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RESEARCH ARTICLE

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Resilient control of networked control systems under deception attacks: A memory-event-triggered communication scheme

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Summary

This paper considers resilient event-triggered control problem for a class of networked systems subject to randomly occurring deception attacks. First, a new memory event-triggered scheme (METS) is proposed to reduce the utilization of communication resources while maintaining desired system performance. Different from some existing event-triggered schemes, some recently released packets are firstly utilized in the proposed METS, which provides a better flexibility to improve the system dynamics. Second, considering the security problem of the networked control systems, a randomly occurring deception attack model is employed where the bounded malicious signals are injected by the adversary. Considering both the effects of METS and deception attack, new type of networked control system model is constructed and the corresponding memory state-feedback controller is designed. Then, sufficient conditions for the asymptotical stability of the systems are derived by using a Lyapunov functional technique. Finally, the obtained results are verified through a pendulum system, which demonstrates the effectiveness of the proposed methods.

KEYWORDS

deception attacks, Lyapunov functional, memory event-triggered control, networked control systems

1 | INTRODUCTION

Control systems over a certain digital networks are referred as networked control systems (NCSs); in an NCS, the components including the sensors, controllers, or actuators are usually distributed and connected to the plant through wired/wireless network. NCSs have been applied in lots of different areas such as environmental monitoring, smart grids, teleoperation control, artificial vehicles, industrial automation, and unmanned marine vehicles.[1-9] In spite of the benefits of NCSs, there are still many tough challenges in NCSs which has to be dealt with. In recent years, great efforts have been paid to NCSs and a rich body of pioneer research studies has emerged to solve the modeling, control, filtering, and estimation problems in NCSs (see other works[10-18] and the references therein). To name a few, Cloosterman et al[10] investigated the stabilization problem of NCSs with time-varying delays. The H_∞ filtering problems of NCSs have been studied in the works of Huang et al[11] and Jiang et al.[12] Using an improved Riccati equation method, the authors considered both the network-induced delays and packets dropout in NCSs simultaneously.[13] It should be noted that a time-triggered scheme is widely used in above mentioned investigations, ie, the sensor samples the output periodically and transmits all the sampled signal to the controller. To guarantee desired system dynamics, the sampling period is chosen in the worst case of the system. As a result, the sampling period is set small at most of the times and a great number of redundant packets are released, which will waste the scarce network resources. In order to overcome this problem, lots of research studies have been developed on how to make better use of the scarce resources while still guaranteeing the system performance.[19-24]

So far, the so-called event-triggered scheme (ETS) has been designed to reduce the packet transmission in the network (see other works[19,21,22,24-27] and the references therein). In ETS strategies, the transmission or not of a packet is determined by a predesigned triggering condition that depends on the state or output of the system. In this way, the number of transmissions is reduced while desired system performance is maintained. For example, in some literature, a typical ETS is given as $t_{k+1} = \min\{t \in \mathbb{R} | (\|x(t_k) - x(t)\|) \geq \sigma(\|x(t)\|)\}$, where $x(t)$ is the current state, $x(t_k)$ is the last released packet, t_k is the most recent released instant, t_{k+1} is the next released instant, and σ is a constant threshold parameter. In the past two decades, different types of triggering conditions have been explored, which can be roughly classified into several categories, such as the absolute ETS,[28] mixed ETS,[29] hybrid ETS,[30] static ETS,[31] dynamic ETS,[32] periodic/discrete ETS,[21,24] adaptive ETS,[33] and distributed ETS.[34,35] It is worth noting that, in order to avoid ZENO phenomenon, Heemels et al[21] and Yeu et al[24] made a trade-off between the time-triggered control and event-triggered control and proposed a periodic/discrete event-triggered control for linear systems. More recently, an adaptive ETS is developed in other works,[33,36-38] wherein the threshold parameter can be adjusted adaptively according to the system dynamics.

It should be pointed out that most of the triggering conditions are designed based on the difference between the *newly sampled signal* $x(t)$ and *the last released packet* $x(t_k)$, that is, $x(t)-x(t_k)$. In those ETSs, when $x(t)-x(t_k)$ is small, the packet $x(t)$ is not likely to be released. However, only the error information is not enough to reflect the full dynamic character of the system. A "smart" ETS should consider more system dynamics so as to make a well trade-off between system performance and communication resource utilization. For example, when the curve of the system dynamic reaches the vertex of the response, the relative error between two sampled signals becomes small therefore the ETS is not likely to release this packet. However, we expect that, at these instants, more sampled signals would be released so as to shorten the transient process. For this purpose, we make one of the first several attempts to design a memory ETS (METS) by using some historic released signals in the triggering condition. Two simple cases are proposed in Section 2.1 to illustrate the effects of the proposed METS.

Along with the pervasive utilization of open yet unprotected communication network, the NCSs are vulnerable to cyber attacks. It is reported in Guo et al[39] that a successful cyber attacks may lead to great serious consequences, including customer information leakage, destruction of infrastructure, and even threat of human lives. As a result, the security problems in NCSs have stimulated increasing attention and numerous outstanding results have been published.[40-45] Among them, deception attacks, as one of the utmost important cyber attacks, can wreck the integrity of the data by modifying its content. More recently, increasing attention has been devoted to the exploration of the deception attacks (see other works[39,46-50]).

Motivated by above observation, the goal of this paper is to design a resilient memory controller for the proposed NCSs subject to randomly occurring deception attacks. A new type of ETS, called METS, is proposed to reduce the number of redundant transmission. In order to implement the METS, two buffers are needed at the event-generator side and the controller side, respectively, which are used to store the historic released signals. Furthermore, considering the security problem of the NCSs, the effect of randomly occurring deception attacks is considered. By using the proposed memory feedback controller, sufficient conditions are obtained to guarantee the asymptotic stability of NCSs. The feedback controller and trigger parameters can be codesigned through solving a set of linear matrix inequalities (LMIs). Finally, a pendulum system example is proposed to validate the feasibility and practicality of the proposed METS and controller design method.

Notation. The notation used here is standard except where otherwise stated. $\mathbb{R}^n$ and $\mathbb{R}^{n\times m}$ denote the n dimensional Euclidean space and $n\times m$ real matrices, respectively. A^T denotes the transpose of the matrix A. $I_{m\times m}$ denotes a matrix with all elements are 1. $X \geq Y$ (respectively, $X > Y$) represent $X - Y$ is positive semidefinite (respectively, positive definite), where X and Y are symmetric matrices. For a vector $x \in \mathbb{R}^n$, we denote by $\|x\| := \sqrt{x^T x}$ its 2-norm. In symmetric block matrices, "$*$" is used to represent an ellipsis for terms that is induced by symmetry.

2 | PROBLEM FORMULATION

Considering the following system:

$$\dot{x}(t) = Ax(t) + Bu(t), \tag{1}$$

where $x(t) \in \mathbb{R}^n$ is the system state vector, $u(t) \in \mathbb{R}^m$ is control input. A and B are parameters with appropriate dimensions, and $u(t)$ is assumed to be 0 before the first packet is received.

