

Event-Triggered Fault-Tolerant Control for Multi-Agent Systems with Polynomial-Form Faults

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Abstract: This paper addresses the fault-tolerant control(FTC) problem in multi-agent systems(MAS), with a focus on actuator faults characterized by polynomial forms. The polynomial model effectively captures a variety of complex fault patterns and enables flexible representation of fault signals through polynomial approximation. Based on this model, a state observer is designed to simultaneously estimate the system states, fault signals, and external disturbances. To reduce communication load, an event-triggered mechanism incorporating an open-loop estimator is introduced. By integrating the observer and the event-triggered mechanism, a distributed FTC protocol is developed, which not only mitigates the impact of actuator faults but also attenuates external disturbances, thereby significantly enhancing system stability. Both theoretical analysis and simulation results demonstrate that the proposed scheme ensures satisfactory consensus performance in MAS.

Keywords: fault-tolerant control; multi-agent systems; polynomial model; event-triggered mechanism

1. Introduction

In contemporary control theory and practice, the notion of MAS is motivated by cooperative swarm phenomena observed in nature. These systems demonstrate distinct advantages in highly automated environments, with representative applications including unmanned surface vessel clusters [1,2], coordinated unmanned aerial vehicle formations [3–5], and intelligent logistics scheduling [6,7]. Accordingly, agents must coordinate their actions during operation under prescribed/common rules to achieve the overall objective. Reaching consensus relies on information exchange, which is pivotal for maintaining system-wide performance and efficiency [8–10].

In real-world implementations, MAS frequently encounter uncertainties including component malfunctions and external disturbances. Such uncertainties may considerably compromise system performance and, in severe cases, result in complete system failure. Consequently, the development of robust FTC schemes becomes essential. Various FTC approaches have been investigated from different perspectives. For instance, topology-reconstruction-based fault-tolerant strategies have been developed to maintain cooperative performance in the presence of agent faults and communication topology variations [11]. Distributed adaptive FTC methods have also been investigated for heterogeneous MASs subject to actuator faults and time-varying communication delays [12]. From the perspective of fault estimation and compensation, observer-based predictive FTC schemes have been developed to actively estimate actuator faults and compensate for their adverse effects [13]. More recently, event-triggered FTC has been further investigated to simultaneously address fault tolerance and communication-efficiency requirements in MASs [14]. These studies demonstrate that FTC technology plays an important role in enhancing system adaptability and robustness and maintaining the desired system performance in the presence of faults and disturbances.

Actuator faults represent one of the most prevalent types of failures and are frequently encountered in MAS [15]. Such faults can arise from multiple sources, including electrical anomalies, human operational errors, or mechanical wear, often preventing the system from achieving its predefined objectives. Consequently, developing FTC strategies

capable of effectively handling actuator faults is essential for ensuring system safety and reliability. However, many existing FTC studies are developed for constant, bounded, or specifically structured actuator faults. Although these formulations facilitate controller and observer design, they may not adequately describe more complicated time-varying fault profiles encountered in practical systems. Polynomial-form fault models provide a more flexible representation and can characterize a broader class of actuator fault behaviors, making FTC design under such models both theoretically and practically relevant [8,16].

Network communication resources in MAS are typically limited, and without proper management, they can significantly compromise cooperative efficiency. Although traditional time-triggered sampling methods offer some improvement, their resource utilization efficiency remains suboptimal. In comparison, event-triggered mechanisms provide a more resource-efficient alternative. Rather than continuously monitoring system states, this approach initiates data transmission and control updates only when predefined triggering conditions are met. For example, Zhao et al. [17] investigated the fast finite-time consensus problem of high-order nonlinear MASs under an event-triggered communication scheme, demonstrating that event-driven information exchange can effectively reduce unnecessary communication while preserving the desired consensus performance. In addition to communication efficiency, secure information exchange has also received increasing attention in networked control systems. For instance, Li et al. [18] investigated encryption/decryption mechanisms and learning-based replay-attack detection for switched systems to improve communication security. More recently, event-triggered mechanisms have also been incorporated into FTC frameworks to simultaneously address communication efficiency and fault accommodation under faults and network attacks [14]. Furthermore, by enforcing a positive lower bound on the inter-event time, Zeno behavior can be effectively excluded. Nevertheless, most existing event-triggered studies primarily focus on reducing communication or sampling frequency, while the joint treatment of communication efficiency, fault estimation, disturbance rejection, and fault-tolerant consensus remains relatively limited. This mechanism substantially reduces communication consumption while maintaining control accuracy. Despite these advances, several issues remain to be further addressed. First, many existing FTC methods for MAS are established for relatively simple or specifically structured actuator faults, which restricts their ability to represent more general time-varying fault behaviors. Second, fault estimation, disturbance rejection, and communication-resource reduction are often considered separately, making it difficult to simultaneously achieve fault accommodation and communication efficiency. Moreover, although event-triggered strategies have been widely investigated for reducing communication burden, their integration with observer-based FTC under general actuator faults and external disturbances remains insufficiently explored. Therefore, developing a unified framework that can characterize diverse actuator faults, estimate system states, faults, and disturbances, and simultaneously reduce communication consumption remains a meaningful problem.

To address the above issues, this paper develops an event-triggered observer-based FTC framework for MAS subject to actuator faults and external disturbances. Polynomial functions are introduced to provide a flexible representation of different actuator fault profiles. On this basis, an observer is constructed to simultaneously estimate the system states, actuator faults, and external disturbances. Furthermore, an event-triggered mechanism incorporating an open-loop estimator is integrated into the FTC design to reduce unnecessary communication while preserving the required consensus performance.

