

# Exam in Automatic Control II

## Reglerteknik II 5hp (1RT495)

**Date:** August 26, 2017

**Venue:** Bergsbrunnagatan 15, sal 2

**Responsible teacher:** Hans Rosth.

**Aiding material:** Calculator, mathematical handbooks, textbooks by Glad & Ljung (Reglerteori/Control theory & Reglerteknik). Additional notes in the textbooks are allowed.

**Preliminary grades:** 23p for grade 3, 33p for grade 4, 43p for grade 5.

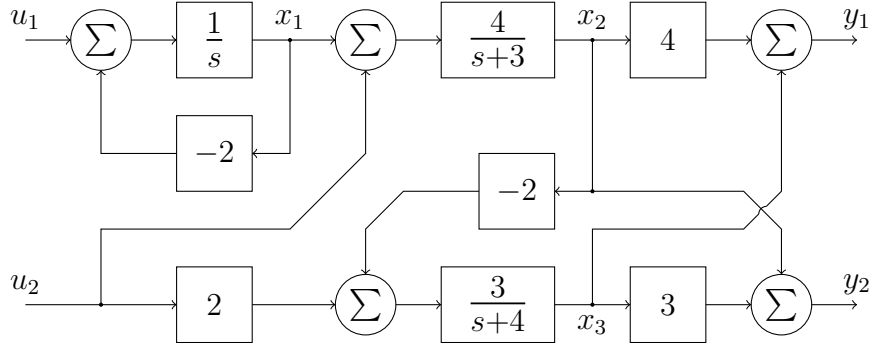
**Use separate sheets** for each problem, i.e. no more than one problem per sheet. Write your exam code on every sheet.

**Important:** Your solutions should be well motivated unless else is stated in the problem formulation! Vague or lacking motivations may lead to a reduced number of points.

**Problem 6** is an alternative to the homework assignments from the spring semester 2017. (In case you choose to hand in a solution to Problem 6 you will be accounted for the best performance of the homework assignments and Problem 6.)

Good luck!

**Problem 1** The block diagram below shows a system with two inputs and two outputs.



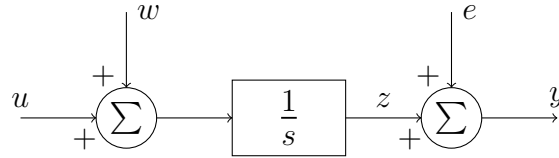
- (a) Give the state space model of the system in the block diagram above, with  $u = [u_1 \ u_2]^T$ ,  $y = [y_1 \ y_2]^T$  and  $x = [x_1 \ x_2 \ x_3]^T$  as input, output and state vector, and with  $x_1$ ,  $x_2$  and  $x_3$  as in the block diagram. **(4p)**
- (b) Is the state space model in (a) stable and/or a minimal realization? **(3p)**

**Problem 2** Consider the discrete-time stochastic process

$$\begin{cases} x(k+1) = \begin{bmatrix} 0.4 & 1 \\ -0.6 & 0 \end{bmatrix} x(k) + \begin{bmatrix} 0.6 \\ 0 \end{bmatrix} v(k), \\ y(k) = \begin{bmatrix} 1 & 0 \end{bmatrix} x(k) + v(k), \end{cases} \quad Ev(k) = 0, \Phi_v(\omega) = 1. \quad (1)$$

- (a) Determine the covariance matrix of the state vector,  $\Pi_x = Ex(k)x(k)^T$ , and the variance of the output,  $Ey(k)^2$ . **(3p)**
- (b) What is the spectrum,  $\Phi_y(\omega)$ , of the output? **(3p)**
- (c) Give the Kalman filter gain,  $K$ , for the  $\hat{x}(k|k-1)$  estimator for (1). **(5p)**  
*Hint:* If you find it necessary you may use that  $P = E\tilde{x}\tilde{x}^T$  is diagonal in this case.

**Problem 3** A simple model describing variations of the level in a water reservoir is given in the block diagram below.



Here the input  $u$  is the controlled net flow into the reservoir,  $z$  is the level and  $y$  is the measured level. There are two independent, zero mean noise sources: the measurement noise,  $e$ , and uncontrolled variations in the net flow,  $w$ .

