



Research article

Exponential synchronization of reaction-diffusion neural networks via intermittent event-triggered control

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Abstract: This work investigated the exponential synchronization (ES) of reaction-diffusion neural networks (RDNNs) via a novel aperiodic intermittent event-triggered control strategy. The proposed scheme enables each network node to independently configure its event-triggered threshold, control interval, and rest interval, thereby reducing unnecessary response-state sampling/transmission and controller updates under the assumption that the drive state is locally available. By constructing a piecewise Lyapunov functional and adopting Dini derivative analysis and graph-theory techniques, sufficient conditions for exponential synchronization were established. Furthermore, the exclusion of Zeno behavior was strictly proven to guarantee the feasibility of the designed event-triggered mechanism. Numerical simulations on a 10-node directed RDNN with fully heterogeneous node-wise configurations and 200 Monte Carlo runs validated the effectiveness and advantage of the proposed algorithm in reducing response-state sampling and transmission as well as controller updates compared with event-triggered synchronous schemes.

Keywords: aperiodic intermittent control, event-triggered control, exponential synchronization, reaction-diffusion neural networks

1. Introduction

In recent years, reaction-diffusion neural networks (RDNNs) with inherent spatiotemporal coupling dynamics have been extensively adopted in image processing and pattern recognition. Spatially distributed sensing and image-perception hardware can be well-modeled by RDNNs. However, such embedded devices suffer from limited communication bandwidth, insufficient computing resources, and strict energy constraints. Traditional continuous-control and periodic-sampling strategies require persistent signal transmission and controller updates, which incur substantial redundant overhead and hardware burden. Therefore, developing resource-efficient

synchronization control schemes for RDNNs is of practical significance for engineering implementations [1–3]. Numerous studies have investigated the dynamical behaviors and synchronization problems of RDNNs, forming a fundamental theoretical framework for spatiotemporal system analysis.

Early studies primarily focused on continuous feedback control based on Lyapunov stability theory. In [1], the synchronization of RDNNs with Dirichlet boundary conditions and infinite delays was studied. In [2], the global exponential stability and periodicity of delayed RDNNs with Dirichlet boundaries were analyzed via improved Lyapunov-Krasovskii functionals. By virtue of the Hardy-Poincaré inequality, an exponential synchronization criterion for fuzzy memristive RDNNs was established in [4]. The intermittent synchronization and H_∞ performance of complex-valued RDNNs were further explored in [5]. For practical applications, event-triggered impulsive control was utilized to realize cluster synchronization and image encryption in [6], while exponential synchronization of coupled RDNNs was achieved via impulsive event-triggered strategies in [7]. In parallel, for delayed neural networks, passivity and stability analysis have been significantly advanced by the allowable delay set flexible fragmentation approach [8], the generalized reciprocally convex inequality [9], event-triggered synchronization under actuator saturation [10], and the monotonically increasing function-based event-triggered sampling scheme [11]. These works provide powerful tools for temporal neural networks, but they do not address the spatial diffusion operator and Dirichlet-boundary-induced dissipation that are essential in RDNNs. Nevertheless, these continuous and periodic control methods rely on persistent sampling and frequent updates, which fail to reduce redundant response-state sampling and transmission as well as controller updates, and cannot satisfy low-power requirements.

To alleviate the heavy resource consumption of continuous control, intermittent control has been widely applied to RDNNs by activating controllers only within discrete time intervals. In [12], periodic intermittent control was adopted for exponential synchronization of delayed RDNNs with stochastic disturbances. Based on time-scale theory, intermittent event-triggered control was developed for complex network synchronization in [13]. Asynchronous intermittent event-triggered stabilization for dynamic networks was studied in [14]. Furthermore, a semi-intermittent switching control was proposed in [15] to achieve fixed-time synchronization of delayed memristive RDNNs. More recently, aperiodic intermittent delayed sampled-data control has been developed for semi-global synchronization of stochastic mixed time-delay systems with Lévy noise [16], asynchronous intermittent control has been used for exponential stability of stochastic highly nonlinear delayed systems with regime-switching diffusion [17], and stability of multi-linked stochastic delayed complex networks with stochastic hybrid impulses has been studied via the Dupire-Itô formula [18]. These results reveal the potential of asynchronous and aperiodic intermittent scheduling. However, their models are mainly finite-dimensional stochastic systems or complex networks without reaction-diffusion dynamics. Consequently, the spatial coupling, homogeneous Dirichlet boundary, and diffusion-induced dissipation of RDNNs cannot be directly captured by the methods in [16–18]. Despite reduced control frequency, most periodic intermittent schemes cannot adapt to real-time system states, resulting in unavoidable sampling redundancy.

As an alternative resource-saving mechanism, event-triggered control updates controllers only when system states exceed predefined thresholds, avoiding periodic sampling waste. In [19] and [20], event-triggered strategies were designed for fixed preassigned-time synchronization of delayed and

memristive neural networks. In [21], switched event-triggered control was used for exponential synchronization of RDNNs. However, most existing event-triggered results concentrate on purely temporal neural networks and ignore the essential spatial diffusion dynamics of RDNNs, which limits their applicability to spatiotemporal coupled systems. In the spatiotemporal setting, security-aware intermittent dynamic event-triggered sampled-data output synchronization for delayed RDNNs [22], asynchronous state estimation for switched nonlinear reaction-diffusion susceptible-infected-recovered (SIR) epidemic models with impulsive effects [23], and quantized control for interconnected partial differential equation (PDE) systems via mobile measurement and control strategies [24] are closely related. Although these works address security, quantization, impulsiveness, and mobile measurement, they do not consider the combination of node-wise asynchronous aperiodic intermittent scheduling and event-triggered RDNN synchronization, nor do they establish Zeno exclusion when the event-triggered sampler is switched off during rest intervals.

Hybrid intermittent event-triggered control further integrates the advantages of intermittent time scheduling and event-driven adaptation, which only executes triggering detection in active control intervals and significantly improves control efficiency. This hybrid framework has been successfully applied to various complex systems. In [25], aperiodically intermittent dynamic event-triggered control was proposed for predefined-time synchronization of stochastic networks. In [26], a hybrid intermittent event-triggered method was designed for robot formation synchronization. Intermittent event-triggered schemes were also developed for output-coupled network synchronization [27], fractional-order fuzzy signed network bipartite synchronization [28], and directed network synchronization under intermittent communication constraints [29]. Moreover, dynamic event-triggered control was adopted to achieve semi-global bipartite consensus of multi-agent systems with input saturation [30], and fault-tolerant secure bipartite consensus against denial-of-service (DoS) attacks and quantization was further realized in [31]. In addition, recent advances on fractional reaction-diffusion complex network synchronization [32], fault-tolerant synchronization of switched complex networks [33], and Pareto-optimal synchronization control of complex networks [34] have further enriched the related literature. Although these works verify the superiority of hybrid control, most results are established for ordinary differential systems without spatial diffusion, which are inapplicable to RDNNs.

In summary, there remain several research gaps in existing RDNN synchronization studies. First, pure continuous or intermittent RDNN control lacks adaptive event-triggered scheduling, resulting in redundant periodic sampling. Second, existing hybrid intermittent event-triggered theories are designed for temporal systems and cannot characterize the spatiotemporal coupling of RDNNs. Third, the coexistence of spatial diffusion, intermittent switching, and event-triggered constraints induces complex jump variations of Lyapunov functionals, while effective stability analysis and Zeno-exclusion theories for such coupled systems are still insufficient. It should be emphasized that the novelty of this paper is not a simple combination of intermittent control and event-triggered control. Rather, it lies in overcoming three intertwined theoretical challenges: the spatial diffusion operator and Dirichlet boundary conditions require a Lyapunov analysis incorporating the Hardy-Poincaré inequality and graph-theoretic coupling estimates; the node-wise asynchronous aperiodic active and rest intervals make the control and rest intervals interleaved among nodes, so synchronous intermittent control methods and purely temporal event-triggered schemes cannot be directly applied; and since the event-triggered sampler is switched off during rest intervals, standard

Zeno-exclusion proofs for continuously active event-triggered mechanisms are not applicable, and a finite-horizon lower bound on inter-event times must be established via parabolic PDE regularity and backward uniqueness.

Motivated by the above issues, this paper proposes a novel aperiodic intermittent event-triggered exponential synchronization control strategy for RDNNs. The designed controller supports flexible configuration of active intervals, rest intervals, and adaptive dynamic thresholds, which adapts well to distributed heterogeneous embedded hardware. By constructing piecewise Lyapunov functionals and combining the Hardy-Poincaré inequality and Dini derivative techniques, sufficient conditions for exponential synchronization are derived. Meanwhile, Zeno behavior is strictly excluded to guarantee physical realizability. The proposed scheme effectively balances synchronization accuracy, convergence speed, and efficiency in reducing response-state sampling and transmission as well as controller updates under locally available drive states, providing a reliable theoretical basis for low-energy spatiotemporal neural network control. It should be noted that the communication-saving interpretation in this paper assumes that $z_i(s, t)$ is locally available at node i . If $z_i(s, t)$ must be transmitted remotely, a continuous z_i channel would be required.

The rest of this paper is organized as follows. Section 3 constructs the mathematical model of the considered system and elaborately designs the aperiodic intermittent event-triggered control strategy. Section 4 presents the main theoretical results of this work. Numerical simulations are carried out in Section 5 to verify the effectiveness of the proposed control scheme. Section 6 concludes the whole paper.

2. Notations

Define $\mathcal{N} = \{1, 2, \dots, N\}$ and $\mathcal{H} = \{0, 1, 2, \dots\}$. Let $\mathbb{R}^n$ be n -dimensional Euclidean space, $\mathbb{R}$ be real numbers, and $\mathbb{R}^+ = [0, +\infty)$. $C^{2,1}(\mathbb{R}^n \times \mathbb{R}^+; \mathbb{R}^+)$ represents the family of all functions $U(s, t)$ on $\mathbb{R}^n \times \mathbb{R}^+$, which is nonnegative and continuously twice differentiable in s and once in t . The superscript “T” denotes the transpose of vectors and $|\cdot|$ denotes the Euclidean norm of a vector. A bounded compact set in $\mathbb{R}^k$ is denoted by Γ with $\text{mes}(\Gamma) > 0$, which represents the measure of Γ . $\psi(s) \in C^1(\Gamma)$ denotes that the first derivative of $\psi(s)$ exists and is continuous in Euclidean space.

