Hybrid-Driven-Based $\mathcal{H}_\infty$ Control for Networked Cascade Control Systems With Actuator Saturations and Stochastic Cyber Attacks

Jinliang Liu, Yuanyuan Gu, Xiangpeng Xie, Dong Yue, and Ju H. Park

***Abstract*—This paper focuses on the hybrid-driven-based $\mathcal{H}_\infty$ control for networked cascade control systems (NCCSs) with actuator saturations and stochastic cyber attacks. In order to relieve the network bandwidth load effectively, a hybrid triggered scheme is introduced, which contains a switch between time-triggered scheme and event-triggered scheme. A newly hybrid-driven-based NCCS model is established by considering the effects of both actuator saturations and stochastic cyber attack, which is an important threat to network security. By using the Lyapunov stability theory, sufficient conditions are obtained to ensure the system stability. Furthermore, both primary controller gain and secondary controller gain are achieved explicitly in terms of linear matrix inequality techniques. Finally, a power plant gas-turbine system is presented to illustrate the usefulness of the designed state feedback controllers.**

***Index Terms*—Actuator saturations, cyber attacks, hybrid triggered scheme, networked cascade control systems (NCCSs).**

I. Introduction

In RECENT years, cascade control has exhibited widely industrial applications such as chemical reactors [1], power plants [2], underwater robots [3], networked control systems (NCSs) [4], and so on. Its success mainly depends on the distinctive structure composed of two control loops where the outer loop is responsible for the stability of the systems and the inner loop is aimed at eliminating the disturbances quickly [4]. NCS is a kind of control system where sensors, controllers and actuators are connected through a communication network [13], the advantages of which are simple installation, easy maintenance and low cost, etc. [5]. It is worth noting that an increasing attention has been paid to the combination of cascade control and NCS in the past decade, which is called networked cascade control systems (NCCSs). For example, a typical kind of NCCS with state feedback controllers is investigated and the sufficient condition for the stability of NCCS as well as the $\mathcal{H}_\infty$ control laws are obtained in [4]. A class of NCCSs based on fieldbus is studied in [6], which is modeled as a finite-dimensional discrete-time linear time-invariant system in terms of augmented state vector method. The stabilization and $\mathcal{H}_\infty$ controller design problems are investigated in [7], which are based on an extended model called singular NCCSs. For singular NCCSs, the problem of dissipative fault-tolerant control synthesis and the issue of exponential passivity analysis are further addressed in [8] and [9], respectively.

However, the introduction of the network also brings about many challenges including network-induced time-delay [10], limited network bandwidth [11], and packet dropout [12], which may deteriorate the performance and destabilize the system. How to prevent the data from redundant signal transmissions has been a fundamental research topic in control and signal processing areas. From an analysis and design point of view [13], time-triggered scheme has been widely adopted for many years since it simply transmits all periodically sampled data to guarantee a desired system performance [14]. However, from a computation and resource occupation point of view [15], it will send unnecessary signals to the bandwidth-limited communication channel and give rise to the waste of network resources in such case that the system state keeps steady [19]. In order to decrease the overload of network bandwidth [16] resulting from the time-triggered scheme, many scholars have proposed various event-triggered schemes [17]. For example, a novel event-triggered scheme is proposed in [14], which can effectively reduce the burden of network bandwidth. The main idea of the event-triggered scheme proposed in [14] is that the newly sampled data whether to be transmitted or not is determined by a threshold. There has been a rich body of research results available in the literature based on the event-triggered scheme mentioned in [14]. For example, $\mathcal{H}_\infty$ filtering problem for sampled-data systems is studied in [18] by adopting the event-triggered scheme in [14] to save communication resources. Peng *et al.* [19] proposed a novel mixed self-triggered and event-triggered scheme to improve the energy efficiency of the wireless sensor networks, which extends the event-triggered scheme proposed in [14].

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Inspired by the event-triggered scheme proposed in [14], the problem concerning decentralized event-triggered $\mathcal{H}_\infty$ control is addressed in [20] for neural networks. By combining the advantages of both time-triggered scheme and event-triggered scheme proposed in [14], a novel hybrid triggered scheme is proposed in [21], which is implemented by a random switching between time-triggered scheme and event-triggered scheme, and the adoption of hybrid triggered scheme can improve the system performance and reduce the network transmission simultaneously. Under the hybrid triggered scheme proposed in [21], the quantized stabilization and the $\mathcal{H}_\infty$ filter design problem for T-S fuzzy systems are investigated in [22] and [23], respectively. In addition, Liu *et al.* [24] designed the resilient observer-based output feedback controller for T-S fuzzy systems under the hybrid triggered scheme [21]. $\mathcal{H}_\infty$ filter design for networked systems [25] and for neural networks [26] are, respectively, addressed by considering the hybrid triggered scheme mentioned in [21].

As is well known, owing to the physical constraints or technological restrictions, saturation phenomena inevitably exist in different kinds of practical systems [31], which may also deteriorate the performance of the systems [32], [33]. Actuator saturation is one of the most important saturation phenomena [34], which has attracted lots of attention. For instance, an anti-windup controller is designed in [35] for singularly perturbed systems with actuator saturation. The issue of adaptive fuzzy tracking control is studied in [36] for nonlinear stochastic systems by considering actuator saturation. Wang *et al.* [37] proposed a global cooperative control framework to address the global leader-follower consensus for multiagent systems subject to actuator saturation. The event-triggered control for linear systems is presented in [38] with actuator saturation and external disturbances.

More recently, due to the open property of data transmission channels, the security problems in NCSs have gained an ever-increasing interest from researchers in the control community [39], [40]. In particular, cyber attacks have become the major threat to network security, which aim to affect the control performance by destroying/modifying certain significant data transmitted over network [41]. Hence, increasing research interests have been paid to exploring the impact coming from various cyber attacks such as denial of service attacks [42], replay attacks [43], and deception attacks [44]. For example, Ding *et al.* [45] investigated the observer-based event-triggering consensus control for a class of discrete-time multiagent systems by considering lossy sensors and cyber-attacks. Distributed event-triggered control problem is addressed in [46] for NCSs with stochastic cyber-attacks. Distributed recursive filter for stochastic systems and distributed event-triggered $\mathcal{H}_\infty$ filter for continuous-time linear-invariant system are separately designed in [47] and [48] over sensor networks, where the deception attacks randomly take place.

Motivated by the previously mentioned results, this paper first investigates the problem of $\mathcal{H}_\infty$ control for NCCSs with hybrid triggered scheme, actuator saturations and stochastic cyber attacks. The main contributions are summarized as follows.

1) The hybrid triggered scheme is first introduced into the $\mathcal{H}_\infty$ controller design problem for NCCSs while taking the effects of actuator saturations and stochastic cyber attacks into consideration.
2) A new model for NCCSs is first constructed by considering the hybrid triggered scheme, actuator saturations and stochastic cyber attacks.
3) Based on the constructed model, the criteria for the considered NCCSs stability are derived by means of Lyapunov stability theory. Moreover, the primary controller gain and the secondary controller gain are obtained simultaneously in terms of linear matrix inequality (LMI) techniques.

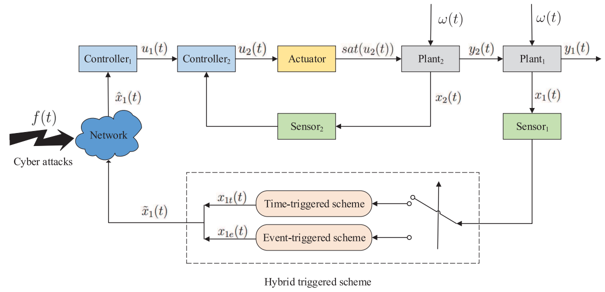

Fig. 1. Structure of hybrid-driven-based $\mathcal{H}_\infty$ controller for NCCSs with actuator saturations and stochastic cyber attacks.

The remainder of this paper is organized as follows. In Section II, problem formulation and preliminaries are outlined and a new model for NCCSs is established. Section III shows the main results concerning the sufficient stabilization conditions for NCCSs and the $\mathcal{H}_\infty$ controller design method. Moreover, both primary controller gain and secondary controller gain are obtained. An illustrative example is given in Section IV to show the usefulness of the design method. Conclusion is presented in Section V.

Notation: $\mathbb{R}^n$ and $\mathbb{R}^{n\times m}$ stand for the n-dimensional Euclidean space and the set of $n\times m$ real matrices, respectively; the superscript T represents matrix transposition; I denotes the identity matrix of appropriate dimension; the notation $X > 0$ for $X \in \mathbb{R}^{n\times n}$ means that the matrix X is real symmetric positive definite; $\mathbb{E}$ is the expectation operator; $*$ refers to the entries caused by symmetry; $\|\cdot\|$ denotes the Euclidean norm; and sym(B) represents the symmetrized expression $B + B^{\mathrm{T}}$.

II. System Description

This paper is concerned with hybrid-driven-based $\mathcal{H}_\infty$ control for NCCSs with actuator saturations and stochastic cyber attacks. As shown in Fig. 1, the structure of cascade control system contains two loops, where the inner loop is made up of secondary plant Plant$_2$, secondary sensor Sensor$_2$, secondary controller Controller$_2$, and actuator, and the outer loop is made up of primary plant Plant$_1$, primary sensor Sensor$_1$, primary controller Controller$_1$, and actuator. A network is assumed to connect the Sensor$_1$ and the Controller$_1$ in the cascade control system, which constitutes the NCCS considered in this paper.

The primary plant Plant$_1$ under consideration is described by the following:

$$\text{Plant}_1: \begin{cases} \dot{x}_1(t) = A_1 x_1(t) + B_1 y_2(t) \\ y_1(t) = C_1 x_1(t) + D_1 \omega(t) \end{cases} \tag{1}$$

where $x_1(t) \in \mathbb{R}^n$ and $y_1(t) \in \mathbb{R}^m$ denote the state vector and the measurement output of Plant_1, respectively; $y_2(t)$ is the measurement output of Plant_2; $\omega(t) \in \mathcal{L}_2[0,\infty)$ is the disturbance input; and A_1, B_1, C_1, and D_1 are the known real constant matrices with appropriate dimensions.