It is desirable to keep the variations of the level as small as possible, at a minimal cost in terms of control power. Therefore the LQG control law  $u = -L\hat{x}$ , which minimizes the cost function

$$V = E [z^2 + \rho^2 u^2], \quad \rho > 0,$$

is used. (The estimate  $\hat{x}$  is obtained from a Kalman filter, which is not considered in this problem.)

(a) In a first approximation it is assumed that both  $w$  and  $e$  are white noise. Find the optimal feedback gain  $L$ , expressed in  $\rho$ . (Use  $x = z$  as state variable.) **(3p)**

(b) It turns out that

$$w(t) = \frac{1}{p+1}v(t),$$

where  $v$  is white noise, is a much better description of  $w$ . The measurement noise,  $e$ , is still assumed to be white. Give a state space representation of the total model, where the dynamics of  $w$  are incorporated. Use the “standard” form, i.e. determine the matrices and vectors  $A$ ,  $B$ ,  $N$ ,  $M$  and  $C$  in

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + Nv_1(t), \\ z(t) = Mx(t), \\ y(t) = Cx(t) + v_2(t). \end{cases}$$

Also, relate  $v_1$  and  $v_2$  to  $v$  and  $e$ . **(4p)**

(c) Find the optimal state feedback gain  $L$  for the total model in (b). **(4p)**

**Problem 4** A double tank system (similar to the one in the MPC demo lab) has the linearized model

$$\begin{cases} \dot{x}(t) = \begin{bmatrix} -1 & 0 \\ 1 & -0.5 \end{bmatrix} x(t) + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u(t), \\ y(t) = \begin{bmatrix} 0 & 1 \end{bmatrix} x(t). \end{cases}$$

Here  $y(t)$  is the water level in the lower tank and  $u(t)$  is the flow into the upper tank (from a pump).

The controller is implemented as a sampling state feedback controller, with a zero-order hold (ZOH) circuit. That is,

$$u(t) = u(kh) \text{ for } kh \leq t < kh + h, \text{ and } u(kh) = -Lx(kh) + mr(kh), \quad (2)$$

where  $h$  is the sampling interval. Discrete-time control design then requires a discrete-time model of the system:

$$\begin{cases} x(kh + h) = Fx(kh) + Gu(kh), \\ y(kh) = Hx(kh) \end{cases} \Leftrightarrow y(kh) = H(qI - F)^{-1}Gu(kh).$$

(a) Determine the ZOH sampled model of the system, i.e. give  $F$ ,  $G$  and  $H$  in the state space model above. The answer should be expressed in the sampling period  $h$ . **(4p)**

(b) The state feedback gain  $L$  in (2) should be determined by use of the pole placement technique. It is found that the performance of the closed loop system would be satisfactory for the *continuous-time* pole polynomial  $s^2 + 2s + 1$  (if a continuous-time controller is used).

What *discrete-time* closed loop pole polynomial,  $q^2 + aq + b$ , should one aim for in order to have an equivalent performance when the sampling controller (2) is used? The answer should be expressed in the sampling period  $h$ . (You need not compute  $L$ .) **(2p)**

(c) For a certain choice of sampling period the ZOH sampled model is

$$y(kh) = \frac{0.5(q + 0.5)}{q^2 - 0.75q + 0.125}u(kh).$$

The desired closed loop pole polynomial is then  $q^2 - 0.5q + 0.0625$ . Determine the value of  $m$  in (2) such that there is unit static gain from  $r$  to  $y$ . **(1p)**

**Problem 5** Specify for each of the following statements whether it is true or false. No motivations required — only answers “true”/“false” are considered!

- (a)  $\Phi(\omega) = \frac{4}{\omega^2 - 4}$  is the spectrum of a continuous-time stochastic process.
- (b) The discrete-time system  $y(k) = \frac{0.2}{q-0.8}u(k)$  has unit static gain.
- (c) White noise is characterized by that its covariance function  $r(\tau)$  is constant and non-zero for all time lags  $\tau$ .
- (d) For a Kalman filter, based on a correct model and full knowledge of the noise, the *output innovations* are white noise.
- (e) For a linear time-invariant (LTI) system LQG design yields an LTI controller.
- (f) With MPC it is not possible to handle bounds on the control input.
- (g) In MPC the computational load typically increases with the *control/input horizon*.