A directed graph, denoted as $\mathcal{G} = (V_1, E)$, consists of a vertex set $V_1 = \{1, 2, \dots, N\}$ and an arc (i, j) set E , which represents connections from an initial vertex i to a terminal vertex j . This digraph $\mathcal{G}$ is considered weighted if each arc (j, i) is assigned a positive weight a_{ij} . In our convention, a_{ij} is positive when there exists an arc from vertex j to vertex i , and it is set to zero otherwise.

For any vector-valued function $\mathbf{x}(s)$ defined on the spatial domain Γ , the $L^2(\Gamma)$ norm is formulated as $\|\mathbf{x}\|_{L^2(\Gamma)}^2 = \int_{\Gamma} |\mathbf{x}(s)|^2 ds$, where $|\cdot|$ denotes the Euclidean norm of vectors.

3. Model description and preliminaries

3.1. Mathematical model

The model established for a directed graph G with N ($N \geq 2$) vertices is as follows:

$$\frac{\partial}{\partial t} z_i(s, t) = \sum_{o=1}^k \frac{\partial}{\partial s_o} \left(B_{io} \frac{\partial z_i(s, t)}{\partial s_o} \right) + f_i(z_i(s, t)) + \sum_{j=1}^N a_{ij} H_{ij}(z_i(s, t), z_j(s, t)), \quad i \in \mathcal{N}, \quad (3.1)$$

where $z_i(s, t)$ is the state of the system at the i -th vertex at time t and spatial position s , with $s = (s_1, s_2, \dots, s_k)^T \in \Gamma \subset \mathbb{R}^k$, $\Gamma = \{(s_1, s_2, \dots, s_k) \mid |s_o| < n_o, n_o > 0, o = 1, 2, \dots, k\}$ is a bounded compact set with positive measure in $\mathbb{R}^k$; the function $f_i(\cdot) : \mathbb{R}^m \rightarrow \mathbb{R}^m$ is continuous; $B_{io} > 0$ is related to the transmission diffusion operator of the i -th vertex along the o -th direction; $H_{ij}(\cdot, \cdot) : \mathbb{R}^m \times \mathbb{R}^m \rightarrow \mathbb{R}^m$ is the coupling form, and a_{ij} denotes the coupling weight.

The homogeneous Dirichlet boundary conditions for drive system (3.1) are as follows:

$$\begin{cases} z_i(s, t) = 0, & (s, t) \in \partial\Gamma \times [0, +\infty), \\ z_i(s, 0) = \phi_i(s, 0), & s \in \Gamma, i \in \mathcal{N}. \end{cases}$$

Define $\phi(s, 0) = (\phi_1^T(s, 0), \phi_2^T(s, 0), \dots, \phi_N^T(s, 0))^T$, with $\phi(\cdot, 0)$ bounded and continuous on Γ . Then, the corresponding response system is:

$$\frac{\partial}{\partial t} w_i(s, t) = \sum_{o=1}^k \frac{\partial}{\partial s_o} \left(B_{io} \frac{\partial w_i(s, t)}{\partial s_o} \right) + f_i(w_i(s, t)) + e_i(s, t) + \sum_{j=1}^N a_{ij} H_{ij}(w_i(s, t), w_j(s, t)), \quad i \in \mathcal{N}, \quad (3.2)$$

and $w_i(s, t)$ is an m -dimensional state vector. Note that $e_i(s, t)$ is piecewise continuous in t and uniformly bounded in $L^\infty(0, T; L^2(\Gamma))$ for any finite $T > 0$. Then, the homogeneous Dirichlet boundary conditions for system (3.2) are:

$$\begin{cases} w_i(s, t) = 0, & (s, t) \in \partial\Gamma \times [0, +\infty), \\ w_i(s, 0) = \varphi_i(s, 0), & s \in \Gamma, i \in \mathcal{N}. \end{cases}$$

Let $\varphi(s, 0) = (\varphi_1^T(s, 0), \varphi_2^T(s, 0), \dots, \varphi_N^T(s, 0))^T$, which is bounded and continuous on Γ . For the aperiodic intermittent event-triggered control strategy, the control input is given by

$$e_i(s, t) = \begin{cases} -\eta_i(w_i(s, t_r^i) - z_i(s, t)), & t \in [t_h^i, s_h^i) \cap [t_r^i, t_{r+1}^i), \\ 0, & \text{otherwise,} \end{cases} \quad (3.3)$$

where $h \in \mathcal{H}$ and $\eta_i > 0$. Here, $[t_h^i, s_h^i)$ and $[s_h^i, t_{h+1}^i)$ denote the control interval and rest interval, respectively. During rest intervals $t \in [s_h^i, t_{h+1}^i)$, the event-triggered sampler is switched off and the controller is inactive, i.e., $e_i(s, t) = 0$. Let t be the current instant, and the state error of the i th node at the sampling time and the last triggering time are defined as $u_i(s, t) = w_i(s, t) - w_i(s, t_r^i)$.

Therefore, for $t \in [t_r^i, t_{r+1}^i)$, it holds that

$$w_i(s, t_r^i) - z_i(s, t) = (w_i(s, t) - z_i(s, t)) + (w_i(s, t_r^i) - w_i(s, t)) = v_i(s, t) - u_i(s, t),$$

and then, one obtains

$$e_i(s, t) = -\eta_i(v_i(s, t) - u_i(s, t)).$$

The next triggering instant t_{r+1}^i is determined by

$$t_{r+1}^i = \inf \left\{ t > t_r^i \mid t \in \bigcup_{h \in \mathcal{H}} [t_h^i, s_h^i), \|u_i(s, t)\|_{L^2(\Gamma)}^2 > \sigma_i \|v_i(s, t)\|_{L^2(\Gamma)}^2 \right\}, \quad (3.4)$$

where $\sigma_i \in (0, 1)$ is an independently designed threshold parameter for each node. The event-triggered detection is only activated during the control intervals $t \in [t_h^i, s_h^i)$. During the rest intervals $t \in [s_h^i, t_{h+1}^i)$, the event-triggering sampler is turned off. If the triggering condition is violated during a rest interval, no triggering event is generated. When the next control interval begins, the sampler is reactivated; if the condition still holds, the controller is updated immediately at the start of that control interval.

Remark 3.1. For each node i , the drive state $z_i(s, t)$ is locally available as a reference and is not transmitted over the communication network. The response state $w_i(s, t)$ is measured locally for event detection. Only the sampled state $w_i(s, t_r^i)$ is transmitted at the triggering instant t_r^i and is held by a zero-order hold until the next triggering instant t_{r+1}^i . The control input $e_i(s, t)$ is computed locally from this held sample and the locally available $z_i(s, t)$. Thus, the proposed event-triggered mechanism reduces response-state sampling and transmission as well as controller updates, but not the transmission of $z_i(s, t)$. The triggering counts in Section 5 refer to response-state sampling and controller updates. If $z_i(s, t)$ is not locally available, Eq (3.3) would require a continuous z_i channel, which is outside the present communication-saving claim.

From drive system (3.1) and response system (3.2), the corresponding error system is obtained as

$$\begin{aligned} \frac{\partial}{\partial t} v_i(s, t) = & \sum_{o=1}^k \frac{\partial}{\partial s_o} \left(B_{io} \frac{\partial}{\partial s_o} v_i(s, t) \right) + f_i(w_i(s, t)) - f_i(z_i(s, t)) + e_i(s, t) \\ & + \sum_{j=1}^N a_{ij} [H_{ij}(w_i(s, t), w_j(s, t)) - H_{ij}(z_i(s, t), z_j(s, t))], \quad i \in \mathcal{N}. \end{aligned} \quad (3.5)$$

Since both $z_i(s, t)$ and $w_i(s, t)$ satisfy homogeneous Dirichlet boundary conditions $z_i|_{\partial\Gamma} = 0$, $w_i|_{\partial\Gamma} = 0$, the synchronization error naturally satisfies the same Dirichlet boundary condition:

$$v_i(s, t) = w_i(s, t) - z_i(s, t) = 0, \quad \forall (s, t) \in \partial\Gamma.$$

For the above error system, assume that its solution $v(s, t) = (v_1^T(s, t), v_2^T(s, t), \dots, v_N^T(s, t))^T \in \mathbb{R}^{mN}$ exists and is unique.

The event-triggered detection is only activated during control intervals $t \in [t_h^i, s_h^i)$. During rest intervals $t \in [s_h^i, t_{h+1}^i)$, the event-triggering sampler is turned off and the controller maintains a constant output.

Definition 3.1. [1] If there exist constants $\varepsilon > 0$ and $M > 1$ such that for $v(s, t) = (v_1^T(s, t), v_2^T(s, t), \dots, v_N^T(s, t))^T \in \mathbb{R}^{mN}$, $s \in \Gamma$, $v(s, 0)$ is bounded and continuous, and satisfies

$$\int_{\Gamma} |v(s, t)|^2 ds \leq M e^{-\varepsilon t} \int_{\Gamma} |v(s, 0)|^2 ds,$$

then system (3.1)–(3.2) achieves exponential synchronization.

Definition 3.2. [12] For the aperiodic intermittent event-triggered control strategy (3.3), if there exist $\gamma_i \in (0, 1)$ and $T_{\gamma_i} \geq 0$ such that

$$T_{con}^i(t_1, t_2) \geq \gamma_i(t_1 - t_2) - T_{\gamma_i}, \quad \forall t_1 > t_2 \geq t_0,$$

$$T_{con}^{ic}(t_1, t_2) \leq (1 - \gamma_i)(t_1 - t_2) + T_{\gamma_i}, \quad \forall t_1 > t_2 \geq t_0,$$

where $T_{con}^i(t_1, t_2)$ and $T_{con}^{ic}(t_1, t_2)$ are the total control interval length and total rest interval length on $[t_2, t_1]$, respectively; γ_i is the average control rate; and T_{γ_i} is the elasticity number.

