

1) Volume balances for the two tanks give

$$\frac{d}{dt}(A_1 h_1) = q_1 + q_0 - q_{12}$$

$$\frac{d}{dt}(A_2 h_2) = q_{12} - q_2$$

which gives the nonlinear state equations

$$\dot{h}_1 = \frac{1}{A_1} u + \frac{1}{A_1} q_0 - \frac{k_{12} \sqrt{h_1 - h_2}}{A_1} = f_1(h_1, u, q_0)$$

$$\dot{h}_2 = \frac{k_{12} \sqrt{h_1 - h_2}}{A_2} - k_2 \sqrt{h_2} = f_2(\dots)$$

a) Linearization around $\bar{h}_1 = 2$ and $\bar{h}_2 = 1$

$$\begin{bmatrix} \Delta \dot{h}_1 \\ \Delta \dot{h}_2 \end{bmatrix} = \underbrace{\begin{bmatrix} \frac{df_1}{dh_1} & \frac{df_1}{dh_2} \\ \frac{df_2}{dh_1} & \frac{df_2}{dh_2} \end{bmatrix}}_A \underbrace{\begin{bmatrix} \Delta h_1 \\ \Delta h_2 \end{bmatrix}}_x + \underbrace{\begin{bmatrix} \frac{df_1}{du} \\ \frac{df_2}{du} \end{bmatrix}}_B \Delta u + \underbrace{\begin{bmatrix} \frac{df_1}{dq_0} \\ \frac{df_2}{dq_0} \end{bmatrix}}_N \Delta q_0$$

$$A = \begin{bmatrix} \frac{-k_{12}}{2A_1 \sqrt{\bar{h}_1 - \bar{h}_2}} & \frac{k_{12}}{2A_1 \sqrt{\bar{h}_1 - \bar{h}_2}} \\ \frac{k_{12}}{2A_2 \sqrt{\bar{h}_1 - \bar{h}_2}} & \frac{-1}{2A_2} \left(\frac{k_{12}}{\sqrt{\bar{h}_1 - \bar{h}_2}} + \frac{k_2}{\sqrt{\bar{h}_2}} \right) \end{bmatrix} = \begin{bmatrix} -0.1 & 0.1 \\ 0.05 & -0.1 \end{bmatrix}$$

$$B = \begin{bmatrix} 1/A_1 \\ 0 \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \end{bmatrix}$$

$$N = \begin{bmatrix} 1/A_1 \\ 0 \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \end{bmatrix}$$

$$\Delta y = \Delta h_2 = \underbrace{\begin{bmatrix} 0 & 1 \end{bmatrix}}_C \begin{bmatrix} \Delta h_1 \\ \Delta h_2 \end{bmatrix}$$

$$\begin{aligned}
 b) \quad G(s) &= C [sI - A]^{-1} B \\
 &= [0 \ 1] \begin{bmatrix} s+0.1 & -0.1 \\ -0.05 & s+0.1 \end{bmatrix}^{-1} \begin{bmatrix} 2 \\ 0 \end{bmatrix} \\
 &= \frac{[0 \ 1]}{(s+0.1)^2 - 0.005} \begin{bmatrix} s+0.1 & -0.1 \\ 0.05 & s+0.1 \end{bmatrix} \begin{bmatrix} 2 \\ 0 \end{bmatrix} \\
 &= \frac{0.1}{s^2 + 0.2s + 0.005}
 \end{aligned}$$

c) Doable if system observable

$$O(A, C) = \begin{bmatrix} C \\ CA \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0.05 & -0.1 \end{bmatrix}$$

$\det O \neq 0 \Rightarrow$ full rank \Rightarrow observable

d) Controller can be made more aggressive, allowing larger control activity by
* reduce q_u

Making the level in tank 1 harder controlled relative to the level in tank 2. This can be achieved by ~~reducing q_u~~

$$* \text{ increasing } q_{11} \text{ in } Q_x = \begin{bmatrix} q_{11} & 0 \\ 0 & 1 \end{bmatrix}$$

e) To get stationary accuracy when having low frequent disturbances, one should (try) add integral action and/or model the disturbance q_0 and estimate disturbance states one answer good enough

