AN LMI APPROACH TO PASSIVITY ANALYSIS FOR UNCERTAIN NEURAL NETWORKS WITH MULTIPLE TIME-VARYING DELAYS

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ABSTRACT

This paper deals with the problem of Passivity analysis for neural networks with multiple time-varying delays subject to norm-bounded time-varying parameter uncertainties. The activation functions are supposed to be bounded and globally Lipschitz continuous. New passivity conditions are proposed by using Lyapunov-Krasovskii functionals and the free-weighting matrix method to relax the existing requirement of derivative of time delays of the system. Passivity conditions are obtained in terms of linear matrix inequalities, which can be investigated easily by using recently developed standard algorithms. Two illustrative examples are provided to demonstrate the effectiveness.

Key words: passivity conditions, linear matrix inequality, neural networks, uncertainty.

I. INTRODUCTION

It has been shown that applications on signal processing, pattern recognition, static image processing, associative memory and combinatorial optimization rely on the analysis of the dynamic behavior of neural networks. Since stability is one of the most important issues related to such behaviors, the study of the stability problem of neural networks has received much attention in recent years and a great number of results on this issue have been reported [1]-[6].

On the other hand, time delays are often encountered in various practical systems such as biological and artificial neural networks, chemical processes, communication and long transmission lines in the pneumatic system [7]-[8]. In electronic implementation of neural networks, many problems such as switching delays, integration, and communication delays have arisen. In such a case, a delay parameter must be introduced into the system model. Study of neural dynamics with consideration of delays becomes particularly important when manufacturing high quality microelectronic neural networks. It is now well known that time delay is one of the main causes of instability and poor performance of neural networks. Therefore, there has been an increasing interest in the delayed neural networks (DNNs), and a great number of results on these topics have been reported in the literature [9]-[15]. Recently, the so-called “neural networks with multiple time-varying delays” were reported in [16]-[17] for the global robust stability.
criteria. Unfortunately, the results in [16] may not be correct in some cases, which has been explained and improved in [17].

An essential property in linear circuit and system theory is passivity. It is well known that applications in the analysis of properties of immittance or hybrid matrices of various classes of networks, inverse problem of linear optimal control, circle criterion, Popov criterion and spectral factorization by algebra have been found in the literature [18]. Recently, the passivity condition has also been related to the neural networks [19]-[22]. The passivity properties of static multilayer neural networks have been studied in [19]. The passivity properties of dynamical neural networks have also been investigated in [20]-[22]. It should be pointed out that the aforementioned results have free time delays. Recently, one application of passivity analysis for uncertain neural networks with time delay has been dealt with in [23], where sufficient conditions for the existence of passivity condition for the uncertain neural networks with time delay have been obtained in terms of LMI s [24]. However, it should be pointed out that no passivity analysis results on uncertain neural networks with multiple time-varying delays are available in the literature, which motivates the present study.

This paper deals with the problem of passivity analysis for uncertain neural networks with multiple time-varying delays. The time delays appear in the neuron activation function, and the parameter uncertainties are assumed to be time-varying but norm-bounded which appear in all the matrices in both the state and the connection weights of neurons. By constructing the Lyapunov-Krasovskii functionals and the free-weighting matrix method to relax the existing requirement of derivative of time delays \( \tau_k(t) < 1 \) \( (k = 1, 2, \ldots, r) \), new passivity analysis conditions are established. These conditions are expressed in terms of LMI s, which can be solved numerically and efficiently by resorting to standard numerical algorithms. Two examples are provided to demonstrate the applicability of the proposed criteria.

