

Article

Data-Driven Event-Triggered Predictive Control for Consensus of Discrete-Time Multi-Agent Systems with Time-Varying Delays

Chang-Jiang Li , Weifeng Xu , Liang Qi *, Zhaoping Du , Jianzhen Li  and Shuxia Ye 

School of Automation, Jiangsu University of Science and Technology, Zhenjiang 212100, China; changjiang.li@hit.edu.cn (C.-J.L.); xuweifeng1119@stu.just.edu.cn (W.X.); duzhaoping98@163.com (Z.D.)

* Correspondence: alfred_02030210@just.edu.cn

Abstract

Consensus control for discrete-time multi-agent systems is increasingly complex when facing unknown dynamics and time-varying communication delays. Although data-driven control has emerged as a powerful tool to bypass model reliance, few existing studies simultaneously address the challenges of delay compensation and limited communication bandwidth. To bridge this gap, this paper proposes a novel data-driven event-triggered predictive control framework. We leverage Willems' fundamental lemma to construct a predictive model directly from historical data, eliminating the need for system identification. Furthermore, an integrated event-triggered mechanism with a dynamic threshold updates control signals only when necessary, effectively reducing transmission load. Theoretical analysis confirms the recursive feasibility and stability of the closed-loop system, while simulations demonstrate that the proposed method achieves robust consensus with significantly reduced event-triggering frequency.

Keywords: time-varying; data-driven; event-triggered; predictive control; consensus

1. Introduction

Communication delays significantly alter multi-agent system states and can induce complex dynamics. Olfati-Saber studied distributed consensus control in multi-agent systems with directed networks, analyzing protocols for fixed/switching topologies and time-delays while establishing connections between algebraic connectivity and system performance [1]. Li established necessary and sufficient conditions for consensus in first-order discrete-time multi-agent systems with communication delays, fully characterizing the exact consensus region in the step-size and delay parameter space [2]. Ma D. developed a MID-based PID control for first-order unstable delayed systems, ensuring guaranteed decay rate, steady-state tracking, and maximum delay robustness through a pseudo-concave optimization [3]. Wang proposed an event-triggered consensus control strategy for second-order multi-agent systems with actuator saturation and input delay, achieving exponential consensus via Lyapunov–Krasovskii methods and LMI-based stability analysis [4]. Ma Q. established the exact delay margin guaranteeing consensus in second-order multi-agent systems under delayed PI control and characterizes the switching behavior between consensus and non-consensus with increasing delay [5]. Yang addressed distributed optimization for continuous-time multi-agent systems with time-varying communication delays by establishing the relationship between optimal solutions and system equilibria, deriving both delay-dependent and delay-independent convergence conditions, and proposing a sampled-data communication scheme for fast-varying delays, with the theoretical results



Academic Editor: Douglas O'Shaughnessy

Received: 11 January 2026

Revised: 3 February 2026

Accepted: 3 February 2026

Published: 9 February 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

supported by simulations and an application [6]. While advancements in electronic hardware continue to reduce signal transmission latency, physical delays remain inevitable in large-scale networked systems. Consequently, control-theoretic approaches, such as Event-Triggered Mechanisms (ETMs) and Model Predictive Control (MPC), have become indispensable for actively compensating for these time-varying delays at the algorithmic level.

With the advancement of electronic information technologies, computer science, and artificial intelligence, the application domains of coordinated control in multi-agent systems have been expanding, while data-driven control strategies are continuously evolving and being updated. Bu proposed a distributed model-free adaptive control method for data-driven consensus tracking of multi-agent systems with unknown nonlinear dynamics under fixed and switching topologies, using only input–output data without requiring model information [7]. Zhou developed two data-driven optimal synchronization control algorithms for leader-follower multiagent systems with unknown dynamics and disturbances, using output error and input data, respectively, to achieve output synchronization while minimizing errors and rejecting disturbances [8]. Zhang proposed a data-driven distributed optimal consensus control method for multi-agent systems with input delays, using a model reduction approach to transform the delayed system into a delay-free form and adopting neural networks to learn control policies online via adaptive dynamic programming [9]. Li proposed a data-driven optimal output cluster synchronization control method for heterogeneous multi-agent systems with disturbances, using adaptive dynamic programming and a distributed adaptive observer to achieve synchronization without knowledge of system matrices [10]. Huang proposed a model-free distributed predictive control scheme for nonlinear multi-agent systems under communication delays, which actively compensates for delays by introducing a consensus-based auxiliary variable and employing dynamic linearization to design a distributed controller, with its stability and effectiveness verified by analysis and simulation [11].

Event-triggered control improves the consistency and efficiency of multi-agent systems while ensuring the operational quality of the system by updating control signals. Dou systematically reviewed event-triggered control for multi-agent systems, focusing on reducing resource consumption, excluding Zeno behavior, and advances in finite-time, fixed-time, and prescribed-time event-triggered consensus strategies [12]. Yang proposed an event-triggered secure consensus control scheme for multi-agent systems under independent multi-channel DoS attacks, establishing sufficient conditions on attack duration and ensuring stability while excluding Zeno behavior [13]. Liu investigated consensus for multi-agent systems with general linear dynamics using an adaptive dynamic event-triggered strategy that relies only on event-triggered information to reduce communication and exclude Zeno behavior [14]. Dong proposed an event-triggered differentially private optimal consensus algorithm to protect agents' state and cost function privacy during computation while maintaining consensus and optimizing performance [15]. Zhang studied an adaptive event-triggered control strategy for leader-following consensus of non-strict feedback multi-agent systems subject to unknown disturbances and full-state constraints [16]. Zhang studied consensus of multi-agent systems with time-varying delays using an event-triggered delayed impulsive control strategy, establishing sufficient conditions under both continuous and periodic event-triggered mechanisms [17]. Milad Abbasi proposed an observer-based asynchronous periodic event-triggered control scheme to achieve consensus in linear multi-agent systems under time-varying communication delays, employing a bank of observers to reduce communication load and deriving LMI-based stability conditions, with effectiveness validated through simulations and experiments on e-puck2 robots [18].

Distributed model predictive control has become one of the main methods for solving the coordination problems of multi-agent systems due to its ability to enable agents to estimate the future dynamic behaviors of their neighbors and achieve optimal control performance for constrained systems. Cheng addressed the discrete-time double-integrator consensus problem for multi-agent systems with directed switching proximity topologies and input constraints via model predictive control protocols that ensure stable consensus under directed spanning tree conditions [19]. Pang proposed an incremental networked predictive control scheme for linear heterogeneous multi-agent systems subject to random delays and packet dropouts, achieving stable cooperative output tracking with zero steady-state error even under plant-model mismatch [20]. Matthias Köhler studied a distributed MPC framework for constrained heterogeneous nonlinear multi-agent systems, achieving cooperative objectives through local optimization of artificial references with guaranteed feasibility and stability [21]. Liu proposed a high-order fully actuated (HOFA) predictive coordination method for networked nonlinear multi-agent systems with communication delays, achieving simultaneous stability and consensus while actively compensating for delays [22]. Su proposed a robust distributed model predictive control scheme for consensus tracking of linear multi-agent systems under additive disturbances and time-varying delays, utilizing a Lyapunov-Razumikhin-based terminal constraint set and LMI conditions to guarantee recursive feasibility and input-to-state stability, with an illustrative example verifying the approach [23].

Research on multi-agent consensus is one of the key issues, and a solid foundation has been established in this area. This paper will also build upon this foundation for further discussion. Yang studies output consensus of heterogeneous linear multi-agent systems on directed graphs using a predictive event-triggered mechanism with internal reference models, significantly reducing communication costs while excluding Zeno behavior [24]. Liu proposed an event-triggered predictive consensus protocol for linear discrete-time multi-agent systems with norm-bounded parameter uncertainties, achieving consensus via local state monitoring and excluding Zeno behavior under LMI-based conditions [25]. Yin investigated a distributed adaptive event-triggered predictive control protocol for discrete-time multi-agent systems with communication delays, reducing network burden and actively compensating delays via a switched time-delay system formulation solvable via linear matrix inequalities [26]. Qin proposed synchronous and asynchronous distributed model predictive control algorithms for optimal output consensus of high-order multi-agent systems, allowing uncoordinated step-sizes and achieving convergence without global synchronization requirements [27]. Tang proposed an event-triggered distributed model predictive control (DMPC) approach for dynamically decoupled systems with coupled objectives, utilizing compatibility constraints and a stability-based triggering condition to reduce communication while preserving feasibility and stability [28]. The main contributions of this article are as follows:

- (1) This paper proposes a novel framework that integrates data-driven, event-triggered, and predictive control techniques to address the consensus problem for discrete-time multi-agent systems with time-varying communication delays.
- (2) Leveraging Willems' fundamental lemma, the proposed controller design relies solely on a pre-collected dataset of system trajectories, eliminating the need for an explicit system model. This makes the approach suitable for systems with unknown or complex dynamics.
- (3) Rigorous theoretical analysis guarantees the framework's Zeno-free behavior, the recursive feasibility of the control law, and the asymptotic stability of the closed-loop system, ensuring consensus is achieved.

