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Research article

A novel network-based adaptive fault-tolerant control of switched nonlinear systems subject to multiple faults under prescribed performance[☆]

Wen-Jing He[a], Shan-Liang Zhu[a,b], Li-Ting Lu[a], Yu-Qun Han[a,b,*]

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

[b] Research Institute for Mathematics and Interdisciplinary Sciences, Qingdao University of Science and Technology, 266061, China

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ABSTRACT

It is the first report about fault-tolerant-based prescribed performance control of switched nonlinear systems under multiple faults. The concerned faults include not only external faults but also actuator faults. In the process of backstepping control design, prescribed performance control is fully considered, and the combination of unknown nonlinear functions is estimated by multi-dimensional Taylor network. Finally, the developed adaptive fault-tolerant control strategy guarantees the boundedness of all controlled signals while prescribed tracking performance is satisfied. In an effort to further manifest the validity of the fault-tolerant controller, a numerical simulation and a practical simulation are introduced.

1. Introduction

As a class of fundamental and significant hybrid systems, switched systems are the abstract model of a considerable number of practical systems, such as robotic arm systems [1], inverted pendulum systems [2], and mass–spring-damping systems [3]. The control of switched nonlinear systems has turned into an essential exploring subject in the industrial control field since its strong application background. Therefore, quite a number of control methods were reported, such as sliding mode control [4], adaptive control [5], H∞ control [6], backstepping control [7,8], and robust control [9]. Significantly, backstepping-based adaptive control approaches have been adopted in a wide variety of systems [10–14]. However, only relying on backstepping-based adaptive control approaches cannot cope with complex and variable nonlinear problems.

Aiming at working out the above problems, fuzzy logic system (FLS), multi-dimensional Taylor network (MTN), and neural network (NN) estimation techniques are introduced into the control process. These estimation techniques are used to handle complex nonlinear problems that arise in various systems, such as large-scale nonlinear systems [15–17], stochastic nonlinear systems [18–20], and discrete nonlinear systems [21–23]. For switched nonlinear systems, although a lot of NN-based or FLS-based achievements [24–27] were reported, the application depth and breadth of MTN-based control methods are far from enough. According to the knowledge of [28–30], it can be seen that MTN technique has the advantages of simple structure, wide applicability, and real-time approximation, which opens up a novel way for switched nonlinear systems control. However, the majority of the above MTN-based research works focus on the input or output constrained systems rather than fault systems.

On the one hand, the systems often encounter various faults in the actual control process, such as external faults, sensor faults, and actuator faults. These faults can deteriorate system performance and even cause system instability. Therefore, many fault-tolerant control strategies were developed and applied to the control problems of a host of fault systems, such as nonlinear systems [31,32], switched nonlinear systems [33,34], stochastic nonlinear systems [35,36], and large-scale nonlinear systems [37,38]. However, these fault-tolerant control results are not necessarily true when multiple faults occur in the systems. In recent years, the authors of [39] proposed a NN-based fault-tolerant control strategy, which provided a wonderful idea for the control of nonlinear systems with external faults and actuator faults. Significantly, a more difficult situation arises from the fact that the controlled objects move from nonlinear systems to switched nonlinear systems. Therefore, it is essential to derive an available fault-tolerant control strategy for switched nonlinear systems with multiple faults. On the other hand, with the development of science and technique, the higher requirements for system steady-state and transient performance bring more and more challenges. Consequently, a host of prescribed performance control research results were developed [17, 40–42]. However, according to our current knowledge, the exploration

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* Correspondence to: School of Mathematics and Physics, Qingdao University of Science and Technology, Qingdao, 266061, China.
E-mail addresses: hewj@mails.qust.edu.cn (W.-J. He), zhushanliang@qust.edu.cn (S.-L. Zhu), litinglu@mails.qust.edu.cn (L.-T. Lu), yuqunhan@qust.edu.cn (Y.-Q. Han).

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of prescribed performance control for switched nonlinear systems with multiple faults remains undeveloped, which is a huge challenge for system control. Therefore, aimed at switched nonlinear systems subject to multiple faults, it has crucial theoretical significance and practical application value to develop a novel fault-tolerant control approach based on the full consideration of prescribed performance control.

In the arbitrary switching control framework, this paper addresses the challenge of balancing system performance and multiple faults. An adaptive MTN control method based on prescribed performance is proposed, which guarantees that all closed-loop signals remain bounded, and tracking error falls within a prescribed range. Through comparative analysis with existing works, the major innovations of this paper are reflected in the following three points:

(i) This paper proposes an adaptive MTN-based fault-tolerant control strategy, which provides a novel way to control switched nonlinear systems with faults. Due to the simple structure of MTN, authors in [28–30,43] extended it to switched nonlinear systems and yielded numerous satisfactory results. However, these results can neither prevent faults from deteriorating system performance nor guarantee that tracking error satisfies the given constraints.

(ii) This paper enhances the fault tolerance of switched nonlinear systems by proposing a cooperative fault-tolerant control strategy. The system can still maintain the required control performance even under actuator faults and abrupt external faults. Although the authors of [33,34] addressed actuator faults for switched nonlinear systems, the case of the system suffering from abrupt external faults remains open. It should be noted that the abrupt external fault encounter on nonlinear systems is easily ignored. Despite the fact that multiple faults problem was studied in [39], the proposed fault-tolerant control strategy can neither be applied to switched nonlinear systems nor meet the given performance requirements.

(iii) In contrast to [17,40,41], the proposed control strategy in this paper not only meets the desired performance, but also has fault tolerance capability, and achieves effective tracking control of the controlled system in an arbitrary switching backstepping control framework. This paper is a valuable work in the field of switched nonlinear systems, which proposes a control strategy that ensures steady-state operation and achieves the desired performance in the presence of actuator faults and abrupt external faults.

2. System description and preliminaries

Analyzing switched nonlinear system with p inputs

$$\begin{cases} \dot{x}_i = h_{i,\sigma(t)}\left(\bar{\boldsymbol{x}}_i\right) x_{i+1} + \ell_{i,\sigma(t)}\left(\bar{\boldsymbol{x}}_i\right), i = 1,2,\ldots,n-1 \\ \dot{x}_n = \bar{\boldsymbol{h}}^{\mathrm{T}}_{n,\sigma(t)}\boldsymbol{v} + \ell_{n,\sigma(t)}\left(\bar{\boldsymbol{x}}_n\right) + E\left(\boldsymbol{x}\right) K\left(t-T\right) \\ y = x_1 \end{cases} \tag{1}$$

with $y \in R$ indicates the system output. $\boldsymbol{v} = \left[v_1, v_2, \ldots, v_p\right]^{\mathrm{T}} \in R^p$ is the input vector of the system. The fault may occur in the components of the control input. $\bar{\boldsymbol{x}}_i = \left[x_1, x_2, \ldots, x_i\right]^{\mathrm{T}} \in R^i$ and $\boldsymbol{x}_n = \left[x_1, x_2, \ldots, x_n\right]^{\mathrm{T}} \in R^n$ expresses the state vector. $\sigma(t) : R_+ \to S = \{1, \ldots, s\}$ defines the switching signal, with s denotes the number of subsystem. For $k \in S$, $\ell_{i,k}(\cdot)$ and $h_{i,k}(\cdot)$ mean the unknown nonlinear functions, and $\ell_{i,k}(\boldsymbol{0}) = 0$. $h_{n_j,k}, j = 1, \ldots, p$ is the known constant, and $\bar{\boldsymbol{h}}_{n,k} = \left[h_{n_1,k}, \ldots, h_{n_p,k}\right]^{\mathrm{T}} \in R^p$. $E(\boldsymbol{x})$ indicates the external fault of the system (1). $K(t-T)$ denotes a diagonal matrix, which is expressed as

$$K(t-T) = \begin{cases} 1, t \geq T \\ 0, t < T \end{cases} \tag{2}$$

with T indicates the time while the external fault occurs.