II. PROBLEM FORMULATION

The dynamic behavior of neural networks with multiple time-varying delays can be described by the following retarded functional differential state equation

\[
x(t) = - (A + \Delta A(t)) x(t) + (W + \Delta W(t)) g(x(t)) + \sum_{k=1}^{r} (W_k + \Delta W_k(t)) g(x(t - \tau_k(t))) + u(t),
\]

where \( x(t) = [x_1(t), \ldots, x_n(t)]^T \in \mathbb{R}^n \) is the state vector, \( g(x(t)) = [g_1(x_1(t)), \ldots, g_n(x_n(t))]^T \in \mathbb{R}^n \) is the neuron activation function with \( g(0) = 0 \), and let \( y(t) = g(x(t)) \) be the output of the neural networks, \( A = \text{diag}(a_1, a_2, \ldots, a_n) > 0 \) is a positive diagonal matrix, \( W_{kn} \) and \( W_{knn} \) \( (k = 1, 2, \ldots, r) \) are the interconnection matrices representing the weighting coefficients of the neurons, \( u(t) \) is the input vector, \( 0 \leq \tau_k(t) \leq \tilde{\tau}_k \) is the time delay of the system, and it is assumed that \( \tau_k(t) \leq d_k < u_k \) for \( k = 1, \ldots, r \), and constant and \( \tau = \max_{1 \leq k \leq r} \{ \tau_k \} \). \( \Delta A(t) \), \( \Delta W(t) \) and \( \Delta W_k(t) (k = 1, 2, \ldots, r) \) are norm-bounded unknown matrices with time-varying parameter uncertainties, which are assumed to be of the form

\[
[\Delta A(t) \quad \Delta W(t) \quad \Delta W_k(t)] = F(t)[N_1 \quad N_2 \quad N_{3k}].
\]

where \( M, N_1, N_2, \) and \( N_{3k} (k = 1, 2, \ldots, r) \) are known real constant matrices, and \( F(\cdot) \in \mathbb{R}^{k \times l} \) is an unknown time-varying matrix function satisfying

\[
F^T(t)F(t) \leq I, \quad \forall t.
\]

The uncertain matrices \( \Delta A(t) \), \( \Delta W(t) \) and \( \Delta W_k(t) (k = 1, 2, \ldots, r) \) are said to be admissible if both (2) and (3) hold.

The following assumption will be made throughout the paper

**Assumption 1:** The activation function \( g(x) \) is nondecreasing, bounded and globally Lipschitz; that is

\[
0 \leq \frac{g_i(x_1) - g_i(x_2)}{x_1 - x_2} \leq a_i, \quad i = 1, 2, \ldots, n.
\]

The purpose of this paper is to develop conditions for the existence of robust passivity analysis for the uncertain neural networks with multiple time-varying delays (1). Specifically, for the given scalar \( \tau \), we are concerned with finding a passivity analysis in the form (1) such that for any time-varying time delay \( \tau_k(t) \) \( (k = 1, 2, \ldots, r) \) satisfying \( 0 \leq \tau_k(t) \leq \tilde{\tau}_k \) and \( \tau = \max_{1 \leq k \leq r} \{ \tau_k \} \), the uncertain DNN is passive, and

\[
\int_0^{\tau} y^T(s) u(s) ds \geq - \lambda \int_0^{\tau} u^T(s) u(s) ds,
\]

under the zero-initial condition for any \( \tau \geq 0 \) and all admissible uncertainties, where \( \lambda \geq 0 \) is a given scalar [25]. Before concluding this section, the following lemma is presented, which will be used to prove the main results in Section III.

**Lemma 1** [26]: Let \( A, D, S, F \) and \( P \) be real matrices of appropriate dimensions with \( P > 0 \) and \( F \) satisfying

\[
DF + (DFS)^T \preceq e^{-1} D D^T + \epsilon S^T S.
\]
III. MAIN RESULTS

The following theorem is first essential for analyzing the robust passive problem for uncertain DNN (1).

