Proceedings of the Estonian Academy of Sciences
2025, **74**, 4, 500–513

https://doi.org/10.3176/proc.2025.4.03

www.eap.ee/proceedings
Estonian Academy Publishers

AUTOMATIC CONTROL THEORY

RESEARCH ARTICLE

Received 1 January 2025
Accepted 5 March 2025
Available online 24 September 2025

Keywords:
multi-agent system, iterative learning control, forgetting factor, random fault, consistency

Corresponding author:
Xingjian Fu
fxj@bistu.edu.cn

Citation:
Li, Y. and Fu, X. 2025. Iterative learning consistency control for multi-agent systems with forgetting factors under random actuator failures. *Proceedings of the Estonian Academy of Sciences*, **74**(4), 500–513.
https://doi.org/10.3176/proc.2025.4.03

Iterative learning consistency control for multi-agent systems with forgetting factors under random actuator failures

Yuhan Li and Xingjian Fu

School of Automation, Beijing Information Science and Technology University, Beijing 100192, China

ABSTRACT

For the discrete linear multi-agent systems with random actuator faults and system disturbances, an iterative learning control strategy with the forgetting factor is proposed. Firstly, the random variation of actuator faults with the number of iterations is considered. A multiplicative stochastic fault model obeying a normal distribution is designed, and the correction mechanism is given. Secondly, an iterative learning consistency control algorithm with a forgetting factor is provided under the consideration of random disturbances in the system. The system stability is analyzed by using the mean square stability theory. A sufficient condition for the consistency in the multi-agent system is given through the relevant mathematical derivation, which makes it possible to realize the state consistency for the discrete multi-agent system under the occurrence of random faults in the actuator. Finally, the feasibility of the algorithm is verified by numerical simulation in a multi-agent system.

1. Introduction

A multi-agent system (MAS) is a computational system composed of interactive agents. In a MAS, the agents can be physical entities or virtual entities [20]. MASs have some applications in various fields, such as artificial intelligence, robot formations, and power systems [3,8,17]. They can be used to solve complex problems such as collaborative task execution, distributed decision making, and cooperative learning. Compared to a single agent, MASs can achieve higher levels of functionality and performance, which improves the robustness of the system. The consistency problem is a key issue in the research of MASs [4].

With the development of the times and advancements in technology, the environment of different industrial scenarios is highly variable. The agents in a MAS are influenced by environmental factors, which presents additional challenges for studying the stability and consensus of MASs. In [12], the control problem of leader-follower consistency of MASs based on an event-triggered mechanism is studied. The predetermined-time consensus problem of a MAS with nonlinear uncertainties was investigated in [12]. The consensus problem of a MAS with input amplitude constraints and input delays was analyzed in [11]. A fully distributed adaptive protocol was designed in [21] and applied to the nonlinear stochastic MAS with uncertain actuator faults.

Iterative learning control is regarded as an important branch of learning control. It is a new type of learning control strategy. It improves control quality by iteratively applying information obtained from previous experiments to obtain control inputs that produce desired output trajectories. This strategy is applied to the controlled systems with repetitive motion characteristics, such as robots performing repetitive tasks and industrial controllers [6]. The iterative learning control tracking problem for a linear continuous switching system was studied by using a D-type iterative learning control algorithm in [1]. The trajectory tracking problem of mobile robots through iterative learning control was studied in [5].

In addition, the study of iterative learning control in a MAS has attracted considerable attention. A P-type iterative learning control algorithm was used in [2], which investigates the question whether discrete time-varying MASs can be consistent in finite time. The iterative learning control method was explored in the study of UAV formation in [7]. The consensus tracking problem of nonlinear MASs under data transmission losses was considered in [10]. The output consensus tracking problem for continuous linear MASs with measurement limitations was studied by using the P-type iterative learning control method in [19]. In order to effectively reduce the impact of false data injection (FDI) attacks, the consensus learning control problem of nonlinear MASs under FDI attacks was studied by Peng in [13]. In [23], the consensus problem of one-sided Lipschitz MASs under deception attacks and random disturbances was solved by using a pulse-based consensus protocol. As can be seen, the first motivation of this paper is to apply iterative learning control algorithms to study the consensus problem in MASs.

According to [16], reducing the dependence on past iterations in the face of uncertain dynamic changes and external disturbances will better adapt to changing system states and improve convergence speed and robustness. As a result, iterative learning control algorithms with forgetting factors have also been extensively studied. The speed control system of diesel generator sets in ship propulsion systems was studied by Huang using the iterative learning control algorithm with a forgetting factor in [9]. In [18], a suitable iterative learning control algorithm with a variable forgetting factor was designed by Wang for the trajectory characteristics of a lower-limb exoskeleton robot. Additionally, in [22], Zhang studied the path tracking problem of mobile robots with repetitive trajectories by introducing a forgetting factor into the PD-type discrete iterative learning control. Another motivation of this paper is to investigate how to introduce a forgetting factor into the iterative learning control algorithm to study the consensus problem in MASs.

Currently, there are relatively few studies on the consensus problem of MASs with random faults. Based on the aforementioned studies, in this paper, an iterative learning control strategy with a forgetting factor is applied to the consensus problem of a discrete linear MAS with random faults in the actuator. The main contributions are as follows:

1. A new external random disturbance model is established. Unlike conventional external disturbances, this paper proposes that the system's own disturbances follow a normal distribution, thereby introducing greater randomness into the system.

2. Considering that actuator faults vary randomly with the iteration steps, this paper introduces a multiplicative random fault model that follows a normal distribution along with a compensation mechanism. This ensures that the fault parameters of the agents are different in each iteration.

3. Compared to traditional iterative learning control methods, this strategy introduces a forgetting factor that reduces the reliance on past states and enables the system to focus more on the latest errors generated during each iteration. This approach can more effectively address the uncertainties arising from changes in the external environment during the operation of the MAS, ensuring that the system retains good robustness in complex and dynamic practical applications. It provides a new perspective for solving the consensus problem of MASs in complex dynamic environments.

Finally, numerical simulations are presented to validate the effectiveness of the proposed algorithm.

2. Graph theory

In the study, graph theory is utilized to describe the network communication topology among agents in a MAS. Each agent in the system is considered as a node, and thus the set of all agents can be represented as a node set $V = \{1, 2, \cdots, N\}$. The set of edges between the nodes is represented as $\varepsilon = V \times V$. The communication between the nodes can be described using the weighted adjacency matrix $A = (a_{ij}) \in R^{n\times n}$. The weights can represent the influence of the information. The three parts above constitute $G = \{V, \varepsilon, A\}$, representing the communication topology of a MAS. In the adjacency matrix $A = (a_{ij}) \in R^{NkN}$, the indices i and j represent two different nodes. The set of neighboring nodes of the i-th node can be represented using $N_i = \{j \in V : (i, j) \in \varepsilon, i \neq j\}$. If $a_{ij} = 0$ exists, it represents $(i, j) \notin \varepsilon$, indicating that there is no communication relationship between the node i and the node j. If the topology graph is an undirected graph, both $(i, j) \in \varepsilon$ and $(j, i) \in \varepsilon$ exist. Otherwise, the topology graph is a directed graph. In graph theory, the Laplacian matrix is an important matrix for analyzing the topology graph G. The Laplacian matrix is defined as follows: $L = D - A$, where $D = diag(d_1, d_2, \cdots, d_n)$ is the in-degree matrix of the topological structure, and the in-degree of the node i is defined as $d_i = \sum_{j=1}^{n} a_{ij}$. Leaders can be one or multiple individuals. Let the set of nodes representing the leaders be denoted as $\overline{V} = V \cup \{v_0\}$, and let $S = diag\{s_1, s_2, \cdots s_N\}$. Here, s_i represents the connection weight, $i \in \{1, 2, \cdots, N\}$. If there is a connection between an agent and a leader, it is denoted as $s_i > 0$; otherwise, it is represented as $s_i = 0$.

