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Linear Matrix Inequality Approach to Stochastic Stabilization of Networked Control System with Markovian Jumping Parameters

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Abstract: This paper is concerned with the stochastic stabilization problem for a class of networked control system (NCS) with destabilizing transmission factors. By introducing the effective sampling instant to model random time delays and successive packet dropouts as two independent Markov chains, NCS is modeled as a discrete-time Markovian jump linear system with mixed integrated Markovian jumping parameters. In this way, a novel framework to analyze the stochastic stabilization problem of NCS is provided. The necessary and sufficient conditions for the stochastic stabilization of the NCS are obtained by the Lyapunov method and the state-feedback controller gain that depends on the delay modes is obtained in terms of the linear matrix inequalities (LMIs) formulation via the Schur complement theory. Finally, numerical examples are provided to illustrate the effectiveness of the proposed method.

Keywords: Linear matrix inequality, Markov chain, networked control system, stochastic stability, time delay.

1. INTRODUCTION

Networked control systems (NCSs) are distributed feedback control systems in which the communications between sensors, actuators and controllers are implemented via a digital communication network with shared restricted bandwidth [1]. Due to the advantages of low installation cost, reduced wiring, easy maintenance and increased system flexibility, NCSs have been widely used in manufacturing systems, monitoring systems, vehicle highway systems, aircraft systems, robots teleoperation, etc. [2]. Despite lots of advantages network brings to the control system, potential issues arise to make the analysis and design of a networked control system complicated. It is known that the main issues are network induced time delays and packet dropouts which may degrade the system performance and even cause system instability [3]. It is significant to overcome the adverse influences induced by network to guarantee the stability and even high dynamic performance of networked control system.

The stability analysis and stabilizing controller design for networked control systems with network induced delays and packet dropouts have received considerable attention in the literature in recent years. In [4], the network induced delay is assumed to be less than one sampling time and the designed stabilizing state feedback gain is constant for different time delay scenarios. In [5, 6], the time delay analysis of the NCS is provided to explain how it affects network systems and an adaptive Smith predictor control scheme is designed. In [7], time delay is considered in an independent layer to design a stabilizing controller based on model predictive control approach. In [8], uncertain long-delayed systems are considered and a robust controller is designed on a unique structure. In [9], the maximum allowable delay bounds are obtained for the stability of NCSs and are used as the basic parameters for a scheduling method for NCSs.

Furthermore, with the development of stochastic control theory, time delays and packet dropouts are considered as stochastic parameters of NCS models in many research works. In [10], time delays are considered as independent distributed random variable. In [11], the dropout process is modeled as an identically independently distributed process and a power spectral density relevant to NCS is considered. [12] extends the results in [11] by assuming that feedback measurements are randomly dropped with a Markov chain distribution. NSCs with packet dropouts are modeled as discrete Markov jump system in [13, 14]. The stabilization problem for a class of discrete-time Markovian jump linear systems with time-delays both in the system state and in the mode signal has been studied in [15]. By choosing distinct Lyapunov ma-

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trices for different system modes and introducing a triple-integral term, [16] proposed a new Lyapunov method to solve the mean square exponential stability and stabilization problems of Markovian jump systems with time delay. The network-induced random delays are modeled as Markov chains such that the closed-loop system is a jump linear system with one mode in [17, 18]. The sequence of transmission intervals is assume as two models, an independent distributed random sequence and a finite state Markov chain in [19]. The stochastic stability of NCSs with time-varying sampling periods and delays driven by two Markov chains are discussed in [20], but the method in [20] did not consider the problem of data packet dropout.

It is worth noting that most of the research results are based on the restrictive assumptions of the time delay and packet drop models. Since time delays and packet dropouts are always integrated as parameters into the system model, the proposed stabilization controllers are delay-independent and conservative. There are no corresponding switchable controllers to stabilize the plant according to different time-delay scenarios. Although some researchers have applied stochastic control theory to the modeling of NCSs, to the best of the authors' knowledge, the stochastic mode dependent stabilization problem of NCSs which have both time-varying network-induced delays and data packet dropouts driven by two Markov chains has not been fully investigated and still remains challenging.

In this paper, the stochastic stability problem of NCS with arbitrary time delays and packet dropouts driven by two separately Markov chains is investigated. The effective sampling instant is introduced so that both time delays less than one sampling period and larger than one sampling period are distinguished and are dealt with in two different ways. Firstly the time axis in every sampling period is split into equidistant small intervals. Then for the time delays less than one sampling period, the delay values can be determined more accurately by multiple small intervals. On the other hand, the time delays larger than one sampling period are dealt as packet drops. Thus, the NCS can be modeled as a discrete-time jump system characterized by Markov chain distributed dropout and time delay processes. Sufficient conditions for the stochastic stabilization of the NCS with packet loss and time-varying delays are obtained by the Lyapunov function method and the mode-dependent stabilizing controller for the closed-loop NCS is designed in terms of the linear matrix inequalities (LMIs) formulation via the Schur complement theory.

The remainder of this paper is organized as follows: Section 2 addresses problem formulation and NCS modeling with time delays and dropouts by introducing the effective sampling instants. Section 3 presents the sufficient conditions for stochastic stability of the NCSs and the mode-dependent stabilizing controller design in terms of LMI approach. A design example is provided to demonstrate the effectiveness of the new approach proposed in this paper in Section 4. This paper concludes with Section 5.

2. PROBLEM FORMULATION

Consider a linear time-invariant plant described by

$$\dot{x}(t) = \mathrm{A}x(t) + \mathrm{B}u(t), \tag{1}$$

where $x(t) \in \Re^n$ is the state vector, $u(t) \in \Re^p$ is the input vector. A, B are constant matrices of appropriate dimensions. Considering a situation that sensor, actuator and controller are sharing the use of a network to exchange data as shown in Fig. 1.

Actuator accepts the digital signal from sensor via some feedback calculated by controller. Data collisions and communication failure will inevitably happen because of limited capacity of transmission channel. Suppose the sampling period h is constant, the sensor is time-driven and the controller and actuator are both event-driven. The time delay from sensor to actuator τ could be less or larger than one sampling period. To establish a unified NCS model, we define an effective sampling instant that means that the time delay of the packet sampled at that instant is within $0 < \tau \le h$. Due to the time varying characteristics of network induced delays, time axis in every sampling period is split into equidistant small intervals and the length of each interval is a. Therefore, every sampling period h is partitioned into l equidistant small intervals and $a = h/l$. If a packet with $\tau \le h$ reaches actuator, it will be used to update the plant mode, and the time delay τ_k takes value from the finite set $\mathrm{T} = a * M = \{a, 2a, \cdots, la\}$, where $M = \{1, 2, \cdots, l\}$. Otherwise, it will be dealt as a dropout packet. The actuator uses a zeroth-order hold (ZOH) to read the control signal from buffer if no new packet arrived at any one sampling period.

