



NORGES TEKNISK- NATURVITENSKAPELIGE UNIVERSITET  
INSTITUTT FOR TEKNISK KYBERNETIKK

Faglig kontakt under eksamen:

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# Eksamen

## TTK 4115 Lineær systemteori

5. desember 2003

Tid: 0900 – 1400

Hjelpemidler: D - Ingen trykte eller håndskrevne hjelpemidler tillatt. Bestemt, enkel kalkulator tillatt.

### Oppgave 1 (10 %)

Anta gitt et system  $\dot{x} = Ax + Bu$  der

$$A = \begin{pmatrix} 1 & 0 \\ -1 & 2 \end{pmatrix}, \quad B = \begin{pmatrix} 1 \\ \alpha \end{pmatrix}$$

der  $\alpha$  er en konstant.

- a) For hvilke verdier av  $\alpha$  er systemet styrbart?
- b) Anta  $\alpha = -4$ . Finn en tilstandstilbakekopling som plasserer egenverdiene til systemet i  $\lambda = -2 \pm i$ .

### Oppgave 2 (25 %)

- a) Anta gitt en  $n \times n$ -matrise  $A$ . Vis at ved diagonalisering kan denne uttrykkes på formen  $A = Q\bar{A}Q^{-1}$ , og angi hvordan matrisene  $\bar{A}$  og  $Q$  kan bestemmes.

- b) Hvilke forutsetninger må  $A$  tilfredstille for at den skal være diagonaliserbar?
- c) Hvilke betingelser må  $A$  tilfredstille for at systemet  $\dot{x} = Ax$  skal være stabilt?
- d) Hvilke betingelser må  $A$  tilfredstille for at systemet  $\dot{x} = Ax$  skal være asymptotisk stabilt?
- e) Anta i det etterfølgende at  $A$  er gitt ved

$$A = \begin{pmatrix} -1 & 2 \\ 1 & 3 \end{pmatrix}$$

Finn en symmetrisk matrise  $M$  som er en løsning til Lyapunov-ligningen

$$A^T M + M A = -I$$

og benytt  $M$  til å bestemme hvorvidt systemet  $\dot{x} = Ax$  er asymptotisk stabilt.

- f) Beregn  $e^{At}$ , når  $A$  er gitt som i punkt e).

### Oppgave 3 (15 %)

- a) Hvilke egenskaper har en *minimal* realisasjon?
- b) Er systemet definert ved transferfunksjonen

$$G(s) = \frac{2(1-s)}{(1+s)(1+4s)}$$

realiserbart? Begrunn.

- c) Finn en tilstandsromrealisasjon for følgende transferfunksjonsmatrise

$$G(s) = \left( -\frac{2}{(1+2s)^2}, \frac{1+s}{1+2s} \right)$$

**Oppgave 4** (20 %)

Vi har et 1. ordens system på følgende form

$$\dot{x} = ax + bu + v, \quad y = x + w$$

der  $x$  er tilstanden,  $u$  er pådraget,  $y$  er en måling,  $v$  er en ukjent forstyrrelse, og  $w$  er målestøy. Parametrene  $a$  og  $b$  er skalare konstanter.

a) Anta det benyttes en tilstandsestimator på formen

$$\dot{\hat{x}} = a\hat{x} + bu, \quad \hat{x}(0) = 0$$

Hvilke ulemper har denne tilstandsestimatoren?

b) Gitt tilstandsestimatoren  $\hat{x} = y$ , diskuter hvilke ulemper denne har.

c) Anta det benyttes en tilstandsestimator på formen

$$\dot{\hat{x}} = a\hat{x} + bu + \ell(y - \hat{x}), \quad \hat{x}(0) = 0$$

Anta i de etterfølgende oppgaver at  $a = -2$ ,  $b = 1$  og  $\ell = 8$ . Vis at transferfunksjonen fra målestøyen  $w$  til tilstandsestimatet  $\hat{x}$  er gitt ved

$$\frac{\hat{x}}{w}(s) = \frac{8}{s + 10}$$

d) Sammenlign fordeler og ulemper til estimatoren fra punkt c) med estimatorene fra punktene a) og b).

