Fault Tolerant Control Scheme for a Class of Interconnected Nonlinear Time Delay Systems Using Event-Triggered Approach

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ABSTRACT In this study, the event-triggered decentralized fault tolerant control (FTC) problem is investigated for a class of interconnected nonlinear time delay systems in strict feedback form with input quantization and actuator faults. The model of interconnected nonlinear time delay systems includes unstructured uncertainties and unmeasurable states. Firstly, the radial basis function neural networks (RBFNNs) are introduced to identify the unstructured uncertainties and time delay functions. An adaptive RBFNNs state observer is constructed to identify the unmeasurable states, which will be used to the design of decentralized fault tolerant controller. By utilizing the adaptive backstepping technique with low pass filter, an event-based decentralized FTC strategy is developed for the considered interconnected nonlinear systems, such that the output signals could track the reference signals, and the stability of the closed loop systems is guaranteed. Finally, the effectiveness of the designed control strategy is illustrated by a practical simulation example.

INDEX TERMS Time delay systems, state observer, fault tolerant control, backstepping control.

I. INTRODUCTION

Recently, the stability analysis and control synthesis on nonlinear systems have been greatly developed, which have expanded from a single nonlinear system to interconnected nonlinear systems with multiple subsystems interconnected [1]. Interconnected nonlinear systems widely exist in the field of industrial production and information network, such as energy production systems, network control systems and motion control systems [2]. To decrease the computational burden of control strategies for interconnected systems, some scholars have proposed decentralized control methods. For a class of MIMO interconnected systems, a finite time decentralized tracking control approach is presented in [3]. An adaptive decentralized stabilization control approach is proposed in [4] for the uncertain nonlinear large-scale systems. Based on the backstepping technique, a decentralized control design approach is developed in [5] for an interconnected nonlinear systems with state-dependent interconnected terms. Due to the incompletely known mechanisms of the models or the transmission delays of signals, the precise models of interconnected systems are not easy to acquire.

Neural learning systems and fuzzy approximation techniques, which can approximate any smooth nonlinear function with arbitrary precision [6], [7], have been used to the control synthesis of uncertain interconnected nonlinear systems. For instance, a decentralized robust $\mathcal{H}_\infty$ controller is designed in [8] for a large-scale interconnected systems utilizing the T-S fuzzy modeling approach. For nonlinear systems in [9], an adaptive robust stabilization scheme is proposed based on the NNs learning component, such that the closed loop control performance is obviously improved.

Quantization is an inevitable and important process in networked control systems. In the past ten years, the quantification problem of linear/nonlinear systems has received widely attentions from many scholars. For example, in [10], a logarithmic quantizer is proposed to solve the nonuniform quantization problem. Compared with the logarithmic quantizer, the hysteretic quantizer proposed in [11] has more quantization levels and could reduce the chattering phenomenon effectively. Different from the input quantization algorithms developed in [10] and [11], a decomposition method is proposed in [12] for the input quantization, it could overcome the technical problem produced by the piecewise quantization. For a nonlinear system with unknown nonlinear terms and input quantization, an adaptive tracking control
scheme is proposed in [13] to reduce the effect of input quantization. Different from [13], the authors in [14] introduce the Nussbaum function into the adaptive prescribed performance control algorithm for decreasing the input quantization effects to the considered nonlinear system with state time delay.

With the wide application of communication networks in the modern industrial systems, the limitation of communication network resources has attracted the attentions of many scholars. The classical time-based control, which need to uninterrupted transmit control signals in real-time, increases the burden and cost of communication. So it is very important to design an effective control strategy that could decrease the burden of communication transmission in the case of limited communication resources. Event-triggered control is an effective strategy, which only transmits a signal when an event is triggered, and could reduce the burden of network transmission and ensure system performance. In [15], a non-fragile controller is designed for a class of networked singular systems with time delay using the event-triggered sampling scheme, which makes the resulting closed-loop system to be regular, impulse-free, asymptotically stable and dissipative. An event triggering mechanism is given in [16] to a nonlinear system, such that the globally finite time stability of the considered system is achieved. In [17], an event-triggered tracking control scheme is proposed for interconnected systems with disturbances, it guarantees the robust stability with a given $H_\infty$ disturbance attenuation level. Different from [17], which does not consider the input quantization problem, the authors in [18] propose an event-triggered decentralized control strategy, it could reduce the quantization error effects to the considered interconnected nonlinear systems.

In practical engineering, the system will encounter all kinds of faults, such as actuator faults, sensor faults, and component faults. The occurrence of faults will lead to system performance degradation and damage the closed loop stability of the plants. Therefore, fault diagnosis and fault tolerant control have gradually become one of the most popular research contents in the field of the automatic control system. Such as an FTC strategy is proposed in [14] for a nonlinear time delay system with actuator faults using backstepping technique and Nussbaum function, and the semi-global boundedness of the closed loop system could be guaranteed. In [19], an output feedback FTC strategy is proposed for the uncertain nonlinear system with actuator faults utilizing event triggering mechanism. In [20], a fault tolerant control strategy is proposed for a class of neutral time delay systems with actuator saturation by using Lyapunov functional approach and LMI technique, which guarantees that the closed-loop system is finite-time stable. It should be pointed out that the considered plants in [14], [19], [20] are the single nonlinear system. The obtained FTC results described above have some limitations in the modern interconnected internet industry manufacturing systems, which are usually modeled as large-scale nonlinear interconnected systems. Recently, some FTC strategies for interconnected systems have been reported to improve safety and reliability. For example, a robust adaptive decentralized FTC scheme is proposed in [21] for a class of interconnected nonlinear systems with unknown interconnected terms utilizing the NNs technique, which could be dealt with by using the corresponding result of graph theory. In [22], an event-triggered decentralized FTC strategy is proposed to alleviate the sharp change of control input caused by actuator faults. To the best of our knowledge, there are few results on event-triggered decentralized FTC strategies for the interconnected nonlinear time delay systems with unmeasurable states, actuator faults, and input quantization.

Base on the above discussions, an event-triggered decentralized FTC strategy relying on RBFNNs state observer is proposed in this paper for the interconnected nonlinear time delay systems with unmeasurable states. It overcomes the difficulties of event-triggered control caused by unstructured uncertainties, input quantization, time delay, and actuator faults. The designed FTC strategy could guarantee the output signals of the considered interconnected systems could track the reference commands well and all signals of the closed loop systems are ultimately uniformly bounded. The main contributions of this paper are listed as follows

(i) Compared with [18], [19], the model of the interconnected systems considered in this paper is more general. It not only includes unstructured uncertainties, unknown interconnected terms, unmeasurable states, but also includes unknown time delay functions and actuator faults.

(ii) In the design of state observer, the RBFNNs are used to approximate the unstructured uncertainties, the time delay functions are compensated by using the adaptive technique, such that the observation accuracy is guaranteed.

(iii) Different from [14], [22], in which the proposed FTC schemes only consider the input quantization problem or event triggering mechanism, the FTC strategy proposed in this paper considers input quantization and event triggering mechanism, simultaneously.

The rest of this paper is organized as follows. The dynamic model of interconnected nonlinear time delay systems with unstructured uncertainties, input quantization, and actuator faults is presented in section 2. Then, an adaptive RBFNNs state observer is designed in Section 3.1. Based on the state observer, an event-triggered decentralized FTC strategy is designed in section 3.2. In Section 4, a simulation result is given to show the feasibility of the presented FTC strategy. Finally, the main conclusions are given in Section 5.

II. PROBLEM DESCRIPTIONS

Consider the following interconnected nonlinear time delay systems, including $N$ interconnected subsystems with input quantization

$$\begin{align*}
\dot{x}_{i,j} &= x_{i,j+1} + f_{i,j} (\bar{x}_{i,j}) + h_{i,j} (y_i, y_i, d_{i,j}) + \Delta_{i,j} (\bar{y}) \\
\dot{x}_{i,m_i} &= q_i (u_i) + f_{i,m_i} (x_i) + h_{i,m_i} (y_i, y_i, d_{i,m_i}) + \Delta_{i,m_i} (\bar{y}) \\
y_i &= x_{i,1}
\end{align*}$$

(1)
where $i = 1, 2, \ldots, N$, $j = 1, 2, \ldots, m_i - 1$, $\bar{x}_{i,j} = [x_{i,1}, x_{i,2}, \ldots, x_{i,j}]^T \in \mathbb{R}^l$ and $\bar{y} = [y_1, y_2, \ldots, y_N]^T \in \mathbb{R}^N$. $x_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,m_i}]^T \in \mathbb{R}^{m_i}$ and $y_i \in \mathbb{R}$ are the the $i$th subsystem states and output signals, respectively. $f_{i,j} (\bar{x}_{i,j})$, $h_{i,j} (\cdot)$, $\Delta_{i,j} (\bar{y})$ and $q_i (u_i), j = 1, 2, \ldots, m_i$ are the unstructured uncertainty functions, the unknown time delay functions, the unknown interconnected terms and the quantized input of the $i$th subsystem. Assume the time derivative of $h_{i,j} (y_i, y_{i,d_{ij}})$ is existence and boundedness with $|h_{i,j} (y_i, y_{i,d_{ij}})| \leq \bar{h}_{i,j} (y_i, y_{i,d_{ij}}), y_{i,d_{ij}} = y_i (t - d_{ij}(t))$ and the time varying delay $d_{ij}(t)$ is known.

According to [11], the hysteresis quantizer $q_i (u_i)$ is introduced as

$$q_i (u_i) = \left\{ \begin{array}{ll}
\frac{u_{ij}}{1 - \delta_i} & \text{if } u_{ij} < |u_i| \\
\frac{u_{i,j}}{1 + \delta_i} & \text{if } u_{ij} > |u_i| \\
0 & \text{otherwise}
\end{array} \right.
$$

where $u_{i,j} = q_l^{1-j} u_{i,\text{min}}$ with $j = 1, 2, \ldots, 0 < q_l < 1, u_{i,\text{min}} > 0$ and $\delta_i = (1 - q_l) / (1 + q_l)$. $q_i (u_i)$ is in the set $U_i = \{0, \pm u_{i,j}, \pm u_{i,j} (1 + \delta_i)\}$ and $u_{i,\text{min}}$ denotes the size of the dead zone.

The quantized input $q_i (u_i)$ could be rewritten as the following decomposition form [12]

$$q_i (u_i) = M_i (u_i) u_i + N_i \quad (2)$$

with

$$M_i (u_i) = \left\{ \begin{array}{ll}
q_i (u_i) & \text{if } |u_i| > u_{i,\text{min}} \\
1 & \text{if } |u_i| \leq u_{i,\text{min}}
\end{array} \right.
$$

$$N_i = \left\{ \begin{array}{ll}
0 & \text{if } |u_i| > u_{i,\text{min}} \\
-u_i & \text{if } |u_i| \leq u_{i,\text{min}}
\end{array} \right.
$$

In this paper, the actuator loss of effectiveness fault and bias fault are considered, the faulty quantized input $q_{f_i} (u_i)$ could be written as [19]

$$q_{f_i} (u_i) = g_i q_i (u_i) + u_{f_i}, \quad i = 1, 2, \ldots, N \quad (3)$$

where $0 < g_i \leq 1$ is the loss of actuator effectiveness factor indicator in the $i$th subsystem and $g_i$ is an unknown constant. $u_{f_i}$ is the unknown time-varying actuator bias fault in the $i$th subsystem.

when $g_i = 1$, it indicates that the actuator of the $i$th subsystem is healthy. When $0 < g_i < 1$, it means that the actuator partially loses its actuating power. According to the efficiency of the actuator, the control performance will be diminished, but still works. For the interconnected systems considered in this paper, systems cannot work when the actuator is totally broken, so the case of $g_i = 0$ is not studied.

Substituting (3) into (1), the considered interconnected nonlinear time delay systems (1) in actuator faulty case are transformed into the following

$$\dot{x}_{i,j} = x_{i,j+1} + f_{i,j} (\bar{x}_{i,j}) + h_{i,j} (y_i, y_{i,d_{ij}}) + \Delta_{i,j} (\bar{y})$$

$$\dot{x}_{i,m_i} = g_i q_i (u_i) + u_{f_i} + f_{i,m_i} (x_i) + h_{i,m_i} (y_i, y_{i,d_{mi}}) + \Delta_{i,m_i} (\bar{y})$$

$$y_i = x_{i,1} \quad (4)$$

Control Objective: The control objective of this paper is to design an event-triggered decentralized FTC strategy relying on a state observer for interconnected nonlinear time delay systems (4) with unmeasurable states, unstructured uncertainties, input quantization, and actuator faults, such that the stability of the whole closed loop systems is guaranteed.

The following assumptions and lemmas are introduced for the stability analysis and control synthesis of systems (4).