Control objective: For the switched nonlinear system (1), the aim of this paper is to explore a MTN-based adaptive fault-tolerant control approach, resulting in the following two points: (i) the boundedness of all controlled signals is guaranteed; (ii) system output y is able to successfully track desired signal y_d, and prescribed performance of tracking error $\gamma(t) = y - y_d$ can be achieved.

According to [39], the actuator fault can be divided into the Loss of effectiveness model and the Lock-in-place model, which are denote as follows:

Loss of effectiveness model

$$v_j(t) = w_j u_j(t) \tag{3}$$

with $j \in \left\{\overline{j_1, \cdots, j_q}\right\} \cap \{1, \ldots, p\}$, $t \geq t_j$. t_j represents the time when the fault appears. u_j defines the control input. v_j represents the control input after the fault. $w_j \in \left[\underline{w}_j, 1\right]$ expresses the still active ratio of actuator after the loss of effectiveness, with $\underline{w}_j$ indicates the lower bound of w_j and $0 < \underline{w}_j < 1$. When $w_j = 1$, it means that there is no fault in the actuator.

Lock-in-place model

$$v_i(t) = \bar{v}_i, i \in \left\{j_1, j_2, \cdots, j_q\right\} \subset \{1, 2, \ldots, p\} \tag{4}$$

with $t \geq t_i$, $\bar{v}_i$ is a fixed constant, which occurs at t_i. t_i indicates the moment when the lock-in-place fault occurs.

Therefore, combining (3) and (4), input vector $\boldsymbol{v}(t)$ in the system (1) is described as

$$\boldsymbol{v}(t) = w\boldsymbol{u}(t) + \kappa\left(\bar{\boldsymbol{v}} - w\boldsymbol{u}(t)\right) \tag{5}$$

with $\kappa_l = \begin{cases} 1, & l\text{–th actuator fault is (4)} \\ 0, & \text{other situations} \end{cases}$, $l = 1, 2, \ldots, p$, $\kappa = diag\left\{\kappa_1, \ldots, \kappa_p\right\}$, $w = diag\left\{w_1, \ldots, w_p\right\}$, $\boldsymbol{u}(t) = \left[u_1(t), u_2(t), \ldots, u_p(t)\right]^{\mathrm{T}}$ indicates the control vector, and $\bar{\boldsymbol{v}} = \left[\bar{v}_1, \bar{v}_2, \ldots, \bar{v}_p\right]^{\mathrm{T}}$ is the constant vector.

The actuator is used to stabilize the system (1) and drive the tracking error to a small neighborhood of origin. Similar to [39], the control framework is constructed as

$$u_j = \rho_j(\boldsymbol{x}) v_0 \tag{6}$$

with $j = 1, 2, \ldots, p$. v_0 indicates the actual control, which will be designed in the backstepping process. The gain function $\rho_j(\boldsymbol{x})$ satisfies the following condition

$$0 \leq \underline{\rho}_j \leq \rho_j(\boldsymbol{x}) \leq \bar{\rho}_j \tag{7}$$

where $\underline{\rho}_j$, $\bar{\rho}_j$ indicate the lower and upper bounds of $\rho_j(\boldsymbol{x})$.

Combining (5) and (6), we can obtain

$$\begin{aligned} \bar{\boldsymbol{h}}^{\mathrm{T}}_{n,k}\boldsymbol{v} &= \bar{\boldsymbol{h}}^{\mathrm{T}}_{n,k}\left[w\boldsymbol{u}(t) + \kappa\left(\bar{\boldsymbol{v}} - w\boldsymbol{u}(t)\right)\right] \\ &= \sum_{j \neq j_1,\ldots,j_p} w_j h_{n_j,k}\rho_j v_0 + \sum_{j = j_1,\ldots,j_p} h_{n_j,k}\bar{v}_j \\ &= h'_{n,k} v_0 + \sum_{j = j_1,\ldots,j_p} h_{n_j,k}\bar{v}_j \end{aligned} \tag{8}$$

with $h'_{n,k} = \sum_{j \neq j_1,\ldots,j_p} w_j h_{n_j,k}\rho_j$.

In order to achieve the control object (ii), with the help of [40], for $\forall t > 0$, tracking error $\gamma(t)$ satisfies the following condition

$$-\varsigma_{\min}\xi(t) \leq \gamma(t) \leq \varsigma_{\max}\xi(t) \tag{9}$$

where $\xi(t) = \left(\xi_0 - \xi_\infty\right)e^{-at} + \xi_\infty$ is a prescribed performance function. a, ξ_0, ξ_∞, $\varsigma_{\max}$, and $\varsigma_{\min}$ are positive design parameters. In addition, $\xi_0 = \xi(0)$ is chosen as $\xi_0 > \xi_\infty$, and $-\varsigma_{\min}\xi(0) \leq \gamma(0) \leq \varsigma_{\max}\xi(0)$. Based on (9), we can get $\gamma(t) \leq \max\left\{\varsigma_{\min}\xi(0), \varsigma_{\max}\xi(0)\right\}$.

Based on the prescribed performance condition (9), for $\forall t \geq 0$, the constrained $\gamma(t)$ is turned into unconstrained ones by the following transformation

$$\gamma(t) = \xi(t) H(\zeta(t)) \tag{10}$$

with ζ indicates transform error. $H(\zeta) = \frac{\varsigma_{\max}e^{\zeta} - \varsigma_{\min}e^{-\zeta}}{e^{\zeta} + e^{-\zeta}}$ denotes a smoothly and strictly increasing function.

Based on (10), the transform error $\zeta(t)$ can be expressed as

$$\zeta(t) = H^{-1}\left(\frac{\gamma(t)}{\xi(t)}\right) = \frac{1}{2}\ln\frac{H + \varsigma_{\min}}{\varsigma_{\max} - H} \tag{11}$$

Therefore, $\dot{\zeta}(t)$ is described as

$$\dot{\zeta}(t) = \eta\left(\dot{\gamma} - \frac{\dot{\xi}\gamma}{\xi}\right) \tag{12}$$

where $\eta = \frac{1}{2\xi}\left(\frac{1}{H+\varsigma_{\min}} - \frac{1}{H-\varsigma_{\max}}\right)$.

Assumption 1 (*[43]*). There exist positive constants q_m, q_M such that $h_{i,k}(\bar{x}_i)$ satisfies $0 < q_m \le \left|h_{i,k}(\bar{x}_i)\right| \le q_M < \infty$. As a general rule, the sign of function $h_{i,k}(\cdot)$ is assumed to be positive.

Assumption 2 (*[29]*). The desired signal y_d and its up to the nth order time derivatives are bounded and continuous.

