12th IEEE International Conference on Control & Automation (ICCA)
Kathmandu, Nepal, June 1-3, 2016

Improved Results on Stability of Markovian Jump Systems with Time-Varying Delays

Pengfei Li[1], Yu Kang[1,2], Yunbo Zhao[3], Hongsheng Xi[1], and Jun Wang[4]

Abstract— **The stochastic stability of Markovian jump systems with time-varying delays is investigated. Three delay-partitioning methods, i.e., partitioning $[0, d_{min}]$, $[d_{min}, d_{max}]$ and both, are considered to derive the delay-range-dependent stability criteria. Different Lyapunov-Krasovskii functionals are consequently constructed for the stochastic stability of the system. The effectiveness of those results are finally domonstrated by a numerical example.**

I. Introduction

As a special class of hybrid systems, Markovian jump linear systems (MJLS) are widely used to model dynamical systems subject to random abrupt changes [1]–[8]. These random changes can be caused by component failures, abrupt environment changes, changing subsystem interconnections, and so forth. Investigations into such system include, for example, stability analysis [8], [9], H_∞ control and filtering [8], [10]–[12], exponential estimates [3], [4], state or output feedback controller design [13], etc.

On the other hand, time delay is ubiquitous, as seen in chemical process, neural networks, etc. Time delay usually degrades the system performance, causes oscillation, or even destabilizes the system. [14] considered systems with interval time-varying delays by using the free weighting matrix method. [15] used the convex combination to get a less conservativeness result. [16] proposed the reciprocally convex approach to overcome shortcomings in [15]. Besides, delay-partitioning method is another popular method to deal with constant delay and time-varying delay [17], [18]. Fridman [19] employed two different partitioning ways to improve the stability criteria. [20] noticed the fact that the positive definiteness of LKF does not necessarily require all involved symmetric matrices in Lyapunov-Krasovskii functional (LKF) to be positive definite. This method is powerful in reducing the conservativeness, and therefore we here apply it to Markovian jump linear systems with time-varying delays for an improved stability criteria.

*This work was supported in part by the National High-tech R&D Program of China (863 Program 2014AA06A503), the National Natural Science Foundation of China (61422307, 61304048 and 61174061) and the Scientific Research Staring Foundation for the Returned Overseas Chinese Scholars, Ministry of Education of China. Authors also gratefully acknowledge supports from the Youth Innovation Promotion Association, Chinese Academy of Sciences, the Youth Top-notch Talent Support Program, the 1000-talent Youth Program and the Youth Yangtze River Scholar

[1]Pengfei Li and Hongsheng Xi are with Department of Automation, University of Science and Technology of China, Hefei, China. Puffylee@mail.ustc.edu.cn

[2]Yu Kang, corresponding author, with Department of Automation and State Key Laboratory of Fire Science, University of Science and Technology of China, Hefei,China and with Key Laboratory of Technology in Geo-Spatial Information Processing and Application System, Chinese Academy of Sciences, Beijing,China.Kangduyu@ustc.edu.cn

[3]Yunbo Zhao is with the College of Information Engineering, Zhejiang University of Technology, Hangzhou, China. ybzhao@zjut.edu.cn

[4]Jun Wang with the Key Lab of Machine Vision and Intelligence Control Technology, Hefei University, Hefei, China. wangj@hfuu.edu.cn

Markovian jump linear systems with time delays have been studied extensively. To name a few, Fei [2] used the delay-partitioning method to deal with MJLS with constant delay, for an improved stability results compared to [21]. Huang [14] constructed new Lyapunov functions by choosing different Lyapunov matrices for different system modes. Zhao [22] improved the stochastic stability criteria with interval time-varying delays. Gao [3] investigated the exponential estimates of Markovian jump systems with mode-dependent time-varying delays.

In this paper, we study the stochastic stability of Markovian jump systems with interval time-varying delay. For different values of d_{min}, we adopt different delay-partitioning strategies with different LKFs: $[0, d_{min}]$ for large d_{min}, $[d_{min}, d_{max}]$ for small d_{min}, and we may also use both partitions for more complicated cases. We use the method in [20] to analyse the constructed LKFs for three different delay-partitioning strategies and derive corresponding LMIs to guarantee both the positive definiteness of LKFs and negative definiteness of derivative of the LKFs.

The rest of the paper is organized as follows. The model of Markovian jump systems with time-varying delays and some preliminaries are introduced in Section II. In Section III, we present the main results for different delay-partitioning methods. A numerical example is shown in Section IV to illustrate the effectiveness of the proposed results. Finally, Section V concludes the paper.

Notations. Throughout this paper, $\mathbb{R}^n$ represents the n-dimensional Euclidean space. For symmetric matrix X, $X > 0$ means that X is positive definite (negative definite) and $X \geq 0$ ($X \leq 0$) means that X is semi-positive definite (semi-negative definite). $diag\{\dots\}$ stands for block diagonal matrix. I_n is the n-dimensional identity matrix and $0_{n\times m}$ is the $n \times m$-dimensional zero matrix. The asterisk $*$ represents a term that is induced by symmetry. For $d > 0, \mathcal{C}^1([-d, 0]; \mathbb{R}^n)$ denotes the class of smooth functions ϕ from $[-d, 0]$ to $\mathbb{R}^n$ with norm $||\phi|| = \sup_{-d\leq\theta\leq 0} |\phi(\theta)|$. $E(.)$ denotes mathematical expectation.

II. Problem formulation

The considered Markovian jump linear system with mode-independent interval time-varying delays is described by

$$\dot{x}(t) = A(r(t))x(t) + A_d(r(t))x(t - d(t)) \tag{1}$$

$$x(t) = \phi(t), \quad t \in [-d_{max}, 0], \quad r(0) = r_0, \tag{2}$$

where $x(t) \in \mathbb{R}^n$ is the n-dimensional vector represents system state vector, $A(r(t)), A_d(r(t))$ are matrix functions of the stochastic jumping process $\{r(t), t \geq 0\}$, $\{r(t)\}$ is a continuous-time Markov process, which takes values in the finite discrete set $\mathcal{S} = \{1, 2, \ldots, N\}$. Let $\Pi = [\pi_{ij}]$, where $i, j = 1, 2, \ldots, N$, denote the transition probability matrix with

$$Pr\{r(t+\Delta) = j | r(t) = i\} = \begin{cases} \pi_{ij}\Delta + o(\Delta) & i \neq j \\ 1 + \pi_{ii}\Delta + o(\Delta) & i = j \end{cases} \tag{3}$$

