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Fault detection filter design for networked systems with cyber attacks[☆]

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ABSTRACT

This paper focuses on the fault detection for networked systems with deception attacks. Firstly, a fault detection filter (FDF) is presented as a residual generator to detect the random occurring fault signal timely in networked systems with the consideration of network delay and deception attacks. Then, by using the Lyapunov stability theory and linear matrix inequality (LMI) techniques, sufficient conditions are presented to guarantee the stability with an H_∞ performance index γ of our proposed fault detection system. Furthermore, the corresponding coefficient matrices of the FDF are also presented with the explicit expressions. Finally, two simulation examples demonstrate the effectiveness and practicability of the designed FDF.

1. Introduction

As technology advances, modern industrial system has been widely exploited in various areas, such as control systems [1–5], networked systems [6–9], cyber-physical systems [10] and aerospace systems [11]. For example, Wang et al. [4] proposed a slow-state feedback control method for a class of discrete-time singularly perturbed switched systems, and [6] studied the sliding mode control for networked fuzzy control singularly perturbed systems. With the higher requirements of reliability and stability in many engineering areas, fault detection [12–15] has gained great attentions over past two decades, for the faults may result in not only poor performance but also the system instability. For instance, fault detection subject to Brownian motion was constructed for nonlinear switched system in Yong et al. [16]; and an event-triggered fault detection method was investigated for nonlinear discrete-time networked systems in Li et al. [17]; Shen et al. [18] used an H_∞ disturbance estimation approach in fault detection for linear discrete time varying systems; an event-triggered H_i/H_∞ optimization fault detection scheme [19] was proposed in discrete time systems.

It is notable that modern industrial systems are connected by network, and control signals are transmitted via network links. Therefore, it is meaningful to consider network-induced effects in fault detection problems, such as packet dropouts [20], limited network resources [21,22] and network delay[23–26]. As an inevitable network-induced effect, network delay

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gains more attentions recently. For example, both network delay and limited network bandwidth resources were considered in Wang et al. [22]; He et al. [23] solved the fault detection problem for a class of discrete-time networked systems with the consideration of network delay and data missing; Wang et al. [24] designed an FDF for a continuous-time networked control systems with the consideration of network delay and packet dropouts; Boem et al. [25] proposed a delay compensation strategy for a distributed fault detection architecture, allowing manage delays and packet losses; fault detection and isolation was investigated in Aslam et al. [26] for a class of delayed non-linear systems under time-varying delay with an event-triggered mechanism. Thus, network delay is also taken into consideration in our FDF design for networked systems.

Besides above network-induced effects, modern industrial system may become vulnerable to malicious cyber attacks [27–32], which can jam data transmission and affect system reliability and stability significantly. Consequently, cyber attacks have received more and more attentions, such as denial of service attacks in Hu et al. [27], replay attacks in Chen et al. [28], deception attacks in Wang et al. [29] and hybird attacks in Liu et al. [30-32]. However, fault detection subject to cyber attacks has not been well studied, which motivates our work in this paper.

As one of the most important attack modes, deception attacks are introduced, when the adversary sends false information, and such attacks may influence fault detection result. Therefore, deception attacks in fault detection should be attached importance to. To our knowledge, there are a few literatures to address the fault detection problem subject to deception attacks. For example, Rhouma et al. [33] investigated a resilient control strategy for network systems with fault detection subject to zero dynamic attacks, which are special cases of deception attacks. There is still a large gap between zero dynamic attacks and deception attacks, which motivates our study of fault detection with deception attacks. In addition, Li et al. [34] studied fault detection problems with deception attacks in discrete-time stochastic systems, which can't be applied in time-continuous system directly.

From the above published results [12–26,33,34], there are two steps for fault detection. The first step is to define an evaluation function and the corresponding evaluation threshold, which are realized in a filter for fault detection. The second is to detect whether faults occur or not, i.e., compare whether the computed result of the evaluation function exceeds the predefined threshold. Therefore, we also investigate some filter designs [35–38] in this paper. Wang et al. [35] researched on the model-based fuzzy $l_2 - l_\infty$ filtering issue for discrete-time semi-Markov jump nonlinear systems. H_∞ filters are designed for discrete-time switched systems with the known sojourn probability in Tian et al. [36]. Chang et al. [37] [38] concerned the filters designed for continuous-time systems. It is different from traditional filter that the filter designed for fault detection in this paper mainly concerns on detecting faults for time-continuous systems with dual effects of transmission delay and deception attacks.

The main contributions of are summarized as follows: (1) A networked system model is constructed with the consideration of the network delay and deception attacks and a Bernoulli random variable is used to describe the launching probability of deception attacks. (2) Sufficient conditions are provided which can guarantee the H_∞ stability of FDF by using Lyapunov stability theory and LMI techniques. (3) The coefficient matrices of the FDF are also presented in explicit expressions calculated by a set of LMIs and two simulation examples are presented to show the effectiveness and practicability of the proposed method.

The rest of this paper is organized as follows: Section 2 describes the framework of fault detection subject to network delay and deception attacks. Section 3 presents sufficient conditions which can ensure the H_∞ stability of FDF with Lyapunov stability theory and LMI techniques. And the FDF coefficient matrices are obtained by a set of LMIs in Section 3. Section 4 provides simulation results to show that the proposed fault detection method is effective and useful. Conclusion follows in Section 5.

Notations: $\mathbb{R}^n$ is defined to represent Eculidean space with appropriate dimensions; and $\mathbb{R}^{n\times m}$ is a set of $n \times m$ real matrices; the superscript -1 and T of a matrix are used to denote its inverse and transpose, respectively; $M > 0$ (or $M > 0$) means that the matrix M is symmetric positive (or negative) definite; I and 0 are the identity matrix and the zero matrix with appropriate dimension, respectively; $*$ represents a symmetrical entry in a matrix; $Diag\{\ldots\}$ is a block-diagonal matrix with the elements of main diagonal listed in the braces; $L_2[0,\infty]$ represents the linear space of square-integrable vector functions over $[0,\infty)$. $E\{\cdot\}$ is the mathematical expectation of a function.

2. Problem description

The fault detection subject to network delay and deception attacks is depicted in Fig. 1 in the continuous time domain. Fig. 1 shows that the plant and FDF are connected through a communication network, so the output signal $y(t)$ of the plant is changed into $\hat{y}(t)$ by taking inevitable network delay and randomly happening deception attacks into consideration. The system is described as follows:

$$\begin{cases} \dot{x}(t) = Ax(t) + B\omega(t) + Ds(t) \\ y(t) = Cx(t) \end{cases} \tag{1}$$

where $x(t) \in \mathbb{R}^n$ is the plant state, $y(t) \in \mathbb{R}^m$ is the output signal, $\omega(t) \in \mathbb{R}^p$ represents the external disturbance, $s(t) \in \mathbb{R}^q$ denotes the randomly occurring fault, and $\omega(t)$, $s(t)$ are both in $L_2[0,\infty]$. The matrices A, B, C and D are given coefficient matrices with appropriate dimensions.

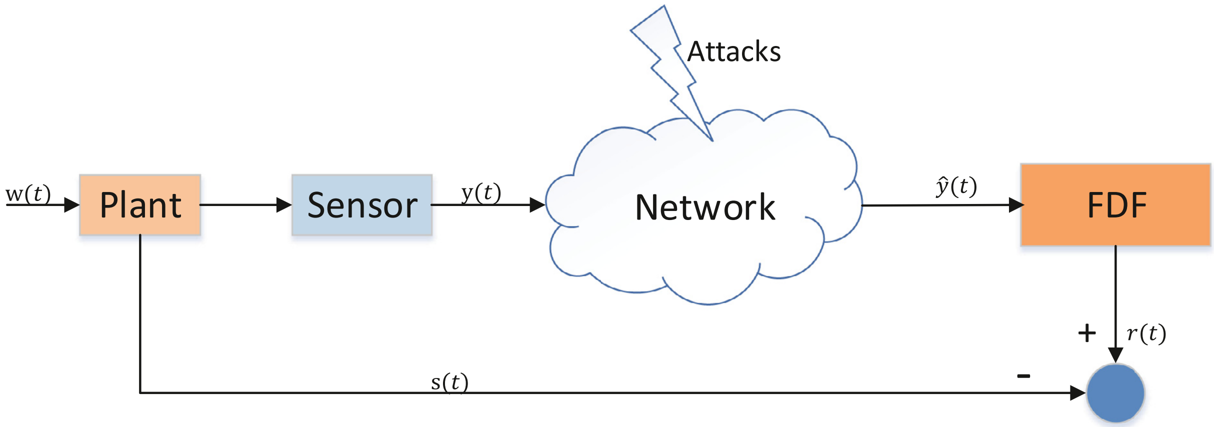


Fig. 1. Fault detection system subject to network delay and deception attacks.

