Adaptive memory-event-triggered $H_\infty$ control for network-based T-S fuzzy systems with asynchronous premise constraints

Yucheng Shi$^1$ | Engang Tian$^2$ | Shibin Shen$^3$ | Xia Zhao$^1$

$^1$ College of Science, University of Shanghai for Science and Technology, Shanghai, China
$^2$ School of Optical-Electrical and Computer Engineering, University of Shanghai for Science and Technology, Shanghai, China
$^3$ School of Electrical and Automation Engineering, Nanjing Normal University, Nanjing, China

Abstract

This paper presents a novel adaptive memory-event-triggered scheme (A-METS) for network-based T-S fuzzy systems with asynchronous premise constraints. Different from the event-triggered scheme (ETS), the proposed A-METS has two characters. First, some recent released packets are applied in deciding whether the current packet is supposed to be released. Second, the triggering parameter can adjust itself according to the variation of the state. It should be pointed out that the proposed adaptive memory-event-triggered scheme can save network recourses and improve the system performance simultaneously when compared with ETS or adaptive ETS. Furthermore, considering the network environment, the asynchronous premise between the fuzzy plant and controller are considered. By resorting to the Lyapunov functional approach, sufficient conditions are derived for the stability and $H_\infty$ performance of the network-based T-S fuzzy systems. For the sake of illustrating the usefulness of the proposed adaptive memory-event-triggered scheme, a tunnel diode circuit example is demonstrated at the end of this paper.

1 | INTRODUCTION

In networked control systems (NCSs), sensors, actuators, controllers and other major features are connected through wire/wireless network, wherein relevant control/measurement signals are transferred through a communication network [1, 2]. The main advantages of NCSs include resource sharing, remote operating and control, increasing flexibility and reliability and so on. Based on these merits, many fruitful results have been proposed (see [3–7] and the references therein). Nowadays, NCSs are used in many fields such as industrial automation, multi-agents systems, unmanned marine vehicles [8–11].

Recently, event-triggered scheme (ETS) has become a hot topic because it can improve the network utilisation effectively by holding back the unnecessary executions. In general, the ETS works as follows, when a new packet is sampled, which is computed through a triggering conditions, if this condition is satisfied, this packet is regarding as “necessary” one and released to the controller, else, it will be dropped. Obviously, the triggering condition plays an utmost key role in the ETS. The parameters in ETS usually contains a triggering threshold, the most recent released packet, the current packets and/or a positive matrix variable to be designed. In most of the studies, a static triggering threshold is used [12–18], which is pre-selected and cannot be adjusted according to the system and network conditions. For example, in [18], fuzzy bipartite tracking control problem for stochastic non-linear multi-agent systems is investigated, where ETS has been applied to reduce the buren of communication. More recently, in order to make the ETS more “smart,” an adaptive ETS (AETS) is introduced [19–22], wherein the threshold can adjust itself according to the system dynamics. To name a few, in [21], an AETS was proposed to mitigate the burden of network-bandwidth for a class of the non-linear systems, where a new adaptive law was presented to achieve the threshold of event-triggering condition on-line. In [22], an AETS was well used in reducing the load frequency of the power system and ensuring resources utilisation. Compared with static ETS, AETS can transmit fewer packets because its threshold is a parameter that can be dynamically adjusted. Although the AETS can further reduce the packets transmission, the system’s dynamic...
may have a degradation when compared with the static ETS. For other kinds of ETS methods, when considering specific media access protocols, a dynamic ETS was proposed in an output-based or decentralised form in [23]. It should be noted that in most of the ETS mentioned above, only the current packets and the newly released packets are used in the event-triggered conditions. As such, some newly released packets were considered, and a memory event-triggered communication scheme (METS) was constructed in [24, 25]. By using the METS, when the system fluctuates wildly, more packets will be released to stabilise the system quickly. However, more packets are probably to be released when compared with static ETS. Therefore, how to design a triggering scheme to give consideration to data transmission and system performance still needs further investigation.

As we all know, T-S fuzzy models have been well paid to characterising non-linear systems, and the common used fuzzy controller design method is parallel distribution compensation (PDC) [26–31]. The T-S fuzzy system is represented by numerous IF-Then rules, which can treat the non-linear system as a fuzzy approximation of multiple local linear models. Therefore, much research enthusiasm has recently been attracted towards the T-S fuzzy systems because of the wide applications in automobile suspension system, the internal combustion engine systems and other fields. [32, 33]. When considering the network-based T-S fuzzy systems, some event-triggered control/filter methods have been concerned in [34–37]. For example, in [37], a new discrete ETS was proposed for T-S fuzzy system. In [38], the problem of tracking control of T-S fuzzy systems is studied, where a novel AETS is employed to save the limited network bandwidth. In these literatures, the premise variables of the system and the fuzzy controller are synchronous. Actually, it is worth noting that the network exists all the time in the process of data transmission, and the asynchronous premise variables will reflect the real situation more truly. Considering this, in [39–41], methods of asynchronous premise reconstruction are designed in terms of the fuzzy systems with ETS. Moreover, for some non-PDC methods, the asynchronous problem is handled by the membership functions with upper and lower bounds [42, 43]. In [44], dynamic output feedback control problem with ETS was investigated to deal with the problem of asynchronous constraints by designing two independent membership functions.

Inspired by the aforementioned discussion, combining the advantages of the AETS and METS, a novel adaptive METS is proposed for network-based T-S fuzzy system with asynchronous premise variables. The main contributions of this paper are summarised as follows:

1) An adaptive memory event-triggered communication scheme (A-METS) is, for the first time, introduced to reduce the number of transmissions effectively and improve the system performance for network-based T-S fuzzy systems.

2) For the sake of ensuring the stability and $H_{\infty}$ performance of the considered systems, an asynchronous premise reconstruction method for T-S fuzzy systems is considered. Correspondingly, the memory fuzzy controller is designed while taking both the effects of the asynchronous premise and A-METS into consideration.

The organisation of this paper is as follows: Section 2 presents an A-METS and asynchronous premise variables for networked T-S fuzzy systems. In Section 3, two theorems are given for the stability and $H_{\infty}$ controller design for the studied systems. A simulation example is presented in Section 4 and Section 5 states conclusions.