Based on the above analysis, the main contributions of this paper can be summarized as follows:

- (1) A unified observer-based FTC framework is developed for MAS subject to actuator faults and external disturbances. Compared with existing FTC approaches that mainly consider constant, bounded, or specifically structured actuator faults, the proposed method employs a polynomial representation to describe a broader class of time-varying fault profiles. By incorporating this fault representation into the augmented observer dynamics, the system states, actuator faults, and external disturbances are estimated simultaneously, providing the information required for distributed fault compensation.
- (2) An event-triggered fault-tolerant consensus strategy incorporating an open-loop estimator is developed based on the obtained estimates. Different from existing studies in which event-triggered communication and fault compensation are generally treated separately, the proposed scheme integrates fault/disturbance estimation, fault-tolerant consensus control, and communication-resource reduction within a unified framework. Moreover, the open-loop estimator provides the required broadcasting information between two consecutive triggering instants, thereby avoiding continuous information transmission. Theoretical analysis establishes the desired consensus performance and excludes Zeno behavior.

2. Preliminaries and Problem Formulation

2.1. Graph Theory

Let $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ denote an undirected graph, where the vertex set is $\mathcal{V} = \{\mathcal{V}_1, \dots, \mathcal{V}_N\}$ and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ denotes the edge set. An edge $(\mathcal{V}_i, \mathcal{V}_j) \in \mathcal{E}$ indicates that agents i and j can exchange information. Since $\mathcal{G}$ is undirected, $(\mathcal{V}_i, \mathcal{V}_j) \in \mathcal{E}$ if and only if $(\mathcal{V}_j, \mathcal{V}_i) \in \mathcal{E}$.

The adjacency matrix $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{N \times N}$ is defined by $a_{ij} = a_{ji} > 0$ if $(\mathcal{V}_i, \mathcal{V}_j) \in \mathcal{E}$ and $a_{ij} = 0$ otherwise, with $a_{ii} = 0$. The graph $\mathcal{G}$ is connected if there exists a path between any two vertices. The neighbor set of vertex i is defined as $\mathcal{N}_i = \{j \in \{1, \dots, N\} \mid a_{ij} > 0\}$.

The Laplacian matrix of $\mathcal{G}$, denoted by $\mathcal{L} = [l_{ij}] \in \mathbb{R}^{N \times N}$, is defined as $l_{ii} = \sum_{j=1}^N a_{ij}$, $l_{ij} = -a_{ij}$, $i \neq j$. For an undirected graph, $\mathcal{L}$ is symmetric. Moreover, if $\mathcal{G}$ is connected, its eigenvalues satisfy

$$0 = \lambda_1(\mathcal{L}) < \lambda_2(\mathcal{L}) \leq \dots \leq \lambda_N(\mathcal{L}),$$

and $\mathcal{L}$ can be orthogonally diagonalized.

2.2. System Modeling

Consider a MAS with N agents, whose i -th agent obeys

$$\begin{aligned} \dot{x}_i(t) &= Ax_i(t) + Bu_i(t) + Ff_i(t) + Dd_i(t), \\ y_i(t) &= Cx_i(t). \end{aligned} \quad (1)$$

Here, $x_i(t) \in \mathbb{R}^n$, $y_i(t) \in \mathbb{R}^p$, $u_i(t) \in \mathbb{R}^m$, $f_i(t) \in \mathbb{R}^{n_f}$, and $d_i(t) \in \mathbb{R}^{n_d}$ denote, respectively, the state, measured output, control input, actuator fault, and exogenous disturbance of agent i . The constant matrices satisfy

$$A \in \mathbb{R}^{n \times n}, B \in \mathbb{R}^{n \times m}, C \in \mathbb{R}^{p \times n}, F \in \mathbb{R}^{n \times n_f}, D \in \mathbb{R}^{n \times n_d}.$$

In this study, the actuator fault $f_i(t) \in \mathbb{R}^{n_f}$ is modeled as a time-varying polynomial of degree $q - 1$:

$$\begin{aligned} f_i(t) &= \kappa_{i,0} + \kappa_{i,1}t + \kappa_{i,2}t^2 + \dots + \kappa_{i,q-1}t^{q-1} \\ &= \sum_{k=0}^{q-1} \kappa_{i,k}t^k, \end{aligned} \quad (2)$$

where $\kappa_{i,k} \in \mathbb{R}^{n_f}$, $k = 0, 1, \dots, q - 1$, are unknown constant coefficient vectors, and $q \in \mathbb{N}$ is a prescribed constant. The notation $f_i^{(r)}(t)$ denotes the r -th time derivative of $f_i(t)$. Since $f_i(t)$ is a polynomial of degree $q - 1$, it follows that $f_i^{(q)}(t) = 0$.

Define

$$z_i(t) = \text{col}\{f_i^{(q-1)}(t), f_i^{(q-2)}(t), \dots, f_i^{(1)}(t)\} \in \mathbb{R}^{(q-1)n_f}.$$

Then, (2) can be equivalently represented as

$$\underbrace{\begin{bmatrix} f_i^{(q)} \\ f_i^{(q-1)} \\ f_i^{(q-2)} \\ \vdots \\ f_i^{(2)} \\ f_i^{(1)} \end{bmatrix}}_{\begin{bmatrix} \dot{z}_i \\ f_i \end{bmatrix}} = \underbrace{\begin{bmatrix} 0 & 0 & \dots & 0 & 0 & 0 \\ I & 0 & \dots & 0 & 0 & 0 \\ 0 & I & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & I & 0 & 0 \\ 0 & 0 & \dots & 0 & I & 0 \end{bmatrix}}_{\begin{bmatrix} \bar{J}_1 & 0 \\ \bar{J}_2 & 0 \end{bmatrix}} \underbrace{\begin{bmatrix} f_i^{(q-1)} \\ f_i^{(q-2)} \\ f_i^{(q-3)} \\ \vdots \\ f_i^{(1)} \\ f_i \end{bmatrix}}_{\begin{bmatrix} z_i \\ f_i \end{bmatrix}}. \quad (3)$$

