Intelligent Control of Performance Constrained Switched Nonlinear Systems With Random Noises and Its Application: An Event-Driven Approach

Xueliang Wang, Jianwei Xia, *Member, IEEE*, Ju H. Park, *Senior Member, IEEE*, Xiangpeng Xie, *Member, IEEE*, and Guoliang Chen

***Abstract*— In this paper, the adaptive fuzzy control of switched stochastic nonlinear systems with set-time prescribed performance based on event-driven mechanism is studied. The creative part of this paper is that based on the set-time performance function, a modified event-triggered strategy that considers asynchronous switching to deteriorate system performance without strict assumptions is presented, which avoids Zeno behavior and saves communication resources. Then, by using backstepping recursive design technique, Itô's differential lemma and mode-dependent average dwell time (MDADT) method, a novel adaptive performance control scheme is proposed, which can ensure that all the variables in the system are semiglobally uniformly ultimately bounded (SGUUB) in probability and the tracking error gets into prescribed boundary no later than an arbitrarily adjusted setting time. Finally, the proposed algorithm is applied to a RLC circuit and its practicability is verified via simulation results.**

***Index Terms*— Fuzzy logic system, event-triggered scheme, multiple Lyapunov function techniques, switched nonlinear system.**

I. Introduction

IN RECENT decades, the electrical circuits and its control methods have been researched deeply in reports [1]–[4]. It is worth noting that the existence of nonlinear dynamics in electrical circuit systems can not be ignored, so the controller design of nonlinear systems has aroused great interest of scholars, and massive excellent achievements have emerged based on neural network or fuzzy approximation approach [5]–[9]. However, the above control schemes are mainly applied for nonstochastic nonlinear systems. An enormous number practical engineering systems are subject to stochastic uncertainty, such as biological system, financial system and chemical reaction process and so on. For non-triangular multi-input and multi-output (MIMO) stochastic nonlinear systems, an adaptive tracking control scheme based on a new stochastic finite-time stability theorem was proposed in [10]. Then, Liu *et al*. [11] studied the control design of nonlinear stochastic systems with state constraints for the first time by constructing two different forms of barrier Lyapunov functions. For discrete-time stochastic nonlinear systems, an adaptive neural control scheme that mitigates the communication burden and improves the tracking accuracy was developed in [12]. Furthermore, for stochastic systems with unmeasurable states, some effective state observers were elegantly designed in [13]–[15] to estimate the unmeasured states.

Unexceptionally, the above researches are both interesting and challenging, but their conclusions are only valid for nonswitched systems. Due to the fact that most systems are difficult to be described by one model in practice. Multi-model switching control have capacious developed foreground in practical systems. For the stability analysis and controller design of switched systems, massive outstanding achievements have been popping up (see [16]–[24]). Especially, the MDADT of milestone was proposed in [24] to analyze the stability of switched systems, which aroused the attention of many scholars. Since then, such method is extended to many kinds of switched systems to relax the restrictions of switching signals and realize the stability of system. To just name a few, Yang *et al*. [25] developed a transition probability-based MDADT switching mechanism for dynamic systems with mixed delays by designing a multiple Lyapunov-Krasovskii functional. In [26], the exponential stability was studied for discrete-time switched positive systems under the framework of MDADT. It was first reported in [27] that the adaptive control scheme for switched nonlinear lower triangular systems under MDADT switching. Nevertheless, up to now, the investigation of the adaptive control for switched nonlinear systems with random noises under MDADT switching is seldom.

Manuscript received 9 January 2022; revised 13 March 2022 and 8 April 2022; accepted 12 May 2022. Date of publication 23 May 2022; date of current version 30 August 2022. This work was supported in part by the National Natural Science Foundation of China under Grant 61973148 and Grant 62003154, in part by the Shandong Provincial Natural Science Foundation under Grant ZR2021JQ23, and in part by the Open Project of Liaocheng University Animal Husbandry Discipline (319312101-01). The work of Ju H. Park was supported by the Korea Government (Ministry of Science and ICT) through the National Research Foundation of Korea (NRF) Grant (2019R1A5A8080290). This article was recommended by Associate Editor W. X. Zheng. *(Corresponding authors: Jianwei Xia; Ju H. Park.)*

Xueliang Wang, Jianwei Xia, and Guoliang Chen are with the School of Mathematics Science, Liaocheng University, Liaocheng 252000, China (e-mail: 1971232758@qq.com; njustxjw@126.com; chenguoliang3936@126.com).

Ju H. Park is with the Department of Electrical Engineering, Yeungnam University, Gyeongsan-si 38541, Republic of Korea (e-mail: jessie@ynu.ac.kr).

Xiangpeng Xie is with the Institute of Advanced Technology, Nanjing University of Posts and Telecommunications, Nanjing 210023, China (e-mail: xiexiangpeng1953@163.com).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TCSI.2022.3175748.

Digital Object Identifier 10.1109/TCSI.2022.3175748

Furthermore, the transient performance of controlled systems is not considered in the above articles. The prescribed performance control (PPC) method was first proposed in [28] and quickly applied to various nonlinear systems, such as large-scale nonlinear systems [29], MIMO nonlinear systems [30], and stochastic nonlinear systems [31], ect. Subsequently, for the convergence time of closed-loop systems, their finite-time adaptive neural networks and fuzzy PPC methods were studied in [32], [33], which effectively solved the problems of slow convergence and low accuracy of traditional adaptive PPC method. Although the above PPC schemes have satisfactory control effects, they have a common disadvantage, that is, the initial value of the performance function depends on the reference signal and the system output. But many industrial systems do not have constraints at the initial time, after the system runs for a certain time, there will be constraints on the system performance, that is, in $[0, T]$, there are no constraints on the system; and after $t > T$, the system has constraints. Therefore, how to design an effective adaptive PPC scheme to deal with this more complex constraint situation is worthy of further research.

On the other hand, event-triggered communication control (ETCC) has attracted widespread attention due to its important role in networked control system [34]–[38]. For the ETCC of the switched systems, an enormous challenge is that the asynchronous switching between the subsystem and the controller is proving elusive. Asynchronous switching is caused by the switch within two consecutive triggering instants. Most of the existing results evade this problem or make strict assumptions about the maximum asynchronous duration, resulting in a lot of restrictions on the applicability of the results in practice, e.g., [39]–[41]. Recently, some excellent reports [42], [43] have been published to solve asynchronous switching to ensure system performance. Unfortunately, the above schemes do not consider stochastic disturbances. In other words, these event-triggered controllers do not be directly applied to switched stochastic nonlinear systems.

In conclusion, we find that the event-triggered fuzzy control methods for switched stochastic nonlinear systems are numbered. Also, the existing methods do not ensure the transient performance of the controlled plant under asynchronous switching. In this paper, a fuzzy set-time PPC scheme is proposed for switched stochastic nonlinear systems. The innovations of this article can be embodied in the following points.

1) By introducing the set-time performance function into the controller design, the proposed adaptive fuzzy set-time PPC scheme not only ensures that the tracking error gets into the predefined constraint region no later than a settable time T, but also eliminates the "initial condition" of the constrained variable e_1 in the traditional PPC scheme.

2) A novel mode-dependent event-triggered mechanism (MDETM) is designed for switched nonlinear systems with random noises considering the impact of asynchronous switching on system performance. The proposed control scheme achieves the expected control effect while mitigating the communication burden.

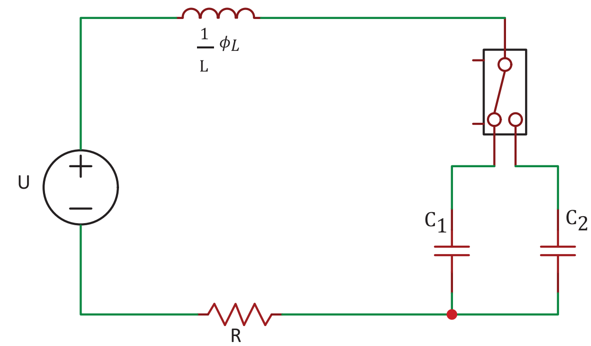

Fig. 1. Schematic diagram of RLC circuit.

3) By using the lower bound of the control gain functions of each subsystem, the individual Lyapunov function is constructed, and a novel event-triggered fuzzy performance controller is designed so that all the variables in the system are bounded.

II. Preliminaries and Problem Formulations

A. Basic Knowledge

Definition 1 [13]: Consider the stochastic system $dx = f(x(t))dt + g(x(t))dw$. Define the differential operator ℓ for C^2 function $V(x)$ as:

$$\ell V = \frac{\partial V}{\partial t} + \frac{\partial V}{\partial x} f + \frac{1}{2} Tr\{g^T \frac{\partial^2 V}{\partial x^2} g\} \tag{1}$$

where $Tr(A)$ is the trace of A.

Lemma 1 [10]: Let $f(Z)$ be a continuous function defined on a compact set $\bar{\Omega}$. Then for any $\tau > 0$, there exists a fuzzy systems $\psi^T S(Z)$ such that

$$\sup_{Z\in\bar{\Omega}} |f(Z) - \psi^T S(Z)| \le \tau.$$

Lemma 2 [8]: For $\forall\ \omega_1 > 0$ and $\omega_2 \in R$, the following result hold

$$0 \le |\omega_2| - \omega_2 \tanh(\frac{\omega_2}{\omega_1}) \le 0.2785\omega_1. \tag{2}$$

B. Problem Statement

Consider switched Itô stochastic nonlinear systems

$$\begin{cases} dx_i = (l_{i,\sigma(t)}(\bar{x}_i)x_{i+1} + f_{i,\sigma(t)}(\bar{x}_i))dt \\ \quad +g^T_{i,\sigma(t)}(\bar{x}_i)dw,\ i = 1, 2, \cdots, n-1, \\ dx_n = (l_{n,\sigma(t)}(\bar{x}_n)u + f_{n,\sigma(t)}(\bar{x}_n))dt \\ \quad +g^T_{n,\sigma(t)}(\bar{x}_n)dw, \\ y = x_1 \end{cases} \tag{3}$$

where $\bar{x}_i = [x_1, \cdots, x_i]^T \in R^i$, $i = 1, 2, \cdots n$, $y \in R$ are the system states, output, respectively. $\sigma(t) : [0, \infty) \to M = \{1, 2, \cdots, d\}$ is a switching signal. $l_{i,p}(\bar{x}_i)$ is known control gain funcation. $f_{i,p}(\bar{x}_i)$ and $g_{i,p}(\bar{x}_i)(1 \le i \le n$, $p \in M)$ are unknown smooth nonlinear functions satisfying local Lipschitz. $w \in R^r$ denotes standard Brownian motion.

Remark 1: The above-mentioned switched stochastic nonlinear system can be applied to the RLC circuit with stochastic perturbations in the capacitor and the inductor. For example, a RLC circuit is shown in Fig. 1, where L is the inductor, R the resistor, C_1, C_2 the two mutual switching capacitor.

Define the tracking error as $e_1 = y - y_d$ with y_d being the reference signal. In this paper, the tracking error need to satisfy

$$-\xi_1(t) < e_1 < \xi_1(t),\ t \geq T > 0 \tag{4}$$

where T is a time parameter, $\xi_1(t)$ is called the set-time performance function and is defined as

$$\xi_1(t) = (\xi_0 - \xi_\infty)e^{-\kappa_1(t-T)} + \xi_\infty \tag{5}$$

where $\xi_0 > \xi_\infty > 0$, $\kappa_1 \geq 0$ are the design parameters.

