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Dynamic event-triggered security control of cyber-physical systems against missing measurements and cyber-attacks ☆

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ABSTRACT

The security control approach is presented for cyber-physical systems (CPSs) with missing measurements and cyber-attacks based on an improved dynamic event-triggered scheme (DETS). The DETS is proposed to decrease the communication workload and reduce the effects of mutation data which may be erroneous. The sensor measurements are assumed to be lost randomly due to the unreliable network. In this paper, an observer-based controller is derived which can be tolerant towards the impacts of the missing measurements and cyber-attacks. The observer-based controller parameters and event-triggered parameter are co-designed. Finally, simulation results verify the validity of the proposed approach.

1. Introduction

Increased attention has been attracted to cyber-physical systems (CPSs), which are complex systems integrated the functions of the computation, communication, and control. These systems have broad application prospects in various areas, such as intelligent transportation systems, power grids, and industrial process control [1]. With the advancement of networked communication and computational abilities, the CPSs can quickly adjust to new situation and provide significant improvement in sensing, actuation and computation [2,3]. However, the signals transmitted among the various components of the system are via wireless network, which are vulnerable to malicious cyber-attacks [4–7]. There is no doubt that severe attacks on CPSs can cause huge economic loss and even threaten human life. Thus, the investigation of the security control issues for CPSs would be of great significance.

Security concerns of CPSs have aroused the enthusiasm of the scholars in science and engineering [8–10]. Since the saboteurs may launch denial-of-service (DoS) attacks [11] and deception attacks [12,13] to destroy the target system by interfering the data transmission. The DoS attacks aim to corrupt the stability of the system by blocking the communication channel, while the deception attacks corrupt the control systems by tempering the transmitted information maliciously [14,15]. For example, in [14], a disturbance rejection controller was developed for nonlinear network control systems (NCSs) under physical and DoS attacks. A distributed attack detection approach was addressed for sensor networks under deception attacks and unknown disturbance and noise in [16]. Until now, a vast amount of energy has been invested into the cyber-attacks against CPSs and a number of control or estimation methods of networked systems have been developed against various types of cyber-attacks. Among the wealth results about cyber-attacks in CPSs, there appear to be a few publications about observer-based control for continuous CPSs subject to DoS attacks [17–19], these approaches fail to work for discrete CPSs in presence of deception attacks and missing measurements, which motivates this article.

Since the networked computation and information exchange are essential in CPSs, it is of great need to make the most efficient use of the constrained bandwidth. Various methods have been

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derived to well utilize the limited network resources [20–24]. Especially, as one effective means to save network resources, event-triggered (ET) schemes are popular with many researchers [25–27]. To mention a few works, two resilient adaptive ET schemes are designed in [28] to avoid some unnecessary data traveling across the network. In [29], a resilient ET scheme was proposed to reduce the bandwidth pressure between the sensor and the filter. A learning-based ET scheme is applied in [30] to economize bandwidth of the network, the triggering threshold of which can be automatically adjusted in response to the variations of latest vehicle state. An ET scheme is applied to investigate the secure leader-following consensus control problem for multi-agent systems with multiple attacks by Liu et al.[31]. However, the dynamic ET control method for NCSs has not been developed to resist the cyber-atacks and randomly missing output measurements, which is still a challenging task.

Motivated by the above analysis, taking malicious cyber-attacks and missing output measurement into account, we are concerned with the stability analysis of a class of discrete NCSs in this article. Note that the network resources have the characteristic of resources-starved and all the system states may be difficult to be measured directly. Our objective is to design an resilient observer-based output feedback controller for the addressed NCSs, which can put up with the cyber-attacks and missing output measurements. The main contributions of this article are as follows. (1) An improved dynamic event-triggered scheme (DETS) is proposed to reduce the network congestion while avoiding some unnecessary abrupt data transmission. (2) A new closed-loop system model is established, which taking into account of the impacts of the cyber-attacks and the missing output measurements. (3) The co-design approach of the observer/controller gains and the triggering matrix of the DETS are presented to guarantee the desired system performance.

2. Preliminaries

The framework of the NCSs under randomly missing output measurements and cyber attacks is given in Fig. 1, where the information flows from sensor to observer and from observer to controller are via unreliable wireless network. For the sake of reducing data update frequency of observer, a DETS is introduced to discard some 'unnecessary' packets with little variation.

The dynamics of the physical plant in Fig. 1 can be modeled as:

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) \\ y(k) = Cx(k) \end{cases} \tag{1}$$

where $x(k) \in \mathbb{R}^{n_x}$ and $y(k) \in \mathbb{R}^{n_y}$ represent the system state vector and the output measurement, respectively. $u(k) \in \mathbb{R}^{n_u}$ stands for the control input. $A \in \mathbb{R}^{n_x \times n_x}, B \in \mathbb{R}^{n_x \times n_u}$ and $C \in \mathbb{R}^{n_y \times n_x}$ are known constant matrices.

