Fault-tolerant Tracking Control for Nonlinear NCSs with Time-delay and Data Loss Failure in Dual-channel Based on Iterative Learning

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Abstract: In this paper, for nonlinear networked control systems (NCSs) with dual-channel data packet loss and time-delay failure, the problem of tracking the desired trajectory is discussed by using PD-type iterative learning control (ILC). In the mathematical modeling of the data transmission process for the NCSs, the dual-channel failure of the measurement channel and the control channel is considered. The data loss and network time-delay are described as the random Bernoulli process with known probability. The sufficient condition to ensure the algorithm convergence is given. This sufficient condition indicates that in the network environment with dual-channel data loss and time-delay, when the system meets the given convergence conditions, the controlled system with input disturbances can converge to the desired trajectory as the number of iterative learning increases. Finally, the simulation example verifies the effectiveness of the proposed method.

Keywords: Networked Control Systems; Fault-tolerant Control; Iterative Learning; Dual-channel

1. INTRODUCTION

With the rapid development of control theory, computer technology and modern network communication technology, the various disciplines intersect each other, and control systems have become more and more complex and diversified, so that the NCSs has also been developed rapidly. The NCSs can easily realize resource sharing, and has the advantages of easy expansion, easy maintenance, and high reliability. These make the NCSs have a wide range of application prospects in many fields such as industrial manufacturing, power system, telemedicine, navigation formation and so on. Therefore, it is a very meaningful subject to study the relevant direction of the NCSs (Ghorbani Saeid et al., 2021; Roy Avinash Kumar et al., 2020; Zhang X et al., 2016).

At present, after decades of development, the study for NCSs have become a research hotspot in the control field (Arman S et al., 2018; Liu K et al., 2015; Mohammad Mahdi Azimi et al., 2021; ZHAO Li et al., 2020).The research on the NCSs mainly involves two aspects. One is the study of control methods, and the other is the study of network scheduling. The research on the control methods mainly considers the influence of time-delay and packet loss on the control system based on the network structure and protocol. By designing the structure and control algorithm for the NCSs, the system can achieve the required performance. The research on network scheduling is to explore an effective scheduling strategy to improve network service quality and performance (Edwin G et al., 2019; Li Hongfei et al., 2021; Tian Zhongda et al., 2021; Zhang H et al., 2017).

Fault-tolerant control is to make the controlled object meet the expected performance, and the system can still maintain stability when a fault occurs. It is necessary to consider the influence of uncertain factors such as system faults, modelling errors, and external disturbances for designing the fault-tolerant control system. The purpose of the current network fault-tolerant control system research is to design an appropriate control mechanism to solve the automatic compensation and various faults suppression such as actuators, sensors, the system itself and associated links, as well as performance optimization problems under different failure modes (Fu Xingjian et al., 2021; Xie C H et al., 2016; Zhu Q et al., 2015).

In the NCSs, network congestion, data transmission competition, system interruption and other reasons will cause data loss. When data loss occurs in the system, the system information transmission is interrupted, which has a major impact on the structure and function for the network system, and even leads to system instability. Data loss is one of the most common failures in NCSs. At present, there have been some research results on the fault-tolerant control of NCSs. According to the impact of data packet loss and induced time-delay on the NCSs performance, many scholars have done research (Chen H et al., 2016; LIU Bin et al., 2018; Mohsen Bahreini et al., 2020). In (LIU Bin et al., 2018), considering the NCSs with actuator failures and distributed time-delays, the design problem for a class of robust fault-tolerant H_∞ controllers is studied. The time-delay and packet loss in the network are treated as equivalent time-delays. In (Mohsen Bahreini et al., 2020), the problems for robust finite-time fault-tolerant stochastic stability and stabilization of the NCSs in the presence of random time-delays and actuator faults are investigated. In (Chen H et al., 2016), The paper considers H_∞ output feedback control for NCSs with time-delay, data packet dropout and disorder, occurred in both sensor-to-controller and controller-to-actuator channels.

A logic data packet processor is used to solve the data packet disorder and data loss is seemed as a special case of the time-delay.

The iterative learning control method was first proposed by Uchiyama in 1978. Since it was proposed, it has been one of the hotspots in the control field (HE Zhiyu et al., 2020; Wang Limin et al., 2020; Wei J et al., 2017; Xiong Wenjun et al., 2021). The basic strategy of this method is as follows. For a kind of nonlinear dynamic system that runs repeatedly on a limited interval, the error information and input information measured in the previous or previous few times are used to correct the input information in the current cycle, so that the repetitive task can do better in this operation. This is repeated until the system output completely tracks the desired trajectory in the entire time interval. In (Dutta Sandip et al., 2020), a simple yet effective optimization method is developed to solve nonlinear conjugate heat transfer. The design technique developed uses linear iterative machine learning model and further optimizes with strategic improvement. In (Li Li et al., 2020), the paper incorporates the set-membership method into the ILC design for a class of linear systems subject to the bounded noise. A new ILC algorithm is given, which not only provides an estimate for the desired input but also determines an ellipsoid of confidence for the estimate. In order to cope with system disturbances in multi-phase batch processes with different dimensions, a hybrid robust control scheme of iterative learning control combined with feedback control is proposed in (Wang L et al., 2018). In addition, the ILC method has also been applied in the actual system (Qiao J Z et al., 2019; ZHOU Ying et al., 2017).

Iterative learning control is a data-based algorithm. The loss of data will have a certain impact on the algorithm convergence, so that the controller cannot work normally. Therefore, the problem of data loss is an important issue in the research of iterative learning control. At the same time, when data is transmitted in the network, there are still problems such as incorrect transmission timing and transmission delay, which increase the uncertainty of the system. It is difficult to establish an accurate mathematical model of the controlled system. As a typical model-free control, iterative learning control does not need to understand the dynamic structure of the controlled object. According to this feature, it can avoid the establishment of accurate mathematical models when studying complex NCSs. Therefore, the analysis and research of NCSs can be simplified by using ILC to study NCSs. In (Zhang YinJun, 2014), the paper deal with the iterative learning control for a class of nonlinear systems with measurement dropouts in the PLC, and studies the P-type iterative learning control algorithm convergence issues. In (Devasia et al., 2016), the article studies ILC where multiple heterogeneous linear subsystems update their input simultaneously based on the error in a collaboratively-controlled desired output. The work proposes an update-partitioning method for co-learning and demonstrates convergence, and iterative learning for each subsystem is convergent. In (BU Xuhui et al., 2012), the paper analyzes the stability of the ILC applied to a class of nonlinear discrete systems with output measurement data dropouts. The data dropout is described as a stochastic Bernoulli process with a given probability. P-type ILC algorithm is derived.

At present, most of the research results are solely aimed at single-channel failures such as data loss between the controller and the actuator or data loss between the sensor and the controller. However, in actual NCSs, data loss failures may exist in two channels, that is, the control input channel (between the controller and the actuator) and the measurement signal channel (between the sensor and the controller). In both channels, the data loss is prone to occur. At the same time, the external disturbances inevitably exist in the two channels. Data loss failures and disturbances will directly affect the convergence and tracking accuracy of the system. Therefore, for a single channel data loss failure or with disturbance, the convergence analysis of the iterative learning control algorithm cannot meet the actual demand. The fault-tolerant control based on iterative learning algorithm should be discussed for NCSs with input disturbance, dual-channel data loss and time-delay.

Based on the above analysis, in this paper, for non-linear NCSs with data loss failure, time-delay and disturbance in dual-channel, PD-type iterative learning control algorithm is used to discuss the stable tracking of the desired trajectory. In NCSs, the failures such as data loss and network time-delay are random. As a random process, Bernoulli sequence can well show the random characteristics, so that Bernoulli random variables can be used to describe the data loss and time-delay in the dual-channel NCSs. In the mathematical modelling for the data transmission process, dual-channel failures are considered. The data loss failure is described as a random Bernoulli process with known probability, that is, if the output data is not lost, the tracking error is used to correct the previous iterative learning control, so as to obtain the current control of the system. If there is data loss, the current control remains unchanged from the previous iteration. The sufficient conditions to ensure the convergence of the algorithm are given and proved. The conclusion shows that when the nonlinear system satisfies the given convergence conditions, under the environment of dual-channel data loss and time-delay, the controlled system with input disturbance can converge to the desired trajectory with the increase of the number of iterative learning. Finally, a simulation example further verifies the effectiveness of the proposed method.