**Assumption 1** [14]: The unknown time delay function $h_{i,j} (y_i, y_{i,d_{ij}})$ satisfies the following inequality

$$|h_{i,j} (y_i, y_{i,d_{ij}})|^2 \leq \bar{h}_{i,j,1}^2 (y_i) + \bar{h}_{i,j,2}^2 (y_{i,d_{ij}})$$

where $j = 1, \ldots, m_i$, $h_{i,j,1} (y_i)$ and $h_{i,j,2} (y_{i,d_{ij}})$ are unknown bounded smooth functions on any compact set.

**Assumption 2** [19]: The unstructured uncertainty function $f_{i,j} (\bar{x}_{i,j})$ satisfies the following local Lipschitz condition

$$|f_{i,j} (\bar{x}_{i,j}) - f_{i,j} (\bar{y}_{i,j})| \leq L_{i,j} \|\bar{x}_{i,j} - \bar{y}_{i,j}\|$$

where $j = 1, \ldots, m_i, L_{i,j} > 0$ is known constant.

**Assumption 3** [23]: The output reference signal $y_{r_i}$ and its first time derivative are known, bounded, and continuous.

**Assumption 4** [24]: The unknown interconnection term $\Delta_{i} (\bar{y})$ is bounded by

$$\|\Delta_{i} (\bar{y})\| \leq \sum_{l=1}^{N} \Psi_{i,l} (|y_l|)$$

where $i = 1, \ldots, N, \Psi_{i,l} (|y_l|) \geq 0$ is an unknown smooth function satisfying $|\Psi_{i,l} (|y_l|) - \Psi_{i,l} (|y_l|)| \leq \tilde{\Psi}_{i,l} (|y_l|), \tilde{\Psi}_{i,l} (y_l) = y_l \tilde{\Psi}_{i,l} (y_l)$, and $\tilde{\Psi}_{i,l} (y_l) = y_l \tilde{\Psi}_{i,l}^* (y_l)$. $\tilde{\Psi}_{i,l} (y_l)$, $\tilde{\Psi}_{i,l}^* (y_l)$, and $\tilde{\Psi}_{i,l}^* (y_l)$ are known smooth functions.
Lemma 1 [14]: For variable $z$ with $\forall z \in R$, the following equation holds
\[
\lim_{z \to 0} \frac{1}{z} \tanh^2 \left( \frac{z}{\omega} \right) = 0
\]
where $\omega \in R^+$ is a constant.

Lemma 2 [18]: The functions $M_i (u_i)$ and $N_i$ in the decomposition form of input quantization $q_i (u_i)$ satisfy the following inequalities
\[
1 - \delta_i \leq M_i (u_i) \leq 1 + \delta_i, \quad |N_i| \leq u_{i,\text{min}}
\]

Lemma 3 [25]: For variable $z$ with $\forall z \in R$, the following inequalities hold
\[
0 \leq |z| - \frac{z^2}{\sqrt{z^2 + \epsilon^2}} \leq \epsilon, \quad |z| - \frac{|z|^2}{|z| + \epsilon} \leq \epsilon \leq |z| + \epsilon
\]
where $\epsilon > 0$ is a constant.

Remark 1: In this paper, a hysteresis quantizer is utilized to quantify the control input signals. Compared with the logarithmic quantizer proposed in [10], the hysteresis quantizer has more detailed quantization levels which could reduce the chattering phenomenon and improve the performance of the fault tolerant control approach designed later.

Remark 2: The assumptions proposed in this paper are reasonable and have been widely used in the published papers. Assumption 1 is a general method to handle the nonlinear time delay problem. Due to the design requirements of state observer, the time delay $d_{i,j}$ is assumed to be known in this study. Assumption 2 is a very common approach to handle the nonlinear unstructured uncertainties. Compared with the global Lipschitz property, the local Lipschitz property means more mild requirements and more practical. Assumption 3 is a very common condition and usually employed to the tracking control design for the interconnected nonlinear systems. Assumption 4 is a common condition for the output-dependent interconnected terms, which has been used in [24] and [26]. In fact, it should be pointed out that $\Psi_{i,1} (|y_{i1}|)$ is class-$K$ function.

III. EVENT-TRIGGERED DECENTRALIZED FTC DESIGN
A. RBFNNs STATE OBSERVER DESIGN
The RBFNNs could be defined as the following form
\[
\varphi_{nn} (X) = W^T S (X)
\]
where $X \in \Omega_X$ and $\Omega_X \subset R^n$ is a compact set. $W = [w_1, w_2, \ldots, w_N]^T \in R^n$ is the weight vector and $S (X) = [s_1 (X), s_2 (X), \ldots, s_n (X)]^T \in R^n$ is the basis function vector with
\[
s_i (X) = \exp \left[ -\frac{(X - \xi_i)^T (X - \xi_i)}{b_i^2} \right]
\]
where $\xi_i = [\xi_{i1}, \xi_{i2}, \ldots, \xi_{i6}]^T \in R^6$ represents the center of the receptive field and $b_i$ denotes the width of the Gaussian function. It is well known that the RBFNNs could identify any unknown smooth function in a compact set $\Omega_X$ [27].

The approximation of unknown smooth function $\varphi (X)$ could be presented as
\[
\varphi (X) = W^* T S (X) + \epsilon (X)
\]
where $W^*$ is an ideal constant weight vector and $\epsilon (X)$ is the approximation error satisfying $|\epsilon (X)| \leq \bar{\epsilon}$ with $\bar{\epsilon}$ is a known positive scalar.

By utilizing the approximation principle of the RBFNNs, the faulty systems (4) are rewritten as follows
\[
\begin{align*}
\dot{x}_{i,1} &= x_{i,2} + f_{i,1} (x_{i,1}) + h_{i,1} (y_i, y_{i,d_{i,1}}) + \Delta f_{i,1} (\hat{y}_i) \\
\dot{x}_{i,k} &= x_{i,k+1} + f_{i,k} (\hat{x}_{i,k}) + \Delta f_{i,k} \\
&+ h_{i,k} (y_i, y_{i,d_{i,k}}) + \Delta h_{i,k} (\hat{y}_i) \\
\dot{x}_{i,m_i} &= g_i q_i (u_i) + u_{f_i} + f_{i,m_i} (\hat{x}_i) + \Delta f_{i,m_i} \\
&+ h_{i,m_i} (y_i, y_{i,d_{i,m_i}}) + \Delta h_{i,m_i} (\hat{y}_i)
\end{align*}
\]
where $k = 2, \ldots, m_i - 1, \Delta f_{i,j} = f_{i,j} (\hat{x}_{i,j}) - f_{i,j} (\hat{x}_{i,j})$ is the estimation of $\hat{x}_{i,j}$.

Based on the RBFNNs approximation results, $f_{i,j} (x_{i,1})$ and $f_{i,j} (\hat{x}_{i,j})$ could be presented as
\[
\begin{align*}
f_{i,1} (x_{i,1}) &= W_{i,1}^T S_{i,1} (x_{i,1}) + \epsilon_{i,1} (x_{i,1}) \\
f_{i,k} (\hat{x}_{i,k}) &= W_{i,k}^T S_{i,k} (\hat{x}_{i,k}) + \epsilon_{i,k} (\hat{x}_{i,k}) \\
f_{i,m_i} (\hat{x}_i) + u_{f_i} &= W_{i,m_i}^T S_{i,m_i} (\hat{x}_{i,m_i}) + \epsilon_{i,m_i} (\hat{x}_{i,m_i})
\end{align*}
\]
where $k = 2, \ldots, m_i - 1, W_{i,j}^*$ is ideal constant weight vectors and $|\epsilon_{i,j} (\hat{x}_{i,j})| \leq \bar{\epsilon}_{i,j}$ with $\bar{\epsilon}_{i,j}$ is a known positive scalar.

Similar to [28], [29], the unstructured uncertainty function $f_{i,m_i} (\hat{x}_i)$ and the unknown bias fault $u_{f_i}$ are approximated by RBFNNs in (6).

Substituting (6) into (5), we have
\[
\begin{align*}
\dot{x}_{i,1} &= x_{i,2} + W_{i,1}^T S_{i,1} (x_{i,1}) + \epsilon_{i,1} (x_{i,1}) \\
&+ h_{i,1} (y_i, y_{i,d_{i,1}}) + \Delta h_{i,1} (\hat{y}_i) \\
\dot{x}_{i,k} &= x_{i,k+1} + W_{i,k}^T S_{i,k} (\hat{x}_{i,k}) + \epsilon_{i,k} (\hat{x}_{i,k}) \\
&+ \Delta f_{i,k} + h_{i,k} (y_i, y_{i,d_{i,k}}) + \Delta h_{i,k} (\hat{y}_i) \\
\dot{x}_{i,m_i} &= g_i q_i (u_i) + W_{i,m_i}^T S_{i,m_i} (\hat{x}_{i,m_i}) + \epsilon_{i,m_i} (\hat{x}_{i,m_i}) \\
&+ h_{i,m_i} (y_i, y_{i,d_{i,m_i}}) + \Delta h_{i,m_i} (\hat{y}_i)
\end{align*}
\]
where $k = 2, \ldots, m_i - 1.$

Since the states $x_{i,j}, j = 2, \ldots, m_i$ are unmeasurable, the adaptive RBFNNs state observer with output feedback is
designed for (4) as

\[
\begin{align*}
\dot{x}_{i,1} &= \dot{x}_{i,2} + \tilde{W}_{i,1}^T S_{i,1} \left( \tilde{x}_{i,1} \right) + \dot{h}_{i,1} (y_i, y_{i,d_{i,1}}) + k_{i,1} (y_i - \tilde{x}_{i,1}) \\
\dot{x}_{i,k} &= \dot{x}_{i,k+1} + \tilde{W}_{i,k}^T S_{i,k} \left( \tilde{x}_{i,k} \right) + \dot{h}_{i,k} (y_i, y_{i,d_{i,k}}) + k_{i,k} (y_i - \tilde{x}_{i,1}) \\
\dot{x}_{i,m_i} &= \dot{g}_i q_i (u_i) + \tilde{W}_{i,m_i}^T S_{i,m_i} \left( \tilde{x}_{i,m_i} \right) + \dot{h}_{i,m_i} (y_i, y_{i,d_{i,m_i}}) + k_{i,m_i} (y_i - \tilde{x}_{i,1}) \\
\hat{y}_i &= \tilde{x}_{i,1}
\end{align*}
\]

where \( k = 2, \ldots, m_i - 1 \), \( \tilde{x}_{i,j} \) and \( \tilde{W}_{i,j} \) are the estimates of \( g_i \), \( x_{i,j} \), \( W_{i,j} \) and \( h_{i,j} \), respectively. The observer gains \( k_{i,1}, \ldots, k_{i,m_i} \) are chosen to make the matrix

\[
A_i = \begin{bmatrix} -k_{i,1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ -k_{i,m_i} & \cdots & 0 \end{bmatrix}
\]

is Hurwitz matrix. Hence, for any given \( Q_i^T = Q_i > 0 \), there must exist a positive definite symmetric matrix \( P_i \) satisfying \( A_i^T P_i + P_i A_i = -Q_i \).

Define the state observation error \( e_{i,j} = x_{i,j} - \tilde{x}_{i,j} \), the estimation error of time delay function \( \hat{h}_{i,j} (y_i, y_{i,d_{i,j}}) = h_{i,j} (y_i, y_{i,d_{i,j}}) - \tilde{h}_{i,j} (y_i, y_{i,d_{i,j}}) \), the estimation error of actuator fault \( \tilde{g}_i = g_i - \hat{g}_i \), and the estimation error of weight vector \( \tilde{W}_{i,j} = W_{i,j}^T - \tilde{W}_{i,j} \), from (7) and (8), the observer error systems are given by

\[
\begin{align*}
\dot{e}_{i,1} &= -k_{i,1} e_{i,1} + e_{i,2} + \tilde{W}_{i,1}^T S_{i,1} \left( x_{i,1} \right) + \dot{h}_{i,1} (y_i, y_{i,d_{i,1}}) + \Delta_1 (\tilde{y}) + e_{i,1} (x_{i,1}) \\
\dot{e}_{i,k} &= -k_{i,k} e_{i,k} + e_{i,k+1} + \tilde{W}_{i,k}^T S_{i,k} \left( \tilde{x}_{i,k} \right) + \dot{h}_{i,k} (y_i, y_{i,d_{i,k}}) + \Delta_1 (\tilde{y}) + e_{i,k} (\tilde{x}_{i,k}) \\
\dot{e}_{i,m_i} &= -k_{i,m_i} e_{i,m_i} + e_{i,m_i+1} + \tilde{W}_{i,m_i}^T S_{i,m_i} \left( \tilde{x}_{i,m_i} \right) + \dot{h}_{i,m_i} (y_i, y_{i,d_{i,m_i}}) + \Delta_1 (\tilde{y}) + e_{i,m_i} (\tilde{x}_{i,m_i}) \\
\dot{\Delta}_{i,m_i} &= \dot{\Delta}_{i,m_i} (\tilde{y}) + \dot{\Delta}_{i,m_i} (\tilde{y}) + e_{i,m_i} (\tilde{x}_{i,m_i}) + \dot{h}_{i,m_i} (y_i, y_{i,d_{i,m_i}}) + \Delta_1 (\tilde{y}) + e_{i,m_i} (\tilde{x}_{i,m_i}) \\
\dot{\Delta}_{i,m_i} &= \dot{\Delta}_{i,m_i} (\tilde{y}) + \dot{\Delta}_{i,m_i} (\tilde{y}) + e_{i,m_i} (\tilde{x}_{i,m_i}) + \dot{h}_{i,m_i} (y_i, y_{i,d_{i,m_i}}) + \Delta_1 (\tilde{y}) + e_{i,m_i} (\tilde{x}_{i,m_i}) \\
\dot{\Delta}_{i,m_i} &= \dot{\Delta}_{i,m_i} (\tilde{y}) + \dot{\Delta}_{i,m_i} (\tilde{y}) + e_{i,m_i} (\tilde{x}_{i,m_i}) + \dot{h}_{i,m_i} (y_i, y_{i,d_{i,m_i}}) + \Delta_1 (\tilde{y}) + e_{i,m_i} (\tilde{x}_{i,m_i}) \\
\end{align*}
\]

where \( k = 2, \ldots, m_i - 1 \).

