Observer-Based Event-Triggered Composite Anti-Disturbance Control for Multi-Agent Systems Under Multiple Disturbances and Stochastic FDIAs

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***Abstract*—This article aims to investigate the security consensus and composite anti-disturbance problems for a class of nonlinear multi-agent systems subjected to stochastic false data injection attacks (FDIAs) and multiple disturbances under a directed communication topology. To attenuate and reject of the negative effects of two types of disturbances, a disturbance observer (DO) is designed to counteract the disturbance produced by exogenous system, and the $\mathcal{H}_\infty$ control method is adopted to attenuate the bounded errors and variables caused by the other type of disturbances and FDIAs simultaneously. To ensure the consensus performance of MASs, an observer-based control strategy is designed, and a novel adaptive compensation technique is proposed to not only evaluate the upper bounds of the unknown but bounded disturbances but also improve the accuracy of the state observer. Furthermore, a novel event-triggered mechanism (ETM) without requiring continuous communication among neighboring agents is developed to reduce the controller update frequency and the communication burden. Meanwhile, Zeno behavior is excluded. Finally, numerical simulations are provided to verify the availability of the designed method.**

***Note to Practitioners*—In multi-agent systems, network security is very important. For example, in smart power grid systems, it is necessary to use the method of state estimation to observe the system to guarantee its safe operation. However, the measured value of the instrument may be affected by FDIAs in the transmission process, thus changing the result of state estimation and causing misjudgment of the system. Similarly, in multi-vehicle systems, FDIAs may destroy the location information of vehicles and cause serious accidents. In addition, the system will be subjected to different types of disturbances in practice, thus reducing the performance of the system. In view of the threat of FDIAs and disturbances to the MAS, a composite anti-disturbance method and an observer-based control strategy are proposed. Meanwhile, to avoid the limitation of communication bandwidth in reality, a novel ETM is developed to save network resources.**

***Index Terms*—Multi-agent systems (MASs), composite anti-disturbance technique, event-triggered control, multiple disturbances, false data injection attacks (FDIAs).**

I. Introduction

Nowadays, multi-agent systems (MASs) have become a research hotspot in the control field because of their strong flexibility, robustness, and reliability, and have been widely used in vehicle coordination, aircraft formation, sensor networks, and so on [1]–[3]. As we all know, reaching consensus among MASs is a prerequisite for them to perform complex tasks. Whereas, in practical applications, MASs will inevitably be affected by disturbances, such as wind, measurement noise, temperature changes, structural vibration, model errors, and so on [4]. Therefore, how to attenuate and reject the disturbances to improve the consensus performance of MASs is a significant research problem.

In recent years, the anti-disturbance control of MASs have been extensively investigated in [5]–[10]. Specifically,

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in [5]–[7], aiming at the disturbance produced by the exogenous system, a disturbance observer (DO) is developed to evaluate the disturbance, and then the estimated value is introduced into the controller to reject the disturbance. For a class of impulsive disturbance or unknown disturbance with no obvious regularity, an $\mathcal{H}_\infty$ control method is developed in [8], [9], which ensures that the MAS can meet the pre-set performance index under the disturbance with finite energy. In [10], an anti-disturbance method based on the upper bound of disturbance is proposed to improve the performance of MASs. However, it is noteworthy that the above results only take into account a single type of disturbance. In fact, MASs are often faced with different types of disturbances, which will lead to the above methods being ineffective in handling the disturbances according to the characteristics of the disturbances, and may even fail and result in the decline of system control accuracy or even instability. For systems with various sources of disturbances, composite hierarchical anti-disturbance control is an effective method [11], and this method has also been used in Markovian jump system, spacecraft control, and so on [12], [13]. However, as far as we know, there are few results reporting the consensus control problem of MASs under multiple disturbances, which inspired us to solve this nontrivial control problem. In addition, due to the complex working environment, MASs are often faced with the threat of cyber attacks, which mainly include denial-of-service (DoS) attacks, replay attacks, false data injection attacks (FDIAs), etc. [14]–[17]. Among these attacks, FDIAs destroy the information by tampering with transmitted data, which has strong concealment [18], [19]. Unfortunately, although the above attacks are highly destructive, most of the existing multi-agent anti-disturbance methods are restricted to the case of secure network [10], [20]. Thus, to better reflect the reality, it is very attractive for us to design a security consensus control strategy that can resist disturbance when MASs are subjected to multiple disturbances and FDIAs.

On the other hand, with the expansion of the scale of MASs, how to reduce the waste of resources has become an urgent problem [21], [22]. To mitigate the consumption of bandwidth and maintain the performance of the system, event-triggered control has been applied to the anti-disturbance control for MASs (see [6], [7], [23]–[27]). To be specific, in [6] and [7], an event-triggered mechanism (ETM) is proposed that does not require continuous communication between neighbor agents to update the triggering condition and thus reduces the communication burden. However, it should be pointed out that the controller needs to continuously obtain the information of the DO, which may lead to unnecessary waste of resources. In [23], a self-triggering algorithm is designed to avoid the continuous monitoring of the triggering condition, while the controller is still continuously updated. [24] and [25] introduce a scheme with the merit that the controller is only updated at the trigger time, but the drawback is that the ETM requires the agent to continuously obtain the neighbor's state, so it cannot effectively reduce the communication load. While some of the results take into account both the reduction of controller updates and the continuous monitoring of the state of the neighbor agents [26], we notice that they are mainly designed based on undirected graphs or assume that the system state is measurable [27]. Indeed, in comparison to undirected graphs, the research of MASs under the directed graphs is more challenging due to the asymmetry of the Laplacian matrix. Furthermore, in some cases, it is difficult or even impossible to obtain the state information of the system [28], [29], and the above-mentioned results will no longer apply. Therefore, how to develop an observer-based event-triggered consensus protocol under a directed graph that requires neither continuous monitoring of the neighbor's information nor constant updating of the controller is another motivation of this paper.

Considering the aforementioned discussions, in this paper, via the event-triggered control, the security consensus and composite anti-disturbance problems are investigated for nonlinear MASs subjected to multiple disturbances and stochastic FDIAs. The difficulties faced in this study are how to design a control strategy to ensure the consensus of the MASs under multiple disturbances and stochastic FDIAs, and how to construct a novel ETM to save communication resources. The main contributions are summarized in the following aspects:

1) A *composite anti-disturbance method* based on disturbance observer and $\mathcal{H}_\infty$ control: In contrast to the secure network environment and single disturbance, FDIAs and multiple disturbances are considered but excluded in [8] and [9]. To attenuate and reject the negative effects of two types of disturbances, a DO is designed to counteract the disturbance produced by exogenous system, and the $\mathcal{H}_\infty$ control method is applied to attenuate bounded disturbance. In addition, rather than just obtaining a uniformly ultimately bounded (UUB) consensus errors as in [30], the $\mathcal{H}_\infty$ control method can also attenuate the bounded errors and variables caused by disturbances and FDIAs to improve the system performance.
2) An output feedback control strategy based on state observer: Different from [20] and [27] which require the state to be measurable, an observer is constructed to estimate the real state of the system. In the meanwhile, the introduction of DO and *adaptive disturbance compensation technique* based on *the estimated value of disturbance upper bound* greatly improve the accuracy of the observer and the consensus performance of the MASs under multiple disturbances, and has no requirements of the preliminary knowledge of the upper bounds on the bounded disturbance signals in [10], [31] and the boundedness assumption of their derivatives as in [32], [33].
3) A novel event-triggered mechanism: Compared with the results which only avoid the continuous communication of the controller [6], [7], [23] or the continuous monitoring of the triggering condition [24], [25], the proposed ETM does not require to transmit information with neighbors all the time and ensures the intermittent communication of the controller, and thus saves network resources and reduces the frequent operation of the physical institutions. Besides, Zeno behavior is ruled out.

Notations: Let $\mathbb{R}^n$ and $\mathbb{R}^{m\times n}$ represent the set of all n-dimensional real column vectors and $m \times n$-order real

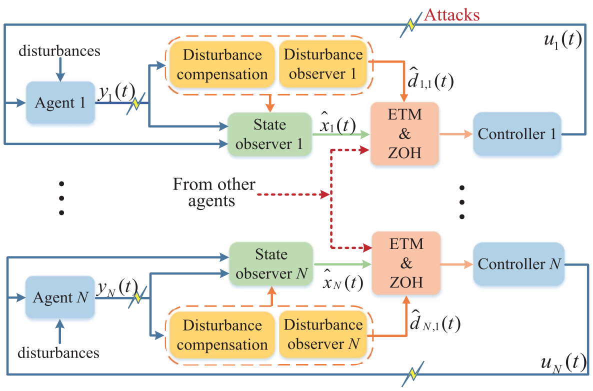


Fig. 1. Framework of MASs under disturbance and FDIAs.

matrices, respectively; matrix I_N is an N-order identity matrix and vector 1_N denotes an N-dimensional column vector with all elements being 1. col$\{\cdot\}$ denotes a column vector and diag$\{\cdot\}$ represents a diagonal matrix. Given a matrix M, $M > 0$ means that M is symmetric and positive definite, and the largest (or smallest) eigenvalue can be denoted by $\lambda_{\max}(\cdot)$(or $\lambda_{\min}(\cdot)$); M^T stands for the transpose of M, and $\text{He}(M) = M + M^T$. Define the expectation operator as $\mathbb{E}\{\cdot\}$ and the infinitesimal operator $\Im$ of the function $V(t)$ is $\Im V(t) = \lim_{\Delta t \to 0^+} \frac{1}{\Delta t}\{\mathbb{E}\{V(t+\Delta t)|t\} - V(t)\}$. The Kronecker product and the Euclidean norm are represented by $\otimes$ and $\|\cdot\|$, respectively.

II. Problem Statement and Preliminaries

The framework of MASs considered in this paper is shown in Fig. 1. When the control signal $u_i(t)$ and output signal $y_i(t)$ of the agent are transmitted, they may be subject to FDIAs, which will reduce the accuracy of the data. In addition, if disturbances occur, the composite anti-disturbance control strategy will ensure the performance of the MASs.

A. Graph Theory

The interaction between N followers can be described by a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$, where $\mathcal{V} = \{1, \cdots, N\}$ is the node set, $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ denotes the set of edges, and $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{N\times N}$ is the adjacency matrix and its element a_{ij} represents the information transmission among agents, i.e., if agent i can communicate with agent j through the edge $\mathcal{E}_{ji}$, then $a_{ij} = 1$; else $a_{ij} = 0$. Assume that $a_{ii} = 0$, $\forall i \in \mathcal{V}$. Define $\mathcal{N}_i = \{j \in \mathcal{V} | \mathcal{E}_{ji} \in \mathcal{E}\}$ as the set of all neighbors of node i, and $\tilde{\mathcal{N}}$ represents the maximum cardinality of the set $\mathcal{N}_i$. Let $\mathcal{D} = \text{diag}\{d_1, \ldots, d_N\}$ be the degree matrix, where $d_i = \sum_{j\in\mathcal{N}_i} a_{ij}$. Then, the Laplacian matrix of graph $\mathcal{G}$ is defined as $\mathcal{L} = \mathcal{D} - \mathcal{A}$. If a leader $\mathcal{V}_0$ is considered, the Laplacian matrix of the new graph $\bar{\mathcal{G}}$ can be written as $\bar{\mathcal{L}} = \begin{bmatrix} 0 & 0_{1\times N} \\ \mathcal{L}_2 & \mathcal{L}_1 \end{bmatrix}$ with $\mathcal{L}_1 = \mathcal{L} + \mathcal{A}_0$, and $\mathcal{A}_0 = \text{diag}\{a_{10}, \ldots, a_{N0}\}$, where $a_{i0} = 1$ if the follower i can get information from the leader directly and $a_{i0} = 0$ otherwise. Besides, the matrix $\mathcal{L}_2$ is expressed as $\mathcal{L}_2 = -\text{col}\{a_{10}, \ldots, a_{N0}\}$.

