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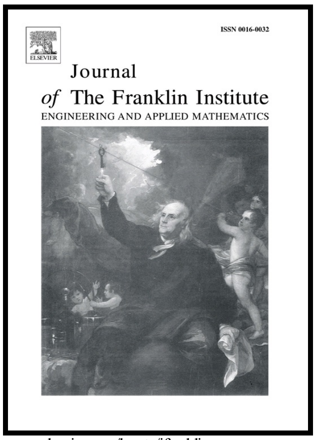

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Adaptive event-triggered control of a class of nonlinear networked systems

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Abstract

This paper investigates an adaptive event-triggered communication scheme (AETCS) for a class of networked Takagi-Sugeno (T-S) fuzzy control systems. The threshold of event-triggering condition has great influence on the maximum allowable number of successive packet losses. Different from the conventional method, the threshold, in this study, is dependent on a novel adaptive law which can be achieved on-line rather than a predefined constant, since the threshold with fixed value is hard to suit the variation of the system. The stability and stabilization criteria are derived by using a new Lyapunov function. Finally, an example is provided to demonstrate the design method.

Key words: Adaptive event-triggered communication scheme; Networked control system; Takagi-Sugeno (T-S) fuzzy model.

1. Introduction

Recently, much attention has been paid to the networked control systems (NCSs) where the control loops are closed through a communication network due to the advantages of its low cost, easy maintenance, high flexibility, simple installation and maintenance[1–6]. Many applications, for example, mobile sensor networks[7], intelligent transportation systems[8], remote surgery[9] and theoretic results[2, 3, 10–12] are reported to cope with the NCSs. Notice that the aforementioned results are based on a periodic execution of control actions. The signal transmission period is pre-set under a worst operation condition while analyzing the stability of the system, which may lead to a conservativeness in the sense of resource usage , such as sampling rate, CPU time. These problem might be concealed by utilizing a better hardware, however, from the perspective of energy conservation, communication capacity and cost, on implementations over wireless sensor, such as CAN (1 MB/s), Zigbee (250 Kb/s) and some battery-powered wireless networks, the limitations of these communication medium should no longer be neglected.

As an alternative of the periodic time-triggered control, event-triggered control schemes have attracted much attention to mitigate the hardware requirement by reducing the "unnecessary" data transmission while guaranteeing the desired levels of control performance in the context of sensor/actuator networks. Compared with the time-triggered control, the tasks are triggered by a sequence of well-designed events rather than periodic time instants with the elapse of time, that is, the data before being releasing into the network are screened by a device which decides whether or not to send the sampling data over the network. A large amount of "unnecessary" data are dropped out actively under this selection mechanism, thus the network resource can be saved to allocate other more important task. In [13], the authors presented

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a decentralized event-triggered implementation, over sensor/actuator networks, of centralized nonlinear controllers. Wang and Lemmon proposed a method for distributed event-triggered control under an assumption that the control system was composed of weakly coupled subsystems in [14]. In [15], the authors developed an event-triggered transmission policy based on a state-estimation. The event-triggered algorithms are designed based on the variation of the Lyapunov functions and a selection of the input variables to be updated [16]. However, a common feature of the aforementioned results on the event-triggering scheme (ETS) is that the controller gains should be known in *prior*. To overcome this drawback, co-designing methods are wildly investigated for both the feedback control gain of the system and the parameters of the event-triggering condition recently, for example, [17–20], and references therein.

The threshold of event-triggering condition may greatly affect the execution of control task. However, the threshold, in the conventional design, being a pre-set constant, is hard to adapt the variation of the system, that is, the event-triggered parameter to be designed should adapt to the external disturbance. Therefore, an on-line optimization is required to for achieving the event-triggering parameter, which is a big challenging issue. To the best of the authors knowledge, up to now, there are few results in the open literature on achieving the threshold of the event-triggering condition for nonlinear systems, which motivates the current work.

Notice that many industrial systems exhibit serious non-linear characteristics, which make the analysis and synthesis for the system more difficult, especially for NCSs. It has been proved that Takagi-Sugeno (T-S) fuzzy models can approximate any continuous functions by a set of conventional linear systems and described by a family of IF-THEN rules [21–23]. Consequently, the study on nonlinear NCSs has received much attentions by using the method of T-S fuzzy model[24–26]. In this paper, we deal with the problem of an adaptive event-triggered fuzzy control for T-S fuzzy model based nonlinear NCSs. The contributions of the paper are as follows. Firstly, a new adaptive data transmitting scheme is developed. The burden of network-bandwidth is mitigated after introducing of the adaptive data-transmitting generator (ADTG), by which the data with less contribution to the control performance or less relative variation from the latest released data are discarded. Secondly, a new adaptive law is put forward to achieve the threshold of event triggering condition on-line. The threshold of the triggering condition becomes an optimal result rather than an arbitrary one with the conventional event-triggered method. Thirdly, To ensure the closed-loop system asymptotic stability under the proposed AETCS, a new Lyapunov-Krasovskii functional is developed and a sufficient condition is given to co-design the parameters of the AETCS and the fuzzy controller.

The remainder of this paper is organized as follows. Section 2 describes the framework of AETCS and the modelling process of the closed-loop NCS under AETCS. In section 3, the stability and stabilization criteria are established with consideration of AETCS. Section 4 gives an example to show the effectiveness of the proposed scheme. The paper is concluded in Section 5.

Notation: $\mathbb{R}^n$ denotes the n-dimensional Euclidean space, $\mathbb{R}^{n\times m}$ is the set of real $n \times m$ matrices. For any positive integer r, $\mathscr{S}_r \triangleq \{1, 2, \cdots, r\}$. I is the identity matrix of appropriate dimensions. $\delta_i \triangleq [\underbrace{0, 0, \cdots, 0}_{i-1}, I, 0, \cdots, 0]_{n\times 7n}$. $\|\cdot\|$ stands for the Euclidean vector norm or spectral norm as appropriate. The notation $X > 0$ (respectively, $X < 0$), for $X \in \mathbb{R}^{n\times n}$ means that the matrix X is a real symmetric positive definite (respectively, negative definite). The asterisk $*$ in a matrix is used to denote term that is induced by symmetry, Matrices, if they are not explicitly stated , are assumed to have compatible dimensions.

2. Problem statement and an AETCS

In this section, we will study the networked control design for a nonlinear system by using a new adaptive event-triggering scheme. Under this scheme, the data with less contribution to the control performance or less relative variation will be discarded to mitigate the network-bandwidth. Then a unified model of networked nonlinear system is presented based on the AETCS.

2.1. The system description

Consider the following nonlinear plant

$$\dot{x}(t) = f(x(t)) + g(x(t))u(t) \tag{1}$$

where $x(t) \in \mathbb{R}^n$ is the state vector and $u(t) \in \mathbb{R}^m$ is the input vector; $f(x), g(x)$ is continuous functions of x, and $f(0) = 0, g(0) = 0$.

