

## Guaranteed Cost Controller Design for Multirate Systems

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**Abstract:** This paper proposes a design method of a guaranteed cost controller for multirate systems. A class of a minimal order observer is used to design the robust controller via linear matrix inequality technique. A numerical example is given to illustrate the proposed method.

**Keywords:** guaranteed cost control, multirate systems, a minimal order observer, LMI

### 1. INTRODUCTION

Instability and bad performance can occur on a controlled system with uncertainties. Therefore, considerable interests have been attracted to studies of robust controller design in recent decades. Moreover, it is desirable to design a controller which not only achieves the stability of the uncertain system but also guarantees an adequate level of performance. One of the approaches to solve this problem is a guaranteed cost control method [1].

Multirate sampling schemes have long been the focus of interest by many control designers [2], [3], [4], [5]. This paper proposes a design method of a guaranteed cost controller for multirate systems. The controller is based on a state-space model and the state variable is estimated by a minimal order multirate observer. The design problem is expressed by matrix inequalities and solved by an iterative algorithm of a linear matrix inequality technique.

### 2. PROBLEM STATEMENT

Consider a discrete-time uncertain system in the form

$$\begin{aligned} \mathbf{x}(k+1) &= (A_0 + \Delta A_0)\mathbf{x}(k) + (B_0 + \Delta B_0)\mathbf{u}(k) \\ \mathbf{y}(k) &= C\mathbf{x}(k) \end{aligned} \quad (1)$$

Assume the output sampling period is greater than that of the input and only  $\mathbf{y}(kNT_s)$  is available, where  $N$  is a positive integer greater than one and  $T_s$  denotes a sampling period. Then, the general form of (1) can be written as follows

$$\begin{aligned} \mathbf{x}(k+N) &= (A + \Delta A)\mathbf{x}(k) + (B + \Delta B)\mathbf{v}(k) \\ \mathbf{y}(k) &= C\mathbf{x}(k) \end{aligned} \quad (2)$$

where

$$\begin{aligned} A &= A_0^N, \Delta A = (A_0 + \Delta A_0)^N - A_0^N, \\ B &= [B_0, A_0 B_0, \dots, A_0^{N-1} B_0], \\ \Delta B &= [\Delta B_0, (A_0 + \Delta A_0)(B_0 + \Delta B_0) - A_0 B_0, \dots, \\ &\quad (A_0 + \Delta A_0)^{N-1}(B_0 + \Delta B_0) - A_0^{N-1} B_0], \\ \mathbf{v}(k) &= [\mathbf{u}^T(k+N-1), \mathbf{u}^T(k+N-2), \dots, \mathbf{u}^T(k)]^T. \end{aligned}$$

Matrices  $A_0$ , and  $B_0$  are known constant real-valued matrices with appropriate dimensions, and  $C$  is restricted to the form of  $C = [O \ I_m]$ .

We assume that the parameter uncertainties  $\Delta A_0(k)$  and  $\Delta B_0(k)$  satisfy the following relations

$$\Delta A_0(k) = D_A F_A(k) E_A, \Delta B_0(k) = D_B F_B(k) E_B \quad (3)$$

where  $F_A(k)$  and  $F_B(k)$  are unknown time-varying and deterministic matrices satisfying

$$F_A^T(k) F_A(k) \leq I, F_B^T(k) F_B(k) \leq I \quad (4)$$

and  $D_A, E_A$  are constant real-valued known matrices with appropriate dimensions.

It is also assumed that the initial state variable  $\mathbf{x}(0)$  is unknown, but their mean and covariance are known, respectively as

$$E[\mathbf{x}(0)] = \mathbf{m}_0 \quad (5)$$

$$E[(\mathbf{x}(0) - \mathbf{m}_0)(\mathbf{x}(0) - \mathbf{m}_0)^T] = \Sigma_0 > O \quad (6)$$

where  $E[\cdot]$  denotes the expected value operator.

The problem considered here is to design a minimal order observer

$$\mathbf{z}(k+N) = D\mathbf{z}(k) + E\mathbf{y}(k) + \sum_{i=0}^{N-1} H_i \mathbf{u}(k+i) \quad (7)$$

$$\hat{\mathbf{x}}(k) = P\mathbf{z}(k) + W\mathbf{y}(k) \quad (8)$$

and a controller

$$\mathbf{v}(k) = K\hat{\mathbf{x}}(k) \quad (9)$$

with

$$K = \begin{bmatrix} K_{N-1} \\ \vdots \\ K_1 \\ K_0 \end{bmatrix}, A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}, D = A_{11} + LA_{21},$$

$$H_i = TA^{N-1-i}B, TA - DT = EC,$$

$$T = [I_{n-m} \ L], PT + WC = I_n, P = [I_{n-m} \ O]^T$$

so as to achieve an upper bound on the following quadratic performance index

$$\begin{aligned} E[J] &= \\ E \left[ \sum_{l=0} \{ \mathbf{x}^T(Nl) Q \mathbf{x}(Nl) + \mathbf{v}^T(Nl) R \mathbf{v}(Nl) \} \right] \end{aligned} \quad (10)$$

associated with the multirate systems (2), where  $Q$  and  $R$  are given symmetric positive-definite matrices.

### 3. MAIN RESULTS

Attention of this study is restricted to  $N = 2$ ,  $\Delta B_0 = 0$  for simplicity of description. The main result of this study is given by Theorem 1.

