



**POLITECNICO**  
MILANO 1863

# Identification and Control of a Quadruple Tank system

## Lecture 2 – Linearization and control design

Lorenzo Nigro, Prof. Riccardo Scattolini

Slides and control schemes by Fabio Bonassi

**Responsible of tutoring activities: Lorenzo Nigro** ([lorenzo.nigro@polimi.it](mailto:lorenzo.nigro@polimi.it))

## Tentative Schedule:

<b>Lecture 1.</b> Modeling, identification, and validation	April 10, 16:15 – 18:15	Online (Webex)
<b>Lecture 2.</b> Design of a PI-based control architecture	April 12, 11:15 – 13:15	Online (Webex)
<b>Lecture 3.</b> Testing of students' LQ control architectures (3 groups)	April 24, 10:30 – 12:30	Lab (IRL)
<b>Lecture 4.</b> Testing of students' LQ control architectures (4 groups)	April 24, 16:00 – 19:00	Lab (IRL)
<b>Lecture 5.</b> Testing of students' LQ control architectures (4 groups)	April 30, 9:30 – 12:30	Lab (IRL)
<b>Lecture 6.</b> Testing of students' LQ control architectures (3 groups)	May 8, 10:30 – 12:30	Lab (IRL)
<b>Lecture 7.</b> Testing of students' LQ control architectures (4 groups)	May 8, 16:00 – 19:00	Lab (IRL)
<b>Lecture 8.</b> Testing of students' LQ control architectures (4 groups)	May 15, 16:00 – 19:00	Lab (IRL)

**Please remember to fill in the attendance form!**

# Register your participation

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# Goals of the second lecture

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- ☐ Linearize the grey-box model of the Quadruple Tank
- ☐ Design a decentralized control system
- ☐ Design a decoupled control system

Nonlinear model under consideration

$$\dot{h}_1 = -\frac{A_1}{S} \sqrt{2gh_1} + \frac{\kappa_2(V_2) \cdot \gamma_2(V_2)}{S} V_2$$

$$\dot{h}_2 = \frac{A_1}{S} \sqrt{2gh_1} - \frac{A_2}{S} \sqrt{2gh_2} + \frac{\kappa_1(V_1) \cdot (1 - \gamma_1(V_1))}{S} V_1$$

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 Identified parameter


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In the following, for simplicity we will denote the grey-box model by

$$\begin{aligned} \dot{x}(t) &= f(x(t), u(t)) \\ y(t) &= C x(t) \end{aligned} \quad x = \begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{bmatrix} \quad u = \begin{bmatrix} V_1 \\ V_2 \end{bmatrix} \quad y = \begin{bmatrix} h_2 \\ h_4 \end{bmatrix}$$


Nonlinear model under consideration

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**Problem:** How do we compute the equilibrium  $(\bar{x}, \bar{u}, \bar{y})$  corresponding to some  $\bar{y}$ ?



We want to solve numerically the following system of equations

$$\begin{cases} 0 = f(\bar{x}, \bar{u}) \\ \bar{y} = C\bar{x} \end{cases}$$

Letting  $z = \begin{bmatrix} \bar{x} \\ \bar{u} \end{bmatrix}$ , computing the equilibrium amounts to finding  $\underline{z} \leq z \leq \bar{z}$  such that  $g(z) = 0$

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$$g(z) = [f(\bar{z}); \tilde{C}\bar{z} - \bar{y}]$$

## Possible solutions:

- **fsolve** – does not support bounds on  $z$
- **Symbolic Toolbox** – does not support numeric maps used for  $\kappa_j(V_j)$  and  $\gamma_j(V_j)$
- **CasADi** – does not support numeric maps used for  $\kappa_j(V_j)$  and  $\gamma_j(V_j)$
- **fmincon** – supports bounds and numeric maps

```
nlconstr = @(z) build_nonlinear_constraints(z, y_bar); % Nonlinear constraints
z_lb = [ eps; eps; eps; eps; 0; 0 ]; % Lower bound on decision variables
z_ub = [ 30; 30; 30; 30; 18; 18 ]; % Upper bound on decision variables
z0 = [ 6; 6; 6; 6; 6; 6 ]; % Initial guess
```

Lower and Upper decision variable bounds

```
z_sol = fmincon(@(z) z(1)+z(3), z0, [], [], [], [], z_lb, z_ub, nlconstr);
```

```
function [ nlcstr_le, nlcstr_eq ] = build_nonlinear_constraints(z, y_bar)
    nlcstr_le = [];
```

```
    nlcstr_eq = [ dynamics_f(z(1:4), z(5:6));
                  y_bar - dynamics_g(z(1:4)) ];
```

```
end
```

```
function x_dot = dynamics_f(x, u)
    x_dot(1) = - A1 / S * sqrt(2 * g * x(1)) + k2(u(2)) * gamma2(u(2)) / S * u(2);
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    x_dot(3) = - A3 / S * sqrt(2 * g * x(3)) + k1(u(1)) * gamma1(u(1)) / S * u(1);
    x_dot(4) = A3 / S * sqrt(2 * g * x(3)) - A4 / S * sqrt(2 * g * x(4)) + k2(u(2)) * (1 - gamma2(u(2))) / S * u(2);
```

```
end
```

```
function y = dynamics_g(x)
    y = [ x(2); x(4) ];
```

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Lower and Upper decision variable bounds  
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Inequalities, equalities

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                  y_bar - dynamics_g(z(1:4)) ];
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```
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```

$$g(z) = \begin{bmatrix} f(\bar{z}); \\ \tilde{C}\bar{z} - \bar{y} \end{bmatrix}$$

