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Research article

Intermittent impulsive control for leader-following consensus of stochastic multi-agent systems with packet dropouts

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Abstract: This paper investigates the leader-following consensus problem of stochastic multi-agent systems (SMASs) with packet dropouts. Specifically, an intermittent impulsive control (IIC) strategy is proposed to reduce communication and control costs, combining the distinct strengths of aperiodic intermittent control and impulsive control techniques. The packet dropout phenomenon, which is described by an auxiliary function, is taken into account. Based on the linear matrix inequality (LMI) technique and the average dwell time algorithm, sufficient Lyapunov-based conditions are derived to ensure that the SMASs achieve mean-square leader-following consensus. Finally, numerical simulations based on the classical Chua's circuit model are presented to illustrate the effectiveness of the derived results.

Keywords: consensus; stochastic multi-agent systems; impulsive control; aperiodic intermittent control; packet dropouts
Mathematics Subject Classification: 34H05

1. Introduction

As an important class of networked control systems, multi-agent systems (MASs) can execute complex tasks beyond the capacity of any single agent by leveraging the interaction and cooperation among agents [1–3]. Over the last decade, the consensus problem of MASs has attracted significant attention from the control community due to its wide applications in various fields, such as formation control, distributed optimization, and sensor networks [4–6]. In practical scenarios, MASs often operate in uncertain environments and are subject to various disturbances. If these stochastic disturbances are not properly addressed, the consensus of stochastic multi-agent systems (SMASs) is highly likely to be compromised. Consequently, investigating the consensus of SMASs holds profound practical significance [7–10].

Packet dropouts are inevitable in networked control systems owing to network congestion, electromagnetic interference, malicious cyber-attacks, and other factors [11–13]. If packet dropouts are not properly addressed, the communication topology or control signals of MASs will be severely disrupted. This not only degrades control performance but may even lead to system instability in severe scenarios. To address this issue, various control strategies have been proposed to mitigate the adverse effects of packet dropouts. For instance, a tolerant containment controller was designed in [14] to ensure finite-time leader-following consensus of MASs in the presence of actuator faults, denial-of-service attacks, and packet dropouts. In [15], the mean-square consensus problem of heterogeneous MASs with packet dropouts was investigated by developing a dynamic output feedback control strategy. Considering energy-dependent packet dropouts, leader-following consensus of MASs was investigated in [16] by designing a feedback control scheme. Note that the above control schemes necessitate continuous control inputs, thereby resulting in substantial control costs. Consequently, this paper is motivated to investigate a novel control strategy for achieving the leader-following consensus of SMASs with packet dropouts.

To achieve consensus in SMASs, various control strategies have been developed, including event-triggered control [17], adaptive control [18], intermittent control [19], and impulsive control [20]. Among these strategies, impulsive control and intermittent control schemes have gained significant attention due to their ability to handle systems with discontinuities and their potential to reduce communication and control costs. These two schemes are detailed below.

Distinct from continuous control strategies, impulsive control actuates the system exclusively at a sequence of discrete time instants, inducing instantaneous state jumps to steer the system dynamics, while allowing the system to evolve continuously without control inputs between consecutive impulses [21–23]. Owing to this characteristic, this mechanism inherently reduces communication burdens, conserves actuator energy, and avoids continuous observation of system states. Consequently, impulsive control has been extensively deployed across a wide spectrum of practical engineering applications, particularly in resource-constrained scenarios such as spacecraft attitude maneuvering, autonomous vehicle coordination, epidemic disease management, and power grid synchronization. Depending on the sequence design of the impulse instants, impulsive control schemes can be classified into two kinds: time-triggered and event-triggered. Time-triggered impulsive control allows the impulse intervals to fluctuate within certain bounds or adhere to an average impulse interval constraint [24–26]. Furthermore, while time-triggered mechanisms are effective, they may still generate redundant control updates. To further optimize resource utilization, event-triggered impulsive control has recently garnered substantial research interest [27–29]. By orchestrating impulse executions exclusively when specific, state-dependent threshold conditions are violated, this scheme minimizes unnecessary communication and control costs.

Intermittent control operates through an alternating sequence of control and free intervals [30–32]. During the control intervals, the control input is applied to steer the system dynamics, whereas during the free intervals, the control is entirely switched off, allowing the system to evolve in an open-loop fashion. This piecewise continuous actuation mechanism aligns with the physical constraints inherent in many real-world engineering applications. For instance, in networked unmanned aerial vehicle formations, mobile sensor networks, and autonomous manufacturing systems, continuous communication and actuation are often unfeasible due to limited onboard battery capacity, constrained communication bandwidth, or the strict necessity to prevent actuator overheating. Based on the temporal arrangement of the control intervals, intermittent control strategies are primarily classified into periodic and aperiodic frameworks. Periodic intermittent control imposes strictly constant durations for both the control and free intervals across all cycles, which considerably simplifies both the engineering implementation and the mathematical stability analysis [33–35]. However, rigidly maintaining periodic switching is often impractical in practice. To address this issue, aperiodic intermittent control relaxes the constant-duration constraint, allowing the control and free intervals to fluctuate dynamically within specific theoretical bounds, thereby offering a more resilient and flexible approach to ensuring system consensus [36–38].

Inspired by the distinct resource-saving advantages of both impulsive control and intermittent control, a few recent efforts have emerged to integrate these two mechanisms for system stabilization [39, 40]. Nevertheless, these preliminary hybrid schemes predominantly focus on deterministic systems operating under ideal network conditions. Different from existing hybrid schemes, the implementation of such a combined strategy for SMASs, particularly in the presence of unreliable network transmissions like packet dropouts, remains a largely unexplored gap. In practical networked environments, packet dropouts can easily disrupt the discontinuous control signals, leading to severe performance degradation. This clear gap motivates the current study to develop a novel intermittent impulsive control (IIC) strategy. By restricting impulsive actuations strictly within the intermittent control intervals and incorporating a compensatory mechanism for packet dropouts, the proposed IIC achieves consensus while significantly reducing communication overhead. The main contributions of this paper are summarized as follows:

(1) An IIC strategy is proposed to restrict impulsive control signals strictly to the control intervals. Meanwhile, the packet dropout phenomenon is considered in the design of the IIC strategy, which enhances the resilience of the control scheme to packet dropouts.
(2) By employing the average dwell time algorithm, sufficient leader-following consensus conditions are derived, which are significantly less conservative than those based on fixed impulsive intervals. These results reveal the relationship among the average impulsive interval, the packet dropout rate, and the minimum control rate.

The remainder of this article is organized as illustrated in Figure 1.

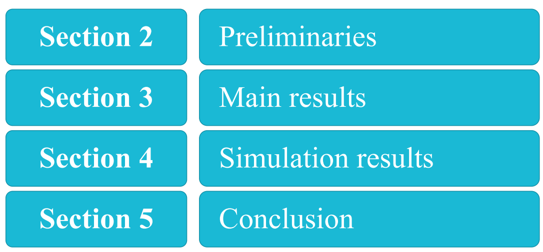


Figure 1. The remainder of this article.

2. Preliminaries

Notations: $\mathbb{R}^m$, $\mathbb{R}^{m\times m}$, and $\mathbb{N}^+$ denote the m-dimensional Euclidean space, the set of $m \times m$ real matrices, and the set of positive integers, respectively. For a real matrix A, $\lambda_{\min}(A)$ and $\lambda_{\max}(A)$ denote its minimum and maximum eigenvalues, respectively. $\mathrm{diag}\{x_1, \ldots, x_n\}$ represents an $n \times n$ diagonal matrix with elements x_i on its main diagonal. I_m indicates the $m \times m$ identity matrix.