*Theorem 1.* If the following matrix inequalities optimization problem;  $\min \{\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3 + \gamma_4\}$  subject to

$$\begin{bmatrix} -S_1 + Q & 0 & 0 & K^T R & (A + BK)^T \\ 0 & -S_2 D^T S_2 & (KP)^T R & (BKP)^T \\ 0 & * & -S_2 & 0 & 0 \\ * & * & 0 & -R & 0 \\ * & * & 0 & 0 & -X \end{bmatrix} < 0 \quad (11)$$

$$\begin{bmatrix} \Psi & E_A^T & \Psi_1 & \Psi_2 & \Psi_3 & \Psi_4 & \Psi_5 & \Psi_6 & \Psi_7 & \Psi_8 & \Psi_9 \\ * & M_0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ * & 0 & M_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ * & 0 & 0 & M_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ * & 0 & 0 & 0 & M_3 & 0 & 0 & 0 & 0 & 0 & 0 \\ * & 0 & 0 & 0 & 0 & M_4 & 0 & 0 & 0 & 0 & 0 \\ * & 0 & 0 & 0 & 0 & 0 & M_5 & 0 & 0 & 0 & 0 \\ * & 0 & 0 & 0 & 0 & 0 & 0 & M_6 & 0 & 0 & 0 \\ * & 0 & 0 & 0 & 0 & 0 & 0 & 0 & M_7 & 0 & 0 \\ * & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & M_8 & 0 \\ * & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & M_9 \end{bmatrix} < 0 \quad (12)$$

$$\begin{aligned} \begin{bmatrix} -X_1 & S_1 A_0 D_A \\ * & -\delta_4 I \end{bmatrix} < 0, & \begin{bmatrix} -X_2 & S_1 D_A \\ * & -\delta_5 I \end{bmatrix} < 0, \\ \begin{bmatrix} -X_3 & S_1 D_A \\ * & -\delta_6 I \end{bmatrix} < 0, & \begin{bmatrix} -X_4 & S_1 D_A \\ * & -\delta_{11} I \end{bmatrix} < 0, \\ \begin{bmatrix} -X_5 & S_1 D_A \\ * & -\delta_{28} I \end{bmatrix} < 0, & \begin{bmatrix} -Y_1 & S_1 A_0 D_A \\ * & -\delta_{13} I \end{bmatrix} < 0, \\ \begin{bmatrix} -Y_2 & S_1 D_A \\ * & -\delta_{14} I \end{bmatrix} < 0, & \begin{bmatrix} -Y_3 & S_1 D_A \\ * & -\delta_{15} I \end{bmatrix} < 0, \\ \begin{bmatrix} -Y_4 & S_1 D_A \\ * & -\delta_{19} I \end{bmatrix} < 0, & \begin{bmatrix} -Y_5 & S_1 D_A \\ * & -\delta_{31} I \end{bmatrix} < 0, \end{aligned} \quad (13)$$

$$\begin{aligned} \sum_{k=1}^n e_{nk}^T \Theta_0 e_{nk} < \gamma_0, & \sum_{k=1}^m e_{mk}^T \Theta_1 e_{mk} < \gamma_1 \\ \sum_{k=1}^m e_{mk}^T \Theta_2 e_{mk} < \gamma_2, & \sum_{k=1}^m e_{mk}^T \Theta_3 e_{mk} < \gamma_3 \end{aligned} \quad (14)$$

$$\begin{bmatrix} -\gamma_4 & w_1^T Y^T & w_2^T Y^T & \dots & w_m^T Y^T \\ Y w_1 & -S_2 & & & \vdots \\ Y w_2 & & \ddots & & \vdots \\ \vdots & & & \ddots & \vdots \\ Y w_m & \dots & \dots & \dots & -S_2 \end{bmatrix} < 0 \quad (15)$$

where

$$\begin{aligned} \Psi &= (\delta_1 + \delta_3 \mu_3 + \mu_a + (\delta_c)_{inv} \epsilon_c + (\delta_e)_{inv} \epsilon_e + \mu_f \\ &+ \delta_4 + \delta_6 \mu_6 + \delta_9 \mu_9 + \mu_g + (\delta_i)_{inv} \mu_i \\ &+ (\delta_l)_{inv} \mu_l + \mu_m + \delta_{13} + \delta_{15} \mu_{15} + \delta_{16} \mu_{16} \\ &+ \delta_{18} \mu_{18} + \delta_{21} + \delta_{23} \mu_{23} + \delta_{24} \mu_{24} + \delta_{26} \mu_{26}) \\ &E_A^T E_A + (\delta_2 + (\delta_b)_{inv} + \mu_d + \delta_5 + (\delta_h)_{inv} \\ &+ \delta_j + \delta_{14} + \delta_{17} \mu_{17} + \delta_{22} + \delta_{25} \mu_{25}) \\ &(E_A A_0)^T E_A A_0, \end{aligned}$$

