Consensus Control of Multi-Agent Systems Using Fault-Estimation-in-the-Loop: Dynamic Event-Triggered Case

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***Abstract*—The paper develops a novel framework of consensus control with fault-estimation-in-the-loop for multi-agent systems (MASs) in the presence of faults. A dynamic event-triggered protocol (DETP) by adding an auxiliary variable is utilized to improve the utilization of communication resources. First, a novel estimator with a noise bias is put forward to estimate the existed fault and then a consensus controller with fault compensation (FC) is adopted to realize the demand of reliability and safety of addressed MASs. Subsequently, a novel consensus control framework with fault-estimation-in-the-loop is developed to achieve the predetermined consensus performance with the l_2-l_∞ constraint by employing the variance analysis and the Lyapunov stability approaches. Furthermore, the desired estimator and controller gains are obtained in light of the solution to an algebraic matrix equation and a linear matrix inequality in a recursive way, respectively. Finally, a simulation result is employed to verify the usefulness of the proposed design framework.**

***Index Terms*—Consensus control, dynamic event-triggered protocol (DETP), fault compensation (FC), fault estimation, multi-agent systems (MASs).**

I. Introduction

In the last decades, the collective behaviors (e.g., consensus and swarming) have been investigated toward multi-agent systems (MASs) due to their extensive implementation in engineering practice such as intelligent transportation systems, sensor networks, and formation control of unmanned air vehicles [1]–[3], and so forth on. As a typical representative, consensus is one of the emerging issues for MASs in the framework of cooperative control. The main goal of consensus, by utilizing local neighboring information, is to construct an appropriate control protocol such that the states of all agents reach some common values where each agent should be able to share its local information between adjacent agents via a shared communication network [4], [5]. To date, a surge of research results under different network environments or dynamic behaviors have been reported in the literature, including, but not limited to, linear MASs with network-induced phenomena or communication scheduling, nonlinear MASs with network-induced phenomena or communication scheduling, MASs subject to cyber-attacks as well as MASs with various constraints [6]–[8].

It should be noted that the interaction of data via the shared communication channels received a lot of attention primarily because of the spatial distribution characteristic of the agents. Compared with traditional networked control systems, the burden of communication has generally increased in practice and, consequently, the probability of data conflicts occurring has increased [9]–[11]. In order to overcome this shortage, some communication scheduling schemes, including event-triggered protocols, stochastic communication protocols as well as Round-Robin protocols, have been employed to govern the exchanges of data, see e.g., [12]–[14] and the references therein. Among these protocols, considerable results based on event-triggered protocols have been devoted to deal with the consensus control issue, where data exchanges occur if and only if some predetermined events occur, see e.g., [15]–[17]. This type of protocol is generally an artificially designed scheme for transmitting information into the application layer and thus its shapes and structures are diverse. It should be emphasised that event functions are usually constructed by real-time relative status/measurement information and fixed trigger thresholds. There is no doubt that these types of protocols lack the capacity to dynamically adjust the burden of communication. As such, from an engineering viewpoint, a dynamic event-triggered protocol (DETP) with time-varying threshold [18]–[21] should release much fewer events while still keeping the same system performance, which gives rise to one of the main motivations of our

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investigation.

It is not uncommon in engineering practice for system components to be subject to faults, which could result in degraded system performance or instability of the treated systems. As such, consideration must be given to the requirement of reliability and safety at the design stage. As an active approach, an adjustable controller can be predeterminately designed in the framework of fault tolerant control (FTC) such that the closed-loop system performance can be satisfied at an admissible level when unpredictable faults occur. For instance, a two-layer framework has been developed in [22] to realize the containment requirement in the presence of faults where the unknown fault coefficient has been estimated and an adaptive tracking controller has been derived. Furthermore, another novel approach should be that the appropriate compensation can be taken in active controllers where fault information (i.e., size and amplitude) can be provided via designed fault estimators. Obviously, the fault estimator will take part in the control closed loop, and hence this kind of approach can be regarded as active FTC using fault-estimation-in-the-loop [23]–[25]. To realize this purpose, the fault should be detected or estimated via observing the system input/output [26]. Nevertheless, most existing literature has been documented based on fault estimation or FTC problem only, see e.g., [27]–[32]. For instance, the states and fault signals have been estimated simultaneously in [27] with torus-event-based protocols and multiple fading measurements. Besides, a distributed FTC strategy has been obtained in [28] to ensure the overall stability for large-scale interconnected systems while the propagation characteristic of occurred faults cannot be taken into account adequately. In summary, the active FTC using fault-estimation-in-the-loop has not yet received much attention for the distributed system.

It is not difficult to find that a large body of accessible results have not been applicable to handle the consensus control issue of MASs with fault-estimation-in-the-loop, not to mention the case where a DETP is a concern. Evidently, consensus control embedded fault estimation for MASs under DETP inevitably encounters the following identified challenges: 1) how to design a consensus controller with fault compensation (FC); 2) how to develop an analysis framework of consensus performance considering the impact from faults; 3) how to design the gains of both fault estimator and controller to realize the addressed consensus.

By the discussions above, this paper endeavours to develop a novel framework of consensus control with fault-estimation-in-the-loop by addressing the above three challenges. The main contributions of this paper are highlighted as three aspects: 1) A novel cooperative framework of consensus control and fault estimation is established for MASs with DETP in the presence of faults; 2) A novel estimator with a noise bias is put forward to estimate the existed fault and then a consensus controller with FC is adopted to realize the desired consensus performance with the l_2-l_∞ constraint; and 3) By employing the variance analysis and the Lyapunov stability approaches, the desired estimator and controller gains are obtained in light of the solution to an algebraic matrix equation and a linear matrix inequality in a recursive way, respectively.

Notations: The notation used is fairly standard if not explicitly. $\mathbf{1}_N$ denotes a vector column with all ones. $\|a\|$ describes the Euclidean norm of the vector a. I_n denotes the n-dimensional identity matrix. $\otimes$ represents the Kronecker product, and the augmentation as $[m_1^T,\ldots,m_N^T]^T$ of vectors $m_1^T,\ldots,m_N^T$ can be denoted to $\mathrm{col}\{m_1,\ldots,m_N\}$.

II. Problem Formulation and Preliminaries

First, let us briefly introduce some necessary information on graphs to describe the communication topology of MASs. A fixed undirected graph is represented by $\mathcal{G}=(\mathcal{V},\mathcal{E},\mathcal{L})$ of order N with the set of nodes $\mathcal{V}=\{1,2,\ldots,N\}$, the set of edges $\mathcal{E}\subseteq\mathcal{V}\times\mathcal{V}$ and the Laplacian matrix $\mathcal{L}=[a_{ij}]_{N\times N}$. Specifically, an edge of $\mathcal{G}$ is represented by the ordered pair (i,j), and if there is an edge between nodes i and j (i.e., $(i,j)\in\mathcal{E}$), then agent j can transmit the information to agent i. Furthermore, such an agent is regarded as a neighbor of agent i, and the neighbors' set is defined as $\mathcal{N}_i=\{j\in\mathcal{V}:(i,j)\in\mathcal{E}\}$. Furthermore, the Laplacian matrix $\mathcal{L}=[a_{ij}]_{N\times N}$ is with $a_{ij}\geq 0$ for $i\neq j$ and $a_{ii}=-\sum_{j=1}^{N}a_{ij}$ where $a_{ij}=-1$ if (i,j) belongs to $\mathcal{E}$ otherwise $a_{ij}=0$.

A. System Models

Consider the following the multi-agent system (MAS) consisting of N agents where the dynamics of the ith agent on the time interval $[0,\ T]$ is expressed by

$$\begin{cases} x_{i,k+1}=\ A_k x_{i,k}+B_k u_{i,k}+D_k\omega_{i,k}+F_k f_{i,k}\\ y_{i,k}=\ C_k x_{i,k}+E_k\nu_{i,k}\\ z_{i,k}=\ H_k x_{i,k}\end{cases}\tag{1}$$

where $x_{i,k}\in\mathbb{R}^{n_x}$ is the system state; $u_{i,k}\in\mathbb{R}^{n_u}$ is the control input; $y_{i,k}\in\mathbb{R}^{n_y}$ is the measurement output; $f_{i,k}\in\mathbb{R}^{n_f}$ is the fault; $z_{i,k}\in\mathbb{R}^{n_z}$ is the controlled output; and $\omega_{i,k}\in\mathbb{R}^{n_\omega}$ and $\nu_{i,k}\in\mathbb{R}^{n_\nu}$ are, respectively, the process noise and measurement noise with means $E\{\omega_{i,k}\}=\mu_{1,i}$ and $E\{\nu_{i,k}\}=\mu_{2,i}$, and covariance matrices $\sigma_{1,i}^2 I$ and $\sigma_{2,i}^2 I$. Note that $\omega_{i,k}$ and $\nu_{i,k}$ are independent and identically distributed sequences. A_k, B_k, C_k, D_k, E_k, F_k and H_k are known time-varying matrices with appropriate dimensions.