The possible cases of packets transmission during the sampling period on timing diagram of the considered NCS with both time delay and packet dropout are shown in Fig. 2. The solid line indicates that the packet arrives at

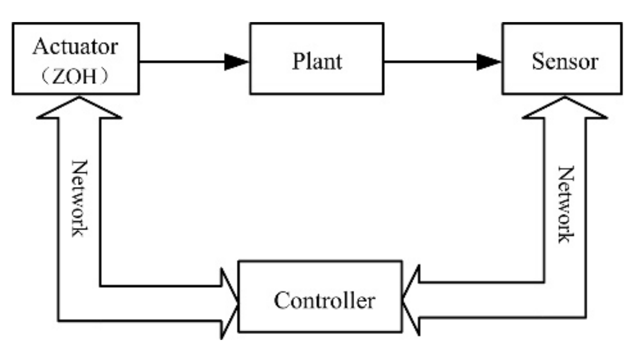

Fig. 1. The structure of NCS.

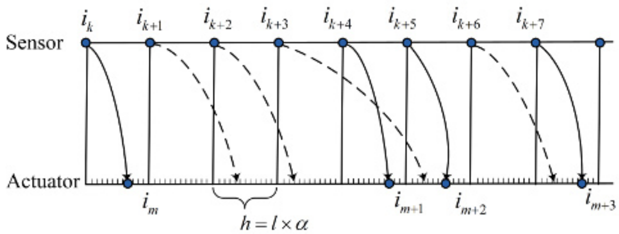

Fig. 2. Transmission conditions of NCS on timing diagram.

the actuator in a sampling period, the time delay of the packet is $\tau \leq h$. The dashed line indicates that the packet is dropped, or that the packet has not reached the actuator within a sampling period.

It can be seen from the timing diagram that as the packet dropout situations change, the control inputs acting on the plant are different from sampling interval to sampling interval. Four cases may arise and are discussed as follows:

Case 1: A packet with $0 < \tau \leq h$ arrived within the current sampling interval and there is no packet dropout within the previous sampling interval, such as the situation on the interval $[t_k, t_{k+1}]$

$$x(k+1) = \Phi x(k) + \Gamma_{0k} u(k) + \Gamma_{1k} u(k-1), \tag{2}$$

where

$$\Phi = e^{Ah}, \Gamma_{0k} = \int_0^{h-\tau_k} e^{As} ds\mathbf{B}, \ \ \Gamma_{1k} = \int_{h-\tau_k}^{h} e^{As} ds\mathbf{B}. \tag{3}$$

In this case, it is easy to see from (3) that the values of system matrices Γ_{0k}, Γ_{1k} are time-varying and determined by τ_k. In this way, the time-varying network induced delay is transformed into the parameter uncertainty of the system matrices. Thus, system (2) is a switched system which contains l subsystem, where the matrices Γ_{0k}, Γ_{1k} are allowed to take values from the finite set $\Psi = \{\hat{\Gamma}_1(\tau_k = a), \hat{\Gamma}_2(\tau_k = 2a), \ldots, \hat{\Gamma}_l(\tau_k = la)\}$, and $\hat{\Gamma}_m$, $m = 1, \ldots, l$ represents the pair of Γ_{0k}, Γ_{1k} . Then system (2) can be written into

$$x(k+1) = \Phi x(k) + \Gamma_{0\sigma(k)} u(k) + \Gamma_{1\sigma(k)} u(k-1), \tag{4}$$

where $\sigma(k)$ is called a switching signal, which is a piecewise constant function.

Case 2: A packet with $0 < \tau \leq h$ arrived within the current sampling interval, but packet-dropouts happened in the last sampling intervals, such as the situation on the interval $[t_{k+4}, t_{k+5}]$

$$x(k+1) = \Phi x(k) + \Gamma_{0k} u(k) + \Gamma_{1k} u(k-d_k), \tag{5}$$

where $\Phi = e^{Ah}$, $\Gamma_{0k} = \int_0^{h-\tau_k} e^{As} ds\mathbf{B}$, $\Gamma_{1k} = \int_{h-\tau_k}^{h} e^{As} ds\mathbf{B}$.

Suppose that the maximum bound of successive dropped packets is d and d_k takes value from a finite set $D = \{1, \cdots, d\}$, then we can conclude that there are d occasions that can describe successive packet-dropouts condition. Together with the time delay situation, system (5) is also a switched system which contains $d \times l$ subsystem. Then system (5) can be written into

$$x(k+1) = \Phi x(k) + \Gamma_{0\sigma(k)} u(k) + \Gamma_{1\sigma(k)} u(k-d_{\sigma(k)}), \tag{6}$$

where $\sigma(k)$ is called a switching signal, which is a piecewise constant function.

Case 3: Packet dropout happens within the current sampling interval, but there is packet with $\tau \leq h$ that reaches actuator within the last sampling interval, such as the situation on the interval $[t_{k+1}, t_{k+2}]$

$$x(k+1) = \Phi x(k) + \Gamma u(k-1), \tag{7}$$

where $\Phi = e^{Ah}$, $\Gamma = \int_0^h e^{As} ds\mathbf{B}$.

Case 4: Packet dropout happens within the current sampling interval and it has still happened within the previous sampling interval, such as the situation on the interval $[t_{k+3}, t_{k+4}]$

$$x(k+1) = \Phi x(k) + \Gamma u(k-d_k). \tag{8}$$

Suppose that the successive packet dropouts at the current sampling instant is d_k which takes value from a finite set $D = \{1, \cdots, d\}$. Then it is easy to see that system (8) contains d subsystems and can be written into

$$x(k+1) = \Phi x(k) + \Gamma u(k-d_{\sigma(k)}), \tag{9}$$

where $\Phi = e^{Ah}$, $\Gamma = \int_0^h e^{As} dsB$.