The aim of this paper is to design hybrid-driven-based $\mathcal{H}_\infty$ controllers for NCCSs with actuator saturations and stochastic cyber attacks. It can be seen from Fig. 1 that $u_1(t)$ is the output of primary controller, as well as a part of the input of secondary controller. The given primary controller and the secondary controller are state feedback as follows:

$$\begin{cases} u_1(t) = K_1\hat{x}_1(t) \\ u_2(t) = u_1(t) + K_2x_2(t) \end{cases} \tag{2}$$

where K_1 and K_2 are the state feedback gain matrices of Controller_1 and Controller_2, respectively; $\hat{x}_1(t)$ is the real input of primary controller; $x_2(t)$ is the state vector of secondary plant; and $u_2(t)$ is the output of secondary controller.

Remark 1: Compared with the structure of common NCSs, the NCCSs have one more loop, which is added to quickly eliminate the disturbances in the inner loop. The key idea of this paper is to design useful primary controller in the outer loop and the secondary controller in the inner loop for NCCSs simultaneously.

Inspired by the idea of [21], a hybrid triggered scheme is introduced to alleviate the load of network bandwidth. As shown in Fig. 1, the hybrid triggered scheme contains a random switch between the "time-triggered scheme" and the "event-triggered scheme."

When the switch turns on the channel of time-triggered scheme, the periodically sampled measurements will be transmitted in time, which implies that the sequence of transmitting instant is t_kh $(k = 1, 2, \ldots)$, where h is a sampling period, t_k $(k = 1, 2, \ldots)$ is a sequence set of positive integers, namely, $\{t_1, t_2, t_3, \ldots\} = \{1, 2, 3, \ldots\}$. In other words, when the latest transmitting instant is t_kh, the next transmitting instant is $t_{k+1}h = t_kh + h$. Suppose η_{t_k} denotes the network-induced time-delay of sensor measurement sampled at the instant t_kh.

Define $\eta(t) = t - t_kh$, as shown in Fig. 1, the sensor measurement can be described as

$$\begin{aligned} & x_{1t}(t) = x_1(t_kh) = x_1(t - \eta(t)) \\ & t \in \left[t_kh + \eta_{t_k}, t_{k+1}h + \eta_{t_{k+1}}\right), \quad k = 1, 2, \ldots \end{aligned} \tag{3}$$

where $0 < \min\{\eta_{t_k}\} \le \eta(t) \le \eta_M$. $\eta_M = h + \max\{\eta_{t_k}, \eta_{t_{k+1}}\} \triangleq h + \overline{\eta}$ and $\overline{\eta}$ is the upper bound of the communication time-delay.

When the switch turns on the channel of event-triggered scheme, the periodically sampled measurements will be transmitted only when they violate the triggering condition. Then the sequence of transmitting instant can be expressed as follows:

$$\begin{aligned} t_{k+1}h = t_kh + \inf_{j\ge1}\Big\{ & jh | e_k^{\mathrm{T}}(t)\Omega e_k(t) \\ & > \lambda x_1^{\mathrm{T}}\left(i_k^jh\right)\Omega x_1\left(i_k^jh\right)\Big\},\ j = 1, 2, \ldots \end{aligned} \tag{4}$$

where $e_k(t) = x_1(t_kh) - x_1(i_k^jh)$, the trigger parameters $\Omega > 0$ will be designed and $\lambda \in [0, 1)$ will be given. t_kh and $i_k^jh = t_kh + jh$ stand for the latest transmitting instant and current sampling instant, respectively.

By considering the effect of network, the transmitted data arriving at primary controller will be hold by zero-order-hold within the time interval $[t_kh + \eta_{t_k}, t_{k+1}h + \eta_{t_{k+1}})$. For development, the interval can be divided into several subintervals, which can be expressed as $[t_kh + \eta_{t_k}, t_{k+1}h + \eta_{t_{k+1}}) = \cup_{j=0}^{d_k}[i_k^jh + \eta_{t_{k+j}}, i_k^jh + h + \eta_{t_{k+1+j}})$, where $d_k = t_{k+1} - t_k - 1$ is similar to the definition in [14]. Define $d(t) = t - i_k^jh$, $t \in [i_k^jh + \eta_{t_{k+j}}, i_k^jh + h + \eta_{t_{k+1+j}})$, $j = 0, 1, 2, \ldots$ It is easy to get the range of $d(t)$ as $0 < \eta_{t_k} \le d(t) \le h + \max\{\eta_{t_k}, \eta_{t_{k+1}}\} = h + \overline{\eta} \triangleq d_M$.

Then, the sensor measurement can be expressed as

$$\begin{aligned} & x_{1e}(t) = x_1(t_kh) = x_1(t - d(t)) + e_k(t) \\ & t \in [t_kh + \eta_{t_k}, t_{k+1}h + \eta_{t_{k+1}}). \end{aligned} \tag{5}$$

In order to explain the random switching rule of hybrid triggered scheme, a Bernoulli random variable $\alpha(t)$ is introduced, where $\alpha(t) \in \{0, 1\}$ and the statistical properties of $\alpha(t)$ are assumed to be $\mathbb{E}\{\alpha(t)\} = \bar{\alpha}$ and $\mathbb{E}\{(\alpha(t) - \bar{\alpha})^2\} = \sigma^2$. Then, as the method proposed in [21], the sensor measurement under hybrid triggered scheme can be described as follows:

$$\tilde{x}_1(t) = \alpha(t)x_{1t}(t) + (1 - \alpha(t))x_{1e}(t). \tag{6}$$

Remark 2: The Bernoulli random variable $\alpha(t)$ shown in (6) is utilized to indicate the switching law from one triggered scheme to another. If $\alpha(t) = 1$, the channel of time-triggered scheme is activated for transmitting. If $\alpha(t) = 0$, the channel of event-triggered scheme is chosen to transmit data.

Remark 3: The hybrid triggered scheme is first proposed in [21] to improve the system performance and reduce the network transmission for NCSs. This paper introduces the hybrid triggered scheme into the analysis and design for NCCSs with actuator saturations and stochastic cyber attacks.

In this paper, it is assumed that the cyber attacks are launched randomly which can be expressed by a nonlinear function $f(x_1(t))$ and the corresponding time delay is assumed as $\tau(t) \in (0, \tau_M]$. Inspired by the method in [41] and [47], a Bernoulli random variable $\beta(t)$ is utilized to govern the stochastic cyber attacks similarly. Furthermore, suppose $\beta(t)$ is subject to Bernoulli distribution and uncorrelated to $\alpha(t)$. When $\beta(t) = 1$, the cyber attacks are implemented; otherwise, when $\beta(t) = 0$, the data transmission is normal. Therefore, under hybrid triggered scheme and stochastic cyber attacks, the real input of primary controller can be represented as

$$\hat{x}_1(t) = \beta(t)f(x_1(t - \tau(t))) + (1 - \beta(t))\tilde{x}_1(t) \tag{7}$$

where $\mathbb{E}\{\beta(t)\} = \bar{\beta}$ and $\mathbb{E}\{(\beta(t) - \bar{\beta})^2\} = \delta^2$.

Remark 4: For the NCCSs considered in this paper, a network is adopted to transmit data from primary sensor Sensor_1 to primary controller Controller_1. In the practical engineering, the data transmission network is susceptible to be attacked by potential cyber attack, which is one of the important factors affecting the network security. It is notable that the successfully cyber attacks possess stochastic characteristic due mainly to the protection of hardware or software, the communication protocols and the randomly fluctuated network conditions (e.g., network load, network congestion, and network transmission rate) [47]. For example, under a (T, N) secret sharing scheme, where a confidential message is divided into N shares and at least T out of N shares can reconstruct the original message, a secure message can be recovered only when T or more shares are successfully delivered by multipath routing protocol. In other words, if the cyber attacks randomly destroy the N different paths such that $T-1$ or less shares eventually arrive at destination host, the secure message will not be recovered [44]. To be more exact, the cyber attacks discussed in this paper belong to stochastic deception attacks, where the way of corrupting the transmission data is to fully substitute it with the attack signals [41].

Remark 5: It should be mentioned that the cyber attacks may be undetectable since the attack signals are strategically generated by malicious adversaries and may relate to system information [40]. This paper assumes the adversaries have access to full state information of Plant_1 (1). Moreover, similar to the description in [26], this paper models the cyber attacks as a nonlinear function associated with system state, which is confined in Assumption 1.

Remark 6: Note that upon the deception attacks occurring at any time during the data transmission over a network, the real measurements are replaced by attack signals which will cheat existing monitoring systems [39] and continue to be transmitted over a network. Thus, the attack signals are also subject to time delays, which are assumed to be bounded by τ_M in this paper.

Then, the controllers of (2) can be rewritten as follows:

$$\begin{cases} u_1(t) = \beta(t)K_1 f(x_1(t-\tau(t))) \\ \qquad + (1-\beta(t))\alpha(t)K_1x_1(t-\eta(t)) \\ \qquad + (1-\beta(t))(1-\alpha(t))K_1x_1(t-d(t)) \\ \qquad + (1-\beta(t))(1-\alpha(t))K_1e_k(t) \\ u_2(t) = u_1(t) + K_2x_2(t). \end{cases} \tag{8}$$

The secondary plant under consideration is described by the following:

$$\text{Plant}_2 : \begin{cases} \dot{x}_2(t) = A_2x_2(t) + A_3x_2(t-\theta(t)) \\ \qquad + B_2\text{sat}(u_2(t)) + B_3\omega(t) \\ y_2(t) = C_2x_2(t) + D_2\omega(t) \end{cases} \tag{9}$$

where $\theta(t) \in (0, \theta_M]$ is a state-delay variable of the Plant_2; A_2, A_3, B_2, B_3, C_2, and D_2 are the known real constant matrices with appropriate dimensions; and $\text{sat}(u_2(t))$ is the saturation function of actuator, which has the similar definition in [34] as $\text{sat}(u_2) = [\text{sat}(u_2^1), \text{sat}(u_2^2), \ldots, \text{sat}(u_2^m)]^{\text{T}} \in \mathbb{R}^m$, where

$$\text{sat}(u_2^i) \triangleq \begin{cases} \rho_i, & u_2^i > \rho_i \\ u_2^i, & -\rho_i \le u_2^i \le \rho_i, \quad i = 1, 2, \ldots, m \\ -\rho_i, & u_2^i < -\rho_i \end{cases} \tag{10}$$

with ρ_i representing the known upper limits of actuator saturation constraints.