B. System Model

Considering a nonlinear MAS consisting of a leader and N followers under a directed graph, the dynamics of the ith follower is given by

$$\begin{cases} \dot{x}_i(t) = & Ax_i(t) + B[u_i(t) + d_{i,1}(t)] + Dd_{i,2}(t) + \phi(x_i(t)), \\ y_i(t) = & Cx_i(t), \ i = 1, \cdots, N, \end{cases} \tag{1}$$

where $x_i(t) \in \mathbb{R}^n$ is the state vector; $u_i(t) \in \mathbb{R}^m$ is the control input signal; $y_i(t) \in \mathbb{R}^p$ is the measured output. A, B, C, and D are known system matrices. $\phi(x_i(t)) \in \mathbb{R}^n$ represents a nonlinear term. Suppose that the matrix pair (A, B, C) is stabilizable and detectable. Besides, two kinds of disturbances $d_{i,1}(t)$ and $d_{i,2}(t)$ are included in (1), where $d_{i,2}(t)$ denote a class of arbitrary bounded but unknown disturbances without a definite model, i.e., $\|d_{i,2}(t)\| \le \bar{d}_{i,2}$, while $d_{i,1}(t) \in \mathbb{R}^m$ represent a class of disturbances with a definite model generated by the following nonlinear exogenous system:

$$\begin{cases} \dot{w}_i(t) = & Ww_i(t) + Ff(w_i(t)), \\ d_{i,1}(t) = & Vw_i(t), \end{cases} \tag{2}$$

where $w_i(t) \in \mathbb{R}^q$ is the state vector of the nonlinear exogenous system; $f(w_i(t))$ is a continuous unknown nonlinear function; W, F, V are known constant matrices, and the pair (W, BV) is assumed to be observable [4].

The leader has the following dynamics:

$$\begin{cases} \dot{x}_0(t) = Ax_0(t) + \phi(x_0(t)), \\ y_0(t) = Cx_0(t), \end{cases} \tag{3}$$

where $x_0(t) \in \mathbb{R}^n$, $y_0(t) \in \mathbb{R}^p$ and $\phi(x_0(t))$ are the state, output, and nonlinear term of the leader, respectively.

Assumption 1 [34]: There is a directed spanning tree with the leader as the root node in graph $\bar{\mathcal{G}}$. $i = 1, 2, \cdots, N$.

Assumption 2: For all vectors $x_1(t)$, $x_2(t) \in \mathbb{R}^n$ and $w_1(t)$, $w_2(t) \in \mathbb{R}^q$, the nonlinear functions $\phi(x_i(t))$ and $f(w_i(t))$ are, respectively, satisfied

$$\begin{aligned} \|\phi(x_2(t)) - \phi(x_1(t))\| &\le \|\Lambda_1(x_2(t) - x_1(t))\|, \\ \|f(w_2(t)) - f(w_1(t))\| &\le \|\Lambda_2(w_2(t) - w_1(t))\|, \end{aligned}$$

where Λ_1 and Λ_2 are symmetric positive definite matrices.

Lemma 1 [34]: When Assumption 1 holds, there exists a matrix $\Theta = \text{diag}\{\theta_1, \cdots, \theta_N\} > 0$, whose element θ_i satisfies $[\theta_1, \cdots, \theta_N]^T = (\mathcal{L}_1^T)^{-1} 1_N$, such that $\tilde{\mathcal{L}} = \Theta\mathcal{L}_1 + \mathcal{L}_1^T\Theta \ge \lambda_0 I_N > 0$, and $\lambda_0 = \lambda_{\min}(\tilde{\mathcal{L}})$. Furthermore, as Θ is a diagonal matrix, its maximum and minimum eigenvalues can be represented by $\theta_{\max} = \max\{\theta_i\}$ and $\theta_{\min} = \min\{\theta_i\}$.

Lemma 2 [35]: Given $x \in \mathbb{R}^{l_1}$, $y \in \mathbb{R}^{l_2}$ and matrix $M_1 \in \mathbb{R}^{l_1\times l_2}$, for any constant $\beta > 0$ and matrix $M_2 \in \mathbb{R}^{l_2\times l_2} > 0$, it holds that

$$2x^T M_1 y \le \beta x^T M_1 M_2 M_1^T x + \beta^{-1} y^T M_2^{-1} y.$$

Remark 1: Without loss of generality, the disturbance model (2) can represent many disturbances in practice. For example, if $F \neq 0$, it can represent a class of non-harmonic disturbance generated by a nonlinear exogenous system; if $F = 0$ and $W = 0$, it can denote unknown constant *disturbance. In addition, when $F = 0$ and W is selected as $\begin{bmatrix} 0 & w_0 \\ -w_0 & 0 \end{bmatrix}$ with $w_0 > 0$, it can represent a kind of harmonic disturbance whose phase and amplitude are unknown, and the frequency is known or unknown depending on whether the harmonic frequency w_0 is known or not [4], [36].*

C. False Data Injection Attack (FDIA) Model

Due to the complex network structure and high dependence on the network in MASs, they are more vulnerable to FDIAs. In this paper, it is assumed that the attack signals occur in the follower's controller-actuator channel and sensor-controller channel, as shown in Fig. 1. Then, taking into account the randomness of the FDIAs, the actual control signal $\tilde{u}_i(t)$ received by the actuator is

$$\tilde{u}_i(t) = u_i(t) + \Gamma_i^u(t)\nu_i^u(t),$$

where $\nu_i^u(t)$ is the attack signal injected into the controller channel, the random variable $\Gamma_i^u(t)$ which obeys the Bernoulli distribution is the attacker's decision variable, and the probabilities of $\Gamma_i^u(t)$ are

$$\text{Prob}\{\Gamma_i^u(t) = 1\} = \chi_i^u, \quad \text{Prob}\{\Gamma_i^u(t) = 0\} = 1 - \chi_i^u,$$

with $\chi_i^u \in [0, 1)$ being a constant.

Similarly, the actual output signal $\tilde{y}_i(t)$ can be written as

$$\tilde{y}_i(t) = y_i(t) + \Gamma_i^y(t)\nu_i^y(t),$$

where $\nu_i^y(t)$ is the attack signal injected into the sensor channel, and the probabilities of random decision variable $\Gamma_i^y(t)$ are:

$$\text{Prob}\{\Gamma_i^y(t) = 1\} = \chi_i^y, \quad \text{Prob}\{\Gamma_i^y(t) = 0\} = 1 - \chi_i^y,$$

with $\chi_i^y \in [0, 1)$ being a constant.

Assumption 3: Define $\nu^u(t) = \text{col}\{\nu_1^u(t), \cdots, \nu_N^u(t)\}$, $\nu^y(t) = \text{col}\{\nu_1^y(t), \cdots, \nu_N^y(t)\}$, and consensus error $\delta_i(t) = x_i(t) - x_0(t)$, then

1) The attack signal $\nu^u(t)$ satisfies $\|\nu^u(t)\|^2 \le \kappa\|\delta(t)\|^2$, where $\delta(t) = \text{col}\{\delta_1(t), \cdots, \delta_N(t)\}$ and $\kappa > 0$.

2) The attack signal $\nu^y(t)$ is bounded, i.e., $\|\nu^y(t)\| \le \bar{\nu}$, where $\bar{\nu} > 0$.

Therefore, under the action of FDIAs, the model of MAS (1) can be represented as

$$\begin{cases} \dot{x}_i(t) = Ax_i(t) + B[\tilde{u}_i(t) + d_{i,1}(t)] + Dd_{i,2}(t) + \phi(x_i(t)), \\ y_i(t) = Cx_i(t), \ i = 1, \cdots, N. \end{cases} \tag{4}$$

Remark 2: In this paper, we consider the FDIAs that simultaneously attack the sensor-controller and controller-actuator channels. Compared with earlier results of attacking a single channel [37], [38], it is more general and challenging to consider this model. Moreover, from the point of view of the attacker, the energy of the FDIAs is often limited, so Assumption 3 is reasonable and common [16], [18], [39].

III. Main Results

In this section, a composite anti-disturbance method is put forward to ensure the consensus of the MASs under multiple disturbances and FDIAs. Meanwhile, a novel ETM is designed, which not only reduces the update rate of the controller, but also avoids continuous monitoring of the neighbors' states. In addition, Zeno behavior will not exhibit in each agent.

A. Observer and Controller Design

Since the state of MAS cannot be measured, a state observer for each agent is proposed as

$$\begin{cases} \dot{\hat{x}}_i(t) = A\hat{x}_i(t) + B[\tilde{u}_i(t) + \hat{d}_{i,1}(t)] + Dg_i(t) + \phi(\hat{x}_i(t)) \\ -L_1(\tilde{y}_i(t) - \hat{y}_i(t)), \\ \hat{y}_i(t) = C\hat{x}_i(t), \ i = 1, \cdots, N, \end{cases} \tag{5}$$

where $\hat{x}_i(t)$, $\hat{y}_i(t)$, and $\hat{d}_{i,1}(t)$ are the estimated values of the state $x_i(t)$, output $y_i(t)$ and disturbance $d_{i,1}(t)$. L_1 is the observer gain matrix to be devised and the disturbance compensation term $g_i(t)$ is designed as

$$g_i(t) = \frac{H(\tilde{y}_i(t) - \hat{y}_i(t))\hat{\bar{d}}_{i,2}^2(t)}{\|H(\tilde{y}_i(t) - \hat{y}_i(t))\| \left\|\hat{\bar{d}}_{i,2}(t)\right\| + \vartheta_i}, \tag{6}$$

where $\vartheta_i > 0$, H is a gain matrix, and the adaptive parameter $\hat{\bar{d}}_{i,2}(t)$ is given by

$$\dot{\hat{\bar{d}}}_{i,2}(t) = -\frac{1}{\eta_i}\vartheta_i\hat{\bar{d}}_{i,2}(t) + \frac{1}{\eta_i}\|H(\tilde{y}_i(t) - \hat{y}_i(t))\|, \tag{7}$$

with η_i being a positive constant. Besides, to resist disturbance $d_{i,1}$, the following DO is considered:

$$\begin{cases} \dot{\hat{\omega}}_i(t) = W\hat{\omega}_i(t) + Ff(\hat{\omega}_i(t)) - L_2(\tilde{y}_i(t) - \hat{y}_i(t)), \\ \hat{d}_{i,1}(t) = V\hat{\omega}_i(t), \end{cases} \tag{8}$$

where $\hat{\omega}_i(t)$ and L_2 are the state and gain matrix of the DO, respectively.

Remark 3: As shown in Fig. 1, to improve the accuracy of the observer under multiple disturbances, the DO (8) and adaptive compensation mechanism $g_i(t)$ in (6) are introduced into the distributed state observer (5), in which the DO is used to estimate the modeling disturbance $d_{i,1}(t)$ and then offset it; for norm bounded disturbance $d_{i,2}(t)$, the adaptive compensation mechanism (6) rejects it by using the estimated value of the upper bound of the disturbance. In addition, it should be pointed out that it only uses the output information which is more convenient to obtain than the state information, and avoids the dependence on the disturbance model by estimating the upper bound of the disturbance, so it is easier to apply to real situations. In the following text, a composite anti-disturbance mechanism based on DO and $\mathcal{H}_\infty$ control method will be developed to ensure the consensus of MASs.

In MASs, the energy consumption of physical institutions is often huge, and a lot of network resources will be occupied in the process of information transmission. Therefore, in order to achieve consensus and reject disturbance under the limited network bandwidth, based on the above analysis, a control law driven by an ETM is developed as follows when $t \in [t_k^i, t_{k+1}^i)$:

$$u_i(t) = -\hat{d}_{i,1}(t_k^i) + cK\Big[\sum\nolimits_{j\in\mathcal{N}_i} a_{ij}(\hat{x}_j(t_k^i) - \hat{x}_i(t_k^i)) + a_{i0}(x_0(t_k^i) - \hat{x}_i(t_k^i))\Big], \quad (9)$$

where $c > 0$ denotes the coupling strength, K is a feedback matrix to be designed, t_k^i is the moment when the kth event of agent i occurs, and its update rule (i.e., event-triggered condition) will be given in (21). In addition, it is necessary to point out that the leader's state is measurable because it can be considered as a command producer [40].

