Fault Detection for Fuzzy Systems with Multiplicative Noises under Periodic Communication Protocols

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***Abstract*—This paper is concerned with the fault detection problem for a class of networked fuzzy systems with multiplicative noises on both system states and measurement outputs. In view of the limited communication capacity, a periodical communication protocol (i.e. the Round-Robin protocol) is adopted to undertake the transmission task between the sensors and the fault detection filter, which leads to periodical delays in the overall system. A Takagi-Sugeno (T-S) fuzzy- model-based fault detection filter is constructed to produce the residual signal and an auxiliary error system is established to facilitate the stability analysis of the error dynamics. With the aid of Lyapunov stability theory, sufficient conditions are obtained that ensure the exponentially mean-square stability of the error dynamics with prescribed H_∞ performance constraint. The desired fault detection filter is designed by solving a convex optimization problem via the semi-definite programme method. A finite-time evaluation function and an adjustable threshold are introduced in order to detect the possible faults effectively. The effectiveness of the proposed fault detection scheme is validated by a numerical simulation example.**

***Index Terms*—Networked system, fuzzy model, multiplicative noises, Round-Robin protocol, periodical communication, fault detection, residual evaluation function, adjustable threshold.**

I. Introduction

In the past two decades, networked control systems (NCSs) have become more and more popular in industrial applications due to their distinct advantages such as flexible structure, far transfer distance, decentralization function, and simple installation. Accordingly, a rich body of literature has been available on various network-induced phenomena including packet dropouts, communication delays, signal quantizations and network congestions, see e.g. [2], [7], [15], [17], [21], [27], [36], [40] and the references therein. A particular cause of network-induced side effect of almost all NCSs is the limited network bandwidth which, to a great extent, prevents the system components (e.g. sensors, actuators and receivers) from hurdle-free communications. Accordingly, significant research attention has been devoted to the investigation on NCSs under limited communication capacity, see e.g. [5], [6], [11], [30], [38]. Among others, the so-called Round-Robin protocol has been widely recognized as an effective means in tackling the communication constraints. The main idea of the Round-Robin scheduling is to assign the transmission opportunity to the communication nodes in a periodic order, thereby dramatically reducing the communication costs. Very recently, the Round-Robin protocol in the network environment has generated considerable research interest from both academy and industry. For instance, a Round-Robin interconnection rule has been designed for a class of distributed observer networks in [35]. In [18], [43], based upon the periodic scheduling mechanism, analysis and synthesis issues of NCSs with Round-Robin protocol have been thoroughly researched by using the time-delay system approach.

As is well known, system faults may degrade the system performance and even cause instability/oscillations leading to cascaded disasters, and fault detection (FD) has proven to be an important area of research with successful applications in a variety of engineering practice [41], [45], [46]. Generally speaking, the first step of model-based FD to design a FD filter to produce a valuable residual signal, and then the second step is to formulate a residual evaluation function to compare with a prescribed threshold. In the past decades, a multitude of FD techniques have been developed and a great number of FD results have been available, see e.g. [20], [24], [25], [44]. In the context of networked systems (e.g. distributed control systems, unattended monitoring systems, remote medical platforms), the FD problem becomes even more critical since the faults might occur more frequently in NCS and seriously jeopardize the system reliability of systems [13]. In [39], the fault detection filtering has been investigated for complex systems with nonhomogeneous Markovian parameters, where the malicious packet losses over communication networks have been considered. On the other hand, an appropriate use of the threshold plays a key role in determining the detection rate and the false alarm rate. Traditionally, the threshold has been chosen as the supremum of the evaluation function in the fault-free case. Such threshold is typically a constant that does not allow adjustment to adapt the changing environment. Recently, the design problem of adaptive thresholds has started to draw some initial research attention. For example, in [1], [20], an adaptive threshold has been studied for the health monitoring of offshore wind-farms and nonlinear systems, respectively.

On another research frontier, for decades, the control and filtering problems for fuzzy systems have been attracting an

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ever-increasing research interest. The fuzzy-logic theory has demonstrated its great superiority in the research of nonlinear systems since Zadeh first proposed the fuzzy set theory. Among various fuzzy approximation models, the Takagi-Sugeno (T-S) fuzzy model is one of the most widely used approaches for studying analysis and synthesis problems of affine nonlinear systems [4]. Under the framework of T-S fuzzy model, the nonlinear plant can be approximated by a set of linear model through local linearization method, where these linear subsystems are smoothly connected by some nonlinear fuzzy membership functions. After tens of years' advances, a large amount of literature have appeared on the analysis/synthesis problems for various nonlinear systems by using the T-S fuzzy model, see e.g. [10], [16], [26], [28], [29], [34], [40] for some representative works. Due to its advantages such as simple installation and maintenance, reduced weight and power requirements, high reliability, etc., the fuzzy networked nonlinear systems have gained many research attention in recent years, see e.g. [10], [27]. When it comes to the fault detection problem, the fuzzy-logic-based approach gives rise to the adaptive nature of the fault detection process [31], [32]. The design of the T-S fuzzy model based fault detector can be easily retrieved in the literature, see e.g. [8], [19], [48].

Summarizing the discussions made so far, it can be concluded that 1) the design of NCSs has become a research focus and the periodical communication protocol (i.e. the Round-Robin protocol) has made it possible to reduce communication burden when the network resource is a concern; 2) the FD problem for NCSs has been well studied and the adaptive threshold selection issue remains open especially in a networked environment; and 3) the fuzzy-model-based analysis approach has proven to be a popular tool in handling nonlinear systems. To this end, a seemingly natural research problem is whether/how we can deal with the FD problem for NCSs under periodical communication protocol. Obviously, such a problem is of both the theoretical importance and practical significance. A thorough literature review reveals that, so far, there have been very few research results on the fault detection problem for networked systems under communication protocols, not to mention the case where the T-S fuzzy model is used as an approximation of certain nonlinear systems as well as the case where the underlying system is subject to multiplicative noises that occur frequently in practice [22]. It is, therefore, the main purpose of this paper to shorten such a gap.

In this paper, we are interested in the fault detection problem for a class of fuzzy networked systems where the desired fault detection filter is implemented under a kind of periodical communication protocol. The contributions of this paper are highlighted as follows: *1) a periodical Round-Robin protocol is introduced to tackle the communication constraints, under which the sensor measurement at the receiving end is presented; 2) the multiplicative noises on both the system states and the measurement outputs are taken into account to describe the interference from a non-ideal environment; 3) an H_∞ fault detection filter is constructed on the basis of the T-S fuzzy model such that the detection error dynamics is exponentially stable in the mean square sense; 4) the difficulty (mainly periodic time-delays) resulting from the combinational use of Round-Robin protocol and zero-order-holders (ZOHs) is effectively overcome by developing the block matrix technique; and 5) an adjustable threshold is suggested that provides more flexibility for the detector design as compared to the traditional case of constant threshold.*

Notation. In this paper, $\mathbb{R}^n$, $\mathbb{R}^{n\times m}$ and $\mathbb{Z}$ $(\mathbb{Z}^+, \mathbb{Z}^-)$ denote, respectively, the n-dimensional Euclidean space, the set of all $n\times m$ real matrices and the set of all integers (nonnegative integers, negative integers). $\|\cdot\|$ refers to the Euclidean norm in $\mathbb{R}^n$. I_n represents the identity matrix of dimension $n\times n$, and I is the identity matrix of compatible dimension. The notation $X\geq Y$ (respectively, $X>Y$), where X and Y are symmetric matrices, means that $X-Y$ is positive semi-definite (respectively, positive definite). For a matrix M, M^T and M^{-1} represent its transpose and inverse, respectively. The shorthand $\mathrm{diag}\{M_1,\ M_2,\dots,\ M_n\}$ denotes a block diagonal matrix with diagonal blocks being the matrices $M_1,\ M_2,\ \dots,\ M_n$. In symmetric block matrices, the symbol '$*$' is used as an ellipsis for terms induced by symmetry. $\lambda_{\max}(\cdot)$ is the maximum eigenvalue. $\mathrm{mod}(a,b)$ represents the unique nonnegative remainder on division of the integer a by the positive integer b. For integers a, b with $a\leq b$, $\mathbb{N}[a,\ b]$ denotes the discrete interval given by $\mathbb{N}[a,\ b]=[a,\ a+1,\cdots,b-1,\ b]$. Matrices, if they are not explicitly stated, are assumed to have compatible dimensions.

