Secure State Estimation for Interval Type-2 Fuzzy Systems With FDI Attacks and Event-Triggered WTOD Protocol

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Abstract—The article designs a secure co-estimation approach for nonlinear systems with false data injection (FDI) attack and network bandwidth limitations, which is described by interval type-2 (IT2) fuzzy system. For mitigating communication load and avoiding network data collision, an event-triggered weighted try-once-discard protocol is implemented to adjust the data transmission frequency. Given the unknown system state and FDI attacks, both of the state observer and the attack observer are put forward. Besides, a new attack compensation controller is proposed under co-design of the observer of the state and FDI attack. The asymptotical stability of the augmented system can be realized by the proposed sufficient conditions for the existence of the fuzzy observer and controller gains, while the prescribed H_{∞} performance requirement can be met. Then the secure controller design method is given accordingly. Finally, the validity of the attained results are provided by simulation examples.

Index Terms—Event-triggered control, false data injection attacks (FDI), interval type-2 fuzzy system, weighted try-once discard protocol.

I. INTRODUCTION

DUE TO the higher and higher requirements of industrial automation and control precision, the control objects are constantly changing and expanding to complex nonlinear

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systems. The existence of the nonlinearity makes the controlled system analysis and design become harder. Nowadays, the Takagi-Sugeno (T-S) fuzzy modeling method is Widely recognized as an effective approach in charactering the nonlinear systems [1], [2], [3]. With membership functions (MFs) and if-then rules, nonlinear networked control systems (NCSs) can be approximated by several linear subsystems [4]. Nowadays, interval type-1 (IT1) fuzzy model and interval type-2 (IT2) fuzzy model are two types of models representing the nonlinear systems [5], [6], [7]. Compared with the former, the advantage of the latter type lies in its flexibility, which can handle the uncertainty in nonlinear systems by the lower and upper MFs [8]. Some control or filtering approach for IT2 fuzzy systems have been proposed, such as the modelpredictive control in [9], finite frequency fault detection filter design in [10] and fault-tolerant control in [11] for interval IT2 fuzzy system. Therefore, control or filtering approaches for T-S fuzzy systems continue to receive attention.

As is known, event-triggering control (ETC) is an prominent method to reduce network communication, the key of which is to reasonably utilize limited network resources (LNR) by managing information transmission frequency and controller execution frequency [12], [13], [14]. Compared with the conventional periodic sampling strategy, the execution of control tasks under the event-triggering mechanism (ETM) depends on the designed event-triggering conditions instead of the fixed time [15], [16], [17]. Therefore, benefiting from ETM, the consumption of computing and LNR can be relieved effectively while maintaining the control performance. So far, a variety of ETMs have been proposed for nonlinear NCSs [18], [19], [20]. For example, to deal with output feedback issues, a novel estimate-based control strategy is designed under the dynamic event-triggering (DET) strategy in [21]. In [22], the DET-based integral sliding-mode controller is presented for nonlinear NCSs by robust adaptive dynamic programming. However, the issue of security-ensured DET combined with try-once-discard protocol are rarely investigated for nonlinear network systems.

In addition to the ETMs, various network scheduling protocols are also efficient methods to make reasonable and effective use of LNR [23], [24], [25]. Network communication protocols are usually used to control the transmission order of data, so as to achieve the purpose of reasonable allocation of LNR [26], [27]. Up to now, many different communication

protocols have been applied in nonlinear NCSs [28], [29]. Compared with other protocols, the data transmission sequence regulated by weighted try-once-discard (WTOD) protocol depends on the maximum weight error of sensor points, which has the advantage of initiative and flexibility. At present, WTOD protocol are highly applied in security controller design [30] and sliding-mode control problem [31]. However, WTOD protocol and DET strategy are rarely simultaneously considered which motivates the current brief.

In the nonlinear NCSs, besides the bandwidth constraint, network security is another problem that has received extensive attention [32], [33], [34]. Due to the open and fragile characteristics of the network, the nonlinear NCSs may compromise with malicious attacks by hackers, resulting in destruction of the transmitted signal authenticity and integrity [35], [36], [37], [38], [39]. In NCSs, there exist different security threats in communication networks, such as false data injection (FDI) attacks [40], [41] and denial-of-service (DoS) attacks [42], [43]. FDI attacks destroy the authenticity of data by injecting malicious data into nonlinear NCSs [44]. In [45], the FDI and DoS attacks are considered in designing the resilient control method for multiarea load frequency control systems. The distributed estimation problem is studied in [46] for multiarea power systems against FDI attacks. Given that the DET strategy, the WTOD protocol and the FDI attacks are not constructed in a framework in the mentioned results. The secure co-estimation problem for nonlinear NCSs is still open and needs to be discussed.

In this article, the secure co-estimation and control approach is proposed for nonlinear NCSs subject to LNR and FDI attacks based on IT2 fuzzy model. In contrast to the existing works, the method proposed in this article exhibits good robustness and has the following significant advantages.

- For easing the network transmission burden, a novel DETTOD protocol is proposed for the nonlinear networked systems under the effect of FDI attacks, under which only one group is accessible to transmit signals over the communication network at the triggering instant. Compared with some existing results [21], [45], the data collisions can be avoided.
- 2) For the IT2 fuzzy model, considering the DETTOD protocol and the FDI attacks, the observers of state and FDI attacks are co-designed and a new observer-based attack compensation controller is presented to ensure the expected system performance while the negative effects of the FDI attacks is suppressed. Different from [30], the developed observer-based controller can automatically estimate and compensate for FDI attacks without extra restrictions on FDI attacks, which has great advantages to avoid the adverse effect of FDI attacks.

Notation: \mathbb{R}^m stands for the *m*-dimensional Euclidean space, I is the identity matrix of appropriate dimensions and 0 represents the zero matrix of compatible dimensions. The superscript T stands for matrix transposition. The symbol diag $\{\ldots\}$ represents a block-diagonal matrix and * stands for the symmetric term in a symmetric block matrix. $||\cdot||$ is the Euclidean norm of a vector and its induced norm of a matrix. The arguments of functions are

sometimes simplified, for example, $h_i(x(k))g_j(\hat{x}(k))$ is donated by $h_{ii}(k)$.

II. PROBLEM DESCRIPTION

A. Interval Type-2 T-S Fuzzy Model

In this article, the *i*th rule of the IT-2 fuzzy model is **Plant Rule** *i*:

IF ϑ_{1x} is W_1^i , ϑ_{2x} is W_2^i , ..., ϑ_{lx} is W_l^i , **THEN**

$$\begin{cases} x(k+1) = A_{i}x(k) + B_{i}(u(k) + a(k)) + D_{i}\omega(k) \\ y(k) = C_{i}x(k) \\ z(k) = M_{i}x(k), i = 1, \dots, s \end{cases}$$
 (1)

where $\vartheta_{vx} = \vartheta_v(x(k))$, W_d^i represents the fuzzy set corresponding to $\vartheta_d(k)$, in which $i=1,2,\ldots,s,\ d=1,2,\ldots,l,\ x(k)\in\mathbb{R}^{n_x},\ u(k)\in\mathbb{R}^{n_u},\ y(k)\in\mathbb{R}^{n_y},\ z(k)\in\mathbb{R}^{n_z}$ and $\omega(k)\in\mathbb{L}_2[0,\infty)$ are the system state, the control input, the measurement output, the control output and the disturbance input, respectively. $a(k)\in\mathbb{R}^{n_u}$ represents the unknown FDI attack signal. $A_i,\ B_i,\ C_i,\ D_i,\$ and M_i are known constant matrices and B_i is assumed to be full column.

