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Intermittent sensor fault detection for stochastic LTV systems with parameter uncertainty and limited resolution

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ABSTRACT
This paper considers the detection problem of intermittent sensor faults in stochastic linear time-varying systems with both parameter uncertainty and limited resolution. By introducing the soft measurement model, a state estimator is designed whose upper bound of estimation error covariance is obtained and minimised at each time step. Based on it, the residual is generated and its relationship with the fault is analysed quantitatively. Then the evaluation function and corresponding detection threshold is given. Our proposed method is recursive and therefore suitable for real-time online applications. At last, two simulation studies are carried out to illustrate the validity of our proposed method.

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1. Introduction

With the rapid development of advanced control and computer technologies, the modern engineering systems have become more automated and complicated. Meanwhile, the increased complexity and automation tend to make the systems more vulnerable. Any faults may have the potential to cause a host of safety, environmental and economic problems, which could even turn into disasters. Therefore, the fault detection technology has received extensive attention from both academia and industry over the past decades (Brás, Rosa, Silvestre, & Oliveira, 2015; Floquet, Barbot, Perruquetti, & Djemai, 2004; Franze & Famularo, 2012; Hajshirmohamadi, Davoodi, Meskin, & Sheikholeslam, 2016; Hwang, Kim, Kim, & Seah, 2010; Jing & Hua, 2008; Ríos, Punta, & Fridman, 2017; Zhang, Zhao, Li, & Liu, 2010).

Among existing studies, tremendous research efforts have been made to fault detection for linear time-varying (LTV) systems. There are mainly two methods that shed insightful lights among the available literature: state estimation-based methods (Ben Hmida, Khémiri, Ragot, & Gossa, 2010; Li & Zhou, 2009; Shen, Ding, & Wang, 2013) and parity space-based methods (Wan, Dong, & Ye, 2013; Zhong, Ding, Han, & Ding, 2010; Zhong, Song, & Ding, 2015). However, they do not consider the multiplicative parameter uncertainty and sensor resolution. Meanwhile, there is always some mismatch between mathematical model and real system. The model uncertainty is inevitable due to the existence of parameter perturbation, external disturbance, and so on. As a result, the robust fault detection has attracted persistent research interest. Generally speaking, two types of uncertainty are often considered: polytopic uncertainty (Blesa, Puig, & Saludes, 2012; Casavola, Famularo, & Franzè, 2005, 2008; Gao, Chen, & Wang, 2008; He, Wang, Ji, & Zhou, 2011; Wei & Verhaegen, 2010; Zhang, Liu, & Wang, 2011) and norm-bounded uncertainty (Ahmadizadeh, Zarei, & Karimi, 2014; He & Liu, 2011; Pourbabaee, Meskin, & Khorasani, 2016; Zhang et al., 2015; Zhuang, Li, & Li, 2016).

As a special kind of fault, the intermittent fault (IF) has received increasing interest recently. Different from permanent fault, the IF is referred to the fault which lasts for a limited period of time and then disappears without any external corrective action, and such a fault is often recurrent (Correcher, García, Morant, Quiles, & Rodríguez, 2012). In practical engineering systems, the IF is a major and common potential safety hazard, seriously threatening the life and property security (Bakhshi, Kunche, & Pecht, 2014; Söderholm, 2007). Hence, it is of vital importance to study the intermittent fault detection (IFD). In recent years, some initial IFD methods have been developed including quantitative methods (Blough, Sullivan, & Masson, 1992; Cai, Liu, & Xie, 2017; Cui, Dong, Bo, & Juszczyk, 2011; Yan, He, & Zhou, 2016; Yaramasu, Cao, Liu, & Wu, 2015) and qualitative methods (Contant, Lafortune, & Teneketzis, 2004; Correcher, Garcia, Morant, Quiles & Blasco-Gimenez, 2003; Ismaeel & Bhatnagar, 1997; Singh, Subramania, Holland, & Davis, 2012; Steadman, Berghout, Olsen, & Sorensen, 2008; Syed, Perinpanayagam, Samie, & Jennions, 2016; Zhang, Lei, & Chang, 2017; Zhou, Huang, Naixue, Qin & Huang, 2015).

Summarising the above discussion, it can be concluded that although the IFD has stirred some initial research interest, the corresponding robust IFD problem for stochastic LTV systems with parameter uncertainty and limited resolution has yet not been adequately addressed. It is due probably to difficulties

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in simultaneously processing noise, parameter uncertainty and resolution. Moreover, the stochastic characteristic of them adds substantial challenge to IFD method design, especially when both the occurrence and disappearance of the fault needs to be detected.

It is worth mentioning that the resolution is an important parameter of sensors, thus being a non-negligible factor for any fault detection issues. However, so far, to the best of our knowledge, this factor has rarely been considered in the fault detection community. Besides, most previous work usually assumes that the model uncertainty has a specific structure. The structure and corresponding parameters are also required to be known beforehand, which sometimes may not be impossible. Moreover, most available results in the literature are within the framework of norm index. In the view of these facts, we are motivated to propose a new IFD method. The main contributions of the paper can be highlighted as follows: (1) *a residual generator is constructed which takes both parameter uncertainty and limited resolution into consideration* ; (2) *the quantitative relationship between the residual and fault is given* ; and (3) *our proposed IFD method is recursive thus can be used for real-time online applications* .

The rest of this paper is organised as follows. In Section 2, the IFD problem for stochastic LTV systems with parameter uncertainty and limited resolution is formulated with some assumptions. In Section 3, the IFD method is designed based on our proposed state estimator. Simulation results are presented in Section 4, and some concluding remarks are given in Section 5.

Notations. Except where otherwise stated, the notations used throughout this paper are fairly standard. $\mathbb{R}^n$ and $\mathbb{R}^{n\times m}$ represent the n-dimensional Euclidean space and the set of all $n \times m$ real matrices, respectively. $\mathbf{0}_{n\times m} \in \mathbb{R}^{n\times m}$ is the null matrix (0 at all entries), and $\mathbf{I}_{n\times n}$ is the identity matrix with n rows and n columns (1 at the (i, i)th entry and 0 elsewhere). The scalar $x^{(i)}$ denotes the ith entry of the vector $\mathbf{x} \in \mathbb{R}^n$. The notation $\mathcal{S}(m, n)$ stands for the set $\{m, m+1, \dots, n\}$,$(m \in \mathbb{Z}, n \in \mathbb{Z}, m \le n)$. $\mathbb{E}_S\{\mathbf{A}\}$ represents the mathematical expectation of a stochastic variable $\mathbf{A}$ over the set S. Given a matrix $\mathbf{A} \in \mathbb{R}^{n\times m}$, row$\{\mathbf{A}, i\}$ denotes the vector $[a_{i1}\ a_{i2}\ \cdots\ a_{im}]^{\mathrm{T}}$. Given a set $\mathcal{V} = \{n_1, n_2, \dots, n_m\}$,$(n_1 \le n_2 \le \cdots \le n_m)$, $\mathrm{col}_{i\in\mathcal{V}}\{\mathbf{A}_i\}$ denotes the block-column matrix $[\mathbf{A}_{n_1}^T\ \mathbf{A}_{n_2}^{\mathrm{T}}\ \cdots\ \mathbf{A}_{n_m}^{\mathrm{T}}]^{\mathrm{T}}$. The notations $\mathrm{p}_{\mathrm{row}}(\mathbf{A})$, $\boldsymbol{\mu}_{\mathbf{A}}$ and $\Sigma_{\mathbf{A}}$ stand for $\mathrm{col}_{i\in\mathcal{S}(1,n)}\{\mathrm{row}\{\mathbf{A}, i\}\}$, $\mathbb{E}\{\mathbf{A}\}$ and $\mathbb{E}\{\mathrm{p}_{\mathrm{row}}(\mathbf{A})\mathrm{p}_{\mathrm{row}}(\mathbf{A})^{\mathrm{T}}\}$, respectively. Scalars are in italic, and matrices are in bold. Matrices, if their dimensions are not explicitly stated, are assumed to be compatible for algebraic operations.

