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Research article

Dynamic event-triggered adaptive finite-time consensus control for multi-agent systems with time-varying actuator faults

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Abstract: In this study, the adaptive finite-time leader-following consensus control for multi-agent systems (MASs) subjected to unknown time-varying actuator faults is reported based on dynamic event-triggering mechanism (DETM). Neural networks (NNs) are used to approximate unknown nonlinear functions. Command filter and compensating signal mechanism are introduced to alleviate the computational burden. Unlike the existing methods, by combining adaptive backstepping method with DETM, a novel finite time control strategy is presented, which can compensate the actuator efficiency successfully, reduce the update frequency of the controller and save resources. At the same time, under the proposed strategy, it is guaranteed that all followers can track the trajectory of the leader in the sense that consensus errors converge to a neighborhood of the origin in finite time, and all signals in the closed-loop system are bounded. Finally, the availability of the designed strategy is validated by two simulation results.

Keywords: leader-following consensus tracking; adaptive finite time control; dynamic event-triggered control (DETC); unknown time-varying actuator faults

1. Introduction

In recent years, the distributed consensus problem in the MASs has been widely studied by many scholars. Remarkably, leader-following consensus control, which is intend to design a control protocol according to local communication so that all followers can track the trajectory of the leader, has been applied to many engineering fields, such as robotic manipulators [1] and grid-connected microgrids [2]. Considering the existence of uncertainties, a large number of adaptive consensus tracking control strategies based on backstepping method have been proposed in [3–6]. Note that the results of the above studies have a common problem, that is, the "explosion of complexity" problem caused by repeated differentiations of the virtual control signals. To tackle this problem, command filter-based backstepping method was proposed in [7]. In line with this method, many excellent research results have been presented in [8–10]. For example, in [10], a novel adaptive command filter backstepping control scheme was advanced, and it was proved that asymptotic tracking could be achieved by a Lyapunov stability analysis. In addition, with regard to stability issues, various types of Lyapunov functions have been offered in [11–14] to analyze the stability and synchronization control. However, the above results mainly discuss stability in infinite time. In many industrial engineering fields, to improve convergence rate and convergence time, systems are required to achieve stable performance and tracking performance in finite time. Based on this, numerous finite time consensus tracking schemes were developed in [15–22]. Nevertheless, actuators of all agents mentioned above are required to operate healthily.

As is known to all, actuator failures often occur during the operation of many practical systems, which can lead to system performance degradation, or may bring adverse impact on the industrial production. In response to this, researchers have focused on fault-tolerant control to compensate the influence caused by actuator faults, see [23–29]. However, the residual fault control rates in the aforementioned literatures were always constants. There is a more practical class of faults composed of time-varying actuation efficiency and time-varying uncontrolled additional faults. In order to deal with such actuator faults, many research results have been presented in [30–37]. For example, in [34], by introducing some integrable auxiliary signals and a new contradiction argument, an adaptive consensus tracking control scheme was given for MASs with time-varying actuator faults. Unfortunately, the control signals of above-mentioned results are needed to have continuous transmission to actuators, which inevitably results in a waste of resources.

Recently, so as to utilize communication resources more effectively and reduce computational expenses, event-triggered control (ETC) has been investigated and has received attention increasingly. Different from the schemes based on event-triggered mechanism (ETM) in [38–47, 49, 50] where the threshold parameters were all fixed constants, DETC schemes with the help of adaptive backstepping method were developed in [48, 51–54], and the threshold parameters were required to be adjusted dynamically. Furthermore, in [55], based on DETM, two intermittent control protocols were introduced depending on whether combined measurement or single measurement was used, which could diminish the update frequency of control protocol in the nonlinear MASs. However, to our knowledge, there are few research results on dynamic event-triggered adaptive finite-time consensus tracking for high-order nonlinear MASs with time-varying actuator faults, which motivates our study.

Inspired by the above mentioned results, this paper will study the problem of adaptive finite-time leader-following consensus via DETC for MASs with time-varying actuator faults. The main contributions are as follows:

1)Unlike the previous results in [27–29], the time-varying actuator faults are studied in this paper. An adaptive leader-following tracking control strategy is presented, which makes consensus errors converge to a small neighborhood of the origin in finite time.

2)To reduce the computational burden, command filter and compensating mechanism are introduced. Besides, different from the schemes based on ETM proposed in [38–45], DETC is proposed. The dynamic event-triggered controller with larger triggering time interval is designed for each follower, which greatly saves communication resources while successfully compensating for actuator efficiency.

Notation

Table 1. The connotation of symbols.

Symbol	Connotation
R	the set of real numbers
R^r	the real r-dimensional space
diag$\{\cdot\}$	diagonal matrix
$A \otimes B$	Kronecker product of matrices A and B
$\lvert \cdot \rvert$	absolute value
$x_{i,q}$, $g_{i,q}$	$x_{i,q}(t)$, $g_{i,q}(\cdot)$

2. System formulation and preliminaries

2.1. System formulation

Consider a class of nonstrict-feedback nonlinear MASs, whose dynamics can be described by

$$\begin{cases} \dot{x}_{i,q} = x_{i,q+1} + g_{i,q}(x_i), \quad q = 1, 2, \ldots, n-1 \\ \dot{x}_{i,n} = u_i + g_{i,n}(x_i), \\ \ \ y_i = x_{i,1}, \quad i = 1, 2, \ldots, N \end{cases} \tag{2.1}$$

where $x_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,n}]^T \in R^n$ represents the ith follower's state, $u_i \in R$ and $y_i \in R$ denote the system input and output, respectively. $g_{i,q}(x_i)$ $(q = 1, 2, \ldots, n)$ are uncertain smooth nonlinear functions satisfying $g_{i,q}(0) = 0$. The actuators of N followers may suffer from failures, which can be modeled as

$$u_i(t) = \varrho_i(t)\bar{u}_i(t) + \breve{u}_i(t), \quad i = 1, 2, \ldots, N, \tag{2.2}$$

where $\varrho_i(t) \in R$ is an unknown time-varying actuation effectiveness, $\bar{u}_i(t)$ represents a control signal which needs to be designed later and $\breve{u}_i(t)$ denotes an unknown additive fault.

Remark 1. *In lots of literature on the MASs consensus control [27–29], there always exists a normal actuator, that is,* $\varrho_i(t) = 1$, $\breve{u}_i(t) = 0$. *However, in practical applications, the actuator may be subject to fault. As shown in (2.2), the time-varying actuation effectiveness and additive fault are presented. In other words, the actuator may resume healthy operation or change from one type of fault to another.*

2.2. Topology theory

The directed graph $\mathcal{Y} = (\mathcal{A}, \mathcal{B})$ is composed of node set $\mathcal{A} = \{1, 2, \ldots, N\}$ and edge set $\mathcal{B} \subseteq \mathcal{A} \times \mathcal{A}$, which is used to denote the interaction between N followers in this study. Define the connectivity matrix as $\mathcal{L} = [l_{ip}]$, namely, $l_{ip} = 1$ in case of having a directed edge from p to i $((p, i) \in \mathcal{B})$, $l_{ip} = 0$ otherwise. Besides, it is required that $l_{ii} = 0$. The neighbors set of node i is expressed as $\mathcal{M}_i = \{p | (p, i) \in \mathcal{B}\}$. $\mathcal{K} = diag\{k_1, k_2, \ldots, k_N\}$ is an in-degree matrix with $k_i = \sum_{p \in \mathcal{M}_i} l_{ip}$. Denote the Laplacian matrix as $\mathcal{C} = \mathcal{K} - \mathcal{L}$. Define the pinning matrix $\mathcal{W} = diag\{w_1, w_2, \ldots, w_N\}$, and $w_i = 1$ indicates there is a directed edge from the leader indexed by 0 to the ith follower, $w_i = 0$ otherwise. And the augmented graph $\bar{\mathcal{Y}}$ can be obtained, which is composed of $\mathcal{Y}$ and edges between some followers and the leader. Additionally, we can get the matrix $\mathcal{D} = \mathcal{C} + \mathcal{W}$.

Control objective: This study is to design an event-triggered controller for every follower with actuator faults, so that y_i can track the output of leader y_d where possible in finite time, and can successfully avoid Zeno phenomenon. To achieve the control objective, some preparatory knowledge will be given in the following.