**Oppgave 5** (15 %)

Følgende system er gitt

$$\begin{aligned} \dot{x} &= -0.4x + 0.1u_d + u \\ y &= x + 0.1v \end{aligned}$$

der  $x$  er tilstanden,  $u_d$  er pådraget,  $y$  er en måling, og  $v$  og  $u$  er hvitstøyprosesser der:

$$\begin{aligned} E[u(t)u(\tau)] &= Q\delta(t - \tau) \\ E[v(t)v(\tau)] &= R\delta(t - \tau) \\ E[u(t)v(\tau)] &= 0 \end{aligned}$$

- a) Sett opp ligningene for Kalman-filteret for dette systemet, og forklar hvilken informasjon som er nødvendig for å beregne tilstandsestimatet.
- b) Anta at  $Q$  økes. Hva skjer med Kalmanforsterkningen?
- c) Anta at  $v$  får større varians på grunn av endringer i sensoren, men at  $R$  holdes konstant i filteret fordi man ikke er klar over dette. Hva skjer nå med Kalmanforsterkningen?
- d) Ved nærmere analyse av spekteret til  $v$ , viser det seg at  $v$  ikke er hvit, men har spektraltettheten:

$$S(\omega) = \frac{1}{\omega^2 + 1}$$

Hva blir ligningene til Kalman-filteret nå?

### **Oppgave 6** (15 %)

Signalet  $v(t)$  er et stasjonært signal definert ved  $V(s) = G(s)W(s)$ , der  $w(t)$  er et normalfordelt hvitstøy-signal med null middelvei og varians 1. Transferfunksjonen  $G(s)$  er definert ved

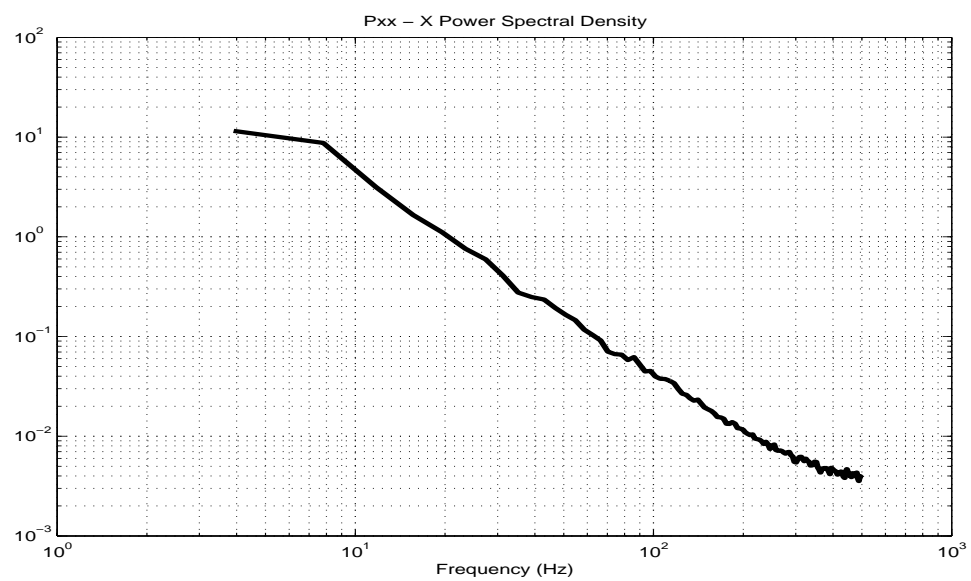
$$G(s) = \frac{K}{1 + Ts}$$

- a) Hva er autokorrelasjonsfunksjonen og effektspektret for signalet  $w(t)$ ?
- b) Vis at effektspektret for signalet  $v(t)$  er

$$S_v(j\omega) = \frac{K^2}{(\omega T)^2 + 1}$$

Hva er autokorrelasjonsfunksjonen?