2. Problem formulation and preliminaries

Consider a class of stochastic LTV systems described by the following state-space model:

$$\begin{aligned}\mathbf{x}(k+1) &= (\mathbf{A}_c(k) + \mathbf{A}_\delta(k))\,\mathbf{x}(k)\\ &\quad + (\mathbf{B}_c(k) + \mathbf{B}_\delta(k))\,\mathbf{u}(k) + \mathbf{w}(k),\end{aligned} \tag{1}$$

$$\mathbf{y}(k) = (\mathbf{C}_c(k) + \mathbf{C}_\delta(k))\,\mathbf{x}(k) + \mathbf{v}(k) + \boldsymbol{\Delta}\left(\mathbf{y}(k)\right) + \mathbf{f}(k), \tag{2}$$

$$\frac{y(k)^{(i)}}{s^{(i)}} \in \mathbb{Z}, i \in \mathcal{S}\left(1, n_{\mathbf{y}}\right), k \in \mathbb{N}. \tag{3}$$

where $\mathbf{x}(k) \in \mathbb{R}^{n_\mathbf{x}}$ is the system state, $\mathbf{u}(k) \in \mathbb{R}^{n_\mathbf{u}}$ is the control input, and $\mathbf{y}(k) \in \mathbb{R}^{n_\mathbf{y}}$ is the measurement output. $\mathbf{w}(k) \in \mathbb{R}^{n_\mathbf{x}}$ is the process noise, and $\mathbf{v}(k) \in \mathbb{R}^{n_\mathbf{y}}$ is the measurement noise. $s^{(i)}$ is the resolution of sensor i, $\Delta(\mathbf{y}(k))$ is the resolution-induced uncertainty, and $\mathbf{f}(k) \in \mathbb{R}^{n_\mathbf{y}}$ is the sensor fault. $\mathbf{A}_c(k) \in \mathbb{R}^{n_\mathbf{x}\times n_\mathbf{x}}$, $\mathbf{B}_c(k) \in \mathbb{R}^{n_\mathbf{x}\times n_\mathbf{u}}$, $\mathbf{C}_c(k) \in \mathbb{R}^{n_\mathbf{y}\times n_\mathbf{x}}$ are known deterministic parameters. $\mathbf{A}_\delta(k) \in \mathbb{R}^{n_\mathbf{x}\times n_\mathbf{x}}$, $\mathbf{B}_\delta(k) \in \mathbb{R}^{n_\mathbf{x}\times n_\mathbf{u}}$, $\mathbf{C}_\delta(k) \in \mathbb{R}^{n_\mathbf{y}\times n_\mathbf{x}}$ are corresponding unknown stochastic parameter uncertainty. The above system is called fault-free system if $\forall k \in \mathbb{N}, \mathbf{f}(k) \equiv \mathbf{0}_{n_\mathbf{y}\times 1}$. Otherwise, it is called faulty system.

The IF is in the following form:

$$\mathbf{f}(k) = \sum_{j=1}^{\infty} \mathbf{f}_j \left(\Gamma\left(k - k_{o,j}\right) - \Gamma\left(k - k_{d,j}\right)\right), \tag{4}$$

where $\Gamma(\cdot)$ is the unit step function. $\mathbf{f}_j$ is the jth fault profile, and $k_{o,j}$, $k_{d,j}$ are corresponding occurrence and disappearance time. The summation is used to describe the IF which occurs and disappears recurrently.

The following assumptions are made throughout this paper.

Assumption 2.1: *The initial state* $\mathbf{x}(0)$ *has the mean* $\bar{\mathbf{x}}_0$, *covariance* $\mathbf{P}_0$, *and second moment* Σ_0. *The noise* $\mathbf{w}(k)$,$\mathbf{v}(k)$ *are zero-mean white processes with covariances* $\Sigma_{\mathbf{w}(k)}$ *and* $\Sigma_{\mathbf{v}(k)}$. *The fault profile* $f_j^{(i)}$ *is much larger than the resolution* $s^{(i)}$, *i.e.* $f_j^{(i)} + 2s^{(i)} \approx f_j^{(i)}$. *Besides, the initial state, noise, and parameter uncertainty are mutually independent of each other.*

Assumption 2.2: *The stochastic parameter uncertainty* $\mathbf{A}_\delta(k)$, $\mathbf{B}_\delta(k)$, $\mathbf{C}_\delta(k)$ *are zero-mean white processes with*

$$\begin{aligned}\mathbb{E}\left\{\mathrm{p}_{\mathrm{row}}\left(\mathbf{A}_\delta(k)\right)\mathrm{p}_{\mathrm{row}}(\mathbf{A}_\delta(k))^{\mathrm{T}}\right\} &= \Sigma_{\mathbf{A}_\delta(k)},\\ \mathbb{E}\left\{\mathrm{p}_{\mathrm{row}}\left(\mathbf{B}_\delta(k)\right)\mathrm{p}_{\mathrm{row}}(\mathbf{B}_\delta(k))^{\mathrm{T}}\right\} &= \Sigma_{\mathbf{B}_\delta(k)},\\ \mathbb{E}\left\{\mathrm{p}_{\mathrm{row}}\left(\mathbf{C}_\delta(k)\right)\mathrm{p}_{\mathrm{row}}(\mathbf{C}_\delta(k))^{\mathrm{T}}\right\} &= \Sigma_{\mathbf{C}_\delta(k)}.\end{aligned} \tag{5}$$

In this paper, our main aim is to design an effective strategy to detect the occurrence and disappearance IF. It is worth mentioning that our proposed method fully considers both model uncertainty and resolution, thus can achieve a favourable detection performance. Our method can also be applied for the permanent fault detection, as the permanent fault is a special case of IF.

3. Main results

In this section, the aforementioned IFD problem will be investigated. Before proceeding further, the following soft measurement model and its property are firstly given.