Here, each I and 0 in (3) denotes $I_{n_f} \in \mathbb{R}^{n_f \times n_f}$ and $0_{n_f \times n_f}$, respectively. Accordingly,

$$\bar{J}_1 \in \mathbb{R}^{(q-1)n_f \times (q-1)n_f}, \quad \bar{J}_2 \in \mathbb{R}^{n_f \times (q-1)n_f}.$$

After rearrangement, the dynamics of the MAS can be expressed as:

$$\begin{cases} \dot{x}_i(t) = Ax_i(t) + Bu_i(t) + Ff_i(t) + Dd_i(t), \\ y_i(t) = Cx_i(t), \\ \dot{z}_i(t) = \bar{J}_1 z_i(t), \\ f_i(t) = \bar{J}_2 z_i(t). \end{cases} \quad (4)$$

The unknown disturbance $d_i(t)$ is produced by an exogenous system, which is represented as follows:

$$\begin{cases} \dot{\omega}_i(t) = \mathcal{W}\omega_i(t) \\ d_i(t) = \mathcal{V}\omega_i(t). \end{cases} \quad (5)$$

Remark 1. The approach effectively models the disturbance via a first-order low-pass structure with a specified cutoff. After parameter tuning, ω_i is replaced by d_i the model is suitable for a wide range of engineering disturbance types.

Assumption 1. (A, B) is controllable, $(\mathcal{W}, \mathcal{V})$ is observable.

Assumption 2. $\text{Rank}(B, F) = \text{Rank}(B)$; $\text{Rank}(B, D) = \text{Rank}(B)$.

2.3. Control Objective

Consider system (1) over a communication graph $\mathcal{G}$. A distributed event-triggered controller $u_i(t)$ achieves leaderless consensus for system (1)

$$\lim_{t \rightarrow \infty} \|x_i(t) - x_j(t)\| = 0, \quad \forall i, j = 1, 2, \dots, N. \quad (6)$$

3. Main Results

This section investigates the FTC problem for system (1) subject to faults and exogenous disturbances. An observer is first constructed to jointly estimate the agent states, the fault, and the disturbance. An event-triggered mechanism with open-loop estimation is then incorporated to improve communication efficiency. Building on these components, a distributed FTC scheme is developed to ensure that the system remains stable and attains the prescribed control objectives in the presence of faults and disturbances.

For systems (1) (2) (5), the following observer is designed:

$$\begin{cases} \dot{\hat{x}}_i(t) = A\hat{x}_i(t) + Bu_i(t) + D\hat{d}_i(t) + F\hat{f}_i(t) + E_1\epsilon_i(t), \\ \dot{\hat{z}}_i(t) = \bar{J}_1\hat{z}_i(t) + E_2\epsilon_i(t), \\ \dot{\hat{\omega}}_i(t) = \mathcal{W}\hat{\omega}_i(t) + E_3\epsilon_i(t), \\ \dot{\hat{f}}_i(t) = \bar{J}_2\hat{z}_i(t) + E_4\epsilon_i(t), \end{cases} \quad (7)$$

where $\epsilon_i(t)$ denotes the relative output error, defined as:

$$\epsilon_i(t) = C(x_i(t) - \hat{x}_i(t)). \quad (8)$$

Here, $\hat{x}_i(t)$, $\hat{z}_i(t)$ and $\hat{\omega}_i(t)$ denote the estimates of $x_i(t)$, $z_i(t)$ and $\omega_i(t)$, respectively. Accordingly, the estimation errors are defined as $e_{x_i}(t) = x_i(t) - \hat{x}_i(t)$, $e_{z_i}(t) = z_i(t) - \hat{z}_i(t)$, $e_{\omega_i}(t) = \omega_i(t) - \hat{\omega}_i(t)$, $e_{f_i}(t) = f_i(t) - \hat{f}_i(t)$.

The augmented estimation error vector formed by these errors is $\bar{e}_i(t) = [e_{x_i}^T(t) \ e_{z_i}^T(t) \ e_{\omega_i}^T(t) \ e_{f_i}^T(t)]^T$. From (1) and (7), the error system of agent i is given by:

$$\begin{aligned} e_{x_i}(t) &= A e_{x_i}(t) + B \mathcal{V} e_{\omega_i}(t) + F e_{f_i}(t) - E_1 \epsilon_i(t), \\ e_{z_i}(t) &= \bar{J}_1 e_{z_i}(t) - E_2 \epsilon_i(t), \\ e_{\omega_i}(t) &= \mathcal{W} e_{\omega_i}(t) - E_3 \epsilon_i(t), \\ \dot{e}_{f_i}(t) &= \bar{J}_2 e_{z_i}(t) - E_4 \epsilon_i(t). \end{aligned} \quad (9)$$

After further aggregation and algebraic simplification of the preceding error system, the following form is obtained:

$$\dot{\bar{e}}_i(t) = \underbrace{\begin{bmatrix} A & 0 & D\mathcal{V} & F \\ 0 & \bar{J}_1 & 0 & 0 \\ 0 & 0 & \mathcal{W} & 0 \\ 0 & \bar{J}_2 & 0 & 0 \end{bmatrix}}_{\bar{A}} \bar{e}_i(t) - \underbrace{\begin{bmatrix} E_1 \\ E_2 \\ E_3 \\ E_4 \end{bmatrix}}_E \epsilon_i(t). \quad (10)$$

where $\bar{e}_i = [e_{x_i}^T \ e_{z_i}^T \ e_{\omega_i}^T \ e_{f_i}^T]^T$.

