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Adaptive Event-Triggered H_∞ Control for Markov Jump Systems with Generally Uncertain Transition Rates

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Abstract

This paper considers the adaptive event-triggered H_∞ control issue for Markov jump systems with generally uncertain transition rates and actuator faults. Compared with the conventional method, an adaptive event-triggered mechanism with a varying threshold is adopted to save the communication resources effectively. The general model of transition rates in Markov jump process includes completely unknown and uncertain bounded as two special models. Based on linear matrix inequalities, the sufficient conditions of the controller design can be obtained to guarantee the closed-loop systems are stochastically stable. Finally, simulation examples are exploited to verify the effectiveness of the proposed control strategy.

Keywords Markov jump systems · Adaptive event-triggered control · Generally uncertain transition rates · Actuator faults

1 Introduction

It is known that Markov jump systems (MJSs) have been extensively applied to manufacturing systems [42], flight control systems [36], networked control systems [8], multi-agent systems [28], and so on. Recently, many relevant results have been reported in [12,17,27,44,47,49,50,57]. It is noted that the transition rates (TRs) of the aforemen-

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tioned control results are assumed to be totally known. However, the accurate values of TRs are usually hard to be estimated in practice. To handle such a problem, many related results have been published [22,33,39,48,52]. Considering the bounded uncertain TRs (BUTRs), the stabilization issue of MJSs was studied in [48]. The authors in [33] discussed the robust control problem for Markovian neural networks with partly unknown TRs (PUTRs). In [22], the sliding mode control method was employed to handle the stabilization problem of MJSs with PUTRs. Furthermore, the generally uncertain TRs (GUTRs) should be considered, in which every TR can be decomposed as estimate value and estimate error. Generally speaking, the GUTR model contains two special cases of BUTR and PUTR. In [15,19,32,55], the stability and stabilization problems of MJSs with GUTRs were studied. The authors in [20] investigated the delay stability issue for neutral MJSs with GUTRs.

It should be remarkable that the communication bandwidth of MJSs is limited, which may result in the problem of network-induced delays. Traditionally, the time-triggered control scheme is adopted, where the sampling signal is uniformly updated in a fixed sampling period. Such a control scheme may result in the unnecessary signal transmission and increase the burden of communication network. To solve this problem, the event-triggered mechanism is regarded as an effective way to save the communication resources in [3,6,11,26,37,40,53,58,60]. In [41], the event-triggered controller for MJSs was designed. Considering the output quantization, the authors in [45] investigated the filter design problem for MJSs by utilizing the event-triggered scheme. Based on the aforementioned analysis results, the event-triggered strategy with a fixed threshold is usually adopted. However, such mechanism with a fixed threshold cannot adapt the changes of the system, which may waste some communication resources. Therefore, it is necessary to propose an adaptive event-triggered scheme with a varying threshold. Based on the adaptive event-triggered method, the authors in [34] designed a fault detection filter for stochastic systems. In [13], an adaptive event-triggered strategy was presented to handle the H_∞ tracking control problem for nonlinear fuzzy systems. By utilizing Takagi-Sugeno fuzzy approach, an adaptive event-triggered controller for uncertain suspension systems was designed in [24].

On the other hand, due to the wear or loss of machinery, the actuator fault is inevitable for MJSs. When actuator fault occurs, the performance of MJSs may be degraded. Thus, many theoretical results subject to actuator fault were presented in [2,4,7,10,18,23,25,59,61]. Considering the actuator fault, the sliding mode control problem for semi-MJSs was studied in [18]. In [23], an adaptive sliding mode controller for MJSs was designed when actuator failure exists. To the best of authors' knowledge, there exist few results on the adaptive event-triggered H_∞ control problem for MJSs with GUTRs and actuator failures, which motivates this study.

Motivated by the aforementioned results, the adaptive event-triggered H_∞ control problem for MJSs with GUTRs and actuator failure is discussed. The main contributions are summarized below:

(1) In contrast to traditional control strategy [21], a new event-triggered mechanism with a varying threshold is designed to reduce the use of transmission bandwidth and save the communication resources.

(2) The GUTR model, in which each TR may be completely unknown or generally uncertain, can be more general than that of both BUTR and PUTR. As a matter of fact, the GUTR model contains two special cases of BUTR and PUTR, which is applied to more practical situations.

The remainder of this paper can be organized below. Section 2 shows the description and preliminaries of MJSs. Section 3 designs the adaptive event-triggered controller. Section 4 gives simulation results to prove the feasibility of the proposed strategy. Finally, we conclude this paper in Sect. 5.

Notations The real symmetric and positive definite matrix can be denoted by the matrix $M > 0$. The matrix transpose and inverse can be represented by the superscripts "T" and "-1", respectively. The m-dimensional Euclidean space and the probability are denoted by $\mathbb{R}^m$ and $\mathrm{P}\{\cdot\}$, respectively. The notation "$*$" represents a symmetric term in the symmetric matrix. The mathematical expectation operator and the unknown TR can be represented by the notations $\mathrm{E}\{\cdot\}$ and "?", respectively. The symbol diag$\{\ldots\}$ denotes a block-diagonal matrix. The space of square integral vector function is used to be denoted by the symbol $\mathcal{L}_2[0, \infty)$.

2 System Description and Preliminaries

2.1 System Model

Consider MJSs in the probability space $(\Omega, \mathcal{F}, \mathcal{P})$:

$$\begin{cases} \dot{\chi}(t) = A(\ell_t)\chi(t) + B(\ell_t)(u(t) + \omega(t)) \\ z(t) = E(\ell_t)\chi(t) + D_v(\ell_t)\omega(t) \end{cases} \tag{1}$$

where $\{\ell_t, t \geq 0\}$ denotes finite-state Markov process in state space $\mathbb{N} = \{1, 2, \ldots, \eta\}$, $\chi(t) \in \mathbb{R}^n$ denotes the state variable, the control input is defined as $u(t) \in \mathbb{R}^m$, $z(t) \in \mathbb{R}^p$ stands for the control output, and $\omega(t) \in \mathbb{R}^m$ denotes the disturbance belonging to $\mathcal{L}_2[0, \infty)$. $A(\ell_t) \in \mathbb{R}^{n\times n}$, $B(\ell_t) \in \mathbb{R}^{n\times m}$, $E(\ell_t) \in \mathbb{R}^{p\times n}$ and $D_v(\ell_t) \in \mathbb{R}^{p\times m}$ represent known matrices. The TR matrix $\Pi = \lambda_{ij}(i, j \in \mathbb{N})$ is written as

$$\Pr\{\ell_{t+\upsilon} = j|\ell_t = i\} = \begin{cases} \lambda_{ij}\upsilon + \alpha(\upsilon), & i \neq j \\ 1 + \lambda_{ii}\upsilon + \alpha(\upsilon), & i = j \end{cases} \tag{2}$$

where $\upsilon > 0$, $\lim_{\upsilon\to 0} \alpha(\upsilon)/\upsilon = 0$, and $\lambda_{ij} > 0$ $(i \neq j)$. In addition, $\lambda_{ii} = -\sum_{j=1, j\neq i}^{\eta} \lambda_{ij}$.

In this paper, it is assumed that the TR matrix Π is uncertain. For instance, the matrix Π for MJSs may be represented as

$$\Pi = \begin{bmatrix} \tilde{\lambda}_{11} + \Lambda_{11} & ? & \tilde{\lambda}_{13} + \Lambda_{13} & \ldots & ? \\ ? & ? & \tilde{\lambda}_{23} + \Lambda_{23} & \ldots & \tilde{\lambda}_{2\eta} + \Lambda_{2\eta} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ ? & \tilde{\lambda}_{\eta 2} + \Lambda_{\eta 2} & ? & \ldots & \tilde{\lambda}_{\eta\eta} + \Lambda_{\eta\eta} \end{bmatrix} \tag{3}$$

where $\tilde{\lambda}_{ij}$ and $\Lambda_{ij} \in [-\vartheta_{ij}, \vartheta_{ij}](\vartheta_{ij} \geq 0)$ denote the estimated value and the estimated error of TR, respectively. Moreover, the values of $\tilde{\lambda}_{ij}$ and ϑ_{ij} are assumed to be known. For convenience, for $\forall i \in \mathbb{N}$, $I^i = I^i_k \bigcup I^i_{uk}$ can be determined by

$$I^i_k \triangleq \Big\{ j : \text{For } \ j \in \mathbb{N}, \ \tilde{\lambda}_{ij} \text{ is assumed to be known} \Big\}$$
$$I^i_{uk} \triangleq \Big\{ j : \text{For } \ j \in \mathbb{N}, \ \tilde{\lambda}_{ij} \text{ is assumed to be unknown} \Big\}$$

In addition, if $I^i_k \neq \varnothing$ holds, the set is defined as $I^i_k = \{k^i_1, k^i_2, \ldots, k^i_J\}$, where $k^i_s \in \mathcal{N}^+$ denotes the sth value in the ith row of matrix Π.

Based on the properties of GUTRs, the following assumptions are given:

Assumption 1 When $I^i_k = \mathbb{N}$, then $\tilde{\lambda}_{ij} - \vartheta_{ij} \geq 0$ $(\forall j \in \mathbb{N}, j \neq i)$, $\tilde{\lambda}_{ii} = -\Sigma^{\eta}_{j=1, j\neq i}\tilde{\lambda}_{ij}$ and $\vartheta_{ii} = \Sigma^{\eta}_{j=1, i\neq j}\vartheta_{ij}$.