In the ideal case, the consensus controller is designed with the following form:

$$u_{i,k}=K_k\sum_{j\in\mathcal{N}_i}a_{ij}(y_{j,k}-y_{i,k})=K_k\phi_{i,k}\tag{2}$$

where K_k is the controller gain matrix to be determined.

In what follows, defining $\xi_{i,k}=[\ x_{i,k}^T\quad f_{i,k}^T\ ]^T$, the augmented system is further written as

$$\begin{cases}\xi_{i,k+1}=\ \bar{A}_k\xi_{i,k}+\bar{B}_k u_{i,k}+\bar{D}_k\omega_{i,k}\\ y_{i,k}=\ \bar{C}_k\xi_{i,k}+E_k\nu_{i,k}\end{cases}\tag{3}$$

where

$$\bar{A}_k=\begin{bmatrix}A_k & F_k\\ 0 & I\end{bmatrix},\ \bar{B}_k=\begin{bmatrix}B_k\\ 0\end{bmatrix}$$

$$\bar{D}_k=\begin{bmatrix}D_k^T & 0\end{bmatrix}^T,\ \bar{C}_k=\begin{bmatrix}C_k & 0\end{bmatrix}.$$

The following assumption is imposed to achieve the main objective.

Assumption 1: The control matrix and the fault matrix satisfy $\text{rank}(B_k, F_k) = \text{rank}(B_k)$, that is, there is a transform matrix M_k such that $F_k = B_k M_k$.

Remark 1: From the engineering point of view, part components of the actuator faults occur, which result in abnormal noises added in the normal control signals or the loss of normal control signals. As such, the assumption $\text{rank}(B_k, F_k) = \text{rank}(B_k)$ is reasonable and of apparent significance in practice.

B. Fault Estimator and Controller Based on Dynamic Event-Triggered Scheme

In this subsection, a set of fault estimators will be designed to compensate the performance loss caused by faults in this paper. Specifically, an estimator on agent i can collect all measurement signals from itself and its neighbours when needed and then estimates the potential faults with the purpose of FC. Furthermore, an event-triggered rule is exploited to adjust the communication burden. Now, let us provide more details about them.

Denote the estimated fault on the estimator i as $\hat{f}_{i,k}$. For presentation convenience, the event-triggered instant sequences on estimator i are defined as $t_0^i < t_1^i < t_2^i < \cdots < t_k^i < \cdots$ and the employed event execution function $\Upsilon(\cdot,\cdot,\cdot,\cdot)$ is as follows:

$$\begin{aligned}&\Upsilon(h_{i,k}^1, h_{i,k}^2, \delta_{i,k}, \varepsilon_i)\\&\quad = h_{i,k}^{1T} h_{i,k}^1 + h_{i,k}^{2T} h_{i,k}^2 - \frac{1}{\tau_i}\delta_{i,k} - \varepsilon_i y_{i,k}^T y_{i,k}\end{aligned} \tag{4}$$

with the gaps $h_{i,k}^1 = y_{i,k} - y_{i,t_k^i}$ and $h_{i,k}^2 = \hat{f}_{i,k} - \hat{f}_{i,t_k^i}$ $(k \in [t_k^i, t_{k+1}^i))$, where y_{i,t_k^i} and $\hat{f}_{i,t_k^i}$ are, respectively, the measurement and the estimated faults on the latest triggering instant t_k^i. τ_i and ε_i are two known positive constants, and $\delta_{i,k}$ is an internal dynamical variable satisfying

$$\begin{cases}\delta_{i,k+1} = \rho_i \delta_{i,k} - h_{i,k}^{1T} h_{i,k}^1 - h_{i,k}^{2T} h_{i,k}^2 + \varepsilon_i y_{i,k}^T y_{i,k}\\ \delta_{i,0} = \delta_0^i\end{cases} \tag{5}$$

with $\delta_0^i \geq 0$ being a predetermined initial condition. Furthermore, $0 < \rho_i < 1$ satisfying $\tau_i \geq 1/\rho_i$ is also a prescribed constant.

In the practical implementation, the event occurs only when the condition $\Upsilon(h_{i,k}^1, h_{i,k}^2, \delta_{i,k}, \varepsilon_i) < 0$ is violated, and hence the event release instants are given recursively as follows:

$$t_{k+1}^i = \inf_{k\in\mathbb{N}}\{k > t_k^i | \Upsilon(h_{i,k}^1, h_{i,k}^2, \delta_{i,k}, \varepsilon_i) > 0\}. \tag{6}$$

Furthermore, in the event instant, the sensor i deployed on the estimator i will immediately broadcast its measurement and estimated fault to its neighbors. In this scenario, the designed fault estimator on $k \in [t_k^i, t_{k+1}^i)$ is in the following form:

$$\begin{aligned}\hat{\xi}_{i,k+1} &= \bar{A}_k \hat{\xi}_{i,k} + \bar{B}_k u_{i,k} + G_{i,k}(y_{i,k} - \hat{y}_{i,k})\\&\quad + \bar{D}_k \mu_{1,i} - G_{i,k} E_k \mu_{2,i}\end{aligned} \tag{7}$$

where $G_{i,k}$ is the parameter matrix to be determined, $\hat{\xi}_{i,k}$ is the estimation of $\xi_{i,k}$ which is the augmentation of states and faults on agent i. Obviously, the second-block-element in $\hat{\xi}_{i,k}$ is just the estimate of fault $f_{i,k}$.

The adopted consensus controller with fault compensation is constructed as follows:

$$\begin{aligned}u_{i,k} &= K_k \sum_{j\in\mathcal{N}_i} a_{ij}(y_{j,t_k^j} - y_{i,t_k^i}) - M_k \sum_{j\in\mathcal{N}_i} a_{ij}(\hat{f}_{j,t_k^j} - \hat{f}_{i,t_k^i})\\&= K_k \phi_{i,k} + K_k \sum_{j\in\mathcal{N}_i} a_{ij}(h_{i,k}^1 - h_{j,k}^1)\\&\quad - M_k \sum_{j\in\mathcal{N}_i} a_{ij}(h_{i,k}^2 - h_{j,k}^2) - M_k \sum_{j\in\mathcal{N}_i} a_{ij}(\hat{f}_{j,k} - \hat{f}_{i,k}).\end{aligned} \tag{8}$$

According to the above illustration, denoting

$$\begin{aligned}&\xi_k = \text{col}_N\{\xi_{i,k}\},\ \hat{\xi}_k = \text{col}_N\{\hat{\xi}_{i,k}\},\ h_k^1 = \text{col}_N\{h_{i,k}^1\}\\&h_k^2 = \text{col}_N\{h_{i,k}^2\},\ \hat{f}_k = \text{col}_N\{\hat{f}_{i,k}\},\ f_k = \text{col}_N\{f_{i,k}\}\\&\nu_k = \text{col}_N\{\nu_{i,k}\},\ \omega_k = \text{col}_N\{\omega_{i,k}\},\ z_k = \text{col}_N\{z_{i,k}\}\end{aligned}$$

and $e_k = \xi_k - \hat{\xi}_k$, then keeping the gaps in mind, one can easily access the estimation error dynamics

$$\begin{aligned}e_{k+1} &= (I_N \otimes \bar{A}_k - G_k \tilde{C}_k) e_k + (I_N \otimes \bar{D}_k)\\&\quad \times (\omega_k - \tilde{\mu}_1) - G_k \tilde{E}_k (\nu_k - \tilde{\mu}_2)\end{aligned} \tag{9}$$

and the closed-loop system

$$\begin{cases}\xi_{k+1} = (I_N \otimes \bar{A}_k + \mathcal{L} \otimes (\bar{B}_k K_k \bar{C}_k))\xi_k\\ \qquad + (\mathcal{L} \otimes \bar{B}_k K_k) h_k^1 - (\mathcal{L} \otimes N_k) h_k^2\\ \qquad + (\mathcal{L} \otimes \bar{B}_k K_k E_k)\nu_k + (I_N \otimes \bar{D}_k)\omega_k\\ \qquad - (\mathcal{L} \otimes \bar{N}_k)\xi_k - (\mathcal{L} \otimes N_k)(\hat{f}_k - f_k)\\ z_k = (I_N \otimes \bar{H}_k)\xi_k\end{cases} \tag{10}$$

where

$$\begin{aligned}&G_k = \text{diag}\{G_{1,k}, G_{2,k}, \ldots, G_{N,k}\}\\&\tilde{C}_k = \text{diag}\{\underbrace{\bar{C}_k, \ldots, \bar{C}_k}_{N}\},\ \tilde{E}_k = \text{diag}\{\underbrace{E_k, \ldots, E_k}_{N}\}\\&\tilde{\mu}_1 = \text{col}_N\{\mu_{1,i}\},\ \tilde{\mu}_2 = \text{col}_N\{\mu_{2,i}\},\ \bar{H}_k = \begin{bmatrix} H_k & 0 \end{bmatrix}\\&N_k = \bar{B}_k M_k = \begin{bmatrix} M_k^T B_k^T & 0 \end{bmatrix}^T\\&\bar{N}_k = \begin{bmatrix} 0 & \bar{B}_k M_k \end{bmatrix}.\end{aligned}$$