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function x_dot = dynamics_f(x, u)
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```
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```

```
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```

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Nonlinear constraints

$$\bar{y} = \begin{bmatrix} 10 \\ 10 \end{bmatrix} \rightarrow \bar{x} = \begin{bmatrix} 24.66 \\ 10 \\ 3.04 \\ 10 \end{bmatrix}, \quad \bar{u} = \begin{bmatrix} 6.60 \\ 9.28 \end{bmatrix}$$



Two approaches:

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2. **By hand**

$$\dot{\delta x} = \left. \frac{\partial f(x, u)}{\partial x} \right|_{\bar{x}, \bar{u}} \delta x + \left. \frac{\partial f(x, u)}{\partial u} \right|_{\bar{x}, \bar{u}} \delta u$$

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$$\delta \dot{h}_1 = -\frac{A_1 \sqrt{2g}}{S \sqrt{\bar{h}_1}} \delta h_1 + \left. \frac{\partial [k_2(V_2) \gamma_2(V_2) V_2]}{\partial V_2} \right|_{\bar{V}_2} \delta V_2$$

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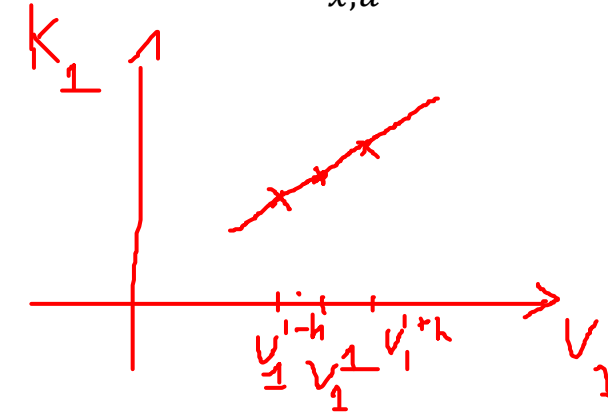
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$$\delta \dot{x} = \left. \frac{\partial f(x, u)}{\partial x} \right|_{\bar{x}, \bar{u}} \delta x + \left. \frac{\partial f(x, u)}{\partial u} \right|_{\bar{x}, \bar{u}} \delta u$$

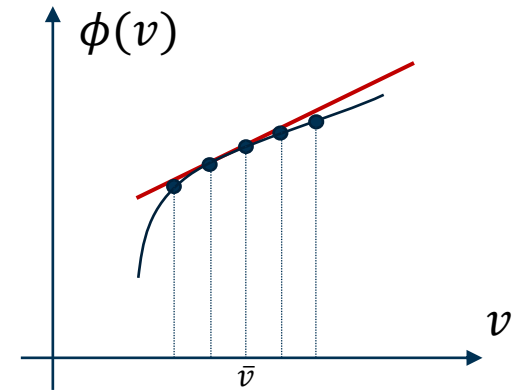


Since  $\kappa_j$  and  $\gamma_j$  are numerical maps, these terms should be **estimated numerically**

# Five-point stencil derivative approximation

$$\left. \frac{d\phi(v)}{dv} \right|_{\bar{v}} \approx \frac{\phi(\bar{v} - 2h) - 8\phi(\bar{v} - h) + 8\phi(\bar{v} + h) - \phi(\bar{v} + 2h)}{12h}$$

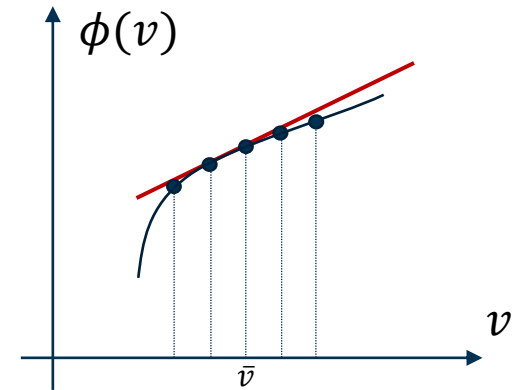
This method can be applied to estimate the “missing derivatives”



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## Resulting linearized model

$$\delta \dot{x} = \begin{bmatrix} -0.01714 & 0 & 0 & 0 \\ 0.01714 & -0.09525 & 0 & 0 \\ 0 & 0 & -0.05238 & 0 \\ 0 & 0 & 0.05238 & 0.099 \end{bmatrix} \delta x + \begin{bmatrix} 0 & 0.09701 \\ 0.1207 & 0 \\ 0.1387 & 0 \\ 0 & 0.1595 \end{bmatrix} \delta u$$

