Optimal Operation and Control of Thermal Energy Systems

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HighEFF

PhD Defence

Overview: Scope

- Optimal operation and control for steam cycles – plantwide perspective

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I Optimal operation and control for steam cycles – plantwide perspective

II Input transformations for linearization, decoupling and feedforward disturbance rejection

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Industry nonlinear static model based calculation block, but little theory

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Academia: heavy mathematical treatment of linearizing nonlinear dynamic systems, but few applications

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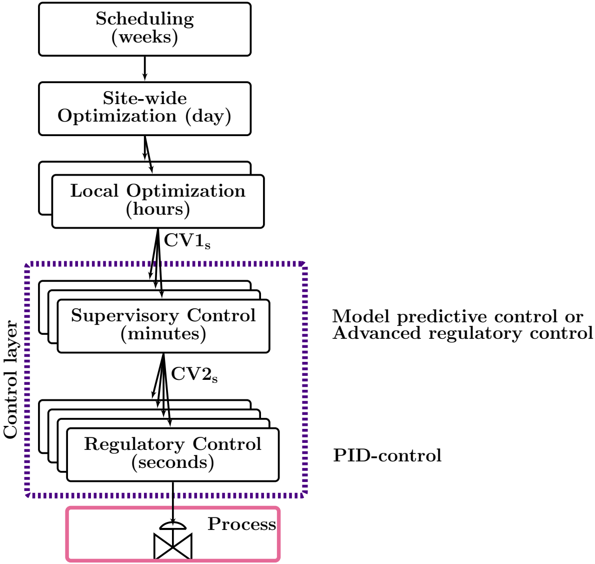
II. Input transformations for linearization, decoupling and feedforward disturbance rejection

Industry	nonlinear static model based calculation block, but little theory
Academia	heavy mathematical treatment of linearizing nonlinear dynamic systems, but few applications

III. Handling constraints on manipulated used for inventory control to balance supply and demand

1. Overview: operation and control



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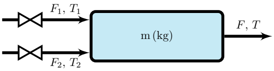

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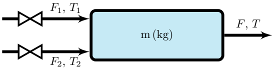

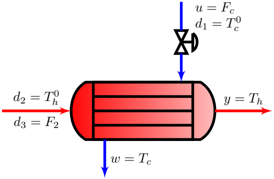

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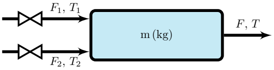

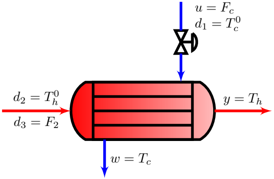

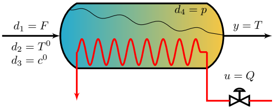

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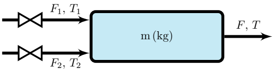

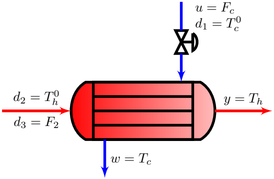

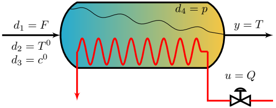

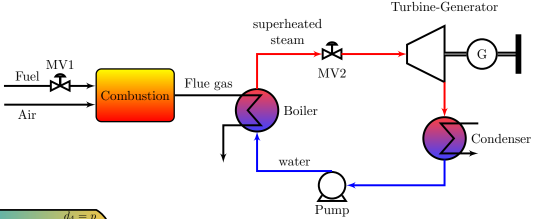

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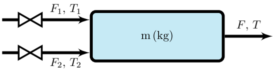

