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观测器为基础的多包传输网络化系统故障检测

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摘要: 研究了基于不确定马尔科夫模型的多包传输网络化系统故障检测问题. 通过引入传输矩阵形式, 部分转移概率矩阵元素未知的马尔科夫跳系统模型被用来描述相邻采样周期不同数据包传输时的相关特性. 基于获得的模型, 利用李雅普若夫方法和随机分析技巧, 建立了线性矩阵不等式形式充分条件, 所得扩展的误差系统满足随机稳定性和H_∞扰动水平. 特别的, 本文的结论可以包含经典马尔科夫模型和切换模型作为其特例. 最后通过仿真例子说明了所用方法的有效性.

关键词: 故障诊断; 网络化系统; 多包传输; 马尔科夫跳系统

中图分类号: TP273　　　**文献标识码**: A

Observer-based fault detection for networked systems with multiple packets transmission pattern

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Abstract: Fault detection problem of multiple packets transmission networked systems with uncertain Markovian jump system model is investigated. By introducing transmission matrix, we build Markovian jump system model with partly unknown transition probabilities to describe the interaction between different packet transmissions in adjacent sampling periods. Based on the obtained model, with the help of Lyapunov method and stochastic analysis techniques, we design mode-dependent fault detection filter in terms of linear matrix inequalities to stabilize stochastically the augmented error system in H-infinity framework. Corresponding results of classical Markovian jump system model and the switched system model can be included as our special cases. The effectiveness of the proposed method is demonstrated by simulation examples.

Key words: fault detection; networked systems; transmission of multiple packets; Markovian jump system

1 Introduction

For modern communication networked systems, physical plants, sensors, actuators and observers are always not located in the same place; thus observer signals are transmitted from one place to another through network[1]. Usually, single packet transmission[2–3] and multiple packets transmission[4–6] are two kinds of data transmission pattern on network-based systems. Although this kind of network-based information transmission systems have many attractive advantages, the introduction of network inevitably brings communication constraints to the systems, which all might be ended up in poor performance or fault.

On the other hand, fault detection of large-scale complex systems is an active research field[7–11]. Recently, fault detection of networked control systems with communication delays and/or missing measurements have been extensively considered by many researchers[12–14]. Actually, few has modeled multiple packets transmission networked systems as Markovian jump systems, and almost no attention has been paid to the study of fault detection for Markovian networked systems with partially unknown transition probabilities, which motivates our investigation.

Different from the previous studies on multiple packets transmission with deterministic systems model[1,6] and Bernoulli random model[4–5], in this paper, Markov chain is introduced to describe the interaction in adjacent sampling period, and Markovian jump systems model with partly unknown transition probabilities is established. Based on the obtained model, by utilizing mode-dependent fault detection filter such as residual generator, fault detection of multiple packets transmission networked systems is formulated as an H_∞ attenuation problem. Furthermore, sufficient conditions for the existence of mode-dependent observer gain matrices and residual weighting matrices are acquired in terms of certain linear matrix inequalities (LMIs), and explicit parameters are characterized if these LMIs are feasible. Finally, simulation examples are presented to demonstrate the effectiveness of the proposed method.

2 Problem statement

Consider the following networked systems:

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$$\begin{cases} x(k+1) = Ax(k) + B_1 d(k) + B_2 f(k), \\ y(k) = Cx(k) + D_1 d(k) + D_2 f(k), \end{cases} \quad (1)$$

where $x(k) \in \mathbb{R}^n$ is the plant's state, $y(k) \in \mathbb{R}^m$ is the outputs. $d(k) \in \mathbb{R}^s$ and $f(k) \in \mathbb{R}^t$ are the disturbance input and fault, respectively, which belong to $\ell_2[0, \infty)$. A, B_1, B_2, C, D_1 and D_2 are known real matrices with the appropriate dimensions. In this paper, we investigate multiple packets transmission networked systems and split the measurement out $y(k)$ into κ separate packets, i.e. $y(k) = [Y_1^{\mathrm{T}}(k) \ \cdots \ Y_\kappa^{\mathrm{T}}(k)]^{\mathrm{T}}$, where $Y_i(k) \in \mathbb{R}^{p_i}$, $p_i \in \mathbb{Z}^+$ and $\sum\limits_{i=1}^{\kappa} p_i = m$.