- c) Anslå verdiene til  $K$  og  $T$  fra følgende estimerte effektspektrum:



Vedlegg til eksamen (Noen nyttige formler og uttrykk)

$$\begin{aligned}
 x(t) &= e^{At}x(0) + \int_0^t e^{A(t-\tau)}Bu(\tau)d\tau \\
 x(k) &= A^kx(0) + \sum_{m=0}^{k-1} A^{k-1-m}Bu(m) \\
 A^{-1} &= \frac{\text{adj}(A)}{\det(A)} \\
 \det(A) &= \sum_{i=1}^n a_{ij}c_{ij} \\
 \text{adj}(A) &= \{c_{ij}\}^T \\
 c_{ij} &= (-1)^{i+j}\det(A_{ij}) \quad (\text{kofaktor}), \quad A_{ij} = \text{undermatrise til } A \\
 \mathcal{C} &= (B \ AB \ A^2B \ \dots \ A^{n-1}B) \\
 \mathcal{O} &= \begin{pmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{n-1} \end{pmatrix} \\
 G(s) &= C(sI - A)^{-1}B + D \\
 G(z) &= C(zI - A)^{-1}B + D \\
 \mathbf{G}(\mathbf{s}) &= \mathbf{G}(\infty) + \mathbf{G}_{\text{sp}}(\mathbf{s}) \\
 d(s) &= s^r + \alpha_1 s^{r-1} + \dots + \alpha_{r-1}s + \alpha_r \\
 \mathbf{G}_{\text{sp}}(s) &= \frac{1}{d(s)}[\mathbf{N}_1 s^{r-1} + \mathbf{N}_2 s^{r-2} + \dots + \mathbf{N}_{r-1}s + \mathbf{N}_r] \\
 \dot{\mathbf{x}} &= \begin{bmatrix} -\alpha_1 \mathbf{I}_p & -\alpha_2 \mathbf{I}_p & \dots & -\alpha_{r-1} \mathbf{I}_p & -\alpha_r \mathbf{I}_p \\ \mathbf{I}_p & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_p & \dots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{I}_p & \mathbf{0} \end{bmatrix} \mathbf{x} + \begin{bmatrix} \mathbf{I}_p \\ \mathbf{0} \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix} \mathbf{u} \\
 \mathbf{y} &= [\mathbf{N}_1 \ \mathbf{N}_2 \ \dots \ \mathbf{N}_{r-1} \ \mathbf{N}_r] \mathbf{x} + \mathbf{G}(\infty) \mathbf{u}
 \end{aligned}$$

Vedlegg til eksamen.

Diskret Kalman-filter:

$$\begin{aligned}
 \mathbf{x}_{k+1} &= \mathbf{\Phi}_k \mathbf{x}_k + \mathbf{w}_k \\
 \mathbf{z}_k &= \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k \\
 E[\mathbf{w}_k \mathbf{w}_i^T] &= \begin{cases} \mathbf{Q}_k, & i = k \\ 0, & i \neq k \end{cases} \\
 E[\mathbf{v}_k \mathbf{v}_i^T] &= \begin{cases} \mathbf{R}_k, & i = k \\ 0, & i \neq k \end{cases} \\
 E[\mathbf{w}_k \mathbf{v}_i^T] &= 0, \forall i, k \\
 \mathbf{P}_k^- &= E[\mathbf{e}_k^- \mathbf{e}_k^{-T}] \\
 \mathbf{P}_k &= E[\mathbf{e}_k \mathbf{e}_k^T] = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_k^- (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)^T + \mathbf{K}_k \mathbf{R}_k \mathbf{K}_k^T \\
 \mathbf{K}_k &= \mathbf{P}_k^- \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R}_k)^{-1} \\
 \mathbf{P}_{k+1}^- &= \mathbf{\Phi}_k \mathbf{P}_k \mathbf{\Phi}_k^T + \mathbf{Q}_k
 \end{aligned}$$

Kontinuerlig Kalman filter:

$$\begin{aligned}
 \dot{\mathbf{x}} &= \mathbf{F}\mathbf{x} + \mathbf{G}\mathbf{u} \\
 \mathbf{z} &= \mathbf{H}\mathbf{x} + \mathbf{v} \\
 E[\mathbf{u}(t)\mathbf{u}(t)^T] &= \mathbf{Q}\delta(t - \tau) \\
 E[\mathbf{v}(t)\mathbf{v}(t)^T] &= \mathbf{R}\delta(t - \tau) \\
 E[\mathbf{u}(t)\mathbf{v}(t)^T] &= 0 \\
 \mathbf{K} &= \mathbf{P}\mathbf{H}^T \mathbf{R}^{-1} \\
 \dot{\mathbf{P}} &= \mathbf{F}\mathbf{P} + \mathbf{P}\mathbf{F}^T - \mathbf{P}\mathbf{H}^T \mathbf{R}^{-1} \mathbf{H}\mathbf{P} + \mathbf{G}\mathbf{Q}\mathbf{G}^T, \quad \mathbf{P}(0) = \mathbf{P}_0
 \end{aligned}$$