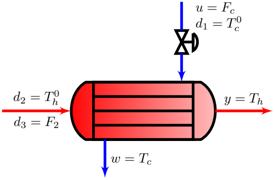

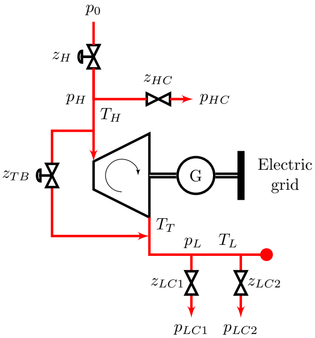

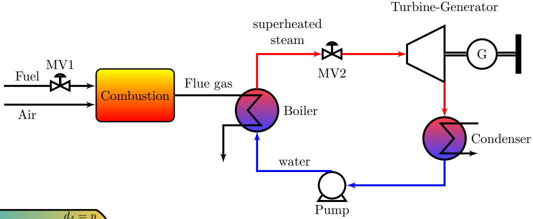

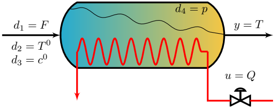

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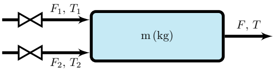
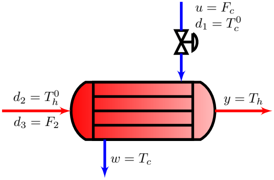
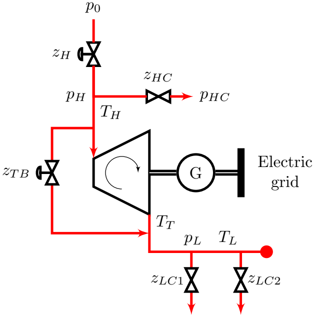
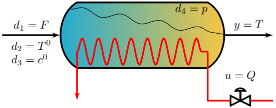
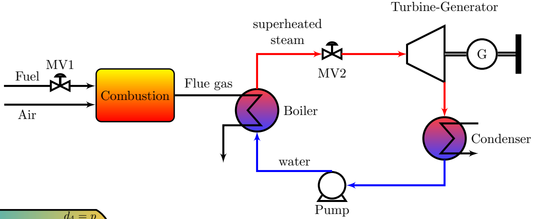
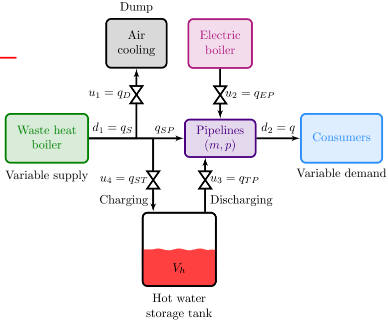




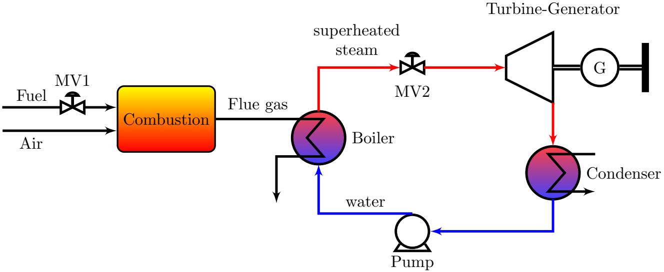








2. Optimal operation and control of steam cycles



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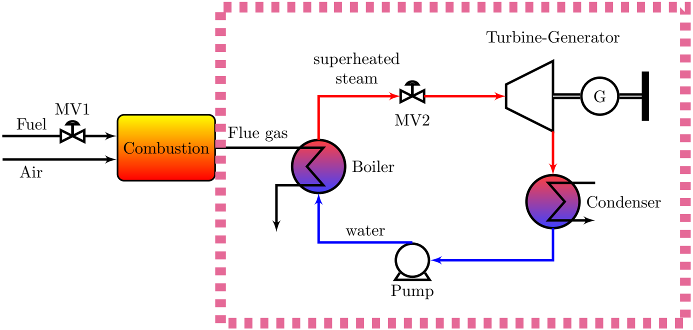