II. Problem Formulation

Consider the following discrete networked fuzzy systems with multiplicative noises:

Plant Rule i:

IF $\theta_1(k)$ is $\mathcal{F}_{i1}$, $\cdots$, $\theta_j(k)$ is $\mathcal{F}_{ij}$, $\cdots$ and $\theta_p(k)$ is $\mathcal{F}_{ip}$, **THEN**

$$\begin{cases} x(k+1) =\big(A_i+\zeta(k)D_i\big)x(k)+B_iu(k) \\ \qquad\qquad +E_i\omega(k)+F_if(k), \\ \quad y(k) =\big(C_i+\xi(k)G_i\big)x(k)+H_i\omega(k), \quad i\in\mathbb{U} \\ \quad x(k) =\phi(k), \quad \forall\, k\in\mathbb{Z}^- \end{cases} \tag{1}$$

where $k\in\mathbb{Z}^+$, $\mathbb{U}=\{1,\ 2,\cdots,r\}$ with r being the number of IF-THEN rules; $\theta(k)=[\theta_1(k),\theta_2(k)\cdots,\theta_p(k)]$ is the premise variable vector; $\mathcal{F}_{ij}$ $(j=1,2,\cdots,p)$ is the fuzzy set; $x(k)\in\mathbb{R}^n$ is the state vector; $u(k)\in\mathbb{R}^{n_u}$ is the control input vector; $y(k)=[y_1(k),y_2(k),\cdots,y_l(k),\cdots,y_s(k)]^T$ is the measured output vector with $y_l(k)\in\mathbb{R}$ being the lth sensor measurement $(l\in\mathbb{S}=\{1,\ 2,\cdots,s\})$; $\phi(k)$ is the initial state; $\zeta(k)\in\mathbb{R}$ and $\xi(k)\in\mathbb{R}$ are the zero-mean multiplicative noises satisfying $\mathbb{E}\{\zeta^2(k)\}=\sigma_\zeta^2$ and $\mathbb{E}\{\xi^2(k)\}=\sigma_\xi^2$, respectively; $\omega(k)\in\mathbb{R}^{n_\omega}$ is the unknown disturbance input which belongs to $l_2[0,N)$ (the space of square summable sequences with the norm of $\|\omega\|_{[0,N]}^2=\mathbb{E}\{\sum_{k=0}^N\|\omega(k)\|^2\}$ [33]); $f(k)\in\mathbb{R}^{n_f}$ is the possible fault signal to be detected; and A_i, D_i, B_i, E_i, F_i, C_i, G_i and H_i are constant matrices with appropriate dimensions.

Remark 1. *As is well known, the system model (1) is actually the local linear models that can be used to approximate a nonlinear plant at any precision through the nonlinear fuzzy membership functions. On the other hand, the multiplicative* *noises not only enter the system states but also appear in the measured outputs. Therefore, the concerned model is closed to engineering practice [42]. In this paper, for simplicity, the second-order statistics of the multiplicative noises is assumed to be known, and $\zeta(k)$ and $\xi(k)$ are uncorrelated with each other.*

In this paper, we assume that the sensors are distributed in different locations from the target networked fuzzy system, and the communication is conducted through shared networks. In order to mitigate the negative influence from the limited communication capacity of the communication network, the Round-Robin protocol is utilized as the communication protocol to schedule the sensors. The so-called Round-Robin protocol can be described by the following rules:

$i)$ all sensors are pre-arranged in a round sequence as the communication nodes;
$ii)$ all communication nodes are orderly allowed to access the channel at a time instant k;
$iii)$ each communication node can only take one unit time of the index k for one communication link.

For illustration purpose, the channel access order of sensors under the Round-Robin protocol is shown in Fig. 1, in which the channel accesses of each sensor node are divided into different round. From the mechanism of Round-Robin scheduling, it can be known that the lth sensor measurement $y_l(k)$ can only be transmitted at the time instant $k = sj + l$ ($j \in \mathbb{Z}^+$). Therefore, a sensor's access to the channel is periodic. On the other hand, in order to maximize the utilization of the received measurements, a set of ZOHs are adopted to store the received sensor measurements, where the data will not be updated until the next renewed measurement arrives.

Denoting $\vec{y}_l(k)$ as the lth sensor measurement at the receiving end, it is verified that

$$\vec{y}_l(k) = \begin{cases} y_l(k - \aleph_k^l), & k - l \geq 0 \\ 0, & k - l < 0 \end{cases} \tag{2}$$

where $\aleph_k^l = \mathrm{mod}(k - l, s)$ is the time-delay induced by the adopted communication protocol and ZOHs. It is obvious that the delay $\aleph_k^l \in \Pi_0$ appears periodically, where $\Pi_0 = \{0,\ 1,\ ,2, \cdots, s-1\}$.

Remark 2. *The Round-Robin protocol serves as an effective method to alleviate the communication burden in network communications with a limited transmission rate. Because of its economic utilization of network bandwidth, the Round-Robin protocol has found wide applications in networked control systems. Moreover, as pointed out in [11], the periodic scheduling method plays an important role in distributed systems (e.g. the microactuator arrays) since the simultaneous communication with multiple subsystems can hardly be achieved. It should be noticed that the preserved measurements in the ZOHs can provide the fault detection filter with full sensor measurements, which are actually the measurement vector $\vec{y}(k)$. Unfortunately, the combinational use of the Round-Robin protocol and the ZOHs would inevitably introduce certain time-varying periodic delays to the received measurements, which will certainly increase the complexity of the design process. Such kind of periodic delays, if not properly handled, would degrade the performance of the fault detector to some extent [12].*

For generating the residual to detect the possible fault in the networked systems, we construct a fuzzy fault detection filter of the following type (which is also called the residual generating system):

Fault detection filter i:
IF θ_1 is $\mathcal{F}_{i1}, \cdots, \theta_j$ is $\mathcal{F}_{ij}, \cdots$ and θ_p is $\mathcal{F}_{ip}$,
THEN

$$\begin{cases} \hat{x}(k+1) = \hat{A}_i \hat{x}(k) + \hat{B}_i \vec{y}(k), \\ \hat{y}(k) = \hat{C}_i \hat{x}(k) + \hat{D}_i \vec{y}(k), \\ r(k) = \hat{y}(k) - f(k), \end{cases} \tag{3}$$

where $\hat{x}(k) \in \mathbb{R}^n$ is the state of the fault detection filter; $\hat{y}(k) \in \mathbb{R}^{n_f}$ is the output of the residual generating system; $r(k)$ is the so-called the residual signal; and $\hat{A}_i$, $\hat{B}_i$, $\hat{C}_i$ and $\hat{D}_i$ are the gain parameters of the concerned fault detection filter to be designed.

For brevity, in what follows, we denote $h_i = h_i(k)$ and

$$\begin{aligned} &\sum_{i_1, i_2, \cdots, i_s = 1}^{r} h_{i_1} h_{i_2} \cdots h_{i_s} \\ = \ &\sum_{i_1=1}^{r} h_{i_1} \sum_{i_2=1}^{r} h_{i_2} \cdots \sum_{i_s=1}^{r} h_{i_s} \quad \text{for } s \in \mathbb{Z}^+. \end{aligned}$$

Define the normalized membership function (also called the fuzzy basis function) as

$$h_i(k) = \frac{\Psi_i(k)}{\sum_{j=1}^{r} \Psi_j(k)}, \tag{4}$$

where $\Psi_i(k) = \prod_{j=1}^{p} \mathfrak{F}_{ij}(\theta_j(k))$ and $\mathfrak{F}_{ij}(\theta_j(k)) > 0$ is the grade of membership of $\theta_j(k)$ in $\mathcal{F}_{ij}$. Apparently, we have

$$0 \leq h_i(k) \leq 1, \quad \sum_{i=1}^{r} h_i(k) = 1, \quad \forall\, k \in \mathbb{Z}^+.$$

Consequently, the defuzzified output of the networked T-S fuzzy model (1) can be presented as

$$\begin{cases} x(k+1) = \sum_{i=1}^{r} h_i(k) \big[\big(A_i + \zeta(k) D_i \big) x(k) + B_i u(k) \\ \qquad\qquad + E_i \omega(k) + F_i f(k) \big], \qquad\qquad i \in \mathbb{U}. \\ y(k) = \sum_{i=1}^{r} h_i(k) \big[\big(C_i + \xi(k) G_i \big) x(k) + H_i \omega(k) \big], \end{cases} \tag{5}$$

By denoting $\hat{B}_i = [\hat{B}_{i\bullet 1} \quad \hat{B}_{i\bullet 2} \cdots \hat{B}_{i\bullet s}]$, $\hat{D}_i = [\hat{D}_{i\bullet 1} \ \ \hat{D}_{i\bullet 2} \cdots \hat{D}_{i\bullet s}]$,

$$C_i = \begin{bmatrix} C_{i\circ 1} \\ C_{i\circ 2} \\ \cdots \\ C_{i\circ s} \end{bmatrix}, \quad G_i = \begin{bmatrix} G_{i\circ 1} \\ G_{i\circ 2} \\ \cdots \\ G_{i\circ s} \end{bmatrix}, \quad H_i = \begin{bmatrix} H_{i\circ 1} \\ H_{i\circ 2} \\ \cdots \\ H_{i\circ s} \end{bmatrix}, \tag{6}$$

