

Article

Fixed-Time Event-Triggered Control for High-Order Nonlinear Multi-Agent Systems Under Unknown Stochastic Time Delays

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Abstract: In this paper, the fixed-time control for high-order nonlinear multi-agent systems under unknown stochastic time delay is investigated via an event-triggered approach. First of all, RBF neural networks are utilized to approximate the system's uncertain nonlinearities. After that, an event-triggered scheme, which is designed with a relative threshold for more flexible control, is proposed to alleviate the communication burden. In consideration of the unknown stochastic time delay in the inter-communication among high-order nonlinear multi-agent systems, the Lyapunov–Krasovskii functional (LKF) is used to construct the system's Lyapunov function, specifically targeting the adverse effects caused by time delay. Further, the fixed-time stability theory is employed to ensure that the convergence time remains independent of the initial values. Finally, the proposed control strategy is validated through numerical simulations.

Keywords: high-order nonlinear multi-agent system; unknown stochastic time delay; event-triggered control; fixed-time stability; Lyapunov–Krasovskii functional

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1. Introduction

High-order nonlinear multi-agent systems are generally composed of a set of sub-systems with high-order nonlinear dynamics, which exhibit great potential in practical applications such as the platoon driving of intelligent vehicles [1], formation flying of unmanned aircraft [2], cooperative working of electro-hydraulic systems [3], etc. During recent decades, fruitful results have been yielded in the control of high-order nonlinear multi-agent systems [4–6]. However, the inherent uncertainty and nonlinearity in these systems significantly enhance the difficulty of the controller design and reduce the control performance [7]. To this end, fuzzy logic functions and neural networks are frequently deployed in the identification of uncertain nonlinear terms in high-order nonlinear multi-agent systems [8–10]. In addition, mutual interactions among subsystems further enhance the difficulty in controlling such a system. In [11], a decentralized nearly optimal controller was designed to cope with the weak interactions between subsystems. The adaptive neural controller was designed to address the strong interconnectivity between subsystems in [12]. With the continuous advancement of research, an increasing number of remarkable achievements have emerged in the control of high-order nonlinear multi-agent systems in recent years [13,14].

For high-order nonlinear multi-agent systems to fulfill given tasks, it is necessary for subsystems to exchange information with each other. However, the limited bandwidth of the communication channel restricts the information transmission between subsystems, which may lead to communication congestion and even system performance reduction. At present, a time-triggered scheme is widely deployed in the control of high-order nonlinear multi-agent systems, which not only exhibits satisfactory control performance but also facilitates system analysis [15–17]. However, such periodical sampling will inevitably cause information redundancy and increase energy consumption [18]. In view of this, the event-triggered mechanism (ETM) has been proposed to execute sampling and control only at specific moments [19], which is more effective in fulfilling control tasks and has gained considerable attention in recent studies [20]. For example, the ETM was introduced to reduce unnecessary information transmission for high-order nonlinear multi-agent systems in [21]. In event-triggered control, the triggering threshold, to a certain extent, determines the system control performance [22]. In [23,24], a relative threshold ETM was designed to diminish the sensing cost and communication burden of the system. In [25], a novel dynamic event-triggered mechanism was proposed for continuous-time boiler turbine systems to reduce the number of controller updates and save system resources. In [26], the bipartite time-varying output formation tracking problem of heterogeneous linear multi-agent systems with disturbances was investigated based on adaptive dynamic event-triggered control.

On the other hand, the stochastic time delay arising from communication congestion is also a critical concern in the control of high-order nonlinear multi-agent systems [27]. Time delay, which may reduce the control performance and even lead to system instability, has been extensively discussed in the literature [27–34]. At present, the methodology for dealing with time delay can be roughly divided into the frequency-domain and time-domain approaches [28]. The results under the frequency-domain method are accurate [29], but it is quite difficult to implement for unknown stochastic time delays, especially time delays in nonlinear systems. The time-domain method, which is mainly based on the Lyapunov stability theory, can cope with unknown stochastic delay systems and has received considerable attention in recent years. Yin et al. comprehensively used the Lyapunov–Krasovskii functional (LKF), bilateral neural network adaptive control, and finite covering lemma to address the constant time delay problem in nonlinear systems [27,30,31]. Further, an adaptive control strategy was proposed for stochastic constant time delay [32]. Recently, the unknown stochastic time delay in nonlinear systems has become a hot topic. Phat et al. [33] addressed the time-varying delay issue of nonlinear fractional-order systems by means of robust finite-time control. In [34], a finite-time stability strategy was utilized to improve the performance of the nonlinear time delay system.

In practical control systems, convergence time is undeniably an important consideration [35]. Presently, finite-time control is frequently employed to enhance the system's transient performance [36–39]. However, the convergence time of finite-time control is influenced by the system's initial values, which may not satisfy some practical requirements [40]. Fixed-time control, which has a predetermined convergence time [41], is regarded as a potential solution to enhance system's transient performance. In [42], a novel sliding mode controller was designed to obtain fixed-time convergence for second-order systems. Subsequently, some fixed-time controllers in the sense of the Lyapunov theory were designed [43–45], which made fixed-time control broaden its applicability and increased its popularity. In [43], a fixed-time controller was designed by combining multiple Lyapunov methods and stochastic analysis theory. The fixed-time event-triggered controller was investigated to obtain satisfactory control performance in [44]. Utilizing a series of new

Lyapunov functions and modified tuning functions, an adaptive fixed-time consensus controller was designed in [45].

Although lots of studies have been devoted to the control of high-order nonlinear multi-agent systems, literature that specifically considers the communication constraints, time delay, and convergence time simultaneously is rarely seen as far as we are concerned. However, these issues are often required at the same time for better control performance in practical applications. Inspired by the above descriptions, this paper designs a fixed-time event-triggered controller for high-order nonlinear multi-agent systems with unknown stochastic time delays. The main contributions are generalized below.

1. The relative threshold ETM designed in this paper can save communication resources compared to the traditional time-triggered mechanism [15–17] and offers more flexibility and adaptability compared to the fixed threshold ETM [46].
2. To tackle prevalent unknown stochastic time delays in high-order nonlinear multi-agent systems, the LKF is introduced to integrate nonlinear time delay functions with the system Lyapunov function. By effectively addressing the time delay functions in the subsequent controller design process, the system exhibits robustness to time delay.
3. The designed fixed-time controller ensures that the system can be semiglobal practical fixed-time stable (SPFTS), wherein the convergence time is solely determined by the designed control parameters and is independent of the system's initial values.

The remainder of this paper is as follows. Section 2 provides preliminary knowledge and problem formulation. Then, the control scheme design and fixed-time stability analysis for high-order nonlinear multi-agent systems are presented in Section 3. Section 4 provides two representative simulation examples to illustrate the theoretical results. Finally, Section 5 concludes this paper.

2. Preliminaries and Problem Formulation

In this section, some mathematical preliminaries are presented, and the problem addressed in this paper is formulated.

2.1. Graph Theory

Define the directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$, where $\mathcal{V} = \{v_1, v_2, \dots, v_N\}$, $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$, and $\mathcal{A} = [a_{ij}]_{N \times N}$ are the set of nodes, the set of directed edges, and a weighted adjacency matrix, respectively. Define $a_{ij} > 0$ if $(v_j, v_i) \in \mathcal{E}$; otherwise, $a_{ij} = 0$. The degree matrix is defined as $\mathcal{D} = \text{diag}\{q_1, q_2, \dots, q_N\}$, where $q_i = \sum_{j \in N_i} a_{ij}$. The Laplace matrix of a directed graph is $L = \mathcal{D} - \mathcal{A}$. Define $\mathcal{B} = \text{diag}\{p_1, p_2, \dots, p_N\}$, and v_0 is the leader, $p_i = 1$, if the i -th node can receive the leader's information and $p_i = 0$ otherwise.

2.2. Lemmas

For a generic dynamical system,

$$\dot{x} = f(x), x(0) = x_0, \quad (1)$$

where $x \in R^n$ and $f(\cdot)$ are system states and nonlinear functions, respectively.

Lemma 1 ([9]). *If there exists a positive definite function $V(x)$ and some parameters satisfying $p > 0$, $q > 0$, $0 < g < 1$, $\mathfrak{k} > 1$, and $0 < \varkappa < \infty$ such that*

$$\dot{V}(x) \leq -pV^g(x) - qV^{\mathfrak{k}}(x) + \varkappa, \quad (2)$$

system (1) is referred to as being semiglobal practical fixed-time stable (SPFTS), and the states of system (1) can reach the following set within the interval $[0, T_f]$:

$$\Omega = \left\{ x \mid V(x) \leq \min \left\{ \left(\frac{\varkappa}{p(1-\iota)} \right)^{\frac{1}{\mathfrak{g}}}, \left(\frac{\varkappa}{q(1-\iota)} \right)^{\frac{1}{\mathfrak{k}}} \right\} \right\}, \quad (3)$$

where the scalar ι satisfies $0 < \iota < 1$, and the settling time $\mathcal{T}_f$ is bound by the fixed-time $\mathcal{T}_{max}$

$$\mathcal{T}_f \leq \mathcal{T}_{max} = \frac{1}{p\iota(1-\mathfrak{g})} + \frac{1}{q\iota(\mathfrak{k}-1)}. \quad (4)$$

Lemma 2 ([24]). If ρ and ς are real variables and $\mathfrak{x}$, $\mathfrak{y}$, and $\mathfrak{z}$ are positive constants, we have

$$|\rho|^{\mathfrak{x}} |\varsigma|^{\mathfrak{y}} \leq \frac{\mathfrak{x}}{\mathfrak{x} + \mathfrak{y}} \mathfrak{z} |\rho|^{\mathfrak{x} + \mathfrak{y}} + \frac{\mathfrak{y}}{\mathfrak{x} + \mathfrak{y}} \mathfrak{z}^{-\frac{\mathfrak{x}}{\mathfrak{y}}} |\varsigma|^{\mathfrak{x} + \mathfrak{y}}. \quad (5)$$

Lemma 3 ([9]). For $\lambda_1, \lambda_2, \dots, \lambda_n \geq 0$ and $m > 0$, if $0 < m < 1$, one can obtain $\sum_{i=1}^n \lambda_i^m \geq \left(\sum_{i=1}^n \lambda_i \right)^m$; otherwise, one has $\sum_{i=1}^n \lambda_i^m \geq n^{1-m} \left(\sum_{i=1}^n \lambda_i \right)^m$.

Lemma 4 ([44]). If $\delta \in \mathbb{R}$ and $\epsilon > 0$, we have

$$0 \leq |\delta| - \delta \tanh\left(\frac{\delta}{\epsilon}\right) \leq 0.2785\epsilon. \quad (6)$$

Lemma 5 ([44]). For $\forall (\gamma, \delta) \in \mathbb{R}^2$, the following inequality holds:

$$\gamma\delta \leq \frac{\eta^{\mathfrak{g}}}{\mathfrak{g}} |\gamma|^{\mathfrak{g}} + \frac{1}{\mathfrak{h}\eta^{\mathfrak{h}}} |\delta|^{\mathfrak{h}}, \quad (7)$$

where $\eta > 0$, $\mathfrak{g} > 1$, $\mathfrak{h} > 1$ and $(\mathfrak{g} - 1)(\mathfrak{h} - 1) = 1$.

Lemma 6 ([9]). Radial basis function neural networks (RBF NNs) are often used to estimate the unknown terms of nonlinear systems due to their excellent approximation ability. An unknown smooth function $\mathcal{F}(Z)$ can be approximated by the following:

$$\mathcal{F}(Z) = \Lambda^T \Xi(Z), \quad (8)$$

where $\Lambda = [w_1, \dots, w_l]^T \in \mathbb{R}^l$ denotes the ideal weight vector, l denotes the node number in the hidden layer, $Z \in \mathbb{R}^n$ is an input vector, $\Xi(Z) = [\xi_1(Z), \dots, \xi_l(Z)]$ represents the basis function vector, and $\xi_i(Z)$ is the Gaussian basis function with the following form:

$$\xi_i(Z) = \exp\left(-\frac{\|X - \epsilon_i\|^2}{l_i^2}\right), i = 1, 2, \dots, l, \quad (9)$$

with ϵ_i denoting the center of the Gaussian kernel and l_i representing the width of the Gaussian kernel.

As is well known, RBF NNs in (8) can uniformly estimate any discrete-time unknown functions with arbitrary accuracy. Further, the unknown function can be rewritten as follows:

$$\mathcal{F}(Z) = \Lambda^T \Xi(Z) + \varepsilon(Z), \quad (10)$$

where Λ and $\varepsilon(Z)$ are the ideal weight vector and estimation error, respectively.