Remark 2: Whether it is the traditional PPC schemes proposed in [29]–[31] or the finite-time PPC schemes proposed in [32], [33], the performance function requires "initial condition", that is, $\xi_1(0)$ satisfies $-\xi_1(0) < e_1(0) < \xi_1(0)$. Obviously, $\xi_1(0)$ introduced in this paper is independent of the initial conditions of the system output and the desired signal.

Our control objectives are as follows:

1) All signals of the controlled systems are SGUUB in probability under MDADT method;

2) The tracking error e_1 gets into a prescribed boundary no later than a settable time T;

3) The designed MDETM is Zeno-free.

To this end, the following mapping is proposed:

$$\chi_1 = \tanh(e_1) \tag{6}$$

meanwhile, the following indirect performance function $\xi_2(t)$ is adopted

$$-\xi_2(t) < \chi_1 < \xi_2(t), \quad t \geq 0 \tag{7}$$

where

$$\xi_2(t) = Ne^{-\kappa_2 t}\frac{(s(t) - s_1)}{s_0} + \tanh(\xi_1),$$

$$s(t) = \begin{cases} (s_0 - \frac{t}{T})e^{1-\frac{t}{T-t}} + s_1, & 0 \leq t < T, \\ s_1, & t \geq T \end{cases}$$

and $N \geq 1$, $\kappa_2 \geq 0$, $s_0 \geq 0$ $s_1 \geq 0$ are the design parameters.

Remark 3: According to the expression of ξ_2, it can be seen from $N \geq 1$, when $t = 0$, we have $\xi_2(0) \geq 1$. Then from $-1 < \chi_1(0) < 1$, it follows that $-\xi_2(0) \leq \chi_1(0) \leq \xi_2(0)$. And the proposed method removes the "initial condition" imposed on the tracking error e_1.

Specially, the following assumptions are imposed.

Assumption 1: (Slow Switching)

(1) There exists a number $\tau_d^* > 0$ (called a dwell time) such that any two switches are separated by at least $\tau_d^* > 0$;

(2) There exist numbers $\tau_{ap} > \tau_d^*$ (called a mode-dependent average dwell time) and $N_{0p} \geq 1$ such that

$$N_{\sigma p}(T, t) \leq N_{0p} + \frac{T_p(T, t)}{\tau_{ap}}, \quad \forall T \geq t \geq 0 \tag{8}$$

where $N_{\sigma p}(T, t)$ is the numbers of times the pth subsystem is activated on $[t, T]$, $T_p(T, t)$ is the total running time of the pth subsystem on $[t, T]$.

Assumption 2: There are two constants $b_{i,m}^p, b_{i,M}^p$ such that $0 < b_{i,m}^p \leq |l_{i,p}(\bar{x}_i)| \leq b_{i,M}^p$. Without losing generality, we assumes that $\text{sign}(l_{i,p}(\bar{x}_i)) > 0$.

Assumption 3: The reference signal $y_d(t)$ and its derivatives $y_d^{(i)}(t)$, $i = 1, 2, \cdots, n$ are known and bounded.

III. Adaptive Fuzzy Control Design Scheme

The development of backstepping design starts by defining the following coordinate transformations

$$\begin{cases} z_1 = \tan(\frac{\pi\chi_1}{2\xi_2}), \\ z_i = x_i - \alpha_{i-1}, \quad i = 2, 3, \cdots, n \end{cases} \tag{9}$$

where α_{i-1} denotes the virtual control signal. To simplify the backstepping process, the virtual signal α_i and the adaptive law $\hat{W}_i$ are chosen as

$$\alpha_1 = -\frac{\rho_2}{\rho_1}(c_1 z_1 + \frac{z_1^3\hat{W}_1}{\pi a_1^2}S_1^T(Z_1)S_1(Z_1)), \tag{10}$$

$$\alpha_i = -c_i z_i - \frac{z_i^3\hat{W}_i}{2a_i^2}S_i^T(Z_i)S_i(Z_i), \quad i = 2, 3, \cdots, n, \tag{11}$$

$$\dot{\hat{W}}_i = \frac{l_i z_i^6}{2a_i^2}S_i^T(Z_i)S_i(Z_i) - l_i\hat{W}_i, \quad i = 1, 2, \cdots, n \tag{12}$$

where $\rho_1 = 1 - \tanh^2(e_1)$, $\rho_2 = \xi_2\cos^2(\frac{\pi\chi_1}{2\xi_2})$, a_i, c_i, l_i represent positive design parameters. $Z_1 = [x_1, \xi_2, \dot{\xi}_2, y_d, \dot{y}_d]^T$, $Z_i = [\bar{x}_i, \hat{W}_1, \hat{W}_2, \cdots, \hat{W}_{i-1}, \xi_2, \dot{\xi}_2, \cdots, \xi_2^{(i)}, y_d, y_d^{(i)}]^T (i \geq 2)$. Define $W_i = \max_{p\in M}\{\frac{\|\psi_{i,p}\|^2}{b_{i,\min}}\}$ with $b_{i,\min} = \min_{p\in M}\{b_{i,m}^p\}$, $\tilde{W}_i = W_i - \hat{W}_i$, $\hat{W}_i$ is the estimation of W_i.

Step 1: From (3) and (9), it follows that

$$dz_1 = \frac{\pi}{2\rho_2}(\rho_1 l_{1,p}(\bar{x}_1)(z_2 + \alpha_1) + \rho_1(f_{1,p}(\bar{x}_1) - \dot{y}_d) - \frac{\chi_1\dot{\xi}_2}{\xi_2})dt + \frac{\pi\rho_1}{2\rho_2}g_{1,p}(\bar{x}_1)dw. \tag{13}$$

The Lyapunov function candidate for the pth switching subsystem is defined as

$$V_{1,p} = \frac{1}{4}z_1^4 + \frac{b_{1,m}^p}{2l_1}\tilde{W}_1^2. \tag{14}$$

Thus, $\ell V_{1,p}$ is given as

$$\ell V_{1,p} = \frac{\pi z_1^3}{2\rho_2}(\rho_1 l_{1,p}(\bar{x}_1)(z_2 + \alpha_1) + \rho_1(f_{1,p}(\bar{x}_1) - \dot{y}_d) - \frac{\chi_1\dot{\xi}_2}{\xi_2}) - \frac{b_{1,m}^p}{l_1}\tilde{W}_1\dot{\hat{W}}_1 + \frac{3\pi^2\rho_1^2}{8\rho_2^2}z_1^2 g_{1,p}^T(\bar{x}_1)g_{1,p}(\bar{x}_1). \tag{15}$$

By using Young's inequality, one has

$$\frac{\pi\rho_1}{2\rho_2}z_1^3 l_{1,p}(\bar{x}_1)z_2 \leq \frac{3}{4}(\frac{\pi}{2})^{4/3}l_{1,p}(\bar{x}_1)z_1^4\rho_1^{4/3}\rho_2^{3/4} + \frac{1}{4}l_{1,p}(\bar{x}_1)z_2^4, \tag{16}$$

$$\frac{3\pi^2\rho_1^2}{8\rho_2^2} z_1^2 g_{1,p}^T(\bar{x}_1) g_{1,p}(\bar{x}_1) \leq \frac{3\pi^4\rho_1^4}{16\rho_2^4} a_1^{-2} z_1^4 \|g_{1,p}(\bar{x}_1)\|^4 + \frac{3}{16}a_1^2. \tag{17}$$

Therefore, (15) can be rewritten as

$$\ell V_{1,p} \leq \frac{\pi\rho_1}{2\rho_2} z_1^3 l_{1,p}(\bar{x}_1)\alpha_1 + \frac{1}{4} l_{1,p} z_2^4 + z_1^3 \bar{f}_{1,p}(Z_1) - \frac{3}{4}z_1^4 - \frac{b_{1,m}^p}{l_1}\tilde{W}_1\dot{\hat{W}}_1 + \frac{3}{16}a_1^2 \tag{18}$$

where $\bar{f}_{1,p}(Z_1) = \rho_1 f_{1,p}(\bar{x}_1) + \frac{3\pi^4\rho_1^4}{16\rho_2^4} a_1^{-2} z_1^4 \|g_{1,p}(\bar{x}_1)\|^4 - \rho_1\dot{y}_d + \frac{3}{4}z_1 + \frac{3}{4}l_{1,p}(\bar{x}_1) z_1^4 \rho_1^{4/3}\rho_2^{4/3} - \frac{\chi_1\dot{\xi}_2}{\xi_2}$. By using fuzzy logic system $\psi_{1,p}^T S_1(Z_1)$ approximate $\bar{f}_{1,p}(Z_1)$, we have

$$\bar{f}_{1,p}(Z_1) = \psi_{1,p}^T S_1(Z_1) + \delta_1^p(Z_1) \tag{19}$$

where $|\delta_1^p(Z_1)| \leq \tau_1$ with $\tau_1 > 0$. According to Young's inequality, it can be given

$$z_1^3 \bar{f}_{1,p}(Z_1) \leq \frac{b_{1,m}^p z_1^6 W_1}{2a_1^2} S_1^T(Z_1) S_1(Z_1) + \frac{1}{2}a_1^2 + \frac{3}{4}z_1^4 + \frac{1}{4}\tau_1^4. \tag{20}$$

Substituting (10), (12) and (20) into (18) yields

$$\ell V_{1,p} \leq -\frac{\pi}{2} c_1 b_{1,m}^p z_1^4 + b_{1,m}^p \tilde{W}_1\hat{W}_1 + \frac{1}{4} l_{1,p}(\bar{x}_1) z_2^4 + \tilde{\Upsilon}_1 \tag{21}$$

where $\tilde{\Upsilon}_1 = \frac{11}{16}a_1^2 + \frac{1}{4}\tau_1^4$.

Step i ($2 \leq i \leq n-1$): From (3) and (9), one has

$$dz_i = (l_{i,p}(\bar{x}_1)(z_{i+1}+\alpha_i) + f_{i,p}(\bar{x}_i) - \ell\alpha_{i-1})dt + (g_{i,p}(\bar{x}_i) - \sum_{j=1}^{i-1}\frac{\partial\alpha_{i-1}}{\partial x_j} g_{j,p}(\bar{x}_j))dw \tag{22}$$

where

$$\ell\alpha_{i-1} = \sum_{j=1}^{i-1}\frac{\partial\alpha_{i-1}}{\partial x_j}(l_{j,p}(\bar{x}_j)x_{j+1} + f_{j,p}(\bar{x}_j)) + \sum_{j=0}^{i-1}\frac{\partial\alpha_{i-1}}{\partial y_d^{(j)}} y_d^{(j+1)} + \sum_{j=1}^{i-1}\frac{\partial\alpha_{i-1}}{\partial\hat{W}_j}\dot{\hat{W}}_j + \frac{1}{2}\sum_{j,s=1}^{i-1}\frac{\partial^2\alpha_{i-1}}{\partial x_j\partial x_s} g_{j,p}^T(\bar{x}_j) g_{s,p}(\bar{x}_s).$$