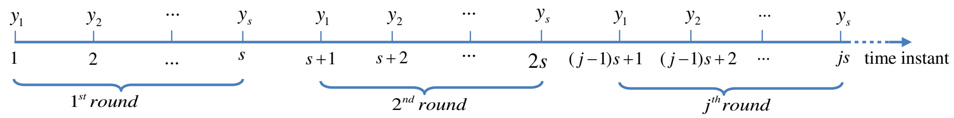

Fig. 1: Access order of sensors under Round-Robin protocol

the fault detection filter (3) can be described by

$$\begin{cases} \hat{x}(k+1) = \frac{1}{s}\sum_{i,j=1}^{r} h_i h_j \sum_{l=1}^{s} \big[\hat{A}_i \hat{x}(k) \\ \quad + s\big(\hat{B}_{i.l} C_{j\circ l} x(k-\aleph_k^l) \\ \quad + \hat{B}_{i.l} G_{j\circ l} \xi(k-\aleph_k^l) x(k-\aleph_k^l) \\ \quad + \hat{B}_{i.l} H_{j\circ l} \omega(k-\aleph_k^l)\big)\big], \\ \hat{y}(k) = \frac{1}{s}\sum_{i,j=1}^{r} h_i h_j \sum_{l=1}^{s} \big[\hat{C}_i \hat{x}(k) \\ \quad + s\big(\hat{D}_{i.l} C_{j\circ l} x(k-\aleph_k^l) \\ \quad + \hat{D}_{i.l} G_{j\circ l} \xi(k-\aleph_k^l) x(k-\aleph_k^l) \\ \quad + \hat{D}_{i.l} H_{j\circ l} \omega(k-\aleph_k^l)\big)\big]. \end{cases} \tag{7}$$

Denoting $\tilde{x}(k) = \hat{x}^T(k) - x^T(k)$, $\theta(k) = \big[x^T(k) \;\; \tilde{x}(k)\big]^T$ and $\nu^T(k) = \big[\omega^T(k) \;\; f^T(k) \;\; u^T(k)\big]$, we immediately obtain the following augmented error dynamics of the fault detection filter:

$$\begin{cases} \theta(k+1) = \frac{1}{s}\sum_{i,j,t=1}^{r} h_i h_j h_t \sum_{l=1}^{s} \big[\bar{A}_{ijt}\theta(k) \\ \quad + \zeta(k)\bar{B}_{jt}\theta(k) + \bar{C}_{ijl}\theta(k-\aleph_k^l) \\ \quad + \xi(k-\aleph_k^l)\bar{D}_{ijl}\theta(k-\aleph_k^l) \\ \quad + \bar{E}_{jt}\nu(k) + \bar{F}_{ijl}\nu(k-\aleph_k^l)\big], \\ r(k) = \frac{1}{s}\sum_{i,j,t=1}^{r} h_i h_j h_t \sum_{l=1}^{s} \big[\bar{G}_i\theta(k) \\ \quad + \bar{H}_{ijl}\theta(k-\aleph_k^l) \\ \quad + \xi(k-\aleph_k^l)\bar{J}_{ijl}\theta(k-\aleph_k^l) \\ \quad + K\nu(k) + \bar{L}_{ijl}\nu(k-\aleph_k^l)\big], \end{cases} \tag{8}$$

where $K = \begin{bmatrix} 0 & -I_{n_f} \end{bmatrix}$,

$$\bar{A}_{ijt} = \begin{bmatrix} A_t & 0 \\ \hat{A}_i - A_j & \hat{A}_i \end{bmatrix}, \quad \bar{C}_{ijl} = \begin{bmatrix} 0 & 0 \\ s\hat{B}_{i.l}C_{j\circ l} & 0 \end{bmatrix},$$
$$\bar{B}_{jt} = \begin{bmatrix} D_t & 0 \\ -D_j & 0 \end{bmatrix}, \quad \bar{E}_{jt} = \begin{bmatrix} E_t & F_t & B_t \\ -E_j & -F_j & -B_j \end{bmatrix},$$
$$\bar{D}_{ijl} = \begin{bmatrix} 0 & 0 \\ s\hat{B}_{i.l}G_{j\circ l} & 0 \end{bmatrix}, \quad \bar{F}_{ijl} = \begin{bmatrix} 0 & 0 \\ s\hat{B}_{i.l}H_{j\circ l} & 0 \end{bmatrix},$$
$$\bar{G}_i = \begin{bmatrix} \hat{C}_i & \hat{C}_i \end{bmatrix}, \quad \bar{H}_{ijl} = \begin{bmatrix} s\hat{D}_{i.l}C_{j\circ l} & 0 \end{bmatrix},$$
$$\bar{J}_{ijl} \begin{bmatrix} s\hat{D}_{i.l}G_{j\circ l} & 0 \end{bmatrix}, \quad \bar{L}_{ijl} = \begin{bmatrix} s\hat{D}_{i.l}H_{j\circ l} & 0 \end{bmatrix}.$$

Definition 1. *The augmented error dynamics (8) with* $\nu(k) \equiv 0$ *is said to be exponentially mean-square stable if there exist two constants* $\alpha > 0$ *and* $\epsilon \in (0,1)$ *such that*

$$\mathbb{E}\left\{\|\theta(k)\|^2\right\} \le \alpha\epsilon^k \sup_{i\in\Pi_0} \mathbb{E}\left\{\|\theta(i)\|^2\right\}, \quad k \in \mathbb{Z}^+.$$

Definition 2. *Under the zero initial condition, if the following disturbance attenuation constraint*

$$\min \gamma \quad s.t. \sum_{k=0}^{\infty} \mathbb{E}\left\{\|r(k)\|^2\right\} \le \gamma^2 \sum_{k=0}^{\infty} \mathbb{E}\left\{\|\upsilon(k)\|^2\right\} \tag{9}$$

is met for all nonzero sequences $\{\upsilon(\cdot)\}$, *where* $\gamma > 0$ *and* $\upsilon(k) = [\nu^T(k) \;\; \nu^T(k-\aleph_k^1) \cdots \nu^T(k-\aleph_k^l) \cdots \nu^T(k-\aleph_k^s)]^T$, *then the fuzzy residual generating system (3) is regarded as an* H_∞ *fault detection filter.*

In this paper, our main purpose is to obtain an H_∞ fuzzy fault detection filter in the form of (3) such that the augmented error dynamics (8) is *exponentially mean-square stable*. Afterwards, based on the residual signal generated by the fuzzy fault detection filter (3), a finite-time residual evaluation function $J(k)$ is established as follows:

$$J(k) = \mathbb{E}\left\{\left(\sum_{\iota=0}^{\mathcal{L}} \|r(k-\iota)\|\right)^{\frac{1}{2}}\right\}, \tag{10}$$

where $\mathcal{L} \in \mathbb{Z}^+$ is the length of the evaluating time horizon. In order to determine the time to alarm, a trigger point (i.e. the threshold J_{th}) needs to be determined. Among various forms of thresholds in specific implementation, a common choice for the threshold is the supremum of the evaluation function in the fault-free case [14], namely,

$$\bar{J}_{th} = \sup_{k\in\mathbb{Z}^+, \xi(k)\neq 0, \zeta(k)\neq 0, \omega(k)\in l_2, u(k)\neq 0, f(k)=0} \mathbb{E}\{J(k)\}. \tag{11}$$

However, it is well known that the above threshold inevitably results in a fixed trigger point, and thus cannot be dynamically adjusted. To solve this problem, we adopt a dynamic threshold as follows:

$$J_{th} = J_{th,\omega} + J_{th,u}, \tag{12}$$

where

$$J_{th,\omega} = \sup_{k\in\mathbb{Z}^+, \xi(k)\neq 0, \zeta(k)\neq 0, \omega(k)\in l_2, u(k)=0, f(k)=0} \mathbb{E}\{J(k)\},$$
$$J_{th,u} = \sup_{k\in\mathbb{Z}^+, \xi(k)\neq 0, \zeta(k)\neq 0, \omega(k)=0, u(k)\neq 0, f(k)=0} \mathbb{E}\{J(k)\}.$$

As pointed out in [47], the constant $J_{th,\omega}$ can be determined off-line, but $J_{th,u}$ can be adjusted on-line by dynamically changing the control input $u(k)$ [47]. Since the residual evaluation function $J(k)$ is influenced by the fault in the target system, the occurred fault can be detected if the value of the finite-time residual evaluation function exceeds the obtained threshold. More specifically, the triggering mechanism of alarm can be described by the following rule:

$$\begin{aligned} J(k) > J_{th} &\Longrightarrow \text{Alarm : fault} \\ J(k) \le J_{th} &\Longrightarrow \text{No alarm: fault free.} \end{aligned} \tag{13}$$

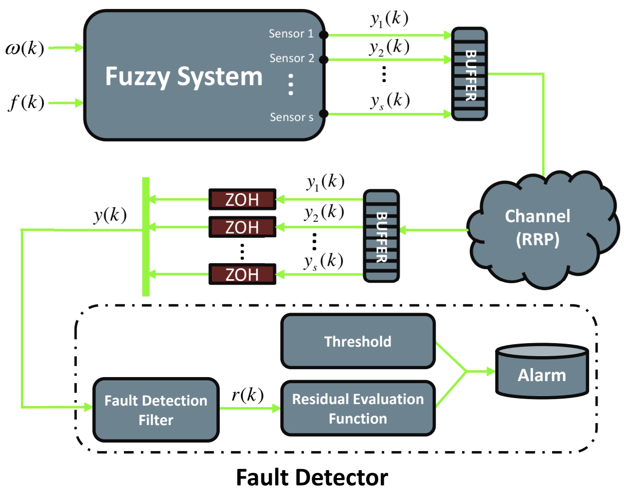

Fig. 2: Fuzzy fault detection system under Round-Robin protocol

For a better illustration, the flowchart of the fault detection procedure under the Round-Robin protocol is shown in Fig. 2.

