International Journal of Innovative Computing, Information and Control
Volume **8**, Number **4**, April **2012**

ICIC International ©2012 ISSN 1349-4198
pp. **2439–2451**

FAULT DETECTION FOR STATE-DELAY FUZZY SYSTEMS SUBJECT TO RANDOM COMMUNICATION DELAY

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Received December 2010; revised June 2011

Abstract. *This paper is concerned with the problem of fault detection for discrete-time state-delay fuzzy systems. It is assumed that the output measurements are subject to random communication delay. The random communication delay is modeled as a finite state Markov process, and it is assumed that the transition probabilities are partially known. The problem addressed is the design of a delay-mode-dependent fuzzy fault detection filter, which is used as a residual generator, such that the estimation error between residual and fault (or, more generally, weighted fault) is as small as possible. Based on a fuzzy Lyapunov functional and Finsler's Lemma, a delay-dependent sufficient condition for the solvability of the problem is established. The fault detection filter parameters can be obtained by solving a set of linear matrix inequalities. A numerical example is given to illustrate the efficiency of the proposed approach.*

Keywords: Fault detection, State-delay fuzzy system, Random communication delay, Fuzzy Lyapunov functional, Partially known transition probabilities

1. **Introduction.** Fault detection and isolation (FDI) for many dynamic systems have attracted great attention. One of the most popular methods to FDI is model-based fault detection one, which is to design a fault detection filter or observer generating a residual to decide whether a fault has occurred in the system [1, 2, 3, 4]. In many real systems, unknown inputs, control inputs and faults are usually coupled. In order to design a robust FDI system, which is sensitive to faults and simultaneously robust to unknown inputs and control inputs, an H_∞-filtering formulation of an FDI problem has been presented [5, 6, 7, 8, 9]. More recently, a great amount of effort has been devoted to the problem of FDI for both continuous-time systems and discrete-time systems in a networked environment [10, 11, 12, 13, 14]. The authors in [10] have studied the design of robust fault detection for networked control systems with large transfer delays, where the networked control system was modeled as a Markovian jump system based on the multirate sampling method together with the augmented state matrix method. The authors in [11] have dealt with the fault detection problem for a class of linear discrete-time systems in a networked environment. In [12], the problem of robust fault estimation has been investigated for a class of uncertain continuous-time linear networked control systems with random communication network-induced delays, which are described by Markov processes. The fault detection problem for continuous-time linear time-invariant systems over IP-based networks has been investigated in [13], in which the statistical characteristics of the network-induced delay are utilized. In [14], the problem of fault detection has been studied for continuous-time linear networked control systems with non-ideal network quality of service, which includes network-induced delay, data dropout and error sequence.

It is well known that most physical systems are nonlinear, and some complex nonlinear systems can often be represented or approximated by Takagi-Sugeno (T-S) fuzzy models [15, 16], which is described by a family of fuzzy IF-THEN rules that represent local linear input/output relations of the system. The overall fuzzy model of the system is achieved by smoothly blending these local linear models together through membership functions. Many methods to stability analysis, controller design and state estimator design of T-S fuzzy systems have been developed, such as a common quadratic Lyapunov function approach [17, 18, 19, 20], a piecewise quadratic Lyapunov function approach [20, 21, 22, 23] and a fuzzy (or non-quadratic) Lyapunov function approach [24, 25, 26, 27].

Recently, there have appeared some results on fault detection for fuzzy dynamic systems in the open literature [28, 29, 30, 31]. Specially, the authors in [31] were concerned with the problem of fault detection for discrete-time fuzzy systems under the assumption that there existed a communication medium between the physical plant and the fault detection filter, and the data packet dropout phenomenon happened intermittently. Communication network-induced delays were not taken into account in [31]. In addition, time delay is frequently encountered in various complex nonlinear systems, such as chemical systems and mechanical systems. To the best of our knowledge, however, the problem of fault detection for discrete-time state-delay fuzzy systems subject to random communication delay remains open. This motivates the present research.

The purpose of this paper is to present a fault detection filter design for discrete-time state-delay fuzzy systems under the consideration that output measurements are subject to random communication delay. It is assumed that the distribution characteristics of communication delays satisfy a Markov chain [10, 11, 12, 32, 33, 34], and the transition probabilities are also assumed to be partly known [35, 36]. Firstly, a delay-dependent sufficient condition for the existence of a delay-mode-dependent fuzzy fault detection filter is established by means of fuzzy Lyapunov functional and Finsler's Lemma. Then, the design of the fuzzy fault detection filter gain is presented. Finally, a numerical example is given to illustrate the efficiency of the proposed conditions.

2. **Problem Statement and Preliminaries.** Consider a class of nonlinear discrete-time state-delayed systems that can be described by the following fuzzy dynamic model with both local analytic linear models and fuzzy membership functions:

$$\begin{aligned}
\text{Rule } i: \quad & \text{IF } \theta_1(k) \text{ is } M_{i1} \text{ and } \cdots \text{ and } \theta_g(k) \text{ is } M_{ig} \\
& \text{THEN } x(k+1) = A_i x(k) + A_{di} x(k-d(k)) + B_i u(k) + D_i \omega(k) + G_i f(k) \\
& \qquad\quad\; y(k) = C x(k) \\
& \qquad\quad\; x(k) = \phi(k), \quad \forall k \in [-\bar{d}, 0], \quad i \in \mathscr{L} \triangleq \{1, 2, \cdots, r\}
\end{aligned} \tag{1}$$

where r denotes the number of inference rules; $\theta(k) = (\theta_1(k), \theta_2(k), \cdots, \theta_g(k))$ some measurable premise variables; M_{ij} $(j = 1, 2, \cdots, g)$ the fuzzy sets; $x(k) \in \mathbb{R}^n$ the state vector; $y(k) \in \mathbb{R}^p$ the measurement output vector; $u(k) \in \mathbb{R}^m$ the known input vector; $\omega(k) \in \mathbb{R}^q$ the unknown disturbance input vector; $f(k) \in \mathbb{R}^l$ the fault to be detected; $\phi(k)$ the given initial condition sequence; $u(k)$, $\omega(k)$ and $f(k)$ belong to $l_2[0, \infty)$. A_i, A_{di}, B_i, D_i, G_i and C are known constant matrices of appropriate dimensions. Time-varying delays $d(k)$ are positive integers satisfying $\underline{d} \le d(k) \le \bar{d}$. Here, $\underline{d}$ and $\bar{d}$ are the known lower and upper bounds of delays, respectively.