2.1 | The memory event-triggered scheme

Before proposing the METS, we first recall the periodic ETS proposed in the work of Yue et al[24]

$$t_{k+1}h = t_k h + \min_{l \in \mathbb{N}} \left\{ lh | e_{k,l}^T W e_{k,l} > \sigma x^T(t_k h) W x(t_k h) \right\}, \tag{2}$$

where $e_{k,l}^T := x(t_k h) - x(t_k h + lh)$ and h is the sampling period, t_k is a integer and $\{t_0, t_1, \dots\} \subset \{0, 1, \dots\}$, which denotes the sequence the sampling instant, $t_k h$ denotes the most recent triggered instant. $t_k h + lh$ represents the sampling time. $l \in \mathbb{N}$ satisfying $l < t_{k+1} - t_k$, $0 < \sigma < 1$ is a predefined threshold parameter, and W is a positive symmetric matrix to be designed.

Remark 1. According to the ETS (2) proposed in the work of Yue et al,[24] it can be found that whether a new sampled packet can be released mainly determines on two factors, the first is the threshold parameter σ, a smaller σ leads to more triggering instants. When σ is fixed, it determines on the error $e_{k,l} = x(t_k h) - x(t_k h + lh)$, a larger $e_{k,l}$ means that the new packet $x(t_k h + lh)$ is more likely to be released. In this paper, an index is defined as $\lambda_{t_k h} := \frac{\|x(t_k h + lh) - x(t_k h)\|}{\|x(t_k h)\|}$, the values of $\lambda_{t_k h}$ demonstrate whether a new sampled signal deserves to be released, obviously, a larger $\lambda_{t_k h}$ means the sampled signal is more likely to be transmitted.

In order to show the limitation of the ETS in (2), a simple case of the system response is given in Figure 1. Assume that the values of the sampled responses are listed in Table 1.

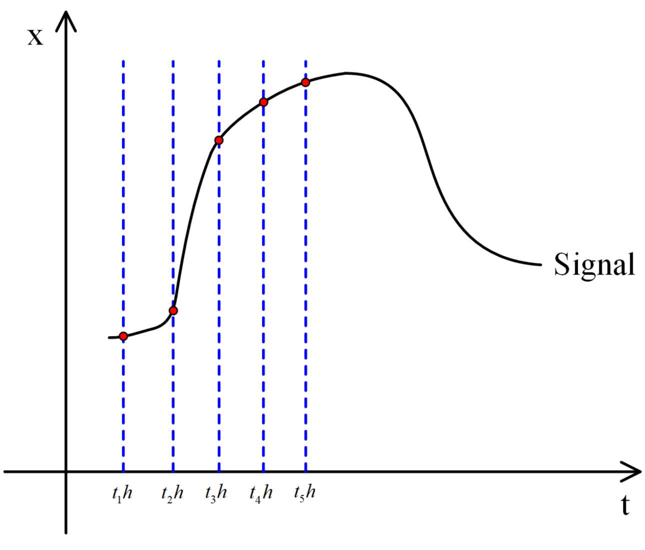

FIGURE 1 A simple case of the system response [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 The values of the system response

	$x(t_1h)$	$x(t_2h)$	$x(t_3h)$	$x(t_4h)$	$x(t_5h)$
values	0.1	0.2	0.6	0.7	0.8
$\lambda_{t_k h}$	–	1.000	2.000	0.167	0.143

From Table 1, it can be found that index $\lambda_{t_k h}$ for packets $x(t_2h)$and $x(t_3h)$ are large but those for the packets $x(t_4h)$ and $x(t_5h)$ are very small. Therefore, as described above, $x(t_4h)$ and $x(t_5h)$ are not likely to be released to the controller. However, the values of $x(t_4h)$ and $x(t_5h)$ are much larger than $x(t_2h)$. Generally speaking, when the response of the system reach the vertex, we usually expect the ETS releasing more packets thus generating more control input, such that the transient process maybe shorten.

From above observation, it can be concluded that some existing ETSs cannot release more packets when the system curve is at the vertex. The reasons may be that only the current and most released packets information is utilized in the ETS. To overcome this problem, a METS is proposed by utilizing the historic released signals, which is described as

$$t_{k+1}h = t_k h + \min_{l\in\mathbb{N}} \left\{ lh | \hat{\varphi}\left(x(t_k h), e_i(t), \sigma\right) > 0 \right\}, \tag{3}$$

where

$$\hat{\varphi}\left(x(t_k h), e_i(t), \sigma\right) := \sum_{i=1}^{m} \mu_i e_i^T(t) W e_i(t) - \sigma \bar{x}^T W \bar{x}$$

with $\bar{x} := \frac{1}{m}\sum_{i=1}^{m} x(t_{k+1-i}h)$, $e_i := x(t_{k-i+1}h) - x(t_k h + lh)$, $\mu_i \in [0,1]$ are the weighting parameters and $\sum_{i=1}^{m} \mu_i = 1$.

Remark 2. In the METS (3), m historic released packets $\{x(t_k h), \ldots, x(t_{k-m+1}h)\}$ are utilized, and if $m = 1$, the METS reduces to the ETS in (2). The weighting parameters μ_i are selected to demonstrate the weights of the released packets. Generally, we regard that the more recent released packets are more important than others. In this paper, we assume that $\mu_i \geq \mu_{i+1} (i = 1, \ldots, m-1)$.

Using the proposed METS (3), for $\mu_1 = 0.6, \mu_2 = 0.2, \mu_3 = 0.2$, the index $\bar{\lambda}_{t_k h} = \frac{\sum_{i=1}^{m} \mu_i |e_i(t)|}{|\bar{x}|}$ for the packets $x(t_4h)$ and $x(t_5h)$ in Figure 1 and Table 1 is, respectively, 0.933 and 0.44. Obviously, they are much larger than those obtained using the ETS (2), that is, the packets $x(t_4h)$ and $x(t_5h)$ are more likely to be released in the METS (3) than by using ETS (2).

In NCSs, the controller will hold the same in the interval $[t_k h + \tau_{t_k}, t_{k+1}h + \tau_{t_{k+1}}) \triangleq \mathcal{I}$, which can be divided into several subintervals as $\mathcal{I} = \bigcup_{l=0}^{l=t_{k+1}-t_k-1} \mathcal{I}_l$, $\mathcal{I}_l = [t_k h + lh + \delta_{t_k}, t_k h + (l+1)h + \delta_{t_k})$ with

$$\delta_{t_k} = \begin{cases} \tau_{t_k}, & l = 0, 1, \ldots, t_{k+1} - t_k - 2, \\ \tau_{t_{k+1}}, & l = t_{k+1} - t_k - 1, \end{cases}$$

where τ_{t_k} and $\tau_{t_{k+1}}$ are transmission delay of the packets $x(t_k h)$ and $x(t_{k+1}h)$, respectively. Define $\tau(t) = t - t_k h - lh$ for $t \in \mathcal{I}_l$, it is clear that $\tau(t)$ is a piecewise function and $0 \leq \tau_{t_k} \leq \tau(t) \leq h + \bar{\tau} \triangleq \tau_M$, where $\bar{\tau}$ is the upper bound of the transmission delay $\{\tau_{t_k}\}$.

