Received: 29 June 2023 | Revised: 15 November 2023 | Accepted: 25 December 2023

DOI: 10.1002/asjc.3317

RESEARCH ARTICLE

WILEY

Adaptive tracking control for a class of nonlinear systems with intermittent actuator faults under prescribe output tracking performance

Li-Ting Lu[1] | Yu-Qun Han[1,2,3] | Dong-Mei Wang[1] | Shan-Liang Zhu[1,2,3] | Qing-Hua Zhou[1]

[1]School of Mathematics and Physics, Qingdao University of Science and Technology, Qingdao, China

[2]Research Institute for Mathematics and Interdisciplinary Sciences, Qingdao University of Science and Technology, Qingdao, China

[3]Qingdao Innovation Center of Artificial Intelligence Ocean Technology, Qingdao, China

Correspondence
Qing-Hua Zhou, School of Mathematics and Physics, Qingdao University of Science and Technology, Qingdao 266061, China.
Email: QinghuaZhouQKD1909@163.com

Abstract

This paper investigates the adaptive tracking control problem of a class of nonlinear systems with intermittent actuator faults and prescribed performance. In the backstepping design process, a performance function is incorporated to ensure that the tracking error adheres to the prescribed performance criteria. Simultaneously, multi-dimensional Taylor networks are used to approximate the unknown nonlinear functions in the system. Subsequently, to avoid jumps in the improved Lyapunov function when faults occur, a boundary estimation method is presented, which effectively compensates for the impact of intermittent actuator faults. Ultimately, based on Lyapunov stability theory, it is proven that all signals of the closed-loop system are bounded, and the tracking error can satisfy the prescribed transient and steady-state performance. Simulation results demonstrate the effectiveness of the proposed scheme.

KEYWORDS

adaptive control, intermittent actuator faults, multi-dimensional Taylor network, nonlinear systems, prescribed performance

1 | INTRODUCTION

Actuators in control systems may encounter partial loss of effectiveness (PLOE) faults or total loss of effectiveness (TLOE) faults during operation. If not managed properly, these faults can lead to system instability. Therefore, addressing actuator faults is an important topic in control systems. So far, numerous effective solutions have been developed to solve this problem, such as pseudo-inverse method [1], sliding mode control [2, 3], multiple-model [4, 5], learning-based approaches [6, 7], and adaptive control [8–13]. Adaptive control is particularly advantageous as it does not require fault detection and diagnosis, and it can adaptively update control parameters by estimating faults or fault-induced uncertainties in real-time. Authors in [9–12] proposed an adaptive control scheme to the tracking control problem in linear systems. Building upon backstepping control technology, the results of [9–12] were extended to nonlinear systems in [8, 13]. However, these control schemes are built on the assumption that the controlled system is either known or possesses simple unknown parameters. In cases where the system is completely unknown, the aforementioned control schemes become ineffective.

To overcome this challenge, several adaptive control schemes based on neural network [14, 15], fuzzy logic [16, 17], or multi-dimensional Taylor network (MTN) [18–20] have been proposed to solve various uncertain nonlinear systems with actuator faults. Among these schemes, MTN has gained widespread attention [21–23] due to its straightforward structure and its ability to swiftly approximate functions. However, it is important to note that all of the previously mentioned control schemes assume a finite number of actuator faults. As highlighted in [24], actuator faults often occur infinitely, leading to the growing prevalence of intermittent faults characterized by frequent oscillations between normal and faulty states. To address the challenge of intermittent actuator faults, authors in [24] pioneered an adaptive modular scheme for a class of multi-input single-output nonlinear systems with intermittent actuator faults, under the assumption that the boundary knowledge of the unknown terms caused by actuator faults is known. Building on the insights from [24], a series of methods [25–27] have been introduced to tackle intermittent actuator faults. Among these, authors in [27] proposed a boundary estimation method that does not require knowledge of uncertain boundaries. It is worth noting that the schemes mentioned earlier [25–27] primarily focus on the steady-state performance of the system and do not take into account the transient performance.

Therefore, in addition to ensuring steady-state performance, improving the transient performance of the system is also of paramount importance. To achieve this goal, the concept of prescribed performance control (PPC) was developed and first introduced in [28]. This control approach employs error transformation technique and introduces a performance function. By adjusting the performance function, it enables the tracking error to satisfy the prescribed transient and steady-state performance (e.g., overshoot, convergence rate, and steady-state error). Given varying performance requirements, numerous performance functions [29–31] have been proposed, and PPC has gained widespread attention in various nonlinear systems, including general nonlinear systems [32, 33], stochastic nonlinear systems [34, 35], large-scale nonlinear systems [36, 37], nonlinear multi-agent systems [38, 39], and switched nonlinear systems [40, 41]. However, as mentioned earlier, the actuator faults often destroy the performance of a system. Despite the considerable number of fault compensation methods developed to date, improving the performance of fault-affected systems remains paramount. Hence, conducting research on applying PPC technology to enhance the performance of nonlinear systems with actuator faults is highly meaningful. Most existing studies [42–45] have primarily focused on a limited number of faults and have not extended their scope to intermittent actuator faults. Therefore, it holds great significance to design a PPC scheme that can effectively address intermittent actuator faults and simultaneously achieve good transient and steady-state performance for the system's tracking error.

Based on the above discussion, this paper focuses on the adaptive tracking control problem of a class of nonlinear systems with prescribed performance and intermittent actuator faults. Compared with existing results, the main contributions of this paper can be summarized as follows:

(1) This article introduces an improved adaptive tracking control scheme for nonlinear systems afflicted by intermittent actuator faults. The scheme ensures that the tracking error complies with prescribed transient and steady-state performance criteria. In contrast to the method primarily focusing on steady-state performance in [25–27], this paper also takes into consideration the transient performance of the tracking error. The adjustment of the parameters of the proposed performance function allows for meeting both transient and steady-state performance requirements.
(2) Differing from the fault model considered in [8, 13], this paper allows for an unlimited occurrence of actuator faults, which is more practical in practical scenarios. Furthermore, unlike the method for handling intermittent actuator faults described in [24], this paper utilizes a boundary estimation approach without requiring knowledge of boundary information.
(3) Although intermittent actuator faults were considered in [24–27], the issue of prescribed performance was not addressed. Similarly, while [32, 33] addressed the issue of prescribed performance, the problem of intermittent actuator faults was not considered. This paper addresses a more representative problem by simultaneously considering both intermittent actuator faults and prescribed performance.

2 | PROBLEM FORMULATION

2.1 | Nonlinear system

Consider a class of uncertain strict-feedback nonlinear systems with intermittent actuator faults described by

$$\begin{cases} \dot{x}_i = x_{i+1} + f_i(\bar{x}_i) + \Delta_i(t) \\ \quad i = 1, 2, \cdots, n-1 \\ \dot{x}_n = \sum_{j=1}^{l} \kappa_j u_j + f_n(\bar{x}_n) + \Delta_n(t) \\ \quad y = x_1 \end{cases} \tag{1}$$

where $\bar{x}_i = [x_1, x_2, \ldots, x_i]^{\mathrm{T}} \in \mathbf{R}^i$, $\bar{x}_n = [x_1, x_2, \ldots, x_n]^{\mathrm{T}} \in \mathbf{R}^n$ and $y \in \mathbf{R}$ represent the system states and output, respectively. $u_j \in \mathbf{R}$ denotes the jth control input of the system. κ_j is an unknown constant which is non-zero. $f_i(\cdot)$ represents an unknown nonlinear function satisfying $f_i(\boldsymbol{0}) = 0$. $\Delta_i(t)$ represents the system disturbance,

TABLE 1 Different types of actuator faults.

Fault types	$\rho_j^q(t)$	$\bar{u}_j^q(t)$
No faults	$\rho_j^q(t)=1$	$\bar{u}_j^q(t)=0$
PLOE	$0<\rho_j^q(t)<1$	$\bar{u}_j^q(t)=0$
TLOE	$\rho_j^q(t)=0$	$\bar{u}_j^q(t)\neq 0$

for which an unknown constant $\bar{\Delta}_i > 0$ exists, such that $|\Delta_i(t)| \leq \bar{\Delta}_i$.

Similar to [46], we denote u_{cj} $(j = 1, 2, \dots, \iota)$ as the input to the jth actuator. In the absence of actuator faults, the output of the actuator u_j equals its input u_{cj}, that is, $u_j = u_{cj}$. If the jth actuator experiences intermittent faults, the fault model can be described as follows:

$$\begin{cases} u_j = \rho_j^q(t)u_{cj} + \bar{u}_j^q(t) \\ \rho_j^q(t)\bar{u}_j^q(t) = 0, t \in [t^q, t^{q+1}) \end{cases} \tag{2}$$

where $j = 1, 2 \dots \iota, q \in N^+$ denotes the number of occurrence of faults, $\rho_j^q(t) \in [0, 1)$ and $\bar{u}_j^q(t)$ represent the unknown time-varying fault parameters, t^q denotes the unknown time of fault occurrence, and $0 \leq t^q < t^{q+1}$. Based on the different values of $\rho_j^q(t)$ and $\bar{u}_j^q(t)$, the actuators can be classified into different types of faults, as shown in Table 1.

Remark 1. In (2), the fault parameters $\rho_j^q(t)$ and $\bar{u}_j^q(t)$ are both unknown time-varying functions, and the fault occurrence number q is also not limited. This indicates that the actuator can transition intermittently an infinite number of times between one fault and another, and the unknown variables t^q, $\rho_j^q(t)$, and $\bar{u}_j^q(t)$ suggest that the fault information is completely unpredictable. Moreover, the actuator fault model (2) is more general compared to previous works [8, 13]. It is applicable not only to actuator faults with uniform interval periods but also to those with non-uniform interval periods.

The objective of the control is to design an adaptive tracking controller for nonlinear system (1) with intermittent actuator faults and prescribed performance such that

P1. All signals of the closed-loop system are bounded.
P2. The system's output y can track the desired output y_d, and the tracking error $e_1(t) = y(t) - y_d(t)$ can meet the specified transient and steady-state tracking performance requirements.

To achieve the above objectives, the following assumptions need to be provided.

Assumption 1. Within each time interval $[t^q, t^{q+1})$, if no more than $\iota - 1$ actuators experience TLOE faults, the remaining actuators can still achieve the control objectives of the system.

Assumption 2. The sign of κ_j is known (i.e., $\mathrm{sgn}(\kappa_j)$ is known), where $j = 1, 2, \dots, \iota$.

Assumption 3. In the case of PLOE faults, there exist unknown constants $\underline{\rho}_j$ such that $0 < \underline{\rho}_j \leq \rho_j^q(t) \leq 1$ for the fault parameter $\rho_j^q(t)$, where $j = 1, 2, \dots, \iota$. In the case of TLOE faults, there exists an unknown constant $\bar{\bar{u}}_j > 0$ such that $\left|\bar{u}_j^q(t)\right| \leq \bar{\bar{u}}_j$ for the fault parameter $\bar{u}_j^q(t)$.

Assumption 4. Reference y_d and its up to n th order derivatives are known and bounded.

Remark 2. Assumption 1 is commonly found in existing literatures [47, 48] to ensure controllability. It should be noted that as long as at least one actuator is not in the TLOE state, it is permissible for the actuators to simultaneously experience either the PLOE or TLOE state. In Assumption 3, $\underline{\rho}_j$ and $\bar{\bar{u}}_j$ represent the bounds of actuator faults with PLOE and TLOE types, which are utilized to guarantee the controllability of the system and are widely adopted in most existing studies [18–20]. Assumptions 2 and 4 are fairly standard assumptions in many literatures [48, 49] addressing the adaptive backstepping control problem. They serve as necessary conditions for the design of the controller.

