Mathematical Biosciences and Engineering

http://www.aimspress.com/journal/mbe

MBE, 21(3): 4724–4741.
DOI: 10.3934/mbe.2024207
Received: 10 January 2024
Revised: 09 February 2024
Accepted: 21 February 2024
Published: 29 February 2024

Research article

Adaptive fuzzy fixed time formation control of state constrained nonlinear multi-agent systems against FDI attacks

Jinxin Du and Lei Liu*

College of Science, Liaoning University of Technology, Jinzhou, China

* **Correspondence:** Email: liuleill@live.cn.

Abstract: In this manuscript, based on nonlinear multi-agent systems (MASs) with full state constraints and considering security control problem under false data injection (FDI) attacks , the fixed-time formation control (FTFC) protocol was designed, which can ensure that all agents follow the required protocol within a fixed time. Fuzzy logic system (FLS) was used to compensate and approximate the uncertain function, which improved safety and robustness of the formation process. Finally, the fixed-time theory and Lyapunov stability theory were addressed to prove the effectiveness of the proposed method, and simulation examples verified the effectiveness of the theory.

Keywords: MASs; full state constraints; fixed-time formation; FDI attacks; backstepping

1. Introduction

Recently, with the continuous progress of information technology and the rapid development of artificial intelligence and swarm intelligence theory, the control technology of multi-agent system (MASs) has become a hot research direction [1–3]. MASs are networks composed of multiple cooperating agents, which can jointly solve complex problems and provide innovative solutions. With the wide application of MASs in various fields, distributed control of MASs has attracted much attention, mainly including consensus control [4], formation control [5–8], containment control [9, 10], etc. Nevertheless, in some practical systems, especially in MASs, there are generally complex nonlinearities and uncertainties that can't be ignored, so the study of nonlinear MASs is of great essence. Because of the existence of nonlinear dynamics, the control problem of nonlinear MASs has become a challenge.

In the field of nonlinear multi-agent control, the key of control is to influence the behavior of the whole system by adjusting the interaction between each agent, and then achieve the control goal in a specific time scale. At present, finite-time control [11–13], fast finite-time control [14, 15], fixed-time control [16–19] and other methods have attracted the attention of many scholars, Cao et al. proposed finite-time control protocols in MASs consensus control in [11], and Du et al. designed a fixed-time consensus control protocol in heterogeneous MASs [17]. Fixed-time control means that the system can reach the required state or goal within a predetermined fixed time. Compared with traditional control methods, fixed-time control could keep the stability and performance within a predetermined time and is not affected by the initial conditions and external disturbances of the system. It was applied in mechanical control, robot control, power system, etc. In addition, with the increasing requirements and limitations in the controlled system and the improvement of system modeling, scholars have proposed various control algorithms and methods, such as sliding mode control [20], adaptive control [21], reinforcement learning [22, 23], and iterative learning control [24], to cope with the challenges of complex and nonlinear systems.

Constraint problems in control systems have become one of the hot research directions [25]. These constraints may involve state constraints [25–27], input constraints [28,29], output constraints [30], etc. Due to the constraints in actual systems, many scholars hammered at formation control and constraint problems of MASs, and they certainly made progress in the theoretical research levels. In the research of MASs formation problem, similar to social networks [31], the relationships between agents are complex. Agents need to be able to perceive the surrounding environment, including detecting the presence and position information of other neighbor agents, complete the coordination and control of complex tasks, and maintain predetermined geometric configurations. However, there are often more complex external conditions and human factors in practical applications.

At present, the security control problem of the control system under the complex network has been a concern, and the most typical attacks are the attacks in control system. Common malicious attacks include FDI attacks [10, 32–34], replay attacks [35], cyber attacks [36], and denial of service (DOS) attacks [37–40]. Among these, FDI attack is a kind of network attack method with strong damage ability to system stability where attackers inject false data into the network to change the state and destroy the stability of the systems. Miao et al. studied the control problem under attack and constraints in cyber-physical systems in [32], and Jiang et al. studied the tracking control problem under attack conditions based on MASs [33].

Considering the universality and destructiveness in practical applications, many scholars are devoted to the study of FDI attacks. Nontheless, there are still few studies on the FDI attacks in the formation control of nonlinear MASs. Therefore, we realize the FTFC of nonlinear MASs under FDI attacks is required and it has more practical application reference value. This paper innovates from the following aspects:

1) Compared with previous control strategies, the FTFC for MASs with full state constraints proposed in this article takes FDI attacks into account. In dealing with the state constraint problem, a novel nonlinear transformation method is employed to transform the system state to an unconstrained state.

2) Integrating backstepping techniques with FTFC strategies, the designed controller can achieve stability during the attack period, and the attack coefficient can also be effectively compensated.

2. System descriptions and preliminaries

2.1. Graph theory

Define $\Xi = (\upsilon, \varepsilon, A)$ being a weighted-undirected graph in communication network, with a cluster of nodes $\upsilon = \{v_1, v_2, \dots, v_N\}$, a cluster of edges $\varepsilon \subseteq \left\{\left(v_i, v_j\right) : v_i, v_j \subseteq \upsilon\right\}$, and $A = \left[a_{ij}\right] \in R^{n\times n}$ representing the adjacency matrix. In the undirected graph Ξ, an edge $\left(v_i, v_j\right)$ is expressed as $v_{ij} = \left(v_i, v_j\right), i \neq j$, and it means that the jth agent is able to deliver the message to the ith agent. The Laplacian matrix $L = \left[l_{ij}\right] \in R^{n\times n}$, associated with the undirected graph Ξ, is structured as

$$L = \left[l_{ij}\right] = D - A$$

where $D = diag\{d_1, \dots, d_n\} = diag\left\{\sum_{j=1}^{n} a_{1j}, \dots, \sum_{j=1}^{n} a_{nj}\right\}$.

2.2. Problem formulation

Consider the nonlinear MASs as

$$\begin{cases} \dot{x}_{i,m} = x_{i,m+1} + f_{i,m}\left(\bar{x}_{i,m}\right) \\ \dot{x}_{i,q} = u_i + f_{i,q}\left(\bar{x}_{i,q}\right) \\ y_i = x_{i,1} \end{cases} \tag{2.1}$$

where $\bar{x}_{i,m} = \left[x_{i,1}, \dots, x_{i,m}\right]^T \in R^m$ and $\bar{x}_{i,q} = \left[x_{i,1}, \dots, x_{i,q}\right]^T \in R^q$ represent state vector of the ith follower, $i = 1, \dots, P$, $m = 1, \dots, q-1$, u_i and y_i are the control input and output of the ith follower, and $f_{i,m}\left(\bar{x}_{i,m}\right)$ and $f_{i,q}\left(\bar{x}_{i,q}\right)$ are both unknown smooth nonlinear functions.

Definition 1: Consider state-dependent parameterized FDI attacks model as

$$\widehat{x}_{i,r} = x_{i,r} + \zeta_s\left(x_{i,r}, t\right) \tag{2.2}$$

where $\widehat{x}_{i,r}$ denotes the state destroyed by FDI attacks, $\zeta_s\left(x_{i,r}, t\right)$ represents the FDI attacks into $x_{i,r}$, $\zeta_s\left(x_{i,r}, t\right)$ is parameterized as $\zeta_s\left(x_{i,r}, t\right) = \varsigma_s(t)\, x_{i,r}$, and $\varsigma_s(t)$ represents the unknown and time-varying signals. The transformed state is denoted as $x_{i,r} = \kappa_s(t)\,\widehat{x}_{i,r}$, $\kappa_s(t) = \left(1 + \varsigma_s(t)\right)^{-1}$.

The dynamic of the leader is scaled as

$$\begin{cases} \dot{x}_{l,m} = x_{l,m+1} \\ \dot{x}_{l,q} = u_l \\ y_l = x_{l,1} \end{cases} \tag{2.3}$$

Consider the case of being attacked, which is modeled as

$$y_l = \kappa_s(t)\,\widehat{y}_l \tag{2.4}$$

Remark 1: The FDI attacks in this paper targets MASs and occurs in both leader and follower agents.