Lemma 1 (*[41]*). *For $\forall\varepsilon > 0$, a continuous nonlinear function $L(\chi)$ defined in a compact set Ω_χ can be estimated by a MTN with form $\boldsymbol{\beta}^{\mathrm{T}} S_{m_n}(\chi)$, such as*

$$L(\chi) = \boldsymbol{\beta}^{*\mathrm{T}} S_{m_n}(\chi) + \delta(\chi) \tag{13}$$

with $S_{m_n}(\chi) = \left[\chi_1, \dots, \chi_n, \chi_1^2, \dots, \chi_n^2, \dots, \chi_1^m, \dots, \chi_n^m\right]^{\mathrm{T}}$ defines the middle layer vector. $\delta(\chi)$ represents the estimation error and satisfies $|\delta(\chi)| \le \varepsilon$. $\chi = \left[\chi_1, \dots, \chi_n\right]^{\mathrm{T}} \in R^n$ means the input vector. $\boldsymbol{\beta}$ expresses the weight vector from the middle layer to the output layer, and $\boldsymbol{\beta}^* := \arg\min_{\beta \in R^l}\left\{\sup_{L \in \Omega_\chi}\left|L(\chi) - \boldsymbol{\beta}^{\mathrm{T}} S_{m_n}(\chi)\right|\right\} \in R^l$.

3. Main works

The weight vector $\boldsymbol{\beta}_{i,k}$ of MTN satisfies $\beta_i = \max\{\|\boldsymbol{\beta}_{i,k}\|^2 : k \in S\}$. β_i is the unknown constant. $\hat{\beta}_i$ indicates the estimated value of β_i and satisfies $\tilde{\beta}_i = \beta_i - \hat{\beta}_i$.

In addition, for the system (1), the following state transformation is defined

$$\begin{cases} z_1 = \zeta(t) - \dfrac{1}{2}\ln\dfrac{\varsigma_{\min}}{\varsigma_{\max}} \\ z_i = x_i - \alpha_{i-1} \end{cases} \tag{14}$$

where $i = 2, \dots, n$, α_i defines virtual control signal, and its detailed structure will be built below.

Combining (1), (8), (12), and (14), the time derivatives of the new variable z_i can be obtained as follows

$$\begin{cases} \dot{z}_1 = \eta\left(h_{1,k}x_2 + \ell_{1,k} - \dot{y}_d - \dfrac{\dot{\xi}\gamma}{\xi}\right) \\ \dot{z}_i = h_{i,k}x_{i+1} + \ell_{i,k} - \dot{\alpha}_{i-1}, i = 2, \dots, n-1 \\ \dot{z}_n = h'_{n,k}v_0 + \sum\limits_{j=j_1,\dots,j_p} h_{n_j,k}\bar{v}_j + \ell_{n,k} + K(t-T)E(\boldsymbol{x}) - \dot{\alpha}_{n-1} \end{cases} \tag{15}$$

where $\dot{\alpha}_i = \sum_{j=1}^{i}\frac{\partial\alpha_i}{\partial x_j}\left(h_{j,k}x_{j+1} + \ell_{j,k}\right) + \sum_{j=1}^{i}\frac{\partial\alpha_i}{\partial\hat{\beta}_j}\dot{\hat{\beta}}_j + \sum_{j=0}^{i}\frac{\partial\alpha_i}{\partial y_d^{(j)}}y_d^{(j+1)}$.

3.1. Adaptive fault-tolerant controller design

The procedure for designing MTN-based fault-tolerant adaptive controller is summarized as n steps.

Step 1: A candidate function V_1 is introduced

$$V_1 = \frac{1}{2}z_1^2 + \frac{1}{2}\tilde{\beta}_1^2 \tag{16}$$

In view of the transformation (14), the time derivative of V_1 is described as

$$\dot{V}_1 = z_1\left[\eta h_{1,k}\left(z_2 + \alpha_1\right) + L_{1,k}\right] - \frac{1}{2}q_M\eta z_1^2 - \frac{1}{2}z_1^2 - \tilde{\beta}_1\dot{\hat{\beta}}_1 \tag{17}$$

with $L_{1,k} = \eta\left(\ell_{1,k} - \dot{y}_d - \frac{\dot{\xi}\gamma}{\xi}\right) + \frac{1}{2}\left(q_M\eta + 1\right)z_1$ is a continuous function.

According to Lemma 1, for $\forall\varepsilon_{1,k} > 0$, the nonlinear function $L_{1,k}$ can be approximated by MTN, which is expressed with the following form

$$L_{1,k} = \boldsymbol{\beta}_{1,k}^{\mathrm{T}} S_{m_1} + \delta_{1,k} \tag{18}$$

where $\left|\delta_{1,k}\right| \le \varepsilon_{1,k}$ represents the estimation error of MTN.

By means of (18) and Young's inequality, the following formula is correct

$$z_1 L_{1,k} \le \frac{1}{2}c_1^2 + \frac{1}{2c_1^2}z_1^2\beta_1 S_{m_1}^{\mathrm{T}} S_{m_1} + \frac{1}{2}z_1^2 + \frac{1}{2}\varepsilon_{1,k}^2 \tag{19}$$

where constant $c_1 > 0$.

Selecting the virtual control signal such as

$$\alpha_1 = -\frac{1}{q_m\eta}\left(\mu_1 z_1 + \frac{1}{2c_1^2}z_1\hat{\beta}_1 S_{m_1}^{\mathrm{T}} S_{m_1}\right) \tag{20}$$

with $\mu_1 > 0$ is a constant.

Next, invoking Young's inequality, the following inequalities are obtained

$$\eta h_{1,k}z_1 z_2 \le \frac{1}{2}q_M\eta\left(z_1^2 + z_2^2\right) \tag{21}$$

$$\eta h_{1,k}z_1\alpha_1 \le -\mu_1 z_1^2 - \frac{1}{2c_1^2}z_1^2\hat{\beta}_1 S_{m_1}^{\mathrm{T}} S_{m_1} \tag{22}$$

Combining (14), (17), (19), (21), and (22), the following formula is correct

$$\dot{V}_1 \le -\mu_1 z_1^2 + \tilde{\beta}_1\left(\frac{1}{2c_1^2}z_1^2 S_{m_1}^{\mathrm{T}} S_{m_1} - \dot{\hat{\beta}}_1\right) + \frac{1}{2}q_M\eta z_2^2 + \frac{1}{2}\left(c_1^2 + \varepsilon_{1,k}^2\right) \tag{23}$$

Step 2: Considering a candidate Lyapunov function V_2 with the following form

$$V_2 = V_1 + \frac{1}{2}z_2^2 + \frac{1}{2}\tilde{\beta}_2^2 \tag{24}$$

On the basis of the transformation (14), the time derivative of the above Lyapunov function can be written as

$$\begin{aligned} \dot{V}_2 = &\dot{V}_1 + z_2\left[h_{2,k}\left(z_3 + \alpha_2\right) + L_{2,k}\right] - \tilde{\beta}_2\dot{\hat{\beta}}_2 \\ &- \left(\frac{1}{2}q_M\eta + \frac{1}{2}q_M + \frac{1}{2}\right)z_2^2 \end{aligned} \tag{25}$$

with $L_{2,k} = \ell_{2,k} - \dot{\alpha}_1 + \frac{1}{2}\left(q_M\eta + q_M + 1\right)z_2$ is a continuous function.

Based on Lemma 1, for $\forall\varepsilon_{2,k} > 0$, the continuous nonlinear function $L_{2,k}$ can be approximated by MTN, which can be indicated as

$$L_{2,k} = \boldsymbol{\beta}_{2,k}^{\mathrm{T}} S_{m_2} + \delta_{2,k} \tag{26}$$

where $\left|\delta_{2,k}\right| \le \varepsilon_{2,k}$ denotes the estimation error of MTN.

