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Fault detection reduced-order filter design for discrete-time Markov jump system with deficient transition information

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Abstract

The paper addresses the fault detection (FD) problem for a class of discrete-time Markov jump linear systems (MJLSs) with deficient transition rates, which simultaneously considers the totally known, partly unknown, and uncertain transition rates. Then, in accordance with the linear matrix inequality (LMI) method and the convexification techniques, a sufficient condition for the existence of FD reduced-order filter over MJLSs with deficient transition information is obtained, which can ensure the error augmented system with the FD reduced-order filter is stochastically stable. In addition, a performance index is given to enhance the robustness of the residual system against deficient transition information and external disturbance, such that the error between the fault and the residual is made as small as possible to reinforce the faults sensitivity. Finally, an illustrative example is employed to show the effectiveness of the proposed design approach.

Keywords: Markov jump linear systems, Fault detection, Deficient transition rate, Reduced-order filter

1 Introduction

During the past decades, Markov jump linear systems (MJLSs) have been received extensive interests in many engineering fields, such as energy system, solar thermal power generation system, networked control system, manufacturing system, financial market system [1, 2]. Many important results have been reported, such as a number of studies on the Markovian jump system on the filter design [3–5], controller design [6], output feedback control [7–10], stability analysis and synthesis [11–13]. In fact, MJLSs are very appropriate to dynamical model systems whose property is subject to random sudden variant due to abrupt external disturbance, shifting of the action spots of a nonlinear system, and repairs of components, thus, in order to ensure the nonlinear system stochastically exponentially stable, the author in [9] proposed a Markovian Lyapunov functional which was been successfully used in the nonlinear systems. In essence, the transition rates (TRs) in the MJLSs are considerable up to now. A large number of traditional analysis and design results have been reported on condition that the exactly known the TRs in the MJLSs [14, 15]. However, it should be pointed that all the mode transition rates can not be acquired totally in lots of engineering plants. That is to say, for a majority of MJLSs, there are three types of transition cases for the MJLSs, e.g., some are known, some are unknown, and others are polytopic uncertain TRs [16, 17]. On the other hand, in many published papers, the unknown TRs and polytopic uncertain TRs in MJLSs have been taken into account separatedly. In reality, in a lot of actual conditions, there are the uncertain TRs and unknown TRs in MJLSs synchronously. To mention a few, the author in [2] investigated continuous-time Markovian jump problems with deficient transition descriptions. In [18], an H_∞ filtering was developed for the two dimensional continuous time MJLSs with deficient transition descriptions. In this way, it is more rational and general to research on the analysis and synthesis of MJLSs with the totally known, uncertain and partly unknown TRs concurrently, which is the main motivation to do my research.

On another research frontier, the fault detection and isolation techniques have gotten a great number of attention in the academic research and practical application

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because of the increasing demand for improving the system reliability and the safety of modern plant operations and reducing costs (see [19]-[29]). The basic design idea of FD is to use the effective methods to generate a residual signal and to construct a common diagnostic residual evaluation function to compare with a beforehand threshold, then an alarm of fault is generated when the value of system residual is larger than the threshold [30, 31]. Hence, in the process of fault detection, residual generation is a very important step, based on this, there are many basic approaches are provided to generate robust residuals that are sensitive to faults, while insensitive to unknown input and noise. In the existing methods, which have been proposed to detect faults, such as full-state observer-based methods [32], optimization-based approach [33], parity relations approach [34], unknown input observers [35, 36], system identification methods [37, 38], nonlinear approach [39, 40], artificial intelligence techniques [41, 42], discrete event systems and hybrid systems [43–46], the fault detection filter method is the most favoured method. However, in many practical applications, high-order models are frequently used to describe physical systems. This brings many difficulties in design of the corresponding FD filter in order to detect faults in a timely way. Moreover, to the knowledge of the authors, there are few results have been reported in the literature on the high-efficiency FD reduced-order filter design. This motivates us to study this work in order to reduce the complexity, computation time of the FD filter design process and save storage space, so as to improve the efficiency of the fault detection, which has great potential in practical applications.

In this paper, the chief aim is to design the FD reduced-order filter for a family of discrete-time MJLSs with deficient TRs, which is more general. By satisfying some performance indexes, the susceptibility to malfunction and the robustness against interference are both enhanced on residual outputs. Through the constructing of the residual generator, the FD design scheme is converted to an H_∞ filtering problem in order that the error between residual and malfunction is minimized at the H_∞ level. Then, the sufficient condition for the existence of the FD filter for the represented systems is obtained via linear matrix inequalities. Finally, a numerical example is presented to show the effectiveness and potential of the developed theoretical result. In fact, the problem of fault detection for MJLSs with deficient TRs should meet many requirements of detection performance and Markov jump process, which leads to the increase difficulty of filter design. Therefore, to the best knowledge of the author, the research on the fault detection reduced-order filters for Markov jump system with deficient transition information is relatively few, which is the third motivation for this research.

The remainder of this paper is organized as follows. In Section 2, the mathematical model of the system is formulated, and then, many preliminary results are shown. The sufficient condition of FD filter for the underlying system is established in Section 3. In Section 4, a simulation example is presented to point out the effectiveness of the proposed approach.

Notations. $\mathbb{R}^n$ denotes the n-dimensional Euclidean space, $\mathbb{R}^{m\times n}$ denotes the set of all $m \times n$ real matrices, and N represents a positive integer. The notation $P > 0$, where P is the symmetric matrix, which means that P is positive definite. In a symmetric matrix, $*$ represents the symmetric element. $\|\cdot\|$ denotes the Euclidean vector norm of a vector, $l_2[0,\infty)$ is the space of all square summable vector functions for $\omega = \{\omega(k)\} \in l_2[0,\infty)$, and its norm is given by $\|\omega\|_2 = \sqrt{\sum_{k=0}^{\infty}\|\omega\|^2}$. The mathematical expectation operator is denoted as $E[\cdot]$, and $\|Z\|_{\varepsilon_2} = \sqrt{E[\sum_{k=0}^{\infty}\|Z\|^2]}$ indicates its norm.