Corresponding to the METS, a memory controller is proposed as

$$u(t) = \sum_{i=1}^{m} K_i x(t_{k-i+1}h), t \in \mathcal{I}. \tag{4}$$

Considering the METS (3) and memory controller (4), for $t \in \mathcal{I}_i$, system (1) can be rewritten as

$$\begin{aligned} \dot{x}(t) &= Ax(t) + \sum_{i=1}^{m} BK_i [x(t - \tau(t)) + e_i(t)], \\ x(t) &= \phi(t), t \in [-\tau_M, 0), \end{aligned} \tag{5}$$

where $\phi(t)$ is the initial condition of $x(t)$. The structure of the NCS with METS is illustrated in Figure 2. In the considered system, in order to implement the METS and memory controller, two buffers are needed to store the past released samples and the length of the buffer is m $(1 \leq m)$.

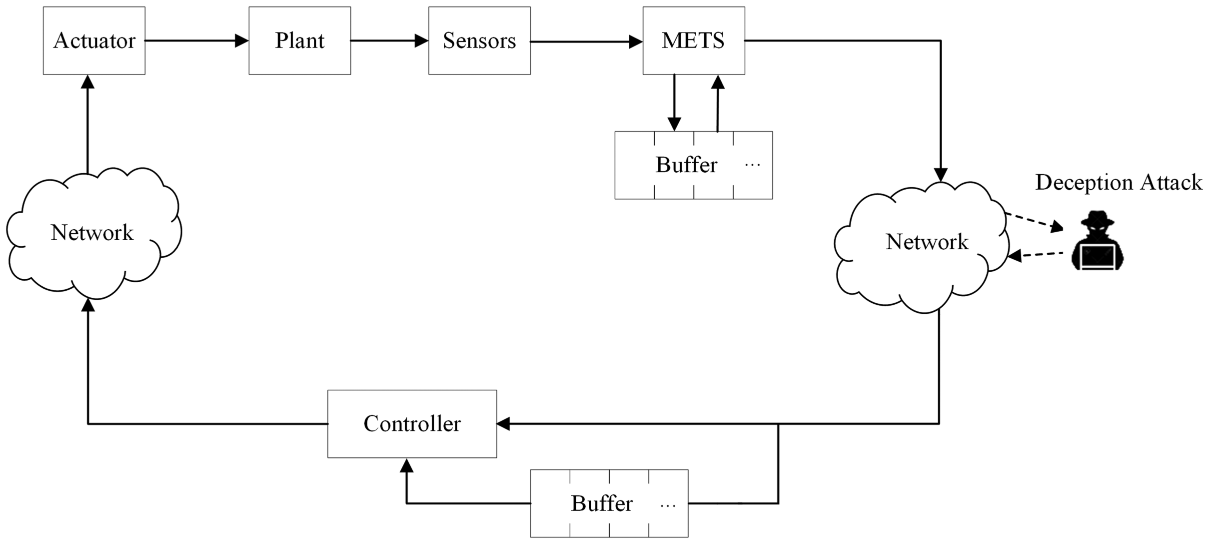

FIGURE 2 The structure of memory event-triggered networked control system under deception attacks. METS, memory event-triggered scheme

2.2 | The deception attack model

In this paper, it is assumed that the attacker can capture the system dynamic $x(t_k h)$ and release aggressive signals $f(x(t-d(t))$ in a random way. When deception attacks happen, the faked signal would join in the buffer of controller together with true signal. It is hard to distinguish the faked signals from the nonattacked one. To get rid of this dilemma, we design the following scheduling rules: at every released instant, *the event-generator will packet m historic released signal* $\{x(t_k h), \dots, x(t_{k-m+1}h)\}$ *and send them to the controller together*. In this way, the NCSs (5) under randomly occurring deception attacks can be expressed as

$$\dot{x}(t) = Ax(t) + \sum_{i=1}^{m} \theta(t) BK_i f_i(x(t-d(t))) + (1-\theta(t)) \sum_{i=1}^{m} BK_i (x(t-\tau(t)) + e_i(t)), \tag{6}$$

where $\theta(t) \in \{0, 1\}$ denotes the occurring probability of deception attacks. When $\theta(t) = 0$, it means there are no attacks, when $\theta(t) = 1$, the original signal $[x(t_k h), \dots, x(t_{k-m+1}h)]$ is captured by the attacker and replaced by a group of aggressive signal $[f_1(x(t-d(t)), \dots, f_m(x(t-d(t))]$. The mathematical characters of $\theta(t)$ are assumed to be known as

$$\mathbb{E}(\theta(t)) = \theta, \mathbb{E}(\theta(t) - \theta)^2 = \theta(1-\theta) \triangleq \gamma^2.$$

The aggressive signals $f_i(x(t-d(t))(i \in \{1, 2, \dots, m\})$ are assumed to satisfy

$$\| f_i(x(t-d(t)) \|_2 \leq \| G_i x(t-d(t)) \|_2, \tag{7}$$

where G_i is respective known matrix representing the upper bound of the nonlinearity $f_i(\cdot)$, $0 \leq d(t) \leq d_M$. Without loss of generality, assume that $G_{\max}$ is the largest one among G_i.

The following infinitesimal operator $\mathcal{L}$ is needed in the main results.

Definition 1 (See the works of Liu et al[51]). For a given function $V : C^B_{F_0}([-\tau_M, 0], R^n) \times S$, its infinitesimal operator $\mathcal{L}$ is defined as

$$\mathcal{L}(V_\eta(t)) = \lim_{\Delta \to +0^+} \frac{1}{\Delta} \left[E(V(\eta_t + \Delta) | \eta_t) - V(\eta_t) \right]. \tag{8}$$

3 | MAIN RESULTS

The purpose of this section is to design the memory controller (4) and METS (3) such that system (6) under randomly occurring deception attacks is asymptotically stable. Firstly, by using Lyapunov functional method, sufficient conditions for the stability of system (6) with given controller feedback gains are derived.

Theorem 1. *For given parameters m, σ, θ, γ, μ_α and matrix sequence $K_\alpha, \alpha \in \{1, \dots, m\}$, system (6) is asymptotically stable if there exist matrices $P > 0, Q_1 > 0, Q_2 > 0, R_1 > 0, R_2 > 0, W > 0$ and N, M, T, S with appropriate dimensions such that*

$$\Omega(i) = \begin{bmatrix} \Omega_{11} & * & * & * & * \\ \Omega_{21}(i) & -R_1 & * & * & * \\ \Omega_{31}(1) & 0 & -R_1 & * & * \\ \Omega_{41}(1) & 0 & 0 & -R_1 & * \\ \Omega_{51} & 0 & 0 & 0 & -P \end{bmatrix} < 0, i = 1, 2 \tag{9}$$

$$\Omega(j) = \begin{bmatrix} \Omega_{11} & * & * & * & * \\ \Omega_{21}(j) & -R_2 & * & * & * \\ \Omega_{31}(2) & 0 & -R_2 & * & * \\ \Omega_{41}(2) & 0 & 0 & -R_2 & * \\ \Omega_{51} & 0 & 0 & 0 & -P \end{bmatrix} < 0, j = 3, 4, \tag{10}$$

where

$$\Omega_{11} = \Psi + \Gamma + \Gamma^T, \Psi = \left[\Psi_{ij}\right]_{4\times 4}$$

$$\Psi_{11}^{11} = PA + A^T P + Q_1 + Q_2, \Psi_{11}^{21} = (1-\theta)\sum_{\alpha=1}^{m} K_\alpha^T B^T P,$$