The following Lyapunov function candidate is defined

$$V_{i,p} = V_{i-1,p} + \frac{1}{4}z_i^4 + \frac{b_{i,m}^p}{2l_i}\tilde{W}_i^2 \tag{23}$$

and then, we have

$$\ell V_{i,p} = \ell V_{i-1,p} + z_i^3(l_{i,p}(\bar{x}_i)(z_{i+1}+\alpha_i) + f_{i,p}(\bar{x}_i) - \ell\alpha_{i-1}) - \frac{b_{i,m}^p}{l_i}\tilde{W}_i\dot{\hat{W}}_i + \frac{3}{2}z_i^2\phi_{i,p}^T(\bar{x}_i)\phi_{i,p}(\bar{x}_i) \tag{24}$$

where $\phi_{i,p}(\bar{x}_i) = g_{i,p}(\bar{x}_i) - \sum_{j=1}^{i-1}\frac{\partial\alpha_{i-1}}{\partial x_j} g_{j,p}(\bar{x}_j)$. By utilizing Young's inequality, the following inequality holds

$$z_i^3 l_{i,p}(\bar{x}_i) z_{i+1} \leq \frac{3}{4} l_{i,p}(\bar{x}_i) z_i^4 + \frac{1}{4} l_{i,p}(\bar{x}_i) z_{i+1}^4, \tag{25}$$

$$\frac{3}{2}z_i^2\phi_{i,p}^T\phi_{i,p} \leq \frac{3}{4}a_i^{-2}z_i^4\|\phi_{i,p}\|^4 + \frac{3}{4}a_i^2. \tag{26}$$

Using (25)-(26), (24) can be rewritten as

$$\ell V_{i,p} \leq \ell V_{i-1,p} + z_i^3 l_{i,p}(\bar{x}_i)\alpha_i + \frac{1}{4}l_{i,p}(\bar{x}_i)z_{i+1}^4 + z_i^3\bar{f}_{i,p}(Z_i) - \frac{3}{4}z_i^4 - \frac{b_{i,m}^p}{l_i}\tilde{W}_i\dot{\hat{W}}_i + \frac{3}{4}a_i^2 - \frac{1}{4}l_{i-1,p}(\bar{x}_{i-1})z_i^4 \tag{27}$$

where $\bar{f}_{i,p}(Z_i) = f_{i,p}(\bar{x}_i) + \frac{3}{4}a_i^{-2}z_i\|\phi_{i,p}\|^4 - \ell\alpha_{i-1} + \frac{3}{4}z_i + \frac{3}{4}l_{i,p}(\bar{x}_i)z_i + \frac{1}{4}l_{i-1,p}(\bar{x}_{i-1})z_i$. Same as (19), it can be given

$$\bar{f}_{i,p}(Z_i) = \psi_{i,p}^T S_i(Z_i) + \delta_i^p(Z_i) \tag{28}$$

where $|\delta_i^p(Z_i)| \leq \tau_i$ with $\tau_i > 0$. Furthermore, the following inequality can be obtained

$$z_i^3\bar{f}_{i,p}(Z_i) \leq \frac{b_{i,m}^p z_i^6 W_i}{2a_i^2} S_i^T(Z_n) S_i(Z_n) + \frac{1}{2}a_i^2 + \frac{3}{4}z_i^4 + \frac{1}{4}\tau_i^4. \tag{29}$$

Substituting (11), (12) and (29) into (27) result in

$$\ell V_{i,p} \leq -\frac{\pi}{2}c_1 b_{1,m}^p z_1^4 - \sum_{j=2}^{i}(c_j b_{j,m}^p z_j^4) + \sum_{j=1}^{i} b_{j,m}^p\tilde{W}_j\hat{W}_j + \frac{1}{4}l_{i,p}(\bar{x}_i)z_{i+1}^4 + \sum_{j=1}^{i}\tilde{\Upsilon}_j \tag{30}$$

where $\tilde{\Upsilon}_j = \sum_{j=1}^{i}(\frac{5}{4}a_j^2 + \frac{1}{4}\tau_j^4)$.

Step n: First, let $\top_0^k = t_k$, $\top_{r+1}^k = t_{k+1}$, $\top_1^k, \top_2^k, \cdots, \top_r^k$ are the switching times on $[t_k, t_{k+1})$. The MDETM is designed as follows

$$\begin{aligned} u^p(t) = &-(1+\lambda)(\alpha_n\tanh(\frac{z_n^3 l_n^p(\bar{x}_n)\alpha_n}{\rho^p}) + \hbar_1\tanh(\frac{z_n^3 l_n^p(\bar{x}_n)\hbar_1}{\rho^p})) \\ &- (\frac{1+\lambda}{1-\lambda})T_w\tanh(\frac{z_n^3 l_n^p(\bar{x}_n)T_w}{\rho^p}), \end{aligned} \tag{31}$$

$$u(t) = u^{\sigma(t_k)}(t_k), \quad t_k \leq t < t_{k+1}, \tag{32}$$

$$t_{k+1} = \inf\{t \in R \,||\beta^{\sigma(t)}(t)| \geq \lambda|u^{\sigma(t_k)}(t_k)| + \epsilon + T_w\}, \tag{33}$$

$$T_w = \begin{cases} |u^{\sigma(t_k)}(\top_1^k) - u^{\sigma(\top_1^k)}(\top_1^k)|, & t \in [\top_1^k, \top_2^k), \\ 0, & \text{otherwise} \end{cases} \tag{34}$$

where $\beta^{\sigma(t)}(t) = u^{\sigma(t_k)}(t_k) - u^{\sigma(t)}(t)$, $\hbar_1 > \frac{\epsilon}{1-\lambda}$. $\epsilon > 0$, $\rho^p > 0$ and $0 < \lambda < 0.5$ are design parameters.

Remark 4: For the studied switched stochastic nonlinear systems, the MDETM that relies on switching signals is cleverly designed, which not only mitigates the communication burden, but also eliminates the impact of asynchronous switching on the system performance.

Remark 5: It can be seen that the triggering error of the designed MDETM is discontinuous at the switching moment, and switching may cause additional continuous triggers, which may lead to Zeno behavior. The introduction of variable T_w effectively avoids the above problems.

From (3) and (9), one has

$$dz_n = (l_{n,p}(\bar{x}_1)u + f_{i,p}(\bar{x}_n) - \ell\alpha_{n-1})dt + (l_{n,p}(\bar{x}_n) - \sum_{j=1}^{n-1}\frac{\partial\alpha_{n-1}}{\partial x_j}l_{j,p}(\bar{x}_j))dw \quad (35)$$

where

$$\begin{aligned}\ell\alpha_{n-1} &= \sum_{j=1}^{n-1}\frac{\partial\alpha_{i-1}}{\partial x_j}(l_{j,p}(\bar{x}_j)x_{j+1} + f_{j,p}(\bar{x}_j)) \\ &\quad + \sum_{j=0}^{n-1}\frac{\partial\alpha_{i-1}}{\partial y_d^{(j)}}y_d^{(j+1)} + \sum_{j=1}^{n-1}\frac{\partial\alpha_{i-1}}{\partial\hat{W}_j}\dot{\hat{W}}_j \\ &\quad + \frac{1}{2}\sum_{j,s=1}^{n-1}\frac{\partial^2\alpha_{i-1}}{\partial x_j\partial x_s}g_{j,p}^T(\bar{x}_j)g_{s,p}(\bar{x}_s).\end{aligned}$$

Define the Lyapunov function candidate

$$V_{n,p} = V_{n-1,p} + \frac{1}{4}z_n^4 + \frac{b_{n,m}^p}{2l_n}\tilde{W}_n^2. \quad (36)$$

From (35) and (36), we have

$$\begin{aligned}\ell V_{n,p} &= \ell V_{n-1,p} + z_n^3(l_{n,p}u + f_{n,p}(\bar{x}_n) - \ell\alpha_{n-1}) \\ &\quad - \frac{b_{n,m}^p}{l_n}\tilde{W}_n\dot{\hat{W}}_n + \frac{3}{2}z_n^2\phi_{n,p}^T(\bar{x}_n)\phi_{n,p}(\bar{x}_n) \quad (37)\end{aligned}$$

where $\phi_{n,p}(\bar{x}_n) = g_{n,p}(\bar{x}_n) - \sum_{j=1}^{n-1}\frac{\partial\alpha_{n-1}}{\partial x_j}g_{j,p}(\bar{x}_j)$. By utilizing Young's inequality, the following inequality holds

$$\frac{3}{2}z_n^2\phi_{n,p}^T\phi_{n,p} \le \frac{3}{4}a_n^{-2}z_n^4\|\phi_{n,p}\|^4 + \frac{3}{4}a_n^2. \quad (38)$$

By substituting (38) into (37), it gets

$$\begin{aligned}\ell V_{n,p} &\le \ell V_{n-1,p} + z_n^3 l_{n,p}(\bar{x}_n)u + z_n^3\bar{f}_{n,p}(Z_n) - \frac{3}{4}z_n^4 \\ &\quad - \frac{b_{n,m}^p}{l_n}\tilde{W}_n\dot{\hat{W}}_n + \frac{3}{4}a_n^2 - \frac{1}{4}l_{n-1,p}(\bar{x}_{n-1})z_n^4 \quad (39)\end{aligned}$$

where $\bar{f}_{n,p}(Z_n) = f_{n,p}(\bar{x}_n) + \frac{3}{4}a_n^{-2}z_n\|\phi_{n,p}\|^4 - \ell\alpha_{n-1} + \frac{3}{4}z_n + \frac{1}{4}l_{n-1,p}(\bar{x}_{n-1})z_n$. Same as (19), one has

$$\bar{f}_{n,p}(Z_i) = \psi_{n,p}^T S_n(Z_n) + \delta_n^p(Z_n) \quad (40)$$

where $|\delta_n^p(Z_n)| \le \tau_n$ with $\tau_n > 0$.

By applying Young's inequality, we have

$$z_n^3\bar{f}_{n,p}(Z_n) \le \frac{b_{n,m}^p z_n^6 W_n}{2a_n^2}S_n^T(Z_n)S_n(Z_n) + \frac{1}{2}a_n^2 + \frac{3}{4}z_n^4 + \frac{1}{4}\tau_n^4. \quad (41)$$

By using (41), (39) can be converted into

$$\begin{aligned}\ell V_{n,p} &\le \ell V_{n-1,p} + \frac{b_{n,m}^p z_n^6 W_n}{2a_n^2}S_n^T(Z_n)S_n(Z_n) \\ &\quad + z_n^3 l_{n,p}(\bar{x}_n)u - \frac{b_{n,m}^p}{l_n}\tilde{W}_n\dot{\hat{W}}_n + \frac{5}{4}a_n^2 \\ &\quad + \frac{1}{4}\tau_n^4 - \frac{1}{4}l_{n-1,p}(\bar{x}_{n-1})z_n^4. \quad (42)\end{aligned}$$

Next, we will divide the system dynamics into two parts for discussion based on whether the pth subsystem is synchronized with the candidate controller within the triggering interval $[t_k, t_{k+1})$.

Part 1: synchronous interval.