Each correct answer scores +1, each incorrect answer scores -1, and omitted answers score 0 points. (Minimal total score is 0 points.) **(7p)**

**Problem 6** *The HW bonus points (from the spring 2017) are exchangeable for this problem.*

Consider the continuous-time stochastic process

$$\dot{x}(t) = Ax(t) + Nv(t), \quad A = \begin{bmatrix} -2 & 0 \\ 1 & -2 \end{bmatrix}, \quad N = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad Ev(t) = 0, \quad \Phi_v(\omega) = 32.$$

- (a) What is the covariance matrix,  $\Pi_x^c = Ex(t)x(t)^T$ , of the state vector for this stochastic process? **(2p)**
- (b) A discrete-time model representation of the stochastic process above is

$$x(kh+h) = Fx(kh) + w(kh), \quad F = e^{Ah}, \quad R_w = Ew(kh)w(kh)^T = \begin{bmatrix} r_1 & r_{12} \\ r_{12} & r_2 \end{bmatrix}.$$

Compute the matrix  $F$  when the sampling period is  $h = 0.5$ . **(1p)**

- (c) In the discrete-time model the process noise is white and vector valued, and its covariance  $R_w$  is a  $2 \times 2$  matrix. The discrete-time model is such that the covariance matrix for its state vector is identical to the one for the continuous-time stochastic process, i.e.,  $\Pi_x^d = Ex(kh)x(kh)^T = Ex(t)x(t)^T = \Pi_x^c$ . Compute  $R_w$  so that this property holds. **(4p)**

**Solutions to the exam in Automatic Control II, 2017-08-26:**

1. (a) From the block diagram we get

$$\begin{aligned} x_1 &= \frac{1}{p}(-2x_1 + u_1) && \Leftrightarrow && px_1 = -2x_1 + u_1, \\ x_2 &= \frac{4}{p+3}(x_1 + u_2) && \Leftrightarrow && px_2 = 4x_1 - 3x_2 + 4u_2, \\ x_3 &= \frac{3}{p+4}(-2x_2 + 2u_2) && \Leftrightarrow && px_3 = -6x_2 - 4x_3 + 6u_2. \end{aligned}$$

We also see that  $y_1 = 4x_2 + x_3$  and  $y_2 = x_2 + 3x_3$ . All together we get

$$\begin{cases} \dot{x}(t) = \begin{bmatrix} -2 & 0 & 0 \\ 4 & -3 & 0 \\ 0 & -6 & -4 \end{bmatrix}^{=A} x(t) + \begin{bmatrix} 1 & 0 \\ 0 & 4 \\ 0 & 6 \end{bmatrix}^{=B} u(t), \\ y(t) = \begin{bmatrix} 0 & 4 & 1 \\ 0 & 1 & 3 \end{bmatrix}^{=C} x(t). \end{cases}$$

(b) The poles are the eigenvalues of  $A$ . Since  $A$  is triangular all eigenvalues are on the diagonal, and these are all negative. Hence the system is stable. Minimal realization  $\Leftrightarrow$  both controllable and observable:

$$\mathcal{S} = [B \quad AB \quad A^2B] = \begin{bmatrix} 1 & 0 & -2 & \dots \\ 0 & 4 & 4 & \dots \\ 0 & 6 & 0 & \dots \end{bmatrix}, \quad \mathcal{O} = \begin{bmatrix} C \\ CA \\ CA^2 \end{bmatrix} = \begin{bmatrix} 0 & 4 & 1 \\ 0 & 1 & 3 \\ 16 & -18 & -12 \\ \vdots & & \end{bmatrix}$$

Both  $\mathcal{S}$  and  $\mathcal{O}$  have full rank (it suffices to check the three first columns and rows). Thus, the system is both controllable and observable, and thereby a minimal realization.

