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Research article

A new approach for accuracy-preassigned finite-time exponential synchronization of neutral-type Cohen–Grossberg memristive neural networks involving multiple time-varying leakage delays

Er-Yong Cong[1,4,*], Yantao Wang[2,3,*], Xian Zhang[2,3] and Li Zhu[1]

[1] Department of Mathematics, Harbin University, Harbin 150086, China
[2] School of Mathematical Science, Heilongjiang University, Harbin 150080, China
[3] Heilongjiang Provincial Key Laboratory of the Theory and Computation of Complex Systems, Heilongjiang University, Harbin 150080, China
[4] Heilongjiang Provincial Key Laboratory of the Intelligent Perception and Intelligent Software, Harbin University, Harbin 150080, China

* **Correspondence:** Email: cey1979@163.com, wangyantao@hlju.edu.cn.

Abstract: We studied the problem of accuracy-preassigned finite-time exponential synchronization of neutral-type Cohen–Grossberg memristive neural networks involving time-varying multiple leakage and transmission delays. First, a novel method was presented to give an estimation formula for solutions of the error system. Then, the estimation formula was used to establish sufficient conditions guaranteeing accuracy-preassigned finite-time exponential synchronization of the considered memristive Cohen–Grossberg neural networks. The obtained sufficient conditions were composed of some linear scalar inequalities that was easy to solve by employing standard tool softwares. Moreover, the approach proposed here was based on the concept of accuracy-preassigned finite-time exponential synchronization, and Lyapunov–Krasovskii functionals or model transformations were not involved, simplifying the theorematic proof. Finally, two numerical examples were given to present the validity of theorematic results.

Keywords: neutral-type memristive Cohen–Grossberg neural networks; accuracy-preassigned finite-time exponential synchronization; leakage delays
Mathematics Subject Classification: 93D20

1. Introduction

Neural networks (NNs) have been the subject of many studies because of their successful applications in various areas such as associative memory [1], autonomous navigation [2], data encryption [3], intelligent control [4], optimization [5,6], controller design [7], pattern recognition [8], spacecraft formation flying [9], and so on. In practice, time delays can cause NNs to oscillate, become unstable, or perform poorly [10, 11]. Researchers have identified several types of delays, including leakage delays [12–14], distributed delays, transmission delays, and neutral delays. In recent years, a number of topics related to delayed NNs, such as stability and stabilization [15–18], dissipativity analysis and control [19,20], passivity and passification [21], state estimation [22], and synchronization control [23–25], have attracted attention from many researchers.

The Cohen–Grossberg NNs (CGNNs) were proposed by Cohen and Grossberg in 1983 [26]. In the past few years, increasing intension in analyzing and control of CGNNs have appeared [27–30]. In 2008, Stanley R. Williams and his team found the practical memristor [31], which verifies Chua's prediction in 1971 [32]. Since the memristor mimics the forgetting and remembering processes in human brains, it has potential to be used as brain-like computers and future computers. In order to more accurately mimic the human brain via NNs, the ordinary resistor of connection weights of CGNNs is replaced by the memristor, resulting in memristive CGNNs. Therefore, memristive CGNNs have more significance in the study of human brain simulation.

Synchronization issues have garnered significant attention and research [33–35], thanks to their applications in image encryption, audio encryption, and secure communication [36–38]. In [39], finite-time synchronization criteria of memristive CGNNs involving time-varying delays were obtained by constructing the appropriate nonlinear transformations and employing the differential inclusion theory. For reaction-diffusion memristive CGNNs, a new definition of quasi-fixed-time synchronization was proposed in [40], and quasi-fixed-time synchronization theorem was investigated by designing an effective controller. In [28], using the reduced-order method based on the differential inclusion theory, the adaptive feedback controller was proposed to achieve global asymptotic synchronization of proportional delay inertial memristive CGNNs. In [41], the exponential synchronization conditions of quaternion-valued memristive CGNNs involving time-varying delays were presented by employing the differential inclusion theory, an improved one-norm method, and the set-valued map theory. For coupled memristive multi-stable CGNNs involving mixed delays, some sufficient conditions guaranteeing multi-synchronization were investigated by utilizing the M-matrix theory, the state-space decomposition, and the fixed point theory [42]. The synchronization issues of fractional-order delayed memristive CGNNs are addressed in [43, 44].

In the above references about finite-time synchronization problem of NNs, the settling-time formula was derived by employed the different radial unbounded function. When the time is larger than the settling time, state variances of error system are always equal to zero in theoretically; however, due to the network noises, model approximation, DoS attacks, and so on, they realistically converge into a small domain containing the origin [45]. In [34], a parameter $\epsilon > 0$ was introduced to describe the small domain. From the angle of application, the positive number ϵ can be viewed as a preassigned accuracy, which should be satisfied whenever considering a finite-time synchronization issue. The relationship between accuracy-preassigned finite-time exponential synchronization in neutral-type Cohen–Grossberg memristive neural networks and Keller-Segel models lies in the exploration of complex dynamical systems and the synchronization phenomena in NNs, particularly under the influence of delays and spatial interactions. Specifically, the concept of accuracy-preassigned finite-time exponential synchronization in the context of neutral-type Cohen–Grossberg memristive neural networks provides a framework for understanding and analyzing synchronization behaviors in Keller-Segel models, particularly in the presence of time-varying delays. Both fields involve the study of complex systems characterized by nonlinear interactions and delays, and they share common mathematical methodologies, including Lyapunov functions, stability theory, and bifurcation analysis, for their theoretical analysis [46,47]. Therefore, it is great to address the accuracy-preassigned finite-time synchronization issue of NNs.

As stated, several researchers have studied the subject on the finite-time synchronization of time-delay memristive CGNNs. Nevertheless, there is no study on the finite-time synchronization of *neutral-type* delayed memristive CGNNs. We seek to address this gap by investigating the accuracy-preassigned finite-time exponential synchronization problem of neutral-type memristive CGNNs involving multiple time-varying leakage and transmission delays. We summarize the significance and contributions of this article below:

- Compared with the current literature, the memristive CGNN model addressed in this article is more general. The model is not only neutral-type but also involves more time-varying delays. Moreover, we provide a new idea to solve the problems related to synchronization of neutral-type memristive delayed CGNNs.
- We introduce a novel method that is ground on the upper-right derivative of solutions of the error system. Especially, instead of the derivative, the upper-right derivative is employed in the theoretical derivation, which is compatible with a new controller that is different from ones in studies.
- The derived synchronization conditions are comprised of simple scalar inequalities that is convenient to implement via the common software tools. Moreover, the synchronization condition can guarantee that the states of the error system converge exponentially into a small range containing the origin under the preassigned accuracy.

The structure of the article is designed below: In Section 2, we provide preliminary results, including the drive and response neutral-type delayed memristive CGNNs model, necessary assumptions, definitions, and lemmas. In Section 3, we present the design method of controller to achieve accuracy-preassigned finite-time exponential synchronization between the drive and response neutral-type delayed memristive CGNNs. In Section 4, we validate the major results through numerical examples. Finally, the conclusions are given in Section 5.

Notations: Let $\langle n\rangle$ be the set $\{1, 2, \dots, n\}$, where n is a positive integer. The symbol $\mathbb{R}$ represents the real number field. The symbols $C(\mathbb{S}_1, \mathbb{S}_2)$ and $C^1(\mathbb{S}_1, \mathbb{S}_2)$ denote the linear spaces over $\mathbb{R}$ of all continuous and continuously differential functions $f : \mathbb{S}_1 \to \mathbb{S}_2$, respectively. The column-vectorizing operator is denoted by $\mathrm{col}(\cdot)$. The symbol $\mathcal{D}^+$ represents the upper-right derivative of functions. The Euclidean norm is denoted by $\|\cdot\|$.

2. Preliminaries

The considered neutral-type memristive CGNN involving multiple time-varying leakage and transmission delays can be written as:

$$\dot{x}_i(t) = \psi_i(x_i(t))\Big[-\varphi_i(x_i(t-\pi_i(t))) + \sum_{j\in\langle n\rangle} a_{ij}(x_i(t))p_j(x_j(t)) + \sum_{j\in\langle n\rangle} b_{ij}(x_i(t))q_j(x_j(t-\eta_{ij}(t)))\Big] + \sum_{j\in\langle n\rangle} s_{ij}\dot{x}_j(t-\varepsilon_{ij}),\ t\geq 0,\ i\in\langle n\rangle, \tag{2.1a}$$

$$x_i(s) = \phi_i^x(s),\ s\in[-\rho,0],\ i\in\langle n\rangle, \tag{2.1b}$$

where n is the number of neurons, $\varepsilon_{ij} > 0$, $\pi_i \in C([0,+\infty),[\check{\pi}_i,\hat{\pi}_i])$ and $\eta_{ij}\in C([0,+\infty),[\check{\eta}_{ij},\hat{\eta}_{ij}])$ are the neutral, leakage, and transmission delays, respectively, $0\leq\check{\pi}_i$, $0\leq\check{\eta}_{ij}$, $x_i : [-\rho,+\infty)\to\mathbb{R}$ are the neuronal states, $\rho = \max\{\hat{\varepsilon},\hat{\pi},\hat{\eta}\}$, $\hat{\varepsilon} = \max\limits_{i,j\in\langle n\rangle}\varepsilon_{ij}$, $\hat{\pi} = \max\limits_{i\in\langle n\rangle}\hat{\pi}_i$, $\hat{\eta} = \max\limits_{i,j\in\langle n\rangle}\hat{\eta}_{ij}$, $\psi_i\in C(\mathbb{R},[\check{\Psi}_i,\hat{\Psi}_i])$ are the amplification functions, $0<\check{\Psi}_i$, $\varphi_i\in C(\mathbb{R},\mathbb{R})$ are the self-signal functions, $\phi_i^x\in C^1([-\rho,0],\mathbb{R})$ refer to the initial functions, $s_{ij}\in\mathbb{R}$, and $p_j, q_j\in C(\mathbb{R},\mathbb{R})$ represent the activation functions. In addition, the connection weights have the form as follows:

$$a_{ij}(\cdot) = \begin{cases}\check{a}_{ij}, & \text{if } |\cdot| > \varpi_i,\\ \hat{a}_{ij}, & \text{if } |\cdot|\leq\varpi_i,\end{cases}\quad b_{ij}(\cdot) = \begin{cases}\check{b}_{ij}, & \text{if } |\cdot| > \varpi_i,\\ \hat{b}_{ij}, & \text{if } |\cdot|\leq\varpi_i,\end{cases} \tag{2.2}$$

here, $\varpi_i > 0$ are the threshold constants, and $\hat{a}_{ij}$, $\check{a}_{ij}$,$\hat{b}_{ij}$, and $\check{b}_{ij}$ are known scalars.

Remark 1. *When $s_{ij} = 0$, $\pi_i(\cdot)\equiv 0$ and $\eta_{ij}(\cdot) = \eta_j(\cdot)$ for all $i,j\in\langle n\rangle$, the NN model* (2.1) *simplifies to memristive CGNNs with time-varying delays [39]. When $\pi_i(\cdot)\equiv 0$, $s_{ij} = 0$, $a_{ij}(\cdot) = a_{ij}$, $b_{ij}(\cdot) = b_{ij}$ and $\eta_{ij}(\cdot) = \eta(\cdot)$ for any $i,j\in\langle n\rangle$, the NN model* (2.1) *reduces to CGNNs with one time-varying transmission delay [48].*

Remark 2. *In some NNs, there are a large number of synapses with different sizes and parallel paths with different lengths, which limits the space range [49]. Therefore, there is always a representative time delay, which is essentially different from the conventional delays, and it broadly exists in the negative feedback terms of the system, which are identified as leakage terms, named leakage delay. The leakage delay is usually incorporated in the study of network modeling. Such a type of time delay often has a tendency to destabilize the NNs and is difficult to handle. Therefore, it is of great practical significance to study the stability of NNs with leakage delays.*

We take the neutral-type memristive CGNN (2.1) as the drive system, which devises a neutral-type memristive CGNN (response system) as follows:

$$\dot{y}_i(t) = \psi_i(y_i(t))\Big[-\varphi_i(y_i(t-\pi_i(t))) + \sum_{j\in\langle n\rangle} a_{ij}(y_i(t))p_j(y_j(t)) + \sum_{j\in\langle n\rangle} b_{ij}(y_i(t))q_j(y_j(t-\eta_{ij}(t)))\Big] + \sum_{j\in\langle n\rangle} s_{ij}\dot{y}_j(t-\varepsilon_{ij})$$

$$+u_i(t),\ t\geq 0, i\in\langle n\rangle, \tag{2.3a}$$

$$y_i(s)=\phi_i^y(s),\ s\in[-\rho,0],\ i\in\langle n\rangle, \tag{2.3b}$$

where $y_i:[-\rho,+\infty)\to\mathbb{R}$ represent the neuronal states, $\phi_i^y\in C^1([-\rho,0],\mathbb{R})$ stand for the initial functions, and $u_i:[0,+\infty)\to\mathbb{R}$ refer to the control inputs.