Let $\mu_i(\theta(k))$ be the normalized fuzzy membership function satisfying

$$\mu_i(\theta(k)) \ge 0, \quad \sum_{i=1}^{r} \mu_i(\theta(k)) = 1. \tag{2}$$

It is assumed that the premise variables do not depend on the input variables $u(k)$. By using a center-average defuzzifier, product fuzzy inference, and singleton fuzzifier, the dynamic fuzzy model (1) can be expressed by the following global model:

$$\begin{aligned} x(k+1) &= A(k)x(k) + A_d(k)x(k-d(k)) + B(k)u(k) + D(k)\omega(k) + G(k)f(k) \\ y(k) &= Cx(k) \end{aligned} \tag{3}$$

where

$$[\ A(k) \quad A_d(k) \quad B(k) \quad D(k) \quad G(k)\ ] = \sum_{i=1}^{r} \mu_i(\theta(k))[\ A_i \quad A_{di} \quad B_i \quad D_i \quad G_i\ ].$$

Let τ_k be the signal transmission delay experienced by the signal containing $y(k)$. In this paper, τ_k is modeled as a homogeneous Markov chain that takes values in $\mathcal{S} = \{0, 1, \cdots, \bar{\tau}\}$ and the transition probability matrix is $\Pi = (\pi_{\alpha\beta})$. That is, time varying delay τ_k jumps from mode α to β with probabilities, which is defined by

$$\pi_{\alpha\beta} = \mathrm{Prob}(\tau_{k+1} = \beta | \tau_k = \alpha),$$

where $\pi_{\alpha\beta} \geq 0$ and $\sum_{\beta=0}^{\bar{\tau}} \pi_{\alpha\beta} = 1$ for all $\alpha, \beta \in \mathcal{S}$.

It is assumed that if there is no new information coming at step $k+1$ (data could be lost or there is a longer delay), then $y(k - \tau_k)$ will be used for state estimation. This means that delay τ_k can increase at mostly 1 each step, that is

$$\mathrm{Prob}(\tau_{k+1} > \tau_k + 1) = 0.$$

Hence, the structured transition probability matrix is given by

$$\Pi = \begin{bmatrix} \pi_{00} & \pi_{01} & 0 & 0 & \cdots & 0 \\ ? & \pi_{11} & \pi_{12} & 0 & \cdots & 0 \\ \pi_{20} & ? & ? & \pi_{23} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \pi_{(\bar{\tau}-1)\bar{\tau}} \\ ? & \pi_{\bar{\tau}1} & ? & \pi_{\bar{\tau}3} & \cdots & \pi_{\bar{\tau}\bar{\tau}} \end{bmatrix}, \tag{4}$$

where ? stands for the inaccessible elements.

For the purpose of residual generation, the following fuzzy fault detection filter is constructed as a residual generator:

$$\begin{aligned} \text{Rule } i: \ & \text{IF } \theta_1(k) \text{ is } M_{i1} \text{ and } \cdots \text{ and } \theta_g(k) \text{ is } M_{ig} \\ & \text{THEN } \hat{x}(k+1) = A_{fi}(\tau_k)\hat{x}(k) + B_{fi}(\tau_k)y(k-\tau_k) \\ & \qquad\quad r(k) = C_{fi}(\tau_k)\hat{x}(k) + D_{fi}(\tau_k)y(k-\tau_k) \end{aligned} \tag{5}$$

where $\hat{x}(k) \in \mathbb{R}^n$ is the filter state vector, and $r(k) \in \mathbb{R}^l$ is the residual signal. $A_{fi}(\tau_k)$, $B_{fi}(\tau_k)$, $C_{fi}(\tau_k)$ and $D_{fi}(\tau_k)$ ($\tau_k \in \mathcal{S}$, $i \in \mathscr{L}$) are the fault detection filter matrices to be determined.

The overall fuzzy filter (5) can be written as

$$\begin{aligned} \hat{x}(k+1) &= \sum_{i=1}^{r} \mu_i(\theta(k))(A_{fi}(\tau_k)\hat{x}(k) + B_{fi}(\tau_k)y(k-\tau_k)) \\ r(k) &= \sum_{i=1}^{r} \mu_i(\theta(k))(C_{fi}(\tau_k)\hat{x}(k) + D_{fi}(\tau_k)y(k-\tau_k)) \end{aligned} \tag{6}$$

For $\tau_k = \alpha \in \mathcal{S}$, we denote

$$A_{fi}(\tau_k) = A_{fi,\alpha}, \quad B_{fi}(\tau_k) = B_{fi,\alpha}, \quad C_{fi}(\tau_k) = C_{fi,\alpha}, \quad D_{fi}(\tau_k) = D_{fi,\alpha}.$$

To improve the performance of the fault detection system, we choose a stable matrix $W(z)$ to weight the fault signal $f(k)$, i.e., $f_w(z) = W(z)f(z)$. Suppose a minimal realization of $f_w(z) = W(z)f(z)$ is

$$\begin{aligned} \bar{x}(k+1) &= A_w\bar{x}(k) + B_w f(k) \\ f_w(k) &= C_w\bar{x}(k) + D_w f(k) \end{aligned} \tag{7}$$

where $\bar{x}(k) \in \mathbb{R}^{n_w}$ is the weighted fault state, $f(k) \in \mathbb{R}^l$ is the original fault and $f_w(k) \in \mathbb{R}^l$ is the weighted fault. A_w, B_w, C_w and D_w are assumed to be known real constant matrices with appropriate dimensions.

Let $e(k) = r(k) - f_w(k)$, $\xi(k) = [x^T(k)\ \ \hat{x}^T(k)\ \ \bar{x}^T(k)]^T, \nu(k) = [u^T(k)\ \ \omega^T(k)\ \ f^T(k)]^T$, then the overall fault detection dynamics can be described as

$$\begin{aligned} \xi(k+1) &= \sum_{i=1}^{r}\mu_i(\theta(k))(\bar{A}_i(\tau_k)\xi(k) + \bar{A}_{di}E\xi(k-d(k)) + \bar{A}_{\tau i}(\tau_k)E\xi(k-\tau_k) + \bar{D}_i\nu(k)) \\ e(k) &= \sum_{i=1}^{r}\mu_i(\theta(k))(\bar{C}_i(\tau_k)\xi(k) + D_{fi}(\tau_k)CE\xi(k-\tau_k) + \bar{E}\nu(k)) \end{aligned} \tag{8}$$

where

$$\begin{aligned} &\bar{A}_i(\tau_k) = \begin{bmatrix} A_i & 0 & 0 \\ 0 & A_{fi}(\tau_k) & 0 \\ 0 & 0 & A_w \end{bmatrix}, \quad \bar{A}_{\tau i}(\tau_k) = \begin{bmatrix} 0 \\ B_{fi}(\tau_k)C \\ 0 \end{bmatrix}, \\ &\bar{A}_{di} = \begin{bmatrix} A_{di} \\ 0 \\ 0 \end{bmatrix}, \quad E = \begin{bmatrix} I & 0 & 0 \end{bmatrix}, \quad \bar{D}_i = \begin{bmatrix} B_i & D_i & G_i \\ 0 & 0 & 0 \\ 0 & 0 & B_w \end{bmatrix}, \\ &\bar{C}_i(\tau_k) = \begin{bmatrix} 0 & C_{fi}(\tau_k) & -C_w \end{bmatrix}, \quad \bar{E} = \begin{bmatrix} 0 & 0 & -D_w \end{bmatrix}. \end{aligned} \tag{9}$$