By the fuzzy modelling approach [27–29], the system (1) can be represented or approximated in a compact (bound closed) set by a T-S fuzzy model, in which the i-th rule of the model is of the form

Plant Rule i **:**

$$\begin{aligned} &\text{If } \theta_1(t) \text{ is } W_1^i \text{ and } \cdots \text{ and } \theta_g(t) \text{ is } W_g^i \text{ Then} \\ &\dot{x}(t) = A_i x(t) + B_i u(t) \end{aligned} \tag{2}$$

where $W_j^i (i \in \mathscr{S}_r, j \in \mathscr{S}_g)$ is the fuzzy set, which is characterized by the membership functions $W_j^i(\theta_j(t))$; r and g are the number of fuzzy rules and fuzzy sets, $\theta(t) = [\theta_1(t), \theta_2(t), \cdots, \theta_g(t)]^T$ is the premise variables; A_i and B_i are constant matrices with compatible dimensions.

By using the center-average defuzzifier, product inference and singleton fuzzifier, the global dynamics of T-S fuzzy system (2) can be expressed as

$$\dot{x}(t) = \sum_{i=1}^{r} h_i(\theta(t)) \left[A_i x(t) + B_i u(t)\right] \tag{3}$$

where

$$h_i(\theta(t)) = \frac{\omega_i(\theta(t))}{\sum_{i=1}^{r} \omega_i(\theta(t))}, \ \omega_i(\theta(t)) = \prod_{j=1}^{g} W_j^i(\theta_j(t)) \tag{4}$$

For $\forall i \in \{1, 2, \cdots, r\}$, $h_i(\theta(t))$ has the properties of $h_i(\theta(t)) \geq 0$ and $\sum_{i=1}^{r} h_i(\theta(t)) = 1$. For notational simplicity, $h_i(\theta(t))$ is written as h_i in the next presentation.

2.2. An adaptive event-triggered communication scheme

The proposed AETCS-based nonlinear networked control system, shown in Fig. 1, consists of a nonlinear continuous controlled plant, a sensor, a sampler, a fuzzy controller and a zero-order holder (ZOH), an actuator and an adaptive data-transmitting generator (ADTG). From the figure, one can see that the proposed framework inherits the traditional NCSs except that the ADTG is introduced before the sampled data accessing the network. However, the AETG is a crucial part of the control system due to the selection of control information greatly depending on it.

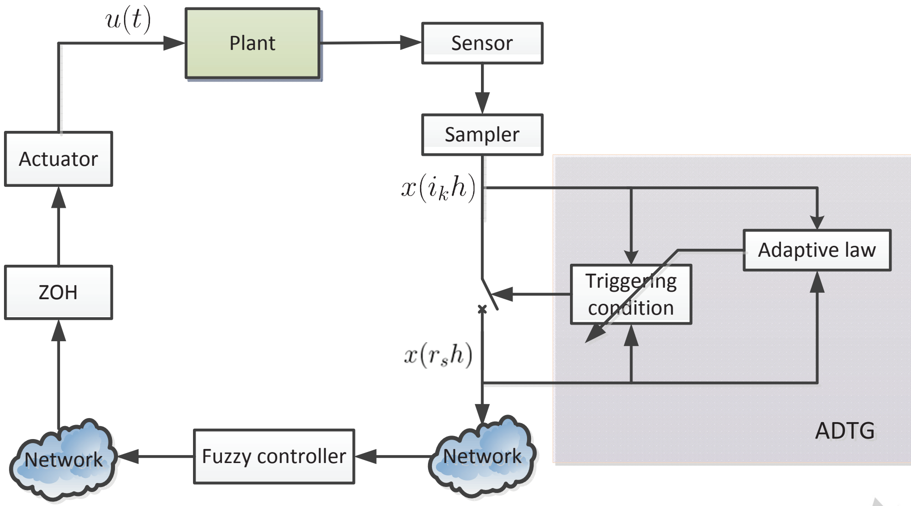

Figure 1: A diagram of AETCS for a nonlinear NCS

Based on the previous work on modelling NCSs, such as [11, 30], we consider the following fuzzy controller under assumptions that: 1) the sensors are clock-driven, controllers and actuators are event-driven; 2) the sampling data are hold by ZOH before the new data are updated; and 3) the data are transmitted over the network by a single packet in every control period h and there are no packet losses.

$$u(t^+) = \sum_{j=1}^{r} h_j K_j x(r_s h), \quad t \in \chi_{r_s} \tag{5}$$

where $\chi_{r_s} \triangleq [r_s h + \tau_{r_s}, r_{s+1} h + \tau_{r_{s+1}})$, K_j $(j \in \mathscr{S}_r)$ is a controller gain to be designed, h is a sampling period, $r_s h$ is a releasing instant broadcasted by ADTG, τ_{r_s} is a network-transmitted delay at $r_s h$.

Fig. 2 gives an example to show the time sequence of the sampling and releasing instant under the AETCS. In Fig. 2, the data are sampled periodically at instant $i_k h$, $(i_k h \in \Omega_1 \triangleq \{0h, 1h, 2h, 3h, 4h, 5h, \cdots\})$, and the data at releasing instant $r_s h$, $(r_s h \in \Omega_2 \triangleq \{r_0 h = 0h, r_1 h = 4h, r_2 h = 6h \cdots\})$ are selected to release into the network and the others are discarded. The control input of the fuzzy system is kept by ZOH during the period $\chi_0 = [0h + \tau_0, 4h + \tau_4), \chi_1 = [4h + \tau_4, 6h + \tau_6), \ldots$.

Remark 1. From the above analysis, one can obviously see that Ω_2 is a subset of Ω_1 and $\sum_{s=0}^{\infty} \chi_{r_s} = [t_0, \infty)$. Further more, the releasing period $\Delta r_s h = r_{s+1} h - r_s h$ is larger than the sampling period h due to the effect of AETCS, which leads to a larger average releasing period $\bar{h}_r = \frac{\sum_{s=1}^{N} \Delta r_s h}{N}$ than h.

ADTG in this study is responsible for deciding wether or not to send the updated sampling data, that is, a decision should be made at every updated instant of the sampler. To expound the mechanism of AETCS clearly , we divide the releasing interval χ_{r_s} into several sampling-like subsets artificially as $\chi_{r_s}^{l} = [r_s h + lh - h + \tau_{r_s}^{l-1}, r_s h + lh + \tau_{r_s}^{l})$ for $l = 1, 2, \cdots, \bar{l}$, where $0\tau_{r_s}^{l}$ takes value of τ_{r_s} and $\tau_{r_{s+1}}$ for $l \leq \bar{l} - 1$ and $l = \bar{l}$, respectively (see Fig. 2). Obviously, $\chi_{r_s} = \cup_{l=1}^{\bar{l}} \chi_{r_s}^{l}$.