Let \( e_i = [e_{i,1}, \ldots, e_{i,m_i}]^T = \tilde{g}_i q_i (u_i) + \Delta f_i + \hat{\Delta}_{i} + e_i + \hat{h}_i + \Delta_1 (\tilde{y}) \),

\[
\begin{align*}
\dot{\Delta}_{i,m_i} &= \dot{\Delta}_{i,m_i} (\tilde{y}) + \dot{\Delta}_{i,m_i} (\tilde{y}) + e_{i,m_i} (\tilde{x}_{i,m_i}) + \dot{h}_{i,m_i} (y_i, y_{i,d_{i,m_i}}) + \Delta_1 (\tilde{y}) + e_{i,m_i} (\tilde{x}_{i,m_i}) \\
\end{align*}
\]

and \( \hat{h}_i = \left[ \tilde{h}_{i,1} (y_i, y_{i,d_{i,1}}), \ldots, \tilde{h}_{i,m_i} (y_i, y_{i,d_{i,m_i}}) \right]^T \). Then, the observer error systems can be written as follows

\[
\begin{align*}
\dot{e}_i &= A_i e_i + B_i \tilde{g}_i q_i (u_i) + \Delta f_i + \hat{\Delta}_{i} + e_i + \hat{h}_i + \Delta_1 (\tilde{y}) \quad (10)
\end{align*}
\]

where \( B_i = \begin{bmatrix} 1 & \cdots & 0 \end{bmatrix} \), \( \Delta f_i = \begin{bmatrix} \Delta f_{i,1}, \ldots, \Delta f_{i,m_i} \end{bmatrix} \) and \( e_i = \begin{bmatrix} e_{i,1}, \ldots, e_{i,m_i} \end{bmatrix} \).

Define the following Lyapunov function candidate as

\[
V_{i,0} = e_i^T P_i e_i + \frac{1}{2 \Pi_i} \tilde{h}_i h_i \quad (11)
\]

where \( \Pi_i > 0 \) is given constant parameter.

Taking the derivative of \( V_{i,0} \) along the trajectory of (10) yields

\[
\dot{V}_{i,0} = e_i^T \left( A_i^T P_i + P_i A_i \right) e_i + 2 e_i^T P_i \Delta f_i + e_i + \frac{1}{\Pi_i} \tilde{h}_i \tilde{h}_i \quad (12)
\]

Design the following adaptive parameter update algorithm for \( h_i \)

\[
\dot{h}_i = \Pi_i \left( 2 P_i e_i - c_h \tilde{h}_i \right) \quad (13)
\]

Substituting (13) into (12), we have

\[
\dot{V}_{i,0} \leq - \left( \lambda_{\min} (Q_i) - 2 - \frac{1}{\Pi_i} \| P_i \|^2 - L_i \right) \| e_i \|^2 + \frac{1}{\Pi_i} \| e_i \|^2 + 2 e_i^T P_i \Delta_1 (\tilde{y}) + e_i + \| P_i \|^2 \sum_{j=1}^{m_i} l_{i,j} \| \tilde{W}_{i,j} \|^2, \quad (15)
\]

From Assumption 2 and Young’s inequality, it is known that the following inequalities hold

\[
\begin{align*}
2 e_i^T P_i \Delta f_i &\leq \| e_i \|^2 + \| P_i \|^2 \| \Delta f_i \|^2 \leq \| e_i \|^2 + \| P_i \|^2 \sum_{j=1}^{m_i} l_{i,j} \| \tilde{W}_{i,j} \|^2, \\
2 e_i^T P_i \Delta_1 (\tilde{y}) &\leq \| e_i \|^2 + \| P_i \|^2 \| \Delta_1 (\tilde{y}) \|^2, \\
\end{align*}
\]

where \( L_i = 1 + \| P_i \|^2 \sum_{j=1}^{m_i} l_{i,j} \) and \( a \) is a positive constant.

Substituting (15) into (14), we have

\[
\dot{V}_{i,0} \leq - \left( \lambda_{\min} (Q_i) - 2 - \frac{1}{\Pi_i} \| P_i \|^2 - L_i \right) \| e_i \|^2 + \frac{1}{\Pi_i} \| e_i \|^2 + 2 e_i^T P_i \Delta_1 (\tilde{y}) + e_i + \| P_i \|^2 \sum_{j=1}^{m_i} l_{i,j} \| \tilde{W}_{i,j} \|^2
\]

where \( \lambda_{\min} (Q_i) \) denotes the minimum eigenvalue of \( Q_i \) and \( R_{i,0} = \| P_i \|^2 \| e_i \|^2 + a \tilde{h}_i h_i + \frac{1}{2 \Pi_i} \| h_i \|_2^2 \).

Remark 3: Compared with [19], in which the unknown time delay function is not considered, the adaptive RBFNNs state observer proposed in this paper could not only observe
the unmeasurable states, but also estimate unknown time delay functions. By using the Lyapunov function, the adaptive update algorithms of unknown time delay functions are obtained, which could compensate for the effects of the unknown time delay functions and improve the observation accuracy.

**B. EVENT-TRIGGERED DECENTRALIZED FTC DESIGN**

In this section, an adaptive decentralized FTC strategy will be designed by employing both event-triggered control and backstepping technique with low pass filter. A simplified diagram of the proposed approach is depicted in Figure 1.

Firstly, the following coordinate transformations are introduced

\[
\begin{align*}
\dot{z}_{i,1} &= y_{i} - y_{ri} \\
\dot{z}_{i,j} &= \dot{x}_{i,j} - \beta_{i,j} \\
\phi_{i,j} &= \beta_{i,j} - \alpha_{i,j-1}
\end{align*}
\]

where \( j = 2, \ldots, m, \alpha_{i,j} \) is the virtual control input, \( \beta_{i,j} \) is the output signal of low pass filter which are presented to avoid the differentiation operation of \( \alpha_{i,j-1} \) and the specific forms will be provided later.

**Step i, 1:** From (17), taking the derivative of \( z_{i,1} \) with respect to time yields

\[
\begin{align*}
\dot{z}_{i,1} &= \dot{y}_{i} - \dot{y}_{ri} \\
&= z_{i,2} + \phi_{i,2} + \alpha_{i,1} + e_{i,2} + W_{i,1}^T S_{i,1} (x_{i,1}) \\
&\quad + \epsilon_{i,1} (x_{i,1}) + \hat{h}_{i,1} (y_{i, y_{d,i,1}}) + \Delta_{i,1} (\hat{y}) - \dot{y}_{ri} \\
&= z_{i,2} + \phi_{i,2} + \alpha_{i,1} + e_{i,2} + W_{i,1}^T S_{i,1} (x_{i,1}) \\
&\quad + \epsilon_{i,1} (x_{i,1}) + \hat{h}_{i,1} (y_{i, y_{d,i,1}}) - \hat{h}_{i,1} (y_{i, y_{d,i,1}}) + \Delta_{i,1} (\hat{y}) - \dot{y}_{ri}
\end{align*}
\]

Define the Lyapunov function candidate as follows

\[
V_{i,1} = V_{i,0} + \frac{1}{2} z_{i,2}^2 + \frac{1}{2} \dot{\hat{h}}_{i,1}^2 - \hat{h}_{i,1} (y_{i, y_{d,i,1}})
\]

with

\[
V_{d,i,j} = \frac{1}{2} e^{\theta_{d,i,j}} \int_{t_{d}-d_{i,j}}^{t} e^{-\vartheta(t-s)} \tilde{h}_{i,12} (y_{i} (s)) ds
\]

where \( y_{ri}, \Delta_{i,1} \) and \( \varrho_{i} \) are the positive scalars and \( \tilde{W}_{i,1} = W_{i,1}^* - W_{i,1} \) and \( \dot{W}_{d,i,j} = \dot{W}_{d}^*_{i,j} - \dot{W}_{d,i,j} \) are the estimation errors of weight vector, \( \tilde{W}_{i,1} \) and \( \dot{W}_{d,i,j} \) are the estimations of \( W_{i,1}^* \) and \( \dot{W}_{d,i,j}^* \), respectively. Assume \( d_{i,j} \) and its time derivatives \( \dot{d}_{i,j} \) are bounded with \( \dot{d}_{i,j} \leq d_{i,j}^T \).

Taking the derivative of \( V_{i,1} \) along the trajectory of (18)

\[
\dot{V}_{i,1} = \dot{V}_{i,0} + z_{i,1} (z_{i,2} + \phi_{i,2} + \alpha_{i,1} + e_{i,2} + W_{i,1}^T S_{i,1} (x_{i,1})) \\
&\quad + \epsilon_{i,1} (x_{i,1}) + \hat{h}_{i,1} (y_{i, y_{d,i,1}}) - \dot{h}_{i,1} (y_{i, y_{d,i,1}}) \\
&\quad + \frac{1}{2} \tilde{W}_{i,1}^T \dot{\tilde{W}}_{i,1} + \frac{1}{2} \tilde{W}_{d,i,j}^T \dot{W}_{d,i,j} + V_{d,i,j}
\]

Taking the derivative of \( V_{d,i,j} \) with respect to time yields

\[
\dot{V}_{d,i,j} \leq -\varrho_{i} V_{d,i,j} + \frac{1}{2} e^{\theta_{d,i,j}} \int_{t_{d}-d_{i,j}}^{t} e^{-\vartheta(t-s)} \tilde{h}_{i,12} (y_{i}) - \frac{1}{2} \tilde{h}_{i,12} (y_{d,i,j})
\]

Based on Young’s inequality, it can be seen that

\[
\begin{align*}
\dot{z}_{i,1} z_{i,2} + z_{i,1} \phi_{i,2} + z_{i,1} e_{i,2} \\
&\leq \frac{3}{2} z_{i,2}^2 + \frac{1}{2} \phi_{i,2}^2 + \frac{1}{2} \epsilon_{i,2}^2 + \frac{1}{2} \| e_{i,2} \|^2, \\
\dot{z}_{i,1} \hat{h}_{i,1} (y_{i, y_{d,i,1}}) \\
&\leq \frac{1}{2} z_{i,1}^2 + \frac{1}{2} \hat{h}_{i,1}^2 (y_{i}) + \frac{1}{2} \tilde{h}_{i,12}^2 (y_{d,i,1}), \\
\dot{z}_{i,1} \tilde{h}_{i,1} (y_{i, y_{d,i,1}}) &\leq \frac{1}{2} z_{i,1}^2 + \frac{1}{2} \tilde{h}_{i,12}^2 (y_{d,i,1}), \\
\dot{z}_{i,1} \Delta_{i,1} (\hat{y}) &\leq z_{i,1} e_{i,1} (x_{i,1}) \\
&\leq z_{i,1}^2 + \frac{1}{2} \| \Delta_{i,1} (\hat{y}) \|^2 + \frac{1}{2} e_{i,1}^2.
\end{align*}
\]

Substituting (16) and (21)-(22) into (20) yields

\[
\dot{V}_{i,1} \leq H_{i,1} + R_{i,0} + \frac{1}{2} z_{i,2}^2 + \frac{7}{2} \tilde{h}_{i,12}^2
\]
\[ +z_{i,1}\alpha_{i,1} + \frac{1}{2}\phi_{i,2}^2 + \phi_{i,2}\dot{\psi}_{i,2} + z_{i,1}\left(\hat{W}_{\delta i}^TS_{\delta i}\right)(x_{i,1}) + \Phi_{i,1}\left(Z_{i,1}\right) - \dot{y}_{ri}\]
\[ + \frac{1}{\gamma_{li,1}}\hat{W}_{\delta i}^T\left(y_{li,1}z_{i,1}S_{li,1}\left(x_{i,1}\right) - \hat{W}_{li,1}\right) + \frac{1}{\Lambda_{li,1}}\hat{W}_{\delta i,li}^T\hat{W}_{\delta i,li} + \frac{1}{2}\left(1-2\tanh^2\left(\frac{z_{i,1}}{w_i}\right)\right)\hat{h}_{i,1}^T(y_i) + \frac{1}{\gamma_i}\dot{\psi}_{i,1} + \frac{1}{\gamma_{li,1}}V_{d,li,1} + \frac{1}{2}\hat{h}_{i,1}^2(y_i, y_i, y_{d,li,1}) \] (23)

where \( H_i,1 = -\left(\lambda_{\min}(Q_i) - \frac{x}{2} - \frac{1}{2}\|P_i\|^2 - \tilde{L}_i\right)\|e_i\|^2 + \left(\alpha + \frac{1}{2}\right)\|\Lambda_i\|\tilde{h}_i\|\tilde{W}_{\delta i}\|^2 + 2\phi_{i,1}^2 + 2\phi_{i,2}^2 + q_i(u_i) - \left(\frac{\Theta_i}{2} - \frac{1}{\mu}\right)\tilde{h}_i\tilde{h}^T_i. \)

It is not difficult to find that the Lyapunov function candidate \( V(y_i, z_{i,1}, \Phi_i,1(Z_{i,1})) \) could be approximated as

\[ \Phi_{i,1}(Z_{i,1}) = W_{\delta i,li}^TS_{\delta i,li}(Z_{i,1}) + \epsilon_{d,li,1}(Z_{i,1}) \] (24)

where \( \epsilon_{d,li,1} \) is a known positive scalar.