Next, an FDF is set to generate the residual signal, which is used to detect whether faults have been happened or not in system (1). The residual generator FDF is described by following system (2).

$$\begin{cases}\dot{x}_F(t) = A_F x_F(t) + B_F \hat{y}(t) \\ r(t) = C_F x_F(t) + D_F \hat{y}(t)\end{cases} \tag{2}$$

where $x_F(t) \in \mathbb{R}^n$ is the state estimation of $x(t)$, $r(t) \in \mathbb{R}^l$ is the residual signal, and $\hat{y}(t)$ denotes the input of the FDF, which is affected by network delay and deception attacks. The matrices A_F, B_F, C_F and D_F are the coefficient matrices with appropriate dimensions to be determined later, which is the main objective of this paper.

In order to detect whether faults $s(t)$ happen in the system (1) or not, an evaluation function $\mathcal{F}(t)$ for residual signal and the corresponding threshold $\mathcal{F}_{th}$ for $\mathcal{F}(t)$ are predefined firstly. As $\mathcal{F}(t)$ is used to evaluate the residual signal, it can be defined by Eq. (3) referred that in Wang et al. [22], where $r(\cdot)$ is the residual signal generated by the system (2). And the corresponding threshold $\mathcal{F}_{th}$ for $\mathcal{F}(t)$ is defined by Eq. (4).

$$\mathcal{F}(t) = \sqrt{\frac{1}{t}\int_0^t r^T(v) r(v) dv} \tag{3}$$

$$\mathcal{F}_{th} = \sup_{\omega(t)\in L_2[0,\infty], s(t)=0} \mathcal{F}(t) \tag{4}$$

With the definition of a residual evaluation function $\mathcal{F}(t)$ and the corresponding threshold $\mathcal{F}_{th}$, the following detection logic (5) is used to detect whether faults occur or not.

$$\begin{cases}\mathcal{F}(t) > \mathcal{F}_{th} \Rightarrow \text{alarm for faults} \\ \mathcal{F}(t) \le \mathcal{F}_{th} \Rightarrow \text{not alarm for no fault}\end{cases} \tag{5}$$

This paper investigates FDF for system (1). As shown in Fig. 1, when the output vector $y(t)$ is transmitted to filter through a communication network. If there is no deception attack during the signal transmission, $\eta(t) \in [0, \eta_M]$ is the generated delay of the communication network, and η_M is the allowable maximum value of $\eta(t)$. Therefore, the input vector $y_1(t)$ is expressed by Eq. (6).

$$y_1(t) = Cx(t - \eta(t)) \tag{6}$$

Suppose that deception attacks occur during the signal transmission, the output vector $y_2(t)$ is influenced not only by network delay but also by deception attacks. Define $d(t) \in [0, d_M]$ as the time-varying delay and $\mathcal{D}(u)$ as a deception attacks function, where d_M is the maximum transmission delay under deception attacks. Then, the input signal $y_2(t)$ can be represented by Eq. (7).

$$y_2(t) = C\mathcal{D}(x(t - d(t))) \tag{7}$$

For any given parameter u, the deception attacks function $\mathcal{D}(u)$ are assumed to satisfy the following constraint [29], where S is the known upper bound matrix of the nonlinearity.

$$\mathcal{D}^T(u)\mathcal{D}(u) \le u^T S^T S u \tag{8}$$

A Bernoulli variable $\beta(t) \in \{0, 1\}$ is exploited to represent that deception attack occurs (or not) at time t, i.e, $\beta(t) = 1$ (or 0). $\bar{\beta}$ is the probability of deception attacks occurring, i.e., $Pr(\beta(t) = 1) = \bar{\beta}$, there are the expectation $E\{\beta(t)\} = \bar{\beta}$ and the mathematical variance $E\{(\beta(t)-\bar{\beta})^2\} = \bar{\beta}(1-\bar{\beta}) = \delta^2$. Therefore, the real input of the filter $\hat{y}(t)$ can be described by Eq. (9) with the consideration of two transmission cases with deception attacks happening randomly $y_1(t)$ and $y_2(t)$.

$$\hat{y}(t) = (1-\beta(t))Cx(t-\eta(t)) + \beta(t)C\mathcal{D}(x(t-d(t))) \tag{9}$$

Substituting Eq. (9) into the system (2), thereby, the filter system can be rewritten as:

$$\begin{cases} \dot{x}_F(t) = A_F x_F(t) + B_F[(1-\beta(t))Cx(t-\eta(t)) + \beta(t)C\mathcal{D}(x(t-d(t)))] \\ r(t) = C_F x_F(t) + D_F[(1-\beta(t))Cx(t-\eta(t)) + \beta(t)C\mathcal{D}(x(t-d(t)))] \end{cases} \tag{10}$$

Let $\zeta(t) = \begin{pmatrix} x^T(t) & x_F^T(t) \end{pmatrix}^T$, $\nu(t) = \begin{pmatrix} \omega^T(t) & s^T(t) \end{pmatrix}^T$, $r_e(t) = r(t) - s(t)$, we can obtain the following augmented system by combining Eqs. (1) and (10):

$$\begin{cases} \dot{\zeta}(t) = \bar{A}_f\zeta(t) + (1-\beta(t))\bar{B}_f H\zeta(t-\eta(t)) + \beta(t)\bar{B}_f\mathcal{D}(H\zeta(t-d(t))) + \bar{D}_f\nu(t) \\ r_e(t) = \bar{C}_f\zeta(t) + (1-\beta(t))\bar{F}_f H\zeta(t-\eta(t)) + \beta(t)\bar{F}_f\mathcal{D}(H\zeta(t-d(t))) + \bar{G}_f\nu(t) \end{cases} \tag{11}$$

where $\bar{A}_f = \begin{pmatrix} A & 0 \\ 0 & A_F \end{pmatrix}$, $\bar{B}_f = \begin{pmatrix} 0 \\ B_F C \end{pmatrix}$, $\bar{D}_f = \begin{pmatrix} B & D \\ 0 & 0 \end{pmatrix}$, $\bar{C}_f = \begin{pmatrix} 0 & C_F \end{pmatrix}$, $\bar{F}_f = D_F C$, $\bar{G}_f = \begin{pmatrix} 0 & -I \end{pmatrix}$, $H = \begin{pmatrix} I & 0 \end{pmatrix}$.

The goal of this paper is to design an FDF such that system (11) can be asymptotically stable with H_∞ performance index γ. Such a system can be achieved if the following inequality (12) holds for all nonzero $\nu(t) \in L_2[0,\infty]$.

$$E\{\int_0^\infty r_e^T(t)r_e(t)dt\} \le \gamma^2 E\{\int_0^\infty \nu^T(t)\nu(t)dt\} \tag{12}$$

where γ is a given scalar.

Definition 1 ([39]). For given function V, the infinitesimal operator $\mathcal{L}$ for variable t of the function is defined as

$$\mathcal{L}V(\zeta(t)) = \lim_{\Delta\to 0^+}\frac{1}{\Delta}[(V(\zeta(t+\Delta)|\zeta(t)) - V(\zeta(t))] \tag{13}$$

Lemma 1 ([40]). *For any vector u, $v \in \mathbb{R}^n$ and positive defined matrix $\Xi \in \mathbb{R}^{n\times n}$ with appropriate dimensions, the constraint (14) is satisfied:*

$$2u^T v \le u^T\Xi u + v^T\Xi^{-1}v \tag{14}$$

Lemma 2 ([41]). *Suppose $\eta(t) \in [0,\eta_M]$, $d(t) \in [0,d_M]$, $\Phi_i (i = 1,\ldots,4)$ are given matrices of appropriate dimensions, then*

$$\eta(t)\Phi_1 + (\eta_M - \eta(t))\Phi_2 + d(t)\Phi_3 + (d_M - d(t))\Phi_4 + \Omega < 0 \tag{15}$$

if and only if the constraints in (16) are all satisfied.

$$\begin{cases} \eta_M\Phi_1 + d_M\Phi_3 + \Omega < 0 \\ \eta_M\Phi_2 + d_M\Phi_3 + \Omega < 0 \\ \eta_M\Phi_1 + d_M\Phi_4 + \Omega < 0 \\ \eta_M\Phi_2 + d_M\Phi_4 + \Omega < 0 \end{cases} \tag{16}$$

3. Main results

In this section, we provide and prove the sufficient conditions to ensure the stability of the system (11) with an H_∞ performance index γ via the Lyapunov stability theory; then, the filter coefficient matrices are determined in Theorem 2 by using LMI techniques.