2 Problem formulation

Consider the following discrete-time MJLS on a complete rate space of the form:

$$
\begin{aligned}
x_{k+1} &= A(r_k)x_k + B(r_k)u_k + E(r_k)\omega_k + F(r_k)f_k, \\
y_k &= C(r_k)x_k + D(r_k)\omega_k + H(r_k)f_k,
\end{aligned}
\tag{1}
$$

where $x_k \in \mathbb{R}^{n_x}$ represents the plant state, $u_k \in \mathbb{R}^{n_u}$ is the known control input, $\omega_k \in \mathbb{R}^{n_d}$ is the exogenous disturbance signal, $f_k \in \mathbb{R}^{n_f}$ is the fault signal to be detected, $y_k \in \mathbb{R}^{n_y}$ is the controlled output, u_k, ω_k and f_k are assumed to belong to $l_2[0,\infty)$. $\{r_k, k > 0\}$ is a discrete-time homogeneous Markov chain, which takes values in a finite set $S = \{1, 2, \ldots, n\}$ with mode transition rates (TRs) $\text{Prob}(r_{k+1} = j \,|\, r_k = i) = \lambda_{ij}$, where $\lambda_{ij} \geq 0$, for all $i, j \in S$ and $\Sigma_{j=1}^{N}\lambda_{ij} = 1$. For $r_k = i,\ i \in S$, the system matrices of the i-th mode are denoted by (A_i, B_i, C_i, D_i), which are known real matrices. In this paper, system (1) is assumed randomly stable, which is a precondition for model design.

Moreover, the TRs of the Markov process be regarded as being polytopic uncertain and partly available; in other words, the transition rate matrix (TRM) $\Lambda = \{\lambda_{ij}\}$ is deemed to belong to a known polytope P_Λ with vertices Λ_s.

$$
P_\Lambda := \left\{ \Lambda \,\middle|\, \Lambda = \sum\nolimits_{s=1}^{M} \alpha_s \Lambda_s;\ \alpha_s \geq 0,\ \sum\nolimits_{s=1}^{M} \alpha_s = 1 \right\},
\tag{2}
$$

where vertices $\Lambda_s = [\lambda_{ij}]_{N\times N},\ i,\ j \in S,\ I = 1,\ 2\cdots M$ are still given TRM containing unknown and uncertain factors. For example, for system (1) with four variation modes, the TRM may be as:

$$\begin{bmatrix} \tilde{\lambda}_{11} & \lambda_{12} & \tilde{\lambda}_{13} & \hat{\lambda}_{14} \\ \hat{\lambda}_{21} & \hat{\lambda}_{22} & \lambda_{23} & \hat{\lambda}_{24} \\ \hat{\lambda}_{31} & \lambda_{32} & \hat{\lambda}_{33} & \lambda_{34} \\ \lambda_{41} & \tilde{\lambda}_{42} & \hat{\lambda}_{43} & \lambda_{44} \end{bmatrix} \tag{3}$$

where the superscripts labeled with "˜" and "ˆ" represent the polytopic uncertainties and unknown TRs, separately, and the others are known TRs. In order to make the notational more clearly, for all $i \in S$, we denote $S = S_k^{(i)} \cup S_{uc}^{(i)} \cup S_{uk}^{(i)}$ as follows:

$$\begin{aligned} S_k^{(i)} &:= \left\{ j : \lambda_{ij} \text{ is known} \right\}, \\ S_{uc}^{(i)} &:= \left\{ j : \tilde{\lambda}_{ij} \text{ is uncertain} \right\}, \\ S_{uk}^{(i)} &:= \left\{ j : \hat{\lambda}_{ij} \text{ is unknown} \right\}. \end{aligned}$$

Also, we define $\lambda_{uk}^{(is)} := \sum_{j\in S_{uk}^{(i)}} \hat{\lambda}_{ij} = 1 - \sum_{j\in S_k^{(i)}} \lambda_{ij} - \sum_{j\in S_{uc}^{(i)}} \tilde{\lambda}_{ij}^{(is)}$.

Remark 1. The transition rates of the MJLSs $\{r_k,\ k \geq 0\}$ have been universally assumed to be some known, some unknown, and some uncertain within given intervals. Hence, the TRM considered in this article is more natural to the MJLSs, which includes the previous three cases. Then, we are interested in designing an FD filter for the underlying system, and its desired structure is considered to be:

$$\begin{aligned} \hat{x}_{k+1} &= A_F(r_k)\hat{x}_k + B_F(r_k)y_k, \\ \hat{r}_k &= C_F(r_k)\hat{x}_k + D_F(r_k)y_k, \end{aligned} \tag{4}$$

where, $\hat{x}_k \in \mathbb{R}^n$ is the state estimation of filter, $\hat{r}_k \in \mathbb{R}^f$ is the residual, and $A_F(r_k)$, $B_F(r_k)$, $C_F(r_k)$, $D_F(r_k)$, and $\forall r_k \in$ I are the matrices to be calculated.

Define $\tilde{x}_k := \begin{bmatrix} x_k^T & \hat{x}_k^T \end{bmatrix}^T$, $e_k := \hat{r}_k - f_k$. Then, by augmenting (1) and (4), the error augmented system is obtained as follows:

$$\begin{aligned} \tilde{x}_{k+1} &= \tilde{A}(r_k)\tilde{x}_k + \tilde{B}(r_k)\psi_k, \\ e_k &= \tilde{C}(r_k)\tilde{x}_k + \tilde{D}(r_k)\psi_k, \end{aligned} \tag{5}$$

where, $\psi_k = [\,u_k^T \quad \omega_k^T \quad f_k^T]^T$ and

$$\tilde{A}(r_k) = \begin{bmatrix} A(r_k) & 0 \\ B_F(r_k)C(r_k) & A_F(r_k) \end{bmatrix},$$

$$\tilde{B}(r_k) = \begin{bmatrix} B(r_k) & E(r_k) & F(r_k) \\ 0 & B_F(r_k)D(r_k) & B_F(r_k)H(r_k) \end{bmatrix},$$

$$\tilde{C}(r_k) = \begin{bmatrix} D_F(r_k)C(r_k) & C_F(r_k) \end{bmatrix},$$

$$\tilde{D}(r_k) = [0 \quad D_F(r_k)D(r_k)D_F(r_k)H(r_k) - I\,].$$

In fact, the error augmented system (5) is also an MJLS with deficient TRM in (3). Now, to describe the main objective of this article more precisely, let us recommend the following definitions for system (5), which are necessary for the later progress.

