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Less Conservative Delay-dependent Asymptotic Stability Criteria for Stochastic Neural Networks of Neutral-type with Distributed Delay

[1]Guoquan Liu, [1,2]Simon X. Yang and [1,3]Yi Chai
[1]College of Automation, Chongqing University, Chongqing 400044, China
[2]School of Engineering, University of Guelph, Guelph, Ontario, Canada N1G2W1, Canada
[3]State Key Laboratory of Power Transmission Equipment and System Security and New Technology of Engineering, Chongqing University, Chongqing, China

Abstract: To deal with the problem of the global asymptotic stability for stochastic neural networks of neutral-type with distributed delay, this study proposed delay-dependent stability criteria based on the Lyapunov-Krasovskii functional method and the Itô's differential formula. In addition, new stability criteria are obtained in terms of linear matrix inequalities (LMIs). More specifically, the obtained results are less conservative, in which the Leibniz-Newton formula and the free-weighting matrix method are employed. At last, two numerical examples are given to show the effect of the proposed LMIs results.

Key words: Delay-dependent asymptotic stability, stochastic neural networks, neutral-type, lyapunov-Krasovskii functional, distributed delay

INTRODUCTION

Over past two decades, artificial neural networks have attracted considerable attention because of their immense potentials of application prospective. Time delay is commonly encountered in the implementation of neural networks due to the finite switching speed of amplifier and it is frequently a source of instability in neural networks (Marcus and Westervelt, 1989; Chen and Zheng, 2009). So it is very important to investigate the stability of delayed neural networks. Recently, a great deal of results have been reported in the literature via various approaches (Wan and Sun, 2005; Zhang *et al*., 2007; Liu *et al*., 2008; Yue *et al*., 2008; Jiang *et al*., 2009; Xiao and Zhang, 2009; Li *et al*., 2009; Chen and Zheng, 2009; Park *et al*., 2009; Zhang and Shi, 2009; Wan and Zhou, 2008; Huang, 2007; Singh, 2010). In addition, many dynamical systems are described with neutral functional differential equations that include neutral delay differential equations. These systems are called neutral neural networks or neutral networks of neutral-type. Recently, the stability analysis for delayed neural networks of neutral-type has drawn particular research attention (Park *et al*., 2008; Chen *et al*., 2010; Su and Chen, 2009; Rakkiyappan and Balasubramaniam, 2008; Feng *et al*., 2009). For example, Park *et al*. (2008) studied the problem of the global asymptotic stability for delayed cellular neural networks of neutral-type. Especially, Rakkiyappan and Balasubramaniam (2008) studied the problem of the global exponential stability for delayed cellular neural networks of neutral-type with discrete and distributed delays and derived some delay-independent sufficient conditions. Also, some delay-dependent conditions for the global asymptotic stability problem are presented by Feng *et al*. (2009). Generally speaking, the delay-dependent results are less conservative than the delay-independent ones, especially when the size of time delay is small. Therefore, much attention has been paid to the delay-dependent type.

Stochastic perturbations, as well as time delays may cause instability and poor performance of many practical systems. But the global asymptotic stability analysis for stochastic neural networks of neutral-type with discrete and unbounded distributed delays is investigated by only a few researchers (Li, 2010; Sakthivel *et al*., 2010). In Li (2010), the Lyapunov-Krasovskii functional method has been developed to deal with the analysis problem of global robust stability for a class of stochastic interval neural networks with continuously distributed delay of neutral-type. In study of Sakthivel *et al*. (2010), exponential stability conditions for stochastic neural networks of neutral-type were proposed under some assumptions. To the best of our knowledge, the stability problem for stochastic delayed neural networks of neutral-type has not been fully investigated which remains as an interesting research topic.

With this motivation, this study has considered the problem of the global asymptotic stability for stochastic

Corresponding Author: Guoquan Liu, College of Automation, Chongqing University, Chongqing 400044, China
Tel: +86013618395665

neural networks of neutral type with unbounded distributed delay. Based on an appropriate Lyapunov-Krasovskii functional and the Itô's differential formula, new stability criterion is obtained in terms of LMIs. More specifically, the obtained condition is less conservative, in which the Leibniz-Newton formula and the free-weighting matrix method are employed. Two numerical examples are shown to illustrate the effectiveness of the proposed method.

SOME PRELIMINARIES

In this study, we consider the following stochastic neural networks of neutral-type with unbounded distributed delay model:

$$d[z(t)-Bz(t-\tau(t))]=\left[-Cz(t)+W_1r(z(t))+W_2r(z(t-\tau(t)))+A\int_{-\infty}^{t}K(t-s)r(z(s))ds+I\right]dt$$
$$+\left[D_0z(t)+D_1\int_{-\infty}^{t}K(t-s)r(z(s))ds+D_2z(t-\tau(t))\right]d\omega(t),\ z(t)=\phi(t),-\infty\le t\le 0 \tag{1}$$

where, $z(t) = [z_1(t), z_2(t), ..., z_n(t)]^T \in \Re^n$ is the neural state vector, $r(z(t))=[r_1(z_1(t)),r_2(z_2(t)),...,r_n(z_n(t))]^T\in\Re^n$ is the neuron activation function. $\tau(t)$ is a scalar representing the delay time. I is a external constant input. $\omega(t)=[\omega_1(t),\omega_2(t),...,\omega_n(t)]^T$ is a Brownian motion defined on a complete probability space (Ω, F, P) with a natural filtration $\{F_t\}\ge 0$ which satisfies E $\{d\omega(t)\} = 0$ and $E\{d\omega^2(t)\}=0$. $C=\mathrm{diag}\{c_1,c_2,...,c_n\}>0, W_1\in\Re^{n\times n}, W_2\in\Re^{n\times n}, A\in\Re^{n\times n}$ and $B\in\Re^{n\times n}$ are the connection weight matrices; $D_0\in\Re^{n\times n}$, $D_1\in\Re^{n\times n}$ and $D_2\in\Re^{n\times n}$ are known real constant matrices. K (t) = diag $\{k_1(t), k_2(t), ..., k_n(t)\}$ is the delay kernel function, k_j is a real valued continuous nonnegative function defined on $[0, +\infty]$ which is assumed to satisfy $\int_0^{\infty}k_j(s)\,ds=1, j=1,2,...,n$. $\phi(t)$ is the initial condition of the neural network $\phi\in\partial^2_{\mathcal{F}_0}\left[(-\infty,0),\Re^n\right]$.