Lemma 3.1. [2] Given positive constants n_o ($o = 1, 2, \dots, k$) and $|s_0| < n_o$, let $\psi(s)$ be a real-valued function in $C^1(\Gamma)$, and $\psi(s) = 0$ on the boundary $\partial\Gamma$ of Γ , i.e., $\psi(s)|_{\partial\Gamma} = 0$. Then

$$\int_{\Gamma} \psi^2(s) ds \leq n_o^2 \int_{\Gamma} \left| \frac{\partial \psi(s)}{\partial s_0} \right|^2 ds.$$

This inequality holds under the homogeneous Dirichlet boundary condition $\psi|_{\partial\Gamma} = 0$, which is consistent with the boundary setting of synchronization error $v_i(s, t)$.

Lemma 3.2. [3] Let $N \geq 2$ hold and ξ_i be the cofactor of the i -th diagonal element in the Laplacian matrix of digraph (G, B) , where $B = (b_{ij})_{N \times N}$. Then

$$\sum_{i,j=1}^N \xi_i b_{ij} F_{ij}(v_i(s, t), v_j(s, t)) = \sum_{\tilde{d} \in \mathbb{Q}} W(\tilde{d}) \sum_{(r,x) \in E(C_{\tilde{d}})} F_{rx}(v_r(s, t), v_x(s, t)),$$

where $F_{ij}(v_i(s, t), v_j(s, t)) : \mathbb{R}^m \times \mathbb{R}^m \rightarrow \mathbb{R}$ ($i, j \in N$) is any function; $W(\tilde{d})$ is the weight of $\tilde{d}$; $C_{\tilde{d}}$ is the directed cycle of $\tilde{d}$; and $\mathbb{Q}$ is the set of all spanning simple cycles of digraph (G, B) . Note that for any $i \in N$, if digraph (G, B) is strongly connected, then $\xi_i > 0$. In this paper, we consider strongly connected digraphs.

Assumption 3.1. For the activation function $f_i(\cdot)$, there exist positive constants α_i such that $f_i(\cdot)$ satisfies:

$$(w_i(s, t) - z_i(s, t))^T (f_i(w_i(s, t)) - f_i(z_i(s, t))) \leq \alpha_i (w_i(s, t) - z_i(s, t))^T (w_i(s, t) - z_i(s, t)).$$

Assumption 3.2. For any $s, \hat{s}, y, \hat{y} \in \mathbb{R}^m$, there exists a constant $\delta_{ij} > 0$ such that

$$|H_{ij}(s, y) - H_{ij}(\hat{s}, \hat{y})| \leq \delta_{ij} (|s - \hat{s}| + |y - \hat{y}|).$$

Assumption 3.3. For any inter-event interval located inside a control interval, i.e., for $t \in [t_r^i, t_{r+1}^i) \cap [t_h^i, s_h^i)$, the event-triggered rule (3.4) guarantees that

$$\|u_i(s, t)\|_{L^2(\Gamma)}^2 \leq \sigma_i \|v_i(s, t)\|_{L^2(\Gamma)}^2.$$

During the rest intervals $t \in [s_h^i, t_{h+1}^i)$, the event-triggering sampler is turned off and the control input is $e_i(s, t) = 0$. Hence the above inequality is not required to hold on rest intervals.

Assumption 3.4. For any functions $u(s)$ and $w(s)$ defined on Γ with $w|_{\partial\Gamma} = 0$, Green's first identity satisfies

$$\int_{\Gamma} u \frac{\partial w}{\partial s_o} ds = \oint_{\partial\Gamma} u w n_0 ds - \int_{\Gamma} w \frac{\partial u}{\partial s_o} ds = - \int_{\Gamma} w \frac{\partial u}{\partial s_o},$$

where the boundary integral vanishes due to the Dirichlet boundary condition $w|_{\partial\Gamma} = 0$.

3.2. Zeno behavior exclusion

Definition 3.3. The closed-loop system does not exhibit Zeno behavior if, for every finite $T > 0$, the triggering sequence $\{t_r^i\}$ has no finite accumulation point in $[0, T]$, or equivalently, only finitely many triggering instants occur in any finite time interval.

Since the event-triggered sampler is switched off during rest intervals, the triggering sequence is only generated within control intervals. Hence it suffices to analyze inter-event times inside control intervals.

Lemma 3.3. If the initial synchronization error satisfies $v_i(\cdot, 0) \not\equiv 0$, then for any finite $T > 0$,

$$\|v_i(\cdot, t)\|_{L^2(\Gamma)} > 0, \quad \forall t \in [0, T].$$

If $v_i(\cdot, 0) \equiv 0$, then $v_i(\cdot, t) \equiv 0$ for all $t \geq 0$, and no further triggering events occur.

Proof. Suppose there exists $t_0 \in [0, T]$ such that $\|v_i(\cdot, t_0)\|_{L^2(\Gamma)} = 0$. Then $v_i(\cdot, t_0) = 0$ a.e. in Γ . By the backward uniqueness of uniformly parabolic equations with Lipschitz nonlinearities, this implies $v_i(\cdot, 0) = 0$ a.e. in Γ , which contradicts $v_i(\cdot, 0) \not\equiv 0$. Hence $\|v_i(\cdot, t)\|_{L^2(\Gamma)} > 0$ for all $t \in [0, T]$. $\square$

Lemma 3.4. Under Assumptions 3.1 and 3.2, for any finite time $T > 0$, the time derivative of the state $w_i(s, t)$ in system (3.2) is uniformly bounded in the $L^2(\Gamma)$ norm over $[0, T]$. That is, there exists a positive constant $L_i(T)$, dependent on T and the system parameters, such that

$$\left\| \frac{\partial w_i(\cdot, t)}{\partial t} \right\|_{L^2(\Gamma)} \leq L_i(T), \quad \forall t \in [0, T]. \quad (3.6)$$

Proof. By the Lipschitz conditions in Assumptions 3.1 and 3.2, and by standard energy estimates for parabolic PDEs, the states w_i and z_i are uniformly bounded in $L^2(\Gamma)$ over $[0, T]$. Consequently, the control term $e_i(s, t)$ satisfies $e_i \in L^\infty(0, T; L^2(\Gamma))$, since it is generated by bounded sampled states and bounded drive states. Rewrite system (3.2) as

$$\frac{\partial w_i}{\partial t} - \sum_{o=1}^k \frac{\partial}{\partial s_o} \left(B_{io} \frac{\partial w_i}{\partial s_o} \right) = f_i(w_i) + e_i(s, t) + \sum_{j=1}^N a_{ij} H_{ij}(w_i, w_j).$$

The right-hand side is uniformly bounded in $L^2(\Gamma)$ for all $t \in [0, T]$, i.e., it belongs to $L^\infty(0, T; L^2(\Gamma))$. By the L^2 -regularity theory for uniformly parabolic equations with homogeneous Dirichlet boundary conditions, we obtain $\partial_t w_i \in L^\infty(0, T; L^2(\Gamma))$. Hence there exists $L_i(T) > 0$ such that the desired inequality holds. The bound $L_i(T)$ depends on the finite time horizon T rather than being a global constant on $[0, \infty)$. $\square$

Based on Lemma 3.4, the measurement error $u_i(s, t) = w_i(s, t) - w_i(s, t_r^i)$ satisfies, for $t \in [t_r^i, t_{r+1}^i)$,

$$\|u_i(\cdot, t)\|_{L^2(\Gamma)} = \left\| \int_{t_r^i}^t \frac{\partial w_i}{\partial \tau} d\tau \right\|_{L^2(\Gamma)} \leq L_i(T)(t - t_r^i).$$

At the triggering instant, by the event-triggered rule (3.4), before the controller is updated, it holds that

$$\|u_i(\cdot, t_{r+1}^{i-})\|_{L^2(\Gamma)} = \sqrt{\sigma_i} \|v_i(\cdot, t_{r+1}^{i-})\|_{L^2(\Gamma)}.$$

Combining the above two relations yields

$$t_{r+1}^i - t_r^i \geq \frac{\sqrt{\sigma_i} \|v_i(\cdot, t_{r+1}^i)\|_{L^2(\Gamma)}}{L_i(T)}. \quad (3.7)$$

Now fix an arbitrary finite $T > 0$. By Lemma 3.3, if $v_i(\cdot, 0) \neq 0$, then $\|v_i(\cdot, t)\|_{L^2(\Gamma)} > 0$ for all $t \in [0, T]$. Since $v_i(\cdot, t)$ is continuous in t as a consequence of parabolic regularity, the extreme value theorem implies that there exists a constant $m_i(T) > 0$ such that

$$\|v_i(\cdot, t)\|_{L^2(\Gamma)} \geq m_i(T), \quad \forall t \in [0, T].$$

Therefore, all inter-event intervals within $[0, T]$ satisfy

$$t_{r+1}^i - t_r^i \geq \tau_i(T) := \frac{\sqrt{\sigma_i} m_i(T)}{L_i(T)} > 0.$$

Consequently, the number of triggering instants in $[0, T]$ is finite; indeed, it is bounded by $T/\tau_i(T) + 1$. Since $T > 0$ is arbitrary, the triggering sequence $\{t_r^i\}$ has no finite accumulation point. Hence the closed-loop system does not exhibit Zeno behavior in the sense of Definition 3.3.

4. Main results

Based on the system formulation, definitions, and preliminary lemmas established in Section 3, we proceed to derive sufficient conditions to guarantee exponential synchronization of the considered reaction-diffusion neural networks under the designed aperiodic intermittent event-triggered control scheme. A piecewise time-varying Lyapunov functional will be constructed and graph theory together with Dini derivative techniques are utilized to obtain the synchronization criteria.

Lemma 4.1. [35] *For any $i \in \mathcal{N}$, suppose that $U_i(v_i(s, t), t) \in C^{2,1}(\mathbb{R}^m \times \mathbb{R}^+; \mathbb{R}^+)$ satisfies the following conditions:*

A1: *There exist positive constants r_i and c_i such that*

$$\int_{\Gamma} r_i |v_i(s, t)|^2 ds \leq U_i(v_i(s, t), t) \leq \int_{\Gamma} c_i |v_i(s, t)|^2 ds.$$

A2: *There exist a positive constant λ and functions $F_{ij}(v_i, v_j)$ ($i, j \in \mathcal{N}$) such that*

$$\frac{dU_i(v_i(s, t), t)}{dt} \leq -\lambda U_i(v_i(s, t), t) + \int_{\Gamma} \sum_{j=1}^N b_{ij} F_{ij}(v_i(s, t), v_j(s, t)) ds.$$

A3: *For each directed cycle $\tilde{\delta}$ in the weighted digraph (G, B) ,*

$$\sum_{(r,x) \in E(C_{\tilde{\delta}})} F_{rx}(v_r(s, t), v_x(s, t)) \leq 0.$$

Then the system (3.1)–(3.2) achieves exponential synchronization.