Define $e(t) = x(r_s h + lh) - x(r_s h)$ and $\Omega_3 \triangleq \{l | e^T(t) \Xi e(t) - \varrho(t) x^T(r_s h + lh) \Xi x(r_s h + lh) \leq 0\}$

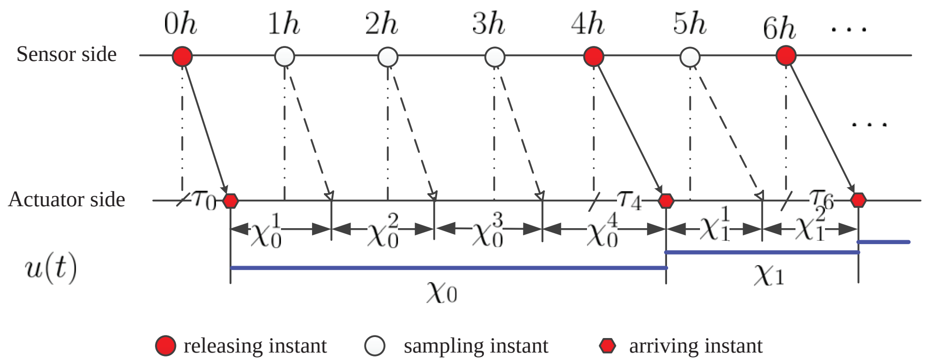

Figure 2: An example of timing diagram for an event-triggered implementation

for $t \in \chi_{r_s}$, then the number of divided subinterval $\bar{l}$ is decided by

$$\bar{l} = \begin{cases} 1 & \Omega_3 = \phi \\ 1 + \max\{l | l \in \Omega_3\} & \text{others} \end{cases} \tag{6}$$

for $t \in \chi_{r_s}$, $\Xi > 0$ is a weight of triggering condition to be designed, and $\varrho(t)$ is a variable of threshold satisfying the following adaptive event-triggering law

$$\dot{\varrho}(t) = \frac{\theta}{\varrho(t)}\left(\frac{1}{\varrho(t)} - \vartheta\right) e^T(t)\Xi e(t) \tag{7}$$

with $0 < \varrho(t) \leq 1$ and $\theta > 0, \vartheta > 0$.

Remark 2. Eq. (6) gives the next releasing instant $r_{s+1}h = r_s h + \bar{l}h$, that is, $\bar{l} - 1$ is the maximum allowable number of successive packet losses. It means that an event will be triggered by ADTG when the updated sampled-data violates the triggering condition

$$e^T(t)\Xi e(t) - \varrho(t)x^T(r_s h + lh)\Xi x(r_s h + lh) \leq 0 \tag{8}$$

otherwise, the sampling data will be discarded. Thus, the number of packet-transmission over the communication network are greatly reduced.

Remark 3. From (7), one can know that if the system tends to be stable at the equilibrium, the error $e(t) = x(r_s h + lh) - x(r_s h)$ accordingly approaches to zero, i.e. $\dot{\varrho}(t) \to 0$, then the threshold converges to a certain value unless there is a new external disturbance destabilizing the system. That is the threshold should be convergent if and only if the system is stable.

Remark 4. If one sets $\theta = 0$ in (7), then the triggering condition in (8) degrades into the conventional ones, such as [17, 18], with the following format

$$e^T(t)\Xi e(t) - \bar{\varrho}x^T(r_s h + lh)\Xi x(r_s h + lh) \leq 0 \tag{9}$$

where $0 < \bar{\varrho} \leq 1$ is a predefined constant. Specially, the above scheme approaches to the time-triggered ones if $\bar{\varrho} \to 0^+$.

Remark 5. From (8), one can see that the threshold variable $\varrho(t)$ has a major effect on the number of the packets transmitted over the network in a certain period. $\varrho(t)$ in (7) is an optimal result regulated by the adaptive law (7) on-line, while the threshold $\bar{\varrho}$ in (9) is a preset constant, by which it can not be accommodated with the varying external disturbance.

2.3. AETCS-based NCSs modelling

Define $\eta(t) = t - (r_s h + lh)$ for $t \in \chi^l_{r_s}$. From the definition of $e(t)$, we have

$$x(r_s h) = x(t - \eta(t)) - e(t) \tag{10}$$

where $\eta_m = \min\{\tau_k\} \le \eta(t) \le h + \max\{\tau_k\} = \eta_M$.

Combining (3), (5) and (10) leads to a closed-loop NCS model

$$\dot{x}(t) \;=\; \sum_{i=1}^{r}\sum_{j=1}^{r} h_i h_j \left[A_i x(t) - B_i K_j e(t) + B_i K_j x(t - \eta(t))\right] \tag{11}$$

Additionally, the adaptive event-triggered condition (8) is equivalent to

$$e^T(t)\Xi e(t) - \varrho(t)x^T(t - \eta(t))\Xi x(t - \eta(t)) \le 0 \tag{12}$$

For the sake of simplicity, we denote $\zeta(t) = [x^T(t)\ x^T(t-\eta_m)\ x^T(t-\eta(t))\ x^T(t-\eta_M)\ e^T(t)$ $\frac{1}{\eta(t)}\int_{t-\eta(t)}^{t} x^T(s)ds\ \ \frac{1}{\bar{\eta}-\eta(t)}\int_{t-\eta_M}^{t-\eta(t)} x^T(s)ds]^T$. Then the system (11) can be rewritten as

$$\dot{x}(t) \;=\; \sum_{i=1}^{r}\sum_{j=1}^{r} h_i h_j \mathcal{A}_{ij}\zeta(t) \tag{13}$$

where $\mathcal{A}_{ij} = \begin{bmatrix} A_i & 0 & B_iK_j & 0 & -B_iK_j & 0 & 0\end{bmatrix}$.

3. Stability analysis and controller design

In this section, we are in position to develop an approach of stability analysis and co-design for fuzzy controller, the weight of event-triggering condition and the threshold of event-triggering condition to the networked T-S fuzzy system (13). Before we give the Theorems, the following lemma are first introduced, which is helpful for deriving our main results.

Lemma 1. [31] For a given matrix $R > 0$, the following inequality holds for all continuously differentiable function ω in $[a, b] \to \mathbb{R}^n$:
$\ell_R(\dot{\omega}) \ge \frac{1}{b-a}(\omega(b) - \omega(a))^T R(\omega(b) - \omega(a)) + \frac{3}{b-a}\tilde{\Omega}^T R\tilde{\Omega}$,
where $\ell_R(\omega) = \int_a^b \omega^T(u)R\omega(u)du$ and $\tilde{\Omega} = \omega(b) + \omega(a) - \frac{2}{b-a}\int_a^b \omega(u)du$.