Dinary-valued function $\sigma_l(k)(l = 1, 2, \cdots, \kappa)$ is used to describe the l-th packet transmission status at discrete time k, i.e., $\sigma_l(k) : \mathbb{Z} \to \{0, 1\}$, where 1 means successful data transmission and 0 means data loss. Specifically, the l-th packets output $Y_l(k)$ is available to observer only corresponding packet access the communication medium, i.e. $\sigma_l(k) = 1$. Otherwise, when $\sigma_l(k) = 0$, the output of l-th packets will be zero by the observer and $Y_l(k)$ will be ignored due to its being unavailable. If we regard $\bar{Y}_l(k)$ as the l-th packets signal received by the observer, we can describe the transmission dynamics of l-th packets as

$$\bar{Y}_l(k) = \sigma_l(k) Y_l(k), \ l = 1, 2, \cdots, \kappa. \quad (2)$$

For given κ, we define the transmission matrix as $M_\kappa \triangleq \{\sigma_1, \sigma_2, \cdots, \sigma_\kappa\}$. Specially, transmission matrix M_κ can be expressed as the following form:

$$\begin{cases} M_\kappa^{0,1} \triangleq \{0, 0, \cdots, 0\}, \\ M_\kappa^{1,1} \triangleq \{1, \underbrace{0, \cdots, 0}\}, \cdots, \\ M_\kappa^{1,\kappa} \triangleq \{\underbrace{0, \cdots, 0}, 0\}, \cdots, \\ M_\kappa^{\kappa-1,1} \triangleq \{\underbrace{1, \cdots, 1}, 0\}, \cdots, \\ M_\kappa^{\kappa-1,\kappa} \triangleq \{0, \underbrace{1, \cdots, 1}\}, \\ M_\kappa^{\kappa,1} \triangleq \{1, 1, \cdots, 1\}. \end{cases} \quad (3)$$

According to above discussion, we achieve the following dynamics model:

$$\bar{y}(k) = M_p^{\mu(k)} y(k), \quad (4)$$

where

$$M_\kappa^{\mu(k)} \in \{M_\kappa^{0,1}; M_\kappa^{1,1}, \cdots, M_\kappa^{1,\kappa}; \cdots; M_\kappa^{\kappa-1,1}, \cdots, M_\kappa^{\kappa-1,\kappa}; M_\kappa^{\kappa,1}\}$$

and

$$\bar{y}(k) = [\bar{Y}_1^{\mathrm{T}}(k) \ \ \bar{Y}_2^{\mathrm{T}}(k) \ \ \cdots \ \ \bar{Y}_\kappa^{\mathrm{T}}(k)]^{\mathrm{T}}.$$

Let $\mu(k)$ be a discrete-time homogeneous Markov chains, which takes values in a finite set $\Im = \{1, 2, \cdots, 2^\kappa\}$ with the transition probabilities matrix $\Lambda = (\rho_{ij})$ given by

$$\rho_{ij} = \mathrm{P}(\mu(k+1)|\mu(k)), \quad (5)$$

where $\rho_{ij} \geqslant 0$, $\forall i, j \in \Im$ and $\sum\limits_{j=1}^{2^\kappa} \rho_{ij} = 1$.

In this paper, an observer-based fault detection filter is constructed as residual generator:

$$\begin{cases} \hat{x}(k+1) = A\hat{x}(k) + L_{\mu(k)}(\bar{y}(k) - \hat{y}(k)), \\ \hat{y}(k) = C\hat{x}(k), \\ r(k) = V_{\mu(k)}(\bar{y}(k) - \hat{y}(k)), \end{cases} \quad (6)$$

where $\hat{x}(k) \in \mathbb{R}^n$ and $\hat{y}(k) \in \mathbb{R}^q$ represent the state and output estimation vectors, respectively, $r(k)$ is the residual signal. Observer gain matrices $L_{\mu(k)}$ and residual weighting matrices $V_{\mu(k)}$ will be designed. Fault detection filters with above structure is assumed to jump synchronously with the modes in (4), which is hereby mode-dependent.

Defining $e_1(k) = x(k) - \hat{x}(k)$, from (1)(4) and (5), we have

$$\begin{aligned} & e_1(k+1) = \\ & [A - L_{\mu(k)}C]e_1(k) - L_{\mu(k)}[M_\kappa^{\mu(k)} - I]Cx(k) + \\ & [B_1 - L_{\mu(k)} M_\kappa^{\mu(k)} D_1]d(k) + \\ & [B_2 - L_{\mu(k)} M_\kappa^{\mu(k)} D_2]f(k). \end{aligned} \quad (7)$$

Combining (1) and (7), denoting $r_e(k) = r(k) - f(k)$, $e(k) = [x^{\mathrm{T}}(k) \quad e_1^{\mathrm{T}}(k)]^{\mathrm{T}}$ and $\omega(k) = [d^{\mathrm{T}}(k) \ f^{\mathrm{T}}(k)]^{\mathrm{T}}$, we obtain the following augmented error system:

$$\begin{cases} e(k+1) = \bar{A}_{\mu(k)} e(k) + \bar{B}_{\mu(k)} \omega(k), \\ r_e(k) = \bar{C}_{\mu(k)} e(k) + \bar{D}_{\mu(k)} \omega(k), \end{cases} \quad (8)$$

where

$$\bar{A}_{\mu(k)} = \begin{bmatrix} A & 0 \\ -L_{\mu(k)} M_\kappa^{\mu(k)} C - L_{\mu(k)} C & A - L_{\mu(k)} C \end{bmatrix},$$

