

CONTROL THEORY

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CONTENT (9-12H, 13-14H)

- Control – an overview
- State space
 - Model & linearization
 - Stabilization
 - Feedback & Linear Quadratic Control
 - Observation & Kalman Filter

System dynamical properties:
Stabilize around equilibrium &
observe with disturbance,
noise and limited information

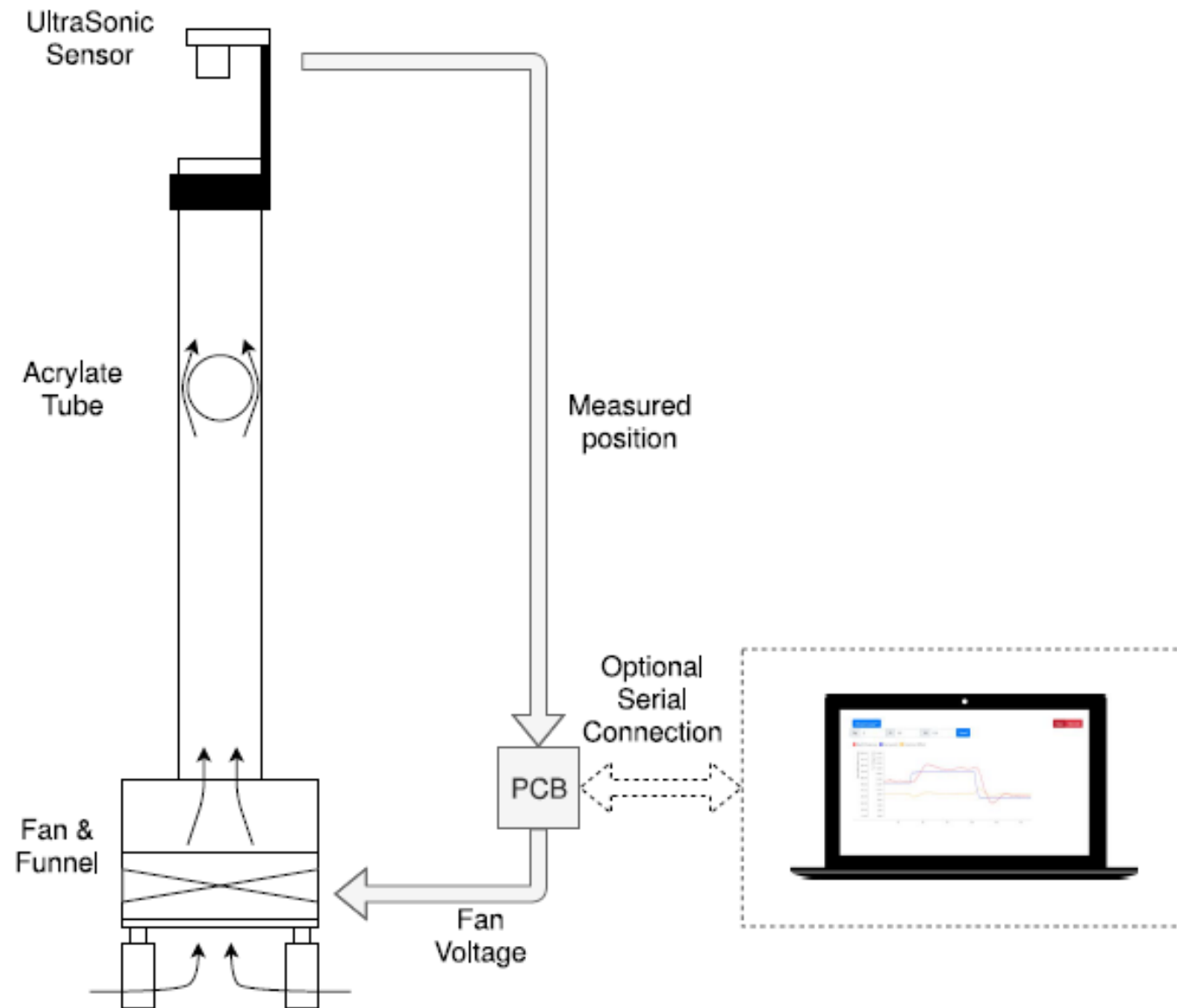
CONTENT (14-17H)

- Control Architectures
 - Input-output models
 - Control Algorithms
 - LQR
 - LQG
 - MIMO control: decoupling
 - Model Predictive control

Assuming stability & observation, how do we get where we want, given constraints, costs, ?

CONTROL: AN OVERVIEW

SYSTEM: LEVITATION OF A BALL



IDEAL PROCESS

= Input fully determines output



Model $m\ddot{x} = -mg + c(v_\ell - \dot{x})^2$

Equilibrium $mg = cv_\ell^2$

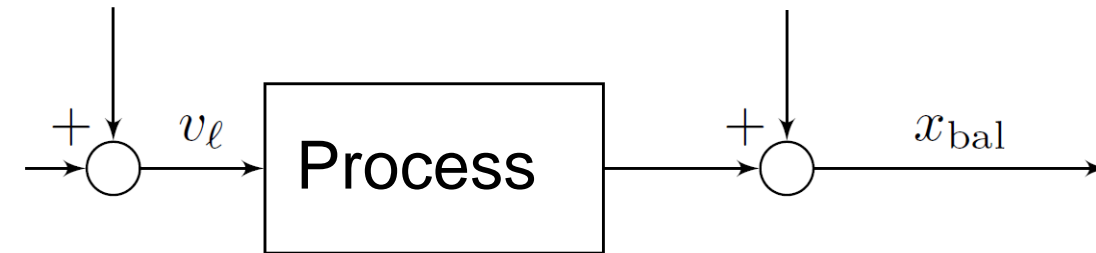
Hard to stabilize

Position difficult to choose

REAL PROCESS

Disturbance

Sensor noise

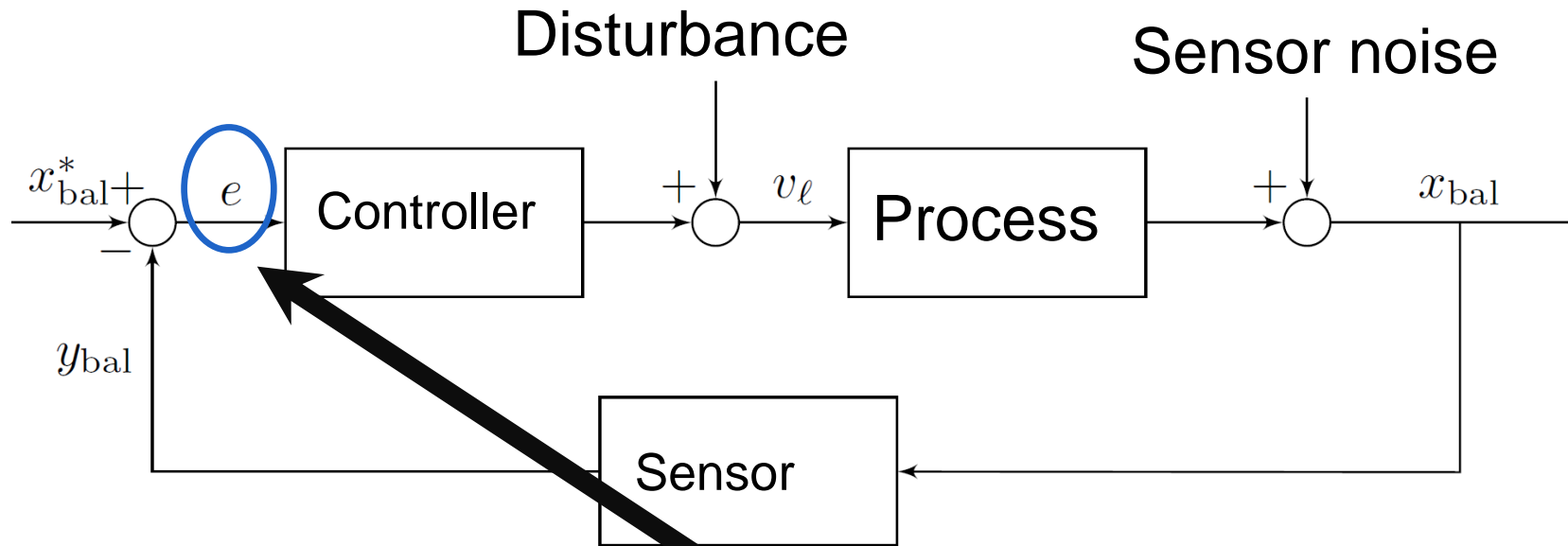


Disturbance: 'Input' we have no control over,

Changes in assumed model

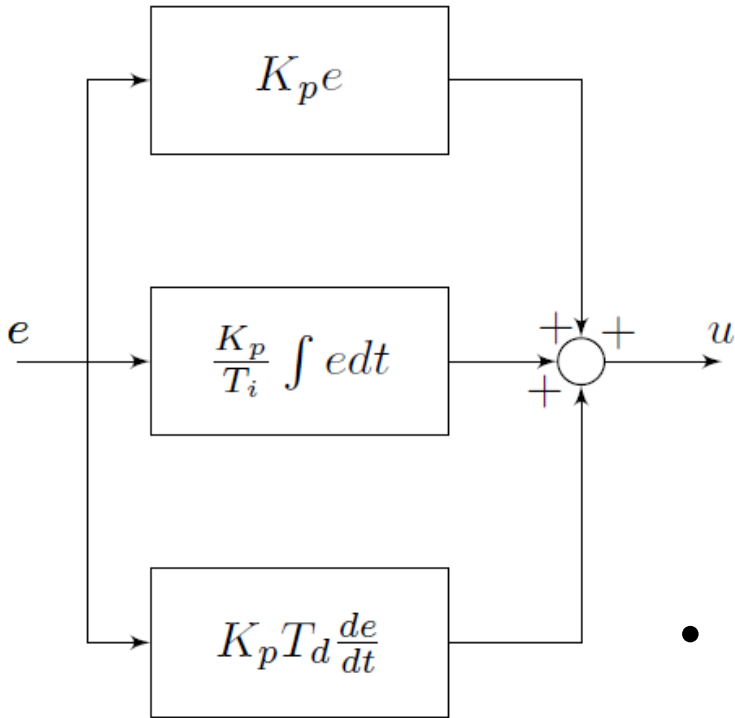
Sensor noise: Sensor never exact

FEEDBACK AND CONTROL ALGORITHM



- Sensor dynamics: Usually much faster than process (e.g. thermocouple)
- Control algorithm: Algorithm to modify input based on measured value and option setpoint
- Optimize speed, energy cost, stabilize, tracking (error=0)

CONTROL ALGORITHM



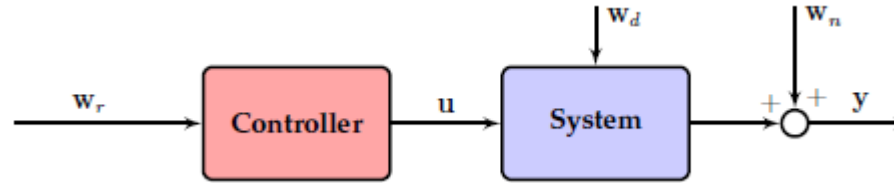
$$u(t) = K_p \left(e(t) + \frac{1}{T_i} \int_0^t e(\tau) d\tau + T_d \frac{de(t)}{dt} \right)$$

$$u(t) = K_p \left(e(t) + \frac{1}{T_i} \sum_{i=0}^n e(i) t_s + T_d \frac{e(t) - e(t - t_s)}{t_s} \right)$$

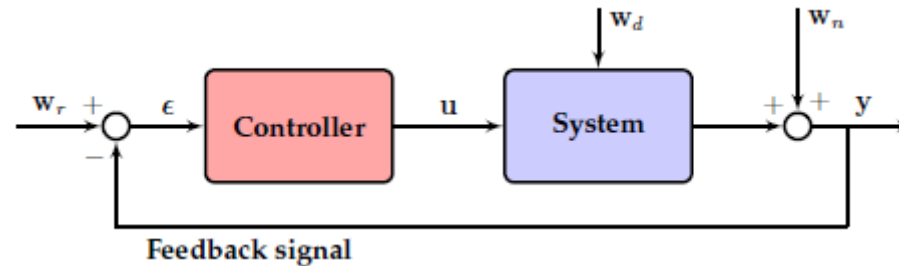
- P: $K_p e(t)$ control as long as there is an error
- I: $\frac{K_p}{T_i} \sum_{i=0}^n e(i) t_s$ control as long as a sum of error
- D: $K_p T_d \frac{e(t) - e(t - t_s)}{t_s}$ control as long as there is a derivative of the error

OPEN VS CLOSD

- Based on history or existing model, provide input



- Based on measured output, provide input



- Fuel rate model $y = u$ cruise control
- Crane positioning

SELF DRIVING

- Vehicle dynamics
 - Tracking road
 - Disturbance road
-
- Sensors & GPS
 - Decide fuel and steer angles based on this information



AEROSPACE

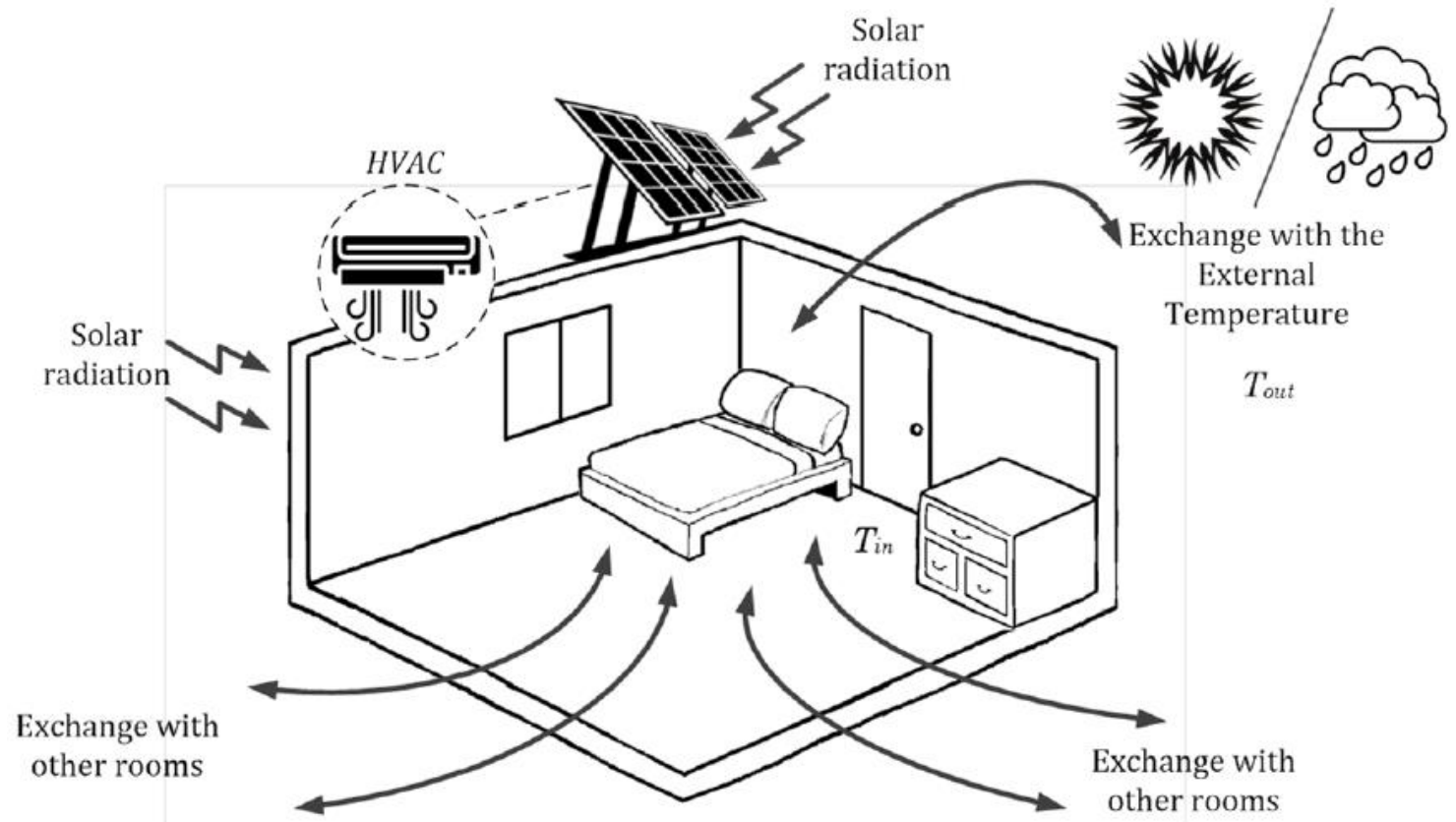
- Rocket dynamics
- Stabilize and desired location
- Side and main thrusters