2.3. Preparatory knowledge

Assumption 1. *[15] The fixed directed graph $\bar{\mathcal{Y}}$ includes a spanning tree with the leader as a root.*

Assumption 2. *The output y_d and $\dot{y}_d$ are continuous, known and bounded functions.*

Assumption 3. *[31] $\varrho_i(t)$ and $\breve{u}_i(t)$ are bounded for $i = 1, 2, \ldots, N$, namely, there exist constants $\varrho_{imin} > 0$ and $\breve{u}_{imax} > 0$, such that $\varrho_{imin} \le \varrho_i(t) \le 1$ and $|\breve{u}_i(t)| \le \breve{u}_{imax}$.*

Remark 2. *Compared with [5], the condition required for the leader's trajectory signal y_d is relaxed in Assumption 2. In other words, it is not required that y_d and its derivatives up to the n-th order are bounded and continuous.*

Remark 3. *Assumption 3 indicates that the actuator has a limited actuation effectiveness. Furthermore, the existence of ϱ_{imin} implies the exclusion of cases where $\varrho_i(t) = 0$ and $\varrho_i(t)$ tends to 0. In other words, the ith follower can be affected by $\bar{u}_i(t)$. Besides, it is required that $\varrho_i(t)$ and $\breve{u}_i(t)$ are bounded, which can contribute to compensating the actuator fault in the following control design.*

Lemma 1. *[40] Define that $\bar{g}(Z)$ is any continuous function over the compact set Ξ and $\varepsilon > 0$, then there is always a radial basis function neural network (RBFNN) $\Phi^{*^T} S(Z)$ such that*

$$\sup_{Z\in\Xi} \left|\bar{g}(Z) - \Phi^T S(Z)\right| \le \varepsilon, \ \ Z \in \Xi \subset R^r, \tag{2.3}$$

where $\Phi^* = [\Phi_1^*, \Phi_2^*, \ldots, \Phi_l^*]^T \in R^l$ with node number $l > 1$ represents the weight vector, and $S(Z) = [s_1(Z), s_2(Z), \ldots, s_l(Z)]^T$. $s_j(Z) = \exp[\frac{-(Z-\vartheta_j)^T(Z-\vartheta_j)}{\hbar^2}](j = 1, 2, \ldots, l)$ are Gaussian functions with the center of receptive field $\vartheta_j = [\vartheta_{j1}, \ldots, \vartheta_{jr}]^T$ and $\hbar$ being the width of $s_j(Z)$. Besides, the ideal constant weight is denoted as $\Phi = \arg\min\{\sup_{Z\in\Xi}\left|\bar{g}(Z) - \Phi^{*^T} S(Z)\right|\}$.

Lemma 2. *[40] Suppose $\breve{\epsilon}_k = [\epsilon_1, \epsilon_2, \ldots, \epsilon_k]^T$, where k is a positive integer. Let $S(\breve{\epsilon}_k) = [s_1(\breve{\epsilon}_k), s_2(\breve{\epsilon}_k), \ldots, s_k(\breve{\epsilon}_k)]^T$ be the RBF vector. Then, for positive integers $m \le n$, one has*

$$S^T(\breve{\epsilon}_n)S(\breve{\epsilon}_n) \le S^T(\breve{\epsilon}_m)S(\breve{\epsilon}_m). \tag{2.4}$$

Lemma 3. *[44] The inequality $0 \le |\mu_1| - \mu_1 \tanh\left(\frac{\mu_1}{\sigma_1}\right) \le 0.2785\sigma_1$ holds for any $\sigma_1 > 0, \mu_1 \in R$.*

Lemma 4. *[31] Let $\delta_1, \delta_2, \ldots, \delta_n \in R$, $0 < a < 1$, then the following inequality holds*

$$\left(\sum_{i=1}^{n} |\delta_i|\right)^a \le \sum_{i=1}^{n} |\delta_i|^a \le n^{1-a}\left(\sum_{i=1}^{n} |\delta_i|\right)^a. \tag{2.5}$$

Lemma 5. *[16,29] For the system $\dot{x} = f(x, u)$, if there exist constants λ, $\xi > 0$, $\pi \in (0, \infty)$, $a \in (0, 1)$, $h \in (0, 1)$ and a continuous function $V(x)$, such that*

$$\beta_1(\|x\|) \le V(x) \le \beta_2(\|x\|),$$

$$\dot{V}(x) \le -\lambda V(x) - \xi V^{a}(x) + \pi,$$

where $\beta_1(.)$ and $\beta_2(.)$ are K_∞-functions, then it is said that the system is practical finite-time stability. Besides, the settling time T satisfies

$$T \le \frac{1}{(1-a)\lambda} \ln \frac{\lambda V^{1-a}(x_0) + h\xi}{\lambda(\frac{\pi}{(1-h)\xi})^{\frac{1-a}{a}} + h\xi}. \tag{2.6}$$

3. Design procedure and stability analysis

3.1. Leader-following consensus control design

In this section, an event-triggered adaptive finite-time control scheme is proposed by backstepping method for system (2.1) subjected to actuator faults. To avoid "explosion of complexity" problem in the process of backstepping design, the first order command filter and compensating mechanism are introduced. The design framework is as follows.

First, define the tracking error and transformation of coordinates as

$$\varsigma_{i,1} = \sum_{p\in\mathcal{M}_i} l_{ip}(y_i - y_p) + \omega_i(y_i - y_d), \tag{3.1}$$

$$\varsigma_{i,q} = x_{i,q} - \check{\alpha}_{i,q}, \tag{3.2}$$

where $q = 2, \ldots, n$. $\check{\alpha}_{i,q}$ is the output signal of command filter, given by

$$\psi_{i,q}\dot{\check{\alpha}}_{i,q} + \check{\alpha}_{i,q} = \alpha_{i,q-1},\ \check{\alpha}_{i,q}(0) = \alpha_{i,q-1}(0),$$

where $\alpha_{i,q-1}$ is as the input signal and $\psi_{i,q}$ is a positive parameter. To deal with the impact of the unachieved portion $(\check{\alpha}_{i,q} - \alpha_{i,q-1})$ caused by the command filter, the compensating signals $\eta_{i,q}$ $(q = 1, 2, \ldots, n)$ are introduced as

$$\dot{\eta}_{i,1} = -\lambda_{i,1}\eta_{i,1} + (k_i + \omega_i)\eta_{i,2} + (k_i + \omega_i)(\check{\alpha}_{i,2} - \alpha_{i,1}) - d_{i,1} sgn(\eta_{i,1}), \tag{3.3}$$

$$\dot{\eta}_{i,q} = -\lambda_{i,q}\eta_{i,q} + \eta_{i,q+1} + (\check{\alpha}_{i,q+1} - \alpha_{i,q}) - d_{i,q} sgn(\eta_{i,q}) - \frac{\ell}{4}\eta_{i,q},\ \ q = 2, 3, \ldots, n-1, \tag{3.4}$$

$$\dot{\eta}_{i,n} = -\lambda_{i,n}\eta_{i,n} - d_{i,n} sgn(\eta_{i,n}) - \frac{1}{4}\eta_{i,n}, \tag{3.5}$$

where $\lambda_{i,q}$, $d_{i,q}$ are positive parameters, and $\eta_{i,q}(0) = 0$. Then, define the compensated tracking errors as $\chi_{i,q} = \varsigma_{i,q} - \eta_{i,q}$.

In order to develop the following backstepping design process smoothly, we define the constant $\theta_i = \max\{\|\Phi_{i,q}\|^2, q = 1, 2, \ldots, n\}$, $i = 1, 2, \ldots, N$. Obviously, θ_i is an unknown constant because $\|\Phi_{i,q}\|$ are unknown. Let $\hat{\theta}_i$ be an estimation of θ_i, and the corresponding estimation error is defined as $\tilde{\theta}_i = \theta_i - \hat{\theta}_i$.

Next, the design procedure will be described detailedly based on backstepping method.

Step 1: From (2.1) and (3.1), we can get that the derivative of $\chi_{i,1}$ is

$$\dot{\chi}_{i,1} = (k_i + \omega_i)(\varsigma_{i,2} + \check{\alpha}_{i,2} + g_{i,1}) - \sum_{p\in\mathcal{M}_i} l_{ip}(x_{p,2} + g_{p,1}) - \omega_i\dot{y}_d - \dot{\eta}_{i,1}. \tag{3.6}$$

Construct the candidate Lyapunov function as

$$V_{i,1} = \frac{\chi_{i,1}^4}{4} + \frac{1}{2\rho_i}\tilde{\theta}_i^2,$$

where ρ_i is a positive parameter. Then from (3.6), we have

$$\dot{V}_{i,1} = \chi_{i,1}^3\left((k_i+\omega_i)(\varsigma_{i,2}+\breve{\alpha}_{i,2}+g_{i,1}) - \sum_{p\in\mathcal{M}_i} l_{ip}(x_{p,2}+g_{p,1}) - \omega_i\dot{y}_d - \dot{\eta}_{i,1}\right) - \frac{1}{\rho_i}\tilde{\theta}_i\dot{\hat{\theta}}_i.$$