$$\delta y = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \delta x$$

**Poles:** -0.0952, -0.0171, -0.0993, -0.0524

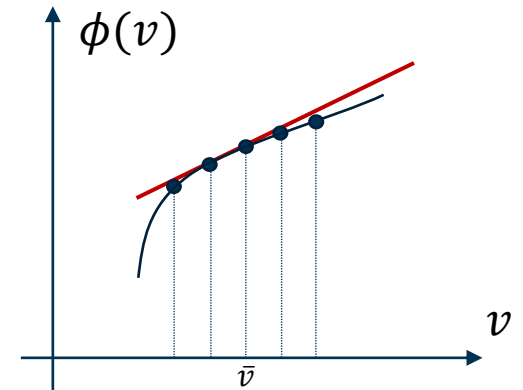
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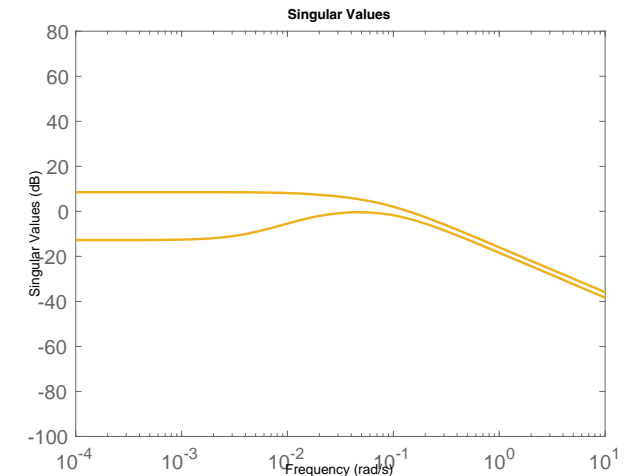
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# Design #1 – Decentralized PI

---

**Idea:** Design two decentralized PI controllers:  $R_1(s)$  to regulate  $G_{11}(s)$ , and  $R_2(s)$  to regulate  $G_{22}(s)$ , or vice versa.

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The input output pairs are decided by inspecting the **Relative Gain Array (RGA)** matrix

$$RGA = G(0) \odot (G(0)^{-1})^T = \begin{bmatrix} \lambda & 1 - \lambda \\ 1 - \lambda & \lambda \end{bmatrix}$$

In our case,  $\lambda \approx 3.3$ , which indicates

- **Very strong coupling** between the variables
- Best pairs:  $(u_1, y_1)$  and  $(u_2, y_2)$