Based on Young's inequality, it can be seen that

\[ z_{i,1}\epsilon_{d,li,1}(Z_{i,1}) \leq \frac{1}{2}\hat{z}_{i,1}^2 + \frac{1}{2}\hat{z}_{d,li,1}^2 \] (25)

The virtual control input \( \alpha_{i,1} \) is designed as follows

\[ \alpha_{i,1} = -\left(r_{i,1} + 4\right)z_{i,1} - \hat{W}_{\delta i}^TS_{\delta i,li}(Z_{i,1}) - z_{i,1}\chi_i(y_i) + \dot{y}_{ri} \] (26)

with

\[ \begin{align*}
\dot{W}_{\delta i,li} &= \gamma_{li,1}\left(z_{i,1}S_{li,1}(x_{i,1}) - c_{li,1}\hat{W}_{li,1}\right) \\
\dot{W}_{\delta i,li} &= \Lambda_{li,1}\left(z_{i,1}S_{li,li}(Z_{i,1}) - c_{d,li,1}\hat{W}_{\delta i,li}\right)
\end{align*} \]

where \( r_{i,1}, \gamma_{li,1} \) and \( c_{li,1} \) are the positive scalars. \( \chi_i(y_i) \) is a design function. The first order low pass filter is designed as follows

\[ k_{i,2}\beta_{i,2} + \beta_{i,2} = \alpha_{i,1}, \beta_{i,2} (0) = \alpha_{i,1} (0) \]

where \( k_{i,2} \) is a positive constant, \( \alpha_{i,1} \) and \( \beta_{i,2} \) are the output and the input of low pass filter, respectively.

By using the definition of \( \Phi_{i,2} = \beta_{i,2} - \alpha_{i,1} \), we have

\[ \Phi_{i,2}\dot{\psi}_{i,2} = \Phi_{i,2}\left(\frac{\alpha_{i,1} - \beta_{i,2}}{k_{i,2}}\right) - \phi_{i,2}\dot{\psi}_{i,2} \leq -\frac{1}{2k_{i,2}}\phi_{i,2}^2 + \frac{1}{2}\phi_{i,2}^2 + \frac{1}{2}M_i^2 \] (27)

where \( |\dot{\psi}_{i,1}| \leq M_i^2 \) is bounded [18].

Substituting (24)-(27) into (23) yields

\[ \dot{V}_{i,1} \leq H_{i,1} + \frac{1}{2}\phi_{i,2}^2 - r_{i,1}\hat{z}_{i,1}^2 - \left(\frac{1}{\kappa_{i,2}} - 1\right)\phi_{i,2}^2 \]
\[ + c_{i,1}\hat{W}_{li,1}\hat{W}_{li,1} + c_{d,li,1}\hat{W}_{\delta i,li}\hat{W}_{\delta i,li} + R_{i,1} \]
\[ + \frac{1}{2}\left(1-2\tanh^2\left(\frac{z_{i,1}}{w_i}\right)\right)\hat{h}_{i,1}^2(y_i) - \dot{\psi}_{i,1}\hat{z}_{i,1}^2 \chi_i(y_i) \]

where \( R_{i,1} = R_{i,1} + \epsilon_{d,li,1}^2 + \epsilon_{d,li,1}^2 + \frac{1}{2}M_i^2 \chi_i(y_i, y_{d,li,1}). \)

Step i, k (2 \leq k \leq m_i - 1): From (17), the derivative of \( \dot{z}_{i,k} \) with respect to time yields

\[ \dot{z}_{i,k} = \dot{\xi}_{i,k} - \beta_{i,k} = \dot{\xi}_{i,k} + \hat{W}_{li,k}^TS_{li,k}\left(\hat{\xi}_{i,k}\right) \]
\[ + \hat{h}_{i,k}(y_i, y_{d,li,k}) + k_{i,k}(y_i - \hat{\xi}_{i,k}) = \hat{z}_{i,k} + \phi_{i,k} + \phi_{i,k}\hat{W}_{li,k}^TS_{li,k}\left(\hat{\xi}_{i,k}\right) \]
\[ + \hat{h}_{i,k}(y_i, y_{d,li,k}) - \hat{h}_{i,k}(y_i, y_{d,li,k}) + k_{i,k}(y_i - \hat{\xi}_{i,k}) \]
\[ - \beta_{i,k} + \hat{W}_{li,k}^TS_{li,k}\left(\hat{\xi}_{i,k}\right) - \hat{W}_{li,k}^TS_{li,k}\left(\hat{\xi}_{i,k}\right) \] (28)

Define the Lyapunov function candidate as follows

\[ V_{i,k} = V_{i,k-1} + \frac{1}{2}\phi_{i,k}^2 + \frac{1}{2}\phi_{i,k+1}^2 + \frac{1}{2\gamma_{li,k}}\hat{W}_{li,k}^T\hat{W}_{li,k} \]
\[ + \frac{1}{2\Lambda_{li,k}}\hat{W}_{d,li,k}^T\hat{W}_{d,li,k} + V_{d,ik} \] (29)

with

\[ V_{d,ik} = \frac{1}{2}e^{\sigma_{d,ik}}e^{-\sigma_{d,ik}}\int_{t-d_{i,k}}^{t} e^{-\sigma_{d,ik}}ds \]

where \( \gamma_{li,k}, \Lambda_{li,k} \) and \( \sigma_{d,ik} \) are the positive scalars. \( \hat{W}_{li,k} = W_{li,k}^* - \hat{W}_{li,k} \) and \( \hat{W}_{d,ik} = W_{d,ik}^* - \hat{W}_{d,ik} \) are the estimation errors of the weight vector. \( \hat{W}_{li,k} \) and \( \hat{W}_{d,ik} \) are the estimations of \( W_{li,k}^* \) and \( W_{d,ik}^* \), respectively. Assume \( d_{i,k} \) and its time derivatives \( \dot{d}_{i,k} \) are bounded with \( \hat{d}_{i,k} \leq \tilde{d}_{i,k} < 1. \)

Taking the derivative of \( V_{i,k} \) along the trajectory of (28) yields

\[ \dot{V}_{i,k} = \dot{V}_{i,k-1} + z_{i,k}\left(\hat{z}_{i,k+1} + \phi_{i,k+1} + \alpha_{i,k}\right) + \hat{W}_{li,k}^TS_{li,k}\left(\hat{\xi}_{i,k}\right) + h_{i,k}(y_i, y_{d,li,k}) \]
\[ + k_{i,k}(y_i - \hat{\xi}_{i,k}) - \hat{h}_{i,k}(y_i, y_{d,li,k}) - \hat{W}_{li,k}^TS_{li,k}\left(\hat{\xi}_{i,k}\right) \]
\[ + \phi_{i,k+1}\hat{W}_{li,k}^T\left(y_i, y_{d,li,k}\right) \]
\[ + \frac{1}{\gamma_{li,k}}\hat{W}_{li,k}^T\left(y_i, y_{d,li,k}\right) - \hat{W}_{li,k}^T\left(y_i, y_{d,li,k}\right) \]
\[ + \frac{1}{\Lambda_{li,k}}\hat{W}_{d,li,k}^T\hat{W}_{d,li,k} + V_{d,ik} \] (30)
Similar to Step i, 1, the following inequalities are obtained

\[
\begin{align*}
&\sum_{i,k} z_{i,k} \phi_{i,k} \leq z_{i,k}^2 + \frac{1}{2} y_{i,k}^2 + \frac{1}{2} z_{i,k}^2 + \frac{1}{2} y_{i,k}^2 + \frac{1}{2} l_{i,k} \tilde{W}_{i,k}^T \tilde{W}_{i,k}, \\
&z_{i,k} \bar{h}_{i,k} (y_{i}, \phi_{i,k}) \leq \frac{1}{2} y_{i,k}^2 + \frac{1}{2} h_{i,k}^2 (y_{i}, \phi_{i,k}), \\
&z_{i,k} \bar{h}_{i,k} (y_{i}, \phi_{i,k}) \leq \frac{1}{2} y_{i,k}^2 + \frac{1}{2} h_{i,k}^2 (y_{i}, \phi_{i,k}), \\
&\phi_{i,k+1} \bar{h}_{i,k+1} \leq -\frac{1}{\kappa_{i,k}} \phi_{i,k+1}^2 + \frac{1}{2} \phi_{i,k+1}^2 + \frac{1}{2} M_{i,k}^2
\end{align*}
\]

\[
\text{(31)}
\]

where \(|\bar{a}_{i,k}| \leq M_{i,k}^2\) is bounded [18].

Substituting (31) into (30) yields

\[
\begin{align*}
\dot{V}_{i,k} &\leq H_{i,k} - \sum_{j=1}^{k} r_{i,j} z_{i,j}^2 - \sum_{j=1}^{k+1} \frac{1}{\kappa_{i,j} - 1} \phi_{i,j}^2 \\
&+ \sum_{j=1}^{k} \frac{1}{2} \left( 1 - 2\tanh^2 \left( \frac{z_{i,j}}{w_{j}} \right) \right) h_{i,j}^2 (y_{i}) + \frac{1}{2} l_{i,j} \tilde{W}_{i,j}^T \tilde{W}_{i,j} \\
&+ \sum_{j=1}^{k-1} c_{i,j} \tilde{W}_{i,j}^T \tilde{W}_{i,j} + \sum_{j=1}^{k} c_{d,j} \tilde{W}_{i,j}^T \tilde{W}_{i,j} + \sum_{j=1}^{k} \gamma_{i,j} \tilde{W}_{i,j}^T \tilde{W}_{i,j} + R_{i,k-1} \\
&- z_{i,1}^2 \tilde{h}_{i,1} (y_{i}) + \frac{1}{2} z_{i,k}^2 + \frac{1}{2} y_{i,k}^2 + \frac{1}{2} \phi_{i,k}^2 + \frac{1}{2} M_{i,k}^2 \\
&+ \frac{1}{2} M_{i,k}^2 + \frac{1}{2} \tilde{h}_{i,k}^2 (y_{i}, \phi_{i,k}) - \tilde{h}_{i,k} (y_{i}) \tilde{W}_{i,k}^T (y_{i}, \phi_{i,k}) \\
&- \frac{1}{2} \sum_{j=1}^{k} \gamma_{i,j} \tilde{W}_{i,j}^T \tilde{W}_{i,j} + \frac{1}{2} \tilde{h}_{i,k}^2 (y_{i}, \phi_{i,k})
\end{align*}
\]

\[
\text{(32)}
\]

where \(\Phi_{i,k} (Z_{i,k}) = \frac{1}{\kappa_{i,k}} \text{tanh}^2 \left( \frac{z_{i,k}}{w_{k}} \right) h_{i,k}^2 (y_{i})\), \(h_{i,k}^2 (y_{i}) = h_{i,k}^2 (y_{i}) + \frac{1}{d} \tilde{h}_{i,k}^2 (y_{i})\) and \(Z_{i,k} = [y_{i}, z_{i,k}]^T\).