According to (3.3), one has

$$\dot{V}_{i,1} = \chi_{i,1}^3\Big((k_i+\omega_i)(\chi_{i,2}+\alpha_{i,1}) + \bar{g}_{i,1}(Z_{i,1}) - \omega_i\dot{y}_d + \lambda_{i,1}\eta_{i,1} + d_{i,1}sgn(\eta_{i,1})\Big) - \frac{1}{\rho_i}\tilde{\theta}_i\dot{\hat{\theta}}_i, \tag{3.7}$$

where $\bar{g}_{i,1}(Z_{i,1}) = (k_i+\omega_i)g_{i,1} - \sum_{p\in\mathcal{M}_i} l_{ip}(x_{p,2}+g_{p,1})$ with $Z_{i,1} = [x_i^T, x_p^T]^T$. In view of Lemma 1, by using RBFNNs to approximate function $\bar{g}_{i,1}(Z_{i,1})$, namely,

$$\bar{g}_{i,1}(Z_{i,1}) = \Phi_{i,1}^T S_{i,1}(Z_{i,1}) + \varepsilon_{i,1}(Z_{i,1}), \quad |\varepsilon_{i,1}(Z_{i,1})| \le \bar{\varepsilon}_{i,1}, \tag{3.8}$$

where $\varepsilon_{i,1}(Z_{i,1})$ denotes the approximation error and $\bar{\varepsilon}_{i,1} > 0$. Through employing Young's inequality and Lemma 2, one can obtain that

$$\chi_{i,1}^3\bar{g}_{i,1}(Z_{i,1}) \le \frac{\theta_i}{2b_{i,1}^2}\chi_{i,1}^6 S_{i,1}^T S_{i,1} + \frac{b_{i,1}^2}{2} + \frac{3}{4}\chi_{i,1}^4 + \frac{\bar{\varepsilon}_{i,1}^4}{4}, \tag{3.9}$$

$$\chi_{i,1}^3 d_{i,1} sgn(\eta_{i,1}) \le \frac{\chi_{i,1}^6}{2} + \frac{d_{i,1}^2}{2}, \tag{3.10}$$

where $S_{i,1} = S_{i,1}(\bar{Z}_{i,1})$ with $\bar{Z}_{i,1} = [x_{i,1}, x_{p,1}]^T$ and $b_{i,1} > 0$ is a parameter to be designed. Then, substituting (3.9) and (3.10) into (3.7), we have

$$\begin{aligned}\dot{V}_{i,1} \le{}& \chi_{i,1}^3\Big((k_i+\omega_i)(\chi_{i,2}+\alpha_{i,1}) - \omega_i\dot{y}_d + \lambda_{i,1}\eta_{i,1}\Big) - \frac{1}{\rho_i}\tilde{\theta}_i\dot{\hat{\theta}}_i + \frac{3}{4}\chi_{i,1}^4 + \frac{\chi_{i,1}^6}{2} + \frac{\theta_i}{2b_{i,1}^2}\chi_{i,1}^6 S_{i,1}^T S_{i,1} \\ &+ \frac{b_{i,1}^2}{2} + \frac{\bar{\varepsilon}_{i,1}^4}{4} + \frac{d_{i,1}^2}{2}. \end{aligned} \tag{3.11}$$

The virtual controller is devised as

$$\alpha_{i,1} = \frac{1}{k_i+\omega_i}\left(-\lambda_{i,1}\varsigma_{i,1} - \frac{\chi_{i,1}^3}{2} - \frac{\chi_{i,1}^3\hat{\theta}_i S_{i,1}^T S_{i,1}}{2b_{i,1}^2} - \xi_{i,1} + \omega_i\dot{y}_d - \frac{3}{4}(1+k_i+\omega_i)\chi_{i,1}\right), \tag{3.12}$$

where $\xi_{i,1} > 0$ is a design parameter. It follows from (3.12) and Young's inequality that

$$\dot{V}_{i,1} \le -\lambda_{i,1}\chi_{i,1}^4 - \xi_{i,1}\chi_{i,1}^3 + (k_i+\omega_i)\chi_{i,1}^3\chi_{i,2} + \frac{\tilde{\theta}_i}{\rho_i}\Big(\frac{\rho_i\chi_{i,1}^6 S_{i,1}^T S_{i,1}}{2b_{i,1}^2} - \dot{\hat{\theta}}_i\Big) - \frac{3}{4}(k_i+\omega_i)\chi_{i,1}^4 + \frac{b_{i,1}^2}{2} + \frac{\bar{\varepsilon}_{i,1}^4}{4} + \frac{d_{i,1}^2}{2}$$

$$\leq -\lambda_{i,1}\chi_{i,1}^4 - \xi_{i,1}\chi_{i,1}^3 + \frac{1}{4}(k_i+\omega_i)\chi_{i,2}^4 + \frac{\tilde{\theta}_i}{\rho_i}(\frac{\rho_i\chi_{i,1}^6 S_{i,1}^T S_{i,1}}{2b_{i,1}^2} - \dot{\hat{\theta}}_i) + \frac{b_{i,1}^2}{2} + \frac{\bar{\varepsilon}_{i,1}^4}{4} + \frac{d_{i,1}^2}{2}.$$

Step q ($q = 2, 3, \ldots, n-1$) : According to (3.2), one has

$$\dot{\chi}_{i,q} = \varsigma_{i,q+1} + \check{\alpha}_{i,q+1} + g_{i,q} - \dot{\check{\alpha}}_{i,q} - \dot{\eta}_{i,q}. \tag{3.13}$$

Choose the following candidate Lyapunov function as

$$V_{i,q} = V_{i,q-1} + \frac{1}{4}\chi_{i,q}^4,$$

then we can derive that

$$\dot{V}_{i,q} = \dot{V}_{i,q-1} + \chi_{i,q}^3\left(\chi_{i,q+1} + \alpha_{i,q} + \bar{g}_{i,q}(Z_{i,q}) - \dot{\check{\alpha}}_{i,q} + \lambda_{i,q}\eta_{i,q} + d_{i,q}sgn(\eta_{i,q}) + \frac{\ell}{4}\eta_{i,q}\right), \tag{3.14}$$

where $\bar{g}_{i,q}(Z_{i,q}) = g_{i,q}$. Similarly, it is obtained from Lemma 1 that

$$\bar{g}_{i,q}(Z_{i,q}) = \Phi_{i,q}^T S_{i,q}(Z_{i,q}) + \varepsilon_{i,q}(Z_{i,q}), \quad |\varepsilon_{i,q}(Z_{i,q})| \leq \bar{\varepsilon}_{i,q}, \tag{3.15}$$

where $\varepsilon_{i,q}(Z_{i,q})$ is the approximation error and $\bar{\varepsilon}_{i,q} > 0$. It follows from Young's inequality and Lemma 2 that

$$\chi_{i,q}^3\bar{g}_{i,q}(Z_{i,q}) \leq \frac{\theta_i}{2b_{i,q}^2}\chi_{i,q}^6 S_{i,q}^T S_{i,q} + \frac{b_{i,q}^2}{2} + \frac{3}{4}\chi_{i,q}^4 + \frac{\bar{\varepsilon}_{i,q}^4}{4}, \tag{3.16}$$

$$\chi_{i,q}^3 d_{i,q}sgn(\eta_{i,q}) \leq \frac{\chi_{i,q}^6}{2} + \frac{d_{i,q}^2}{2}, \tag{3.17}$$

where $S_{i,p} = S_{i,p}(\bar{Z}_{i,p})$ with $\bar{Z}_{i,p} = [x_{i,1}, x_{i,2}, \ldots, x_{i,p}]^T$ and $b_{i,p} > 0$ is a parameter. By plugging (3.16) and (3.17) into (3.14), one can obtain that

$$\dot{V}_{i,q} \leq \dot{V}_{i,q-1} + \chi_{i,q}^3\left(\chi_{i,q+1} + \alpha_{i,q} - \dot{\check{\alpha}}_{i,q} + \lambda_{i,q}\eta_{i,q} + \frac{\ell}{4}\eta_{i,q}\right) + \frac{\theta_i}{2b_{i,q}^2}\chi_{i,q}^6 S_{i,q}^T S_{i,q} + \frac{3}{4}\chi_{i,q}^4 + \frac{\chi_{i,q}^6}{2} + \frac{b_{i,q}^2}{2} + \frac{\bar{\varepsilon}_{i,q}^4}{4} + \frac{d_{i,q}^2}{2}.$$

Then the virtual controller $\alpha_{i,q}$ can be constructed as

$$\alpha_{i,q} = -\lambda_{i,q}\varsigma_{i,q} - \frac{\chi_{i,q}^3}{2} - \frac{\chi_{i,q}^3\hat{\theta}_i S_{i,q}^T S_{i,q}}{2b_{i,q}^2} - \xi_{i,q} - \frac{3}{2}\chi_{i,q} - \frac{\ell\varsigma_{i,q}}{4} + \dot{\check{\alpha}}_{i,q}, \tag{3.18}$$

where $\xi_{i,q}$ is a positive parameter to be designed. Using Young's inequality, we have

$$\dot{V}_{i,q} \leq -\sum_{v=1}^{q}\lambda_{i,v}\chi_{i,v}^4 - \sum_{v=1}^{q}\xi_{i,v}\chi_{i,v}^3 + \frac{1}{4}\chi_{i,q+1}^4 + \frac{\tilde{\theta}_i}{\rho_i}\left(\sum_{v=1}^{q}\frac{\rho_i\chi_{i,v}^6 S_{i,v}^T S_{i,v}}{2b_{i,v}^2} - \dot{\hat{\theta}}_i\right) + \sum_{v=1}^{q}\left(\frac{b_{i,v}^2}{2} + \frac{\bar{\varepsilon}_{i,v}^4}{4} + \frac{d_{i,v}^2}{2}\right).$$