Let $\boldsymbol{\mathcal{Y}}(k) = (\mathbf{C}_c(k) + \mathbf{C}_\delta(k))\mathbf{x}(k) + \mathbf{v}(k) + \mathbf{f}(k)$, we have

$$y(k)^{(i)} \Rightarrow \mathcal{Y}(k)^{(i)} \in S\left(y(k)^{(i)}\right), \tag{6}$$

where the set $S(y(k)^{(i)})$ is decided by the following rule:

$$S\left(y(k)^{(i)}\right) = \begin{cases} \left[y(k)^{(i)}, \quad y(k)^{(i)} + s^{(i)}\right), y(k)^{(i)} > 0, \\ \left(-s^{(i)}, s^{(i)}\right), \quad y(k)^{(i)} = 0, \\ \left(y(k)^{(i)} - s^{(i)}, y(k)^{(i)}\right], \quad \left(y(k)^{(i)} - s^{(i)}, y(k)^{(i)}\right]. \end{cases} \tag{7}$$

Then we can get the soft measurement model

$$\mathbf{Y}(k) = (\mathbf{C}_c(k) + \mathbf{C}_\delta(k))\,\mathbf{x}(k) + \mathbf{v}(k) + \boldsymbol{\Delta}(\mathbf{Y}(k)) + \mathbf{f}(k), \tag{8}$$

where the soft measurement output is decided by

$$Y(k)^{(i)} = \mathbb{E}_{S\left(y(k)^{(i)}\right)}\left\{\mathcal{Y}(k)^{(i)}\right\}. \tag{9}$$

In this paper, the system is measured by the sensor with non-zero resolution. We can only know which set the perfect measurement $\boldsymbol{\mathcal{Y}}(k)$ belongs to, but we can get the soft measurement output $\mathbf{Y}(k)$ according to the information of real measurement output $\mathbf{y}(k)$ and system model. Below is the basic property of our proposed soft measurement model.

Theorem 3.1: *Consider system* (1)–(3), *the resolution-induced uncertainty* $\Delta(\mathbf{Y}(k))$ *of the soft measurement model* (8) *satisfies*

$$\mathbb{E}\left\{\Delta(\mathbf{Y}(k))^{(i)}\right\} = 0, \tag{10}$$

$$\mathbb{E}\left\{\left\|\Delta(\mathbf{Y}(k))^{(i)}\right\|_2\right\} \le \mathbb{E}\left\{\left\|\Delta\left(y(k)\right)^{(i)}\right\|_2\right\}, \tag{11}$$

$$\mathbb{E}\left\{\left\|\Delta(\mathbf{Y}(k))^{(i)}\right\|_2\right\} = \mathbb{E}\left\{\left\|\Delta\left(y(k)\right)^{(i)}\right\|_2\right\} \Leftrightarrow Y(k)^{(i)} = y(k)^{(i)}. \tag{12}$$

Proof: The proof of the theorem is straightforward, thus omitted here. ■

Let $\hat{\mathbf{x}}(k)$ be the state estimate, and $\tilde{\mathbf{x}}(k) = \mathbf{x}(k) - \hat{\mathbf{x}}(k)$ be the state estimation error. The corresponding state estimation error covariance is $\mathbf{P}_\mathbf{x}(k) = \mathbb{E}\{\tilde{\mathbf{x}}(k)\tilde{\mathbf{x}}(k)^{\mathrm{T}}\}$. Our proposed state estimator is as follows:

$$\begin{aligned}\hat{\mathbf{x}}(k) &= \mathbf{A}_c(k-1)\,\hat{\mathbf{x}}(k-1) + \mathbf{B}_c(k-1)\,\mathbf{u}(k-1) \\ &\quad + \mathbf{K}_\mathbf{x}(k)\left(\mathbf{Y}(k) - \mathbf{C}_c(k)\,\mathbf{A}_c(k-1)\,\hat{\mathbf{x}}(k-1)\right. \\ &\quad \left.-\mathbf{C}_c(k)\,\mathbf{B}_c(k-1)\,\mathbf{u}(k-1)\right),\end{aligned} \tag{13}$$

where $\mathbf{K}_\mathbf{x}(k)$ is the state estimation gain which can be designed according to the following theorem.

Theorem 3.2: *Consider the fault-free system* (1)–(3) *with state estimator* (13) *and positive scalar* $\alpha_l, l \in \mathcal{S}(1,5)$, *the upper bound of the state estimation error covariance is*

$$\begin{aligned}\mathcal{P}_\mathbf{x}(k) &= \mathbf{K}_\mathbf{x}(k)\,\mathbf{Q}(k)\,\mathbf{K}_\mathbf{x}(k)^{\mathrm{T}} - \mathbf{K}_\mathbf{x}(k)\,\mathbf{C}_c(k)\,\mathbf{H}(k) \\ &\quad - \mathbf{H}(k)\,\mathbf{C}_c(k)^{\mathrm{T}}\mathbf{K}_\mathbf{x}(k)^{\mathrm{T}} + \mathbf{H}(k).\end{aligned} \tag{14}$$

It is minimised if and only if

$$\mathbf{K}_\mathbf{x}(k) = \mathbf{H}(k)\,\mathbf{C}_c(k)^{\mathrm{T}}\mathbf{Q}(k)^{-1}, \tag{15}$$

and the corresponding minimum upper bound is

$$\mathcal{P}_\mathbf{x}(k) = \left(\mathbf{I}_{n_\mathbf{x}\times n_\mathbf{x}} - \mathbf{K}_\mathbf{x}(k)\,\mathbf{C}_c(k)\right)\mathbf{H}(k), \tag{16}$$

where

$$\begin{aligned}\mathbf{H}(k) &= (1+\alpha_1)\,\mathbf{A}_c(k-1)\,\mathcal{P}_\mathbf{x}(k-1)\,\mathbf{A}_c(k-1)^{\mathrm{T}} \\ &\quad + (1+\alpha_2)\,\Sigma_{\mathbf{A}_\delta(k-1)\mathbf{x}(k-1)} \\ &\quad + (1+\alpha_3)\,\Sigma_{\mathbf{B}_\delta(k-1)\mathbf{u}(k-1)} + (1+\alpha_4)\,\Sigma_{\mathbf{w}(k-1)},\end{aligned} \tag{17}$$