In what follows, let

$$\begin{aligned}\bar{\xi}_k &= [\ \bar{\xi}_{1,k}^T \quad \bar{\xi}_{2,k}^T \quad \cdots \quad \bar{\xi}_{N,k}^T\ ]^T\\ \bar{z}_k &= [\ \bar{z}_{1,k}^T \quad \bar{z}_{2,k}^T \quad \cdots \quad \bar{z}_{N,k}^T\ ]^T\end{aligned}$$

where $\bar{\xi}_{i,k} = \xi_{i,k} - (1/N)\sum_{i=0}^N \xi_{i,k}$. Noticing that $\bar{\xi}_k = (\bar{\Phi} \otimes I_{n_x+n_f})\xi_k$ and $\bar{z}_k = (\bar{\Phi} \otimes I_{n_z}) z_k$ with $\bar{\Phi} = I_N - (1/N)\mathbf{1}_N \mathbf{1}_N^T$, one can derive that

$$\begin{cases}\bar{\xi}_{k+1} = ((I_N \otimes \bar{A}_k) + \mathcal{L} \otimes \bar{B}_k K_k \bar{C}_k))\bar{\xi}_k\\ \qquad + (\mathcal{L} \otimes \bar{B}_k K_k) h_k^1 - (\mathcal{L} \otimes N_k) h_k^2\\ \qquad + (\mathcal{L} \otimes \bar{B}_k K_k E_k)\nu_k + (\bar{\Phi} \otimes \bar{D}_k)\omega_k\\ \qquad - (I_N \otimes \bar{N}_k)\bar{\xi}_k - (\mathcal{L} \otimes N_k)\Xi e_k\\ \bar{z}_k = (I_N \otimes \bar{H}_k)\bar{\xi}_k\end{cases} \tag{11}$$

where

$$\Xi = \begin{bmatrix} 0 & -I & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & -I & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 0 & -I \end{bmatrix}.$$

Defining variables

$$d_k = [\omega_k^T \ \ \nu_k^T]^T, \ \ h_k = [h_k^{1T} \ h_k^{2T}]^T$$

the above closed-loop system can be rewritten as follows

$$\begin{cases} \bar{\xi}_{k+1} = A_k\bar{\xi}_k + F_k e_k + B_k h_k + D_k d_k \\ \bar{z}_k = H_k\bar{\xi}_k \end{cases} \tag{12}$$

where

$$\mathcal{A}_k = I_N \otimes \bar{A}_k + \mathcal{L}\otimes(\bar{B}_k K_k \bar{C}_k) - \mathcal{L}\otimes\bar{N}_k$$

$$\mathcal{B}_k = \begin{bmatrix} \mathcal{L}\otimes\bar{B}_k K_k & -(\mathcal{L}\otimes N_k) \end{bmatrix}$$

$$\mathcal{D}_k = \begin{bmatrix} \bar{\Phi}\otimes\bar{D}_k & \mathcal{L}\otimes\bar{B}_k K_k E_k \end{bmatrix}$$

$$\mathcal{H}_k = I_N \otimes \bar{H}_k, \ \ F_k = -(\mathcal{L}\otimes N_k)\Xi.$$

Remark 2: In order to improve the reliability and safety, the controller input should integrate some compensation to make up for the impact from occurred faults. Usually, a virtual system [22] or a dynamic compensator [23]–[25] can be employed to give rise to the desired control signal for the fault compensation. When MAS is a concern, the fault propagation is not considered if only the fault from the agent itself is compensated in the designed controller [25]. Fortunately, the fault propagation can be avoided via the utilization of a virtual system in the upper layer [22]. Compared with the existing literature, the propagation characteristics of the faults occurring in different agents are taken into account in this paper via the employed compensation $M_k \sum_{j\in\mathcal{N}_i} a_{ij}(\hat{f}_{j,t_k^j} - \hat{f}_{i,t_k^i})$ while the impact from external noises is also suppressed via embedding the statistical characteristic of noises.

In this paper, our aim is to design both the fault estimator gain G_k and the controller gain K_k such that the closed-loop system (12) reaches the pre-specified finite-horizon consensus performance with the given l_2-l_∞ constraint on the interval $[0, T]$. Specifically, the paper expects to the following two requirements:

1) By resorting to the collected local measurements, design a fault estimator (7) such that, based on estimate error dynamics (9), an upper bound of covariance matrices is achieved, that is, there is a positive definite matrix Γ_k guaranteeing $E\{e_k e_k^T\} \le \Gamma_k$ in least-squares sense;

2) In light of the estimated fault, design a fault-compensated consensus controller (8) such that the following l_2-l_∞ consensus performance is achieved for the closed-loop system (12)

$$\begin{aligned} E\{\sup\|\bar{z}_k\|^2\} < \gamma^2 \sum_{k=0}^{T} \Big\{ &\|d_k\|^2 + \lambda_{\max}\{\tilde{\mathcal{D}}_k\}\mathrm{trace}\{W\} \\ &+ \lambda_{\max}\{\tilde{\mathcal{E}}_k\}\mathrm{trace}\{V\}\Big\} + \gamma^2 E\Big\{\bar{\xi}_0^T \bar{\mathcal{Q}}_0 \bar{\xi}_0 \\ &+ e_0^T \bar{\mathcal{M}}_0 e_0 + \sum_{i=1}^{N} \frac{1}{\tau_i}\delta_{i,0}\Big\} \end{aligned} \tag{13}$$

where $\gamma > 0$ is a prescribed scalar, $\bar{\mathcal{Q}}_0 > 0$ and $\bar{\mathcal{M}}_0 > 0$ are two known weighted matrices.

III. Main Results

In this section, the error dynamics is first analyzed by using the least-squares approach to estimate the occurred faults. The consensus performance with the l_2-l_∞ constraint is then guaranteed for the closed-loop system with the formulated gains. To this end, the following lemmas are necessary.

Lemma 1 [33]: Assume that the map $\mathcal{W}_k(\cdot) : [0, T]\times\mathbb{R}^{n_x} \to \mathbb{R}^{n_x}$ is a positive-definite matrix function. If $\mathcal{W}(U_1) \le \mathcal{W}(U_2)$ for $0 \le U_1 \le U_2$ with $U_1 = U_1^T$ and $U_2 = U_2^T$, then the solutions $N_{k+1} = \mathcal{W}_k(N_k)$ and $M_{k+1} \le \mathcal{W}(M_k)$ with the initial condition $M_0 = N_0$ satisfy $M_{k+1} \le N_{k+1}$.

The following lemma can be easily realized along with a similar line in [19].

Lemma 2: For the dynamic event-triggering conditions (5) and (6) with $\delta_{i,0} \ge 0$ $(1 \le i \le N)$, $\delta_{i,k}$ satisfies $\delta_{i,k} \ge 0$ for all $k \in \mathbb{R}$ if there exist scalars ρ_i and τ_i such that $\rho_i\tau_i \ge 1$.

Remark 3: The above lemma definitely discloses the behavior of internal dynamic variable $\delta_{i,k}$, whose non-negativity caters for the requirement of practical engineering. Furthermore, such a variable provides more adjusting capability in comparison with traditional condition $h_{i,k}^{1T}h_{i,k}^1 + h_{i,k}^{2T}h_{i,k}^2 - \varepsilon_i y_{i,k}^T y_{i,k}$.

A. Performance Analysis and Gain Design of the Fault Estimator

In this subsection, let us discuss the performance of the fault estimator and its gain design in the least-squares sense. Specifically, the upper bound of the estimator error covariance is presented and the estimator gain is designed to guarantee that such an upper bound is minimized.

Theorem 1: The adopted fault estimator (7) with G_k is unbiased, and the upper bound of covariance matrices of estimation error dynamics (9) on the time interval $[0, T]$ satisfies the following iterative equation:

$$\begin{aligned} \Gamma_{k+1} = &(I_N\otimes\bar{A}_k - G_k\tilde{C}_k)\Gamma_k(I_N\otimes\bar{A}_k - G_k\tilde{C}_k)^T \\ &+ (I_N\otimes\bar{D}_k)W(I_N\otimes\bar{D}_k^T) + G_k\tilde{E}_k V\tilde{E}_k^T G_k^T \end{aligned} \tag{14}$$

where

$$W = \mathrm{diag}\{\sigma_{1,1}^2 I, \sigma_{1,2}^2 I, \ldots, \sigma_{1,N}^2 I\}$$

$$V = \mathrm{diag}\{\sigma_{2,1}^2 I, \sigma_{2,2}^2 I, \ldots, \sigma_{2,N}^2 I\}.$$

Proof: First, it follows from (9) that

$$\begin{aligned} E\{e_{k+1}\} &= E\{(I_N\otimes\bar{A}_k - G_k\tilde{C}_k)e_k \\ &\quad - G_k\tilde{E}_k(\nu_k - \tilde{\mu}_2) + (I_N\otimes\bar{D}_k)(\omega_k - \tilde{\mu}_1)\} \\ &= (I_N\otimes\bar{A}_k - G_k\tilde{C}_k)E\{e_k\} \end{aligned}$$

which means that the adopted fault estimator (7) is unbiased if the initial condition $E\{e_0\} = 0$.