Theorem 1. *With known parameters η_M, d_M, $\bar{\beta}$, $\bar{A}_f$, $\bar{B}_f$, $\bar{C}_f$, $\bar{D}_f$, $\bar{F}_f$, $\bar{G}_f$ and matrix S, augmented system (11) with the consideration of deception attacks is asymptotically stable with an H_∞ performance index γ, if there are positive definite matrices P, Q_i and R_i $(i = 1, 2)$, and free weight matrices U, V, M, N, such that the following matrix inequalities can be held:*

$$\Psi(s) = \begin{bmatrix} \Sigma_{11}+\Gamma+\Gamma^T & * & * & * & * & * & * \\ \Sigma_{21} & -I & * & * & * & * & * \\ \Sigma_{31} & 0 & -I & * & * & * & * \\ \Sigma_{41} & 0 & 0 & -I & * & * & * \\ \Sigma_{51} & 0 & 0 & 0 & \Sigma_{55} & * & * \\ \Sigma_{61} & 0 & 0 & 0 & 0 & \Sigma_{66} & * \\ \Sigma_{71}(s) & 0 & 0 & 0 & 0 & 0 & \Sigma_{77} \end{bmatrix} < 0, s = 1,2,3,4 \tag{17}$$

where

$$\Sigma_{11} = \begin{bmatrix} P\bar{A}_f + \bar{A}_f^T P + Q_1 + Q_2 & * & * & * & * & * & * \\ \bar{\beta}_1 H^T \bar{B}_f^T P & 0 & * & * & * & * & * \\ 0 & 0 & -Q_1 & * & * & * & * \\ 0 & 0 & 0 & 0 & * & * & * \\ 0 & 0 & 0 & 0 & -Q_2 & * & * \\ \bar{\beta}\bar{B}_f^T P & 0 & 0 & 0 & 0 & -\bar{\beta} I & * \\ \bar{D}_f^T P & 0 & 0 & 0 & 0 & 0 & -\gamma^2 I \end{bmatrix}$$

$$\begin{aligned}
\Sigma_{21} &= \begin{bmatrix} 0 & 0 & 0 & \sqrt{\bar{\beta}} SH & 0 & 0 & 0 \end{bmatrix}, \Sigma_{31} = \begin{bmatrix} \bar{C}_f & \bar{\beta}_1 \bar{F}_f H & 0 & 0 & 0 & \bar{F}_f & \bar{G}_f \end{bmatrix} \\
\Sigma_{41} &= \begin{bmatrix} 0 & \delta \bar{F}_f H & 0 & 0 & 0 & -\delta \bar{F}_f & 0 \end{bmatrix}, \Sigma_{55} = \Sigma_{66} = Diag\{-PR_1^{-1}P, -PR_2^{-1}P\} \\
\Sigma_{51} &= \begin{bmatrix} \sqrt{\eta_M} P\bar{A}_f & \sqrt{\eta_M}\bar{\beta}_1 P\bar{B}_f H & 0 & 0 & 0 & \sqrt{\eta_M}\bar{\beta} P\bar{B}_f & \sqrt{\eta_M} P\bar{D}_f \\ \sqrt{d_M} P\bar{A}_f & \sqrt{d_M}\bar{\beta}_1 P\bar{B}_f H & 0 & 0 & 0 & \sqrt{d_M}\bar{\beta} P\bar{B}_f & \sqrt{d_M} P\bar{D}_f \end{bmatrix} \\
\Sigma_{61} &= \begin{bmatrix} 0 & \sqrt{\eta_M}\delta P\bar{B}_f H & 0 & 0 & 0 & -\sqrt{\eta_M}\delta P\bar{B}_f & 0 \\ 0 & \sqrt{d_M}\delta P\bar{B}_f H & 0 & 0 & 0 & -\sqrt{d_M}\delta P\bar{B}_f & 0 \end{bmatrix}, \Sigma_{77} = Diag\{-R_1, -R_2\} \\
\Sigma_{71}(1) &= \begin{bmatrix} \sqrt{\eta_M} U^T \\ \sqrt{d_M} M^T \end{bmatrix}, \Sigma_{71}(2) = \begin{bmatrix} \sqrt{\eta_M} U^T \\ \sqrt{d_M} N^T \end{bmatrix}, \Sigma_{71}(3) = \begin{bmatrix} \sqrt{\eta_M} V^T \\ \sqrt{d_M} M^T \end{bmatrix}, \Sigma_{71}(4) = \begin{bmatrix} \sqrt{\eta_M} V^T \\ \sqrt{d_M} N^T \end{bmatrix} \\
\Gamma &= \begin{bmatrix} U+M & V-U & -V & N-M & -N & 0 & 0 \end{bmatrix}, \bar{\beta}_1 = 1 - \bar{\beta} \\
U^T &= \begin{bmatrix} U_1^T & U_2^T & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, V^T = \begin{bmatrix} 0 & V_2^T & V_3^T & 0 & 0 & 0 & 0 \end{bmatrix} \\
M^T &= \begin{bmatrix} M_1^T & 0 & 0 & M_4^T & 0 & 0 & 0 \end{bmatrix}, N^T = \begin{bmatrix} 0 & 0 & 0 & N_4^T & N_5^T & 0 & 0 \end{bmatrix}
\end{aligned}$$

Proof. The Lyapunov function $V(t)$ can be constructed as

$$V(t) = V_1(t) + V_2(t) + V_3(t), \tag{18}$$

with

$$\begin{aligned}
V_1(t) &= \zeta^T(t) P \zeta(t), V_2(t) = \int_{t-\eta_M}^{t} \zeta^T(s) Q_1 \zeta(s) ds + \int_{t-d_M}^{t} \zeta^T(s) Q_2 \zeta(s) ds, \\
V_3(t) &= \int_{t-\eta_M}^{t} \int_s^t \dot{\zeta}^T(v) R_1 \dot{\zeta}(v) dv ds + \int_{t-d_M}^{t} \int_s^t \dot{\zeta}^T(v) R_2 \dot{\zeta}(v) dv ds.
\end{aligned}$$

Then, taking the infinitesimal operator given in Definition 1 and the mathematical expectation of $V_k(t)$ of Eq. (18), one can derive

$$E\{\mathcal{L}V_1(t)\} = 2\zeta^T(t) P \mathcal{A}, \tag{19}$$

$$E\{\mathcal{L}V_2(t)\} = \zeta^T(t)(Q_1 + Q_2)\zeta(t) - \zeta^T(t-\eta_M) Q_1 \zeta(t-\eta_M) - \zeta^T(t-d_M) Q_2 \zeta(t-d_M), \tag{20}$$

$$E\{\mathcal{L}V_3(t)\} = E\{\dot{\zeta}^T(t) R \dot{\zeta}(t)\} - \int_{t-\eta_M}^{t} \dot{\zeta}(v)^T(s) R_1 \dot{\zeta}(s) ds - \int_{t-d_M}^{t} \dot{\zeta}^T(s) R_2 \dot{\zeta}(s) ds, \tag{21}$$

in which

$$E\{\dot{\zeta}^T(t) R \dot{\zeta}(t)\} = E[\mathcal{A} + (\bar{\beta} - \beta(t))\mathcal{A}_1]^T R [\mathcal{A} + (\bar{\beta} - \beta(t))\mathcal{A}_1] = \mathcal{A}^T R \mathcal{A} + \delta^2 \mathcal{A}_1^T R \mathcal{A}_1 \tag{22}$$

where $\mathcal{A} = \bar{A}_f \zeta(t) + (1-\bar{\beta})\bar{B}_f H \zeta(t-\eta(t)) + \bar{\beta}\bar{B}_f \mathcal{D}(H\zeta(t-d(t))) + \bar{D}_f v(t)$, $\mathcal{A}_1 = \bar{B}_f H \zeta(t-\eta(t)) - \bar{B}_f \mathcal{D}(H\zeta(t-d(t)))$, $R = \eta_M R_1 + d_M R_2$.

Applying the free-weighting matrices method [42], one can get that:

$$\pi_1 = 2\xi^T(t) U[\zeta(t) - \zeta(t-\eta(t)) - \int_{t-\eta(t)}^{t} \dot{\zeta}(s) ds] = 0, \tag{23}$$

$$\pi_2 = 2\xi^T(t) V[\zeta(t-\eta(t)) - \zeta(t-\eta_M) - \int_{t-\eta_M}^{t-\eta(t)} \dot{\zeta}(s) ds] = 0, \tag{24}$$

$$\pi_3 = 2\xi^T(t) M[\zeta(t) - \zeta(t-d(t)) - \int_{t-d(t)}^{t} \dot{\zeta}(s) ds] = 0, \tag{25}$$

$$\pi_4 = 2\xi^T(t)N[\zeta(t-d(t)) - \zeta(t-d_M) - \int_{t-d_M}^{t-d(t)} \dot{\zeta}(s)ds] = 0, \tag{26}$$

where U, V, M, N are free-weighting matrices with appropriate dimensions,and
$\xi(t) = \begin{bmatrix}\zeta^T(t) & \zeta^T(t-\eta(t)) & \zeta^T(t-\eta_M) & \zeta^T(t-d(t)) & \zeta^T(t-d_M) & \mathcal{D}^T(H\zeta(t-d(t))) & \nu^T(t)\end{bmatrix}^T$.