Definition 1. [16] A discrete-time stochastic system (5) is said to be stochastically stable if for $\psi_k = 0, k \geq 0$ and every initial condition $\tilde{x}_0 \in \mathbb{R}^{n_x}$ and $r_0 \in S$ the following holds: $E\left\{ \sum_{k=0}^{\infty} \left\| \tilde{x}_k \right\|^2 \left| \tilde{x}_0, r_0 \right. \right\} < \infty$.

Definition 2. [6] Given the disturbance input $\omega_k \in l_2[\,0,\infty)$, a scalar $\gamma > 0$, system (5) is stochastically stable and has an H_∞ performance index γ if the following two conditions are satisfied:

1) When $\omega_k = 0, k \geq 0$, system (5) is stochastically stable in the sense of Definition 1.

2) When $\omega_k \neq 0, k \geq 0$, under zero initial conditions, the following inequality holds:

$$E\left\{ \sum_{K=0}^{\infty} \|e_k\|^2 \right\} < \gamma^2 E\left\{ \sum_{K=0}^{\infty} \|\omega_k\|^2 \right\} \tag{6}$$

As a consequence, the main purposes of this paper are to determine matrices $\{A_F(r_k),\ B_F(r_k),\ C_F(r_k),\ D_F(r_k)\}$ in system (4), such that the augmented error system (5) is randomly stable with a reliable H_∞ performance level γ with deficient transition information. Finally, the discrete-time MJLS (1) will be assumed to be stable in the end. Moreover, in order to detect the fault f_k, the residual evaluation function is designed as $J(\hat{r}_g) = \sqrt{\sum_{g=k_0}^{k_0+L} \hat{r}_g^T \hat{r}_g}$, where k_0 denotes the initial evaluation time instant. The fault f_k can be detected by the following steps.

i) Select a threshold $J_{\text{th}} \triangleq \sup_{d\in l_2, f=0} E\left[J(\hat{r}_k)\right]$.

ii) Based on the above result, the fault f_k can be detected by comparing $J(\hat{r}_k)$ and J_{th}.

iii)When $J(\hat{r}_k) \geq J_{\text{th}}$, there are some faults, we should give an alarm; when $J(\hat{r}_k) < J_{\text{th}}$, there are no faults.

Before proceeding further, we give the following lemma on the H_∞ performance analysis of system (5) with completely known TRs, which will be used in the derivation of our main results.

Lemma 1. (see([3])) Given the disturbance input $\omega_k \in l_2[\,0,\infty)$, for the MJLS (5) with completely known TRs and a given scalar $\gamma > 0$, if the coupled inequalities

$$\begin{bmatrix} \tilde{A}_i^T \eta_i \tilde{A}_i - P_i + \tilde{C}_i^T \tilde{C}_i & \tilde{A}_i^T \eta_i \tilde{B}_i + \tilde{C}_i^T \tilde{D}_i \\ * & -\left(\gamma^2 I - \tilde{B}_i^T \eta_i \tilde{B}_i - \tilde{D}_i^T \tilde{D}\right) \end{bmatrix} < 0,\ \forall i \in I, \tag{7}$$

where $\eta_i := \sum_{j=1}^{N} \lambda_{ij} P_j$ have a resolvable matrices $P =$

$\{P_1, P_2, \ldots P_N\}$ such that the MJLS (5) with totally known TRs is randomly stable with an H_∞ performance index γ.

3 Main results

In this section, based on Lemma 1, firstly, we will introduce an H_∞ performance analysis criterion for the error augmented system (5) and further focus on the design of the FD reduced-order filter for MJLS (1) with deficient mode information.

3.1 H_∞ FD filter with deficient transition information performance analysis

The following lemma presents an H_∞ FD filter performance analysis criterion for the underlying augmented error system in (5) with deficient TRs.

Lemma 2. Let $\gamma > 0$ be a given scalar; if there are positive-definite symmetric matrices $P = \{P_1, P_2, \ldots P_N\}$ such that LMI (8) holds, then the error augmented system in (5) with deficient transition information is randomly stable with a guaranteed H_∞ performance index γ and satisfies (6).

$$\begin{bmatrix} -\left(\eta_j^{(is)}\right)^{-1} & 0 & \tilde{A}_i & \tilde{B}_i \\ * & -I & \tilde{C}_i & \tilde{D}_i \\ * & * & -P_i & 0 \\ * & * & * & -\gamma^2 I \end{bmatrix} < 0 \tag{8}$$

where

$$\eta_j^{(is)} := \sum_{j\in S_k^{(i)}} \lambda_{ij}P_j + \sum_{j\in S_{uc}^{(i)}} \tilde{\lambda}_{ij}^{(s)} P_j + \sum_{j\in S_{uk}^{(i)}} \hat{\lambda}_{uk} P_j,$$

$$\sum_{j\in S_{uk}^{(i)}} \hat{\lambda}_{uk} := 1 - \sum_{j\in S_k^{(i)}} \lambda_{ij} - \sum_{j\in S_{uc}^{(i)}} \tilde{\lambda}_{ij}^{(s)}.$$

Proof. By virtue of Lemma 1, it is shown that system (5) with totally known TRs is randomly stable with an H_∞ performance γ, when matrix inequality (7) holds. Now due to $\Sigma_{j=1}^N \lambda_{ij} = 1$ and with deficient TRs, we rewrite the term

$$\Sigma_{j=1}^N \lambda_{ij}P_j = \sum_{j\in S_k^{(i)}} \lambda_{ij}P_j + \sum_{j\in S_{uc}^{(i)}} \left(\sum_{s=1}^M \alpha_s \tilde{\lambda}_{ij}^{(s)}\right) P_j + \sum_{j\in S_{uk}^{(i)}} \hat{\lambda}_{uk} P_j\,. \tag{9}$$

Considering the fact that $0 \le \alpha_s \le 1$, $\sum_{s=1}^M \alpha_s = 1$, (9) can be rewritten as

$$\Sigma_{j=1}^N \lambda_{ij}P_j = \sum_{s=1}^M \alpha_s \left(\sum_{j\in S_k^{(i)}} \lambda_{ij}P_j + \sum_{j\in S_{uc}^{(i)}} \tilde{\lambda}_{ij}^{(s)} P_j + \sum_{j\in S_{uk}^{(i)}} \hat{\lambda}_{uk} P_j\right) = \eta_j^{(is)}.$$