3. Problem description

The MAS composed of n agents is considered in this paper. Each agent is characterized by the same identical dynamic structure, although the parameters differ among agents. For the j-th agent in the MAS, the following linear discrete system is considered:

$$\begin{cases} x_{k,j}(t+1) = A_t x_{k,j}(t) + B_t u_{k,j}(t) + \omega(t), \\ y_{k,j}(t) = C_t x_{k,j}(t), \end{cases} \tag{1}$$

where k represents the iteration number and $x_{k,j}(t)$, $u_{k,j}(t)$, $y_{k,j}(t)$ represent the control state, control input, and control output of the j-th agent at the k-th iteration, respectively; $\omega(t)$ represents the disturbance experienced by the system, which follows a continuous distribution $\mathrm{P}(\omega(t) > 0) = 1$. Additionally, $E[\omega(t)] = \mu$, $E[(\omega(t) - \mu)^2] = \sigma^2$. A_t,B_t, and C_t are the corresponding time-varying coefficient matrices.

The desired trajectory $y_d(t)$ of the MAS is given. $y_d(t)$ is considered a virtual leader, labeled as 0, while the remaining agents are treated as followers, labeled as $j \in [1, 2, \cdots, n]$. It is assumed that the desired trajectory $y_d(t)$ is directly accessible only to partial agents. Thus, $G = \{V, \overline{\varepsilon}, \overline{A}\}$ represents the complete communication topology, $\overline{\varepsilon}$ denotes the set of edges, and $\overline{A}$ represents the adjacency matrix.

Actuator faults between the agents are considered in this paper, where the faults are represented by a random multiplicative variable $\alpha_{k,j}(t)$. The fault information received by the j-th agent from the i-th agent is denoted by $z_{k,j,i}(t)$, which can be expressed as:

$$z_{k,j,i}(t) = \alpha_{k,j,i}(t) y_{k,i}(t). \tag{2}$$

The following assumptions are provided for the MAS and the random fault variable to facilitate further analysis.

Assumption 1. The fault gain $\alpha_{k,j}(t)$ follows a continuous distribution $\mathrm{P}(\alpha_{k,j}(t) > 0) = 1$. Additionally, $E[\alpha_{k,j,i}(t)] = \mu$ and $E[(\alpha_{k,j,i}(t) - \mu)^2] = \sigma^2$ are the parameters of the system, where μ is a known constant.

Assumption 2. The desired trajectory $y_d(t)$ is achievable, as there exist an initial state $y_d(t)$ and an input $y_d(t)$ for the system such that:

$$\begin{cases} x_d(t+1) = A_t x_d(t) + B_t u_d(t), \\ y_d(t) = C_t x_d(t). \end{cases} \tag{3}$$

Assumption 3. When $t = 0$, the system state $x_{k,j}(0)$ equals the desired state $x_d(0)$.

Assumption 4. Matrices B and C are full rank.

Assumption 5. The graph $G = \{V, \overline{\varepsilon}, \overline{A}\}$ contains a spanning tree, and the virtual leader is the root of the spanning tree.

Remark 1. Assumption 5 is a sufficient condition for achieving consensus tracking in the MAS. If there exists an isolated agent in the system that cannot access the desired trajectory, its output will never converge to the desired value, regardless of the number of iterations. As a result, the system will fail to reach a consensus state.

For the MAS (1), the control objective is to design an appropriate iterative learning control algorithm. As the number of iterations increases, under the condition that only a subset of the agents has access to the desired trajectory, the goal for the output of each agent is to converge to the desired trajectory. That is, the system should satisfy:

$$\lim_{k \to \infty} E\left[\|y_d(t) - y_{k,j}(t)\|\right]^2 = 0, \forall t \in [0, 1, 2, \cdots n]. \tag{4}$$

4. Iterative learning consistency control for multi-agent systems

In Section 2, it is known that there exists a multiplicative random fault variable $\alpha_{k,j,i}(t)$ in the outputs among the agents. This causes the fault-affected information $z_{k,j,i}(t)$ received by the j-th agent to be unsuitable for direct use as the actual output of the corresponding agent in iterative learning consensus control. Therefore, the following correction is first performed on the outputs of the MAS affected by actuator faults:

$$\bar{z}_{k,j,i}(t) = \mu^{-1} z_{k,j,i}(t) = \mu^{-1}\alpha_{k,j,i}(t) y_{k,j}(t). \tag{5}$$

Remark 2. Due to Assumption 1, the mean value of $\mu^{-1}\alpha_{k,j,i}(t)y_{k,j}(t)$ in (5) is zero. It ensures that the corrected signal serves as an unbiased estimate of the original output. This allows the corrected signal to be effectively applied in the consensus learning scheme.

In the general case of MAS consensus research, the consensus error of the j-th agent at the k-th iteration is:

$$\begin{aligned} \xi_{k,j}(t) &= \sum_{i\in N_i} a_{ji}\left(y_{k,i}(t) - y_{k,j}(t)\right) + s_j\left(y_d(t) - y_{k,j}(t)\right) \\ &= \sum_{i\in N_i} a_{ji}\left(e_{k,j}(t) - e_{k,i}(t)\right) + s_j e_{k,j}(t). \end{aligned} \tag{6}$$

Unlike the general case, due to the output correction in this paper, the consensus error of the j-th agent at the k-th iteration is defined as:

$$\begin{aligned} \xi_{k,j}(t) &= \sum_{i\in N_j} a_{ji}\left(\bar{z}_{k,j,i}(t) - y_{k,j}(t)\right) + s_j\left(y_d(t) - y_{k,j}(t)\right) \\ &= \sum_{i\in N_j} a_{ji}\left(\mu^{-1}\alpha_{k,j,i}(t)y_{k,i}(t) - y_{k,j}(t)\right) + s_j\left(y_d(t) - y_{k,j}(t)\right) \\ &= \sum_{i\in N_j} a_{ji}\left(y_{k,i}(t) - y_{k,j}(t) - (1-\mu^{-1}\alpha_{k,j,i}(t))y_{k,i}(t)\right) + s_j\left(y_d(t) - y_{k,j}(t)\right) \\ &= \sum_{i\in N_j} a_{ji}\left(y_{k,i}(t) - y_{k,j}(t)\right) + s_j\left(y_d(t) - y_{k,j}(t)\right) - \sum_{i\in N_j} a_{ji}(1-\mu^{-1}\alpha_{k,j,i}(t))y_{k,i}(t) \\ &= \sum_{i\in N_j} a_{ji}\left(y_{k,i}(t) - y_{k,j}(t)\right) + s_j e_{k,j}(t) + \sum_{i\in N_j} a_{ji}(1-\mu^{-1}\alpha_{k,j,i}(t))\left(e_{k,j}(t) - y_d(t)\right), \end{aligned} \tag{7}$$

where $e_{k,j}(t) = y_d(t) - y_{k,j}(t)$ is the actual tracking error of the j-th agent.