Remark 4.1. Note that the piecewise function $\theta_i(t)$ defined in (4.3) is continuous at the switching instants t_h^i and s_h^i , but it is not differentiable at these points due to the presence of the $\min\{\cdot\}$ operator. To ensure the rigor of the subsequent stability analysis, all derivatives of the Lyapunov functional $U_i(t)$ are understood in the sense of the upper-right-hand Dini derivative, which is defined as $D^+U_i(t) = \limsup_{\Delta t \rightarrow 0^+} \frac{U_i(t+\Delta t) - U_i(t)}{\Delta t}$. For Lipschitz continuous functions, the Dini derivative always exists and coincides with the ordinary derivative almost everywhere. For notational clarity, we explicitly use $D^+U_i(t)$ at switching and triggering instants. On intervals where $U_i(t)$ is continuously differentiable, $D^+U_i(t)$ coincides with the ordinary derivative $\dot{U}_i(t)$. The piecewise nature of $U_i(t)$ does not mean that differentiation is avoided; rather, the functional is differentiated piecewise on each smooth subinterval, while the upper-right Dini derivative is used at nonsmooth switching and triggering points.

Theorem 4.1. For any $i \in \mathcal{N}$, if there exist positive constants κ_i such that

$$\kappa_i(1 - \gamma_i) - 2 \sum_{o=1}^k \frac{B_{io}}{n_o^2} + 2\alpha_i + \eta_i(\sigma_i - 1) + 2 \sum_{j=1}^N a_{ij}\delta_{ij}(e^{\kappa_i T_{\gamma_i}} + 1) < 0, \quad (4.1)$$

$$-\kappa_i\gamma_i - 2 \sum_{o=1}^k \frac{B_{io}}{n_o^2} + 2\alpha_i + 2 \sum_{j=1}^N a_{ij}\delta_{ij}(e^{\kappa_i T_{\gamma_i}} + 1) < 0, \quad (4.2)$$

under the aperiodic event-triggered control strategy (3.3), system (3.1)–(3.2) achieves exponential synchronization.

Proof. The Lyapunov functional $U_i(t)$ is piecewise defined and may be nonsmooth at t_h^i, s_h^i, t_r^i . Hence, the classical derivative may not exist at these points. We adopt the upper-right-hand Dini derivative $D^+U_i(t)$. On each smooth subinterval, $U_i(t)$ is continuously differentiable, so $D^+U_i(t) = \dot{U}_i(t)$. At the switching and triggering instants, $U_i(t)$ is continuous, and only the right-hand derivative may change due to the controller update. Define $U_i(v_i(s, t), t) \triangleq U_i(t) = \int_{\Gamma} e^{\theta_i(t)} |v_i(s, t)|^2 ds$. The function $\theta_i(t)$ satisfies

$$\theta_i(t) = \begin{cases} \kappa_i T_{\gamma_i}, & t \in [t_0^i, s_0^i), \\ g_i(t, t_h^i), & t \in [t_h^i, s_h^i), \\ \theta_i(s_h^i) - \kappa_i \gamma_i (t - s_h^i), & t \in [s_h^i, t_{h+1}^i), \end{cases} \quad (4.3)$$

where $g_i(t, t_h^i) = \min\{\kappa_i T_{\gamma_i}, \theta_i(t_h^i) + \kappa_i(1 - \gamma_i)(t - t_h^i)\}$.

From (4.3), we can deduce that $\theta_i(t) \leq \kappa_i T_{\gamma_i}$, and further obtain

$$D^+\theta_i(t) \leq \begin{cases} \kappa_i(1 - \gamma_i), & t \in [t_h^i, s_h^i), \\ -\kappa_i\gamma_i, & t \in [s_h^i, t_{h+1}^i). \end{cases} \quad (4.4)$$

For any fixed $t \geq t_0$, let $t_i^* := \max\{s \in [t_0, t] : \theta_i(s) = \kappa_i T_{\gamma_i}\}$, which is the latest time such that $\theta_i(s)$ reaches $\kappa_i T_{\gamma_i}$. If $t_i^* = t$, then $\theta_i(t) = \kappa_i T_{\gamma_i} \geq 0$. If $t_i^* < t$, then $\theta_i(s) < \kappa_i T_{\gamma_i}$ for all $s \in (t_i^*, t]$, so the $\min\{\cdot\}$ term in (4.3) is not saturated. Hence, on $(t_i^*, t]$, the inequality in (4.4) becomes equality on control intervals, i.e., $D^+\theta_i(s) = \kappa_i(1 - \gamma_i)$, and on rest intervals, it is $D^+\theta_i(s) = -\kappa_i\gamma_i$. Therefore,

$\theta_i(t) = \theta_i(t_i^*) + \kappa_i(1 - \gamma_i)T_{\text{con}}^i(t_i^*, t) - \kappa_i\gamma_i T_{\text{rest}}^i(t_i^*, t)$, where $T_{\text{con}}^i(t_i^*, t)$ and $T_{\text{rest}}^i(t_i^*, t)$ denote the total control time and total rest time on $[t_i^*, t]$, respectively. By Definition 3.2, $T_{\text{con}}^i(t_i^*, t) \geq \gamma_i(t - t_i^*) - T_{\gamma_i}$ and $T_{\text{rest}}^i(t_i^*, t) \leq (1 - \gamma_i)(t - t_i^*) + T_{\gamma_i}$. Substituting these inequalities and noting that $\theta_i(t_i^*) = \kappa_i T_{\gamma_i}$, we obtain $\theta_i(t) \geq \kappa_i T_{\gamma_i} + \kappa_i(1 - \gamma_i)[\gamma_i(t - t_i^*) - T_{\gamma_i}] - \kappa_i\gamma_i[(1 - \gamma_i)(t - t_i^*) + T_{\gamma_i}] = \kappa_i T_{\gamma_i} - \kappa_i T_{\gamma_i} = 0$. Thus $0 \leq \theta_i(t) \leq \kappa_i T_{\gamma_i}$ holds for all $t \geq t_0$, which rigorously justifies the use of $\theta_i(t) \geq 0$ in the subsequent Lyapunov analysis.

$$\begin{aligned}\theta_i(t) &= \theta_i(t_i^*) + \kappa_i(1 - \gamma_i)T_{\text{con}}^i(t_i^*, t) - \kappa_i\gamma_i T_{\text{con}}^{ic}(t_i^*, t) \\ &\geq \kappa_i T_{\gamma_i} + \kappa_i(1 - \gamma_i)[\gamma_i(t - t_i^*) - T_{\gamma_i}] - \kappa_i\gamma_i[(1 - \gamma_i)(t - t_i^*) + T_{\gamma_i}] \\ &= \kappa_i T_{\gamma_i} - \kappa_i T_{\gamma_i} = 0,\end{aligned}$$

where $T_{\text{con}}^i(t_i^*, t)$ represents the total control time of node i on $[t_i^*, t]$, and $T_{\text{con}}^{ic}(t_i^*, t)$ denotes the total rest time of node i over $[t_i^*, t]$.

From the above derivation, it holds that $0 \leq \theta_i(t) \leq \kappa_i T_{\gamma_i}$. For $t \geq 0$, it yields $1 = e^0 \leq e^{\theta_i(t)} \leq e^{\kappa_i T_{\gamma_i}}$,

$$\int_{\Gamma} |v_i(s, t)|^2 ds \leq \int_{\Gamma} e^{\theta_i(t)} |v_i(s, t)|^2 ds \leq \int_{\Gamma} e^{\kappa_i T_{\gamma_i}} |v_i(s, t)|^2 ds.$$

According to Theorem 4.1, taking $r_i = 1$ and $c_i = e^{\kappa_i T_{\gamma_i}}$, it can be verified that condition A1 holds. When the system is in the control interval $t \in [t_h^i, s_h^i)$ and the triggering time $t \in [t_r^i, t_{r+1}^i)$, combining with (3.5), the Lyapunov functional is formulated as $U_i(t) = \int_{\Gamma} e^{\theta_i(t)} |v_i(s, t)|^2 ds$.

Taking the upper-right-hand Dini derivative of $U_i(t)$ on a smooth subinterval, the following result is yielded:

$$\begin{aligned}D^+ U_i(t) &= \int_{\Gamma} \left[e^{\theta_i(t)} \dot{\theta}_i(t) |v_i(s, t)|^2 + 2e^{\theta_i(t)} v_i^T(s, t) \frac{\partial v_i(s, t)}{\partial t} \right] ds \\ &= e^{\theta_i(t)} \int_{\Gamma} \left[\dot{\theta}_i(t) |v_i(s, t)|^2 + 2v_i^T(s, t) \left(\sum_{o=1}^k \frac{\partial}{\partial s_o} \left(B_{io} \frac{\partial v_i(s, t)}{\partial s_o} \right) + f_i(w_i(s, t)) - f_i(z_i(s, t)) \right) \right. \\ &\quad \left. + e_i(s, t) + \sum_{j=1}^N a_{ij} (H_{ij}(w_i(s, t), w_j(s, t)) - H_{ij}(z_i(s, t), z_j(s, t))) \right] ds.\end{aligned}\quad (4.5)$$

Next, each term in (4.5) is separately divided and estimated. First, the nonlinear coupling term is bounded in accordance with Assumption 3.2.

$$\begin{aligned}&e^{\theta_i(t)} v_i^T(s, t) \sum_{j=1}^N a_{ij} [H_{ij}(w_i(s, t), w_j(s, t)) - H_{ij}(z_i(s, t), z_j(s, t))] \\ &\leq e^{\theta_i(t)} v_i^T(s, t) \sum_{j=1}^N a_{ij} \delta_{ij} (|w_i(s, t) - z_i(s, t)| + |w_j(s, t) - z_j(s, t)|) \\ &= e^{\theta_i(t)} v_i^T(s, t) \sum_{j=1}^N a_{ij} \delta_{ij} (|v_i(s, t)| + |v_j(s, t)|) \\ &= \sum_{j=1}^N a_{ij} \delta_{ij} (e^{\theta_i(t)} |v_i(s, t)|^2 + e^{\theta_i(t)} |v_i(s, t)| |v_j(s, t)|).\end{aligned}\quad (4.6)$$