Borrowed the main idea of [34], the saturation function $\text{sat}(u_2(t))$ can be represented by a linear $u_2(t)$ and a nonlinear $\phi(u_2(t))$, namely

$$\text{sat}(u_2(t)) = u_2(t) - \phi(u_2(t)). \tag{11}$$

The dead-zone nonlinearity function $\phi(u_2(t))$ satisfies the condition: there $\exists\ 0 < \varepsilon < 1$, such that

$$\varepsilon u_2^{\text{T}}(t)u_2(t) \ge \phi^{\text{T}}(u_2(t))\phi(u_2(t)) \tag{12}$$

where $\varepsilon = \max\{\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_m\}$.

Remark 7: According to the proof in [34], the ε in (12) is dependent on the factors as ρ_i and u_2^i in (10), namely, for $i = 1, 2, \ldots, m$, $\varepsilon_i \ge (1-(\rho_i/|u_2^i|_{\max}))^2$, where $|u_2^i|_{\max}$ stands for the maximum amplitude of control input $u_2^i(t)$.

Substitute $u_2(t)$ in (8) into (11) and then the actuator saturation function $\text{sat}(u_2(t))$ can be rewritten as

$$\begin{aligned} \text{sat}(u_2(t)) = &(1-\beta(t))\alpha(t)K_1x_1(t-\eta(t)) \\ &+ (1-\beta(t))(1-\alpha(t))K_1x_1(t-d(t)) \\ &+ (1-\beta(t))(1-\alpha(t))K_1e_k(t) \\ &+ \beta(t)K_1f(x_1(t-\tau(t))) \\ &+ K_2x_2(t) - \phi(u_2(t)). \end{aligned} \tag{13}$$

By combining (1), (9), and (13), it can yield a new model for NCCSs as follows:

$$\begin{cases} \dot{x}_1(t) = A_1x_1(t) + B_1C_2x_2(t) + B_1D_2\omega(t) \\ \dot{x}_2(t) = A_2x_2(t) + A_3x_2(t-\theta(t)) \\ \qquad + (1-\beta(t))\alpha(t)B_2K_1x_1(t-\eta(t)) \\ \qquad + (1-\beta(t))(1-\alpha(t))B_2K_1x_1(t-d(t)) \\ \qquad + (1-\beta(t))(1-\alpha(t))B_2K_1e_k(t) \\ \qquad + \beta(t)B_2K_1f(x_1(t-\tau(t))) \\ \qquad + B_2K_2x_2(t) - B_2\phi(u_2(t)) + B_3\omega(t) \\ y_1(t) = C_1x_1(t) + D_1\omega(t). \end{cases} \tag{14}$$

In the following, an assumption and two lemmas are introduced, which are helpful to derive our desired results.

Assumption 1 [26]: Assume that the following condition of nonlinear function $f(x)$ holds, which is introduced to restraint the cyber attacks

$$\|f(x)\|^2 \le \|Fx\|^2 \tag{15}$$

where F is a constant matrix standing for the upper bound of the nonlinearity.

Lemma 1 [27]: Consider a given matrix $R = R^{\text{T}} > 0$. Then, for all continuously differentiable function $\dot{x}(t)$ in $[a, b] \to \mathbb{R}^n$, the following inequality holds:

$$-\int_a^b \dot{x}^{\text{T}}(s)R\dot{x}(s)ds \le -\frac{1}{b-a}\begin{bmatrix}\Pi_1 \\ \Pi_2\end{bmatrix}^{\text{T}}\begin{bmatrix}R & * \\ 0 & 3R\end{bmatrix}\begin{bmatrix}\Pi_1 \\ \Pi_2\end{bmatrix} \tag{16}$$

where

$$\Pi_1 = x(b) - x(a)$$

$$\Pi_2 = x(b) + x(a) - \frac{2}{b-a}\int_a^b x(s)ds.$$

Lemma 2 [28]: Suppose that there exists a matrix $M \in \mathbb{R}^{n\times n}$ satisfying that $\begin{bmatrix}R & * \\ M & R\end{bmatrix} \ge 0$ for given symmetric positive definite matrices $R \in \mathbb{R}^{n\times n}$. Then, for any scalar $\theta \in (0, 1)$, the following inequality holds:

$$\begin{bmatrix}\frac{1}{\theta}R & 0 \\ 0 & \frac{1}{1-\theta}R\end{bmatrix} \ge \begin{bmatrix}R & * \\ M & R\end{bmatrix}. \tag{17}$$

The aim of this paper is to design the hybrid-driven-based controllers (2) for NCCS (14), such that, in the presence of actuator saturations (12) and stochastic cyber attacks (15), the NCCS (14) is mean-square asymptotically stable, and $\mathcal{H}_\infty$ performance constraint is satisfied. More specifically, the following requirements are satisfied.

1) The NCCS (14) with $\omega(t) = 0$ is asymptotically stable in the mean-square sense.
2) Under the zero-initial condition, the inequality $\mathbb{E}\{\int_0^\infty \|y_1(s)\|^2 ds\} < \gamma^2 \mathbb{E}\{\int_0^\infty \|\omega(s)\|^2 ds\}$ holds for all nonzero $\omega(t) \in \mathcal{L}_2[0, \infty)$ and prescribed scalar $\gamma > 0$.

III. Main Results

In this section, the stability conditions for system (14) will be derived based on the Lyapunov–Krasovskii function method and the state feedback controllers (2) will be designed by means of LMI-based approaches [29]. The research results are stated as follows.

Theorem 1: For given positive scalars $\bar{\alpha}$, $\bar{\beta}$, γ, and $0 < \varepsilon < 1$, the upper bound of time-delays $\eta_M > 0$, $d_M > 0$, $\tau_M > 0$, and $\theta_M > 0$, trigger parameter λ, and matrices F, K_1, and K_2, the system (14) is asymptotically stable in the mean-square sense if there exist matrices $P_1 > 0$, $P_2 > 0$, $Q_i > 0$, $R_i > 0$ $(i = 1, 2, 3, 4)$, $\Omega > 0$, and M_i, N_i, S_i, W_i $(i = 1, 2, 3, 4)$ with appropriate dimensions such that

$$\Phi = \begin{bmatrix} \Phi_1 & * \\ \Phi_2 & \Phi_3 \end{bmatrix} < 0 \tag{18}$$

$$\Theta_i = \begin{bmatrix} R_i & * & * & * \\ 0 & 3R_i & * & * \\ U_{i_1} & U_{i_2} & R_i & * \\ U_{i_3} & U_{i_4} & 0 & 3R_i \end{bmatrix} \geq 0, i = 1, 2, 3, 4 \tag{19}$$

where

$$U_1 = M, \quad U_2 = N, \quad U_3 = S, \quad U_4 = W$$

$$\Phi_1 = \begin{bmatrix} \Phi_{11} & * & * & * & * & * & * \\ \Psi_1 & \Psi_{11} & * & * & * & * & * \\ \Psi_2 & 0 & \Psi_{22} + \lambda\Omega & * & * & * & * \\ \Psi_3 & 0 & 0 & \Psi_{33} & * & * & * \\ \Phi_{12} & \Phi_{13} & \Phi_{14} & 0 & \Phi_{15} & * & * \\ 0 & 0 & 0 & 0 & \Psi_4 & \Psi_{44} & * \\ \Phi_{16} & 0 & 0 & 0 & \Phi_{17} & 0 & \Phi_{18} \end{bmatrix}$$

$$\Phi_{11} = \mathrm{sym}(P_1 A_1) + \sum_{j=1}^{3}(Q_j - 4R_j), \quad \Phi_{12} = C_2^{\mathrm{T}} B_1^{\mathrm{T}} P_1$$

$$\Phi_{13} = \begin{bmatrix} \bar{\beta}_1 \bar{\alpha} P_2 B_2 K_1 & 0 & 0 & 0 \end{bmatrix}, \quad \bar{\beta}_1 = 1 - \bar{\beta}$$

$$\Phi_{14} = \begin{bmatrix} \bar{\beta}_1 \bar{\alpha}_1 P_2 B_2 K_1 & 0 & 0 & 0 \end{bmatrix}, \quad \bar{\alpha}_1 = 1 - \bar{\alpha}$$

$$\Phi_{15} = \mathrm{sym}(P_2 A_2 + P_2 B_2 K_2) + Q_4 - 4R_4$$

$$\Phi_{16} = \begin{bmatrix} 0 & 0 & 0 & \Upsilon_3 \end{bmatrix}^{\mathrm{T}}, \quad \Upsilon_3 = P_1 B_1 D_2$$

$$\Phi_{17} = \begin{bmatrix} \bar{\beta}_1 \bar{\alpha}_1 P_2 B_2 K_1 & \bar{\beta} P_2 B_2 K_1 & -P_2 B_2 & P_2 B_3 \end{bmatrix}^{\mathrm{T}}$$

$$\Phi_{18} = \mathrm{diag}\{-\Omega, -\bar{\beta} I, -I, -\gamma^2 I\}$$

$$\Psi_i = \begin{bmatrix} -2R_i^{\mathrm{T}} - \sum_{j=1}^{4} U_{i_j}^{\mathrm{T}} & \Psi_{i2}^{\mathrm{T}} & 6R_i^{\mathrm{T}} & 2U_{i_3}^{\mathrm{T}} + 2U_{i_4}^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}$$

$$\Psi_{i2}^{\mathrm{T}} = U_{i_1}^{\mathrm{T}} + U_{i_2}^{\mathrm{T}} - U_{i_3}^{\mathrm{T}} - U_{i_4}^{\mathrm{T}}, \quad i = 1, 2, 3, 4$$

$$\Psi_{ii}^{\mathrm{T}} = \begin{bmatrix} \Xi_{i1} & * & * & * \\ \Xi_{i2} & -Q_i - 4R_i & * & * \\ \Xi_{i3} & -2U_{i_2}^{\mathrm{T}} + 2U_{i_4}^{\mathrm{T}} & -12R_i & * \\ \Xi_{i4} & 6R_i & -4U_{i_4} & -12R_i \end{bmatrix}$$

$$\Xi_{i1} = -8R_i + \mathrm{sym}(U_{i_1} - U_{i_2} + U_{i_3} - U_{i_4})$$

$$\Xi_{i2} = -2R_i - U_{i_1} + U_{i_2} + U_{i_3} - U_{i_4}$$

$$\Xi_{i3} = 6R_i + 2U_{i_2}^{\mathrm{T}} + 2U_{i_4}^{\mathrm{T}}, \quad \Xi_{i4} = 6R_i - 2U_{i_3} + 2U_{i_4}$$