For $\tau_k = \alpha \in \mathcal{S}$, we denote $\bar{A}_i(\tau_k = \alpha)$, $\bar{A}_{\tau i}(\tau_k = \alpha)$ and $\bar{C}_i(\tau_k = \alpha)$ as $\bar{A}_{i,\alpha}$, $\bar{A}_{\tau i,\alpha}$ and $\bar{C}_{i,\alpha}$, respectively.

Suppose that the initial state and initial mode of system (8) are $\xi(k) = \psi(k)$, $\forall k \in [-\tau, 0](\tau = \max\{\bar{d}, \bar{\tau}\})$ and τ_0, respectively. Then, we adopt the definition in [37] for the stochastic stability.

Definition 2.1. *The fault detection system (8) ($\nu(k) = 0$) is said to be stochastically stable, if the following condition*

$$\mathbb{E}\left[\sum_{k=0}^{\infty}\|\xi(\psi,\tau_0)\|^2|\psi,\tau_0\right] < \infty$$

holds for every initial state ψ and initial mode τ_0.

The fault detection problem to be addressed in this paper can be stated as the following steps.

Step 1: Generate a residual signal, which is based on a filter in the form of (6). The filter is designed such that the resulting overall fault detection system is stochastically stable when $\nu(k) = 0$, and under zero initial condition and for all nonzero $\nu(k) \in l_2[0, \infty)$, the following holds:

$$\mathbb{E}\left[\sqrt{\sum_{k=0}^{\infty}e^T(k)e(k)}\right] < \gamma\left(\sum_{k=0}^{\infty}\nu^T(k)\nu(k)\right)^{\frac{1}{2}} \tag{10}$$

for a given scalar $\gamma > 0$.

Step 2: Select a residual evaluation function. In this paper, we consider the following residual evaluation function:

$$J(r) = \left(\sum_{k=k_0}^{k_0+T} r^T(k)r(k)\right)^{\frac{1}{2}} \tag{11}$$

where k_0 denotes the initial evaluation time instant and T denotes the evaluation time steps.

Step 3: Select a threshold $J_{\text{th}} = \sup_{\omega\in l_2, u\in l_2, f=0} \mathbb{E}[J(r)]$.

Step 4: Detect the fault $f(k)$ by comparing $J(r)$ with J_{th}. When the evaluation value is larger than the threshold, an alarm of fault is generated. That is,

$$\begin{cases} J(r) > J_{\text{th}} & \Rightarrow \quad \text{with faults} \Rightarrow \quad \text{alarm} \\ J(r) \le J_{\text{th}} & \Rightarrow \quad \text{no faults.} \end{cases}$$

Lemma 2.1. *(Finsler's Lemma)* [38] *Let $x \in \mathbb{R}^n$, $Q = Q^T \in \mathbb{R}^{n\times n}$ and $H \in \mathbb{R}^{m\times n}$ such that* $\text{rank}(H) = r < n$. *Then the following statements are equivalent:*

1. $x^TQx < 0 \quad \forall x \neq 0$ such that $Hx = 0$.

2. $\exists W \in \mathbb{R}^{n\times m}$, $Q + WH + H^TW^T < 0$.

For convenience, for $\alpha \in \mathcal{S}$ we denote $P_{i,\alpha} = P_i(\tau_k = \alpha)$, $i \in \mathscr{L}$ and

$$\mathcal{S}_{\mathcal{K}}^{\alpha} \triangleq \{\beta : \text{ if } \pi_{\alpha\beta} \text{ is known}\}, \quad \mathcal{S}_{\mathcal{UK}}^{\alpha} \triangleq \{\beta : \text{ if } \pi_{\alpha\beta} \text{ is unknown}\}. \tag{12}$$

3. **Main Results.** In this section, the delay-dependent stochastic stability with an H_∞ performance of fault detection system (8) is first analyzed. Then, a delay-mode-dependent fault detection filter in the form of (6) is designed based on the obtained stability criterion.

Theorem 3.1. *Given a positive scalar $\gamma > 0$ and a fault detection filter in the form of (6), the fault detection system (8) is stochastically stable with an H_∞ performance γ if there exist matrices $P_{i,\alpha} > 0$, $M_{i,\alpha} > 0$, $N_{i,\alpha} > 0$, $U_{i,\alpha} = \begin{bmatrix} U_{11i,\alpha} & U_{12i,\alpha} \\ U_{12i,\alpha}^T & U_{22i,\alpha} \end{bmatrix} > 0$, $T_{i,\alpha} = \begin{bmatrix} T_{11i,\alpha} & T_{12i,\alpha} \\ T_{12i,\alpha}^T & T_{22i,\alpha} \end{bmatrix} > 0$, $\tilde{S}_{i,\alpha}$, $Q > 0$, $R > 0$, $W > 0$, $Z > 0$, $X_{1i,\alpha}$, $X_{2i,\alpha}$, $Y_{1i,\alpha}$, $Y_{2i,\alpha}$ ($\alpha \in \mathcal{S}$, $i \in \mathscr{L}$) such that the following linear matrix inequalities hold for $\alpha \in \mathcal{S}$:*

$$\begin{bmatrix} \Theta_{iil,\alpha}^{(s)} & \tilde{C}_{i,\alpha}^T \\ \tilde{C}_{i,\alpha} & -I \end{bmatrix} < 0, \quad i, l \in \mathscr{L}, \quad s = 1, 2, \tag{13}$$