2 | PROBLEM FORMULATION

2.1 | Network-based T-S fuzzy systems

Considering a non-linear system which is denoted as

$$ R^e : \text{If} \, \xi_1(x(t)) \in \mathcal{E}_i^1, \ldots, \text{and} \, \xi_g(x(t)) \in \mathcal{E}_g^g. $$

Then

$$ \begin{align*}
\dot{x}(t) &= A_i x(t) + B_i u(t) + R_{ij} \omega(t), \\
\xi(t) &= C_i x(t) + D_i u(t),
\end{align*} \tag{1} $$

where $x(t) \in \mathbb{R}^n$ and $u(t) \in \mathbb{R}^m$ are the state and input vector, respectively. $\omega(t) \in \mathcal{L}_1[0, \infty)$ denotes the external disturbance signal, $\xi(t) \in \mathbb{R}^g$ represents the system output, $i = 1, 2, \ldots, r$, $r$ is the number of IF-THEN rules, $\mathcal{E}_i^j$ are fuzzy sets and $\xi_j(x(t))(j = 1, 2, \ldots, g)$ represent premise variables and define $\xi(x(t)) = [\xi_1(x(t)), \ldots, \xi_g(x(t))]^T$. $A_i$, $B_i$, $C_i$, $R_{ij}$ and $D_i$ are known constant matrices with appropriate dimensions.

The global fuzzy system can be derived by means of the weighted average of multiple local linear models

$$ \begin{align*}
\dot{x}(t) &= \sum_{i=1}^{r} \lambda_i \xi(x(t))(A_i x(t) + B_i u(t) + R_{ij} \omega(t)), \\
\xi(t) &= \sum_{i=1}^{r} \lambda_i \xi(x(t))(C_i x(t) + D_i u(t)),
\end{align*} \tag{2} $$

where

$$ \lambda_i \xi(x(t)) = \frac{\prod_{j=1}^{g} \mathcal{E}_j^j(\xi_j(x(t)))}{\sum_{i=1}^{r} \prod_{j=1}^{g} \mathcal{E}_j^j(\xi_j(x(t)))} \geq 0, \tag{3} $$

$\mathcal{E}_j^j(\xi_j(x(t)))$ is the membership value of $\xi_j(x(t))$ in $\mathcal{E}_j^j$ and $\sum_{i=1}^{r} \lambda_i \xi(x(t)) = 1$.

Considering the impact of the network environment, the premise variables at the controller should be $\xi(x(t_k))$, the $i$th controller rule is

$$ R^e : \text{If} \, \xi_1(x(t_k)) \in \mathcal{E}_i^1, \ldots, \text{and} \, \xi_g(x(t_k)) \in \mathcal{E}_g^g. $$

Then $u(t) = K_i x(t_k)$, $j = 1, 2, \ldots, r$, \tag{4}
where \( K_j \) are controller gain to be determined later.

### 2.2 Network-based T-S fuzzy controller with asynchronous premise constraints

Similar to the analysis of [14], we define \( \tau_{tkh} \) as the communication delay of the sampled packet \( x(t_k b) \) and \( \tau(l) = t - (t_k b + lb) \), \( b \) is the sampling period. The control input will remain the same in the interval \( [t_k b + \tau_{tkh}, t_{k+1} b + \tau_{tkh+1}] \). Using virtual partition method, the interval is divided into the following sub-intervals

\[
\begin{align*}
\mathcal{R}_0 &= [t_k b + \tau_{tkh}, t_{k+1} b + \tau_{tkh}], \\
\mathcal{R}_l &= [t_k b + lb + \tau_{tkh}, t_{k+1} b + lb + \tau_{tkh}], \quad l = 1, 2, ..., d_k - 1, \\
\mathcal{R}_{d_k} &= [t_k b + lb + \tau_{tkh}, t_{k+1} b + lb + \tau_{tkh+1}],
\end{align*}
\]

where \( \mathcal{R} = \bigcup_{l=0}^{d_k} \mathcal{R}_l \), \( \tau \) is the upper boundary of \{\tau_{tkh}\}. \( \tau(l) \) satisfies the following inequality for \( t \in \mathcal{R}_l \)

\[
0 \leq \tau_{tk} \leq \tau(l) \leq b + \tau \triangleq \tau_{M}, \quad \tau(l) = 1. \tag{6}
\]

Then, the fuzzy controller is easily obtained

\[
u(t) = \sum_{j=1}^{r} \lambda_j \psi_j(x(t_k b)) K_j x(t - \tau(l)). \tag{7}\]

Combining (7) and (9) together, for \( j = 1, 2, ..., r \), we conclude that

\[
u(t) = \sum_{j=1}^{r} \mu_j \lambda_j \psi_j(x(t)) K_j x(t - \tau(l)). \tag{13}\]

### 2.3 The adaptive memory event-triggered scheme

Firstly, let us review the static ETS proposed in [14] is expressed as

\[
\begin{align*}
t_{k+1} b &= t_k b + \min \left\{ lb \in \mathbb{N} \mid \| \Phi \| T \Phi x(t_k b) > \rho (t_k b) \right\}, \tag{14}
\end{align*}
\]

where \( e_{k,i} = (t_k b) - x(t_k b + lb), i \in \mathbb{N} \), \( \Phi \) is a triggered parameters and \( \rho \) is a given arbitrary scalar.

**Remark 1.** In the ETS (14), it is obvious that the triggering threshold \( \rho \) and the error \( e_{k,i} \) both determine whether a newly sampled packet is transmitted. For example, a smaller \( \rho \) and a larger \( e_{k,i} \) will give rise to more triggering instants, that is, the more packets are probably to be transmitted.

In this paper, combining the advantages of AETS and METS, an A-METS is proposed, which is described as

\[
\begin{align*}
t_{k+1} b &= t_k b + \min \left\{ lb \in \mathbb{N} \mid \| \Phi \| T \Phi x(t_k b) > \rho (t_k b) \right\}, \tag{15}
\end{align*}
\]

where \( e_{k,i} = (t_k b) - x(t_k b + lb), i \in \mathbb{N} \), \( \Phi \) is a triggered parameters satisfying \( 0 \leq \sigma_p \leq 1 \).

Different from the predetermined \( \rho \) in (14), \( \rho(t_k b) \) in (15) can be adaptively adjusted based on the following rule:

\[
\rho(t_{k+1} b) = \max \{ \bar{\rho}, \nu \rho(t_k b) \}, \tag{16}
\]

where \( \bar{\rho} > 0 \), and the parameter \( \nu \) is determined by

\[
\nu = \begin{cases} 
0, & \text{if } \| x(t_{k+1} b) \| \geq \| x(t_k b) \| \\
1 - \frac{2 \alpha}{\pi} \arctan \frac{\| x(t_{k+1} b) \| - \| x(t_k b) \|}{\| x(t_k b) \|}, & \text{otherwise}
\end{cases}, \tag{17}
\]

where we set \( \alpha > 0 \). The initial of \( \rho(t_k b) \) is given as \( \rho(0) = \bar{\rho} \). From (16), we can see that \( \bar{\rho} \) is the lower bound of \( \rho(t_k b) \) and a larger \( \alpha \) will result a larger change rate of \( \rho(t_k b) \).
Remark 2. Obviously, the function arctan(⋅) in (16) is a bounded function, that is, arctan(⋅) ∈ \((-\frac{\pi}{2}, \frac{\pi}{2})\). The system can adaptively adjust the triggered threshold parameter \(\varrho(t)\) based on this feature. For example, if ||\(x(t_b)\)|| > ||\(x(t_{b+1})\)||, one can derive that \(\varrho(t_b) > \varrho(t_{b+1})\). Consequently, a smaller \(\varrho(t_{b+1})\) will lead to a higher communication efficiency. In reverse, a larger value of \(\varrho(t_{b+1})\) can obtain a lower transmission efficiency.

