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Hybrid Event-Triggered Filtering for Nonlinear Markov Jump Systems With Stochastic Cyber-Attacks

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ABSTRACT This paper studies the problem of H_∞ filtering for nonlinear Markov jump systems based on Takagi-Sugeno model. Firstly, we propose a hybrid event-triggered mechanism with an adjustable threshold, which not only helps to save more limited communication resources, but also excludes Zeno behavior while preserving the merits of continuous triggering. Secondly, given the threat of cyber-attacks to network security, a stochastic variable is introduced to describe the considered deception attacks in filter design. Thirdly, a less restrictive Lyapunov-Krasovskii functional (LKF), which is not required to be continuous and positive definite in a triggering interval, is constructed to establish sufficient condition on the exponential mean-square stability for the filtering error system with a weighted H_∞ performance. Meanwhile, co-design of the desired filter and event-triggered mechanism is achieved. Finally, a tunnel diode circuit system is provided to illustrate the effectiveness and advantage of the obtained results.

INDEX TERMS Markov jump systems, Takagi-Sugeno (T-S) fuzzy systems, adaptive event-triggered mechanism, H_∞ filtering, cyber-attacks.

I. INTRODUCTION

With the rapid development of technologies on computer networks and communication, networked control systems (NCSs) have attracted much attention in recent decades [1]–[4]. The signal transmission among system components, such as plant, sensor, controller, actuator, ect., is conducted through communication networks. Communication networks are facing big challenge because of the increasing complexity of NCSs and ensuing frequent information interaction. How to develop effective communication protocols for reducing the communication workload has thus been a hotspot.

Event-triggered communication mechanism (ETCM) is introduced to save limited communication resources. When an ETCM is applied in NCSs, it plays an important role in determining the update of target signal. The signal is updated only if a predefined condition is violated. Thus, compared with the periodic sampling method, ETCM can greatly reduce unnecessary data update. As its efficiency in avoiding redundant packet transmission, ETCM has been intensively studied and widely used in the research of control and filtering problem [5]–[12]. For a feasible ETCM, it should guarantee a positive minimum inter-event time. This is an essential prerequisite. As stated in [13], if a positive minimum inter-event time can not be ensured, an infinite number of events maybe generated in a finite time interval, which is so-called Zeno behavior [14] and make the ETCM of no practical significance. Therefore, sampled-data-based ETCM has been proposed to exclude the Zeno behavior [15]–[19]. For example, the authors in [17] proposed a discrete ETCM that depends on nonuniformly sampled state to investigate the stabilization problem of neural-network-based control systems, the triggering condition is only verified at some nonuniform sampling instants. Obviously, a positive minimum inter-event time is guaranteed by the nonzero lower bound of sampling interval. To further reduce the number of transmitted data packets, a periodic sampling data based ETCM, the threshold of which is adaptively adjustable, was developed in [16] for

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studying the H_∞ filtering problem of nonlinear NCSs. Noted that the ETCM based on sampling avoids Zeno behavior but does not use all the available information. It is likely to miss some key measurements if the sampling period has not been set properly, thereby affect the filtering effect. To take advantage of the continuous-time measurements and guarantee a positive lower bound on the inter-event intervals, hybrid ETCMs were put forward in [20]–[22] by introducing a constant waiting time and combining it with continuous event-triggering condition. Under this mechanism, each time the target signal is updated, a new round of continuous evaluation of the event-triggering condition is carried out after predetermine time. Thus, hybrid ETCM contributes to transmitting data packet more accurately while avoiding Zeno phenomenon.

It is well known that nonlinearity is a common feature of many practical systems. Due to the great capacity in approximating nonlinear systems by a set of linear systems via IF-THEN rules, T-S fuzzy model has been widely applied in the study of nonlinear systems [23]–[26]. In addition, unexpected changes may happen in the plant structure because of the existence of component failures and the other abrupt phenomena. To model such situation appropriately and obtain more applicable results, Markov jump parameters have been intensively considered [27]–[31]. Moreover, as one of the fundamental issues in the field of control, filtering problem has always been concerned [32]–[35]. Especially, given that unreliable links, which could significantly degrade the performance of NCSs, exist in communication channels inevitably, a large number of results of filter design under the influence of various network-induced factors have been reported in the literature [36]–[40]. To mention a few, in [36], the reliable $\mathcal{L}_2-\mathcal{L}_\infty$ asynchronous filtering problem was studied for the T-S fuzzy Markov jump system with sensor failures. By designing an event-based filter, the distributed filtering problem over wireless sensor networks with stochastic measurement fading was addressed in [39]. Recently, owing to the openness of communication channel, cyber-attacks have become the major threat to network security [41]–[43]. Filtering problems considering the impact of different cyber-attacks have thus drawn increasing attention [44]–[46]. However, to the authors' knowledge, no results are available in the literature on the hybrid and adaptive ETCM-based filtering for nonlinear Makov jump systems with cyber-attacks, which is the motivation of this paper.

Inspired by the above discussion, this paper focuses on addressing the H_∞ filtering problem for nonlinear Markov jump systems based on T-S fuzzy model. There are three main contributions:

1) To save more limited communication resources, a hybrid ETCM with an adjustable threshold is proposed. This mechanism can not only preserve the merits of continuous triggering, but also exclude Zeno behavior.
2) Considering the threat of cyber-attacks to network security, a stochastic variable is introduced to describe the considered deception attacks in filter design.
3) The constructed LKF is neither continuous nor positive definite in a triggering interval, less conservative result is thus expected to be obtained.

Notations: The notations used throughout this paper are fairly standard. $sym\{M\} = M + M^T$. $col\{\cdot\}$ denotes a column vector. $diag\{\cdot\}$ denotes a diagonal matrix. $\lambda_{\max}(M)$ ($\lambda_{\min}(M)$) denotes the maximum (minimum) eigenvalue of matrix M. I and 0 denote the identity matrix and zero matrix with appropriate dimensions, respectively. I_n, 0_n and $0_{n\times m}$ denote $n\times n$ identity matrix, $n\times n$ zero matrix and $n\times m$ zero matrix, respectively. Notation $\|\cdot\|$ denotes the Euclidean norm. $Pr\{\cdot\}$ denotes the occurrence probability of a event. $\mathbb{E}\{\cdot\}$ denotes the mathematical expectation. Matrices, if their dimensions are not explicitly stated, are assumed to have compatible dimensions.

II. PROBLEM DESCRIPTION AND PRELIMINARIES

Consider the following nonlinear Markov jump system modeled by a T-S fuzzy system.

Plant rule i: IF $\vartheta_1(t)$ is θ_{i1}, $\vartheta_2(t)$ is θ_{i2}, $\cdots$, and $\vartheta_r(t)$ is θ_{ir}, THEN

$$\begin{cases} \dot{x}(t) = A_i(v(t))x(t) + B_i(v(t))\omega(t) \\ y(t) = C_i(v(t))x(t) \\ z(t) = E_i(v(t))x(t) + F_i(v(t))\omega(t) \end{cases} \tag{1}$$

where $\theta_{i\ell}$ ($i \in \mathcal{N} = \{1, 2, \cdots, N\}$, $\ell \in \{1, 2, \cdots, r\}$) is the fuzzy sets with N IF-THEN rules, and $\vartheta_\ell(t)$ is the premise variable. $x(t) \in \mathcal{R}^{d_x}$, $y(t) \in \mathcal{R}^{d_y}$, $z(t) \in \mathcal{R}^{d_z}$ and $\omega(t) \in \mathcal{R}^{d_\omega}$ are the state vector, the measurement output, the signal to be estimated and the disturbance belonging to $\mathcal{L}_2[0, \infty)$, respectively. $A_i(v(t))$, $B_i(v(t))$, $C_i(v(t))$, $E_i(v(t))$ and $F_i(v(t))$ are known matrices with compatible dimensions. $\{v(t), t \geq 0\}$ is a right-continuous Markovian chain on a complete probability space $(\Omega, \mathcal{F}, \{\mathcal{F}\}_{t\geq 0}, \mathcal{P})$. It takes values in $\mathcal{M} = \{1, 2, \cdots, M\}$ with generator $\Pi = (\pi_{pq})_{M\times M}$ ($p, q \in \mathcal{M}$) given by

$$Pr\{v(t+\Delta t) = q | v(t) = p\} = \begin{cases} \pi_{pq}\Delta t + o(\Delta t), & q \neq p \\ 1 + \pi_{pp}\Delta t + o(\Delta t), & q = p \end{cases}$$

where $\Delta t > 0$, $\lim_{\Delta t\to 0} \frac{o(\Delta t)}{\Delta t} = 0$. M is the number of mode. $\pi_{pq} \geq 0$ ($q \neq p$) is the transition rate from mode p at time t to mode q at time $t + \Delta t$, and $\pi_{pp} = -\sum_{q=1,q\neq p}^{M} \pi_{pq}$.

