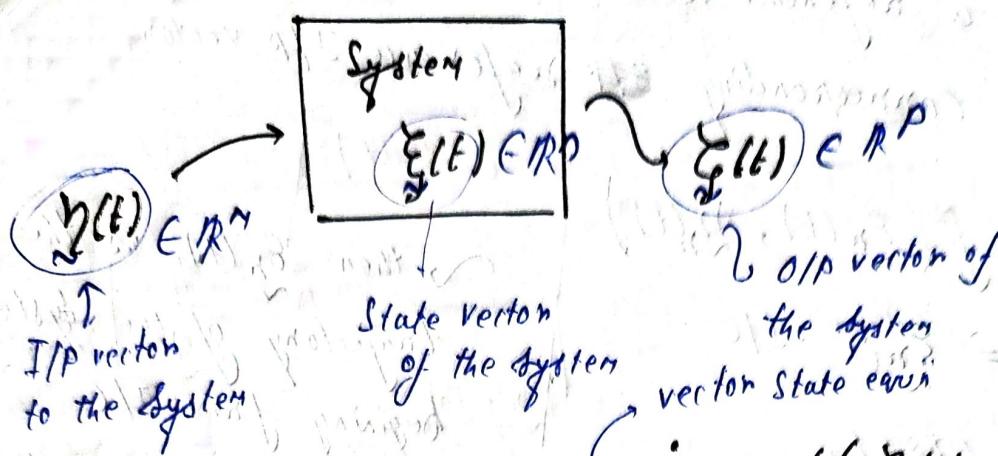


Week-01

AE777 (Optimal Space Flight Control)

Lec-01

Optimal Space Flight Control
Lec-01
Week-01
AE777
Objectives:
1. To understand the basic concepts of optimal control theory.
2. To learn how to solve the optimal control problems using Pontryagin's Maximum Principle.
3. To understand the application of optimal control theory in aerospace engineering.
4. To learn how to implement optimal control algorithms in MATLAB.



- The system is governed by

$$\dot{x}(t) = f(x(t), y(t))$$

$$\text{I/C: } x(t_i) = \sum x_i$$

$$z(t) = h(x(t), y(t))$$

O/P eqn

② Determining Whether the system is Linear or NOT!

→ the system is said to be linear if

$$\text{for I/P vector: } y(t) = c_1 y_1(t) + c_2 y_2(t)$$

$$\text{the O/P vector: } z(t) = c_1 z_1(t) + c_2 z_2(t)$$

where $z_1(t)$ is the O/P for I/P $y_1(t)$

$z_2(t)$ is O/P of I/P $y_2(t)$

- If the functional $f(\cdot)$ & $h(\cdot)$ are continuous in some time intv. $t_i \leq t \leq t_f$, if they do NOT contain Non-Linear functions of the state vector $x(t)$ & I/P vector $y(t)$, then the system is linear in the given time intv. $t_i \leq t \leq t_f$.

Linearization:

$\tilde{e}_n(t)$ \rightarrow a reference state vector

\sim $\tilde{n}_n(t)$ \rightarrow corresponding ~~ref~~ reference I/P vector.

$$\dot{\tilde{e}}_n(t) = f(\tilde{e}_n(t), \tilde{n}_n(t))$$

$$\sim \tilde{e}_n(t_i) = \tilde{e}_{n_i} : \text{I/C}$$

for $t_i \leq t \leq t_f$

\sim then $\tilde{e}_n(t)$ is the trajectory of the system beginning from I/C

\tilde{e}_{n_i} & $\tilde{n}_n(t)$ is the corresponding control history in the time interv. $t_i \leq t \leq t_f$.

$$\begin{cases} \tilde{e}(t) = \tilde{e}_n(t) + \tilde{z}(t) \\ \tilde{n}(t) = \tilde{n}_n(t) + \tilde{u}(t) \end{cases} \quad \begin{matrix} \text{arbitrarily} \\ \text{small} \\ \text{state} \\ \text{+ control} \\ \text{deviations} \end{matrix}$$

Perturbed solution

$$\text{Subject to I/C: } \tilde{e}_n(t_i) = \tilde{e}_{n_i} \quad \Rightarrow \quad \tilde{z}(t_i) = \tilde{e}_i - \tilde{e}_n$$

Now, assume that the vector functional $f(\cdot)$ possesses continuous derivatives w.r.t. state & control variables upto an ∞ Order at the reference solution $(\tilde{e}_n, \tilde{n}_n)$, we expand the state equation about the reference

solution:

$$\tilde{e}(t) - \tilde{e}_n(t) = f(\tilde{e}(t), \tilde{n}(t)) - f(\tilde{e}_n(t), \tilde{n}_n(t))$$

$$= f(\tilde{e}_n(t) + \tilde{z}(t), \tilde{n}_n(t) + \tilde{u}(t))$$

$$- f(\tilde{e}_n(t), \tilde{n}_n(t))$$

$$= f(\tilde{e}_n(t), \tilde{n}_n(t)) + \left[\frac{\partial f}{\partial \tilde{e}} \Big|_{(\tilde{e}_n, \tilde{n}_n)} \cdot \tilde{z}(t) \right]$$

$$+ \left[\frac{\partial f}{\partial \tilde{n}} \Big|_{(\tilde{e}_n, \tilde{n}_n)} \cdot \tilde{u}(t) \right]$$

$$+ O(HoT_x)$$

$$- f(\tilde{e}_n(t), \tilde{n}_n(t))$$

Neglect the HOTS! (Good when $\dot{x}(t)$ & $\dot{u}(t)$ are very small;
or ignored)

$$\text{So, } \dot{\tilde{x}}(t) - \dot{\tilde{x}_n}(t) = \frac{\partial f}{\partial \tilde{x}} \Big|_{(\tilde{x}_n, \tilde{u}_n)} \cdot \tilde{x}(t) + \frac{\partial f}{\partial u} \Big|_{(\tilde{x}_n, \tilde{u}_n)} \cdot \tilde{u}(t)$$

$$\Rightarrow \boxed{\dot{\tilde{x}}(t) = \underline{\underline{A}} \cdot \tilde{x}(t) + \underline{\underline{B}} \cdot \tilde{u}(t)} \quad \begin{matrix} \text{subject to IC:} \\ \tilde{x}(t_0) = \underline{\underline{x}} \end{matrix}$$

where $\underline{\underline{A}} = \frac{\partial f}{\partial \tilde{x}} \Big|_{(\tilde{x}_n, \tilde{u}_n)}$ & $\underline{\underline{B}} = \frac{\partial f}{\partial \tilde{u}} \Big|_{(\tilde{x}_n, \tilde{u}_n)}$

Linearized
State Equation

(Linearized about the
reference solution)

$$\dot{\tilde{x}}(t) = h \left(\tilde{x}(t), \tilde{u}(t) \right)$$

for $t_i \leq t \leq t_f$

$\tilde{x}(t)$ \sim state
variable

$\tilde{u}(t)$ \sim I/P variable

$\tilde{y}(t)$ \sim O/P variable

$$\begin{aligned} \dot{\tilde{x}}(t) &= h \left(\tilde{x}(t), \tilde{u}(t) \right) \\ &= h \left(\tilde{x}_n(t) + \tilde{x}(t), \tilde{u}_n(t) + \tilde{u}(t) \right) \end{aligned}$$

assuming that the vector functional $h(\cdot)$ looks continuous
derivative w.r.t. state & control variables upto an ∞ order at
the reference solution $(\tilde{x}_n(t), \tilde{u}_n(t))$, we expand the O/P eqn
about the reference solution.

$$\begin{aligned} \dot{\tilde{x}}(t) - \dot{\tilde{x}_n}(t) &= h \left(\tilde{x}_n(t) + \tilde{x}(t), \tilde{u}_n(t) + \tilde{u}(t) \right) \\ &\quad - h \left(\tilde{x}_n(t), \tilde{u}_n(t) \right) \end{aligned}$$

$$\begin{aligned} &= h \left(\tilde{x}_n(t), \tilde{u}_n(t) \right) + \left(\frac{\partial h}{\partial \tilde{x}} \Big|_{(\tilde{x}_n, \tilde{u}_n)} \cdot \tilde{x}(t) \right. \\ &\quad \left. + \frac{\partial h}{\partial \tilde{u}} \Big|_{(\tilde{x}_n, \tilde{u}_n)} \cdot \tilde{u}(t) \right) \\ &\quad + \text{HOTS} \\ &\quad - h \left(\tilde{x}_n(t), \tilde{u}_n(t) \right) \end{aligned}$$

$$e) \dot{\tilde{y}}(t) - \tilde{g}_n(t) = \frac{\partial h}{\partial \tilde{x}} \Big|_{(\tilde{x}_n, \tilde{y}_n)} \tilde{g}(t) + \frac{\partial h}{\partial \tilde{y}} \Big|_{(\tilde{x}_n, \tilde{y}_n)} \tilde{y}(t)$$

~~$\tilde{y}(t)$~~

$\tilde{y}(t) = C \cdot \tilde{g}(t) + D \cdot \tilde{y}(t)$

where $C = \frac{\partial h}{\partial \tilde{x}} \Big|_{(\tilde{x}_n, \tilde{y}_n)}$, $D = \frac{\partial h}{\partial \tilde{y}} \Big|_{(\tilde{x}_n, \tilde{y}_n)}$

Linearized O/P

(Linearized about the reference solns.)

