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Fuzzy-Model-Based Robust Fault Detection With Stochastic Mixed Time Delays and Successive Packet Dropouts

Hongli Dong, Member, IEEE, Zidong Wang, Senior Member, IEEE, James Lam, Senior Member, IEEE, and Huijun Gao, Senior Member, IEEE

Abstract—This paper is concerned with the network-based robust fault detection problem for a class of uncertain discrete-time Takagi–Sugeno fuzzy systems with stochastic mixed time delays and successive packet dropouts. The mixed time delays comprise both the multiple discrete time delays and the infinite distributed delays. A sequence of stochastic variables is introduced to govern the random occurrences of the discrete time delays, distributed time delays, and successive packet dropouts, where all the stochastic variables are mutually independent but obey the Bernoulli distribution. The main purpose of this paper is to design a fuzzy fault detection filter such that the overall fault detection dynamics is exponentially stable in the mean square and, at the same time, the error between the residual signal and the fault signal is made as small as possible. Sufficient conditions are first established via intensive stochastic analysis for the existence of the desired fuzzy fault detection filters, and then, the corresponding solvability conditions for the desired filter gains are established. In addition, the optimal performance index for the addressed robust fuzzy fault detection problem is obtained by solving an auxiliary convex optimization problem. An illustrative example is provided to show the usefulness and effectiveness of the proposed design method.

Index Terms—Discrete-time fuzzy systems, fault detection, networked control systems (NCSs), packet dropouts, randomly occurring mixed time delays.

I. INTRODUCTION

OVer the past decades, the fault detection problem has been an active field of research because of the ever increasing demand for higher performance, higher safety, and reliability standards [3], [24], [28], [31]. Generally speaking, a fault detection process consists of constructing a residual signal and computing a residual evaluation function which can then be compared with a predefined threshold. When the residual exceeds the threshold, the fault is detected, and an alarm of fault is generated. As is well known, for a fault detection problem, the residual signal should be made sensitive to faults (in order to detect faults in a timely way) and robust to modeling errors or disturbances (in order to avoid false alarms). Recently, the model-based approaches to fault detection problems have been widely adopted for dynamic systems. The main idea of these approaches is to introduce a performance index and then convert the fault detection problem into an associated optimization problem. Accordingly, a variety of important results have been reported in the literature. For example, the fault detection problems have been addressed in [37] for linear time-varying systems, in [39] for singular systems, in [16] and [32] for sampled-data systems, in [28] for stochastic systems, in [38] for Markovian jump linear systems, and in [12] and [23] for networked control systems (NCSs). It is worth noting that most of the aforementioned results are concerned with linear models.

Nonlinearities are recognized to exist universally in practical systems. Takagi–Sugeno (T–S) fuzzy models have proven to be capable of approximating any smooth nonlinear systems to any specified accuracy within any compact set, which is achieved by smoothly blending a family of local linear models through fuzzy membership functions. Based on this local linearity, many complex nonlinear systems can be represented by using T–S fuzzy models. As a result, the last decade has witnessed a rapidly growing interest in T–S fuzzy systems, and many important results have been reported in the literature. To mention a few, the stability and stabilization problems of the fuzzy systems have been addressed in [4], [9], [11], [14], and [35]. The filtering problems have been investigated in [8] and [18], and the control problems have been studied in [2], [10], [17], [21], and [29]. Since nonlinear systems can be approximated by T–S fuzzy models, an applicable design scheme of the fault detectors for nonlinear systems can be transformed into the fault detection problem for T–S fuzzy systems [28].
On another active research front, NCSs have received a great deal of attention in recent years owing to their successful applications in a wide range of areas such as industrial automation, aerospace, nuclear power station, and internet-based control [5], [6], [12], [13], [20], [25], [33], [34]. The research into NCSs has mainly focused on the network-induced challenging problems, such as communication delays and data packet dropouts that could degrade the system performances or even cause fault. Over the past few years, compared with the rich literature on filtering and control problems for NCSs, only a limited number of results have been available on the fault detection problems of NCSs with time delays. For example, the fault detection problem has been investigated for a class of discrete-time networked linear systems with constant time delays [12]. In [36], the fault detection problem for NCSs has been studied where the communication delays are described as a random Markov jump process. It is worth mentioning that most of the reported results have been concerned with the discrete time delays. Another kind of time delays, namely, distributed time delays, has been largely overlooked due mainly to the complexity and difficulty. The application insight of the distributed delays has been widely recognized, and a number of results involving continuously distributed delays have been published (see, e.g., [15], [26], and [30]). The distributed delays in the discrete-time setting, on the other hand, have received little attention despite their application significance in digital control systems [27]. Furthermore, it is fairly unrealistic to assume that the discrete-time distributed delays are deterministic in a networked environment. Instead, due to the unpredictable changes of the network conditions, the discrete-time distributed delays may occur in a probabilistic way. As such, it makes practical sense to investigate how the randomly occurring phenomena (e.g., discrete time delay, distributed time delay, and packet dropout) affect the dynamic behavior of the NCSs as well as the fault detection process.

A thorough literature review on the fault detection problems for NCSs and fuzzy control systems has revealed that, up to now, little attention has been paid to the study of fault detection for nonlinear NCSs with both communication delays and packet dropouts, particularly when the randomly occurring phenomena (e.g., discrete time delay, distributed time delay, and packet dropout) affect the dynamic behavior of the NCSs as well as the fault detection process.

Fig. 1. Framework of the fuzzy fault detection filter design over network environments.

A specified Bernoulli distribution. 2) The investigation on the T–S fuzzy model is carried out for a class of complex systems that account for the modeling errors, disturbance rejection attenuation, probabilistic delay, and packet dropouts within the same framework. 3) Stochastic analysis is conducted to enforce multiple requirements, including the $H_{\infty}$-norm constraints, the fault detection specification, and the usual mean-square convergence of the detection errors.