The main intend of this article is to design a controller based on the observed state $\hat{x}(k)$. The observer-based controller model is constructed as follows:

$$\begin{cases} \hat{x}(k+1) = A\hat{x}(k) + Bu(k) + L(\tilde{y}(k) - C\hat{x}(k)) \\ u(k) = K\tilde{x}(k) \end{cases} \tag{2}$$

where $\hat{x}(k) \in \mathbb{R}^{n_x}$ represents the observer state, $\tilde{x}(k) \in \mathbb{R}^{n_x}$ stands for the signal received by controller and $\tilde{y}(k) \in \mathbb{R}^{n_y}$ is the data received by observer. The models of $\tilde{x}(k)$ and $\tilde{y}(k)$ will be given later. $L \in \mathbb{R}^{n_x \times n_y}$ and $K \in \mathbb{R}^{n_u \times n_x}$ are observer gain and controller gain to be determined.

Remark 1. Notice that the randomly occurring information missing and cyber-attacks are often encountered in many practical systems. The output measurement $y(k)$ and the observer state

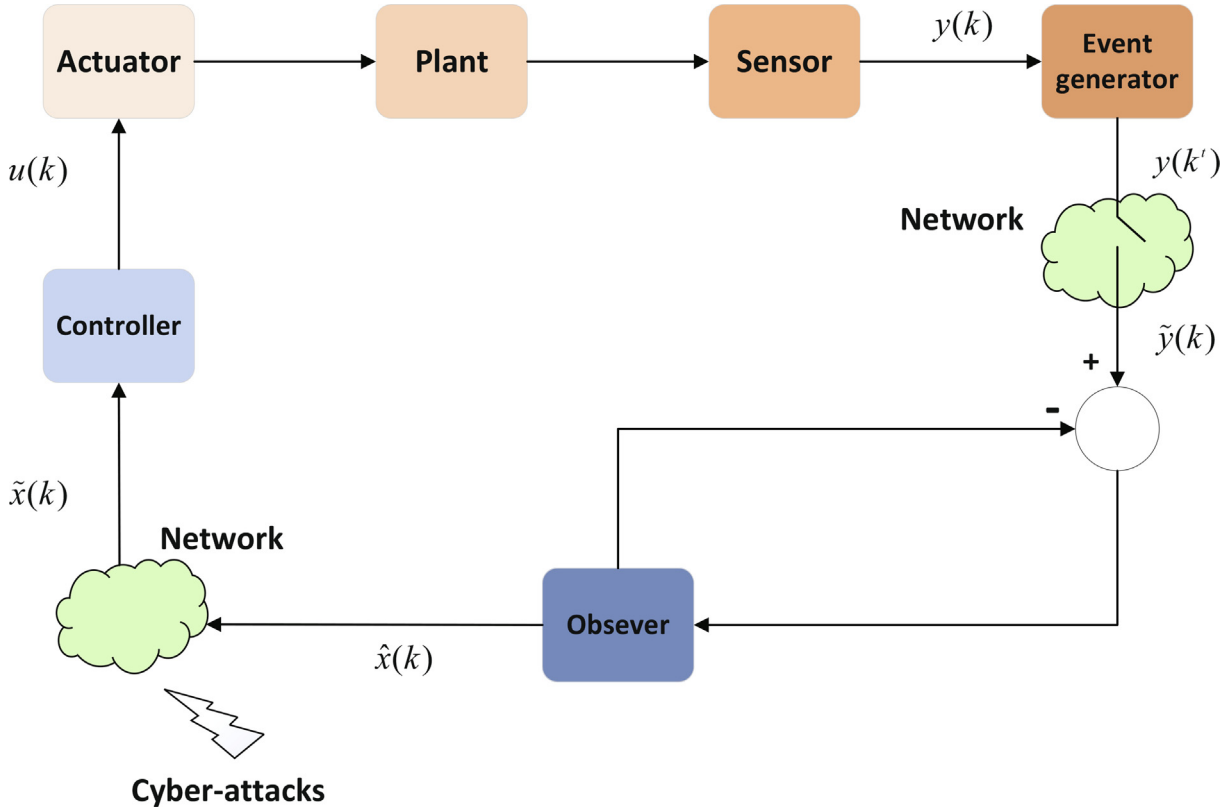

Fig. 1. The structure of dynamic ET NCSs with cyber-attacks and missing output measurements.

$\hat{x}(k)$being transmitted via the unreliable network may be different with the real observer input $\bar{y}(k)$and the controller input $\bar{x}(k)$, that is, $\bar{y}(k)$ is not equal to $y(k)$and $\bar{x}(k)$ is not equal to $\hat{x}(k)$.

A dynamic ET generator is introduced between the sensor and the observer to reduce the frequency of signals released into the network as shown in Fig. 1. The following condition is employed for event-based update of the observer:

$$\begin{cases} \lambda\phi(k) > \theta(k) \\ \phi(k) = e^T(k)Me(k) - \delta y^T\left(k^t\right)My\left(k^t\right) \end{cases} \tag{3}$$

where δ and λ are known positive constants, $e(k) = y\left(k^t\right) - y\left(k^t + \Delta\right)$ in which

$$y\left(k^t + \Delta\right) \triangleq \mu\left[y(k) - y\left(k^t\right)\right] + y\left(k^t\right) \tag{4}$$

with μ is an adjustment factor satisfying $\mu \in (0, 1]$, k^t stands for the triggering instant, $y\left(k^t\right)$ denotes the latest signal released by the dynamic ET generator, and the auxiliary offset variable $\theta(k)$ is denoted as:

$$\begin{cases} \theta(k+1) = \sigma\theta(k) - \phi(k) \\ \theta(0) \geqslant 0 \end{cases} \tag{5}$$

with σ is a constant in $(0, 1)$, λ and σ satisfy $\lambda\sigma \geqslant 1$ which can ensure $\theta(k) \geqslant 0$ for any $k \in \mathbb{N}, \mathbb{N} = \{1, 2, 3, \cdots\}$ according to Lemma 1 in [25].