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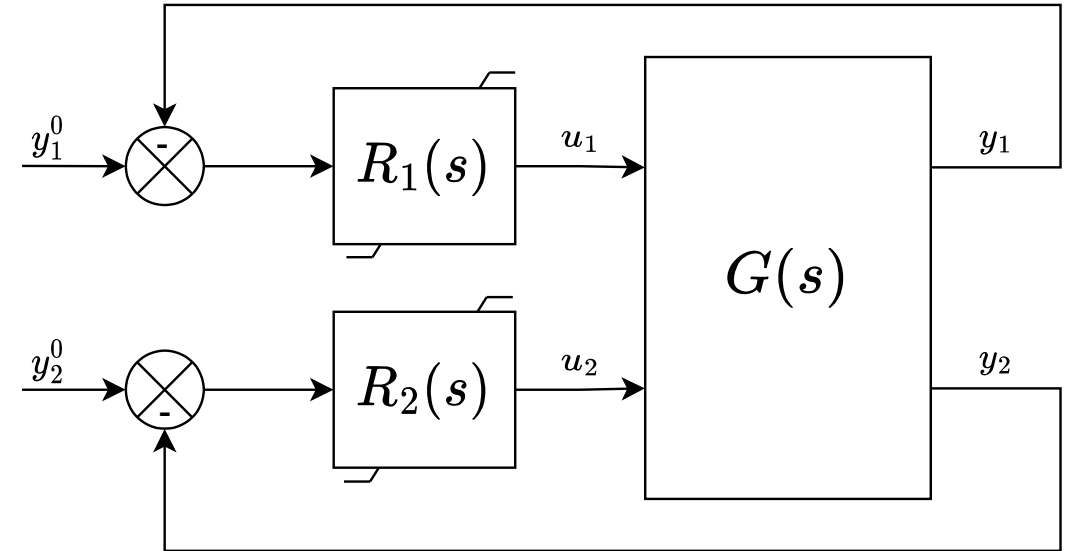
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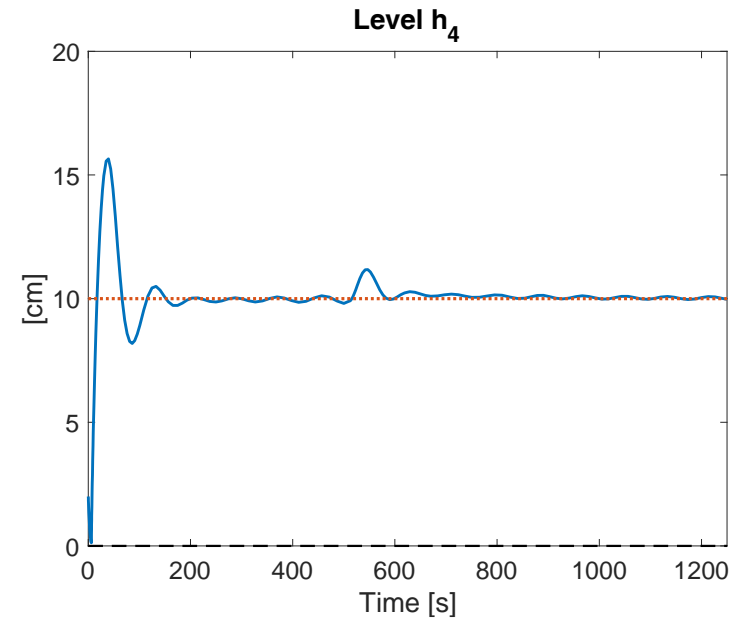
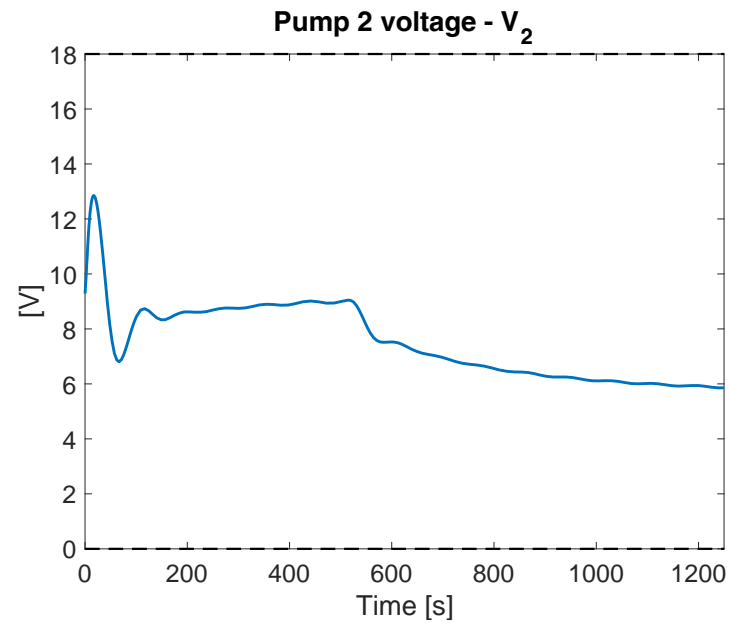
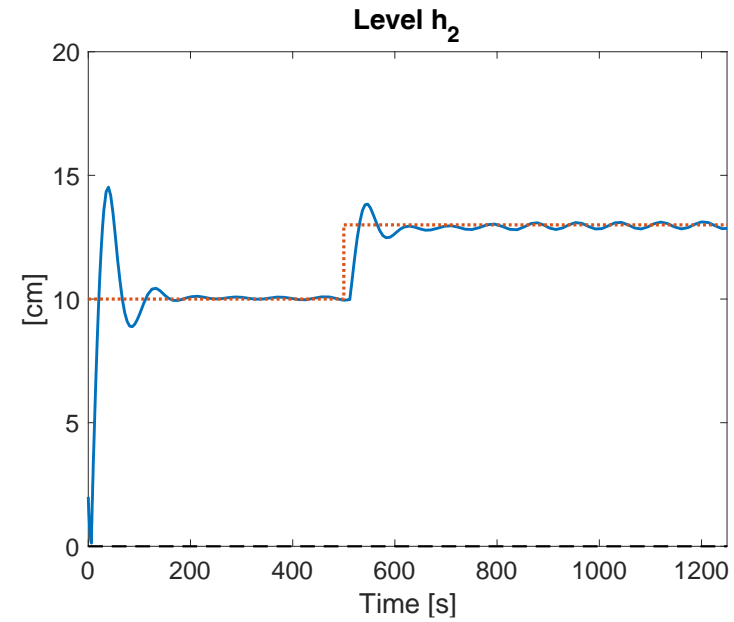
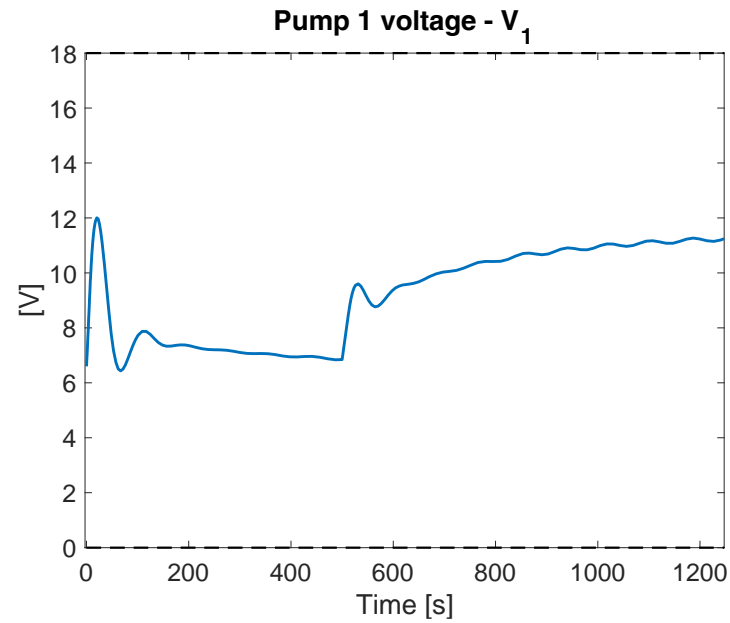
- **Very strong coupling** between the variables
- Best pairs:  $(u_1, y_1)$  and  $(u_2, y_2)$

**Remark:** Don't forget to equip the regulator with some **anti-windup** action!



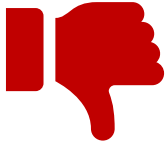
```
R1 = pidtune(Gs(1, 1), 'PI', 0.05);
R2 = pidtune(Gs(2, 2), 'PI', 0.05);
```

# Design #1 – Performances





- Very **easy to design**, it's just 1 line of code for the RGA and 1 line for the regulator design
- Allows to easily include control saturation and anti-windup strategies



- In cases where there are strong cross-couplings ( $\lambda > 1$ ), may not work well.
- Naïve scheme: in general, it may **lead to instability!**

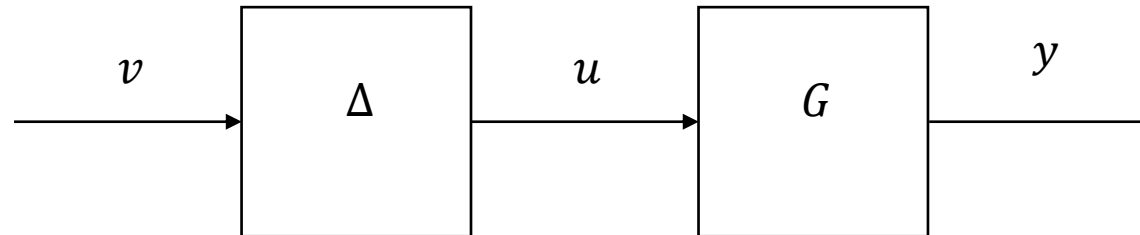
We can do something better, resorting to a “decoupler”!



