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Research article

Consensus of multi-agent system with disturbance based on dynamical event-triggered control

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Abstract: This study addresses the consensus problem of multi-agent systems (MAS) subject to external disturbance. Considering the presence of external disturbance factors, a theoretical analysis of consensus for distributed MAS is conducted. First, a state observer and an adaptive disturbance observer are designed to estimate both the node states and disturbance states of each agent in the system. Subsequently, a dynamic event-triggered control strategy is formulated based on the estimated values from the observers. Notably, the dynamic event-triggered strategy incorporates dynamically adjustable parameters, offering enhanced flexibility compared to conventional static event-triggered strategies. Using Lyapunov stability theory and inequality techniques, sufficient conditions for achieving consensus in disturbed MAS are derived. Finally, a numerical example is provided to demonstrate the effectiveness of the observers, control strategies, and theoretical results. This work provides new solutions for the consensus control of heterogeneous MAS with external disturbance, where both the obsever and the dynamic event-triggered controller are equipped with adjustable parameters, rendering the approach more practical for real-world applications.

Keywords: multi-agent systems; disturbance rejection; dynamic event-triggered control; adaptive control; consensus

1. Introduction

The consensus problem of multi-agent systems (MAS) is one of the core topics in the field of distributed control. Consensus control aims to drive the states or outputs of all agents to converge to a common value through local information exchange, which is fundamental for achieving collective intelligent collaboration. In recent years, with the increasing scale and complexity of systems, the consensus problem of MAS has attracted considerable attention from scholars, and its theories and methods are continuously being enriched and developed.

However, compared with ideal MAS, various external disturbance are commonly present in practical applications, such as random noise, external interference, communication delays, and modeling uncertainties. The existence of disturbance can affect the motion states of the agents, leading to system instability and poor performance. Effective control strategies should be implemented to reduce or even eliminate the adverse effects of disturbance on the system. Therefore, when applying the research findings on MAS consensus to real-world scenarios, it is particularly important to consider the disturbance the system faces. Nevertheless, studying the consensus problem of MAS with disturbance is considerably more challenging. Wang et al. [1] considered the distributed consensus control problem of second-order MAS with directed networks subject to disturbance. Unlike existing work, they proposed a local composite disturbance observer that can asymptotically estimate the precise state of local disturbance asymptotically. Luo et al. [2] introduced an observer-based distributed event-triggered strategy where each agent's triggering time sequence is different, and the time-varying delay controller updates only at the triggering instants, effectively reducing communication overhead. Li et al. [3] was the first to attempt to apply the active disturbance rejection control method to the consensus analysis of a class of second-order stochastic MAS with undirected connected network topologies and disturbance. While substantial research has been devoted to disturbance rejection in MAS, such as robust control, disturbance observer-based methods, and H_∞ control, the consensus problem for heterogeneous MAS under unknown disturbance remains an area open for further exploration, specifically within a dynamic event-triggered control framework that incorporates an adaptive disturbance observer. Therefore, how to construct such a framework and design an efficient controller to achieve consensus is the main focus of this paper.

However, achieving consensus under disturbance introduces a fundamental design conflict with the resource constraints prevalent in real networked systems. On the one hand, effective disturbance rejection typically demands continuous or high-frequency control updates to actively compensate for perturbations, which can lead to significant communication and energy costs. On the other hand, control strategies designed primarily for resource conservation, such as standard event-triggered control, inherently reduce the frequency of control updates. This sporadic activation can weaken the system's ability to counteract disturbance in real time, as the control input remains unchanged between triggering instants, potentially allowing disturbance to have a greater impact on the system's state before being corrected. Therefore, reconciling the trade-off between robustness against disturbance and efficiency in resource usage constitutes a critical yet challenging problem for practical MAS applications. Recent works have explored hybrid frameworks that combine disturbance observers with event-triggered mechanisms. For instance, Li et al. [4] integrates an extended state observer into an event-triggered scheme to handle mismatched disturbance in MAS. However, such approaches often employ static triggering thresholds, which may lead to conservative performance or excessive triggering in the face of varying disturbance, as discussed in the analyses of event-triggered control limitations [5].

In general, the consensus problem in MAS can be approached from two aspects. One is to achieve consensus by changing the system's own topological structure, such as adjusting the coupling strength between nodes or increasing the connections between nodes; the other is to apply external control to the system by designing suitable external inputs. Due to the many limitations and impracticality of promoting system consensus by changing the network's own topological structure in actual systems, the controller design method is widely applied. To date, many effective consensus control strategies have been proposed by scholars, including pinning control [6], adaptive control [7–9], sampling control [10], impulsive control [11], and event-triggered control [12, 13]. Among them, adaptive control can provide adaptive strategies for time-varying parameters and continuously adjust parameters through adaptive rules, thereby effectively tuning the system to achieve consensus and possessing strong flexibility. Event-triggered control determines the signal transmission situation at the next moment by pre-designing suitable triggering conditions, and control is activated only when the system's error signal meets the preset triggering conditions.

In recent decades, the application of event-triggered control has become increasingly widespread, commonly including adaptive event-triggered control [14], distributed event-triggered control [15], self-triggered control [16], dynamic event-triggered control [17], and hybrid event-triggered control [18]. Among them, dynamic event-triggered control is the most widely used, characterised by the introduction of internal dynamic variables that adaptively adjust the event-triggered conditions, further improving resource utilization efficiency while ensuring system stability. Xu [17] proposed two event-triggered control strategies, based on nonlinear relative state and absolute state coupling using projection operator techniques, and designed corresponding dynamic event-triggered strategies. As the name suggests, hybrid event-triggered mechanisms combine event-triggered control with adaptive control, sampling control, pinning control, and other control methods, thereby constructing a more efficient control framework.

Based on recent progress in the consensus of MAS and event-triggered control methods, this paper conducts an in-depth analysis to address the consensus problem of heterogenous MAS with disturbance. The main contributions of this paper are as follows.

