Hindawi Publishing Corporation
Abstract and Applied Analysis
Volume 2014, Article ID 597298, 8 pages
http://dx.doi.org/10.1155/2014/597298

Research Article

Finite-Time Boundedness for a Class of Delayed Markovian Jumping Neural Networks with Partly Unknown Transition Probabilities

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Received 11 November 2013; Accepted 8 December 2013; Published 6 January 2014

Academic Editor: Zhengguang Wu

This paper is concerned with the problem of finite-time boundedness for a class of delayed Markovian jumping neural networks with partly unknown transition probabilities. By introducing the appropriate stochastic Lyapunov-Krasovskii functional and the concept of stochastically finite-time stochastic boundedness for Markovian jumping neural networks, a new method is proposed to guarantee that the state trajectory remains in a bounded region of the state space over a prespecified finite-time interval. Finally, numerical examples are given to illustrate the effectiveness and reduced conservativeness of the proposed results.

1. Introduction

Over the past decades, delayed neural networks have been successfully applied in the pattern recognition, signal processing, image processing, and pattern recognition problems. However, these successful applications mostly rely on the dynamic behaviors of delayed neural networks and some of these applications are dependent on stability of the equilibria of neural networks. Up to now, there have been a large number of results related to dynamical behaviors of delayed neural networks [1–8].

On the one, in the past few decades, Markovian jump systems have gained special research attention. Such class of systems is a special class of stochastic hybrid systems, which may switch from one to another at the different time. Such as component failures, sudden environmental disturbance and abrupt variations of a nonlinear system [9–11]. Moreover, it is shown that such jumping can be decided by a Markovian chain [12]. For the linear Markovian jumping systems, many important issues have been devoted extensively such as stability, stabilization, control synthesis, and filter design [13–16]. In reality, however, it is worth mentioning that most of the gotten results are based on the implicit assumptions that the complete knowledge of transition probabilities is known. It is known that in most situations, the transition probabilities rate of Markovian jump systems and networks is not known; it is difficult to obtain all the transition probabilities. Therefore, it is of great importance to investigate the partly unknown transition probabilities. Very recently, the systems with partially unknown transition probabilities have been fully investigated and many important results have been obtained; for a recent survey on this topic and related questions, one can refer to [17–23]. However, it has been shown that the existing delay-dependent results are conservative.

On the other hand, the practical problems which described system stay as not exceeding a given threshold over finite-time interval are considered. Compared with classical Lyapunov stability, finite-time stability was studied to tackle the transient behavior of systems in the finite-time interval. Recently, the concept of finite-time stability has been revisited in the terms of linear matrix inequalities (LMIs); some results have been obtained to guarantee that system is finite-time stable and finite-time bounded [24–39]. To the best of our knowledge, the finite-time stability analysis for Markovian jumping neural networks with mode-dependent time-varying delays and partially known transition rates has not been tackled, and such a situation motivates our present study.

The main contribution of this paper lies in proposing a novel method for finite-time boundedness of delayed Markovian jumping neural networks with partly unknown transition probabilities. The considered system is more general than the systems with completely known or completely unknown transition probabilities, which can be regarded as two special cases of the one tackled here. In contrast to study on Markovian jumping neural networks with time delays, the knowledge of the unknown elements is not required in our method. By employing the appropriate Lyapunov-Krasovskii functional, the sufficient conditions are obtained to ensure that the system does not exceed a given threshold in a specified time interval. The finite-time bounded criteria can be tackled in the form of LMIs. Finally, numerical examples are given to demonstrate that the derived results are less conservative and more useful than some existent ones.

2. Preliminaries

Given a probability space (Ω, F, P) where Ω, F and P, respectively, represents the sample space, the algebra of events and the probability measure which defined on Ω. In this paper, we consider the following n-neuron Markovian jumping neural network over the space (Ω, F, P) described by

$$\begin{gathered}\dot{x}(t) = -A_{r_t} x(t) + B_{r_t} f(x(t)) + C_{r_t} f\left(x\left(t - \tau_{r_t}(t)\right)\right) + J \\ x(t) = \phi(t), \quad t \in [-\tau, 0),\end{gathered} \tag{1}$$

where $x(t) = [x_1(t), x_2(t), \ldots, x_n(t)]^{\top}$ represents the neural state vector of the system, $f(x(t)) = [f_1(x_1(t)), f_2(x_2(t)), \ldots, f_n(x_n(t))]^{\top}$ is the nonlinear activation function with the initial condition $f(0) = 0$, $A_{r_t} = \operatorname{diag}\{a_1(r_t), a_2(r_t), \ldots, a_n(r_t)\}$ describes the rate with each neuron which would reset its potential to resting state in isolation, $B_{r_t} = [b_{ij}(r_t)]_{n\times n}$ and $C_{r_t} = [c_{ij}(r_t)]$ are the connection weight matrices and the delayed connection weight matrices, respectively, and $J = [J_1, J_2, \ldots, J_n]^{\top}$ denotes a constant external input vector. $\tau_{r_t}(t)$ are the time-varying delays which satisfy

$$\begin{gathered}0 \le \tau_{r_t}(t) \le \tau_{r_t}, \\ 0 \le \dot{\tau}_{r_t}(t) \le d_{r_t} \le 1,\end{gathered} \tag{2}$$

where τ_{r_t} and d_{r_t} are constant scalars and $\tau = \max_{r_t}\{\tau_{r_t}\}$, $d = \max_{r_t}\{d_{r_t}\}$.