Accordingly, the augmented error system can be expressed as:

$$\dot{\bar{e}}_i(t) = \bar{A}\bar{e}_i(t) - E\epsilon_i(t). \quad (11)$$

Since the designed system operates through the cooperation of N agents, define the stacked error vector as $\bar{e}(t) = [\bar{e}_1^T(t) \ \dots \ \bar{e}_N^T(t)]^T$.

The global error system for the N agents is given by:

$$\dot{\bar{e}}(t) = [I_N \otimes (\bar{A} - E\bar{C})]\bar{e}(t) \quad (12)$$

where $\bar{C} = [C, 0, 0, 0]$.

Theorem 1. The error system in (12) is asymptotically stable provided that there exists a symmetric positive definite matrix $P_1 > 0$ satisfying the following linear matrix inequality.

$$P_1\bar{A} + \bar{A}^T P_1 - Y\bar{C} - \bar{C}^T Y^T < 0 \quad (13)$$

where $Y = P_1 E$.

Proof. Define the following Lyapunov function:

$$V_1(t) = \bar{e}^T(t)(I_n \otimes P_1)\bar{e}(t) \quad (14)$$

the $\dot{V}_1(t)$ is derived as

$$\dot{V}_1(t) = \bar{e}^T(t)[I_N \otimes (P_1\bar{A} + \bar{A}^T P_1 - Y\bar{C} - \bar{C}^T Y^T)]\bar{e}(t). \quad (15)$$

By Theorem 1, it follows that $\dot{V}_1(t) < 0$ along the trajectories. Consequently, the global estimation error system (12) is asymptotically stable. This concludes the design of the observer and its stability proof.

To improve the utilization of communication resources and avoid unnecessary transmissions, an event-triggered mechanism is employed to update the control signals. This mechanism adopts a threshold rule that leverages adjacency-based broadcast information, thereby reducing redundant communication. For agent i , let $\{t_0^i, t_1^i, \dots, t_{k_i}^i, \dots\}$ denote the event times within $[t_0, t)$, and let $N_e(t_0, t)$ be the number of events occurring on $[t_0, t)$. An event is generated whenever the proactive-update condition of agent i is satisfied. For $t \in [t_{k_i}^i, t_{k_i+1}^i)$, the following FTC law is applied:

$$u_i(t) = -K_1 \hat{\bar{x}}_i(t) + K_2 \Omega_i(x_{j \in N_i}^e(t)) \quad (16)$$

Here, $K_1 = [K_x, 0, K_w, K_f]$ denotes the compensation-based estimation gain, and $\hat{\bar{x}}_i(t) = [\hat{x}_i^T(t), \hat{z}_i^T(t), \hat{w}_i^T(t), \hat{f}_i^T(t)]^T$ is the stacked estimate of agent i . The matrix $K_2 \in \mathbb{R}^{m \times n}$ represents the broadcast weighting matrix induced by the adjacency relations. The broadcast term is defined by

$$\Omega_i(x_{j \in N_i}^e(t)) = \sum_{j \in \mathcal{N}_i} a_{ij} (x_j^e(t) - x_i^e(t)), \quad (17)$$

where a_{ij} denotes the (i, j) -th entry of the adjacency matrix $\mathcal{A}$ associated with graph $\mathcal{G}$. The variable $x_i^e(t)$ denotes the broadcast estimate of agent i generated from its most recently triggered state. Specifically, $t_{k_i}^i(t)$ denotes the latest successful triggering instant of agent i before time t , and the broadcast estimate is initialized by

$$x_i^e(t_{k_i}^i(t)) = x_i(t_{k_i}^i(t)). \quad (18)$$

Similarly, for neighboring agents, $x_j^e(t)$ denotes the broadcast estimate of agent j generated from its most recently triggered state $x_j(t_{k_j}^j)$. For $t \in [t_{k_j}^j, t_{k_j+1}^j)$, the dynamics of the adjacency-broadcast variable are given by

$$\dot{x}_j^e(t) = Ax_j^e(t), \quad x_j^e(t_{k_j}^j) = x_j(t_{k_j}^j). \quad (19)$$

Define the event-triggered error as $\rho_i(t) = x_i^e(t) - x_i(t)$. The event-triggering scheme $\{t_{k_i}^i\}_{k_i \in \mathbb{N}}$ determines the activation sequence by imposing the following temporal constraints:

$$\|\rho_i(t)\| \leq \xi_i \|\Omega_i(x_{i \in \mathcal{N}_i}^s(t))\| \quad (20)$$

where $\xi_i > 0$ denotes the triggering threshold. This guarantees that the update law $u_i(t)$ in (16) is executed only provided that the event-triggered error $\rho_i(t)$ satisfies the neighborhood-based triggering condition.

By substituting (16) into (1), the dynamic equation for agent i is derived as:

$$\begin{aligned} \dot{x}_i(t) = & (A - BK_x)x_i(t) + BK_1\bar{e}_i(t) \\ & + BK_2 \sum_{j \in \mathcal{N}_i} a_{ij}(x_j(t) - x_i(t)) \\ & + BK_2 \sum_{j \in \mathcal{N}_i} a_{ij}(\rho_j(t) - \rho_i(t)) \end{aligned} \quad (21)$$

this directly leads to

$$\begin{aligned} \dot{x}(t) = & [I_n \otimes (A - BK_x) - \mathcal{L} \otimes BK_2]x(t) \\ & + (I_n \otimes BK_1)\bar{e}(t) - (\mathcal{L} \otimes BK_2)\rho(t) \end{aligned} \quad (22)$$

where $x(t) = \text{col}(x_i(t))$, $\bar{e}(t) = \text{col}(\bar{e}_i(t))$, $\rho(t) = \text{col}(\rho_i(t))$. The graph Laplacian matrix is denoted by $\mathcal{L}$. $\square$

Assumption 3. The graph $\mathcal{G}$ is undirected and connected.