Through the singleton fuzzifier, product inference and the center average defuzzifier, the T-S fuzzy system (1) with $v(t) = p$ is inferred as

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{N} \lambda_i(\vartheta(t)) \left(A_{ip}x(t) + B_{ip}\omega(t)\right) \\ y(t) = \sum_{i=1}^{N} \lambda_i(\vartheta(t)) \left(C_{ip}x(t)\right) \\ z(t) = \sum_{i=1}^{N} \lambda_i(\vartheta(t)) \left(E_{ip}x(t) + F_{ip}\omega(t)\right) \end{cases} \tag{2}$$

where $\vartheta(t) = col\{\vartheta_1(t), \vartheta_2(t), \cdots, \vartheta_r(t)\}$, $\lambda_i(\vartheta(t))$ denotes the normalized membership function satisfying $\lambda_i(\vartheta(t)) = \frac{\prod_{\ell=1}^{r}\theta_{i\ell}(\vartheta_\ell(t))}{\sum_{i=1}^{N}\prod_{\ell=1}^{r}\theta_{i\ell}(\vartheta_\ell(t))} \geq 0$ and $\sum_{i=1}^{N}\lambda_i(\vartheta(t)) = 1$. $\theta_{i\ell}(\vartheta_\ell(t))$ is the grade of membership of $\vartheta_\ell(t)$ in $\theta_{i\ell}$. In the following, $\lambda_i(\vartheta(t))$ is written as λ_i for brevity.

In order to save the limited communication resources, we adopt an event generator to determine whether the current measurement output $y(t)$ should be transmit or not. i_k is denoted as the last trigger instant, then the next trigger instant i_{k+1} is determined by

$$i_{k+1} = \min\{t \geq s_k | (y(t) - y(i_k))^T \Psi (y(t) - y(i_k)) > \psi(i_k) y^T(i_k) \Psi y(i_k)\} \quad (3)$$

where $\Psi > 0$ is a weighting matrix to be determined, $\psi(i_k) = \psi_1(1 + \psi_2 \exp(-\|y(i_k)\|))$ is a dynamically adjustable threshold with constants $\psi_1, \psi_2 \in [0, 1)$. $s_k = i_k + \tau$ where $\tau > 0$ is silent time.

Remark 1: It is worth noting that ETCM (3) is a new hybrid and adaptive event-triggered mechanism. On the one hand, after each time the measurement output $y(t)$ has been updated, event generator comes to a halt for τ time and then continuously evaluates the triggering condition in (3). Unlike the sampled-data-based ETCM, hybrid ETCM is based on continuous-time measurements. Thus, this kind of ETCM contributes to transmitting data packet more accurately while excluding Zeno behavior. On the other hand, threshold $\psi(i_k)$ is adaptively adjustable. For example, if $\|y(i_{k+1})\| > \|y(i_k)\|$, $\psi(i_{k+1}) < \psi(i_k)$ can be derived, i.e., in this case, ETCM (3) adopts smaller $\psi(i_{k+1})$ to set a high communication frequency for transmitting as many valuable measurement output signals as possible. And if $\|y(i_{k+1})\| < \|y(i_k)\|$, $\psi(i_{k+1}) > \psi(i_k)$ can be derived, i.e., larger $\psi(i_{k+1})$ is adopted to set a low communication frequency for reducing the communication burden.

Remark 2: When $\psi_1 = \psi_2 = 0$, $\psi(i_k) \equiv 0$, ETCM (3) reduces to the periodic sampling mechanism with period τ. When $\psi_1 \neq 0$ and $\psi_2 = 0$, $\psi(i_k) = \psi_1$, ETCM (3) reduces to the hybrid event-triggered mechanism with static threshold. Thus, compared with the event-triggered mechanism proposed in [20], [21], ETCM (3) is more general.

Additionally, due to the openness of communication channels, it is vulnerable to cyber-attacks, and cyber-attacks are the major threat to network security. Thus, the influence of deception attacks is considered in the transmission of measurement output $y(t)$. When the network is subject to deception attacks, the transmitted signal is fully substituted by the attack signal $f(y(t))$. Considering that the successful cyber-attacks occur randomly because of the protection of hardware or software, ect, a stochastic variable $\beta(t)$, which is Bernoulli distributed and takes value in the set $\{0, 1\}$, is introduced, and $Pr\{\beta(t) = 1\} = \beta$, where β denotes the probability that deception attacks does not occur.

Therefore, under the influence of event-triggered mechanism and stochastic deception attacks, the actual measurement output transmitted to the filter is presented as

$$\widehat{y}(t) = \beta(t)y(i_k) + (1 - \beta(t))f(y(t)), \quad t \in [i_k, i_{k+1}) \quad (4)$$

Remark 3: In (4), when $\beta(t) = 1$, the actual measurement output transmitted to the filter is $y(i_k)$, in other words, there is no cyber-attack occurring in the transmission of signal. When $\beta(t) = 0$, $\widehat{y}(t) = f(y(t))$, which means that the network is subject to deception attack, malicious signal $f(y(t))$ fully substitute the measurement output.

The following full-order filter is designed for system (2).

$$\begin{cases} \dot{\widehat{x}}(t) = \sum_{j=1}^{N} \lambda_j(\vartheta(t)) \left(\widehat{A}_{jp}\widehat{x}(t) + \widehat{B}_{jp}\widehat{y}(t)\right) \\ \widehat{z}(t) = \sum_{j=1}^{N} \lambda_j(\vartheta(t)) \left(\widehat{E}_{jp}\widehat{x}(t)\right), \quad t \in [i_k, i_{k+1}) \end{cases} \quad (5)$$

where $\widehat{x}(t)$ and $\widehat{z}(t)$ are the estimation of $x(t)$ and $z(t)$, respectively. $\widehat{A}_{jp}$, $\widehat{B}_{jp}$ and $\widehat{E}_{jp}$ are the filter gains to be determined.

By introducing

$$\alpha(t) = \begin{cases} 1, & t \in [i_k, s_k); \\ 0, & t \in [s_k, i_{k+1}), \end{cases}$$
$$\tau(t) = t - i_k \leq \tau, \quad t \in [i_k, s_k),$$
$$e(t) = y(i_k) - y(t), \quad t \in [s_k, i_{k+1}),$$

$y(i_k)$ can be rewritten as

$$y(i_k) = \alpha(t)y(t - \tau(t)) + (1 - \alpha(t))(e(t) + y(t)) \quad (6)$$

Furthermore, denoting $\widetilde{x}(t) = col\{x(t), \widehat{x}(t)\}$, $\widetilde{z}(t) = z(t) - \widehat{z}(t)$, we can obtain the following filtering error system based on (2), (4), (5) and (6).

$$\begin{cases} \dot{\widetilde{x}}(t) = \mathcal{A}_{ijp\lambda}\widetilde{x}(t) + \beta g(\alpha(t), \widetilde{x}(t), \widetilde{x}(t - \tau(t)), e(t)) \\ \qquad + (1 - \beta)\mathcal{C}_{jp\lambda} f(y(t)) + \mathcal{D}_{ip\lambda}\omega(t) \\ \qquad + (\beta(t) - \beta) g(\alpha(t), \widetilde{x}(t), \widetilde{x}(t - \tau(t)), e(t)) \\ \qquad - (\beta(t) - \beta)\mathcal{C}_{jp\lambda} f(y(t)) \\ \widetilde{z}(t) = \mathcal{E}_{ijp\lambda}\widetilde{x}(t) + \mathcal{F}_{ip\lambda}\omega(t), \ t \in [i_k, i_{k+1}) \end{cases} \quad (7)$$

where $g(\alpha(t), \widetilde{x}(t), \widetilde{x}(t - \tau(t)), e(t)) = \alpha(t)\mathcal{B}_{ijp\lambda}\widetilde{x}(t - \tau(t)) + (1 - \alpha(t))(\mathcal{B}_{ijp\lambda}\widetilde{x}(t) + \mathcal{C}_{jp\lambda}e(t))$ and

$$\mathcal{A}_{ijp\lambda} = \sum_{i=1}^{N}\sum_{j=1}^{N}\lambda_i\lambda_j\mathcal{A}_{ijp}, \quad \mathcal{A}_{ijp} = \begin{bmatrix} A_{ip} & 0 \\ 0 & \widehat{A}_{jp} \end{bmatrix}$$

$$\mathcal{B}_{ijp\lambda} = \sum_{i=1}^{N}\sum_{j=1}^{N}\lambda_i\lambda_j\mathcal{B}_{ijp}, \quad \mathcal{B}_{ijp} = \begin{bmatrix} 0 & 0 \\ \widehat{B}_{jp}C_{ip} & 0 \end{bmatrix}$$

$$\mathcal{E}_{ijp\lambda} = \sum_{i=1}^{N}\sum_{j=1}^{N}\lambda_i\lambda_j\mathcal{E}_{ijp}, \quad \mathcal{E}_{ijp} = \begin{bmatrix} E_i & -\widehat{E}_j \end{bmatrix}$$

$$\mathcal{C}_{jp\lambda} = \sum_{j=1}^{N}\lambda_j\mathcal{C}_{jp}, \ \mathcal{C}_{jp} = \begin{bmatrix} 0 \\ \widehat{B}_{jp} \end{bmatrix}$$

$$\mathcal{D}_{ip\lambda} = \sum_{i=1}^{N}\lambda_i\mathcal{D}_{ip}, \ \mathcal{D}_{ip} = \begin{bmatrix} B_{ip} \\ 0 \end{bmatrix}, \ \mathcal{F}_{ip\lambda} = \sum_{i=1}^{N}\lambda_i F_{ip}.$$

Before developing the main results, the following assumption and definitions are needed.