C is the O/P Coeff. Matrix

D is direct transition

if $D(t) = 0 \Rightarrow$ System is "proper"

$$\tilde{g}(t) = \tilde{g}(t) - \tilde{g}_n(t)$$

$$\tilde{y}(t) = \tilde{y}(t) - \tilde{y}_n(t)$$

$$\tilde{y}(t) = \tilde{y}(t) - \tilde{y}_n(t)$$

Given: $\dot{\tilde{x}} = f(\tilde{x}, \tilde{y}, t)$ State vector
 $\tilde{g}(t_i) = \tilde{g}_i$: IC Input
 $\tilde{y} = h(\tilde{x}, \tilde{y}, t)$ O/P vector.

Consider the reference solution:
 $\tilde{x}_n = \tilde{x}_n(t)$ & \tilde{y}_n such that:
 $\tilde{x}_n = \tilde{x}_n(t)$
 $\tilde{y}_n = \tilde{y}_n(t)$
 $\tilde{g}_n = \tilde{g}_n(t)$

On linearizing about the reference solution,

$$\dot{\tilde{y}}(t) = A \cdot \tilde{g}(t) + B(t) \cdot \tilde{y}(t)$$

$$\tilde{y}(t) = C(t) \cdot \tilde{g}(t) + D(t) \cdot \tilde{y}(t)$$

$$A = \frac{\partial f}{\partial \tilde{x}} \Big|_{(\tilde{x}_n, \tilde{y}_n)}$$

$$B = \frac{\partial f}{\partial \tilde{y}} \Big|_{(\tilde{x}_n, \tilde{y}_n)}$$

where $A = \frac{\partial f}{\partial \tilde{x}} \Big|_{(\tilde{x}_n, \tilde{y}_n)}$, $B = \frac{\partial f}{\partial \tilde{y}} \Big|_{(\tilde{x}_n, \tilde{y}_n)}$, $C = \frac{\partial h}{\partial \tilde{x}} \Big|_{(\tilde{x}_n, \tilde{y}_n)}$, $D = \frac{\partial h}{\partial \tilde{y}} \Big|_{(\tilde{x}_n, \tilde{y}_n)}$

① Solution to Linear State Equations:

$$\tilde{z}(t) = A(t) \cdot \tilde{z}(t) + B(t) \cdot y(t) \quad \rightarrow, \textcircled{i}$$

subject to IC: $\tilde{z}(t_i) = \tilde{z}_i$

is expressed as $\tilde{z}(t) = \text{homogenous solution} + \text{particular solution}$
 $\tilde{z}(t) = \tilde{\Phi}(t, t_i) \tilde{z}_i + \int_{t_i}^t \tilde{\Phi}(t, \tau) B(\tau) y(\tau) d\tau$ where $t \geq t_i$

• Homogeneous Solution:

$$\tilde{z}(t) = A(t) \cdot \tilde{z}(t)$$

$$\tilde{z}(t) = \tilde{\Phi}(t, t_i) \tilde{z}_i$$

↳ State Transition Matrix (STM)

has the following properties:

$$\tilde{\Phi}(t_i, t_i) = I$$

$$\tilde{\Phi}(t_i, t) = \tilde{\Phi}(t, t_i)^{-1}$$

$$\tilde{\Phi}(t_i, t_f) = \tilde{\Phi}(t_i, t_0) \tilde{\Phi}(t_0, t_f)$$

where $t_i \leq t_0 \leq t_f$

$$\frac{d \tilde{\Phi}(t, t_i)}{dt} = A(t) \cdot \tilde{\Phi}(t, t_i)$$

General solution to eqns. \textcircled{i}

$$\tilde{z}(t) = \tilde{\Phi}(t, t_i) \tilde{z}_i + \int_{t_i}^t \tilde{\Phi}(t, \tau) B(\tau) y(\tau) d\tau, \quad t \geq t_i$$

O/P: $y(t) = C(t) \tilde{z}(t) + D(t) u(t)$

$$y(t) = C \cdot \tilde{\Phi}(t, t_i) \tilde{z}_i + \int_{t_i}^t (C \cdot \tilde{\Phi}(t, \tau) B(\tau) y(\tau) + D(t) \delta(t-\tau) f(\tau)) d\tau$$

so

$$\tilde{y}(t) = C(t) \cdot \tilde{\Phi}(t, t_i) \cdot \tilde{z}_i + \int_{t_i}^t [C(t) \tilde{\Phi}(t, \tau) B(\tau) + D(t) \delta(t-\tau)] y(\tau) d\tau$$

$t_i \leq t \leq t_f$

$$\text{So, } \tilde{y}(t) = \underline{\Phi}(t, t_i) \tilde{z}_i + \int_{t_i}^t \underline{\Phi}(t, \tau) \underline{B}(\tau) \cdot \underline{Q}(\tau) d\tau, \quad t_i \leq t$$

$$\tilde{y}(t) = \underline{C} \cdot \underline{\Phi}(t, t_i) \cdot \tilde{z}_i + \int_{t_i}^t [\underline{C} \underline{\Phi}(t, \tau) \underline{B}(\tau) \underline{y}(\tau) + \underline{D}(t) \cdot \delta(t-\tau) \cdot \underline{G}(\tau)] d\tau$$

Convolution integral
of the linear
system.

$\delta(t-\tau)$ is Dirac Delta function
representing a unit
impulse applied at $t=\tau$

① When $\underline{C} \cdot \underline{z}_i = 0$, then $\tilde{y}(t) = \int_{t_i}^t \underline{B} \underline{G}(t, \tau) \underline{u}(\tau) d\tau$

Input response
matrix

$$\underline{G}(t, \tau) = \underline{C}(t) \underline{\Phi}(t, \tau) \underline{B}(\tau) + \underline{D}(t) \cdot \delta(t-\tau) \quad \tau \leq t$$

when $\underline{u}(\tau) = \delta(t-\tau)$ i.e. when the input is a unit impulse

then, $\tilde{y}(t) = \int_{t_i}^t \underline{G}(t, \tau) \delta(t-\tau) d\tau$

Impulse response
matrix

$\underline{G}(t, \tau)_{ij}$ is the value of the i^{th} O/P variable at time t ,
when the j^{th} I/P variable is a unit impulse
function applied at time τ , subject to zero
Initial conditions, $\tilde{z}_i = 0$

Step response
matrix

$$\underline{s}(t, t_i) = \int_{t_i}^t \underline{G}(t, \tau) d\tau, \quad t_i \leq t$$

$\underline{G}(t, \tau) \sim$ Impulse response matrix.

$$\underline{S}(t, t_i) = \int_{t_i}^t \underline{G}(t, \tau) d\tau$$

Step response matrix!

$$\underline{S}(t, t_i) = \int_{t_i}^t \underline{G}(t, \tau) d\tau \quad t_i < t \leq T$$

$\underline{S}(t, t_i)_{ij}$ is the value of i th o/p at time t when the j th I/P variable is a unit step applied at time t_i , subject to $0 \leq t \leq T$, $q_i = 0$

① Linear Time Invariant System:

(LTI system)

the linear system's properties are invariant wrt time, i.e. $\underline{A}, \underline{B}, \underline{C}, \underline{D}$ are independent of time, t .

$$\underline{\dot{q}}(t) = \underline{A} \cdot \underline{q}(t) + \underline{B} \cdot \underline{y}(t)$$

$$\underline{y}(t) = \underline{C} \cdot \underline{q}(t) + \underline{D} \cdot \underline{u}(t)$$

$$\underline{\dot{q}}(t_i) = \underline{\dot{q}_i}$$

$$\underline{\Phi}(t, t_i) = e^{\underline{A}(t-t_i)}$$

for LTI system,

where

$$e^{\underline{A}(t-t_i)} = \underline{I} + \underline{A}(t-t_i) + \frac{1}{2!} \underline{A}^2(t-t_i)^2 + \frac{1}{3!} \underline{A}^3(t-t_i)^3 + \dots$$

$$\dot{\underline{x}} = \underline{A} \cdot \underline{x} + \underline{B} \cdot \underline{u}$$

in Laplace variable.