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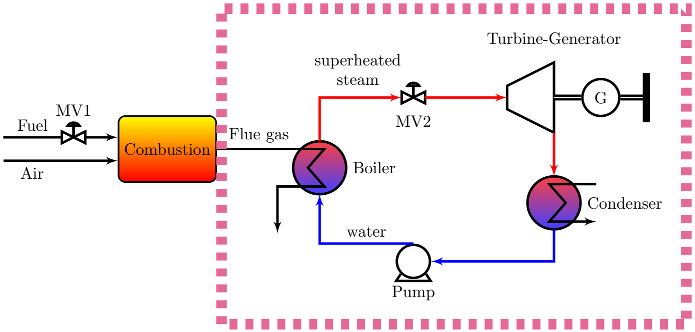
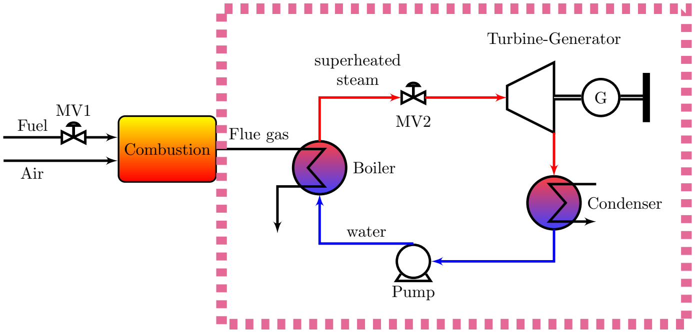


I. Identify operational objectives
(steady-state)

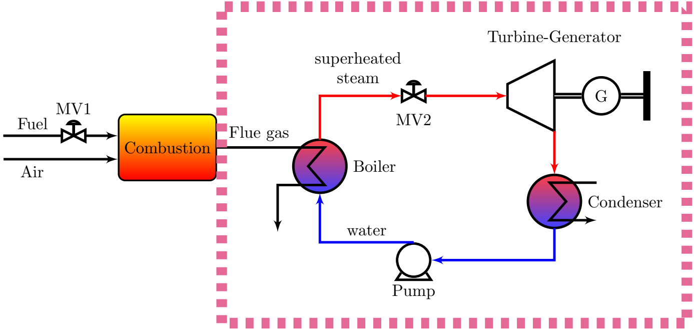
2. Optimal operation and control of steam cycles



I. Identify operational objectives (steady-state)

II. Analyze performance of different control strategies (dynamic)

2. Optimal operation and control of steam cycles



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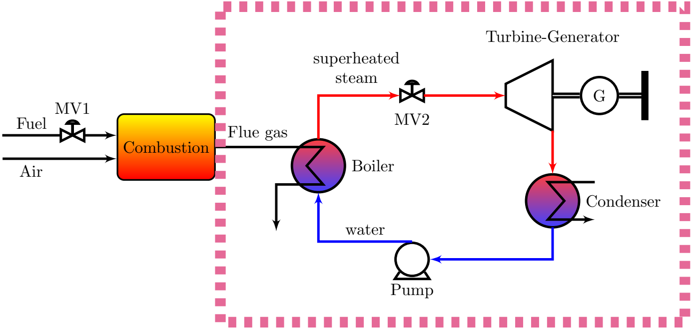
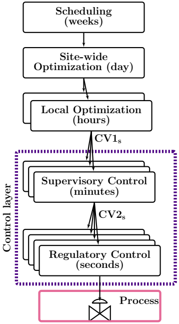
Framework: plantwide control

2. Optimal operation and control of steam cycles





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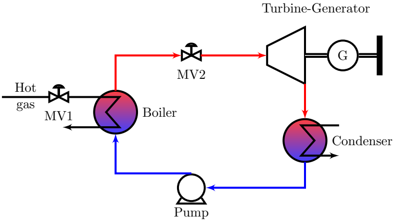

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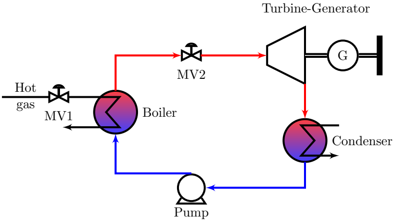
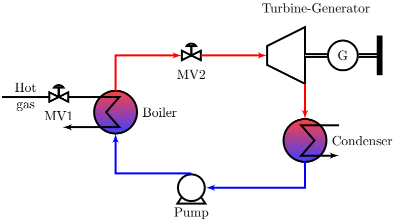