Lemma 1 ([47]). *For any scalar function $\chi > 0$ and $z_f \in \mathbf{R}$, the inequality $0 \leq |z_f| - \frac{z_f^2}{\sqrt{z_f^2+\chi^2}} < \chi$ holds.*

2.2 | Multi-dimensional Taylor network

The MTN is a unique neural network consisting of three layers: the input layer, the middle layer, and the output layer. The topological depiction of the MTN is illustrated in Figure 1. In this diagram, $z_1, z_2, \dots, z_n$ represent the inputs of the MTN. The middle layer encompasses a polynomial combination of these inputs, effectively mapping the input space to a new space. The mathematical expression for the output layer is as follows:

$$f_{MTN}(\boldsymbol{Z}) = \boldsymbol{\theta}^{\mathrm{T}} S_{m_n}(\boldsymbol{Z}) \tag{3}$$

where $\boldsymbol{Z} = [z_1, z_2, \dots z_n]^{\mathrm{T}} \in \Omega_{\boldsymbol{Z}} \subset \mathbf{R}^n, \boldsymbol{\theta} = [\theta_1, \theta_2, \dots, \theta_l]^{\mathrm{T}} \in \mathbf{R}^l$ are the input vector and the weight vector of the MTN. The form of element of vector $S_{m_n}(\boldsymbol{Z})$ is $\prod_{i,j=1}^{n} s_i^{\sigma_i} s_j^{\sigma_j}$, where σ_i and σ_j are nonnegative integers and

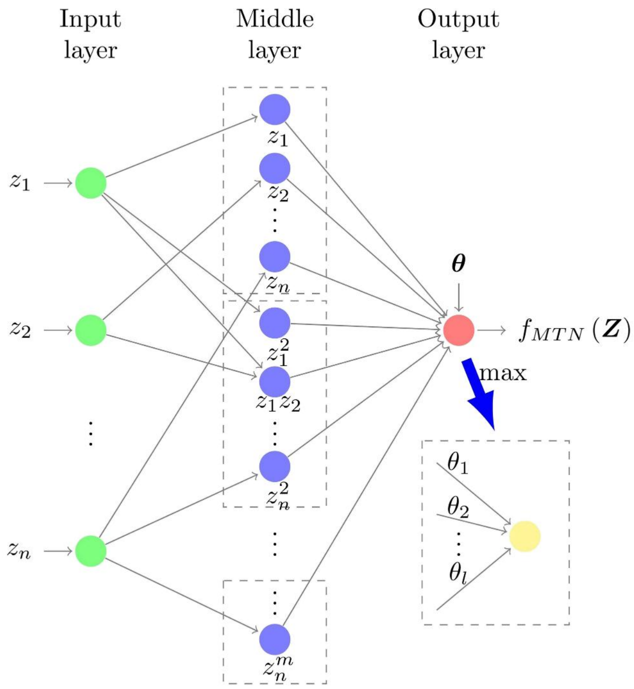


FIGURE 1 Topological structure of a multi-dimensional Taylor network (MTN).

satisfy $1 \leq \sigma_i + \sigma_j \leq m$, that is,

$$S_{m_n}(\boldsymbol{Z}) = [\underbrace{z_1, \ldots, z_n}_{1term}, \underbrace{z_1^2, z_1 z_2, \ldots, z_n^2}_{2term}, \ldots, \underbrace{z_1^m, \ldots, z_n^m}_{mterm}]^T \in \mathbf{R}^l \tag{4}$$

where n and l are the number of input dimensions and the middle layer of the MTN, respectively.

Lemma 2 ([50]). *For any given continuous function $f(\boldsymbol{Z})$ defined in a bounded closed set $\Omega_{\boldsymbol{Z}} \subset R^n$, for any $\varepsilon > 0$, there exist a MTN, such that*

$$f(\boldsymbol{Z}) = \boldsymbol{\theta}^{*\mathrm{T}} S_{m_n}(\boldsymbol{Z}) + \delta(\boldsymbol{Z}), \ |\delta(\boldsymbol{Z})| \leq \varepsilon \tag{5}$$

where $\delta(\boldsymbol{Z})$ is the approximation error, $\boldsymbol{\theta}^* = \left[\theta_1^*, \theta_2^*, \ldots, \theta_l^*\right]^{\mathrm{T}} \in R^l$ is the ideal constant weight vector and defined as $\boldsymbol{\theta}^* := \arg\min_{\boldsymbol{\theta} \in \boldsymbol{R}^l} \left\{ \sup_{\boldsymbol{Z} \in \boldsymbol{\Omega}_Z} \left| \delta(\boldsymbol{Z}) - \boldsymbol{\theta}^{\mathrm{T}} S_{m_n}(\boldsymbol{Z}) \right| \right\}$.

Remark 3. The structure of MTN has been outlined in [51, 52]. It is worth noting that, compared to neural networks, MTN has a simpler structure. The intermediate layers of a MTN consist of polynomial arrays involving only addition and multiplication operations. This simplicity greatly reduces the computational complexity. Additionally, the input–output characteristics of MTN are complex and dynamic, whereas most neural networks have single and static input-output characteristics. This implies that MTN has advantages such as ease of implementation, and strong learning capabilities. Overall, MTN offers a wide adaptability to the practical control of dynamic systems.

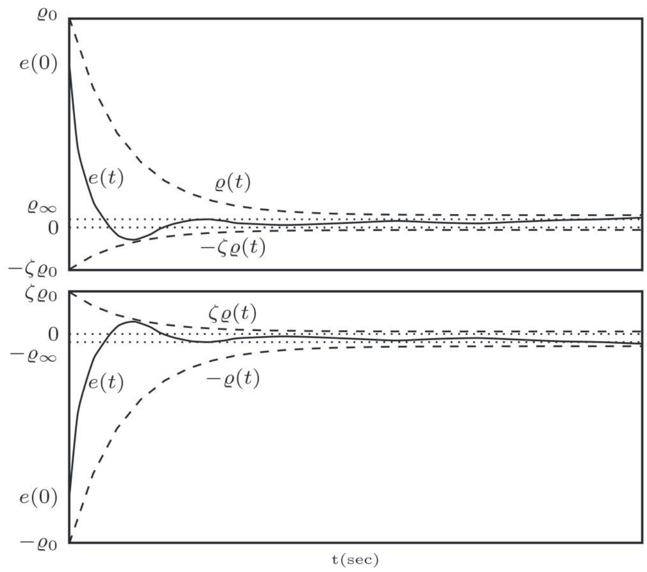


FIGURE 2 Tracking error prescribed performance.

3 | ADAPTIVE TRACKING CONTROLLER DESIGN

3.1 | Transformed system

In order to meet the transient and steady-state performance requirements of tracking error, error transformation is first performed in this paper, and the following decreasing performance function is selected:

$$\varrho(t) = (\varrho_0 - \varrho_\infty)e^{-\upsilon t} + \varrho_\infty \tag{6}$$

where υ is a positive constant that can adjust the convergence speed of the system. $\varrho_0 = \varrho(0) > 0$, $\varrho_\infty = \lim_{t\to\infty} \varrho(t) > 0$. If, for $t > 0$, the tracking error $e_1(t)$ satisfies

$$\begin{cases} -\zeta\varrho(t) < e_1(t) < \varrho(t) \ , \text{if } e_1(0) > 0 \\ -\varrho(t) < e_1(t) < \zeta\varrho(t) \ , \text{if } e_1(0) < 0 \end{cases} \tag{7}$$

and then control objective P2 can be achieved, where $0 \leq \zeta \leq 1$. The constant ϱ_∞ represents the maximum allowable value of $e_1(t)$ when the system reaches steady state, and ϱ_0 represents the maximum allowable value of $e_1(t)$ during transient periods. The appropriate selection of the performance function $\varrho(t)$ and the constant ζ imposes performance boundaries on the system's tracking error, as shown in Figure 2.

As same as [53], this paper proposes an error transformation that can equivalently transform a nonlinear system with constrained tracking error behavior into a system without such behavior. The transformation is defined by the following equation:

$$e_1(t) = \varrho(t)S(z_1) \tag{8}$$

where z_1 is the transformed error, $S(z_1)$ is a smooth and increasing function and meets the following properties:

$$\begin{cases} \lim_{z_1\to\infty} S(z_1) = 1, \lim_{z_1\to-\infty} S(z_1) = -\zeta, -\zeta < S(z_1) < 1 & \text{, if } e_1(0) > 0 \\ \lim_{z_1\to\infty} S(z_1) = \zeta, \lim_{z_1\to-\infty} S(z_1) = -1, -1 < S(z_1) < \zeta & \text{, if } e_1(0) < 0 \end{cases}.$$

In this article, a function $S(z_1)$ satisfying these properties is chosen as $S(z_1) = \begin{cases} \frac{e^{z_1}-\zeta e^{-z_1}}{e^{z_1}+e^{-z_1}} & \text{, if } e_1(0) > 0 \\ \frac{\zeta e^{z_1}-e^{-z_1}}{e^{z_1}+e^{-z_1}} & \text{, if } e_1(0) < 0 \end{cases}$. Then, based on (8), the inverse transformation can be obtained as follows:

$$z_1 = S^{-1}\left(\frac{e_1}{\varrho}\right) = \begin{cases} \frac{1}{2}\ln\left(\frac{e_1/\varrho+\zeta}{1-e_1/\varrho}\right) & \text{, if } e_1(0) > 0 \\ \frac{1}{2}\ln\left(\frac{e_1/\varrho+1}{\zeta-e_1/\varrho}\right) & \text{, if } e_1(0) < 0 \end{cases} \tag{9}$$

with its derivative being $\dot{z}_1 = \begin{cases} \frac{1}{2\varrho}\left(\frac{1}{e_1/\varrho+\zeta} - \frac{1}{e_1/\varrho-1}\right)\left(\dot{e}_1 - \frac{\dot{\varrho}}{\varrho}e_1\right) & \text{, if } e_1(0) > 0 \\ \frac{1}{2\varrho}\left(\frac{1}{(e_1/\varrho+1}-\frac{1}{(e_1/\varrho-\zeta}\right)\left(\dot{e}_1 - \frac{\dot{\varrho}}{\varrho}e_1\right) & \text{, if } e_1(0) < 0 \end{cases}$.

Subsequently, according to $e_1 = y - y_d$, and in conjunction with (1), we get

$$\dot{z}_1 = r\left(-v + x_2 + f_1(\bar{x}_1) + \Delta_1(t)\right) \tag{10}$$

where $r = \begin{cases} \frac{1}{2\varrho}\left(\frac{1}{e_1/\varrho+\zeta} - \frac{1}{e_1/\varrho-1}\right) & \text{, if } e_1(0) > 0 \\ \frac{1}{2\varrho}\left(\frac{1}{(e_1/\varrho+1}-\frac{1}{e_1/\varrho-\zeta}\right) & \text{, if } e_1(0) < 0 \end{cases}$, $v = \dot{y}_d + \frac{\dot{\varrho}}{\varrho}e_1$. Thus, the equivalent system after the transformation is

$$\begin{cases} \dot{z}_1 = r\left(-v + x_2 + f_1(\bar{x}_1) + \Delta_1(t)\right) \\ \dot{x}_2 = x_3 + f_2(\bar{x}_2) + \Delta_2(t) \\ \cdots \\ \dot{x}_n = \sum_{j=1}^{l} \kappa_j u_j + f_n(\bar{x}_n) + \Delta_n(t) \end{cases} \tag{11}$$

According to the properties of $S(z_1)$, it can be concluded that $r > 0$. So (11) remains in strict feedback form. The system (1) is invariant under the error transformation (8).

Remark 4. (1) If $e_1(0) = 0$, then $\zeta = 0$ cannot be chosen, as it would result in $z_1(0)$ being infinite. However, $S(z_1)$ can still be defined, and in this case, treating $e_1(0)$ as either less than or greater than zero has no effect on the analysis.

