## Asychronous Control for Markov Jump Lure's Systems With Control Saturation

Abstract—The abstract here.

I. INTRODUCTION

II. PRELIMINARIES

Consider a class of discrete-time MJLS on a probability space  $(\Omega, \mathcal{F}, \mathcal{P})$ :

$$\begin{cases} x_{k+1} = A_{r(k)}x_k + F_{r(k)}\varphi(y_k) + B_{r(k)}u_k \\ + E_{r(k)}^x w_k, \quad y_k = C_{r(k)}x_k, \\ z_k = C_{r(k)}^z x_k + G_{r(k)}^z \varphi(y_k) + D_{r(k)}^z u_k \\ + E_{r(k)}^z w_k \end{cases}$$
(1)

where  $x_k \in \mathbb{R}^{n_x}, u_k \in \mathbb{R}^{n_u}, y_k \in \mathbb{R}^{n_y}, z_k \in \mathbb{R}^{n_z}$ , and  $w_k \in \mathbb{R}^{n_w}$  represent the state, the control input, the output related to the nonlinearity, the controlled output and the exogenous disturbance vector respectively.  $A_{r(k)}, F_{r(k)}, B_{r(k)}, E^x_{r(k)}, C^z_{r(k)}, G^z_{r(k)}, D^z_{r(k)}$  and  $E^z_{r(k)}$  represent the time-varying system matrices, all of which are preknown and real.  $\{r(k), k \geq 0\}$  is a Markov chain taking values in a positive integer set  $\mathcal{N} = \{1, 2, \dots, N\}$  with mode TPs:

$$\Pr\{r(k+1) = i | r(k) = i\} = \pi_{ii}$$
 (2)

Clearly, for all  $i, j \in \mathcal{N}$ ,  $\pi_{ij} \in [0, 1]$ , and  $\sum_{j=0}^{N} \pi_{ij} = 1$  for each mode i. The system matrices in (1) at instant k can be expressed as  $A_i, F_i, B_i, E_i^x, C_i^z, G_i^z, D_i^z$  and  $E_i^z$ , which are real known constant matrices with appropriate dimensions, and the related transition probability matrix is described as  $\Pi = \{\pi_{ij}\}.$ 

**Assumption 1:** The function  $\varphi(\cdot): \mathbb{R}^{n_y} \to \mathbb{R}^{n_y}$  satisfies:

- (1)  $\varphi(0) = 0$  and
- (2) there exists a diagonal positive definite matrix  $\Omega \in \mathbb{R}^{p \times p}$  such that:

$$\varphi_{(\ell)}(y)[\varphi(y) - \Omega y]_{(\ell)} \le 0. \tag{3}$$

where for all  $y \in \mathbb{R}^p$ ,  $\ell \in \{1, ..., p\}$ . And in this case we say that the nonlinearity  $\varphi(\cdot)$  satisfies it's own cone bounded sector conditions and to be decentralized. According to (3) we have:

$$SC(y, \Lambda) := \varphi'(y)\Lambda[\varphi(y) - \Omega y] \le 0,$$
 (4)

where  $\Lambda$  is any diagonal positive semidefinite matrix, and  $\Omega$  is pre-given. From the Assumption 1, we get:

$$[\Omega y]_{(\ell)}[\varphi(y) - \Omega y]_{(\ell)} \le 0, \tag{5}$$

which implies:

$$0 \le \varphi'(y) \Lambda \varphi(y) \le \varphi'(y) \Lambda \Omega y \le y' \Omega \Lambda \Omega y \tag{6}$$

**Definition 1:** System (1) is said to be locally stochastically stable if for  $w_(k) = 0$  and any initial condition  $x_0 \in \mathcal{D}_0$ ,  $r_0 \in \mathcal{N}$ , the following formulation holds:

$$||x||_2^2 = \sum_{k=0}^{\infty} \mathbb{E}[||x_k||^2] < \infty.$$
 (7)

Where in this case the set  $\mathcal{D}_0 \subset \mathbb{R}^p$  is said to be the domain of stochastic stability of the origin.

Define  $\mathcal{F}_k$  as the  $\sigma$ -field generated by the random variables  $x_k$  and r(k). We define next the class of exogenous disturbances with bounded energy and the finite  $\ell_2$ -induced norm.