where $\Delta > 0, \lim_{\Delta \to 0^+} o(\Delta)/\Delta = 0$, and $\pi_{ij} \geq 0$, for $i \neq j$, is the transition rate from mode i at time t to mode j at time $t + \Delta$, with $\pi_{ii} = -\sum_{j \neq i} \pi_{ij}$ for each mode $i \in \mathcal{S}$. $d(t)$ denotes the mode-independent time-varying state delay in the above Markovian jump system, and satisfies

$$0 \leq d_{min} \leq d(t) \leq d_{max} < \infty \tag{4}$$

$$\dot{d}(t) \leq \mu \tag{5}$$

where d_{min}, d_{max} and μ are constant and independent of mode $r(t)$. $\phi(t) \in \mathcal{C}^1([-d_{max}, 0]; \mathbb{R}^n)$ and $r(0) = r_0$ are initial conditions of the system state and mode, respectively. For the simplicity of notations, $r(t) = i \in \mathcal{S}$, $A(r(t))$ and $A_d(r(t))$ are denoted as A_i and A_{di}.

Let $x_t = x(t+s), -d_{max} \leq s \leq 0$. According to [5] and [1], $\{(x_t, r(t)), t \geq 0\}$ is a Markov process with initial state $(\phi(.), r(0))$. Let $\mathcal{L}$ is the weak infinitesimal operator of the stochastic process $\{(x_t, r(t))\}$, $\mathcal{L}$ acting on $V(x_t, i, t)$ is defined as follows,

$$\begin{aligned} &\mathcal{L}V(x_t, i, t) \\ &= \lim_{\Delta \to 0^+} \frac{1}{\Delta}[E\{V(x(t+\Delta), r(t+\Delta), t+\Delta) | x_t, r(t) = i\} \\ &\quad - V(x_t, i, t)] \end{aligned} \tag{6}$$

Next, we'll introduce the definition of the stochastic stability and some useful lemmas.

Definition 1: Markovian jump system (1) with (2) is said to be stochastically stable if, for any initial state $\phi(t)$ and initial mode r_0, the following condition is satisfied

$$\lim_{t \to \infty} E\left\{\int_0^t x^T(t)x(t)dt | \phi, r_0\right\} < \infty \tag{7}$$

Lemma 1 (Jensen's inequality [23]): For any constant symmetry matrix $M \in \mathbb{R}^{n \times n}$ with $M > 0$, scalars $b > a$, vector function $\omega : [a, b] \to \mathbb{R}^m$ such that the integrations in the following are well defined, then

$$\int_a^b \omega^T(t) M \omega(t) dt \geq \frac{1}{b-a}\left[\int_a^b \omega(t)dt\right]^T M \left[\int_a^b \omega(t)dt\right]$$

Lemma 2 ([16]): Let $f_i : \mathbb{R}^m \to \mathbb{R}$ $(i = 1, 2, \ldots, N)$ have positive values in an open subset $\mathcal{D}$ of $\mathbb{R}^m$. Then, the reciprocally convex combination of f_i over $\mathcal{D}$ satisfies

$$\min_{\{\beta_i | \beta_i > 0, \sum_i \beta_i = 1\}} \sum_i \frac{1}{\beta_i} f_i(t) = \sum_i f_i(t) + \max_{g_{i,j}(t)} \sum_{i \neq j} g_{i,j}(t)$$

subject to

$$\left\{g_{i,j} : \mathbb{R}^m \to \mathbb{R}, g_{j,i}(t) = g_{i,j}(t), \begin{bmatrix} f_i(t) & g_{i,j}(t) \\ g_{i,j}(t) & f_j(t) \end{bmatrix} \geq 0\right\}.$$

III. MAIN RESULTS

In this section, three different delay-partitioning methods are used to deal with the mode-independent time-varying delay. The first method is to divide the interval $[0, d_{min}]$ into r parts. This method fails if $d_{min} = 0$. Thus the second method is proposed to partition the interval to $[d_{min}, d_{max}]$. The third method is the combination of the first two.

A. The partition of $[0, d_{min}]$

For the simplicity of notations, denote $d_0 = d_{min}$ and $d_1 = d_{max}$.

Theorem 1: Given scalars $d_0 > 0, d_1, \mu$ and partitioning parts r, the system (1) is stochastically stable if there exist positive definite matrices $M > 0, R > 0, R_i > 0, Z_i > 0, (i \in \mathcal{S})$ and $Z > 0$, real symmetric matrices P_i, Q, Q_i, S, S_i and real matrices Y_i, such that the following LMIs hold for $i = 1, 2, \ldots, N$:

$$\Xi_3 > 0 \tag{8}$$

$$S + \frac{Z}{d_1} > 0 \tag{9}$$

$$\Sigma_1 = \begin{bmatrix} \Xi_1 & -Z_i & -Z \\ * & d_1 S_i + Z_i & 0 \\ * & * & S + \frac{Z}{d_1} \end{bmatrix} > 0 \tag{10}$$

$$\Sigma_2 = \begin{bmatrix} \frac{P_i}{2} + \frac{d_0}{2r}R + R_i & -R_i W_r & -R W_r \\ * & \Xi_2 & 0 \\ * & * & \Xi_3 \end{bmatrix} > 0 \tag{11}$$

$$\Lambda_1 < 0 \tag{12}$$

$$\Theta_{3i} = \begin{bmatrix} \frac{\Phi}{2} + W_2^T \Lambda_1 W_2 & -W_2^T \Lambda_1 W_r \\ * & W_r^T \Lambda_1 W_r + \frac{d_0}{r}\Lambda_2 \end{bmatrix} < 0 \tag{13}$$

$$\Lambda_3 < 0 \tag{14}$$

$$\Theta_{4i} = \begin{bmatrix} \frac{d_1 \Phi}{2(d_1 - d_0)} + W_2^T \Lambda_3 W_2 & -W_2^T \Lambda_3 \\ * & \Lambda_3 + d_1 \Lambda_4 \end{bmatrix} < 0 \tag{15}$$

$$\begin{bmatrix} \frac{Z_i}{d_1 - d_0} & Y_i \\ Y_i^T & \frac{Z_i}{d_1 - d_0} \end{bmatrix} \geq 0 \tag{16}$$

where

$$\begin{aligned} \Phi &= W_2^T P_i W_1 + W_1^T P_i W_2 + W_2^T(\sum_{j=1}^N \pi_{ij} P_j + M) W_2 \\ &+ W_3^T Q_i W_3 - W_4^T Q_i W_4 - (1-\mu) W_5^T M W_5 \\ &+ \frac{d_0}{r} W_3^T Q W_3 - \frac{r}{d_0}(W_2 - W_6)^T R_i (W_2 - W_6) \\ &+ W_1^T(\frac{d_0 R_i}{r} + \frac{d_0^2 R}{2r^2} + (d_1 - d_0) Z_i + \frac{d_1^2 - d_0^2}{2} Z) W_1 \\ &+ W_7^T S_i W_7 - W_8^T S_i W_8 \\ &- \begin{bmatrix} W_5 - W_7 \\ W_5 - W_8 \end{bmatrix}^T \begin{bmatrix} \frac{Z_i}{d_1 - d_0} & Y_i \\ Y_i^T & \frac{Z_i}{d_1 - d_0} \end{bmatrix} \begin{bmatrix} W_5 - W_7 \\ W_5 - W_8 \end{bmatrix} \end{aligned}$$

$$W_1 = [A_i, \ 0_{n \times (r+1)n}, \ A_{di}]; \quad W_2 = [I_n, \ 0_{n \times (r+2)n}]$$