Remark 4: In some existing event-triggered anti-disturbance results based on DO for MASs (see [6], [7]), they only avoid continuous information transmission between neighbor agents, but still need to constantly obtain the state of the DO, resulting in frequent operation of the controller. However, the controller designed in (9) is updated only when the trigger rule is met, so that its lifetime can be improved. Meanwhile, the output feedback control strategy does not need to assume that the state can be obtained as in [20] and [27], which makes this method more challenging.

Denoting $e_{x_i}(t) = x_i(t) - \hat{x}_i(t)$ as the state estimation error, and disturbance error is represented by $e_{\omega_i}(t) = \omega_i(t) - \hat{\omega}_i(t)$. Then, let $e_i(t) = \begin{bmatrix} e_{x_i}^T(t) & e_{\omega_i}^T(t)\end{bmatrix}^T$, according to (2), (4), (5) and (8), one can derive the following augmented error system:

$$\dot{e}_i(t) = (\bar{A} + \bar{L}\bar{C})e_i(t) + \bar{D}(d_{i,2}(t) - g_i(t)) + \bar{F}\varphi_i(t) + \bar{L}\Gamma_i^y(t)\nu_i^y(t) \quad (10)$$

with $\bar{A} = \begin{bmatrix} A & BV \\ 0 & W\end{bmatrix}$, $\bar{L} = \begin{bmatrix} L_1 \\ L_2\end{bmatrix}$, $\bar{C} = \begin{bmatrix} C & 0\end{bmatrix}$, $\bar{D} = \begin{bmatrix} D \\ 0\end{bmatrix}$, $\bar{F} = \begin{bmatrix} I & 0 \\ 0 & F\end{bmatrix}$, $\varphi_i(t) = \begin{bmatrix} \phi(x_i(t)) - \phi(\hat{x}_i(t)) \\ f(\omega_i(t)) - f(\hat{\omega}_i(t))\end{bmatrix}$. Next, define $e(t) = \text{col}\{e_1(t), \cdots, e_N(t)\}$, it follows from (10) that

$$\dot{e}(t) = [I_N \otimes (\bar{A} + \bar{L}\bar{C})]e(t) + (I_N \otimes \bar{D})(d_2(t) - g(t)) + [\Gamma^y(t) \otimes \bar{L}]\nu^y(t) + (I_N \otimes \bar{F})\varphi(t),$$

where

$$g(t) = \text{col}\{g_1(t), \cdots, g_N(t)\}, \Gamma^y(t) = \text{diag}\{\Gamma_1^y(t), \cdots, \Gamma_N^y(t)\},$$
$$d_2(t) = \text{col}\{d_{1,2}(t), \cdots, d_{N,2}(t)\}, \varphi(t) = \text{col}\{\varphi_1(t), \cdots, \varphi_N(t)\}.$$

Next, the parameter design methods of state observer and DO are summarized in Theorem 1.

Theorem 1: Consider the MAS (1) subjected to multiple disturbances and FDIAs. Under Assumptions 1-3, for given positive parameters β_1, β_2, and ϵ, if there exist matrices Q and H and a symmetric positive definite matrix P_1 such that

$$\begin{bmatrix} \text{He}(P_1\bar{A} + Q\bar{C}) + \beta_1\Lambda^T\Lambda & P_1\bar{F} & Q \\ * & -\beta_1 I_n & 0 \\ * & * & -\beta_2 I_n\end{bmatrix} < 0, \quad (11)$$

$$\begin{bmatrix} -\epsilon I & P_1\bar{D} - \bar{C}^T H^T \\ * & -\epsilon I\end{bmatrix} < 0, \quad (12)$$

hold with $\Lambda = \text{diag}\{\Lambda_1, \Lambda_2\}$, and the observer gain $\bar{L}$ is designed as $\bar{L} = P_1^{-1}Q$. Then, if we choose the state observer and disturbance observer as in (5) and (8), the state estimation error $e_{x_i}(t)$ and disturbance estimation error $e_{\omega_i}(t)$ are UUB.

Proof: Choose a Lyapunov function as follows

$$V_1(t) = e^T(t)(I_N \otimes P_1)e(t) + \sum_{i=1}^N \eta_i e_{\bar{d}_{i,2}}^2(t), \quad (13)$$

where $\eta_i > 0$ and $e_{\bar{d}_{i,2}}(t) = \bar{d}_{i,2} - \hat{\bar{d}}_{i,2}(t)$. Next, by calculating $\Im V_1(t)$ and taking mathematical expectations, we obtain

$$\begin{aligned}\mathbb{E}\{\Im V_1(t)\} = \mathbb{E}\{&e^T(t)[I_N \otimes (P_1(\bar{A} + \bar{L}\bar{C}) + (\bar{A} + \bar{L}\bar{C})^T P_1)] \\ &\times e(t) + 2e^T(t)(I_N \otimes P_1\bar{D})[d_2(t) - g(t)] \\ &+ 2e^T(t)(I_N \otimes P_1\bar{F})\varphi(t) + 2e^T(t)[\Gamma^y(t) \\ &\otimes P_1\bar{L}]\nu^y(t) + 2\sum_{i=1}^N \eta_i e_{\bar{d}_{i,2}}(t)\dot{e}_{\bar{d}_{i,2}}(t)\}. \quad (14)\end{aligned}$$

From Young's inequality and Assumption 2, it yields

$$\begin{aligned}&\mathbb{E}\{2e^T(t)(I_N \otimes P_1\bar{F})\varphi(t)\} \\ &\quad \le \mathbb{E}\{e^T(t)[I_N \otimes (\frac{1}{\beta_1}P_1\bar{F}\bar{F}^T P_1 + \beta_1\Lambda^T\Lambda)]e(t)\}. \quad (15)\end{aligned}$$

Denote $\mathbb{E}\{\Gamma^y(t)\} = \bar{\Gamma}^y$ with $\bar{\Gamma}^y = \text{diag}\{\chi_1^y, \cdots, \chi_N^y\}$. Based on Lemma 2, one can deduce that

$$\begin{aligned}&\mathbb{E}\{2e^T(t)(\Gamma^y(t) \otimes P_1\bar{L})\nu^y(t)\} \\ &\quad \le \mathbb{E}\{\frac{1}{\beta_2}e^T(t)(I_N \otimes P_1\bar{L}\bar{L}^T P_1)e(t) + \beta_2\lambda_{\max}(\bar{\Gamma}^{y^T}\bar{\Gamma}^y)\bar{\nu}^2\}. \quad (16)\end{aligned}$$

Notice that if $\epsilon > 0$ is selected small enough, $P_1\bar{D} = \bar{C}^T H^T$ can be achieved from LMI (12) [10]. In addition, by the definition of $e_{\bar{d}_{i,2}}(t)$ in (13), it is known that $\dot{e}_{\bar{d}_{i,2}}(t) = \frac{1}{\eta_i}\vartheta_i\hat{\bar{d}}_{i,2}(t) - \frac{1}{\eta_i}\|H(\tilde{y}_i(t) - \hat{y}_i(t))\|$. Then, combined with (6), it can be derived

$$\begin{aligned}&2\mathbb{E}\left\{e^T(t)(I_N \otimes P_1\bar{D})[d_2(t) - g(t)] + \sum_{i=1}^N \eta_i e_{\bar{d}_{i,2}}(t)\dot{e}_{\bar{d}_{i,2}}(t)\right\} \\ &\le 2\mathbb{E}\left\{\sum_{i=1}^N \left\|e_i^T(t)P_1\bar{D}\right\|\bar{d}_{i,2} - \sum_{i=1}^N e_i^T(t)P_1\bar{D} \right. \\ &\quad \times \frac{H(\tilde{y}_i(t) - \hat{y}_i(t))\hat{\bar{d}}_{i,2}^2(t)}{\|H(\tilde{y}_i(t) - \hat{y}_i(t))\|\left\|\hat{\bar{d}}_{i,2}(t)\right\| + \vartheta_i} + \sum_{i=1}^N \vartheta_i e_{\bar{d}_{i,2}}(t)\hat{\bar{d}}_{i,2}(t) \\ &\quad \left. - \sum_{i=1}^N e_{\bar{d}_{i,2}}(t)\|H(\tilde{y}_i(t) - \hat{y}_i(t))\|\right\} \\ &\le 2\mathbb{E}\left\{\sum_{i=1}^N \left\|e_i^T(t)P_1\bar{D} + \nu_i^{y^T}(t)\chi_i^{y^T}H^T\right\|\bar{d}_{i,2} + \sum_{i=1}^N \varpi_i\bar{d}_{i,2} \right. \\ &\quad - \sum_{i=1}^N \frac{[e_i^T(t)P_1\bar{D} + \nu_i^{y^T}(t)\chi_i^{y^T}H^T]H[\bar{C}e_i(t) + \chi_i^y\nu_i^y(t)]\hat{\bar{d}}_{i,2}^2(t)}{\left\|H[\bar{C}e_i(t) + \chi_i^y\nu_i^y(t)]\right\|\left\|\hat{\bar{d}}_{i,2}(t)\right\| + \vartheta_i} \\ &\quad + \sum_{i=1}^N \vartheta_i e_{\bar{d}_{i,2}}(t)\hat{\bar{d}}_{i,2}(t) - \sum_{i=1}^N e_{\bar{d}_{i,2}}(t)\left\|H[\bar{C}e_i(t) + \chi_i^y\nu_i^y(t)]\right\| \\ &\quad \left. + \sum_{i=1}^N \nu_i^{y^T}(t)\chi_i^{y^T}H^T\frac{H[\bar{C}e_i(t) + \chi_i^y\nu_i^y(t)]\hat{\bar{d}}_{i,2}^2(t)}{\left\|H[\bar{C}e_i(t) + \chi_i^y\nu_i^y(t)]\right\|\left\|\hat{\bar{d}}_{i,2}(t)\right\| + \vartheta_i}\right\}\end{aligned}$$

$$
\begin{aligned}
&\leq 2\mathbb{E}\Bigg\{\sum_{i=1}^{N}\left\|e_i^T(t)P_1\bar{D}+\nu_i^{y^T}(t)\chi_i^{y^T}H^T\right\|\left\|\hat{\bar{d}}_{i,2}(t)\right\|+\sum_{i=1}^{N}\varpi_i\bar{d}_{i,2}\\
&\quad-\sum_{i=1}^{N}\frac{[e_i^T(t)P_1\bar{D}+\nu_i^{y^T}(t)\chi_i^{y^T}H^T][H\bar{C}e_i(t)+H\chi_i^y\nu_i^y(t)]}{\left\|H[\bar{C}e_i(t)+\chi_i^y\nu_i^y(t)]\right\|\left\|\hat{\bar{d}}_{i,2}(t)\right\|+\vartheta_i}\\
&\quad\times\hat{\bar{d}}_{i,2}^2(t)+\sum_{i=1}^{N}\vartheta_i e_{\bar{d}_{i,2}}(t)(\bar{d}_{i,2}-e_{\bar{d}_{i,2}}(t))+\sum_{i=1}^{N}\left\|\hat{\bar{d}}_{i,2}(t)\right\|\\
&\quad\times\left\|\nu_i^{y^T}(t)\chi_i^{y^T}H^T\right\|\\
&\leq \mathbb{E}\Bigg\{2\sum_{i=1}^{N}\vartheta_i+2\sum_{i=1}^{N}\varpi_i\bar{d}_{i,2}-2\sum_{i=1}^{N}\vartheta_i e_{\bar{d}_{i,2}}^2(t)+\beta_3\\
&\quad\times\sum_{i=1}^{N}\vartheta_i e_{\bar{d}_{i,2}}^2(t)+\frac{1}{\beta_3}\sum_{i=1}^{N}\vartheta_i\bar{d}_{i,2}^2(t)+2\sum_{i=1}^{N}\left\|\nu_i^{y^T}(t)\chi_i^{y^T}H^T\right\|\\
&\quad\times\bar{d}_{i,2}+\sum_{i=1}^{N}\vartheta_i\|e_{\bar{d}_{i,2}}(t)\|+\sum_{i=1}^{N}\frac{1}{\vartheta_i}\left\|\nu_i^{y^T}(t)\chi_i^{y^T}H^T\right\|^2\Bigg\}\\
&\leq \mathbb{E}\Bigg\{2\sum_{i=1}^{N}\vartheta_i+6\sum_{i=1}^{N}\left\|\nu_i^{y^T}(t)\chi_i^{y^T}H^T\right\|\bar{d}_{i,2}+\frac{1}{\beta_3}\sum_{i=1}^{N}\vartheta_i\bar{d}_{i,2}^2\\
&\quad-(1-\beta_3)\sum_{i=1}^{N}\vartheta_i e_{\bar{d}_{i,2}}^2(t)+\sum_{i=1}^{N}\frac{1}{\vartheta_i}\left\|\nu_i^{y^T}(t)\chi_i^{y^T}H^T\right\|^2\Bigg\},
\end{aligned}\tag{17}
$$