Notation: The notation used in this paper is fairly standard. The superscript “T” stands for matrix transposition, $\mathbb{R}^n$ denotes the $n$-dimensional Euclidean space, and $\mathbb{R}^{m \times n}$ is the set of all real matrices of dimension $m \times n$. The set of all nonpositive integers is denoted by $\mathbb{Z}^-$. Zero represents zero matrix of compatible dimensions. The $n$-dimensional identity matrix is denoted as $I_n$ or simply $I$, if no confusion is caused. The notation $P > 0$ means that $P$ is real symmetric and positive definite. $I_2[0, \infty)$ is the space of square summable sequences. $\text{tr}(M)$ refers to the trace of the matrix $M$. The notation $\|A\|$ refers to the norm of a matrix $A$ defined by $\|A\| = \sqrt{\text{tr}(A^T A)}$, and $\|\cdot\|_2$ stands for the usual $l_2$ norm. In symmetric block matrices or complex matrix expressions, we use an asterisk “*” to represent a term that is induced by symmetry, and $\text{diag}\{\cdots\}$ stands for a block-diagonal matrix. In addition, $\mathbb{E}\{x\}$ and $\mathbb{E}\{x|y\}$ will, respectively, denote the expectation of the stochastic variable $x$ and expectation of $x$ conditional on $y$. $\text{Prob}\{\cdot\}$ means the occurrence probability of the event “·.” The symbol $\circ$ denotes the Kronecker product. Matrices, if their dimensions are not explicitly stated, are assumed to be compatible for algebraic operations.

II. PROBLEM FORMULATION

In this paper, we consider the fault detection problem for a class of uncertain discrete-time fuzzy systems with stochastic mixed time delays and successive packet dropouts in NCSs, where the framework is shown in Fig. 1. The sensors are connected to the fault detection filter via a network which is subject to possible successive packet dropouts.

A. Physical Plant

Consider a discrete-time nonlinear system with stochastic mixed time delays which can be represented by the following
T–S fuzzy dynamic model:

△ **Plant Rule i:** IF \( \theta_1(k) \) is \( M_{i1} \) and \( \theta_2(k) \) is \( M_{i2} \) and \( \cdots \) and \( \theta_p(k) \) is \( M_{ip} \), THEN

\[
x(k + 1) = A_i x(k) + A_{d1i} \sum_{m=1}^{h} \alpha_m(k) x(k - \tau_m(k))
+ \beta_i A_{d2i} \sum_{d=1}^{\infty} \mu_d x(k - d) + D_{1i} w(k) + C_i f(k)
\]

where \( x_1(k) \) is the fuzzy set, \( r \) is the number of IF–THEN rules, and \( \theta(k) = [\theta_1(k), \theta_2(k), \ldots, \theta_p(k)] \) is the premise variable vector. \( x_1(k) \in \mathbb{R}^n \) represents the state vector; \( y_1(k) \in \mathbb{R}^m \) is the process output; \( u(k) \in \mathbb{R}^l \) is the input; \( f(k) \in \mathbb{R}^l \) is the disturbance input; \( \eta(k) \in \mathbb{R}^m \) is the fault to be detected; \( G_i \) are constant positive integers representing the lower and upper bounds on the communication delay. \( \forall k \in \mathbb{Z}^- \), the global dynamics of the T–S fuzzy systems (1) can be inferred as follows:

\[
x(k + 1) = \sum_{i=1}^{r} h_i(\theta(k)) \times \left[ A_i x(k) + A_{d1i} \sum_{m=1}^{h} \alpha_m(k) x(k - \tau_m(k))
+ \beta_i A_{d2i} \sum_{d=1}^{\infty} \mu_d x(k - d)
+ D_{1i} w(k) + C_i f(k) \right]
\]

\[
y(k) = \sum_{i=1}^{r} h_i(\theta(k)) [C_i x(k) + D_{2i} w(k)]
\]

where \( \alpha_m(k) \) and \( \beta_i \) are constant positive integers representing the lower and upper bounds on the communication delay, respectively. The constants \( \mu_d \geq 0 \) (\( d = 1, 2, \ldots, \infty \)) satisfy the following convergence conditions:

\[
\hat{\mu} := \sum_{d=1}^{\infty} \mu_d < +\infty.
\]

To account for the phenomena of randomly occurring discrete time delays and distributed time delays, we introduce the stochastic variables \( \alpha_m(k) \in \mathbb{R} \) (\( m = 1, 2, \ldots, h \)) and \( \beta(k) \in \mathbb{R} \), which are mutually independent Bernoulli-distributed white sequences and also independent with the premise variables \( \theta(k) \). Natural assumptions on \( \alpha_m(k) \) and \( \beta_i \) are as follows:

\[
\text{Prob} \{ \alpha_m(k) = 1 \} = \mathbb{E} \{ \alpha_m(k) \} = \bar{\alpha}_m
\]
\[
\text{Prob} \{ \alpha_m(k) = 0 \} = 1 - \bar{\alpha}_m
\]
\[
\text{Prob} \{ \beta(k) = 1 \} = \mathbb{E} \{ \beta(k) \} = \tilde{\beta}
\]
\[
\text{Prob} \{ \beta(k) = 0 \} = 1 - \tilde{\beta}
\]

**Remark 1:** In model (1), both the discrete time-delay term \( x(k - \tau_m(k)) \) and the distributed time-delay term \( \sum_{d=1}^{\infty} \mu_d x(k - d) \) behave probabilistically due to the introduction of the stochastic variables \( \alpha_m(k) \) and \( \beta_i \). As such, they are called randomly occurring mixed time delays. Note that the term \( \sum_{d=1}^{\infty} \mu_d x(k - d) \) may be considered as the discretization of the semi-infinite integral form \( \int_{-\infty}^{\infty} h(t-s)x(s)ds \) in the continuous-time system. It is noted that distributed delays occur very often in practical systems and have attracted much attention in the literature (see, e.g., [15] and [30]). Most results have been concerned with the continuous deterministic time delays, and there have been very few results for randomly occurring mixed time delays particularly when the fault detection problem becomes a research focus.

By using a center average defuzzifier, product interference, and a singleton fuzzifier, the global dynamics of the T–S fuzzy systems (1) can be inferred as follows:

\[
x(k + 1) = \sum_{i=1}^{r} h_i(\theta(k)) \times \left[ A_i x(k) + A_{d1i} \sum_{m=1}^{h} \alpha_m(k) x(k - \tau_m(k))
+ \beta_i A_{d2i} \sum_{d=1}^{\infty} \mu_d x(k - d)
+ D_{1i} w(k) + C_i f(k) \right]
\]

\[
y(k) = \sum_{i=1}^{r} h_i(\theta(k)) [C_i x(k) + D_{2i} w(k)]
\]
B. Communication Channel with Packet Dropouts

In this paper, we assume that an unreliable network medium is present between the physical plant and the fault detection filter, and the packet dropout phenomenon constitutes another focus of our present research. The signal received by the fault detection filter can be described by

$$y_f(k) = \gamma(k)y(k) + (1 - \gamma(k))y_f(k - 1) \quad (6)$$

where $y_f(k) \in \mathbb{R}^m$ is the actual measurement signal of $y(k)$ and $\gamma(k) \in \mathbb{R}$ is a binary distributed random variable with $\text{Prob}\{\gamma(k) = 1\} = \mathbb{E}\{\gamma(k)\} = \gamma$ and $\text{Prob}\{\gamma(k) = 0\} = 1 - \gamma$. In this paper, we assume that the premise variables $\theta(k)$ do not depend on the stochastic variables $\alpha(k), \beta(k),$ and $\gamma(k)$. In addition, all the stochastic variables are assumed to be mutually independent Bernoulli-distributed white sequences.