(2) When $e_1(0) > 0$, the upper bound for the prescribed performance is $\lim_{z_1\to\infty} S(z_1)\varrho(t) = \varrho(t)$, and the lower bound is $\lim_{z_1\to-\infty} S(z_1)\varrho(t) = -\zeta\varrho(t)$. When $e_1(0) < 0$, the upper bound is $\lim_{z_1\to\infty} S(z_1)\varrho(t) = \zeta\varrho(t)$, and the lower bound is $\lim_{z_1\to-\infty} S(z_1)\varrho(t) = -\varrho(t)$.

(3) According to (6)–(9), the tracking error $e_1(t)$ of the system is transformed into a new variable z_1. If z_1 is bounded, then $e_1(t)$ will always be able to be preserved within the range of $(-\zeta\varrho(t), \varrho(t))$ or $(-\varrho(t), \zeta\varrho(t))$.

Remark 5. Many improved performance functions, such as finite-time convergence [54], fragility-avoidance prescribed performance [55, 56], have been developed to meet specific performance requirements. However, this often results in complex formulations of the performance function, which can hinder the engineering implementation of the PPC algorithm. In this study, a simpler and more feasible performance function structure is adopted for ease of implementation.

3.2 | Controller design

In this section, in the framework of backstepping technique, this paper proposes an adaptive tracking controller for the nonlinear system (1) with intermittent actuator faults and prescribed performance.

First, the following coordinate transformation is given

$$\begin{cases} z_1 = S^{-1}\left(\frac{e_1}{\varrho}\right) \\ z_{i+1} = x_{i+1} - \alpha_i, 1 \le i \le n-1 \end{cases} \tag{12}$$

where α_i represents the virtual control signal, which will be designed later in this paper.

Now, we begin to design the controller.

Step 1: Choosing the first Lyapunov function as follows

$$V_1 = \frac{1}{2}z_1^2 + \frac{1}{2}\tilde{\boldsymbol{\theta}}_1^{\mathrm{T}}\boldsymbol{\tau}_1^{-1}\tilde{\boldsymbol{\theta}}_1 \tag{13}$$

where $\boldsymbol{\tau}_1 > 0$ is an arbitrary positive definite matrix, $\boldsymbol{\theta}_1$ represents the weight vector of the MTN, $\hat{\boldsymbol{\theta}}_1$ represents the estimation of $\boldsymbol{\theta}_1$, and $\tilde{\boldsymbol{\theta}}_1 = \boldsymbol{\theta}_1 - \hat{\boldsymbol{\theta}}_1$ represents the parameter error vector.

Thus, according to (10) and (13), its derivative with respect to time is

$$\dot{V}_1 = z_1\left(-rv + rx_2 + rf_1(\bar{x}_1) + r\Delta_1(t)\right) - \tilde{\boldsymbol{\theta}}_1^{\mathrm{T}}\boldsymbol{\tau}_1^{-1}\dot{\hat{\boldsymbol{\theta}}}_1 \tag{14}$$

Next, using Young's inequality, we obtain

$$z_1 r\Delta_1(t) \le \frac{1}{2}r^2 z_1^2 + \frac{1}{2}\bar{\Delta}_1^2 \tag{15}$$

Naturally, substituting (15) into (14), we obtain

$$\dot{V}_1 \leq z_1 \bar{f}_1 + r z_1 x_2 - \frac{1}{2} z_1^2 + \frac{1}{2}\bar{\Delta}_1^2 - \tilde{\theta}_1^{\mathrm{T}} \tau_1^{-1} \dot{\hat{\theta}}_1 \tag{16}$$

where $\bar{f}_1 = -rv + r f_1(\bar{x}_1) + \frac{1}{2} r^2 z_1 + \frac{1}{2} z_1$.

Given that $f_1(\bar{x}_1)$ is not known, $\bar{f}_1$ remains an unknown function. According to Lemma 2, leveraging the approximation properties of MTN, it is possible to employ a MTN for estimating $\bar{f}_1$. More specifically, for any $\varepsilon_1 > 0$, there exists

$$\bar{f}_1 = \theta_1^{\mathrm{T}} S_{m_1}(\boldsymbol{Z}_1) + \delta_1(\boldsymbol{Z}_1), \ |\delta_1(\boldsymbol{Z}_1)| \leq \varepsilon_1 \tag{17}$$

where $\boldsymbol{Z}_1 = [z_1]^{\mathrm{T}}$, and $\delta_1(\boldsymbol{Z}_1)$ is the approximation error.

Subsequently, substituting (17) into (16) and applying the Young's inequality along with (12), we obtain

$$\dot{V}_1 \leq z_1 \left(r z_2 + r\alpha_1 + \theta_1^{\mathrm{T}} S_{m_1} \right) + \frac{1}{2}\varepsilon_1^2 + \frac{1}{2}\bar{\Delta}_1^2 - \tilde{\theta}_1^{\mathrm{T}} \tau_1^{-1} \dot{\hat{\theta}}_1 \tag{18}$$

Thus, the virtual control signal α_1 is designed as follows:

$$\alpha_1 = -\frac{1}{r}\left(k_1 z_1 + \hat{\theta}_1^{\mathrm{T}} S_{m_1}(\boldsymbol{Z}_1) \right) \tag{19}$$

where $k_1 > 0$ is a design parameter.

Then, substituting (19) into (18) yields

$$\dot{V}_1 \leq -k_1 z_1^2 + z_1 r z_2 + \frac{1}{2}\varepsilon_1^2 + \frac{1}{2}\bar{\Delta}_1^2 + \tilde{\theta}_1^{\mathrm{T}} \left(z_1 S_{m_1} - \tau_1^{-1} \dot{\hat{\theta}}_1 \right) \tag{20}$$

Clearly, we can choose the adaptive law $\dot{\hat{\theta}}_1$ as

$$\dot{\hat{\theta}}_1 = z_1 \tau_1 S_{m_1}(\boldsymbol{Z}_1) - \eta_1 \tau_1 \hat{\theta}_1 \tag{21}$$

where $\eta_1 > 0$ is a design parameter.

Eventually, substituting (21) into (20), we obtain

$$\dot{V}_1 \leq -k_1 z_1^2 + z_1 r z_2 + \frac{1}{2}\varepsilon_1^2 + \frac{1}{2}\bar{\Delta}_1^2 + \eta_1 \tilde{\theta}_1^{\mathrm{T}} \hat{\theta}_1 \tag{22}$$

Step 2: Choosing the second Lyapunov function as follows:

$$V_2 = V_1 + \frac{1}{2} z_2^2 + \frac{1}{2}\tilde{\theta}_2^{\mathrm{T}} \tau_2^{-1} \tilde{\theta}_2 \tag{23}$$

where $\tau_2 > 0$ is an arbitrary positive definite matrix, θ_2 represents the weight vector of the MTN, $\hat{\theta}_2$ represents the estimation of θ_2, and $\tilde{\theta}_2 = \theta_2 - \hat{\theta}_2$ represents the parameter error vector.

Based on (11), (12), and (23), its derivative with respect to time is

$$\dot{V}_2 = \dot{V}_1 + z_2 \left(x_3 + f(\bar{x}_2) + \Delta_2(t) - \dot{\alpha}_1 \right) - \tilde{\theta}_2^{\mathrm{T}} \tau_2^{-1} \dot{\hat{\theta}}_2 \tag{24}$$

Next, using Young's inequality, we obtain

$$z_2 \Delta_2(t) \leq \frac{1}{2} z_2^2 + \frac{1}{2}\bar{\Delta}_2^2 \tag{25}$$

Naturally, substituting (25) into (24), we obtain

$$\dot{V}_2 \leq \dot{V}_1 + z_2 \bar{f}_2 + z_2 x_3 - r z_1 z_2 - \frac{1}{2} z_2^2 + \frac{1}{2}\bar{\Delta}_2^2 - \tilde{\theta}_2^{\mathrm{T}} \tau_2^{-1} \dot{\hat{\theta}}_2 \tag{26}$$

where $\bar{f}_2 = f_2(\bar{x}_2) - \dot{\alpha}_1 + r z_1 + z_2$.

Similar to step 1, $\bar{f}_2$ is also an unknown function. According to Lemma 2, leveraging the approximation properties of MTN, it is possible to employ a MTN for estimating $\bar{f}_2$. More specifically, for any $\varepsilon_2 > 0$, there exists

$$\bar{f}_2 = \theta_2^{\mathrm{T}} S_{m_2}(\boldsymbol{Z}_2) + \delta_2(\boldsymbol{Z}_2), \ |\delta_2(\boldsymbol{Z}_2)| \leq \varepsilon_2 \tag{27}$$

where $\boldsymbol{Z}_2 = [z_1, z_2]^{\mathrm{T}}$ and $\delta_2(\boldsymbol{Z}_2)$ is the approximation error.

Subsequently, substituting (27) into (26) and applying the Young's inequality along with (12), we obtain

$$\dot{V}_2 \leq \dot{V}_1 + z_2 \left(z_3 + \alpha_2 + \theta_2^{\mathrm{T}} S_{m_2} \right) + \frac{1}{2}\varepsilon_2^2 + \frac{1}{2}\bar{\Delta}_2^2 - r z_1 z_2 - \tilde{\theta}_2^{\mathrm{T}} \tau_2^{-1} \dot{\hat{\theta}}_1 \tag{28}$$

Thus, the virtual control signal α_2 is designed as follows:

$$\alpha_2 = -k_2 z_2 - \hat{\theta}_2^{\mathrm{T}} S_{m_2}(\boldsymbol{Z}_2) \tag{29}$$

where $k_2 > 0$ is a design parameter.

Then, substituting (29) into (28) and according to (20) yields

$$\dot{V}_2 \leq -\sum_{\lambda=1}^{2} k_\lambda z_\lambda^2 + \sum_{\lambda=1}^{2} \frac{1}{2}\varepsilon_\lambda^2 + \sum_{\lambda=1}^{2} \frac{1}{2}\bar{\Delta}_\lambda^2 + \tilde{\theta}_2^{\mathrm{T}} \left(z_2 S_{m_2} - \tau_2^{-1} \dot{\hat{\theta}}_2 \right) + \eta_1 \tilde{\theta}_1^{\mathrm{T}} \hat{\theta}_1 + z_2 z_3 \tag{30}$$

Clearly, we can choose the adaptive law $\dot{\hat{\theta}}_2$ as

$$\dot{\hat{\theta}}_2 = z_2 \tau_2 S_{m_2}(\boldsymbol{Z}_2) - \eta_2 \tau_2 \hat{\theta}_2 \tag{31}$$

where $\eta_2 > 0$ is a design parameter.

Eventually, substituting (31) into (30), we obtain

$$\dot{V}_2 \leq -\sum_{\lambda=1}^{2} k_\lambda z_\lambda^2 + \sum_{\lambda=1}^{2} \frac{1}{2}\varepsilon_\lambda^2 + \sum_{\lambda=1}^{2} \frac{1}{2}\bar{\Delta}_\lambda^2 + \sum_{\lambda=1}^{2} \eta_\lambda \tilde{\theta}_\lambda^{\mathrm{T}} \hat{\theta}_\lambda + z_2 z_3 \tag{32}$$

Step i ($i = 3, \ldots, n-1$): Choosing the ith Lyapunov function as follows:

$$V_i = V_{i-1} + \frac{1}{2} z_i^2 + \frac{1}{2}\tilde{\theta}_i^{\mathrm{T}} \tau_i^{-1} \tilde{\theta}_i \tag{33}$$

where $\tau_i > 0$ is an arbitrary positive definite matrix, θ_i represents the weight vector of the MTN, $\hat{\theta}_i$ represents the estimation of θ_i, and $\tilde{\theta}_i = \theta_i - \hat{\theta}_i$ represents the parameter error vector.