Similar to Step i, 1, \(\Phi_{i,k} (Z_{i,k})\) is an unknown smooth function. According to Lemma 1, when \(Z_{i,k} = 0\), \(\Phi_{i,k} (Z_{i,k})\) will avoid the singular phenomenon. Hence, by utilizing the RBFNNs, \(\Phi_{i,k} (Z_{i,k})\) could be approximated as

\[
\Phi_{i,k} (Z_{i,k}) = W_{d,i,k}^* S_{d,i,k} (Z_{i,k}) + \varepsilon_{d,i,k} (Z_{i,k})
\]

\[
\text{(33)}
\]

where \(\varepsilon_{d,i,k} (Z_{i,k}) \leq \tilde{\varepsilon}_{d,i,k}\) and \(\tilde{\varepsilon}_{d,i,k}\) is a known positive scalar.

Based on Young’s inequality, it can be seen that

\[
\begin{align*}
\sum_{i,k} z_{i,k} \varepsilon_{d,i,k} (Z_{i,k}) &\leq \frac{1}{2} z_{i,k}^2 + \frac{1}{2} \varepsilon_{d,i,k}^2
\end{align*}
\]

\[
\text{(34)}
\]

Design the virtual control input \(\alpha_{i,k}\) as follows

\[
\alpha_{i,k} = -\left( r_{i,k} + \frac{7}{2} \right) z_{i,k} - \tilde{W}_{i,k}^T S_{i,k} (\tilde{x}_{i,k}) - \tilde{W}_{d,i,k}^T S_{d,i,k} (Z_{i,k}) - \tilde{W}_{d,i,k}^T S_{d,i,k} (Z_{i,k}) - k_{i,k} (y_{i} - \tilde{x}_{i,1}) + \tilde{\beta}_{i,k}
\]

\[
\text{(35)}
\]

with

\[
\begin{align*}
\tilde{W}_{i,k} &= \frac{1}{2} \phi_{i,k}^2 (y_{i}) + \sum_{j=1}^{k} c_{i,j} \tilde{W}_{i,j} \tilde{W}_{i,j} \\
\tilde{W}_{d,i,k} &= \Lambda_{i,k} \left( z_{i,k} S_{d,i,k} (Z_{i,k}) - c_{d,i,k} \tilde{W}_{d,i,k} \right)
\end{align*}
\]

where \(r_{i,k}, c_{i,k}\) and \(c_{d,i,k}\) are the positive scalars. Substituting (33)-(35) into (32) yields

\[
\dot{V}_{i,k} \leq H_{i,k} - \sum_{j=1}^{k} r_{i,j} z_{i,j}^2 - \sum_{j=1}^{k+1} \frac{1}{\kappa_{i,j} - 1} \phi_{i,j}^2 \\
+ \sum_{j=1}^{k} \frac{1}{2} \left( 1 - 2\tanh^2 \left( \frac{z_{i,j}}{w_{j}} \right) \right) h_{i,j}^2 (y_{i}) + \sum_{j=1}^{k} c_{i,j} \tilde{W}_{i,j}^T \tilde{W}_{i,j} \\
+ \sum_{j=1}^{k} c_{d,j} \tilde{W}_{i,j}^T \tilde{W}_{i,j} + \sum_{j=1}^{k} \gamma_{i,j} \tilde{W}_{i,j}^T \tilde{W}_{i,j} + R_{i,k-1} \\
+ \frac{1}{2} M_{i,k}^2 + \frac{1}{2} \tilde{h}_{i,k}^2 (y_{i}, \phi_{i,k}) - \tilde{h}_{i,k} (y_{i}) \tilde{W}_{i,k}^T (y_{i}, \phi_{i,k}) \\
- \frac{1}{2} \sum_{j=1}^{k} \gamma_{i,j} \tilde{W}_{i,j}^T \tilde{W}_{i,j} + \frac{1}{2} \tilde{h}_{i,k}^2 (y_{i}, \phi_{i,k})
\]

\[
\text{(36)}
\]

Define the following Lyapunov function

\[
\begin{align*}
V_{i,m} &= V_{i,m-1} + \frac{1}{2} z_{i,m}^2 \\
&+ \frac{1}{2} \alpha_{i,m} \tilde{W}_{i,m}^T \tilde{W}_{i,m} + \frac{1}{2} \alpha_{i,m} \tilde{W}_{d,i,m}^T \tilde{W}_{d,i,m} \\
&+ \frac{1}{2} \sigma_{i,m} \tilde{\beta}_{i,m}^2 + \frac{1}{2} \sigma_{i,m} \tilde{\beta}_{i,m}^2 + V_{d,i,m}
\end{align*}
\]

\[
\text{(37)}
\]

with

\[
V_{d,i,m} = \frac{1}{2} \int_{0}^{t} e^{\gamma_{d,i,m}} e^{-\sigma_{d,i,m}} c_{d,i,m} (y_{i}(s)) \text{ds}
\]

where \(\gamma_{d,i,m}, \Lambda_{i,m}, \sigma_{d,i,m}, \beta_{i,m}\) and \(\alpha_{i,m}\) are the positive scalars. \(\tilde{W}_{i,m}, \tilde{W}_{d,i,m}, \tilde{W}_{d,i,m}, \tilde{G}_{i}, \tilde{G}_{i}, \tilde{\beta}_{i,m}\) and \(\tilde{\beta}_{i,m}\) are the estimations of \(W_{i,m}, W_{d,i,m}, G_{i}, \text{ and } \beta_{i,m}\), respectively.
Assume $d_{i,m}$ and its time derivatives $\dot{d}_{i,m}$ are bounded with $\dot{d}_{i,m} \leq d_{i,m}^T < 1$.

Taking the derivative of $V_{i,m}$ along the trajectory of (36)

$$
\dot{V}_{i,m} = \dot{V}_{i,m-1} + z_{i,m} (\hat{g}(d_{i,m}(u_i)) + k_{i,m} (y_i - \hat{x}_{i,1})) + h_{i,m} (y_i, y_i, d_{i,m}) - \dot{\beta}_{i,m} \\
= \dot{W}_{i,m}^T S_{i,m} (\hat{x}_{i,m}) + h_{i,m} (y_i, y_i, d_{i,m}) - \dot{\beta}_{i,m} \\
= \frac{1}{\gamma_{i,m}} W_{i,m}^T (\gamma_{i,m} z_{i,m} S_{i,m} (\hat{x}_{i,m}) - \dot{W}_{i,m}) \\
+ \frac{1}{\Lambda_{i,m}} \dot{W}_{d,i,m} \dot{W}_{d,i,m} + \frac{1}{\sigma_{gi}} \hat{g}_{i} + \frac{g_{i}}{\sigma_{pi}} \hat{\rho}_{i} \hat{\rho}_{i} + \dot{V}_{d,i,m}
$$

(38)

Based on Young’s inequality, it can be obtained that

$$
-z_{i,m} \hat{W}_{i,m}^T S_{i,m} (\hat{x}_{i,m}) \leq \frac{1}{2} z_{i,m}^2,
$$

(39)

$$
\frac{1}{2} l_{i,m} \dot{W}_{i,m}^T \dot{W}_{i,m},
$$

(40)

$$
\frac{1}{2} h_{i,m}^T (y_i) + \frac{1}{2} h_{i,m}^T (y_i, d_{i,m}) \leq \frac{1}{2} z_{i,m}^2,
$$

(41)

Substituting (39)-(41) into (38), then it can be obtained that

$$
\dot{V}_{i,m} \leq H_{i,1} - \sum_{j=1}^{m_l} \frac{1}{2} \left( 1 - 2 \tanh^2 \left( \frac{z_{i,m}^2}{W_{j}} \right) \right) h_{i,j}^T (y_i) + \sum_{j=1}^{m_l} c_{i,j} \dot{W}_{i,j} \dot{W}_{i,j} \\
+ \sum_{j=1}^{m_l} \frac{1}{2} l_{i,j} \dot{W}_{i,j} \dot{W}_{i,j} + \sum_{j=2}^{m_l} \frac{1}{2} l_{i,j} \dot{W}_{i,j} \dot{W}_{i,j} + R_{i,m,-1} \\
+ \frac{1}{2} h_{i,m}^2 (y_i, y_i, d_{i,m}) - \dot{\beta}_{i,m} \\
\dot{W}_{i,m} (\gamma_{i,m} z_{i,m} S_{i,m} (\hat{x}_{i,m}) - \dot{W}_{i,m}) \\
+ \frac{1}{\Lambda_{i,m}} \dot{W}_{d,i,m} \dot{W}_{d,i,m} + \frac{1}{\sigma_{gi}} \hat{g}_{i} + \frac{g_{i}}{\sigma_{pi}} \hat{\rho}_{i} \hat{\rho}_{i} \\
- \sum_{j=1}^{m_l} q_{i} V_{d,i} + \frac{1}{2} h_{i,m}^2 (y_i, y_i, d_{i,m}) - \dot{\beta}_{i,m} \gamma_{i,m} \chi (\tilde{y})
$$

(42)

where $\Phi_{i,m} (Z_{i,m}) = \frac{1}{2} \tanh^2 \left( \frac{z_{i,m}^2}{W_{i,m}} \right) h_{i,m}^T (y_i) + \frac{g_{i} \rho_{i}}{\sigma_{pi}} h_{i,m}^T (y_i) + Z_{i,m} = \left[ y_i, z_{i,m} \right]^T$.

Similar to step 1, $\Phi_{i,m} (Z_{i,m})$ is an unknown smooth function. According to Lemma 1, when $Z_{i,m} = 0$, $\Phi_{i,m} (Z_{i,m})$ will avoid the singular phenomenon. Hence, by utilizing the RBFNNs, $\Phi_{i,m} (Z_{i,m})$ could be approximated as

$$
\Phi_{i,m} (Z_{i,m}) = W_{i,m}^T S_{i,m} (Z_{i,m}) + \epsilon_{i,m} (Z_{i,m})
$$

(43)

where $| \epsilon_{d,i,m} (Z_{i,m}) | \leq \epsilon_{d,i,m}$ and $\epsilon_{d,i,m}$ is a known positive scalar.

Based on Young’s inequality, it can be obtained that

$$
Z_{i,m} \epsilon_{d,i,m} (Z_{i,m}) \leq \frac{1}{2} \dot{Z}_{i,m}^2 + \frac{1}{2} \epsilon_{d,i,m}^2
$$

(44)

Substituting (43)-(44) into (42), we can obtain

$$
\dot{V}_{i,m} \leq H_{i,1} - \sum_{j=1}^{m_l} \frac{1}{2} \left( 1 - 2 \tanh^2 \left( \frac{z_{i,m}^2}{W_{j}} \right) \right) h_{i,j}^T (y_i) + \sum_{j=1}^{m_l} c_{i,j} \dot{W}_{i,j} \dot{W}_{i,j} \\
+ \sum_{j=1}^{m_l} \frac{1}{2} l_{i,j} \dot{W}_{i,j} \dot{W}_{i,j} + \sum_{j=2}^{m_l} \frac{1}{2} l_{i,j} \dot{W}_{i,j} \dot{W}_{i,j} + R_{i,m,-1} \\
+ \frac{1}{2} h_{i,m}^2 (y_i, y_i, d_{i,m}) - \dot{\beta}_{i,m} \\
\dot{W}_{i,m} (\gamma_{i,m} z_{i,m} S_{i,m} (\hat{x}_{i,m}) - \dot{W}_{i,m}) \\
+ \frac{1}{\Lambda_{i,m}} \dot{W}_{d,i,m} \dot{W}_{d,i,m} + \frac{1}{\sigma_{gi}} \hat{g}_{i} + \frac{g_{i}}{\sigma_{pi}} \hat{\rho}_{i} \hat{\rho}_{i} \\
- \sum_{j=1}^{m_l} q_{i} V_{d,i} + \frac{1}{2} h_{i,m}^2 (y_i, y_i, d_{i,m}) - \dot{\beta}_{i,m} \gamma_{i,m} \chi (\tilde{y})
$$

(45)

where $\alpha_{i,m}$ is the virtual control input and has the following form

$$
\alpha_{i,m} = - \left( r_{i,m} + \frac{5}{2} \right) z_{i,m} \dot{W}_{i,m} S_{i,m} (\hat{x}_{i,m}) \\
- \dot{W}_{d,i,m} S_{d,i,m} (Z_{i,m}) + \dot{\beta}_{i,m} \\
- k_{i,m} (y_i - \hat{x}_{i,1}) - \dot{z}_{i,m} \hat{g}_{i} \gamma_{i,m} \chi (\tilde{y}) + \frac{1}{\Lambda_{i,m}} \dot{Z}_{i,m} - \sum_{j=1}^{m_l} q_{i} V_{d,i} + \frac{1}{2} h_{i,m}^2 (y_i, y_i, d_{i,m}) - \dot{\beta}_{i,m} \gamma_{i,m} \chi (\tilde{y})
$$

(46)

with

$$
\dot{W}_{i,m} = \gamma_{i,m} Z_{i,m} S_{i,m} (\hat{x}_{i,m}) - c_{i,m} \dot{W}_{i,m} \\
\dot{W}_{d,i,m} = \Lambda_{i,m} Z_{i,m} S_{d,i,m} (Z_{i,m}) - c_{d,i,m} \dot{W}_{d,i,m}
$$

(47)
where

\[
\begin{align*}
\dot{v}_i(t) &= \hat{\beta}_i \dot{v}_i(t) \\
\ddot{v}_i(t) &= -\left(1 + \eta_i\right) \left(\frac{z_{i,m} \sigma^2_{i,m}}{(1 - \delta_i) \sqrt{\frac{z_{i,m} \sigma^2_{i,m} + r_i^2}{\sqrt{z_{i,m} \sigma^2_{i,m} + r_i^2}}}}\right) \\
&\quad + \frac{z_{i,m} \sigma^2_{i,m}}{(1 - \delta_i) \sqrt{\frac{z_{i,m} \sigma^2_{i,m} + r_i^2}{\sqrt{z_{i,m} \sigma^2_{i,m} + r_i^2}}}} \dot{\hat{g}}_i - \sigma_{gi} v_i(t) z_{i,m} - c_{gi} \ddot{g}_i \hat{\beta}_i - \frac{\hat{p}_{i}}{\sigma_{pi}} \ddot{\hat{g}}_i
\end{align*}
\]

with \( \sigma_i > \frac{\eta(1 + \delta) \lambda_0}{1 - \eta_i} \). \( \tau_i, c_{gi} \) and \( c_{pi} \) are the positive scalars.

