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• **Supplementary File** •

Observer-Based Event-Triggered Asynchronous Control of Networked Markovian Jump Systems Under Deception Attacks

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Appendix A Preliminaries

Assumption 1. [1] The control input matrix B_i, $\forall i \in \ell$ is constant with full column rank, that is, $Rank(B_i) = n_u, B_i = B$. Then, the singular-value decomposition of B can be obtained of the form $B = Z_1 \begin{bmatrix} Z_2 \\ 0 \end{bmatrix} Z_3$, where $Z_1 \in R^{n_x \times n_x}$, $Z_2 \in R^{n_u \times n_u}$, $Z_3 \in R^{n_u \times n_u}$, $Z_1^T Z_1 = I$, and $Z_3^T Z_3 = I$.

Definition 1. [2] Choose $V(\bar{x}(k), r_k)$ as Lyapunov function of system (9). Define a differential operator $\Delta V(\bar{x}(k), r_k)$ as

$$\Delta V(\bar{x}(k), r_k) = E\left[V(\bar{x}(k+1), r_{k+1}) - V(\bar{x}(k), r_k) \mid \bar{x}(k), r_k\right].$$

Definition 2. [3] Consider the stochastic system (9). If there exists a Lyapunov function $V(\bar{x}(k), r_k) : R^{2n^x} \to R$, two constants $c_1 > 0$ and $c_2 > 0$, and K_∞ functions α_1 and α_2, such that

$$\begin{cases} \alpha_1(\|\bar{x}(k)\|) \leqslant V(\bar{x}(k), r_k) \leqslant \alpha_2(\|\bar{x}(k)\|), \\ \Delta V(\bar{x}(k), r_k) \leqslant -c_1 V(\bar{x}(k), r_k) + c_2, \end{cases}$$

for all $\bar{x} \in R^{2n^x}$, $k > 0$. Then, there exists unique strong solution of system (9), and the system is bounded in probability.

Appendix B The Proof of Lemma 1

The dynamic equation of $\tilde{W}(k)$ using (7) can be derived as

$$\tilde{W}(k+1) = \tilde{W}(k) - \sigma \hat{W}(k) - \frac{\eta S(V^T \hat{x}(k_s)) z^T(k+1)}{1 + \|S(V^T \hat{x}(k_s))\|^2 \|z(k+1)\|^2}. \tag{B1}$$

Then choose the following Lyapunov function

$$V_{\tilde{W}}(k) = \mathrm{tr}\{\tilde{W}^T(k)\tilde{W}(k)\}. \tag{B2}$$

For convenience, we denote

$$\vartheta_S(k) = \frac{S(V^T \hat{x}(k_s))}{1 + \|S(V^T \hat{x}(k_s))\|^2 \|z(k+1)\|^2}. \tag{B3}$$

Then, the first difference of (B2) along (B1) and (B3) is expressed as

$$\begin{aligned} \Delta V_{\tilde{W}}(k) &= \mathrm{tr}\{\tilde{W}^T(k+1)\tilde{W}(k+1) - \tilde{W}^T(k)\tilde{W}(k)\} \\ &= \mathrm{tr}\Big\{\sigma^2 \hat{W}^T(k)\hat{W}(k) + \eta^2 \vartheta_S^T(k)\vartheta_S(k) z^2(k+1) - 2\sigma \tilde{W}^T(k)\hat{W}(k) - 2\eta \tilde{W}^T(k)\vartheta_S(k) z(k+1) \\ &\quad + 2\sigma\eta \hat{W}^T(k)\vartheta_S(k) z(k+1)\Big\}. \end{aligned} \tag{B4}$$

Moreover, according to the fact $\vartheta_S^T(k)\vartheta_S(k)z^2(k+1) \leqslant \frac{1}{4}$, and applying the Young's inequality, one has

$$\begin{cases} \eta^2 \vartheta_S^T(k)\vartheta_S(k) z^2(k+1) \leqslant \dfrac{\eta^2}{4}, \\ -2\eta \tilde{W}^T(k)\vartheta_S(k) z(k+1) \leqslant \dfrac{\tilde{W}^T(k)\tilde{W}(k)}{4\gamma} + \gamma\eta^2, \\ 2\sigma\eta \hat{W}^T(k)\vartheta_S(k) z(k+1) \leqslant \sigma^2 \hat{W}^T(k)\hat{W}(k) + \dfrac{\eta^2}{4}. \end{cases} \tag{B5}$$