**Theorem 1:** Suppose Assumption 1 holds and $\lambda \geq 0$ and $\mu$ are given constant scalars, then the DNN (1) for a 11 delays $\tau_k(t)$ $(k = 1, 2, \ldots, r)$ satisfying $0 \leq \tau_k(t) \leq \overline{\tau_k}$ and $\overline{\tau_k} = \max_{1 \leq k \leq r} \{\overline{\tau_k}\}$ is passivity condition if there exists scalars $\overline{\tau_k} \leq d_k < u_k$, $k = 1, \ldots, r$, $\epsilon_1 > 0$ and matrices $P > 0$, $\sum_{k=1}^r \overline{Q_k} > 0$, $k = 1, \ldots, r$ and diagonal matrix $S = \text{diag} (\delta_1, \delta_2, \ldots, \delta_r) > 0$, $H = (A_1, A_2, \ldots, A_r)$ and $\Gamma = \text{diag} (\alpha_1, \alpha_2, \ldots, \alpha_r) \geq 0$, and any appropriate dimensional matrices $R_1$, $R_2$, $R_3$ $(k = 1, 2, \ldots, r)$, $R_4 < 0$, $R_5$ such that the following LMI holds

$$
\begin{bmatrix}
\Omega & RM & \epsilon_1 N^T \\
M^T R^T & -\epsilon_1 & 0 \\
\epsilon_1 N & 0 & -\epsilon_1
\end{bmatrix} < 0,
$$

(7)

where

$$
R = [R_k, R_{k-1}, \ldots, R_2, R_1, R_0]_r^T \\
N = [N_k, \ldots, N_2, N_1, 0]_r^T
$$

$$
\Omega =
\begin{bmatrix}
\begin{bmatrix}
A^T R_k^T + A R_k^T & -R_k W^T + A^T R_k^T & \ldots & -R_k W^T + A^T R_k^T \\
R_k W^T + A R_k^T & -R_k W^T + A^T R_k^T & \ldots & -R_k W^T + A^T R_k^T \\
& \ddots & \ddots & \ddots \\
& & \ddots & \ddots & \ddots \\
R_0 & R_1 & \ldots & R_k & R_k \\
R_{k-1} & R_k & \ldots & R_k & R_k \\
& \ldots & \ldots & \ldots & \ldots \\
R_2 & R_3 & \ldots & R_k & R_k
\end{bmatrix}
\end{bmatrix} + H - \text{diag}(\delta_1, \delta_2, \ldots, \delta_r) - \Gamma^T \Gamma
$$

**Proof:** Define the following Lyapunov-Krasovskii functional candidate for DNN (1) as

$$
V_2(x(t)) = \sum_{i=1}^r s_i \int_0^{x_i(t)} \phi_i(\alpha) d\alpha,
$$

(10)

$$
V_3(x(t)) = \sum_{k=1}^r \int_{\tau_k(t)}^t g^T(x(\alpha)) Q_k g(x(\alpha)) d\alpha
$$

(11)

where $S = \text{diag} (\delta_1, \delta_2, \ldots, \delta_r)$. For any appropriately dimensional matrices $R_1$, $R_2$, $R_3$ $(k = 1, 2, \ldots, r)$, $R_4$, $R_5$, the following equation is true

$$
2 \dot{x}^T(t) R_1 + g^T(x(t)) + \sum_{k=1}^r g^T(x(t - \tau_k(t))) R_3k
$$

$$
+ \dot{x}^T(t) R_4 + u^T(t) R_5 \times \left[-(A + \Delta A(t)) x(t) \right.
$$

$$
+ (W + \Delta W(t)) f(x(t))
$$

$$
+ \sum_{k=1}^r (W_k + \Delta W_k(t)) f(x(t - \tau_k(t))) + u(t) - \dot{x}(t) \right)
$$

$$
= 0
$$

(12)