Invoking (26) and Young's inequality, the following inequality holds

$$z_2 L_{2,k} \le \frac{1}{2}c_2^2 + \frac{1}{2c_2^2}z_2^2\beta_2 S_{m_2}^{\mathrm{T}} S_{m_2} + \frac{1}{2}z_2^2 + \frac{1}{2}\varepsilon_{2,k}^2 \tag{27}$$

where constant $c_2 > 0$.

Defining the virtual control signal as

$$\alpha_2 = -\frac{1}{q_m}\left(\mu_2 z_2 + \frac{1}{2c_2^2}z_2\hat{\beta}_2 S_{m_2}^{\mathrm{T}} S_{m_2}\right) \tag{28}$$

with $\mu_2 > 0$ is a constant.

The following inequalities are derived from (28) and Young's inequality

$$h_{2,k}z_2 z_3 \le \frac{1}{2}q_M z_2^2 + \frac{1}{2}q_M z_3^2 \tag{29}$$

$$h_{2,k}z_2\alpha_2 \le -\mu_2 z_2^2 - \frac{1}{2c_2^2}z_2^2\hat{\beta}_2 S_{m_2}^{\mathrm{T}} S_{m_2} \tag{30}$$

Combining (14), (23), (25), (27), (29), and (30), the following formula is correct

$$\dot{V}_2 \leq -\sum_{j=1}^{2}\mu_j z_j^2 + \sum_{j=1}^{2}\tilde{\beta}_j\left(\frac{1}{2c_j^2}z_j^2 S_{m_j}^{\mathrm{T}} S_{m_j} - \dot{\hat{\beta}}_j\right) + \frac{1}{2}q_M z_3^2 + \frac{1}{2}\sum_{j=1}^{2}\left(c_j^2 + \varepsilon_{j,k}^2\right) \tag{31}$$

Step $i\,(3 \leq i \leq n-1)$: Constructing the candidate Lyapunov function V_i as

$$V_i = V_{i-1} + \frac{1}{2}z_i^2 + \frac{1}{2}\tilde{\beta}_i^2 \tag{32}$$

According to the transformation (14), $\dot{V}_i$ is described as

$$\dot{V}_i = z_i\left[h_{i,k}\left(\alpha_i + z_{i+1}\right) + L_{i,k}\right] - \tilde{\beta}_i\dot{\hat{\beta}}_i - \left(q_M + \frac{1}{2}\right)z_i^2 + \dot{V}_{i-1} \tag{33}$$

with $L_{i,k} = \ell_{i,k} - \dot{\alpha}_{i-1} + \left(q_M + \frac{1}{2}\right)z_i$ is a continuous function.

With the help of Lemma 1, for $\forall\varepsilon_{i,k} > 0$, the nonlinear function $L_{i,k}$ can be approximated by MTN, which can be written as

$$L_{i,k} = \beta_{i,k}^{\mathrm{T}} S_{m_i} + \delta_{i,k} \tag{34}$$

where $|\delta_{i,k}| \leq \varepsilon_{i,k}$ defines the estimation error of MTN.

Based on (34) and Young's inequality, the following inequality holds

$$z_i L_{i,k} \leq \frac{1}{2}c_i^2 + \frac{1}{2c_i^2}z_i^2\beta_i S_{m_i}^{\mathrm{T}} S_{m_i} + \frac{1}{2}z_i^2 + \frac{1}{2}\varepsilon_{i,k}^2 \tag{35}$$

where constant $c_i > 0$.

The virtual control signal is selected as

$$\alpha_i = -\frac{1}{q_m}\left(\mu_i z_i + \frac{1}{2c_i^2}z_i\hat{\beta}_i S_{m_i}^{\mathrm{T}} S_{m_i}\right) \tag{36}$$

with $\mu_i > 0$ is a constant.

Similarly, from Young's inequality, we arrive at the following inequalities

$$h_{i,k}z_i z_{i+1} \leq \frac{1}{2}q_M z_i^2 + \frac{1}{2}q_M z_{i+1}^2 \tag{37}$$

$$h_{i,k}z_i\alpha_i \leq -\mu_i z_i^2 - \frac{1}{2c_i^2}z_i^2\hat{\beta}_i S_{m_i}^{\mathrm{T}} S_{m_i} \tag{38}$$

Combining (14), (31), (33), (35), (37), (38), and mathematical derivation, the following formula is correct

$$\dot{V}_i \leq -\sum_{j=1}^{i}\mu_j z_j^2 + \sum_{j=1}^{i}\tilde{\beta}_j\left(\frac{1}{2c_j^2}z_j^2 S_{m_j}^{\mathrm{T}} S_{m_j} - \dot{\hat{\beta}}_j\right) + \frac{1}{2}q_M z_{i+1}^2 + \frac{1}{2}\sum_{j=1}^{i}\left(c_j^2 + \varepsilon_{j,k}^2\right) \tag{39}$$

Step n: In accordance with the recurrence method, we introduce the nth candidate Lyapunov function V_n as

$$V_n = V_{n-1} + \frac{1}{2}z_n^2 + \frac{1}{2}\tilde{\beta}_n^2 + \frac{1}{2}\tilde{\beta}^2 \tag{40}$$

with $\tilde{\beta} = \beta - \hat{\beta}$ denotes the estimate error. $\hat{\beta}$ expresses the estimated value of β. $\beta = \|\boldsymbol{\beta}\|^2$ is the unknown constant. $\boldsymbol{\beta}$ denotes the weight vector of MTN.

Thus, the time derivative of V_n is written as

$$\dot{V}_n = z_n\left(\sum_{j=j_1,\ldots,j_p} h_{n_j,k}\bar{v}_j + L_{n,k} + K(t-T)E(\boldsymbol{x})\right) + z_n h'_{n,k}v_0 - \frac{1}{2}\left(q_M + 1\right)z_n^2 - \tilde{\beta}_n\dot{\hat{\beta}}_n - \tilde{\beta}\dot{\hat{\beta}} + \dot{V}_{n-1} \tag{41}$$

with $L_{n,k} = \ell_{n,k} - \dot{\alpha}_{n-1} + \frac{q_M+1}{2}z_n$ is a continuous function.

In the light of Lemma 1, for $\forall\varepsilon_{n,k} > 0$, the combination of the nonlinear functions $L_{n,k}$ can be approximated by MTN, which can be described as

$$L_{n,k} = \boldsymbol{\beta}_{n,k}^{\mathrm{T}} S_{m_n} + \delta_{n,k} \tag{42}$$

where $|\delta_{n,k}| \leq \varepsilon_{n,k}$ means the estimation error of MTN.

Invoking (42) and Young's inequality, the following inequality holds

$$\begin{aligned} z_n L_{n,k} &\leq \frac{1}{2}c_n^2 + \frac{1}{2c_n^2}z_n^2\left\|\boldsymbol{\beta}_{n,k}\right\|^2 S_{m_n}^{\mathrm{T}} S_{m_n} + \frac{1}{2}z_n^2 + \frac{1}{2}\varepsilon_{n,k}^2 \\ &\leq \frac{1}{2}c_n^2 + \frac{1}{2c_n^2}z_n^2\beta_n S_{m_n}^{\mathrm{T}} S_{m_n} + \frac{1}{2}z_n^2 + \frac{1}{2}\varepsilon_{n,k}^2 \end{aligned} \tag{43}$$

with $c_n > 0$ is a constant.