Autokorrelasjon:

$$\begin{aligned}
 R_X(\tau) &= E[X(t)X(t + \tau)] \text{ (Stasjonær prosess)} \\
 R_X(t_1, t_2) &= E[X(t_1)X(t_2)] \text{ (Ikke stasjonær prosess)} \\
 Y(s) &= G(s)U(s) \Rightarrow \\
 R_y(t_1, t_2) &= E[y(t_1)y(t_2)] \\
 &= \int_0^{t_1} \int_0^{t_2} g(\xi)g(\eta)E[u(t_1 - \xi)u(t_2 - \eta)] d\xi d\eta \text{ (Transient analyse)}
 \end{aligned}$$

Minste kvadraters estimering:

$$\begin{aligned}V(\bar{\theta}) &= \frac{1}{2}(\mathcal{Y}_N - \Phi_N \bar{\theta})^T (\mathcal{Y}_N - \Phi_N \bar{\theta}) \\E[\hat{\theta} \hat{\theta}^T] &= \hat{\sigma}_e^2 (\Phi_N^T \Phi_N)^{-1} \\ \hat{\sigma}_e^2 &= \frac{2}{N-p} V(\hat{\theta})\end{aligned}$$





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# Exam

## TTK 4115 Linear systems

5. December 2003

Time: 0900 – 1400

Supporting materials: D - No printed or handwritten material allowed. Specific, simple calculator allowed.

### Oppgave 1 (10 %)

Given a system  $\dot{x} = Ax + Bu$  where

$$A = \begin{pmatrix} 1 & 0 \\ -1 & 2 \end{pmatrix}, \quad B = \begin{pmatrix} 1 \\ \alpha \end{pmatrix}$$

where  $\alpha$  is a constant.

- a) For what values of  $\alpha$  is the system controllable?
- b) Assume that  $\alpha = -4$ . Find a state feedback control law that places the systems eigenvalues in  $\lambda = -2 \pm i$ .

### Oppgave 2 (25 %)

- a) Let  $A$  be a given  $n \times n$ -matrix. Show that by diagonalization the matrix can be represented as  $A = Q\bar{A}Q^{-1}$ , and state how the matrices  $\bar{A}$  and  $Q$  can be determined.

- b) Which conditions must  $A$  satisfy to ensure that the matrix is diagonalizable?
- c) Which conditions must  $A$  satisfy to ensure that the system  $\dot{x} = Ax$  is stable?
- d) Which conditions must  $A$  satisfy to ensure that the system  $\dot{x} = Ax$  is asymptotically stable?
- e) From now on let  $A$  be given by

$$A = \begin{pmatrix} -1 & 2 \\ 1 & 3 \end{pmatrix}$$

Find a symmetric matrix  $M$  that solves the Lyapunov-equation

$$A^T M + M A = -I$$

and use  $M$  to determine if the system  $\dot{x} = Ax$  is asymptotically stable.

- f) Calculate  $e^{At}$ , where  $A$  is as defined in e).

### Oppgave 3 (15 %)

- a) What properties does *minimal* realization have?
- b) Is the system defined by the following transfer function

$$G(s) = \frac{2(1-s)}{(1+s)(1+4s)}$$

realizable? Justify your answer.

- c) Find a state space representation of the following transfer function matrix

$$G(s) = \begin{pmatrix} -\frac{2}{(1+2s)^2}, & \frac{1+s}{1+2s} \end{pmatrix}$$

**Oppgave 4** (20 %)

Given the following first order system

$$\dot{x} = ax + bu + v, \quad y = x + w$$

where  $x$  is the state,  $u$  is the input,  $y$  is the measurement,  $v$  is an unknown disturbance, and  $w$  is measurement noise. The parameters  $a$  and  $b$  are scalar constants.

a) Assume that a state estimator on the form

$$\dot{\hat{x}} = a\hat{x} + bu, \quad \hat{x}(0) = 0$$

is used. Which disadvantages does this estimator have?

b) Given the state estimator  $\hat{x} = y$ , discuss the disadvantages with this approach.

c) Assume that a state estimator on the form

$$\dot{\hat{x}} = a\hat{x} + bu + \ell(y - \hat{x}), \quad \hat{x}(0) = 0$$

is used. From now on, let  $a = -2$ ,  $b = 1$  and  $\ell = 8$ . Show that the transfer function from the measurement noise  $w$  to the state estimate  $\hat{x}$  is given by

$$\frac{\hat{x}}{w}(s) = \frac{8}{s + 10}$$

d) Compare advantages and disadvantages of the estimator from exercise c) with the estimators from a) and b).