Remark 3. In some existing work, AETS and METS have been investigated yet. AETS has the advantage of reducing the transmission of packets effectively and saving limited bandwidth [22]. METS has the advantage of utilising some historic signals to improve the performance of the system [24, 25]. In this paper, considering the advantages of both AETS and METS, an A-METS is proposed. In the A-METS (15), \(m\) is view as the number of the historic released packets to reflect the existence of memory. It is clear that the A-METS becomes the traditional AETS when \(m = 1\). The weighting parameters \(\sigma_\omega\) can illustrate the significance of the released packets. Usually, we view the newly released packets as more important. Therefore, it is assumed to be \(\sigma_\omega > \sigma_\omega_{k+1}\), \((k = 1, 2, \ldots, m - 1)\).

For convenience, \(\lambda_i(\xi(\tau(t)))\) is written as \(\lambda_i\), according to (15), the expression of memory fuzzy controller is obtained as

\[
n(t) = \sum_{i=1}^{r} \sum_{j=1}^{m} \mu_i A_i K_{ij} \xi(t - \tau(t)) + \epsilon_i, \quad t \in \mathcal{R}.
\]

Substituting (18) into (2) leads to the following fuzzy system:

\[
\begin{align*}
\dot{x}(t) &= A_i x(t) + B_{ij} \xi(t - \tau(t)) + \epsilon_i + B_{ij} \omega(t), \\
\dot{z}(t) &= C_i x(t) + D_{ij} \xi(t - \tau(t)) + \epsilon_i, \quad t \in \mathcal{R},
\end{align*}
\]

where

\[
\begin{align*}
A_i &= \sum_{j=1}^{r} \sum_{j=1}^{m} \mu_i A_i, \quad B_{ij} = \sum_{j=1}^{r} \sum_{j=1}^{m} \mu_i A_i B_{ij}, \\
C_i &= \sum_{j=1}^{r} \sum_{j=1}^{m} \mu_i A_i C_{ij}, \quad D_{ij} = \sum_{j=1}^{r} \sum_{j=1}^{m} \mu_i A_i D_{ij}, \\
B_{ij} &= \sum_{j=1}^{r} \sum_{j=1}^{m} \mu_i B_{ij}.
\end{align*}
\]

By using the proposed A-METS, the purpose of this paper is to design the fuzzy memory feedback controller, such that the following two requirements are satisfied.

1) The system (19) is asymptotically stable with \(\omega(t) = 0\).

2) Under zero initial condition, for any non-zero \(\omega(t) \in \mathcal{L}_2[0, \infty]\) and a prescribed index \(\gamma\), such that inequality \(||\tau(t)||_2 \leq \gamma ||\omega(t)||_2\) holds.

3.1 MAIN RESULTS

We aim to exploit a method for the sake of ensuring stability and designing controller for the studied systems. First of all, the following three lemmas are given for obtaining the desired results. Then, the sufficient condition that ensures the \(H_{\infty}\) performance is established.

**Lemma 1.** [45] For arbitrary matrices \(Y_1, Y_2\) and \(\Delta\) with compatible dimensions, \(\tau(t)\) is the network-induced delay satisfies \(\tau(t) \in [0, \tau_M]\), the following inequality:

\[
\tau(t) Y_1 + [\tau_M - \tau(t)] Y_2 + \Delta < 0
\]

holds if and only if

\[
\begin{align*}
\tau_M Y_1 + \Delta &< 0, \\
\tau_M Y_2 + \Delta &< 0.
\end{align*}
\]

**Lemma 2.** [46] For arbitrary vector \(a, b \in \mathbb{R}^{n \times 1}\), positive definite matrix \(F \in \mathbb{R}^{n \times n}\), we have the inequality

\[
2 a^T b \leq a^T F^{-1} a + b^T F b.
\]

**Lemma 3.** [46] For arbitrary variable \(\varepsilon\), and \(H, D, P\) are some real matrices with compatible dimensions and \(||P|| \leq 1\), the following inequality is true

\[
HPD + D^T P^T H^T \leq \varepsilon^{-1} H H^T + \varepsilon D^T D.
\]

**Theorem 1.** For given scalars \(\tau_M, \gamma, \delta, \sigma_\omega, \eta_1, \eta_2, m\), and matrix \(K_{ij}\), the system (19) is asymptotically stable if there exist matrices \(P > 0, S_1 > 0, S_2 > 0, L_1 > 0, L_2 > 0\) and some free matrices \(U, G, W\) with compatible dimensions such that the following matrix inequalities hold for \(i, j = 1, 2, \ldots, r, i < j\).
where
\[
\begin{align*}
\Omega_{11}^{ij} &= \Phi^{ij} + \Gamma + \Gamma^T + 2\tau_{M}\mathcal{J}L_1\Sigma_{1}^{ij} \nonumber \\
\Sigma_{11}^{ij} &= \Phi^{ij} + \Gamma + \Gamma^T \nonumber \\
\Phi^{ij} &= |\Phi^{ij}|_{3\times 3} \nonumber \\
(\Phi^{ij})_{11}^{11} &= A_i^T P + P A_i + S_1 - L_1 \nonumber \\
(\Phi^{ij})_{11}^{21} &= \Sigma_{m=1}^{m} K_{i_{m}} B_{i_{m}} P (\Phi^{ij})_{22}^{22} = \hat{\Phi} \nonumber \\
(\Phi^{ij})_{21}^{21} &= L_1 (\Phi^{ij})_{21}^{21} = B_{i_{m}} P \nonumber \\
(\Phi^{ij})_{22}^{22} &= \text{diag} \{-S_1, -L_1, -T^2 I\} \nonumber \\
(\Phi^{ij})_{31}^{31} &= \left[K_{i_{m}} B_{i_{m}} P, \frac{\hat{\Phi}}{m!}\right]_{m \times 2} \nonumber \\
(\Phi^{ij})_{33}^{33} &= \frac{\hat{\Phi}}{m!} \Phi \cdot I_{m} + \text{diag}\{-\sigma_1 \Phi, \ldots, -\sigma_m \Phi\} \nonumber \\
\Gamma &= [U + W, G - U, -G, -W, 0, 0, \ldots, 0] \nonumber \\
\Sigma_{1}^{ij} &= \left[A_i, \Sigma_{m=1}^{m} B_i K_{i_{m}} 0, 0, B_{i_{m}}, B_{i_{m}}, \ldots, B_{i_{m}} K_{i_{m}} \right] \nonumber \\
\Sigma_{2}^{ij} &= \left[C_i, \Sigma_{m=1}^{m} D_i K_{i_{m}} 0, 0, 0, D_i K_{i_{m}}, \ldots, D_i K_{i_{m}} \right] \nonumber \\
\Omega_{21}^{ij} &= \text{col} \left[\sqrt{M} S_1 \Sigma_{1}^{ij}, \sqrt{M} G T, \sqrt{M} L_2 \Sigma_{1}^{ij}, \Sigma_{2}^{ij} \right] \nonumber \\
\Sigma_{21}^{ij} &= \text{col} \left[\sqrt{M} S_1 \Sigma_{1}^{ij}, \sqrt{M} U T, \sqrt{M} W T, \Sigma_{2}^{ij} \right] \nonumber \\
\mathcal{J} &= \text{col}[L, 0, 0, -L, 0, 0, \ldots, 0] \nonumber \\
\Omega_{22} &= \text{diag}\{-S_2, -S_2, -L_2, -I\} \nonumber \\
\Sigma_{22} &= \text{diag}\{-S_2, -S_2, -S_2, -L_2\} - I \nonumber 
\end{align*}
\]