where $0<\beta_3<1$, and $\varpi_i=\left\|e_i^T(t)P_1\bar{D}\right\|+\left\|\nu_i^{y^T}(t)\chi_i^{y^T}H^T\right\|-\left\|e_i^T(t)P_1\bar{D}+\nu_i^{y^T}(t)\chi_i^{y^T}H^T\right\|\leq 2\left\|\nu_i^{y^T}(t)\chi_i^{y^T}H^T\right\|$. Furthermore, let $Q=P_1\bar{L}$, and substituting (15)-(17) into (14), we can obtain

$$
\begin{aligned}
&\mathbb{E}\{\Im V_1(t)\}\\
&\quad\leq \mathbb{E}\{-e^T(t)(I_N\otimes\Xi_1)e(t)-(1-\beta_3)\sum_{i=1}^{N}\vartheta_i e_{\bar{d}_{i,2}}^2(t)+\Delta\}\\
&\quad\leq \mathbb{E}\Bigg\{-\frac{\lambda_{\min}(\Xi_1)}{\lambda_{\max}(P_1)}e^T(t)(I_N\otimes P_1)e(t)-\frac{(1-\beta_3)\underline{\vartheta}}{\bar{\eta}}\\
&\qquad\times\sum_{i=1}^{N}\vartheta_i e_{\bar{d}_{i,2}}^2(t)+\Delta\Bigg\}
\end{aligned}\tag{18}
$$

with $\Xi_1=-(P_1\bar{A}+\bar{A}^TP_1+Q\bar{C}+\bar{C}^TQ^T+\frac{1}{\beta_1}P_1\bar{F}\bar{F}^TP_1+\beta_1\Lambda^T\Lambda+\frac{1}{\beta_2}QQ^T)$, $\Delta=\beta_2\lambda_{\max}(\bar{\Gamma}^{y^T}\bar{\Gamma}^y)\bar{\nu}^2+2\sum_{i=1}^{N}\vartheta_i+6\sum_{i=1}^{N}\|\nu_i^{y^T}(t)\chi_i^{y^T}H^T\|\bar{d}_{i,2}+\frac{1}{\beta_3}\sum_{i=1}^{N}\vartheta_i\bar{d}_{i,2}^2+\sum_{i=1}^{N}\frac{1}{\vartheta_i}\|\nu_i^{y^T}(t)\chi_i^{y^T}H^T\|^2>0$. Then, by applying Schur complement Lemma to (11), it holds that $\Xi_1>0$, and (18) can be rewritten as

$$\mathbb{E}\{\Im V_1(t)\}\leq\mathbb{E}\{-\alpha V_1(t)+\Delta\},\tag{19}$$

where $\alpha=\min\left\{\frac{\lambda_{\min}(\Xi_1)}{\lambda_{\max}(P_1)},\frac{(1-\beta_3)\underline{\vartheta}}{\bar{\eta}}\right\}$, $\bar{\eta}=\max\{\eta_1,\cdots,\eta_N\}$, and $\underline{\vartheta}=\min\{\vartheta_1,\cdots,\vartheta_N\}$, which implies that $V_1(t)$ is bounded. Therefore, the estimation errors $e_{x_i}(t)$, $e_{w_i}(t)$, and $e_{\bar{d}_{i,2}}(t)$ are UUB. The proof is completed. ■

Remark 5: It can be seen from the state observer (5) and disturbance observer (8) that attack signals $\nu_i^y(t)$ and $\nu_i^u(t)$ are included. Although they are unknown to us, these attack signals have specific values in practice, and once Assumption 3 is satisfied, the designed observers can ensure that the estimation errors $e_{x_i}(t)$ and $e_{w_i}(t)$ are UUB. On the other hand, compared with the result of anti-disturbance using the upper bound of disturbance, the proposed method does not need to assume that the upper bound of disturbance is known as in [10], [31]. Furthermore, unlike the disturbance rejection control method based on extended state observer in [32], which requires that the disturbance and its derivatives are bounded and satisfies $\lim_{t\to\infty}\dot{d}(t)=0$, the proposed disturbance compensation method (6) only needs to ensure that the disturbance is bounded. In addition, according to (19), we can know that the estimation errors $e_{x_i}(t)$, $e_{w_i}(t)$, and $e_{\bar{d}_{i,2}}(t)$ are affected by the energy and frequency of FDIAs and the upper bound of disturbance $d_{i,2}(t)$, so we must adjust the parameters to minimize the above estimation errors to improve the accuracy.

B. Consensus Performance Analysis

In this subsection, sufficient conditions for MAS (1) and (3) subjected to multiple disturbances and FDIAs are obtained to achieve $\mathcal{H}_\infty$ consensus performance. First, the state of followers under FDIAs can be obtained by substituting (9) into (4) as follows:

$$
\begin{aligned}
\dot{x}_i(t)&=Ax_i(t)+B\Big[-\hat{d}_{i,1}(t_k^i)+cK\Big(\sum\nolimits_{j\in\mathcal{N}_i}a_{ij}(\hat{x}_j(t_k^i)\\
&\quad-\hat{x}_i(t_k^i))+a_{i0}(x_0(t_k^i)-\hat{x}_i(t_k^i))\Big)+\Gamma_i^u(t)\nu_i^u(t)+d_{i,1}(t)\Big]\\
&\quad+Dd_{i,2}(t)+\phi(x_i(t)).
\end{aligned}\tag{20}
$$

Before moving forward, for each agent, denote $\varepsilon_i(t)=\hat{x}_i(t_k^i)-\hat{x}_i(t)$, $\varepsilon_{i0}(t)=x_0(t_k^i)-x_0(t)$, and $\tilde{\varepsilon}_i(t)=\hat{d}_{i,1}(t_k^i)-\hat{d}_{i,1}(t)$ as measurement errors, and the time sequence $\{t_k^i\}$ is generated by

$$t_{k+1}^i=\inf\{t>t_k^i|r_i(t)>0\}\tag{21}$$

and

$$
\begin{aligned}
&r_i(t)\\
&\quad=\theta_i\Big(\rho_1\left\|B^TP_2\varepsilon_i(t)\right\|^2+\rho_2a_{i0}\left\|B^TP_2\varepsilon_{i0}(t)\right\|^2+\beta_5\|\tilde{\varepsilon}_i(t)\|^2\Big)\\
&\qquad-\hbar_{i1}\theta_i\Bigg(\Bigg\|B^TP_2\sum_{j\in\mathcal{N}_i}a_{ij}(\hat{x}_j(t_k^i)-\hat{x}_i(t_k^i))\Bigg\|^2+\left\|B^TP_2a_{i0}\right.\\
&\qquad\left.\times(x_0(t_k^i)-\hat{x}_i(t_k^i))\right\|^2\Bigg)-\hbar_{i2}\theta_i\left\|\hat{\bar{d}}_{i,2}(t)\right\|^2-\upsilon_i\ell_ie^{-\upsilon_it}
\end{aligned}\tag{22}
$$

with $\rho_1=\kappa_1c+\hbar_1(1+1/\kappa_2)(\theta_{\max}/\theta_{\min})\lambda_{\max}(\mathcal{L}^T\mathcal{L})+\hbar_1(1+1/\kappa_3)(1+1/\kappa_4)$, $\rho_2=\kappa_1c+\hbar_1(1+1/\kappa_3)(1+\kappa_4)$, $\hbar_1=\max\{\hbar_{i1}\}$, $\max\{\hbar_{i2}\}\leq\frac{2\sigma^2}{3}$, and $\hbar_{i1}$, $\hbar_{i2}$, β_5, υ_i, ℓ_i being positive constants. In addition, the remaining parameters will be given in Theorem 2.

Remark 6: Unlike the ETM in [26] which uses state-independent thresholds, in the design process of the ETM, we adopt a dynamically adjustable threshold based on system performance, so as to achieve a better balance in saving resources and improving control performance. Meanwhile, it is worth pointing out that the introduction of estimated value $\hat{\bar{d}}_{i,2}(t)$ and exponential term $\upsilon_i\ell_ie^{-\upsilon_it}$ can facilitate the $\mathcal{H}_\infty$ consensus analysis and the exclusion of Zeno behavior.

Recall that $\delta_i(t) = x_i(t) - x_0(t)$. Then, let $\delta(t) = \{\delta_1(t), \cdots, \delta_N(t)\}$, and combining (3) and (20) yields

$$\begin{aligned}\dot{\delta}(t) = &(I_N \otimes A - c\mathcal{L}_1 \otimes BK)\delta(t) + (c\mathcal{L}_1 \otimes BK)e_x(t)\\ &-(c\mathcal{L}_1 \otimes BK)\varepsilon(t) + (c\mathcal{A}_0 \otimes BK)\varepsilon_0(t) - (I_N \otimes B)\\ &\times\tilde{\varepsilon}(t) + (I_N \otimes BV)e_w(t) + [\Gamma^u(t) \otimes B]\nu^u(t) + (I_N\\ &\otimes D)d_2(t) + \phi(x) - \tilde{\phi}(x_0),\end{aligned} \tag{23}$$

where

$$\begin{aligned}&e_x(t)=\mathrm{col}\{e_{x_1}(t), \cdots, e_{x_N}(t)\}, \varepsilon_0(t)=\mathrm{col}\{\varepsilon_{10}(t), \cdots, \varepsilon_{N0}(t)\},\\ &\varepsilon(t)=\mathrm{col}\{\varepsilon_1(t), \cdots, \varepsilon_N(t)\}, e_w(t)=\mathrm{col}\{e_{w_1}(t), \cdots, e_{w_N}(t)\},\\ &\tilde{\varepsilon}(t)=\mathrm{col}\{\tilde{\varepsilon}_1(t), \cdots, \tilde{\varepsilon}_N(t)\}, \Gamma^u(t)=\mathrm{diag}\{\Gamma_1^u(t), \cdots, \Gamma_N^u(t)\},\\ &\phi(x) - \tilde{\phi}(x_0)=\mathrm{col}\{\phi(x_1) - \phi(x_0), \cdots, \phi(x_N) - \phi(x_0)\}.\end{aligned}$$

Next, the $\mathcal{H}_\infty$ consensus problem for MASs can be solved by Theorem 2.