Based on above analysis, NCS can be seen as a complex switched system and the trigger of every subsystem is time delays τ_k and successive packet dropouts d_k. Suppose that the successive effective sampling instants are $0 = i_0 < i_1 < i_2 \ldots < i_m < \ldots$, thus during the interval $[i_m, i_{m+1})$, we can get

$$\begin{aligned}
x(i_m+1) &= \Phi x(i_m) + \Gamma u(i_m-1), \\
x(i_m+2) &= \Phi^2 x(i_m) + (\Phi\Gamma + \Gamma) u(i_m-1), \\
&\vdots \\
x(i_{m+1}-1) &= \Phi^{i_{m+1}-i_m-1} x(i_m) \\
&\quad + (\Phi^{i_{m+1}-i_m-2}\Gamma + \cdots + \Gamma) u(i_m-1), \\
x(i_{m+1}) &= \Phi x(i_{m+1}-1) + \Gamma_{0(i_{m+1}-1)} u(i_{m+1}-1) \\
&\quad + \Gamma_{1(i_{m+1}-1)} u(i_m-1).
\end{aligned} \tag{10}$$

Then, to sum up the state equations above, NCS can be written into a unified form based on the newly defined effective sampling instant as follows:

$$\begin{aligned}
x(i_{m+1}) = &\Phi^{i_{m+1}-i_m} x(i_m) + \Gamma_{0(i_{m+1}-1)} u(i_{m+1}-1) \\
&+ (\Phi^{i_{m+1}-i_m-1}\Gamma + \Phi^{i_{m+1}-i_m-2}\Gamma + \cdots
\end{aligned}$$

$$+\Phi\Gamma+\Gamma_{1(i_{m+1}-1)})u(i_m-1). \quad (11)$$

Thus, the system (10) with fixed sampling time has been transformed into the system (11) with variable sampling time. In this paper, actuator executes in a zero order hold (ZOH) fashion between two successive sampling instants. Therefore, the state feedback controller is described as follows during the interval $[i_m-1+\tau_m, i_{m+1}-1+\tau_{m+1})$

$$u(i_{m+1}-1)=K_m x(i_{m+1}-1), \quad (12)$$

where K_m is the candidate state feedback gain matrix, which is related to the transmission delay τ_m of the successive packet dropouts between instant i_m and i_{m+1}.

Define a new augmented state $z(m+1)=[x(i_{m+1}) \quad x(i_{m+1}-1) \quad \cdots \quad x(i_m+1) \quad x(i_m)\ u(i_{m+1}-1)]^T$, then system (11) can be rewritten as the following augmented closed-loop system

$$z(m+1)=\bar{\mathrm{A}}(m)z(m), \quad (13)$$

where

$$\bar{\mathrm{A}}(m)=\begin{bmatrix} \Gamma_{0(i_{m+1}-1)}K_m & \hat{\Phi}_{(i_{m+1}-1)} \\ \hat{K}_m & \hat{I} \end{bmatrix}, \quad (14)$$

$$\hat{\Phi}_{(i_{m+1}-1)}=\begin{bmatrix} 0 & \cdots & \Phi^{i_{m+1}-i_m} & 0 & \Pi \end{bmatrix},$$

$$\hat{K}_m=\begin{bmatrix} I & \cdots & 0 & 0 & K_m \end{bmatrix}^T,$$

$$\hat{I}=\begin{bmatrix} 0 & 0 \\ \tilde{I} & 0 \end{bmatrix},\ \tilde{I}=\begin{bmatrix} 0 & \cdots & I \\ 0 & \cdots & 0 \end{bmatrix},$$

$$\Pi=\Phi^{i_{m+1}-i_m-1}\Gamma+\Phi^{i_{m+1}-i_m-2}\Gamma+\cdots+\Phi\Gamma +\Gamma_{1(i_{m+1}-1)}. \quad (15)$$

3. MAIN RESULTS

In Section 2, d_m is defined as the number of dropped packet between two successive effective sampling instants i_m and i_{m+1}, and based on the four cases described in section 2 we can conclude that d_m takes value from a finite set $\Omega=\{0,1,\cdots,d\}$. Also in section 2, we mentioned that packet only with $\tau \leq h$ will be acted on the plant. Thus, τ_m takes value from the finite set $\mathrm{M}=\{a,2a,\cdots,la\}$ and the upper bound is h.

In this paper, we assume that random delays τ_m and packet dropouts d_m are two independent Markov chains that take values in M and Ω with the following transition probabilities

$$\omega_{pi}=\Pr(\tau_{m+1}=ia|\tau_m=pa),\ \forall i,p\in \mathrm{M},$$
$$\lambda_{qj}=\Pr(d_{m+1}=j|d_m=q),\ \forall j,q\in\Omega, \quad (16)$$

where $\omega_{pi},\ \lambda_{qj}\geq 0$ and

$$\sum_{i=1}^{l}\omega_{pi}=1,\quad \sum_{j=0}^{d}\lambda_{qj}=1. \quad (17)$$

The transition probability matrixes are defined by

$$\Theta=\begin{bmatrix} \omega_{11} & \omega_{12} & \cdots & \omega_{1l} \\ \omega_{21} & \omega_{22} & \cdots & \omega_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ \omega_{l1} & \omega_{l2} & \cdots & \omega_{ll} \end{bmatrix},$$

$$\Pi=\begin{bmatrix} \lambda_{00} & \lambda_{01} & \cdots & \lambda_{0d} \\ \lambda_{10} & \lambda_{11} & \cdots & \lambda_{1d} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{d0} & \lambda_{d1} & \cdots & \lambda_{dd} \end{bmatrix}. \quad (18)$$

Remark 1: Random delays and packet dropouts are driven by two independent Markov chains. The value of next state of effective instants is only related with the value of current state of effective instants. In other words, if we know the values of time delays τ_{m-1} and packet dropouts d_{m-1} at effective instant i_m, then we can obtain the value of τ_m and d_m at effective instant i_{m+1}.