$W_3 = [I_{rn},\ 0_{rn\times 3n}]$; $\quad W_4 = [0_{rn\times n},\ I_{rn},\ 0_{rn\times 2n}]$
$W_5 = [0_{n\times(r+2)n},\ I_n]$; $\quad W_6 = [0_{n\times n},\ I_n,\ 0_{n\times(r+1)n}]$
$W_7 = [0_{n\times rn}, I_n, 0_{n\times 2n}]$; $\quad W_8 = [0_{n\times(r+1)n}, I_n, 0_{n\times n}]$
$W_r = [I_n,\ 0_{n\times(r-1)n}]$

$$\Xi_1 = \frac{d_1 P_i}{2(d_1-d_0)} + \frac{d_1+d_0}{2}Z + Z_i$$

$$\Xi_2 = \frac{d_0}{r}Q_i + W_r^T R_i W_r \quad \Xi_3 = Q + \frac{r}{d_0}W_r^T R W_r$$

$$\Lambda_1 = \sum_{j=1}^{N}\pi_{ij}R_j - R; \qquad \Lambda_2 = \sum_{j=1}^{N}\pi_{ij}Q_j - Q$$

$$\Lambda_3 = \sum_{j=1}^{N}\pi_{ij}Z_j - Z; \qquad \Lambda_4 = \sum_{j=1}^{N}\pi_{ij}S_j - S$$

Proof: Consider the following Lyapunov-Krasovskii functional(LKF):

$$V(x_t,i,t) = V_1(x_t,i,t) + V_2(x_t,i,t) + V_3(x_t,i,t) \quad (17)$$

where

$$V_1(x_t,i,t) = x^T(t)P_i x(t) + \int_{t-d(t)}^{t} x^T(s)Mx(s)ds$$

$$\begin{aligned} V_2(x_t,i,t) = &\int_{t-\frac{d_0}{r}}^{t} \eta_1^T(s)Q_i\eta_1(s)ds \\ &+ \int_{-\frac{d_0}{r}}^{0}\int_{t+\theta}^{t}\eta_1^T(s)Q\eta_1(s)dsd\theta \\ &+ \int_{-\frac{d_0}{r}}^{0}\int_{t+\theta}^{t}\dot{x}^T(s)R_i\dot{x}(s)dsd\theta \\ &+ \int_{-\frac{d_0}{r}}^{0}\int_{\theta}^{0}\int_{t+\beta}^{t}\dot{x}^T(s)R\dot{x}(s)dsd\beta d\theta \end{aligned}$$

$$\begin{aligned} V_3(x_t,i,t) = &\int_{t-d_1}^{t-d_0} x^T(s)S_i x(s)ds \\ &+ \int_{-d_1}^{-d_0}\int_{t+\theta}^{t} x^T(s)Sx(s)dsd\theta \\ &+ \int_{-d_1}^{-d_0}\int_{t+\theta}^{t}\dot{x}^T(s)Z_i\dot{x}(s)dsd\theta \\ &+ \int_{-d_1}^{-d_0}\int_{\theta}^{0}\int_{t+\beta}^{t}\dot{x}^T(s)Z\dot{x}(s)dsd\beta d\theta \end{aligned}$$

with$\eta_1(s) = \left[x^T(s),\ x^T(s-\frac{d_0}{r}),\ldots,x^T(s-\frac{(r-1)d_0}{r})\right]^T$ and $M>0,\ R_i>0,\ R>0,\ Z_i>0$ and $Z>0$.

Firstly, we use Lemma 1 to get a lower bound of the proposed LKF. Notice that

$$\begin{aligned} &\int_{-\frac{d_0}{r}}^{0}\int_{\theta}^{0}\int_{t+\beta}^{t}\dot{x}^T(s)R\dot{x}(s)dsd\beta d\theta \\ &\geq \frac{d_0}{2r}x^T(t)Rx(t) - \frac{2r}{d_0}\int_{-\frac{d_0}{r}}^{0}x^T(t)R\int_{t+\theta}^{t}W_r\eta_1(s)dsd\theta \\ &\quad + \frac{r}{d_0}\int_{-\frac{d_0}{r}}^{0}\int_{t+\theta}^{t}\eta_1^T(s)W_r^T RW_r\eta_1(s)dsd\theta. \end{aligned}$$

we have

$$\begin{aligned} &V_2(x_t,i,t) + x^T(t)\frac{P_i}{2}x(t) \\ &\geq x^T(t)(\frac{P_i}{2} + \frac{d_0 R}{2r})x(t) + \frac{r}{d_0}\int_{t-\frac{d_1}{r}}^{t}\eta_1^T(s)\frac{d_0}{r}Q_i\eta_1(s)ds \\ &- \frac{2r}{d_0}\int_{-\frac{d_0}{r}}^{0}x^T(t)R\int_{t+\theta}^{t}W_r\eta_1(s)dsd\theta \\ &+ \frac{r}{d_0}\int_{-\frac{d_0}{r}}^{0}\left[\int_{t+\theta}^{t}\eta_1(s)ds\right]^T(Q + \frac{rW_r^T RW_r}{d_0})\left[\int_{t+\theta}^{t}\eta_1(s)ds\right]d\theta \\ &+ \frac{r}{d_0}\int_{t-\frac{d_0}{r}}^{t}\left[x(t) - W_r\eta_1(s)\right]^T R_i\left[x(t) - W_r\eta_1(s)\right]ds \\ &= \frac{r}{d_0}\int_{t-\frac{d_0}{r}}^{t}\zeta_1^T\Sigma_1\zeta_1 ds \end{aligned}$$

where $\zeta_1 = [x^T(t)\ \ \eta_1^T(s)\ \ \int_{t+\theta}^{t}\eta_1^T(s)ds]^T$.