$$\begin{aligned} \Psi_1 &= A^T S_1 A_0 D_A, \quad \Psi_2 = A^T S_1 D_A, \\ \Psi_3 &= (E_A A_0)^T, \quad \Psi_4 = (BK)^T, \quad \Psi_5 = (E_A B_0 K_0)^T, \\ \Psi_6 &= (BKP)^T, \quad \Psi_7 = (E_A B_0 K_0 P)^T, \\ \Psi_8 &= Z_C A_0 D_A, \quad \Psi_9 = Z_C D_A, \\ M_0 &= -\text{diag}\{(\delta_b)_{inv}(\mu_b)_{inv}, (\delta_c)_{inv}(\mu_c)_{inv}, \\ &\delta_{7inv} \mu_{7inv}, (\delta_h)_{inv}(\mu_h)_{inv}, (\delta_i)_{inv}(\mu_i)_{inv}\}, \\ M_1 &= -\delta_1, \quad M_2 = -\text{diag}\{\delta_2, \delta_3, \delta_{10}, \delta_{27} inv\}, \\ M_3 &= -\text{diag}\{(\delta_e)_{inv}(\mu_e)_{inv}, \delta_{8inv} \mu_{8inv}, (\delta_l)_{inv} \mu_l\}, \\ M_4 &= -\text{diag}\{X_{1inv}, X_{2inv}, X_{3inv}, X_{4inv}, X_{5inv}\}, \\ M_5 &= -\text{diag}\{\delta_7, \delta_8, \delta_9 \epsilon_{9inv}, \delta_{10inv}, \delta_{11inv}, \\ &\delta_{12inv} \mu_{12inv}, \delta_{19inv}, \delta_{20inv} \mu_{20inv}\}, \\ M_6 &= -\text{diag}\{Y_{1inv}, Y_{2inv}, Y_{3inv}, Y_{4inv}, Y_{5inv}\}, \\ M_7 &= -\text{diag}\{\delta_{16}, \delta_{17}, \delta_{18} \epsilon_{18inv}, \delta_{20}, \delta_{24}, \delta_{25}, \\ &\delta_{26inv} \epsilon_{26inv}, \delta_{27}, \delta_{28}, \delta_{29}, \mu_{30inv}, \delta_{31}, \mu_{32}\}, \\ M_8 &= -\delta_{21}, \quad M_9 = -\text{diag}\{\delta_{22}, \delta_{23}, \delta_{29} inv\}, \\ Y &= S_2 L, \quad Z = [S_2 \quad Y], \\ \Theta_0 &= \frac{1}{2} (S_1 (\Sigma_0 + m_0 m_0^T) + (\Sigma_0 + m_0 m_0^T)^T S_1), \\ \Theta_1 &= \frac{1}{2} (S_2 \Sigma_{11} + \Sigma_{11} S_2), \quad \Theta_2 = \frac{1}{2} (Y \Sigma_{21} + \Sigma_{21}^T Y^T), \\ \Theta_3 &= \frac{1}{2} (Y^T \Sigma_{12} + \Sigma_{12}^T Y), \quad \Sigma_{22}^{1/2} = [w_1, w_2, \dots, w_m], \\ \Sigma_0 &= \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}, \quad e_{ik} = [0_{k-1}^T \quad 1 \quad 0_{i-k}^T]^T, \end{aligned}$$

has a set of solutions  $S_1 > 0$ ,  $X > 0$ ,  $X_l > 0$ ,  $(X_l)_{inv} > 0$ ,  $Y_l > 0$ ,  $(Y_l)_{inv} > 0$ , where  $l = 1, \dots, 5$ ,  $Y$ ,  $Z$ ,  $\gamma_0$ ,  $\gamma_1$ ,  $\gamma_2$ ,  $\gamma_3$ ,  $\gamma_4$  and positive scalars  $\delta_1$ ,  $\delta_2$ ,  $\delta_3$ , and so on which satisfy the inverse relation such as  $X = S_1^{-1}$ ,  $(X_l)_{inv} = X_l^{-1}$  and so on, then the minimal order observer-based control law (7)-(9) is a guaranteed cost controller which gives the minimum expected value of the guaranteed cost

$$\begin{aligned} E[J] &= E \left[ x^T(0) S_1 x(0) + \xi^T(0) S_2 \xi(0) \right] \\ &= \min \{ \gamma_0 + \gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 \} \end{aligned} \quad (16)$$

where  $\xi(k) = z(k) - T x(k)$  is the estimated error of the minimal order observer.

*Remark 1:* Since (11)-(13) have a constraint of the inverse relations and nonlinear terms, an iterative algorithm via LMI approach is introduced to solve [6].

Before giving a proof of theorem 1, a key lemma is introduced.

*Lemma 1.* [7] Given matrices  $D$  and  $E$  of appropriate dimensions, and  $F(k)$  be a matrix function satisfying  $F(k)^T F(k) \leq I$ , then for any  $\alpha > 0$ , the following inequality holds

$$D F(k) E + E^T F(k)^T E^T \leq \alpha D D^T + \alpha^{-1} E^T E.$$

*Proof of Theorem 1.*

Equations (2) and (7)-(9) yield the closed-loop system

$$\begin{bmatrix} x(k+2) \\ \xi(k+2) \end{bmatrix} = \begin{bmatrix} \Phi_1 & \Phi_2 \\ \Phi_3 & \Phi_4 \end{bmatrix} \begin{bmatrix} x(k) \\ \xi(k) \end{bmatrix} \quad (17)$$

where

$$\begin{aligned}\Phi_1 &= A + \Delta A(k) + BK, \quad \Phi_2 = (B + \Delta B(k))KP, \\ \Phi_3 &= -T\Delta A(k), \quad \Phi_4 = D - T\Delta B(k)KP.\end{aligned}$$

Consider a candidate of Lyapunov function as

$$V(k) = \mathbf{x}^T(k)S_1\mathbf{x}(k) + \boldsymbol{\xi}^T S_2 \boldsymbol{\xi}(k) \quad (18)$$

then,

$$\begin{aligned}\Delta V(k) &= V(k+2) - V(k) \\ &= \begin{bmatrix} \mathbf{x}^T(k) \\ \boldsymbol{\xi}^T(k) \end{bmatrix} \begin{bmatrix} \Lambda_1 & \Lambda_2 \\ * & \Lambda_3 \end{bmatrix} \begin{bmatrix} \mathbf{x}(k) \\ \boldsymbol{\xi}(k) \end{bmatrix} \quad (19)\end{aligned}$$

where

$$\begin{aligned}\Lambda_1 &= (A + \Delta A(k) + (B + \Delta B(k))K)^T S_1 \\ &\quad (A + \Delta A(k) + (B + \Delta B(k))K) \\ &\quad + (-T\Delta A(k))^T S_2 (-T\Delta A(k)) - S_1, \\ \Lambda_2 &= (A + \Delta A(k) + (B + \Delta B(k))K)^T S_1 \\ &\quad (B + \Delta B(k))KP + (-T\Delta A(k))^T S_2 \\ &\quad (D - T\Delta B(k)KP), \\ \Lambda_3 &= (D - T\Delta B(k)KP)^T S_2 (D - T\Delta B(k)KP) \\ &\quad + ((B + \Delta B(k))KP)^T S_1 (B + \Delta B(k))KP \\ &\quad - S_2.\end{aligned}$$