2. PROBLEM STATEMENT

Consider the following nonlinear system

$$\begin{cases} x_k(t+1) = f\left(x_k(t),t\right) + A\left(x_k(t),t\right)u_k(t) \\ +\eta(t) \\ y_k(t) = B\left(x_k(t),t\right)u_k(t) \end{cases} \tag{1}$$

Where the discrete time $t \in \{0,1,\cdots T\}$ is denoted as $t \in [0,T]$. $x_k(t) \in R^n$ is the state vector. $u_k(t) \in R^m$ is the input vector. $y_k(t) \in R^m$ is the output vector. $f(\cdot), A(\cdot)$ and $B(\cdot)$ is a smooth function. $\eta(t)$ is the input disturbance. The subscript k represents the number of iterations.

For the nonlinear system (1) in a finite time, the following assumptions are given.

Assumption 1 The non-linear function $f(\cdot)$ and $A(\cdot)$ satisfy the Lipschintz condition, that is, there are constants k_f and k_a that satisfy

$$\|f(x_1(t),t)-f(x_2(t),t)\| \le k_f \|x_1(t)-x_2(t)\|$$
$$\|A(x_1(t),t)-A(x_2(t),t)\| \le k_a \|x_1(t)-x_2(t)\|$$

Assumption 2 Non-linear functions $A(\cdot)$ and $B(\cdot)$ are bounded for the state $x_k(t)$, and there are constants k_c and b_d that satisfy $|A(\cdot)| \le k_c$ and $|B(\cdot)| \le b_d$.

Assumption 3 The initial conditions of the nonlinear system are satisfied as

$$x_k(0) = x_d(0) \tag{2}$$

Where $x_k(0)$ and $x_d(0)$ are the initial states and the desired states of the system in the k_{th} run respectively.

For the system (1), the control law is designed as follows

$$\tilde{u}_{k+1}(t) = \tilde{u}_k(t) + \Gamma\tilde{e}_k(t) + L(\tilde{e}_k(t) - \tilde{e}_k(t-1)) \tag{3}$$

Where $\tilde{e}_k(t) = y_d(t) - \tilde{y}_k(t)$. Γ is P-type matrix, and L is D-type matrix.

Due to network constraints, there are often dual-channel data loss situations in NCSs. One is the data loss caused by the network failure when the output signal of the sensor is transmitted to the controller. The other is the data loss caused by the network failure when the control signal from the controller is transmitted to the actuator.

In NCSs, the network transmission channel can be regarded as a random switch. When the switch is closed, the data transmission is successful. When the switch is off, data transmission fails, that is, data loss occurs. The success rate of data transmission is the probability that the switch is closed. Assume that $y_k(t)$ represents the measured output of the controlled object, and $u_k(t)$ is the control input. $\tilde{y}_k(t)$ is the measurement data received at the controller input, and $\tilde{u}_k(t)$ is the control input given by the output. α and β are Bernoulli random variables satisfying independent distribution

$$\mathrm{P}[\alpha = 1] = \bar{\alpha}, 0 \le \bar{\alpha} \le 1 \tag{4}$$

$$\mathrm{P}[\beta = 1] = \bar{\beta}, 0 \le \bar{\beta} \le 1 \tag{5}$$

$\bar{\alpha}$ and $\bar{\beta}$ indicate the success rate of data transmission. $\mathrm{P}\{\cdot\}$ represents the mathematical expectation of $\{\cdot\}$. When $\alpha=1$, the measurement output data transmission is successful. When $\alpha=0$, the measurement output data transmission fails. When $\beta=1$, the control input data transmission is successful; when $\beta=0$, the control input data transmission fails.

For the network time-delay, suppose that $0 \le n_1 \le 1$ and $0 \le n_2 \le 1$ are independent distribution Bernoulli random time-delay factors. When $n_1=1$, there is no transmission time-delay in the channel between the sensor and the controller, and when $n_1=0$, there is the time-delay in data transmission. When $n_2=1$, there is no transmission delay in the data channel between the controller and the actuator, and when $n_2=0$, there is the time-delay0 in data transmission.

In addition, the data loss random variable and the transmission delay random variable are not completely independent. Whether the network control system has time-delay or not is related to whether there is data loss in the network.

Therefore, the conditional probabilities of no time-delay in network system transmission are

$$\begin{aligned} &\mathrm{P}[\alpha = 1, n_1 = 1] \\ &= \mathrm{P}[\alpha = 1]\mathrm{P}[n_1 = 1|\alpha = 1] = \bar{\alpha}\bar{n}_1 \end{aligned} \tag{6}$$

$$\begin{aligned} &\mathrm{P}[\beta = 1, n_2 = 1] \\ &= \mathrm{P}[\beta = 1]\mathrm{P}[n_2 = 1|\beta = 1] = \bar{\beta}\bar{n}_2 \end{aligned} \tag{7}$$

When there is a transmission time-delay in the NCSs, the conditional probabilities are

$$\begin{aligned} &\mathrm{P}[\alpha = 1, n_1 = 0] = \mathrm{P}[\alpha = 1]\mathrm{P}[n_1 = 0|\alpha = 1] \\ &= \bar{\alpha}(1 - \bar{n}_1) \end{aligned} \tag{8}$$

$$\begin{aligned} &\mathrm{P}[\beta = 1, n_2 = 0] = \mathrm{P}[\beta = 1]\mathrm{P}[n_2 = 0|\beta = 1] \\ &= \bar{\beta}(1 - \bar{n}_2) \end{aligned} \tag{9}$$

In summary, in the k_{th} iteration, the system output signal with data loss and transmission time-delay disturbance can be expressed as

$$\tilde{y}_k(t) = \alpha[n_1 y_k(t) + (1 - n_1) y_k(t-1)] \tag{10}$$

$$u_k(t) = \beta[n_2 \tilde{u}_k(t) + (1 - n_2)\tilde{u}_k(t-1)] \tag{11}$$

3. CONVERGENCE ANALYSIS

The following main conclusions can be obtained for the above statements.

Theorem For the nonlinear system (1), the Assumptions 1-Assumptions 3 are satisfied and the system has data loss failure, time-delay and input disturbances in dual-channel. When the iterative learning controller (3) is used, for all the k and $t \in [0, \mathrm{T}]$, $\gamma_k = \|1 - \bar{\beta}\bar{n}_2(\Gamma + L)\bar{\alpha}\bar{n}_1 B(x_k(t))\| < 1$ holds, then $\lim_{k\to\infty} \varepsilon\{\|y_k(t)\|\} = y_d(t)$.

Proof: the tracking error at the k_{th} iteration is

$$e_k(t) = y_d(t) - y_k(t) \tag{12}$$

From the system (1), get

$$\begin{aligned} e_k(t) &= B(x_d(t))u_d(t) - B(x_k(t))u_k(t) \\ &= B(x_d(t))u_d(t) - B(x_k(t))u_k(t) \\ &+ B(x_k(t))u_d(t) - B(x_k(t))u_d(t) \\ &= \left(B(x_d(t)) - B(x_k(t))\right)u_d(t) \\ &+ B(x_k(t))\Delta u_k(t) \end{aligned} \tag{13}$$

Where, the system error is $e_k(t) = y_d(t) - y_k(t)$. $\Delta u_k(t) = u_d(t) - u_k(t)$.

