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Quasi-Mittag-Leffler synchronization of delayed fractional-order Cohen-Grossberg inertial neural networks with uncertain parameters

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ABSTRACT

In this work, the quasi-Mittag-Leffler (QML) synchronization problem of fractional-order Cohen–Grossberg inertial neural networks (FOCGINNs) in the presence of uncertain parameters and time-varying delays is investigated. Initially, two control strategies, namely, a state-feedback controller and an adaptive controller, are developed to achieve QML synchronization. By employing these control strategies, sufficient synchronization conditions are established using Lyapunov stability theory in connection with the fractional-order Halanay inequality and the Razumikhin approach. Moreover, explicit synchronization error bounds are derived using the Mittag–Leffler function. Finally, numerical simulations validate the theoretical results, demonstrating the effectiveness of both controllers and confirming the robustness of the proposed synchronization framework.

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1. Introduction

A neural network (NN) is an artificial intelligence model inspired by the human brain. It can solve many types of technological problems and promote technological breakthroughs. In recent decades, NNs have gained significant attention in the field of dynamical system research due to their diverse applications, including associative memory,[1] pattern recognition,[2] and image processing.[3] Since time delays are inherent in practical systems and can significantly impair system performance, they may also induce complex dynamical behaviors, including oscillations[4] and bifurcations,[5,6] thereby motivating further investigation of delayed NN systems. As a result, delayed NNs have been extensively studied, and numerous findings have been documented in the existing literature.[7–10] Most existing studies on NN dynamics and synchronization have been limited to integer-order NNs. In contrast, the superior modeling capabilities of fractional calculus, characterised by its infinite memory and hereditary properties, are driving the development of fractional-order neural networks (FONNs). Recent research has highlighted the application of fractional calculus in NNs for stability, synchronization, optimization, and parameter training,[11] demonstrating its growing importance in the modeling and analysis of complex neural dynamics. The Cohen–Grossberg neural network (CGNN) model was originally introduced in 1983.[12] This general framework encompasses several well-known NN models, including bidirectional associative memory (BAM), Hopfield, and cellular NNs. The dynamical behavior of this model has attracted considerable attention in the literature.[13–15] In particular, numerous studies have investigated its stability,[16,17] stabilization,[18,19] and synchronization properties.[20,21]

Synchronization is a dynamical phenomenon in which systems with distinct initial conditions

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gradually achieve a desired relationship through mutual interactions or external control inputs. Extensive research has been devoted to synchronization in NNs,[20–22] motivated by its potential applications in areas such as cryptography, image processing, and secure information transmission. Recently, synchronization of fractional-order (FO) systems has attracted research interest and has progressed into an active research area, with various synchronization types such as finite-time,[23] projective,[24] quasi,[25] and complete synchronization. The synchronization analysis of delayed fractional-order Cohen–Grossberg neural networks (FOCGNNs) remains to be explored, which is one of the reasons behind this study. Notably, synchronization of delayed FOCGNNs has received considerable research attention and remains an active research topic.[26–28] Moreover, parameter uncertainties may arise in practical systems due to modeling inaccuracies and external perturbations, potentially affecting their dynamical behavior. Therefore, analyzing synchronization of NNs subject to time-varying delay (TVD) and parameter uncertainties is essential for ensuring reliable synchronization performance.

Compared with linear controllers,[29] nonlinear controllers,[30] and impulsive controllers,[31] adaptive controllers can reduce control costs while ensuring stable performance. Therefore, to achieve synchronization in NNs under uncertainties, the design of effective adaptive control schemes is important. Most research focuses on NNs defined solely by the first-order derivatives of state variables, neglecting the impact of inertial effects on system dynamics. To address this limitation, we focus on NNs that incorporate inertial effects. The concept of inertial NNs was introduced by Babcock and Westervelt in 1986 with the integration of inductors into traditional neural circuit models.[32] They demonstrated that the presence of inertial terms can result in complex and unusual dynamical phenomena, such as chaos, oscillatory behaviour, and instability. It should be noted that the incorporation of inertial effects into neural systems has specific biological backgrounds. The incorporation of inertial terms into CGNNs has significantly enriched their dynamical behaviors, and as a result, this topic has attracted considerable research interest, with several studies reported in the literature.[33–35] **Table 1** presents a comparison between the current study and previous research.

Inspired by the previous discussions, the QML synchronization of delayed FOCGNNs with parameter uncertainties and inertial terms will be investigated, and the major contributions are as follows:

- A fractional-order Cohen-Grossberg inertial neural network (FOCGINN) system of Caputo type with uncertain parameters and TVDs is considered. Through an appropriate variable transformation, the FOCGINNs are equivalently converted into the standard FOCGNN framework.
- To achieve QML synchronization between the FOCGINNs, state-feedback and adaptive control mechanisms are employed. The state-feedback controller stabilizes the synchronization error system, while the adaptive controller dynamically adjusts the control gains to accommodate parameter uncertainties.
- By utilizing the FO Halanay inequality and the Razumikhin technique, sufficient synchronization criteria are established by the Lyapunov stability theory, and the synchronization error bounds are explicitly estimated.

The remainder of this paper is organized as follows: Section 2 covers the basic definitions and lemmas. The model formulations are presented in Section 3. Section 4 discusses the main results in two subsections, one with a state-feedback controller and another with an adaptive controller. Numerical results and concluding remarks are provided in Sections 5 and 6, respectively.

Table 1. Comparison of recent literature with the proposed work

Study	**Fractional-order**	**Cohen-grossberg**	**Delay**	**Inertial term**	**QML**	**Uncertain parameters**
[27]	✓	✓	✓	-	-	-
[34]	✓	✓	-	✓	-	-
[36]	✓	-	✓	-	-	-
[37]	✓	✓	✓	-	-	-
[38]	✓	✓	✓	✓	-	-
[39]	✓	-	-	-	✓	-
This study	✓	✓	✓	✓	✓	✓

2. Preliminaries

Definition 1. [40] *Consider the function* $\mathfrak{C}(t) \in \mathbb{C}([a,b] \to \mathbb{R})$*, and let its Caputo fractional derivative of order* ϕ *be described as*

$$ {}^{C}{}_{0}\mathcal{D}_{t}^{\phi}\mathfrak{C}(t) = \frac{1}{\Gamma(1-\phi)} \int_{0}^{t} \frac{\mathfrak{C}^{'}(q)}{(t-q)^{\phi}} dq. $$

For ease of notation, the Caputo fractional derivative operator ${}^{C}{}_{0}\mathcal{D}_{t}^{\phi}$ *is hereafter denoted by* ${}_{0}\mathcal{D}_{t}^{\phi}$.

Definition 2. [40] *The one-parameter Mittag-Leffler (ML) function is*

$$ \mathcal{E}_{\theta}(v) = \sum_{k=0}^{\infty} \frac{v^{k}}{\Gamma(\theta k+1)}, \quad \mu > 0, $$

and the of two-parameter ML function is

$$ \mathcal{E}_{\theta,\hat{\theta}}(v) = \sum_{k=0}^{\infty} \frac{v^{k}}{\Gamma(\theta k+\hat{\theta})}, \quad \theta > 0, \hat{\theta} > 0. $$

Lemma 1. [41] *Let* $\mathfrak{C}(t) \in \mathbb{C}([t_0,+\infty] \to \mathbb{R})$ *and* $\phi \in (0,1)$*. Then*

$$ {}_{0}\mathcal{D}_{t}^{\phi}\mathfrak{C}^{2}(t) \leq 2\mathfrak{C}(t){}_{0}\mathcal{D}_{t}^{\phi}\mathfrak{C}(t). $$

Lemma 2. [42] *Consider the function* $\mathfrak{C}(t) \in \mathbb{C}([t_0,+\infty] \to \mathbb{R})$ *and* $\forall \mathfrak{K}^{*} \in \mathbb{R}$*. Then the following inequality holds:*

$$ {}_{0}\mathcal{D}_{t}^{\phi}[\mathfrak{C}(t)-\mathfrak{K}^{*}]^{2} \leq 2[\mathfrak{C}(t)-\mathfrak{K}^{*}]{}_{0}\mathcal{D}_{t}^{\phi}\mathfrak{C}(t). $$

3. Model formulation

The uncertain delayed FOCGINN is defined as

$$ \begin{aligned} {}_{0}\mathcal{D}_{t}^{2\phi}\alpha_i(t) &= -S_i\,{}_{0}\mathcal{D}_{t}^{\phi}\alpha_i(t) - \mathfrak{A}_i(\alpha_i(t)) \\ &\Big[\mathfrak{g}_i(\alpha_i(t)) - \sum_{j=1}^{n}(\mathfrak{P}_{ij}+\Delta\mathfrak{P}_{ij})\mathfrak{f}_{1j}(\alpha_j(t)) \\ &- \sum_{j=1}^{n}(\mathfrak{Q}_{ij}+\Delta\mathfrak{Q}_{ij})\mathfrak{f}_{2j}(\alpha_j(t-\eta(t)) \\ &- \mathfrak{I}_i(t)\Big], \end{aligned} \tag{1} $$

where $i = 1,2,\ldots,n$, $\alpha_i(t)$ refers to the i^{th} neuron state at time t, $\mathfrak{A}_i(\cdot)$ represents the amplification function, and $\mathfrak{g}_i(\cdot)$ refers to the behavior function. $\mathfrak{P}_{ij}$ and $\mathfrak{Q}_{ij}$ represent the connection weights between the states i and j. $f(\cdot)$ denotes the activation function. $\eta(t)$ and $\mathfrak{I}_i(t)$ represent the TVD and external input, respectively. $\Delta\mathfrak{P}_{ij}$ and $\Delta\mathfrak{Q}_{ij}$ denote the parameter uncertainties, which are bounded and described by

$$ |\Delta\mathfrak{P}_{ij}| \leq \Lambda_{ij} \quad and \quad |\Delta\mathfrak{Q}_{ij}| \leq \Gamma_{ij} $$

where $\Lambda_{ij} > 0$ and $\Gamma_{ij} > 0$.