Similarly, we can obtain,

$$V_3(x_t,i,t) + x^T(t)\frac{P_i}{2}x(t) \geq \frac{1}{d_1}\int_{t-d_1}^{t-d_0}\zeta_2^T\Sigma_2\zeta_2 ds$$

where $\zeta_2 = [x^T(t)\ \ x^T(s)\ \ \int_{t+\theta}^{t}x^T(s)ds]^T$. If (10) and (11) hold, then $V(x_t,i,t) > 0$.

In order to show that $\mathcal{L}V(x_t,i,t) < 0$. we get

$$\begin{aligned} &\mathcal{L}V_3(x_t,i,t) \leq x^T(t-d_0)S_i x(t-d_0) + (d_1-d_0)x^T(t)Sx(t) \\ &\quad - x^T(t-d_1)S_i x(t-d_1) - \int_{t-d_1}^{t-d_0}\dot{x}^T(s)Z_i\dot{x}(s)ds \\ &\quad + \int_{t-d_1}^{t-d_0}x^T(s)(\sum_{j=1}^{N}\pi_{ij}S_j - S)x(s)ds \\ &\quad + \dot{x}^T(t)[(d_1-d_0)Z_i + \frac{d_1^2-d_0^2}{2}Z]\dot{x}(t) \\ &\quad + \int_{-d_1}^{-d_0}\int_{t+\theta}^{t}\dot{x}^T(s)(\sum_{j=1}^{N}\pi_{ij}Z_j - Z)\dot{x}(s)dsd\theta \end{aligned} \quad (18)$$

Suppose that $d_0 < d(t) < d_1$, then by using Lemma 1 and Lemma 2, it yields that

$$\begin{aligned} &-\int_{t-d_1}^{t-d_0}\dot{x}^T(s)Z_i\dot{x}(s)ds \\ &\leq -\begin{bmatrix} x(t-d(t)) - x(t-d_0) \\ x(t-d(t)) - x(t-d_1)\end{bmatrix}^T \begin{bmatrix} \frac{Z_i}{d_1-d_0} & Y_i \\ * & \frac{Z_i}{d_1-d_0}\end{bmatrix} \\ &\quad \begin{bmatrix} x(t-d(t)) - x(t-d_0) \\ x(t-d(t)) - x(t-d_1)\end{bmatrix} \end{aligned} \quad (19)$$

When $d(t) = d_0$ or $d(t) = d_1$, the above inequality still holds since $x(t-d(t)) - x(t-d_0) = 0$ or $x(t-d(t)) - x(t-d_1) = 0$. Similarly, we can also get the upper bound of $\mathcal{L}V_1(x_t,i,t)$ and $\mathcal{L}V_2(x_t,i,t)$, and together with (18), (19), we can obtain

$$\begin{aligned} &\mathcal{L}V(x_t,i,t) \leq \xi^T(t)\Phi\xi(t) \\ &\quad + \int_{t-\frac{d_0}{r}}^{t}\eta_1^T(s)\Lambda_2\eta_1(s)ds + \int_{-\frac{d_0}{r}}^{0}\int_{t+\theta}^{t}\dot{x}^T(s)\Lambda_1\dot{x}(s)dsd\theta \\ &\quad + \int_{t-d_1}^{t-d_0}x^T(s)\Lambda_4 x(s)ds + \int_{-d_1}^{-d_0}\int_{t+\theta}^{t}\dot{x}^T(s)\Lambda_3\dot{x}(s)dsd\theta \end{aligned}$$

where $\xi(t) = \left[\eta_1^T(t), x^T(t-d_0), x^T(t-d_1), x^T(t-d(t))\right]^T$.

If (12) and (14) hold, we use Lemma 1 once again and obtain the following inequality,

$$\mathcal{L}V(x_t,i,t) \leq \frac{r}{d_0}\int_{t-\frac{d_0}{r}}^{t} \zeta_3^T(t)\Theta_{3i}\zeta_3(t) + \frac{1}{d_1}\int_{t-d_1}^{t-d_0} \zeta_4^T(t)\Theta_{4i}\zeta_4(t)$$

where $\zeta_3 = [\xi^T(t),\ \eta_1^T(s)]^T$ and $\zeta_4 = [\xi^T(t),\ x^T(s)]^T$. If the conditions (13) and (15) both hold, then $\mathcal{L}V(x_t,i,t) < 0$.

Under the conditions $V(x_t,i,t) > 0$ and $\mathcal{L}V(x_t,i,t) < 0$, similar with [4], we can easily show the system (1) is stochastically stable, so the procedure is omitted for brevity. This completes the proof. ■

B. *The partition of* $[d_{min}, d_{max}]$

In this section, the interval $[d_{min}, d_{max}]$ is uniformly divided into m parts, i.e. $[d_{min}, d_{max}] = \bigcup_{k=1}^{m}[d_{k-1}, d_k]$, where $d_0 = d_{min}$, $d_m = d_{max}$ and $d_k = \frac{m-k}{m}d_0 + \frac{k}{m}d_m$. Let $d_{ij} = d_i - d_j$, and then $d_{k(k-1)} = \frac{d_{m0}}{m}$.

Theorem 2: Given scalars $d_0 \geq 0, d_m$ and partitioning parts m, the system (1) is stochastically stable if there exist positive definite matrices $M > 0, R > 0, R_i > 0$ $(i \in \mathcal{S}), Z_{il} > 0, Z_l > 0$ $(l = 1,2,\ldots,m)$, real symmetric matrices P_i, Q, Q_i, S, S_i and real matrices Y_{il}, such that the following LMIs hold for $i = 1,2,\ldots,N$:

$$Q + \frac{R}{d_0} > 0 \qquad (20)$$

$$\begin{bmatrix} \frac{P_i}{2} + \frac{d_0 R}{2} + R_i & -R_i & -R \\ * & R_i + d_0 Q_i & 0 \\ * & * & Q + \frac{R}{d_0} \end{bmatrix} > 0 \qquad (21)$$

$$\Xi_{33} > 0 \qquad (22)$$

$$\begin{bmatrix} \Xi_{11} & -\Xi_{12} & -\Xi_{13} \\ * & \Xi_{22} & 0 \\ * & * & \Xi_{33} \end{bmatrix} > 0 \qquad (23)$$