**Definition 2**: For  $\gamma > 0$ , set  $W_{\gamma}$  is defined as follows:

$$\mathcal{W}_{\gamma} := \{ w = \{ w_k \}_{k \in \mathbb{N}}; w_k \in \mathbb{R}^m, k \in \mathbb{N}, w_k \text{ is}$$

$$\mathcal{F}_k\text{-measureable, and } \|w\|_2^2 = \sum_{k=0}^{\infty} \mathbb{E}(\|w_k\|)^2 < \frac{1}{\gamma} \}.$$
 (8)

The finite  $\ell_2$ -induced gain associated with the closed-loop system (1) with  $x_0=0$  between the disturbance  $w=\{w_k\}_{k\in\mathbb{N}}$  and controlled output  $z=\{z_k\}_{k\in\mathbb{N}}$  is equal or less than  $\sqrt{\varrho}$  if for every  $w\in\mathcal{W}_\gamma$  then we have

$$\frac{1}{\varrho} \|z\|_2^2 = \frac{1}{\varrho} \sum_{k=0}^{\infty} \mathbb{E} \left[ \|z_k\|^2 \right] \le \|w\|_2^2 = \sum_{k=0}^{\infty} \mathbb{E} \left[ \|w_k\|^2 \right]. \tag{9}$$

In this paper, we consider the following controller:

$$u_k = K_{\sigma(k)} x_k + \Gamma_{\sigma(k)} \varphi(y_k) \tag{10}$$

where  $K_{\sigma(k)} \in \mathbb{N}^{n_u \times n_x}$  is a time-varying controller gain matrix, and  $\Gamma_{\sigma(k)} \in \mathbb{N}^{n_u \times n_y}$  is a time-varying nonlinear output feedback gain matrix. The parameter  $\{\sigma(k), k \geq 0\}$  takes values in another pre-given positive integer set, which is marked as  $\mathcal{M} = \{1, 2, \dots, M\}$  subject to the pre-known conditional probability matrix  $\Phi = \{\mu_{im}\}$ , the probabilities of which are defined by

$$\Pr\{\sigma(k) = \phi | r(k) = i\} = \mu_{i\phi}. \tag{11}$$

Where for all  $i \in \mathcal{N}, \phi \in \mathcal{M}, \mu_{i\phi} \in [0, 1]$ , and  $\sum_{\phi=1}^{M} \mu_{i\phi} = 1$  for each  $i \in \mathcal{N}$ .

Combing the asynchronous controller (10) and system (1) we have the following closed system:

$$\begin{cases} x_{k+1} = \bar{A}_{i\theta}x_k + \bar{F}_{i\theta}\varphi_i(C_ix_k) + E_i^x w_k \\ z_k = \bar{C}_{i\theta}x_k + \bar{G}_{i\theta}\varphi_i(C_ix_k) + E_i^z w_k \end{cases}$$
(12)

Where, for  $i \in \mathcal{N}, \phi \in \mathcal{M}$ 

$$\begin{split} \bar{A}_{i\phi} &= A_i + B_i K_{\phi}, \qquad \bar{F}_{i\phi} = F_i + B_i \Gamma_{i\phi} \\ \bar{C}^z_{i\phi} &= C^z_i + D^z_i K_{\phi}, \qquad \bar{G}^z_{i\phi} = G^z_i + D^z_i \Gamma_{\phi} \end{split}$$

III. MAIN RESULT

$$\begin{cases} x_{k+1} = \bar{A}_{i\theta}x_k + \bar{F}_{i\theta}\varphi_i(C_ix_k) + E_i^x w_k \\ z_k = \bar{C}_{i\theta}x_k + \bar{G}_{i\theta}\varphi_i(C_ix_k) + E_i^z w_k \end{cases}$$

System (12) with  $x_0=0$  and  $w_k=0$  is stochastically stable, if for all  $i\in\mathcal{N}$  and  $\phi\in\mathcal{M}$ , there exist positive definite matrices  $\bar{P}_i\in\mathbb{R}^{n_x\times n_x},\ R_{i\phi}\in\mathbb{R}^{(n_x+n_y)\times (n_x+n_y)}$ , matrices  $K_\phi\in\mathbb{R}^{n_u\times n_x},\ \Gamma_\phi\in\mathbb{R}^{n_u\times n_y}$  and positive semidefinite matrix  $T_i\in\mathbb{R}^{n_y}$  to ensure (13) and (14) hold.