Based on (11), (12), and (33), its derivative with respect to time is

$$\dot{V}_i = \dot{V}_{i-1} + z_i \left(x_{i+1} + f(\bar{x}_i) + \Delta_i(t) - \dot{\alpha}_{i-1} \right) - \tilde{\theta}_i^{\mathrm{T}} \tau_i^{-1} \dot{\hat{\theta}}_i \tag{34}$$

Next, using the Young's inequality, we obtain

$$z_i \Delta_i(t) \leq \frac{1}{2} z_i^2 + \frac{1}{2} \bar{\Delta}_i^2 \tag{35}$$

Naturally, substituting (35) into (34), we obtain

$$\dot{V}_i \leq \dot{V}_{i-1} + z_i \bar{f}_i + z_i x_{i+1} - z_{i-1} z_i - \frac{1}{2} z_i^2 + \frac{1}{2} \bar{\Delta}_i^2 - \tilde{\theta}_i^{\mathrm{T}} \boldsymbol{\tau}_i^{-1} \dot{\hat{\theta}}_i \tag{36}$$

where $\bar{f}_i = f_i(\bar{x}_i) - \dot{\alpha}_{i-1} + z_i + z_{i-1}$.

Similar to step 1, $\bar{f}_i$ is also an unknown function. According to Lemma 2, leveraging the approximation properties of MTN, it is possible to employ a MTN for estimating $\bar{f}_i$. More specifically, for any $\varepsilon_i > 0$, there exists

$$\bar{f}_i = \boldsymbol{\theta}_i^{\mathrm{T}} S_{m_i}(\boldsymbol{Z}_i) + \delta_i(\boldsymbol{Z}_i), \; |\delta_i(\boldsymbol{Z}_i)| \leq \varepsilon_i \tag{37}$$

where $\boldsymbol{Z}_i = [z_1, z_2, \ldots, z_i]^{\mathrm{T}}$ and $\delta_i(\boldsymbol{Z}_i)$ is the approximation error.

Subsequently, substituting (37) into (36) and applying the Young's inequality along with (12), we obtain

$$\begin{aligned} \dot{V}_i \leq\; & \dot{V}_{i-1} + z_i \left(z_{i+1} + \alpha_i + \boldsymbol{\theta}_i^{\mathrm{T}} S_{m_i} \right) + \frac{1}{2}\varepsilon_i^2 + \frac{1}{2}\bar{\Delta}_i^2 \\ & - \tilde{\boldsymbol{\theta}}_i^{\mathrm{T}} \boldsymbol{\tau}_i^{-1} \dot{\hat{\boldsymbol{\theta}}}_i - z_{i-1} z_i \end{aligned} \tag{38}$$

Thus, the virtual control signal α_i is designed as follows:

$$\alpha_i = -k_i z_i - \hat{\boldsymbol{\theta}}_i^{\mathrm{T}} S_{m_i}(\boldsymbol{Z}_i) \tag{39}$$

where $k_i > 0$ is a design parameter.

Then, substituting (39) into (38) yields

$$\begin{aligned} \dot{V}_i \leq & -\sum_{\lambda=1}^{i} k_\lambda z_\lambda^2 + \sum_{\lambda=1}^{i} \frac{1}{2}\varepsilon_\lambda^2 + \sum_{\lambda=1}^{i} \frac{1}{2}\bar{\Delta}_\lambda^2 + \sum_{\lambda=1}^{i-1} \eta_\lambda \tilde{\boldsymbol{\theta}}_\lambda^{\mathrm{T}} \hat{\boldsymbol{\theta}}_\lambda \\ & + \tilde{\boldsymbol{\theta}}_i^{\mathrm{T}} \left(z_i S_{m_i} - \boldsymbol{\tau}_i^{-1} \dot{\hat{\boldsymbol{\theta}}}_i \right) + z_i z_{i+1} \end{aligned} \tag{40}$$

Clearly, we can choose the adaptive law $\dot{\hat{\boldsymbol{\theta}}}_i$ as

$$\dot{\hat{\boldsymbol{\theta}}}_i = z_i \boldsymbol{\tau}_i S_{m_i}(\boldsymbol{Z}_i) - \eta_i \boldsymbol{\tau}_i \hat{\boldsymbol{\theta}}_i \tag{41}$$

where $\eta_i > 0$ is a design parameter.

Eventually, substituting (41) into (40), we obtain

$$\dot{V}_i \leq -\sum_{\lambda=1}^{i} k_\lambda z_\lambda^2 + \sum_{\lambda=1}^{i} \frac{1}{2}\varepsilon_\lambda^2 + \sum_{\lambda=1}^{i} \frac{1}{2}\bar{\Delta}_\lambda^2 + \sum_{\lambda=1}^{i} \eta_\lambda \tilde{\boldsymbol{\theta}}_\lambda^{\mathrm{T}} \hat{\boldsymbol{\theta}}_\lambda + z_i z_{i+1} \tag{42}$$

Step n: By (2) and (11), we have

$$\dot{z}_n = \sum_{j=1}^{\iota} \kappa_j \rho_j^q(t) u_{cj} + \sum_{j=1}^{\iota} \kappa_j \bar{u}_j^q(t) + f_n(\bar{x}_n) + \Delta_n(t) - \dot{\alpha}_{n-1} \tag{43}$$

According to Assumption 3, when $t > 0$, $\sum_{j=1}^{\iota} |\kappa_j| \rho_j^q \geq min\left\{ |\kappa_1| \underline{\rho}_1^q, |\kappa_2| \underline{\rho}_2^q, \cdots, |\kappa_\iota| \underline{\rho}_\iota^q \right\}$. So $\inf_{t\geq 0} \sum_{j=1}^{\iota} |\kappa_j| \rho_j^q \geq min\left\{ |\kappa_1| \underline{\rho}_1^q, |\kappa_2| \underline{\rho}_2^q, \cdots, |\kappa_\iota| \underline{\rho}_\iota^q \right\}$. To compensate for intermittent actuator faults, a definition is introduced as

$$\breve{\pi} = \inf_{t\geq 0} \sum_{j=1}^{\iota} |\kappa_j| \rho_j^q, \quad \omega = \frac{1}{\breve{\pi}} \tag{44}$$

Choosing the nth Lyapunov function as follows:

$$V_n = V_{n-1} + \frac{1}{2} z_n^2 + \frac{1}{2} \tilde{\boldsymbol{\theta}}_n^{\mathrm{T}} \boldsymbol{\tau}_n^{-1} \tilde{\boldsymbol{\theta}}_n + \frac{\breve{\pi}}{2\tau} \tilde{\omega}^2 \tag{45}$$

where $\boldsymbol{\tau}_n > 0$ is an arbitrary positive definite matrix, τ is a constant, $\boldsymbol{\theta}_n$ represents the weight vector of the MTN, $\hat{\boldsymbol{\theta}}_n$ represents the estimate of $\boldsymbol{\theta}_n$, $\tilde{\boldsymbol{\theta}}_n = \boldsymbol{\theta}_n - \hat{\boldsymbol{\theta}}_n$ represents the parameter error vector, and $\tilde{\omega} = \omega - \hat{\omega}$ is the parameter estimate.

According to (43) and (45) along with (11) and (12), the time derivative of the Lyapunov function can be obtained as follows:

$$\begin{aligned} \dot{V}_n = \; & \dot{V}_{n-1} + z_n \left(\sum_{j=1}^{\iota} \kappa_j \rho_j^q(t) u_{cj} + \sum_{j=1}^{\iota} \kappa_j \bar{u}_j^q(t) \right) \\ & + z_n \left(f_n(\bar{x}_n) + \Delta_n(t) - \dot{\alpha}_{n-1} \right) - \tilde{\boldsymbol{\theta}}_n^{\mathrm{T}} \boldsymbol{\tau}_n^{-1} \dot{\hat{\boldsymbol{\theta}}}_n - \frac{\breve{\pi}}{\tau} \tilde{\omega} \dot{\hat{\omega}} \end{aligned} \tag{46}$$

Next, using the Young's inequality, we obtain

$$z_n \Delta_n(t) \leq \frac{1}{2} z_n^2 + \frac{1}{2} \bar{\Delta}_n^2 \tag{47}$$

Substituting (47) into (46) and under Assumption 3, we obtain

$$\begin{aligned} \dot{V}_n \leq \; & \dot{V}_{n-1} + z_n \sum_{j=1}^{\iota} \kappa_j \rho_j^q u_{cj} + z_n \bar{f}_n - \frac{1}{2} z_n^2 - z_{n-1} z_n \\ & + \frac{1}{2} \bar{\Delta}_n^2 - \tilde{\boldsymbol{\theta}}_n^{\mathrm{T}} \boldsymbol{\eta}_n^{-1} \dot{\hat{\boldsymbol{\theta}}}_n - \frac{\breve{\pi}}{\tau} \tilde{\omega} \dot{\hat{\omega}} \end{aligned} \tag{48}$$

where $\bar{f}_n = \sum_{j=1}^{\iota} \kappa_j \bar{\bar{u}}_j + f_n(\bar{x}_n) - \dot{\alpha}_{n-1} + z_n + z_{n-1}$.

Similar to step 1, $\bar{f}_n$ is also an unknown function. According to Lemma 2, leveraging the approximation properties of MTN, it is possible to employ a MTN for estimating $\bar{f}_n$. More specifically, for $\forall \varepsilon_n > 0$, there exists

$$\bar{f}_n = \boldsymbol{\theta}_n^{\mathrm{T}} S_{m_n}(\boldsymbol{Z}_n) + \delta_n(\boldsymbol{Z}_n), \; |\delta_n(\boldsymbol{Z}_n)| \leq \varepsilon_n \tag{49}$$

where $\boldsymbol{Z}_n = [z_1, z_2, \ldots, z_n]^{\mathrm{T}}$, and $\delta_n(\boldsymbol{Z}_n)$ denotes the approximation error.

Substituting (49) into (48), using (40) and applying the Young's inequality yields

$$
\begin{aligned}
\dot{V}_n \leq & -\sum_{\lambda=1}^{n-1} k_\lambda z_\lambda^2+\sum_{\lambda=1}^{n-1} \frac{1}{2} \varepsilon_\lambda^2+\sum_{\lambda=1}^{n-1} \frac{1}{2} \bar{\Delta}_\lambda^2+\sum_{\lambda=1}^{n-1} \eta_\lambda \tilde{\theta}_\lambda^{\mathrm{T}} \hat{\theta}_\lambda \\
& +z_n\left(\sum_{j=1}^{l} \kappa_j \rho_j^q u_{cj}+\theta_n^{\mathrm{T}} S_{m_n}\right)+\frac{1}{2} \varepsilon_n^2+\frac{1}{2} \bar{\Delta}_n^2 \\
& -\tilde{\theta}_n^{\mathrm{T}} \tau_n^{-1} \dot{\hat{\theta}}_n-\frac{\breve{\pi}}{\tau} \tilde{\omega} \dot{\hat{\omega}}
\end{aligned} \tag{50}
$$

Thus, the virtual control signal α_n and $\dot{\hat{\theta}}_n$ is designed as follows:

$$
\alpha_n=k_n z_n+\hat{\theta}_n^{\mathrm{T}} S_{m_n}\left(\boldsymbol{Z}_n\right) \tag{51}
$$

$$
\dot{\hat{\theta}}_n=\tau_n S_{m_n} z_n-\eta_n \tau_n \hat{\theta}_n \tag{52}
$$

where $k_n>0$, $\eta_n>0$ are design parameters.

