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Research article

Finite-time synchronization of delayed complex dynamical networks via sampled-data controller

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Abstract: This paper focused on the finite-time synchronization problem of complex dynamical networks (CDNs) with time-varying delay under sampled-data control schemes. A pinning control approach based on sampled-data was designed to achieve synchronization criteria. Developing a new looped Lyapunov functional with delayed information and sampling instants yielded sufficient conditions as linear matrix inequalities. The suggested CDNs were synchronized with one another since the derived criteria guaranteed the error CDN's asymptotic stability. A numerical example and corresponding simulation results confirmed the proposed control scheme's effectiveness.

Keywords: complex dynamical networks; finite-time synchronization; time-varying delay; pinning control; linear matrix inequalities

1. Introduction

A complex dynamical networks (CDNs) generally comprises a large-scale arrangement of interconnected nodes, where all nodes resemble a dynamical network. The dynamical networks are often represented by a differential equation that includes a coupling term between the various nodes involved in the dynamics. However, the network structure enables and limits dynamic behaviors within the network. In real life, complex networks can be modeled in many areas, such as biological systems, complex circuits, social networks, food webs, power grids, the World Wide Web, electricity distribution networks, and epidemiology, and it is attractive in both industry and academic areas [1,2]. These applications make it attractive to study CDNs. In addition, time-delays occur in CDNs owing to component capabilities, and congestion often exists in complex networks during acquisition and signal transmission [3, 4]. Thus, it's crucial to consider the effects of time-varying delay on complex networks. Hence, coupled differential equations can be used to describe a wide range of interesting collective phenomena in CDNs, including spatiotemporal chaos, synchronization, and self-organization [5, 6]. The dynamical nodes of complex networks exhibit a fascinating and essential property, namely, synchronization, which has been extensively studied in [7]. Synchronization is a significant nonlinear phenomenon that has played a vital role in the dynamic features of complex network fields in recent years [8, 9]. Subsequently, the investigation focused on the synchronization issue between all dynamic nodes in a complex network, which denotes that every node in a complex network over time aligns with every other node. This phenomenon is significant because it may be observed in daily life, including the synchronous transfer of signals (analog or digital) in communication networks and engineering applications, which require synchronization for rapid convergence.

Typically, synchronization in complex networks does not occur spontaneously and requires external controls. Therefore, a complex network synchronization control is critical. To attain synchronization, numerous efficient control strategies have been put forward, including observer [10], adaptive [11], feedback [12], pinning [13] controls, and so on. Controlling all nodes simultaneously is very difficult because it causes problems such as high costs and difficulty in increasing the control. As a result, controlling a complex network through controllers is typically challenging, and a natural technique to maintain a complicated network is pinning a few of the nodes [14]. Therefore, specific nodes within a complex network need to be controlled to reduce problems and enhance feasibility, called pinning control. This strategy only requires some key nodes to control the complex network comprehensively (see [15, 16]). Pinned control and dynamic feedback quantizers have recently been employed to achieve finite-horizon H_∞ synchronization for CDNs [17]. Using a pinning control technique, the authors in [18, 19] examined a complex network synchronization with or without time-varying delay couplings.

Furthermore, sampled-data control (SDC) is gaining popularity in stabilizing the system with appropriate and good control performance. In [20], the sampled-data synchronization control issue was studied for general CDNs with time-varying delays. A sufficient condition was derived to ensure asymptotic stability in the error system, apply the widely used Jensen inequality, and create the planned sampled-data feedback controller. However, the sampling period is essential for improving the control performance. In particular, a long sampling period can result in limited communication bandwidth and capacity. Hence, researchers focused on improving the large sampling period using different approaches, including continuous Lyapunov functionals (LFs) [21] and discontinuous LFs [22]. The looped functions have received much attention among researchers due to their fundamentally positive definite only in sampling instants, resulting in less conservative stability criteria in terms of the sampling period. A Lyapunov function $V(t)$ is said to be a looped LF if it satisfies

$$V_i(t_q) = V_i(t_{q+1}) = 0.$$

The key advantage of looped LFs is a relaxed constraint on the positivity of $V_i(t)$ at the sample instants t_q and t_{q+1}. Additionally, it utilizes the whole information of $x(t_q)$ to $x(t)$ and $x(t)$ to $x(t_{q+1})$. Therefore, looped LFs have gained interest in SDC stability analysis [23, 24]. To date, the synchronization of CDNs has been defined over infinite time intervals. Finite-time synchronization (FTS) optimizes the convergence or settling time. To this aim, FTS techniques have been derived for time-varying delayed complex networks [25–27] to achieve stability or synchronization in finite-time. FTS in CDNs has attracted more attention in specific fields, such as [28, 29], where FTS occurs when the error system reaches the origin within finite-time.The works mentioned on FTS are that the derived conditions do not include information on two-sided looped functionals in FTS. To our knowledge, finite-time CDNs with two-sided looped LFs have yet to be considered for synchronization of delayed CDNs.

Motivated by the analysis mentioned above, designing two-sided looped functionals in the delayed CDNs for FTS is the primary goal of this study. Based on the above explanation, the main implications of this study are as follows:

- The synchronization issue between the isolated node CDNs and the i^{th} node CDNs with time-varying delay is investigated under SDC-based pinning control, and improved looped LFs are constructed to check the stability of the proposed approach in terms of linear matrix inequalities (LMIs).
- The information of $x(t_q)$ to $x(t)$ and $x(t)$ to $x(t_{q+1})$ and the upper bound of the time-varying delay are involved in the proposed looped LFs.
- The derived sufficient conditions guarantee the FTS for the error states of the CDNs with time-varying delay. The numerical example and its simulation results prove the effectiveness of the proposed criteria.