Unlike the general P-type iterative learning control algorithm, a P-type iterative learning control law with a forgetting factor is adopted. The distributed control scheme is as follows:

$$u_{k+1,j}(t) = \sigma u_{k,j}(t) + \lambda_k \Gamma \xi_{k,j}(t+1), \tag{8}$$

where $\sigma (0 < \sigma < 1)$ is the forgetting factor, Γ is the iterative learning gain matrix, and λ_k is a decreasing sequence. Let

$$\begin{aligned} x_k(t) &= \left[x_{k,1}{}^T(t), x^T{}_{k,2}(t), \cdots, x^T{}_{k,n}(t)\right]^T, \\ y_k(t) &= \left[y_{k,1}{}^T(t), y^T{}_{k,2}(t), \cdots, y^T{}_{k,n}(t)\right]^T, \\ u_k(t) &= \left[u_{k,1}{}^T(t), u^T{}_{k,2}(t), \cdots, u^T{}_{k,n}(t)\right]^T, \\ e_k(t) &= \left[e^T_{k,1}(t), e^T_{k,2}(t), \cdots, e^T_{k,n}(t)\right]^T, \\ A_c &= diag\left\{A_{c,1}, A_{c,2}, \cdots, A_{c,n}\right\}, \\ \Upsilon_{k,i}(t) &= \left[1-\mu^{-1}\alpha_{k,1,i}(t), 1-\mu^{-1}\alpha_{k,2,i}(t), \cdots, 1-\mu^{-1}\alpha_{k,n,i}(t)\right]^T, \\ \Upsilon_k(t) &= \left[\Upsilon_{k,1}(t), \Upsilon_{k,2}(t), \cdots, \Upsilon_{k,n}(t)\right]^T, \\ \Gamma &= diag\{\Gamma_1, \Gamma_2, \cdots, \Gamma_n\}. \end{aligned}$$

Here, $A_{c,j}$ represents the j-th row of the adjacency matrix A.

The MAS (1) can then be written in a compact form as

$$\begin{cases} x_k(t+1) = (I_n \otimes A_t)x_k(t) + (I_n \otimes B_t)u_k(t) + \omega(t), \\ y_k(t) = (I_n \otimes C_t)x_k(t). \end{cases} \tag{9}$$

Similarly, (8) can be written in a compact form as

$$\begin{aligned} u_{k+1}(t) = \sigma u_k(t) + \lambda_k[(L+D) \otimes \Gamma]e_k(t+1) + \lambda_k \Upsilon_k(t+1)[A_c \otimes \Gamma]e_k(t+1) \\ - \lambda_k \Upsilon_k(t+1)[A_c \otimes \Gamma](1_n \otimes y_d(t+1)). \end{aligned} \tag{10}$$

To simplify the expression, the following inductive processing is applied to (9).
Let

$$u_k = [u_k(0)^T, u_k(1)^T, \cdots, u_k(N-1)^T]^T,$$
$$y_k = [y_k(1)^T, y_k(2)^T, \cdots, y_k(N)^T]^T,$$

where u_k and y_k represent the input and output at the corresponding time of each iteration, respectively.

It can be obtained as

$$y_k = Gu_k + Hx_k(0) + M\omega, \tag{11}$$

$$y_d = Gu_d + Hx_d(0), \tag{12}$$

where

$$G = \begin{pmatrix} I_n \otimes C_t B_t & 0 & 0 & 0 \\ I_n \otimes C_t A_t B_t & I_n \otimes C_t B_t & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ I_n \otimes C A_t^{N-1} B_t & I_n \otimes C_t A_t^{N-2} B_t & \cdots & I_n \otimes C_t B_t \end{pmatrix}, \quad H = \begin{pmatrix} (I_n \otimes C_t A_t)^T \\ (I_n \otimes C_t A_t^2)^T \\ \vdots \\ (I_n \otimes C_t A_t^N)^T \end{pmatrix},$$

$$M = \begin{pmatrix} I_n \otimes C_t & 0 & 0 & 0 \\ I_n \otimes C_t A_t & I_n \otimes C_t & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ I_n \otimes C_t A_t^{N-1} & I_n \otimes C_t A_t^{N-2} & \cdots & I_n \otimes C_t \end{pmatrix}.$$

Let $\Delta u_k = u_d - u_k$. Combining (10), (11), (12), and Assumption 3, the following can be obtained:

$$\begin{aligned} u_{k+1}(t) &= \sigma u_k + \lambda_k \Psi_1 e_k + \lambda_k \Upsilon_k \Psi_2 e_k - \lambda_k \Upsilon_k \Psi_2 Y_d \\ &= \sigma u_k + \lambda_k \Psi_1 (G\Delta u_k - M\omega) + \lambda_k \Upsilon_k \Psi_2 (G\Delta u_k - M\omega) - \lambda_k \Upsilon_k \Psi_2 Y \\ &= \sigma u_k + \lambda_k \Psi_1 G\Delta u_k + \lambda_k \Upsilon_k \Psi_2 G\Delta u_k - \lambda_k \Psi_1 M\omega - \lambda_k \Upsilon_k \Psi_2 M\omega - \lambda_k \Upsilon_k \Psi_2 Y_d, \end{aligned} \tag{13}$$

where

$$\Psi_1 = (L+D) \otimes \Gamma,$$
$$\Psi_2 = A_c \otimes \Gamma,$$
$$\Upsilon_k = diag\{\Upsilon_k(1), \Upsilon_k(2), \cdots, \Upsilon_k(N)\}.$$

For the convergence analysis, the following necessary lemmas are provided.

Lemma 1. *If the learning gain matrix* Γ *satisfies the condition that all eigenvalues of the matrix* $\Gamma C_t B_t$ *are positive real numbers, then the matrix* $-(L+D) \otimes (\Gamma C_t B_t)$ *is stable.*

Lemma 2. [14] *Let* $\{\xi_k, k = 1, 2, \cdots\}$, $\{\tau_k, k = 1, 2, \cdots\}$, *and* $\{\chi_k, k = 1, 2, \cdots\}$ *be real sequences, and assume they satisfy*

$$0 < \tau_k < 1, \quad \chi_k \geq 0, \quad \tau_k \to 0, \quad \sum_{k=1}^{\infty} \tau_k = \infty,$$

and $\xi_{k+1} \leq (1-\tau_k)\xi_k + \chi_k$. *Then, the equation* $\lim_{k\to\infty} \xi_k = \lim_{k\to\infty} \chi_k/\tau_k$ *holds under the condition that the limit on the right-hand side exists. Furthermore, if* $\chi_k/\tau_k \to 0$ *and* $\xi_k \geq 0$, *then* $\lim_{k\to\infty} \xi_k = 0$.

Theorem 1. *Considering the stability of the MAS (1) under Assumptions 1–5. If* Γ *is designed such that the eigenvalues of* $\Gamma C_t B_t$ *are all positive real numbers, then the learning consensus scheme ensures that the input errors of all agents converge to 0 in the mean square sense,* $\lim_{k\to\infty} E\left[\left\|u_d(t) - u_{k,j}(t)\right\|\right]^2 = 0$. *Consequently, the tracking errors* $E\left[\|y_d(t) - y_{k,j}(t)\|\right]^2$ *of all agents also converge to 0 in the mean square sense.*

Proof. From (13), the input error expression can be obtained as:

$$\begin{aligned}\Delta u_{k+1} &= \sigma\Delta u_k - \lambda_k\Psi_1 G\Delta u_k - \lambda_k\Upsilon_k\Psi_2 G\Delta u_k + \lambda_k\Psi_1 M\omega \\ &\quad + \lambda_k\Upsilon_k\Psi_2 M\omega + \lambda_k\Upsilon_k\Psi_2 Y_d.\end{aligned} \tag{14}$$

Since the eigenvalues of the matrix $\Gamma C_t B_t$ are all positive real numbers, by Lemma 2, $-(L + D)\otimes(\Gamma C_t B_t)$ is stable, noting that $-(L + D) \otimes (\Gamma C_t B_t)$ is a block lower triangular matrix, and $\Psi_1 G$ is the diagonal block. It can be deduced that all eigenvalues of $\Psi_1 G$ have positive real parts. Therefore, there exists a positive definite matrix P such that the equation $\Theta^T P + \Theta P = I(\Theta = \Psi_1 G)$ holds.