Consider FOCGINNs (1) as a drive system, and let its associated response system be defined as

$$ \begin{aligned} {}_{0}\mathcal{D}_{t}^{2\phi}\beta_i(t) &= -S_i\,{}_{0}\mathcal{D}_{t}^{\phi}\beta_i(t) \\ &- \mathfrak{A}_i(\beta_i(t))[\mathfrak{g}_i(\beta_i(t)) \\ &- \sum_{j=1}^{n}(\mathfrak{P}_{ij}+\Delta\mathfrak{P}_{ij})\mathfrak{f}_{1j}(\beta_j(t)) \\ &- \sum_{j=1}^{n}(\mathfrak{Q}_{ij}+\Delta\mathfrak{Q}_{ij})\mathfrak{f}_{2j}(\beta_j(t-\eta(t)) \\ &- \mathfrak{I}_i(t)+\mathfrak{U}_i(t)], \end{aligned} \tag{2} $$

where $\mathfrak{U}_i(t)$ denotes the controller and is designed later.

For systems (1) and (2), we use the following variable transformation:

$$ \begin{aligned} \mathfrak{R}_{\alpha i}(t) &= {}_{0}\mathcal{D}_{t}^{\phi}\alpha_i(t) + \alpha_i(t), \\ \mathfrak{R}_{\beta i}(t) &= {}_{0}\mathcal{D}_{t}^{\phi}\beta_i(t) + \beta_i(t). \end{aligned} $$

Then systems (1) and (2) are equivalent to

$$ \begin{cases} {}_{0}\mathcal{D}_{t}^{\phi}\alpha_i(t) = -\alpha_i(t) + \mathfrak{R}_{\alpha i}(t), \\ {}_{0}\mathcal{D}_{t}^{\phi}\mathfrak{R}_{\alpha i}(t) = -(\mathfrak{S}_i-1)\mathfrak{R}_{\alpha i}(t) \\ -(1-\mathfrak{S}_i)\alpha_i(t) \\ -\mathfrak{A}_i(\alpha_i(t))\Big[\mathfrak{g}_i(\alpha_i(t)) \\ -\sum_{j=1}^{n}(\mathfrak{P}_{ij}+\Delta\mathfrak{P}_{ij})\mathfrak{f}_{1j}(\alpha_j(t)) \\ -\sum_{j=1}^{n}(\mathfrak{Q}_{ij}+\Delta\mathfrak{Q}_{ij})\times \\ \mathfrak{f}_{2j}(\alpha_j(t-\eta(t))) - \mathfrak{I}_i(t)\Big] \end{cases} \tag{3} $$

and

$$ \begin{cases} {}_{0}\mathcal{D}_{t}^{\phi}\beta_i(t) = -\beta_i(t) + \mathfrak{R}_{\beta i}(t), \\ {}_{0}\mathcal{D}_{t}^{\phi}\mathfrak{R}_{\beta i}(t) = -(\mathfrak{S}_i-1)\mathfrak{R}_{\beta i}(t) \\ -(1-\mathfrak{S}_i)\beta_i(t) \\ -\mathfrak{A}_i(\beta_i(t))\Big[\mathfrak{g}_i(\beta_i(t)) \\ -\sum_{j=1}^{n}(\mathfrak{P}_{ij}+\Delta\mathfrak{P}_{ij})\mathfrak{f}_{1j}(\beta_j(t)) \\ -\sum_{j=1}^{n}(\mathfrak{Q}_{ij}+\Delta\mathfrak{Q}_{ij})\times \\ \mathfrak{f}_{2j}(\beta_j(t-\eta(t))) - \mathfrak{I}_i(t)+\mathfrak{U}_i(t)\Big]. \end{cases} \tag{4} $$

Consider the error states $\mathfrak{E}_i(t) = \beta_i(t) - \alpha_i(t)$ and $\mathfrak{E}_{\mathfrak{R}i}(t) = \mathfrak{R}_{\beta i}(t) - \mathfrak{R}_{\alpha i}(t)$. From systems (3) and (4), the error system is obtained as follows:

$$ \begin{cases} {}_{0}\mathcal{D}_{t}^{\phi}\mathfrak{E}_i(t) \\ = -\mathfrak{E}_i(t) + \mathfrak{E}_{\mathfrak{R}i}(t) \\ {}_{0}\mathcal{D}_{t}^{\phi}\mathfrak{E}_{\mathfrak{R}i}(t) \\ = -(\mathfrak{S}_i-1)\mathfrak{E}_{\mathfrak{R}i}(t) - (1-\mathfrak{S}_i)\mathfrak{E}_i(t) \\ -\mathfrak{A}_i(\beta_i(t))\mathfrak{g}_i(\beta_i(t)) + \mathfrak{A}_i(\alpha_i(t))\mathfrak{g}_i(\alpha_i(t)) \\ +\mathfrak{A}_i(\beta_i(t))\sum_{j=1}^{n}(\mathfrak{P}_{ij}+\Delta\mathfrak{P}_{ij})\mathfrak{f}_{1j}(\beta_j(t)) \\ -\mathfrak{A}_i(\alpha_i(t))\sum_{j=1}^{n}(\mathfrak{P}_{ij}+\Delta\mathfrak{P}_{ij})\mathfrak{f}_{1j}(\alpha_j(t)) \\ +\mathfrak{A}_i(\beta_i(t))\sum_{j=1}^{n}(\mathfrak{Q}_{ij}+\Delta\mathfrak{Q}_{ij}) \\ \mathfrak{f}_{2j}(\beta_j(t-\eta(t))) \end{cases} \tag{5} $$

$$\begin{cases} -\mathfrak{A}_i(\alpha_i(t))\sum_{j=1}^{n}(\mathfrak{Q}_{ij}+\Delta\mathfrak{Q}_{ij}) \\ \mathfrak{f}_{2j}(\alpha_j(t-\eta(t)) \\ +\mathfrak{A}_i(\beta_i(t))\mathfrak{I}_i(t)-\mathfrak{A}_i(\beta_i(t))\mathfrak{I}_i(t)+\mathfrak{U}_i(t). \end{cases}$$

For the subsequent analysis, we use the following hypotheses.

H1: For every $\wr, \hat{\wr} \in \mathbb{R}$, there exist $\mathfrak{X}_j > 0$ and $\mathfrak{Y}_j > 0$ such that

$$|f_{1j}(\wr) - f_{1j}(\hat{\wr})| \leq \mathfrak{X}_j|\wr - \hat{\wr}|,$$
$$|f_{2j}(\wr) - f_{2j}(\hat{\wr})| \leq \mathfrak{Y}_j|\wr - \hat{\wr}|.$$

H2: For every $\mathfrak{d} \in \mathbb{R}$, there exist constants $l_j^x > 0, l_j^\tau > 0$ and $\tilde{l}_j > 0$ satisfying the following:

$$|f_{1j}(\mathfrak{d})| \leq l_j^x, \quad |f_{2j}(\mathfrak{d})| \leq l_j^\tau, \quad |\mathfrak{I}_i(\mathfrak{d})| \leq \tilde{l}_i.$$

H3: Consider the function $\xi_i(\alpha_i) = \mathfrak{A}_i(\alpha_i)\mathfrak{g}_i(\alpha_i)$, which has a bounded derivative with respect to α_i and satisfies the following inequality:

$$0 \leq \underline{\xi}_i \leq \xi_i'(\alpha_i) \leq \bar{\xi}_i, \quad i = 1, 2, \ldots, n,$$

where $\underline{\xi}_i > 0$ and $\bar{\xi}_i > 0$.

H4: Consider the function $\mathfrak{A}_i(\alpha_i(t))$ $(i = 1, 2, \ldots, n)$, which is bounded and has a bounded derivative and satisfies the following inequality:

$$0 \leq \underline{\mathfrak{A}}_i \leq \mathfrak{A}_i(\alpha_i(t)) \leq \bar{\mathfrak{A}}_i, \quad |\mathfrak{A}_i'(\cdot)| \leq \lambda_i,$$

where $\underline{\mathfrak{A}}_i > 0, \bar{\mathfrak{A}}_i > 0$ and $\lambda_i > 0$.