The event triggering mechanism is given as follows

\[
t_{i,k+1} = \inf \{ t \in \mathbb{R} | |\beta_i(t)| \geq \eta_i |u_i(t)| + \omega_i \}
\]

where \( 0 < \eta_i < 1 \) and \( \omega_i > 0 \) are design parameters, \( \beta_i(t) = v_i(t) - u_i(t) \) denotes the measurement error.

Besides, according to the event-triggered mechanism, there exists \( |\xi_{i,1}(t)| \leq 1 \) and \( |\xi_{i,2}(t)| \leq 1 \) satisfying \( v_i(t) = (1 + \xi_{i,1}(t) \eta_i) u_i(t) + \xi_{i,2}(t) \omega_i \) in the time interval \( [t_{i,k}, t_{i,k+1}) \). Therefore, we can obtain the control input \( u_i \) during the event triggering

\[
\begin{align*}
\dot{v}_i(t) &= \frac{v_i(t)}{1 + \xi_{i,1}(t) \eta_i} - \frac{\xi_{i,2}(t) \omega_i}{1 + \xi_{i,1}(t) \eta_i}
\end{align*}
\]

Substituting (46) and (48) into (45), then we have

\[
\begin{align*}
V_{i,m_i}[t_{i,k+1} - t_{i,k}] &\leq H_{i} - \sum_{j=1}^{m_i} \frac{1}{2} \left(1 - 2 \tanh^2 \left(\frac{z_{i,j} \sigma_{i,j}}{w_j}\right)\right) \hat{W}_{i,j}^T \hat{W}_{i,j} + \sum_{j=1}^{m_i} c_{d,j} \hat{W}_{i,j}^T \hat{W}_{i,j} \\
&\quad + \sum_{j=1}^{m_i} c_{d,j} \hat{W}_{i,j}^T \hat{W}_{i,j} + \frac{1}{2} \sum_{j=2}^{m_i} l_{i,j} \hat{W}_{i,j}^T \hat{W}_{i,j} + \frac{1}{2} z_{i,m_i} \hat{g}_i M_i(u_i) (v_i(t)) \left(1 + \xi_{i,1}(t) \eta_i - \frac{\xi_{i,2}(t) \omega_i}{1 + \xi_{i,1}(t) \eta_i}\right) \\
&\quad + z_{i,m_i} \hat{g}_i N_i - z_{i,m_i} \sigma^2_{i,m_i} \frac{2}{\sqrt{z_{i,m_i} \sigma^2_{i,m_i} + r_i^2}} |u_{i,min} + \lambda_i| \\
&\quad + R_{i,m_i - 1} + \frac{1}{2} \hat{r}_i^2 \sigma_{i,m_i} \hat{g}_i M_i(u_i) + \frac{c_{gi}}{\sigma_{gi}} \hat{g}_i - \frac{g_{c_{pi}}}{\sigma_{pi}} \hat{p}_{i} \hat{\beta}_i \\
&\quad - \sum_{j=1}^{m_i} Q_{V_d,j} \dot{y}_j + \frac{1}{2} \hat{r}_i^2 \sigma_{i,m_i} \hat{g}_i M_i(u_i) \left(y_i, y_i, d_m, d_i\right) - \frac{1}{2} z_{i,1,2} \chi(t)
\end{align*}
\]

**Remark 4:** Suppose that \( t = t_{i,k} \) is the current moment, then \( t_{i,k}, k \in \mathbb{N}^+ \) can be regarded as the triggering instant of the current event, the control input \( u_i \) will be update and held as a constant \( v_i(t_{i,k}) \) in the time interval \( t \in [t_{i,k}, t_{i,k+1}) \). Once the mechanism is triggered again, \( t_{i,k+1} \) can be regarded as the triggering instant of the next event, the control input \( u_i \) will be update as \( v_i(t_{i,k+1}) \).

**Remark 5:** It could be found that the design object of event triggering mechanism is \( u_i \), not the quantized signal \( q_i (u_i) \). This is because the input quantization \( q_i (u_i) \) has been expressed as the decomposition form \( M_i(u_i) u_i + N_i \), and according to Lemma 1, the decomposition form could be dealt with into an appropriate linear function only related to \( u_i \). Utilizing this approach to design the event triggering mechanism could also achieve the desired control results. But it should be pointed out that the control object of event triggering mechanism is the quantized control input signals \( q_i (u_i) \) in the actual systems.

In this position, the main result of this paper is given in the form of Theorem 1.

**Theorem 1:** Consider the interconnected nonlinear time delay systems (4) under the Assumptions 1-5, the event-triggered adaptive decentralized FTC strategy (47) relying on the RBFNNs state observer (8) guarantees that the tracking errors converge to a small neighborhood near the origin, and all the signals of the closed loop systems are ultimately uniformly bounded by selecting the appropriate parameters. Besides, there exists \( t_i^* > 0 \) such that the inter-execution intervals \( \{t_{i,k+1} - t_{i,k}\} \geq t_i^*, k \in \mathbb{N}^+ \).

**Proof:** According to Lemmas 2-3 and (47), the following inequalities are derived

\[
\begin{align*}
&z_{i,m_i} \hat{g}_i M_i (u_i) \left(\frac{v_i(t)}{1 + \xi_{i,1}(t) \eta_i} - \frac{\xi_{i,2}(t) \omega_i}{1 + \xi_{i,1}(t) \eta_i}\right) \\
&\leq z_{i,m_i} \hat{g}_i M_i (u_i) + z_{i,m_i} \hat{g}_i M_i (u_i) \frac{v_i(t)}{1 + \xi_{i,1}(t) \eta_i} + |z_{i,m_i} \hat{g}_i M_i (u_i) \xi_{i,2}(t) \omega_i| \\
&\leq -\frac{\hat{\beta}_i}{1 - \delta_i} \left(1 - \delta_i\right) \left(\frac{z_{i,m_i} \sigma^2_{i,m_i}}{(1 - \delta_i) \sqrt{\frac{z_{i,m_i} \sigma^2_{i,m_i} + r_i^2}{\sqrt{z_{i,m_i} \sigma^2_{i,m_i} + r_i^2}}} + \frac{z_{i,m_i} \sigma^2_{i,m_i}}{(1 - \delta_i) \sqrt{\frac{z_{i,m_i} \sigma^2_{i,m_i} + r_i^2}{\sqrt{z_{i,m_i} \sigma^2_{i,m_i} + r_i^2}}} + r_i^2}\right) + |z_{i,m_i} \hat{g}_i (1 + \delta_i) \omega_i| \\
&\leq -z_{i,m_i} \sigma_{i,m_i} \omega_i + 2 \tau_i + \frac{|z_{i,m_i} \hat{g}_i (1 + \delta_i) \omega_i|}{1 - \eta_i} \\
&\leq -z_{i,m_i} \sigma_{i,m_i} \omega_i + 2 \tau_i \\
&\leq -z_{i,m_i} \sigma_{i,m_i} \omega_i + 2 \tau_i + \frac{|z_{i,m_i} \hat{g}_i (1 + \delta_i) \omega_i|}{1 - \eta_i}
\end{align*}
\]

and

\[
\begin{align*}
z_{i,m_i} \hat{g}_i N_i - z_{i,m_i} \sigma^2_{i,m_i} \frac{2}{\sqrt{z_{i,m_i} \sigma^2_{i,m_i} + r_i^2}} |u_{i,min} + \lambda_i| \\
&\leq z_{i,m_i} \hat{g}_i |u_{i,min} - \frac{z_{i,m_i} \sigma^2_{i,m_i} \frac{2}{\sqrt{z_{i,m_i} \sigma^2_{i,m_i} + r_i^2}} |u_{i,min} + \lambda_i|}{z_{i,m_i} \hat{g}_i |u_{i,min} + \lambda_i|} \\
&\leq \frac{|z_{i,m_i} \hat{g}_i |u_{i,min} + \lambda_i|}{z_{i,m_i} \hat{g}_i |u_{i,min} + \lambda_i|} \leq \tilde{\lambda}_i
\end{align*}
\]

Based on Young’s inequality, we have

\[
\begin{align*}
\hat{W}_{i,j} \hat{W}_{i,j} &\leq -\frac{1}{2} \hat{W}_{i,j} \hat{W}_{i,j} + \frac{1}{2} \hat{W}_{i,j} \hat{W}_{i,j} \\
\hat{W}_{i,j} \hat{W}_{i,j} &\leq -\frac{1}{2} \hat{W}_{i,j} \hat{W}_{i,j} + \frac{1}{2} \hat{W}_{i,j} \hat{W}_{i,j} \\
\hat{g}_i \hat{g}_i &\leq -\frac{1}{2} \hat{g}_i \hat{g}_i + \frac{1}{2} \hat{g}_i \hat{g}_i
\end{align*}
\]
It seems to be conservative that suppose there exists a large positive constant $\Xi_i$ satisfying $u_i^2 \leq \Xi_i$, but in practical engineering, the actuator could not output infinite control power, the control input must be bounded.

$$2e_i^T P_i B_i \delta_i (u_i) \leq \| e_i \|^2 + \| P_i \|^2 \Xi_i^2 (M_i (u_i) u_i + N_i)^2$$

$$\leq \| e_i \|^2 + 2\| P_i \|^2 \left( (1 + \delta_i^2) \Xi_i + u_{i,min}^2 \right) \Xi_i^2$$

(53)

According to the Assumption 4, one has

$$\| \Delta_i (\tilde{y}^i) \|^2$$

$$\leq \left( \sum_{i=1}^N \Psi_{i,i}^2 (\| y_i \|) \right)^2 \leq N \sum_{i=1}^N \Psi_{i,i}^2 (\| y_i \|)$$

$$\leq N \sum_{i=1}^N \left( 2\Psi_{i,i}^2 (2 \| z_i,1 \|) + 2\Psi_{i,i}^2 (2 \| y_i \|) \right)$$

$$\leq N \sum_{i=1}^N 8\psi_{i,i}^2 \left( \Psi_{i,i}^2 (2 \| z_i,1 \|) + \Psi_{i,i}^2 (2 \| z_i,1 \|) \right)^2 + B_i$$

(54)

where $B_i$ is a constant with $B_i \geq 2N \sum_{i=1}^N \Psi_{i,i}^2 (2 \| y_i \|)$.