1) A state and disturbance estimation mechanism based on an adaptive state observer and disturbance observer has been designed, which can simultaneously estimate the state of the node and the disturbance. Compared with traditional methods that estimate only the state or only the disturbance, this observer is capable of obtaining accurate estimates of both state and disturbance with weaker prior information. Additionally, it is suitable for different types of disturbance models, enhancing the system's robustness to uncertainty.
2) A dynamic event-triggered control strategy with dynamically adjustable parameters has been proposed. The event-triggered control introduced in this paper incorporates dynamic parameters $\eta_i(t)$, allowing real-time adjustment of the triggering threshold. Compared with traditional static event-triggered control, this method effectively reduces the frequency of control updates while ensuring consensus, thereby lowering system resource consumption.
3) Through rigorous theoretical derivation, this paper proves that the system will not exhibit Zeno behaviour under the proposed event-triggered control, and the adaptive coupling strength $k_i(t)$ in the controller remains bounded, thus avoiding engineering issues such as infinite gain growth and actuator saturation, and enhancing the practicality and feasibility of this control strategy in actual networked systems.

Unlike conventional static event-triggered consensus protocols [19] which rely on fixed thresholds and lack any mechanism for disturbance compensation, our dynamic event-triggered strategy integrated with an adaptive disturbance observer simultaneously achieves robust consensus and resource efficiency. Furthermore, compared to disturbance observer-based control methods without event-triggering [20], our framework explicitly reduces communication and computational overhead while maintaining comparable disturbance rejection performance. In contrast to adaptive consensus controllers where coupling strengths may grow unboundedly [21], our design ensures all adaptive gains remain bounded, preventing actuator saturation and enhancing practical implementability.

2. Notations and some preliminaries

2.1. Notations

First, we introduce the notations used in this paper. $\mathbb{R}$ and $\mathbb{Z}_+$ denote the sets of real numbers and positive integers, while $\mathbb{R}^n$ and $\mathbb{R}^{n\times m}$ signify the sets of n-dimensional real vectors and $n \times m$ real matrices. For a symmetric matrix M, $M > 0$ indicates that M is positive. Furthermore, $\lambda_{\max}(M)$ and $\lambda_{\min}(M)$ denote the maximum and minimum eigenvalues, respectively. Finally, $A = (a_{ij})_{N\times N}$ is the weighted adjacency matrix of an undirected graph $\mathcal{G}$, and the corresponding Laplacian matrix is defined as $L = (l_{ij})_{N\times N}$ with $l_{ij} = -a_{ij}$ for $i \neq j$ and $l_{ij} = \sum_{i\neq j} a_{ij}$ for $i = j$. The symbol I denotes the identity matrix. $tr(\cdot)$ denotes the trace of a matrix. It's worth noting that capital letters denote matrices and lowercase letters denote vectors.

2.2. Necessary preliminaries

Lemma 1. *[22] There are two vectors $x, y \in \mathbb{R}^n$, and one has $x^T y = tr(xy^T)$.*

Assumption 1. *Suppose D_i in (3.3) is a bounded constant matrix, and $\|D_i\| \leq d$.*

3. Main results

3.1. Network model

In this paper, we consider a MAS with one leader node and N follower nodes. The dynamics for the leader node are given by

$$\begin{cases} \dot{x}_0(t) = Ax_0(t) \\ y_0(t) = Cx_0(t), \end{cases} \tag{3.1}$$

and the dynamics of the follower nodes are

$$\begin{cases} \dot{x}_i(t) = Ax_i(t) + u_i(t) + E_1\delta_i(t) \\ y_i(t) = Cx_i(t) + E_2\delta_i(t), \end{cases} \tag{3.2}$$

where $i = 1, 2, \cdots, N$. $x_i(t) \in \mathbb{R}^{n_1}$ and $y_i(t) \in \mathbb{R}^{n_2}$ represent the state vector and the output vector of the i-th agent, respectively. A, C, E_1, and E_2 are constant matrices of appropriate dimensions. Furthermore, $u_i(t) \in \mathbb{R}^{n_1}$ and $\delta_i(t) \in \mathbb{R}^m$ denote the controller and disturbance of the i-th agent in the MAS (3.2). The disturbance satisfies the following equation:

$$\dot{\delta}_i(t) = D_i\delta_i(t), \tag{3.3}$$

where the unknown constant matrix D_i is the coefficient matrix of the external disturbance equation. It is worth noting that the topological graph corresponding to the MAS studied in this paper is an undirected connected graph.

Remark 1. *For complex networks, signals are inevitably affected by factors such as network bandwidth and transmission media during transmission between various network nodes, causing disturbance and leading to some uncertainties in the network.*

Remark 2. *The system dynamics (3.2) consider the case where the input matrix is the identity matrix. This is a standard and frequently adopted assumption in consensus problem formulations. This choice serves to simplify the exposition and highlight the core design principles of the proposed observer and event-triggered controller. It is important to note that this assumption does not fundamentally restrict the practical applicability of the method. For a system with a general, known, and invertible input matrix B, the control law can be readily generalized by considering a transformed control input. The core framework, including the structure of the adaptive disturbance observer, the design of the dynamic event-triggering condition based on* $\eta_i(t)$*, and the associated stability analysis, remains conceptually valid and can be extended accordingly. The presented case of* $B = I$ *thus provides a clear and foundational blueprint for the integrated co-design strategy under external disturbance.*

Remark 3. *The disturbance model* $\dot{\delta}_i(t) = D_i\delta_i(t)$ *in (3.3) is capable of describing many common disturbance types encountered in real-world multi-agent systems. For example, when* $D_i = 0$*, the model represents constant disturbance such as steady-state wind forces acting on unmanned aerial vehicles during hover or terrain-induced biases in ground robot localization. When* D_i *contains purely imaginary eigenvalues, the model generates sinusoidal disturbance, which can represent periodic vibrations in mechanical structures or oscillatory load variations in power networks. Furthermore, when* D_i *is unknown, the adaptive estimation mechanism in (3.5) enables online identification of the disturbance dynamics, making the framework applicable to scenarios where precise prior knowledge of the disturbance model is unavailable. This modeling approach has been widely adopted in practical applications including robotic manipulators, autonomous vehicles, and power systems, as documented in the disturbance observer literature.*