Thus, with deficient transition information, (7) can be rewritten as

$$\begin{bmatrix} \tilde{A}_i^T \eta_i \tilde{A}_i - P_i + \tilde{C}_i^T \tilde{C}_i & \tilde{A}_i^T \eta_i \tilde{B}_i + \tilde{C}_i^T \tilde{D}_i \\ * & -\left(\gamma^2 I - \tilde{B}_i^T \eta_i \tilde{B}_i - \tilde{D}_i^T \tilde{D}_i\right) \end{bmatrix}$$

$$= \sum_{s=1}^M \alpha_s \begin{bmatrix} \tilde{A}_i^T \eta_j^{(is)} \tilde{A}_i - P_i + \tilde{C}_i^T \tilde{C}_i & \tilde{A}_i^T \eta_j^{(is)} \tilde{B}_i + \tilde{C}_i^T \tilde{D}_i \\ * & -\left(\gamma^2 I - \tilde{B}_i^T \eta_j^{(is)} \tilde{B}_i - \tilde{D}_i^T \tilde{D}_i\right) \end{bmatrix}. \tag{10}$$

Then, the right-hand side (RHS) of equality (10) can be further processed as

$$\text{RHS}(10) = \begin{bmatrix} \tilde{A}_i^T \eta_j^{(is)} \tilde{A}_i - P_i + \tilde{C}_i^T \tilde{C}_i & \tilde{A}_i^T \eta_j^{(is)} \tilde{B}_i + \tilde{C}_i^T \tilde{D}_i \\ * & -\left(\gamma^2 I - \tilde{B}_i^T \eta_j^{(is)} \tilde{B}_i - \tilde{D}_i^T \tilde{D}_i\right) \end{bmatrix}. \tag{11}$$

The RHS of equality (11) can be decomposed into the following form:

$$\begin{aligned} \text{RHS}(11) &= \begin{bmatrix} \tilde{A}_i^T \eta_j^{(is)} \tilde{A}_i & \tilde{A}_i^T \eta_j^{(is)} \tilde{B}_i \\ * & \tilde{B}_i^T \eta_j^{(is)} \tilde{B}_i \end{bmatrix} + \begin{bmatrix} -P_i + \tilde{C}_i^T \tilde{C}_i & \tilde{C}_i^T \tilde{D}_i \\ * & -\gamma^2 I + \tilde{D}_i^T \tilde{D}_i \end{bmatrix} \\ &= \begin{bmatrix} \tilde{A}_i^T \eta_j^{(is)} \tilde{A}_i & \tilde{A}_i^T \eta_j^{(is)} \tilde{B}_i \\ * & \tilde{B}_i^T \eta_j^{(is)} \tilde{B}_i \end{bmatrix} + \begin{bmatrix} \tilde{C}_i^T \tilde{C}_i & \tilde{C}_i^T \tilde{D}_i \\ * & \tilde{D}_i^T \tilde{D}_i \end{bmatrix} + \begin{bmatrix} -P_i & 0 \\ * & -\gamma^2 I \end{bmatrix} \end{aligned} \tag{12}$$

In fact, by Schur complement, RHS (12) is equivalent to

$$\begin{aligned} \text{RHS}(12) &= \begin{bmatrix} -I & \tilde{C}_i & \tilde{D} \\ \tilde{C}_i^T & -P_i & 0 \\ \tilde{D}_i^T & 0 & -\gamma^2 I \end{bmatrix} + \begin{bmatrix} \tilde{A}_i^T \eta_j^{(is)} \tilde{A}_i & \tilde{A}_i^T \eta_j^{(is)} \tilde{B}_i \\ * & \tilde{B}_i^T \eta_j^{(is)} \tilde{B}_i \end{bmatrix} \\ &= \begin{bmatrix} -(\eta_j^{(is)})^{-1} & 0 & \tilde{A}_i & \tilde{B}_i \\ * & -I & \tilde{C}_i & \tilde{D}_i \\ * & * & -P_i & 0 \\ * & * & * & -\gamma^2 I \end{bmatrix} < 0. \end{aligned} \tag{13}$$

This completes the proof of the lemma. □

Remark 2. Lemma 2 presents an H_∞ performance analysis criterion for a family of MJLSs with deficient TRs. However, it is shown that there are coupling terms in the system matrices inequality (8), which structural constraint significantly augments the level of design conservatism. Thus, it incurs some difficulties for fault detection filter synthesis problem. To overcome these difficulties, the slack matrix method can be adopted here in order to obtain the following improved criterion for augmented error system (5).

3.2 Design of H_∞ FD reduced-order filter

The next step is to translate the H_∞ FD reduced-order filter design problem into a model-matching problem. In the following theorem, a sufficient condition is provided for the existence of an admissible H_∞ FD reduced-order filter with the deficient transition probabilities (3).

Theorem 1. *Consider system (1) with deficient transition information, for given* $\gamma > 0$*, determine the matrices* $A_{Fi} = M_{i(2)}^{-1}\tilde{A}_i$, $B_{Fi} = M_{i(2)}^{-1}\tilde{B}_i$, $C_{Fi} = \tilde{C}_i$, $D_{Fi} = \tilde{D}_i$, *then the FD reduced-order filter (4) is found so that the augmented error system (5) is randomly stable with an* H_∞ *performance index* γ*, if there exist positive-definite symmetric matrices* $P_i = \begin{bmatrix} P_{i(1)} & P_{i(2)} \\ * & P_{i(3)} \end{bmatrix} \in R^{(n_x+n_r)\times(n_x+n_r)}$, $M_i = \begin{bmatrix} M_{i(1)} & TM_{i(2)} \\ * & M_{i(3)} \end{bmatrix} \in R^{(n_x+n_r)\times(n_x+n_r)}$, *and* $\tilde{A}_{ri}, \tilde{B}_{ri}, \tilde{C}_{ri}, \tilde{D}_{ri}$, $\forall i \in I$, *satisfy the following LMIs:*