If the dynamic ET condition (3) is met, the "required" output measurement will be put into the wireless network, while the data with a little variation will be dropped. Then we obtain the next triggering time k^{t+1} as follows:

$$k^{t+1} = \min\left\{k \in \mathbb{N} | k > k^t, k \text{ satisfying } (3)\right\} \tag{6}$$

Remark 2. From the definition of k^t, one can easily see that the set of triggering times $\left\{k^t | t \in \mathbb{N}\right\}$ is the subset of $\mathbb{N}$.

Remark 3. Considering that the mutation data may be easier to satisfy dynamic ET condition (3) than normal data, one set the error $e(k) = y\left(k^t\right) - y\left(k^t + \Delta\right)$ with the definition of $y\left(k^t + \Delta\right)$ in (4) rather than $e(k) = y\left(k^t\right) - y(k)$ to avoid the mutation data being mistakenly released into the network.

Remark 4. In (4), if we let $\mu = 1, y\left(k^t + \Delta\right)$ will be equal to $y(k)$ and the error $e(k) = y\left(k^t\right) - y\left(k^t + \Delta\right)$ will be $e(k) = y\left(k^t\right) - y(k)$, that is, the triggering condition (3) becomes the case in [32]. If $0 < \mu < 1$, the value of $y\left(k^t + \Delta\right)$ will range from $y\left(k^t\right)$ to $y(k)$. In particular, if $\mu = \frac{1}{2}, y\left(k^t + \Delta\right)$ will equal to the average between $y\left(k^t\right)$ and $y(k)$. Consequently, the designed triggering condition (3) can avoid the erroneous events in some extent.

Since the information losses may occur during being transmitted via the Sensor-to-Observer communication channel, the stochastic variable $\alpha(k)$ is applied to account for this phenomenon. The presentation of the observer input is:

$$\tilde{y}(k) = \alpha(k)y\left(k^t\right) = \alpha(k)\left[Cx(k) + \frac{1}{\mu}e(k)\right] \tag{7}$$

where $\alpha(k) \in \{0, 1\}$ satisfying the following constraints:

$$\mathbb{E}(\alpha(k)) = \bar{\alpha}, \mathbb{E}(1 - \alpha(k)) = 1 - \bar{\alpha} \tag{8}$$

In the presence of malicious cyber-attacks, the transmitted data over the network will be modified and the controller cannot receive the real observer state. A nonlinear function (NF) $\varrho(\hat{x}(k))$ is utilized to characterize the cyber-attacks sent by the malicious opponent. The controller input can be expressed as

$$\tilde{x}(k) = \hat{x}(k) + \beta(k)\varrho(\hat{x}(k)) \tag{9}$$

where $\beta(k) \in \{0, 1\}$ and

$$\mathbb{E}(\beta(k)) = \bar{\beta}, \mathbb{E}(1 - \beta(k)) = 1 - \bar{\alpha}, \tag{10}$$

Remark 5. It should be noted that $\beta(k) = 1$ in (9) represents that the system is subject to cyber-attacks which will tamper the real data packets, in this case, the real controller input is denoted by (9). Otherwise, $\beta(k) = 0$, this means the network does not experience the cyber-attacks, and the input of the controller is $\hat{x}(k)$.

Define $\epsilon(k) \triangleq x(k) - \hat{x}(k)$, from (1), (2) and (9), the system state $x(k+1)$ can be computed as:

$$\begin{aligned} x(k+1) = {} & (A + BK)\hat{x}(k) + A\epsilon(k) + \bar{\beta}BK\varrho(\hat{x}(k)) \\ & + \left(\beta(k) - \bar{\beta}\right)BK\varrho(\hat{x}(k)) \end{aligned} \tag{11}$$

and observer state $\hat{x}(k+1)$ can be obtained from (2), (7) and (9):

$$\begin{aligned} \hat{x}(k+1) = {} & [A + BK + (\bar{\alpha} - 1)LC]\hat{x}(k) + \bar{\alpha}LC\epsilon(k) + \frac{\bar{\alpha}}{\mu}Le(k) \\ & + \bar{\beta}BK\varrho(\hat{x}(k)) + (\alpha(k) - \bar{\alpha}) \\ & \times \left[LC\hat{x}(k) + LC\epsilon(k) + \frac{1}{\mu}Le(k)\right] \\ & + \left(\beta(k) - \bar{\beta}\right)BK\varrho(\hat{x}(k)). \end{aligned} \tag{12}$$

Then, we can derive the error $\epsilon(k+1)$ from (11) and (12):

$$\begin{aligned} \epsilon(k+1) = {} & -(\bar{\alpha} - 1)LC\hat{x}(k) + (A - \bar{\alpha}LC)\epsilon(k) - \frac{\bar{\alpha}}{\mu}Le(k) \\ & - (\alpha(k) - \bar{\alpha})\left[LC\hat{x}(k) + LC\epsilon(k) + \frac{1}{\mu}Le(k)\right]. \end{aligned} \tag{13}$$