Remark 1. This assumption is often employed to investigate the stability of neural networks. It is worth noting that if this assumption is not true, corresponding time-delays are not a continuous function belonging to a given interval; neither the lower nor upper bounds for time-varying delays are available. Therefore, it may lead to more conservativeness.

Let the random form process $\{r_t, t \ge 0\}$ be the Markovian stochastic process taking values on the finite set $\mathcal{N} = \{1, 2, \ldots, N\}$ with transition rate matrix $\Omega = \{\mu_{ij}\}$, $i, j \in \mathcal{N}$; namely, for $r_t = i$, $r_{t+1} = j$, one has

$$\Pr\left(r_{t+h} = j \mid r_t = i\right) = \begin{cases}\mu_{ij} h + o(h), & \text{if } j \ne i \\ 1 + \mu_{ii} h + o(h), & \text{if } j = i,\end{cases} \tag{3}$$

where $h > 0$, $\lim_{h\to 0}(o(h)/h) = 0$, and $\mu \ge 0$ $(i, j \in \mathcal{N}, j \ne i)$, denote switching rate from mode i at time t to mode j at time $t + h$. For all $i \in \mathcal{N}$, $\mu_{ii} = -\sum_{j=1, j\ne i} \mu_{ij}$. Moreover, the Markovian process transition matrix Ω is defined as follows:

$$\Omega = \begin{bmatrix}\mu_{11} & \mu_{12} & \cdots & \mu_{1N} \\ \mu_{21} & \mu_{22} & \cdots & \mu_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{N1} & \mu_{N2} & \cdots & \mu_{NN}\end{bmatrix}. \tag{4}$$

Moreover, the transition rates of jumping process in this paper are considered to be partly accessed; that is, some elements in matrix Ω are unknown. Therefore, the transition rates matrix Ω which is Markovian jump system (1) may be as follows:

$$\Omega = \begin{bmatrix}\mu_{11} & ? & \cdots & \mu_{1N} \\ ? & \mu_{22} & \cdots & ? \\ \vdots & \vdots & \ddots & \vdots \\ ? & ? & \cdots & \mu_{NN}\end{bmatrix}, \tag{5}$$

where ? represents the inaccessible elements. For notational clarity, for all $i \in \mathcal{N}$, we denote $\mathcal{N} = \mathcal{N}^i_{\mathcal{K}} + \mathcal{N}^i_{\mathcal{UK}}$ and we denote that

$$\begin{gathered}\mathcal{N}^i_{\mathcal{K}} \equiv \left\{j : \mu_{ij} \text{ is known}\right\}, \\ \mathcal{N}^i_{\mathcal{UK}} \equiv \left\{j : \mu_{ij} \text{ is unknown}\right\}.\end{gathered} \tag{6}$$

Moreover, if $\mathcal{N}^i_{\mathcal{K}} \ne \emptyset$, $\mathcal{N}^i_{\mathcal{K}}$ and $\mathcal{N}^i_{\mathcal{UK}}$ can be further described, respectively, as

$$\begin{gathered}\mathcal{N}^i_{\mathcal{K}} = \left\{\mathcal{K}^i_1, \mathcal{K}^i_2, \ldots, \mathcal{K}^i_m\right\}, \\ \mathcal{N}^i_{\mathcal{UK}} = \left\{\mathcal{UK}^i_1, \mathcal{UK}^i_2, \ldots, \mathcal{UK}^i_{N-m}\right\},\end{gathered} \tag{7}$$

where $\mathcal{N}^i_m \in \mathbb{Z}^+$ represents the mth known element with the index $\mathcal{N}^i_m$ in the ith row of matrix Ω. $\mathcal{UN}^i_{N-m} \in \mathbb{Z}^+$ represents the $N-m$th unknown element with the index $\mathcal{UN}^i_{Nm}$ in the ith row of matrix Ω.

Set $\mathcal{N}$ contains N modes of system (1) and, for $r_t = i \in \mathcal{N}$, the system matrices of the ith mode are denoted by A_i, B_i, and C_i, which are considered to be real known with appropriate dimensions.

Remark 2. The Markovian jump process $\{r_t, t \ge 0\}$ in the literature is always assumed μ_{ij} ether to be completely known ($\mathcal{N}^i_{\mathcal{K}}$) or completely unknown ($\mathcal{N}^i_{\mathcal{UK}}$). Therefore, our transition probabilities matrix considered in this paper is more general than the Markovian jump systems and therefore covers the existing ones.

Assumption 3. The neuron state-based nonlinear function $f(x(t))$ considered in Markovian jump system (1) is bounded and satisfies

$$0 \le \frac{f_s(\varsigma_1) - f_s(\varsigma_2)}{\varsigma_1 - \varsigma_2} \le \gamma_s, \quad s = 1, 2, \ldots, n \tag{8}$$

for all $\varsigma_1, \varsigma_2 \in \mathcal{R}$, with γ_s being known real constants with $s = 1, 2, \ldots, n$.