Integral action

Introduce the integral state:

$$x_I = \int^t r - y dt \Rightarrow \dot{x}_I = r - y \approx r - \Delta h_2$$

add the state to the state space model

$$\begin{bmatrix} \dot{\Delta h}_1 \\ \dot{\Delta h}_2 \\ \dot{x}_I \end{bmatrix} = \underbrace{\begin{bmatrix} -0.1 & 0.1 & 0 \\ 0.05 & -0.1 & 0 \\ 0 & -1 & 0 \end{bmatrix}}_{A_e} \underbrace{\begin{bmatrix} \Delta h_1 \\ \Delta h_2 \\ \Delta x_I \end{bmatrix}}_{x_e} + \underbrace{\begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix}}_{B_e} \Delta u + \underbrace{\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}}_{D_e} r$$

Modify the cost function to (for example)

$$J = E \left\{ \begin{bmatrix} \Delta h_1 \\ \Delta h_2 \\ x_I \end{bmatrix} \begin{bmatrix} q_{11} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & q_I \end{bmatrix} \begin{bmatrix} \Delta h_1 \\ \Delta h_2 \\ x_I \end{bmatrix} + q_u \Delta u^2 \right\}$$

Minimizing J gives

$$u = -L_e \hat{x}_e$$

where $\hat{x}_e = [\hat{x} \ x_I]$, \hat{x} being the estimated levels using a Kalman filter. The integral state should not be estimated!

The feedback gain is given by the stationary Riccati eqns ($S > 0$)

$$A_e^T S + S A_e + Q_x - S B_e q_u^{-1} B_e^T S = 0$$
$$L_e = \frac{1}{q_u} B_e^T S = [L \ L_I]$$

while the estimator is given by

$$\dot{\hat{x}} = A \hat{x} + B \Delta u + K (\Delta y - C \Delta x)$$

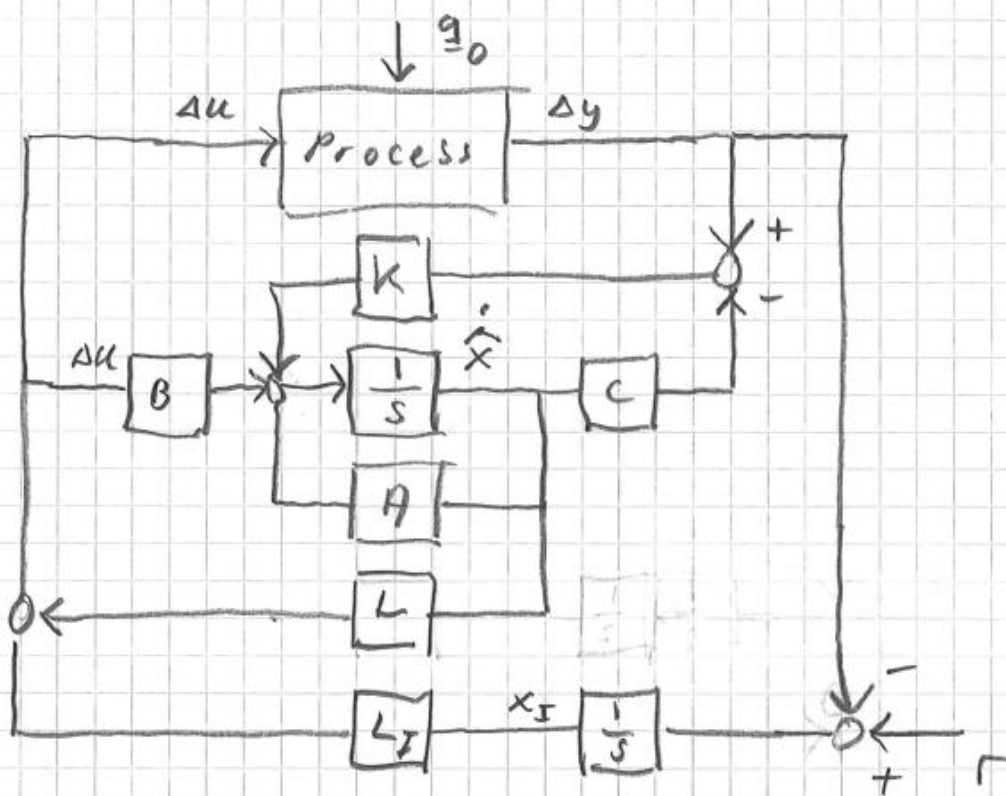
where K is the solution to $(P > 0)$

$$K = PC^T R_2^{-1}$$

$$AP + PAT - PC^T R_2^{-1} CP + NR_1 N^T = 0$$

where R_1 is the intensity of the process disturbance and R_2 is the intensity of the measurement noise. Those are assumed independent here.