2.3. Problem Statement

Consider the following high-order nonlinear multi-agent time delay system:

$$\begin{cases} \dot{x}_{i,m}(t) = x_{i,m+1}(t) + \mathfrak{L}_{i,m}(\bar{x}_{i,m}(t - \tau_{i,m})) + \mathfrak{d}_{i,m}(\bar{x}_{i,m}(t)), \\ \dot{x}_{i,n_i}(t) = u_i(t) + \mathfrak{L}_{i,n_i}(x_{i,n_i}(t - \tau_{i,n_i})) + \mathfrak{d}_{i,n_i}(x_{i,n_i}(t)), \\ y_i = x_{i,1}, i = 1, \dots, N; m = 1, \dots, n_i - 1. \end{cases}, \quad (11)$$

where $x_i = [x_{i,1}, x_{i,2}, \dots, x_{i,n_i}]^T \in \mathbb{R}^{n_i}$, $u_i(t) \in \mathbb{R}$, and $y_i \in \mathbb{R}$ are the states, input, and output of the i th subsystem, respectively. $\mathfrak{L}_{i,m}(\bar{x}_{i,m}(t - \tau_{i,m}))$ represents the unknown smooth nonlinear time delay function, $\tau_{i,m}$ is the unknown stochastic state delay, and $\mathfrak{d}_{i,m}(\bar{x}_{i,m}(t))$ is the external disturbance. Here, $x_i(t - \tau_{i,m})$ is written as $x_i(\tau_{i,m})$ for simplicity.

The main objective of this paper is to design the control input u_i for the high-order nonlinear multi-agent time delay system (11) such that the following are true:

1. The output y_i can track the reference signal y_0 within a fixed time, and all the closed-loop signals are SPFTS.
2. The communication resources are significantly reduced with the introduction of the event-triggered mechanism.
3. The system can remain stable in the presence of unknown stochastic time delays.

Here are several important assumptions for the subsequent controller design.

Assumption 1. The desired signal $y_0(t)$ and its m th-order derivatives $y_0^{(m)}(m = 1, 2, \dots, n)$ are continuous and bound.

Assumption 2. The time delay function $\mathfrak{L}_{i,m}(\bar{x}_{i,m})$ satisfies $|\mathfrak{L}_{i,m}(\bar{x}_{i,m})| \leq \sum_{g=1}^m \mathfrak{J}_{i,m,g}(x_{i,g})$, where $\mathfrak{J}_{i,m,g}(x_{i,g})$ is an unknown bounded positive function.

Assumption 3. For an unknown positive function $\mathfrak{J}_{i,m,h}(x_{i,h})$, we have the following inequalities:

$$\frac{1}{2} \sum_{m=1}^{n_i} \sum_{v=1}^{n_i} \sum_{g=1}^v \int_{t-\tau_{i,v}}^t \mathfrak{J}_{i,v,g}^2(x_{i,g}(s)) ds = \mathfrak{b} \leq \mathfrak{B}, \quad (12)$$

$$\frac{1}{2} \sum_{m=1}^{n_i} \sum_{j \in N_i} \sum_{v=1}^{n_i} \sum_{g=1}^v \int_{t-\tau_{i,v}}^t \mathfrak{J}_{j,v,g}^2(x_{j,g}(s)) ds = \mathfrak{c} \leq \mathfrak{C}, \quad (13)$$

where $\mathfrak{b}$, $\mathfrak{c}$, $\mathfrak{B}$, $\mathfrak{C}$ are positive constants.

Assumption 4. The external disturbance $\mathfrak{d}_{i,m}(\bar{x}_{i,m}(t))$ satisfies $|\mathfrak{d}_{i,m}(\bar{x}_{i,m}(t))| \leq |\sigma_{i,m}(\bar{x}_{i,m}(t))|$, where $\sigma_{i,m}(\bar{x}_{i,m}(t))$ is an unknown function.

Remark 1. It is important to emphasize that the above four assumptions presented in this paper are both essential and reasonable. Assumption 1 serves as a foundational premise and is extensively prevalent in the backstepping-based controller design of high-order nonlinear systems [9,13,17]. In addition, this assumption is also coherent with some practical systems, such as the double-rod hydraulic position servo system [47], the uncertain quadrotor UAV system [48], the unmanned underwater vehicle pole attitude control system [49], etc. Since the time delay functions in the system is bound, it is reasonable that Assumption 2 assumes the upper bound of the time delay function to be $\sum_{g=1}^m \mathfrak{J}_{i,m,g}(x_{i,g})$. Additionally, it is clear that the integrals and summations of bound functions are also bound; thus, Assumption 3 is equally reasonable. Assumption 4 is widely validated by extensive experiments, as detailed in [50].

3. Main Results

The fixed-time event-triggered controller is constructed in this section, and the structure of the proposed strategy is displayed in Figure 1. Combining RBF NNs, the fixed-time stability theory, and the Lyapunov–Krasovskii functional, the virtual control law and adap-

tive law of the system are built by virtue of the backstepping technique. Then, the control signal is further obtained through the ETM, allowing for appropriate control of the system.

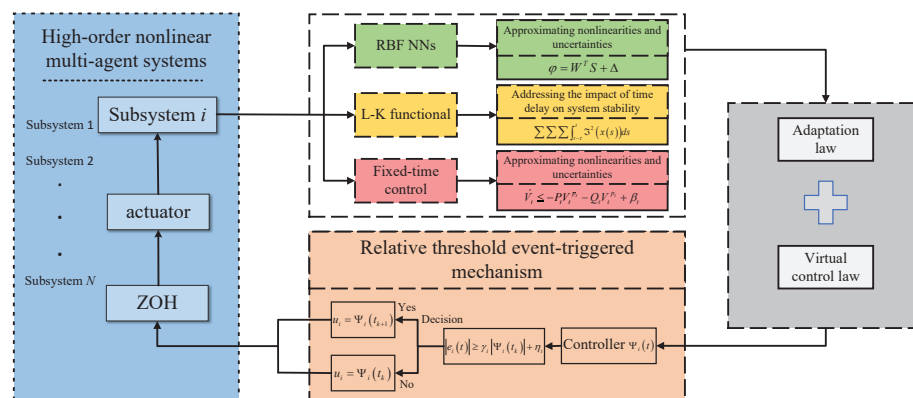


Figure 1. Structural diagram of the controller design.

3.1. Event-Triggered Mechanism Design

Define $\mathbf{e}_i(t) = \Psi_i(t) - \Psi_i(t_k)$, where t and t_k are the current time and the previous triggering time, and Ψ_i is the control signal. Then, the triggering event will only be executed when the following inequality holds:

$$|\mathbf{e}_i(t)| \geq \gamma_i |\Psi_i(t_k)| + \eta_i, \quad (14)$$

where $\gamma_i \in (0, 1)$ and $\eta_i > 0$ are two positive parameters.

Then, the triggering time t_{k+1} can be expressed as follows:

$$t_{k+1} = \inf\{t > t_k \mid |\mathbf{e}_i(t)| \geq \gamma_i |\Psi_i(t_k)| + \eta_i\}. \quad (15)$$

Then, we have the following formula:

$$\Psi_i(t) = (1 + \mathfrak{w}_1(t)\gamma_i)u_i(t) + \mathfrak{w}_2(t)\eta_i, \quad t \in [t_k, t_{k+1}), \quad (16)$$

where $u_i(t)$ is the control input, η_i is a positive parameter, and $\mathfrak{w}_1(t)$ and $\mathfrak{w}_2(t)$ are time-varying parameters with $|\mathfrak{w}_1(t)| \leq 1$ and $|\mathfrak{w}_2(t)| \leq 1$.

Further, the actuator signal $u_i(t)$ can be written as follows:

$$u_i(t) = \frac{\Psi_i(t)}{1 + \mathfrak{w}_1(t)\gamma_i} - \frac{\mathfrak{w}_2(t)\eta_i}{1 + \mathfrak{w}_1(t)\gamma_i}. \quad (17)$$

3.2. Fixed-Time Event-Triggered Controller Design Under Unknown Stochastic Time Delay

The tracking errors of each system are constructed as follows:

$$\begin{cases} z_{i,1} = \sum_{j \in N_i} \mathfrak{a}_{i,j}(x_{i,1} - x_{j,1}) + p_i(x_{i,1} - y_0), \\ z_{i,r} = x_{i,r} - \alpha_{i,r-1}, r = 2, \dots, n_i. \end{cases}, \quad (18)$$

where $\alpha_{i,q}$ ($q = 1, 2, \dots, n_i$) is the virtual control law, and $\mathfrak{a}_{i,j}$ is the element of the adjacency matrix $\mathcal{A}$.

Step $i, 1$: Construct the Lyapunov function as follows:

$$V_{i,1} = \frac{1}{2}z_{i,1}^2 + \frac{1}{2} \int_{t-\tau_{i,1}}^t \mathfrak{J}_{i,1,1}^2(x_{i,1}(s))ds + \frac{1}{2} \sum_{j \in N_i} \int_{t-\tau_{j,1}}^t \mathfrak{J}_{j,1,1}^2(x_{j,1}(s))ds. \quad (19)$$

The derivative of $V_{i,1}$ is as follows:

$$\begin{aligned} \dot{V}_{i,1} = & z_{i,1}((p_i + q_i)(z_{i,2} + \alpha_{i,1} + \mathfrak{L}_{i,1}(\bar{x}_{i,1}(\tau_{i,1})) + \mathfrak{d}_{i,1}(\bar{x}_{i,1})) - \sum_{j \in N_i} a_{i,j}(x_{j,2} + \mathfrak{L}_{j,1}(\bar{x}_{j,1}(\tau_{j,1})) \\ & + \mathfrak{d}_{j,1}(\bar{x}_{j,1}(t))) - p_i \dot{y}_0) + \frac{1}{2} \mathfrak{J}_{i,1,1}^2(x_{i,1}(t)) - \frac{1}{2} \mathfrak{J}_{i,1,1}^2(x_{i,1}(\tau_{i,1})) + \frac{1}{2} \sum_{j \in N_i} \mathfrak{J}_{j,1,1}^2(x_{j,1}(t)) \\ & - \frac{1}{2} \sum_{j \in N_i} \mathfrak{J}_{j,1,1}^2(x_{j,1}(\tau_{j,1})). \end{aligned} \quad (20)$$

According to Lemma 5, one has the following:

$$z_{i,1} \mathfrak{L}_{i,1}(\bar{x}_{i,1}(\tau_{i,1})) \leq \frac{(p_i + q_i)z_{i,1}^2}{2} + \frac{\mathfrak{J}_{i,1,1}^2(x_{i,1}(\tau_{i,1}))}{2(p_i + q_i)}, \quad (21)$$

$$z_{i,1} \mathfrak{d}_{i,1}(x_{i,1}) \leq \frac{(p_i + q_i)b_{i,0,0}^2}{2} + \frac{z_{i,1}^2 \sigma_{i,1}^2}{2(p_i + q_i)b_{i,0,0}^2}, \quad (22)$$

$$z_{i,1} \mathfrak{L}_{j,1}(\bar{x}_{j,1}(\tau_{j,1})) \leq \frac{z_{i,1}^2}{2} + \frac{\mathfrak{J}_{j,1,1}^2(x_{j,1}(\tau_{j,1}))}{2}, \quad (23)$$

$$z_{i,1} \mathfrak{d}_{j,1}(x_{j,1}) \leq \frac{b_{j,1,1}^2}{2} + \frac{z_{i,1}^2 \sigma_{j,1}^2}{2b_{j,1,1}^2}, \quad (24)$$

where $b_{i,0,0}$ and $b_{j,1,1}$ are positive constants.

Substituting (21)–(24) into (20) yields the following:

$$\begin{aligned} \dot{V}_{i,1} \leq & z_{i,1}[(p_i + q_i)(z_{i,2} + \alpha_{i,1}) + \frac{1}{2}z_{i,1}(p_i + q_i)^2 + \frac{z_{i,1}\sigma_{i,1}^2}{2b_{i,0,0}^2} - \sum_{j \in N_i} a_{i,j}(x_{j,2} - \frac{1}{2}z_{i,1} - \frac{z_{i,1}\sigma_{j,1}^2}{2b_{j,1,1}^2}) \\ & - p_i \dot{y}_0] + \frac{(p_i + q_i)^2 b_{i,0,0}^2}{2} + \sum_{j \in N_i} \frac{b_{j,1,1}^2}{2} + \frac{1}{2} \mathfrak{J}_{i,1,1}^2(x_{i,1}(t)) + \frac{1}{2} \sum_{j \in N_i} \mathfrak{J}_{j,1,1}^2(x_{j,1}(t)) \\ = & z_{i,1}[(p_i + q_i)(z_{i,2} + \alpha_{i,1}) - \sum_{j \in N_i} a_{i,j}x_{j,2} - p_i \dot{y}_0 + \mathcal{F}_{i,1}] + \frac{b_{i,1,1}^2}{2} + \sum_{j \in N_i} \frac{b_{j,1,1}^2}{2} \\ & + \frac{1}{2} \mathfrak{J}_{i,1,1}^2(x_{i,1}(t)) + \frac{1}{2} \sum_{j \in N_i} \mathfrak{J}_{j,1,1}^2(x_{j,1}(t)), \end{aligned} \quad (25)$$

where $\mathcal{F}_{i,1} = \frac{1}{2}z_{i,1}(p_i + q_i)^2 + \frac{z_{i,1}\sigma_{i,1}^2}{2b_{i,0,0}^2} + \sum_{j \in N_i} a_{i,j}(\frac{1}{2}z_{i,1} + \frac{z_{i,1}\sigma_{j,1}^2}{2b_{j,1,1}^2})$ and $b_{i,1,1}^2 = (p_i + q_i)^2 b_{i,0,0}^2$.

According to Lemma 6, we have the following:

$$\mathcal{F}_{i,1} = \Lambda_{i,1}^T \Xi_{i,1} + \varepsilon_{i,1}, \quad (26)$$

where $|\varepsilon_{i,1}| \leq \mathfrak{g}_{i,1}$ and $\mathfrak{g}_{i,1} > 0$.