It should be noted that by using the Brouwer fixed-point theorem, there should exist at least the one equilibrium point for system (1). Assuming that $x^* = [x_1^*, x_2^*, \ldots, x_n^*]^\top$ is the equilibrium point of (1) and using the transformation $z(\cdot) = x(\cdot) - x^*$, system (1) can be converted to the following system:

$$\dot{z}(t) = -A_{r_t} z(t) + B_{r_t} g(z(t)) + C_{r_t} g\left(z\left(t - \tau_{r_t}(t)\right)\right), \tag{9}$$

where $z(t) = [z_1(t), z_2(t), \ldots, z_n(t)]^\top$, $g(z(\cdot)) = [g_1(z_1(x(t))), g_2(x(t)), \ldots, g_n(x(t))]^\top$, and $g_i(z_i(z_i(\cdot))) = f_i(z_i(\cdot) + x_i^*) - f_i(x_i^*)$, $i = 1, 2, \ldots, n$. According to Assumption 3, one can obtain that

$$0 \le \frac{g_i(z_i(t))}{z_i(t)} \le \gamma_i, \quad g_i(0) = 0,\ i = 1, 2, \ldots, n. \tag{10}$$

Definition 4 (see [33]). The nominal time-delayed Markovian jumping neural networks (1) are said to be stochastically finite-time bounded with respect to (c_1, c_2, T), if

$$\begin{gathered}\mathbb{E}\|x(t_1)\|^2 \le c_1 \Longrightarrow \mathbb{E}\|x(t_2)\|^2 \le c_2, \\ t_1 \in [-\tau, 0], \quad t_2 \in [0, T].\end{gathered} \tag{11}$$

Definition 5 (see [34]). Let $V(x_t, r_t)$ be a stochastic positive functional and define its weak infinitesimal operator as

$$\begin{aligned}&\pounds V(x_t, r_t = i) \\ &\quad = \lim_{\Delta \to 0} \frac{1}{\Delta}\left[\mathbb{E}\{V(x_{t+\Delta}, r_{t+\Delta}) \mid x_t, r_t = i\} - V(x_t, r_t = i)\right].\end{aligned} \tag{12}$$

3. Finite-Time H_∞ Performance Analysis

In this section, one method would be employed to analyze the finite-time stability of Markovian jump systems with partial information on transition probabilities.

Theorem 6. *Given a time constant $T > 0$, the delayed Markovian jumping neural networks* (1) *are stochastically finite-time bounded with respect to (c_1, c_2, T), if there exist a positive constant $\eta > 0$, mode-dependent symmetric positive-definite matrices $P_i > 0$, $Q_{1i} > 0$, $Q_{2i} > 0$, $W_1 > 0$, $W_2 > 0$ $(i \in \mathcal{N})$, a set of symmetric matrices S_v $(v = 1, 2, \ldots, N)$, any appropriately dimensioned matrices M_i, N_i $(i \in \mathcal{N})$, Γ_s, and scalars λ_l $(l = 1, 2, \ldots, 6)$ such that the following matrix inequalities hold:*

$$\begin{gathered}
\sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} Q_{1j} - \left(1 + \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij}\right) W_1 + \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} Q_{1i} < 0, \\
Q_{1j} - W_1 + Q_{1i} < 0, \quad j \in \mathcal{N}^i_{\mathcal{UK}},\ j \ne i, \\
Q_{1j} - W_1 + Q_{1i} < 0, \quad j \in \mathcal{N}^i_{\mathcal{UK}},\ j = i, \\
\sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} Q_{2j} - \left(1 + \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij}\right) W_2 + \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} Q_{2i} < 0, \\
Q_{2j} - W_2 + Q_{2i} < 0, \quad j \in \mathcal{N}^i_{\mathcal{UK}},\ j \ne i, \\
Q_{2j} - W_2 + Q_{2i} < 0, \quad j \in \mathcal{N}^i_{\mathcal{UK}},\ j = i,
\end{gathered}$$

$$\begin{aligned}
\Sigma_i = {} & e_1\left(1 + \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij}\right)\left(-P_i A_i - A_i^\top P_i\right) e_1^\top \\
& + e_1 \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} P_j e_1^\top + 2 e_1 P_i B_i e_3^\top + 2 e_1 P_i C_i e_4 + e_1 Q_{1i} e_1^\top \\
& - \left(1 - d_i - \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} \tau_j\right) e_2 Q_{1i} e_2^\top + e_3 Q_{2i} e_3^\top \\
& - (1 - d_i) e_4 Q_{2i} e_4^\top + \sum_{j=1}^{N} \mu_{ij} \tau_j e_4 Q_{2i} e_4^\top \\
& + \tau e_1 W_1 e_1^\top + \tau e_3 W_2 e_3^\top + e_1 \Gamma_s M_i \Gamma_s e_1^\top \\
& - e_3 M_i e_3^\top + e_2 \Gamma_s N_i \Gamma_s e_2^\top - e_4 N_i e_4^\top \\
& - e_1 \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} S_v e_1^\top < 0,
\end{aligned}$$

$$\begin{gathered}
e_1\left(-P_i A_i - A_i^\top P_i + P_j - S_v\right) e_1^\top + e_2 \tau_j Q_{2i} e_2^\top < 0, \\
j \in \mathcal{N}^i_{\mathcal{UK}}, \quad j \ne i, \\
e_1\left(-P_i A_i - A_i^\top P_i + P_j - S_v\right) e_1^\top + e_2 \tau_j Q_{2i} e_2^\top > 0, \\
j \in \mathcal{N}^i_{\mathcal{UK}}, \quad j = i,
\end{gathered} \tag{13}$$

$$c_1 e^{\eta T}\left(\lambda_2 + \tau\lambda_3 + \tau\overline{\gamma}_s^2\lambda_4 + \tau^2\lambda_5 + \tau^2\overline{\gamma}_s^2\lambda_6\right) < \lambda_1 c_2, \tag{14}$$

where

$$\begin{gathered}
\lambda_1 = \max_{i \in \mathcal{N}} \lambda_{\min}(P_i), \qquad \lambda_2 = \max_{i \in \mathcal{N}} \lambda_{\max}(P_i), \\
\lambda_3 = \max_{i \in \mathcal{N}} \lambda_{\max}(Q_{1i}), \qquad \lambda_4 = \max_{i \in \mathcal{N}} \lambda_{\max}(Q_{2i}), \\
\lambda_5 = \lambda_{\max}(W_1), \qquad \lambda_6 = \lambda_{\max}(W_2), \qquad \overline{\gamma}_s = \max_s(\gamma_s).
\end{gathered} \tag{15}$$