Definition 2: Given any initial formation tracking errors $\|x_i(t_0) - x_l(t_0) - h_i\| \in R$, one has

$$\lim_{t\to t_0+T} \|x_i(t) - x_l(t) - \hbar_i\| = 0,\ t \geq t_0 + T \tag{2.5}$$

where T denotes the settling time for secure fixed-time formation tracking control, and $\hbar_i = [h_{i,1}, \cdots, h_{i,m}]^T \in R^m$ represents the anticipated position vector between the ith agent and the leader.

Remark 2: The time-varying structure h_i of MASs in the paper is bounded, and its time derivative exists, that is, there exist $\hat{h}_i$ and $\bar{h}_i$ such that $|h_i| < \hat{h}_i$, $|\dot{h}_i| < \bar{h}_i$. Moreover, when $h_i = 0$, the formation control in this paper can be transformed into consensus tracking control.

Assumption 1 [32]: For the false data $\zeta_s(x_{i,r}, t)$, there exists $\bar{\zeta}_s$, satisfying: $\zeta_s(x_{i,m}, t) < \bar{\zeta}_i$, and the signals $\varsigma_s(t)$ are positive and meet the following conditions: $\underline{\varsigma}_s < \varsigma_s(t) < \bar{\varsigma}_s$, $\underline{\varsigma}_s$ and $\bar{\varsigma}_s$ stand by the unknown constants, the coefficient of attack $\kappa_s(t)$ is bounded, and $|\kappa_s(t)| \le \bar{\kappa}_s$.

Assumption 2: There exists an edge at least between each follower and the leader (root).

Lemma 1 [3]: The undirected graph Ξ is connected if, and only if, the Laplacian matrix is irreducible.

Lemma 2 [18]: In continuously normalized and radiationally unconstrained functions $V(\mathbb{Z})$, for any $\mathbb{Z}(t) \in R$, satisfy: $V(\mathbb{Z}) \le -\sigma V^{\iota}(\mathbb{Z}) - \upsilon V^{\tau}(\mathbb{Z})$, where $\sigma > 0, \upsilon > 0$, $\iota > 1$, $0 < \tau < 1$ are constants and the system can achieve fixed-time stability within $T = \frac{1}{\upsilon(1-\tau)} + \frac{1}{\sigma(1-\iota)}$.

Lemma 3 [28]: For any variables $\bar{a}$, $\bar{b}$ and positive constants ϑ_1, ϑ_2, and ϑ_3, one has

$$|\bar{a}|^{\vartheta_1}\left|\bar{b}\right|^{\vartheta_2} \le \frac{\vartheta_1}{\vartheta_1 + \vartheta_2}\vartheta_3|\bar{a}|^{\vartheta_1+\vartheta_2} + \frac{\vartheta_2}{\vartheta_1 + \vartheta_2}\vartheta_3^{\frac{\vartheta_1}{\vartheta_2}}\left|\bar{b}\right|^{\vartheta_1+\vartheta_2} \tag{2.6}$$

Lemma 4 [41]: For any $\lambda_i \in R$, the inequalities hold

$$\sum\nolimits_{j=1}^{Q} |\lambda_i|^m \ge \begin{cases} \left(\sum_{j=1}^{Q} |\lambda_i|\right)^m & 0 < m \le 1 \\ Q^{1-m}\left(\sum_{j=1}^{Q} |\lambda_i|\right)^m & 1 < m < +\infty \end{cases} \tag{2.7}$$

2.3. Fuzzy logic system

Lemma 5 [12]: $\omega(x)$ denotes a continuous but unknown function, and the domain is the compact set γ. For constant $\theta > 0$, the FLS $f(x) = W^T\Psi(x)$ satisfy the following:

$$\sup_{x\in\nu} \left|\omega(x) - W^T\Psi(x)\right| \le \theta \tag{2.8}$$

where $x = \left(x_1, x_2, \ldots, x_q\right)^T$, $\Psi(x) = [\Psi_1(x), \Psi_2(x), \ldots, \Psi_L(x)]^T$, $\Psi_{\mathrm{p}}(x)$ is the fuzzy basis function, and $W = [W_1, \ldots, W_P]^T$ stands by the ideal weight vector.

Control objective: The principal objective of this article is to devise adaptive fuzzy FTFC controllers such that MASs with full state constraints satisfy the following:

1) Each follower in MASs can achieve fixed-time formation control in the case of FDI attacks.
2) The states of MASs are all bounded by the constraints and the closed-loop signals of the system are bounded.

3. Main results

3.1. Adaptive controller design

The coordinates are converted as

$$z_{i,m} = \frac{x_{i,m}}{k_c^2 - x_{i,m}^2} \tag{3.1}$$

where k_c denotes known smooth constants constraints on $x_{i,m}$, $\left|x_{i,m}\right| < k_c$ and define $\Phi_{i,m} = k_c^2 - x_{i,m}^2$, $\mu_{i,m} = \left(k_c^2 + x_{i,m}^2\right) / \left(k_c^2 - x_{i,m}^2\right)^2$.

The formation tracking error is determined as

$$e_{i,m} = \sum_{j=1}^{N_i} a_{ij} \left((z_{i,m} - h_i) - \left(z_{j,m} - h_j\right) \right) + b_i \left(z_{i,m} - h_i - \alpha_0\right) \tag{3.2}$$

$$e_{i,m} = z_{i,m} - \kappa_s \frac{\alpha_{i,m-1}}{\Phi_{i,m}} \tag{3.3}$$

$$\alpha_0 = \frac{y_l}{k_c^2 - y_l^2} \tag{3.4}$$

Step 1: The constrained system under attack can be constructed as

$$z_{i,1} = \frac{x_{i,1}}{k_c^2 - x_{i,1}^2} \tag{3.5}$$

According to (3.1), take the derivative with respect to $z_{i,1}$, and one has

$$\dot{z}_{i,1} = \mu_{i,1} \dot{x}_{i,1} = \mu_{i,1} \left(x_{i,2} + f_{i,1} \left(\bar{x}_{i,1}\right)\right) \tag{3.6}$$

where $\mu_{i,1} = k_c^2 + x_{i,1}^2 / \left(k_c^2 - x_{i,1}^2\right)^2$.

The formation tracking errors are defined as

$$e_{i,1} = \sum_{j=1}^{N_i} a_{ij} \left((z_{i,1} - h_i) - \left(z_{j,1} - h_j\right) \right) + b_i \left(z_{i,1} - h_i - \alpha_0\right) \tag{3.7}$$

then, one has

$$E = (L + B) \left(Z_f - \hbar_i - I_N y_l\right) \tag{3.8}$$

where $E = \left[e_{i,1}, \cdots, e_{P,1}\right]^T \in R^P$, $Z_f = \left[z_{i,1}, \ldots, z_{P,1}\right]^T$.

The unknown nonlinear function is defined as

$$G_{i,1} \left(M_{i,1}\right) = \mu_{i,1} f_{i,1} \left(\bar{x}_{i,1}\right) - \mu_l \dot{y}_l \tag{3.9}$$

From the FLSs, it follows that

$$G_{i,1} \left(M_{i,1}\right) = W_{i,1}^T \Psi_{i,1} \left(M_{i,1}\right) + \varepsilon_{i,1} \left(M_{i,1}\right) \tag{3.10}$$

where $\Psi_{i,1} \left(M_{i,1}\right) \in R^{\upsilon_m}$ stands by fuzzy basis function vector, υ_m denotes the numbers of fuzzy rules, $\left\|W_{i,m}\right\| \leq \bar{W}_{i,m}$, $\left|\varepsilon_{i,m} \left(M_{i,m}\right)\right| \leq \bar{\varepsilon}_{i,m}$, and $m = 1, 2, \ldots q$.

Define

$$V_1 = \frac{1}{2} E^T (L + B)^{-1} E + \sum_{i=1}^{P} \frac{1}{2\upsilon_{i,1}} \tilde{\omega}_{i,1}^2 + \sum_{i=1}^{P} \frac{1}{2\varpi_{i,1}} \tilde{\kappa}_s^2 \tag{3.11}$$

where $\tilde{\omega}_{i,m} = \omega_{i,m} - \hat{\omega}_{i,m}$, $\hat{\omega}_{i,m}$ stands by the estimation of $\omega_{i,m}$, $\tilde{\kappa}_s = \kappa_s - \hat{\kappa}_s$, $\hat{\kappa}_s$ stands by the estimation of κ_s, $\upsilon_{i,1} = 2\varphi_{i,1}/(2\varphi_{i,1} - 1)$, and $\varpi_{i,1} = 2\psi_{i,1}/(2\psi_{i,1} - 1)$.