Assumption 2 When $I^i_k \neq \mathbb{N}$ and $i \in I^i_k$, we have $\tilde{\lambda}_{ij} - \vartheta_{ij} \geq 0$ $(\forall j \in \mathbb{N}, j \neq i)$, $\tilde{\lambda}_{ii} + \vartheta_{ii} \leq 0$ and $\Sigma_{j \in I^i_k}\tilde{\lambda}_{ij} \leq 0$.

Assumption 3 When $I^i_k \neq \mathbb{N}$ and $i \notin I^i_k$, we have $\tilde{\lambda}_{ij} - \vartheta_{ij} \geq 0$ $(\forall j \in \mathbb{N})$.

Based on the characteristics of the TRs, we have $0 \leq \tilde{\lambda}_{ij} - \vartheta_{ij} \leq \lambda_{ij} \leq \tilde{\lambda}_{ij} + \vartheta_{ij} (j \neq i)$ and $\tilde{\lambda}_{ii} - \vartheta_{ii} \leq \lambda_{ii} \leq \tilde{\lambda}_{ii} + \vartheta_{ii} \leq 0$. Hence, the three assumptions are reasonable and feasible.

Remark 1 If $I^i_{uk} = \varnothing$, $\forall i \in \mathbb{N}$, matrix (3) will be turned into a BUTR matrix. When $\vartheta_{ij} = 0$, $\forall i \in \mathbb{N}$, $\forall j \in I^i_k$, matrix (3) can be transformed into a PUTR matrix.

Define $\lambda^i_k \triangleq \sum_{j \in I^i_k} \lambda_{ij}$. When MJSs work in the ith mode, the systems are reformulated as

$$\begin{cases} \dot{\chi}(t) = A_i \chi(t) + B_i(u(t) + \omega(t)) \\ z(t) = E_i \chi(t) + D_{vi}\omega(t) \end{cases} \tag{4}$$

where the matrices $A(\ell_t)$, $B(\ell_t)$, $E(\ell_t)$ and $D_v(\ell_t)$ can be replaced by matrices A_i, B_i, E_i and D_{vi}, respectively.

2.2 Adaptive Event-Triggered Control Strategy

As is well known, the states of MJSs are sent to the state-feedback controller by the communication network. However, many redundant signal transmission may increase the burden of communication network. Hence, an adaptive event-triggered method is introduced to handle this problem. Figure 1 plots the framework of an adaptive event-triggered control system, where the network-induced delay is considered, and the system states are sampled based on the sampling period $T > 0$. Moreover, $t_k T$

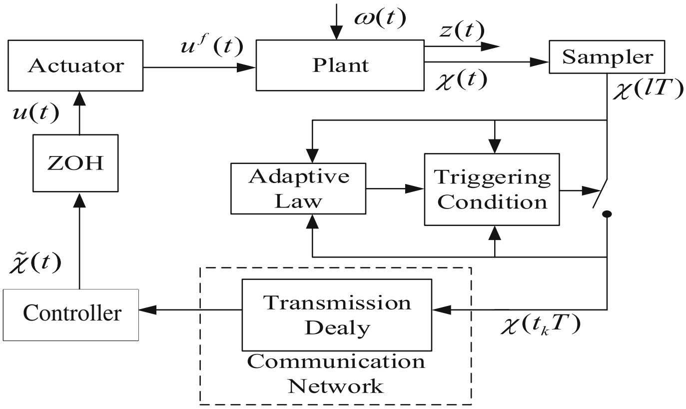


Fig. 1 The structure of adaptive event-triggered control system

and lT stand for the latest triggered instant and the sampling instant, respectively. The next triggered instant condition is deduced by

$$t_{k+1} = t_k + \min\{lT|[\chi(t_kT + lT) - \chi(t_kT)]^{\mathrm{T}} W_i[\chi(t_kT + lT) - \chi(t_kT)]\} \\ \geq \epsilon_i(t)\chi^{\mathrm{T}}(t_kT)W_i\chi(t_kT) \tag{5}$$

where $W_i > 0$ for each i denotes a weighting matrix to be determined and $\epsilon_i(t)$ stands for the event-triggered threshold. The present sampled data and the latest transmitted one are denoted by $\chi(t_kT + lT)$ and $\chi(t_kT)$, respectively. When the above inequality (5) is established, $\chi(t_kT + lT)$ will be transferred to the controller side. The adaptive law [14,56] is constructed as

$$\dot{\epsilon}_i(t) = \frac{1}{\epsilon_i(t)}\left[\frac{1}{\epsilon_i(t)} - \epsilon_0\right] e^{\mathrm{T}}(t)W_ie(t) \tag{6}$$

where $\epsilon_0 > 0$ denotes a pre-given constant and $e(t) = \chi(t_kT) - \chi(t_kT + lT)$ is the relative error value.

Remark 2 According to the formula in (6), the threshold can be changed by the variation of system modes. If the error value $e(t)$ approaches to 0, $\dot{\epsilon}_i(t) = 0$, which implies that the threshold $\epsilon_i(t)$ will become a constant. Suppose that the condition $\epsilon_0 = \frac{1}{\epsilon_i(0)}$ holds, then $\dot{\epsilon}_i(t) = 0$, the proposed control strategy (5) will become the traditional event-triggered condition [54,64]:

$$t_{k+1} = t_k + \min\{lT|[\chi(t_kT + lT) - \chi(t_kT)]^{\mathrm{T}} W_i[\chi(t_kT + lT) \\ - \chi(t_kT)]\} \geq \bar{\epsilon}\chi^{\mathrm{T}}(t_kT)W_i\chi(t_kT)$$

where $\bar{\epsilon} \in [0, 1)$ denotes a pre-given scalar.

The triggered instants are assumed to be t_0T, t_1T, t_2T, ..., where t_0 denotes the initial time. Since the time-varying network delays should not be ignored, the correspondent sensor data will be received by the controller at the instants $t_0T+\tau_0, t_1T+\tau_1, t_2T+\tau_2, \cdots$, respectively. Thus, the control input is represented as

$$\tilde{\chi}(t) = \chi(t_kT), \quad t \in [t_kT + \tau_{t_k}, t_{k+1}T + \tau_{t_{k+1}}) \tag{7}$$

According to the existing results [16], the next triggered instant is assumed to be $t_{k+1} = t_k + lT$. Divide the interval $[t_kT + \tau_{t_k}, t_{k+1}T + \tau_{t_{k+1}})$ into $\bigcup_{p=1}^{l-1} T_p$, where $T_p = [t_kT + pT + \tau_{t_k+pT}, t_kT + (p+1)T + \tau_{t_{k+1}+(p+1)}T)$. The time delay $\tau(t)$ can be defined as $\tau(t) = t - t_kT - pT, t \in T_p$, and satisfies $\tau_l \leq \tau(t) < T + \tau_u$, where τ_l and τ_u denote the minimum and maximum value of $\tau(t)$, respectively.

The expression of state $\chi(t_kT)$ can be determined as follows:

$$\chi(t_kT) = \chi(t - \tau(t)) + e(t), \quad t \in [t_kT + \tau_{t_k}, t_{k+1}T + \tau_{t_{k+1}}) \tag{8}$$

then, we design the following state-feedback controller

$$u(t) = \mathcal{K}_i\tilde{\chi}(t), \quad t \in [t_kT + \tau_{t_k}, t_{k+1}T + \tau_{t_{k+1}}) \tag{9}$$

where $\mathcal{K}_i \in \mathbb{R}^{m\times n}$ ($\forall i \in \mathbb{N}$) represent the controller gains.

2.3 Actuator Failure Model

In the extreme working environment, the MJSs may suffer from actuator failure. To address it thoroughly, the failure model is modeled as

$$u^f(t) = \rho u(t), \quad \rho \in [0, 1] \tag{10}$$

where ρ stands for a scalar.

Remark 3 In the failure model, $\rho = 0$ denotes that the actuator is completely failed, $\rho = 1$ represents that the actuator cannot be failed, $0 < \rho < 1$ means that the actuator occurs partial failure.

Combining (4), (7), (8), (9) with (10), the closed-loop system is constructed as follows:

$$\begin{cases} \dot{\chi}(t) = A_i\chi(t) + \rho B_i\mathcal{K}_i\chi(t-\tau(t)) + \rho B_i\mathcal{K}_i e(t) + B_i\omega(t) \\ z(t) = E_i\chi(t) + D_{vi}\omega(t) \end{cases} \tag{11}$$

In this section, we need to introduce following definitions and lemmas to obtain the main results.