Proof. We consider the following the stochastic Lyapunov-Krasovskii functional:

$$V(z_t, r_t) = \sum_{l=1}^{4} V_l(z_t, r_t), \tag{16}$$

where

$$\begin{aligned}
V_1(z_t, r_t) &= z^\top(t) P_{r_t} z(t), \\
V_2(z_t, r_t) &= \int_{t-\tau_{r_t}(t)}^{t} z^\top(s) Q_{1r_t} z(s)\, ds, \\
V_3(z_t, r_t) &= \int_{t-\tau_{r_t}(t)}^{t} g^\top(z(s)) Q_{2r_t} g(z(s))\, ds, \\
V_4(z_t, r_t) &= \int_{-\tau}^{0}\int_{t+\theta}^{t} z^\top(s) W_1 z(s)\, ds\, d\theta \\
&\quad + \int_{-\tau}^{0}\int_{t+\theta}^{t} g^\top(z(s)) W_2 g(z(s))\, ds\, d\theta
\end{aligned} \tag{17}$$

with P_i, Q_{1i}, Q_{2i}, $(i = 1, 2, \ldots, N)$, W_1, and W_2 being positive definite matrices and

$$\sum_{j=1}^{N} \mu_{ij} Q_{1j} < W_1, \tag{18}$$

$$\sum_{j=1}^{N} \mu_{ij} Q_{2j} < W_2. \tag{19}$$

For notational simplicity, let

$$\xi(t) = \left[z^{\top}(t), z^{\top}(t-\tau_i(t)), g^{\top}(z(t)), g^{\top}(z(t-\tau_i(t)))\right]^{\top},$$
$$e_s = \Big[\underbrace{0,\ldots,0}_{s-1}, I, \underbrace{0,\ldots,0}_{4-s}\Big]^{\top}, \quad s = 1, \ldots, 4. \tag{20}$$

Let £ be the infinitesimal generator of random process $\{z_t, t \geq 0\}$; then for each $r_t = i$, $i \in \mathcal{N}$, we can obtain that

$$\begin{aligned}
£V_1(z_t, i) &= 2z^{\top}(t) P_i \dot{z}(t) + z^{\top}(t) \sum_{j=1}^{N} \mu_{ij} P_j z(t) \\
&= \xi^{\top}(t) e_1 \left(-P_i A_i - A_i^{\top} P_i + \sum_{j=1}^{N} \mu_{ij} P_j\right) e_1^{\top} \xi(t) \\
&\quad + 2\xi^{\top}(t) e_1 P_i B_i e_3^{\top} \xi(t) + 2\xi^{\top}(t) e_1 P_i C_i e_4 \xi(t), \\
£V_2(z_t, i) &= \lim_{\Delta \to 0^+} \frac{1}{\Delta} \mathbb{E} \\
&\quad \times \left\{ \left[\int_{t+\Delta-\tau_{r_{t+\Delta}}(t+\Delta)}^{t+\Delta} z^{\top}(s) Q_{1r_{t+\Delta}} z(s)\, ds \mid r_t = i \right] \right. \\
&\quad \left. - \int_{t-\tau_i(t)}^{t} z^{\top}(s) Q_{1i} z(s)\, ds \right\} \\
&= \lim_{\Delta \to 0^+} \frac{1}{\Delta} \left\{ \int_{t+\Delta-\tau_i(t+\Delta)-\sum_{j=1}^{N}(\mu_{ij}\Delta+o(\Delta))\tau_j(t+\Delta)}^{t+\Delta} z^{\top}(s) \right. \\
&\quad \times \left[Q_{1i} + \sum_{j=1}^{N} (\mu_{ij}\Delta + o(\Delta)) \right] z(s)\, ds \\
&\quad \left. - \int_{t-\tau_i(t)}^{t} z^{\top}(s) Q_{1i} z(s)\, ds \right\} \\
&= \lim_{\Delta \to 0^+} \frac{1}{\Delta} \left\{ \int_{t+\Delta-\tau_i(t+\Delta)-\sum_{j=1}^{N}(\mu_{ij}\Delta+o(\Delta))\tau_j(t+\Delta)}^{t+\Delta} \right. \\
&\quad \times z^{\top}(s) Q_{1i} z(s)\, ds \\
&\quad \left. - \int_{t-\tau_i(t)}^{t} z^{\top}(s) Q_{1i} z(s)\, ds \right\} \\
&\quad + \lim_{\Delta \to 0^+} \frac{1}{\Delta} \int_{t+\Delta-\tau_i(t+\Delta)-\sum_{j=1}^{N}(\mu_{ij}\Delta+o(\Delta))\tau_j(t+\Delta)}^{t+\Delta} z^{\top}(s) \\
&\quad \times \sum_{j=1}^{N} (\mu_{ij}\Delta + o(\Delta)) \\
&\quad \times Q_{1j} z(s)\, ds \\
&= \lim_{\Delta \to 0^+} \frac{1}{\Delta} \int_{t}^{t+\Delta} z^{\top}(s) Q_{1i} z(s)\, ds \\
&\quad + \lim_{\Delta \to 0^+} \frac{1}{\Delta} \int_{t+\Delta-\tau_i(t+\Delta)-\sum_{j=1}^{N}(\mu_{ij}\Delta+o(\Delta))\tau_j(t+\Delta)}^{t+\Delta} \\
&\quad \times z^{\top}(s) \sum_{j=1}^{N} (\mu_{ij}\Delta + o(\Delta)) \\
&\quad \times Q_{1j} z(s)\, ds \\
&= \xi^{\top}(t) e_1 Q_{1i} e_1^{\top} \xi(t) - \left(1 - \dot{\tau}_i(t) - \sum_{j=1}^{N} \mu_{ij} \tau_j(t)\right) \\
&\quad \times \xi^{\top}(t) e_2 Q_{1i} e_2^{\top} \xi(t) \\
&\quad + \int_{t-\tau_i(t)}^{t} z^{\top}(s) \left(\sum_{j=1}^{N} \mu_{ij} Q_{1j}\right) z(s)\, ds \\
&\leq \xi^{\top}(t) e_1 Q_{1i} e_1^{\top} \xi(t) - \left(1 - d_i - \sum_{j=1}^{N} \mu_{ij} \tau_j(t)\right) \\
&\quad \times \xi^{\top}(t) e_2 Q_{1i} e_2^{\top} \xi(t) \\
&\quad + \int_{t-\tau_i(t)}^{t} z^{\top}(s) \left(\sum_{j=1}^{N} \mu_{ij} Q_{1j}\right) z(s)\, ds.
\end{aligned} \tag{21}$$