Remark 1. *The practical significance of the above hypotheses is explained as follows. H1 assumes Lipschitz continuity of the activation functions $f_{1j}(\cdot)$ and $f_{2j}(\cdot)$, which ensures that bounded variations in neuronal states produce proportionally bounded variations in the corresponding activation outputs. Such regularity is commonly adopted in NN stability and synchronization analysis. H2 imposes boundedness on the activation and interaction functions, ensuring that the nonlinear responses and inter-neuronal interactions remain within finite ranges, which is consistent with bounded operating ranges commonly considered in NN models. H3 requires the combined function $\xi_i(\alpha_i) = \mathfrak{A}_i(\alpha_i)\mathfrak{g}_i(\alpha_i)$ to be bounded and non-decreasing, which provides a controlled nonlinear response and facilitates the estimation of the Cohen–Grossberg terms in the synchronization analysis. H4 assumes that the amplification function $\mathfrak{A}_i(\alpha_i(t))$ is positive and bounded with a bounded derivative, ensuring that the amplification mechanism remains finite and varies at a controlled rate. These properties are practically meaningful for describing regular and bounded neuronal dynamics and are essential for establishing the stability and synchronization conditions of the considered system.*

Definition 3. [36] *System (1) is said to attain QML synchronization with system (2), with an error bound $\mathfrak{e}$ and the rate of convergence θ, if for all initial states satisfiying $\mathfrak{E}(s)$ $(s \in [\eta_{\max}, 0])$, there exist constants $\mathfrak{M} > 0, c > 0$, and $t_\eta > 0$ such that for $\forall t > t_\eta$, the error state satisfies*

$$\|\mathfrak{E}(t)\| \leq \{\mathfrak{M}\mathcal{E}_\phi(-\theta t^\phi)\}^c + \mathfrak{e}.$$

Remark 2. *When $\mathfrak{e} = 0$, the QML synchronization reduces to the ML synchronization. For $\phi = 1$ and $\mathfrak{e} = 0$, the system achieves exponential synchronization.*

Remark 3. *In,[36] the authors explored QML projective synchronization in delayed FONNs with mismatched parameters. In,[37] the authors studied the quasi-synchronization of FOCGNNs. In contrast to,[36,37] this work analyzes the QML synchronization of delayed FOCGNNs with uncertain parameters and inertial effects.*

Lemma 3. [43] *Consider a positive definite function $\mathfrak{C}(t)$ that satisfies the following*

$${}_0\mathcal{D}_t^\phi \mathfrak{C}(t) \leq -\Theta_1\mathfrak{C}(t) + \Theta_2 \max_{t-\eta(t)\leq s\leq t} \mathfrak{C}(s) + \Theta_3,$$
$$t > 0, \mathfrak{C}(s) = |\nu(s)|, \quad \eta_{\max} \leq s \leq 0,$$

where $\Theta_2 \geq 0, \Theta_3 \geq 0, \Theta_1 + \Theta_2 \leq 0$ and $\eta(t) \in [0, \eta_{\max}]$. Then there exists $\mathfrak{M}$ such that the following holds

$$\mathfrak{C}(t) \leq \mathfrak{M}\mathcal{E}_\phi(\kappa t^\phi) - \frac{\Theta_3}{\Theta_1 + \Theta_2}$$

for all $t \geq \eta(t) + 1$, where the parameter κ is defined as

$$\kappa = \sup_{t-\eta(t)\geq 1}\{\hat{\kappa}|\hat{\kappa} - \Theta_1 - \Theta_2\frac{\mathcal{E}_\phi(\hat{\kappa}(t-\eta(t))^\phi)}{\mathcal{E}_\phi(\hat{\kappa}t^\phi)} = 0\}.$$

Lemma 4. [44] *Consider non-negative functions $\mathfrak{C}(t)$ and $\hat{\mathfrak{C}}(t)$ that are continuous on $[0, +\infty]$, with $\mathfrak{C}(t)$ bounded on $[-\eta_{\max}, 0]$, satisfiying*

$${}_0\mathcal{D}_t^\phi(\mathfrak{C}(t) + \hat{\mathfrak{C}}(t)) \leq -\Theta_1\mathfrak{C}(t) + \Theta_2 \sup_{t-\eta(t)\leq s\leq t} \mathfrak{C}(s) + \Theta_3,$$

where $\phi \in (0, 1), \Theta_1 > \Theta_2 > 0$ and $\Theta_3 \geq 0$. For any $\mathcal{W} > 0$, there exists $T > 0$ such that

$$\mathfrak{C}(t) \leq \frac{\left(\mathfrak{C}(0) + \hat{\mathfrak{C}}(0) - \frac{\Theta_3}{\Theta_1}\right)\mathcal{E}_\phi(-\Theta_1 t^\phi) + \frac{\Theta_3}{\Theta_1}}{1 - \frac{\Theta_2}{\Theta_1}} + \mathcal{W},$$

$t > T$.

4. Main results

This section explores the FOCGINN's QML synchronization criteria through two different controller types: state-feedback controllers and adaptive controllers.

4.1. State-feedback controllers

The state-feedback control scheme is proposed as

$$\mathfrak{U}_i(t) = -\mathfrak{K}_{ai}\mathfrak{E}_i(t) - \mathfrak{K}_{bi}\mathfrak{E}_{\mathfrak{R}i}(t), \tag{6}$$

where $\mathfrak{K}_{ai} > 0$ and $\mathfrak{K}_{bi} > 0$ are control gains.

Theorem 1. *Under hypotheses (H2)–(H4), if the control parameters $\mathcal{K}_{ai}$ and $\mathcal{K}_{bi}$ satisfiying the following conditions*

$$\begin{cases} \mathfrak{I}_a = min(\mathfrak{I}_1, \mathfrak{I}_2) \geq 0, \\ \mathfrak{I}_b = \max_{1\leq i\leq n}\Big\{\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij} + \Gamma_{ij}|)\mathfrak{Y}_j\Big\} \geq 0, \\ \mathfrak{I}_c = \sum_{i=1}^{n}\sum_{j=1}^{n}\Big[(\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij} + \Lambda_{ij}|)l_x)^2 \\ +(\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij} + \Gamma_{ij}|)l_\tau)^2\Big] \geq 0, \end{cases} \tag{7}$$

where

$$\mathfrak{I}_1 = \min_{1\leq i\leq n}\Big\{\underline{\xi}_i + 2 + \lambda_i\tilde{l}_i + |\mathfrak{S}_i| - \sum_{j=1}^{n}\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij} + \Lambda_{ij}|)\mathfrak{X}_j + \mathfrak{K}_{ai}\Big\},$$

$$\mathfrak{I}_2 = \min_{1\leq i\leq n}\Big\{\underline{\xi}_i + \lambda_i\tilde{l}_i + 3|\mathfrak{S}_i| - 4 - 4n + \mathfrak{K}_{ai} + 2\mathfrak{K}_{bi} - \sum_{j=1}^{n}\big[\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij} + \Lambda_{ij}|)\mathfrak{X}_j - \bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij} + \Gamma_{ij}|)\mathfrak{Y}_j\Big\},$$

then system (1) can achieve QML synchronization with system (2) under controller (6) with an error bound $\sqrt{\frac{\mathfrak{I}_c}{\mathfrak{I}_a - \mathfrak{I}_b}}$.

Proof Let us consider the Lyapunov function

$$\mathfrak{V}(t) = \sum_{i=1}^{n}\mathfrak{E}_i^2(t) + \sum_{i=1}^{n}\mathfrak{E}_{\mathfrak{R}i}^2(t). \tag{8}$$

Taking the fractional derivative of (8) based on Lemma 1 along (5), we have

$$\begin{aligned} {}_0\mathcal{D}_t^{\phi}\mathfrak{V}(t) &= 2\sum_{i=1}^{n}\mathfrak{E}_i(t){}_0\mathcal{D}_t^{\phi}\mathfrak{E}_i(t) \\ &+ 2\sum_{i=1}^{n}\mathfrak{E}_{\mathfrak{R}i}(t){}_0\mathcal{D}_t^{\phi}\mathfrak{E}_{\mathfrak{R}i}(t) \\ \leq& 2\sum_{i=1}^{n}\mathfrak{E}_i(t)\Big[\mathfrak{E}_{\mathfrak{R}i}(t) - \mathfrak{E}_i(t)\Big] \\ &+ 2\sum_{i=1}^{n}\mathfrak{E}_{\mathfrak{R}i}(t)\Big[-(\mathfrak{S}_i - 1)\mathfrak{E}_{\mathfrak{R}i}(t) \\ &- (1 - \mathfrak{S}_i)\mathfrak{E}_i(t) - \mathfrak{A}_i(\beta_i(t))\mathfrak{g}_i(\beta_i(t)) \\ &+ \mathfrak{A}_i(\alpha_i(t))\mathfrak{g}_i(\alpha_i(t)) \\ &+ \mathfrak{A}_i(\beta_i(t))\sum_{j=1}^{n}(\mathfrak{P}_{ij} + \Delta\mathfrak{P}_{ij})\mathfrak{f}_{1j}(\beta_j(t)) \\ &- \mathfrak{A}_i(\alpha_i(t))\sum_{j=1}^{n}(\mathfrak{P}_{ij} + \Delta\mathfrak{P}_{ij})\mathfrak{f}_{1j}(\alpha_j(t)) \\ &+ \mathfrak{A}_i(\beta_i(t))\sum_{j=1}^{n}(\mathfrak{Q}_{ij} + \Delta\mathfrak{Q}_{ij})\mathfrak{f}_{2j}(\beta_j(t - \eta(t)) \\ &- \mathfrak{A}_i(\alpha_i(t))\sum_{j=1}^{n}(\mathfrak{Q}_{ij} + \Delta\mathfrak{Q}_{ij})\mathfrak{f}_{2j}(\alpha_j(t - \eta(t)) \\ &+ \mathfrak{A}_i(\beta_i(t))\mathfrak{I}_i(t) - \mathfrak{A}_i(\beta_i(t))\mathfrak{I}_i(t) \\ &- \mathfrak{K}_{ai}\mathfrak{E}_i(t) - \mathfrak{K}_{bi}\mathfrak{E}_{\mathfrak{R}i}(t)\Big]. \end{aligned} \tag{9}$$