3.2. Design of an adaptive observer

In this paper, we consider the consensus problem of a MAS with disturbance in an undirected connect graph. To estimate the states of nodes and disturbance, an adaptive observer is designed as follows:

$$\begin{cases} \dot{\hat{x}}_i(t) = A\hat{x}_i(t) + u_i(t) + E_1\hat{\delta}_i(t) + G_{i1}(y_i(t) - \hat{y}_i(t)) \\ \hat{y}_i(t) = C\hat{x}_i(t) + E_2\hat{\delta}_i(t), \end{cases} \tag{3.4}$$

and

$$\begin{cases} \dot{\hat{\delta}}_i(t) = \hat{D}_i(t)\hat{\delta}_i(t) + G_{i2}(y_i(t) - \hat{y}_i(t)) \\ \dot{\hat{D}}_i(t) = P_i\tilde{y}_i(t)\hat{\delta}_i^T(t), \end{cases} \tag{3.5}$$

where $\hat{x}_i(t)$, $\hat{y}_i(t)$, and $\hat{\delta}_i(t)$ are the estimates of $x_i(t)$, $y_i(t)$, and $\delta_i(t)$, respectively. Furthermore, $G_{i1} \in \mathbb{R}^{n_1\times n_2}$ and $G_{i2} \in \mathbb{R}^{m\times n_2}$ are the control gain matrices of the observers (3.4) and (3.5). P_i is a constant matrix of suitable dimensions. Define the observation errors $\tilde{x}_i(t) = x_i(t) - \hat{x}_i(t)$, $\tilde{y}_i(t) = y_i(t) - \hat{y}_i(t)$ and $\tilde{\delta}_i(t) = \delta_i(t) - \hat{\delta}_i(t)$, where $i = 1, 2, \cdots, N$. Then, we establish the observation error system as follows:

$$\begin{cases} \dot{\tilde{x}}_i(t) = (A - G_{i1}C)\tilde{x}_i(t) + (E_1 - G_{i1}E_2)\tilde{\delta}_i(t) \\ \dot{\tilde{\delta}}_i(t) = -G_{i2}C\tilde{x}_i(t) + (D_i - G_{i2}E_2)\tilde{\delta}_i(t) + (D_i - \hat{D}_i(t))\hat{\delta}_i(t). \end{cases} \tag{3.6}$$

Let $z_i(t) = (x_i^T(t), \delta_i^T(t))^T$ and $\hat{z}_i(t) = (\hat{x}_i^T(t), \hat{\delta}_i^T(t))^T$; one can conclude $\tilde{z}_i(t) = (\tilde{x}_i^T(t), \tilde{\delta}_i^T(t))^T$. Then, the observation error system can be rewritten as

$$\dot{\tilde{z}}_i(t) = \begin{pmatrix} A - G_{i1}C & E_1 - G_{i1}E_2 \\ -G_{i2}C & D_i - G_{i2}E_2 \end{pmatrix} \tilde{z}_i(t) + \begin{pmatrix} 0_{n_1 \times m} \\ I_m \end{pmatrix} (D_i - \hat{D}_i(t)) \begin{pmatrix} 0_{m \times n_1} & I_m \end{pmatrix} \hat{z}_i(t). \tag{3.7}$$

The first theorem of this paper is given below:

Theorem 1. *For the MAS (3.1) and (3.2), based on the designed observers (3.4) and (3.5), if there exists a matrix P_i such that*

$$H_i > 0, \lambda_{\max}\{H_i U_i + U_i^T H_i\} + 2d\lambda_{\max}\{H_i^T H_i\} < 0, \tag{3.8}$$

where $H_i = \begin{pmatrix} H_{i1} & (P_iC)^T \\ P_iC & P_iE_2 \end{pmatrix}$, $U_i = \begin{pmatrix} A - G_{i1}C & E_1 - G_{i1}E_2 \\ -G_{i2}C & -G_{i2}E_2 \end{pmatrix}$, *then the designed adaptive observer can estimate the state and disturbance of the i-th node. Thus, the observation error eventually converges to 0.*

Proof. Firstly, we construct the Lyapunov function:

$$V_i(t) = \tilde{z}_i^T(t) H_i \tilde{z}_i(t) + 2tr\tilde{D}_i^T(t)\tilde{D}_i(t), i = 1, 2, \cdots, N \tag{3.9}$$

where $\tilde{D}_i(t) = D_i - \hat{D}_i(t)$, and H_i is a positive definite matrix.

Then, calculating $\dot{V}_i(t)$ and substituting the trajectories of (3.7) into $\dot{V}_i(t)$, one can conclude

$$\begin{aligned} \dot{V}_i(t) =& 2\tilde{z}_i^T(t) H_i \dot{\tilde{z}}_i(t) + 2tr\tilde{D}_i^T(t)\dot{\tilde{D}}_i(t) \\ =& 2\tilde{z}_i^T(t) H_i (\begin{pmatrix} A - G_{i1}C & E_1 - G_{i1}E_2 \\ -G_{i2}C & -G_{i2}E_2 \end{pmatrix} \tilde{z}_i(t) + \begin{pmatrix} O_{n_1 \times m} \\ I_m \end{pmatrix} D_i \begin{pmatrix} O_{m \times n_1} & I_m \end{pmatrix} \tilde{z}_i(t) \\ &+ \begin{pmatrix} O_{n_1 \times m} \\ I_m \end{pmatrix} (D_i - \hat{D}_i(t)) \begin{pmatrix} O_{m \times n_1} & I_m \end{pmatrix} \hat{z}_i(t)) - 2tr\tilde{D}_i^T(t)\dot{\hat{D}}_i(t). \end{aligned} \tag{3.10}$$

Note that $U_i = \begin{pmatrix} A - G_{i1}C & E_1 - G_{i1}E_2 \\ -G_{i2}C & -G_{i2}E_2 \end{pmatrix}$ and $Q = \begin{pmatrix} O_{n_1 \times m} \\ I_m \end{pmatrix}$. Then, $\dot{V}_i(t)$ can be rewritten as:

$$\dot{V}_i(t) = 2\tilde{z}_i^T(t) H_i (U_i \tilde{z}_i(t) + Q D_i Q^T \tilde{z}_i(t) + Q\tilde{D}_i(t) Q^T \hat{z}_i(t)) - 2tr\tilde{D}_i^T(t)\dot{\hat{D}}_i(t). \tag{3.11}$$

After that, from Lemma 1, one can obtain

$$\begin{aligned} &2\tilde{z}_i^T(t) H_i Q \tilde{D}_i(t) Q^T \hat{z}_i(t) - 2tr\tilde{D}_i^T(t)\dot{\hat{D}}_i(t) \\ =& 2tr\tilde{D}_i^T(t) Q^T H_i \tilde{z}_i(t) \hat{z}_i^T(t) Q - 2tr\tilde{D}_i^T(t) P_i \tilde{y}_i(t) \hat{\delta}_i^T(t) \\ =& 0. \end{aligned} \tag{3.12}$$

Substituting (3.12) into (3.11)

$$\begin{aligned} \dot{V}_i(t) =& 2\tilde{z}_i^T(t) H_i (U_i \tilde{z}_i(t) + Q D_i Q^T \tilde{z}_i(t)) \\ \leq& \tilde{z}_i^T(t)(H_i U_i + U_i^T H_i) + 2\tilde{z}_i^T(t) d\lambda_{\max}\{H_i^T H_i\} \tilde{z}_i(t) \\ =& \tilde{z}_i^T(t)(H_i U_i + U_i^T H_i + 2d\lambda_{\max}\{H_i^T H_i\}) \tilde{z}_i(t) \\ <& 0. \end{aligned} \tag{3.13}$$

This result implies that the observation error $\tilde{z}_i(t) \to 0$ when $t \to +\infty$. Thus, the designed adaptive observers (3.4) and (3.5) can observe the node states and disturbance states of the MAS (3.1) and (3.2).