Let $\eta(k) = \begin{bmatrix} \hat{x}^T(k) & \epsilon^T(k) \end{bmatrix}^T$, the following augmented system can be derived

$$\begin{aligned} \eta(k+1) = {} & \bar{A}\eta(k) + \frac{\bar{\alpha}}{\mu}\bar{L}e(k) + \bar{\beta}\bar{B}\varrho(\hat{x}(k)) + \left(\beta(k) - \bar{\beta}\right)\bar{B}\varrho(\hat{x}(k)) \\ & + (\alpha(k) - \bar{\alpha})\left[\bar{L}_c\eta(k) + \frac{1}{\mu}\bar{L}e(k)\right], \end{aligned} \tag{14}$$

where

$$\bar{A} = \begin{bmatrix} A + BK + (\bar{\alpha} - 1)LC & \bar{\alpha}LC \\ -(\bar{\alpha} - 1)LC & A - \bar{\alpha}LC \end{bmatrix}, \bar{L} = \begin{bmatrix} L \\ -L \end{bmatrix}, \bar{B} = \begin{bmatrix} BK \\ 0 \end{bmatrix},$$

$$\bar{L}_c = \begin{bmatrix} LC & LC \\ -LC & -LC \end{bmatrix}.$$

Then, the dynamic ET control issue for NCSs (1) with missing measurements and cyber-attacks is transformed into the stability issue of (14). In deriving our main results, the following lemma and assumption are needed.

Lemma 1. [32] For $B \in \mathbb{R}^{n_x \times n_u}, rank(B) = n_u$, the singular value decomposition of B is $B = U\begin{bmatrix} S^T & 0 \end{bmatrix}^T V^T$, where $U^T U = I, V^T V = I$. For $\overline{P} \triangleq UP_1U^T, P_1 = \begin{bmatrix} M & * \\ 0 & N \end{bmatrix}, M \in \mathbb{R}^{n_q \times n_q}, N \in \mathbb{R}^{(n_x - n_q) \times (n_x - n_q)}$, there exists $\widetilde{P} = \left(V^T\right)^{-1}S^{-1}MSV^T$ satisfying $\overline{P}B = B\widetilde{P}$.

Assumption 1. The matrix B is a full rank matrix.

Assumption 2. The NF $\varrho(\hat{x}(k))$ satisfies the following condition

$$\varrho^T(\hat{x}(k))\varrho(\hat{x}(k)) \leqslant \hat{x}^T(k)\Gamma^T\Gamma\hat{x}(k). \tag{15}$$

where Γ is a known matrix.

Remark 6. Compared with the event-triggered scheme with preset triggering parameter in [5,25,33,34], an auxiliary variable $\theta(k)$ is introduced into the DETS in this paper to adjust the amount of data transmission via network. Larger trigger interval will be determined by DETS than that by event-triggered scheme with preset triggering parameter which has been proved in [35].

3. Main Results

A new ET observer-based control algorithm is developed in this section for the augmented system (14). Moreover, the co-design approach of controller gain, the observer gain, and dynamic ET parameter will be shown.

Theorem 1. *For given scalars $\lambda > 0, \delta > 0, \mu \in (0,1], \sigma \in (0,1)$ $\bar{\alpha} \in (0,1)$ and $\bar{\beta} \in (0,1)$ and matrix Γ, the augmented system (14) is asymptotic stable if there exist matrices $\bar{P} > 0, M > 0, Y$ and Z such that*

$$\Sigma_2 = \begin{bmatrix} \Omega_{11} & * & * & * & * \\ \Omega_{21} & \mathcal{P} & * & * & * \\ \rho_\beta\Omega_{31} & 0 & \mathcal{P} & * & * \\ \rho_\alpha\Omega_{41} & 0 & 0 & \mathcal{P} & * \\ \Omega_{51} & 0 & 0 & 0 & -I \end{bmatrix} < 0 \tag{16}$$

where

$$\Omega_{11} = \begin{bmatrix} -\bar{P}^T - \delta\kappa C^T MC & * & * & * \\ -\delta\kappa C^T MC & -\bar{P}^T - \delta\kappa C^T MC & * & * \\ -\frac{\delta}{\mu}\kappa MC & -\frac{\delta}{\mu}\kappa MC & \kappa\left(1-\frac{\delta}{\mu^2}\right)M & * \\ 0 & 0 & 0 & -I \end{bmatrix},$$

$$\Omega_{21} = \begin{bmatrix} \bar{P}^T A + BY + (\bar{\alpha}-1)ZC & \bar{\alpha}ZC & \frac{\bar{\alpha}}{\mu}Z & \bar{\beta}BY \\ -(\bar{\alpha}-1)ZC & \bar{P}^T A - \bar{\alpha}ZC & -\frac{\bar{\alpha}}{\mu}Z & 0 \end{bmatrix},$$

$$\Omega_{31} = \begin{bmatrix} 0 & 0 & 0 & BY \\ 0 & 0 & 0 & 0 \end{bmatrix}, \Omega_{41} = \begin{bmatrix} ZC & ZC & \frac{1}{\mu}ZC & 0 \\ -ZC & -ZC & -\frac{1}{\mu}ZC & 0 \end{bmatrix},$$