For system (1), the following assumptions are given:

Assumption 1: The matrix in system (1) satisfies $\rho(B)<1$ where the notation $\rho(B)$ denotes the spectral radius of B

Assumption 2: The time-varying delay satisfies:

$$0\le\tau(t)\le\tau, \dot{\tau}(t)\le\tau_d<1 \tag{2}$$

where τ and τ_d are known constants.

Assumption 3: The activation functions $r_i(.)$ (i = 1,2, ..., n) are bounded and satisfy the following Lipschitz condition:

$$|r_i(\eta_1)-r_i(\eta_2)|\le|\vartheta_i(\eta_1-\eta_2)|, i=1,2,...,n, \eta_1,\eta_2\in\Re^n \tag{3}$$

where $\vartheta_i\in\Re^{n\times n}$ for i = 1, 2, ..., n are known constant matrices.

Assume $z^*=[z_1^*,z_2^*,...,z_n^*]^T$ is an equilibrium point of system (1). It can be easily derive that the transformation puts $x_i=z_i-z_i^*$ system (1) into the following system:

$$d[x(t)-Bx(t-\tau(t))]=\left[-Cx(t)+W_1f(x(t))+W_2f(x(t-\tau(t)))+A\int_{-\infty}^{t}K(t-s)f(x(s))ds\right]dt$$
$$+\left[D_0x(t)+D_1\int_{-\infty}^{t}K(t-s)f(x(s))ds+D_2x(t-\tau(t))\right]d\omega(t) \tag{4}$$

where:

$$x(t)=[x_1(t),x_2(t),...,x_n(t)]^T\in\Re^n,$$
$$f(x(t))=[f_1(x_1(t)),f_2(x_2(t)),...,f_n(x_n(t))]^T\in\Re^n,$$
$$f_j(x_j(t))=r(x_j(t))+z_j^*)-r_j(z_j^*)$$

Since the function $r_i(.)$ satisfies the hypothesis Assumption. It is easy to note that $f_i(.)$ satisfies:

$$|f_i(\eta)|\le|\vartheta_i\eta|, i=1,2,...,n, \vartheta_i\in\Re^n \tag{5}$$

which is equivalent to:

$$f_i^T(\eta)f_i(\eta)\le\eta^T\vartheta_i^T\vartheta_i\eta, i=1,2,...,n, f_i(\eta_i)=0 \tag{6}$$

For the sake of simplicity, the following notations are adopted:

$$y(t)=-Cx(t)+W_1f(x(t))+W_2f(x(t-\tau(t)))+A\int_{-\infty}^{t}K(t-s)f(x(s))ds \tag{7}$$

$$g(t)=D_0x(t)+D_1\int_{-\infty}^{t}K(t-s)f(x(s))ds+D_2x(t-\tau(t)) \tag{8}$$

Then system (4) is transformed to:

$$d[x(t)-Bx(t-\tau(t))]=y(t)dt+g(t)d\omega(t) \tag{9}$$

Before presenting the main results, let us introduce the following Definition and Lemmas:

Definition 1: For the stochastic neural networks of neutral-type (4) and every, $\phi\in\partial^2_{\mathcal{F}_0}$, the trivial solution is globally asymptotically stable in the mean square if:

$$\lim_{x\to+\infty}E\|(x,\phi)\|^2=0 \tag{10}$$

Lemma 1: (Schur complement (Boyd *et al*., 1994): For a given matrix:

$$\Pi = \begin{bmatrix} \Pi_{11} & \Pi_{12} \\ \Pi_{12}^T & \Pi_{22} \end{bmatrix}$$

with $\Pi_{11} = \Pi_{11}^T$, $\Pi_{22} = \Pi_{22}^T$ then following conditions are equivalent:

$$\begin{aligned} &(1)\ \Pi<0, \\ &(2)\ \Pi_{22}<0, \Pi_{11} - \Pi_{12}\Pi_{22}^{-1}\Pi_{12}^T < 0, \\ &(2)\ \Pi_{11}<0, \Pi_{22} - \Pi_{12}^T\Pi_{11}^{-1}\Pi_{12} < 0 \end{aligned} \tag{11}$$

Lemma 2: (Gu, 2000): For any constant matrix M > 0, any scalars a and b with a<b and a vector function x (t): $[a,b] \rightarrow \Re^n$ such that the integrals concerned as well defined, the following holds:

$$\left[\int_a^b x(s)\,ds\right]^T M \left[\int_a^b x(s)\,ds\right] \le (b-a)\int_a^b x^T(s)\,Mx(s)\,ds \tag{12}$$

Lemma 3: For any real vectors a, b and any matrix M > 0 with appropriate dimensions, it follows that:

$$2a^Tb \le a^TMa + b^TM^{-1}b \tag{13}$$

STABILITY ANALYSIS

Here, we discussed global asymptotic stability of system (4). Based on the Lyapunov-Krasovskii functional and the Itô's differential formula, novel stability criteria are obtained in terms of LMIs.