Define the consensus error as $e_i(t) = x_i(t) - \bar{x}(t)$, $\bar{x}(t) = \frac{1}{N} \sum_{j=1}^N x_j(t)$. Stack the vectors as $e(t) = \text{col}(e_1(t), \dots, e_N(t))$, $x(t) = \text{col}(x_1(t), \dots, x_N(t))$. Then the stacked error admits the compact form $e(t) = (\mathcal{M} \otimes I_n)x(t)$, $\mathcal{M} = I_N - \frac{1}{N}\mathbf{1}_N\mathbf{1}_N^T$.

Under Assumption 3, there exists an orthogonal matrix $\Gamma = [\frac{1}{\sqrt{N}}, \gamma_2, \gamma_3, \dots, \gamma_N]$, where $\gamma_i \in \mathbb{R}^N$ for $i = 2, 3, \dots, N$ are orthogonal eigenvectors of the Laplacian $\mathcal{L}$ associated with the eigenvalues $\lambda_i(\mathcal{L})$. Consequently, the following properties hold: $\Gamma\Gamma^T = I_N$, $\mathcal{L}\mathcal{M} = \mathcal{Y}\mathcal{M} = \mathcal{L}\gamma\gamma^T = \mathcal{M} = I_N - \frac{1}{N}\mathbf{1}_N\mathbf{1}_N^T$, $\Gamma^T\mathcal{L}\Gamma = \text{diag}\{0, \lambda_i(\mathcal{L})\}$.

Accordingly, the global state consensus error is given by:

$$\begin{aligned} \dot{e}(t) = & [I_N \otimes (A - BK_x) - \mathcal{L} \otimes BK_2]e(t) \\ & + (\mathcal{M} \otimes BK_1)\bar{e}(t) - (\mathcal{L} \otimes BK_2)\rho(t) \end{aligned} \quad (23)$$

Theorem 2. Let $\iota > 0$. If there exist symmetric positive definite matrices $P_2, Q_1, Q_2 \in \mathbb{R}^{n \times n}$, $R \in \mathbb{R}^{m \times m}$ and $K_x \in \mathbb{R}^{m \times n}$ satisfying the following conditions:

$$-Q_1 - P_2BK_x - K_x^TB^TP_2 + Q_2 < 0 \quad (24)$$

Assuming Theorem 1 holds, the following additional conditions must be satisfied:

$$P_1\bar{A} + \bar{A}^TP_1 - R\bar{C} - \bar{C}^TR^T + \sigma_1P_1 + \mu_1I_{n_a} < 0. \quad (25)$$

Then, under the event-triggered condition (20), the MAS (1) endowed with the FTC protocols (16) achieves exponential consensus, where $\mu_1 = \frac{\iota p_1 \lambda_{\max}^2(\mathcal{M})H_1^2}{\lambda_{\min}(Q_2)}$, $\sigma_1 \leq \frac{(q_1 q_2 - q_2 - q_1)\lambda_{\min}(Q_2)}{q_1 q_2 \lambda_{\max}(P_2)} - \frac{2\xi^2 q_2 \lambda_N^4(\mathcal{L})H_2^2}{(1 - 2\xi^2 \lambda_N^2(\mathcal{L})\lambda_{\min}(Q_2)\lambda_{\max}(P_2))}$, $n_a = n + n_z + n_d + n_f$ and the event triggered threshold requirement is fulfilled by $\bar{\xi} \in (0, \sqrt{\frac{1}{2\lambda_N^2(\mathcal{L})}})$.

Let $K_\omega = (B^TB)^{-1}B^TD\mathcal{V}$ denote the disturbance-estimation gain matrix, $K_f = (B^TB)^{-1}B^TF$ the fault-

estimation gain matrix, $K_2 = \tau R^{-1} B^T P_2$, $\tau \geq \frac{1}{2\lambda_2(\mathcal{L})}$ the adjacency-information-based broadcasting matrices, and $H_1 = \|P_2 B K_1\|$, $H_2 = \|P_2 B K_2\|$ positive scalars, the agent group will achieve leaderless consensus.

Proof. Consider the Lyapunov function $V_2(t) = e^T(t)(I_n \otimes P_2)e(t)$. Under the solvable ARE $P_2 A + A^T P_2 - P_2 B B^T P_2 + Q_1 = 0$, the LMI (24) and condition $\tau \geq \frac{1}{2\lambda_2(\mathcal{L})}$ the derivative is given by:

$$\begin{aligned} \dot{V}_2(t) = & e^T(t) [I_N \otimes (P_2(A - BK_x) + (A - BK_x)^T P_2) \\ & - 2(\mathcal{L} \otimes P_2 B K_2)] e(t) + 2e^T(t)(\mathcal{M} \otimes P_2 B K_1) \bar{e}(t) \\ & - 2e^T(t)(\mathcal{L} \otimes P_2 B K_2) \delta(t). \end{aligned} \quad (26)$$

Applying Young's inequality (for any $m > 0$), hence:

$$\begin{aligned} \dot{V}_2(t) \leq & -\lambda_{\min}(Q_2) \sum_{i=1}^N \check{e}_i^T(t) \check{e}_i(t) \\ & + H_1 \sum_{i=1}^N (m_1 \lambda_{\max}^2(\mathcal{M}) \check{e}_i^T(t) \check{e}_i(t) + m_1^{-1} \check{e}_i^T(t) \check{e}_i(t)) \\ & + H_2 \sum_{i=1}^N (m_2 \lambda_N^2(\mathcal{L}) \check{e}_i^T(t) \check{e}_i(t) + m_2^{-1} \check{\rho}_i^T(t) \check{\rho}_i(t)) \end{aligned} \quad (27)$$

where $\check{e}(t) = \text{col}(\check{e}_i(t)) = (\Gamma^T \otimes I_n) \bar{e}(t)$, $\check{\rho}(t) = \text{col}(\check{\rho}_i(t)) = (\Gamma^T \otimes I_n) \rho(t)$, $\check{e}(t) = \text{col}(\check{e}_i(t)) = (\Gamma^T \otimes I_{n_a}) e(t)$.