The MTN technique can be used to deal with the external fault $E(\boldsymbol{x})$, similar to the work of (43), for $\forall\varepsilon > 0$, which can be obtained

$$\begin{aligned} z_n K(t-T)E(\boldsymbol{x}) &\leq z_n\boldsymbol{\beta}^{\mathrm{T}} S_{m_n} + z_n\delta \\ &\leq \frac{1}{2}c^2 + \frac{1}{2c^2}z_n^2\|\boldsymbol{\beta}\|^2 S_{m_n}^{\mathrm{T}} S_{m_n} + \frac{1}{2}z_n^2 + \frac{1}{2}\varepsilon^2 \\ &\leq \frac{1}{2}c^2 + \frac{1}{2c^2}z_n^2\beta S_{m_n}^{\mathrm{T}} S_{m_n} + \frac{1}{2}z_n^2 + \frac{1}{2}\varepsilon^2 \end{aligned} \tag{44}$$

with $c > 0$ is a constant, and $|\delta| \leq \varepsilon$ represents the estimation error of MTN.

In order to achieve fault-tolerant control of the fault system (1), actual control signal is structured as $v_0 = v_n + v_F$, and

$$v_n = -\frac{1}{h'_{n,k}}\left(\mu_n z_n + \frac{1}{2c_n^2}z_n\hat{\beta}_n S_{m_n}^{\mathrm{T}} S_{m_n}\right) - \frac{1}{h'_{n,k}}\sum_{j=j_1,\ldots,j_p} h_{n_j,k}\bar{v}_j \tag{45}$$

$$v_F = -\frac{1}{2h'_{n,k}}\left(z_n + \frac{1}{c^2}z_n\hat{\beta} S_{m_n}^{\mathrm{T}} S_{m_n}\right) \tag{46}$$

with $\mu_n > 0$ is a constant. The structure of v_n ensures that the system (1) can be effectively controlled, even when the actuator fault occurs. v_F is mainly used to deal with effect of the external fault.

Combining (41), (43), (44), (45), and (46), the following inequality can be obtained

$$\dot{V}_n \leq -\sum_{j=1}^{n}\mu_j z_j^2 + \sum_{j=1}^{n}\tilde{\beta}_j\left(\frac{1}{2c_j^2}z_j^2 S_{m_j}^{\mathrm{T}} S_{m_j} - \dot{\hat{\beta}}_j\right) + \tilde{\beta}\left(\frac{1}{2c^2}z_n^2 S_{m_n}^{\mathrm{T}} S_{m_n} - \dot{\hat{\beta}}\right) + \frac{1}{2}\left(c^2 + \varepsilon^2\right) + \frac{1}{2}\sum_{j=1}^{n}\left(c_j^2 + \varepsilon_{j,\max}^2\right) \tag{47}$$

with $\varepsilon_{j,\max} = \max\left\{\varepsilon_{j,k} | k \in S\right\}$.

Remark 1. Although the prescribed performance control issue of switched nonlinear systems is considered by [40], the proposed control strategy cannot ensure the stability of the controlled system while it is suffering from multiple faults. In addition, compared with [40], a more complex performance control problem is discussed, and an adaptive MTN-based fault-tolerant controller is proposed, which realizes the prescribed performance control of the switched fault system with a relatively simple control structure.

3.2. Stability analysis

Theorem 1. *The problem of prescribed performance control of the switched nonlinear system (1) with multiple faults is addressed. When the actual control signals are constructed as (45), (46), the virtual control signals are selected as (20), (28), (36), and the adaptive control laws of the following form are considered*

$$\dot{\hat{\beta}} = -\Lambda\hat{\beta} + \frac{1}{2c^2}z_n^2 S_{m_n}^{\mathrm{T}} S_{m_n} \tag{48}$$

$$\dot{\hat{\beta}}_j = -\Lambda_j\hat{\beta}_j + \frac{1}{2c_j^2}z_j^2 S_{m_j}^{\mathrm{T}} S_{m_j} \tag{49}$$

where $j = 1, 2, \ldots, n$, $\Lambda > 0$ and $\Lambda_j > 0$ are constants, then, it can be concluded that the following two points are correct:

(i) All signals are bounded for the closed-loop system;

(ii) System output y is able to successfully track desired signal y_d. Furthermore, tracking error $y - y_d$ guarantees the given prescribed tracking performance.

Proof. For the system (1), constructing the Lyapunov function as

$$V = V_n = \frac{1}{2}\sum_{j=1}^{n} z_j + \frac{1}{2}\sum_{j=1}^{n} \tilde{\beta}_j^2 + \frac{1}{2}\tilde{\beta}^2 \tag{50}$$

On the basis of (47), (48), and (49), $\dot{V}$ is derived as

$$\begin{aligned}\dot{V} \le &- \sum_{j=1}^{n} \mu_j z_j^2 + \frac{1}{2}\sum_{j=1}^{n}\left(c_j^2 + \varepsilon_{j,\max}^2\right) \\ &+ \frac{1}{2}\left(c^2 + \varepsilon^2\right) + \sum_{j=1}^{n} \Lambda_j \tilde{\beta}_j \hat{\beta}_j + \Lambda \tilde{\beta}\hat{\beta}\end{aligned} \tag{51}$$

By utilizing Young's inequality, the following inequalities are correct

$$\Lambda \tilde{\beta}\hat{\beta} \le -\frac{1}{2}\Lambda \tilde{\beta}^2 + \frac{1}{2}\Lambda \beta^2 \tag{52}$$

$$\sum_{j=1}^{n} \Lambda_j \tilde{\beta}_j \hat{\beta}_j \le -\frac{1}{2}\Lambda_{\min}\sum_{j=1}^{n} \tilde{\beta}_j^2 + \frac{1}{2}\sum_{j=1}^{n} \Lambda_j \beta_j^2 \tag{53}$$

with $\Lambda_{\min} = \min\left\{\Lambda_j | j = 1, \ldots, n\right\}$.

Substituting (52), (53) into (51), the following formula can be obtained

$$\begin{aligned}\dot{V} \le &- \sum_{j=1}^{n} \mu_j z_j^2 + \sum_{j=1}^{n} \frac{1}{2}\left(c_j^2 + \varepsilon_{j,\max}^2\right) + \frac{1}{2}\left(c^2 + \varepsilon^2\right) \\ &- \frac{1}{2}\Lambda \tilde{\beta}^2 + \frac{1}{2}\Lambda \beta^2 - \frac{1}{2}\Lambda_{\min}\sum_{j=1}^{n} \tilde{\beta}_j^2 + \frac{1}{2}\sum_{j=1}^{n} \Lambda_j \beta_j^2 \\ \le &- BV + C\end{aligned} \tag{54}$$

with $C = \frac{1}{2}\left(c^2 + \varepsilon^2\right) + \frac{1}{2}\sum_{j=1}^{n} \Lambda_j \beta_j^2 + \frac{1}{2}\sum_{j=1}^{n}\left(c_j^2 + \varepsilon_{j,\max}^2\right) + \frac{1}{2}\Lambda \beta^2$ and $B = \min\left\{2\mu_j, \Lambda, \Lambda_j | j = 1, 2, \ldots, n\right\}$.

By integrating (54), we can get

$$0 \le V \le \left[V(0) - \frac{C}{B}\right] e^{-Bt} + \frac{C}{B} \tag{55}$$

Based on (55), using the similar analysis method in [40], Theorem 1 is proved.

In conclusion, the design process of adaptive controller constructed in this paper can be summarized as Fig. 1.