Theorem 1: For given scalars τ, τ_d satisfy $0 \le \tau(t) \le \tau, \dot{\tau}(t) \le \tau_d < 1$ system (4) is globally asymptotically stable in the mean square, if there exist positive define matrices $P, Q_{11}, Q_{22}, Q_{33}, R, Z$, any matrices $Q_{12}, M_j, N_j, (j=1,2,...,7)$, positive define diagonal matrix E, positive scalars ε_1, ε_2 such that the following LMIs holds:

$$\Gamma = \begin{bmatrix} \Gamma_{11} & \Gamma_{12} & \Gamma_{13} & \Gamma_{14} & \Gamma_{15} \\ * & -\Gamma_{22} & 0 & 0 & 0 \\ * & * & -\Gamma_{33} & 0 & 0 \\ * & * & * & -\Gamma_{44} & 0 \\ * & * & * & * & -\Gamma_{55} \end{bmatrix} < 0 \tag{14}$$

$$Q = \begin{bmatrix} Q_{11} & Q_{12} \\ * & Q_{22} \end{bmatrix} > 0 \tag{15}$$

where:

$$\begin{aligned} &\Gamma_{11} = [\varphi_{ij}]_{7\times7}, \Gamma_{12} = \Gamma_{13} = [N_i]_{7\times1}, \\ &\Gamma_{14} = \begin{bmatrix} D_0^TP & 0 & 0 & D_1^TP & D_2^TP & 0 & 0 \end{bmatrix}^T, \\ &\Gamma_{15} = \begin{bmatrix} D_0^TZ & 0 & 0 & D_1^TZ & D_2^TZ & 0 & 0 \end{bmatrix}^T, \\ &\Gamma_{22} = R, \Gamma_{33} = Z, \Gamma_{44} = P, \Gamma_{55} = Z \end{aligned}$$

with:

$$\begin{aligned} &\varphi_{1,1} = Q_{11} + Q_{33} - M_1C - C^TM_1^T + N_1 + N_1^T + \varepsilon_1\vartheta_1^T\vartheta_1, \\ &\varphi_{1,2} = -C^TM_2^T + M_1W_1 + N_2^T, \varphi_{1,3} = -C^TM_3^T + M_1W_2 + N_3^T, \\ &\varphi_{1,4} = -C^TM_4^T + M_1A + N_4^T, \varphi_{1,5} = -C^TM_5^T + N_5^T - N_1B - N_1, \\ &\varphi_{1,6} = -C^TM_6^T + N_6^T + N_1B, \varphi_{1,7} = P - C^TM_7^T - M_1 + N_7^T, \\ &\varphi_{2,2} = Q_{22} + E + M_2W_1 + W_1^TM_2^T - \varepsilon_1 I, \\ &\varphi_{2,3} = W_1^TM_3^T + M_2W_2, \varphi_{2,4} = W_1^TM_4^T + M_2A, \\ &\varphi_{2,5} = W_1^TM_5^T - N_2B - N_2 - (1-\tau_d)Q_{12}, \varphi_{2,6} = W_1^TM_6^T + N_2B, \\ &\varphi_{2,7} = W_1^TM_7^T - M_2, \varphi_{3,3} = -(1-\tau_d)Q_{22} + M_3W_2 + W_2^TM_3^T \\ &-\varepsilon_2 I, \varphi_{3,4} = W_2^TM_4^T + M_3A, \varphi_{3,5} = W_2^TM_5^T - N_3B - N_3, \\ &\varphi_{3,6} = W_2^TM_6^T + N_3B, \varphi_{3,7} = W_2^TM_7^T - M_3, \\ &\varphi_{4,4} = -E + M_4A + A^TM_4^T, \varphi_{4,5} = A^TM_5^T - N_4B - N_4, \\ &\varphi_{4,6} = A^TM_6^T + N_4B, \varphi_{4,7} = A^TM_7^T - M_4, \\ &\varphi_{5,5} = -(1-\tau_d)Q_{11} - N_5B - B^TN_5^T - N_5 - N_5^T - \varepsilon_2\vartheta_2^T\vartheta_2, \\ &\varphi_{5,6} = -B^TN_6^T - N_6^T + N_5B, \varphi_{5,7} = -M_5 - B^TN_7^T - N_7^T, \\ &\varphi_{6,6} = -Q_{33}(1-2\tau_d) + N_6B + B^TN_6^T, \varphi_{6,7} = -M_6 + B^TN_7^T, \\ &\varphi_{7,7} = \tau^2R - M_7 - M_7^T \end{aligned}$$

Proof: Using Lemma 1 (Schur complement), LMI (14) can be transformed to:

$$\Pi = \Gamma_{11} + NR^{-1}N^T + NZ^{-1}N^T + \Gamma_{14}\Gamma_{44}^{-1}\Gamma_{14}^T + \Gamma_{15}\Gamma_{55}^{-1}\Gamma_{15}^T < 0 \tag{16}$$

where, $\Gamma_{11}, \Gamma_{14}, \Gamma_{15}, \Gamma_{44}, \Gamma_{55}$ are defined in Theorem 1.

From (6), the following inequalities can be obtained easily:

$$f^T(x(t))\,f(x(t)) - x^T(t)\vartheta_1^T\vartheta_1 x(t) \le 0 \tag{17}$$

$$f^T(x(t-\tau(t)))\,f(x(t-\tau(t))) - x^T(t-\tau(t))\,\vartheta_2^T\vartheta_2 x(t-\tau(t)) \le 0 \tag{18}$$

Noticing that, for any scalars $\varepsilon_i > 0$, i = 1, 2, there exist:

$$0 \le \varepsilon_1\left[x^T(t)\,\vartheta_1^T\vartheta_1 x(t) - f^T(x(t))\,f(x(t))\right] \tag{19}$$

$$0 \le \varepsilon_2\left[x^T(t-\tau(t))\,\vartheta_2^T\vartheta_2 x(t-\tau(t)) - f^T(x(t-\tau(t)))\,f(x(t-\tau(t)))\right] \tag{20}$$