By using the inequality of means, one has

$$\begin{aligned}
 & \sum_{j=1}^N a_{ij} \delta_{ij} (e^{\theta_i(t)} |v_i(s, t)|^2 + e^{\theta_i(t)} |v_i(s, t)| |v_j(s, t)|) \\
 & \leq \sum_{j=1}^N a_{ij} \delta_{ij} \left(e^{\theta_i(t)} |v_i(s, t)|^2 + \frac{1}{2} (e^{\theta_i(t)} |v_i(s, t)|)^2 + \frac{1}{2} |v_j(s, t)|^2 \right) \\
 & = \sum_{j=1}^N a_{ij} \delta_{ij} \left(e^{\theta_i(t)} |v_i(s, t)|^2 + \frac{1}{2} e^{2\theta_i(t)} |v_i(s, t)|^2 + \frac{1}{2} |v_j(s, t)|^2 \right) \\
 & = \sum_{j=1}^N a_{ij} \delta_{ij} \left((e^{\theta_i(t)} + e^{2\theta_i(t)}) |v_i(s, t)|^2 - \frac{1}{2} e^{2\theta_i(t)} |v_i(s, t)|^2 + \frac{1}{2} |v_j(s, t)|^2 \right). \tag{4.7}
 \end{aligned}$$

Since $e^{\theta_i(t)} \geq 1$, it follows that

$$\begin{aligned}
 & \sum_{j=1}^N a_{ij} \delta_{ij} \left((e^{\theta_i(t)} + e^{2\theta_i(t)}) |v_i(s, t)|^2 - \frac{1}{2} e^{2\theta_i(t)} |v_i(s, t)|^2 + \frac{1}{2} |v_j(s, t)|^2 \right) \\
 & \leq \sum_{j=1}^N a_{ij} \delta_{ij} \left((e^{\theta_i(t)} + e^{2\theta_i(t)}) |v_i(s, t)|^2 - \frac{1}{2} |v_i(s, t)|^2 + \frac{1}{2} |v_j(s, t)|^2 \right) \\
 & = \sum_{j=1}^N a_{ij} \delta_{ij} ((e^{\theta_i(t)} + e^{2\theta_i(t)}) |v_i(s, t)|^2) + \frac{1}{2} \sum_{j=1}^N a_{ij} \delta_{ij} (|v_j(s, t)|^2 - |v_i(s, t)|^2). \tag{4.8}
 \end{aligned}$$

Next, from the aperiodic intermittent event-triggered control strategy (3.3) together with Assumption 3.3, the following relation is obtained:

$$\begin{aligned}
 & 2 \int_{\Gamma} v_i^T(s, t) e_i(s, t) ds = -2\eta_i \int_{\Gamma} v_i^T(s, t) (w_i(s, t_r^i) - z_i(s, t)) ds \\
 & = -2\eta_i \int_{\Gamma} v_i^T(s, t) (v_i(s, t) - u_i(s, t)) ds = -2\eta_i \int_{\Gamma} |v_i(s, t)|^2 ds + 2\eta_i \int_{\Gamma} v_i^T(s, t) u_i(s, t) ds \\
 & \leq -\eta_i \int_{\Gamma} |v_i(s, t)|^2 ds + \eta_i \int_{\Gamma} |u_i(s, t)|^2 ds \leq (\sigma_i - 1) \eta_i \int_{\Gamma} |v_i(s, t)|^2 ds. \tag{4.9}
 \end{aligned}$$

Then, by using the exchange law of summation and integration, Assumption 3.4, boundary conditions of synchronization error, and Lemma 3.1, one has

$$\begin{aligned}
 & \int_{\Gamma} 2v_i^T(s, t) \sum_{o=1}^k \frac{\partial}{\partial s_o} \left(B_{io} \frac{\partial v_i(s, t)}{\partial s_o} \right) ds = 2 \sum_{o=1}^k B_{io} \int_{\Gamma} v_i^T(s, t) \frac{\partial^2 v_i(s, t)}{\partial s_o^2} ds \\
 & = 2 \sum_{o=1}^k B_{io} \left(\oint_{\partial \Gamma} v_i^T(s, t) \frac{\partial v_i(s, t)}{\partial s_o} n_o ds - \int_{\Gamma} \frac{\partial v_i(s, t)}{\partial s_o} \frac{\partial v_i^T(s, t)}{\partial s_o} ds \right) \\
 & = -2 \sum_{o=1}^k B_{io} \int_{\Gamma} \frac{\partial v_i(s, t)}{\partial s_o} \frac{\partial v_i^T(s, t)}{\partial s_o} ds = -2 \sum_{o=1}^k B_{io} \int_{\Gamma} \left| \frac{\partial v_i(s, t)}{\partial s_o} \right|^2 ds
 \end{aligned}$$

$$\leq -2 \sum_{o=1}^k B_{io} \frac{1}{n_o^2} \int_{\Gamma} |v_i(s, t)|^2 ds = \int_{\Gamma} -2 \sum_{o=1}^k \frac{B_{io}}{n_o^2} |v_i(s, t)|^2 ds. \quad (4.10)$$

Finally, from Assumption 3.1, one obtains

$$2 \int_{\Gamma} v_i^T(s, t) (f_i(w_i(s, t)) - f_i(z_i(s, t))) ds \leq 2 \int_{\Gamma} \alpha_i v_i^T(s, t) v_i(s, t) ds = 2 \int_{\Gamma} \alpha_i |v_i(s, t)|^2 ds. \quad (4.11)$$

Combining (4.6)–(4.11), we simplify formula (4.5):

$$\begin{aligned} D^+ U_i(t) &= e^{\theta_i(t)} \left[\int_{\Gamma} \dot{\theta}_i(t) |v_i(s, t)|^2 ds + 2 \int_{\Gamma} v_i^T(s, t) \left(\sum_{o=1}^k \frac{\partial}{\partial s_o} \left(B_{io} \frac{\partial v_i(s, t)}{\partial s_o} \right) + f_i(w_i(s, t)) - f_i(z_i(s, t)) \right) \right. \\ &\quad \left. + e_i(s, t) + \sum_{j=1}^N a_{ij} [H_{ij}(w_i(s, t), w_j(s, t)) - H_{ij}(z_i(s, t), z_j(s, t))] ds \right] \\ &\leq \left[\kappa_i (1 - \gamma_i) - 2 \sum_{o=1}^k \frac{B_{io}}{n_o^2} + 2\alpha_i + 2 \sum_{j=1}^N a_{ij} \delta_{ij} (e^{\theta_i(t)} + 1) + \eta_i (\sigma_i - 1) \right] U_i(t) \\ &\quad + \int_{\Gamma} \sum_{j=1}^N a_{ij} \delta_{ij} (|v_j(s, t)|^2 - |v_i(s, t)|^2) ds \\ &\leq \left[\kappa_i (1 - \gamma_i) - 2 \sum_{o=1}^k \frac{B_{io}}{n_o^2} + 2 \sum_{j=1}^N a_{ij} \delta_{ij} (e^{\kappa_i T \gamma_i} + 1) + \eta_i (\sigma_i - 1) \right] U_i(t) \\ &\quad + \int_{\Gamma} \sum_{j=1}^N b_{ij} F_{ij}(v_i(s, t), v_j(s, t)) ds, \end{aligned} \quad (4.12)$$

where $b_{ij} = a_{ij} \delta_{ij}$ and $F_{ij}(v_i(s, t), v_j(s, t)) \triangleq |v_j(s, t)|^2 - |v_i(s, t)|^2$. Thus, condition A3 is satisfied.

Similarly, when the system is in the rest interval $t \in [s_h^i, t_{h+1}^i)$, one has $e_i(s, t) = 0$.

$$\begin{aligned} D^+ U_i(t) &= \int_{\Gamma} \left[e^{\theta_i(t)} \dot{\theta}_i(t) |v_i(s, t)|^2 + e^{\theta_i(t)} 2 v_i^T(s, t) \frac{\partial v_i(s, t)}{\partial t} \right] ds \\ &= e^{\theta_i(t)} \left[\int_{\Gamma} \dot{\theta}_i(t) |v_i(s, t)|^2 ds + 2 \int_{\Gamma} v_i^T(s, t) \left(\sum_{o=1}^k \frac{\partial}{\partial s_o} \left(B_{io} \frac{\partial v_i(s, t)}{\partial s_o} \right) + f_i(w_i(s, t)) - f_i(z_i(s, t)) \right) \right. \\ &\quad \left. + \sum_{j=1}^N a_{ij} [H_{ij}(w_i(s, t), w_j(s, t)) - H_{ij}(z_i(s, t), z_j(s, t))] ds \right] \\ &\leq \left[-\kappa_i \gamma_i - 2 \sum_{o=1}^k \frac{B_{io}}{n_o^2} + 2\alpha_i + 2 \sum_{j=1}^N a_{ij} \delta_{ij} (e^{\theta_i(t)} + 1) \right] U_i(t) + \int_{\Gamma} \sum_{j=1}^N b_{ij} F_{ij}(v_i(s, t), v_j(s, t)) ds \\ &\leq \left[-\kappa_i \gamma_i - 2 \sum_{o=1}^k \frac{B_{io}}{n_o^2} + 2\alpha_i + 2 \sum_{j=1}^N a_{ij} \delta_{ij} (e^{\kappa_i T \gamma_i} + 1) \right] U_i(t) + \int_{\Gamma} \sum_{j=1}^N b_{ij} F_{ij}(v_i(s, t), v_j(s, t)) ds. \end{aligned} \quad (4.14)$$

Therefore, for all $t \geq 0$, one can conclude that

$$\frac{dU_i(t)}{dt} \leq -\lambda U_i(t) + \int_{\Gamma} \sum_{j=1}^N b_{ij} F_{ij}(v_i(s, t), v_j(s, t)) ds.$$