Remark 2: The dropout model (6) has been introduced in [19] to describe the successive packet dropouts. For example, if $\gamma(k) = 1$, we have $y(k) = y_f(k)$, which means that there is no packet dropout. If $\gamma(k) = 0$ but $\gamma(k - 1) = 1$, we have $y(k) = y_f(k - 1)$, which means that the measured output at time point $k$ is missing but one at time point $k - 1$ has been received. As shown in [22], it is easy to further confirm that (6) can be a model for multiple consecutive packet dropouts where the latest measurement received in the buffers will be utilized if the current measurement is lost during packet transmissions. Such a scheme is certainly more realistic than the one setting the measurement signals to zero when the current measurements are lost [6], [8], [25].

C. Fuzzy Fault Detection Filter

As discussed previously, the key step of fault detection schemes is the construction of a dynamic system called a fault detection observer/filter, in which the residual signal is generated in order to determine whether a fault has occurred or not [28].

In this paper, for the physical plant represented by (1) and (5), we adopt a fuzzy fault detection filter whose model is described as follows:

\[ \Delta \text{ Filter Rule i: If } \theta_1(k) = M_{11} \text{ and } \theta_2(k) = M_{12} \text{ and } \cdots \text{ and } \theta_p(k) = M_{1p}, \text{ THEN} \]

\[ \hat{x}(k + 1) = A_{f1}\hat{x}(k) + B_{f1}y_f(k) \]

\[ r(k) = C_{f1}\hat{x}(k) + D_{f1}y_f(k) \quad (7) \]

where $\hat{x}(k) \in \mathbb{R}^n$ represents the filter state vector, $r(k) \in \mathbb{R}^l$ is the so-called residual that is compatible with the fault vector $f(k)$, and $A_{f1}, B_{f1}, C_{f1}, D_{f1}$ are appropriately dimensioned filter matrices to be determined. Then, the overall fuzzy fault detection filter can be represented in the following form:

\[ \hat{x}(k + 1) = \sum_{i=1}^{r} h_i [A_{fi}\hat{x}(k) + B_{fi}y_f(k)] \]

\[ r(k) = \sum_{i=1}^{r} h_i [C_{fi}\hat{x}(k) + D_{fi}y_f(k)]. \quad (8) \]

Our aim in this paper is to design a fault detection filter of the form in (7) that makes the error between residual signal $r(k)$ and fault signal $f(k)$ as small as possible. From (5), (6), and (8), we have the overall fault detection dynamics governed by the following system:

\[ \eta(k + 1) = \sum_{i=1}^{r} \sum_{j=1}^{r} h_i h_j \left[ \begin{array}{c} A_{ij}\eta(k) + \gamma(k)A_{ij} \end{array} \right] \eta(k) \]

\[ + \sum_{m=1}^{h} (\hat{A}_{d1mi} + \alpha_m(k)\hat{A}_{d1i}) \eta(k - \tau_m(k)) \]

\[ + (\hat{A}_{d2i} + \beta(k)\hat{A}_{d2i}) \sum_{d=1}^{\infty} \mu_d\eta(k - d) \]

\[ + (\hat{B}_{ij} + \gamma(k)\hat{B}_{ij}) v(k) \quad (9) \]

\[ e(k) = \sum_{i=1}^{r} \sum_{j=1}^{r} h_i h_j \left[ \begin{array}{c} C_{ij}\eta(k) + \gamma(k)\hat{C}_{ij} \end{array} \right] \eta(k) \]

\[ + (\hat{D}_{ij} + \gamma(k)\hat{D}_{ij}) v(k) \quad (10) \]

where

\[ \eta(k) = [x^T(k) \quad x^T(k) \quad y_f^T(k - 1)]^T \]

\[ e(k) = r(k) - f(k) \quad v(k) = [w^T(k) \quad f^T(k)]^T \]

\[ \hat{A}_{d1mi} = \text{diag}\{\alpha(m)A_{d1i}, 0, 0\} \]

\[ \hat{A}_{d2i} = \text{diag}\{\alpha(m)A_{d2i}, 0, 0\} \]

\[ \hat{C}_{ij} = \text{diag}\{\alpha(m)C_{fj}, C_{fj}, (1 - \gamma)D_{fj}\} \]

\[ \hat{C}_{ij} = [D_{fj}C_{fj} \quad 0 - D_{fj}] \]

\[ \hat{A}_{ij} = \left[ \begin{array}{ccc} A_{fj} & 0 & 0 \\ \beta & 0 & 0 \\ 0 & -B_{fj} & C_{fj} \end{array} \right] \quad (11) \]

\[ \hat{B}_{ij} = \left[ \begin{array}{ccc} B_{d1i} & 0 & 0 \\ 0 & 0 & 0 \end{array} \right] \quad \hat{B}_{ij} = \left[ \begin{array}{ccc} 0 & 0 & 0 \\ 0 & 0 & 0 \end{array} \right] \]

with $\alpha_m(k) = \alpha_m(k - 1) - \alpha_m$, $\beta(k) = \beta(k - 1) - \beta$, and $\gamma(k) = \gamma(k - 1) - \gamma$. It is clear that $\mathbb{E}\{\hat{\alpha}_m(k)\} = 0$, $\mathbb{E}\{\hat{\beta}(k)\} = 0$, $\mathbb{E}\{\gamma(k)\} = 0$ and $\mathbb{E}\{\gamma^2(k)\} = \alpha_m(1 - \alpha_m)$, $\mathbb{E}\{\beta^2(k)\} = \beta(1 - \beta)$, $\mathbb{E}\{\gamma^2(k)\} = \gamma(1 - \gamma)$.