2. (a) The covariance matrix solves the discrete-time Lyapunov equation,  $\Pi_x = F\Pi_x F^T + NRN^T$  (can be used directly since  $v$  is white noise), where  $R = 1$  in this case. Here we have

$$F = \begin{bmatrix} 0.4 & 1 \\ -0.6 & 0 \end{bmatrix}, \quad N = \begin{bmatrix} 0.6 \\ 0 \end{bmatrix}. \quad \text{Setting } \Pi_x = \begin{bmatrix} \pi_1 & \pi_{12} \\ \pi_{12} & \pi_2 \end{bmatrix}$$

and spelling out the Lyapunov equation, the following equation system is obtained:

$$\begin{cases} \pi_1 = 0.16\pi_1 + 0.8\pi_{12} + \pi_2 + 0.36, \\ \pi_{12} = -0.24\pi_1 - 0.6\pi_{12}, \\ \pi_2 = 0.36\pi_1, \end{cases} \quad \Leftrightarrow \begin{cases} \pi_1 = \frac{0.36}{0.6} = 0.6, \\ \pi_{12} = -\frac{0.24}{1.6} \cdot 0.6 = -0.09, \\ \pi_2 = 0.36 \cdot 0.6 = 0.216. \end{cases}$$

Since  $y = Hx + v$  we get  $Ey^2 = E[(Hx + v)(Hx + v)^T] = H\Pi_x H^T + R_v = \pi_1 + R_v$  (since  $x(k)$  and  $v(k)$  are uncorrelated). Hence

$$\Pi_x = \begin{bmatrix} 0.6 & -0.09 \\ -0.09 & 0.216 \end{bmatrix}, \quad Ey^2 = \pi_1 + R_v = 0.6 + 1 = 1.6.$$

(b) The output spectrum is  $\Phi_y(\omega) = |G(e^{i\omega})|^2 \Phi_v(\omega)$ . The system (1) is on observer canonical form so we get  $G(q) = \frac{0.6q}{q^2 - 0.4q + 0.6} + 1 = \frac{q^2 + 0.2q + 0.6}{q^2 - 0.4q + 0.6}$  (can also use  $G(q) = H(qI - F)^{-1}N + 1$ ), and since  $\Phi_v(\omega) = 1$  we have

$$\begin{aligned} \Phi_y(\omega) &= \frac{e^{-i2\omega} + 0.2e^{-i\omega} + 0.6}{e^{-i2\omega} - 0.4e^{-i\omega} + 0.6} \cdot \frac{e^{i2\omega} + 0.2e^{i\omega} + 0.6}{e^{i2\omega} - 0.4e^{i\omega} + 0.6} \\ &= \frac{1 + 0.2^2 + 0.6^2 + (0.2 + 0.2 \cdot 0.6)(e^{i\omega} + e^{-i\omega}) + 0.6(e^{i2\omega} + e^{i2\omega})}{1 + (-0.4)^2 + 0.6^2 + (-0.4 - 0.4 \cdot 0.6)(e^{i\omega} + e^{-i\omega}) + 0.6(e^{i2\omega} + e^{i2\omega})} \\ &= \frac{1.40 + 0.32(e^{i\omega} + e^{-i\omega}) + 0.6(e^{i2\omega} + e^{-i2\omega})}{1.52 - 0.64(e^{i\omega} + e^{-i\omega}) + 0.6(e^{i2\omega} + e^{-i2\omega})} = \frac{1.40 + 0.64 \cos \omega + 1.2 \cos 2\omega}{1.52 - 1.28 \cos \omega + 1.2 \cos 2\omega}. \end{aligned}$$

(c) Notice that (1) is on *innovations form* if  $F - NH$  is stable (has all eigenvalues inside the unit circle). Here  $\det(qI - F + NH) = q^2 + 0.2q + 0.6 \Rightarrow$  eigenvalues in  $-0.1 \pm i\sqrt{0.59}$ , which is inside the unit circle. Hence the system is on innovations form, and then the Kalman gain is  $K = N$  — see Eq. (5.83) in Glad/Ljung (this holds for discrete-time systems as well). Thus, without solving any DARE we can directly state that

$$K = N = \begin{bmatrix} 0.6 \\ 0 \end{bmatrix}.$$

(Of course it is possible and correct to obtain  $K$  by solving the DARE. The solution then is  $P = 0$ ! Note though that  $R_1 = R_2 = R_{12} = 1$ !)