Definition 1 [23] The stochastic positive functional candidate is denoted by $\mathcal{V}(\chi(t), \ell_t, t \geq 0) = \mathcal{V}(\chi(t), i)$, and the infinitesimal operator $\mathcal{LV}(\chi(t), i)$ is written as

$$\mathcal{LV}(\chi(t), i) = \lim_{\triangle\to 0^+} \frac{1}{\triangle}\left[E\{\mathcal{V}(\chi(t+\triangle), \ell_{t+\triangle})|\chi(t), \ell_t = i\} - \mathcal{V}(\chi(t), i)\right]$$

Definition 2 [38,51] When $u(t) = 0$, system (11) is stochastically stable, for the initial conditions $\chi(0)$ and $r_0 \in \mathbb{N}$, the condition holds:

$$\mathrm{E}\left\{\int_0^{\infty} \|\chi(t)\|^2 dt | \chi(0), r_0)\right\} < +\infty$$

Lemma 1 [1,30] *Given a positive constant ζ, system (11) with the H_∞ performance is said to be stochastically stable, for all non-zero $\omega(t) \in \mathcal{L}_2[0, \infty)$, it holds that*

$$\int_0^{\infty} \|z(t)\|^2 \mathrm{d}t \leq \zeta^2 \int_0^{\infty} \|\omega(t)\|^2 \mathrm{d}t$$

Lemma 2 [15] *If there exist any real constant ϱ and any matrix ψ, the matrix inequality can be described as*

$$\varrho(\psi + \psi^{\mathrm{T}}) \leq \varrho^2 T + \psi T^{-1} \psi^{\mathrm{T}}, \quad T > 0$$

3 Main Results

3.1 Performance Analysis

By adopting the adaptive event-triggered scheme, sufficient conditions of the controller design are obtained to guarantee that MJSs with the H_∞ performance are stochastic stable by the following theorem.

Theorem 1 *For known positive constants τ_1, τ_2, T, ϵ_0 and a scalar ζ, the closed-loop system (11) with GUTRs is stochastically stable and satisfies the H_∞ performance, if there exist matrices $P_i > 0$, $Q_1 > 0$, $Q_2 > 0$, $Q_{1i} > 0$, $Q_{2i} > 0$, $G_1 > 0$, $G_2 > 0$, and control gains $\mathcal{K}_i$, for $\forall i \in \mathbb{N}$ such that*

$$\begin{bmatrix} \Psi_{1i} & P_1 - P_i & \ldots & P_{i-1} - P_i & P_{i+1} - P_i & \ldots & P_s - P_i \\ * & -H_{i1} & \ldots & 0 & 0 & \ldots & 0 \\ * & * & \ddots & \vdots & \vdots & \vdots & \vdots \\ * & * & * & -H_{i(i-1)} & 0 & \vdots & \vdots \\ * & * & * & * & -H_{i(i+1)} & \vdots & \vdots \\ * & * & * & * & * & \ddots & \vdots \\ * & * & * & * & * & * & -H_{is} \end{bmatrix} < 0, \quad i \in I_k^i \text{ and } I_{uk}^i = \varnothing \quad (12)$$

$$\begin{bmatrix} \Psi_{2i} & P_{k_1^i} - P_l & \ldots & P_{k_m^i} - P_l \\ * & -M_{ik_1^i l} & \ldots & 0 \\ * & * & \ddots & \vdots \\ * & * & * & -M_{ik_m^i l} \end{bmatrix} < 0, \quad i \in I_k^i \text{ and } I_{uk}^i \neq \varnothing \quad (13)$$

$$\begin{bmatrix} \Psi_{3i} & P_{k_1^i} - P_i & \dots & P_{k_m^i} - P_i \\ * & -L_{ik_1^i} & \dots & 0 \\ & & \ddots & \vdots \\ * & * & & \\ * & * & * & -L_{ik_m^i} \end{bmatrix} < 0, \quad i \notin I_k^i, \ \forall j \in I_{uk}^i \tag{14}$$

$$\sum_{j=1}^{\eta} \lambda_{ij} Q_1(j) \leq Q_1 \tag{15}$$

$$\sum_{j=1}^{\eta} \lambda_{ij} Q_2(j) \leq Q_2 \tag{16}$$

$$\sum_{j=1}^{\eta} \frac{1}{2}\epsilon_j^2(t) \leq 0 \tag{17}$$

where

$$\Psi_{1i} = \begin{bmatrix} \Psi_{11i} & \Psi_{12i} & \Psi_{13i} \\ * & \Psi_{22i} & \Psi_{23i} \\ * & * & \Psi_{33i} \end{bmatrix}, \quad \Psi_{2i} = \begin{bmatrix} \Psi_{21i} & \Psi_{12i} & \Psi_{13i} \\ * & \Psi_{22i} & \Psi_{23i} \\ * & * & \Psi_{33i} \end{bmatrix},$$

$$\Psi_{3i} = \begin{bmatrix} \Psi_{31i} & \Psi_{12i} & \Psi_{13i} \\ * & \Psi_{22i} & \Psi_{23i} \\ * & * & \Psi_{33i} \end{bmatrix}$$

$$\Psi_{11i} = \begin{bmatrix} \Gamma_{1i} & \Gamma_{12i} \\ * & \Gamma_{22i} \end{bmatrix}, \quad \Psi_{21i} = \begin{bmatrix} \Gamma_{2i} & \Gamma_{12i} \\ * & \Gamma_{22i} \end{bmatrix}, \quad \Psi_{31i} = \begin{bmatrix} \Gamma_{3i} & \Gamma_{12i} \\ * & \Gamma_{22i} \end{bmatrix},$$

$$\Gamma_{31i} = -2G_2 + W_i$$

$$\Gamma_{12i} = \begin{bmatrix} \rho \mathcal{K}_i^{\mathrm{T}} B_i^{\mathrm{T}} P_i \\ G_1^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}, \quad \Gamma_{22i} = \begin{bmatrix} \Gamma_{31i} & G_2 \\ * & \Gamma_{33i} \end{bmatrix}, \quad \Gamma_{33i} = -Q_{1i} - G_1 - G_2$$

$$\Psi_{12i} = \begin{bmatrix} 0 & \rho P_i B_i \mathcal{K}_i & P_i B_i + E_i^{\mathrm{T}} D_{vi} \\ G_2 & W_i & 0 \\ 0 & 0 & 0 \end{bmatrix},$$

$$\Psi_{13i} = \begin{bmatrix} \tau_1 A_i^{\mathrm{T}} & (\tau_2 - \tau_1) A_i^{\mathrm{T}} \\ \tau_1 \rho \mathcal{K}_i^{\mathrm{T}} B_i^{\mathrm{T}} & \rho(\tau_2 - \tau_1)\mathcal{K}_i^{\mathrm{T}} B_i^{\mathrm{T}} \\ 0 & 0 \end{bmatrix}$$

$$\Psi_{22i} = \begin{bmatrix} -Q_{2i} - G_2 & 0 & 0 \\ * & (1-\epsilon_0) W_i & 0 \\ * & * & D_{vi}^{\mathrm{T}} D_{vi} - \zeta^2 I \end{bmatrix},$$

$$\Psi_{23i} = \begin{bmatrix} 0 & 0 \\ \tau_1 \rho \mathcal{K}_i^{\mathrm{T}} B_i^{\mathrm{T}} & (\tau_2 - \tau_1)\rho K_i^{\mathrm{T}} B_i^{\mathrm{T}} \\ \tau_1 B_i^{\mathrm{T}} & (\tau_2 - \tau_1) B_i^{\mathrm{T}} \end{bmatrix}$$

$$\Gamma_i = A_i^{\mathrm{T}} P_i + P_i A_i + Q_{1i} + Q_{2i} + \tau_1 Q_1 + \tau_2 Q_2 - G_1 + E_i^{\mathrm{T}} E_i,$$

$$\Psi_{33i} = \mathrm{diag}\left\{ -G_1^{-1}, -G_2^{-1} \right\}$$

$$\begin{aligned}
\varGamma_{1i} &= \varGamma_i + \sum_{j=1, j\neq i}^{\eta} \tilde{\lambda}_{ij}(P_j - P_i) + \sum_{j=1, j\neq i}^{\eta} \frac{\vartheta_{ij}^2}{4} H_{ij}, \\
\varGamma_{2i} &= \varGamma_i + \sum_{j\in I_k^i} \tilde{\lambda}_{ij}(P_j - P_l) + \sum_{j\in I_k^i} \frac{\vartheta_{ij}^2}{4} M_{ijl} \\
\varGamma_{3i} &= \varGamma_i + \sum_{j\in I_k^i} \tilde{\lambda}_{ij}(P_j - P_l) + \sum_{j\in I_k^i} \frac{\vartheta_{ij}^2}{4} L_{ij}, \quad \tau_1 = \tau_l, \quad \tau_2 = \tau_u + T
\end{aligned}$$

Proof Define the Lyapunov–Krasovskii functional as

$$\mathcal{V}(\chi(t), \ell_t, t) = \sum_{i=1}^{5} \mathcal{V}_i(\chi(t), \ell_t, t) \tag{18}$$

where

$$\begin{aligned}
\mathcal{V}_1(\chi(t), \ell_t, t) &= \chi^{\mathrm{T}}(t) P(\ell_t) \chi(t) \\
\mathcal{V}_2(\chi(t), \ell_t, t) &= \int_{t-\tau_1}^{t} \chi^{\mathrm{T}}(\delta) Q_1(\ell_t) \chi(\delta) \mathrm{d}\delta + \int_{t-\tau_2}^{t} \chi^{\mathrm{T}}(\delta) Q_2(\ell_t) \chi(\delta) \mathrm{d}\delta \\
\mathcal{V}_3(\chi(t), \ell_t, t) &= \int_{-\tau_1}^{0} \int_{t+\delta}^{t} \chi^{\mathrm{T}}(\theta) Q_1 \chi(\theta) \mathrm{d}\theta \mathrm{d}\delta + \int_{-\tau_2}^{0} \int_{t+\delta}^{t} \chi^{\mathrm{T}}(\theta) Q_2 \chi(\theta) \mathrm{d}\theta \mathrm{d}\delta \\
\mathcal{V}_4(\chi(t), \ell_t, t) &= \tau_1 \int_{-\tau_1}^{0} \int_{t+\delta}^{t} \dot{\chi}^{\mathrm{T}}(\theta) G_1 \dot{\chi}(\theta) \mathrm{d}\theta \mathrm{d}\delta \\
&\quad + (\tau_2 - \tau_1) \int_{-\tau_2}^{-\tau_1} \int_{t+\delta}^{t} \dot{\chi}^{\mathrm{T}}(\theta) G_2 \dot{\chi}(\theta) \mathrm{d}\theta \mathrm{d}\delta \\
\mathcal{V}_5(\chi(t), \ell_t, t) &= \frac{1}{2} \epsilon^2(\ell_t)
\end{aligned}$$