Assumption 1: The attack signal function $f(y(t)) = col\{f_1(y_1(t)), f_2(y_2(t)), \cdots, f_{d_y}(y_{d_y}(t))\}$ is assumed to be nonlinear and satisfy the following condition for any scalar $\varsigma \neq 0$,

$$\ell_i^- \leq \frac{f_i(\varsigma)}{\varsigma} \leq \ell_i^+, \quad (i = 1, 2, \cdots, d_y) \tag{8}$$

where ℓ_i^- and ℓ_i^+ are known constants. In addition, we denote $\ell_i = \max\{|\ell_i^-|, |\ell_i^+|\}$ and $\mathcal{L} = diag\{\ell_1, \ell_2, \cdots, \ell_{d_y}\}$.

Remark 4: Different from the existing assumptions on deception attack function in [42], [44], the constants ℓ_i^-, ℓ_i^+ in (8) can be positive, negative and zero, which means that this type of deception attack function contains Lipschitz bounded function as its special case. Thus, the deception attack function considered here is more general.

Definition 1: The filtering error system (7) is said to be exponentially mean-square stable with $\omega(t) \equiv 0$ if there exist positive scalars a and b such that

$$\mathbb{E}\{\|\tilde{x}(t)\|^2\} \leq ae^{-bt}\mathbb{E}\{\|\tilde{x}(0)\|^2\}.$$

Definition 2: For given positive scalars ρ and γ, the filtering error system (7) is said to be exponentially mean-square stable with a weighted H_∞ performance γ if system (7) is exponentially mean-square stable and under the zero initial condition, the following inequality holds for any non-zero $\omega(t) \in \mathcal{L}_2[0, \infty)$,

$$\mathbb{E}\left\{\int_0^\infty e^{-\rho s}\tilde{z}^T(s)\tilde{z}(s)ds\right\} \leq \gamma^2 \int_0^\infty \omega^T(s)\omega(s)ds.$$

III. MAIN RESULTS

In this section, the exponential mean-square stability analysis for system (7) is conducted firstly, sufficient condition under which system (7) is exponentially mean-square stable and satisfies a weighted H_∞ performance γ is presented in Theorem 1. Then, based on the proposed condition in Theorem 1, a filter design method is provided in Theorem 2. For convenience, we firstly define the following block entry matrices:

$$\mathcal{I}_i = [0_{2d_x,(i-1)2d_x}, I_{2d_x}, 0_{2d_x,(5-i)2d_x+d_y+d_\omega}] \quad (i = 1, 2, \cdots, 5)$$
$$\mathcal{I}_{s1} = [0_{d_x,(s-1)2d_x}, I_{d_x}, 0_{d_x}, 0_{d_x,(5-s)2d_x+d_y+d_\omega}]$$
$$\mathcal{I}_{s2} = [0_{d_x,(s-1)2d_x}, 0_{d_x}, I_{d_x}, 0_{d_x,(5-s)2d_x+d_y+d_\omega}] \quad (s = 1, 2, 3)$$
$$\mathcal{I}_6 = [0_{d_y,10d_x}, I_{d_y}, 0_{d_y,d_\omega}], \ \mathcal{I}_7 = [0_{d_\omega,10d_x}, 0_{d_\omega,d_y}, I_{d_\omega}]$$
$$\mathcal{J}_1 = [I_{2d_x}, 0_{2d_x,2d_x+2d_y+d_\omega}]$$
$$\mathcal{J}_2 = [0_{2d_x}, I_{2d_x}, 0_{2d_x,2d_y+d_\omega}]$$
$$\mathcal{J}_{11} = [I_{d_x}, 0_{d_x,3d_x+2d_y+d_\omega}]$$
$$\mathcal{J}_{12} = [0_{d_x}, I_{d_x}, 0_{d_x,2d_x+2d_y+d_\omega}]$$
$$\mathcal{J}_{21} = [0_{d_x,2d_x}, I_{d_x}, 0_{d_x,d_x+2d_y+d_\omega}]$$
$$\mathcal{J}_{22} = [0_{d_x,3d_x}, I_{d_x}, 0_{d_x,2d_y+d_\omega}]$$
$$\mathcal{J}_3 = [0_{d_y,4d_x}, I_{d_y}, 0_{d_y,d_y+d_\omega}]$$
$$\mathcal{J}_4 = [0_{d_y,4d_x+d_y}, I_{d_y}, 0_{d_y,d_\omega}], \ \mathcal{J}_5 = [0_{d_\omega,4d_x+2d_y}, I_{d_\omega}],$$

and the other notations are defined as

$$\varpi_1(t) = \tau(t)\tilde{x}(t), \ \varpi_2(t) = \tau(t)\dot{\tilde{x}}(t)$$
$$\eta_1(t) = col\{\tilde{x}(t), \tilde{x}(t-\tau(t))\}$$
$$\eta_2(t) = col\{\tilde{x}(t), \dot{\tilde{x}}(t), \tilde{x}(t-\tau(t)), \varpi_1(t), \varpi_2(t)\}$$
$$\eta_3(t) = col\{\tilde{x}(t), \dot{\tilde{x}}(t), \tilde{x}(t-\tau(t)), \varpi_1(t), \varpi_2(t), f(y(t)), \omega(t)\}$$
$$\eta_4(t) = col\{\tilde{x}(t), \dot{\tilde{x}}(t), e(t), f(y(t)), \omega(t)\}$$
$$\mathscr{C}_{ip} = [C_{ip}, 0_{2d_x}], \ \mathcal{J}(t) = \tilde{z}^T(t)\tilde{z}(t) - \gamma^2\omega^T(t)\omega(t).$$

Theorem 1: For given scalars τ, ψ_1, ψ_2, ρ, $\mu \geq 1$ satisfying $\ln\mu - \rho\tau < 0$, system (7) is exponentially mean-square stable with a weighted H_∞ performance γ if there exist positive definite matrices Ψ, $\mathcal{P}_p$, $\mathcal{S}_m$, $\mathcal{Q}$, positive definite diagonal matrix $\mathcal{V} = diag\{v_1, v_2, \cdots, v_{d_y}\}$, arbitrary matrices $\mathcal{R}$, $\mathcal{H}$, $\mathcal{G}$, $\mathcal{K}_1$ and $\mathcal{K}_2$, such that $\forall i, j \in \mathcal{N}$ $(j > i)$, $p, m \in \mathcal{M}$, the following inequalities hold:

$$\begin{bmatrix} \mathscr{U}_{iip}(0) & \mathscr{V}_{iip}^T \\ * & -I \end{bmatrix} < 0 \tag{9}$$

$$\begin{bmatrix} \mathscr{U}_{iip}(\tau) & \mathscr{V}_{iip}^T & \sqrt{\tau}\mathscr{W}^T \\ * & -I & 0 \\ * & * & -e^{\rho\tau}\mathcal{Q} \end{bmatrix} < 0 \tag{10}$$

$$\begin{bmatrix} \mathscr{U}_{ijp}(0) + \mathscr{U}_{jip}(0) & \mathscr{V}_{ijp}^T & \mathscr{V}_{jip}^T \\ * & -I & 0 \\ * & * & -I \end{bmatrix} < 0 \tag{11}$$

$$\begin{bmatrix} \mathscr{U}_{ijp}(\tau) + \mathscr{U}_{jip}(\tau) & \mathscr{V}_{ijp}^T & \mathscr{V}_{jip}^T & \sqrt{2\tau}\mathscr{W}^T \\ * & -I & 0 & 0 \\ * & * & -I & 0 \\ * & * & * & -e^{\rho\tau}\mathcal{Q} \end{bmatrix} < 0 \tag{12}$$

$$\begin{bmatrix} \mathscr{M}_{iim} & \mathscr{N}_{iim}^T \\ * & -I \end{bmatrix} < 0 \tag{13}$$

$$\begin{bmatrix} \mathscr{M}_{ijm} + \mathscr{M}_{jim} & \mathscr{N}_{ijm}^T & \mathscr{N}_{jim}^T \\ * & -I & 0 \\ * & * & -I \end{bmatrix} < 0 \tag{14}$$

$$\mathcal{S}_m \leq \mathcal{P}_p, \quad \mathcal{P}_p \leq \mu\mathcal{S}_m \tag{15}$$

where $\mathscr{U}_{ijp}(\tau(t)) = \mathscr{U}_{ijp}^1 + \mathscr{U}_{ip}(\tau(t))$, $\mathscr{V}_{ijp} = \mathcal{E}_{ijp}\mathcal{I}_1 + F_{ip}\mathcal{I}_7$, $\mathscr{W} = \mathcal{G}[\mathcal{I}_1^T, \mathcal{I}_3^T]^T$ and $\mathscr{M}_{ijm} = \mathscr{M}_{ijm}^1 + \mathscr{M}_{im}$, $\mathscr{N}_{ijm} = \mathcal{E}_{ijm}\mathcal{J}_1 + F_{im}\mathcal{J}_5$ with