# Design #2 – Backward-decoupled PI

**Idea:** Design  $\Gamma_{12}(s)$  and  $\Gamma_{21}(s)$  so that

$$G(s)\Delta(s) = \begin{bmatrix} G_{11}(s) & 0 \\ 0 & G_{22}(s) \end{bmatrix}$$



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$$G(s)\Delta(s) = \begin{bmatrix} G_{11}(s) & 0 \\ 0 & G_{22}(s) \end{bmatrix}$$

If  $G(s)$  is asymptotically stable and does not have unstable zeros, one can use

$$\Delta(s) = \left( I - \begin{bmatrix} 0 & \Gamma_{12}(s) \\ \Gamma_{21}(s) & 0 \end{bmatrix} \right)^{-1}$$

$$\left. \begin{aligned} \Gamma_{12}(s) &= -\frac{G_{12}(s)}{G_{11}(s)} = -\frac{0.0138}{s + 0.017} \\ \Gamma_{21}(s) &= -\frac{G_{21}(s)}{G_{22}(s)} = -\frac{0.0456}{s + 0.052} \end{aligned} \right\} \text{(strictly proper)}$$

# Design #2 – Backward-decoupled PI

**Idea:** Design  $\Gamma_{12}(s)$  and  $\Gamma_{21}(s)$  so that

$$G(s)\Delta(s) = \begin{bmatrix} G_{11}(s) & 0 \\ 0 & G_{22}(s) \end{bmatrix}$$

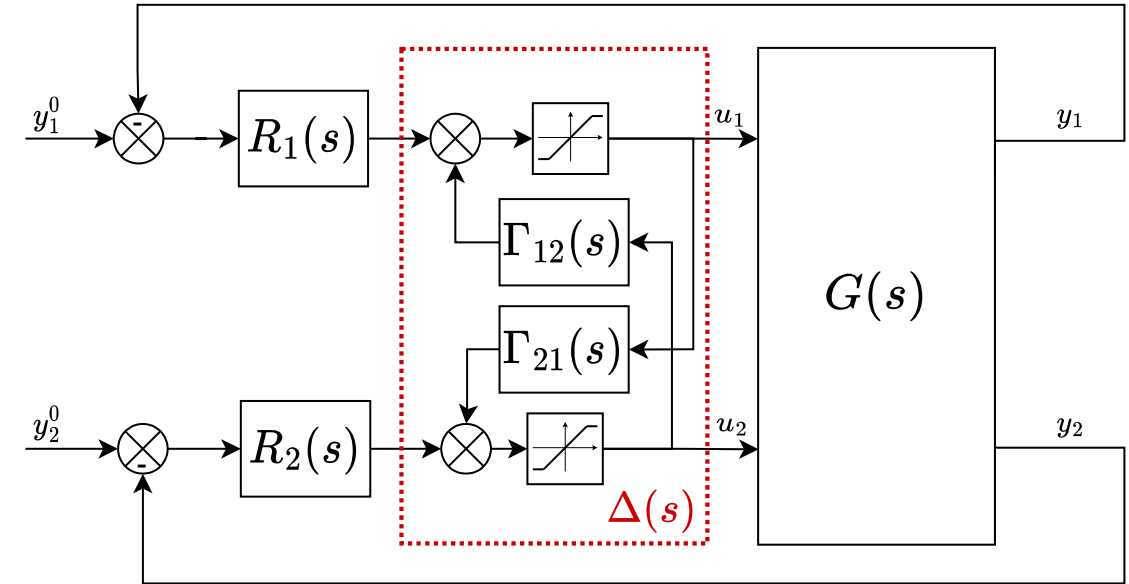
If  $G(s)$  is asymptotically stable and does not have unstable zeros, one can use