$$\begin{bmatrix} -R_{i\theta} & \mathscr{H}_{i\phi} \\ * & \mathscr{P}_i \end{bmatrix} < 0 \tag{13}$$

$$\begin{bmatrix} \mathcal{S}_{i\phi} & \mathcal{N}_{i\phi} \\ * & \mathcal{Z}_{i\phi} \end{bmatrix} < 0 \tag{14}$$

where

$$\mathcal{H}_{i\phi} = \begin{bmatrix} \sqrt{\pi_{i1}} \hat{A}_{i\phi} \\ \sqrt{\pi_{i2}} \hat{A}_{i\phi} \\ \vdots \\ \sqrt{\pi_{i_N}} \hat{A}_{i\phi} \end{bmatrix}, \mathcal{P}_{i\phi} = \operatorname{diag} \{ -\bar{P}_1, -\bar{P}_2, \dots, -\bar{P}_N \}$$

$$\hat{A}_{i\theta} = \begin{bmatrix} \bar{A}_{i\theta} & \bar{F}_{i\theta} \end{bmatrix}$$

$$\mathcal{S}_{i\phi} = \begin{bmatrix} -P_i & 0 \\ * & H_{i\phi} \end{bmatrix}$$

$$\mathcal{N}_{i\phi} = \begin{bmatrix} \sqrt{u_{i1}} \begin{bmatrix} \bar{P}_i \\ R_{i1} \end{bmatrix} & \dots & \sqrt{u_{iM}} \begin{bmatrix} \bar{P}_i \\ R_{iM} \end{bmatrix} \end{bmatrix}$$

$$\mathcal{L}_{i\phi} = \operatorname{diag} \left\{ \begin{bmatrix} -I \\ -R_{i1} \end{bmatrix}, \dots, \begin{bmatrix} -I \\ -R_{iM} \end{bmatrix} \right\}$$

$$H_{i\theta} = \begin{bmatrix} -I & C_i' \Omega_i T_i \\ * & -2T_i \end{bmatrix}$$

Proof: Construct a Lyapunov function in the form of (15).

$$V(k, x_k, r(k)) = x_k' P_{r(k)} x_k$$
 (15)

Where  $P_{r(k)}=\bar{P}_{r(k)}^{-1}$ . Let  $\mathbb{E}\{\Delta V(k)\}=\mathbb{E}\{V(k+1,x_{k+1},r(k+1)=j|x_k,r(k)=i\}-V(k,x_k,i)$  and it is easy to find that

$$\mathbb{E}\{\Delta V(k)\} = \mathbb{E}\{x_{k+1}^{'} X_{i} x_{k+1}\} - V(k, x_{k}, i)$$
 (16)

Where  $X_i = \sum_{j=1}^N \pi_{ij} P_j$ . Based on system (12) we can further obtain

$$\mathbb{E}\{x_{k+1}'X_{i}x_{k+1}\} = \sum_{\phi=1}^{M} u_{i\phi}\hat{x}_{k}'\hat{A}_{i\phi}'X_{i}\hat{A}_{i\phi}\hat{x}_{k}$$

$$= \hat{x}_{k}' \Big(\sum_{\phi=1}^{M} u_{i\phi}\hat{A}_{i\phi}'X_{i}\hat{A}_{i\phi}\Big)\hat{x}_{k}$$
(17)

Where  $\hat{x}_{k} = (x_{k}^{'}, \varphi_{i}^{'}(C_{i}x_{k}))^{'}$ . Which implies

$$\mathbb{E}\{\Delta V(k)\} = \hat{x}_k' \Big( \sum_{\phi=1}^M u_{i\phi} \hat{A}_{i\phi}' X_i \hat{A}_{i\phi} \Big) \hat{x}_k - V(k, x_k, i)$$
 (18)