For the *i*th rule, the firing strength h_{ix} belongs to the interval set S_i with $S_i = [\underline{h}_{ix}, \overline{h}_{ix}]$, where $\underline{h}_{ix} = \prod_{d=1}^l \underline{W}_d^i(\vartheta_{dx})$ and $\overline{h}_{ix} = \prod_{d=1}^l \overline{W}_d^i(\vartheta_{dx})$ stand for the lower and upper membership value, respectively. In addition, $\overline{W}_d^i(\vartheta_{dx}) \in [0, 1]$ and $\underline{W}_d^i(\vartheta_{dx}) \in [0, 1]$ are the lower and upper MFs, respectively.

The model of the overall system (1) is inferred as

$$\begin{cases} x(k+1) = \sum_{i=1}^{s} h_{ix}[A_{i}x(k) + B_{i}(u(k) + a(k)) \\ + D_{i}\omega(k)] \\ y(k) = \sum_{i=1}^{s} h_{ix}C_{i}x(k) \\ z(k) = \sum_{i=1}^{s} h_{ix}M_{i}x(k) \end{cases}$$
(2)

where

$$h_{ix} = \frac{\varrho_{ix}}{\sum_{i=1}^{s} \varrho_{ix}}$$

which is the normalized membership and satisfies $h_{ix} \ge 0$ and $\sum_{i=1}^{s} h_{ix} = 1$. $\varrho_{ix} = \underline{\alpha}_{ix} \underline{h}_{ix} + \overline{\alpha}_{ix} \overline{h}_{ix}$, in which $0 \le \underline{\alpha}_{ix} \le 1$ and $0 \le \overline{\alpha}_{ix} \le 1$ are the nonlinear weighting functions (NWFs) with $\underline{\alpha}_{ix} + \overline{\alpha}_{ix} = 1$.

Remark 1: In this article, the interaction channel between the actuator and controller are assumed to be attacked by hackers injecting FDI attacks, resulting in abnormal noise added to the normal control signal or loss of the normal control signal. Therefore, the attack signal a(k) is used in this article to describe the corresponding negative impacts.

B. DETTOD Protocol

In NCSs, the issue of LNR may cause data collisions and network congestion, significantly degrade system performance, and even destabilize the system. Given this, a novel scheduling protocol is presented to determine whether the signals of sensor nodes will be transmitted through a communication network with bandwidth constraints. Specifically, partition sensor measurement $y(k) = [y_1(k), y_2(k), \dots, y_{n_y}(k)]$, the transmitted sensor measurements should satisfy the DET condition first, whether or not the component $y_i(k)$, $i = 1, \dots, n_y$ will be sent into network is governed by WTOD protocol.

To reduce unnecessary channel occupancy and save LNR, a new DET strategy is implemented between sensors and observers. Then, we define the following ETM:

$$t_{n+1} = \min_{k \in \mathbb{N}^+} \{ k | k > t_n, \, \psi(k) \ge 0 \}$$
 (3)

where $\psi(k) = \chi^T(k)\Omega\chi(k) - \sigma(t_n)y^T(k)\Omega y(k)$ and $\chi(k) = y(k) - y(t_n)$, $k \in [t_n, t_{n+1})$. Among them, y(k) is the current sampled signal and $y(t_n)$ is the latest triggering measurement signal. $\sigma(t_n) \in (0, 1)$ and $\Omega > 0$ are the event-triggered threshold and the weighting matrix, respectively.

The threshold variable $\sigma(t_n)$ in (3) is designed as

$$\begin{cases} \sigma(t_n) = \lambda \cdot g(t_n) \\ g(t_n) = 1 - \frac{1}{1 + \beta \cdot e^{-(||x(t_n)|| - ||x(t_{n-1})||)}} \end{cases}$$
(4)

with $\lambda \in (0, 1]$ and $\beta > 0$ being given constants.

It is observed from (3) that the measuring signal will be granted transfer permission if and only if the condition $\psi(k) \ge 0$ holds.

Remark 2: The event-triggered threshold $\sigma(t_n)$ shown in (4) can vary with the change of state evolution. When $||x(t_n)|| < ||x(t_{n-1})||$, it means the system state tends to be stable, then $\sigma(t_n)$ will increase and the trigger frequency will decrease. $||x(t_n)|| \ge ||x(t_{n-1})||$ indicates the system state is unstable, under this case, $\sigma(t_n)$ will reduce and the sampled state will easily be triggered. Therefore, the dynamic ETM threshold $\sigma(t_n)$ designed in this work can help enhance the adaptivity of the ETM. In addition, λ and $\beta > 0$ are pregiven in practice.

For the purpose of further relieve the data collisions, WTOD protocol is introduced to identify the sensor nodes that are granted access to the network. Under WTOD protocol, only one triggered components $y_i(t_n)$ can pass through the communication network. By utilizing a zero-order holder (ZOH), the updated rule of the observer input is

$$\bar{y}_i(k) = \begin{cases} y_i(t_n), & i = \delta(t_n) \\ \bar{y}_i(k-1), & \text{otherwise.} \end{cases}$$
 (5)

where $\delta(t_n)$ denotes the corresponding sensor point obtains the permission of data transmission at the moment t_n , and $\delta(t_n)$ can be expressed as

$$\delta(t_n) = \arg \max_{1 \le i \le n_y} (y_i(t_n) - \bar{y}_i(k-1))^T Q_i(y_i(t_n) - \bar{y}_i(k-1))$$
(6)

where Q_i is a known matrix and $\bar{y}_i(t_{n-1})$ stands for the last transmitted signal.

Define

$$\iota(i) = \begin{cases} 0, & i \neq 0 \\ 1, & i = 0. \end{cases}$$
 (7)

Under the proposed DETTOD protocol's update principle (3), (5), and (6), $\bar{y}(k)$ is expressed as

$$\bar{y}(k) = \Phi_{\delta(t_n)} y(t_n) + \left(I - \Phi_{\delta(t_n)} \right) \bar{y}(k-1) \tag{8}$$

where $\Phi_i \triangleq \text{diag}\{\iota(i-1)I, \iota(i-2)I, \dots, \iota(\delta(t_n)-n_y)I\}$ $(1 \leq \delta(t_n) \leq n_y)$.

Remark 3: Different from the existing event triggered mechanisms, the DETTOD protocol in this article can further

reduce the transmission amount and avoid data collisions. The DETTOD protocol is proposed by organically combining the merits of DET strategy and WTOD protocol. If the current data $y(t_n)$ is triggered by the DET strategy (3), the triggered signal $y(t_n)$ will be scheduled by the WTOD protocol. Only one component $y_i(t_n)$ with the largest weighted error from the last reported value can be permitted to be sent for transmission. Thus, the occurrences of network congestions can be effectively avoided.

Remark 4: Here, the DETTOD protocol is employed to deal with the issue of limited communication capacity in the controlled system. It should be mentioned that this protocol can also be extended to regulate the signal transmission in the fault-tolerant control problem in [11] and the fault estimation for fuzzy systems in [7], which will be our future work.

C. FDI Attacks Model

Similar to [47], the FDI attack signal a(k) in (1) is represented as

$$\begin{cases} \eta(k+1) = E\eta(k) \\ a(k) = F\eta(k) \end{cases}$$
 (9)

where $\eta(k) \in \mathbb{R}^{n_{\eta}}$, $E \in \mathbb{R}^{n_{\eta} \times n_{\eta}}$ and $F \in \mathbb{R}^{n_{u} \times n_{\eta}}$.