Theorem 2: Assume that Assumptions 1-3 hold. For given positive scalars $\kappa_{1,2,3}$, $\beta_i (i = 4, \cdots, 7)$, and σ, if there exists matrix $P_2 > 0$ such that

$$\begin{bmatrix}\Phi_{11} & P_2^{-1} & P_2^{-1}\Lambda_1^T & P_2^{-1}\\ * & -\dfrac{1}{\beta_6\kappa\lambda_{\max}^2(\tilde{\Gamma}^u)}I_n & 0 & 0\\ * & * & -\dfrac{1}{\beta_7}I_n & 0\\ * & * & * & -I_n\end{bmatrix} < 0, \tag{24}$$

$$\begin{aligned}&\Big[2\hbar_1\Big((1 + \kappa_2)(\tilde{\mathcal{N}} + \sqrt{N\tilde{\mathcal{N}}})^2 + 1 + \kappa_3\Big) + \beta_4 c\Big]\\ &\quad\times\lambda_{\max}(P_2BB^TP_2) < \sigma^2,\end{aligned} \tag{25}$$

with $\Phi_{11} = AP_2^{-1} + P_2^{-1}A^T + \Big(\frac{c\lambda_{\max}(\mathcal{L}_1^T\mathcal{L}_1)\lambda_{\max}(\Theta)}{\beta_4\lambda_{\min}(\Theta)} + \frac{1}{\beta_5} + \frac{1}{\beta_6} + \frac{c\lambda_{\max}(\mathcal{L}_1^T\mathcal{L}_1)\lambda_{\max}(\Theta)}{\kappa_1\lambda_{\min}(\Theta)} + \frac{c}{\kappa_1} + 2\hbar_1\Big((1 + \kappa_2)(\tilde{\mathcal{N}} + \sqrt{N\tilde{\mathcal{N}}})^2 + 1 + \kappa_3\Big) - \frac{c\lambda_0}{\lambda_{\max}(\Theta)}\Big)BB^T + \frac{1}{\sigma^2}BVV^TB^T + \frac{4}{\sigma^2}DD^T + \frac{1}{\beta_7}I$*, and the scalar κ is defined in Assumption 3. Then, in the presence of multiple disturbances and FDIAs, under the consensus control protocol (9) and ETM (21), the $\mathcal{H}_\infty$ consensus performance can be guaranteed, i.e.,*

$$\begin{aligned}&\mathbb{E}\Big\{\int_0^{t_f}\delta^T(t)(\Theta \otimes I)\delta(t)dt\Big\}\\ &\quad\le \mathbb{E}\Big\{\sigma^2\int_0^{t_f}\zeta^T(t)(I \otimes \Theta)\zeta(t)dt + V_2(0)\Big\}\end{aligned} \tag{26}$$

with σ is the error attenuation level, $\zeta(t) = \mathrm{col}\{e_x(t), e_w(t), e_{\bar{d}_2}(t), \hat{\hat{d}}_2(t)\}$, *and the controller gain matrix is $K = B^TP_2$.*

Proof: Constructing a Lyapunov function candidate as

$$V_2(t) = \delta^T(t)(\Theta \otimes P_2)\delta(t) + \sum_{i=1}^N \ell_i e^{-\upsilon_i t} \tag{27}$$

in which $P_2, \ell_i, \upsilon_i > 0$ such that $V_2(t) > 0$. Based on the definition of $\Im V(t)$, it follows from (23) and (27) by taking mathematical expectations that

$$\begin{aligned}\mathbb{E}\{\Im V_2(t)\} = &\mathbb{E}\{\delta^T(t)[\Theta \otimes (P_2A + A^TP_2) - c\Theta\mathcal{L}_1 \otimes P_2BK\\ &-c\mathcal{L}_1{}^T\Theta \otimes K^TB^TP_2]\delta(t) + 2\delta^T(t)(c\Theta\mathcal{L}_1\\ &\otimes P_2BK)e_x(t) - 2\delta^T(t)(c\Theta\mathcal{L}_1 \otimes P_2BK)\varepsilon(t)\\ &+2\delta^T(t)(c\Theta\mathcal{A}_0 \otimes P_2BK)\varepsilon_0(t) - 2\delta^T(t)(\Theta\\ &\otimes P_2B)\tilde{\varepsilon}(t) + 2\delta^T(t)(\Theta \otimes P_2BV)e_w(t)\\ &+2\delta^T(t)(\Theta\Gamma^u(t) \otimes P_2B)\nu^u(t) + 2\delta^T(t)(\Theta\\ &\otimes P_2D)d_2(t) + 2\delta^T(t)(\Theta \otimes P_2)[\phi(x) - \tilde{\phi}(x_0)]\\ &-\sum_{i=1}^N \ell_i\upsilon_i e^{-\upsilon_i t}\}.\end{aligned} \tag{28}$$

Using Lemma 2, it is not difficult to obtain that

$$\begin{aligned}&\mathbb{E}\{2\delta^T(t)(c\Theta\mathcal{L}_1 \otimes P_2BK)e_x(t)\}\\ &\le \mathbb{E}\Big\{\frac{c\lambda_{\max}(\mathcal{L}_1^T\mathcal{L}_1)\lambda_{\max}(\Theta)}{\beta_4\lambda_{\min}(\Theta)}\delta^T(t)(\Theta \otimes P_2BB^TP_2)\delta(t)\\ &\quad+\beta_4 c e_x^T(t)(\Theta \otimes P_2BB^TP_2)e_x(t)\Big\}\end{aligned} \tag{29}$$

and

$$\begin{aligned}\mathbb{E}\{-2\delta^T(t)(\Theta \otimes P_2B)\tilde{\varepsilon}(t)\} \le &\mathbb{E}\{\frac{1}{\beta_5}\delta^T(t)(\Theta \otimes P_2BB^TP_2)\delta(t)\\ &+\beta_5\tilde{\varepsilon}^T(t)(\Theta \otimes I)\tilde{\varepsilon}(t)\}.\end{aligned} \tag{30}$$

Subsequently, let $\mathbb{E}\{\Gamma^u(t)\} = \tilde{\Gamma}^u$, where $\tilde{\Gamma}^u = \mathrm{diag}\{\chi_1^u, \cdots, \chi_N^u\}$. Based on Young's inequality and Assumption 2, by following the similar steps in (29) and (30), we can conclude that

$$\begin{aligned}&\mathbb{E}\{\Im V_2(t)\}\\ &\le \mathbb{E}\Big\{\delta^T(t)[\Theta \otimes (P_2A + A^TP_2) - c\Theta\mathcal{L}_1 \otimes P_2BK - c\mathcal{L}_1{}^T\Theta\\ &\quad\otimes K^TB^TP_2]\delta(t) + \delta^T(t)\Big[\Theta \otimes \Big(\frac{c\lambda_{\max}(\mathcal{L}_1^T\mathcal{L}_1)\lambda_{\max}(\Theta)}{\beta_4\lambda_{\min}(\Theta)}\\ &\quad\times P_2BB^TP_2 + \frac{c\lambda_{\max}(\mathcal{L}_1^T\mathcal{L}_1)\lambda_{\max}(\Theta)}{\kappa_1\lambda_{\min}(\Theta)}P_2BB^TP_2 + \frac{c}{\kappa_1}\\ &\quad\times P_2BB^TP_2 + \frac{1}{\beta_5}P_2BB^TP_2 + \frac{1}{\sigma^2}P_2BVV^TB^TP_2\\ &\quad+\frac{1}{\beta_6}P_2BB^TP_2 + \frac{4}{\sigma^2}P_2DD^TP_2 + \frac{1}{\beta_7}P_2P_2 + \beta_7\Lambda_1^T\Lambda_1\Big)\Big]\\ &\quad\times\delta(t) + \beta_4 c e_x^T(t)(\Theta \otimes P_2BB^TP_2)e_x(t) + \kappa_1 c\varepsilon^T(t)(\Theta\\ &\quad\otimes P_2BB^TP_2)\varepsilon(t) + \kappa_1 c\sum_{i=1}^N\theta_i a_{i0}\varepsilon_{i0}^T(t)P_2BB^TP_2\varepsilon_{i0}(t)\\ &\quad+\beta_5\tilde{\varepsilon}^T(t)(\Theta \otimes I)\tilde{\varepsilon}(t) + \sigma^2 e_w^T(t)(\Theta \otimes I)e_w(t) + \beta_6\\ &\quad\times\lambda_{\max}^2(\tilde{\Gamma}^u)\nu^{u^T}(t)(\Theta \otimes I)\nu^u(t) + \frac{\sigma^2}{4}d_2^T(t)(\Theta \otimes I)d_2(t)\\ &\quad-\sum_{i=1}^N\ell_i\upsilon_i e^{-\upsilon_i t}\Big\}.\end{aligned} \tag{31}$$

Further, in each event interval $[t_k^i, t_{k+1}^i)$, with the event-triggered condition (21), it is obvious that

$$\begin{aligned}&\rho_1\sum_{i=1}^N\theta_i\big\|B^TP_2\varepsilon_i(t)\big\|^2 + \rho_2\sum_{i=1}^N\theta_i a_{i0}\big\|B^TP_2\varepsilon_{i0}(t)\big\|^2\\ &\quad+\beta_5\sum_{i=1}^N\theta_i\|\tilde{\varepsilon}_i(t)\|^2\end{aligned}$$

$$\leq \hbar_1 \sum_{i=1}^{N} \theta_i \Big(\Big\| B^T P_2 \sum_{j\in\mathcal{N}_i} a_{ij}(\hat{x}_j(t_k^i) - \hat{x}_i(t_k^i)) \Big\|^2 + \big\| B^T P_2 \times a_{i0}(x_0(t_k^i) - \hat{x}_i(t_k^i)) \big\|^2 \Big) + \frac{2\sigma^2}{3} \sum_{i=1}^{N} \theta_i \Big\| \hat{\bar{d}}_{i,2}(t) \Big\|^2 + \sum_{i=1}^{N} \upsilon_i \ell_i e^{-\upsilon_i t}, \tag{32}$$

where

$$\begin{aligned}
&\theta_i \Big\| B^T P_2 \sum_{j\in\mathcal{N}_i} a_{ij}(\hat{x}_j(t_k^i) - \hat{x}_i(t_k^i)) \Big\|^2 + \theta_i \big\| B^T P_2 a_{i0} \times (x_0(t_k^i) - \hat{x}_i(t_k^i)) \big\|^2 \\
&\leq \theta_i \bigg(\Big\| B^T P_2 \sum_{j\in\mathcal{N}_i} a_{ij}(\hat{x}_j(t) - \hat{x}_i(t)) \Big\| + \Big\| B^T P_2 \sum_{j\in\mathcal{N}_i} a_{ij} \times (\varepsilon_j(t) - \varepsilon_i(t)) \Big\| \bigg)^2 + \theta_i \big(\big\| B^T P_2 a_{i0}(x_0(t) - \hat{x}_i(t)) \big\| \\
&\quad + \big\| B^T P_2 a_{i0}(\varepsilon_{i0}(t) - \varepsilon_i(t)) \big\| \big)^2 \\
&\leq (1+\kappa_2)\theta_i \Big\| B^T P_2 \sum_{j\in\mathcal{N}_i} a_{ij}(\hat{x}_j(t) - \hat{x}_i(t)) \Big\|^2 + (1+\frac{1}{\kappa_2})\theta_i \times \Big\| B^T P_2 \sum_{j\in\mathcal{N}_i} a_{ij}(\varepsilon_j(t) - \varepsilon_i(t)) \Big\|^2 + (1+\kappa_3)\theta_i \big\| B^T P_2 \\
&\quad \times a_{i0}(x_0(t) - \hat{x}_i(t)) \|^2 + (1+\frac{1}{\kappa_3})\theta_i \big\| B^T P_2 a_{i0}(\varepsilon_{i0}(t) - \varepsilon_i(t)) \|^2
\end{aligned} \tag{33}$$

can be obtained according to the additive property of norm and Young's inequality. To simplify the analysis, define $p_i(t) = x_0(t) - \hat{x}_i(t)$, $q_i(t) = \sum_{j\in\mathcal{N}_i} a_{ij}(\hat{x}_j(t) - \hat{x}_i(t))$. Next, we accumulate the items in (33) from agent 1 to agent N, respectively. By the relationship $p_i(t) = e_{x_i}(t) - \delta_i(t)$, the following inequality is obtained:

$$\begin{aligned}
\sum_{i=1}^{N} \theta_i \big\| B^T P_2 a_{i0} p_i(t) \big\|^2 &\leq \Big\| (\sqrt{\Theta} \otimes B^T P_2) p(t) \Big\|^2 \\
&\leq 2 \Big\| (\sqrt{\Theta} \otimes B^T P_2)\delta(t) \Big\|^2 + 2 \Big\| (\sqrt{\Theta} \otimes B^T P_2) e_x(t) \Big\|^2,
\end{aligned} \tag{34}$$

where $p(t) = \mathrm{col}\{p_1(t), \cdots, p_N(t)\}$, and one has

$$\sum_{i=1}^{N} \theta_i \big\| B^T P_2 q_i(t) \big\|^2 \leq (\tilde{\mathcal{N}} + \sqrt{N\tilde{\mathcal{N}}})^2 \Big\| (\sqrt{\Theta} \otimes B^T P_2) p(t) \Big\|^2 \tag{35}$$

since $\big\| B^T P_2 q_i(t) \big\| \leq \sum_{j\in\mathcal{N}_i} a_{ij} \big(\big\| B^T P_2 p_i(t) \big\| + \big\| B^T P_2 p_j(t) \big\| \big) \leq \tilde{\mathcal{N}} \big\| B^T P_2 p_i(t) \big\| + \sqrt{\tilde{\mathcal{N}}} \big\| (I_N \otimes B^T P_2) p(t) \big\|$. Moreover, notice that

$$\begin{aligned}
\sum_{i=1}^{N} \theta_i \Big\| B^T P_2 \sum_{j\in\mathcal{N}_i} a_{ij}(\varepsilon_j(t) - \varepsilon_i(t)) \Big\|^2 &= \Big\| (\sqrt{\Theta}\mathcal{L} \otimes B^T P_2)\varepsilon(t) \Big\|^2 \\
&\leq \frac{\lambda_{\max}(\Theta)}{\lambda_{\min}(\Theta)} \lambda_{\max}(\mathcal{L}^T \mathcal{L}) \varepsilon^T(t)(\Theta \otimes P_2 B B^T P_2)\varepsilon(t)
\end{aligned} \tag{36}$$

and

$$\begin{aligned}
&\sum_{i=1}^{N} \theta_i \big\| B^T P_2 a_{i0}(\varepsilon_{i0}(t) - \varepsilon_i(t)) \big\|^2 \\
&\leq \sum_{i=1}^{N} \theta_i \big(a_{i0} \big\| B^T P_2 \varepsilon_{i0}(t) \big\| + a_{i0} \big\| B^T P_2 \varepsilon_i(t) \big\| \big)^2 \\
&\leq (1+\kappa_4) \sum_{i=1}^{N} \theta_i a_{i0} \big\| B^T P_2 \varepsilon_{i0}(t) \big\|^2 + (1+\frac{1}{\kappa_4}) \sum_{i=1}^{N} \theta_i \times \big\| B^T P_2 \varepsilon_i(t) \big\|^2.
\end{aligned} \tag{37}$$

Then, it can be inferred from (32)-(37) that

$$\begin{aligned}
&\rho_1 \sum_{i=1}^{N} \theta_i \big\| B^T P_2 \varepsilon_i(t) \big\|^2 + \rho_2 \sum_{i=1}^{N} \theta_i a_{i0} \big\| B^T P_2 \varepsilon_{i0}(t) \big\|^2 + \beta_5 \sum_{i=1}^{N} \theta_i \|\tilde{\varepsilon}_i(t)\|^2 \\
&\leq 2\hbar_1(1+\kappa_2)(\tilde{\mathcal{N}} + \sqrt{N\tilde{\mathcal{N}}})^2 \Big(\Big\| (\sqrt{\Theta} \otimes B^T P_2)\delta(t) \Big\|^2 + \Big\| (\sqrt{\Theta} \otimes B^T P_2) e_x(t) \Big\|^2 \Big) + \hbar_1(1+\frac{1}{\kappa_2}) \frac{\lambda_{\max}(\Theta)}{\lambda_{\min}(\Theta)} \\
&\quad \times \lambda_{\max}(\mathcal{L}^T \mathcal{L}) \varepsilon^T(t)(\Theta \otimes P_2 B B^T P_2)\varepsilon(t) + 2\hbar_1(1+\kappa_3) \times \Big(\Big\| (\sqrt{\Theta} \otimes B^T P_2)\delta(t) \Big\|^2 + \Big\| (\sqrt{\Theta} \otimes B^T P_2) e_x(t) \Big\|^2 \Big) \\
&\quad + \hbar_1(1+\frac{1}{\kappa_3}) \Big((1+\kappa_4) \sum_{i=1}^{N} \theta_i a_{i0} \big\| B^T P_2 \varepsilon_{i0}(t) \big\|^2 + (1+\frac{1}{\kappa_4}) \sum_{i=1}^{N} \theta_i \big\| B^T P_2 \varepsilon_i(t) \big\|^2 \Big) + \frac{2\sigma^2}{3} \sum_{i=1}^{N} \theta_i \Big\| \hat{\bar{d}}_{i,2}(t) \Big\|^2 \\
&\quad + \sum_{i=1}^{N} \upsilon_i \ell_i e^{-\upsilon_i t}.
\end{aligned} \tag{38}$$

Recall that ρ_1 and ρ_2 are defined in (22). By combining similar terms on both sides of inequality (38), it yields

$$\begin{aligned}
&\kappa_1 c \varepsilon^T(t)(\Theta \otimes P_2 B B^T P_2)\varepsilon(t) + \kappa_1 c \sum_{i=1}^{N} \theta_i a_{i0} \varepsilon_{i0}^T(t) P_2 B \times B^T P_2 \varepsilon_{i0}(t) + \beta_5 \tilde{\varepsilon}^T(t)(\Theta \otimes I)\tilde{\varepsilon}(t) \\
&\leq 2\hbar_1 \Big[(1+\kappa_2)(\tilde{\mathcal{N}} + \sqrt{N\tilde{\mathcal{N}}})^2 + 1 + \kappa_3 \Big] \times \Big(\delta^T(t)(\Theta \otimes P_2 B B^T P_2)\delta(t) + e_x^T(t)(\Theta \otimes P_2 B B^T P_2) e_x(t) \Big) \\
&\quad + \frac{2\sigma^2}{3} \hat{\bar{d}}_2^T(t)(\Theta \otimes I)\hat{\bar{d}}_2(t) + \sum_{i=1}^{N} \upsilon_i \ell_i e^{-\upsilon_i t},
\end{aligned} \tag{39}$$

where $\hat{\bar{d}}_2(t) = \mathrm{col}\{\hat{\bar{d}}_{1,2}(t), \cdots, \hat{\bar{d}}_{N,2}(t)\}$. Additionally, it is clear that

$$\begin{aligned}
&\frac{\sigma^2}{4} d_2^T(t)(\Theta \otimes I) d_2(t) + \frac{2\sigma^2}{3} \hat{\bar{d}}_2^T(t)(\Theta \otimes I)\hat{\bar{d}}_2(t) \\
&\leq \frac{\sigma^2}{4} [(e_{\bar{d}_2}(t) + \hat{\bar{d}}_2(t))^T (\Theta \otimes I)(e_{\bar{d}_2}(t) + \hat{\bar{d}}_2(t))] + \frac{2\sigma^2}{3} \times \hat{\bar{d}}_2^T(t)(\Theta \otimes I)\hat{\bar{d}}_2(t) \\
&\leq \frac{\sigma^2}{4} [e_{\bar{d}_2}^T(t)(\Theta \otimes I) e_{\bar{d}_2}(t) + 3 e_{\bar{d}_2}^T(t)(\Theta \otimes I) e_{\bar{d}_2}(t)
\end{aligned}$$

$$
\begin{aligned}
&+\frac{1}{3}\hat{\tilde{d}}_2^T(t)(\Theta\otimes I)\hat{\tilde{d}}_2(t)+\hat{\tilde{d}}_2^T(t)(\Theta\otimes I)\hat{\tilde{d}}_2(t)]\\
&+\frac{2\sigma^2}{3}\hat{\tilde{d}}_2^T(t)(\Theta\otimes I)\hat{\tilde{d}}_2(t)\\
\le\ &\sigma^2 e_{\tilde{d}_2}^T(t)(\Theta\otimes I)e_{\tilde{d}_2}(t)+\sigma^2\hat{\tilde{d}}_2^T(t)(\Theta\otimes I)\hat{\tilde{d}}_2(t). \quad (40)
\end{aligned}
$$

In what follows, to analyze the $\mathcal{H}_\infty$ stability of MASs under multiple disturbances and FDIAs, consider a function as

$$
\aleph(t)=\mathbb{E}\{\Im V_2(t)+\delta^T(t)(\Theta\otimes I)\delta(t)\ -\sigma^2\zeta^T(t)(I\otimes\Theta)\zeta(t)\}. \quad (41)
$$

Then, according to Lemma 1 and Assumption 3, by substituting (31), (39), and (40) into (41), it attains

$$
\begin{aligned}
&\aleph(t)\\
&\le\mathbb{E}\Bigg\{\delta^T(t)\Bigg[\Theta\otimes\Bigg(P_2A+A^TP_2+\Bigg(\frac{c\lambda_{\max}(\mathcal{L}_1^T\mathcal{L}_1)\lambda_{\max}(\Theta)}{\beta_4\lambda_{\min}(\Theta)}\\
&\quad+\frac{1}{\beta_5}+\frac{1}{\beta_6}+\frac{c\lambda_{\max}(\mathcal{L}_1^T\mathcal{L}_1)\lambda_{\max}(\Theta)}{\kappa_1\lambda_{\min}(\Theta)}+\frac{c}{\kappa_1}+2\hbar_1\\
&\quad\times\Big((1+\kappa_2)(\tilde{\mathcal{N}}+\sqrt{N\tilde{\mathcal{N}}})^2+1+\kappa_3\Big)\Bigg)P_2BB^TP_2+\frac{1}{\sigma^2}\\
&\quad\times P_2BVV^TB^TP_2+\beta_6\kappa\lambda_{\max}^2(\tilde{\Gamma}^u)I+\frac{4}{\sigma^2}P_2DD^TP_2\\
&\quad+\frac{1}{\beta_7}P_2P_2+\beta_7\Lambda_1^T\Lambda_1\Bigg)-c\lambda_0\otimes P_2BB^TP_2\Bigg]\delta(t)\\
&\quad+\Big[2\hbar_1\Big((1+\kappa_2)(\tilde{\mathcal{N}}+\sqrt{N\tilde{\mathcal{N}}})^2+1+\kappa_3\Big)+\beta_4c\Big]\\
&\quad\times\lambda_{\max}(P_2BB^TP_2)e_x^T(t)(\Theta\otimes I)e_x(t)+\sigma^2e_\omega^T(t)(\Theta\otimes I)\\
&\quad\times e_\omega(t)+\sigma^2e_{\tilde{d}_2}^T(t)(\Theta\otimes I)e_{\tilde{d}_2}(t)+\sigma^2\hat{\tilde{d}}_2^T(t)(\Theta\otimes I)\hat{\tilde{d}}_2(t)\\
&\quad-\sum_{i=1}^N\ell_i\upsilon_ie^{-\upsilon_it}+\sum_{i=1}^N\upsilon_i\ell_ie^{-\upsilon_it}+\delta^T(t)(\Theta\otimes I)\delta(t)\\
&\quad-\sigma^2\zeta^T(t)(I\otimes\Theta)\zeta(t)\Bigg\}.
\end{aligned}
$$

From (24) and (25), one can conclude that $\aleph(t)<0$ by using Schur complement. Integrating both sides of $\aleph(t)<0$, the following inequality can be obtained:

$$
\begin{aligned}
&\mathbb{E}\Bigg\{V_2(t_f)-V_2(0)+\int_0^{t_f}\delta^T(t)(\Theta\otimes I)\delta(t)dt\Bigg\}\\
&\qquad\le\mathbb{E}\Bigg\{\sigma^2\int_0^{t_f}\zeta^T(t)(I\otimes\Theta)\zeta(t)dt\Bigg\}, \quad (42)
\end{aligned}
$$

which indicates that (26) holds. This completes the proof. ■

Remark 7: For the matrix P_2 in Theorem 2, the solution process is given in Algorithm 1. Since (25) is a constant constraint, we can easily satisfy it by adjusting parameters. Besides, it should be pointed out that the solution of matrix P_2 depends on the Laplacian matrix of the system, so it is not fully distributed. As an extension, this will be one of the tasks we will consider in the future. In the selection of parameters of the ETM (21), the tradeoff between better system performance and control actions and communication resource consumption need to be considered. For example, if $\hbar_{i1}$, $\hbar_{i2}$, and ℓ_i are smaller, the more times of triggering, the more frequent controller updates, and the better system performance, but the communication burden will increase, and vice versa.