At this time, $\sigma(t) = \sigma(t_k) = p$, $T_w = 0$. From (31)-(33), we have $u^p(t) = (1 + \vartheta_1(t)\lambda)u^p(t_k) + \vartheta_2(t)\epsilon,\ \forall t \in [t_k, t_{k+1})$, where $\vartheta_1(t) \in [-1, 1], \vartheta_2(t) \in [-1, 1]$. Then, the actual controller can be expressed as

$$u = u^p(t_k) = \frac{u^p(t)}{1 + \vartheta_1\lambda} - \frac{\vartheta_2\epsilon}{1 + \vartheta_1\lambda}. \quad (43)$$

Therefore, (42) can be repeated as

$$\begin{aligned}\ell V_{n,p} &\le \ell V_{n-1,p} + \frac{b_{n,m}^p z_n^6 W_n}{2a_n^2}S_n^T(Z_n)S_n(Z_n) + \frac{5}{4}a_n^2 \\ &\quad + \frac{1}{1 + \vartheta_1\lambda}z_n^3 l_{n,p}(\bar{x}_n)u^p(t) - \frac{\vartheta_2\epsilon}{1 + \vartheta_1\lambda}z_n^3 l_{n,p}(\bar{x}_n) \\ &\quad - \frac{b_{n,m}^p}{l_n}\tilde{W}_n\dot{\hat{W}}_n + \frac{1}{4}\tau_n^4 - \frac{1}{4}l_{n-1,p}(\bar{x}_{n-1})z_n^4. \quad (44)\end{aligned}$$

Based on $\frac{z_n^3 l_n^p(\bar{x}_n)u^p(t)}{1+\vartheta_1\lambda} \le \frac{z_n^3 l_n^p(\bar{x}_n)u^p(t)}{1+\lambda}$, $l_n^p(\bar{x}_n)|\frac{\vartheta_2\epsilon}{1+\vartheta_1\lambda}| \le l_n^p(\bar{x}_n)\frac{\epsilon}{1-\lambda}$, $\hbar_1 > \frac{\epsilon}{1-\lambda}$, it follows that

$$\begin{aligned}\ell V_{n,p} &\le \ell V_{n-1,p} + \frac{b_{n,m}^p z_n^6 W_n}{2a_n^2}S_n^T(Z_n)S_n(Z_n) - \frac{b_{n,m}^p}{l_n}\tilde{W}_n\dot{\hat{W}}_n \\ &\quad - \frac{1 + \lambda}{1 + \vartheta_1\lambda}z_n^3 l_{n,p}(\bar{x}_n)(\alpha_n \tanh(\frac{z_n^3 l_n^p(\bar{x}_n)\alpha_n}{\rho^p}) \\ &\quad + \hbar_1 \tanh(\frac{z_n^3 l_n^p(\bar{x}_n)\hbar_1}{\rho^p})) - \frac{\vartheta_2\epsilon}{1 + \vartheta_1\lambda}z_n^3 l_{n,p}(\bar{x}_n) \\ &\quad + \frac{5}{4}a_n^2 + \frac{1}{4}\tau_n^4 - \frac{1}{4}l_{n-1,p}(\bar{x}_{n-1})z_n^4 \\ &\le \ell V_{n-1,p} + \frac{b_{n,m}^p z_n^6 W_n}{2a_n^2}S_n^T(Z_n)S_n(Z_n) - \frac{b_{n,m}^p}{l_n}\tilde{W}_n\dot{\hat{W}}_n \\ &\quad + \frac{5}{4}a_n^2 + \frac{1}{4}\tau_n^4 - \frac{1}{4}l_{n-1,p}(\bar{x}_{n-1})z_n^4 + 0.557\rho^p \\ &\quad + z_n^3 l_{n,p}(\bar{x}_n)\alpha_n. \quad (45)\end{aligned}$$

Using a process similar to Step i, it gets

$$\begin{aligned}\ell V_{n,p} &\le -\frac{\pi}{2}c_1 b_{1,m}^p z_1^4 - \sum_{j=2}^{n}(c_j b_{j,m}^p z_j^4) + \sum_{j=1}^{n}b_{j,m}^p\tilde{W}_j\hat{W}_j \\ &\quad + \sum_{j=1}^{n-1}\tilde{\Upsilon}_j + \frac{5}{4}a_n^2 + \frac{1}{4}\tau_n^4 + 0.557\rho^p. \quad (46)\end{aligned}$$

By means of Young's inequality, we get

$$\sum_{j=1}^{n}b_{j,m}^p\tilde{W}_j\hat{W}_j \le -\frac{1}{2}\sum_{j=1}^{n}b_{j,m}^p\tilde{W}_j^2 + \frac{1}{2}\sum_{j=1}^{n}b_{j,\max}W_j^2 \quad (47)$$

where $b_{j,\max} = \max_{p\in\mathcal{H}}\{b_{j,M}^p\}$. Then, (46) becomes

$$\ell V_{n,p} \le -\frac{\pi}{2}c_1 b_{1,m}^p z_1^4 - \sum_{j=2}^{n}(c_j b_{j,m}^p z_j^4) - \frac{1}{2}\sum_{j=1}^{n}b_{j,m}^p\tilde{W}_j^2 + \Delta_p \quad (48)$$

where $\Delta_p = \sum_{j=1}^{n-1}\tilde{\Upsilon}_j + \frac{1}{2}\sum_{j=1}^{n}b_{j,\max}W_j^2 + \frac{5}{4}a_n^2 + \frac{1}{4}\tau_n^4 + 0.557\rho^p$.

Part 2: asynchronous interval.

① If $\sigma(t_k) \neq p$, $\sigma(t) = p$ with $t \in [\top_1^k, \top_2^k)$. At this moment, the MDETM (33) can ensure that

$$|u^{\sigma(t_k)}(t_k) - u^p(t)| \leq \lambda |u^{\sigma(t_k)}(t_k)| + T_w + \epsilon. \tag{49}$$

Similar to the derivation in Part 1, we have

$$z_n^3 l_n^p(\bar{x}_n)u(t) = z_n^3 l_n^p(\bar{x}_n)u^{\sigma(t_k)}(t_k) \leq \frac{z_n^3 l_n^p(\bar{x}_n)u^p(t)}{1+\lambda} + |z_n^3 l_n^p(\bar{x}_n)\frac{\epsilon + T_w}{1-\lambda}|. \tag{50}$$

Take the same steps as Part 1 to get

$$\begin{aligned}\ell V_{n,p} \leq& -\frac{\pi}{2}c_1 b_{1,m}^p z_1^4 - \sum_{j=2}^n (c_j b_{j,m}^p z_j^4) - \frac{1}{2}\sum_{j=1}^n b_{j,m}^p \tilde{W}_j^2 + \Delta_p \\ &+ |\frac{z_n^3 l_n^p(\bar{x}_n)T_w}{1-\lambda}| - \frac{z_n^3 l_n^p(\bar{x}_n)T_w}{1-\lambda}\tanh(\frac{z_n^3 l_n^p(\bar{x}_n)T_w}{\rho^p}) \\ \leq& -\frac{\pi}{2}c_1 b_{1,m}^p z_1^4 - \sum_{j=2}^n (c_j b_{j,m}^p z_j^4) - \frac{1}{2}\sum_{j=1}^n b_{j,m}^p \tilde{W}_j^2 \\ &+ \Delta_p + 0.557\rho^p. \end{aligned}\tag{51}$$

② This interval is nonempty only if $r > 1$. At this time, $\sigma(t_k) \neq p$, $\sigma(t) = p$ with $t \in [\top_i^k, \top_{i+1}^k)$, $i = 2, \cdots, r$. The MDETM (33) is the same as Part 1 to ensure

$$|u^{\sigma(t_k)}(t_k) - u^p(t)| \leq \lambda |u^{\sigma(t_k)}(t_k)| + \epsilon. \tag{52}$$

Then, using the similar derivation given in Part 1, we get

$$z_n^3 l_n^p(\bar{x}_n)u(t) = z_n^3 l_n^p(\bar{x}_n)u^{\sigma(t_k)}(t_k) \leq \frac{z_n^3 l_n^p(\bar{x}_n)u^p(t)}{1+\lambda} + z_n^3 l_n^p(\bar{x}_n)\frac{\epsilon}{1-\lambda}. \tag{53}$$

It can be obtained by using the same procedure as in Part 1

$$\ell V_{n,p} \leq -\frac{\pi}{2}c_1 b_{1,m}^p z_1^4 - \sum_{j=2}^n (c_j b_{j,m}^p z_j^4) - \frac{1}{2}\sum_{j=1}^n b_{j,m}^p \tilde{W}_j^2 + \Delta_p. \tag{54}$$

The synchronous/asynchronous discussion between the subsystem and the candidate controller is completed. Next, by selecting the Lyapunov function candidate $V_p = V_{n,p}$, we have

$$\ell V_p \leq -\eta_p V_p + \Lambda \tag{55}$$

where $\eta_p = \min\{2\pi c_1 b_{1,m}^p, 4c_i b_{i,m}^p, l_1, l_i, i = 2, 3, \cdots, n\}$, $\Lambda = \max\{\Delta_p + 0.557\rho^p, p \in M\}$.

Theorem 1: For the switched stochastic nonlinear systems (3) under Assumptions 1-3. The actual controller (32), the adaptive law (12) and the MDETM (31)-(34) are constructed for $\sigma(t)$ with MDADT $\tau_{ap} \geq \tau_{ap}^* = \frac{ln\mu_p}{\eta_p}$, $\mu_p = \max\{\frac{b_{i,m}^p}{b_{i,m}^k}, 1, i = 1, 2, \cdots, n, \forall k \in M\}$, it can ensure the following:

1) All the resulting system signals are SGUUB in probability.

2) The tracking error e_1 gets into a prescribed boundary no later than a setting time.

3) The designed MDETM is Zeno-free.

Proof. First of all, we prove that all signals of the control system are bounded, and the discussion is divided into two cases.

Case 1: When $\mu_p = 1 (p \in M)$, we get $V_p = V_q, \forall p, q \in M$. Therefore, the common Lyapunov function $V = V_p$ for all subsystems satisfies (55), which means

$$E\{V(t)\} \leq V(0) + \frac{\Lambda}{\eta_{\min}} \quad \forall t \geq 0 \tag{56}$$

where $\eta_{\min} = \min\{\eta_p, p \in M\}$. Therefore, it can be concluded that all the signals in the control system are SGUUB.

Case 2: When $\exists \mu_{p,q} > 1 (p, q \in M)$. There are functions $\underline{\gamma}, \overline{\gamma} \in K_\infty$, such that $\underline{\gamma}(\|Y\|) \leq V_p(Y) \leq \overline{\gamma}(\|Y\|)$, for an arbitrary $T > 0$, let $t_0 = 0$ and $t_1, t_2, \cdots, t_s, t_{s+1}, \cdots, t_{N_\sigma(0,T)}$ are the switching times on $[0, T]$, in which $N_\sigma(T, 0) = \sum_{p=1}^d N_{\sigma p}(T, 0)$, $p \in M$.