$$\bar{B}_{\mu(k)} = \begin{bmatrix} B_1 & B_2 \\ B_1 - L_{\mu(k)} M_\kappa^{\mu(k)} D_1 & B_2 - L_{\mu(k)} M_\kappa^{\mu(k)} D_2 \end{bmatrix},$$

$$\bar{C}_{\mu(k)} = [V_{\mu(k)} M_\kappa^{\mu(k)} C - V_{\mu(k)} C \quad V_{\mu(k)} C],$$

$$\bar{D}_{\mu(k)} = [V_{\mu(k)} M_\kappa^{\mu(k)} D_1 \quad V_{\mu(k)} M_\kappa^{\mu(k)} D_2 - I].$$

$r_e(k)$ is the residual error which contains information on both the time and location of the occurrence of stochastic fault.

Definition 1 Augmented filtering error system (8) is said to be stochastically stable for $\omega(k) = 0$ and initial condition $e(0)$ and $\mu(0)$, the following holds:

$$\mathrm{E}\{\sum_{k=0}^{\infty} \|e(k)\|^2 | e(0), \mu(0)\} < \infty.$$

With Definition 1, the original fault detection filter design problem for system (1) can be further converted into H_∞ filtering problem: find fault detection filter parameters $L_{\mu(k)}$ and $V_{\mu(k)}$ such that the augmented error systems (8) is stochastically stable and the infimum of γ is made as small as possible in the feasibility of

$$\sum_{k=0}^{\infty} \mathrm{E}\{\|r_e(k)\|^2\} \leqslant \gamma^2 \sum_{k=0}^{\infty} \|\omega(k)\|^2, \quad (9)$$

for all nonzero $\omega(k)$, where $\gamma > 0$ is a given disturbance attenuation level.

In this paper, threshold J_{th} and residual evolution function $J(r_e)(k)$ are selected as

$$J(r_e)(k) = \mathrm{E}\{\sum_{k=k_0}^{k_0+\varrho} r_e^{\mathrm{T}}(k) r_e(k)\}^{\frac{1}{2}},$$

$$J_{\mathrm{th}} = \sup_{d(k) \in \ell_2, f(k)=0} J(r_e)(k),$$

respectively, where k_0 is the initial evaluation time instant and ϱ is the evaluation time steps. Therefore, we can detect the fault by comparing $J_{\rm th}$ and $J(r_e)(k)$ with the following test:

$$\begin{cases} J(r_e)(k) \geqslant J_{\rm th} \Longrightarrow \text{alarm for fault}, \\ J(r_e)(k) < J_{\rm th} \Longrightarrow \text{no fault}. \end{cases} \tag{10}$$

3 Main results and proofs

In this section, sufficient conditions on the existence of OBFDF would be given, and mode-dependent fault detection filters would be constructed. For notation clarity, $\forall i \in \Im$, we denote $\Im = \Im_K^i + \Im_{UK}^i$ with $\Im_K^i \triangleq \{j : \rho_{ij}$ is known$\}$ and $\Im_{UK}^i \triangleq \{j : \rho_{ij}$ is unknown$\}$.

Theorem 1 For given scalar $\gamma > 0$, augmented filtering error system (8) with partly unknown transition probabilities is stochastically stable and satisfies the H_∞ noise attenuation level (9), if there exist matrices $P_i (i \in \Im)$ such that following matrix inequalities hold:

$$\begin{bmatrix} -P_i & 0 & \bar{C}_i^{\rm T} & \bar{A}_i^{\rm T}\Upsilon_j \\ * & -\gamma^2 I & \bar{D}_i^{\rm T} & \bar{B}_i^{\rm T}\Upsilon_j \\ * & * & -I & 0 \\ * & * & * & -\Upsilon_j \end{bmatrix} < 0, \tag{11}$$

$$\Upsilon_j \triangleq \begin{bmatrix} \Upsilon_{j1} & \Upsilon_{j2} \\ * & \Upsilon_{j3} \end{bmatrix} \triangleq \frac{1}{\rho_K^i} \sum_{j\in\Im_K^i} \rho_{ij} \begin{bmatrix} P_{j1} & P_{j2} \\ * & P_{j3} \end{bmatrix},$$
$$j \in \Im_K^i, \tag{12}$$

$$\Upsilon_j \triangleq \begin{bmatrix} P_{j1} & P_{j2} \\ * & P_{j3} \end{bmatrix},\ j \in \Im_{UK}^i, \tag{13}$$

where $\rho_K^i = \sum\limits_{j\in\Im_K^i} \rho_{ij}$.