Algorithm 1

Step 1: Select the appropriate parameters $\kappa_{1,2,3}$, $\beta_i(i=4,\cdots,7)$, c, $\hbar_1$ and σ;
Step 2: **If** LMI (24) is feasible **then**
  go to **Step 3**;
 else
  go to **Step 1**;
Step 3: Calculate $\lambda_{\max}(P_2BB^TP_2)$ using the matrix P_2 solved by LMI (24), and substitute it into (25);
Step 4: **If** (25) is satisfied **then**
  output P_2;
 else
  go to **Step 1**.

Remark 8: From Theorem 1 and based on the definition of $e_{\tilde{d}_{i,2}}(t)$ in (13), we know that $e_x(t)$, $e_\omega(t)$, $e_{\tilde{d}_2}(t)$, and $\hat{\tilde{d}}_2(t)$ are UUB. Then, in the consensus analysis, we can treat them as disturbances and attenuate them by using the $\mathcal{H}_\infty$ control strategy [4], [41]. Hence, compared with a single anti-disturbance mechanism [6], [8], the composite anti-disturbance mechanism based on DO and $\mathcal{H}_\infty$ control strategy is more helpful to improve the anti-disturbance ability of MASs subjected to various sources of disturbances. Moreover, it is worth mentioning that the observer-based event-triggered composite anti-disturbance control method is developed based on the directed interaction topology, which has a wider application than undirected graph.

C. Exclusion of Zeno Behavior

In this part, we will show that the proposed event-triggered mechanism is Zeno-free, and the main result is given in Theorem 3.

Theorem 3: Under the consensus control protocol (9) driven by the ETM (21), due to the minimum time between events is positive, Zeno behavior is ruled out in MASs, i.e.,

$$
t_{k+1}^i-t_k^i\ge\frac{1}{\|\mathrm{M}\|}\ln\Bigg(\frac{\|\mathrm{M}\|\sqrt{\upsilon_i\ell_ie^{-\upsilon_it}}}{\|\Omega_i\|\alpha_k^i}+1\Bigg)>0, \quad (43)
$$

where $\Omega_i=\mathrm{diag}\{\sqrt{\theta_i\rho_1}B^TP_2,\sqrt{\theta_i\rho_2a_{i0}}B^TP_2,\sqrt{\theta_i\beta_5}V\}$, M *and* α_k^i *are defined in (45).*

Proof: Define $\bar{\varepsilon}_i(t)=\hat{\omega}_i(t_k^i)-\hat{\omega}_i(t)$, we then have $\tilde{\varepsilon}_i(t)=V\bar{\varepsilon}_i(t)$. Thus, the event-triggered function (22) can be rewritten as

$$
\begin{aligned}
r_i(t)=\ &\bar{e}_i^T(t)\Omega_i^T\Omega_i\bar{e}_i(t)\\
&-\hbar_{i1}\theta_i\Bigg(\Bigg\|B^TP_2\sum_{j\in\mathcal{N}_i}a_{ij}(\hat{x}_j(t_k^i)-\hat{x}_i(t_k^i))\Bigg\|^2\\
&\quad+\big\|B^TP_2a_{i0}(x_0(t_k^i)-\hat{x}_i(t_k^i))\big\|^2\Bigg)\\
&-\hbar_{i2}\theta_i\Big\|\hat{\tilde{d}}_{i,2}(t)\Big\|^2-\upsilon_i\ell_ie^{-\upsilon_it}, \quad (44)
\end{aligned}
$$

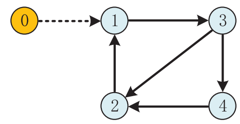


Fig. 2. Communication topology.

where $\bar{e}_i(t) = \text{col}\{\varepsilon_i(t), \varepsilon_{i0}(t), \bar{\varepsilon}_i(t)\}$. For each agent, $\forall t \in [t_k^i, t_{k+1}^i)$, the derivative of $\|\bar{e}_i(t)\|$ satisfies

$$\|\dot{\bar{e}}_i(t)\| = \left\| -\begin{bmatrix} \dot{\hat{x}}_i(t) \\ \dot{x}_0(t) \\ \dot{\hat{w}}_i(t) \end{bmatrix} \right\| \le \|\mathrm{M}\|\|\bar{e}_i(t)\| + \alpha_k^i, \tag{45}$$

in which $\mathrm{M} = \text{diag}\{A, A, W\}$, and

$$0 < \alpha_k^i = \|\mathrm{M}_1\|\bar{\nu} + \left\| \begin{bmatrix} -A\hat{x}_i(t_k^i) - B[\tilde{u}_i(t) + \hat{d}_{i,1}(t)] - Dg_i(t) \\ -\phi(\hat{x}_i(t)) + L_1 Ce_{x_i}(t) \\ -Ax_0(t_k^i) - \phi(x_0(t)) \\ -W\hat{w}_i(t_k^i) - Ff(\hat{w}_i(t)) + L_2 Ce_{x_i}(t) \end{bmatrix} \right\|$$

with $\mathrm{M}_1 = \text{diag}\{L_1, 0, L_2\}$. It follows from (45) that

$$\|\bar{e}_i(t)\| \le \frac{\alpha_k^i}{\|\mathrm{M}\|}\left(e^{\|\mathrm{M}\|(t-t_k^i)} - 1\right). \tag{46}$$

Obviously, (46) can be converted into $\|\Omega_i \bar{e}_i(t)\| \le \frac{\|\Omega_i\|\alpha_k^i}{\|\mathrm{M}\|}\left(e^{\|\mathrm{M}\|(t-t_k^i)} - 1\right)$. Then, by the ETM (21) with event-triggered function (44), one can achieve that

$$\sqrt{\upsilon_i \ell_i e^{-\upsilon_i t}} \le \frac{\|\Omega_i\|\alpha_k^i}{\|\mathrm{M}\|}\left(e^{\|\mathrm{M}\|(t_{k+1}^i - t_k^i)} - 1\right) \tag{47}$$

By solving (47), it shows that $t_{k+1}^i - t_k^i > 0$ is valid. Hence, Theorem 3 holds. ∎

IV. Simulation Examples

This section provides numerical examples to demonstrate the validity of our results. Consider MAS consisting of one leader and four followers, whose network structure is depicted in Fig. 2. The system matrices of (1) and (2) are selected as

$$A = \begin{bmatrix} -2.9 & 0.3 & 0.4 & 1.2 \\ -0.1 & -0.2 & 0.6 & 1.5 \\ 1.2 & 2.1 & -2.8 & 3.4 \\ 1 & -2 & -2.5 & -2.5 \end{bmatrix}, \quad B = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ -1 & 0.5 \\ -0.1 & 0.2 \end{bmatrix},$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix}, \quad D = \begin{bmatrix} 0.1 & 0.1 & -0.1 & -0.1 \end{bmatrix}^T,$$

$$W = \begin{bmatrix} 0 & 0.1 \\ -0.1 & 0 \end{bmatrix}, \quad F = \begin{bmatrix} -0.27 & -0.2 \\ 0.28 & 0 \end{bmatrix}, \quad V = \begin{bmatrix} 0.4 & 0.5 \\ 0.5 & 0.2 \end{bmatrix}.$$

The nonlinear functions $\phi(x_i(t))$ and $f(w_i(t))$ are given as $\phi(x_i) = [0, 0, 0, 0.01\sin(x_{i1}(t))]^T$ and $f(w_i(t)) = [0.01\sin(w_{i1}(t)), 0]^T$, respectively. Then, according to Assumption 2, one has $\Lambda_1 = \text{diag}\{0.01, 0.01, 0.01, 0.01\}$ and $\Lambda_2 = \text{diag}\{0.01, 0.01\}$. In addition, it can be obtained from Fig. 2 and Lemma 1 that $\lambda_0 = 1.7859$ and $\Theta = \text{diag}\{4, 2.5, 7, 3.5\}$. Next, select the appropriate values for the positive scalars β_1, β_2, and ϵ, by using the LMI Toolbox in Matlab to solve (11) and (12) in Theorem 1, we get the observer gain L_1, L_2 and gain matrix H as

TABLE I
Initial State Values of Each Agent

Initial values	Agent 0	Agent 1	Agent 2	Agent 3	Agent 4
$x_{i1}/\hat{x}_{i1}$	-0.3/-0.3	-0.3/-0.1	0.4/0.1	0.25/0.3	0.6/0.8
$x_{i2}/\hat{x}_{i2}$	0.5/0.5	0.4/0.2	-0.2/0.2	0.1/0.4	-0.2/-0.6
$x_{i3}/\hat{x}_{i3}$	0.2/0.2	-0.3/0	0.3/0.3	0.15/0.1	0.3/0.1
$x_{i4}/\hat{x}_{i4}$	-0.8/-0.8	0.3/0.3	0.2/-0.1	-0.1/0.2	-0.4/-0.2

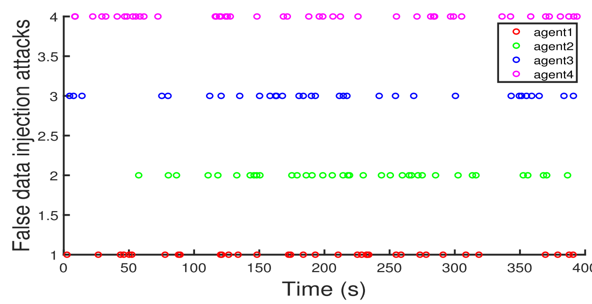


Fig. 3. The attack moments of the FDIAs on each agent.

$$L_1 = \begin{bmatrix} -0.5251 & -0.3762 & 0.1873 \\ -0.3761 & -1.4251 & 0.9100 \\ 0.0862 & 0.2073 & -0.8614 \\ 0.1011 & 0.7028 & -0.9898 \end{bmatrix},$$

$$L_2 = \begin{bmatrix} -0.2387 & -0.7350 & -0.0121 \\ -0.3048 & -0.7429 & 0.4430 \end{bmatrix},$$

$$H = \begin{bmatrix} 0.0188 & -0.0051 & -0.0115 \end{bmatrix}.$$

Without loss of generality, it is assumed that FDIAs will occur on all agents, the probabilities of FDIAs are given as $\chi_i^u = \chi_i^y = 0.02$ $(i = 1, 2)$ and $\chi_i^u = \chi_i^y = 0.03$ $(i = 3, 4)$, and the attack energy limit parameters are set as $\kappa = 0.1$ and $\bar{\nu} = 0.1$. Then, choose $\kappa_1 = 2$, $\kappa_2 = \kappa_3 = \beta_4 = \beta_6 = \beta_7 = 10$, $\beta_5 = 0.5$, $\sigma = 1.41$, $c = 0.08$ and $\hbar_1 = 0.005$, based on Theorem 2, one can get the matrix P_2 and the gain matrix K are

$$P_2 = \begin{bmatrix} 0.3795 & 0.1339 & 0.0007 & 0.3258 \\ 0.1339 & 1.4411 & 0.1882 & 0.7283 \\ 0.0007 & 0.1882 & 0.3893 & 0.0623 \\ 0.3258 & 0.7283 & 0.0623 & 1.0152 \end{bmatrix},$$

$$K = \begin{bmatrix} -0.0333 & -0.2610 & -0.3955 & -0.1638 \\ 0.0655 & 0.2398 & 0.2071 & 0.2342 \end{bmatrix}.$$

In the simulation, the disturbances $d_{i,2}(t)$ are simulated by $d_{1,2}(t) = 0.2e^{-0.1t}\sin(5t)$, $d_{2,2}(t) = 0.3e^{-0.1t}\sin(5t)$, $d_{3,2}(t) = \frac{\sin(2t)}{3+t}$ and $d_{4,2}(t) = e^{-0.2t}\sin(5t)$. Furthermore, the initial conditions of external disturbance (2) and disturbance observer (8) are chosen as $w_i(0) = i * [0.1 \quad 0.2]^T$ and $\hat{w}_i(0) = i * [-0.1 \quad 0.1]^T$, where $i = 1, \cdots, 4$. In addition, the initial state values of each agent are shown in Table I.