Denoting  $h_{i\phi} = \text{diag}\{P_i, I_{n_x+n_y}, \{\text{diag}(I_{n_x}, R_{i\phi}^{-1})_{\phi=1}^M\}\}$  and using  $h_{i\phi}$  to pre- and post-multiplying the inequality given in (14), respectively, then we can get

$$\begin{bmatrix} \begin{bmatrix} -P_i & 0 \\ * & H_{i\phi} \end{bmatrix} & \sqrt{u_{i1}} \begin{bmatrix} I \\ & I \end{bmatrix} & \cdots & \sqrt{u_{iM}} \begin{bmatrix} I \\ & I \end{bmatrix} \\ \sqrt{u_{i1}} \begin{bmatrix} I \\ & I \end{bmatrix} & \begin{bmatrix} -I \\ & -R_{i1}^{-1} \end{bmatrix} & \\ \vdots & & \ddots & \\ \sqrt{u_{iM}} \begin{bmatrix} I \\ & I \end{bmatrix} & \begin{bmatrix} -I \\ & -R_{iM}^{-1} \end{bmatrix} \end{bmatrix} < 0$$

Applying Schur complement, we can get

$$\sum_{\phi=1}^{M} u_{i\phi} \begin{bmatrix} I & 0 \\ * & R_{i\phi} \end{bmatrix} + \begin{bmatrix} -P_{i} & 0 \\ * & H_{i\phi} \end{bmatrix} < 0 \tag{19}$$

(19) multiply  $(x_k^{'}, \hat{x}_k^{'})^{'}$  on left and it's transpose on the right. We get

$$\hat{x}_{k}^{'} \sum_{\phi=1}^{M} u_{i\phi} R_{i\phi} \hat{x}_{k} - x_{k}^{'} P_{i} x_{k} - 2SC(i, x_{k}, T_{i}) < 0$$
 (20)

Applying Schur complement to inequality (13). We can obtain

$$\hat{A}_{i\phi}X_i\hat{A}_{i\phi} < R_{i\phi} \tag{21}$$

Combining inequalities (20) and (21), it's easy to find that

$$\hat{x}_{k}^{'} \sum_{\phi=1}^{M} u_{i\phi} (\hat{A}_{i\phi} X_{i} \hat{A}_{i\phi}) \hat{x}_{k} - x_{k}^{'} P_{i} x_{k} - 2SC(i, x_{k}, T_{i}) < 0$$
(22)

Combining inequalities (18) and (22), it is easy to obtain that

$$\mathbb{E}\{\Delta V(k)\} - 2SC(i, x_k, T_i) < 0 \tag{23}$$

Furthermore, noticing the condition given in (4), we further have  $\mathbb{E}\{\Delta V(k)\}$  < 0, which completes the proof.

Theorem 2: For each mode  $i \in \mathcal{N}$  and  $\phi \in \mathcal{M}$ , if there exist positive-definite matrices  $\bar{P}_i \in \mathbb{R}^{n_x \times n_x}$  and  $R_{i\phi} \in \mathbb{R}^{(n_x + n_y + n_w) \times (n_x + n_y + n_w)}$ , matrices  $K_{\phi} \in \mathbb{N}^{n_u \times n_x}$ ,  $\Gamma_{\phi} \in \mathbb{R}^{n_u \times n_y}$ , positive semi-definite matrix  $T_i \in \mathbb{R}^{n_y \times n_y}$  and a positive scalar  $\gamma$ , such that the following LMIs are verified

$$\begin{bmatrix} -R_{i\theta} & \mathscr{H}_{i\phi} \\ * & \mathscr{P}_i \end{bmatrix} < 0 \tag{24}$$

$$\begin{bmatrix} \mathcal{S}_{i\phi} & \mathcal{N}_{i\phi} \\ * & \mathcal{L}_{i\phi} \end{bmatrix} < 0 \tag{25}$$

Where

$$\mathcal{H}_{i\phi} = \begin{bmatrix} \sqrt{\pi_{i1}} \hat{A}_{i\phi} \\ \sqrt{\pi_{i2}} \hat{A}_{i\phi} \\ \vdots \\ \sqrt{\pi_{i_N}} \hat{A}_{i\phi} \end{bmatrix}^{'}, \quad \mathcal{S}_{i\phi} = \begin{bmatrix} -P_i & 0 \\ * & H_{i\phi} \end{bmatrix}$$

$$\mathcal{P}_{i\phi} = \operatorname{diag} \{ -\bar{P}_1, -\bar{P}_2, \dots, -\bar{P}_N, -I^{n_w \times n_w} \}$$