**Proof.** Considering the following Lyapunov function
\[
V(t, x) = V_1(t, x) + V_2(t, x) + V_3(t, x),
\]
where
\[
\begin{align*}
V_1(t, x) &= x^T(t)P x(t) 
\end{align*}
\]
\[
\begin{align*}
V_2(t, x) &= \int_{t-\tau_M}^{t} x^T(\tau)S_1 x(\tau) \ d\tau 
+ \int_{t-\tau_M}^{t} \int_{\tau}^{t} x^T(\tau)S_2 x(\tau) \ d\tau \ d\zeta 
\end{align*}
\]
\[
\begin{align*}
V_3(t, x) &= [\tau_M - \tau(t)] \left\{ x^T(t) - x^T(t) \right\} L_1 [x(t) - x(t)] 
+ \int_{\tau(t)}^{t} x^T(\tau)L_2 x(\tau) \ d\tau 
\end{align*}
\]
and \(P, S_1, S_2, L_1, L_2\) are positive definite matrices, \(x_k = i_k b + \theta + \tau_k\). From the proposed A-METS in (15), we obtain easily that, for \(t \in \mathcal{R}_1\),
\[
\begin{align*}
\sum_{p=1}^{m} \sigma_{i_{p}}^{t} \Phi_{i_{p}} 
\end{align*}
\]
\[
\begin{align*}
&\leq \hat{\rho} \left[ \frac{1}{m} \sum_{p=1}^{m} (e_{i_{p}} + x(t) - x(t)) \right]^{T} 
\Phi \left[ \frac{1}{m} \sum_{p=1}^{m} (e_{i_{p}} + x(t) - x(t)) \right].
\end{align*}
\]
Taking derivation on \(V(t, x)\) and using \(\frac{d}{dt} x(t_k) = 0\), which yields
\[
\begin{align*}
V_1(t, x) &= 2 \sum_{i=1}^{m} \sum_{j=1}^{m} \mu_i \lambda_j \dot{x^T}(t) P \lambda \dot{x}(t) 
+ B_i K_{i_{p}} (x(t) - x(t)) + e_{i_{p}} + B_{i_{m}} w(t)] 
\end{align*}
\]
\[
\begin{align*}
V_2(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber 
\end{align*}
\]
\[
\begin{align*}
V_3(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_4(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_5(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_6(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_7(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_8(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_9(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_{10}(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_{11}(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_{12}(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_{13}(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_{14}(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_{15}(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_{16}(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_{17}(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \nonumber
\end{align*}
\]
\[
\begin{align*}
V_{18}(t, x) &= x^T(t)S_1 x(t) - x(t) - x(t) - x(t) \n
From (28)–(31), we can easily derive
\[
\dot{V}(t, x(t)) = \dot{V}_1(t, x(t)) + \dot{V}_2(t, x(t)) + \dot{V}_3(t, x(t)) + U_1 + U_2 + U_3
\]
\[
\leq \sum_{i=1}^{r} \sum_{j=1}^{r} \mu_i \lambda_i \omega^T(t) (\Theta^{ij} + \Theta^j) \omega(t)\]
\[-\chi^T(t) \chi(t) + \gamma^2 \omega^T(t) \omega(t)\]
where
\[
\Theta^{ij} = \Phi^{ij} + \left[(\tau_M - T_c) + \sum_{j=1}^{r} \mu_j \lambda_j \omega^T(t) \right] \left[ \Sigma_{ij}^1 \right]^T L_2 \Sigma_{ij}^1 + G \Sigma_{ij}^{-1} G^T
\]
\[+ 2 \tau L_1 \Sigma_{ij}^1 \right] + \left( \Sigma_{ij}^2 \right)^T \Sigma_{ij}^2 + \sum \sum \tau \left[T_0^{-1} U^T + W L_1^{-1} W^T \right]
\]
\[
(33)
\]
From Lemma 1 and (32) and (33), we derive
\[
\dot{V}(t, x(t)) + \chi^T(t) \chi(t) - \gamma^2 \omega^T(t) \omega(t)
\]
\[
\leq \sum_{i=1}^{r} \sum_{j=1}^{r} \mu_i \lambda_i \omega^T(t) \left[ \Omega_{ij}^1 - \left( \Omega_{21}^j \right)^T \Omega_{22}^{-1} \Omega_{21}^j + \Xi_{ij}^1 \right]
\]
\[-\left( \Xi_{ij}^2 \right)^T \Xi_{22}^{-1} \Xi_{ij}^2 \right) \omega(t)
\]
\[
= \sum_{i=1}^{r} \sum_{j=1}^{r} \mu_i \lambda_i \omega^T(t) \left[ \Omega_{ij}^1 + \sum_{i=1}^{r} \mu_i \lambda_i \omega^T(t) \left[ \Sigma_{ij}^1 \right]^T L_2 \Sigma_{ij}^1 \right]
\]
\[-\left( \Xi_{ij}^2 \right)^T \Xi_{22}^{-1} \Xi_{ij}^2 \right) \omega(t)
\]
\[
(34)
\]
where $\Omega_{ij}^1$, $\Omega_{ij}^2$, $\Xi_{ij}^1$, $\Xi_{ij}^2$, $\Xi_{22}^1$ are given in Theorem 1.