The error system related to the drive-response neutral-type memristive CGNNs (2.1) and (2.3) is expressed as:

$$\begin{aligned}\dot{e}_i(t)=&[-\psi_i(y_i(t))\varphi_i(y_i(t-\pi_i(t)))+\psi_i(x_i(t))\varphi_i(x_i(t-\pi_i(t)))]\\&+\sum_{j\in\langle n\rangle}\Big[\psi_i(y_i(t))a_{ij}(y_i(t))p_j(y_j(t))-\psi_i(x_i(t))a_{ij}(x_i(t))p_j(x_j(t))\Big]\\&+\sum_{j\in\langle n\rangle}\Big[\psi_i(y_i(t))b_{ij}(y_i(t))q_j(y_j(t-\eta_{ij}(t)))-\psi_i(x_i(t))b_{ij}(x_i(t))q_j(x_j(t-\eta_{ij}(t)))\Big]\\&+\sum_{j\in\langle n\rangle}s_{ij}\dot{e}_j(t-\varepsilon_{ij})+u_i(t),\ t\geq 0,\ i\in\langle n\rangle,\end{aligned} \tag{2.4a}$$

$$e_i(s)=\phi_i(s),\ s\in[-\rho,0],\ i\in\langle n\rangle, \tag{2.4b}$$

where $\phi_i(s)=\phi_i^y(s)-\phi_i^x(s)$ and $e_i(t)=y_i(t)-x_i(t)$.

Definition 1. *For any initial function $\phi(\cdot)$, we say that the neutral-type memristive CGNNs* (2.1) *and* (2.3) *achieve accuracy-preassigned finite-time exponential synchronization, if for given an accuracy $\epsilon>0$, there are $\hat{T}>0$ and $u_i(t)$ $(i\in\langle n\rangle)$ such that the state vector, $e(t):=\mathrm{col}\big(e_1(t),\dots,e_n(t)\big)$ satisfies $\|e(t)\|<\epsilon$ whenever $t>\hat{T}$. The constant $\hat{T}$ is called the settling time.*

The following assumptions are required.

A_1: [44] For every $i\in\langle n\rangle$, there are positive numbers P_i, Q_i, $\hat{P}_i$, and $\hat{Q}_i$ satisfying:
$|p_i(\kappa)|\leq\hat{P}_i$, $|p_i(\kappa)-p_i(\iota)|\leq P_i|\kappa-\iota|$,
$|q_i(\kappa)|\leq\hat{Q}_i$, $|q_i(\kappa)-q_i(\iota)|\leq Q_i|\kappa-\iota|$, $\kappa,\iota\in\mathbb{R}$.

A_2: For every $i\in\langle n\rangle$, there are positive numbers Ψ_i and Φ_i, satisfying:
$|\psi_i(\kappa_1)\varphi_i(\kappa_2)-\psi_i(\iota_1)\varphi_i(\iota_2)|\leq\Psi_i|\kappa_1-\iota_1|+\Phi_i|\kappa_2-\iota_2|$, $\kappa_1,\kappa_2,\iota_1,\iota_2\in\mathbb{R}$.
In the case without the leakage delay, it is chosen that $\kappa_1=\kappa_2$ and $\iota_1=\iota_2$ [44].

Remark 3. *In Assumptions A_1 and A_2, we require the amplification function or activation functions to be bounded continuous and satisfy Lipschitz continuity. Otherwise, the NN system may experience problems such as gradient explosion or model degradation. There are also many research results that can handle discontinuous activation functions [44].*

We aim to design controllers $u_i(t)$ $(i\in\langle n\rangle)$ such that the drive-response neutral-type memristive CGNNs (2.1) and (2.3) achieve accuracy-preassigned finite-time exponential synchronization. To this end, the following conclusion is needed.

Lemma 1. *Set $\bar{b}_{ij}=\max\{|\check{b}_{ij}|,|\hat{b}_{ij}|\}$ and $\bar{a}_{ij}=\max\{|\check{a}_{ij}|,|\hat{a}_{ij}|\}$. Then, under assumption A_1, there are:*

$$|\psi_i(y_i(s))a_{ij}(y_i(s))p_j(y_j(s))-\psi_i(x_i(s))a_{ij}(x_i(s))p_j(x_j(s))|$$

$$\leq \hat{\Psi}_i \bar{a}_{ij} P_j |e_j(s)| + \hat{\Psi}_i \hat{P}_j |\hat{a}_{ij} - \check{a}_{ij}| + \hat{P}_j \bar{a}_{ij} (\hat{\Psi}_i - \check{\Psi}_i),\ i, j \in \langle n \rangle, s \geq 0, \tag{2.5}$$

$$\begin{aligned} &|\psi_i(y_i(s)) b_{ij}(y_i(s)) q_j(y_j(s - \eta_{ij}(s))) - \psi_i(x_i(s)) b_{ij}(x_i(s)) q_j(x_j(s - \eta_{ij}(s)))| \\ \leq &\hat{\Psi}_i \bar{b}_{ij} Q_j |e_j(s - \eta_{ij}(s))| + \hat{\Psi}_i \hat{Q}_j |\hat{b}_{ij} - \check{b}_{ij}| + \hat{Q}_j \bar{b}_{ij} (\hat{\Psi}_i - \check{\Psi}_i),\ i, j \in \langle n \rangle, s \geq 0. \end{aligned} \tag{2.6}$$

Proof. We prove only (2.5), since the other is similar. It follows from $\psi_i \in C(\mathbb{R}, [\check{\Psi}_i, \hat{\Psi}_i])$, $\bar{a}_{ij} = \max\{|\check{a}_{ij}|\,|\hat{a}_{ij}|\}$, (2.2) and assumption A_1 that

$$\begin{aligned} &|\psi_i(y_i(s)) a_{ij}(y_i(s)) p_j(y_j(s)) - \psi_i(x_i(s)) a_{ij}(x_i(s)) p_j(x_j(s))| \\ =&|\psi_i(y_i(s)) a_{ij}(y_i(s)) p_j(y_j(s)) - \psi_i(y_i(s)) a_{ij}(y_i(s)) p_j(x_j(s)) \\ &+ \psi_i(y_i(s)) a_{ij}(y_i(s)) p_j(x_j(s)) - \psi_i(y_i(s)) a_{ij}(x_i(s)) p_j(x_j(s)) \\ &+ \psi_i(y_i(s)) a_{ij}(x_i(s)) p_j(x_j(s)) - \psi_i(x_i(s)) a_{ij}(x_i(s)) p_j(x_j(s))| \\ \leq &\hat{\Psi}_i \bar{a}_{ij} P_j |e_j(s)| + \hat{\Psi}_i \hat{P}_j |\hat{a}_{ij} - \check{a}_{ij}| + \hat{P}_j \bar{a}_{ij} (\hat{\Psi}_i - \check{\Psi}_i),\ i, j \in \langle n \rangle, s \geq 0. \end{aligned}$$

□

3. Accuracy-preassigned fixed-time exponential synchronization

Throughout this section, we assume that assumptions A_1 and A_2 hold. To realize accuracy-preassigned finite-time exponential synchronization between neutral-type memristive CGNNs (2.1) and (2.3), we design the following controllers:

$$u_i(t) = -K_i \left(e_i(t) - \sum_{j \in \langle n \rangle} s_{ij} e_j(t - \varepsilon_{ij}) \right),\ i \in \langle n \rangle,\ t \geq 0, \tag{3.1}$$

where $K_i > 0$ represent the controller gains.

Theorem 1. *Under the controller* (3.1)*, each solution of the error system* (2.4) *meets the following relation:*

$$|e_i(t)| \leq \sum_{\ell=0}^{5} \partial_{i\ell}(t) + \tfrac{\Upsilon_i}{K_i},\ i \in \langle n \rangle,\ t \geq 0, \tag{3.2}$$

where

$\partial_{i0}(t) = \mathrm{e}^{-K_i t} \|\phi\|_\rho \left(1 + \sum_{j \in \langle n \rangle} |s_{ij}|\right)$, $\|\phi\|_\rho = \max\limits_{i \in \langle n \rangle} \sup\limits_{s \in [-\rho, 0]} \max\left\{|\phi_i(s)|, |\dot{\phi}_i(s)|\right\}$,

$\partial_{i1}(t) = \sum_{j \in \langle n \rangle} |s_{ij}| |e_j(t - \varepsilon_{ij})|$,

$\partial_{i2}(t) = \Psi_i \int_0^t \mathrm{e}^{K_i(s-t)} |e_i(s)| \mathrm{d}s$,

$\partial_{i3}(t) = \Phi_i \int_0^t \mathrm{e}^{K_i(s-t)} |e_i(s - \pi_i(s))| \mathrm{d}s$,

$\partial_{i4}(t) = \hat{\Psi}_i \sum_{j \in \langle n \rangle} \int_0^t \mathrm{e}^{K_i(s-t)} \bar{a}_{ij} P_j |e_j(s)| \mathrm{d}s$,

$\partial_{i5}(t) = \hat{\Psi}_i \sum_{j \in \langle n \rangle} \int_0^t \mathrm{e}^{K_i(s-t)} \bar{b}_{ij} Q_j |e_j(s - \eta_{ij}(s))| \mathrm{d}s$,

$\Upsilon_i = (\hat{\Psi}_i - \check{\Psi}_i) \sum\limits_{j \in \langle n \rangle} \left(\bar{a}_{ij} \hat{P}_j + \bar{b}_{ij} \hat{Q}_j\right) + \hat{\Psi}_i \sum\limits_{j \in \langle n \rangle} \left(|\hat{a}_{ij} - \check{a}_{ij}| \hat{P}_j + |\hat{b}_{ij} - \check{b}_{ij}| \hat{Q}_j\right)$.