Step n: In the last step, we will design the event-triggered controller based on actuator failures. The DETM is considered as follows:

$$\bar{u}_i(t) = \varpi_i(t^i_\iota), \quad \forall t \in [t^i_\iota, t^i_{\iota+1}), \tag{3.19}$$

$$t^i_{\iota+1} = \inf\left\{t \in R \middle| \, |z_i(t)| \geq \gamma_i(t)|\bar{u}_i(t)| + \Delta_i\right\}, \tag{3.20}$$

$$\dot{\gamma}_i(t) = -\beta_i\gamma_i^2(t), \tag{3.21}$$

where $\varpi_i(t)$ is the control signal to be designed next, t^i_ι denotes the update time, $z_i(t) = \varpi_i(t) - \bar{u}_i(t)$ is the measurement error , $\Delta_i > 0$ and $\beta_i > 0$ are parameters. Moreover, it can be seen that $\forall\gamma_i(0) \in (0, 1)$, we have $\gamma_i(t) \in (0, 1)$. According to (3.20), we can obtain that $\forall t \in [t^i_\iota, t^i_{\iota+1})$, $|z_i(t)| \leq \gamma_i(t)|\bar{u}_i(t)| + \Delta_i$, then it is concluded that $\varpi_i(t) = (1 + \zeta_{i,1}(t)\gamma_i(t))\bar{u}_i(t) + \zeta_{i,2}(t)\Delta_i$ with $|\zeta_{i,1}(t)| \leq 1$ and $|\zeta_{i,2}(t)| \leq 1$. Hence, $\bar{u}_i(t)$ can be expressed as

$$\bar{u}_i(t) = \frac{\varpi_i(t)}{1 + \zeta_{i,1}(t)\gamma_i(t)} - \frac{\zeta_{i,2}(t)\Delta_i}{1 + \zeta_{i,1}(t)\gamma_i(t)}. \tag{3.22}$$

According to (3.2), one has

$$\dot{\chi}_{i,n} = \varrho_i(t)\bar{u}_i + \breve{u}_i + g_{i,n} - \dot{\breve{\alpha}}_{i,n} - \dot{\eta}_{i,n}. \tag{3.23}$$

Define the Lyapunov function candidate as

$$V_{i,n} = V_{i,n-1} + \frac{1}{4}\chi^4_{i,n}.$$

From (3.5), one has

$$\dot{V}_{i,n} = \dot{V}_{i,n-1} + \chi^3_{i,n}\left(\varrho_i(t)\bar{u}_i + \breve{u}_i + \bar{g}_{i,n}(Z_{i,n}) - \dot{\breve{\alpha}}_{i,n} + \lambda_{i,n}\eta_{i,n} + d_{i,n}sgn(\eta_{i,n}) + \frac{1}{4}\eta_{i,n}\right), \tag{3.24}$$

where $\bar{g}_{i,n}(Z_{i,n}) = g_{i,n}$. And we can get from the similar process (3.15) that

$$\bar{g}_{i,n}(Z_{i,n}) = \Phi^T_{i,n}S_{i,n}(Z_{i,n}) + \varepsilon_{i,n}(Z_{i,n}), \quad |\varepsilon_{i,n}(Z_{i,n})| \leq \bar{\varepsilon}_{i,n}, \tag{3.25}$$

where $\varepsilon_{i,n}(Z_{i,n})$ represents the approximation error and $\bar{\varepsilon}_{i,n} > 0$. From Young's inequality and Assumption 3, it can be derived that

$$\chi^3_{i,n}\breve{u}_i \leq \frac{3}{4}\chi^4_{i,n} + \frac{1}{4}\breve{u}^4_{imax}, \tag{3.26}$$

$$\chi^3_{i,n}\bar{g}_{i,n}(Z_{i,n}) \leq \frac{\theta_i}{2b^2_{i,n}}\chi^6_{i,n}S^T_{i,n}S_{i,n} + \frac{b^2_{i,n}}{2} + \frac{3}{4}\chi^4_{i,n} + \frac{\bar{\varepsilon}^4_{i,n}}{4}, \tag{3.27}$$

$$\chi^3_{i,n}d_{i,n}sgn(\eta_{i,n}) \leq \frac{\chi^6_{i,n}}{2} + \frac{d^2_{i,n}}{2}, \tag{3.28}$$

where $S_{i,n} = S_{i,n}(\bar{Z}_{i,n})$ with $\bar{Z}_{i,n} = Z_{i,n}$ and the design parameter $b_{i,n} > 0$. By substituting (3.22) and (3.26)–(3.28) into (3.24) yields

$$\dot{V}_{i,n} \leq \dot{V}_{i,n-1} + \chi^3_{i,n}\left(\varrho_i(t)\left(\frac{\varpi_i(t)}{1 + \zeta_{i,1}(t)\gamma_i(t)} - \frac{\zeta_{i,2}(t)\Delta_i}{1 + \zeta_{i,1}(t)\gamma_i(t)}\right) - \dot{\breve{\alpha}}_{i,n} + \lambda_{i,n}\eta_{i,n} + \frac{1}{4}\eta_{i,n}\right) + \frac{3}{2}\chi^4_{i,n}$$

$$+\frac{\theta_i}{2b_{i,n}^2}\chi_{i,n}^6 S_{i,n}^T S_{i,n}+\frac{\chi_{i,n}^6}{2}+\frac{1}{4}\breve{u}_{imax}^4+\frac{b_{i,n}^2}{2}+\frac{\bar{\varepsilon}_{i,n}^4}{4}+\frac{d_{i,n}^2}{2}$$
$$\le -\sum_{v=1}^{n}\lambda_{i,v}\chi_{i,v}^4-\sum_{v=1}^{n}\xi_{i,v}\chi_{i,v}^3+\frac{\tilde{\theta}_i}{\rho_i}\left(\sum_{v=1}^{n}\frac{\rho_i\chi_{i,v}^6 S_{i,v}^T S_{i,v}}{2b_{i,v}^2}-\dot{\hat{\theta}}_i\right)+\sum_{v=1}^{n}\left(\frac{b_{i,v}^2}{2}+\frac{\bar{\varepsilon}_{i,v}^4}{4}+\frac{d_{i,v}^2}{2}+\frac{1}{4}\breve{u}_{imax}^4\right)$$
$$+\chi_{i,n}^3\varrho_i(t)\left(\frac{\varpi_i(t)}{1+\zeta_{i,1}(t)\gamma_i(t)}-\frac{\zeta_{i,2}(t)\Delta_i}{1+\zeta_{i,1}(t)\gamma_i(t)}\right)+\varrho_{imin}|\chi_{i,n}^3\alpha_{i,n}|, \tag{3.29}$$

where $\alpha_{i,n}=\frac{1}{\varrho_{imin}}\left(-\lambda_{i,n}\varsigma_{i,n}-\frac{\chi_{i,n}^3}{2}-\frac{\chi_{i,n}^3\hat{\theta}_i S_{i,n}^T S_{i,n}}{2b_{i,n}^2}-\xi_{i,n}-\frac{3}{2}\chi_{i,n}-\frac{\varsigma_{i,n}}{4}+\dot{\breve{\alpha}}_{i,n}\right)$ and $\xi_{i,n}>0$ is a parameter. The event-triggered controller $\varpi_i(t)$ and the adaptive law $\hat{\theta}_i$ are devised in the following:

$$\varpi_i(t)=-(1+\gamma_i(t))\left(\alpha_{i,n}\tanh\frac{\chi_{i,n}^3\alpha_{i,n}}{\sigma_i}+\bar{o}_i\tanh\frac{\chi_{i,n}^3\bar{o}_i}{\sigma_i}\right), \tag{3.30}$$
$$\dot{\hat{\theta}}_i=\sum_{v=1}^{n}\frac{\rho_i\chi_{i,v}^6 S_{i,v}^T S_{i,v}}{2b_{i,v}^2}-\Lambda_i\hat{\theta}_i, \tag{3.31}$$

where $\bar{o}_i>0$ and $\varrho_{imin}\bar{o}_i>\frac{\Delta_i}{1-\gamma_i}$. Owing to $0<\varrho_{imin}\le\varrho_i(t)\le 1$, $|\zeta_{i,1}(t)|\le 1$, $|\zeta_{i,2}(t)|\le 1$ and $x\tanh x\ge 0$, we can get that

$$\varrho_i(t)\chi_{i,n}^3\frac{\varpi_i(t)}{1+\zeta_{i,1}(t)\gamma_i(t)}\le -\varrho_{imin}\chi_{i,n}^3\alpha_{i,n}\tanh\frac{\chi_{i,n}^3\alpha_{i,n}}{\sigma_i}-\varrho_{imin}\chi_{i,n}^3\bar{o}_i\tanh\frac{\chi_{i,n}^3\bar{o}_i}{\sigma_i}, \tag{3.32}$$
$$\varrho_i(t)\chi_{i,n}^3\frac{\zeta_{i,2}(t)\Delta_i}{1+\zeta_{i,1}(t)\gamma_i(t)}\le\left|\frac{\chi_{i,n}^3\Delta_i}{1-\gamma_i}\right|. \tag{3.33}$$