□

3.3. Design of a dynamic event-triggered controller

First, this paper studies the consensus problem of a MAS with a leader node. Consensus error of the i-th node is defined as $e_i(t) = x_i(t) - x_0(t)$, where $i = 1, 2, \cdots, N$. Combining the MAS (3.1) and (3.2), the consensus error system can be written as

$$\dot{e}_i(t) = Ae_i(t) + E_1\delta_i(t) + u_i(t), i = 1, 2, \cdots N. \tag{3.14}$$

In order to compensate for the effects of disturbance in the network, we design an adaptive controller based on a dynamic event-triggered mechanism as follows:

$$\begin{aligned} u_i(t) =& k_i(t)\Sigma_{j=1}^{N} a_{ij}(\hat{x}_j(t^j_{k_j}) - \hat{x}_i(t^i_{k_i}) + \gamma_i(x_0(t) - \hat{x}_i(t^i_{k_i})) \\ &- E_1\hat{\delta}_i(t), \end{aligned} \tag{3.15}$$

where $i = 1, 2, \cdots, N$, $k_i(t) \geq 0$ represents the bounded coupling strength with $\max\{k_i(t)\} = \bar{k}$, and γ_i represents the pinning control gain. Moreover, $t^i_{k_i}$ are the triggering instants of the i-th node and $t \in [t^i_{k_i}, t^i_{k_i+1})$.

Define $\varepsilon_i(t) = \hat{x}_i(t) - \hat{x}_i(t^i_{k_i})$, where $t \in [t^i_{k_i}, t^i_{k_i+1})$. For i-th node, we design the following event-triggered mechanism:

$$\begin{cases} t^i_1 = 0, \\ t^i_{k_i+1} = \inf\{t | t > t^i_{k_i} : \eta_i(t) \leq \frac{1}{\xi_i}[r_3 e^{-\alpha t} + r_4 \varepsilon_i^T(t)\varepsilon_i(t)]\}, \end{cases} \tag{3.16}$$

where $\xi_i > 0$, $r_1 < 0$, $r_3 < 0$, $r_4 > 0$, $r_3 > \frac{r_2 r_4}{r_1}$, and $r_1 + \frac{1}{c_2} < r_4$. Furthermore, $\eta_i(t)$ is a dynamic value that follows the adaptive law:

$$\dot{\eta}_i(t) = -\xi_i\eta_i(t) + r_1\varepsilon_i^T(t)\varepsilon_i(t) + r_2 e^{-\alpha t}, i = 1, 2, \cdots, N. \tag{3.17}$$

It is important to emphasize that the initial value of $\eta_i(t)$ is defined as $\eta_i(0) > 0$.

The vectors $e(t) = (e_1^T(t), e_2^T(t), \cdots, e_N^T(t))^T, \varepsilon(t) = (\varepsilon_1^T(t), \varepsilon_2^T(t), \cdots, \varepsilon_N^T(t))^T$, $\tilde{x}(t) = (\tilde{x}_1^T(t), \tilde{x}_2^T(t), \cdots, \tilde{x}_N^T(t))^T, \tilde{\delta}(t) = (\tilde{\delta}_1^T(t), \tilde{\delta}_2^T(t), \cdots, \tilde{\delta}_N^T(t))^T$ are defined, and the error system (3.14) can be rewritten as follows:

$$\dot{e}(t) =(I_N \otimes A)e(t) + (I_N \otimes E_1)\tilde{\delta}(t) + (K(t)(L + \Gamma) \otimes I_n)(\tilde{x}(t) - e(t) + \varepsilon(t)), \tag{3.18}$$

where the matrices $K(t) = diag\{k_1(t), k_2(t), \cdots, k_N(t)\}$ and $\Gamma = diag\{\gamma_1, \gamma_2, \cdots, \gamma_N\}$.

Remark 4. *The controller design in (3.15) is distinct from the adaptive consensus protocols in [23–25]. Those protocols employ coupling strengths updated by explicit adaptive laws, which may lead to unbounded growth. In contrast, the coupling gain in our design is specifically configured as a bounded and time-varying parameter. This is a deliberate co-design choice to prevent excessive control effort and actuator saturation. The core adaptive mechanisms of our proposed framework are located elsewhere, namely within the adaptive disturbance observer in (3.4) and (3.5) for online perturbation estimation, and the dynamic event-triggering mechanism in (3.16) and (3.17), where the internal dynamic variable adjusts the triggering threshold. Therefore, our strategy achieves a balance of robustness and resource efficiency not through an unbounded adaptive coupling strength, but through the integration of a bounded control gain with dedicated adaptive modules for observation and triggering.*

Proposition 2. *The dynamic value $\eta_i(t) > 0$ in the event-triggered function (3.16) for $i = 1, 2, \cdots, N$.*

Proof. Combining (3.16) and (3.17), one can obtain

$$\dot{\eta}_i(t) + (1 - \frac{r_1}{r_4})\xi_i \eta_i(t) > 0. \tag{3.19}$$

Noting that constant $\Phi = (1 - \frac{r_1}{r_4})\xi_i$, then

$$\dot{\eta}_i(t) + \Phi \eta_i(t) > 0, \tag{3.20}$$

Finally, one obtains

$$\eta_i(t) > e^{-\Phi t} \eta_i(0) > 0. \tag{3.21}$$

□

Remark 5. *For leader nodes, it is unreasonable to define an event-triggered controller. As evidenced in the reference [26], a fully asynchronous event-triggered controller that utilizes real-time information from the leader is more effective in achieving consensus in multi-agent systems. Therefore, the controller in this paper (3.15) uses real-time information from the leader.*