Remark 4. *The inequality* (3.2) *is different from the respective conclusions in [11, 24, 25].*

Proof. It is obvious from (2.4a) that

$$\begin{aligned}
&\mathcal{D}^+\left|e_i(t)-\sum_{j\in\langle n\rangle}s_{ij}e_j(t-\varepsilon_{ij})\right| \\
=&E_i(t)\left(\dot{e}_i(t)-\sum_{j\in\langle n\rangle}s_{ij}\dot{e}_j(t-\varepsilon_{ij})\right) \\
=&E_i(t)[-\psi_i(y_i(t))\varphi_i(y_i(t-\pi_i(t)))+\psi_i(x_i(t))\varphi_i(x_i(t-\pi_i(t)))]+E_i(t)\sum_{j\in\langle n\rangle}[\psi_i(y_i(t))a_{ij}(y_i(t))p_j(y_j(t)) \\
&-\psi_i(x_i(t))a_{ij}(x_i(t))p_j(x_j(t))]+E_i(t)\sum_{j\in\langle n\rangle}[\psi_i(y_i(t))b_{ij}(y_i(t))q_j(y_j(t-\eta_{ij}(t))) \\
&-\psi_i(x_i(t))b_{ij}(x_i(t))q_j(x_j(t-\eta_{ij}(t)))]+E_i(t)u_i(t),\ t\geq 0,\ i\in\langle n\rangle,
\end{aligned}$$

where $E_i(t)=\operatorname{sgn}\left(e_i(t)-\sum_{j\in\langle n\rangle}s_{ij}e_j(t-\varepsilon_{ij})\right)$, and hence,

$$\begin{aligned}
&\mathcal{D}^+\left(\mathrm{e}^{K_it}\left|e_i(t)-\sum_{j\in\langle n\rangle}s_{ij}e_j(t-\varepsilon_{ij})\right|\right) \\
=&\mathrm{e}^{K_it}\left(K_i\left|e_i(t)-\sum_{j\in\langle n\rangle}s_{ij}e_j(t-\varepsilon_{ij})\right|+E_i(t)[-\psi_i(y_i(t))\varphi_i(y_i(t-\pi_i(t)))+\psi_i(x_i(t))\varphi_i(x_i(t-\pi_i(t)))]\right. \\
&+E_i(t)\sum_{j\in\langle n\rangle}\left[\psi_i(y_i(t))a_{ij}(y_i(t))p_j(y_j(t))-\psi_i(x_i(t))a_{ij}(x_i(t))p_j(x_j(t))\right]+E_i(t)u_i(t) \\
&\left.+E_i(t)\sum_{j\in\langle n\rangle}[\psi_i(y_i(t))b_{ij}(y_i(t))q_j(y_j(t-\eta_{ij}(t)))-\psi_i(x_i(t))b_{ij}(x_i(t))q_j(x_j(t-\eta_{ij}(t)))]\right),\ t\geq 0,\ i\in\langle n\rangle.
\end{aligned} \tag{3.3}$$

This, together with (3.1), assumption A_2, and Lemma 1, derives that

$$\begin{aligned}
&\mathcal{D}^+\left(\mathrm{e}^{K_it}\left|e_i(t)-\sum_{j\in\langle n\rangle}s_{ij}e_j(t-\varepsilon_{ij})\right|\right) \\
\leq&\mathrm{e}^{K_it}\left(\left|\psi_i(y_i(t))\varphi_i(y_i(t-\pi_i(t)))-\psi_i(x_i(t))\varphi_i(x_i(t-\pi_i(t)))\right|\right. \\
&+\sum_{j\in\langle n\rangle}\left|\psi_i(y_i(t))a_{ij}(y_i(t))p_j(y_j(t))-\psi_i(x_i(t))a_{ij}(x_i(t))p_j(x_j(t))\right| \\
&\left.+\sum_{j\in\langle n\rangle}\left|\psi_i(y_i(t))b_{ij}(y_i(t))q_j(y_j(t-\eta_{ij}(t)))-\psi_i(x_i(t))b_{ij}(x_i(t))q_j(x_j(t-\eta_{ij}(t)))\right|\right) \\
\leq&\mathrm{e}^{K_it}\Psi_i|e_i(t)|+\mathrm{e}^{K_it}\Phi_i|e_i(t-\pi_i(t))|+\mathrm{e}^{K_it}\hat{\Psi}_i\sum_{j\in\langle n\rangle}\bar{a}_{ij}P_j|e_j(t)| \\
&+\mathrm{e}^{K_it}\hat{\Psi}_i\sum_{j\in\langle n\rangle}\bar{b}_{ij}Q_j|e_j(t-\eta_{ij}(t))|+\mathrm{e}^{K_it}\Upsilon_i,\ t\geq 0,\ i\in\langle n\rangle.
\end{aligned} \tag{3.4}$$

Taking an integration on both sides of (3.4) from 0 to t, we have

$$|e_i(t)| \le \mathrm{e}^{-K_i t}\left|e_i(0) - \sum_{j\in\langle n\rangle} s_{ij}e_j(-\varepsilon_{ij})\right| + \sum_{\ell=1}^{5}\partial_{i\ell}(t) + \tfrac{\Upsilon_i}{K_i},\ i\in\langle n\rangle,\ t\ge 0,$$

and hence (3.2) holds. □

Theorem 2. *For given positive numbers ς, ϵ and λ, assume that $g = \frac{(1-\varsigma)\epsilon}{\sqrt{n}}$, and there are scalars $l_i(>1)$ and $K_i(>\lambda)$ such that*

$$\ln l_i + \ln\|\phi\|_\rho - \ln\tfrac{\varsigma\epsilon}{\sqrt{n}} > 0,\ i\in\langle n\rangle, \tag{3.5a}$$

$$\sum_{j\in\langle n\rangle}\left(\frac{\frac{1}{n}+|s_{ij}|}{l_i} + \frac{l_j\Omega_{ij}}{l_i}\right) + \frac{\Psi_i+\Phi_i\mathrm{e}^{\lambda\hat{\pi}_i}}{K_i-\lambda} < 1,\ i\in\langle n\rangle, \tag{3.5b}$$

$$\sum_{j\in\langle n\rangle}|s_{ij}| + \frac{\frac{\Upsilon_i}{g}+\Psi_i+\Phi_i+\hat{\Psi}_i\sum_{j\in\langle n\rangle}\left(\bar{a}_{ij}P_j+\bar{b}_{ij}Q_j\right)}{K_i} < 1,\ i\in\langle n\rangle, \tag{3.5c}$$

where $\Omega_{ij} = |s_{ij}|\mathrm{e}^{\lambda\varepsilon_{ij}} + \frac{\hat{\Psi}_i\left(\bar{a}_{ij}P_j+\bar{b}_{ij}Q_j\mathrm{e}^{\lambda\hat{\eta}_{ij}}\right)}{K_i-\lambda}$. Then,

(i) $|e_i(t)| \le l_i\|\phi\|_\rho\mathrm{e}^{-\lambda t} + g$ for any $t\ge-\rho$ and $i\in\langle n\rangle$;

(ii) The controller (3.1) can guarantee that the neutral-type memristive CGNNs (2.1) and (2.3) achieve accuracy-preassigned finite-time exponential synchronization within the settling time:

$$\hat{T} := \frac{\ln L + \ln\|\phi\|_\rho - \ln\frac{\varsigma\epsilon}{\sqrt{n}}}{\lambda}, \tag{3.6}$$

where $L = \max_{i\in\langle n\rangle} l_i$.

Proof. In the proof, we suppose that $\phi_i \in C^1([-\rho,0],\mathbb{R}),\ i\in\langle n\rangle$ are finite but can be chosen arbitrarily, and $e_i(t)$ ($i\in\langle n\rangle$) is the corresponding solution of the error system (2.4).

(i) It is obvious when $t\in[-\rho,0]$. We assert that (i) is correct for $t\ge-\rho$; otherwise, there exist $T>0$ and $v\in\langle n\rangle$, satisfying

$$|e_i(t)| \le l_i\|\phi\|_\rho\mathrm{e}^{-\lambda t} + g, t\in[-\rho,T], i\in\langle n\rangle, \tag{3.7}$$

$$|e_v(T)| = l_v\|\phi\|_\rho\mathrm{e}^{-\lambda T} + g. \tag{3.8}$$

For any given $s\in[0,T]$, we can obtain from (3.7) and (3.8), $\varepsilon_{vj}>0$, $\pi_v(\cdot)\in[\check{\pi}_v,\hat{\pi}_v]$ and $\eta_{vj}(\cdot)\in[\check{\eta}_{vj},\hat{\eta}_{vj}]$ that

$$|e_j(s-\varepsilon_{vj})| \le \mathrm{e}^{\lambda\varepsilon_{vj}}l_j\|\phi\|_\rho\mathrm{e}^{-\lambda s} + g,$$

$$
\begin{aligned}
|e_j(s-\eta_{vj}(s))| &\le e^{\lambda\hat{\eta}_{vj}} l_j \|\phi\|_\rho e^{-\lambda s} + g,\\
|e_v(s-\pi_v(s))| &\le e^{\lambda\hat{\pi}_v} l_v \|\phi\|_\rho e^{-\lambda s} + g.
\end{aligned} \tag{3.9}
$$

Noting that

$$
\int_0^T e^{K_v(s-T)} ds \le \tfrac{1}{K_v}, \quad \int_0^T e^{(K_v-\lambda)s-K_vT} ds = e^{-\lambda T}\int_0^T e^{(K_v-\lambda)(s-T)} ds \le \tfrac{e^{-\lambda T}}{K_v-\lambda},
$$

we have from (3.9) that

$$
\begin{aligned}
&\partial_{v1}(T) \le \sum_{j\in\langle n\rangle} |s_{vj}| e^{\lambda\varepsilon_{vj}} l_j \|\phi\|_\rho e^{-\lambda T} + g\sum_{j\in\langle n\rangle} |s_{vj}|,\\
&\partial_{v2}(T) \le \Psi_v \tfrac{1}{K_v-\lambda} l_v \|\phi\|_\rho e^{-\lambda T} + g\Psi_v \tfrac{1}{K_v},\\
&\partial_{v3}(T) \le \Phi_v \tfrac{e^{\lambda\hat{\pi}_v}}{K_v-\lambda} l_v \|\phi\|_\rho e^{-\lambda T} + g\Phi_v \tfrac{1}{K_v},\\
&\partial_{v4}(T) \le \hat{\Psi}_v \sum_{j\in\langle n\rangle} \tfrac{\bar{a}_{vj}P_j}{K_v-\lambda} l_j \|\phi\|_\rho e^{-\lambda T} + g\hat{\Psi}_v \sum_{j\in\langle n\rangle} \bar{a}_{vj}P_j \tfrac{1}{K_v},\\
&\partial_{v5}(T) \le \hat{\Psi}_v \sum_{j\in\langle n\rangle} \tfrac{\bar{b}_{vj}Q_j e^{\lambda\hat{\eta}_{vj}}}{K_v-\lambda} l_j \|\phi\|_\rho e^{-\lambda T} + g\hat{\Psi}_v \sum_{j\in\langle n\rangle} \bar{b}_{vj}Q_j \tfrac{1}{K_v}.
\end{aligned}
$$

It follows from (3.2) that

$$
\begin{aligned}
|e_v(T)| \le & l_v \|\phi\|_\rho e^{-\lambda T}\left(\frac{\Psi_v+\Phi_v e^{\lambda\hat{\pi}_v}}{K_v-\lambda} + \sum_{j\in\langle n\rangle}\left(\frac{\frac{1}{n}+|s_{vj}|}{l_v} + \frac{l_j\Omega_{vj}}{l_v}\right)\right)\\
&+ g\left(\sum_{j\in\langle n\rangle}|s_{vj}| + \frac{\frac{\Upsilon_v}{g}+\Psi_v+\Phi_v+\hat{\Psi}_v\sum_{j\in\langle n\rangle}\left(\bar{a}_{vj}P_j+\bar{b}_{vj}Q_j\right)}{K_v}\right).
\end{aligned}
$$

This, combined with (3.5c), means that $|e_v(T)| < l_v\|\phi\|_\rho e^{-\lambda T} + g$, which contradicts (3.8). Therefore, (i) holds.

(ii) When $t > \hat{T}$, one has from (i) and (3.6) that

$$
|e_i(t)| \le L\|\phi\|_\rho e^{-\lambda t} + g \le L\|\phi\|_\rho e^{-\lambda\hat{T}} + \tfrac{(1-\varsigma)\epsilon}{\sqrt{n}} < \tfrac{\varsigma\epsilon}{\sqrt{n}} + \tfrac{(1-\varsigma)\epsilon}{\sqrt{n}} = \tfrac{\epsilon}{\sqrt{n}}, i\in\langle n\rangle,
$$

hence,

$$
\|e(t)\| < \epsilon,\ t > \hat{T}.
$$

In accordance with Definition 1, the controller (3.1) can guarantee that the neutral-type memristive CGNNs (2.1) and (2.3) achieve accuracy-preassigned finite-time exponential synchronization within the settling time given by (3.6). □

Remark 5. *Theorem 2 presents the existence and design approach of a novel controller that can be used to establish accuracy-preassigned finite-time exponential synchronization between the drive-response neutral-type memristive CGNNs* (2.1) *and* (2.3).