By H1 and H2, we obtain

$$\begin{aligned} &\mathfrak{A}_i(\beta_i(t))\mathfrak{g}_i(\beta_i(t)) - \mathfrak{A}_i(\alpha_i(t))\mathfrak{g}_i(\alpha_i(t)) \\ &\qquad = \xi_i^{'}(\chi_i(t))(\beta_i(t) - \alpha_i(t)), \\ &\mathfrak{A}_i(\beta_i(t)) - \mathfrak{A}_i(\alpha_i(t)) \\ &\qquad = \mathfrak{A}^{'}(\hat{\chi}_i(t))(\beta_i(t) - \alpha_i(t)), \end{aligned}$$

where $\chi_i(t)$ and $\hat{\chi}(t)$ lie between $\beta_i(t)$ and $\alpha_i(t)$. Therefore, we have

$$\begin{aligned} &-2\sum_{i=1}^{n}\mathfrak{E}_{\mathfrak{R}i}(t)\Big(\mathfrak{A}_i(\beta_i(t))\mathfrak{g}_i(\beta_i(t)) \\ &-\mathfrak{A}_i(\alpha_i(t))\mathfrak{g}_i(\alpha_i(t))\Big) \\ &= -2\sum_{i=1}^{n}\mathfrak{E}_{\mathfrak{R}i}(t)\Big(\xi_i^{'}(\chi_i(t))\mathfrak{E}_i(t)\Big) \\ &\leq -2\sum_{i=1}^{n}\underline{\xi}_i|\mathfrak{E}_{\mathfrak{R}i}(t)||\mathfrak{E}_i(t)| \\ &\leq -\sum_{i=1}^{n}\underline{\xi}_i[\mathfrak{E}_{\mathfrak{R}i}^2(t) + \mathfrak{E}_i^2(t)]. \end{aligned} \tag{10}$$

Similarly,

$$\begin{aligned} &2\sum_{i=1}^{n}\mathfrak{E}_{\mathfrak{R}i}(t)\Big[\mathfrak{A}_i(\beta_i(t)) - \mathfrak{A}_i(\alpha_i(t))\Big]\mathfrak{I}_i(t) \\ &= -2\sum_{i=1}^{n}\mathfrak{E}_{\mathfrak{R}i}(t)\Big[\mathfrak{A}_i^{'}(\hat{\chi}_i(t))\mathfrak{E}_i(t)\mathfrak{I}_i(t)\Big] \\ &\leq -2\sum_{i=1}^{n}\lambda_i\tilde{l}_i|\mathfrak{E}_{\mathfrak{R}i}(t)||\mathfrak{E}_i(t)| \\ &\leq -\sum_{i=1}^{n}\lambda_i\tilde{l}_i\Big[\mathfrak{E}_{\mathfrak{R}i}^2(t) + \mathfrak{E}_i^2(t)\Big], \end{aligned} \tag{11}$$

and

$$\begin{aligned} &2\sum_{i=1}^{n}\mathfrak{E}_{\mathfrak{R}i}(t)\Big[-(\mathfrak{S}_i - 1)\mathfrak{E}_{\mathfrak{R}i}(t) \\ &-(1 - \mathfrak{S}_i)\mathfrak{E}_i(t)\Big] \\ &= -2\sum_{i=1}^{n}\mathfrak{E}_{\mathfrak{R}i}(t)(\mathfrak{S}_i - 1)\mathfrak{E}_{\mathfrak{R}i}(t) \end{aligned} \tag{12}$$

$$
\begin{aligned}
&- 2\sum_{i=1}^{n}\mathfrak{E}_{\Re i}(t)(1-\mathfrak{S}_i)\mathfrak{E}_i(t)\\
&\le -2\sum_{i=1}^{n}(|\mathfrak{S}_i-1|)\mathfrak{E}^2_{\Re i}(t)\\
&\quad -\sum_{i=1}^{n}(|1-\mathfrak{S}_i|)\Big[\mathfrak{E}^2_{\Re i}(t)+\mathfrak{E}^2_i(t)\Big].
\end{aligned}
$$

According to (H1)–(H2) and (H4), we obtain

$$
\begin{aligned}
&2\sum_{i=1}^{n}\mathfrak{E}_{\Re i}(t)\sum_{j=1}^{n}(\mathfrak{P}_{ij}+\Delta\mathfrak{P}_{ij})\times\\
&\Big[\mathfrak{A}_i(\beta_i(t))\mathfrak{f}_{1j}(\beta_j(t))-\mathfrak{A}_i(\alpha_i(t))\mathfrak{f}_{1j}(\alpha_j(t))\Big]\\
&=2\sum_{i=1}^{n}\mathfrak{E}_{\Re i}(t)\sum_{j=1}^{n}(\mathfrak{P}_{ij}+\Delta\mathfrak{P}_{ij})\times\\
&\quad\Big[\mathfrak{A}_i(\beta_i(t))\mathfrak{f}_{1j}(\beta_j(t))-\mathfrak{A}_i(\beta_i(t))\mathfrak{f}_{1j}(\alpha_j(t))\\
&\quad+\mathfrak{A}_i(\beta_i(t))\mathfrak{f}_{1j}(\alpha_j(t))-\mathfrak{A}_i(\alpha_i(t))\mathfrak{f}_{1j}(\alpha_j(t))\Big]\\
&=2\sum_{i=1}^{n}\mathfrak{E}_{\Re i}(t)\mathfrak{A}_i(\beta_i(t))\sum_{j=1}^{n}(\mathfrak{P}_{ij}+\Delta\mathfrak{P}_{ij})\times\\
&\quad\Big[\mathfrak{f}_{1j}(\beta_j(t))-\mathfrak{f}_{1j}(\alpha_j(t))\Big]\\
&+2\sum_{i=1}^{n}\mathfrak{E}_{\Re i}(t)(\mathfrak{A}_i(\beta_i(t))\\
&\quad-\mathfrak{A}_i(\alpha_i(t)))\sum_{j=1}^{n}(\mathfrak{P}_{ij}+\Delta\mathfrak{P}_{ij})\mathfrak{f}_{1j}(\alpha_j(t))\\
&\le 2\sum_{i=1}^{n}\sum_{j=1}^{n}\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}|+\Lambda_{ij})\mathfrak{X}_j|\mathfrak{E}_{\Re i}(t)||\mathfrak{E}_i(t)|\\
&\quad+2\sum_{i=1}^{n}\sum_{j=1}^{n}2\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}|+\Lambda_{ij})l_x|\mathfrak{E}_{\Re i}(t)|\\
&\le\sum_{i=1}^{n}\sum_{j=1}^{n}\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}|+\Lambda_{ij})\mathfrak{X}_j\Big[\mathfrak{E}^2_{\Re i}(t)+\mathfrak{E}^2_i(t)\Big]\\
&\quad+2\sum_{i=1}^{n}\sum_{j=1}^{n}\Big[\mathfrak{E}^2_{\Re i}(t)+(\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}|+\Lambda_{ij})l_x)^2\Big].
\end{aligned}
\tag{13}
$$

Similarly,

$$
\begin{aligned}
&2\sum_{i=1}^{n}\mathfrak{E}_{\Re i}(t)\sum_{j=1}^{n}(\mathfrak{Q}_{ij}+\Delta\mathfrak{Q}_{ij})\Big[\mathfrak{A}_i(\beta_i(t))\times\\
&\mathfrak{f}_{2j}(\beta_j(t-\eta(t)))-\mathfrak{A}_i(\alpha_i(t))\mathfrak{f}_{2j}\\
&(\alpha_j(t-\eta(t)))\Big]\\
&=2\sum_{i=1}^{n}\mathfrak{E}_{\Re i}(t)\sum_{j=1}^{n}(\mathfrak{Q}_{ij}+\Delta\mathfrak{Q}_{ij})\Big[\mathfrak{A}_i(\beta_i(t))\times\\
&\quad\mathfrak{f}_{2j}(\beta_j(t-\eta(t)))-\mathfrak{A}_i(\beta_i(t))\mathfrak{f}_{2j}(\alpha_j(t-\eta(t)))\\
&\quad+\mathfrak{A}_i(\beta_i(t))\mathfrak{f}_{2j}(\alpha_j(t-\eta(t)))\\
&\quad-\mathfrak{A}_i(\alpha_i(t))\mathfrak{f}_{2j}(\alpha_j(t-\eta(t)))\Big]\\
&=2\sum_{i=1}^{n}\mathfrak{E}_{\Re i}(t)\mathfrak{A}_i(\beta_i(t))\sum_{j=1}^{n}(\mathfrak{Q}_{ij}+\Delta\mathfrak{Q}_{ij})\\
&\quad\Big[\mathfrak{f}_{2j}(\beta_j(t-\eta(t)))-\mathfrak{f}_{2j}(\alpha_j(t-\eta(t)))\Big]\\
&\quad+2\sum_{i=1}^{n}\mathfrak{E}_{\Re i}(t)\Big[\mathfrak{A}_i(\beta_i(t))-\mathfrak{A}_i(\alpha_i(t))\Big]\times\\
&\quad\sum_{j=1}^{n}(\mathfrak{Q}_{ij}+\Delta\mathfrak{Q}_{ij})\mathfrak{f}_{2j}(\alpha_j(t-\eta(t)))\\
&\le 2\sum_{i=1}^{n}\sum_{j=1}^{n}\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}|+\Gamma_{ij})\mathfrak{Y}_j|\mathfrak{E}_{\Re i}(t)||\\
&\mathfrak{E}_i(t-\eta(t))|\\
&\quad+2\sum_{i=1}^{n}\sum_{j=1}^{n}2\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}|+\Gamma_{ij})l_\tau|\mathfrak{E}_{\Re i}(t)|\\
&\le\sum_{i=1}^{n}\sum_{j=1}^{n}\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}|+\Gamma_{ij})\mathfrak{Y}_j\Big[\mathfrak{E}^2_{\Re i}(t)\\
&+\mathfrak{E}^2_i(t-\eta(t))\Big]\\
&\quad+2\sum_{i=1}^{n}\sum_{j=1}^{n}\Big[\mathfrak{E}^2_{\Re i}(t)+(\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}|+\Gamma_{ij})l_\tau)^2\Big]
\end{aligned}
\tag{14}
$$

and

$$
\begin{aligned}
&-2\sum_{i=1}^{n}\mathfrak{E}_{\Re i}(t)(\mathfrak{K}_{1i}\mathfrak{E}_i(t)+\mathfrak{K}_{2i}\mathfrak{E}_{\Re i}(t))\\
&\le -2\sum_{i=1}^{n}\mathfrak{K}_{ai}|\mathfrak{E}_{\Re i}(t)||\mathfrak{E}_i(t)|\\
&\quad-2\sum_{i=1}^{n}\mathfrak{K}_{bi}|\mathfrak{E}_{\Re i}(t)||\mathfrak{E}_{\Re i}(t)|\\
&\le -\sum_{i=1}^{n}\mathfrak{K}_{ai}\Big[\mathfrak{E}^2_{\Re i}(t)+\mathfrak{E}^2_i(t)\Big]\\
&\quad-2\sum_{i=1}^{n}\mathfrak{K}_{bi}\mathfrak{E}^2_{\Re i}(t).
\end{aligned}
\tag{15}
$$