Then, substituting (51) and (52) into (50), we obtain

$$
\begin{aligned}
\dot{V}_n \leq & -\sum_{\lambda=1}^{n} k_\lambda z_\lambda^2+\sum_{\lambda=1}^{n} \frac{1}{2} \varepsilon_\lambda^2+\sum_{\lambda=1}^{n} \frac{1}{2} \bar{\Delta}_\lambda^2+\sum_{\lambda=1}^{n} \eta_\lambda \tilde{\theta}_\lambda^{\mathrm{T}} \hat{\theta}_\lambda \\
& +z_n\left(\sum_{j=1}^{l} \kappa_j \rho_j^q u_{cj}+\alpha_n\right)-\frac{\breve{\pi}}{\tau} \tilde{\omega} \dot{\hat{\omega}}
\end{aligned} \tag{53}
$$

Clearly, we can design the controller u_{cj} and the parameter adaptive law $\dot{\hat{\omega}}$ as

$$
u_{cj}=-\operatorname{sgn}\left(\kappa_j\right) \frac{z_n \hat{\omega}^2 \alpha_n^2}{\sqrt{z_n^2 \hat{\omega}^2 \alpha_n^2+\chi^2}} \tag{54}
$$

$$
\dot{\hat{\omega}}=\tau \alpha_n z_n-c \hat{\omega} \tag{55}
$$

where $c>0$ is a design parameter. According to [47], χ is a smooth and bounded function that is strictly positive and satisfies $\int_{t_0}^{\infty} \chi(\gamma) \mathrm{d}\gamma \leq \bar{\chi} \leq \infty$. Based on Lemma 1, [57], and (54) and (55), we have

$$
z_n \sum_{j=1}^{l} \kappa_j \rho_j^q u_{cj} \leq-\breve{\pi} \frac{z_n^2 \hat{\omega}^2 \alpha_n^2}{\sqrt{z_n^2 \hat{\omega}^2 \alpha_n^2+\chi^2}} \leq \breve{\pi} \chi-z_n \breve{\pi} \hat{\omega} \alpha_n \tag{56}
$$

$$
z_n \alpha_n-\breve{\pi} z_n \hat{\omega} \alpha_n-\breve{\pi} z_n \tilde{\omega} \alpha_n=0 \tag{57}
$$

Eventually, substituting (56) and (57) into (53), we obtain

$$
\begin{aligned}
\dot{V}_n \leq & -\sum_{\lambda=1}^{n} k_\lambda z_\lambda^2+\sum_{\lambda=1}^{n} \frac{1}{2} \varepsilon_\lambda^2+\sum_{\lambda=1}^{n} \frac{1}{2} \bar{\Delta}_\lambda^2+\sum_{\lambda=1}^{n} \eta_\lambda \tilde{\theta}_\lambda^{\mathrm{T}} \hat{\theta}_\lambda \\
& +\frac{\breve{\pi} c}{\tau} \tilde{\omega} \hat{\omega}+\breve{\pi} \chi
\end{aligned} \tag{58}
$$

3.3 | Stability analysis

Theorem 1. *If the strict-feedback nonlinear system (1) with intermittent actuator faults satisfies Assumptions 1–4 and the initial conditions are bounded, then the controller (54), virtual control signals (19), (39), and (51), adaptive laws (21), (41), and (52), fault parameter estimation law (55) can ensure that*

1. *All signals of the closed-loop system are bounded.*
2. *The system's output y can track the desired output y_d, and the tracking error $e_1(t)=y(t)-y_d(t)$ can meet the prescribed transient and steady-state tracking performance requirements.*

Proof. For the entire system, consider the following Lyapunov function:

$$
V=V_n=\frac{1}{2} \sum_{\lambda=1}^{n} z_\lambda^2+\frac{1}{2} \sum_{\lambda=1}^{n} \tilde{\theta}_\lambda^{\mathrm{T}} \tau_\lambda^{-1} \tilde{\theta}_\lambda+\frac{\breve{\pi}}{2 \tau} \tilde{\omega}^2 \tag{59}
$$

By (58) and (59), we have

$$
\begin{aligned}
\dot{V}=\dot{V}_n \leq & -\sum_{\lambda=1}^{n} k_\lambda z_\lambda^2+\sum_{\lambda=1}^{n} \frac{1}{2} \varepsilon_\lambda^2+\sum_{\lambda=1}^{n} \frac{1}{2} \bar{\Delta}_\lambda^2 \\
& +\sum_{\lambda=1}^{n} \eta_\lambda \tilde{\theta}_\lambda^{\mathrm{T}} \hat{\theta}_\lambda+\frac{\breve{\pi} c}{\tau} \tilde{\omega} \hat{\omega}+\breve{\pi} \chi
\end{aligned} \tag{60}
$$

Subsequently, from the definitions of $\hat{\theta}_\lambda$ and $\hat{\omega}$ and by employing the Young's inequality, we have

$$
\sum_{\lambda=1}^{n} \eta_\lambda \tilde{\theta}_\lambda^{\mathrm{T}} \hat{\theta}_\lambda \leq \frac{1}{2} \sum_{\lambda=1}^{n} \eta_\lambda\left\|\theta_\lambda\right\|^2-\tilde{\eta} \sum_{\lambda=1}^{n} \tilde{\theta}_\lambda^{\mathrm{T}} \tau_\lambda^{-1} \tilde{\theta}_\lambda \tag{61}
$$

$$
c \tilde{\omega} \hat{\omega} \leq-\frac{1}{2} c \tilde{\omega}^2+\frac{1}{2} c \omega^2 \tag{62}
$$

where $\tilde{\eta}=\min \left\{\tilde{\eta}_1, \tilde{\eta}_2, \ldots, \tilde{\eta}_n\right\}$, $\tilde{\eta}_\lambda=\frac{\eta_\lambda}{2 \lambda_{max}\left(\tau_\lambda^{-1}\right)}$, and $\lambda_{max}\left(\tau_\lambda^{-1}\right)$ represents the maximum eigenvalue of the matrix τ_λ^{-1}.

Naturally, substituting (61) and (62) into (60), we obtain

$$
\begin{aligned}
\dot{V} \leq & -\sum_{\lambda=1}^{n} k_\lambda z_\lambda^2+\sum_{\lambda=1}^{n} \frac{1}{2} \varepsilon_\lambda^2+\sum_{\lambda=1}^{n} \frac{1}{2} \bar{\Delta}_\lambda^2+\frac{1}{2} \sum_{\lambda=1}^{n} \eta_\lambda\left\|\theta_\lambda\right\|^2 \\
& -\tilde{\eta} \sum_{\lambda=1}^{n} \tilde{\theta}_\lambda^{\mathrm{T}} \tau_\lambda^{-1} \tilde{\theta}_\lambda-\frac{\breve{\pi} c}{2 \tau} \tilde{\omega}^2+\frac{\breve{\pi} c}{2 \tau} \omega^2+\breve{\pi} \chi \leq-a V+b
\end{aligned} \tag{63}
$$

where $a=\min \left\{a_1, a_2, \ldots, a_n\right\}$, $a_i=\min \left\{2 k_\lambda, \tilde{\eta}, c\right\}$, $b=\sum_{\lambda=1}^n \frac{1}{2} \varepsilon_\lambda^2+\sum_{\lambda=1}^n \frac{1}{2} \bar{\Delta}_\lambda^2+\frac{1}{2} \sum_{\lambda=1}^n \eta_\lambda\left\|\theta_\lambda\right\|^2+\frac{\breve{\pi} c}{2 \tau} \omega^2+\breve{\pi} \chi$, $\lambda=1,2, \ldots n$.

Then, integrate (63) over the interval $[0, t]$

$$
0 \leq V \leq V(0) e^{-a t}+\frac{b}{a} \tag{64}
$$

By using (59) and (64), it is obvious that all signals of the closed-loop system are bounded. Since z_1 is bounded, according to Remark 4, $e_1(t)$ is also bounded and can meet the prescribed tracking performance. This completes the proof of Theorem1. □

Remark 6. Based on the above, an adaptive tracking controller is proposed for the nonlinear strict-feedback system with intermittent actuator faults and prescribed performance. The specific control structure is shown in Figure 3.

4 | SIMULATION RESULTS

This section aims to substantiate the effectiveness and advancement of the proposed method through the utilization of a numerical example and a practical example.

Example 1. Considering the third-order nonlinear system with intermittent actuator faults as follows:

$$\begin{cases} \dot{x}_1 = x_2 + 0.1\sin x_1 \\ \dot{x}_2 = x_3 + 0.2x_2 \\ \dot{x}_3 = \kappa_1 u_1 + \kappa_2 u_2 + 0.8x_3 + \sin t \\ y = x_1 \end{cases} \tag{65}$$

where $\kappa_1 = 1$ and $\kappa_2 = 2$.

The actuator fault model is chosen as follows:

$$u_1 = \begin{cases} 0.6u_{c1} & \text{if } t \in [j\mathrm{T}^*, (j+1)\mathrm{T}^*) \\ u_{c1} & \text{others} \end{cases} \tag{66}$$

$$u_2 = \begin{cases} \sin t & \text{if } t \in [j\mathrm{T}^*, (j+1)\mathrm{T}^*) \\ u_{c2} & \text{others} \end{cases} \tag{67}$$

where $j = 1, 3...$, and $T^* = 10s$. From (66) and (67), it can be observed that during each time interval of jT^*,

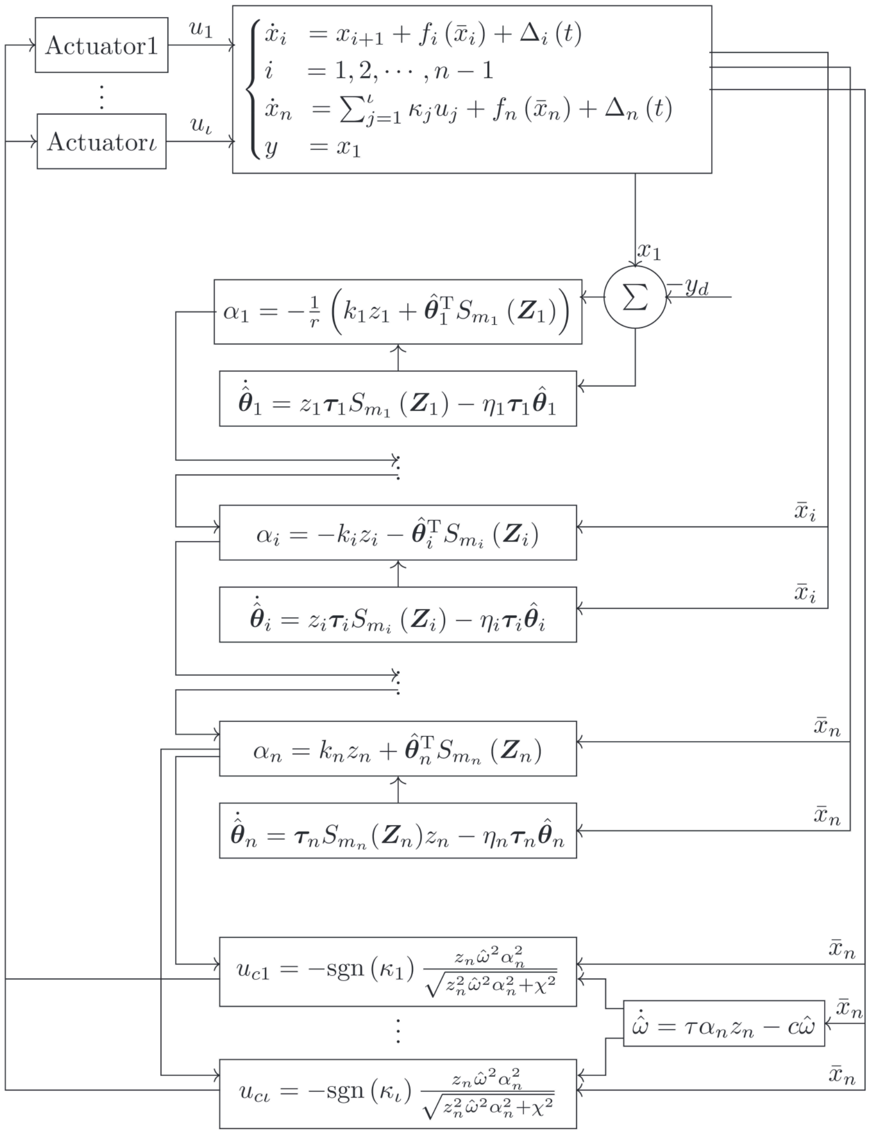


FIGURE 3 Block diagram of control system.