Therefore, similarly to the proof in [15], a Lyapunov function $V_k = (\Delta u_k^T)P(\Delta u_k)$ is defined. By substituting the input error expression (14) into the system, the following can be obtained:

$$\begin{aligned}V_{k+1} &= (\Delta u_{k+1}^T)P(\Delta u_{k+1}) \\ &= \sigma^2\Delta u_k^T P\Delta u_k + \lambda_k^2\Delta u_k^T\Theta^T P\Theta\Delta u_k + \lambda_k^2\Delta u_k^T(\Upsilon_k\Psi_2 G)^T P\Upsilon_k\Psi_2 G\Delta u_k \\ &\quad + \lambda_k^2(\Psi_1 M\omega)^T P(\Psi_1 M\omega) + \lambda_k^2(\Upsilon_k\Psi_2 M\omega)^T P\Upsilon_k\Psi_2 M\omega \\ &\quad + \lambda_k^2(\Upsilon_k\Psi_2 Y_d)^T P\Upsilon_k\Psi_2 Y_d - \sigma\lambda_k\Delta u_k^T[P\Theta + \Theta^T P]\Delta u_k \\ &\quad - \lambda_k\sigma\Delta u_k^T[P\Upsilon_k\Psi_2 G + (\Upsilon_k\Psi_2 G)^T P]\Delta u_k - 2\sigma\lambda_k\Delta u_k^T P\Omega_1\Delta u_0 \\ &\quad + 2\sigma\lambda_k\Delta u_k^T P\Psi_1 M\omega + 2\sigma\lambda_k\Delta u_k^T P\Upsilon_k\Psi_2 M\omega + 2\sigma\lambda_k\Delta u_k^T P\Upsilon_k\Psi_2 Y_d \\ &\quad + \lambda_k^2\Delta u_k^T[\Theta^T P\Upsilon_k\Psi_2 G + (\Upsilon_k\Psi_2 G)^T P\Theta]\Delta u_k \\ &\quad - 2\lambda_k^2\Delta u_k^T\Theta^T P\Psi_1 M\omega - 2\lambda_k^2\Delta u_k^T\Theta^T P\Upsilon_k\Psi_2 M\omega - 2\lambda_k^2\Delta u_k^T\Theta^T P\Upsilon_k\Psi_2 Y_d \\ &\quad - 2\lambda_k^2\Delta u_k^T(\Upsilon_k\Psi_2 G)^T P\Psi_1 M\omega - 2\lambda_k^2\Delta u_k^T(\Upsilon_k\Psi_2 G)^T P\Upsilon_k\Psi_2 M\omega \\ &\quad - 2{\lambda_k}^2{\Delta u_k}^T(\Upsilon_k\Psi_2 G)^T P\Upsilon_k\Psi_2 Y_d \\ &\quad + 2\lambda_k^2(\Psi_1 M\omega)^T P\Upsilon_k\Psi_2 M\omega + 2\lambda_k^2(\Psi_1 M\omega)^T P\Upsilon_k\Psi_2 Y_d \\ &\quad + 2\lambda_k^2(\Upsilon_k\Psi_2 M\omega)^T P\Upsilon_k\Psi_2 Y_d.\end{aligned} \tag{15}$$

An δ-algebra is defined as
$\mathcal{F}_k \triangleq \delta\left\{x_{l,j}, y_{l,j}(t), u_{l,j}(t), \theta_{l,j,i}(t), \omega_{l,j}(t), 0 \le t \le N, 1 \le l \le k, 1 \le j, i \le n\right\}$, representing the set of all events caused by random variables up to the k-th iteration. Since the input at the k-th iteration is generated using information from the previous iteration, it is evident that $\Delta u_k \in \mathcal{F}_{k-1}$, while Υ_k and ω are independent of $\mathcal{F}_k$. Thus, by the definitions of Υ_k and ω, we have $E[\Upsilon_k] = 0$ and $E[\omega_k] = 0$. Consequently, the following can be obtained:

$$\begin{aligned}&\mathrm{E}\left[{\Delta u_k}^T[P\Upsilon_k\Psi_2 G + (\Upsilon_k\Psi_2 G)^T P]\Delta u_k \mid \mathcal{F}_{k-1}\right] = 0, \\ &\mathrm{E}\left[{\Delta u_k}^T P\Psi_1 M\omega \mid \mathcal{F}_{k-1}\right] = 0, \\ &\mathrm{E}\left[{\Delta u_k}^T P\Upsilon_k\Psi_2 M\omega \mid \mathcal{F}_{k-1}\right] = 0, \\ &\mathrm{E}\left[{\Delta u_k}^T P\Upsilon_k\Psi_2 Y_d \mid \mathcal{F}_{k-1}\right] = 0, \\ &\mathrm{E}\left[\Delta u_k^T[\Theta^T P\Upsilon_k\Psi_2 G + (\Upsilon_k\Psi_2 G)^T P\Theta]\Delta u_k \mid \mathcal{F}_{k-1}\right] = 0, \\ &\mathrm{E}\left[{\Delta u_k}^T\Theta^T P\Psi_1 M\omega \mid \mathcal{F}_{k-1}\right] = 0, \\ &\mathrm{E}\left[{\Delta u_k}^T\Theta^T P\Upsilon_k\Psi_2 M\omega \mid \mathcal{F}_{k-1}\right] = 0, \\ &\mathrm{E}\left[{\Delta u_k}^T\Theta^T P\Upsilon_k\Psi_2 Y_d \mid \mathcal{F}_{k-1}\right] = 0, \\ &\mathrm{E}\left[\Delta u_k^T(\Upsilon_k\Psi_2 G)^T P\Psi_1 M\omega \mid \mathcal{F}_{k-1}\right] = 0, \\ &\mathrm{E}\left[\Delta u_k^T(\Upsilon_k\Psi_2 G)^T P\Upsilon_k\Psi_2 M\omega \mid \mathcal{F}_{k-1}\right] = 0, \\ &\mathrm{E}\left[(\Psi_1 M\omega)^T P\Upsilon_k\Psi_2 M\omega \mid \mathcal{F}_{k-1}\right] = 0, \\ &\mathrm{E}\left[(\Psi_1 M\omega)^T P\Upsilon_k\Psi_2 Y_d \mid \mathcal{F}_{k-1}\right] = 0, \\ &\mathrm{E}\left[(\Upsilon_k\Psi_2 M\omega)^T P\Upsilon_k\Psi_2 Y_d \mid \mathcal{F}_{k-1}\right] = 0.\end{aligned} \tag{16}$$