$$\underline{\lambda} \left\{ \underline{x} \right\}$$

$$\underline{\delta} \underline{s} e^{\underline{C}}$$

$$\text{hence } X(s) = \underline{\lambda} \left\{ x(t) \right\}(s)$$

$$\underline{\delta} X(s) - \underline{x}(t=0) = \underline{A} \cdot \underline{\lambda} \left\{ x(s) \right\} + \underline{B} \cdot \underline{U}(s)$$

$$U(s) = \underline{\lambda} \left\{ u(t) \right\}(s)$$

$$\Rightarrow \underline{\delta} X(s) - \underline{x}_0 = \underline{A} \cdot \underline{\lambda} \left\{ x(s) \right\} + \underline{B} \cdot \underline{U}(s)$$

$$\Rightarrow (\underline{\delta} \underline{s} - \underline{A}) \cdot \underline{\lambda} \left\{ x(s) \right\} = \underline{x}_0 + \underline{B} \cdot \underline{U}(s)$$

$$\Rightarrow \underline{\lambda} \left\{ x(s) \right\} = (\underline{\delta} \underline{s} - \underline{A})^{-1} \underline{x}_0 + (\underline{\delta} \underline{s} - \underline{A})^{-1} \cdot \underline{B} \cdot \underline{U}(s)$$

$$\underline{x}(t=0) = \underline{x}_0$$

For homogeneous LTI system: $\underline{Q}(s) = \underline{0}$

$$\underline{x}(s) = (\underline{\delta} \underline{s} - \underline{A})^{-1} \underline{x}_0$$

$$\underline{x}(t) = \underline{\lambda}^{-1} \left\{ (\underline{\delta} \underline{s} - \underline{A})^{-1} \right\} \underline{x}_0$$

where
 $t \geq t_i$

$$\text{so, } e^{\underline{A}(t-t_i)} = \underline{\lambda}^{-1} \left\{ (\underline{\delta} \underline{s} - \underline{A})^{-1} \right\}, \text{ where } t_i = 0$$

$$\text{i.e. } \underline{e}^{\underline{A}t} = \underline{\lambda}^{-1} \left\{ (\underline{\delta} \underline{s} - \underline{A})^{-1} \right\}$$

where $t_i = 0$

For a generalized LTI system:

$$\underline{x}(t) = e^{\underline{A}(t-t_i)} \underline{x}_i + \int_{t_i}^t e^{\underline{A}(t-\tau)} \cdot \underline{B} \cdot \underline{u}(\tau) d\tau$$

when $t_i = 0 \Rightarrow \underline{x}(t_i=0) = \underline{x}_0$

$$\text{then, } \underline{x}(t) = e^{\underline{A}t} \underline{x}_0 + \int_0^t e^{\underline{A}(t-\tau)} \cdot \underline{B} \cdot \underline{u}(\tau) d\tau$$

for an asymptotically stable system.

$\rightarrow 0$ as $t \rightarrow \infty$ or finite value (or steady state)
as $t \rightarrow \infty$ or assumes some functional form as that of the IIP Pforced response

$$\tilde{y}(t) = \underline{C} \cdot \underline{x}(t) + \underline{D} \cdot \tilde{u}(t)$$

$$\left\{ \begin{array}{l} \underline{x}(t) \\ \tilde{u}(t) \end{array} \right\}$$

$$\tilde{y}(s) = \underline{C} \cdot \underline{x}(s) + \underline{D} \cdot \tilde{u}(s)$$

for LTI system, with $\underline{x}(t=0) = \underline{0}$

$$\tilde{y}(s) = \underline{C}(\underline{sI} - \underline{A})^{-1} \tilde{u}(s) + [\underline{C}(\underline{sI} - \underline{A})^{-1} \cdot \underline{B} + \underline{D}] \underline{U}(s)$$

↓
for LTI system, subject to 0 ICS
i.e. $y(0) = \dot{y}(0) = \ddot{y}(0) = \dots = 0$

$$\boxed{\tilde{y}(s) = \underline{G}_I(s) \cdot \underline{U}(s)}$$

Transfer Matrix

$\underline{G}_I(s) = \lambda \left\{ \text{Impulse Response Matrix subjected to 0 ICS} \right\}$

$\underline{G}_I(s) = \frac{\text{numerators}}{\text{Denom}}$ \curvearrowright zeros of the system.
 \curvearrowright poles of the system.

" eigenvalues of \underline{A}

$$\star \boxed{\underline{G}_I(s) = \underline{C} \cdot (\underline{sI} - \underline{A})^{-1} \cdot \underline{B} + \underline{D}}$$

\therefore for LTI system with 0 ICS.
i.e. $\underline{x}(t_i=0) = \underline{0}, \forall i \in \mathbb{N}$

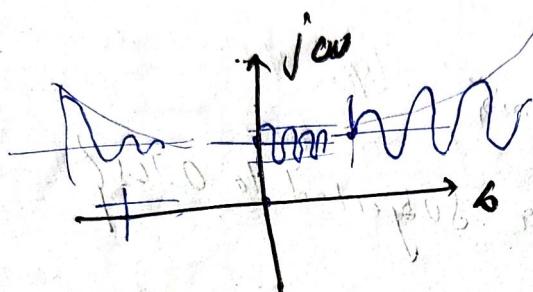
① Stability Criteria for a LTI system with OICs

$$\cancel{\det(\delta I - A) = 0} \quad (\delta I - A) \cdot \underline{\underline{X}}/\delta = 0$$

↓ eigenvalues ↓ eigenvectors

Characteristic "eigen" of the system.

- the Eigenvalue of the linear system is obtained from $\det(\delta I - A) = 0$



$$(\delta + j\omega)$$

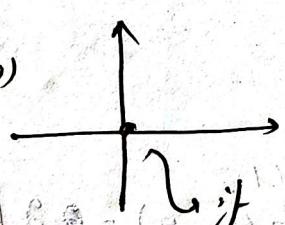
growth (or decay)
of amplitude of the
characteristic
vector about the equl. pt.

frequency of
oscillation of the
characteristic
vector about the equl. pt.

~~stable~~
asymptotically stable
Marginally
Unstable.

of oscillatory behaviour of const. amplitude
⇒ const. signal + oscillations.

In notes AE777 (Lec 2)
they are
called
'stable'



$$\delta + \delta \cdot (0 + j\omega)$$

if p no. of poles are at origin

$$\text{then } f(t) = k_1 + k_2 t^1 + k_3 t^2 + \dots + k_p t^{p-1} + \dots$$

for $p > 1$ system is unstable

$p = 1$ system is ~~marginally~~

may be stable (but Not asymptotically stable!)

① Calculation of State Transition Matrix (LTI)

Homogeneous state eqn of LTI system : $\dot{x} = Ax$

$$\text{State Transition Matrix, } \Phi(t, t_i) = e^{-A(t-t_i)}$$

$$\text{where } e^{At} = \mathcal{L}^{-1}\{(sI - A)^{-1}\}$$

sE is the Laplace variable.

② Partial fraction Expansion

Consider a rational function, $F(s) = \frac{N(s)}{D(s)}$

whose poles are $P_1, P_2, \dots, P_{N-1}, P_N$

of multiplicity 1, i.e. simple poles

$$\text{then } F(s) = \left[\frac{r_1}{s-P_1} + \frac{r_2}{s-P_2} + \dots + \frac{r_{N-1}}{s-P_{N-1}} \right] + \left[\frac{r_{N_1}}{s-P_N} + \frac{r_{N_2}}{(s-P_N)^2} + \dots + \frac{r_{N_K}}{(s-P_N)^K} \right]$$

Where $r_1, r_2, \dots, r_{N-1}, r_N, r_{N_1}, r_{N_2}, \dots, r_{N_K}$

$\underbrace{\text{M. n residues}}$ $\underbrace{\text{R. K. residues}}$

total = $K + N-1$ residues.

Where, $r_i = \lim_{s \rightarrow P_i} (s - P_i) F(s) ; 1 \leq i \leq N-1$

$$r_i = \lim_{s \rightarrow P_i} \frac{d^{(K-i)}}{ds^{(K-i)}} (s - P_i)^K F(s) ; 1 \leq i \leq K$$

$$r_{N_i} = \lim_{s \rightarrow P_N} \frac{d^{(K-i)}}{ds^{(K-i)}} (s - P_N)^K F(s) ; 1 \leq i \leq K$$

④ Controllability : (of a LTI system)

property of a system where it is possible to move the system from "any" initial state $\tilde{y}(t_i)$ to any given final state $\tilde{z}(t_f)$ solely by the application of I/P vector, $y(t)$ acting in a finite control interval $t_i \leq t \leq t_f$

✓ In an uncontrollable system

it may be possible to move between some specific states by applying control I/P.