$$\begin{bmatrix} \Theta_{ijl,\alpha}^{(s)} + \Theta_{jil,\alpha}^{(s)} & \tilde{C}_{i,\alpha}^T & \tilde{C}_{j,\alpha}^T \\ \tilde{C}_{i,\alpha} & -I & 0 \\ \tilde{C}_{j,\alpha} & 0 & -I \end{bmatrix} < 0, \quad l \in \mathscr{L}, \quad 1 \le i < j \le r, \quad s = 1, 2, \tag{14}$$

$$\sum_{\beta\in\mathcal{S}_{\mathcal{K}}^{\alpha}} \pi_{\alpha\beta} P_{l,\beta} < M_{l,\alpha}, \quad l \in \mathscr{L}, \tag{15}$$

$$P_{l,\beta} < N_{l,\alpha}, \quad \beta \in \mathcal{S}_{\mathcal{UK}}^{\alpha}, \quad l \in \mathscr{L}, \tag{16}$$

$$\begin{bmatrix} U_{11i,\alpha} & U_{12i,\alpha} & X_{1i,\alpha} \\ U_{12i,\alpha}^T & U_{22i,\alpha} & X_{2i,\alpha} \\ X_{1i,\alpha}^T & X_{2i,\alpha}^T & Z \end{bmatrix} \ge 0, \quad i \in \mathscr{L}, \tag{17}$$

$$\begin{bmatrix} T_{11i,\alpha} & T_{12i,\alpha} & Y_{1i,\alpha} \\ T_{12i,\alpha}^T & T_{22i,\alpha} & Y_{2i,\alpha} \\ Y_{1i,\alpha}^T & Y_{2i,\alpha}^T & Z \end{bmatrix} \ge 0, \quad i \in \mathscr{L}, \tag{18}$$

where

$$\Theta_{ijl,\alpha}^{(s)} = \Phi_{il,\alpha}^{(s)} + \tilde{S}_{j,\alpha}\Gamma_{i,\alpha} + \Gamma_{i,\alpha}^T\tilde{S}_{j,\alpha}^T, \quad s = 1, 2,$$

$$\Phi_{il,\alpha}^{(s)} = \begin{bmatrix} \Phi_{11l,\alpha} & -\bar{\tau}E^TZE & 0 & 0 & 0 & 0 \\ * & \Phi_{22i,\alpha}^{(s)} & 0 & \Phi_{24i,\alpha}^{(s)} & 0 & 0 \\ * & * & -W & 0 & 0 & 0 \\ * & * & * & \Phi_{44i,\alpha}^{(s)} & \Phi_{45i,\alpha}^{(s)} & 0 \\ * & * & * & * & \Phi_{55i,\alpha}^{(s)} & 0 \\ * & * & * & * & * & -\gamma^2 I \end{bmatrix}, \quad s = 1, 2,$$

$$\Phi_{11l,\alpha} = \bar{\tau}E^TZE + M_{l,\alpha} + N_{l,\alpha},$$
$$\Phi_{22i,\alpha}^{(1)} = -P_{i,\alpha} + E^T[\bar{\tau}Z + (\bar{\tau}+1)Q + (\bar{d} - \underline{d} + 1)W + R + X_{1i,\alpha} + X_{1i,\alpha}^T + \bar{\tau}U_{11i,\alpha}]E,$$
$$\Phi_{24i,\alpha}^{(1)} = -E^TX_{1i,\alpha} + E^TX_{2i,\alpha}^T + \bar{\tau}E^TU_{12i,\alpha},$$
$$\Phi_{44i,\alpha}^{(1)} = -Q - X_{2i,\alpha} - X_{2i,\alpha}^T + Y_{1i,\alpha} + Y_{1i,\alpha}^T + \bar{\tau}U_{22i,\alpha},$$
$$\Phi_{45i,\alpha}^{(1)} = -Y_{1i,\alpha} + Y_{2i,\alpha}^T, \quad \Phi_{55i,\alpha}^{(1)} = -R - Y_{2i,\alpha} - Y_{2i,\alpha}^T,$$
$$\Phi_{22i,\alpha}^{(2)} = -P_{i,\alpha} + E^T[\bar{\tau}Z + (\bar{\tau}+1)Q + (\bar{d} - \underline{d} + 1)W + R + X_{1i,\alpha} + X_{1i,\alpha}^T]E,$$
$$\Phi_{24i,\alpha}^{(2)} = -E^TX_{1i,\alpha} + E^TX_{2i,\alpha}^T,$$
$$\Phi_{44i,\alpha}^{(2)} = -Q - X_{2i,\alpha} - X_{2i,\alpha}^T + Y_{1i,\alpha} + Y_{1i,\alpha}^T + \bar{\tau}T_{11i,\alpha},$$
$$\Phi_{45i,\alpha}^{(2)} = -Y_{1i,\alpha} + Y_{2i,\alpha}^T + \bar{\tau}T_{12i,\alpha}, \quad \Phi_{55i,\alpha}^{(2)} = -R - Y_{2i,\alpha} - Y_{2i,\alpha}^T + \bar{\tau}T_{22i,\alpha},$$
$$\Gamma_{i,\alpha} = \begin{bmatrix} -I & \bar{A}_{i,\alpha} & \bar{A}_{di} & \bar{A}_{\tau i,\alpha} & 0 & \bar{D}_i \end{bmatrix},$$

and $\tilde{C}_{i,\alpha} = \begin{bmatrix} 0 & \bar{C}_{i,\alpha} & 0 & D_{fi,\alpha}C & 0 & \bar{E} \end{bmatrix}$ *with* $\bar{A}_{i,\alpha}$, $\bar{A}_{di}$, $\bar{A}_{\tau i,\alpha}$, $\bar{D}_i$, $\bar{C}_{i,\alpha}$, $\bar{E}$ *defined in (9).*

Proof: The proof is cut off due to space limitation.