Consider the following a lyapunov-krasoskill functional for system (4) as follows:

$$V(t) = V_1(t) + V_2(t) + V_3(t) + V_4(t) + V_5(t) \tag{21}$$

where:

$$V_1(t) = [x(t) - Bx(t-\tau(t))]^T P[x(t) - Bx(t-\tau(t))],$$
$$V_2(t) = \int_{t-\tau(t)}^{t} \begin{bmatrix} x(s) \\ f(x(s)) \end{bmatrix}^T \begin{bmatrix} Q_{11} & Q_{12} \\ * & Q_{22} \end{bmatrix} \begin{bmatrix} x(s) \\ f(x(s)) \end{bmatrix} ds + \int_{t-2\tau(t)}^{t} x^T(s)\, Q_{33} x(s)\, ds,$$
$$V_3(t) = \tau \int_{-\tau}^{0}\int_{t+\beta}^{t} y^T(s)\, Ry(s)\, ds d\beta,$$
$$V_4(t) = \int_{-\tau}^{0}\int_{t+\beta}^{t} g^T(s)\, Zg(s)\, ds d\beta,$$
$$V_5(t) = \sum_{0}^{n} e_i \int_0^{\infty}\int_{t-\sigma}^{t} k_i(\sigma)\, f_i^2(x_i(s))\, ds d\sigma$$

and $P, Q_{11}, Q_{22}, Q_{33}, R, Z$ are positive matrices.

By it ô's differential formula, the stochastic derivative of V (t) along the trajectory of system (4) is given by:

$$dV(t) = \{\mathcal{L}V(t)\}\, dt + \{[x(t) - Bx(t-\tau(t))]^T Pg(t)\}\, d\omega(t) \tag{22}$$

where:

$$\mathcal{L}V(t) = \mathcal{L}V_1(t) + \mathcal{L}V_2(t) + \mathcal{L}V_3(t) + \mathcal{L}V_4(t) + \mathcal{L}V_5(t) \tag{23}$$

$$\begin{aligned} \mathcal{L}V_1(t) &= 2[x(t) - Bx(t-\tau(t))]^T Py(t) + g^T(t)Pg(t) \\ &= 2[x(t) - Bx(t-\tau(t))]^T Py(t) + \left[D_0 x(t) + D_1\int_{-\infty}^{t} K(t-s)f(x(s))ds + D_2 x(t-\tau(t))\right]^T \\ &\times P\left[D_0 x(t) + D_1\int_{-\infty}^{t} K(t-s)f(x(s))ds + D_2 x(t-\tau(t))\right] \end{aligned} \tag{24}$$

$$\begin{aligned} \mathcal{L}V_2(t) &= \begin{bmatrix} x(t) \\ f(x(t)) \end{bmatrix}^T \begin{bmatrix} Q_{11} & Q_{12} \\ * & Q_{22} \end{bmatrix} \begin{bmatrix} x(t) \\ f(x(t)) \end{bmatrix} - (1-\dot{\tau}(t)) \begin{bmatrix} x(t-\tau(t)) \\ f(x(t-\tau(t))) \end{bmatrix}^T \begin{bmatrix} Q_{11} & Q_{12} \\ * & Q_{22} \end{bmatrix} \\ &\times \begin{bmatrix} x(t-\tau(t)) \\ f(x(t-\tau(t))) \end{bmatrix} + x^T(t)Q_{33}x(t) - (1-2\dot{\tau}(t))x^T(t-2\tau(t))Q_{33}x(t-2\tau(t)) \\ &\le \begin{bmatrix} x(t) \\ f(x(t)) \end{bmatrix}^T \begin{bmatrix} Q_{11} & Q_{12} \\ * & Q_{22} \end{bmatrix} \begin{bmatrix} x(t) \\ f(x(t)) \end{bmatrix} - (1-\tau_d) \begin{bmatrix} x(t-\tau(t)) \\ f(x(t-\tau(t))) \end{bmatrix}^T \begin{bmatrix} Q_{11} & Q_{12} \\ * & Q_{22} \end{bmatrix} \\ &\times \begin{bmatrix} x(t-\tau(t)) \\ f(x(t-\tau(t))) \end{bmatrix} + x^T(t)Q_{33}x(t) - (1-2\tau_d)x^T(t-2\tau(t))Q_{33}x(t-2\tau(t)) \end{aligned} \tag{25}$$

$$\mathcal{L}V_3(t) = \tau^2 y^T(t)\, Ry(t) - \tau\int_{t-\tau}^{t} y^T(s)Ry(s)\, ds \tag{26}$$

$$\begin{aligned} \mathcal{L}V_4(t) &= \tau g^T(t)Zg(t) - \int_{t-\tau}^{t} g^T(s)Zg(s)ds \\ &\le \tau\left[D_0 x(t) + D_1\int_{-\infty}^{t} K(t-s)f(x(s))ds + D_2 x(t-\tau(t))\right]^T \\ &\times Z\left[D_0 x(t) + D_1\int_{-\infty}^{t} K(t-s)f(x(s))ds + D_2 x(t-\tau(t))\right] - \int_{t-\tau(t)}^{t} g^T(s)Zg(s)ds \end{aligned} \tag{27}$$

$$\begin{aligned} \mathcal{L}V_5(t) &= \sum_{j=1}^{n} e_j\int_0^{\infty} k_j(\delta) f_j^2(x_i(t))d\delta - \sum_{j=1}^{n} e_j\int_0^{\infty} k_j(\delta) f_j^2(x_j(t-\delta))\, d\delta \\ &= f^T(x(t))Ef(x(t)) - \sum_{j=1}^{n} e_j\int_0^{\infty} k_j(\delta)d\delta\int_0^{\infty} k_j(\delta) f_j^2(x_j(t-\delta))\, d\delta \\ &\le f^T(x(t))Ef(x(t)) - \sum_{j=1}^{n} e_j\left(\int_0^{\infty} k_j(\delta)\, f(x_j(t-\delta))\, d\delta\right)^2 \end{aligned} \tag{28}$$