∞ time may be required to change between arbitrary states!

For a system to be "controllable" all its state ~~on~~ variables, must be influenced either directly or indirectly by the control I/P, ~~if~~

if there is a subsystem that is unaffected by control I/P then the whole system is uncontrollable!

⇒ an LTI system is Controllable $\Leftrightarrow P = (B \ A \ B \ A^2 \ B \ \dots \ A^{n-1} \ B)$
 at $\begin{pmatrix} A & B \\ A^2 & B \\ \vdots & \vdots \\ A^{n-1} & B \end{pmatrix}$ must have rank n , $\exists \in \mathbb{R}^n$
 controllability test
 if $\begin{pmatrix} A & B \\ A^2 & B \\ \vdots & \vdots \\ A^{n-1} & B \end{pmatrix}$ is not full rank then the system is uncontrollable.

⇒ for an uncontrollable system: we can isolate controllable part from the uncontrollable part using LT such that the transformed system's coeff. matrix is partitioned into controllable & uncontrollable subsystem.

if the uncontrollable part is stable

Then the system is

said to be stabilizable

④ A controllable system which is unstable, can be stabilized using a feedback control system.

⑤ Observability: (of a LTI system)

→ it is defined as the ability of an arbitrary state $\tilde{x}(t)$, of a linear system to be determined from a finite record of the O/P $y(t)$, $t \geq T$, when NO input acts on the system!
 (unforced LTI system)

for a forced linear system $u(t)$ should be known in the period of observation $t \geq t_i$

For a system to be "Observable", the O/P variables must be either directly or indirectly be affected by the state variables!

⇒ an unforced LTI system is observable $\Leftrightarrow \boxed{N} = [C^T A^T C^T (A^T)^2 C^T \dots (A^T)^{n-1} C^T]$
 $(u(t) = 0)$

$\tilde{x} = A \cdot \tilde{x} + B \cdot u$ → Observability test matrix.
 $y = C \cdot \tilde{x} + D \cdot u \quad (u = 0)$ Must have rank n
 else ~~Unobservable~~

If there is subsystem that leaves the O/P vector unaffected then the entire system is Unobservable!

⑥ For an unobservable system: we can isolate unobservable part from observable part

if the unobservable part of the system is stable
 then the system is Detectable

⑦ ✓ The Observability (or atleast detectability) of a plant allows the design of an Observer to estimate the actual state of the plant by an estimated $\tilde{x}(t)$ from measurement of the O/P $y(t)$
 if knowledge of applied I/P $u(t)$

therefore Observer is also called State estimator for the plant!

① State Feedback Control of LTI System: [Design of "Regulator"]

a LTI system $\left\{ \begin{array}{l} \dot{x}_{nx1} = A_{nx1}x_{nx1} + B_{nx1}y \\ y = C_{nx1}x_{nx1} + D_{nx1}u \end{array} \right.$

$y \in R^q$

$u \in R^p$

if the uncontrollable part is stable \Rightarrow $C_{nx1}A_{nx1}^n = 0 \Rightarrow$ system is proper

for a stabilizable plant, the overall closed loop system is made stable via Linear Static Feedback

Control law $u = -K_{=Mn} \dot{x}_{nx1} \Rightarrow$ "Regulator"

K : regulator gain matrix

$$\dot{x}_{nx1} = (A - B \cdot K) \dot{x}_{nx1}$$

$$B \cdot \dot{x}_{nx1}$$

regulator dynamic matrix on the dynamic matrix

"regulation" entire system is observable we select K such that $(A - B \cdot K)$ has all its EVs on left place

dynamic matrix is Hurwitz

② Method for selecting K :

Method 1: Auerman's formula: [applicable when $B \cdot y \in R^n$]

(System is asymptotically stable)

$$K = \frac{(P \cdot W)}{\det(P \cdot W)} (\hat{a} - a)^{-1}$$

$$a = (a_n \ a_{n-1} \ a_{n-2} \dots \ a_2 \ a_1)$$

$$\hat{a} = (\hat{a}_n \ \hat{a}_{n-1} \ \hat{a}_{n-2} \ \dots \ \hat{a}_2 \ \hat{a}_1) \sim \det(\delta I - \underline{A - B \cdot K})$$

controllability test matrix

$$P = (B \ \underline{A \cdot B} \ \underline{A^2 \cdot B} \ \dots \ \underline{A^{n-1} \cdot B})$$

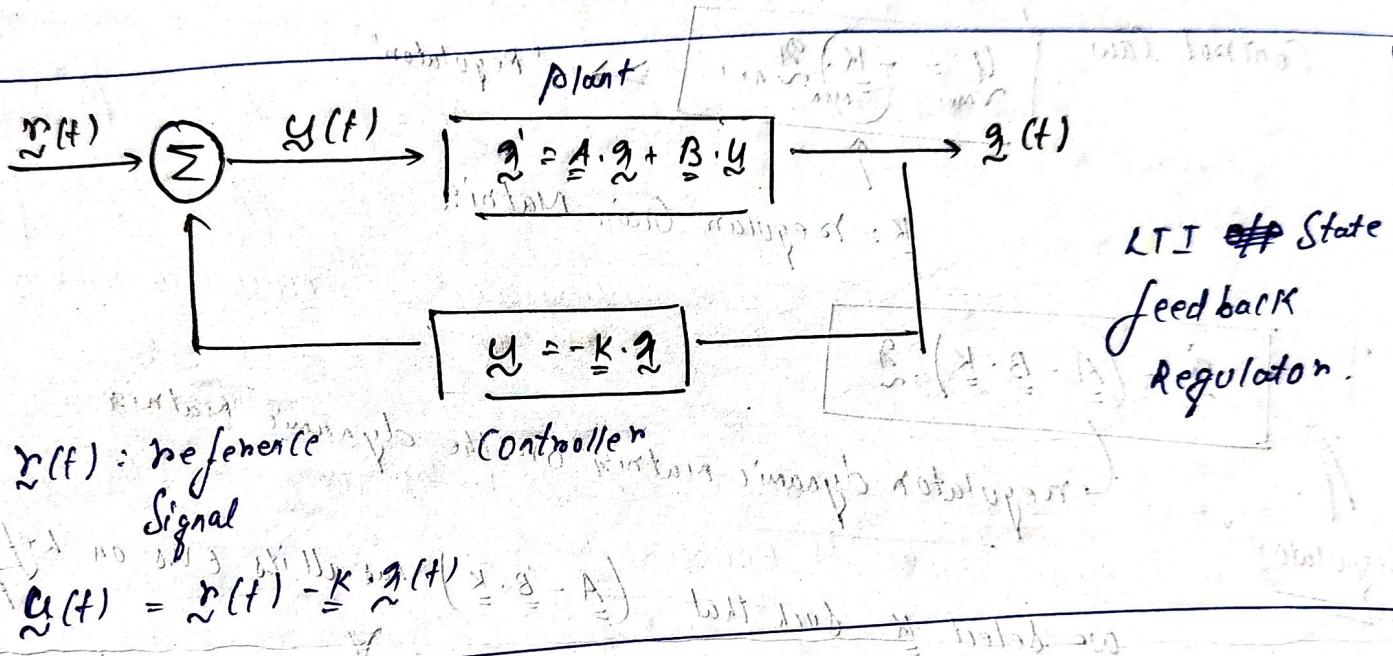
$$\begin{aligned} \det(\delta I - A) &= \delta^n + a_{n-1}\delta^{n-1} + a_{n-2}\delta^{n-2} + \dots + a_2\delta + a_1 \\ &= \delta^n + \hat{a}_n\delta^{n-1} + \hat{a}_{n-1}\delta^{n-2} + \dots + \hat{a}_2\delta + \hat{a}_1 \end{aligned}$$

$\underline{W} = \begin{pmatrix} 1 & a_n & a_{n-1} & \dots & a_4 & a_3 & a_2 \\ 0 & 1 & a_n & \dots & a_5 & a_4 & a_3 \\ 0 & 0 & 1 & \dots & a_6 & a_5 & a_4 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 1 & a_n & a_{n-1} \\ 0 & 0 & 0 & \dots & 0 & 1 & a_n \\ 0 & 0 & 0 & \dots & 0 & 0 & 1 \end{pmatrix}$

Upper triangular, Toeplitz matrix

Method

(ii) Knowing the roots or comparing with the desired characteristic eqn.
 $\det(\underline{\alpha}I - \underline{A} - \underline{B}\underline{k})$



$$\begin{bmatrix} 1 & (V_1 \cdot A) & (B - V_1 \cdot B) & (V_1 \cdot C) & X \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$(V_1 \cdot A - B) \cdot B = (V_1 \cdot A - B) \cdot B = 0$$

$$V_1 \cdot A \cdot B = V_1 \cdot A \cdot B = 0$$

O/P feedback Control of LTI Systems [Design of "Observer"]

The state vector $\tilde{x}(t)$ is often NOT measurable (because some state variables may not be any physical quantities) even if they are physically meaningful variable, sometimes measuring them won't be of any help!