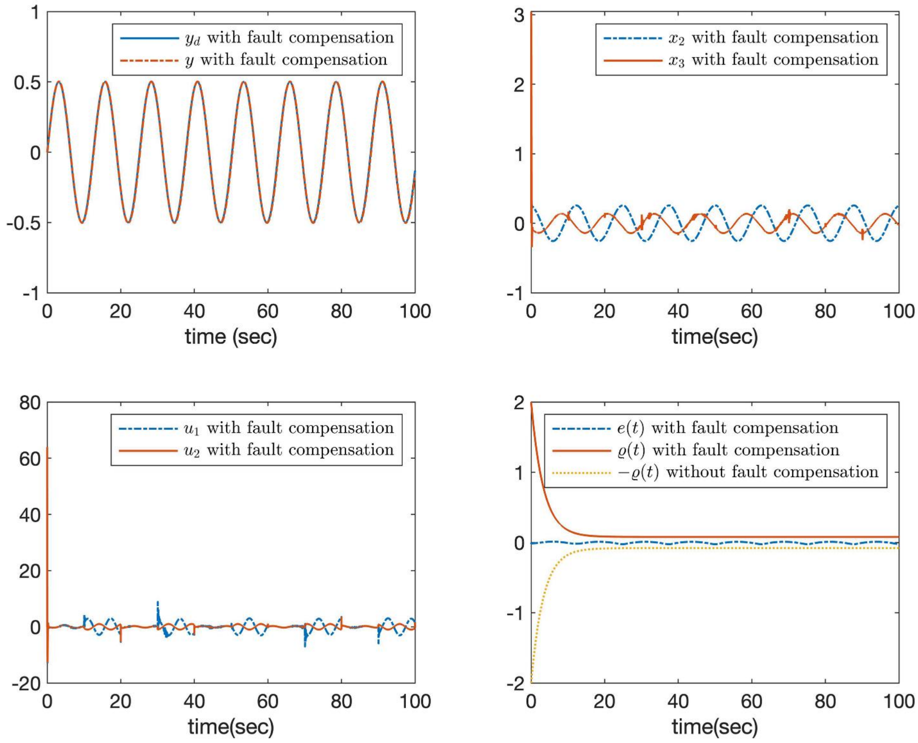


FIGURE 4 The trajectories of system states, control inputs, and tracking error with fault compensation.

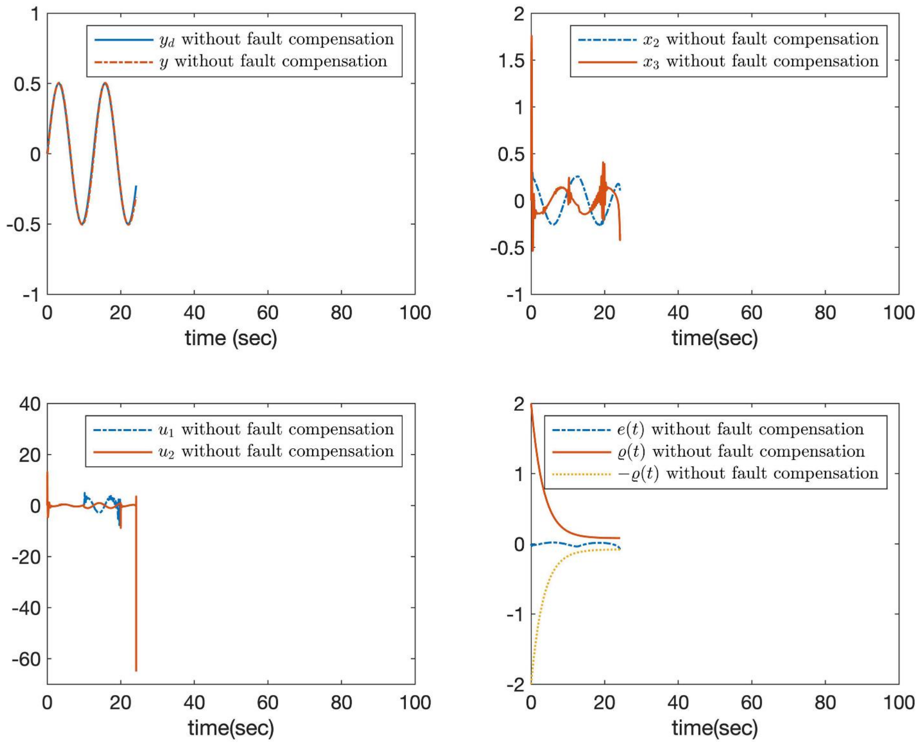


FIGURE 5 The trajectories of system states, control inputs, and tracking error without fault compensation.

the output of the first actuator in the system will lose 60% of its effectiveness, while the second actuator will be locked at $u_2 = \sin t$. In the remaining time intervals, both actuators will operate without any faults.

For system (65), the virtual control signals are $\alpha_1 = -\frac{1}{r}\left(k_1 z_1 + \hat{\theta}_1^{\mathrm{T}} S_{m_1}(\boldsymbol{Z}_1)\right)$, $\alpha_2 = -k_2 z_2 - \hat{\theta}_2^{\mathrm{T}} S_{m_2}(\boldsymbol{Z}_2)$, $\alpha_3 = k_3 z_3 + \hat{\theta}_3^{\mathrm{T}} S_{m_3}(\boldsymbol{Z}_3)$, the adaptive laws are $\dot{\hat{\theta}}_1 = z_1 \boldsymbol{\tau}_1 S_{m_1}(\boldsymbol{Z}_1) - \eta_1 \boldsymbol{\tau}_1 \hat{\theta}_1$, $\dot{\hat{\theta}}_2 = z_2 \boldsymbol{\tau}_2 S_{m_2}(\boldsymbol{Z}_2) - \eta_2 \boldsymbol{\tau}_2 \hat{\theta}_2$, $\dot{\hat{\theta}}_3 = z_3 \boldsymbol{\tau}_3 S_{m_3}(\boldsymbol{Z}_3) - \eta_3 \boldsymbol{\tau}_3 \hat{\theta}_3$, $\dot{\hat{\omega}} = \tau \alpha_3 z_3 - c\hat{\omega}$ and the controllers are $u_{c1} = -\mathrm{sgn}(\kappa_1)\frac{z_3 \hat{\omega}^2 \alpha_3^2}{\sqrt{z_3^2 \hat{\omega}^2 \alpha_3^2 + \chi^2}}$, $u_{c2} = -\mathrm{sgn}(\kappa_2)\frac{z_3 \hat{\omega}^2 \alpha_3^2}{\sqrt{z_3^2 \hat{\omega}^2 \alpha_3^2 + \chi^2}}$. Furthermore, $z_1 = x_1 - y_d$, $z_2 = x_2 - \alpha_1$, $z_3 =$

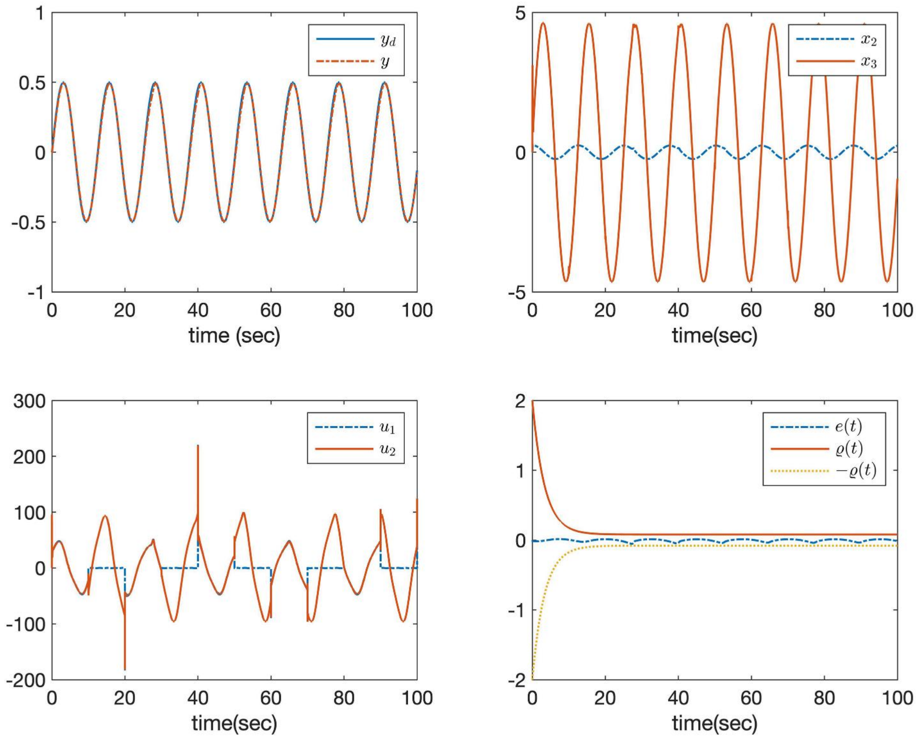


FIGURE 6 The trajectories of system states, control inputs, and tracking error.

$x_3 - \alpha_2$, and $\chi = 0.5e^{-0.5t}$, the desired trajectory is selected as $y_d = 0.5\sin(0.5\text{t})$. The prescribe performance function is chosen as $\varrho(t) = (2-0.08)e^{-t} + 0.08$. The system initial values are $x_1(0) = x_2(0) = x_3(0) = 0$. The design parameters are selected as $k_1 = 9.5$, $k_2 = 30$, $k_3 = 180$, $\boldsymbol{\tau}_1 = 0.2\boldsymbol{I}_5$, $\boldsymbol{\tau}_2 = 0.1\boldsymbol{I}_9$, $\boldsymbol{\tau}_3 = 0.1\boldsymbol{I}_9$, $\tau = 1$, $\eta_1 = 0.1$, $\eta_2 = 0.1$, $\eta_3 = 0.1$, and $c = 1$.

The simulation results are presented in Figure 4. Based on Figure 4, it can be observed that despite intermittent actuator failures occurring in the controller, the system output y is still able to effectively track the desired output y_d. Throughout the process, the tracking error $e_1(t)$ consistently remains within the prescribed performance range, demonstrating outstanding performance.

In order to further validate the effectiveness of the proposed adaptive fault compensation controller, we only use the virtual controllers α_1, α_2, α_3 and the adaptive laws $\theta_1, \theta_2, \theta_3$ to control the system (65). The simulation is conducted with the same chosen parameters as before, and the simulation results are shown in Figure 5. From Figure 5, it is evident that although the system output y initially tracks the reference signal y_d, when a fault occurs and there is no fault compensator to mitigate its effects, the system starts to become unstable. The control input exhibits significant oscillations, and the output fails to keep up with the reference signal, thereby failing to meet the system's performance requirements.