Definition: With system (10) and every initial conditions $\psi$, the fault detection dynamics in (10) is said to be exponentially mean square stable if, in case of $v(k) = 0$, there exist constants $\delta > 0$ and $0 < \kappa < 1$ such that

\[ \mathbb{E}\left\{\|\eta(k)\|^2\right\} \leq \delta k^\kappa \sup_{i \in \mathbb{Z}^+} \mathbb{E}\left\{\|\psi(i)\|^2\right\} \quad \forall k \geq 0. \]
To this end, the fault detection problem to be addressed in this paper can be described by the following two steps.

Step 1) Generate a residual signal. For system (1), design a fuzzy fault detection filter in the form of (7) to generate a residual signal \( r(k) \). Furthermore, the filter is designed so that the overall fault detection system (10) is exponentially mean square stable with the following \( \mathcal{H}_\infty \) performance constraint under zero initial condition:

\[
\sum_{k=0}^{\infty} E \left\{ \| e(k) \|^2 \right\} \leq \gamma^2 \sum_{k=0}^{\infty} \| v(k) \|^2
\]  

(12)

where \( v(k) \neq 0 \) and \( \gamma > 0 \) is made as small as possible in the feasibility of (12).

Step 2) Set up a fault detection measure. In this paper, we adopt a residual evaluation stage, including an evaluation function \( J(k) \) and a threshold \( J_{th} \) of the following form:

\[
J(k) = \left\{ \sum_{k=s-L}^{k=s} r(T) r(k) \right\}^{\frac{1}{2}}, \quad J_{th} = \sup_{\omega \in \mathcal{W}, j=0} E \left\{ J(k) \right\}
\]

(13)

where \( L \) denotes the length of the finite evaluating time horizon. Based on (13), the occurrence of faults can be detected by comparing \( J(k) \) with \( J_{th} \) according to the following rule:

- \( J(k) > J_{th} \implies \) with faults \( \implies \) alarm
- \( J(k) \leq J_{th} \implies \) no faults.

### III. MAIN RESULTS

**Lemma 1 [15]:** Let \( \mathcal{M} \in \mathbb{R}^{n \times n} \) be a positive semidefinite matrix, \( x_i \in \mathbb{R}^n \), and constant \( \alpha_i > 0 \) (i = 1, 2, ..., \( \infty \)). If the series concerned is convergent, then we have

\[
\left( \sum_{i=1}^{\infty} a_i x_i \right)^T \mathcal{M} \left( \sum_{i=1}^{\infty} a_i x_i \right) \leq \left( \sum_{i=1}^{\infty} a_i \right) \left( \sum_{i=1}^{\infty} a_i x_i \mathcal{M} x_i \right).
\]

(14)

**Lemma 2 (S-procedure):** Let \( L = L^T \) and \( H \) and \( E \) be real matrices of appropriate dimensions with \( F \) satisfying \( F E^T \leq I \). Then, \( L + H F E + E^T F^T H^T < 0 \), if and only if there exists a positive scalar \( \varepsilon > 0 \) such that \( L + \varepsilon^{-1} H H^T + \varepsilon E^T E < 0 \) or equivalently

\[
\begin{bmatrix}
L & \varepsilon E^T \\
H^T & -\varepsilon I \\
E & 0 \\
\varepsilon E & -\varepsilon I
\end{bmatrix} < 0.
\]

(15)

**Lemma 3 [10]:** For any real matrices \( X_{ij} \) for \( i, j = 1, 2, ..., r \) and \( \Lambda > 0 \) with appropriate dimensions, we have

\[
\sum_{i=1}^{r} \sum_{j=1}^{r} \sum_{k=1}^{r} h_i h_j h_k h_l X_{ij}^T X_{kl} A X_{kl} \leq \sum_{i=1}^{r} \sum_{j=1}^{r} h_i h_j X_{ij}^T A X_{ij}.
\]

(16)

For convenience of presentation, we first discuss the nominal system of (10) (i.e., without parameter uncertainty \( \Delta A_i \)) and will eventually extend our main results to the general case. We have the following analysis result that serves as a theoretical basis for the subsequent design problem.

**Theorem 1:** Consider the nominal fuzzy system of (1) with given filter parameters and a prescribed \( \mathcal{H}_\infty \) performance \( \gamma > 0 \). The nominal fuzzy fault detection system in (10) is exponentially mean square stable with a disturbance attenuation level \( \gamma \) if there exist matrices \( P > 0, Q_k > 0 \) (\( k = 1, 2, \ldots, h \)), and \( R > 0 \) satisfying

\[
\Psi_{ii}^T P \Psi_{ii} + \tilde{A}^T \tilde{A} + \tilde{B}^T \tilde{B} < 0
\]

(17)

\[
\Psi_{ij}^T \tilde{P} (\tilde{P} + \tilde{B}_i) + (\tilde{P} + \tilde{B}_j) \tilde{P} (\tilde{P} + \tilde{B}_j) + 2(\tilde{P} + \tilde{B}_j) < 0
\]

(18)

where

\[
\tilde{A}_i = [g \tilde{A}_i 0 0 g \tilde{B}_i] \quad \tilde{B}_i = [\tilde{A}^T \tilde{C}^T] \quad \tilde{B}_i = [\tilde{A}^T \tilde{C}^T]_i
\]

\[
\tilde{C}_i = [\tilde{C}_i 0 0 \tilde{D}_i] \quad \Psi_{ij} = [\tilde{A}_i^T \tilde{C}^T]_j
\]

\[
\tilde{C}_i = [g \tilde{C}_i 0 0 g \tilde{D}_i] \quad \tilde{P} = \text{diag}(P, I)
\]

\[
\tilde{P}_j = \text{diag}(\tilde{P}_j, -\gamma I) \quad \tilde{P}_j = \text{diag}(Q_k, F_{ij}, \tilde{A}_{d_{ij}})
\]

\[
\tilde{Q}_k = \sum_{k=1}^{h} (d_{\text{max}} - d_{\text{min}} + 1) Q_k + \mu R - P
\]

\[
F_{ij} = \tilde{A}_{d_{ij}} \tilde{P} \tilde{A}_{d_{ij}} - \tilde{Q} \tilde{A}_{d_{ij}} = \gamma^2 \tilde{A}_{d_{ij}}^T P \tilde{A}_{d_{ij}} \frac{1}{R} P
\]

\[
\tilde{Q} = \text{diag}(Q_1, \ldots, Q_h) \quad \tilde{A}_{d_{ij}} = \tilde{A}_{d_{ij}} \tilde{\tilde{A}}_{d_{ij}}
\]

\[
\gamma^2 = \tilde{\beta}(1 - \tilde{\beta}).
\]