III. Main Results

The following lemmas will be used in the proofs of our main results.

Lemma 1. *(Schur Complement) [3] Let the constant matrices Σ_1, Σ_2, Σ_3 be given where $\Sigma_1=\Sigma_1^T$ and $0<\Sigma_2=\Sigma_2^T$. Then, $\Sigma_1-\Sigma_3^T\Sigma_2^{-1}\Sigma_3\geq 0$ if and only if*

$$\begin{bmatrix}\Sigma_1 & \Sigma_3^T\\ \Sigma_3 & \Sigma_2\end{bmatrix}\geq 0 \quad\text{or}\quad \begin{bmatrix}\Sigma_2 & \Sigma_3\\ \Sigma_3^T & \Sigma_1\end{bmatrix}\geq 0.$$

Lemma 2. *Let $R\in\mathbb{R}^{2n\times 2n}$ be a positive definite matrix. For any real vectors $X_{ijtl}\in\mathbb{R}^{2n}$ and $X_{abcd}\in\mathbb{R}^{2n}$ with $i,j,t,a,b,c\in\mathbb{U}$ and $l,d\in\mathbb{S}$, we have*

$$\begin{aligned}&\frac{1}{s}\sum_{i,j,t,a,b,c=1}^{r}h_ih_jh_th_ah_bh_c\sum_{l=1}^{s}\sum_{d=1}^{s}X_{ijtl}^TRX_{abcd}\\ \leq&\sum_{i,j,t=1}^{r}h_ih_jh_t\sum_{l=1}^{s}X_{ijtl}^TRX_{ijtl},\end{aligned}\tag{14}$$

where $h_z\geq 0$ and $\sum_{z=1}^{r}h_z=1$ with $z\in\mathbb{U}$.

Proof: Similar to the proof of Lemma 2 in [9], let us recall the well-known inequality

$$2X^TRY\leq X^TRX+Y^TRY,$$

where X and Y are any vectors belonging to $\mathbb{R}^{2n}$. Then, it follows that one easily has

$$\begin{aligned}&\frac{2}{s}\sum_{i,j,t,a,b,c=1}^{r}h_ih_jh_th_ah_bh_c\sum_{l=1}^{s}\sum_{d=1}^{s}X_{ijtl}^TRX_{abcd}\\ \leq&\frac{1}{s}\sum_{i,j,t,a,b,c=1}^{r}h_ih_jh_th_ah_bh_c\sum_{l=1}^{s}\sum_{d=1}^{s}\Big(X_{ijtl}^TRX_{ijtl}\\ &+X_{abcd}^TRX_{abcd}\Big)\\ =&2\sum_{i,j,t=1}^{r}h_ih_jh_t\sum_{l=1}^{s}X_{ijtl}^TRX_{ijtl},\end{aligned}$$

which completes the proof. ■

For the fault detection problem, it is always a prerequisite to generate the residual signal in order to establish the residual evaluation function latter. In what follows, we shall concentrate upon the analysis and synthesis of the proposed fuzzy fault detection filter, where the exponentially mean-square stability of the augmented error dynamics and the H_∞ disturbance attenuation performance will be simultaneously addressed.

A. Stability and H_∞ performance analysis

Theorem 1. *Let the parameters (i.e., $\hat{A}_i$, $\hat{B}_i$, $\hat{C}_i$ and $\hat{D}_i$) of the fault detection filter be given. The error dynamics (8) is exponentially mean-square stable and the residual-generating system (3) is an H_∞ fault detection filter under the Round-Robin scheduling if there exist two positive definite matrices P and Q such that the following semi-definite problem is feasible*

$$\min\gamma\quad s.t.\ \bar{\Omega}^{ijtl}<0,\quad i,j,t\in\mathbb{U}\ \text{and}\ l\in\mathbb{S}\tag{15}$$

where $\bar{\Omega}_3^{ijtl}=\mathrm{diag}\{-Q^{-1},\,-I_{n_f},\,-Q^{-1},\,-I_{n_f}\}$,

$$\begin{aligned}\bar{\Omega}^{ijtl}&=\begin{bmatrix}\bar{\Omega}_1^{ijtl} & *\\ \bar{\Omega}_2^{ijtl} & \bar{\Omega}_3^{ijtl}\end{bmatrix},\quad \Lambda_1=Q-sP-\sigma_\zeta^2\bar{B}_{jt}^TQ\bar{B}_{jt},\\ \bar{\Omega}_1^{ijtl}&=\mathrm{diag}\{-\Lambda_1,\,-sP,\,-\gamma^2I_{(n_\omega+n_f)},\,-s\gamma^2I_{(n_\omega+n_f)}\},\\ \bar{\Omega}_2^{ijtl}&=\begin{bmatrix}0 & \sigma_\xi\bar{D}_{ijl} & 0 & 0\\ 0 & \sigma_\xi\bar{J}_{ijl} & 0 & 0\\ \bar{A}_{ijt} & \bar{C}_{ijl} & \bar{E}_{jt} & \bar{F}_{ijl}\\ \bar{G}_i & \bar{H}_{ijl} & K & \bar{L}_{ijl}\end{bmatrix}.\end{aligned}$$

Proof: Define $\Psi_t(k)=\{\theta(k),\ \theta(k-1),\cdots,\theta(k-t)\}$ and $\hbar(k)=\bigcup_{t=1}^{\infty}\Psi_t(k)$. Choose a Lyapunov-Krasovskii function candidate as follows

$$V(k)=\sum_{i=1}^{2}V_i(k),\tag{16}$$

where

$$\begin{aligned}V_1(k)&=\theta^T(k)Q\theta(k),\\ V_2(k)&=\sum_{l=1}^{s}\sum_{\tau(k)=-\aleph_k^l}^{-1}\theta^T(k+\tau(k))P\theta(k+\tau(k)).\end{aligned}$$

Letting $\nu(k)=0$, we compute the difference of $V(k)$ along the trajectory of the error dynamics (8) as follows:

$$\mathbb{E}\{V(k+1)-V(k)|\hbar(k)\}$$

$$
\begin{aligned}
= & \frac{1}{s^2}\sum_{i,j,t,a,b,c=1}^{r} h_ih_jh_th_ah_bh_c\sum_{l=1}^{s}\sum_{d=1}^{s} \\
& \times\mathbb{E}\Big\{\big[\bar{A}_{ijt}\theta(k)+\zeta(k)\bar{B}_{jt}\theta(k)+\bar{C}_{ijl}\theta(k-\aleph_k^l) \\
& +\xi(k-\aleph_k^l)\bar{D}_{ijl}\theta(k-\aleph_k^l)\big]^TQ \\
& \times\big[\bar{A}_{ab}\theta(k)+\zeta(k)\bar{B}_b\theta(k)+\bar{C}_{abd}\theta(k-\aleph_k^c) \\
& +\xi(k-\aleph_k^c)\bar{D}_{abd}\theta(k-\aleph_k^c)\big]-\theta^T(k)Q\theta(k)\Big\} \\
& +\sum_{l=1}^{s}\mathbb{E}\Big\{\theta^T(k)P\theta(k)-\theta^T(k-\aleph_k^l)P\theta(k-\aleph_k^l)\Big\} \\
= & \frac{1}{s^2}\sum_{i,j,t,a,b,c=1}^{r} h_ih_jh_th_ah_bh_c\sum_{l=1}^{s}\sum_{d=1}^{s} \\
& \times\mathbb{E}\Big\{\big[\bar{A}_{ijt}\theta(k)+\zeta(k)\bar{B}_{jt}\theta(k)+\bar{C}_{ijl}\theta(k-\aleph_k^l) \\
& +\xi(k-\aleph_k^l)\bar{D}_{ijl}\theta(k-\aleph_k^l)\big]^TQ\big[\bar{A}_{ab}\theta(k) \\
& +\zeta(k)\bar{B}_b\theta(k)+\bar{C}_{abd}\theta(k-\aleph_k^c) \\
& +\xi(k-\aleph_k^c)\bar{D}_{abd}\theta(k-\aleph_k^c)\big]-\theta^T(k)(Q-sP)\theta(k) \\
& -s\theta^T(k-\aleph_k^l)P\theta(k-\aleph_k^l)\Big\}. \qquad (17)
\end{aligned}
$$

It follows from Lemma 2 that

$$
\begin{aligned}
& \mathbb{E}\big\{V(k+1)-V(k)\big|\hbar(k)\big\} \\
\le & \frac{1}{s}\sum_{i,j,t=1}^{r}h_ih_jh_t\sum_{l=1}^{s}\mathbb{E}\Big\{\big[\bar{A}_{ijt}\theta(k)+\zeta(k)\bar{B}_{jt}\theta(k) \\
& +\bar{C}_{ijl}\theta(k-\aleph_k^l)+\xi(k-\aleph_k^l)\bar{D}_{ijl}\theta(k-\aleph_k^l)\big]^TQ \\
& \times\big[\bar{A}_{ijt}\theta(k)+\zeta(k)\bar{B}_{jt}\theta(k)+\bar{C}_{ijl}\theta(k-\aleph_k^l) \\
& +\xi(k-\aleph_k^l)\bar{D}_{ijl}\theta(k-\aleph_k^l)\big]-\theta^T(k)(Q-sP)\theta(k) \\
& -s\theta^T(k-\aleph_k^l)P\theta(k-\aleph_k^l)\Big\}. \qquad (18)
\end{aligned}
$$