In addition,

$$\begin{aligned}
&\mathrm{E}\left[\Delta u_k^T \Theta^T P \Theta \Delta u_k \mid \mathcal{F}_{k-1}\right] \le (\Delta u_k)^T \mathrm{E}[\Theta^T P \Theta \mid \mathcal{F}_{k-1}] \Delta u_k \\
&\le \rho_1 (\Delta u_k)^T P \Delta u_k = \rho_1 V_k, \\
&\mathbb{E}\left[\Delta u_k^T (\Upsilon_k \Psi_2 G)^T P \Upsilon_k \Psi_2 G \Delta u_k \mid \mathcal{F}_{k-1}\right] \\
&\le (\Delta u_k)^T \mathrm{E}[(\Upsilon_k \Psi_2 G)^T P \Upsilon_k \Psi_2 G \mid \mathcal{F}_{k-1}] \Delta u_k \\
&\le \rho_2 (\Delta u_k)^T P \Delta u_k = \rho_2 V_k, \\
&\mathbb{E}\left[(\Psi_1 M \omega)^T P (\Psi_1 M \omega) \mid \mathcal{F}_{k-1}\right] \le \rho_3, \\
&\mathbb{E}\left[(\Upsilon_k \Psi_2 M \omega)^T P \Upsilon_k \Psi_2 M \omega \mid \mathcal{F}_{k-1}\right] \le \rho_4, \\
&\mathrm{E}\left[(\Upsilon_k \Psi_2 Y_d)^T P \Upsilon_k \Psi_2 Y_d \mid \mathcal{F}_{k-1}\right] \le \rho_5,
\end{aligned} \tag{17}$$

where $\rho_* \ge 0$, and $* = 1, 2, 3, 4, 5$ are appropriate constants.

$$\begin{aligned}
\mathrm{E}[\Delta u_k{}^T [P\Theta + \Theta^T P] \Delta u_k \mid \mathcal{F}_{k-1}] &= \mathrm{E}\left[\Delta u_k^T \Delta u_k \mid \mathcal{F}_{k-1}\right] \\
&\ge \rho_6 V_k,
\end{aligned} \tag{18}$$

where ρ_6 is a constant satisfying $I \ge \rho_6 P$.

Since P is a positive definite matrix, it can be written as $P = P^{\frac{1}{2}} P^{\frac{1}{2}}$. Thus, the following can be obtained:

$$\begin{aligned}
&-2\Delta u_k{}^T (\Upsilon_k \Psi_2 G)^T P \Upsilon_k \Psi_2 Y_d \le 2 \left| \underbrace{\Delta u_k{}^T (\Upsilon_k \Psi_2 G)^T P^{\frac{1}{2}}}_{a^T} \underbrace{P^{\frac{1}{2}} \Upsilon_k \Psi_2 Y_d}_{b^T} \right| \\
&\le \underbrace{\Delta u_k{}^T (\Upsilon_k \Psi_2 G)^T P \Upsilon_k \Psi_2 G \Delta u_k}_{a^T a} + \underbrace{(\Upsilon_k \Psi_2 Y_d)^T P \Upsilon_k \Psi_2 Y_d}_{b^T b}.
\end{aligned} \tag{19}$$

Therefore,

$$\mathrm{E}\left[-2\Delta u_k^T (\Upsilon_k \Psi_2 G)^T P \Upsilon_k \Psi_2 Y_d \mid \mathcal{F}_{k-1}\right] \le \rho_2 V + \rho_5. \tag{20}$$

Combining (15)–(18) and (20), the following can be obtained:

$$\begin{aligned}
&\mathrm{E}[V_{k+1} \mid \mathcal{F}_{k-1}] \\
&\le \sigma^2 V_k + \lambda_k^2 \rho_1 V_k + \lambda_k^2 \rho_2 V_k + \lambda_k^2 \rho_3 + \lambda_k^2 \rho_4 + \lambda_k^2 \rho_5 \\
&- \lambda_k \sigma \rho_6 V_k + \lambda_k^2 \rho_2 V_k + \lambda_k^2 \rho_5 \\
&= \sigma^2 V_k - \sigma \lambda_k \rho_6 V_k + \lambda_k^2 \rho_1 V_k + 2\lambda_k^2 \rho_2 V_k + \lambda_k^2 \rho_3 + \lambda_k^2 \rho_4 + 2\lambda_k^2 \rho_5 \\
&= \sigma^2 \left[(V_k - \frac{\lambda_k \rho_6}{\sigma} V_k + \frac{\lambda_k^2 \rho_1}{\sigma^2} V_k + \frac{2\lambda_k^2 \rho_2}{\sigma^2} V_k) + \frac{(\lambda_k^2 \rho_3 + \lambda_k^2 \rho_4 + 2\lambda_k^2 \rho_5)}{\sigma^2} \right] \\
&\le (V_k - \frac{\lambda_k \rho_6}{\sigma} V_k + \frac{\lambda_k^2 \rho_1}{\sigma^2} V_k + \frac{2\lambda_k^2 \rho_2}{\sigma^2} V_k) + \frac{(\lambda_k^2 \rho_3 + \lambda_k^2 \rho_4 + 2\lambda_k^2 \rho_5)}{\sigma^2} \\
&= \left(1 - \frac{\lambda_k \rho_6}{\sigma} + \frac{\lambda_k^2 \rho_1}{\sigma^2} + \frac{2\lambda_k^2 \rho_2}{\sigma^2}\right) V_k + \frac{(\lambda_k^2 \rho_3 + \lambda_k^2 \rho_4 + 2\lambda_k^2 \rho_5)}{\sigma^2} \\
&= \left[1 - \frac{1}{\sigma} \lambda_k \left(\rho_6 - \frac{\lambda_k \rho_1}{\sigma} - \frac{2\lambda_k \rho_2}{\sigma}\right)\right] V_k + \frac{(\lambda_k^2 \rho_3 + \lambda_k^2 \rho_4 + 2\lambda_k^2 \rho_5)}{\sigma^2}.
\end{aligned} \tag{21}$$

Taking the expectation on both sides of (21), the following can be obtained:

$$\mathrm{E}[V_{k+1}] \le (1 - p_k)\, \mathrm{E}[V_k] + q_k, \tag{22}$$

where $p_k = \frac{1}{\sigma}\lambda_k\left[\rho_6 - \lambda_k\left(\frac{\rho_1+2\rho_2}{\sigma}\right)\right]$ and $q_k = \frac{(\lambda_k{}^2\rho_3+\lambda_k{}^2\rho_4+2\lambda_k{}^2\rho_5)}{\sigma^2}$. By Lemma 2, $\mathbb{E}[V_k]$,p_k, and q_k correspond to ξ_k,τ_k, and χ_k, respectively. Since $\lambda_k \to 0$, when k is sufficiently large, by proper scaling, the following can be obtained: $\lambda_k\left(\frac{\rho_1+2\rho_2}{\sigma}\right) \le (1/2)\rho_6$,

$$\begin{aligned}\frac{q_k}{p_k} &= \frac{\frac{1}{\sigma^2}(\lambda_k^2\rho_3 + \lambda_k^2\rho_4 + 2\lambda_k^2\rho_5)}{\frac{1}{\sigma}\lambda_k\left[\rho_6 - \lambda_k\left(\frac{\rho_1+2\rho_2}{\sigma}\right)\right]} = \frac{\lambda_k^2(\rho_3 + \rho_4 + 2\rho_5)}{\sigma\lambda_k\left[\rho_6 - \lambda_k\left(\frac{\rho_1+2\rho_2}{\sigma}\right)\right]}\\ &\le \frac{\lambda_k(\rho_3 + \rho_4 + 2\rho_5)}{\sigma\rho_6}\underset{k\to\infty}{\longrightarrow} 0.\end{aligned}$$

By Lemma 2, when $k \to \infty$, $\mathrm{E}[V_k] \to 0$, $\lim_{k\to\infty}\mathbb{E}[\|u_d - u_k\|^2] = 0$. Consequently, $\lim_{k\to\infty}\mathbb{E}[\|y_d - y_k\|^2] = 0$. This proof indicates that the designed iterative learning consensus control scheme with a forgetting factor can achieve consensus convergence in the MAS.