Consider the piecewise continuous function $H(t) = e^{\lambda_{\sigma(t)}t}V_{\sigma(t)}(Y(t))$. From (55), on each interval $[t_j, t_{j+1})$, one has

$$\dot{H}(t) \leq \lambda_{\sigma(t)}e^{\lambda_{\sigma(t)}t}V_{\sigma(t)}(Y(t)) + e^{\lambda_{\sigma(t)}t}\dot{V}_{\sigma(t)}(Y(t)). \tag{57}$$

Invoking the fact $E[dw(t)] = 0$, we have

$$\begin{aligned} E\left\{\int_{t_j}^{t_{j+1}} \dot{H}(t)\mathrm{d}t\right\} &= E\{H(t_{j+1}^-)\} - E\{H(t_j)\} \\ &\leq E\left\{\int_{t_j}^{t_{j+1}} e^{\lambda_{\sigma(t)}t}\Lambda \mathrm{d}t\right\}. \end{aligned}\tag{58}$$

It is shown from $V_p(Y(t)) \leq \mu_p V_q(Y(t))$, one has

$$\begin{aligned} E\{H(t_{j+1})\} \leq& \mu_{\sigma(t_{j+1})}E\left\{e^{(\eta_{\sigma(t_{j+1})} - \eta_{\sigma(t_j)})t_{j+1}}H(t_{j+1}^-)\right\} \\ \leq& \prod_{i=0}^j \mu_{\sigma(t_{i+1})}E\left\{e^{\sum_{i=0}^j(\eta_{\sigma(t_{i+1})} - \eta_{\sigma(t_i)})t_{i+1}}H(t_0)\right\} \\ &+ E\left\{\sum_{l=0}^j\left(Q_{1,l}\int_{t_l}^{t_{l+1}} e^{\eta_{\sigma(t_l)}t}\Lambda \mathrm{d}t\right)\right\} \end{aligned}\tag{59}$$

where $Q_{1,l} = \prod_{i=l}^j \mu_{\sigma(t_{i+1})}\exp\left\{\sum_{i=l}^j(\eta_{\sigma(t_{i+1})} - \eta_{\sigma(t_i)})t_{i+1}\right\}$. Hence

$$\begin{aligned} E\{H(T^-)\} \leq& E\{Q_2 H(0)\} + E\left\{\int_{t_{N_\sigma(T,0)}}^T \Lambda e^{\eta_{\sigma(t_{N_\sigma(T,0)})}t}\mathrm{d}t\right\} \\ &+ E\left\{\sum_{l=0}^{N_\sigma(T,0)-1}\left(Q_{2,l}\int_{t_l}^{t_{l+1}} e^{\eta_{\sigma(t_l)}t}\Lambda \mathrm{d}t\right)\right\} \end{aligned}\tag{60}$$

where

$$Q_2 = \prod_{i=0}^{N_\sigma(T,0)-1}\mu_{\sigma(t_{i+1})}\exp\left\{\sum_{i=0}^{N_\sigma(T,0)-1}(\eta_{\sigma(t_{i+1})} - \eta_{\sigma(t_i)})t_{i+1}\right\},$$

$$Q_{2,l}=\prod_{i=l}^{N_\sigma(T,0)-1}\mu_{\sigma(t_{i+1})}\exp\left\{\sum_{i=l}^{N_\sigma(T,0)-1}(\eta_{\sigma(t_{i+1})}-\eta_{\sigma(t_i)})t_{i+1}\right\}.$$

Then get from (60) that

$$\begin{aligned}
&E\{V_{\sigma(T^-)}(Y(T))\}\\
&\quad\le E\left\{Q_3V_{\sigma(0)}(Y(0))\right\}\\
&\qquad+E\left\{\sum_{s=0}^{N_\sigma(T,0)-1}\left(Q_{3,l}\int_{t_l}^{t_{l+1}}e^{\eta_{\sigma(t_l)}t}\Lambda\mathrm{d}t\right)\right\}\\
&\qquad+E\left\{e^{-\eta_{\sigma(t_{N_\sigma(T,0)})}T}\int_{t_{N_\sigma(T,0)}}^{T}\Lambda e^{\eta_{\sigma(t_{N_\sigma(T,0)})}t}\mathrm{d}t\right\}\\
&\quad\le E\{\bar{Q}_3V_{\sigma(0)}(Y(0))\}\\
&\qquad+E\left\{\sum_{l=0}^{N_\sigma(T,0)-1}\left(\bar{Q}_{3,l}e^{-\varepsilon_{\min}t_{l+1}}\int_{t_l}^{t_{l+1}}e^{\varepsilon_{\min}t}\Lambda\mathrm{d}t\right)\right\}\\
&\qquad+E\left\{e^{-\varepsilon_{\min}T}\int_{t_{N_\sigma(T,0)}}^{T}\Lambda e^{\varepsilon_{\min}t}\mathrm{d}t\right\}\\
&\quad\le E\left\{\tilde{Q}_3V_{\sigma(0)}(Y(0))\right\}\\
&\qquad+E\left\{\sum_{l=0}^{N_\sigma(T,0)-1}\left(\tilde{Q}_{3,l}e^{-\varepsilon_{\min}t_{l+1}}\int_{t_l}^{t_{l+1}}e^{\varepsilon_{\min}t}\Lambda\mathrm{d}t\right)\right\}\\
&\qquad+E\left\{e^{-\varepsilon_{\min}T}\int_{t_{N_\sigma(T,0)}}^{T}\Lambda e^{\varepsilon_{\min}t}\mathrm{d}t\right\}
\end{aligned}\tag{61}$$

where

$$\begin{aligned}
Q_3=&\prod_{j=0}^{N_\sigma(T,0)-1}\mu_{\sigma(t_{j+1})}\exp\left\{\sum_{j=0}^{N_\sigma(T,0)-1}(\eta_{\sigma(t_{j+1})}\right.\\
&\left.-\eta_{\sigma(t_j)})t_{j+1}-\eta_{\sigma(t_{N_\sigma(T,0)})}T+\eta_{\sigma(t_0)}t_0\right\},\\
Q_{3,l}=&\prod_{i=l}^{N_\sigma(T,0)-1}\mu_{\sigma(t_{i+1})}\exp\left\{\sum_{i=l}^{N_\sigma(T,0)-1}(\eta_{\sigma(t_{i+1})}\right.\\
&\left.-\eta_{\sigma(t_i)})t_{i+1}-\eta_{\sigma(t_{N_\sigma(T,0)})}T\right\},\\
\bar{Q}_3=&\prod_{p=1}^{d}\mu_p^{N_{\sigma p}}\exp\left\{-\sum_{p=1}^{H}[\eta_p\sum_{l\in\phi}(t_{l+1}-t_l)]\right.\\
&\left.-\eta_{\sigma(t_{N_\sigma})}(T-t_{N_\sigma})\right\},\\
\bar{Q}_{3,l}=&\prod_{i=l}^{N_\sigma(T,0)-1}\mu_{\sigma(t_{i+1})}\exp\left\{\sum_{i=l}^{N_\sigma(T,0)-1}(\eta_{\sigma(t_{i+1})}\right.\\
&\left.-\eta_{\sigma(t_i)})t_{i+1}-\eta_{\sigma(t_{N_\sigma})}T+\eta_{\sigma(t_l)}t_{l+1}\right\},\\
\tilde{Q}_3=&\exp\left\{\sum_{p=1}^{d}N_{0p}\ln\mu_p\right\}\exp\left\{\sum_{p=1}^{d}\frac{T_p}{\tau_{ap}}\ln\mu_p-\sum_{p=1}^{d}\eta_pT_p\right\},\\
\tilde{Q}_{3,l}=&\prod_{p=1}^{d}\mu_p^{N_{\sigma p}(T,t_{l+1})}\exp\left\{-\sum_{p=1}^{d}\eta_pT_p(T,t_{l+1})\right\},
\end{aligned}$$

$\phi(p)$ stands for the set of l satisfying $\sigma(t_l)=p, t_l\in\{t_0,t_1,\cdots t_s,t_{s+1},\cdots t_{N_\sigma-1}\}$, and $\varepsilon_{\min}=\min\{\varepsilon_p, p\in M\}$ with $\varepsilon_p\in(0,\eta_p-\ln\mu_p/\tau_{ap})$.

Then, from $\tau_{ap}\ge(\ln\mu_p/\eta_p)$ together with (8) get

$$\begin{aligned}
&E\{V_{\sigma(T^-)}(Y(T))\}\\
&\quad\le E\{Q_4V_{\sigma(0)}(Y(0))\}+E\left\{e^{-\varepsilon_{\min}T}\int_{t_{N_\sigma(T,0)}}^{T}\Lambda e^{\varepsilon_{\min}t}\mathrm{d}t\right\}\\
&\qquad+E\left\{\sum_{l=0}^{N_\sigma(T,0)-1}\left(\prod_{p=1}^{d}\mu_p^{N_{0p}}e^{\sum_{p=1}^{d}(\eta_p-\varepsilon_p)T_p(T,t_{l+1})}\right.\right.\\
&\qquad\quad\left.\left.\cdot e^{-\sum_{p=1}^{d}\eta_pT_p(T,t_{l+1})}e^{-\varepsilon_{\min}t_{l+1}}\int_{t_l}^{t_{l+1}}e^{\varepsilon_{\min}t}\Lambda\mathrm{d}t\right)\right\}\\
&\quad\le E\{Q_4V_{\sigma(0)}(X(0))\}+E\left\{e^{-\varepsilon_{\min}T}\int_{t_{N_\sigma(T,0)}}^{T}\Lambda e^{\varepsilon_{\min}t}\mathrm{d}t\right\}\\
&\qquad+E\left\{\sum_{l=0}^{N_\sigma(T,0)-1}\left(\prod_{p=1}^{d}\mu_p^{N_{0p}}e^{-\varepsilon_{\min}(T-t_{l+1})}\right.\right.\\
&\qquad\quad\left.\left.\cdot e^{-\varepsilon_{\min}t_{l+1}}\int_{t_l}^{t_{l+1}}e^{\varepsilon_{\min}t}\Lambda\mathrm{d}t\right)\right\}\\
&\quad\le E\{Q_4V_{\sigma(0)}(Y(0))\}\\
&\qquad+E\left\{\prod_{p=1}^{d}\mu_p^{N_{0p}}e^{-\varepsilon_{\min}T}\int_0^T\Lambda e^{\varepsilon_{\min}t}\mathrm{d}t\right\}\\
&\quad\le e^{\sum_{p=1}^{d}N_{0p}\ln\mu_p}e^{\max_{p\in M}((\ln\mu_p/\tau_{ap})-\eta_p)T}E\{\overline{\gamma}(\|Y(0)\|)\}\\
&\qquad+\prod_{p=1}^{H}\mu_p^{N_{0p}}\frac{\Lambda}{\varepsilon_{\min}}
\end{aligned}\tag{62}$$

where $Q_4=\exp\{\sum_{p=1}^{H}N_{0p}\ln\mu_p\}\exp\{\sum_{p=1}^{H}(\frac{T_p}{\tau_{ap}}-\eta_p)T_p\}$.

Therefore, all signals in the control system are SGUUB under MDADT method. Furthermore, we need to prove that $-\xi_1(t)<e_1<\xi_1(t), t\ge T>0$. With the help of the boundedness of z_1 and $\tan(\pm\frac{\pi}{2})=\infty$, it follows that

$$-\xi_2(t)<\chi_1<\xi_2(t).\tag{63}$$

From (6) and (7), we have

$$-\xi_2(t)<\tanh(e_1)<\xi_2(t).\tag{64}$$

According to the expression of $\xi_2(t)$, when $T\ge t$, we can obtain

$$0<\xi_2(t)=\tanh(\xi_1(t)).\tag{65}$$

Upon using (64) and (65), it is shown that $-\xi_1(t)<e_1<\xi_1(t), t\ge T$.

Finally, according to the number of switches between two continuous triggering instants, three cases are used to prove that the designed MDETM is Zeno-free.

Case 1 Triggering Interval With No Switch: Let $\sigma(t)=p$ for all $t\in[t_k,t_{k+1})$. Upon utilizing the definition of $\beta^p(t)$, one has

$$\frac{d}{dt}|\beta^p|=sign(\beta^p)\dot{\beta}^p\le|\dot{u}^p(t)|.$$

With the help of (31), it follows that u^p is differentiable and $\dot{u}^p$ is bounded. From $\beta^p(t_k) = 0$ and $\lim_{t \to t_{k+1}} \beta^p(t) = (\lambda|u^p(t_k)| + \epsilon)$ to get $t_{k+1} - t_k \geq (\lambda|u^p(t_k)| + \epsilon)/\varrho_1 > 0$, where ϱ_1 is a positive constant satisfying $|\dot{u}^p| \leq \varrho_1$.

