



Article

Fractional-Order Dynamic Event-Triggered-Based Adaptive Fuzzy Predefined-Time Consensus Tracking Control for Euler–Lagrange Systems with Actuator Faults

Zhenlin Wang ¹ , Seiji Hashimoto ^{1,*} , Song Xu ² and Takahiro Kawaguchi ¹

¹ Division of Electronics and Informatics, Gunma University, Kiryu 376-8515, Japan; zhenlinwang8689@gmail.com (Z.W.)

² College of Automation, Jiangsu University of Science and Technology, Zhenjiang 212000, China

* Correspondence: hashimotos@gunma-u.ac.jp

Abstract

This paper investigates the predefined-time leader–follower consensus tracking problem for multiple Euler–Lagrange systems subject to actuator faults under a fractional-order dynamic event-triggered framework. First, to guarantee the convergence-time requirement, nonsingular predefined-time terms are embedded into the backstepping design, such that the consensus tracking errors can enter a small residual set within a predefined time. Then, a fractional-order dynamic event-triggered mechanism is introduced to determine the update instants of the sampled actuator input, in which the fractional-order auxiliary variable is used to incorporate historical triggering information into the threshold dynamics. Moreover, adaptive laws and fuzzy logic systems (FLSs) are employed to compensate for actuator faults and model uncertainties. Furthermore, based on predefined-time Lyapunov analysis, it is proved that all closed-loop signals are bounded and predefined-time consensus tracking performance is achieved. Finally, simulation results verify the effectiveness of the proposed method.

Keywords: Euler–Lagrange systems; adaptive fault-tolerant control; fuzzy logic systems; fractional-order dynamic event-triggered control; predefined-time consensus control

1. Introduction

Multi-agent systems (MASs) have attracted considerable attention due to their ability to accomplish cooperative tasks through distributed information exchange [1]. Owing to their scalability, flexibility, and distributed decision-making capability, MASs have been widely applied in many engineering fields, such as robotic manipulators [2], intelligent transportation systems [3], and industrial automation [4]. Euler–Lagrange systems provide a general modeling framework for describing the dynamics of agents in many engineering MASs [5]. As a fundamental problem in cooperative control, leader–follower consensus tracking of multiple Euler–Lagrange systems aims to make all followers track a reference signal generated by a leader through local information exchange [6,7]. However, in practical implementations, communication constraints, convergence-time requirements, and actuator faults should also be considered.

To reduce frequent communication and actuator input updates, event-triggered control has been introduced into multiple Euler–Lagrange systems. Wang et al. developed a fully distributed event-triggered adaptive fuzzy consensus control method for multiple uncertain Euler–Lagrange systems [8]. The model-independent event-based consensus



Academic Editor: Carlo Cattani

Received: 11 June 2026

Revised: 23 July 2026

Accepted: 31 July 2026

Published: 4 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

problem of multiple Euler–Lagrange systems subject to input disturbances was further investigated in [9]. These methods effectively reduce unnecessary communication and control updates. However, their triggering conditions mainly depend on instantaneous system information, resulting in limited flexibility in threshold adjustment. To overcome this limitation, dynamic event-triggered mechanisms have been investigated. A periodic event-based sliding-mode tracking controller incorporating a dynamic triggering variable was developed for Euler–Lagrange systems in [10]. For multi-leader UAV formations, Wang et al. developed an adaptive finite-time fault-tolerant control with distributed two-channel dynamic event-triggered method [11]. Ren et al. designed a method of finite-time distributed tracking control with dynamic event-triggered for networked multi-UAV systems [12]. Through the incorporation of auxiliary dynamic variables into the triggering conditions, these investigations improve the flexibility of threshold adjustment and reduce unnecessary control updates. However, the auxiliary threshold variables in these methods are governed by integer-order differential equations, and the nonlocal memory of historical triggering information is not explicitly incorporated into the threshold evolution. Fractional-order operators can incorporate both current and historical triggering information into the threshold dynamics. Therefore, introducing fractional-order dynamics into the event-triggering mechanism provides a more flexible way to balance the control update frequency and consensus tracking performance. Despite these potential advantages, fractional-order dynamic event-triggered consensus tracking for multiple Euler–Lagrange systems remains insufficiently investigated, while reducing control updates alone cannot guarantee that the tracking errors converge within a predefined time.

Although event-triggered control reduces actuator input updates, convergence-time performance remains an important issue in consensus tracking control [13]. To improve convergence speed, Liu et al. and Gong et al. respectively studied fixed-time consensus tracking problems for nonlinear MASs with directed communication networks and second-order MASs with disturbances [14,15]. These results guarantee that the convergence-time upper bound is independent of initial conditions. However, this upper bound is still determined by control parameters and cannot be specified in advance according to task requirements. Compared with fixed-time control, the method of predefined-time control allows the convergence time to be specified as a design parameter. To meet stricter time requirements, Wang et al. proposed a method of prescribed-time consensus and containment control for networked Euler–Lagrange systems, while the considered agents are mainly first-order systems [16]. Ni et al. investigated predefined-time consensus tracking for networked systems with second-order dynamics [17]. Zou et al. addressed the predefined-time output-feedback consensus tracking problem for Euler–Lagrange systems with disturbances [18]. Yoo and Park further studied dynamic event-triggered prescribed-time consensus tracking for nonlinear time-delay networked systems in [19]. However, fractional-order event-triggered predefined-time consensus tracking for multiple Euler–Lagrange systems remains insufficiently investigated.

In practical Euler–Lagrange systems, actuator faults may occur due to long-term operation [20], mechanical wear [21], device aging [22], or varying operating conditions [23]. As a result, the actual actuator input may deviate from the designed control signal, which can degrade cooperative tracking performance or even affect closed-loop stability [24]. Moreover, actuator faults occurring in one agent may affect the cooperative behavior of the whole group [25]. Therefore, fault-tolerant cooperative control for Euler–Lagrange systems with actuator faults has attracted increasing attention. For networked Euler–Lagrange and multi-manipulator systems with actuator faults, distributed robust fault-tolerant control, event-triggered consensus control, finite-time formation-containment control, and fuzzy adaptive containment control have been investigated in [26–29]; however, these meth-

ods do not achieve predefined-time fault-tolerant consensus tracking. Shi et al. further proposed a predefined-time event-triggered sliding-mode control method for uncertain Euler–Lagrange dynamic systems with actuator faults [30], but the fractional-order dynamic event-triggered consensus tracking problem for multiple Euler–Lagrange systems was not considered. Nevertheless, predefined-time fault-tolerant consensus tracking for multiple Euler–Lagrange systems under fractional-order dynamic event-triggered control still needs further investigation.

Based on the above discussion, this paper addresses the predefined-time leader–follower consensus tracking problem for multiple Euler–Lagrange systems subject to actuator faults under a fractional-order event-triggered framework. The virtual leader information is available only to a subset of followers. A fractional-order dynamic event-triggered mechanism and an adaptive fuzzy fault-tolerant controller are developed. It is proved that all closed-loop signals are bounded and that the consensus tracking errors enter a small residual set within a predefined time. The main contributions of this paper are summarized as follows:

- Different from the finite/fixed-time control methods [18,19], this paper investigates predefined-time consensus tracking for multiple Euler–Lagrange systems in which the settling time can be specified in advance and depends only on simple adjustment parameters rather than the initial conditions or complicated design parameters. A smooth predefined-time control approach is developed by smoothly switching between the state-dependent fractional-power and cubic terms. Unlike the methods in [16,17], which may suffer from singularity problems, the nonsingular predefined-time terms are incorporated into the backstepping design in this paper and the consensus tracking errors can converge to a small residual set within a predefined time.
- Compared with the integer-order dynamic event-triggered method in [12], this paper develops a fractional-order dynamic event-triggered mechanism for multiple Euler–Lagrange systems. The fractional-order auxiliary variable is introduced into the threshold dynamics, such that historical triggering information can be used in the triggering decision. The proposed mechanism reduces unnecessary triggering events while improving consensus tracking accuracy.
- Compared with the fault-tolerant Euler–Lagrange and multi-manipulator control methods in [26–30], this paper simultaneously considers predefined-time consensus tracking and fractional-order dynamic event-triggered input updating. An adaptive fault-tolerant compensation mechanism and an auxiliary system are introduced to handle actuator faults, and fault-tolerant consensus tracking is achieved within the proposed predefined-time event-triggered framework.

The rest of this paper is organized as follows. The problem formulation, preliminaries, and basic assumptions are given in Section 2. The controller design and stability analysis are presented in Section 3. Simulation results for networked robotic manipulators are provided in Section 4. The conclusion is given in Section 5.

2. Problem Formulation and Preliminaries

2.1. Graph Theory

Consider a multi-agent system composed of N agents. Its communication topology $\mathcal{G}$ can be represented as a weighted undirected graph $\mathcal{G} = (\mathcal{W}, \mathcal{E}, \mathcal{A})$, where $\mathcal{W} = \{1, 2, \dots, N\}$ and $\mathcal{E} \subseteq \mathcal{W} \times \mathcal{W}$ represent the node set and edge set, respectively. If $(i, j) \in \mathcal{E}$, then agents i and j can exchange information with each other. The adjacency matrix of graph $\mathcal{G}$ is defined as $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{N \times N}$, where $a_{ij} = a_{ji} > 0$ if $(i, j) \in \mathcal{E}$, otherwise $a_{ij} = 0$. In this paper, $a_{ii} = 0$, $i = 1, 2, \dots, N$.

Furthermore, the neighbor set of agent i is defined as $\mathcal{N}_i = \{j \in \mathcal{W} : (i, j) \in \mathcal{E}\}$. The Laplacian matrix associated with graph $\mathcal{G}$ is defined as $\mathcal{L} = [l_{ij}] \in \mathbb{R}^{N \times N}$, where $l_{ij} = -a_{ij}$ for $i \neq j$, and $l_{ii} = \sum_{j=1, j \neq i}^N a_{ij}$. Since $\mathcal{G}$ is undirected, the Laplacian matrix $\mathcal{L}$ is symmetric and positive semi-definite. It can be verified that $\mathcal{L}\mathbf{1}_N = 0$, where $\mathbf{1}_N \in \mathbb{R}^N$ is the vector with all entries equal to one.

A leader-follower architecture is considered in this paper, where the reference signal is generated by a virtual leader. Let $\mu_i \geq 0$ denote the connection weight between the i -th agent and the virtual leader. If $\mu_i > 0$, the i -th agent can directly obtain the reference signal; otherwise, $\mu_i = 0$. Define $\mathcal{B} = \text{diag}\{\mu_1, \mu_2, \dots, \mu_N\}$ and $\mathcal{H} = \mathcal{L} + \mathcal{B}$. In this paper, the communication graph $\mathcal{G}$ is fixed, undirected, and connected, and at least one follower can directly obtain the reference signal from the virtual leader. Under these conditions, $\mathcal{H}$ is symmetric positive definite.

2.2. System Model

This paper considers a networked Euler–Lagrange system composed of N agents. The dynamics of the i -th agent are described by

$$M_i(X_i)\ddot{X}_i + C_i(X_i, \dot{X}_i)\dot{X}_i + G_i(X_i) = u_i^a + d_i(t), \quad i = 1, 2, \dots, N, \quad (1)$$

where $X_i \in \mathbb{R}^n$, $\dot{X}_i \in \mathbb{R}^n$, and $\ddot{X}_i \in \mathbb{R}^n$ are the position, velocity, and acceleration vectors of the i -th agent, respectively. $M_i(X_i) \in \mathbb{R}^{n \times n}$, $C_i(X_i, \dot{X}_i) \in \mathbb{R}^{n \times n}$ and $G_i(X_i) \in \mathbb{R}^n$ represent the inertia matrix, Coriolis and centrifugal matrix, and gravity vector, respectively. Moreover, $u_i^a \in \mathbb{R}^n$ and $d_i(t) \in \mathbb{R}^n$ are the actual actuator input and external disturbance, respectively.

For convenience of controller design, define $q_{i1} = X_i$, $q_{i2} = \dot{X}_i$. In the following controller design, the Euler–Lagrange dynamics are rewritten in the following second-order state-space form:

$$\begin{cases} \dot{q}_{i1} = q_{i2}, \\ \dot{q}_{i2} = B_i(q_{i1})u_i^a + \Phi_i(q_{i1}, q_{i2}) + \Delta_i(q_{i1}, t), \end{cases} \quad i = 1, 2, \dots, N, \quad (2)$$

where $B_i(q_{i1}) = M_i^{-1}(q_{i1})$, $\Phi_i(q_{i1}, q_{i2}) = -M_i^{-1}(q_{i1})[C_i(q_{i1}, q_{i2})q_{i2} + G_i(q_{i1})]$, and $\Delta_i(q_{i1}, t) = M_i^{-1}(q_{i1})d_i(t)$.

To achieve consensus tracking, a reference signal $q_d(t) \in \mathbb{R}^n$ is generated by the virtual leader. Define the tracking error vector as $\delta = [\delta_1^\top, \delta_2^\top, \dots, \delta_N^\top]^\top$, with $\delta_i = q_{i1} - q_d(t)$.

Using the communication weights defined in the graph $\mathcal{G}$, the consensus error variable is defined as

$$z_{i1} = \sum_{j=1}^N a_{ij}(q_{i1} - q_{j1}) + \mu_i(q_{i1} - q_d(t)), \quad (3)$$

where a_{ij} and $\mu_i \geq 0$ denote the adjacency weight and the leader connection weight, respectively. In vector form, it can be written as $z_1 = (\mathcal{H} \otimes I_n)\delta$, where $z_1 = [z_{11}^\top, z_{21}^\top, \dots, z_{N1}^\top]^\top$ and $\mathcal{H} = \mathcal{L} + \mathcal{B}$.

2.3. Actuator Fault Model

In practical Euler–Lagrange systems, actuator faults may occur due to efficiency degradation, partial loss of effectiveness, or unexpected bias signals. In this paper, the actual actuator input $u_i^a(t)$ of agent i is modeled as

$$u_i^a(t) = \Gamma_i(t)u_{si}(t) + J_i(t), \quad (4)$$

where $u_{si}(t) \in \mathbb{R}^n$ denotes the sampled control signal generated by the event-triggered mechanism, $\Gamma_i(t) \in \mathbb{R}^{n \times n}$ represents the actuator effectiveness matrix, and $J_i(t) \in \mathbb{R}^n$ denotes the actuator bias fault.