Remark 6. *The error system* (2.4) *contains multiple delays and some coupling terms of two or three functions, which becomes hard for synchronizing CGNNs* (2.1) *and* (2.3). *To overcome this difficult problem, we design controller* (3.1) *to deal with the neutral delays and introduce the parameter* ς *to eliminate the couplings among amplification functions, self-signal functions, and activation functions.*

Remark 7. *As mentioned in the Introduction section, the positive number ϵ is viewed as a preassigned accuracy, which has to be satisfied considering a finite-time synchronization issue. Thus, ϵ is usually a small positive number, which implies that* $\ln \frac{\varsigma\epsilon}{\sqrt{n}} < 0$, *and hence for given initial functions, the feasibility of* (3.5a) *can be easily guaranteed. Then,* (3.5b) *and* (3.5c) *can be satisfied by choosing appropriately the positive numbers l_i and K_i, $i \in \langle n \rangle$.*

Noting that the nonlinear inequalities in (3.5) are not convenient to solve, we provide the following conclusion:

Corollary 1. *For given positive constants ς, ϵ, and λ, assume that there are positive numbers τ, r_i, and h_i ($i \in \langle n \rangle$) such that*

$$r_j \leq r_i \tau, \ i, j \in \langle n \rangle, \tag{3.10a}$$

$$h_i \left(1 - \sum_{j \in \langle n \rangle} \tau |s_{ij}| \mathrm{e}^{\lambda \varepsilon_{ij}} \right) - \lambda \left(r_i - \sum_{j \in \langle n \rangle} r_j |s_{ij}| \mathrm{e}^{\lambda \varepsilon_{ij}} \right) - r_i (\Psi_i + \Phi_i \mathrm{e}^{\lambda \hat{\pi}_i}) - \sum_{j \in \langle n \rangle} r_j \hat{\Psi}_i \left(\bar{a}_{ij} P_j + \bar{b}_{ij} Q_j \mathrm{e}^{\lambda \hat{\eta}_{ij}} \right) > 0, i \in \langle n \rangle, \tag{3.10b}$$

$$h_i \left(1 - \sum_{j \in \langle n \rangle} |s_{ij}| \right) - r_i \left(\frac{\sqrt{n} \Upsilon_i}{(1-\varsigma)\epsilon} + \Psi_i + \Phi_i + \hat{\Psi}_i \sum_{j \in \langle n \rangle} \left(\bar{a}_{ij} P_j + \bar{b}_{ij} Q_j \right) \right) > 0, \ i \in \langle n \rangle. \tag{3.10c}$$

Then, the controller (3.1) with $K_i = h_i r_i^{-1}$ ($i \in \langle n \rangle$) can ensure that the neutral-type memristive CGNNs (2.1) and (2.3) achieve accuracy-preassigned finite-time exponential synchronization within the settling time given in (3.6).

Proof. For any $i \in \langle n \rangle$, it follows from (3.10) and $K_i = h_i r_i^{-1}$ that (3.5c) holds, and

$$K_i \left(r_i - \sum_{j \in \langle n \rangle} r_j |s_{ij}| \mathrm{e}^{\lambda \varepsilon_{ij}} \right) - \lambda \left(r_i - \sum_{j \in \langle n \rangle} r_j |s_{ij}| \mathrm{e}^{\lambda \varepsilon_{ij}} \right) - r_i (\Psi_i + \Phi_i \mathrm{e}^{\lambda \hat{\pi}_i}) - \sum_{j \in \langle n \rangle} r_j \hat{\Psi}_i \left(\bar{a}_{ij} P_j + \bar{b}_{ij} Q_j \mathrm{e}^{\lambda \hat{\eta}_{ij}} \right) > 0,$$

and hence,

$$(K_i - \lambda) r_i - r_i (\Psi_i + \Phi_i \mathrm{e}^{\lambda \hat{\pi}_i}) - (K_i - \lambda) \sum_{j \in \langle n \rangle} r_j |s_{ij}| \mathrm{e}^{\lambda \varepsilon_{ij}} - \sum_{j \in \langle n \rangle} r_j \hat{\Psi}_i \left(\bar{a}_{ij} P_j + \bar{b}_{ij} Q_j \mathrm{e}^{\lambda \hat{\eta}_{ij}} \right) > 0,$$

that is,

$$(K_i - \lambda) r_i - r_i (\Psi_i + \Phi_i \mathrm{e}^{\lambda \hat{\pi}_i}) - (K_i - \lambda) \sum_{j \in \langle n \rangle} r_j \Omega_{ij} > 0. \tag{3.11}$$

Furthermore,

$$r_i - r_i \frac{\Psi_i + \Phi_i \mathrm{e}^{\lambda \hat{\pi}_i}}{K_i - \lambda} - \sum_{j \in \langle n \rangle} r_j \Omega_{ij} > 0,$$

that is,

$$\sum_{j\in\langle n\rangle}\frac{r_j\Omega_{ij}}{r_i}+\frac{\Psi_i+\Phi_i e^{\lambda\hat{\pi}_i}}{K_i-\lambda}<1.$$

Thus, there exist $l_i > 1$ ($i \in \langle n\rangle$) such that (3.5a) and (3.5b) hold. By Theorem 2, the controller (3.1) with $K_i = h_i r_i^{-1}$ ($i \in \langle n\rangle$) can guarantee that the neutral-type memristive CGNNs (2.1) and (2.3) achieve accuracy-preassigned finite-time exponential synchronization within the settling time given in (3.6). □

Remark 8. *From Theorem 2 and Corollary 1, one can conclude that the positive numbers l_i ($i \in \langle n\rangle$) in the settling time can be obtained based on the following steps:*

Step 1. Take appropriate values of positive numbers ς, ϵ, and λ;

Step 2. Find positive numbers τ, r_i and h_i ($i \in \langle n\rangle$) such that the linear scalar inequalities in (3.10) are feasible;

Step 3. Calculate the controller gains K_i by $K_i = h_i r_i^{-1}$, $i \in \langle n\rangle$;

Step 4. Find positive numbers l_i ($i \in \langle n\rangle$) such that the scalar inequalities in (3.5a) and (3.5b) are feasible.

When $s_{ij} = 0$, $\pi_i(t) \equiv 0$, and $\eta_{ij}(t) = \eta_j(t)$ for all $t \geq 0$ and $i, j \in \langle n\rangle$, the NN models (2.1) and (2.3) simplify to memristive CGNNs with time-varying delays:

$$\begin{aligned}\dot{x}_i(t) =&\psi_i(x_i(t))\Big[-\varphi_i(x_i(t))+\sum_{j\in\langle n\rangle}a_{ij}(x_i(t))p_j(x_j(t))\\&+\sum_{j\in\langle n\rangle}b_{ij}(x_i(t))q_j(x_j(t-\eta_j(t)))\Big],\ t\geq 0,\ i\in\langle n\rangle,\end{aligned}\tag{3.12a}$$

$$x_i(s) =\phi_i^x(s),\ s\in[-\rho,0],\ i\in\langle n\rangle,\tag{3.12b}$$

and

$$\begin{aligned}\dot{y}_i(t) =&\psi_i(y_i(t))\Big[-\varphi_i(y_i(t))+\sum_{j\in\langle n\rangle}a_{ij}(y_i(t))p_j(y_j(t))\\&+\sum_{j\in\langle n\rangle}b_{ij}(y_i(t))q_j(y_j(t-\eta_j(t)))\Big]+u_i(t),\ t\geq 0, i\in\langle n\rangle,\end{aligned}\tag{3.13a}$$

$$y_i(s) = \phi_i^y(s),\ s\in[-\rho,0],\ i\in\langle n\rangle,\tag{3.13b}$$

respectively. Furthermore, the error system is as follows:

$$\dot{e}_i(t) =[-\psi_i(y_i(t))\varphi_i(y_i(t))+\psi_i(x_i(t))\varphi_i(x_i(t))]$$

$$+\sum_{j\in\langle n\rangle}\Big[\psi_i(y_i(t))a_{ij}(y_i(t))p_j(y_j(t))-\psi_i(x_i(t))a_{ij}(x_i(t))p_j(x_j(t))\Big]$$
$$+\sum_{j\in\langle n\rangle}\Big[\psi_i(y_i(t))b_{ij}(y_i(t))q_j(y_j(t-\eta_j(t)))-\psi_i(x_i(t))b_{ij}(x_i(t))q_j(y_j(t-\eta_j(t)))\Big]$$
$$+u_i(t),\ i\in\langle n\rangle,\ t\geq 0, \tag{3.14a}$$

$$e_i(s)=\phi_i(s),\ i\in\langle n\rangle,\ s\in[-\rho,0], \tag{3.14b}$$

where

$$u_i(t)=-K_ie_i(t),\ t\geq 0,\ i\in\langle n\rangle, \tag{3.15}$$

and $K_i>0$ stand for the controller gains.

Now, we can obtain the following conclusion.

Corollary 2. *For given positive constants ς, ϵ, and λ, assume that there are positive numbers $\tilde{l}_i$ and $\tilde{h}_i$, such that*

$$\tilde{h}_i-\lambda\tilde{l}_i-\hat{\Psi}_i\sum_{j\in\langle n\rangle}(\tilde{l}_j+1)\left(\bar{a}_{ij}P_j+\bar{b}_{ij}Q_j\mathrm{e}^{\lambda\hat{\eta}_j}\right)-(\Psi_i+\Phi_i)(\tilde{l}_i+1)>0,\ i\in\langle n\rangle, \tag{3.16a}$$

$$\ln(\tilde{l}_i+1)+\ln\|\phi\|_\rho-\ln\tfrac{\varsigma\epsilon}{\sqrt{n}}>0,\ i\in\langle n\rangle, \tag{3.16b}$$

$$\tilde{h}_i-\tilde{l}_i\left(\tfrac{\sqrt{n}\Upsilon_i}{(1-\varsigma)\epsilon}+\Psi_i+\Phi_i+\hat{\Psi}_i\sum_{j\in\langle n\rangle}\left(\bar{a}_{ij}P_j+\bar{b}_{ij}Q_j\right)\right)>0,\ i\in\langle n\rangle. \tag{3.16c}$$

Then, the controller (3.15) with $K_i=\tilde{h}_i\tilde{l}_i^{-1}$ $(i\in\langle n\rangle)$ can guarantee that the memristive CGNNs (3.12) and (3.13) achieve accuracy-preassigned finite-time exponential synchronization within the settling time given in (3.6) with $L=\max_{i\in\langle n\rangle}(\tilde{l}_i+1)$.

Proof. In light of (3.16a) and $K_i=\tilde{h}_i\tilde{l}_i^{-1}$ $(i\in\langle n\rangle)$, we have

$$(K_i-\lambda)\tilde{l}_i-\hat{\Psi}_i\sum_{j\in\langle n\rangle}(\tilde{l}_j+1)\left(\bar{a}_{ij}P_j+\bar{b}_{ij}Q_j\mathrm{e}^{\lambda\hat{\eta}_j}\right)-(\Psi_i+\Phi_i)(\tilde{l}_i+1)>0,\ i\in\langle n\rangle.$$

Set $l_i=\tilde{l}_i+1$, $i\in\langle n\rangle$. Then,

$$(K_i-\lambda)(l_i-1)-\hat{\Psi}_i\sum_{j\in\langle n\rangle}l_j\left(\bar{a}_{ij}P_j+\bar{b}_{ij}Q_j\mathrm{e}^{\lambda\hat{\eta}_j}\right)-(\Psi_i+\Phi_i)l_i>0,\ i\in\langle n\rangle,$$

that is,

$$\tfrac{1}{l_i}+\sum_{j\in\langle n\rangle}\tfrac{l_j\tilde{\Omega}_{ij}}{l_i}+\tfrac{\Psi_i+\Phi_i}{K_i-\lambda}<1,\ i\in\langle n\rangle, \tag{3.17}$$

where $\tilde{\Omega}_{ij}=\frac{\hat{\Psi}_i\left(\bar{a}_{ij}P_j+\bar{b}_{ij}Q_j\mathrm{e}^{\lambda\hat{\eta}_j}\right)}{K_i-\lambda}$. By Theorem 2, (3.16b) and (3.16c), the controller (3.15) with $K_i=\tilde{h}_i\tilde{l}_i^{-1}$ $(i\in\langle n\rangle)$ can guarantee that the memristive CGNNs (3.12) and (3.13) achieve accuracy-preassigned finite-time exponential synchronization within the settling time given in (3.6) with $L=\max_{i\in\langle n\rangle}(\tilde{l}_i+1)$. □

Remark 9. *In [39], finite-time synchronization criteria of memristive CGNNs* (3.12) *and* (3.13) *are derived by employing the differential inclusion theory and constructing the appropriate nonlinear transformations. Compared with the results obtained in [39], Corollary 2 provides a simpler synchronization criterion. In addition, our method can cause the states of the error system to move directly to the preassigned range containing the origin, which avoids the two-stage procedures required in [39].*

4. Numerical examples

To verify the applicability of the results obtained in this article, the following two examples are provided.