- (4) The effectiveness of the method is validated through simulations, which also reveal the dual impact of the prediction horizon (N_p); a longer horizon not only enhances control performance (e.g., faster convergence) but also significantly reduces the total number of event triggers, thereby lowering communication overhead.

This paper is organized as follows: Section 2 provides some preliminaries. Section 3 gives the mathematical derivation and main results. Numerical examples and experimental verifications are proposed in Section 4. Section 5 concludes the article.

2. Preliminaries

Given a nonnegative adjacency matrix $\mathcal{A} \in \mathbb{R}_{\geq 0}^{N \times N}$, the associated directed graph is denoted by $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$, where $\mathcal{V} = 1, 2, \dots, N$ is the vertex set and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ represents the set of directed edges such that $(i, j) \in \mathcal{E}$ iff $a_{ij} > 0$. The Laplacian matrix $\mathcal{L}$ of the graph $\mathcal{G}$ is defined as $\mathcal{L} = \mathcal{D} - \mathcal{A}$, where $\mathcal{D} = \text{diag}(d_1, d_2, \dots, d_N)$ is the degree matrix with $d_i = \sum_{j=1}^N a_{ij}$. A fundamental property of $\mathcal{L}$ is that it possesses a zero row sum, i.e., $\mathcal{L}\mathbf{1}_N = \mathbf{0}_N$, where $\mathbf{1}_N$ and $\mathbf{0}_N$ denote the N -dimensional all-one and all-zero vectors, respectively.

The graph $\mathcal{G}$ is said to contain a directed spanning tree if there exists at least one root vertex from which every other vertex is reachable via a directed path. Given a collection of directed graphs $\mathcal{G}_1, \mathcal{G}_2, \dots, \mathcal{G}_k$ sharing the same vertex set $\mathcal{V}$, their union is defined as the directed graph with vertex set $\mathcal{V}$ and edge set given by $\bigcup i = 1^k \mathcal{E}_i$. $\|\cdot\|$ represents the corresponding Euclidean norm. $I_n \in \mathbb{R}^{n \times n}$ denotes an $n \times n$ -dimensional identity matrix.

3. Main Results

3.1. Event-Triggered Design

Consider a discrete-time multi-agent system composed of N agents. The dynamics of each agent is described by the following second-order model:

$$\begin{aligned} x_i(k+1) &= x_i(k) + hv_i(k) \\ v_i(k+1) &= v_i(k) + hu_i(k) \end{aligned} \quad (1)$$

where $x_i(k) \in \mathbb{R}$ are the position variable of the i -th agent, $v_i(k) \in \mathbb{R}$ are the velocity variable of the i -th agent and $u_i(k) \in \mathbb{R}$ are the control input of the i -th agent. The parameter h is the sampling period of the discrete-time system.

The Laplacian matrix of the graph $\mathcal{G}(\mathcal{A}(k))$ is denoted by $\mathcal{L}(k)$. To ensure consensus in system (1) under time-varying delays, a control protocol is formulated using relative position and velocity measurements:

$$\begin{aligned} u_i(k) = & - \sum_{j \in N_i} a_{ij}(k) \left(\alpha (x_i(k - \tau(k)) - x_j(k - \tau(k))) \right. \\ & \left. + (v_i(k - \tau(k)) - v_j(k - \tau(k))) \right) \end{aligned} \quad (2)$$

where N_i denotes the set of neighbors of agent i , $\alpha > 0$ is a control gain, and $\tau(k)$ is a time-varying unknown but bounded communication delay satisfying

$$0 \leq \tau(k) \leq \tau_{max} \quad (3)$$

in which 0 and τ_{max} represent the known lower and upper bounds of the delay, respectively.

This paper aims to develop an event-triggered control strategy to achieve consensus in system (1) from any initial condition.

$$\begin{aligned}\lim_{k \rightarrow \infty} \|x_i(k) - x_j(k)\| &= 0 \\ \lim_{k \rightarrow \infty} \|v_i(k) - v_j(k)\| &= 0\end{aligned}\quad (4)$$

for all $i, j \in \{1, 2, \dots, N\}$

To reduce unnecessary communication, an event-triggered mechanism is introduced in this paper. Under this mechanism, each agent i broadcasts its current state to its neighbors only when a specific triggering condition is satisfied. The discrete time instants at which these triggers occur form a sequence. The timestamp of the s -th event trigger for agent i is denoted by t_s^i , and thus the complete sequence of its triggering instants can be represented as $\{t_1^i, t_2^i, \dots, t_s^i\}$.

Between two consecutive triggering instants (e.g., t_s^i and t_{s+1}^i), that is, for $k \in [t_s^i, t_{s+1}^i - 1]$, agent i 's neighbors continuously use the state information broadcast at time t_s^i . To mathematically formalize this, the latest triggering instant at any time step k is defined as follows:

$$\hat{k}_i(k) \triangleq \max_{s \in \mathbb{N}^+} \{t_s^i | t_s^i \leq k\} \quad (5)$$

To streamline the subsequent derivation, the symbol $\hat{k}_i$ is substituted for $\hat{k}_i(k)$. The measurement error of agent i at time k is defined as the difference between its current state and the most recent state:

$$\begin{aligned}e_{x,i}(k) &= x_i(\hat{k}_i) - x_i(k) \\ e_{v,i}(k) &= v_i(\hat{k}_i) - v_i(k)\end{aligned}\quad (6)$$

Let $\hat{x}_i(k) = x_i(\hat{k}_i)$ and $\hat{v}_i(k) = v_i(\hat{k}_i)$. Under the event-triggered mechanism, control protocol (2) is modified to

$$\begin{aligned}u_i(k) &= - \sum_{j \in N_i} a_{ij}(k) \left(\alpha(\hat{x}_i(k - \tau(k)) - \hat{x}_j(k - \tau(k))) \right. \\ &\quad \left. + (\hat{v}_i(k - \tau(k)) - \hat{v}_j(k - \tau(k))) \right)\end{aligned}\quad (7)$$

The local neighborhood error for agent i is defined as follows:

$$\zeta_i(k) = - \sum_{j \in N_i} a_{ij}(k) \left(\alpha(x_i(k) - x_j(k)) + (v_i(k) - v_j(k)) \right) \quad (8)$$

To formulate a fully distributed triggering condition that relies only on locally available information, it defines an estimated neighborhood error based on the last broadcasted states from neighbors:

$$\hat{\zeta}_i(k) = - \sum_{j \in N_i} a_{ij}(k) \left(\alpha(\hat{x}_i(k) - \hat{x}_j(k)) + (\hat{v}_i(k) - \hat{v}_j(k)) \right) \quad (9)$$

The measurement error vector is defined as

$$e_i(k) = \begin{bmatrix} \alpha e_{x,i}^T(k) & e_{v,i}^T(k) \end{bmatrix}^T \quad (10)$$

The sequence of triggering instants $\{t_s^i\}$ is recursively generated according to the following rule. Given the s -th triggering instant t_s^i , the next triggering instant t_{s+1}^i is determined as follows:

$$t_{s+1}^i = \min\{k > t_s^i \mid f_i(k) > 0\} \quad (11)$$

where the event-triggering function $f_i(k)$ is designed as follows:

$$f_i(k) = \|e_i(k)\|^2 - \sigma_i \|\hat{\zeta}_i(k - \tau(k))\|^2 - c_i \rho^k \quad (12)$$

and $0 < \sigma_i < 1$ is an adjustable parameter, $c_i > 0$ is a positive constant, and $\rho \in (0, 1)$ denotes a decay rate.

It is important to clarify how the system ensures the validity of the control signals despite relying on discontinuous updates. The use of the last broadcast state $\hat{x}_j(k)$ effectively functions as a Zero-Order Hold (ZOH) mechanism for inter-agent communication. Although this introduces a discrepancy (defined as the measurement error $e_i(k)$) between the broadcast value and the actual real-time state, this error is not arbitrary. The correctness of the scheme is actively guaranteed by the event-triggering condition (12). This condition serves as a dynamic bounding constraint: it enforces that the measurement error $e_i(k)$ remains strictly within a permissible range governed by the threshold function $\sigma_i \|\hat{\zeta}_i\|^2 + c_i \rho^k$. Consequently, the information used by neighbors is mathematically guaranteed to be a sufficiently accurate approximation of the true state to maintain system stability, as any deviation exceeding this safety margin will instantaneously trigger a state update.

It is worth noting that the event-triggering threshold is not a fixed constant but a dynamically vanishing quantity, which is crucial for achieving asymptotic consensus rather than merely bounded consensus. The threshold consists of two components: a state-dependent term, $\sigma_i \|\hat{\zeta}_i(k - \tau(k))\|^2$, and a time-dependent term $c_i \rho^k$. As the closed-loop system stabilizes, the neighborhood consensus error $\hat{\zeta}_i$ converges to zero, causing the state-dependent term to vanish. Simultaneously, the time-dependent term deterministically decays to zero as $k \rightarrow \infty$ due to $\rho \in (0, 1)$. This vanishing threshold design compels the measurement error $e_i(k)$ to also converge to zero, thereby enabling the system to achieve precise asymptotic consensus.