Lemma 2. [32] For given positive integers n,m,a scalar α in the interval $(0, 1)$, a given $n \times n$-matrix $R > 0$, two matrices W_1 and W_2 in $\mathbb{R}^{n\times m}$. Define, for all vector ξ in $\mathbb{R}^m$, the function $\Theta(\alpha, U)$ given by: $\Theta(\alpha, R) = \frac{1}{\alpha}\xi^T W_1^T R W_1 \xi + \frac{1}{1-\alpha}\xi^T W_2^T R W_2 \xi$

Then, if there exists a matrix U in $\mathbb{R}^{n\times n}$ such that $\begin{pmatrix} R & U \\ * & R \end{pmatrix} > 0$,then the following inequality holds

$$\min \Theta(\alpha, R) \ge \begin{pmatrix} W_1\xi \\ W_2\xi \end{pmatrix}^T \begin{pmatrix} R & U \\ * & R \end{pmatrix}\begin{pmatrix} W_1\xi \\ W_2\xi \end{pmatrix}.$$

Lemma 3. [32] For any constant matrix $R \in \mathbb{R}^{n\times n}$, $R > 0$, scalars $\bar{\tau}_1 \le \tau(t) \le \bar{\tau}_2$, and vector function $\dot{x} : [-\bar{\tau}_2, -\bar{\tau}_1] \to \mathbb{R}^n$ such that the following integration is well defined, it holds that

$$-(\bar{\tau}_2 - \bar{\tau}_1)\int_{t-\bar{\tau}_2}^{t-\bar{\tau}_1} \dot{x}^T(s)R\dot{x}(s)ds \le \begin{bmatrix} x(t-\bar{\tau}_1) \\ x(t-\bar{\tau}_2)\end{bmatrix}^T \begin{bmatrix} -R & * \\ R & -R\end{bmatrix}\begin{bmatrix} x(t-\bar{\tau}_1) \\ x(t-\bar{\tau}_2)\end{bmatrix} \tag{14}$$

Theorem 1. For given positive scalars η_m, η_M, ϑ and matrix K_j ($j \in \mathscr{S}_r$), if there exist real matrices $P > 0, Q_1 > 0, Q_2 > 0, R_1 > 0, R_2 > 0, \Xi > 0$ with appropriate dimensions satisfying the following LMI conditions:

$$\begin{bmatrix} \Omega_{ii} & * \\ \mathscr{R}\mathcal{A}_{ii} & -\mathscr{R} \end{bmatrix} < 0 \qquad i \in \mathscr{S}_r \tag{15}$$

$$\begin{bmatrix} \Omega_{ij} + \Omega_{ji} & * \\ \mathscr{R}(\mathcal{A}_{ij} + \mathcal{A}_{ji}) & -\mathscr{R} \end{bmatrix} < 0 \qquad i < j \ (i, j \in \mathscr{S}_r) \tag{16}$$

$$\begin{bmatrix} \bar{R}_2 & * \\ U & \bar{R}_2 \end{bmatrix} > 0 \tag{17}$$

where

$$\begin{aligned}
\Omega_{ij} &= \delta_1^T P\mathcal{A}_{ij} + \mathcal{A}_{ij}^T P\delta_1 + diag\{Q_1 + Q_2, -Q_1, \Xi, -Q_2, -\vartheta\Xi, 0, 0\} \\
&- \begin{bmatrix} W_1 \\ W_2 \end{bmatrix}^T \begin{bmatrix} \bar{R} & * \\ U & \bar{R} \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix}^T \begin{bmatrix} -R_1 & * \\ R_1 & -R_1 \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix} \\
\mathcal{A}_{ij} &= \begin{bmatrix} A_i & 0 & B_iK_j & 0 & -B_iK_j & 0 & 0 \end{bmatrix} \\
W_1 &= \begin{bmatrix} \delta_1 - \delta_3 \\ \delta_1 + \delta_3 - 2\delta_6 \end{bmatrix}, W_2 = \begin{bmatrix} \delta_3 - \delta_4 \\ \delta_3 + \delta_4 - 2\delta_7 \end{bmatrix}, \\
\bar{R}_2 &= diag\{R_2, 3R_2\}, \mathscr{R} = \eta_m R_1 + \eta_M R_2
\end{aligned}$$

Then, the closed-loop system (11) is asymptotically stable under the proposed event-triggering condition (8) with adaptive law (7).

Proof: Consider the following Lyapunov functional candidate

$$\begin{aligned}
V(t) &= V_1(t) + V_2(t) + V_3(t) + V_4(t) \\
V_1(t) &= x^T(t)Px(t) \\
V_2(t) &= \int_{t-\eta_m}^{t} x^T(s)Q_1x(s)ds + \int_{t-\eta_M}^{t} x^T(s)Q_2x(s)ds \\
V_3(t) &= \eta_m \int_{t-\eta_m}^{t} \int_{s}^{t} \dot{x}^T(v)R_1\dot{x}(v)dvds + \eta_M \int_{t-\eta_M}^{t} \int_{s}^{t} \dot{x}^T(v)R_2\dot{x}(v)dvds \\
V_4(t) &= \frac{1}{2}\varrho^2(t)
\end{aligned}$$

Since

$$-\eta_M \int_{t-\eta_M}^{t} \dot{x}^T(s)R_2\dot{x}(s)ds = -\eta_M \int_{t-\eta(t)}^{t} \dot{x}^T(s)R_2\dot{x}(s)ds - \eta_M \int_{t-\eta_M}^{t-\eta(t)} \dot{x}^T(s)R_2\dot{x}(s)ds$$

Then by using Lemma 1 and Lemma 2, we have

$$
\begin{aligned}
-\eta_M \int_{t-\eta_M}^{t} \dot{x}^T(s)R_2\dot{x}(s)ds &\leq -\frac{\eta_M}{\eta(t)}\zeta^T(t)(\delta_1-\delta_3)^T R_2(\delta_1-\delta_3)\zeta(t) \\
&- \frac{3\eta_M}{\eta(t)}\zeta^T(t)(\delta_1+\delta_3-2\delta_6)^T R_2(\delta_1+\delta_3-2\delta_6)\zeta(t) \\
&- \frac{\eta_M}{\eta_M-\eta(t)}\zeta^T(t)(\delta_3-\delta_4)^T R_2(\delta_3-\delta_4)\zeta(t) \\
&- \frac{3\eta_M}{\eta_M-\eta(t)}\zeta^T(t)(\delta_3+\delta_4-2\delta_7)^T R_2(\delta_3+\delta_4-2\delta_7)\zeta(t) \\
&= -\frac{\eta_M}{\eta(t)}\zeta^T(t)W_1^T\bar{R}_2W_1\zeta(t) - \frac{\eta_M}{\eta_M-\eta(t)}\zeta^T(t)W_2^T\bar{R}_2W_2\zeta(t) \\
&= -\frac{1}{\alpha}\zeta^T(t)W_1^T\bar{R}_2W_1\zeta(t) - \frac{1}{1-\alpha}\zeta^T(t)W_2^T\bar{R}_2W_2\zeta(t) \\
&\leq -\zeta^T(t)\begin{bmatrix} W_1 \\ W_2 \end{bmatrix}^T \begin{bmatrix} \bar{R}_2 & * \\ U & \bar{R}_2 \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \end{bmatrix}\zeta(t)
\end{aligned}
$$

where $0 < \alpha = \frac{\eta(t)}{\eta_M} \leq 1$.