$$\begin{aligned}\mathbf{Q}(k) &= \mathbf{C}_c(k)\,\mathbf{H}(k)\,\mathbf{C}_c(k)^{\mathrm{T}} + (1+\alpha_2)\,\Sigma_{\mathbf{C}_\delta(k)\mathbf{A}_c(k-1)\mathbf{x}(k-1)} \\ &\quad + (1+\alpha_2)\,\Sigma_{\mathbf{C}_\delta(k)\mathbf{A}_\delta(k-1)\mathbf{x}(k-1)} \\ &\quad + \mathbb{E}\left\{\mathbf{C}_\delta(k)\left(\mathbf{A}_c(k-1)\,\bar{\boldsymbol{x}}(k-1)\,\mathbf{u}(k-1)^{\mathrm{T}}\mathbf{B}_c\right.\right. \\ &\quad \times \left.\left.(k-1)^{\mathrm{T}}\right)\mathbf{C}_\delta(k)^{\mathrm{T}}\right\} \\ &\quad + \mathbb{E}\left\{\mathbf{C}_\delta(k)\left(\mathbf{B}_c(k-1)\,\mathbf{u}(k-1)\right.\right. \\ &\quad \times \left.\left.\bar{\boldsymbol{x}}(k-1)^{\mathrm{T}}\mathbf{A}_c(k-1)^{\mathrm{T}}\right)\mathbf{C}_\delta(k)^{\mathrm{T}}\right\} \\ &\quad + (1+\alpha_3)\,\Sigma_{\mathbf{C}_\delta(k)\mathbf{B}_c(k-1)\mathbf{u}(k-1)} + (1+\alpha_3)\,\Sigma_{\mathbf{C}_\delta(k)\mathbf{B}_\delta(k-1)\mathbf{u}(k-1)} \\ &\quad + (1+\alpha_4)\,\Sigma_{\mathbf{C}_\delta(k)\mathbf{w}(k-1)} + (1+\alpha_5)\,\Sigma_{\mathbf{v}(k)} \\ &\quad + \sum_{l=1}^{5}\left(\alpha_l^{-1}\mathrm{tr}\left(\Sigma_{\boldsymbol{\Delta}(\mathbf{Y}(k))}\right)\mathbf{I}_{n_\mathbf{y}\times n_\mathbf{y}}\right) + \mathrm{tr}\left(\Sigma_{\boldsymbol{\Delta}(\mathbf{Y}(k))}\right)\mathbf{I}_{n_\mathbf{y}\times n_\mathbf{y}}.\end{aligned} \tag{18}$$

The above state estimator is employed to generate the residual as follows:

$$\mathbf{r}(k) = \mathbf{Y}(k) - \mathbf{C}_c(k)\,\hat{\mathbf{x}}(k). \tag{19}$$

Next, we will fully analyse the influence of the fault on the residual.

Theorem 3.3: *The residual* (19) *of the faulty system* (1)–(3) *is related to the fault by*

$$\mathbf{r}(k) \approx \mathbf{r}_o(k) + \left(\mathbf{I}_{n_\mathbf{y}\times n_\mathbf{y}} + \mathbf{C}_c(k)\,\mathbf{S}(k)\right)\mathbf{f}(k) + \mathbf{C}_c(k)\,\mathbf{s}(k), \tag{20}$$

where $\mathbf{r}_o(k)$ *is the residual of the corresponding fault-free system, and* $\mathbf{S}(k)$, $\mathbf{s}(k)$ *have the following recursive forms*:

$$\begin{aligned}\mathbf{S}(k) &= \left(\mathbf{A}_c(k-1) - \mathbf{K}_\mathbf{x}(k)\,\mathbf{C}_c(k)\,\mathbf{A}_c(k-1)\right)\mathbf{S}(k-1) \\ &\quad - \mathbf{K}_\mathbf{x}(k),\end{aligned} \tag{21}$$

$$\mathbf{s}(k)=\begin{cases}-\left(\mathbf{K_x}(k)+\mathbf{S}(k)\right)\mathbf{f}(k)+\left(\mathbf{A}_c(k-1)\right.\\ \left.-\mathbf{K_x}(k)\mathbf{C}_c(k)\mathbf{A}_c(k-1)\right)\mathbf{s}(k-1), \quad k=k_{o,j},\\ \left(\mathbf{A}_c(k-1)-\mathbf{K_x}(k)\mathbf{C}_c(k)\mathbf{A}_c(k-1)\right)\\ \left(\mathbf{S}(k-1)\mathbf{f}(k-1)+\mathbf{s}(k-1)\right), \quad k=k_{d,j},\\ \left(\mathbf{A}_c(k-1)-\mathbf{K_x}(k)\mathbf{C}_c(k)\mathbf{A}_c(k-1)\right)\mathbf{s}(k-1),\\ \quad k\in\mathcal{S}\left(k_{d,j}+1,k_{o,j+1}-1\right),\\ \mathbf{0}_{n_\mathrm{x}\times 1}, \quad \text{otherwise.}\end{cases} \tag{22}$$

Proof: According to (1), (8), and (13), we can get the dynamic of the state estimation error as follows:

$$\begin{aligned}\tilde{\mathbf{x}}(k)&=\left(\mathbf{A}_c(k-1)-\mathbf{K_x}(k)\mathbf{C}_c(k)\mathbf{A}_c(k-1)\right)\tilde{\mathbf{x}}(k-1)\\&\quad+\left(\mathbf{A}_\delta(k-1)-\mathbf{K_x}(k)\left(\mathbf{C}_c(k)\mathbf{A}_\delta(k-1)\right.\right.\\&\quad\left.\left.+\mathbf{C}_\delta(k)\mathbf{A}_c(k-1)+\mathbf{C}_\delta(k)\mathbf{A}_\delta(k-1)\right)\right)\mathbf{x}(k-1)\\&\quad+\left(\mathbf{B}_\delta(k-1)-\mathbf{K_x}(k)\left(\mathbf{C}_c(k)\mathbf{B}_\delta(k-1)\right.\right.\\&\quad\left.\left.+\mathbf{C}_\delta(k)\mathbf{B}_c(k-1)+\mathbf{C}_\delta(k)\mathbf{B}_\delta(k-1)\right)\right)\mathbf{u}(k-1)\\&\quad+\left(\mathbf{I}_{n_\mathrm{x}\times n_\mathrm{x}}-\mathbf{K_x}(k)\left(\mathbf{C}_c(k)+\mathbf{C}_\delta(k)\right)\right)\mathbf{w}(k-1)\\&\quad-\mathbf{K_x}(k)\mathbf{v}(k)-\mathbf{K_x}(k)\boldsymbol{\Delta}\left(\mathbf{Y}(k)\right)-\mathbf{K_x}(k)\mathbf{f}(k)\\&=\mathbf{L}(k)\tilde{\mathbf{x}}(k-1)+\mathbf{N}(k)\mathbf{x}(k-1)+\mathbf{M}(k)\mathbf{u}(k-1)\\&\quad+\mathbf{U}(k)\mathbf{w}(k-1)-\mathbf{K_x}(k)\mathbf{v}(k)-\mathbf{K_x}(k)\boldsymbol{\Delta}\left(\mathbf{Y}(k)\right)\\&\quad-\mathbf{K_x}(k)\mathbf{f}(k),\end{aligned} \tag{23}$$

where

$$\begin{aligned}\mathbf{L}(k)&=\left(\mathbf{A}_c(k-1)-\mathbf{K_x}(k)\mathbf{C}_c(k)\mathbf{A}_c(k-1)\right),\\ \mathbf{N}(k)&=\left(\mathbf{A}_\delta(k-1)-\mathbf{K_x}(k)\left(\mathbf{C}_c(k)\mathbf{A}_\delta(k-1)\right.\right.\\&\quad\left.\left.+\mathbf{C}_\delta(k)\mathbf{A}_c(k-1)+\mathbf{C}_\delta(k)\mathbf{A}_\delta(k-1)\right)\right),\\ \mathbf{M}(k)&=\left(\mathbf{B}_\delta(k-1)-\mathbf{K_x}(k)\left(\mathbf{C}_c(k)\mathbf{B}_\delta(k-1)\right.\right.\\&\quad\left.\left.+\mathbf{C}_\delta(k)\mathbf{B}_c(k-1)+\mathbf{C}_\delta(k)\mathbf{B}_\delta(k-1)\right)\right),\\ \mathbf{U}(k)&=\left(\mathbf{I}_{n_\mathrm{x}\times n_\mathrm{x}}-\mathbf{K_x}(k)\left(\mathbf{C}_c(k)+\mathbf{C}_\delta(k)\right)\right).\end{aligned} \tag{24}$$