$$\begin{bmatrix} \Theta_1 & \Theta_2 & 0 & \Theta_4 & TM_{i(2)}A_{Fi} & \Theta_6 \\ * & \Theta_3 & 0 & \Theta_5 & M_{i(2)}A_{Fi} & \Theta_7 \\ * & * & -I & D_{Fi}C_i & C_{Fi} & \Theta_8 \\ * & * & * & -P_{i(1)} & -P_{i(2)} & 0 \\ * & * & * & * & -P_{i(3)} & 0 \\ * & * & * & * & * & -\gamma^2 I \end{bmatrix} < 0, \quad (14)$$

where

$$\eta_{j(m)}^{(is)} := \sum_{j\in S_k^{(i)}} \lambda_{ij}P_{j(m)} + \sum_{j\in S_{uc}^{(i)}} \tilde{\lambda}_{ij}^{(s)}P_{j(m)} + \sum_{j\in S_{uk}^{(i)}} \hat{\lambda}_{uk}P_{j(m)},$$
$$m = 1,2,3, \sum_{j\in S_{uk}^{(i)}} \hat{\lambda}_{uk} := 1 - \sum_{j\in S_k^{(i)}} \lambda_{ij} - \sum_{j\in S_{uc}^{(i)}} \tilde{\lambda}_{ij}^{(s)}, \quad (15)$$

$\Theta_1 = \eta_{j(1)}^{(is)} - M_{i(1)} - M_{i(1)}^T$,
$\Theta_2 = \eta_{j(2)}^{(is)} - HM_{i(2)} - M_{i(3)}^T$,
$\Theta_3 = \eta_{j(3)}^{(is)} - M_{i(2)} - M_{i(2)}^T$,
$\Theta_4 = M_{i(1)}A_i + TM_{i(2)}B_{Fi}C$,
$\Theta_5 = M_{i(3)}A_i + M_{i(2)}B_{Fi}C_i$,
$\Theta_6 = \begin{bmatrix} M_{i(1)}B_i & M_{i(1)}E_i + TM_{i(2)}B_{Fi}D & M_{i(1)}F_i + TM_{i(2)}B_{Fi}H_i \end{bmatrix}$,
$\Theta_7 = \begin{bmatrix} M_{i(3)}B_i & M_{i(3)}E_i + M_{i(2)}B_{Fi}D_i & M_{i(3)}F_i + M_{i(2)}B_{Fi}H_i \end{bmatrix}$,
$\Theta_8 = \begin{bmatrix} 0 & D_{Fi}D_i & D_{Fi}H_i - I \end{bmatrix}$.

Proof. Based on Lemma 2, accomplishing a congruence transformation with (8) using given matrix $\{M_i \quad I \quad I \quad I\}$ yields the following inequality

$$\begin{bmatrix} -M_i\left(\eta_j^{(is)}\right)^{-1}M_i^T & 0 & M_i\tilde{A}_i & M_i\tilde{B}_i \\ * & -I & \tilde{C}_i & \tilde{D}_i \\ * & * & -P_i & 0 \\ * & * & * & -\gamma^2 I \end{bmatrix} < 0, \quad (16)$$

For an discretionary matrix M_i, $\forall i \in I$, we have the following inequality established:

$$\left(\eta_j^T - M_i^T\right)\eta_j^{-1}\left(\eta_j - M_i^T\right) \geq 0. \quad (17)$$

We expand (17), then, get the following bounding inequality:

$$\eta_j^T - M_i^T - M_i^T \geq -M_i^T\eta_j^{-1}M_i^T. \quad (18)$$

It can be easily obtained the following form:

$$\begin{bmatrix} \eta_j^{(is)} - M_i - M_i^T & 0 & M_i\tilde{A}_i & M_i\tilde{B}_i \\ * & -I & \tilde{C}_i & \tilde{D}_i \\ * & * & -P_i & 0 \\ * & * & * & -\gamma^2 I \end{bmatrix} < 0. \quad (19)$$

In (19), in order to further research, we assume that the matrix P, M have the following forms:

$$P_i := \begin{bmatrix} P_{i(1)} & P_{i(2)} \\ * & P_{i(3)} \end{bmatrix}, \ M_i := \begin{bmatrix} M_{i(1)} & M_{i(2)} \\ * & M_{i(3)} \end{bmatrix}, \ i \in I. \quad (20)$$

For H_∞ FD filter design purpose, we choose the slack matrix M_i as:

$$M_i := \begin{bmatrix} M_{i(1)} & TM_{(2)} \\ M_{i(3)} & M_{(4)} \end{bmatrix}, \ i \in I, \quad (21)$$

where

$T := \begin{bmatrix} I_{n_r} & O_{n_r\times(n_x-n_r)} \end{bmatrix}^T$, $M_{i(1)} \in R^{n_x\times n_x}$, $M_{i(3)} \in R^{n_r\times n_x}$, $M_{(2)} \in R^{n_r\times n_r}$, *and* $M_{(4)} \in R^{n_r\times n_r}$.

Then, according to formula (21), performing the following congruent transformation

$$\begin{bmatrix} M_i + M_i^T \end{bmatrix} = \begin{bmatrix} M_{i(1)} + M_{i(1)}^T & TM_{(2)} + M_{i(3)}^T \\ * & M_{(4)} + M_{(4)}^T \end{bmatrix}, \quad (22)$$

by $\begin{bmatrix} I & 0 \\ * & M_{(2)}M_{(4)}^{-1} \end{bmatrix}$ yields

$$
\begin{bmatrix} I & 0 \\ * & M_{(2)}M_{(4)}^{-1} \end{bmatrix}
\begin{bmatrix} M_{i(1)}+M_{i(1)}^T & TM_{(2)}+M_{i(3)}^T \\ M_{i(3)} & M_{(4)}+M_{(4)}^T \end{bmatrix}
\begin{bmatrix} I & 0 \\ * & M_{(4)}^{-T}M_{(2)}^T \end{bmatrix}
= \begin{bmatrix} M_{i(1)}+M_{i(1)}^T & TM_{(2)}M_{(4)}^{-T}M_{(2)}^T+M_{i(3)}^TM_{(4)}^{-T}M_{(2)}^T \\ * & M_{(2)}M_{(4)}^{-T}M_{(2)}^T+M_{(2)}M_{(4)}^{-1}M_{(2)}^T \end{bmatrix}
= \begin{bmatrix} M_{i(1)}+M_{i(1)}^T & TM_{i(2)}+M_{i(3)} \\ * & M_{i(2)}+M_{i(2)}^T \end{bmatrix}. \tag{23}
$$