Introducing auxiliary positive scalars $m_1, m_2 > 0$, it follows that

$$\begin{aligned} \dot{V}_2(t) \leq & -\left(1 - \frac{1}{q_1} - \frac{1}{q_2}\right) \lambda_{\min}(Q_2) \sum_{i=1}^N \check{e}_i^T(t) \check{e}_i(t) \\ & + \frac{q_1 H_1^2 \lambda_{\max}^2(\mathcal{M})}{\lambda_{\min}(Q_2)} \sum_{i=1}^N \check{e}_i^T(t) \check{e}_i(t) \\ & + \frac{q_2 H_2^2 \lambda_N^2(\mathcal{L})}{\lambda_{\min}(Q_2)} \sum_{i=1}^N \check{\rho}_i^T(t) \check{\rho}_i(t) \end{aligned} \quad (28)$$

where $q_1, q_2 > 0$.

Since the broadcast state satisfies $x^e(t) = \rho(t) + x(t)$, $x^e(t) = \text{col}(x_i^e(t))$, it follows that

$$\Omega(x_{j \in \mathcal{N}_i}^e(t)) = -(\mathcal{L} \otimes I_n)(\rho(t) + x(t)), \quad (29)$$

where $\Omega(x_{j \in \mathcal{N}_i}^e(t)) = \text{col}(\Omega_i(x_{j \in \mathcal{N}_i}^e(t)))$, $\Omega_i(x_{j \in \mathcal{N}_i}(t)) = \sum_{j \in \mathcal{N}_i} (x_j(t) - x_i(t))$.

By the triangle inequality and $\|(\mathcal{L} \otimes I_n) \rho\| \leq \lambda_N(\mathcal{L}) \|\rho\|$, we obtain

$$\|\Omega(x_{j \in \mathcal{N}_i}^e(t))\| \leq \|\Omega(x_{j \in \mathcal{N}_i}(t))\| + \lambda_N(\mathcal{L}) \|\rho(t)\|. \quad (30)$$

Furthermore, using $\Gamma(x_{j \in \mathcal{N}_i}(t)) = -(\mathcal{L} \otimes I_n)x(t)$ and the projector $\mathcal{M} = I_N - \frac{1}{N} \mathbf{1}_N \mathbf{1}_N^T$, for which $\mathcal{L}\mathcal{M} = \mathcal{M}\mathcal{L} = \mathcal{L}$, we have

$$\begin{aligned} \|\Omega(x_{j \in \mathcal{N}_i}(t))\|^2 & \leq \lambda_N^2(\mathcal{L}) x^T(t) (\mathcal{M}^2 \otimes I_n) x(t) \\ & = \lambda_N^2(\mathcal{L}) e^T(t) e(t). \end{aligned} \quad (31)$$

Therefore $\|\rho(t)\|^2 \leq \frac{2\bar{\xi}^2 \lambda_N^2(\mathcal{L})}{1 - 2\bar{\xi}^2 \lambda_N^2(\mathcal{L})} \|e(t)\|^2$ where $\bar{\xi} = \max_{i=1, \dots, N} \xi_i$.

On any event-triggered activation interval, define the composite Lyapunov function $V_3(t) = V_2(t) + \frac{1}{\iota} V_1(t)$, $\iota > 0$. Accordingly, its derivative can be written as

$$\begin{aligned} \dot{V}_3(t) & \leq -\sigma_1 \lambda_{\max}(P_2) e^T(t) (I_n \otimes I_n) e(t) \\ & \quad - \frac{\sigma_1}{\iota} \bar{e}^T(t) (I_n \otimes P_1) \bar{e}(t) \\ & \leq -\sigma_1 V_3(t). \end{aligned} \quad (32)$$

Therefore, agent consensus is achieved, and the proof is complete. $\square$

Remark 2. Under the event-triggered mechanism, the control update sequence $\{t_{k_i}^i\}_{k_i \in \mathbb{N}}$ of agent i is determined by $t_{k_i+1}^i = t_{k_i}^i + \Delta_{k_i}$,

$$\Delta_{k_i} := \max \left\{ \inf_{t > t_{k_i}^i} \{t - t_{k_i}^i \mid \|\rho_i(t)\| = \xi_i \|\Omega_i(x(t))\|\}, \theta_i \right\}. \quad (33)$$

where $\theta_i > 0$ and $\xi_i > 0$ are preset scalars. Since $\Delta_{k_i} \geq \theta_i > 0$ holds for all k_i , the inter-execution intervals are uniformly lower-bounded, and thus Zeno behavior is excluded.

4. Simulation Results

A four-agent model is employed to validate the feasibility of the proposed scheme. The key parameters of the model are specified by the following known matrices:

$$A = \begin{bmatrix} 0.25 & 1.02 & 0.08 & 2.5 \\ -0.4 & -1.01 & 0 & -4 \\ 0.10 & 1.31 & -0.70 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.18 \\ 7.6 \\ 4.5 \\ 0 \end{bmatrix} \quad F = \begin{bmatrix} 0.35 \\ 15.18 \\ 9 \\ 0 \end{bmatrix} \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$D = [0.0352 \quad 1.5184 \quad 0.8980 \quad 0]^T$$

The interconnection topology among the agents is shown in Figure 1.