When the data loss and transmission time-delay are included in the system, it can be obtained from the equation (10)

$$\begin{aligned} \tilde{e}_k(t) &= y_d(t) - \tilde{y}_k(t) = \alpha n_1\left(y_d(t) - y_k(t)\right) \\ &+ \alpha(1-n_1)\left(y_d(t-1) - y_k(t-1)\right) \\ &+ \alpha(1-n_1)\left(y_d(t) - y_d(t-1)\right) \\ &= \alpha n_1 e_k(t) + \alpha(1-n_1)e_k(t-1) \\ &+ \alpha(1-n_1)\Delta y_d(t) \end{aligned} \tag{14}$$

Where $\Delta y_d(t) = y_d(t) - y_d(t-1)$ can be ignored, and the equation (14) can be sorted into

$$\tilde{e}_k(t) = \alpha n_1 e_k(t) + \alpha(1-n_1)e_k(t-1) \tag{15}$$

From the equation (11)

$$\begin{aligned} u_{k+1}(t) - u_k(t) &= \beta\left(n_2\tilde{u}_{k+1}(t) \right. \\ &\left. + (1-n_2)\tilde{u}_{k+1}(t-1)\right) \\ &- \beta\left(n_2\tilde{u}_k(t) - (1-n_2)\tilde{u}_k(t-1)\right) \\ &= \beta n_2\left(\tilde{u}_{k+1}(t) - \tilde{u}_k(t)\right) \\ &+ \beta(1-n_2)\left(\tilde{u}_{k+1}(t-1) - \tilde{u}_k(t-1)\right) \end{aligned} \tag{16}$$

Substituting the iterative learning control law (3) into the equation (16)

$$\begin{aligned} u_{k+1}(t) &= u_k(t) + \beta n_2\left(\tilde{u}_{k+1}(t) - \tilde{u}_k(t)\right) \\ &+ \beta(1-n_2)\left(\tilde{u}_{k+1}(t) - \tilde{u}_k(t-1)\right) \\ &= u_k(t) + \beta n_2\left[\Gamma\tilde{e}_k(t) + L\left(\tilde{e}_k(t) - \tilde{e}_k(t-1)\right)\right] \\ &+ \beta(1-n_2)\left[\Gamma\tilde{e}_k(t-1) + L\left(\tilde{e}_k(t-1) - \tilde{e}_k(t-2)\right)\right] \\ &= u_k(t) + \tilde{m}_1\tilde{e}_k(t) + \tilde{m}_2\tilde{e}_k(t-1) + \tilde{m}_3\tilde{e}_k(t-2) \end{aligned} \tag{17}$$

Where $\tilde{m}_1 = \beta n_2(\Gamma + L)$, $\tilde{m}_3 = -\beta(1-n_2)L$,

$\tilde{m}_2 = \beta(1-n_2)(\Gamma + L) - \beta n_2 L$.

Then

$$\begin{aligned} u_{k+1}(t) &= u_k(t) + \tilde{m}_1\left[\alpha n_1 e_k(t) + \alpha(1-n_1)e_k(t-1)\right] \\ &+ \tilde{m}_2\left[\alpha n_1 e_k(t-1) + \alpha(1-n_1)e_k(t-2)\right] \\ &+ \tilde{m}_3\left[\alpha n_1 e_k(t-2) + \alpha(1-n_1)e_k(t-3)\right] \\ &= u_k(t) + m_1 e_k(t) + m_2 e_k(t-1) + m_3 e_k(t-2) \\ &+ m_4 e_k(t-3) \end{aligned} \tag{18}$$

Where $m_1 = \tilde{m}_1\alpha n_1$, $m_2 = \tilde{m}_1\alpha(1-n_1) + \tilde{m}_2\alpha n_1$,

$m_3 = \tilde{m}_2\alpha(1-n_1) + \tilde{m}_3\alpha n_1$, $m_4 = \tilde{m}_3\alpha(1-n_1)$

Subtract $u_d(t)$ from both sides of the equation (18)

$$\begin{aligned} \Delta u_{k+1}(t) &= \Delta u_k(t) - m_1 e_k(t) - m_2 e_k(t-1) \\ &- m_3 e_k(t-2) - m_4 e_k(t-3) \end{aligned} \tag{19}$$

Substituting the equation (13) into the equation (19)

$$\begin{aligned} \Delta u_{k+1}(t) &= \Delta u_k(t) \\ &- m_1\left[\left(B(x_d(t)) - B(x_k(t))\right)u_d(t) \right. \\ &\left. + B(x_k(t))\Delta u_k(t)\right] - m_2\left[\left(B(x_d(t-1)) \right.\right. \\ &\left.\left. - B(x_k(t-1))\right)u_d(t-1) + B(x_k(t-1))\Delta u_k(t-1)\right] \\ &- m_3\left[\left(B(x_d(t-2)) - B(x_k(t-2))\right)u_d(t-2) \right. \\ &\left. + B(x_k(t-2))\Delta u_k(t-2)\right] - m_4\left[\left(B(x_d(t-3)) \right.\right. \\ &\left.\left. - B(x_k(t-3))\right)u_d(t-3) + B(x_k(t-3))\Delta u_k(t-3)\right] \end{aligned} \tag{20}$$

Simplification

$$\begin{aligned} \Delta u_{k+1}(t) &= \left(1 - m_1 B(x_k(t))\right)\Delta u_k(t) \\ &- m_2 B(x_k(t-1))\Delta u_k(t-1) \\ &- m_3 B(x_k(t-2))\Delta u_k(t-2) \\ &- m_4 B(x_k(t-3))\Delta u_k(t-3) \\ &- m_1\left[\left(B(x_d(t)) - B(x_k(t))\right)u_d(t)\right] \\ &- m_2\left[\left(B(x_d(t-1)) - B(x_k(t-1))\right)u_d(t-1)\right] \\ &- m_3\left[\left(B(x_d(t-2)) - B(x_k(t-2))\right)u_d(t-2)\right] \\ &- m_4\left[\left(B(x_d(t-3)) - B(x_k(t-3))\right)u_d(t-3)\right] \end{aligned} \tag{21}$$

Take the norm for both ends of the equation (21)

$$\begin{aligned} \left\|\Delta u_{k+1}(t)\right\| &\le \left\|1 - m_1 B(x_k(t))\right\|\left\|\Delta u_k(t)\right\| \\ &+ \left\|m_2 B(x_k(t-1))\right\|\left\|\Delta u_k(t-1)\right\| \\ &+ \left\|m_3 B(x_k(t-2))\right\|\left\|\Delta u_k(t-2)\right\| \\ &+ \left\|m_4 B(x_k(t-3))\right\|\left\|\Delta u_k(t-3)\right\| \\ &+ \left\|m_1\right\|\left\|B(x_d(t)) - B(x_k(t))\right\|\left\|u_d(t)\right\| \end{aligned}$$

$$+\|m_4\|\left\|B\left(x_d(t-3)\right)-B\left(x_k(t-3)\right)\right\|\|u_d(t-3)\|$$
$$+\|m_2\|\left\|B\left(x_d(t-1)\right)-B\left(x_k(t-1)\right)\right\|\|u_d(t-1)\| \quad (22)$$
$$+\|m_3\|\left\|B\left(x_d(t-2)\right)-B\left(x_k(t-2)\right)\right\|\|u_d(t-2)\|$$

According to the Assumption 1

$$\begin{aligned}
\|\Delta u_{k+1}(t)\| &\le \left\|1-m_1B\left(x_k(t)\right)\right\|\|\Delta u_k(t)\| \\
&+\left\|m_2B\left(x_k(t-1)\right)\right\|\|\Delta u_k(t-1)\| \\
&+\left\|m_3B\left(x_k(t-2)\right)\right\|\|\Delta u_k(t-2)\| \\
&+\left\|m_4B\left(x_k(t-3)\right)\right\|\|\Delta u_k(t-3)\| \\
&+\|k_1m_1\|\|\Delta x_k(t)\|+\|k_1m_2\|\|\Delta x_k(t-1)\| \\
&+\|k_1m_3\|\|\Delta x_k(t-2)\|+\|k_1m_4\|\|\Delta x_k(t-3)\|
\end{aligned} \quad (23)$$

where $k_1=k_bb_u, b_u=\sup_{t\in[0,T]} u_d(t)$.