$$\Delta(s) = \left( I - \begin{bmatrix} 0 & \Gamma_{12}(s) \\ \Gamma_{21}(s) & 0 \end{bmatrix} \right)^{-1}$$

$$\Gamma_{12}(s) = -\frac{G_{12}(s)}{G_{11}(s)} = -\frac{0.0138}{s + 0.017}$$

$$\Gamma_{21}(s) = -\frac{G_{21}(s)}{G_{22}(s)} = -\frac{0.0456}{s + 0.052}$$

(strictly)  
proper



$R_1(s)$  and  $R_2(s)$  can be then designed based on  $G_{11}(s)$  and  $G_{22}(s)$

# Design #2 – Backward-decoupled PI w/ Anti-windup

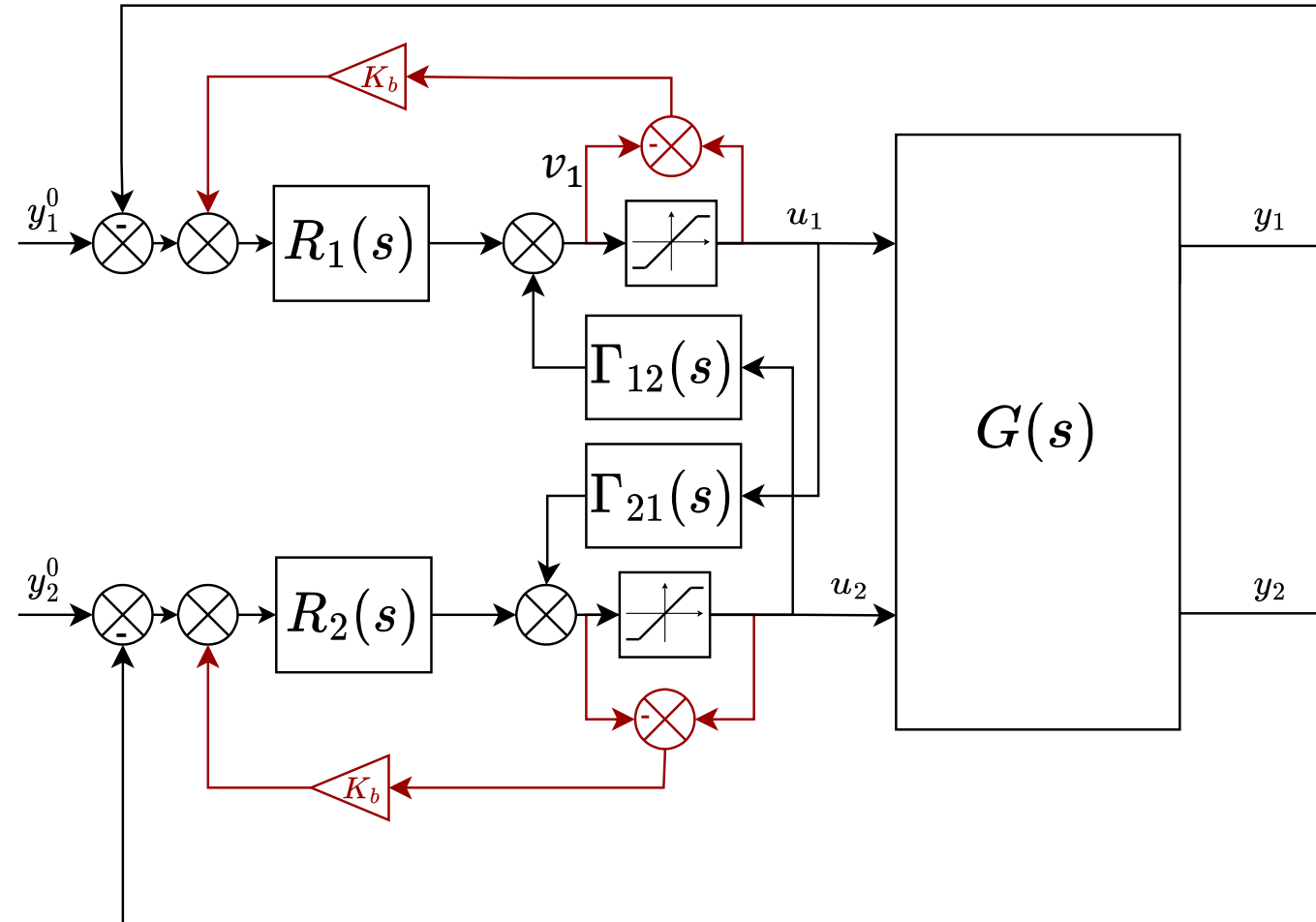
If

$$v_1 > u_{max}$$

Then

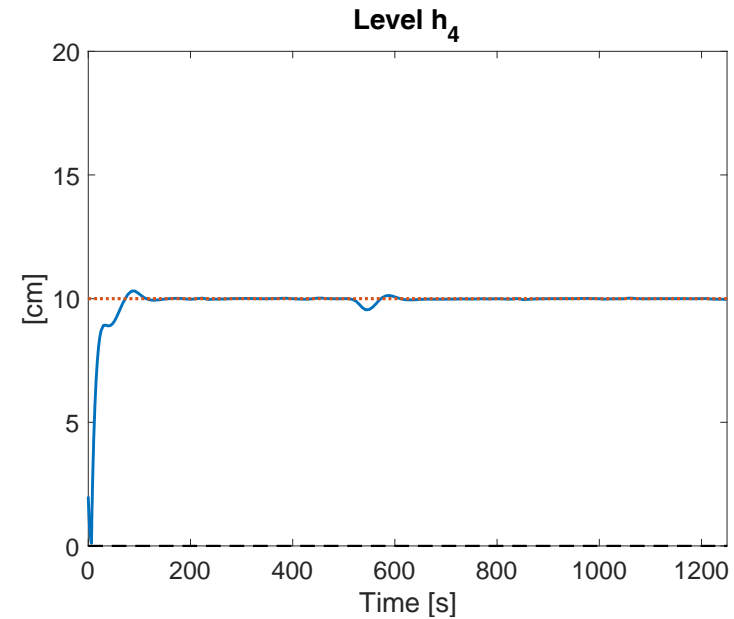
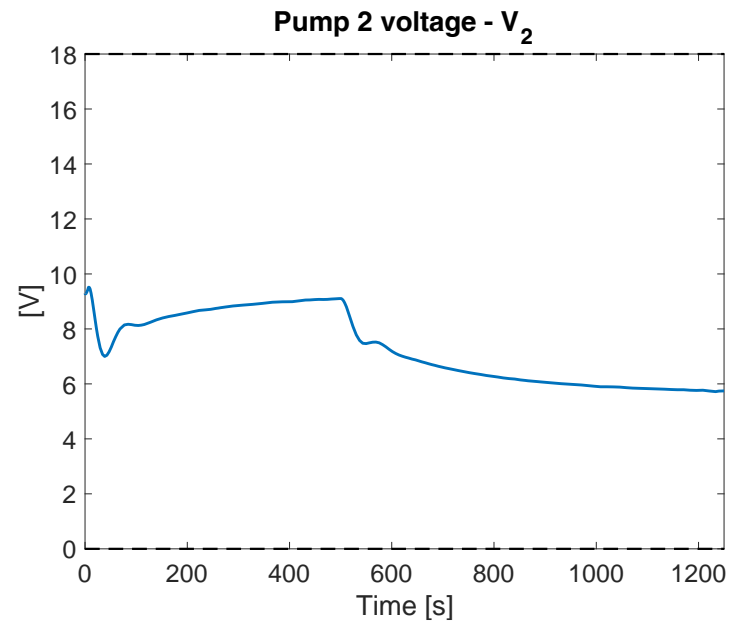
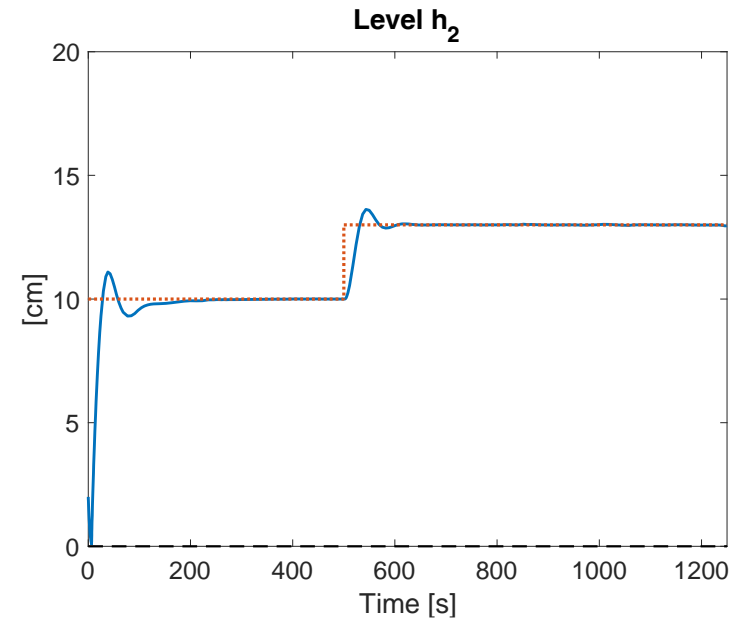
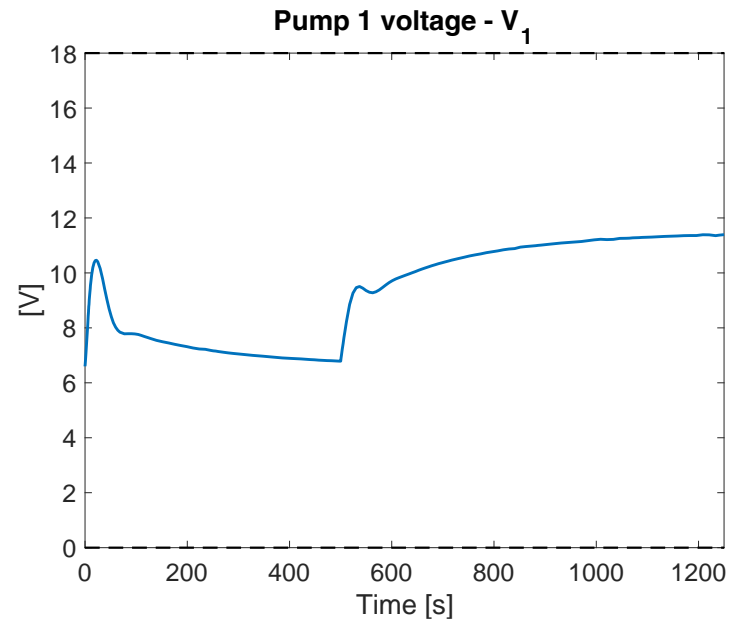
$$-v_1 + u_1 < 0$$

Reducing the input  
of the regulator



$K_b$  is the backcalculation gain

# Design #2 – Performances





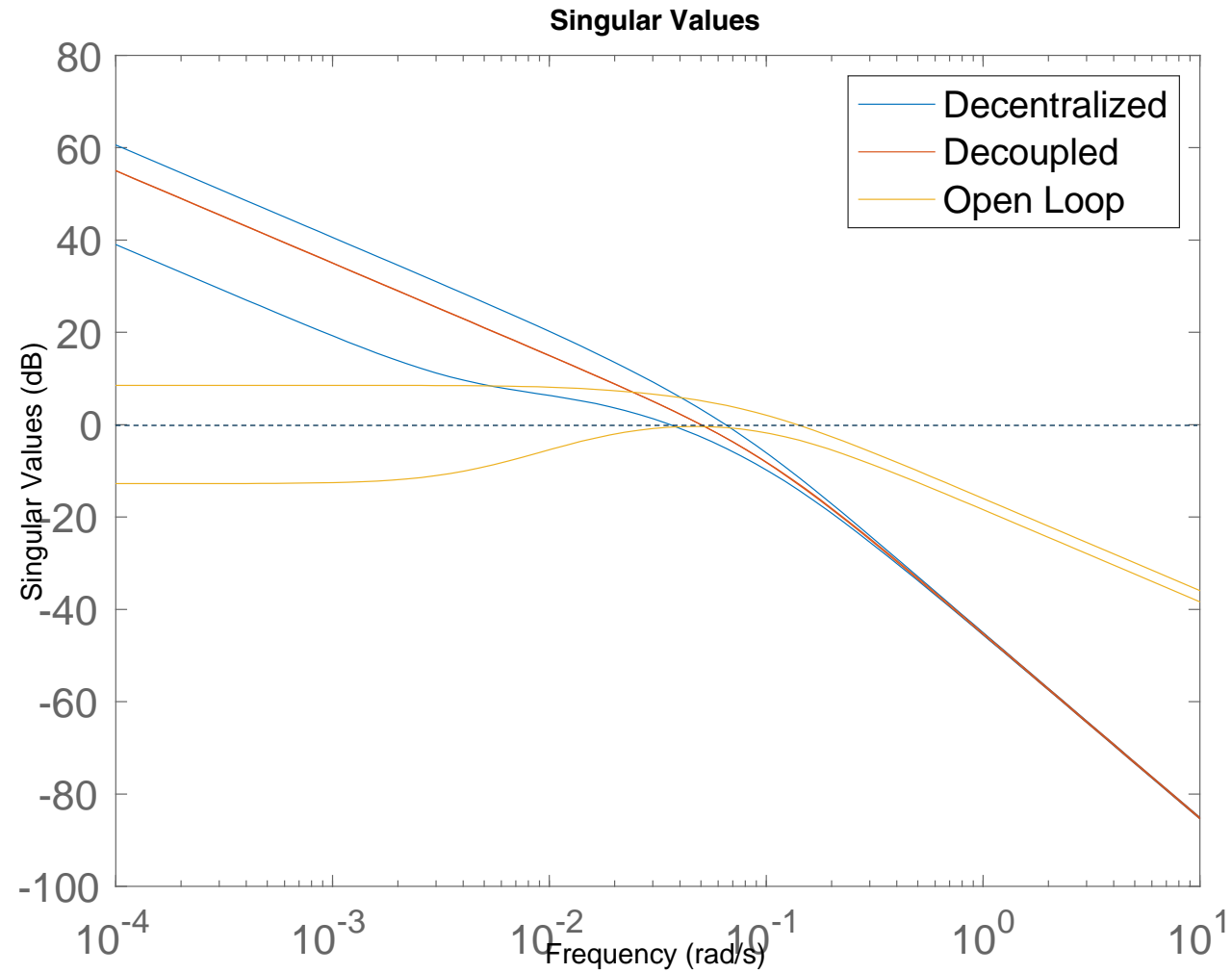
- Stability and performance guarantees even for strongly coupled systems



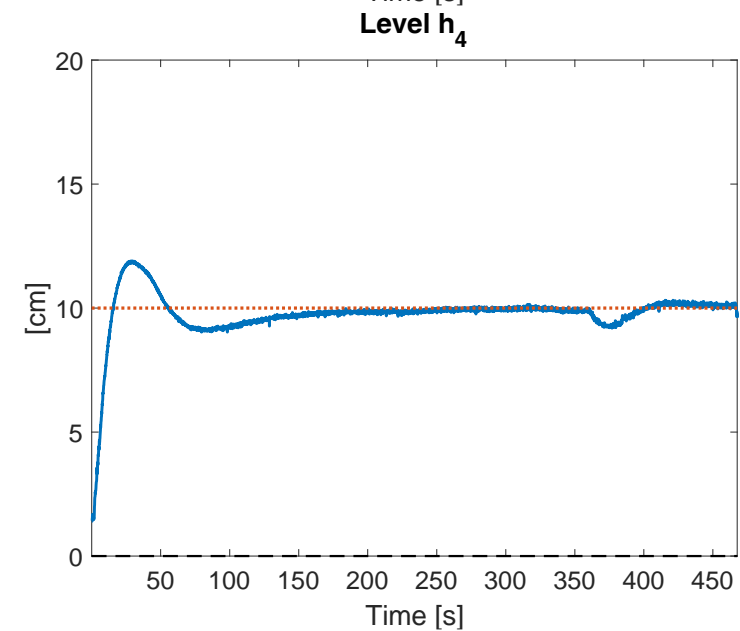
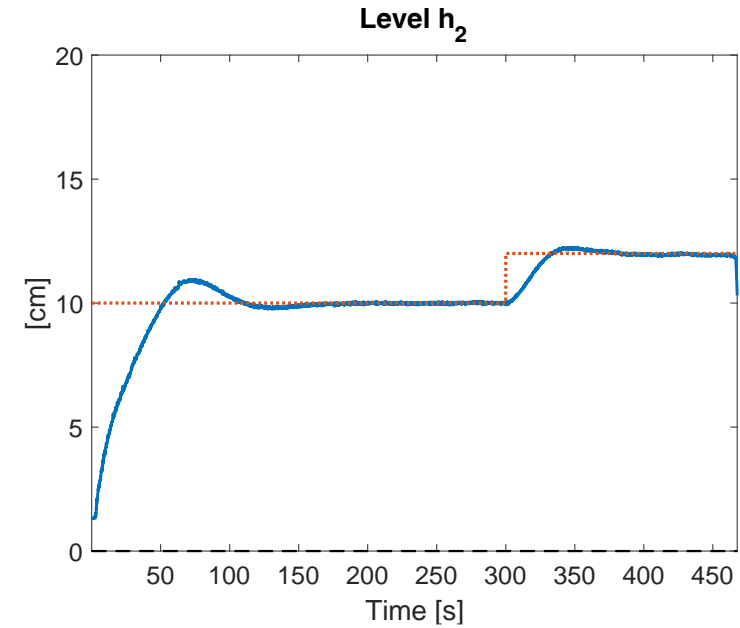