**3. (a)** A state space representation is

$$\dot{x} = u + w, \quad z = x, \quad y = x + e.$$

Theorem 9.1  $\Rightarrow L = Q_2^{-1}B^T S$ , where  $S = S^T > 0$  solves the CARE  $0 = A^T S + SA + M^T Q_1 M - SBQ_2^{-1}B^T S$ . Here  $Q_1 = 1$ ,  $Q_2 = \rho^2$ ,  $A = 0$ ,  $B = 1$  and  $M = 1$ , leading to

$$0 = 1 - S^2/\rho^2 \quad \Rightarrow \quad S = \rho,$$

and then  $L = \rho^{-2}\rho = 1/\rho$ .

(b) We have that  $pw = -w + v$ , and therefore

$$\begin{cases} \dot{z} = w + u, \\ \dot{w} = -w + v, \\ z = z, \\ y = z + e \end{cases} \Leftrightarrow \begin{cases} \dot{x} = \begin{bmatrix} 0 & 1 \\ 0 & -1 \end{bmatrix} x + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u + \begin{bmatrix} 0 \\ 1 \end{bmatrix} v, \\ z = \begin{bmatrix} 1 & 0 \end{bmatrix} x, \\ y = \begin{bmatrix} 1 & 0 \end{bmatrix} x + e, \end{cases}$$

with  $x = [z \ w]^T$ .

(c) The CARE becomes

$$\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} s_1 & s_{12} \\ s_{12} & s_2 \end{bmatrix} + \begin{bmatrix} s_1 & s_{12} \\ s_{12} & s_2 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 0 & -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} [1 \ 0] \\ - \begin{bmatrix} s_1 & s_{12} \\ s_{12} & s_2 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} \rho^{-2} [1 \ 0] \begin{bmatrix} s_1 & s_{12} \\ s_{12} & s_2 \end{bmatrix},$$

which, taken element by element, leads to the equation system

$$\begin{cases} 0 = 1 - s_1^2/\rho^2, \\ 0 = s_1 - s_{12} - s_1 s_{12}/\rho^2, \\ 0 = 2s_{12} - 2s_2 - s_{12}^2/\rho^2, \end{cases} \Rightarrow \begin{cases} s_1 = \rho, \\ s_{12} = \frac{s_1}{1 + s_1/\rho^2} = \frac{\rho^2}{\rho + 1}, \\ s_2 = (2 - s_{12}/\rho^2) s_{12}/2 = \frac{\rho^2(2\rho + 1)}{2(\rho + 1)^2}. \end{cases}$$

The state feedback gain is then  $L = \rho^{-2} [s_1 \ s_{12}] = [1/\rho \ 1/(\rho + 1)]$ .

4. (a) Use Theorem 4.1. Then we need  $e^{At}$ , which is obtained by the Laplace transform:

$$\mathcal{L}[e^{At}] = (sI - A)^{-1} = \begin{bmatrix} s+1 & 0 \\ -1 & s+0.5 \end{bmatrix}^{-1} = \begin{bmatrix} \frac{1}{s+1} & 0 \\ \frac{1}{(s+1)(s+0.5)} & \frac{1}{s+0.5} \end{bmatrix}, \\ \Leftrightarrow e^{At} = \begin{bmatrix} e^{-t} & 0 \\ 2(e^{-0.5t} - e^{-t}) & e^{-0.5t} \end{bmatrix}$$

Hence,

$$F = e^{Ah} = \begin{bmatrix} e^{-h} & 0 \\ 2(e^{-0.5h} - e^{-h}) & e^{-0.5h} \end{bmatrix}, \quad H = C = [0 \ 1], \\ G = \int_0^h e^{At} B dt = \int_0^h \begin{bmatrix} e^{-t} \\ 2(e^{-0.5t} - e^{-t}) \end{bmatrix} dt = \begin{bmatrix} 1 - e^{-h} \\ 2 - 4e^{-0.5h} + 2e^{-h} \end{bmatrix}.$$

(b) For ZOH sampling continuous-time poles  $p$  are mapped on discrete-time poles  $e^{ph}$ . The continuous-time pole polynomial here corresponds to a double pole in  $-1$ , so the corresponding discrete-time poles should be a double pole in  $e^{-h}$ . This corresponds to the discrete-time pole polynomial  $(q - e^{-h})^2 = q^2 - 2e^{-h}q + e^{-2h}$ .