Similar to the process above, it yields

$$\begin{aligned}
£V_3(z_t, i) &\leq \xi^{\top}(t) e_3 Q_{2i} e_3^{\top} \xi(t) - (1 - d_i) \xi^{\top}(t) e_4 Q_{2i} e_4^{\top} \xi(t) \\
&\quad + \sum_{j=1}^{N} \mu_{ij} \tau_j(t) \xi^{\top}(t) e_4 Q_{2i} e_4^{\top} \xi(t) \\
&\quad + \int_{t-\tau_i(t)}^{t} g^{\top}(z(s)) \left(\sum_{j=1}^{N} \mu_{ij} Q_{2i}\right) g(z(s))\, ds, \\
£V_4(z_t, i) &= \tau \xi^{\top}(t) e_1 W_1 e_1^{\top} \xi(t) - \int_{t-\tau}^{t} z^{\top}(s) W_1 z(s)\, ds \\
&\quad + \tau \xi^{\top}(t) e_3 W_2 e_3^{\top} \xi(t) \\
&\quad - \int_{t-\tau}^{t} g^{\top}(z(s)) W_2 g(z(s))\, ds.
\end{aligned} \tag{22}$$

From (18) and (19), we obtain that

$$\begin{aligned}
&\int_{t-\tau_i(t)}^{t} z^{\top}(s) \left(\sum_{j=1}^{N} \mu_{ij} Q_{1j}\right) z(s)\, ds \\
&\quad \leq \int_{t-\tau}^{t} z^{\top}(s) \left(\sum_{j=1}^{N} \mu_{ij} Q_{1j}\right) z(s)\, ds \\
&\quad \leq \int_{t-\tau}^{t} z^{\top}(s) W_1 z(s)\, ds,
\end{aligned}$$

$$\int_{t-\tau_i(t)}^{t} g^{\top}(z(s)) \left(\sum_{j=1}^{N} \mu_{ij} Q_{2j} \right) g(z(s))\, ds$$
$$\leq \int_{t-\tau}^{t} g^{\top}(z(s)) \left(\sum_{j=1}^{N} \mu_{ij} Q_{2j} \right) g(z(s))\, ds$$
$$\leq \int_{t-\tau}^{t} g^{\top}(z(s)) W_2 g(z(s))\, ds. \tag{23}$$

Also, it results from (10) that for any appropriately dimensioned matrices M_i, N_i, $(i = 1, 2, \ldots, N)$, one can obtain

$$0 \leq \xi^{\top}(t) e_1 \Gamma_s M_i \Gamma_s e_1^{\top} \xi(t) - \xi^{\top}(t) e_3 M_i e_3^{\top} \xi(t),$$
$$0 \leq \xi^{\top}(t) e_2 \Gamma_s N_i \Gamma_s e_2^{\top} \xi(t) - \xi^{\top}(t) e_4 N_i e_4^{\top} \xi(t). \tag{24}$$

From (16)–(24), we have

$$\pounds V(z_t, i) \leq \xi^{\top}(t) \Xi_i \xi(t), \tag{25}$$

where

$$\begin{aligned}
\Xi_i = {} & e_1 \left(-P_i A_i - A_i^{\top} P_i + \sum_{j=1}^{N} \mu_{ij} P_j \right) e_1^{\top} \\
& + 2 e_1 P_i B_i e_3^{\top} + 2 e_1 P_i C_i e_4 + e_1 Q_{1i} e_1^{\top} \\
& - \left(1 - d_i - \sum_{j=1}^{N} \mu_{ij} \tau_j \right) e_2 Q_{1i} e_2^{\top} \\
& + e_3 Q_{2i} e_3^{\top} - (1 - d_i) e_4 Q_{2i} e_4^{\top} \\
& + \sum_{j=1}^{N} \mu_{ij} \tau_j e_4 Q_{2i} e_4^{\top} + \tau e_1 W_1 e_1^{\top} \\
& + \tau e_3 W_2 e_3^{\top} + e_1 \Gamma_s M_i \Gamma_s e_1^{\top} - e_3 M_i e_3^{\top} \\
& + e_2 \Gamma_s N_i \Gamma_s e_2^{\top} - e_4 N_i e_4^{\top}.
\end{aligned} \tag{26}$$