Remark 5: In this article, the FDI attack model (9) under consideration is more universal by comparison with some existing models [40], [45], [46]. Specifically, the attacker destroys the transmitted signal by arbitrarily controlling the matrices E and F. As a Hurwitz matrix, the matrix E is usually chosen to limit the bounds of the injected signal a(k). Furthermore, in an effort to make the research more convincing, it is assumed here that all the underlying system information is possible to be maliciously accessed by FDI attackers.

D. Observer-Based Fuzzy Controller

For handling the influences of DETTOD protocol and FDI attacks, the form of the fuzzy controller are designed as

Controller Rule *j*:

IF
$$\epsilon_{1\hat{x}}$$
 is N_1^j , $\epsilon_{2\hat{x}}$ is N_2^j , ..., $\epsilon_{p\hat{x}}$ is N_p^j ,

$$\begin{cases}
\hat{x}(k+1) = A_{j}\hat{x}(k) + B_{j}(u(k) + a(k)) + L_{j,\delta(t_{n})} \\
(C_{j}\hat{x}(k) - \bar{y}(k)) \\
\hat{y}(k) = C_{j}\hat{x}(k) \\
u(k) = K_{j,\delta(t_{n})}C_{j}\hat{x}(k) - \hat{a}(k), j = 1, \dots, s
\end{cases}$$
(10)

where $\epsilon_{w\hat{x}} = \epsilon_w(\hat{x}(k)) \ \hat{x}(k)$ is the state estimate, u(k) is the compensation controller under the effect of FDI attacks and $\delta(t_n) = 1, 2, ..., n_y$. $L_{j,\delta(t_n)}$ and $K_{j,\delta(t_n)}$ stand for the fuzzy observer gains and the fuzzy controller gains to be devised, respectively.

Denoted the following interval sets as the firing strength of the *j*th rule:

$$T_j = [\underline{g}_{j\hat{x}}, \overline{g}_{j\hat{x}}]$$

where $\underline{g}_{j\hat{x}} = \prod_{b=1}^p \underline{N}_b^j(\epsilon_{b\hat{x}})$ and $\overline{g}_{j\hat{x}} = \prod_{b=1}^p \overline{N}_b^j(\epsilon_{b\hat{x}})$ stand for the lower and upper membership value, respectively. In

addition, $\overline{N}_b^j(\epsilon_{b\hat{x}}) \in [0, 1]$ and $\underline{N}_b^j(\epsilon_{b\hat{x}}) \in [0, 1]$ are the lower and upper MFs, respectively.

Thus, the overall observer-based fuzzy controller is formulated as

$$\begin{cases} \hat{x}(k+1) = \sum_{j=1}^{s} g_{j\hat{x}} [A_j \hat{x}(k) + B_j(u(k) + a(k)) \\ + L_{j,\delta(t_n)} (C_j \hat{x}(k) - \bar{y}(k))] \\ \hat{y}(k) = \sum_{j=1}^{s} g_{j\hat{x}} C_j \hat{x}(k) \\ u(k) = \sum_{j=1}^{s} g_{j\hat{x}} [K_{j,\delta(t_n)} C_j \hat{x}(k) - \hat{a}(k)] \end{cases}$$
(11)

where

$$g_{j\hat{x}} = \frac{\kappa_{j\hat{x}}}{\sum_{i=1}^{s} \kappa_{j\hat{x}}}$$

which is the normalized membership and satisfies $g_{j\hat{x}} \geq 0$ and $\sum_{j=1}^{s} g_{j\hat{x}} = 1$. Besides, $\kappa_{j\hat{x}} = \underline{c}_{j\hat{x}}\underline{g}_{j\hat{x}} + \overline{c}_{j\hat{x}}\overline{g}_{j\hat{x}}$, in which $\underline{c}_{j\hat{x}}$ and $\overline{c}_{j\hat{x}}$ taking values in [0, 1] are NWFs with $\underline{c}_{i\hat{x}} + \overline{c}_{j\hat{x}} = 1$ and the attack estimation $\hat{a}(k) = F\hat{\eta}(k)$.

E. FDI Attacks Observer

In an effort to estimate the magnitude of unknown FDI attack signal a(k), the intermediate variable $\eta(k)$ in (9) should be estimated. Obviously, the solution of system (9) is unique under given initial conditions. Thus, for a given matrix $G_{\delta(t_n)}$, there is a unique solution m = m(k) denoted by

$$m(k) = \eta(k) - G_{\delta(t_n)}\hat{x}(k) \tag{12}$$

for the following system,

$$m(k+1) = \sum_{j=1}^{s} g_{j\hat{x}} [(E - G_{\delta(t_{n+1})} B_{j} F) m(k) + (EG_{\delta(t_{n})} - G_{\delta(t_{n+1})} A_{j} - G_{\delta(t_{n+1})} B_{j} F G_{\delta(t_{n})}) \hat{x}(k) - G_{\delta(t_{n+1})} B_{j} u(k) - G_{\delta(t_{n+1})} L_{j,\delta(t_{n})} (C_{j} \hat{x}(k) - \bar{y}(k))]$$
(13)

which can be derived from (2), (9), (11), and (12).

Assume that there exists a unique solution to (13), the solution $\eta = \eta(k)$ of (9) can be determined uniquely with

$$\eta(k) = m(k) + G_{\delta(t_n)}\hat{x}(k). \tag{14}$$

Based on the previous analysis, the designed indirect-attack observer can described as

$$\begin{cases}
\hat{m}(k+1) = \sum_{j=1}^{s} g_{j\hat{x}} [(E - G_{\delta(t_{n+1})} B_{j}F) \hat{m}(k) \\
+ (EG_{\delta(t_{n})} - G_{\delta(t_{n+1})} A_{j} \\
- G_{\delta(t_{n+1})} B_{j}FG_{\delta(t_{n})}) \hat{x}(k) - G_{\delta(t_{n+1})} B_{j}u(k) \\
- G_{\delta(t_{n+1})} L_{j,\delta(t_{n})} (C_{j}\hat{x}(k) - \bar{y}(k))] \\
\hat{\eta}(k+1) = \hat{m}(k+1) + G_{\delta(t_{n+1})} \hat{x}(k+1), \\
j = 1, \dots, s, \delta(t_{n}) = 1, 2, \dots, n_{y}.
\end{cases} (15)$$

Define $e_x(k) = x(k) - \hat{x}(k)$ and $e_{\eta}(k) = \eta(k) - \hat{\eta}(k)$. According to (2), (9), (11), (13), and (15), it can be inferred that

$$x(k+1) = \sum_{i=1}^{s} \sum_{j=1}^{s} h_{ij}(k) [(A_i + B_i K_{j,\delta(t_n)} C_j) x(k) - B_i K_{j,\delta(t_n)} C_j e_x(k) + B_i F e_{\eta}(k) + D_i \omega(k)]$$
(16)

$$\hat{x}(k+1) = \sum_{i=1}^{s} \sum_{j=1}^{s} h_{ij}(k) [(A_j + B_j K_{j,\delta(t_n)} C_j$$

$$+L_{j,\delta(t_{n})}C_{j} - L_{j,\delta(t_{n})}\Phi_{\delta(t_{n})}C_{i})x(k) + (-A_{j} - B_{i}K_{j,\delta(t_{n})}C_{j} - L_{j,\delta(t_{n})}C_{j})e_{x}(k) + B_{j}Fe_{\eta}(k) + L_{j,\delta(t_{n})}\Phi_{\delta(t_{n})}\chi(k) - L_{j,\delta(t_{n})}(I - \Phi_{\delta(t_{n})})\bar{y}(k - 1)]$$
(17)
$$e_{\eta}(k+1) = m(k+1) - \hat{m}(k+1) = \sum_{j=1}^{s} g_{j\hat{x}}[(E - G_{\delta(t_{n+1})}B_{j}F)e_{\eta}(k)]$$
(18)
$$e_{x}(k+1) = \sum_{i=1}^{s} \sum_{j=1}^{s} h_{ij}(k)\{[(A_{i} - A_{j}) + (B_{i} - B_{j})K_{j,\delta(t_{n})}C_{j} + L_{j,\delta(t_{n})}C_{i} - C_{j})]x(k) + [(A_{j} - (B_{i} - B_{j})K_{j,\delta(t_{n})}C_{j} + L_{j,\delta(t_{n})}\Phi_{\delta(t_{n})}\chi(k)$$

$$e_{x}(k) + (B_{i} - B_{j})Fe_{\eta}(k) - L_{i,\delta(t_{n})}\Phi_{\delta(t_{n})}\chi(k)$$