Theorem 1. *The parameters of the event-triggered mechanism are chosen within the following ranges: $c_i > 0, \rho \in (0, 1)$, ensuring that the system can avoid Zeno behavior.*

Proof of Theorem 1. There exists a positive lower bound on the time interval between t_s^i and t_{s+1}^i .

Let $T_s^i = t_{s+1}^i - t_s^i$ denote the inter-event time between the s -th triggering instants of agent i . It is necessary to prove that there exists a constant $T_{\min} > 0$, independent of s and i , such that $T_s^i > T_{\min}$ for all s, i .

Consider an arbitrary triggering instant, denoted as k_s^i . By definition, the measurement error is reset to zero at this instant, i.e., $e_i(t_s^i) = 0$. To analyze the evolution of the error between two consecutive triggering instants t_s^i and t_{s+1}^i , it considers any time step k satisfying $t_s^i \leq k \leq t_{s+1}^i - 1$. Within this specific interval, the value of the latest triggering instant $\hat{k}_i$ for the error terms $e_i(k)$ and $e_i(k + 1)$ remains fixed at t_s^i . Consequently, the one-step difference of the error can be analyzed as follows:

At any time instant $k > t_s^i$, consider the one-step difference of the error vector:

$$e_i(k + 1) - e_i(k) = \begin{bmatrix} \alpha(e_{x,i}(k + 1) - e_{x,i}(k)) \\ e_{v,i}(k + 1) - e_{v,i}(k) \end{bmatrix} \quad (13)$$

The validity of the following one-step error derivation is restricted to the interval between two triggering instants. Specifically, for any time step k within the range $[t_s^i, t_{s+1}^i - 1)$, the latest triggering instant used to define the error is invariant and equal to t_s^i . Based on Definition (6) of the measurement error and System (1), the following expression can be derived:

$$\begin{aligned} e_{x,i}(k+1) - e_{x,i}(k) &= (x_i(t_s^i) - x_i(k+1)) - (x_i(t_s^i) - x_i(k)) \\ &= x_i(k) - x_i(k+1) - hv_i(k) \\ e_{v,i}(k+1) - e_{v,i}(k) &= (v_i(t_s^i) - v_i(k+1)) - (v_i(t_s^i) - v_i(k)) \\ &= v_i(k) - v_i(k+1) - hu_i(k) \end{aligned} \quad (14)$$

The error vector can be represented in the form of

$$e_i(k+1) = e_i(k) - h \begin{bmatrix} \alpha v_i(k) \\ u_i(k) \end{bmatrix} \quad (15)$$

By applying the triangle inequality, an upper bound on the norm can be obtained as follows:

$$\|e_i(k+1)\| \leq \|e_i(k)\| + h \left\| \begin{bmatrix} \alpha v_i(k) \\ u_i(k) \end{bmatrix} \right\| \quad (16)$$

The existence of this bound is guaranteed by the controller design itself: the input $u_i(k)$ is inherently bounded by constraint (C2) in (25), which, for a finite initial state, ensures the state trajectory remains bounded over any finite time interval, including $[t_s^i, t_{s+1}^i)$. This implies that there exists a positive constant M_i such that for all k , the following inequality holds:

$$h \left\| \begin{bmatrix} \alpha v_i(k) \\ u_i(k) \end{bmatrix} \right\| \leq M_i \quad (17)$$

Beginning at $k = k_s^i$, $\|e_i(t_s^i)\| = 0$, successive application of the above inequality over Δk iterations yields the following:

$$\|e_i(k_s^i + \Delta k)\| \leq \sum_{i=0}^{\Delta k-1} M_i = \Delta k \cdot M_i \quad (18)$$

The next triggering instant k_{s+1}^i is defined as the first time instant after t_s^i at which the triggering condition is satisfied. According to the triggering function $f_i(k)$, this condition is given by the following:

$$\|e_i(k)\|^2 > \sigma_i \|\hat{\zeta}_i(k - \tau(k))\|^2 + c_i \rho^k \quad (19)$$

At the triggering instant t_{s+1}^i , the following condition must be satisfied: $\|e_i(t_{s+1}^i)\|^2 > c_i \rho^{t_{s+1}^i}$

Let $\Delta k = T_s^i = t_{s+1}^i - t_s^i$. By integrating the above-derived upper bound on the error growth, it follows that

$$(\Delta k \cdot M_i)^2 \geq \|e_i(t_s^i + \Delta k)\|^2 = \|e_i(t_{s+1}^i)\|^2 > c_i \rho^{t_{s+1}^i} \quad (20)$$

A lower bound for Δk can be explicitly solved:

$$\Delta k > \frac{\sqrt{c_i \rho^{t_{s+1}^i}}}{M_i} \quad (21)$$

Since $c_i > 0$ and $\rho \in (0, 1)$, the right-hand side remains strictly positive. Consequently, the minimum time interval between two consecutive triggering events, denoted by T_{min} , is strictly greater than zero. This guarantees that the number of triggering events within any finite time period is finite, thereby effectively excluding Zeno behavior. $\square$

3.2. Data-Driven Predictive Model Construction

The primary predictive technique employed in this study is a Data-Driven Model Predictive Control (DDMPC) framework, mathematically founded on Willems' Fundamental Lemma. Unlike traditional identification-based methods, this approach utilizes a subspace-based representation, where historical input-state data is organized into Hankel matrices. This structure enables the direct prediction of future system trajectories from pre-collected data without the explicit identification of parametric state-space matrices. Guided by this theory, an offline data-collection experiment is first conducted.

The fundamental lemma by Willems states that any trajectory generated by a linear time-invariant (LTI) system lies in the linear span of a sufficiently rich set of previously collected "basis trajectories" from the same system [29]. This theory enables the prediction of the system's future behavior based solely on historical data.

Guided by the aforementioned theory, an offline data-collection experiment is first conducted in this work. Specifically, a persistently exciting input sequence $u(0), u(1), \dots, u(T-1)$ is applied to a single-agent system, and the corresponding state sequence $\xi(0), \xi(1), \dots, \xi(T-1)$ is recorded simultaneously.

The collected one-dimensional time-series data is structured into two-dimensional Hankel matrices using a sliding window technique. Since the state vector $\xi(k) = [x(k)^T, v(k)^T]^T \in \mathbb{R}^{2n}$ is $2n$ -dimensional and the input $u_i(k) \in \mathbb{R}$ is n -dimensional, the input Hankel matrix $U_{data} \in \mathbb{R}^{L \times c}$ and the state Hankel matrix $\Xi_{data} \in \mathbb{R}^{2L \times c}$ are constructed as follows:

$$U_{data} = \begin{bmatrix} u(0) & u(1) & \cdots & u(T-L) \\ u(1) & u(2) & \cdots & u(T-L+1) \\ \vdots & \vdots & \ddots & \vdots \\ u(L-1) & u(L) & \cdots & u(T-1) \end{bmatrix} \quad (22)$$

$$\Xi_{data} = \begin{bmatrix} \xi(0) & \xi(1) & \cdots & \xi(T-L) \\ \xi(1) & \xi(2) & \cdots & \xi(T-L+1) \\ \vdots & \vdots & \ddots & \vdots \\ \xi(L-1) & \xi(L) & \cdots & \xi(T-1) \end{bmatrix} \quad (23)$$

where $c = T - L + 1$ is the number of columns, representing the number of valid basis trajectories extracted from data of total length T .

A core assumption of this work is that all agents in the multi-agent network share identical linear time-invariant (LTI) dynamics. Therefore, data collected offline from a single agent is sufficient to describe the behavior of any agent in the network.

To construct the predictive model, we partition the Hankel matrices row-wise. Let T_p be the length of the past data window and N_p be the prediction horizon, such that $L = T_p + N_p$. It partitions Ξ_{data} into two blocks: $\Xi_p \in \mathbb{R}^{2T_p \times c}$, formed by the first $2T_p$ rows, representing past state trajectories; and $\Xi_{future} \in \mathbb{R}^{2N_p \times c}$, formed by the subsequent $2N_p$ rows, representing future state trajectories. Similarly, $U_{future} \in \mathbb{R}^{N_p \times c}$ is formed by the last N_p rows of U_{data} .

According to Willems' fundamental lemma [29], for any agent i , any valid trajectory starting from its current state $\zeta_i(k)$ is guaranteed to have a unique coefficient vector $g_i \in \mathbb{R}^c$ that satisfies the following relation:

$$\begin{bmatrix} \zeta_{i,init} \\ u_{i,future} \\ \tilde{\zeta}_{i,future} \end{bmatrix} = \begin{bmatrix} \Xi_P \\ U_{future} \\ \Xi_{future} \end{bmatrix} g_i \quad (24)$$

where the initial state constraint is $\zeta_{i,init} = \zeta_i(k)$, $u_{i,future}$ and $\tilde{\zeta}_{i,future}$ are the future input and state sequences over the prediction horizon N_P .