$$\begin{aligned}
\mathscr{U}_{ijp}^1 &= sym\{(\mathcal{I}_1^T\mathcal{K}_1^T + \mathcal{I}_2^T\mathcal{K}_2^T)(-\mathcal{I}_2 + \mathcal{A}_{ijp}\mathcal{I}_1 + \beta\mathcal{B}_{ijp}\mathcal{I}_3 \\
&\quad +(1-\beta)\mathcal{C}_{jp}\mathcal{I}_6 + \mathcal{D}_{ip}\mathcal{I}_7)\} \\
\mathscr{U}_{ip}(\tau(t)) &= (\tau - \tau(t))\mathcal{I}_2^T\mathcal{Q}\mathcal{I}_2 + sym\{[\mathcal{I}_1^T, \mathcal{I}_2^T, \mathcal{I}_3^T, \mathcal{I}_4^T, \mathcal{I}_5^T] \\
&\quad \times\mathcal{H}[\mathcal{I}_4^T - \tau(t)\mathcal{I}_1^T, \mathcal{I}_5^T - \tau(t)\mathcal{I}_2^T]^T\} + \sum_{q=1}^{M}\pi_{pq}\mathcal{I}_1^T\mathcal{P}_q\mathcal{I}_1 \\
&\quad +(\tau - \tau(t))sym\{[\mathcal{I}_2^T, \mathcal{I}_1^T + \mathcal{I}_5^T]\mathcal{R}[\mathcal{I}_1^T, \mathcal{I}_3^T, \mathcal{I}_4^T]^T + [\mathcal{I}_1^T \\
&\quad -\mathcal{I}_3^T, \mathcal{I}_4^T]\mathcal{R}[\mathcal{I}_2^T, 0, \mathcal{I}_1^T + \mathcal{I}_5^T]^T + \rho[\mathcal{I}_1^T - \mathcal{I}_3^T, \mathcal{I}_4^T]\mathcal{R}[\mathcal{I}_1^T, \\
&\quad \mathcal{I}_3^T, \mathcal{I}_4^T]^T\} + sym\{\mathcal{I}_1^T\mathcal{P}_p\mathcal{I}_2 + e^{-\rho\tau}[\mathcal{I}_1^T, \mathcal{I}_3^T]\mathcal{G}^T(\mathcal{I}_1 - \mathcal{I}_3) \\
&\quad -[\mathcal{I}_1^T - \mathcal{I}_3^T, \mathcal{I}_4^T]\mathcal{R}[\mathcal{I}_1^T, \mathcal{I}_3^T, \mathcal{I}_4^T]^T\} + \rho\mathcal{I}_1^T\mathcal{P}_p\mathcal{I}_1 - \gamma^2\mathcal{I}_7^T\mathcal{I}_7 \\
&\quad -\mathcal{I}_6^T\mathcal{V}\mathcal{I}_6 + \mathscr{C}_{ip}^T\mathcal{L}^T\mathcal{V}\mathcal{L}\mathscr{C}_{ip}
\end{aligned}$$

$$\begin{aligned}
&\mathscr{M}^1_{ijm} \\
&= sym\{(\mathcal{J}_1^T\mathcal{K}_1^T + \mathcal{J}_2^T\mathcal{K}_2^T)(-\mathcal{J}_2 + (\mathcal{A}_{ijm} + \beta\mathcal{B}_{ijm}) \\
&\quad \times\mathcal{J}_1 + \beta\mathcal{C}_{jm}\mathcal{J}_3 + (1-\beta)\mathcal{C}_{jm}\mathcal{J}_4 + \mathcal{D}_{im}\mathcal{J}_5)\} \\
&\mathscr{M}_{im} \\
&= sym\{\mathcal{J}_1^T\mathcal{S}_m\mathcal{J}_2\} + \sum_{n=1}^{N}\pi_{mn}\mathcal{J}_1^T\mathcal{S}_n\mathcal{J}_1 + \rho\mathcal{J}_1^T\mathcal{S}_m\mathcal{J}_1 \\
&\quad -\gamma^2\mathcal{J}_5^T\mathcal{J}_5 - \mathcal{J}_3^T\Psi\mathcal{J}_3 - \mathcal{J}_4^T\mathcal{V}\mathcal{J}_4 + \mathcal{J}_1^T\mathscr{C}_{im}^T\mathcal{L}^T\mathcal{V}\mathcal{L}\mathscr{C}_{im}\mathcal{J}_1 \\
&\quad +\psi_1(\mathcal{J}_3 + \mathscr{C}_{im}\mathcal{J}_1)^T\Psi(\mathcal{J}_3 + \mathscr{C}_{im}\mathcal{J}_1).
\end{aligned}$$

Proof: Consider the following LKF for system (7):

$$V(t, v(t)) = \begin{cases} V_1(t, v(t)), & t \in [i_k, s_k) \\ V_2(t, v(t)), & t \in [s_k, i_{k+1}) \end{cases} \tag{16}$$

where $V_1(t, v(t)) = \tilde{x}^T(t)\mathcal{P}(v(t))\tilde{x}(t) + W_1(t) + W_2(t)$ and $V_2(t, v(t)) = \tilde{x}^T(t)\mathcal{S}(v(t))\tilde{x}(t)$ with

$$\begin{aligned}
W_1(t) &= (\tau - \tau(t))\int_{t-\tau(t)}^{t} e^{\rho(s-t)}\dot{\tilde{x}}^T(s)\mathcal{Q}\dot{\tilde{x}}(s)ds \\
W_2(t) &= 2(\tau - \tau(t)) \\
&\quad \times\begin{bmatrix}\tilde{x}(t) - \tilde{x}(t-\tau(t)) \\ \varpi_1(t)\end{bmatrix}^T \mathcal{R}\begin{bmatrix}\tilde{x}(t) \\ \tilde{x}(t-\tau(t)) \\ \varpi_1(t)\end{bmatrix}
\end{aligned}$$

Firstly, we can easily check that $W_1(i_k) = W_1(s_k^-) = W_2(i_k) = W_2(s_k^-) = 0$. Therefore, the relationship between $V_1(t, v(t)$ and $V_2(t, v(t))$ can be derived from (15) as

$$V_2(s_k, v(s_k)) \le V_1(s_k^-, v(s_k^-)) \tag{17}$$

$$V_1(i_k, v(i_k)) \le \mu V_2(i_k^-, v(i_k^-)) \tag{18}$$

Secondly, when $t \in [i_k, s_k)$, we denote $v(t) = p$. Then, from $\alpha(t) = 1$ and (7), $\mathbb{E}\{\dot{\tilde{x}}(t)\} = \mathcal{A}_{ijp\lambda}\tilde{x}(t) + \beta\mathcal{B}_{ijp\lambda}\tilde{x}(t - \tau(t)) + (1-\beta)\mathcal{C}_{jp\lambda}f(y(t)) + \mathcal{D}_{ip\lambda}\omega(t)$ can be obtained, and it holds that

$$\begin{aligned}
&\mathscr{L}V_1(t, v(t)) + \rho V_1(t, v(t)) + \mathcal{J}(t) \\
&= 2\tilde{x}^T(t)\mathcal{P}_p\dot{\tilde{x}}(t) + \sum_{q=1}^{M}\pi_{pq}\tilde{x}^T(t)\mathcal{P}_q\tilde{x}(t) + \rho\tilde{x}^T(t)\mathcal{P}_p\tilde{x}(t) \\
&\quad +(\tau - \tau(t))\dot{\tilde{x}}^T(t)\mathcal{Q}\dot{\tilde{x}}(t) - \int_{t-\tau(t)}^{t} e^{\rho(s-t)}\dot{\tilde{x}}^T(s)\mathcal{Q}\dot{\tilde{x}}(s)ds \\
&\quad -2\begin{bmatrix}\tilde{x}(t) - \tilde{x}(i_k) \\ \varpi_1(t)\end{bmatrix}^T \mathcal{R}\begin{bmatrix}\tilde{x}(t) \\ \tilde{x}(i_k) \\ \varpi_1(t)\end{bmatrix} \\
&\quad +2(\tau - \tau(t))\begin{bmatrix}\dot{\tilde{x}}(t) \\ \tilde{x}(t) + \varpi_2(t)\end{bmatrix}^T \mathcal{R}\begin{bmatrix}\tilde{x}(t) \\ \tilde{x}(i_k) \\ \varpi_1(t)\end{bmatrix} \\
&\quad +2(\tau - \tau(t))\begin{bmatrix}\tilde{x}(t) - \tilde{x}(i_k) \\ \varpi_1(t)\end{bmatrix}^T \mathcal{R}\begin{bmatrix}\dot{\tilde{x}}(t) \\ 0 \\ \tilde{x}(t) + \varpi_2(t)\end{bmatrix} \\
&\quad +2\rho(\tau - \tau(t))\begin{bmatrix}\tilde{x}(t) - \tilde{x}(i_k) \\ \varpi_1(t)\end{bmatrix}^T \mathcal{R}\begin{bmatrix}\tilde{x}(t) \\ \tilde{x}(i_k) \\ \varpi_1(t)\end{bmatrix} \\
&\quad +(\mathcal{E}_{ijp\lambda}\tilde{x}(t) + \mathcal{F}_{ip\lambda}\omega(t))^T(\mathcal{E}_{ijp\lambda}\tilde{x}(t) + \mathcal{F}_{ip\lambda}\omega(t)) \\
&\quad -\gamma^2\omega^T(t)\omega(t)
\end{aligned} \tag{19}$$