According to Definition 1, we have

$$\begin{aligned}
\mathcal{L}\mathcal{V}_1(\chi(t), \ell_t, t) &= \dot{\chi}^{\mathrm{T}}(t) P_i \chi(t) + \chi^{\mathrm{T}}(t) P_i \dot{\chi}(t) + \chi^{\mathrm{T}}(t) \left(\sum_{j=1}^{\eta} \pi_{ij} P_j \right) \chi(t) \\
\mathcal{L}\mathcal{V}_2(\chi(t), \ell_t, t) &= \chi^{\mathrm{T}}(t) Q_{1i} \chi(t) - \chi^{\mathrm{T}}(t-\tau_1) Q_{1i} \chi(t-\tau_1) \\
&\quad + \int_{t-\tau_1}^{t} \chi^{\mathrm{T}}(\delta) \left(\sum_{j=1}^{\eta} \pi_{ij} Q_{1j} \right) \chi(\delta) \mathrm{d}\delta \\
&\quad + \chi^{\mathrm{T}}(t) Q_{2i} \chi(t) - \chi^{\mathrm{T}}(t-\tau_2) Q_{2i} \chi(t-\tau_2) \\
&\quad + \int_{t-\tau_2}^{t} \chi^{\mathrm{T}}(\delta) \left(\sum_{j=1}^{\eta} \pi_{ij} Q_{2j} \right) \chi(\delta) \mathrm{d}\delta
\end{aligned}$$

$$\begin{aligned}
\mathcal{L}\mathcal{V}_3(\chi(t),\ell_t,t) &= \tau_1\chi^{\mathrm{T}}(t)Q_1\chi(t) - \int_{t-\tau_1}^{t}\chi^{\mathrm{T}}(\delta)Q_1\chi(\delta)\mathrm{d}\delta + \tau_2\chi^{\mathrm{T}}(t)Q_2\chi(t)\\
&\quad - \int_{t-\tau_2}^{t}\chi^{\mathrm{T}}(\delta)Q_2\chi(\delta)\mathrm{d}\delta\\
\mathcal{L}\mathcal{V}_4(\chi(t),\ell_t,t) &= \tau_1^2\dot{\chi}^{\mathrm{T}}(t)G_1\dot{\chi}(t) + (\tau_2-\tau_1)^2\dot{\chi}^{\mathrm{T}}(t)G_2\dot{\chi}(t)\\
&\quad - \tau_1\int_{t-\tau_1}^{t}\dot{\chi}^{\mathrm{T}}(\delta)G_1\dot{\chi}(\delta)\mathrm{d}\delta\\
&\quad - (\tau_2-\tau_1)\int_{t-\tau_2}^{t-\tau_1}\dot{\chi}^{\mathrm{T}}(\delta)G_2\dot{\chi}(\delta)\mathrm{d}\delta\\
\mathcal{L}\mathcal{V}_5(\chi(t),\ell_t,t) &= \left[\frac{1}{\epsilon_i(t)} - \epsilon_0\right]e^{\mathrm{T}}(t)W_ie(t) + \frac{1}{2}\sum_{j=1}^{\eta}\lambda_{ij}\epsilon_j^2(t)
\end{aligned}$$

From (15) and (16), we can infer that

$$\int_{t-\tau_1}^{t}\chi^{\mathrm{T}}(\delta)\left(\sum_{j=1}^{\eta}\lambda_{ij}Q_{1j}\right)\chi(\delta)\mathrm{d}\delta \le \int_{t-\tau_1}^{t}\chi^{\mathrm{T}}(\delta)Q_1\chi(\delta)\mathrm{d}\delta$$

$$\int_{t-\tau_2}^{t}\chi^{\mathrm{T}}(\delta)\left(\sum_{j=1}^{\eta}\lambda_{ij}Q_{2j}\right)\chi(\delta)\mathrm{d}\delta \le \int_{t-\tau_2}^{t}\chi^{\mathrm{T}}(\delta)Q_2\chi(\delta)\mathrm{d}\delta$$

By using the Jensen's inequality [31,35], we have

$$-\tau_1\int_{t-\tau_1}^{t}\dot{\chi}^{\mathrm{T}}(\delta)G_1\dot{\chi}(\delta)\mathrm{d}\delta \le \begin{bmatrix}\chi(t)\\ \chi(t-\tau_1)\end{bmatrix}^{\mathrm{T}}\begin{bmatrix}-G_1 & G_1\\ * & -G_1\end{bmatrix}\begin{bmatrix}\chi(t)\\ \chi(t-\tau_1)\end{bmatrix}$$

$$\begin{aligned}
-(\tau_2-\tau_1)\int_{t-\tau_2}^{t-\tau_1}\dot{\chi}^{\mathrm{T}}(\delta)G_2\dot{\chi}(\delta)\mathrm{d}\delta &\le \begin{bmatrix}\chi(t-\tau(t))\\ \chi(t-\tau_1)\\ \chi(t-\tau_2)\end{bmatrix}^{\mathrm{T}}\begin{bmatrix}-2G_2 & G_2 & G_2\\ * & -G_2 & 0\\ * & * & -G_2\end{bmatrix}\\
&\quad \begin{bmatrix}\chi(t-\tau(t))\\ \chi(t-\tau_1)\\ \chi(t-\tau_2)\end{bmatrix}
\end{aligned}$$

Combining (5) with (6), the following inequality can be obtained

$$\begin{aligned}
\epsilon_i(t)\dot{\epsilon}_i(t) &= \left[\frac{1}{\epsilon_i(t)} - \epsilon_0\right]e^{\mathrm{T}}(t)W_ie(t) + \sum_{j=1}^{\eta}\lambda_{ij}\frac{1}{2}\epsilon_j^2(t)\\
&\le [\chi(t-\tau(t))+e(t)]^{\mathrm{T}}\,W_i\,[\chi(t-\tau(t))+e(t)] - \epsilon_0e^{\mathrm{T}}(t)W_ie(t)\\
&= \begin{bmatrix}\chi(t-\tau(t))\\ e(t)\end{bmatrix}^{\mathrm{T}}\begin{bmatrix}W_i & W_i\\ * & (1-\epsilon_0)W_i\end{bmatrix}\begin{bmatrix}\chi(t-\tau(t))\\ e(t)\end{bmatrix}
\end{aligned}$$

Let $\xi^{\mathrm{T}}(t) = [\chi^{\mathrm{T}}(t)\ \ \chi^{\mathrm{T}}(t-\tau(t))\ \ \chi^{\mathrm{T}}(t-\tau_1)\ \ \chi^{\mathrm{T}}(t-\tau_2)\ \ e^{\mathrm{T}}(t)]$, one can have

$$\mathcal{LV}(\chi(t), \ell_t, t) \leq \xi^{\mathrm{T}}(t)\Xi_i\xi(t)$$

where

$$\Xi_i = \begin{bmatrix} \Xi_{11i} + \sum_{j=1}^{\eta}\lambda_{ij}P_j & \Xi_{12i} & G_1 & 0 & \Xi_{15i} \\ * & \Xi_{22i} & G_2 & G_2 & \Xi_{25i} \\ * & * & -Q_{1i} - G_1 - G_2 & 0 & 0 \\ * & * & * & -Q_{2i} - G_2 & 0 \\ * & * & * & * & \Xi_{55i} \end{bmatrix}$$

$$\begin{aligned}
\Xi_{11i} &= A_i^{\mathrm{T}}P_i + P_iA_i + Q_{1i} + Q_{2i} + \tau_1 Q_1 + \tau_2 Q_2 + \tau_1^2 A_i^{\mathrm{T}}G_1A_i \\
&\quad + (\tau_2 - \tau_1)^2 A_i^{\mathrm{T}}G_2A_i - G_1 \\
\Xi_{12i} &= \rho P_iB_i\mathcal{K}_i + \tau_1^2\rho A_i^{\mathrm{T}}G_1B_i\mathcal{K}_i + (\tau_2-\tau_1)^2\rho A_i^{\mathrm{T}}G_2B_i\mathcal{K}_i \\
\Xi_{15i} &= \rho P_iB_i\mathcal{K}_i + \tau_1^2\rho A_i^{\mathrm{T}}G_1B_i\mathcal{K}_i + (\tau_2-\tau_1)^2\rho A_i^{\mathrm{T}}G_2B_i\mathcal{K}_i \\
\Xi_{22i} &= \tau_1^2\rho^2\mathcal{K}_i^{\mathrm{T}}B_i^{\mathrm{T}}G_1B_i\mathcal{K}_i - 2G_2 + (\tau_2-\tau_1)^2\rho^2\mathcal{K}_i^{\mathrm{T}}B_i^{\mathrm{T}}G_2B_i\mathcal{K}_i + W_i \\
\Xi_{25i} &= \tau_1^2\rho^2\mathcal{K}_i^{\mathrm{T}}B_i^{\mathrm{T}}G_1B_i\mathcal{K}_i + (\tau_2-\tau_1)^2\rho^2 K_i^{\mathrm{T}}B_i^{\mathrm{T}}G_2B_i\mathcal{K}_i + W_i \\
\Xi_{55i} &= \tau_1^2\rho^2\mathcal{K}_i^{\mathrm{T}}B_i^{\mathrm{T}}G_1B_i\mathcal{K}_i + (1-\epsilon_0)W_i + (\tau_2-\tau_1)^2\rho^2\mathcal{K}_i^{\mathrm{T}}B_i^{\mathrm{T}}G_2B_i\mathcal{K}_i
\end{aligned} \tag{19}$$

According to Schur complement, conditions (12)–(14) can guarantee $\Xi_i < 0$, which means that $\mathcal{LV}(\chi(t), \ell_t, t) < 0$ for $\forall\xi(t) \neq 0$. Then, system (11) is stochastically stable when $\omega(t) = 0$.