<https://users.ugent.be/~kdkemele/rocket2018/>



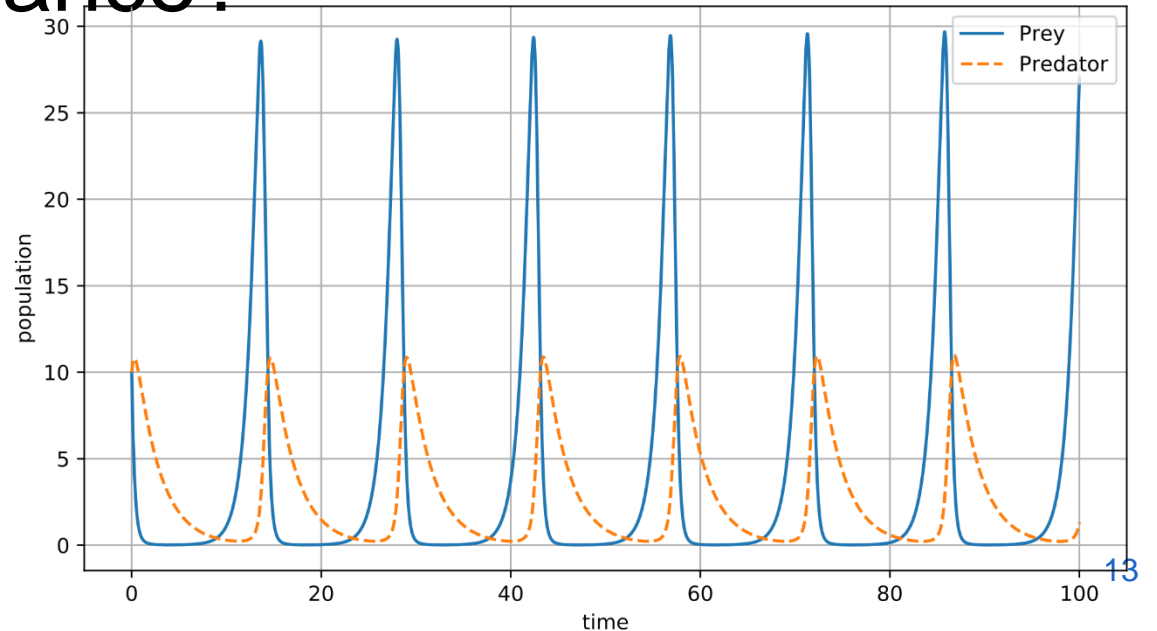
HEATING

- Heating room
- Disturbance (window, sun)
- Lowering energy use
- Energy balance



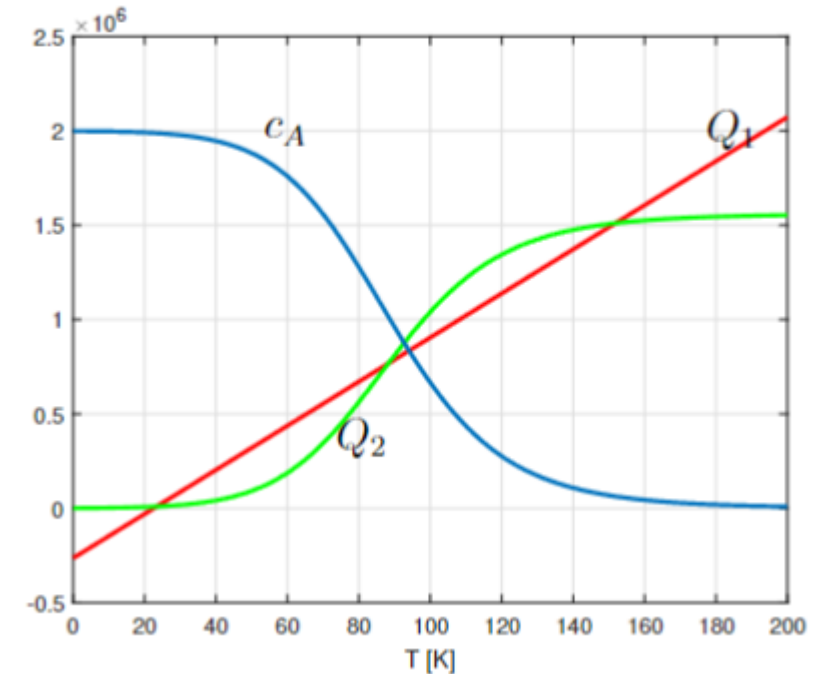
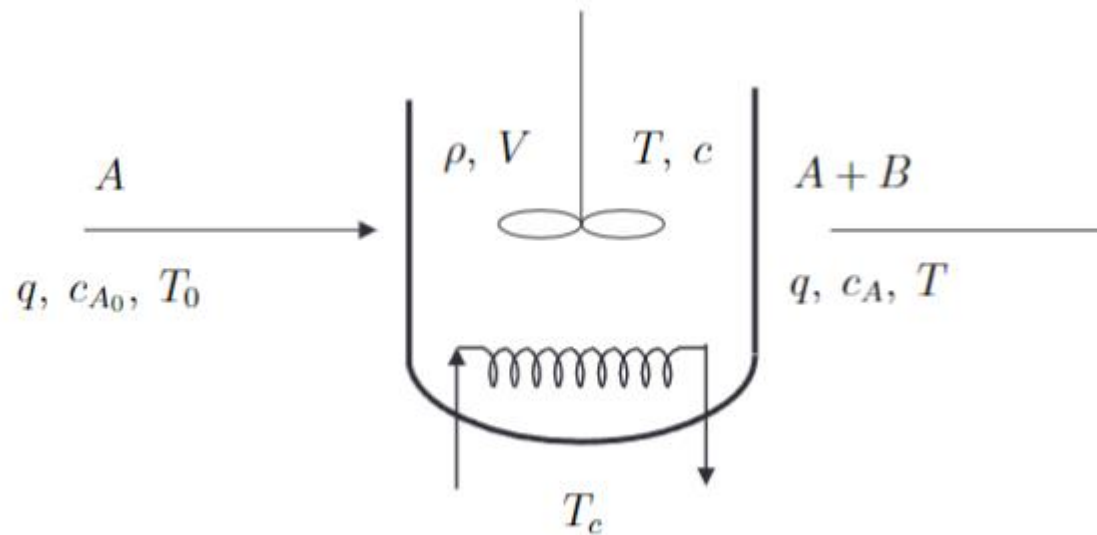
PREDATOR PREY/ INFECTION

- Many prey -> many predators
- Too much competition and less food -> less predators
- Less predators -> more prey
- Competition model
- What happens with disturbance?

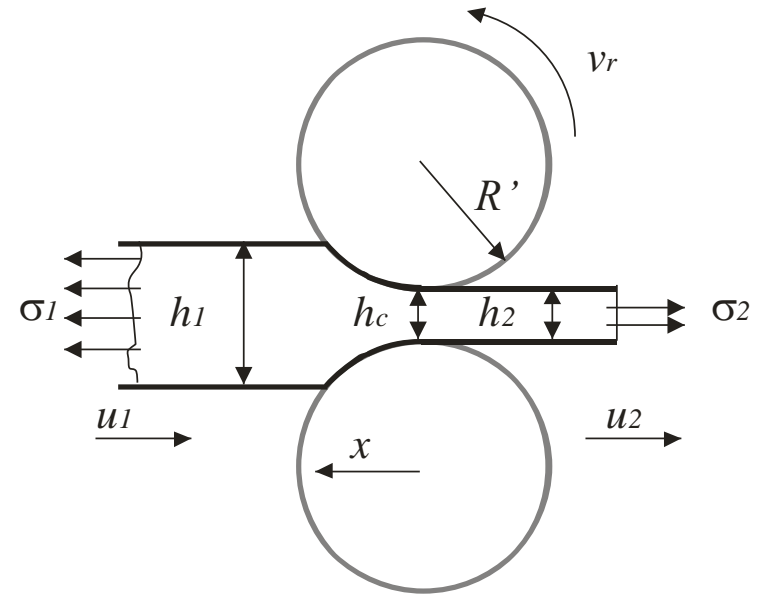
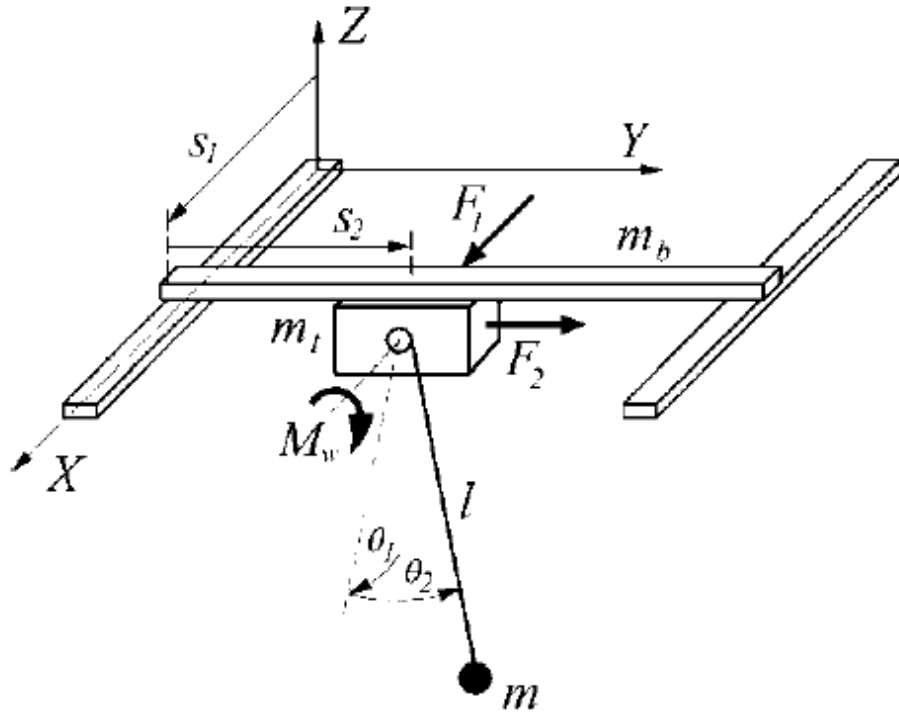


(BIO) CHEMICAL REACTOR

- Balance Removed heat = generated heat
- ‘Instable’ points might provide best generation of substance B
- Feedback

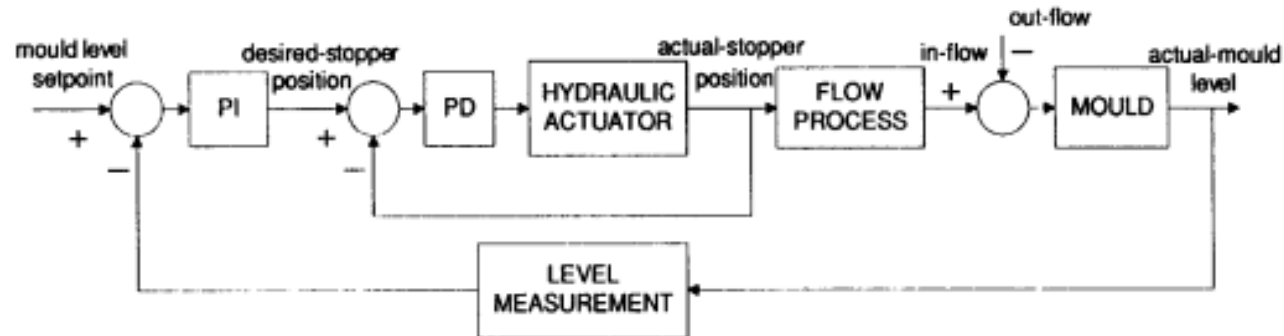
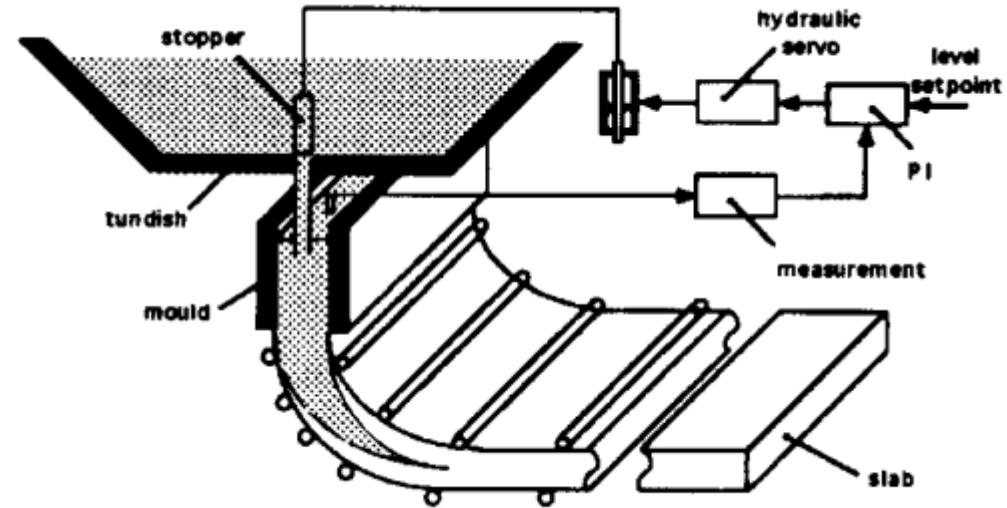


STEEL FACTORY



CONTINUOUS CASTER

- Level of steel control
- Determines quality
- Two cascades systems
 1. Stopper (fast)
 2. Level of caster (slow)



STATE SPACE

MATRICES AND VECTORS

Matrix

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{bmatrix} \in \mathbb{R}^{n \times m}$$

Determinant

$$\det(A) = \begin{vmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{vmatrix} \in \mathbb{R}$$

$$\det(A) = \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix} = a_{11} \cdot a_{22} - a_{12} \cdot a_{21}$$

Vectors

$$x = [x_1 \quad \cdots \quad x_m] \in \mathbb{R}^{1 \times m}$$

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^{n \times 1}$$

EIGENVECTORS AND VALUES

- Matrix maps column vector into another one with transformation:

$$y = Ax, A \in \mathbb{R}^{n \times n}$$

Rotation matrix: $A = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix}$

- Eigenvector v maps to itself with a factor λ (= eigenvalue)

$$v\lambda = Av$$

EIGENVECTORS AND VALUES: STEPS

$$v\lambda = Av \Rightarrow 0 = (A - I\lambda)v$$

Determine n eigenvalues λ : $\det(A - I\lambda) = 0$

Then compute n eigenvectors

$$(A - I\lambda_i)v_i = 0$$

EIGENVECTOR AND VALUES: DIAGONALIZATION

$$V = [v_1 \ v_2 \ \dots \ v_n] \text{ and } \Lambda = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$$

$$V\Lambda = AV$$

$$V^{-1}V\Lambda = V^{-1}AV$$

$$\Lambda = V^{-1}AV$$

BASIC MATHEMATICS: TAYLOR SERIES

- $f(x) \approx f(a) + f'(a)(x - a) + \frac{f''(a)(x-a)^2}{2} + \dots$
- Change of coordinates $(x - a) = \Delta x$
- $$f(x, y, z) \approx f(a, b, c) + \frac{\partial f(a, b, c)}{\partial x} \left(\underbrace{x - a}_{\Delta x} \right) +$$
$$\frac{\partial f(a, b, c)}{\partial y} \left(\underbrace{y - b}_{\Delta y} \right) + \frac{\partial f(a, b, c)}{\partial z} \left(\underbrace{z - c}_{\Delta z} \right)$$

MODELS

Let of Linear Time Invariant first order ODEs (LTI systems)

$$\dot{x} = Ax + Bu$$

$$y = Cx + Du$$

- State vector $x \in \mathbb{R}^{n \times 1}$
- Input vector $u \in \mathbb{R}^{p \times 1}$ (How to intervene in dynamics)
 - Disturbances (inputs, but not from us)
- Output vector $y \in \mathbb{R}^{q \times 1}$ (What we can measure)
- $A \in \mathbb{R}^{n \times n}$: System Matrix
- $B \in \mathbb{R}^{n \times p}$: Input Matrix
- $C \in \mathbb{R}^{q \times n}$: Output Matrix

MODELS: DISCRETE TIME

Set of linear Difference equations:

$$x_{k+1} = A_d x_k + B_d u_k$$

$$y_k = C_d x_k + D_d u_k$$

- Used in Model Predictive control
- Conversion Continuous to discrete time:

$$A_d = e^{A\Delta t},$$

$$B_d = \int_0^{\Delta t} e^{A\tau} B \, d\tau,$$

$$C_d = C,$$

$$D_d = D.$$

LINEARIZATION

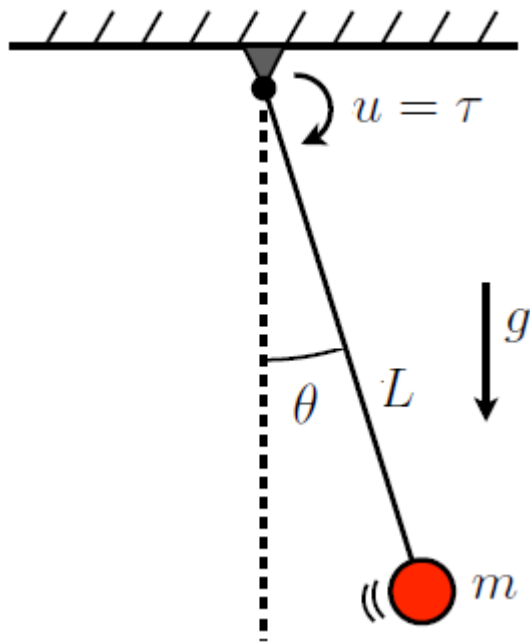
$$\dot{x} = f(x, u)$$

$$y = g(x, u)$$

Taylor series around operational or equilibrium point
 $(\dot{x} = 0), (\bar{x}, \bar{u})$

$$f(\Delta x, \Delta u) \approx f(\bar{x}, \bar{u}) + \underbrace{\frac{\partial f(\bar{x}, \bar{u})}{\partial x}}_A \Delta x + \underbrace{\frac{\partial f(\bar{x}, \bar{u})}{\partial u}}_B \Delta u$$