Remark 3.1. *With the similar idea of Theorem 3.1 in* [36]*, slack matrices* $M_{i,\alpha}$ *and* $N_{i,\alpha}$ *(*$i \in \mathscr{L}$*,* $\alpha \in \mathcal{S}$*) are introduced in Theorem 3.1. For the case that the transition probabilities are completely known, the corresponding* H_∞ *performance analysis result can be readily obtained from Theorem 3.1 by removing the terms induced by the introduction of* $N_{i,\alpha}$*, i.e.,* $\Phi_{11l,\alpha}$ *(*$l \in \mathscr{L}$*,* $\alpha \in \mathcal{S}$*) in Theorem 3.1 modified as* $\Phi_{11l,\alpha} = \bar{\tau}E^TZE + M_{l,\alpha}$ *and inequality (16) removed.*

Remark 3.2. *It is noted that the result presented by Theorem 3.1 is obtained by using a mode-dependent fuzzy Lyapunov functional and mode-dependent slack matrices* $X_{1i,\alpha}$*,* $X_{2i,\alpha}$*,* $Y_{1i,\alpha}$*,* $Y_{2i,\alpha}$*,* $U_{i,\alpha}$*,* $T_{i,\alpha}$*,* $\tilde{S}_{i,\alpha}$ *(*$i \in \mathscr{L}$*,* $\alpha \in \mathcal{S}$*). In addition, the convex combination technique is applied in the proof Theorem 3.1. Therefore, the potential conservatism is reduced. In the meanwhile, it should be pointed out that the introduction of free-weight matrices* $X_{1i,\alpha}$*,* $X_{2i,\alpha}$*,* $Y_{1i,\alpha}$*,* $Y_{2i,\alpha}$*,* $U_{i,\alpha}$*,* $T_{i,\alpha}$*,* $\tilde{S}_{i,\alpha}$ *(*$i \in \mathscr{L}$*,* $\alpha \in \mathcal{S}$*) may lead to a increase in the computational demand. Moreover, the conditions in Theorem 3.1 are still sufficient ones, which could be further improved in terms of conservatism. In order to obtain less conservative results, a delay partitioning method developed in the literature, such as in* [39]*, may be applied.*

We are now in a position to present the main result in this section.

Theorem 3.2. *Given a positive scalar* $\gamma > 0$*, the fault detection system (8) is stochastically stable with an* H_∞ *performance* γ *if for there exist matrices* $P_{i,\alpha} > 0$*,* $M_{i,\alpha} > 0$*,* $N_{i,\alpha} > 0$*,* $U_{i,\alpha} = \begin{bmatrix} U_{11i,\alpha} & U_{12i,\alpha} \\ U_{12i,\alpha}^T & U_{22i,\alpha} \end{bmatrix} > 0$*,* $T_{i,\alpha} = \begin{bmatrix} T_{11i,\alpha} & T_{12i,\alpha} \\ T_{12i,\alpha}^T & T_{22i,\alpha} \end{bmatrix} > 0$*,* $S_{11i,\alpha}$*,* $S_{21i,\alpha}$*,* $S_{22,\alpha}$*,* $F_{i,\alpha}$*,* $\hat{A}_{fi,\alpha}$*,* $\hat{B}_{fi,\alpha}$*,* $\hat{C}_{fi,\alpha}$*,* $\hat{D}_{fi,\alpha}$*,* $Q > 0$*,* $R > 0$*,* $W > 0$*,* $Z > 0$*,* $X_{1i,\alpha}$*,* $X_{2i,\alpha}$*,* $Y_{1i,\alpha}$*,* $Y_{2i,\alpha}$ *(*$\alpha \in \mathcal{S}$*,* $i \in \mathscr{L}$*) satisfying the following linear matrix inequalities for some given scalars*

ρ_α, $\alpha \in \mathcal{S}$:

$$\begin{bmatrix} \Psi^{(s)}_{iil,\alpha} & \breve{C}^T_{i,\alpha} \\ \breve{C}_{i,\alpha} & -I \end{bmatrix} < 0, \quad i, l \in \mathscr{L}, \quad s = 1, 2, \tag{19}$$

$$\begin{bmatrix} \Psi^{(s)}_{ijl,\alpha} + \Psi^{(s)}_{jil,\alpha} & \breve{C}^T_{i,\alpha} & \breve{C}^T_{j,\alpha} \\ \breve{C}_{i,\alpha} & -I & 0 \\ \breve{C}_{j,\alpha} & 0 & -I \end{bmatrix} < 0, \quad l \in \mathscr{L}, \quad 1 \le i < j \le r, \quad s = 1, 2, \tag{20}$$

$$\sum_{\beta \in \mathcal{S}^\alpha_{\mathcal{K}}} \pi_{\alpha\beta} P_{l,\beta} < M_{l,\alpha}, \quad l \in \mathscr{L}, \tag{21}$$

$$P_{l,\beta} < N_{l,\alpha},\ \beta \in \mathcal{S}^\alpha_{\mathcal{UK}}, \quad l \in \mathscr{L}, \tag{22}$$

$$\begin{bmatrix} U_{11i,\alpha} & U_{12i,\alpha} & X_{1i,\alpha} \\ U^T_{12i,\alpha} & U_{22i,\alpha} & X_{2i,\alpha} \\ X^T_{1i,\alpha} & X^T_{2i,\alpha} & Z \end{bmatrix} \ge 0, \quad i \in \mathscr{L}, \tag{23}$$

$$\begin{bmatrix} T_{11i,\alpha} & T_{12i,\alpha} & Y_{1i,\alpha} \\ T^T_{12i,\alpha} & T_{22i,\alpha} & Y_{2i,\alpha} \\ Y^T_{1i,\alpha} & Y^T_{2i,\alpha} & Z \end{bmatrix} \ge 0, \quad i \in \mathscr{L}, \tag{24}$$

where

$$\breve{C}_{i,\alpha} = \begin{bmatrix} 0 & \hat{C}_{i,\alpha} & 0 & \hat{D}_{fi,\alpha}C & 0 & \bar{E} \end{bmatrix},$$

$$\hat{C}_{i,\alpha} = \begin{bmatrix} 0 & \hat{C}_{fi,\alpha} & -C_w \end{bmatrix}, \quad \bar{E} = \begin{bmatrix} 0 & 0 & -D_w \end{bmatrix},$$

$$\Psi^{(s)}_{ijl,\alpha} = \begin{bmatrix} \Psi_{11ijl,\alpha} & \Psi_{12ij,\alpha} & \Psi_{13ij,\alpha} & \Psi_{14ij,\alpha} & 0 & \Psi_{16ij,\alpha} \\ * & \Psi^{(s)}_{22i,\alpha} & 0 & \Psi^{(s)}_{24i,\alpha} & 0 & 0 \\ * & * & -W & 0 & 0 & 0 \\ * & * & * & \Psi^{(s)}_{44i,\alpha} & \Psi^{(s)}_{45i,\alpha} & 0 \\ * & * & * & * & \Psi^{(s)}_{55i,\alpha} & 0 \\ * & * & * & * & * & -\gamma^2 I \end{bmatrix}, \quad s = 1, 2,$$

$$\Psi_{11ijl,\alpha} = \bar{\tau}E^T Z E + M_{l,\alpha} + N_{l,\alpha} - diag\{S_{i,\alpha} + S^T_{i,\alpha}, F_{i,\alpha} + F^T_{i,\alpha}\},$$