(c) The closed loop system will be

$$y(kh) = \frac{0.5(q + 0.5)}{q^2 - 0.5q + 0.0625} mr(kh) = G_c(q)mr(kh).$$

Static gain corresponds to setting  $q = 1$ . In order to have unit static gain we must have

$$1 = G_c(1)m = \frac{0.5(1 + 0.5)m}{1 - 0.5 + 0.0625} \Leftrightarrow m = \frac{1 - 0.5 + 0.0625}{0.5(1 + 0.5)} = \frac{0.5625}{0.75} = 0.75.$$



**5. (a)** False (A spectrum is always non-negative); **(b)** True (Set  $q = 1$ ); **(c)** False (For white noise  $r(\tau) = 0$  for  $\tau \neq 0$ ); **(d)** True (Theorem 5.3?); **(e)** True (Theorem 9.1); **(f)** False (This is handled by the numerical optimization); **(g)** True (Control horizon = dimension of the optimization problem)

**6. (a)**  $\Pi_x^c$  solves the continuous-time Lyapunov equation,  $0 = A\Pi_x^c + \Pi_x^c A^T + NR_v N^T$ :

$$\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} -2 & 0 \\ 1 & -2 \end{bmatrix} \begin{bmatrix} \pi_1 & \pi_{12} \\ \pi_{12} & \pi_2 \end{bmatrix} + \begin{bmatrix} \pi_1 & \pi_{12} \\ \pi_{12} & \pi_2 \end{bmatrix} \begin{bmatrix} -2 & 1 \\ 0 & -2 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} 32 \begin{bmatrix} 1 & 0 \end{bmatrix} \Leftrightarrow$$

$$\begin{cases} 0 = -4\pi_1 + 32, \\ 0 = \pi_1 - 4\pi_{12}, \\ 0 = 2(\pi_{12} - 2\pi_2), \end{cases} \Leftrightarrow \begin{cases} \pi_1 = 8, \\ \pi_{12} = 2, \\ \pi_2 = 1, \end{cases} \Leftrightarrow \Pi_x^c = \begin{bmatrix} 8 & 2 \\ 2 & 1 \end{bmatrix}.$$

**(b)** Use that  $\mathcal{L}[e^{At}] = (sI - A)^{-1}$ :

$$(sI - A)^{-1} = \begin{bmatrix} s+2 & 0 \\ -1 & s+2 \end{bmatrix}^{-1} = \begin{bmatrix} \frac{1}{s+2} & 0 \\ \frac{1}{(s+2)^2} & \frac{1}{s+2} \end{bmatrix} \Leftrightarrow e^{At} = \begin{bmatrix} e^{-2t} & 0 \\ te^{-2t} & e^{-2t} \end{bmatrix}$$

Thus

$$F = \begin{bmatrix} e^{-1} & 0 \\ 0.5e^{-1} & e^{-1} \end{bmatrix} = e^{-1} \begin{bmatrix} 1 & 0 \\ 0.5 & 1 \end{bmatrix}.$$

**(c)** Use the discrete-time Lyapunov equation,  $\Pi_x^d = F\Pi_x^d F^T + R_w$  and that  $\Pi_x^d = \Pi_x^c \Rightarrow$

$$R_w = \Pi_x^c - F\Pi_x^c F^T = \begin{bmatrix} 8 & 2 \\ 2 & 1 \end{bmatrix} - e^{-1} \begin{bmatrix} 1 & 0 \\ 0.5 & 1 \end{bmatrix} \begin{bmatrix} 8 & 2 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0.5 \\ 0 & 1 \end{bmatrix} e^{-1} = \begin{bmatrix} 8(1 - e^{-2}) & 2 - 6e^{-2} \\ 2 - 6e^{-2} & 1 - 5e^{-2} \end{bmatrix}.$$