PENDULUM



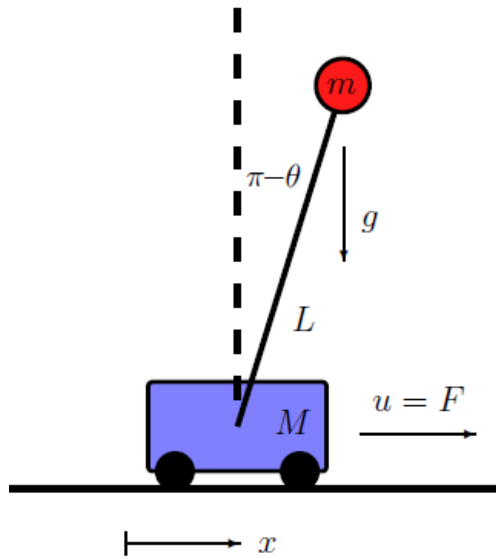
$$\ddot{\theta} = -\frac{g}{L} \sin \theta + u$$

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \theta \\ \dot{\theta} \end{bmatrix} \implies \frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} x_2 \\ -(g/L) \sin(x_1) + u \end{bmatrix}.$$

$$\underbrace{\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ g/L & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u}_{\text{pendulum up, } \lambda = \pm \sqrt{g/L}}$$

$$\underbrace{\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -g/L & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u}_{\text{pendulum down, } \lambda = \pm i \sqrt{g/L}}$$

PENDULUM ON CART = CRANE



$b = 1$ (up)

$b = -1$ (down)

$$\dot{x} = v,$$

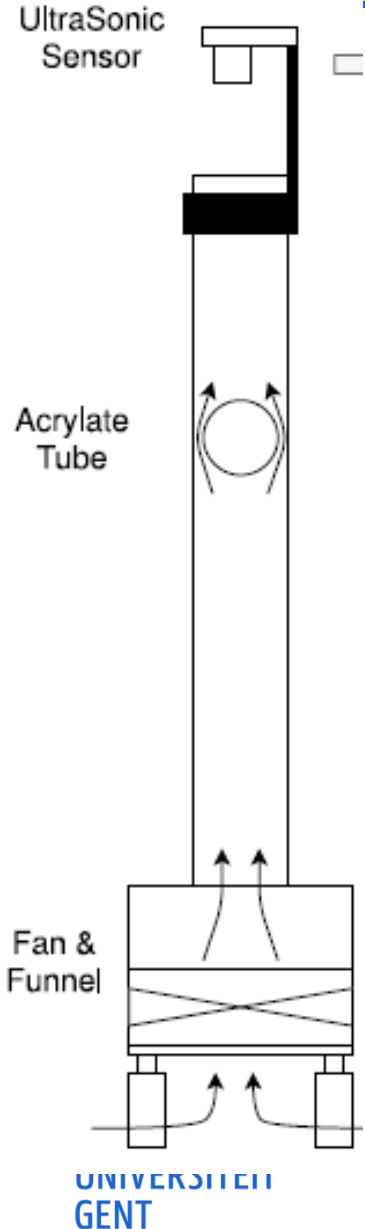
$$\dot{v} = \frac{-m^2 L^2 g \cos(\theta) \sin(\theta) + mL^2 (mL\omega^2 \sin(\theta) - \delta v) + mL^2 u}{mL^2 (M + m(1 - \cos(\theta)^2))},$$

$$\dot{\theta} = \omega,$$

$$\dot{\omega} = \frac{(m + M)mgL \sin(\theta) - mL \cos(\theta) (mL\omega^2 \sin(\theta) - \delta v) - mL \cos(\theta) u}{mL^2 (M + m(1 - \cos(\theta)^2))}.$$

$$\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -\delta/M & bmg/M & 0 \\ 0 & 0 & 0 & 1 \\ 0 & -b\delta/ML & -b(m + M)g/ML & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} 0 \\ 1/M \\ 0 \\ b/ML \end{bmatrix} u$$

EVITATION OF BALL



$$m\ddot{x} = -mg + c(v_\ell - \dot{x})^2$$

$$mg = cv_\ell^2$$

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & -2\sqrt{\frac{mg}{c}} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 2\sqrt{\frac{mg}{c}} \end{bmatrix} u$$

$$y = [1 \ 0] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + [0]u$$

We only measure position

COMPETITION MODEL

$x_1(t)$: Rabbit population

$x_2(t)$: Sheep population

$$\dot{x}_1 = x_1(3 - x_1 - 2x_2)$$

$$\dot{x}_2 = x_2(2 - x_1 - x_2)$$

$$A = \begin{bmatrix} 3 - 2\bar{x}_1 - 2\bar{x}_2 & -2\bar{x}_1 \\ -\bar{x}_2 & 2 - \bar{x}_1 - 2\bar{x}_2 \end{bmatrix}$$

$$\begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 2 \end{bmatrix}, \begin{bmatrix} 3 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$



EIGENVALUES & EIGENVECTORS

- Autonomous system: $\dot{x} = Ax$
- Solution $x(t) = e^{At}x(0)$ $e^{At} \text{ ???}$ $A \in \mathbb{R}^{n \times n}$
- Eigenvalues/vectors of A , Λ and V
- Eigenmodes $Vz(t) = x$
- $V\dot{z} = AVz \Rightarrow V^{-1}V\dot{z} = V^{-1}AVz$
- $\dot{z} = \Lambda z \Rightarrow z(t) = e^{\Lambda t}z(0)$

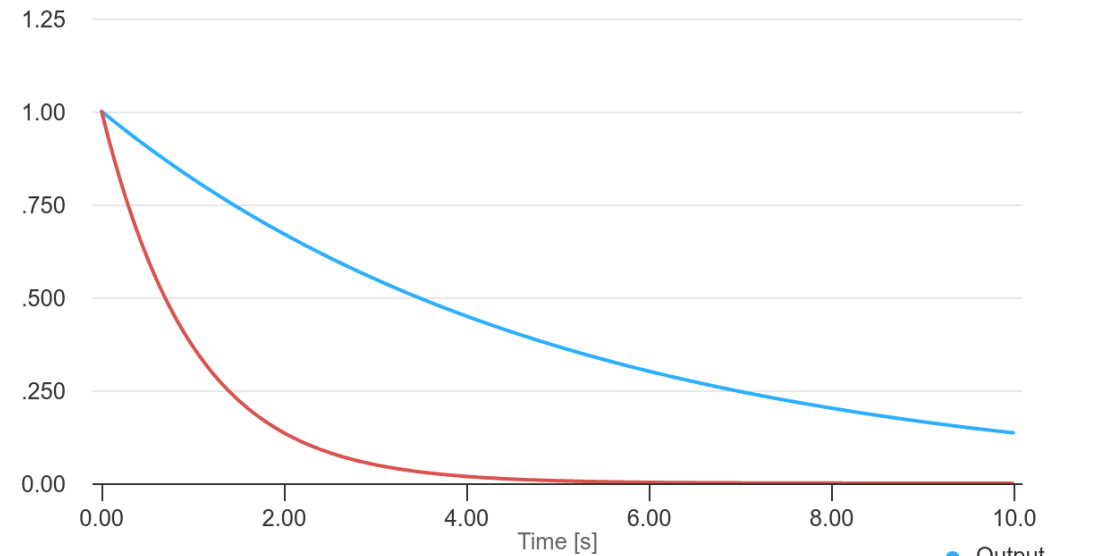
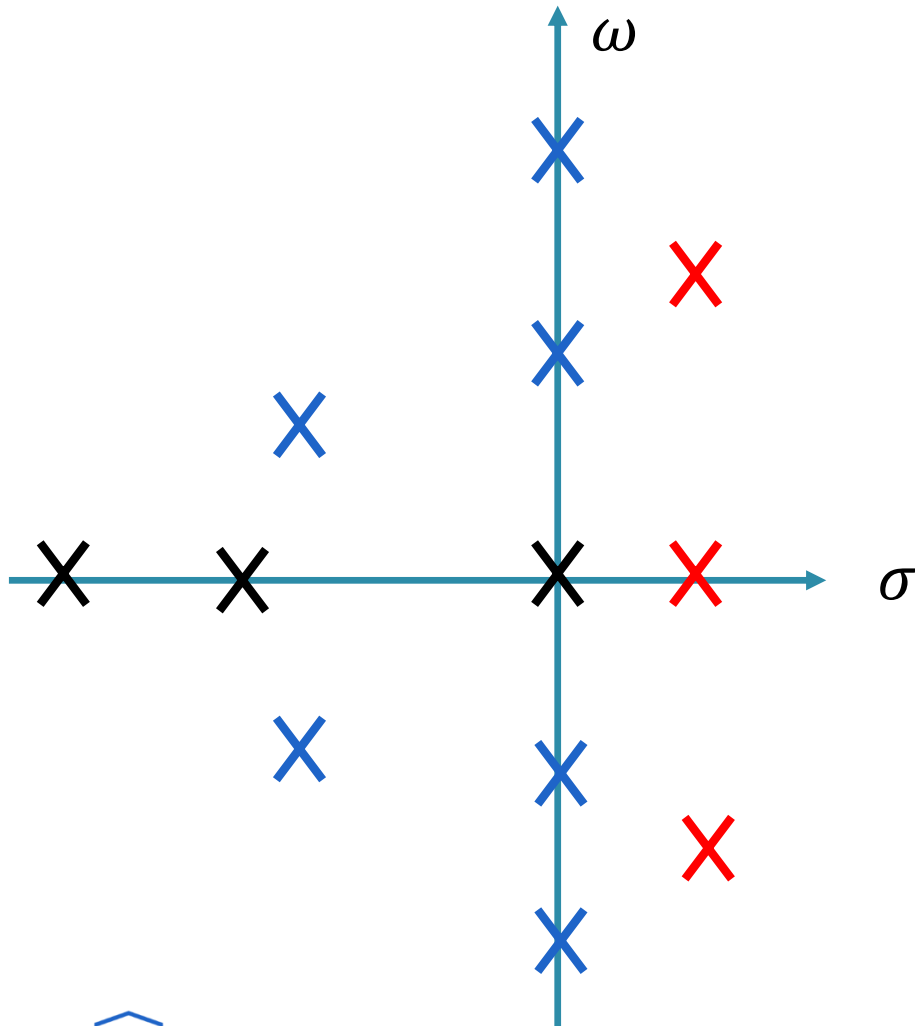
$$e^{\Lambda t} = \begin{bmatrix} e^{\lambda_1 t} & 0 & \dots & 0 \\ 0 & e^{\lambda_2 t} & \dots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \dots & e^{\lambda_n t} \end{bmatrix} \in \mathbb{R}^{n \times n}$$

EIGENVALUES & EIGENVECTORS

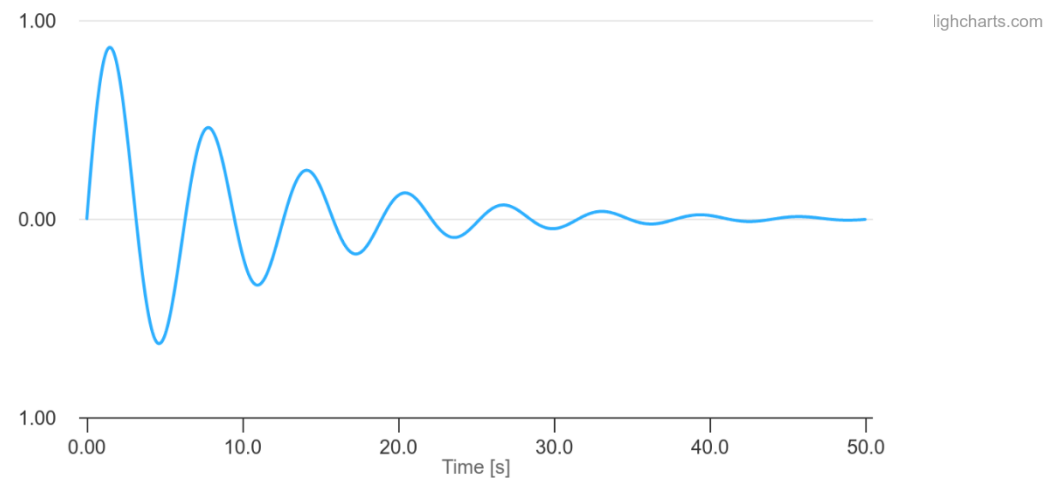
- $\dot{x} = Ax \Rightarrow \dot{x} = V\Lambda V^{-1}x$
- Solution $x(t) = e^{V\Lambda V^{-1}t}x(0) \Rightarrow V e^{\Lambda t} V^{-1}x(0)$
- $x_k(t) = \sum_{i=1}^n v_i(k) e^{\lambda_i t} v_i^{-1}(k)x_i(0)$
- $\lambda_i = \sigma_i + j\omega_i$

What types of time responses are there??

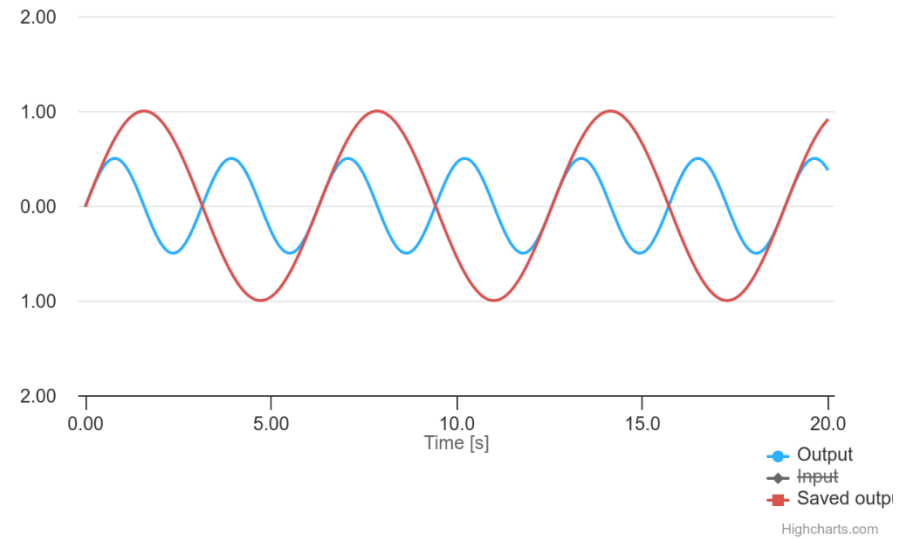
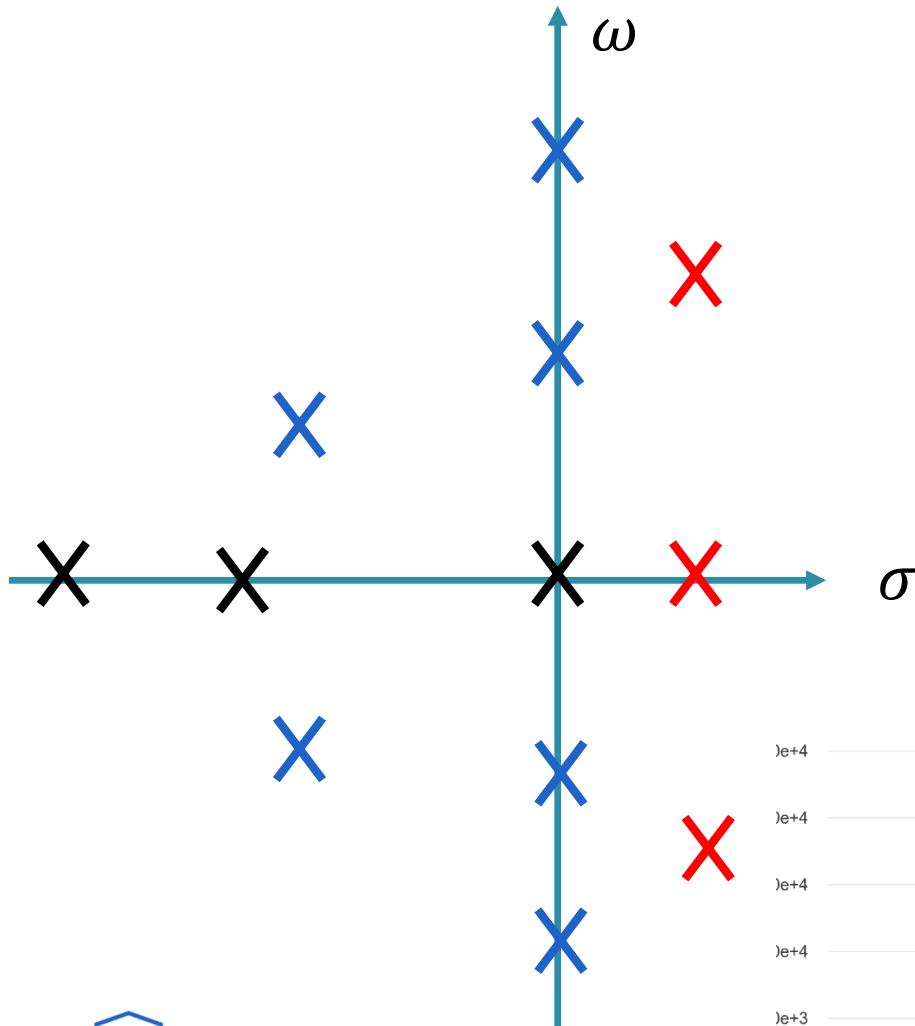
EIGENVALUES & STABILITY