Furthermore, we can obtain the dynamic of the residual

$$\mathbf{r}(k)=\mathbf{C}_c(k)\tilde{\mathbf{x}}(k)+\mathbf{C}_\delta(k)\mathbf{x}(k)+\mathbf{v}(k)+\boldsymbol{\Delta}\left(\mathbf{Y}(k)\right)+\mathbf{f}(k). \tag{25}$$

Let us define a variable $\boldsymbol{\varphi}(k)$ as follows:

$$\boldsymbol{\varphi}(k)=\tilde{\mathbf{x}}(k)-\mathbf{S}(k)\mathbf{f}(k)-\mathbf{s}(k). \tag{26}$$

By resorting to (21)–(23), and (26), it can be obtained that

$$\begin{aligned}\boldsymbol{\varphi}(k+1)&\approx\mathbf{L}(k+1)\boldsymbol{\varphi}(k)+\mathbf{N}(k+1)\mathbf{x}(k)\\&\quad+\mathbf{M}(k+1)\mathbf{u}(k)+\mathbf{U}(k+1)\mathbf{w}(k)\\&\quad-\mathbf{K_x}(k+1)\mathbf{v}(k+1)\\&\quad-\mathbf{K_x}(k+1)\boldsymbol{\Delta}_o\left(\mathbf{Y}(k+1)\right),\end{aligned} \tag{27}$$

where $\Delta_o(\mathbf{Y}(k+1))$ denotes the resolution-induced uncertainty of the fault-free system. Similarly, we can get the dynamic of the state estimation error and residual for the corresponding fault-free system:

$$\begin{aligned}\tilde{\mathbf{x}}_o(k+1)&=\mathbf{L}(k+1)\tilde{\mathbf{x}}_o(k)+\mathbf{N}(k+1)\mathbf{x}(k)\\&\quad+\mathbf{M}(k+1)\mathbf{u}(k)+\mathbf{U}(k+1)\mathbf{w}(k)\\&\quad-\mathbf{K_x}(k+1)\mathbf{v}(k+1)\\&\quad-\mathbf{K_x}(k+1)\boldsymbol{\Delta}_o\left(\mathbf{Y}(k+1)\right),\end{aligned} \tag{28}$$

$$\mathbf{r}_o(k)=\mathbf{C}_c(k)\tilde{\mathbf{x}}_o(k)+\mathbf{C}_\delta(k)\mathbf{x}(k)+\mathbf{v}(k)+\boldsymbol{\Delta}_o\left(\mathbf{Y}(k)\right). \tag{29}$$

It then follows immediately from (25) to (29) that

$$\mathbf{r}(k)\approx\mathbf{r}_o(k)+\left(\mathbf{I}_{n_\mathrm{y}\times n_\mathrm{y}}+\mathbf{C}_c(k)\mathbf{S}(k)\right)\mathbf{f}(k)+\mathbf{C}_c(k)\mathbf{s}(k), \tag{30}$$

which completes the proof. ■

It can be seen that the residual is influenced by the fault additively and not cumulatively, thus can be utilised for IF detection. The following corollary gives the condition of fault detectability.

Corollary 3.1: *Consider the faulty system* (1)–(3) *with residual* (19), *then the fault is detectable if the following condition holds*:

$$\begin{aligned}&\left(\mathbf{I}_{n_\mathrm{y}\times n_\mathrm{y}}+\mathbf{C}_c(k)\mathbf{S}(k)\right)\mathbf{f}(k)+\mathbf{C}_c(k)\mathbf{s}(k)\neq\mathbf{0}_{n_\mathrm{y}\times 1},\\&k\in\left[k_{o,j},k_{d,j}-1\right],\end{aligned} \tag{31}$$

where $\mathbf{r}_o(k)$ *is the residual of the fault-free system, and* $\mathbf{S}(k)$, $\mathbf{s}(k)$ *are defined in* (21) *and* (22).

In this paper, the detection statistic is in the following square form:

$$T_D(k)=\mathbf{r}(k)^{\mathrm{T}}\mathbf{r}(k). \tag{32}$$

The basic property of above statistic is presented in the following theorem.

Theorem 3.4: *Consider the fault-free system* (1)–(3) *with residual* (19) *and positive scalar* $\alpha_l, l\in\mathcal{S}(1,5)$, *the expectation of the detection statistic* (32) *satisfies*

$$\mathbb{E}\left\{T_D(k)\right\}\leq J_{th}(k), \tag{33}$$

where $\boldsymbol{\mathcal{P}}_\mathbf{x}(k)$ *is defined in* (16), *and* $J_{th}(k)$ *is as follows*:

$$\begin{aligned}J_{th}(k)&=\left(1+\alpha_1+\alpha_2+\alpha_3\right)\mathrm{tr}\left(\mathbf{C}_c(k)\boldsymbol{\mathcal{P}}_\mathbf{x}(k)\mathbf{C}_c(k)\right)\\&\quad+\left(1+{\alpha_1}^{-1}+\alpha_4\right)\mathrm{tr}\left(\Sigma_{\mathbf{C}_\delta(k)\mathbf{x}(k)}\right)\\&\quad+\left(1+{\alpha_2}^{-1}+\alpha_5\right)\mathrm{tr}\left(\Sigma_{\mathbf{v}(k)}\right)\\&\quad+\left(1+{\alpha_3}^{-1}+{\alpha_4}^{-1}+{\alpha_5}^{-1}\right)\mathrm{tr}\left(\Sigma_{\boldsymbol{\Delta}(\mathbf{Y}(k))}\right).\end{aligned} \tag{34}$$

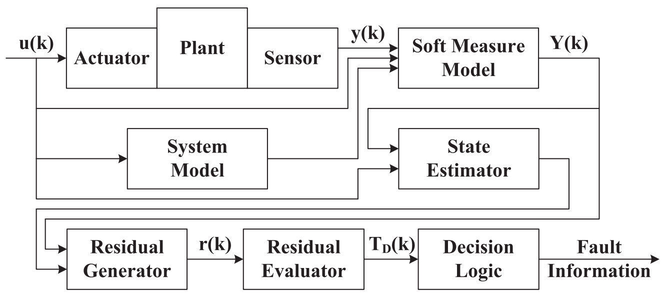

Figure 1. The schematic diagram of our proposed IFD method.