$$\hat{A}_{i\theta} = \begin{bmatrix} \bar{A}_{i\theta} & \bar{F}_{i\theta} & E_i^x \end{bmatrix}, \quad \hat{A}_{i\theta}^z = \begin{bmatrix} \bar{C}_{i\theta}^z & \bar{G}_{i\theta}^z & E_i^z \end{bmatrix}$$

$$\mathcal{N}_{i\phi} = \begin{bmatrix} \sqrt{u_{i1}} \begin{bmatrix} \bar{P}_i \\ R_{i1} \end{bmatrix} & \dots & \sqrt{u_{iM}} \begin{bmatrix} \bar{P}_i \\ R_{iM} \end{bmatrix} \end{bmatrix}$$

$$\mathcal{L}_{i\phi} = \operatorname{diag} \left\{ \begin{bmatrix} -I \\ -R_{i1} \end{bmatrix}, \dots, \begin{bmatrix} -I \\ -R_{iM} \end{bmatrix} \right\}$$

$$H_{i\theta} = \begin{bmatrix} -I_{n_x} & C_i' \Omega_i T_i & 0 \\ * & -2T_i & 0 \\ \vdots & & & 2T_i \end{bmatrix}$$

then system (12) with  $x_0 = 0$  and  $w \in \mathcal{W}_{\gamma}$  is stochastically stable and the  $l_2$ -gain of the closed system is strictly less or equal to  $\gamma$ .

Proof: We first select (16) as the Lyapunov function and  $P_{r(k)} = \bar{P}_{r(k)}^{-1}$ . Similar to the proof of theorem 1, we can obtain that

$$\mathbb{E}\{\Delta V(k)\} = \hat{x}_k' \Big( \sum_{\phi=1}^M u_{i\phi} \hat{A}_{i\phi}' X_i \hat{A}_{i\phi} \Big) \hat{x}_k - V(k, x_k, i)$$
 (26)

Where  $\hat{x}_k = (x_k^{'}, \varphi_i^{'}(C_ix_k), w_k^{'})^{'}, X_i = \sum_{j=1}^N \pi_{ij}P_j$ Denoting  $h_{i\phi} = \mathrm{diag}\{P_i, I_{n_x+n_y+n_w}, \{\mathrm{diag}(I_{n_x}, R_{i\phi}^{-1})_{\phi=1}^M\}\}$  and using  $h_{i\phi}$  to pre- and post-multiplying the inequality given in (25), respectively, then we can obtain

$$\begin{bmatrix} \begin{bmatrix} -P_i & 0 \\ * & H_{i\phi} \end{bmatrix} & \sqrt{u_{i1}} \begin{bmatrix} I \\ & I \end{bmatrix} & \cdots & \sqrt{u_{iM}} \begin{bmatrix} I \\ & I \end{bmatrix} \\ \sqrt{u_{i1}} \begin{bmatrix} I \\ & I \end{bmatrix} & \begin{bmatrix} -I \\ & -R_{i1}^{-1} \end{bmatrix} & \\ \vdots & & \ddots & \\ \sqrt{u_{iM}} \begin{bmatrix} I \\ & I \end{bmatrix} & \begin{bmatrix} -I \\ & -R_{iM}^{-1} \end{bmatrix} \end{bmatrix} <$$

Applying Schur complement, we can get

$$\sum_{\phi=1}^{M} u_{i\phi} \begin{bmatrix} I & 0 \\ * & R_{i\phi} \end{bmatrix} + \begin{bmatrix} -P_i & 0 \\ * & H_{i\phi} \end{bmatrix} < 0 \tag{27}$$

(27) multiply  $(x_k^{'}, \hat{x}_k^{'})^{'}$  on left and it's transpose on the right.

$$\hat{x}_{k}^{'}(\sum_{\phi=1}^{M}u_{i\phi}R_{i\phi})\hat{x}_{k} - x_{k}^{'}P_{i}x_{k} - 2SC(i, x_{k}, T_{i}) - \gamma^{2}w_{k}^{'}w_{k} < 0$$
(28)

Applying Schur complement to inequality (24). We can obtain

$$\hat{A}_{i\phi}X_i\hat{A}_{i\phi} + (\hat{A}_{i\phi}^z)'\hat{A}_{i\phi}^z < R_{i\phi} \tag{29}$$