The actuator effectiveness matrix is defined as $\Gamma_i(t) = \text{diag}\{\kappa_{i1}(t), \kappa_{i2}(t), \dots, \kappa_{in}(t)\}$, where $\kappa_{ik}(t)$ represents the effectiveness coefficient of the k -th actuator of agent i . If $\kappa_{ik}(t) = 1$, the corresponding actuator operates without effectiveness loss; if $0 < \kappa_{ik}(t) < 1$, the actuator suffers from partial loss of effectiveness.

2.4. Fractional-Order Dynamic Event-Triggered Mechanism

To decrease unnecessary updates of the control input while using historical triggering information, a fractional-order dynamic event-triggered mechanism is introduced. For agent i , $u_{ei}(t) \in \mathbb{R}^n$ and $u_{si}(t) \in \mathbb{R}^n$ represent the continuous control signal and the sampled control signal, respectively.

For $t \in [t_r^i, t_{r+1}^i)$, the sampled control signal is defined as

$$u_{si}(t) = u_{ei}(t_r^i), \quad t \in [t_r^i, t_{r+1}^i), \quad (5)$$

where t_r^i denotes the r -th triggering instant of agent i .

The event-triggering error is defined as

$$e_{ui}(t) = u_{si}(t) - u_{ei}(t). \quad (6)$$

The triggering instant is determined by

$$t_{r+1}^i = \inf \left\{ t > t_r^i \mid h_i \|u_{si}(t)\| - \|e_{ui}(t)\| + m_i(t) \leq 0 \right\}, \quad (7)$$

where $0 < h_i < 1$ and $m_i(0) > 0$.

Different from the conventional integer-order dynamic event-triggered mechanism, the auxiliary triggering variable $m_i(t)$ is updated by the following fractional-order dynamic law

$${}^C D_t^{\alpha_{FD}} m_i(t) = -\Pi_1 m_i(t) + \Pi_2 [2 + \tanh(h_i \|u_{si}(t)\| - \|e_{ui}(t)\|)], \quad (8)$$

where $0 < \alpha_{FD} < 1$, ${}^C D_t^{\alpha_{FD}}$ denotes the Caputo fractional derivative.

Let $\chi_i(t) = h_i \|u_{si}(t)\| - \|e_{ui}(t)\|$. Since $-1 < \tanh(\chi_i(t)) < 1$, one has $1 < 2 + \tanh(\chi_i(t)) < 3$. It follows from the dynamic law of $m_i(t)$ that

$${}^C D_t^{\alpha_{FD}} m_i(t) \geq -\Pi_1 m_i(t) + \Pi_2, \quad {}^C D_t^{\alpha_{FD}} m_i(t) \leq -\Pi_1 m_i(t) + 3\Pi_2. \quad (9)$$

Applying the fractional-order comparison principle to these two differential estimates gives

$$0 < m_i^* \leq m_i(t) \leq \bar{m}_i, \quad (10)$$

where

$$m_i^* = \min \left\{ m_i(0), \frac{\Pi_2}{\Pi_1} \right\}, \quad \bar{m}_i = \max \left\{ m_i(0), \frac{3\Pi_2}{\Pi_1} \right\}. \quad (11)$$

Therefore, under $m_i(0) > 0$, $\Pi_1 > 0$, and $\Pi_2 > 0$, the auxiliary triggering variable $m_i(t)$ remains positive and bounded.

Using the Caputo fractional derivative, $m_i(t)$ can be expressed in the following integral form:

$$m_i(t) = m_i(0) + \frac{1}{\Gamma(\alpha_{FD})} \int_0^t (t-s)^{\alpha_{FD}-1} [-\Pi_1 m_i(s) + \Pi_2 (2 + \tanh(h_i \|u_{si}(s)\| - \|e_{ui}(s)\|))] ds. \quad (12)$$

This expression shows that the evolution of $m_i(t)$ depends on the historical triggering information over $[0, t]$.

For $t \in [t_r^i, t_{r+1}^i)$, the triggering condition implies

$$\|e_{ui}(t)\| \leq h_i \|u_{si}(t)\| + m_i(t). \quad (13)$$

For subsequent stability analysis, there exist time-varying variables $v_1(t)$ and $v_2(t)$ satisfying $\|v_1(t)\| \leq 1$ and $\|v_2(t)\| \leq 1$ such that

$$e_{ui}(t) = -h_i v_1(t) u_{si}(t) - v_2(t) m_i(t). \quad (14)$$

Combining the above equation with $e_{ui}(t) = u_{si}(t) - u_{ei}(t)$ yields

$$u_{si}(t) = (1 + h_i v_1(t))^{-1} (u_{ei}(t) - v_2(t) m_i(t)). \quad (15)$$

Remark 1. When $m_i(t) = 0$, the proposed triggering mechanism reduces to the static event-triggered mechanism. Since $m_i(t)$ remains positive, the dynamic threshold relaxes the triggering condition and helps avoid unnecessary actuator input updates. Different from the conventional integer-order dynamic event-triggered mechanism, the auxiliary variable $m_i(t)$ is generated by a fractional-order dynamic law. From the integral form of $m_i(t)$, the current threshold depends on the historical evolution of the triggering condition over $[0, t]$. Therefore, the triggering decision is affected not only by the current triggering error, but also by past triggering information. In addition, the fractional order α_{FD} affects the memory weight in the threshold dynamics and provides an additional degree of freedom for the event-triggered design. This feature gives the proposed mechanism more flexibility in balancing the control update frequency and consensus tracking accuracy.

Control objective: This paper aims to design an adaptive fuzzy fractional-order dynamic event-triggered controller for each Euler–Lagrange agent such that all followers can achieve predefined-time tracking of the reference signal generated by the virtual leader, despite unknown nonlinearities, external disturbances, and actuator faults. Specifically, the consensus tracking errors enter a small residual set within the predefined time T_c , while all signals in the closed-loop system remain bounded.

2.5. Lemmas and Assumptions

Lemma 1 ([13]). Consider a positive definite Lyapunov function $V(t)$. If there exist positive constants c_1, c_2, T_c, Λ , and a constant $0 < \vartheta < 1$ such that

$$\dot{V} \leq -c_1 V^{1-\frac{\vartheta}{2}} - c_2 V^{1+\frac{\vartheta}{2}} + \Lambda, \quad (16)$$

then the closed-loop system is predefined-time stable. Moreover, the settling time satisfies $T \leq \frac{\pi}{\vartheta \sqrt{c_1 c_2}}$. Therefore, if the control parameters are selected such that $\sqrt{c_1 c_2} \geq \frac{\pi}{\vartheta T_c}$, the convergence time can be predefined by T_c .

Lemma 2 ([31]). For any $x \in \mathbb{R}$ and any constant $\varepsilon > 0$, the following inequality holds:

$$0 \leq |x| - x \tanh\left(\frac{x}{\varepsilon}\right) \leq 0.2785\varepsilon. \quad (17)$$

Lemma 3 ([32]). For any $x, y \in \mathbb{R}$ and any constant $\eta > 0$, the following inequality holds:

$$xy \leq \frac{\eta}{2}x^2 + \frac{1}{2\eta}y^2. \quad (18)$$

Lemma 4 ([32]). For any vector $x \in \mathbb{R}^n$ and any constant $\varepsilon > 0$, the following inequality holds:

$$0 \leq \|x\| - \frac{x^\top x}{\sqrt{x^\top x + \varepsilon^2}} \leq \varepsilon. \quad (19)$$

Lemma 5 ([33]). For $x_i \geq 0$, $i = 1, 2, \dots, N$, and $0 < r_{l1} < 1$, the following inequality holds:

$$\sum_{i=1}^N x_i^{r_{l1}} \geq \left(\sum_{i=1}^N x_i \right)^{r_{l1}}. \quad (20)$$

For $r_{l2} > 1$, the following inequality holds:

$$\sum_{i=1}^N x_i^{r_{l2}} \geq N^{1-r_{l2}} \left(\sum_{i=1}^N x_i \right)^{r_{l2}}. \quad (21)$$

Lemma 6. For any $x \in \mathbb{R}$ and $\alpha_{le} > 0$, define

$$\text{sig}^{\alpha_{le}}(x) = |x|^{\alpha_{le}} \text{sgn}(x).$$

Then, $x \text{sig}^{\alpha_{le}}(x) = |x|^{\alpha_{le}+1}$.

Assumption 1. The reference signal $q_d(t)$, $\dot{q}_d(t)$, and $\ddot{q}_d(t)$ are continuous and bounded.

Assumption 2. The actuator effectiveness factors $\kappa_{ik}(t)$ are unknown but strictly positive, and the actuator bias fault $J_i(t)$ is unknown but bounded. Specifically, there exist unknown positive constants $\underline{\kappa}_i$, $\bar{\kappa}_i$, and $\bar{J}_i$ such that

$$0 < \underline{\kappa}_i \leq \kappa_{ik}(t) \leq 1, \quad k = 1, 2, \dots, n, \quad \|J_i(t)\| \leq \bar{J}_i. \quad (22)$$

Assumption 3. The external disturbance $\Delta_i(q_{i1}, t)$, the fuzzy approximation error $\rho_i(x_i)$, and the actuator bias fault term $B_i J_i(t)$ are bounded. Therefore, for the lumped uncertainty $\Delta_{\Xi_i} = \rho_i(x_i) + B_i J_i(t) + \Delta_i$, there exists an unknown positive constant Ξ_i such that

$$\|\Delta_{\Xi_i}(t)\| \leq \Xi_i. \quad (23)$$

3. Controller Design and Stability Analysis

3.1. Event-Based Predefined-Time Fuzzy Consensus Control

To facilitate the controller design, the local consensus tracking error z_{i1} is defined as

$$z_{i1} = \sum_{j=1}^N a_{ij}(q_{i1} - q_{j1}) + \mu_i(q_{i1} - q_d). \quad (24)$$

The leader-following tracking error is defined as $\delta_i = q_{i1} - q_d$, and the stacked tracking error vector is given by $\delta = [\delta_1, \delta_2, \dots, \delta_N]^\top$. Then, the vector form of (24) can be written as

$$z_1 = [z_{11}, z_{21}, \dots, z_{N1}]^\top = \mathcal{H}\delta, \quad (25)$$

where $\mathcal{H} = \mathcal{L} + \mathcal{B}$ is symmetric positive definite.

Based on the backstepping technique, the second backstepping error variable z_{i2} is introduced as

$$z_{i2} = q_{i2} - \alpha_{i1}. \quad (26)$$

Step 1: In this step, q_{i2} is regarded as a virtual control input, and the virtual control law α_{i1} is designed to stabilize z_{i1} .

Consider the following Lyapunov function V_1

$$V_1 = \frac{1}{2} \delta^\top (\mathcal{L} + \mathcal{B}) \delta = \frac{1}{2} \delta^\top \mathcal{H} \delta. \quad (27)$$

Since $\mathcal{H}$ is symmetric positive definite, V_1 is positive definite with respect to δ , and the derivative of tracking error δ_i can be obtained that

$$\dot{\delta}_i = \dot{q}_{i1} - \dot{q}_d = q_{i2} - \dot{q}_d = z_{i2} + \alpha_{i1} - \dot{q}_d. \quad (28)$$

Then, the derivative of V_1 is obtained as

$$\dot{V}_1 = \delta^\top \mathcal{H} \dot{\delta} = z_1^\top \dot{\delta} = \sum_{i=1}^N z_{i1}^\top \dot{\delta}_i = \sum_{i=1}^N z_{i1}^\top (z_{i2} + \alpha_{i1} - \dot{q}_d). \quad (29)$$

The virtual control law is designed as

$$\alpha_{i1} = - \frac{z_{i1} \bar{\alpha}_{i1}^\top \bar{\alpha}_{i1}}{\sqrt{z_{i1}^\top z_{i1} \bar{\alpha}_{i1}^\top \bar{\alpha}_{i1} + \varepsilon_{i1}^2}}, \quad (30)$$

where $\varepsilon_{i1} > 0$ is a positive constant, and

$$\bar{\alpha}_{i1} = k_{i1} z_{i1} + k_{i1} \beta_{i1} + k_{i2} \text{sig}^{\gamma_2}(z_{i1}) - \dot{q}_d, \quad (31)$$

where $0 < \varrho < 1$, $\gamma_1 = 1 - \varrho$, and $\gamma_2 = 1 + \varrho$. Following the predefined-time design method, the gains are selected as $k_{i1} = \pi / (2^{1-\varrho/2} \varrho T_c)$ and $k_{i2} = \pi n^{\varrho/2} 2^{\varrho/2-1} / (\varrho T_c)$. Here, $T_c > 0$ is the predefined time and n denotes the system dimension.

To avoid the possible singularity caused by the fractional power term near the origin, β_{i1} is defined as

$$\beta_{i1}(z_{i1}) = \begin{cases} \text{sig}^{\gamma_1}(z_{i1}), & |z_{i1}| \geq \pi_{i1}, \\ \eta_1 z_{i1} + \eta_2 z_{i1}^3, & |z_{i1}| < \pi_{i1}. \end{cases} \quad (32)$$

where $\pi_{i1} \in (0, 1)$ is a small threshold, and $\eta_1 = \frac{3-\gamma_1}{2} \pi_{i1}^{\gamma_1-1}$, $\eta_2 = \frac{\gamma_1-1}{2} \pi_{i1}^{\gamma_1-3}$. With this selection, $\beta_{i1}(z_{i1})$ is continuous near the origin and avoids the possible singularity caused by the fractional power term.

Using Lemma 4 and substituting (30) into (29), it follows that

$$\begin{aligned} \dot{V}_1 &= \sum_{i=1}^N \left[z_{i1}^\top z_{i2} - \frac{z_{i1}^\top z_{i1} \bar{\alpha}_{i1}^\top \bar{\alpha}_{i1}}{\sqrt{z_{i1}^\top z_{i1} \bar{\alpha}_{i1}^\top \bar{\alpha}_{i1} + \varepsilon_{i1}^2}} - z_{i1}^\top \dot{q}_d \right] \\ &\leq \sum_{i=1}^N \left[z_{i1}^\top z_{i2} - z_{i1}^\top \bar{\alpha}_{i1} + \varepsilon_{i1} - z_{i1}^\top \dot{q}_d \right]. \end{aligned} \quad (33)$$

Substituting (31) into (33), it can obtain that

$$\dot{V}_1 \leq \sum_{i=1}^N \left[z_{i1}^\top z_{i2} - k_{i1} z_{i1}^\top z_{i1} - k_{i1} z_{i1}^\top \beta_{i1} - k_{i2} |z_{i1}|^{\gamma_2+1} + \varepsilon_{i1} \right]. \quad (34)$$

For the term

$$L_1 = - \sum_{i=1}^N k_{i1} z_{i1}^\top \beta_{i1}, \quad (35)$$

According to the definition of β_{i1} , the following two cases are considered.