Example 1. *In neutral-type memristive CGNNs* (2.1) *and* (2.3)*, we choose* $n = 2$*, and*

$$\psi_1(\cdot) = 0.01\sin^2(\cdot) + 0.01,\ \psi_2(\cdot) = 0.01\cos^2(\cdot) + 0.02,$$
$$\varphi_1(\cdot) = 0.5 + 0.1\sin(\cdot),\ \varphi_2(\cdot) = 0.7 + 0.1\cos(\cdot),$$
$$[\check{a}_{ij}]_{2\times 2} = \begin{bmatrix} 2.5 & -0.1 \\ -1.9 & 2 \end{bmatrix},\ [\hat{a}_{ij}]_{2\times 2} = \begin{bmatrix} 2.3 & -0.13 \\ -1.7 & 1.8 \end{bmatrix},$$
$$[\check{b}_{ij}]_{2\times 2} = \begin{bmatrix} -1.1 & 0.22 \\ 1.15 & -3.5 \end{bmatrix},\ [\hat{b}_{ij}]_{2\times 2} = \begin{bmatrix} -1.3 & 0.3 \\ 1.2 & -3.7 \end{bmatrix},$$
$$[s_{ij}]_{2\times 2} = \begin{bmatrix} 0.1 & 0.02 \\ -0.03 & 01 \end{bmatrix},\ \varpi_1 = 0.3,\ \varpi_2 = 0.2,$$
$$\varepsilon_{11} = 0.01,\ \varepsilon_{12} = 0,\ \varepsilon_{21} = 0.02,\ \varepsilon_{22} = 0.03,$$
$$\pi_1(\cdot) = 0.1|\sin(\cdot)|,\ \pi_2(\cdot) = 0.1|\cos(\cdot)|,$$
$$\eta_{11}(t) = \frac{e^t}{1+10e^t},\ \eta_{12}(t) = \frac{e^t}{1+20e^t},\ \eta_{21}(t) = \frac{e^t}{1+30e^t},\ \eta_{22}(t) = \frac{e^t}{1+40e^t},$$
$$p_j(v) = q_j(v) = \frac{0.1}{1+e^{-v}},\ j = 1, 2,\ t \geq 0,\ v \in \mathbb{R},$$
$$\phi_1^x(s) \equiv 0.6,\ \phi_2^x(s) \equiv -0.4,\ \phi_1^y(s) \equiv -0.6,\ \phi_2^y(s) \equiv -0.4,\ s \in [-0.1, 0].$$

It is clear that $\hat{\varepsilon} = 0.03$, $\rho = \hat{\pi} = \hat{\eta} = 0.1$, $\hat{\Psi}_1 = 0.02$, $\check{\Psi}_1 = 0.01$, $\hat{\Psi}_2 = 0.03$, $\check{\Psi}_2 = 0.02$, $\bar{a}_{11} = 2.5$, $\bar{a}_{12} = 0.13$, $\bar{a}_{21} = 1.9$, $\bar{a}_{22} = 2$, $\bar{b}_{11} = 1.3$, $\bar{b}_{12} = 0.3$, $\bar{b}_{21} = 1.2$, $\bar{b}_{22} = 3.7$, and $\|\phi\|_\rho = 1.2$. Set $\Phi_1 = 0.002$, $\Phi_2 = 0.003$, $\Psi_1 = 0.006$, $\Psi_2 = 0.008$, and $P_i = \hat{P}_i = Q_i = \hat{Q}_i = 0.1$, $i \in \langle 2 \rangle$. Then, assumptions A_1 and A_2 are satisfied. For $\varsigma = 0.001$, $\lambda = 1.5$, and $\epsilon = 0.04$, using the software tool YALMIP, one can gain the following feasible solution to the inequalities in (3.10):

$$\tau = 1.0100,\ r_1 = r_2 = 0.0010,\ h_1 = 0.0019,\ h_2 = 0.0016,$$

hence, $K_1 = 1.9494$ and $K_2 = 1.6471$. Then, it can be obtained that $l_1 = 1.5299$ and $l_2 = 1.6353$ by solving the inequalities in (3.5a) and (3.5b), hence, $L = 1.6353$ and $\hat{T} = 7.4316$. By Corollary 1, the controller (3.1) can guarantee that the neutral-type memristive CGNNs (2.1) and (2.3) achieve accuracy-preassigned finite-time exponential synchronization within the settling time $\hat{T}$.

Under the designed controller (3.1), the state trajectories of the considered neutral-type memristive CGNNs are presented in Figures 1 and 2, and the corresponding errors and their norms are given in Figures 3 and 4. From these four figures, it can be observed that the errors with the controller exhibit a gradual convergence towards zero. In addition, without the controller, Figures 5 and 6 illustrate the state trajectories of the considered neutral-type memristive CGNNs. Consequently, to resolve the synchronization issue, it is of paramount importance to design an appropriate controller to ensure that the states of considered error system gradually reduce the origin.

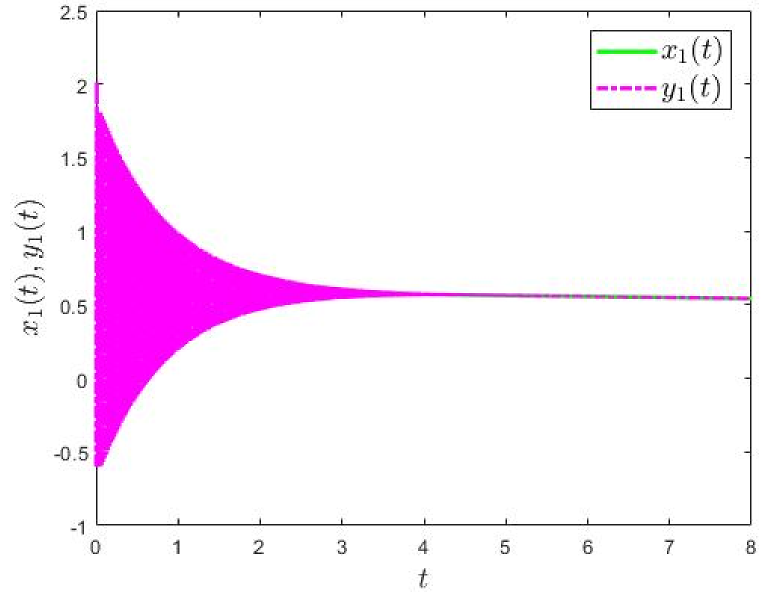

Figure 1. State trajectories $x_1(t)$ and $y_1(t)$ of the considered CGNNs with the controller in Example 1.

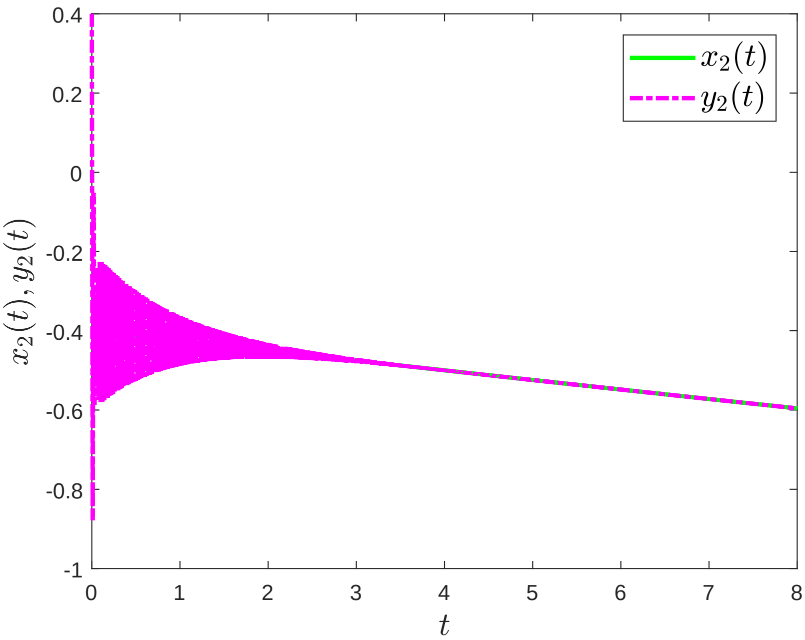

Figure 2. State trajectories $x_2(t)$ and $y_2(t)$ of the considered CGNNs with the controller in Example 1.

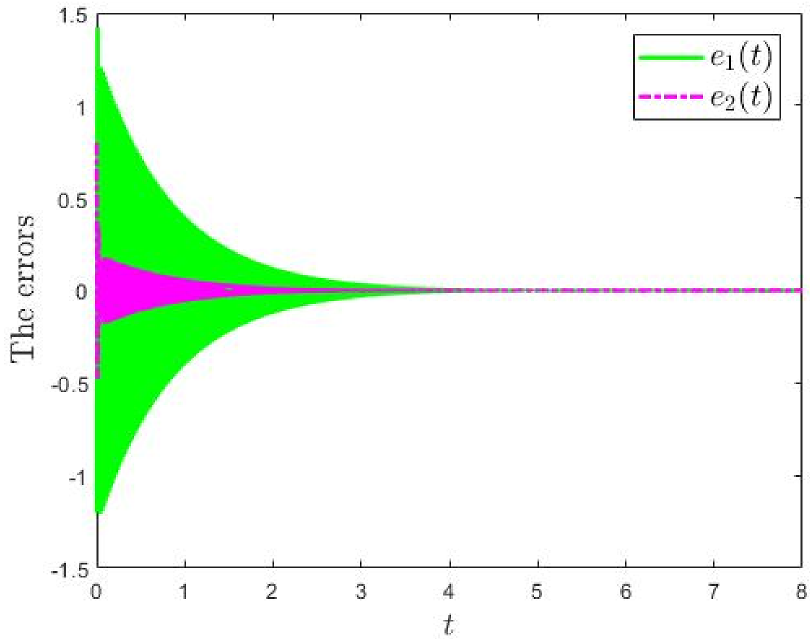

Figure 3. Error curves with the controller in Example 1.

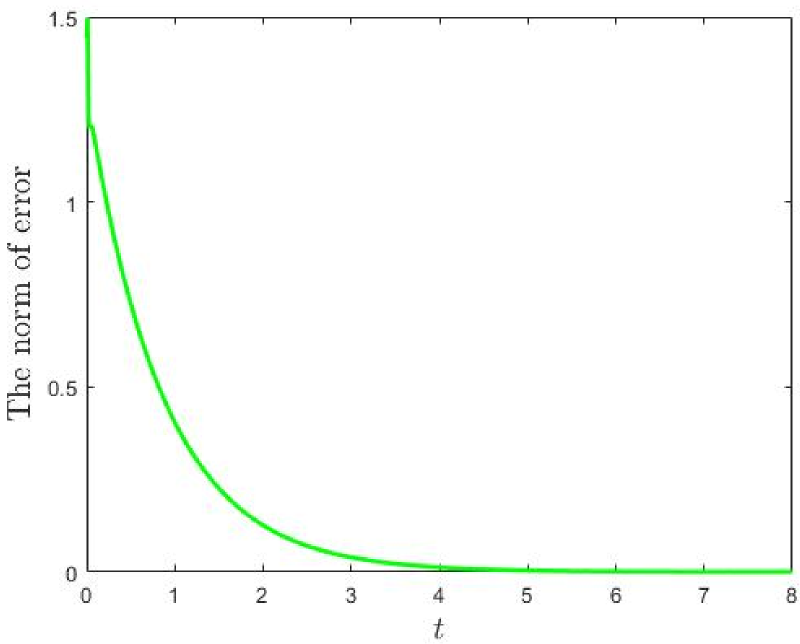

Figure 4. Norm curves of errors in Example 1.