Define $\varphi_1 = \Omega_{ij}^1 + \gamma \Omega_{ij}^2 - \left( \Omega_{21}^j \right)^T \Omega_{22}^{-1} \Omega_{21}^j$, $\varphi_2 = \Omega_{ij}^1 + \gamma \Omega_{ij}^2 - \left( \Omega_{21}^j \right)^T \Omega_{22}^{-1} \Omega_{21}^j$, by using Schur Complement, for $j = 1, 2, (24)–(27)$ imply
\[
\Omega_{ij}^1 - \left( \Omega_{21}^j \right)^T \Omega_{22}^{-1} \Omega_{21}^j < 0, \quad (35)
\]
\[
\Xi_{ij}^1 - \left( \Xi_{22}^1 \right)^T \Xi_{22}^{-1} \Xi_{ij}^2 < 0, \quad (36)
\]
\[
\varphi_1 - \varphi_2 \left( \Xi_{22}^1 \right)^T \Xi_{22}^{-1} \Xi_{ij}^1 < 0, \quad (37)
\]
\[
(38)
\]
Considering (37) and (38) with $\left( \varphi_2 - \frac{\mu_j}{\mu_i} \right) \left( \Omega_{ij}^1 \right)^T \Omega_{ij}^2 < 0$, $(\varphi_2 - \frac{\mu_j}{\mu_i} \left( \Xi_{22}^1 \right)^T \Xi_{22}^{-1} \Xi_{ij}^1 < 0$, for $j = 1, 2$, we obtain
\[
\varphi_1 - \frac{\mu_i}{\mu_j} \left( \Omega_{ij}^1 \right)^T \Omega_{ij}^2 < 0, \quad (39)
\]
\[
\varphi_2 - \frac{\mu_i}{\mu_j} \left( \Xi_{22}^1 \right)^T \Xi_{22}^{-1} \Xi_{ij}^1 < 0, \quad (40)
\]
Define
\[
\kappa_1 = \frac{\varphi_1 - \mu_i}{\mu_j} \varphi_2, \quad \kappa_2 = \frac{\mu_i}{\mu_j} \varphi_2 - \varphi_1.
\]
Combining (39) and (40), for $j = 1, 2$, we can easily derive
\[
\sum_{j=1}^{2} \kappa_j \left[ \varphi_1 - \frac{\mu_i}{\mu_j} \left( \Omega_{ij}^1 \right)^T \Omega_{ij}^2 < 0, \quad (42)
\right.
\]
\[
\sum_{j=1}^{2} \kappa_j \left[ \varphi_2 - \frac{\mu_i}{\mu_j} \left( \Xi_{22}^1 \right)^T \Xi_{22}^{-1} \Xi_{ij}^1 < 0, \quad (43)
\right.
\]
which yields
\[
\Omega_{ij}^1 + \frac{\mu_i}{\mu_j} \Omega_{ij}^2 - \left( \Omega_{21}^j \right)^T \Omega_{22}^{-1} \Omega_{21}^j - \frac{\mu_i}{\mu_j} \left( \Omega_{ij}^1 \right)^T \Omega_{ij}^2 < 0, \quad (44)
\]
\[
\Xi_{ij}^1 + \frac{\mu_i}{\mu_j} \Xi_{22}^1 - \left( \Xi_{22}^1 \right)^T \Xi_{22}^{-1} \Xi_{ij}^1 - \frac{\mu_i}{\mu_j} \left( \Xi_{ij}^1 \right)^T \Xi_{22}^1 < 0, \quad (45)
\]
From (34), (35), (36), (44) and (45), we derive
\[
\dot{V}(t, x(t)) + \chi^T(t) \chi(t) - \gamma^2 \omega^T(t) \omega(t) \leq 0. \quad (46)
\]
Integrating both sides of (46) from 0 to $\infty$, we derive $\left\| \chi(t) \right\|_2 \leq \gamma^2 \left\| \omega(t) \right\|_2$ under zero initial condition.

From the inequalities (24)–(27), it can be concluded that when $\omega(t) = 0$, there exists a positive scalar $\chi > 0$ such that $\dot{V}(t, x(t)) \leq -\chi \left\| x(t) \right\|_2^2$, which implies system (19) is asymptotically stable with $H_\infty$ performance. The proof has been completed.

**Theorem 2.** For given scalars $\tau_M$, $\Sigma$, $\theta$, $\sigma$, $\eta$, $\eta_2$, $\delta_1$, $\delta_2$, $\delta_3$, $\mu$, and $\gamma$, the system (19) is asymptotically stable with $H_\infty$ performance $\gamma$, the memory controller gains is $K_{jp} = Y_{jp}^{-1}$, if there exist $X > 0$, $\delta_1 > 0$, $\delta_2 > 0$, $\delta_3 > 0$, $L_1 > 0$, $L_2 > 0$ and matrices $Y_{jp}$ $p = 1, 2, ..., m$, $U$, $W$, $V$...
and \( \hat{\mathcal{C}} \), with compatible dimensions such that

\[
\begin{bmatrix}
\hat{\Omega}^i_{11} & * \\
\hat{\Omega}^i_{21} & \hat{\Omega}^i_{22}
\end{bmatrix} < 0,
\]

(47)

\[
\begin{bmatrix}
\hat{\Xi}^i_{11} & * \\
\hat{\Xi}^i_{21} & \hat{\Xi}^i_{22}
\end{bmatrix} < 0,
\]

(48)

\[
\begin{bmatrix}
\hat{\Omega}^i_{11} + \eta_i \hat{\Omega}^i_{11} & * & * \\
\hat{\Omega}^i_{21} & \hat{\Omega}^i_{22} & * \\
\sqrt{\mu_i} \hat{\Omega}^i_{21} & 0 & \hat{\Omega}^i_{22}
\end{bmatrix} < 0, \quad i = 1, 2,
\]

(49)

\[
\begin{bmatrix}
\hat{\Xi}^i_{11} + \eta_i \hat{\Xi}^i_{11} & * & * \\
\hat{\Xi}^i_{21} & \hat{\Xi}^i_{22} & * \\
\sqrt{\mu_i} \hat{\Xi}^i_{21} & 0 & \hat{\Xi}^i_{22}
\end{bmatrix} < 0, \quad i = 1, 2,
\]

(50)

where

\[
\hat{\Omega}^i_{11} = \Omega^i_{11} = \Phi^i + \Gamma + \Gamma^T
\]

\[
(\Phi^i)_{11} = X^T A_f + A_f X + \frac{1}{2}(\frac{1}{2} I_2) - L_1
\]

\[
(\Phi^i)_{11} = \sum_{p=1}^m X_p^T B_{ij}^T, \quad (\Phi^i)_{21} = B_{ij}^T
\]

\[
(\Phi^i)_{22} = \text{diag} \left\{ -3\delta_i, -3\delta_i, -\gamma^2 I \right\}
\]

\[
(\Phi^i)_{31} = \begin{bmatrix} Y_{ij}^TB_{ij}^T, \frac{\bar{\gamma}}{m^2} \Phi \end{bmatrix}
\]