$$\Omega_{51} = [\Gamma \quad 0 \quad 0 \quad 0],$$

$$\rho_\beta = \sqrt{(1-\bar{\beta})\bar{\beta}}, \rho_\alpha = \sqrt{(1-\bar{\alpha})\bar{\alpha}}, \kappa = \sigma - 1 - \frac{1}{\lambda},$$

$$\mathcal{P} = diag\{-\bar{P}, -\bar{P}\}.$$

Then, the observer-based controller gains can be designed as

$$K = \widetilde{P}^{-1}Y \tag{17}$$

$$L = \bar{P}^{-1}Z \tag{18}$$

where $\widetilde{P} = \left(V^T\right)^{-1}S^{-1}MSV^T$ and the symbols V, S and M are given in Lemma 1.

Proof. Construct the following Lyapunov functional candidate for system (14)

$$V(k) = \eta^T(k)P\eta(k) - \frac{1}{\lambda}\theta(k) \tag{19}$$

Define the forward difference of $V(k)$ as $\Delta V(k) \triangleq V(k+1) - V(k)$. The expectation of $\Delta V(k)$ is

$$\begin{aligned} \mathbb{E}\{\Delta V(k)\} &= \left[\overline{A}\eta(k) + \tfrac{\bar{\alpha}}{\mu}\overline{L}e(k) + \bar{\beta}\overline{B}\varrho(\hat{x}(k))\right]^T \\ &\quad \times P\left[\overline{A}\eta(k) + \tfrac{\bar{\alpha}}{\mu}\overline{L}e(k) + \bar{\beta}\overline{B}\varrho(\hat{x}(k))\right] \\ &\quad + \bar{\alpha}(1-\bar{\alpha})\left[\overline{L}_c\eta(k) + \tfrac{1}{\mu}\overline{L}e(k)\right]^T P\left[\overline{L}_c\eta(k) + \tfrac{1}{\mu}\overline{L}e(k)\right] \\ &\quad + \bar{\beta}(1-\bar{\beta})\varrho^T(\hat{x}(k))\overline{B}^T P\overline{B}\varrho(\hat{x}(k)) - \eta^T(k)P\eta(k) \\ &\quad + \tfrac{1}{\lambda}(\sigma-1)\theta(k) - \tfrac{1}{\lambda}\left[e^T(k)Me(k) - \delta y\left(k^t\right)My\left(k^t\right)\right] \\ &= \xi^T(k)\Big[\Theta_1 + \mathcal{A}^T P\mathcal{A} + \bar{\beta}(1-\bar{\beta})\mathcal{B}^T P\mathcal{B} \\ &\quad + \bar{\alpha}(1-\bar{\alpha})\mathcal{C}^T P\mathcal{C}\Big]\xi(k) + \tfrac{1}{\lambda}(\sigma-1)\theta(k) \end{aligned} \tag{20}$$

where $\mathcal{A} = \begin{bmatrix} \overline{A} & \frac{\bar{\alpha}}{\mu}\overline{L} & \bar{\beta}\overline{B} \end{bmatrix}, \mathcal{B} = \begin{bmatrix} 0 & 0 & \overline{B} \end{bmatrix}, \mathcal{C} = \begin{bmatrix} \overline{L}_c & \frac{1}{\mu}\overline{L} & 0 \end{bmatrix}, \xi(k) = \begin{bmatrix} \eta^T(k) & e^T(k) & \varrho^T(\hat{x}(k)) \end{bmatrix}^T$, and

$$\Theta_1 = \begin{bmatrix} -P + \frac{\delta}{\lambda}I_{12}^T C^T MCI_{12} & * & * \\ \frac{\delta}{\mu\lambda}MCI_{12} & \frac{1}{\lambda}\left(\frac{\delta}{\mu^2}-1\right)M & * \\ 0 & 0 & 0 \end{bmatrix},$$

with $I_{12} = [I \quad I]$.

Notice that $0 < \sigma < 1$, the following inequality can be easily deduced from (3):

$$\frac{1}{\lambda}(\sigma-1)\theta(k) \leqslant (\sigma-1)\left[e^T(k)Me(k) - \delta y\left(k^t\right)My\left(k^t\right)\right] \tag{21}$$

Combining (3), (15) and (21), one can obtain

$$\begin{aligned} \mathbb{E}\{\Delta V(k)\} &\leqslant \xi^T(k)\Big[\Theta_1 + \mathcal{A}^T P\mathcal{A} + \bar{\beta}(1-\bar{\beta})\mathcal{B}^T P\mathcal{B} \\ &\quad + \bar{\alpha}(1-\bar{\alpha})\mathcal{C}^T P\mathcal{C}\Big]\xi(k) \\ &\quad + (\sigma-1)\Big\{e^T(k)Me(k) - \delta\left[CI_{12}\eta(k) + \tfrac{1}{\mu}e(k)\right]^T \\ &\quad \times M\left[CI_{12}\eta(k) + \tfrac{1}{\mu}e(k)\right]\Big\} - \eta^T(k)P\eta(k) \\ &\quad + \eta^T(k)I_1^T\Gamma^T\Gamma I_1\eta(k) - \varrho^T(\hat{x}(k))\varrho(\hat{x}(k)) \\ &= \xi^T(k)\Big[\Theta_2 + \mathcal{A}^T P\mathcal{A} + \bar{\beta}(1-\bar{\beta})\mathcal{B}^T P\mathcal{B} \\ &\quad + \bar{\alpha}(1-\bar{\alpha})\mathcal{C}^T P\mathcal{C} + \mathcal{D}^T\mathcal{D}\Big]\xi(k) \end{aligned} \tag{22}$$