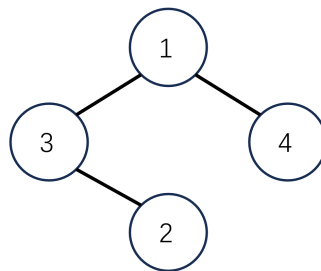


Figure 1. Communication topology.

The associated Laplacian matrix is given by:

$$\mathcal{L} = \begin{bmatrix} 2 & 0 & -1 & -1 \\ 0 & 1 & -1 & 0 \\ -1 & -1 & 2 & 0 \\ -1 & 0 & 0 & 1 \end{bmatrix}$$

To assess the stability of the system under external disturbances, the unknown external disruptions, denoted as $d_i(t)$ are incorporated as specified in (5). The corresponding parameters are defined accordingly.

$$\mathcal{W} = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}, \mathcal{V} = [2 \quad 0].$$

Agent failures, which can be described by a polynomial form, are specified as follows:

$$f_i(t) = \begin{cases} 0, & \text{if } t < 2, \\ 1 + \sin 2t, & \text{if } 2 \leq t \leq 13, \\ 0, & \text{if } t > 13. \end{cases} \quad (34)$$

Through computation, the observer gain matrix is obtained as:

$$E_1 = \begin{bmatrix} 5.7 & 2.6 \\ 56.2 & 17.1 \\ 41.2 & 17.6 \\ 6.5 & 2.1 \end{bmatrix}, E_2 = \begin{bmatrix} 6.1 & 1.4 \\ 19.5 & 3.9 \\ 29.7 & 7.1 \end{bmatrix},$$

$$E_3 = \begin{bmatrix} -27.7 & -6 \\ -19.5 & -4.3 \end{bmatrix}, E_4 = [17.7 \quad 3.5].$$

Figure 2 shows the actuator fault $f_i(t)$ and its estimate $\hat{f}_i(t)$ for each agent. The blue solid line represents the actual fault signal, while the red dashed line denotes the estimated signal. It can be observed that a system fault occurs at $t = 2$ s, and the designed observer effectively tracks this fault, demonstrating its capability for accurate fault estimation.

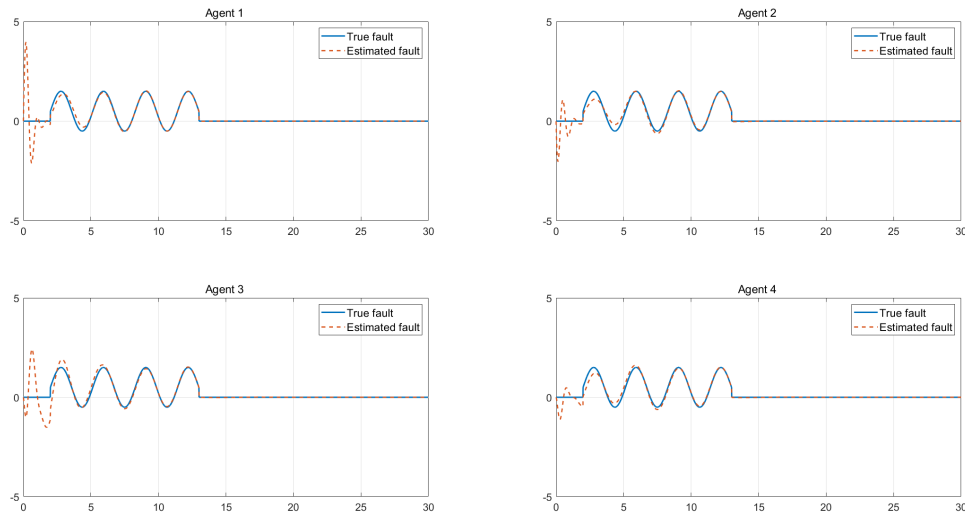


Figure 2. Actuator fault $f_i(t)$ and its estimate $\hat{f}_i(t)$ for Agents 1–4.

Figure 3 shows the external disturbance $d_i(t)$ and its estimate $\hat{d}_i(t)$ for each agent, where the blue solid line represents the actual disturbance signal and the red dashed line corresponds to the estimated signal. Under the assumption that the system is subject to persistent external disturbances, the results show that the designed observer can accurately estimate this continuous disturbance signal.

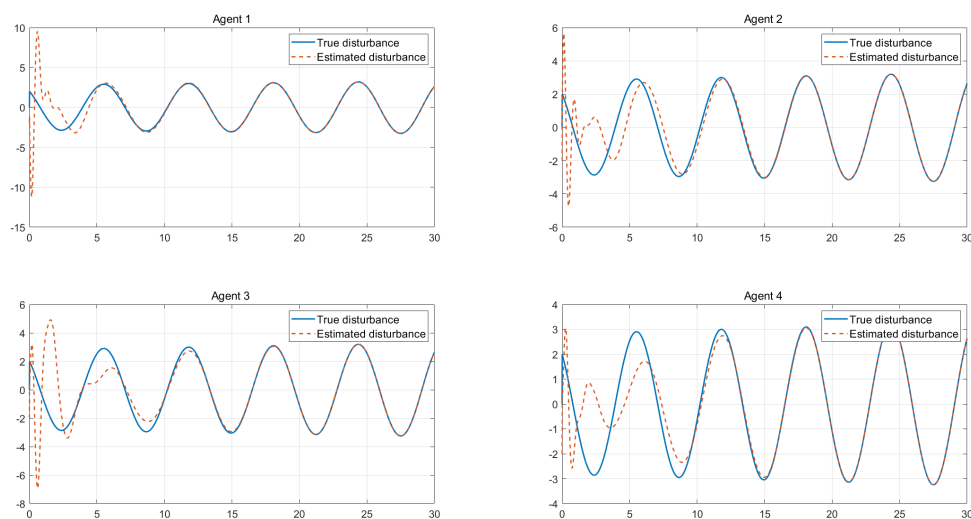


Figure 3. External disturbance $d_i(t)$ and its estimate $\hat{d}_i(t)$ for Agents 1–4.