(51)

\[
(\Phi^i)_{33} = \frac{\bar{\gamma}}{m^2} \Phi \cdot I_n + \text{diag}(-\sigma_i \Phi, \ldots, -\sigma_i \Phi)
\]

\[
\Gamma = [U + \|V\|, \hat{\mathcal{C}} - \hat{\mathcal{C}} - \|V\|, 0, 0, \ldots, 0]
\]

\[
\mathcal{F} = \text{col}[X, 0, 0, -X, 0, 0, \ldots, 0]
\]

\[
\hat{\Sigma}_1 = \begin{bmatrix} A_1 X, \sum_{p=1}^m B_1 Y_{jp}, 0, 0, B_{ai} B_1 Y, \ldots, B_1 Y_{jm} \end{bmatrix}
\]

\[
\hat{\Sigma}_2 = \begin{bmatrix} C_1 X, \sum_{p=1}^m D_1 Y_{jp}, 0, 0, 0, D_1 Y_{11}, \ldots, D_1 Y_{jm} \end{bmatrix}
\]

\[
\bar{\Omega}^i_{21} = \text{col} \begin{bmatrix} \sqrt{\tau_M \Sigma^i_1}, \sqrt{\tau_M \Sigma^i_2}, \sqrt{\tau_M \Sigma^i_1}, \sqrt{\tau_M \Sigma^i_2}, \sqrt{\tau_M \Sigma^i_1}, \sqrt{\tau_M \Sigma^i_2} \end{bmatrix}
\]

\[
\hat{\Xi}^i_{21} = \text{col} \begin{bmatrix} \sqrt{\tau_M \Sigma^i_1}, \sqrt{\tau_M \Sigma^i_1}, \sqrt{\tau_M \Sigma^i_1}, \sqrt{\tau_M \Sigma^i_2}, \sqrt{\tau_M \Sigma^i_2}, \sqrt{\tau_M \Sigma^i_2} \end{bmatrix}
\]

The proof has been completed.

Remark 4. Noticing that the existence of non-linear items \(-X^T \hat{\mathcal{C}} \), \(-X^T \hat{\mathcal{C}} \), \(-X^T \hat{\mathcal{C}} \) cannot be ensured. However, if \( \bar{\rho} \) is too large, (47)–(50) cannot be solved straightly by LMI toolbox. Therefore, we substitute non-linear items \( X^T \hat{\mathcal{C}} X \), \( X^T \hat{\mathcal{C}} X \), \( X^T \hat{\mathcal{C}} X \) with \( \delta_1^2 \delta_2^2 \), where \( \delta_1 > 0 \) is a scalar. Generally, there are two methods in the literature to deal with non-linear items. One method is the CCL algorithm, which transfers the feasible solutions of non-linear matrix inequalities to a non-linear optimisation problem involving LMI conditions. Another method is the linearisation of non-linear method. In this paper, we have used the second method and enlarge some items, therefore, and that has created some conservatism. However, the less conservative results based on CCL generally than those based on linearisation of non-linear method. It should be pointed out that although CCL can effectively reduce the conservativeness of this paper, the main work of this article is to handle adaptive memory-event-triggered \( H_{\infty} \) control for network-based T-S fuzzy systems with asynchronous premise constraints. Therefore, CCL approach has not been considered.

Remark 5. For a preselect threshold \( \bar{\rho} \), the performance index \( \gamma \), triggered parameter \( \Phi \) and memory fuzzy controller gains \( K_{ij} \) can be obtained from Theorem 2. Too large \( \bar{\rho} \) will result fewer packets need to be transmitted. However, if \( \bar{\rho} \) is too large, (47)–(50) maybe infeasible, that is, the performance of the system cannot be ensured.
4 | AN ILLUSTRATIVE EXAMPLE

A case study on tunnel diode circuit [44] as shown in Figure 1 is carried out in this section to demonstrate the efficacy of proposed method, the diode is described as \( i_D(t) = 0.002v_D(t) + 0.01i_D(t) \), based on Kirchhoff Laws and let \( x_1(t) = r(t) \) and \( x_2(t) = i(t) \), and set \( C = 20mF, L = 1000mH \) and \( R = 10\Omega \), we can obtain

\[
\begin{align*}
\dot{x}_1(t) &= -0.1x_1(t) - 0.5x_1^2(t) + 50x_2(t) \\
\dot{x}_2(t) &= -x_1(t) - 10x_2(t) + u(t) + \omega(t), \\
\dot{\zeta}(t) &= x_1(t)
\end{align*}
\]

where \( \zeta(t) \) and \( \omega(t) \) are the controlled output and disturbance noise, respectively.

In this paper, two fuzzy rules are used, for example, as shown in Figure 2. Supposing that \(-3 \leq x_1(t) \leq 3\), the system (52) can be approximately expressed by the system (19), where

\[
\begin{align*}
A_1 &= \begin{bmatrix} -0.1 & 50 \\ -1 & -10 \end{bmatrix}, A_2 = \begin{bmatrix} -4.6 & 50 \\ -1 & -10 \end{bmatrix} \\
B_1 &= \begin{bmatrix} 0 & 1 \end{bmatrix}^T, \quad B_2 = \begin{bmatrix} 0 & 1 \end{bmatrix}^T \\
C_1 &= \begin{bmatrix} 1 & 0 \end{bmatrix}, \quad C_2 = \begin{bmatrix} 1 & 0 \end{bmatrix} \\
B_{w1} &= \begin{bmatrix} 0 & 1 \end{bmatrix}^T, \quad B_{w2} = \begin{bmatrix} 0 & 1 \end{bmatrix}^T
\end{align*}
\]

For the simulation purpose, under the initial condition \( x(0) = [0.5, -0.2]^T \), we assume

\[
\omega(t) = \begin{cases} 0.2e^{-0.03(t-5)}\sin(0.05t), & \text{if } t \in [0, 5] \\
0, & \text{otherwise.} \end{cases}
\]

Using the proposed A-METS, we set \( m = 3 \), the memory weighting parameters with \( \sigma_1 = 0.7, \sigma_2 = 0.2, \sigma_3 = 0.1 \), accordingly. The other parameters are chosen as \( \tau_M = 0.2, \gamma = 2, \delta_1 = 3, \delta_2 = 1.8, \delta_3 = 1.8, \eta_1 = 0.8, \eta_2 = 1.25, \alpha = 0.27 \) and sampling period \( h = 0.02s \), and the lower bound of the dynamic threshold \( \hat{\rho} = 0.5 \). Correspondingly, \( K_j \) and \( \Phi \) are obtained as follows by applying Theorem 2

\[
\Phi = \begin{bmatrix} 2.3351 & 5.0450 \\ 5.0450 & 21.0839 \end{bmatrix},
\]

\[
K_{11} = [-0.0268 - 0.4969], \quad K_{12} = [-0.0323 - 0.2159],
\]

\[
K_{13} = [-0.0333 - 0.1597], \quad K_{21} = [0.2577 - 1.7223],
\]

\[
K_{22} = [0.0726 - 0.4853], \quad K_{23} = [0.0356 - 0.2381].
\]