Remark 1. Theoretically, the validity of the data-driven representation relies on the Persistency of Excitation (PE) of the offline input sequence. In our implementation, we ensure that the offline control input u_{data} is persistently exciting of order L , guaranteeing that the Hankel matrix $\mathcal{H}_L(u_{data})$ has full row rank. Furthermore, to handle potential measurement noise and avoid numerical ill-conditioning, Tikhonov regularization is employed in the optimization formulation. By penalizing the norm of the coefficient vector g (i.e., adding a term $\lambda_g \|g\|^2$ to the cost function), we relax the rigid equality constraints. This regularization acts as a robustness margin, ensuring that the solver finds a smooth control solution even when the data is corrupted by mild noise.

3.3. Input-Constrained Model Predictive Control Formulation

At each triggering instant k for agent i , its optimal control policy is determined by solving a data-driven finite-horizon optimization problem, which is formulated as follows:

$$g_i^*(k) = \arg \min_{g_i \in \mathbb{R}^c} J_i(g_i, k)$$

Objective Function: $J_i(g_i, k)$:

$$J_i(g_i, k) = \sum_{l=0}^{N_P-1} \left[\sum_{j \in N_i} \|\tilde{\zeta}_{i,l}^{pred}(g_i) - \hat{\zeta}_{j,l}^{\tau(k)}(g_i)\|_Q^2 + \|u_{i,l}^{pred}(g_i)\|_R^2 \right] \quad (25)$$

$$s.t. \tilde{\zeta}_i(k) = \Xi_{i,P} g_i \quad \textbf{(C1)}$$

$$u_{min} \leq u_{i,l}^{pred}(g_i) \leq u_{max}, \forall l \in 0, \dots, N_P - 1 \quad \textbf{(C2)}$$

$\sum_{j \in N_i} \|\tilde{\zeta}_{i,l}^{pred}(g_i) - \hat{\zeta}_{j,l}^{\tau(k)}(g_i)\|_Q^2$ represents the consensus cost term, which serves as the core mechanism for driving the system toward consensus. It penalizes deviations between the planned trajectory of agent i and the time-delayed planned trajectories of its neighbors j . By minimizing this cost, the controller proactively computes a future path that reduces discrepancies with neighboring agents. $\|u_{i,l}^{pred}(g_i)\|_R^2$ represents the control effort cost, which quantifies the physical energy or resources required to execute the control actions. This term ensures the uniqueness and smoothness of the solution to the optimization problem. The weighting matrices $Q \geq 0$ (positive semi-definite) and $R > 0$ (positive definite) are design parameters.

At the triggering instant k , agent i computes the complete optimal future control sequence $u_i(k|k) = [u_{i,0}^*, u_{i,1}^*, \dots, u_{i,N_P-1}^*]^T$. However, the entire sequence is not implemented; instead, the agent applies only the first control input $u_{i,0}^*$ from this sequence to the system. Upon the arrival of the subsequent triggering instant k' , agent i first measures its new current state $\zeta_i(k')$ and then repeats the entire optimization procedure described above to compute a new optimal control sequence based on the updated information.

Remark 2. Although the presented framework focuses on homogeneous linear systems, it offers broad extensibility. For heterogeneous agents, the consensus protocol remains valid by simply constructing individual Hankel matrices from agent-specific datasets. For mild model mismatches or data noise, the proposed controller exhibits inherent robustness due to the receding horizon mechanism, which actively compensates for prediction errors via real-time state feedback updates. Future work will further explore extensions to nonlinear dynamics, potentially by integrating Koopman operator theory.

3.4. Implementation Procedure

To facilitate the practical application of the proposed theoretical framework, the complete execution workflow of the Data-Driven Event-Triggered Predictive Control (DD-ETPC) strategy is summarized in Table 1. This procedure delineates the offline data processing phase and the online recursive control loop.

Table 1. Data-driven event-triggered predictive control strategy.

Require: Pre-collected dataset $\{u_{data}, \xi_{data}\}$; Weighting matrices Q, R ; Parameters σ_i, c_i, ρ ; Prediction horizon N_p .

1. Offline Phase:

Construct Hankel matrices $U_P, U_{future}, \Xi_P, \Xi_{future}$ using (22) and (23) based on the sliding window technique.

2. Online Phase:

For time instant $k = 0, 1, 2, \dots$ **do**

For each agent $i \in \{1, \dots, N\}$ **do**

 Measure current state $\xi_i(k)$ and compute measurement error $e_i(k)$ via (6).

 Check event-triggering condition: Is Equation (12) satisfied?

If condition is satisfied ($f_i(k) > 0$) **then**

 Update triggering instant $t_s^i \leftarrow k$.

 Broadcast current state $\hat{\xi}_i(k)$ to neighbors.

 Solve Optimization Problem (25) to find optimal coefficient vector g_i^* .

 Compute optimal control input $u_i(k) = u_{i,0}^*$ from the sequence.

 Apply $u_i(k)$ to the system.

Else

 Maintain silence (no broadcast).

 Apply control input based on the tail of the previous sequence.

End If

End For

 System state evolves to $k + 1$.

End For

3.5. Convergence Analysis for Multi-Agent Consensus

Assumption 1. The communication graph among the agents is assumed to be strongly connected and permanently contain a directed spanning tree.

Theorem 2. The following proof of recursive feasibility relies on the standard assumption that the input constraint set is admissible for a zero control input, i.e., $u_{\min} \leq 0 \leq u_{\max}$. Under Assumptions 1, the closed-loop control system (1)—composed of the Objective Function (25) and the event-triggering mechanism (12)—is asymptotically stable, and all agents achieve asymptotic consensus.

Proof of Theorem 2. This proof requires demonstrating recursive feasibility and asymptotic stability.

First, recursive feasibility is considered. Using mathematical induction, we demonstrate that if the optimization problem is feasible at a triggering instant k , it remains feasible at the next triggering instant k' .

Assume that at triggering instant k , agent i successfully solves the optimization problem, obtaining the optimal solution $g_i^*(k)$ and the corresponding optimal control sequence $u_i^*(k|k)$. Considering the subsequent triggering instant k' for agent i , we construct a candidate control sequence $u_i^{cand}(k'|k')$, which consists of the tail portion of the optimal sequence from time k and a zero control input:

$$u_i^{cand}(k' + l|k') = \begin{cases} u_i^*(k + l + 1|k), & l = 0, \dots, N_p - 2 \\ 0, & l = N_p - 1 \end{cases}$$

This candidate control sequence, driving the system starting from the actual state $\xi_i(k')$, forms a valid system trajectory. By the existence of the data-driven representation, there is guaranteed to exist a coefficient vector $g_i^{cand}(k')$ capable of generating this trajectory and satisfying the initial state constraint $\xi_i(k') = \Xi_{i,init} g_i^{cand}(k')$.

For the first $N_p - 1$ elements of the sequence $l = (0, \dots, N_p - 2)$, we have $u_i^{cand}(k' + l|k')$. By the inductive hypothesis, these control inputs form part of the optimal sequence computed at time k . Hence, they already satisfy the input constraints, i.e., $u_{min} \leq u_i^{cand}(k' + l|k') \leq u_{max}$.

For the final element of the sequence ($l = N_p - 1$), we have $u_i^{cand}(k' + N_p - 1|k') = 0$. According to C2, the zero control input also satisfies the constraints, i.e., $u_{min} \leq 0 \leq u_{max}$.

Thus, a candidate vector $g_i^{cand}(k')$ has been constructed for the optimization problem at time k' , which satisfies all constraints. Therefore, if the problem is feasible at time k , it must also be feasible at time k' . Recursive feasibility of the optimization problem is guaranteed.

Define the Lyapunov function candidate for the multi-agent system as the summation of the individual optimal cost functions of all agents:

$$V(k) = \sum_{i=1}^N J_i^*(\hat{k}_i)$$

where $J_i^*(\hat{k}_i)$ denotes the optimal cost value obtained by agent i by solving optimization problem at its most recent triggering instant $\hat{k}_i \leq k$. Since the stage cost is nonnegative, it follows that $V(k) \geq 0$. Consider agent i , which is triggered at time instant k' (its previous triggering instant being k). By the principle of optimality, have $J_i^*(k') \leq J_i(g_i^{cand}(k'))$.

The relationship between the cost of the candidate solution and the optimal cost from the previous time step is given by:

$$J_i(g_i^{cand}(k')) = J_i^*(k) - L_i(k) + L_i(\xi_i^*(k + N_p|k), 0, k')$$

where $L_i(k) = \sum_{j \in N_i} \|\xi_i(k) - \hat{\xi}_j(k - \tau(k))\|_Q^2 + \|u_i(k)\|_R^2$ denotes the actual stage cost incurred at time k . This yields the evolution of the Lyapunov function over one triggering interval:

$$J_i^*(k') - J_i^*(k) \leq -L_i(k) + L_i(\xi_i^*(k + N_p|k), 0, k')$$

The variation of the global Lyapunov function at time instant k satisfies the following relation:

$$V(k') - V(k) \leq -L_i(k) + L_i(\xi_i^*(k + N_p|k), 0, k') \quad (26)$$

Summing both sides of Inequality (26) from the initial triggering instant k_0 to an arbitrary subsequent triggering instant k_M , and denoting the sequence of triggered agents during this process as $i_0, i_1, \dots, i_{M-1}$, yields the following cumulative relation:

$$\sum_{s=0}^{M-1} [V(t_{s+1}) - V(t_s)] \leq - \sum_{s=0}^{M-1} L_{i_s}(t_s) + \sum_{s=0}^{M-1} L_{i_s}(\xi_{i_s}^*(t_s + N_P|t_s), 0, t_{s+1}) \quad (27)$$

Rearranging the inequality yields the following:

$$\sum_{s=0}^{M-1} L_{i_s}(t_s) \leq V(t_0) - V(t_M) + \sum_{s=0}^{M-1} L_{i_s}(\xi_{i_s}^*(t_s + N_P|t_s), 0, t_{s+1}) \quad (28)$$

where $V(t_0)$ denotes the system's initial optimal cost, which is a finite and positive quantity. Given that $J_i^* \geq 0$ is satisfied, it concludes that $-V(t_M) \leq 0$.