Using Lemma 3, we obtain

$$
\begin{aligned}
\dot{V}_3(t) &\leq \dot{x}^T(t)(\eta_m R_1 + \eta_M R_2)\dot{x}(t) + \begin{bmatrix} x(t) \\ x(t-\eta_m) \end{bmatrix}^T \begin{bmatrix} -R_1 & R_1 \\ R_1 & -R_1 \end{bmatrix} \begin{bmatrix} x(t) \\ x(t-\eta_m) \end{bmatrix} \\
&- \zeta^T(t)\begin{bmatrix} W_1 \\ W_2 \end{bmatrix}^T \begin{bmatrix} \bar{R}_2 & * \\ U & \bar{R}_2 \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \end{bmatrix}\zeta(t)
\end{aligned} \tag{18}
$$

Recalling the adaptive law (7) and the triggering condition (12) follows

$$
\begin{aligned}
\dot{V}_4(t) &= \varrho(t)\dot{\varrho}(t) \\
&= \frac{1}{\varrho(t)}e^T(t)\Xi e(t) - \vartheta e^T(t)\Xi e(t) \\
&\leq x^T(t-\eta(t))\Xi x(t-\eta(t)) - \vartheta e^T(t)\Xi e(t)
\end{aligned} \tag{19}
$$

Combining (18) and (19) yields

$$
\begin{aligned}
\dot{V}(t) &\leq \sum_{i=1}^{r}\sum_{j=1}^{r} h_i h_j \Big\{ 2x^T(t)P\mathcal{A}_{ij}\zeta(t) + x^T(t)(Q_1+Q_2)x(t) \\
&- x^T(t-\eta_m)Q_1x(t-\eta_m) - x^T(t-\eta_M)Q_2x^T(t-\eta_M) \\
&+ \zeta^T(t)\mathcal{A}_{ij}^T(\eta_m R_1 + \eta_M R_2)\mathcal{A}_{ij}\zeta(t) + \begin{bmatrix} x(t) \\ x(t-\eta_m) \end{bmatrix}^T \begin{bmatrix} -R_1 & R_1 \\ R_1 & -R_1 \end{bmatrix} \begin{bmatrix} x(t) \\ x(t-\eta_m) \end{bmatrix} \\
&- \zeta^T(t)\begin{bmatrix} W_1 \\ W_2 \end{bmatrix}^T \begin{bmatrix} \bar{R}_2 & * \\ U & \bar{R}_2 \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \end{bmatrix}\zeta(t) \\
&+ x^T(t-\eta(t))\Xi x(t-\eta(t)) - \vartheta e^T(t)\Xi e(t) \Big\} \\
&= \sum_{i=1}^{r}\sum_{j=1}^{r} h_i h_j \zeta^T(t)\left\{ \Omega_{ij} + \mathcal{A}_{ij}^T\mathscr{R}\mathcal{A}_{ij} \right\}\zeta(t)
\end{aligned}
$$

$$= \sum_{i=1}^{r} h_i^2 \zeta^T(t) \left\{ \Omega_{ii} + \mathcal{A}_{ii}^T \mathscr{R} \mathcal{A}_{ii} \right\} \zeta(t)$$
$$+ \sum_{i=1}^{r} \sum_{i<j}^{r} h_i h_j \zeta^T(t) \left\{ \Omega_{ij} + \Omega_{ji} + (\mathcal{A}_{ij}^T + \mathcal{A}_{ji}^T) \mathscr{R} (\mathcal{A}_{ij} + \mathcal{A}_{ji}) \right\} \zeta(t)$$

By using Schur complements, we can conclude that (15), (16) and (17) are sufficient conditions to guarrentee $\dot{V}(t) < 0$, which further implies the closed-loop system (11) is asymptotically stable from Lyapunov stability theory. The proof is completed. ■

Remark 6. θ in (8) to can be used to regulate the convergent rate of the threshold $\varrho(t)$. For convenience, we let $\theta = 1$ in Theorem 1 and the subsequent results.

As the statement in Remark 4, if we choose $\theta = 0$ in (7), the proposed AETCS turns to be a conventional event-triggered scheme with the format of (9). By using a similar method, we can achieve the following corollary.

Corollary 1. For given positive scalars $\eta_m, \eta_M, \bar{\varrho}$ and matrix K_j ($j \in \mathscr{S}_r$), if there exist real matrices $P > 0, Q_1 > 0, Q_2 > 0, R_1 > 0, R_2 > 0, \Xi > 0$ with appropriate dimensions satisfying the following LMI conditions:

$$\begin{bmatrix} \hat{\Omega}_{ii} & * \\ \mathscr{R}\mathcal{A}_{ii} & -\mathscr{R} \end{bmatrix} < 0 \qquad i \in \mathscr{S}_r \tag{20}$$
$$\begin{bmatrix} \hat{\Omega}_{ij} + \hat{\Omega}_{ji} & * \\ \mathscr{R}(\mathcal{A}_{ij} + \mathcal{A}_{ji}) & -\mathscr{R} \end{bmatrix} < 0 \qquad i < j\ (i, j \in \mathscr{S}_r) \tag{21}$$
$$\begin{bmatrix} \bar{R}_2 & * \\ U & \bar{R}_2 \end{bmatrix} > 0 \tag{22}$$

where

$$\hat{\Omega}_{ij} = \delta_1^T P \mathcal{A}_{ij} + \mathcal{A}_{ij}^T P \delta_1 + diag\{Q_1 + Q_2, -Q_1, \bar{\varrho}\Xi, -Q_2, -\Xi, 0, 0\}$$
$$- \begin{bmatrix} W_1 \\ W_2 \end{bmatrix}^T \begin{bmatrix} \bar{R} & * \\ U & \bar{R} \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix}^T \begin{bmatrix} -R_1 & * \\ R_1 & -R_1 \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix}$$

and the other parameters are defined in Theorem 1. Then the closed-loop system (11) with the event-triggered scheme in (9) is asymptotically stable.

Next, based on Theorem 1, a sufficient condition for co-designing of the weight of event-triggered condition Ξ and the controller gain K_j ($j \in \mathscr{S}_r$) will be presented.

Theorem 2. For given positive scalars $\eta_m, \eta_M, \vartheta$ and μ_k ($k = 1, 2$), if there exist real matrices $X > 0, \bar{Q}_1 > 0, \bar{Q}_2 > 0, \tilde{R}_1 > 0, \tilde{R}_2 > 0, \Xi$ and Y_j ($j \in \mathscr{S}_r$) with appropriate dimensions satisfying the following LMI conditions:

$$\begin{bmatrix} \bar{\Omega}_{ii} & * \\ \bar{\mathcal{A}}_{ii} & \bar{\Upsilon}_1 \end{bmatrix} < 0 \qquad i \in \mathscr{S}_r \tag{23}$$
$$\begin{bmatrix} \bar{\Omega}_{ij} + \bar{\Omega}_{ji} & * \\ \bar{\mathcal{A}}_{ij} + \bar{\mathcal{A}}_{ji} & \bar{\Upsilon}_2 \end{bmatrix} < 0 \qquad i < j\ (i, j \in \mathscr{S}_r) \tag{24}$$
$$\begin{bmatrix} \bar{\mathcal{R}}_2 & * \\ \bar{U} & \bar{\mathcal{R}}_2 \end{bmatrix} > 0 \tag{25}$$