We can see from (13) that system matrix $\bar{A}(m)$ is finally determined by τ_m and d_m. Consistent with prior analysis in section 2, NCS can be viewed as a complex switched system and the trigger of every subsystem is time delays τ_k and d_k. In the system, both time delays and packet dropouts are time varying and their probability distribution are regulated by the Markov chain. Therefore, system (13) can be seen as a discrete-time Markovian jump linear system with finite jump modes varying in a finite set which is combined by sets M and Ω. Here, we further identified the stochastic characteristic of time delays and packet dropouts to convert the closed-loop system (13) into a discrete-time Markovian jump linear system. Let us define a compact set I to denote jump modes of (13), then we can get $I=\{1,2,3...,l*(d+1)\}$. Define $\hat{A}(p,q)$ as the jump modes determined by $\tau_m=p$ and $d_m=q$, $K(p,q)$ as the mode-dependent state feedback controller gain, then augmented system (13) can be transformed into a discrete-time Markovian jump linear system

$$z(m+1)=\hat{\mathbf{A}}(p,q)z(m),\ \forall p\in \mathrm{M}, q\in\Omega, \quad (19)$$

where

$$\hat{\mathrm{A}}(p,q)=\begin{bmatrix} \Gamma_0(\tau_m)K(p,q) & \hat{\Phi}(\tau_m) \\ \hat{K}(p,q) & \hat{I} \end{bmatrix}, \quad (20)$$

$$\hat{\Phi}=\begin{bmatrix} 0 & \cdots & \Phi^{d_m+1} & 0 & \hat{\Pi} \end{bmatrix},$$

$$\hat{K}=\begin{bmatrix} I & \cdots & 0 & 0 & K(p,q) \end{bmatrix}^T,$$

$$\hat{I}=\begin{bmatrix} 0 & 0 \\ \tilde{I} & 0 \end{bmatrix},\ \tilde{I}=\begin{bmatrix} 0 & \cdots & I \\ 0 & \cdots & 0 \end{bmatrix},$$

$$\hat{\Pi}=\Phi^{d_m}\Gamma+\Phi^{d_m-1}\Gamma+\cdots+\Phi\Gamma+\Gamma_1(\tau_m). \quad (21)$$

Thus, the augmented closed-loop system (13) with the time delays and packet dropouts has been converted to a discrete-time Markovian jump linear system (19) with finite jump modes, and the two systems have the same dimension. First, the definition of stochastic stability is given [21].

Definition 1: For initial state $z_0 = z(0)$ and initial distributions $\tau_0 = \tau(0) \in \mathrm{M}$ and $d_0 = d(0) \in \Omega$, if there exists a finite matrix $\mathbf{Q} > 0$ satisfying

$$E(\sum_{m=0}^{\infty} \|z(m)\|^2 | z_0, \tau_0, d_0) < z_0^T \mathbf{Q} z_0.$$

Then the system (19) is stochastically stable.

Theorem 1: If there exist symmetric positive definite matrices $\mathbf{X}(p,q) > 0, p \in M, q \in \Omega$ satisfying

$$\begin{bmatrix} \mathbf{X}(p,q) & \mathbf{X}(p,q)\mathbf{U}(p,q) \\ \mathbf{U^T}(p,q)\mathbf{X^T}(p,q) & \Lambda \end{bmatrix} > 0,$$
$$p = 1,2,\ldots,l, \ \ q = 0,1,2,\ldots,d, \tag{22}$$

where

$$\mathbf{U}(p,q) = [\sqrt{\omega_{p1}\lambda_{q0}}\hat{\mathbf{A}}^\mathbf{T}(1,0)\cdots\sqrt{\omega_{pl}\lambda_{qd}}\hat{\mathbf{A}}^\mathbf{T}(l,d)],$$
$$\Lambda = diag\{\mathbf{X}(1,0),\cdots,\mathbf{X}(l,d)\}. \tag{23}$$

Then, the system (19) is stochastically stable.

Proof: Consider the following form of the Lyapunov function:

$$V(m) = z^T(m)\mathbf{P}(p,q)z(m), \tag{24}$$

where

$$\mathbf{P}(p,q) = \mathbf{X^{-1}}(p,q). \tag{25}$$

Then, we have

$$\begin{aligned} &E(\Delta V) \\ &= E(V(m+1) - V(m)) \\ &= E(z^T(m+1) \\ &\quad \times \mathbf{P}(\tau_{m+1}, d_{m+1})z(m+1)|z(m), \tau_m = p, d_m = q) \\ &\quad - z^T(m)\mathbf{P}(p,q)z(m) \\ &= \sum_{j=0}^{d}\sum_{i=1}^{l}\lambda_{qj}\omega_{pi}z^T(m)\hat{\mathbf{A}}^\mathbf{T}(i,j)\mathbf{P}(i,j)\hat{\mathbf{A}}(i,j)z(m) \\ &\quad - z^T(m)\mathbf{P}(p,q)z(m) \\ &= z^T(m)\big[\sum_{j=0}^{d}\sum_{i=1}^{l}\lambda_{qj}\omega_{pi}\hat{\mathbf{A}}^\mathbf{T}(i,j)\mathbf{P}(i,j)\hat{A}(i,j) \\ &\quad - \mathbf{P}(p,q)\big]z(m) \\ &= z^T(m)V(p,q)z(m), \end{aligned} \tag{26}$$

where $V(p,q) = \sum_{j=0}^{d}\sum_{i=1}^{l}\lambda_{qj}\omega_{pi}\hat{A}^T(i,j)\mathbf{P}(i,j)\hat{A}(i,j) - \mathbf{P}(p,q)$. If $V(p,q) < 0$, then

$$\begin{aligned} E(\Delta V) &= E(V(m+1) - V(m)) \\ &\le -\lambda_{\min}(-V(p,q))z^T(m)z(m) \\ &\le -\alpha z^T(m)z(m) = -\alpha\|z(m)\|^2, \end{aligned} \tag{27}$$

where $\alpha = \inf\{\lambda_{\min}(-V(p,q)), p \in M, q \in \Omega\} > 0$. From the previous inequality(27), for any integer $G \ge 1$, we have

$$E(V(G+1)) - E(V(0)) \le -\alpha E\{\sum_{m=0}^{G}\|z(m)\|^2\}, \tag{28}$$

which implies

$$E\{\sum_{m=0}^{\infty}\|z(m)\|^2\} \le \frac{1}{\alpha}E(V(0)) = \frac{1}{\alpha}z_0^T\mathbf{P}(\tau_0, d_0)z_0. \tag{29}$$

Thus, from Definition 1, if $V(p,q) < 0$, the system (19) is stochastically stable. From the definition of $V(p,q)$, the stochastic stability of system (19) is equivalent to:

$$\begin{aligned} &V(p,q) \\ &= \sum_{j=0}^{d}\sum_{i=1}^{l}\lambda_{qj}\omega_{pi}\hat{A}^T(i,j)\mathbf{P}(i,j)\hat{A}(i,j) - \mathbf{P}(p,q) \\ &< 0. \end{aligned} \tag{30}$$

By Schur complement, (30) is equivalent to:

$$\begin{bmatrix} \mathbf{P}(p,q) & \mathbf{U}(p,q) \\ \mathbf{U^T}(p,q) & \Lambda \end{bmatrix} > 0,$$
$$p = 1,2,\ldots,l, \ \ q = 0,1,2,\ldots,d, \tag{31}$$

where $\mathbf{U}$(p,q) and Λ have been defined in (23).