By introducing  $\bar{\mathbf{z}}(k)$  and  $\Omega$ , the equation (19) can be written as

$$\begin{aligned}\Delta V(k) &= \bar{\mathbf{z}}^T(k)\Omega\bar{\mathbf{z}}(k) \\ &\quad - \{\mathbf{x}^T(k)Q\mathbf{x}(k) + \mathbf{v}^T(k)R\mathbf{v}(k)\} \quad (20)\end{aligned}$$

where

$$\bar{\mathbf{z}}(k) = \begin{bmatrix} \mathbf{x}(k) \\ \boldsymbol{\xi}(k) \end{bmatrix}, \quad \Omega = \begin{bmatrix} \bar{\Lambda}_1 & \bar{\Lambda}_2 \\ * & \bar{\Lambda}_3 \end{bmatrix},$$

$$\begin{aligned}\bar{\Lambda}_1 &= (A + \Delta A(k) + (B + \Delta B(k))K)^T S_1 \\ &\quad (A + \Delta A(k) + (B + \Delta B(k))K) \\ &\quad + (-T\Delta A(k))^T S_2 (-T\Delta A(k)) - S_1 \\ &\quad + Q + K^T RK \\ \bar{\Lambda}_2 &= (A + \Delta A(k) + (B + \Delta B(k))K)^T S_1 \\ &\quad (B + \Delta B(k))KP + (-T\Delta A(k))^T S_2 \\ &\quad (D - T\Delta B(k)KP) + K^T RKP \\ \bar{\Lambda}_3 &= (D - T\Delta B(k)KP)^T S_2 (D - T\Delta B(k)KP) \\ &\quad + ((B + \Delta B(k))KP)^T S_1 (B + \Delta B(k))KP \\ &\quad - S_2 + (KP)^T RKP.\end{aligned}$$

Under the condition

$$\Omega < 0 \quad (21)$$

the equation (20) leads to

$$\Delta V(k) < -\{\mathbf{x}^T(k)Q\mathbf{x}(k) + \mathbf{v}^T(k)R\mathbf{v}(k)\} < 0 \quad (22)$$

for any  $\mathbf{x}(k) \neq \mathbf{0}$  and the closed-loop system is asymptotically stable.

Here, the condition (21) is investigated below. By applying Lemma 1 to (21), the parameter uncertainties can be written down

$$\begin{aligned}2\mathbf{x}^T(k)\Delta A^T(k)S_1 A\mathbf{x}(k) \\ \leq \mathbf{x}^T(k)\{(\delta_1 + \delta_3\mu_3)E_A^T E_A + \delta_1^{-1}A^T S_1 A_0 D_A \\ (S_1 A_0 D_A)^T A + \delta_2(E_A A_0)^T E_A A_0 \\ + (\delta_2^{-1} + \delta_3^{-1})A^T S_1 D_A D_A^T S_1 A\}\mathbf{x}(k) \quad (23)\end{aligned}$$

$$\begin{aligned}\mathbf{x}^T(k)\Delta A^T(k)S_1 \Delta A\mathbf{x}(k) \\ \leq \mathbf{x}^T(k)\{(\delta_b^{-1} + \mu_d + \delta_e\mu_e)(E_A A_0)^T E_A A_0 \\ + (\mu_a + \delta_b\mu_b + \delta_c\mu_c + \delta_c^{-1}\epsilon_c + \delta_e\mu_e + \mu_f) \\ E_A^T E_A\}\mathbf{x}(k) \quad (24)\end{aligned}$$

$$\begin{aligned}2\mathbf{x}^T(k)\Delta A^T(k)S_1 BK\mathbf{x}(k) \\ \leq \mathbf{x}^T(k)\{(\delta_4 + \delta_6\mu_6)E_A^T E_A + \delta_5(E_A A_0)^T E_A A_0 \\ + \delta_4^{-1}K^T B^T S_1 A_0 D_A (S_1 A_0 D_A)^T BK \\ + (\delta_5^{-1} + \delta_6^{-1})K^T B^T S_1 D_A (S_1 D_A)^T BK\}\mathbf{x}(k) \quad (25)\end{aligned}$$

$$\begin{aligned}2\mathbf{x}^T(k)\Delta A^T(k)S_1 \Delta B K\mathbf{x}(k) \\ \leq \mathbf{x}^T(k)\{(\delta_7\mu_7 + \delta_9\mu_9)E_A^T E_A \\ + \delta_8\mu_8(E_A A_0)^T E_A A_0 + (\delta_7^{-1} + \delta_8^{-1} + \delta_9^{-1}\epsilon_9) \\ (E_A B_0 K_0)^T E_A B_0 K_0\}\mathbf{x}(k) \quad (26)\end{aligned}$$

$$\begin{aligned}2\mathbf{x}^T(k)K^T \Delta B^T(k)S_1 A\mathbf{x}(k) \\ \leq \mathbf{x}^T(k)\{\delta_{10}(E_A B_0 K_0)^T E_A B_0 K_0 \\ + \delta_{10}^{-1}A^T S_1 D_A D_A^T S_1 A\}\mathbf{x}(k) \quad (27)\end{aligned}$$

$$\begin{aligned}2\mathbf{x}^T(k)K^T \Delta B^T(k)S_1 BK\mathbf{x}(k) \\ \leq \mathbf{x}^T(k)\{\delta_{11}(E_A B_0 K_0)^T E_A B_0 K_0 \\ + \delta_{11}^{-1}(BK)^T S_1 D_A D_A^T S_1 BK\}\mathbf{x}(k) \quad (28)\end{aligned}$$

$$\begin{aligned}2\mathbf{x}^T(k)K^T \Delta B^T(k)S_1 \Delta B(k)K\mathbf{x}(k) \\ \leq \mathbf{x}^T(k)\{\delta_{12}\mu_{12}(E_A B_0 K_0)^T E_A B_0 K_0\}\mathbf{x}(k) \quad (29)\end{aligned}$$