By employing Lemma 1, it can be obtained that

$$-2\xi^T(t)U\int_{t-\eta(t)}^{t} \dot{\zeta}(s)ds \le \eta(t)\xi^T(t)UR_1^{-1}U^T\xi(t) + \int_{t-\eta(t)}^{t} \dot{\zeta}^T(s)R_1\dot{\zeta}(s)ds, \tag{27}$$

$$-2\xi(t)^TV\int_{t-\eta_M}^{t-\eta(t)} \dot{\zeta}(s)ds \le (\eta_M - \eta(t))\xi^T(t)VR_1^{-1}V^T\xi(t) + \int_{t-\eta_M}^{t-\eta(t)} \dot{\zeta}^T(s)R_1\dot{\zeta}(s)ds, \tag{28}$$

$$-2\xi^T(t)M\int_{t-d(t)}^{t} \dot{\zeta}(s)ds \le d(t)\xi^T(t)MR_2^{-1}M^T\xi(t) + \int_{t-d(t)}^{t} \dot{\zeta}^T(s)R_2\dot{\zeta}(s)ds, \tag{29}$$

$$-2\xi^T(t)N\int_{t-d_M}^{t-d(t)} \dot{\zeta}(s)ds \le (d_M - d(t))\xi^T(t)NR_2^{-1}N^T\xi(t) + \int_{t-d_M}^{t-d(t)} \dot{\zeta}^T(s)R_2\dot{\zeta}(s)ds, \tag{30}$$

Notice that

$$E\left\{\gamma_e^T(t)\gamma_e(t)\right\} = E\left\{\left[\mathcal{B} + \left(\bar{\beta} - \beta(t)\right)\mathcal{B}_1\right]^T\left[\mathcal{B} + \left(\bar{\beta} - \beta(t)\right)\mathcal{B}_1\right]\right\} = \mathcal{B}^T\mathcal{B} + \delta^2\mathcal{B}_1^T\mathcal{B}_1 \tag{31}$$

where $\mathcal{B} = \bar{C}_f\zeta(t) + (1-\bar{\beta})\bar{F}_fH\zeta(t-\eta(t)) + \bar{\beta}\bar{F}_f\mathcal{D}(H\zeta(t-d(t))) + \bar{G}_f\nu(t)$, $\mathcal{B}_1 = \bar{F}_fH\zeta(t-\eta(t)) - \bar{F}_f\mathcal{D}(H\zeta(t-d(t)))$.

The inequality (8) can be rewritten as the inequality (32).

$$\mathcal{D}^T(H\zeta(t-d(t)))\mathcal{D}(H\zeta(t-d(t))) \le (H\zeta(t-d(t)))^TS^TS(H\zeta(t-d(t))). \tag{32}$$

Combining Eqs. (19)–(32), it has

$$\begin{aligned}
&E\{\mathcal{L}V(t) + r_e^T(t)r_e(t) - \gamma^2\nu^T(t)\nu(t)\} \\
&\le 2\zeta^T(t)P\mathcal{A} + \zeta^T(t)(Q_1+Q_2)\zeta(t) - \zeta^T(t-\eta_M)Q_1\zeta(t-\eta_M) - \zeta^T(t-d_M)Q_2\zeta(t-d_M) \\
&+ \mathcal{A}^TR\mathcal{A} + \delta^2\mathcal{A}_1^TR\mathcal{A}_1 - \int_{t-\eta_M}^{t} \dot{\zeta}^T(s)R_1\dot{\zeta}(s)ds - \int_{t-d_M}^{t} \dot{\zeta}^T(s)R_2\dot{\zeta}(s)ds + \mathcal{B}^T\mathcal{B} + \delta^2\mathcal{B}_1^T\mathcal{B}_1 \\
&- \gamma^2\nu^T(t)\nu(t) + \bar{\beta}(H\zeta(t-d(t)))^TS^TS(H\zeta(t-d(t))) - \bar{\beta}\mathcal{D}(H\zeta(t-d(t)))^T\mathcal{D}(H\zeta(t-d(t))) \\
&\le 2\zeta^T(t)P\mathcal{A} + \zeta^T(t)(Q_1+Q_2)\zeta(t) - \zeta^T(t-\eta_M)Q_1\zeta(t-\eta_M) - \zeta^T(t-d_M)Q_2\zeta(t-d_M) \\
&+ \mathcal{A}^TR\mathcal{A} + \delta^2\mathcal{A}_1^TR\mathcal{A}_1 + \mathcal{B}^T\mathcal{B} + \delta^2\mathcal{B}_1^T\mathcal{B}_1 - \gamma^2\nu^T(t)\nu(t) + 2\xi(t)^TU[\zeta(t) - \zeta(t-\eta(t))] \\
&+ 2\xi(t)^TV[\zeta(t-\eta(t)) - \zeta(t-\eta_M)] + 2\xi(t)^TM[\zeta(t) - \zeta(t-d(t))] \\
&+ 2\xi(t)^TN[\zeta(t-d(t)) - \zeta(t-d_M)] + \eta(t)\xi(t)^TUR_1^{-1}U^T\xi(t) \\
&+ (\eta_M - \eta(t))\xi(t)^TVR_1^{-1}V^T\xi(t) + d(t)\xi(t)^TMR_2^{-1}M^T\xi(t) \\
&+ (d_M - d(t))\xi(t)^TNR_2^{-1}N^T\xi(t) + \bar{\beta}(H\zeta(t-d(t)))^TS^TS(H\zeta(t-d(t))) \\
&- \bar{\beta}\mathcal{D}^T(H\zeta(t-d(t)))\mathcal{D}(H\zeta(t-d(t)))
\end{aligned} \tag{33}$$

With the application of Lemma 2 and Schur complement in the inequality (33), one can easily obtain that the inequalities (17) are the sufficient conditions for $E\{\mathcal{L}V(t) + \gamma_e^T(t)\gamma_e(t) - \gamma^2\nu^T(t)\nu(t)\} < 0$.

In order to prove the stability with the H_∞ performance index γ of the augmented system (11), one first construct the following function according to the inequality (12):

$$\begin{aligned}
\mathcal{J}(t) &= E\{\textstyle\int_0^t r_e^T(s)r_e(s)ds\} - \gamma^2E\{\int_0^t \nu^T(s)\nu(s)ds\} \\
&= E\{\textstyle\int_0^t r_e^T(s)r_e(s) - \gamma^2\nu^T(s)\nu(s)ds\}
\end{aligned} \tag{34}$$

It follows that

$$\begin{aligned}
\mathcal{J}(t) &= E\{\textstyle\int_0^t \gamma_e^T(s)\gamma_e(s) - \gamma^2\nu^T(s)\nu(s) + \mathcal{L}V(s)ds - V(t)\} \\
&\le \textstyle\int_0^t E\{\gamma_e^T(s)\gamma_e(s) - \gamma^2\nu^T(s)\nu(s) + \mathcal{L}V(s)ds\}
\end{aligned} \tag{35}$$

With $E\{\mathcal{L}V(t) + r_e^T(t)r_e(t) - \gamma^2\nu^T(t)\nu(t)\} < 0$, one can easily derive that $\mathcal{J}(t) < 0$ under zero initial condition, when letting $t \to \infty$, which ensures that the augmented system (11) is asymptotically stable with the H_∞ performance index γ.

The proof is finished. □

Theorem 2. *With known parameters η_M, d_M, $\bar{\beta}$, ε_i $(i = 1, 2)$ and matrix S, if there exist matrices $P_1 > 0$, $\bar{P}_3 > 0$, $\tilde{Q}_i > 0$, $\tilde{R}_i > 0$, $\tilde{U}$, $\tilde{V}$, $\tilde{M}$, $\tilde{N}$, $\hat{A}_f$, $\hat{B}_f$, $\hat{C}_f$, $\hat{D}_f$ with appropriate dimensions, the augmented system (11) is asymptotically stable with an H_∞ performance index γ, if the following conditions hold.*

$$\tilde{\Psi}(s) = \begin{bmatrix} \tilde{\Sigma}_{11} & * & * & * & * & * & * \\ \tilde{\Sigma}_{21} & -I & * & * & * & * & * \\ \tilde{\Sigma}_{31} & 0 & -I & * & * & * & * \\ \tilde{\Sigma}_{41} & 0 & 0 & -I & * & * & * \\ \tilde{\Sigma}_{51} & 0 & 0 & 0 & \tilde{\Sigma}_{55} & * & * \\ \tilde{\Sigma}_{61} & 0 & 0 & 0 & 0 & \tilde{\Sigma}_{66} & * \\ \tilde{\Sigma}_{71}(s) & 0 & 0 & 0 & 0 & 0 & \tilde{\Sigma}_{77} \end{bmatrix} < 0, s = 1, 2, 3, 4 \tag{36}$$

$$P_1 - \bar{P}_3 > 0 \tag{37}$$

where

$$\tilde{\Sigma}_{11} = \begin{bmatrix} \tilde{\Lambda}_1 & * & * & * & * & * & * \\ \bar{\beta}_1\tilde{\Lambda}_2 & 0 & * & * & * & * & * \\ 0 & 0 & -\tilde{Q}_1 & * & * & * & * \\ 0 & 0 & 0 & 0 & * & * & * \\ 0 & 0 & 0 & 0 & -\tilde{Q}_2 & * & * \\ \bar{\beta}\tilde{\Lambda}_3 & 0 & 0 & 0 & 0 & -\bar{\beta}I & * \\ \tilde{\Lambda}_4 & 0 & 0 & 0 & 0 & 0 & -\gamma^2 I \end{bmatrix}$$