Define $\mathbf{H}(p,q) = diag\{\mathbf{P}^{-1}(p,q), \mathbf{I_{00}}, \ldots, \mathbf{I_{ld}}\}$, and premultiply and post-multiply (31) by $\mathbf{H}(p,q)$, we get (22) holds. The stochastic stability of system (19) is obtained. This completes the proof. □

Next, a design method of stabilizing controller for NCS is presented. Let us denote the following matrixes:

$$\tilde{\mathbf{A}}(p,q) = \begin{bmatrix} 0 & \hat{\Phi}(\tau_m) \\ I_{I0} & \hat{I} \end{bmatrix}, \ \tilde{\mathbf{B}}(p,q) = \begin{bmatrix} \Gamma_0(\tau_m) \\ I_{0I} \end{bmatrix},$$
$$\tilde{\mathbf{K}}(p,q) = \begin{bmatrix} K(p,q) & 0 \end{bmatrix}, \tag{32}$$

where

$$I_{I0} = \begin{bmatrix} I & \cdots & 0 & 0 & 0 \end{bmatrix}^T,$$
$$I_{0I} = \begin{bmatrix} 0 & \cdots & 0 & 0 & I \end{bmatrix}^T. \tag{33}$$

Then, system (19) can be rewritten into the following form:

$$z(m+1) = [\tilde{\mathbf{A}}(p,q) + \tilde{\mathbf{B}}(p,q)\tilde{\mathbf{K}}(p,q)]z(m). \tag{34}$$

In order to develop a design algorithm for a state feedback controller that stabilizes the discrete-time Markovian jump linear system as described in Section 2, The Matrices $\tilde{A}(p,q)$, $\tilde{B}(p,q)$, $\tilde{K}(p,q)$ in (32) are defined in the form of Partitioned Matrices as follows:

$$\begin{aligned}
\tilde{\mathbf{A}}(p,q) &= \begin{bmatrix} \tilde{\mathbf{A}}(p,q)_{11} & \tilde{\mathbf{A}}(p,q)_{12} \\ \tilde{\mathbf{A}}(p,q)_{21} & \tilde{\mathbf{A}}(p,q)_{22} \end{bmatrix}, \\
\tilde{\mathbf{B}}(p,q) &= \begin{bmatrix} \tilde{\mathbf{B}}(p,q)_{11} \\ \tilde{\mathbf{B}}(p,q)_{21} \end{bmatrix}, \\
\tilde{\mathbf{K}}(p,q) &= \begin{bmatrix} \tilde{\mathbf{K}}(p,q)_{11} & \tilde{\mathbf{K}}(p,q)_{12} \end{bmatrix}. \quad (35)
\end{aligned}$$

Theorem 2: If there exist symmetric positive definite matrices $\mathbf{G}(m,n)$ and $\mathbf{V}(m,n)$, matrices $\mathbf{R}(m,n)(\forall m \in M, n \in \Omega)$ satisfying

$$\begin{bmatrix} \mathbf{G}(p,q) & \mathbf{0} & \Xi_1 \\ * & \mathbf{V}(p,q) & \Xi_2 \\ * & * & Z \end{bmatrix} > 0, \ \forall p \in M, \ q \in \Omega, \quad (36)$$

and

$$\begin{aligned}
\Xi_1 &= [\sqrt{\omega_{p1}\lambda_{q0}}\Pi(1,0) \cdots \sqrt{\omega_{pl}\lambda_{qd}}\Pi(l,d)], \\
\Xi_2 &= [\sqrt{\omega_{p1}\lambda_{q0}}\Phi(1,0) \cdots \sqrt{\omega_{pl}\lambda_{qd}}\Phi(l,d)], \\
Z &= diag\{diag\{\mathbf{G}(1,0), \mathbf{V}(1,0)\}, \ldots, \\
&\qquad diag\{\mathbf{G}(l,d), \mathbf{V}(l,d)\}\}, \\
\Pi(i,j) &= \begin{bmatrix} \tilde{\mathbf{A}}(i,j)_{11}\mathbf{G}(p,q) + \tilde{\mathbf{B}}(i,j)_{11}\mathbf{R}(p,q) \\ \tilde{\mathbf{A}}(i,j)_{21}\mathbf{G}(p,q) + \tilde{\mathbf{B}}(i,j)_{21}\mathbf{R}(p,q) \end{bmatrix}^T, \\
\Phi(i,j) &= \begin{bmatrix} \tilde{\mathbf{A}}(i,j)_{12}\mathbf{V}(p,q) \\ \tilde{\mathbf{A}}(i,j)_{22}\mathbf{V}(p,q) \end{bmatrix}^T. \quad (37)
\end{aligned}$$

Then, the system (19) is stochastically stable and the mode-dependent state feedback controller is given by

$$\mathbf{K}(p,q) = \mathbf{R}(p,q)\mathbf{G}^{-1}(p,q), \ \ p \in M, \ \ q \in \Omega. \quad (38)$$

Proof: Assume that there exist symmetric positive definite matrices $\mathbf{G}(p,q)$ and $\mathbf{V}(p,q)$, matrices $\mathbf{R}(p,q)(\forall p \in M, q \in \Omega)$ such that (36) is satisfied. From (38) we get

$$\mathbf{R}(p,q) = \mathbf{K}(p,q)\mathbf{G}(p,q), \ \ p \in M, \ \ q \in \Omega. \quad (39)$$