Under the adaptive event-triggered mechanism, we will prove that MJSs with the H_∞ performance are stochastically stable if $\omega(t) \neq 0$. Thus, the following equality holds

$$\begin{aligned}
\mathcal{LV}(\chi(t), \ell_t, t) = {}& \xi^{\mathrm{T}}(t)\Xi_i\xi(t) + 2\chi^{\mathrm{T}}(t)P_iB_i\omega(t) + 2\tau_1^2\chi^{\mathrm{T}}(t)A_i^{\mathrm{T}}G_1B_i\omega(t) \\
&+ 2\tau_1^2\rho\chi^{\mathrm{T}}(t-\tau(t))\mathcal{K}_i^{\mathrm{T}}B_i^{\mathrm{T}}G_1B_i\omega(t) + 2\tau_1^2\rho e^{\mathrm{T}}(t)\mathcal{K}_i^{\mathrm{T}}B_i^{\mathrm{T}}G_1B_i\omega(t) \\
&+ \tau_1^2\omega^{\mathrm{T}}(t)B_i^{\mathrm{T}}G_1B_i\omega(t) + 2(\tau_2-\tau_1)^2\chi^{\mathrm{T}}(t)A_i^{\mathrm{T}}G_2B_i\omega(t) \\
&+ 2(\tau_2-\tau_1)^2\rho\chi^{\mathrm{T}}(t-\tau(t))\mathcal{K}_i^{\mathrm{T}}B_i^{\mathrm{T}}G_2B_i\omega(t) \\
&+ 2(\tau_2-\tau_1)^2\rho e^{\mathrm{T}}(t)\mathcal{K}_i^{\mathrm{T}}B_i^{\mathrm{T}}G_2B_i\omega(t) \\
&+ (\tau_2-\tau_1)^2\omega^{\mathrm{T}}(t)B_i^{\mathrm{T}}G_2B_i\omega(t)
\end{aligned}$$

Based on the definition of $E\mathcal{V}(\chi(t), \ell_t, t) = E\int_0^\infty \mathcal{LV}(\chi(t), \ell_t, t)dt > 0$, the system performance satisfies the following condition:

$$\begin{aligned}
L &\leq E\left\{\int_0^\infty z^{\mathrm{T}}(t)z(t) - \zeta^2\omega^{\mathrm{T}}(t)\omega(t) + \mathcal{LV}(\chi(t), \ell_t, t)\right\}\mathrm{d}t \\
&= E\int_0^\infty \hbar^{\mathrm{T}}(t)\Pi_i\hbar(t)\mathrm{d}t
\end{aligned}$$

where

$$\hbar^{\mathrm{T}}(t) = [\xi^{\mathrm{T}}(t) \;\; \omega^{\mathrm{T}}(t)]$$

$$\Pi_i = \begin{bmatrix} \Pi_{11i} + \sum_{j=1}^{\eta} \lambda_{ij} P_j & \Pi_{12i} & G_1 & 0 & \Pi_{15i} & \Pi_{16i} \\ * & \Pi_{22i} & G_2 & G_2 & \Pi_{25i} & \Pi_{26i} \\ * & * & \Pi_{33i} & 0 & 0 & 0 \\ * & * & * & -Q_{2i} - G_2 & 0 & 0 \\ * & * & * & * & \Pi_{55i} & \Pi_{56i} \\ * & * & * & * & * & \Pi_{66i} \end{bmatrix}$$

$$\Pi_{11i} = \Xi_{11i} + E_i^{\mathrm{T}} E_i, \quad \Pi_{12i} = \Xi_{12i}, \quad \Pi_{15i} = \Xi_{15i}, \quad \Pi_{22i} = \Xi_{22i}$$

$$\Pi_{16i} = P_i B_i + \tau_1^2 A_i^{\mathrm{T}} G_1 B_i + (\tau_2 - \tau_1)^2 A_i^2 G_2 B_i + E_i^{\mathrm{T}} D_{vi}$$

$$\Pi_{25i} = \Xi_{25i}, \quad \Pi_{33i} = -Q_{1i} - G_1 - G_2, \quad \Pi_{55i} = \Xi_{55i}$$

$$\Pi_{26i} = \tau_1^2 \rho \mathcal{K}_i^{\mathrm{T}} B_i^{\mathrm{T}} G_1 B_i + (\tau_2 - \tau_1)^2 \rho \mathcal{K}_i^{\mathrm{T}} B_i^{\mathrm{T}} G_2 B_i$$

$$\Pi_{56i} = \tau_1^2 \rho \mathcal{K}_i^{\mathrm{T}} B_i^{\mathrm{T}} G_1 B_i + (\tau_2 - \tau_1)^2 \rho \mathcal{K}_i^{\mathrm{T}} B_i^{\mathrm{T}} G_2 B_i$$

$$\Pi_{66i} = \tau_1^2 B_i^{\mathrm{T}} G_1 B_i + (\tau_2 - \tau_1)^2 B_i^{\mathrm{T}} G_2 B_i + D_{vi}^{\mathrm{T}} D_{vi} - \zeta^2 I$$

Consider system (11) with the GUTRs matrix, similar to [20], $\Pi_{11i} + \sum_{j=1}^{\eta} \lambda_{ij} P_j$ can be divided into three situations for discussion.

Case 1 When $i \in I_k^i$ and $I_{uk}^i = \varnothing$, by Assumption 1, such that

$$\begin{aligned} \Phi_{1i} = \Pi_{11i} + \sum_{j=1}^{\eta} \lambda_{ij} P_j &= \Pi_{11i} + \sum_{j=1, j\neq i}^{\eta} \lambda_{ij}(P_j - P_i) \\ &= \sum_{j=1, j\neq i}^{\eta} \tilde{\lambda}_{ij}(P_j - P_i) + \sum_{j=1, j\neq i}^{\eta} \Lambda_{ij}(P_j - P_i) \end{aligned}$$

then employing Lemma 2, it follows that

$$\begin{aligned} \sum_{j=1, j\neq i}^{\eta} \Lambda_{ij}(P_j - P_i) &= \sum_{j=1, j\neq i}^{\eta} \left[\frac{1}{2}\Lambda_{ij}(P_j - P_i) + \frac{1}{2}\Lambda_{ij}(P_j - P_i)\right] \\ &\leq \sum_{j=1, i\neq i}^{\eta} \left(\left(\frac{1}{2}\Lambda_{ij}\right)^2 H_{ij} + (P_j - P_i) H_{ij}^{-1}(P_j - P_i)\right)\right) \\ &\leq \sum_{j=1, j\neq i}^{\eta} \left(\frac{\vartheta_{ij}^2}{4} H_{ij} + (P_j - P_i) H_{ij}^{-1}(P_j - P_i)\right) \end{aligned}$$

from inequality (12), we can obtain $\Phi_{1i} < 0$ by Schur complement.

Case 2 When $i \in I_k^i$ and $I_{uk}^i \neq \varnothing$, by Assumption 2, for $\forall l \in I_{uk}^i$, we obtain

$$\begin{aligned}\Phi_{2i} &\leq \Pi_{11i} + \sum_{j\in I_k^i} \lambda_{ij} P_j - \sum_{j\in I_k^i} \lambda_{ij} P_l \\ &= \Pi_{11i} + \sum_{j\in I_k^i} \tilde{\lambda}_{ij}(P_j - P_l) + \sum_{j\in I_k^i} \Lambda_{ij}(P_j - P_l)\end{aligned}$$

after using Lemma 2, the following inequality holds

$$\begin{aligned}\sum_{j\in I_k^i} \Lambda_{ij}(P_j - P_l) &= \sum_{j\in I_k^i} \left[\frac{1}{2}\Lambda_{ij}(P_j - P_l) + \frac{1}{2}\Lambda_{ij}(P_j - P_l)\right] \\ &\leq \sum_{j\in I_k^i} \left[\left(\frac{1}{2}\Lambda_{ij}\right)^2 M_{ijl} + (P_j - P_l)M_{ijl}^{-1}(P_j - P_l)\right] \\ &\leq \sum_{j\in I_k^i} \left[\left(\frac{1}{4}\vartheta_{ij}\right)^2 M_{ijl} + (P_j - P_l)M_{ijl}^{-1}(P_j - P_l)\right]\end{aligned}$$

by Schur complement and inequality (13), it follows that $\Phi_{2i} < 0$.