Thus, matrix M_i in (21) can been directly specified the following general form:

$$
M_i := \begin{bmatrix} M_{i(1)} & TM_{i(2)} \\ M_{i(3)} & M_{i(2)} \end{bmatrix},\ i \in I. \tag{24}
$$

It is shown that in this way the matrix variable $M_{i(2)}$ can be absorbed by the filter model gain variables A_{Fi} and B_{Fi} by introducing

$$
\tilde{A}_i := M_{i(2)}A_{Fi},\ \tilde{B}_i := M_{i(2)}B_{Fi}. \tag{25}
$$

This feature enables one to make no congruent transformation to the original matrix inequality, and all the slack variables can be set as Markov switching. Further define matrix variables

$$
\tilde{C}_i = C_{Fi},\ \tilde{D}_i = D_{Fi},\ \eta_j^{(is)} = \begin{bmatrix} \eta_{1j}^{(is)} & \eta_{2j}^{(is)} \\ * & \eta_{3j}^{(is)} \end{bmatrix}. \tag{26}
$$

Then, we replace matrices M_i given by (24) into (19); together with the admissible filter parameter, matrices are defined in (25) and (26). Finally, we can get (14) exactly. This completes the proof. □

Remark 3. Up until now, it has shown that the main result presented in Theorem 1 that not only provides performance index γ^* but also gives a numerically efficient and reliable approach to determine the corresponding gains of an admissible FD reduced-order filter in (4) by using Matlab software. In order to acquire a receivable H_∞ FD reduced-order filter with γ made as small as possible in (6), it is necessary to calculate the inequality (14) in Theorem 1 iteratively. Also, it can be derived from (14) that the design FD reduced-order filter and the corresponding error between residual and fault should be different on the basis of the different degree of deficient statistics of mode transitions. The main goal is to make the error as small as possible. To illustrate the feasibility and effectiveness of the proposed FD scheme, a numerical example will be given in the next section.

4 Numerical example

For simplicity, we only consider the addressed FD problem for a discrete-time MJLS with deficient transition information. Consider MJLS (1) with four operation modes, and the following matrices:

$$
A_1 = \begin{bmatrix} 0.05 & -0.27 & 0.44 & 0.39 \\ 0.55 & 0.33 & 0.38 & 0.55 \\ 0.1 & 0.17 & 0.27 & 0.44 \\ 0.05 & 0.22 & 0.16 & 0.11 \end{bmatrix},
A_2 = \begin{bmatrix} 0.11 & -0.17 & 0.27 & 0.44 \\ 0.55 & 0.06 & 0.22 & 0.55 \\ 0.05 & 0.17 & 0.28 & 0.44 \\ 0.17 & 0.05 & 0.06 & -0.11 \end{bmatrix},
$$

$$
A_3 = \begin{bmatrix} 0.16 & 0.06 & -0.02 & 0.18 \\ 0.04 & -0.37 & 0.53 & -0.04 \\ -0.08 & -0.32 & -0.05 & -0.11 \\ -0.17 & 0.4 & 0.04 & 0.29 \end{bmatrix},
A_4 = \begin{bmatrix} 0.23 & 0.01 & -0.55 & -0.38 \\ -0.33 & 0.36 & -0.48 & -0.1 \\ -0.20 & -0.45 & 0.1 & -0.19 \\ 0.23 & 0.16 & 0.5 & -0.3 \end{bmatrix},
$$

$B_1 = [0.5;\ 0.2;\ 0.3;\ 0.1]$, $B_2 = [-0.8; -0.2; -0.1; -1]$,
$B_3 = [0.2; -0.2; -0.1; 0.1]$, $B_4 = [0.9; -1.1; -0.7; -1.2]$,
$C_1 = [1\ \ 0.1\ \ 0.2\ \ -0.3]$, $C_2 = [0.5\ \ -0.8\ \ 0.3\ 0.5]$,
$C_3 = [1.4\ \ 0.7\ \ 0.2\ \ -0.8]$, $C_4 = [-0.71.2\ 1.2\ \ -0.6]$,
$D_1 = D_2 = D_3 = D_4 = 0.5$,
$E_1 = E_2 = E_3 = E_4 = [0.08;\ 0.12;\ 0.50;\ 0.29]$,
$F_1 = F_2 = F_3 = F_4 = [1;\ -1;\ -1;\ 1]$,
$H_1 = H_2 = H_3 = H_4 = [-1]$.

In order to make the simulation simplification, we consider the known control input $u(k)$ is simulated by step signal with amplitude 0.2 for $k = 0, 1, 2, \ldots, 300$. The exogenous disturbance input ω_k is given by white noise signal with amplitude less than 0.5. The fault signal f_k is:

$$
f_k = \begin{cases} 2, 100 \le k \le 200, \\ 0, \text{others}. \end{cases}
$$

Now, four cases for different transition rate matrix (TRM) are shown in Table 1, and the simulation result of Markov chain r_k is given in Fig. 1.

Table 1 Four different TRMs

Case1: completely known TRM	Case 2: polytopic uncertain TRM
$\begin{bmatrix} 0.3 & 0.2 & 0.1 & 0.4 \\ 0.3 & 0.2 & 0.3 & 0.2 \\ 0.1 & 0.5 & 0.3 & 0.1 \\ 0.2 & 0.2 & 0.1 & 0.5 \end{bmatrix}$	$\begin{bmatrix} 0.3 & 0.2 & \hat{\lambda}_{13} & \hat{\lambda}_{14} \\ \hat{\lambda}_{21} & \hat{\lambda}_{22} & \hat{\lambda}_{23} & \hat{\lambda}_{24} \\ \tilde{\lambda}_{31} & \hat{\lambda}_{32} & \tilde{\lambda}_{33} & \hat{\lambda}_{34} \\ \hat{\lambda}_{41} & \hat{\lambda}_{42} & 0.1 & 0.5 \end{bmatrix}$
Case 3: partly known TRM	Case4: completely unknown TRM
$\begin{bmatrix} 0.3 & 0.2 & \hat{\lambda}_{13} & \hat{\lambda}_{14} \\ \hat{\lambda}_{21} & \hat{\lambda}_{22} & 0.3 & \hat{\lambda}_{24} \\ \hat{\lambda}_{31} & \hat{\lambda}_{32} & \hat{\lambda}_{33} & \hat{\lambda}_{34} \\ \hat{\lambda}_{41} & \hat{\lambda}_{42} & 0.1 & 0.5 \end{bmatrix}$	$\begin{bmatrix} \hat{\lambda}_{11} & \hat{\lambda}_{12} & \hat{\lambda}_{13} & \hat{\lambda}_{14} \\ \hat{\lambda}_{21} & \hat{\lambda}_{22} & \hat{\lambda}_{23} & \hat{\lambda}_{24} \\ \hat{\lambda}_{31} & \hat{\lambda}_{32} & \hat{\lambda}_{33} & \hat{\lambda}_{34} \\ \hat{\lambda}_{41} & \hat{\lambda}_{42} & \hat{\lambda}_{43} & \hat{\lambda}_{44} \end{bmatrix}$