Since the system input $u_i(k)$ is always constrained within the interval $[u_{min}, u_{max}]$, and the system is stabilizable, it follows that the state trajectory $\xi_i(k)$ is guaranteed to be bounded provided that the initial state is bounded. Consequently, the value of the stage cost function $L_i(\xi, u, k)$ must also lie within a finite range.

The objective of the MPC controller is to minimize the cumulative cost over the prediction horizon of N_P steps. To achieve this, the controller must drive the system state toward regions with lower cost within the prediction horizon. If the prediction horizon N_P is sufficiently long, the terminal state of the optimal trajectory, $\xi_{i_s}^*(t_s + N_P|t_s)$ will lie in close proximity to the consensus state. Consequently, the value of the cost term $L_{i_s}(\xi_{i_s}^*(t_s + N_P|t_s), 0, t_{s+1})$ will be significantly small.

Moreover, since $\{L_{i_s}(t_s)\}$ constitutes a sequence of nonnegative terms whose partial sums are bounded, it follows from the convergence criterion for nonnegative series that

$$\sum_{s=0}^{\infty} L_{i_s}(t_s) < \infty \quad (29)$$

According to the necessary condition for the convergence of a series—that its general term must tend to zero—the following can be concluded:

$$\lim_{k \rightarrow \infty} L_i(k) = 0, \forall i \in \{1, \dots, N\} \quad (30)$$

This result is the cornerstone of the consensus proof. Based on the fact that $L_i(k) \rightarrow 0$ and that the weighting matrices Q and R are positive definite, two key preliminary results:

- (1) The control inputs converge to zero: $\lim_{k \rightarrow \infty} u_i(k) = 0$
- (2) The state of agent i converges to the last broadcasted state of its neighbors: $\lim_{k \rightarrow \infty} \|\xi_i(k) - \hat{\xi}_j(k - \tau(k))\| = 0, \forall j \in N_i$.

First, velocity consensus is proven. From result (1), the velocity dynamics $v_i(k+1) = v_i(k) + hu_i(k)$ imply that $\lim_{k \rightarrow \infty} \|v_i(k+1) - v_i(k)\| = 0$. This shows that for each agent, the velocity sequence $\{u_i(k)\}$ is a Cauchy sequence, which guarantees its convergence to a constant value. A critical property of a convergent sequence is that for any bounded interval, such as the delay $\tau(k)$, the difference between terms also vanishes, i.e., $\lim_{k \rightarrow \infty} \|v_j(k) - v_j(k - \tau(k))\| = 0$.

Furthermore, as the system stabilizes, the state-dependent part of the event-triggering threshold, $\hat{\xi}_i$ converges to zero, and the time-dependent term $c_i \rho^k$ also decays to zero. Since Zeno's behavior is excluded (Theorem 1), the inter-event times are strictly positive. This is

only possible if the measurement error that drives the trigger also converges to zero. Thus, it holds that $\lim_{k \rightarrow \infty} \|e_j(k)\| = \lim_{k \rightarrow \infty} \|\hat{\xi}_j(k) - \xi_j(k)\| = 0$ for all agents.

Now, consider the triangle inequality:

$$\begin{aligned} \|\xi_i(k) - \xi_j(k - \tau(k))\| &\leq \|\xi_i(k) - \hat{\xi}_j(k - \tau(k))\| \\ &\quad + \|\hat{\xi}_j(k - \tau(k)) - \xi_j(k - \tau(k))\| \end{aligned}$$

The first term on the right-hand side converges to zero due to result (2). The second term is the measurement error $\|e_j(k - \tau(k))\|$, which also converges to zero. This definitively proves that $\lim_{k \rightarrow \infty} \|\xi_i(k) - \xi_j(k - \tau(k))\| = 0$.

Finally, velocity consensus is proven using another application of the triangle inequality:

$$\|v_i(k) - v_j(k)\| \leq \|v_i(k) - v_j(k - \tau(k))\| + \|v_j(k - \tau(k)) - v_j(k)\|$$

As shown above, both terms on the right-hand side converge to zero. This leads directly to the conclusion of velocity consensus across all neighbors. By Assumption 1, this extends to the entire network:

$$\lim_{k \rightarrow \infty} \|v_i(k) - v_j(k)\| = 0$$

Since $\lim_{k \rightarrow \infty} u_i(k) = 0$ and measurement errors vanish, it is implied that the neighborhood error $\lim_{k \rightarrow \infty} \zeta_i(k) = 0$. From the definition of $\zeta_i(k)$ in (8):

$$\lim_{k \rightarrow \infty} \sum_{j \in N_i} a_{ij}(k) (\alpha(x_i(k) - x_j(k)) + (v_i(k) - v_j(k))) = 0$$

Given that the velocity difference term converges to zero, the equation simplifies to

$$\lim_{k \rightarrow \infty} \sum_{j \in N_i} a_{ij}(k) (\alpha(x_i(k) - x_j(k))) = 0$$

This expression indicates that the vector of position differences lies in the null space of the graph Laplacian. Under Assumption 1, the null space is spanned by the vector $[\mathbf{1}, \mathbf{1}, \dots, \mathbf{1}]^T$. This condition can only be satisfied if all position differences are zero. Therefore, position consensus is achieved:

$$\lim_{k \rightarrow \infty} \|x_i(k) - x_j(k)\| = 0$$

Thus, the asymptotic consensus of the system state is proven. $\square$

It is worth noting that data-driven approaches must contend with empirical factors characterized by high variance, such as measurement noise or unmodeled disturbances. The proposed framework inherently handles these fluctuations through the receding horizon principle and the event-triggered mechanism. Specifically, at each triggering instant k , the optimization problem (25) is solved based on the current actual state feedback $\xi_i(k)$, rather than relying solely on open-loop predictions. This feedback loop allows the controller to compensate for accumulated deviations caused by data variance. Furthermore, the event-triggering condition (12) acts as a dynamic supervisor: if high variance leads to a sudden increase in the measurement error $e_i(k)$ that exceeds the threshold, the mechanism forces an immediate update of the control input. This ensures that the system maintains robust consensus performance even in the presence of fluctuating empirical factors.

4. Numerical Examples

In this section, a set of comparative experiments is conducted to validate the effectiveness of the proposed theory through simulations. The system model is constructed based on Equation (1), with the time delay set to $0 < \tau(k) < 3$. The initial states and velocities of the multi-agent system are configured as $x_1(0) = 0, x_2(0) = 2, x_3(0) = 5, x_4(0) = -1$ and $v_1(0) = 5, v_2(0) = 3, v_3(0) = -5, v_4(0) = -2$, respectively. Furthermore, the communication topology is designed as follows:

$$\mathcal{A} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix}$$

In this example, the parameters are selected as follows: $h = 0.01, \alpha = 0.9, \sigma_i = 0.02, c_i = 0.1, \rho = 0.99$. Figures 1–3 present the simulation outcomes for the agent positions, velocities, and event-triggering instants under a prediction horizon of $N_P = 10$. Figures 4–6 show the simulation results obtained with a prediction horizon $N_P = 20$, including the evolution of multi-agent positions, velocities, and the corresponding event-triggering instants. Figures 7–9 depict the simulation results for a prediction horizon of $N_P = 30$, demonstrating the resulting multi-agent position/velocity profiles and the event-triggering behavior.

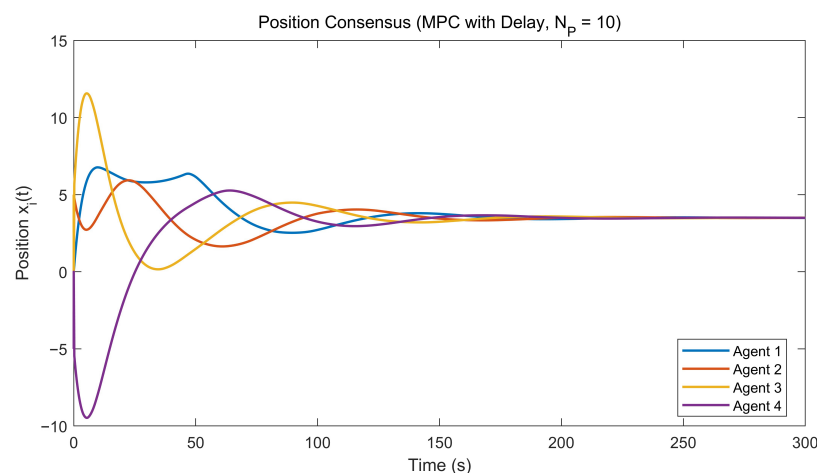


Figure 1. The positions of all agents ($N_P = 10$).