Take the derivative of V_1, and it obtains

$$\begin{aligned}\dot{V}_1 &= \sum_{i=1}^{P}\left(e_{i,1}\left(\dot{z}_{i,1} - \dot{h}_i - \mu_l\dot{y}_l\right) - \frac{1}{\upsilon_{i,1}}\tilde{\omega}_{i,1}\dot{\hat{\omega}}_{i,1} - \frac{1}{\varpi_{i,1}}\tilde{\kappa}_s\dot{\hat{\kappa}}_s\right)\\ &= \sum_{i=1}^{P}\left(e_{i,1}\left(\mu_{i,1}\Phi_{i,2}e_{i,2}+\frac{1}{\kappa_s}\widehat{\mu}_{i,1}\alpha_{i,1} - \dot{h}_i + W_{i,1}^T\Psi_{i,1} + \varepsilon_{i,1}\right) - \frac{1}{\upsilon_{i,1}}\tilde{\omega}_{i,1}\dot{\hat{\omega}}_{i,1} - \frac{1}{\varpi_{i,1}}\tilde{\kappa}_s\dot{\hat{\kappa}}_s\right)\end{aligned} \tag{3.12}$$

According to Young's inequality,

$$e_{i,1}W_{i,1}^T\Psi_{i,1} \leq \frac{1}{2}d_{i,1}^2 + \frac{1}{2d_{i,1}^2}\bar{W}_{i,1}^2\Psi_{i,1}^T\Psi_{i,1}e_{i,1}^2 \tag{3.13}$$

$$e_{i,1}\varepsilon_{i,1} \leq \frac{1}{4}e_{i,1}^2 + \bar{\varepsilon}_{i,1}^2 \tag{3.14}$$

$$-e_i\dot{h}_i \leq \frac{1}{4}e_i^2 + \bar{h}_i^2 \tag{3.15}$$

where $d_{i,j}$ represents the positive design parameter.

The virtual controller is designed as

$$\alpha_{i,1} = -\frac{1}{\widehat{\mu}_{i,1}}\left(\frac{\widehat{e}_{i,1}}{2} + \frac{\Psi_{i,1}^T\Psi_{i,1}}{2d_{i,1}^2}\widehat{e}_{i,1}\hat{\omega}_{i,1} + c_{i,1}\widehat{e}_{i,1}^{\gamma_1} + \bar{c}_{i,1}\widehat{e}_{i,1}^{\gamma_2}\right) \tag{3.16}$$

Substituing (3.13)–(3.16) into (3.12), one has

$$\dot{V}_1 \leq \sum_{i=1}^{P}\left(\mu_{i,1}\Phi_{i,2}e_{i,1}e_{i,2} - c_{i,1}e_{i,1}^{\gamma_1} - \bar{c}_{i,1}e_{i,1}^{\gamma_2} - \frac{1}{\upsilon_{i,1}}\tilde{\omega}_{i,1}\left(\dot{\hat{\omega}}_{i,1} - \frac{\Psi_{i,1}^T\Psi_{i,1}}{2d_{i,1}^2}e_{i,1}^2\right) + \frac{1}{\varpi_{i,1}}\tilde{\kappa}_{i,1}\dot{\hat{\kappa}}_{i,1} + \Delta_{i,1}\right) \tag{3.17}$$

where $\Delta_{i,1} = \frac{1}{2}d_{i,1}^2 + \bar{\varepsilon}_{i,1}^2 + \bar{h}_i^2$.

Step $p(2 \leq p \leq q-1)$: The derivative of $e_{i,p}$ is scaled as

$$\dot{e}_{i,p} = \dot{z}_{i,p} - \left(\kappa_s\frac{\alpha_{i,p-1}}{\Phi_{i,p}}\right)' \tag{3.18}$$

The unknown nonlinear function is defined as

$$G_{i,p}\left(M_{i,p}\right) = \mu_{i,p}f_{i,p}\left(\bar{x}_{i,p}\right) - \left(\kappa_s\frac{\alpha_{i,p-1}}{\Phi_{i,p}}\right)' \tag{3.19}$$

From the FLSs, it obtains

$$G_{i,p}\left(M_{i,p}\right) = W_{i,p}^{*T}\Psi_{i,p}\left(M_{i,p}\right) + \varepsilon_{i,p}\left(M_{i,p}\right) \tag{3.20}$$

where $M_{i,p} = \left[x_{i,1}, \cdots, x_{i,p}, \hat{\omega}_{i,1}, \cdots, \hat{\omega}_{i,p-1}\right]^T$, $\Psi_{i,p}\left(M_{i,p}\right)$ stands for fuzzy basis function, $W_{i,p}^{*T}$ denotes the optimal weight vector, and $\varepsilon_{i,p}\left(M_{i,p}\right)$ denotes the error of approximation.

The Lyapunov function is chosen as

$$V_p = V_{p-1} + \sum_{i=1}^{P} \frac{1}{2} e_{i,p}^2 + \sum_{i=1}^{P} \frac{1}{2\upsilon_{i,p}} \tilde{\omega}_{i,p}^2 + \sum_{i=1}^{P} \frac{1}{2\varpi_{i,p}} \tilde{\kappa}_s^2 \tag{3.21}$$

Take the derivative of (3.21), and it obtains

$$\dot{V}_p = \dot{V}_{p-1} + \sum_{i=1}^{P_{p+1}} \left(\mu_{i,p} \Phi_{i,p+1} e_{i,p} e_{i,p+1} + e_{i,p} \left(\frac{1}{\kappa_s} \widehat{\mu}_{i,p} \alpha_{i,p} + W_{i,p}^T \Psi_{i,p} + \varepsilon_{i,p} \right) - \frac{1}{\upsilon_{i,p}} \tilde{\omega}_{i,p} \dot{\hat{\omega}}_{i,p} - \frac{1}{\varpi_{i,p}} \tilde{\kappa}_s \dot{\hat{\kappa}}_s \right) \tag{3.22}$$

According to Young's inequality,

$$e_{i,p} W_{i,p}^T \Psi_{i,p} \leq \frac{1}{2} d_{i,p}^2 + \frac{1}{2d_{i,p}^2} \bar{W}_{i,p}^2 \Psi_{i,p}^T \Psi_{i,p} e_{i,p}^2 \tag{3.23}$$

$$e_{i,p} \varepsilon_{i,p} \leq \frac{1}{2} e_{i,p}^2 + \frac{1}{2} \bar{\varepsilon}_{i,p}^2 \tag{3.24}$$

The virtual controller is

$$\alpha_{i,p} = -\frac{1}{\widehat{\mu}_{i,p}} \left(\widehat{\mu}_{i,p-1} \widehat{\Phi}_{i,p} \widehat{e}_{i,p-1} + \frac{\widehat{e}_{i,p}}{2} + \frac{\Psi_{i,p}^T \Psi_{i,p}}{2d_{i,p}^2} \widehat{e}_{i,p} \hat{\omega}_{i,p} + c_{i,p} \widehat{e}_{i,p}^{\gamma_1} + \bar{c}_{i,p} \widehat{e}_{i,p}^{\gamma_2} \right) \tag{3.25}$$

$$\begin{aligned} \dot{V}_p \leq & \sum_{m=1}^{p-1} \sum_{i=1}^{P} \left(-c_{i,m} e_{i,m}^{1+\gamma_1} - \bar{c}_{i,m} e_{i,m}^{1+\gamma_2} - \frac{1}{\upsilon_{i,p}} \tilde{\omega}_{i,m} \left(\dot{\hat{\omega}}_{i,m} - \frac{\Psi_{i,m}^T \Psi_{i,m}}{2d_{i,m}^2} e_{i,m}^2 \right) - \frac{1}{\varpi_{i,p}} \tilde{\kappa}_s \dot{\hat{\kappa}}_s + \Delta_{i,p} \right) \\ & + \sum_{m=1}^{p} \mu_{i,p-1} \Phi_{i,p} e_{i,p-1} e_{i,p} \end{aligned} \tag{3.26}$$