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Substituting (B5) into (B4), and noting that

$$\mathrm{tr}\left\{-2\sigma\tilde{W}^T(k)\hat{W}(k)\right\} = \mathrm{tr}\Big\{-\sigma\hat{W}^T(k)\hat{W}(k) - \sigma\tilde{W}^T(k)\tilde{W}(k) + \sigma W^T W\Big\},$$

we have

$$\Delta V_{\tilde{W}}(k) \leqslant -\left(\sigma - \frac{1}{4\gamma}\right)\|\tilde{W}(k)\|_F^2 - \sigma(1-\sigma)\|\hat{W}(k)\|_F^2 + \delta_w, \tag{B6}$$

where $\delta_w = \sigma\cdot\|W\|_F^2 + (0.5+\gamma)\eta^2$, and $\|\cdot\|_F$ is the Frobenius norm.

It can be seen from (B6) that the following inequality

$$\Delta V_{\tilde{W}}(k) \leqslant -\kappa\|\tilde{W}(k)\|_F^2 + \delta_w, \tag{B7}$$

holds as long as $\frac{1}{4\gamma} < \sigma < 1$, $\gamma > 1$, and $\kappa = \sigma - \frac{1}{4\gamma}$. Further, condition $\frac{1}{4\gamma} < \sigma < 1$ holds, which means that $0 < \kappa < 1$. According to the Lyapunov theory [4], the NN weight estimation error $\tilde{W}(k)$ is bounded in probability with any bounded initial NN weight estimation $\hat{W}(0)$. ■

Appendix C The Proof of Theorem 1

Choose the Lyapunov function candidate as

$$V(k) = V_{\bar{x}}(k, x(k), r(k)) + \mu V_{\tilde{W}}(k), \tag{C1}$$

where $\mu > 0$ is a constant parameter, and

$$V_{\bar{x}}(k, x(k), r(k)) = \bar{x}^T(k)P_{r_k}\bar{x}(k), \quad V_{\tilde{W}}(k) = \mathrm{tr}\{\tilde{W}^T(k)\tilde{W}(k)\}.$$

Define $\bar{P}_i = \sum_{j\in\mathcal{L}}^N \pi_{ij}P_j$, then the first difference of $V_{\bar{x}}(k)$ along (9) is expressed as

$$\begin{aligned}\Delta V_{\bar{x}}(k) &= E\left\{V_{\bar{x}}(k+1, x(k+1), r(k+1))|x(k), r(k)=i\right\} - V_{\bar{x}}(k, x(k), i)\\ &= \bar{x}^T(k+1)\left(\sum_{m=1}^M \varpi_{im}\sum_{j=1}^N \pi_{ij}P_j\right)\bar{x}(k+1) - \bar{x}^T(k)P_i\bar{x}(k)\\ &= \sum_{m=1}^M \varpi_{im}\Big(\bar{A}_{im}\bar{x}(k) + \bar{B}_{im}e_{ET}(k) + \bar{H}_{im}\left(\tilde{W}^T(k)S(V^T\hat{x}(k_s)) - \varepsilon(\hat{x}(k_s)) - w(k)\right)\Big)^T\bar{P}_i\Big(\bar{A}_{im}\bar{x}(k)\\ &\quad + \bar{B}_{im}e_{ET}(k) + \bar{H}_{im}\left(\tilde{W}^T(k)S(V^T\hat{x}(k_s)) - \varepsilon(\hat{x}(k_s)) - w(k)\right)\Big) - \bar{x}^T(k)P_i\bar{x}(k),\end{aligned}$$