Example 2. To further validate the effectiveness of the proposed approach, we consider a three-order single-joint robotic system [58] with intermittent actuator faults, represented as follows:

$$\begin{cases} D\ddot{q} + B\dot{q} + N\sin(q) + (q^2+1)\dot{q} = \check{\tau} \\ M\dot{\check{\tau}} + J\check{\tau} + (q+\dot{q})^2\check{\tau} = u_1 + u_2 - K_m\dot{q} \end{cases} \tag{68}$$

where q, $\dot{q}$, and $\ddot{q}$ represent joint position, velocity, and acceleration, respectively. The variables $\check{\tau}$ and $\dot{\check{\tau}}$ represent motor rotation angle and angular velocity, while u_1 and u_2 represent the control input signals for the motors. Additionally, the terms $(q^2+1)\dot{q}$ and $(q+\dot{q})^2\check{\tau}$ represent external disturbances. To facilitate the simulation, we define the variables $x_1 = q$, $x_2 = \dot{q}$, and $x_3 = \check{\tau}$. Furthermore, the system parameters are chosen as $D = 1\text{kgm}^2$, $B = 1\text{Nms/rad}$, $M = 0.05\text{H}$, $K_m = 10\text{Nm/A}$, $J = 0.5\Omega$, $N = 10\text{Nm}$.

The actuator fault model is chosen as follows:

$$u_1 = \begin{cases} 0.3\sin 3\text{t} \ \text{ if } t \in [j\text{T}^*, (j+1)\text{T}^*) \\ u_{c1} \qquad\qquad \text{others} \end{cases} \tag{69}$$

$$u_2 = \begin{cases} 0.3u_{c2} \ \text{ if } t \in [j\text{T}^*, (j+1)\text{T}^*) \\ u_{c2} \qquad\qquad \text{others} \end{cases} \tag{70}$$

where $j = 1, 3\ldots$, and $T^* = 10s$. From (59) and (70), it can be observed that during each time interval of jT^*, the output of the first actuator in the system will be locked at $u_1 = 0.3\sin 3\text{t}$, while the second actuator will lose 30% of its effectiveness. In the remaining time intervals, both actuators will operate without any faults.

For system (68), the virtual control signals are $\alpha_1 = -\frac{1}{r}\left(k_1 z_1 + \hat{\theta}_1^{\mathrm{T}} S_{m_1}(\boldsymbol{Z}_1)\right)$, $\alpha_2 = -k_2 z_2 - \hat{\theta}_2^{\mathrm{T}} S_{m_2}(\boldsymbol{Z}_2)$, $\alpha_3 = k_3 z_3 + \hat{\theta}_3^{\mathrm{T}} S_{m_3}(\boldsymbol{Z}_3)$, the adaptive laws are $\dot{\hat{\theta}}_1 = z_1 \boldsymbol{\tau}_1 S_{m_1}(\boldsymbol{Z}_1) - \eta_1 \boldsymbol{\tau}_1 \hat{\theta}_1$, $\dot{\hat{\theta}}_2 = z_2 \boldsymbol{\tau}_2 S_{m_2}(\boldsymbol{Z}_2) - \eta_2 \boldsymbol{\tau}_2 \hat{\theta}_2$, $\dot{\hat{\theta}}_3 = z_3 \boldsymbol{\tau}_3 S_{m_3}(\boldsymbol{Z}_3) - \eta_3 \boldsymbol{\tau}_3 \hat{\theta}_3$, $\dot{\hat{\omega}} = \tau \alpha_3 z_3 - c\hat{\omega}$ and the controllers are $u_{c1} = -\mathrm{sgn}(\kappa_1) \frac{z_3 \hat{\omega}^2 \alpha_3^2}{\sqrt{z_3^2 \hat{\omega}^2 \alpha_3^2 + \chi^2}}$, $u_{c2} = -\mathrm{sgn}(\kappa_2) \frac{z_3 \hat{\omega}^2 \alpha_3^2}{\sqrt{z_3^2 \hat{\omega}^2 \alpha_3^2 + \chi^2}}$. Similarly, $z_1 = x_1 - y_d$, $z_2 = x_2 - \alpha_1$, $z_3 = x_3 - \alpha_2$, and $\chi = 0.5e^{-0.5t}$, the desired trajectory is selected as $y_d = 0.5\sin(0.5t)$. The prescribe performance function is chosen as $\varrho(t) = (2 - 0.08)e^{-t} + 0.08$. The system initial values are $x_1(0) = x_2(0) = x_3(0) = 0$. The design parameters are selected as $k_1 = 9.5$, $k_2 = 30$, $k_3 = 180$, $\boldsymbol{\tau}_1 = 0.2\boldsymbol{I}_5$, $\boldsymbol{\tau}_2 = 0.1\boldsymbol{I}_9$, $\boldsymbol{\tau}_3 = 0.1\boldsymbol{I}_9$, $\tau = 1$, $\eta_1 = 0.1$, $\eta_2 = 0.1$, $\eta_3 = 0.1$, and $c = 1$.

The simulation results are presented in Figure 6. From Figure 6, it is apparent that despite intermittent actuator failures, the system output y can effectively track the desired output y_d with high precision. Throughout the operation, the tracking error consistently remains within the prescribed performance range, demonstrating the system's robustness and its capability to compensate for actuator faults.

Remark 7. It is worth noting that the parameter selection is only a sufficient condition to ensure stability of a controlled system. The introduction of χ is aimed at achieving faster convergence of the error compensation system, while the introduction of k_i, $\boldsymbol{\tau}_i$, and η_i is intended to ensure optimal tracking performance. Increasing k_i, $\boldsymbol{\tau}_i$, and η_i, and reducing χ may lead to an increase in the magnitude of the control signal. Therefore, in the application of control design, it is important to consider a balance between better tracking performance and control input by selecting appropriate design parameters.

5 | CONCLUSION

In this paper, a novel adaptive controller is developed for nonlinear strict-feedback systems with intermittent actuator faults and prescribed performance. To address the issue of prescribed performance, a performance function is proposed and incorporated in the backstepping design process to achieve the desired performance requirements through error transformation techniques. MTN is employed to approximate unknown nonlinear functions. Subsequently, the problem of intermittent actuator failures is effectively addressed through a boundary estimation algorithm. Lastly, simulation results effectively validate the effectiveness of the proposed approach.

It is worth noting that the results obtained in this paper only guarantee that the tracking error remains within a certain range. However, in practical applications, achieving convergence within a limited time is often required. Therefore, the next step should consider combining finite-time [59] and fixed-time [60] stability theories to design an adaptive fault compensation controller for nonlinear systems with intermittent actuator failures.

AUTHOR CONTRIBUTIONS

Li-Ting Lu: Software; writing—original draft. **Yu-Qun Han:** Formal analysis; methodology; resources; writing—review and editing. **Dong-Mei Wang:** software. **Shanliang Zhu:** resources; supervision. **Qing-Hua Zhou:** Formal analysis; methodology; resources.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

ORCID

Yu-Qun Han https://orcid.org/0000-0002-9055-2954
Dong-Mei Wang https://orcid.org/0000-0002-4073-6392
Shan-Liang Zhu https://orcid.org/0000-0002-6194-3614
Qing-Hua Zhou https://orcid.org/0009-0006-2610-1549

REFERENCES

1. Z. Gao and P. J. Antsaklis, *Stability of the pseudo-inverse method for reconfigurable control systems*, Int. J. Control **53** (1991), no. 3, 717–729.
2. J. H. Qin, Q. C. Ma, H. J. Gao, and W. X. Zheng, *Fault-tolerant cooperative tracking control via integral sliding mode control technique*, IEEE/ASME Trans. Mechatron. **23** (2018), no. 1, 342–351.
3. X. Yu, P. Li, and Y. Zhang, *The design of fixed-time observer and finite-time fault-tolerant control for hypersonic gliding vehicles*, IEEE Trans. Ind. Electron. **65** (2018), no. 5, 4135–4144.
4. L. J. Liu, K. Shi, X. F. Yuan, and Q. X. Li, *Multiple model-based fault-tolerant control system for distributed drive electric vehicle*, J. Brazilian Soc. Mech. Sci. Eng. **41** (2019), 1–15.
5. Y. J. Ma, G. Tao, B. Jiang, and Y. H. Cheng, *Multiple-model adaptive control for spacecraft under sign errors in actuator response*, J. Guid., Control, Dyn. **39** (2016), no. 3, 628–641.
6. Z. X. Liu, C. Yuan, Y. M. Zhang, and J. Luo, *A learning-based fault tolerant tracking control of an unmanned quadrotor helicopter*, J. Intell. Robot. Syst. **84** (2016), 145–162.
7. F. K. Zhang, W. M. Wu, R. Song, and C. Wang, *Dynamic learning-based fault tolerant control for robotic manipulators with actuator faults*, J. Franklin Inst. **360** (2023), no. 2, 862–886.
8. J. P. Cai, C. Y. Wen, H. Y. Su, and Z. T. Liu, *Robust adaptive failure compensation of hysteretic actuators for a class of uncertain*