Take expectations on both ends of the inequality (23)

$$\begin{aligned}
\varepsilon\{\|\Delta u_{k+1}(t)\|\} &\le \|1-\bar{m}_1B(x_k(t))\|\varepsilon\{\|\Delta u_k(t)\|\} \\
&+\left\|\bar{m}_2B\left(x_k(t-1)\right)\right\|\varepsilon\{\|\Delta u_k(t-1)\|\} \\
&+\left\|\bar{m}_3B\left(x_k(t-2)\right)\right\|\varepsilon\{\|\Delta u_k(t-2)\|\} \\
&+\left\|\bar{m}_4B\left(x_k(t-3)\right)\right\|\varepsilon\{\|\Delta u_k(t-3)\|\} \\
&+\|k_1\bar{m}_1\|\varepsilon\{\|\Delta x_k(t)\|\} \\
&+\|k_1\bar{m}_2\|\varepsilon\{\|\Delta x_k(t-1)\|\}+\|k_1\bar{m}_3\|\varepsilon\{\|\Delta x_k(t-2)\|\} \\
&+\|k_1\bar{m}_4\|\varepsilon\{\|\Delta x_k(t-3)\|\}
\end{aligned} \quad (24)$$

Where $\bar{m}_1=\bar{\beta}\bar{n}_2(\Gamma+L)\bar{\alpha}\bar{n}_1,\ \bar{m}_2=\bar{\beta}\bar{n}_2(\Gamma+L)\bar{\alpha}(1-\bar{n}_1)$

$+\left[\bar{\beta}(1-\bar{n}_2)(\Gamma+L)-\bar{\beta}\bar{n}_2L\right]\bar{\alpha}\bar{n}_1,\quad \bar{m}_3=\left[\bar{\beta}(1-\bar{n}_2)\right.$

$\left.\times(\Gamma+L)-\bar{\beta}\bar{n}_2L\right]\bar{\alpha}(1-\bar{n}_1)-\bar{\beta}(1-\bar{n}_2)L\bar{\alpha}\bar{n}_1,$

$\bar{m}_4=-\bar{\beta}(1-\bar{n}_2)L\bar{\alpha}(1-\bar{n}_1).$

Then

$$\begin{aligned}
\Delta x_k(t) &= x_d(t)-x_k(t) \\
&= f\left(x_d(t-1)\right)+A\left(x_d(t-1)\right)u_d(t-1) \\
&-f\left(x_k(t-1)\right)-A\left(x_k(t-1)\right)u_k(t-1) \\
&= f\left(x_d(t-1)\right)-f\left(x_k(t-1)\right) \\
&+A\left(x_d(t-1)\right)u_d(t-1)-A\left(x_k(t-1)\right)u_d(t-1) \\
&+A\left(x_k(t-1)\right)u_d(t-1)-A\left(x_k(t-1)\right)u_k(t-1)
\end{aligned} \quad (25)$$

From then equation (25)

$$\begin{aligned}
\Delta x_k(t) &= f\left(x_d(t-1)\right)-f\left(x_k(t-1)\right) \\
&+\left(A\left(x_d(t-1)\right)-A\left(x_k(t-1)\right)\right)u_d(t-1) \\
&+A\left(x_k(t-1)\right)\Delta u_k(t-1)
\end{aligned} \quad (26)$$

Both ends of the equation (26) are normed

$$\begin{aligned}
\|\Delta x_k(t)\| &\le \left\|f\left(x_d(t-1)\right)-f\left(x_k(t-1)\right)\right\| \\
&+\left\|A\left(x_d(t-1)\right)-A\left(x_k(t-1)\right)\right\|\|u_d(t-1)\| \\
&+\left\|A\left(x_k(t-1)\right)\right\|\|\Delta u_k(t-1)\|+\left\|A\left(x_k(t-1)\right)\right\|
\end{aligned} \quad (27)$$

According to the Assumption 1 and Assumption 2

$$\begin{aligned}
\|\Delta x_k(t)\| &\le k_f\|\Delta x_k(t-1)\| \\
&+k_a\|\Delta x_k(t-1)\|\|b_u\|+k_c\|\Delta u_k(t-1)\| \\
&= k_2\|\Delta x_k(t-1)\|+k_3\|\Delta u_k(t-1)\| \\
&\le k_2\left[k_f\|\Delta x_k(t-2)\|+k_a\|\Delta x_k(t-2)\|\|b_u\|\right. \\
&\left.+k_3\|\Delta u_k(t-2)\|\right]+k_3\|\Delta u_k(t-1)\| \\
&= k_2\left[k_2\|\Delta x_k(t-2)\|+k_3\|\Delta u_k(t-2)\|\right] \\
&+k_3\|\Delta u_k(t-1)\| \\
&\le k_2^t\|\Delta x_k(0)\|+k_3\sum_{q=1}^{t}k_2^{q-1}\|\Delta u_k(t-q)\|
\end{aligned} \quad (28)$$

Where $k_2=k_f+k_ab_u, k_3=k_c$.

According to the Assumption 3

$$\|\Delta x_k(0)\|=\|x_d(0)-x_k(0)\|=0 \quad (29)$$

Then

$$\|\Delta x_k(t)\|\le k_3\sum_{q=1}^{t}k_2^{q-1}\|\Delta u_k(t-q)\| \quad (30)$$

The equation (30) is taken as mathematical expectation

$$\varepsilon\{\|\Delta x_k(t)\|\}\le k_3\sum_{p=1}^{t}k_2^{q-1}\varepsilon\{\|\Delta u_k(t-q)\|\} \quad (31)$$

Then

$$\begin{aligned}
\varepsilon\{\|\Delta u_{k+1}(t)\|\} &\le \left\|1-\bar{m}_1B\left(x_k(t)\right)\right\|\varepsilon\{\|\Delta u_k(t)\|\} \\
&+\left\|\bar{m}_2B\left(x_k(t-1)\right)\right\|\ \varepsilon\{\|\Delta u_k(t-1)\|\} \\
&+\left\|\bar{m}_3B\left(x_k(t-2)\right)\right\|\varepsilon\{\|\Delta u_k(t-2)\|\} \\
&+\|k_1\bar{m}_1\|k_3\sum_{q=1}^{t}k_2^{q-1}\cdot\varepsilon\{\|\Delta u_k(t-q)\|\} \\
&+\|k_1\bar{m}_2\|k_3\sum_{q=1}^{t-1}k_2^{q-1}\ \varepsilon\{\|\Delta u_k(t-q-1)\|\} \\
&+\|\bar{m}_4B(x_k(t-3))\|\varepsilon\{\|\Delta u_k(t-3)\|\}
\end{aligned}$$

$$+\|k_1\bar{m}_3\|k_3\sum_{q=1}^{t-2}k_2^{q-1}\varepsilon\left\{\|\Delta u_k(t-q-2)\|\right\}$$
$$+\|k_1\bar{m}_4\|k_3\sum_{p=1}^{t-3}k_2^{q-1}\varepsilon\left\{\|\Delta u_k(t-q-3)\|\right\} \quad (32)$$

Namely

$$\begin{aligned}&\varepsilon\left\{\|\Delta u_{k+1}(t)\|\right\}=\gamma_k\varepsilon\left\{\|\Delta u_k(t)\|\right\}\\&+\gamma_{k1}\varepsilon\left\{\|\Delta u_k(t-1)\|\right\}+\gamma_{k2}\varepsilon\left\{\|\Delta u_k(t-2)\|\right\}\\&+\gamma_{k3}\varepsilon\left\{\|\Delta u_k(t-3)\|\right\}+\sum_{q=1}^{t}\omega_{k,q}\varepsilon\left\{\|\Delta u_k(t-q)\|\right\}\\&+\sum_{p=1}^{t-1}\omega_{k1,p}\varepsilon\left\{\|\Delta u_k(t-p-1)\|\right\}\\&+\sum_{p=1}^{t-2}\omega_{k2,p}\varepsilon\left\{\|\Delta u_k(t-p-2)\|\right\}\\&+\sum_{q=1}^{t-3}\omega_{k3,q}\varepsilon\left\{\|\Delta u_k(t-q-3)\|\right\}\end{aligned} \quad (33)$$