where

$$\Theta_2 = \begin{bmatrix} -P - \delta(\sigma - 1 - \frac{1}{\lambda})I_{12}^T C^T MCI_{12} & * & * \\ -\frac{\delta}{\mu}(\sigma - 1 - \frac{1}{\lambda})MCI_{12} & (\sigma - 1 - \frac{1}{\lambda})\left(1 - \frac{\delta}{\mu^2}\right)M & * \\ 0 & 0 & -I \end{bmatrix},$$

and $\mathcal{D} = [\Gamma I_1 \quad 0 \quad 0], I_1 = [I \quad 0]$.

According to schur complement, we can conclude that $\mathbb{E}\{\Delta V(k)\} \leqslant 0$ from the following inequality

$$\Sigma_1 = \begin{bmatrix} \Theta_2 & * & * & * & * \\ P\mathcal{A} & -P & * & * & * \\ \rho_\beta P\mathcal{B} & 0 & -P & * & * \\ \rho_\alpha P\mathcal{C} & 0 & 0 & -P & * \\ \mathcal{D} & 0 & 0 & 0 & -I \end{bmatrix} < 0 \tag{23}$$

then the asymptotic stability of system (14) can be ensured.

In the following, the explicit form of the observer-based controller gains will be presented. Let $P = \begin{bmatrix} \bar{P} & * \\ 0 & \bar{P} \end{bmatrix}$. For $B \in \mathbb{R}^{n_x \times n_u}, rank(B) = n_u$, By using Lemma 1, there exists

$\widetilde{P} = \left(V^T\right)^{-1} S^{-1} M S V^T$ satisfying $\overline{P}B = B\widetilde{P}$. Define $Y \triangleq \widetilde{P}K$ and $Z \triangleq \overline{P}L$, then (16) can be derived from (23). This completes the proof.

When the network channel between the observer and controller works normally, which means the cyber-attacks are in absent, the closed loop system model (14) can be rewritten as

$$\eta(k+1) = \overline{A}\eta(k) + \frac{\bar{\alpha}}{\mu}\overline{L}e(k) + (\alpha(k) - \bar{\alpha})\left[\overline{L}_c\eta(k) + \frac{1}{\mu}\overline{L}e(k)\right]. \tag{24}$$

The expressions of $\overline{A}, \overline{L}$ and $\overline{L}_c$ are given in (14).

By the same derivation process as Theorem 1, based on (24), the observer-based controller design approach can be derived for system (1) with missing output measurements and DETS.

Corollary 1. *For given scalars $\lambda > 0, \delta > 0, \mu \in (0,1], \sigma \in (0,1)$ and $\bar{\alpha} \in (0,1)$ and matrix Γ, the augmented system (24) is asymptotic stable if there exist matrices $\bar{P} > 0, M > 0, Y$ and Z such that*

$$\Sigma_3 = \begin{bmatrix} \Phi_{11} & * & * \\ \Phi_{21} & \mathcal{P} & * \\ \rho_\alpha \Phi_{31} & 0 & \mathcal{P} \end{bmatrix} < 0 \tag{25}$$

where

$$\Phi_{11} = \begin{bmatrix} -\bar{P}^T - \delta\kappa C^T M C & * & * \\ -\delta\kappa C^T M C & -\bar{P}^T - \delta\kappa C^T M C & * \\ -\frac{\delta}{\mu}\kappa M C & -\frac{\delta}{\mu}\kappa M C & \kappa\left(1 - \frac{\delta}{\mu^2}\right)M \end{bmatrix},$$

$$\Phi_{21} = \begin{bmatrix} \bar{P}A + BY + \left(\bar{\alpha} - 1\right)ZC & \bar{\alpha}ZC & \frac{\bar{\alpha}}{\mu}Z \\ -\left(\bar{\alpha} - 1\right)ZC & \bar{P}A - \bar{\alpha}ZC & -\frac{\bar{\alpha}}{\mu}Z \end{bmatrix},$$

$$\Phi_{31} = \begin{bmatrix} ZC & ZC & \frac{1}{\mu}Z \\ -ZC & -ZC & -\frac{1}{\mu}Z \end{bmatrix},$$

$$\rho_\alpha = \sqrt{\bar{\alpha}\left(1 - \bar{\alpha}\right)}, \kappa = \sigma - 1 - \tfrac{1}{\lambda}, \mathcal{P} = diag\left\{-\bar{P}, -\bar{P}\right\}.$$

The observer-based controller gains are designed as (17) and (18).

Remark 7. The main challenges in deriving the control method in Theorem 1 is how to construct an dynamic event-triggered scheme to reduce the network congestion while avoiding some unnecessary abrupt data transmission, and how to deal with the impacts of the cyber-attacks and the missing output measurements. Inspired by References [25,33], the difficulties are overcome and a secure co-design approach of the observer/controller gains and the DETS matrix are presented to guarantee the desired system performance.