Case 2 (Triggering Interval With One Switch): Assume that the switch occurs at $\top_1^k \in (t_k, t_{k+1})$. Noting that, it can be seen from $|u^{\sigma(t_k)}(t_k) - u^{\top_1^k}(\top_1^k)| < \lambda|u^{\sigma(t_k)}(t_k)| + \epsilon + T_w$ that no additional trigger will be generated at $\top_1^k$. From case 1, $\frac{d}{dt}|\beta^{\sigma(t_k)}| \leq \varrho_1$ can be obtained in $(t_k, \top_1^k)$. As in case 1, it can be guaranteed that $\frac{d}{dt}|\beta^{\sigma(\top_1^k)}| \leq \varrho_2$ in $(\top_1^k, t_{k+1})$, where ϱ_2 is a positive constant. It is shown from the above analysis that $t_{k+1} - t_k \geq (\lambda|u^{\sigma(t_k)}(t_k)| + \epsilon)/\{\max \varrho_1, \varrho_2\} > 0$.

Case 3 (Triggering Interval With Multiple Switches): N_k is the number of switches on the kth triggering interval, and obviously $t_{k+1} - t_k \geq N_k \tau_d^* > 0$.

Based on the above analysis, the designed MDETM is Zeno-free. The proof is completed.

Remark 6: To prove the stability of the switched system based on the multiple Lyapunov function techniques, it is important to construct the relationship between any two Lyapunov functions. In this paper, the cumulative relationship of two Lyapunov functions is found by using uniform coordinate transformation and common adaptive law for all subsystems.

IV. Simulation Examples

In this section, the effectiveness of the proposed theoretical results is verified by numerical example and practical example.

Example 1: Consider the following numerical example

$$\begin{cases} \dot{x}_1 = (l_{1,\sigma(t)}(\bar{x}_1)x_2)dt, \\ \dot{x}_2 = (l_{2,\sigma(t)}(\bar{x}_2)u + f_{2,\sigma(t)}(\bar{x}_2))dt \\ \qquad + g_{2,\sigma(t)}^T(\bar{x}_2)dw, \\ y = x_1 \end{cases} \tag{66}$$

where $\sigma(t) : [0, \infty) \to M = \{1, 2\}$, $l_{1,1} = 1 + 0.3\cos(x_1)$, $l_{1,2} = 1 + 0.5\cos(x_1)$, $l_{2,1} = 1 + 0.7\sin(x_1 x_2)$, $l_{2,2} = 1 + 0.6\cos(x_1 x_2)$, $f_{2,1} = 0.1\sin(x_1)$, $f_{2,2} = 0.1\cos(x_1^2)$, $g_{2,1}^T = x_1\sin(x_1)$, $g_{2,2}^T = \sin(x_1)$. The desired signal $y_d(t) = 0.7\sin(t)$. The following membership functions are selected:

$$\begin{aligned} &\mu F_i^1 = e^{-0.5(x_i+1.5)^2}, \quad \mu F_i^2 = e^{-0.5(x_i+1)^2}, \\ &\mu F_i^3 = e^{-0.5(x_i+0.5)^2}, \quad \mu F_i^4 = e^{-0.5(x_i)^2}, \\ &\mu F_i^5 = e^{-0.5(x_i-0.5)^2}, \quad \mu F_i^6 = e^{-0.5(x_i-1)^2}, \\ &\mu F_i^7 = e^{-0.5(x_i-1.5)^2}. \end{aligned}$$

The initial conditions are $[x_1(0), x_2(0)]^T = [-0.5, 0.4]^T$, $\hat{W}_1(0) = 15$, $\hat{W}_2(0) = 4$. The design parameters are chosen as $a_1 = 10$, $c_1 = 5$, $l_1 = 0.8$, $a_2 = 10$, $c_2 = 1$, $l_2 = 0.7$, $\lambda = 0.3$, $\hbar_1 = 5$, $\epsilon = 2$, $\rho^1 = 1$, $\rho^2 = 0.8$, $\xi_0 = 0.1$, $\xi_\infty = 0.01$, $\kappa_1 = 0.7$, $s_0 = 5$, $s_1 = 3$, $\kappa_2 = 20$, $N = 10$ and the setting time $T = 2$s. Furthermore, it is shown from $\mu_1 = 1.4$, $\eta_1 = 0.7$, $\mu_2 = 1.3$, $\eta_2 = 0.7$ that $\tau_{a1} \geq 0.4807$, $\tau_{a2} \geq 0.4110$.

The simulation results are shown in Figs. 2-8. Fig. 2 displays the tracking performance of the output y. Fig. 3 depicts the control effect of tracking error e_1, and e_1 gets into a prescribed boundary no later than a setting time $T = 2$s without $-\xi_1(0) \leq e_1(0) \leq \xi_1(0)$. The system state x_2 and the adaptive parameters $\hat{W}_1$, $\hat{W}_2$ are described in Figs. 4 and 5, respectively. The trajectory of control input u is shown in Fig. 6. Fig. 7 gives the time interval of event-triggered. Finally, the responses of the switching signal is illustrated in Fig. 8.

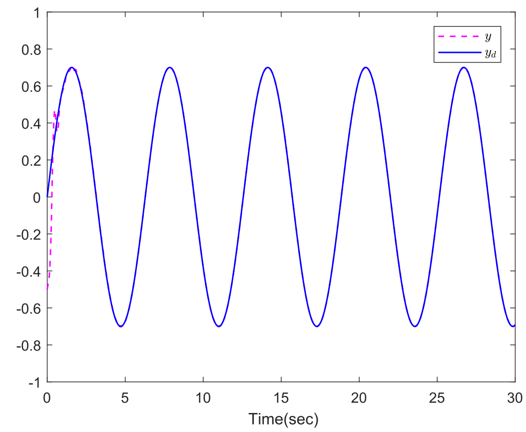

Fig. 2. Responses of tracking performance in Example 1.

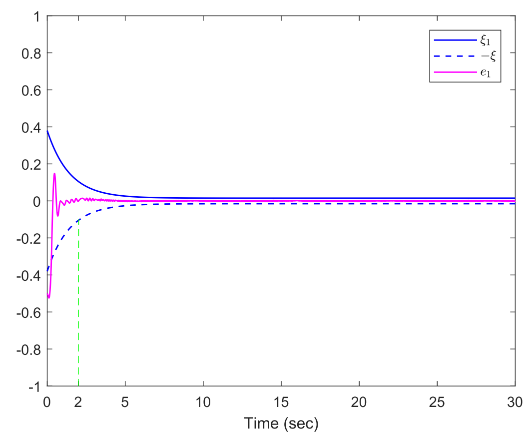

Fig. 3. Responses of control effect in Example 1.

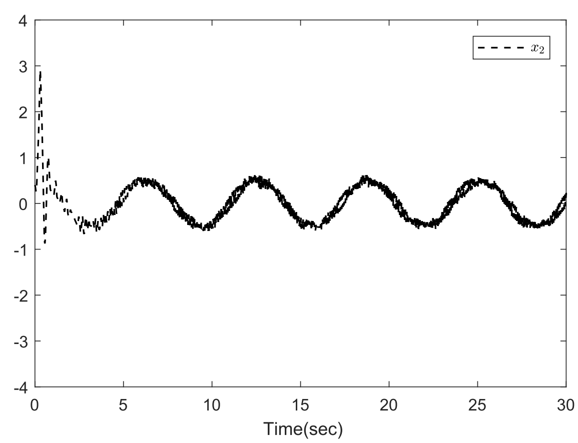

Fig. 4. Responses of x_2 in Example 1.

Example 2: In order to verify the practicability of the proposed control method, the RLC circuit given in [16] is

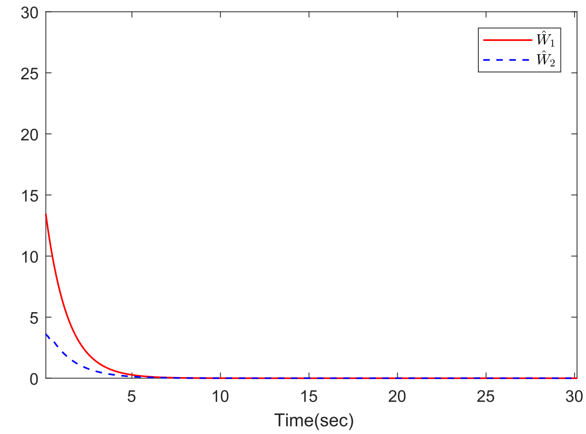

Fig. 5. Responses of $\hat{W}_1$ and $\hat{W}_2$ in Example 1.

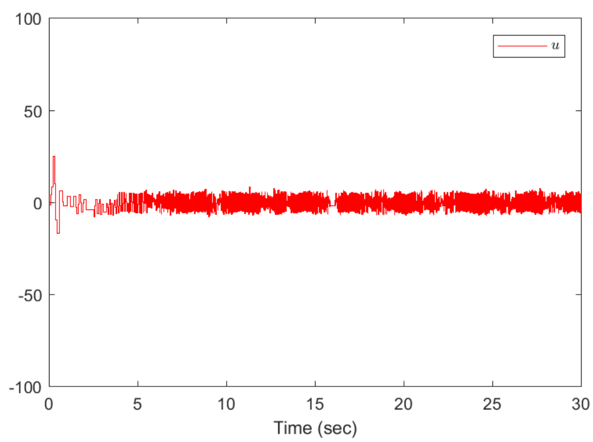

Fig. 6. Responses of control input u in Example 1.

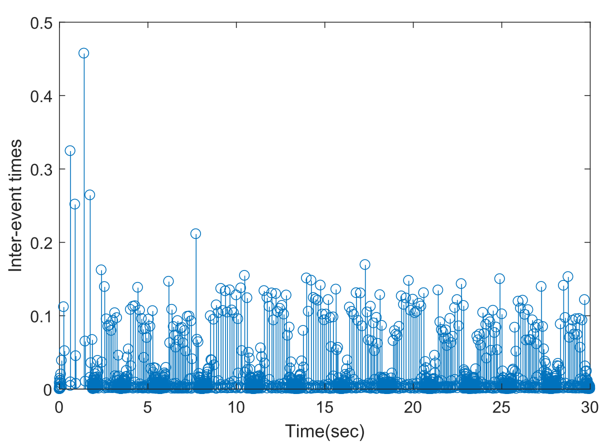

Fig. 7. Inter-event times in Example 1.

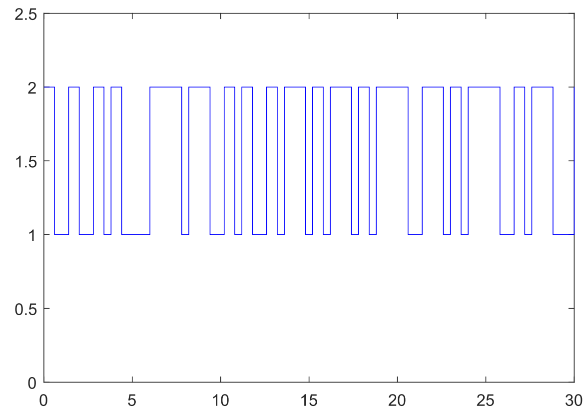

Fig. 8. Responses of switching signal in Example 1.