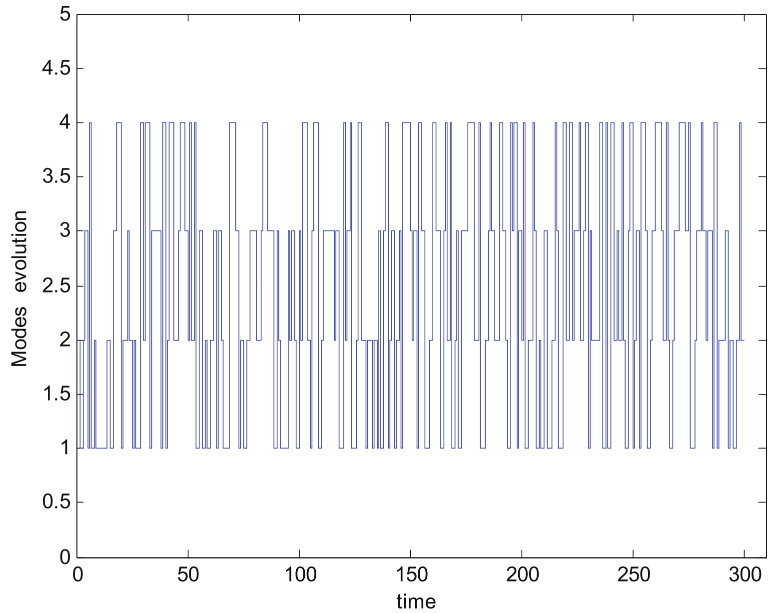

Fig. 1 Modes evolution

For case 2, the TRM includes three vertices $\Delta_r,\ r = 1,2,3$, and their third row $\Delta_r^3,\ r = 1,2,3$, are given by

$$\Delta_1^3 = \left[\, 0.5\ \hat{\lambda}_{32}\ 0.2\ \hat{\lambda}_{34} \,\right],$$
$$\Delta_2^3 = \left[\, 0.35\ \hat{\lambda}_{32}\ 0.42\ \hat{\lambda}_{34} \,\right],$$
$$\Delta_3^3 = \left[\, 0.2\ \hat{\lambda}_{32}\ 0.36\ \hat{\lambda}_{34} \,\right].$$

Applying Theorem 1 through the Matlab LMI Toolbox, the gains of an admissible FD filter in the form of (4) for four different TRMs in Table 1 are acquired respectively.

Obviously, it is seen from Fig. 2, which presents the generated residual signals $\hat{r}_k$, that the more transition rate information we have known, the smaller the generated