Consider an SMAS with M followers and one leader, which dynamics are given by

$$\begin{cases} \mathrm{d}r_i(t) = [Ar_i(t) + Bf(r_i(t)) + u_i(t)]\mathrm{d}t + \sigma(r_i(t))\mathrm{d}W(t), \\ \mathrm{d}r_0(t) = [Ar_0(t) + Bf(r_0(t))]\mathrm{d}t + \sigma(r_0(t))\mathrm{d}W(t), \end{cases} \tag{2.1}$$

where $i \in \{1, 2, \ldots, M\}$, $r_i(t) \in \mathbb{R}^m$ denotes the state of the i-th follower, $r_0(t) \in \mathbb{R}^m$ indicates the state of the leader, $A, B \in \mathbb{R}^{m\times m}$ are constant matrices, $f : \mathbb{R}^m \to \mathbb{R}^m$ and $\sigma : \mathbb{R}^m \to \mathbb{R}^m$ are nonlinear functions, $u_i(t)$ denotes the control input for the i-th follower, and $W(t)$ denotes a standard scalar Brownian motion defined on a complete probability space $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t\geq t_0}, \mathbb{P})$.

Remark 2.1. *It is important to clarify that system (2.1) utilizes a common Brownian motion $W(t)$ for all agents. Physically, this assumption aligns with scenarios where the multi-agent system operates in a compact formation and is subjected to uniform environmental disturbances, such as identical wind gusts or global electromagnetic interferences. Broadening the proposed architecture to accommodate independent stochastic perturbations, such as assigning the distinct Brownian motion $W_i(t)$ across respective agents, inevitably injects nonvanishing diffusion elements into the underlying error dynamics. Consequently, exact mean-square consensus would generally degrade to practical consensus, which remains a challenging and significant topic for our future research.*

The communication topology among the followers is described as an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ and $\mathcal{E}$ are the sets of nodes and edges, respectively. The set of neighbors of the i-th follower is denoted by $\mathcal{N}_i = \{j \in \{1, 2, \ldots, M\} : (i, j) \in \mathcal{E}\}$. The adjacency matrix $\mathcal{A} = [a_{ij}]_{M\times M}$ of the graph $\mathcal{G}$ is presented by

$$a_{ij} = \begin{cases} 1, & \text{if } (i, j) \in \mathcal{E}, \\ 0, & \text{otherwise}, \end{cases} \text{ and } a_{ij} = a_{ji}, i \neq j.$$

The Laplacian matrix of $\mathcal{G}$ is given by $\mathcal{L} = [l_{ij}]_{M\times M}$, where

$$l_{ij} = \begin{cases} \sum_{j=1, j\neq i}^{M} a_{ij}, & \text{if } i = j, \\ -a_{ij}, & \text{if } i \neq j. \end{cases}$$

Denote $\mathcal{D} = \mathrm{diag}\{d_1, d_2, \ldots, d_M\}$, where $d_i > 0$ means that the i-th follower can receive information from the leader, and $d_i = 0$ otherwise. Let $\mathcal{H} = \mathcal{L} + \mathcal{D}$.

Assumption 2.1. *[10] The graph $\mathcal{G}$ is connected, and at least one follower can receive information from the leader.*

Assumption 2.2. *[9] The nonlinear function $f(\cdot)$ satisfies the following Lipschitz conditions: There exists a diagonal matrix $\Gamma \in \mathbb{R}^{m\times m}$ such that for all $x, y \in \mathbb{R}^m$,*

$$\|f(x) - f(y)\| \leq \|\Gamma(x - y)\|.$$

Assumption 2.3. *[10] The nonlinear function $\sigma(\cdot)$ satisfies the following constraint: There exists a positive definite matrix $\Sigma \in \mathbb{R}^{m\times m}$ such that for all $x, y \in \mathbb{R}^m$,*

$$trace[(\sigma(x) - \sigma(y))^\top(\sigma(x) - \sigma(y))] \le (x - y)^\top\Sigma(x - y).$$

Let $\xi_i(t) = r_i(t) - r_0(t)$ denote the consensus error of the i-th follower. Then, the error system can be derived from (2.1) as follows:

$$\mathrm{d}\xi_i(t) = [A\xi_i(t) + B\tilde{f}(\xi_i(t)) + u_i(t)]\mathrm{d}t + \tilde{\sigma}(\xi_i(t))\mathrm{d}W(t), \tag{2.2}$$

where $\tilde{f}(\xi_i(t)) = f(r_i(t)) - f(r_0(t))$, $\tilde{\sigma}(\xi_i(t)) = \sigma(r_i(t)) - \sigma(r_0(t))$. Define $\xi(t) = [\xi_1^\top(t), \xi_2^\top(t), \dots, \xi_M^\top(t)]^\top$. Then system (2.2) is expressed in a compact form:

$$\mathrm{d}\xi(t) = [(I_M \otimes A)\xi(t) + (I_M \otimes B)\mathscr{F}(\xi(t)) + u(t)]\mathrm{d}t + \mathscr{G}(\xi(t))\mathrm{d}W(t), \tag{2.3}$$

where $\mathscr{F}(\xi(t)) = [\tilde{f}^\top(\xi_1(t)), \tilde{f}^\top(\xi_2(t)), \dots, \tilde{f}^\top(\xi_M(t))]^\top$, $\mathscr{G}(\xi(t)) = [\tilde{\sigma}^\top(\xi_1(t)), \tilde{\sigma}^\top(\xi_2(t))^\top, \dots, \tilde{\sigma}^\top(\xi_M(t))]^\top$, and $u(t) = [u_1^\top(t), u_2^\top(t), \dots, u_M^\top(t)]^\top$.

Lemma 2.1. *[41] Under Assumption 2.1, the matrix $\mathcal{H}$ associated with the undirected and balanced communication graph is symmetric positive definite.*

Definition 2.1. *[8] SMAS* (2.1) *is said to achieve exponential leader-following consensus in mean square if there exist two positive constants φ and ε such that, for any initial condition, the error system* (2.3) *satisfies*

$$\mathbf{E}\{\|\xi(t)\|^2\} \le \varepsilon e^{-\varphi(t-t_0)}\mathbf{E}\{\|\xi(t_0)\|^2\}, \forall t \ge t_0.$$

3. Main results

The objective of this paper is to develop an IIC strategy that ensures leader-following consensus of SMAS (2.1) in the presence of packet dropouts.

3.1. The IIC strategy design

Let $\mathbb{C}_k = [t_{k-1}, t_{k-1} + \Xi_k)$ and $\mathbb{F}_k = [t_{k-1} + \Xi_k, t_k)$ denote the kth control interval and the kth free interval of intermittent control, respectively, where $k \in \mathbb{N}^+$, $t_k - t_{k-1}$ is the kth intermittent period, and Ξ_k denotes the duration of the kth control interval. Considering the packet dropout phenomenon, the IIC strategy for the i-th follower is designed as follows:

$$u_i(t) = \begin{cases} \beta(t)\chi \sum_{k=1}^{\infty} \sum_{s_k=1}^{\eta_k} \vartheta_i(t)\delta(t - t_{k,s_k}), & t \in \mathbb{C}_k, \\ 0, & t \in \mathbb{F}_k, \end{cases} \tag{3.1}$$

where $\vartheta_i(t) = \sum_{j\in\mathcal{N}_i} a_{ij}(r_j(t) - r_i(t)) - d_i(r_i(t) - r_0(t))$, $\delta(\cdot)$ indicates the Dirac function, $\chi > 0$ is the control gain, η_k is the number of impulses within the kth control interval, t_{k,s_k} stands for the s_kth impulsive instant in the kth control interval, and $\beta(t)$ denotes the packet dropout variable, which is defined as

$$\beta(t) = \begin{cases} 1, & \text{if the control signal is transmitted,} \\ 0, & \text{if the control signal is lost.} \end{cases}$$