Case 3 When $i \notin I_k^i$, by Assumption 3, we have

$$\begin{aligned}\Phi_{3i} &\leq \Pi_{11i} + \sum_{j\in I_k^i} \lambda_{ij} P_j + \sum_{j\in I_{uk}^i, j\neq i} \lambda_{ij} P_i + \lambda_{ii} P_i \\ &= \Pi_{11i} + \sum_{j\in I_k^i} \lambda_{ij} P_j + \left(-\lambda_{ii} - \sum_{j\in I_k^i} \lambda_{ij}\right) P_i + \lambda_{ii} P_i \\ &= \Pi_{11i} + \sum_{j\in I_k^i} \tilde{\lambda}_{ij}(P_j - P_i) + \sum_{j\in I_k^i} \Lambda_{ij}(P_j - P_i)\end{aligned}$$

by employing Lemma 2, it follows that

$$\begin{aligned}\sum_{j\in I_k^i} \Lambda_{ij}(P_j - P_i) &\leq \sum_{j\in I_k^i} \left[\left(\frac{1}{2}\Lambda_{ij}\right)^2 L_{ij} + (P_j - P_i)L_{ij}^{-1}(P_j - P_i)\right] \\ &\leq \sum_{j\in I_k^i} \left[\frac{\vartheta_{ij}^2}{4} L_{ij} + (P_j - P_i)L_{ij}^{-1}(P_j - P_i)\right]\end{aligned}$$

from inequality (14), it is easily obtained $\Phi_{3i} < 0$ by Schur complement.

The following condition can be derived

$$\mathrm{E}\left(\sup_{0\neq\omega(t)\in\mathcal{L}_2}\frac{\|z(t)\|}{\|\omega(t)\|}\right)<\zeta$$

according to Schur complement, one can obtain $\Pi_i < 0$ by conditions (12)–(17). According to Definition 2, the resulting system (11) with the H_∞ performance is stochastically stable. The proof is finished. □

3.2 Controller Design

A solution of the controller design will be presented for the closed-loop system (11).

Theorem 2 *Given positive constants $\tau_1, \tau_2, k_1, k_2, \epsilon_0, \zeta$, if there exist matrices $P_i > 0$, $H_{ij} > 0$, $M_{ijl} > 0$, $L_{ij} > 0$, $Q_{1i} > 0$, $Q_{2i} > 0$, $Q_1 > 0$, $Q_2 > 0$, $G_1 > 0$, $G_2 > 0$, $X_i > 0$ and control gains $\bar{\mathcal{K}}_i$, such that for $\forall i \in \mathbb{N}$,*

$$\begin{bmatrix} \hat{\Psi}_{1i} & P_1-P_i & \dots & P_{i-1}-P_i & P_{i+1}-P_i & \dots & P_s-P_i \\ * & -H_{i1} & \dots & 0 & 0 & \dots & 0 \\ * & * & \ddots & \vdots & \vdots & \vdots & \vdots \\ * & * & * & -H_{i(i-1)} & 0 & \vdots & \vdots \\ * & * & * & * & -H_{i(i+1)} & \vdots & \vdots \\ * & * & * & * & * & \ddots & \vdots \\ * & * & * & * & * & * & -H_{is} \end{bmatrix} < 0, \quad i \in I_k^i \text{ and } I_{uk}^i = \varnothing \tag{20}$$

$$\begin{bmatrix} \hat{\Psi}_{2i} & P_{k_1^i}-P_l & \dots & P_{k_m^i}-P_l \\ * & -M_{ik_1^i l} & \dots & 0 \\ * & * & \ddots & \vdots \\ * & * & * & -M_{ik_m^i l} \end{bmatrix} < 0, \quad i \in I_k^i \text{ and } I_{uk}^i \neq \varnothing \tag{21}$$

$$\begin{bmatrix} \hat{\Psi}_{3i} & P_{k_1^i}-P_i & \dots & P_{k_m^i}-P_i \\ * & -L_{ik_1^i} & \dots & 0 \\ * & * & \ddots & \vdots \\ * & * & * & -L_{ik_m^i} \end{bmatrix} < 0, \quad i \notin I_k^i,\ \forall j \in I_{uk}^i \tag{22}$$

$$P_i B_i = B_i X_i \tag{23}$$

where

$$
\hat{\Psi}_{1i} = \begin{bmatrix} \hat{\Psi}_{11i} & \hat{\Psi}_{12i} & \hat{\Psi}_{13i} \\ * & \hat{\Psi}_{22i} & \hat{\Psi}_{23i} \\ * & * & \hat{\Psi}_{33i} \end{bmatrix}, \quad \hat{\Psi}_{2i} = \begin{bmatrix} \hat{\Psi}_{21i} & \hat{\Psi}_{12i} & \hat{\Psi}_{13i} \\ * & \hat{\Psi}_{22i} & \hat{\Psi}_{23i} \\ * & * & \hat{\Psi}_{33i} \end{bmatrix},
$$

$$
\hat{\Psi}_{3i} = \begin{bmatrix} \hat{\Psi}_{31i} & \hat{\Psi}_{12i} & \hat{\Psi}_{13i} \\ * & \hat{\Psi}_{22i} & \hat{\Psi}_{23i} \\ * & * & \hat{\Psi}_{33i} \end{bmatrix}
$$

$$
\hat{\Psi}_{11i} = \begin{bmatrix} \hat{\Gamma}_{1i} & \hat{\Gamma}_{12i} \\ * & \hat{\Gamma}_{22i} \end{bmatrix}, \quad \hat{\Psi}_{21i} = \begin{bmatrix} \hat{\Gamma}_{2i} & \hat{\Gamma}_{12i} \\ * & \hat{\Gamma}_{22i} \end{bmatrix},
$$

$$
\hat{\Psi}_{31i} = \begin{bmatrix} \hat{\Gamma}_{3i} & \hat{\Gamma}_{12i} \\ * & \hat{\Gamma}_{22i} \end{bmatrix}, \quad \hat{\Gamma}_{31i} = -2G_2 + W_i
$$

$$
\hat{\Gamma}_{12i} = \begin{bmatrix} \rho \bar{\mathcal{K}}_i^{\mathrm{T}} B_i^{\mathrm{T}} \\ R_1^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}, \quad \hat{\Gamma}_{22i} = \begin{bmatrix} \hat{\Gamma}_{31i} & G_2 \\ * & \hat{\Gamma}_{33i} \end{bmatrix},
$$

$$
\hat{\Psi}_{33i} = \begin{bmatrix} -2k_1 P + k_1^2 G_1 & 0 \\ * & -2k_2 P + k_2^2 G_2 \end{bmatrix}
$$

$$
\hat{\Psi}_{12i} = \begin{bmatrix} 0 & \rho B_i \bar{\mathcal{K}}_i & P_i B_i + E_i^{\mathrm{T}} D_{vi} \\ G_2 & W_i & 0 \\ 0 & 0 & 0 \end{bmatrix},
$$

$$
\hat{\Psi}_{13i} = \begin{bmatrix} \tau_1 A_i^{\mathrm{T}} P & (\tau_2 - \tau_1) A_i^{\mathrm{T}} P \\ \tau_1 \rho \bar{\mathcal{K}}_i^{\mathrm{T}} B_i^{\mathrm{T}} & \rho(\tau_2 - \tau_1) \bar{\mathcal{K}}_i^{\mathrm{T}} B_i^{\mathrm{T}} \\ 0 & 0 \end{bmatrix}
$$

$$
\hat{\Psi}_{22i} = \begin{bmatrix} -Q_{2i} - G_2 & 0 & 0 \\ * & (1-\epsilon_0) W_i & 0 \\ * & * & D_{vi}^{\mathrm{T}} D_{vi} - \zeta^2 I \end{bmatrix},
$$

$$
\hat{\Psi}_{23i} = \begin{bmatrix} 0 & 0 \\ \tau_1 \rho \bar{\mathcal{K}}_i^{\mathrm{T}} B_i^{\mathrm{T}} & (\tau_2 - \tau_1) \rho \bar{\mathcal{K}}_i^{\mathrm{T}} B_i^{\mathrm{T}} \\ \tau_1 B_i^{\mathrm{T}} P & (\tau_2 - \tau_1) B_i^{\mathrm{T}} P \end{bmatrix}
$$

$$
\hat{\Gamma}_i = A_i^{\mathrm{T}} P_i + P_i A_i + Q_{1i} + Q_{2i} + \tau_1 Q_1 + \tau_2 Q_2 - G_1 + E_i^{\mathrm{T}} E_i,
$$

$$
\hat{\Gamma}_{33i} = -Q_{1i} - G_1 - G_2
$$

$$
\hat{\Gamma}_{1i} = \hat{\Gamma}_i + \sum_{j=1, j\neq i}^{\eta} \tilde{\lambda}_{ij}(P_j - P_i) + \sum_{j=1, j\neq i}^{\eta} \frac{\vartheta_{ij}^2}{4} H_{ij},
$$

$$
\hat{\Gamma}_{2i} = \hat{\Gamma}_i + \sum_{j \in I_k^i} \tilde{\lambda}_{ij}(P_j - P_l) + \sum_{j \in I_k^i} \frac{\vartheta_{ij}^2}{4} M_{ijl}
$$

$$
\hat{\Gamma}_{3i} = \hat{\Gamma}_i + \sum_{j \in I_k^i} \tilde{\lambda}_{ij}(P_j - P_l) + \sum_{j \in I_k^i} \frac{\vartheta_{ij}^2}{4} L_{ij}
$$

under the adaptive event-triggered mechanism, system (11) with GUTRs is stochastically stable and meets the H_∞ performance. Furthermore, if the linear matrix inequalities (LMIs) (20)–(22) have feasible solutions, the desired H_∞ controller gains $\mathcal{K}_i$ are calculated by

$$\mathcal{K}_i = X_i^{-1}\bar{\mathcal{K}}_i \tag{24}$$

Proof For $k_\varsigma > 0$, $\varsigma = 1, 2$, one has

$$(k_\varsigma G_\varsigma - P_i)G_\varsigma^{-1}(k_\varsigma G_\varsigma - P_i) \geq 0$$

which implies

$$-P_i G_\varsigma^{-1} P_i \leq k_\varsigma^2 G_\varsigma - 2k_\varsigma P_i, \quad \varsigma = 1, 2$$

Replacing $k_\varsigma^2 G_\varsigma - 2k_\varsigma P_i$ with $-P_i G_\varsigma^{-1} P_i$ in LMIs (20)–(22).