Where $\gamma_{k1}=\left\|\bar{m}_2B\left(x_k(t-1)\right)\right\|$, $\gamma_{k2}=\left\|\bar{m}_3B\left(x_k(t-2)\right)\right\|$,

$\gamma_{k3}=\left\|\bar{m}_4B\left(x_k(t-3)\right)\right\|$, $\omega_{k,q}=\|k_1\bar{m}_1\|k_3k_2^{q-1}$,

$\omega_{k1,q}=\|k_1\bar{m}_2\|k_3k_2^{q-1}$, $\omega_{k2,q}=\|k_1\bar{m}_3\|k_3k_2^{q-1}$,

$\omega_{k3,q}=\|k_1\bar{m}_4\|k_3k_2^{q-1}$,
$\gamma_k=\left\|1-\bar{m}_1B\left(x_k(t)\right)\right\|=\left\|1-\bar{\beta}\bar{n}_2(\Gamma+L)\bar{\alpha}\bar{n}_1B\left(x_k(t)\right)\right\|$. Expand the equation (33) from $t=0$ to $t=T$

$$\varepsilon\left\{\|\Delta u_{k+1}(0)\|\right\}\le\gamma_k\varepsilon\left\{\|\Delta u_k(0)\|\right\} \quad (34)$$

$$\begin{aligned}&\varepsilon\left\{\|\Delta u_{k+1}(1)\|\right\}\le\gamma_k\varepsilon\left\{\|\Delta u_k(1)\|\right\}\\&\quad+\left(\gamma_{k1}+\omega_{k,1}\right)\varepsilon\left\{\|\Delta u_k(0)\|\right\}\\&=\gamma_k\varepsilon\left\{\|\Delta u_k(1)\|\right\}+\upsilon_{1,0}\varepsilon\left\{\|\Delta u_k(0)\|\right\}\end{aligned} \quad (35)$$

$$\begin{aligned}&\varepsilon\left\{\|\Delta u_{k+1}(2)\|\right\}\le\gamma_k\varepsilon\left\{\|\Delta u_k(2)\|\right\}\\&+\left(\gamma_{k1}+\omega_{k,1}\right)\varepsilon\left\{\|\Delta u_k(1)\|\right\}\\&+\left(\gamma_{k2}+\omega_{k,2}+\omega_{k1,1}\right)\varepsilon\left\{\|\Delta u_k(0)\|\right\}\\&=\gamma_k\varepsilon\left\{\|\Delta u_k(2)\|\right\}+\upsilon_{2,1}\varepsilon\left\{\|\Delta u_k(1)\|\right\}\\&+\upsilon_{2,0}\varepsilon\left\{\|\Delta u_k(0)\|\right\}\end{aligned} \quad (36)$$

$$\begin{aligned}&\varepsilon\left\{\|\Delta u_{k+1}(3)\|\right\}\le\gamma_k\varepsilon\left\{\|\Delta u_k(3)\|\right\}\\&+\left(\gamma_{k1}+\omega_{k,1}\right)\varepsilon\left\{\|\Delta u_k(2)\|\right\}\\&+\left(\gamma_{k2}+\omega_{k,2}+\omega_{k1,1}\right)\varepsilon\left\{\|\Delta u_k(1)\|\right\}\\&+\left(\gamma_{k3}+\omega_{k,3}+\omega_{k1,2}+\omega_{k2,1}\right)\varepsilon\left\{\|\Delta u_k(0)\|\right\}\\&=\gamma_k\varepsilon\left\{\|\Delta u_k(3)\|\right\}+\upsilon_{3,2}\varepsilon\left\{\|\Delta u_k(2)\|\right\}\\&+\upsilon_{3,1}\varepsilon\left\{\|\Delta u_k(1)\|\right\}+\upsilon_{3,0}\varepsilon\left\{\|\Delta u_k(0)\|\right\}\end{aligned} \quad (37)$$

Where $\upsilon_{1,0}=\gamma_{k1}+\omega_{k,1}$, $\upsilon_{2,1}=\gamma_{k1}+\omega_{k,1}$,

$\upsilon_{2,0}=\gamma_{k2}+\omega_{k,2}+\omega_{k1,1}$, $\upsilon_{3,0}=\gamma_{k3}+\omega_{k,3}+\omega_{k1,2}+\omega_{k2,1}$

$\upsilon_{3,2}=\gamma_{k1}+\omega_{k,1}$, $\upsilon_{3,1}=\gamma_{k2}+\omega_{k,2}+\omega_{k1,1}$.

Then

$$\begin{aligned}&\varepsilon\left\{\|\Delta u_{k+1}(T)\|\right\}\le\gamma_k\varepsilon\left\{\|\Delta u_k(T)\|\right\}\\&+\upsilon_{T,T\text{-}1}\varepsilon\left\{\|\Delta u_k(T-1)\|\right\}+\upsilon_{T,T\text{-}2}\varepsilon\left\{\|\Delta u_k(T-2)\|\right\}\\&+\upsilon_{T,T\text{-}3}\varepsilon\left\{\|\Delta u_k(T-3)\|\right\}+\upsilon_{4,T\text{-}4}\varepsilon\left\{\|\Delta u_k(T-4)\|\right\}\\&+\cdots+\upsilon_{T,0}\varepsilon\left\{\|\Delta u_k(0)\|\right\}\end{aligned} \quad (38)$$

The matrix form can be expressed as

$$u_{k+1}=\phi_k u_k \quad (39)$$

Where

$$u_{k+1}=\begin{pmatrix}\varepsilon\{u_{k+1}(0)\}\\\varepsilon\{u_{k+1}(1)\}\\\varepsilon\{u_{k+1}(2)\}\\\vdots\\\varepsilon\{u_{k+1}(T)\}\end{pmatrix},u_k=\begin{pmatrix}\varepsilon\{u_k(0)\}\\\varepsilon\{u_k(1)\}\\\varepsilon\{u_k(2)\}\\\vdots\\\varepsilon\{u_k(T)\}\end{pmatrix},$$

$$\phi_k=\begin{pmatrix}\gamma_k&0&0&\cdots&0\\\upsilon_{1,0}&\gamma_k&0&\cdots&0\\\upsilon_{2,0}&\upsilon_{2,1}&\ddots&\vdots&\vdots\\\vdots&\vdots&\vdots&\gamma_k&0\\\upsilon_{T,0}&\upsilon_{T,1}&\cdots&\upsilon_{T,T-1}&\gamma_k\end{pmatrix}$$

If all the eigenvalues of ϕ_k are in the unit circle, when $k\to\infty$, for $t\in[0,T]$, $\varepsilon\left\{\delta u_k(t)\right\}\to 0$. Therefore, if $\gamma_k=\left\|1-\bar{\beta}\bar{n}_2(\Gamma+L)\bar{\alpha}\bar{n}_1B\left(x_k(t)\right)\right\|<1$ holds for all k and t, then there is $\lim_{k\to\infty}\varepsilon\left\{\|\Delta u_k(t)\|\right\}=0$. From the Assumption 3, $\lim_{k\to\infty}\varepsilon\left\{\|y_k(t)\|\right\}=y_d(t)$ holds. The proof is complete.

4. SIMULATION RESEARCH

Consider the following nonlinear system

$$\begin{cases}x_k(t+1)=\sin\left(x_k(t)\right)+0.2\left(1-x_k(t)\right)u_k(t)\\+\cos(2t)\\y_k(t)=\cos^2\left(x_k(t)\right)+u_k(t)\end{cases} \quad (40)$$

Let $y_k(t)=\cos(\pi t/300)+5\sin(\pi t/300)$ is the desired tracking trajectory of the system. $x_k(0)=1$ and $x_d(0)=1$ are the initial states. The initial input is $u_0(t)=0$, where $t\in[0,1,2,\cdots 600]$.