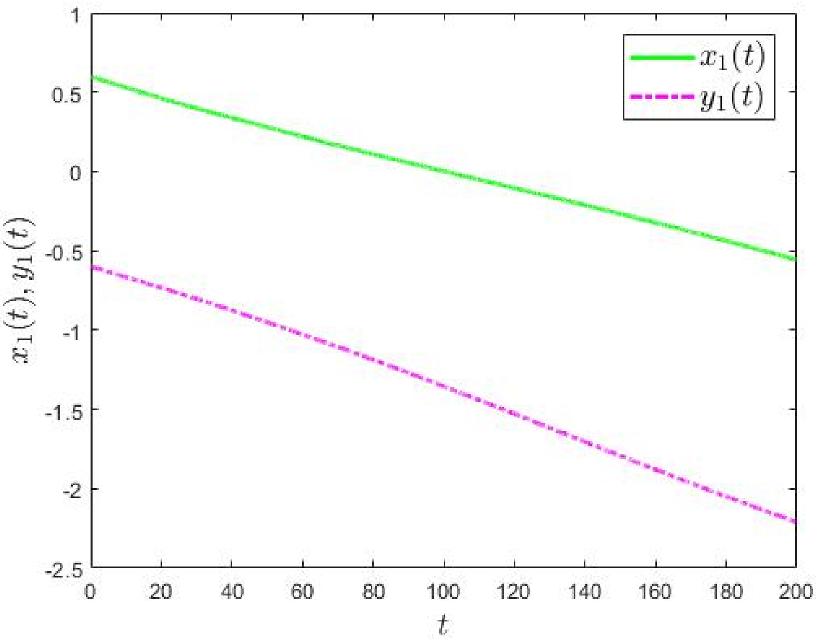

Figure 5. State trajectories $x_1(t)$ and $y_1(t)$ of the considered CGNNs without the controller in Example 1.

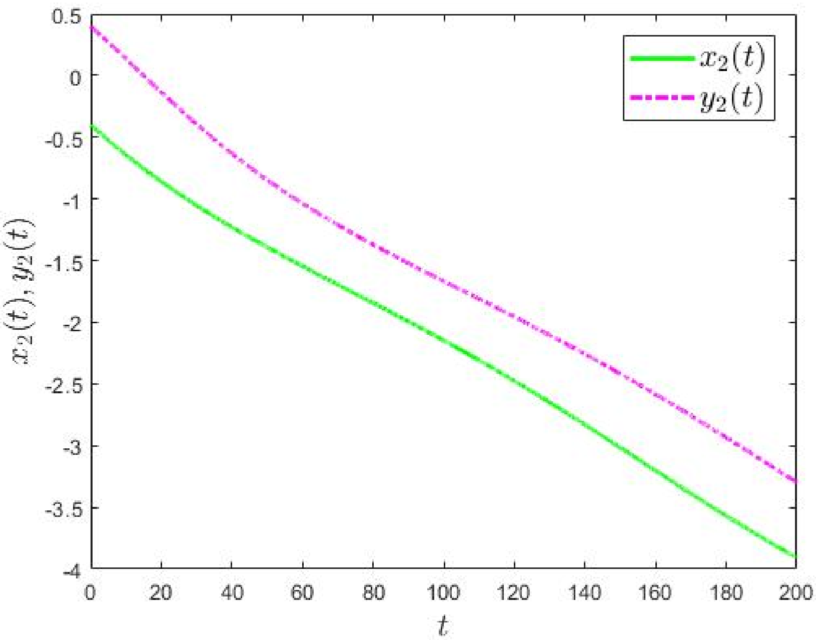

Figure 6. State trajectories $x_2(t)$ and $y_2(t)$ of the considered CGNNs without the controller in Example 1.

It is seen from (3.6) that the settling time $\hat{T}$ is affected by parameter ς, the preassigned accuracy ϵ, the norm $||\phi||_\rho$ of initial function, and the decay rate λ, which is explained by Tables 1–4. From which, it is concluded that the settling time $\hat{T}$ is positively dependent on the norm $||\phi||_\rho$ of initial function, and negatively dependent on parameter ς, the preassigned accuracy ϵ, or the decay rate λ.

Table 1. The relation between the settling time $\hat{T}$ and ς when $\epsilon = 0.04$, $||\phi||_\rho = 1.2$, $\lambda = 1.5$, and $||\phi||_\rho = 1.2$.

Parameter	Parameter value					
ς	0.001	0.002	0.003	0.004	0.005	0.006
$\hat{T}$	7.4316	6.9695	6.9692	6.5074	6.3587	6.2371

Table 2. The relation between the settling time $\hat{T}$ and ϵ when $\varsigma = 0.001$, $||\phi||_\rho = 1.2$, and $||\phi||_\rho = 1.2$.

Parameter	Parameter value					
ϵ	0.03	0.04	0.05	0.06	0.07	0.08
$\hat{T}$	7.5792	7.4316	7.2828	7.1613	7.0585	6.9695

Table 3. The relation between the settling time $\hat{T}$ and $||\phi||_\rho$ when $\varsigma = 0.001$, $\epsilon = 0.04$, and $\lambda = 1.5$.

Parameter	Parameter value					
$\|\|\phi\|\|_\rho$	1.2	12	120	1200	12000	12000
$\hat{T}$	7.4316	8.9666	10.5016	12.0367	13.5717	15.1068

Table 4. The relation between the settling time $\hat{T}$ and λ when $\varsigma = 0.001$, $\epsilon = 0.04$, and $||\phi||_\rho = 1.2$.

Parameter	Parameter value					
λ	1.0	1.1	1.2	1.3	1.4	1.5
$\hat{T}$	11.0848	10.0798	9.3218	8.5938	7.9707	7.4316

Example 2. *In memristive CGNNs* (3.12) *and* (3.13)*, we choose* $n = 2$*, and*

$$
\begin{aligned}
&\psi_1(\cdot) = 0.15 - 0.01\sin(\cdot),\ \psi_2(\cdot) = 0.03\cos^2(\cdot),\\
&\varphi_1(\cdot) = 0.2 + 0.1\sin(\cdot),\ \varphi_2(\cdot) = 0.2 + 0.1\cos(\cdot),\\
&\varpi_1 = 0.3,\ \varpi_2 = 0.2,\\
&[\check{a}_{ij}]_{2\times 2} = \begin{bmatrix} 2.2 & -0.12 \\ -1.9 & 2 \end{bmatrix},\ [\hat{a}_{ij}]_{2\times 2} = \begin{bmatrix} 2.0 & -0.15 \\ -2.1 & 1.8 \end{bmatrix},\\
&[\check{b}_{ij}]_{2\times 2} = \begin{bmatrix} -1.15 & 0.24 \\ 1.05 & -2.5 \end{bmatrix},\ [\hat{b}_{ij}]_{2\times 2} = \begin{bmatrix} -0.95 & 0.2 \\ 0.95 & -2.7 \end{bmatrix},\\
&p_j(\cdot) = q_j(\cdot) = 0.1\tanh(\cdot),\ \eta_j(t) = \tfrac{e^t}{1+10e^t},\ j = 1, 2,\ t \geq 0,\\
&\phi_1^x(s) \equiv 6,\ \phi_2^x(s) \equiv -4,\ \phi_1^y(s) \equiv -6,\ \phi_2^y(s) \equiv -4,\ s \in [-0.1, 0].
\end{aligned}
$$

It is clear that $\rho = \hat{\eta}_j = 0.1$, $\hat{\Psi}_1 = 0.16$, $\check{\Psi}_1 = 0.14$, $\hat{\Psi}_2 = 0.03$, $\check{\Psi}_2 = 0$, $\bar{a}_{11} = 2.2$, $\bar{a}_{12} = 0.15$, $\bar{a}_{21} = 2.1$, $\bar{a}_{22} = 2.0$, $\bar{b}_{11} = 1.15$, $\bar{b}_{12} = 0.24$, $\bar{b}_{21} = 1.05$, $\bar{b}_{22} = 2.7$, and $||\phi||_\rho = 12$. Set $\Phi_1 = 0.016$, $\Phi_2 = \Psi_1 = 0.003$, $\Psi_2 = 0.009$ and $P_i = \hat{P}_i = Q_i = \hat{Q}_i = 0.1$, $i \in \langle 2 \rangle$. Then, assumptions A_1 and A_2

are satisfied. For $\varsigma = 0.001$, $\lambda = 1.4$, and $\epsilon = 0.04$, using the software tool YALMIP, one can gain the following feasible solution to the inequalities in Corollary 2:

$$\tilde{l}_1 = 0.8581,\ \tilde{l}_2 = 0.6604,\ \tilde{h}_1 = 1.4189,\ \tilde{h}_2 = 1.3082,$$

hence, $K_1 = 1.6536$, $K_2 = 1.9809$, $L = 0.8581$, and $\hat{T} = 9.6983$. By Corollary 2, the controller (3.15) can guarantee that the considered memristive CGNNs achieve accuracy-preassigned finite-time exponential synchronization within the settling time $\hat{T}$.

Under the designed controller (3.15), the state trajectories of the considered memristive CGNNs are presented in Figures 7 and 8, and the corresponding errors and their norms are given in Figures 9 and 10. From these four figures, it can be observed that the errors with the controller exhibit a gradual convergence towards zero. In addition, without the controller, Figures 11 and 12 illustrate the state trajectories of the considered memristive CGNNs. Consequently, to resolve the synchronization issue, it is of paramount importance to design an appropriate controller to ensure that the states of the considered error system gradually reduce the origin.

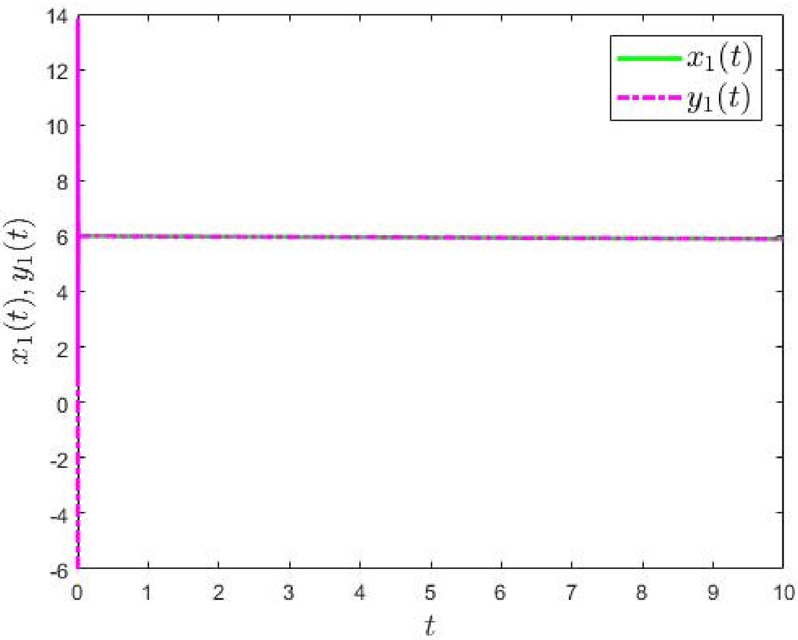

Figure 7. State trajectories $x_1(t)$ and $y_1(t)$ of the considered CGNNs with the controller in Example 2.

