_{01} = \begin{bmatrix} 0.2962 & -0.1245 & -0.0147 \end{bmatrix}, \\ & K_{11} = \begin{bmatrix} 0.2962 & -0.1245 & -0.0147 \end{bmatrix}, \\ & K_{02} = \begin{bmatrix} 0.1106 & -0.0215 & -0.0176 \end{bmatrix}, \\ & K_{12} = \begin{bmatrix} 0.1106 & -0.0215 & -0.0176 \end{bmatrix}. \end{split}$$



FIGURE 6. The closed-Loop system status x_1 .



FIGURE 7. The closed-Loop system status x_2 .



FIGURE 8. The closed-Loop system status x_3 .

V. CONCLUSION

The two-mode-dependent state feedback controller design method for a kind of networked Markov system with random time-delay is researched in this paper. The S/C time-delay and the C/A time-delay are both considered, the sufficient conditions on the stochastic stability of the closed-loop system and the solution of the controller gain matrix are given. The numerical simulation shows that the controller designed in this paper is superior to the mode-independent controller.

REFERENCES

 T. Li, X. Tang, J. Ge, and S. Fei, "Event-based fault-tolerant control for networked control systems applied to aircraft engine system," *Inf. Sci.*, vol. 512, pp. 1063–1077, Feb. 2020.

- [2] W. Ding, Z. Mao, B. Jiang, and W. Chen, "Fault detection for a class of nonlinear networked control systems with Markov transfer delays and stochastic packet drops," *Circuits, Syst., Signal Process.*, vol. 34, no. 4, pp. 1211–1231, Apr. 2015.
- [3] J. Wang, M. Chen, H. Shen, J. H. Park, and Z. Wu, "A Markov jump model approach to reliable event-triggered retarded dynamic output feedback *H*_∞ control for networked systems," *Nonlinear Anal., Hybrid Syst.*, vol. 26, pp. 137–150, 2017.
- [4] W. He and Y. Dong, "Adaptive fuzzy neural network control for a constrained robot using impedance learning," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 4, pp. 1174–1186, Apr. 2018.
- [5] H.-J. Yao, "Exponential stability control for nonlinear uncertain networked systems with time delay," *J. Discrete Math. Sci. Cryptogr.*, vol. 21, no. 2, pp. 563–569, Feb. 2018.
- [6] L. Zhao, H. Xu, Y. Yuan, and H. Yang, "Stabilization for networked control systems subject to actuator saturation and network-induced delays," *Neurocomputing*, vol. 267, pp. 354–361, Dec. 2017.
- [7] T. G. Oliveira, R. M. Palhares, V. C. S. Campos, P. S. Queiroz, and E. N. Gonçalves, "Improved takagi-sugeno fuzzy output tracking control for nonlinear networked control systems," *J. Franklin Inst.*, vol. 354, no. 16, pp. 7280–7305, Nov. 2017.
- [8] P. Li, Y. Kang, Y.-B. Zhao, and Z. Yuan, "Packet-based model predictive control for networked control systems with random packet losses," in *Proc. IEEE Conf. Decis. Control (CDC)*, Dec. 2018, pp. 3457–3462.
- [9] Y. Zhang, F. Yang, Y. Zhu, J. Chen, and J. Zhu, "*H*_∞ filtering for networked control systems with randomly occurring consecutive packet losses," in *Proc. Austral. New Zealand Control Conf. (ANZCC)*, Dec. 2017, pp. 6–10.
- [10] X. Li, J. Wang, and S. Sun, "Robust H_∞ filtering for network-based systems with delayed and missing measurements," *Control Theory Appl.*, vol. 30, no. 11, pp. 1401–1407, 2013.
- [11] S.-L. Sun, "Optimal linear estimators for discrete-time systems with one-step random delays and multiple packet dropouts," *Acta Automatica Sinica*, vol. 38, no. 3, pp. 349–354, Mar. 2012.
- [12] J. Zhang, J. Lam, and Y. Xia, "Output feedback delay compensation control for networked control systems with random delays," *Inf. Sci.*, vol. 265, pp. 154–166, May 2014.
- [13] J. Dong and W.-J. Kim, "Markov-chain-based output feedback control for stabilization of networked control systems with random time delays and packet losses," *Int. J. Control, Autom. Syst.*, vol. 10, no. 5, pp. 1013–1022, Oct. 2012.
- [14] Y.-F. Wang, Z.-X. Li, H.-Y. Chen, L.-D. Quan, and X.-R. Guo, "Design for nonlinear networked control systems with time delay governed by Markov chain with partly unknown transition probabilities," *Math. Problems Eng.*, vol. 2015, Sep. 2015, Art. no. 604246.
- [15] L. Qiu, B. Xu, and S. Li, " \mathcal{H}_{∞} control for networked control systems with mode-dependent time-delays," *Control Decis.*, vol. 26, no. 4, pp. 571–576, 2011.
- [16] Y.-G. Sun and Q.-Z. Gao, "Stability and stabilization of networked control system with forward and backward random time delays," *Math. Problems Eng.*, vol. 2012, Jan. 2012, Art. no. 834643.
- [17] Z. Wang, Y. Liu, and X. Liu, "Exponential stabilization of a class of stochastic system with Markovian jump parameters and mode-dependent mixed time-delays," *IEEE Trans. Autom. Control*, vol. 55, no. 7, pp. 1656–1662, Jul. 2010.
- [18] L. Zhang, Y. Leng, and P. Colaneri, "Stability and stabilization of discretetime semi-Markov jump linear systems via semi-Markov kernel approach," *IEEE Trans. Autom. Control*, vol. 61, no. 2, pp. 503–508, Feb. 2016.
- [19] L. Zhang, Z. Ning, and P. Shi, "Input—Output approach to control for fuzzy Markov jump systems with time-varying delays and uncertain packet dropout rate," *IEEE Trans. Cybern.*, vol. 45, no. 11, pp. 2449–2460, Nov. 2015.
- [20] X. Song, Y. Men, J. Zhou, J. Zhao, and H. Shen, "Event-triggered \mathcal{H}_{∞} control for networked discrete-time Markov jump systems with repeated scalar nonlinearities," *Appl. Math. Comput.*, vol. 298, pp. 123–132, Apr. 2017.
- [21] X. Kui and Y. Wang, "Stabilization for networked markovian jump systems with partly unknown transition probabilities," *Control Eng. China*, vol. 25, no. 12, p. 27, 2018.
- [22] L. Zhang, Y. Shi, T. Chen, and B. Huang, "A new method for stabilization of networked control systems with random delays," *IEEE Trans. Autom. Control*, vol. 50, no. 8, pp. 1177–1181, Aug. 2005.