According to the strict inequalities in conditions (4.1) and (4.2), it directly follows that $\mu_i = \kappa_i(1 - \gamma_i) - 2 \sum_{o=1}^k \frac{B_{io}}{n_o^2} + 2\alpha_i + 2 \sum_{j=1}^N a_{ij} \delta_{ij} (e^{\kappa_i T_{\gamma_i}} + 1) + \eta_i(\sigma_i - 1) < 0$ and $v_i = -\kappa_i \gamma_i - 2 \sum_{o=1}^k \frac{B_{io}}{n_o^2} + 2\alpha_i + 2 \sum_{j=1}^N a_{ij} \delta_{ij} (e^{\kappa_i T_{\gamma_i}} + 1) < 0$. Thus, for each node i , we define the local exponential decay rate $\lambda_i = \min\{-\mu_i, -v_i\}$. Then the global exponential synchronization rate is $\lambda = \min_{i \in \mathcal{N}} \lambda_i = \min_{i \in \mathcal{N}} \{-\mu_i, -v_i\} > 0$, which strictly satisfies the requirement of exponential synchronization in Definition 3.1. Consequently, condition A2 is satisfied, and then the conditions in Theorem 4.1 hold. Hence, the system (3.1)–(3.2) achieves exponential synchronization (ES) via aperiodic intermittent control. $\square$

Remark 4.2. The convergence rate λ is derived under a sufficient condition, whose conservatism mainly comes from the bounding of coupling terms and the uniform estimation over all nodes. Compared with the common quadratic Lyapunov functional with fixed weighting, the proposed piecewise time-varying Lyapunov functional can adaptively adjust the decay rates and the growth rates in control and rest intervals, respectively, which effectively reduces the conservatism of the synchronization criterion and is more suitable for intermittent switching systems. When equality holds in conditions (4.1) or (4.2), i.e., $\mu_i = 0$ or $v_i = 0$, the corresponding decay rate reduces to zero, and the closed-loop system can only achieve uniform boundedness of synchronization errors rather than exponential synchronization. Therefore, strict inequalities are necessary to guarantee a positive exponential convergence rate, which is consistent with the definition of exponential synchronization. Tighter coupling-specific bounds may be obtained by retaining the graph Laplacian or spanning-tree weights, or by solving LMI-based conditions.

5. Numerical simulations

In this section, we adopt a 10-node, directed, networked reaction-diffusion neural network to verify the proposed control strategy. Each node is independently configured with its own event-triggered threshold, control interval, rest interval, average control rate, and elasticity number, so as to validate the generality of the theoretical results for fully heterogeneous node-wise configurations. Let $\mathcal{N} = \{1, 2, \dots, 10\}$. A 10-node reaction-diffusion neural-network model is constructed based on the directed graph (G, B) , as given below:

$$\frac{\partial}{\partial t} z_i(s, t) = B_i \frac{\partial^2 z_i(s, t)}{\partial s^2} + \arctan(z_i(s, t)) + \sum_{j=1}^{10} a_{ij} \delta_{ij} z_i(s, t) + \sum_{j=1}^{10} a_{ij} \delta_{ij} z_j(s, t), i \in \mathcal{N}, \quad (5.1)$$

and the corresponding response system is given by:

$$\frac{\partial}{\partial t} w_i(s, t) = B_i \frac{\partial^2 w_i(s, t)}{\partial s^2} + \arctan(w_i(s, t)) + e_i(s, t) + \sum_{j=1}^{10} a_{ij} \delta_{ij} w_i(s, t) + \sum_{j=1}^{10} a_{ij} \delta_{ij} w_j(s, t), i \in \mathcal{N}. \quad (5.2)$$

Then, the error system is described by

$$\frac{\partial}{\partial t} v_i(s, t) = B_i \frac{\partial^2 v_i(s, t)}{\partial s^2} + \arctan(w_i(s, t)) - \arctan(z_i(s, t)) + e_i(s, t) + \sum_{j=1}^{10} a_{ij} \delta_{ij} [v_i(s, t) + v_j(s, t)], i \in \mathcal{N}.$$

The initial states of systems (5.1) and (5.2), together with the values of η_i and B_{io} , are given in Table 1.

Table 1. Initial states and parameters.

i	$z_i(s, 0)$	$w_i(s, 0)$	η_i	B_{io}
1	$11.2 \sin^6(\pi s)$	$4 \sin^4(\pi s)$	0.56	5
2	$3 \sin^4(\pi s)$	$4 \sin^5(\pi s)$	0.78	5
3	$\sin^3(\pi s)$	$3.8 \sin^3(\pi s)$	0.89	5
4	$12 \sin^6(\pi s)$	$4.2 \sin^5(\pi s)$	0.86	5
5	$6 \sin^4(\pi s)$	$4.8 \sin^3(\pi s)$	0.99	5
6	$0.5 \sin^3(\pi s)$	$\sin^4(\pi s)$	0.97	5
7	$11.8 \sin^6(\pi s)$	$4.5 \sin^5(\pi s)$	0.67	5
8	$7.2 \sin^4(\pi s)$	$3.8 \sin^3(\pi s)$	0.87	5
9	$\sin^3(\pi s)$	$4 \sin^2(\pi s)$	0.69	5
10	$13.2 \sin^6(\pi s)$	$3 \sin^3(\pi s)$	0.89	5

The elements of the Laplacian matrix of the directed graph (G, B) are given in Table 2:

Table 2. Laplacian matrix elements.

$a_{21} = 0.023$	$a_{32} = 0.031$	$a_{43} = 0.011$	$a_{54} = 0.002$
$a_{65} = 0.016$	$a_{76} = 0.018$	$a_{87} = 0.032$	$a_{98} = 0.009$
$a_{10,9} = 0.017$	$a_{1,10} = 0.031$		

The remaining a_{ij} are all equal to 0. It also follows that

$$(w_i(s, t) - z_i(s, t))^T (\arctan(w_i(s, t)) - \arctan(z_i(s, t))) \leq (w_i(s, t) - z_i(s, t))^T (w_i(s, t) - z_i(s, t))$$

and

$$|\delta_{ij}(w_i(s, t) + w_j(s, t)) - \delta_{ij}(z_i(s, t) + z_j(s, t))| \leq \delta_{ij} |v_i(s, t) + v_j(s, t)|.$$

The control intervals for each node are set as

$$\bigcup_{h=0}^{\infty} ([h + a_i, h + b_i) \cup [h + c_i, h + d_i)),$$

where a_i, b_i, c_i, d_i are independently designed for each node, as listed in Table 3.

Table 3. Independent aperiodic control-interval parameters for each node.

Node i	a_i	b_i	c_i	d_i	Control interval
1	0.02	0.42	0.48	0.93	$\cup_{h=0}^{\infty}([h + 0.02, h + 0.42) \cup [h + 0.48, h + 0.93))$
2	0.05	0.46	0.52	0.96	$\cup_{h=0}^{\infty}([h + 0.05, h + 0.46) \cup [h + 0.52, h + 0.96))$
3	0.01	0.39	0.47	0.89	$\cup_{h=0}^{\infty}([h + 0.01, h + 0.39) \cup [h + 0.47, h + 0.89))$
4	0.07	0.48	0.54	0.98	$\cup_{h=0}^{\infty}([h + 0.07, h + 0.48) \cup [h + 0.54, h + 0.98))$
5	0.03	0.38	0.45	0.85	$\cup_{h=0}^{\infty}([h + 0.03, h + 0.38) \cup [h + 0.45, h + 0.85))$
6	0.08	0.49	0.56	0.99	$\cup_{h=0}^{\infty}([h + 0.08, h + 0.49) \cup [h + 0.56, h + 0.99))$
7	0.04	0.42	0.50	0.92	$\cup_{h=0}^{\infty}([h + 0.04, h + 0.42) \cup [h + 0.50, h + 0.92))$
8	0.06	0.47	0.53	0.95	$\cup_{h=0}^{\infty}([h + 0.06, h + 0.47) \cup [h + 0.53, h + 0.95))$
9	0.02	0.37	0.44	0.82	$\cup_{h=0}^{\infty}([h + 0.02, h + 0.37) \cup [h + 0.44, h + 0.82))$
10	0.09	0.50	0.57	0.98	$\cup_{h=0}^{\infty}([h + 0.09, h + 0.50) \cup [h + 0.57, h + 0.98))$

The event-triggered thresholds for each node are given in the following Table 4:

Table 4. Independent event-triggered thresholds for each node.

Node i	1	2	3	4	5	6	7	8	9	10
σ_i	0.052	0.061	0.073	0.048	0.082	0.056	0.069	0.091	0.064	0.077

Let $\kappa_i = 1$. The parameters γ_i and T_{γ_i} are listed in Table 5:

Table 5. Independent γ_i and T_{γ_i} for each node.

Node i	1	2	3	4	5	6	7	8	9	10
γ_i	0.85	0.85	0.80	0.85	0.75	0.84	0.80	0.83	0.73	0.82
T_{γ_i}	0.085	0.078	0.082	0.091	0.145	0.132	0.140	0.076	0.155	0.118

Substituting the above fully heterogeneous parameters into conditions (4.1) and (4.2) of Theorem 4.1 yields

$$\begin{aligned}
 \max \{\mu_i\} &= \max \{ -0.2561, -2.4914, -4.5004, -6.6274, -8.6548, \\
 &\quad -10.6919, -12.3510, -14.4923, -16.3415, -18.5738 \} < 0, \\
 \max \{v_i\} &= \max \{ -0.7205, -2.7543, -4.6707, -6.8039, -8.7414, \\
 &\quad -10.7715, -12.7226, -14.6969, -16.6910, -18.7477 \} < 0.
 \end{aligned}$$

The numerical results show that all μ_i and v_i are strictly negative, which fully satisfies the strict inequality conditions of Theorem 4.1.