Replacing $\mathbf{R}(p,q)$ in (36) by $\mathbf{K}(p,q)\mathbf{G}(p,q)$, and denote

$$\mathbf{X}(p,q) = \begin{bmatrix} \mathbf{G}(p,q) & \\ & \mathbf{V}(p,q) \end{bmatrix}, \quad (40)$$

we can get

$$\begin{bmatrix} \mathbf{X}(p,q) & \Delta_{1,0} & \cdots & \Delta_{i,j} & \cdots & \Delta_{l,d} \\ * & \mathbf{X}(1,0) & \cdots & 0 & \cdots & 0 \\ * & * & \ddots & 0 & \cdots & 0 \\ * & * & \cdots & \mathbf{X}(i,j) & \cdots & 0 \\ * & * & \cdots & * & \ddots & 0 \\ * & * & \cdots & * & \cdots & \mathbf{X}(l,d) \end{bmatrix},$$

$$\begin{aligned}
\Delta_{1,0} &= \sqrt{\omega_{p1}\lambda_{q0}}\mathbf{H}^T(1,0)\mathbf{X}(p,q), \\
\Delta_{i,j} &= \sqrt{\omega_{pi}\lambda_{qj}}\mathbf{H}^T(i,j)\mathbf{X}(p,q), \\
\Delta_{l,d} &= \sqrt{\omega_{pl}\lambda_{qd}}\mathbf{H}^T(l,d)\mathbf{X}(p,q), \\
i &= 1,2,\ldots,l, \ \ j = 0,1,2,\ldots,d, \quad (41)
\end{aligned}$$

where

$$\mathbf{H}(i,j) = \begin{bmatrix} \tilde{\mathbf{A}}(i,j)_{11} + \tilde{\mathbf{B}}(i,j)_{11}K(p,q) & \tilde{\mathbf{A}}(i,j)_{12} \\ \tilde{\mathbf{A}}(i,j)_{21} + \tilde{\mathbf{B}}(i,j)_{21}K(p,q) & \tilde{\mathbf{A}}(i,j)_{22} \end{bmatrix}. \quad (42)$$

Notice that

$$\begin{aligned}
Z =& diag\{diag\{\mathbf{G}(1,0), \mathbf{V}(1,0)\}, \ldots, \\
& diag\{\mathbf{G}(l,d), \mathbf{V}(l,d)\}\} \\
=& diag\{\mathbf{X}(1,0), \cdots \mathbf{X}(l,d)\} \\
=& \Lambda, \quad (43)
\end{aligned}$$

and

$$\begin{aligned}
&\mathbf{H}(i,j) = \tilde{A}(i,j) + \tilde{B}(i,j)K(i,j), \\
&i = 1,2,\ldots,l, \ \ j = 0,1,2,\ldots,d. \quad (44)
\end{aligned}$$

Therefore, (41) can be written into the following form

$$\begin{aligned}
&\begin{bmatrix} \mathbf{X}(p,q) & \mathbf{X}(p,q)\mathrm{T} \\ * & \Lambda \end{bmatrix} > 0, \\
&\mathrm{T} = [\sqrt{\omega_{p1}\lambda_{q0}}H^{\mathbf{T}}(1,0) \cdots \sqrt{\omega_{pl}\lambda_{qd}}H^{\mathbf{T}}(l,d)], \\
&p = 1,2,\ldots,l, \ \ q = 0,1,2,\ldots,d. \quad (45)
\end{aligned}$$

According to Theorem 1, the system (19) is stochastically stable and the mode-dependent state feedback controller gain is given by $\mathbf{K}(m,n) = \mathbf{R}(m,n)\mathbf{G}^{-1}(m,n)$. This completes the proof. □

4. SIMULATION AND EXPERIMENT

In this section, numerical and practical examples are presented to illustrate the effectiveness of the proposed methods for stochastic stability problem of NCS. As mentioned in section 3, the transmission delay τ_m takes value from the finite set which consists of a series of equidistant small intervals. In the following two examples, both sampling periods are $0.03s$, and the time axis in every sampling period is split into 3 equidistant small intervals and the length of each interval is $0.01s$. Then τ_m takes value from the set $M = \{0.01s, 0.02s, 0.03s\}$. And we use the case that the bound of consecutive dropped packets $d = 2$, then d_m takes value from the set $\Omega = \{0,1,2\}$. Thus, both the Markov chains of time delays and packet dropouts have three operation modes.

Two different transmission conditions of network are considered to validate the effectiveness of the design method:

1) The first network transmission condition

In this network transmission condition, the transition probability matrices of time delays and packet dropouts are given by the matrices Θ_1 and Π_1. We can found that the values of the first column of the matrices are much larger than the values of the third column. That means that the probability of jumping from the current network transmission condition to the good network transmission condition is greater than the poor network transmission condition.

$$\Theta_1 = \begin{bmatrix} 0.5 & 0.3 & 0.2 \\ 0.7 & 0.2 & 0.1 \\ 0.6 & 0.2 & 0.2 \end{bmatrix}, \quad \Pi_1 = \begin{bmatrix} 0.5 & 0.2 & 0.3 \\ 0.5 & 0.4 & 0.1 \\ 0.6 & 0.3 & 0.1 \end{bmatrix}. \tag{46}$$

2) The second network transmission condition

In order to better verify the effectiveness of proposed control method, the second network condition with different transition probability matrices is considered. The representation of transition probability matrices which are given by Θ_2 and Π_2. Compared with the first network transmission condition, the values of the first column are much less than the values of the third column in Θ_2 and Π_2. That represents a poor network transmission condition and the probability of jumping from the current network transmission condition to the good network transmission condition is far less than the poor network transmission condition.

$$\Theta_2 = \begin{bmatrix} 0.2 & 0.3 & 0.5 \\ 0.1 & 0.2 & 0.7 \\ 0.2 & 0.2 & 0.6 \end{bmatrix}, \quad \Pi_2 = \begin{bmatrix} 0.3 & 0.2 & 0.5 \\ 0.1 & 0.4 & 0.5 \\ 0.1 & 0.3 & 0.6 \end{bmatrix}. \tag{47}$$

4.1. Numerical example

In this example, let us consider the following nominal continuous time system

$$\dot{x} = \begin{bmatrix} 0 & 1 \\ -2 & -3 \end{bmatrix} x + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u \tag{48}$$

for the plant which is controlled by the discrete-time Markovian jumping process proposed in Section 2, all possible jump modes are determined by two Markovian jumping parameters τ_m and d_m. The Matlab LMI Control Toolbox is used to solve the LMI feasible problem presented in Theorem 2. Table 1 shows the results of the mode-dependent controller gains in the first network transmission condition. The state trajectories of NCS with the proposed feedback control law in this network transmission condition are shown in Fig. 3. It can be seen that the networked control system is stochastically stable when time delays and packet dropouts happen during data transmission. In the second network transmission condition, for the same plant and the same Markovian jumping parameters τ_m and d_m, mode-dependent controller gains of all possible jump modes also can be obtained by solving the LMI feasible problem presented in Theorem 2. Table 2 shows the results of the mode-dependent controller gains of this case. In this case, the state trajectories of NCS with the feedback control law presented in Table 2 is shown in Fig. 4. Compared with the first network condition, the second network condition is relatively poor. It can be seen that the stability of networked control system still can be guaranteed, but the overshoot of the system states becomes larger, and the stabilization regulating time becomes longer in this situation.