5. Simulation

In this section, the results obtained are validated by simulation. In this paper, we consider MASs consisting of four followers and one virtual leader. The communication topology is shown in Fig. 1.

The virtual leader is numbered 0, and the followers are numbered 1–4. Based on the interaction signal values of each agent, the adjacency matrix of the system can be derived as $A = \begin{bmatrix}0 & 2 & 2 & 0\\1 & 0 & 0 & 1\\1 & 0 & 0 & 1\\0 & 2 & 2 & 0\end{bmatrix}$, the degree matrix $D = \begin{bmatrix}4 & 0 & 0 & 0\\0 & 2 & 0 & 0\\0 & 0 & 2 & 0\\0 & 0 & 0 & 4\end{bmatrix}$. Therefore, due to graph theory in Section 2, the Laplacian matrix can be obtained as

$$L = D - A = \begin{bmatrix}4 & -2 & -2 & 0\\-1 & 2 & 0 & -1\\-1 & 0 & 2 & -1\\0 & -2 & -2 & -4\end{bmatrix}.$$

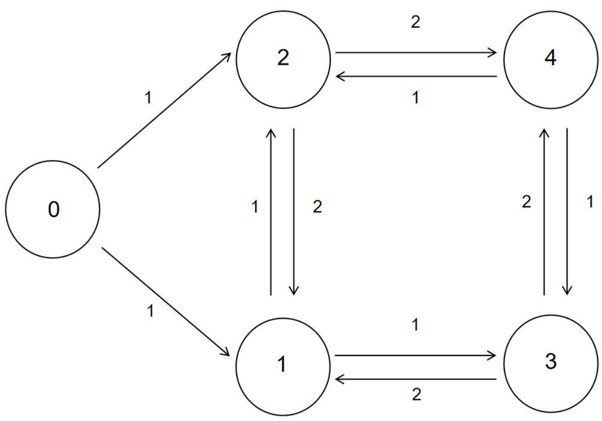

Fig. 1. System communication topology.

Additionally, only the followers 1 and 2 can directly receive information from the virtual leader 0. So it can be obtained as

$$S = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

The matrix of time-varying coefficients for designing the dynamic model of the system is as follows:

$$A_t = \begin{bmatrix} 0.02\sin 0.01t & -0.2 & 0.01t \\ 0.2 & -0.02t & -0.04\sin 0.5t \\ 0.1 & 0.1 & 0.2 + 0.05\cos 0.2t \end{bmatrix},$$

$$B_t = \begin{bmatrix} 1 - 0.5\sin 0.5t & 0 \\ 0.01t & 0.01t \\ 0 & 1 + 0.1\sin 0.5t \end{bmatrix},$$

$$C_t = \begin{bmatrix} 0.2 + 0.1\sin 0.5t & 0.1 & -0.1 \\ 0 & 0.1 & 0.4 - 0.1\sin 0.4t \end{bmatrix}.$$

Consider the desired trajectory of the virtual leader 0 as $y_d = \begin{bmatrix} \sin\frac{t}{4} \\ \cos\frac{t}{4} \end{bmatrix}$, $t \in [0, 30]$. For convenience of analysis, the initial states of the four agents are chosen as $[0, 0, 0]^T$ and the control inputs are chosen as $[0, 0]^T$. The random disturbance is denoted as $\omega(t) \sim N(0.9, 0.1^2)$, and the actuator random fault is denoted as $\alpha(t) \sim N(0.95, 0.1^2)$. The sequence of decreasing iterative learning gains is denoted as $\lambda_k = 0.95^k$. The initial iterative learning gain matrix is chosen as $\Gamma = \begin{bmatrix} 0.4 & 0 & 0 & 0 \\ 0 & 0.4 & 0 & 0 \\ 0 & 0 & 0.4 & 0 \\ 0 & 0 & 0 & 0.4 \end{bmatrix}$.

The iterative learning forgetting factor is chosen as $\sigma = 0.90$.

The random fault values of the actuator at each iteration are given in Fig. 2. It can be seen that for each iteration of the MAS, the values of the actuator faults are not the same. It reflects the randomness, which is more suitable for complex dynamic changes in the actual engineering applications.

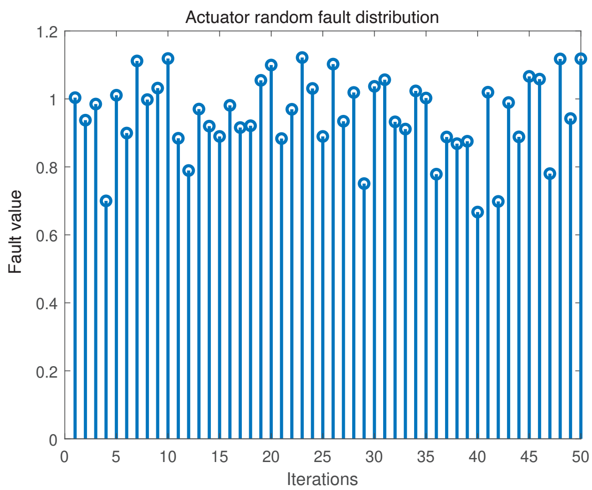

Fig. 2. Distribution of actuator random faults with iteration.

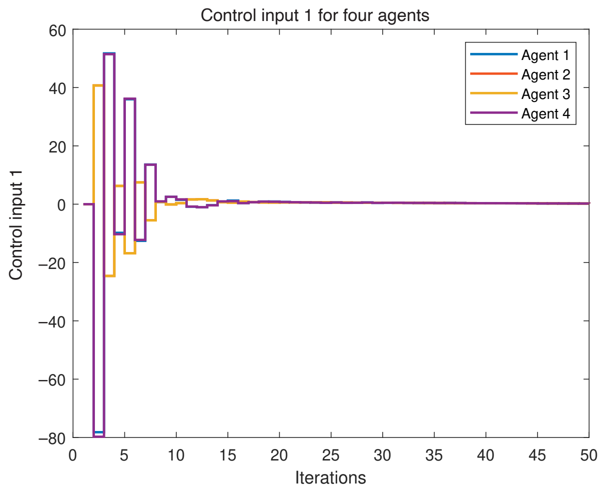

Fig. 3. Variation of control input component 1 for four agents with iteration.

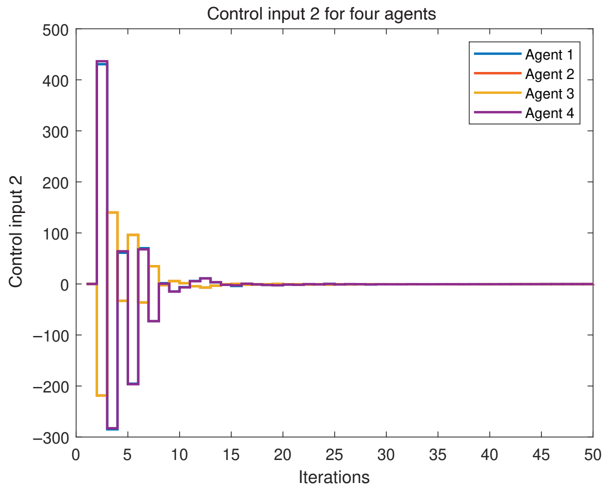

Fig. 4. Variation of control input component 2 for four agents with iteration.