(19)

**Proof:** Choose a Lyapunov functional candidate as

\[
V(k) = \sum_{i=1}^{3} V_i(k)
\]

(20)
with \( P > 0 \), \( R > 0 \), and \( Q_j > 0 \) \((j = 1, 2, \ldots, h)\) being matrices to be determined. Then, along the trajectory of system (10), we have

\[
\mathbb{E}\{\Delta V_1(k)\} = \mathbb{E}\left\{\sum_{i=1}^{r} \sum_{j=1}^{r} \sum_{s=1}^{r} h_i h_j h_s h_t \left( \hat{A}_{ij} + \hat{\gamma}(k) \hat{A}_{ij} \right) \eta(k) \right. \\
+ \sum_{m=1}^{h} (\hat{A}_{d1mi} + \hat{\alpha}_m(k) \hat{A}_{d1i}) \eta(k - \tau_m(k)) \\
+ (\hat{A}_{d2i} + \hat{\beta}(k) \hat{A}_{d2i}) \sum_{d=1}^{\infty} \eta_d \eta(k - d) \\
+ (\hat{B}_{ij} + \hat{\gamma}(k) \hat{B}_{ij}) v(k) \right. \\
+ \left( \hat{A}_{sl} + \hat{\gamma}(k) \hat{A}_{sl} \right) \eta(k) \\
+ \sum_{m=1}^{h} (\hat{A}_{d1ms} + \hat{\alpha}_m(k) \hat{A}_{d1s}) \eta(k - \tau_m(k)) \\
+ (\hat{A}_{d2s} + \hat{\beta}(k) \hat{A}_{d2s}) \sum_{d=1}^{\infty} \eta_d \eta(k - d) \\
+ (\hat{B}_{sl} + \hat{\gamma}(k) \hat{B}_{sl}) v(k) \\
- \eta^T(k) P \eta(k) \left\}.
\]

(21)

Next, by applying Lemma 1, it can be derived that

\[
\mathbb{E}\{\Delta V_2(k)\} \leq \mathbb{E}\left\{\hat{\mu}^T(k) R \eta(k) - \frac{1}{\hat{\mu}} \left( \sum_{d=1}^{\infty} \mu_d \eta(k - d) \right)^T \right. \\
\times R \left( \sum_{d=1}^{\infty} \mu_d \eta(k - d) \right) \left\}
\]

(22)

\[
\mathbb{E}\{\Delta V_3(k)\} \leq \mathbb{E}\left\{ \sum_{j=1}^{h} \left( \eta^T(k) Q_j \eta(k) - \eta^T(k - \tau_j(k)) \right) \\
\times Q_j \eta(k - \tau_j(k)) \\
+ \sum_{j=1}^{h} (d_{\max} - d_{\min}) \eta^T(k) Q_j \eta(k) \right\}.
\]

(23)

For notational convenience, we denote

\[
\hat{\xi}(k) = \left[ \eta^T(k) \eta^T(k - \tau) \sum_{d=1}^{\infty} \mu_d \eta^T(k - d) \right]^T \\
\xi(k) = \left[ \tilde{\xi}^T(k) \eta^T(k) \right]^T \mathbf{P}_{ij} = \text{diag}\{\hat{P}_{ij}, 0\} \\
\eta(k - \tau) = \left[ \eta^T(k - \tau_1(k)) \cdots \eta^T(k - \tau_h(k)) \right]^T \\
\mathcal{A}_{ij} = [A_{ij} \hat{Z}_{1mi} \hat{A}_{d2i}] \quad \hat{A}_{ij} = [g \hat{A}_{ij} 0 0].
\]

(24)

In the following, we first prove the exponential stability of the fault detection dynamics system (10) with \( v(k) = 0 \). Considering (20)–(24) and by using Lemma 3, we have

\[
\mathbb{E}\{\Delta V(k)\} \leq \mathbb{E}\left\{ \sum_{i=1}^{r} \sum_{j=1}^{r} \sum_{s=1}^{r} h_i h_j h_s h_t \xi^T(k) \\
\times \left( A_{ii}^T P A_{sti} + \hat{A}_{ij}^T P \hat{A}_{sti} + \hat{P}_{ii} \right) \xi(k) \right\} \\
+ \frac{1}{2} \sum_{i,j=1, i \neq j}^{r} h_i h_j \xi^T(k) \\
\times \left( (A_{ij} + \hat{A}_{ij})^T P (A_{ij} + \hat{A}_{ij}) + (\hat{A}_{ij} + \hat{A}_{ji})^T \right. \\
\times P (\hat{A}_{ij} + \hat{A}_{ji}) + 2(\hat{P}_{ij} + \hat{P}_{ji}) \right\} \xi(k) \right\}.
\]

(25)

By utilizing the Schur Complement Lemma [1], we know that \( \mathbb{E}\{\Delta V(k)\} < 0 \) if (17) and (18) are true. Furthermore, along the same line of the proof for Theorem 1 in [25], it can be concluded that the discrete-time nominal fuzzy system of (10) with \( v(k) = 0 \) is exponentially mean square stable.

Now, let us establish the \( H_\infty \) performance of the nominal fuzzy system of (10). Assume zero initial condition, and introduce the following index:

\[
J(n) = \mathbb{E}\left\{ \frac{\mathbb{E}\{\Delta V(k)\}}{1} \mathbb{E}\{\xi^T(k) v(k) - \gamma^2 v^T(k) v(k)\} \right\} \\
\leq \mathbb{E}\left\{ \frac{\mathbb{E}\{\Delta V(k)\}}{1} \mathbb{E}\{\xi^T(k) v(k) + \Delta V(k)\} \right\}.
\]