Block scheme:



Adding disturbance model

Assume we have identified disturbance model such that

$$\Delta g_{\pm 0} = G_v(s) v_i$$

where v is assumed to be WGN

This can then be written on state space form

$$\dot{x}_v = A_v x_v + B_v v_i$$

$$\Delta g_{\pm 0} = C_v x_v$$

The original state space model is then extended with these states to get

$$\begin{bmatrix} \dot{\Delta h}_1 \\ \dot{\Delta h}_2 \\ \dot{x}_v \end{bmatrix} = \underbrace{\begin{bmatrix} -0.1 & 0.1 & C_v \\ 0.05 & -0.1 & 0 \\ 0 & 0 & A_v \end{bmatrix}}_{A_d} \underbrace{\begin{bmatrix} \Delta h_1 \\ \Delta h_2 \\ x_v \end{bmatrix}}_{x_{ed}} + \underbrace{\begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix}}_{B_d} \Delta u + \underbrace{\begin{bmatrix} 0 \\ 0 \\ B_v \end{bmatrix}}_{N_d} v_i$$

$$\Delta y = \underbrace{\begin{bmatrix} 0 & 1 & 0 \end{bmatrix}}_{C_d} \underbrace{x_{ed}}_{\text{vector}} + v_2$$

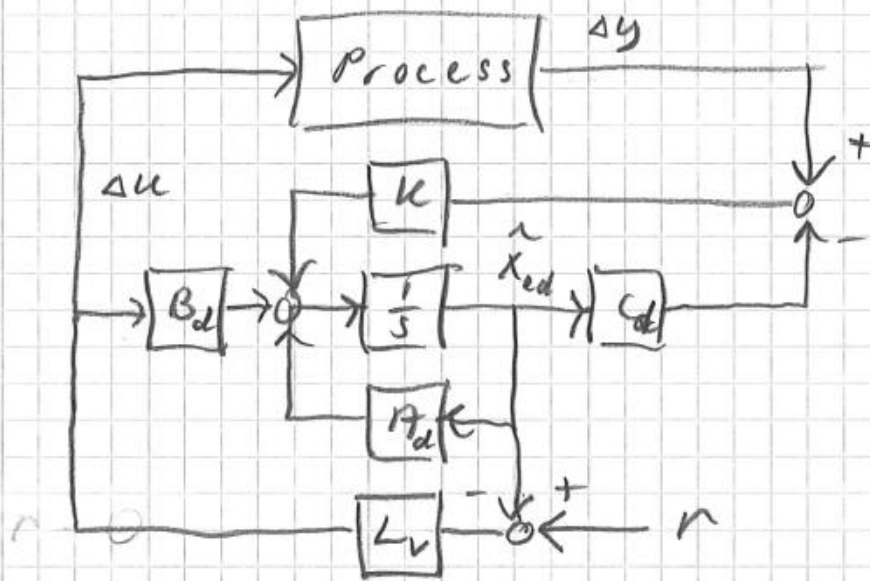
Now x_{ed} is estimated with a Kalman filter for $(A_d, B_d$ and $N_d)$ and the LQG feedback is calculated for the same model with zero cost on the disturbance states, i.e.

$$J = E \left\{ \underbrace{[\Delta h_1, \Delta h_2, x_v]}_{\text{new } Q_x} \begin{bmatrix} q_{11} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta h_1 \\ \Delta h_2 \\ x_v \end{bmatrix} + r_u \Delta u^2 \right\}$$

The stationary Riccati eqns then give L_v such that the optimal feedback is

$$\Delta u = -L_v \begin{bmatrix} \hat{\Delta h}_1 \\ \hat{\Delta h}_2 \\ x_v \end{bmatrix}$$

The block scheme is the std for LQG



2.

$$a) \quad G(s) = \frac{Y(s)}{U(s)} = \frac{e^{-Ts}}{1+s}$$

$$\Rightarrow \dot{y}(t) + y(t) = u(t-T)$$

$$\begin{cases} \dot{x}(t) = -x(t) + u(t-T) \\ y(t) = x(t) \end{cases}$$

Sampling with $h=T$ gives

$$x(k+1) = \varphi x(k) + \gamma u(k-1)$$

where $\varphi = e^{-T}$
 $\gamma = \int_0^T e^{-\tau} d\tau = \left[-e^{-\tau} \right]_0^T = 1 - e^{-T}$