Notations: The n-dimensional Euclidean space is denoted by $\mathbb{R}^n$, the set of all $n \times n$ real matrices is $\mathbb{R}^{n\times n}$, positive real numbers are denoted by $\mathbb{R}^+$, and an identity matrix is denoted by I_n. The maximum and minimum eigenvalues of a real symmetric matrix Q are denoted by $\lambda_{\max}(Q)$ and $\lambda_{\min}(Q)$, respectively. $Q > 0$ or $Q < 0$ indicates the positive definite or negative definite matrix of Q. The symmetric terms in the symmetric matrix are shown by "$*$". The transpose of the matrix X is represented by X^T. $\|\cdot\|$ represents the norm of a Euclidean vector. Kronecker product is represented as "$\otimes$".

2. Preliminaries and problem formulations

This paper considers CDNs with identical nodes "N". The tracking target is denoted by node index 0, and other nodes $1, 2, ..., N$ are denoted by usual nodes within the network. The representation of the tracking target as an isolated node is explained by

$$\dot{x}_0(t) = Ax_0(t) + f(x_0(t - \tau(t))), \tag{2.1}$$

where target node's state vector is denoted by

$$x_0(t) \in \mathbb{R}^n$$

and

$$f(\cdot, \cdot) : \mathbb{R}^n \times \mathbb{R}^+ \longrightarrow \mathbb{R}^n$$

denotes the nonlinear functions and expresses the dynamics of the nodes. $A \in \mathbb{R}^{n\times n}$ is a constant real matrix. $\tau(t)$ represents the time-varying delay,

$$0 < \tau(t) \leq \tau, \quad \dot{\tau}(t) \leq \mu,$$

where

$$\tau > 0$$

and

$$0 < \mu < 1$$

are known constants.The i^{th} node of dynamics is represented below as:

$$\dot{x}_\mathrm{i}(t) = Ax_\mathrm{i}(t) + f(x_\mathrm{i}(t - \tau(t))) + \mathfrak{C}\sum_{\mathrm{j}=1}^{N} b_{\mathrm{ij}}\Gamma x_\mathrm{j}(t),$$

where $\mathrm{i} = 1, 2, ..., N$; the state vector of the i^{th} node is

$$x_\mathrm{i}(t) = (x_{\mathrm{i}1}(t), x_{\mathrm{i}2}(t), ..., x_{\mathrm{i}n}(t))^T \in \mathbb{R}^n.$$

The coupling strength of the whole network is $\mathfrak{C}$. To show the topology of the network, the coupling matrix is

$$B = (b_{\mathrm{ij}}) \in \mathbb{R}^{N\times N}.$$

$b_{\mathrm{ij}} > 0$ if node i is able to receive information from node j; otherwise,

$$b_{\mathrm{ij}} = 0 \ (\mathrm{i} \neq \mathrm{j}).$$

Then,

$$b_{\mathrm{ii}} = -\sum_{\mathrm{j}\neq\mathrm{i}}^{N} b_{\mathrm{ij}}$$

denoted as diagonal elements. The internal coupling matrix,

$$\Gamma = \mathrm{diag}\{\delta_1, \delta_2, ..., \delta_n\} \in \mathbb{R}^{n\times n}$$

is semi-positive definite and signifies the precise connection relationship between two nodes. If two nodes communicate at i^{th} state, then

$$\delta_i > 0,$$

otherwise,

$$\delta_i = 0.$$

Achieving synchronization in large-scale networks by controlling all nodes is more challenging. Thus, pinning control selects specific network nodes for m nodes that are pinned ($1 \leq m \leq N$); the set of all nodes are

$$\mathcal{N} = \{1, 2, ..., N\}$$

and the set of pinned nodes are

$$\mathcal{M} = \{1, 2, ..., m\}.$$

The CDNs with pinning controller are given below as:

$$\begin{aligned}\dot{x}_\mathrm{i}(t) =& Ax_\mathrm{i}(t) + f(x_\mathrm{i}(t - \tau(t))) \\ &+ \mathfrak{C}\sum_{\mathrm{j}=1}^{N} b_{\mathrm{ij}}\Gamma x_\mathrm{j}(t) + u_\mathrm{i}(t), \ \ \mathrm{i} \in \mathcal{M}.\end{aligned} \tag{2.2}$$

Let us consider the SDC as follows:

$$u_\mathrm{i}(t) = K(x_\mathrm{i}(t_q) - x_0(t_q)), \quad t_q \leq t < t_{q+1}, \tag{2.3}$$

where $\mathrm{i} = 1, 2, ..., N$ and $K \in \mathbb{R}^{n\times n}$ is a control gain matrix. The h_q is a sampling interval that satisfies

$$0 < h_m \leq h_q \leq h_M$$

and is denoted by

$$h_q = t_{q+1} - t_q,$$

where $q \in \mathbb{N}$. Then, substitute (2.3) in (2.2), and we get

$$\begin{aligned}\dot{x}_\mathrm{i}(t) =& Ax_\mathrm{i}(t) + f(x_\mathrm{i}(t - \tau(t))) + \mathfrak{C}\sum_{\mathrm{j}=1}^{N} b_{\mathrm{ij}}\Gamma x_\mathrm{j}(t) \\ &+ K(x_\mathrm{i}(t_q) - x_0(t_q)), \quad t \in [t_q, t_{q+1}), \mathrm{i} \in \mathcal{M}.\end{aligned} \tag{2.4}$$