Proof: By resorting to the property of matrix inequality and trace, we have

$$\begin{aligned}
\mathbb{E}\{T_D(k)\} &= \mathrm{tr}\left(\mathbb{E}\left\{\mathbf{r}(k)^{\mathrm{T}}\mathbf{r}(k)\right\}\right)\\
&= \mathrm{tr}\left(\mathbb{E}\left\{(\mathbf{C}_c(k)\tilde{\mathbf{x}}(k)+\mathbf{C}_\delta(k)\mathbf{x}(k)+\mathbf{v}(k)+\mathbf{\Delta}(\mathbf{Y}(k)))^{\mathrm{T}}\right.\right.\\
&\quad \left.\left.\times(\mathbf{C}_c(k)\tilde{\mathbf{x}}(k)+\mathbf{C}_\delta(k)\mathbf{x}(k)+\mathbf{v}(k)+\mathbf{\Delta}(\mathbf{Y}(k)))\right\}\right)\\
&\le (1+\alpha_1+\alpha_2+\alpha_3)\,\mathrm{tr}\left(\mathbf{C}_c(k)\mathcal{P}_{\mathbf{x}}(k)\mathbf{C}_c(k)\right)\\
&\quad + \left(1+\alpha_1{}^{-1}+\alpha_4\right)\mathrm{tr}\left(\Sigma_{\mathbf{C}_\delta(k)\mathbf{x}(k)}\right)\\
&\quad + \left(1+\alpha_2{}^{-1}+\alpha_5\right)\mathrm{tr}\left(\Sigma_{\mathbf{v}(k)}\right)\\
&\quad + \left(1+\alpha_3{}^{-1}+\alpha_4{}^{-1}+\alpha_5{}^{-1}\right)\mathrm{tr}\left(\Sigma_{\mathbf{\Delta}(\mathbf{Y}(k))}\right).
\end{aligned} \tag{35}$$

The proof of the theorem is thus completed. ■

It is obvious that the fault detection threshold $J_{th}(k)$ is less than $4\mathrm{tr}(\mathbf{C}_c(k)\mathcal{P}_{\mathbf{x}}(k)\mathbf{C}_c(k)) + 3\mathrm{tr}(\Sigma_{\mathbf{C}_\delta(k)\mathbf{x}(k)}) + 3\mathrm{tr}(\Sigma_{\mathbf{v}(k)}) + 4\mathrm{tr}(\Sigma_{\Delta(\mathbf{Y}(k))})$.

By setting the detection threshold $J_D(k)$ as follows:

$$J_D(k) = J_{th}(k), \tag{36}$$

we can then make fault detection by the following logic:

$$\begin{aligned}
T_D(k) > J_D(k) &\Rightarrow \text{with fault} \Rightarrow \text{fault alarm},\\
T_D(k) \le J_D(k) &\Rightarrow \text{no fault} \Rightarrow \text{fault release}.
\end{aligned} \tag{37}$$

According to the above analysis, our proposed IFD method can now be summarised in Figure 1.

4. Simulation example

4.1 Example A

To illustrate the validity of the proposed IFD method, we consider a stochastic LTV system with following parameters:

$$\mathbf{A}_c(k) = \begin{bmatrix} 0.97 & 0.4+0.01\cos(0.13k)\\ 0.13+0.02\sin(0.13k) & -0.76 \end{bmatrix},$$

$$\mathbf{B}_c(k) = \begin{bmatrix} 0.15+0.03\cos(0.12k)\\ 0.18+0.04\sin(0.15k) \end{bmatrix},$$

$$\mathbf{C}_c(k) = \begin{bmatrix} 0.75+0.03\sin(0.13k) & 0.64\\ 0.83 & 0.71+0.02\cos(0.14k) \end{bmatrix}.$$

In our simulation, the initial state, process noise, and measurement noise are mutually independent zero-mean white processes with covariances $\Sigma_{\mathbf{x}(0)} = \mathbf{I}_{n_\mathbf{x}\times n_\mathbf{x}}\times 10^{-6}$, $\Sigma_{\mathbf{w}(k)} = 1.3\mathbf{I}_{n_\mathbf{x}\times n_\mathbf{x}}\times 10^{-4}$, and $\Sigma_{\mathbf{v}(k)} = 1.5\mathbf{I}_{n_\mathbf{x}\times n_\mathbf{x}}\times 10^{-4}$, respectively. The resolution is $\mathbf{s}(k) = [0.001\ \ 0.001]^{\mathrm{T}}$. The uncertain parameter matrices are mutually independent zero-mean white processes with covariances:

$$\Sigma_{\mathbf{A}_\delta(k)} = \begin{bmatrix} 1.6+0.2\cos(0.12k) & & & \\ & 1.2 & & \\ & & 1.3 & \\ & & & 1.5+0.4\sin(0.16k) \end{bmatrix} \times 10^{-3},$$

$$\Sigma_{\mathbf{B}_\delta(k)} = \begin{bmatrix} 1.3 & \\ & 1.4+0.3\sin(0.21k) \end{bmatrix} \times 10^{-2},$$

$$\Sigma_{\mathbf{C}_\delta(k)} = \begin{bmatrix} 1.2+0.5\cos(0.13k) & & & \\ & 1.4+0.6\sin(0.2k) & & \\ & & 1.8+0.4\sin(0.15k) & \\ & & & 1.6 \end{bmatrix} \times 10^{-5}.$$

In order to demonstrate the effectiveness of our proposed method, three different fault cases are all taken into consideration.

Case 1: The fault occurs only in sensor 1 as follows:

$$\mathbf{f}(k) = \begin{cases} [0.2\quad 0]^{\mathrm{T}}, & k \in [201, 240],\\ [0.28\quad 0]^{\mathrm{T}}, & k \in [501, 540],\\ [0.16\quad 0]^{\mathrm{T}}, & k \in [801, 860],\\ [0\quad 0]^{\mathrm{T}}, & \text{otherwise}. \end{cases}$$

Case 2: The fault occurs only in sensor 2 as follows:

$$\mathbf{f}(k) = \begin{cases} [0\quad 0.16]^{\mathrm{T}}, & k \in [201, 240],\\ [0\quad 0.25]^{\mathrm{T}}, & k \in [501, 540],\\ [0\quad 0.2]^{\mathrm{T}}, & k \in [801, 860],\\ [0\quad 0]^{\mathrm{T}}, & \text{otherwise}. \end{cases}$$

Case 3: The fault occurs both in sensor 1 and 2 as follows:

$$\mathbf{f}(k) = \begin{cases} [0.26\quad 0.13]^{\mathrm{T}}, & k \in [201, 240],\\ [0.12\quad 0.3]^{\mathrm{T}}, & k \in [501, 540],\\ [0.32\quad 0.2]^{\mathrm{T}}, & k \in [801, 860],\\ [0\quad 0]^{\mathrm{T}}, & \text{otherwise}. \end{cases}$$

Simulation results are shown in Figures 2–5. Figure 2 presents the mean square resolution-induced uncertainty of the sensors. We can observe that the mean square resolution-induced uncertainty of soft measurement model is less than that of the real measurement model. The IFD results are shown in Figures 3–5. It can be seen that our method (OM) has a better performance than the present method (PM), which is due to the efforts we have made in handling both stochastic uncertainty and limited sensor resolution.