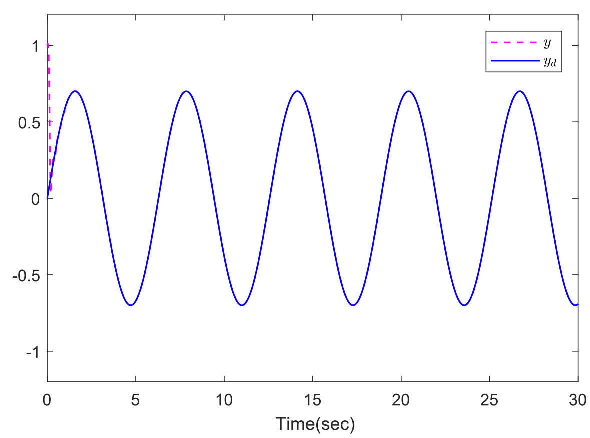

Fig. 9. Responses of tracking performance in Example 7.

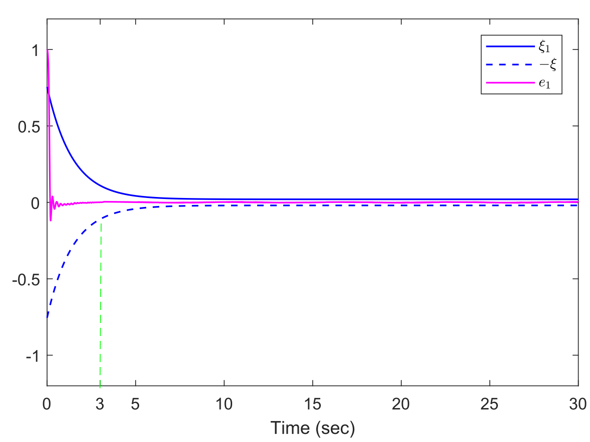

Fig. 10. Responses of control effect in Example 2.

considered.

$$\begin{cases} \dot{x}_1 = x_2 dt, \\ \dot{x}_2 = (u - \dfrac{1}{C_{\sigma(t)}} - \dfrac{R}{L} x_2) dt + \dfrac{1}{L} x_2 \sin(x_1) dw \end{cases} \tag{67}$$

where $L = 1H$, $C_1 = 0.5F$, $C_1 = 0.8F$, $R = 0.1\Omega$. Define $x_1 = q_c$, $x_2 = \phi_L$.

The membership functions are the same as Example 1. The initial conditions are $[x_1(0), x_2(0)]^T = [1, 0.8]^T$, $\hat{W}_1(0) = 1$, $\hat{W}_2(0) = 1$. The design parameters are chosen as $a_1 = 1$, $c_1 = 25$, $l_1 = 0.5$, $a_2 = 5$, $c_2 = 5$, $l_2 = 0.1$, $\lambda = 0.3$, $\hbar_1 = 0.25$, $\epsilon = 0.1$, $\rho^1 = 1$, $\rho^2 = 0.8$, $\xi_0 = 0.1$, $\xi_\infty = 0.01$, $\kappa_1 = 0.7$, $s_0 = 5$, $s_1 = 3$, $\kappa_2 = 20$, $N = 10$ and the setting time $T = 3$s. Especially, we get $\mu_1 = \mu_2 = 1$, which means that a common Lyapunov function can be found for system (67), and Theorem 1 holds under arbitrary switching signals.

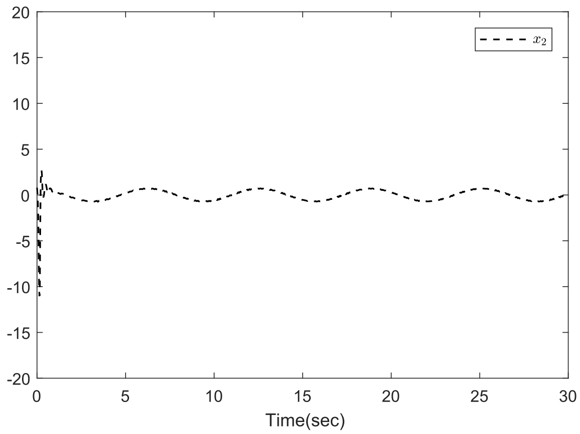

Fig. 11. Responses of x_2 in Example 2.

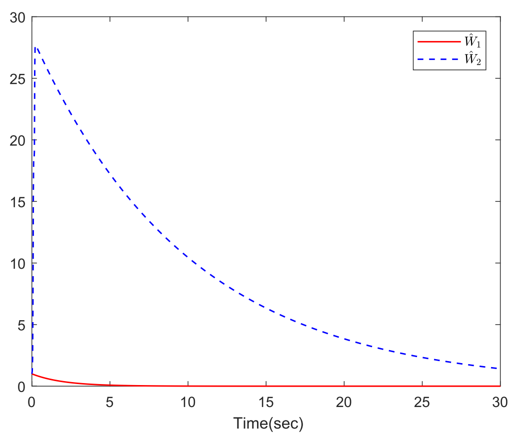

Fig. 12. Responses of $\hat{W}_1$ and $\hat{W}_2$ in Example 2.

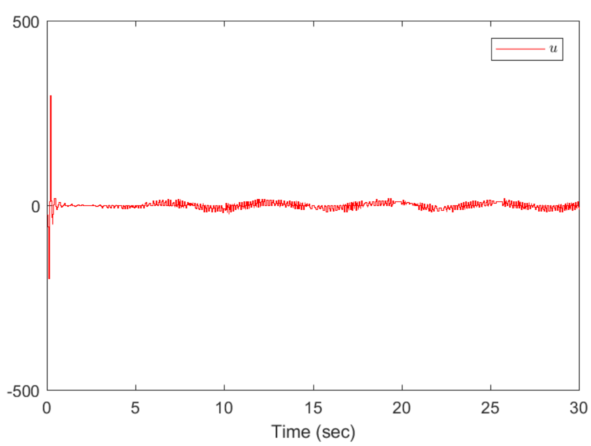

Fig. 13. Responses of control input u in Example 2.

The simulation results for the RLC circuit are shown in Figs. 9-15. From Figs. 9-10, we can see that e_1 can be constrained in performance function no later than a setting time $T = 3$s without $-\xi_1(0) \leq e_1(0) \leq \xi_1(0)$. Figs. 11-13 display the boundedness of x_2, $\hat{W}_1$, $\hat{W}_2$ and u. The trajectories of the trigger time interval and the system signal are shown in Figs. 14 and 15. Simulation results verify the practicality of the proposed control algorithm.

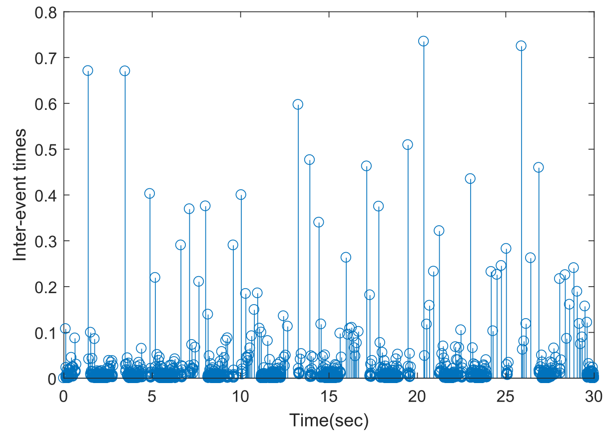

Fig. 14. Inter-event times in Example 2.

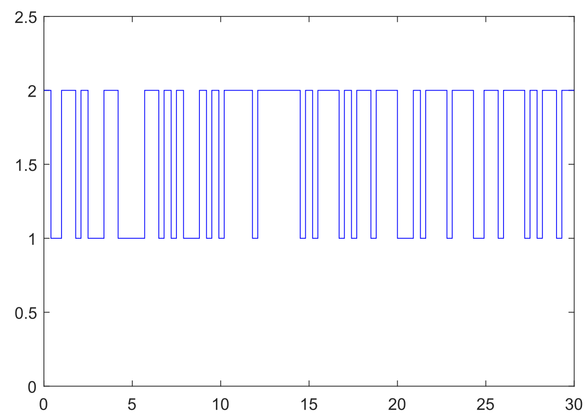

Fig. 15. Responses of switching signal in Example 2.

V. Conclusion

Based on the event-triggered strategy, this paper solves the problem of fuzzy control for stochastic switched nonlinear systems with set-time predefined performance. Combined with MDADT method and Lyapunov function stability analysis, a fuzzy performance algorithm is proposed. The contribution of this study is to introduce the MDETM into the performance control design of switched stochastic nonlinear systems. The proposed control algorithm can not only ensure that the tracking error enters the predefined region no later than a setting time, but also overcome the adverse impact of asynchronous switching on the system performance. Finally, the theoretical results are verified by two simulation examples. In the future, we will study the set-time PPC design of MIMO systems, large-scale systems and multi-agent systems.

References

[1] Y. Wang, P. Shi, Q. Wang, and D. Duan, "Exponential H_∞ filtering for singular Markovian jump systems with mixed mode-dependent time-varying delay," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 60, no. 9, pp. 2440–2452, Feb. 2013.

[2] Y. Wang, P. Shi, and H. Yan, "Reliable control of fuzzy singularly perturbed systems and its application to electronic circuits," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 65, no. 10, pp. 3519–3528, Oct. 2018.

[3] X. Song, J. Man, S. Song, and C. K. Ahn, "Finite-time fault estimation and tolerant control for nonlinear interconnected distributed parameter systems with Markovian switching channels," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 69, no. 3, pp. 1347–1359, Mar. 2022, doi: 10.1109/TCSI.2021.3129372.

[4] B. Zhang, C. Dou, D. Yue, J. H. Park, and Z. Zhang, "Attack-defense evolutionary game strategy for uploading channel in consensus-based secondary control of islanded microgrid considering DoS attack," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 69, no. 2, pp. 821–834, Feb. 2022, doi: 10.1109/TCSI.2021.3120080.

[5] L. Zhao, X. Chen, J. Yu, and P. Shi, "Output feedback-based neural adaptive finite-time containment control of non-strict feedback nonlinear multi-agent systems," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 69, no. 2, pp. 847–858, Feb. 2022, doi: 10.1109/TCSI.2021.3124485.

[6] Q. Zhou, S. Zhao, H. Li, R. Lu, and C. Wu, "Adaptive neural network tracking control for robotic manipulators with dead zone," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 12, pp. 3611–3620, Dec. 2019.

[7] Y. Li, T. Yang, and S. Tong, "Adaptive neural networks finite-time optimal control for a class of nonlinear systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 11, pp. 4451–4460, Nov. 2020.

[8] H. Liang, G. Liu, H. Zhang, and T. Huang, "Neural-network-based event-triggered adaptive control of nonaffine nonlinear multiagent systems with dynamic uncertainties," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 5, pp. 2239–2250, May 2020.

[9] Y.-J. Liu, W. Zhao, L. Liu, D. Li, S. Tong, and C. L. P. Chen, "Adaptive neural network control for a class of nonlinear systems with function constraints on states," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Sep. 14, 2021, doi: 10.1109/TNNLS.2021.3107600.

[10] S. Sui, C. L. P. Chen, and S. Tong, "Fuzzy adaptive finite-time control design for nontriangular stochastic nonlinear systems," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 1, pp. 172–184, Jan. 2019.

[11] Y.-J. Liu, S. Lu, S. Tong, X. Chen, C. L. P. Chen, and D.-J. Li, "Adaptive control-based Barrier Lyapunov functions for a class of stochastic nonlinear systems with full state constraints," *Automatica*, vol. 87, pp. 83–93, Jan. 2018.

[12] M. Wang, Z. Wang, Y. Chen, and W. Sheng, "Event-based adaptive neural tracking control for discrete-time stochastic nonlinear systems: A triggering threshold compensation strategy," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 6, pp. 1968–1981, Jun. 2020.