It can be inferred from Lemma 5 that

$$z_{i,1} \mathcal{F}_{i,1} \leq |z_{i,1}|(\|\Lambda_{i,1}\| \|\Xi_{i,1}\| + \mathfrak{g}_{i,1}) \leq \frac{z_{i,1}^2}{2c_{i,1}^2} \|\Lambda_{i,1}\|^2 \|\Xi_{i,1}\|^2 + \frac{1}{2}c_{i,1}^2 + \frac{z_{i,1}^2}{2} + \frac{1}{2}\mathfrak{g}_{i,1}^2, \quad (27)$$

where $c_{i,1}$ is a positive parameter.

Define the estimation error $\tilde{\theta}_i$ as follows:

$$\tilde{\theta}_i = \theta_i - \hat{\theta}_i, \quad (28)$$

where $\theta_i = \max\{\|\Lambda_{i,j}\|^2, j = 1, 2, \dots, n_i\}$, and $\hat{\theta}_i$ is the estimation value of θ_i .

Let $\vartheta_{i,r} > 0$ and $\nu_{i,r} > 0$ ($r = 1, 2, \dots, n_i$) be the designed parameters. Then, the virtual control law $\alpha_{i,1}$ can be designed as follows:

$$\alpha_{i,1} = \frac{1}{p_i + q_i} \left(-\vartheta_{i,1} z_{i,1}^{2\rho_1-1} - \nu_{i,1} z_{i,1}^{2\rho_2-1} + \sum_{j \in N_i} a_{i,j} x_{j,2} - \frac{1}{2} z_{i,1} + p_i \dot{y}_0 - \frac{z_{i,1}}{2c_{i,1}^2} \hat{\theta}_i \Xi_{i,1}^T \Xi_{i,1} \right). \quad (29)$$

Substituting (26)–(29) into (25), we have

$$\begin{aligned} \dot{V}_{i,1} \leq & -\vartheta_{i,1} z_{i,1}^{2\rho_1-1} - \nu_{i,1} z_{i,1}^{2\rho_2-1} + (p_i + q_i) z_{i,1} z_{i,2} + \frac{z_{i,1}^2}{2c_{i,1}^2} (\|\Lambda_{i,1}\|^2 - \hat{\theta}_i) S_{i,1}^T S_{i,1} \\ & + \frac{1}{2} \mathcal{J}_{i,1,1}^2(x_{i,1}(t)) + \frac{1}{2} \sum_{j \in N_i} \mathcal{J}_{j,1,1}^2(x_{j,1}(t)) + \frac{1}{2} c_{i,1}^2 + \frac{1}{2} g_{i,1}^2 + \frac{b_{i,1,1}^2}{2} + \sum_{j \in N_i} \frac{b_{j,1,1}^2}{2}. \end{aligned} \quad (30)$$

Step $i, 2$: Construct the Lyapunov function as follows:

$$V_{i,2} = V_{i,1} + \frac{1}{2} z_{i,2}^2 + \frac{1}{2} \sum_{v=1}^2 \sum_{g=1}^v \int_{t-\tau_{i,v}}^t \mathcal{J}_{i,v,g}^2(x_{i,g}(s)) ds + \frac{1}{2} \sum_{j \in N_i} \sum_{v=1}^2 \sum_{g=1}^v \int_{t-\tau_{i,v}}^t \mathcal{J}_{j,v,g}^2(x_{j,g}(s)) ds. \quad (31)$$

The time derivative of (31) is as follows:

$$\begin{aligned} \dot{V}_{i,2} = & \dot{V}_{i,1} + z_{i,2} (z_{i,3} + \alpha_{i,2} + \mathcal{L}_{i,2}(\bar{x}_{i,2}(\tau_{i,2})) + \mathfrak{d}_{i,2}(\bar{x}_{i,2}) - \dot{\alpha}_{i,1}) + \frac{1}{2} \sum_{v=1}^2 \sum_{g=1}^v \left[\mathcal{J}_{i,v,g}^2(x_{i,g}(t)) \right. \\ & \left. - \mathcal{J}_{i,v,g}^2(x_{i,g}(\tau_{i,v})) \right] + \frac{1}{2} \sum_{j \in N_i} \sum_{v=1}^2 \sum_{g=1}^k \left[\mathcal{J}_{j,v,g}^2(x_{j,g}(t)) - \mathcal{J}_{j,v,g}^2(x_{j,g}(\tau_{i,v})) \right]. \end{aligned} \quad (32)$$

Based on Lemma 5, one has the following:

$$z_{i,2} \mathcal{L}_{i,2}(\bar{x}_{i,2}(\tau_{i,2})) \leq \frac{z_{i,2}^2}{2} + \frac{1}{2} \sum_{g=1}^2 \mathcal{J}_{i,2,g}^2(x_{i,g}(\tau_{i,2})), \quad (33)$$

$$z_{i,2} \mathfrak{d}_{i,2}(\bar{x}_{i,2}) \leq \frac{b_{i,2,2}^2}{2} + \frac{z_{i,2}^2 \sigma_{i,2}^2(\bar{x}_{i,2})}{2b_{i,2,2}^2}, \quad (34)$$

where $b_{i,2,2}$ is a positive constant.

The time derivative of $\alpha_{i,1}$ is as follows:

$$\begin{aligned} \dot{\alpha}_{i,1} = & \frac{\partial \alpha_{i,1}}{\partial x_{i,1}} \dot{x}_{i,1} + \sum_{j \in N_i} \sum_{v=1}^2 \frac{\partial \alpha_{i,1}}{\partial x_{j,v}} \dot{x}_{j,v} + \frac{\partial \alpha_{i,1}}{\partial \hat{\theta}_i} \dot{\hat{\theta}}_i + \sum_{v=0}^1 \frac{\partial \alpha_{i,1}}{\partial y_0^{(v)}} \dot{y}_0^{(v+1)} \\ = & \mathcal{R}_1 + \frac{\partial \alpha_{i,1}}{\partial x_{i,1}} (\mathcal{L}_{i,1}(x_{i,1}(\tau_{i,1})) + \mathfrak{d}_{i,1}(\bar{x}_{i,1})) + \sum_{j \in N_i} \sum_{v=1}^2 \frac{\partial \alpha_{i,1}}{\partial x_{j,v}} (\mathcal{L}_{j,v}(\bar{x}_{j,v}(\tau_{j,v})) + \mathfrak{d}_{j,v}(\bar{x}_{j,v})), \end{aligned} \quad (35)$$

$$\text{where } \mathcal{R}_1 = \frac{\partial \alpha_{i,1}}{\partial x_{i,1}} x_{i,2} + \sum_{j \in N_i} \sum_{v=1}^2 \frac{\partial \alpha_{i,1}}{\partial x_{j,v}} x_{j,v+1} + \frac{\partial \alpha_{i,1}}{\partial \hat{\theta}_i} \dot{\hat{\theta}}_i + \sum_{v=0}^1 \frac{\partial \alpha_{i,1}}{\partial y_0^{(v)}} \dot{y}_0^{(v+1)}.$$

According to Lemma 5, one has the following:

$$-z_{i,2} \frac{\partial \alpha_{i,1}}{\partial x_{i,1}} \mathcal{L}_{i,1}(\bar{x}_{i,1}(\tau_{i,1})) \leq \frac{z_{i,2}^2}{2} \left(\frac{\partial \alpha_{i,1}}{\partial x_{i,1}} \right)^2 + \frac{1}{2} \mathcal{J}_{i,1,1}^2(x_{i,1}(\tau_{i,1})), \quad (36)$$

$$-z_{i,2} \frac{\partial \alpha_{i,1}}{\partial x_{i,1}} \mathfrak{d}_{i,1}(x_{i,1}) \leq \frac{z_{i,2}^2 \sigma_{i,1}^2}{2b_{i,2,1}^2} + \frac{1}{2} b_{i,2,1}^2, \quad (37)$$

$$-z_{i,2} \sum_{j \in N_i} \sum_{v=1}^2 \frac{\partial \alpha_{i,1}}{\partial x_{j,v}} \mathfrak{L}_{j,v}(\bar{x}_{j,v}(\tau_{j,v})) \leq \sum_{j \in N_i} \sum_{v=1}^2 \left(\frac{z_{i,2}^2}{2} \left(\frac{\partial \alpha_{i,1}}{\partial x_{j,v}} \right)^2 + \frac{1}{2} \sum_{g=1}^v \mathfrak{J}_{j,v,g}^2(x_{j,g}(\tau_{j,v})) \right), \quad (38)$$

$$-z_{i,2} \sum_{j \in N_i} \sum_{v=1}^2 \frac{\partial \alpha_{i,1}}{\partial x_{j,v}} \mathfrak{d}_{j,v}(\bar{x}_{j,v}) \leq \sum_{j \in N_i} \sum_{v=1}^2 \left(\frac{z_{i,2}^2 \sigma_{j,v}^2}{2b_{j,2,v}^2} \left(\frac{\partial \alpha_{i,1}}{\partial x_{j,v}} \right)^2 + \frac{1}{2} b_{j,2,v}^2 \right). \quad (39)$$

Substituting (33)–(39) into (32) yields the following:

$$\begin{aligned} \dot{V}_{i,2} &\leq \dot{V}_{i,1} + z_{i,2}(z_{i,3} + \alpha_{i,2} - \mathcal{R}_1) + \frac{1}{2} z_{i,2}^2 + \frac{1}{2} \sum_{g=1}^2 \mathfrak{J}_{i,2,g}^2(x_{i,g}(\tau_{i,2})) + \frac{b_{i,2,2}^2}{2} + \frac{z_{i,2}^2 \sigma_{i,2}^2(\bar{x}_{i,2})}{2b_{i,2,2}^2} \\ &\quad + \frac{z_{i,2}^2}{2} \left(\frac{\partial \alpha_{i,1}}{\partial x_{i,1}} \right)^2 + \frac{1}{2} \mathfrak{J}_{i,1,1}^2(x_{i,1}(\tau_{i,1})) + \frac{z_{i,2}^2 \sigma_{i,1}^2}{2b_{i,2,1}^2} + \frac{1}{2} b_{i,2,1}^2 + \sum_{j \in N_i} \sum_{v=1}^2 \left(\frac{z_{i,2}^2}{2} \left(\frac{\partial \alpha_{i,1}}{\partial x_{j,v}} \right)^2 \right. \\ &\quad \left. + \frac{1}{2} \sum_{g=1}^v \mathfrak{J}_{j,v,g}^2(x_{j,g}(\tau_{j,v})) \right) + \sum_{j \in N_i} \sum_{v=1}^2 \left(\frac{z_{i,2}^2 \sigma_{j,v}^2}{2b_{j,2,v}^2} \left(\frac{\partial \alpha_{i,1}}{\partial x_{j,v}} \right)^2 + \frac{1}{2} b_{j,2,v}^2 \right) \\ &\quad + \frac{1}{2} \sum_{v=1}^2 \sum_{h=1}^v [\mathfrak{J}_{i,v,g}^2(x_{i,g}(t)) - \mathfrak{J}_{i,v,g}^2(x_{i,g}(\tau_{i,v}))] \\ &\quad + \frac{1}{2} \sum_{j \in N_i} \sum_{v=1}^2 \sum_{g=1}^v [\mathfrak{J}_{j,v,g}^2(x_{j,g}(t)) - \mathfrak{J}_{j,v,g}^2(x_{j,g}(\tau_{i,v}))] \\ &= \dot{V}_{i,1} + z_{i,2}(z_{i,3} + \alpha_{i,2} + \mathcal{F}_{i,2}) + \frac{1}{2} z_{i,2}^2 + \frac{b_{i,2,2}^2}{2} + \frac{1}{2} b_{i,2,1}^2 + \sum_{j \in N_i} \sum_{v=1}^2 \frac{1}{2} b_{j,2,v}^2 \\ &\quad + \frac{1}{2} \sum_{v=1}^2 \sum_{g=1}^v \mathfrak{J}_{i,v,g}^2(x_{i,g}(t)) + \frac{1}{2} \sum_{j \in N_i} \sum_{v=1}^2 \sum_{g=1}^v \mathfrak{J}_{j,v,g}^2(x_{j,g}(t)) \\ \text{where } \mathcal{F}_{i,2} &= \frac{z_{i,2} \sigma_{i,2}^2(\bar{x}_{i,2})}{2b_{i,2,2}^2} + \frac{z_{i,2}}{2} \left(\frac{\partial \alpha_{i,1}}{\partial x_{i,1}} \right)^2 + \sum_{j \in N_i} \sum_{v=1}^2 \left(\frac{z_{i,2}}{2} \left(\frac{\partial \alpha_{i,1}}{\partial x_{j,v}} \right)^2 + \frac{z_{i,2} \sigma_{j,k}^2}{2b_{j,2,v}^2} \left(\frac{\partial \alpha_{i,1}}{\partial x_{j,v}} \right)^2 \right) + \\ &\quad \frac{z_{i,2} \sigma_{i,1}^2}{2b_{i,2,1}^2} - \mathcal{R}_1. \end{aligned} \quad (40)$$

According to Lemma 6, we have the following:

$$\mathcal{F}_{i,2} = \Lambda_{i,2}^T \Xi_{i,2} + \varepsilon_{i,2}, \quad (41)$$

where $|\varepsilon_{i,2}| \leq \mathfrak{g}_{i,2}$ and $\mathfrak{g}_{i,2} > 0$.