Proof For the stability analysis of augmented error system (8), we construct the following stochastic Lyapunov function:

$$V(\Im(k)) = e^{\rm T}(k)P_{\mu(k)}e(k),$$

where $P_{\mu(k)} > 0 (\mu(k) \in \Im)$ are positive definite matrices. Calculating the difference of $V(x(k))$ along the augmented error system (8) with $\omega(k) = 0$ and taking the mathematical expectation, we have

$$\begin{aligned} &\mathrm{E}\{\Delta e V(\Im(k))\} = \\ &\mathrm{E}\{V(\Im(k+1)) - V(\Im(k))\} \leqslant \\ &e^{\rm T}(k+1) \sum_{j\in\Im_K} \rho_{ij} P_j e(k+1) - e^{\rm T}(k)P_i e(k) = \\ &e^{\rm T}(k+1)[\sum_{j\in\Im_K^i} \rho_{ij} + \sum_{j\in\Im_{UK}^i} \rho_{ij}]P_j e(k+1) - \\ &e^{\rm T}(k)[\sum_{j\in\Im_K^i} \rho_{ij} + \sum_{j\in\Im_{UK}^i} \rho_{ij}]P_i e(k) = \\ &e^{\rm T}(k)[\vec{A}_i{}^{\rm T} + \sum_{j\in\Im_{UK}^i} \rho_{ij}\vec{A}_j{}^{\rm T}]e(k), \end{aligned} \tag{14}$$

where $\vec{A}_i{}^{\rm T} = \bar{A}_i^{\rm T}\boldsymbol{P}_K^i\bar{A}_i - \rho_K^i P_i$, $\vec{A}_j{}^{\rm T} = \bar{A}_i^{\rm T}P_j\bar{A}_i - P_i$, $\boldsymbol{P}_K^i = \sum\limits_{j\in\Im_K^i} \rho_{ij}P_j$.

By Schur complement, (11) implies $\vec{A}_i < 0$ and $\vec{A}_j < 0$. Thus we have

$$\begin{aligned} &\mathrm{E}\{\Delta V(\Im(k))\} \leqslant \\ &-\sum_{j\in\Im_{UK}^i} \rho_{ij} \min_j \lambda_{\min}(-\vec{A}_j{}^{\rm T})e^{\rm T}(k)e(k) - \\ &\lambda_{\min}(-\vec{A}_i{}^{\rm T})e^{\rm T}(k)e(k). \end{aligned} \tag{15}$$

Then the stochastic stability can be obtained by similar main line as [14].

On the other hand, under zero initial condition, for $\omega(k) \neq 0$ in (8), we consider the following performance index:

$$J = \mathrm{E}\sum_{k=0}^{\infty} [r_e^{\rm T}(k)r_e(k) - \gamma^2 w^{\rm T}(k)w(k)]. \tag{16}$$

Let

$$\xi(k) = [e^{\rm T}(k) \quad \omega^{\rm T}(k)]^{\rm T},$$

we have

$$\begin{aligned} &J \leqslant \\ &\sum_{k=0}^{\infty} \mathrm{E}[\Delta V(k) + r_e^{\rm T}(k)r_e(k) - \gamma^2 w^{\rm T}(k)w(k)] = \\ &\sum_{k=0}^{\infty} \mathrm{E}[(\varXi_1^i + \rho_K^i\varXi_2^i) + \rho_{ij}(\bar{\varXi}_1^i + \rho_K^i\varXi_2^i)], \end{aligned} \tag{17}$$

where

$$\varXi_1^i = \begin{bmatrix} \bar{A}_i^{\rm T}\boldsymbol{P}_K^i\bar{A}_i & \bar{A}_i^{\rm T}\boldsymbol{P}_K^i\bar{B}_i \\ * & \bar{B}_i^{\rm T}\boldsymbol{P}_K^i\bar{B}_i \end{bmatrix},$$

$$\bar{\varXi}_1^i = \begin{bmatrix} \bar{A}_i^{\rm T}P_j\bar{A}_i & \bar{A}_i^{\rm T}P_j\bar{B}_i \\ * & \bar{B}_i^{\rm T}P_j\bar{B}_i \end{bmatrix},$$

$$\varXi_2^i = \begin{bmatrix} \bar{C}_i^{\rm T}\bar{C}_i - P_i & \bar{C}_i^{\rm T}\bar{D}_i \\ * & \bar{D}_i^{\rm T}\bar{D}_i - \gamma^2 I \end{bmatrix}.$$

By Schur complement, (11) is equivalent to $(\varXi_1^i + \rho_K^i\varXi_2^i) + \rho_{ij}(\bar{\varXi}_1^i + \rho_K^i\varXi_2^i) < 0$, which implies $J < 0$, that is $\mathrm{E}\{\|r_e(k)\|_2\} \leqslant \gamma\|\omega(k)\|_2$, so the proof is completed.