Subsequently, let us compute the covariance of estimation error dynamics (9). Recalling the definition of covariance matrix, we calculate P_{k+1} along with the trajectory (9) that

$$\begin{aligned}P_{k+1} &= E\{e_{k+1}e_{k+1}^T\}\\ &= E\{[(I_N\otimes\bar{A}_k - G_k\tilde{C}_k)e_k - G_k\tilde{E}_k(\nu_k-\tilde{\mu}_2)\\ &\quad + (I_N\otimes\bar{D}_k)(\omega_k-\tilde{\mu}_1)][(I_N\otimes\bar{A}_k - G_k\tilde{C}_k)e_k\\ &\quad + (I_N\otimes\bar{D}_k)(\omega_k-\tilde{\mu}_1) - G_k\tilde{E}_k(\nu_k-\tilde{\mu}_2)]^T\}\\ &= (I_N\otimes\bar{A}_k - G_k\tilde{C}_k)P_k(I_N\otimes\bar{A}_k - G_k\tilde{C}_k)^T\\ &\quad + (I_N\otimes\bar{D}_k)W(I_N\otimes\bar{D}_k)^T + G_k\tilde{E}_kV\tilde{E}_k^TG_k^T.\end{aligned}$$

Noting Lemma 1, we can find that the obtained matrix Γ_k via the iterative equation (14) ensures $P_k \le \Gamma_k$ when the initial condition $\Gamma_0 \ge P_0$. ■

For the purpose of determining the estimator parameter, taking the partial derivation of trace Γ_{k+1} in regard to G_k into consideration, one obtains

$$\begin{aligned}\frac{\partial \mathrm{tr}(\Gamma_{k+1})}{\partial G_k} &= -(I_N\otimes\bar{A}_k)\Gamma_k\tilde{C}_k^T - \tilde{C}_k\Gamma_k(I_N\otimes\bar{A}_k)^T\\ &\quad + G_k\tilde{C}_k\Gamma_k\tilde{C}_k^T + \tilde{C}_k\Gamma_k\tilde{C}_k^TG_k^T\\ &\quad + G_k\tilde{E}_kV\tilde{E}_k^T + \tilde{E}_kV\tilde{E}_k^TG_k^T. \qquad (15)\end{aligned}$$

Now, the estimator parameter G_k can be determined by minimizing the trace of matrix Γ_{k+1}, whose analytical solution is provided in the following theorem.

Theorem 2: The adopted fault estimator (7) is unbiased, and the upper bound of its estimation error covariance on the time interval [0, T] is minimized via the following designed gain

$$G_k = (I_N\otimes\bar{A}_k)\Gamma_k\tilde{C}_k^T(\tilde{C}_k\Gamma_k\tilde{C}_k^T - \tilde{E}_kV\tilde{E}_k^T)^{-1} \qquad (16)$$

where the given initial matrix Γ_0 is a diagonal one.

B. Controller Design With Fault Compensation

In the above subsection, the desired fault estimator is designed in the mean square sense. In what follows, a fault tolerant controller is discussed with the help of obtained estimated faults in this subsection.

Theorem 3: Consider the MAS (1) under DETP (4) with two predetermined parameters ρ_i $(0<\rho_i<1)$ and τ_i $(\tau_i>0)$ meeting $\rho_i\tau_i \ge 1$ $(i\in\{1,\dots,N\})$. Let positive scalars γ and ε_i, two weighted matrices $\bar{\mathcal{Q}}_0$ and $\bar{\mathcal{M}}_0$, as well as two gain matrices K_k and G_k be given. The consensus performance (13) with the l_2-l_∞ constraint is achieved for the closed-loop system (12) if there exist two positive matrices $\mathcal{Q}_k$ and $\mathcal{M}_k$ (satisfying $\mathcal{Q}_0 \le \bar{\mathcal{Q}}_0$ and $\mathcal{M}_0 \le \bar{\mathcal{M}}_0$), and a constant $\kappa>0$ such that, for all $0\le k\le T$, the following linear matrix inequalities:

$$\Xi_k = \begin{bmatrix} \Xi_k^{11} & * & * & * & *\\ 0 & \Xi_k^{22} & * & * & *\\ \Xi_k^{31} & 0 & \Xi_k^{33} & * & *\\ \Xi_k^{41} & 0 & \Xi_k^{43} & \Xi_k^{44} & *\\ 0 & 0 & 0 & 0 & \vec{\Lambda}_3 \end{bmatrix} < 0 \qquad (17)$$

$$\begin{bmatrix} \mathcal{Q}_k & * \\ \mathcal{H}_k & \gamma^2 I \end{bmatrix} > 0 \qquad (18)$$

hold, where

$$\begin{aligned}\Xi_k^{11} &= \mathcal{A}_k^T\mathcal{Q}_{k+1}\mathcal{A}_k + \mathcal{C}_k^T\vec{\Lambda}_1\mathcal{C}_k - \mathcal{Q}_k\\ \Xi_k^{22} &= \mathcal{F}_k^T\mathcal{Q}_{k+1}\mathcal{F}_k + \tilde{\mathcal{A}}_k - \mathcal{M}_k\\ \Xi_k^{31} &= \mathcal{A}_k^T\mathcal{Q}_{k+1}\mathcal{B}_k,\ \Xi_k^{33} = \mathcal{B}_k^T\mathcal{Q}_{k+1}\mathcal{B}_k - \vec{\Lambda}_2\\ \Xi_k^{41} &= \mathcal{A}_k^T\mathcal{Q}_{k+1}\mathcal{D}_k + \mathcal{C}_k^T\vec{\Lambda}_1\mathcal{E}_k,\ \Xi_k^{43} = \mathcal{B}_k^T\mathcal{Q}_{k+1}\mathcal{D}_k\\ \Xi_k^{44} &= \mathcal{D}_k^T\mathcal{Q}_{k+1}\mathcal{D}_k + \mathcal{E}_k^T\vec{\Lambda}_1\mathcal{E}_k - \gamma^2 I\\ \vec{\Lambda}_1 &= \mathrm{diag}\Big\{\varepsilon_1\Big(\frac{1}{\tau_1}+\kappa\Big)I,\dots,\varepsilon_N\Big(\frac{1}{\tau_N}+\kappa\Big)I\Big\}\\ \vec{\Lambda}_2 &= \kappa I + \mathrm{diag}\Big\{\underbrace{\frac{1}{\tau_1}I,\frac{1}{\tau_1}I,\dots,\frac{1}{\tau_N}I,\frac{1}{\tau_N}I}_{2N}\Big\}\\ \vec{\Lambda}_3 &= \mathrm{diag}\Big\{\frac{\rho_1-1+\kappa}{\tau_1}I,\dots,\frac{\rho_N-1+\kappa}{\tau_N}I\Big\}.\end{aligned}$$

Proof: To begin with, the Lyapunov function is adopted as follows:

$$V_k = V_1(\bar{\xi}_k) + V_2(e_k) + V_3(\delta_k) \qquad (19)$$

where

$$V_1(\bar{\xi}_k) = \bar{\xi}_k^T\mathcal{Q}_k\bar{\xi}_k,\ \ V_2(e_k) = e_k^T\mathcal{M}_ke_k,\ \ V_3(\delta_k) = \frac{1}{\tau}\delta_k$$

and then the difference of V_k is written

$$\Delta V_k = \Delta V_1(\bar{\xi}_k) + \Delta V_2(e_k) + \Delta V_3(\delta_k) \qquad (20)$$

where

$$\begin{aligned}\Delta V_1(\bar{\xi}_k) &= E\{V_1(\bar{\xi}_{k+1})|\bar{\xi}_k\} - V_1(\bar{\xi}_k)\\ \Delta V_2(e_k) &= E\{V_2(e_{k+1})|e_k\} - V_2(e_k)\\ \Delta V_3(\delta_k) &= E\{V_3(\delta_{k+1})|\delta_k\} - V_3(\delta_k).\end{aligned}$$