Similar to (27), one has

$$z_{i,2} \mathcal{F}_{i,2} \leq |z_{i,2}| (\|\Lambda_{i,2}\| \|\Xi_{i,2}\| + \mathfrak{g}_{i,2}) \leq \frac{z_{i,2}^2}{2c_{i,2}^2} \|\Lambda_{i,2}\|^2 \Xi_{i,2}^T \Xi_{i,2} + \frac{1}{2} c_{i,2}^2 + \frac{z_{i,2}^2}{2} + \frac{1}{2} \mathfrak{g}_{i,2}^2, \quad (42)$$

where $c_{i,2}$ is a positive parameter.

Similar to (29), $\alpha_{i,2}$ can be designed as follows:

$$\alpha_{i,2} = -\vartheta_{i,2} z_{i,2}^{2\rho_1-1} - \nu_{i,2} z_{i,2}^{2\rho_2-1} - z_{i,2} + (p_i + q_i) z_{i,1} - \frac{z_{i,2}}{2c_{i,2}^2} \hat{\theta}_i \Xi_{i,2}^T \Xi_{i,2}. \quad (43)$$

Substituting (41)–(43) into (40) yields the following:

$$\begin{aligned} \dot{V}_{i,2} &\leq - \sum_{m=1}^2 \vartheta_{i,m} z_{i,m}^{2\rho_1} - \sum_{m=1}^2 \nu_{i,m} z_{i,m}^{2\rho_2} + z_{i,2} z_{i,3} + \sum_{m=1}^2 \frac{z_{i,m}^2}{2c_{i,m}^2} (\|\Lambda_{i,m}\|^2 - \hat{\theta}_i) S_{i,2}^T S_{i,2} \\ &\quad + \frac{1}{2} \sum_{m=1}^2 \sum_{v=1}^m \sum_{g=1}^k \left(\mathfrak{J}_{i,v,g}^2(x_{i,g}(t)) + \sum_{j \in N_i} \mathfrak{J}_{j,v,g}^2(x_{j,g}(t)) \right) + \frac{1}{2} \sum_{m=1}^2 (c_{i,m}^2 + \mathfrak{g}_{i,m}^2) \\ &\quad + \frac{1}{2} \sum_{v=1}^2 \sum_{g=1}^v \left(b_{i,v,g}^2 + \sum_{j \in N_i} b_{j,v,g}^2 \right). \end{aligned} \quad (44)$$

Step i, r ($r = 3, \dots, n_i - 1$): Design the Lyapunov function as follows:

$$V_{i,r} = V_{i,r-1} + \frac{1}{2} z_{i,r}^2 + \frac{1}{2} \sum_{v=1}^r \sum_{g=1}^v \int_{t-\tau_{i,v}}^t \mathfrak{J}_{i,v,g}^2(x_{i,g}(s)) ds + \frac{1}{2} \sum_{j \in N_i} \sum_{v=1}^r \sum_{g=1}^v \int_{t-\tau_{j,v}}^t \mathfrak{J}_{j,v,g}^2(x_{j,g}(s)) ds. \quad (45)$$

Similar to (43), we have

$$\alpha_{i,r} = -\vartheta_{i,r} z_{i,r}^{2\rho_1-1} - \nu_{i,r} z_{i,r}^{2\rho_2-1} - z_{i,r} - z_{i,r-1} - \frac{z_{i,r}}{2c_{i,r}^2} \hat{\theta}_i \Xi_{i,r}^T \Xi_{i,r}. \quad (46)$$

Then, the following inequality can be obtained:

$$\begin{aligned} \dot{V}_{i,r} \leq & - \sum_{m=1}^r \vartheta_{i,m} z_{i,m}^{2\rho_1} - \sum_{m=1}^r \nu_{i,m} z_{i,m}^{2\rho_2} + z_{i,r} z_{i,r+1} + \sum_{m=1}^r \frac{z_{i,m}^2}{2c_{i,m}^2} (\|\Lambda_{i,m}\|^2 - \hat{\theta}_i) \Xi_{i,m}^T \Xi_{i,m} \\ & + \frac{1}{2} \sum_{m=1}^r \sum_{v=1}^m \sum_{g=1}^v \left(\mathfrak{J}_{i,v,g}^2(x_{i,g}(t)) + \sum_{j \in N_i} \mathfrak{J}_{j,v,g}^2(x_{j,g}(t)) \right) + \frac{1}{2} \sum_{m=2}^r (c_{i,m}^2 + \mathfrak{g}_{i,m}^2) \\ & + \frac{1}{2} \sum_{v=1}^r \sum_{g=1}^v \left(b_{i,v,g}^2 + \sum_{j \in N_i} b_{j,v,g}^2 \right). \end{aligned} \quad (47)$$

Step i, n_i : The Lyapunov function can be constructed as follows:

$$\begin{aligned} V_{i,n_i} = & V_{i,n_i-1} + \frac{1}{2} \sum_{v=1}^{n_i} \sum_{g=1}^v \int_{t-\tau_{i,v}}^t \mathfrak{J}_{i,v,g}^2(x_{i,g}(s)) ds + \frac{1}{2} \sum_{j \in N_i} \sum_{v=1}^{n_i} \sum_{g=1}^v \int_{t-\tau_{j,v}}^t \mathfrak{J}_{j,v,g}^2(x_{j,g}(s)) ds \\ & + \frac{1}{2} \hat{\theta}_i^2 + \frac{1}{2} z_{i,n_i}^2. \end{aligned} \quad (48)$$

The time derivative of the above function is as follows:

$$\begin{aligned} \dot{V}_{i,n_i} = & \dot{V}_{i,n_i-1} + z_{i,n_i} (u_i + \mathfrak{L}_{i,n_i}(\bar{x}_{i,n_i}(\tau_{i,n_i})) + \mathfrak{d}_{i,n_i}(\bar{x}_{i,n_i}) - \dot{\alpha}_{i,n_i-1}) - \tilde{\theta}_i \dot{\hat{\theta}}_i \\ & + \frac{1}{2} \sum_{v=1}^{n_i} \sum_{g=1}^v (\mathfrak{J}_{i,v,g}^2(x_{i,g}(t)) \mathfrak{J}_{i,v,g}^2(x_{i,g}(\tau_{i,v}))) + \frac{1}{2} \sum_{j \in N_i} \sum_{v=1}^2 \sum_{g=1}^{n_i} (\mathfrak{J}_{j,v,g}^2(x_{j,g}(t)) \\ & - \sum_{j \in N_i} \mathfrak{J}_{j,v,g}^2(x_{j,g}(\tau_{i,v}))). \end{aligned} \quad (49)$$

Combining Lemma 5, we have the following inequalities:

$$z_{i,n_i} \mathfrak{L}_{i,n_i}(\bar{x}_{i,n_i}(\tau_{i,n_i})) \leq \frac{z_{i,n_i}^2}{2} + \frac{1}{2} \sum_{g=1}^{n_i} \mathfrak{J}_{i,n_i,g}^2(x_{i,n_i}(\tau_{i,n_i})), \quad (50)$$

$$z_{i,n_i} \mathfrak{d}_{i,n_i}(\bar{x}_{i,n_i}) \leq \frac{b_{i,n_i,n_i}^2}{2} + \frac{z_{i,n_i}^2 \sigma_{i,n_i}^2(\bar{x}_{i,n_i})}{2b_{i,n_i,n_i}^2}, \quad (51)$$

where b_{i,n_i,n_i} is a positive constant.

The derivative of α_{i,n_i-1} is as follows:

$$\begin{aligned} \dot{\alpha}_{i,n_i-1} = & \mathcal{R}_{n_i-1} + \sum_{v=1}^{n_i-1} \frac{\partial \alpha_{i,n_i-1}}{\partial x_{i,v}} (\mathfrak{L}_{i,v}(\bar{x}_{i,v}(\tau_{i,v})) + \mathfrak{d}_{i,v}(\bar{x}_{i,v})) + \sum_{v=1}^{n_i} \sum_{j \in N_i} \frac{\partial \alpha_{i,n_i-1}}{\partial x_{j,v}} (\mathfrak{L}_{j,v}(\bar{x}_{j,v}(\tau_{j,v})) \\ & + \mathfrak{d}_{j,v}(\bar{x}_{j,v})), \end{aligned} \quad (52)$$

$$\text{where } \mathcal{R}_{n_i-1} = \sum_{v=1}^{n_i-1} \frac{\partial \alpha_{i,n_i-1}}{\partial x_{i,v}} x_{i,v+1} + \sum_{v=1}^{n_i} \sum_{j \in N_i} \frac{\partial \alpha_{i,n_i-1}}{\partial x_{j,v}} x_{j,v+1} + \sum_{v=0}^{n_i-1} \frac{\partial \alpha_{i,n_i-1}}{\partial y_0^{(v)}} y_0^{(v+1)} + \frac{\partial \alpha_{i,n_i-1}}{\partial \hat{\theta}_i} \dot{\hat{\theta}}_i.$$

According to Lemma 5, one has

$$-\sum_{k=1}^{n_i-1} z_{i,n_i} \frac{\partial \alpha_{i,n_i-1}}{\partial x_{i,v}} \mathfrak{L}_{i,v}(\bar{x}_{i,v}(\tau_{i,v})) \leq \sum_{v=1}^{n_i-1} \left(\frac{z_{i,n_i}^2}{2} \left(\frac{\partial \alpha_{i,n_i-1}}{\partial x_{i,v}} \right)^2 + \frac{1}{2} \sum_{g=1}^v \mathfrak{I}_{i,v,g}^2(\bar{x}_{i,v}(\tau_{i,v})) \right), \quad (53)$$

$$-\sum_{v=1}^{n_i-1} z_{i,n_i} \frac{\partial \alpha_{i,n_i-1}}{\partial x_{i,v}} \mathfrak{d}_{i,v}(\bar{x}_{i,v}) \leq \sum_{v=1}^{n_i-1} \left(\frac{z_{i,n_i}^2 \sigma_{i,v}^2}{2b_{i,n_i,v}^2} + \frac{1}{2} b_{i,n_i,v}^2 \right), \quad (54)$$

$$-\sum_{j \in N_i} \sum_{v=1}^{n_i} z_{i,n_i} \frac{\partial \alpha_{i,n_i-1}}{\partial x_{j,v}} \mathfrak{L}_{j,v}(\bar{x}_{j,v}(\tau_{j,v})) \leq \sum_{j \in N_i} \sum_{v=1}^{n_i} \left(\frac{z_{i,n_i}^2}{2} \left(\frac{\partial \alpha_{i,n_i-1}}{\partial x_{j,v}} \right)^2 + \frac{1}{2} \sum_{g=1}^v \mathfrak{I}_{j,v,g}^2(\bar{x}_{j,g}(\tau_{j,v})) \right), \quad (55)$$

$$-\sum_{j \in N_i} \sum_{v=1}^2 z_{i,n_i} \frac{\partial \alpha_{i,n_i-1}}{\partial x_{j,v}} \mathfrak{d}_{j,v}(\bar{x}_{j,v}) \leq \sum_{j \in N_i} \sum_{v=1}^{n_i} \left(\frac{z_{i,n_i}^2 \sigma_{j,v}^2}{2b_{j,n_i,k}^2} \left(\frac{\partial \alpha_{i,n_i-1}}{\partial x_{j,v}} \right)^2 + \frac{1}{2} b_{j,n_i,v}^2 \right). \quad (56)$$

Substituting (50)–(56) into (49), the following inequality can be obtained:

$$\begin{aligned} \dot{V}_{i,n_i} \leq & \dot{V}_{i,n_i-1} + z_{i,n_i} (u_i(t) + \mathcal{F}_{i,n_i}) - \tilde{\theta}_i \dot{\hat{\theta}}_i + \frac{1}{2} z_{i,n_i}^2 + \frac{b_{i,n_i,n_i}^2}{2} + \frac{1}{2} \sum_{v=1}^{n_i-1} b_{i,n_i,v}^2 + \sum_{j \in N_i} \sum_{v=1}^{n_i} \frac{1}{2} b_{j,n_i,v}^2 \\ & + \frac{1}{2} \sum_{v=1}^{n_i} \sum_{g=1}^v \mathfrak{I}_{i,v,g}^2(x_{i,g}(t)) + \frac{1}{2} \sum_{j \in N_i} \sum_{v=1}^{n_i} \sum_{g=1}^v \mathfrak{I}_{j,v,g}^2(x_{j,g}(t)), \end{aligned} \quad (57)$$

$$\begin{aligned} \text{where } \mathcal{F}_{i,n_i} = & \frac{z_{i,n_i} \sigma_{i,n_i}^2(\bar{x}_{i,n_i})}{2b_{i,n_i,n_i}^2} + \sum_{j \in N_i} \sum_{v=1}^{n_i} \left(\frac{z_{i,n_i}^2}{2} \left(\frac{\partial \alpha_{i,n_i-1}}{\partial x_{j,v}} \right)^2 + \frac{z_{i,n_i} \sigma_{j,v}^2}{2b_{j,n_i,v}^2} \left(\frac{\partial \alpha_{i,n_i-1}}{\partial x_{j,v}} \right)^2 \right) + \\ & \sum_{v=1}^{n_i-1} \frac{z_{i,n_i}}{2} \left(\frac{\partial \alpha_{i,n_i-1}}{\partial x_{i,v}} \right)^2 \sum_{v=1}^{n_i-1} \frac{z_{i,n_i} \sigma_{i,v}^2}{2b_{i,n_i,v}^2} - \mathcal{R}_{n_i-1}. \end{aligned}$$

According to Lemma 6, we can obtain the following:

$$\mathcal{F}_{i,n_i} = \Lambda_{i,n_i}^T \Xi_{i,n_i} + \varepsilon_{i,n_i}, \quad (58)$$

where $|\varepsilon_{i,n_i}| \leq \mathfrak{g}_{i,n_i}$ and $\mathfrak{g}_{i,n_i} > 0$.