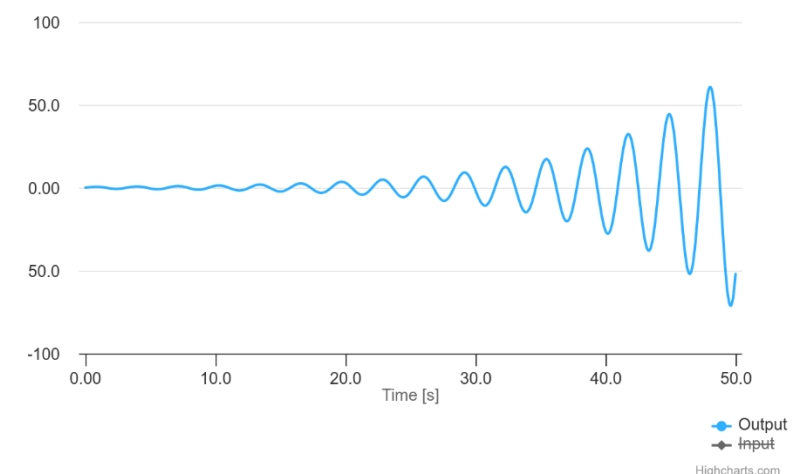
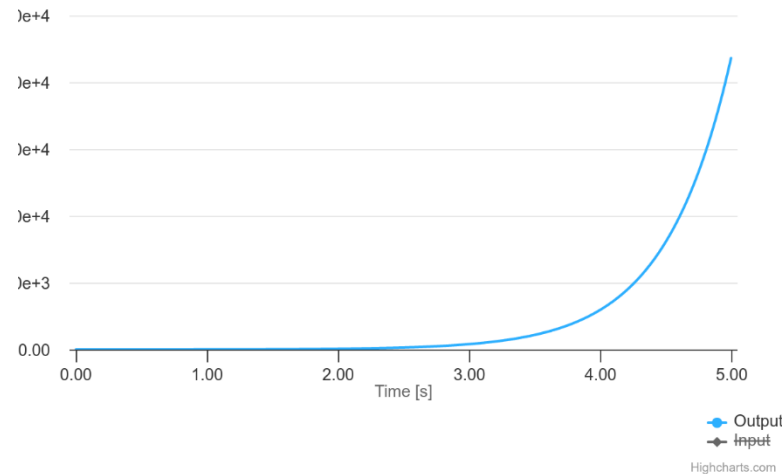
Oscillations
Process
Unstable



EIGENVALUES & STABILITY



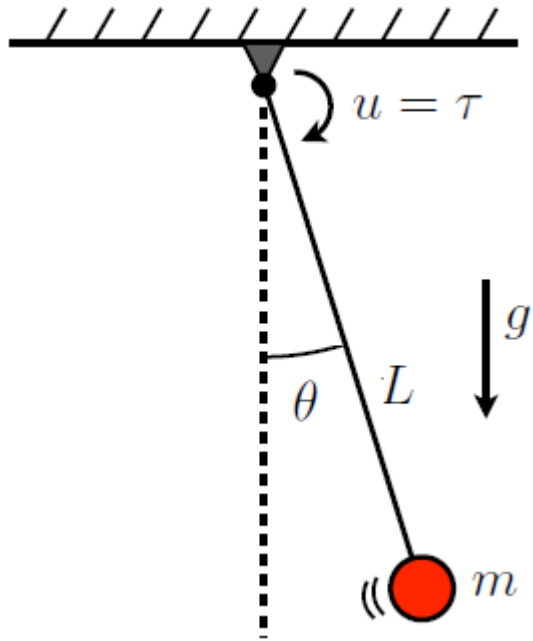
Oscillations
Process
Unstable



EIGENVALUES, EIGENVECTORS & STABILITY

- Eigenvalues in dynamical system meaning:
 - Stability & Speed
 - Response is exponential of eigenvalues, weighted by eigenvectors
 - (if $x(0)$ is an eigenvector, you stay on this vector)

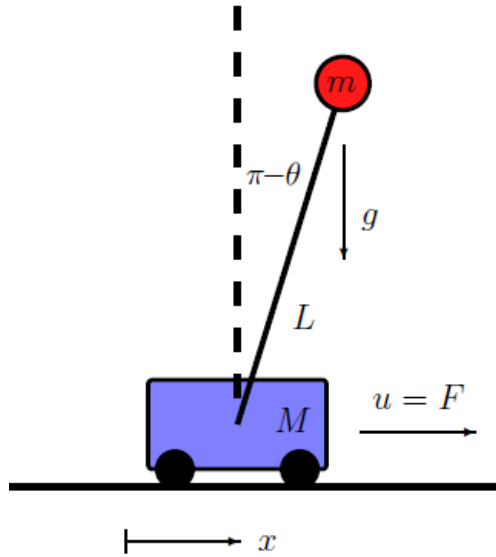
PENDULUM



$$\underbrace{\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ g/L & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u}_{\text{pendulum up, } \lambda = \pm \sqrt{g/L}}$$

$$\underbrace{\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -g/L & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u}_{\text{pendulum down, } \lambda = \pm i \sqrt{g/L}}$$

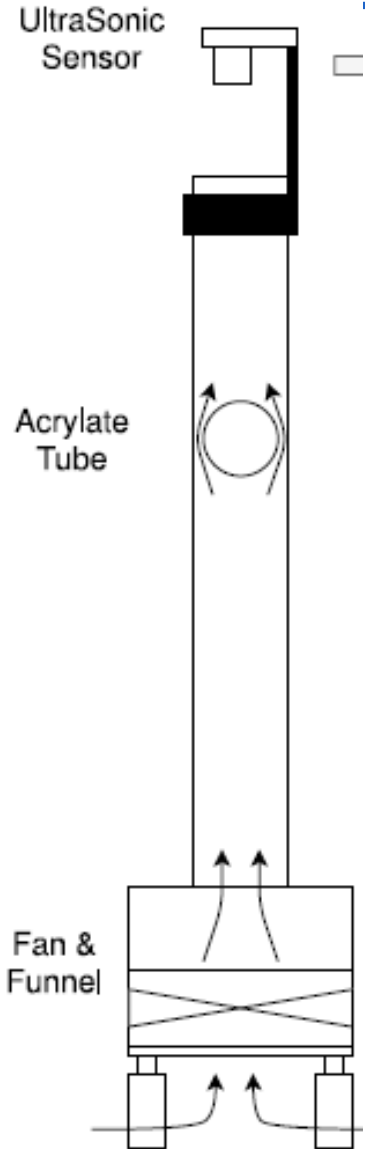
PENDULUM ON CART = CRANE



$$\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -\delta/M & bmg/M & 0 \\ 0 & 0 & 0 & 1 \\ 0 & -b\delta/ML & -b(m+M)g/ML & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} 0 \\ 1/M \\ 0 \\ b/ML \end{bmatrix} u$$

SHOW IN PYTHON

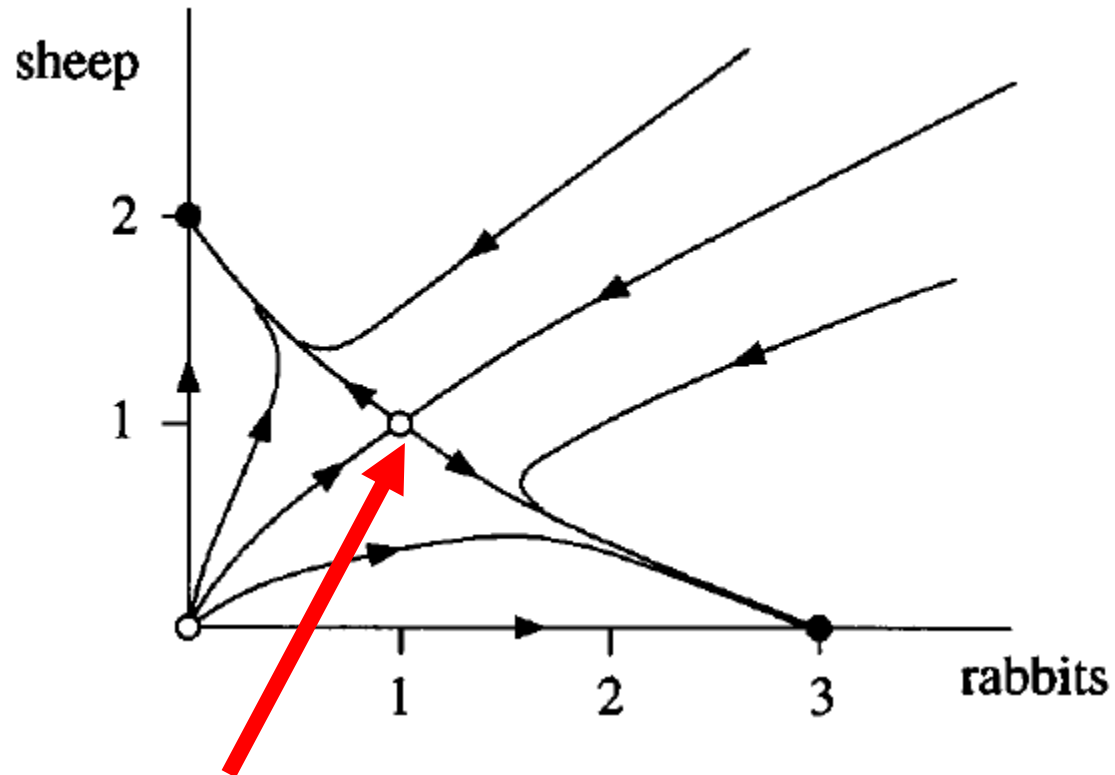
LEVITATION OF BALL



$$\begin{bmatrix} \dot{x}_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & -2\sqrt{\frac{mg}{c}} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 2\sqrt{\frac{mg}{c}} \end{bmatrix} u$$

$$\lambda_{1,2} = 0, -2\sqrt{\frac{mg}{c}}$$

COMPETITION MODEL



Intervene by adding/removing sheep or rabbits
=FEEDBACK

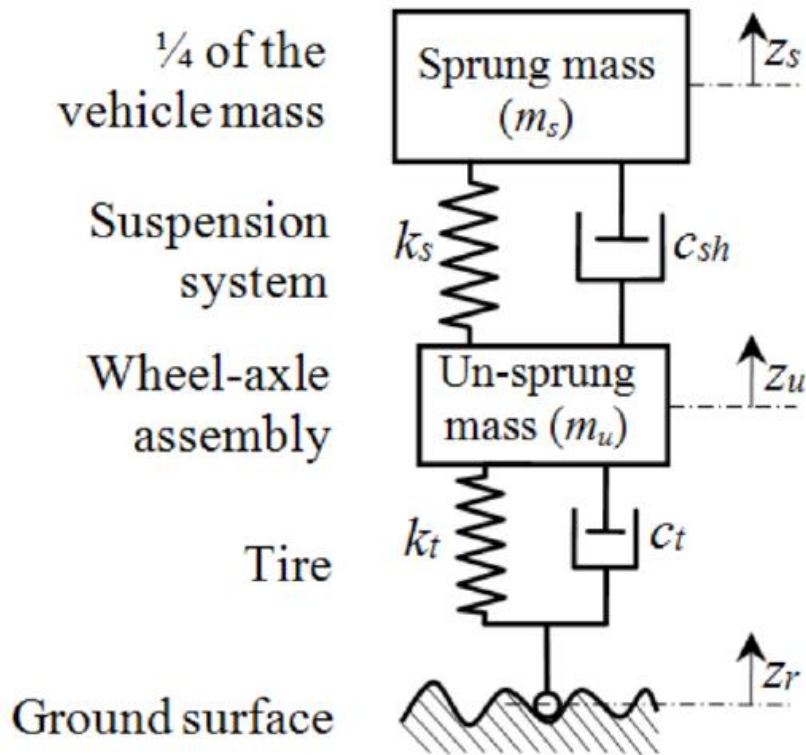
$$\begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 2 \end{bmatrix}, \begin{bmatrix} 3 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$



'FORCED' RESPONSE

- $\dot{x} = Ax + Bu$
- $x(t) = \int_0^t e^{A(t-\tau)} Bu(\tau) d\tau$ (convolution integral)
- Forced response
 - Transient determined by eigenvalues & vectors
 - Steady state part, weighted version of u
- Python example: Intro to control toolbox
- Response to frequency: gain and phase
- See later (Input/Output & Laplace)

EXAMPLE FORCED: SUSPENSION



Parameter	Value
Sprung mass m_s	332 kg
Unsprung mass m_u	100 kg
Suspension spring k_s	48000 N/m
Tire spring k_t	200 000 N/m
Suspension damper c_s	1000 Nm/s

Lajqi, S., & Pehan, S. (2012).

Designs and optimizations of active and semi-active non-linear suspension systems for a terrain vehicle.

Strojniški vestnik-Journal of Mechanical Engineering, 58(12), 732-743.

STATE FEEDBACK

- Eigenvalues determine stability, speed & oscillations
- Can we choose u such that we can change the eigenvalues? STATE FEEDBACK = $u = -Kx$

$$\dot{x} = Ax + Bu$$

$$\dot{x} = \underbrace{(A - BK)}_{\text{New system matrix}} x$$

- Requires **FULL** state knowledge

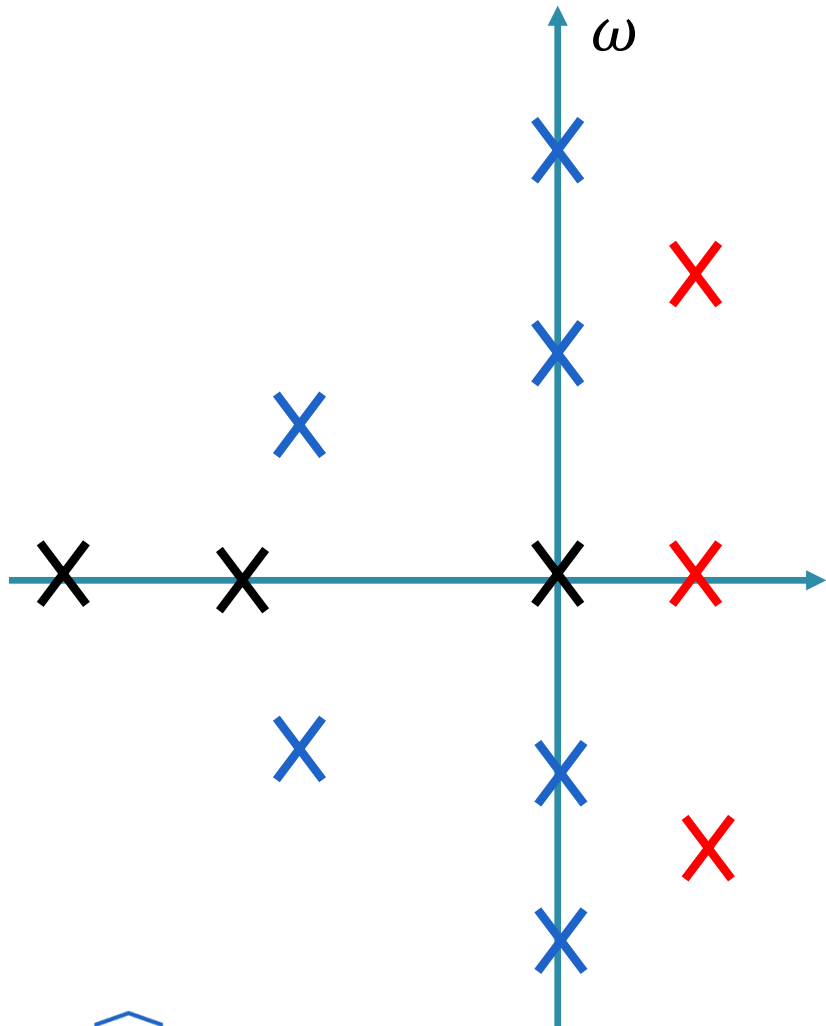
CONTROLLABILITY

- Controllability matrix

$$C = [B \ AB \ A^2B \ \dots \ A^{n-1}B]$$

- If rank matrix is n , system is controllable
 - Arbitrary eigenvalue placement through state feedback $u = -Kx$
 - Reachability: any state x can be reached in finite time, for some u
 - Python inverted pendulum