By Cauchy-Schwarz inequality, we have

$$\begin{aligned}\Delta V_{\bar{x}}(k) \leqslant \sum_{m=1}^M \varpi_{im}\Big\{&\bar{x}^T(k)\left(2\bar{A}_{im}^T\bar{P}_i\bar{A}_{im}\right)\bar{x}(k) + 4\Big(\bar{B}_{im}e_{ET}(k)\Big)^T\bar{P}_i\Big(\bar{B}_{im}e_{ET}(k)\Big)\\ &+ 4\Big(\bar{H}_{im}\left(\tilde{W}^T(k)S(V^T\hat{x}(k_s)) - \varepsilon(\hat{x}(k_s)) - w(k)\right)\Big)^T\bar{P}_i\times\\ &\Big(\bar{H}_{im}\left(\tilde{W}^T(k)S(V^T\hat{x}(k_s)) - \varepsilon(\hat{x}(k_s)) - w(k)\right)\Big)\Big\} - \bar{x}^T(k)P_i\bar{x}(k).\end{aligned} \tag{C2}$$

Specially, the second term on the right of inequality (C2) leads to

$$\begin{aligned}&4\sum_{m=1}^M \varpi_{im}\Big(\bar{B}_{im}e_{ET}(k)\Big)^T\bar{P}_i\Big(\bar{B}_{im}e_{ET}(k)\Big)\\ \leqslant &\sum_{m=1}^M \varpi_{im}\Big\{4e_{ET}^T(k)\bar{B}_{im}^T\bar{P}_i\bar{B}_{im}e_{ET}(k) + \rho\hat{x}^T(k_s)N_m\hat{x}(k_s) - e_{ET}^T(k)M_m e_{ET}(k)\Big\}\\ = &\sum_{m=1}^M \varpi_{im}\Big\{e_{ET}^T(k)(4\bar{B}_{im}^T\bar{P}_i\bar{B}_{im} + \rho N_m - M_m)e_{ET}(k) + \rho\bar{x}^T(k)\bar{N}_{1m}\bar{x}(k) + 2\rho\bar{x}^T(k)\bar{N}_{2m}e_{ET}(k)\Big\}.\end{aligned} \tag{C3}$$

Moreover, according to $\|S(\cdot)\| \leqslant S_{\max}$, $\|\varepsilon(\cdot)\| \leqslant \varepsilon_{\max}$, and $\|w(k)\| \leqslant w_{\max}$, the third term on the right of inequality (C2) leads to

$$\begin{aligned}&4\sum_{m=1}^M \varpi_{im}\Big(\bar{H}_{im}\left(\tilde{W}^T(k)S(V^T\hat{x}(k_s)) - \varepsilon(\hat{x}(k_s)) - w(k)\right)\Big)^T\bar{P}_i\Big(\bar{H}_{im}\left(\tilde{W}^T(k)S(V^T\hat{x}(k_s)) - \varepsilon(\hat{x}(k_s)) - w(k)\right)\Big)\\ \leqslant &\, 12\sup_{i\in\mathcal{L}, m\in\mathcal{S}}\left\{\lambda_{\max}(\bar{H}_{im}^T\bar{P}_i\bar{H}_{im})\right\}\left(S_{\max}^2\|\tilde{W}(k)\|_F^2 + \varepsilon_{\max}^2 + w_{\max}^2\right).\end{aligned} \tag{C4}$$

Based on inequalities (C3)-(C4), the first difference of $V_{\bar{x}}(k)$ can arrive at

$$\Delta V_{\bar{x}}(k) \leqslant \sum_{m=1}^M \varpi_{im}\Big\{\bar{x}^T(k)\left(2\bar{A}_{im}^T\bar{P}_i\bar{A}_{im} + \rho\bar{N}_{1m}\right)\bar{x}(k) + e_{ET}^T(k)\left(4\bar{B}_{im}^T\bar{P}_i\bar{B}_{im} - M_m\right)e_{ET}(k) + 2\rho\bar{x}^T(k)\bar{N}_{2m}e_{ET}(k)\Big\}$$

$$-\bar{x}^T(k)(P_i)\bar{x}(k)+12\sup_{i\in\mathcal{L},m\in\mathcal{S}}\left\{\lambda_{\max}(\bar{H}_{im}^T\bar{P}_i\bar{H}_{im})\right\}\left(S_{\max}^2\|\tilde{W}(k)\|_F^2+\varepsilon_{\max}^2+w_{\max}^2\right). \tag{C5}$$