Based on Lemma 5, we have

$$z_{i,n_i} \mathcal{F}_{i,n_i} \leq |z_{i,n_i}| (\|\Lambda_{i,n_i}\| \|\Xi_{i,n_i}\| + \mathfrak{g}_{i,n_i}) \leq \frac{z_{i,n_i}^2}{2c_{i,n_i}^2} \|\Lambda_{i,n_i}\|^2 \Xi_{i,n_i}^T \Xi_{i,n_i} + \frac{1}{2} c_{i,n_i}^2 + \frac{z_{i,n_i}^2}{2} + \frac{1}{2} \mathfrak{g}_{i,n_i}^2, \quad (59)$$

where c_{i,n_i} is a designed parameter.

Construct the virtual control law α_{i,n_i} as follows:

$$\alpha_{i,n_i} = -\vartheta_{i,n_i} z_{i,n_i}^{2\rho_1-1} - \nu_{i,n_i} z_{i,n_i}^{2\rho_2-1} - z_{i,n_i} - z_{i,n_i-1} - \frac{z_{i,n_i}}{2c_{i,n_i}^2} \hat{\theta}_i \Xi_{i,n_i}^T \Xi_{i,n_i}. \quad (60)$$

Substituting (58)–(60) into (57), one has

$$\begin{aligned} \dot{V}_{i,n_i} \leq & -\sum_{m=1}^{n_i} \vartheta_{i,m} z_{i,m}^{2\rho_1} - \sum_{m=1}^{n_i} \nu_{i,m} z_{i,m}^{2\rho_2} - \tilde{\theta}_i \dot{\hat{\theta}}_i + \sum_{m=1}^{n_i} \frac{z_{i,m}^2}{2c_{i,m}^2} (\|\Lambda_{i,m}\|^2 - \hat{\theta}_i) S_{i,2}^T S_{i,2} \\ & + \frac{1}{2} \sum_{m=1}^{n_i} \sum_{k=1}^m \sum_{g=1}^v \left(\mathfrak{I}_{i,v,g}^2(x_{i,g}(t)) + \sum_{j \in N_i} \mathfrak{I}_{j,v,g}^2(x_{j,g}(t)) \right) + z_{i,n_i} (u_i(t) - \alpha_{i,n_i}) \\ & + \frac{1}{2} \sum_{m=1}^{n_i} (c_{i,m}^2 + \mathfrak{g}_{i,m}^2) + \frac{1}{2} \sum_{v=1}^{n_i} \sum_{g=1}^v \left(b_{i,v,g}^2 + \sum_{j \in N_i} b_{j,v,g}^2 \right). \end{aligned} \quad (61)$$

The parameter updating law $\hat{\theta}_i$ can be constructed as follows:

$$\dot{\hat{\theta}}_i = -\lambda_i \hat{\theta}_i + \sum_{m=1}^{n_i} \frac{z_{i,m}^2}{2c_{i,m}^2 h_{i,j}^2} \Xi_{i,m}^T \Xi_{i,m}, \quad (62)$$

where λ_i is a designed parameter.

Based on Lemma 5, we have the following:

$$\begin{aligned} \sum_{j=1}^{n_i} \frac{z_{i,j}^2}{2c_{i,j}^2 h_{i,j}^2} (\|\Lambda_{i,j}\|^2 - \hat{\theta}_i) \Xi_{i,j}^T \Xi_{i,j} - \tilde{\theta}_i \dot{\hat{\theta}}_i &= \sum_{j=1}^{n_i} \frac{z_{i,j}^2}{2c_{i,j}^2 h_{i,j}^2} (\|\Lambda_{i,j}\|^2 - \hat{\theta}_i) \Xi_{i,j}^T \Xi_{i,j} \\ &\quad - \sum_{j=1}^{n_i} \frac{z_{i,j}^2}{2c_{i,j}^2 h_{i,j}^2} \tilde{\theta}_i \Xi_{i,j}^T \Xi_{i,j} + \lambda_i \tilde{\theta}_i \hat{\theta}_i \leq \lambda_i \tilde{\theta}_i \hat{\theta}_i. \end{aligned} \quad (63)$$

Substituting (62)–(63) into (61), we have the following:

$$\begin{aligned} \dot{V}_{i,n_i} &\leq - \sum_{m=1}^{n_i} \vartheta_{i,m} z_{i,m}^{2\rho_1} - \sum_{m=1}^{n_i} \nu_{i,m} z_{i,m}^{2\rho_2} + \frac{1}{2} \sum_{m=1}^{n_i} \sum_{v=1}^m \sum_{g=1}^v \left(\mathcal{J}_{i,v,g}^2(x_{i,g}(t)) + \sum_{j \in N_i} \mathcal{J}_{j,v,g}^2(x_{j,g}(t)) \right) \\ &\quad + \lambda_i \tilde{\theta}_i \hat{\theta}_i + z_{i,n_i}(u_i(t) - \alpha_{i,n_i}) + \frac{1}{2} \sum_{m=1}^{n_i} (c_{i,m}^2 + \mathfrak{g}_{i,m}^2) + \frac{1}{2} \sum_{v=1}^{n_i} \sum_{g=1}^v \left(b_{i,v,g}^2 + \sum_{j \in N_i} b_{j,v,g}^2 \right). \end{aligned} \quad (64)$$

Based on the proposed ETM (15), controller $\Psi_i(t)$ can be designed as follows:

$$\Psi_i(t) = -(1 + \gamma_i) \left[\alpha_{i,n_i} \tanh\left(\frac{z_{i,n_i} \alpha_{i,n_i}}{\mu_i}\right) + \bar{\eta}_i \tanh\left(\frac{\bar{\eta}_i z_{i,n_i}}{\mu_i}\right) \right]. \quad (65)$$

Invoking (17), (65), and Lemma 4, $z_{i,n_i}(u_i - \alpha_{i,n_i})$ in (64) can be written as follows:

$$\begin{aligned} z_{i,n_i}(u_i - \alpha_{i,n_i}) &= z_{i,n_i} \left(\frac{\Psi_i(t)}{1 + \mathfrak{w}_1(t)\gamma_i} - \frac{\mathfrak{w}_2(t)\eta_i}{1 + \mathfrak{w}_1(t)\gamma_i} - \alpha_{i,n_i} \right) \leq \frac{z_{i,n_i} \Psi_i(t)}{1 + \mathfrak{w}_1(t)\gamma_i} + \frac{z_{i,n_i} \eta_i}{1 - \gamma_i} \\ &\quad - z_{i,n_i} \alpha_{i,n_i} \leq -z_{i,n_i} \alpha_{i,n_i} \tanh\left(\frac{z_{i,n_i} \alpha_{i,n_i}}{\mu_i}\right) - z_{i,n_i} \bar{\eta}_i \tanh\left(\frac{z_{i,n_i} \bar{\eta}_i}{\mu_i}\right) \\ &\quad + |z_{i,n_i} \bar{\eta}_i| + |z_{i,n_i} \alpha_{i,n_i}| \leq 0.557 \mu_i. \end{aligned} \quad (66)$$

Thus, it follows from (64) and (66) that

$$\begin{aligned} \dot{V}_{i,n_i} &\leq - \sum_{m=1}^{n_i} \vartheta_{i,m} z_{i,m}^{2\rho_1} - \sum_{m=1}^{n_i} \nu_{i,m} z_{i,m}^{2\rho_2} + \frac{1}{2} \sum_{m=1}^{n_i} \sum_{v=1}^m \sum_{g=1}^v \left(\mathcal{J}_{i,v,g}^2(x_{i,g}(t)) + \sum_{j \in N_i} \mathcal{J}_{j,v,g}^2(x_{j,g}(t)) \right) \\ &\quad + \lambda_i \tilde{\theta}_i \hat{\theta}_i + 0.557 \mu_i + \frac{1}{2} \sum_{m=1}^{n_i} (c_{i,m}^2 + \mathfrak{g}_{i,m}^2) + \frac{1}{2} \sum_{v=1}^{n_i} \sum_{g=1}^v \left(b_{i,v,g}^2 + \sum_{j \in N_i} b_{j,v,g}^2 \right). \end{aligned} \quad (67)$$

3.3. Fixed-Time Stability Analysis

Based on the above theoretical derivation, we have the following theorem.

Theorem 1. *Based on Assumptions 1–4, the high-order nonlinear multi-agent time delay system (11), governed by the controller (65) and event-triggered mechanism (15), can achieve semiglobal practical fixed-time stability. In addition, there exists a minimum time interval $t_{\min}$ between the triggering instance; thus, Zeno behavior will be avoided.*

Proof. According to Lemma 2, one can obtain the following:

$$\lambda_i \tilde{\theta}_i \hat{\theta}_i = \lambda_i (\theta_i - \hat{\theta}_i) \hat{\theta}_i = \lambda_i (\theta_i \hat{\theta}_i - \hat{\theta}_i^2) \leq \frac{1}{2} \lambda_i \theta_i^2 - \frac{1}{2} \lambda_i \tilde{\theta}_i^2. \quad (68)$$

According to Lemma 5, we have the following inequality:

$$-\tilde{\theta}_i^2 \leq -\left(\frac{1}{2} \tilde{\theta}_i^2\right)^{\rho_1} - \left(\frac{1}{2} \tilde{\theta}_i^2\right)^{\rho_2} + (1 - \rho_1) \rho_1^{\frac{\rho_1}{1-\rho_1}}. \quad (69)$$

The Lyapunov function of system (11) can be chosen as follows:

$$V_i(t) = V_{i,n_i}(t). \quad (70)$$

Then, the derivative of (70) can be obtained:

$$\begin{aligned} \dot{V}_i(t) \leq & - \sum_{m=1}^{n_i} \vartheta_{i,m} z_{i,m}^{2\rho_1} - \sum_{m=1}^{n_i} v_{i,m} z_{i,m}^{2\rho_2} + \frac{1}{2} \sum_{m=1}^{n_i} \sum_{v=1}^m \sum_{g=1}^v \left(\mathfrak{I}_{i,v,g}^2(x_{i,v}(t)) + \sum_{j \in N_i} \mathfrak{I}_{j,v,g}^2(x_{j,g}(t)) \right) \\ & + \lambda_i \tilde{\theta}_i \hat{\theta}_i + 0.557\mu_i + \frac{1}{2} \sum_{m=1}^{n_i} (c_{i,m}^2 + \mathfrak{g}_{i,m}^2) + \frac{1}{2} \sum_{v=1}^{n_i} \sum_{g=1}^v \left(b_{i,v,g}^2 + \sum_{j \in N_i} b_{j,v,g}^2 \right). \end{aligned} \quad (71)$$

Combining (68) and (69), we can obtain the following:

$$\begin{aligned} \dot{V}_i(t) \leq & - \sum_{m=1}^{n_i} \vartheta_{i,m} z_{i,m}^{2\rho_1} - \sum_{m=1}^{n_i} v_{i,m} z_{i,m}^{2\rho_2} + \frac{1}{2} \sum_{m=1}^{n_i} \sum_{v=1}^m \sum_{g=1}^v \left(\mathfrak{I}_{i,v,g}^2(x_{i,g}(t)) + \sum_{j \in N_i} \mathfrak{I}_{j,v,g}^2(x_{j,g}(t)) \right) \\ & + 0.557\mu_i + \frac{1}{2} \lambda_i \theta_i^2 + \frac{1}{2} \sum_{m=1}^{n_i} (c_{i,m}^2 + \mathfrak{g}_{i,m}^2) + \frac{1}{2} \sum_{v=1}^{n_i} \sum_{g=1}^v \left(b_{i,v,g}^2 + \sum_{j \in N_i} b_{j,v,g}^2 \right) \\ & - \frac{1}{2} \lambda_i \left(\frac{1}{2} \tilde{\theta}_i^2 \right)^{\rho_1} - \frac{1}{2} \lambda_i \left(\frac{1}{2} \tilde{\theta}_i^2 \right)^{\rho_2} + \frac{\lambda_i}{2} (1 - \rho_1) \rho_1^{\frac{\rho_1}{1-\rho_1}} \\ \leq & - \mathfrak{T}_1 \left(\sum_{m=1}^{n_i} \frac{1}{2} z_{i,m}^2 \right)^{\rho_1} - \mathfrak{T}_2 \left(\sum_{m=1}^{n_i} \frac{1}{2} z_{i,m}^2 \right)^{\rho_2} - \frac{1}{2} \lambda_i \left(\frac{1}{2} \tilde{\theta}_i^2 \right)^{\rho_1} - \frac{1}{2} \lambda_i \left(\frac{1}{2} \tilde{\theta}_i^2 \right)^{\rho_2} + \mathfrak{A}, \end{aligned} \quad (72)$$

$$\begin{aligned} \text{where } & \frac{1}{2} \sum_{m=1}^{n_i} \sum_{v=1}^m \sum_{g=1}^v \left(\mathfrak{I}_{i,v,g}^2(x_{i,g}(t)) + \sum_{j \in N_i} \mathfrak{I}_{j,v,g}^2(x_{j,g}(t)) \right) + 0.557\mu_i + \frac{1}{2} \lambda_i \theta_i^2 + \frac{1}{2} \sum_{m=2}^{n_i} (c_{i,m}^2 + \mathfrak{g}_{i,m}^2) \\ & + \frac{1}{2} \sum_{v=1}^{n_i} \sum_{g=1}^v \left(b_{i,v,g}^2 + \sum_{j \in N_i} b_{j,v,g}^2 \right) + \frac{\lambda_i}{2} (1 - \rho_1) \rho_1^{\frac{\rho_1}{1-\rho_1}} \leq \mathfrak{A}, \text{ and } \mathfrak{A} \text{ is a positive constant.} \\ & \mathfrak{T}_1 = 2^{\rho_1} n_i^{1-\rho_1} \min\{\vartheta_{i,m}, m = 1, \dots, n_i\}, \mathfrak{T}_2 = 2^{\rho_2} n_i^{1-\rho_2} \min\{v_{i,m}, m = 1, \dots, n_i\}. \end{aligned}$$