Define $\Upsilon = \mathrm{diag}\{I, I, I, I, I, I, P^{-1}, P^{-1}\}$, pre- and post-multiplying both sides of (20)–(22) with Υ. Then, conditions (12)–(14) can be obtained.

It is known that the above equality (23) can be written as [5,9]

$$\mathrm{tr}[(P_i B_i - B_i X_i)^{\mathrm{T}}(P_i B_i - B_i X_i)] = 0$$

then, the following constraint condition is obtained

$$(P_i B_i - B_i X_i)^{\mathrm{T}}(P_i B_i - B_i X_i) < \varpi_i I$$

where ϖ_i denotes a small positive scalar. Then, we have

$$\begin{bmatrix} -\varpi_i I & (P_i B_i - B_i X_i)^{\mathrm{T}} \\ * & -I \end{bmatrix} < 0 \tag{25}$$

the adaptive event-triggered control problem will be translated into the minimization problem: min ϖ_i, subject to (20)–(22) and (25). The proof is finished. □

4 Simulation Examples

We present a numerical example and a practical example to show the availability of the proposed adaptive event-triggered control method for MJSs.

Example 1 Consider the system (1) with four subsystems, the parameter matrices are shown as follows:

Fig. 2 The threshold $\epsilon_1(t)$

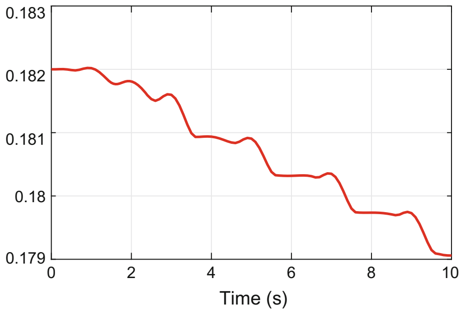
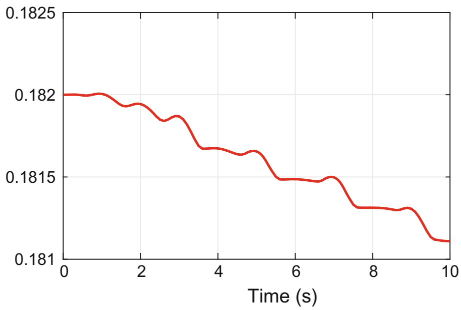


Fig. 3 The threshold $\epsilon_2(t)$



$$A_1 = \begin{bmatrix} -1.56 & 1.5 & 0.4 \\ 0 & -3.279 & -2.1 \\ 0 & 2.928 & -2.082 \end{bmatrix}, \quad A_2 = \begin{bmatrix} -1.56 & 1.5 & 0.2 \\ 0 & -4.279 & -2.3 \\ 0 & 2.928 & -2.282 \end{bmatrix}$$

$$A_3 = \begin{bmatrix} -1.56 & 1.5 & 0.2 \\ 0 & -5.279 & -2.3 \\ 0 & 2.928 & -2.882 \end{bmatrix}, \quad A_4 = \begin{bmatrix} -1.56 & 1.5 & 0.2 \\ 0 & -6.279 & -2.3 \\ 0 & 2.928 & -2.182 \end{bmatrix}$$

$$B_1 = \begin{bmatrix} 0.04 \\ 0.02 \\ -0.01 \end{bmatrix}, \quad B_2 = \begin{bmatrix} 0.02 \\ 0.01 \\ -0.01 \end{bmatrix}, \quad B_3 = \begin{bmatrix} 0.02 \\ 0.01 \\ -0.02 \end{bmatrix}, \quad B_4 = \begin{bmatrix} 0.01 \\ 0.01 \\ -0.02 \end{bmatrix}$$

$$E_1 = \begin{bmatrix} 0.2 & 0.1 & 0 \end{bmatrix}, \quad E_2 = \begin{bmatrix} 0.2 & 0 & 0.2 \end{bmatrix}, \quad E_3 = \begin{bmatrix} 0.1 & 0.1 & 0 \end{bmatrix}$$

$$E_4 = \begin{bmatrix} 0.1 & 0.1 & 0 \end{bmatrix}, \quad D_{v1} = D_{v2} = 0.2, \quad D_{v3} = D_{v4} = 0.1$$

The GUTR matrix is given as

$$\Pi = \begin{bmatrix} -1.4 & 1 + \Lambda_{12} & ? & ? \\ ? & -1.9 & 1.7 & ? \\ 1.2 & ? & -1.6 + \Lambda_{33} & ? \\ 1.6 & ? & ? & -1.8 \end{bmatrix}$$

where $\Lambda_{12} \in [-0.1, 0.1]$ and $\Lambda_{33} \in [-0.2, 0.2]$.

The external disturbance of four subsystems is defined as $\omega(t) = \exp(-t)\sqrt{x_1^2 + x_2^2 + x_3^2}$, and the initial condition is taken as $\chi(0) = [0.4 \; -1 \; 0.8]^{\mathrm{T}}$. Given

Fig. 4 The threshold $\epsilon_3(t)$

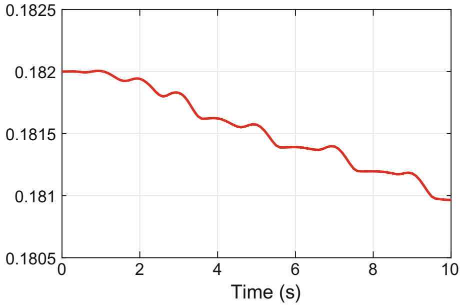


Fig. 5 The threshold $\epsilon_4(t)$

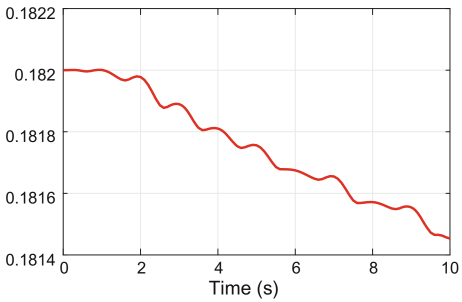


Fig. 6 Release instants under adaptive event-triggered mechanism

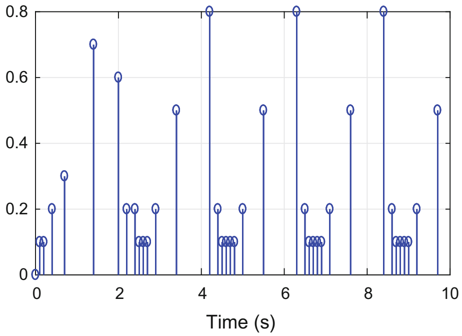
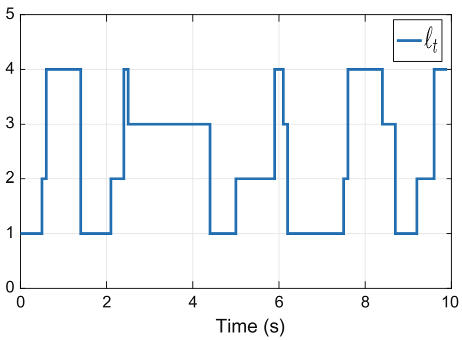


Fig. 7 The switching signal ℓ_t



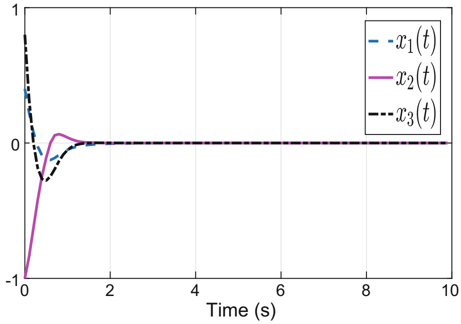


Fig. 8 The state responses of the closed-loop system

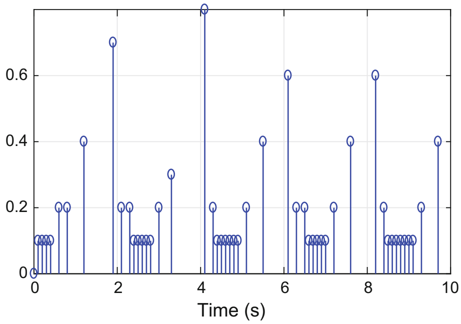


Fig. 9 Release instants under traditional event-triggered mechanism

the scalars $T = 0.1$, $\epsilon_0 = 400$, $\tau_l = 0.01$, $\tau_u = 0.02$, $k_i = 1$ $(i = 1, 2)$ and $\rho = 0.6$. By solving LMIs (20)–(22), under the condition of optimal $\zeta = 4.1182$, the controller gains are calculated as follows:

$$\mathcal{K}_1 = \begin{bmatrix} -1.2297 & -0.3082 & 0.2568 \end{bmatrix}, \quad \mathcal{K}_2 = \begin{bmatrix} -1.9164 & -0.5327 & 0.9166 \end{bmatrix}$$
$$\mathcal{K}_3 = \begin{bmatrix} -1.5019 & -0.3277 & 1.0780 \end{bmatrix}, \quad \mathcal{K}_4 = \begin{bmatrix} -1.1650 & -0.4260 & 1.8073 \end{bmatrix}$$