$$\tilde{\Sigma}_{21} = \begin{bmatrix} 0 & 0 & 0 & \sqrt{\bar{\beta}}SH & 0 & 0 & 0 \end{bmatrix}, \tilde{\Sigma}_{31} = \begin{bmatrix} \tilde{C}_f & \overline{\beta}_1\overline{F}_f H & 0 & 0 & 0 & \overline{F}_f & \overline{G}_f \end{bmatrix}$$
$$\tilde{\Sigma}_{41} = \begin{bmatrix} 0 & \delta\overline{F}_f H & 0 & 0 & 0 & -\delta\overline{F}_f & 0 \end{bmatrix}, \tilde{\Sigma}_{55} = \tilde{\Sigma}_{66} = Diag\left\{-2\varepsilon_1\tilde{P} + \varepsilon_1^2\tilde{R}_1, -2\varepsilon_2\tilde{P} + \varepsilon_2^2\tilde{R}_2\right\}$$
$$\tilde{\Sigma}_{51} = \begin{bmatrix} \sqrt{\eta_M}\Pi_1 & \sqrt{\eta_M}\overline{\beta}_1\Pi_2^T & 0 & 0 & 0 & \sqrt{\eta_M}\overline{\beta}\Pi_3^T & \sqrt{\eta_M}\Pi_4^T \\ \sqrt{d_M}\Pi_1 & \sqrt{d_M}\overline{\beta}_1\Pi_2^T & 0 & 0 & 0 & \sqrt{d_M}\overline{\beta}\Pi_3^T & \sqrt{d_M}\Pi_4^T \end{bmatrix}$$
$$\tilde{\Sigma}_{61} = \begin{bmatrix} 0 & \sqrt{\eta_M}\delta\Pi_2^T & 0 & 0 & 0 & -\sqrt{\eta_M}\delta\Pi_3^T & 0 \\ 0 & \sqrt{d_M}\delta\Pi_2^T & 0 & 0 & 0 & -\sqrt{d_M}\delta\Pi_3^T & 0 \end{bmatrix}, \tilde{\Sigma}_{77} = Diag\left\{-\tilde{R}_1, -\tilde{R}_2\right\}$$

$$\tilde{\Sigma}_{71}(1) = \begin{bmatrix} \sqrt{\eta_M}\tilde{U}^T \\ \sqrt{d_M}\tilde{M}^T \end{bmatrix}, \tilde{\Sigma}_{71}(2) = \begin{bmatrix} \sqrt{\eta_M}\tilde{U}^T \\ \sqrt{d_M}\tilde{N}^T \end{bmatrix}, \tilde{\Sigma}_{71}(3) = \begin{bmatrix} \sqrt{\eta_M}\tilde{V}^T \\ \sqrt{d_M}\tilde{M}^T \end{bmatrix}, \tilde{\Sigma}_{71}(4) = \begin{bmatrix} \sqrt{\eta_M}\tilde{V}^T \\ \sqrt{d_M}\tilde{N}^T \end{bmatrix}$$
$$\tilde{\Lambda}_1 = \Pi_1 + \Pi_1^T + \tilde{Q}_1 + \tilde{Q}_2 + \tilde{\Gamma} + \tilde{\Gamma}^T, \tilde{\Gamma} = \begin{bmatrix} \tilde{U} + \tilde{M} & \tilde{V} - \tilde{U} & -\tilde{V} & \tilde{N} - \tilde{M} & -\tilde{N} & 0 & 0 \end{bmatrix}$$
$$\Pi_1 = \begin{bmatrix} P_1 A & \hat{A}_f \\ \bar{P}_3 A & \hat{A}_f \end{bmatrix}, \tilde{\Lambda}_2 = \Pi_2 = \begin{bmatrix} C^T\hat{B}_f^T & C^T\hat{B}_f^T \\ 0 & 0 \end{bmatrix}, \tilde{\Lambda}_3 = \Pi_3 = \begin{bmatrix} C^T\hat{B}_f^T & C^T\hat{B}_f^T \end{bmatrix}$$
$$\tilde{\Lambda}_4 = \Pi_4 = \begin{bmatrix} B^T P_1 & B^T\bar{P}_3 \\ D^T P_1 & D^T\bar{P}_3 \end{bmatrix}$$

Moreover, if the conditions above are held, the filter coefficient matrices of system (2) can be designed by

$$\begin{cases} A_F = \hat{A}_f\bar{P}_3^{-1}, \\ B_F = \hat{B}_f, \\ C_F = \hat{C}_f\bar{P}_3^{-1}, \\ D_F = \hat{D}_f. \end{cases} \tag{38}$$

Proof. For any positive definite matrices P, R_i and scalar $\varepsilon_i > 0$ with $i = 1, 2$, the following inequality (39) holds.

$$(R_i - \varepsilon_i^{-1}P)R_i^{-1}(R_i - \varepsilon_i^{-1}P) \geq 0. \tag{39}$$

Then, one can get:

$$-PR_i^{-1}P \leq -2\varepsilon_i P + \varepsilon_i^2 R_i. \tag{40}$$

Therefore, the inequalities in (41) are the sufficient conditions for those in (17)

$$\Psi(s)=\begin{bmatrix}\Sigma_{11}+\Gamma+\Gamma^T & * & * & * & * & * & * \\ \Sigma_{21} & -I & * & * & * & * & * \\ \Sigma_{31} & 0 & -I & * & * & * & * \\ \Sigma_{41} & 0 & 0 & -I & * & * & * \\ \Sigma_{51} & 0 & 0 & 0 & \hat{\Sigma}_{55} & * & * \\ \Sigma_{61} & 0 & 0 & 0 & 0 & \hat{\Sigma}_{66} & * \\ \Sigma_{71}(s) & 0 & 0 & 0 & 0 & 0 & \Sigma_{77}\end{bmatrix}<0, s=1,2,3,4 \tag{41}$$

where $\hat{\Sigma}_{55}=\hat{\Sigma}_{66}=Diag\{-2\varepsilon_1\tilde{P}+\varepsilon_1^2\tilde{R}_1,-2\varepsilon_2\tilde{P}+\varepsilon_2^2\tilde{R}_2\}$.

If exist the matrices $P_1>0$, $P_3>0$ and P_2, we define $P=\begin{bmatrix}P_1 & * \\ P_2 & P_3\end{bmatrix}$, $E=\begin{bmatrix}I & 0 \\ 0 & P_2^TP_3^{-1}\end{bmatrix}$, $\bar{P}_3=P_2^TP_3^{-1}P_2$, $\Theta=Diag\{\underbrace{E,\dots,E}_{5},\underbrace{I,\dots,I}_{5},E,E,E\}$.

According to Schur complement, $P>0$ is equivalent to $P_1-\bar{P}_3>0$.

Define $\tilde{R}_i=ER_iE^T$ $(i=1,2)$, $\tilde{U}=EUE^T$, $\tilde{V}=EVE^T$, $\tilde{M}=EME^T$, $\tilde{N}=ENE^T$, $\tilde{\Gamma}=E\Gamma E^T$. Then pre- and post-multiply Eq. (41) with Θ and Θ^T, respectively, one can have Eq. (36). Define variables

$$\begin{cases}\hat{A}_f=\tilde{A}_f\bar{P}_3, \tilde{A}_f=P_2^TA_FP_2^{-T},\\ \hat{B}_f=P_2^TB_F,\\ \hat{C}_f=\tilde{C}_F\bar{P}_3, \tilde{C}_F=C_FP_2^{-T},\\ \hat{D}_f=D_F.\end{cases} \tag{42}$$

According to the analysis above, the filter parameters (A_F,B_F,C_F,D_F) in system (2) can be replaced by $(P_2^{-T}\tilde{A}_fP_2^T,P_2^{-T}\hat{B}_f,\tilde{C}_fP_2^T,\hat{D}_f)$, the filter system can be rewritten as

$$\begin{cases}\dot{x}_F(t)=P_2^{-T}\tilde{A}_fP_2^Tx_F(t)+P_2^{-T}\hat{B}_f\hat{y}(t),\\ r(t)=\tilde{C}_fP_2^Tx_F(t)+\hat{D}_f\hat{y}(t).\end{cases} \tag{43}$$

Defining $\tilde{x}_F(t)=P_2^Tx_F(t)$, from Eq. (43), one can get

$$\begin{cases}\dot{\tilde{x}}_F(t)=\tilde{A}_f\tilde{x}_F(t)+\hat{B}_f\hat{y}(t),\\ r(t)=\tilde{C}_f\tilde{x}_F(t)+\hat{D}_f\hat{y}(t).\end{cases} \tag{44}$$

Then, comparing system (44) with system (2), the filter coefficient matrices can be chosen as $(\tilde{A}_f,\hat{B}_f,\tilde{C}_f,\hat{D}_f)$. With $\hat{A}_f=\tilde{A}_f\bar{P}_3$ and $\hat{C}_f=\tilde{C}_f\bar{P}_3$ defined in (42), the filter coefficient matrices are given by Eq. (38).

The proof is finished. □

4. Simulation results

Simulation works in MATLAB are carried out to validate the effectiveness of our proposed fault detection approach for networked systems by the following two examples, a simple numerical experiment in Example 1 and a motion coordinate system of an Unmanned Surface Vehicles (USV) in Example 2.