Step q: Derivation of $e_{i,q}$ is scaled as

$$\dot{e}_{i,q} = \mu_{i,q} \left(u_i + f_{i,q} \left(\bar{x}_{i,q} \right) \right) - \left(\kappa_s \frac{\alpha_{i,q-1}}{\Phi_{i,q}} \right)' \tag{3.27}$$

The unknown nonlinear function is defined as

$$G_{i,q} \left(M_{i,q} \right) = \mu_{i,q} f_{i,q} \left(\bar{x}_{i,q} \right) - \left(\kappa_s \frac{\alpha_{i,q-1}}{\Phi_{i,q}} \right)' \tag{3.28}$$

From the FLSs, it obtains

$$G_{i,q} \left(M_{i,q} \right) = W_{i,q}^{*T} \Psi_{i,q} \left(M_{i,q} \right) + \varepsilon_{i,q} \left(M_{i,q} \right) \tag{3.29}$$

where $M_{i,q} = \left[x_{i,1}, \cdots, x_{i,q}, \hat{\omega}_{i,1}, \cdots, \hat{\omega}_{i,q-1} \right]^T$, $\Psi_{i,q} \left(M_{i,q} \right)$ stands for fuzzy basis function, $W_{i,q}^{*T}$ denotes the optimal weight vector, and $\varepsilon_{i,q} \left(M_{i,q} \right)$ denotes the error of approximation.

Choose the Lyapunov function

$$V_q = V_{q-1} + \sum_{i=1}^{P} \frac{1}{2} e_{i,q}^2 + \sum_{i=1}^{P} \frac{1}{2\upsilon_{i,q}} \tilde{\omega}_{i,q}^2 + \sum_{i=1}^{P} \frac{1}{2\varpi_{i,q}} \tilde{\kappa}_s^2 \tag{3.30}$$

The actual controller is derived as

$$u_i = -\frac{1}{\widehat{\mu}_{i,q}} \left(\widehat{\mu}_{i,q-1} \widehat{\Phi}_{i,q} \widehat{e}_{i,q-1} + \frac{\widehat{e}_{i,q}}{2} + \frac{\Psi_{i,q}^T \Psi_{i,q}}{2d_{i,q}^2} \widehat{e}_{i,q} \hat{\omega}_{i,q} + c_{i,q} \widehat{e}_{i,q}^{\gamma_1} + \bar{c}_{i,q} \widehat{e}_{i,q}^{\gamma_2} \right) \tag{3.31}$$

The adaptive law of design parameters is

$$\dot{\hat{\omega}}_{i,m} = -\upsilon_{i,m} \sigma_{i,m} \hat{\omega}_{i,m} + \upsilon_{i,m} \frac{\Psi_{i,m}^T \Psi_{i,m} e_{i,m}^2}{2d_{i,m}^2} \tag{3.32}$$

$$\dot{\hat{\kappa}}_s = -\varpi_{i,m} r_{i,m} \hat{\kappa}_s \tag{3.33}$$

where $\sigma_{i,m}$ and $r_{i,m}$ are design positive constants.

We then obtain

$$\dot{V}_q \leq \sum_{m=1}^{q} \sum_{i=1}^{P} \left(-c_{i,m} e_{i,m}^{1+\gamma_1} - \bar{c}_{i,m} e_{i,m}^{1+\gamma_2} + \sigma_{i,m} \tilde{\omega}_{i,m} \hat{\omega}_{i,m} + r_{i,m} \tilde{\kappa}_s \hat{\kappa}_s \right) + \Delta_m \tag{3.34}$$

where $\Delta_m = \sum_{m=1}^{q} \sum_{i=1}^{P} \Delta_{i,m}$.

3.2. Stability analysis

Theorem 1: For the high order MASs (2.1) with full state constraints under FDI attacks (2.2), with Assumptions 1–2, design virtual controllers (3.16) and (3.25), actual controllers (3.31), and choosing adaptation laws (3.32) and (3.33), boundedness of the MASs state can be achieved and the formation tracking error can fluctuate around zero with FTFC.

Proof of the Theorem 1:

Substituing (3.11), (3.21), and (3.30), we have

$$V_q = \frac{1}{2} E^T (L+B)^{-1} E + \sum_{m=2}^{q} \sum_{i=1}^{P} \frac{1}{2} e_{i,m}^2 + \sum_{m=1}^{q} \sum_{i=1}^{P} \frac{1}{2\upsilon_{i,m}} \tilde{\omega}_{i,m}^2 + \sum_{m=1}^{q} \sum_{i=1}^{P} \frac{1}{2\varpi_{i,m}} \tilde{\kappa}_s^2 \tag{3.35}$$

From Young's inequality,

$$\sigma_{i,m} \tilde{\omega}_{i,m} \hat{\omega}_{i,m} \leq -\frac{\sigma_{i,m}}{\upsilon_{i,m}} \tilde{\omega}_{i,m}^2 + \frac{\varphi_{i,m} \sigma_{i,m}}{2} \omega_{i,m}^2 \tag{3.36}$$

$$r_{i,m} \tilde{\kappa}_s \hat{\kappa}_s \leq -\frac{r_{i,m}}{\varpi_{i,m}} \tilde{\kappa}_s^2 + \frac{r_{i,m} \psi_{i,m}}{2} \kappa_s^2 \tag{3.37}$$

then we get

$$
\begin{aligned}
\dot{V}_q \leq & \sum_{m=1}^{q}\sum_{i=1}^{P}\sigma_{i,m}\left(\frac{\tilde{\omega}_{i,m}^2}{2\upsilon_{i,m}}\right)^{\frac{1+\gamma_1}{2}} + a\left(\sum_{m=1}^{q}\sum_{i=1}^{P}\left(\frac{\tilde{\omega}_{i,m}^2}{2\upsilon_{i,m}}\right)^{\frac{1+\gamma_2}{2}}\right) + \bar{\Delta}_{i,q} \\
& - a\sum_{m=1}^{q}\sum_{i=1}^{P}\frac{\tilde{\omega}_{i,m}^2}{2\upsilon_{i,m}} + \sum_{m=1}^{q}\sum_{i=1}^{P} r_{i,m}\left(\frac{\tilde{\kappa}_s^2}{2\varpi_{i,m}}\right)^{\frac{1+\gamma_1}{2}} - \sum_{m=1}^{q}\sum_{i=1}^{P}\frac{r_{i,m}}{2\varpi_{i,m}}\tilde{\kappa}_s^2 \\
& - a\left(\sum_{m=1}^{q}\sum_{i=1}^{P}\left(\left(e_{i,m}^2\right)^{\frac{1+\gamma_1}{2}} + \left(\tilde{\omega}_{i,m}^2\right)^{\frac{1+\gamma_1}{2}} + \left(\tilde{\kappa}_s^2\right)^{\frac{1+\gamma_1}{2}}\right)\right) \\
& - b\left(\sum_{m=1}^{q}\sum_{i=1}^{P}\left(\left(e_{i,m}^2\right)^{\frac{1+\gamma_2}{2}} + \left(\tilde{\omega}_{i,m}^2\right)^{\frac{1+\gamma_2}{2}} + \left(\tilde{\kappa}_s^2\right)^{\frac{1+\gamma_2}{2}}\right)\right) \\
& + b\sum_{m=1}^{q}\sum_{i=1}^{P}\left(\frac{\tilde{\kappa}_s^2}{2\varpi_{i,m}}\right)^{\frac{1+\gamma_2}{2}} - b\sum_{m=1}^{q}\sum_{i=1}^{P}\frac{r_{i,m}}{2\varpi_{i,m}}\tilde{\kappa}_s^2 - \sum_{m=1}^{q}\sum_{i=1}^{P}\frac{\sigma_{i,m}}{2\upsilon_{i,m}}\tilde{\omega}_{i,m}^2
\end{aligned} \tag{3.38}
$$

where $\bar{\Delta}_{i,q} = \sum_{m=1}^{q}\sum_{i=1}^{P}\left(\frac{r_{i,m}\psi_{i,m}}{2}\kappa_s^2 + \frac{\varphi_{i,m}\sigma_{i,m}}{2}\omega_{i,m}^2\right)$.