In all simulations, $z_i(s, t)$ is assumed to be locally available and is not transmitted over the communication network. The reported triggering counts refer to response-state sampling and transmission events as well as controller update events. All three schemes adopt the event-triggered (ET) mechanism with the same thresholds as in Table 4, and differ only in the scheduling and

synchronous or asynchronous update mechanisms. Scheme 1 is the proposed asynchronous aperiodic intermittent event-triggered control, where each node independently configures σ_i , the control interval, the rest interval, γ_i , and T_{γ_i} , and only the controller of the triggered node is updated during its own control interval. Scheme 2 is the periodic synchronous ET, where all nodes share a common period $T = 1$, a common control interval $[h, h + 0.5)$, and a common rest interval $[h + 0.5, h + 1)$. During the control interval, if $\max_i \{\|u_i(s, t)\|_{L^2(\Gamma)}^2 - \sigma_i \|v_i(s, t)\|_{L^2(\Gamma)}^2\} > 0$, all nodes update their controllers simultaneously, so the total number of control updates is $10m$ for m global triggering events. Scheme 3 is the aperiodic synchronous ET, where all nodes share the same aperiodic control or rest-interval sequence $\bigcup_{h=0}^{\infty} ([h + 0.04, h + 0.46) \cup [h + 0.53, h + 0.94))$ with identical thresholds to Table 4, and the synchronous triggering rule is the same as in Scheme 2.

Each run adds random perturbations to the initial states as $z_i(s, 0) \leftarrow z_i(s, 0)(1 + 0.05\xi_i)$ and $w_i(s, 0) \leftarrow w_i(s, 0)(1 + 0.05\zeta_i)$, where ξ_i, ζ_i are standard normal random variables. The three schemes use the same random seeds and the same perturbations for fair comparison. A total of $M = 200$ independent Monte Carlo runs are performed. For the convergence time, average triggering times per node, and total control updates, we report the mean $\pm$ standard deviation, 95% confidence intervals, Wilcoxon rank-sum test p -values between the proposed scheme and the synchronous event-triggered schemes, and Cohen's d effect size for the control updates. The convergence time is defined as $T_{\text{conv}} = \inf\{t > 0 : \max_{1 \leq i \leq 10} \|v_i(\cdot, t)\|_{L^2(\Gamma)}^2 \leq 10^{-3}\}$.

Table 6. Performance comparison of three event-triggered control schemes (200 Monte Carlo runs). Triggering counts refer to response-state sampling and controller updates; z_i is locally available and not counted.

Scheme	Convergence time / s	Avg trigger/node	Total updates	p -value
Proposed: asynchronous aperiodic ETC	1.8588 ± 0.0083	380.2 ± 3.0	3802.2 ± 29.8	—
Periodic synchronous ETC	2.1200 ± 0.0081	634.0 ± 11.3	6340.0 ± 112.5	< 0.0001
Aperiodic synchronous ETC	1.9158 ± 0.0082	1248.2 ± 12.3	12481.6 ± 123.2	< 0.0001

Table 6 presents the fair comparison results under 200 Monte Carlo runs, where all three schemes adopt the event-triggered mechanism with the same σ_i as in Table 4. From Table 6, the proposed asynchronous aperiodic scheme achieves faster convergence than both synchronous event-triggered schemes, and the Wilcoxon rank-sum tests confirm that the differences are statistically significant ($p < 0.0001$ for both comparisons). On average, the proposed scheme converges in 1.8588 s, which is 12.3% faster than the periodic synchronous scheme and 3.0% faster than the aperiodic synchronous scheme. The standard deviation of the convergence time of the proposed scheme is 0.0083, comparable to those of the synchronous schemes (0.0081 and 0.0082), indicating similar robustness. More importantly, the proposed scheme requires only 380.2 triggering events per node on average, totaling 3802.2 control updates across all nodes, whereas the periodic and aperiodic synchronous schemes demand 6340.0 and 12,481.6 control updates, respectively. The Wilcoxon rank-sum test confirms that the proposed scheme significantly reduces the total number of control updates ($p < 0.0001$), with a reduction of 40.0% compared to the periodic synchronous scheme and 69.5% compared to the aperiodic synchronous scheme. Figure 1 compares the evolution of the maximum synchronization error $E(t) = \max_{1 \leq i \leq 10} \int_{\Gamma} |v_i(s, t)|^2 ds$ under the three event-triggered schemes, with

shaded regions indicating standard deviations over 200 Monte Carlo runs. The dashed line denotes the convergence threshold 10^{-3} , and the subgraph shows the local amplification of error curves within $t \in [0, 1]$. All three schemes achieve exponential convergence, while the proposed scheme exhibits the fastest convergence and the smallest error, which is consistent with the theoretical prediction in Theorem 4.1. In summary, the revised simulation validates that the proposed strategy is applicable to fully heterogeneous node-wise configurations with independent thresholds, control intervals, and rest intervals; that the 200 Monte Carlo runs and statistical tests support its advantages in both robustness and controller-update savings under the local availability of the drive state; and that compared with synchronous event-triggered schemes using the same thresholds, the proposed asynchronous aperiodic scheme has significant advantages in reducing control updates, and the comparison is fair.

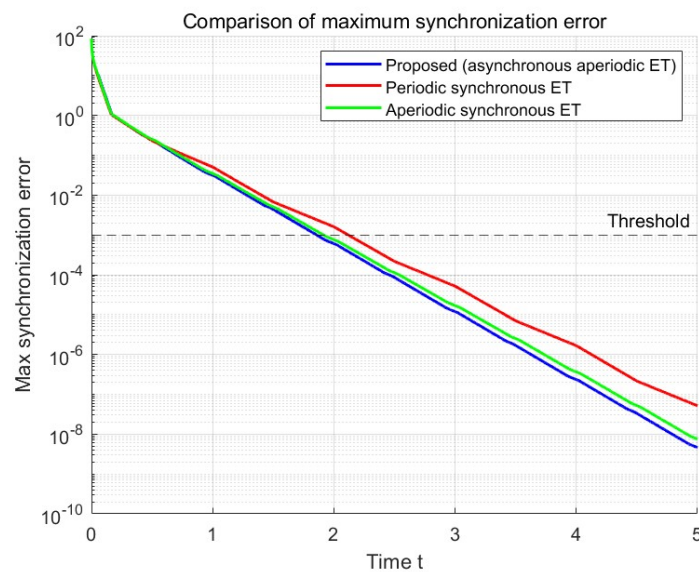


Figure 1. Comparison of maximum synchronization error $\max_{1 \leq i \leq 10} \int_T |v_i(s, t)|^2 ds$ under three event-triggered control schemes. The dashed line denotes the convergence threshold 10^{-3} .

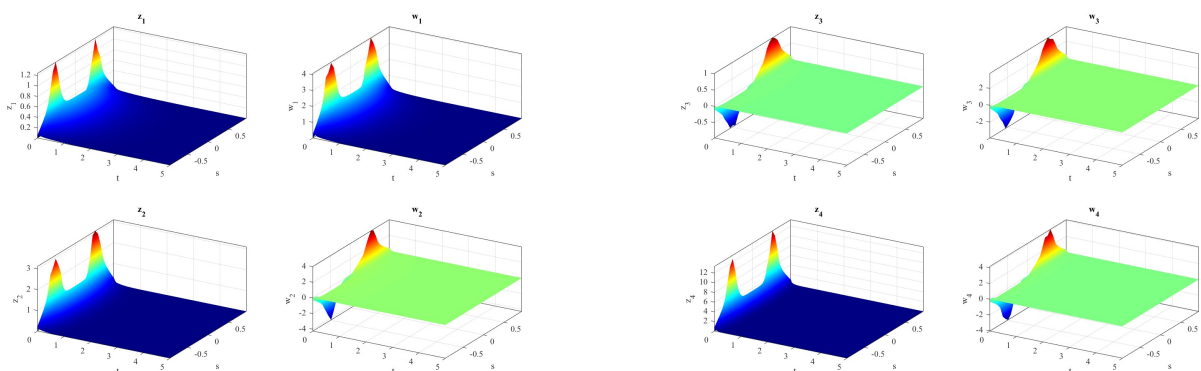


Figure 2. Simulations of the drive systems z_1, z_2, z_3, z_4 and the response systems w_1, w_2, w_3, w_4 , respectively.

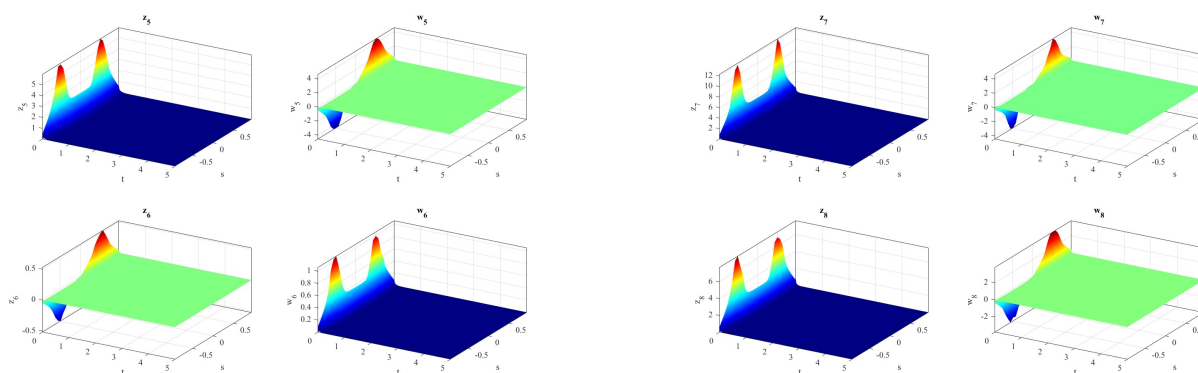


Figure 3. Simulations of the drive systems z_5, z_6, z_7, z_8 and the response systems w_5, w_6, w_7, w_8 , respectively.

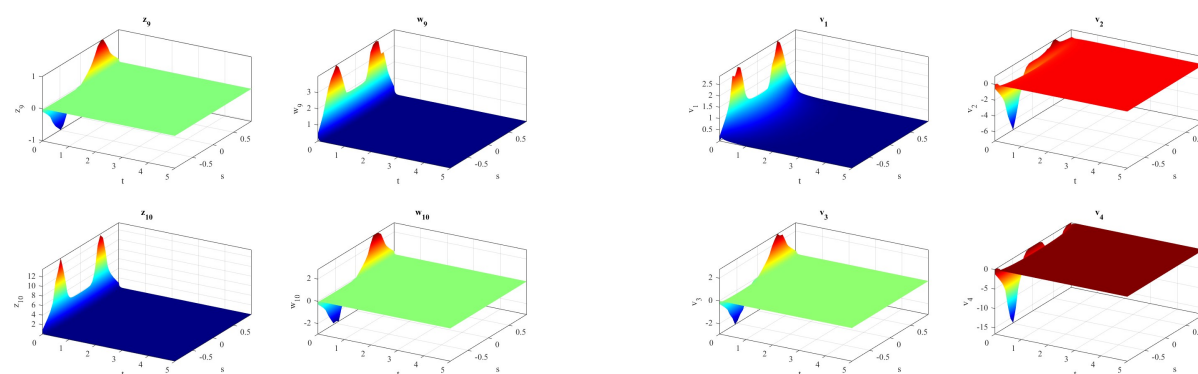


Figure 4. Simulations of the drive systems z_9, z_{10} , the response systems w_9, w_{10} , and the error systems v_1, v_2, v_3 , and v_4 (left to right, respectively).