Example 1. The practical coefficient matrices A, B, C and D in the system (1) are given as follows.

$$A=\begin{pmatrix}-2 & 0\\ 0 & -1\end{pmatrix}, B=\begin{pmatrix}0.01\\ 0.02\end{pmatrix}, C=\begin{pmatrix}1 & 0\end{pmatrix}, D=\begin{pmatrix}0.9\\ 0.8\end{pmatrix}.$$

The external disturbance $\omega(t)$ is a uniformly distributed random signal in the range of $[-1,1]$. For the sake of simplicity, the delay functions $\eta(t)$ and $d(t)$ are also set as uniformly distributed random functions in the ranges of $[0,\eta_M]$ and $[0,d_M]$, respectively. The deception attacks function $\mathcal{D}(x(t))$, the matrix S and the fault signal $s(t)$ are described respectively as follows.

$$\mathcal{D}(x(t))=\begin{pmatrix}-\tanh(0.3x_2(t))\\ -\tanh(0.6x_1(t))\end{pmatrix}, S=\begin{pmatrix}0.6 & 0\\ 0 & 0.3\end{pmatrix}, s(t)=\begin{cases}10, t\in[2,6]\\ 0, \text{otherwise}\end{cases}$$

The numerical experiment for the augmented system (11) is performed for $t\in[0,20s]$ and the sample time is set as 0.1s. Set $d_M=0.15$s, $\eta_M=0.2$s, $\gamma=7$ and ε_i $(i=1,2)$ for augment system (11). The probability of deception attacks is described as $\bar{\beta}$. In our simulations, $\beta(t)$ is set as 0.1 and the distribution of $\beta(t)$ is given in Fig. 2. In Fig. 2, there are several blue vertical lines at some moments, which means a deception attack happens at that time, i.e, $\beta(t)=1$ at time t. The times of

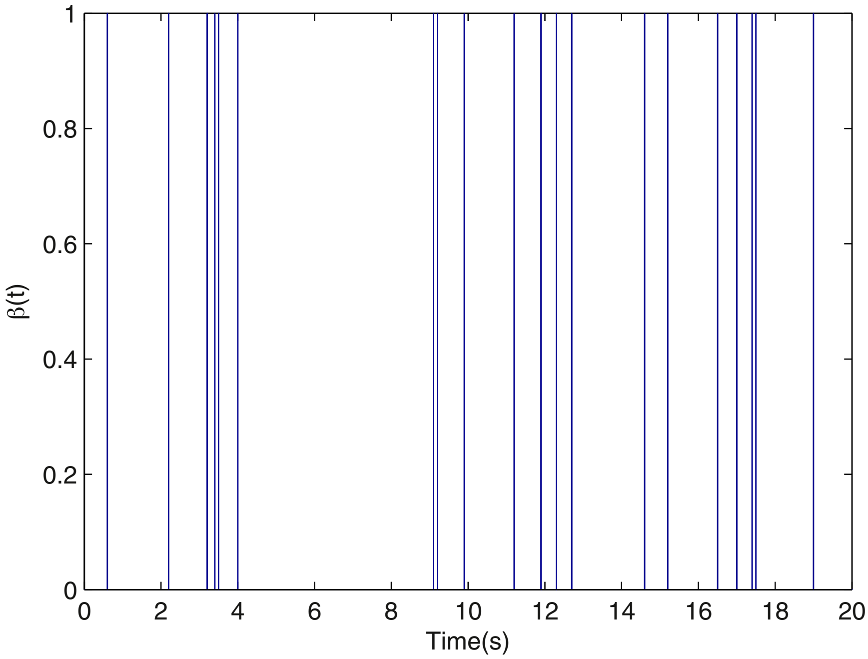


Fig. 2. Bernoulli variable $\beta(t)$ with $\bar{\beta} = 0.1$.

deception attacks occurring are affected by the probability $\bar{\beta}$, which means that there may be more vertical lines in Fig. 2 if $\bar{\beta}$ is larger.

Based on Matlab/LMIs toolbox and applying Theorem 2, the following parameter matrices can be computed.

$$\overline{P}_3 = \begin{pmatrix} 73.4371 & -26.0365 \\ -26.0365 & 55.0036 \end{pmatrix}, \hat{A}_f = 10^3 * \begin{pmatrix} -8.4337 & 0.0537 \\ 0.1184 & -8.3843 \end{pmatrix},$$

$$\hat{B}_f = \begin{pmatrix} 1.0415 \\ -0.6129 \end{pmatrix}, \hat{C}_f = \begin{pmatrix} -0.2191 & 0.6647 \end{pmatrix}, \hat{D}_f = 0.4220 \tag{45}$$

.

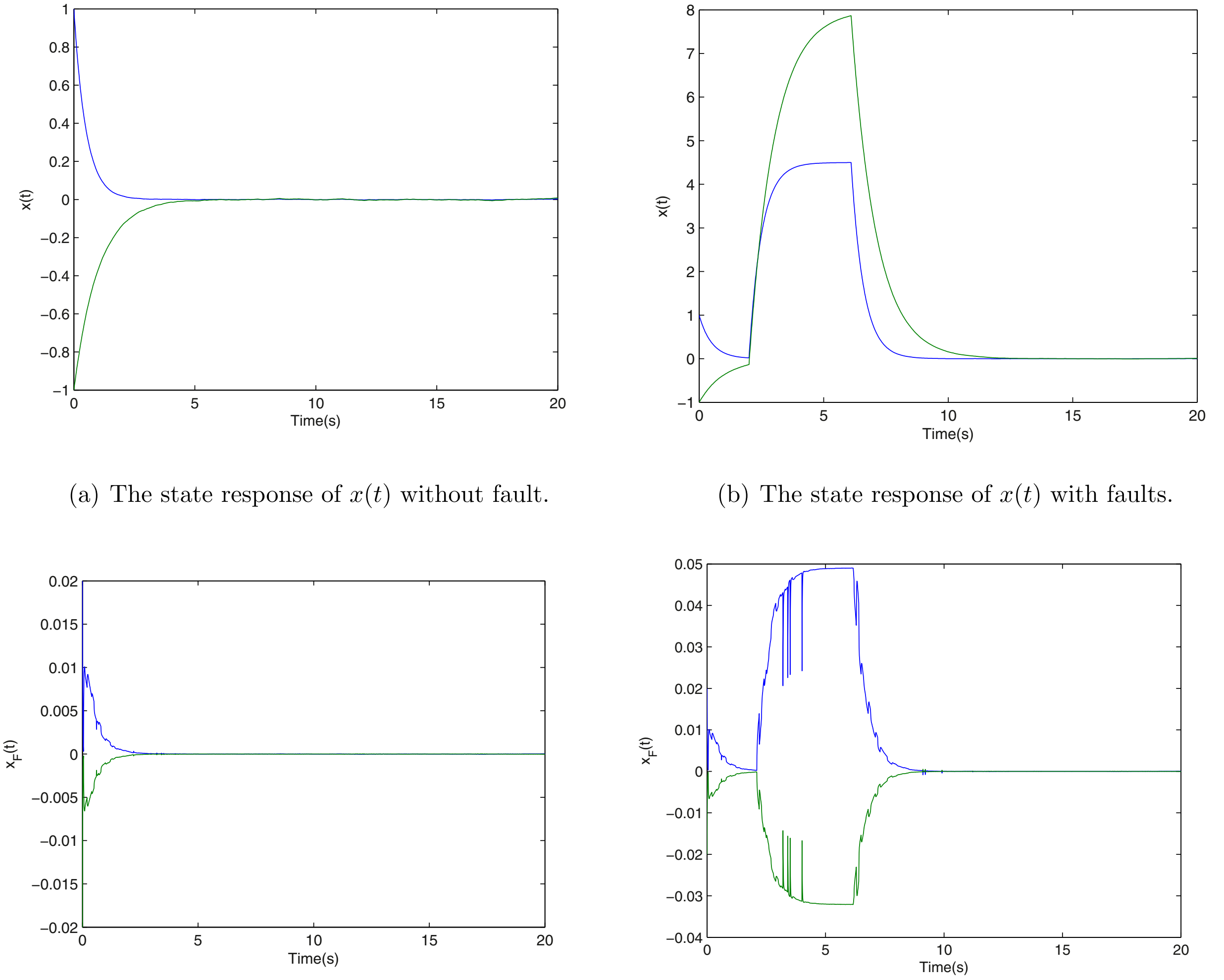
With Eq. (38), the coefficient matrices of FDF system (2) are given as follows.

$$A_F = \begin{pmatrix} -137.5865 & -64.1515 \\ -63.0055 & -182.2560 \end{pmatrix}, B_F = \begin{pmatrix} 1.0415 \\ -0.6129 \end{pmatrix}, C_F = \begin{pmatrix} 0.0016 & 0.0128 \end{pmatrix}, D_F = 0.4220.$$

Supposing that the initial states are given as $x(0) = \begin{pmatrix} 1 & -1 \end{pmatrix}^T$, $x_F(0) = \begin{pmatrix} 0.02 & -0.02 \end{pmatrix}^T$, the state response $\zeta(t) = \begin{bmatrix} x^T(t) & x_F^T(t) \end{bmatrix}^T$ and the residual response $r_e(t)$ of the corresponding augmented system (11) are presented by Fig. 3 and Fig. 4. The state responses of $x(t)$ without/with faults are given in Fig. 3(a) and (b), while that of $x_F(t)$ without/with faults are presented in Fig. 3(c) and (d). Fig. 3 shows that the state response of the corresponding augmented system composed by the state $x(t)$ and the state $x_F(t)$ is stable, which is also proved by Theorem 1. Fig. 4 illustrates that the residual response $r_e(t)$ can detect the occurrence of the fault immediately.