Along the trajectory of the nominal system of (10) and taking (11), (24), and (25) into consideration, we have

\[
J(n) \leq \mathbb{E}\left\{ \sum_{k=0}^{n} \sum_{i=1}^{r} \sum_{j=1}^{r} \sum_{s=1}^{r} h_i h_j h_s h_t \xi^T(k) \\
\times (\Psi_{ij}^T P \Psi_{st} + \hat{\Psi}_{ij}^T P \hat{\Psi}_{st} + \hat{\Psi}_{ii}) \xi(k) \right\} \\
\leq \mathbb{E}\left\{ \sum_{k=0}^{n} \left\{ \sum_{i=1}^{r} h_i^2 \xi^T(k) \\
\times (\Psi_{ij}^T P \Psi_{ii} + \hat{\Psi}_{ij}^T P \hat{\Psi}_{ii} + \hat{\Psi}_{ii}) \xi(k) \right\} \\
+ \frac{1}{2} \sum_{i,j=1, i \neq j}^{r} h_i h_j \xi^T(k) \\
\times [\Psi_{ij} + \hat{\Psi}_{ji}]^T P (\Psi_{ij} + \hat{\Psi}_{ji}) + (\Psi_{ij} + \hat{\Psi}_{ji})^T P (\hat{\Psi}_{ij} + \hat{\Psi}_{ji}) \right\} + 2(\hat{\Psi}_{ij} + \hat{\Psi}_{ji}) \xi(k) \right\}.
\]

(26)
which leads to $J(n) < 0$ by considering Theorem 1. Letting $n \to \infty$, we obtain
\[
\sum_{k=0}^{\infty} \mathbb{E} \left\{ \| e(k) \|^2 \right\} \leq \gamma^2 \sum_{k=0}^{\infty} \| r(k) \|^2
\]
which is equivalent to the inequality in (12), and therefore, the proof of Theorem 1 is complete.

Having established the analysis results, we are now in a position to deal with the fuzzy fault detection filter design problem.

**Theorem 2:** Consider the nominal fuzzy system of (10), and let $\gamma > 0$ be a given scalar. A desired full-order fault detection filter of the form (7) exists if there exist matrices $P > 0$, $R > 0$, and $Q_k > 0$ ($k = 1, 2, \ldots, h$) and matrices $X_i$ and $K_i$ satisfying
\[
\begin{align*}
\Omega_1 &= \begin{bmatrix} \bar{P}_{i} & \cdots & \bar{P} \end{bmatrix} \begin{bmatrix} \Gamma_{ii} \end{bmatrix} < 0, & i = 1, 2, \ldots, r \\
\Omega_2 &= \begin{bmatrix} 2(\bar{P}_{ij} + \bar{P}_{ji}) \end{bmatrix} \begin{bmatrix} \Gamma_{ij} + \Gamma_{ji} \end{bmatrix} < 0, & 1 \leq i < j \leq r
\end{align*}
\]
where
\[
\begin{align*}
\Gamma_{11ij} &= \begin{bmatrix} P \hat{A}_{0i} + X_i \hat{R}_{1i} & P \hat{Z}_{1mi} \\
K_i \hat{R}_{1i} & 0 \end{bmatrix} \\
\Gamma_{12ij} &= \begin{bmatrix} P \hat{A}_{d2i} + \gamma X_i \hat{R}_{2ij} \end{bmatrix} \\
0 & \begin{bmatrix} E_0 + \gamma K_i \hat{R}_{2ij} \end{bmatrix} \\
\Gamma_{21ij} &= \begin{bmatrix} gP \hat{A}_{1i} + gX_i \hat{R}_{1ij} \end{bmatrix} \\
0 & \begin{bmatrix} gK_i \hat{R}_{1ij} \end{bmatrix} \\
\Gamma_{22ij} &= \begin{bmatrix} 0 & gP \hat{D}_{0i} + gX_i \hat{R}_{2ij} \\
0 & gK_i \hat{R}_{2ij} \end{bmatrix}
\end{align*}
\]
\[
\begin{align*}
\hat{R}_{1i} &= \begin{bmatrix} 0 & I & 0 \\
\gamma C_j & 0 & (1 - \gamma)I \end{bmatrix} & \Gamma_{ij} &= \begin{bmatrix} \Gamma_{11ij} & \Gamma_{12ij} \\
\Gamma_{21ij} & \Gamma_{22ij} \end{bmatrix} \\
\hat{A}_{0i} &= \begin{bmatrix} A_i & 0 & 0 \\
\gamma C_j & 0 & (1 - \gamma)I \end{bmatrix} & \hat{A}_{1i} &= \begin{bmatrix} 0 & 0 & 0 \\
0 & 0 & 0 \end{bmatrix} \\
\hat{B}_{0i} &= \begin{bmatrix} D_{1i} & G_i \\
\gamma D_{2i} & 0 \end{bmatrix} & \hat{D}_{0i} &= \begin{bmatrix} 0 & 0 & 0 \\
0 & 0 & 0 \end{bmatrix} \\
\hat{R}_{2ij} &= \begin{bmatrix} 0 & 0 \\
D_{2ij} & 0 \end{bmatrix} & \hat{R}_{4ij} &= \begin{bmatrix} 0 & 0 \\
C_j & 0 \end{bmatrix} & \hat{E}_0 &= \begin{bmatrix} 0 & -I \end{bmatrix}
\end{align*}
\]
and $\bar{P}_i$ and $\bar{P}$ are defined in Theorem 1. Furthermore, if $(P, R, Q_k, X_i, K_i)$ is a feasible solution of (27) and (28), then the fault detection filter parameters in the form of (7) are given as follows:
\[
[A_{fi} B_{fi}] = (\hat{E}^T P \hat{E})^{-1} \hat{E}^T X_i \quad [C_{fi} D_{fi}] = K_i,
\]
and $P_i$ and $\bar{P}$ are defined in Theorem 1. Furthermore, if $(P, R, Q_k, X_i, K_i)$ is a feasible solution of (27) and (28), then the fault detection filter parameters in the form of (7) are given as follows:
\[
\begin{align*}
&\begin{bmatrix} \Omega_1 & \epsilon_{i} \hat{E}_a \\
\hat{H}_{a}^T_{ai} & \epsilon_{i} \hat{E}_a \end{bmatrix} < 0, & i = 1, 2, \ldots, r \\
&\begin{bmatrix} \Omega_2 & \epsilon_{i} \hat{E}_a \\
\hat{H}_{a}^T_{ai} & \epsilon_{i} \hat{E}_a \end{bmatrix} < 0, & 1 \leq i < j \leq r
\end{align*}
\]
where
\[
\begin{align*}
\hat{H}_{a} &= \begin{bmatrix} 0 & 0 & 0 & 0 \end{bmatrix} \\
\hat{E}_a &= \begin{bmatrix} 0 & 0 & 0 \end{bmatrix} \\
\hat{H} &= \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}
\end{align*}
\]
and \( \Omega_1 \) and \( \Omega_2 \) are defined in Theorem 2. Moreover, if \((P,R,Q_k,X_i,K_i,\varepsilon_{ij})\) is a feasible solution of (35) and (36), then the fault detection filter parameters in the form of (7) are given as follows:

\[
[A_{fi} \ B_{fi}] = (E^TPE)^{-1}E^TXi \quad [C_{fi} \ D_{fi}] = Ki. \tag{38}
\]

**Proof:** Replace \(A_i\) in (27) and (28) with \(A_i + H_{ai}F(k)E_i\), and rewrite (27) and (28) in the following form:

\[
\Omega_1 + H_{ai}F(k)E_a + E_a^TF(k)H_{ai}^T < 0
\]
\[
\Omega_2 + (H_{ai} + H_{aj})F(k)E_a + E_a^TF(k)(H_{ai} + H_{aj})^T < 0
\]

where the corresponding parameters have been defined in (37). According to Lemma 2, we can easily obtain (35) and (36), and the proof is then complete.