By using Lemma 2, it follows that:

$$-\tau\int_{t-\tau}^{t} y^T(s)Ry(s)ds \le -\left[\int_{t-\tau(t)}^{t} y(s)ds\right]^T R\left[\int_{t-\tau(t)}^{t} y(s)ds\right] \tag{29}$$

$$\begin{aligned} &-\sum_{j=1}^{n} e_j\left(\int_0^{\infty} k_j(\delta) f(x_j(t-\delta))\, d\delta\right)^2 \\ &\le -\left(\int_{-\infty}^{t} K(t-s)f(x(s))ds\right)^T E\left(\int_{-\infty}^{t} K(t-s)f(x(s))\, ds\right) \end{aligned} \tag{30}$$

From (7) and the Newton-Leibniz formula, the following equations are true for free-weighting matrices M and N with appropriate dimensions:

$$0 = 2\xi^T(t)M\left[-Cx(t) + W_1 f(x(t)) + W_2 f(x(t-\tau(t))) + A\int_{-\infty}^{t} K(t-s)f(x(s))ds - y(t)\right] \tag{31}$$

$$0 = 2\xi^T(t)N\begin{bmatrix} x(t) - Bx(t-\tau(t)) - x(t-\tau(t)) + Bx(t-2\tau(t)) \\ -\int_{t-\tau(t)}^{t} y(s)ds - \int_{t-\tau(t)}^{t} g(s)d\omega(s) \end{bmatrix} \tag{32}$$

where:

$$\xi^T(t) = \begin{bmatrix} x^T(t), f^T(x(t)), f^T(x(t-\tau(t))), \left(\int_{-\infty}^{t} K(t-s)f(x(s))ds\right)^T, \\ x^T(t-\tau(t)), x^T(t-2\tau(t)), y^T(t) \end{bmatrix}$$

From Lemma 3, it can be obtained as:

$$-2\xi^T(t)N\int_{t-\tau(t)}^{t} y(s)ds \le \xi^T(t)NR^{-1}N^T\xi(t) + \left[\int_{t-\tau(t)}^{t} y(s)ds\right]^T R\left[\int_{t-\tau(t)}^{t} y(s)ds\right] \tag{33}$$

$$-2\xi^T(t)N\int_{t-\tau(t)}^{t} g(s)\, d\omega(s) \le \xi^T(t)NZ^{-1}N^T\xi(t) + \left[\int_{t-\tau(t)}^{t} g(s)\, d\omega(s)\right]^T Z\left[\int_{t-\tau(t)}^{t} g(s)\, d\omega(s)\right] \tag{34}$$

Then, combining (19), (20) and (23)-(34) together, we can obtain that:

$$\begin{aligned} dV(t) &\le \left\{\xi^T(t)\Pi\xi(t) - \int_{t-\tau(t)}^{t} g^T(s)Zg(s)ds + \left[\int_{t-\tau(t)}^{t} g(s)d\omega(s)\right]^T Z\left[\int_{t-\tau(t)}^{t} g(s)\, d\omega(s)\right]\right\}dt \\ &+ [x(t) - Bx(t-\tau(t))]^T Pg(t)\, d\omega(t) \end{aligned} \tag{35}$$

It is obvious that for $\Pi < 0$ and there exists a scalar $\delta > 0$ such that:

$$\Pi + \mathrm{diag}\{\delta I, 0, 0, 0, 0, 0, 0\} < 0 \quad (36)$$

Taking the mathematical expectation of both sides of (35), using:

$$E\left\{\int_{t-\tau(t)}^{t} g^T(s)\, Z g(s)\, ds\right\} = E\left\{\left[\int_{t-\tau(t)}^{t} g(s) d\omega(s)\right]^T Z \left[\int_{t-\tau(t)}^{t} g(s)\, d\omega(s)\right]\right\} \quad (37)$$

And considering (36), we have:

$$\frac{dEV(t)}{dt} \le E\{\xi^T(t)\Pi\xi(t)\} \le -\delta E\|x(t)\|^2 \quad (38)$$

Where, E is the mathematical expectation operator.

Then by using the Lyapunov-Krasovskii stability theorem, we can conclude that the stochastic delayed neural networks of neutral-type (4) is globally asymptotically stable if (14) and (15) hold. This completes the proof of Theorem 1.

Remark 1: The criterion given in Theorem 1 is delay-dependent. It is well known that the delay-dependent criteria are less conservative than delay-independent criteria when the time delay is small

Remark 2: Note that the conditions (14) and (15) are given as LMIs. Therefore, by using the MATLAB LMI Toolbox, it is straightforward to check the feasibility of (14) and (15) without turning any parameters

Based on the proof of Theorem 1, we have the following results.

Case 1: If we drop out the unbounded distributed delay and system (4) can be simplified to:

$$\begin{aligned} d[x(t) - Bx(t-\tau(t))] &= [-Cx(t) + W_1 f(x(t)) + W_2 f(x(t-\tau(t)))]dt \\ &\quad + [D_0 x(t) + D_2 x(t-\tau(t))]d\omega(t) \end{aligned} \quad (39)$$

Corollary 2: For given scalars τ, τ_d satisfy $0 \le \tau(t) \le \tau, \dot{\tau}(t) \le \tau_d < 1$ system (39) is globally asymptotically stable in the mean square, if there exist positive define matrices $P, Q_{11}, Q_{22}, Q_{33}, R, Z$, any matrices $Q_{12}, M_j, N_j (j = 1, 2, ..., 6)$ positive scalars ε_1, ε_2 such that the following LMIs holds:

$$\tilde{\Gamma} = \begin{bmatrix} \tilde{\Gamma}_{11} & \tilde{\Gamma}_{12} & \tilde{\Gamma}_{13} & \tilde{\Gamma}_{14} & \tilde{\Gamma}_{15} \\ * & -\tilde{\Gamma}_{22} & 0 & 0 & 0 \\ * & * & -\tilde{\Gamma}_{33} & 0 & 0 \\ * & * & * & -\tilde{\Gamma}_{44} & 0 \\ * & * & * & * & -\tilde{\Gamma}_{55} \end{bmatrix} < 0 \quad (40)$$