Define the synchronization error of CDNs as

$$\mathrm{e}_\mathrm{i}(t) = x_\mathrm{i}(t) - x_0(t).$$

Then, we get that the error dynamics of the complex network becomes:

$$\begin{aligned}\dot{\mathrm{e}}_{\mathrm{i}}(t) =& A\mathrm{e}_{\mathrm{i}}(t) + F(e_{\mathrm{i}}(t-\tau(t))) + \mathfrak{C}\sum_{\mathrm{j}=1}^{N} b_{ij}\Gamma \mathrm{e}_{\mathrm{j}}(t) \\ &+ K\mathrm{e}_{\mathrm{i}}(t_q), \quad t \in [t_q, t_{q+1}),\ \mathrm{i} \in \mathcal{M},\end{aligned} \tag{2.5}$$

where,

$$F(\mathrm{e}_{\mathrm{i}}(t-\tau(t))) = f(x_{\mathrm{i}}(t-\tau(t))) - f(x_0(t-\tau(t))).$$

For simplicity, the error system can be rewritten as follows:

$$\begin{aligned}\dot{E}(t) =& (I_N \otimes A)E(t) + F(E(t-\tau(t))) \\ &+ \mathfrak{C}(B\otimes\Gamma)E(t) + \tilde{K}E(t_q), \quad t \in [t_q, t_{q+1}).\end{aligned} \tag{2.6}$$

If we let

$$\begin{aligned}E(t) &= (\mathrm{e}_1^T(t), \mathrm{e}_2^T(t), ..., \mathrm{e}_N^T(t)),\\ F(E(t-\tau(t))) &= F^T(\mathrm{e}_1(t-\tau(t))), ..., F^T(\mathrm{e}_N(t-\tau(t))),\\ \tilde{K} &= diag\{\overbrace{K, K, ..., K}^{\mathcal{M}}\}.\end{aligned}$$

Assumption 2.1. *The nonlinear function satisfies the following condition as similar in [30],*

$$[F(x) - F(y) - U(x-y)]^T[F(x) - F(y) - V(x-y)] \le 0,$$

where $x, y \in \mathbb{R}^n$ *and* U, V *are known real-valued matrices.*

Lemma 2.1. *[31] For any positive symmetric constant matrix*

$$M \in \mathbb{R}^{n\times n},$$

scalars $\mathtt{r}_1, \mathtt{r}_2$ *satisfy*

$$\mathtt{r}_1 < \mathtt{r}_2,$$

a vector function

$$F : [\mathtt{r}_1, \mathtt{r}_2] \longrightarrow \mathbb{R}^n$$

such that the integrations concerned are well-defined, then

$$\left(\int_{\mathtt{r}_1}^{\mathtt{r}_2} F(s)ds\right)^T M\left(\int_{\mathtt{r}_1}^{\mathtt{r}_2} F(s)ds\right) \le (\mathtt{r}_2 - \mathtt{r}_1) \times \int_{\mathtt{r}_1}^{\mathtt{r}_2} F^T(s)MF(s)ds.$$

Lemma 2.2. *[32] Let* $r(t)$ *be a differentiable function,*

$$r(t) : [t_q, t] \longrightarrow \mathbb{R}^n.$$

For any positive matrix $W \in \mathbb{R}^n$*, any matrices* S_1 *and* $S_2 \in \mathbb{R}^{k\times n}$*, and any vector* $\xi(t)$*, the following inequality holds:*

$$\begin{aligned}-\int_{t_q}^{t} \dot{r}^T(s)W\dot{r}(s)ds \le& 2\zeta^T(t)(S_1\phi_1 + S_2\phi_2) + (t-t_q)\zeta^T(t)\\ &\times (S_1W^{-1}S_1^T + \frac{1}{3}S_2W^{-1}S_2^T)\zeta(t),\end{aligned}$$

where

$$\begin{aligned}\phi_1 &= r(t) - r(t_q),\\ \phi_2 &= r(t) + r(t_q) - \frac{2}{t-t_q}\int_{t_q}^{t} r(s)ds.\end{aligned}$$

Definition 2.1. *Given that* Q *is a positive matrix,* c_1, c_2, T *is the positive constants with* $c_1 < c_2$*, and the error system is FTS with respect to* (c_1, c_2, T)*, if*

$$\begin{aligned}&sup_{-\tau\le\theta\le 0}\{E^T(\theta)QE(\theta),\ \dot{E}^T(\theta)Q\dot{E}(\theta),\\ &F^T(E(\theta))QF(E(\theta))\} < c_1 \Rightarrow\ E^T(t)QE(t) < c_2,\ \forall\, t \in [0, T].\end{aligned}$$

3. Main results

In this section, the looped LFs, assumption and lemmas are used to construct the stability criteria for the error system (2.6) and were summarized as follows:

Theorem 3.1. *For given constants*

$$h_M \ge h_m > 0,$$

scalar α*, and unknown control gain matrix* K*, the CDNs (2.6) can achieve FTS with respect to* (c_1, c_2, T) *with* $c_1 < c_2$*, if there exist symmetric matrices*

$$\begin{aligned}&Q_i > 0 \in \mathbb{R}^{N\times N}\ (i = 1, 2, ..., 9),\\ &J \in \mathbb{R}^{N\times N}, \quad P_{1b} \in \mathbb{R}^{N\times N}, \quad P_{2b} \in \mathbb{R}^{N\times N},\\ &P_{3b} \in \mathbb{R}^{N\times N}, \quad P_{4b} \in \mathbb{R}^{N\times N} (b = 1, 2, 3), \quad F \in \mathbb{R}^{N\times N}\end{aligned}$$

and a scalars $\lambda > 0,\ \omega > 0$*, such that the following LMIs hold:*

$$\begin{bmatrix}\varphi + h_q\bar{\varphi}_1 & \sqrt{h_q}P_1^T & \sqrt{h_q}P_2^T\\ * & -Q_7 & 0\\ * & * & -3Q_7\end{bmatrix} < 0, \tag{3.1}$$

$$\begin{bmatrix} \varphi + h_q\bar{\varphi}_2 & \sqrt{h_q}P_3^T & \sqrt{h_q}P_4^T \\ * & -Q_6 & 0 \\ * & * & -3Q_6 \end{bmatrix} < 0 \tag{3.2}$$

and

$$e^{\omega T}c_1[\lambda_{max}(Q_1)+\tau\lambda_{max}(Q_2)+\tau^2\lambda_{max}(Q_3)+\tau\lambda_{max}(Q_4)] < c_2. \tag{3.3}$$

For simplicity,

$$\varphi = \varphi_{\iota,\jmath},\ \ \bar{\varphi}_1 = \bar{\varphi}_{1(\iota,\jmath)},\ \ \bar{\varphi}_2 = \bar{\varphi}_{2(\iota,\jmath)},\ \ \iota,\jmath = 1,2,...,10.$$

Here,

$$\begin{aligned}
\varphi_{1,1} =& -\frac{1}{\tau}Q_3 + Q_9 - Q_8 + Q_4 + 2AJ + 2P_{31} + 2P_{41} \\
& - 2P_{11} + 2P_{21} - 2\lambda U + 2\mathfrak{C}(B\otimes\Gamma)J - \omega Q_1, \\
\varphi_{1,2} =& Q_1 - J + \alpha A^TJ^T + \mathfrak{C}(B\otimes\Gamma)J^T, \\
\varphi_{1,3} =& -Q_{51} + Q_{52}^T - P_{31} + P_{41} + Q_8 + KJ + P_{32}^T + P_{42}^T, \\
\varphi_{1,4} =& -Q_{52} + Q_{53} + P_{11} + P_{21} - Q_9 - P_{12}^T + P_{22}^T, \\
\varphi_{1,5} =& \frac{1}{\tau}Q_3,\ \ \varphi_{1,7} = \lambda V,\ \ \varphi_{1,8} = J, \\
\varphi_{1,9} =& -2P_{21} + P_{23}^T - P_{13}^T, \\
\varphi_{1,10} =& -2P_{41} + P_{33}^T + P_{43}^T,\ \ \varphi_{2,2} = \tau Q_3 - 2\alpha J, \\
\varphi_{2,3} =& \alpha JK,\ \ \varphi_{2,8} = \alpha J, \\
\varphi_{3,3} =& 2Q_{51} - 2P_{32} + 2P_{42} - Q_8, \\
\varphi_{3,10} =& -2P_{42} - P_{33}^T + P_{43}^T, \\
\varphi_{4,4} =& -2Q_{53} + 2P_{12} + 2P_{22} + Q_9, \\
\varphi_{4,9} =& -P_{22} + P_{13}^T + P_{23}^T,\ \ \ \varphi_{5,5} = -\frac{1}{\tau}Q_3, \\
\varphi_{6,6} =& -2\lambda U - (1-\mu)Q_4,\ \varphi_{6,8} = \lambda V, \\
\varphi_{7,7} =& Q_2 - 2\lambda I,\ \varphi_{8,8} = -(1-\mu)Q_2 - 2\lambda I,\ \varphi_{9,9} = -4P_{23}, \\
\varphi_{10,10} =& -4P_{43},\ \bar{\varphi}_{1(1,2)} = Q_8,\ \bar{\varphi}_{1(2,2)} = Q_6, \\
\bar{\varphi}_{1(2,3)} =& 51 - Q_8^T,\ \bar{\varphi}_{1(2,4)} = Q_{52},\ \bar{\varphi}_{2(1,2)} = Q_9,\ \bar{\varphi}_{2(2,2)} = Q_7, \\
\bar{\varphi}_{2(2,3)} =& Q_{52}^T,\ \bar{\varphi}_{2(2,4)} = Q_{53} - Q_9^T.
\end{aligned}$$

Then,

$$K = J^{-1}F$$

is a control gain matrix.

Proof. Choose the LFs as follows:

$$V(t) = \sum_{\mathrm{i}=1}^{8} V_{\mathrm{i}}(t), \tag{3.4}$$

where

$$\begin{aligned}
V_1(t) =& E^T(t)Q_1E(t), \\
V_2(t) =& \int_{t-\tau(t)}^{t} F^T(E(s))Q_2F(E(s))ds, \\
V_3(t) =& \int_{-\tau}^{o}\int_{t+\theta}^{t} \dot{E}^T(s)Q_3\dot{E}(s)dsd\theta, \\
V_4(t) =& \int_{t-\tau(t)}^{t} E^T(s)Q_4E(s)ds, \\
V_5(t) =& 2\Upsilon^TQ_5\begin{bmatrix} E(t_q) \\ E(t_{q+1}) \end{bmatrix}, \\
V_6(t) =& (t_{q+1}-t)\int_{t_q}^{t} \dot{E}^T(s)Q_6\dot{E}(s)ds \\
& -(t-t_q)\int_{t}^{t_{q+1}} \dot{E}^T(s)Q_7\dot{E}(s)ds, \\
V_7(t) =& (t_{q+1}-t)[E(t)-E(t_q)]^TQ_8[E(t)-E(t_q)], \\
V_8(t) =& (t-t_q)[E(t_{q+1})-E(t)]^TQ_9[E(t_{q+1})-E(t)].
\end{aligned}$$