Thus, one obtains

$$a = \min\left\{c_{i,m}, \sigma_{i,m}(1/2\upsilon_{i,m})^{\frac{1+\gamma_1}{2}}, r_{i,m}(1/2\varpi_{i,m})^{\frac{1+\gamma_1}{2}}, \sigma_{i,m}\right\} \tag{3.39}$$

$$b = \min\left\{\bar{c}_{i,m},\ \sigma_{i,m}(1/2\upsilon_{i,m})^{\frac{1+\gamma_2}{2}}, r_{i,m}(1/2\varpi_{i,m})^{\frac{1+\gamma_2}{2}}, r_{i,m}\right\} \tag{3.40}$$

From Lemma 3, we get

$$\sum_{m=1}^{q}\sum_{i=1}^{P}\left(\frac{\tilde{\omega}_{i,m}^2}{2\upsilon_{i,m}}\right)^{\frac{1+\gamma_2}{2}} \leq \sum_{m=1}^{q}\sum_{i=1}^{P}\left(\frac{\tilde{\omega}_{i,m}^2}{2\upsilon_{i,m}}\right) + \Lambda_1 \tag{3.41}$$

$$\sum_{m=1}^{q}\sum_{i=1}^{P}\left(\frac{\tilde{\kappa}_s^2}{2\varpi_{i,m}}\right)^{\frac{1+\gamma_2}{2}} \leq \sum_{m=1}^{q}\sum_{i=1}^{P}\left(\frac{\tilde{\kappa}_s^2}{2\varpi_{i,m}}\right) + \Lambda_1 \tag{3.42}$$

where $\Lambda_1 = \left(\frac{1-\gamma_2}{2}\right)\left(\frac{1+\gamma_2}{2}\right)^{\frac{1+\gamma_2}{1-\gamma_2}}$

Define $c_r = \max\left\{\lambda_{\max}\left[(L+B)^{-1}\right], \frac{1}{2}, \frac{1}{2\upsilon_{i,m}}, \frac{1}{2\varpi_{i,m}}\right\}$

$$V_q \leq c_r\left(\sum_{m=2}^{q}\sum_{i=1}^{P}e_{i,m}^2 + \sum_{m=1}^{q}\sum_{i=1}^{P}\tilde{\omega}_{i,m}^2 + \sum_{m=1}^{q}\sum_{i=1}^{P}\tilde{\kappa}_s^2\right) \tag{3.43}$$

$$V_q^{\frac{1+\gamma_1}{2}} \leq c_s\left(\sum_{m=2}^{q}\sum_{i=1}^{P}e_{i,m}^{1+\gamma_1} + \sum_{m=1}^{q}\sum_{i=1}^{P}\tilde{\omega}_{i,m}^{1+\gamma_1} + \sum_{m=1}^{q}\sum_{i=1}^{P}\tilde{\kappa}_s^{1+\gamma_1}\right) \tag{3.44}$$

From Lemma 4, one has

$$V_q^{\frac{1+\gamma_2}{2}} \leq \bar{c}_s \left(\sum_{m=2}^{q} \sum_{i=1}^{P} e_{i,m}^{1+\gamma_2} + \sum_{m=1}^{q} \sum_{i=1}^{P} \tilde{\omega}_{i,m}^{1+\gamma_2} + \sum_{m=1}^{q} \sum_{i=1}^{P} \tilde{\kappa}_s^{1+\gamma_2} \right) \tag{3.45}$$

where $c_s = 3^{\frac{\gamma_1-1}{2}} c_r^{\frac{1+\gamma_1}{2}}, \bar{c}_s = c_r^{\frac{1+\gamma_2}{2}}$.

From above, we get

$$\begin{aligned} \dot{V}_q \leq & -\ell_1 V_q^{\gamma} - \ell_2 V_q^{\bar{\gamma}} + \sum_{m=1}^{q} \sum_{i=1}^{P} \left(\sigma_{i,m} \left(\frac{\tilde{\omega}_{i,m}^2}{2\upsilon_{i,m}} \right)^{\frac{1+\gamma_1}{2}} - \frac{\sigma_{i,m}}{2\upsilon_{i,m}} \tilde{\omega}_{i,m}^2 \right) \\ & + \sum_{m=1}^{q} \sum_{i=1}^{P} \left(r_{i,m} \left(\frac{\tilde{\kappa}_s^2}{2\varpi_{i,m}} \right)^{\frac{1+\gamma_1}{2}} - \frac{r_{i,m}}{2\varpi_{i,m}} \tilde{\kappa}_s^2 \right) + \Lambda_0 \end{aligned} \tag{3.46}$$

where $\ell_1 = \frac{a}{c_s} > 0$, $\ell_2 = \frac{b}{\bar{c}_s} > 0$, $0 < \bar{\gamma} = \frac{1+\gamma_2}{2} < 1$, $\gamma = \frac{1+\gamma_1}{2} > 1$, $\Lambda_0 = \bar{\Delta}_{i,q} + a\Lambda_1 + b\Lambda_1$.

Suppose that there are unknown constants $\Gamma_{i,m}$ and $\Pi_{i,m}$, which satisfy: $\left|\tilde{\omega}_{i,m}\right| \leq \Gamma_{i,m}, |\tilde{\kappa}_s| \leq \Pi_{i,m}$

If $\Gamma_{i,m} < \sqrt{2\upsilon_{i,m}}$, one has

$$\sum_{m=1}^{q} \sum_{i=1}^{P} \left(\sigma_{i,m} \left(\frac{\tilde{\omega}_{i,m}^2}{2\upsilon_{i,m}} \right)^{\frac{1+\gamma_1}{2}} - \frac{\sigma_{i,m}}{2\upsilon_{i,m}} \tilde{\omega}_{i,m}^2 \right) < 0 \tag{3.47}$$

With $\Gamma_{i,m} \geq \sqrt{2\upsilon_{i,m}}$, one obtains

$$\sum_{m=1}^{q} \sum_{i=1}^{P} \left(\sigma_{i,m} \left(\frac{\tilde{\omega}_{i,m}^2}{2\upsilon_{i,m}} \right)^{\frac{1+\gamma_1}{2}} - \frac{\sigma_{i,m}}{2\upsilon_{i,m}} \tilde{\omega}_{i,m}^2 \right) \leq \Xi_1 \tag{3.48}$$

where $\Xi_1 = \sum_{m=1}^{q} \sum_{i=1}^{P} \sigma_{i,m} \left(\frac{\Gamma_{i,m}^2}{2\upsilon_{i,m}} \right)^{\frac{1+\gamma_1}{2}} - \frac{\sigma_{i,m}}{2\upsilon_{i,m}} \Gamma_{i,m}^2$

If $\Pi_{i,m} < \sqrt{2\varpi_{i,m}}$, it gets

$$\sum_{m=1}^{q} \sum_{i=1}^{P} \left(r_{i,m} \left(\frac{\tilde{\kappa}_s^2}{2\varpi_{i,m}} \right)^{\frac{1+\gamma_1}{2}} - \frac{r_{i,m}}{2\varpi_{i,m}} \tilde{\kappa}_s^2 \right) < 0 \tag{3.49}$$

If $\Pi_{i,m} \geq \sqrt{2\varpi_{i,m}}$, one obtains

$$\sum_{m=1}^{q} \sum_{i=1}^{P} \left(r_{i,m} \left(\frac{\tilde{\kappa}_s^2}{2\varpi_{i,m}} \right)^{\frac{1+\gamma_1}{2}} - \frac{r_{i,m}}{2\varpi_{i,m}} \tilde{\kappa}_s^2 \right) \leq \Xi_2 \tag{3.50}$$

where $\Xi_2 = \sum_{m=1}^{q} \sum_{i=1}^{P} r_{i,m} \left(\frac{\Pi_{i,m}^2}{2\varpi_{i,m}} \right)^{\frac{1+\gamma_1}{2}} - \frac{r_{i,m}}{2\varpi_{i,m}} \Pi_{i,m}^2$.