$$Q = \begin{bmatrix} Q_{11} & Q_{12} \\ * & Q_{22} \end{bmatrix} > 0 \quad (41)$$

where:

$$\tilde{\Gamma}_{11} = [\tilde{\varphi}_{ij}]_{6\times 6}, \tilde{\Gamma}_{12} = \tilde{\Gamma}_{13} = [N_i]_{6\times 1},$$
$$\tilde{\Gamma}_{14} = \begin{bmatrix} D_0^T P & 0 & 0 & 0 & D_2^T P & 0 \end{bmatrix}^T,$$
$$\tilde{\Gamma}_{15} = \begin{bmatrix} D_0^T Z & 0 & 0 & 0 & D_2^T Z & 0 \end{bmatrix}^T,$$
$$\Gamma_{22} = R, \Gamma_{33} = Z, \Gamma_{44} = P, \Gamma_{55} = Z$$

with:

$$\tilde{\varphi}_{1,1} = Q_{11} + Q_{33} - M_1 C - C^T M_1^T + N_1 + N_1^T + \varepsilon_1 \vartheta_1^T \vartheta_1,$$
$$\tilde{\varphi}_{1,2} = -C^T M_2^T + M_1 W_1 + N_2^T, \tilde{\varphi}_{1,3} = -C^T M_3^T + M_1 W_2 + N_3^T,$$
$$\tilde{\varphi}_{1,4} = -C^T M_4^T + N_4^T - N_1 B - N_1, \tilde{\varphi}_{1,5} = -C^T M_5^T + N_5^T + N_1 B,$$
$$\tilde{\varphi}_{1,6} = P - C^T M_6^T - M_1 + N_6^T, \tilde{\varphi}_{2,2} = Q_{22} + M_2 W_1 + W_1^T M_2^T - \varepsilon_1 I,$$
$$\tilde{\varphi}_{2,3} = W_1^T M_3^T + M_2 W_2, \tilde{\varphi}_{2,4} = W_1^T M_4^T - N_2 B - N_2 - (1-\tau_d) Q_{12},$$
$$\tilde{\varphi}_{2,5} = W_1^T M_5^T + N_2 B, \tilde{\varphi}_{2,6} = W_1^T M_6^T - M_2,$$
$$\tilde{\varphi}_{3,3} = -(1-\tau_d) Q_{22} + M_3 W_2 + W_2^T M_3^T - \varepsilon_2 I,$$
$$\tilde{\varphi}_{3,4} = W_2^T M_4^T - N_3 B - N_3,$$
$$\tilde{\varphi}_{3,5} = W_2^T M_5^T + N_3 B, \tilde{\varphi}_{3,6} = W_2^T M_6^T - M_3,$$
$$\tilde{\varphi}_{4,4} = -(1-\tau_d) Q_{11} - N_4 B - B^T N_4^T - N_4 - N_4^T - \varepsilon_2 \vartheta_2^T \vartheta_2,$$
$$\tilde{\varphi}_{4,5} = -B^T N_5^T - N_5^T + N_4 B, \tilde{\varphi}_{4,6} = -M_4 - B^T N_6^T - N_6^T,$$
$$\tilde{\varphi}_{5,5} = -Q_{33}(1 - 2\tau_d) + N_5 B + B^T N_5^T, \tilde{\varphi}_{5,6} = -M_5 + B^T N_6^T,$$
$$\tilde{\varphi}_{6,6} = \tau^2 R - M_6 - M_6^T$$

Proof: It is similar to the proof of Theorem 1.

Remark 3: The system (39) has been intensively in the literatures, such as (Chen *et al*., 2010; Su and Chen, 2009). The Corollary 2 provides a complementary method to results in (Chen *et al*., 2010; Su and Chen, 2009).

Case 2: If there are no stochastic disturbances and system (4) can be described as:

$$d[x(t) - Bx(t-\tau(t))] = \left[-Cx(t) + W_1 f(x(t)) + W_2 f(x(t-\tau(t))) + A\int_{-\infty}^{t} K(t-s) f(x(s)) ds\right] dt \quad (42)$$

Corollary 3: For given scalars τ, τ_d satisfy $0 \le \tau(t) \le \tau, \dot{\tau}(t) \le \tau_d < 1$ system (42) is globally asymptotically stable in the mean square, if there exist positive define matrices P, Q_{11}, Q_{22}, R any matrices $Q_{12}, M_j, N_j (j = 1, 2, ..., 6)$, positive define diagonal matrix E, positive scalars ε_1, ε_2 such that the following LMIs holds:

$$\bar{\Gamma} = \begin{bmatrix} \bar{\Gamma}_{11} & \tilde{\Gamma}_{12} \\ * & -\Gamma_{22} \end{bmatrix} < 0 \quad (43)$$

$$Q = \begin{bmatrix} Q_{11} & Q_{12} \\ * & Q_{22} \end{bmatrix} > 0 \quad (44)$$

where:

$$\bar{\Gamma}_{11} = [\bar{\varphi}_{ij}]_{6\times 6}, \Gamma_{12} = [N_i]_{6\times 1}, \Gamma_{22} = R$$

with:

$$\begin{aligned}
&\bar{\varphi}_{1,1} = Q_{11} - M_1 C - C^T M_1^T + N_1 + N_1^T + \varepsilon_1 \vartheta_1^T \vartheta_1, \\
&\bar{\varphi}_{1,2} = -C^T M_2^T + M_1 W_1 + N_2^T, \\
&\bar{\varphi}_{1,3} = -C^T M_3^T + M_1 W_2 + N_3^T, \bar{\varphi}_{1,4} = -C^T M_4^T + M_1 A + N_4^T, \\
&\bar{\varphi}_{1,5} = -C^T M_5^T + N_5^T - N_1 B, \bar{\varphi}_{1,6} = P - C^T M_6^T - M_1 + N_6^T, \\
&\bar{\varphi}_{2,2} = Q_{22} + E + M_2 W_1 + W_1^T M_2^T - \varepsilon_1 I, \\
&\bar{\varphi}_{2,3} = W_1^T M_3^T + M_2 W_2, \bar{\varphi}_{2,4} = W_1^T M_4^T + M_2 A, \\
&\bar{\varphi}_{2,5} = W_1^T M_5^T - N_2 B - (1-\tau_d) Q_{12}, \\
&\bar{\varphi}_{2,6} = W_1^T M_6^T - M_2, \bar{\varphi}_{3,3} = -(1-\tau_d) Q_{22} + M_3 W_2 + W_2^T M_3^T - \varepsilon_2 I, \\
&\bar{\varphi}_{3,4} = W_2^T M_4^T + M_3 A, \bar{\varphi}_{3,5} = W_2^T M_5^T - N_3 B, \\
&\bar{\varphi}_{3,6} = W_2^T M_6^T - M_3, \bar{\varphi}_{4,4} = -E + M_4 A + A^T M_4^T, \\
&\bar{\varphi}_{4,5} = A^T M_5^T - N_4 B, \bar{\varphi}_{4,6} = A^T M_6^T - M_4, \\
&\bar{\varphi}_{5,5} = -(1-\tau_d) Q_{11} - N_5 B - B^T N_5^T - \varepsilon_2 \vartheta_2^T \vartheta_2, \\
&\bar{\varphi}_{5,6} = -M_5 - B^T N_6^T, \bar{\varphi}_{6,6} = \tau^2 R - M_6 - M_6^T
\end{aligned}$$

Proof: It is similar to the proof of Theorem 1.

Remark 4: If we choose $\tau(t) \equiv \tau$ in (42), that is the time delay sections satisfy constant delay and from (42) we can obtain the corresponding stability criterion which is similar to that of Feng *et al.* (2009), so Feng *et al.* (2009) is a special case of this paper and our results extend the results by Feng *et al.* (2009)

NUMERICAL EXAMPLES

Here, two examples are given to demonstrate the proposed results.

Example 1: Consider a two-neuron stochastic delayed neural network of neutral-type (4) with the following parameters (Example 1 of Li, 2010):

$$C = \begin{bmatrix} 7.5 & 0 \\ 0 & 5.25 \end{bmatrix}, W_1 = \begin{bmatrix} 0.1 & -0.1 \\ -0.06 & 0.02 \end{bmatrix}, W_2 = \begin{bmatrix} -0.1 & -1 \\ 0.15 & 0.07 \end{bmatrix},$$
$$A = \begin{bmatrix} 0.32 & 0.02 \\ -0.17 & 0.24 \end{bmatrix}, B = \begin{bmatrix} 0.15 & 0 \\ 0 & 0.15 \end{bmatrix},$$
$$\tau(t) = 0.2 - 0.1\sin(t), D_0 = D_1 = 0.1I, D_2 = 0$$

Let $\tau = 0.3, \tau_d = 0.1, \vartheta_1 = 0.2I, \vartheta_1 = 0.1I$. Now, solving the LMIs (14) and (15) in Theorem 1, by using Matlab LMI Control toolbox, one can find that system (4) described by Example 1 is globally asymptotically stable in the mean square. Then, one gets a feasible solution as follows:

$$P = \begin{bmatrix} 36.7771 & 0.5867 \\ 0.5867 & 38.4582 \end{bmatrix}, Q_{11} = \begin{bmatrix} 32.6963 & 0.1285 \\ 0.1285 & 32.8239 \end{bmatrix},$$
$$Q_{12} = \begin{bmatrix} -0.4362 & 0.1871 \\ 0.1871 & -0.2904 \end{bmatrix}, Q_{22} = \begin{bmatrix} 14.8573 & -0.0438 \\ -0.0438 & 14.8465 \end{bmatrix},$$
$$Q_{33} = \begin{bmatrix} 34.3079 & 0.1046 \\ 0.1046 & 34.3269 \end{bmatrix}, R = \begin{bmatrix} 30.6104 & 0.0138 \\ 0.0138 & 30.7508 \end{bmatrix},$$
$$Z = \begin{bmatrix} 31.7368 & 0.0003 \\ 0.0003 & 31.7358 \end{bmatrix}, E = \{25.5797 \quad 25.5797\},$$
$$\varepsilon_1 = 58.5111, \varepsilon_2 = 22.8341,$$
$$M_1 = \begin{bmatrix} 7.1361 & 0.0475 \\ 0.0475 & 9.5694 \end{bmatrix}, M_2 = \begin{bmatrix} 0.0711 & -0.0197 \\ -0.0197 & -0.0173 \end{bmatrix},$$
$$M_3 = \begin{bmatrix} -0.0255 & 0.0020 \\ 0.0020 & -0.0289 \end{bmatrix}, M_4 = \begin{bmatrix} 0.0120 & -0.0473 \\ -0.0473 & -0.0286 \end{bmatrix},$$
$$M_5 = \begin{bmatrix} 0.3926 & -0.1051 \\ -0.1051 & 0.5371 \end{bmatrix}, M_6 = \begin{bmatrix} 4.5062 & 0.1510 \\ 0.1510 & 6.0783 \end{bmatrix},$$
$$M_7 = \begin{bmatrix} -0.0952 & -0.5062 \\ -0.5062 & 0.8118 \end{bmatrix}, N_1 = \begin{bmatrix} -0.1038 & 0.0858 \\ 0.0858 & 0.0849 \end{bmatrix},$$
$$N_2 = \begin{bmatrix} 0.5515 & -0.0271 \\ -0.0271 & 0.4632 \end{bmatrix}, N_3 = \begin{bmatrix} -0.1460 & 0.0017 \\ 0.0017 & -0.1493 \end{bmatrix},$$
$$N_4 = \begin{bmatrix} -0.0416 & 0.0366 \\ 0.0366 & -0.0102 \end{bmatrix}, N_5 = \begin{bmatrix} 0.2198 & -0.0260 \\ -0.0260 & 0.1884 \end{bmatrix},$$
$$N_6 = \begin{bmatrix} -1.0419 & 0.0707 \\ 0.0707 & -0.8277 \end{bmatrix}, N_7 = \begin{bmatrix} 0.0064 & -0.0709 \\ -0.0709 & -0.1059 \end{bmatrix}$$

For this example, it can be founded in Li (2010) that the maximum allowable delay bound with $\tau(t) = \mu(t)$ was 0.3. However, by applying Theorem 1 to the above Example 1, one can obtain the maximum allowable delay bound with $\tau d = 0.1$ is 1.0599e+004. Therefore, the proposed result show Theorem 1 gives a large delay bound than the result given in Li (2010).