Here,

$$\Upsilon^T = col\{(t_{q+1}-t)(E(t)-E(t_q)),\ (t-t_q)(E(t)-E(t_{q+1}))\}^T,$$

$$Q_5 = \begin{bmatrix} Q_{51} & Q_{52} \\ * & Q_{53} \end{bmatrix}.$$

The derivative of V(t) along state trajectories can be calculated as

$$\dot{V}_1(t) = 2E^T(t)Q_1\dot{E}(t), \tag{3.5}$$

$$\begin{aligned}
\dot{V}_2(t) \le& F^T(E(t))Q_2F(E(t)) - (1-\mu)F^T \\
& (E(t-\tau(t))Q_2F(E(t-\tau(t))),
\end{aligned} \tag{3.6}$$

$$\dot{V}_3(t) = \tau(\dot{E}^T(t)Q_3\dot{E}(t)) - \int_{t-\tau}^{t} \dot{E}^T(s)Q_3\dot{E}(s)ds, \tag{3.7}$$

$$\dot{V}_4(t) \le E^T(t)Q_4E(t) - (1-\mu)E^T(t-\tau(t))Q_4E(t-\tau(t)), \tag{3.8}$$

$$\dot{V}_5(t) = 2\left(\begin{bmatrix} (t_{q+1}-t)\dot{E}(t) - E(t) + E(t_q) \\ (t-t_q)\dot{E}(t) + E(t) - E(t_{q+1}) \end{bmatrix}^T Q_5 \begin{bmatrix} E(t_q) \\ E(t_{q+1}) \end{bmatrix}\right), \tag{3.9}$$

$$\begin{aligned}
\dot{V}_6(t) =& -\int_{t_q}^{t} \dot{E}^T(s)Q_6\dot{E}(s)ds + (t_{q+1}-t)\dot{E}^T(t)Q_6\dot{E}(t) \\
& -\int_{t}^{t_{q+1}} \dot{E}^T(s)Q_7\dot{E}(s)ds + (t-t_q)\dot{E}^T(t)Q_7\dot{E}(t),
\end{aligned} \tag{3.10}$$

$$\dot{V}_7(t) = -[E(t)-E(t_q)]^TQ_8[E(t)-E(t_q)]$$

$$+ 2(t_{q+1} - t)[E(t) - E(t_q)]^T Q_8 \dot{E}(t), \tag{3.11}$$

$$\begin{aligned}\dot{V}_8(t) =&[E(t_{q+1}) - E(t)]^T Q_9 [E(t_{q+1}) - E(t)]\\ &- 2(t - t_q)[E(t_{q+1}) - E(t)]^T Q_9 \dot{E}(t).\end{aligned} \tag{3.12}$$

By using Lemma 2.1 in (3.7) to process the integral part, we get

$$\begin{aligned}-\int_{t-\tau}^{t} \dot{E}^T(s) Q_3 \dot{E}(s) ds \leq& -\frac{1}{\tau}[(E^T(t) - E^T(t-\tau)) Q_3\\ &\times (E(t) - E(t-\tau))].\end{aligned} \tag{3.13}$$

By applying 2.2 in $\dot{V}_6(t)$, the integral terms are estimated as:

$$\begin{aligned}&-\int_{t}^{t_{q+1}} \dot{E}^T(s) Q_7 \dot{E}(s) ds \leq 2\zeta^T(t)(P_1\phi_1 + P_2\phi_2)\\ &+ (t_{q+1} - t)\zeta^T(t)(P_1 Q_7^{-1} P_1^T + \frac{1}{3} P_2 Q_7^{-1} P_2^T)\zeta(t),\end{aligned} \tag{3.14}$$

$$\begin{aligned}&-\int_{t_q}^{t} \dot{E}^T(s) Q_6 \dot{E}(s) ds \leq 2\zeta^T(t)(P_3\phi_3 + P_4\phi_4)\\ &+ (t - t_q)\zeta^T(t)(P_3 Q_6^{-1} P_3^T + \frac{1}{3} P_4 Q_6^{-1} P_4^T)\zeta(t),\end{aligned} \tag{3.15}$$

where,

$$\begin{aligned}\phi_1 &= E(t_{q+1}) - E(t),\\ \phi_2 &= E(t_{q+1}) + E(t) - \frac{2}{t_{q+1} - t}\int_{t}^{t_{q+1}} E(s) ds,\\ \phi_3 &= E(t) - E(t_q),\\ \phi_4 &= E(t) + E(t_q) - \frac{2}{t - t_q}\int_{t_q}^{t} E(s) ds,\\ P_1^T &= \begin{bmatrix} P_{11}^T & 0 & 0 & P_{12}^T & 0 & 0 & 0 & 0 & P_{13}^T & 0 \end{bmatrix},\\ P_2^T &= \begin{bmatrix} P_{21}^T & 0 & 0 & P_{22}^T & 0 & 0 & 0 & 0 & P_{23}^T & 0 \end{bmatrix},\\ P_3^T &= \begin{bmatrix} P_{31}^T & 0 & P_{32}^T & 0 & 0 & 0 & 0 & 0 & 0 & P_{33}^T \end{bmatrix},\\ P_4^T &= \begin{bmatrix} P_{41}^T & 0 & P_{42}^T & 0 & 0 & 0 & 0 & 0 & 0 & P_{43}^T \end{bmatrix}.\end{aligned}$$