According to Assumption 3, one has

$$\begin{aligned} \dot{V}_i(t) \leq & - \mathfrak{T}_3 \left(\sum_{m=1}^{n_i} \frac{1}{2} z_{i,m}^2 + \frac{1}{2} \tilde{\theta}_i^2 \right)^{\rho_1} - \mathfrak{T}_4 \left(\sum_{m=1}^{n_i} \frac{1}{2} z_{i,m}^2 + \frac{1}{2} \tilde{\theta}_i^2 \right)^{\rho_2} - \mathfrak{t}_1 \mathfrak{b}^{\rho_1} - \mathfrak{t}_2 \mathfrak{b}^{\rho_2} - \mathfrak{f}_1 \mathfrak{c}^{\rho_1} \\ & - \mathfrak{f}_2 \mathfrak{c}^{\rho_2} + \mathfrak{t}_1 \mathfrak{B}^{\rho_1} + \mathfrak{t}_2 \mathfrak{B}^{\rho_2} + \mathfrak{f}_1 \mathfrak{C}^{\rho_1} + \mathfrak{f}_2 \mathfrak{C}^{\rho_2} + \mathfrak{A} \\ \leq & - \mathfrak{p} \left(\sum_{m=1}^{n_i} \frac{1}{2} z_{i,m}^2 + \frac{1}{2} \tilde{\theta}_i^2 + \mathfrak{b} + \mathfrak{c} \right)^{\rho_1} - \mathfrak{q} \left(\sum_{m=1}^{n_i} \frac{1}{2} z_{i,m}^2 + \frac{1}{2} \tilde{\theta}_i^2 + \mathfrak{b} + \mathfrak{c} \right)^{\rho_2} + \mathfrak{x} \\ = & - \mathfrak{p} V^{\rho_1}(x) - \mathfrak{q} V^{\rho_2}(x) + \mathfrak{x}, \end{aligned} \quad (73)$$

$$\begin{aligned} \text{where } & \mathfrak{t}_1, \mathfrak{t}_2, \mathfrak{f}_1, \text{ and } \mathfrak{f}_2 \text{ are positive constants, } \mathfrak{T}_3 = 2^{1-\rho_1} \min\{\mathfrak{T}_1, \frac{1}{2} \lambda_i\}, \mathfrak{T}_4 = \min\{\mathfrak{T}_2, \frac{1}{2} \lambda_i\}, \\ & \mathfrak{T}_5 = 2^{1-\rho_1} \min\{\mathfrak{T}_3, \mathfrak{t}_1\}, \mathfrak{T}_6 = \min\{\mathfrak{T}_4, \mathfrak{t}_2\}, \mathfrak{p} = 2^{1-\rho_1} \min\{\mathfrak{T}_5, \mathfrak{f}_1\}, \mathfrak{q} = \min\{\mathfrak{T}_6, \mathfrak{f}_2\}, \text{ and} \\ & \mathfrak{x} = \mathfrak{t}_1 \mathfrak{B}^{\rho_1} + \mathfrak{t}_2 \mathfrak{B}^{\rho_2} + \mathfrak{f}_1 \mathfrak{C}^{\rho_1} + \mathfrak{f}_2 \mathfrak{C}^{\rho_2} + \mathfrak{A}. \end{aligned}$$

According to Lemma 1, we know that system (11) is SPFTS, and its settling time $\mathcal{T}_f$ is bound by $\mathcal{T}_{\max}$:

$$\mathcal{T}_f \leq \mathcal{T}_{\max} := \frac{1}{\mathfrak{p}\iota(1-\rho_1)} + \frac{1}{\mathfrak{q}\iota(\rho_2-1)}, \quad (74)$$

with $0 < \iota < 1$ as a positive parameter.

Next, we will prove that the event-triggered mechanism in Section 3.1 will not cause the Zeno phenomenon.

According to the designed event-triggered mechanism (15), we have

$$\mathfrak{e}_i(t) = \Psi_i(t) - \Psi_i(t_k). \quad (75)$$

Since $\Psi_i(t)$ is continuous, the following equation can be obtained:

$$\dot{\mathfrak{e}}_i(t) = \dot{\Psi}_i(t), \quad \forall t \in [t_k, t_{k+1}). \quad (76)$$

Further, one can obtain the following:

$$|\dot{\Psi}_i(t)| \leq \mathfrak{M} \quad \forall t \in [t_k, t_{k+1}), \quad (77)$$

where $\mathfrak{M} > 0$ is the upper bound.

According to the designed event-triggered mechanism, we have the following equations:

$$\mathfrak{e}_i(t_k) = 0, \quad (78)$$

$$|\mathfrak{e}_i(t_{k+1}^-)| = \gamma_i |\Psi_i(t_k)| + \eta_i \geq \eta_i. \quad (79)$$

Combining (76)–(79), we have the following:

$$|\dot{\mathfrak{e}}_i(t_k)| = \frac{|\mathfrak{e}_i(t_{k+1}^-) - \mathfrak{e}_i(t_k)|}{t_{k+1} - t_k} = \frac{\gamma_i |\Psi_i(t_k)| + \eta_i}{t_{k+1} - t_k} \leq \mathfrak{M} \quad (80)$$

From (80), we can obtain the following inequality:

$$t_{k+1} - t_k \geq \frac{\gamma_i |\Psi_i(t_k)| + \eta_i}{\mathfrak{M}} \geq \frac{\eta_i}{\mathfrak{M}}. \quad (81)$$

Let $t_{\min} \triangleq \frac{\eta_i}{\mathfrak{M}}$; hence, Zeno behavior is effectively avoided, i.e., $t_{k+1} - t_k \geq t_{\min}$ with $t_{\min} > 0$.

This completes the proof. $\square$

4. Simulation Results

Here, two representative examples are employed to validate the effectiveness of the designed control strategy.

4.1. Example 1

Consider the following nonlinear multi-agent system:

$$\begin{cases} \dot{x}_{i,1}(t) = x_{i,2}(t) + \mathfrak{L}_{i,1}(\bar{x}_{i,1}(t - \tau_{i,1})) + \mathfrak{d}_{i,1}(\bar{x}_{i,1}(t)), \\ \dot{x}_{i,2}(t) = x_{i,3}(t) + \mathfrak{L}_{i,2}(\bar{x}_{i,2}(t - \tau_{i,2})) + \mathfrak{d}_{i,2}(\bar{x}_{i,2}(t)), \\ \dot{x}_{i,3}(t) = u_i(t) + \mathfrak{L}_{i,3}(\bar{x}_{i,3}(t - \tau_{i,3})) + \mathfrak{d}_{i,3}(x_{i,3}(t)), \\ y_i = x_{i,1}, i = 1, 2. \end{cases}, \quad (82)$$

where $\mathfrak{L}_{i,1} = 0.6x_{i,1}(t - 0.1)$, $\mathfrak{L}_{i,2} = 0.4x_{i,2}(t - 0.03|\sin(t)|)$, $\mathfrak{L}_{i,3} = 0.2x_{i,1}(t - 0.1)\sin(x_{i,2}(t - 0.03|\sin(t)|) + x_{i,3}(t - 0.02|\cos(t)|))$, $\mathfrak{d}_{i,1} = 0.3\sin(x_{i,1})$, $\mathfrak{d}_{i,2} = 0.5\cos(x_{i,1} + x_{i,2})$, and $\mathfrak{d}_{i,3} = 0.8x_{i,1}x_{i,2} + \cos(x_{i,3})$.

The desired signal is $y_0 = 0.4\sin(0.5t) + 1.5\sin(t)$. The control parameters are chosen as $\gamma_1 = \gamma_2 = 0.5$, $\eta_1 = \eta_2 = 20$, $\bar{\eta} = 5$, $\vartheta_{1,1} = \vartheta_{2,1} = 15$, $\nu_{1,1} = \nu_{2,1} = 12$, $\vartheta_{1,2} = 14$, $\vartheta_{2,2} = 11$, $\nu_{1,2} = \nu_{2,2} = 13$, $\vartheta_{1,3} = 12$, $\vartheta_{2,3} = 15$, $\nu_{1,3} = 15$, $\nu_{2,3} = 18$, $\lambda_1 = 1$, $\lambda_2 = 3$, and $\rho_1 = 9/11$, $\rho_2 = 11/9$. The initial values of system states and tracking errors are set as $x_{1,1} = x_{2,1} = 0.01$, $x_{1,2} = 1.2$, $x_{1,3} = 2.5$, $x_{2,2} = 1.5$, $x_{2,3} = 3.3$, and $z_{i,j} = 0.5 (i = 1, 2; j = 1, 2, 3)$. The simulation step is selected as 0.01 s. The communication topology of the high-order nonlinear multi-agent system is designed as in Figure 2.

The radial basic functions are selected as $s_1(z_{i,j}) = \exp\left[-\frac{(z_{i,j}-1)^2}{0.5}\right]$, $s_2(z_{i,j}) = \exp\left[-\frac{(z_{i,j}-0.5)^2}{0.5}\right]$, $s_3(z_{i,j}) = \exp\left[-\frac{(z_{i,j}-0)^2}{0.5}\right]$, $s_4(z_{i,j}) = \exp\left[-\frac{(z_{i,j}+0.5)^2}{0.5}\right]$, and $s_5(z_{i,j}) = \exp\left[-\frac{(z_{i,j}+1)^2}{0.5}\right]$.

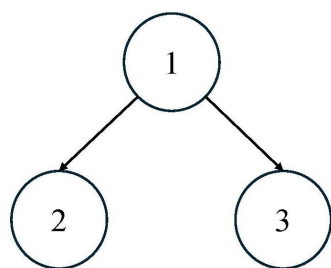


Figure 2. The topology of example 1.

The simulation results are shown in Figures 3–7.

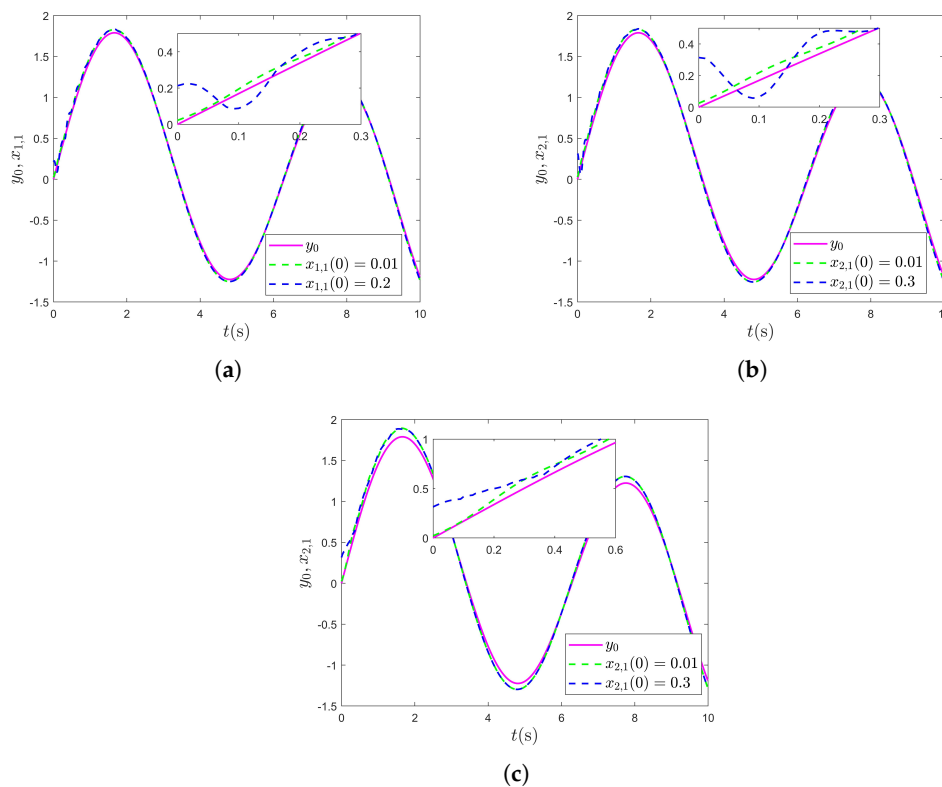


Figure 3. The output of the subsystems. (a) The output of subsystem 1; (b) the output of subsystem 2; (c) the output of subsystem 2 under asymptotic stability in reference [51].