According to (3.29)–(3.33) and Lemma 3, one has

$$\dot{V}_{i,n}\le -\sum_{v=1}^{n}\lambda_{i,v}\chi_{i,v}^4-\sum_{v=1}^{n}\xi_{i,v}\chi_{i,v}^3+\frac{\Lambda_i}{\rho_i}\tilde{\theta}_i\hat{\theta}_i+\sum_{v=1}^{n}\left(\frac{b_{i,v}^2}{2}+\frac{\bar{\varepsilon}_{i,v}^4}{4}+\frac{d_{i,v}^2}{2}+\frac{1}{4}\breve{u}_{imax}^4\right)+0.557\varrho_{imin}\sigma_i. \tag{3.34}$$

Remark 4. *As shown in (3.19)–(3.21), one of the characteristics of DETC is that the threshold parameter $\gamma_i(t)$ can be dynamically adjusted. If supposing $\gamma_i(0)=0$, $\Delta_i\neq 0$ and $\beta_i=0$, (3.21) changes into $t_{\iota+1}^i=\inf\left\{t\in R\middle|\,|z_i(t)|\ge\Delta_i\right\}$, which is the classical sample-data control. Moreover, if setting $\gamma_i(0)\neq 0$, $\Delta_i\neq 0$ and $\beta_i=0$, the proposed DETC becomes the static event-triggered control. Therefore, by comparison, DETC is more flexible. Besides, DETC has a larger average triggering time interval and fewer communication times, which can contribute to reducing the update frequency of the controller, saving communication resources and improving the utilization rate of resources.*

Step n+1: For the compensating system, the following Lyapunov function is constructed as

$$V_{i,n+1}=\frac{1}{4}\sum_{q=1}^{n}\eta_{i,q}^4.$$

From (3.3)–(3.5), we have

$$\dot{V}_{i,n+1}=-\sum_{q=1}^{n}\lambda_{i,q}\eta_{i,q}^4-\sum_{q=1}^{n}d_{i,q}sgn(\eta_{i,q})\eta_{i,q}^3+(k_i+\omega_i)\eta_{i,1}^3\eta_{i,2}+\sum_{q=2}^{n-1}\eta_{i,q}^3\eta_{i,q+1}-\sum_{q=2}^{n-1}\frac{\ell}{4}\eta_{i,q}^4$$

$$-\frac{1}{4}\eta_{i,n}^4+(k_i+\omega_i)(\breve{\alpha}_{i,2}-\alpha_{i,1})\eta_{i,1}^3+\sum_{q=2}^{n-1}(\breve{\alpha}_{i,q+1}-\alpha_{i,q})\eta_{i,q}^3. \tag{3.35}$$

It follows from Young's inequality that

$$\begin{aligned}(k_i+\omega_i)\eta_{i,1}^3\eta_{i,2}&\leq\frac{3}{4}(k_i+\omega_i)\eta_{i,1}^4+\frac{1}{4}(k_i+\omega_i)\eta_{i,2}^4,\\ \eta_{i,q}^3\eta_{i,q+1}&\leq\frac{3}{4}\eta_{i,q}^4+\frac{1}{4}\eta_{i,q+1}^4,\end{aligned}$$

and from [26], for $q=1,2,\ldots,n-1$, it is gained that $\|\breve{\alpha}_{i,q+1}-\alpha_{i,q}\|\leq\tau_{i,q}$ in the time T_{i1} where $\tau_{i,q}$ are positive constants. Hence, (3.35) can be written as

$$\begin{aligned}\dot{V}_{i,n+1}&\leq-\Big(\lambda_{i,1}-\frac{3}{4}(k_i+\omega_i)\Big)\eta_{i,1}^4-\sum_{q=2}^{n}(\lambda_{i,q}-\frac{3}{4})\eta_{i,q}^4-\sum_{q=1}^{n}d_{i,q}|\eta_{i,q}|^3+(k_i+\omega_i)\tau_{i,1}|\eta_{i,1}|^3+\sum_{q=2}^{n-1}\tau_{i,q}|\eta_{i,q}|^3\\ &\leq-\lambda_iV_{i,n+1}-d_iV_{i,n+1}^{\frac{3}{4}},\end{aligned} \tag{3.36}$$

where $\lambda_i=4\min\left\{\lambda_{i,1}-\frac{3}{4}(k_i+\omega_i),\lambda_{i,q}-\frac{3}{4}\right\}$, $d_i=2\sqrt{2}\Big(\min\{d_{i,q}\}-\max\{(k_i+\omega_i)\tau_{i,1},\tau_{i,q}\}\Big)$ and $d_i>0$ can be satisfied by choosing suitable parameters. A candidate Lyapunov function is selected as $V_i=V_{i,n}+V_{i,n+1}$, then from (3.34), we have

$$\dot{V}_i\leq-\sum_{v=1}^{n}\bar{\lambda}_i(\frac{1}{4}\chi_{i,v}^4)-\sum_{v=1}^{n}\bar{\xi}_i(\frac{1}{4}\chi_{i,q}^4)^{\frac{3}{4}}-\lambda_iV_{i,n+1}-d_iV_{i,n+1}^{\frac{3}{4}}+\frac{\Lambda_i}{\rho_i}\tilde{\theta}_i\hat{\theta}_i+\Pi_i, \tag{3.37}$$

where $\bar{\lambda}_i=4\min\{\lambda_{i,v}\}$, $\bar{\xi}_i=2\sqrt{2}\min\{\xi_{i,v}\}$ and $\Pi_i=\sum_{v=1}^{n}\left(\frac{b_{i,v}^2}{2}+\frac{\bar{\varepsilon}_{i,v}^4}{4}+\frac{d_{i,v}^2}{2}+\frac{1}{4}\breve{u}_{imax}^4\right)+0.557\varrho_{imin}\sigma_i$. Choose the whole Lyapunov function candidate as $V=\sum_{i=1}^{N}V_i$, then the derivative of V can be gained that

$$\dot{V}\leq-\sum_{i=1}^{N}\sum_{v=1}^{n}\bar{\lambda}_i(\frac{1}{4}\chi_{i,v}^4)-\sum_{i=1}^{N}\sum_{v=1}^{n}\bar{\xi}_i(\frac{1}{4}\chi_{i,q}^4)^{\frac{3}{4}}-\sum_{i=1}^{N}\lambda_iV_{i,n+1}-\sum_{i=1}^{N}d_iV_{i,n+1}^{\frac{3}{4}}+\sum_{i=1}^{N}\frac{\Lambda_i}{\rho_i}\tilde{\theta}_i\hat{\theta}_i+\sum_{i=1}^{N}\Pi_i. \tag{3.38}$$

3.2. Stability analysis

Theorem 1. *Consider the MAS (2.1) with actuator faults (2.2) satisfying Assumption 1–3, if virtual controllers (3.12) and (3.18), actual controller (3.19), adaptive laws (3.31) and the compensating signals (3.3)–(3.5) are designed under event-triggered mechanism (3.20) and (3.21), then it can be guaranteed that 1) all signals in the closed-loop system are bounded; 2) the tracking errors converge into a small neighborhood of the origin in finite time; 3) Zeno behavior is effectively elimitated.*

Proof: We can know from Young's inequality that

$$\frac{\Lambda_i}{\rho_i}\tilde{\theta}_i\hat{\theta}_i\leq-\frac{\Lambda_i}{2\rho_i}\tilde{\theta}_i^2+\frac{\Lambda_i}{2\rho_i}\theta_i^2\leq-\frac{\Lambda_i}{8\rho_i}\tilde{\theta}_i^2-\Lambda_i(\frac{\tilde{\theta}_i^2}{2\rho_i})^{\frac{3}{4}}+\pi_i, \tag{3.39}$$

where $\pi_i = \frac{\Lambda_i}{4} + \frac{\Lambda_i}{2\rho_i}\theta_i^2$. With the help of Lemma 4 and by substituting (3.39) into (3.38), one has

$$\dot{V} \leq -\sum_{i=1}^{N}\sum_{v=1}^{n}\bar{\lambda}_i(\frac{1}{4}\chi_{i,v}^4) - \sum_{i=1}^{N}\frac{\Lambda_i}{8\rho_i}\tilde{\theta}_i^2 - \sum_{i=1}^{N}\sum_{v=1}^{n}\bar{\xi}_i(\frac{1}{4}\chi_{i,q}^4)^{\frac{3}{4}} - \sum_{i=1}^{N}\Lambda_i(\frac{\tilde{\theta}_i^2}{2\rho_i})^{\frac{3}{4}} - \lambda_i V_{i,n+1} - \sum_{i=1}^{N} d_i V_{i,n+1}^{\frac{3}{4}} + \Pi$$
$$\leq -\lambda V - \xi V^{\frac{3}{4}} + \Pi, \tag{3.40}$$