**Oppgave 5** (15 %)

Given the following system

$$\begin{aligned} \dot{x} &= -0.4x + 0.1u_d + u \\ y &= x + 0.1v \end{aligned}$$

where  $x$  is the state,  $u_d$  is the input,  $y$  is the measurement, and  $v$  and  $u$  are white noise processes where:

$$\begin{aligned} E[u(t)u(\tau)] &= Q\delta(t - \tau) \\ E[v(t)v(\tau)] &= R\delta(t - \tau) \\ E[u(t)v(\tau)] &= 0 \end{aligned}$$

- a) Define the Kalman filter equations for the system and explain what information is needed to compute the state estimate.
- b) Assume that  $Q$  is increased. How does this affect the Kalman gain?
- c) Assume that the variance in  $v$  increases due to changes in the sensor, and since we are not aware of this,  $R$  is kept constant in the filter. How does this affect the Kalman gain?
- d) Analyzes of the power spectrum of  $v$  reveals that  $v$  is no white noise process, but has the following power spectral density:

$$S(\omega) = \frac{1}{\omega^2 + 1}$$

Define the Kalman filter equations in this case.

### **Oppgave 6** (15 %)

The signal  $v(t)$  is a stationary signal defined by  $V(s) = G(s)W(s)$ , where  $w(t)$  is a Gaussian distributed white noise signal with zero mean and unit variance. The transfer function  $G(s)$  is defined by

$$G(s) = \frac{K}{1 + Ts}$$

- a) Find the power spectral density function and the autocorrelation function for the signal  $w(t)$ .
- b) Show that the power spectral density function for the signal  $v(t)$  is

$$S_v(j\omega) = \frac{K^2}{(\omega T)^2 + 1}$$

Find the autocorrelation function.

- c) Find approximate values of  $K$  and  $T$  from the following estimated effect spectrum:



Attachment to the exam (Some useful formulas and expressions)

$$\begin{aligned}
 x(t) &= e^{At}x(0) + \int_0^t e^{A(t-\tau)}Bu(\tau)d\tau \\
 x(k) &= A^kx(0) + \sum_{m=0}^{k-1} A^{k-1-m}Bu(m) \\
 A^{-1} &= \frac{adj(A)}{det(A)} \\
 det(A) &= \sum_{i=1}^n a_{ij}c_{ij} \\
 adj(A) &= \{c_{ij}\}^T \\
 c_{ij} &= (-1)^{i+j}det(A_{ij}) \quad (\text{cofactor}), \quad A_{ij} = \text{sub matrix of } A \\
 \mathcal{C} &= (B \ AB \ A^2B \ \dots \ A^{n-1}B) \\
 \mathcal{O} &= \begin{pmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{n-1} \end{pmatrix} \\
 G(s) &= C(sI - A)^{-1}B + D \\
 G(z) &= C(zI - A)^{-1}B + D \\
 \mathbf{G}(\mathbf{s}) &= \mathbf{G}(\infty) + \mathbf{G}_{\text{sp}}(\mathbf{s}) \\
 d(s) &= s^r + \alpha_1s^{r-1} + \dots + \alpha_{r-1}s + \alpha_r \\
 \mathbf{G}_{\text{sp}}(s) &= \frac{1}{d(s)}[\mathbf{N}_1s^{r-1} + \mathbf{N}_2s^{r-2} + \dots + \mathbf{N}_{r-1}s + \mathbf{N}_r] \\
 \dot{\mathbf{x}} &= \begin{bmatrix} -\alpha_1\mathbf{I}_p & -\alpha_2\mathbf{I}_p & \dots & -\alpha_{r-1}\mathbf{I}_p & -\alpha_r\mathbf{I}_p \\ \mathbf{I}_p & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_p & \dots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{I}_p & \mathbf{0} \end{bmatrix} \mathbf{x} + \begin{bmatrix} \mathbf{I}_p \\ \mathbf{0} \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix} \mathbf{u} \\
 \mathbf{y} &= [\mathbf{N}_1 \ \mathbf{N}_2 \ \dots \ \mathbf{N}_{r-1} \ \mathbf{N}_r] \mathbf{x} + \mathbf{G}(\infty)\mathbf{u}
 \end{aligned}$$

Attachment to the exam.