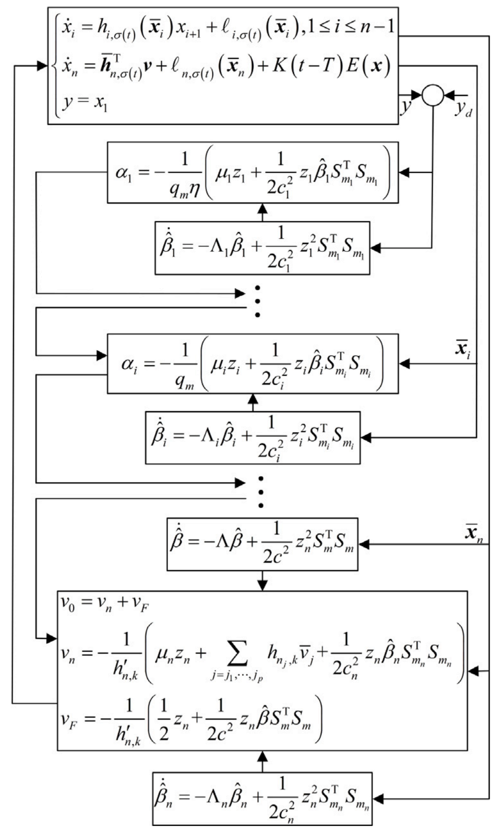

Fig. 1. Adaptive control framework.

4. Simulation result

Example 1. Considering a class of third-order switched nonlinear system subject to multiple faults, which is governed by the following form

$$\begin{cases}\dot{x}_1 = h_{1,k}x_2 + \ell_{1,k} \\ \dot{x}_2 = h_{2,k}x_3 + \ell_{2,k} \\ \dot{x}_3 = h_{3_1,k}v_1 + h_{3_2,k}v_2 + \ell_{3,k} + K(t-T)E \\ y = x_1\end{cases} \tag{56}$$

where the initial conditions are $x_1(0) = 0.01$, $x_2(0) = x_3(0) = 0.1$, $k \in S = \{1, 2\}$, $h_{3_1,1} = 4$, $h_{3_2,1} = 2$, $h_{3_1,2} = 2$, $h_{3_2,2} = 1$, $y_d = 0.5(\sin 0.5t + \sin 0.25t)$. $K(t-T)$ is expressed as (2) and $T = 25s$. The external fault is selected as $E(\boldsymbol{x}) = x_1x_2x_3$. The nonlinear functions are set to $\ell_{1,1} = 0.1x_1 \sin x_1$, $\ell_{1,2} = 0.2x_1 \cos x_1$, $\ell_{2,1} = 0.2x_1^2 x_2$, $\ell_{2,2} = 0.1x_1 x_2^2$, $\ell_{3,1} = 0.2x_2 x_3^2$, $\ell_{3,2} = 0.1x_2^2 x_3$, $h_{1,1} = 0.1\cos x_1 + 0.8$, $h_{1,2} = 0.1\sin x_1 + 1$, $h_{2,1} = h_{2,2} = 1$. The parameters in prescribed performance function are designed as $\xi_0 = 3$, $\xi_\infty = 0.2$, $a = 1$, $\varsigma_{\min} = 0.8$, $\varsigma_{\max} = 1$. The parameters of the fault-tolerant MTN-based controller proposed are designed as $c = 1$, $c_1 = c_2 = c_3 = 1$, $q_m = 0.8$, $\Lambda = \Lambda_1 = \Lambda_2 = \Lambda_3 = 1$, $\mu_1 = 15$, $\mu_2 = 8$, $\mu_3 = 5$. For $t > 15s$, actuator faults are indicated as $v_1 = 0.5u_1 = 0.5v_0$ and $v_2 = \bar{v}_2 = 10$, with $\omega_1 = \omega_2 = 0.5$, $\rho_1 = \rho_2 = 1$. So we can get $h'_{3,1} = 2$, $h'_{3,2} = 1$, $\sum_{j=j_1,j_2} h_{n_j,1}\bar{v}_j = 20$, and $\sum_{j=j_1,j_2} h_{n_j,2}\bar{v}_j = 10$. The simulation results are displayed in Figs. 2–7. Fig. 2 describes that system output successfully track desired signal. Fig. 3 reveals that the tracking error satisfies the predetermined constraints and steady-state performance. Figs. 2–3 show that the tracking performance of this paper is satisfactory. Fig. 4 illustrates the bounded control input, and it can be found that when the time reaches $15s$, the actual control input subject to faults can be divided into the lock-in-place input v_1 and the loss of effectiveness input v_2. Fig. 5 displays the trajectory of the external fault input v_F. Figs. 6–7 depict the state variables x_2, x_3, and the switching signal, respectively. It follows from Figs. 2–7, one can see that the controller developed in this paper can achieve the control objects.

Example 2. The continuous stirred tank reactor subject to two modes feed stream [28] is described as the switched nonlinear system with multiple faults as follows

$$\begin{cases}\dot{x}_1 = x_1 + \ell_{1,k} \\ \dot{x}_2 = h_{2_1,k}v_1 + h_{2_2,k}v_2 + K(t-T)E \\ y = x_1\end{cases} \tag{57}$$

with the initial conditions are $x_1(0) = x_2(0) = 0$, $k \in S = \{1, 2\}$, $h_{2_1,1} = h_{2_2,1} = 2$, $h_{2_1,2} = h_{2_2,2} = 1$, $y_d = 0.5(\sin t + \sin 0.5t)$. The external fault is selected as $E(\boldsymbol{x}) = x_1x_2$. $K(t-T)$ is described as (2), and $T = 25$ s. The nonlinear functions are set to $\ell_{1,1} = -0.1x_1$, $\ell_{1,2} = x_1$. The parameters in prescribed performance function are designed as $\xi_0 = 3$, $\xi_\infty = 0.2$, $a = 1$, $\varsigma_{\min} = 1$, $\varsigma_{\max} = 1$. The parameters of the fault-tolerant

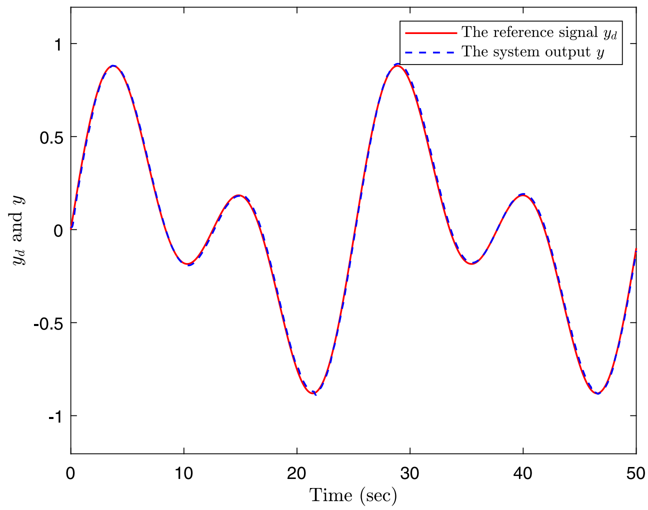

Fig. 2. The trajectories of y_d and y of Example 1.