In (9), substituting (10)–(15), we obtain

$$
\begin{aligned}
&{}_0\mathcal{D}^{\phi}_t\mathfrak{V}(t)\\
&\quad=-\sum_{i=1}^{n}\{\underline{\xi}_i+2+\lambda_i\tilde{l}_i+|\mathfrak{S}_i|\\
&\quad-\sum_{j=1}^{n}\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}
\end{aligned}
$$

$$
\begin{aligned}
&+\Lambda_{ij}|)\mathfrak{X}_j+\mathfrak{K}_{ai}\}\mathfrak{E}_i^2(t)\\
&-\sum_{i=1}^{n}\{\underline{\xi}_i+\lambda_i\tilde{l}_i+3|\mathfrak{S}_i|\\
&-4-4n+\mathfrak{K}_{ai}+2\mathfrak{K}_{bi}\\
&-\sum_{j=1}^{n}\big[\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}+\Lambda_{ij}|)\mathfrak{X}_j\\
&-\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}+\Gamma_{ij}|)\mathfrak{Y}_j\big]\}\mathfrak{E}_{\Re i}(t)\\
&+\sum_{i=1}^{n}\sum_{j=1}^{n}\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}+\Gamma_{ij}|)\mathfrak{Y}_j\mathfrak{E}_i^2(t-\eta(t))\\
&+\sum_{i=1}^{n}\sum_{j=1}^{n}\Big[(\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}+\Lambda_{ij}|)l_x)^2\\
&\quad+(\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}+\Gamma_{ij}|)l_\tau)^2\Big]\\
&\le-\mathfrak{I}_1\sum_{i=1}^{n}\mathfrak{E}_i^2(t)-\mathfrak{I}_2\sum_{i=1}^{n}\mathfrak{E}_{\Re i}^2(t)\\
&+\mathfrak{I}_b\sum_{i=1}^{n}\mathfrak{E}_i^2(t-\eta(t))+\mathfrak{I}_c
\end{aligned}
$$

where

$$
\begin{aligned}
\mathfrak{I}_1=&\min_{1\le i\le n}\{\underline{\xi}_i+2+\lambda_i\tilde{l}_i+|\mathfrak{S}_i|\\
&-\sum_{j=1}^{n}\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}+\Lambda_{ij}|)\mathfrak{X}_j+\mathfrak{K}_{ai}\},\\
\mathfrak{I}_2=&\min_{1\le i\le n}\{\underline{\xi}_i+\lambda_i\tilde{l}_i+3|\mathfrak{S}_i|-4-4n\\
&+\mathfrak{K}_{ai}+2\mathfrak{K}_{bi}\\
&-\sum_{j=1}^{n}\big[\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}\\
&+\Lambda_{ij}|)\mathfrak{X}_j-\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}+\Gamma_{ij}|)\mathfrak{Y}_j\},
\end{aligned}
$$

$$
\begin{aligned}
\mathfrak{I}_b=&\max_{1\le i\le n}\{\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}+\Gamma_{ij}|)\mathfrak{Y}_j\},\\
\mathfrak{I}_c=&\sum_{i=1}^{n}\sum_{j=1}^{n}\Big[(\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}+\Lambda_{ij}|)l_x)^2\\
&+(\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}+\Gamma_{ij}|)l_\tau)^2\big],\\
\mathfrak{I}_a=&min(\mathfrak{I}_1,\mathfrak{I}_2).
\end{aligned}
$$

Applying the fractional-order Razumikhin technique, we obtain

$$
\begin{aligned}
{}_0\mathcal{D}_t^{\phi}\mathfrak{V}(t)\le&-\mathfrak{I}_a\mathfrak{V}(t)+\mathfrak{I}_b\\
&\max_{t-\eta(t)\le s\le t}\mathfrak{V}(s)+\mathfrak{I}_c.
\end{aligned}
\tag{16}
$$

By using Lemma 3, we have

$$
\mathfrak{V}(t)\le\mathfrak{M}\mathcal{E}_\phi(-\theta t^\phi)+\frac{\mathfrak{I}_c}{\mathfrak{I}_a-\mathfrak{I}_b},
$$

where

$$
\theta=\sup_{t-\eta(t)\ge1}\{\hat{\theta}|\hat{\theta}-\mathfrak{I}_a-\mathfrak{I}_b\frac{\mathcal{E}_\phi(\hat{\theta}(t-\eta(t))^\phi)}{\mathcal{E}_\phi(\hat{\theta}t^\phi)}=0\}.
$$

From this we obtain

$$
\begin{aligned}
\|\mathfrak{E}(t)\|\le&\|\mathfrak{E}(t)\|+\|\mathfrak{E}_{\Re}(t)\|\\
\le&\{\mathfrak{M}\mathcal{E}_\phi(\theta t^\phi)\}^{\frac{1}{2}}+\frac{\sqrt{\mathfrak{I}_c}}{\sqrt{\mathfrak{I}_a-\mathfrak{I}_b}},
\end{aligned}
$$

which confirms that system (1) achieves QML synchronization with system (2), with convergence rate θ and error bound $\frac{\sqrt{\mathfrak{I}_c}}{\sqrt{\mathfrak{I}_a-\mathfrak{I}_b}}$.

4.2. Adaptive controller

However, selecting the controller gains $\mathcal{K}_{ai}$ and $\mathcal{K}_{bi}$ in controller (6) is challenging, as they must be chosen sufficiently large to satisfy condition (7), which may lead to a conservative design, especially when dealing with uncertain systems. So to overcome this limitation in this section, we adopt the adaptive controller, which can tune its gain automatically to enhance the system performance. The adaptive controller for the system (5) is constructed as

$$
\begin{aligned}
&\mathfrak{U}_i(t)=\mathfrak{K}_{ai}(t)\mathfrak{E}_{\Re i}(t)+\mathfrak{K}_{bi}(t)\mathfrak{E}_i(t)\,\mathrm{sign}(\mathfrak{E}_{\Re i}(t)),\\
&{}_0\mathcal{D}_t^{\phi}\mathfrak{K}_{ai}(t)=-\pi_{ai}\mathfrak{E}_{\Re i}^2(t),\\
&{}_0\mathcal{D}_t^{\phi}\mathfrak{K}_{bi}(t)=-\pi_{bi}|\mathfrak{E}_i(t)||\mathfrak{E}_{\Re i}(t)|,
\end{aligned}
\tag{17}
$$

where $\pi_{ai}>0$ and $\pi_{bi}>0$.

Theorem 2. *Under the hypotheses (H1)-(H4), if there exist constants π_{ai} and π_{bi} such that*

$$
\begin{cases}
\beth_a:=min(\beth_1,\beth_2)\ge0,\\
\beth_b:=\max_{1\le i\le n}\{\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}+\Gamma_{ij}|)\mathfrak{Y}_j\},\\
\beth_c:=\sum_{i=1}^{n}\sum_{j=1}^{n}\Big[(\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}+\Lambda_{ij}|)l_x)^2\\
+(\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}+\Gamma_{ij}|)l_\tau)^2\big]\ge0,
\end{cases}
\tag{18}
$$

where

$$
\begin{aligned}
\beth_1=&\min_{1\le i\le n}\{\underline{\xi}_i+2+\lambda_i\tilde{l}_i+|\mathfrak{S}_i|+\mathfrak{K}_b^*\\
&-\sum_{j=1}^{n}\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}+\Lambda_{ij}|)\mathfrak{X}_j\},\\
\beth_2=&\min_{1\le i\le n}\{\underline{\xi}_i+\lambda_i\tilde{l}_i+3|\mathfrak{S}_i|-4-4n\\
&+2\mathfrak{K}_a^*+\mathfrak{K}_b^*\\
&-\sum_{j=1}^{n}\big[\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}+\Lambda_{ij}|)\mathfrak{X}_j-\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}\\
&+\Gamma_{ij}|)\mathfrak{Y}_j\},\\
\beth_b=&\max_{1\le i\le n}\{\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}+\Gamma_{ij}|)\mathfrak{Y}_j\},\\
\beth_c=&\sum_{i=1}^{n}\sum_{j=1}^{n}\Big[(\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij}+\Lambda_{ij}|)l_x)^2\\
&+(\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij}+\Gamma_{ij}|)l_\tau)^2\big],\\
\beth_a=&min(\beth_1,\beth_2),
\end{aligned}
$$

then system (1) can achieve the QML synchronization with the system (2) under the controller (17) with an error bound $\sqrt{\frac{\beth_c}{\beth_a-\beth_b}}$.