Applying the well-known inequality $2X^TY \le X^TX + Y^TY$ and Jensen's integral inequality, we can deduce the following inequality for any appropriate dimensional matrix $\mathcal{G}$.

$$\begin{aligned}
&-\int_{t-\tau(t)}^{t} e^{\rho(s-t)}\dot{\tilde{x}}^T(s)\mathcal{Q}\dot{\tilde{x}}(s)ds \\
&\quad \le \tau(t)\eta_1^T(t)e^{-\rho\tau}\mathcal{G}^T\mathcal{Q}^{-1}\mathcal{G}\eta_1(t) \\
&\quad\quad +2e^{-\rho\tau}\eta_1^T(t)\mathcal{G}^T(\tilde{x}(t) - \tilde{x}(t-\tau(t)))
\end{aligned} \tag{20}$$

In addition, from Assumption 1, it holds for any positive definite diagonal matrix $\mathcal{V}$ that

$$y^T(t)\mathcal{L}^T\mathcal{V}\mathcal{L}y(t) - f^T(y(t))\mathcal{V}f(y(t)) \ge 0 \tag{21}$$

Besides, for arbitrary matrices $\mathcal{H}$, $\mathcal{K}_1$ and $\mathcal{K}_2$ with compatible dimensions, it is easy to obtain the following two equalities.

$$0 = 2\eta_2^T(t)\mathcal{H}\begin{bmatrix}\varpi_1(t) - \tau(t)\tilde{x}(t) \\ \varpi_2(t) - \tau(t)\dot{\tilde{x}}(t)\end{bmatrix} \tag{22}$$

$$\begin{aligned}
0 &= 2\mathbb{E}\Big\{(\tilde{x}^T(t)\mathcal{K}_1^T + \dot{\tilde{x}}^T(t)\mathcal{K}_2^T)(-\dot{\tilde{x}}(t) + \mathcal{A}_{ijp\lambda}\tilde{x}(t) \\
&\quad +\beta\mathcal{B}_{ijp\lambda}\tilde{x}(t-\tau(t)) + (1-\beta)\mathcal{C}_{jp\lambda}f(y(t)) \\
&\quad +\mathcal{D}_{ip\lambda}\omega(t))\Big\}
\end{aligned} \tag{23}$$

Combining (19)–(23), we have

$$\begin{aligned}
&\mathbb{E}\{\mathscr{L}V_1(t, v(t)) + \rho V_1(t, v(t)) + \mathcal{J}(t)\} \\
&\quad \le \eta_3^T(t)\Big\{\sum_{i=1}^{N}\sum_{j=1}^{N}\lambda_i\lambda_j\mathscr{X}_{ijp}(\tau(t))\Big\}\eta_3(t)
\end{aligned}$$

where $\mathscr{X}_{ijp}(\tau(t)) = \mathscr{U}_{ijp}(\tau(t)) + \tau(t)\mathscr{W}^T(e^{\rho\tau}\mathcal{Q})^{-1}\mathscr{W} + \mathscr{V}_{ijp}^T\mathscr{V}_{ijp}$.

By using Schur Complement and convex combination, we can derive from (9)–(12) that $\sum_{i=1}^{N}\sum_{j=1}^{N}\lambda_i\lambda_j\mathscr{X}_{ijp}(\tau(t)) < 0$, i.e.,

$$\mathbb{E}\{\mathscr{L}V_1(t, v(t)) + \rho V_1(t, v(t)) + \mathcal{J}(t)\} \le 0 \tag{24}$$

Similarly, when $t \in [s_k, i_{k+1})$, we denote $v(t) = m$. Then, from $\alpha(t) = 0$ and (7), $\mathbb{E}\{\dot{\tilde{x}}(t)\} = (\mathcal{A}_{ijp\lambda} + \beta\mathcal{B}_{ijp\lambda})\tilde{x}(t) + \beta\mathcal{C}_{jp\lambda}e(t) + (1-\beta)\mathcal{C}_{jp\lambda}f(y(t)) + \mathcal{D}_{ip\lambda}\omega(t)$ can be obtained. There holds that

$$\begin{aligned}
&\mathbb{E}\{\mathscr{L}V_2(t, v(t)) + \rho V_2(t, v(t)) + \mathcal{J}(t)\} \\
&\le \mathbb{E}\Big\{2\tilde{x}^T(t)\mathcal{S}_m\dot{\tilde{x}}(t) + \sum_{n=1}^{M}\pi_{mn}\tilde{x}^T(t)\mathcal{S}_m\tilde{x}(t) \\
&\quad +\rho\tilde{x}^T(t)\mathcal{S}_m\tilde{x}(t) - \gamma^2\omega^T(t)\omega(t) \\
&\quad +(\mathcal{E}_{ijp\lambda}\tilde{x}(t) + \mathcal{F}_{ip\lambda}\omega(t))^T(\mathcal{E}_{ijp\lambda}\tilde{x}(t) + \mathcal{F}_{ip\lambda}\omega(t)) \\
&\quad +2(\tilde{x}^T(t)\mathcal{K}_1^T + \dot{\tilde{x}}^T(t)\mathcal{K}_2^T)(-\dot{\tilde{x}}(t) + \mathcal{A}_{ijm\lambda}\tilde{x}(t) \\
&\quad +\beta\mathcal{B}_{ijm\lambda}\tilde{x}(t) + \beta\mathcal{C}_{jm\lambda}e(t) + \mathcal{D}_{im\lambda}\omega(t) \\
&\quad +(1-\beta)\mathcal{C}_{jm\lambda}f(y(t))) - e^T(t)\Psi e(t) \\
&\quad +\psi_1(e(t) + y(t))^T\Psi(e(t) + y(t)) + y^T(t)\mathcal{L}^T\mathcal{V}\mathcal{L}y(t) \\
&\quad -f^T(y(t))\mathcal{V}f(y(t))\Big\} \le \eta_4^T(t)\Big\{\sum_{i=1}^{N}\sum_{j=1}^{N}\lambda_i\lambda_j\mathscr{Y}_{ijm}\Big\}\eta_4(t)
\end{aligned}$$

where $\mathscr{Y}_{ijm} = \mathscr{M}_{ijm} + \mathscr{N}_{ijm}^T \mathscr{N}_{ijm}$. By using Schur Complement, we can derive from (13) and (14) that $\sum_{i=1}^{N}\sum_{j=1}^{N} \lambda_i \lambda_j \mathscr{Y}_{ij} < 0$, i.e.,

$$\mathbb{E}\{\mathscr{L}V_2(t, v(t)) + \rho V_2(t, v(t)) + \mathcal{J}(t)\} \leq 0 \quad (25)$$

When $\omega(t) \equiv 0$, $\mathcal{J}(t) = \tilde{z}^T(t)\tilde{z}(t) \geq 0$. Thus, it can be derived from (24) and (25) that

$$\mathbb{E}\{\mathscr{L}V_1(t, v(t)) + \rho V_1(t, v(t))\} \leq 0 \quad (26)$$

$$\mathbb{E}\{\mathscr{L}V_2(t, v(t)) + \rho V_2(t, v(t))\} \leq 0 \quad (27)$$

For $t \in [i_k, i_{k+1})$, without loss of generality, we assume $t \in [s_k, i_{k+1})$. Denote $\mathscr{T}(0, t)$ as the triggered times over time interval $(0, t)$, $\mathscr{T}(0, t) \leq \frac{t}{\tau}$ obviously. From (17), (18), (26) and (27), we have

$$\begin{aligned}\mathbb{E}\{V(t, v(t))\} &= \mathbb{E}\{V_2(t, v(t))\}\\ &\leq e^{-\rho(t-s_k)}\mathbb{E}\{V_2(s_k, v(s_k))\}\\ &\leq e^{-\rho(t-i_k)}\mathbb{E}\{V_1(i_k, v(i_k))\}\\ &\leq \mu^{\mathscr{T}(0,t)}e^{-\rho t}\mathbb{E}\{V_1(0, v(0))\}\\ &\leq e^{(\frac{\ln\mu}{\tau}-\rho)t}\mathbb{E}\{V_1(0, v(0))\}.\end{aligned}$$

Noting that $\ln\mu - \rho\tau < 0$, it holds that $\frac{\ln\mu}{\tau} - \rho < 0$, and thus there exist a positive scalar ρ^* such that $\mathbb{E}\{V(t, v(t))\} \leq e^{-\rho^* t}\mathbb{E}\{V_1(0, v(0))\}$. Moreover, we can obtain from (16) that $V_2(t, v(t)) \geq \min_{m\in\mathcal{M}}\{\lambda_{\min}(\mathcal{S}_m)\}\|\tilde{x}(t)\|^2$ and $V_1(0, v(0)) \leq \max_{p\in\mathcal{M}}\{\lambda_{\max}(\mathcal{P}_p)\}\|\tilde{x}(0)\|^2$. Therefore, we have

$$\mathbb{E}\{\|\tilde{x}(t)\|^2\} \leq \frac{\max_{p\in\mathcal{M}}\{\lambda_{\max}(\mathcal{P}_p)\}}{\min_{m\in\mathcal{M}}\{\lambda_{\min}(\mathcal{S}_m)\}}e^{-\rho^* t}\mathbb{E}\{\|\tilde{x}(0)\|^2\}$$

That is to say, system (7) is exponentially mean-square stable.