Discrete Kalman-filter:

$$\begin{aligned}
 \mathbf{x}_{k+1} &= \mathbf{\Phi}_k \mathbf{x}_k + \mathbf{w}_k \\
 \mathbf{z}_k &= \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k \\
 E[\mathbf{w}_k \mathbf{w}_i^T] &= \begin{cases} \mathbf{Q}_k, & i = k \\ 0, & i \neq k \end{cases} \\
 E[\mathbf{v}_k \mathbf{v}_i^T] &= \begin{cases} \mathbf{R}_k, & i = k \\ 0, & i \neq k \end{cases} \\
 E[\mathbf{w}_k \mathbf{v}_i^T] &= 0, \forall i, k \\
 \mathbf{P}_k^- &= E[\mathbf{e}_k^- \mathbf{e}_k^{-T}] \\
 \mathbf{P}_k &= E[\mathbf{e}_k \mathbf{e}_k^T] = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_k^- (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)^T + \mathbf{K}_k \mathbf{R}_k \mathbf{K}_k^T \\
 \mathbf{K}_k &= \mathbf{P}_k^- \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R}_k)^{-1} \\
 \mathbf{P}_{k+1}^- &= \mathbf{\Phi}_k \mathbf{P}_k \mathbf{\Phi}_k^T + \mathbf{Q}_k
 \end{aligned}$$

Continuous Kalman filter:

$$\begin{aligned}
 \dot{\mathbf{x}} &= \mathbf{F}\mathbf{x} + \mathbf{G}\mathbf{u} \\
 \mathbf{z} &= \mathbf{H}\mathbf{x} + \mathbf{v} \\
 E[\mathbf{u}(t)\mathbf{u}(t)^T] &= \mathbf{Q}\delta(t - \tau) \\
 E[\mathbf{v}(t)\mathbf{v}(t)^T] &= \mathbf{R}\delta(t - \tau) \\
 E[\mathbf{u}(t)\mathbf{v}(t)^T] &= 0 \\
 \mathbf{K} &= \mathbf{P}\mathbf{H}^T \mathbf{R}^{-1} \\
 \dot{\mathbf{P}} &= \mathbf{F}\mathbf{P} + \mathbf{P}\mathbf{F}^T - \mathbf{P}\mathbf{H}^T \mathbf{R}^{-1} \mathbf{H}\mathbf{P} + \mathbf{G}\mathbf{Q}\mathbf{G}^T, \quad \mathbf{P}(0) = \mathbf{P}_0
 \end{aligned}$$

Autocorrelation:

$$\begin{aligned}
 R_X(\tau) &= E[X(t)X(t + \tau)] \text{ (Stationary process)} \\
 R_X(t_1, t_2) &= E[X(t_1)X(t_2)] \text{ (Non-stationary process)} \\
 Y(s) &= G(s)U(s) \Rightarrow \\
 R_y(t_1, t_2) &= E[y(t_1)y(t_2)] \\
 &= \int_0^{t_1} \int_0^{t_2} g(\xi)g(\eta)E[u(t_1 - \xi)u(t_2 - \eta)]d\xi d\eta \text{ (Transient analyzes)}
 \end{aligned}$$

Least squares estimation:

$$\begin{aligned}
 V(\bar{\theta}) &= \frac{1}{2}(\mathcal{Y}_N - \Phi_N \bar{\theta})^T (\mathcal{Y}_N - \Phi_N \bar{\theta}) \\
 E[\hat{\theta}\hat{\theta}^T] &= \hat{\sigma}_e^2 (\Phi_N^T \Phi_N)^{-1} \\
 \hat{\sigma}_e^2 &= \frac{2}{N - p} V(\hat{\theta})
 \end{aligned}$$