Proof. Let's consider the Lyapunov function as

$$\mathfrak{V}_2(t) = \mathfrak{V}_a(t) + \mathfrak{V}_b(t), \tag{19}$$

where

$$\mathfrak{V}_a(t) = \sum_{i=1}^{n} \mathfrak{E}_i^2(t) + \sum_{i=1}^{n} \mathfrak{E}_{\Re i}^2(t),$$

$$\mathfrak{V}_b(t) = \sum_{i=1}^{n} \frac{1}{\pi_{ai}}(\mathfrak{K}_{ai}(t) - \mathfrak{K}_a^*)^2 + \sum_{i=1}^{n} \frac{1}{\pi_{bi}}(\mathfrak{K}_{bi}(t) - \mathfrak{K}_b^*)^2.$$

By computing the fractional derivative of $\mathfrak{V}_a(t)$ according Lemma 2 along (5), we obtain

$$\begin{aligned}
&{}_0\mathcal{D}_t^{\phi}\mathfrak{V}_a(t)\\
&\le 2\sum_{i=1}^{n} \mathfrak{E}_i(t)\,{}_0\mathcal{D}_t^{\phi}\mathfrak{E}_i(t) + 2\sum_{i=1}^{n} \mathfrak{E}_{\Re i}(t)\,{}_0\mathcal{D}_t^{\phi}\mathfrak{E}_{\Re i}(t)\\
&\le 2\sum_{i=1}^{n} \mathfrak{E}_i(t)\Big[\mathfrak{E}_{\Re i}(t) - \mathfrak{E}_i(t)\Big] + 2\sum_{i=1}^{n} \mathfrak{E}_{\Re i}(t)\times\\
&\Big[-(\mathfrak{S}_i - 1)\mathfrak{E}_{\Re i}(t) - (1-\mathfrak{S}_i)\mathfrak{E}_i(t)\\
&- \mathfrak{A}_i(\beta_i(t))\mathfrak{g}_i(\beta_i(t)) + \mathfrak{A}_i(\alpha_i(t))\mathfrak{g}_i(\alpha_i(t))\\
&+ \mathfrak{A}_i(\beta_i(t))\sum_{j=1}^{n}(\mathfrak{P}_{ij} + \Delta\mathfrak{P}_{ij})\mathfrak{f}_{1j}(\beta_j(t))\\
&- \mathfrak{A}_i(\alpha_i(t))\sum_{j=1}^{n}(\mathfrak{P}_{ij} + \Delta\mathfrak{P}_{ij})\mathfrak{f}_{1j}(\alpha_j(t))\\
&+ \mathfrak{A}_i(\beta_i(t))\sum_{j=1}^{n}(\mathfrak{Q}_{ij} + \Delta\mathfrak{Q}_{ij})\mathfrak{f}_{1j}(\beta_j(t-\eta(t)))\\
&+ \mathfrak{A}_i(\alpha_i(t))\sum_{j=1}^{n}(\mathfrak{Q}_{ij} + \Delta\mathfrak{Q}_{ij})\mathfrak{f}_{1j}(\alpha_j(t-\eta(t)))\\
&+ \mathfrak{A}_i(\beta_i(t))\mathfrak{I}_i(t) - \mathfrak{A}_i(\beta_i(t))\mathfrak{I}_i(t)\\
&+ \mathfrak{K}_{ai}(t)\mathfrak{E}_{\Re i}(t)\\
&+ \mathfrak{K}_{bi}|\mathfrak{E}_i(t)|sign(\mathfrak{E}_{\Re i}(t))\Big].
\end{aligned} \tag{20}$$

The fractional derivative of $\mathfrak{V}_b(t)$ is

$$\begin{aligned}
{}_0\mathcal{D}_t^{\phi}\mathfrak{V}_b(t) &\le -2\sum_{i=1}^{n}(\mathfrak{K}_{ai}(t) - \mathfrak{K}_a^*)\mathfrak{E}_{\Re i}^2(t)\\
&- 2\sum_{i=1}^{n}(\mathfrak{K}_{ai}(t) - \mathfrak{K}_b^*)|\mathfrak{E}_i(t)||\mathfrak{E}_{\Re i}(t)|.
\end{aligned} \tag{21}$$

From (20) and (21) we derive ${}_0\mathcal{D}_t^{\phi}\mathfrak{V}_2(t)$. The remaining steps are similar to Theorem 1. Therefore, we obtain

$$\begin{aligned}
{}_0\mathcal{D}_t^{\phi}\mathfrak{V}_2(t) &= {}_0\mathcal{D}_t^{\phi}\mathfrak{V}_a(t) + {}_0\mathcal{D}_t^{\phi}\mathfrak{V}_b(t)\\
&\le -\sum_{i=1}^{n}\{\underline{\xi}_i + 2 + \lambda_i\tilde{l}_i + |\mathfrak{S}_i| + \mathfrak{K}_b^*\\
&- \sum_{j=1}^{n}\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij} + \Lambda_{ij}|)\mathfrak{X}_j\}\mathfrak{E}_i^2(t)\\
&- \sum_{i=1}^{n}\{\underline{\xi}_i + \lambda_i\tilde{l}_i\\
&+ 3|\mathfrak{S}_i| - 4 - 4n + 2\mathfrak{K}_a^* + \mathfrak{K}_b^*\\
&- \sum_{j=1}^{n}\big[\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij} + \Lambda_{ij}|)\mathfrak{X}_j\\
&- \bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij} + \Gamma_{ij}|)\mathfrak{Y}_j\big]\}\mathfrak{E}_{\Re i}(t)\\
&+ \sum_{i=1}^{n}\sum_{j=1}^{n}\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij} + \Gamma_{ij}|)\mathfrak{Y}_j\mathfrak{E}_i^2(t-\eta(t))\\
&+ \sum_{i=1}^{n}\sum_{j=1}^{n}\Big[(\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij} + \Lambda_{ij}|)l_x)^2\\
&+ (\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij} + \Gamma_{ij}|)l_\tau)^2\Big]\\
&\le -\beth_1\sum_{i=1}^{n}\mathfrak{E}_i^2(t) - \beth_2\sum_{i=1}^{n}\mathfrak{E}_{\Re i}^2(t)\\
&+ \beth_b\sum_{i=1}^{n}\mathfrak{E}_i^2(t-\eta(t)) + \beth_c
\end{aligned}$$

where

$$\begin{aligned}
\beth_1 &= \min_{1\le i\le n}\{\underline{\xi}_i + 2 + \lambda_i\tilde{l}_i + |\mathfrak{S}_i| + \mathfrak{K}_b^*\\
&\quad - \sum_{j=1}^{n}\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij} + \Lambda_{ij}|)\mathfrak{X}_j\},\\
\beth_2 &= \min_{1\le i\le n}\{\underline{\xi}_i + \lambda_i\tilde{l}_i + 3|\mathfrak{S}_i| - 4\\
&\quad - 4n + 2\mathfrak{K}_a^* + \mathfrak{K}_b^*\\
&\quad - \sum_{j=1}^{n}\big[\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij} + \Lambda_{ij}|)\mathfrak{X}_j\\
&\quad - \bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij} + \Gamma_{ij}|)\mathfrak{Y}_j\},\\
\beth_b &= \max_{1\le i\le n}\{\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij} + \Gamma_{ij}|)\mathfrak{Y}_j\},\\
\beth_c &= \sum_{i=1}^{n}\sum_{j=1}^{n}\Big[(\bar{\mathfrak{A}}_i(|\mathfrak{P}_{ij} + \Lambda_{ij}|)l_x)^2\\
&\quad + (\bar{\mathfrak{A}}_i(|\mathfrak{Q}_{ij} + \Gamma_{ij}|)l_\tau)^2\big],\\
\beth_a &= min(\beth_1, \beth_2),
\end{aligned}$$

Applying the fractional-order Razumikhin technique, we obtain

$$\begin{aligned}
{}_0\mathcal{D}_t^{\phi}\mathfrak{V}_2(t) &\le -\beth_a\mathfrak{V}(t) + \beth_b\\
&\sup_{t-\eta(t)\le s\le t}\mathfrak{V}(s) + \beth_c.
\end{aligned} \tag{22}$$

By Lemma 2 and for any $\mathcal{W} > 0$,

$$\mathfrak{V}_2(t) \leq \frac{\left(\mathfrak{V}_a(0)+\mathfrak{V}_b(0)-\frac{\beth_c}{\beth_a}\right)\mathcal{E}_\phi(-\beth_a t^\phi)+\frac{\beth_c}{\beth_a}}{1-\frac{\beth_b}{\beth_a}}+\mathcal{W}.$$

Consequently, taking $\mathcal{W}\to 0$, we obtain

$$\begin{aligned}\|\mathfrak{E}(t)\| \leq & \|\mathfrak{E}(t)\|+\|\mathfrak{E}_{\Re}(t)\| \\ \leq & \{\mathcal{W}_\nu \mathfrak{E}_\phi(-\beth_a t^\phi)\}^{\frac{1}{2}}+\sqrt{\frac{\beth_c}{\beth_a-\beth_b}}\end{aligned}$$

where $\mathcal{W}_\nu = \frac{\left(\mathfrak{V}_a(0)+\mathfrak{V}_b(0)-\frac{\beth_c}{\beth_a}\right)}{1-\frac{\beth_b}{\beth_a}}$, which confirms that system (1) achieves QML synchronization with system (2), with convergence rate θ and error bound $\frac{\sqrt{\beth_c}}{\sqrt{\beth_a-\beth_b}}$. □