Case 1: If $|z_{i1}| \geq \pi_{i1}$, one has

$$L_1 = - \sum_{i=1}^N k_{i1} |z_{i1}|^{\gamma_1+1}. \quad (36)$$

Case 2: If $|z_{i1}| < \pi_{i1}$, using a generalized Young-type inequality, one obtains

$$\begin{aligned} L_1 &= - \sum_{i=1}^N k_{i1} z_{i1}^\top (\eta_1 z_{i1} + \eta_2 z_{i1}^3) \\ &\leq - \sum_{i=1}^N k_{i1} |z_{i1}|^{\gamma_1+1} + \sum_{i=1}^N k_{i1} z_{i1}^\top z_{i1} + \bar{K} \left(\frac{1-\gamma_1}{2} \right) \bar{\gamma} \end{aligned} \quad (37)$$

where $\bar{K} = \min_{i=1,\dots,N} \{k_{i1}\}$, and $\bar{\gamma} > 0$ is an auxiliary constant introduced in the inequality used to bound the residual term caused by the smooth approximation.

Combining the above two cases, it follows that

$$L_1 \leq - \sum_{i=1}^N k_{i1} |z_{i1}|^{\gamma_1+1} + \sum_{i=1}^N k_{i1} z_{i1}^\top z_{i1} + \bar{K} \left(\frac{1-\gamma_1}{2} \right) \bar{\gamma}. \quad (38)$$

Therefore, it follows from (34) and (38) that

$$\dot{V}_1 \leq \sum_{i=1}^N \left[z_{i1}^\top z_{i2} - k_{i1} |z_{i1}|^{\gamma_1+1} - k_{i2} |z_{i1}|^{\gamma_2+1} + \varepsilon_{i1} \right] + \bar{K} \left(\frac{1-\gamma_1}{2} \right) \bar{\gamma}. \quad (39)$$

Step 2: In this step, the actual control input u_{si} is designed to stabilize z_{i2} , while the unknown nonlinearities, actuator faults, and lumped uncertainties are compensated.

Consider the following Lyapunov candidate function V_2

$$V_2 = \frac{1}{2} \sum_{i=1}^N z_{i2}^\top z_{i2}. \quad (40)$$

The function V_2 is introduced to evaluate the effect of the actual control input on the stabilization of z_{i2} .

$$\begin{aligned} \dot{z}_{i2} &= \dot{q}_{i2} - \dot{\alpha}_{i1} \\ &= B_i u_i + \Phi_i + \Delta_i - \dot{\alpha}_{i1} \\ &= B_i \Gamma_i u_{si} + B_i J_i(t) + \Phi_i + \Delta_i - \dot{\alpha}_{i1}. \end{aligned} \quad (41)$$

To effectively handle the lumped unknown nonlinear function $F_i(x_i) = \Phi_i - \dot{\alpha}_{i1}$, a fuzzy logic system is introduced [8]:

$$F_i(x_i) = \Phi_i - \dot{\alpha}_{i1} = W_i^{*\top} \phi_i(x_i) + \rho_i(x_i), \quad (42)$$

where $x_i = [q_{i1}^\top, q_{i2}^\top]^\top$ denotes the input vector of the FLS, W_i^* is the ideal weight matrix, $\phi_i(x_i)$ is the fuzzy basis-function vector, and $\rho_i(x_i)$ is the bounded approximation error satisfying $\|\rho_i(x_i)\| \leq \bar{\rho}_i$.

Substituting (42) into (41), the derivative of z_{i2} can be given by

$$\dot{z}_{i2} = B_i \Gamma_i u_{si} + \Delta_i + W_i^{*\top} \phi_i(x_i) + \rho_i(x_i) + B_i J_i(t). \quad (43)$$

Denote $a_{i0} = \inf_{t \geq 0}(\Gamma_i)$ as the lower bound of Γ_i , and define $\zeta_i = \frac{1}{a_{i0}}$. Then, $\dot{V}_2$ can be given by

$$\dot{V}_2 = \sum_{i=1}^N z_{i2}^\top \left[B_i \Gamma_i u_{si} + W_i^* \phi_i(x_i) + \Delta_{\Xi_i} \right] \quad (44)$$

where $\Delta_{\Xi_i} = \rho_i(x_i) + B_i J_i(t) + \Delta_i$ denotes the lumped uncertainty consisting of the external disturbance, the fuzzy approximation error, and the actuator bias fault term. According to Assumption 3, there exists an unknown positive constant Ξ_i such that $\|\Delta_{\Xi_i}\| \leq \Xi_i$.

The corresponding estimation errors are defined as

$$\begin{cases} \tilde{W}_i = W_i^* - \hat{W}_i, \\ \tilde{\zeta}_i = \zeta_i - \hat{\zeta}_i, \\ \tilde{\Xi}_i = \Xi_i - \hat{\Xi}_i. \end{cases} \quad (45)$$

To avoid the possible singularity caused by the fractional power term near the origin, the auxiliary function β_{i2} is introduced as

$$\beta_{i2}(z_{i2}) = \begin{cases} \text{sig}^{\gamma_1}(z_{i2}), & |z_{i2}| \geq \pi_{i2}, \\ \eta_3 z_{i2} + \eta_4 z_{i2}^3, & |z_{i2}| < \pi_{i2}, \end{cases} \quad (46)$$

where $\pi_{i2} \in (0, 1)$, $\eta_3 = \frac{3-\gamma_1}{2} \pi_{i2}^{\gamma_1-1}$, and $\eta_4 = \frac{\gamma_1-1}{2} \pi_{i2}^{\gamma_1-3}$. This smooth approximation avoids the possible singularity near the origin.

The role of β_{i2} is similar to β_{i1} , which provides the desired nonlinear damping term while maintaining smoothness around the origin.

Moreover, since $B_i(q_{i1})$ is bounded on the compact set, there exists a positive constant $\bar{B}_i$ such that $\|B_i(q_{i1})\| \leq \bar{B}_i$. According to the fractional-order dynamic event-triggered mechanism, the sampled input u_{si} can be represented by the continuous signal u_{ei} , the bounded auxiliary variable $m_i(t)$, and two bounded time-varying functions $v_1(t)$ and $v_2(t)$. Since $m_i(t)$ is positive and bounded, there exists a positive constant $\bar{m}_i$ such that $0 < m_i(t) \leq \bar{m}_i$. Moreover, since $|v_1(t)| \leq 1$, $|v_2(t)| \leq 1$, and $0 < h_i < 1$, define $m_{ei} = \frac{\bar{m}_i}{1-h_i}$. Then, one has

$$\left| \frac{v_2(t)m_i(t)}{1+v_1(t)h_i} \right| \leq m_{ei}. \quad (47)$$

Based on the above analysis, the auxiliary control signal β_i is constructed as follows.

$$\begin{aligned} \beta_i = & \hat{W}_i^\top \phi_i(x_i) + \tanh\left(\frac{z_{i2}}{d_{i1}}\right) \hat{\Xi}_i + z_{i1} + k_{i3} z_{i2} \\ & + k_{i1} \beta_{i2}(z_{i2}) + k_{i2} \text{sig}^{\gamma_2}(z_{i2}) + \bar{B}_i^2 m_{ei}^2 z_{i2}, \end{aligned} \quad (48)$$

where the term $\hat{W}_i^\top \phi_i(x_i)$ is used to compensate for the unknown nonlinear function. The hyperbolic tangent term is introduced to handle the lumped bounded uncertainty. The term z_{i1} is used to cancel the coupling term generated in Step 1. The terms involving k_{i1} , k_{i2} , and k_{i3} provide the required damping effects for z_{i2} , while the last term is used to dominate the event-triggering error.

The sampled control input u_{si} is generated from u_{ei} through the fractional-order dynamic event-triggered mechanism, and the continuous control signal u_{ei} is designed as

$$u_{ei} = -B_i^{-1}(1+h_i)z_{i2} \frac{\hat{\zeta}_i^2 \beta_i^\top \beta_i}{\sqrt{z_{i2}^\top z_{i2} \hat{\zeta}_i^2 \beta_i^\top \beta_i + \varepsilon_{i2}^2}} \quad (49)$$

where $\varepsilon_{i2} > 0$ is a small design constant.

From the actuator fault assumption and the definition of a_{i0} , one has $0 < a_{i0} \leq \Gamma_i(t) \leq \bar{\Gamma}_i$. Therefore,

$$z_{i2}^\top B_i \Gamma_i u_{ei}(t) = - (1 + h_i) z_{i2}^\top \Gamma_i z_{i2} \frac{\hat{\zeta}_i^2 \beta_i^\top \beta_i}{\sqrt{z_{i2}^\top z_{i2} \hat{\zeta}_i^2 \beta_i^\top \beta_i + \varepsilon_{i2}^2}} \leq 0. \quad (50)$$

Using Young's inequality, it follows that

$$-\frac{m_i(t)}{1 + v_1(t)h_i} z_{i2}^\top B_i \Gamma_i v_2(t) \leq m_{ei} \bar{B}_i |\bar{\Gamma}_i| |z_{i2}| \leq \bar{B}_i^2 z_{i2}^\top z_{i2} m_{ei}^2 + \frac{|\bar{\Gamma}_i|^2}{4}. \quad (51)$$

By substituting (15) into $z_{i2}^\top B_i \Gamma_i u_{si}(t)$ and according to Lemma 4 and Young's inequality, one obtains

$$\begin{aligned} z_{i2}^\top B_i \Gamma_i u_{si}(t) &= \frac{z_{i2}^\top B_i \Gamma_i u_{ei}(t)}{1 + v_1(t)h_i} - \frac{z_{i2}^\top B_i \Gamma_i v_2(t)m_i(t)}{1 + v_1(t)h_i} \\ &\leq \frac{z_{i2}^\top B_i \Gamma_i u_{ei}(t)}{1 + h_i} + z_{i2}^\top z_{i2} \bar{B}_i^2 m_{ei}^2 + \frac{|\bar{\Gamma}_i|^2}{4} \\ &\leq -a_{i0} \frac{z_{i2}^\top z_{i2} \hat{\zeta}_i^2 \beta_i^\top \beta_i}{\sqrt{z_{i2}^\top z_{i2} \hat{\zeta}_i^2 \beta_i^\top \beta_i + \varepsilon_{i2}^2}} + \bar{B}_i^2 z_{i2}^\top z_{i2} m_{ei}^2 + \frac{|\bar{\Gamma}_i|^2}{4} \\ &\leq -a_{i0} \hat{\zeta}_i z_{i2}^\top \beta_i + a_{i0} \varepsilon_{i2} + \bar{B}_i^2 z_{i2}^\top z_{i2} m_{ei}^2 + \frac{|\bar{\Gamma}_i|^2}{4}. \end{aligned} \quad (52)$$

By using Assumption 3 and Lemma 2, it can be obtained that

$$\begin{aligned} z_{i2}^\top \Delta_{\Xi_i} - z_{i2}^\top \hat{\Xi}_i \tanh\left(\frac{z_{i2}}{d_{i1}}\right) &\leq |z_{i2}| \Xi_i - z_{i2}^\top \hat{\Xi}_i \tanh\left(\frac{z_{i2}}{d_{i1}}\right) \\ &= \Xi_i \left[|z_{i2}| - z_{i2}^\top \tanh\left(\frac{z_{i2}}{d_{i1}}\right) \right] + \tilde{\Xi}_i z_{i2}^\top \tanh\left(\frac{z_{i2}}{d_{i1}}\right) \\ &\leq 0.2785 d_{i1} \Xi_i + \tilde{\Xi}_i z_{i2}^\top \tanh\left(\frac{z_{i2}}{d_{i1}}\right). \end{aligned} \quad (53)$$

The derivative of V_2 can be derived as

$$\begin{aligned} \dot{V}_2 &\leq \sum_{i=1}^N \left[a_{i0} \varepsilon_{i2} - a_{i0} \hat{\zeta}_i z_{i2}^\top \beta_i + \bar{B}_i^2 z_{i2}^\top z_{i2} m_{ei}^2 + \frac{|\bar{\Gamma}_i|^2}{4} + z_{i2}^\top W_i^{*\top} \phi_i(x_i) + z_{i2}^\top \Delta_{\Xi_i} \right] \\ &\leq \sum_{i=1}^N \left[a_{i0} \varepsilon_{i2} + a_{i0} \tilde{\zeta}_i z_{i2}^\top \beta_i + z_{i2}^\top \tilde{W}_i^\top \phi_i(x_i) + z_{i2}^\top \tilde{\Xi}_i \tanh\left(\frac{z_{i2}}{d_{i1}}\right) - z_{i2}^\top z_{i1} \right. \\ &\quad \left. - k_{i3} z_{i2}^\top z_{i2} - k_{i1} z_{i2}^\top \beta_{i2}(z_{i2}) - k_{i2} |z_{i2}|^{\gamma_2+1} + 0.2785 d_{i1} \Xi_i + \frac{|\bar{\Gamma}_i|^2}{4} \right]. \end{aligned} \quad (54)$$

For the term

$$L_2 = - \sum_{i=1}^N k_{i1} z_{i2}^\top \beta_{i2}(z_{i2}), \quad (55)$$

according to the definition of $\beta_{i2}(z_{i2})$, the following two cases are considered.

Case 1: If $|z_{i2}| \geq \pi_{i2}$, then

$$\beta_{i2}(z_{i2}) = \text{sig}^{\gamma_1}(z_{i2}), \quad (56)$$

and hence

$$L_2 = - \sum_{i=1}^N k_{i1} |z_{i2}|^{\gamma_1+1}. \quad (57)$$

Case 2: If $|z_{i2}| < \pi_{i2}$, then

$$\beta_{i2}(z_{i2}) = \eta_3 z_{i2} + \eta_4 z_{i2}^3. \quad (58)$$

By using the same generalized Young-type inequality as that used for L_1 , one obtains

$$\begin{aligned} L_2 &= - \sum_{i=1}^N k_{i1} z_{i2}^\top (\eta_3 z_{i2} + \eta_4 z_{i2}^3) \\ &\leq - \sum_{i=1}^N k_{i1} |z_{i2}|^{\gamma_1+1} + \sum_{i=1}^N k_{i1} z_{i2}^\top z_{i2} + \bar{K} \left(\frac{1-\gamma_1}{2} \right) \bar{\gamma}. \end{aligned} \quad (59)$$

Combining the above two cases gives

$$L_2 \leq - \sum_{i=1}^N k_{i1} |z_{i2}|^{\gamma_1+1} + \sum_{i=1}^N k_{i1} z_{i2}^\top z_{i2} + \bar{K} \left(\frac{1-\gamma_1}{2} \right) \bar{\gamma}, \quad (60)$$

where $\bar{K}$ and $\bar{\gamma}$ are the positive constants introduced in the estimate of L_1 .