POLE PLACEMENT



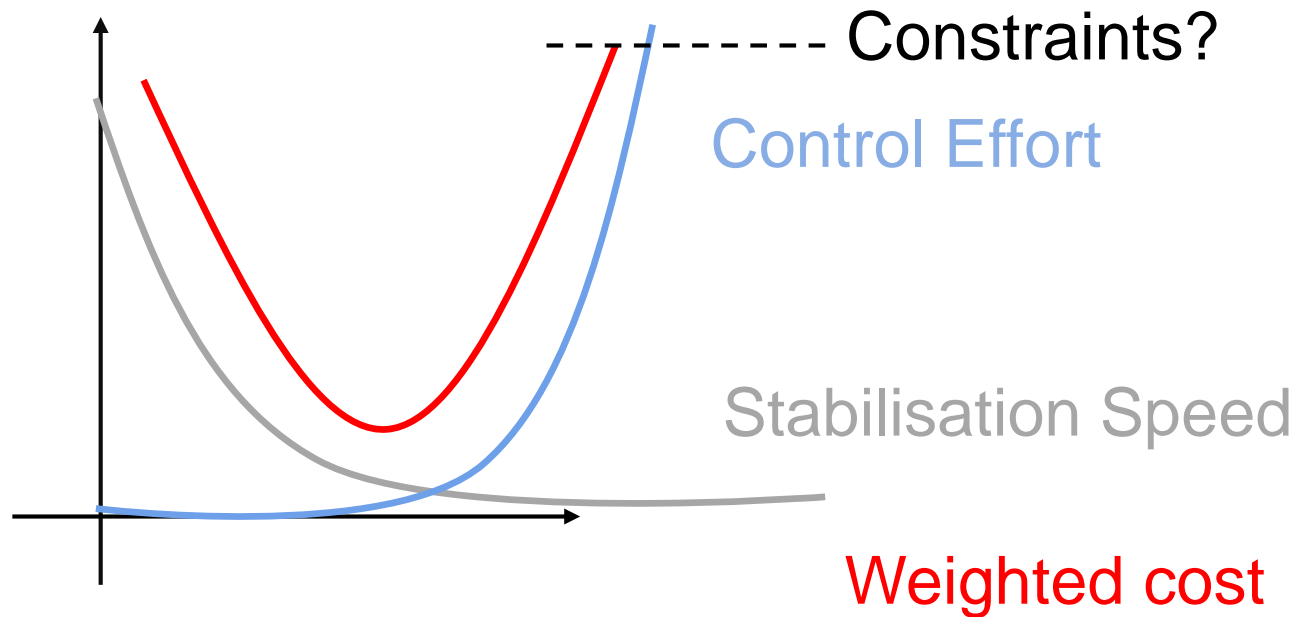
- Eigenvalue on the real axis
- As negative as possible?

$$\dot{x} = \underbrace{(A - BK)}_{\text{New system matrix}} x$$

- σ – Python command 'Place'
- Inverted pendulum example

POLE PLACEMENT

- Why is there a balance?
- Nonlinear might not be actually stable??

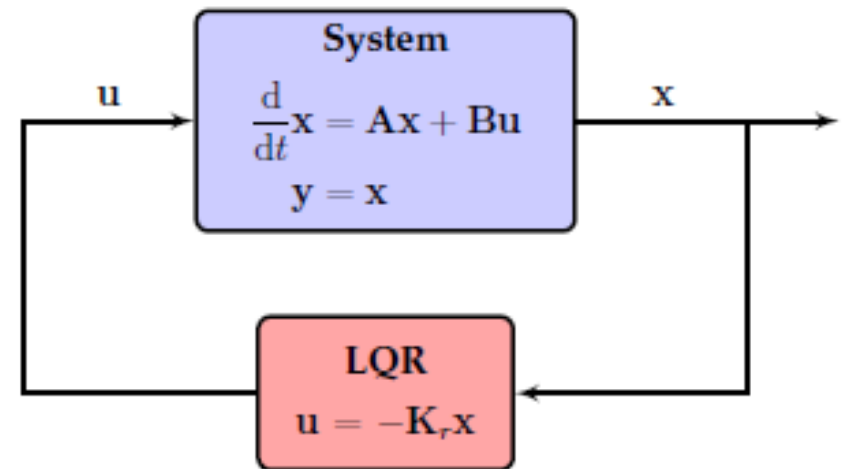


DESIGNING FEEDBACK: LINEAR QUADRATIC CONTROL

- Controllability means a $u = -Kx$ can stabilize and change eigenvalues. How to choose K ?
- *Weight optimization between fast stabilization and input cost*
- $J = \int_0^\infty (\textcolor{red}{x}^T \textcolor{red}{Q} \textcolor{red}{x} + \textcolor{green}{u}^T \textcolor{green}{R} \textcolor{green}{u}) dt \quad J = \sum_{n=0}^\infty x^T Q x + u^T R u$
 - Q : Weight matrix states
 - R : Weight matrix input (“Energy”)

DESIGNING FEEDBACK: LINEAR QUADRATIC CONTROL

- $J = \sum_{n=0}^{\infty} x^T Q x + u^T R u$
- Optimal $K_r = R^{-1} B^T S$
- Where S is the solution of a 'stationary Ricatti' equation:
 - $A^T S + S A - S B R^{-1} B^T S + Q = 0$
 - Inverted pendulum example

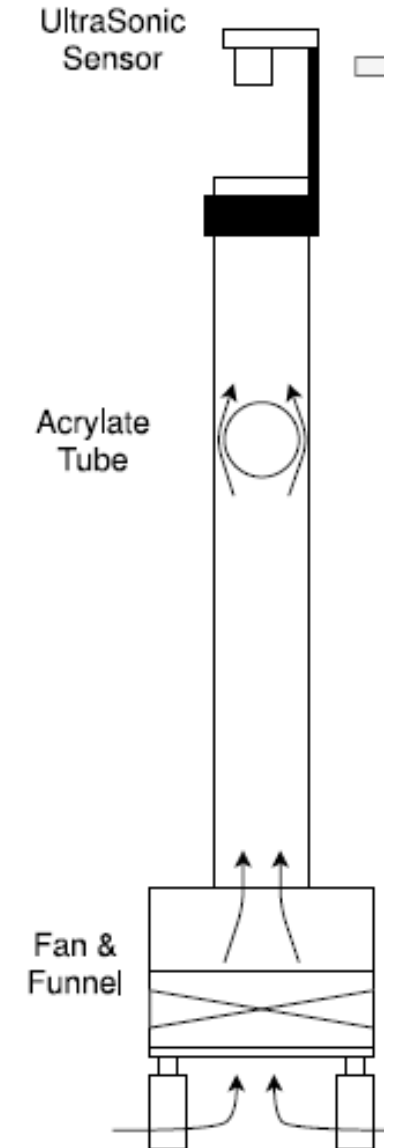


DESIGNING FEEDBACK: LQR REFERENCE

- We want $x = x_r$
- $\dot{x}^* = Ax^* + Bu^*$ where $x^* = x - x_r$ and $u^* = u - u_r$
- Stable if $u^* = -Kx^*$
- $0 = Ax_r + Bu_r$
- So same optimization holds, different meaning input cost

STATE ESTIMATION

- Until now: Knowledge full state x
- Output equation! $y = Cx + Du$
- Not all state can be measured because of limited sensors, measurement locations



OBSERVABILITY

- Observability matrix $O = \begin{bmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{n-1} \end{bmatrix}$
- If rank matrix is n , system is observable
 - any state x can be estimated from y in finite time, for some u
 - Similar like controllability second meaning!

OBSERVER

Estimated dynamics based on y

$$\begin{aligned}\dot{\hat{x}} &= A\hat{x} + Bu + K_f(\mathbf{y} - \hat{y}) \\ \hat{y} &= C\hat{x}\end{aligned}$$

$$\dot{\hat{x}} = (A - K_f C)\hat{x} + [B \ K_f] \begin{bmatrix} u \\ y \end{bmatrix}$$

Estimation error dynamics: $\epsilon = x - \hat{x}$

$$\dot{\epsilon} = (A - K_f C)\epsilon$$

Pole placement/stabilisation! But how to choose K_f ?

KALMAN FILTER

Observer gain optimization under system and measurement noise

$$\begin{aligned}\dot{x} &= Ax + Bu + w_d, & w_d &\in \mathbb{R}^{n \times 1}, \text{ in } \mathcal{N}(0, \sigma_d^2) \\ y &= Cx + Du + w_n, & w_n &\in \mathcal{N}(0, \sigma_n^2)\end{aligned}$$

$$\mathbb{E}(w_d) = \mathbb{E}(w_n) = 0 \quad \mathbb{E}(w_d w_d^T) = V_d \quad \mathbb{E}(w_n w_n^T) = V_n$$

$$\dot{\epsilon} = (A - K_f C)\epsilon + w_d - K_f v_k \quad J = \mathbb{E}(\epsilon \epsilon^T)$$

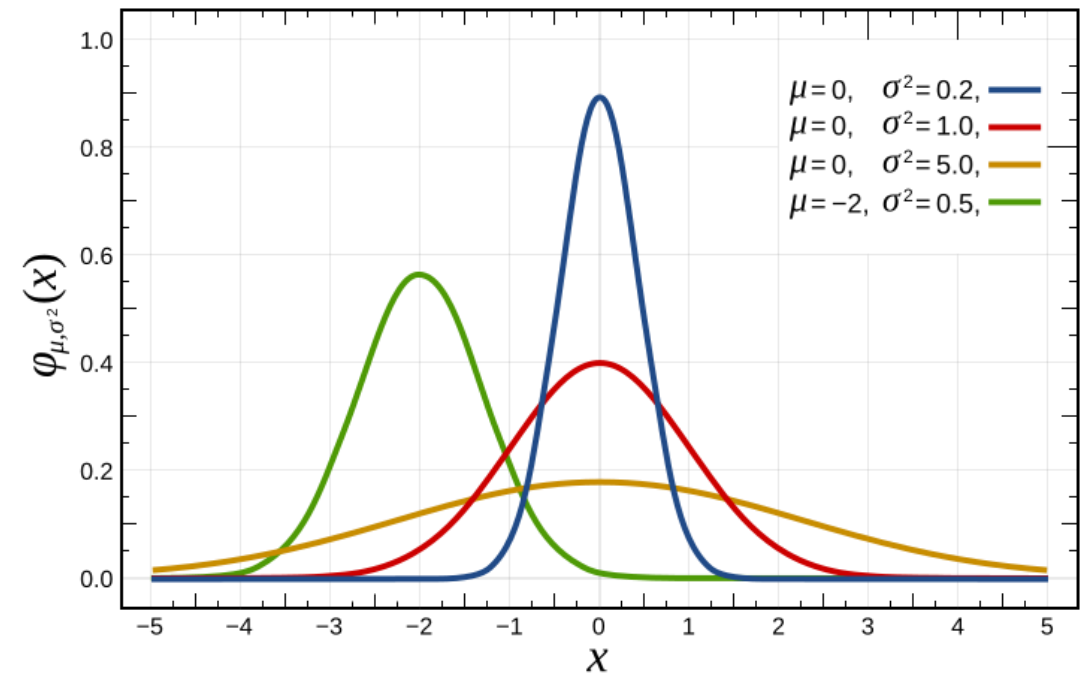
$$\text{Optimal } K_f = SC^T V_n^{-1}$$

Where S is the solution of a 'stationary Ricatti' equation:

$$SA^T + AS - SC^T V_n^{-1} CS + V_d = 0$$

Large input noise: Trust measurement, more gain

Large output noise: Trust estimation, less gain



ESTIMATION & CONTROL

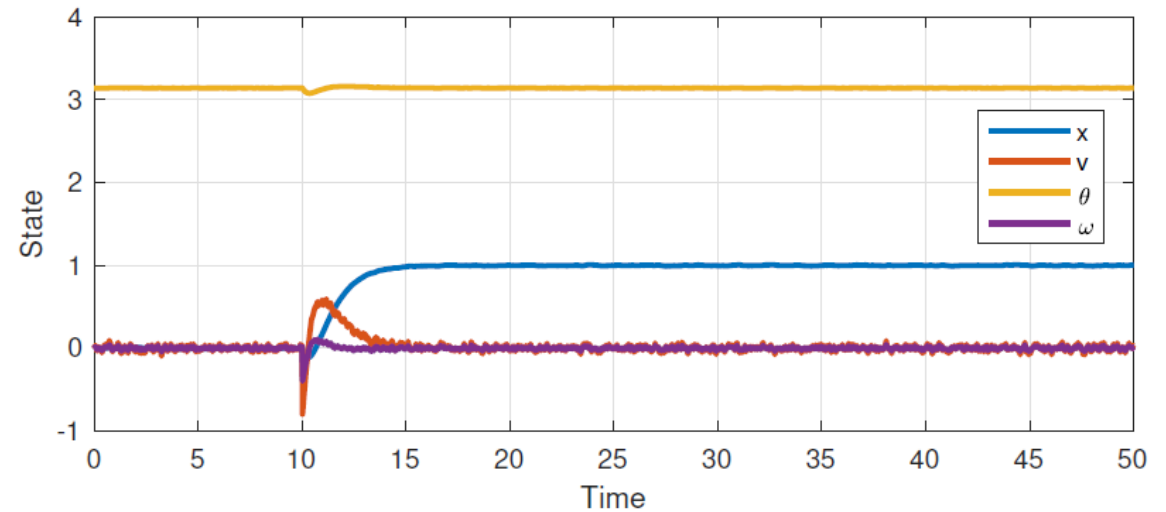
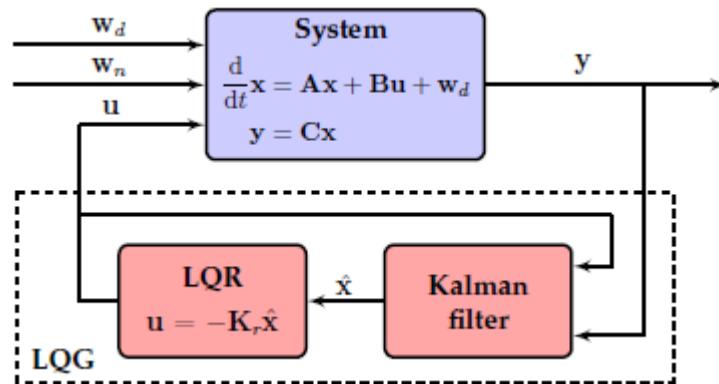
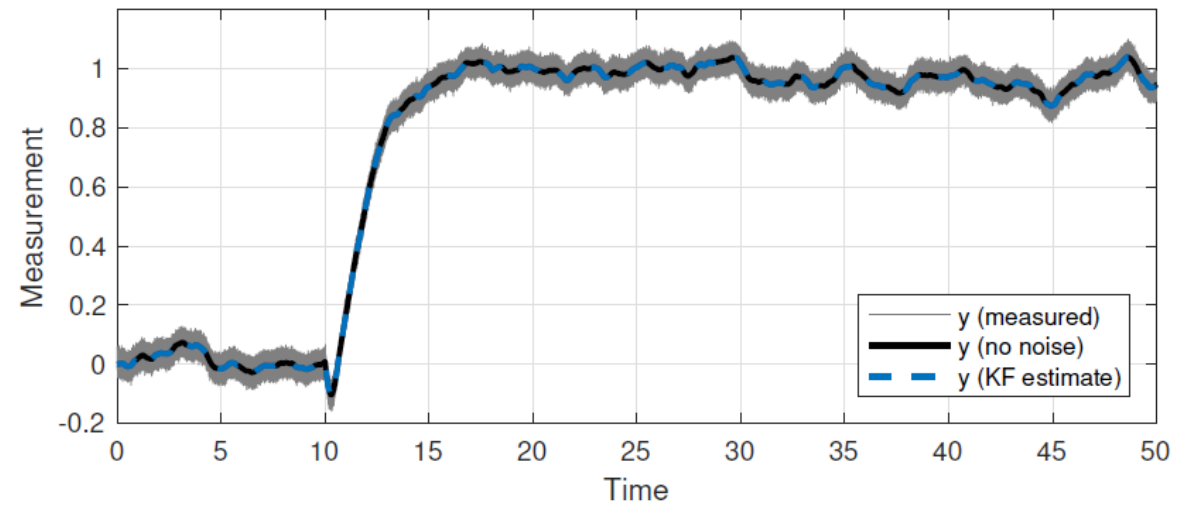


Figure 8.18: Output response using LQG feedback control.



EXAMPLE: INVERTED PENDULUM

- Robustness? Does control still work if model estimation wrong?
- <https://www.youtube.com/watch?v=D3bbIng-Kcc>

ADVANCED TOPICS?

- Nonlinear Kalman
- Reduced observer (not all states)
- Stopgap: Linear Parameter varying:
$$\dot{x} = A(t)x + B(t)u$$
- Advanced libraries usually MATLAB & SIMULINK

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- Linear Systems (Course Ghent University, Gert De Cooman)
- Control System Design and Management (Course University of Newcastle, Julio Braslavsky)
- Brunton, S. L., & Kutz, J. N. (2022). *Data-driven science and engineering: Machine learning, dynamical systems, and control*. Cambridge University Press.
- Chevalier, A., Dekemele, K., Juchem, J., & Loccufier, M. (2021). Student feedback on educational innovation in control engineering: active learning in practice. *IEEE Transactions on Education*, 64(4), 432-437.
- Strogatz, S. H. (2018). *Nonlinear dynamics and chaos: with applications to physics, biology, chemistry, and engineering*. CRC press.