nonlinear systems, IEEE Trans. Autom. Control **58** (2013), no. 9, 2388–2394.
9. W. Chen and J. Jiang, *Fault-tolerant control against stuck actuator faults*, IEE Proc.-Control Theory Appl. **152** (2005), no. 2, 138–146.
10. G. Tao, S. Chen, and S. M. Joshi, *An adaptive actuator failure compensation controller using output feedback*, IEEE Trans. Autom. Control **47** (2002), no. 3, 506–511.
11. G. Tao, S. M. Joshi, and X. Ma, *Adaptive state feedback and tracking control of systems with actuator failures*, IEEE Trans. Autom. Control **46** (2001), no. 1, 78–95.
12. G. Tao, *Direct adaptive actuator failure compensation control: a tutorial*, J. Control Decision **1** (2014), no. 1, 75–101.
13. W. Wang and C. Y. Wen, *Adaptive actuator failure compensation control of uncertain nonlinear systems with guaranteed transient performance*, Automatica **46** (2010), no. 12, 2082–2091.
14. H. Liu, Y. P. Pan, J. Cao, H. X. Wang, and Y. Zhou, *Adaptive neural network backstepping control of fractional-order nonlinear systems with actuator faults*, IEEE Trans. Neural Netw. Learn. Syst. **31** (2020), no. 12, 5166–5177.
15. H. Q. Wang, W. Bai, and P. X. P. Liu, *Finite-time adaptive fault-tolerant control for nonlinear systems with multiple faults*, IEEE/CAA J. Autom. Sin. **6** (2019), no. 6, 1417–1427.
16. P. Li and G. H. Yang, *Backstepping adaptive fuzzy control of uncertain nonlinear systems against actuator faults*, J. Control Theory Appl. **7** (2009), no. 3, 248–256.
17. H. Q. Wang, P. X. P. Liu, X. D. Zhao, and X. P. Liu, *Adaptive fuzzy finite-time control of nonlinear systems with actuator faults*, IEEE Trans. Cybern. **50** (2019), no. 5, 1786–1797.
18. A. Bali, U. P. Singh, and R. Kumar, *Multi-dimensional Taylor network-based fault-tolerant control for nonlinear systems with unmodeled dynamics and actuator faults*, Neural Process. Lett. **2022** (2022), 1–27.
19. N. Li, Y. Q. Han, W. J. He, and S. L. Zhu, *A novel network-based controller design for a class of stochastic nonlinear systems with multiple faults and full state constraints*, Int. J. Control (2023), DOI 10.1080/00207179.2022.2163297.
20. M. X. Wang, S. L. Zhu, S. M. Liu, Y. Du, and Y. Q. Han, *Design of adaptive finite-time fault-tolerant controller for stochastic nonlinear systems with multiple faults*, IEEE Trans. Autom. Sci. Eng. **20** (2023), no. 4, 2492–2502. DOI 10.1109/TASE.2022.3206328.
21. Y. Q. Han, *Adaptive tracking control of a class of nonlinear systems with unknown dead-zone output: a multi-dimensional Taylor network (MTN)-based approach*, Int. J. Control **94** (2021), no. 11, 3161–3170.
22. Y. Q. Han and H. S. Yan, *Observer-based multi-dimensional Taylor network decentralised adaptive tracking control of large-scale stochastic nonlinear systems*, Int. J. Control **93** (2020), no. 7, 1605–1618.
23. H. S. Yan and Y. Q. Han, *Decentralized adaptive multi-dimensional Taylor network tracking control for a class of large-scale stochastic nonlinear systems*, Int. J. Adapt. Control Signal Process. **33** (2019), no. 4, 664–683.
24. W. Wang and C. Y. Wen, *Adaptive compensation for infinite number of actuator failures or faults*, Automatica **47** (2011), no. 10, 2197–2210.
25. G. Y. Lai, Z. Liu, C. L. P. Chen, Y. Zhang, and X. Chen, *Adaptive compensation for infinite number of time-varying actuator failures in fuzzy tracking control of uncertain nonlinear systems*, IEEE Trans. Fuzzy Syst. **26** (2017), no. 2, 474–486.
26. G. Y. Lai, C. Y. Wen, Z. Liu, Y. Zhang, C. L. P. Chen, and S. L. Xie, *Adaptive compensation for infinite number of actuator failures/faults using output feedback control*, Inform. Sci. **399** (2017), 1–12.
27. C. Wang, C. Wen, X. Zhang, and J. Huang, *Output-feedback adaptive control for a class of MIMO nonlinear systems with actuator and sensor faults*, J. Franklin Inst. **357** (2020), no. 12, 7962–7982.
28. C. P. Bechlioulis and G. A. Rovithakis, *Adaptive control with guaranteed transient and steady state tracking error bounds for strict feedback systems*, Automatica **45** (2009), no. 2, 532–538.
29. X. W. Bu, B. X. Jiang, et al., *Hypersonic tracking control under actuator saturations via readjusting prescribed performance functions*, ISA Trans. **134** (2023), 74–85.
30. X. W. Bu, B. X. Jiang, and H. M. Lei, *Low-complexity fuzzy neural control of constrained waverider vehicles via fragility-free prescribed performance approach*, IEEE Trans. Fuzzy Syst. (2022), DOI 10.1109/TFUZZ.2022.3217378.
31. X. Bu, Q. Qi, and B. Jiang, *A simplified finite-time fuzzy neural controller with prescribed performance applied to waverider aircraft*, IEEE Trans. Fuzzy Syst. **30** (2021), no. 7, 2529–2537.
32. D. Y. Duan, L. Chu, and Y. Q. Han, *Multi-dimensional Taylor network-based adaptive funnel tracking control of a class of nonlinear systems with prescribed performance*, IEEE Access **8** (2020), 132265–132272.
33. Y. Q. Han, N. Li, W. J. He, and S. L. Zhu, *Adaptive multi-dimensional Taylor network funnel control of a class of nonlinear systems with asymmetric input saturation*, Int. J. Adapt. Control Sig. Process. **35** (2021), no. 5, 713–726.
34. X. Y. Ouyang, L. B. Wu, N. N. Zhao, and C. Gao, *Event-triggered adaptive prescribed performance control for a class of pure-feedback stochastic nonlinear systems with input saturation constraints*, Int. J. Syst. Sci. **51** (2020), no. 12, 2238–2257.
35. S. Sui, C. L. P. Chen, and S. C. Tong, *A novel adaptive NN prescribed performance control for stochastic nonlinear systems*, IEEE Trans. Neural Netw. Learn. Syst. **32** (2020), no. 7, 3196–3205.
36. Y. Q. Han, *Design of decentralized adaptive control approach for large-scale nonlinear systems subjected to input delays under prescribed performance*, Nonlinear Dyn. **106** (2021), no. 1, 565–582.
37. S. L. Zhu and Y. Q. Han, *Adaptive decentralized prescribed performance control for a class of large-scale nonlinear systems subject to nonsymmetric input saturations*, Neural Comput. Appl. **34** (2022), no. 13, 11123–11140.
38. W. Wang, H. J. Liang, Y. N. Pan, and T. S. Li, *Prescribed performance adaptive fuzzy containment control for nonlinear multiagent systems using disturbance observer*, IEEE Trans. Cybern. **50** (2020), no. 9, 3879–3891.
39. Z. W. Wu, T. P. Zhang, X. N. Xia, and Y. Hua, *Finite-time adaptive neural command filtered control for non-strict feedback uncertain multi-agent systems including prescribed performance and input nonlinearities*, Appl. Math. Comput. **421** (2022), 126953.
40. Y. M. Li and S. C. Tong, *Adaptive neural networks prescribed performance control design for switched interconnected uncertain nonlinear systems*, IEEE Trans. Neural Netw. Learn. Syst. **29** (2017), no. 7, 3059–3068.
41. Y. M. Li, S. C. Tong, L. Liu, and G. Feng, *Adaptive output-feedback control design with prescribed performance for switched nonlinear systems*, Automatica **80** (2017), 225–231.

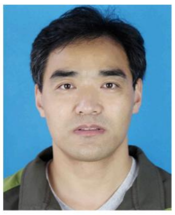
42. H. H. Pan, D. Zhang, W. C. Sun, and X. H. Yu, *Event-triggered adaptive asymptotic tracking control of uncertain MIMO nonlinear systems with actuator faults*, IEEE Trans. Cybern. **52** (2022), no. 9, 8655–8667.
43. H. Q. Wang, W. Bai, X. D. Zhao, and P. X. P. Liu, *Finite-time-prescribed performance-based adaptive fuzzy control for strict-feedback nonlinear systems with dynamic uncertainty and actuator faults*, IEEE Trans. Cybern. **52** (2022), no. 7, 6959–6971.
44. D. Zhai, L. W. An, J. H. Li, and Q. L. Zhang, *Adaptive fuzzy fault-tolerant control with guaranteed tracking performance for nonlinear strict-feedback systems*, Fuzzy Sets Syst. **302** (2016), 82–100.
45. L. L. Zhang and G. H. Yang, *Adaptive fuzzy prescribed performance control of nonlinear systems with hysteretic actuator nonlinearity and faults*, IEEE Trans. Syst. Man. Cybern. Syst. **48** (2018), no. 12, 2349–2358.
46. Y. Q. Nai and Q. Y. Yang, *Adaptive neural output feedback fault tolerant control for a class of uncertain nonlinear systems with intermittent actuator faults*, Neurocomputing **377** (2020), 145–158.
47. C. L. Wang, C. Y. Wen, and Y. Lin, *Decentralized adaptive backstepping control for a class of interconnected nonlinear systems with unknown actuator failures*, J. Franklin Inst. **352** (2015), no. 3, 835–850.
48. W. Wu and S. C. Tong, *Fuzzy adaptive consensus control for nonlinear multiagent systems with intermittent actuator faults*, IEEE Trans. Cybern. **53** (2023), no. 5, 2969–2979.
49. Y. X. Li and G. H. Yang, *Adaptive asymptotic tracking control of uncertain nonlinear systems with input quantization and actuator faults*, Automatica **72** (2016), 177–185.
50. Y. Lin, H. S. Yan, B. Zhou, et al., *Nonlinear time series prediction method based on multi-dimensional Taylor network and its applications*, Control Decis. **29** (2014), no. 5, 795–801.
51. L. Chu, T. Gao, M. X. Wang, Y. Q. Han, and S. L. Zhu, *Adaptive decentralized control for large-scale nonlinear systems with finite-time output constraints by multi-dimensional Taylor network*, Asian J. Control **24** (2022), no. 4, 1769–1779.
52. M. X. Wang, S. L. Zhu, and Y. Q. Han, *Multi-dimensional Taylor network-based control for a class of nonlinear stochastic systems with full state time-varying constraints and the finite-time output constraint*, Asian J. Control **24** (2022), no. 6, 3311–3325.
53. C. P. Bechlioulis and G. A. Rovithakis, *Robust adaptive control of feedback linearizable MIMO nonlinear systems with prescribed performance*, IEEE Trans. Autom. Control **53** (2008), no. 9, 2090–2099.
54. X. W. Bu, B. X. Jiang, and H. M. Lei, *Performance guaranteed finite-time non-affine control of waverider vehicles without function-approximation*, IEEE Trans. Intell. Transp. Syst. **24** (2022), no. 3, 3252–3262.
55. X. W. Bu, C. C. Hua, M. L. Lv, and Z. H. Wu, *Flight control of waverider vehicles with fragility-avoidance prescribed performance*, IEEE Trans. Aerosp. Electron. Syst. (2023), DOI 10.1109/TAES.2023.3251314.
56. X. W. Bu, M. L. Lv, H. M. Lei, and J. D. Cao, *Fuzzy neural pseudo control with prescribed performance for waverider vehicles: a fragility-avoidance approach*, IEEE Trans. Cybern. (2023), DOI 10.1109/TCYB.2023.3255925.
57. J. Long, W. Wang, J. S. Huang, J. Zhou, and K. X. Liu, *Distributed adaptive control for asymptotically consensus tracking of uncertain nonlinear systems with intermittent actuator faults and directed communication topology*, IEEE Trans. Cybern. **51** (2019), no. 8, 4050–4061.
58. Y. S. Yang, G. Feng, and J. S. Ren, *A combined backstepping and small-gain approach to robust adaptive fuzzy control for strict-feedback nonlinear systems*, IEEE Trans. Syst., Man, Cybern. - Part A. Syst. Humans **34** (2004), no. 3, 406–420.
59. H. Q. Wang, K. Xu, and H. G. Zhang, *Adaptive finite-time tracking control of nonlinear systems with dynamics uncertainties*, IEEE Trans. Autom. Control **68** (2023), no. 9, 5737–5744.
60. H. Q. Wang, M. Chen, and X. P. Liu, *Fuzzy adaptive fixed-time quantized feedback control for a class of nonlinear systems*, Acta. Autom. Sin. **47** (2021), no. 12, 2823–2830.

AUTHOR BIOGRAPHIES

Li-Ting Lu received the BS degree in mathematics and applied mathematics from Guangzhou University, Guangzhou, China, in 2021. She is currently pursuing MS degree with the Qingdao University of Science and Technology. Her current research interests include fault-tolerant control, nonlinear multi-agent systems, adaptive control, and neural networks.

Yu-Qun Han received the BS degree in mathematics and applied mathematics and the MS degree in applied mathematics from Qingdao University of Science and Technology, Qingdao, China, in 2010 and 2013, respectively, and the PhD degree in control theory and control engineering form Southeast University, Nanjing, China, in 2018. He has been with the School of Mathematics and Physics, Qingdao University of Science and Technology, Qingdao, China, since December 2018. His current research interests include nonlinear system control, stochastic nonlinear system control, adaptive control, and neural networks.

Dong-Mei Wang received the BS degree in statistics from Yan tai University, Yantai, China, in 2022. She is currently pursuing the MS degree with the Qingdao University of Science and Technology. Her current research interests include stochastic nonlinear systems, event-triggered control, adaptive control, and neural networks.



Shan-Liang Zhu received the PhD degree in college of electromechanical engineering form Qingdao Science and Technology University in 2020 and the MS degree in school of mathematical sciences from the Ocean University of China in 2004. He is currently an Associate Professor with Qingdao Science and Technology University. His research interests include differential dynamic system, data-driven control, machine learning, and their applications.

Qing-Hua Zhou received the PhD degree in applied mathematics from Nanjing University, Nanjing, China, in 2007. She is currently a Professor with the School of Mathematics and Physics, Qingdao University of Science and Technology, Qingdao, China. She has published over 40 refereed journal and conference papers. Her research interests include nonlinear dynamic systems, neural networks, and control theory.

How to cite this article: L.-T. Lu, Y.-Q. Han, D.-M. Wang, S.-L. Zhu, and Q.-H. Zhou, *Adaptive tracking control for a class of nonlinear systems with intermittent actuator faults under prescribe output tracking performance*, Asian J. Control. **26** (2024), 2011–2025, DOI 10.1002/asjc.3317.