Figure 4 shows the state-estimation error $e_{x_i}(t) = x_i(t) - \hat{x}_i(t)$ for each agent. The state-estimation errors asymptotically converge to zero, verifying the state-estimation performance of the designed observer.

Figure 5 illustrates the consensus error of the system. Under the proposed FTC scheme, the system error eventually converges to zero, achieving the intended control objective. Furthermore, the designed event-triggered scheme incorporates an open-loop estimator, enabling agents to update their states based on the open-loop estimated information even when no event is triggered, rather than remaining static. This mechanism contributes to enhanced system stability.

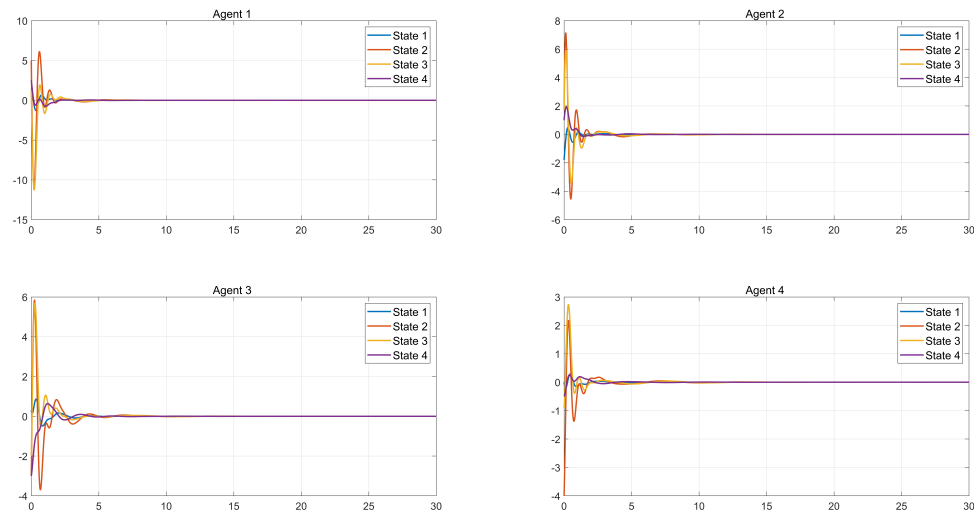


Figure 4. State-estimation error for Agents 1–4.

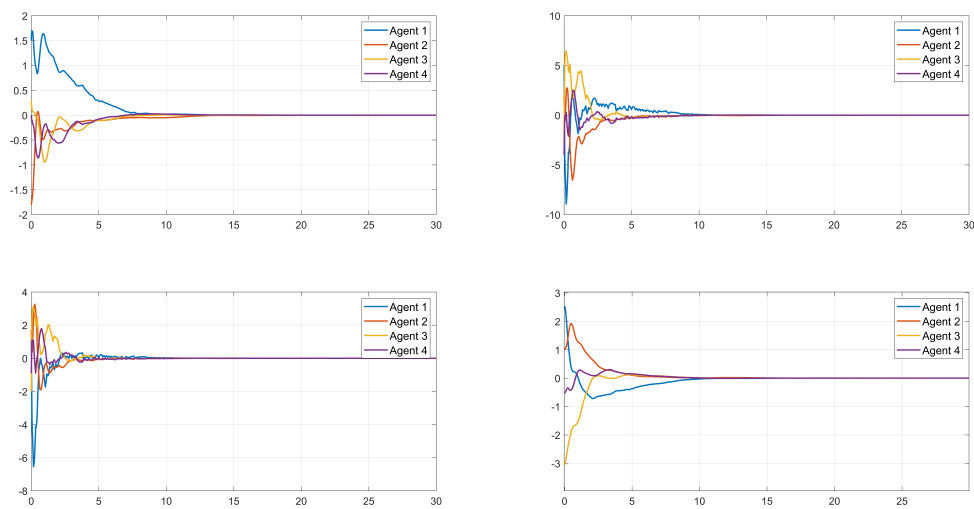


Figure 5. Consensus error for Agents 1–4.

The proposed framework simultaneously addresses polynomial-form actuator faults, external disturbances, state/fault/disturbance estimation, and event-triggered fault-tolerant consensus control. The results in Figures 2–5 verify the feasibility and effectiveness of the proposed framework under the considered conditions.

5. Conclusions

This paper investigates the FTC of MAS subject to actuator faults and external disturbances. The actuator faults are modeled using polynomial functions, which are capable of representing a wider range of fault types. Based on this model, a state observer is designed to simultaneously estimate the system states, fault signals, and disturbance signals. To reduce communication load, an event-triggered scheme incorporating an open-loop estimator is developed. By integrating the observer and the event-triggered scheme, an FTC strategy is formulated to mitigate the impact of faults and disturbances on the system, and its effectiveness is verified through simulations. Future work will focus on enhancing the observer design to extend its estimation capability to a broader variety of fault patterns.

Author Contributions

K.F.: writing—original draft, writing—review & editing, software; X.Q.: validation; O.O.R.: visualization; G.P.: conceptualization, resources, supervision; C.H.: investigation. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Not applicable.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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