where

$$\begin{aligned}\bar{\Omega}_{ij} &= \delta_1^T\bar{\mathcal{A}}_{ij} + \bar{\mathcal{A}}_{ij}^T\delta_1 + diag\{\bar{Q}_1 + \bar{Q}_2, -\bar{Q}_1, \bar{\Xi}, -\bar{Q}_2, -\vartheta\bar{\Xi}, 0, 0\} \\ &- \begin{bmatrix} W_1 \\ W_2 \end{bmatrix}^T \begin{bmatrix} \mathcal{R}_2 & * \\ \bar{U} & \mathcal{R}_2 \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix}^T \begin{bmatrix} -\tilde{R}_1 & * \\ \tilde{R}_1 & -\tilde{R}_1 \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix}\end{aligned}$$

$$\begin{aligned}\bar{\mathcal{A}}_{ij} &= \begin{bmatrix} A_iX & 0 & B_iY_j & 0 & -B_iY_j & 0 & 0 \end{bmatrix} \\ W_1 &= \begin{bmatrix} \delta_1 - \delta_3 \\ \delta_1 + \delta_3 - 2\delta_6 \end{bmatrix}, W_2 = \begin{bmatrix} \delta_3 - \delta_4 \\ \delta_3 + \delta_4 - 2\delta_7 \end{bmatrix}, \\ \mathcal{R}_2 &= diag\{\tilde{R}_2, 3\tilde{R}_2\}, \bar{\Upsilon}_k = -2\mu_k X + \mu_k^2\tilde{\mathscr{R}}, \\ \tilde{\mathscr{R}} &= \eta_m\tilde{R}_1 + \eta_M\tilde{R}_2\end{aligned}$$

Then the closed-loop system (11) is asymptotically stable under the proposed event-triggering condition (8). Moreover, the controller gain in (5) is given by $K_j = Y_jX^{-1}$, and the adaptive law of the AETCS can be achieved on-line by

$$\dot{\varrho}(t) = \frac{1}{\varrho(t)}\left(\frac{1}{\varrho(t)} - \vartheta\right)e^T(t)X^{-1}\bar{\Xi}X^{-1}e(t) \tag{26}$$

Proof: Pre- and post-multiplying (15) and (16) with diag$\{I, P\mathscr{R}^{-1}\}$, diag$\{I, P\mathscr{R}^{-1}\}$ and theirs transposes, we have

$$\begin{bmatrix} \Omega_{ii} & * \\ P\mathcal{A}_{ii} & -P\mathscr{R}^{-1}P \end{bmatrix} < 0 \qquad i \in \mathscr{S}_r \tag{27}$$

$$\begin{bmatrix} \Omega_{ij} + \Omega_{ji} & * \\ P(\mathcal{A}_{ij} + \mathcal{A}_{ji}) & -P\mathscr{R}^{-1}P \end{bmatrix} < 0 \qquad i < j \in \mathscr{S}_r \tag{28}$$

It is noted that

$$(\mu_k\mathscr{R} - P)\mathscr{R}^{-1}(\mu_k\mathscr{R} - P) \geq 0 \tag{29}$$

where μ_k $(k = 1, 2)$ is a positive scalar. Then it is true that

$$-P\mathscr{R}^{-1}P \leq -2\mu_kP + \mu_k^2\mathscr{R} \tag{30}$$

It follows that

$$\begin{bmatrix} \Omega_{ii} & * \\ P\mathcal{A}_{ii} & -\Upsilon_1 \end{bmatrix} < 0 \qquad i \in \mathscr{S}_r \tag{31}$$

$$\begin{bmatrix} \Omega_{ij} + \Omega_{ji} & * \\ P(\mathcal{A}_{ij} + \mathcal{A}_{ji}) & -\Upsilon_2 \end{bmatrix} < 0 \qquad i < j \in \mathscr{S}_r \tag{32}$$

where $\Upsilon_k = -2\mu_kP + \mu_k^2\mathscr{R}$.

Define $X = P^{-1}, \bar{Q}_1 = XQ_1X, \bar{Q}_2 = XQ_2X, \tilde{R}_1 = XR_1X, \tilde{R}_2 = XR_2X, \bar{U} = XUX, Y = KX$, $J = $ diag$\{X, X, X, X, X, X, X\}$. It can obviously see that Eq. (31) and (32) are equivalent to Eq. (15) and (16) by pre- and post-multiplying (31) and (32) with diag$\{J, X\}$ and theirs transposes, respectively. Similarly, we can conclude that (25) is equivalent to (17). This completes the proof. ■

Remark 7. A cone complementary linearization (CCL) algorithm is an alternate algorithm to deal with the non-convex problem [33]. Althouth CCL algorithm can get a less conservative result than those based on the inequality (29), we need more auxiliary variables to solve LMIs. If the nonlinear system with more T-S fuzzy rules and high dimension, the extra computation load is very significant. Therefore, the inequality (29) is used in this study to solve this problem.

Similarly, the following results can be obtained if one uses the event triggering condition with the format of (9).

Corollary 2. For given positive scalars $\eta_m, \eta_M, \underline{\varrho}$ and μ_k $(k = 1, 2)$, if there exist real matrices $X > 0, \bar{Q}_1 > 0, \bar{Q}_2 > 0, \tilde{R}_1 > 0, \tilde{R}_2 > 0, \bar{\Xi}$ and Y_j $(j \in \mathscr{S}_r)$ with appropriate dimensions satisfying the following LMI conditions:

$$\begin{bmatrix} \tilde{\Omega}_{ii} & * \\ \bar{\mathcal{A}}_{ii} & \Upsilon_1 \end{bmatrix} < 0 \qquad i \in \mathscr{S}_r \tag{33}$$

$$\begin{bmatrix} \tilde{\Omega}_{ij} + \tilde{\Omega}_{ji} & * \\ \bar{\mathcal{A}}_{ij} + \bar{\mathcal{A}}_{ji} & \Upsilon_2 \end{bmatrix} < 0 \qquad i < j \; (i, j \in \mathscr{S}_r) \tag{34}$$

$$\begin{bmatrix} \bar{\mathcal{R}}_2 & * \\ \bar{U} & \bar{\mathcal{R}}_2 \end{bmatrix} > 0 \tag{35}$$

where

$$\begin{aligned} \tilde{\Omega}_{ij} &= \delta_1^T \bar{\mathcal{A}}_{ij} + \bar{\mathcal{A}}_{ij}^T \delta_1 + diag\{\bar{Q}_1 + \bar{Q}_2, -\bar{Q}_1, \underline{\varrho}\bar{\Xi}, -\bar{Q}_2, -\bar{\Xi}, 0, 0\} \\ &- \begin{bmatrix} W_1 \\ W_2 \end{bmatrix}^T \begin{bmatrix} \bar{\mathcal{R}}_2 & * \\ \bar{U} & \bar{\mathcal{R}}_2 \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix}^T \begin{bmatrix} -\tilde{R}_1 & * \\ \tilde{R}_1 & -\tilde{R}_1 \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix} \end{aligned}$$

and the others parameters are defined in Theorem 2. Then the closed-loop system (11) is asymptotically stable under the event-triggering condition with the format of (9). Moreover, the weight of event-triggered condition (9) is determined by $\Xi = X^{-1}\bar{\Xi}X^{-1}$ and the controller gain in (5) is given by $K_j = Y_j X^{-1}$.