Remark 6. *It is worth noting that fully asynchronous event-triggered control refers to each agent sampling only at its own triggering instants. This control strategy can further reduce computational resource consumption and improve system energy efficiency compared twith traditional event-triggered control strategies, especially in energy-constrained environments.*

Theorem 3. *Based on Assumption 1, if the following two conditions are satisfied*

$$\lambda_{\max}\{2A + c_1 E_1 E_1^T\} + 2\bar{k}\|L + \Gamma\|(1 + c_2 \bar{k}\|L + \Gamma\|) < 0 \tag{3.22}$$

and

$$\lambda_{\max}\{H_i U_i + U_i^T H_i\} + 2d\lambda_{\max}\{H_i^T H_i\} + \max\{\frac{1}{c_1}, \frac{1}{c_2}\} < 0, \tag{3.23}$$

then the MAS (3.1) and (3.2) can achieve consensus under the action of controller (3.15) and event-triggering mechanism (3.16).

Proof. First, construct the function:

$$\hat{V}_1(t) = e^T(t)e(t) + \Sigma_{i=1}^N \eta_i(t) + \Sigma_{i=1}^N V_i(t), \tag{3.24}$$

where $i = 1, 2, \cdots, N$. Then, calculating $\dot{\hat{V}}_1(t)$ and substituting the trajectories of (3.18) into $\dot{\hat{V}}_1(t)$ when

$t \in [t^i_{k_i}, t^i_{k_i+1})$,

$$
\begin{aligned}
\dot{\hat{V}}_1(t) =& 2e^T(t)\dot{e}(t) + \sum_{i=1}^{N} \dot{\eta}_i(t) + \sum_{i=1}^{N} \dot{V}_i(t) \\
=& 2e^T(t)[(I_N \otimes A)e(t) + (I_N \otimes E_1)\tilde{\delta}(t) + (K(t)(L+\Gamma) \otimes I_n)(\tilde{x}(t) - e(t) + \varepsilon(t))] \\
&+ \sum_{i=1}^{N}(-\xi_i\eta_i(t) + r_1\varepsilon_i^T(t)\varepsilon_i(t) + r_2 e^{-\alpha t}) + \sum_{i=1}^{N} \dot{V}_i(t) \\
\leq& e^T(t)[I_N \otimes (2A + c_1E_1E_1^T)]e(t) + \frac{1}{c_1}\tilde{\delta}^T(t)\tilde{\delta}(t) + 2e^T(t)(K(t)(L+\Gamma) \otimes I_n) \\
&(\tilde{x}(t) - e(t) + \varepsilon(t)) + \sum_{i=1}^{N} \dot{V}_i(t) + \sum_{i=1}^{N}(-\xi_i\eta_i(t) + r_1\varepsilon_i^T(t)\varepsilon_i(t) + r_2 e^{-\alpha t}) \\
\leq& e^T(t)[I_N \otimes (2A + c_1E_1E_1^T) - 2(K(t)(L+\Gamma) \otimes I_n) + 2c_2(K(t)(L+\Gamma)^2K(t)) \otimes I_n]e(t) \\
&+ \frac{1}{c_1}\tilde{\delta}^T(t)\tilde{\delta}(t) + \frac{1}{c_2}\tilde{x}^T(t)\tilde{x}(t) + \sum_{i=1}^{N}(-\xi_i\eta_i(t) + (r_1 + \frac{1}{c_2})\varepsilon_i^T(t)\varepsilon_i(t) + r_2 e^{-\alpha t}) \\
&+ \sum_{i=1}^{N} \dot{V}_i(t).
\end{aligned} \tag{3.25}
$$

Combining the event-triggered mechanism (3.16), one can obtain

$$
\begin{aligned}
&-\xi_i\eta_i(t) + (r_1 + \frac{1}{c_2})\varepsilon_i^T(t)\varepsilon_i(t) + r_2 e^{-\alpha t} \\
\leq& (r_1 + \frac{1}{c_2} - r_4)\varepsilon_i^T(t)\varepsilon_i(t) + (r_2 - r_3)e^{-\alpha t} \\
\leq& (r_2 - r_3)e^{-\alpha t}.
\end{aligned} \tag{3.26}
$$

Substituting (3.26) into (3.25) yields

$$
\begin{aligned}
\dot{\hat{V}}_1(t) \leq& e^T(t)[I_N \otimes (2A + c_1E_1E_1^T) - 2(K(t)(L+\Gamma) \otimes I_n) + 2c_2(K(t)(L+\Gamma)^2K(t)) \otimes I_n]e(t) \\
&+ \frac{1}{c_1}\tilde{\delta}^T(t)\tilde{\delta}(t) + \frac{1}{c_2}\tilde{x}^T(t)\tilde{x}(t) + \sum_{i=1}^{N} \dot{V}_i(t) \\
\leq& e^T(t)[\lambda_{\max}\{2A + c_1E_1E_1^T\}2\bar{k}\|L+\Gamma\|(1 + c_2\bar{k}\|L+\Gamma\|)]e(t) + (r_2 - r_3)e^{-\alpha t} \\
&+ \frac{1}{c_1}\tilde{\delta}^T(t)\tilde{\delta}(t) + \frac{1}{c_2}\tilde{x}^T(t)\tilde{x}(t) + \sum_{i=1}^{N}(\tilde{z}_i^T(t)(H_iU_i + U_i^TH_i + 2d\lambda_{\max}\{H_i^TH_i\})\tilde{z}_i(t)) \\
<& (r_2 - r_3)e^{-\alpha t}.
\end{aligned} \tag{3.27}
$$

Thereby, it follows from (3.27) that

$$
\begin{cases}
\hat{V}_1(+\infty) \geq 0, \\
\hat{V}_1(+\infty) \leq \hat{V}_1(0) + \frac{r_2 - r_3}{\alpha}.
\end{cases} \tag{3.28}
$$

Finally, we conclude that the MAS (3.1) and (3.2) can achieve quasi-consensus under the action of the controller (3.15). □

3.4. Exclusion of zeno behavior

Theorem 4. *The MAS (3.1) and (3.2) will not exhibit Zeno behavior under the action of controller (3.15) and event-triggering mechanism (3.16).*