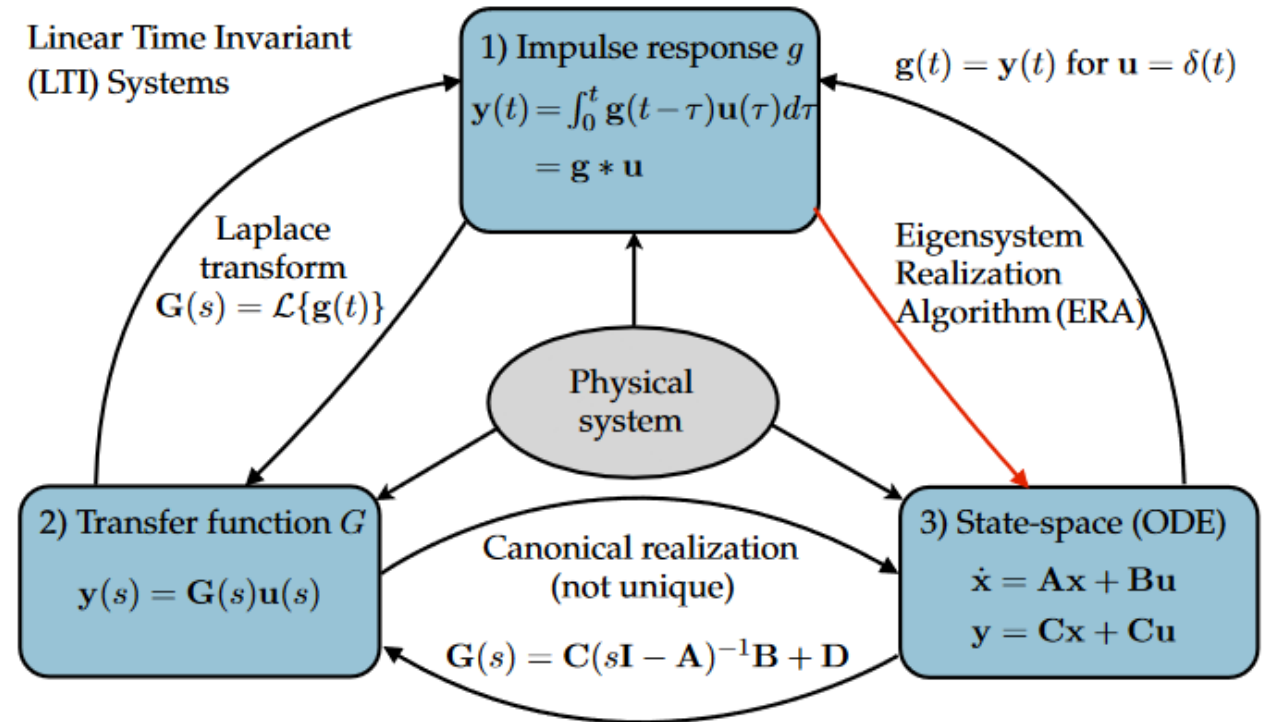
INPUT-OUTPUT MODELS

LAPLACE TRANSFORM

- The Laplace transform:

$$\begin{aligned}\mathcal{L}\left\{\frac{d}{dt}f(t)\right\} &= \int_{0^-}^{\infty} \underbrace{\frac{d}{dt}f(t)}_{dv} \underbrace{e^{-st}}_u dt \\ &= \left[f(t)e^{-st}\right]_{t=0^-}^{t=\infty} - \int_{0^-}^{\infty} f(t)(-se^{-st})dt \\ &= f(0^-) + s\mathcal{L}\{f(t)\}.\end{aligned}$$

- In short: to go from differential - to algebraic equations



FROM STATE-SPACE TO INPUT-OUTPUT MODELS

- We are interested in the relationship between the inputs and (measurable) outputs (i.e. not necessarily all the states)
- Consider a linear system

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du \end{cases}$$

Often: $D = 0$
 $G(s) = C(sI - A)^{-1}$

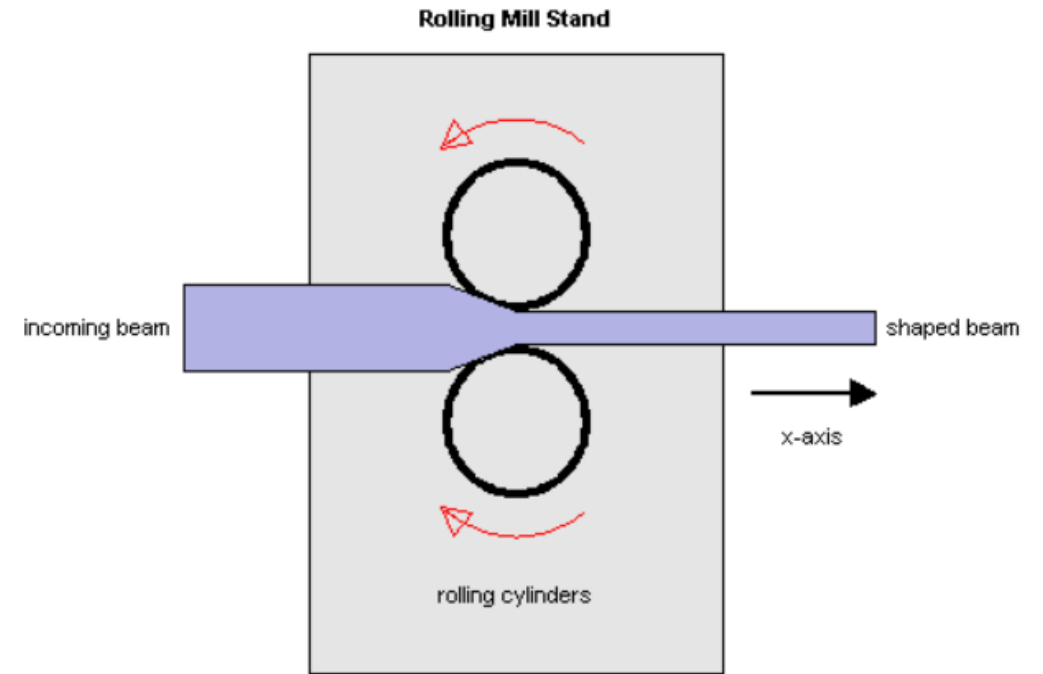
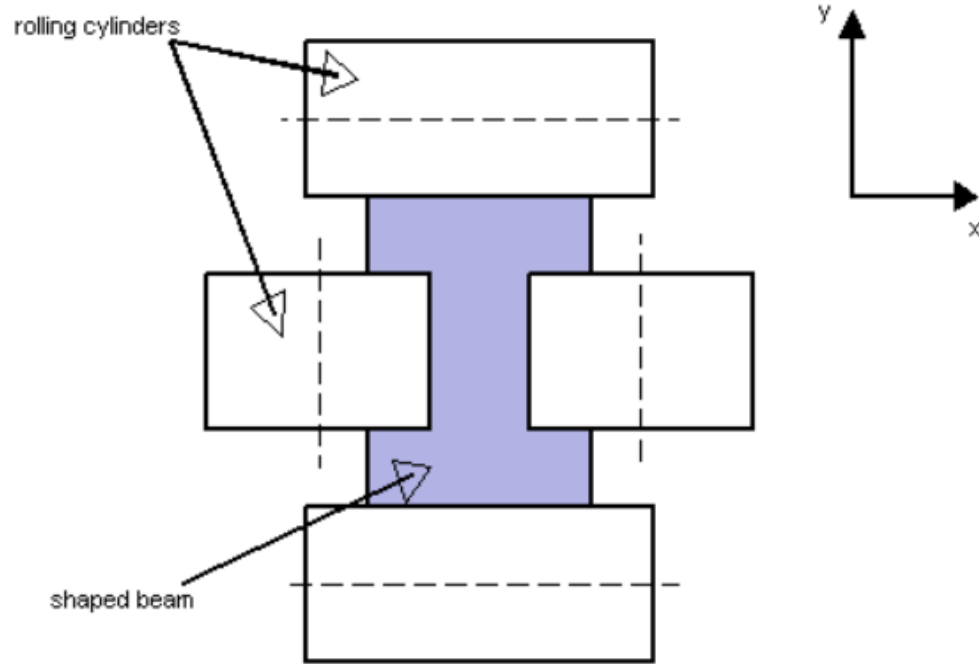
- Laplace transform:

$$\begin{cases} sX = AX + BU \\ Y = CX + DU \end{cases}$$

$$\implies Y = \underbrace{\left[C(sI - A)^{-1} + D \right]}_{G(s)} U$$

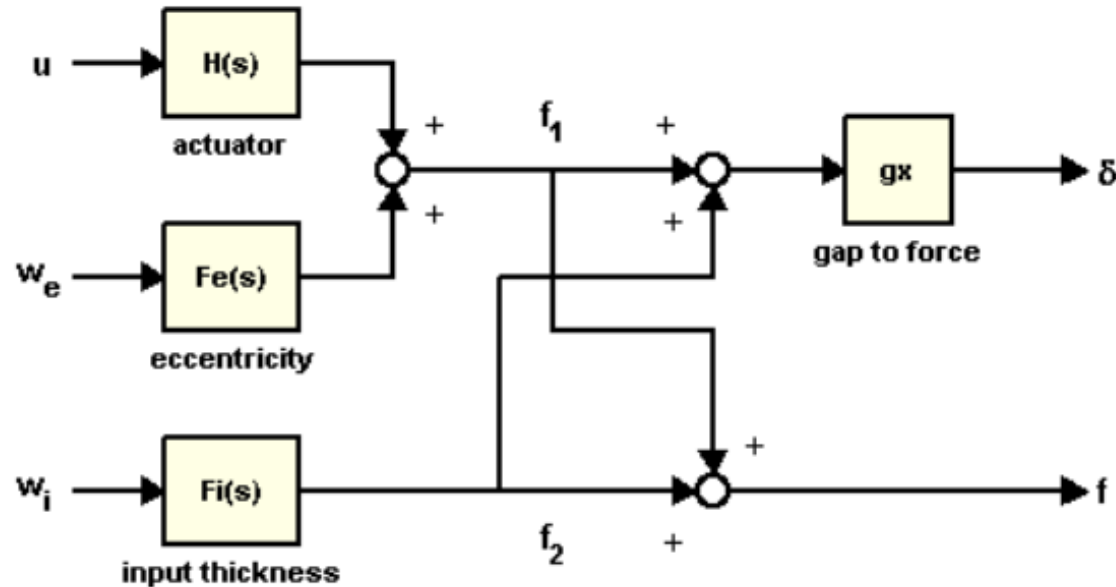
MIMO CONTROL

BEAM ROLLING: EXAMPLE



- Goal: track static reference thickness w_r

BEAM ROLLING: PROCESS (X-DIRECTION)



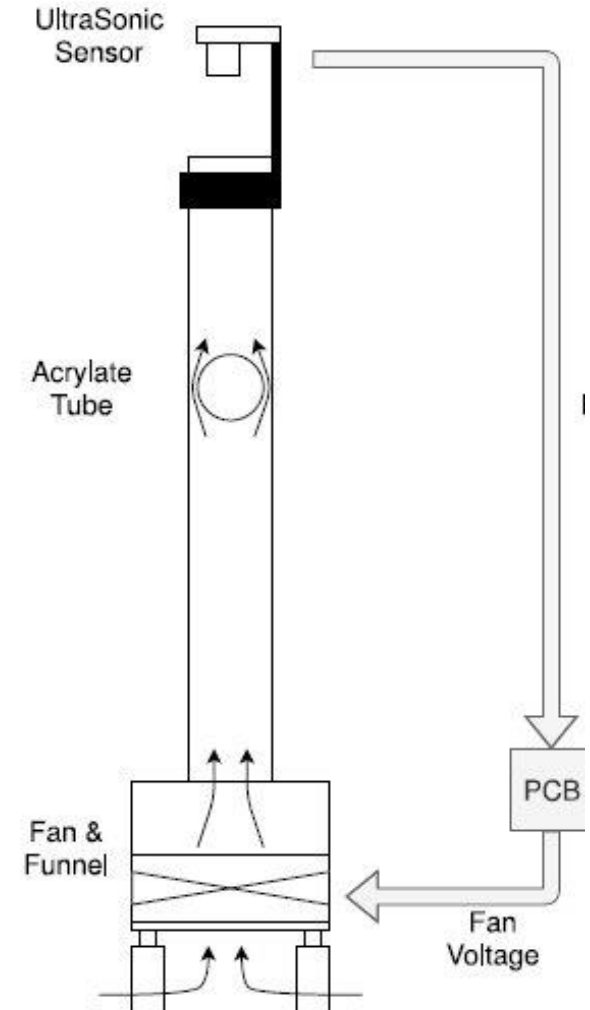
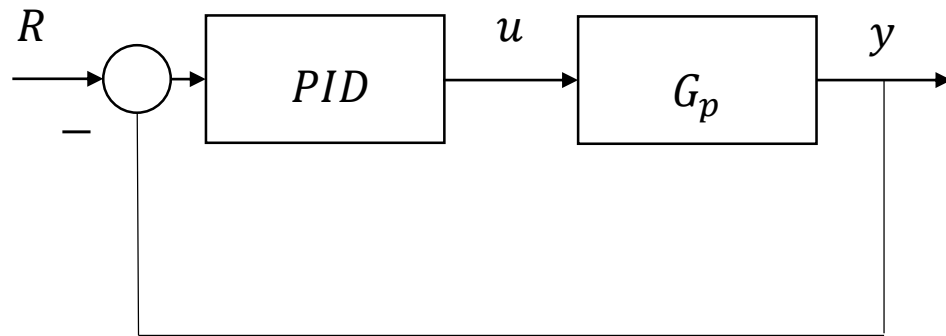
- u : controlled input
- w_e : eccentricity (disturbance)
- w_i : input thickness (disturbance)
- δ : gap thickness (not measurable)
- f : rolling force (measurable)

- Dynamics

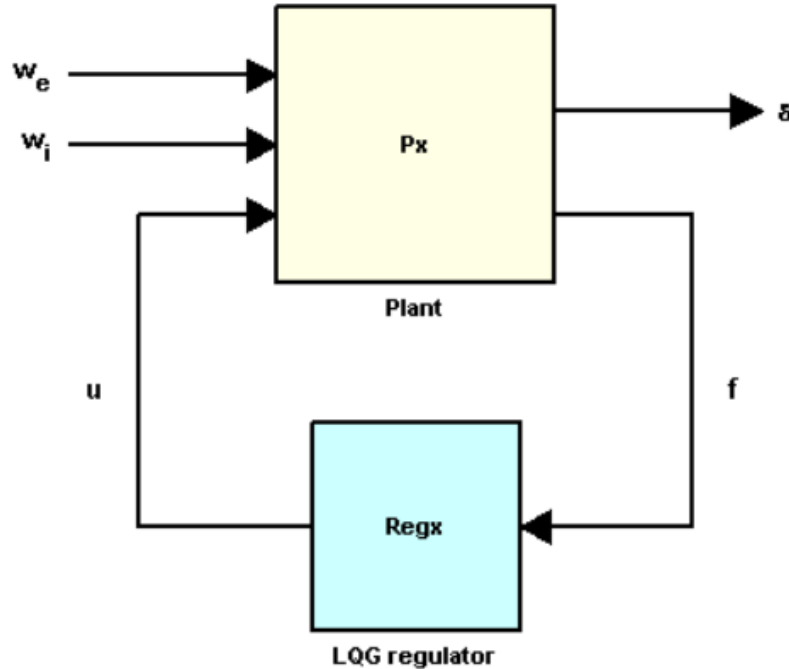
$$H_x = \frac{2.4 \times 10^8}{s^2 + 72s + 90^2} \quad F_{ex} = \frac{3 \times 10^4 s}{s^2 + 0.125s + 6^2} \quad F_{ix} = \frac{10^4}{s + 0.05}$$

BASIC CONTROL: PID

- Easy tuning rules:
 - Oscillation test results in K_u
 - E.g. Ziegler-Nichols: K_P, K_I, K_D
- More involved tuning based on some quality labels:
 - Overshoot
 - Settling time



BEAM ROLLING: LQR CONTROL (X-DIRECTION)



- Define cost function:

$$C(u) = \int_0^{\infty} y^T Q y + u^T R u dt$$

- Wherein

$$Q \in \mathbb{R}^{p \times p}$$

$$R \in \mathbb{R}^{m \times m}$$

- Result: control law

$$u = -K(x - w_r), \quad K \in \mathbb{R}^{m \times n}$$

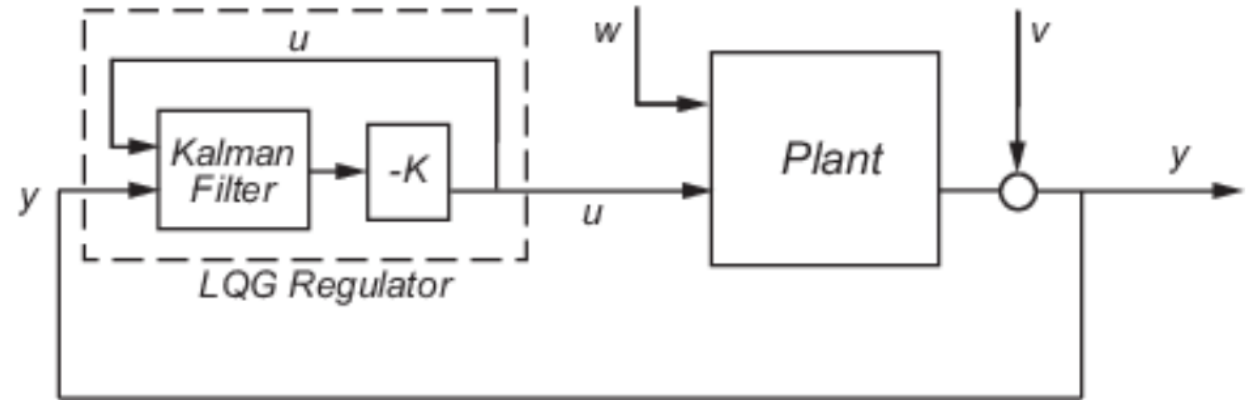
- But...