4. Numerical simulation

A numerical instance is utilized to verify the feasibility of the proposed control methods. Consider system (1) with the following parameters:

$$A = \begin{bmatrix} 0.1 & 0.2 & 0.6 & 0.1 \\ 0.5 & 0.2 & -0.2 & 0.1 \\ 0.7 & 0.5 & 0.4 & -0.3 \\ 0.2 & 0.1 & 0.3 & 0.6 \end{bmatrix}, B = \begin{bmatrix} 0.1 & 0.2 \\ 2.679 & 1 \\ 1.136 & -3.146 \\ 1.136 & 0 \end{bmatrix},$$

$$C = \begin{bmatrix} 0.6 & 0.5 \\ 0.8 & 0.9 \\ 0.3 & 0.7 \\ -0.2 & 1 \end{bmatrix}^T.$$

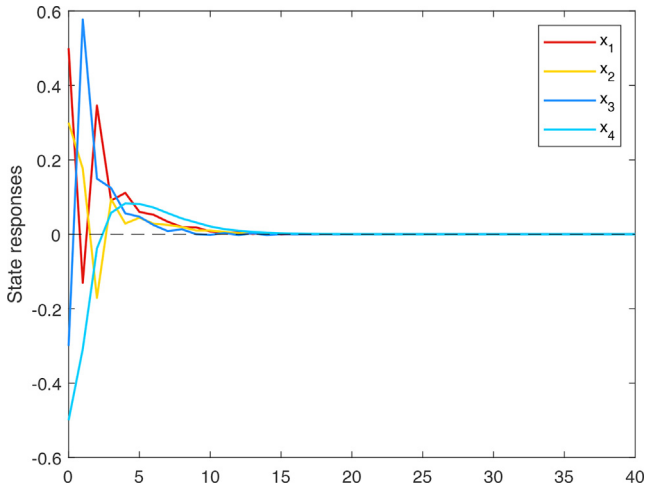

Fig. 2. State response.

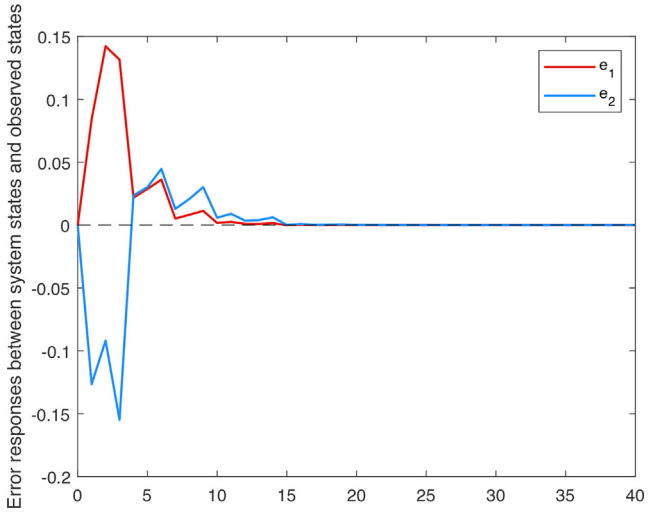

Fig. 3. Error responses between system states and observed states.

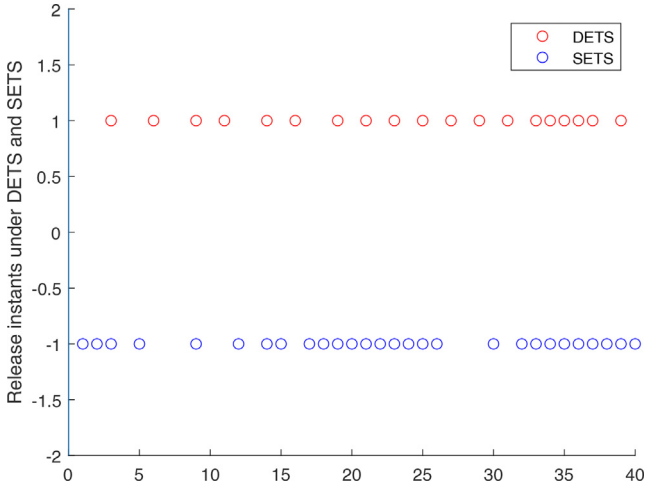

Fig. 4. Triggering instants under DETM and SETM.

The dynamic ET parameters are $\lambda = 10, \delta = 0.03, \sigma = 0.2, \mu = \frac{1}{3}$ and the initial auxiliary offset variable $\theta(0) = 10$. $\bar{\alpha} = 0.7, \bar{\beta} = 0.3$, and

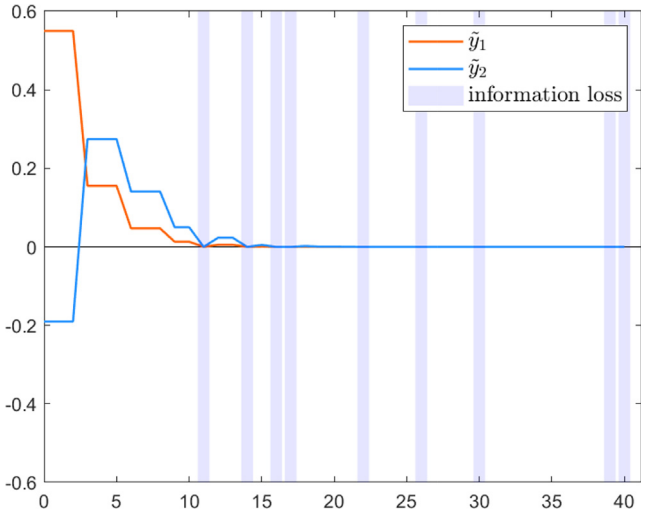

Fig. 5. The observer input with random information losses.