Proof. According to the measuring error $\varepsilon_i(t) = \hat{x}_i(t) - \hat{x}_i(t^i_{k_i})$, where $t \in [t^i_{k_i}, t^i_{k_i+1})$, one can obtain:

$$\begin{aligned} D^+\|\varepsilon_i(t)\| \leq &\|\dot{\varepsilon}_i(t)\| = \|\dot{\hat{x}}_i(t)\| \\ =&\|A\hat{x}_i(t) + k_i(t)(-\Sigma_{j=1}^N l_{ij}\hat{x}_j(x^j_{k_j}) + \gamma_i(x_0(t) - \hat{x}_i(t^i_{k_i}))) \\ &+ E_1\hat{\delta}_i(t) + G_{i1}(y_i(t) - \hat{y}_i(t))\| \\ \leq&\|A(x_i(t) - \tilde{x}_i(t)) + E_1(\delta_i(t) - \tilde{\delta}_i(t)) + G_{i1}(C\tilde{x}_i(t) + E_2\tilde{\delta}_i(t))\| \\ &+ \|k_i(t)(-\Sigma_{j=1}^N l_{ij}\hat{x}_j(t^j_{k_j}) + \gamma_i(x_0(t) - \hat{x}_i(t^i_{k_i})))\| \\ =&\Lambda_i(t) + \bar{k}\iota, \end{aligned} \tag{3.29}$$

where $i = 1, 2, \cdots, N$. Then, let $\| - \Sigma_{j=1}^N l_{ij}\hat{x}_j(t^j_{k_j}) + \gamma_i(x_0(t) - \hat{x}_i(t^i_{k_i}))\| = \iota$ and $\Lambda_i(t) = \|A(x_i(t) - \tilde{x}_i(t)) + E_1(\delta_i(t) - \tilde{\delta}_i(t)) + G_{i1}(C\tilde{x}_i(t) + E_2\tilde{\delta}_i(t))\|$. Moreover, Theorem 1 and Theorem 2 have proved that $x_i(t)$, $\delta_i(t)$, $\tilde{x}_i(t)$, and $\tilde{\delta}_i(t)$ are bounded vectors, so one can conclude that there exists $\Lambda > 0$ such that $\Lambda_i(t) \leq \Lambda$. Ultimately, one can rewrite (3.29) as follows:

$$\|\varepsilon_i(t)\|' \leq \Lambda + \bar{k}\iota. \tag{3.30}$$

Integrating (3.30) from t to $t^i_{k_i}$, we get

$$\|\varepsilon_i(t)\| \leq (\Lambda + \bar{k}\iota)(t - t^i_{k_i}). \tag{3.31}$$

Therefore, letting $t = t^i_{k_i+1}$ in (3.31), we get

$$\|\varepsilon_i(t^i_{k_i+1})\| \leq (\Lambda + \bar{k}\iota)\|t^i_{k_i+1} - t^i_{k_i}\|. \tag{3.32}$$

At the same time, combining the event-triggered mechanism (3.16), one can conclude

$$\begin{aligned} &\frac{1}{r_4}[\xi_i\eta_i(t^i_{k_i+1}) - r_3e^{-\alpha t^i_{k_i+1}}] \\ \leq&\varepsilon_i^T(t^i_{k_i+1})\varepsilon_i(t^i_{k_i+1}) \\ \leq&[(\Lambda + \bar{k}\iota)\|t^i_{k_i+1} - t^i_{k_i}\|]^2. \end{aligned} \tag{3.33}$$

If Zeno exists, $t^i_{k_i+1} - t^i_{k_i} = 0$ in (3.33), then the resulting $\frac{1}{r_4}[\xi_i\eta_i(t^i_{k_i+1}) - r_3e^{-\alpha t^i_{k_i+1}}] \leq 0$ contradicts $\xi_i > 0$, $r_3 < 0$, and $r_4 > 0$ in the event-triggered mechanism (3.16). Therefore, the behavior of Zeno can be excluded. □

Remark 7. *The proposed dynamic event-triggered controller (3.15) together with the adaptive mechanism (3.16) is designed as a direct solution to the robustness-resource efficiency trade-off highlighted in the introduction. Its core innovation lies in the co-design integration of an adaptive disturbance observer and a dynamic event-triggered mechanism within a unified framework, which* *enables simultaneous disturbance compensation and resource-aware control. The triggering condition is governed by the internal dynamic variable $\eta_i(t)$ that evolves online, allowing the update strategy to adapt dynamically in response to the real-time consensus error $e_i(t)$. This offers superior flexibility and efficiency compared to static triggering schemes. Furthermore, the design provides practical guarantees by analytically excluding Zeno behavior and ensuring the boundedness of the time-varying coupling gains $k_i(t)$. These features collectively prevent unrealistic infinite triggering and actuator saturation, thereby enhancing the practical feasibility of the proposed control strategy.*

4. Numerical simulation

This section presents numerical simulations of the control strategy design and theoretical analysis presented in Section 3, thereby demonstrating the validity of the control strategy design and theoretical results.

Consider a MAS with four nodes, where 1, 2, 3, 4, and 5 represent five follower nodes and node 0 represents the leader node. The leader node is pinned to the first follower node, the third follower node, and the forth follower node, so the Laplacian matrix of the system is $L = \begin{bmatrix} 1 & 0 & -1 & 0 & 0 \\ 0 & 2 & -1 & 0 & -1 \\ -1 & -1 & 2 & 0 & 0 \\ 0 & 0 & 0 & 1 & -1 \\ 0 & -1 & 0 & -1 & 2 \end{bmatrix}$ and the corresponding undirected topological graph is shown in Figure 1. Each node's state and disturbance are assumed to be one-dimensional. The initial states $x_i(0)$ of all nodes in the system and the initial disturbance states $\delta_i(0)$ are selected as random numbers between -2 and 2, where $i = 0, 1, \cdots, 5$. The coefficient matrices in systems (3.1) and (3.2) are chosen as $A = -12, E_1 = 1.17, E_2 = 14.2628$, and $C = -8.9142$ according to the theorem conditions.

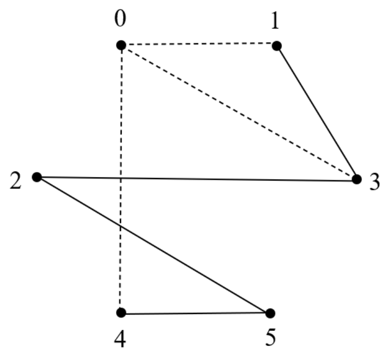

Figure 1. Undirected network topology of multi-agent system with disturbance.