Introduce $x_2(k) = u(k-1)$, which gives

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \end{bmatrix} = \begin{bmatrix} e^{-T} & 1-e^{-T} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(k)$$

$$\tilde{x}(k+1) = A \tilde{x}(k) + B u(k)$$

$$y(k) = \underbrace{[1 \ 0]}_C \tilde{x}(k)$$

$$\begin{aligned}
 b) \quad u(k) &= -L \tilde{x}(k) \\
 &= -[l_1 \quad l_2] \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix}
 \end{aligned}$$

Closed loop system

$$\tilde{x}(k+1) = (A - BL)\tilde{x}(k)$$

Poles equals the eigen values of $A - BL$

$$\begin{aligned}
 P(\lambda) &= \det(\lambda I - A + BL) \\
 &\equiv (\lambda - 0.25)^2 \\
 &= \lambda^2 - 0.5\lambda + 0.0625
 \end{aligned}$$

$$T = \ln 2 \Rightarrow A = \begin{bmatrix} 0.5 & 0.5 \\ 0 & 0 \end{bmatrix}$$

$$\begin{aligned}
 P(\lambda) &= \det \begin{bmatrix} \lambda - 0.5 & -0.5 \\ l_1 & \lambda + l_2 \end{bmatrix} \\
 &= \lambda^2 + \lambda(l_2 - 0.5) + 0.5(l_1 - l_2)
 \end{aligned}$$

Polynomial identification

$$\begin{aligned}
 l_2 - 0.5 &= -0.5 \Rightarrow l_2 = 0 \\
 0.5(l_1 - l_2) &= 0.0625 \Rightarrow l_1 = l_2 + 0.125 \\
 &= 0.125
 \end{aligned}$$

$$\begin{aligned}
 \therefore u_{FB}(k) &= -0.125 x_1(k) \\
 &= -0.125 (0.5 x_1(k-1) + 0.5 x_2(k-1)) \\
 &= -0.0625 y(k-1) - 0.0625 u_{FB}(k-1)
 \end{aligned}$$

$$\Rightarrow u_{FB}(k) = \frac{-0.0625 z^{-1}}{1 + 0.0625 z^{-1}} y(k)$$

$H(z)$

$$\begin{aligned}
 c) \quad u(k) &= K_r r(k) - H(z) y(k) \\
 y(k) &= x_1(k) \\
 &= 0,5 x_1(k-1) + 0,5 u(k-2)
 \end{aligned}$$

System is stable \Rightarrow we can assume steady-state

$$\begin{cases}
 \bar{u} = K_r \bar{r} - H(1) \bar{y} \\
 \bar{y} = 0,5 \bar{y} + 0,5 \bar{u} \quad \Rightarrow \quad \bar{y} = \bar{u}
 \end{cases}$$

$$\Rightarrow \bar{y} = K_r \bar{r} - H(1) \bar{y}$$

$$\bar{y} = \frac{K_r}{1 + H(1)} \bar{r} \equiv \bar{r} \quad (\text{correct gain})$$

$$K_r = 1 + H(1) = 1 - \frac{0,0625}{1 + 0,0625} = \underline{\underline{0,9412}}$$

3.

$$\dot{x} = \underbrace{\begin{bmatrix} -0.5 & 1 & 1 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix}}_A x + \underbrace{\begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}}_B u$$

$$y = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix}}_C x + \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}}_D u$$

Observability matrix

$$A^2 = \begin{bmatrix} 0.25 & -1 & -1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$Q = \begin{bmatrix} C \\ CA \\ CA^2 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ -0.5 & 1 & 1 \\ 0 & -1 & -1 \\ 0.25 & -1.5 & -1.5 \\ 0 & 1 & 1 \end{bmatrix}$$

2nd & 3rd column equal

Rank = 2 \Rightarrow Not observable

Is the system stable?

$$\det(\lambda I - A) = \det \begin{bmatrix} \lambda + 0.5 & -1 & -1 \\ 0 & \lambda + 1 & 0 \\ 0 & 0 & \lambda + 1 \end{bmatrix}$$

$$= (\lambda + 0.5)(\lambda + 1)(\lambda + 1) = 0$$

All eigenvalues in LHP \Rightarrow stable

\Rightarrow Unobservable states must be stable

\Rightarrow Detectable

Controllability matrix

$$\mathcal{S} = [B \quad AB \quad A^2B]$$

$$= \begin{bmatrix} 0 & 1 & 1 & -0.5 & x & x \\ 1 & 0 & -1 & 0 & x & x \\ 0 & 1 & 0 & -1 & x & x \end{bmatrix}$$

Linearly independent \Rightarrow rank = 3

\therefore Controllable

\Rightarrow Stabilizable

4.

a) All step responses look like step responses of 1st order systems with no time delay, i.e.

$$G_{ij}(s) = \frac{K_{ij}}{1 + sT_{ij}} \quad , \quad i, j = 1, 2$$

The gains K_{ij} are the final value (since step size is 1) and the time constants are the times when approx. 63% of the change has occurred.