Remark 3.1. *In contrast to existing intermittent control schemes, such as [33–36], the proposed IIC strategy introduces an impulsive control technique within the control interval of intermittent control. Specifically, the system benefits from the free intervals $\mathbb{F}_k$ where control is entirely switched off. Within the active control intervals $\mathbb{C}_k$, the continuous control input is replaced by a sequence of discrete impulses at instants t_{k,s_k}. Consequently, during the active intervals, the communication network is only triggered, and the actuator is only energized, at these specific discrete instants. Between any two consecutive impulses, the actuator output is zero, and no information is transmitted. This mechanism significantly reduces the communication bandwidth occupancy and actuator energy consumption compared to conventional intermittent controllers. Furthermore, compared with existing IIC strategies [39, 40] that strictly assume ideal and continuous transmission of impulsive signals, the proposed framework is significantly more resilient. It explicitly accommodates the unreliability of communication networks by quantifying the tolerable packet dropout rate $\overline{\rho}$ and balancing it with the minimum control rate ψ, thereby successfully overcoming the aforementioned challenge.*

Remark 3.2. *While event-triggered mechanisms excel at saving resources, they generally necessitate continuous or high-frequency state monitoring to accurately evaluate the triggering conditions. In practical networked environments characterized by severe packet dropouts, relying on real-time state transmissions to trigger events becomes highly vulnerable. Missing a critical event-triggered control packet could easily cause the threshold conditions to be violated for an extended period, leading to system instability. Therefore, this paper adopts a time-triggered IIC approach to establish a more resilient baseline against inevitable data loss.*

For the design of the IIC strategy, sequences $\{t_k\}$ and $\{\Xi_k\}$ satisfy the following conditions:

$$\begin{cases} 0 < \Xi_k < t_k - t_{k-1}, \forall k \in \mathbb{N}^+, \\ \lim_{k\to\infty} t_k = \infty. \end{cases}$$

Denote the minimum control rate as $\psi = \Xi/\Lambda$, where $\Xi = \inf_{k\in\mathbb{N}^+}\{\Xi_k\}$ and $\Lambda = \sup_{k\in\mathbb{N}^+}\{t_k - t_{k-1}\}$.

Then the sequence $\{t_{k,s_k}\}$ satisfies $0 \le t_0 < t_{1,1} < \cdots < t_{1,\eta_1} < t_1 < t_{2,1} < \cdots < t_{k,\eta_k} < t_k < \cdots$ and $\lim_{k\to\infty} t_{k,s_k} = \infty$.

It follows from (2.3) and (3.1) that the closed-loop error system can be expressed as

$$\begin{cases} \begin{cases} \mathrm{d}\xi(t) = [(I_M \otimes A)\xi(t) + (I_M \otimes B)\mathscr{F}(\xi(t))]\mathrm{d}t + \mathscr{G}(\xi(t))\mathrm{d}W(t), \ t \ne t_{k,s_k} \in \mathbb{C}_k, \\ \Delta\xi(t) = -\beta(t)\chi(\mathcal{H} \otimes I_m)\xi(t^-), \ t = t_{k,s_k} \in \mathbb{C}_k, \end{cases} \\ \mathrm{d}\xi(t) = [(I_M \otimes A)\xi(t) + (I_M \otimes B)\mathscr{F}(\xi(t))]\mathrm{d}t + \mathscr{G}(\xi(t))\mathrm{d}W(t), \ t \in \mathbb{F}_k, \end{cases} \tag{3.2}$$

where $\Delta\xi(t) = \xi(t^+) - \xi(t^-)$. Assume that the state of system (3.2) is right continuous at t_{k,s_k}, i.e., $\xi(t_{k,s_k}^+) = \xi(t_{k,s_k})$.

Denoting $\Upsilon : \{t_{k,s_k}\} \to \{\Upsilon_0, \Upsilon_1\}$, one has

$$\Upsilon(t) = \begin{cases} \Upsilon_0, & \text{if } \beta(t_{k,s_k}) = 0, \\ \Upsilon_1, & \text{if } \beta(t_{k,s_k}) = 1, \end{cases}$$

where $\Upsilon_0 = I_{Mm}$ and $\Upsilon_1 = I_{Mm} - \chi(\mathcal{H} \otimes I_m)$. Then, system (3.2) is rewritten as

$$\begin{cases} \begin{cases} \mathrm{d}\xi(t) = [(I_M \otimes A)\xi(t) + (I_M \otimes B)\mathscr{F}(\xi(t))]\mathrm{d}t + \mathscr{G}(\xi(t))\mathrm{d}W(t), \ t \ne t_{k,s_k} \in \mathbb{C}_k, \\ \xi(t) = \Upsilon(t)\xi(t^-), \ t = t_{k,s_k} \in \mathbb{C}_k, \end{cases} \\ \mathrm{d}\xi(t) = [(I_M \otimes A)\xi(t) + (I_M \otimes B)\mathscr{F}(\xi(t))]\mathrm{d}t + \mathscr{G}(\xi(t))\mathrm{d}W(t), \ t \in \mathbb{F}_k. \end{cases} \tag{3.3}$$

Let $\mathcal{R}_1(t,t_0)$ and $\mathcal{R}_2(t,t_0)$ be the ideal and actual numbers of impulses generated over the interval $[t_0,t]$, respectively. Then, the packet dropout rate is defined as $\rho(t) = 1 - \frac{\mathcal{R}_2(t,t_0)}{\mathcal{R}_1(t,t_0)}$. We assume that the packet dropout rate satisfies $\limsup_{t\to\infty}\rho(t) \le \bar{\rho}$, where $\bar{\rho} \in [0,1)$ is a constant.

Definition 3.1. *[40] If there exist two scalar ϖ and $\mathcal{K}$ such that*

$$\frac{\sum_{i=1}^{k}\Xi_k}{\varpi} - \mathcal{K} \le \mathcal{R}_1(t_k,t_0), \forall k \in \mathbb{N},$$

then ϖ and $\mathcal{K}$ are called the intermittent average impulsive interval and the intermittent elasticity number, respectively.

Remark 3.3. *The primary purpose of Definition 3.1 is to relax the conservative constraint of strict step-by-step upper bounds on impulsive intervals by evaluating them in an average sense. Physically, the constant ϖ represents the macroscopic average time elapsed between two consecutive impulses during the active control intervals. The constant $\mathcal{K}$ serves as an elasticity bound, allowing the impulsive signals to be transiently clustered or sparsely distributed, provided that the average interval remains constrained by ϖ.*

3.2. Leader-following consensus analysis

Herein, some sufficient conditions are derived to guarantee that leader-following consensus of SMAS (2.1) with packet dropouts can be achieved via IIC (3.1).

Theorem 3.1. *Suppose that Assumptions 2.1–2.3 hold. If there exist two positive definite matrices $\mathcal{Z}, \Theta \in \mathbb{R}^{m\times m}$ and two scalars α, γ such that*

$$\mathcal{Z} < \gamma I_m, \tag{3.4}$$

$$\begin{bmatrix} \Psi & \mathcal{Z}B \\ * & -\Theta \end{bmatrix} < 0, \tag{3.5}$$

$$\varphi_1 = -\frac{(1-\bar{\rho})\psi}{\varpi}\ln\zeta - \alpha > 0, \tag{3.6}$$

where $\Psi = \mathcal{Z}A + A^\top\mathcal{Z} + \Gamma\Theta\Gamma + \gamma\lambda_{\max}(\Sigma)I_m - \alpha\mathcal{Z}$, $\zeta = \lambda_{\max}((I_M - \chi\mathcal{H})^\top(I_M - \chi\mathcal{H}))$, then SMAS (2.1) *with packet dropouts can achieve leader-following consensus in mean square under the IIC strategy* (3.1).