$$\Lambda_1 < 0 \qquad (24)$$

$$\begin{bmatrix} \frac{\Omega+\Omega_l}{2} + W_2^T\Lambda_1 W_2 & -W_2^T\Lambda_1 \\ * & d_0\Lambda_2 + \Lambda_1 \end{bmatrix} < 0 \qquad (25)$$

$$\Xi < 0 \qquad (26)$$

$$\begin{bmatrix} \frac{m(\Omega+\Omega_l)}{2d_{m0}} + W_2^T W_e^T \Xi W_e W_2 & -W_2^T W_e^T \Xi \\ * & \Lambda_4 + \Xi \end{bmatrix} < 0 \qquad (27)$$

$$\begin{bmatrix} \frac{mZ_{il}}{d_{m0}} & Y_{il} \\ * & \frac{mZ_{il}}{d_{m0}} \end{bmatrix} \geq 0 \qquad (28)$$

where

$$\Omega = W_2^T P_i W_1 + W_1^T P_i W_2 + W_2^T(\sum_{j=1}^{N}\pi_{ij}P_j + Q_i + M + d_0 Q)W_2 - W_6^T Q_i W_6 - (1-\mu)W_5^T M W_5 + W_1^T(d_0 R_i + \frac{d_0^2}{2}R + \frac{d_{m0}}{m}\sum_{k=1}^{m} Z_{ik} + \sum_{k=1}^{m}\frac{d_k^2 - d_{k-1}^2}{2}Z_k)W_1 + W_3^T(\frac{d_{m0}}{m}S + S_i)W_3 - W_4^T S_i W_4 - \frac{1}{d_0}(W_2 - W_6)^T R_i (W_2 - W_6)$$

$$\Omega_l = -\frac{m}{d_{m0}}\sum_{k=1,k\neq l}^{m}(W_{k+6} - W_{k+5})^T Z_{ik}(W_{k+6} - W_{k+5}) - \begin{bmatrix} W_5 - W_{l+6} \\ W_5 - W_{l+5} \end{bmatrix}^T \begin{bmatrix} \frac{mZ_{il}}{d_{m0}} & Y_{il} \\ * & \frac{mZ_{il}}{d_{m0}} \end{bmatrix} \begin{bmatrix} W_5 - W_{l+6} \\ W_5 - W_{l+5} \end{bmatrix}$$

$$W_1 = [A_i,\ 0_{n\times(m+1)n},\ A_{di}]; \quad W_2 = [I_n,\ 0_{n\times(m+2)n}];$$
$$W_3 = [0_{mn\times n},\ I_{mn},\ 0_{mn\times 2n}];$$
$$W_4 = [0_{mn\times 2n},\ I_{mn},\ 0_{mn\times n}];$$
$$W_5 = [0_{n\times(m+2)n},\ I_n]; \quad W_6 = [0_{n\times n},\ I_n,\ 0_{n\times(m+1)n}];$$
$$W_{k+6} = [0_{n\times(k+1)n}, I_n, 0_{n\times(m-k+1)n}]; \quad k = 1,2,\ldots,m$$
$$W_e = [I_n, I_n, \ldots, I_n]_{n\times mn}^T$$

$$\Lambda_{3k} = \sum_{j=1}^{N}\pi_{ij}Z_{jk} - Z_k \quad k = 1,2,\ldots,m$$

$$\Xi = diag\left\{\frac{\Lambda_{31}}{d_1}, \frac{\Lambda_{32}}{d_2}, \ldots, \frac{\Lambda_{3m}}{d_m}\right\}$$

$$\Xi_{11} = \frac{mP_i}{2d_{m0}} + \frac{d_{m0}}{2m}\sum_{k=1}^{m}\frac{Z_k}{d_k} + \sum_{k=1}^{N}\frac{Z_{ik}}{d_k}$$

$$\Xi_{12} = \left[\frac{Z_{i1}}{d_1}, \frac{Z_{i2}}{d_2}, \ldots, \frac{Z_{im}}{d_m}\right]; \quad \Xi_{13} = \left[\frac{Z_1}{d_1}, \frac{Z_2}{d_2}, \ldots, \frac{Z_m}{d_m}\right]$$

$$\Xi_{22} = diag\left\{\frac{Z_{i1}}{d_1}, \frac{Z_{i2}}{d_2}, \ldots, \frac{Z_{im}}{d_m}\right\} + S_i$$

$$\Xi_{33} = diag\left\{\frac{Z_1}{d_1}, \frac{Z_2}{d_2}, \ldots, \frac{Z_m}{d_m}\right\} + S$$

$\Lambda_1, \Lambda_2, \Lambda_4$ is the same with Theorem 1.

Proof: The theorem can be proved by construct the following LKF.

$$V(x_t,i,t) = V_1(x_t,i,t) + V_4(x_t,i,t) + V_5(x_t,i,t) \qquad (29)$$

where $V_1(x_t,i,t)$ is the same as in Theorem 1, and

$$V_4(x_t,i,t) = \int_{t-d_0}^{t} x^T(s)Q_i x(s)ds + \int_{-d_0}^{0}\int_{t+\theta}^{t} x^T(s)Qx(s)dsd\theta + \int_{-d_0}^{0}\int_{t+\theta}^{t}\dot{x}^T(s)R_i\dot{x}(s)dsd\theta + \int_{-d_0}^{0}\int_{\theta}^{0}\int_{t+\beta}^{t}\dot{x}^T(s)R\dot{x}(s)dsd\beta d\theta$$

$$V_5(x_t,i,t) = \int_{t-\frac{d_{m0}}{m}}^{t}\eta_2^T(s)S_i\eta_2(s)ds + \int_{-\frac{d_{m0}}{m}}^{0}\int_{t+\theta}^{t}\eta_2^T(s)S\eta_2(s)dsd\theta + \sum_{k=1}^{m}\int_{-d_k}^{-d_{k-1}}\int_{t+\theta}^{t}\dot{x}^T(s)Z_{ik}\dot{x}(s)dsd\theta$$

$$+\sum_{k=1}^{m}\int_{-d_k}^{-d_{k-1}}\int_{\theta}^{0}\int_{t+\beta}^{t}\dot{x}^T(s)Z_k\dot{x}(s)dsd\beta d\theta$$

with$\eta_2(s)=[x^T(s-d_0),\ x^T(s-d_1),\dots,x^T(s-d_{m-1})]^T$ and $P_i>0,\ M>0,\ R_i>0,\ R>0,\ Z_{ik}>0$ and $Z_k>0$. Since $Z_k>0$, we have

$$\int_{-d_k}^{-d_{k-1}}\int_{\theta}^{0}\int_{t+\beta}^{t}\dot{x}^T(s)Z_k\dot{x}(s)dsd\beta d\theta \geq \int_{-d_k}^{-d_{k-1}}\int_{\theta}^{-d_{k-1}}\int_{t+\beta}^{t}\dot{x}^T(s)Z_k\dot{x}(s)dsd\beta d\theta$$