To satisfy the conditions of Theorem 1, the coefficients $G_{11} = 1.2191, G_{12} = 1.1819, D_1 = 0.803, P_1 = 0.5609; G_{21} = 0.0269, G_{22} = 1.1721, D_2 = 0.912, P_2 = 0.0897; G_{31} = 0.0172, G_{32} = 0.7539, D_3 = 0.7943, P_3 = 0.2531; G_{41} = 0.5123, G_{42} = 0.6348, D_4 = 0.7215, P_4 = 0.3726; G_{51} = 0.4087, G_{52} = 0.8924, D_5 = 0.8562, P_5 = 0.2149$ are selected for observers (3.4) and (3.5). Figures 2 and 3 illustrate the observation error trajectories for the node states and disturbance states, respectively. Figure 4 shows the trajectory of the values $\hat{D}_i(t)$ in the adaptive disturbance observer (3.5).

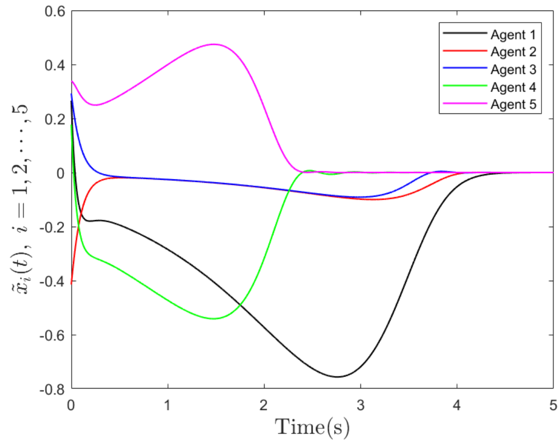

Figure 2. Trajectory of observation errors of node states.

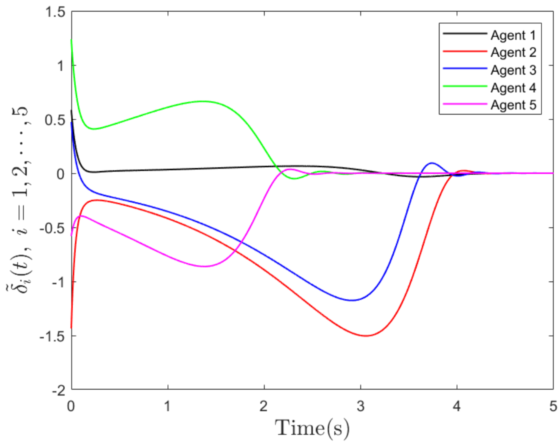

Figure 3. Trajectory of observation errors of disturbance.

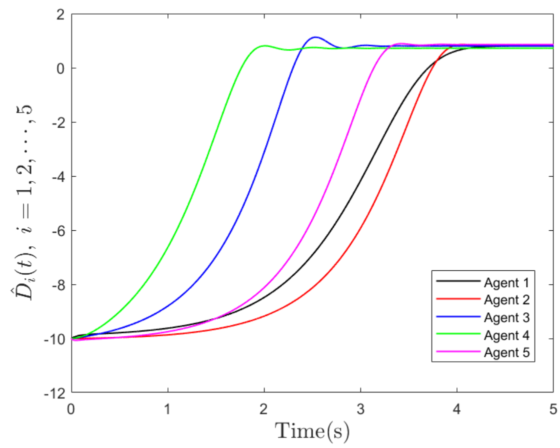

Figure 4. Trajectory of value $\hat{D}_i(t)$ in adaptive observer (3.5).

As illustrated in Figures 2 and 3, the observation error ultimately converges to zero, indicating the effectiveness of the observers.

In the dynamic event-triggered controller (3.15), the coefficients $\gamma_2 = \gamma_5 = 0, \gamma_1 = \gamma_3 = \gamma_4 = 1$ are selected, and the coupling strengths are set as $k_1(t) = k_2(t) = \frac{\sin t}{2}$ and $k_3(t) = k_4(t) = k_5(t) = \frac{\cos t}{4}$. In addition, the coefficients in the dynamic event-triggered controller (3.16) and the dynamic change rate (3.17) are set to $\xi_1 = \xi_2 = \xi_3 = \xi_4 = \xi_5 = 2, r_1 = -1, r_2 = 0.6, r_3 = -0.5$, and $r_4 = 1$ to satisfy the conditions of Theorem 3. The simulation results are shown in Figures 5–7. Among them, Figure 5 is the trajectory graph of the consensus error, and Figures 6 and 7 are the trajectory graphs of the event-triggered controller values $\eta_i(t)$ and the event-triggered instants graph of the MAS under the event-triggered strategy (3.16), respectively. From Figure 5, it can be seen that the consensus error ultimately converges to zero.

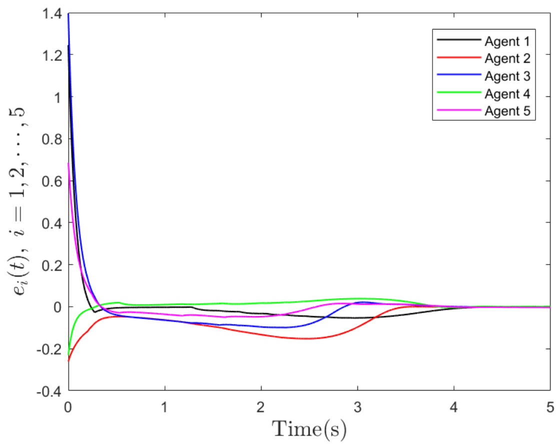

Figure 5. The consensus error trajectory of the MAS (3.1) and (3.2).

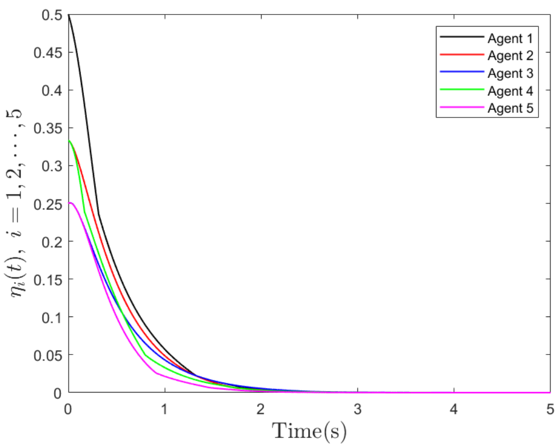

Figure 6. Trajectory of event-triggered controller values $\eta_i(t)$.