Combining inequalities (28) and (29), it's easy to find that

$$\hat{x}_{k}^{'} \left( \sum_{\phi=1}^{M} u_{i\phi} (\hat{A}_{i\phi} X_{i} \hat{A}_{i\phi} + (\hat{A}_{i\phi}^{z})^{'} \hat{A}_{i\phi}^{z}) \right) \hat{x}_{k} - x_{k}^{'} P_{i} x_{k}$$

$$- 2SC(i, x_{k}, T_{i}) - \gamma^{2} w_{k}^{'} w_{k} < 0$$
(30)

Which implies

$$\mathbb{E}\{\Delta V(k)\} + \mathbb{E}\{z_{k}^{'}z_{k}\} - \gamma^{2}w_{k}^{'}w_{k} - 2SC(i, x_{k}, T_{i}) < 0$$
 (31)

Furthermore, noticing the condition given in (4), we further have  $\mathbb{E}\{\Delta V(k)\} + \mathbb{E}\{z_k^{'}z_k\} - \gamma^2 w_k^{'}w_k < 0$ , which means

$$\mathbb{E}\{\Delta V(k) + z_k' z_k - \gamma^2 w_k' w_k | x_k, r(k) = i\} < 0$$
 (32)

Noting the zero initial condition, we can conclude that  $\frac{\|z\|_2}{\|w\|_2} < \gamma$  is satisfied, which completes the proof.

Remark: It's easy to find that, if (24) and (25) holds, the asynchronous controller can be designed based on Theorem 2. The optimal  $l_2$  performance  $\gamma^*$  can be obtained via dealing with the optimal problem as follows:

min 
$$\sigma$$
 subject to (24) and (25) with  $\sigma=\gamma^2$  (33)   
 IV. Numerical Example

In this section, we provide an example to verify the validity of proposed methods. Consider the Markov jump Lur'e system (1) with following data:  $\mathcal{N} = \{1, 2\}, \ \mathcal{M} = \{1, 2\}$ 

given in (25), respectively, then we can obtain 
$$A_1 = \begin{bmatrix} 0.4 & 0.4 \\ 0.2 & 1 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 1.1 & 0.6 \\ 0.3 & 0.4 \end{bmatrix}$$
 
$$A_1 = \begin{bmatrix} 0.4 & 0.4 \\ 0.2 & 1 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 1.1 & 0.6 \\ 0.3 & 0.4 \end{bmatrix}$$
 
$$B_1 = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}, \quad B_2 = \begin{bmatrix} 0.7 \\ 0.5 \end{bmatrix}, \quad F_1 = \begin{bmatrix} 1 \\ 1.2 \end{bmatrix}, \quad F_2 = \begin{bmatrix} 1.2 \\ 1 \end{bmatrix}$$
 
$$C_1 = \begin{bmatrix} 0.9 \\ 0.5 \end{bmatrix}, \quad C_2 = \begin{bmatrix} -1 \\ 0.7 \end{bmatrix}, \quad C_1^z = \begin{bmatrix} 0.2 \\ 0 \end{bmatrix}, \quad C_1^z = \begin{bmatrix} 0.1 \\ 0.1 \end{bmatrix}$$
 
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$$C_1 = \begin{bmatrix} 0.9 \\ 0.5 \end{bmatrix}, \quad C_2 = \begin{bmatrix} 0.4 \\ 0.3 \end{bmatrix}, \quad C_1^z = \begin{bmatrix} 0.1 \\ 0.1 \end{bmatrix}$$
 
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$$C_1 = \begin{bmatrix} 0.1 \\ 0.1 \end{bmatrix}, \quad C_1^z = \begin{bmatrix} 0.1 \\ 0.1 \end{bmatrix},$$

We can get following controller gain matrices by solving the LMIs in (24) and (25):

$$K_1 = \begin{bmatrix} -1.0266 & -1.2008 \end{bmatrix}, \quad \Gamma_1 = -2.4363$$
  
 $K_2 = \begin{bmatrix} -1.1812 & -0.9191 \end{bmatrix}, \quad \Gamma_2 = -2.2642$ 

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## REFERENCES

[1] H. Kopka and P. W. Daly, *A Guide to LETEX*, 3rd ed. Harlow, England: Addison-Wesley, 1999.