$$S_{i,\alpha} = \begin{bmatrix} S_{11i,\alpha} & \rho_\alpha S_{22,\alpha} \\ S_{21i,\alpha} & S_{22,\alpha} \end{bmatrix}, \quad \Psi_{12ij,\alpha} = \begin{bmatrix} S_{11j,\alpha}A_i - \bar{\tau}Z & \rho_\alpha \hat{A}_{fi,\alpha} & 0 \\ S_{21j,\alpha}A_i & \hat{A}_{fi,\alpha} & 0 \\ 0 & 0 & F_{j,\alpha}A_w \end{bmatrix},$$

$$\Psi_{13ij,\alpha} = \begin{bmatrix} S_{11j,\alpha}A_{di} \\ S_{21j,\alpha}A_{di} \\ 0 \end{bmatrix}, \quad \Psi_{14ij,\alpha} = \begin{bmatrix} \rho_\alpha \hat{B}_{fi,\alpha}C \\ \hat{B}_{fi,\alpha}C \\ 0 \end{bmatrix},$$

$$\Psi_{16ij,\alpha} = \begin{bmatrix} S_{11j,\alpha}B_i & S_{11j,\alpha}D_i & S_{11j,\alpha}G_i \\ S_{21j,\alpha}B_i & S_{21j,\alpha}D_i & S_{21j,\alpha}G_i \\ 0 & 0 & F_{j,\alpha}B_w \end{bmatrix},$$

$$\Psi^{(1)}_{22i,\alpha} = -P_{i,\alpha} + E^T[\bar{\tau}Z + (\bar{\tau}+1)Q + (\bar{d} - \underline{d} + 1)W + R + X_{1i,\alpha} + X^T_{1i,\alpha} + \bar{\tau}U_{11i,\alpha}]E,$$
$$\Psi^{(1)}_{24i,\alpha} = -E^T X_{1i,\alpha} + E^T X^T_{2i,\alpha} + \bar{\tau}E^T U_{12i,\alpha},$$
$$\Psi^{(1)}_{44i,\alpha} = -Q - X_{2i,\alpha} - X^T_{2i,\alpha} + Y_{1i,\alpha} + Y^T_{1i,\alpha} + \bar{\tau}U_{22i,\alpha},$$
$$\Psi^{(1)}_{45i,\alpha} = -Y_{1i,\alpha} + Y^T_{2i,\alpha}, \quad \Psi^{(1)}_{55i,\alpha} = -R - Y_{2i,\alpha} - Y^T_{2i,\alpha},$$
$$\Psi^{(2)}_{22i,\alpha} = -P_{i,\alpha} + E^T[\bar{\tau}Z + (\bar{\tau}+1)Q + (\bar{d} - \underline{d} + 1)W + R + X_{1i,\alpha} + X^T_{1i,\alpha}]E,$$
$$\Psi^{(2)}_{24i,\alpha} = -E^T X_{1i,\alpha} + E^T X^T_{2i,\alpha},$$
$$\Psi^{(2)}_{44i,\alpha} = -Q - X_{2i,\alpha} - X^T_{2i,\alpha} + Y_{1i,\alpha} + Y^T_{1i,\alpha} + \bar{\tau}T_{11i,\alpha},$$
$$\Psi^{(2)}_{45i,\alpha} = -Y_{1i,\alpha} + Y^T_{2i,\alpha} + \bar{\tau}T_{12i,\alpha}, \quad \Psi^{(2)}_{55i,\alpha} = -R - Y_{2i,\alpha} - Y^T_{2i,\alpha} + \bar{\tau}T_{22i,\alpha}.$$

Moreover, a suitable fault detection filter matrices in (5) is given by

$$\begin{bmatrix} A_{fi,\alpha} & B_{fi,\alpha} \\ C_{fi,\alpha} & D_{fi,\alpha} \end{bmatrix} = \begin{bmatrix} S_{22,\alpha}^{-1} & 0 \\ 0 & I \end{bmatrix} \begin{bmatrix} \hat{A}_{fi,\alpha} & \hat{B}_{fi,\alpha} \\ \hat{C}_{fi,\alpha} & \hat{D}_{fi,\alpha} \end{bmatrix}, \quad i \in \mathscr{L}, \ \alpha \in \mathcal{S}. \tag{25}$$

Proof: Choose the relaxed variable $\tilde{S}_{i,\alpha}, \alpha \in \mathcal{S}$ introduced in Theorem 3.1 as

$$\tilde{S}_{i,\alpha} = \begin{bmatrix} \text{diag}\{S_{i,\alpha}, F_{i,\alpha}\} \\ 0_{(5n+n_w+m+q+l)\times(2n+n_w)} \end{bmatrix}, \quad S_{i,\alpha} = \begin{bmatrix} S_{11i,\alpha} & \rho_\alpha S_{22,\alpha} \\ S_{21i,\alpha} & S_{22,\alpha} \end{bmatrix} \tag{26}$$

where $S_{11i,\alpha} \in \mathbb{R}^{n\times n}$, $S_{21i,\alpha} \in \mathbb{R}^{n\times n}$, $S_{22,\alpha} \in \mathbb{R}^{n\times n}$, $F_{i,\alpha} \in \mathbb{R}^{n_w\times n_w}$, $i \in \mathscr{L}$, and $\rho_\alpha, \alpha \in \mathcal{S}$ are scalar tuning parameters.

By substituting the matrix $\tilde{S}_{i,\alpha}$ defined in (26) into (13) and (14) in Theorem 3.1 and introducing

$$\hat{A}_{fi,\alpha} = S_{22,\alpha}A_{fi,\alpha}, \ \hat{B}_{fi,\alpha} = S_{22,\alpha}B_{fi,\alpha}, \ \hat{C}_{fi,\alpha} = C_{fi,\alpha}, \ \hat{D}_{fi,\alpha} = D_{fi,\alpha} \tag{27}$$

it follows that (19) and (20) guarantee (13) and (14), respectively.

On the other hand, it follows from (13) and (14) that $S_{i,\alpha} + S_{i,\alpha}^T > 0$, $\alpha \in \mathcal{S}$. Therefore, $S_{i,\alpha}$, $i \in \mathscr{L}$, $\alpha \in \mathcal{S}$ are nonsingular, which implies that $S_{22,\alpha}$, $\alpha \in \mathcal{S}$ are nonsingular. Hence, (25) is equivalent to (27), and the proof is completed.