4. A numerical example

In this section, an example of networked control for an unstable batch reactor [34] is used to demonstrate the effectiveness of the proposed approach.

Example 1. Consider the following nonlinear mass-spring system

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= -0.01x_1(t) - 0.67x_1^3(t) + u(t) \end{aligned}$$

Choose fuzzy membership function as $h_1(t) = 1 - x_1^2(t)$ and $h_2(t) = 1 - h_1(t)$, where $x_1 \in [-1, 1]$. The following fuzzy model is also used to model aforementioned nonlinear system:

$$\begin{aligned} R^1 &: \text{ If } x_1(t) \text{ is } h_1(t) \\ &\quad\; \text{Then } \dot{x}(t) = A_1 x(t) + B_1 u(t) \\ R^2 &: \text{ If } x_1(t) \text{ is } h_2(t) \\ &\quad\; \text{Then } \dot{x}(t) = A_2 x(t) + B_2 u(t) \end{aligned}$$

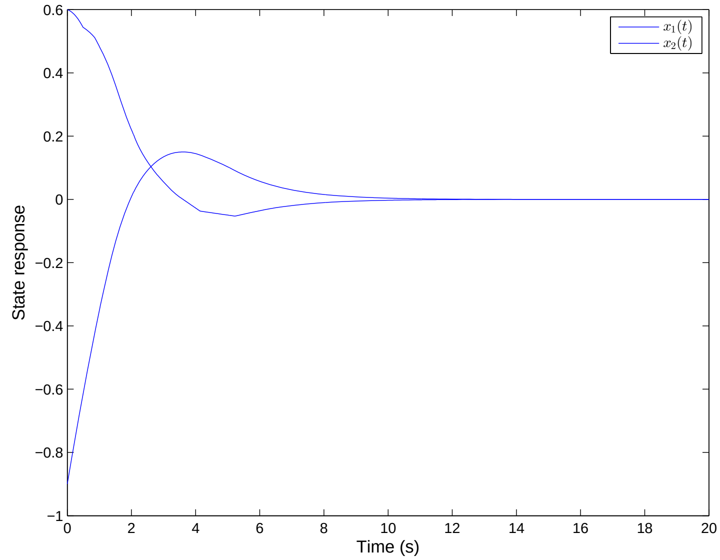

Figure 3: The state trajectories of $x(t)$ under AETCS

where

$$A_1 = \begin{bmatrix} 0 & 1 \\ -0.01 & 0 \end{bmatrix}, A_2 = \begin{bmatrix} 0 & 1 \\ -0.68 & 0 \end{bmatrix}, B_1 = B_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Assume $\eta_m = 0.01$ and $\eta_M = 0.2$ respectively. Using Theorem 2 with $\vartheta = 20, \mu_k = 1$ ($k = 1, 2$), we can obtain the feedback gain in (5) and the weight of event-triggering condition in (8) are give by

$$K_1 = \begin{bmatrix} -0.2590 & -0.9220 \end{bmatrix}, K_2 = \begin{bmatrix} 0.1528 & -1.0964 \end{bmatrix} \tag{36}$$

$$\Xi = \begin{bmatrix} 2.4780 & -2.1003 \\ -2.1003 & 2.4347 \end{bmatrix}, \tag{37}$$

Set the sampling period $h = 0.2s$. Under the initial condition $\phi^T(t) = [-0.9\ 0.6]$, the responses of the system with AETCS are shown in Fig. (3)- Fig. (6). The state trajectories of the system, shown in Fig. 3, demonstrates the effectiveness of the proposed adaptive event-triggered transmission strategy. The control input with the time sequences of the packets is presented in Fig. 4, where the periodic sampling instant, the broadcast instant and the arriving instant of the data at actuator side are depicted by "$\cdot$", "$\circ$ " and "$*$", respectively. From Fig. 4, we can know that: 1) Some sampling data are discarded before accessing the network due to the execution of ADTG; 2) The value of the released data transmitted over the network are kept a constant in the time interval $t \in \chi_{r_s}$ by ZOH; and 3) There exists a network-induced delay from the broadcasting instant at sensor side to the arriving instant at actuator side. As can be seen from Fig. 5 that the threshold of AETCS is regulated continually till the error reaches to a stable state. In this case, the threshold $\varrho(t)$ converges to 0.0504 finally. Fig. 6 shows the maximum number of successive packet losses, which further demonstrates the effect of the adaptive event-triggered scheme on the network-transmitted mechanism.

To compare performance of the proposed AETCS with the conventional ETS, we choose the threshold $\bar{\rho}$ of ETS in (9) as 0.0504, which is a stable value of AETCS in the above case.

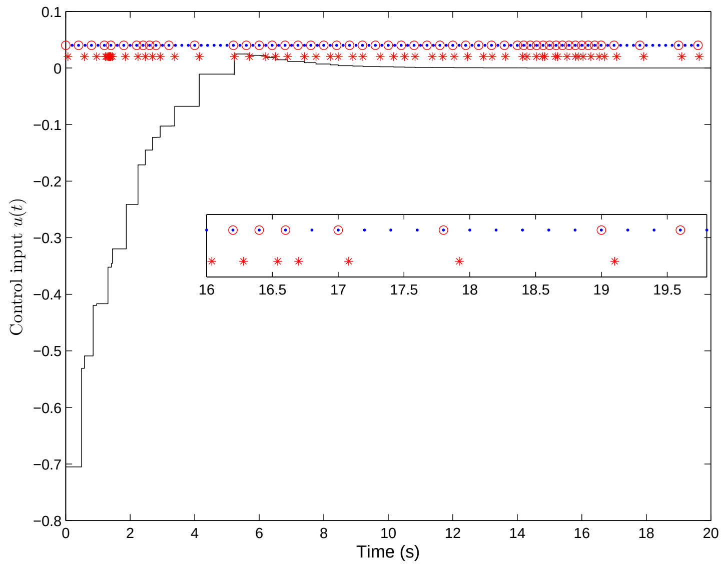

Figure 4: The control input $u(t)$ of the system with AETCS

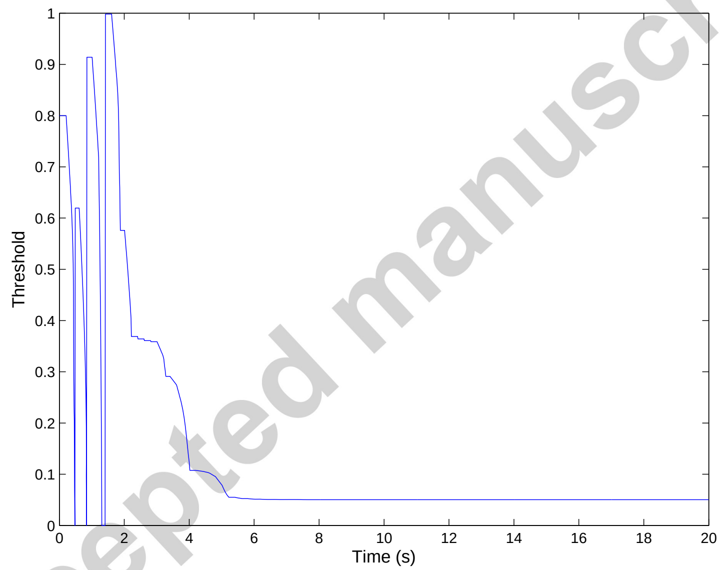

Figure 5: The threshold $\varrho(t)$ of the system with AETCS

By using Corollary 2, we can obtain the related parameters as follows

$$K_1 = \begin{bmatrix} -0.2589 & -0.8222 \end{bmatrix}, K_2 = \begin{bmatrix} 0.1531 & -1.0967 \end{bmatrix} \tag{38}$$

$$\Xi = \begin{bmatrix} 48.8018 & -41.3477 \\ -41.3477 & 47.8804 \end{bmatrix}, \tag{39}$$