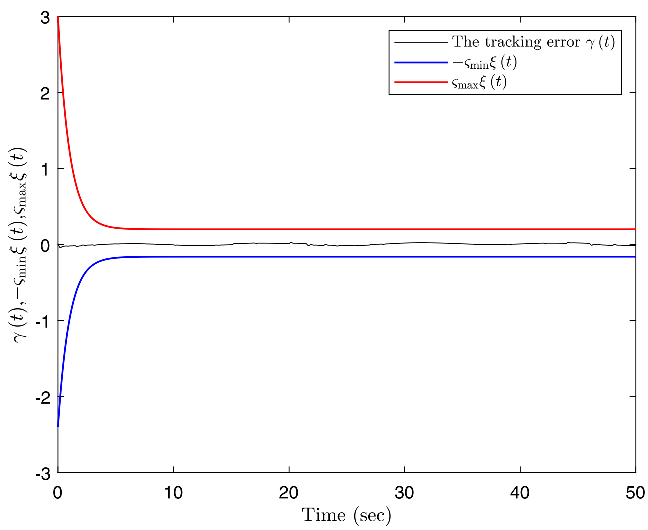

Fig. 3. The trajectories of $\gamma(t)$, $-\varsigma_{\min}\xi(t)$, and $\varsigma_{\max}\xi(t)$ of Example 1.

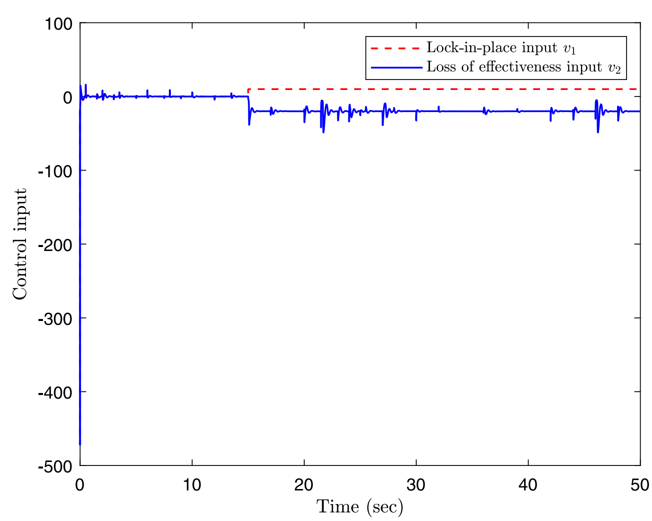

Fig. 4. Trajectories of system inputs v_1, v_2 in Example 1.

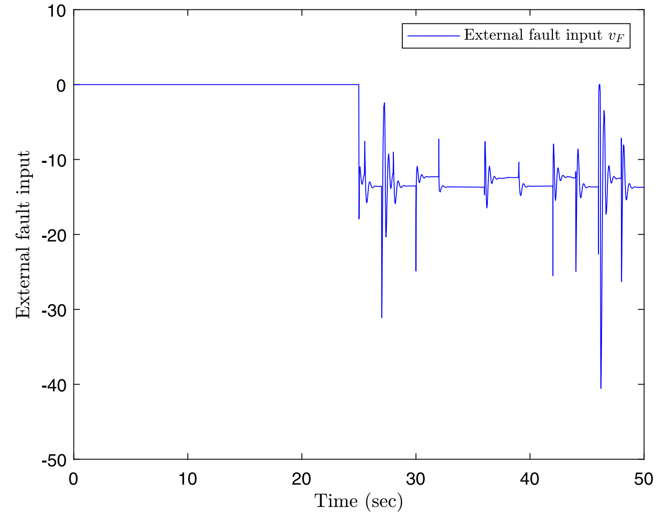

Fig. 5. Trajectory of external fault input v_F of Example 1.

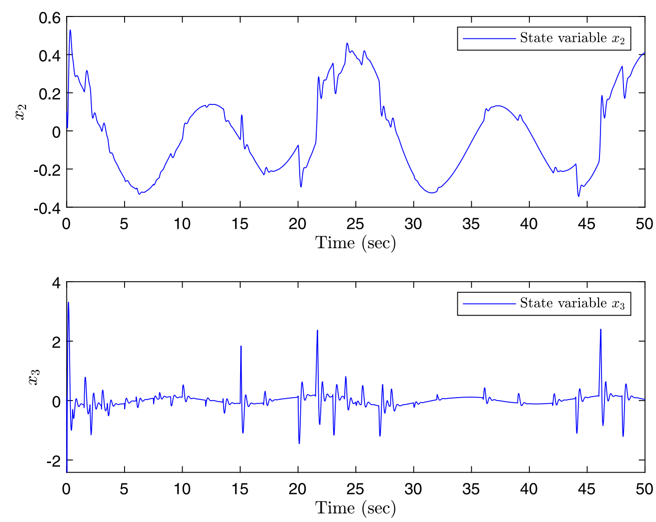

Fig. 6. Trajectories of state variables x_2, x_3 of Example 1.

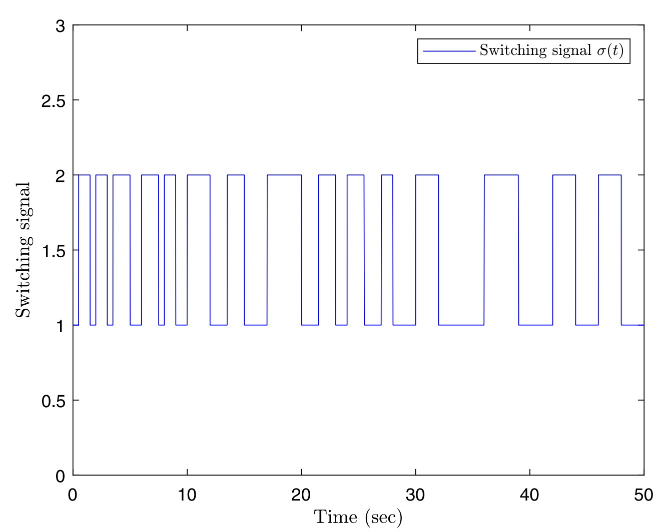

Fig. 7. Trajectory of switching signal $\sigma(t)$ of Example 1.

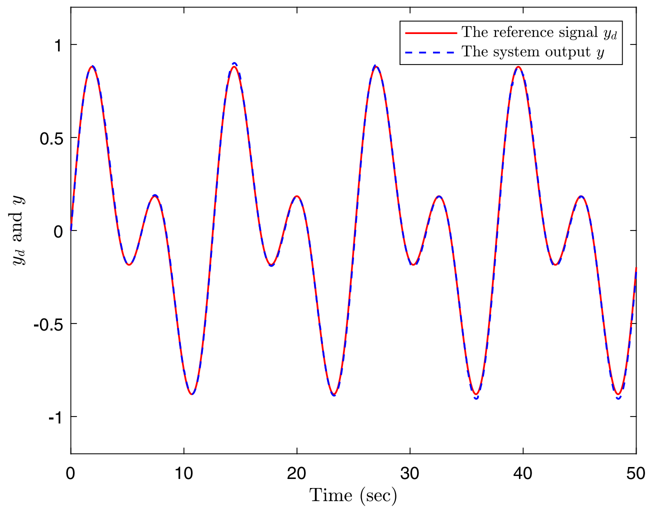

Fig. 8. The trajectories of y_d and y of Example 2.