Now the following inequality is obtained by 2.1, where U, V are diagonal matrices, and for any $\lambda > 0$,

$$\begin{aligned}0 \leq& -2\lambda[F(E(t)) - \mathrm{U}(E(t))]^T[F(E(t)) - \mathrm{V}(E(t))]\\ &- 2\lambda[F(E(t-\tau(t))) - \mathrm{U}(E(t-\tau(t)))]^T\\ &\times [F(E(t-\tau(t))) - \mathrm{V}(E(t-\tau(t)))].\end{aligned} \tag{3.16}$$

For any non-singular matrix J with appropriate dimensions and scalar α, the Eq (2.6) is given as follows:

$$\begin{aligned}0 =& 2[E^T(t) + \alpha\dot{E}^T(t)]J[AE(t) + F(E(t-\tau(t)))\\ &+ \mathfrak{C}(B \otimes \Gamma)E(t) + KE(t_q) - \dot{E}(t)].\end{aligned} \tag{3.17}$$

Let,

$$\begin{aligned}\zeta^T(t) =&\Big[E^T(t)\dot{E}^T(t)E^T(t_q)E^T(t_{q+1})E^T(t-\tau)E^T(t-\tau(t))\\ &F^T(E(t))F^T(E(t-\tau(t)))\frac{1}{t_{q+1} - t}\int_{t}^{t_{q+1}} E^T(s) ds\\ &\frac{1}{t - t_q}\int_{t_q}^{t} E^T(s) ds\Big].\end{aligned} \tag{3.18}$$

Thus, by adding (3.5) to (3.17) inequalities, we get

$$\begin{aligned}\dot{V}(t) &\leq \zeta^T(t)\ \Xi(t)\ \zeta(t) \qquad (3.19)\\ &= \zeta^T(t)\left[\frac{t_{q+1} - t}{h_q}(\varphi + h_q\hat{\varphi}_1) + \frac{t - t_q}{h_q}(\varphi + h_q\hat{\varphi}_2)\right]\zeta(t),\end{aligned}$$

where,

$$\Xi(t) = \varphi + \hat{\varphi}_1 + \hat{\varphi}_2,$$

with

$$\hat{\varphi}_1 = \bar{\varphi}_1 + P_1 Q_7^{-1} P_1^T + \frac{1}{3} P_2 Q_7^{-1} P_2^T,$$

and

$$\hat{\varphi}_2 = \bar{\varphi}_2 + P_3 Q_6^{-1} P_3^T + \frac{1}{3} P_4 Q_6^{-1} P_4^T.$$

Then, it can be clearly verified that

$$\Xi(t) < 0$$

are convex in $t \in [t_q, t_{q+1})$ if, and only if,

$$\varphi + h_q\hat{\varphi}_1 < 0, \tag{3.20}$$

$$\varphi + h_q\hat{\varphi}_2 < 0. \tag{3.21}$$

Therefore, by applying the Schur complement in Eqs (3.19) and (3.20), one can get LMIs (3.1) and (3.2), and it can be shown that

$$\dot{V}(t) < 0.$$

Thus, the error system is asymptotically stable.

Notice that,

$$V(t) \geq \left(E^T(t) Q_1 E(t)\right).$$

According to (3.1) and (3.2), one has

$$\zeta^T(t)\left[\Xi(t)+\begin{pmatrix}-\omega Q_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\end{pmatrix}\right]\zeta(t),$$

i.e.,

$$\zeta^T(t)\ \Xi(t)\ \zeta(t) - E^T(t)\omega Q_1 E(t) < 0. \tag{3.22}$$

We have

$$\dot{V}(t) < \omega V(t). \tag{3.23}$$

Integrating from 0 to T in (3.22), with $t \in [0,T]$, it follows that

$$e^{-\omega t}V(t) < V(0). \tag{3.24}$$

Then, by the Definition 2.1 of $V_i(t)$ ($i = 1,2,3,4$), we can obtain that

$$\begin{aligned}
V(0) \leq & V_1(0)+V_2(0)+V_3(0)+V_4(0)\\
\leq & E^T(0)Q_1E(0)+\int_{-\tau(0)}^{0}F^T(E(s))Q_2F(E(s))ds\\
& +\int_{-\tau}^{0}\int_{\theta}^{0}\dot{E}^T(s)Q_3\dot{E}(s)dsd\theta+\int_{-\tau(0)}^{0}E^T(s)Q_4E(s)ds\\
\leq & \lambda_{max}(Q_1)E^T(0)E(0)\\
& +\tau\lambda_{max}(Q_2)sup_{-\tau\leq\theta\leq 0}\{F^T(E(\theta))F(E(\theta))\}\\
& +\tau^2\lambda_{max}(Q_3)sup_{-\tau\leq\theta\leq 0}\{\dot{E}^T(\theta)\dot{E}(\theta)\}\\
& +\tau\lambda_{max}(Q_4)sup_{-\tau\leq\theta\leq 0}\{E^T(\theta)E(\theta)\}\\
\leq & \Big(\lambda_{max}(Q_1)+\tau\lambda_{max}(Q_2)+\tau^2\lambda_{max}(Q_3)\\
& +\tau\lambda_{max}(Q_4)\Big)\times sup_{-\tau\leq\theta\leq 0}\{E^T(\theta)E(\theta),\\
& \dot{E}^T(\theta)\dot{E}(\theta),F^T(E(\theta))F(E(\theta))\}\\
\leq & c_1\Big(\lambda_{max}(Q_1)+\tau\lambda_{max}(Q_2)+\tau^2\lambda_{max}(Q_3)+\tau\lambda_{max}(Q_4)\Big).
\end{aligned} \tag{3.25}$$