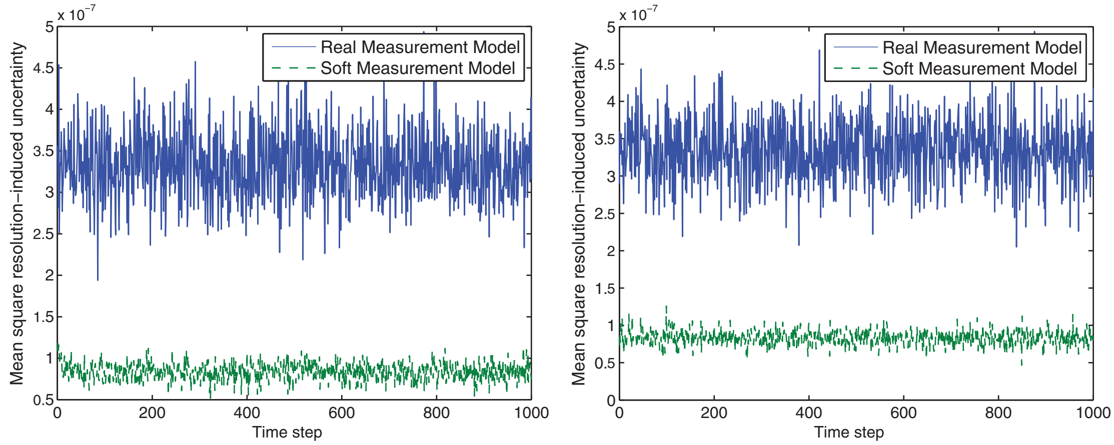

Figure 2. Mean square resolution-induced uncertainty. (a) Sensor 1 (b) Sensor 2.

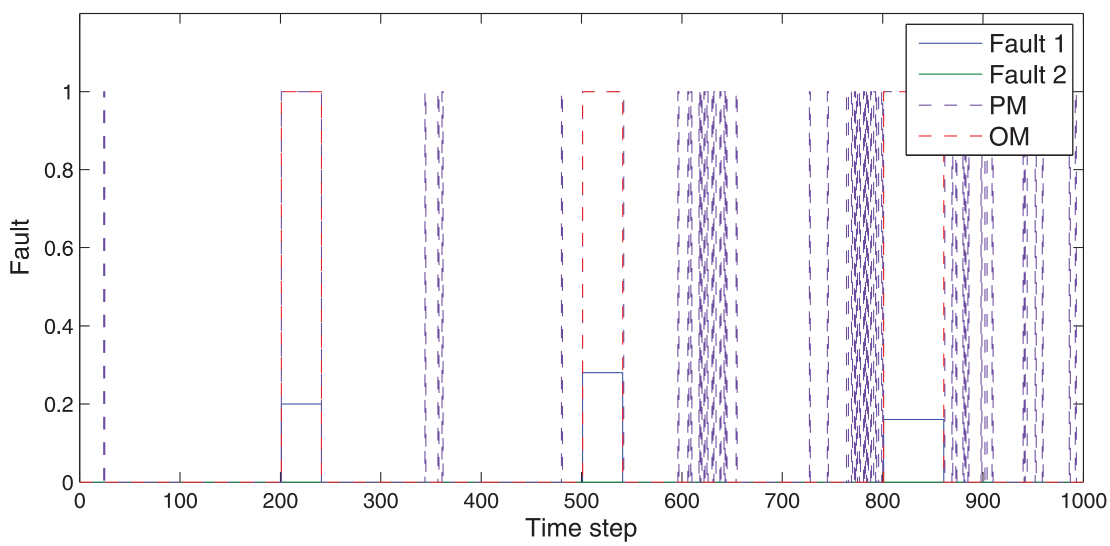

Figure 3. Case 1: The IF and detection result.

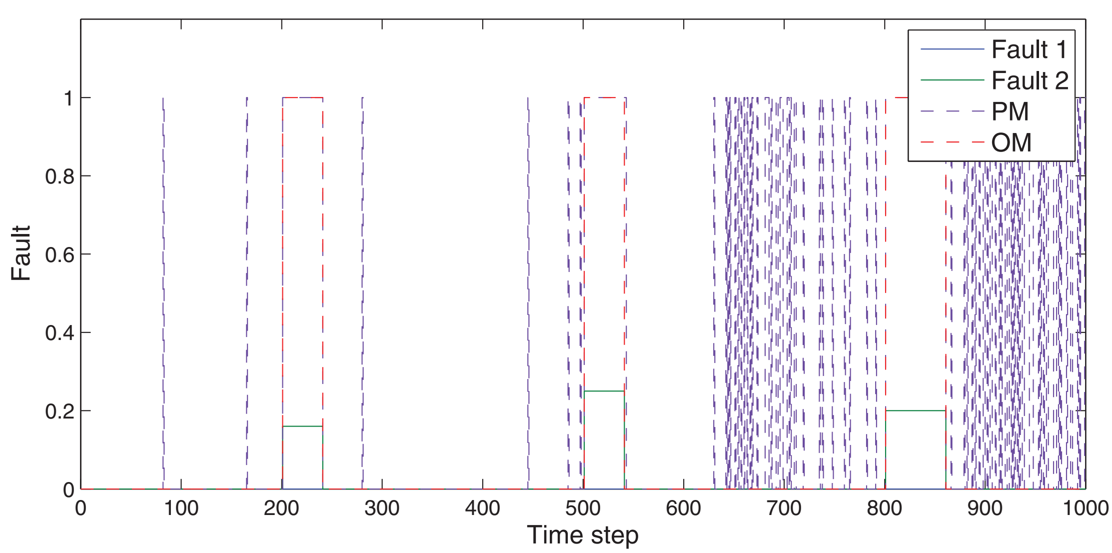

Figure 4. Case 2: The IF and detection result.