When $\omega(t) \neq 0$, similarly, from (17), (18), (24) and (25), we have

$$\begin{aligned}&\mathbb{E}\{V(t, v(t))\} = \mathbb{E}\{V_2(t, v(t))\}\\ &\leq e^{-\rho(t-s_k)}\mathbb{E}\{V_2(s_k, v(s_k))\} - \int_{s_k}^{t} e^{-\rho(t-s)}\mathbb{E}\{\mathcal{J}(s)\}ds\\ &\leq e^{-\rho(t-s_k)}\mathbb{E}\{V_1(s_k^-, v(s_k^-))\} - \int_{s_k}^{t} e^{-\rho(t-s)}\mathbb{E}\{\mathcal{J}(s)\}ds\\ &\leq e^{-\rho(t-i_k)}\mathbb{E}\{V_1(i_k, v(i_k))\} - \int_{i_k}^{t} e^{-\rho(t-s)}\mathbb{E}\{\mathcal{J}(s)\}ds\\ &\leq \mu e^{-\rho(t-i_k)}\mathbb{E}\{V_2(i_k^-, v(i_k^-))\}\\ &\quad - \int_{i_k}^{t} e^{-\rho(t-s)}\mathbb{E}\{\mathcal{J}(s)\}ds\\ &\leq \mu e^{-\rho(t-s_{k-1})}\mathbb{E}\{V_2(s_{k-1}, v(s_{k-1}))\}\\ &\quad - \mu\int_{s_{k-1}}^{i_k} e^{-\rho(t-s)}\mathbb{E}\{\mathcal{J}(s)\}ds\\ &\quad - \int_{i_k}^{t} e^{-\rho(t-s)}\mathbb{E}\{\mathcal{J}(s)\}ds\\ &\leq \mu^{\mathscr{T}(0,t)}e^{-\rho t}\mathbb{E}\{V_1(0, v(0))\}\\ &\quad - \int_{0}^{t} \mu^{\mathscr{T}(s,t)}e^{-\rho(t-s)}\mathbb{E}\{\mathcal{J}(s)\}ds.\end{aligned}$$

Under the conditions of $V_1(0, v(0)) = 0$ and $V_2(t, v(t)) \geq 0$, we can easily obtain

$$\begin{aligned}&\int_0^t \mu^{\mathscr{T}(s,t)}e^{-\rho(t-s)}\mathbb{E}\{\tilde{z}^T(s)\tilde{z}(s)\}ds\\ &\qquad \leq \gamma^2\int_0^t \mu^{\mathscr{T}(s,t)}e^{-\rho(t-s)}\omega^T(s)\omega(s)ds. \quad (28)\end{aligned}$$

By multiplying both side of inequality (28) with $\mu^{-\mathscr{T}(0,t)}$, we obtain

$$\begin{aligned}&\int_0^t e^{-\rho(t-s)-\mathscr{T}(0,s)\ln\mu}\mathbb{E}\{\tilde{z}^T(s)\tilde{z}(s)\}ds\\ &\qquad \leq \gamma^2\int_0^t e^{-\rho(t-s)-\mathscr{T}(0,s)\ln\mu}\omega^T(s)\omega(s)ds. \quad (29)\end{aligned}$$

where $\mathscr{T}(0, s)\ln\mu \leq \rho s$ because $\mathscr{T}(0, s) \leq \frac{s}{\tau}$ and $\ln\mu - \rho\tau < 0$. Thus, we further obtain

$$\begin{aligned}&\int_0^t e^{-\rho(t-s)-\rho s}\mathbb{E}\{\tilde{z}^T(s)\tilde{z}(s)\}ds\\ &\qquad \leq \gamma^2\int_0^t e^{-\rho(t-s)}\omega^T(s)\omega(s)ds. \quad (30)\end{aligned}$$

Integrating inequality (30) from $t = 0$ to $t = +\infty$, it can be deduced that

$$\int_0^\infty e^{-\rho s}\mathbb{E}\{\tilde{z}^T(s)\tilde{z}(s)\}ds \leq \gamma^2\int_0^\infty \omega^T(s)\omega(s)ds.$$

which means that system (7) satisfies a weighted H_∞ performance γ. This completes the proof.

Remark 5: The LKF constructed in (16) has the following three features.

1) It is not required to be continuous since $V(i_k, v(i_k)) \neq V(i_k^-, v(i_k^-))$ and $V(s_k, v(s_k)) \neq V(s_k^-, v(s_k^-))$.

2) The non-positive definiteness of $V(t, v(t))$ is allowed since matrix $\mathcal{R}$ is arbitrary.

3) The available information on the sawtooth structure of $\tau(t)$ is fully considered.

Base on these relaxation and consideration, less conservative result is expected to be obtained.

Theorem 2: For given scalars τ, ψ_1, ψ_2, ρ, $\mu \geq 1$ satisfying $\ln\mu - \rho\tau < 0$, system (7) is exponentially mean-square stable with a weighted H_∞ performance γ if there exist positive definite matrices Ψ, $\mathcal{P}_p$, $\mathcal{S}_m$, $\mathcal{Q}$, positive definite diagonal matrix $\mathcal{V} = diag\{v_1, v_2, \cdots, v_{d_y}\}$, arbitrary matrices $\mathcal{R}$, $\mathcal{H}$, $\mathcal{G}$, $\mathcal{K}_{11}$, $\mathcal{K}_{12}$, $\mathcal{K}_{21}$, $\mathcal{K}_{22}$ $\tilde{A}_{j\kappa}$, $\tilde{B}_{j\kappa}$, $\tilde{E}_{jk}$ ($\kappa \in \{p, m\}$) and any invertible matrix $\mathcal{K}_{13}$, such that $\forall i, j \in \mathcal{N}$ $(j > i)$, $p, m \in \mathcal{M}$, (15) and the following linear matrix inequalities (LMIs) hold:

$$\begin{bmatrix}\tilde{\mathscr{U}}_{iip}(0) & \tilde{\mathscr{V}}_{iip}^T\\ * & -I\end{bmatrix} < 0 \quad (31)$$

$$\begin{bmatrix}\tilde{\mathscr{U}}_{iip}(\tau) & \tilde{\mathscr{V}}_{iip}^T & \sqrt{\tau}\mathscr{W}^T\\ * & -I & 0\\ * & * & -e^{\rho\tau}\mathcal{Q}\end{bmatrix} < 0 \quad (32)$$

$$\begin{bmatrix}\tilde{\mathscr{U}}_{ijp}(0) + \tilde{\mathscr{U}}_{jip}(0) & \tilde{\mathscr{V}}_{ijp}^T & \tilde{\mathscr{V}}_{jip}^T\\ * & -I & 0\\ * & * & -I\end{bmatrix} < 0 \quad (33)$$

$$\begin{bmatrix} \widetilde{\mathscr{U}}_{ijp}(\tau)+\widetilde{\mathscr{U}}_{jip}(\tau) & \widetilde{\mathscr{V}}_{ijp}^T & \widetilde{\mathscr{V}}_{jip}^T & \sqrt{2\tau}\mathscr{W}^T \\ * & -I & 0 & 0 \\ * & * & -I & 0 \\ * & * & * & -e^{\rho\tau}Q \end{bmatrix} < 0 \quad (34)$$

$$\begin{bmatrix} \widetilde{\mathscr{M}}_{iim} & \widetilde{\mathscr{N}}_{iim}^T \\ * & -I \end{bmatrix} < 0 \quad (35)$$

$$\begin{bmatrix} \widetilde{\mathscr{M}}_{ijm}+\widetilde{\mathscr{M}}_{jim} & \widetilde{\mathscr{N}}_{ijm}^T & \widetilde{\mathscr{N}}_{jim}^T \\ * & -I & 0 \\ * & * & -I \end{bmatrix} < 0 \quad (36)$$

where $\widetilde{\mathscr{U}}_{ijp}(\tau(t)) = \mathscr{U}_{ijp}^2 + \mathscr{U}_{ip}(\tau(t))$, $\widetilde{\mathscr{V}}_{ijp} = E_{ip}\mathcal{I}_{11} - \widetilde{E}_{jp}\mathcal{I}_{12} + F_{ip}\mathcal{I}_7$, and $\widetilde{\mathscr{M}}_{ijm} = \mathscr{M}_{ijm}^2 + \mathscr{M}_{im}$, $\widetilde{\mathscr{N}}_{ijm} = E_{im}\mathcal{J}_{11} - \widetilde{E}_{jm}\mathcal{J}_{12} + F_{im}\mathcal{J}_5$ with