To deal with the output-dependent interconnected terms, we design the following function

$$\chi_i (\tilde{y}) = 8N \left( a + \frac{1}{2} \right) \sum_{i=1}^{N} \left( \tilde{\Psi}_{i,i}^2 (2 \| z_i,1 \|) \right)$$

$$+ \tilde{\Psi}_{i,i}^2 (2 \| z_i,1 \|)$$

(55)

Substituting (50)-(55) into (49), then we have

$$\dot{V}_{i,m_i} \leq -\left( \lambda_{\min} (Q_i) - \frac{7}{2} - \frac{1}{a} \| P_i \|^2 - \tilde{L}_i \right) \| e_i \|^2$$

$$- \left( \frac{c_{i,i}}{2} - \| P_i \|^2 \tilde{l}_{i,i} \right) \tilde{W}_{i,i}^T \tilde{W}_{i,i} - \sum_{j=1}^{m_i} r_{i,j} \tilde{z}_{i,j}^2$$

$$- \sum_{j=2}^{m_i} \left( \frac{c_{i,j}}{2} - \| P_i \|^2 \tilde{l}_{i,j} - \frac{1}{2} \tilde{l}_{i,j} \right) \tilde{W}_{i,j}^T \tilde{W}_{i,j}$$

$$- \sum_{j=1}^{m_i} \left( \frac{c_{d,i}}{2} \tilde{W}_{d,i}^T \tilde{W}_{d,i} - \sum_{j=1}^{m_i} \left( \frac{1}{\kappa_{i,j}} - 1 \right) \phi_{i,j}^2 \right)$$

$$+ \sum_{j=1}^{m_i} \frac{1}{2} \left( 1 - 2\tanh^2 \left( \frac{z_{i,j}}{w_j} \right) \right) h_{i,j}^+ (y_i) - \frac{g\| c_{pi} \|^2}{2\sigma_{pi}} \tilde{h}_i^2$$

$$- \left( \frac{c_{gi}}{2\sigma_{gi}} - 2\| P_i \|^2 \left( (1 + \delta_i^2) \Xi_i + u_{i,min}^2 \right) \right) \tilde{g}_i^2 + R_{i,m_i}$$

$$- \sum_{j=1}^{m_i} \theta_i \tilde{V}_{d,i,j} - \left( \frac{c_{h,i}}{2} - \frac{1}{2\tilde{l}_i} \right) \tilde{h}_i^2$$

(56)

To the whole interconnected systems, the Lyapunov function is designed as

$$V = \sum_{i=1}^N V_{i,m_i}$$

Taking the derivative of $V$ with respect to time yields

$$\dot{V} \leq \sum_{i=1}^N \left[ - \left( \lambda_{\min} (Q_i) - \frac{7}{2} - \frac{1}{a} \| P_i \|^2 - \tilde{L}_i \right) \| e_i \|^2$$

$$- \left( \frac{c_{i,i}}{2} - \| P_i \|^2 \tilde{l}_{i,i} \right) \tilde{W}_{i,i}^T \tilde{W}_{i,i} - \sum_{j=1}^{m_i} r_{i,j} \tilde{z}_{i,j}^2$$

$$- \sum_{j=2}^{m_i} \left( \frac{c_{i,j}}{2} - \| P_i \|^2 \tilde{l}_{i,j} - \frac{1}{2} \tilde{l}_{i,j} \right) \tilde{W}_{i,j}^T \tilde{W}_{i,j}$$

$$- \sum_{j=1}^{m_i} \left( \frac{c_{d,i}}{2} \tilde{W}_{d,i}^T \tilde{W}_{d,i} - \sum_{j=1}^{m_i} \left( \frac{1}{\kappa_{i,j}} - 1 \right) \phi_{i,j}^2 \right)$$

$$- \sum_{j=2}^{m_i} \left( \frac{1}{\kappa_{i,j}} - 1 \right) \phi_{i,j}^2 - \frac{g\| c_{pi} \|^2}{2\sigma_{pi}} \tilde{h}_i^2 - \sum_{j=1}^{m_i} \theta_i \tilde{V}_{d,i,j} - \left( \frac{c_{h,i}}{2} - \frac{1}{2\tilde{l}_i} \right) \tilde{h}_i^2$$

$$- \left( \frac{c_{gi}}{2\sigma_{gi}} - 2\| P_i \|^2 \left( (1 + \delta_i^2) \Xi_i + u_{i,min}^2 \right) \right) \tilde{g}_i^2$$

$$+ \sum_{i=1}^N \sum_{j=1}^{m_i} \frac{1}{2} \left( 1 - 2\tanh^2 \left( \frac{z_{i,j}}{w_j} \right) \right) h_{i,j}^+ (y_i) + \sum_{i=1}^N R_{i,m_i}$$

(57)

On the basis of Assumption 3 and the properties of $\tanh (\cdot)$, there exists a positive constant $Y_{i,j}$ satisfying

$$\frac{1}{2} \left( 1 - 2\tanh^2 \left( \frac{z_{i,j}}{w_j} \right) \right) h_{i,j}^+ (y_i) \leq Y_{i,j}$$

Furthermore, we can obtain as follows

$$\dot{V} \leq -\mu V + M$$

(58)

where

$$0 < \mu \leq \min_{1 \leq i \leq N, 1 \leq j \leq m_i} \left\{ \frac{\lambda_{\min} (Q_i) - \frac{7}{2} - \frac{1}{a} \| P_i \|^2 - \tilde{L}_i}{\lambda_{\max} (P_i)} \right\}$$

$$2\gamma_{i,1} \left( \frac{c_{i,1}}{2} - \| P_i \|^2 \tilde{l}_{i,1} \right), \lambda_{i,j} d_{i,j}, 2r_{i,j}, 2 \left( \frac{1}{\kappa_{i,j}} - 1 \right),$$

$$2\gamma_{i,j} \left( \frac{c_{i,j}}{2} - \| P_i \|^2 \tilde{l}_{i,j} - \frac{1}{2} \tilde{l}_{i,j} \right), 2 \left( \frac{c_{h,i}}{2} - \frac{1}{2\tilde{l}_i} \right),$$

$$2 \left( \frac{c_{gi}}{2\sigma_{gi}} - 2\| P_i \|^2 \left( (1 + \delta_i^2) \Xi_i + u_{i,min}^2 \right) \right) \tilde{g}_i^2$$

and

$$M = \sum_{i=1}^N R_{i,m_i} + \sum_{i=1}^N m_i Y_{i,j}.$$
Multiplying on both sides of (58) by $e^{\mu t}$, and then integrating over $[0, t)$ generates
\[ V \leq V(0) e^{-\mu t} + M \mu \left(1 - e^{-\mu t}\right) \]
\[ \leq V(0) e^{-\mu t} + M \mu \]  
(59)

According to Lyapunov stability theory, it can be known from (59) that all signals for the interconnected systems are ultimately uniformly bounded. Furthermore, the tracking error $z_{i,1} = y_i - y_{ri}$ satisfies
\[ \sum_{i=1}^{N} \frac{1}{2} z_{i,1}^2 \leq V(0) e^{-\mu t} + \frac{2M}{\mu} \]
We can obtain
\[ |z_{i,1}| \leq \sqrt{2V(0)} e^{-\mu t} + \sqrt{\frac{2M}{\mu}} \]

According to the above inequalities, $z_{i,1}$ could be regulated into a small set and the size of set can be reduced by choosing the appropriate parameters, such as $P_i$, $a$, $L_i$, $r_i$, $y_{ri}$ and $d_{q,i}$ soon on. When $t \to \infty$, $e^{-\mu t} \to 0$, and $J \geq \frac{2M}{\mu}$, when $t \geq T^*$, $|z_{i,1}| \leq J$. Hence, the tracking errors converge to a neighborhood near the origin.

Considering $\beta_i(t) = v_i(t) - u_i(t)$, one can obtain that
\[ \frac{d}{dt} \beta_i(t) = \frac{d}{dt} \beta_i^2(t) = \text{sign} (\beta_i(t)) |\beta_i(t)| \leq |\dot{v}_i(t)| \]

According to the proven part of Theorem 1, all signals are bounded in the closed loop systems. Hence, it can be assured that $|\dot{v}_i(t)| \leq \xi_i$ with $\xi_i > 0$. It is easy to know that $\beta_i(t_{k,k}) = 0$ and $\lim_{t \to t_{k,k+1}} \beta_i(t_{k,k}) = \eta_i |u_i(t_{k,k}) + \omega_i$. Then, we could obtain that
\[ \eta_i |u_i(t_{k,k}) + \omega_i| \leq \xi_i \]

Therefore, there exists a lower bound of inter-execution time interval $T^*$ such that $t_{k,k+1} - t_{k,k} \geq T^*$ and $t_{k,k}^* \geq \eta_i |u_i(t_{k,k}) + \omega_i| \geq \frac{\xi_i}{\omega_i} > 0$, in other words, the Zeno-behavior is avoided in this paper.

Remark 6: Different from the event-triggered FTC strategy proposed in [19] utilizing the control signal $u_i$ directly, in this paper, the event-triggered FTC strategy first quantizes the input signal into piecewise constant $q_i(u_i)$, and then utilizes the event triggering mechanism to send the quantized control input signals $q_i(u_i)$ to the actuator in the form of aperiodic piecewise constant, which could further reduce the communication frequency between the controllers and the actuators compared with [19].

Remark 7: In [18], the event-triggered decentralized control approach is designed for the interconnected nonlinear systems with unmeasurable states and input quantization. But the time delay and the actuator faults issues are not further studied in [18], while this paper is concerned with the event-triggered decentralized FTC strategy for the interconnected nonlinear time delay systems with input quantization, unmeasurable states, and actuator faults. Hence, this paper could be regarded as the extension and supplement of [18].

Remark 8: In the process of stability analysis of the closed-loop system, the selected Lyapunov function $V_{i,k}$ includes $V_{d,ik}$, which is designed for the unknown time delay function $h_{ij} (y_i, y_{d,j})$, such that the derived decentralized FTC scheme could tolerate the effects of the unknown time delay function to the considered closed loop systems.

IV. SIMULATION RESULTS

In this section, the event-triggered decentralized FTC strategy proposed in this paper is applied to two interconnected two-stage chemical reactors with delayed recycle streams described as follows
\[
\begin{align*}
\dot{x}_{1,1} &= -\frac{1}{A_{1,1}} x_{1,1} - B_{1,1} x_{1,1} + \frac{1 - C_{1,2}}{D_{1,1}} x_{1,2} + M_{1,1} \sin (x_{1,1} + x_{2,1}) \nonumber \\
\dot{x}_{1,2} &= -\frac{1}{A_{1,2}} x_{1,2} - B_{1,2} x_{1,2} + \frac{C_{1,1}}{D_{1,2}} x_{1,1} (t - d_1) + u_1 + M_{1,2} \sin (x_{2,1}) \\
\dot{x}_{2,1} &= -\frac{1}{A_{2,1}} x_{2,1} - B_{2,1} x_{2,1} + \frac{1 - C_{2,2}}{D_{2,1}} x_{2,2} + M_{2,1} \sin (x_{1,1}) \\
\dot{x}_{2,2} &= -\frac{1}{A_{2,2}} x_{2,2} - B_{2,2} x_{2,2} + \frac{C_{2,1}}{D_{2,2}} x_{2,1} (t - d_2) + u_2 + M_{2,2} \sin (x_{1,1} - x_{2,1}) \\
y_1 &= x_{1,1} \\
y_2 &= x_{2,1}
\end{align*}
\]
where $x_{1,1}, x_{1,2}, x_{2,1}$ and $x_{2,2}$ are the compositions, $A_{1,1}, A_{1,2}, A_{2,1}$ and $A_{2,2}$ are the reactor residence times, $C_{1,1}, C_{1,2}, C_{2,1}$ and $C_{2,2}$ are the recycle flow rates, $D_{1,1}, D_{1,2}, D_{2,1}$ and $D_{2,2}$ are reactor volumes, $B_{1,1}, B_{1,2}, B_{2,1}$ and $B_{2,2}$ are the reaction constants. The parameters are given as $A_{1,1} = A_{1,2} = A_{2,1} = A_{2,2} = 50, B_{1,1} = B_{1,2} = 0.03, B_{2,1} = B_{2,2} = 0.04, C_{1,1} = C_{1,2} = C_{2,1} = C_{2,2} = 0.5, D_{1,1} = D_{1,2} = D_{2,1} = D_{2,2} = 0.5, M_{1,1} = M_{2,1} = M_{2,2} = 0.1$ and $M_{1,2} = 0.2$. The known time-varying delays are given as $d_1 = 0.2 (1 + 0.4 \sin (2t))$ and $d_2 = 0.3 (1 + 0.4 \sin (2t))$. The output reference signals are given as $y_{r,1} = \sin (t)$ and $y_{r,2} = \cos (t)$.