The residual evaluation function response $\mathcal{F}(t)$ described by Eq. (3) is depicted in Fig. 5. The results of $\mathcal{F}(t)$ with/without faults are described by the red dash dot line and the blue dashed line in Fig. 5, respectively. From Fig. 5, the fault detection threshold $\mathcal{F}_{th}$ is chosen as 0.3190, which is defined by Eq. (4). Fig. 5 also shows that system fault appeared at $t = 2.5468$ s, i.e., the fault detection time is $t = 0.5468$ s after the fault occurring.

Example 2. Consider a simple motion coordinate system of a USV borrowed from Wang et al. [22], which only the motion in sway, yaw and roll is considered in our simulations, and the rest factors is modeled as external disturbance, such as heave, surge, and pitch. The corresponding motion system is described with the formation (46), where $\upsilon(t)$, $r(t)$, $p(t)$, $\phi(t)$, $\psi(t)$ and $\delta(t)$ are corresponding to the sway velocity caused by the rudder motion, yaw velocity, roll velocity, roll angle,



(a) The state response of $x(t)$ without fault.

(b) The state response of $x(t)$ with faults.

(c) The state response of $x_F(t)$ without fault.

(d) The state response of $x_F(t)$ with faults.

Fig. 3. The state response of augmented system.

heading angle and rudder angle [22].

$$\begin{cases} \dot{\upsilon}(t) = -\frac{1}{T_\upsilon}\upsilon(t) + \frac{K_{d\upsilon}}{T_\upsilon}\delta(t) \\ \dot{r}(t) = \frac{K_{\upsilon r}}{T_r}\upsilon(t) - \frac{1}{T_r}r(t) + \frac{K_{dr}}{T_r}\delta(t) + \frac{1}{T_r}\omega_\psi(t) \\ \dot{p}(t) = \omega_n^2 K_{\upsilon p}\upsilon(t) - 2\zeta\omega_n p(t) - \omega^2\phi(t) + \omega_n^2 K_{dp}\delta(t) + \omega_n^2\omega_\phi(t) \\ \dot{\phi}(t) = p(t) \\ \dot{\psi}(t) = r(t) \end{cases} \tag{46}$$

Set $x(t) = [\upsilon^T(t) \quad r^T(t) \quad \psi^T(t)p^T(t) \quad \phi^T(t)]^T$, $\omega(t) = \left[\omega_\psi^T(t) \quad \omega_\phi^T(t)\right]^T$ as the external disturbance where $\omega\psi(t)$ and $\omega\phi(t)$ denote the influence of wave on $\psi(t)$ and $\phi(t)$, $\delta(t) = Kx(t)$ as the system input, and then we can rewrite the system (46) as (47):

$$\dot{x}(t) = (A_0 + A_1K)x(t) + B\omega(t) \tag{47}$$

where

$$A_0 = \begin{pmatrix} -\frac{1}{T_\upsilon} & 0 & 0 & 0 & 0 \\ \frac{K_{\upsilon r}}{T_r} & -\frac{1}{T_r} & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ \omega_n^2 K_{\upsilon p} & 0 & 0 & -2\zeta\omega_n & -\omega_n^2 \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix}, A_1 = \begin{pmatrix} \frac{K_{d\upsilon}}{T_\upsilon} \\ \frac{K_{dr}}{T_r} \\ 0 \\ \omega_n^2 K_{dp} \\ 0 \end{pmatrix}, B = \begin{pmatrix} 0 & 0 \\ \frac{1}{T_r} & 0 \\ 0 & 0 \\ 0 & \omega_n^2 \\ 0 & 0 \end{pmatrix}.$$

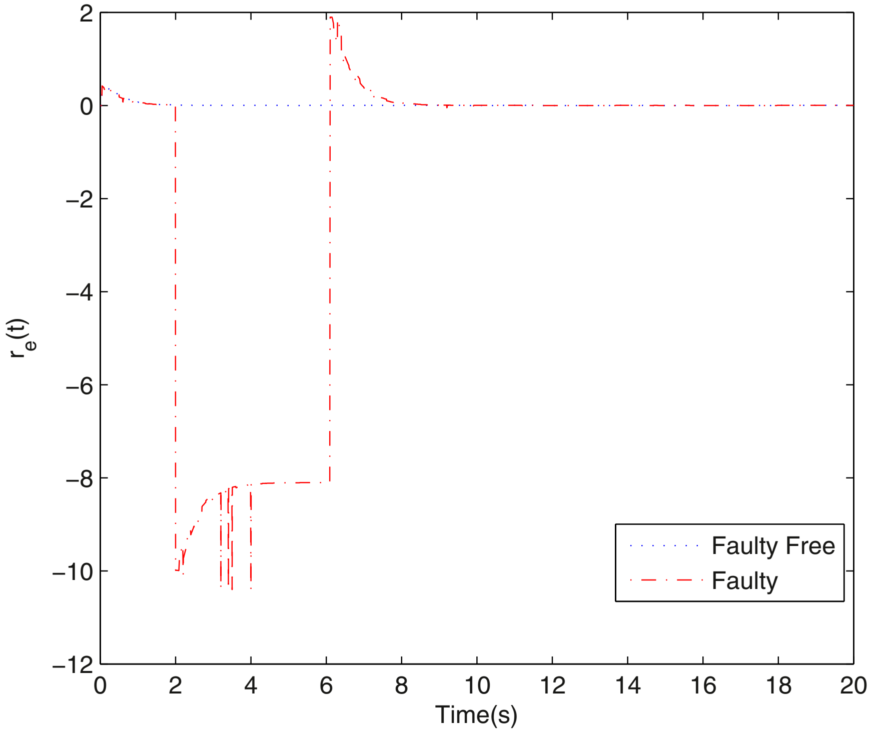


Fig. 4. Residual response $r_e(t)$ in Example 1.

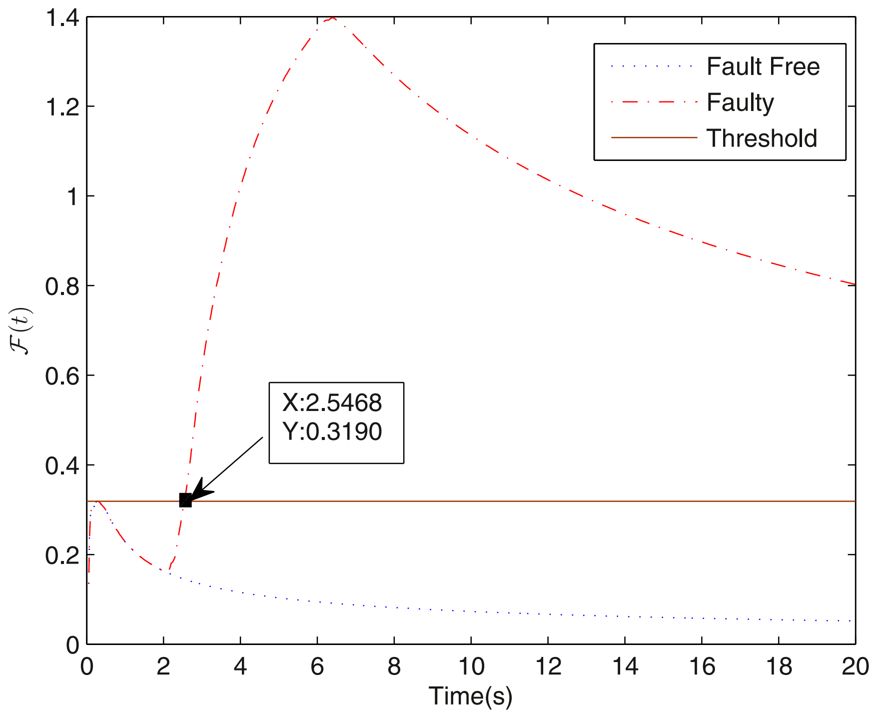


Fig. 5. Residual evaluation function $\mathcal{F}(t)$ in Example 1.