Theorem 2 For given scalar $\gamma > 0$, if there exist matrices $P_{i1}, P_{i2}, P_{i3}, \bar{L}_i, \bar{V}_i, X_i, Y_i, U_i (i \in \Im)$, such that the following LMIs hold:

$$\begin{bmatrix} \varTheta_{11}^i & 0 & \varTheta_{12}^i \\ * & \varTheta_{22}^i & \varTheta_{23}^i \\ * & * & \varTheta_{33}^i \end{bmatrix} < 0, \tag{18}$$

where

$$\varTheta_{33}^i = \begin{bmatrix} -I & 0 & 0 \\ * & \Upsilon_{1i} - X_i - X_i^{\rm T} & \Upsilon_{2i} - Y_i - U_i^{\rm T} \\ * & * & \Upsilon_{3i} - Y_i - Y_i^{\rm T} \end{bmatrix},$$

$$\varTheta_{12}^i = \begin{bmatrix} \varTheta_{121}^i & A^{\rm T}X_i^{\rm T} - \varTheta_{122}^i & A^{\rm T}U_i^{\rm T} - \varTheta_{122}^i \\ C^{\rm T}\bar{V}_i^{\rm T} & A^{\rm T}Y_i^{\rm T} - C^{\rm T}\bar{L}_i^{\rm T} & A^{\rm T}Y_i^{\rm T} - C^{\rm T}\bar{L}_i^{\rm T} \end{bmatrix},$$

$$\varTheta_{23}^i = \begin{bmatrix} D_1^{\rm T}M_\kappa^i\bar{V}_i^{\rm T} & B_1^{\rm T}X_i^{\rm T} + \varTheta_{231}^i & B_1^{\rm T}U_i^{\rm T} + \varTheta_{231}^i \\ C^{\rm T}\bar{V}_i^{\rm T} & B_2^{\rm T}X_i^{\rm T} + \varTheta_{232}^i & B_2^{\rm T}U_i^{\rm T} + \varTheta_{232}^i \end{bmatrix},$$

$$\varTheta_{22}^i = \mathrm{diag}\{-\gamma^2 I, -\gamma^2 I\},$$
$$\varTheta_{121}^i = C^{\rm T}M_\kappa^i\bar{V}_i^{\rm T} - C^{\rm T}\bar{V}_i^{\rm T},$$
$$\varTheta_{122}^i = C^{\rm T}\bar{L}_i^{\rm T} + C^{\rm T}M_\kappa^i\bar{L}_i^{\rm T},$$
$$\varTheta_{231}^i = B_1^{\rm T}Y_i^{\rm T} - D_1^{\rm T}M_\kappa^i\bar{L}_i^{\rm T},$$
$$\varTheta_{232}^i = B_2^{\rm T}Y_i^{\rm T} - D_2^{\rm T}M_\kappa^i\bar{L}_i^{\rm T}.$$

Then, the augmented error system (8) is stochastically stable (or stable for any switching sequence if $\Im_K^i = \varnothing$, for all $i \in \Im$) with H_∞ attenuation performance. Moreover, if LMIs (18) have feasible solution, mode-dependent filters is given by

$$L_i = Y_i^{-1}\bar{L}_i,\ V_i = \bar{V}_i,\ i \in \Im. \tag{19}$$

Proof Denoting $J = \mathrm{diag}\{I, I, I, \Upsilon_j^{-1}R_i^{\mathrm{T}}\}$, pre- and post multiplying (11) by J^{T} and J, respectively, we have

$$\begin{bmatrix} -P_i & 0 & \bar{C}_i^{\mathrm{T}} & \bar{A}_i^{\mathrm{T}}R_i^{\mathrm{T}} \\ * & -\gamma^2 I & \bar{D}_i^{\mathrm{T}} & \bar{B}_i^{\mathrm{T}}R_i^{\mathrm{T}} \\ * & * & -I & 0 \\ * & * & * & -R_i^{\mathrm{T}}\Upsilon_j^{-1}R_i^{\mathrm{T}} \end{bmatrix} < 0. \quad (20)$$

For an arbitrary matrix $R_i = \begin{bmatrix} X_i & Y_i \\ U_i & Y_i \end{bmatrix}$, $i \in \Im$, assuming Y_i is inverse, we have the following fact:

$$\begin{cases} (\frac{1}{\rho_K^1}\boldsymbol{P}_K^i - R_i)(\frac{1}{\rho_K^1}\boldsymbol{P}_K^i)^{-1}(\frac{1}{\rho_K^1}\boldsymbol{P}_K^i - R_i)^{\mathrm{T}} \geqslant 0, \\ (P_j - R_i)P_j^{-1}(P_j - R_i)^{\mathrm{T}} \geqslant 0. \end{cases} \quad (21)$$

Then, we have $\Upsilon_j - R_i - R_i^{\mathrm{T}} \geqslant -R_i\Upsilon_j^{-1}R_i^{\mathrm{T}}$, and (20) can rewrite as

$$\begin{bmatrix} -P_i & 0 & \bar{C}_i^{\mathrm{T}} & \bar{A}_i^{\mathrm{T}}R_i^{\mathrm{T}} \\ * & -\gamma^2 I & \bar{D}_i^{\mathrm{T}} & \bar{B}_i^{\mathrm{T}}R_i^{\mathrm{T}} \\ * & * & -I & 0 \\ * & * & * & \Upsilon_j - R_i - R_i^{\mathrm{T}} \end{bmatrix} < 0. \quad (22)$$

Further define matrices variables

$$P_i = \begin{bmatrix} P_{i1} & P_{i2} \\ * & P_{i3} \end{bmatrix},\ \bar{L}_i = Y_iL_i,\ \bar{V}_i = V_i.$$

Replacing $\bar{L}_i = Y_iL_i$, $\bar{V}_i = V_i$ into (22), we readily obtain (18). The proof is completed.