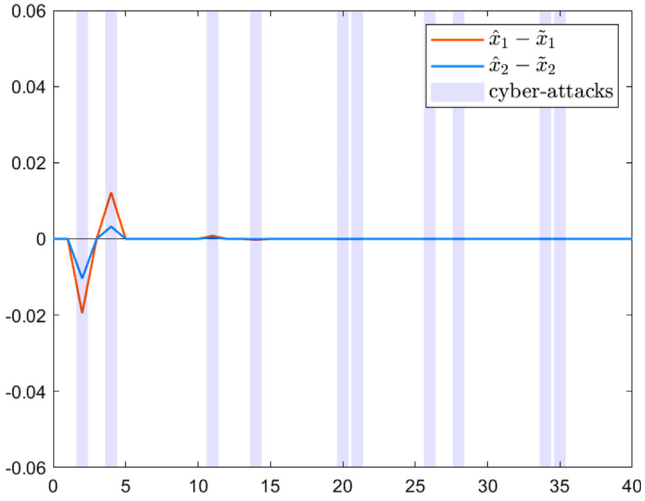

Fig. 6. The error between the signals at the observer side and the controller side subject to cyber-attacks.

the initial state and the initial observer state are $x(0) = [0.5 \quad 0.3 \quad -0.3 \quad -0.5]^T$, $\hat{x}(0) = [1 \quad 0 \quad -1 \quad 0]^T$. The NF meeting Assumption 2 is $\varrho(\hat{x}(k)) = diag\{0.2\sin(k), 0.1\sin(k), 0.3\sin(k), 0.2sin(k)\} \times \hat{x}(k)$with $\Gamma = diag\{0.2, 0.1, 0.3, 0.2\}$

Then, by solving LMI conditions given by Theorem 1, dynamic ET matrix M, observer gain L and controller gain K can be calculated as

$$M = \begin{bmatrix} 1.6665 & -0.4617 \\ -0.4617 & 0.8610 \end{bmatrix},$$

$$L = \begin{bmatrix} 0.0366 & 0.0272 & 0.0917 & 0.0145 \\ 0.0151 & 0.0332 & 0.0532 & 0.0389 \end{bmatrix}^T,$$

$$K = \begin{bmatrix} -0.0634 & -0.0365 & -0.0210 & -0.0332 \\ 0.0853 & 0.0846 & 0.1157 & -0.0158 \end{bmatrix}.$$

The simulation results are given in Fig. 2–6. Fig. 2 shows the system state converges to zero which illustrates the designed controller can ensure the stability of the augmented system. Fig. 3 depicts the error between system state and observer state which implies the effectiveness of the observer. The releasing instants of DETS and static ET scheme are shown in Fig. 4. Within the simulation interval, 28 data have been triggered under static ET scheme, while only 19 signals have been released into the wireless network under DETS. In other words, 47.5% signals takes up bandwidth resources under DETS, while 70% sampled signals are released under static ET scheme. The observer input $\tilde{y}(k)$ with random information loss is depicted in Fig. 5, from which we can see the observer input $\tilde{y}(k)$ will turn to zero when information missing happens. The error between the signals at the observer side $\hat{x}(k)$ and the controller side $\tilde{x}(k)$ subject to cyber-attacks is displayed in Fig. 6. Under the influence of malicious attacks, the signal $\tilde{x}(k)$ will suddenly deviate from the normal value $\hat{x}(k)$. From the above simulation results, we can see the validity and merit of the proposed methods is illustrated.

5. Conclusions

In this article, the problem of dynamic ET observer-based control has been solved for a class of NCSs with missing output measurements and malicious cyber-attacks. A novel DETS is developed to make effective use of the constrained network resources. Considering the situation of unreliable communication network and limited networked resources, a new model has been proposed to reflect the phenomena of the missing output measurements and randomly occurring cyber-attacks under the adopted DETS. The observer gain, controller gain, and the parameters of the DETS have been co-designed. Finally, the validity of the proposed control algorithm has been checked by the simulation results. In the future, we will extend the proposed DETS into the consensus control of mutiagent systems and sensor networks.

CRediT authorship contribution statement

Lijuan Zha: Conceptualization, Methodology, Investigation, Formal analysis, Resources, Writing - original draft, Writing - review & editing. **Rongfei Liao:** Writing - original draft, Data curation, Validation, Formal analysis. **Jinliang Liu:** Investigation, Resources, Formal analysis, Writing - review & editing. **Jinde Cao:** Conceptualization, Supervision, Methodology, Project administration. **Xiangpeng Xie:** Investigation, Writing - review & editing, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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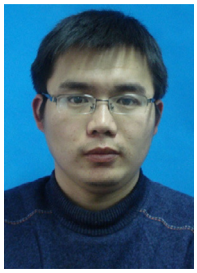

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