Figure 3a–c shows the output of the two subsystems with different initial values, where Figure 3a,b is obtained under fixed-time control, while Figure 3c is executed by the asymptotically stable control in reference [51]. From Figure 3a,b, it can be observed that the system has satisfactory control performance for different initial values, and the convergence time is short (about 0.3 s). From Figure 3c, it is evident that the convergence time is relatively long and influenced by the initial values; the control performance is relatively poor as well. Through the above analysis, we know that the fixed-time control strategy has better control performance compared with the asymptotic stable control strategy, its convergence time is shorter, and it is not affected by the initial value, which is more favorable in practical applications.

Figure 4 displays both the actuator and control signals of the two subsystems. It can be observed that until the next triggering event, the system actuator signal u remains unchanged compared with the previous triggering moment. This demonstrates that the utilization of the ETM effectively preserves communication resources, which allows for more efficient utilization of communication resources in the system.

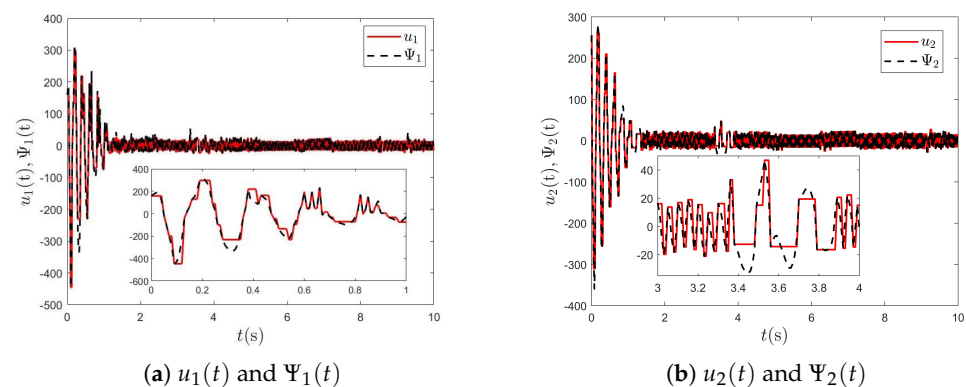


Figure 4. Actuator and control signals of the two subsystems.

Figure 5 illustrates the triggering interval between consecutive events of the two subsystems. The figure clearly demonstrates that the length of the triggering interval is nonuniform, with the majority of intervals being larger than the sampling interval (0.01 s). This observation further validates the effectiveness of event-triggered mechanisms in conserving communication resources.

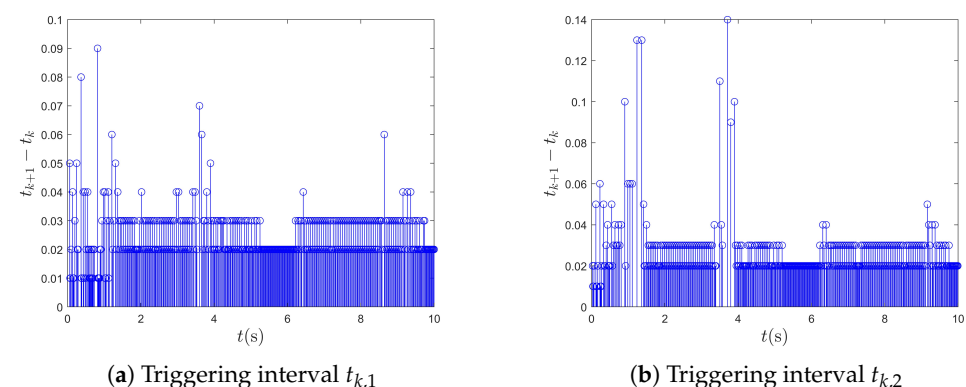


Figure 5. Triggering intervals of the two subsystems.

Figures 6 and 7 show system tracking errors under a time delay. It is observed that the system exhibits rapid fluctuations in tracking errors near the origin and converges to zero in a very short time, showing the effectiveness of the fixed-time control strategy. Also, the robustness of high-order multi-agent nonlinear systems to time delays under the Lyapunov–Krasovskii functional approach is validated.

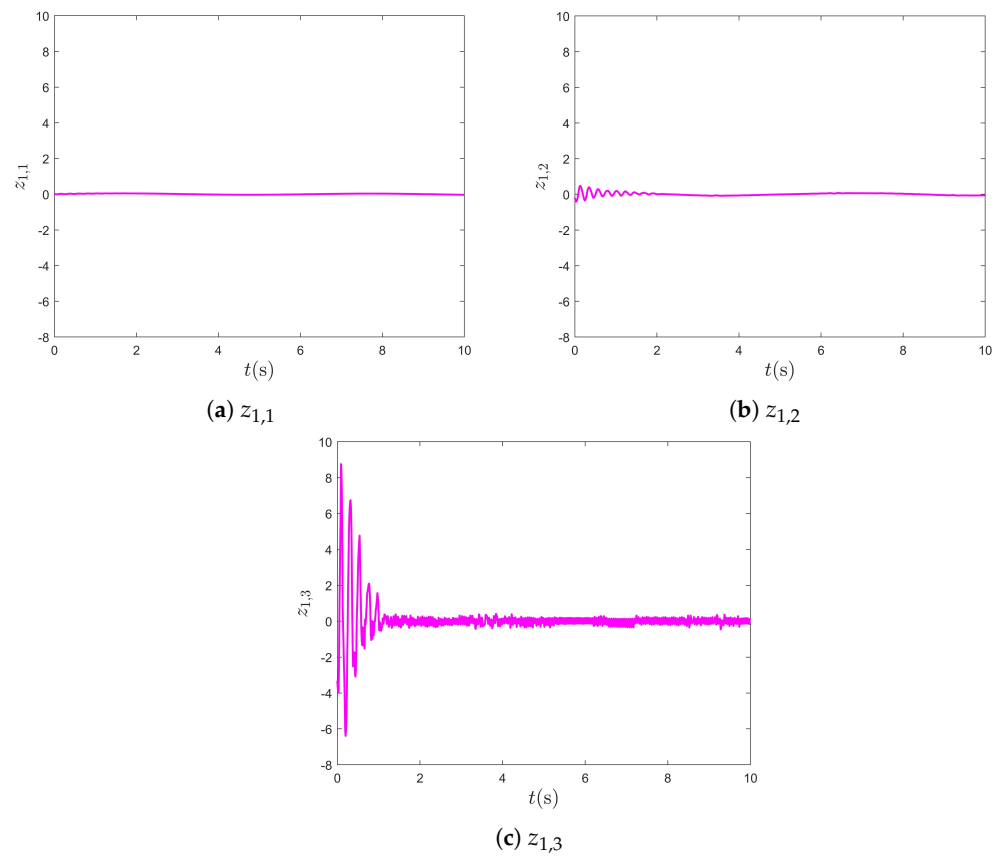


Figure 6. Tracking errors of subsystem 1.

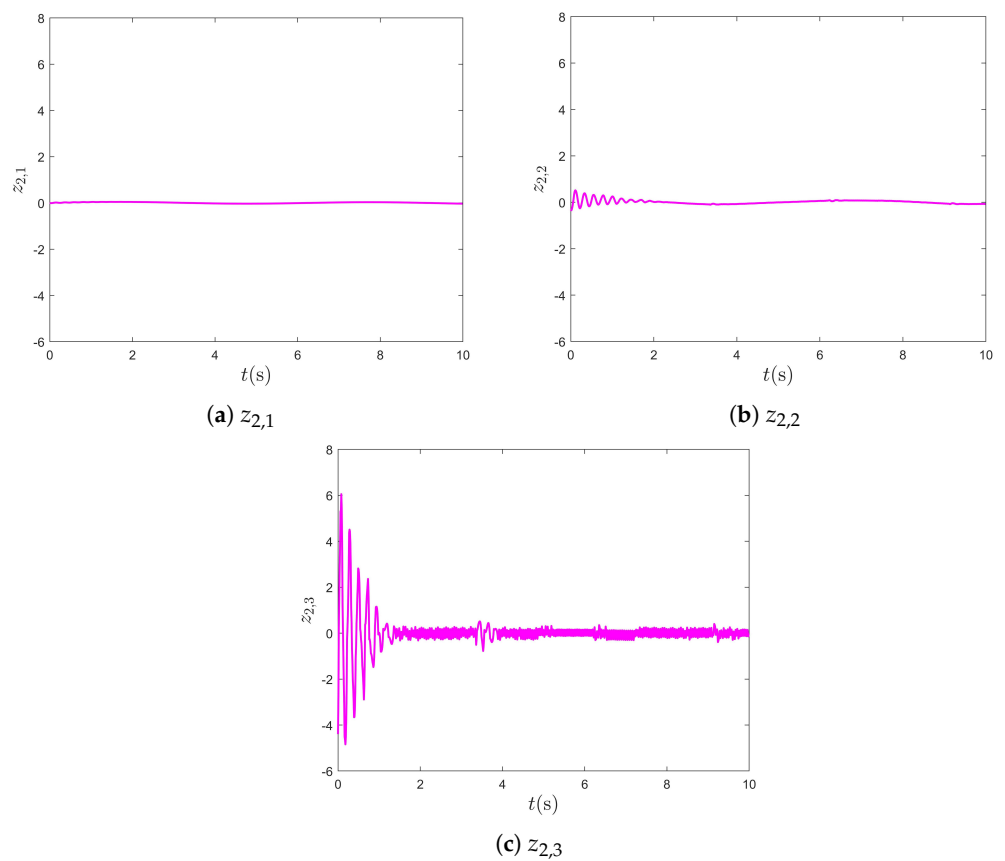


Figure 7. Tracking errors of subsystem 2.

In addition, a comparison with the time-triggered control approach for high-order nonlinear multi-agent systems in the literature [5] is conducted, and the results are listed in Table 1.

Table 1. Number of triggering events (NTE) and transmission percentages.

	Sampling Times	NET	Percentage
Sub1	1000	387	38.7%
Sub2	1000	216	21.6%
Literature [5]	1000	1000	100%

From Table 1, we can see that the number of triggering events (NTE) was significantly reduced under the event-triggered scheme, which saved lots of communication resources in the control of high-order nonlinear multi-agent systems.

From the above simulation results and analysis, it can be concluded that the controller designed in this paper demonstrates remarkable capability in maintaining stability and ensuring good control performance under unknown stochastic time delays, confirming the effectiveness of the designed controller.

4.2. Example 2

In this simulation, a vehicle platoon system is employed to showcase the superiority of the control scheme. The model of a vehicle platoon system with a time delay is illustrated as follows:

$$\begin{cases} \dot{p}_i = q_i(t - \tau_{i,1}), \\ \dot{q}_i = w_i(t - \tau_{i,2}), \\ \dot{w}_i = -\frac{1}{\chi_i} \left(\dot{q}_i + \frac{\xi_i A_i C_{d_i}}{2\mathcal{M}_i} q_i^2 + \frac{\kappa_i}{\mathcal{M}_i} \right) - \frac{\xi_i A_i C_{d_i} q_i(t - \tau_{i,1}) w_i(t - \tau_{i,2})}{\mathcal{M}_i} + \frac{1}{\chi_i \mathcal{M}_i} u_i, \end{cases} \quad 1 \leq i \leq 2. \quad (83)$$

where p_i , q_i , and w_i are the position, velocity, and acceleration of the i th vehicle, respectively. u_i is the control input of the i th vehicle's engine, with $u_i > 0$ representing the throttle input and $u_i < 0$ representing the brake input. ξ_i represents the specific mass of the air. For the i th vehicle, χ_i is the engine's time constant, $\mathcal{M}_i$ is the vehicle mass, A_i represents the cross-sectional area, C_{d_i} depicts the drag coefficient, $\frac{\xi_i A_i C_{d_i}}{2\mathcal{M}_i}$ is the air resistance, and κ_i displays the mechanical drag.

To better illustrate the simulation results, the velocity of the leader is taken as the desired signal:

$$q_0 = \begin{cases} 9.8 \sin\left(\frac{\pi t}{21}\right) & 0 \leq t < 9.5 \\ 9.8 & 9.5 \leq t \leq 50.5 \\ 9.8 \sin\left(\frac{\pi t}{21}\right) & 50.5 < t \leq 60 \end{cases} \quad (84)$$

The parameters are selected as $\xi_i = 1.3 \text{ kg/m}^3$, $\chi_i = 0.24$, $\mathcal{M}_i = 1460 \text{ kg}$, $A_i = 2.3 \text{ m}^2$, $C_{d_i} = 0.36$, and $\kappa_i = 5.1 \text{ N}$. The control parameters are chosen as $\gamma_1 = \gamma_2 = 0.5$, $\eta_1 = \eta_2 = 10$, $\bar{\eta} = 5$, $\vartheta_{1,1} = \vartheta_{2,1} = 15$, $v_{1,1} = v_{2,1} = 5$, $\vartheta_{1,2} = \vartheta_{2,2} = v_{1,2} = 15$, $v_{2,2} = 13$, $v_{1,3} = 12$, $v_{2,3} = v_{1,3} = 25$, $v_{2,3} = 15$, $\lambda_1 = 1$, $\lambda_2 = 3$, and $\rho_1 = 9/11$, $\rho_2 = 11/9$. The initial values of system's states and tracking errors are set as $p_1 = 39.98$, $q_1 = 0.05$, $w_1 = 3.5$, $p_2 = 29.98$, $q_2 = 0.05$, $w_2 = 2.6$, and $z_{i,j} = 0.5 (i = 1, 2; j = 1, 2, 3)$. The stochastic time delays are set as $\tau_{i,1} = 0.05$ and $\tau_{i,2} = 0.01|\cos(t)|$. The simulation step is selected as 0.01 s. The communication topology of the vehicle platoon system is designed as in Figure 8.