From (C3) and (C5), we finally have the overall first difference $\Delta V(k)$ as

$$\begin{aligned}\Delta V(k)&=\Delta V_{\bar{x}}(k)+\mu\Delta V_{\tilde{W}}(k)\\&\leqslant\sum_{m=1}^{M}\varpi_{im}\left\{\bar{x}^T(k)\left(2\bar{A}_{im}^T\bar{P}_i\bar{A}_{im}+\rho\bar{N}_{1m}\right)\bar{x}(k)+e_{ET}^T(k)\left(4\bar{B}_{im}^T\bar{P}_i\bar{B}_{im}-M_m\right)e_{ET}(k)+2\rho\bar{x}^T(k)\bar{N}_{2m}e_{ET}(k)\right\}\\&\quad-\bar{x}^T(k)P_i\bar{x}(k)+12\sup_{i\in\mathcal{L},m\in\mathcal{S}}\left\{\lambda_{\max}(\bar{H}_{im}^T\bar{P}_i\bar{H}_{im})\right\}\left(S_{\max}^2\|\tilde{W}(k)\|_F^2+\varepsilon_{\max}^2+w_{\max}^2\right)-\mu\kappa\|\tilde{W}(k)\|_F^2+\mu\delta_w\\&=\xi^T(k)\Phi_{im}\xi(k)+\left(12\sup_{i\in\mathcal{L},m\in\mathcal{S}}\left\{\lambda_{\max}(\bar{H}_{im}^T\bar{P}_i\bar{H}_{im})\right\}S_{\max}^2-\mu\kappa\right)\|\tilde{W}(k)\|_F^2+\delta_M,\end{aligned} \tag{C6}$$

where

$$\xi(k)=\left[\bar{x}^T(k)\ \ e_{ET}^T(k)\right]^T,\quad \delta_M=\mu\delta_w+12\sup_{i\in\mathcal{L},m\in\mathcal{S}}\left\{\lambda_{\max}(\bar{H}_{im}^T\bar{P}_i\bar{H}_{im})\right\}(\varepsilon_{\max}^2+w_{\max}^2),$$

$$\Phi_{im}=\sum_{m=1}^{M}\varpi_{im}\begin{bmatrix}2\bar{A}_{im}^T\bar{P}_i\bar{A}_{im}+\rho\bar{N}_{1m} & \rho\bar{N}_{2m}\\ * & 4\bar{B}_{im}^T\bar{P}_i\bar{B}_{im}-M_m\end{bmatrix}-\begin{bmatrix}P_i & 0\\0 & 0\end{bmatrix}.$$

By using the same proof technique in [5], conditions (10)-(11) can guarantee that $\Phi_{im}<0$, for all $i\in\mathcal{L}$, $m\in\mathcal{S}$. Therefore, in view of conditions (10)-(12), we have

$$\Delta V(k)\leqslant\inf_{i\in\mathcal{L},m\in\mathcal{S}}\{\lambda_{\min}(\Phi_{im})\}\|\xi(k)\|^2+\left(12\sup_{i\in\mathcal{L},m\in\mathcal{S}}\left\{\lambda_{\max}(\bar{H}_{im}^T\bar{P}_i\bar{H}_{im})\right\}S_{\max}^2-\mu\kappa\right)\|\tilde{W}(k)\|_F^2+\delta_M. \tag{C7}$$

From the above inequality, there exists a small constant $\tau>0$ such that $\Delta V(k)\leqslant-\tau V(k)+\delta_M$. Then, all signals of the closed-loop system are bounded in probability. This complete the proof. ■

Appendix D Design of Observer-Based Controller

Based on Theorem 1 and singular-value decomposition, the solvability for the event-triggered observer-based controller design problem under deception attacks is presented.