$$\Psi_{11}^{22} = \sigma W, \Psi_{22} = \mathrm{diag}\{-Q_1, 0, -Q_2\},$$

$$\Psi_{31} = \left[(1-\theta)K_\alpha^T B^T P \ \ \tfrac{\sigma}{m} W\right]_{m\times 2}, \Psi_{41} = \left[\theta K_\alpha^T B^T P \ \ 0\right]_{m\times 2},$$

$$\Psi_{33} = \frac{\sigma}{m^2} W \cdot I_m + \mathrm{diag}\{-\mu_1 W, \dots, -\mu_m W\},$$

$$\Psi_{44} = \mathrm{diag}\{-\theta P, \dots, -\theta P\}, \Omega_{21}(1) = \sqrt{\tau_M} N^T, \Omega_{21}(2) = \sqrt{\tau_M} M^T,$$

$$\Omega_{21}(3) = \sqrt{d_M} T^T, \Omega_{21}(4) = \sqrt{d_M} S^T, \Omega_{31}(1) = \sqrt{\tau_M} R_1 \mathcal{A},$$

$$\Omega_{31}(2) = \sqrt{d_M} R_2 \mathcal{A}, \Omega_{41}(1) = \sqrt{\tau_M} R_1 \mathcal{B}, \Omega_{41}(2) = \sqrt{d_M} R_2 \mathcal{B},$$

$$\Omega_{51} = \left[0 \ 0 \ 0 \ \sqrt{m\theta} G_{\max} P \ 0 \ \cdots \ 0 \ 0\right],$$

$$\Gamma = \left[N + T \ \ -N + M \ \ -M \ \ -T + S \ \ -S \ \ 0 \ \cdots \ 0\right],$$

$$\mathcal{A} = \left[A \ \ (1-\theta)\textstyle\sum_{\alpha=1}^{m} BK_\alpha \ \ 0 \ 0 \ 0 \ \ (1-\theta)\bar{K} \ \ \theta\bar{K}\right],$$

$$\mathcal{B} = \left[0 \ \ -\gamma \textstyle\sum_{\alpha=1}^{m} BK_\alpha \ \ 0 \ 0 \ 0 \ \ -\gamma\bar{K} \ \ \gamma\bar{K}\right],$$

$$\bar{K} = \left[BK_1 \ \cdots \ BK_m\right].$$

Proof. Construct the following Lyapunov functional as

$$V(t) = V_1(t) + V_2(t) + V_3(t), \tag{11}$$

where

$$
\begin{aligned}
V_1(t) &= x^T(t)Px(t)\\
V_2(t) &= \int_{t-\tau_M}^{t} x^T(s)Q_1x(s)\,ds + \int_{t-d_M}^{t} x^T(s)Q_2x(s)ds\\
V_3(t) &= \int_{t-\tau_M}^{t}\int_{s}^{t} \dot{x}^T(v)R_1\dot{x}(v)\,dvds + \int_{t-d_M}^{t}\int_{s}^{t} \dot{x}^T(v)R_2\dot{x}(v)dvds.
\end{aligned}
$$

From the definition of e_α, $\tau(t)$, $\bar{x}$ and the triggering algorithm (3), it can be seen that, for $t \in \mathcal{I}_i$,

$$\sum_{\alpha=1}^{m}\mu_\alpha e_\alpha^T W e_\alpha \leq \sigma\left[\frac{1}{m}\sum_{\alpha=1}^{m}(x(t-\tau(t))) + e_\alpha\right]^T W\left[\frac{1}{m}\sum_{\alpha=1}^{m}(x(t-\tau(t))) + e_\alpha\right].$$

From the definition of $f_i(x(t-d(t)))$ in (7), the following inequality exists:

$$-\sum_{i=1}^{m}x^T(t-d(t))G_iPG_ix(t-d(t)) + \sum_{i=1}^{m}f_i^T(x(t-d(t)))Pf_i(x(t-d(t))) \leq 0.$$

Applying the infinitesimal operator defined in Definition 1 and taking expectation on both sides of (11), we can obtain

$$
\begin{aligned}
E(\mathcal{L}(V(t))) \leq{}& 2x^T(t)P\left[Ax(t) + \theta B\left(\sum_{\alpha=1}^{m}K_\alpha(f_\alpha(x(t-d(t)))) + (1-\theta)B\sum_{\alpha=1}^{m}K_\alpha(x(t-\tau(t)) - e_\alpha)\right]\right.\\
&+ x^T(t)Q_1x(t) - x^T(t-\tau_M)Q_1x(t-\tau_M) + x^T(t)Q_2x(t) - x^T(t-d_M)Q_2x(t-d_M)\\
&+ \tau_M\dot{x}^T(t)R_1\dot{x}(t) - \int_{t-\tau_M}^{t}\dot{x}^T(s)R_1\dot{x}(s)ds + d_M\dot{x}^T(t)R_2\dot{x}(t) - \int_{t-d_M}^{t}\dot{x}^T(s)R_2\dot{x}(s)ds\\
&- 2\xi^T(t)N\left[x(t) - x(t-\tau(t)) - \int_{t-\tau(t)}^{t}\dot{x}(s)ds\right] - 2\xi^T(t)M\cdot\\
&\left[x(t-\tau(t)) - x(t-\tau_M) - \int_{t-\tau_M}^{t-\tau(t)}\dot{x}(s)ds\right] - 2\xi^T(t)T\left[x(t) - x(t-d(t)) - \int_{t-d(t)}^{t}\dot{x}(s)ds\right]\\
&- 2\xi^T(t)S\left[x(t-d(t)) - x(t-d_M) - \int_{t-d_M}^{t-d(t)}\dot{x}(s)ds\right]\\
&- \sum_{\alpha=1}^{m}\mu_\alpha e_\alpha^T(t)We_\alpha(t) + \sigma\left[\frac{1}{m}\sum_{\alpha=1}^{m}(e_\alpha + x(t-\tau(t)))\right]^T W\left[\frac{1}{m}\sum_{\alpha=1}^{m}(e_\alpha + x(t-\tau(t)))\right]\\
&+ \sum_{i=1}^{m}\theta x^T(t-d(t))G_iPG_ix(t-d(t)) - \theta\sum_{i=1}^{m}f_i^T(x(t-d(t)))Pf_i(x(t-d(t))),
\end{aligned}
$$

where

$$\xi^T(t) = \left[x^T(t)\ x^T(t-\tau(t))\ x^T(t-\tau_M)\ x^T(t-d(t))\ x^T(t-d_M)\ e_1^T\ \ldots\ e_m^T\ f_1^T\ \ldots\ f_m^T\right].$$

Notice that

$$E\left(\tau_M\dot{x}^T(t)R_1\dot{x}(t)\right) = \xi^T(t)\left(\Omega_{31}^T(1)R_1^{-1}\Omega_{31}(1) + \Omega_{41}^T(1)R_1^{-1}\Omega_{41}(1)\right)\xi(t)$$

$$E\left(d_M\dot{x}^T(t)R_2\dot{x}(t)\right) = \xi^T(t)\left(\Omega_{31}^T(2)R_2^{-1}\Omega_{31}(2) + \Omega_{41}^T(2)R_2^{-1}\Omega_{41}(2)\right)\xi(t)$$