For trajectory tracking with data loss and time-delay in network system, simulation studies are done according to different conditions.

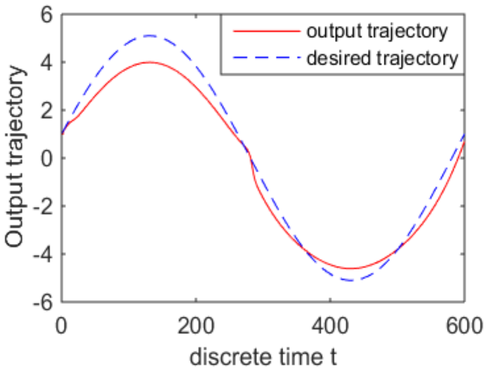

Fig. 1. Output curves in 2nd iteration.

1) Let $\bar{\alpha}=\bar{\beta}=1, \bar{n}_1=\bar{n}_2=1$. That is, there is no data loss and time-delay.

The gain parameters in the iterative learning control law is chosen as $\Gamma=0.85$ and $L=0.1$. It can be known from the theorem that under the action of the iterative learning control law (3), the gain parameters Γ, L and other parameter values satisfy the convergence condition.

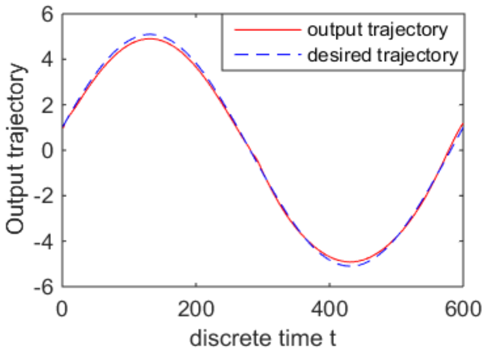

Fig. 2. Output curves in 3rd iteration.

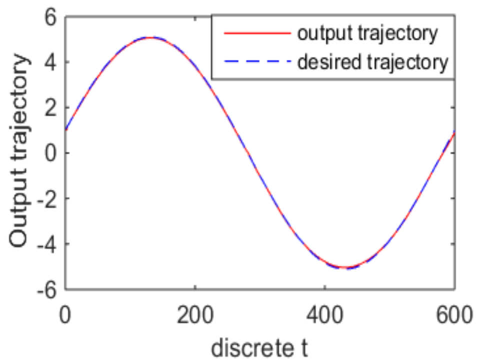

Fig. 3. Output curves in 4th iteration.

The tracking curves in the second iteration are shown in Fig.1. The tracking curves in the third iteration are shown in Fig.2. The tracking curves in the 4th iteration are shown in Fig.3. Convergence process of the maximum error absolute value during 10 iterations is shown in Fig.4.

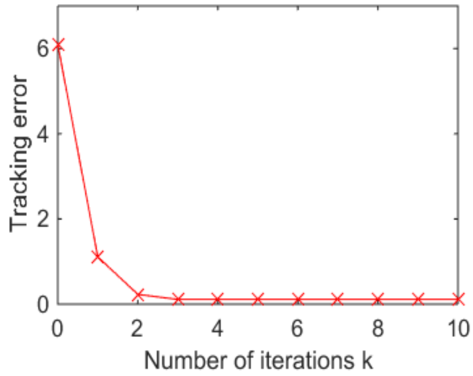

Fig. 4. Convergence process of the maximum error absolute value during 10 iterations.

It can be seen from Fig.1 to Fig.4 that the system output can better track the desired output when the number of iterations $k=4$.

2)Let $\bar{\alpha}=0.9, \bar{\beta}=0.9, \bar{n}_1=0.9, \bar{n}_2=0.8$

The gain parameters in the iterative learning control law is chosen as $\Gamma=0.75$ and $L=0.15$. It can be known from the theorem that under the action of the iterative learning control law (3), the gain parameters Γ, L and other parameter values satisfy the convergence condition.

The tracking curves in the second iteration are shown in Fig.5. The tracking curves in the third iteration are shown in Fig.6. The tracking curves in the 5th iteration are shown in Fig.7. Convergence process of the maximum error absolute value during 10 iterations is shown in Fig.8.

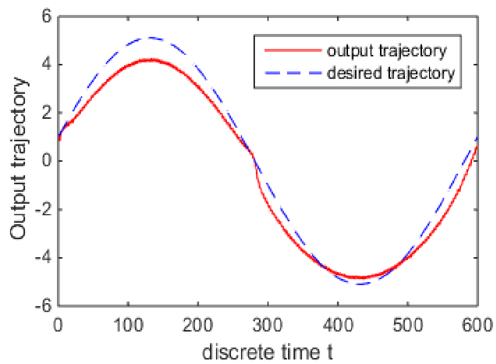

Fig. 5. Output curves in 2nd iteration.

It can be seen from Fig.5 to Fig.8 that the system output can better track the desired output when the number of iterations $k=5$.

In this case, the method proposed in this paper is compared with the other existing methods (Jia Yanlong, 2019). In the NCSs, the random failure of data packet loss and the transmission time-delay are not completely independent.

Time-delay and data loss will affect the tracking speed and accuracy of the output curve. There are only conditions for the successful data transmission without considering the transmission time-delay factors in the paper (Jia Yanlong, 2019). When the method is used for simulation, the value of the data loss rate can be increased by 20% (and let λ_1=0.6, λ_2=1). The tracking curves in the 4th iteration and the 8th iteration are shown in Fig.9 and Fig.10, respectively.

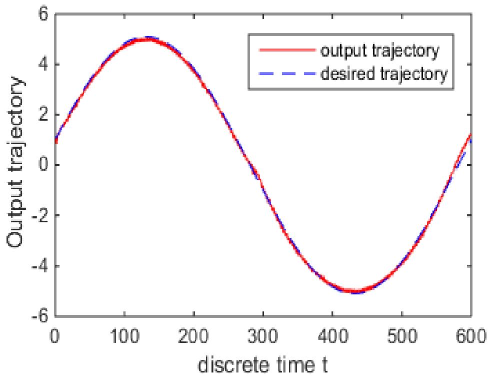

Fig. 6. Output curves in 3rd iteration.

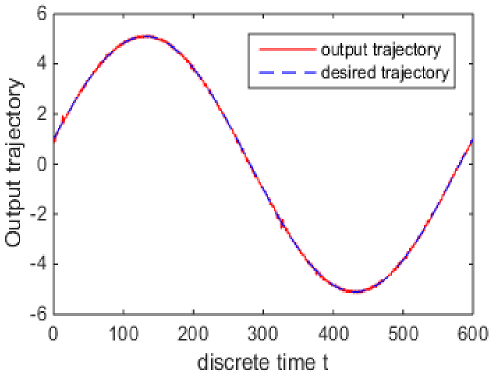

Fig. 7. Output curves in 5th iteration.

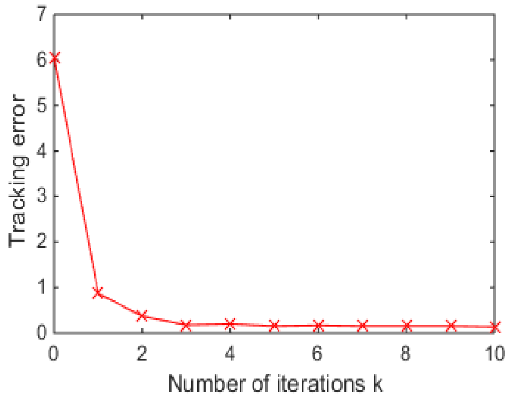

Fig. 8. Convergence process of the maximum error absolute value during 10 iterations.

Since the transmission time-delay in NCSs is not considered, the number of iterations for the system output curves to track the desired output curves has obviously increased.