$$\begin{aligned}\mathbf{x}^T(k)\Delta A^T(k)T^T S_2 T\Delta A(k)\mathbf{x}(k) \\ \leq \mathbf{x}^T(k)\{(\mu_g + \delta_h\mu_h + \delta_i\mu_i + \delta_i^{-1}\epsilon_i + \delta_l^{-1}\epsilon_l + \mu_m) \\ E_A^T E_A + (\delta_h^{-1} + \delta_j + \delta_l\mu_l)E_A^T E_A\}\mathbf{x}(k) \quad (30)\end{aligned}$$

$$\begin{aligned}2\mathbf{x}^T(k)\Delta A^T(k)S_1 BKP\boldsymbol{\xi}(k) \\ \leq \mathbf{x}^T(k)\{(\delta_{13} + \delta_{15}\mu_{15})E_A^T E_A + \delta_{14}(E_A A_0)^T \\ E_A A_0\}\mathbf{x}(k) + \boldsymbol{\xi}^T(k)\{\delta_{13}^{-1}(E_A B_0 K_0 P)^T \\ S_1 A_0 D_A (S_1 A_0 D_A)^T E_A B_0 K_0 P + (\delta_{14}^{-1} + \delta_{15}^{-1}) \\ (E_A B_0 K_0 P)^T S_1 D_A (S_1 D_A)^T E_A B_0 K_0 P\}\boldsymbol{\xi}(k) \quad (31)\end{aligned}$$

$$\begin{aligned}2\mathbf{x}^T(k)\Delta A^T(k)S_1 \Delta B K P\boldsymbol{\xi}(k) \\ \leq \mathbf{x}^T(k)\{(\delta_{16}\mu_{16} + \delta_{18}\mu_{18})E_A^T E_A \\ + \delta_{17}\mu_{17}(E_A A_0)^T E_A A_0\}\mathbf{x}(k) \\ + \boldsymbol{\xi}^T(k)\{(\delta_{16}^{-1} + \delta_{17}^{-1} + \delta_{18}^{-1}\epsilon_{18})(E_A B_0 K_0 P)^T \\ E_A B_0 K_0 P\}\boldsymbol{\xi}(k) \quad (32)\end{aligned}$$

$$\begin{aligned}
& 2\mathbf{x}^T(k)K^T\Delta B^T(k)S_1BKP\xi(k) \\
& \leq \mathbf{x}^T(k)\{\delta_{19}(E_A B_0 K_0)^T E_A B_0 K_0\}\mathbf{x}(k) \\
& \quad + \xi^T(k)\{\delta_{19}^{-1}(BKP)^T S_1 D_A D_A^T S_1 BKP\}\xi(k) \quad (33)
\end{aligned}$$

$$\begin{aligned}
& 2\mathbf{x}^T(k)K^T\Delta B^T(k)S_1\Delta BKP\xi(k) \\
& \leq \mathbf{x}^T(k)\{\delta_{20}\mu_{20}(E_A B_0 K_0)^T E_A B_0 K_0\}\mathbf{x}(k) \\
& \quad + \xi^T(k)\{\delta_{20}^{-1}(E_A B_0 K_0 P)^T E_A B_0 K_0 P\}\xi(k) \quad (34)
\end{aligned}$$

$$\begin{aligned}
& -2\mathbf{x}^T(k)\Delta A^T(k)T^T S_2 D\xi(k) \\
& \leq \mathbf{x}^T(k)\{(\delta_{21} + \delta_{23}\mu_{23})E_A^T E_A \\
& \quad + \delta_{22}(E_A A_0)^T E_A A_0\}\mathbf{x}(k) \\
& \quad + \xi^T(k)\{\delta_{21}^{-1}Z_C A_0 D_A (Z_C A_0 D_A)^T \\
& \quad + (\delta_{22}^{-1} + \delta_{23}^{-1})Z_C D_A (Z_C D_A)^T\}\xi(k) \quad (35)
\end{aligned}$$

$$\begin{aligned}
& 2\mathbf{x}^T(k)\Delta A^T(k)T^T S_2 T\Delta B(k)KP\xi(k) \\
& \leq \mathbf{x}^T(k)\{(\delta_{24}\mu_{24} + \delta_{26}\mu_{26})E_A^T E_A \\
& \quad + \delta_{25}\mu_{25}(E_A A_0)^T E_A A_0\}\mathbf{x}(k) \\
& \quad + \xi^T(k)\{(\delta_{24}^{-1} + \delta_{25}^{-1} + \delta_{26}^{-1}\epsilon_{26}) \\
& \quad (E_A B_0 K_0 P)^T E_A B_0 K_0 P\}\xi(k) \quad (36)
\end{aligned}$$

$$\begin{aligned}
& 2\mathbf{x}^T(k)A^T S_1 \Delta B(k)KP\xi(k) \\
& \leq \mathbf{x}^T(k)\{\delta_{27}A^T S_1 D_A D_A^T S_1 A\}\mathbf{x}(k) \\
& \quad + \xi^T(k)\{\delta_{27}^{-1}(E_A B_0 K_0 P)^T E_A B_0 K_0 P\}\xi(k) \quad (37)
\end{aligned}$$

$$\begin{aligned}
& 2\mathbf{x}^T(k)K^T B^T S_1 \Delta B(k)KP\xi(k) \\
& \leq \mathbf{x}^T(k)\{\delta_{28}(BK)^T S_1 D_A D_A^T S_1 BK\}\mathbf{x}(k) \\
& \quad + \xi^T(k)\{\delta_{28}^{-1}(E_A B_0 K_0 P)^T E_A B_0 K_0 P\}\xi(k) \quad (38)
\end{aligned}$$

$$\begin{aligned}
& -2\xi^T(k)D^T S_2 T\Delta B(k)KP\xi(k) \\
& \leq \xi^T(k)\{\delta_{29}Z_C D_A (Z_C D_A)^T \\
& \quad + \delta_{29}^{-1}(E_A B_0 K_0 P)^T E_A B_0 K_0 P\}\xi(k) \quad (39)
\end{aligned}$$