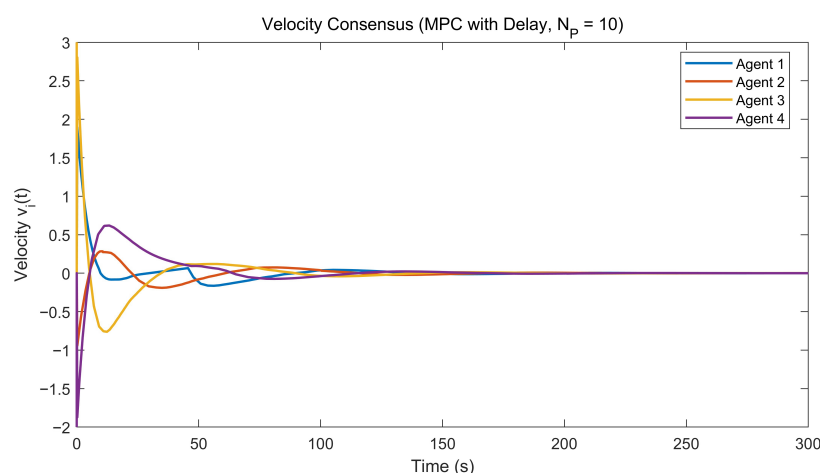


Figure 2. Velocity trajectories of all agents with prediction horizon ($N_P = 10$).

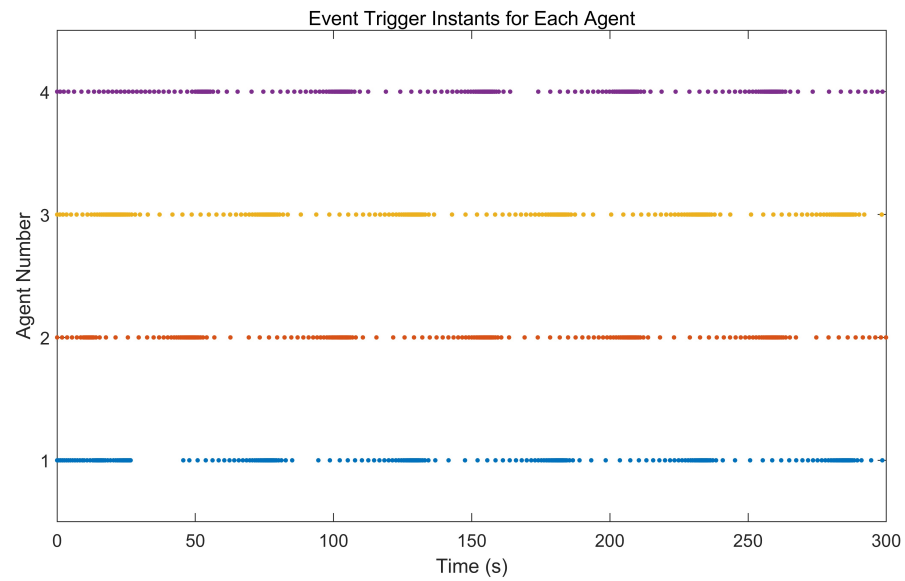


Figure 3. The triggering instants of all agents ($N_P = 10$).

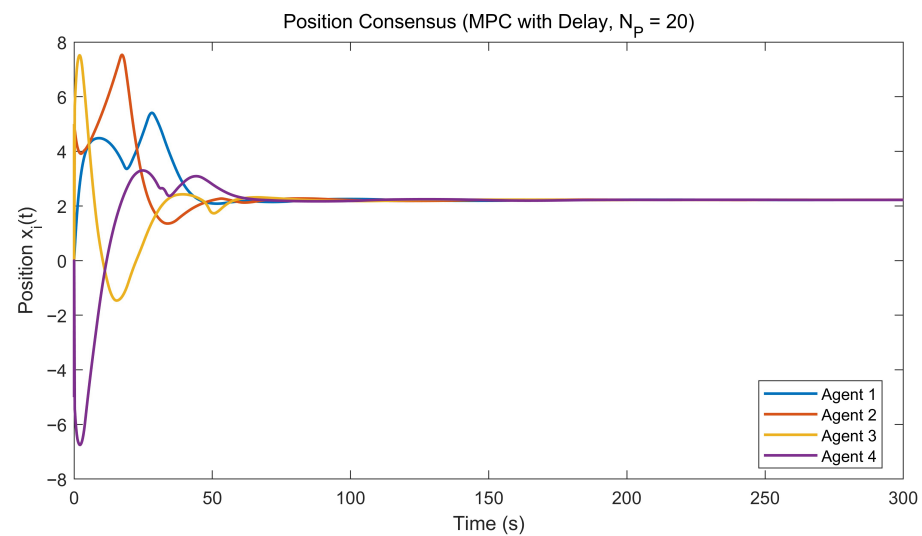


Figure 4. The positions of all agents ($N_P = 20$).

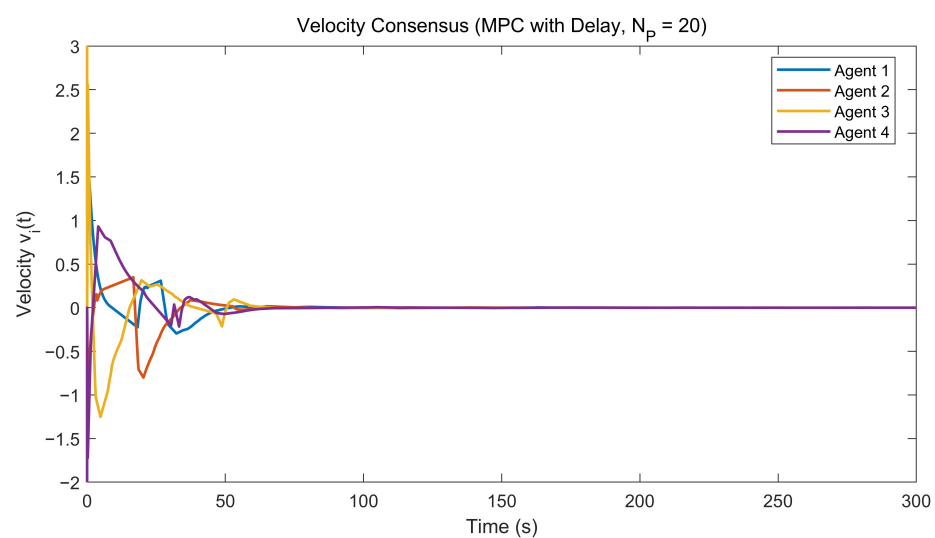


Figure 5. Velocity trajectories of all agents with prediction horizon ($N_P = 20$).

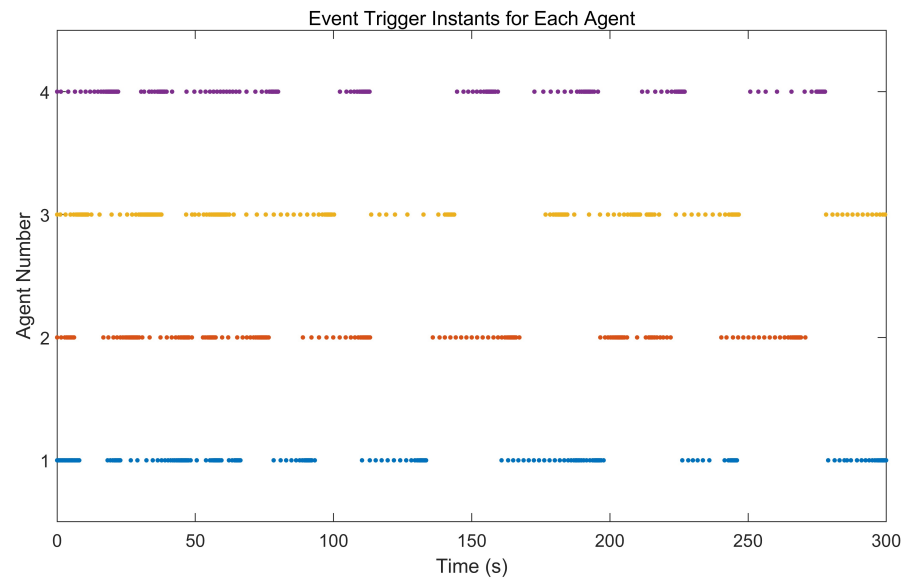


Figure 6. The triggering instants of all agents ($N_P = 20$).