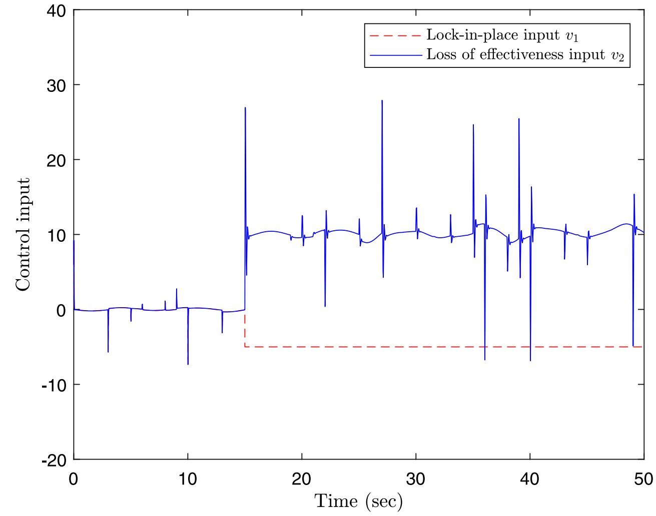

Fig. 10. The trajectories of system inputs v_1, v_2 of Example 2.

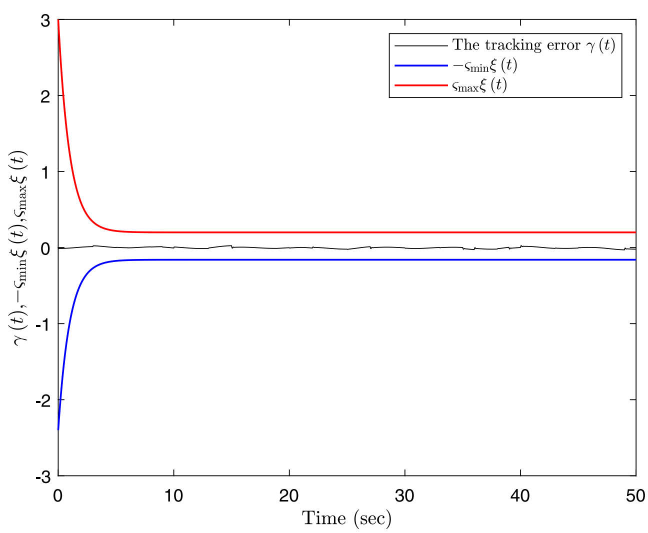

Fig. 9. The trajectories of $\gamma(t)$, $-\varsigma_{\min}\xi(t)$, and $\varsigma_{\max}\xi(t)$ of Example 2.

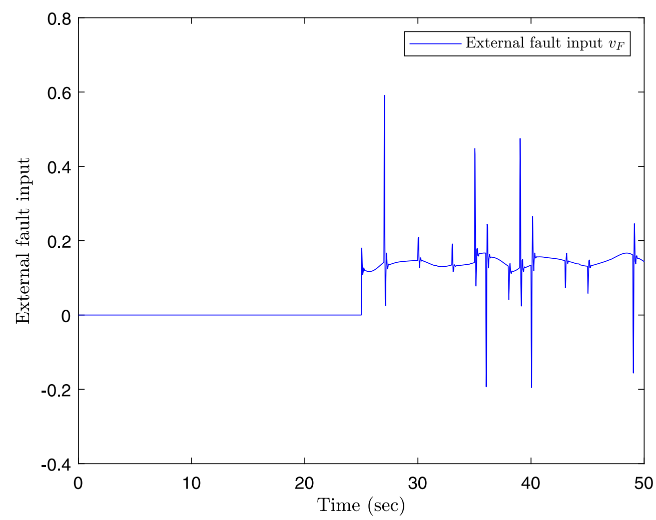

Fig. 11. The trajectory of external fault input v_F of Example 2.

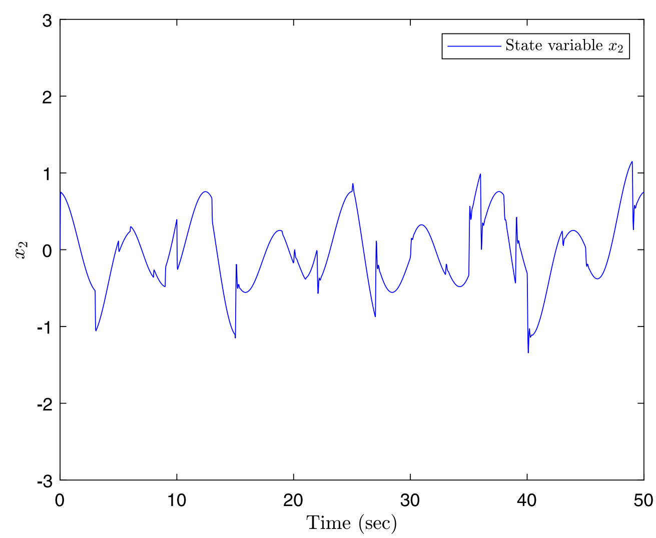

Fig. 12. The trajectory of state variables x_2 of Example 2.

MTN-based controller are designed as $c = c_1 = c_2 = 1$, $\Lambda_1 = \Lambda_2 = \Lambda = 1$, $q_m = 0.5$, $\mu_1 = 25$, $\mu_2 = 50$. For $t > 15s$, actuator faults are indicated as $v_1 = 0.5u_1 = 0.5v_0$ and $v_2 = \bar{v}_2 = -5$, with $\omega_1 = \omega_2 = 0.5$, $\rho_1 = \rho_2 = 1$. So, we can get $h'_{3,1} = h'_{3,2} = 1$ and $\sum_{j=j_1,j_2} h_{n_j,1}\bar{v}_j = \sum_{j=j_1,j_2} h_{n_j,2}\bar{v}_j = 2$. The simulation results are displayed in Figs. 8–13.

Figs. 8–13 further verify that the fault-tolerant MTN-based controller proposed can also achieve superior tracking control in practical systems.

5. Conclusion

The prescribed performance control of switched nonlinear systems with multiple faults is researched. The multiple faults considered in this paper include actuator faults and external faults. Firstly, prescribed performance is given careful consideration in the control process. Secondly, the MTN technique is utilized to estimate unknown nonlinear functions. Thirdly, a new adaptive fault-tolerant control strategy is explored. It needs to be emphasized that the tracking issue of switched nonlinear systems subject to multiple faults and prescribed performance

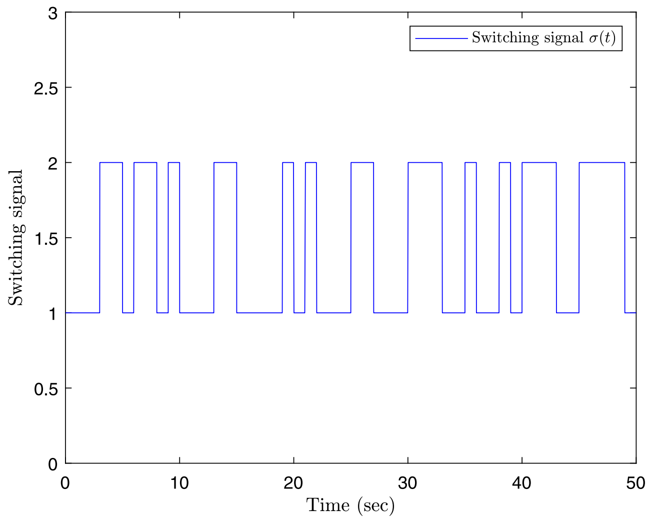

Fig. 13. The trajectory of switching signal $\sigma(t)$ of Example 2.

is first worked out by MTN-based fault-tolerant control. Finally, two examples further indicate that the control strategy developed can acquire the prescribed performance control object. Future research focuses on how to achieve global control of switched nonlinear systems with unmodeled external faults.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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