$$\begin{aligned} \mathscr{U}_{ijp}^2 = sym\Big\{&(\mathcal{I}_{11}^T\mathcal{K}_{11}^T + \mathcal{I}_{12}^T\mathcal{K}_{12}^T)A_{ip}\mathcal{I}_{11} \\ &+ (\mathcal{I}_{21}^T\mathcal{K}_{21}^T + \mathcal{I}_{22}^T\mathcal{K}_{22}^T)A_{ip}\mathcal{I}_{11} \\ &+ (\mathcal{I}_{11}^T + \mathcal{I}_{12}^T + \mathcal{I}_{21}^T + \mathcal{I}_{22}^T)\widetilde{A}_{jp}\mathcal{I}_{12} \\ &+ \beta(\mathcal{I}_{11}^T + \mathcal{I}_{12}^T + \mathcal{I}_{21}^T + \mathcal{I}_{22}^T)\widetilde{B}_{jp}C_{ip}\mathcal{I}_{31} \\ &+ (1-\beta)(\mathcal{I}_{11}^T + \mathcal{I}_{12}^T + \mathcal{I}_{21}^T + \mathcal{I}_{22}^T)\widetilde{B}_{jp}\mathcal{I}_6 \\ &+ (\mathcal{I}_1^T\mathcal{K}_1^T + \mathcal{I}_2^T\mathcal{K}_2^T)(-\mathcal{I}_2 + \mathcal{D}_{ip}\mathcal{I}_7)\Big\} \end{aligned}$$

$$\begin{aligned} \mathscr{M}_{ijm}^2 = sym\Big\{&(\mathcal{J}_{11}^T\mathcal{K}_{11}^T + \mathcal{J}_{12}^T\mathcal{K}_{12}^T)A_{im}\mathcal{J}_{11} \\ &+ (\mathcal{J}_{21}^T\mathcal{K}_{21}^T + \mathcal{J}_{22}^T\mathcal{K}_{22}^T)A_{im}\mathcal{J}_{11} \\ &+ (\mathcal{J}_{11}^T + \mathcal{J}_{12}^T + \mathcal{J}_{21}^T + \mathcal{J}_{22}^T)\widetilde{A}_{jm}\mathcal{J}_{12} \\ &+ \beta(\mathcal{J}_{11}^T + \mathcal{J}_{12}^T + \mathcal{J}_{21}^T + \mathcal{J}_{22}^T)\widetilde{B}_{jm}C_{im}\mathcal{J}_{11} \\ &+ \beta(\mathcal{J}_{11}^T + \mathcal{J}_{12}^T + \mathcal{J}_{21}^T + \mathcal{J}_{22}^T)\widetilde{B}_{jm}\mathcal{J}_3 \\ &+ (1-\beta)(\mathcal{J}_{11}^T + \mathcal{J}_{12}^T + \mathcal{J}_{21}^T + \mathcal{J}_{22}^T)\widetilde{B}_{jm}\mathcal{J}_4 \\ &+ (\mathcal{J}_1^T\mathcal{K}_1^T + \mathcal{J}_2^T\mathcal{K}_2^T)(-\mathcal{J}_2 + \mathcal{D}_{im}\mathcal{J}_5)\Big\} \end{aligned}$$

Moreover, the filter gains can be given as

$$\widehat{A}_{j\kappa} = (K_{13}^T)^{-1}\widetilde{A}_{j\kappa}, \quad \widehat{B}_{j\kappa} = (K_{13}^T)^{-1}\widetilde{B}_{j\kappa}, \quad \widehat{E}_{j\kappa} = \widetilde{E}_{j\kappa}. \tag{37}$$

Proof: Define $\mathcal{I}_s = \begin{bmatrix} \mathcal{I}_{s1} \\ \mathcal{I}_{s2} \end{bmatrix}$ $(s = 1, 2, 3)$, $\mathcal{J}_s = \begin{bmatrix} \mathcal{J}_{s1} \\ \mathcal{J}_{s2} \end{bmatrix}$ $(s = 1, 2)$, $\mathcal{K}_1 = \begin{bmatrix} \mathcal{K}_{11} & \mathcal{K}_{12} \\ \mathcal{K}_{13} & \mathcal{K}_{13} \end{bmatrix}$ and $\mathcal{K}_2 = \begin{bmatrix} \mathcal{K}_{21} & \mathcal{K}_{22} \\ \mathcal{K}_{13} & \mathcal{K}_{13} \end{bmatrix}$. From (37) and system (7), it is easy to check that (31)–(36) are equivalent to (9)–(14). This completes the proof.

IV. NUMERICAL EXAMPLE

In this section, a numerical example is provided to demonstrate the effectiveness and advantage of the results obtained in this paper.

Example 1: We apply the proposed filter design method to a tunnel diode circuit system [47], the schematic diagram of which is given in Figure 1.

Similar to [36], the tunnel diode circuit system can be modeled by T-S fuzzy system (1). The system matrices and the membership functions are given as

$$A_{11} = \begin{bmatrix} -0.1 & 50 \\ -1 & -10 \end{bmatrix}, \quad A_{21} = \begin{bmatrix} -4.6 & 50 \\ -1 & -10 \end{bmatrix}$$

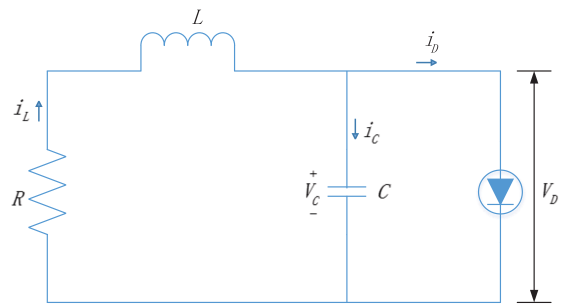

FIGURE 1. Tunnel diode circuit.

$$A_{12} = \begin{bmatrix} -0.11 & 50.1 \\ -1 & -10.1 \end{bmatrix}, \quad A_{22} = \begin{bmatrix} -4.5 & 50 \\ -1.1 & -10 \end{bmatrix}$$

$$B_{11} = B_{21} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad B_{12} = \begin{bmatrix} 0 \\ 1.1 \end{bmatrix}, \quad B_{22} = \begin{bmatrix} 0 \\ 0.9 \end{bmatrix}$$

$$C_{11} = C_{21} = \begin{bmatrix} 1 & 0 \end{bmatrix}, \quad C_{12} = \begin{bmatrix} 1.1 & 0 \end{bmatrix}$$

$$C_{22} = \begin{bmatrix} 0.9 & 0 \end{bmatrix}, \quad E_{11} = E_{21} = E_{22} = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

$$E_{12} = \begin{bmatrix} 1.5 & 0 \end{bmatrix}, \quad F_{11} = F_{21} = F_{12} = F_{22} = 0.1$$

$$\lambda_1 = \begin{cases} \dfrac{3 + x_1(t)}{3}, & -3 \le x_1(t) \le 0; \\ \dfrac{3 - x_1(t)}{3}, & 0 \le x_1(t) \le 3; \\ 0, & \text{otherwise}, \end{cases} \quad \lambda_2 = 1 - \lambda_1,$$

and the transition rate matrix is given as

$$\Pi = \begin{bmatrix} -6 & 6 \\ 4 & -4 \end{bmatrix}.$$

We assume that the deception attack signal $f(y(t)) = 0.1y(t) + \tanh(0.1y(t))$ and the occurrence probability of a successful deception attack is 0.3, thus $\mathcal{L} = 0.2$ and $\beta = 0.7$ can be easily obtained. In addition, we set $\mu = 1.1$, $\rho = 1.95$, $\tau = 0.05$, $\psi_1 = 0.15$ and $\psi_2 = 0.2$.

By solving the LMIs in Theorem 2, we get the optimal H_∞ performance $\gamma_{\min} = 2.0013$, and weighting matrix $\Psi = 0.0395$ is achieved, the corresponding filter gains are obtained as (To save space, we do not list all the filter gains):

$$\widehat{A}_{11} = \begin{bmatrix} -3.0987 & 55.2556 \\ -0.0986 & -2.0252 \end{bmatrix},$$

$$\widehat{A}_{21} = \begin{bmatrix} -3.0827 & 56.8321 \\ -0.0991 & -2.0746 \end{bmatrix},$$

$$\widehat{A}_{12} = \begin{bmatrix} -3.0969 & 56.7800 \\ -0.1016 & -1.7827 \end{bmatrix},$$

$$\widehat{A}_{22} = \begin{bmatrix} -3.0853 & 55.4330 \\ -0.1038 & -1.9517 \end{bmatrix}.$$

Supposing the external disturbance $\omega(t) = \sin(0.1t)e^{-0.1t}$ and the initial state $x(t) = \widehat{x}(t) = \begin{bmatrix} 1 & -1 \end{bmatrix}^T$. The simulation results are shown in Figure 2 to Figure 7. Figure 2 shows the release instants and intervals of signal $y(t)$, and the trigger times is found to be 43. Figure 3 and Figure 4 present the state trajectories of $z(t)$, $\widehat{z}(t)$ and $\widetilde{z}(t)$, respectively. From Figure 2 to Figure 4, we can conclude that the hybrid and adaptive ETCM-based filter designed here works well in estimation while reducing the communication burden.