Next, applying the same parameters, the proposed A-METS reduces to the AEITS when \( m = 1 \), \( K_j \) and \( \Phi \) are computed as

\[
\Phi = \begin{bmatrix} 0.7350 & 1.5846 \\ 1.5846 & 6.5432 \end{bmatrix},
\]

\[
K_1 = [-0.1281 - 0.7313], \quad K_2 = [-0.2785 - 1.9783].
\]

With the asynchronous premise variables, the numbers of transmitted packets among AEITS, METS and the proposed A-METS are listed in Table 1. By using the proposed A-METS, the state responses, release intervals, the trajectory of adaptive threshold \( \rho(t) \) are shown in Figures 3–5, respectively. Figure 6 depicts the curve of the circuit control input, we can see that \( u(t) \) tends to initial state after a short oscillation, which indicates a good control performance. Obviously, the threshold \( \rho(t) \) is dynamically adjusted in terms of the variation of the state, while ensuring the control performance and stability of the system. The state responses, release instants and intervals under METS and AEITS are shown in Figures 7–10, respectively.
FIGURE 3  State responses under A-METS with asynchronous premise

FIGURE 4  Release intervals under A-METS with asynchronous premise

FIGURE 5  the trajectory of adaptive threshold $\rho(t)$ in (15) with $\rho = 0.5$

FIGURE 6  The curve of the circuit control input under A-METS with asynchronous premise

FIGURE 7  State responses under METS with asynchronous premise

FIGURE 8  Release intervals under METS with asynchronous premise
TABLE 1  The number of transmitted packets under different schemes with asynchronous constraints

| $\bar{\rho}$ | AETS | METS | A-METS |
|-------------|------|------|--------|
| 0           | 500  | 500  | 500    |
| 0.1         | 198  | 292  | 286    |
| 0.2         | 147  | 205  | 194    |
| 0.3         | 127  | 160  | 148    |
| 0.4         | 110  | 129  | 118    |
| 0.5         | 86   | 107  | 96     |

Comparing Figures 3 and 7, it can be found that the overshoot and settling time are almost the same. Further, we can see that the proposed A-METS can transmit less packets than METS from Table 1. Therefore, the proposed A-METS can achieve similar system performance by using less packets, thus more communication resource can be saved.

From Table 1 and Figures 3 and 9, we can see that although the proposed A-METS can transmit more packets than AETS, the overshoot and settling time outperform the AETS. It is worth to point out there are properly more packets released at the beginning time $t \in [0, 2s]$ when the states have a drastic change (see Figure 4). That is, the proposed A-METS can improve the performance of the system.

From Table 1 and the figures, we can conclude that (i) the packets transmitted by proposed A-METS are less than the METS and larger than AETS ; (ii) the proposed A-METS by transmitting fewer packets can achieve the similar system performance to METS. Both the system performance of the A-METS and METS are better than that of AETS. Further, compared with the AETS, the proposed A-METS will release more packets when the state of the system fluctuates severely, which makes the responses of the system reach the stable more quickly. That is, the proposed A-METS can give consideration to the data transmission reduction and system performance improving, simultaneously.

5 | CONCLUSION

An adaptive METS has been investigated for networked T-S fuzzy systems with asynchronous premise variables. An adaptive METS has been employed to save the communication resources and effectively reduce data packets transmission through utilizing historical packets. The memory fuzzy controller has been designed by constructing the asynchronous premise variables. Sufficient conditions of the system have been derived by using the Lyapunov theory. Simulation results have been presented to illustrate the efficacy of the proposed method. It should be noted that $H_{\infty}$ control problem is considered in this paper; however, filtering problem has also been given much attention recently. Therefore, how to consider an adaptive memory-event-triggered $H_{\infty}$ filtering problem for networked T-S fuzzy systems with asynchronous constraints is one of our future work.

ACKNOWLEDGMENTS

This work was supported in part by the National Natural Science Foundation of China under Grants 61903252, 61773218 and in part by Program for Professor of Special Appointment (Eastern Scholar) at Shanghai Institutions of Higher Learning.