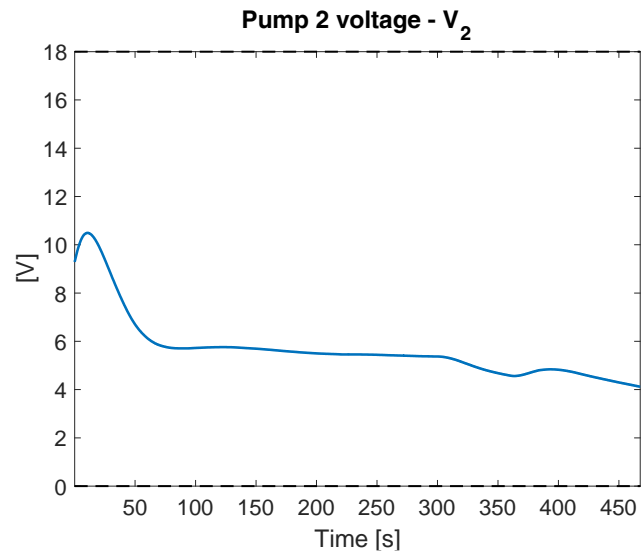
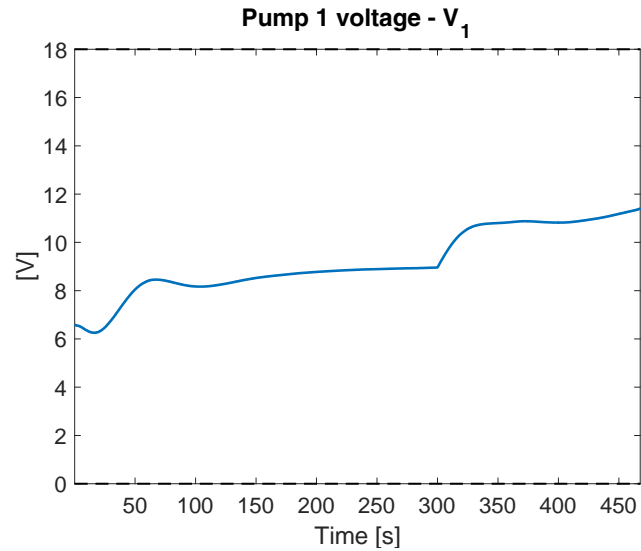
- Slightly harder design, anti-windup not trivial
- Model-sensitive: inaccurate models could lead to worse performances than decentralized PIs



# Comparison of the singular values



# Validation on the real apparatus



# Instructions for the lab experiments

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1. **Make sure your group is selected** (see WeBeep) TODO
2. **Fill your availabilities:** <https://doodle.com/meeting/participate/id/b6z6Oy9b>



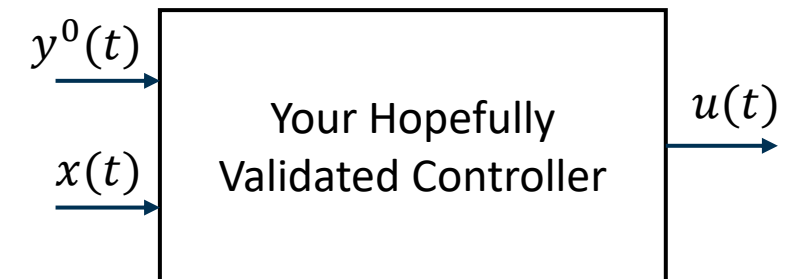
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3. I'll communicate the schedules on next Wednesday

4. Prepare:

- A .mat file with all and only the necessary parameters (gains, variables, equilibria, ecc)
- A Simulink scheme containing a subsystem having
  - $y^0(t)$  and  $x(t)/y(t)$  as inputs
  - $u(t)$  as output
  - All the components must be discrete-time blocks having sampling time  $\tau_s = 0.01s$





**Thanks for your attention!**