The variation of the two control input components of the four following agents along the iteration axis is shown in Fig. 3 and Fig. 4, respectively. It can be seen that when the forgetting factor is 0.9, with the increase in the number of iterations, the control input component 1 and the control input component 2 of the four agents both converge to 0 in a finite amount of time around the 20th iteration under the random fault of the actuator, and consistency is achieved.

The changes in the three state components of the four following agents along the iteration axis are shown in Fig. 5, Fig. 6, and Fig. 7, respectively. It can be seen from Figs 5 and 6 that, with the increase in the number of iterations, the state component 1 and the state component 2 of the four agents converge to a stable value around the 20th iteration under random actuator failure. However, the curves show slight jitter due to the randomness of the actuator failure, though this is not significant, and consistency is essentially achieved. From Fig. 7, it can be observed that the state component 3 of the four agents also tends to stabilize at the 20th iteration, performing better relative to the state components 1 and 2.

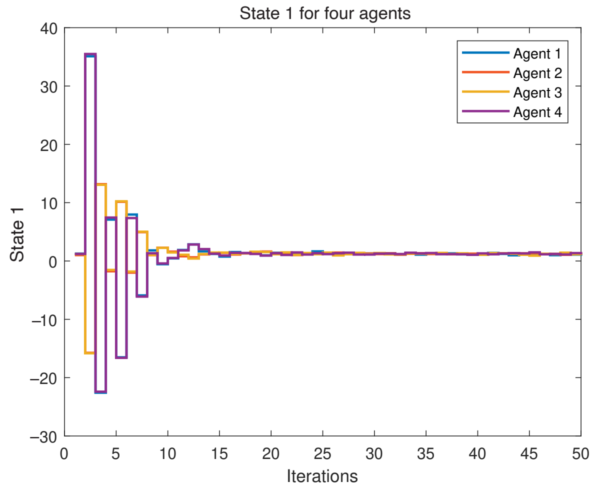

Fig. 5. Variation of state component 1 for four agents with iteration.

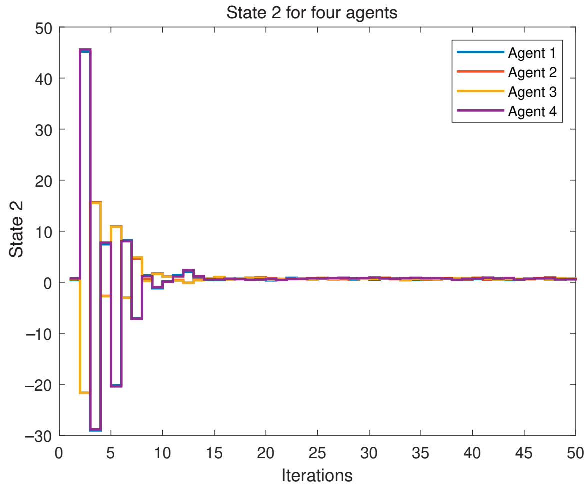

Fig. 6. Variation of state component 2 for four agents with iteration.

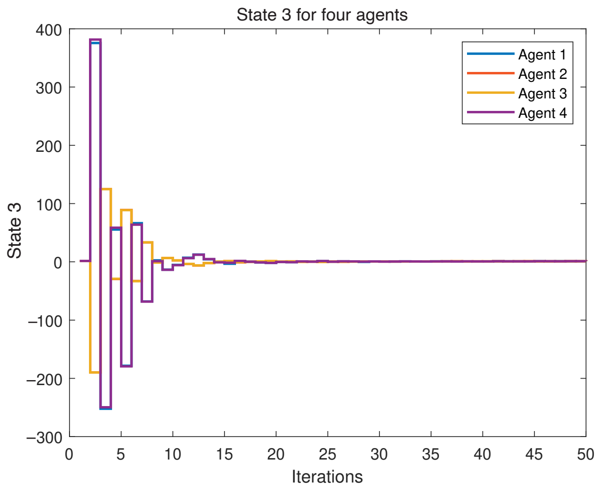

Fig. 7. Variation of state component 3 for four agents with iteration.

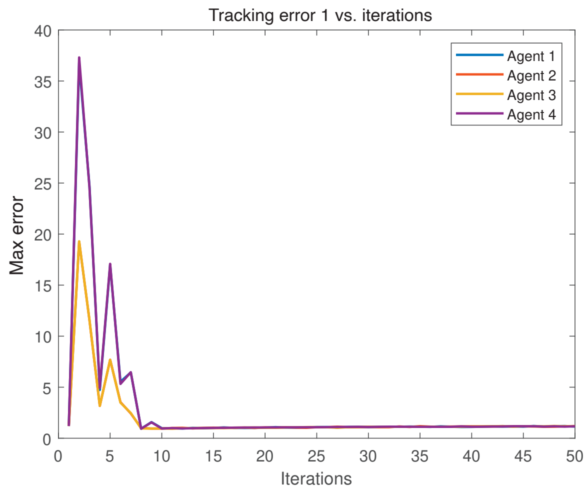

Fig. 8. Variation of tracking error 1 for four agents with iteration.

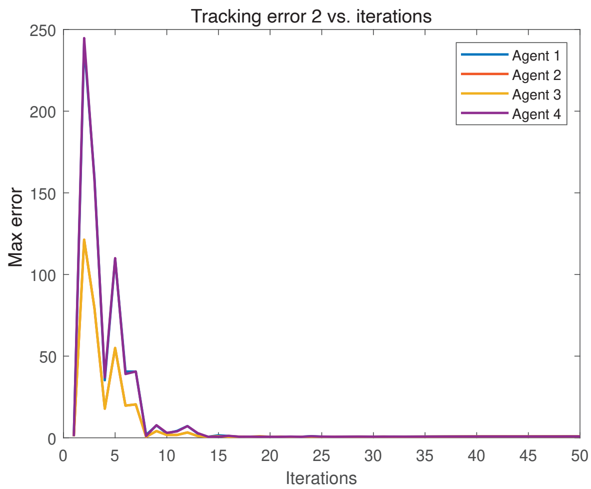

Fig. 9. Variation of tracking error 2 for four agents with iteration.

The change in tracking error of the four following agents along the iteration axis is shown in Fig. 8 and Fig. 9, respectively. It can be seen from the figures that under the random fault of the actuator, the tracking error component 1 of the four agents tends to reach the same value at the 20th iteration. Considering the randomness of the faults, the error does not converge to 0 but gradually tends to decrease. The tracking error component 2 of the four agents converges to 0 at about the 20th iteration, and tracking consistency control is essentially achieved.

6. Conclusions

In this paper, the P-type iterative learning control method, which introduces a forgetting factor, is applied to a discrete linear multi-agent system subject to random disturbances. By introducing a forgetting factor, reliance on past states is diminished, thereby enhancing the system's adaptability to random actuator faults and preserving the consistency of the multi-agent system. Drawing upon the stability theory of mean-square significance, a sufficient condition for the ultimate convergence of system consistency error is derived and presented. It ensured that consistency is achieved in the mean-square sense. Numerical simulations confirm that the proposed control method demonstrates robustness in discrete linear multi-agent systems in the presence of random actuator faults and disturbances.

Data availability statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Acknowledgments

This work was supported by the National Natural Science Foundation of China under grant No. 62103057. The publication costs of this article were partially covered by the Estonian Academy of Sciences.