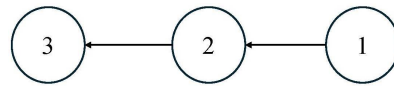


Figure 8. The topology of Example 2.

Figure 9 displays the states of the vehicle platoon. A closer analysis of the figure indicates that each vehicle smoothly transitioned through three stages: acceleration, cruising, and deceleration. Importantly, the follower vehicle showcases its impressive ability to accurately follow the leader and maintain the pre-defined distance between the vehicles, which highlights the performance of the entire platoon system under a time delay.

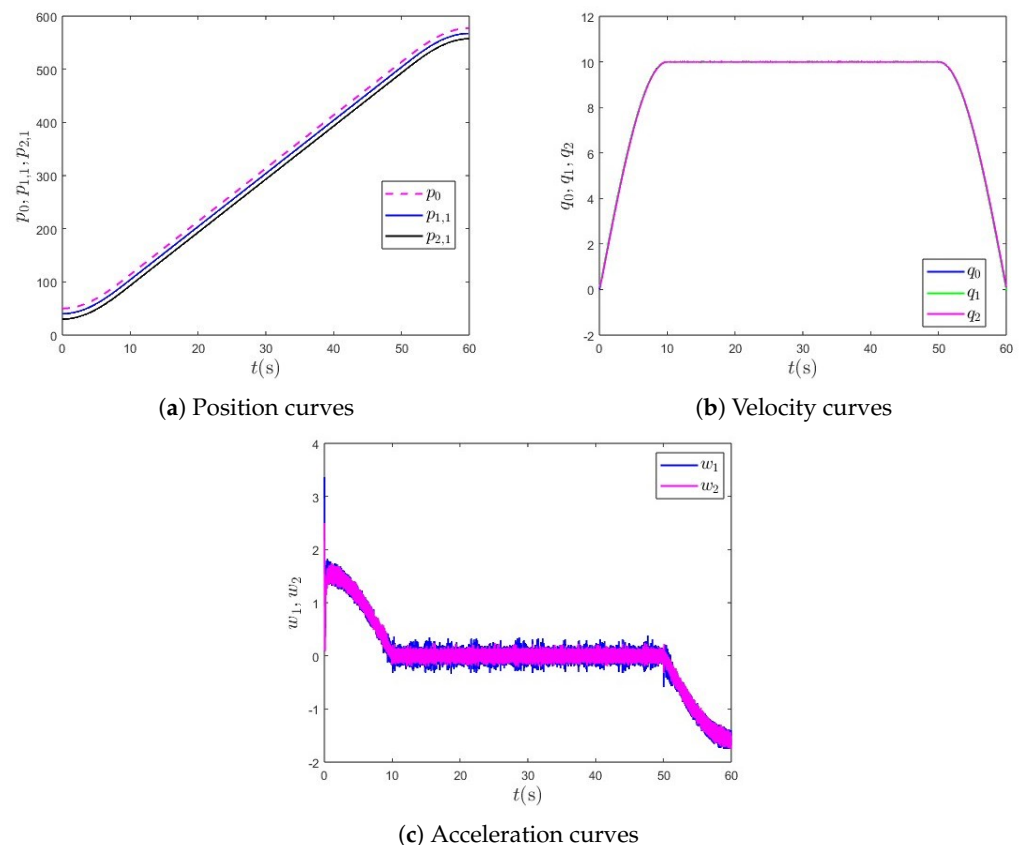


Figure 9. The states of the vehicle platoon.

Figure 10 shows the actuator and control signals of two followers. It is clear that the control signal $\Psi(t)$ is continuous while the actuator signal $u(t)$ is discrete. The actuator signal $u(t)$ remains unchanged until the next triggering moment, which conserves sufficient communication resources compared to the time-triggered approach.

Similar to Figure 5, Figure 11 represents the time intervals for the ETM. It is observed that the majority of triggering intervals are larger than the sampling time of 0.01 s. This finding serves as evidence for the resource-saving capability of the ETM.

Figures 12 and 13 illustrate the tracking errors of two follower vehicles, both displaying fluctuations near the origin. This consistent behavior reinforces the significant control performance achieved by the entire vehicle platoon system in the presence of a time delay.

To further illustrate the effectiveness of the proposed event-triggered method in saving communication resources, a comparison with the literature [3] is performed, and the results are listed in Table 2.

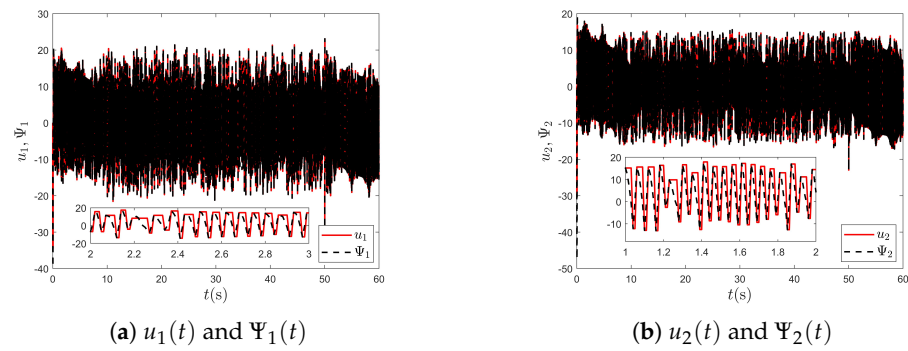


Figure 10. Actuator and control signals of the followers.

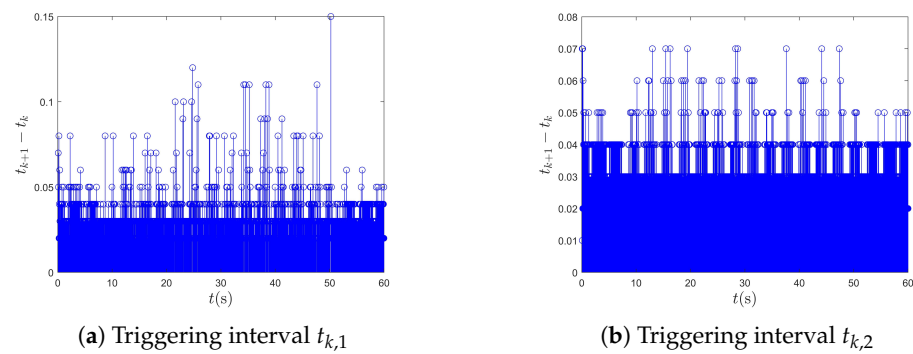


Figure 11. Triggering intervals of the followers.

Table 2. Number of triggering events (NTE) and transmission percentages.

	Sampling Times	NET	Percentage
Vehicle 1	6000	2547	42.45%
Vehicle 2	6000	1275	21.25%
Literature [3]	6000	6000	100%

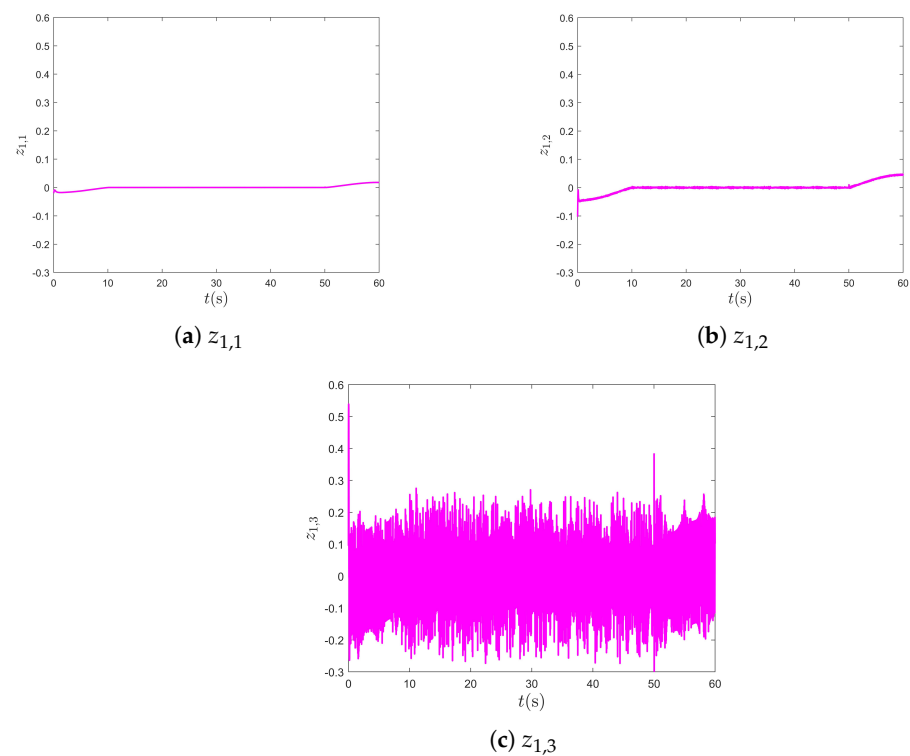


Figure 12. Tracking errors of follower 1.

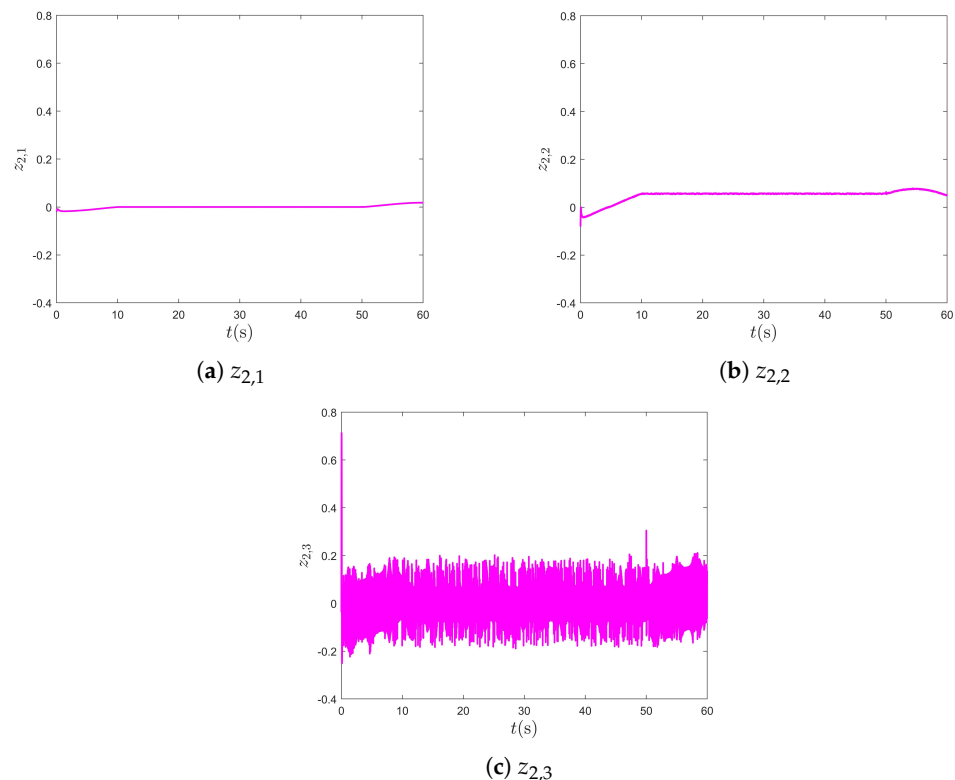


Figure 13. Tracking errors of follower 2.

Table 2 shows the number of triggering events (NTE) and transmission percentages of the two following vehicles. Compared with the time-triggered scheme utilized in [3], the event-triggered approach proposed in this paper obviously saves a lot of network resources, which, therefore, can improve the communication efficiency between vehicles.

The simulation results clearly demonstrate that the presence of time delays does not hinder the smooth operation of the entire vehicle platoon system. This finding provides further evidence to support the validity of the proposed control strategy, as it successfully mitigates the negative impact of time delays on system stability.

5. Conclusions

In this paper, a fixed-time event-triggered controller is proposed for a high-order nonlinear multi-agent system with unknown stochastic time delay. Firstly, RBF NNs are employed to deal with the uncertain nonlinearities within the system. Then, the ETM is designed to decrease the execution time of the controller, thereby saving communication resources. Subsequently, the utilization of the Lyapunov–Krasovskii functional plays a crucial role in mitigating the impact of time delays on system stability. Further, the fixed-time stability theory is used to enhance the system’s transient performance. Finally, the effectiveness and feasibility of the designed controller are further verified through two representative simulations.

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