$x???$



LQG CONTROL

- Boils down to: Kalman + LQR



- Kalman to estimate the state

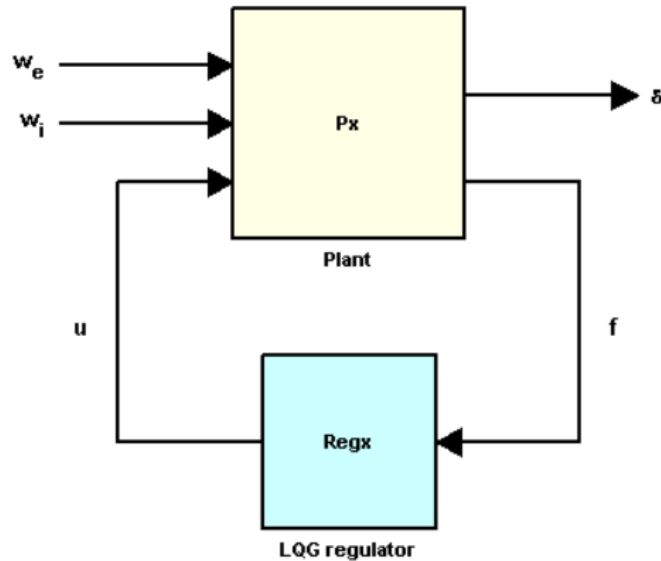
$$y \xrightarrow{F_{Kalman}} \hat{x}$$

- LQR, using an estimate of the full state:

$$u = -K\hat{x}, \quad K \in \mathbb{R}^{m \times n}$$

- u : plant input
- y : plant output
- w : input disturbance
- v : output disturbance

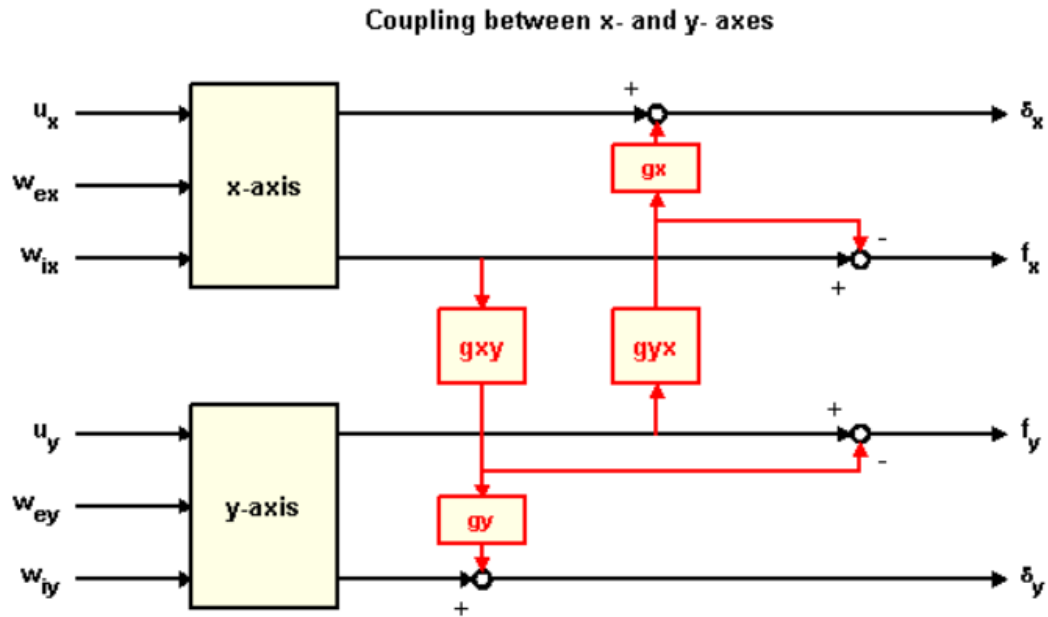
BEAM ROLLING: LQG CONTROL (X-DIRECTION)



- u : controlled input
- w_e : disturbance (eccentricity)
- w_i : disturbance (input thickness)
- δ : gap thickness (not measurable)
- f : rolling force (measurable)

Python implementation

BEAM ROLLING: X & Y DIRECTION



- Interactions exist:
 - Example: Poisson coefficient
- Complicating control:
 - Input u_x influences f_y
 - Input u_y influences f_x
 - Cross coupling
- How to deal with this?

DECOUPLED CONTROL

- Coupling between u_i and y_j exist
- How to deal with this?
 1. Ignore coupling (Decentralised Control):
 - LQR or LQG for separated models → suboptimal solution
 - ‘What is good for one might be bad for the other’
 2. Take coupling into account (Centralised Control):
 - Difficult to comprehend
 - LQR or LQG: complicated model and often suboptimal
 3. Decouple in control scheme!
- To what degree do u_j and y_i interact?
 - Relative Gain Array (RGA)

DECOUPLED CONTROL: RELATIVE GAIN ARRAY (1)

- Consider the input-output model: $y(s) = G(s)u(s)$
- Gain from u_j to y_i (all other loops open):
- Gain from u_j to y_i (all other loops closed):

$$\left. \frac{\partial y_i}{\partial u_j} \right|_{u_k = \text{cst}, k \neq j} = g_{ij}$$

$$\left. \frac{\partial y_i}{\partial u_j} \right|_{y_k = \text{cst}, k \neq j} = \hat{g}_{ij}$$

- Relative gain:

$$\lambda_{ij} := \frac{g_{ij}}{\hat{g}_{ij}} = [G]_{ij} [G^{-1}]_{ji}$$

- With:

$$\hat{g}_{ij} = \frac{1}{[G^{-1}]_{ij}}$$

DECOUPLED CONTROL: RELATIVE GAIN ARRAY (2)

- Apply a step input Δu_j keeping u_k constant ($k \neq j$) and measure the output change Δy_i

$$g_{ij} = \left. \frac{\Delta y_i}{\Delta u_j} \right|_{u_k = \text{cst}, k \neq j}$$

- Apply a step input Δu_j keeping y_k constant ($k \neq j$) (i.e. keeping all other loops closed and measure the output change Δy_i)

$$\hat{g}_{ij} = \left. \frac{\Delta y_i}{\Delta u_j} \right|_{y_k = \text{cst}, k \neq j}$$

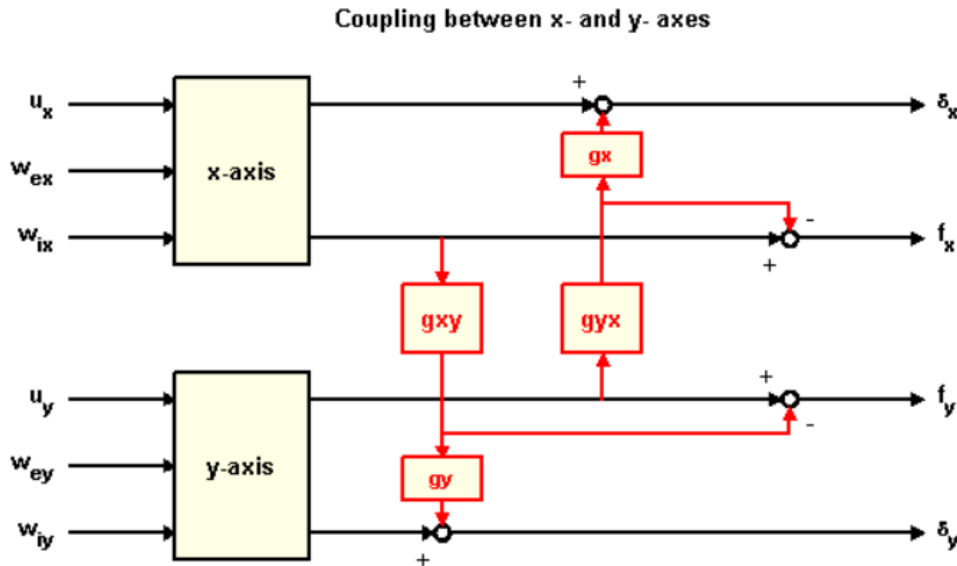
BEAM ROLLING: DECOUPLING CONTROL (1)

- Input-output model:

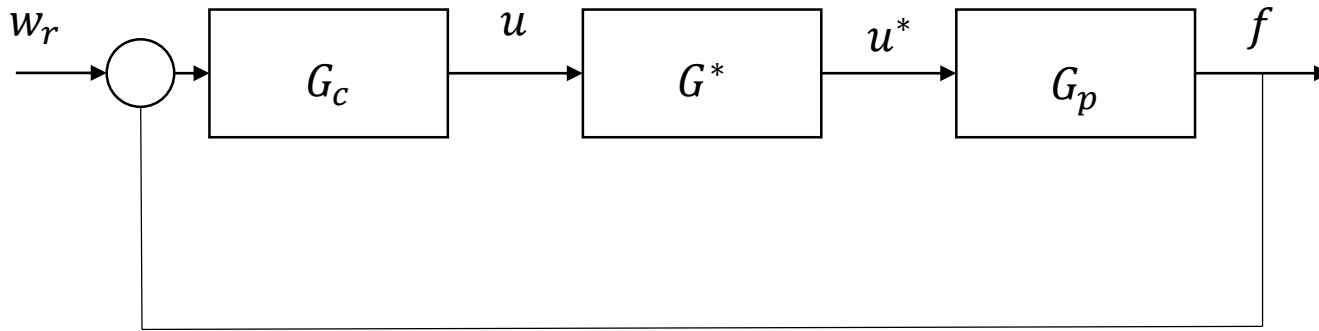
$$y(s) = G(s)u(s), \quad G(s) \in \mathbb{R}^{4 \times 6}$$

- With:

$$y = \begin{bmatrix} \delta_x \\ f_x \\ \delta_y \\ f_y \end{bmatrix} \quad \& \quad u = \begin{bmatrix} u_x \\ w_{ex} \\ w_{ix} \\ u_y \\ w_{ey} \\ w_{iy} \end{bmatrix}$$



BEAM ROLLING: DECOUPLING CONTROL (2)



- G^* such that inputs and outputs are decoupled i.e. no interaction between u_x and f_y and u_y and f_x
- We aim at static decoupling: $\lim_{s \rightarrow 0} sG(s) = \tilde{G}_{stat}$

$G^*? \rightarrow$ Exercise

BEAM ROLLING: DECOUPLING CONTROL (3)

- We aim at static decoupling: $\lim_{s \rightarrow 0} sG(s) = \tilde{G}_{stat}$
- Consider the new input-output model:

$$\begin{bmatrix} f_x \\ f_y \end{bmatrix} = \tilde{G}_{stat} \begin{bmatrix} u_x \\ u_y \end{bmatrix}$$

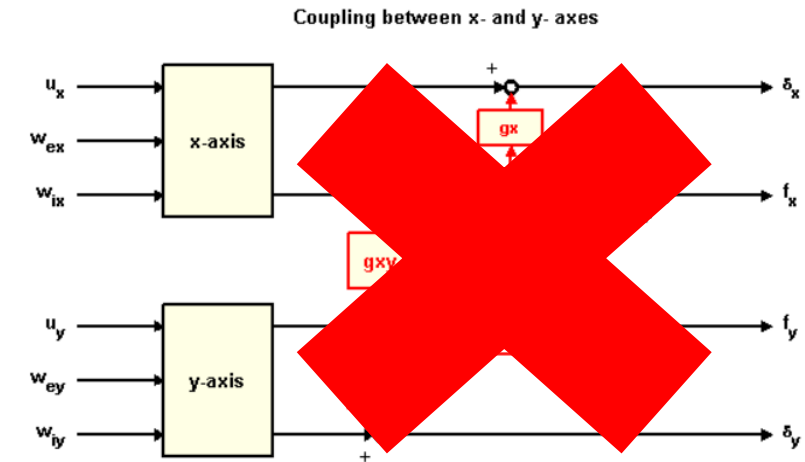
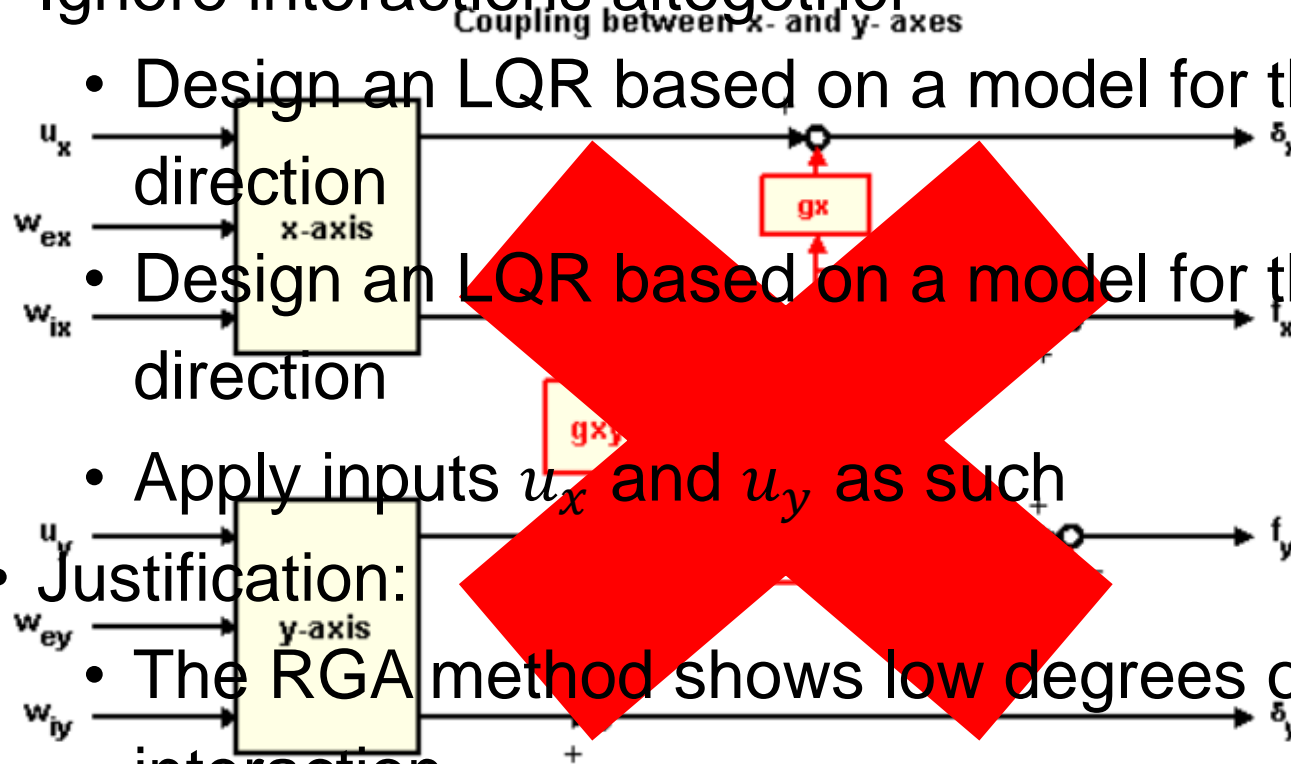
- Wherein:

$$\tilde{G}_{stat} = \begin{bmatrix} 29629.63 & -95686.98 \\ -28148.15 & 100723.14 \end{bmatrix}$$

- Goal: find \tilde{G}_{stat}^* for $y = \tilde{G}_{stat} \tilde{G}_{stat}^* u$ such that y and u are decoupled

BEAM ROLLING: DECENTRALISED CONTROL

- Ignore interactions altogether
 - Design an LQR based on a model for the x-direction
 - Design an LQR based on a model for the y-direction
 - Apply inputs u_x and u_y as such
- Justification:
 - The RGA method shows low degrees of interaction
 - Note: coupling w_e & w_i w.r.t. f are not considered