3.2. Stability Analysis

The stability result is presented in the following theorem.

Theorem 1. Under Assumptions 1–3, consider the networked Euler–Lagrange systems with unknown nonlinearities, external disturbances, and actuator faults. Suppose that the communication topology is fixed, undirected, and connected, and the leader signal is available to at least one follower. If the proposed adaptive fuzzy fractional-order dynamic event-triggered fault-tolerant controller is used together with the adaptive laws, then the following results are obtained:

- (1) All closed-loop signals remain bounded.
- (2) The consensus tracking errors enter a small residual set within the predefined time T_c .

Proof. For the stability analysis of the closed-loop system, construct the following global Lyapunov function V :

$$V = V_1 + V_2 + \sum_{i=1}^N \frac{1}{2\lambda_{i1}} \|\tilde{W}_i\|^2 + \frac{1}{2} \sum_{i=1}^N \frac{a_{i0}}{\lambda_{i2}} \tilde{\zeta}_i^2 + \frac{1}{2} \sum_{i=1}^N \frac{1}{\lambda_{i3}} \tilde{\Xi}_i^2 \quad (61)$$

where $\lambda_{i1} > 0$, $\lambda_{i2} > 0$, and $\lambda_{i3} > 0$ are adaptive gains.

Then, the derivative of V satisfies

$$\begin{aligned} \dot{V} &\leq \sum_{i=1}^N \left[z_{i1}^\top z_{i2} - k_{i1} |z_{i1}|^{\gamma_1+1} - k_{i2} |z_{i1}|^{\gamma_2+1} + \bar{K} \left(\frac{1-\gamma_1}{2} \right) \bar{\gamma} + \varepsilon_{i1} \right] + \sum_{i=1}^N \left[a_{i0} \varepsilon_{i2} + a_{i0} \tilde{\zeta}_i z_{i2}^\top \beta_i \right. \\ &\quad \left. + z_{i2}^\top \tilde{W}_i^\top \phi_i(x_i) + z_{i2}^\top \tilde{\Xi}_i \tanh \left(\frac{z_{i2}}{d_{i1}} \right) + 0.2785 d_{i1} \Xi_i - z_{i2}^\top z_{i1} - k_{i3} z_{i2}^\top z_{i2} + \frac{|\bar{\Gamma}_i|^2}{4} \right] \\ &\quad + \sum_{i=1}^N \left[-k_{i1} |z_{i2}|^{\gamma_1+1} + k_{i1} z_{i2}^\top z_{i2} + \bar{K} \left(\frac{1-\gamma_1}{2} \right) \bar{\gamma} \right] - \sum_{i=1}^N k_{i2} |z_{i2}|^{\gamma_2+1} \\ &\quad - \sum_{i=1}^N \frac{1}{\lambda_{i1}} \text{tr}(\tilde{W}_i^\top \hat{W}_i) - \sum_{i=1}^N \frac{a_{i0}}{\lambda_{i2}} \tilde{\zeta}_i \dot{\tilde{\zeta}}_i - \sum_{i=1}^N \frac{1}{\lambda_{i3}} \tilde{\Xi}_i \dot{\tilde{\Xi}}_i. \end{aligned} \quad (62)$$

Design the adaptive laws as follows:

$$\dot{\hat{W}}_i = \lambda_{i1} \phi_i(x_i) z_{i2}^\top - \lambda_{i1} \hat{W}_i, \quad (63)$$

$$\dot{\hat{\zeta}}_i = \lambda_{i2} z_{i2}^\top \beta_i - \lambda_{i2} \hat{\zeta}_i, \quad (64)$$

$$\dot{\hat{\Xi}}_i = \lambda_{i3} z_{i2}^\top \tanh\left(\frac{z_{i2}}{d_{i1}}\right) - \lambda_{i3} \hat{\Xi}_i. \quad (65)$$

Substituting the adaptive laws into the derivative of V , it can be obtained that $-\frac{1}{\lambda_{i1}} \text{tr}(\tilde{W}_i^\top \dot{\hat{W}}_i) = -\text{tr}(\tilde{W}_i^\top \phi_i(x_i) z_{i2}^\top) + \text{tr}(\tilde{W}_i^\top \hat{W}_i)$. Since $z_{i2}^\top \tilde{W}_i^\top \phi_i(x_i) = \text{tr}(\tilde{W}_i^\top \phi_i(x_i) z_{i2}^\top)$, the terms involving $\phi_i(x_i) z_{i2}^\top$ cancel each other. Similarly,

$$-\frac{a_{i0}}{\lambda_{i2}} \tilde{\zeta}_i \dot{\hat{\zeta}}_i = -a_{i0} \tilde{\zeta}_i z_{i2}^\top \beta_i + a_{i0} \tilde{\zeta}_i \hat{\zeta}_i, \quad (66)$$

and

$$-\frac{1}{\lambda_{i3}} \tilde{\Xi}_i \dot{\hat{\Xi}}_i = -\tilde{\Xi}_i z_{i2}^\top \tanh\left(\frac{z_{i2}}{d_{i1}}\right) + \tilde{\Xi}_i \hat{\Xi}_i. \quad (67)$$

Therefore, the corresponding cross terms in $\dot{V}$ cancel. Moreover, since $z_{i1}^\top z_{i2} = z_{i2}^\top z_{i1}$, the coupling terms between V_1 and V_2 also cancel, leaving only the parameter leakage terms $\text{tr}(\tilde{W}_i^\top \hat{W}_i)$, $a_{i0} \tilde{\zeta}_i \hat{\zeta}_i$, $\tilde{\Xi}_i \hat{\Xi}_i$.

Therefore, the derivative of V can be given by

$$\begin{aligned} \dot{V} \leq & \sum_{i=1}^N \left[-k_{i1} |z_{i1}|^{\gamma_1+1} - k_{i2} |z_{i1}|^{\gamma_2+1} - k_{i1} |z_{i2}|^{\gamma_1+1} - k_{i2} |z_{i2}|^{\gamma_2+1} \right. \\ & \left. + 2\bar{K} \left(\frac{1-\gamma_1}{2} \right) \bar{\gamma} + \varepsilon_{i1} + a_{i0} \varepsilon_{i2} + 0.2785 d_{i1} \Xi_i + \frac{|\bar{\Gamma}_i|^2}{4} \right] \\ & + \sum_{i=1}^N \left[\text{tr}(\tilde{W}_i^\top \hat{W}_i) + a_{i0} \tilde{\zeta}_i \hat{\zeta}_i + \tilde{\Xi}_i \hat{\Xi}_i \right]. \end{aligned} \quad (68)$$

By choosing $\gamma_1 = 1 - \varrho$ and $\gamma_2 = 1 + \varrho$, the above inequality can be rewritten as

$$\begin{aligned} \dot{V} \leq & - \sum_{i=1}^N \left[k_{i1} (z_{i1}^\top z_{i1})^{1-\frac{\varrho}{2}} + k_{i2} (z_{i1}^\top z_{i1})^{1+\frac{\varrho}{2}} \right] - \sum_{i=1}^N \left[k_{i1} (z_{i2}^\top z_{i2})^{1-\frac{\varrho}{2}} + k_{i2} (z_{i2}^\top z_{i2})^{1+\frac{\varrho}{2}} \right] \\ & + \sum_{i=1}^N \left[\varepsilon_{i1} + a_{i0} \varepsilon_{i2} + 2\bar{K} \left(\frac{1-\gamma_1}{2} \right) \bar{\gamma} + 0.2785 d_{i1} \Xi_i + \frac{|\bar{\Gamma}_i|^2}{4} \right] \\ & + \sum_{i=1}^N \left[\text{tr}(\tilde{W}_i^\top \hat{W}_i) + a_{i0} \tilde{\zeta}_i \hat{\zeta}_i + \tilde{\Xi}_i \hat{\Xi}_i \right]. \end{aligned} \quad (69)$$

By using Young's inequality, the following inequalities hold

$$\text{tr}(\tilde{W}_i^\top \hat{W}_i) \leq -\frac{1}{2} \text{tr}(\tilde{W}_i^\top \tilde{W}_i) + \frac{1}{2} \text{tr}(W_i^{*\top} W_i^*), \quad (70)$$

$$a_{i0} \tilde{\zeta}_i \hat{\zeta}_i \leq -\frac{a_{i0}}{2} \tilde{\zeta}_i^2 + \frac{a_{i0}}{2} \zeta_i^2, \quad (71)$$

$$\tilde{\Xi}_i \hat{\Xi}_i \leq -\frac{1}{2} \tilde{\Xi}_i^2 + \frac{1}{2} \Xi_i^2. \quad (72)$$

Substituting the above inequalities into the derivative of V , it can be obtained that

$$\begin{aligned} \dot{V} \leq & - \sum_{i=1}^N \left[k_{i1} (z_{i1}^\top z_{i1})^{1-\frac{\rho}{2}} + k_{i2} (z_{i1}^\top z_{i1})^{1+\frac{\rho}{2}} \right] - \sum_{i=1}^N \left[k_{i1} (z_{i2}^\top z_{i2})^{1-\frac{\rho}{2}} + k_{i2} (z_{i2}^\top z_{i2})^{1+\frac{\rho}{2}} \right] \\ & + \sum_{i=1}^N \left[\varepsilon_{i1} + a_{i0} \varepsilon_{i2} + 2\bar{K} \left(\frac{1-\gamma_1}{2} \right) \bar{\gamma} + 0.2785 d_{i1} \Xi_i + \frac{|\bar{\Gamma}_i|^2}{4} \right] \\ & + \sum_{i=1}^N \left[\frac{1}{2} \text{tr}(\tilde{W}_i^* \tilde{W}_i^*) + \frac{a_{i0}}{2} \zeta_i^2 + \frac{1}{2} \Xi_i^2 \right] - \sum_{i=1}^N \frac{1}{2} \text{tr}(\tilde{W}_i^\top \tilde{W}_i) - \sum_{i=1}^N \frac{a_{i0}}{2} \tilde{\zeta}_i^2 - \sum_{i=1}^N \frac{1}{2} \tilde{\Xi}_i^2. \end{aligned} \quad (73)$$

To further transform the negative quadratic terms into the predefined-time form, the following inequalities are used.

$$- \text{tr}(\tilde{W}_i^\top \tilde{W}_i) \leq - \left(\frac{1}{2} \text{tr}(\tilde{W}_i^\top \tilde{W}_i) \right)^{1-\frac{\rho}{2}} - \left(\frac{1}{2} \text{tr}(\tilde{W}_i^\top \tilde{W}_i) \right)^{1+\frac{\rho}{2}} + v_{W_i}, \quad (74)$$

$$- \tilde{\zeta}_i^2 \leq - \left(\frac{1}{2} \tilde{\zeta}_i^2 \right)^{1-\frac{\rho}{2}} - \left(\frac{1}{2} \tilde{\zeta}_i^2 \right)^{1+\frac{\rho}{2}} + v_{\zeta_i}, \quad (75)$$

$$- \tilde{\Xi}_i^2 \leq - \left(\frac{1}{2} \tilde{\Xi}_i^2 \right)^{1-\frac{\rho}{2}} - \left(\frac{1}{2} \tilde{\Xi}_i^2 \right)^{1+\frac{\rho}{2}} + v_{\Xi_i}, \quad (76)$$

where $v_{W_i} = \frac{\rho}{2} \left(1 - \frac{\rho}{2} \right)^{\frac{2-\rho}{\rho}} + (\bar{W}_i^2)^{1+\frac{\rho}{2}}$, $v_{\zeta_i} = \frac{\rho}{2} \left(1 - \frac{\rho}{2} \right)^{\frac{2-\rho}{\rho}} + (\bar{\zeta}_i^2)^{1+\frac{\rho}{2}}$, and $v_{\Xi_i} = \frac{\rho}{2} \left(1 - \frac{\rho}{2} \right)^{\frac{2-\rho}{\rho}} + (\bar{\Xi}_i^2)^{1+\frac{\rho}{2}}$ with $\|\tilde{W}_i\| \leq \bar{W}_i$, $|\tilde{\zeta}_i| \leq \bar{\zeta}_i$, and $|\tilde{\Xi}_i| \leq \bar{\Xi}_i$.

Then, it can be obtained that

$$\begin{aligned} - \frac{1}{2} \sum_{i=1}^N \frac{1}{2} \text{tr}(\tilde{W}_i^\top \tilde{W}_i) & \leq - \frac{1}{2} \sum_{i=1}^N \left(\frac{1}{2} \text{tr}(\tilde{W}_i^\top \tilde{W}_i) \right)^{1-\frac{\rho}{2}} - \frac{1}{2} \sum_{i=1}^N \left(\frac{1}{2} \text{tr}(\tilde{W}_i^\top \tilde{W}_i) \right)^{1+\frac{\rho}{2}} + \sum_{i=1}^N \frac{1}{2} v_{W_i} \\ & = - \sum_{i=1}^N \frac{1}{2} \frac{1}{\frac{1}{\lambda_{i1}}^{1-\frac{\rho}{2}}} \left(\frac{1}{2\lambda_{i1}} \text{tr}(\tilde{W}_i^\top \tilde{W}_i) \right)^{1-\frac{\rho}{2}} - \sum_{i=1}^N \frac{1}{2} \frac{1}{\frac{1}{\lambda_{i1}}^{1+\frac{\rho}{2}}} \left(\frac{1}{2\lambda_{i1}} \text{tr}(\tilde{W}_i^\top \tilde{W}_i) \right)^{1+\frac{\rho}{2}} + \sum_{i=1}^N \frac{1}{2} v_{W_i}, \end{aligned} \quad (77)$$

$$\begin{aligned} - \sum_{i=1}^N \frac{a_{i0}}{2} \tilde{\zeta}_i^2 & \leq - \sum_{i=1}^N \frac{a_{i0}}{2} \left(\frac{1}{2} \tilde{\zeta}_i^2 \right)^{1-\frac{\rho}{2}} - \sum_{i=1}^N \frac{a_{i0}}{2} \left(\frac{1}{2} \tilde{\zeta}_i^2 \right)^{1+\frac{\rho}{2}} + \sum_{i=1}^N \frac{a_{i0}}{2} v_{\zeta_i} \\ & = - \sum_{i=1}^N \frac{a_{i0}}{2} \frac{1}{\left(\frac{a_{i0}}{\lambda_{i2}} \right)^{1-\frac{\rho}{2}}} \left(\frac{a_{i0}}{2\lambda_{i2}} \tilde{\zeta}_i^2 \right)^{1-\frac{\rho}{2}} - \sum_{i=1}^N \frac{a_{i0}}{2} \frac{1}{\left(\frac{a_{i0}}{\lambda_{i2}} \right)^{1+\frac{\rho}{2}}} \left(\frac{a_{i0}}{2\lambda_{i2}} \tilde{\zeta}_i^2 \right)^{1+\frac{\rho}{2}} + \sum_{i=1}^N \frac{a_{i0}}{2} v_{\zeta_i}, \end{aligned} \quad (78)$$

$$\begin{aligned} - \sum_{i=1}^N \frac{1}{2} \tilde{\Xi}_i^2 & \leq - \sum_{i=1}^N \frac{1}{2} \left(\frac{1}{2} \tilde{\Xi}_i^2 \right)^{1-\frac{\rho}{2}} - \sum_{i=1}^N \frac{1}{2} \left(\frac{1}{2} \tilde{\Xi}_i^2 \right)^{1+\frac{\rho}{2}} + \sum_{i=1}^N \frac{1}{2} v_{\Xi_i} \\ & = - \sum_{i=1}^N \frac{1}{2} \frac{1}{\frac{1}{\lambda_{i3}}^{1-\frac{\rho}{2}}} \left(\frac{1}{2\lambda_{i3}} \tilde{\Xi}_i^2 \right)^{1-\frac{\rho}{2}} - \sum_{i=1}^N \frac{1}{2} \frac{1}{\frac{1}{\lambda_{i3}}^{1+\frac{\rho}{2}}} \left(\frac{1}{2\lambda_{i3}} \tilde{\Xi}_i^2 \right)^{1+\frac{\rho}{2}} + \sum_{i=1}^N \frac{1}{2} v_{\Xi_i}. \end{aligned} \quad (79)$$