- [23] Y. Shi and B. Yu, "Output feedback stabilization of networked control systems with random delays modeled by Markov chains," *IEEE Trans. Autom. Control*, vol. 54, no. 7, pp. 1668–1674, Jun. 2009.
- [24] X. Jiang, Q.-L. Han, and X. Yu, "Stability criteria for linear discretetime systems with interval-like time-varying delay," in *Proc. Amer. Control Conf.*, 2005, pp. 2817–2822.
- [25] M. Liu and W. Yang, "Network-based filtering for stochastic Markovian jump systems with application to PWM-driven boost converter," *Circuits, Syst., Signal Process.*, vol. 36, no. 8, pp. 3071–3097, Aug. 2017.



HENG LI was born in Hunan, China, in 1963. He received the B.S. and M.S. degrees in civil engineering from Tongji University, in 1984 and 1987, respectively, and the Ph.D. degree in architectural science from the University of Sydney, Australia, in 1993.

From 1993 to 1995, he was a Lecturer with James Cook University. From 1996 to 1997, he was a Senior Lecture, with the Civil Engineering Department, Monash University. Since 1997, he

was gradually promoted from Associate Professor to Chair Professor of construction informatics with The Hong Kong Polytechnic University. He has authored two books and more than 500 articles. His research interests include building information modeling, robotics, functional materials, and the Internet of Things.

Dr. Li was a recipient of the National Award from Chinese Ministry of Education, in 2015, and the Gold Prize of Geneva Innovation 2019. He is also a Review Editor of *Automation in Construction*.



YANFENG WANG was born in Liaocheng, Shandong, China, in 1980. He received the M.S. degrees in operations research and cybernetics and the Ph.D. degree in control theory and control engineering from Northeastern University, in 2007 and 2013, respectively.

He is currently an Associate Professor with the School of Engineering, Huzhou University, Huzhou, Zhejiang, China. He has authored three books and more than 30 articles. He has been

supported by the National Natural Science Funds of China and Natural Science Funds of Zhejiang Province. His main research areas are networked control systems, fault detection, and fault-tolerant control.



PING HE was born in Huilongya, Nanchong, Sichuan, China, in November 1990. He received the B.S. degree in automation from the Sichuan University of Science and Engineering, Zigong, Sichuan, China, in June 2012, the M.S. degree in control science and engineering from North-eastern University, Shenyang, Liaoning, China, in July 2014, and the Ph.D. degree in electrome-chanical engineering from the Universidade de Macau, Taipa, Macau, in June 2017.