O/P feedback control law:

Only the physically measurable variables \rightarrow O/P vector, $\tilde{y}(t)$ are used for feedback!

a General Non-linear time varying system / plant:

$$\text{state eqn: } \dot{\tilde{x}} = f(\tilde{x}(t), \tilde{u}(t))$$

$$\text{O/P eqn: } \tilde{y} = h(\tilde{x}(t), \tilde{u}(t))$$

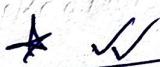
$$y = g(\tilde{y}(t)) : \text{Static control law.}$$

The O/P feedback control $\tilde{u} = g(\tilde{y}(t), \tilde{z}(t)) : \text{dynamic control law.}$

$$\text{where } \tilde{z} = T(\tilde{y}(t), \tilde{x}(t))$$

O/P exp: (Dynamic Feedback Control)

↳ Observer based Control where $\tilde{x}(t) = \hat{x}(t)$ Function $(\tilde{y}(t), \tilde{u}(t))$



the system is observable (or atleast detectable)



We can build Observer!

✓ Observer is an essential tool for building practical systems with the help of O/P feedback!

The state eqn of a LTI ~~sys~~ observer for a plant:

$$\left\{ \begin{array}{l} \hat{x}(t) = A \cdot \hat{x}(t) + B \cdot U(t) \\ Y(t) = C \cdot \hat{x}(t) + D \cdot U(t) \end{array} \right.$$

In order to ensure that

$$\hat{x}(t) \rightarrow x(t) \text{ as } t \rightarrow \infty$$

we should select L in such a fashion that $(A - L \cdot C)$ is Hurwitz, i.e. all EVs of $(A - L \cdot C)$ are on Left Hand Side.

$$\hat{x} = \overset{\circ}{A} \hat{x} + \overset{\circ}{B} \cdot Y + \overset{\circ}{L} \cdot \overset{\circ}{U}$$

observer's
dynamic
matrix

Gain
Matrix

$$A = \overset{\circ}{A} - \overset{\circ}{L} \cdot C$$

$$(A - L \cdot C) \beta = B$$

$$(A - L \cdot C)^T = A^T - L^T \cdot C^T$$

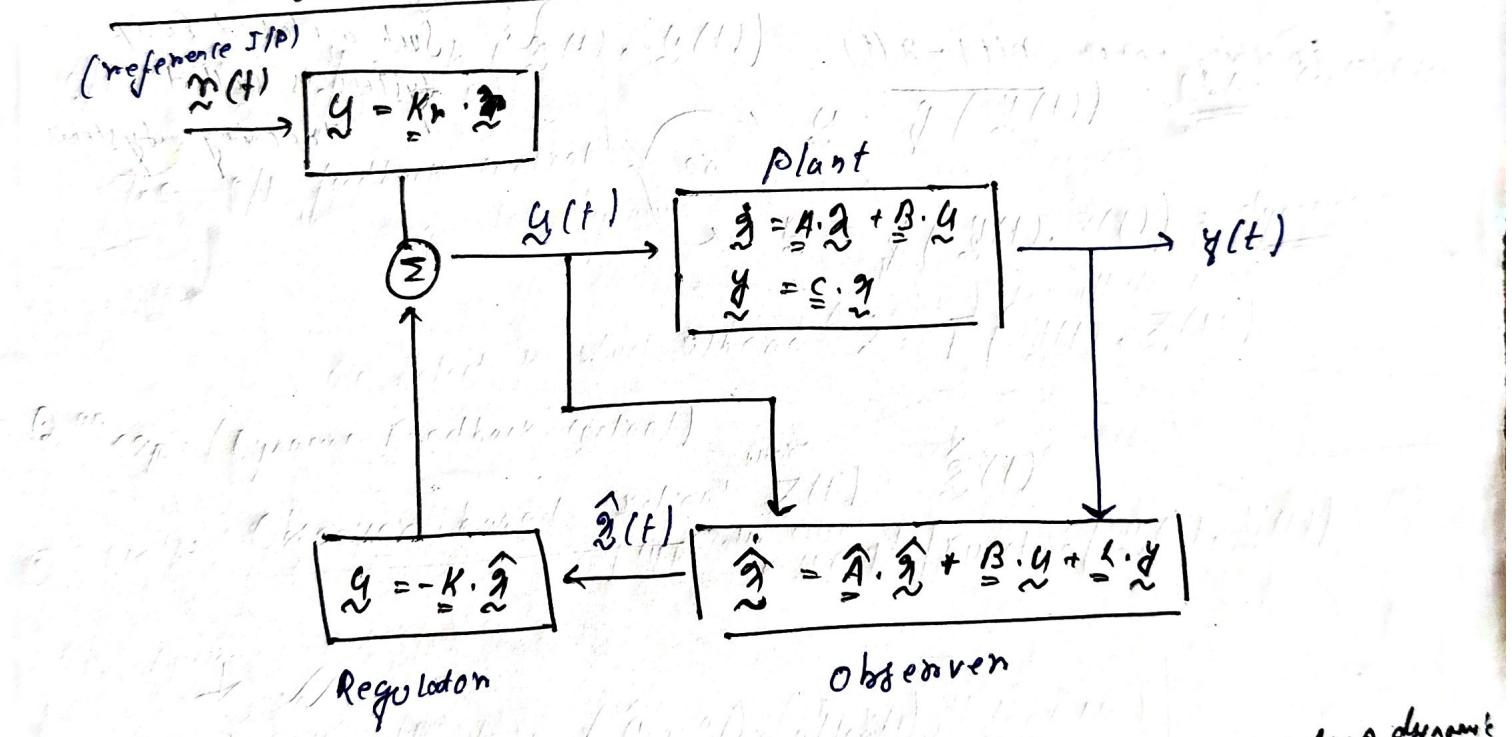
$$(A^T - L^T \cdot C^T) \beta = B^T$$

$$\left[\begin{array}{c} \text{Constraints (positivity)} \\ \text{Constraints (stability)} \\ \text{Constraints (observability)} \end{array} \right]$$

Further validation of plant behavior by simulation

On stabilizable & detectable plant we can build
 on putting together Regulator } \Rightarrow Compensator \sim a state of feedback system
 with dynamic feedback law
 designed separately
 Separation principle
 for the design of a stable, observer based compensator

* LTI O/P feedback Compensation:



* State eqns of LTI Compensation:

$$\begin{aligned}
 \dot{\tilde{z}}_{\text{ctrl}} &= \frac{A \cdot \tilde{y}_1 - B \cdot K \cdot \tilde{z}_{\text{ctrl}}}{M_{\text{ctrl}}} \\
 \dot{\tilde{z}}_{\text{ctrl}} &= \left(A - B \cdot K - L \cdot C \right) \cdot \tilde{z}_{\text{ctrl}} + \frac{L \cdot C \cdot \tilde{y}}{M_{\text{ctrl}}} \\
 \end{aligned} \quad \left. \right\} \quad \dot{\tilde{x}} = \bar{A} \cdot \tilde{x} \quad \text{where } \bar{A} = \begin{pmatrix} A & -B \cdot K \\ A - B \cdot K - L \cdot C & L \cdot C \end{pmatrix}$$

$$\tilde{x} = (\tilde{z}^T, \tilde{z}'^T)^T$$

Suppose a reference signal $\tilde{r}(t) \in \mathbb{R}^n$ acts on the compensated system; then $\tilde{y}(t) = \tilde{n}(t) - K \cdot \hat{x}$

$$\text{So, } \dot{\tilde{x}} = \tilde{A} \cdot \tilde{x} + \tilde{B} \cdot \tilde{n}$$

$$\text{where } \tilde{A} = \begin{pmatrix} A & -B \cdot K \\ 0 & I_n \end{pmatrix} \text{ and } \tilde{B} = \begin{pmatrix} B \\ 0 \end{pmatrix}$$