Based on Lemma 5, it can be obtained that

$$\begin{aligned}
\dot{V} \leq & - \sum_{i=1}^N k_{i1} 2^{1-\frac{\varrho}{2}} \left(\frac{1}{2} z_{i1}^\top z_{i1} \right)^{1-\frac{\varrho}{2}} - \sum_{i=1}^N k_{i2} 2^{1+\frac{\varrho}{2}} \left(\frac{1}{2} z_{i1}^\top z_{i1} \right)^{1+\frac{\varrho}{2}} - \sum_{i=1}^N k_{i1} 2^{1-\frac{\varrho}{2}} \left(\frac{1}{2} z_{i2}^\top z_{i2} \right)^{1-\frac{\varrho}{2}} \\
& - \sum_{i=1}^N k_{i2} 2^{1+\frac{\varrho}{2}} \left(\frac{1}{2} z_{i2}^\top z_{i2} \right)^{1+\frac{\varrho}{2}} - \sum_{i=1}^N \frac{\lambda_{i1}^{1-\frac{\varrho}{2}}}{2} \left(\frac{1}{2\lambda_{i1}} \text{tr}(\tilde{W}_i^\top \tilde{W}_i) \right)^{1-\frac{\varrho}{2}} \\
& - \sum_{i=1}^N \frac{\lambda_{i1}^{1+\frac{\varrho}{2}}}{2} \left(\frac{1}{2\lambda_{i1}} \text{tr}(\tilde{W}_i^\top \tilde{W}_i) \right)^{1+\frac{\varrho}{2}} - \sum_{i=1}^N \frac{\lambda_{i2}^{1-\frac{\varrho}{2}}}{2} a_{i0}^{\frac{\varrho}{2}} \left(\frac{a_{i0}}{2\lambda_{i2}} \tilde{\zeta}_i^2 \right)^{1-\frac{\varrho}{2}} \\
& - \sum_{i=1}^N \frac{\lambda_{i2}^{1+\frac{\varrho}{2}}}{2} a_{i0}^{-\frac{\varrho}{2}} \left(\frac{a_{i0}}{2\lambda_{i2}} \tilde{\zeta}_i^2 \right)^{1+\frac{\varrho}{2}} - \sum_{i=1}^N \frac{\lambda_{i3}^{1-\frac{\varrho}{2}}}{2} \left(\frac{1}{2\lambda_{i3}} \tilde{\Xi}_i^2 \right)^{1-\frac{\varrho}{2}} \\
& - \sum_{i=1}^N \frac{\lambda_{i3}^{1+\frac{\varrho}{2}}}{2} \left(\frac{1}{2\lambda_{i3}} \tilde{\Xi}_i^2 \right)^{1+\frac{\varrho}{2}} + \sum_{i=1}^N \left[\varepsilon_{i1} + a_{i0} \varepsilon_{i2} + 2\bar{K} \left(\frac{1-\gamma_1}{2} \right) \bar{\gamma} + 0.2785 d_{i1} \Xi_i + \frac{|\bar{\Gamma}_i|^2}{4} \right] \\
& + \sum_{i=1}^N \left[\frac{1}{2} \text{tr}(W_i^{*\top} W_i^*) + \frac{a_{i0}}{2} \zeta_i^2 + \frac{1}{2} \Xi_i^2 \right] + \sum_{i=1}^N \left(\frac{1}{2} v_{W_i} + \frac{a_{i0}}{2} v_{\zeta_i} + \frac{1}{2} v_{\Xi_i} \right).
\end{aligned} \tag{80}$$

Based on the above inequality and Lemma 5, the negative terms can be further collected into a compact form. Define

$$V = \sum_{i=1}^N \left(\frac{1}{2} z_{i1}^\top z_{i1} + \frac{1}{2} z_{i2}^\top z_{i2} + \frac{1}{2\lambda_{i1}} \|\tilde{W}_i\|^2 + \frac{a_{i0}}{2\lambda_{i2}} \tilde{\zeta}_i^2 + \frac{1}{2\lambda_{i3}} \tilde{\Xi}_i^2 \right). \tag{81}$$

The coefficients C_{i1} and C_{i2} are selected as the minimum coefficients of the negative terms with powers $1 - \varrho/2$ and $1 + \varrho/2$, respectively. Since V consists of $5N$ nonnegative components, Lemma 5 is applied to collect these terms. For the power $1 - \varrho/2$, the corresponding terms are bounded by $V^{1-\varrho/2}$, while for the power $1 + \varrho/2$, the factor $(5N)^{-\varrho/2}$ is introduced. Therefore, all negative terms can be combined into the compact predefined-time inequality for $\dot{V}$.

It follows that there exist positive constants $\bar{C}_1$, $\bar{C}_2$, and Λ such that

$$\dot{V} \leq -\bar{C}_1 V^{1-\frac{\varrho}{2}} - \bar{C}_2 V^{1+\frac{\varrho}{2}} + \Lambda, \tag{82}$$

where the local coefficients are defined as

$$C_{i1} = \min \left\{ k_{i1} 2^{1-\frac{\varrho}{2}}, \frac{\lambda_{i1}^{1-\frac{\varrho}{2}}}{2}, \frac{\lambda_{i2}^{1-\frac{\varrho}{2}}}{2} a_{i0}^{\frac{\varrho}{2}}, \frac{\lambda_{i3}^{1-\frac{\varrho}{2}}}{2} \right\}, \tag{83}$$

$$C_{i2} = \min \left\{ k_{i2} 2^{1+\frac{\varrho}{2}}, \frac{\lambda_{i1}^{1+\frac{\varrho}{2}}}{2}, \frac{\lambda_{i2}^{1+\frac{\varrho}{2}}}{2} a_{i0}^{-\frac{\varrho}{2}}, \frac{\lambda_{i3}^{1+\frac{\varrho}{2}}}{2} \right\}. \tag{84}$$

Here, C_{i1} and C_{i2} denote the local minimum coefficients, and $\bar{C}_1$ and $\bar{C}_2$ are the corresponding global positive constants which satisfy $\bar{C}_1 = \min_{i=1,\dots,N} \{C_{i1}\}$, and $\bar{C}_2 = (5N)^{-\frac{\varrho}{2}} \min_{i=1,\dots,N} \{C_{i2}\}$. Moreover, Λ collects all bounded residual terms, given by

$$\begin{aligned}
\Lambda = & \sum_{i=1}^N \left[\varepsilon_{i1} + a_{i0} \varepsilon_{i2} + 2\bar{K} \left(\frac{1-\gamma_1}{2} \right) \bar{\gamma} + 0.2785 d_{i1} \Xi_i + \frac{|\bar{\Gamma}_i|^2}{4} \right. \\
& \left. + \frac{1}{2} \text{tr}(W_i^{*\top} W_i^*) + \frac{a_{i0}}{2} \zeta_i^2 + \frac{1}{2} \Xi_i^2 + \frac{1}{2} v_{W_i} + \frac{a_{i0}}{2} v_{\zeta_i} + \frac{1}{2} v_{\Xi_i} \right].
\end{aligned} \tag{85}$$

If the control parameters are selected such that $\bar{C}_1 \geq \frac{\pi}{\varrho T_c}$ and $\bar{C}_2 \geq \frac{\pi}{\varrho T_c}$, then

$$\dot{V} \leq -\frac{\pi}{\varrho T_c} \left(V^{1-\frac{\varrho}{2}} + V^{1+\frac{\varrho}{2}} \right) + \Lambda. \quad (86)$$

With $c_1 = c_2 = \pi/(\varrho T_c)$ and $\vartheta = \varrho$, the derived inequality satisfies the condition in Lemma 1, since $\sqrt{c_1 c_2} = \pi/(\varrho T_c)$. Hence, the closed-loop system is predefined-time stable. All closed-loop signals are bounded, and the consensus tracking errors converge to a small residual set within the predefined time T_c .

The proposed fractional-order dynamic event-triggered mechanism can exclude Zeno behavior. After each triggering instant t_r^i , the event-triggering error satisfies $e_{ui}(t_r^i) = 0$. Since all closed-loop signals are bounded, the continuous control signal $u_{ei}(t)$ is bounded and locally Lipschitz, and hence there exists a positive constant $\bar{d}_i$ such that $\|\dot{e}_{ui}(t)\| \leq \bar{d}_i$ for $t \in [t_r^i, t_{r+1}^i)$. Therefore, $\|e_{ui}(t)\| \leq \bar{d}_i(t - t_r^i)$. According to the triggering condition, the next triggering instant can occur only when $\|e_{ui}(t)\| \geq h_i \|u_{si}(t)\| + m_i(t) \geq m_i^*$. Consequently, the inter-event time satisfies $t_{r+1}^i - t_r^i \geq \frac{m_i^*}{\bar{d}_i} > 0$. Hence, Zeno behavior is avoided. $\square$

Remark 2. The residual bound Λ is mainly affected by the approximation error, actuator bias fault, event-triggering error, and the robust compensation parameters. Smaller values of ε_{i1} , ε_{i2} , and d_{i1} can reduce part of the residual bound, while larger control gains help increase C_1 and C_2 to satisfy the predefined-time condition. Therefore, the proposed controller provides a tradeoff among tracking accuracy, convergence speed, and control/update effort.

Remark 3. It should be noted that, compared with the integer-order dynamic and static event-triggered mechanisms, the numerical implementation of the Caputo fractional-order dynamic law requires historical triggering information and therefore introduces additional computational and storage burdens. These additional burdens arise from the update of the auxiliary triggering variable $m_i(t)$ and do not change the remaining controller structure or the stability analysis. Meanwhile, the historical information enables $m_i(t)$ to reflect the past evolution of the triggering condition, while the fractional order α_{FD} provides an additional degree of freedom for adjusting the triggering threshold. The simulation results in Section 4 show that this additional computational burden is accompanied by fewer control input updates and smaller final tracking errors, reflecting a trade-off between computational burden and control performance.

Remark 4. In this paper, the stability analysis relies on the symmetry and positive definiteness of the Laplacian matrix of the undirected connected communication graph. For a directed graph, the designed distributed predefined-time consensus algorithm, the dynamic event-triggered mechanism, and the adaptive fault-tolerant method are still valid. However, the stability analysis for Euler-Lagrange systems cannot be achieved since the Laplacian matrix of the directed graph is nonsymmetric. Additional conditions such as strong connectivity, weight balance, or the existence of a leader-rooted directed spanning tree may be required. Therefore, extending the proposed distributed predefined-time fault-tolerant control algorithm to a directed graph or switching graph is a direction of future work.

Remark 5. The proposed control scheme in this paper is based on the undirected connected graph, where at least one follower can directly obtain leader information, and the communication graph is delay-free. If these conditions are violated, the system performance may degrade, and even result in system instability. For example, a temporary disconnection of the communication graph may interrupt information exchange among some agents and enlarge the consensus tracking errors. Large communication delays may increase the mismatch between sampled information and actual

system states, thereby affecting the convergence speed and residual errors. In addition, temporary unavailability of the leader information may prevent some followers from updating their reference signals in time, which may weaken the predefined-time tracking performance. Therefore, the stability and robustness under these assumption-violating cases cannot be directly guaranteed by the present theoretical results, and require separate analysis with additional connectivity conditions, delay constraints, and information recovery mechanisms.

4. Simulation

In this section, two examples are conducted to verify the effectiveness of the proposed adaptive fuzzy fractional-order event-triggered fault-tolerant predefined-time consensus control scheme.

Example 1. As a representative example of the Euler–Lagrange systems considered in Section 2, a networked multi-manipulator system composed of four two-link robotic manipulators is considered. For the i -th robotic manipulator, the dynamics are described by

$$M(q_i)\ddot{q}_i + C(q_i, \dot{q}_i)\dot{q}_i + G(q_i) = u_i^a + d_i(t), \quad i = 1, 2, 3, 4, \quad (87)$$

where $q_i = [q_{i1}, q_{i2}]^\top \in \mathbb{R}^2$ and $\dot{q}_i = [\dot{q}_{i1}, \dot{q}_{i2}]^\top \in \mathbb{R}^2$ denote the joint position and velocity vectors, respectively. The actual actuator input is denoted by $u_i^a \in \mathbb{R}^2$, and $d_i(t) \in \mathbb{R}^2$ is the external disturbance.

The inertia matrix, Coriolis and centrifugal matrix, and gravity vector are given as

$$M(q_i) = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}, \quad C(q_i, \dot{q}_i) = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix}, \quad G(q_i) = \begin{bmatrix} G_1 \\ G_2 \end{bmatrix}. \quad (88)$$

The detailed expressions of M_{ij} , C_{ij} , and G_i are listed in Table 1. The physical parameters are selected as $m_1 = m_2 = 5$, $l_1 = l_2 = 0.4$, $g = 9.8$. The reference trajectory generated by the virtual leader is chosen as $q_d(t) = [1.2 \sin(\pi t), 0.8 \cos(\pi t)]^\top$. The external disturbance acting on the i -th robotic manipulator is set as $d_i(t) = [0.12 \sin(1.2t + 0.2i), 0.1 \cos(0.9t + 0.3i)]^\top$.