REFERENCES

1. Zhang, W., et al.: Stability of networked control systems. IEEE Contr. Syst. Mag. 21(1), 84–99 (2001)
2. Yang, T., et al.: New study of controller design for networked control systems. IET Control Theory Appli. 4(7), 1109–1121 (2010)
3. Tian, E., et al.: Probabilistic-constrained filtering for a class of nonlinear systems with improved static event-triggered communication. Int. J. Robust Nonlinear Control 29(5), 1484–1498 (2019)
4. Tian, E., et al.: Chance-constrained $H_{\infty}$ control for a class of time-varying systems with stochastic nonlinearities: the finite-horizon case. Automatica 107, 296–305 (2019)
5. Ju, Y., et al.: Fault detection for discrete time-delay networked systems with round robin protocol in finite-frequency domain. Int. J. Syst. Sci. 50(13), 2497–2509 (2019)
6. Zhao, X., et al.: Probability-constrained tracking control for a class of time-varying nonlinear stochastic systems. J. Frankl. Inst. 355(5), 2689–2702 (2018)
7. Peng, C., Sun, H.: Switching-like event-triggered control for networked control systems under malicious denial of service attacks. IEEE Trans. Autom. Control 65, 3943–3949 (2020) (10.1109/TAC.2020.2989773)
8. Zhang, X.M., et al.: Networked control systems: a survey of trends and techniques. IEEE/CAA J. Autom. Sinica 7(1), 1–17 (2019)
9. Liang, H., et al.: Containment control of semi-markovian multiagent systems with switching topologies. IEEE Trans. Syst. Man Cybern. Syst. (2019) (10.1109/TSMC.2019.2946248).
10. Peng, C., et al.: Consensus of multiagent systems with nonlinear dynamics using an integrated sampled-data-based event-triggered communication scheme. IEEE Trans. Syst. Man Cybern. Syst. 49(3), 589–599 (2018)
11. Wang, Y.L., et al.: Network-based T–S fuzzy dynamic positioning controller design for unmanned marine vehicles. IEEE Trans. Cybern. 48(9), 2750–2763 (2018)
12. Peng, C., et al.: Resilient event-triggered $H_{\infty}$ load frequency control for networked power systems with energy-limited DoS attacks. IEEE Trans. Power Syst. 32(5), 4110–4118 (2017)
13. Hu, S., et al.: Resilient event-triggered controller synthesis of networked control systems under periodic DoS jamming attacks. IEEE Trans. Cybern. 49(12), 4271–4281 (2018)
14. Yue, D., et al.: A delay system method for designing event-triggered controllers of networked control systems. IEEE Trans. Autom. Control 58(2), 475–481 (2012)
15. Hu, S., et al.: Observer-based event-triggered control for networked linear systems subject to denial-of-service attacks. IEEE Trans. Cybern. 50(5), 1952–1964 (2019)
16. Peng, C., Zhang, J.: Event-triggered output-feedback $H_{\infty}$ control for networked control systems with time-varying sampling. IET Control Theory Appl. 9(9), 1384–1391 (2015)
17. Wei, G., et al.: Event-triggered control for discrete-time systems with unknown nonlinearities: An interval observer-based approach. Int. J. Syst. Sci. 51(6), 1019–1031 (2020)
18. Liang, H., et al.: Event-triggered fuzzy bipartite tracking control for networked systems based on distributed reduced-order observers. IEEE Trans. Fuzzy Syst. 2020, https://doi.org/10.1109/TFUZZ.2020.2982618
19. Gu, Z., et al.: An adaptive event-triggering scheme for networked interconnected control system with stochastic uncertainty. Int. J. Robust Nonlinear Control 27(2), 236–251 (2017)
20. Liu, J., et al.: Secure adaptive-event-triggered filter design with input constraint and hybrid cyber attack. IEEE Trans. Cybern. (2020), https://doi.org/10.1109/TTCYB.2020.3037572
21. Gu, Z., et al.: Adaptive event-triggered control of a class of nonlinear networked systems. J. Franklin. Inst. 354(9), 3854–3871 (2017)
22. Peng, C., et al.: Adaptive event-triggering $H_{\infty}$ load frequency control for network-based power systems. IEEE Trans. Ind. Electron. 65(2), 1685–1694 (2017)
23. Do˘alı, V., et al.: Output-based and decentralized dynamic event-triggered control with guaranteed $L_2$-gain performance and zero-freeness. IEEE Trans. Autom. Control 62(1), 34–49 (2016)
24. Tian, E., Peng, C.: Memory-based event-triggering $H_{\infty}$ load frequency control for power systems under deception attacks. IEEE Trans. Cybern. 50, 4610–4618 (2020), https://doi.org/10.1109/TCYB.2020.2972384
25. Sun, X., et al.: Memory-event-trigger-based secure control of cloud-aided active suspension systems against deception attacks. Inf. Sci. 543, 1–17 (2020), https://doi.org/10.1016/j.ins.2020.06.059
26. Gu, Z., et al.: Memory-based continuous event-triggered control for networked TS fuzzy systems against cyber-attacks. IEEE Trans. Fuzzy Syst. (2020), (10.1109/TFUZZ.2020.3012771).
27. Xie, X., et al.: Further studies on control synthesis of discrete-time T–S fuzzy systems via useful matrix equalities. IEEE Trans. Fuzzy Syst. 22(4), 1026–1031 (2013)
28. Zhang, H., et al.: Fuzzy model-based robust networked control for a class of nonlinear systems. IEEE Trans. Syst. Man Cybern. A, Syst. Humans 39(2), 437–447 (2009)
29. Liu, J., et al.: Security distributed state estimation for nonlinear networked systems against DoS attacks. Int. J. Robust Nonlinear Control 30(3), 1156–1180 (2020)
30. Huang, L., et al.: Improved stability criteria for T–S fuzzy systems with time-varying delay via convex analysis approach. IET Control Theory Appl. 10(15), 1888–1895 (2016)
31. Lam, H.: Stability analysis of T–S fuzzy control systems using parameter-dependent Lyapunov function. IET Control Theory Appl. 3(6), 750–762 (2009)
32. Wang, W.Y., et al.: Hierarchical T–S fuzzy-neural control of anti-lock braking system and active suspension in a vehicle. Automatica 48(8), 1698–1706 (2012)
33. Piltan, E., et al.: Design model free fuzzy sliding mode control: Applied to internal combustion engine. Int. J. Eng. 5(4), 302–312 (2011)
34. Sun, Y., et al.: Event-triggered filtering for nonlinear networked discrete-time systems. IEEE Trans. Ind. Electron. 62(11), 7163–7170 (2015)
35. Jiang, X., Han, Q.L.: On designing fuzzy controllers for a class of nonlinear networked control systems. IEEE Trans. Fuzzy Syst. 16(4), 1050–1060 (2008)
36. Hu, S., et al.: Event-triggered controller design of nonlinear discrete-time networked control systems in T–S fuzzy model. Appl. Soft Comput. 30, 400–411 (2015)
37. Peng, C., et al.: To transmit or not to transmit: A discrete event-triggered communication scheme for networked Takagi–Sugeno fuzzy systems. IEEE Trans. Fuzzy Syst. 21(1), 164–170 (2012)
38. Gu, Z., et al.: $H_{\infty}$ tracking control of nonlinear networked systems with a novel adaptive event-triggered communication scheme. J. Franklin. Inst. 354(8), 3540–3553 (2017)
39. Peng, C., et al.: Relaxed stability and stabilisation conditions of networked fuzzy control systems subject to asynchronous grades of membership. IEEE Trans. Fuzzy Syst. 22(5), 1101–1112 (2013)
40. Liu, Y., et al.: Event-based reliable dissipative filtering for T–S fuzzy systems with asynchronous constraints. IEEE Trans. Fuzzy Syst. 26(4), 2089–2098 (2017)
41. Wang, X.L., Yang, G.H.: Event-triggered $H_{\infty}$ control for TS fuzzy systems via new asynchronous premise reconstruction approach. IEEE Trans. Cybern. (2019), https://doi.org/10.1109/TTCYB.2019.2956736
42. Li, H., et al.: Event-triggered fault detection of nonlinear networked systems. IEEE Trans. Cybern. 47(4), 1041–1052 (2016)
43. Pan, Y., Yang, G.H.: Event-triggered fault detection filter design for nonlinear networked systems. IEEE Trans. Syst. Man Cybern. Syst. 48(11), 1851–1862 (2017)
44. Ran, G.T., et al.: Event-triggered dynamic output feedback control for networked T–S fuzzy systems with asynchronous premise variables. IEEE Access 6, 78740–78750 (2018)
45. Tian, E., et al.: Delay-dependent robust $H_{\infty}$ control for T–S fuzzy system with interval time-varying delay. Fuzzy Sets Syst. 160(12), 1708–1719 (2009)
46. Cao, Y.Y., et al.: Delay-dependent robust $H_{\infty}$ control for uncertain systems with time-varying delays. IEE Proc., Control Theory Appli. 145(3), 338–344 (1998)

How to cite this article: Shi Y, Tian E, Shen S, Zhao X. Adaptive memory-event-triggered $H_{\infty}$ control for network-based T–S fuzzy systems with asynchronous premise constraints. IET Control Theory Appl. 2021;15:534–544. https://doi.org/10.1049/cth2.12059