By following this,

$$V_i(t)\ (i = 5,6,7,8)$$

becomes zero, when $t = 0$, i.e.,

$$V_5(0) = V_6(0) = V_7(0) = V_8(0) = 0.$$

Combining the (3.23) and (3.24) inequalities, we get

$$\begin{aligned}
\Big(E^T(t)Q_1E(t)\Big) &\leq V(t) < e^{\omega t}V(0)\\
&\leq e^{\omega t}c_1\{\lambda_{max}(Q_1)+\tau\lambda_{max}(Q_2)\\
&\quad +\tau^2\lambda_{max}(Q_3)+\tau\lambda_{max}(Q_4)\}.
\end{aligned}$$

Therefore,

$$\begin{aligned}
&\Big(E^T(t)Q_1E(t)\Big)\\
&< e^{\omega T}c_1[\lambda_{max}(Q_1)+\tau\lambda_{max}(Q_2)+\tau^2\lambda_{max}(Q_3)+\tau\lambda_{max}(Q_4)]\\
&< c_2.
\end{aligned}$$

In Theorem 3.1, under (3.3), we can obtain

$$\Big(E^T(t)Q_1E(t)\Big) < c_2$$

for all $t \in [0,T]$. Subsequently, the system achieves FTS concerning c_1, c_2, T. Hence, the theorem completes. □

Remark 3.1. *In [24], for sampling information of the system, they considered one-sided looped LFs. In Eq (3.4), we proposed two-sided looped LFs in the stability analysis of CDNs with time-varying delay. Therefore, utilizing sampling information from the interval t_q to t and t to t_{q+1}, it helps to reduce the convergence of the system.*

Remark 3.2. *The conditions (3.1)–(3.3) can be turned into standard LMIs by fixing the ω value. By the definition of FTS, the synchronization error stays within the time interval of which we fixed. Specifically, the condition (3.3) is undertaken by the following LMI conditions,*

$$\begin{aligned}
&\theta_1 I < Q_1 < \theta_2 I,\\
&0 < Q_2 < \theta_3 I,\\
&0 < Q_3 < \theta_4 I,\\
&0 < Q_4 < \theta_5 I,\\
&c_1\theta_2 + c_1\tau\theta_3 + c_1\tau^2\theta_4 + c_1\tau\theta_5 < c_2\theta_1 e^{-\omega T},
\end{aligned}$$

for some positive numbers θ_1–θ_5.

Remark 3.3. *Here, c_1, c_2, and T values are all predetermined in the numerical problem. Definition 2.1 says that CDNs are FTS when constrained by an initial state error. The synchronization error remains bounded within the specified time limit. Additionally, scalar value ω is fixed, and T value increases with c_1 decreases or c_2 increases.*

Remark 3.4. *The evaluation techniques presented in the researches [33–36] are entirely distinct from the methods introduced in Theorem 3.1. A two-sided LF is designed for the FTS of the delayed CDNs. First, we investigated the delayed CDNs under SDC with looped LFs for stability analysis. Second, we introduced the upper bound of time-varying delay in the looped LF. Third, the sufficient conditions are derived for FTS. Therefore, the results presented in this paper provide a new approach for studying FTS, which leads a less conservatism.*

Remark 3.5. *Based on Theorem 3.1, we have calculated the number of decision variables as $20n^2 + 6n + 1$ for the derived conditions. Here, the computational complexity depends on the order of n^2, i.e., $O(n^2)$. The computational complexity is increased if n becomes a large value.*

4. Numerical example

This section illustrates the numerical example to demonstrate the effectiveness of the network synchronization criteria. Consider three nodes in the CDNs. The pinning nodes are considered as the first two nodes in the following parameters:

$$A = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix},$$

$$B = \begin{bmatrix} -1 & 0 & 1 \\ 0 & -1 & 1 \\ 1 & 1 & -2 \end{bmatrix},$$

$$\Gamma = I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

and

$$f(x_i(t)) = \begin{bmatrix} -0.5x_{i1} + \tanh(0.2x_{i1}) + 0.2x_{i2} \\ 0.95x_{i2} - \tanh(0.75x_{i2}) \end{bmatrix}.$$

The Assumption 2.1 is satisfied with

$$U = \begin{bmatrix} -0.5 & 0.2 \\ 0 & 0.95 \end{bmatrix},$$

$$V = \begin{bmatrix} -0.3 & 0.2 \\ 0 & 0.2 \end{bmatrix}.$$

Let us consider

$$\alpha = 0.2, \quad \tau = 0.5, \quad \tau(t) = 0.3 + 0.2sint, \quad \mu = 0.2.$$

A comparison with the existing method for determining the maximum sampling period h_M is shown in Table 1. By taking $\mathfrak{C} = 0.1$, Table 1 shows a comparison between the existing result, and it shows that our approach yields a less conservative outcome than the existing work in [24].

Table 1. Maximum sampling period for $\mathfrak{C} = 0.1$.