$$\Upsilon_1 = P_2 B_2 K_1, \quad \Upsilon_2 = P_2 B_2 K_2, \quad \sigma = \sqrt{\bar{\alpha}\bar{\alpha}_1}, \quad \delta = \sqrt{\bar{\beta}\bar{\beta}_1}$$

$$\Phi_2 = \begin{bmatrix} \Phi_{21} & \Phi_{22} & \Phi_{23} \\ \Phi_{24} & \Phi_{25} & \Phi_{26} \\ \Phi_{27} & \Phi_{28} & \Phi_{29} \end{bmatrix}, \quad \Phi_3 = \mathrm{diag}\{\Phi_{31}, \Phi_{32}, \Phi_{33}\}$$

$$\Phi_{21} = \begin{bmatrix} \eta_M P_1 A_1 & 0_{1\times 8} \\ d_M P_1 A_1 & 0_{1\times 8} \\ \tau_M P_1 A_1 & 0_{1\times 8} \end{bmatrix}, \quad \Phi_{23} = \begin{bmatrix} 0_{1\times 3} & \eta_M \Upsilon_3 \\ 0_{1\times 3} & d_M \Upsilon_3 \\ 0_{1\times 3} & \tau_M \Upsilon_3 \end{bmatrix}$$

$$\Phi_{22} = \begin{bmatrix} 0_{1\times 4} & \eta_M P_1 B_1 C_2 & 0_{1\times 4} \\ 0_{1\times 4} & d_M P_1 B_1 C_2 & 0_{1\times 4} \\ 0_{1\times 4} & \tau_M P_1 B_1 C_2 & 0_{1\times 4} \end{bmatrix}$$

$$\Phi_{24} = \begin{bmatrix} 0 & \bar{\beta}_1 \bar{\alpha} \theta_M \Upsilon_1 & 0_{1\times 3} & \bar{\beta}_1 \bar{\alpha}_1 \theta_M \Upsilon_1 & 0_{1\times 3} \\ 0 & \sigma \bar{\beta}_1 \theta_M \Upsilon_1 & 0_{1\times 3} & -\sigma \bar{\beta}_1 \theta_M \Upsilon_1 & 0_{1\times 3} \\ 0 & -\delta \bar{\alpha} \theta_M \Upsilon_1 & 0_{1\times 3} & -\delta \bar{\alpha}_1 \theta_M \Upsilon_1 & 0_{1\times 3} \\ 0 & -\sigma \delta \theta_M \Upsilon_1 & 0_{1\times 3} & \sigma \delta \theta_M \Upsilon_1 & 0_{1\times 3} \end{bmatrix}$$

$$\Phi_{25} = \begin{bmatrix} 0_{1\times 4} & \theta_M P_2 A_2 + \theta_M \Upsilon_2 & \theta_M P_2 A_3 & 0_{1\times 3} \\ 0_{1\times 4} & 0 & 0 & 0_{1\times 3} \\ 0_{1\times 4} & 0 & 0 & 0_{1\times 3} \\ 0_{1\times 4} & 0 & 0 & 0_{1\times 3} \end{bmatrix}$$

$$\Phi_{26} = \begin{bmatrix} \bar{\beta}_1 \bar{\alpha}_1 \theta_M \Upsilon_1 & \bar{\beta} \theta_M \Upsilon_1 & -\theta_M P_2 B_2 & \theta_M P_2 B_3 \\ -\sigma \bar{\beta}_1 \theta_M \Upsilon_1 & 0 & 0 & 0 \\ -\delta \bar{\alpha}_1 \theta_M \Upsilon_1 & \delta \theta_M \Upsilon_1 & 0 & 0 \\ \sigma \delta \theta_M \Upsilon_1 & 0 & 0 & 0 \end{bmatrix}$$

$$\Phi_{27} = \begin{bmatrix} 0 & 0 & 0_{1\times 3} & 0 & 0_{1\times 3} \\ 0 & \sqrt{\varepsilon}\bar{\beta}_1 \bar{\alpha} K_1 & 0_{1\times 3} & \sqrt{\varepsilon}\bar{\beta}_1 \bar{\alpha}_1 K_1 & 0_{1\times 3} \\ 0 & \sqrt{\varepsilon}\bar{\beta}_1 \sigma K_1 & 0_{1\times 3} & -\sqrt{\varepsilon}\bar{\beta}_1 \sigma K_1 & 0_{1\times 3} \\ 0 & -\sqrt{\varepsilon}\bar{\alpha}\delta K_1 & 0_{1\times 3} & -\sqrt{\varepsilon}\bar{\alpha}_1 \delta K_1 & 0_{1\times 3} \\ 0 & -\sqrt{\varepsilon}\sigma\delta K_1 & 0_{1\times 3} & \sqrt{\varepsilon}\sigma\delta K_1 & 0_{1\times 3} \\ C_1 & 0 & 0_{1\times 3} & 0 & 0_{1\times 3} \end{bmatrix}$$

$$\Phi_{28} = \begin{bmatrix} \sqrt{\bar{\beta}} F & 0_{1\times 3} & 0 & 0_{1\times 4} \\ 0 & 0_{1\times 3} & \sqrt{\varepsilon} K_2 & 0_{1\times 4} \\ 0 & 0_{1\times 3} & 0 & 0_{1\times 4} \\ 0 & 0_{1\times 3} & 0 & 0_{1\times 4} \\ 0 & 0_{1\times 3} & 0 & 0_{1\times 4} \\ 0 & 0_{1\times 3} & 0 & 0_{1\times 4} \end{bmatrix}$$

$$\Phi_{29} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ \sqrt{\varepsilon}\bar{\beta}_1 \bar{\alpha}_1 K_1 & \sqrt{\varepsilon}\bar{\beta} K_1 & 0 & 0 \\ -\sqrt{\varepsilon}\bar{\beta}_1 \sigma K_1 & 0 & 0 & 0 \\ -\sqrt{\varepsilon}\bar{\alpha}_1 \delta K_1 & \sqrt{\varepsilon}\delta K_1 & 0 & 0 \\ \sqrt{\varepsilon}\sigma\delta K_1 & 0 & 0 & 0 \\ 0 & 0 & 0 & D_1 \end{bmatrix}$$

$$\Phi_{31} = \mathrm{diag}\{-P_1 R_1^{-1} P_1, -P_1 R_2^{-1} P_1, -P_1 R_3^{-1} P_1\}$$

$$\Phi_{32} = \mathrm{diag}\{-P_2 R_4^{-1} P_2, -P_2 R_4^{-1} P_2, -P_2 R_4^{-1} P_2 - P_2 R_4^{-1} P_2\}$$

$$\Phi_{33} = \mathrm{diag}\{-I, -I, -I, -I, -I, -I\}.$$

Proof: See Appendix A. ∎

Theorem 1 presents the sufficient conditions, which guarantee the asymptotical stability of the system (14) in the mean-square sense. Based on the results in Theorem 1, the following theorem is devoted to designing the controllers in the form of (2).

Theorem 2: For given positive scalars $\bar{\alpha}$, $\bar{\beta}$, η_M, d_M, τ_M, θ_M, λ, ε, γ, ϵ_1, ϵ_2, ϵ_3, ϵ_4, and ϵ_f and matrix F, the system (14) is mean-square asymptotically stable if there exist positive matrices $X_1 > 0$, $X_2 > 0$, $\tilde{Q}_1 > 0$, $\tilde{Q}_2 > 0$, $\tilde{Q}_3 > 0$, $\hat{Q}_4 > 0$, $\tilde{R}_1 > 0$, $\tilde{R}_2 > 0$, $\tilde{R}_3 > 0$, $\hat{R}_4 > 0$, $\tilde{\Omega} > 0$, $\tilde{M}_i$, $\tilde{N}_i$, $\tilde{S}_i$, $\hat{W}_i$ (i = 1, 2, 3, 4), and Y_1, Y_2 with appropriate dimensions such that the following LMIs hold

$$\tilde{\Phi} = \begin{bmatrix} \tilde{\Phi}_1 & * \\ \tilde{\Phi}_2 & \tilde{\Phi}_3 \end{bmatrix} < 0 \tag{20}$$

$$\tilde{\Theta}_i = \begin{bmatrix} \tilde{R}_i & * & * & * \\ 0 & 3\tilde{R}_i & * & * \\ \tilde{U}_{i_1} & \tilde{U}_{i_2} & \tilde{R}_i & * \\ \tilde{U}_{i_3} & \tilde{U}_{i_4} & 0 & 3\tilde{R}_i \end{bmatrix} \geq 0,\ i = 1, 2, 3 \tag{21}$$

$$\hat{\Theta}_4 = \begin{bmatrix} \hat{R}_4 & * & * & * \\ 0 & 3\hat{R}_4 & * & * \\ \hat{W}_1 & \hat{W}_2 & \hat{R}_4 & * \\ \hat{W}_3 & \hat{W}_4 & 0 & 3\hat{R}_4 \end{bmatrix} \geq 0 \tag{22}$$

where $\tilde{\Phi}$, $\tilde{\Theta}_i$ $(i = 1, 2, 3)$, and $\hat{\Theta}_4$ are, respectively, derived from Φ, Θ_i $(i = 1, 2, 3)$, and Θ_4 by substitute U_i $(i = 1, 2, 3)$, W, Ω, R_i $(i = 1, 2, 3)$, R_4, P_1A_1, P_1B_1, P_2A_2, P_2B_2, P_2A_3, P_2B_3, C_1, F, K_1, K_2, $\bar{\beta}I$, $-P_1R_i^{-1}P_1$ $(i = 1, 2, 3)$, and $-P_2R_4^{-1}P_2$ with $\tilde{U}_i$ $(i = 1, 2, 3)$, $\hat{W}$, $\tilde{\Omega}$, $\tilde{R}_i$ $(i = 1, 2, 3)$, $\hat{R}_4$, A_1X_1, B_1, A_2X_2, B_2, A_3X_2, B_3, C_1X_1, FX_1, Y_1, Y_2, $-2\bar{\beta}\epsilon_f X_1 + \bar{\beta}\epsilon_f^2 I$, $-2\epsilon_i X_1 + \epsilon_i^2 \tilde{R}_i$ $(i = 1, 2, 3)$, and $-2\epsilon_4 X_2 + \epsilon_4^2 \hat{R}_4$ accordingly. Other symbols have been defined in Theorem 1.