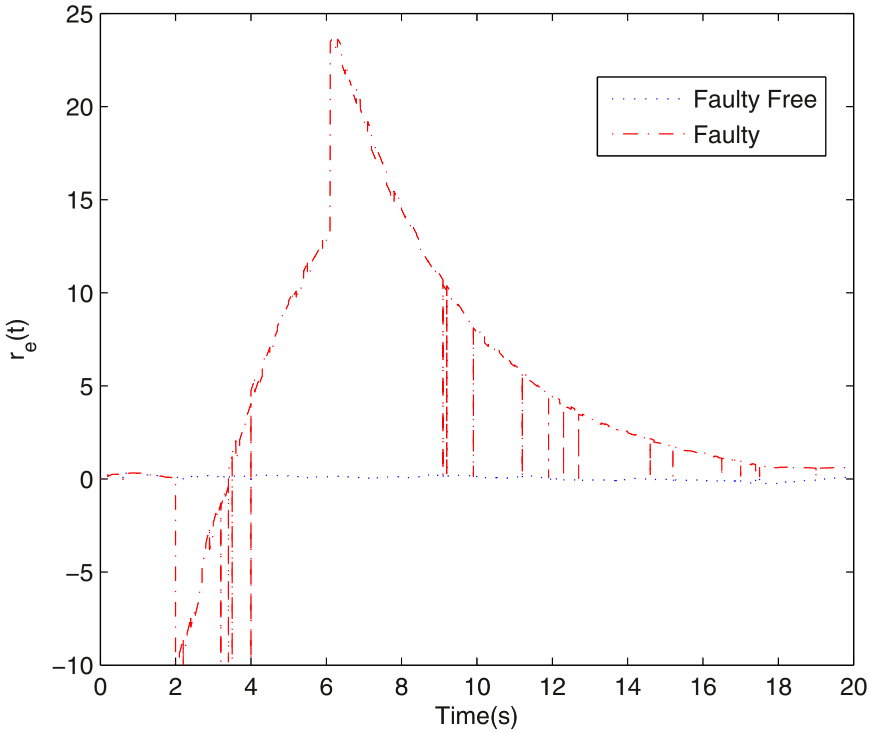


Fig. 6. Residual response $r_e(t)$ in Example 2.

Taking the fault $s(t)$ into consideration and setting $A = A_0 + A_1K$, the system (47) can be changed into (1).

The simulation parameters of the motion system are also referred to Wang et al. [22] to demonstrate the effectiveness of our scheme, and the numerical value of the parameters are set as: $T_\upsilon = 0.5263$, $T_r = 0.4211$, $K_{dr} = -0.0103$, $K_{dp} = -0.0202$, $K_{d\upsilon} = 0.0380$, $K_{\upsilon p} = 0.7980$, $K_{\upsilon r} = -0.4600$, $\omega_n = 1.6300$, $\zeta = 2.0840$, and suppose $K = \begin{pmatrix}1.1118 & 3.4650 & 6.6327 & -1.5691 & 3.1662\end{pmatrix}$, $C = \begin{pmatrix}1 & 0.8 & 1 & -1 & 0.6\end{pmatrix}$, $D = \begin{pmatrix}0.6 & -1 & 2 & 0.8 & 1\end{pmatrix}^T$. The coefficient matrices A and B can be derived as follows:

$$A = \begin{pmatrix} -1.8197 & 0.2502 & 0.4789 & -0.1133 & 0.2286 \\ -1.1196 & -2.4595 & -0.1618 & 0.0383 & -0.0773 \\ 0 & 1.0000 & 0 & 0 & 0 \\ 2.0605 & -0.1861 & -0.3562 & -6.7095 & -2.8269 \\ 0 & 0 & 0 & 1.0000 & 0 \end{pmatrix}, B = \begin{pmatrix} 0 & 0 \\ 2.375 & 0 \\ 0 & 0 \\ 0 & 2.6569 \\ 0 & 0 \end{pmatrix}$$

The deception attack $\mathcal{D}(x(t))$, the matrix S and the initial states of $x(0)$ & $x_F(0)$ are described as follows. The rest parameters are set as that in Example 1, such as the distribution of $\beta(t)$, the fault funtion $s(t)$, the delay $\eta(t)$ & $d(t)$ and so on.

$$\mathcal{D}(x(t)) = \begin{pmatrix} -tanh(0.4x_5(t)) \\ -tanh(0.6x_1(t)) \\ -tanh(0.3x_2(t)) \\ -tanh(0.2x_3(t)) \\ -tanh(0.5x_4(t)) \end{pmatrix}, S = \begin{pmatrix} 0.6 & 0 & 0 & 0 & 0 \\ & 0.3 & 0 & 0 & 0 \\ & * & 0.2 & 0 & 0 \\ & * & * & 0.5 & 0 \\ & * & * & * & 0.4 \end{pmatrix}, x(0) = \begin{pmatrix} 0 \\ 0.1 \\ 0.3 \\ 0.8 \\ 0.6 \end{pmatrix}, x_F(0) = \begin{pmatrix} 0.2 \\ -0.2 \\ -0.1 \\ -0.3 \\ -0.8 \end{pmatrix}.$$

Based on Matlab/LMIs toolbox and applying Theorem 2, the coefficient matrices of FDF system (2) can be computed.

$$A_f = 10^4 * \begin{pmatrix} -0.1486 & 0.0557 & -0.2789 & -0.0580 & -0.1282 \\ 0.0551 & -1.2416 & 0.1828 & 0.3198 & -0.1232 \\ -0.2790 & 0.1831 & -1.1588 & 0.0235 & -0.1011 \\ -0.0574 & 0.3200 & 0.0228 & -3.4888 & 0.7080 \\ -0.1286 & -0.1232 & -0.1009 & 0.7091 & -1.2551 \end{pmatrix},$$

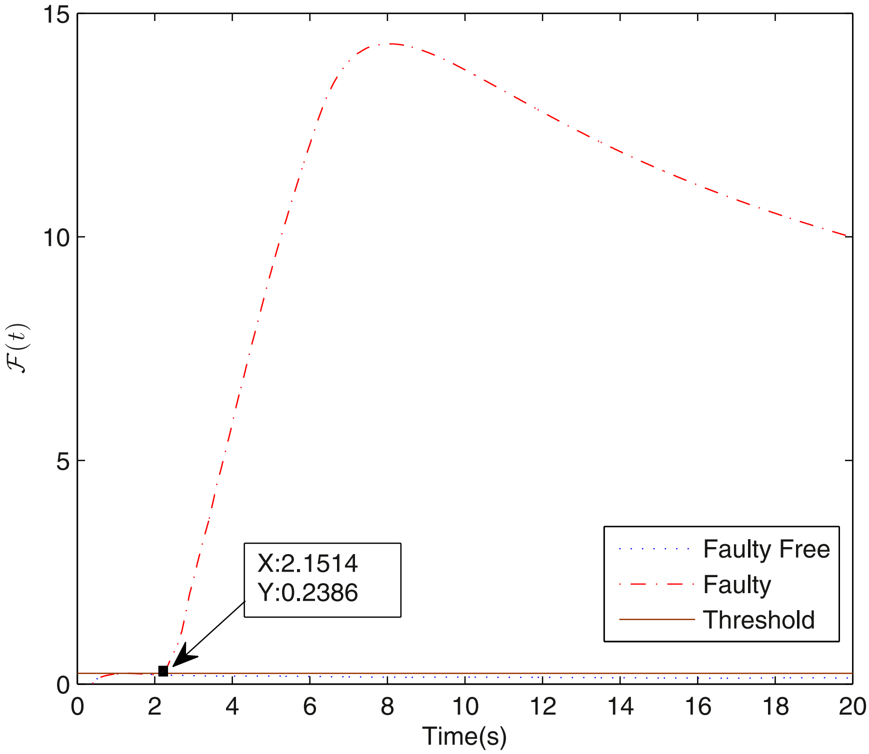


Fig. 7. Residual evaluation function $\mathcal{F}(t)$ in Example 2.

$$B_f = \begin{pmatrix} -20.9742 \\ -1.7510 \\ 4.5846 \\ 1.2078 \\ 0.5044 \end{pmatrix}, C_f = \begin{pmatrix} 0.0111 \\ -0.0074 \\ 0.0340 \\ -0.0207 \\ 0.0257 \end{pmatrix}^T, D_f = 0.3297.$$

The residual response $r_e(t)$ and the residual evaluation function response $\mathcal{F}(t)$ for Example 2 are described in Figs. 6 and 7. Fig. 6 illustrates that the residual response $r_e(t)$ can detect the occurrence of the fault immediately. From Fig. 7, the fault detection threshold $\mathcal{F}_{th}$ is chosen as 0.2386, which is defined by Eq. (4). Fig. 7 also shows that system fault appeared at $t = 2.1514$s, i.e., the fault detection time is $t = 0.1514$s after the fault occurring, which means that our fault detection scheme can detect the fault in a very short time in a motion system for a USV.

5. Conclusion

In this paper, a fault detection system is established for networked systems by taking network delay and deception attacks into consideration. Firstly, an FDF is designed for networked system with the consideration of network delay and deception attacks. Particularly, a Bernoulli variable $\beta(t)$ is used to denote whether deception attacks occur in system (11). Then, with the application of Lyapunov stability theory and LMI techniques, sufficient conditions and the corresponding FDF coefficient matrices are derived to ensure the stability with an H_∞ performance index γ. Finally, two simulation examples demonstrate the effectiveness and usefulness of the proposed approach. There are many research interests to draw attentions in the future. For example, event-triggering should be introduced to our fault detection systems with the consideration of limited network bandwidth resources. Moreover, the design of FDF systems with the consideration of packet dropout and hybrid attacks is also a challenging and meaningful work.

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