Defining

$$\eta^T(t,s) = \left[\, \xi^T(t)\ \dot{x}^T(s) \,\right].$$

We can further conclude that

$$\begin{aligned}
E(\mathcal{L}(V(t))) < {} & \frac{1}{\tau_M}\int_{t-\tau(t)}^{t} \eta^T(t,s)F_1\eta(t,s)ds + \frac{1}{\tau_M}\int_{t-\tau_M}^{t-\tau(t)} \eta^T(t,s)F_2\eta(t,s)ds \\
& + \frac{1}{d_M}\int_{t-d(t)}^{t} \eta^T(t,s)F_3\eta(t,s)ds + \frac{1}{d_M}\int_{t-d_M}^{t-d(t)} \eta^T(t,s)F_4\eta(t,s)ds \\
& + m\theta x^T(t-d(t))G_{\max}PG_{\max}x(t-d(t)),
\end{aligned}$$

where

$$F_i = \begin{bmatrix} \Omega_{11} + \Omega_{31}(1)^T R_1^{-1}\Omega_{31}(1) + \Omega_{41}(1)^T R_1^{-1}\Omega_{41}(1) & * \\ \Omega_{21}(i) & -R_1 \end{bmatrix}, i = \{1,2\}.$$

$$F_j = \begin{bmatrix} \Omega_{11} + \Omega_{31}(2)^T R_2^{-1}\Omega_{31}(2) + \Omega_{41}(2)^T R_2^{-1}\Omega_{41}(2) & * \\ \Omega_{21}(j) & -R_2 \end{bmatrix}, j = \{3,4\}.$$

Using Schur Complement, one can obtain from (9) and (10) that, for $t \in [t_kh + \tau_k, t_{k+1}h + \tau_{k+1}]$,

$$E(\mathcal{L}(V(t))) < 0.$$

This completes the proof. □

Remark 3. Generally speaking, the conservatism of the results mainly comes from two aspects, the first is the selection of the parameters μ_i and the second is the used Lyapunov functional technique. As for the first aspect, how to choose a group of parameters μ_i to obtain an optimal result is still open. In this paper, we have tried different groups parameters to obtain a relative good one. For the second aspect, to deal with cross items $\int_{t-\tau_M}^{t} \dot{x}^T(s)R_1\dot{x}(s)ds$ and $\int_{t-d_M}^{t} \dot{x}^T(s)R_2\dot{x}(s)ds$, a simple but efficient method has been used in the proof, however, the conservatism can be further improved by using some new proposed methods, such as the method in the work of Zhang and Han.[52]

In the following, a criterion is provided to design the state-feedback gains under deception attacks and METS (3).

Theorem 2. *For given parameters σ, m, θ, γ, μ_i, ρ_1, and ρ_2, system (6) under randomly occurring deception attacks and METS is asymptotical stability, if there exist matrices $X > 0$, $\tilde{Q}_1 > 0$, $\tilde{Q}_2 > 0$, $\tilde{R}_1 > 0$, $\tilde{R}_2 > 0$, $\tilde{W} > 0$, $\tilde{N}$, $\tilde{M}$, $\tilde{T}$, $\tilde{S}$, $Y_\alpha, (\alpha = 1, 2, \dots, m)$ of appropriate dimensions such that*

$$\Xi(i) = \begin{bmatrix} \Xi_{11} & * & * & * & * \\ \Xi_{21}(i) & -\tilde{R}_1 & * & * & * \\ \Xi_{31}(1) & 0 & \Phi(\tilde{R}_1) & * & * \\ \Xi_{41}(1) & 0 & 0 & \Phi(\tilde{R}_1) & * \\ \Xi_{51} & 0 & 0 & 0 & -X \end{bmatrix} < 0, i = 1, 2 \tag{12}$$

$$\Xi(j) = \begin{bmatrix} \Xi_{11} & * & * & * & * \\ \Xi_{21}(j) & -\tilde{R}_2 & * & * & * \\ \Xi_{31}(2) & 0 & \Phi(\tilde{R}_2) & * & * \\ \Xi_{41}(2) & 0 & 0 & \Phi(\tilde{R}_2) & * \\ \Xi_{51} & 0 & 0 & 0 & -X \end{bmatrix} < 0, j = 3, 4, \tag{13}$$

the memory controller gains are $K_\alpha = Y_\alpha X^{-1}$, where

$$\Xi_{11} = \tilde{\Psi} + \tilde{\Gamma} + \tilde{\Gamma}^T, \tilde{\Psi} = \left[\tilde{\Psi}_{ij}\right]_{4\times 4}, \tilde{\Psi}_{11}^{11} = AX + XA^T + \tilde{Q}_1 + \tilde{Q}_2,$$

$$\tilde{\Psi}_{11}^{21} = (1-\theta)\sum_{\alpha=1}^{m} Y_\alpha^T B^T, \tilde{\Psi}_{11}^{22} = \sigma \tilde{W}, \tilde{\Psi}_{22} = \ \operatorname{diag}\{-\tilde{Q}_1, 0, -\tilde{Q}_2\},$$

$$\Phi(\tilde{R}_1) = \rho_1^2 \tilde{R}_1 - 2\rho_1 X, \Phi(\tilde{R}_2) = \rho_2^2 \tilde{R}_2 - 2\rho_2 X,$$

$$\tilde{\Psi}_{31} = \left[(1-\theta)Y_\alpha^T B^T \ \ \tfrac{\sigma}{m}\tilde{W}\right]_{m\times 2}, \tilde{\Psi}_{33} = \frac{\sigma}{m^2}\tilde{W}\cdot I_m + \operatorname{diag}\left\{-\mu_1 \tilde{W}, \ \dots, -\mu_m \tilde{W}\right\},$$

$$\tilde{\Psi}_{41} = \left[\theta Y_\alpha^T B^T \ \ 0\right]_{m\times 2}, \Psi_{44} = \operatorname{diag}\{-\theta X, \ \dots, -\theta X\},$$

$$\Xi_{21}(1) = \sqrt{\tau_M}\tilde{N}^T, \Xi_{21}(2) = \sqrt{\tau_M}\tilde{M}^T, \Xi_{21}(3) = \sqrt{d_M}\tilde{T}^T, \Xi_{21}(4) = \sqrt{d_M}\tilde{S}^T,$$

$$\tilde{\Gamma} = \left[\tilde{N} + \tilde{T} \ \ -\tilde{N} + \tilde{M} \ \ -\tilde{M} \ \ -\tilde{T} + \tilde{S} \ \ -\tilde{S} \ \ 0 \ \ 0 \ \cdots \ 0\right],$$

$$\Xi_{31}(1) = \sqrt{\tau_M}\tilde{\mathcal{A}}, \Xi_{31}(2) = \sqrt{d_M}\tilde{\mathcal{A}}, \Xi_{41}(1) = \sqrt{\tau_M}\tilde{\mathcal{B}}, \Xi_{41}(2) = \sqrt{d_M}\tilde{\mathcal{B}},$$

$$\Xi_{51} = \left[0 \ 0 \ 0 \ \sqrt{m\theta}G_{\max}X \ 0 \ 0 \ 0 \ \cdots \ 0 \ 0\right]_{m\times(5+2m)},$$