5. Numerical simulation

Example 1. *Consider the 2-D delayed FOCGINN systems (1) and (2) with the following parameters:*
$\phi = 0.98, \Delta\mathfrak{P}_{ij} = \Delta\mathfrak{Q}_{ij} = 0.1\cos(t), i,j = 1,2.$

$$\mathfrak{S} = \begin{bmatrix} 1.1 & 0 \\ 0 & 1.1 \end{bmatrix},\quad \mathfrak{P} = \begin{bmatrix} 1.3 & 1.2 \\ 1.1 & -1.2 \end{bmatrix} \text{ and}$$

$$\mathfrak{Q} = \begin{bmatrix} 1.2 & -1.5 \\ -1.5 & 1.5 \end{bmatrix}.$$

The functions in the systems are $\mathfrak{A}_i(\alpha_i(t)) = 0.4\alpha_i(t), = \mathfrak{A}_i(\beta_i(t)) = 0.4\beta_i(t), \mathfrak{g}_i(\alpha_i(t)) = 0.3[1+\frac{1}{1+|\alpha_i(t)|}], \mathfrak{g}_i(\beta_i(t)) = 0.3[1+\frac{1}{1+|\beta_i(t)|}], \mathfrak{f}_{1j}(\cdot) = \mathfrak{f}_{2j}(\cdot) = 0.5\tanh(\cdot)$ *and* $\mathfrak{I}_i(t) = 0$. *With the initial conditions* $\alpha_1(0) = 0.2, \alpha_2(0) = -1.1, \beta_1(0) = -0.3$, *and* $\beta_2(0) = -1.8$, *the phase trajectories of system (1) are displayed in* ***Figure 1****. From hypotheses (H1)-(H2), we obtain the following values by calculation:* $\underline{\mathfrak{A}}_i = \bar{\mathfrak{A}}_i = 0.9, \lambda_i = 0.3, \xi_i = 0.18, \mathfrak{X}_i = \mathfrak{Y}_i = l_i^x = l_i^\tau = \tilde{l}_i = 1, i = 1,2.$

The controller parameters are adopted as $\mathfrak{K}_{ai} = 2.6, \mathfrak{K}_{bi} = 2.6$. *With the help of controller (6) and the conditions of Theorem 1, we obtain the synchronization error bound as* $\frac{\sqrt{\beth_c}}{\sqrt{\beth_a-\beth_b}} = 0.9571$. *These results show that systems (1) and (2) achieve QML synchronization.* ***Figures 2*** *and* ***3*** *show the state behavior of systems (1) and (2) under controller (6), and* ***Figure 4*** *shows the synchronization error together with the actual and theoretical bounds.*

Example 2. *Consider the 3-D delayed FOCGINN system with the following parameters:* $\phi = 0.88, \mathfrak{S} = diag(1.01, 1.01, 1.01), \Delta\mathfrak{P}_{ij} = \mathfrak{Q}_{ij} = 0.3\cos(t), i,j = 1,2.$

$$\mathfrak{P} = \begin{bmatrix} 1.3 & 0.2 & 1.4 \\ -0.9 & -1.2 & 1.1 \\ 1.1 & -1.2 & 1.1 \end{bmatrix},$$

$$\mathfrak{Q} = \begin{bmatrix} 1.2 & -1.5 & 2.1 \\ -1.5 & 1.5 & 1.1 \\ 2.1 & 1.1 & 1.1 \end{bmatrix}$$

The functions inthe systems are $\mathfrak{A}_i(\alpha_i(t)) = 0.4\alpha_i(t), \mathfrak{A}_i(\beta_i(t)) = 0.4\beta_i(t), \mathfrak{g}_i(\alpha_i(t)) = 0.4[2+\frac{1}{1+|\alpha_i(t)|}], \mathfrak{g}_i(\beta_i(t)) = 0.4[2+\frac{1}{1+|\beta_i(t)|}], \mathfrak{f}_{1j}(\cdot) = \mathfrak{f}_{2j}(\cdot) = 0.5\tanh(\cdot), \eta(t) = 0.3+(sin(2.9t))$ *and* $\mathfrak{I}_i(t) = 0$. *With the initial conditions* $\alpha_1(0), = 0.2, \alpha_2(0) = 1.4, \alpha_3(0) = 0.1, \beta_1(0) = -0.3, \beta_2(0) = 1.6$, *and* $\beta_3(0) = 1.1$, *the phase trajectories of system (1) are displayed in* ***Figure 5****. From hypotheses (H1)-(H4), we obtain the following parameters by calculation:* $\underline{\mathfrak{A}}_i = \bar{\mathfrak{A}}_i = 0.9, \lambda_i = 0.3, \xi_i = 0.18, \mathfrak{X}_i = \mathfrak{Y}_i = l_i^x = l_i^\tau = \tilde{l}_i = 1, i = 1,2,3.$ *This example relies on Theorem 2. The adaptive controller (17) is employed, and the control parameters are selected according to the adaptive law as* $\pi_{a1} = 4.2, \pi_{a2} = 4.2, \pi_{a3} = 4.2, \pi_{b1} = 2.1, \pi_{b2} = 2.3, \pi_{b3} = 4.2$. *Based on the controller (17), systems (1) and (2) attain QML synchronization with the error bound* $\frac{\sqrt{\beth_c}}{\sqrt{\beth_a-\beth_b}} = 0.6757$. ***Figures 6–8*** *depict the state responses of systems (1) and (2) in the presence of adaptive controller (17), and the synchronization error bound is displayed in* ***Figure 9****. The adaptive gain trajectories are illustrated in* ***Figures 10*** *and* ***11****.*

Table 2 compares the synchronization error bounds of system (5) based on the proposed controllers. The adaptive controller reduces the theoretical and actual error bounds by 29.4% and 83.8%, respectively, compared with the state-feedback controller, indicating improved synchronization accuracy.

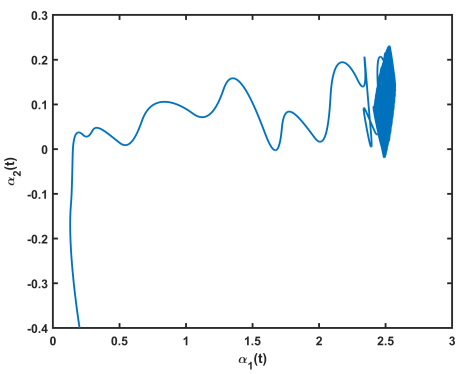


Figure 1. Phase trajectories of system (1)

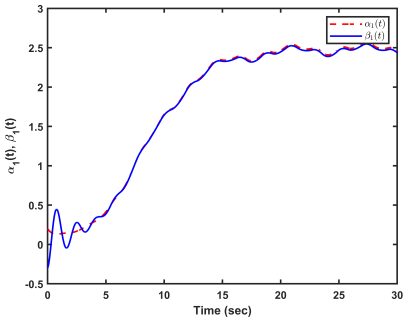


Figure 2. Time responses of the drive and response systems under controller (6)

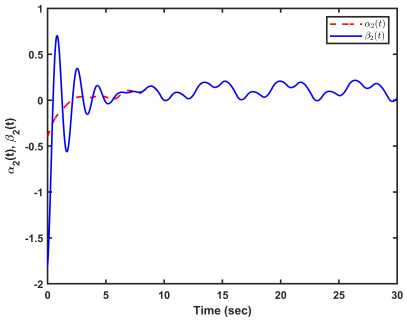


Figure 3. Time responses of the drive and response systems under controller (6)

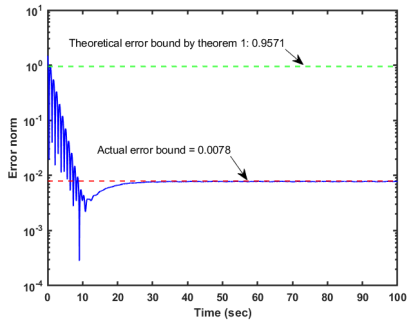


Figure 4. Time evolution of $\|\mathfrak{E}(t)\|$ under controller (6)

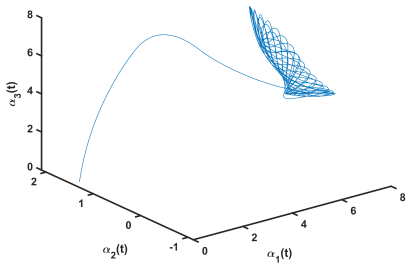


Figure 5. Phase trajectories of system (1)

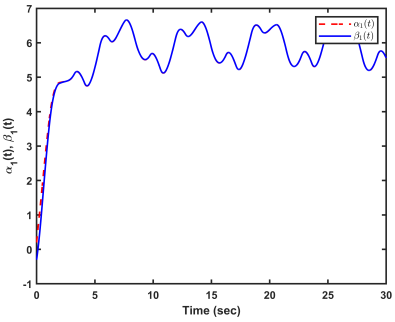


Figure 6. Time responses of the drive and response systems under controller (17)

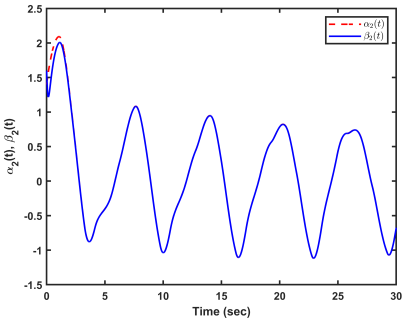


Figure 7. Time responses of the drive and response systems under controller (17)