Table 1. Dynamic terms of the two-link robotic manipulator.

Term	Expression
M_{11}	$(m_1 + m_2)l_1^2 + m_2l_2^2 + 2m_2l_1l_2 \cos q_{i2}$
M_{12}	$m_2(l_2^2 + l_1l_2 \cos q_{i2})$
M_{21}	M_{12}
M_{22}	$m_2l_2^2$
C_{11}	$-m_2l_1l_2\dot{q}_{i2} \sin q_{i2}$
C_{12}	$m_2l_1l_2(\dot{q}_{i1} + \dot{q}_{i2}) \sin q_{i2}$
C_{21}	$m_2l_1l_2\dot{q}_{i1} \sin q_{i2}$
C_{22}	0
G_1	$m_2l_2g \cos(q_{i1} + q_{i2}) + (m_1 + m_2)l_1g \cos q_{i1}$
G_2	$m_2l_2g \cos(q_{i1} + q_{i2})$

The communication topology among the four robotic manipulators and the virtual leader is specified by $\mathcal{A} = \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{bmatrix}$ and $\mathcal{B} = \text{diag}\{1, 0, 0, 1\}$. Thus, manipulators 1 and 4 can directly obtain the leader signal, and the leader information can be transmitted

to all manipulators through the communication graph. The initial conditions are selected as $q_1(0) = [0, 0.1]^\top$, $q_2(0) = [0.2, 0.1]^\top$, $q_3(0) = [0.1, 0.1]^\top$, $q_4(0) = [0.3, 0.1]^\top$, and $\dot{q}_1(0) = \dot{q}_2(0) = \dot{q}_3(0) = \dot{q}_4(0) = [0.1, 0.1]^\top$. The simulation is performed over $[0, 10]$ s with a fixed sampling step of 0.001 s. The fractional-order dynamic event-triggered parameters are selected as $\alpha_{FD} = 0.72$, $h_i = 0.014$, $\Pi_1 = 1.15$, $\Pi_2 = 0.006$, and $m_i(0) = 0.003$. The predefined-time and control parameters are chosen as $T_c = 3$ s, $\varrho = 0.16$. The adaptive parameters are initialized as $\hat{W}_i(0) = 0.011_{9 \times 2}$, $\hat{\zeta}_i(0) = 0.18$, and $\hat{\Xi}_i(0) = 0.08$, $i = 1, 2, 3, 4$, with adaptive gains $\lambda_{i1} = 0.030$, $\lambda_{i2} = 0.050$, and $\lambda_{i3} = 0.050$.

The fault injection instants are selected as $t_1^f = 1.50$ s, $t_2^f = 3.00$ s, $t_3^f = 4.50$ s, $t_4^f = 6.00$ s. Before the fault occurs, $\Gamma_i(t) = I_2$ and $J_i(t) = 0$. After the fault occurs, the actuator effectiveness factors and bias faults are given by

$$\begin{aligned}\Gamma_1(t) &= \text{diag}\{0.78 + 0.035 \sin(0.8t), 0.82 + 0.030 \cos(0.6t)\}, \\ \Gamma_2(t) &= \text{diag}\{0.75 + 0.040 \cos(0.7t), 0.80 + 0.035 \sin(0.8t)\}, \\ \Gamma_3(t) &= \text{diag}\{0.78 + 0.040 \sin(0.6t), 0.82 + 0.035 \cos(0.9t)\}, \\ \Gamma_4(t) &= \text{diag}\{0.74 + 0.040 \cos(0.8t), 0.77 + 0.040 \sin(0.7t)\}, \\ J_1(t) &= [0.060 \sin(0.9t), -0.055 \cos(0.7t)]^\top, \quad t \geq t_1^f, \\ J_2(t) &= [-0.070 \cos(0.8t), 0.060 \sin(0.6t)]^\top, \quad t \geq t_2^f, \\ J_3(t) &= [0.060 \sin(0.7t), 0.050 \cos(0.8t)]^\top, \quad t \geq t_3^f, \\ J_4(t) &= [-0.075 \sin(0.6t), 0.065 \cos(0.9t)]^\top, \quad t \geq t_4^f.\end{aligned}$$

In the simulation, the lower bounds of the two actuator effectiveness factors are set as 0.68 and 0.70, respectively.

Following the fuzzy logic techniques in [8,29], the fuzzy rules are formulated as follows, and Gaussian membership functions are selected: IF x_{i1} is A_{j1} AND x_{i2} is A_{j2} AND x_{i3} is A_{j3} AND x_{i4} is A_{j4} , THEN the corresponding consequent is $\hat{w}_{ij}$, where $\hat{w}_{ij}$ is the j -th row of $\hat{W}_i$. The antecedent fuzzy sets are described by the Gaussian membership functions

$$\mu_{j\ell}(x_{i\ell}) = \exp\left(-\frac{(x_{i\ell} - c_{j\ell})^2}{\sigma^2}\right), \quad (89)$$

where $c_{j\ell}$ is the ℓ -th component of the center c_j and $\sigma = 3.2$ is the common width. The normalized firing strength of the j -th rule is calculated as

$$\phi_{ij}(x_i) = \frac{\prod_{\ell=1}^4 \mu_{j\ell}(x_{i\ell})}{\sum_{r=1}^9 \prod_{\ell=1}^4 \mu_{r\ell}(x_{i\ell})}. \quad (90)$$

The fuzzy approximation is then given by $\hat{F}_i(x_i) = \hat{W}_i^\top \phi_i(x_i)$. The centers of the nine rules are listed in Table 2.

Table 2. Centers of the Gaussian membership functions used in the FLS.

Rule j	c_{j1}	c_{j2}	c_{j3}	c_{j4}
1	−1.2	−1.2	−4	−4
2	−0.6	−0.6	−2	−2
3	0	0	0	0
4	0.6	0.6	2	2
5	1.2	1.2	4	4
6	−1.2	1.2	−3	3
7	1.2	−1.2	3	−3
8	−0.3	0.9	−1	2
9	0.9	−0.3	2	−1

For comparison, a Nussbaum-type method, an integer-order dynamic event-triggered mechanism (DETC), and a static event-triggered mechanism (SETC) are also simulated under the same initial conditions, reference trajectory, actuator faults, and disturbances.

The following results are presented to demonstrate the tracking performance, bounded control input, fractional-order triggering behavior, adaptive parameter evolution, and comparative advantages of the proposed control scheme.

Figures 1 and 2 show the tracking trajectories of the first and second joint components, respectively. It can be observed that all robotic manipulators track the desired trajectories after a short transient process. Although actuator faults are injected at different instants, the tracking trajectories remain bounded and no divergence occurs. This indicates that the proposed adaptive fuzzy fractional-order event-triggered fault-tolerant controller can maintain satisfactory tracking performance in the presence of actuator degradation and external disturbances.

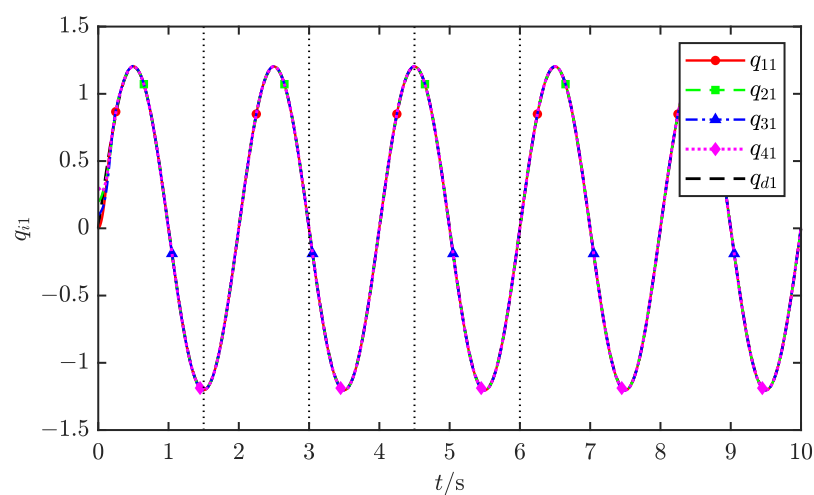


Figure 1. Tracking trajectories of the first joint component.

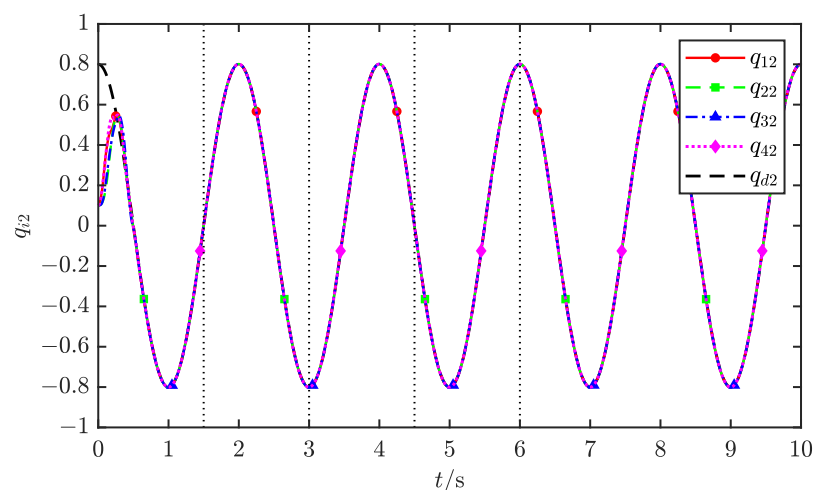


Figure 2. Tracking trajectories of the second joint component.

Figure 3 depicts the tracking and consensus error norms under actuator faults. The vertical dashed lines denote the fault injection instants. It can be seen that the error decreases rapidly during the initial transient stage and then remains within a small bounded region. Quantitatively, the tracking error norm at $T_c = 3$ s is 0.007865, the final tracking error norm is 0.007559, and the maximum tracking error norm after 3 s is 0.010373. The RMS tracking

error norm over the whole simulation interval is 0.150113. These results are consistent with the predefined-time tracking property obtained in the theoretical analysis.

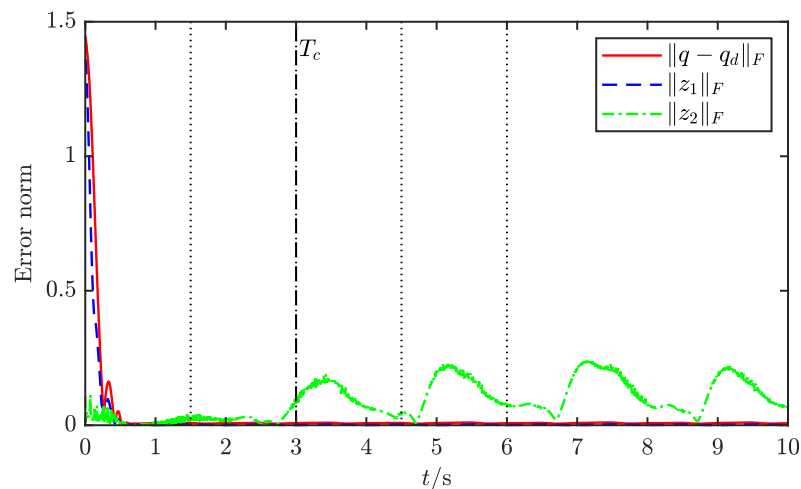


Figure 3. Tracking and consensus error norms under actuator faults.

Figure 4 presents the actual actuator inputs generated by the proposed method. The control signals remain bounded throughout the simulation interval, and only moderate variations appear after the actuator faults occur. This result shows that the proposed scheme can compensate for the adverse effects of actuator faults without producing excessive control oscillations.

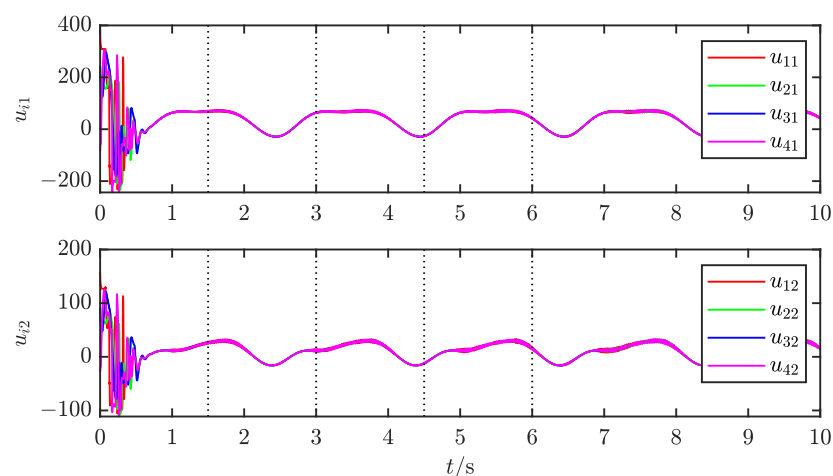


Figure 4. Actual actuator inputs of the proposed method.

Figure 5 illustrates the fractional-order event-triggering behavior. The triggering instants are distributed over the simulation interval rather than being generated at every sampling instant. In this simulation, the four robotic manipulators generate 5115, 3728, 3480, and 4494 triggered updates, respectively, and the total number of triggered updates is 16,817. Since the total number of possible periodic updates is $4 \times 10,000 = 40,000$, the update saving rate is approximately 57.96%. The dynamic triggering variables remain positive and bounded, which is consistent with the design of the fractional-order event-triggered mechanism.

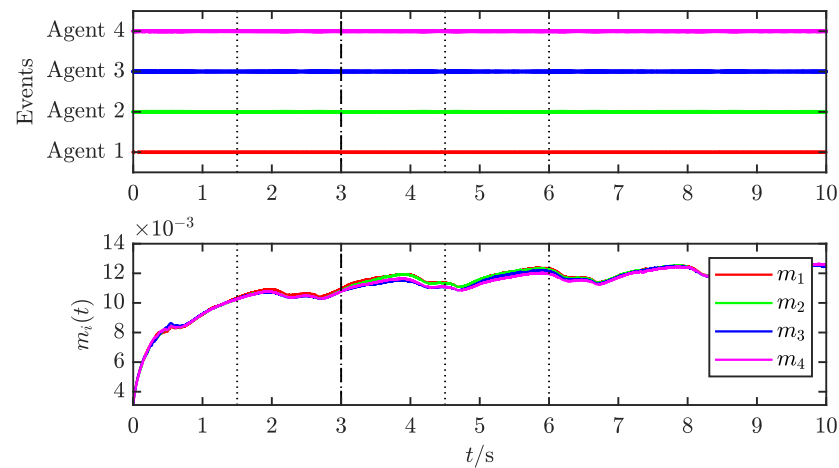


Figure 5. Memory-based fractional-order event-triggering behavior.