Then

$$\begin{aligned}&\sum_{k=1}^{m}\int_{-d_k}^{-d_{k-1}}\int_{\theta}^{-d_{k-1}}\int_{t+\beta}^{t}\dot{x}^T(s)Z_k\dot{x}(s)dsd\beta d\theta\\ &\leq \frac{d_{m0}^2}{2m^2}x^T(t)\sum_{k=1}^{m}\frac{Z_k}{d_k}x(t)\\ &\quad -2\int_{-\frac{d_{m0}}{m}}^{0}x^T(t)\int_{t+\theta}^{t}\Xi_{13}\eta_2(s)dsd\theta\\ &\quad +\int_{-\frac{d_{m0}}{m}}^{0}\int_{t+\theta}^{t}\eta_2^T(s)diag\left\{\frac{Z_1}{d_1},\frac{Z_2}{d_2},\dots,\frac{Z_m}{d_m}\right\}\eta_2(s)dsd\theta\end{aligned}$$

The framework of proof for $V(x_t,i,t)>0$ is similar to Theorem 1, and thus is omitted here. Hence, if (20)-(23) hold, then $V(x_t,i,t)>0$.

The proof of $\mathcal{L}V(x_t,i,t)<0$ is almost the same as Theorem 1, except for the handling method of $-\sum_{k=1}^{m}\int_{t-d_k}^{t-d_{k-1}}\dot{x}^T(\theta)Z_{ik}\dot{x}(\theta)d\theta$. Assuming that $d(t)\in[d_{l-1},d_l]$, $l=1,2,\dots,m$ yields

$$\begin{aligned}&-\sum_{k=1}^{m}\int_{t-d_k}^{t-d_{k-1}}\dot{x}^T(\theta)Z_{ik}\dot{x}(\theta)d\theta\\ &\leq -\frac{m}{d_{m0}}\sum_{k=1,k\neq l}^{m}[x(t-d_{k-1})-x(t-d_k)]^TZ_{ik}\\ &\qquad [x(t-d_{k-1})-x(t-d_k)]\\ &\quad -\begin{bmatrix}x(t-d(t))-x(t-d_l)\\ x(t-d(t))-x(t-d_{l-1})\end{bmatrix}^T\begin{bmatrix}\frac{mZ_{il}}{d_{m0}} & Y_{il}\\ * & \frac{mZ_{il}}{d_{m0}}\end{bmatrix}\\ &\quad \begin{bmatrix}x(t-d(t))-x(t-d_l)\\ x(t-d(t))-x(t-d_{l-1})\end{bmatrix}\end{aligned}$$

where the condition (28) must be satisfied. By some calculations, we can conclude that if (24)-(28) hold, then $\mathcal{L}V(x_t,i,t)<0$.

The procedure of proving stochastically stable is similar to that of Theorem 1 and is thus omitted here. ■

C. Divide both $[0,d_{min}]$ *and* $[d_{min},d_{max}]$

In this section, we partition $[0,d_{min}]$ into r parts and $[d_{min},d_{max}]$ into m parts at the same time, and then derive the corresponding stochastic stability criterion. Denote $\eta_1(s)=[x^T(s),\ x^T(s-\frac{d_0}{r}),\dots,x^T(s-\frac{(r-1)d_0}{r})]^T$ and $\eta_2(s)=[x^T(s-d_0),\ x^T(s-d_1),\dots,x^T(s-d_{m-1})]^T$, where $d_0,\ d_1,\dots,\ d_m$ is the same as in previous section.

Theorem 3: Given scalars $d_0\geq 0, d_m,\mu$ and the partitioning parts r,m, the system (1) is stochastically stable if there exist real matrices $M>0,R>0,R_i>0,Z_{il}>0,(i\in\mathcal{S})$ and $Z_l>0$ $(l=1,2,\dots,m)$, real symmetric matrices P_i,Q,Q_i,S,S_i and real matrices Y_{il} such that (8) (11) (12) (24) (25) (28) (30) and the following LMIs hold for $i=1,2,\dots,N$:

$$\begin{bmatrix}\frac{\Omega+\Omega_l}{2}+W_2^T\Lambda_1W_2 & -W_2^T\Lambda_1W_r\\ * & W_r^T\Lambda_1W_r+\frac{d_0}{r}\Lambda_2\end{bmatrix}<0 \qquad (30)$$

$$\begin{bmatrix}\frac{m(\Omega+\Omega_l)}{2d_{m0}}+W_2^TW_e^T\Xi W_eW_2 & -W_2^TW_e^T\Xi\\ * & \Lambda_4+\Xi\end{bmatrix}<0 \qquad (31)$$

where

$$\begin{aligned}\Omega &= W_2^TP_iW_1+W_1^TP_iW_2+W_2^T(\sum_{j=1}^{N}\pi_{ij}P_j+M)W_2\\ &\quad +W_3^TQ_iW_3-W_4^TQ_iW_4-(1-\mu)W_7^TMW_7\\ &\quad +\frac{d_0}{r}W_3^TQW_3+W_1^T(\frac{d_0}{r}R_i+\frac{d_0^2}{2r^2}R+\frac{d_{m0}}{m}\sum_{k=1}^{m}Z_{ik}\\ &\quad +\sum_{k=1}^{m}\frac{d_k^2-d_{k-1}^2}{2}Z_k)W_1+W_5^T(\frac{d_{m0}}{m}S+S_i)W_5\\ &\quad -W_6^TS_iW_6-\frac{r}{d_0}(W_2-W_8)^TR_i(W_2-W_8)\end{aligned}$$

$$\begin{aligned}\Omega_l &= -\frac{m}{d_{m0}}\sum_{k=1,k\neq l}^{m}(W_{k+8}-W_{k+9})^TZ_{ik}(W_{k+8}-W_{k+9})\\ &\quad -\begin{bmatrix}W_7-W_{l+9}\\ W_7-W_{l+8}\end{bmatrix}^T\begin{bmatrix}\frac{mZ_{il}}{d_{m0}} & Y_{il}\\ * & \frac{mZ_{il}}{d_{m0}}\end{bmatrix}\begin{bmatrix}W_7-W_{l+9}\\ W_7-W_{l+8}\end{bmatrix}\end{aligned}$$