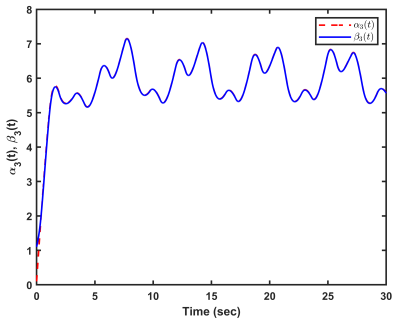


Figure 8. Time responses of the drive and response systems under controller (17)

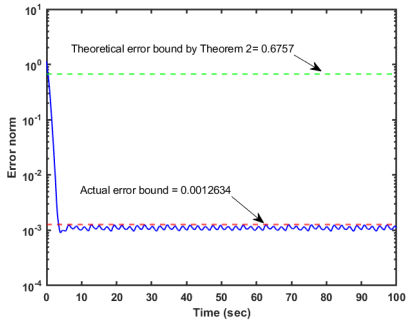


Figure 9. Time evolution of $\|\mathfrak{E}(t)\|$ under controller (17)

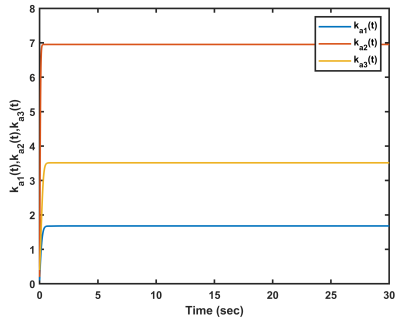


Figure 10. Time responses of the adaptive gains $\mathfrak{K}_{ai}, (i = 1, 2, 3)$

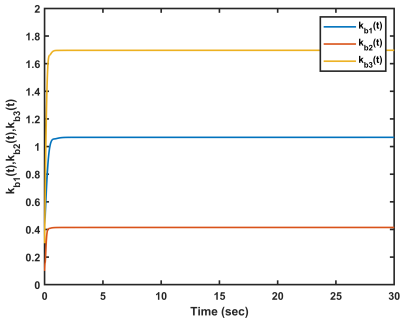


Figure 11. Time responses of the adaptive gains $\mathfrak{K}_{bi}, (i = 1, 2, 3)$

Table 2. Comparison of the proposed controllers based on error bounds

Proposed controllers	Theoretical error bound	Actual error bound
(6)	0.9571	0.0078
(17)	0.6757	0.0012634
Reduction using adaptive controller (%)	29.4%	83.8%

Example 3. *Consider the 2-D delayed FOCGINN systems (1) and (2) with the following parameters:* $\Delta\mathfrak{P}_{ij} = \Delta\mathfrak{Q}_{ij} = 0.5\sin(t)$,

$$\mathfrak{S} = \begin{bmatrix} 1.01 & 0 \\ 0 & 1.01 \end{bmatrix}, \quad \mathfrak{P} = \begin{bmatrix} 3.3 & 0.2 \\ -0.9 & -1.2 \end{bmatrix},$$

$$\mathfrak{Q} = \begin{bmatrix} 2.2 & -1.5 \\ -1.5 & 1.5 \end{bmatrix}$$

The functions in the systems are $\mathfrak{A}_i(\alpha_i(t)) = 0.2\alpha_i(t), = \mathfrak{A}_i(\beta_i(t)) = 0.2\beta_i(t), \mathfrak{g}_i(\alpha_i(t)) = 0.5[2 + \frac{1}{1+|\alpha_i(t)|}], \mathfrak{g}_i(\beta_i(t)) = 0.5[2 + \frac{1}{1+|\beta_i(t)|}], \mathfrak{f}_{1j}(\cdot) = \mathfrak{f}_{2j}(\cdot) = 0.5\tanh(\cdot), \mathfrak{I}_i(t) = 0$ *and* $\eta(t) = \frac{e^t}{e^T+1}$. *The initial conditions are* $\alpha_1(0) = 0.2, \alpha_2(0) = -1.1, \beta_1(0) = -0.3$, *and* $\beta_2(0) = -1.8$. *Then, the phase trajectories of the delayed FOCGINNs are depicted in* ***Figures 12–14*** *for different fractional orders. For the fractional order* $\phi = 0.77$, *from hypotheses (H1)-(H4), we obtain the following parameters by calculation:* $\underline{\mathfrak{A}}_i = \bar{\mathfrak{A}}_i = 0.6, \lambda_i = 0.5, \xi_i = 0.38, \mathfrak{X}_i = \mathfrak{Y}_i = l_i^x = l_i^\tau = \tilde{l}_i = 1, i = 1, 2$. *This example relies on Theorem 2. We employ adaptive controller (17) and choose the control parameters according to the adaptive law as* $\pi_{a1} = 2.2, \pi_{a2} = 2.2, \pi_{b1} = 4.1, \pi_{b2} = 4.3$. *Using controller (17), systems (1) and (2) attain QML synchronization.* ***Figures 15*** *and* ***16*** *depict the state response of the systems (1) and (2) under the presence of the adaptive controller (17), and its synchronization error bound is displayed in* ***Figure 17***. ***Table 3*** *compares the error-state convergence times of the proposed synchronization scheme with existing literature models.*

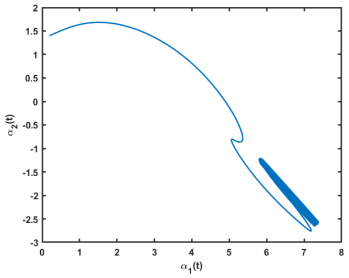


Figure 12. Phase trajectories of system (1) for $\phi = 0.77$

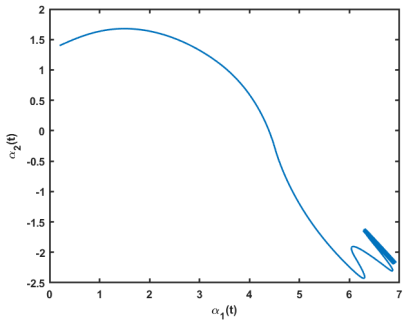


Figure 13. Phase trajectories of system (1) for $\phi = 0.88$

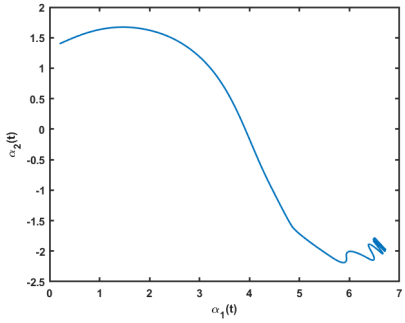


Figure 14. Phase trajectories of system (1) for $\phi = 0.99$

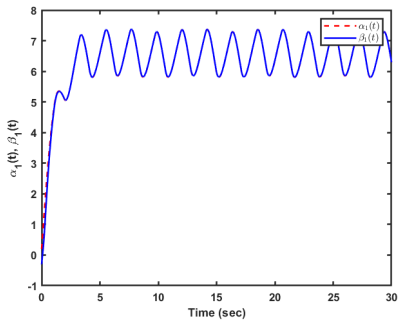


Figure 15. Time responses of the drive and response systems under controller (17)

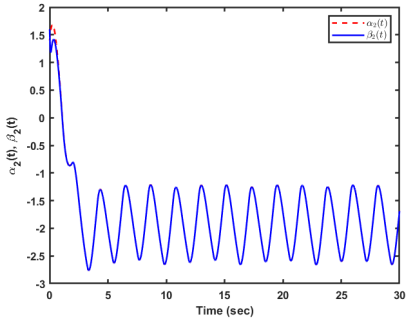


Figure 16. Time responses of the drive and response systems under controller (17)

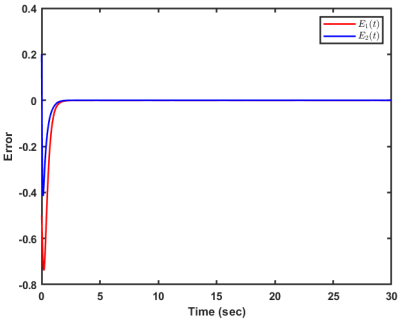


Figure 17. Synchronization error in Example 3

Table 3. Comparison of convergence times

Method	Convergence time (s)
[37]	5
[45]	4
Proposed	3.02

6. Conclusion

This work addressed the QML synchronization analysis of delayed FOCGINNs with uncertain parameters. The FOCGINN was successfully converted into an equivalent standard FOCGNN by applying an appropriate variable transformation. To attain QML synchronization, two control approaches, namely, a state-feedback controller and an adaptive controller, were proposed and implemented. Based on these controllers, using Lyapunov stability theory and the proposed lemmas, sufficient conditions for attaining QML synchronization were established through two theorems. To highlight the applicability of the derived outcomes, numerical simulation examples were presented. However, the present study is limited to theoretical synchronization analysis and numerical validation, without considering practical engineering implementation or experimental validation. As a future direction, the proposed synchronization framework will be extended to secure communication applications, with particular emphasis on developing an application-oriented encryption scheme based on synchronized neural dynamics.

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Conflict of interest

The authors declare they have no competing interests.

Author contributions

Conceptualization: Pavithra Ganeshan, Dharani Shanmugavel
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Investigation: Pavithra Ganeshan
Methodology: Dharani Shanmugavel
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Validation: Sivakumar Muthusamy
Visualization: Sivakumar Muthusamy
Writing-original draft: Pavithra Ganeshan
Writing-review & editing: Dharani Shanmugavel, Sivakumar Muthusamy

Availability of data

Not applicable.

AI tools statement

All authors confirm that no AI tools were used in the preparation of this manuscript.

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