Theorem 1. Consider the closed-loop system (9). For given $0\leqslant\rho<1$, if there exists matrices $R_{1im}>0$, $R_{2im}>0$, $P_{1i}>0$, $P_{2i}>0$, $\bar{P}_{1i}>0$, $\bar{P}_{2i}>0$, X_1, X_2, X_3, $\bar{K}_m$, and $\bar{L}_m$, scalars $0<\kappa<1$, $\mu>0$, $\lambda_1>0$, such that $\forall i\in\mathcal{L}$, $m\in\mathcal{S}$

$$\sum_{m=1}^{M}\varpi_{im}\mathrm{diag}\{R_{1im},R_{2im}\}<\mathrm{diag}\{P_{1i},P_{2i}\}, \tag{D1}$$

$$\begin{bmatrix}\Psi_{11} & 0 & \sqrt{2}\Psi_{13} & 0\\ * & \Psi_{11} & 0 & 2\Psi_{24}\\ * & * & \Psi_{33} & \Psi_{34}\\ * & * & * & -M_m\end{bmatrix}<0, \tag{D2}$$

$$12\lambda_1S_{\max}^2-\mu\kappa<0, \tag{D3}$$

$$\begin{bmatrix}\Psi_{11} & \Psi_{12}\\ * & -\lambda_1\end{bmatrix}<0, \tag{D4}$$

hold, where

$$\Psi_{11}=\mathrm{diag}\left\{\bar{P}_{1i}-X-X^T,\bar{P}_{2i}-X-X^T\right\},\quad \Psi_{13}=\begin{bmatrix}XA_i+Z_1\tilde{K}_m & Z_1\tilde{K}_m\\ XA_m-XA_i+\bar{L}_mC_m-\bar{L}_mC_i & XA_m+\bar{L}_mC_m\end{bmatrix},$$

$$\Psi_{12}=\begin{bmatrix}-Z_1\tilde{K}_m\\0\end{bmatrix},\quad \Psi_{24}=\begin{bmatrix}Z_1\tilde{K}_m\\0\end{bmatrix},\quad \Psi_{33}=\begin{bmatrix}\rho N_m-R_{1im} & \rho N_m\\ * & \rho N_m-R_{2im}\end{bmatrix},\quad \Psi_{34}=\begin{bmatrix}\rho N_m\\ \rho N_m\end{bmatrix},\quad \tilde{K}_m=\begin{bmatrix}\bar{K}_m\\0\end{bmatrix}$$

Then, with bounded initial values and Assumption 1, all signals of closed-loop system (9) are bounded in probability under the observer-based event-triggered controller (8) and the NN weight estimates $\hat{W}(k)$ (9). Moreover, the controller and observer gains are given as

$$K_m=X_1^{-1}\bar{K}_m,\quad L_m=X^{-1}\bar{L}_m. \tag{D5}$$

Proof: Based on Schur complement, condition (11) can be rewritten as

$$\begin{bmatrix}\Lambda_{11} & \Lambda_{12}\\ * & \Lambda_{22}\end{bmatrix}<0, \tag{D6}$$

where $\Lambda_{11} = \mathrm{diag}\{-\bar{P}_i, -\bar{P}_i\}$, $\Lambda_{12} = \mathrm{diag}\{\sqrt{2}\bar{P}_i\bar{A}_{im}, 2\bar{P}_i\bar{B}_{im}\}$, $\Lambda_{22} = \begin{bmatrix} \rho\bar{N}_{1m} - R_{im} & \rho\bar{N}_{2m} \\ * & -M_m \end{bmatrix}$.

Then, assuming X be an arbitrary matrix, after pre- and post-multiplying $\mathrm{diag}\{X\bar{P}_i^{-1}, X\bar{P}_i^{-1}, I, I\}$ and its transpose to (D6), one has

$$\begin{bmatrix} \bar{\Lambda}_{11} & \bar{\Lambda}_{11} \\ * & \Lambda_{22} \end{bmatrix} < 0, \tag{D7}$$

where $\bar{\Lambda}_{11} = \mathrm{diag}\{-X\bar{P}_i^{-1}X^T, -X\bar{P}_i^{-1}X^T\}$, $\bar{\Lambda}_{12} = \mathrm{diag}\{\sqrt{2}X\bar{A}_{im}, 2X\bar{B}_{im}\}$.