with

$$\tilde{\mathcal{A}} = \left[AX \ \ (1-\theta)\textstyle\sum_{\alpha=1}^m BY_\alpha \ \ 0 \ 0 \ 0 \ (1-\theta)\tilde{Y} \ \ \theta\tilde{Y}\right],$$

$$\tilde{\mathcal{B}} = \left[0 \ \ -\gamma\textstyle\sum_{\alpha=1}^m BY_\alpha \ \ 0 \ 0 \ 0 \ -\gamma\tilde{Y} \ \ \gamma\tilde{Y}\right],$$

$$\tilde{Y} = \left[BY_1 \ \cdots \ BY_m\right].$$

Proof. Define $X = P^{-1}$, premultiply and postmultiply (9) and (10) with diag$(X, \ \dots, X, R_l^{-1}, R_l^{-1}, X)$, respectively, and define new matrix variables $\tilde{Q}_l = XQ_lX$, $\tilde{R}_l = XR_lX(l = 1, 2)$, $\tilde{W} = XWX$, $\tilde{\Upsilon}$ =diag$(X, \ \dots, X)\Upsilon X(\Upsilon = N, M, T, S)$, (12) and (13) can be obtained together with the following inequality:

$$-X\tilde{R}_i^{-1}X \le \rho_i^2\tilde{R}_i - 2\rho_i X, i = 1, 2.$$

□

Remark 4. Theorem 2 has proposed a sufficient condition to deal with codesign problem of controller and METS parameters, which are shown in terms of LMIs. Generally speaking, the interior-point LMI solvers are faster than some convex optimization algorithms. The complexity of LMI computations is polynomial time which is bounded by $\mathcal{O}(\mathcal{M}\mathcal{N}^3 log(\mathcal{V}/\varepsilon))$, where ε is relative accuracy set for algorithm, $\mathcal{V}$ is data-dependant scaling factor, $\mathcal{M}$ is the total row size of LMIs, and $\mathcal{N}$ is the number of scalar decision variables. Here, we assume that the system's dimension is n and involved variable's dimension can be determined by $x_j(t) \in \mathbb{R}$ and $f_i(x(t)) \in \mathbb{R}^n, i \in \{1, 2, \dots, m\}$. Then, for Theorem 2, $\mathcal{M} = n(2m+8)+mn$ and $\mathcal{N} = n[3n+2+m+4(5+2m)]+5+m$. Therefore, the computational complexity of Theorem 2 can be expressed as $\mathcal{O}(n^7)$, which depends polynomially on the system's size.

For $m = 1$ and $u(t) = Kx(t_kh)$, a corollary can be easily derived from Theorem 2.

Corollary 1. *For given parameters σ, θ, γ, and ρ, system (6) is asymptotical stability if there exist matrices of $X > 0$, $\tilde{Q}_1 > 0$, $\tilde{Q}_2 > 0$, $\tilde{R}_1 > 0$, $\tilde{R}_2 > 0$, $\tilde{W} > 0$, $\tilde{N}$, $\tilde{M}$, $\tilde{T}$, $\tilde{S}$, Y of appropriate dimensions such that $i = 1, 2$, $j = 3, 4$:*

$$\hat{\Xi}(i) = \begin{bmatrix} \hat{\Xi}_{11} & * & * & * & * \\ \tilde{\Xi}_{21}(i) & -\tilde{R}_1 & * & * & * \\ \hat{\Xi}_{31}(1) & 0 & \Phi(\tilde{R}_1) & * & * \\ \hat{\Xi}_{41}(1) & 0 & 0 & \Phi(\tilde{R}_1) & * \\ \hat{\Xi}_{51} & 0 & 0 & 0 & -X \end{bmatrix} < 0, i = 1, \tag{14}$$

$$\hat{\Xi}(j)=\begin{bmatrix}\hat{\Xi}_{11} & * & * & * & * \\ \hat{\Xi}_{21}(j) & -\tilde{R}_2 & * & * & * \\ \hat{\Xi}_{31}(2) & 0 & \Phi(\tilde{R}_2) & * & * \\ \hat{\Xi}_{41}(2) & 0 & 0 & \Phi(\tilde{R}_2) & * \\ \hat{\Xi}_{51} & 0 & 0 & 0 & -X\end{bmatrix}<0, j=3,4, \tag{15}$$

where

$$\hat{\Xi}_{11}=\hat{\Psi}+\hat{\Gamma}+\hat{\Gamma}^T, \hat{\Psi}=\left[\hat{\Psi}_{ij}\right]_{4\times 4}, \hat{\Psi}_{11}^{11}=\tilde{\Psi}_{11}^{11}, \hat{\Psi}_{11}^{22}=\tilde{\Psi}_{11}^{22},$$

$$\hat{\Psi}_{22}=\tilde{\Psi}_{22}, \hat{\Psi}_{11}^{21}=(1-\theta)Y^TB^T, \hat{\Psi}_{31}=\left[(1-\theta)Y^TB^T \;\; \sigma\tilde{W}\right],$$

$$\hat{\Psi}_{33}=-\tilde{W}+\sigma\tilde{W}, \hat{\Psi}_{41}=\left[\theta Y^TB^T \;\; 0\right], \hat{\Psi}_{44}=-\theta X,$$

$$\hat{\Gamma}=\left[\tilde{N}+\tilde{T} \;\; -\tilde{N}+\tilde{M} \;\; -\tilde{M} \;\; -\tilde{T}+\tilde{S} \;\; -\tilde{S} \;\; 0 \;\; 0\right],$$

$$\hat{\Xi}_{31}(1)=\sqrt{\tau_M}\hat{\mathcal{A}}, \hat{\Xi}_{31}(2)=\sqrt{d_M}\hat{\mathcal{A}}, \hat{\Xi}_{41}(1)=\sqrt{\tau_M}\hat{\mathcal{B}},$$

$$\hat{\Xi}_{41}(2)=\sqrt{d_M}\hat{\mathcal{B}}, \hat{\Xi}_{51}=\left[0 \;\; 0 \;\; 0 \;\; \sqrt{\theta}GX \;\; 0 \;\; 0 \;\; 0\right],$$

$$\hat{\mathcal{A}}=\left[AX \;\; (1-\theta)BY \;\; 0 \;\; 0 \;\; 0 \;\; (1-\theta)BY \;\; \theta BY\right],$$

$$\hat{\mathcal{B}}=\left[0 \;\; -\gamma BY \;\; 0 \;\; 0 \;\; 0 \;\; -\gamma BY \;\; \gamma BY\right],$$

the controller feedback gain can be designed as $K=YX^{-1}$.

4 | AN ILLUSTRATIVE EXAMPLE

Considering a pendulum system borrowed from Yue et al,[24] the system parameters are

$$A=\begin{bmatrix}0 & 1 & 0 & 0 \\ 0 & 0 & \frac{-mg}{M} & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & \frac{g}{l} & 0\end{bmatrix}, \quad B=\begin{bmatrix}0 \\ \frac{1}{M} \\ 0 \\ \frac{-1}{Ml}\end{bmatrix},$$

where $M=10$ is the cart mass and $m=1$ is the mass of the pendulum bob, $l=3$ is the length of the pendulum arm and $g=10$ is gravitational acceleration. The eigenvalue of A is $\{0, 0, 1.8257, -1.8257\}$; obviously, the system is unstable without a controller. The states $[x_1 \;\; x_2 \;\; x_3 \;\; x_4]=[y \;\; \dot{y} \;\; \omega \;\; \dot{\omega}]$, where $x_i(i=1,2,3,4)$, are the cart's position, the cart's velocity, the pendulum bob's angle, and the pendulum's angular velocity, respectively. The initial state $\phi(t)=[0.98 \;\; 0 \;\; 0.2 \;\; 0]^T$.