where $\Pi = \sum_{i=1}^{N}(\Pi_i + \pi_i)$, $\lambda = \min\{\bar{\lambda}_i, \frac{1}{4}\Lambda_i, \lambda_i\}$ and $\xi = \min\{\bar{\xi}_i, \Lambda_i, d_i\}$, $i = 1, 2, \dots, n$. It follows from (3.40) that $\dot{V} \leq -\lambda V + \Pi$, namely, $V \leq (V(t_0) - \frac{\Pi}{\lambda})e^{-\lambda(t-t_0)} + \frac{\Pi}{\lambda} \leq V(t_0) + \frac{\Pi}{\lambda}$. Therefore, all signals in the closed-loop system remain bounded. According to Lemma 5, we can conclude that $V \leq (\frac{\Pi}{(1-h)\xi})^{\frac{4}{3}}$ in a finite time T for $h \in (0, 1)$. Thus, it is derived that $|\varsigma_{i,q}| \leq 2\sqrt{2}\left(\frac{\Pi}{(1-h)\xi}\right)^{\frac{1}{3}}$. Due to $\varsigma_1 = \mathcal{D}(y - (1_N \otimes y_d))$ with $\varsigma_1 = [\varsigma_{1,1}, \varsigma_{2,1}, \dots, \varsigma_{N,1}]^T$ and $y = [y_{1,1}, y_{2,1}, \dots, y_{N,1}]^T$, thus $|y_i - y_d| \leq \frac{2\sqrt{2}\left(\frac{\Pi}{(1-h)\xi}\right)^{\frac{1}{3}}}{\mu}$, where μ denotes the least singular value of $\mathcal{D}$. Moreover, T satisfies

$$T \leq \max\{T_{i,1}\} + \frac{4}{\lambda}\ln\frac{\lambda V^{\frac{1}{4}}(t_0) + h\xi}{\lambda(\frac{\Pi}{(1-h)\xi})^{\frac{1}{3}} + h\xi}. \tag{3.41}$$

Next, we will demonstrate that Zeno phenomenon can be excluded under the proposed scheme, namely, there exists $t_\star^i > 0$, such that $t_{l+1}^i - t_l^i \geq t_\star^i$ with $l \in Z^+$. Owing to $z_i(t) = \varpi_i(t) - \bar{u}_i(t)$, we have $\forall t \in [t_l^i, t_{l+1}^i)$,

$$\frac{d}{dt}|z_i| = \frac{d}{dt}\sqrt{z_i \times z_i} = sgn(z_i)\dot{z}_i \leq |\dot{\varpi}_i|. \tag{3.42}$$

Furthermore, it follows from (3.30) that ϖ_i is differentiable and $\dot{\varpi}_i$ is a continuous function of bounded signals. Hence, it can be obtained that $|\dot{\varpi}_i| \leq \varpi_i^*$, where $\varpi_i^* > 0$ is a constant. Because of $z_i(t_l^i) = 0$ and $\lim_{t\to t_{l+1}^i} z_i(t) = \gamma_i|\bar{u}_i(t_l^i)| + \Delta_i$, therefore $t_\star^i \geq \frac{\gamma_i|\bar{u}_i(t_l^i)|+\Delta_i}{\varpi_i^*}$. In conclusion, the Zeno behavior is prevented.

4. Simulation results

In this section, two simulation examples are given to verify the effectiveness of the proposed control scheme.

Example 1: Consider the following multi-agent system

$$\begin{cases} \dot{x}_{i,1} = x_{i,2} + g_{i,1}(x_{i,1}, x_{i,2}), \\ \dot{x}_{i,2} = u_i + g_{i,2}(x_{i,1}, x_{i,2}), \quad i = 1, 2, 3, 4, \end{cases} \tag{4.1}$$

where $g_{1,1} = 0.05\sin(x_{1,1} - x_{1,2})$, $g_{1,2} = 0.01\sin(x_{1,1})\cos(x_{1,2})$, $g_{2,1} = 0.01x_{2,1}\cos(x_{2,2})$, $g_{2,2} = 0.03\sin(0.5(x_{2,1} - x_{2,2}))$, $g_{3,1} = 0.02\exp(-x_{3,1})\cos(x_{3,2})$, $g_{3,2} = 0.02\sin(0.3(x_{3,1} - x_{3,2}))$, $g_{4,1} = 0.05\exp(-x_{4,1})\cos(x_{4,2})$, $g_{4,2} = 0.01\sin(x_{4,1} - x_{4,2})$. The actuator fault models for four followers are defined as

$$u_1 = (0.8 + 0.1\cos(-0.5t))\bar{u}_1 + 0.3\sin t,\quad u_2 = (0.7 + 0.1\sin(-0.6t))\bar{u}_2 + 0.3\sin t,$$
$$u_3 = (0.6 + 0.2\sin(-0.5t))\bar{u}_3 + 0.3\sin t,\quad u_4 = (0.5 + 0.1\cos(-0.7t))\bar{u}_4 + 0.3\sin t.$$

The communication topology of four followers and one leader is shown in Figure 1. And the Laplacian matrix and the pinning matrix can be described as

$$C = \begin{pmatrix} 1 & 0 & -1 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 1 \end{pmatrix}, \qquad \mathcal{W} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}.$$

Moreover, the output of leader is $y_d = \sin(0.5t)$. Our control objective is to make the output of each follower y_i track y_d in finite time. NNs are used to approximate the unknown nonlinear functions $\bar{g}_{i,q}(Z_{i,q})$ $(i = 1,2,3,4, q = 1,2)$. $\Phi^{*T}_{i,q}S_{i,q}(Z_{i,q})$ contains 11 nodes, and the centers ϑ_j are evenly distributed in $[-2.5, 2.5]$ with width of 2. Besides, the initial conditions are selected as $x(0) = [0.1, 0.1, 0.1, 0.2, 0.2, 0.1, 0.4, 0.3]^T$, $\gamma(0) = [0.5, 0.5, 0.3, 0.5]^T$, $\theta(0) = [0.1, 0.2, 0.3, 0.4]^T$, $\eta_{i,q}(0) = 0$ and $\breve{\alpha}_{i,2}(0) = 0$, $i = 1,2,3,4$, $q = 1,2$. To achieve the control objective, the design parameters are chosen as $\lambda_{i,q} = 15$, $b_{i,q} = 10$, $\xi_{i,q} = 0.1$, $d_{1,q} = d_{2,1} = 0.25$, $d_{2,2} = d_{3,q} = d_{4,q} = 0.5$, $\Lambda_i = 0.6$, $\beta_i = 0.5$, $\rho_1 = \rho_2 = \rho_4 = 15$, $\rho_3 = 10$, $\psi_i = 0.05$, $\bar{o}_1 = \bar{o}_2 = \bar{o}_3 = 50$, $\bar{o}_4 = 60$, $\Delta_i = 3$ and $\sigma_i = 0.2$, $i = 1,2,3,4$, $q = 1,2$.

The simulation results under the proposed control strategy are depicted in Figures 2–7. As shown in Figure 2, each follower's output y_i can well track the leader's output y_d.

Figures 3 and 4 show the input signals $\bar{u}_i$ of four followers. The trajectories of dynamic trigger time intervals $t^i_{\iota+1} - t^i_\iota$ are exhibited in Figures 5 and 6, and the event-triggered numbers of four followers are shown in Table 2. It is clearly seen that the amount of computation and communication resources are considerably reduced. At last, Figure 7 displays the boundedness of the adaptive laws $\hat{\theta}_i (i = 1,2,3,4)$.

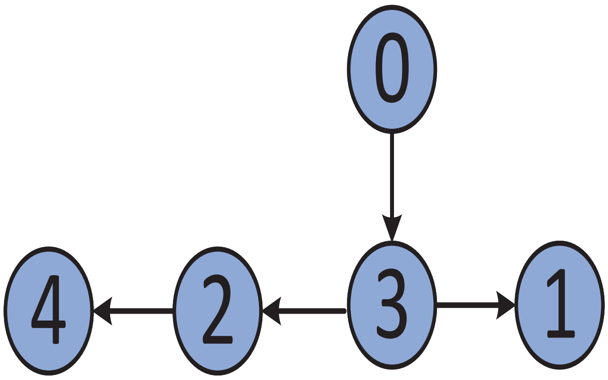

Figure 1. Communication topology in Example 1.

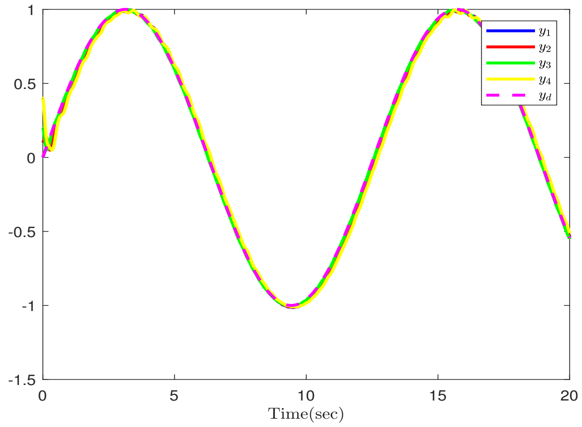

Figure 2. The trajectories of $y_i (i = 1, 2, 3, 4)$ and y_d in Example 1.