Noting the fact that $(\bar{P}_i - X)\bar{P}_i(\bar{P}_i - X)^T \geqslant 0$, we can achieve $\bar{P}_i - X - X^T \geqslant -X\bar{P}_i^{-1}X^T$. Then, a sufficient condition to guarantee (D7) is obtained as

$$\begin{bmatrix} \hat{\Lambda}_{11} & \bar{\Lambda}_{11} \\ * & \Lambda_{22} \end{bmatrix} < 0. \tag{D8}$$

where $\hat{\Lambda}_{11} = \mathrm{diag}\{\bar{P}_i - X - X^T, \bar{P}_i - X - X^T\}$.

Now, we are in the position to proof that conditions (10) and (D8) can be guaranteed by (D1)-(D2). For this purpose, let the matrices $\bar{P}_i$, P_i, R_{im} and X in (D8) have the following forms:

$$\bar{P}_i = \mathrm{diag}\{\bar{P}_{1i}, \bar{P}_{2i}\}, P_i = \mathrm{diag}\{P_{1i}, P_{2i}\}, R_{im} = \mathrm{diag}\{R_{1im}, R_{2im}\}, \bar{X} = \mathrm{diag}\{X, X\}, X = Z_1 \begin{bmatrix} X_1 Z_3^T Z_2^{-1} & X_2 \\ 0 & X_3 \end{bmatrix} Z_1^T. \tag{D9}$$

According to Assumption 1 and the definition of X, one immediately obtains

$$XBK_m = Z_1 \begin{bmatrix} X_1 Z_3^T Z_2^{-1} & X_2 \\ 0 & X_3 \end{bmatrix} Z_1^T Z_1 \begin{bmatrix} Z_2 \\ 0 \end{bmatrix} Z_3 K_m = Z_1 \begin{bmatrix} X_1 \\ 0 \end{bmatrix} K_m. \tag{D10}$$

Substituting (D9) and (D10) into (11), and denoting $\bar{K}_m = X_1 K_m$ and $\bar{L}_m = XL_m$, it is easy to obtain inequalities (D1)-(D2).

Using the similar technique, it is easy to proof that (D3)-(D4) can ensure condition (12) holds. The proof is finished. ■

Appendix E Simulations

In this section, the proposed method is evaluated by a simulation example. Consider the MJS (1) with parameters

$$A_1 = \begin{bmatrix} 1.1 & 0 \\ 0 & 0.5 \end{bmatrix}, A_2 = \begin{bmatrix} 1.2 & 0 \\ 0 & -0.3 \end{bmatrix}, A_3 = \begin{bmatrix} 0.5 & 0 \\ 0 & -1.1 \end{bmatrix}, B_1 = B_2 = B_3 = \begin{bmatrix} 0.1 \\ 0.1 \end{bmatrix}, C_1 = \begin{bmatrix} 0.1 \\ 0.2 \end{bmatrix}, C_2 = \begin{bmatrix} 0.3 \\ 0.1 \end{bmatrix}, C_3 = \begin{bmatrix} 0.2 \\ 0.1 \end{bmatrix}.$$

The transition matrices of $r(k)$ and $\tau(k)$ are as follows

$$\pi = \begin{bmatrix} 0.1 & 0.8 & 0.1 \\ 0.3 & 0.4 & 0.3 \\ 0.5 & 0.2 & 0.3 \end{bmatrix}, \quad \varpi = \begin{bmatrix} 0.4 & 0.4 & 0.2 \\ 0.2 & 0.6 & 0.2 \\ 0.3 & 0.2 & 0.5 \end{bmatrix}.$$