Table 1. The mode-dependent controller gains of numerical plant in the 1st network condition.

	$\tau_1 = 0.01s$	$\tau_2 = 0.02s$	$\tau_3 = 0.03s$
$d_1 = 0$	$K(1,1) = \begin{bmatrix} -1.9671 \\ -2.0383 \end{bmatrix}$	$K(1,2) = \begin{bmatrix} -1.7651 \\ -2.0361 \end{bmatrix}$	$K(1,3) = \begin{bmatrix} -1.3305 \\ -1.7727 \end{bmatrix}$
$d_2 = 1$	$K(2,1) = \begin{bmatrix} -2.0382 \\ -2.1718 \end{bmatrix}$	$K(2,2) = \begin{bmatrix} -1.7881 \\ -2.1606 \end{bmatrix}$	$K(2,3) = \begin{bmatrix} -1.3491 \\ -1.9053 \end{bmatrix}$
$d_3 = 2$	$K(3,1) = \begin{bmatrix} -2.1217 \\ -2.3359 \end{bmatrix}$	$K(3,2) = \begin{bmatrix} -1.8281 \\ -2.3215 \end{bmatrix}$	$K(3,3) = \begin{bmatrix} -1.3809 \\ -2.0703 \end{bmatrix}$

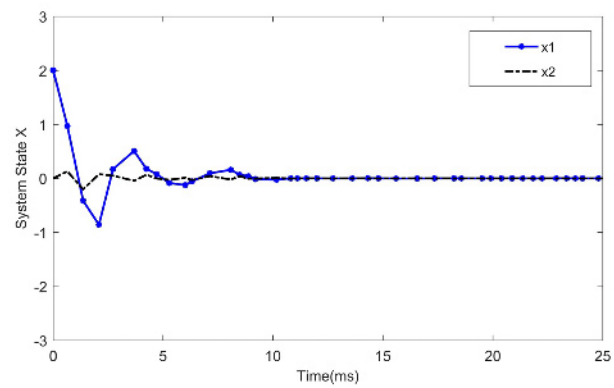

Fig. 3. States trajectory of NCS with the 1st network condition.

Table 2. The mode-dependent controller gains of numerical plant in the 2nd network condition.

	$\tau_1 = 0.01s$	$\tau_2 = 0.02s$	$\tau_3 = 0.03s$
$d_1 = 0$	$K(1,1) = \begin{bmatrix} -3.2185 \\ -3.3905 \end{bmatrix}$	$K(1,2) = \begin{bmatrix} -2.1173 \\ -2.5085 \end{bmatrix}$	$K(1,3) = \begin{bmatrix} -1.4184 \\ -1.9773 \end{bmatrix}$
$d_2 = 1$	$K(2,1) = \begin{bmatrix} -3.5930 \\ -3.9012 \end{bmatrix}$	$K(2,2) = \begin{bmatrix} -2.1538 \\ -2.6780 \end{bmatrix}$	$K(2,3) = \begin{bmatrix} -1.4165 \\ -2.0919 \end{bmatrix}$
$d_3 = 2$	$K(3,1) = \begin{bmatrix} -4.4467 \\ -5.0579 \end{bmatrix}$	$K(3,2) = \begin{bmatrix} -2.2931 \\ -3.0258 \end{bmatrix}$	$K(3,3) = \begin{bmatrix} -1.4417 \\ -2.2870 \end{bmatrix}$

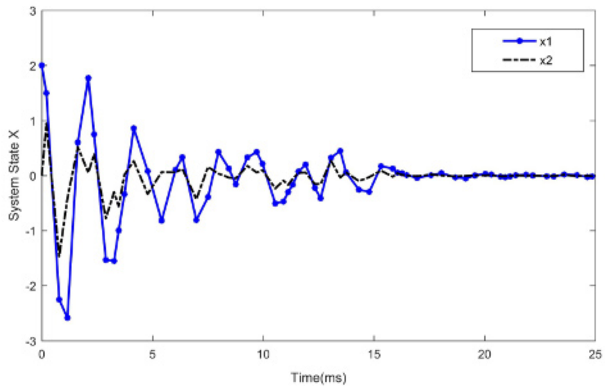

Fig. 4. States trajectory of NCS with the 2nd network condition.

4.2. Practical example

To further validate the proposed method, a servo motor control system which consists of a dc motor, load plate, speed and angle sensors is considered in this section. This servo motor system was identified in [22]. To construct NCS with the servo motor system, a test rig was built based on two ARM 9 embedded boards. The two boards are used, one on the controller side and the other on the plant side, and are connected through the network. The kernel chip of the embedded board is ATMEL's AT91RM9200, which is a high-performance 32-bit RISC micro-controller for Ethernet-based embedded systems. A 10M/100M self-adaptive network controller is integrated in the chip, and the chip also has a high computing performance and can work at speeds up to 180 MHz. Two-channel 16-bit high-speed analog-digital(A/D) converters and eight-channel 16-bit high-speed A/D converters in the controller board provide I/O interfaces for the controlled plant.

The model of the motor control plant was identified and written into a third-order system with the following state-space from

$$\dot{x} = \begin{bmatrix} 1.12 & 0.213 & -0.335 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} x + \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} u,$$
$$y = \begin{bmatrix} 0.0541 & 0.1150 & 0.0001 \end{bmatrix} x. \tag{49}$$

The discrete-time Markovian jumping process is also used to control the servo motor plant and the same Markovian jumping parameters τ_m and d_m are used to determine all possible jump modes. Based on Theorem 2, the LMI feasible problem is solved and the results of the mode-dependent controller gains in the first network transmission condition are showed in Table 3. The output of the servo motor system with the solved controller gains in the first network transmission condition are shown in Fig. 5.