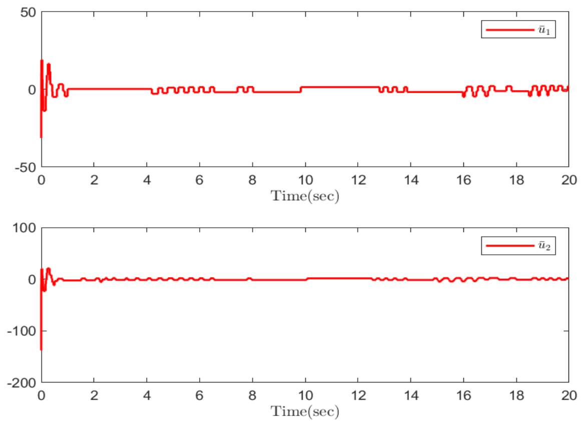

Figure 3. The trajectories of control input signals $\bar{u}_1$ and $\bar{u}_2$ in Example 1.

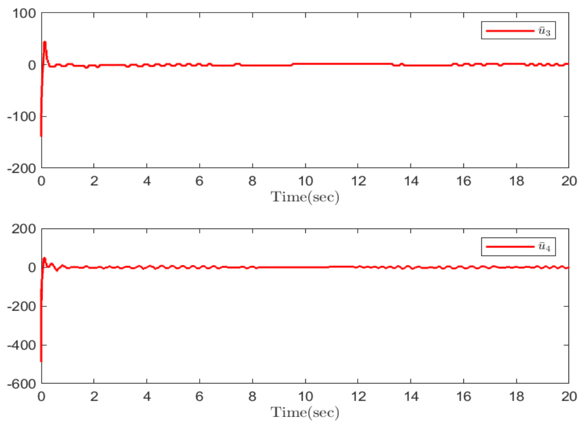

Figure 4. The trajectories of control input signals $\bar{u}_3$ and $\bar{u}_4$ in Example 1.

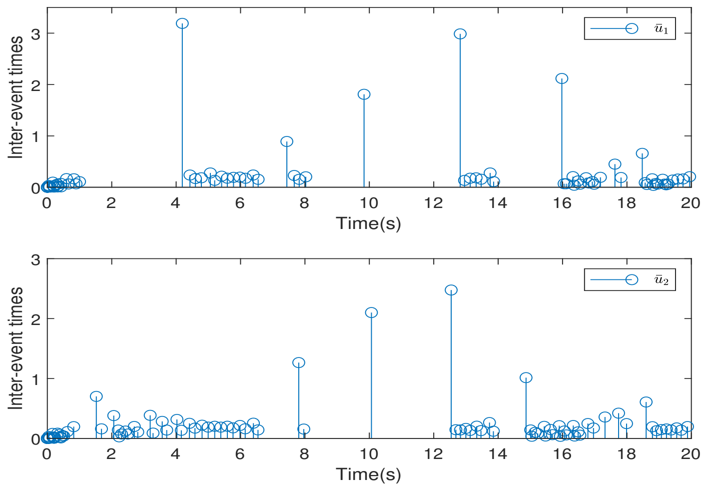

Figure 5. The trigger time intervals of $\bar{u}_1$ and $\bar{u}_2$ in Example 1.

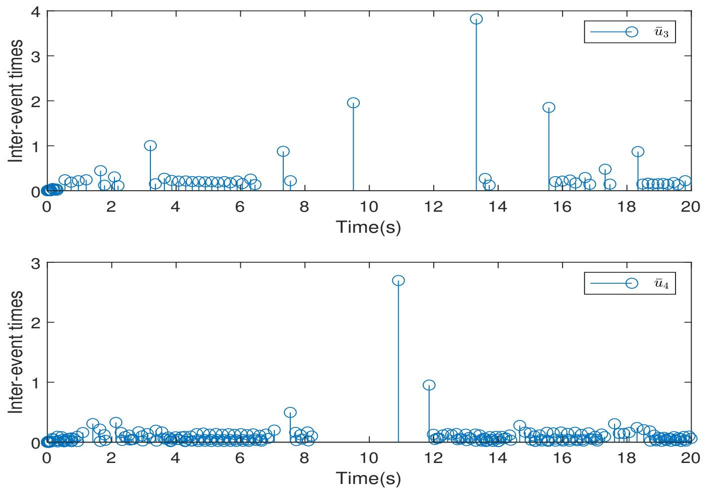

Figure 6. The trigger time intervals of $\bar{u}_3$ and $\bar{u}_4$ in Example 1.

Table 2. The number of triggers of each follower in Example 1.

Agent(node)	1	2	3	4
The number of triggers	81	100	71	229

Example 2: To prove that the proposed scheme is applicable in practice, the multiple single-link robot manipulator systems (SRMSs) are considered. According to [29], suppose that there are four followers and the SRMS is described as

$$M\ddot{q}_i + B\dot{q}_i + N\sin(\dot{q}_i) = I_i, \quad i = 1, 2, 3, 4, \tag{4.2}$$

where $M = \frac{J}{K_\tau} + \frac{mL_0^2}{3K_\tau} + \frac{M_0L_0^2}{K_\tau} + \frac{2M_0R_0^2}{5K_\tau}$, $N = \frac{mL_0G}{2K_\tau} + \frac{M_0L_0G}{K_\tau}$ and $B = \frac{B_0}{K_\tau}$, q_i and I_i are the angular position and motor armature current, respectively. In [29], the designed parameters $M = 1, B = 1, N = 1$ have been given. Define $x_{i,1} = q_i, x_{i,2} = \dot{q}_i, u_i = I_i$, (4.2) can be rewritten as

$$\begin{aligned}\dot{x}_{i,1} &= x_{i,2} + g_{i,1},\\ \dot{x}_{i,2} &= u_i + g_{i,2},\end{aligned} \tag{4.3}$$

where $g_{i,1} = 0,\ g_{i,2} = 10\sin(x_{i,1}) - x_{i,2}$. The actuator fault models for four followers are defined as

$$u_1 = (0.6 + 0.1\cos(-0.5t))\bar{u}_1 + 0.3\sin t,\quad u_2 = (0.5 + 0.25\sin(-0.6t))\bar{u}_2 + 0.3\sin t,$$
$$u_3 = (0.7 + 0.2\sin(-0.5t))\bar{u}_3 + 0.3\sin t,\quad u_4 = (0.3 + 0.25\cos(-0.7t))\bar{u}_4 + 0.3\sin t.$$

The communication relationship between the four followers and the leader is depicted in Figure 8. Therefore, based on Figure 8, the Laplacian matrix C and the pinning matrix $\mathcal{W}$ are expressed as

$$C = \begin{pmatrix} 1 & -1 & 0 & 0\\ 0 & 1 & -1 & 0\\ 0 & -1 & 1 & 0\\ 0 & 0 & -1 & 1\end{pmatrix},\qquad \mathcal{W} = \begin{pmatrix} 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0\\ 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 0\end{pmatrix}.$$

And the leader's output is $y_d = 0.5\sin t$. The initial conditions are the same as in Example 1, and the parameters are designed as $\lambda_{1,q} = \lambda_{2,q} = \lambda_{4,1} = 65$, $\lambda_{3,q} = \lambda_{4,2} = 60$, $b_{i,q} = 10$, $\xi_{i,q} = 0.01$, $d_{i,q} = 0.01$, $\Lambda_i = 2$, $\beta_i = 2$, $\rho_i = 20$, $\psi_1 = \psi_2 = \psi_3 = 0.05$, $\psi_4 = 0.12$, $\bar{o}_1 = \bar{o}_2 = \bar{o}_4 = 50$, $\bar{o}_3 = 45$, $\Delta_1 = 4$, $\Delta_2 = \Delta_3 = 1$, $\Delta_4 = 5$ and $\sigma_i = 0.1$, $i = 1, 2, 3, 4$, $q = 1, 2$.

Figures 9–14 display the simulation results of our devised scheme. The output curves are shown in Figure 9, which indicates that the desired consensus can be achieved in finite time. Figure 10 illustrates the trajectories of the adaptive laws $\hat{\theta}_i (i = 1, 2, 3, 4)$. The trajectories of $\bar{u}_i (i = 1, 2, 3, 4)$ are drawn in Figures 11 and 12, and the trigger time intervals are reflected in Figures 13 and 14. Furthermore, the event-triggered numbers of four followers are presented in Table 3. In conformity with the simulation results, the control scheme can be well applied in the SRMSs.