Based on (16)–(18), we can derive:

$$\begin{cases} \xi(k+1) = \sum_{i=1}^{s} \sum_{j=1}^{s} h_{ij}(k) [\vec{A}_{ij,\delta(t_n)} \xi(k) \\ + \vec{B}_{j,\delta(t_n)} \chi(k) + \vec{D}_i \omega(k)] \\ z(k) = \sum_{i=1}^{s} h_{ix} M_i x(k) \end{cases}$$
(20)

 $+L_{i\delta(t_{m})}(I-\Phi_{\delta(t_{m})})\bar{y}(k-1)+D_{i}\omega(k)\}.$ (19)

where

$$\xi(k) = [x^{I}(k) \quad \bar{y}^{I}(k-1) \quad e_{x}^{I}(k) \quad e_{\eta}^{I}(k)]^{I}$$

$$\vec{A}_{ij,\delta(t_{n})} = \begin{bmatrix} \Pi_{11} & 0 & -B_{i}K_{j,\delta(t_{n})}C_{j} & B_{i}F \\ \Phi_{\delta(t_{n})}C_{i} & \Gamma(t_{n}) & 0 & 0 \\ \Pi_{31} & \Pi_{32} & \Pi_{33} & \Pi_{34} \\ 0 & 0 & 0 & \Pi_{44} \end{bmatrix}$$

$$\vec{B}_{j,\delta(t_{n})} = \begin{bmatrix} 0 \\ -\Phi_{\delta(t_{n})} \\ -L_{j,\delta(t_{n})}\Phi_{\delta(t_{n})} \\ -L_{j,\delta(t_{n})}\Phi_{\delta(t_{n})} \end{bmatrix}, \vec{D}_{i} = \begin{bmatrix} D_{i} \\ 0 \\ D_{i} \\ 0 \end{bmatrix}$$

$$\Pi_{11} = A_{i} + B_{i}K_{j,\delta(t_{n})}C_{j}, \Gamma(t_{n}) = I - \Phi_{\delta(t_{n})}$$

$$\Pi_{31} = (A_{i} - A_{j}) + (B_{i} - B_{j})K_{j,\delta(t_{n})}C_{j} + L_{j,\delta(t_{n})}$$

$$(\Phi_{\delta(t_{n})}C_{i} - C_{j})$$

$$\Pi_{32} = L_{j,\delta(t_{n})}\Gamma(t_{n})$$

$$\Pi_{33} = A_{j} - (B_{i} - B_{j})K_{j,\delta(t_{n})}C_{j} + L_{j,\delta(t_{n})}C_{j}$$

$$\Pi_{34} = (B_{i} - B_{j})F, \Pi_{44} = E - G_{\delta(t_{n+1})}B_{j}F.$$

Definition 1: For any $\zeta > 0$, the mean-square stability of (20) is said to be achieved if there exists $M(\zeta) > 0$ such that $||\xi(k)||^2 < \zeta$, k > 0 when $||\xi(0)||^2 < M(\zeta)$. In addition, the global mean-square asymptotical stability is ensured if $\lim ||\xi(k)||^2 = 0$ for any initial condition.

In the following, we are devoted to investigate the control method of nonlinear NCSs (2) with DETTOD protocol under FDI attacks. With the designed observer-based controller, the following requirements are satisfied.

- 1) The asymptotical stability of (20) is achieved when $\omega(k) \equiv 0$.
- 2) Under the zero-initial condition, the below condition holds

$$\sum_{k=0}^{\infty} ||z(k)||^2 < \gamma^2 \sum_{k=0}^{\infty} ||\omega(k)||^2.$$
 (21)

III. MAIN RESULTS

Note that the imperfectly matched MFs of controlled plant (2) and the observed-based controller (11) lead to the existence of $\sum_{i=1}^{s} \sum_{j=1}^{s} h_{ij}(k)$ in (19) and (20). For handling this, similar to [15], we define the lower and the global upper bound of $h_{ij}(k)$ as \underline{u}_{ij} and \overline{u}_{ij} . The slack matrices $\underline{R}_{ij} \geq 0$ and $\overline{R}_{ij} \geq 0$ satisfy the conditions as follow:

$$\sum_{i=1}^{s} \sum_{j=1}^{s} \left(h_{ij}(k) - \underline{u}_{ij} \right) \underline{R}_{ij} \ge 0$$
 (22)

$$\sum_{i=1}^{s} \sum_{j=1}^{s} (\overline{u}_{ij} - h_{ij}(k)) \overline{R}_{ij} \ge 0.$$
 (23)

Next, to achieve the stability of the addressed system, a sufficient condition will be developed in Theorem 1. Afterward, the co-design method of the state observer gains $L_{j,\delta(t_n)}$, the attack observer gains $G_{\delta(t_n)}$ and controller gains $K_{j,\delta(t_n)}$ will be acquired in Theorem 2.

Theorem 1: For given $\Omega > 0$, $\lambda \in (0,1]$, the state observer gains $L_{j,\delta(t_n)}$, the attack observer gains $G_{\delta(t_n)}$, controller gains $K_{j,\delta(t_n)}$ and predefined H_{∞} performance index γ , the system (20) is globally mean-square asymptotically stable and performance constraint (21) is achieved if there exist scalars $\mu_q(k) > 0$, matrices $\underline{R}_{ij} > 0$, $\overline{R}_{ij} > 0$ and $P_r > 0$ with $i, j = 1, 2, \ldots, s$ and $r = 1, 2, \ldots, n_y$, such that

$$\Xi_{ij,r} - \overline{R}_{ij} + \underline{R}_{ij} + \sum_{i=1}^{s} \sum_{i=1}^{s} \left(\overline{u}_{ij} \overline{R}_{ij} - \underline{u}_{ij} \underline{R}_{ij} \right) < 0 \qquad (24)$$

where

$$\Xi_{ij,r} = \begin{bmatrix} \Xi_{i,r}^{11} & * & * & * \\ \Xi^{21} & \Xi^{22} & * & * \\ 0 & 0 & -\gamma^{2}I & * \\ \bar{A}_{ij,r} & \bar{B}_{j,r} & \bar{D}_{i} & -P_{r+1}^{-1} \end{bmatrix}$$

$$\Xi_{i,r}^{11} = -P_{r} + \lambda H_{1}^{T} C_{i}^{T} \Omega C_{i} H_{1} + H_{1}^{T} M_{i}^{T} M_{i} H_{1}$$

$$- \sum_{q=1}^{n_{y}} \mu_{q}(k) (C_{i} H_{1} - H_{2})^{T} \tilde{Q}_{q}(C_{i} H_{1} - H_{2})$$

$$\Xi^{21} = - \sum_{q=1}^{n_{y}} \mu_{q}(k) \tilde{Q}_{q}(C_{i} H_{1} - H_{2})$$