Adding $+ 2 g^T(x(t)) H x(t) - 2 g^T(x(t)) H x(t)$ and (12) to $\dot{V}(x(t))$ yields

$$
\dot{V}(x(t)) \leq 2 \dot{x}^T(t) P x(t) + 2 g^T(x(t)) S x(t)
$$

$$
+ \sum_{k=1}^r g^T(x(t)) Q_k g(x(t))
$$

$$
- \sum_{k=1}^r (1 - d_k) g^T(x(t - \tau_k(t))) Q_k g(x(t - \tau_k(t)))
$$

$$
- 2 \dot{x}^T(t) R_1 + g^T(x(t)) + \sum_{k=1}^r g^T(x(t - \tau_k(t))) R_3k
$$

$$
+ x^T(t) R_4 + u^T(t) R_5 \times \left[-(A + \Delta A(t)) x(t) \right.
$$

$$
+ (W + \Delta W(t)) f(x(t))
$$

$$
+ \sum_{k=1}^r (W_k + \Delta W_k(t)) f(x(t - \tau_k(t))) + u(t) - \dot{x}(t) \right)
$$

$$
+ 2 g^T(x(t)) H x(t) - 2 g^T(x(t)) H x(t),
$$

(13)

where the diagonal matrix $H = (\delta_1, \delta_2, \ldots, \delta_r) > 0$.

Using Assumption 1 and Lemma 1, it can be shown that

$$
+ 2 g^T(x(t)) H x(t) \leq - 2 g^T(x(t)) H \Gamma^T g(x(t))
$$

(14)

in which $\Gamma = \text{diag} (\alpha_1, \alpha_2, \ldots, \alpha_r) \geq 0$ and

$$
- 2 \dot{x}^T(t) R_1 + g^T(x(t)) + \sum_{k=1}^r g^T(x(t - \tau_k(t))) R_3k
$$

$$
+ \dot{x}^T(t) R_4 + u^T(t) R_5 \times \left[-(A + \Delta A(t)) x(t) + (W + \Delta W(t)) f(x(t))
$$

$$
+ \sum_{k=1}^r (W_k + \Delta W_k(t)) f(x(t - \tau_k(t))) + u(t) - \dot{x}(t) \right)
$$

$$
= 0
$$

(12)
\[
+ \sum_{k=1}^{t} (W_k + \Delta W_k(t)) f(x(t-t_k(t)))+u(t)-\dot{x}(t)\right), \\
\leq e^T(t)\Pi e(t) + \varepsilon_1^{-1}e^T(t)RM M^T R^T e(t) \\
+ \varepsilon_1 e^T(t)N^T Ne(t),
\]

where
\[
\varepsilon_1 = \frac{\varepsilon_1}{\varepsilon_1}
\]
\[
\Omega = \begin{bmatrix}
\dot{R}_k + R^A & -R^W + H + A^T R_k & -R_W t + A^T R_k & -R_W t + A^T R_k \\
R_k - R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k \\
R_k - R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k \\
R_k - R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k \\
-\varepsilon_1^{-1}RM M^T R^T + \varepsilon_1 N^T N)e(t),
\]

Substituting (14)-(15) into (13) and arranging terms yields
\[
\hat{V}(x(t)) \leq e^T(t)\Sigma e(t),
\]

where
\[
\Sigma = \begin{bmatrix}
A_r R_k + R^A & R_k - R^W + H^T - A^T R_k & -R^W t + A^T R_k & -R^W t + A^T R_k \\
R_k - R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k \\
R_k - R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k \\
R_k - R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k \\
\end{bmatrix}
\]

Let \( y(t) = g(x(t)) \) be the output of the neural networks. Finally, it follows from (5) that
\[
\hat{V}(x(t)) - 2y^T(t)u(t) - \lambda u^T(t)u(t) \leq e^T(t)\Omega e(t),
\]

where
\[
\Omega = \begin{bmatrix}
A_r R_k + R^A & -R^W + H^T - A^T R_k & -R^W t + A^T R_k & -R^W t + A^T R_k \\
R_k - R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k \\
R_k - R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k \\
R_k - R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k & -R^W + W^T R_k \\
\end{bmatrix}
\]