By the fact that $\sum_{j \in \mathcal{N}} \mu_{ij} = 0$, we can rewrite Ξ_i as

$$\begin{aligned}
\Xi_i = {} & e_1 \left(-P_i A_i - A_i^{\top} P_i + \sum_{j=1}^{N} \mu_{ij} P_j \right) e_1^{\top} \\
& + 2 e_1 P_i B_i e_3^{\top} + 2 e_1 P_i C_i e_4 + e_1 Q_{1i} e_1^{\top} \\
& - \left(1 - d_i - \sum_{j=1}^{N} \mu_{ij} \tau_j \right) e_2 Q_{1i} e_2^{\top} \\
& + e_3 Q_{2i} e_3^{\top} - (1 - d_i) e_4 Q_{2i} e_4^{\top} \\
& + \sum_{j=1}^{N} \mu_{ij} \tau_j e_4 Q_{2i} e_4^{\top} + \tau e_1 W_1 e_1^{\top} \\
& + \tau e_3 W_2 e_3^{\top} + e_1 \Gamma_s M_i \Gamma_s e_1^{\top} - e_3 M_i e_3^{\top} \\
& + e_2 \Gamma_s N_i \Gamma_s e_2^{\top} - e_4 N_i e_4^{\top} \\
& - e_1 \sum_{j=1}^{N} \mu_{ij} \left(P_i A_i + A_i^{\top} P_i + S_v \right) e_1^{\top}.
\end{aligned} \tag{27}$$

Thus, from (6), we have

$$\begin{aligned}
\Xi_i = {} & e_1 \left(1 + \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} \right) \left(-P_i A_i - A_i^{\top} P_i \right) e_1^{\top} \\
& + e_1 \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} P_j e_1^{\top} + 2 e_1 P_i B_i e_3^{\top} \\
& + 2 e_1 P_i C_i e_4 + e_1 Q_{1i} e_1^{\top} \\
& - \left(1 - d_i - \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} \tau_j \right) e_2 Q_{1i} e_2^{\top} + e_3 Q_{2i} e_3^{\top} \\
& - (1 - d_i) e_4 Q_{2i} e_4^{\top} + \sum_{j=1}^{N} \mu_{ij} \tau_j e_4 Q_{2i} e_4^{\top} \\
& + \tau e_1 W_1 e_1^{\top} + \tau e_3 W_2 e_3^{\top} + e_1 \Gamma_s M_i \Gamma_s e_1^{\top} \\
& - e_3 M_i e_3^{\top} + e_2 \Gamma_s N_i \Gamma_s e_2^{\top} - e_4 N_i e_4^{\top} \\
& - e_1 \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} S_v e_1^{\top} \\
& + \sum_{j \in \mathcal{N}^i_{\mathcal{UK}}} \mu_{ij} \left[e_1 \left(-P_i A_i - A_i^{\top} P_i + P_j - S_v \right) e_1^{\top} \right. \\
& \qquad \left. + e_2 \tau_j Q_{2i} e_2^{\top} \right].
\end{aligned} \tag{28}$$

Then, for $j \in \mathcal{N}^i_{\mathcal{UK}}$ and if $i \in \mathcal{N}^i_{\mathcal{K}}$, $\Xi_i < 0$ can be guaranteed. On the other hand, for $j \in \mathcal{N}^i_{\mathcal{UK}}$ and if $i \notin \mathcal{N}^i_{\mathcal{K}}$, Ξ_i can be further expressed as

$$\begin{aligned}
\Xi_i = {} & e_1 \left(1 + \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} \right) \left(-P_i A_i - A_i^{\top} P_i \right) e_1^{\top} \\
& + e_1 \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} P_j e_1^{\top} + 2 e_1 P_i B_i e_3^{\top} \\
& + 2 e_1 P_i C_i e_4 + e_1 Q_{1i} e_1^{\top} \\
& - \left(1 - d_i - \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} \tau_j \right) e_2 Q_{1i} e_2^{\top} + e_3 Q_{2i} e_3^{\top} \\
& - (1 - d_i) e_4 Q_{2i} e_4^{\top} + \sum_{j=1}^{N} \mu_{ij} \tau_j e_4 Q_{2i} e_4^{\top} \\
& + \tau e_1 W_1 e_1^{\top} + \tau e_3 W_2 e_3^{\top} + e_1 \Gamma_s M_i \Gamma_s e_1^{\top} \\
& - e_3 M_i e_3^{\top} + e_2 \Gamma_s N_i \Gamma_s e_2^{\top} - e_4 N_i e_4^{\top} \\
& - e_1 \sum_{j \in \mathcal{N}^i_{\mathcal{K}}} \mu_{ij} S_v e_1^{\top} \\
& + \sum_{j \in \mathcal{N}^i_{\mathcal{UK}}, j \neq i} \mu_{ij} \left[e_1 \left(-P_i A_i - A_i^{\top} P_i + P_j - S_v \right) e_1^{\top} \right. \\
& \qquad \left. + e_2 \tau_j Q_{2i} e_2^{\top} \right] + \mu_{ii} \\
& \qquad \times \left[e_1 \left(-P_i A_i - A_i^{\top} P_i + P_j - S_v \right) e_1^{\top} \right. \\
& \qquad \left. + e_2 \tau_j Q_{2i} e_2^{\top} \right].
\end{aligned} \tag{29}$$