[13] H. Ma, H. Li, H. Liang, and G. Dong, "Adaptive fuzzy event-triggered control for stochastic nonlinear systems with full state constraints and actuator faults," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 11, pp. 2242–2254, Nov. 2019.

[14] C. Hua, K. Li, and X. Guan, "Event-based dynamic output feedback adaptive fuzzy control for stochastic nonlinear systems," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 5, pp. 3004–3015, Oct. 2018.

[15] H. Min, S. Xu, B. Zhang, and Q. Ma, "Output-feedback control for stochastic nonlinear systems subject to input saturation and time-varying delay," *IEEE Trans. Autom. Control*, vol. 64, no. 1, pp. 359–364, Jan. 2019.

[16] G. L. Chen, C. C. Fan, J. Lam, J. Sun, and J. W. Xia, "Aperiodic sampled-data controller design for switched It$\hat{o}$ stochastic Markovian jump systems," *Syst. Control Lett.*, vol. 157, Nov. 2021, Art. no. 105031.

[17] B. Zhang, W. X. Zheng, and S. Xu, "Filtering of Markovian jump delay systems based on a new performance index," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 60, no. 5, pp. 1250–1263, May 2013.

[18] H. Ren, G. Zong, and H. R. Karimi, "Asynchronous finite-time filtering of networked switched systems and its application: An event-driven method," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 66, no. 1, pp. 391–402, Jan. 2019.

[19] X. Zhao, L. Zhang, P. Shi, and M. Liu, "Stability of switched positive linear systems with average dwell time switching," *Automatica*, vol. 48, no. 6, pp. 1132–1137, 2012.

[20] Y. Zhu, Z. Zhong, M. Basin, and D. Zhou, "A descriptor system approach to stability and stabilization of discrete-time switched PWA systems," *IEEE Trans. Automat. Control*, vol. 63, no. 10, pp. 3456–3463, Oct. 2018.

[21] W. Qi, G. Zong, and W. X. Zheng, "Adaptive event-triggered SMC for stochastic switching systems with semi-Markov process and application to boost converter circuit model," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 68, no. 2, pp. 786–796, Feb. 2021.

[22] Y. Zhu, W. X. Zheng, and D. Zhou, "Quasi-synchronization of discrete-time Lur'e-type switched systems with parameter mismatches and relaxed PDT constraints," *IEEE Trans. Cybern.*, vol. 50, no. 5, pp. 2026–2037, May 2020.

[23] B. Niu, D. Wang, N. D. Alotaibi, and F. E. Alsaadi, "Adaptive neural state-feedback tracking control of stochastic nonlinear switched systems: An average dwell-time method," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 4, pp. 1076–1087, Apr. 2019.

[24] X. Zhao, L. Zhang, P. Shi, and M. Liu, "Stability and stabilization of switched linear systems with mode-dependent average dwell time," *IEEE Trans. Autom. Control*, vol. 57, no. 7, pp. 1809–1815, Jul. 2012.

[25] X. Yang, Y. Liu, J. Cao, and L. Rutkowski, "Synchronization of coupled time-delay neural networks with mode-dependent average dwell time switching," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 12, pp. 5483–5496, Dec. 2020.

[26] X. Li, S.-L. Du, and X. Zhao, "Stability and ℓ_1-gain analysis for switched positive systems with MDADT based on quasi-time-dependent approach," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 51, no. 9, pp. 5846–5854, Sep. 2021.

[27] B. Niu, P. Zhao, J.-D. Liu, H.-J. Ma, and Y.-J. Liu, "Global adaptive control of switched uncertain nonlinear systems: An improved MDADT method," *Automatica*, vol. 115, May 2020, Art. no. 108872.

[28] C. P. Bechlioulis and G. A. Rovithakis, "Robust adaptive control of feedback linearizable MIMO nonlinear systems with prescribed performance," *IEEE Trans. Autom. Control*, vol. 53, no. 9, pp. 2090–2099, Oct. 2008.

[29] Y. Li and S. Tong, "Adaptive neural networks prescribed performance control design for switched interconnected uncertain nonlinear systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 7, pp. 3059–3068, Jul. 2018.

[30] X. Wang, Q. Wang, and C. Sun, "Prescribed performance fault-tolerant control for uncertain nonlinear MIMO system using actor-critic learning structure," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Feb. 25, 2021, doi: 10.1109/TNNLS.2021.3057482.

[31] Q. Zhou, H. Li, L. Wang, and R. Lu, "Prescribed performance observer-based adaptive fuzzy control for nonstrict-feedback stochastic nonlinear systems," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 10, pp. 1747–1758, Oct. 2018.

[32] S. Sui, C. L. P. Chen, and S. Tong, "A novel adaptive NN prescribed performance control for stochastic nonlinear systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 7, pp. 3196–3205, Jul. 2021.

[33] G. Cui, J. Yu, and P. Shi, "Observer-based finite-time adaptive fuzzy control with prescribed performance for nonstrict-feedback nonlinear systems," *IEEE Trans. Fuzzy Syst.*, vol. 30, no. 3, pp. 767–778, Mar. 2022, doi: 10.1109/TFUZZ.2020.3048518.

[34] G. Chen, D. Yao, H. Li, Q. Zhou, and R. Lu, "Saturated threshold event-triggered control for multiagent systems under sensor attacks and its application to UAVs," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 69, no. 2, pp. 884–895, Feb. 2022, doi: 10.1109/TCSI.2021.3116670.

[35] Z.-G. Wu, Y. Xu, Y.-J. Pan, H. Su, and Y. Tang, "Event-triggered control for consensus problem in multi-agent systems with quantized relative state measurements and external disturbance," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 65, no. 7, pp. 2232–2242, Jul. 2018.

[36] N. Zhao, P. Shi, W. Xing, and C. P. Lim, "Event-triggered control for networked systems under denial of service attacks and applications," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 69, no. 2, pp. 811–820, Feb. 2022, doi: 10.1109/TCSI.2021.3116278.

[37] T. Li, D. Yang, X. Xie, and H. Zhang, "Event-triggered control of nonlinear discrete-time system with unknown dynamics based on HDP (λ)," *IEEE Trans. Cybern.*, early access, Feb. 2, 2021, doi: 10.1109/TCYB.2020.3044595.

[38] H. Li, Y. Wu, M. Chen, and R. Lu, "Adaptive multigradient recursive reinforcement learning event-triggered tracking control for multiagent systems," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Jul. 1, 2021, doi: 10.1109/TNNLS.2021.3090570.

[39] T.-F. Li, J. Fu, F. Deng, and T. Chai, "Stabilization of switched linear neutral systems: An event-triggered sampling control scheme," *IEEE Trans. Autom. Control*, vol. 63, no. 10, pp. 3537–3544, Oct. 2018.

[40] X. Qing, L. Zhou, H. C. W. Daniel, and G. Lu, "Event-triggered control of continuous-time switched linear systems," *IEEE Trans. Autom. Control*, vol. 64, no. 4, pp. 1710–1717, Apr. 2019.

[41] H. Meng, H.-T. Zhang, Z. Wang, and G. Chen, "Event-triggered control for semiglobal robust consensus of a class of nonlinear uncertain multiagent systems," *IEEE Trans. Autom. Control*, vol. 65, no. 4, pp. 1683–1690, Apr. 2020.

[42] J. Lian and C. Li, "Event-triggered control for a class of switched uncertain nonlinear systems," *Syst. Control Lett.*, vol. 135, Jan. 2020, Art. no. 104592.

[43] L. Long and F. Wang, "Dynamic event-triggered adaptive NN control for switched uncertain nonlinear systems," *IEEE Trans. Cybern.*, early access, Aug. 16, 2021, doi: 10.1109/TCYB.2021.3088636.

Xueliang Wang received the B.Sc. degree in mathematics and applied mathematics from Liaocheng University, where he is currently pursuing the M.S. degree in systems sciences. His current research interests include nonlinear systems, switched systems, adaptive control, and their applications.

Jianwei Xia (Member, IEEE) received the B.Sc. degree in mathematics and applied mathematics from Liaocheng University, Liaocheng, China, in 2001, the M.S. degree in automatic engineering from Qufu Normal University, Qufu, China, in 2004, and the Ph.D. degree in automatic control from the Nanjing University of Science and Technology, Nanjing, China, in 2007. From 2010 to 2012, he was a Post-Doctoral Research Associate with the School of Automation, Southeast University, Nanjing. From 2013 to 2014, he was a Post-Doctoral Research Associate with the Department of Electrical Engineering, Yeungnam University, Gyeongsan-si, South Korea. He is a Professor with the School of Mathematics Science, Liaocheng University. His current research interests include nonlinear systems control, robust control, stochastic systems, and neural networks.

Ju H. Park (Senior Member, IEEE) received the Ph.D. degree in electronics and electrical engineering from the Pohang University of Science and Technology (POSTECH), Pohang-si, Republic of Korea, in 1997.

From May 1997 to February 2000, he was a Research Associate with the Engineering Research Center-Automation Research Center, POSTECH. He joined Yeungnam University, Gyeongsan-si, Republic of Korea, in March 2000, where he is currently the Chuma Chair Professor. He is a coauthor of the monographs *Recent Advances in Control and Filtering of Dynamic Systems With Constrained Signals* (Springer-Nature, New York, NY, USA, 2018) and *Dynamic Systems With Time Delays: Stability and Control* (Springer-Nature, 2019). His research interests include robust control and filtering, neural/complex networks, fuzzy systems, multiagent systems, and chaotic systems. He has published a number of articles in these areas. He is a fellow of the Korean Academy of Science and Technology (KAST). Since 2015, he has been a recipient of the Highly Cited Researchers Award by Clarivate Analytics (formerly, Thomson Reuters) and listed in three fields: engineering, computer sciences, and mathematics in 2019, 2020, and 2021. He also serves as an Editor for the *International Journal of Control, Automation and Systems*. He is also a/an Subject Editor/Advisory Editor/Associate Editor/Editorial Board Member of several international journals, including *IET Control Theory and Applications*, *Applied Mathematics and Computation*, *Journal of The Franklin Institute*, *Nonlinear Dynamics*, *Engineering Reports*, *Cogent Engineering*, the IEEE TRANSACTIONS ON FUZZY SYSTEMS, the IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS, and the IEEE TRANSACTIONS ON CYBERNETICS. He is an Editor of an edited volume *Recent Advances in Control Problems of Dynamical Systems and Networks* (Springer-Nature, 2020).

Xiangpeng Xie (Member, IEEE) received the B.S. and Ph.D. degrees in engineering from Northeastern University, Shenyang, China, in 2004 and 2010, respectively. From 2012 to 2014, he was a Post-Doctoral Fellow with the Department of Control Science and Engineering, Huazhong University of Science and Technology. He is currently a Professor with the Institute of Advanced Technology, Nanjing University of Posts and Telecommunications, Nanjing, China. His research interests include fuzzy modeling and control synthesis, state estimations, optimization in process industries, and intelligent optimization algorithms.

Guoliang Chen received the Ph.D. degree in control science and engineering from the School of Automation, Beijing Institute of Technology, Beijing, China, in 2020. From March 2019 to August 2019, he was a Research Associate with the Department of Mechanical Engineering, The University of Hong Kong, Hong Kong. He is currently a Lecturer with the School of Mathematics Science, Liaocheng University. His current research interests include robust control, time-delay systems, sampled-data systems, stochastic systems, and neural networks.