$$\Xi^{22} = -\Omega - \sum_{q=1}^{n_{y}} \mu_{q}(k) \tilde{Q}_{q}$$

$$H_{1} = \begin{bmatrix} I & 0 & 0 & 0 \end{bmatrix}$$

$$\tilde{Q}_{q} = \tilde{Q}_{q} - \tilde{Q}_{r}, \tilde{Q}_{q} \triangleq \operatorname{diag}\{Q_{1}, \dots, Q_{n_{y}}\} \Phi_{q}$$

$$H_{2} = \begin{bmatrix} 0 & I & 0 & 0 \end{bmatrix}, r = \delta(t_{n}).$$

Proof: Construct a Lyapunov-Krasovskii function as

$$V(k) = \xi^{T}(k)P_{r}\xi(k). \tag{25}$$

From (20), one can derive

$$\Delta V(k) = V(k+1) - V(k)$$

$$= \sum_{i=1}^{s} \sum_{j=1}^{s} h_{ij}(k) \left[\vec{A}_{ij,r} \xi(k) \right]$$

$$+\vec{B}_{j,r}\chi(k) + \vec{D}_{i}\omega(k) \Big]^{T} P_{r+1} \Big[\vec{A}_{ij,r}\xi(k) + \vec{B}_{j,r}\chi(k) + \vec{D}_{i}\omega(k) \Big] - \xi^{T}(k) P_{r}\xi(k).$$
 (26)

Noting (6), we have

$$(y_r(t_n) - \bar{y}_r(k-1))^T Q_r(y_r(t_n) - \bar{y}_r(k-1))$$

$$\geq (y_q(t_n) - \bar{y}_q(k-1))^T Q_q(y_q(t_n) - \bar{y}_q(k-1))$$
 (27)

and it further indicates

$$(y(t_n) - \bar{y}(k-1))^T \bar{Q}_r(y(t_n) - \bar{y}(k-1)) \ge (y(t_n) - \bar{y}(k-1))^T \bar{Q}_q(y(t_n) - \bar{y}(k-1)).$$
 (28)

Based on (1), (3), and (28), we can concluded that

$$\begin{bmatrix}
C_i x(k) - \chi(k) - \bar{y}(k-1)
\end{bmatrix}^T \times (\bar{Q}_q - \bar{Q}_r) \\
\times \left[C_i x(k) - \chi(k) - \bar{y}(k-1)\right] \le 0.$$
(29)

In light of (3), (26), and (29), we can get

$$\Delta V(k) \leq \sum_{i=1}^{s} \sum_{j=1}^{s} h_{ij}(k) \left[\vec{A}_{ij,r} \xi(k) + \vec{B}_{j,r} \chi(k) + \vec{D}_{i} \omega(k) \right]^{T} P_{r+1}
\left[\vec{A}_{ij,r} \xi(k) + \vec{B}_{j,r} \chi(k) + \vec{D}_{i} \omega(k) \right] - \xi^{T}(k) P_{r} \xi(k)
- \chi^{T}(k) \Omega \chi(k) + \lambda \xi^{T}(k) H_{1}^{T} C_{i}^{T} \Omega C_{i} H_{1} \xi(k)
- \sum_{q=1}^{n_{y}} \mu_{q}(k) \left[(C_{i} H_{1} - H_{2}) \xi(k) - \chi(k) \right]^{T}
(\bar{Q}_{q} - \bar{Q}_{r}) \left[(C_{i} H_{1} - H_{2}) \xi(k) - \chi(k) \right].$$
(30)

According to schur complement, it can derive that

$$\Delta V(k) \le \tau^{T}(k) \left(\bar{\Xi}_{i,r} + \tilde{\Upsilon}_{ii,r}^{T} P_{r+1}^{-1} \tilde{\Upsilon}_{ij,r} \right) \tau(k)$$
 (31)

where

$$\begin{split} \boldsymbol{\tau}^T(k) &= \begin{bmatrix} \boldsymbol{\xi}^T(k) & \boldsymbol{\chi}^T(k) & \boldsymbol{\omega}^T(k) \end{bmatrix} \\ \bar{\Xi}_{i,r} &= \begin{bmatrix} \Xi_{i,r}^{11} & * & * \\ \Xi^{21} & \Xi^{22} & * \\ 0 & 0 & -\gamma^2 I \end{bmatrix} \\ \tilde{\Upsilon}_{ij,r} &= \begin{bmatrix} \vec{A}_{ij,r} & \vec{B}_{j,r} & \vec{D}_i \end{bmatrix}. \end{split}$$

For any nonzero $\omega(k)$, H_{∞} performance requirement of the augmented system (20) will be taken into account under the zero-initial condition. From (22), (23), and (30), it can follows that:

$$\Delta V(k) + z^{T}(k)z(k) - \gamma^{2}\omega^{T}(k)\omega(k)$$

$$= \sum_{i=1}^{s} \sum_{j=1}^{s} h_{ij}(k)\tau^{T}(k)\Xi_{ij,r}\tau(k)$$

$$\leq \sum_{i=1}^{s} \sum_{j=1}^{s} h_{ij}(k)\tau(k) \left[\Xi_{ij,r} + \underline{R}_{ij} - \overline{R}_{ij} + \sum_{o=1}^{s} \sum_{t=1}^{s} (\overline{u}_{ot}\overline{R}_{ot} - \underline{u}_{ot}\underline{R}_{ot})\right] \tau(k).$$
(32)

Apparently, from (24) and (32), we can derive H_{∞} performance (21) is held.

When $\omega(k) \equiv 0$, we can get from (31) that

$$\Delta V(k) \le \sum_{i=1}^{s} \sum_{j=1}^{s} h_{ij}(k) \bar{\tau}^{T}(k) \Big(\tilde{\Xi}_{ij,r} + \Upsilon_{ij,r}^{T} P_{r+1}^{-1} \Upsilon_{ij,r} \Big) \bar{\tau}(k)$$
(33)

where

$$\begin{split} \bar{\tau}(k) &= \begin{bmatrix} \xi^T(k) & \chi^T(k) \end{bmatrix}^T \\ \tilde{\Xi}_{ij,r} &= \begin{bmatrix} \Xi_{i,r}^{11} & * \\ \Xi_{21}^{21} & \Xi_{22} \end{bmatrix}, \Upsilon_{ij,r} &= \begin{bmatrix} \tilde{A}_{ij,r} & \tilde{B}_{j,r} \end{bmatrix}. \end{split}$$

One can easily derive $\Delta V(k) < 0$ with $\omega(k) \equiv 0$ from (24) and (33). Therefore, the augmented system can be inferred to be asymptotically stable by the Lyapunov theory.

This completes the proof.

Based on the sufficient conditions in Theorem 1, next, we will present the co-design method of the state observer gains, the attack observer gains and controller gains.