References

1. Bu, X., Hou, Z. and Yu, F. Iterative learning control for a class of linear continuous-time switched systems. *Control Theory Appl*., 2012, **29**(8), 1051–1056 (in Chinese).
2. Cao, W. and Sun, M. Finite-time consensus iterative learning control of discrete time-varying multi-agent systems. *Control Decis*., 2019, **34**(4), 891–896 (in Chinese). https://doi.org/10.13195/j.kzyjc.2017.1362
3. Cheng, C., Chen, Z., Guo, Z. and Li, N. Research and development of simulation training platform for multi-agent collaborative decision-making. *J. Syst. Simul.*, 2023, **35**(12), 2669–2679 (in Chinese). https://doi.org/10.16182/j.issn1004731x.joss.23-FZ0821
4. Ding, D., Zhao, X., Zhao, B., Gao, G. and Liu, C. Quantized iterative learning control for second-order multi-agent systems. *J. Proj. Rockets Missile Guid*., 2019, **39**(06), 75–82 (in Chinese). https://doi.org/10.15892/j.cnki.djzdxb.2019.06.017
5. Fan, X., Ming, S., Yao, J. and Yang, J. An improved iterative learning control for mobile robot trajectory tracking. *Fire Control Command Control*, 2023, **48**(07), 29–34 (in Chinese).
6. Gu, L., Wang, Y. and Ma, L. Cooperative formation control of multi-agent systems based on iterative learning. *Control Eng. China*, 2021, **28**(11), 2178–2184 (in Chinese). https://doi.org/10.14107/j.cnki.kzgc.20200933
7. Hock, A. and Schoellig, A. P. Distributed iterative learning control for multi-agent systems. *Auton. Robot*., 2019, **43**, 1989–2010.
8. Hou, R. and Bu, X. Leader-follower iterative learning formation control for robots with arbitrary initial position. *Comput. Eng. Appl*., 2020, **56**(20), 226–231 (in Chinese).
9. Huang, A. M. and Xinglei He, B. Diesel generator speed control based on variable forgetting factor iterative learning method. In *2023 11th International Conference on Power Electronics and ECCE Asia (ICPE 2023 - ECCE Asia), Jeju Island, Republic of Korea, 22–25 May 2023*. IEEE, 2023,1123–1128. https://doi.org/10.23919/ICPE2023-ECCEAsia54778.2023.10213922
10. Liang, J., Bu, X. and Liu, J. Iterative learning consensus tracking control for a class of multi-agent systems with data dropouts. *Comput. Eng. Appl*., 2018, **54**(20), 42–47, 53 (in Chinese).
11. Liu, W., Wang, Y., Ma, X. and Liu, J. Consensus control for input-delay multi-agent system with input constraint. *Syst. Eng. Electr*on., 2024, **46**(9), 3176–3184 (in Chinese).
12. Liu, Y., Yang, H., Liu, F., Li, Y. and Yang, Y. Active disturbance rejection control for multi-agent systems based on distributed event-triggered strategy. *Control Theory Appl*., 2020, **37**(05), 969–977 (in Chinese).
13. Peng, H., Lin, N. and Chi, R. Gain-varying P-type ILC for nonlinear multi-agent systems against FDI attacks. In *2024 IEEE 13th Data Driven Control and Learning Systems Conference (DDCLS), Kaifeng, China, 17–19 May 2024*. IEEE, 2024, 972–976. https://doi.org/10.1109/DDCLS61622.2024.10606801
14. Qu, G., Shen, D. and Yu, X. Batch-based learning consensus of multiagent systems with faded neighborhood information. *IEEE Trans. Neural Netw. Learn. Syst*., 2023, **34**(6), 2965–2977. https://doi.org/10.1109/TNNLS.2021.3110684
15. Shen, D. and Qu, G. Performance enhancement of learning tracking systems over fading channels with multiplicative and additive randomness. *IEEE Trans. Neural Netw. Learn. Syst*., 2020, **31**(4), 1196–1210. https://doi.org/10.1109/TNNLS.2019.2919510
16. Shi, C. and Lin, H. Developments of research and application for iterative learning. *Control. Meas. Control Technol*., 2004, **2**, 1–3, 7 (in Chinese). https://doi.org/10.19708/j.ckjs.2004.02.001
17. Wang, D., Sun, Q. and Su, H. Cooperative distributed real-time intelligent optimization of multi-microgrid systems. *Control Decis*., 2024, **39**(11), 3801–3809 (in Chinese). https://doi.org/10.13195/j.kzyjc.2023.1122
18. Wang, F., Shi, P., Li, S., Zhao, S. and Liu, W. Trajectory control of lower limb exoskeleton robot with variable forgetting factor. In *2016 12th World Congress on Intelligent Control and Automation (WCICA), Guilin, China, 12–15 June 2016*. IEEE, 2016, 1502–1507. https://doi.org/10.1109/WCICA.2016.7578429
19. Wei, Y., Li, Z., Du, Y. and Chen, Y. Iterative learning control for consensus of measurement-constrained linear multi-agent systems. *Control Theory Appl*., 2021, **38**(7), 963–970 (in Chinese).
20. Wu, Q. and Liu, S. Iterative learning control of multi-agent consensus with initial error correction. *Comput. Eng. Appl*., 2014, **50**(1), 29–35 (in Chinese).
21. Xiao, G., Wang, J. and Meng, D. Adaptive finite-time consensus for stochastic multiagent systems with uncertain actuator faults. *IEEE Trans. Control Netw. Syst*., 2023, **10**(4), 1899–1912. https://doi.org/10.1109/TCNS.2023.3250473
22. Zhang, T., Fang, J., Teng, Y., Wang, X., Zhang, Y. and Chen, X. Path-tracking of mobile robot using PD-type iterative learning control with forgetting factor. In *2023 35th Chinese Control and Decision Conference (CCDC), Yichtang, China, 20–22 May 2023*. IEEE, 2023, 864–869. https://doi.org/10.1109/CCDC58219.2023.10326632
23. Zhang, Z., Ma, T., Su, X. and Ma, X. Impulsive consensus of one-sided Lipschitz multi-agent systems with deception attacks and stochastic perturbation. *IEEE Trans. Artif. Intell.*, 2024, **5**(3), 1328–1338. https://doi.org/10.1109/TAI.2023.3289163

Mitmeagendiliste süsteemide iteratiivne õppimiskonsistentsuse juhtimine unustamisteguritega täiturmehhanismide juhuslike tõrgete korral

Yuhan Li ja Xingjian Fu

Diskreetsete lineaarsete mitmeagendiliste süsteemide jaoks, mille täiturmehhanismis esineb juhuslikke tõrkeid ja süsteemi häiringuid, on töötatud välja unustamisteguriga iteratiivse õppimise juhtimise strateegia. Esiteks on vaadeldud täiturmehhanismi tõrgete juhuslikku varieeruvust iteratsioonide arvu suurenedes. Selleks on koostatud normaaljaotusele alluv multiplikatiivne stohhastiline tõrkemudel ja parandamismehhanism. Teiseks on töötatud välja unustamisteguriga iteratiivne õppimiskonsistentsuse juhtimise algoritm, mis arvestab süsteemi juhuslikke häiringuid. Süsteemi stabiilsust on analüüsitud keskmise ruutvea alusel. Tuletatud on piisavuse tingimus mitmeagendilise süsteemi konsistentsuse saavutamiseks, mis võimaldab tagada diskreetse mitmeagendilise süsteemi olekute konsistentsuse ka täiturmehhanismi juhuslike tõrgete korral. Väljatöötatud algoritmi valideerimiseks on teostatud numbrilised simulatsioonid mitmeagendilises süsteemis.