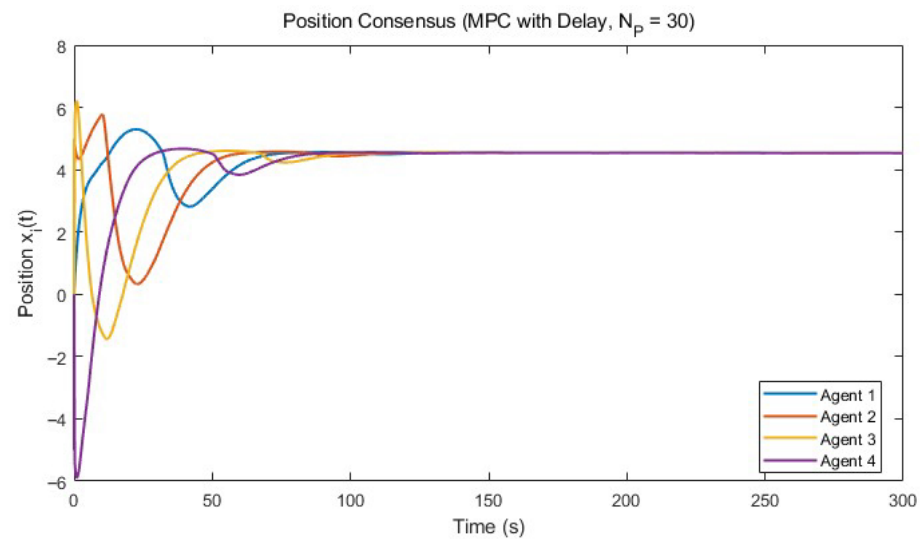


Figure 7. The positions of all agents ($N_P = 30$).

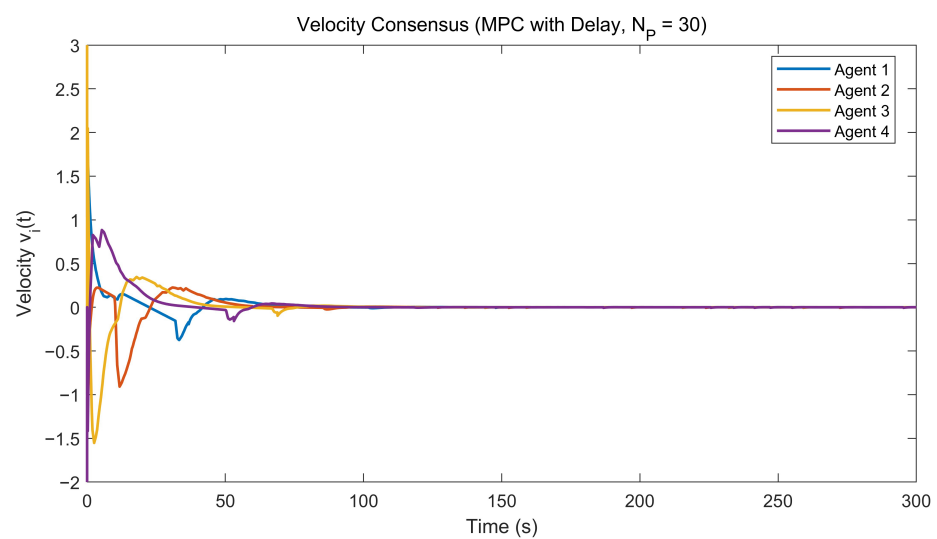


Figure 8. Velocity trajectories of all agents ($N_P = 30$).

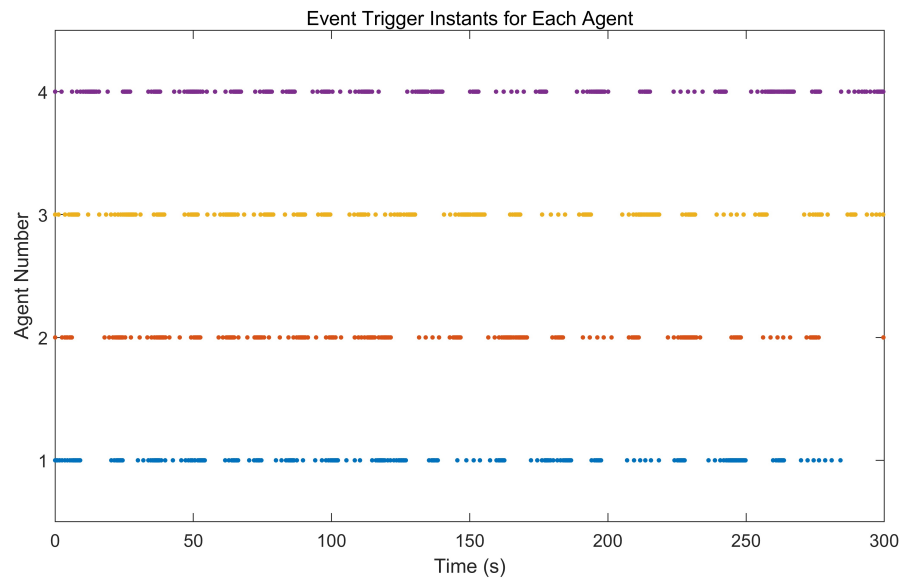


Figure 9. The triggering instants of all agents ($N_P = 30$).

The results confirm that the proposed control protocol successfully drives all agents to achieve consensus in both position and velocity for all tested prediction horizons. A longer prediction horizon yields superior control performance. As N_P increases from 10 to 30, the system exhibits a faster convergence speed and smaller overshoots, as visually demonstrated in the position and velocity trajectory plots. A critical finding is the inverse relationship between the prediction horizon length and the communication frequency. As shown in the comparative bar chart Figure 10, increasing N_P significantly reduces the total number of event triggers for every agent.

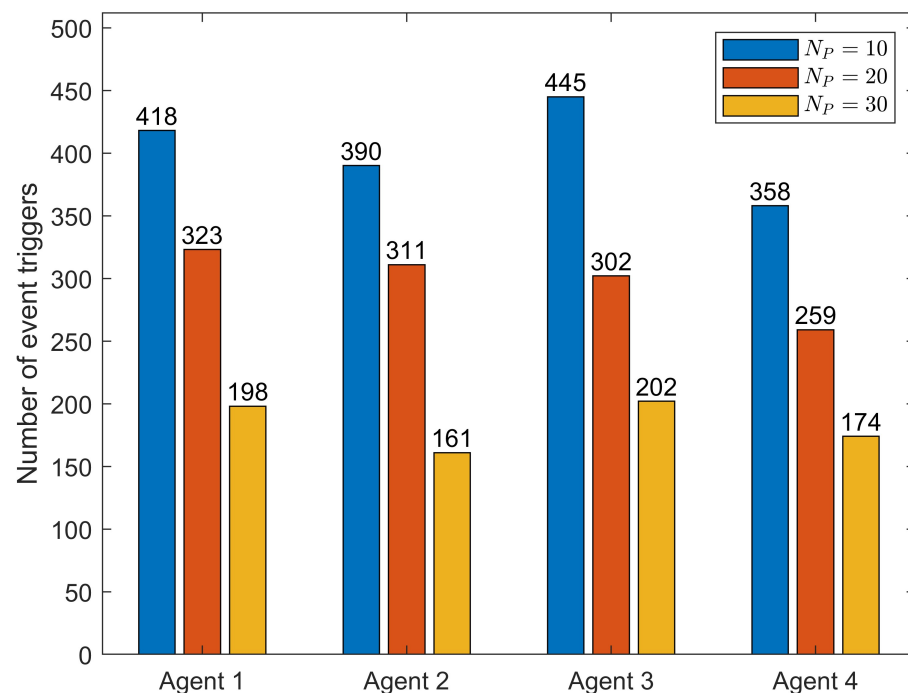


Figure 10. Comparison of the event-triggering frequency of the multi-agent system under different prediction horizons N_P .

5. Conclusions

To further evaluate the proposed framework, it is essential to discuss the results in relation to existing methodologies reported in the literature [7,30].

Comparison with Model-Based Strategies: Traditional event-triggered consensus protocols, such as those reviewed in [30], typically rely on accurate system matrices (A , B) to compute control laws. While effective under ideal conditions, their performance degrades significantly when parametric uncertainties or modeling errors exist. In contrast, our DD-ETPC framework leverages Willems' fundamental lemma to generate control actions directly from data, effectively eliminating the sensitivity to modeling mismatches.

Comparison with Standard Data-Driven Methods: Although other data-driven approaches (e.g., [7]) avoid model reliance, they often lack an explicit mechanism to compensate for time-varying communication delays. Our method distinguishes itself by integrating Predictive Control. The receding horizon mechanism allows agents to predict future states and actively compensate for delays during transmission gaps, ensuring smoother convergence and higher stability margins compared to non-predictive schemes.