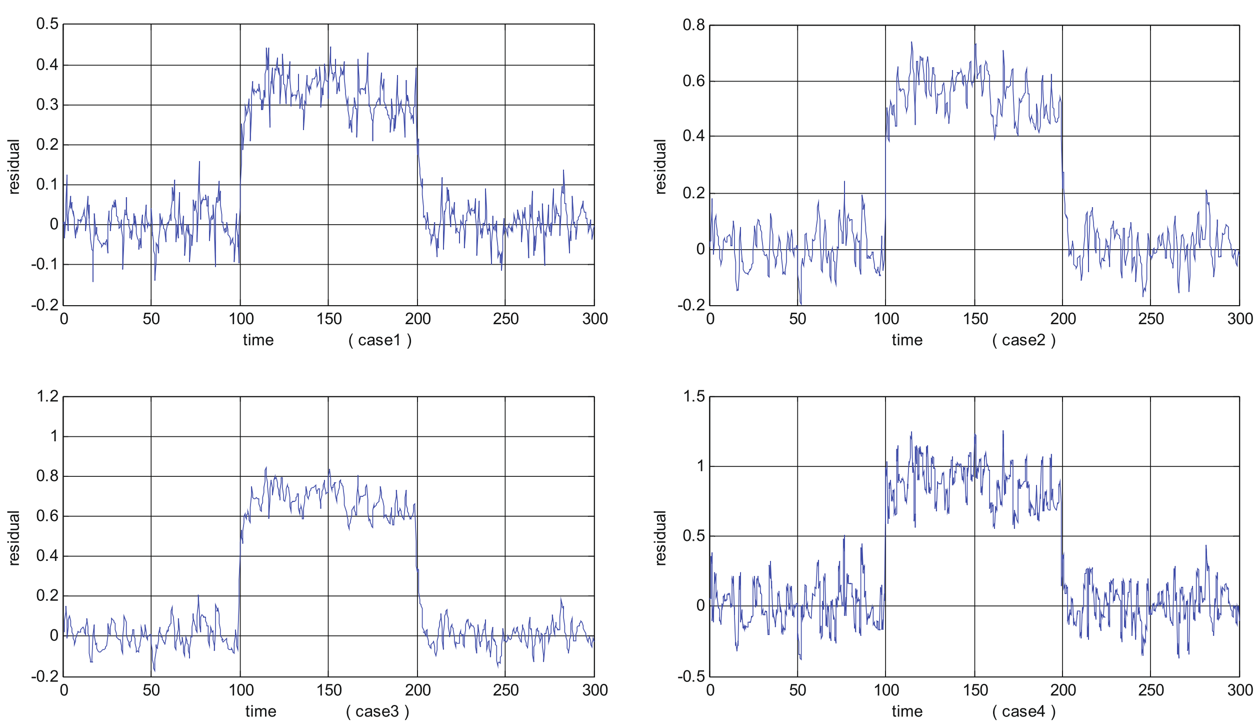

Fig. 2 Generated residual

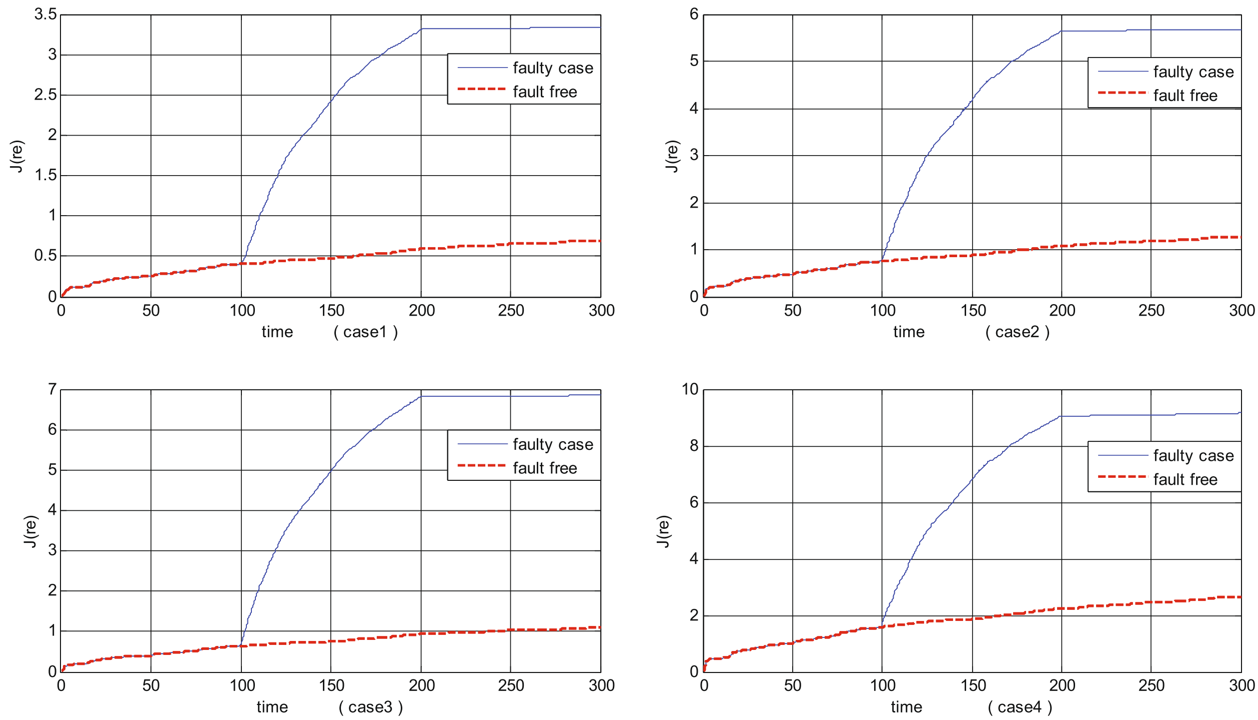

Fig. 3 Evolution of J(rF)

residual $\hat{r}_k$ will become, e.g., the generated residual value in case 2 is the smaller than the residual value in case 3. The simulation results of polytopic uncertain effect better than partly known and completely unknown.

In the following, Fig. 3 displays the evolution of $J(\hat{r}_k) = \sqrt{\sum_{k=k_0}^{k_0+L} \hat{r}_k^T \hat{r}_k}$ for both faulty case and fault-free case, respectively. It can be concluded from Fig. 3 that, when the fault occurs, the residual and the residual evaluation function have obvious change and the H_∞ performance indices for the error augmented system (5) in case 2 are better than those in case 3 and case 4.

According to the path in Fig. 1 and the residual threshold $J_{\mathrm{th}} = \sup_{d\in l_2, f=0} E[\sqrt{\sum_{k=k_0}^{k_0+L} \hat{r}_k^T \hat{r}_k}]$, for the four different TRM cases, the optimal H_∞ performance indices and the corresponding time steps for the FD are obtained in Tables 2 and 3. The filter gain is set to 0.1. From the computation results, it can be also shown that the FD capability in case 2 is stronger than that in case 3 and case 4. From the comparison results of the same-order FD filters, it is clear to see that the fault detection results in polytopic uncertain TRs are less conservative than those in incompletely known and completely unknown TRs. The more polytopic uncertain knowledge in the TRM, the faster sensitivity to faults will be taken and the better fault detection performance the filter can attain. The time steps to detect the fault have been shortened. Finally, comparing Tables 2 and 3, we can find that FD speed with the reduced-order filter is faster than that with full-order filter in the same case. Thus, it declares the effectiveness of the designed FD reduced-order filter for MJLSs with deficient transition information.

Table 2 Computation results for four different reduced-order FD filter cases

Transition rate matrix	$J_{\min}$	Time steps
Completely known (case 1)	2.0057	102
Polytopic uncertain (case 2)	2.5169	103
Partly known (case 3)	2.6306	105
Completely unknown (case 4)	3.3299	107

Table 3 Computation results for four different full-order FD filter cases

Transition rate matrix	$J_{\min}$	Time steps
Completely known (case 1)	2.0032	104
Polytopic uncertain (case 2)	2.4527	106
Partly known (case 3)	2.5062	107
Completely unknown (case 4)	3.2015	109

5 Conclusion

In this paper, a fault detection approach is proposed for discrete-time MJLSs with deficient transition information. The main contribution of our study is the introduction of Markov jump system with deficient transition information in fault detection reduced-order filter design. Special emphasis is polytopic uncertain entries have been included in deficient transition information. The underlying systems are more general, where the deficient transition descriptions are assumed to be completely known, polytopic uncertain, partly unknown, and completely unknown transition rates. Based on the linear matrix inequality approach and the linear convex optimization, a sufficient condition of FD reduced-order filter for MJLS with deficient transition information is obtained, such that the augmented error system is stochastically stable. Then, the changes of the fault signal approximately equal to the changes of the residual signal. Finally, a numerical simulation example has been given to illustrate the effectiveness of the proposed design approach. An interesting topic for future works includes fault detection and fault-tolerant control methods for nonhomogeneous Markov process in the nonlinear systems.

Competing interests
The authors declare that they have no competing interests.

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