Through all above, it can be obtained that

$$\dot{V}_q \leq -\ell_1 V_q^{\gamma} - \ell_2 V_q^{\bar{\gamma}} + \bar{\Lambda}_0 \tag{3.51}$$

To sum up, all the states of MASs are bounded within $T \leq 1/\ell_2 (1-\beta)(1-\bar{\gamma}) + 1/\ell_1 (\gamma - 1)$, and β denotes a constant that satisfies: $\bar{\Lambda}_0 \leq \ell_2 \beta V_q^{\bar{\gamma}}$.

Remark 3: The MASs in this paper are full state constrained, $x_{i,m}$ satisfying $-k_c < x_{i,m} < k_c$, and since $z_{i,m}$ is bounded, the states are all in a compact set.

4. Simulations

In this section, MASs consist of the leader and 4 followers, and the adjacency matrix A represents

$$A = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{pmatrix} \tag{4.1}$$

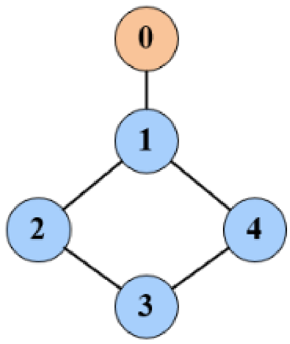

Figure 1. Communication topology.

The relationships between leader and followers are $B = diag\{1, 0, 0, 0\}$, and the Laplacian matrix is in the form of

$$L = \begin{pmatrix} 2 & -1 & 0 & -1 \\ -1 & 2 & -1 & 0 \\ 0 & -1 & 2 & -1 \\ -1 & 0 & -1 & 2 \end{pmatrix}. \tag{4.2}$$

Figure 1 shows the communication topology of MASs.

The followers are modeled as

$$\begin{cases} \dot{x}_{i,1} = 0.1 \sin(x_{i,1}) + x_{i,2} \\ \dot{x}_{i,2} = 0.1 \sin(x_{i,1}) x_{i,2} + u_i \quad i = 1, 2, 3, 4 \\ y_i = x_{i,1} \end{cases} \tag{4.3}$$

where the state of systems satisfies: $|x_{i,1}| < k_{c1} = 0.7$, $|x_{i,2}| < k_{c2} = 1.9$.

The leader trajectory is $x_{l.1} = 0.8 \sin(2.5t)$, and the formation coefficient is $h_1 = h_2 = h_3 = h_4 = 2.2 \cos(2.5t)$. The fuzzy membership function is set as $\mu_{F_{i1}}^{P} = \exp[-(z_{i,1} + 0.25P)^2 - (z_{i,2} + 0.25P)^2]$,

$\mu^{P}_{F_{i2}} = \exp[-(z_{i,1} + 0.25P)^2 - (z_{i,2} + 0.25P)^2 - (x_{l,1} + 0.25P)^2 - (\dot{x}_{l,1} + 0.25P)^2 - (\ddot{x}_{l,1} + 0.25P)^2]$, selecting attack weight $\varsigma_s(t) = -0.18 - 0.42\cos(t)$ and the initial value is $x_{i,1}(0) = 0$, $x_{i,2}(0) = 0.45$, $\omega_{i,j}(0) = 0$. $\kappa_{i,j}(0) = 0$. The design parameters are set as $\gamma_1 = 1.3$, $\gamma_2 = 0.9$, $d_{i,j} = 1.5$, $\sigma_{i,j} = 2.5$, $r_{i,j} = 2$, $c_{i,1} = 0.1$,$c_{i,2} = 20$, $\bar{c}_{1,1} = \bar{c}_{2,1} = 5$, $\bar{c}_{3,1} = \bar{c}_{4,1} = 0.1$, $\bar{c}_{i,2} = 0.1$, $i = 1, 2, 3, 4$, $j = 1, 2$.

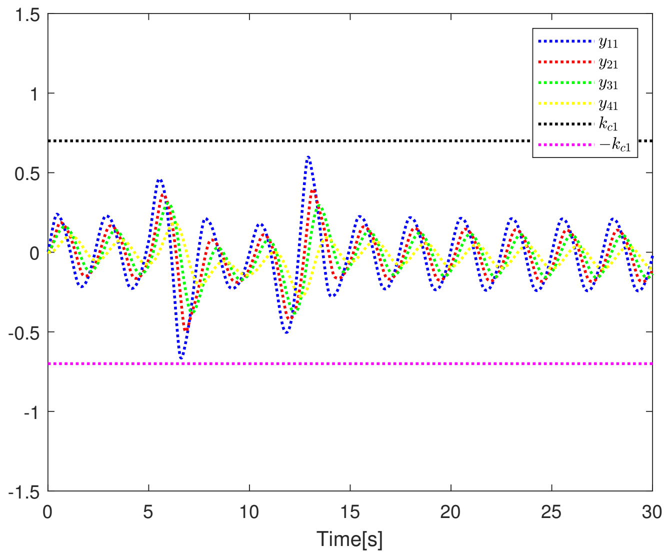

Figure 2. The output signal of agents under FDI attacks.

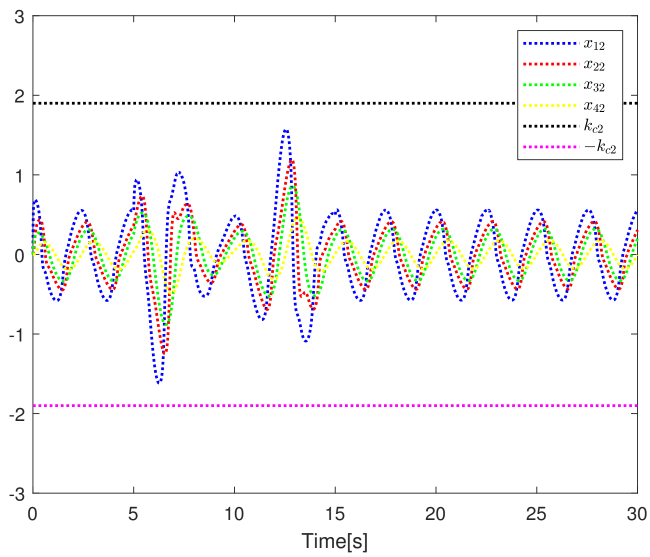

Figure 3. The states of agents under FDI attacks.

The simulation results are shown in Figure 2 to Figure 7. The follower agents in Figure 2 can maintain the predetermined formation trajectory in the constrained state, and the tracking effects meet

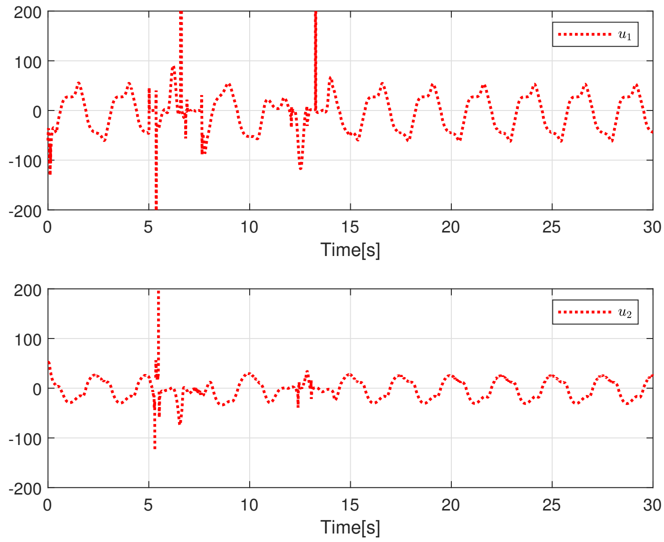

Figure 4. The control inputs of agent 1 and 2.