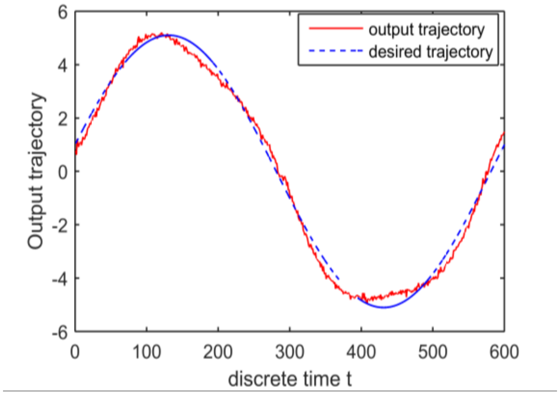

Fig. 9. Output curves in 4th iteration.

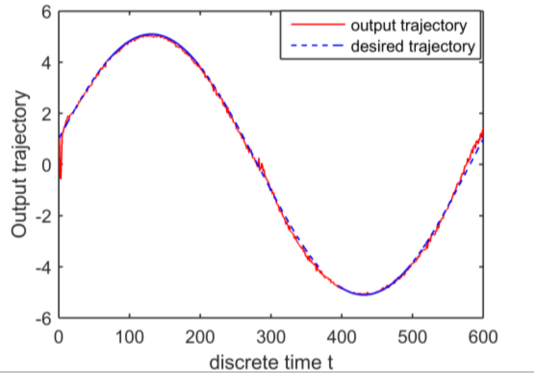

Fig. 10. Output curves in 8th iteration.

3) Let $\bar{\alpha} = 0.7, \bar{\beta} = 0.85, \bar{n}_1 = 0.7, \bar{n}_2 = 0.7$

The gain parameters in the iterative learning control law is chosen as $\Gamma = 0.65$ and $L = 0.2$. It can be known from the theorem that under the action of the iterative learning control law (3), the gain parameters Γ, L and other parameter values satisfy the convergence condition.

The tracking curves in the second iteration are shown in Fig.11. The tracking curves in the 5th iteration are shown in Fig.12. The tracking curves in the 10th iteration are shown in Fig.13. Convergence process of the maximum error absolute value during 15 iterations is shown in Fig.14.

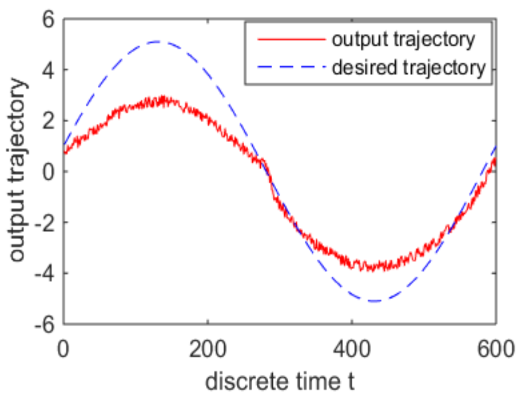

Fig. 11. Output curves in 2nd iteration.

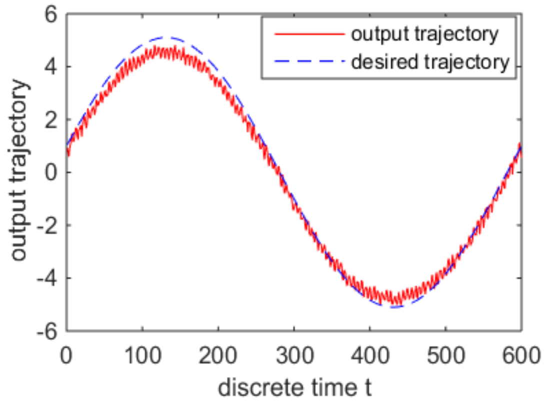

Fig. 12. Output curves in 5th iteration.

It can be seen from Fig.11 to Fig.14 that the system output can better track the desired output curves when the number of iterations $k = 10$.

By using the method (Jia Yanlong, 2019), the tracking curves in the 10th iteration and the 16th iteration are shown in Fig.15 and Fig.16. It can be seen that the number of iterations has also obviously increased.

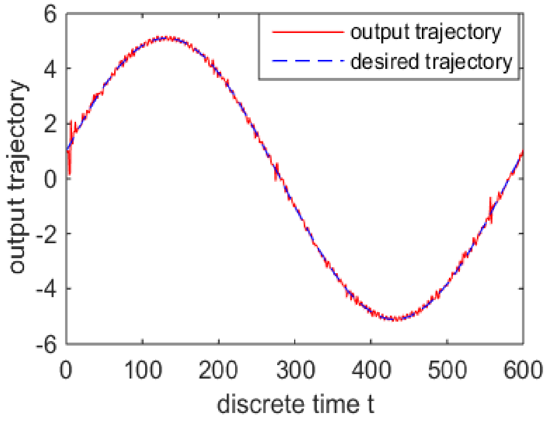

Fig. 13. Output curves in 10th iteration.

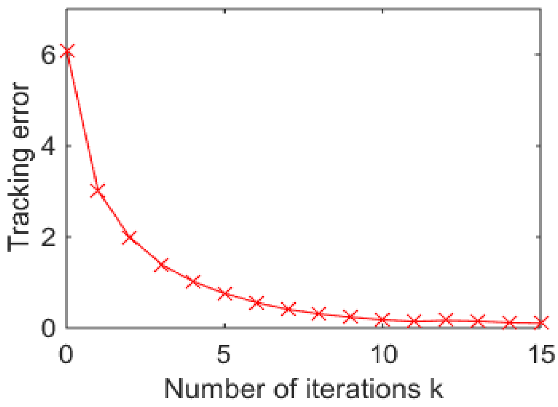

Fig. 14. Convergence process of the maximum error absolute value during 15 iterations.

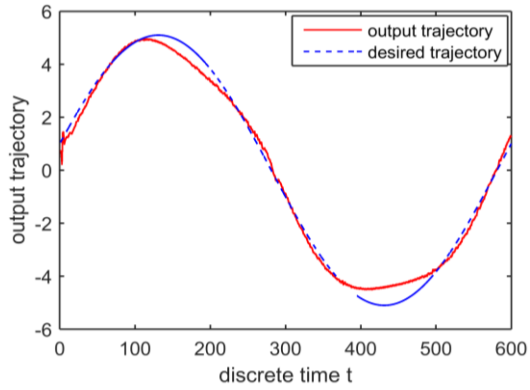

Fig. 15. Output curves in 10th iteration.

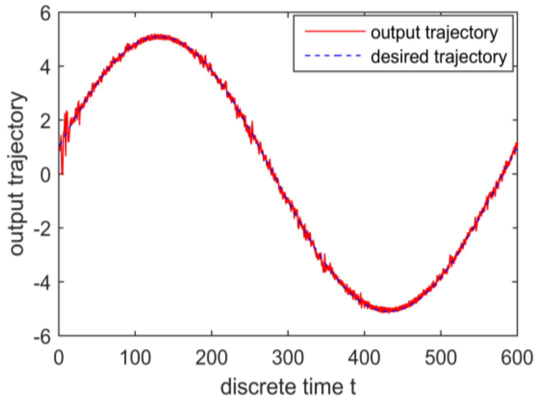

Fig. 16. Output curves in 16th iteration.

4)Let $\bar{\alpha} = 0.7, \bar{\beta} = 0.85, \bar{n}_1 = 0.7, \bar{n}_2 = 0.8$

The gain parameters in the iterative learning control law is chosen as $\Gamma = 5$ and $L = 8$. It can be known from the theorem that under the action of the iterative learning control law (3), the gain parameters Γ, L and other parameter values do not satisfy the convergence condition.

The tracking curves in the 30th iteration are shown in Fig.17. It can be seen from Fig.17 that the system output tracking is relatively poor when the number of iterations $k = 30$.