By noting $\mathbb{E}\{\zeta^2(k)\}=\sigma_\zeta^2$ and $\mathbb{E}\{\xi^2(k)\}=\sigma_\xi^2$, we obtain

$$
\begin{aligned}
& \mathbb{E}\big\{V(k+1)-V(k)\big|\hbar(k)\big\} \\
\le & \frac{1}{s}\sum_{i,j,t=1}^{r}h_ih_jh_t\sum_{l=1}^{s}\mathbb{E}\Big\{\big[\bar{A}_{ijt}\theta(k)+\bar{C}_{ijl}\theta(k-\aleph_k^l)\big]^T \\
& \times Q\big[\bar{A}_{ijt}\theta(k)+\bar{C}_{ijl}\theta(k-\aleph_k^l)\big] \\
& -\theta^T(k)(Q-sP-\sigma_\zeta^2\bar{B}_{jt}^TQ\bar{B}_{jt})\theta(k) \\
& -s\theta^T(k-\aleph_k^l)P\theta(k-\aleph_k^l) \\
& +\sigma_\xi^2\theta^T(k-\aleph_k^l)\bar{D}_{ijl}^TQ\bar{D}_{ijl}\theta^T(k-\aleph_k^l)\Big\} \\
\le & \frac{1}{s}\sum_{i,j,t=1}^{r}h_ih_jh_t\sum_{l=1}^{s}\mathbb{E}\big\{\tilde{\theta}^T(k)\widetilde{\Omega}_0^{ijtl}\tilde{\theta}(k)\big\}, \qquad (19)
\end{aligned}
$$

where $\tilde{\theta}(k)=\big[\theta^T(k)\quad \theta^T(k-\aleph_k^l)\big]^T$,

$$
\begin{aligned}
&\tilde{\Lambda}_1=-\bar{A}_{ijt}^TQ\bar{A}_{ijt}+Q-sP-\sigma_\zeta^2\bar{B}_{jt}^TQ\bar{B}_{jt}, \\
&\tilde{\Lambda}_2=sP-\sigma_\xi^2\bar{D}_{ijl}^TQ\bar{D}_{ijl}-\bar{C}_{ijl}^TQ\bar{C}_{ijl}, \\
&\widetilde{\Omega}_0^{ijtl}=\begin{bmatrix}-\tilde{\Lambda}_1 & * \\ \bar{C}_{ijl}^TQ\bar{C}_{ijl} & -\tilde{\Lambda}_2\end{bmatrix}.
\end{aligned}
$$

Denoting

$$
\bar{\Omega}_0^{ijtl}=\begin{bmatrix}-\Lambda_1 & * & * & * \\ 0 & -sP & * & * \\ 0 & \sigma_\xi\bar{D}_{ijl} & -Q^{-1} & * \\ \bar{A}_{ijt} & \bar{C}_{ijl} & 0 & -Q^{-1}\end{bmatrix}, \qquad (20)
$$

it can be found that $\bar{\Omega}_0^{ijtl}$ is a principal submatrix of $\bar{\Omega}^{ijtl}$. Subsequently, $\bar{\Omega}_0^{ijtl}<0$ can be inferred by $\bar{\Omega}^{ijtl}<0$ in (15) which, according to the Schur Complement (Lemma 1), further implies $\widetilde{\Omega}_0^{ijtl}<0$. Therefore, one has

$$
\begin{aligned}
& \mathbb{E}\big\{V(k+1)-V(k)\big|\hbar(k)\big\} \\
\le & \frac{1}{s}\sum_{i,j,t=1}^{r}h_ih_jh_t\sum_{l=1}^{s}\mathbb{E}\big\{\tilde{\theta}^T(k)\widetilde{\Omega}_0^{ijtl}\tilde{\theta}(k)\big\} \\
\le & \lambda_{\max}(\widetilde{\Omega}_0^{ijtl})\mathbb{E}\big\{\big\|\tilde{x}(k)\big\|^2\big\} \\
< & 0. \qquad (21)
\end{aligned}
$$

According to the definition of $V(k)$ in (16), we obtain

$$
\begin{aligned}
& \lambda_{\min}(Q)\mathbb{E}\big\{\big\|\tilde{x}(k)\big\|^2\big\}\le\mathbb{E}\big\{V(k)\big\} \\
\le & \lambda_{\max}(Q)\mathbb{E}\big\{\big\|\tilde{x}(k)\big\|^2\big\} \\
& +s\lambda_{\max}(P)\mathbb{E}\big\{\sum_{\tau=-s+1}^{-1}\big\|\tilde{x}(k+\tau)\big\|^2\big\}. \qquad (22)
\end{aligned}
$$

For any given scalar $\mu>1$ and a sufficiently large k, it follows from (21) and (22) that

$$
\begin{aligned}
& \mathbb{E}\big\{\mu^kV(k)\big\} \\
=&\mathbb{E}\Big\{V(0)+\sum_{i=0}^{k-1}\big(\mu^{i+1}(V(i+1)-V(i)) \\
& +\mu^i(\mu-1)V(i)\big)\Big\} \\
\le&\lambda_{\max}(Q)\mathbb{E}\big\{\big\|\tilde{x}(0)\big\|^2\big\}+s\lambda_{\max}(P)\mathbb{E}\big\{\sum_{\tau=-s+1}^{-1}\big\|\tilde{x}(\tau)\big\|^2\big\} \\
& +\big(\mu\lambda_{\max}(\widetilde{\Omega}_0^{ijtl})+(\mu-1)\lambda_{\max}(Q)\big)\sum_{i=0}^{k-1}\mu^i\mathbb{E}\big\{\big\|\tilde{x}(i)\big\|^2\big\} \\
& +(\mu-1)s\lambda_{\max}(P)\sum_{i=0}^{k-1}\sum_{j=-s+1}^{-1}\mu^i\mathbb{E}\big\{\big\|\tilde{x}(i+j)\big\|^2\big\} \\
\le&\lambda_{\max}(Q)\mathbb{E}\big\{\big\|\tilde{x}(0)\big\|^2\big\}+s\lambda_{\max}(P)\mathbb{E}\big\{\sum_{\tau=-s+1}^{-1}\big\|\tilde{x}(\tau)\big\|^2\big\} \\
& +\big(\mu\lambda_{\max}(\widetilde{\Omega}_0^{ijtl})+(\mu-1)\lambda_{\max}(Q)\big)\sum_{i=0}^{k-1}\mu^i\mathbb{E}\big\{\big\|\tilde{x}(i)\big\|^2\big\} \\
& +(\mu-1)s\lambda_{\max}(P)\Bigg((s-1)\mu^{s-1}\sum_{j=-s+1}^{-1}\mathbb{E}\big\{\big\|\tilde{x}(j)\big\|^2\big\} \\
& +\Bigg(\sum_{j=0}^{k-s}\sum_{t=1}^{s-1}+\sum_{j=k-s+1}^{k-1}\sum_{t=1}^{k-j}\Bigg)\mu^j\mu^t\mathbb{E}\big\{\big\|\tilde{x}(j)\big\|^2\big\}\Bigg) \\
\le&\lambda_{\max}(Q)\mathbb{E}\big\{\big\|\tilde{x}(0)\big\|^2\big\}+s\lambda_{\max}(P)\mathbb{E}\big\{\sum_{\tau=-s+1}^{-1}\big\|\tilde{x}(\tau)\big\|^2\big\}
\end{aligned}
$$

$$
\begin{aligned}
&+\left(\mu\lambda_{\max}(\widetilde{\Omega}_0^{ijtl})+(\mu-1)\lambda_{\max}(Q)\right)\sum_{i=0}^{k-1}\mu^i\mathbb{E}\{\|\tilde{x}(i)\|^2\}\\
&+(\mu-1)s\lambda_{\max}(P)\\
&\times\Bigg((s-1)^2\mu^{s-1}\sup_{j\in\mathbb{N}[-s+1,\,0]}\mathbb{E}\{\|\tilde{x}(j)\|^2\}\\
&+(s-1)\mu^{s-1}\sum_{j=0}^{k-1}\mu^j\mathbb{E}\{\|\tilde{x}(j)\|^2\}\Bigg)\\
\le& a_1(\mu)\sup_{j\in\mathbb{N}[-s+1,\,0]}\mathbb{E}\{\|\tilde{x}(j)\|^2\}\\
&+a_2(\mu)\sum_{j=0}^{k}\mu^j\mathbb{E}\{\|\tilde{x}(j)\|^2\},
\end{aligned}\tag{23}
$$

where

$$
\begin{aligned}
a_1(\mu) &= \lambda_{\max}(Q)+s\lambda_{\max}(P)(s-1)\\
&\quad+(\mu-1)s\lambda_{\max}(P)(s-1)^2\mu^{s-1},\\
a_2(\mu) &= \mu\lambda_{\max}(\widetilde{\Omega}_0^{ijtl})+(\mu-1)\lambda_{\max}(Q)\\
&\quad+(\mu-1)s\lambda_{\max}(P)(s-1)\mu^{s-1}.
\end{aligned}
$$