Furthermore, the inherent robustness of the proposed predictive framework against time-varying delays suggests its potential applicability in enhancing the security of multi-agent systems against availability attacks, such as DoS jamming. This paper has presented a systematic investigation into the consensus control of discrete-time multi-agent systems subject to time-varying delays. Addressing the specific research objectives outlined in the Introduction, the primary contributions and findings are summarized as follows:

- (1) First, we have established a robust data-driven event-triggered predictive control framework. By seamlessly integrating predictive control with an event-triggered mechanism, this architecture effectively mitigates the adverse effects of unknown system dynamics and time-varying communication delays, ensuring reliable consensus under resource-constrained conditions.
- (2) Second, distinct from traditional model-based paradigms, our approach utilizes Willems' fundamental lemma to construct predictive models directly from historical input-state trajectories. This methodology circumvents the need for explicit system identification, thereby enhancing the system's adaptability to complex or hard-to-model environments.
- (3) Third, rigorous theoretical analysis has substantiated the recursive feasibility of the proposed optimization algorithm and the asymptotic stability of the closed-loop system. Crucially, we have mathematically derived a positive lower bound for inter-event times, guaranteeing the exclusion of Zeno behavior and ensuring the physical implementability of the controller.
- (4) Finally, extensive numerical simulations have validated the efficacy of the proposed strategy. The results explicitly elucidate the dual impact of the prediction horizon (N_P): a larger horizon not only accelerates consensus convergence but also significantly suppresses the frequency of event triggers, revealing a quantifiable trade-off between computational foresight and communication overhead.

Author Contributions: Conceptualization: C.-J.L.; Methodology: C.-J.L. and W.X.; Software: C.-J.L. and W.X.; Validation: L.Q., Z.D., and J.L.; Investigation: L.Q., Z.D., and J.L.; Resources: C.-J.L.; Writing—original draft preparation: C.-J.L. and W.X.; Writing—review and editing: C.-J.L., W.X., and L.Q.; Visualization: W.X.; Project administration: C.-J.L. and S.Y.; Funding acquisition: C.-J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported in part by the National Science Foundation of China under grant No. 62441308.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

Symbol	Description
N	Number of agents in the system
$\mathcal{G}, \mathcal{L}, \mathcal{A}$	Communication graph, Laplacian matrix, and adjacency matrix
$x_i(k), v_i(k)$	Position and velocity of agent i at time step k
$u_i(k)$	Control input of agent i
$\tau(k)$	Time-varying communication delay
$e_i(k)$	Measurement error at time k
t_s^i	The s -th triggering instant for agent i
N_p	Prediction horizon length
Q, R	Positive definite weighting matrices for state and input
$J_i(g_i, k)$	Cost function for the predictive optimization problem

References

1. Olfati-Saber, R.; Murray, R.M. Consensus problems in networks of agents with switching topology and time-delays. *IEEE Trans. Autom. Control* **2004**, *49*, 1520–1533.
2. Li, X.; Liu, J.C.; Li, X.G. Consensus of first-order discrete-time multi-agent systems with time delays. *J. Frankl. Inst.* **2019**, *356*, 5315–5331.
3. Ma, D.; Boussaada, I.; Chen, J.; Bonnet, C.; Niculescu, S.I.; Chen, J. PID control design for first-order delay systems via MID pole placement: Performance vs. robustness. *Automatica* **2022**, *137*, 110102.
4. Wang, J.; Luo, X.; Yan, J.; Guan, X. Event-triggered consensus control for second-order multi-agent system subject to saturation and time delay. *J. Frankl. Inst.* **2021**, *358*, 4895–4916.
5. Ma, Q.; Xu, S. Consensus switching of second-order multiagent systems with time delay. *IEEE Trans. Cybern.* **2022**, *52*, 3349–3353.
6. Yang, S.; Liu, Q.; Wang, J. Distributed optimization based on a multiagent system in the presence of communication delays. *IEEE Trans. Syst. Man Cybern. Syst.* **2016**, *47*, 717–728.
7. Bu, X.; Hou, Z.; Zhang, H. Data-Driven Multiagent Systems Consensus Tracking Using Model Free Adaptive Control. *IEEE Trans. Neural Netw. Learn. Syst.* **2018**, *29*, 1514–1524.
8. Zhou, Y.; Li, D.; Gao, F. Data-Driven Optimal Synchronization Control for Leader-Follower Multiagent Systems. *IEEE Trans. Syst. Man Cybern. Syst.* **2023**, *53*, 495–503.
9. Zhang, H.; Yue, D.; Dou, C.; Zhao, W.; Xie, X. Data-Driven Distributed Optimal Consensus Control for Unknown Multiagent Systems With Input-Delay. *IEEE Trans. Cybern.* **2019**, *49*, 2095–2105.
10. Li, H.; Wei, Q. Data-Driven Optimal Output Cluster Synchronization Control of Heterogeneous Multi-Agent Systems. *IEEE Trans. Autom. Sci. Eng.* **2024**, *21*, 3910–3920.
11. Huang, Y.; Liu, G.P.; Yu, Y.; Hu, W. Data-driven distributed predictive tracking control for heterogeneous nonlinear multiagent systems with communication delays. *IEEE Trans. Autom. Control* **2024**, *69*, 4786–4792.
12. Dou, Y.; Xing, G.; Ma, A.; Zhao, G. A review of event-triggered consensus control in multi-agent systems. *J. Control Decis.* **2025**, *12*, 1–23.
13. Yang, Y.; Li, Y.; Yue, D. Event-trigger-based consensus secure control of linear multi-agent systems under DoS attacks over multiple transmission channels. *Sci. China Inf. Sci.* **2020**, *63*, 150208.
14. Liu, K.; Ji, Z. Dynamic Event-Triggered Consensus of General Linear Multi-Agent Systems With Adaptive Strategy. *IEEE Trans. Circuits Syst. II Express Briefs* **2022**, *69*, 3440–3444.
15. Dong, T.; Zhu, H.; Hu, W. Event-trigger optimal consensus for multi-agent system subject to differential privacy. *Int. J. Control Autom. Syst.* **2021**, *19*, 2940–2949.
16. Zhang, X.Z.; Lan, J.; Liu, Y.J.; Liu, L. Adaptive event-triggered control of multi-agent systems with state constraints and unknown disturbances. *IET Control Theory Appl.* **2021**, *17*, 2171–2182.
17. Zhang, W.; Chen, J.; Wen, S.; Huang, T. Event-Triggered Random Delayed Impulsive Consensus of Multi-Agent Systems With Time-Varying Delay. *IEEE Trans. Emerg. Top. Comput. Intell.* **2025**, *9*, 2059–2064.

18. Abbasi, M.; Marquez, H.J. Observer-based event-triggered consensus control of multi-agent systems with time-varying communication delays. *IEEE Trans. Autom. Sci. Eng.* **2023**, *21*, 6336–6346.
19. Cheng, Z.; Zhang, H.T.; Fan, M.C.; Chen, G. Distributed Consensus of Multi-Agent Systems With Input Constraints: A Model Predictive Control Approach. *IEEE Trans. Circuits Syst. I Regul. Pap.* **2015**, *62*, 825–834.
20. Pang, Y.; Zhao, X. Bayesian spatio-temporal graph transformer network (b-star) for multi-aircraft trajectory prediction. *Knowl.-Based Syst.* **2022**, *249*, 108998.
21. Köhler, M.; Müller, M.A.; Allgöwer, F. Distributed Model Predictive Control for Dynamic Cooperation of Multi-Agent Systems. *arXiv* **2025**, arXiv:2504.00225.
22. Liu, G.P. Coordination of Networked Nonlinear Multi-Agents Using a High-Order Fully Actuated Predictive Control Strategy. *IEEE/CAA J. Autom. Sin.* **2022**, *9*, 615–623.
23. Su, Y.; Shi, Y.; Sun, C. Distributed model predictive control for tracking consensus of linear multiagent systems with additive disturbances and time-varying communication delays. *IEEE Trans. Cybern.* **2019**, *51*, 3813–3823.
24. Yang, Q.; Sun, J.; Chen, J. Output Consensus for Heterogeneous Linear Multiagent Systems With a Predictive Event-Triggered Mechanism. *IEEE Trans. Cybern.* **2021**, *51*, 1993–2005.
25. Liu, X.; Xuan, Y.; Zhang, Z.; Diao, Z.; Mu, Z.; Li, Z. Event-triggered consensus for discrete-time multi-agent systems with parameter uncertainties based on a predictive control scheme. *J. Syst. Sci. Complex.* **2020**, *33*, 706–724.
26. Yin, X.; Yue, D.; Hu, S.; Zhang, H. Distributed adaptive model-based event-triggered predictive control for consensus of multiagent systems. *Int. J. Robust Nonlinear Control* **2018**, *28*, 6180–6201.
27. Qin D.; Jin Z.; Zhang, Z.; Asynchronous event-triggered distributed predictive control for multiagent systems with parameterized synchronization constraints *IEEE Transactions on Automatic Control.* **2023**, *69*, 403–409.
28. Tang, X.; Li, M.; Wei, S.; Ding, B. Event-triggered synchronous distributed model predictive control for multi-agent systems. *Int. J. Control Autom. Syst.* **2021**, *19*, 1273–1282.
29. Van Waarde, H.J.; De Persis, C.; Camlibel, M.K.; Tesi, P. Willems’ Fundamental Lemma for State-Space Systems and Its Extension to Multiple Datasets. *IEEE Control Syst. Lett.* **2020**, *4*, 602–607.
30. Li, Y.; Wang, X.; Sun, J.; Wang, G.; Chen, J. Data-driven consensus control of fully distributed event-triggered multi-agent systems. *Sci. China Inf. Sci.* **2023**, *66*, 152202.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.