Theorem 2: For given $\Omega > 0$, $\lambda \in (0, 1]$, system (20) is be globally mean-square asymptotically stable and performance constraint (21) is guaranteed if there exist scalars $\mu_q(k) > 0$, $\underline{R}_{ij} > 0$, $\overline{R}_{ij} > 0$, $P_r = \text{diag}\{P_{1,r}, P_{2,r}, P_{3,r}, P_{4,r}\} > 0$, $K_{j,r}$, $L_{j,r}$ and G_r for any $i, j = 1, 2, \ldots, s$ and $r = 1, 2, \ldots, n_y$, such that

$$\Psi_{ij,r} - \overline{R}_{ij} + \underline{R}_{ij} + \sum_{i=1}^{s} \sum_{j=1}^{s} \left(\overline{u}_{ij} \overline{R}_{ij} - \underline{u}_{ij} \underline{R}_{ij} \right) < 0$$
 (34)

where

$$\begin{split} \Psi_{ij,r} &= \begin{bmatrix} \bar{\Psi}_{i,r} & * \\ \tilde{\Upsilon}_{ij,r} \, P_{r+1} - 2I \end{bmatrix} \\ \bar{\Psi}_{i,r} &= \begin{bmatrix} \Psi_{11} & * & * & * & * & * \\ 0 & \Psi_{22} & * & * & * & * \\ 0 & 0 & -P_{3,r} & * & * & * \\ 0 & 0 & 0 & -P_{4,r} & * & * \\ \Psi_{51} & \Psi_{52} & 0 & 0 & \Psi_{55} & * \\ 0 & 0 & 0 & 0 & 0 & -\gamma^2 I \end{bmatrix} \end{split}$$

$$\Psi_{11} = -P_{1,r} + \lambda C_i^T \Omega C_i + M_i^T M_i - \sum_{q=1}^{n_y} \mu_q(k) C_i^T \tilde{Q}_q C_i$$

$$\Psi_{22} = -P_{2,r} - \sum_{q=1}^{n_y} \mu_q(k) \tilde{Q}_q$$

$$\Psi_{51} = \sum_{q=1}^{n_y} \mu_q(k) \tilde{Q}_q C_i, \Psi_{52} = -\sum_{q=1}^{n_y} \mu_q(k) \tilde{Q}_q$$

$$\Psi_{55} = -\Omega - \sum_{q=1}^{n_y} \mu_q(k) \tilde{Q}_q.$$

Proof: In light of (20) and (24), we can get

$$\bar{\Psi}_{i,r} + \tilde{\Upsilon}_{ij,r}^T P_{r+1} \tilde{\Upsilon}_{ij,r}
\leq \sum_{i=1}^s \sum_{j=1}^s h_{ij}(k) \left(\bar{\Psi}_{i,r} + \tilde{\Upsilon}_{ij,r}^T P_{r+1} \tilde{\Upsilon}_{ij,r} \right)$$
(35)

TABLE I UPPER AND LOWER MFS OF (2)

Lower bounds	Upper bounds
$\underline{\underline{W_{1x_1}^1} = 1 - e^{-\frac{x_1^2(k)}{1.2}}}$	$\overline{W}_{1x_1}^1 = 0.25e^{-\frac{x_1^2(k)}{0.4}}$
$\underline{W}_{2x_1}^1 = 1 - 0.25e^{-\frac{x_1^2(k)}{0.2}}$	$\overline{W}_{2x_1}^1 = e^{-\frac{x_1^2(k)}{1.6}}$
$\underline{W}_{1x_1}^2 = 0.4e^{-\frac{x_1^2(k)}{0.3}}$	$\overline{W}_{1x_1}^2 = e^{-\frac{x_1^2(k)}{2.4}}$
$\underline{W_{2x_1}^2} = 1 - e^{-\frac{x_1^2(k)}{2.4}}$	$\overline{W}_{2x_1}^2 = 1 - 0.4e^{-\frac{x_1^2(k)}{0.3}}$

where

$$\tilde{\Upsilon}_{ij,r} = \begin{bmatrix} \vec{A}_{ij,r} & \vec{B}_{j,r} & \vec{D}_i \end{bmatrix}.$$

According to Schur complement, $\Psi_{ij,r} < 0$ is equivalent to

$$\begin{bmatrix} \bar{\Psi}_{i,r} & * \\ \tilde{\Upsilon}_{ij,r} & -P_{r+1}^{-1} \end{bmatrix} < 0$$
 (36)

where

$$-P_{r+1}^{-1} = \operatorname{diag}\{-P_{1,r+1}^{-1}, -P_{2,r+1}^{-1}, -P_{3,r+1}^{-1}, -P_{4,r+1}^{-1}\}.$$

Obviously, the fact of

$$(P_{r+1} - I)^T P_{r+1}^{-1} (P_{r+1} - I) \ge 0$$

implies

$$P_{r+1} - 2I \ge -P_{r+1}^{-1}$$

Based on the above related reasoning, the condition (34) can be ensured. This completes the proof.

IV. NUMERICAL SIMULATION

In this section, the derived control method will be applied to a numerical example and a practical example with aim to validate the effectiveness the developed method on IT2 systems with FDI attacks and DETTOD protocol.

Example 1: Consider system (1) with parameters as

$$A_{1} = \begin{bmatrix} 0.8506 & 0.2093 \\ -0.4039 & 0.5167 \end{bmatrix}, A_{2} = \begin{bmatrix} 0.6632 & 0.2583 \\ -0.3909 & 0.6537 \end{bmatrix}$$

$$B_{1} = \begin{bmatrix} 0.3129 & 0.2521 \\ 0.2148 & 0.4133 \end{bmatrix}, B_{2} = \begin{bmatrix} 0.4205 & 0.1576 \\ 0.2147 & 0.4389 \end{bmatrix}$$

$$C_{1} = \begin{bmatrix} 2.5 & -1.2 \\ -1.6 & 2 \end{bmatrix}, C_{2} = \begin{bmatrix} 2.4 & -1.2 \\ -1.5 & 2 \end{bmatrix}$$

$$D_{1} = \begin{bmatrix} 0.3121 & 0.2153 \\ 0.0156 & 0.3224 \end{bmatrix}, D_{2} = \begin{bmatrix} 0.4181 & 0.1114 \\ 0.0265 & 0.2131 \end{bmatrix}$$

$$M_{1} = \begin{bmatrix} 0.5789 & -0.1850 \end{bmatrix}, M_{2} = \begin{bmatrix} 0.6062 & -0.4630 \end{bmatrix}$$

and the initial conditions are set to be $x(0) = [0.2 - 0.1]^T$ and $\hat{x}(0) = [0 \ 0]^T$. Besides, the upper and lower MFs of (2) and (11) are given in Tables I and II. Let

$$\underline{\alpha}_{ix} = 1 - \cos^2(x_1(k)), \, \overline{\alpha}_{ix} = 1 - \underline{\alpha}_{ix}$$

$$c_{i\hat{x}} = 1 - \cos^2(\hat{x}_1(k)), \, \overline{c}_{i\hat{x}} = 1 - c_{i\hat{x}}.$$

TABLE II UPPER AND LOWER MFS OF (11)

Lower bounds	Upper bounds
$\underline{N_{1x_1}^1} = e^{-\frac{x_1^2(k)}{0.6}}$	$\overline{N}_{1x_1}^1 = \underline{N}_1^1(x_1(k))$
$\underline{N}_{2x_1}^1 = e^{-\frac{x_1^2(k)}{0.6}}$	$\overline{N}_{2x_1}^1 = \underline{N}_2^1(x_1(k))$
$\underline{N}_{1x_1}^2 = e^{-\frac{x_1^2(k)}{0.4}}$	$\overline{N}_{1x_1}^2 = \underline{N}_1^2(x_1(k))$
$\underline{N_{2x_1}^2} = e^{-\frac{x_1^2(k)}{0.4}}$	$\overline{N}_{2x_1}^2 = \underline{N}_2^2(x_1(k))$

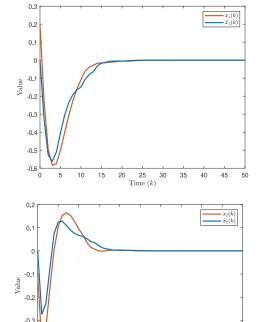


Fig. 1. States evolution $x_1(k)$ and $x_2(k)$ with their observation.