The initial conditions of the system, the observer, and the NN weight estimate are set as $x(0) = [15 \quad 15]^T$, $\hat{x}(0) = [0 \quad 0]^T$, and $\hat{W}(0) = 0.1$, respectively. The external disturbance signal is $w(k) = \sin(2k)$, while the malicious information is assumed to be $\Phi(\hat{x}(k_s)) = \sin(k\pi/20)\sqrt{\hat{x}_1^2(k_s) + \hat{x}_2^2(k_s)} + \sin(k\pi/10)$. Other parameters of event-triggered NN weight updating law are selected as $\sigma = 0.01$, $\eta = 0.9$, $l = 18$, $\rho = 0.5$, $\kappa = 0.6$. By solving the LMIs (D1)-(D4) in Theorem 2, the following gains are obtained

$$K_1 = \begin{bmatrix} -0.5789 & 2.8668 \end{bmatrix}, K_2 = \begin{bmatrix} -0.5340 & 2.8851 \end{bmatrix}, K_3 = \begin{bmatrix} -0.2887 & 2.8851 \end{bmatrix}, L_1 = \begin{bmatrix} -1.8636 \\ -0.2727 \end{bmatrix}, L_2 = \begin{bmatrix} -2.4167 \\ -0.4722 \end{bmatrix}, L_3 = \begin{bmatrix} -1.7222 \\ 2.7219 \end{bmatrix}.$$

Figure E1 depicts the jump modes of original system and observer simultaneously. The inter-execution intervals of the ETM are described in Figure E2, while Figure E3 displays the curves of deception attacks and their estimation. The norm of NN estimate weight matrix $\hat{W}(k)$ is shown in Figure E4. The state trajectories under deception attacks are plotted in Figures E5-E6. The state curves with NN technique are shown in Figures E7-E8, which demonstrate the effectiveness of the design method.

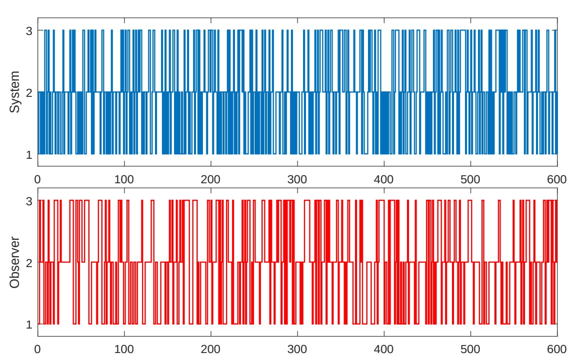

Figure E1 Mode evolutions of system and observer.

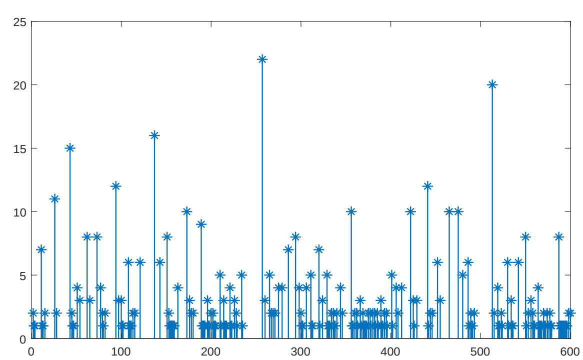

Figure E2 Inter-execution intervals of ETM.

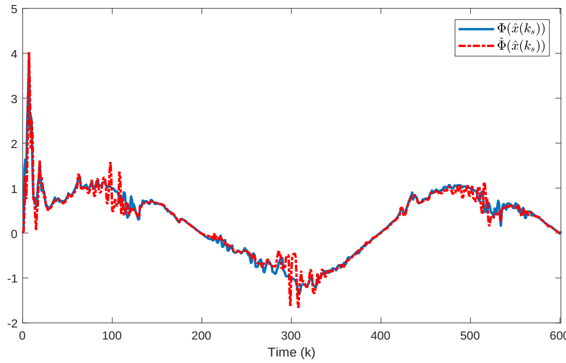

Figure E3 The evolution of deception attacks and their estimation.