Proof. Consider the Lyapunov function candidate as follows:

$$V(t,\xi(t)) = \xi^\top(t)(I_M \otimes \mathcal{Z})\xi(t).$$

Based on the Itô formula [42], when $t \ne t_{k,s_k}$, one has

$$\mathrm{d}V(t,\xi(t)) = \mathscr{L}V(t)\mathrm{d}t + V_\xi(t)\mathscr{G}(\xi(t))\mathrm{d}W(t),$$

where

$$V_\xi(t) = \left(\frac{\partial V(t,\xi(t))}{\partial \xi_1(t)}, \ldots, \frac{\partial V(t,\xi(t))}{\partial \xi_M(t)}\right)$$

and $\mathscr{L}$ is the infinitesimal operator that is defined as

$$\begin{aligned}\mathscr{L}V(t,\xi(t)) = {} & 2\xi^\top(t)(I_M\otimes\mathcal{Z})[(I_M\otimes A)\xi(t)+(I_M\otimes B)\mathscr{F}(\xi(t))]\\ & +\mathrm{trace}[\mathscr{G}^\top(\xi(t))(I_M\otimes\mathcal{Z})\mathscr{G}(\xi(t))].\end{aligned} \tag{3.7}$$

Under Assumptions 2.2 and 2.3, it yields that

$$2\xi^\top(t)(I_M\otimes\mathcal{Z})(I_M\otimes B)\mathscr{F}(\xi(t)) \le \xi^\top(t)(I_M\otimes(\mathcal{Z}B\Theta^{-1}B^\top\mathcal{Z}+\Gamma\Theta\Gamma))\xi(t) \tag{3.8}$$

and

$$\mathrm{trace}[\mathscr{G}^\top(\xi(t))(I_M\otimes\mathcal{Z})\mathscr{G}(\xi(t))] \le \gamma\lambda_{\max}(\Sigma)\xi^\top(t)\xi(t). \tag{3.9}$$

Substituting (3.8) and (3.9) into (3.7), one has

$$\begin{aligned}\mathscr{L}V(t,\xi(t)) &\le \xi^\top(t)(I_M\otimes(\mathcal{Z}A+A^\top\mathcal{Z}+\Gamma\Theta\Gamma+\mathcal{Z}B\Theta^{-1}B^\top\mathcal{Z}+\gamma\lambda_{\max}(\Sigma)I_m))\xi(t)\\ &\le \alpha V(t,\xi(t)).\end{aligned} \tag{3.10}$$

Let ω be a sufficiently small scalar such that $t+\omega\in(t_{k,s_k-1},t_{k,s_k})$. Then, it follows that

$$\mathbf{E}\{V(t+\omega,\xi(t+\omega))\}-\mathbf{E}\{V(t,\xi(t))\} \le \int_t^{t+\omega}\alpha\mathbf{E}\{V(s,\xi(s))\}\mathrm{d}s.$$

When $\omega\to 0^+$, we have

$$\begin{aligned}D^+\mathbf{E}\{V(t,\xi(t))\} &= \mathbf{E}\{\mathscr{L}V(t,\xi(t))\}\\ &\le \alpha\mathbf{E}\{V(t,\xi(t))\},\end{aligned}$$

then it yields that

$$\mathbf{E}\{V(t,\xi(t))\} \le e^{\alpha(t-t_{k,s_k-1})}\mathbf{E}\{V(t_{k,s_k-1},\xi(t_{k,s_k-1}))\} \tag{3.11}$$

for any $t\in[t_{k,s_k-1},t_{k,s_k})$.

Correspondingly, for any $t\in\mathbb{F}_k$, one has

$$\mathbf{E}\{V(t,\xi(t))\} \le e^{\alpha(t-t_{k-1}-\Xi_k)}\mathbf{E}\{V(t_{k-1}+\Xi_k,\xi(t_{k-1}+\Xi_k))\}. \tag{3.12}$$

When $t=t_{k,s_k}\in\mathbb{C}_k$, it follows that

$$\begin{aligned}\mathbf{E}\{V(t_{k,s_k},\xi(t_{k,s_k}))\} &= \mathbf{E}\{\xi^\top(t_{k,s_k})(I_M\otimes\mathcal{Z})\xi(t_{k,s_k})\}\\ &= \mathbf{E}\{\xi^\top(t^-_{k,s_k})\Upsilon^\top(t_{k,s_k})(I_M\otimes\mathcal{Z})\Upsilon(t_{k,s_k})\xi(t^-_{k,s_k})\}.\end{aligned}$$

Based on the definition of $\Upsilon(t)$, when $\Upsilon(t)=\Upsilon_1$, it yields that

$$\mathbf{E}\{V(t_{k,s_k},\xi(t_{k,s_k}))\} \le \zeta\mathbf{E}\{V(t^-_{k,s_k},\xi(t^-_{k,s_k}))\}.$$

From $\Upsilon(t)=\Upsilon_0$, one has

$$\mathbf{E}\{V(t_{k,s_k},\xi(t_{k,s_k}))\} = \mathbf{E}\{V(t^-_{k,s_k},\xi(t^-_{k,s_k}))\}.$$

Then, we obtain

$$\begin{cases}\mathbf{E}\{V(t_{k,s_k},\xi(t_{k,s_k}))\} \le e^{\ln\zeta}\mathbf{E}\{V(t^-_{k,s_k},\xi(t^-_{k,s_k}))\}, \text{ if } \beta(t_{k,s_k})=1,\\ \mathbf{E}\{V(t_{k,s_k},\xi(t_{k,s_k}))\} = \mathbf{E}\{V(t^-_{k,s_k},\xi(t^-_{k,s_k}))\}, \text{ if } \beta(t_{k,s_k})=0.\end{cases} \tag{3.13}$$

For simplicity, (3.13) can be written as

$$\mathbf{E}\{V(t_{k,s_k},\xi(t_{k,s_k}))\} \le e^{\beta(t_{k,s_k})\ln\zeta}\mathbf{E}\{V(t^-_{k,s_k},\xi(t^-_{k,s_k}))\}. \tag{3.14}$$

For any $t \in [t_0, t_{1,1})$, from (3.11), one has

$$\mathbf{E}\{V(t,\xi(t))\} \le e^{\alpha(t-t_0)}\mathbf{E}\{V(t_0,\xi(t_0))\}.$$

For any $t \in [t_{1,1}, t_{1,2})$, it follows from (3.14) that

$$\begin{aligned}\mathbf{E}\{V(t,\xi(t))\} &\le e^{\alpha(t-t_{1,1})}\mathbf{E}\{V(t_{0,1},\xi(t_{1,1}))\}\\ &\le e^{\alpha(t-t_{1,1})}e^{\beta(t_{1,1})\ln\zeta}\mathbf{E}\{V(t^-_{1,1},\xi(t^-_{1,1}))\}\\ &\le e^{\beta(t_{1,1})\ln\zeta+\alpha(t-t_0)}\mathbf{E}\{V(t_0,\xi(t_0))\}.\end{aligned}$$

For any $t \in \mathbb{F}_0$, based on (3.12), we have

$$\begin{aligned}\mathbf{E}\{V(t,\xi(t))\} &\le e^{\alpha(t-t_0-\Xi_0)}\mathbf{E}\{V(t_0+\Xi_0,\xi(t_0+\Xi_0))\}\\ &\le e^{[\beta(t_{1,1})+\beta(t_{1,2})+\ldots+\beta(t_{1,\eta_1})]\ln\zeta+\alpha(t-t_0)}\mathbf{E}\{V(t_0,\xi(t_0))\}.\end{aligned}$$