Remark 1 As [15], the conclusions of Theorem 2 are comprehensive and which include traditional MJLS[11] and switched systems under arbitrary switching[10] as its special case. Thus the proposed method in this paper is more general.

Remark 2 Note that (18) are LMIs over both the matrix variables and the prescribed scalars γ^2. This implies that γ^2 can be included as optimization variables for LMIs (18), which allow us to obtain the minimum H_∞ attenuation level for the overall augmented error systems (8). The sub-optimal mode-dependent fault detection filter can be found by solving the following problem:

$$\min_{X_i, Y_i, U_i, P_i, \bar{L}_i, \bar{V}_i} \text{ s.t.(18)}, \quad (23)$$

4 Illustrative example

Consider the networked systems (1) with the following parameters:

$$A = \begin{bmatrix} -0.2 & 0 \\ 0.3 & -0.1 \end{bmatrix},\ C = \begin{bmatrix} 0.2 & -0.1 \\ 0 & 0.4 \end{bmatrix},$$

$$B_2 = \begin{bmatrix} 0.3 \\ 0 \end{bmatrix},\ B_1 = \begin{bmatrix} 0.4 \\ -0.18 \end{bmatrix},$$

$$D_1 = \begin{bmatrix} -0.1 \\ 0.18 \end{bmatrix},\ D_2 = \begin{bmatrix} 0 \\ 0.32 \end{bmatrix}.$$

If we investigate two packets transmission NCSs, according to the transmission pattern presented in Section 2, the transmission matrices can be constructed as

$$M_2^{2,1} \triangleq \mathrm{diag}\{1, 1\},\ M_2^{0,1} \triangleq \mathrm{diag}\{0, 0\},$$

$$M_2^{1,1} \triangleq \mathrm{diag}\{1, 0\},\ M_2^{1,2} \triangleq \mathrm{diag}\{0, 1\}.$$

Then corresponding transition probability matrix cases are listed in Table 1, where '?' means that element is unknown.

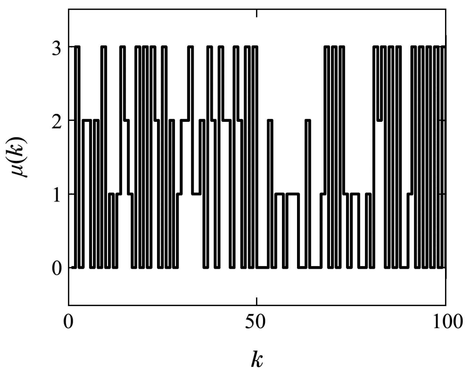
Table 1 Different transition probabilities matrices

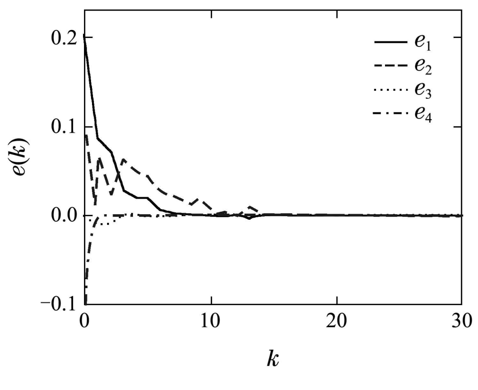
Completely known	Partly unknown	Partly unkown
$\begin{bmatrix} 0.1 & 0.2 & 0.3 & 0.4 \\ 0.2 & 0.6 & 0.1 & 0.1 \\ 0.5 & 0.1 & 0.2 & 0.2 \\ 0.6 & 0.1 & 0.2 & 0.1 \end{bmatrix}$	$\begin{bmatrix} 0.1 & 0.2 & 0.3 & 0.4 \\ ? & 0.6 & ? & 0.1 \\ 0.5 & ? & ? & ? \\ 0.6 & 0.1 & 0.2 & 0.1 \end{bmatrix}$	$\begin{bmatrix} ? & ? & ? & ? \\ ? & ? & ? & ? \\ ? & ? & ? & ? \\ ? & ? & ? & ? \end{bmatrix}$

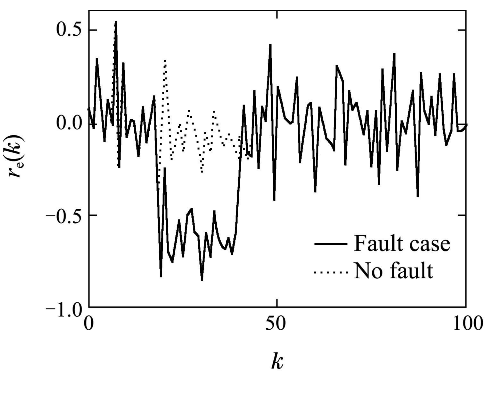
By solving (18), the sub-optimal performance indices are obtained for three different transition probabilities cases, and the computation results are listed in Table 2.