If \( \Omega + \varepsilon_1^{-1}RM M^T R^T + \varepsilon_1 N^T N < 0 \), then
\[
\hat{V}(x(t)) - 2y^T(t)u(t) - \lambda u^T(t)u(t) < 0
\]
and from which it follows that
\[
2 \int_{t_0}^{t_1} y^T(t)u(t)dt > V(x(t_1)) - V(x(t_0)) - \lambda \int_{t_0}^{t_1} u^T(t)u(t)dt.
\]

Since \( V(x(t)) > 0 \) for \( x(t) \neq 0 \) and \( V(x(t)) = 0 \) for \( x(t) = 0 \), it follows that as \( t_1 \to +\infty \) that the uncertain DNN (1) is a globally robust passivity condition. By the Schur complement, it is easy to verify that \( \hat{V}(x(t)) - 2y^T(t)u(t) - \lambda u^T(t)u(t) < 0 \) is equivalent to (7). This completes the proof.
IV. ILLUSTRATIVE EXAMPLES

Example 1: Consider an uncertain DNN in (1) with parameters as

\[
A = \begin{bmatrix} 1.2 & 0 \\ 0 & 2.6 \end{bmatrix}, \quad W = \begin{bmatrix} -0.34 & 0.44 \\ 0.44 & 0.1 \end{bmatrix},
\]

\[
W_1 = \begin{bmatrix} 0.05 & -1.35 \\ -1.51 & 0.35 \end{bmatrix}, \quad W_2 = \begin{bmatrix} 0.4 & -1.2 \\ 0.85 & -0.78 \end{bmatrix},
\]

\[
M = \begin{bmatrix} 0.1 & -0.2 \\ 0.2 & 0.3 \end{bmatrix}, \quad N_1 = \begin{bmatrix} 0.02 & 0.02 \\ 0.02 & 0.01 \end{bmatrix},
\]

\[
N_2 = \begin{bmatrix} -0.03 & 0.01 \\ 0.03 & 0.02 \end{bmatrix}, \quad N_3 = \begin{bmatrix} 0.01 & -0.01 \\ 0.01 & 0.03 \end{bmatrix},
\]

\[
N_{32} = \begin{bmatrix} 0.01 & -0.01 \\ 0.01 & 0.03 \end{bmatrix}.
\]

In this example, assume that the time delay satisfies

\[0 \leq \tau_1(t) \leq u_1 = 0.5 \quad \text{and} \quad 0 \leq \tau_2(t) \leq u_2 = 0.5.\]

Furthermore, the activation functions in this example are assumed to satisfy Assumption 1 with \(\alpha_1 = 0.3, \alpha_2 = 0.4.\) Then, it can be shown that Corollary 5 in [27] and [17, 23, 28] do not satisfy the robustly passivity condition of the delayed system. However, by the Matlab LMI Control Toolbox, it is found that the proposed criteria Eq. (7) is feasible as follows

\[
P = \begin{bmatrix} 0.8490 & -0.2148 \\ -0.2148 & 1.3934 \end{bmatrix}, \quad Q_1 = \begin{bmatrix} 4.5389 & -0.7392 \\ -0.7392 & 4.4922 \end{bmatrix},
\]

\[
Q_2 = \begin{bmatrix} 3.0769 & -0.8018 \\ -0.8018 & 3.8747 \end{bmatrix}, \quad S = \begin{bmatrix} 0.8896 & 0 \\ 0 & 0.7804 \end{bmatrix},
\]

\[
H = \begin{bmatrix} 1.6457 & 0 \\ 0 & 2.4718 \end{bmatrix}, \quad \varepsilon = 2.5585.
\]

Therefore, by Theorem 1, the uncertain neural network with multiple time-varying delays satisfies the robustly passivity condition in the sense of (5) when \(\lambda = 2.4383.\) This implies that for this example the robustly passivity condition in Theorem 1 is less conservative than those in [17, 23, 27, 28].