$$\begin{aligned}
& 2\xi^T(k)(T\Delta B(k)KP)^T S_2 T\Delta B(k)KP\xi(k) \\
& \leq \xi^T(k)\{\mu_{30}(E_A B_0 K_0 P)^T E_A B_0 K_0 P\}\xi(k) \quad (40)
\end{aligned}$$

$$\begin{aligned}
& 2\xi^T(k)(BKP)^T S_1 T\Delta B(k)KP\xi(k) \\
& \leq \xi^T(k)\{\delta_{31}(BKP)^T S_1 D_A D_A^T S_1 BKP \\
& \quad + \delta_{31}^{-1}(E_A B_0 K_0 P)^T E_A B_0 K_0 P\}\xi(k) \quad (41)
\end{aligned}$$

$$\begin{aligned}
& 2\xi^T(k)(B(k)KP)^T S_1 \Delta B(k)KP\xi(k) \\
& \leq \xi^T(k)\{\mu_{32}(E_A B_0 K_0 P)^T E_A B_0 K_0 P\}\xi(k) \quad (42)
\end{aligned}$$

Since there are some inequalities in (23)-(42) that can not be built to LMIs directly, we define new variables to solve

these problems.

$$\begin{aligned}
& \frac{1}{\delta_4}S_1 A_0 D_A (S_1 A_0 D_A)^T \leq X_1, \quad \frac{1}{\delta_5}S_1 D_A (S_1 D_A)^T \leq X_2, \\
& \frac{1}{\delta_5}S_1 D_A (S_1 D_A)^T \leq X_3, \quad \frac{1}{\delta_{11}}S_1 D_A (S_1 D_A)^T \leq X_4, \\
& \delta_{28}S_1 D_A (S_1 D_A)^T \leq X_5, \\
& \frac{1}{\delta_{13}}S_1 A_0 D_A (S_1 A_0 D_A)^T \leq Y_1, \quad \frac{1}{\delta_{14}}S_1 D_A (S_1 D_A)^T \leq Y_2, \\
& \frac{1}{\delta_{15}}S_1 D_A (S_1 D_A)^T \leq Y_3, \quad \frac{1}{\delta_{19}}S_1 D_A (S_1 D_A)^T \leq Y_4, \\
& \delta_{31}S_1 D_A (S_1 D_A)^T \leq Y_5, \quad (43)
\end{aligned}$$

By using Schur complement, (23)-(42) lead to (12). Ignoring parameter uncertainties,  $\Omega$  in (20) equivalent to

$$\begin{bmatrix} -S_1 + Q & 0 & 0 & K^T R & (A + BK)^T S_1 \\ 0 & -S_2 & D^T S_2 (KP)^T R & (BKP)^T S_1 & \\ 0 & * & -S_2 & 0 & 0 \\ * & * & 0 & -R & 0 \\ * & * & 0 & 0 & -S_1 \end{bmatrix} < 0 \quad (44)$$

Pre- and post-multiplying (44) by  $\text{diag}(I, I, I, I, S_1^{-1})$  on both sides, denoting  $X = S_1^{-1}$  and using Schur Complement lead to (11). Further, summing (22) from 0 to  $\infty$  yields

$$\begin{aligned}
J &= \sum_{k=2i, i=0} (\mathbf{x}^T(k)Q\mathbf{x}(k) + \mathbf{v}^T(k)R\mathbf{v}(k)) \\
&< \mathbf{x}^T(0)S_1\mathbf{x}(0) + \xi^T(0)S_2\xi(0) \\
&= J^* \quad (45)
\end{aligned}$$

where  $i$  is positive integer and  $J^*$  denotes the guaranteed cost. Here, we consider the optimal expected value of the guaranteed cost. It is calculated as

$$E[J^*] = \text{tr}S_1 E[\mathbf{x}(0)\mathbf{x}^T(0)] + \text{tr}S_2 E[\xi(0)\xi^T(0)] \quad (46)$$

A relation between mean and covariance of  $\mathbf{x}(0)$  is given by

$$\Sigma_0 = E[\mathbf{x}(0)\mathbf{x}^T(0)] - \mathbf{m}_0\mathbf{m}_0^T \quad (47)$$

Substituting (47) into (46) results in

$$\begin{aligned}
E[J^*] &= \text{tr}S_1(\Sigma_0 + \mathbf{m}_0\mathbf{m}_0^T) \\
& \quad + \text{tr}S_2 E[(z(0) - T\mathbf{x}(0))(z(0) - T\mathbf{x}(0))^T] \quad (48)
\end{aligned}$$

Here, it is readily seen from (48) that

$$\begin{aligned}
& E[(z(0) - T\mathbf{x}(0))(z(0) - T\mathbf{x}(0))^T] \\
& = T\Sigma_0 T^T + (z(0) - T\mathbf{m}_0)(z(0) - T\mathbf{m}_0)^T, \quad (49)
\end{aligned}$$

Next, consider positive scalars  $\gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4$ , satisfying the following inequalities

$$\text{tr}S_1(\Sigma_0 + \mathbf{m}_0\mathbf{m}_0^T) < \gamma_0 \quad (50)$$

$$\text{tr}S_2\Sigma_{11} < \gamma_1 \quad (51)$$

$$\text{tr}S_2 L\Sigma_{21} < \gamma_2 \quad (52)$$

$$\text{tr}S_2\Sigma_{12}L^T < \gamma_3 \quad (53)$$

$$\text{tr}S_2 L\Sigma_{22}L^T < \gamma_4 \quad (54)$$

Minimizing  $\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3 + \gamma_4$  results in giving  $\min E[J^*]$ . By recalling  $\text{tr}(AB) = \text{tr}(BA)$ , (50)-(53) lead to (14). Next, by denoting  $\Sigma_{22}^{1/2} = [\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_m]$ , equation (54) is calculated as

$$\begin{aligned} \text{tr} S_2 L \Sigma_{22} L^T &= \mathbf{w}_1^T Y^T S_2^{-1} Y \mathbf{w}_1 + \mathbf{w}_2^T Y^T S_2^{-1} Y \mathbf{w}_2 \\ &\quad + \dots + \mathbf{w}_m^T Y^T S_2^{-1} Y \mathbf{w}_m \\ &= [\mathbf{w}_1^T Y^T \quad \mathbf{w}_2^T Y^T \quad \dots \quad \mathbf{w}_m^T Y^T] S_2^{-1} \begin{bmatrix} Y \mathbf{w}_1 \\ Y \mathbf{w}_2 \\ \vdots \\ Y \mathbf{w}_m \end{bmatrix} < \gamma_4 \end{aligned} \quad (55)$$