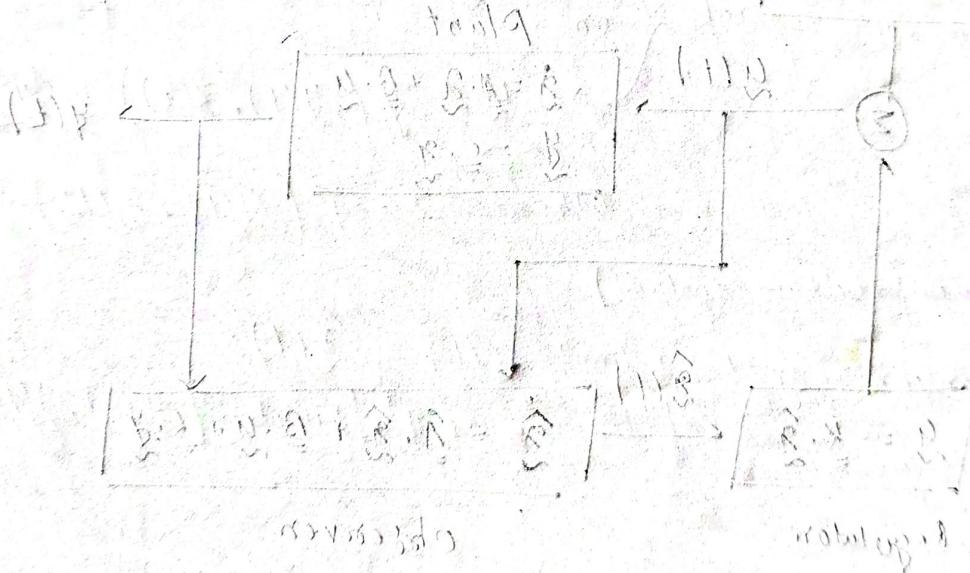
$$B \cdot \lambda + C \cdot (I_n - \tilde{A})^{-1} = \begin{pmatrix} A - B \cdot K - C \cdot I_n & C \cdot I_n \\ 0 & I_n \end{pmatrix}$$

to make the plant's state, $\tilde{x}(t) \rightarrow \tilde{n}(t)$, we introduce a feedforward gain K_n :

$$\tilde{y}(t) = K_n \cdot \tilde{n} - K \cdot \hat{x}$$

~~the~~ $\tilde{n}(t) \rightarrow x(t)$ as $t \rightarrow \infty$ irrespective of $\tilde{r}(t) \neq \tilde{n}(t)$
 tracking error $\underline{\tilde{n}(t) - x(t)}$

Such a closed loop system is called Tracking system!



$$\tilde{x} \cdot \tilde{B} = x \cdot S$$

$$(A - B \cdot K - C \cdot I_n) = \tilde{A}$$

$$(A - B \cdot K - C \cdot I_n) = S$$

Single Variable Optimization:

Consider a function $\lambda(u) \in \mathbb{R}$ of a scalar variable $u \in \mathbb{R}$
 assume that $\lambda(u)$ possesses continuous derivatives of upto and order
 i.e. consider $\lambda(u) \in \mathbb{R}$, $u \in \mathbb{R}$ such that $\lambda''(u)$ is continuous [These assumptions are there in both "sufficient" & "necessary" condition]

Necessary Condition

Suppose $u = u^*$ is the point where $\lambda(u)$ achieves minimum
 provided $u \in \mathbb{R}$ (i.e. $u \in$ whole of the \mathbb{R} or not to any particular subset of \mathbb{R})
 = there is NO constraint on u .

$$\left. \frac{d\lambda}{du} \right|_{u=u^*} = 0$$

$$\left. \frac{d^2\lambda}{du^2} \right|_{u=u^*} \geq 0$$

Sufficient Condition

if at $u = u^*$; $\left. \frac{d\lambda}{du} \right|_{u=u^*} = 0$
 $\left. \frac{d^2\lambda}{du^2} \right|_{u=u^*} > 0$
 provided $u \in \mathbb{R}$ (i.e. no constraint placed on u)
 $u = u^*$ is a point of minima
 if at $u = u^*$ (necessary condition) it satisfied } then $u = u^*$ is stationary pt. !!
 Stationary pts: all those pts. where $\frac{d\lambda(u)}{du} = 0$

$$\text{if at } u = u^*; \left. \frac{d\lambda}{du} \right|_{u=u^*} = 0$$

[provided no constraint is placed on u]

$u = u^*$
is singular point

$$\left. \frac{d^2\lambda}{du^2} \right|_{u=u^*} < 0$$

$u = u^*$ is pt. of maxima

$$\left. \frac{d^2\lambda}{du^2} \right|_{u=u^*} > 0$$

$u = u^*$ is pt. of minima.

$$\left. \frac{d^2\lambda}{du^2} \right|_{u=u^*} = 0$$

We can't decide!

→ In order to determine whether a singular point is a minimum point, an additional condition needs to be specified (called an equation of constraint)

- *
① prior applying the "necessary" & "sufficient" conditions you should make sure that $\lambda(y)$ poses continuous pd of upto 2nd order wrt y .
if $\lambda(y)$ does NOT poses continuous pd of upto 2nd order wrt y
then you can ^{written} apply the "necessary" condition non the "sufficient" condition!

All the EVs of a symmetric matrix are real!

Let A be a symmetric matrix of $Q(z) = z^T \cdot A \cdot z$ be the corresponding quadratic form.

A is called +ve semi-definite if $Q(z) \geq 0 \forall z$
 A is called +ve definite if $Q(z) > 0 \forall z \neq 0$

if all its EVs are > 0 \Leftrightarrow EVs of A are +ve

② Multi Variable Optimization :

Consider a function $L(u) \in \mathbb{R}$, $u \in \mathbb{R}^n$

such that $L(u)$ possess continuous partial derivative of upto and order m . cont. of

Necessary

① Suppose $u = u^*$ is the point where $L(u)$ achieves minima
 condition for apt. to be minima!

↓ provided that there is no constraint on u

$$\frac{\partial L}{\partial u} \Big|_{u=u^*} = 0$$

$$\frac{\partial^2 L}{\partial u^2} \Big|_{u=u^*} \geq 0$$

$$L_u = \frac{\partial L(u)}{\partial u} = \left(\frac{\partial L}{\partial u_1}, \frac{\partial L}{\partial u_2}, \dots, \frac{\partial L}{\partial u_n} \right) \in \mathbb{R}^{1 \times n}$$

$$L_{uu} = \frac{\partial^2 L(u)}{\partial u^2} = \begin{pmatrix} \frac{\partial^2 L}{\partial u_1^2} & \frac{\partial^2 L}{\partial u_1 \partial u_2} & \dots & \frac{\partial^2 L}{\partial u_1 \partial u_n} \\ \frac{\partial^2 L}{\partial u_2 \partial u_1} & \frac{\partial^2 L}{\partial u_2^2} & \dots & \frac{\partial^2 L}{\partial u_2 \partial u_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 L}{\partial u_n \partial u_1} & \frac{\partial^2 L}{\partial u_n \partial u_2} & \dots & \frac{\partial^2 L}{\partial u_n^2} \end{pmatrix} \in \mathbb{R}^{n \times n}$$

if it is symmetric
hence all its EVA are real

$$u = (u_1, u_2, u_3, \dots, u_n)^T \in \mathbb{R}^{n \times 1}$$

$$\begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{pmatrix}$$

(in part ①)
hence L_{uu} is semi-positive definite. \Leftrightarrow all EVA of L_{uu} are ≥ 0

Stationary points are points where $\frac{\partial L}{\partial \dot{y}} = 0$

i) if at $\dot{y} = \dot{y}^*$, $\left. \frac{\partial L}{\partial \dot{y}} \right|_{\dot{y}=\dot{y}^*} = 0$

Sufficient condition
for pt. to be minima provided that there is no constraint on u

ii) provided $\dot{y} \in \mathbb{R}^n$ has no constraint

$$\left. \frac{\partial^2 L}{\partial u^2} \right|_{\dot{y}=\dot{y}^*} > 0 \quad \text{if } \quad \textcircled{i}$$

$\dot{y} = \dot{y}^*$ is a point of minima

In part i) L_{uu} is +ve definite matrix

\Leftrightarrow all EVs of $L_{uu} > 0$

* if any of EVs of $L_{uu} = 0$ then $\dot{y} = \dot{y}^*$ will be a singular point!
(In such case we will need additional constraints to determine whether a singular point is minima or not)

if at $\dot{y} = \dot{y}^*$; $\left. \frac{\partial L}{\partial \dot{y}} \right|_{\dot{y}=\dot{y}^*} = 0$ & $\left. \frac{\partial^2 L}{\partial u^2} \right|_{\dot{y}=\dot{y}^*, u=u^*} > 0$ \Rightarrow $\dot{y} = \dot{y}^*$ is pt. of minima minima
(provided no constraint is placed on u)

$\left. \frac{\partial^2 L}{\partial u^2} \right|_{\dot{y}=\dot{y}^*, u=u^*} < 0 \Rightarrow$ $\dot{y} = \dot{y}^*$ is pt. of maxima
 $\left. \frac{\partial^2 L}{\partial u^2} \right|_{\dot{y}=\dot{y}^*, u=u^*} = 0 \Rightarrow$ we can't decide!
[$u = u^*$ is singular pt.]

provided $f_{\dot{y}}$ is not

singular

if at $\underline{y} = \underline{y}^*$; $\frac{\partial L}{\partial \underline{y}} \Big|_{\underline{y} = \underline{y}^*} = 0$ & $\frac{\partial^2 L}{\partial \underline{y}^2} \Big|_{\underline{y} = \underline{y}^*} = M$
 $(\underline{y}^* \text{ stationary pt.})$

if all Eigenvalues of $M \rightarrow > 0$

$\underline{y} = \underline{y}^*$ is a pt. of
maxima

< 0

if some EVs of M are 0

$\underline{y} = \underline{y}^*$ is a pt. of
maxima

else

$\underline{y} = \underline{y}^*$ is a singular point.

else $\underline{y} = \underline{y}^*$ is a saddle pt.