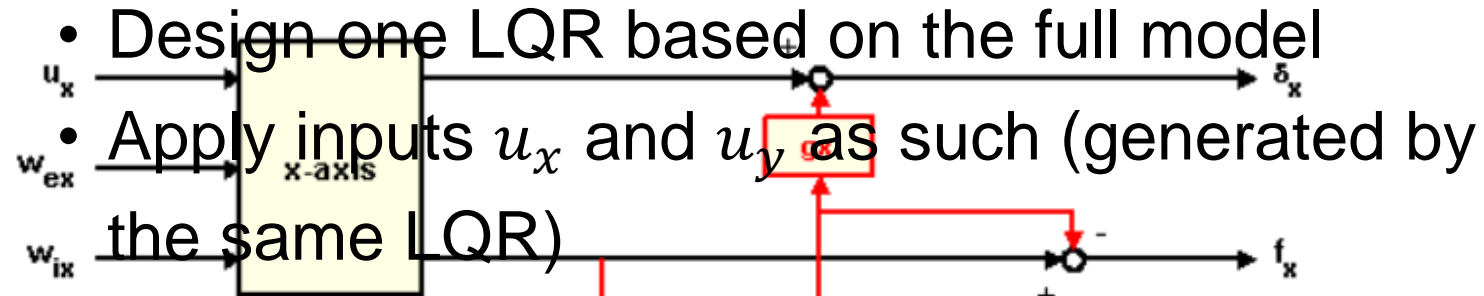


RGA-matrix

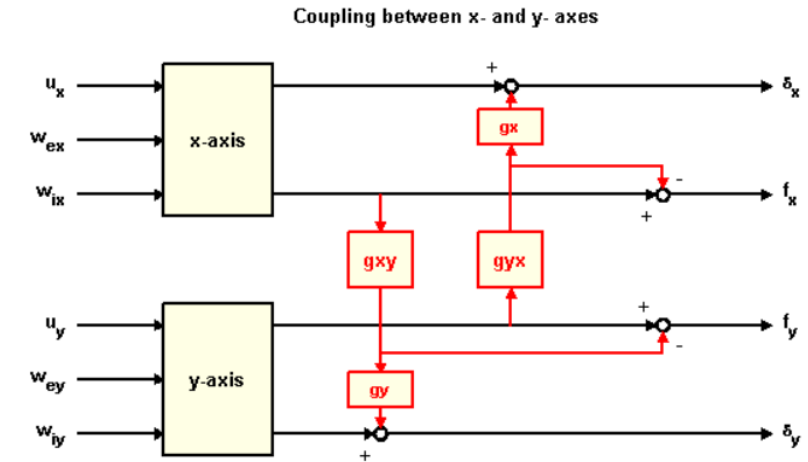
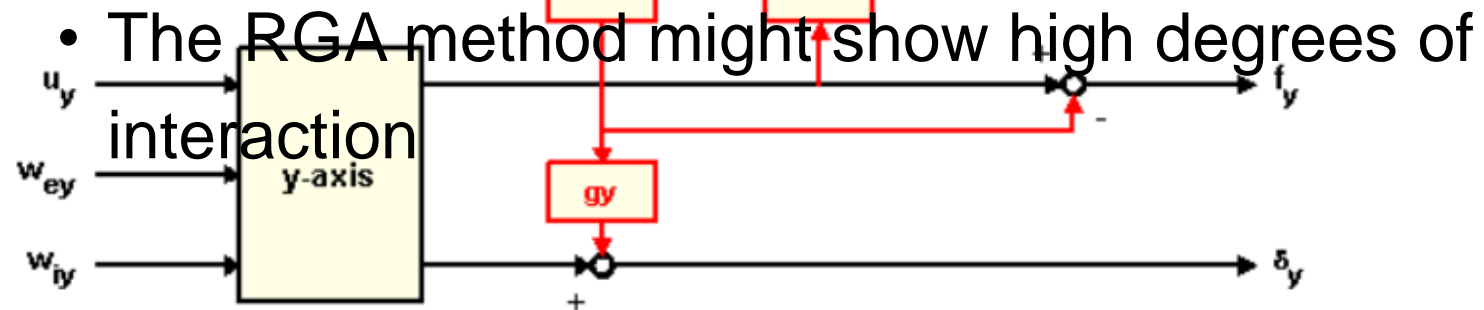
$$\Lambda = \begin{bmatrix} 1.014 & -0.014 \\ -0.014 & 1.014 \end{bmatrix}$$

BEAM ROLLING: CENTRALISED CONTROL

- Model the plant completely (including interactions)

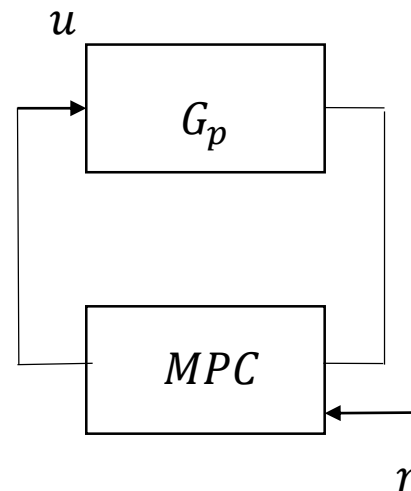


- Justification:



MODEL PREDICTIVE CONTROL (MPC):

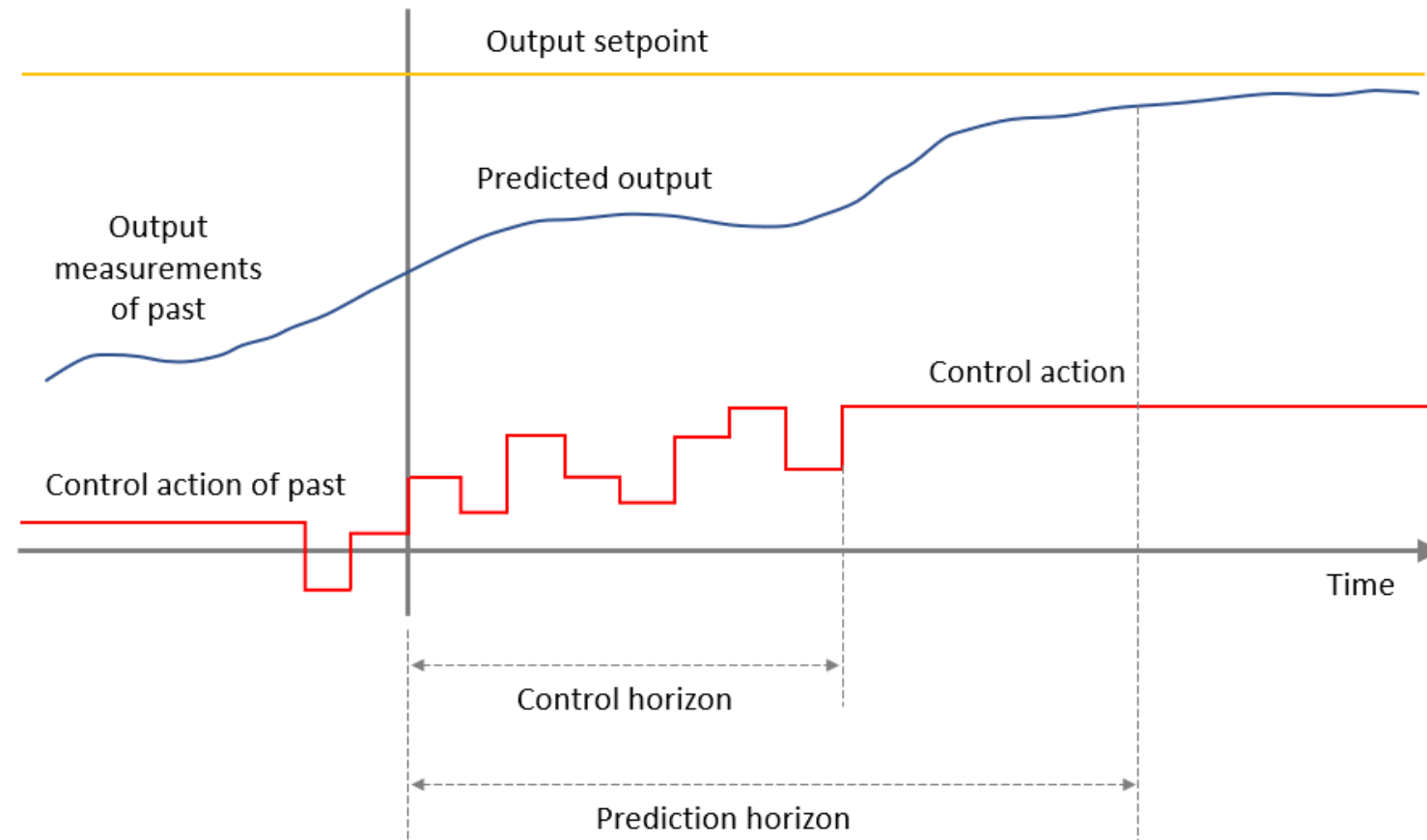
- Unaddressed topics so far:
 - Constraint equations
 - Nonlinear models
 - Dead time
 - Dealing measured disturbances
- → MPC



MPC:

MPC :

- Feedback control for MIMO systems
- Input based on real-time optimisation
- Optimisation based on current state and predicted future output



Current time t
SYMO training

MPC

- Based on a model (state-space):

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) \\ y(k) = Cx(k) + Du(k) \end{cases}$$

- And a well-defined cost function: $J(x, u, y)$
- Taking into account some constraints:

$$U_{i,min} \leq u_i(k) \leq U_{i,max}$$

$$X_{i,min} \leq x_i(t) \leq X_{i,max}$$

- Minimisation of the cost function, based on the predicted output $y(t+k|t), k = 1 \dots N$ (and therefore the predicted error) results in $u(t+k|t), k = 1 \dots N$ over the prediction horizon

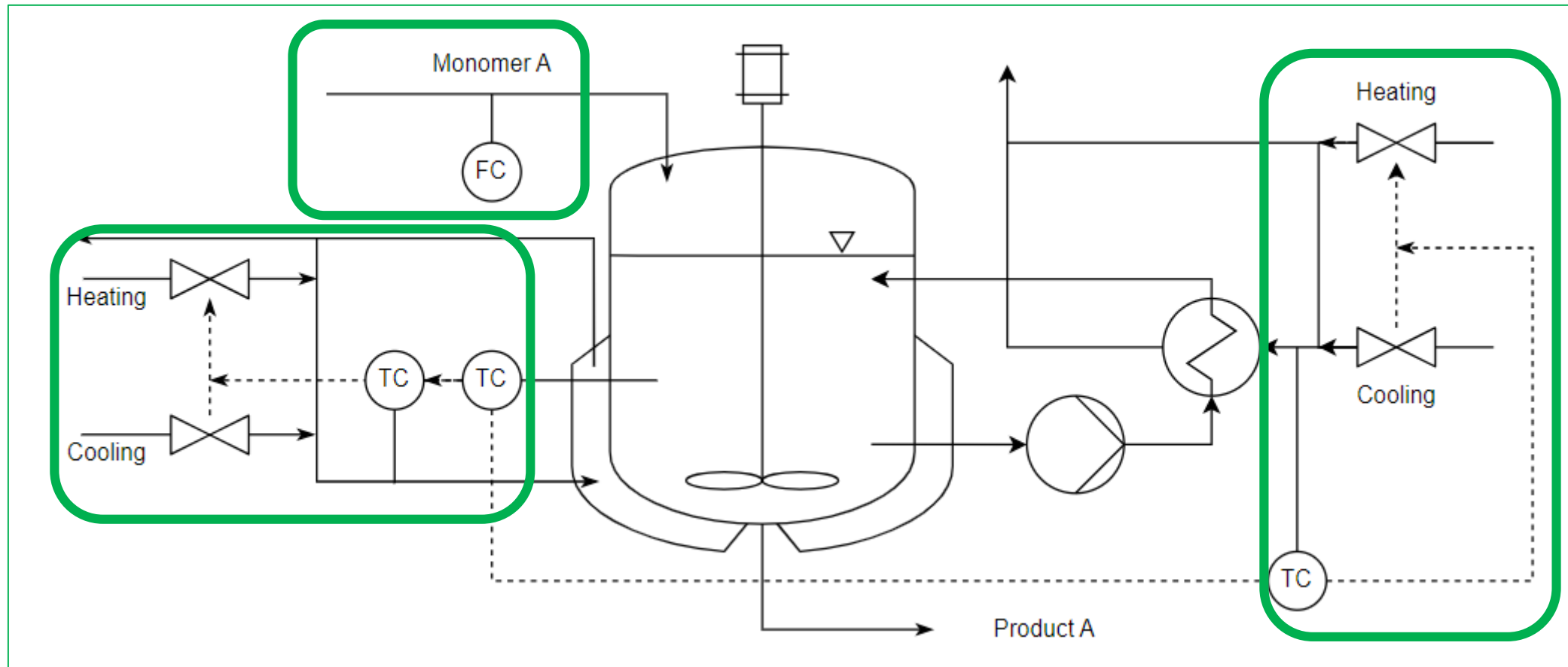
- Only $u(t+1|t)$ applied

Possibly: $(N_u < N)$

$$u(t+k) = \begin{cases} u(t+k), & k < N_u \\ u(t+N_u), & k \geq N_u \end{cases}$$

PROCESS: INDUSTRIAL POLYMERISATION REACTOR

Input



MODEL THROUGH CONSERVATION

$$\begin{aligned}
 \dot{m}_W &= \dot{m}_F \omega_{W,F} \\
 \dot{m}_A &= \dot{m}_F \omega_{A,F} - k_{R1} m_{A,R} - k_{R2} m_{AWT} m_A / m_{ges}, \\
 \dot{m}_P &= k_{R1} m_{A,R} + p_1 k_{R2} m_{AWT} m_A / m_{ges}, \\
 \dot{T}_R &= 1/(c_{p,R} m_{ges}) [\dot{m}_F c_{p,F} (T_F - T_R) + \Delta H_R k_{R1} m_{A,R} - k_K A (T_R - T_S) \\
 &\quad - \dot{m}_{AWT} c_{p,R} (T_R - T_{EK})], \\
 \dot{T}_S &= 1/(c_{p,S} m_S) [k_K A (T_R - T_S) - k_K A (T_S - T_M)], \\
 \dot{T}_M &= 1/(c_{p,W} m_{M,KW}) [\dot{m}_{M,KW} c_{p,W} (T_M^{IN} - T_M) \\
 &\quad + k_K A (T_S - T_M)] + k_K A (T_S - T_M), \\
 \dot{T}_{EK} &= 1/(c_{p,R} m_{AWT}) [\dot{m}_{AWT} c_{p,W} (T_R - T_{EK}) - \alpha (T_{EK} - T_{AWT}) \\
 &\quad + k_{R2} m_A m_{AWT} \Delta H_R / m_{ges}], \\
 \dot{T}_{AWT} &= [\dot{m}_{AWT,KW} c_{p,W} (T_{AWT}^{IN} - T_{AWT}) - \alpha (T_{AWT} - T_{EK})] / (c_{p,W} m_{AWT,KW}),
 \end{aligned}$$

Parameter uncertainty

$$m_F^{acc} = \dot{m}_F$$

$$T_{adiab} = \frac{\Delta H_R}{c_{p,R}} \frac{m_A}{m_A + m_W + m_P} + T_R$$

$$\begin{aligned}
 U &= m_P / (m_A + m_P), \\
 m_{ges} &= m_W + m_A + m_P, \\
 k_{R1} &= k_0 e^{\frac{-E_a}{R(T_R + 273.15)}} (k_{U1} (1 - U) + k_{U2} U), \\
 k_{R2} &= k_0 e^{\frac{-E_a}{R(T_{EK} + 273.15)}} (k_{U1} (1 - U) + k_{U2} U), \\
 k_K &= (m_W k_{WS} + m_A k_{AS} + m_P k_{PS}) / m_{ges}, \\
 m_{A,R} &= m_A - m_A m_{AWT} / m_{ges}.
 \end{aligned}$$

CONSTRAINTS

Control	Min.	Max.	Unit
\dot{m}_F	0	30,000	kg h ⁻¹
T_M^{IN}	60	100	°C
T_{AWT}^{IN}	60	100	°C

State	Init. cond.	Min.	Max.	Unit
m_W	10,000	0	inf.	kg
m_A	853	0	inf.	kg
m_P	26.5	0	inf.	kg
T_R	90.0	$T_{set} - 2.0$	$T_{set} + 2.0$	°C
T_S	90.0	0	100	°C
T_M	90.0	0	100	°C
T_{EK}	35.0	0	100	°C
T_{AWT}	35.0	0	100	°C
T_{adiab}	104.897	0	109	°C
m_F^{acc}	0	0	30,000	kg



OBJECTIVE

- Produce $m_P = 20680 \text{ kg}$ as fast as possible
- Smooth control performance: penalty on input changes

$$J(x, u, z) = \sum_{k=0}^N \left(\underbrace{l(x_k, z_k, u_k, p_k, p_{tv,k})}_{\text{Lagrange term}} + \underbrace{\Delta u_k^T R \Delta u_k}_{\text{r-term}} \right) + \underbrace{m(x_{N+1})}_{\text{Mayer term}}$$