From now on, calculating the difference of $\Delta V_1(\cdot)$ and $\Delta V_2(\cdot)$ along the trajectory of system (12), one has

$$\begin{aligned}E\{\Delta V_1(\bar{\xi}_k)\} &= E\Big\{\bar{\xi}_{k+1}^T\mathcal{Q}_{k+1}\bar{\xi}_{k+1} - \bar{\xi}_k^T\mathcal{Q}_k\bar{\xi}_k\Big\}\\ &= E\Big\{\Big(\mathcal{A}_k\bar{\xi}_k + \mathcal{F}_ke_k + \mathcal{B}_kh_k + \mathcal{D}_kd_k\Big)^T\mathcal{Q}_{k+1}\\ &\quad\times\Big(\mathcal{A}_k\bar{\xi}_k + \mathcal{F}_ke_k + \mathcal{B}_kh_k + \mathcal{D}_kd_k\Big) - \bar{\xi}_k^T\mathcal{Q}_k\bar{\xi}_k\Big\}\\ &= E\Big\{\bar{\xi}_k^T(\mathcal{A}_k^T\mathcal{Q}_{k+1}\mathcal{A}_k - \mathcal{Q}_k)\bar{\xi}_k + 2\bar{\xi}_k^T\mathcal{A}_k^T\mathcal{Q}_{k+1}\mathcal{B}_kh_k\\ &\quad + 2\bar{\xi}_k^T\mathcal{A}_k^T\mathcal{Q}_{k+1}\mathcal{D}_kd_k + 2h_k^T\mathcal{B}_k^T\mathcal{Q}_{k+1}\mathcal{D}_kd_k\\ &\quad + e_k^T\mathcal{F}_k^T\mathcal{Q}_{k+1}\mathcal{F}_ke_k + h_k^T\mathcal{B}_k^T\mathcal{Q}_{k+1}\mathcal{B}_kh_k\\ &\quad + d_k^T\mathcal{D}_k^T\mathcal{Q}_{k+1}\mathcal{D}_kd_k\Big\}. \qquad (21)\end{aligned}$$

and

$$\begin{aligned}E\{\Delta V_2(e_k)\} &= E\{e_{k+1}^T\mathcal{M}_{k+1}e_{k+1} - e_k^T\mathcal{M}_ke_k\}\\ &= E\{[(I_N\otimes\bar{A}_k - G_k\tilde{C}_k)e_k - G_k\tilde{E}_k(\nu_k-\tilde{\mu}_2)\\ &\quad + (I_N\otimes\bar{D}_k)(\omega_k-\tilde{\mu}_1)]^T\mathcal{M}_{k+1}[(I_N\otimes\bar{A}_k\\ &\quad - G_k\tilde{C}_k)e_k + (I_N\otimes\bar{D}_k)(\omega_k-\tilde{\mu}_1)\\ &\quad - G_k\tilde{E}_k(\nu_k-\tilde{\mu}_2)] - e_k^T\mathcal{M}_ke_k\}\\ &\le e_k^T(\tilde{\mathcal{A}}_k - \mathcal{M}_k)e_k + \lambda_{\max}\{\tilde{\mathcal{D}}_k\}\mathrm{trace}\{W\}\\ &\quad + \lambda_{\max}\{\tilde{\mathcal{E}}_k\}\mathrm{trace}\{V\} \qquad (22)\end{aligned}$$

where

$$\tilde{\mathcal{A}}_k = (I_N \otimes \bar{A}_k - G_k\tilde{C}_k)^T \mathcal{M}_{k+1}(I_N \otimes \bar{A}_k - G_k\tilde{C}_k)$$
$$\tilde{\mathcal{D}}_k = (I_N \otimes \bar{D}_k)^T \mathcal{M}_{k+1}(I_N \otimes \bar{D}_k)$$
$$\tilde{\mathcal{E}}_k = (G_k\tilde{E}_k)^T \mathcal{M}_{k+1} G_k \tilde{E}_k.$$

Similarly, we can derive $\Delta V_3(\cdot)$ along the trajectory (5) that

$$\begin{aligned} E\{\Delta V_3(\delta_k)\} &= E\Big\{\sum_{i=1}^{N}\frac{1}{\tau_i}(\delta_{i,k+1}-\delta_{i,k})\Big\} \\ &= E\Big\{\sum_{i=1}^{N}\frac{1}{\tau_i}(\rho_i\delta_{i,k} - h_{i,k}^{1T}h_{i,k}^{1} \\ &\quad - h_{i,k}^{2T}h_{i,k}^{2} + \varepsilon_i y_{i,k}^T y_{i,k} - \delta_{i,k})\Big\} \\ &= E\Big\{\sum_{i=1}^{N}\frac{\rho_i-1}{\tau_i}\delta_{i,k} + \bar{\xi}_k^T C_k \Lambda_1 C_k \bar{\xi}_k - h_k^T \Lambda_2 h_k \\ &\quad + 2\bar{\xi}_k^T C_k \Lambda_1 \mathcal{E}_k d_k + d_k^T \mathcal{E}_k^T \Lambda_1 \mathcal{E}_k d_k\Big\} \end{aligned} \tag{23}$$

where

$$\Lambda_1 = \mathrm{diag}\left\{\frac{\varepsilon_1}{\tau_1}I, \ldots, \frac{\varepsilon_N}{\tau_N}I\right\},$$
$$\Lambda_2 = \mathrm{diag}\left\{\underbrace{\frac{1}{\tau_1}I, \frac{1}{\tau_1}I, \ldots, \frac{1}{\tau_N}I, \frac{1}{\tau_N}I}_{2N}\right\}$$
$$C_k = I_N \otimes \bar{C}_k,\ \ \mathcal{E}_k = \begin{bmatrix} 0 & (I_N \otimes E_k) \end{bmatrix}.$$

Denoting $\eta_k = [\ \bar{\xi}_k^T \quad e_k^T \quad h_k^T \quad d_k^T \quad \bar{\delta}_k^T\ ]^T$ and $\bar{\delta}_k = [\delta_{1,k}^{\frac{1}{2}} \ \cdots \ \delta_{N,k}^{\frac{1}{2}}]^T$, and substituting (21)–(23) into (20) lead to

$$\begin{aligned} E\{\Delta V_k\} &= E\Big\{\bar{\xi}_k^T(\mathcal{A}_k^T Q_{k+1}\mathcal{A}_k + C_k^T\Lambda_1 C_k - Q_k)\bar{\xi}_k \\ &\quad + 2\bar{\xi}_k^T \mathcal{A}_k^T Q_{k+1}\mathcal{B}_k h_k + 2\bar{\xi}_k^T(\mathcal{A}_k^T Q_{k+1}\mathcal{D}_k \\ &\quad + C_k^T\Lambda_1\mathcal{E}_k)d_k + h_k^T(\mathcal{B}_k^T Q_{k+1}\mathcal{B}_k - \Lambda_2)h_k \\ &\quad + e_k^T\mathcal{F}_k^T Q_{k+1}\mathcal{F}_k e_k + e_k^T(\tilde{\mathcal{A}}_k - \mathcal{M}_k)e_k \\ &\quad + \lambda_{\max}\{\tilde{\mathcal{D}}_k\}\mathrm{trace}\{W\} + \lambda_{\max}\{\tilde{\mathcal{E}}_k\}\mathrm{trace}\{V\} \\ &\quad + 2h_k^T\mathcal{B}_k^T Q_{k+1}\mathcal{D}_k d_k + d_k^T(\mathcal{E}_k^T\Lambda_1\mathcal{E}_k \\ &\quad + \mathcal{D}_k^T Q_{k+1}\mathcal{D}_k)d_k + \sum_{i=1}^{N}\frac{\rho_i-1}{\tau_i}\delta_{i,k}\Big\} \\ &= E\Big\{\eta_k^T\bar{\Xi}_k\eta_k\Big\} + \lambda_{\max}\{\tilde{\mathcal{D}}_k\}\mathrm{trace}\{W\} \\ &\quad + \lambda_{\max}\{\tilde{\mathcal{E}}_k\}\mathrm{trace}\{V\} \end{aligned} \tag{24}$$

where

$$\bar{\Xi}_k = \begin{bmatrix} \bar{\Xi}_k^{11} & * & * & * & * \\ 0 & \Xi_k^{22} & * & * & * \\ \Xi_k^{31} & 0 & \bar{\Xi}_k^{33} & * & * \\ \bar{\Xi}_k^{41} & 0 & \Xi_k^{43} & \bar{\Xi}_k^{44} & * \\ 0 & 0 & 0 & 0 & \bar{\Xi}_k^{55} \end{bmatrix}$$

$$\bar{\Xi}_k^{11} = \mathcal{A}_k^T Q_{k+1}\mathcal{A}_k + C_k^T\Lambda_1 C_k - Q_k$$
$$\bar{\Xi}_k^{33} = \mathcal{B}_k^T Q_{k+1}\mathcal{B}_k - \Lambda_2$$
$$\bar{\Xi}_k^{41} = \mathcal{A}_k^T Q_{k+1}\mathcal{D}_k + C_k^T\Lambda_1\mathcal{E}_k$$
$$\bar{\Xi}_k^{44} = \mathcal{D}_k^T Q_{k+1}\mathcal{D}_k + \mathcal{E}_k^T\Lambda_1\mathcal{E}_k$$
$$\bar{\Xi}_k^{55} = \mathrm{diag}\left\{\frac{\rho_1-1}{\tau_1}I, \ldots, \frac{\rho_N-1}{\tau_N}I\right\}.$$

Meanwhile, reviewing (4), it is not difficult to obtain that

$$h_{i,k}^{1T}h_{i,k}^{1} + h_{i,k}^{2T}h_{i,k}^{2} - \frac{1}{\tau_i}\delta_{i,k} - \varepsilon_i y_{i,k}^T y_{i,k} \le 0. \tag{25}$$