Moreover, the desired state feedback gain of primary controller is given by

$$K_1 = Y_1 X_1^{-1} \tag{23}$$

and the desired state feedback gain of secondary controller is given by

$$K_2 = Y_2 X_2^{-1}. \tag{24}$$

Proof: See Appendix B. ■

IV. Simulation Examples

In this section, a simulation example is given to illustrate the usefulness of the proposed approach in this paper. The example is based on a power plant gas-turbine system, the schematic diagram of which is shown in Fig. 2, where the turbine is driven by superheated gas. It should be pointed that the proper temperature of superheated gas plays an especially important role in ensuring the turbine work successfully. In the gas generation process, the three-way plug valve receives air from blower and then send it to two sides. On the one hand, the air functions as a combustion improver in the burning of fuel oil to generate superheated gas. On the other hand, the air takes for cooling the superheated gas.

In order to generate superheated gas with proper temperature, the networked cascade control is adopted, where the outlet gas temperature and the cooling air temperature are measured by primary sensor Sensor$_1$ and secondary sensor Sensor$_2$, respectively. The communication between Sensor$_1$ and primary controller Controller$_1$ relies on a network, and the output of Controller$_1$ is the input of the secondary controller Controller$_2$, which controls the three-way-plus-valve to modulate the two-side air output and thus the proper gas temperature can be guaranteed.

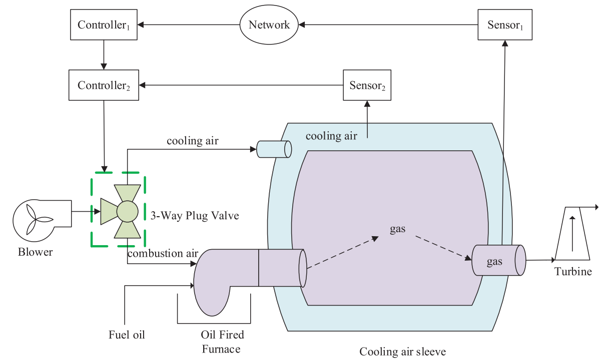

Fig. 2. Schematic of NCCS for gas-turbine system.

Consider the power plant gas-turbine system [7] with state-space representation of the primary plant (1) as

$$\begin{cases} \dot{x}_1(t) = \begin{bmatrix} -1 & 0 \\ -1 & -2 \end{bmatrix} x_1(t) + \begin{bmatrix} 2 \\ 0.1 \end{bmatrix} y_2(t) \\ y_1(t) = \begin{bmatrix} 0 & 0.1 \end{bmatrix} x_1(t) + 0.2\omega(t) \end{cases}$$

and the state-space representation of the secondary plant (9) as

$$\begin{cases} \dot{x}_2(t) = \begin{bmatrix} 1.3 & 1 \\ 0.2 & 0 \end{bmatrix} x_2(t) + \begin{bmatrix} 0.2 & 0.1 \\ 0.2 & 1 \end{bmatrix} x_2(t - \theta(t)) \\ \qquad + \begin{bmatrix} 0.2 \\ 1 \end{bmatrix} \mathrm{sat}(u_2(t)) + \begin{bmatrix} -0.4 \\ 0.1 \end{bmatrix} \omega(t) \\ y_2(t) = \begin{bmatrix} -0.3 & 0.1 \end{bmatrix} x_2(t) + 0.1\omega(t). \end{cases}$$

The initial states of the two plants are given as $x_{10} = \begin{bmatrix} -3 & 0 \end{bmatrix}^{\mathrm{T}}$ and $x_{20} = \begin{bmatrix} -1 & 1 \end{bmatrix}^{\mathrm{T}}$.

The external disturbance is assumed as

$$\omega(t) = \begin{cases} 0.1 \sin(2\pi t), & 0 \leq t \leq 10 \\ 0, & \text{otherwise.} \end{cases}$$

The nonlinear signal of cyber attacks is chosen as

$$f(x_1(t)) = \begin{bmatrix} -\tanh(0.02x_{11}(t)) \\ -\tanh(0.1x_{12}(t)) \end{bmatrix}.$$

It can be seen from Assumption 1 that when the nonlinearity bound is specified as $F = \mathrm{diag}\{0.02, 0.1\}$, the condition (15) can be guaranteed.

In the following, by taking the actuator saturations and stochastic cyber attacks into consideration, three possible cases concerning the different schemes of data transmission, which is indicated by the random variable $\alpha(t)$, will be presented to illustrate the usefulness of designed $\mathcal{H}_\infty$ state feedback controllers.

Case 1: Given $\bar{\alpha} = 0.25$, the data from primary sensor to primary controller is transmitted via hybrid triggered scheme. Choose sampling period $h = 0.1$ s, and assume scalars as $\bar{\beta} = 0.02$, $\eta_M = 0.5$, $d_M = 0.5$, $\tau_M = 0.2$, $\theta_M = 0.2$, $\lambda = 0.16$, $\varepsilon = 0.2$, $\gamma = 2$, and $\epsilon_1 = \epsilon_2 = \epsilon_3 = \epsilon_4 = \epsilon_f = 1$.

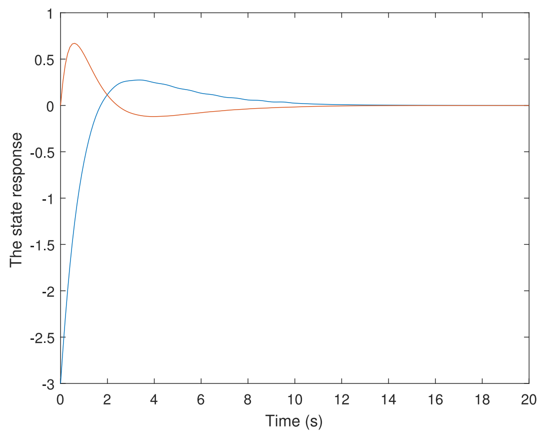

Fig. 3. State responses of primary plant in case 1.

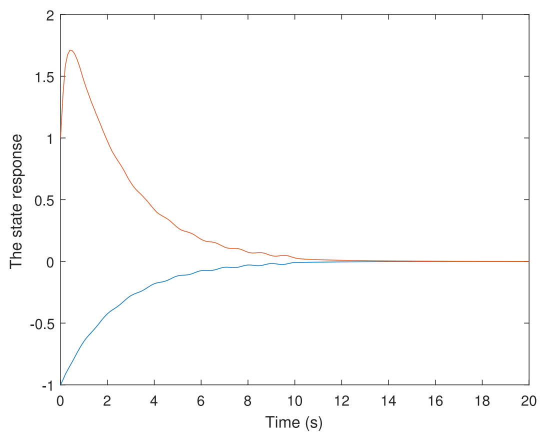

Fig. 4. State responses of secondary plant in case 1.

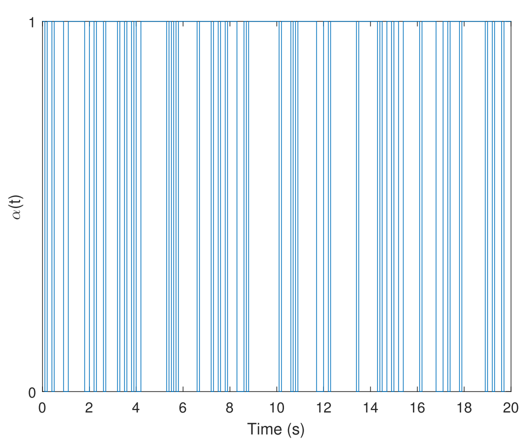

Fig. 5. $\alpha(t)$ with $\bar{\alpha} = 0.25$ in case 1.

By applying Theorem 2, the gains of state feedback controllers are achieved as $K_1 = \begin{bmatrix} -0.0066 & 0.0002 \end{bmatrix}$ and $K_2 = \begin{bmatrix} -11.1586 & -6.1972 \end{bmatrix}$ and event-triggered matrix is $\Omega = \begin{bmatrix} 0.1181 & 0.0539 \\ 0.0539 & 0.1587 \end{bmatrix}$. The state responses of primary plant and secondary plant with actuator saturations and stochastic cyber attacks are shown in Figs. 3 and 4, respectively. The Bernoulli distribution random variable $\alpha(t)$ is depicted in Fig. 5, which is introduced to indicate the switch rule in hybrid triggered scheme. In addition, $\beta(t)$ governing the occurrence of cyber attacks is shown in Fig. 6 with given expectation.

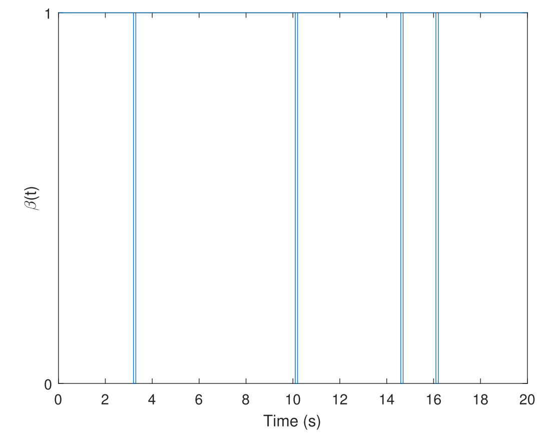

Fig. 6. $\beta(t)$ with $\bar{\beta} = 0.02$ in case 1.

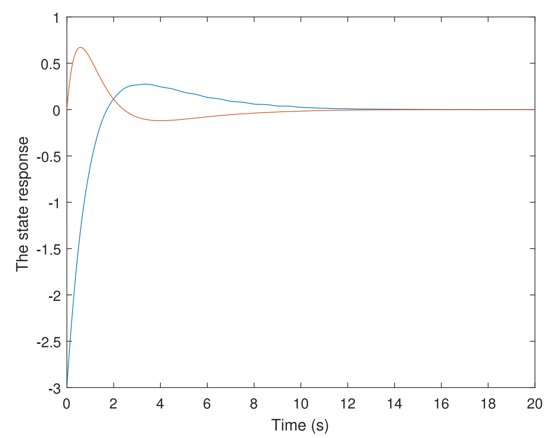

Fig. 7. State responses of primary plant in case 2.