In this example, the deception attacks are assumed to be

$$f_i(x(t))=[\tanh(0.05x_1(t);-\tanh(0.1x_2(t)); \;\; \tanh(0.05x_3(t);-\tanh(0.1x_4(t))].$$

The upper bound matrices $G_i=G_{\max}=\text{diag}\{0.05, 0.1, 0.05, 0.1\}$ which satisfies the constraint $\|f_i(x(t-d(t))\|_2 \leq \|G_ix(t-d(t))\|_2$. Other parameters are set as $d_M=0.06$ s and $\rho_1=\rho_2=0.53$.

In order to show the effectiveness of the proposed METS and the resilient control design method, two cases are proposed. In Case 1, we assume that there is no deception attack in the system. In Case 2, when considering the randomly occurring deception attacks, the simulation results show that the proposed resilient control method is effective.

Case 1. Suppose that there are no deception attacks occurring. Set $\tau_M=h+\bar{\tau}=0.14$ s, which shows a trade-off between the sampling period h and allowable communication delay bound $\bar{\tau}$. In this case, we choose $h=0.1$ s and

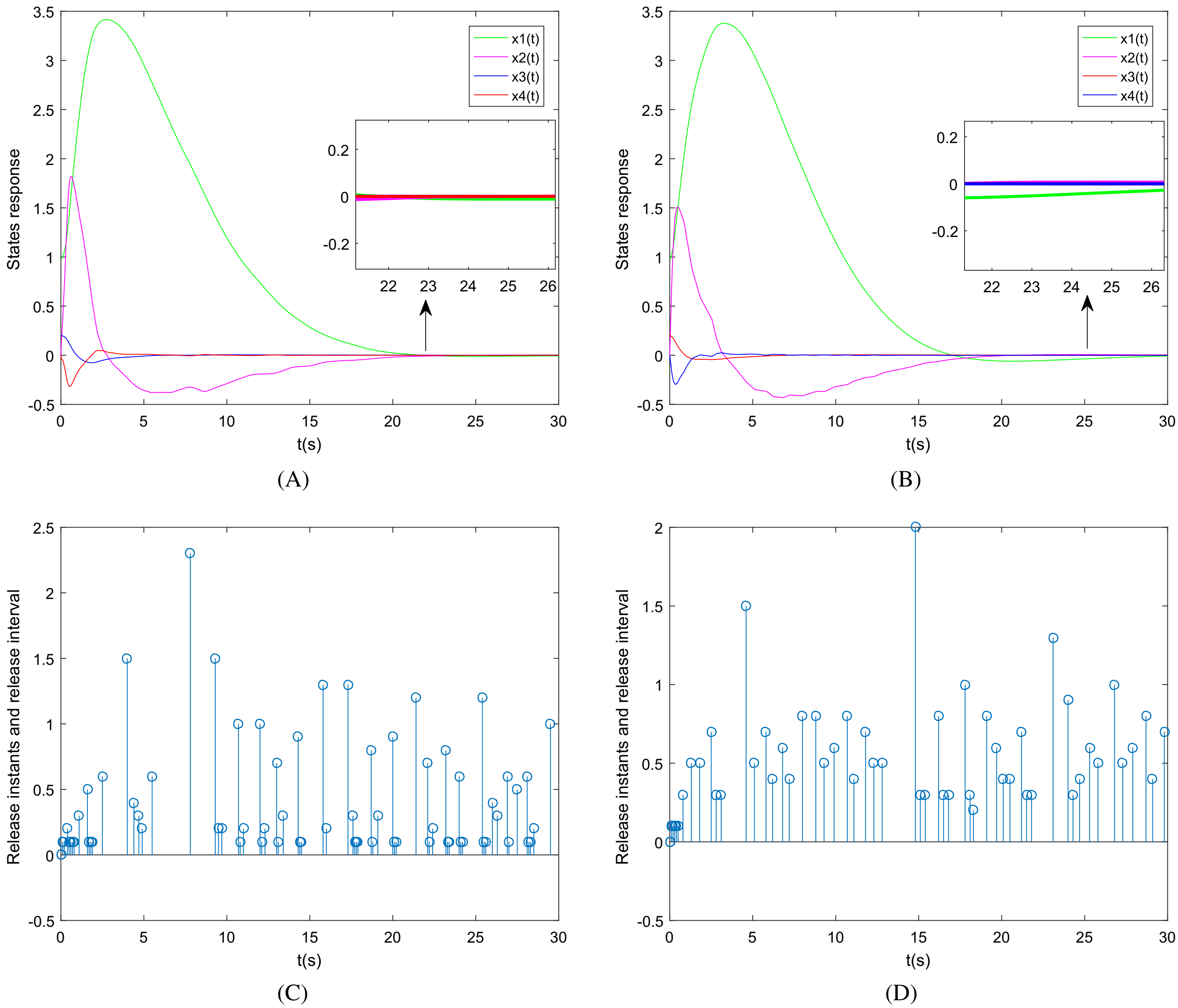

FIGURE 3 Simulation results of Case 1. (A) State responses of memory event-triggered scheme (METS) with $m = 3$; (B) State responses of event-triggered scheme (ETS) in the work of Yue et al[24]; (C) Release intervals of METS with $m = 3$; (D) Release intervals of ETS in the work of Yue et al[24] [Colour figure can be viewed at wileyonlinelibrary.com]

$\bar{\tau} = 0.04$s. Firstly, recalling the ETS method in the work of Yue et al,[24] for $\sigma = 0.2$, the state-feedback controller gain and the triggering parameter W are obtained as

$$K = \begin{bmatrix} 1.3305 & 8.2129 & 301.1510 & 167.1794 \end{bmatrix},$$
$$W = \begin{bmatrix} 0.0009 & 0.0046 & 0.1514 & 0.0841 \\ 0.0046 & 0.0289 & 0.9162 & 0.5104 \\ 0.1514 & 0.9162 & 32.9649 & 18.3005 \\ 0.0841 & 0.5104 & 18.3005 & 10.1673 \end{bmatrix}.$$

In this simulation, 55 packets are released by using the ETS in the work of Yue et al,[24] the state responses and release intervals are shown in Figure 3B and Figure 3D, respectively.