Keeping the above inequality in mind, (24) yields

$$\begin{aligned} E\{\Delta V_k\} &\le E\Big\{\eta_k^T\bar{\Xi}_k\eta_k + \lambda_{\max}\{\tilde{\mathcal{D}}_k\}\mathrm{trace}\{W\} + \lambda_{\max}\{\tilde{\mathcal{E}}_k\}\mathrm{trace}\{V\} \\ &\quad - \sum_{i=1}^{N}\kappa\Big(h_{i,k}^{1T}h_{i,k}^{1} + h_{i,k}^{2T}h_{i,k}^{2} - \frac{1}{\tau_i}\delta_{i,k} - \varepsilon_i y_{i,k}^T y_{i,k}\Big)\Big\} \\ &= E\Big\{\eta_k^T\bar{\Xi}_k\eta_k + \sum_{i=1}^{N}\frac{\kappa}{\tau_i}\delta_{i,k} + \kappa(\bar{\xi}_k^T C_k^T\bar{\Lambda}_1 C_k\bar{\xi}_k \\ &\quad + 2\bar{\xi}_k^T C_k^T\bar{\Lambda}_1\mathcal{E}_k d_k + d_k^T\mathcal{E}_k^T\bar{\Lambda}_1\mathcal{E}_k d_k) - \kappa h_k^T h_k \\ &\quad + \lambda_{\max}\{\tilde{\mathcal{D}}_k\}\mathrm{trace}\{W\} + \lambda_{\max}\{\tilde{\mathcal{E}}_k\}\mathrm{trace}\{V\}\Big\} \\ &= E\Big\{\eta_k^T\tilde{\Xi}_k\eta_k\Big\} + \lambda_{\max}\{\tilde{\mathcal{D}}_k\}\mathrm{trace}\{W\} \\ &\quad + \lambda_{\max}\{\tilde{\mathcal{E}}_k\}\mathrm{trace}\{V\} \end{aligned} \tag{26}$$

where

$$\tilde{\Xi}_k = \begin{bmatrix} \Xi_k^{11} & * & * & * & * \\ 0 & \Xi_k^{22} & * & * & * \\ \Xi_k^{31} & 0 & \Xi_k^{33} & * & * \\ \Xi_k^{41} & 0 & \Xi_k^{43} & \tilde{\Xi}_k^{44} & * \\ 0 & 0 & 0 & 0 & \vec{\Lambda}_3 \end{bmatrix}$$
$$\tilde{\Xi}_k^{44} = \mathcal{D}_k^T Q_{k+1}\mathcal{D}_k + \mathcal{E}_k^T\vec{\Lambda}_1\mathcal{E}_k$$
$$\vec{\Lambda}_1 = \mathrm{diag}\{\varepsilon_1 I, \ldots, \varepsilon_N I\}.$$

In what follows, let us investigate the consensus performance with the l_2-l_∞ constraint for the MAS. To this end, it is easy to see that

$$\begin{aligned} &E\Big\{V_k - V_0 - \gamma^2\sum_{k=0}^{T}\Big(d_k^T d_k \\ &\quad + \lambda_{\max}\{\tilde{\mathcal{D}}_k\}\mathrm{trace}\{W\} + \lambda_{\max}\{\tilde{\mathcal{E}}_k\}\mathrm{trace}\{V\}\Big)\Big\} \\ &= E\Big\{\sum_{k=0}^{T}\Delta V_k - \gamma^2\sum_{k=0}^{T}\Big(d_k^T d_k \\ &\quad + \lambda_{\max}\{\tilde{\mathcal{D}}_k\}\mathrm{trace}\{W\} + \lambda_{\max}\{\tilde{\mathcal{E}}_k\}\mathrm{trace}\{V\}\Big)\Big\} \\ &\le \sum_{k=0}^{T}E\Big\{\eta_k^T\Xi_k\eta_k\Big\} \\ &\le 0 \end{aligned} \tag{27}$$

which means

$$E\{V_k\} \le \sum_{k=0}^{T} \gamma^2 \Big\{ d_k^T d_k + \lambda_{\max}\{\tilde{\mathcal{D}}_k\}\text{trace}\{W\} + \lambda_{\max}\{\tilde{\mathcal{E}}_k\}\text{trace}\{V\}\Big\} + E\{V_0\}. \tag{28}$$

Finally, the inequality (18) implies that $\mathcal{H}_k^T \mathcal{H}_k < \gamma^2 Q_k$ holds. Considering $\bar{z}_k$, one has

$$\begin{aligned} \bar{z}_k^T \bar{z}_k &= \bar{\xi}_k^T \mathcal{H}_k^T \mathcal{H}_k \bar{\xi}_k \\ &\le \gamma^2 \bar{\xi}_k^T Q_k \bar{\xi}_k \\ &\le \gamma^2 \left(\bar{\xi}_k^T Q_k \bar{\xi}_k + e_k^T \mathcal{M}_k e_k + \frac{1}{\tau}\delta_k \right) \\ &= V_k. \end{aligned} \tag{29}$$

Taking the conditions $Q_0 \le \bar{Q}_0$ and $\mathcal{M}_0 \le \bar{\mathcal{M}}_0$ as well as the above inequality into consideration, and (29), one has

$$\begin{aligned} E\{\sup\|\bar{z}_k\|^2\} \le \sum_{k=0}^{T} \gamma^2 \Big\{ & d_k^T d_k + \lambda_{\max}\{\tilde{\mathcal{D}}_k\}\text{trace}\{W\} \\ & + \lambda_{\max}\{\tilde{\mathcal{E}}_k\}\text{trace}\{V\}\Big\} \\ & + \gamma^2 E\Big\{ \bar{\xi}_0^T \bar{Q}_0 \bar{\xi}_0 + e_0^T \bar{\mathcal{M}}_0 e_0 + \sum_{i=1}^{N} \frac{1}{\tau_i}\delta_{i,0} \Big\} \end{aligned} \tag{30}$$

which means that the consensus performance is satisfied with the l_2-l_∞ constraint over a given finite horizon. ■

Next, the controller gains are obtained based on the linear matrix inequality technique.

Theorem 4: Consider the MAS (1) under DETP (4) with two predetermined parameters ρ_i $(0 < \rho_i < 1)$ and τ_i $(\tau_i > 0)$ meeting $\rho_i \tau_i \ge 1$ $(i \in \{1, \ldots, N\})$. Let positive scalars γ and ε_i as well as two weighted matrices $\bar{Q}_0$ and $\bar{\mathcal{M}}_0$ be given. The consensus performance (13) with the l_2-l_∞ constraint is achieved for the closed-loop system (12) if there exist the positive matrices Q_k and $\mathcal{M}_k$ (satisfying $Q_0 \le \bar{Q}_0$ and $\mathcal{M}_0 \le \bar{\mathcal{M}}_0$), matrices $G_{11,k}$, $G_{12,k}$ and $G_{22,k}$ and $\bar{K}_k$, and a constant $\kappa > 0$ such that, for all $0 \le k \le T$, the following linear matrix inequalities:

$$\begin{cases} \Sigma_k = \begin{bmatrix} \Sigma_k^{11} & * \\ \bar{\Sigma}_k^{21} & \bar{\Sigma}_k^{22} \end{bmatrix} < 0 & \text{(31a)} \\ \begin{bmatrix} Q_k & * \\ \mathcal{H}_k & \gamma^2 I \end{bmatrix} > 0 & \text{(31b)} \end{cases}$$

hold, where

$$\Sigma_k^{11} = \begin{bmatrix} \bar{\Sigma}_k^{11} & * & * & * & * \\ 0 & -\mathcal{M}_k & * & * & * \\ 0 & 0 & -\vec{\Lambda}_2 & * & * \\ C_k^T \vec{\Lambda}_1 \mathcal{E}_k & 0 & 0 & \bar{\Sigma}_k^{33} & * \\ 0 & 0 & 0 & 0 & \vec{\Lambda}_3 \end{bmatrix}$$

$$\bar{\Sigma}_k^{11} = C_k^T \vec{\Lambda}_1 C_k - Q_k, \ \ \tilde{\mathcal{A}}_k^2 = I_N \otimes \bar{A}_k - G_k \tilde{C}_k$$

$$\bar{\Sigma}_k^{21} = \begin{bmatrix} \tilde{\mathcal{A}}_k^1 & 0 & \tilde{\mathcal{B}}_k & \tilde{\mathcal{D}}_k & 0 \\ 0 & \mathcal{F}_k & 0 & 0 & 0 \\ 0 & \tilde{\mathcal{A}}_k^2 & 0 & 0 & 0 \end{bmatrix}$$

$$\bar{\Sigma}_k^{22} = \begin{bmatrix} Q_{k+1} - \mathcal{G}_k - \mathcal{G}_k^T & 0 & 0 \\ 0 & -Q_{k+1} & 0 \\ 0 & 0 & -\mathcal{M}_{k+1} \end{bmatrix}$$

$$\bar{\Sigma}_k^{33} = \mathcal{E}_k^T \vec{\Lambda}_1 \mathcal{E}_k - \gamma^2 I, \ \ \mathcal{G}_k = I_N \otimes G_{1k} W_k$$

$$\tilde{\mathcal{A}}_k^1 = I_N \otimes G_{1k} W_k \bar{A}_k + \mathcal{L} \otimes \tilde{K}_k \bar{C}_k - \mathcal{L} \otimes G_{1k} W_k \bar{N}_k$$

$$\tilde{\mathcal{B}}_k = \begin{bmatrix} \mathcal{L} \otimes \tilde{K}_k & -\mathcal{L} \otimes G_{1k} W_k N_k \end{bmatrix}$$

$$\tilde{\mathcal{D}}_k = \begin{bmatrix} \bar{\Phi} \otimes G_{1k} W_k \bar{D}_k & \mathcal{L} \otimes \tilde{K}_k E_k \end{bmatrix}$$

$$G_{1k} = \begin{bmatrix} G_{11k} & G_{12k} \\ 0 & G_{22k} \end{bmatrix}$$

$$W_k = \begin{bmatrix} \bar{B}_k (\bar{B}_k^T \bar{B}_k)^{-1} & (\bar{B}_k^T)^{\perp} \end{bmatrix}^T$$

$$\tilde{K}_k = \begin{bmatrix} \bar{K}_k^T & 0 \end{bmatrix}^T = G_{1k} W_k \bar{B}_k K_k.$$

Furthermore, when the above inequality is solvable, the expression of controller gain is determined by $K_k = G_{11k}^{-1} \bar{K}_k$.