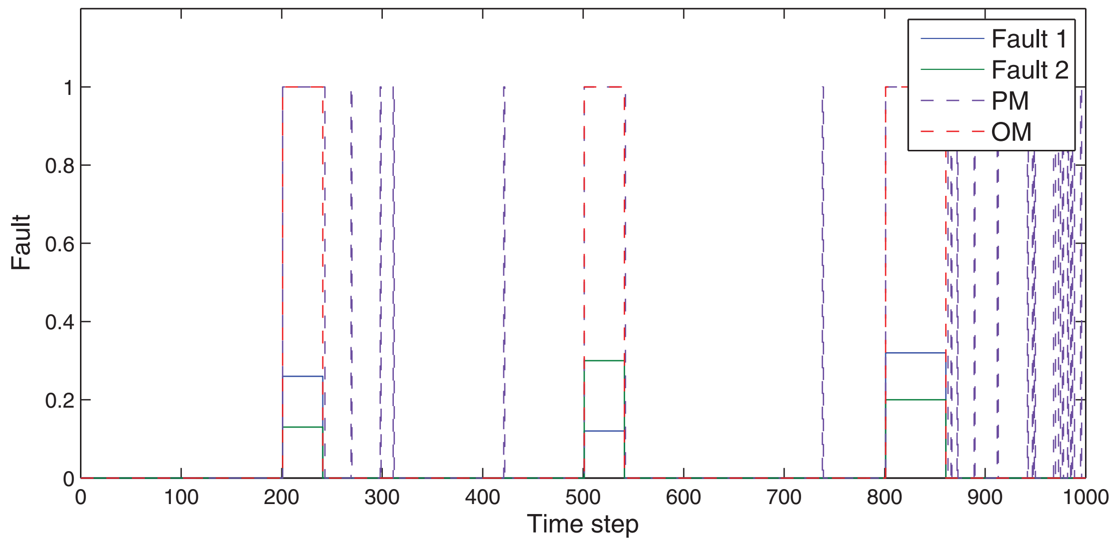

Figure 5. Case 3: The IF and detection result.

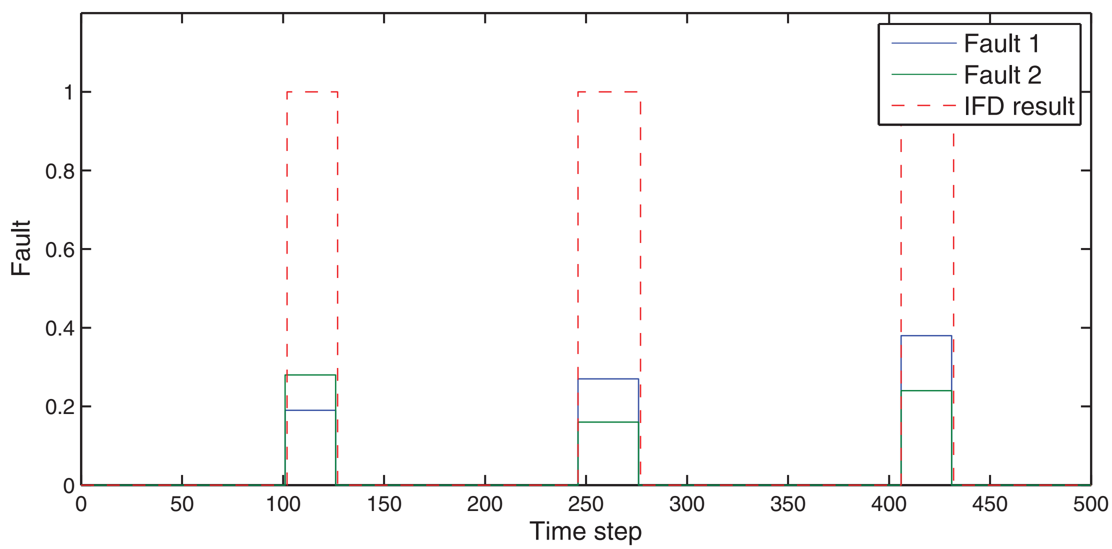

Figure 6. CSTR: The IF and detection result.

4.2 Example B

Consider a non-isothermal continuous stirred tank reactor (CSTR) where an irreversible exothermic reaction takes place. In the reactor, the reactant A is converted to the product B via the chemical reaction $A \to B$. The CSTR has a heating jacket which supplies or removes the heat from the reactor. The identified parameters for the linear model of the CSTR are as follows:

$$\mathbf{A}_c(k) = \begin{bmatrix} 0.9655 & -0.0005 \\ 1.43 & 1.0181 \end{bmatrix},$$

$$\mathbf{B}_c(k) = \begin{bmatrix} 5.24 \times 10^{-3} & -8.09 \times 10^{-9} \\ -1.16 \times 10^{-2} & 4.57 \times 10^{-6} \end{bmatrix}, \quad \text{and}$$

$$\mathbf{C}_c(k) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

In our simulation, the initial state, process noise, and measurement noise are mutually independent zero-mean white processes with covariances $\Sigma_{\mathbf{x}(0)} = 1.2\mathbf{I}_{n_\mathbf{x} \times n_\mathbf{x}} \times 10^{-6}$, $\Sigma_{\mathbf{w}(k)} = \mathbf{I}_{n_\mathbf{x} \times n_\mathbf{x}} \times 10^{-4}$, and $\Sigma_{\mathbf{v}(k)} = \mathbf{I}_{n_\mathbf{x} \times n_\mathbf{x}} \times 10^{-4}$, respectively. The resolution is $\mathbf{s}(k) = [0.001 \;\; 0.001]^{\mathrm{T}}$. The uncertain parameter matrices are mutually independent zero-mean white processes with covariances $\Sigma_{\mathbf{C}_\delta(k)} = \mathbf{0}_{(n_\mathbf{y} n_\mathbf{x}) \times (n_\mathbf{y} n_\mathbf{x})}$,

$$\Sigma_{\mathbf{A}_\delta(k)} = \begin{bmatrix} 1.2 & & & \\ & 1.5 + 0.2\sin(0.1k) & & \\ & & 1.3 + 0.1\cos(0.2k) & \\ & & & 1.4 \end{bmatrix} \times 10^{-6},$$

$$\Sigma_{\mathbf{B}_\delta(k)} = \begin{bmatrix} 1.1 + 0.2\cos(0.1k) & & & \\ & 1.6 & & \\ & & 1.4 + 0.1\cos(0.1k) & \\ & & & 1.5 \end{bmatrix} \times 10^{-6}.$$

The fault of the CSTR is as follows:

$$\mathbf{f}(k) = \begin{cases} [0.19 \quad 0.28]^{\mathrm{T}}, & k \in [101, 125], \\ [0.27 \quad 0.16]^{\mathrm{T}}, & k \in [246, 275], \\ [0.38 \quad 0.24]^{\mathrm{T}}, & k \in [406, 430], \\ [0 \quad 0]^{\mathrm{T}}, & \text{otherwise.} \end{cases}$$

It can be seen from Figure 6 that our proposed method has a favourable performance.

5. Conclusion

In this paper, the IFD problem has been investigated for stochastic LTV systems with parameter uncertainty and limited resolution. We have designed a state estimator at the criterion of minimum mean square error to ensure that the upper bound of the estimation error covariance is minimised at each time step. Based on it, we have constructed a recursive residual generator which does not depend on any structural information of uncertainty. Furthermore, we have also made quantitative analysis of the influence of the fault on it in details. Subsequently, we have evaluated the residual and set corresponding detection threshold. It is worth mentioning that our proposed IFD method fully considers parameter uncertainty and limited resolution thus can achieve favourable detection performance. Finally, we have demonstrated the effectiveness and applicability of our method through two simulation examples.

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