With the aid of (3.6), for any $t \ge t_0$, it yields that

$$\begin{aligned}\mathbf{E}\{V(t,\xi(t))\} &\le e^{(1-\bar{\rho})\frac{(\frac{t-t_0}{\Lambda}-1)\Xi}{\varpi}\ln\zeta+\alpha(t-t_0)}\mathbf{E}\{V(t,\xi(t_0))\}\\ &\le e^{\frac{(\bar{\rho}-1)\Xi}{\varpi}\ln\zeta-\varphi_1(t-t_0)}\mathbf{E}\{V(t,\xi(t_0))\}.\end{aligned}$$

Let $\varepsilon_1 = \frac{\lambda_{\max}(\mathcal{Z})}{\lambda_{\min}(\mathcal{Z})}e^{\frac{(\bar{\rho}-1)\Xi}{\varpi}\ln\zeta}$, then it follows that

$$\mathbf{E}\{\|\xi(t)\|^2\} \le \varepsilon_1 e^{-\varphi_1(t-t_0)}\mathbf{E}\{\|\xi(t_0)\|^2\}.$$

Consequently, leader-following consensus of SMAS (2.1) with packet dropouts can be achieved via the IIC strategy. The proof is completed. ■

Remark 3.4. *Different from existing works on the consensus of SMASs, such as [17–20], the proposed approach effectively accommodates packet dropouts. Specifically, since the impulsive mechanism must be contractive (*$\ln\zeta < 0$*), the decay rate condition in* (3.6) *can be equivalently rewritten as* $\frac{(1-\bar{\rho})\psi}{\varpi}(-\ln\zeta) > \alpha$. *This inequality explicitly quantifies the trade-off: An increased packet dropout rate* $\bar{\rho}$ *linearly reduces the effective transmission proportion* $(1-\bar{\rho})$. *To counterbalance this loss and guarantee that the control effect strictly overcomes the continuous divergence rate* α*, this necessitates either a larger minimum control rate* ψ *or a smaller intermittent average impulsive interval* ϖ. *In other words, a more frequent loss of impulsive signals requires a higher control rate or more frequent impulses to compensate for the adverse effects.*

Remark 3.5. *For the error system* (3.3) *to achieve convergence when* $\alpha > 0$*, it inherently requires* $\ln\zeta < 0$*, which translates to* $\zeta < 1$*. The condition* $\lambda_{max}((I_M-\chi\mathcal{H})^\top(I_M-\chi\mathcal{H})) < 1$ *dictates that the impulsive controller must be strictly contractive. Specifically, the instantaneous state jumps induced by the impulses must compress the consensus error sufficiently to compensate for the divergence accumulated during the continuous dynamics and the information loss caused by packet dropouts. Consequently, the control gain* χ *cannot be selected arbitrarily; it must be carefully co-designed with the topological matrix* $\mathcal{H}$ *to guarantee that all eigenvalues of* $I_M-\chi\mathcal{H}$ *lie strictly within the unit circle.*

Remark 3.6. *If there is no packet dropout, i.e.,* $\bar{\rho} = 0$*, then the sufficient conditions for achieving leader-following consensus of SMAS* (2.1) *can be derived from Theorem 3.1. In addition, if the packet dropout rate* $\overline{\rho}$ *approaches or equals 1,* $1-\overline{\rho}$ *becomes zero. In this case, the decay rate condition* (3.6) *can never be satisfied for any unstable open-loop system.*

Remark 3.7. *The minimum control rate* ψ *is a critical parameter for IIC* (3.1)*. If* $\psi = 0$*, then the control input is always zero, and thus the system cannot achieve leader-following consensus. On the other hand, if* $\psi = 1$*, then IIC* (3.1) *switches to the impulsive controller. In this case, Theorem 3.1 is still valid. Therefore, this paper does not consider the special case of* $\psi = 0$*.*

Consider a class of MASs without stochastic disturbances, which can be described as

$$\begin{cases} \dot{r}_i(t) = Ar_i(t) + Bf(r_i(t)) + u_i(t), \\ \dot{r}_0(t) = Ar_0(t) + Bf(r_0(t)). \end{cases} \tag{3.15}$$

Under IIC (3.1), the error system is given by

$$\begin{cases} \begin{cases} \dot{\xi}(t) = (I_M \otimes A)\xi(t) + (I_M \otimes B)\mathscr{F}(\xi(t)),\ t \neq t_{k,s_k} \in \mathbb{C}_k, \\ \xi(t) = \Upsilon(t)\xi(t^-),\ t = t_{k,s_k} \in \mathbb{C}_k, \end{cases} \\ \dot{\xi}(t) = (I_M \otimes A)\xi(t) + (I_M \otimes B)\mathscr{F}(\xi(t)),\ t \in \mathbb{F}_k. \end{cases} \tag{3.16}$$

Corollary 3.1. *Under Assumptions 2.1 and 2.2, if there is a positive definite matrix* $\mathcal{Z} \in \mathbb{R}^{m\times m}$ *and a scalar* α_1 *such that*

$$\begin{bmatrix} \Psi_1 & \mathcal{Z}B \\ * & -\Theta \end{bmatrix} < 0, \tag{3.17}$$

$$\varphi_2 = -\frac{(1-\bar{\rho})\psi}{\varpi}\ln\zeta - \alpha_1 > 0, \tag{3.18}$$

where $\Psi_1 = \mathcal{Z}A + A^\top\mathcal{Z} + \Gamma\Theta\Gamma - \alpha_1\mathcal{Z}$*,* $\zeta = \lambda_{\max}((I_M - \chi\mathcal{H})^\top(I_M - \chi\mathcal{H}))$*, then MASs* (3.15) *can achieve leader-following consensus by means of IIC* (3.1)*.*

Proof. For $t \neq t_{k,s_k}$, it follows from (3.17) that

$$\begin{aligned} D^+V(t,\xi(t)) &\leq \xi^\top(t)(I_M \otimes (\mathcal{Z}A + A^\top\mathcal{Z} + \Gamma\Theta\Gamma + \mathcal{Z}B\Theta^{-1}B^\top\mathcal{Z}))\xi(t) \\ &\leq \alpha_1 V(t,\xi(t)). \end{aligned}$$

Then, one has

$$\begin{cases} V(t,\xi(t)) \leq V(t_{k,s_k-1},\xi(t_{k,s_k-1}))e^{\alpha_1(t-t_{k,s_k-1})},\ \text{if } t \in [t_{k,s_k-1}, t_{k,s_k}), \\ V(t,\xi(t)) \leq V(t_{k-1}+\Xi_k,\xi(t_{k-1}+\Xi_k))e^{\alpha_1(t-t_{k-1}-\Xi_k)},\ \text{if } t \in \mathbb{F}_k. \end{cases}$$

The remainder of the proof is omitted as it is similar to that of Theorem 3.1. ■

Remark 3.8. *Corollary 3.1 represents a special case of the main theoretical framework. When the stochastic disturbances vanish, the stochastic error system naturally reduces to a deterministic one. Consequently, the sufficient conditions for achieving consensus can be directly deduced from Theorem 3.1, bypassing the need for mean-square expectations.*

4. Simulation results

In this section, a numerical example is provided to illustrate the effectiveness of the derived results. A classical Chua's chaotic system is given by

$$\dot{r}(t) = Ar(t) + Bf(r(t)), \tag{4.1}$$

where $r(t) = [r_1(t), r_2(t), r_3(t)]^\top$ denotes the state vector, $f(r(t)) = [0.5(|r_1(t) + 1| - |r_1(t) - 1|), 0, 0]^\top$, and A and B are the system matrices that are defined as

$$A = \begin{bmatrix} -2.2362 & 9.2156 & 0 \\ 1 & -1 & 1 \\ 0 & -15.9946 & 0 \end{bmatrix}$$

and

$$B = \begin{bmatrix} 4.5355 & 0 & 0 \\ 0 & 4.5355 & 0 \\ 0 & 0 & 4.5355 \end{bmatrix},$$

respectively.