From December 2015 to November 2018, he was an Adjunct Associate Professor with the Department of Automation, Sichuan University of Science and Engineering. From August 2017 to August 2019, he was a Postdoctoral Research Fellow with the Emerging Technologies Institute, The University of Hong Kong, and Smart Construction Laboratory, The Hong Kong Polytechnic University. Since December 2018, he has been a Full Professor with the School of Intelligent Systems Science and Engineering, Jinan University, Zhuhai, Guangdong, China. He has authored one book and more than 40 articles. His research interests include sensor networks, complex networks, multiagent systems, artificial intelligence, control theory, and control engineering.

Dr. Ping was a recipient of the Liaoning Province of China Master's Thesis Award for Excellence, in March 2015, and the IEEE Robotics & Automation Society Finalist of Best Paper Award, in July 2018. He is the Reviewer Member for *Mathematical Reviews* of American Mathematical Society (Reviewer Number: 139695). He also serves as a Section Editor of *Automatika: Journal for Control, Measurement, Electronics, Computing and Communications,* an Academic Editor of *PLOS ONE,* and an Associate Editor of *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering* and *The Journal of Engineering* (IET).



XIAOYUE SUN was born in Jiaxing, China, in 1996. She received the B.S. degree in engineering from Huzhou University, Huzhou, China, in June 2019, where she is currently pursuing the M.S. degree.

Her research interests include networked control system fault detection and fault tolerant control.



WEI WEI (Senior Member, IEEE) received the M.S. and Ph.D. degrees from Xi'an Jiaotong University, Xi'an, China, in 2005 and 2011, respectively. He is currently an Associate Professor with the School of Computer Science and Engineering, Xi'an University of Technology, Xi'an. He has published around 100 research articles in international conferences and journals. His current research interests include the area of wireless networks, wireless sensor networks, image process-

ing, mobile computing, distributed computing, and pervasive computing, the Internet of Things, and sensor data clouds. He ran many funded research projects as a Principal Investigator and a Technical Member. He is a Senior Member of the China Computer Federation (CCF). He is an Editorial Board Member of *Future Generation Computer System*, IEEE Access, *Ad Hoc & Sensor Wireless Sensor Network*, Institute of Electronics, Information and Communication Engineers, and *KSII Transactions on Internet and Information Systems*. He is a TPC Member of many conferences and a Regular Reviewer of the IEEE TRANSACTIONS ON PARALLEL AND DISTRIBUTED SYSTEMS, the IEEE TRANSACTIONS ON IMAGE PROCESSING, the IEEE TRANSACTIONS ON MOBILE COMPUTING, the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, the *Journal of Network and Computer Applications*, and so on.



HAOYANG MI received the bachelor's and Ph.D. degrees from the College of Mechanical and Automotive, South China University of Technology, Guangzhou, China, in 2010 and 2015, respectively. He was a Postdoctoral Researcher with the University of Wisconsin–Madison, USA, from 2016 to 2018, and a Research Fellow with The Hong Kong Polytechnic University, from 2018 to 2019. He is currently an Associate Professor with the National Engineering Research Center for Advanced Poly-

mer Processing Technology, Zhengzhou University. He has published nearly 100 SCI journal publications so far, with a total citation more than 2000 and an H-index of 27. He has applied 17 U.S. and China patents, and composed a book chapter. He also directs several projects on artificial intelligence and flexible sensors, and serves as a Regular Reviewer for many journals. His current researches focus on intelligent materials, artificial intelligence, detection technology, automation device, and flexible sensors.



YANGMIN LI (Senior Member, IEEE) received the B.S. and M.S. degrees in mechanical engineering from Jilin University, Changchun, China, in 1985 and 1988, respectively, and the Ph.D. degree in mechanical engineering from Tianjin University, Tianjin, China, in 1994. He started his academic career, in 1994, as a Lecturer of the Mechatronics Department, South China University of Technology, Guangzhou, China. He was a Fellow of the International Institute for Software

Technology, United Nations University (UNU/IIST), from May to November 1996, a Visiting Scholar with the University of Cincinnati, in 1996, and a Postdoctoral Research Associate with Purdue University, West Lafayette, USA, in 1997. He was an Assistant Professor, in 1997, an Associate Professor, in 2001, and a Full Professor, from 2007 to 2016, with the University of Macau. He is currently a Full Professor with the Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong. He has authored and coauthored 420 scientific articles in journals and conferences. His research interests include micro/nanomanipulation, compliant mechanism, precision engineering, robotics, and multibody dynamics and control.

Dr. Li is an Associate Editor of the IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING, *Mechatronics*, IEEE ACCESS, and the *International Journal of Control, Automation, and Systems*.