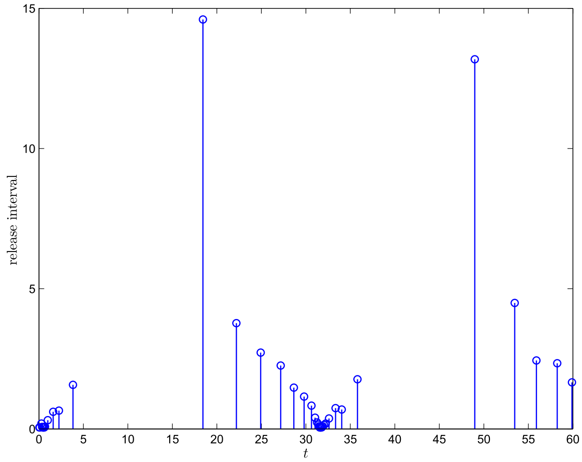

FIGURE 2. The release instants and release intervals under $\psi_1 = 0.15$, $\psi_2 = 0.2$.

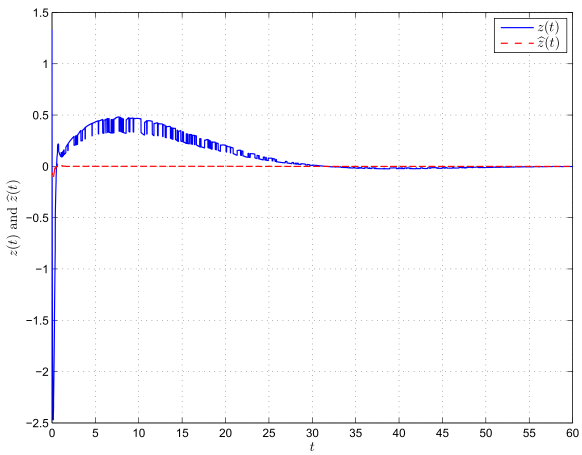

FIGURE 3. The state trajectories of $z(t)$ and $\hat{z}(t)$.

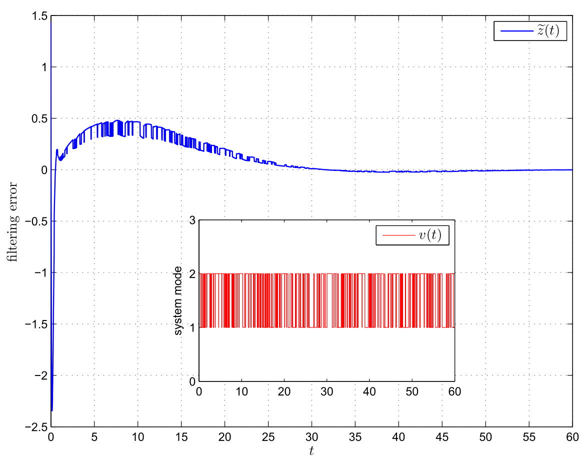

FIGURE 4. The mode evolution and state trajectory of $\tilde{z}(t)$.

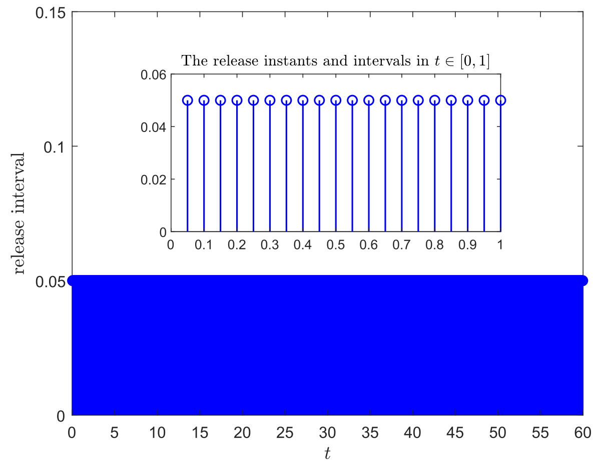

FIGURE 5. The release instants and release intervals under $\psi_1 = \psi_2 = 0$.

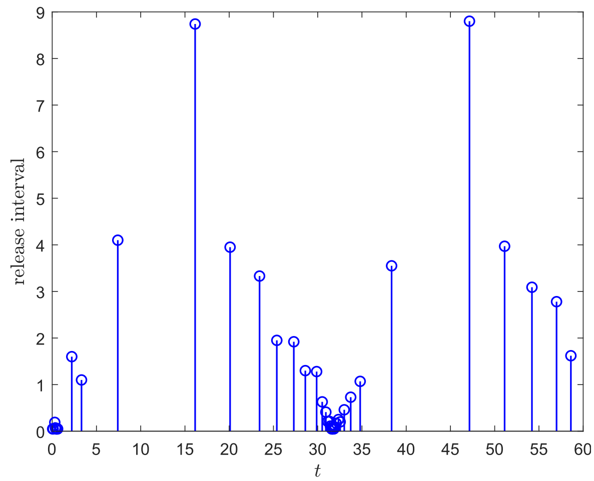

FIGURE 6. The release instants and release intervals under $\psi_1 = 0.15$, $\psi_2 = 0$.

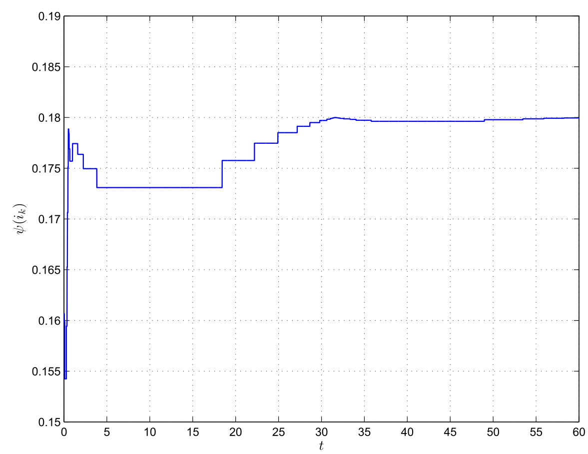

FIGURE 7. The evolution of $\psi(i_k)$.

Additionally, Figure 5 and Figure 6 show the release instants and intervals of signal $y(t)$ under $\psi_1 = \psi_2 = 0$ and $\psi_1 = 0.15$, $\psi_2 = 0$, respectively. By comparing with the result presented in Figure 2, more trigger times can be found in Figures 5 and 6. Figure 7 presents the evolution of the threshold $\psi(i_k)$, from which we can find that the value of $\psi(i_k)$ is dynamically changing. Notably, the value of $\psi(i_k)$ starts to become larger as the value of $\tilde{z}(t)$ is approaching zero, i.e., compared with the ETCM with constant threshold, the adaptive ETCM proposed here has the advantage in saving more communication resource, especially when the filtering is about to be done.

TABLE 1. The trigger times under different communication schemes.

trigger times	$\tau = 0.05$	$\tau = 0.07$	$\tau = 0.09$
periodic sampling method	1199	857	666
static ETCM	51	49	45
adaptive ETCM	49	44	42

TABLE 2. The optimal H_∞ performance $\gamma_{\min}$ for different values of τ and β.

$\gamma_{\min}$	$\beta = 0$	$\beta = 0.3$	$\beta = 0.5$	$\beta = 0.7$	$\beta = 1$
$\tau = 0.5$	1.6882	1.6816	1.6230	1.5399	1.4592
$\tau = 1.5$	1.6905	1.6895	1.6826	1.6768	1.6709
$\tau = 2.5$	1.7072	1.7072	1.7071	1.7067	1.7059

In order to make my point more convincing, we make a comparison of the trigger times obtained by using periodic sampling method ($\psi_1 = \psi_2 = 0$), static ETCM ($\psi_1 \neq 0$, $\psi_2 = 0$) and adaptive ETCM (3) ($\psi_1 \neq 0$, $\psi_2 \neq 0$). Setting the simulation time as 60, the trigger times under different communication schemes is listed in Table 1. From Table 1, it can be clearly seen that adaptive ETCM (3) achieve the least trigger times. Thus, the hybrid and adaptive ETCM proposed here is superior to the existing ETCM in [20], [21] and the periodic sampling method.

To illustrate the relationship among the optimal H_∞ performance $\gamma_{\min}$, τ and β, Table 2 is provided. By solving the LMIs in Theorem 2 under $\mu = 1.1$, $\rho = 0.2$, $\psi_1 = 0.15$ and $\psi_2 = 0.2$, Table 2 lists the optimal H_∞ performance $\gamma_{\min}$ for different values of τ and β.

Two trends are shown in Table 2. One is that for the same value of τ, the value of $\gamma_{\min}$ decreases as the value of β increases, i.e., cyber-attacks impair the performance of a system. It is thus necessary to consider the factor of cyber-attacks in filter design. The other is that for the same value of β, the value of $\gamma_{\min}$ increases as the value of τ increases, which means that the disturbance attenuation performance of the system degrades with the decrease of data transmission. Therefore, it is a tradeoff between system performance and utilization of communication resource.

V. CONCLUSION

We proposed a new hybrid and adaptive event-triggered mechanism, by which the workload of communication network has been largely reduced. Considering the influence of stochastic deception attacks, an event-based filter has been designed for the nonlinear Makov jump systems. Based on the LKF with less restriction, a sufficient condition has been developed on the exponential mean-square stability for the filtering error system with a weighted H_∞ performance. The effectiveness and advantage of the obtained results have finally been illustrated by a tunnel diode circuit system. The present method can be extended to the stabilization of nonlinear networked systems with unreliable links that may be a topic for the future research.

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