$\underline{y} = \underline{y}^*$ is a saddle point if some EVs of $\frac{\partial^2 L}{\partial \underline{y}^2}$ are +ve &
some EVs are -ve

if a pt. $\underline{y} = \underline{y}^*$ does not satisfy the sufficient conditions check
manually! (primarily by plotting graph)

⑤ In the previous lecture we had ~~studied~~ studied how an objective function is optimized w.r.t static variables, when there are NO constraint placed upon their values!

- In this lecture we will extend the treatment to multivariable optimization on when static equality constraints are imposed on the variables of optimization!

⑥ Objective function: $\mathcal{L}(\underline{\mathbf{z}}, \underline{\mathbf{y}}) \in \mathbb{R}$
Control variable: $\underline{\mathbf{z}} \in \mathbb{R}^n$
State variable: $\underline{\mathbf{y}} \in \mathbb{R}^m$

static equality constraint: $f(\underline{\mathbf{z}}, \underline{\mathbf{y}}) = \underline{\mathbf{0}}_{n \times 1} \rightarrow \textcircled{i}$

here $f: \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n$ is a smooth mapping function i.e. it passes continuous Pds wrt $\underline{\mathbf{z}}$ & $\underline{\mathbf{y}}$

This constraint should give a unique $\underline{\mathbf{z}}$ for a given $\underline{\mathbf{y}}$

also assume that $\mathcal{L}(\underline{\mathbf{z}}, \underline{\mathbf{y}})$ passes continuous Pds wrt $\underline{\mathbf{z}}$ & $\underline{\mathbf{y}}$

An arbitrary small variation in control variable, $\underline{\mathbf{y}}$ causes a small corresponding change in state variable, $\underline{\mathbf{z}}$ in order to satisfy eqn "i"

$$df = \underline{\mathbf{0}}_{n \times 1}$$

$$\Rightarrow \int_{\underline{\mathbf{z}}_{n \times n}} d\underline{\mathbf{z}}_{n \times 1} + \int_{\underline{\mathbf{y}}_{m \times 1}} d\underline{\mathbf{y}}_{m \times 1} = \underline{\mathbf{0}}_{n \times 1} \rightarrow \textcircled{ii}$$

$$\underline{\mathbf{f}}_z = \left(\frac{\partial f}{\partial \underline{\mathbf{z}}} \right)_{n \times n}$$

$$\underline{\mathbf{f}}_y = \left(\frac{\partial f}{\partial \underline{\mathbf{y}}} \right)_{n \times m}$$

$d\underline{\mathbf{z}} = -\underline{\mathbf{f}}_z^{-1} d\underline{\mathbf{y}}$

$d\underline{\mathbf{y}}$

provided $\underline{\mathbf{f}}_z$ is NOT singular.

Stationary Condition: Suppose $\tilde{y} = \tilde{y}^*$ is the point which ~~minimizes~~ minimizes $L(\tilde{x}, \tilde{y})$ subject to constraint (i)

(\tilde{y}^*
stationary
pt.)

↓ then

$$\frac{\partial L(\tilde{x}, \tilde{y})}{\partial \tilde{y}} \Big|_{\tilde{y}=\tilde{y}^*} = 0$$

$$\Rightarrow \cancel{\left(\lambda_x \cdot d\tilde{x} + \lambda_u \cdot d\tilde{y} \right)} \Big|_{\tilde{y}=\tilde{y}^*} = 0$$

$$\lambda_x = \left(\frac{\partial L}{\partial \tilde{x}} \right) \text{ } \cancel{1 \times n} \quad (ii)$$

$$\lambda_u = \left(\frac{\partial L}{\partial \tilde{y}} \right) \text{ } \cancel{1 \times n}$$

Combining both (i) & (ii) we have

$$\left(\lambda_u - \lambda_x \cdot f_2^{-1} \cdot d\tilde{x} \right) \cdot d\tilde{u} = 0$$

$$\left(\lambda_u - \lambda_x \cdot f_2^{-1} \cdot f_u \right) \Big|_{\tilde{y}=\tilde{y}^*} = 0$$

You will have n eqns.

use there n eqns + (i) to get \tilde{y}^*

Q. Problem: minimize $\lambda(\mathbf{z}, \mathbf{y})$ subject to the constraint

$$f(\mathbf{z}, \mathbf{y}) = \mathbf{Q}_{n \times 1}$$

Algo:

Step I:

objective func: $\lambda(\mathbf{z}, \mathbf{y}) \in \mathbb{R}$

equality constraint: $f(\mathbf{z}, \mathbf{y}) = \mathbf{Q}_{n \times 1}$

$$\in \mathbb{R}^{n \times 1} \quad \in \mathbb{R}^{M \times 1}$$

Step II:

check whether $f(\mathbf{z}, \mathbf{y})$ poses continuous ads
wrt \mathbf{z} & \mathbf{y}

$$\frac{\partial f}{\partial \mathbf{z}}_{n \times n}, \frac{\partial f}{\partial \mathbf{y}}_{n \times M}$$

Check ($\frac{\partial f}{\partial \mathbf{z}}$)

$$x(\mathbf{z}, \mathbf{y})$$

wrt \mathbf{z} & \mathbf{y}

$$\frac{\partial x}{\partial \mathbf{z}}_{n \times n}, \frac{\partial x}{\partial \mathbf{y}}_{n \times M}$$

If both of the conditions are satisfied then proceed!!

Step III:

If minimization is wrt \mathbf{z} .

$$d\mathbf{f} = \mathbf{0}_{n \times 1}$$

$$\Rightarrow d\mathbf{f} = \frac{\partial f}{\partial \mathbf{z}} \cdot d\mathbf{z} + \frac{\partial f}{\partial \mathbf{y}} \cdot d\mathbf{y} = \mathbf{0}_{n \times 1}$$

then

$$\Rightarrow \frac{\partial \mathbf{f}}{\partial \mathbf{z}}_{n \times n} = -\left(\frac{\partial f}{\partial \mathbf{z}} \cdot \frac{\partial f}{\partial \mathbf{y}}\right) \cdot d\mathbf{y}_{M \times 1}$$

f_g should be Non Singular.

If minimization is wrt \mathbf{y}

$$d\mathbf{f} = -\left(\frac{\partial f}{\partial \mathbf{y}} \cdot \frac{\partial f}{\partial \mathbf{z}}\right) \cdot d\mathbf{z}_{n \times 1}$$

\rightarrow NOTE: the way by which the problem has been set up the minimization has to be always wrt \mathbf{y}

Step IV: at $\tilde{y} = \tilde{y}^*$

$$\begin{aligned} \cancel{\text{Let } d\tilde{x} = 0} \\ \Rightarrow \lambda_2 \cdot \frac{d\tilde{x}}{\tilde{x}_{nn}} + \lambda_4 \cdot \frac{d\tilde{y}}{\tilde{y}_{nn}} = 0 \\ \Rightarrow \left(\lambda_2 - \lambda_2 \cdot \frac{f_x^{-1}}{\tilde{x}_{nn}} \cdot \frac{f_y}{\tilde{y}_{nn}} \right) \cdot d\tilde{y}_{nn} = 0 \end{aligned}$$

$$\lambda_4 - \lambda_2 \cdot \frac{f_x^{-1}}{\tilde{x}_{nn}} \cdot \frac{f_y}{\tilde{y}_{nn}} = 0$$

→ \star

Step V: use eqn \star of $f(\tilde{x}, \tilde{y}) = 0$

→ (and ... and $\sqrt{\star}$ to get \tilde{x}^* & the corresponding \tilde{y}^* !)