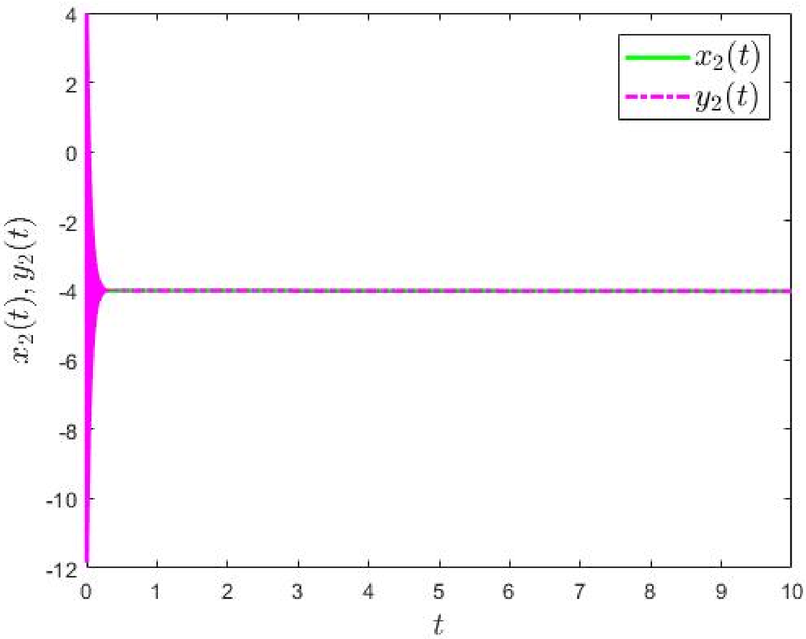

Figure 8. State trajectories $x_2(t)$ and $y_2(t)$ of the considered CGNNs with the controller in Example 2.

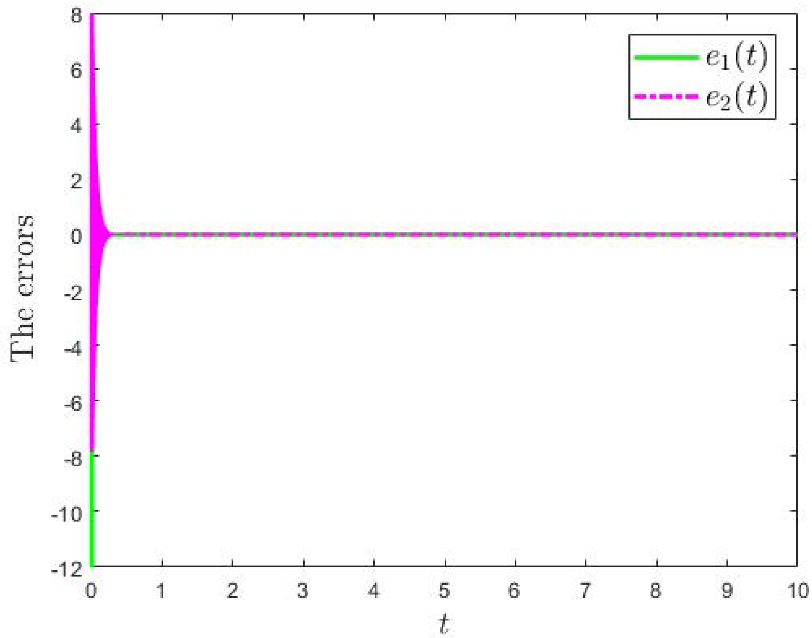

Figure 9. The error curves with the controller in Example 2.

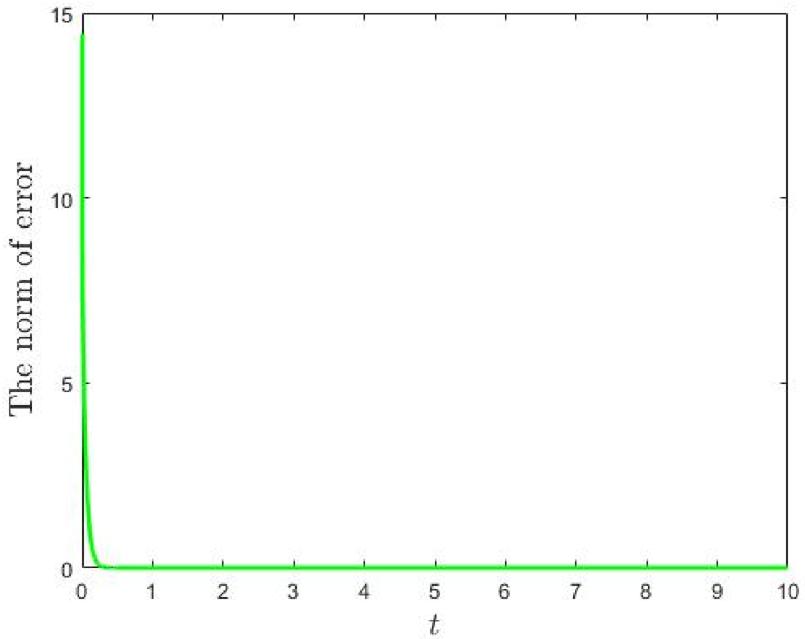

Figure 10. The norm curves with the errors in Example 2.

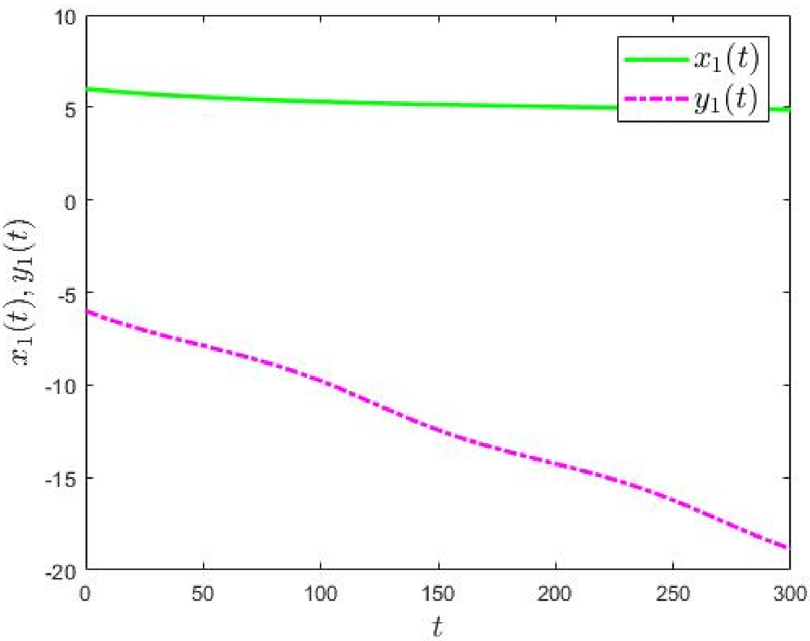

Figure 11. State trajectories $x_1(t)$ and $y_1(t)$ of the considered CGNNs without the controller in Example 2.

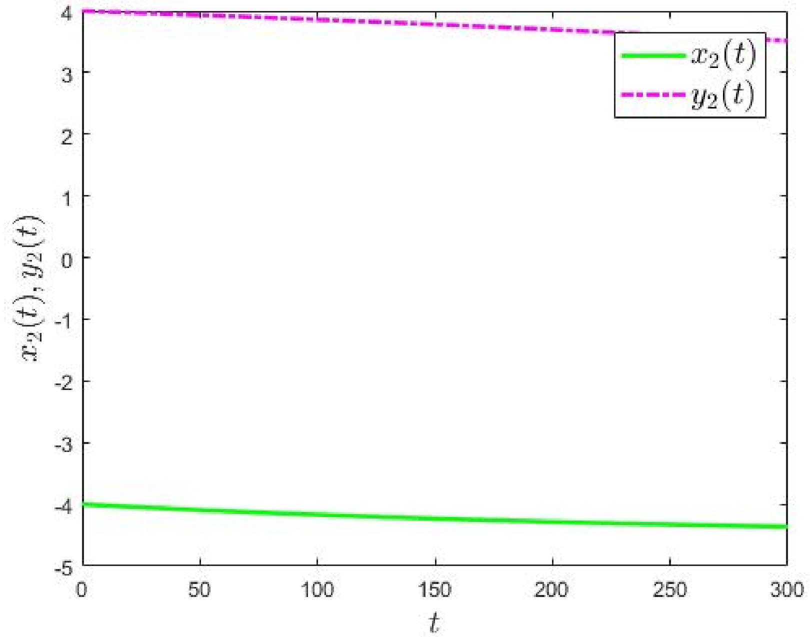

Figure 12. State trajectories $x_2(t)$ and $y_2(t)$ of the considered CGNNs without the controller in Example 2.

5. Conclusions

For a class of neutral-type memristive CGNNs with time-varying multiple leakage and transmission delays, we examine the problem of accuracy-preassigned finite-time exponential synchronization control. By proposing an upper-right derivative-based direct method, a novel controller that is related to neutral delays is presented to achieve accuracy-preassigned finite-time exponential synchronization of the drive and response neutral-type memristive CGNNs. The investigated synchronization conditions are composed of several scalar inequalities that can be checked via the standard software tools. Finally, two numerical examples present the effectiveness of the designed controller. This study fills the gap by presenting sufficient conditions guaranteeing the accuracy-preassigned finite-time exponential synchronization of neutral-type memristive CGNNs with multiple time-varying leakage delays and transmission delays.

Author contributions

Er-Yong Cong: Writing-review & editing, writing-original draft, validation, investigation, conceptualization; Yantao Wang: Writing-review & editing, resources, methodology, conceptualization; Xian Zhang: Writing-review & editing, resources, methodology, conceptualization; Li Zhu: Writing-review & editing, visualization, software, investigation, funding acquisition. All authors have read and approved the final version of the manuscript for publication.

Use of Generative-AI tools declaration

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

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Conflict of interest

All authors declare no conflicts of interest in this paper.

References

1. B. Hu, Z.-H. Guan, G. Chen, F. L. Lewis, Multistability of delayed hybrid impulsive neural networks with application to associative memories, *IEEE T. Neur. Net. Lear.*, **30** (2019), 1537–1551. http://doi.org/10.1109/TNNLS.2018.2870553
2. S. S. Song, J. Liu, J. N. Guo, J. Wang, Y. X. Xie, J.-H. Cui, Neural-network-based AUV navigation for fast-changing environments, *IEEE Internet Things*, **7** (2020), 9773–9783. http://doi.org/10.1109/JIOT.2020.2988313
3. Z. Y. Dong, X. Wang, X. Zhang, M. J. Hu, T. N. Dinh,Global exponential synchronization of discrete-time high-order switched neural networks and its application to multi-channel audio encryption, *Nonlinear Anal.-Hybri.*, **47** (2023), 101291. http://doi.org/10.1016/j.nahs.2022.101291
4. Y. D. Wang, J. W. Xia, Z. Wang, H. Shen, Design of a fault-tolerant output-feedback controller for thickness control in cold rolling mills, *Appl. Math. Comput.*, **369** (2020), 124841. http://doi.org/10.1016/j.amc.2019.124841
5. C. J. Li, X. H. Yu, T. W. Huang, G. Chen, X. He, A generalized Hopfield network for nonsmooth constrained convex optimization: Lie derivative approach, *IEEE T. Neur. Net. Lear.*, **27** (2016) 308–321. http://doi.org/10.1109/TNNLS.2015.2496658
6. C. X. Huang, B. W. Liu, H. D. Yang, J. D. Cao, Positive almost periodicity on SICNNs incorporating mixed delays and D-operator, *Nonlinear Anal.-Model.*, **27** (2022), 719–739. http://doi.org/10.15388/namc.2022.27.27417
7. X. Wang, G. H. Yang, Fault-tolerant consensus tracking control for linear multiagent systems under switching directed network, *IEEE T. Cybernetics*, **50** (2020), 1921–1930. http://doi.org/10.1109/TCYB.2019.2901542
8. E. Cuevas, M.-A. Diaz-Cortes, E. Mezura-Montes, Corner detection of intensity images with cellular neural networks (CNN) and evolutionary techniques, *Neurocomputing*, **347** (2019), 82–93. http://doi.org/10.1016/j.neucom.2019.03.014