Table 2 Minimum γ^* for different transition cases

Completely known	Partly unknown	Partly unkown
0.9821	1.2374	1.6549







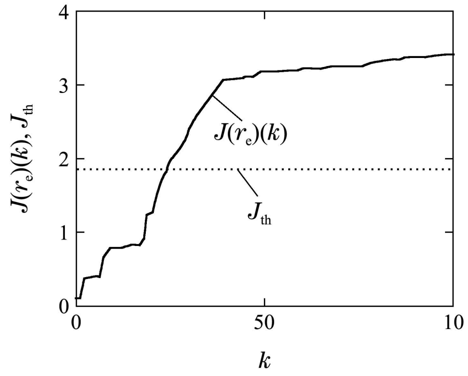


Fig. 1 Corresponding simulations of Case I

In this example, the H_∞ performance level is taken as $\gamma = 1.2$. By using the MATLAB LMI Toolbox, the mode-dependent fault detection filter $L_i^j, V_i^j (i = 1, 2, 3, 4; j = 1, 2, 3)$ can be designed. To demonstrate the effectiveness of designed filter, an unknown disturbance $d(k)$ is assumed to be band-limited white noise with power of 0.05. The fault signal $f(k)$ is simulated as a square wave of 1 amplitude that occurred from 20 to 40 steps. The initial values of the state of the augmented error system is chosen as $e(0) = [0.2\ \ -0.1\ \ 0\ \ 0.1]^{\mathrm{T}}$. For the possible realizations of modes $\mu(k)$ in case I, II and III, corresponding error response $e(k)$, residual estimation signal $r_e(k)$, threshold $J_{\rm th}$ and evolution of residual evaluation function $J(r_e)(k)$ are shown in Figs.1−3, respectively. For given $k_0 = 0$ and $\varrho = 100$, the threshold and residual evaluation function values are obtained in Table 3. From Table 3, we know that when $k =$ 26, 29 and 28, $J(r_e)(k) \geqslant J_{\rm th}$ for the first time, thus the fault can be detected by 6, 9 and 8 time steps after its occurrence, respectively. It is clearly observed from the simulation that the augmented error system (8) are stochastically stable with given H_∞ performance level, and the fault can also be detected effectively.