Moreover, it is not difficult to see that $a_1(1)>0$ and $a_2(1)<0$. Because $a_1(\mu)$ and $a_2(\mu)$ are continuous functions of μ, we can infer that there must exist a scalar $z>1$ such that

$$a_1(z)>0,\quad a_2(z)<0. \tag{24}$$

Subsequently, the following inequality is true

$$
\begin{aligned}
&\mathbb{E}\{\|\tilde{x}(k)\|^2\}\\
\le&\sum_{j=0}^{k}\mu^{j-k}\mathbb{E}\{\|\tilde{x}(j)\|^2\}\\
\le&\mu^{-k}\frac{a_1(z)}{-a_2(z)}\left(\sup_{j\in\mathbb{N}[-s+1,\,0]}\mathbb{E}\{\|\tilde{x}(j)\|^2\}-\mathbb{E}\{z^kV(k)\}\right)\\
\le&\frac{a_1(z)}{-a_2(z)}\mu^{-k}\sup_{j\in\mathbb{N}[-s+1,\,0]}\mathbb{E}\{\|\tilde{x}(j)\|^2\}.
\end{aligned}\tag{25}
$$

By Definition 1, the augmented error dynamics (8) is *exponentially stable* in the mean square sense, and the proof is completed.

Now, we will show the H_∞ disturbance attenuation performance (9) under the zero initial condition for all nonzero sequences $\{\nu(\cdot)\}$. It follows from the augmented error dynamics (8) that

$$
\begin{aligned}
&\mathbb{E}\{V(k+1)-V(k)+\|r(k)\|^2-\gamma^2\|\upsilon(k)\|^2|\hbar(k)\}\\
=&\frac{1}{s^2}\sum_{i,j,t,a,b,c=1}^{r}h_ih_jh_th_ah_bh_c\sum_{l=1}^{s}\sum_{d=1}^{s}\\
&\times\mathbb{E}\Big\{\big[\bar{A}_{ijt}\theta(k)+\zeta(k)\bar{B}_{jt}\theta(k)+\bar{C}_{ijl}\theta(k-\aleph_k^l)\\
&+\xi(k-\aleph_k^l)\bar{D}_{ijl}\theta(k-\aleph_k^l)+\bar{E}_{jt}\nu(k)+\bar{F}_{ijl}\nu(k-\aleph_k^l)\big]^T\\
&\times Q\big[\bar{A}_{ab}\theta(k)+\zeta(k)\bar{B}_b\theta(k)+\bar{C}_{abd}\theta(k-\aleph_k^l)\\
&+\xi(k-\aleph_k^c)\bar{D}_{abd}\theta(k-\aleph_k^l)+\bar{E}_b\nu(k)+\bar{F}_{abd}\nu(k-\aleph_k^c)\big]\\
&-\theta^T(k)(Q-sP)\theta(k)-s\theta^T(k-\aleph_k^l)P\theta(k-\aleph_k^l)\\
&+\big[\bar{G}_i\theta(k)+\bar{H}_{ijl}\theta(k-\aleph_k^l)+\xi(k-\aleph_k^l)\bar{J}_{ijl}\theta(k-\aleph_k^l)\\
&+K\nu(k)+\bar{L}_{ijl}\nu(k-\aleph_k^l)\big]^T\big[\bar{G}_a\theta(k)+\bar{H}_{abd}\theta(k-\aleph_k^c)\\
&+\xi(k-\aleph_k^c)\bar{J}_{abd}\theta(k-\aleph_k^c)+K\nu(k)+\bar{L}_{abd}\nu(k-\aleph_k^c)\big]\\
&-\gamma^2\nu^T(k)\nu(k)-s\gamma^2\nu^T(k-\aleph_k^l)\nu(k-\aleph_k^l)\Big\}\\
\le&\frac{1}{s}\sum_{i,j,t=1}^{r}h_ih_jh_t\sum_{l=1}^{s}\mathbb{E}\Big\{\big[\bar{A}_{ijt}\theta(k)+\bar{C}_{ijl}\theta(k-\aleph_k^l)\\
&+\bar{E}_{jt}\nu(k)+\bar{F}_{ijl}\nu(k-\aleph_k^l)\big]^TQ\big[\bar{A}_{ijt}\theta(k)+\bar{C}_{ijl}\theta(k-\aleph_k^l)\\
&+\bar{E}_{jt}\nu(k)+\bar{F}_{ijl}\nu(k-\aleph_k^l)\big]+\big[\bar{G}_i\theta(k)+\bar{H}_{ijl}\theta(k-\aleph_k^l)\\
&+K\nu(k)+\bar{L}_{ijl}\nu(k-\aleph_k^l)\big]^T\big[\bar{G}_i\theta(k)+\bar{H}_{ijl}\theta(k-\aleph_k^l)\\
&+K\nu(k)+\bar{L}_{ijl}\nu(k-\aleph_k^l)\big]-s\theta^T(k-\aleph_k^l)P\theta(k-\aleph_k^l)\\
&+\sigma_\xi^2\theta^T(k-\aleph_k^l)\bar{D}_{ijl}^TQ\bar{D}_{ijl}\theta(k-\aleph_k^l)\\
&+\sigma_\xi^2\theta^T(k-\aleph_k^l)\bar{J}_{ijl}^T\bar{J}_{ijl}\theta(k-\aleph_k^l)\\
&-\theta^T(k)(Q-sP-\sigma_\zeta^2\bar{B}_{jt}^TQ\bar{B}_{jt})\theta(k)\\
&-\gamma^2\nu^T(k)\nu(k)-s\gamma^2\nu^T(k-\aleph_k^l)\nu(k-\aleph_k^l)\Big\}.
\end{aligned}\tag{26}
$$

Taking advantage of the Schur Complement (Lemma 1) again, it can be seen from the matrix inequalities (15) that

$$
\begin{aligned}
&\mathbb{E}\{V(k+1)-V(k)+\|r(k)\|^2-\gamma^2\|\upsilon(k)\|^2|\hbar(k)\}\\
\le&\frac{1}{s}\sum_{i,j,t=1}^{r}h_ih_jh_t\sum_{l=1}^{s}\mathbb{E}\{\tilde{\theta}^T(k)\bar{\Omega}^{ijtl}\tilde{\theta}(k)\}\\
<&0,
\end{aligned}\tag{27}
$$

where $\tilde{\theta}(k)=\begin{bmatrix}\theta^T(k) & \theta^T(k-\aleph_k^l) & \nu(k) & \nu(k-\aleph_k^l)\end{bmatrix}^T$. By further taking the zero initial condition and $V(k)\ge 0$ into account, summing up both sides of the inequality (27) from 0 to ∞ yields

$$\sum_{k=0}^{\infty}\mathbb{E}\left\{\|r(k)\|^2\right\}\le\gamma^2\sum_{k=0}^{\infty}\mathbb{E}\left\{\|\upsilon(k)\|^2\right\}. \tag{28}$$

According to Definition 2, the residual-generating system (3) is an H_∞ fault detection filter, which completes the proof. ■

Up to now, the *exponentially mean-square stability* of the augmented error dynamics (8) and the H_∞ performance have been thoroughly discussed. Nevertheless, the nonlinear term Q^{-1} in $\bar{\Omega}^{ijtl}$ brings great difficulties to the semi-definite problem in Theorem 1. For this issue, we shall turn to a traceable algorithm for designing the desired fault detection filter by introducing a slack matrix variable in the next subsection.

B. Synthesis of fuzzy fault detection filter

Theorem 2. *For the given structure of the fault detection filter (3), assume that there exist invertible matrix* $S=\mathrm{diag}\{S_1,\ S_2\}$*, matrices* $\hat{\mathscr{A}}_i$*,* $\hat{\mathscr{B}}_{i\bullet l}$*,* $\hat{C}_i$*,* $\hat{D}_{i\bullet l}$*, and matrices* $P>0$ *and* $Q>0$ *such that the following semi-definite problem is feasible*

$$\min\gamma\quad s.t.\ \Omega^{ijtl}<0\quad i,j,t\in\mathbb{U}\ \text{and}\ l\in\mathbb{S} \tag{29}$$

where $\Lambda_5=-Q+S^T+S$*,*

$$\Omega^{ijtl}=\begin{bmatrix}\bar{\Omega}_1^{ijtl} & *\\ \Omega_2^{ijtl} & \Omega_3^{ijtl}\end{bmatrix},\quad \bar{\mathscr{E}}_{jt}=\begin{bmatrix}S_1E_t & S_1F_tS_1B\\ -S_2E_j & -S_2F_jS_2B\end{bmatrix},$$

$$\Omega_2^{ijtl}=\begin{bmatrix}0 & \sigma_\xi\bar{\mathscr{D}}_{ijl} & 0 & 0\\ 0 & \sigma_\xi\bar{J}_{ijl} & 0 & 0\\ \bar{\mathscr{A}}_{ijt} & \bar{\mathscr{C}}_{ijl} & \bar{\mathscr{E}}_{jt} & \bar{\mathscr{F}}_{ijl}\\ \bar{G}_i & \bar{H}_{ijl} & K & \bar{L}_{ijl}\end{bmatrix},$$
$$\Omega_3^{ijtl}=\mathrm{diag}\{-\Lambda_5,\ -I_{n_f},\ -\Lambda_5,\ -I_{n_f}\},$$
$$\bar{\mathscr{A}}_{ijt}=\begin{bmatrix}S_1A_t & 0\\ \hat{\mathscr{A}}_i-S_2A_j & \hat{\mathscr{A}}_i\end{bmatrix},\quad \bar{\mathscr{C}}_{ijl}=\begin{bmatrix}0 & 0\\ s\hat{\mathscr{B}}_{i.l}C_{j\circ l} & 0\end{bmatrix},$$
$$\bar{\mathscr{D}}_{ijl}=\begin{bmatrix}0 & 0\\ s\hat{\mathscr{B}}_{i.l}G_{j\circ l} & 0\end{bmatrix},\quad \bar{\mathscr{F}}_{ijl}=\begin{bmatrix}0 & 0\\ s\hat{\mathscr{B}}_{i.l}H_{j\circ l} & 0\end{bmatrix}.$$