As shown in Table 3, the total number of triggered updates varies from 16,774 to 16,884, corresponding to saving rates between 57.79% and 58.07%. Meanwhile, the RMS tracking error, final tracking error, and post- T_c peak error remain close to their baseline values. These results indicate that Π_1 and Π_2 affect the triggering behavior, while the proposed method maintains similar update-saving and tracking performance over the considered parameter range.

Table 3. Quantitative comparison under different values of Π_1 and Π_2 .

Π_1	Π_2	RMS(e)	Final(e)	Peak $_{t \geq T_c}$	Updates	Saving Rate
0.85	0.006	0.150113	0.007554	0.010341	16774	58.07%
1.15	0.006	0.150113	0.007559	0.010373	16817	57.96%
1.45	0.006	0.150113	0.007557	0.010428	16797	58.01%
1.15	0.004	0.150113	0.007548	0.010353	16884	57.79%
1.15	0.008	0.150113	0.007553	0.010432	16827	57.93%

Figure 6 gives the trajectories of the adaptive parameters. It can be seen that the adaptive parameters remain bounded during the whole simulation process. This verifies that the adaptive fuzzy approximation and robust adaptive terms do not lead to parameter divergence under actuator faults and external disturbances.

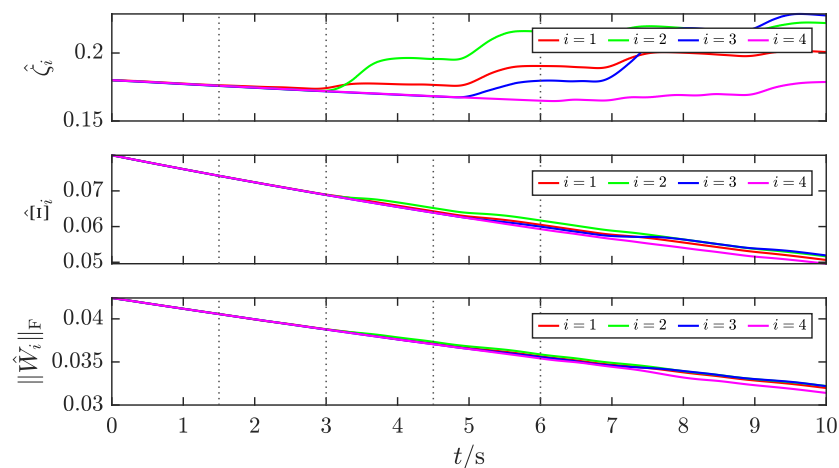


Figure 6. Trajectories of adaptive parameters.

To further demonstrate the advantage of the proposed fault-tolerant design, Figure 7 compares the proposed method with a Nussbaum-type method. The upper subfigure shows the tracking error, and the lower subfigure shows the actual control input. The Nussbaum-type method can still realize bounded tracking, but larger error fluctuations can be observed after the actuator faults occur. Moreover, the corresponding actuator input contains more obvious oscillations. In contrast, the proposed controller achieves a smaller post-transient tracking peak and smoother actuator inputs without relying on oscillatory Nussbaum-type gain adjustment. As shown in Table 4, the proposed method reduces the post- T_c peak tracking error by 71.22% and the input energy by 18.13%.

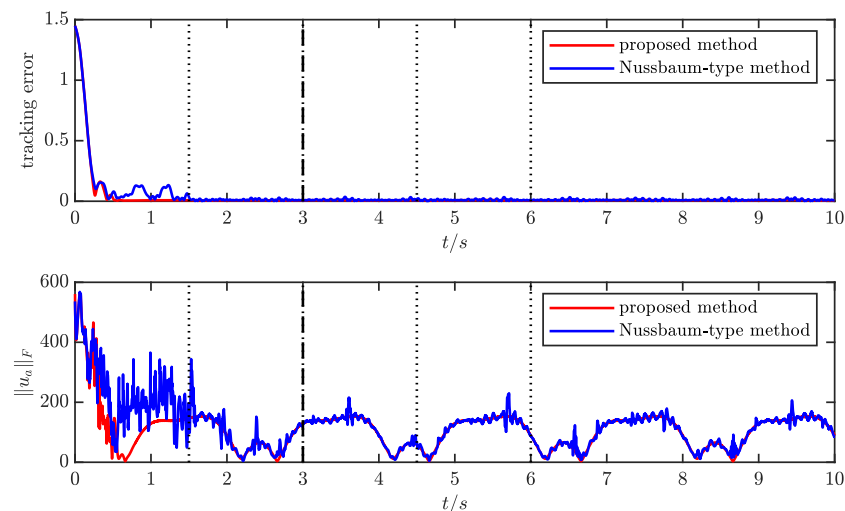


Figure 7. Comparison with the Nussbaum-type method.

Table 4. Tracking performance comparison with the Nussbaum-type method.

Case	$\text{RMS}(e)$	$\text{RMS}_{t \geq T_c}(e)$	$\text{Peak}_{t \geq T_c}$	$\text{Final}(e)$	$\text{Mean}\ u_a\ $
Proposed method	0.150113	0.008023	0.010373	0.007559	109.850
Nussbaum-type method	0.152682	0.012855	0.036041	0.010339	122.239

Figure 8 compares the tracking error norms under the proposed fractional-order event-triggered mechanism (MFETC), the integer-order dynamic event-triggered mechanism (DETC), and the static event-triggered mechanism (SETC). It can be observed that all three mechanisms maintain bounded tracking errors. However, the DETC and SETC cases exhibit larger post-transient error peaks, while the MFETC case maintains a smoother post-transient error profile. The quantitative comparison is summarized in Table 5. These results show that the MFETC mechanism achieves the smallest post- T_c peak error and final error among the three mechanisms, indicating that the proposed fractional-order dynamic event-triggered mechanism can better exploit historical triggering information to improve post-transient tracking accuracy.

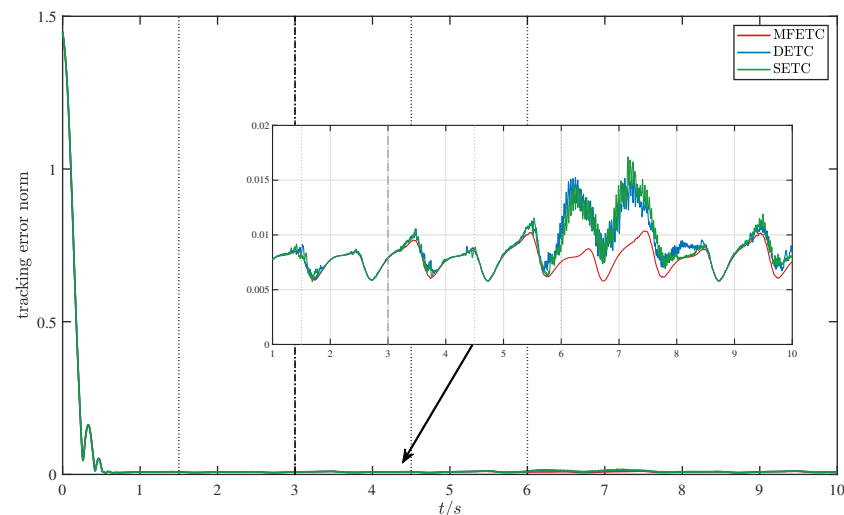


Figure 8. Tracking comparison under different event-triggered mechanisms.

Table 5. Quantitative comparison under different event-triggered mechanisms.

Mechanism	RMS(e)	Final(e)	Peak $_{t \geq T_c}$	Updates	Saving Rate
MFETC	0.150113	0.007559	0.010373	16817	57.96%
DETC	0.150452	0.008501	0.015399	18392	54.02%
SETC	0.150452	0.007996	0.017142	18534	53.67%

Example 2. To further verify the applicability of the proposed method to different Euler–Lagrange systems, four heterogeneous single-link robotic manipulators are considered. The dynamics of the i -th manipulator are described by

$$M_i \ddot{q}_i + b_i \dot{q}_i + m_{p,i} g l_i \sin(q_i) + f_i(q_i, \dot{q}_i) = u_i^a + d_i(t), \quad (91)$$

where $M_i = m_{p,i} l_i^2$, q_i and $\dot{q}_i$ denote the angular position and velocity, respectively, $m_{p,i}$ is the link mass, l_i is the link length, b_i is the damping coefficient, $f_i(q_i, \dot{q}_i)$ represents the unknown nonlinear dynamics, and $d_i(t)$ is the external disturbance. The physical parameters of the four manipulators are given in Table 6.

Table 6. Physical parameters of the heterogeneous single-link robotic manipulators.

Agent i	$m_{p,i}$	l_i	b_i
1	1.60	0.85	0.72
2	2.00	1.00	0.95
3	2.35	0.92	1.18
4	1.80	1.08	0.84

The gravitational acceleration is set to $g = 9.8$. To represent heterogeneous model uncertainties, the unknown nonlinear functions are chosen as $f_1(q_1, \dot{q}_1) = 0.18 \sin(2q_1) + \frac{0.10\dot{q}_1|\dot{q}_1|}{1+|\dot{q}_1|}$, $f_2(q_2, \dot{q}_2) = 0.14 \cos(1.7q_2) + \frac{0.12\dot{q}_2|\dot{q}_2|}{1+|\dot{q}_2|}$, $f_3(q_3, \dot{q}_3) = 0.20 \sin(1.5q_3) + \frac{0.08\dot{q}_3|\dot{q}_3|}{1+|\dot{q}_3|}$, $f_4(q_4, \dot{q}_4) = 0.16 \cos(1.9q_4) + \frac{0.11\dot{q}_4|\dot{q}_4|}{1+|\dot{q}_4|}$. Meanwhile, the bounded external disturbances imposed on the four agents are $d_1(t) = 0.055 \sin(1.10t + 0.2)$, $d_2(t) = 0.050 \cos(0.95t + 0.5)$, $d_3(t) = 0.060 \sin(1.20t + 0.8)$, $d_4(t) = 0.052 \cos(1.05t + 1.1)$. For the cooperative tracking task, the same communication topology and leader-access matrix as those in Example 1 are adopted, and the reference signal generated by the virtual leader is selected as $q_d(t) = 0.90 \sin(0.85\pi t) + 0.18 \cos(0.30\pi t)$.

To evaluate the fault-tolerant performance under different actuator failures, faults are introduced into the four agents at $t_1^f = 1.2$ s, $t_2^f = 2.1$ s, $t_3^f = 3.4$ s, and $t_4^f = 4.6$ s. Before t_i^f , the i -th actuator operates normally, namely, $\Gamma_i(t) = 1$ and $J_i(t) = 0$. At t_i^f , the actuator parameters switch to the following time-varying fault profiles:

$$\begin{aligned}\Gamma_1(t) &= 0.62 + 0.035 \sin(0.75t), & J_1(t) &= 0.16 \sin(0.90t), & t &\geq t_1^f, \\ \Gamma_2(t) &= 0.70 + 0.040 \cos(0.65t), & J_2(t) &= -0.18 \cos(0.75t), & t &\geq t_2^f, \\ \Gamma_3(t) &= 0.58 + 0.030 \sin(0.55t), & J_3(t) &= 0.14 \cos(0.85t), & t &\geq t_3^f, \\ \Gamma_4(t) &= 0.66 + 0.035 \cos(0.80t), & J_4(t) &= -0.17 \sin(0.70t), & t &\geq t_4^f.\end{aligned}$$

The corresponding lower bounds of the actuator effectiveness factors are 0.585, 0.660, 0.550, and 0.625, respectively. Thus, all actuator effectiveness factors remain strictly positive and satisfy Assumption 2.

With the above system and fault settings, the initial positions are set to $q(0) = [0.51, 0.52, 0.53, 0.54]^\top$, and the initial velocities satisfy $\dot{q}_i(0) = 0$. The simulation is performed over $[0, 8]$ s with a fixed sampling step of 0.001 s. The predefined time is set to $T_c = 3$ s with $\varrho = 0.16$, while the remaining controller parameters are $k_{i3} = 24$, $\pi_{i1} = \pi_{i2} = 0.02$, $d_{i1} = 0.45$, $\varepsilon_{i1} = 0.025$, and $\varepsilon_{i2} = 0.75$. The fractional-order dynamic event-triggered parameters are $\alpha_{FD} = 0.72$, $h_i = 0.014$, $\Pi_1 = 1.15$, $\Pi_2 = 0.006$, and $m_i(0) = 0.003$. To implement the adaptive fuzzy approximation, the FLS input is selected as $x_i = [q_i, \dot{q}_i]^\top$. Nine normalized Gaussian fuzzy rules are employed, whose centers are taken from $\{-1.2, 0, 1.2\} \times \{-3, 0, 3\}$, with a common width of $\sigma = 2.2$. The adaptive parameters are initialized as $\hat{W}_i(0) = 0.01 \mathbf{1}_{9 \times 1}$, $\hat{\xi}_i(0) = 0.20$, and $\hat{\Xi}_i(0) = 0.10$, with adaptive gains $\lambda_{i1} = 0.035$ and $\lambda_{i2} = \lambda_{i3} = 0.060$.

Figure 9 presents the tracking trajectories of the four single-link robotic manipulators. Despite the heterogeneous physical parameters, unknown nonlinear dynamics, external disturbances, and actuator faults, all followers track the reference signal generated by the virtual leader. Figure 10 shows the tracking error norm. The error decreases rapidly during the initial transient stage and enters a small residual region within the predefined time $T_c = 3$ s. The tracking error norm at T_c is 0.018978, the final tracking error norm is 0.003324, and the maximum tracking error norm after T_c is 0.019183. Figure 11 illustrates the triggering instants and the corresponding dynamic triggering variables. The four agents generate 2401, 2880, 2891, and 2629 triggered updates, respectively. The total number of triggered updates is 10801, whereas the total number of possible periodic updates is $4 \times 8000 = 32,000$. Therefore, the control-input update saving rate is approximately 66.25%. Moreover, all dynamic triggering variables remain positive and bounded during the simulation. Figure 12 depicts the actual actuator inputs under actuator effectiveness loss and bias faults. The actuator inputs remain bounded after the occurrence of the faults. Together with the tracking results, this further verifies that the proposed method can maintain predefined-time tracking performance for heterogeneous single-link Euler–Lagrange systems under unknown nonlinearities, external disturbances, and actuator faults.