**Remark 3:** In Theorem 3, the fuzzy fault detection filter is designed such that the overall fault detection dynamics is exponentially stable in the mean square and, at the same time, the error between the residual signal and the fault signal is made exponentially stable in the mean square and, at the same time, the proof is then complete.

**IV. An Illustrative Example**

In this section, we use a nonlinear pendulum to demonstrate the effectiveness and applicability of the proposed method. The pendulum system is modified from [7] by adding one damping term for stability of the system. It is assumed that two components of the system (i.e., angle and angular velocity) are randomly perturbed by time delays. The equations of motion of the pendulum are described as follows:

\[
\dot{\theta}(t) = \lambda \theta(t) + \alpha_1(t)(1 - \lambda)\dot{\theta}(t - d(t)) + \alpha_2(t)(1 - \lambda)\theta(t - d(t)) + \beta(t) \int_{-\infty}^{t} \lambda(t - s)\theta(s)ds
\]
\[
\dot{\theta}(t) = -g \sin(\theta(t)) + (b/\ell m) \left[\lambda \theta(t) + (1 - \lambda)\dot{\theta}(t - d(t))\right] + \left(\frac{3}{2}(1 - \frac{q}{m} \cos^2(\theta(t)))\right) + w_1(t)
\]
\[
y(t) = \sin(\theta(t)) + \bar{\theta}(t) + w_2(t)
\]

where \( \theta \) denotes the angle of the pendulum from the vertical, \( \bar{\theta} \) is the angular velocity, \( g = 9.8 \text{ m/s}^2 \) is the gravity constant, \( m \) is the mass of the pendulum, \( a = 1/(m + M) \), \( M \) is the mass of the cart, \( l \) is the length of the pendulum, \( b \) is the damping coefficient of the pendulum around the pivot, and \( w_1 \) and \( w_2 \) are the disturbance applied to the cart and measurement noise, respectively. In this simulation, the pendulum parameters are chosen as \( m = 2 \text{ kg}, M = 8 \text{ kg}, l = 0.5 \text{ m}, b = 0.7 \text{ N} \cdot \text{m/s}, \) and the retarded coefficient \( \lambda = 0.6 \).

Letting \( x_1(t) = \theta(t) \) and \( x_2(t) = \bar{\theta}(t) \), we linearize the plant around the origin \( x = (\pm \pi/2) \) and \( x = (\pm \pi/3) \) and consider the differences between the linearized local model and the original nonlinear model as the uncertainties. By discretizing the plant with a sampling period of 0.05 s, we obtain the following discrete-time T–S fuzzy model:

\[
x(k + 1) = \sum_{i=1}^{3} h_i(\theta(k))
\]
\[
\times \left[ (A_i + \Delta A_i(k))x(k) + A_{d1}(m=1)^{h} \alpha_m(k)x(k - \tau_m(k)) + \beta(k)A_{d2}x(k - d) + D_{1w}(k) \right]
\]
\[
y(k) = \sum_{i=1}^{3} h_i(\theta(k)) [C_i x(k) + D_{2w}(k) ].
\]

The model parameters are given as follows:

\[
A_1 = \begin{bmatrix} 1.000 & 0.0450 \\ 0.8558 & 0.7894 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 1.000 & 0.0450 \\ -0.4679 & 0.8055 \end{bmatrix},
\]
\[
A_{d11} = A_{d12} = A_{d13} = \begin{bmatrix} 0.14 & 0.02 \\ 0 & 0.094 \end{bmatrix}, \quad A_{d21} = A_{d22} = A_{d23} = \begin{bmatrix} 0 & 0.12 \\ 0.1 & 0.02 \end{bmatrix},
\]
\[
D_{11} = D_{12} = D_{13} = \begin{bmatrix} 0 & 1 \end{bmatrix}^T, \quad C_1 = \begin{bmatrix} 0.9949 & 0.9 \end{bmatrix},
\]
\[
C_2 = \begin{bmatrix} 0.8270 & 0.9 \end{bmatrix}, \quad C_3 = \begin{bmatrix} 0.6366 & 0.9 \end{bmatrix},
\]
\[
H_{a1} = H_{a2} = H_{a3} = \begin{bmatrix} 0.2 & 0.01 \end{bmatrix}^T, \quad E_a = \begin{bmatrix} 0 & 2 \end{bmatrix},
\]
\[
F(k) = \sin(k), \quad D_{21} = D_{22} = D_{23} = 1.
\]

and the membership functions are shown in Fig. 2. Assume that the time-varying communication delays \( \tau_1(k) \) and \( \tau_2(k) \) are random variables whose elements are uniformly distributed in the interval [2, 6], and

\[
\bar{\alpha}_1 = \mathbb{E} \{ \alpha_1(k) \} = 0.8, \quad \bar{\alpha}_2 = \mathbb{E} \{ \alpha_2(k) \} = 0.6
\]
\[
\bar{\beta} = \mathbb{E} \{ \beta(k) \} = 0.9.
\]

Choosing the constants \( \mu_d = 2^{-3-d} \), we can easily find that \( \bar{\mu} = \sum_{d=1}^{\infty} \mu_d = 2^{-3} < \sum_{d=1}^{\infty} d\mu_d = 2^{-2} < \infty \), which satisfies the convergence condition (4).
Assume that there are faults on the angular velocity of the pendulum, with fault matrices given by

\[
G_1 = \begin{bmatrix} 0.9887 & -0.0180 \\ -0.0032 & 0.0172 \end{bmatrix},
G_2 = \begin{bmatrix} 0.9033 & -0.0172 \\ -0.0032 & 0.0172 \end{bmatrix},
G_3 = \begin{bmatrix} 0.6237 & 0.0180 \\ 0.0032 & 0.0172 \end{bmatrix}.
\]