Case 2: When $\bar{\alpha} = 1$, the data transmission from primary sensor to primary controller is implemented by time-triggered scheme. Choose sampling period $h = 0.01$ s, and for given $\bar{\beta} = 0.02$, $\eta_M = 0.5$, $d_M = 0.5$, $\tau_M = 0.2$, $\theta_M = 0.2$, $\lambda = 0$, $\varepsilon = 0.2$, $\gamma = 2$, and $\epsilon_1 = \epsilon_2 = \epsilon_3 = \epsilon_4 = \epsilon_f = 1$. According to Theorem 2, the controller feedback gains are calculated as $K_1 = \begin{bmatrix} -0.0125 & -0.0009 \end{bmatrix}$ and $K_2 = \begin{bmatrix} -11.1506 & -6.2001 \end{bmatrix}$. Figs. 7 and 8 show the state responses of primary plant and secondary plant, respectively. The saturation control signal $\text{sat}(u_2(t))$ is depicted in Fig. 9 with red solid line while the original control signal is with blue dashed.

Case 3: If $\bar{\alpha} = 0$, the data transmission from primary sensor to primary controller is under event-triggered scheme. Choose sampling period $h = 0.1$s, and set $\bar{\beta} = 0.02$, $\eta_M = 0.5$, $d_M = 0.5$, $\tau_M = 0.2$, $\theta_M = 0.2$, $\lambda = 0.16$, $\varepsilon = 0.2$, $\gamma = 2$, and $\epsilon_1 = \epsilon_2 = \epsilon_3 = \epsilon_4 = \epsilon_f = 1$. By using Theorem 2, the gains of state feedback controllers are obtained as $K_1 = \begin{bmatrix} -0.0101 & -0.0009 \end{bmatrix}$ and $K_2 = \begin{bmatrix} -11.1411 & -6.1938 \end{bmatrix}$ and event-triggered matrix is $\Omega = \begin{bmatrix} 0.1178 & 0.0538 \\ 0.0538 & 0.1584 \end{bmatrix}$. The state responses of the primary plant and secondary plant with actuator saturations and stochastic cyber attacks are presented in

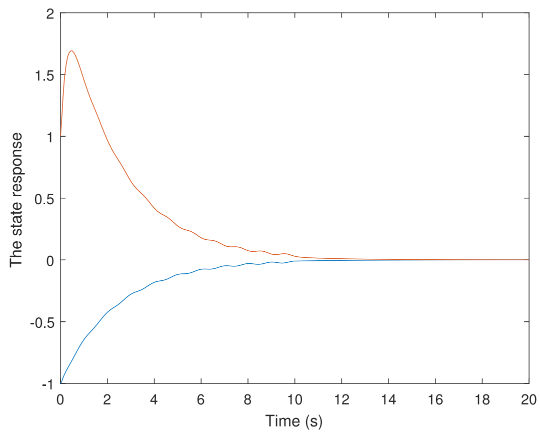

Fig. 8. State responses of secondary plant in case 2.

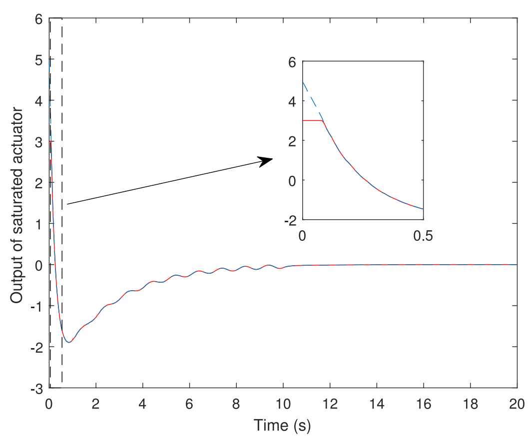

Fig. 9. Output of saturated actuator in case 2.

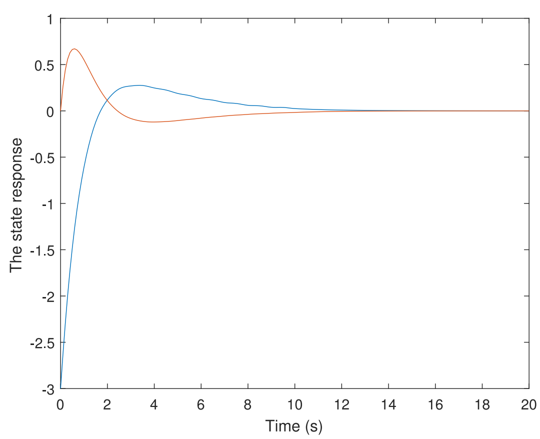

Fig. 10. State responses of primary plant in case 3.

Figs. 10 and 11, respectively. The communication instants and communication intervals are given in Fig. 12.

According to Theorem 2, the gain matrices of $\mathcal{H}_\infty$ primary and secondary controllers as well as the event-triggered matrix can be calculated. Figs. 3, 4, 7, 8, 10, and 11 show the state responses under different situations, which illustrate that the system can be stabilized by the design approach proposed in this paper. From the figures of state responses above, it can be easily seen that the system performance is degraded by

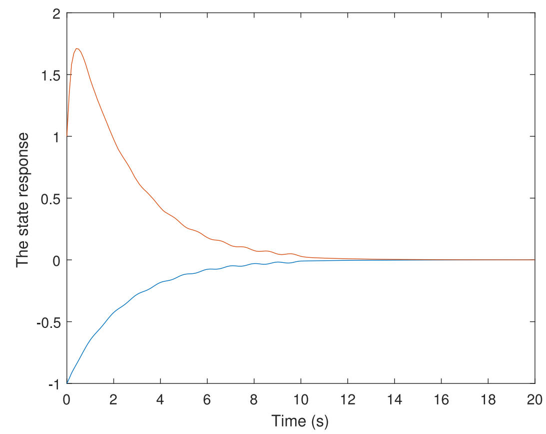

Fig. 11. State responses of secondary plant in case 3.

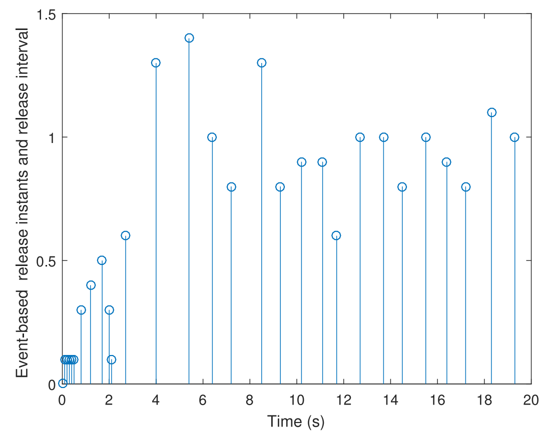

Fig. 12. Release instants and release interval in case 3.

actuator saturations and stochastic cyber attacks. Fig. 12 shows that the transmission frequency is degraded obviously by using event-triggered scheme. Consequently, the burden of network bandwidth can be reduced significantly.

V. Conclusion

This paper addresses the issue about $\mathcal{H}_\infty$ control for hybrid-driven-based NCCSs with actuator saturations and stochastic cyber attacks. A hybrid triggered scheme is introduced to reduce the burden of network bandwidth, where a Bernoulli distribution random variable is utilized to describe the switching rule between the time-triggered scheme and the event-triggered scheme. By taking hybrid triggered scheme, stochastic cyber attacks and actuator saturations into account, a new model for NCCSs is established. Sufficient conditions for the stability of the NCCS are derived by employing Lyapunov stability theory. Moreover, the state feedback gains of both primary controller and secondary controller are obtained in terms of LMI techniques. The simulation example confirms the usefulness of the designed state feedback controllers when considering hybrid triggered scheme, actuator saturations, and stochastic cyber attacks. In our future research, the functional observers will be designed to detect and isolate those attacks in order to make the controller further robust against the cyber attacks.

APPENDIX A
PROOF OF THEOREM 1

Choose a Lyapunov–Krasovskii functional candidate for system (14)

$$V(t) = V_1(t) + V_2(t) + V_3(t) \tag{25}$$

where

$$\begin{aligned}
V_1(t) &= x_1^{\mathrm{T}}(t)P_1x_1(t) + x_2^{\mathrm{T}}(t)P_2x_2(t)\\
V_2(t) &= \sum_{i=1}^{3}\int_{t-r_i}^{t} x_1^{\mathrm{T}}(s)Q_ix_1(s)ds\\
&\quad + \int_{t-\theta_M}^{t} x_2^{\mathrm{T}}(s)Q_4x_2(s)ds\\
V_3(t) &= \sum_{i=1}^{3} r_i\int_{t-r_i}^{t}\int_{s}^{t} \dot{x}_1^{\mathrm{T}}(v)R_i\dot{x}_1(v)dvds\\
&\quad + \theta_M\int_{t-\theta_M}^{t}\int_{s}^{t} \dot{x}_2^{\mathrm{T}}(v)R_4\dot{x}_2(v)dvds
\end{aligned}$$

and $r_1 = \eta_M$, $r_2 = d_M$, $r_3 = \eta_M$, $Q_j > 0$, and $R_j > 0$ $(j = 1, 2, 3, 4)$.