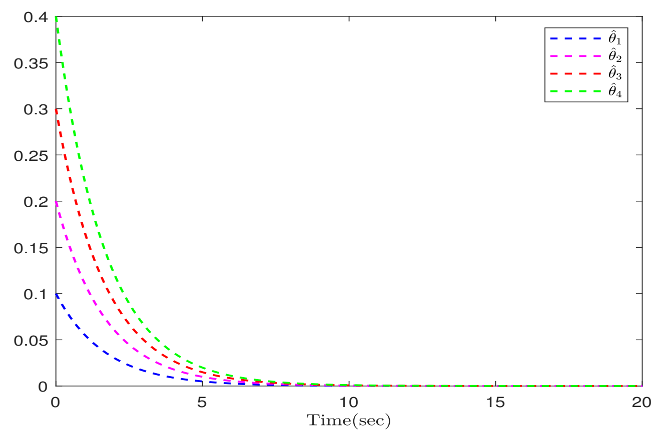

Figure 7. he trajectories of the adaptive laws $\hat{\theta}_i (i = 1, 2, 3, 4)$ in Example 1.

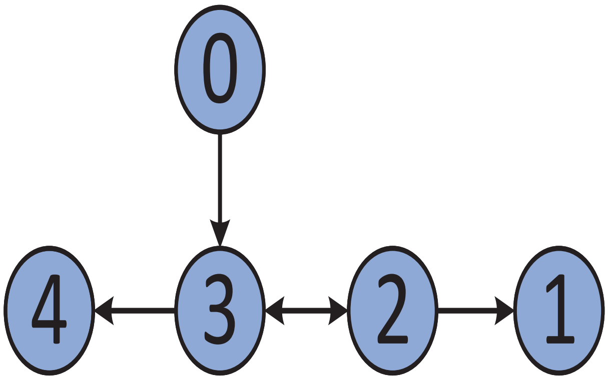

Figure 8. Communication topology in Example 2.

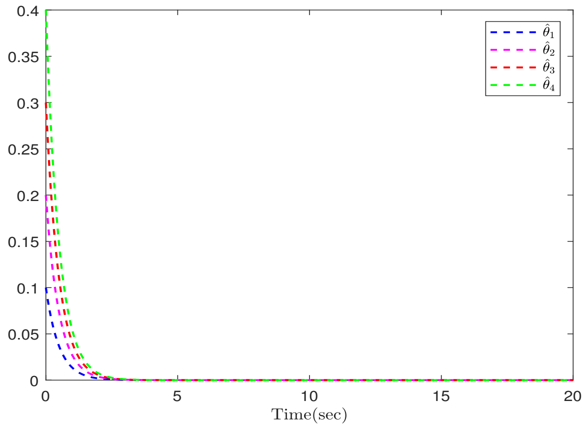

Figure 10. The trajectories of the adaptive laws $\hat{\theta}_i(i = 1, 2, 3, 4)$ in Example 2.

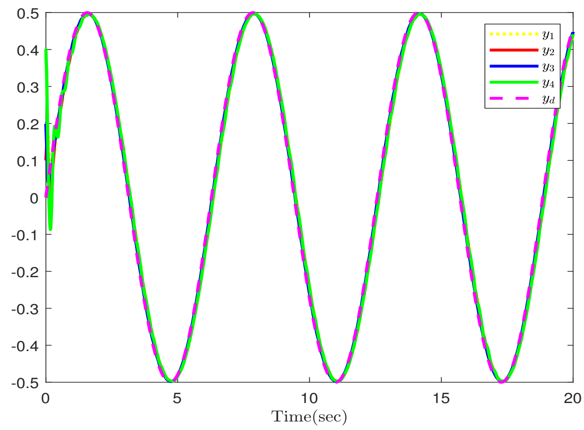

Figure 9. The trajectories of $y_i(i = 1, 2, 3, 4)$ and y_d in Example 2.

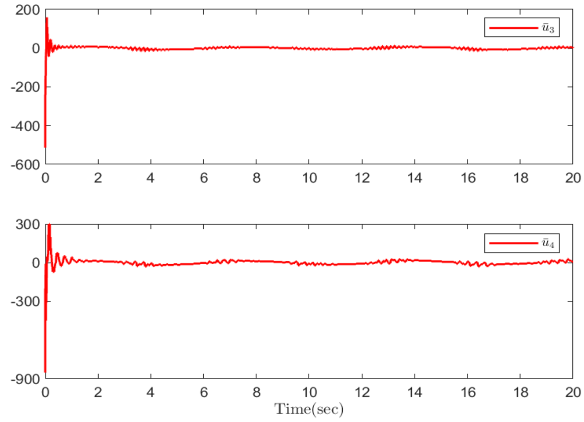

Figure 12. The trajectories of control input signals $\bar{u}_3$ and $\bar{u}_4$ in Example 2.

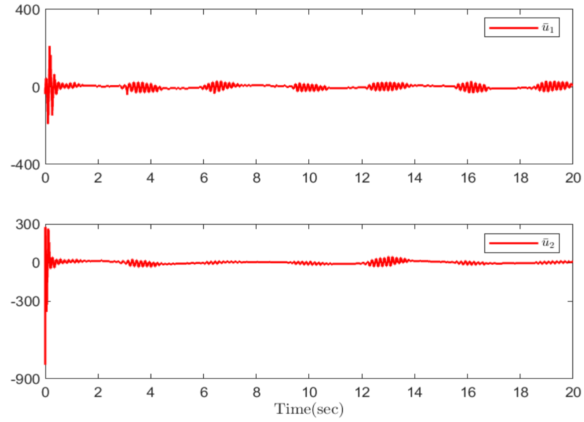

Figure 11. The trajectories of control input signals $\bar{u}_1$ and $\bar{u}_2$ in Example 2.

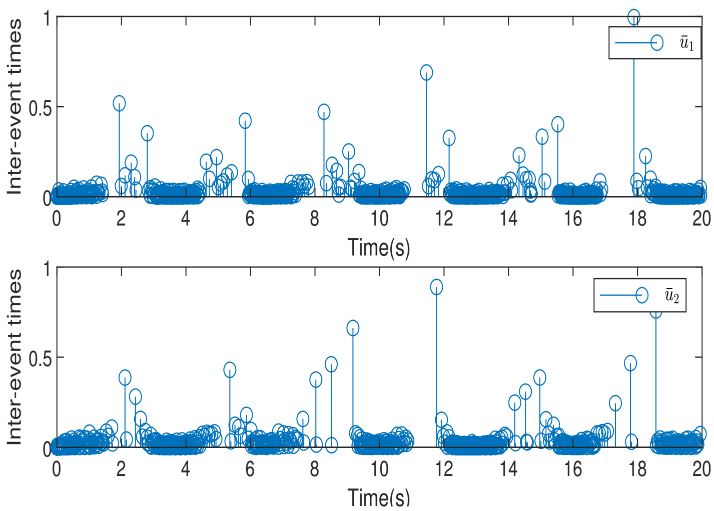

Figure 13. The trigger time intervals of $\bar{u}_1$ and $\bar{u}_2$ in Example 2.

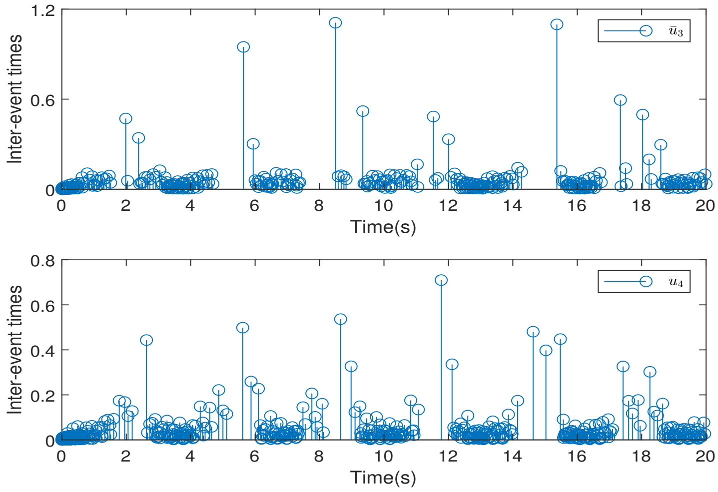

Figure 14. The trigger time intervals of $\bar{u}_3$ and $\bar{u}_4$ in Example 2.

Table 3. The number of triggers of each follower in Example 2.

Agent(node)	1	2	3	4
The number of triggers	362	685	390	289

5. Conclusions

In this paper, with a view towards leader-following consensus tracking, an adaptive finite-time DETC scheme has been proposed for MASs with unknown time-varying actuator faults. Based on adaptive backstepping method, neural network approximation technique and command filter technique, the actuator efficiency has been compensated successfully. Moreover, the DETM has been given for each follower to reduce the update frequency of controller and mitigate the communication burden. In the light of the presented control scheme, leader-following consensus has been achieved in finite time and all signals of the closed-loop system are bounded. In the future, we will tend to study the consensus tracking problem of multiple leaders with time-varying actuator failures in switching topology.

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Conflict of interest

The authors declare there is no conflict of interest.

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