Example 2: Consider the following four-neuron delayed neural network of neutral-type:

$$d[x(t) - Bx(t-\tau(t))] = \begin{bmatrix} -Cx(t) + W_1 f(x(t)) + W_2 f(x(t-\tau(t))) \\ +A\int_{-\infty}^{t} K(t-s) f(x(s)) ds \end{bmatrix} dt \quad (45)$$

where:

$$A = \begin{bmatrix} 0.0265 & 0.1157 & 0.0578 & -0.0930 \\ 0.3186 & -0.1363 & -0.0859 & 0.0742 \\ 0.2037 & -0.2049 & 0.0112 & 0.1457 \\ -0.3161 & -0.2469 & -0.0736 & 0.4224 \end{bmatrix},$$

$$B = \begin{bmatrix} -0.3054 & 0.3682 & 0.1761 & -0.0235 \\ -0.0546 & -0.2089 & -0.0754 & 0.2668 \\ 0.4563 & 0.0023 & 0.1440 & 0.6928 \\ -0.0115 & -0.2349 & 0.2004 & 0.1574 \end{bmatrix},$$

$$C = \begin{bmatrix} 1.6305 & 0 & 0 & 0 \\ 0 & 1.9221 & 0 & 0 \\ 0 & 0 & 2.5973 & 0 \\ 0 & 0 & 0 & 1.3775 \end{bmatrix},$$

$$W_1 = \begin{bmatrix} -2.5573 & -1.3813 & 1.9574 & -1.1398 \\ -1.0226 & -0.8845 & 0.5045 & -0.2111 \\ 1.0378 & 1.5532 & 0.6645 & 1.1902 \\ -0.3898 & 0.7079 & -0.3398 & -2.3162 \end{bmatrix},$$

$$W_2 = \begin{bmatrix} 0.2853 & -0.0793 & 0.4694 & 0.5354 \\ -0.5955 & 1.3352 & -0.9036 & 0.5529 \\ -0.1497 & -0.6065 & -0.1641 & -0.2037 \\ -0.4348 & -1.3474 & -0.6275 & -2.2543 \end{bmatrix}$$

Let $\tau = 1.83, \tau_d = 0, \vartheta_1 = 0.5I, \vartheta_1 = 0.4I$ Now, solving the LMIs (43) and (44) in Corollary 3, by using Matlab LMI Control toolbox, one can find that system (45) described by Example 2 is globally asymptotically stable. Then, one can get a part of feasible solution as follows:

$$P = 10^4 \times \begin{bmatrix} 0.5144 & -0.0614 & -0.0268 & 0.1155 \\ -0.0614 & 1.0395 & 0.1249 & 0.0126 \\ -0.0268 & 0.1249 & 0.8019 & -0.0633 \\ 0.1155 & 0.0126 & -0.0633 & 0.4730 \end{bmatrix},$$

$$Q_{11} = 10^3 \times \begin{bmatrix} 3.4615 & -0.8680 & 0.3696 & 0.6203 \\ -0.8680 & 5.5258 & 0.0752 & 0.3859 \\ 0.3696 & 0.0752 & 4.8772 & 0.1869 \\ 0.6203 & 0.3859 & 0.1869 & 1.9832 \end{bmatrix},$$

$$Q_{22} = 10^3 \times \begin{bmatrix} 3.9580 & -1.6007 & 1.1810 & -0.7181 \\ -1.6007 & 4.8063 & -0.8356 & 0.6035 \\ 1.1810 & -0.8356 & 0.6035 & -0.1509 \\ -0.7181 & 0.3859 & -0.1509 & 3.7652 \end{bmatrix},$$

$$R = 10^3 \times \begin{bmatrix} 0.3665 & -0.3617 & 0.1740 & -0.0416 \\ -0.3617 & 1.2453 & 0.2478 & 0.1946 \\ 0.1740 & 0.2478 & 0.7027 & 0.1079 \\ -0.0416 & 0.1946 & 0.1079 & 0.2567 \end{bmatrix}$$

$$E = 10^3 \times \{5.6211 \quad 5.6211 \quad 5.6211\},$$

$$\varepsilon_1 = 4.0801e{+}003, \varepsilon_2 = 2.2259e{+}004$$

If we let $\tau = 2, \tau_d = 0$, the condition by Feng *et al.* (2009) is not feasible, but using Corollary 3, one can find system (45) is globally asymptotically stable. Therefore, the proposed result is less conservative by Feng *et al.* (2009).

CONCLUSIONS

In this study, the asymptotic stability of stochastic neural networks of neutral-type with unbounded distributed delay. Based an appropriate Lyapunov-Krasovskii functional and the Itô's differential formula, new delay-dependent stability criteria are proposed in terms of LMIs. In addition, the obtained results are less conservative, in which the Leibniz-Newton formula and the free-weighting matrix method are employed. Finally, the validity and effectiveness of the proposed results is verified through two numerical examples. To the best of our knowledge, up to now, the robust stability analysis problems for uncertain stochastic neural networks of neutral-type with time-varying delays have not been investigated, so the future work will focus on the global robust stability of the proposed system.

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