Example 2: Consider an uncertain DNN in (1) with parameters as

\[
A = \begin{bmatrix} 2.7644 & 0 & 0 \\ 0 & 10.3781 & 0 \\ 0 & 0 & 5.3674 \end{bmatrix},
\]

\[
W = \begin{bmatrix} -0.5041 & 0.3754 & -0.2796 \\ -0.0130 & 0.3501 & -0.3767 \\ -0.5553 & -0.2586 & 0.4629 \end{bmatrix},
\]

\[
W_1 = \begin{bmatrix} 0.1988 & 0.2501 & -1.1382 \\ -0.1199 & 2.1522 & 0.1974 \\ -0.1067 & 0.2318 & -1.1486 \end{bmatrix},
\]

\[
W_2 = \begin{bmatrix} 0.2651 & -3.1608 & -2.0491 \\ 3.1859 & -0.1573 & -2.4687 \\ 2.0368 & -1.3633 & 0.5776 \end{bmatrix},
\]

\[
M = \begin{bmatrix} 0.1 & 0 & 0 \\ 0 & 0.3 & 0 \\ 0 & 0 & 0.2 \end{bmatrix}, \quad N_1 = \begin{bmatrix} 0.02 & -0.1 & 0.1 \\ 0.1 & 0.2 & 0.3 \\ 0.2 & 0.3 & 0.1 \end{bmatrix},
\]

\[
N_2 = \begin{bmatrix} -0.02 & 0.1 & 0 \\ 0.01 & 0.02 & 0.03 \\ 0.03 & 0.02 & 0.01 \end{bmatrix},
\]

\[
N_{31} = \begin{bmatrix} 0.01 & 0.02 & 0.3 \\ 0.03 & 0.01 & 0.02 \\ 0.02 & 0.01 & 0.03 \end{bmatrix}, \quad N_{32} = \begin{bmatrix} 0.01 & 0.02 & 0.3 \\ 0.02 & 0.01 & 0.03 \\ 0.01 & 0.03 & 0.02 \end{bmatrix}.
\]

In this example, assume that the time delay satisfies

\[0 \leq \tau_1(t) \leq u_1 = 0.5 \quad \text{and} \quad 0 \leq \tau_2(t) \leq u_2 = 0.5.\]

The activation functions in this example are assumed to satisfy Assumption 1 with

\[\alpha_1 = 0.0446, \quad \alpha_2 = 0.5079, \quad \alpha_3 = 0.6158.\]

For this example, it can be verified that [30, 31] do not satisfy the robustly passivity condition of the delayed system. Now, by the Matlab LMI Control Toolbox, a solution to the LMI (7) in this paper is given as

\[
P = \begin{bmatrix} 0.5121 & -0.1796 & -0.2272 \\ -0.1796 & 1.3243 & -0.2349 \\ -0.2272 & -0.2349 & 1.4665 \end{bmatrix},
\]

\[
Q_1 = \begin{bmatrix} 2.8627 & -0.1629 & -0.0015 \\ -0.1629 & 2.4913 & 0.0393 \\ -0.0015 & 0.0393 & 2.4203 \end{bmatrix}.
\]
Therefore, by Theorem 1, the uncertain neural network with multiple time-varying delays satisfy the robustly passivity condition in the sense of (5) when \( \lambda = 2.3070 \). This shows that for this example the robustly passivity condition in Theorem 1 is less conservative than those in [29, 30].

V. CONCLUSIONS

An LMI approach to passivity analysis for uncertain neural networks with multiple time-varying delays has been proposed in this paper. New passivity conditions are proposed by using Lyapunov-Krasovskii functionals and the free–weighting matrix method to relax the existing requirement of derivative of time delays of the system. As a result, we do establish theoretically that our passivity conditions have been proposed in terms of LMIs, which can be checked easily by using recently developed standard algorithms. Two examples have shown the effectiveness of the proposed criteria in this paper.

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