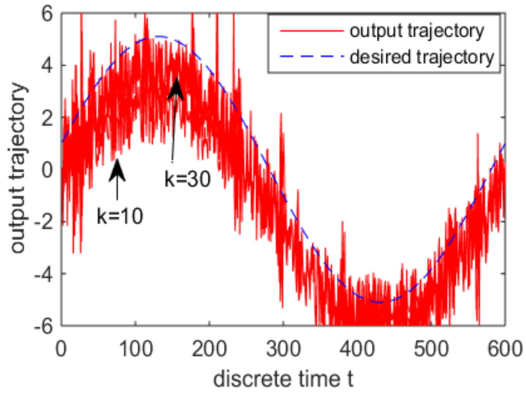

Fig. 17. Output curves in 30th iteration.

Through simulation research, it is known that the trajectory tracking speed of the system output is affected when there is data loss and network time-delay. When the data loss rate and time-delay occurrence rate increase, the convergence speed of the system slows down. The number of iterations required to track the desired trajectory of the system output also increases. At the same time, since the parameter values satisfy the convergence condition of the theorem, the system can remain stable. But when the selected parameters do not meet the convergence conditions, the output tracking effect of the system is very poor.

In general, the control method proposed in this paper effectively reduces the impact of the time-delay disturbances and data loss failures disturbances on the system performance, and enhances the system robustness. When the data loss rate is relatively high (20%~30%) in dual channels, the system still has good tracking performance, which shows that the iterative learning algorithm is indeed effective and feasible.

5. CONCLUSIONS

For the nonlinear NCSs with dual-channel data packet loss and time-delay failure, the fault-tolerant control of trajectory tracking is studied based on iterative learning algorithm. Bernoulli random variables with known probabilities are used to describe data loss and time-delay. The failure model is established. The PD-type iterative learning fault-tolerant control algorithm is proposed and the robust convergence conditions are given. Finally, the simulation study is done. The simulation results show that when the system parameters and random variable values meet the given dynamic convergence conditions, under the dual-channel data packet loss failure and time-delay conditions, the method in this paper has fast convergence of the trajectory, which is useful for tracking the desired curves. It effectively reduces the impact of data packet loss and time-delay disturbance on system performance, which verifies the effectiveness of the control algorithm.

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REFERENCES

Arman S, Alireza A, and Mohammad A A F, et al. (2018). Security challenges of networked control systems. Sustainable Interdependent Networks. 145(2), 77-95.

Bu Xuhui,YU Fashan,Hou Zhongsheng and WANG Fuzhong. (2012). Iterative learning control for a class of nonlinear systems with measurement dropouts. Control Theory & Applications. 29(11),1458-1464.

Chen H, Gao J, Shi T and Lu R. (2016). H_∞ control for networked control systems with time delay, datapacket dropout and disorder. Neurocomputing. 179(C),211-218.

Devasia and Santosh.(2016). Iterative learning control with time-partitioned update for collaborative output tracking. Automatica, 69, 258-264.

Dutta Sandip and Smith Reid.(2020). Nonlinear Optimization of Turbine Conjugate Heat Transfer with Iterative Machine Learning and Training Sample Replacement. Energies,13(17), 4587.

Edwin G.W. Peters, Damian Marelli and Daniel E, et al.(2019). Predictive control for networked systems affected by correlated packet loss. International Journal of Robust and Nonlinear Control, 29(15),5078-5094.

Fu Xingjian and Geng Xinyao. (2021). Fault Estimation and Robust Fault-tolerant Control for Singular Markov Switching Systems with Mixed Time-Delays and UAV Applications. Control Engineering and Applied Informatics,23(2), 53-66.

Ghorbani Saeid, Safavi Ali Akbar and Naghavi S Vahid. (2021). Event-triggered robust model predictive control for Lipschitz nonlinear networked control systems subject to communication delays. Transactions of the Institute of Measurement and Control,43(5), 1126-1142.

He Zhiyu and XU Ning.(2020). Research on Automatic Train Operation Algorithm Based on Non-parametric Iterative Learning Control. Journal of the China Railway Society. 42(12),90-96.

Jia Yanlong. (2019). Application of Iterative Learning Control to Networked Control Systems with Data Dropouts. Yanshan University.

Li Hongfei, Pan Jie and Zhang Xiaoyu, et al.(2021). Integral-based event-triggered fault estimation and impulsive fault-tolerant control for networked control systems applied to underwater vehicles. Neurocomputing, 442(02), 36-47.

Li Li, Liu Yang,Yang Zhile and Tan Jiubin.(2020). Method to improve convergence performance of iterative learning control systems with bounded noise. Journal of the Franklin Institute,357(3),1644-1670.

Liu Bin,Zhou He,LI Yulong and Cui Yangyang. (2018). Fault-tolerant H_∞ Control for Networked Control Systems with Actuator Failures and Distributed Delays. Control and Instruments in Chemical Industry. 45(5), 348-352.

Liu K, Fridman E and Johansson K H. (2015). Networked control with stochastic scheduling. IEEE Transactions on Automatic Control, 60(11), 3071-3076.

Mohammad Mahdi Azimi, Ali Akbar Afzalian and Reza Ghaderi.(2021). Decentralized stabilization of a class of large scale networked control systems based on modified event-triggered scheme. International Journal of Dynamics and Control, 9(1),149-159.

Mohsen Bahreini and Jafar Zarei.(2020). Robust finitetime fault-tolerant control for networked control systems with random delays: A Markovian jump system approach. Nonlinear Analysis: Hybrid Systems,36(05),45-52.

Qiao J Z, Wu H and Zhu Y, et al.(2019). Anti-disturbance iterative learning tracking control for space manipulators with repetitive reference trajectory.Assembly Automation, 39, 401-409.

Roy Avinash Kumar and Srinivasan K. (2020). State estimation for a networked control system with packet delay, packet dropouts and uncertain observation in S-E and C-A channels. Optimal Control Applications and Methods, 41(6),2094-2114.

Tian Zhongda.(2021). Networked control system time-delay compensation based on PI-based dynamic matrix control. at-Automatisierungstechnik, 69(1),41-51.

Wang L, Shen Y and Yu J, et al.(2018). Robust iterative learning control for multi-phase batch processes: an average dwell-time method with 2D convergence indexes. International Journal of Systems Science, 49, 324-343.

Wang Limin,Yu Jingxian,Li Ping,Li Haisheng and Zhang Ridong.(2020). A 2D-FM model-based robust iterative learning model predictive control for batch processes. ISA Transactions,110(10),271-282.

Wei J, Zhang Y and Bao H.(2017). An exploration on adaptive iterative learning control for a class of commensurate high-order uncertain nonlinear fractional order systems. IEEE/CAA Journal of automatica sinica, 5, 618-627.

Xie C H and Yang G H. (2016). Data-based fault-tolerant control for uncertain linear systems with actuator faults. IET Control Theory & Applications.10(3),265-272.

Xiong Wenjun, Ho Daniel W.C. and Wen Shifan.(2021). A periodic iterative learning scheme for finite-iteration tracking of discrete networks based on FlexRay communication protocol. Information Sciences,548,344-356.

Zhou Ying and He Lei. (2017). Iterative learning control for linear motor system with control delay and measurement dropout. Control and Decision. 32(08),1434-1438.

Zhu Q, Lu K and Xie G, et al.(2015). Guaranteed cost fault-tolerant control for networked control systems with sensor faults. Mathematical Problems in Engineering, (6),1-9.

Zhang H , Zhang Z and Wang Z, et al. (2017). New Results on Stability and Stabilization of Networked Control Systems with Short Time-Varying Delay. IEEE Transactions on Cybernetics, 46(12),2772-2781.

Zhang X, Han Q L and Yu X. (2016). Survey on Recent Advances in Networked Control Systems. IEEE Transactions on Industrial Informatics, 12(5),1740-1752.

Zhang YinJun.(2014). Data Loss for Power Line Communication of Nonlinear Systems Iterative Learning Control. Advanced Materials Research,3569,537-540.

Zhao Li and Jiang Dongnian.(2020). Co-design of robust fault-tolerant control and communication for NCS based on AETCS. Journal of Yangzhou University(Natural Science Edition). 23(4),42-47