The FDI attacks are set with

$$E = \begin{bmatrix} -0.1 & 0 \\ 0 & -0.1 \end{bmatrix}, F = \begin{bmatrix} 2.7532 & -0.1203 \\ -0.1203 & 2.5189 \end{bmatrix}$$

and the weighted coefficients of the DETTOD are

$$Q_1 = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix}, Q_2 = \begin{bmatrix} 0.6 & 0 \\ 0 & 0.6 \end{bmatrix}.$$

Under the DETTOD protocol, only one group has permission to transmit signals over the communication network at the triggering instant t_n . Based on the signals being transmitted, $\delta(t_n) \in \{1, 2\}$. The global boundary values in (22) and (23) are set as $\underline{u}_{11} = 0$, $\overline{u}_{11} = 0.048$, $\underline{u}_{12} = 0$, $\overline{u}_{12} = 0.028$, $\underline{u}_{21} = 0.051$, $\overline{u}_{21} = 0.302$, $\underline{u}_{22} = 0.150$, $\overline{u}_{22} = 0.449$. Other parameters are selected as $\gamma = 2$, $\lambda = 0.4$, $\Omega = \text{diag}\{1.5, 2.2\}$, $\omega(k) = [-0.8e^{-0.35k} -0.8e^{0.5-0.35k}]^T$.

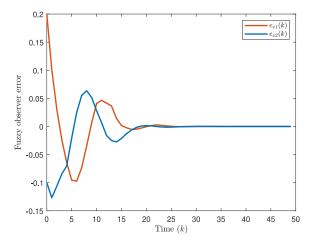


Fig. 2. Trajectories of state estimation error responses $e_x(k)$.

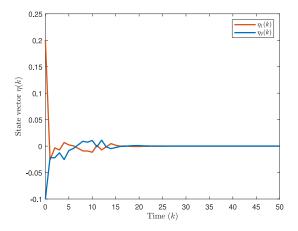


Fig. 3. Intermediate variable responses $\eta(k)$.

Afterwards, by Theorem 2, the state observer gains $L_{j,\delta(t_n)}$, the attack observer gains $G_{\delta(t_n)}$ and the controller gains $K_{j,\delta(t_n)}$ can be calculated as

$$L_{11} = \begin{bmatrix} -0.2495 & 0.0000 \\ 0.1610 & -0.0411 \end{bmatrix}, L_{12} = \begin{bmatrix} -0.1576 & 0.0265 \\ 0.0146 & -0.2148 \end{bmatrix}$$

$$L_{21} = \begin{bmatrix} -0.1782 & -0.0874 \\ 0.1386 & -0.0867 \end{bmatrix}, L_{22} = \begin{bmatrix} -0.0187 & 0.0223 \\ 0.0222 & -0.2339 \end{bmatrix}$$

$$G_{1} = \begin{bmatrix} 0.1223 & -0.0510 \\ -0.0620 & 0.1210 \end{bmatrix}, G_{2} = \begin{bmatrix} 0.1223 & -0.0510 \\ -0.0620 & 0.1210 \end{bmatrix}$$

$$K_{11} = \begin{bmatrix} -0.5553 & -0.2345 \\ 0.0145 & -0.4043 \end{bmatrix}, K_{12} = \begin{bmatrix} -0.5759 & -0.2083 \\ 0.0304 & -0.4296 \end{bmatrix}$$

$$K_{21} = \begin{bmatrix} -0.9861 & -0.6557 \\ 0.3955 & -0.0354 \end{bmatrix}, K_{22} = \begin{bmatrix} -1.0623 & -0.7627 \\ 0.4642 & 0.0597 \end{bmatrix}.$$

Based on the parameters above, the system states and their observations are presented in Fig. 1. Fig. 2 implies that the errors between system states and observer states converge to zero. Obviously, we can conclude that the designed observer will effectively predict its state to be measured under the FDI attacks.

Besides, the intermediate variable $\eta(k)$ and the unmeasurable FDI attacks estimation error $e_{\eta}(k)$ are drawn in Figs. 3 and 4, respectively. Fig. 5 depicts the responses of the control input u(k), which indicates the proposed observer-based attack

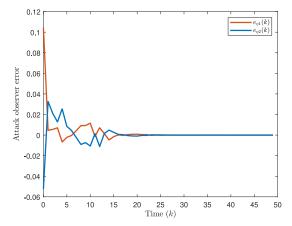


Fig. 4. Trajectories of FDI attacks estimation error $e_{\eta}(k)$.

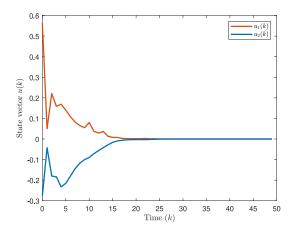


Fig. 5. Control input u(k).

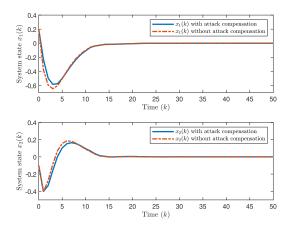


Fig. 6. System state x(k) with and without attack compensation.

compensation controller can effectively stabilize the augumented system.

The curves of the system state x(k) and control input u(k) with and without attack compensation have been plotted in Figs. 6 and 7, which clearly demonstrates the better performance can be achieved by using the developed compensation method.

To better illustrate the advance of the adopted DETTOD protocol, the comparison results on the average interval under our scheme and other schemes in [15], [17], and [48] are

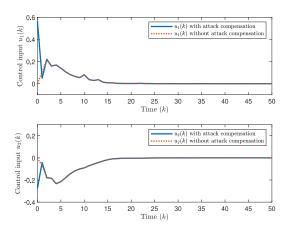


Fig. 7. Control input u(k) with and without attack compensation.

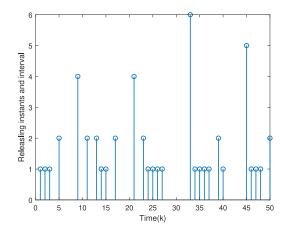


Fig. 8. Triggering instants and intervals under DETTOD protocol.

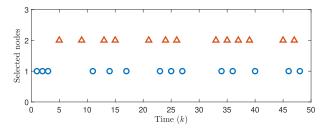


Fig. 9. Selected transmission node governed by WTOD protocol.

TABLE III
AVERAGE SAMPLING PERIOD BY DIFFERENT TRIGGERING SCHEMES

Event-triggering scheme	Average period
The scheme in this paper	0.5686
The scheme (Theorem 1) in [15]	0.5131
The scheme in [17]	0.4816
The scheme (Theorem 5.1) in [48]	0.3917

presented in Table III. The triggering time and departure interval under the DETTOD protocol are plotted in Fig. 8. The selected transmission node governed by WTOD protocol is shown in Fig. 9. From the simulation results, one can see data conflict can be avoided and the pressure on network transmission is also alleviated, which exhibit the advantageous of the proposed DETTOD approach.

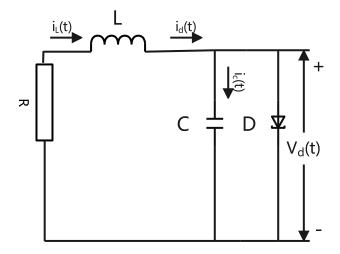


Fig. 10. Tunnel diode circuit system model.

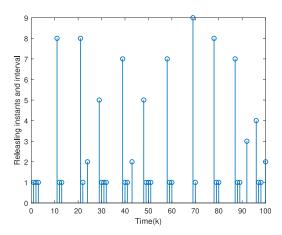


Fig. 11. Triggering instants and interval for tunnel diode circuit system model.