It is assumed that the unknown actuator faults considered in this study have the following forms
\[
\begin{align*}
q_{f,1} (u_1) &= \begin{cases} 
q_1 (u_1), & t \leq 5 \\
0.6 q_1 (u_1) + 2, & 5 < t \leq 20
\end{cases}
\end{align*}
\]
\[
\begin{align*}
q_{f,2} (u_2) &= \begin{cases} 
q_2 (u_2), & t \leq 5 \\
0.5 q_2 (u_2) + 1, & 5 < t \leq 20
\end{cases}
\end{align*}
\]
The design parameters of the state observer (8) are selected as $k_{1,1} = k_{1,2} = 30$ and $k_{2,1} = k_{2,2} = 40$. The design parameters of input quantization $q_i (u_i)$ in (2) are selected as $\eta_1 = \eta_2 = 0.5, w_1 = w_2 = 1$. The design parameters for
The design parameters of decentralized fault tolerant controllers developed in this study are selected as $r_{1,1} = 10$, $r_{1,2} = 20$, $r_{2,1} = 13$, $r_{2,2} = 5$, $c_{1,1} = c_{1,2} = 50$, $c_{2,1} = c_{2,2} = 15$, $c_{d,11} = c_{d,12} = 0.2$, $c_{d,21} = c_{d,22} = 0.3$, $\lambda_1 = 0.01$, $\lambda_2 = 0.01$, $\tau_1 = \tau_2 = 0.01$. The initial states are given

input quantization are selected as $\delta_1 = \delta_2 = 0.2$, $u_{1,\text{min}} = u_{2,\text{min}} = 0.1$. The design parameters of decentralized fault tolerant controllers developed in this study are selected as $r_{1,1} = 10$, $r_{1,2} = 20$, $r_{2,1} = 13$, $r_{2,2} = 5$, $c_{1,1} = c_{1,2} = 50$, $c_{2,1} = c_{2,2} = 15$, $c_{d,11} = c_{d,12} = 0.2$, $c_{d,21} = c_{d,22} = 0.3$, $\kappa_1 = 0.02$, $\kappa_2 = 0.01$, $\gamma_{1,1} = \gamma_{1,2} = 0.02$, $\gamma_{2,1} = \gamma_{2,2} = 0.03$, $\Lambda_{1,1} = \Lambda_{1,2} = 10$, $\Lambda_{2,1} = \Lambda_{2,2} = 13$, $\Pi_1 = \Pi_2 = 2$, $c_{h,1} = 0.05$, $c_{h,2} = 0.5$, $\sigma_{g1} = \sigma_{g2} = 0.06$, $\sigma_{g2} = \sigma_{g2} = 0.04$, $c_{g1} = c_{g1} = 0.003$, $c_{g2} = c_{g2} = 0.003$. The initial states are given

\begin{align*}
&\text{FIGURE 2. Trajectory of } x_{11}, \hat{x}_{11}, x_{21} \text{ and } \hat{x}_{21} \text{ using state observer designed in this paper.} \\
&\text{FIGURE 3. Trajectory of } x_{12}, \hat{x}_{12}, x_{22} \text{ and } \hat{x}_{22} \text{ using state observer designed in this paper.} \\
&\text{FIGURE 4. Trajectory of } y_1, y_{r1}, y_2 \text{ and } y_{r2} \text{ using FTC designed in this paper.}
\end{align*}
as $x_1(0) = [0.2, 0.2]^T$ and $x_2(0) = [0.2, 0.2]^T$. All the other initial values are selected as 0.1.

By utilizing the event-triggered decentralized FTC strategy proposed in this paper to the interconnected delayed chemical reactor systems, the corresponding simulation results are shown in Figure 2-8, where Figure 2 and 3 show the state estimation curves of $x_{12}$ and $x_{22}$, it can be seen that the RBFNNs state observer designed in this paper could observe the unmeasurable states well. Figure 4 shows the output signal tracking performance of the interconnected nonlinear time delay systems. Furthermore, tracking errors are depicted in Figure 5. It is not difficult to find that the FTC strategy
proposed in this study could guarantee the output signals of the interconnected systems track the reference signals well in spite of the existence of actuator faults and input quantization. Figure 6 shows the estimated values of actuator fault. Figure 7 shows the control input curves, which clearly show the effectiveness of the event triggering mechanism. As shown in the above figures that all signals of the closed loop systems are ultimately uniformly bounded. Figure 8 shows the
occurrence instants and time intervals of events. After calculation, it can be obtained that the number of triggers, in subsystem 1, is 460 with the number of non-triggering events is 3541 and the number of triggers, in subsystem 2, is 212 with the number of non-triggering events is 3789. Base on the above simulation result, it is known that the
FIGURE 14. Trajectory of $q_1(u_1)$ and $q_2(u_2)$ using FTC scheme in [19].

FIGURE 15. Inter-event intervals of subsystem 1 and subsystem 2 in [19].

The event-triggered decentralized FTC strategy proposed in this paper can effectively reduce the communication frequency and save communication resources.

In order to illustrate the advantages of the proposed FTC strategy, some simulations comparisons are shown as follows. The FTC strategy proposed in [19], which does not consider the time delay problem and input quantization, are adopted to control the considered interconnected delayed chemical reactor systems, and the corresponding simulation results are displayed in Figure 9-15. Figure 9 and 10 show the estimated curves of the unmeasured state variable $x_{12}$ and $x_{22}$. Figure 11 shows the output signals and their reference signals. Figure 12 shows the tracking error curves. It is easy to find that the tracking performance is poor and the tracking errors have greater oscillation when actuator faults occur. The estimation curves of actuator fault are given in Figures 13. Figure 14 shows the control input curves of the interconnected systems. As shown in Figures 15, the occurrence instants and time intervals of events are depicted.

From the above comparisons, it can be seen that the FTC strategy proposed in [19] could not fully overcome the effects of time delay and quantization errors, it leads to the poor state estimation and output tracking performance for the considered interconnected delayed systems. Therefore, the FTC control strategy designed in [19] has the certain application limitations. On this basis of the result obtained in [19], the improved event-triggered decentralized FTC strategy developed in this paper could overcome the effects of time delay and quantization errors to the closed loop systems. Meanwhile, the good state estimation and output tracking performance are also guaranteed.

V. CONCLUSION

In this paper, an event-triggered decentralized FTC strategy is proposed for a class of interconnected nonlinear time delay systems in strict feedback form with input quantization and actuator faults. The unstructured uncertainties and the unmeasurable states are considered in the interconnected systems. The RBFNNs technique is used to approximate the unstructured uncertainties and unknown time delay functions. To obtained the unmeasurable states, a state observer is designed utilizing the RBFNNs technique. The adaptive backstepping technique with low pass filter is adopted to design the event-triggered decentralized FTC strategy, it could guarantee that the tracking errors can converge to a small neighborhood near the origin and all signals of the closed loop systems are ultimately uniformly bounded.

Finally, a simulation example is presented to show the
effectiveness of the proposed strategy. In our future work, the event-based decentralized fault tolerant control problem will be investigated for the nonlinear interconnected nonlinear time delay systems in sensor faulty case.

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REFERENCES

[1] D. T. Gavel and D. D. Stiljak, “Decentralized adaptive control: Structural conditions for stability,” IEEE Trans. Autom. Control, vol. 34, no. 4, pp. 413–426, Apr. 1989.
[2] L. Shi and S. K. Singh, “Decentralized adaptive controller design for large-scale systems with higher order interconnections,” IEEE Trans. Autom. Control, vol. 37, no. 8, pp. 1106–1118, Aug. 1992.
[3] X. Jin, “Adaptive decentralized finite-time output tracking control for MIMO interconnected nonlinear systems with output constraints and actuator faults,” Int. J. Robust Nonlinear Control, vol. 28, no. 5, pp. 1808–1829, Mar. 2018.
[4] M. Chen and G. Tao, “Adaptive fault-tolerant control of uncertain nonlinear large-scale systems with unknown dead zone,” IEEE Trans. Cybern., vol. 46, no. 8, pp. 1851–1862, Aug. 2016.
[5] X. J. Li and G. H. Yang, “Adaptive decentralized control for a class of interconnected nonlinear systems via backstepping approach and graph theory,” Automatica, vol. 76, no. 1, pp. 1407–1415, 2017.
[6] F. W. Lewis, S. Jagannathan, and A. Yesildirek, Neural Network Control of Robot Manipulators and Non-Linear Systems. Boca Raton, FL, USA: CRC Press, 1998.
[7] L.-X. Wang, “Stable adaptive fuzzy control of nonlinear systems,” IEEE Trans. Fuzzy Syst., vol. 1, no. 2, pp. 146–155, May 1993.
[8] W. Ji, S. Fu, H. Chen, and J. Qiu, “Asynchronous decentralized fuzzy observer-based output feedback control of nonlinear large-scale systems,” Int. J. Fuzzy Syst., vol. 21, no. 1, pp. 19–32, Feb. 2019.
[9] D. Wang, D. Liu, C. Mu, and Y. Zhang, “Neural network learning and robust stabilization of nonlinear systems with dynamic uncertainties,” IEEE Trans. Neural Netw. Learn. Syst., vol. 29, no. 4, pp. 1342–1351, Apr. 2018.
[10] T. Hayakawa, H. Ishii, and K. Tsumura, “Adaptive quantized control for linear uncertain discrete-time systems,” Automatica, vol. 45, no. 3, pp. 692–700, Mar. 2009.
[11] J. Zhou, C. Wen, and G. Yang, “Adaptive backstepping stabilization of nonlinear uncertain systems with quantized input signal,” IEEE Trans. Autom. Control, vol. 59, no. 2, pp. 460–464, Feb. 2014.
[12] Z. Liu, F. Wang, Y. Zhang, and C. L. Philip Chen, “Fuzzy adaptive quantized control for a class of stochastic nonlinear uncertain systems,” IEEE Trans. Cybern., vol. 46, no. 2, pp. 524–534, Feb. 2016.
[13] Q.-Y. Fan, G.-H. Yang, and D. Ye, “Quantization-based adaptive actor-critic tracking control with tracking error constraints,” IEEE Trans. Neural Netw. Learn. Syst., vol. 29, no. 4, pp. 970–980, Apr. 2018.
[14] C.-C. Wang and G.-H. Yang, “Prescribed performance adaptive fault-tolerant tracking control for nonlinear time-delay systems with input quantization and unknown control directions,” Neurocomputing, vol. 311, no. 5, pp. 333–343, Oct. 2018.
[15] R. Sakhthivel, S. Santra, B. Kaviarasan, and K. Venkatacharubub, “Disipative analysis for network-based singular systems with non-fragile controller and event-triggered sampling scheme,” J. Franklin Inst., vol. 354, no. 12, pp. 4739–4761, Aug. 2017.
[16] C. H. Zhang and G. H. Yang, “Event-triggered practical finite-time output feedback stabilization of a class of uncertain nonlinear systems,” Int. J. Robust Nonlinear Control, vol. 29, no. 10, pp. 3078–3092, 2019.
[17] J. Zhou, J.-W. Zhu, W.-A. Zhang, and L. Yu, “Event-triggered dynamic output feedback tracking control for large-scale interconnected systems with disturbances,” J. Franklin Inst., vol. 356, no. 17, pp. 10547–10563, Nov. 2019.
[18] C.-C. Wang and G.-H. Yang, “Event-triggered decentralized output-feedback control for interconnected nonlinear systems with input quantization,” J. Franklin Inst., vol. 356, no. 13, pp. 7028–7048, Sep. 2019.
[19] C.-H. Zhang and G.-H. Yang, “Event-triggered adaptive output feedback control for a class of uncertain nonlinear systems with actuator failures,” IEEE Trans. Cybern., vol. 50, no. 1, pp. 201–210, Jan. 2020.
[20] R. Sakhthivel, M. Joby, C. Wang, and B. Kaviarasan, “Finite-time fault-tolerant control of neutral systems against actuator saturation and nonlinear actuator faults,” Appl. Math. Comput., vol. 332, pp. 425–436, Sep. 2018.
[21] X.-J. Li and G.-H. Yang, “Neural-Network-Based adaptive decentralized fault-tolerant control for a class of interconnected nonlinear systems,” IEEE Trans. Neural Netw. Learn. Syst., vol. 29, no. 1, pp. 144–155, Jan. 2018.
[22] Y. H. Choi and S. J. Yoo, “Event-triggered decentralized adaptive fault-tolerant control of uncertain interconnected nonlinear systems with actuator failures,” ISA Trans., vol. 77, no. 2, pp. 77–89, Jun. 2018.
[23] Y.-X. Li and G.-H. Yang, “Event-triggered adaptive backstepping control for parametric strict-feedback nonlinear systems,” Int. J. Robust Nonlinear Control, vol. 28, no. 3, pp. 976–1000, Feb. 2018.
[24] L. Zhang, C. Hua, G. Cheng, K. Li, and X. Guan, “Decentralized adaptive output feedback fault detection and control for uncertain nonlinear interconnected systems,” IEEE Trans. Cybern., vol. 50, no. 3, pp. 955–945, Mar. 2020.
[25] Y. Li, C. Wang, X. Cai, L. Li, and G. Wang, “Neural-network-based distributed adaptive asymptotically consensus tracking control for non-linear multigent systems with input quantization and actuator faults,” Neurocomputing, vol. 349, no. 2, pp. 64–76, Jul. 2019.
[26] S. J. Yoo, “Output-feedback fault detection and accommodation of uncertain interconnected systems with time-delayed nonlinear faults,” IEEE Trans. Syst., Man, Cybern., Syst., vol. 47, no. 5, pp. 758–766, May 2017.
[27] X. Zheng and Q. Shen, “Neural network-based adaptive fault-tolerant control for a class of high-order strict-feedback nonlinear systems,” IEEE Access, vol. 8, pp. 56510–56517, 2020.
[28] Y. Li, Z. Ma, and S. Tong, “Adaptive fuzzy fault-tolerant control of nontriangular structure nonlinear systems with error constraint,” IEEE Trans. Fuzzy Syst., vol. 26, no. 4, pp. 2062–2074, Aug. 2018.
[29] M. Qian, Z. Zheng, and P. Cheng, “Adaptive NFTSM-based fault tolerant control for a class of nonlinear system with actuator fault and saturation,” IEEE Access, vol. 7, pp. 107083–107095, 2019.