Then, under the Round-Robin scheduling, the augmented error dynamics (8) is exponentially mean-square stable and the disturbance attenuation constraint (9) is also met. Moreover, the other gain parameters of the concerned H_∞ fault detection filter $\hat{A}_j$, $\hat{B}_i$, and $\hat{D}_i$ are characterized by

$$\begin{aligned}&\hat{B}_i=\left[S_2^{-1}\hat{\mathscr{B}}_{i.1}\ \ S_2^{-1}\hat{\mathscr{B}}_{i.2}\cdots S_2^{-1}\hat{\mathscr{B}}_{i.s}\right],\\ &\hat{A}_i=S_2^{-1}\hat{\mathscr{A}}_i,\quad \hat{D}_i=\left[\hat{D}_{i.1}\ \ \hat{D}_{i.2}\cdots\hat{D}_{i.s}\right].\end{aligned}\tag{30}$$

Proof: Noticing the relationship (30), pre- and post-multiplying both sides of $\Omega^{ijtl}<0$ with $\mathrm{diag}\{I_{2n},\ I_{2n},\ I_{n_f+n_\omega+n_u},\ I_{s(n_f+n_\omega+n_u)},\ S^{-1},\ I_{2n},\ S^{-1},\ I_{n_f}\}$ and its transpose yield

$$\begin{bmatrix}\bar{\Omega}_1^{ijtl} & *\\ \widetilde{\Omega}_2^{ijtl} & \widetilde{\Omega}_3^{ijtl}\end{bmatrix}<0,\tag{31}$$

where $Q_s=-S^{-1}QS^{-T}+S^{-1}+S^{-T}$, $\widetilde{\Omega}_3^{ijtl}=\mathrm{diag}\{-Q_s,\ -I_{n_f},\ -Q_s,\ -I_{n_f}\}$ and

$$\widetilde{\Omega}_2^{ijtl}=\begin{bmatrix}0 & \sigma_\xi\bar{D}_{ijl} & 0 & 0\\ 0 & \sigma_\xi\bar{J}_{ijl} & 0 & 0\\ \bar{A}_{ijt} & \bar{C}_{ijl} & \bar{E}_{jt} & \bar{F}_{ijl}\\ \bar{G}_i & \bar{H}_{ijl} & K & \bar{L}_{ijl}\end{bmatrix}.$$

On the other hand, one can infer from $Q>0$ that

$$\begin{aligned}Q^{-1}-Q_s &= Q^{-1}+S^{-1}QS^{-T}-S^{-T}-S^{-1}\\ &= [S^{-1}-Q^{-1}]QS^{-T}-[S^{-1}-Q^{-1}]\\ &= [S^{-T}-Q^{-1}]^TQ[S^{-T}-Q^{-1}]\\ &\geq 0,\end{aligned}\tag{32}$$

which means $\bar{\Omega}^{ijtl}<\Omega^{ijtl}<0$, and the proof is complete. ■

So far, the H_∞ fuzzy fault detection filter has been designed to generate the desired residual signal.

Remark 3. *Theorem 1 provides the sufficient conditions for the existence of the concerned fuzzy fault detection filter such that the exponentially mean-square stability of the error dynamics (8) and the optimal H_∞ disturbance attenuation performance are met simultaneously. It should be noticed that the effects of both the multiplicative noises and the periodic communication Round-Robin protocol are reflected in the main results, and the complexity induced by the Round-Robin protocol is effectively reduced by developing a so-called block matrix method. The derivation of the desired fault detection filter is addressed in Theorem 2, where the established conditions can be verified readily by using the numerically efficient LMI toolbox in Matlab software. The residual generated by the desired fault detection filter can be used as the evaluation function (10), and the threshold (12) can be determined accordingly. Thereafter, the possible fault in the networked fuzzy system can be detected according to the rule (13). On the other hand, it can be seen from (2) and (3) that the time-varying delay $\aleph_k^l$ is a key factor to influence the performance of the fault detection filter. Therefore, we know from $\aleph_k^l=\mathrm{mod}(k-l,s)$ that the dimension of the measured output vector $y(k)$ and the measurement vector $\vec{y}(k)$ can greatly affect fault detection result. As discussed previously, the designed adaptive threshold is superior to the traditional constant one since the current threshold can be adjusted by shifting the control input vector $u(k)$.*

IV. Illustrative Example

In this section, we present a numerical example to demonstrate the feasibility of the proposed algorithm. Consider a discrete-time networked fuzzy system (1) with three measurement sensors (i.e. $s=3$). Take the number of IF-THEN rules $r=2$ and the other parameters as follows:

$$A_1=\begin{bmatrix}-0.4223 & -0.1022\\ -0.0235 & -0.1002\end{bmatrix},\ D_2=\begin{bmatrix}0.3841 & 0.2671\\ 0.0323 & 0.0154\end{bmatrix},$$
$$E_1=\begin{bmatrix}-0.4102\\ -0.3205\end{bmatrix},\ F_1=\begin{bmatrix}-0.4036\\ -0.0085\end{bmatrix},\ B_1=\begin{bmatrix}0.6231\\ -0.3251\end{bmatrix},$$
$$A_2=\begin{bmatrix}0.3125 & 0.1035\\ 0.3231 & 0.1705\end{bmatrix},\ D_1=\begin{bmatrix}-0.2334 & -0.1253\\ -0.4869 & -0.0254\end{bmatrix},$$
$$E_2=\begin{bmatrix}0.0065\\ -0.4008\end{bmatrix},\ F_2=\begin{bmatrix}-0.5045\\ 0.1007\end{bmatrix},\ B_2=\begin{bmatrix}-06423\\ -0.3251\end{bmatrix},$$
$$C_1=\begin{bmatrix}-0.3152 & -0.4523\\ -0.0561 & -0.1357\\ -0.0025 & 0.0058\end{bmatrix},\ H_1=\begin{bmatrix}-0.0254\\ -0.3251\\ -0.0005\end{bmatrix},$$
$$G_1=\begin{bmatrix}-0.4058 & 0.0169\\ 0.2363 & -0.2895\\ 0.1004 & 0.1710\end{bmatrix},\ H_2=\begin{bmatrix}0.2854\\ 0.0304\\ 0.3588\end{bmatrix},$$
$$C_2=\begin{bmatrix}0.0085 & -0.1006\\ -0.1036 & -0.0025\\ 0.0552 & 0.1035\end{bmatrix},\ G_2=\begin{bmatrix}0.2221 & 0.4016\\ 0.0059 & 0.0336\\ 0.1235 & 0.0410\end{bmatrix}.$$

The variances of the zero-mean multiplicative noises $\zeta(k)$ and $\xi(k)$ are set to be $\sigma_\zeta=1.1$ and $\sigma_\xi=1.4$, respectively.