Remark 3.3. *Note that the conditions in Theorem 3.2 involve tuning parameters ρ_α, $\alpha \in \mathcal{S}$. When the scalar parameters ρ_α, $\alpha \in \mathcal{S}$ are given, the conditions in Theorem 3.2 are strict linear matrix inequalities and can be solved by using the LMI toolbox* [40]*. Moreover, if $A_{fi}(\tau_k) = A_{f1}(\tau_k)$, $B_{fi}(\tau_k) = B_{f1}(\tau_k)$, $C_{fi}(\tau_k) = C_{f1}(\tau_k)$, $D_{fi}(\tau_k) = D_{f1}(\tau_k), \forall \tau_k \in \mathcal{S}$, then the fault detection filter (5) becomes a fuzzy-rule-independent one. Theorem 3.1 and Theorem 3.2 in this paper can also handle the problem of fuzzy-rule-independent fault detection filter design as a special case.*

4. Numerical Example.

The following example will show the effectiveness of the proposed design method in the last section.

Example 4.1. *Consider a tunnel-diode circuit modified from* [41] *by ignoring the disturbance term of the measurement output:*

$$\begin{aligned} \dot{x}_1(t) &= -0.1x_1(t) - 0.5x_1^3(t) + 50x_2(t), \\ \dot{x}_2(t) &= -x_1(t) - 10x_2(t) + w(t), \\ y(t) &= x_1(t), \end{aligned} \tag{28}$$

where $x_1(t) = v_C(t)$, $x_2(t) = i_L(t)$, and $v_C(t)$ and $i_L(t)$ are the capacitor voltage and inductance current, respectively. With a sampling time $T = 0.02s$ and the assumption that $|x_1(k)| \le 3$, the circuit system (28) can be approximated by the following T-S model [25, 31]*:*

$$\begin{aligned} \textit{Rule } i: \ & \textit{IF } x_1(k) \textit{ is } M_i(x_1(k)), \\ & \textit{THEN } x(k+1) = A_i x(k) + D_i \omega(k), \\ & \qquad y(k) = Cx(k), \quad i = 1, 2, \end{aligned} \tag{29}$$

where

$$A_1 = \begin{bmatrix} 0.9887 & 0.9024 \\ -0.0180 & 0.8100 \end{bmatrix}, \ A_2 = \begin{bmatrix} 0.9033 & 0.8617 \\ -0.0172 & 0.8103 \end{bmatrix},$$

$$D_1 = \begin{bmatrix} 0.0093 \\ 0.0181 \end{bmatrix}, \ D_2 = \begin{bmatrix} 0.0091 \\ 0.0181 \end{bmatrix}, \ C = \begin{bmatrix} 1 & 0 \end{bmatrix},$$

and the membership functions are given by

$$\mu_1(x_1(k)) = \begin{cases} \dfrac{x_1(k)+3}{3}, & -3 \le x_1(k) \le 0, \\ 0, & x_1(k) < -3, \\ \dfrac{3-x_1(k)}{3}, & 0 \le x_1(k) \le 3, \\ 0, & x_1(k) > 3, \end{cases} \quad \text{and} \quad \mu_2(x_1(k)) = 1 - \mu_1(x_1(k)).$$

For simulation, it is assumed that there are state-delay and faults in the model, and the corresponding matrix parameters are given by

$$A_{d1} = \begin{bmatrix} 0.0093 & 0.0976 \\ -0.002 & -0.01 \end{bmatrix}, \; A_{d2} = \begin{bmatrix} 0.00463 & 0.1383 \\ -0.0028 & -0.013 \end{bmatrix}, \; G_1 = G_2 = \begin{bmatrix} 1 \\ 0.8 \end{bmatrix}.$$

The weighting matrix $W(z)$ in $f_w(z) = W(z)f(z)$ is supposed to be $W(z) = (0.5z)/(z-0.5)$. Its state-space realization is given as (7) with $A_w = 0.5$, $B_w = 0.25$, $C_w = 1$ and $D_w = 0.5$.

Suppose that $\underline{d} = 3$, $\bar{d} = 5$, $\bar{\tau} = 2$ and the transition probability matrix is

$$\Pi = \begin{bmatrix} 0.3 & 0.7 & 0 \\ 0.3 & ? & ? \\ 0.3 & 0.1 & 0.6 \end{bmatrix}.$$

Then, for $\gamma = 2$, $\rho_1 = 0.05$, $\rho_2 = 0.04$, $\rho_3 = 5$, solving LMIs (19)-(24) yields the following fault detection filter gain matrices:

$$A_{f1,0} = \begin{bmatrix} 0.0033 & -0.0133 \\ -0.0001 & 0.0069 \end{bmatrix}, \quad A_{f2,0} = \begin{bmatrix} 0.0034 & -0.0223 \\ -0.0001 & 0.0071 \end{bmatrix}$$
$$A_{f1,1} = 10^{-3} \times \begin{bmatrix} 0.9128 & -0.1023 \\ -0.0454 & -0.2915 \end{bmatrix}, \quad A_{f2,1} = 10^{-3} \times \begin{bmatrix} -0.7492 & -0.2158 \\ 0.0395 & 0.3776 \end{bmatrix}$$
$$A_{f1,2} = \begin{bmatrix} 0.4672 & 0.0437 \\ -0.0107 & 0.2889 \end{bmatrix}, \quad A_{f2,2} = \begin{bmatrix} 0.4080 & -0.0160 \\ -0.0091 & 0.2999 \end{bmatrix}$$
$$B_{f1,0} = \begin{bmatrix} -0.0054 \\ 0.0004 \end{bmatrix}, \quad B_{f2,0} = \begin{bmatrix} -0.0046 \\ 0.0003 \end{bmatrix}, \quad B_{f1,1} = \begin{bmatrix} -0.0065 \\ 0.0003 \end{bmatrix}$$
$$B_{f2,1} = \begin{bmatrix} -0.0063 \\ 0.0003 \end{bmatrix}, \quad B_{f1,2} = \begin{bmatrix} -0.3216 \\ 0.0102 \end{bmatrix}, \quad B_{f2,2} = \begin{bmatrix} -0.2934 \\ 0.0091 \end{bmatrix}$$
$$C_{f1,0} = 10^{-4} \times \begin{bmatrix} -0.0139 & -0.1973 \end{bmatrix}, \quad C_{f2,0} = 10^{-5} \times \begin{bmatrix} 0.0295 & 0.7304 \end{bmatrix}$$
$$C_{f1,1} = 10^{-4} \times \begin{bmatrix} -0.0361 & 0.7316 \end{bmatrix}, \quad C_{f2,1} = 10^{-3} \times \begin{bmatrix} 0.0014 & 0.1057 \end{bmatrix}$$
$$C_{f1,2} = 10^{-4} \times \begin{bmatrix} -0.0343 & -0.4655 \end{bmatrix}, \quad C_{f2,2} = 10^{-4} \times \begin{bmatrix} -0.0267 & -0.3941 \end{bmatrix}$$
$$D_{f1,0} = 1.6667 \times 10^{-5}, \quad D_{f2,0} = 1.5290 \times 10^{-5}, \quad D_{f1,1} = -2.4305 \times 10^{-8}$$
$$D_{f2,1} = -8.9852 \times 10^{-8}, \quad D_{f1,2} = 8.6017 \times 10^{-6}, \quad D_{f2,2} = 8.7673 \times 10^{-6}.$$