Remark 8. *The simulation results presented in Figures 2–8 are produced from nondimensional numerical experiments intended to illustrate algorithmic behaviour rather than measurements obtained from a physical platform. Consequently, the horizontal axes denote nondimensional* *simulation time and the plotted state values are normalized numerical quantities.*

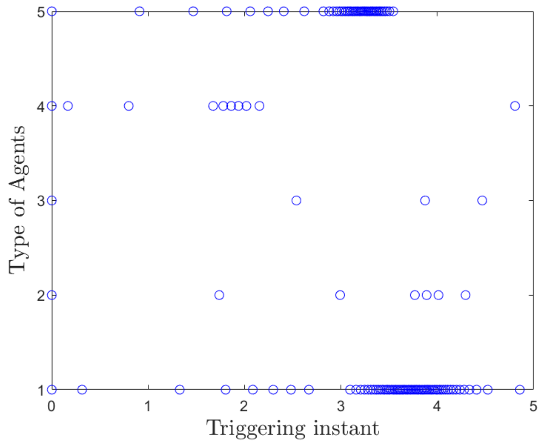

Figure 7. Event-triggered instants graph under strategy (3.16) of the MAS (3.1) and (3.2).

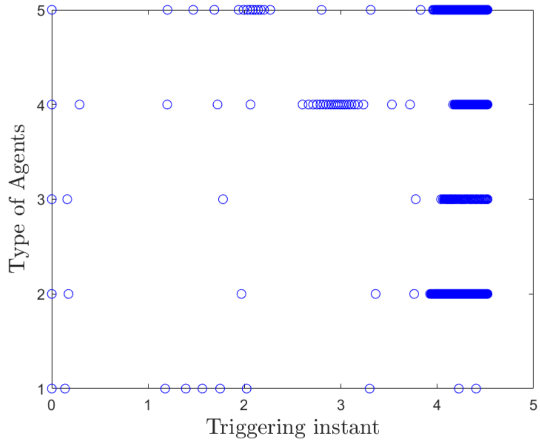

Figure 8. Event-triggered instants graph under static event-triggered control with fixed threshold 3.5.

Remark 9. *The numerical examples focus on validating the disturbance observer, the adaptive estimation law, and the dynamic event-triggered controller under the linear noise assumptions stated earlier. Full implementation and comparison with nonlinear non-Gaussian methods, such as Gaussian mixture unscented smoothing or particle filtering, would require replacing the observer with a Gaussian mixture model(GMM)-based smoother or a particle filter and designing comparable evaluation metrics for estimator bias, variance, and computational cost. This will be carried out as part of a dedicated follow up study.*

Remark 10. *The proposed framework finds a natural application in cooperative multi-robot systems, such as a team of robots transporting an object over uneven terrain. In this scenario, each robot (agent) is subject to unknown time-varying disturbance due to ground irregularities and wheel* *slippage. The adaptive disturbance observer enables each robot to simultaneously estimate its own motion state and the external disturbance in real time, using only local sensor measurements. The dynamic event-triggered controller, governed by the internal variable $\eta_i(t)$, then determines when to broadcast state information and update the control signal. This mechanism allows the system to significantly reduce communication and computation during steady or mildly disturbed operations, while ensuring prompt updates when disturbance or consensus errors grow. Consequently, the robotic team achieves consensus on a common trajectory, accomplishing the cooperative task with enhanced energy efficiency and robustness against terrain-induced uncertainties. This example illustrates how the integrated observer-controller-trigger design maps onto real-world systems operating under practical constraints of limited resources and environmental disturbance.*

Figure 8 shows the agentwise triggering time sequences for the static event-triggered baseline and for the proposed dynamic event-triggered law. The static baseline implements fixed threshold conditions and produces a markedly larger number of triggers across agents. This elevated trigger frequency implies higher communication and computational load and reflects the inherent inflexibility of a static threshold approach, which cannot modulate sensitivity in response to changing estimation errors or disturbance statistics. The dynamic event-triggered law, on the other hand, adapts its triggering condition through time-varying gains and adaptive terms, which reduces redundant transmissions while maintaining comparable convergence and disturbance rejection. The figure therefore illustrates that the static trigger is simple but less flexible and less communication efficient than the dynamic scheme used in this work.

5. Conclusions

In this paper, the consensus problem of MAS with disturbance has been studied. An adaptive observer has been designed to simultaneously estimate the states of the system and the disturbance present in the MAS (3.1) and (3.2). This observer ensures accurate tracking of node states and disturbance, thereby enhancing the system's robustness against uncertainties. Additionally, regarding the system consensus problem, a dynamic event-triggered strategy has been proposed. By enabling real-time state monitoring and adaptive triggering, dynamic event-triggered strategies handle parameter changes and external disturbance more effectively than static strategies and are thus preferable for the MAS subject to disturbance. Unlike some existing adaptive control strategies where coupling strengths may grow unboundedly, the proposed controller ensures bounded adaptive gains, thus avoiding overly conservative control efforts and enhancing practical applicability. Finally, the effectiveness of the theoretical results has been demonstrated through numerical simulation. In future work, the current framework could be extended to the MAS with directed switching topologies or time-delayed communications, which are more reflective of real-world networked systems. Experimental validation on physical platforms, such as robotic networks, smart grids, or autonomous vehicle platoons, would be be a valuable step toward translating theoretical contributions into practical applications. Furthermore, robust state estimation in complex environments may require methods that explicitly address non-Gaussian and strongly nonlinear uncertainty. Candidate approaches include Gaussian mixture unscented Rauch-Tung-Striebel smoothing for multimodal noise [27], filtering frameworks built on Gaussian noise model jump assumptions for intermittent [28] or jump-type measurement noise, particle filters for highly nonlinear dynamics, and recent score based estimators. These approaches can improve robustness to heavy-tailed or multimodal disturbance but impose greater computational and theoretical challenges. As follow-up work we plan to integrate selected GMM and jump-noise filters with our disturbance observer, to test the combined schemes on unstable and oscillatory plant matrices, and to report quantitative comparisons of estimation accuracy, disturbance rejection performance, and computation cost.

Use of AI tools declaration

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

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Conflict of interest

The authors declare there is no conflict of interest.

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