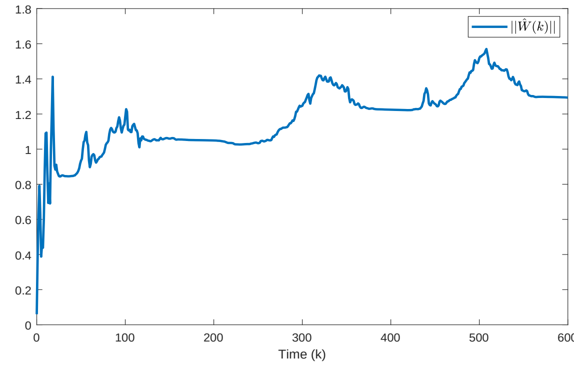

Figure E4 The trajectory of NN weight estimation $\|\hat{W}(k)\|_F$.

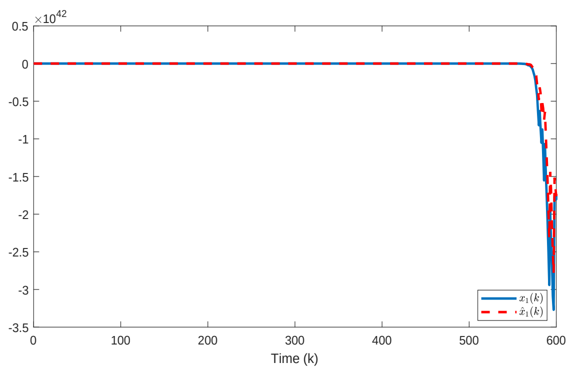

Figure E5 System state $x_1(k)$ and its estimation under deception attacks (without NN).

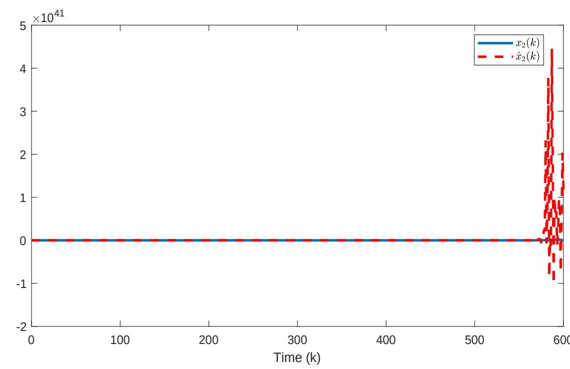

Figure E6 System state $x_2(k)$ and its estimation under deception attacks (without NN).

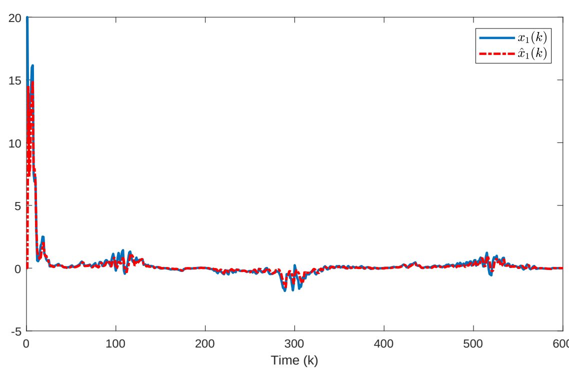

Figure E7 System state $x_1(k)$ and its estimation under deception attacks (with NN).

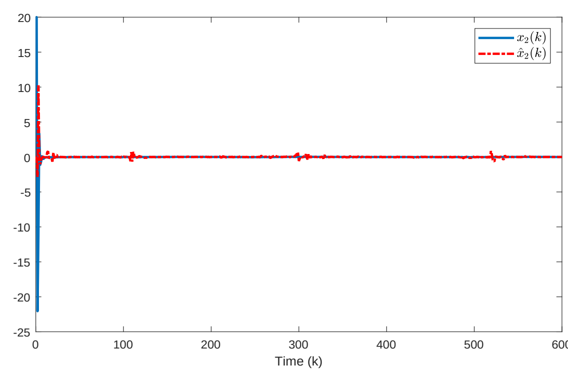

Figure E8 System state $x_2(k)$ and its estimation under deception attacks (with NN).

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