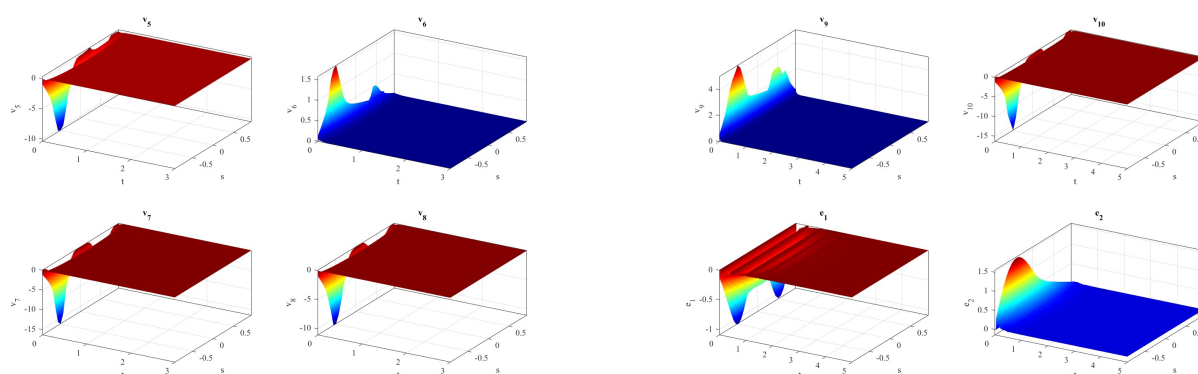


Figure 5. Simulations of the error systems $v_5, v_6, v_7, v_8, v_9, v_{10}$ and the controllers e_1, e_2 , respectively.

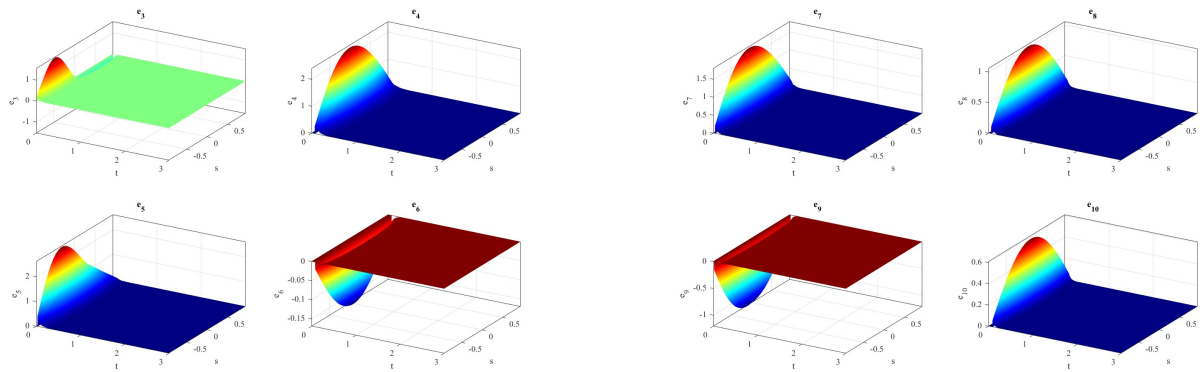


Figure 6. Simulations of the controllers e_3 , e_4 , e_5 , e_6 , e_7 , e_8 , e_9 , and e_{10} , respectively.

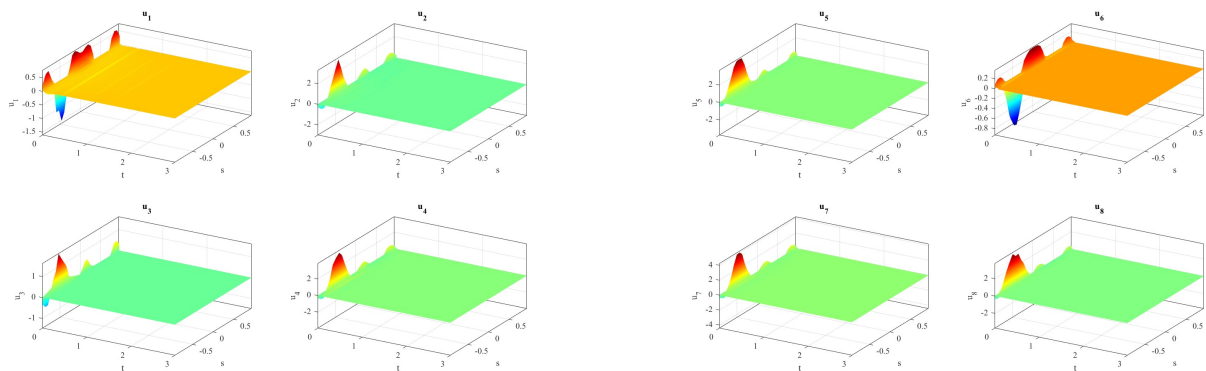


Figure 7. Spatiotemporal evolution of event-triggering error $u_i(s, t) = w_i(s, t) - w_i(s, t_r^i)$ for nodes 1–8.

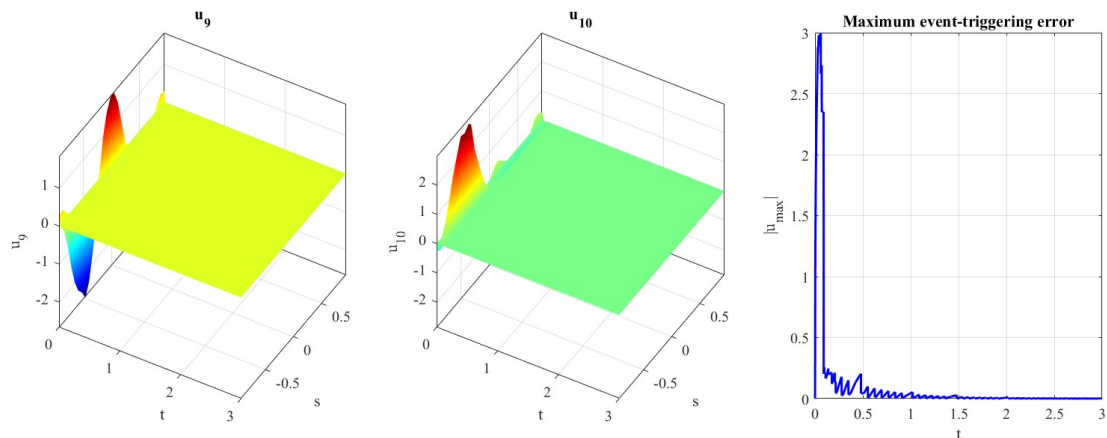


Figure 8. Spatiotemporal evolution of event-triggering error $u_i(s, t) = w_i(s, t) - w_i(s, t_r^i)$ for nodes 9–10, and time evolution of the maximum event-triggering error $|u_{\max}|$ (left to right, respectively).

Figures 2–5 depict the spatiotemporal evolution of the drive and response systems for all nodes. It can be observed that, despite the fully heterogeneous initial states, the response systems rapidly track the drive systems under the designed asynchronous, aperiodic, intermittent event-triggered control protocol. The spatiotemporal profiles of synchronization errors in Figures 2–5 reveal that the errors of all nodes decay rapidly within $t < 1$ and stay below the magnitude of 10^{-3} , which verifies the exponential convergence rate derived in Theorem 4.1. The control signals e_i are only activated in the aperiodic control intervals when the event-triggered condition is satisfied, reflected by the sparse sharp pulses in Figure 6. This demonstrates that the proposed strategy effectively reduces unnecessary energy consumption caused by continuous control updates. The event-triggered error u_i is strictly constrained within the threshold as shown in Figure 7, and the maximum error $|u_{\max}|$ tends to zero after $t > 1$ in Figure 8. This reveals that nearly no control updates are required for the system at the steady state.

6. Conclusions

This paper proposes a novel asynchronous, aperiodic, event-triggered intermittent control strategy to investigate the exponential synchronization of networked reaction-diffusion systems. Unlike existing studies, each node in the network is configured with independent triggering thresholds, control intervals, and rest intervals, which improves the control accuracy and flexibility. A new Lyapunov function is constructed in this paper. Combined with graph theory and inequality techniques, sufficient conditions for synchronization are derived. Numerical simulations under fully heterogeneous node-wise configurations and fair comparisons with event-triggered synchronous schemes verify the effectiveness, robustness, and efficiency of the proposed algorithm in reducing response-state sampling and transmission as well as controller updates, under the assumption that the drive state is locally available. On the basis of the current method, future research will focus on the exponential synchronization of stochastic reaction-diffusion systems with random perturbations, the design of dynamic and adaptive event-triggered aperiodic intermittent control schemes with lower communication and computation costs, and further relaxation of constraints on network topologies and coupling delays.

Use of AI tools declaration

During the preparation of this work the authors used Doubao and DeepSeek in order to translate the manuscript into English, restructure the Introduction section, and generate a condensed version of the excessively long Conclusion. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication. Furthermore, we would like to clarify that all core research content, academic viewpoints, data arguments, and the remaining proofs were independently completed by the authors. AI tools did not participate in core academic processes such as research design, data processing, or conclusion derivation. The authors strictly adhered to academic integrity norms and the relevant requirements of the journal.

Acknowledgments

This work was partially supported by the National Natural Science Foundation of China under Grant No. 62373143, the Key Project of Hunan Provincial Education Department (22A0406), the Project

of Zhuzhou Double Innovation Excellent Talent (2024-7), and the General Science and Technology Project of Department of Education of Jiangxi Province (Grant No. GJJ2202916).

Conflict of interest

The authors declare there are no conflicts of interest.

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