Example 2: Consider the following tunnel diode circuit system plotted in Fig. 10 [49]:

$$i_d(t) = -0.2v_d(t) - 0.01v_d^3(t)$$

where $i_d(t)$ is the current and $v_d(t)$ is the voltage of the tunnel. Define $x_1(t) = v_d(t)$ and $x_2(t) = i_d(t)$, $f(v_d(t)) = 0.2 + 0.01v_d^2(t)$. The adopted circuit system model can be written as

$$\begin{cases} \dot{x}_1(t) = \frac{f(v_d(t))}{C} x_1(t) + \frac{1}{C} x_2(t) \\ \dot{x}_2(t) = -\frac{1}{L} x_1(t) - \frac{R}{L} x_2(t) + \frac{1}{L} u(t) \end{cases}$$
(37)

Let the capacitance C = 0.1F, the inductance L = 1H, the resistances $R = 3\Omega$ and $x_1(t) \in [-3, 3]$, one can get $f_{\text{max}} = 0.29$, $f_{\text{min}} = 0.2$. Then the following two fuzzy rules can be gotten.

Plant Rule F_1 : **IF** $x_1(t)$ is 0, **THEN**

$$\dot{x}(t) = \bar{A}_1 x(t) + \bar{B}_1 u(t)$$

Plant Rule F_2 : **IF** $x_1(t)$ is ± 3 , **THEN**

$$\dot{x}(t) = \bar{A}_2 x(t) + \bar{B}_2 u(t)$$

where

$$\bar{A}_1 = \begin{bmatrix} f_{\min} & 10 \\ -1 & -1 \end{bmatrix}, \bar{A}_2 = \begin{bmatrix} f_{\max} & 10 \\ -1 & -1 \end{bmatrix}, \bar{B}_1 = \bar{B}_2 = \begin{bmatrix} 1.2 & 0 \\ 0 & 1 \end{bmatrix}.$$

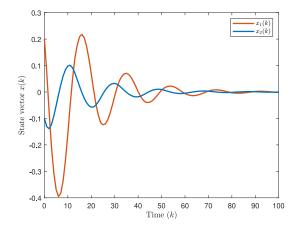


Fig. 12. State responses of tunnel diode circuit system model.

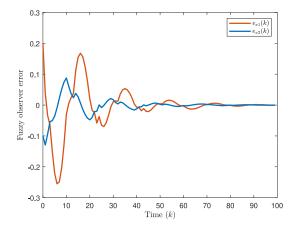


Fig. 13. Trajectories of state estimation error in Example 2.

Based on the method in [15], the lower and upper MFs can be derived as $\overline{h}_{1x} = \underline{h}_{1x} = (f_{\text{max}} - f(v_d(t))/f_{\text{max}} - f_{\text{min}})$, $\overline{h}_{2x} = 1 - \underline{h}_{1x}$, $\underline{h}_{2x} = 1 - \overline{h}_{1x}$. The lower and upper MFs of the controller are chosen as $\underline{g}_{1\hat{x}_1} = 1 - (1/9)e^{-\hat{x}_1(k)}$, $\overline{g}_{1\hat{x}_1} = 1 - (1/27)e^{-\hat{x}_1(k)}$, $\underline{g}_{2\hat{x}_1} = 1 - \overline{g}_{1\hat{x}_1}$, $\overline{g}_{2\hat{x}_1} = 1 - \underline{g}_{1\hat{x}_1}$, $\underline{c}_{\beta\hat{x}_1} = 0.6$, $\overline{c}_{\beta\hat{x}_1} = 0.4$, where $\beta = 1, 2$.

Discretizing the above system with sampling period T = 0.1s, one can derive

$$\begin{cases} x(k+1) = \sum_{i=1}^{2} h_{1x_1} [A_i x(k) + B_i (u(k) + a(k)) \\ + D_i \omega(k)] \\ y(k) = \sum_{i=1}^{2} h_{1x_1} C_i x(k) \\ z(k) = \sum_{i=1}^{2} h_{1x_1} M_i x(k) \end{cases}$$

where

$$A_{1} = \begin{bmatrix} 0.9716 & 0.9454 \\ -0.09454 & 0.8581 \end{bmatrix}, A_{2} = \begin{bmatrix} 0.9805 & 0.9498 \\ -0.09498 & 0.858 \end{bmatrix}$$

$$B_{1} = \begin{bmatrix} 0.1192 & 0.0483 \\ -0.005796 & 0.09358 \end{bmatrix}, B_{2} = \begin{bmatrix} 0.1198 & 0.04845 \\ -0.005813 & 0.09357 \end{bmatrix}$$

$$C_{1} = C_{2} = \begin{bmatrix} 1 & 0.8 \\ 1.1 & 1 \end{bmatrix}, D_{1} = D_{2} = \begin{bmatrix} 0.01 & 0.02 \\ 0.03 & 0.01 \end{bmatrix}$$

$$M_{1} = M_{2} = \begin{bmatrix} 0.1 & 0.1 \end{bmatrix}.$$

According to the control design method in Theorem 2, one has

$$L_{11} = \begin{bmatrix} -0.5191 & -0.1892 \\ -0.1659 & -0.0810 \end{bmatrix}, L_{12} = \begin{bmatrix} -0.1687 & -0.5284 \\ -0.0462 & -0.2076 \end{bmatrix}$$

$$L_{21} = \begin{bmatrix} -0.4512 & -0.2287 \\ -0.1432 & -0.0934 \end{bmatrix}, L_{22} = \begin{bmatrix} -0.2004 & -0.4920 \\ -0.0551 & -0.1943 \end{bmatrix}$$

$$G_{1} = \begin{bmatrix} 0.2980 & -0.1355 \\ 0.0343 & 0.4074 \end{bmatrix}, G_{2} = \begin{bmatrix} 0.2980 & -0.1355 \\ 0.0343 & 0.4074 \end{bmatrix}$$

$$K_{11} = \begin{bmatrix} -16.0177 & 10.7585 \\ 45.2571 & -40.9185 \end{bmatrix}, K_{12} = \begin{bmatrix} -16.0156 & 10.7568 \\ 45.2568 & -40.9182 \end{bmatrix}$$

$$K_{21} = \begin{bmatrix} -15.9990 & 10.7407 \\ 45.2514 & -40.9132 \end{bmatrix}, K_{22} = \begin{bmatrix} -15.9996 & 10.7411 \\ 45.2515 & -40.9133 \end{bmatrix}.$$

By applying the DETTOD protocol, the transmitted signal will be first determined by the event triggering conditions in (3), then, the triggered signal will be scheduled by the WTOD protocol, which not only saves communication resources solves the data conflicts issue in network. In Fig. 11, the triggering instants and interval under the DETTOD protocol is presented. It can be clearly observed that less triggering instants are generated under the proposed method in our article compared with the periodic time-triggered scheme. Figs. 12 and 13 show the trajectories of state response and state estimation error under the designed control method, respectively. We can see that the overall transient performance of the designed mechanism is excellent. This means that more network communication burden can be reduced under the same conditions, which further evidences the efficiency of using the proposed DETTOD protocol.

V. CONCLUSION

A fuzzy co-estimation of state and attacks problem for nonlinear NCSs has been addressed under FDI attacks in this article. A novel DETTOD protocol has been presented to reduce the probability of data conflict and relieve the pressure of network transmission, which is organically combined of the DET strategy and the WTOD protocol. Moreover, a sufficient condition ensuring the asymptotic stability as well as the prescribed H_{∞} performance requirement has been proposed for the constructed augmented system. Comprehensively taking the FDI attack and the DETTOD protocol into consideration, a fuzzy observer-based attack compensation controller and FDI attacks observer of the augmented nonlinear IT2 fuzzy system is proposed. Finally, the feasibility of the proposed theoretical findings are illustrated by two simulation examples. The future work will include fault tolerant control for cyber-physical system under hybrid attacks and LNR, and filtering design of complex networks with DETTOD protocol.

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