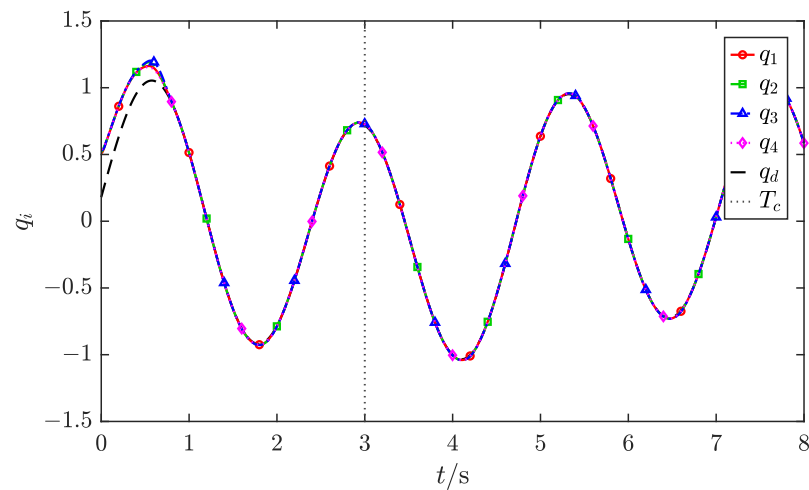


Figure 9. Tracking trajectories of the heterogeneous single-link robotic manipulators.

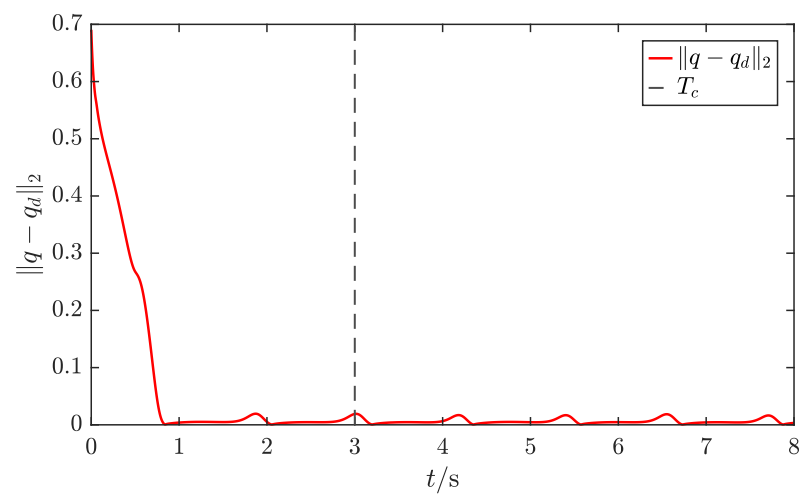


Figure 10. Tracking

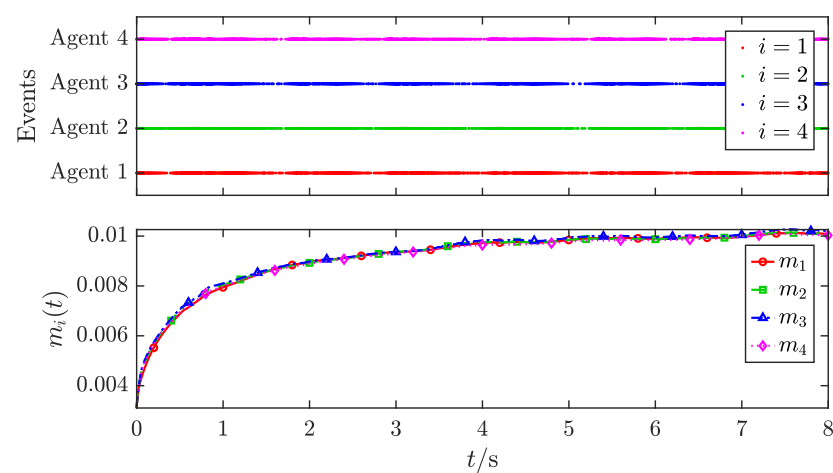


Figure 11. Triggering instants and dynamic triggering variables in Example 2.

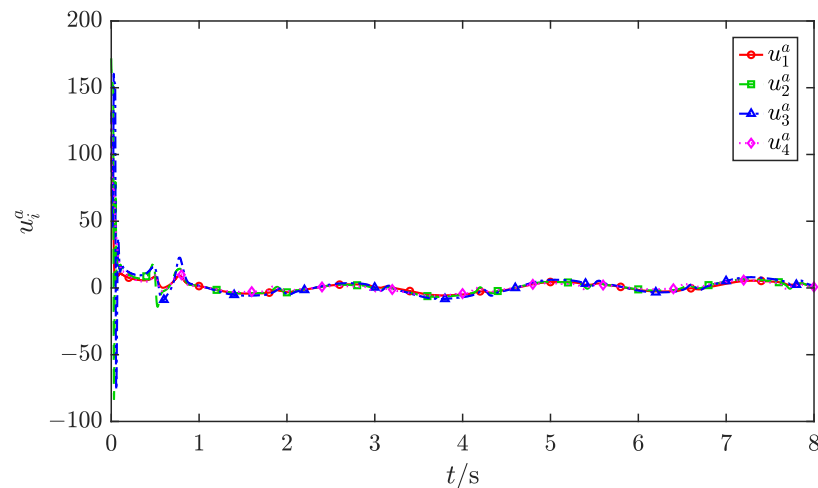


Figure 12. Actual actuator inputs in Example 2.

5. Conclusions

This paper investigated the predefined-time consensus tracking control problem for networked robotic manipulators with actuator faults, unknown nonlinearities, and external disturbances. An adaptive fuzzy fractional-order dynamic event-triggered fault-tolerant control scheme was proposed by combining nonsingular predefined-time backstepping design, fractional-order dynamic event-triggered updating, and adaptive fuzzy fault compensation. The fractional-order triggering variable was introduced to incorporate historical triggering information into the threshold dynamics, while adaptive fuzzy approximation and robust compensation terms were used to handle model uncertainties and actuator faults. Based on Lyapunov analysis, it was proved that all closed-loop signals are bounded and that the tracking errors converge to a small residual set within the predefined time. Simulation results on networked two-link robotic manipulators demonstrated the tracking performance, fault-tolerant capability, and comparative advantages of the proposed method over the Nussbaum-type method, the integer-order dynamic event-triggered mechanism, and the static event-triggered mechanism in the considered case. An additional example involving heterogeneous single-link Euler–Lagrange agents provided further simulation evidence for the effectiveness of the proposed scheme under a different system model and fault scenario. Future work will focus on experimental validation and on extending the proposed scheme to more general communication settings, including directed and switching interaction graphs, temporarily disconnected networks, large communication delays, and incomplete leader information.

Author Contributions: Methodology, Z.W., S.H., S.X. and T.K.; Software, Z.W. and T.K.; Writing—original draft preparation, Z.W. and S.X.; Writing—review and editing, S.H. and T.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Olfati-Saber, R.; Fax, J.A.; Murray, R.M. Consensus and cooperation in networked multi-agent systems. *Proc. IEEE* **2007**, *95*, 215–233.

2. Gai, X.; Xu, C.; Liu, Y.; Feng, Q.; Wang, S. Applications of multi-robotic arms to assist agricultural production: A review. *AgriEngineering* **2025**, *7*, 192.
3. Long, M.; Chung, E. Multi-agent reinforcement learning for cooperative transit signal priority to promote headway adherence. *IEEE Trans. Intell. Transp. Syst.* **2025**, *26*, 3588–3602.
4. Sakurada, L.; de la Prieta, F.; Leitão, P. An agent-based approach for implementing asset administration shell type 3. *IEEE Access* **2025**, *13*, 206617–206638.
5. Hu, Y.; Yan, H.; Wang, M.; Hu, X.; Li, Z. Fuzzy observer-based input/output event-triggered control for Euler–Lagrange systems with guaranteed performance and input saturation. *IEEE Trans. Fuzzy Syst.* **2024**, *32*, 2077–2088.
6. Qin, J.; Ma, Q.; Shi, Y.; Wang, L. Recent advances in consensus of multi-agent systems: A brief survey. *IEEE Trans. Ind. Electron.* **2017**, *64*, 4972–4983.
7. Xia, L.; Li, Q.; Song, R.; Guo, L.; Lewis, F.A. Novel event-triggered control for time-varying leader–follower MASs on directed graphs. *IEEE Trans. Syst. Man Cybern. Syst.* **2025**, *55*, 7911–7921.
8. Wang, A.; Liu, L.; Qiu, J.; Feng, G. Leader-following consensus of multiple uncertain Euler–Lagrange systems via fully distributed event-triggered adaptive fuzzy control. *IEEE Trans. Cybern.* **2024**, *54*, 76–86.
9. Zhang, R.; Huang, J. Fully event-triggered practical leader-following consensus of multiple Euler–Lagrange systems over switching networks. *IEEE Trans. Cybern.* **2024**, *54*, 7566–7575.
10. Narayanan, G.; Karthikeyan, R.; Lee, S.; Ahn, S. Intelligent resilient security control for fractional-order multiagent networked systems using reinforcement learning and event-triggered communication mechanism. *IEEE Trans. Cybern.* **2025**, *55*, 5103–5116.
11. Xu, B.; Li, B. Dynamic event-triggered consensus for fractional-order multi-agent systems without intergroup balance condition. *Fractal Fract.* **2023**, *7*, 268.
12. Wang, L.; Dong, J. Reset event-triggered adaptive fuzzy consensus for nonlinear fractional-order multiagent systems with actuator faults. *IEEE Trans. Cybern.* **2023**, *53*, 1868–1879.
13. Jiménez-Rodríguez, E.; Muñoz-Vázquez, A.J.; Sánchez-Torres, J.D.; Defoort, M.; Loukianov, A.G. A Lyapunov-like characterization of predefined-time stability. *IEEE Trans. Autom. Control.* **2020**, *65*, 4922–4927.
14. Liu, Y.; Yang, G.-H. Neural learning-based fixed-time consensus tracking control for nonlinear multiagent systems with directed communication networks. *IEEE Trans. Neural Netw. Learn. Syst.* **2021**, *32*, 639–652.
15. Gong, J.; Wang, F.; Liu, Z.; Chen, Z. Practical fixed-time consensus tracking for second-order multi-agent systems with mismatched disturbances. *IEEE Trans. Signal Inf. Process. Netw.* **2023**, *9*, 761–769.
16. Wang, Y.; Song, Y.; Hill, D.J.; Krstic, M. Prescribed-time consensus and containment control of networked multiagent systems. *IEEE Trans. Cybern.* **2019**, *49*, 1138–1147.
17. Ni, J.; Liu, L.; Tang, Y.; Liu, C. Predefined-time consensus tracking of second-order multiagent systems. *IEEE Trans. Syst. Man Cybern. Syst.* **2021**, *51*, 2550–2560.
18. Zou, A.-M.; Liu, Y.; Hou, Z.-G.; Hu, Z. Practical predefined-time output-feedback consensus tracking control for multiagent systems. *IEEE Trans. Cybern.* **2023**, *53*, 5311–5322.
19. Yoo, S.J.; Park, B.S. Dynamic event-triggered prescribed-time consensus tracking of nonlinear time-delay multiagent systems by output feedback. *Fractal Fract.* **2024**, *8*, 545.
20. Li, C.; Li, P.; Zheng, C.-B.; Guo, H.; Dong, Z. Event-triggered active fault-tolerant predictive control for networked multi-agent systems with actuator faults and random communication constraints. *Appl. Sci.* **2025**, *15*, 6317.
21. Zhang, Y.; Jiang, J. Bibliographical review on reconfigurable fault-tolerant control systems. *Annu. Rev. Control* **2008**, *32*, 229–252.
22. Ye, Z.; Cheng, Y.; Yu, Z.; Jiang, B. Distributed adaptive fault-tolerant control for leaderless/leader–follower multi-agent systems against actuator and sensor faults. *Electronics* **2023**, *12*, 2924.
23. Shi, J.; Chen, X.; Xing, S.; Liu, A.; Chen, C. Robust cooperative fault-tolerant control for uncertain multi-agent systems subject to actuator faults. *Sensors* **2024**, *24*, 2651.
24. Su, Y.; Shan, Q.; Liang, H.; Li, T.; Zhang, H. Event-based adaptive optimal fault-tolerant consensus control for uncertain nonlinear multiagent systems with actuator failures. *IEEE Trans. Syst. Man Cybern. Syst.* **2025**, *55*, 7273–7287.
25. Yang, P.; Ding, Y.; Shen, Z.; Feng, K. Integral non-singular terminal sliding mode consensus control for multi-agent systems with disturbance and actuator faults based on finite-time observer. *Entropy* **2022**, *24*, 1068.
26. Dong, J.; Tan, J.; Jing, G.; Li, Y.; Wang, H. Distributed robust fault-tolerant control of networked Euler–Lagrange systems with time delays. *Int. J. Robust Nonlinear Control* **2024**, *34*, 3091–3108.
27. Li, J.; Zhao, W.; Liang, Y.; Wu, Z.; Zhao, L. Event-triggered consensus control for a class of uncertain multiple Euler–Lagrange systems with actuator faults. *Discret. Contin. Dyn. Syst. Ser. S* **2024**, *17*, 2839–2854.
28. Li, Y.; Xu, T.; Yang, R.; Wang, M. Distributed adaptive finite-time fault-tolerant formation-containment control for networked Euler–Lagrange systems under directed communication interactions. *Neurocomputing* **2023**, *560*, 126839.
29. Shan, H.; Jiang, Y.; Liang, H.; Wang, S.; Lam, H.-K. Fuzzy adaptive containment control for nonlinear multi-manipulator systems with actuator faults and predefined accuracy. *IEEE Trans. Netw. Sci. Eng.* **2024**, *11*, 1510–1523.

30. Shi, Y.; Yan, H.; Hu, Y.; Wang, M.; Li, Z. Predefined-time event-triggered sliding mode control of uncertain Euler–Lagrange dynamic systems with actuator faults. *Int. J. Syst. Sci.* **2025**, *56*, 3558–3570.
31. Polycarpou, M.M.; Ioannou, P.A. A robust adaptive nonlinear control design. *Automatica* **1996**, *32*, 423–427.
32. Liu, S.; Niu, H.; Zhang, L.; Guo, X. Adaptive compound second-order terminal sliding mode control for the longitudinal attitude control of the fully submerged hydrofoil vessel. *Adv. Mech. Eng.* **2019**, *11*, 1687814019895637.
33. Zuo, Z. Nonsingular fixed-time consensus tracking for second-order multi-agent networks. *Automatica* **2015**, *54*, 305–309.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.