Further, Schur complement derives (15) from (55).  $\square$

It is noted that the inequalities (11)-(13) cannot be solved directly by LMI because they contain the matrices  $S_1, X, X_l, (X_l)_{inv}, Y_l, (Y_l)_{inv}$  and scalars such as  $\delta_7, \delta_{7inv}, \delta_8, \delta_{8inv}$  and so on which satisfy the inverse relations. In addition, nonlinear terms also appeared. Therefore, algorithm in [8] should be modified. Here, we apply the cone complementarity linearization approach and propose the iterative algorithm to solve.

#### 4. A NUMERICAL EXAMPLE

Consider a continuous-time system with the following transfer function

$$G(s) = \frac{1 + \beta}{s(s + 1 + \alpha)}$$

where  $\alpha$  and  $\beta$  are the uncertainties.

We can convert it to the state space form as follows.

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \begin{bmatrix} -1 - \alpha & 0 \\ 1 & 0 \end{bmatrix} \mathbf{x}(t) + \begin{bmatrix} 1 + \beta \\ 0 \end{bmatrix} \mathbf{u}(t) \\ \mathbf{y}(t) &= [0 \quad 1] \mathbf{x}(t) \end{aligned}$$

Then, the discrete-time form is

$$\begin{aligned} \mathbf{x}(k+1) &= \left\{ \begin{bmatrix} 1 - T_s & 0 \\ T_s & 1 \end{bmatrix} + \begin{bmatrix} \Delta a_1 & 0 \\ \Delta a_2 & 0 \end{bmatrix} \right\} \mathbf{x}(k) \\ &\quad + \left\{ \begin{bmatrix} T_s \\ 0 \end{bmatrix} + \begin{bmatrix} \Delta b_1 \\ \Delta b_2 \end{bmatrix} \right\} \mathbf{u}(k) \\ \mathbf{y}(k) &= [0 \quad 1] \mathbf{x}(k) \end{aligned}$$

with  $T_s = 0.1$ ,  $\Delta a_1 = 0.006$ ,  $\Delta a_2 = -0.006$ ,  $\Delta b_1 = \Delta b_2 = 0$ ,

The following parameters are given

$$\mathbf{m}_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \quad \Sigma_0 = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix}, \quad R = 0.01, \quad Q = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.2 \end{bmatrix}.$$

Applying Theorem 1 with  $j_{max} = 1000$ ,  $\gamma_{min} = 0.0001$ ,  $\kappa = 0.0001$  and initial  $\gamma = 2$ , there exist symmetric positive definite matrices and scalars

$$\begin{aligned} S_1 &= \begin{bmatrix} 0.59437490 & 0.06831873 \\ 0.06831873 & 0.59066350 \end{bmatrix}, \\ X &= \begin{bmatrix} 1.70510875 & -0.19722036 \\ -0.19722036 & 1.71582268 \end{bmatrix}, \end{aligned}$$

$$\begin{aligned} X_1 &= \begin{bmatrix} 1.01021505 & -0.01003115 \\ -0.01003115 & 1.00987028 \end{bmatrix}, \\ X_{1inv} &= \begin{bmatrix} 0.98998587 & 0.00983363 \\ 0.00983363 & 0.99032386 \end{bmatrix}, \\ X_2 &= \begin{bmatrix} 1.01266942 & -0.01244290 \\ -0.01244290 & 1.01224011 \end{bmatrix}, \\ X_{2inv} &= \begin{bmatrix} 0.98763825 & 0.01214048 \\ 0.01214048 & 0.98805712 \end{bmatrix}, \\ X_3 &= \begin{bmatrix} 1.01266945 & -0.01244292 \\ -0.01244292 & 1.01224015 \end{bmatrix}, \\ X_{3inv} &= \begin{bmatrix} 0.98763822 & 0.01214050 \\ 0.01214050 & 0.98805708 \end{bmatrix}, \end{aligned}$$

$$\begin{aligned} X_4 &= \begin{bmatrix} 1.01274069 & -0.01251263 \\ -0.01251263 & 1.01230841 \end{bmatrix}, \\ X_{4inv} &= \begin{bmatrix} 0.98757041 & 0.01220686 \\ 0.01220686 & 0.98799212 \end{bmatrix}, \\ X_5 &= \begin{bmatrix} 1.01274065 & -0.01251263 \\ -0.01251263 & 1.01230838 \end{bmatrix}, \\ X_{5inv} &= \begin{bmatrix} 0.98757044 & 0.01220686 \\ 0.01220686 & 0.98799215 \end{bmatrix}, \end{aligned}$$

$$\begin{aligned} Y_1 &= \begin{bmatrix} 1.01020000 & -0.01001977 \\ -0.01001977 & 1.00984678 \end{bmatrix}, \\ Y_{1inv} &= \begin{bmatrix} 0.99000041 & 0.00982286 \\ 0.00982286 & 0.99034668 \end{bmatrix}, \\ Y_2 &= \begin{bmatrix} 1.01265435 & -0.01243153 \\ -0.01243153 & 1.01221660 \end{bmatrix}, \\ Y_{2inv} &= \begin{bmatrix} 0.98765268 & 0.01212985 \\ 0.01212985 & 0.98807980 \end{bmatrix}, \\ Y_3 &= \begin{bmatrix} 1.01265439 & -0.01243155 \\ -0.01243155 & 1.01221662 \end{bmatrix}, \\ Y_{3inv} &= \begin{bmatrix} 0.98765264 & 0.01212987 \\ 0.01212987 & 0.98807978 \end{bmatrix}, \\ Y_4 &= \begin{bmatrix} 1.01272557 & -0.01250124 \\ -0.01250124 & 1.01228488 \end{bmatrix}, \\ Y_{4inv} &= \begin{bmatrix} 0.98758487 & 0.01219620 \\ 0.01219620 & 0.98801482 \end{bmatrix}, \\ Y_5 &= \begin{bmatrix} 1.01272556 & -0.01250124 \\ -0.01250124 & 1.01228487 \end{bmatrix}, \\ Y_{5inv} &= \begin{bmatrix} 0.98758488 & 0.01219620 \\ 0.01219620 & 0.98801482 \end{bmatrix}, \end{aligned}$$