By resorting to the solver of mincx in LMI toolbox, the convex optimization problem (29) is solved and the H_∞ performance index is optimized as $\gamma_{min}=1.1409$, where the feasible solutions of the positive definite matrices Q and P as well as the invertible matrices S_1 and S_2 are listed below:

$$P=\begin{bmatrix}0.03330 & -0.00322 & 0 & 0\\ -0.00322 & 0.05446 & 0 & 0\\ 0 & 0 & 0.00006 & -0.00004\\ 0 & 0 & -0.00004 & 0.00013\end{bmatrix},$$
$$Q=\begin{bmatrix}0.33648 & 0.06371 & -0.00411 & 0.00003\\ 0.06371 & 0.23834 & 0.00003 & -0.00124\\ -0.00411 & 0.00003 & 0.01148 & 0.00724\\ 0.00003 & -0.00124 & 0.00724 & 0.01809\end{bmatrix},$$
$$S_1=\begin{bmatrix}0.28780 & 0.04682\\ 0.04683 & 0.17911\end{bmatrix},\quad S_2=\begin{bmatrix}0.06347 & 0.14937\\ 0.14937 & 0.41285\end{bmatrix}.$$

Subsequently, the gain matrices of the concerned fault detection filter are obtained as follows:

$$\hat{A}_1 = \begin{bmatrix} -0.2882 & 0.1503 \\ -0.0590 & -0.2604 \end{bmatrix}, \quad \hat{A}_2 = \begin{bmatrix} 0.0557 & 0.2925 \\ 0.0080 & -0.0742 \end{bmatrix},$$

$$\hat{B}_1 = \begin{bmatrix} -0.0865 & -0.1572 & -0.2684 \\ -0.1688 & -0.3580 & -0.6317 \end{bmatrix},$$

$$\hat{B}_2 = \begin{bmatrix} 0.0134 & -0.1674 & -0.1674 \\ -0.2845 & -0.3631 & -0.3631 \end{bmatrix},$$

$$\hat{C}_1 = \begin{bmatrix} 0.0082 & 0.0060 \end{bmatrix}, \quad \hat{C}_2 = \begin{bmatrix} 0.01093 & -0.0053 \end{bmatrix},$$

$$\hat{D}_1 = \begin{bmatrix} -0.0477 & -0.1354 & -0.2734 \end{bmatrix},$$

$$\hat{D}_2 = \begin{bmatrix} -0.0296 & -0.1272 & -0.1660 \end{bmatrix}.$$

By now, an H_∞ fault detection filter has been designed under the framework of the T-S fuzzy model.

For simulation purpose, we adopt the normalized membership functions as

$$h_1 = \frac{\sin^2(x_1(k))}{2 + \cos(x_1(k))}, \quad h_2 = 1 - \frac{\sin^2(x_1(k))}{2 + \cos(x_1(k))}.$$

The multiplicative noises are taken as

$$\zeta(k) = -10^{-\mathrm{tg}^{-1}(k)} \frac{\sin(4k)}{\sin(k)} \left(\mathrm{tg}^{-1}(k)\right)^2 \varepsilon(k)$$

with $\varepsilon(k)$ being uniformly distributed over $[0, \ 1]$, and $\xi(k) = \mathrm{tg}^{-1}(k)\zeta(k)$. Let the control input be $u(k) = 0.12e^{\sin(k\mathrm{ctg}^{-1}(k))}\mathrm{tg}^{-1}(k\cos(k))$, the disturbance input be $\omega(k) = e^{-10k}$, the initial state be $\phi(k) = 0$ ($\forall k \in \mathbb{Z}^-$), the evaluating time horizon be $\mathcal{L} = 15$, and the fault be

$$f(k) = \begin{cases} 0.05ke^{\frac{-k}{80}}, & 30 \le k \le 120 \\ 0, & \text{else.} \end{cases}$$

By using the designed fault detection filter (3), the residual signal is steadily generated once the sensor measurements are communicated to the fault detection filter. Fig. 3 shows the evolutions of the residual with fault and fault free, which indicates that the residual will appear even if the fault does not occur. When the fault arises in the fuzzy system, the curve of residual signal yields a surge, and it begins to flatten when the fault disappeared. Evaluation of the residual is shown in Fig. 4, where it can be seen that the growth of the residual evaluation function starts to slacken when the fault disappears in the target networked fuzzy systems.

With help of the designed residual evaluation function (10), the threshold is determined as $J_{th} = 0.0636$ after 100 runs of Monte Carlo simulations. By checking the values of the residual evaluation function $J(k)$, we find that $J(k) = 0.0666$ exceeds the threshold at the time instant $k = 37$ for the first time, and the alarm apparatus can thus be triggered, which means that the fault in the target system is successfully detected with only 7 time instants behind. The evaluation of the residual without fuzzy rules is shown in Fig. 5, from which one knows $J(k) = 0.0647$ exceeds the threshold when $k = 61$. In other words, the non-fuzzy fault detection result largely lags behind the fault occurrence, which thus demonstrates the superiority of the studied scheme.

On the other hand, the measurement model (2) implies that the time delays induced by the Round-Robin protocol vary periodically. Trajectories of the residual with and without the multiplicative noises and interference input are shown in Fig. 6, from which we can see that the multiplicative noises $\zeta(k)$ and $\xi(k)$, the interference $\omega(k)$ can all produce a dash to the residual signal.

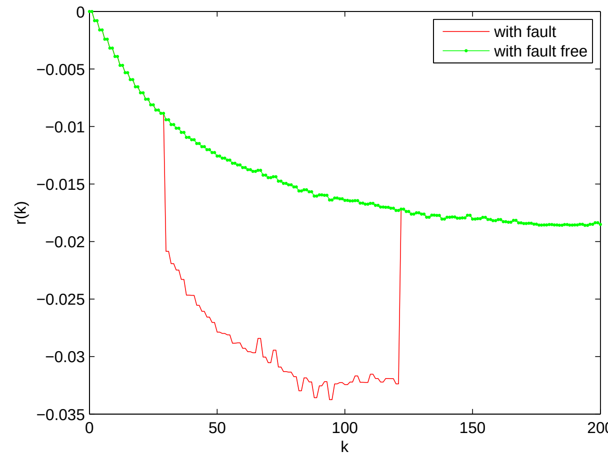

Fig. 3: Residual signal

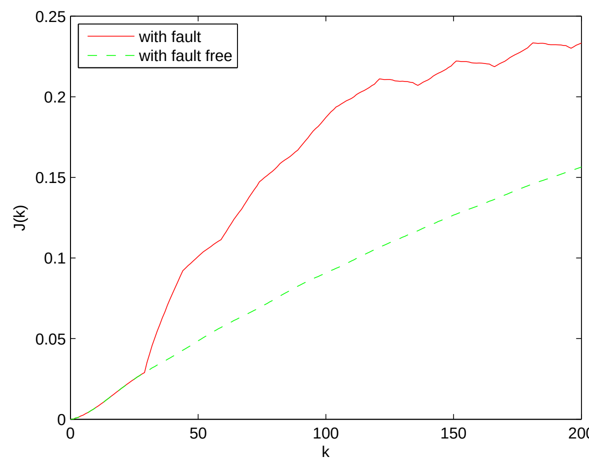

Fig. 4: Residual evaluation

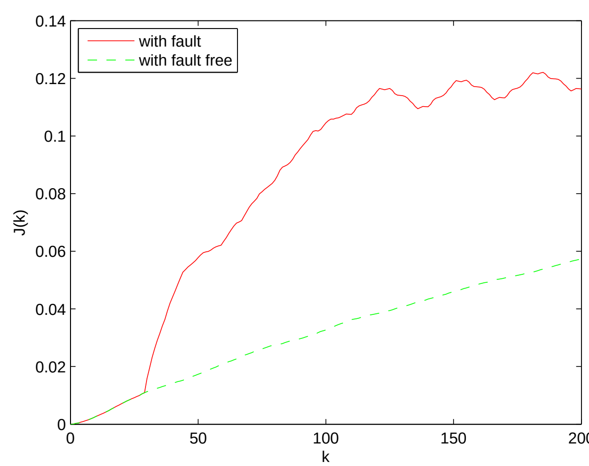

Fig. 5: Residual evaluation without fuzzy rules

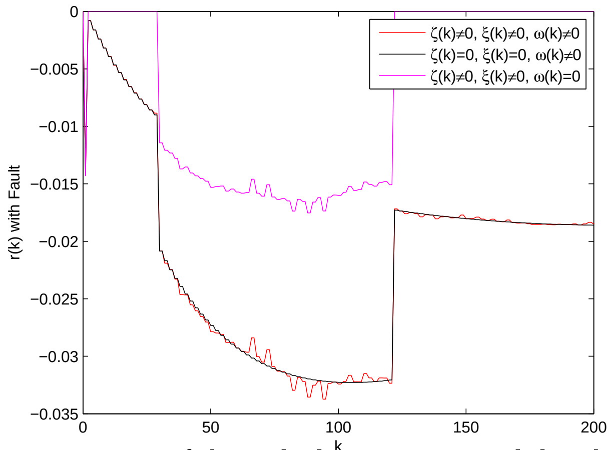

Fig. 6: Impact of the multiplicative noises and disturbance input to the residual

V. Conclusions

The fuzzy fault detection problem has been addressed for a class of T-S fuzzy networked systems in this paper. A novel communication scheduling solution has been used to deal with the communication constraints and the ZOHs have been used to improve the utilization of the received sensor measurements. In the framework of T-S fuzzy model, the structure of an H_∞ fuzzy fault detection filter embedded in the concerned fault detector has been suggested. The explicit expression of the desired fault detection filter has been characterized by solutions to a set of LMI constraints. To efficiently detect the fault occurred in the networked fuzzy systems, a finite-time residual evaluation function and the threshold consisting of constant and adjustable parts have been designed. On the other hand, the low requirement on bandwidth under Round-Robin protocol makes it can be widely used to some special applications such as the fault detection of the underwater power system, the forest fire monitoring and the remote medical diagnosis, etc. Moreover, for energy saving purpose, the event-triggered strategy can play an important role in the low-power network communication, see. e.g. [23]. Therefore, the above topics under Round-Robin protocol will constitute our further research directions.

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