9. H. J. Li, Y. L. Zhu, L. Jing, Y. Wang, Consensus of second-order delayed nonlinear multi-agent systems via node-based distributed adaptive completely intermittent protocols, *Appl. Math. Comput.*, **326** (2018), 1–15. http://doi.org/10.1016/j.amc.2018.01.005

10. X. Zhang, X. H. Meng, Y. T. Wang, C. Y. Liu, Bounded real lemmas for inertial neural networks with unbounded mixed delays and state-dependent switching, *Commun. Nonlinear Sci.*, **119** (2023), 107075. http://doi.org/10.1016/j.cnsns.2022.107075

11. X. Zhang, Z. J. Zhang, Y. T. Wang, X. Wang, New global exponential stability conditions for nonlinear delayed differential systems with three kinds of time-varying delays, *Nonlinearity*, **37** (2024), 095014. http://doi.org/10.1088/1361-6544/ad6126

12. A. Pratap, R. Raja, J. D. Cao, G. Rajchakit, F. E. Alsaadi, Further synchronization in finite time analysis for time-varying delayed fractional order memristive competitive neural networks with leakage delay, *Neurocomputing*, **317** (2018), 110–126. http://doi.org/10.1016/j.neucom.2018.08.016

13. B. W. Liu, Finite-time stability of CNNs with neutral proportional delays and time-varying leakage delays, *Math. Method. Appl. Sci.*, **40** (2017), 167–174. http://doi.org/10.1002/mma.3976

14. V. Gokulakrishnan, R. Srinivasan, M. S. Ali, G. Rajchakit, G. Thak ur, Novel LMI-based adaptive boundary synchronisation of fractional-order fuzzy reaction–diffusion BAM neural networks with leakage delay, *Int. J. Syst. Sci.*, **54** (2023), 2975–2998. http://doi.org/10.1080/00207721.2023.2250491

15. R. X. Li, J. D. Cao, M. Abdel-Aty, Exponential input-to-state stability of quaternion-valued memristive neural networks: Continuous and discrete cases, *Int. J. Adapt. Control*, **39** (2024), 372–382. http://doi.org/10.1002/acs.3943

16. P. Wang, Z. Wang, X. Huang, H. Shen, Dynamic event-triggered control for delayed switched neural networks: A merging signal scheme, *Int. J. Robust Nonlin.*, **33** (2023), 11374–11391. http://doi.org/10.1002/rnc.6950

17. Z. Y. Dong, X. Wang, X. Zhang,A nonsingular M-matrix-based global exponential stability analysis of higher-order delayed discrete-time Cohen–Grossberg neural networks , *Appl. Math. Comput.*, **385** (2020), 125401. http://doi.org/10.1016/j.amc.2020.125401

18. H.-B. Zeng, Y.-J. Chen, Y. He, X.-M. Zhang, A delay-derivative-dependent switched system model method for stability analysis of linear systems with time-varying delay, *Automatica*, **175** (2025), 112183. http://doi.org/10.1016/j.automatica.2025.112183

19. Y. Xue, K. R. Tu, C. Y. Liu, X. Zhang, Non-fragile extended dissipative synchronization control for uncertain discrete-time neural networks with leakage and unbounded time-varying delays , *Chaos Soliton. Fract.*, **185** (2024), 115072. http://doi.org/10.1016/j.chaos.2024.115072

20. K. R. Tu, Y. Xue, X. Zhang, Observer-based resilient dissipativity control for discrete-time memristor-based neural networks with unbounded or bounded time-varying delays, *Neural Networks*, **175** (2024), 106279. http://doi.org/10.1016/j.neunet.2024.106279

21. K. R. Tu, Y. Xue, X. Zhang, A new approach based on system solutions for passivity analysis of discrete-time memristor-based neural networks with time-varying delays, *Appl. Math. Comput.*, **469** (2024), 128551. http://doi.org/10.1016/j.amc.2024.128551

22. L. Luo, J. G. Jian, S. Zheng, Non-fragile state estimation for second-order memristive neural networks with unbounded time-varying delays, *Int. J. Adapt. Control*, **36** (2022), 88–103. http://doi.org/10.1002/acs.3343

23. P. Anbalagan, R. Ramachandran, J. Alzabut, E. Hincal, M. Niezabitowski, Improved results on finite-time passivity and synchronization problem for fractional-order memristor-based competitive neural networks: Interval matrix approach, *Fractal Fract.*, **6** (2022), 36. http://doi.org/10.3390/fractalfract6010036

24. S. L. Yuan, Y. T. Wang, X. Zhang, Global exponential synchronization of switching neural networks with leakage time-varying delays, *Commun. Nonlinear Sci.*, **133** (2024), 107979. http://doi.org/10.1016/j.cnsns.2024.107979

25. W. T. Hua, Y. T. Wang, C. Y. Liu, New method for global exponential synchronization of multi-link memristive neural networks with three kinds of time-varying delays, *Appl. Math. Comput.*, **471** (2024), 128593. http://doi.org/10.1016/j.amc.2024.128593

26. M. A. Cohen, S. Grossberg, Absolute stability of global pattern formation and parallel memory storage by competitive neural networks, *IEEE T. Syst. Man Cy.*, **13** (1983), 815–826. http://doi.org/10.1109/TSMC.1983.6313075

27. C. Wang, H. Zhang, D. L. Wen, M. Q. Shen, L. W. Li, Z. H. Zhang, Novel passivity and dissipativity criteria for discrete-time fractional generalized delayed Cohen–Grossberg neural networks, *Commun. Nonlinear Sci.*, **133** (2024), 107960. http://doi.org/10.1016/j.cnsns.2024.107960

28. Q. Li, L. Q. Zhou, Global asymptotic synchronization of inertial memristive Cohen–Grossberg neural networks with proportional delays, *Commun. Nonlinear Sci.*, **123** (2023), 107295. http://doi.org/10.1016/j.cnsns.2023.107295

29. X. Wang, J. D. Cao, B. Yang, F. B. Chen, Fast fixed-time synchronization control analysis for a class of coupled delayed Cohen-Grossberg neural networks, *J. Franklin I.*, **359** (2022), 1612–1639. http://doi.org/10.1016/j.jfranklin.2022.01.026

30. H. B. Jia, D. M. Luo, J. Wang, H. Shen, Fixed-time synchronization for inertial Cohen–Grossberg delayed neural networks: An event-triggered approach, *Knowl.-Based Syst.*, **250** (2022), 109104. http://doi.org/10.1016/j.knosys.2022.109104

31. D. B. Strukov, G. S. Snider, D. R. Stewart, R. S. Williams, Erratum: The missing memristor found, *Nature*, **453** (2009), 1154. http://doi.org/10.1038/nature08166

32. L. Chua, Memristor–the missing circuit element, *IEEE Transactions on Circuit Theory*, **18** (1971), 507–519. http://doi.org/10.1109/TCT.1971.1083337

33. H.-B. Zeng, Z.-L. Zhai, H. C. Yan, W. Wang, A new looped functional to synchronize neural networks with sampled-data control, *IEEE T. Neur. Net. Lear.*, **33** (2022), 406–415. http://doi.org/10.1109/TNNLS.2020.3027862

34. S. L. Yuan, Y. T. Wang, X. N. Yang, X. Zhang, Accuracy-preassigned fixed-time synchronization of switching inertial neural networks with time-varying leakage and mixed delays, *Neurocomputing*, **617** (2025), 128958. http://doi.org/10.1016/j.neucom.2024.128958

35. J. B. Lan, X. Wang, X. Zhang, Global robust exponential synchronization of interval BAM neural networks with multiple time-varying delays, *Circuits Syst. Signal Process.*, **43** (2024), 2417–2170. http://doi.org/10.1007/s00034-023-02584-z
36. J. Liu, L. Shu, Q. Chen, S. M. Zhong, Fixed-time synchronization criteria of fuzzy inertial neural networks via Lyapunov functions with indefinite derivatives and its application to image encryption, *Fuzzy Set. Syst.*, **459** (2023), 22–42. http://doi.org/10.1016/j.fss.2022.08.002
37. F. Wei, G. C. Chen, Z. G. Zeng, N. Gunasekaran, Finite/fixed-time synchronization of inertial memristive neural networks by interval matrix method for secure communication, *Neural Networks*, **167** (2023), 168–182. http://doi.org/10.1016/j.neunet.2023.08.015
38. P. Kowsalya, S. S. Mohanrasu, A. Kashkynbayev, P. Gokul, R. Rakkiyapp an, Fixed-time synchronization of inertial Cohen–Grossberg neural networks with state dependent delayed impulse control and its application to multi-image encryption, *Chaos Soliton. Fract.*, **181** (2024), 114693. http://dx.doi.org/10.1016/j.chaos.2024.114693
39. Y. C. Shi, J. D. Cao, Finite-time synchronization of memristive Cohen–Grossberg neural networks with time delays, *Neurocomputing*, **377** (2020), 159–167. http://doi.org/10.1016/j.neucom.2019.10.036
40. F. M. Ren, M. H. Jiang, H. Xu, M. Q. Li, Quasi fixed-time synchronization of memristive Cohen–Grossberg neural networks with reaction-diffusion, *Neurocomputing*, **415** (2020), 74–83. http://doi.org/10.1016/j.neucom.2020.07.071
41. Y. Z. Cheng, Y. C. Shi, J. Guo, Exponential synchronization of quaternion-valued memristor-based Cohen–Grossberg neural networks with time-varying delays: norm method, *Cogn. Neurodyn.*, **18** (2024), 1943–1953. http://doi.org/10.1007/s11571-023-10057-x
42. L. B. Peng, D. J. Bi, X. F. Li, H. Li, Y. Tang, Y. L. Xie, Multi-synchronization of coupled multi-stable memristive Cohen–Grossberg neural networks with mixed time-delays, *Expert Syst. Appl.*, **255** (2024), 124501. http://doi.org/10.1016/j.eswa.2024.124501
43. F. F. Du, J.-G. Lu, Novel methods of finite-time synchronization of fractional-order delayed memristor-based Cohen–Grossberg neural networks, *Nonlinear Dyn.*, **111** (2023), 18985–19001. http://doi.org/10.1007/s11071-023-08880-2
44. X. Y. Cui, M. W. Zheng, Y. P. Zhang, M. M. Yuan, H. Zhao, Y. M. Zhang, Predefined-time synchronization of time-varying delay fractional-order Cohen–Grossberg neural network based on memristor, *Commun. Nonlinear Sci.*, **139** (2024), 108294. http://doi.org/10.1016/j.cnsns.2024.108294
45. X. Wang, J. H. Park, H. Liu, X. Zhang, Cooperative output-feedback secure control of distributed linear cyber-physical systems resist intermittent DoS attacks, *IEEE T. Cybernetics*, **51** (2021), 4924–4933. http://doi.org/10.1109/TCYB.2020.3034374
46. A. Columbu, R. D. Fuentes, S. Frassu, Uniform-in-time boundedness in a class of local and nonlocal nonlinear attraction-repulsion chemotaxis models with logistics, *Nonlinear Anal.-Real*, **79** (2024), 104135. http://doi.org/10.1016/j.nonrwa.2024.104135
47. T. X. Li, D. Acosta-Soba, A. Columbu, G. Viglialoro, Dissipative gradient nonlinearities prevent δ-formations in local and nonlocal attraction-repulsion chemotaxis models, *Stud. Appl. Math.*, **154** (2025), e70018. http://doi.org/10.1111/sapm.70018

48. J. C. Huang, X. M. Wu, Z. W. Tu, Exponential synchronization of Cohen-Grossberg neural networks with delays, *IEEE Access*, **11** (2023), 49992–49999. http://doi.org/10.1109/ACCESS.2023.3277986

49. K. Gopalsamy, Leakage delays in BAM, *J. Math. Anal. Appl.*, **325** (2007), 1117–1132. http://doi.org/10.1016/j.jmaa.2006.02.039