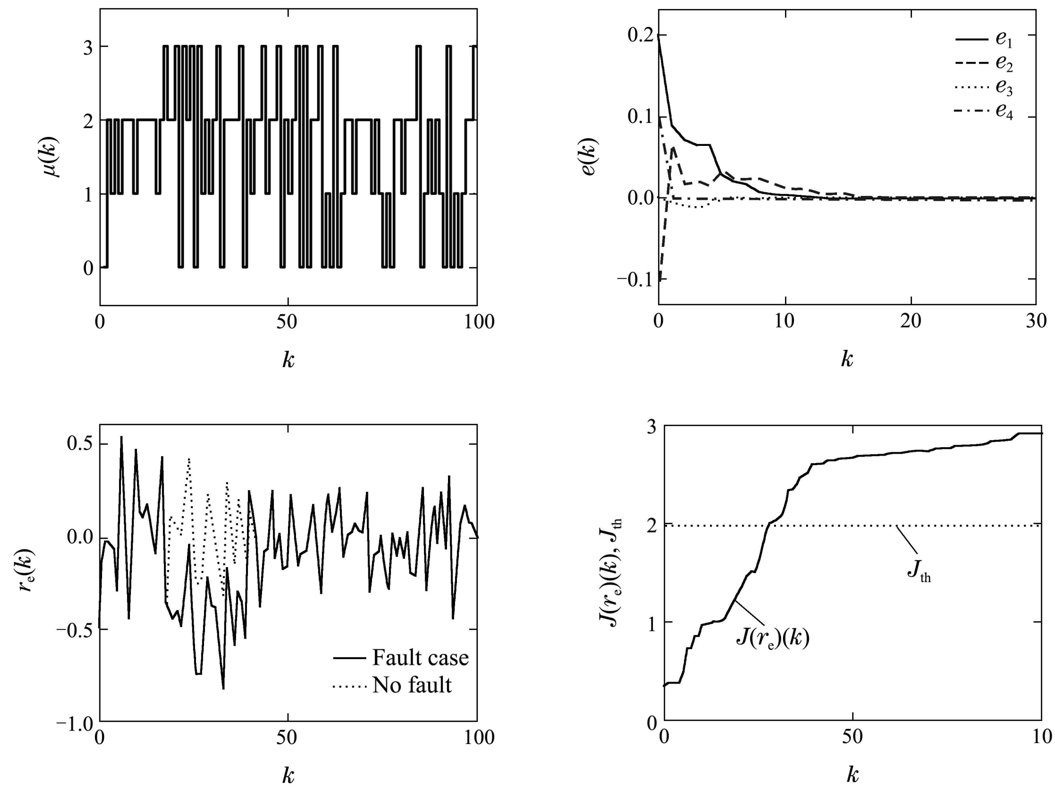
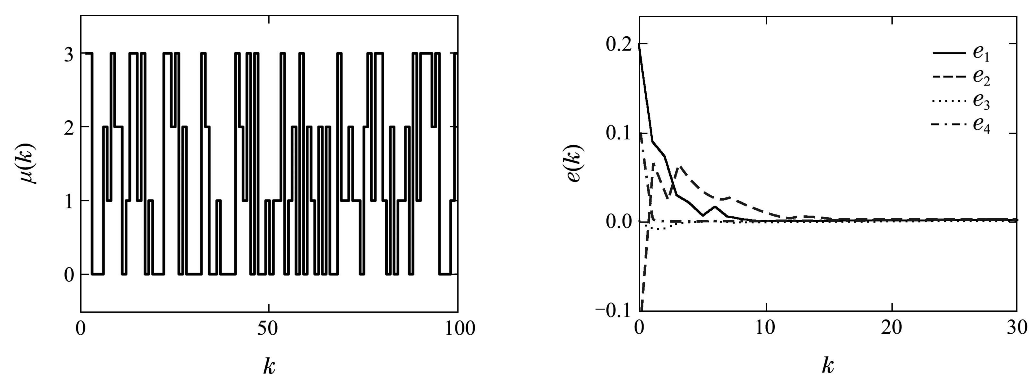


Fig. 2 Corresponding simulations of Case II



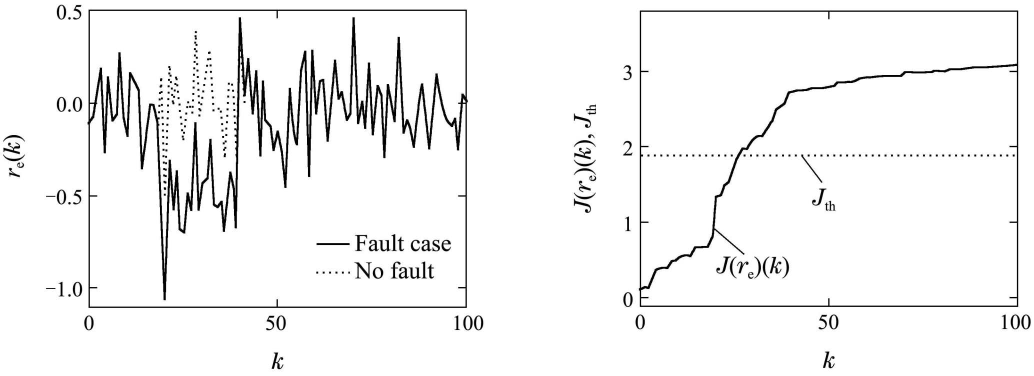


Fig. 3 Corresponding simulations of Case III

Table 3 Corresponding threshold $J_{\rm th}$ and residual evolution function value $J(r_e)(k)$ for different cases

Completely known	Partly unknown	Partly unkown
$J_{\rm th}=1.8594$ $J(r_e)(25)=1.8302\leqslant J_{\rm th}\leqslant$ $J(r_e)(26)=1.9684$	$J_{\rm th}=1.9688$ $J(r_e)(28)=1.9189\leqslant J_{\rm th}\leqslant$ $J(r_e)(29)=1.9985$	$J_{\rm th}=1.8798$ $J(r_e)(27)=1.8740\leqslant J_{\rm th}\leqslant$ $J(r_e)(28)=1.9628$

5 Conclusions

In this paper, the fault detection problem has been addressed for multiple packets transmission networked systems. Considering the interaction of different packets in adjacent sampling period and the difficulty in obtaining precise transition probabilities of Markovian jump systems, by introducing transmission matrix, Markovian jump system with partially unknown transition probabilities is introduced to model this kind of data transmission pattern. Then, we have derived a sufficient condition under which the augmented error system is stochastically stable and the residual estimation error satisfies performance constraint for all nonzero exogenous disturbances under the zero-initial condition. The main attribution is design mode-dependent observer-based fault detection filter such that the error between residual signal and fault signal is made as small as possible. Numerical example is given to illustrate the effectiveness of proposed techniques.

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