Proof: First, in terms of the Schur complement lemma, (17) is written as follows:

$$\Sigma_k = \begin{bmatrix} \Sigma_k^{11} & * \\ \Sigma_k^{21} & \Sigma_k^{22} \end{bmatrix} < 0 \tag{32}$$

where

$$\Sigma_k^{21} = \begin{bmatrix} \mathcal{A}_k & 0 & \mathcal{B}_k & \mathcal{D}_k & 0 \\ 0 & \mathcal{F}_k & 0 & 0 & 0 \\ 0 & \tilde{\mathcal{A}}_k^2 & 0 & 0 & 0 \end{bmatrix}$$

$$\Sigma_k^{22} = \begin{bmatrix} -Q_{k+1}^{-1} & 0 & 0 \\ 0 & -Q_{k+1}^{-1} & 0 \\ 0 & 0 & -\mathcal{M}_{k+1}^{-1} \end{bmatrix}.$$

In what follows, pre-multiplying and post-multiplying inequality (32) by $\text{diag}\{I, I, I, I, I, \mathcal{G}_k, Q_{k+1}, \mathcal{M}_{k+1}\}$ and $\text{diag}\{I, I, I, I, I, \mathcal{G}_k^T, Q_{k+1}^T, \mathcal{M}_{k+1}\}$, respectively lead to

$$\Sigma_k = \begin{bmatrix} \Sigma_k^{11} & * \\ \bar{\Sigma}_k^{21} & \tilde{\Sigma}_k^{22} \end{bmatrix} < 0 \tag{33}$$

where

$$\tilde{\Sigma}_k^{22} = \begin{bmatrix} -\mathcal{G}_k Q_{k+1}^{-1} \mathcal{G}_k^T & 0 & 0 \\ 0 & -Q_{k+1} & 0 \\ 0 & 0 & -\mathcal{M}_{k+1} \end{bmatrix}.$$

Then, by means of the inequality

$$-\mathcal{G}_k Q_{k+1}^{-1} \mathcal{G}_k^T \le Q_{k+1} - \mathcal{G}_k - \mathcal{G}_k^T$$

the above inequality can be guaranteed by the following one

$$\begin{bmatrix} \Sigma_k^{11} & * \\ \bar{\Sigma}_k^{21} & \bar{\Sigma}_k^{22} \end{bmatrix} < 0. \tag{34}$$

Hence, the proof is completed. ■

Remark 4: The focus of this paper is on designing a consensus controller with fault-estimation-in-the-loop under DETP. Some sufficient conditions are derived in four theorems to achieve the predetermined consensus performance by resorting to the variance analysis and the stability analysis. Specifically, Theorems 1 and 2 deal with the issue of fault estimation, which provides the compensation information in the consensus controller. From these two theorems, we can find that (14) describes the iterative formula of error variance and the gain of fault estimator minimizing the above variance is determined by (16). Furthermore, based on the desired estimate of faults via Theorems 1 and 2, Theorems 3 and 4 handle the problems of the consensus analysis and gain design of the desired consensus controller, respectively. In Theorem 3, the condition (17) is related with consensus performance while the condition (18) comes from the requirement of the l_2-l_∞ constraint.

Remark 5: In comparison with the co-design based on linear matrix inequalities in [22]–[25], the paper proposes a novel cooperative framework under which the desired estimator and controller parameters are, respectively, gained by the solution of an algebraic matrix formula and a linear matrix inequality in a recursive way. It is not difficult to see that, in the process of estimator and controller design, some crucial features have been embodied to reflect the complexity which comprise: 1) the time-varying system parameters (A_k, B_k, C_k, D_k, E_k, F_k, H_k); 2) the dynamic trigger thresholds (internal dynamic variable $\delta_{i,k}$); 3) the fault estimation approach (the optimal estimation (14) and (16) in the least-squares sense); and 4) the distributed FTC mechanism (the compensation term $M_k \sum_{j\in\mathcal{N}_i} a_{ij}(\hat{f}_{j,t_k^j} - \hat{f}_{i,t_k^i})$ in (8)).

IV. Simulation Results

In this section, a simulation example is executed to illustrate the validity of the presented method for the MAS (1) with DETP. Consider corresponding parameters with

$$A_k = \begin{bmatrix} 0.99 + 0.05\cos(0.4k) & -0.45 \\ -0.10 & -0.73 - 0.1\cos(0.5k) \end{bmatrix}$$

$$B_k = \begin{bmatrix} 1 \\ 0.25 \end{bmatrix},\ D_k = \begin{bmatrix} 0.3 \\ 0.08 \end{bmatrix},\ F_k = \begin{bmatrix} 1 \\ 0.25 \end{bmatrix}$$

$$C_k = \begin{bmatrix} 1.05 & 0.1 \end{bmatrix},\ E_k = \begin{bmatrix} 0.2 & 0.3 \end{bmatrix}$$

$$H_k = \begin{bmatrix} 0.2 & 0.1 \end{bmatrix},\ M_k = 1.$$

In the simulation, the finite horizon is $[0, 45]$. Besides, we choose the initial conditions $x_{1,0} = [0.1\ \ 0.1]^T$, $x_{2,0} = [0.13\ \ 0.15]^T$, $x_{3,0} = [0.16\ \ 0.20]^T$, $x_{4,0} = [0.19\ \ 0.25]^T$, $x_{5,0} = [0.22\ \ 0.30]^T$. As shown in Fig. 1, consider five agents whose topology is given by an undirected communication graph $\mathcal{G}$ with the set of nodes $\mathcal{V} = \{1,2,3,4,5\}$ and the associated adjacency matrix $\mathcal{L}$ given as follows:

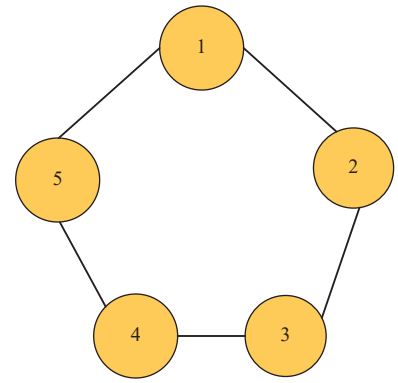

Fig. 1. Communication topology among five agents.

$$\mathcal{L} = \begin{bmatrix} -1 & 0.5 & 0 & 0 & 0.5 \\ 0.5 & -1 & 0.5 & 0 & 0 \\ 0 & 0.5 & -1 & 0.5 & 0 \\ 0 & 0 & 0.5 & -1 & 0.5 \\ 0.5 & 0 & 0 & 0.5 & -1 \end{bmatrix}.$$

The means are set as $\mu_{1,i} = 0.1$ and $\mu_{2,i} = 0.1$. The covariances are chosen as $\sigma_{1,i}^2 = 0.1$ and $\sigma_{2,i}^2 = 0.4$. In (4) and (5), the threshold and the dynamic variable are given as $\varepsilon_1 = \varepsilon_4 = 0.5$, $\varepsilon_2 = \varepsilon_5 = 0.6$, $\varepsilon_3 = 0.7$, $\delta_0^1 = \delta_0^4 = \delta_0^5 = 1$, and $\delta_0^3 = \delta_0^4 = 2$, respectively. The other parameters are chosen as $\tau_i = 4$ and $\rho_i = 0.5$ ($i \in \{1,\ldots,5\}$). The fault signals are created as:

$$f_{i,k} = \begin{cases} -0.1 - 0.02\sin(0.04k), & k > 10 \\ 0, & \text{otherwise} \end{cases}$$

where i belongs to $\{1,\ldots,5\}$.