By taking derivation and expectation on $V_i(t)$ $(i = 1, 2, 3)$, it can be obtained that

$$\mathbb{E}\{\dot{V}_1(t)\} = 2x_1^{\mathrm{T}}(t)P_1\dot{x}_1(t) + 2\mathbb{E}\{x_2^{\mathrm{T}}(t)P_2\dot{x}_2(t)\} \tag{26}$$

$$\begin{aligned}
\mathbb{E}\{\dot{V}_2(t)\} &= \sum_{i=1}^{3}x_1^{\mathrm{T}}(t)Q_ix_1(t) + x_2^{\mathrm{T}}(t)Q_4x_2(t)\\
&\quad - \sum_{i=1}^{3}x_1^{\mathrm{T}}(t-r_i)Q_ix_1(t-r_i)\\
&\quad - x_2^{\mathrm{T}}(t-\theta_M)Q_4x_2(t-\theta_M)
\end{aligned} \tag{27}$$

$$\begin{aligned}
\mathbb{E}\{\dot{V}_3(t)\} &= \dot{x}_1^{\mathrm{T}}(t)\left(\eta_M^2R_1 + d_M^2R_2 + \tau_M^2R_3\right)\dot{x}_1(t)\\
&\quad + \mathbb{E}\left\{\dot{x}_2^{\mathrm{T}}(t)\theta_M^2R_4\dot{x}_2(t)\right\}\\
&\quad - \theta_M\int_{t-\theta_M}^{t}\dot{x}_2^{\mathrm{T}}(v)R_4\dot{x}_2(v)dv\\
&\quad - \sum_{i=1}^{3}r_i\int_{t-r_i}^{t}\dot{x}_1^{\mathrm{T}}(v)R_i\dot{x}_1(v)dv.
\end{aligned} \tag{28}$$

Notice that

$$2\mathbb{E}\{x_2^{\mathrm{T}}(t)P_2\dot{x}_2(t)\} = 2x_2^{\mathrm{T}}(t)P_2[\mathbb{A}_0 + \mathbb{A}_1]$$

where

$$\begin{aligned}
\mathbb{A}_0 &= (A_2 + B_2K_2)x_2(t) + A_3x_2(t-\theta(t))\\
&\quad - B_2\phi(u_2(t)) + B_3\omega(t)\\
\mathbb{A}_1 &= \left(1-\bar{\beta}\right)\bar{\alpha}B_2K_1x_1(t-\eta(t))\\
&\quad + \left(1-\bar{\beta}\right)(1-\bar{\alpha})B_2K_1x_1(t-d(t))\\
&\quad + \left(1-\bar{\beta}\right)(1-\bar{\alpha})B_2K_1e_k(t)\\
&\quad + \bar{\beta}B_2K_1f(x_1(t-\tau(t)))
\end{aligned}$$

since the random variables $\alpha(t)$ and $\beta(t)$ are assumed to be uncorrelated to each other and $\mathbb{E}\{\alpha(t)\} = \bar{\alpha}$, $\mathbb{E}\{\beta(t)\} = \bar{\beta}$.

Notice that

$$\begin{aligned}
\dot{x}_2(t) &= \mathcal{A}_0 + (\alpha(t)-\bar{\alpha})\mathcal{A}_1 + \left(\beta(t)-\bar{\beta}\right)\mathcal{A}_2\\
&\quad + (\alpha(t)-\bar{\alpha})\left(\beta(t)-\bar{\beta}\right)\mathcal{A}_3
\end{aligned}$$

where

$$\begin{aligned}
\mathcal{A}_0 &= \mathbb{A}_0 + \bar{\beta}B_2K_1f(x_1(t-\tau(t))) + \left(1-\bar{\beta}\right)\mathbb{A}_2\\
\mathcal{A}_1 &= \left(1-\bar{\beta}\right)\mathbb{A}_3,\ \ \mathcal{A}_3 = -\mathbb{A}_3\\
\mathcal{A}_2 &= B_2K_1f(x_1(t-\tau(t))) - \mathbb{A}_2\\
\mathbb{A}_2 &= \bar{\alpha}B_2K_1x_1(t-\eta(t)) + (1-\bar{\alpha})B_2K_1x_1(t-d(t))\\
&\quad + (1-\bar{\alpha})B_2K_1e_k(t)\\
\mathbb{A}_3 &= B_2K_1x_1(t-\eta(t)) - B_2K_1x_1(t-d(t))\\
&\quad - B_2K_1e_k(t).
\end{aligned}$$

Furthermore

$$\begin{aligned}
&\mathbb{E}\{\alpha(t)-\bar{\alpha}\} = 0, \mathbb{E}\left\{(\alpha(t)-\bar{\alpha})^2\right\} = \sigma^2\\
&\mathbb{E}\{\beta(t)-\bar{\beta}\} = 0, \mathbb{E}\left\{\left(\beta(t)-\bar{\beta}\right)^2\right\} = \delta^2.
\end{aligned}$$

Therefore

$$\begin{aligned}
\mathbb{E}\left\{\dot{x}_2^{\mathrm{T}}(t)\theta_M^2R_4\dot{x}_2(t)\right\} &= \mathcal{A}_0^{\mathrm{T}}\theta_M^2R_4\mathcal{A}_0 + \sigma^2\mathcal{A}_1^{\mathrm{T}}\theta_M^2R_4\mathcal{A}_1\\
&\quad + \delta^2\mathcal{A}_2^{\mathrm{T}}\theta_M^2R_4\mathcal{A}_2 + \sigma^2\delta^2\mathcal{A}_3^{\mathrm{T}}\theta_M^2R_4\mathcal{A}_3.
\end{aligned} \tag{29}$$

Define

$$\begin{aligned}
\varrho_1 &= \begin{bmatrix} x_1^{\mathrm{T}}(t-\eta(t)) & x_1^{\mathrm{T}}(t-\eta_M) & \varrho_{11}\end{bmatrix}^{\mathrm{T}}\\
\varrho_2 &= \begin{bmatrix} x_1^{\mathrm{T}}(t-d(t)) & x_1^{\mathrm{T}}(t-d_M) & \varrho_{22}\end{bmatrix}^{\mathrm{T}}\\
\varrho_3 &= \begin{bmatrix} x_1^{\mathrm{T}}(t-\tau(t)) & x_1^{\mathrm{T}}(t-\tau_M) & \varrho_{33}\end{bmatrix}^{\mathrm{T}}\\
\varrho_4 &= \begin{bmatrix} x_2^{\mathrm{T}}(t-\theta(t)) & x_2^{\mathrm{T}}(t-\theta_M) & \varrho_{44}\end{bmatrix}^{\mathrm{T}}
\end{aligned}$$

where

$$\begin{aligned}
\varrho_{11} &= \begin{bmatrix} \frac{1}{\eta(t)}\int_{t-\eta(t)}^{t}x_1^{\mathrm{T}}(s)ds & \frac{1}{\eta_M-\eta(t)}\int_{t-\eta_M}^{t-\eta(t)}x_1^{\mathrm{T}}(s)ds\end{bmatrix}\\
\varrho_{22} &= \begin{bmatrix} \frac{1}{d(t)}\int_{t-d(t)}^{t}x_1^{\mathrm{T}}(s)ds & \frac{1}{d_M-d(t)}\int_{t-d_M}^{t-d(t)}x_1^{\mathrm{T}}(s)ds\end{bmatrix}\\
\varrho_{33} &= \begin{bmatrix} \frac{1}{\tau(t)}\int_{t-\tau(t)}^{t}x_1^{\mathrm{T}}(s)ds & \frac{1}{\tau_M-\tau(t)}\int_{t-\tau_M}^{t-\tau(t)}x_1^{\mathrm{T}}(s)ds\end{bmatrix}\\
\varrho_{44} &= \begin{bmatrix} \frac{1}{\theta(t)}\int_{t-\theta(t)}^{t}x_2^{\mathrm{T}}(s)ds & \frac{1}{\theta_M-\theta(t)}\int_{t-\theta_M}^{t-\theta(t)}x_2^{\mathrm{T}}(s)ds\end{bmatrix}.
\end{aligned}$$

By employing Lemma 1, it can be derived easily that

$$\begin{aligned}
&-\theta_M\int_{t-\theta(t)}^{t}\dot{x}_2^{\mathrm{T}}(s)R_4\dot{x}_2(s)ds\\
&\quad \le -\frac{\theta_M}{\theta(t)}\begin{bmatrix}\Pi_{41}\\ \Pi_{42}\end{bmatrix}^{\mathrm{T}}\begin{bmatrix}R_4 & *\\ 0 & 3R_4\end{bmatrix}\begin{bmatrix}\Pi_{41}\\ \Pi_{42}\end{bmatrix}
\end{aligned} \tag{30}$$

$$\begin{aligned}
&-\theta_M\int_{t-\theta_M}^{t-\theta(t)}\dot{x}_2^{\mathrm{T}}(s)R_4\dot{x}_2(s)ds\\
&\quad \le -\frac{\theta_M}{\theta_M-\theta(t)}\begin{bmatrix}\Pi_{43}\\ \Pi_{44}\end{bmatrix}^{\mathrm{T}}\begin{bmatrix}R_4 & *\\ 0 & 3R_4\end{bmatrix}\begin{bmatrix}\Pi_{43}\\ \Pi_{44}\end{bmatrix}
\end{aligned} \tag{31}$$

where $\Pi_{41} = x_2(t) - e_1\varrho_4$, $\Pi_{42} = x_2(t) + e_1\varrho_4 - 2e_3\varrho_4$, $\Pi_{43} = e_1\varrho_4 - e_2\varrho_4$, $\Pi_{44} = e_1\varrho_4 + e_2\varrho_4 - 2e_4\varrho_4$, and e_i $(i = 1, 2, 3, 4)$ are compatible row-block matrices with ith block of an identify matrix.

Then, the following bounding inequality can be obtained by applying Lemma 2 to (30) and (31):

$$-\theta_M \int_{t-\theta_M}^{t} \dot{x}_2^{\mathrm{T}}(s) R_4 \dot{x}_2(s) ds \leq -\begin{bmatrix} \Pi_{41} \\ \Pi_{42} \\ \Pi_{43} \\ \Pi_{44} \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} R_4 & * & * & * \\ 0 & 3R_4 & * & * \\ W_1 & W_2 & R_4 & * \\ W_3 & W_4 & 0 & 3R_4 \end{bmatrix} \begin{bmatrix} \Pi_{41} \\ \Pi_{42} \\ \Pi_{43} \\ \Pi_{44} \end{bmatrix}. \quad (32)$$

Similarly, using Lemmas 1 and 2, we can get the estimation of the other integral terms in (28) as follows:

$$-\sum_{i=1}^{3} r_i \int_{t-r_i}^{t} \dot{x}_1^{\mathrm{T}}(s) R_i \dot{x}_1(s) ds \leq -\sum_{i=1}^{3} \begin{bmatrix} \Pi_{i1} \\ \Pi_{i2} \\ \Pi_{i3} \\ \Pi_{i4} \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} R_i & * & * & * \\ 0 & 3R_i & * & * \\ U_{i_1} & U_{i_2} & R_i & * \\ U_{i_3} & U_{i_4} & 0 & 3R_i \end{bmatrix} \begin{bmatrix} \Pi_{i1} \\ \Pi_{i2} \\ \Pi_{i3} \\ \Pi_{i4} \end{bmatrix} \quad (33)$$

where $U_1 = M, U_2 = N, U_3 = S, \Pi_{i1} = x_1(t) - e_1\varrho_i, \Pi_{i2} = x_1(t) + e_1\varrho_i - 2e_3\varrho_i, \Pi_{i3} = e_1\varrho_i - e_2\varrho_i$, and $\Pi_{i4} = e_1\varrho_i + e_2\varrho_i - 2e_4\varrho_i$ $(i = 1, 2, 3)$.