Similarly, (18) and (19) can be rewritten, respectively, as

$$\begin{aligned}&\left\{\sum_{j\in\mathcal{N}^i_{\mathcal{K}}}\mu_{ij}Q_{1j}-\left(1+\sum_{j\in\mathcal{N}^i_{\mathcal{K}}}\mu_{ij}\right)W_1+\sum_{j\in\mathcal{N}^i_{\mathcal{K}}}\mu_{ij}Q_{1i}\right\}\\&\quad+\sum_{j\in\mathcal{N}^i_{\mathcal{UK}},j\neq i}\mu_{ij}\left[Q_{1j}-W_1+Q_{1i}\right]\\&\quad+\mu_{ii}\left[Q_{1j}-W_1+Q_{1i}\right]<0,\\&\left\{\sum_{j\in\mathcal{N}^i_{\mathcal{K}}}\mu_{ij}Q_{2j}-\left(1+\sum_{j\in\mathcal{N}^i_{\mathcal{K}}}\mu_{ij}\right)W_2+\sum_{j\in\mathcal{N}^i_{\mathcal{K}}}\mu_{ij}Q_{2i}\right\}\\&\quad+\sum_{j\in\mathcal{N}^i_{\mathcal{UK}},j\neq i}\mu_{ij}\left[Q_{2j}-W_2+Q_{2i}\right]\\&\quad+\mu_{ii}\left[Q_{2j}-W_2+Q_{2i}\right]<0.\end{aligned}\tag{30}$$

It is well known that $\mu_{ii}=-\sum_{j=1,j\neq i}^{N}\mu_{ij}<0$; according to (6), one can also obtain

$$\pounds V\left(z_t,i\right)<0.\tag{31}$$

On the other hand, from (32) and the needed constant $\eta>0$, it yields that

$$\mathbb{E}\left\{\pounds V\left(z_t,r_t\right)\right\}<\eta\mathbb{E}\left\{V\left(z_t,r_t\right)\right\},\tag{32}$$

from which we can easily get that

$$e^{-\eta t}\mathbb{E}\left\{V\left(z_t,r_t\right)\right\}<\mathbb{E}\left\{V\left(z_0,r_0\right)\right\}.\tag{33}$$

Note that $0\le t\le T$; we can obtain the following inequality:

$$\begin{aligned}\mathbb{E}\left\{V\left(z_t,r_t\right)\right\}&<e^{\eta t}\mathbb{E}\left\{V\left(x_0,r_0\right)\right\}\\&=e^{\eta t}\left[z^{\top}(0)P_{r_t}z(0)+\int_{-\tau_{r_t}(t)}z^{\top}(s)Q_{1r_t}z(s)\,ds\right.\\&\quad+\int_{-\tau_{r_t}(t)}g^{\top}(z(s))Q_{2r_t}g(z(s))\,ds\\&\quad+\int_{-\tau}^{0}\int_{\theta}^{0}z^{\top}(s)W_1z(s)\,ds\\&\quad\left.+\int_{-\tau}^{0}\int_{\theta}^{0}g^{\top}(z(s))W_1g(z(s))\,ds\right]\\&<e^{\alpha t}\left[\max_{i\in\mathcal{N}}\lambda_{\max}\left(P_i\right)+\tau\max_{i\in\mathcal{N}}\lambda_{\max}\left(Q_{1i}\right)\right.\\&\quad+\tau\overline{\gamma}_s^2\max_{i\in\mathcal{N}}\lambda_{\max}\left(Q_{2i}\right)\\&\quad\left.+\tau^2\lambda_{\max}\left(W_1\right)+\tau^2\overline{\gamma}_s^2\lambda_{\max}\left(W_2\right)\right]\\&\quad\times\sup_{-\tau\le s\le 0}\left\{x^{\top}(s)x(s)\right\}\\&\le c_1e^{\eta T}\left(\lambda_2+\tau\lambda_3+\tau\overline{\gamma}_s^2\lambda_4+\tau^2\lambda_5+\tau^2\overline{\gamma}_s^2\lambda_6\right).\end{aligned}\tag{34}$$

On the other hand, from (16), we can get

$$\mathbb{E}\left\{z^{\top}(t)P_iz(t)\right\}\ge\max_{i\in\mathcal{N}}\lambda_{\min}\left(P_i\right)\mathbb{E}\|z(t)\|^2.\tag{35}$$

Then, we can obtain

$$\mathbb{E}\|z(t)\|^2<\frac{c_1e^{\eta T}\left(\lambda_2+\tau\lambda_3+\tau\overline{\gamma}_s^2\lambda_4+\tau^2\lambda_5+\tau^2\overline{\gamma}_s^2\lambda_6\right)}{\lambda_1}.\tag{36}$$

By condition (14), we can obtain

$$\mathbb{E}\|z(t)\|^2<c_2.\tag{37}$$

By Definition 4, we conclude that Markovian jump system (1) is stochastically finite-time bounded with respect to (c_1,c_2,T). □

Remark 7. In this paper, it is in contrast with existing results for delay-dependent Markovian jump systems with partly unknown transition probabilities, and another different method is presented to tackle the unknown elements in the transition matrix. Compared with [33], some slack matrix variables S_v are introduced in this paper based on the probability identity $\sum_{j=1}^{N}\mu_{ij}=0$, which leads to less conservativeness than [33].

Remark 8. Theorem 6 develops a finite-time bounded criterion of Markovian jumping neural networks with time-varying delays and partially known transition rates. Theorem 6 makes full use of the information of the subsystems' upper bounds of the time-varying delays, which also brings us the less conservativeness.