$$\begin{aligned}&W_1=[A_i,\ 0_{n\times(m+r)n},\ A_{di}];\quad W_2=[I_n,\ 0_{n\times(r+m+1)n}];\\ &W_3=[I_{rn},\ 0_{rn\times(m+2)n}];\\ &W_4=[0_{rn\times n},\ I_{rn},\ 0_{rn\times(m+1)n}];\\ &W_5=[0_{mn\times rn},\ I_{mn},\ 0_{mn\times 2n}];\\ &W_6=[0_{mn\times(r+1)n},\ I_{mn},\ 0_{mn\times n}];\\ &W_7=[0_{n\times(m+r+1)n},\ I_n];\ W_8=[0_{n\times n},\ I_n,\ 0_{n\times(r+m)n}];\\ &W_9=[0_{n\times rn},\ I_n,\ 0_{mn\times n}];\\ &W_{9+k}=[0_{n\times(k+r)n},I_n,0_{n\times(m-k+1)n}];\quad k=1,2,\dots,m\\ &W_e=[I_n,I_n,\dots,I_n]^T_{n\times mn}\end{aligned}$$

and $\Lambda_1,\Lambda_2,\Lambda_3,\Lambda_4,\Xi,\Xi_{11},\Xi_{12},\Xi_{13},\Xi_{22}$ and Ξ_{33} are the same in Theorem 2.

Proof: Consider the following LKF:

$$V(x_t,i,t)=V_1(x_t,i,t)+V_2(x_t,i,t)+V_5(x_t,i,t)$$

where $V_1(x_t,i,t),V_2(x_t,i,t)$ and $V_5(x_t,i,t)$ are the same in Theorem 1 and Theorem 2. The rest of the proof can be easily obtain by Theorem 1 and Theorem 2, so it's omitted here. ■

Remark 1: This theorem is a generalization of Theorem 1 and Theorem 2. When $r=1$, Theorem 3 is equivalent to Theorem 2. When $m=1$, Theorem 3 is an approximation of Theorem 1. So we can choose proper values of r and m to achieve a better result than that of Theorem 1 and Theorem 2.

IV. ILLUSTRATIVE EXAMPLE

In this section, we provide an example to demonstrate the reduced conservativeness of the proposed criteria.

Consider the Markovian jump linear system in (1) with two operation modes whose system matrices and transition probability matrix are given as follows [21],

$$A_1 = \begin{bmatrix} -3.4888 & 0.8057 \\ -0.6451 & -3.2684 \end{bmatrix} \quad A_{d1} = \begin{bmatrix} -0.8620 & -1.2919 \\ -0.6841 & -2.0729 \end{bmatrix}$$
$$A_2 = \begin{bmatrix} -2.4898 & 0.2895 \\ 1.3396 & -0.0211 \end{bmatrix} \quad A_{d2} = \begin{bmatrix} -2.8306 & 0.4978 \\ -0.8436 & -1.0115 \end{bmatrix}$$
$$\Pi = \begin{bmatrix} -0.1 & 0.1 \\ 0.8 & -0.8 \end{bmatrix}$$

Assume $\mu = 0.2$, we compare the results in Theorem 1, Theorem 2 and 3 with the results derived in [3], [22]. Notice that Theorem 1 in [3] is the mean square exponentially stability criterion. Similar as in [4], let $\mu_1 = \mu_2$ and let $\lambda \to 0$, then $\frac{e^{\lambda h_2} - e^{\lambda h_1}}{\lambda} \to h_2 - h_1$, $\frac{e^{\lambda h_1/m} - 1}{\lambda} \to \frac{h_1}{m}$, and then we obtain the stochastic stability criterion. The lower bound d_{min} is given with different values and the maximum allowable upper bound d_{max} is calculated by different theorems, as listed in Table I.

TABLE I: Comparsion of the allowable upper bound values of $d(t)$ for different d_{min}

d_{min}	0.1	0.3	0.5	0.7	0.9
Zhao *et al.* [22]	0.6639	0.6714	0.6688	-	-
Gao *et al.* [3],$m = 1$	0.6569	0.6676	0.6700	-	-
Gao *et al.* [3],$m = 2$	0.6582	0.6829	0.7184	0.7568	-
Gao *et al.* [3],$m = 3$	0.6585	0.6862	0.7258	0.7678	-
Theorem 1, $r = 1$	0.8392	0.8614	0.8900	0.9648	1.0206
Theorem 1, $r = 2$	0.8403	0.8711	0.9181	1.0052	1.0868
Theorem 1, $r = 3$	0.8406	0.8748	0.9253	1.0134	1.1001
Theorem 2, $m = 1$	0.8393	0.8589	0.8818	0.9621	1.0206
Theorem 2, $m = 2$	0.9004	0.8972	0.9198	0.9793	1.0225
Theorem 2, $m = 3$	0.9328	0.9197	0.9320	0.9829	1.0233
Theorem 3, $r = m = 2$	0.9017	0.9110	0.9510	1.0235	1.0882

As can be seen from Table I, when $d_{min} = 0.7$ or 0.9, the results of [3] and [22] are no more applicable. However, we can get d_{max} by using Theorem 1, Theorem 2 and Theorem 3. When d_{min} is small, e.g., $0.1, 0.3$, Theorem 2 ensures better results than Theorem 1, and is vice verse for $d_{min} = 0.7$ or 0.9. In addition, if $d_{min} = 0.5$, which is about half of d_{max}, better results can be achieved by using Theorem 3 with $r = 2, m = 2$ than that of Theorem 1 with $r = 3$ or Theorem 2 with $m = 3$.

V. CONCLUSIONS

Stochastic stability of Markovian jump systems with time-varying delay is investigated in this work. With different delay-partitioning methods and different LKFs, new stochastic stability criteria are obtained, the effectiveness of which is verified by numerical examples. Furthermore, a state feedback controller can also be designed based on these stability criteria.