By recalling the restricted condition (4), the triggering condition, which should be violated when transmitting the sampled data under event-triggered scheme, is as follows:

$$\lambda x_1^{\mathrm{T}}(t - d(t))\Omega x_1(t - d(t)) - e_k^{\mathrm{T}}(t)\Omega e_k(t) \geq 0. \quad (34)$$

From Assumption 1, the following inequality condition can be obtained:

$$\bar{\beta} x_1^{\mathrm{T}}(t - \tau(t)) F^{\mathrm{T}} F x_1(t - \tau(t)) - \bar{\beta} f^{\mathrm{T}}(x_1(t - \tau(t))) f(x_1(t - \tau(t))) \geq 0. \quad (35)$$

Reconsider the inequality (12) about nonlinear function $\phi(u_2(t))$, namely

$$\varepsilon u_2^{\mathrm{T}}(t) u_2(t) - \phi^{\mathrm{T}}(u_2(t))\phi(u_2(t)) \geq 0. \quad (36)$$

Note that

$$u_2(t) = \mathcal{B}_0 + (\alpha(t) - \bar{\alpha})\mathcal{B}_1 + \big(\beta(t) - \bar{\beta}\big)\mathcal{B}_2 + (\alpha(t) - \bar{\alpha})\big(\beta(t) - \bar{\beta}\big)\mathcal{B}_3$$

where

$$\begin{aligned}
\mathcal{B}_0 &= \big(1 - \bar{\beta}\big)\bar{\alpha} K_1 x_1(t - \eta(t)) \\
&\quad + \big(1 - \bar{\beta}\big)(1 - \bar{\alpha}) K_1 x_1(t - d(t)) \\
&\quad + K_2 x_2(t) + \bar{\beta} K_1 f(x_1(t - \tau(t))) \\
&\quad + \big(1 - \bar{\beta}\big)(1 - \bar{\alpha}) K_1 e_k(t) \\
\mathcal{B}_1 &= \big(1 - \bar{\beta}\big) K_1 x_1(t - \eta(t)) + \big(1 - \bar{\beta}\big) K_1 x_1(t - d(t)) \\
&\quad + \big(1 - \bar{\beta}\big) K_1 e_k(t) \\
\mathcal{B}_2 &= -\bar{\alpha} K_1 x_1(t - \eta(t)) - (1 - \bar{\alpha}) K_1 x_1(t - d(t)) \\
&\quad + K_1 f(x_1(t - \tau(t))) - (1 - \bar{\alpha}) K_1 e_k(t) \\
\mathcal{B}_3 &= -K_1 x_1(t - \eta(t)) + K_1 x_1(t - d(t)) + K_1 e_k(t).
\end{aligned}$$

Therefore, it is easy to get that

$$\mathbb{E}\big\{\varepsilon u_2^{\mathrm{T}}(t) u_2(t)\big\} = \varepsilon \mathcal{B}_0^{\mathrm{T}} \mathcal{B}_0 + \sigma^2 \varepsilon \mathcal{B}_1^{\mathrm{T}} \mathcal{B}_1 + \delta^2 \varepsilon \mathcal{B}_2^{\mathrm{T}} \mathcal{B}_2 + \sigma^2 \delta^2 \varepsilon \mathcal{B}_3^{\mathrm{T}} \mathcal{B}_3. \quad (37)$$

Define $\xi(t) = [x_1^{\mathrm{T}}(t), \varrho_1^{\mathrm{T}}, \varrho_2^{\mathrm{T}}, \varrho_3^{\mathrm{T}}, x_2^{\mathrm{T}}(t), \varrho_4^{\mathrm{T}}, e_k^{\mathrm{T}}(t), f^{\mathrm{T}}(x_1(t - \tau(t))), \phi^{\mathrm{T}}(u_2(t)), \omega^{\mathrm{T}}(t)]^{\mathrm{T}}$. By combining (26)–(37) and utilizing Schur complement lemma [30], it yields

$$\mathbb{E}\big\{\dot{V}(t)\big\} + \mathbb{E}\big\{y_1^{\mathrm{T}}(t) y_1(t)\big\} - \gamma^2 \mathbb{E}\big\{\omega^{\mathrm{T}}(t)\omega(t)\big\} < \xi^{\mathrm{T}}(t)\Phi\xi(t). \quad (38)$$

Since $\Phi < 0$ can be ensured by (18) and (19), it can be concluded from (38) that

$$\mathbb{E}\big\{\dot{V}(t)\big\} + \mathbb{E}\big\{y_1^{\mathrm{T}}(t) y_1(t)\big\} - \gamma^2 \mathbb{E}\big\{\omega^{\mathrm{T}}(t)\omega(t)\big\} < 0. \quad (39)$$

When $\omega(t) = 0$, (39) means $\mathbb{E}\big\{\dot{V}(t)\big\} < 0$. Due to $V(t) > 0, \mathbb{E}\big\{\dot{V}(t)\big\} < 0$, it is easy to yield that $\lim_{t\to\infty} \mathbb{E}\big\{\|\bar{x}(t)\|^2\big\} = 0$ for any initial conditions, where $\bar{x}(t) = \big[x_1^{\mathrm{T}}(t)\ x_2^{\mathrm{T}}(t)\big]^{\mathrm{T}}$. Therefore, system (14) is mean-square asymptotically stable in the case of $\omega(t) = 0$.

When $\omega(t)$ is nonzero, by integrating both sides of (39) from 0 to t, it can be derived that

$$V(t) - V(0) + \mathbb{E}\left\{\int_0^t y_1^{\mathrm{T}}(s) y_1(s) ds\right\} - \gamma^2 \mathbb{E}\left\{\int_0^t \omega^{\mathrm{T}}(s)\omega(s) ds\right\} < 0. \quad (40)$$

Letting $t \to \infty$ and under the zero-initial condition, it can be obtained from (40) that

$$\mathbb{E}\left\{\int_0^\infty y_1^{\mathrm{T}}(s) y_1(s) ds\right\} < \gamma^2 \mathbb{E}\left\{\int_0^\infty \omega^{\mathrm{T}}(s)\omega(s) ds\right\} \quad (41)$$

which means the specified $\mathcal{H}_\infty$ norm constraint is satisfied.

This completes the proof.

Appendix B
Proof of Theorem 2

Due to $(R_k - \epsilon_k^{-1} P_1) R_k^{-1} (R_k - \epsilon_k^{-1} P_1) \geq 0,\ (k = 1, 2, 3)$, it can be obtained that

$$-P_1 R_k^{-1} P_1 \leq -2\epsilon_k P_1 + \epsilon_k^2 R_k,\ (k = 1, 2, 3). \quad (42)$$

Similarly

$$-P_2 R_4^{-1} P_2 \leq -2\epsilon_4 P_2 + \epsilon_4^2 R_4 \quad (43)$$

and then

$$\bar{\Phi} < 0 \quad (44)$$

can guarantee (18) holds, where $\bar{\Phi}$ is obtained by substituting the terms Φ_{31} and Φ_{32} with $\bar{\Phi}_{31} = \mathrm{diag}\{-2\epsilon_1 P_1 + \epsilon_1^2 R_1, -2\epsilon_2 P_1 + \epsilon_2^2 R_2, -2\epsilon_3 P_1 + \epsilon_3^2 R_3\}$ and $\bar{\Phi}_{32} = \mathrm{diag}\{-2\epsilon_4 P_2 + \epsilon_4^2 R_4, -2\epsilon_4 P_2 + \epsilon_4^2 R_4, -2\epsilon_4 P_2 + \epsilon_4^2 R_4, -2\epsilon_4 P_2 + \epsilon_4^2 R_4\}$, respectively.

Define $X_1 = P_1^{-1}$, $X_2 = P_2^{-1}$, $\tilde{Q}_j = X_1 Q_j X_1$, $\tilde{R}_j = X_1 R_j X_1$ $(j = 1, 2, 3)$, $\hat{Q}_4 = X_2 Q_4 X_2$, $\hat{R}_4 = X_2 R_4 X_2$, $\tilde{U}_{1_k} = \tilde{M}_k = X_1 M_k X_1$, $\tilde{U}_{2_k} = \tilde{N}_k = X_1 N_k X_1$, $\tilde{U}_{3_k} = \tilde{S}_k = X_1 S_k X_1$, and $\hat{W}_k = X_2 W_k X_2$ $(k = 1, 2, 3, 4)$ and then $\tilde{\Theta}_i$ $(i = 1, 2, 3)$ and $\hat{\Theta}_4$ are obtained by pre- and post-multiplying both sides of Θ_i $(i = 1, 2, 3)$ and Θ_4 with $\mathrm{diag}\{X_1, X_1, X_1, X_1\}$ and $\mathrm{diag}\{X_2, X_2, X_2, X_2\}$, respectively.

Moreover, define $Y_1 = K_1X_1$, $Y_2 = K_2X_2$. Pre- and post-multiply both sides of (44) with $\text{diag}\{\underbrace{X_1, X_1, \ldots, X_1}_{13}, \underbrace{X_2, X_2, \ldots, X_2}_{5}, X_1, X_1, I, I, X_1, X_1, X_1, X_2, X_2, X_2, X_2, \underbrace{I, I, \ldots, I}_{6}\}$, and then substitute $-2\bar{\beta}\epsilon_f X_1 + \bar{\beta}\epsilon_f^2 I$ into $-\bar{\beta}X_1IX_1$. As a result, the (20) can be derived from (44) to guarantee the system (14) mean-square asymptotically stable, and the desired state feedback gain both of primary controller in (23) and secondary controller in (24) can be obtained at the same time.

This completes the proof.

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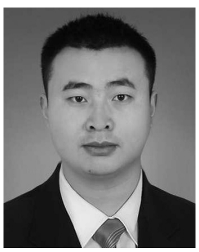

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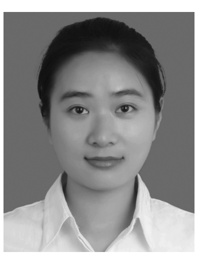

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