Next, by using the proposed METS, for $m = 3$ and the weighting parameters $\mu_1 = 0.5, \mu_2 = 0.3, \mu_3 = 0.2$. Applying Theorem 2, one can obtain the feedback gains and the triggering parameter W as

$$
\begin{aligned}
K_1 &= \begin{bmatrix} 0.5090 & 3.2000 & 118.6998 & 65.9017 \end{bmatrix}, \\
K_2 &= \begin{bmatrix} 0.3060 & 1.9231 & 71.3362 & 39.6064 \end{bmatrix}, \\
K_3 &= \begin{bmatrix} 0.2045 & 1.2852 & 47.6650 & 26.4648 \end{bmatrix}, \\
W &= \begin{bmatrix} 0.0001 & 0.0004 & 0.0144 & 0.0080 \\ 0.0004 & 0.0029 & 0.0867 & 0.0485 \\ 0.0144 & 0.0867 & 3.1386 & 1.7420 \\ 0.0080 & 0.0485 & 1.7420 & 0.9693 \end{bmatrix}.
\end{aligned}
$$

In this case, by using the proposed METS, there are 68 packets released to the controller, the state responses and release intervals of the METS are shown in Figure 3A and Figure 3C, respectively.

Compared the simulation results of the ETS in the work of Yue et al[24] and METS, it can be found that more packets are released by the METS at the beginning time, especially during the interval $t \in [0, 5]$; as a result, the settling time can be obviously shortened. That is, the METS can improve the transient performance by adjusting the packet transmission distribution according to the dynamics of the system.

Case 2. Considering the randomly occurring deception attacks, the occurring probability is chosen as $\theta = 0.1$ and $\sigma = 0.1$. Set $\tau_M = h + \bar{\tau} = 0.11\,\text{s}, h = 0.07\,\text{s}$ and $\bar{\tau} = 0.04\,\text{s}$. Firstly, if we do not utilize the historic release information, by using Corollary 1, there is no feasible solution for the system with deception attacks. Next, by using the proposed METS, for the same $\mu_i, (i = 1, 2, 3)$ in Case 1, by using Theorem 2, the controller feedback gains and triggering parameters W are obtained as

$$
\begin{aligned}
K_1 &= \begin{bmatrix} 1.4496 & 6.6060 & 147.6022 & 82.4861 \end{bmatrix}, \\
K_2 &= \begin{bmatrix} 1.2446 & 5.5255 & 122.9560 & 68.6888 \end{bmatrix}, \\
K_3 &= \begin{bmatrix} 1.0550 & 4.6204 & 102.6059 & 57.3089 \end{bmatrix}, \\
W &= 10^4 \times \begin{bmatrix} 0.0003 & 0.0008 & 0.0156 & 0.0087 \\ 0.0008 & 0.0034 & 0.0645 & 0.0363 \\ 0.0156 & 0.0645 & 1.3667 & 0.7637 \\ 0.0087 & 0.0363 & 0.7637 & 0.4275 \end{bmatrix}.
\end{aligned}
$$

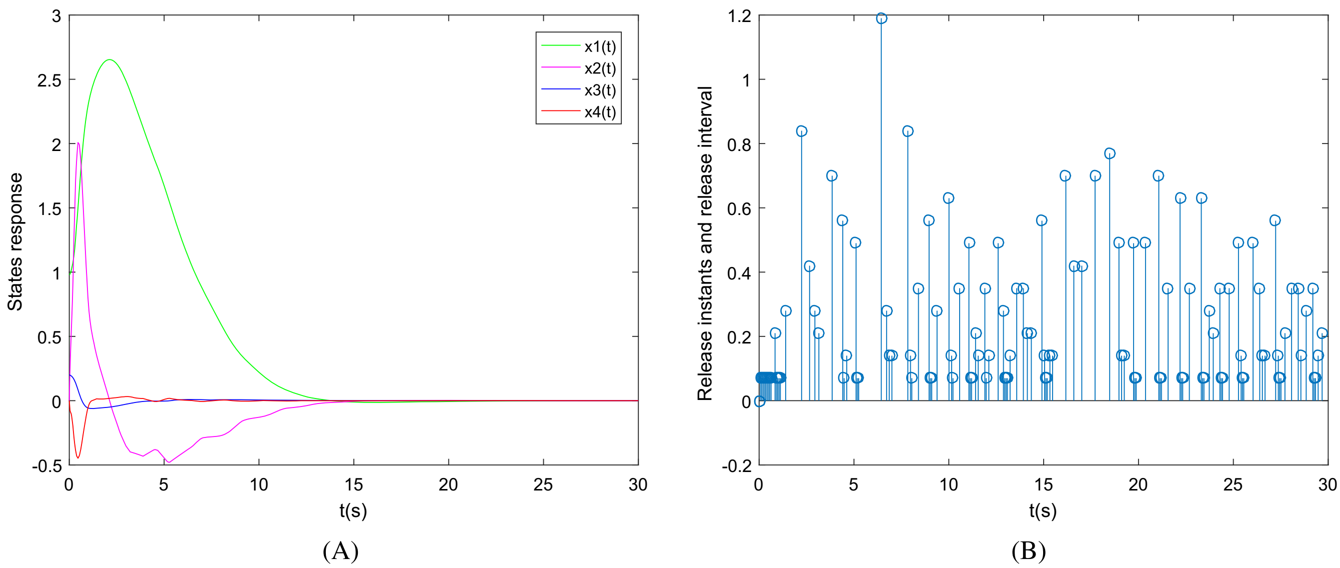

FIGURE 4 Simulation results of Case 2. (A) State responses of memory event-triggered scheme (METS) with $m = 3$; (B) Release intervals of METS with $m = 3$; [Colour figure can be viewed at wileyonlinelibrary.com]

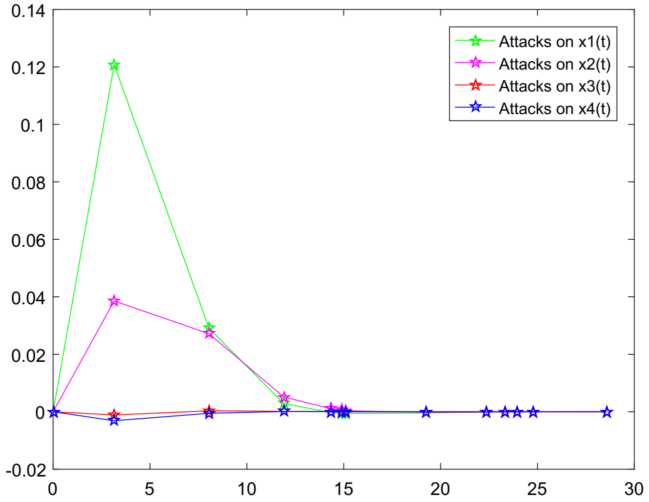

FIGURE 5 The occurring instants of the random deception attacks [Colour figure can be viewed at wileyonlinelibrary.com]

The state responses and release instants are shown in Figure 4 and the deception attack instants are illustrated in Figure 5. From Figures 4 and 5, it can be found that, by using the proposed METS and resilient memory control method, the system can be stabilized in the case of random deception attacks.

5 | CONCLUSION

In this paper, a METS has been proposed for the resilient control of NCSs under deception attacks. The information of some historic released packets has been employed in the proposed METS to trigger more packets at some special instants, especially, at the crest or trough of the system curve. Considering both the METS and deception attacks, new kind of networked control systems model has been built. Based on a Lyapunov functional method, a resilient memory control technique has been designed, sufficient conditions for the asymptotical stability have been derived. Then, controller feedback gains and triggering matrix can be codesigned by solving some LMIs. A simulation example has been proposed to demonstrate the effectiveness of the proposed design method.

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