In order to save communication resources and obtain good consensus performance at the same time, let $\kappa_4 = 10$, and one has $\rho_1 = 0.2722$ and $\rho_2 = 0.1661$. Then, by selecting the appropriate values for other parameters, the simulation results

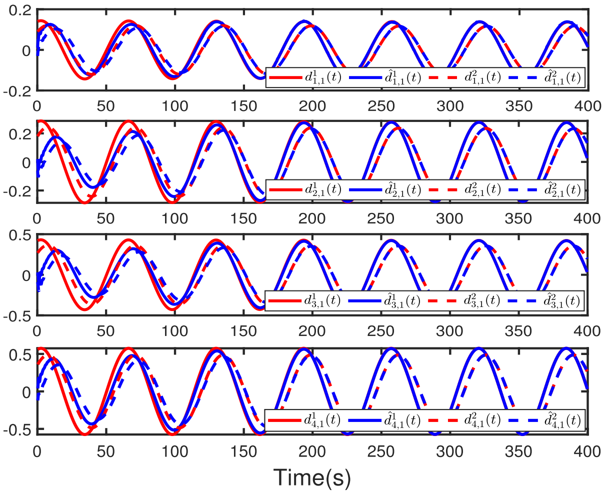


Fig. 4. The disturbances $d_{i,1}(t)$ and their estimated values $\hat{d}_{i,1}(t)$ $(i = 1, \cdots, 4)$.

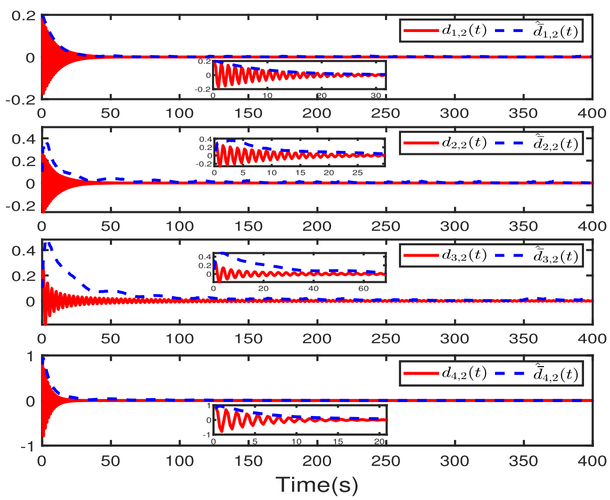


Fig. 5. The disturbances $d_{i,2}(t)$ and the adaptive parameters $\hat{\bar{d}}_{i,2}(t)(i = 1, \cdots, 4)$.

are given in Figs. 3–8. The attack moments of the FDIAs on each agent are plotted in Fig. 3. Fig. 4 shows the disturbance signals $d_{i,1}(t) = [d_{i,1}^1(t), d_{i,1}^2(t)]^T$ and their observed values $\hat{d}_{i,1}(t) = [\hat{d}_{i,1}^1(t), \hat{d}_{i,1}^2(t)]^T$. The disturbances $d_{i,2}(t)$ and the adaptive parameters $\hat{\bar{d}}_{i,2}(t)$ are depicted in Fig. 5. We can see from Figs. 4–5 that the designed DO (8) and adaptive law (7) can achieve good estimation performance under FDIAs, which can play an effective role in anti-disturbance. Fig. 6 represents the evaluated errors of the state observer (5) with respect to $x_i(t)$. We can find that the introduction of DO and $g_i(t)$ ensures the accuracy of the observer. Let $\tilde{J}(t) = \frac{1}{N}\sqrt{\sum_{i=1}^{N} \|x_i(t) - x_0(t)\|^2}$ be the consensus error, then we plot the consensus error of the MASs in Fig. 7, from which we can find that in the presence of multiple disturbances and FDIAs, the proposed composite anti-disturbance control protocol (9) based on ETM (21) shows a good ability to ensure consensus of the MAS and reject disturbances. The triggering instants and intervals of different agents are presented in Fig. 8, which indicates that communication resources are saved and Zeno behavior does not occur.

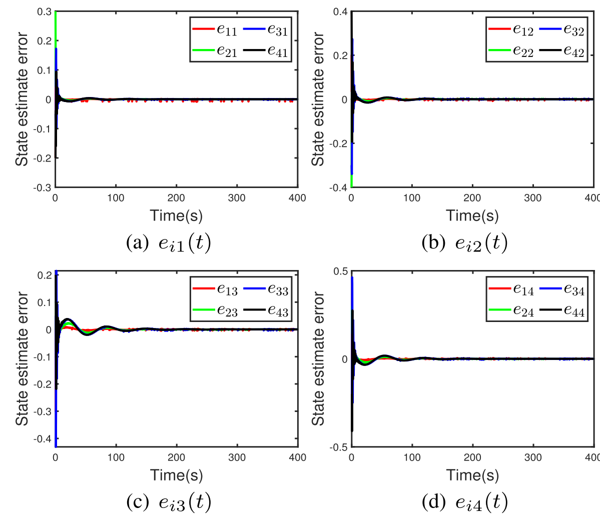


Fig. 6. Observer errors of four agents.

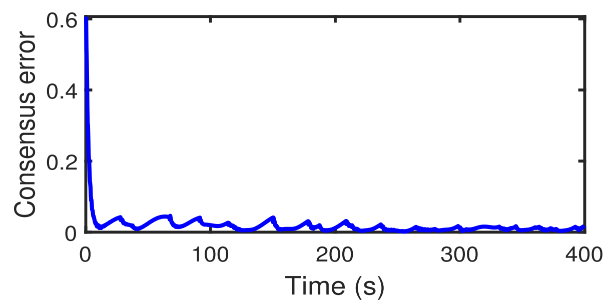


Fig. 7. Consensus error $\tilde{J}(t)$ under control scheme (9).

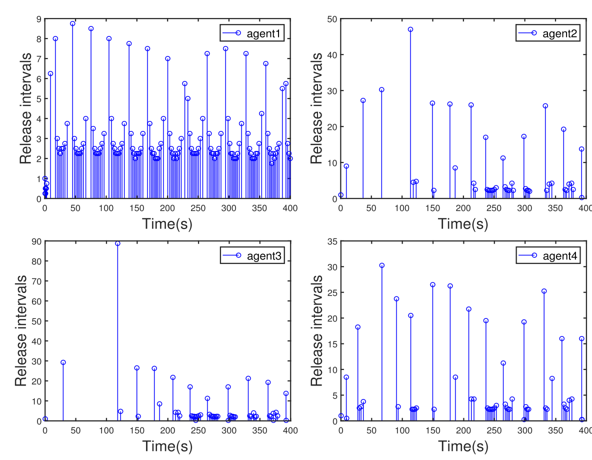
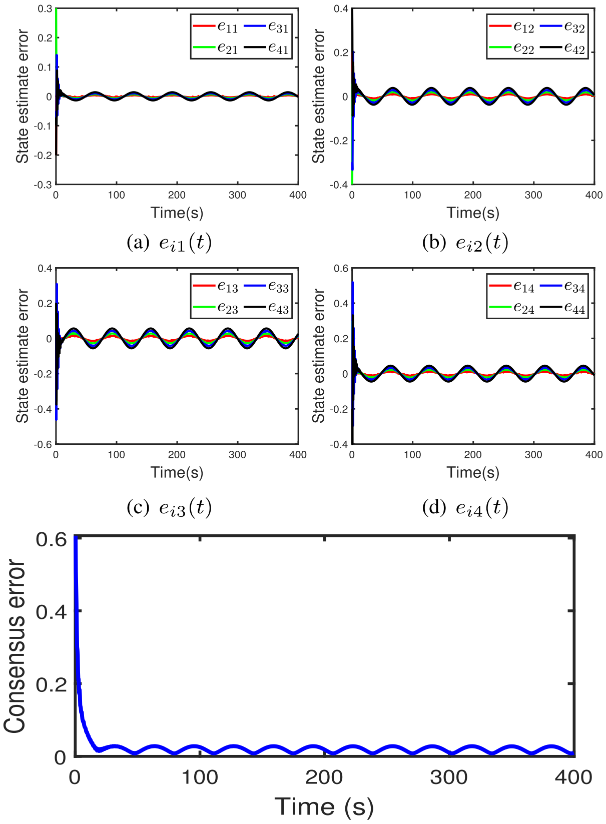


Fig. 8. The occurrence time and interval of events on each agent.

On the other hand, to demonstrate the advantages of the designed control strategy, the observer errors and consensus errors under the method in [40] are depicted in Fig. 9. By comparison, we can see that this method can not guarantee the performance of observer and consensus performance under multiple disturbances and FDIAs, while our method works very well. In addition, the number of trigger points of each agent under different methods is shown in Table II. In view of the above results, we can conclude that the proposed method



(a) $e_{i1}(t)$ (b) $e_{i2}(t)$

(c) $e_{i3}(t)$ (d) $e_{i4}(t)$

(e) Consensus error $\tilde{J}(t)$

Fig. 9. Observer errors and consensus error under the method in [40].

TABLE II
THE NUMBER OF TRIGGER POINTS OF EACH AGENT UNDER DIFFERENT METHODS

Methods \ Agents		1	2	3	4
Control Scheme (9)	CON	133	46	51	54
	NEI	133	46	51	54
Method in [40]	CON	148	84	135	92
	NEI	1600	1600	1600	1600

* CON denotes the number of controller updates, and NEI represents the number of communications between each follower and its neighbors.

can not only achieve good control performance, but also save network resources and reduce the communication burden.

V. CONCLUSION

This work develops an event-triggered control strategy to solve the security consensus problem for MASs under multiple disturbances and FDIAs. We have designed a composite anti-disturbance control strategy based on DO and $\mathcal{H}_\infty$ control, which ensures the consensus performance of MASs under multiple disturbances and FDIAs. For the purpose of reducing the transmission load, a novel ETM is designed and Zeno behavior is avoided. In addition, it is worth mentioning that the proposed ETM does not require continuous monitoring of the neighbors' information, and the controller does not need continuous updating. In the end, the validity of the proposed method is exemplified by simulation results. Our future work will focus on more general nonlinear MASs with directed switching communication topologies and fully distributed event-triggered control. In addition, how to further optimize the ETM to reduce the number of parameters and extend the static ETM to an adaptive ETM are also our objectives.

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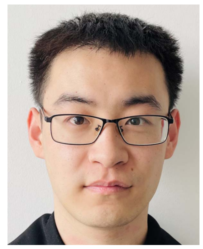

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