Method	h_M
[24]	1.62
Theorem 1	1.75

From Table 1, the proposed method is shown to be superior than the existing method in [24]. Using h_M and Theorem 3.1, we can arrive at the following feasible solutions:

$$c_1 = 0.1, \quad c_2 = 2.36,$$

and

$$T = 6$$

to verify Theorem 3.1 to get feasible for the value

$$\omega = 0.002$$

with respect to (c_1, c_2, T) and using Matlab LMI toolbox to obtained the control gain matrix

$$K = J^{-1}F$$

as

$$K = \begin{bmatrix} -0.1975 & -0.0008 \\ -0.0006 & -0.1971 \end{bmatrix}.$$

Let's consider the initial conditions for the three nodes as

$$x_0(0) = [1 \ -2]^T,$$

$$x_1(0) = [3 \ -5]^T,$$

$$x_2(0) = [6 \ \ -2]^T,$$
$$x_3(0) = [-4 \ \ 3]^T.$$

Under the proposed CDNs with time-varying delay in Theorem 3.1, Figure 1 shows the behavior of the proposed SDC. Figure 2 shows the error system (2.6) with j (j = 1, 2) with the gain matrix converging to origin at finite-time T.

Additionally, we obtained the state response (2.4) with j (j = 1, 2) of the nodes in Figures 3 and 4, respectively. Hence, one can see from these figures that the desired performance of the CDNs was achieved through synchronization using a designed controller.

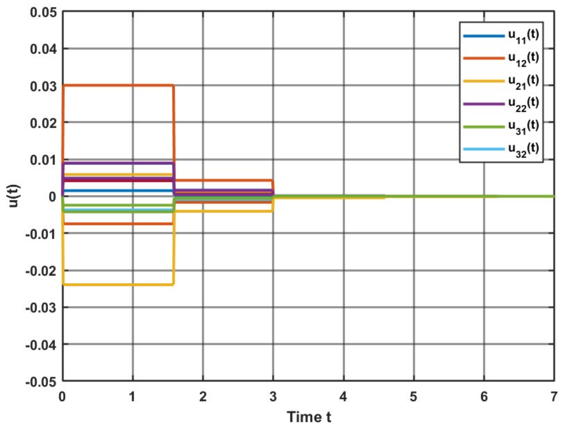

Figure 1. Control input $u(t)$.

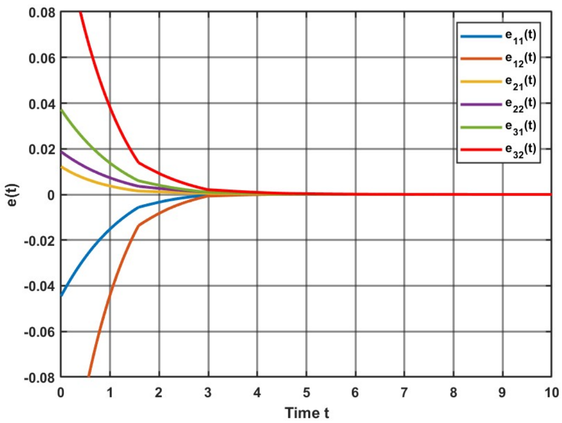

Figure 2. State response of the error system with $u(t)$.

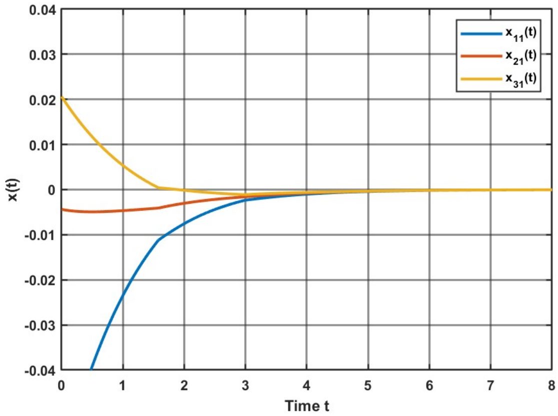

Figure 3. State response of node $j = 1$.

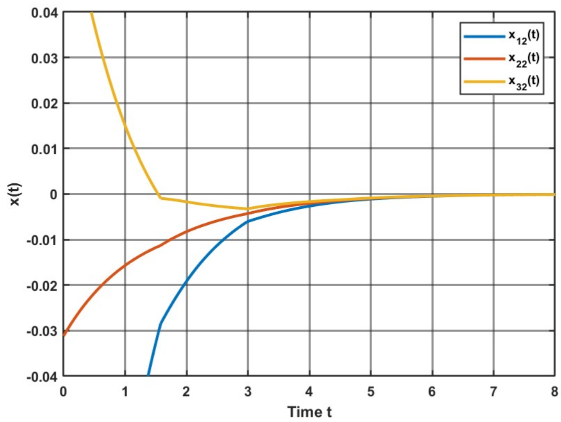

Figure 4. State response of node $j = 2$.

5. Conclusions

This article presented the design of a FTS problem for the CDNs with time-varying delay using an SDC. Synchronization criteria were obtained using the appropriate looped LF method with integral terms. The SDC is designed to achieve FTS, and the gain matrix is obtained by solving the corresponding LMIs. Numerical examples are given to demonstrate the effectiveness of the synchronization criteria in finite time. In [37], stochastic switching is used to study switched Takagi-Sugeno fuzzy systems, where they considered mode-dependent event-triggered control for the switched systems. Therefore, the future direction of the work will focus on applying the switching method to study the proposed CDNs and determining the synchronization criteria with the stochastic switching signal under the mode-dependent event-triggered control scheme.

Use of Generative-AI tools declaration

The authors declare that they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare that there are no conflicts of interest.

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