For the case that the transition probability matrix given by

$$\Pi = \begin{bmatrix} 0.3 & 0.7 & 0 \\ 0.3 & 0.4 & 0.3 \\ 0.3 & 0.1 & 0.6 \end{bmatrix},$$

a possible evolution of delay modes with the initial mode $\tau_0 = 0$ is shown in Figure 1.

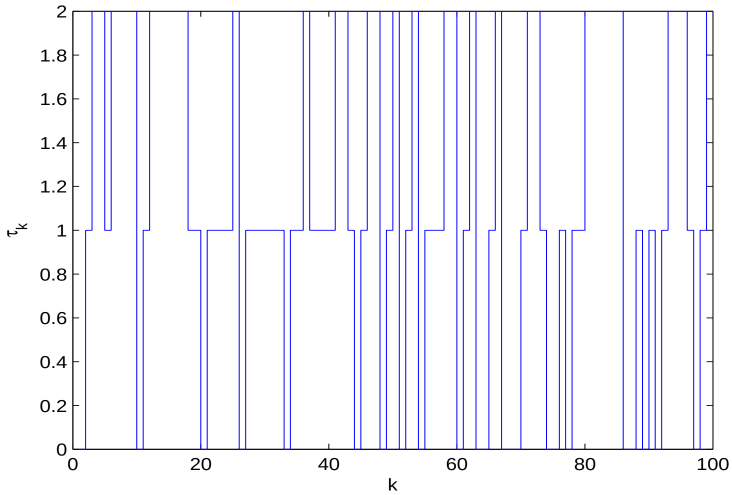

FIGURE 1. Delay modes evolution

Assume that the unknown input $\omega(k)$ is

$$\omega(k) = \begin{cases} 0.01\exp(-0.04k)\cos(0.03\pi k), & 0 \le k \le 100 \\ 0, & \textit{others} \end{cases}$$

and the fault signal $f(k)$ is a square wave of unit amplitude occurred for $k = 30, 31, \cdots, 60$, that is,

$$f(k) = \begin{cases} 1, & 30 \le k \le 60 \\ 0, & \textit{others.} \end{cases}$$

Then the generated residual signal $r(k)$ is shown in Figure 2 and Figure 3 presents the evaluation function of $J(r)$. Selecting a threshold $J_{th} = 1.3211 \times 10^{-6}$, one has $5.8147 \times 10^{-7} = J(32) < J_{th} < J(33) = 4.9040 \times 10^{-5}$. This means that fault $f(k)$ can be detected 3 time steps after its occurrence.

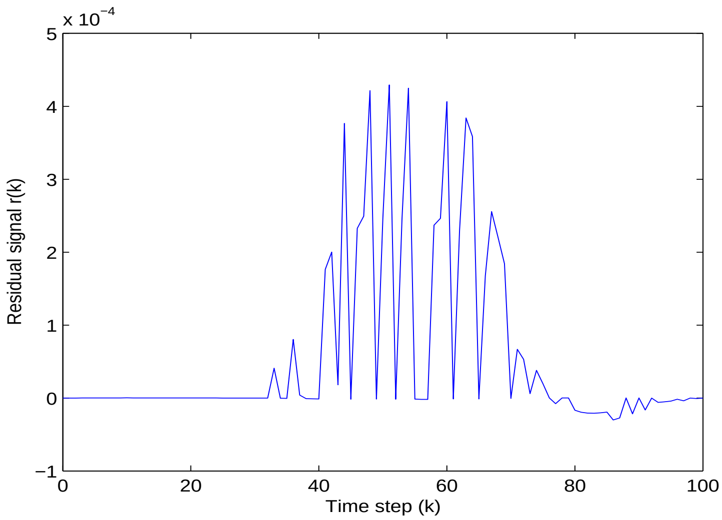

FIGURE 2. Residual signal $r(k)$

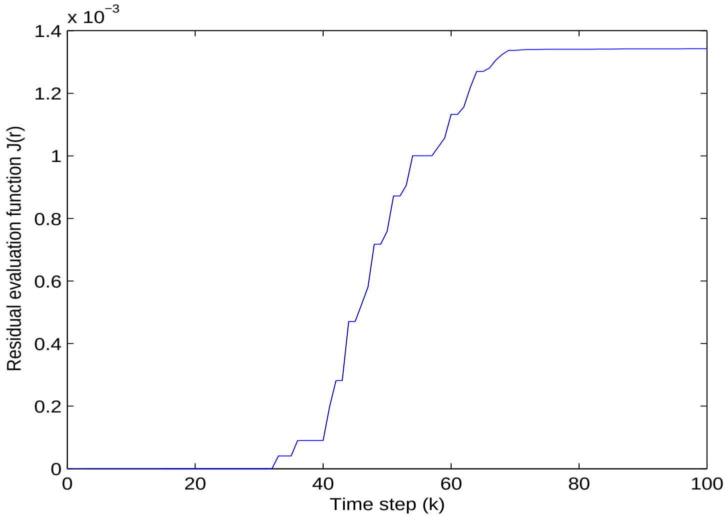

Figure 3. Evaluation function of $J(r)$

5. **Conclusions.** In this paper, a design approach of fault detection filters has been developed for discrete-time state-delay fuzzy systems subject to random communication delay modeled by a Markov chain. The transition probabilities are assumed to be partially known. A fuzzy Lyapunov functional method and Finsler's Lemma are employed to derive sufficient conditions for the existence of a delay-mode-dependent fuzzy fault detection filter. It has been shown that the fault detection filter gains can be obtained by solving a set of linear matrix inequalities. A simulation example has been presented to demonstrate the effectiveness of the proposed method.

Acknowledgment. This work was supported by National Natural Science Foundation of China under Grants No. 61174065, No. 61174066 and No. 61004027, Natural Science Foundation from Jiangsu Province No. BK2010275, Qing Lan Project from the Jiangsu Provincial Department for Education. The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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