Fig. 7 and Fig 8 show the state trajectories of the system and the number of successive packet losses under the ETS with the parameters in (38)-(39) and the same initial conditions with AETCS above. From the state responses of the system in Fig. 3 and Fig. 7, one can see that the state variation is bigger in the period of 0-8s than the one in the period of 8-12s. Table 4 shows that the numble of packet-sampling (NPS) is 40 in the period of 0-8s under the sampling period $h = 0.2$s; and the number of packet-loss (NPL) is 20 by using the proposed

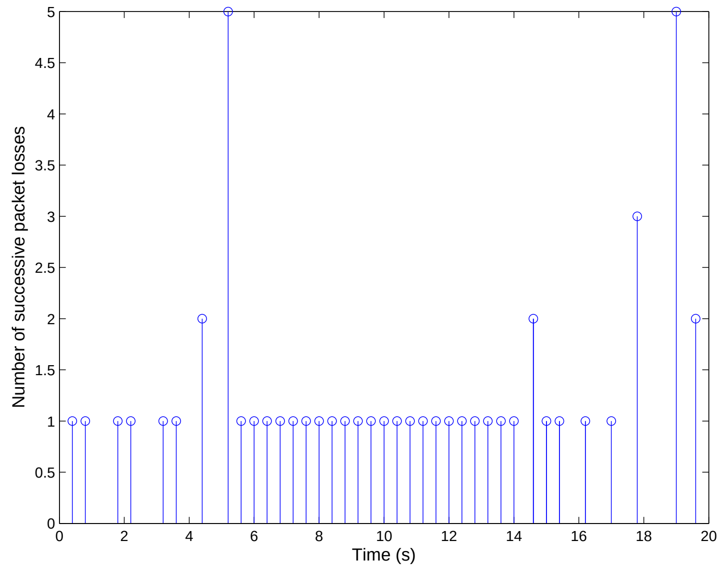

Figure 6: The maximum number of successive packet losses $\bar{l}$ under AETCS

AETCS and 30 by using ETS. While 34 and 32 data-packets are discarded by using AETCS and ETS in the period of 8-20s, respectively. In the period of 0-8s, 50% of sampling packets are used to adapt with the variation of the system, which is 25% more than the one by using ETS. To meet this requirement, the threshold is regulated continually during this period. A better performance can be got by the proposed AETCS than the conventional ETS due to the more "necessary" sampling data being transmitted over the network, which can be illustrated by comparing Fig. 3 withFig. 7. During the period of 8-12s, the system approaches to steady state, NPL is roughly same due to a nearly same threshold during this period.

Table 1: The packet-loss under AETCS and ETS

		0-8s	8-20s
NPS		40	60
NPL	AETCS	20	34
	ETS	30	32

5. Conclusion

In this paper, a novel adaptive event-triggered communication scheme is presented for a class of networked T-S fuzzy systems. The threshold of the event-triggered condition can be achieved by the proposed adaptive law on-line, rather than a preset constant in the conventional event-triggered scheme. A new Lyapunov function is constructed tactfully with consideration of the adaptive law and the stabilization criterion is derived in terms of matrix inequalities by which the weight of the triggering condition and the feedback gain can be obtained simultaneously. Simulation results show that the network resource can be saved to allocate other communication task by using the proposed AETCS.

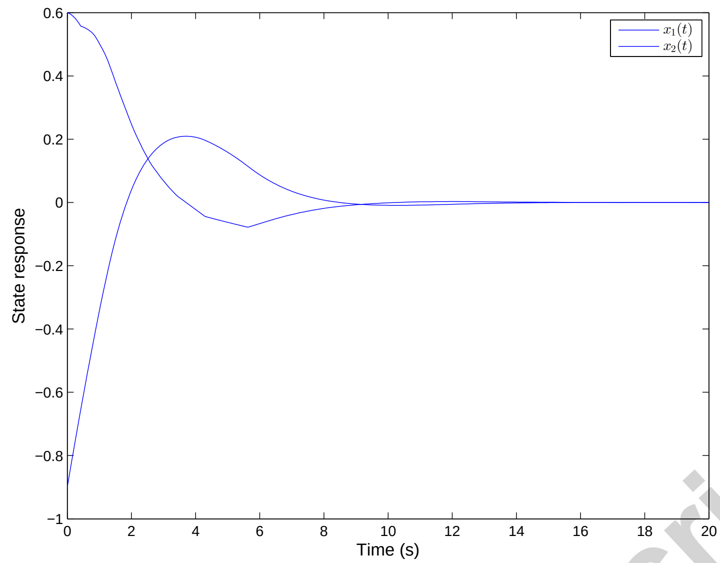

Figure 7: The state trajectories of $x(t)$ of the system with ETS in (9)

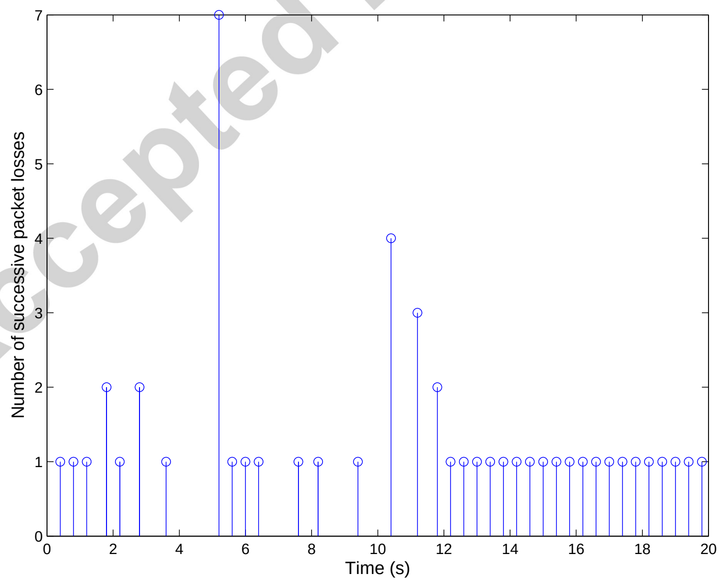

Figure 8: The maximum number of successive packet losses $\bar{l}$ under ETS in (9)

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