$$\begin{aligned} \delta_7 &= 0.99999956, \quad \delta_{7inv} = 1.00000043, \\ \delta_8 &= 0.99999954, \quad \delta_{8inv} = 1.00000045, \\ \delta_{10} &= 1.01620314, \quad \delta_{10inv} = 0.98405521, \\ \delta_{11} &= 1.01881851, \quad \delta_{11inv} = 0.98152908, \\ \delta_{19} &= 1.01881845, \quad \delta_{19inv} = 0.98152913, \\ \delta_{20} &= 1.00000016, \quad \delta_{20inv} = 0.99999983, \\ \delta_{26} &= 1.22843365, \quad \delta_{26inv} = 0.81404477, \\ \delta_{27} &= 0.98405535, \quad \delta_{27inv} = 1.01620299, \end{aligned}$$

$$\delta_{29} = 0.99551922, \delta_{29inv} = 1.00450094,$$

$$\delta_{31} = 0.98152928, \delta_{31inv} = 1.01881829,$$

which satisfy LMIs in (11)-(15) and their inverse relations.

Further, we obtain a solution

$$L = 0.25348223,$$

$$K = \begin{bmatrix} -0.04861597 & 0.19639255 \\ -0.06175519 & -0.39112435 \end{bmatrix},$$

$$E = 0.51274725,$$

$$H_1 = 0.10000000, H_0 = 0.09253482,$$

$$W = \begin{bmatrix} -0.25348223 \\ 1.00000000 \end{bmatrix}, \bar{\gamma} = E[J^*] = 0.140625.$$

Figure 1 displays the transition of guaranteed cost. The mark + shows that a feasible solution cannot be obtained for the guaranteed cost candidate  $\bar{\gamma}$  and the optimal performance index is greater than +. Trajectories of states and estimate error are depicted in Figs. 2-3 with  $x(0) = [-0.1 \ 0.2]^T$ . The control inputs are illustrated in Fig. 4

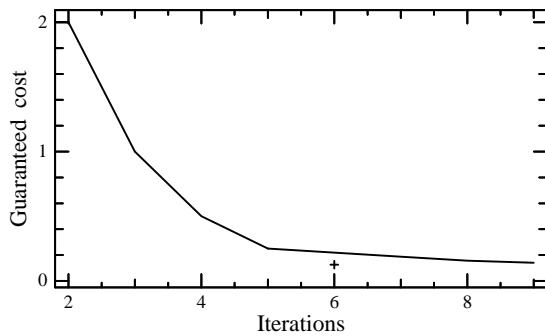


Fig. 1 Trajectory of the guaranteed cost.

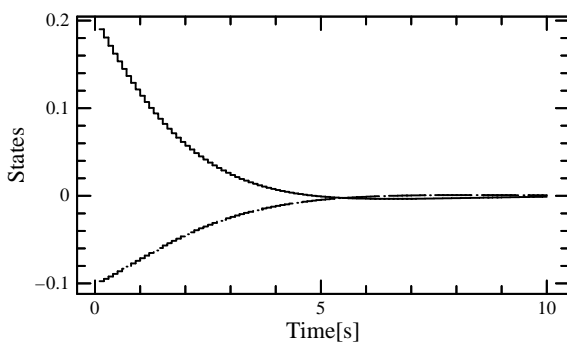


Fig. 2 Trajectories of states  $x_1$  (---) and  $x_2$  (-).

## 5. CONCLUSION

This paper discusses a minimal order observer-based guaranteed cost control design for multirate systems. A sufficient condition for the existence of state feedback guaranteed cost controllers is derived on the basis of the LMI feasible solutions.

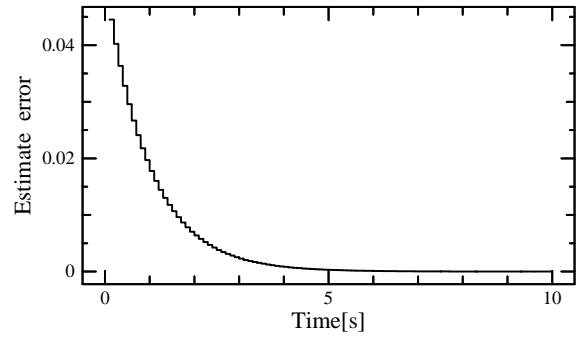


Fig. 3 Trajectory of estimate error  $\xi$ .

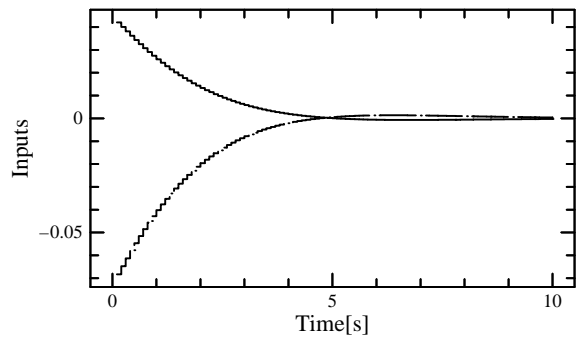


Fig. 4 Control inputs  $u(k)$  (---) and  $u(k+1)$  (-).

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