REFERENCES

[1] M. H. Davis, *Markov Models and Optimization*. CRC Press, 1993, vol. 49.
[2] Z. Fei, H. Gao, and P. Shi, "New results on stabilization of markovian jump systems with time delay," *Automatica*, vol. 45, no. 10, pp. 2300–2306, 2009.
[3] H. Gao, Z. Fei, J. Lam, and B. Du, "Further results on exponential estimates of markovian jump systems with mode-dependent time-varying delays," *IEEE Transactions on Automatic Control*, vol. 56, no. 1, pp. 223–229, 2011.
[4] H. Huang, G. Feng, and X. Chen, "Stability and stabilization of markovian jump systems with time delay via new lyapunov functionals," *Circuits and Systems I: Regular Papers, IEEE Transactions on*, vol. 59, no. 10, pp. 2413–2421, 2012.
[5] Z. Shu, J. Lam, and S. Xu, "Robust stabilization of markovian delay systems with delay-dependent exponential estimates," *Automatica*, vol. 42, no. 11, pp. 2001–2008, 2006.
[6] M. Sun, J. Lam, S. Xu, and Y. Zou, "Robust exponential stabilization for markovian jump systems with mode-dependent input delay," *Automatica*, vol. 43, no. 10, pp. 1799–1807, 2007.
[7] E.-K. Boukas, *Stochastic switching systems: analysis and design*. Berlin,Germany: Birkhauser, 2007.
[8] O. L. do Valle Costa, M. D. Fragoso, and M. G. Todorov, *Continuous-time Markov jump linear systems*. London, U.K: Springer-Verlag, 2012.
[9] X. Feng, K. Loparo, Y. Ji, H. J. Chizeck *et al.*, "Stochastic stability properties of jump linear systems," *IEEE Transactions on Automatic Control*, vol. 37, no. 1, pp. 38–53, 1992.
[10] Y. Y. Cao and J. Lam, "Robust $H\infty$ control of uncertain Markovian jump systems with time-delay," *IEEE Transactions on Automatic Control*, vol. 45, no. 1, pp. 77–83, 2000.
[11] J. Cheng, H. Zhu, S. Zhong, Y. Zeng, and X. Dong, "Finite-time $H\infty$ control for a class of markovian jump systems with mode-dependent time-varying delays via new lyapunov functionals," *ISA transactions*, vol. 52, no. 6, pp. 768–774, 2013.
[12] S. Xu, T. Chen, and J. Lam, "Robust $H\infty$ filtering for uncertain markovian jump systems with mode-dependent time delays," *IEEE Transactions on Automatic Control*, vol. 48, no. 5, pp. 900–907, 2003.
[13] J. Yu, J. Tan, H. Jiang, and H. Liu, "Dynamic output feedback control for markovian jump systems with time-varying delays," *IET Control Theory & Applications*, vol. 6, no. 6, pp. 803–812, 2012.
[14] Y. He, Q.-G. Wang, C. Lin, and M. Wu, "Delay-range-dependent stability for systems with time-varying delay," *Automatica*, vol. 43, no. 2, pp. 371–376, 2007.
[15] H. Shao, "New delay-dependent stability criteria for systems with interval delay," *Automatica*, vol. 45, no. 3, pp. 744–749, 2009.
[16] P. Park, J. W. Ko, and C. Jeong, "Reciprocally convex approach to stability of systems with time-varying delays," *Automatica*, vol. 47, no. 1, pp. 235–238, 2011.
[17] J. Lam, H. Gao, and C. Wang, "Stability analysis for continuous systems with two additive time-varying delay components," *Systems & Control Letters*, vol. 56, no. 1, pp. 16–24, 2007.
[18] S. Mou, H. Gao, W. Qiang, and K. Chen, "New delay-dependent exponential stability for neural networks with time delay," *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, vol. 38, no. 2, pp. 571–576, 2008.
[19] E. Fridman, U. Shaked, and K. Liu, "New conditions for delay-derivative-dependent stability," *Automatica*, vol. 45, no. 11, pp. 2723–2727, 2009.
[20] S. Xu, J. Lam, B. Zhang, and Y. Zou, "New insight into delay-dependent stability of time-delay systems," *International Journal of Robust and Nonlinear Control*, 2013.
[21] S. Xu, J. Lam, and X. Mao, "Delay-dependent h control and filtering for uncertain markovian jump systems with time-varying delays," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 54, no. 9, pp. 2070–2077, 2007.
[22] X. D. Zhao and Q. S. Zeng, "Delay-dependent stability analysis for Markovian jump systems with interval time-varying-delays," *International Journal of Automation and Computing*, vol. 7, no. 2, pp. 224–229, 2010.
[23] K. Gu, J. Chen, and V. L. Kharitonov, *Stability of time-delay systems*. Springer Science & Business Media, 2003.

Engineering Village™

1. Improved results on stability of Markovian jump systems with time-varying delays

Accession number: 20163102669707
Authors: Li, Pengfei (1); Kang, Yu (1, 2); Zhao, Yunbo (3); Xi, Hongsheng (1); Wang, Jun (4)
Author affiliation: (1) Department of Automation, University of Science and Technology of China, Hefei, China; (2) Key Laboratory of Technology in Geo-Spatial Information Processing and Application System, Chinese Academy of Sciences, Beijing, China; (3) College of Information Engineering, Zhejiang University of Technology, Hangzhou, China; (4) Key Lab of Machine Vision and Intelligence Control Technology, Hefei University, Hefei, China
Corresponding author: Kang, Yu(Kangduyu@ustc.edu.cn)
Source title: IEEE International Conference on Control and Automation, ICCA
Abbreviated source title: IEEE Int. Conf. Control Autom., ICCA
Volume: 2016-July
Monograph title: 12th IEEE International Conference on Control and Automation, ICCA 2016
Issue date: July 5, 2016
Publication year: 2016
Pages: 626-631
Article number: 7505348
Language: English
ISSN: 19483449
E-ISSN: 19483457
ISBN-13: 9781509017386
Document type: Conference article (CA)
Conference name: 12th IEEE International Conference on Control and Automation, ICCA 2016
Conference date: June 1, 2016 - June 3, 2016
Conference location: Kathmandu, Nepal
Conference code: 122601
Publisher: IEEE Computer Society
Abstract: The stochastic stability of Markovian jump systems with time-varying delays is investigated. Three delay-partitioning methods, i.e., partitioning [0, dmin], [dmin, dmax] and both, are considered to derive the delay-range-dependent stability criteria. Different Lyapunov-Krasovskii functionals are consequently constructed for the stochastic stability of the system. The effectiveness of those results are finally domonstrated by a numerical example. © 2016 IEEE.
Number of references: 23
Main heading: Stability criteria
Controlled terms: Lyapunov functions - Markov processes - Stability - Stochastic systems - System stability - Time delay - Time varying control systems
Uncontrolled terms: Delay partitioning - Delay-range-dependent - Lyapunov-Krasovskii functionals - Markovian jump systems - Stochastic stability - Time varying- delays
Classification code: 713 Electronic Circuits - 731.1 Control Systems - 921 Mathematics - 922.1 Probability Theory - 961 Systems Science
DOI: 10.1109/ICCA.2016.7505348
Compendex references: YES
Database: Compendex
Compilation and indexing terms, Copyright 2016 Elsevier Inc.
Data Provider: Engineering Village