The simulation results are illustrated in Figs. 2, 3, 4, 5, 6, 7, and 8. For four operation modes, the trajectories of adaptive threshold $\epsilon_i(t)$ are described in Figs. 2, 3, 4, and 5. It is observed that $\epsilon_i(t)$ can be adjusted in terms of the variation of system. Figures 6 and 7 show the adaptive event-triggered release instants and the switching signals, respectively. It can be seen from Fig. 6 that only 38% communication resources are utilized. Figure 8 plots the state responses of the closed-loop system. It is noted that the designed adaptive even-triggered controller can make the state responses of the closed-loop system converge to zero quickly.

To illustrate the advantage of adaptive event-triggered mechanism, we consider the traditional control strategy for MJSs. Similar to [54], define the threshold $\bar{\epsilon} = 0.182$, and the other parameters are same as Example 1. Based on the traditional event-triggered scheme, the release instants are plotted in Fig. 9. It is noted that only 49% sampled data are released. The comparisons of the different scheme are presented in Table 1. Therefore, we can conclude that the designed adaptive event-triggered mechanism can economize more network resources than the traditional scheme.

Table 1 The different network transmission schemes

Event-triggered strategy	Release times
Adaptive scheme	38
Traditional scheme in [54]	49
Periodic sampling scheme	100

Fig. 10 The threshold $\epsilon_1(t)$

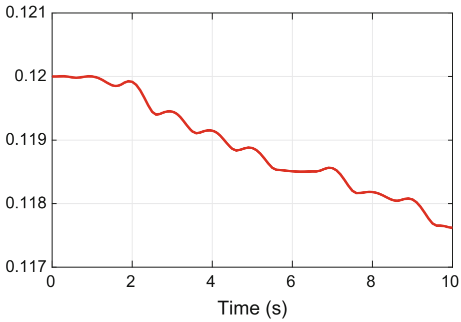
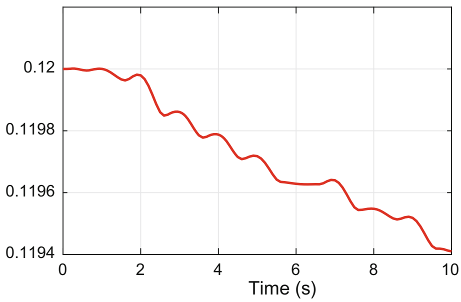


Fig. 11 The threshold $\epsilon_2(t)$



Example 2 For MJSs (1), the matrix A_i is acquired from the model of an F-404 aircraft engine system in [43]

$$\begin{bmatrix} -1.46 & 0 & 2.428 \\ 0.1643 + 0.5\varphi(t) & -0.4 + \varphi(t) & -0.3788 \\ 0.3107 & 0 & -2.23 \end{bmatrix}$$

where $\varphi(t)$ denotes the uncertain parameter following a Markov process ℓ_t with four modes. When $\ell_t = 1, 2, 3, 4$, the uncertainty $\varphi(t)$ can take values as -5, -6, -7 and -8, respectively. The other parameters for such system are same as Example 1.

The GUTR matrix is given as

$$\Pi = \begin{bmatrix} -2.4 & 2.2 + \Lambda_{12} & ? & ? \\ ? & -1.9 & 1.7 & ? \\ 1.2 & ? & -1.8 + \Lambda_{33} & ? \\ 2.6 & ? & ? & -2.8 \end{bmatrix}$$

Fig. 12 The threshold $\epsilon_3(t)$

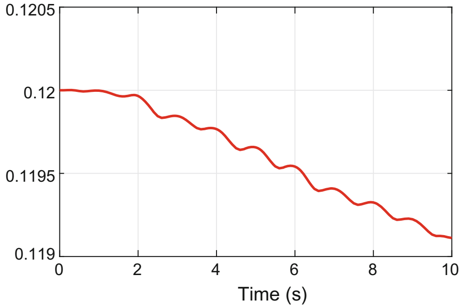


Fig. 13 The threshold $\epsilon_4(t)$

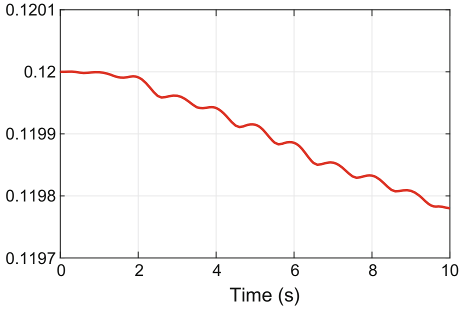


Fig. 14 Release instants under adaptive event-triggered mechanism

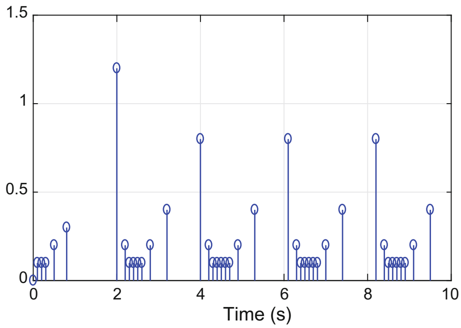
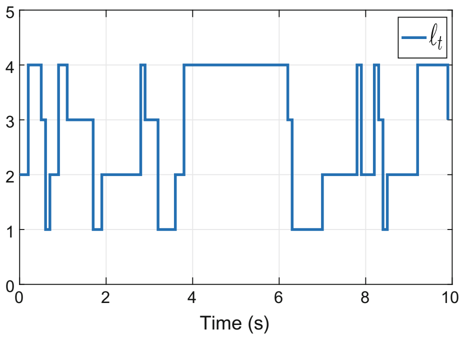


Fig. 15 The switching signal ℓ_t



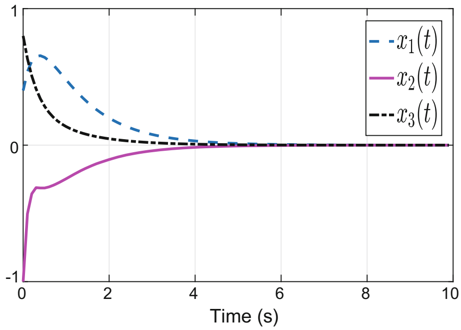


Fig. 16 The state responses of the closed-loop system

where $\Lambda_{12} \in [-0.1, 0.1]$ and $\Lambda_{33} \in [-0.2, 0.2]$.

By solving LMIs (20)–(22), under the condition of optimal $\zeta = 3.9988$, the controller gains are computed as follows:

$$\mathcal{K}_1 = \begin{bmatrix} -1.1474 & -0.1452 & 0.5407 \end{bmatrix}, \quad \mathcal{K}_2 = \begin{bmatrix} -2.1323 & -0.3618 & 1.0058 \end{bmatrix}$$
$$\mathcal{K}_3 = \begin{bmatrix} -1.3973 & -0.2435 & 1.4350 \end{bmatrix}, \quad \mathcal{K}_4 = \begin{bmatrix} -2.2730 & -0.9361 & 2.3924 \end{bmatrix}$$

For four operation modes, the trajectories of adaptive threshold $\epsilon_i(t)$ are described in Figs. 10, 11, 12, and 13, respectively. It is noted that $\epsilon_i(t)$ can be dynamically adjusted according to the adaptive law. Based on the adaptive event-triggered mechanism, the release instants are plotted in Fig. 14. The switching signals are depicted in Fig. 15. The state responses of the closed-loop system are presented in Fig. 16. It is easy to derive that the state trajectories of the closed-loop system approach zero quickly.

Remark 4 In [37], the event-triggered control scheme with a fixed threshold was designed, which could not change itself to satisfy the variation of systems. Hence, it is necessary to present an adaptive event-triggered method with a varying threshold. From Figs. 6, 9 and Table 1, the adaptive event-triggered scheme can save more communication resources than the traditional one.

5 Conclusion

This paper has investigated the adaptive event-triggered H_∞ control problem for MJSs with GUTRs and actuator faults. Compared with the traditional method, an adaptive event-triggered strategy has been introduced to save the communication resources effectively. In the controller design, the actuator failure model has been developed to improve the system reliability. According to the Lyapunov stability approach, the stability conditions for MJSs with the H_∞ performance can be obtained. Finally, the validity of the proposed control approach has been verified by two simulation results. In future work, we will focus on solving the adaptive event-triggered control problem for multi-agent systems [29,46,62,63].

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Compliance with Ethical Standards

Conflict of interest The authors declare that there is no conflict of interest.

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