With the same servo motor plant and the same Markovian jumping parameters, the mode-dependent controller gains of all possible jump modes in the second network transmission condition can be obtained. Table 4 shows the results of the mode-dependent controller gains of this case. The output of the NCS with the feedback control law presented in Table 4 is shown in Fig. 6.

Compared Fig. 5 and Fig. 6, we can find that the deterioration of the network condition introduces larger overshoot of the system states and longer stabilization regulating time, but the system stability still can be guaranteed

Table 3. The mode-dependent controller gains of servo system in the 1st network condition.

	$\tau_1 = 0.01s$	$\tau_2 = 0.02s$	$\tau_3 = 0.03s$
$d_1 = 0$	$K(1,1) = \begin{bmatrix} -0.0167 \\ -0.0216 \\ -0.0254 \end{bmatrix}$	$K(1,2) = \begin{bmatrix} -0.0071 \\ -0.0512 \\ -0.0308 \end{bmatrix}$	$K(1,3) = \begin{bmatrix} -0.0422 \\ -0.0047 \\ -0.0112 \end{bmatrix}$
$d_2 = 1$	$K(2,1) = \begin{bmatrix} -0.0171 \\ -0.0150 \\ -0.0378 \end{bmatrix}$	$K(2,2) = \begin{bmatrix} -0.0144 \\ -0.0202 \\ -0.0064 \end{bmatrix}$	$K(2,3) = \begin{bmatrix} -0.0269 \\ -0.0041 \\ -0.0117 \end{bmatrix}$
$d_3 = 2$	$K(3,1) = \begin{bmatrix} -0.0078 \\ -0.0142 \\ -0.0311 \end{bmatrix}$	$K(3,2) = \begin{bmatrix} -0.0104 \\ -0.0204 \\ -0.0159 \end{bmatrix}$	$K(3,3) = \begin{bmatrix} -0.0173 \\ -0.0094 \\ -0.0227 \end{bmatrix}$

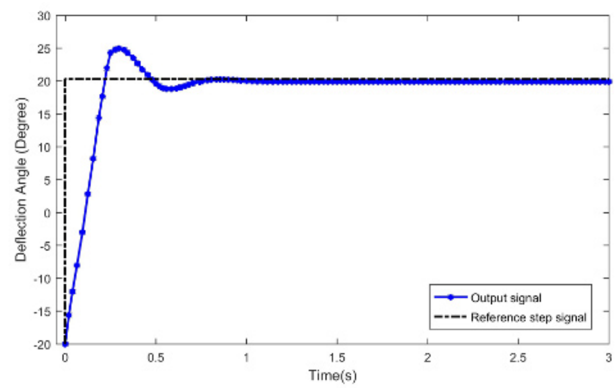

Fig. 5. Output of servo system with the 1st network condition.

Table 4. The mode-dependent controller gains of servo system in the 2nd network condition.

	$\tau_1 = 0.01s$	$\tau_2 = 0.02s$	$\tau_3 = 0.03s$
$d_1 = 0$	$K(1,1) = \begin{bmatrix} -0.0260 \\ -0.0146 \\ -0.0159 \end{bmatrix}$	$K(1,2) = \begin{bmatrix} -0.0152 \\ -0.0097 \\ -0.0215 \end{bmatrix}$	$K(1,3) = \begin{bmatrix} -0.0144 \\ -0.0095 \\ -0.0221 \end{bmatrix}$
$d_2 = 1$	$K(2,1) = \begin{bmatrix} -0.0182 \\ -0.0037 \\ -0.0347 \end{bmatrix}$	$K(2,2) = \begin{bmatrix} -0.0173 \\ -0.0315 \\ -0.0061 \end{bmatrix}$	$K(2,3) = \begin{bmatrix} -0.0228 \\ -0.0029 \\ -0.0157 \end{bmatrix}$
$d_3 = 2$	$K(3,1) = \begin{bmatrix} -0.0171 \\ -0.0192 \\ -0.0067 \end{bmatrix}$	$K(3,2) = \begin{bmatrix} -0.0144 \\ -0.0059 \\ -0.0163 \end{bmatrix}$	$K(3,3) = \begin{bmatrix} -0.0162 \\ -0.0133 \\ -0.0071 \end{bmatrix}$

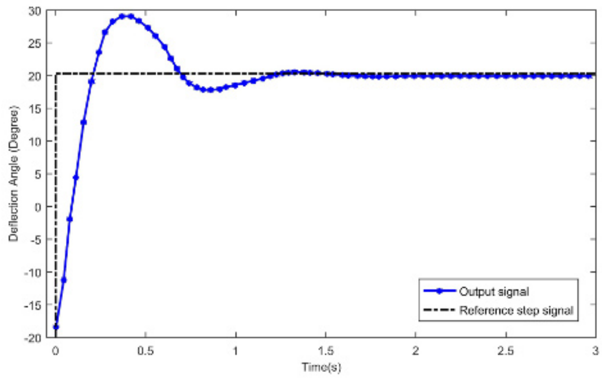

Fig. 6. Output of servo system with the 2nd network condition

with the proposed control law in these two network conditions.

From simulation results above, we can see that with the deterioration of network condition which means the probability of larger delay and more packet drop in Markovian jumping process, the dynamic performance of the system is affected, but the closed-loop NCS with communication limits are effectively stabilized with the mode-dependent state feedback controller obtained by Theorem 2. The results show the effectiveness of the proposed method in this paper.

5. CONCLUSION

The stochastic stability problem of networked control system with destabilizing transmission factors is studied in this paper. Instead of only considering one destabilizing transmission factor with some stochastic distribution, time delays and dropouts processes are characterized by two separately Markov chains to model NCS as a discrete-time Markovian jump system. The effective instant is introduced to establish the relationship between the transmission factors and stability of NCSs. Both time delays less than one sampling period and larger than one sampling period are considered and are dealt with in two different ways. Sufficient conditions for the stochastic stabilization of the NCS with time-varying delays and packet loss are obtained by the Lyapunov function method and the mode-dependent stabilizing controller for the closed-loop NCS is designed in terms of the linear matrix inequalities (LMIs) formulation via the Schur complement theory. Finally numerical examples are given to illustrate the effectiveness of the proposed strategy for the stochastic stabilizing controller over NCS.

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