Remark 9. In our paper, $\tau_i(t)$ and $\dot{\tau}_i(t)$ may indicate the different upper bounds during various time-delay intervals which satisfies condition (2), respectively. However, in existing work, for example, [17], $\tau_i(t)$ and $\dot{\tau}_i(t)$ are always extended to $\tau_i(t)\le\tau=\max\{\tau_i,i\in\mathcal{N}\}$ and $0\le\dot{\tau}_i(t)\le d=\max\{d_i,i\in\mathcal{N}\}$, respectively, which may inevitably lead to the conservativeness. Therefore, in order to reduce the conservatism, the cases above are taken into account by employing the stochastic Lyapunov-Krasovskii functional (16).

4. Illustrative Example

Example 1. Consider a class of delayed Markovian jumping neural networks (9) with two operation modes in [33]:

$$\begin{aligned}&A_1=\begin{bmatrix}2&0\\0&1\end{bmatrix},\qquad A_2=\begin{bmatrix}3&0\\0&2\end{bmatrix},\qquad B_1=\begin{bmatrix}0.5&1\\-0.2&0.5\end{bmatrix},\\&B_2=\begin{bmatrix}1.1&1\\-0.2&0.1\end{bmatrix},\qquad C_1=\begin{bmatrix}0.9&0.1\\-0.1&0.1\end{bmatrix},\\&C_2=\begin{bmatrix}0.3&-0.8\\0.1&0.2\end{bmatrix},\qquad\Gamma_s=I_2.\end{aligned}\tag{38}$$

The mode switching is governed by a Markov chain that has the following transition rate matrix:

$$\Omega=\begin{bmatrix}-0.5&0.5\\0.3&-0.3\end{bmatrix}.\tag{39}$$

In this paper, let the initial values for $c_1 = 0.25$, $T = 2$, $\eta = 1$, and time-varying delay be $\tau_1(t) = \tau_2(t) = 0.2 \times |\cos t|$, which means that $\tau = 0.2$ and $d = 0.2$. Through Theorem 6 and optimization over value c_2, it yields that delayed Markovian jumping neural networks (9) are finite-time bounded with respect to (c_1, c_2, T) with minimal $c_2 = 5.0312$ while minimal c_2 in [33] is 5.4296, which shows the less conservative result in this paper.

Example 2. Consider a class of delayed Markovian jumping neural networks (9) with partially known transition rates and operation modes described as follows:

$$A_1 = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}, \qquad A_2 = \begin{bmatrix} 2.2 & 0 \\ 0 & 1.5 \end{bmatrix}, \qquad A_3 = \begin{bmatrix} 2.3 & 0 \\ 0 & 2.5 \end{bmatrix},$$
$$B_1 = \begin{bmatrix} 1 & 1 \\ -1 & -1 \end{bmatrix}, \qquad B_2 = \begin{bmatrix} 1 & 0.6 \\ 0.1 & 0.3 \end{bmatrix},$$
$$B_3 = \begin{bmatrix} 0.3 & 0.2 \\ 0.4 & 0.1 \end{bmatrix}, \qquad C_1 = \begin{bmatrix} 0.88 & 1 \\ 1 & 1 \end{bmatrix},$$
$$C_2 = \begin{bmatrix} 1 & -0.1 \\ 0.1 & 0.2 \end{bmatrix}, \qquad C_3 = \begin{bmatrix} 0.5 & 0.7 \\ 0.7 & 0.4 \end{bmatrix}, \qquad \Gamma_s = I_2. \tag{40}$$

The three cases of the transition rates matrices are considered as

$$\text{Case I: } \Omega = \begin{bmatrix} -0.8 & 0.3 & 0.5 \\ 0.1 & -0.8 & 0.7 \\ 0.7 & 0.4 & -1.1 \end{bmatrix},$$
$$\text{Case II: } \Omega = \begin{bmatrix} -0.8 & ? & ? \\ 0.1 & -0.8 & 0.7 \\ 0.7 & 0.4 & -1.1 \end{bmatrix}, \tag{41}$$
$$\text{Case III: } \Omega = \begin{bmatrix} -0.8 & ? & ? \\ ? & -0.8 & ? \\ 0.7 & 0.4 & -1.1 \end{bmatrix}.$$

With the same mode switching rates, initial values and time-varying delays, through Theorem 6 and optimization over value c_2, it yields that in Case I, $c_2 = 4.8124$; in Case II, $c_2 = 4.6121$; in Case III, $c_2 = 4.5372$. Therefore, the delayed Markovian jumping neural networks (9) are finite-time bounded with respect to (c_1, c_2, T).

Remark 10. The accessibility of the jumping process $\{r_t, t \geq 0\}$ in the existing literature is commonly assumed to be completely accessible or completely unaccessible. Note that the transition probabilities are still viewed as accessible in this paper. Therefore, the transition probabilities matrix considered in this paper is more general assumption than Markovian jump systems.

5. Conclusions

Unlike most existing research results focusing on Lyapunov stability property of Markovian jump system, our paper investigated finite-time stability which concerns the boundedness of state during the delayed Markovian jump interval. In this paper, we have examined the problems of finite-time boundedness for a class of delayed Markovian jumping neural networks with partly unknown transition probabilities. Based on the analysis result, the static state feedback finite-time boundedness is given. Although the derived result is not in LMIs form, we can turn it into LMIs feasibility problem by fixing some parameters. At last, numerical examples are also given to demonstrate the effectiveness of the proposed approach.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgment

This work was supported by the Natural Science Foundation of Hainan province (111002).

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