Consider an SMAS consisting of one leader and 10 followers, where the leader and followers are described by system (4.1) with stochastic disturbances. Then, the dynamics of the i-th follower and the leader are given by

$$\begin{cases} \mathrm{d}r_i(t) = [Ar_i(t) + Bf(r_i(t)) + u_i(t)]\mathrm{d}t + \sigma(r_i(t))\mathrm{d}W(t), \\ \mathrm{d}r_0(t) = [Ar_0(t) + Bf(r_0(t))]\mathrm{d}t + \sigma(r_0(t))\mathrm{d}W(t), \end{cases}$$

where $\sigma(r) = \tanh(r)$. The communication topology of the SMAS is displayed in Figure 2. It is easy to verify that these functions satisfy Assumptions 2.2 and 2.3 with the corresponding parameter matrices chosen as $\Gamma = \mathrm{diag}\{1, 0, 0\}$ and $\Sigma = \mathrm{diag}\{1, 1, 1\}$, respectively.

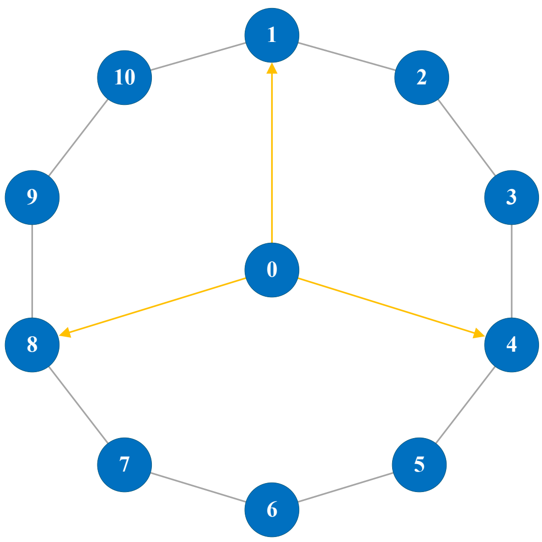


Figure 2. The communication topology of the SMAS.

Figure 3 plots 50 sample trajectories of the leader with the initial state $r_0(0) = [0.15, 0.1, 0.2]^\top$. The initial states of the 10 followers are randomly generated within the interval $[-3, 3]$. The sample trajectories of the SMAS without any control input are depicted in Figure 4. It indicates that the followers cannot track the leader.

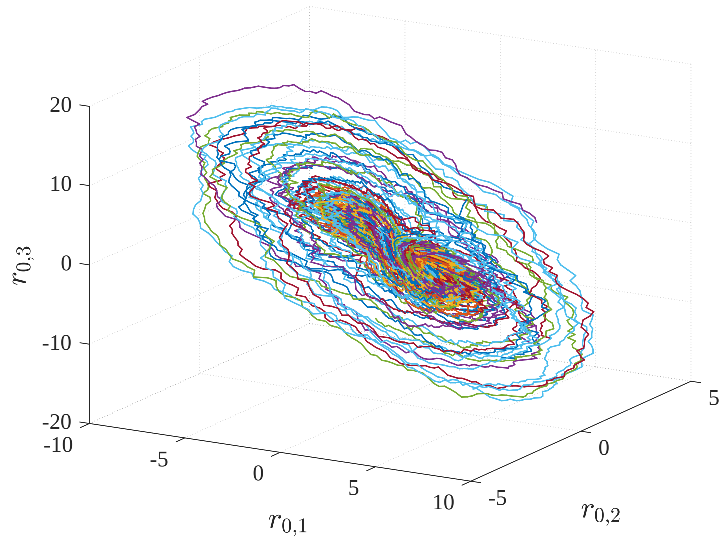
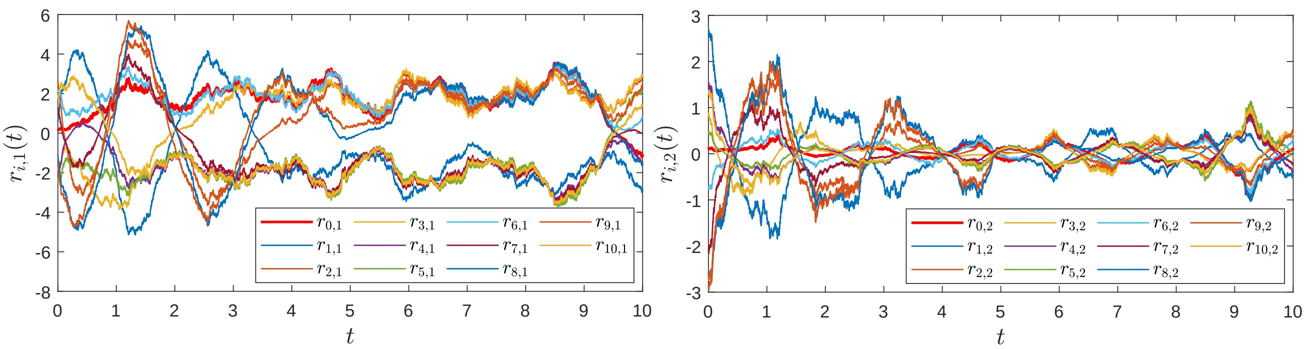
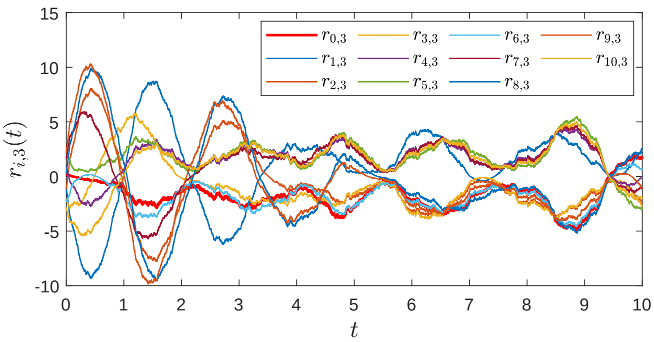


Figure 3. 50 sample trajectories of the leader.



(a) Sample trajectories of $r_{i1}(t), i = 0, \ldots, 10$.

(b) Sample trajectories of $r_{i2}(t), i = 0, \ldots, 10$.



(c) Sample trajectories of $r_{i3}(t), i = 0, \ldots, 10$.

Figure 4. Sample trajectories of the SMAS without any control input.

Given $\alpha = 22$, a group of feasible solutions to linear matrix inequalities (LMIs) (3.4) and (3.5) is obtained as

$$\mathcal{Z} = \begin{bmatrix} 0.2900 & 0.1534 & 0.0328 \\ 0.1534 & 0.8387 & -0.1719 \\ 0.0328 & -0.1719 & 0.2579 \end{bmatrix},$$

$$\Theta = \begin{bmatrix} 2.5509 & 0.3372 & 0.3220 \\ 0.3372 & 4.2949 & -0.3750 \\ 0.3220 & -0.3750 & 2.0153 \end{bmatrix},$$

and $\gamma = 1.9543$. By setting $\chi = 0.43$, $\psi = 0.7$, $\varpi = 0.005$, $\mathcal{K} = 7$, $\bar{\rho} = 0.2$, and $\Xi = \Xi_k = 0.14$ for $k \in \mathbb{N}^+$, one has $\varphi_1 \approx 1.0897$.