$$\begin{aligned} \text{from eqn 2: } & \frac{\partial f}{\partial x}(\tilde{x}, \tilde{y}) = 0 \\ & (\lambda_2 - \lambda_2 \cdot f_x^{-1} \cdot f_y) \cdot \tilde{x}_{nn} = 0 \rightarrow ① \\ \text{from eqn 3: } & \frac{\partial f}{\partial y}(\tilde{x}, \tilde{y}) = 0 \\ & (\lambda_4 - \lambda_2 \cdot f_x^{-1} \cdot f_y) \cdot \tilde{y}_{nn} = 0 \rightarrow ② \end{aligned}$$

$$\begin{aligned} \text{from eqn 5: } & \left(\frac{\partial f}{\partial x} \right)_{\tilde{y} = \tilde{y}^*} = 0 \\ & \left[\lambda_2 - \lambda_2 \cdot f_x^{-1} \cdot f_y \right]_{\tilde{y} = \tilde{y}^*} = 0 \rightarrow ③ \end{aligned}$$

$$\begin{aligned} \text{from eqn 6: } & \left(\frac{\partial f}{\partial y} \right)_{\tilde{x} = \tilde{x}^*} = 0 \\ & \left[\lambda_4 - \lambda_2 \cdot f_x^{-1} \cdot f_y \right]_{\tilde{x} = \tilde{x}^*} = 0 \rightarrow ④ \end{aligned}$$

$$\begin{cases} \text{eqn 3: } \lambda_2 - \lambda_2 \cdot f_x^{-1} \cdot f_y = 0 \\ \text{eqn 4: } \lambda_4 - \lambda_2 \cdot f_x^{-1} \cdot f_y = 0 \end{cases}$$

① Lagrange Multipliers: λ

The problem of minimizing $f(\tilde{x}, \tilde{y})$ w.r.t \tilde{x} , subject to $\tilde{g}(\tilde{x}, \tilde{y}) = 0$

is well posed only if $\begin{cases} df = \tilde{Q}_{n \times 1} \\ dg = 0 \end{cases}$ are consistent linear equation in the arbitrary small variations $d\tilde{x} = 0 \quad d\tilde{y} = 0$

$$\begin{cases} f_{\tilde{x}} \cdot d\tilde{x}_{n \times 1} + f_{\tilde{y}} \cdot d\tilde{y}_{n \times 1} = \tilde{Q}_{n \times 1} \\ g_{\tilde{x}} \cdot d\tilde{x}_{n \times 1} + g_{\tilde{y}} \cdot d\tilde{y}_{n \times 1} = 0 \end{cases}$$

$$\begin{cases} f_{\tilde{x}} \cdot d\tilde{x}_{n \times 1} + \lambda g_{\tilde{x}} \cdot d\tilde{x}_{n \times 1} = 0 \\ f_{\tilde{y}} \cdot d\tilde{y}_{n \times 1} + \lambda g_{\tilde{y}} \cdot d\tilde{y}_{n \times 1} = 0 \end{cases}$$

for this to be consistent, we must be able to find $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_n)^T \in \mathbb{R}^n$

such that

$$\lambda g_{\tilde{x}} + (\lambda^T)_{nn} \cdot f_{\tilde{x}}_{n \times 1} = \tilde{Q}_{1 \times n}$$

$$\lambda g_{\tilde{y}} + (\lambda^T)_{nn} \cdot f_{\tilde{y}}_{n \times 1} = \tilde{Q}_{1 \times n}$$

if the matrix $f_{\tilde{x}}^{-1}$ exists only then λ exists!!

then from ① we have

$$\lambda^T_{1 \times n} = -\lambda g_{\tilde{x}}_{1 \times n} \cdot f_{\tilde{x}}^{-1}_{n \times n}$$

$$\lambda^T_{1 \times n} = -\left(\frac{\partial L}{\partial f}\right)_{d\tilde{y}=0}$$

putting this back in ② we have,

from

$$\left(\lambda^T_{1 \times n} - \lambda g_{\tilde{x}}_{1 \times n} \cdot f_{\tilde{x}}^{-1}_{n \times n} \cdot f_{\tilde{y}}_{n \times 1} \right) = \tilde{Q}_{1 \times n}$$

using this & $f(\tilde{x}, \tilde{y}) = 0$

we can get hold of \tilde{x}^* & \tilde{y}^* !!

② Hamiltonian Formulation : \rightarrow LAGRANGIAN (L)

$$H(\tilde{z}, \tilde{y}, \lambda) \equiv \lambda(\tilde{z}, \tilde{y}) + (\lambda^T)_{nx1} f(\tilde{z}, \tilde{y})_{nx1}$$

The problem of minimising the Lagrangian, $L(\tilde{z}, \tilde{y})$ w.r.t \tilde{y}

subject to $f(\tilde{z}, \tilde{y}) = 0_{nx1}$ is

minimising $H(\tilde{z}, \tilde{y}, \lambda)$ w.r.t \tilde{y}

- So, $dH = \frac{\lambda_{\tilde{z}}}{\sim_{1x1}} d\tilde{z}_{nx1} + \frac{\lambda_u}{\sim_{1xM}} d\tilde{y}_{Mx1}$

- at stationary pt. $\tilde{y} = \tilde{y}^*$, $dH = 0$

now, $\frac{\lambda_{\tilde{z}}}{\sim_{1x1}} = \frac{\lambda_{\tilde{z}}}{\sim_{1x1}} + (\lambda^T)_{nx1} \frac{f_{\tilde{z}}}{\sim_{nx1}}$

$\frac{\lambda_u}{\sim_{1xM}} = \frac{\lambda_u}{\sim_{1xM}} + (\lambda^T)_{nxM} \frac{f_u}{\sim_{nxM}}$

- to find λ , impose $\frac{\lambda_{\tilde{z}}}{\sim_{1x1}} = 0$ @ stationary pt.

- $\frac{\lambda_u}{\sim_{1xM}} \equiv \left(\frac{\lambda_u}{\sim_{1xM}} - \frac{\lambda_{\tilde{z}}}{\sim_{1x1}} \cdot \frac{f_{\tilde{z}}}{\sim_{nx1}} \right) \cdot \frac{f_u}{\sim_{nxM}}$

- as $\frac{\lambda_u}{\sim_{1xM}} = 0_{1xM}$ @ stationary pt.

So, $\left(\frac{\lambda_u}{\sim_{1xM}} - \frac{\lambda_{\tilde{z}}}{\sim_{1x1}} \cdot \frac{f_{\tilde{z}}}{\sim_{nx1}} \cdot \frac{f_u}{\sim_{nxM}} \right) = 0_{1xM}$

$f(\tilde{z}, \tilde{y}) = 0_{nx1}$

Gives us $\tilde{y}^* \neq \tilde{y}^*$.

$$\frac{\partial}{\partial z} (z^T \cdot A \cdot z) = z^T / (A^T + A) \quad [\text{in numerator layout}]$$

$$\left[\begin{array}{l} \frac{\partial}{\partial z} (A \cdot z) = A \\ \frac{\partial}{\partial z} (z^T \cdot A) = A^T \end{array} \right]$$

$$\frac{\partial (Vg)}{\partial z} = g \frac{\partial V}{\partial z}$$

$$\frac{\partial (A \cdot g)}{\partial z} = A \cdot \left(\frac{\partial g}{\partial z} \right)$$

$$\boxed{A \cdot A^T = I_n} \quad \left| \begin{array}{c} n \times n \\ n \times n \\ n \times n \end{array} \right. \leq 0 \quad \text{equivalent to } A^T \cdot A = I_n$$

$$\left(\frac{\partial V}{\partial z} \cdot A \cdot g + A^T \cdot \frac{\partial g}{\partial z} \right) = 0$$

$$\boxed{A^T \cdot A = I_n} \quad \left| \begin{array}{c} n \times n \\ n \times n \\ n \times n \end{array} \right. \quad \min_{n \times n} = 0$$

$$A^T \cdot A = (B, C)$$

$$B, C \in \mathbb{R}^{m \times m}$$

$$\int_{-\infty}^{\infty} f(a-x) g(x) dx = g(a)$$

$$\int_{a-\epsilon_1}^{a+\epsilon_2} f(a-x) g(x) dx = g(a)$$

① $L^{-1} \left\{ \frac{af+b}{s^2 + 2\zeta\omega s + \omega^2} \right\}; 0 \leq \zeta \leq 1$

$$= e^{-\zeta\omega t} \left[a \cos(\omega\sqrt{1-\zeta^2}t) + \frac{(b-a\zeta\omega)}{\omega\sqrt{1-\zeta^2}} \sin(\omega\sqrt{1-\zeta^2}t) \right]$$

Where $0 \leq \zeta \leq 1$

② A problem is well posed if :

Well posed problems have
a good chance to be solved
numerically with a stable
algo!

- A solution exists
 - The solution is unique
 - The solution depends continuously
on the data (boundary & I.C.s)
- Problems which do NOT satisfy
these criteria are ill-posed problems!!