This gives

$$G_{11}(s) \approx \frac{5}{1+s} \quad G_{12} \approx \frac{2}{1+s}$$

$$G_{21}(s) \approx \frac{7.5}{1+0.5s} = \frac{15}{2+s}$$

$$G_{22}(s) \approx \frac{0.5}{1+0.5s} = \frac{1}{2+s}$$

$$\Rightarrow G(s) = \begin{bmatrix} \frac{5}{s+1} & \frac{2}{s+1} \\ \frac{15}{s+2} & \frac{1}{s+2} \end{bmatrix} = \frac{1}{(s+1)(s+2)} \begin{bmatrix} 5(s+2) & 2(s+2) \\ 15(s+1) & (s+1) \end{bmatrix}$$

b) $\text{Re } G_A(G(j\omega)) = G(j\omega) * G^{-T}(j\omega)$

$$G^{-1}(s) = \frac{1}{25} \begin{bmatrix} -(s+1) & 2(s+2) \\ 15(s+1) & -5(s+2) \end{bmatrix}$$

$$G(s) * G^{-T}(s) = \begin{bmatrix} \frac{-5}{25} & \frac{30}{25} \\ \frac{30}{25} & \frac{-5}{25} \end{bmatrix} = \begin{bmatrix} -0.2 & 1.2 \\ 1.2 & -0.2 \end{bmatrix}$$

Thus RGA does not depend on w in this case.

Negative diagonal elements \Rightarrow we should avoid diagonal pairing

Off diagonal elements close to 1

\Rightarrow Choose pairing $y_1 \leftrightarrow u_2$
 $y_2 \leftrightarrow u_1$

Alt. from plot only

From plot we see that

$$G(0) = \begin{bmatrix} 5 & 2 \\ 7.5 & 0.5 \end{bmatrix}$$

$$RGA(G(0)) = G(0) \cdot * G^{-T}(0)$$

$$= \begin{bmatrix} 5 & 2 \\ 7.5 & 0.5 \end{bmatrix} \cdot * \frac{1}{2.5 - 15} \begin{bmatrix} 0.5 & -7.5 \\ -2 & 5 \end{bmatrix}$$

$$= \begin{bmatrix} -0.2 & 1.2 \\ 1.2 & -0.2 \end{bmatrix}$$

Avoid diagonal coupling \Rightarrow only option is

$$y_1 \leftrightarrow u_2$$

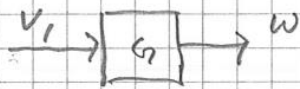
$$y_2 \leftrightarrow u_1$$

5.

$$\dot{x} = -x + u + w$$

$$\Phi_w = \frac{1}{1+\omega^2}$$

Spectral factorization gives that we can construct disturbance w as



where $v_1 \sim WN(0, 1)$ and $G_1(j\omega)G_1(-j\omega) = \Phi_w(\omega)$

$$\Phi_w(\omega) = \frac{1}{(1+j\omega)} \frac{1}{(1-j\omega)}$$

$$\Rightarrow w(t) = \frac{1}{1+p} v_1(t)$$

$$(1+p)w = w + \dot{w} = v_1$$

Extended state space model:

$$\begin{bmatrix} \dot{x} \\ \dot{w} \end{bmatrix} = \underbrace{\begin{bmatrix} -1 & 1 \\ 0 & -1 \end{bmatrix}}_{A_e} \underbrace{\begin{bmatrix} x \\ w \end{bmatrix}}_{x_e} + \underbrace{\begin{bmatrix} 1 \\ 0 \end{bmatrix}}_{B_e} u + \underbrace{\begin{bmatrix} 0 \\ 1 \end{bmatrix}}_{N_e} v_1$$

$$y = \underbrace{\begin{bmatrix} 1 & 0 \end{bmatrix}}_{C_e} \begin{bmatrix} x \\ w \end{bmatrix} + v$$

where $v_2 \sim WN(0, 1)$ and v_1, v_2 are independent ($\Rightarrow R_1=1, R_2=1, R_{12}=0$)

The optimal observer (minimizing the variance of the estimation error) is the continuous time Kalman filter, i.e.