Let the probability of \( \hat{\gamma}(k) \) be given by \( \bar{\gamma} = 0.7 \). Applying Theorem 3, we can obtain the desired \( \mathcal{H}_\infty \) filter parameters as follows:

\[
A_{f1} = \begin{bmatrix} -0.3879 & -0.4043 \\ -0.3840 & 0.4032 \end{bmatrix},
A_{f2} = \begin{bmatrix} 0.4279 & -0.4243 \\ -0.4840 & -0.5132 \end{bmatrix},
A_{f3} = \begin{bmatrix} 0.3868 & 0.4093 \\ 0.5420 & 0.5132 \end{bmatrix},
B_{f1} = \begin{bmatrix} -0.4690 \\ -0.4690 \end{bmatrix},
B_{f2} = \begin{bmatrix} 0.5679 \\ 0.4420 \end{bmatrix},
B_{f3} = \begin{bmatrix} -0.3868 \\ -0.3420 \end{bmatrix},
C_{f1} = \begin{bmatrix} -0.7846 \\ -0.6585 \end{bmatrix},
C_{f2} = \begin{bmatrix} -0.7579 \\ -0.5664 \end{bmatrix},
C_{f3} = \begin{bmatrix} -0.5052 \\ 0.4335 \end{bmatrix},
D_{f1} = -3.5656, D_{f2} = -1.3585, D_{f3} = -0.1792
\]

with the optimized performance index \( \gamma^* = 1.1598 \).

Now, let us show how the probabilities in the measurement (6) affect the \( \mathcal{H}_\infty \) performance of the fault detection filtering process. In Fig. 3, after 100 Monte Carlo simulations, the plot of the average optimal disturbance attenuation level \( \gamma^* \) versus the probability of packet dropouts is provided. It can be seen clearly that a better performance can be achieved with less missing measurements.

To further illustrate the effectiveness of the designed fault detection filter, for \( k = 0, 1, \ldots, 150 \), let the fault signal \( f(k) \) be given as

\[
f(k) = \begin{cases} 1, & 50 \leq k \leq 100 \\ 0, & \text{else} \end{cases}
\]

First, in the case that the initial conditions \( \psi(k), \forall k \in \mathbb{Z}^+ \), \( \psi \in \mathbb{R}^2 \) are 200 random state vectors whose elements are uniformly distributed in the interval \([0, 0.1]\), \( \tau_1(0) = 3 \), \( \tau_2(0) = 4 \), \( x(0) = [\pi/8 \ 0]^T \), \( \bar{x}(0) = [0 \ 0]^T \), \( y_f(-1) = 0 \), \( T = 20 \), and the external disturbance is \( w(k) = 0 \). The residual signal \( r(k) \) and evolution of residual evaluation function \( J(k) \) are shown in Figs. 4 and 5, respectively, which indicate that the designed filter can detect the fault effectively when it occurs.

Next, assume that the disturbance is given by

\[
w(k) = \begin{cases} 0.5 \times \text{rand}[0, 1], & 30 \leq k \leq 130 \\ 0, & \text{else} \end{cases}
\]

where the \text{rand} function generates arrays of random numbers whose elements are uniformly distributed in the interval \([0, 1]\).

The \text{rand} distribution of successive packet dropout numbers is shown in Fig. 6, from which we can see that if the number on the \( Y \)-axis is zero, it means that the current measurement output of the physical plant is transmitted to the fault detection filter successfully. Furthermore, when the number is \( i (i = 1, 2, \ldots) \), it means that we have experienced \( i \) successive packet dropouts and the received measurement at the time \( k - i \) will be used for current estimation. The residual signal \( r(k) \) and evolution...
Fig. 5. Evolution of residual evaluation function $J(k)$ without $w(k)$.

Fig. 6. Distribution of the packet dropout number under $\bar{\gamma} = 0.7$.

Fig. 7. Residual signal with $w(k)$.

Fig. 8. Evolution of residual evaluation function $J(k)$ with $w(k)$ in (41).

Fig. 9. Evolution of residual evaluation function $J(k)$ with $w(k) = 1 \times \text{rand}[0, 1], 30 \leq k \leq 130$.

of residual evaluation function $J(k)$ are shown in Figs. 7 and 8, respectively. It can be seen that the residual not only can reflect the fault in time but also detect the fault without confusing it with the disturbance $w(k)$.

Remark 4: In the simulation, we increase the magnitude of $w(k)$ in (41) with hope to see how a larger disturbance would influence the performance of the fault detection filter. For example, we take $w(k)$ as $1 \times \text{rand}[0, 1]$ and $2 \times \text{rand}[0, 1]$ and then show the corresponding evolutions of residual evaluation function $J(k)$ in Figs. 9 and 10, respectively. For simulation purpose, the threshold is selected as $J_{\text{th}} = \sup_{f=0} \mathbb{E}\left\{\sum_{k=0}^{200} r^T(k)r(k)\right\}^{1/2}$, and accordingly, it can be obtained that $J_{\text{th}} = 1.2643$ in Fig. 9 after 200 Monte Carlo simulations with no faults. From Fig. 9, it can be seen that $1.1036 = J(111) < J_{\text{th}} < J(112) = 1.3657$, which means that the fault can be detected in 12 time steps after its occurrence. Similarly, we can conclude from Fig. 10 that the fault can be detected in 21 time steps after its occurrence. From simulation results, it can be clearly observed that, the smaller $w(k)$ we have, the smaller the threshold we obtain and the faster the fault detection will take.

V. CONCLUSION

In this paper, we have addressed the robust fault detection problem for a class of uncertain discrete-time T–S fuzzy systems. The robust fault detection filter is designed by solving the Riccati equation. The sufficient condition for the existence of the filter is given in terms of algebraic Riccati equations. Two simulation examples are presented to demonstrate the effectiveness of the proposed approach.
systems comprising randomly occurred mixed time delays and successive packet dropouts. The mixed time delays involve both the multiple time-varying discrete delays and the infinite distributed delays. The successive packet dropouts are modeled by a stochastic variable satisfying the Bernoulli random binary distribution. A fuzzy fault detection filter has been designed such that the fault detection dynamics is exponentially stable while preserving a guaranteed performance. A practical simulation example has been used to demonstrate the effectiveness of the fault detection techniques presented in this paper.

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