Under the aforementioned parameter configurations, Figure 5 displays the sequence $\{t_{k,s_k}\}$ of IIC (3.1) when $\varpi = 0.005$ and $\bar{\rho} = 0.2$, where the red and blue lines represent the impulsive instants with and without packet dropouts, respectively. Figure 6 depicts the trajectory of $\mathbf{E}\{\|\xi(t)\|^2\}$ under the IIC strategy, which shows that leader-following consensus is achieved in mean square, thereby validating the effectiveness of Theorem 3.1.

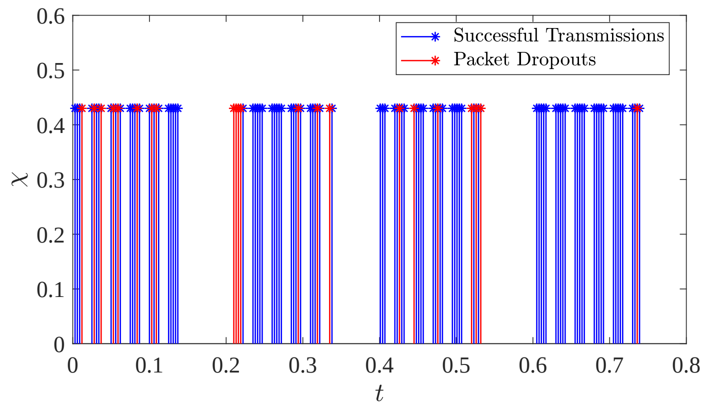


Figure 5. The sequence $\{t_{k,s_k}\}$ of IIC (3.1) with $\varpi = 0.005$ and $\bar{\rho} = 0.2$.

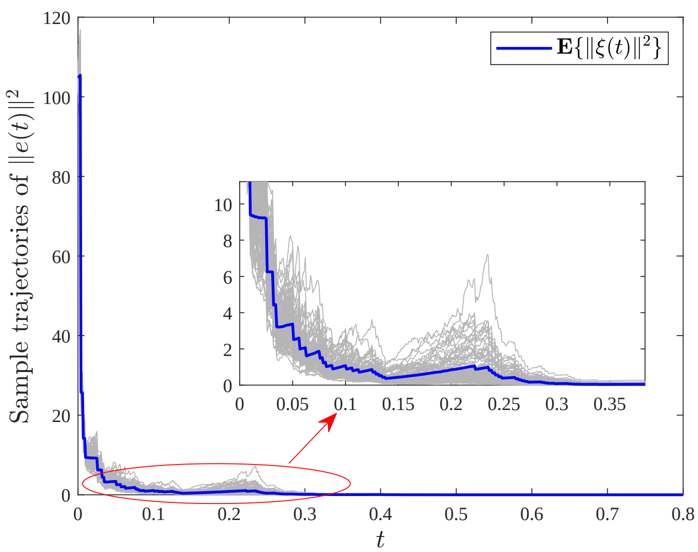


Figure 6. The trajectory of $\mathbf{E}\{\|\xi(t)\|^2\}$ under the IIC strategy and $\bar{\rho} = 0.2$.

Remark 4.1. *It is worth noting that to strictly align with the theoretical assumption* $\limsup_{t\to\infty}\rho(t) \leq \bar{\rho}$*, the packet dropout sequences in the simulations are generated using a constrained random mechanism. Specifically, the dropouts occur randomly but are subjected to a moving-window constraint, ensuring that the actual dropout ratio never exceeds the predefined upper bound* $\bar{\rho}$ *over time.*

Remark 4.2. *It should be pointed out that the expected trajectory of* $\mathbf{E}[\|\xi(t)\|^2]$ *depicted in Figure 6 is numerically approximated by computing the ensemble average over 500 independent Monte Carlo sample paths, where 100 sample trajectories are displayed.*

Furthermore, the parameter settings are the same as above, except that $\bar{\rho} = 0.35$. Set $\varpi = 0.004$ to ensure Theorem 3.1 holds. Then, we have $\varphi_1 \approx 1.4504$. Figure 7 displays the sequence $\{t_{k,s_k}\}$ of IIC (3.1) when $\varpi = 0.004$ and $\bar{\rho} = 0.35$. Figure 8 depicts the trajectory of $\mathbf{E}\{\|\xi(t)\|^2\}$ under the IIC strategy, which means that a higher packet dropout rate $\bar{\rho}$ necessitates a smaller intermittent average impulsive interval ϖ to ensure that the decay rate φ_1 satisfies (3.6).

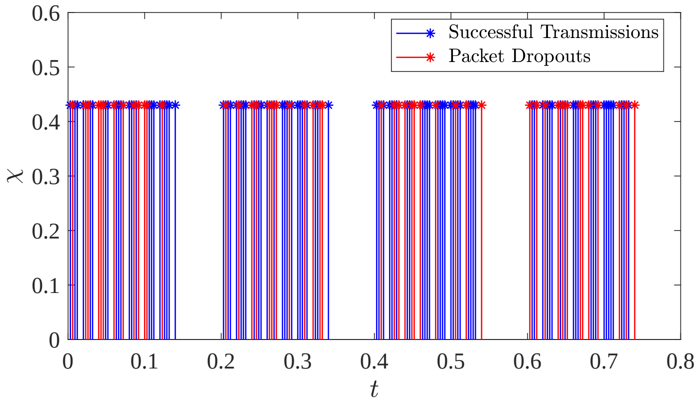


Figure 7. The sequence $\{t_{k,s_k}\}$ of IIC (3.1) with $\varpi = 0.004$ and $\bar{\rho} = 0.35$.

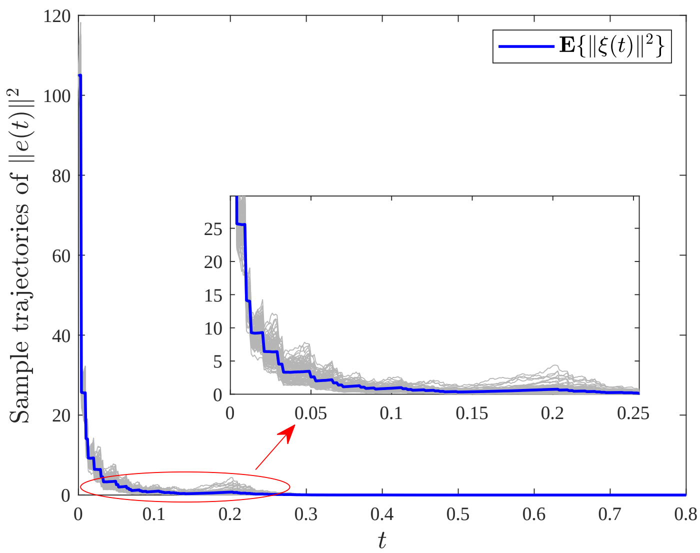


Figure 8. The trajectory of $\mathbf{E}\{\|\xi(t)\|^2\}$ under the IIC strategy and $\bar{\rho} = 0.35$.

In addition, consider an MAS composed of one leader and 10 followers, where the leader and followers are described by system (4.1). Then, the dynamics of the ith follower and the leader are given by

$$\begin{cases} \dot{r}_i(t) = Ar_i(t) + Bf(r_i(t)) + u_i(t), \\ \dot{r}_0(t) = Ar_0(t) + Bf(r_0(t)). \end{cases}$$

Consider the same communication topology as that of the SMAS. The leader has a double scroll chaotic attractor with initial condition $r_0(0) = [0.15, 0.1, 0.2]^\top$, as shown in Figure 9.