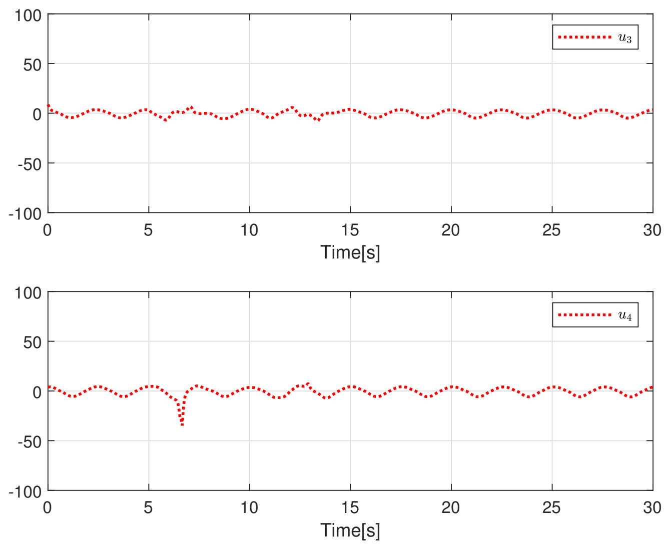

Figure 5. The control inputs of agent 3 and 4.

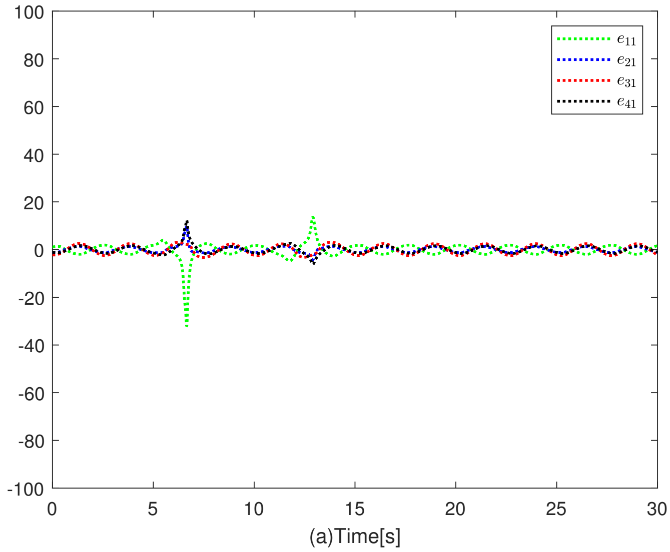

Figure 6. Tracking error of the agents.

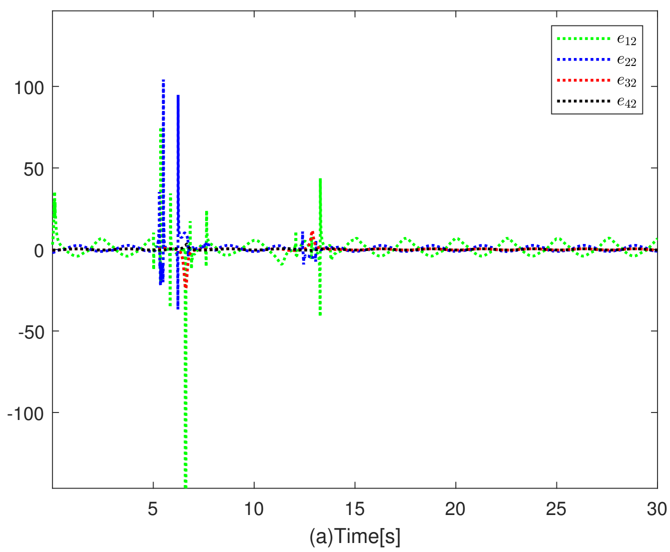

Figure 7. State error of the agents.

expectation and conform to the constraint range. The state output of the agents are shown in Figure 3, which conform to the constraint bound. Figures 4 and 5 illustrate the control inputs of the four groups of agents. Figure 6 illustrates the tracking error of the agents, and it can be seen that the tracking errors of the agents stably converge around zero. Figure 7 shows the state error of the formation process, and the convergence effect reaches the expected standard. During the simulation, the FDI attacks time is set within 5-15s, and the proposed method can still maintain the stability of MASs formation control after FDI attacks.

5. Conclusions

In this paper, for the nonlinear MASs with full state constraints, the fixed-time formation strategy is proposed under FDI attacks conditions, the coordinate transformation is used to deal with the attacks state and the system state constraints, the nonlinear transformation method is used to remove the influence between the full state constraints and topological relations, and the FLS is used to approximate the uncertain function. An adaptive fuzzy fixed-time formation controller is designed based on backstepping method, and the effectiveness of the controller is verified by simulation examples. In the following work, we will work on MASs formation control under complex types of attacks.

Use of AI tools declaration

The authors stated that no artificial intelligence (AI) tools were used at the time of writing this article.

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China under Grants 62333009, in part by the Liaoning Revitalization Talents Program under Grant XLYC2202014, and in part by the Key Projects in Liaoning Province under Grant JYTZD2023085.

Conflict of interest

The authors declare that there is no competing financial interest or personal relationship that could have appeared to influence the work reported in this paper.

References

1. X. W. Dong, G. Q. Hu, Time-varying formation control for general linear multi-agent systems with switching directed topologies, *Automatica*, **73** (2016), 47–55. https://doi.org/10.1016/j.automatica.2016.06.024
2. T. Guo, J. Han, C. Zhou, J. Zhou, Multi-leader-follower group consensus of stochastic time-delay multi-agent systems subject to Markov switching topology, *Math. Biosci. Eng.*, **19** (2022), 7504–7520. https://doi.org/10.3934/mbe.2022353

3. H. Q. Hou, Y. J. Liu, J. Lan, L. Liu, Adaptive fuzzy fixed time time-varying formation control for heterogeneous multiagent systems with full state constraints, *IEEE Trans. Fuzzy Syst.*, **31** (2022), 1152–1162. https://doi.org/10.1109/TFUZZ.2022.3195609

4. L. Wang, J. Dong, C. Xi, Event-triggered adaptive consensus for fuzzy output-constrained multi-agent systems with observers, *J. Frankl. Inst.*, **19** (2022), 7504–7520. https://doi.org/10.1016/j.jfranklin.2019.09.033

5. Q. Shi, T. S. Li, J. Q. Li, C. L. P. Chen, Y. Xiao, Q. H. Shan, Adaptive leader-following formation control with collision avoidance for a class of second-order nonlinear multi-agent systems, *Neurocomputing*, **350** (2019), 282–290. https://doi.org/10.1016/j.neucom.2019.03.045

6. S. Zhang, L. Tang, Y. J. Liu, Formation deployment control of multi-agent systems modeled with PDE, *Math. Biosci. Eng.*, **19** (2022), 13541–13559. https://doi.org/10.3934/mbe.2022632

7. S. Zhao, Affine formation maneuver control of multiagent systems, *IEEE Trans. Autom. Control*, **63** (2018), 4140–4155. https://doi.org/10.1109/TAC.2018.2798805

8. Y. Yang, Y. Xiao, T. S. Li, Attacks on formation control for multiagent systems, *IEEE Trans. Cybern.*, **52** (2022), 12805–12817. https://doi.org/10.1109/TCYB.2021.3089375

9. H. Liu, G. Xie, L. Wang, Necessary and sufficient conditions for containment control of networked multi-agent systems, *Automatica*, **48** (2012), 1415–1422. https://doi.org/10.1016/j.automatica.2012.05.010

10. H. Chu, S. Gorbachev, D. Yue, C. Dou, Output formation containment for multiagent systems under multipoint multipattern FDI attacks: A resilient impulsive compensation control approach, *IEEE Trans. Cybern.*, (2023), 1–12. https://doi.org/10.1109/TCYB.2023.3319647

11. Y. Cao, W. Ren, Finite-time consensus for multi-agent networks with unknown inherent nonlinear dynamics, *Automatica*, **50** (2014), 2648–2656. https://doi.org/10.1016/j.automatica.2014.08.028

12. S. Sui, C. L. P. Chen, S. C. Tong, Fuzzy adaptive finite-time control design for nontriangular stochastic nonlinear systems, *IEEE Trans. Fuzzy Syst.*, **27** (2019), 172–184. https://doi.org/10.1109/TFUZZ.2018.2882167

13. Y. L. Cai, H. G. Zhang, Y. Liu, Q. He, Distributed bipartite finite-time event-triggered output consensus for heterogeneous linear multi-agent systems under directed signed communication topology, *Appl. Math. Comput.*, **378** (2020), 125162. https://doi.org/10.1016/j.amc.2020.125162