$$\dot{\hat{x}}_e = A_e x_e + B_e u + K(y - C_e \hat{x}_e)$$

where K is the solution to (Theorem 5.4)

$$K = P C_e^T R_2^{-1} = \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} \frac{1}{1} = \underline{\underline{\begin{bmatrix} P_{11} \\ P_{12} \end{bmatrix}}}$$

$$A P + P A^T - P C_e^T R_2^{-1} (P C_e^T)^T + N_e R_1 N_e^T = 0$$

$$\begin{bmatrix} -1 & 1 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} + \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix} \begin{bmatrix} -1 & 0 \\ 1 & -1 \end{bmatrix} - \begin{bmatrix} P_{11} \\ P_{12} \end{bmatrix} \begin{bmatrix} P_{11} & P_{12} \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \begin{bmatrix} 0 & 1 \end{bmatrix} = 0$$

$$\left. \begin{array}{l} (1,1): (-P_{11} + P_{12})^2 - P_{11}^2 = 0 \\ (1,2): -P_{12} + P_{22} - P_{12} - P_{11}P_{12} = 0 \\ (2,2): -P_{22}^2 - P_{12}^2 + 1 = 0 \end{array} \right\} \Rightarrow P \text{ choose solution where } P > 0$$

This eqn system is too hard to solve by hand.

However, it was stated that

$$P_{11} \equiv \text{Var}\{\hat{x} - x\} = 0.2$$

$$(1,1) \Rightarrow P_{12} = P_{11} + \frac{1}{2} P_{11}^2 = 0.2 + \frac{0.04}{2} = 0.22$$

$$\Rightarrow K = \begin{bmatrix} 0.2 \\ 0.22 \end{bmatrix}$$

$$\begin{aligned} \begin{bmatrix} \dot{\hat{x}} \\ \dot{\hat{w}} \end{bmatrix} &= \begin{bmatrix} -1 & 1 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} \hat{x} \\ \hat{w} \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u + \begin{bmatrix} 0.2 \\ 0.22 \end{bmatrix} (y - \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} \hat{x} \\ \hat{w} \end{bmatrix}) \\ &= \begin{bmatrix} -1.2 & 1 \\ -0.22 & -1 \end{bmatrix} \begin{bmatrix} \hat{x} \\ \hat{w} \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u + \begin{bmatrix} 0.2 \\ 0.22 \end{bmatrix} y \end{aligned}$$

w scalar and can be modelled using spectral factorization means that w can be modelled as the output of a stable transfer fn $G(s) = \frac{B(s)}{A(s)}$

Written on observer canonical form this transfer fn can be realized as

$$\begin{bmatrix} \dot{w} \\ \dot{x}_w \end{bmatrix} = \underbrace{\begin{bmatrix} -a_1 & 1 & 0 & \dots \\ -a_2 & 0 & 1 & \dots \\ \vdots & & & \ddots \end{bmatrix}}_{A_w} \begin{bmatrix} w \\ x_w \end{bmatrix} + \underbrace{\begin{bmatrix} b_1 \\ b_2 \\ \vdots \end{bmatrix}}_{B_w} v_1, \quad v_1 \sim WN$$

Adding this to the original model

$$\begin{bmatrix} \dot{x} \\ \dot{w} \\ \dot{x}_w \end{bmatrix} = \underbrace{\begin{bmatrix} A & N & 0 & \dots & 0 \\ 0 & & A_w & & \end{bmatrix}}_{A_e} \begin{bmatrix} x \\ w \\ x_w \end{bmatrix} + \underbrace{\begin{bmatrix} B \\ 0 \end{bmatrix}}_{N_c} u + \underbrace{\begin{bmatrix} 0 \\ B_w \end{bmatrix}}_{N_c} v_1$$

$$y = \underbrace{\begin{bmatrix} C & 0 \end{bmatrix}}_{C_e} \begin{bmatrix} x \\ w \\ x_w \end{bmatrix} + v_2$$

Requirements for \exists Kalman filter are stated in Lemma 5.1. For this problem they are

- (i) R, γ, D (obviously fullfilled)
 - (ii) (A_e, C_e) detectable
 - (iii) (A_e, R_1) stabilizable
- } Fullfilled if A_e is stable

A stable, A_w stable $\det(\lambda I - A_e) =$
 $= \det(\lambda I - A) \det(\lambda I - A_w) \Rightarrow A_e$ stable
 \therefore Yes, one can always determine a KF!