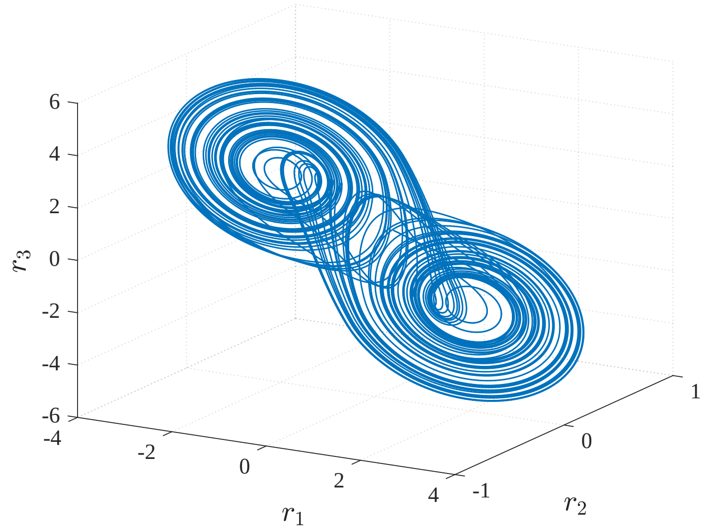


Figure 9. The phase diagram of the leader.

Given $\alpha_1 = 12$, a group of feasible solutions to LMI (3.17) is given by

$$\mathcal{Z} = \begin{bmatrix} 0.2063 & 0.0601 & 0.0935 \\ 0.0601 & 0.4485 & 0.0041 \\ 0.0935 & 0.0041 & 0.0898 \end{bmatrix}$$

and

$$\Theta = \begin{bmatrix} 1.5456 & 0.0297 & 0.5588 \\ 0.0297 & 2.3318 & 0.1414 \\ 0.5588 & 0.1414 & 0.5631 \end{bmatrix}.$$

Set $\chi = 0.38$, $\psi = 0.6$, $\varpi = 0.006$, $\mathcal{K} = 5$, $\bar{\rho} = 0.3$, and $\Xi = \Xi_k = 0.12$ for $k \in \mathbb{N}^+$, and then the decay rate is evaluated as $\varphi_1 = 0.67454 > 0$. The initial states of the 10 followers are randomly generated within the interval $[-3, 3]$.

With these parameters, Figure 10 presents the sequence $\{t_{k,s_k}\}$ of IIC (3.1) for the MAS, where the pink and green lines denote the impulsive instants with and without packet dropouts, respectively. The evolution of $\xi_i(t), i = 1, \ldots, 10$ under the IIC strategy is displayed in Figure 11, which shows that leader-following consensus is achieved, thereby validating the effectiveness of Corollary 3.1.

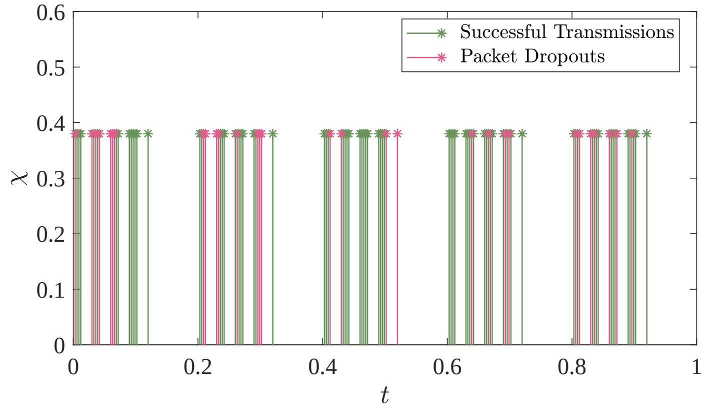
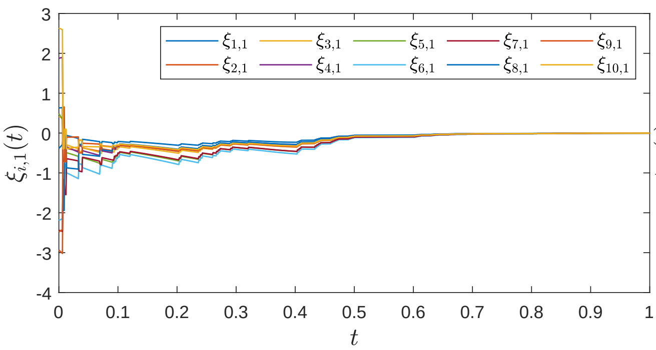
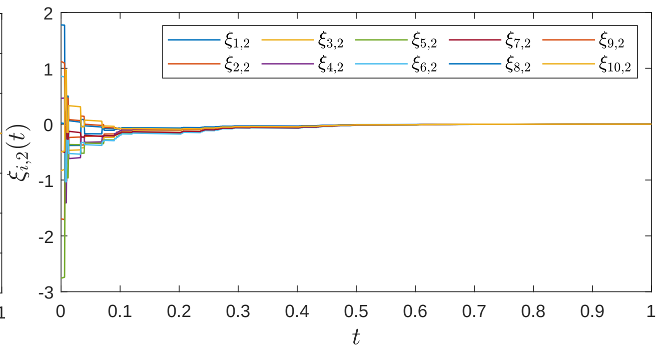


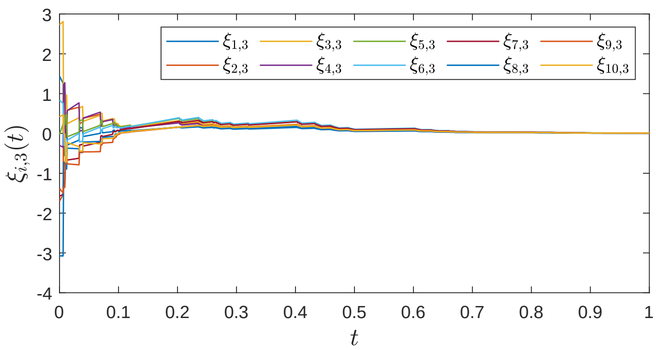
Figure 10. The sequence $\{t_{k,s_k}\}$ of IIC (3.1) with $\varpi = 0.006$ and $\mathcal{K} = 5$.



(a) Evolution of $\xi_{i1}(t), i = 1, \ldots, 10$.



(b) Evolution of $\xi_{i2}(t), i = 1, \ldots, 10$.



(c) Evolution of $\xi_{i3}(t), i = 1, \ldots, 10$.

Figure 11. Evolution of $\xi_i(t), i = 1, \ldots, 10$ under the IIC strategy.

Remark 4.3. *It should be pointed out that the scalar α dictates the tolerated divergence rate of the continuous dynamics and directly influences the final decay rate φ_1. There is an inherent trade-off in the parameter tuning: A larger α relaxes the LMI constraints but decelerates the overall convergence speed. The values $\alpha = 22$ and $\alpha_1 = 12$ are not globally optimal but rather feasible solutions determined via an iterative search algorithm, calibrated to guarantee rapid convergence.*

5. Conclusions

In this paper, we investigate an IIC strategy to achieve leader-following consensus of SMASs with packet dropouts. Under the proposed control framework, the impulsive instants occur exclusively within the control intervals. Furthermore, packet dropouts are described by an auxiliary function. Sufficient conditions are derived to guarantee that leader-following consensus can be achieved in mean square under the proposed IIC strategy. The obtained results reveal the relationship among the average impulsive interval, the packet dropout rate, and the minimum control rate. Finally, a numerical example is provided to illustrate the effectiveness of the derived results. In the future, we will further investigate the consensus problem of SMASs subject to asynchronous packet dropouts within the agent-to-agent communication channels.

Author contributions

Jiawei Zhuang: Funding acquisition, methodology, writing–original draft, writing–review & editing; Dacai Liu: Funding acquisition, investigation, writing–review & editing; Jiacheng Xu: Software, visualization; Lin Fu: Formal analysis, validation; Changrun Chen: Software, visualization. All authors have read and approved the final version of the manuscript for publication.

Use of Generative-AI tools declaration

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

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Conflict of interest

The authors declare that they have no conflict of interest.

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