14. J. Lan, Y. J. Liu, T. Y. Xu, S. C. Tong, L. Liu, Adaptive fuzzy fast finite-time formation control for second-order MASs based on capability boundaries of agents, *IEEE Trans. Fuzzy Syst.*, **30** (2021), 3905–3917. https://doi.org/10.1109/TFUZZ.2021.3133903

15. H. Q. Wang, K. Xu, P. X. P. Liu, J. F. Qiao, Adaptive fuzzy fast finite-time dynamic surface tracking control for nonlinear systems, *IEEE Trans. Circuits I*, **68** (2021), 4337–4348. https://doi.org/10.1109/TCSI.2021.3098830

16. D. J. Yao, C. X. Dou, N. Zhao, T. J. Zhang, Practical fixed-time adaptive consensus control for a class of multi-agent systems with full state constraints and input delay, *Neurocomputing*, **446** (2021), 156–164. https://doi.org/10.1016/j.neucom.2021.03.032

17. H. B. Du, G. H. Wen, D. Wu, Y. Y. Cheng, J. H. Lü, Distributed fixed-time consensus for nonlinear heterogeneous multi-agent systems, *Automatica*, **113** (2020), 108797. https://doi.org/10.1016/j.automatica.2019.108797

18. M. Chen, H. Wang, X. Liu, Adaptive fuzzy practical fixed-time tracking control of nonlinear systems, *IEEE Trans. Fuzzy Syst.*, **29** (2021), 664–673. https://doi.org/10.1109/TFUZZ.2019.2959972

19. Y. L. Cai, H. Zhang, Y. Wang, Z. Gao, Q. He, Adaptive bipartite fixed-time time-varying output formation-containment tracking of heterogeneous linear multiagent systems, *IEEE Trans. Neural Networks Learn. Syst.*, **33** (2021), 4688–4698. https://doi.org/10.1109/TNNLS.2021.3059763

20. J. Qin, G. Zhang, W. X. Zheng, Y. Kang, Adaptive sliding mode consensus tracking for second-order nonlinear multiagent systems with actuator faults, *IEEE Trans. Cybern.*, **49** (2019), 1605–1615. https://doi.org/10.1109/TCYB.2018.2805167

21. D. P. Li, D. J. Li, Adaptive neural tracking control for nonlinear time-delay systems with full state constraints, *IEEE Trans. Syst. Man Cybern. Syst.*, **47** (2017), 1590–1601. https://doi.org/10.1109/TSMC.2016.2637063

22. T. S. Li, W. W. Bai, Q. Liu, Y. Long, C. L. P. Chen, Distributed fault-tolerant containment control protocols for the discrete-time multi-agent systems via reinforcement learning method, *IEEE Trans. Neural Networks Learn. Syst.*, **34** (2021), 3979–3991. https://doi.org/10.1109/TNNLS.2021.3121403

23. Q. He, Z. Feng, H. Fang, X. W. Wang, L. Zhao, Y. D. Yao, et al., A blockchain-based scheme for secure data offloading in healthcare with deep reinforcement learning, *IEEE/ACM Trans. Networks*, **2023** (2023), 1–16. https://doi.org/10.1109/TNET.2023.3274631

24. P. Lin, W. Ren, Y. Song, Distributed multi-agent optimization subject to nonidentical constraints and communication delays, *Automatica*, **65** (2016), 120–131. https://doi.org/10.1016/j.automatica.2015.11.014

25. K. Zhao, Y. Song, Removing the feasibility conditions imposed on tracking control designs for state-constrained strict-feedback systems, *IEEE Trans. Autom. Control*, **64** (2018), 1265–1272. https://doi.org/10.1109/TAC.2018.2845707

26. W. Zhao, Y. J. Liu, L. Liu, Observer-based adaptive fuzzy tracking control using integral barrier Lyapunov functionals for a nonlinear system with full state constraints, *IEEE /CAA J. Autom. Sin.*, **8** (2021), 617–627. https://doi.org/10.1109/JAS.2021.1003877

27. D. P. Li, H. G. Han, J. F. Qiao, Adaptive NN controller of nonlinear state-dependent constrained systems with unknown control direction, *IEEE Trans. Neural Networks Learn. Syst.* , **35** (2024), 913–922. https://doi.org/10.1109/TNNLS.2022.3177839

28. M. Chen, S. S. Ge, B. Ren, Adaptive tracking control of uncertain MIMO nonlinear systems with input constraints, *Automatica*, **4** (2011), 452–465. https://doi.org/10.1016/j.automatica.2011.01.025

29. J. J. Fu, G. H. Wen, W. W. Yu, T. W. Huang, X. H. Yu, Consensus of second-order multiagent systems with both velocity and input constraints, *IEEE Trans. Ind. Electron.*, **66** (2018), 7946–7955. https://doi.org/10.1109/TIE.2018.2879292

30. B. Fan, Q. Yang, S. Jagannathan, Y. Sun, Output-constrained control of nonaffine multiagent systems with partially unknown control directions, *IEEE Trans. Autom. Control*, **64** (2019), 3936–3942. https://doi.org/10.1109/TAC.2019.2892391

31. Q. He, H. Fang, J. Zhang, X. Wang, Dynamic opinion maximization in social networks, *IEEE Trans. Knowl. Data Eng.*, **35** (2023), 350–361. https://doi.org/10.1109/TKDE.2021.3077491

32. B. Miao, H. Wang, Y. J. Liu, L. Liu, Adaptive security control against false data injection attacks in cyber-physical systems, *IEEE J. Emerging Sel. Top. Circuits Syst.*, **13** (2023), 743–751. https://doi.org/10.1109/JETCAS.2023.3253483

33. Y. Jiang, B. Niu, X. Wang, X. Zhao, H. Wang, B. Yan, Distributed finite-time consensus tracking control for nonlinear multi-agent systems with FDI attacks and application to single-link robots, *IEEE Trans. Circuits II*, **70** (2022), 1505–1509. https://doi.org/10.1109/TCSII.2022.3220359

34. A. Mousavi, K. Aryankia, R. R. Selmic, A distributed FDI cyber-attack detection in discrete-time nonlinear multi-agent systems using neural networks, *Eur. J. Control*, **66** (2022), 100646. https://doi.org/10.1016/j.ejcon.2022.100646

35. M. Nadeem, A. Arshad, S. Riaz, A secure architecture to protect the network from replay attacks during client-to-client data transmission, *Appl. Sci.*, **12** (2022), 8143. https://doi.org/10.3390/app12168143

36. Z. Gu, P. Shi, D. Yue, S. Yan, X. Xie, Memory-based continuous event-triggered control for networked T-S fuzzy systems against cyberattacks, *IEEE Trans. Fuzzy Syst.*, **29** (2020), 3118–3129. https://doi.org/10.1109/TFUZZ.2020.3012771

37. W. Qi, Y. Hou, J. H. Park, G. Zong, J. Cao, J. Cheng, SMC for discrete-time networked semi-Markovian switching systems with random DoS attacks and applications, *IEEE Trans. Syst. Man Cybern. Syst.*, **53** (2022), 7504–7520. https://doi.org/10.1109/TSMC.2022.3211322

38. H. Zhang, P. Cheng, L. Shi, J. Chen, Optimal DoS attack scheduling in wireless networked control system, *IEEE Trans. Control Syst. Technol.*, **24** (2015), 843–852. https://doi.org/10.1109/TSMC.2022.3211322

39. Y. Zhang, Z. G. Wu, P. Shi, Event/self-triggered control for leader-following consensus over unreliable network with DoS attacks, *IEEE Trans. Neural Networks Learn. Syst.*, **30** (2019), 3137–3149. https://doi.org/10.1109/TNNLS.2018.2890119

40. Z. Gu, C. K. Ahn, D. Yue, X. Xie, Event-triggered H∞ filtering for T-S fuzzy-model-based nonlinear networked systems with multisensors against dos attacks, *IEEE Trans. Cybern.*, **52** (2022), 5311–5321. https://doi.org/10.1109/TCYB.2020.3030028

41. B. L. Tian, Z. Y. Zuo, H. Wang, Leader–follower fixed-time consensus of multi-agent systems with high-order integrator dynamics, *Int. J. Control*, **90** (2017), 1420–1427. https://doi.org/10.1080/00207179.2016.1207101