The simulation results are shown in Figs. 2–6. Fig. 2 depicts the fault estimation signal for agents 1, 2, 4, 5. Therefore, it is easy to see from Fig. 2 that the designed fault estimation method is applicable. The state trajectories of five agents are depicted with the designed control scheme in Figs. 4–5. Fig. 3 shows the controlled outputs without and with FC for agents 1, 2, 4, 5. One can obtain that the proposed FC scheme performs quite well. Fig. 6 depicts the event-triggered release instants under DETP. It should be pointed out that the triggering instants are mainly focused on the time interval $[0, 20]$. The main reason should be that the consensus performance of the addressed MAS cannot be achieved at the beginning and hence their state trajectories need to be dynamically adjusted. In this scenario, the condition $\Upsilon(h_{i,k}^1, h_{i,k}^2, \delta_{i,k}, \varepsilon_i) > 0$ is easier to be satisfied and hence the measurements and estimated faults need to be transmitted. Surely, the number of information transmission and the update times of protocols are significantly reduced.

V. Conclusions

The paper has proposed a novel consensus control framework with fault-estimation-in-the-loop for the MASs under DETP. For the sake of mitigating unnecessary data communications and improving the utilization of communication resources, DETP has been utilized by adding an auxiliary variable,

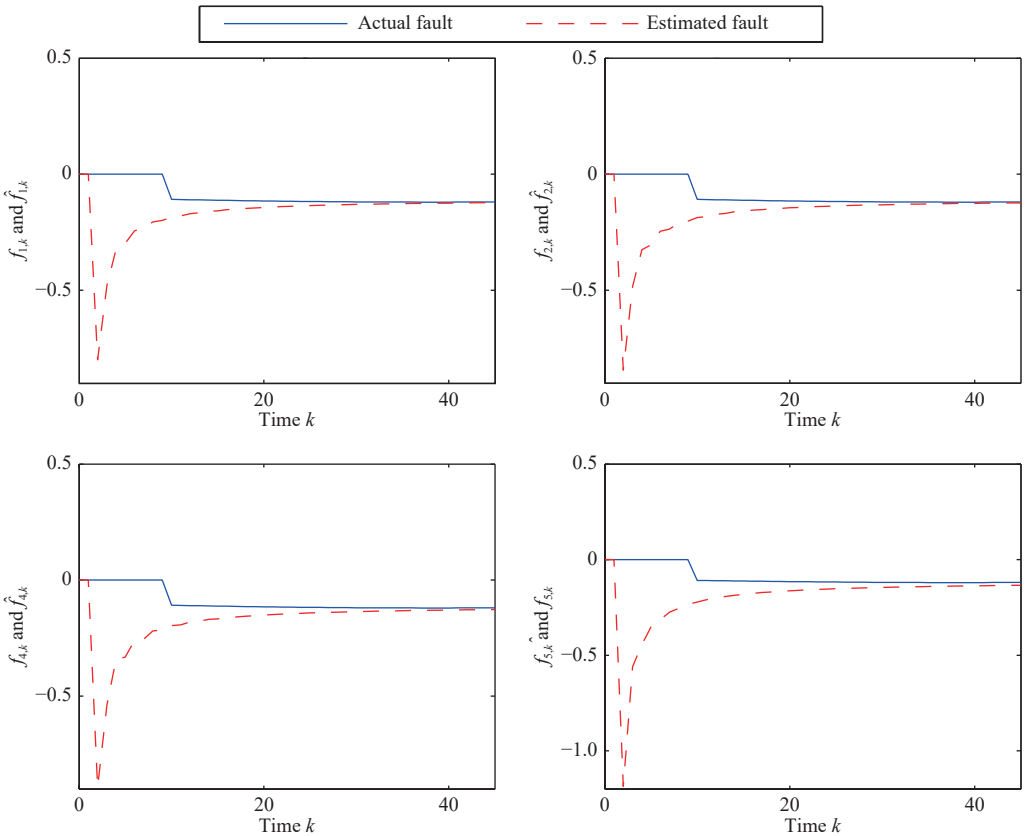

Fig. 2. Actual fault and its estimation.

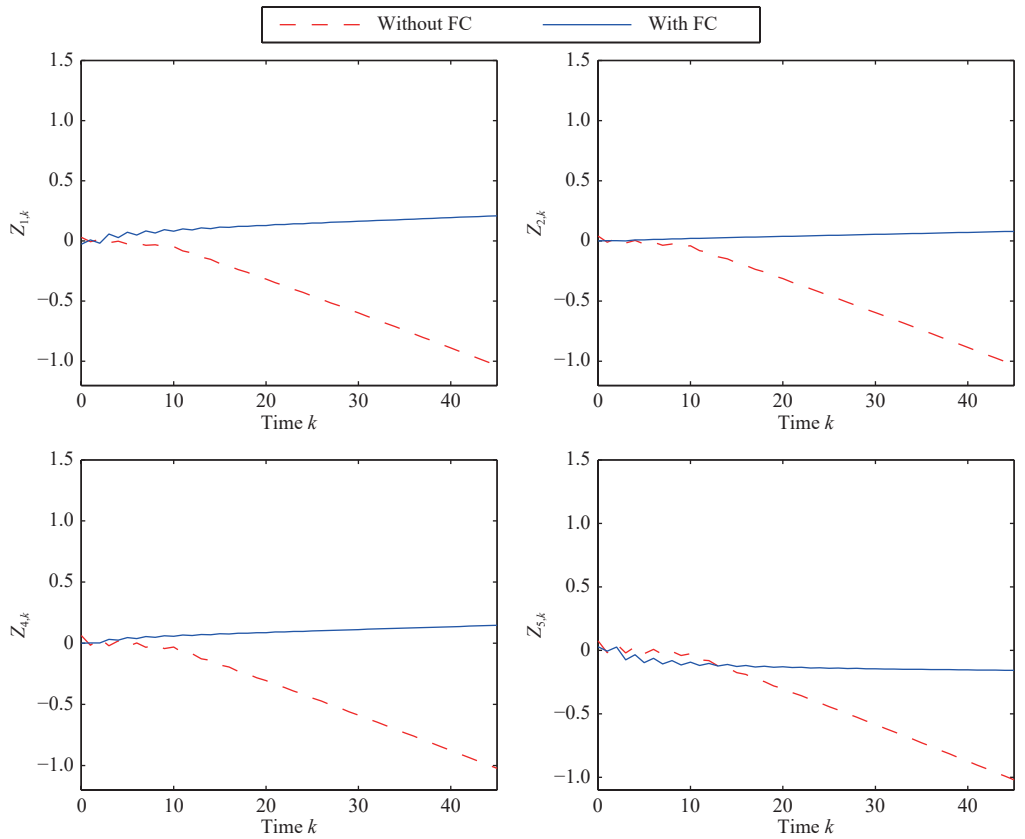

Fig. 3. The controlled output without FC and with FC.

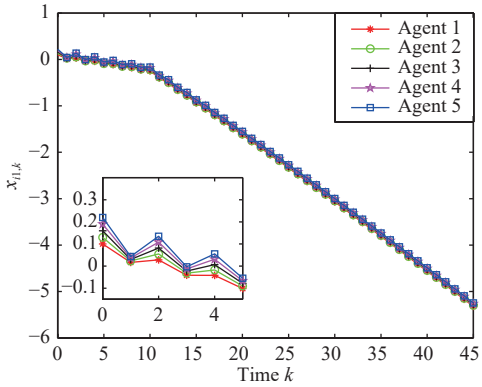

Fig. 4. State trajectories $x_{i1,k}$ of five agents.

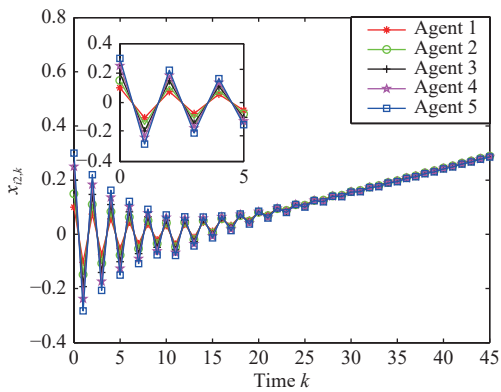

Fig. 5. State trajectories $x_{i2,k}$ of five agents.

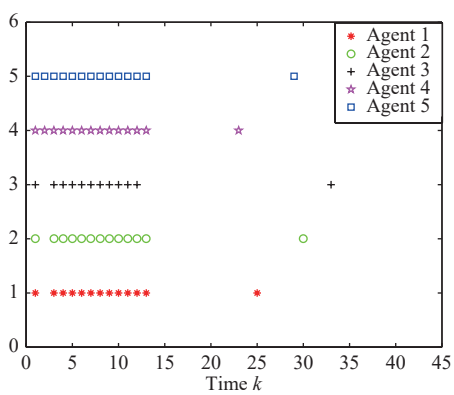

Fig. 6. Triggered instants of five agents.

where each agent transmits the measurement only when a predetermined triggering function is satisfied. Besides, according to utilizing the variance analysis and the Lyapunov stability approaches, the predetermined consensus performance with the l_2-l_∞ constraint has been guaranteed. Furthermore, the desired estimator and controller gains have been obtained in light of the solution to an algebraic matrix equation and a linear matrix inequality in a recursive way, respectively. At last, a simulation result has been provided to verify the effectiveness of the proposed approach. Further research topics include the extension of our results to more general consensus issues with both communication protocols and cyber-attacks [34]–[36].

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