Control objectives:

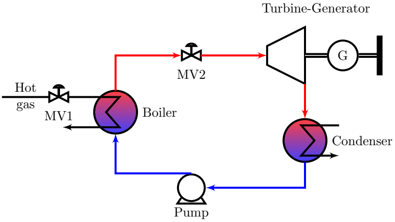
2. Optimal operation and control of steam cycles



Control objectives:

- Long time scale:
  - achieve optimal economic operation

2. Optimal operation and control of steam cycles

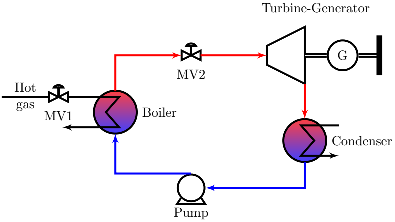


Control objectives:

I Long time scale:
- achieve optimal economic operation

II Short time scale:
- grid frequency regulation
- stabilize the plant
- reject local disturbances

2. Optimal operation and control of steam cycles



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Operational objectives:

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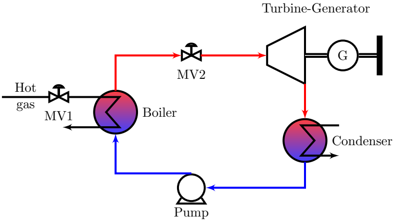

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Operational objectives:

I Produce energy:
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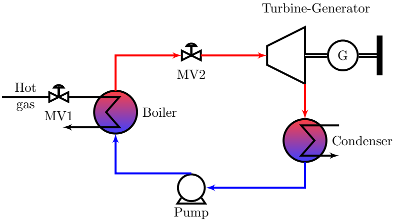
- steam
- electric power and steam

2. Optimal operation and control of steam cycles



Control objectives:

I Long time scale:
- achieve optimal economic operation

II Short time scale:
- grid frequency regulation
- stabilize the plant
- reject local disturbances

Operational objectives:

I Produce energy:
- electric power
- steam
- electric power and steam

II Process a given amount of by-product:
- waste gases
- biomass residues

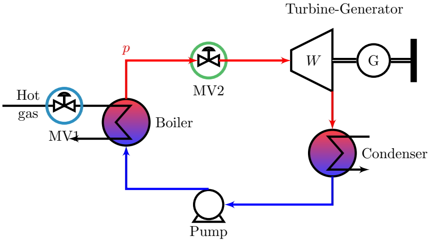
2. Optimal operation and control of steam cycles: steady-state analysis

Degrees of freedom

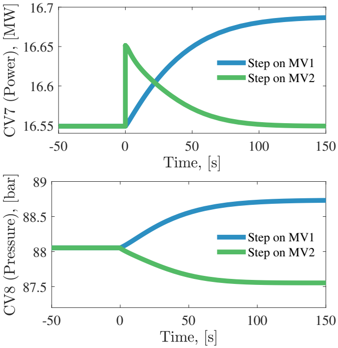
→ 2 after stabilizing the process and controlling the active constraints

MV1 Hot gas flow rate

MV2 Steam turbine valve



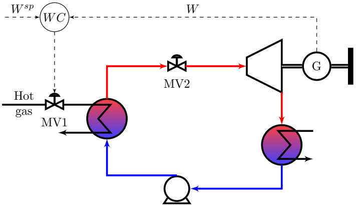
Steps on MV1 and MV2



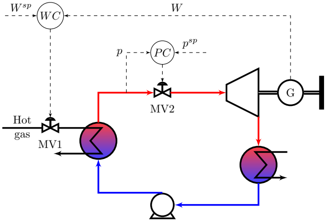
2. Optimal operation and control of steam cycles: dynamic analysis

Operation modes – industrial standards

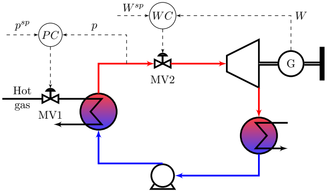
Floating pressure



Boiler Driven



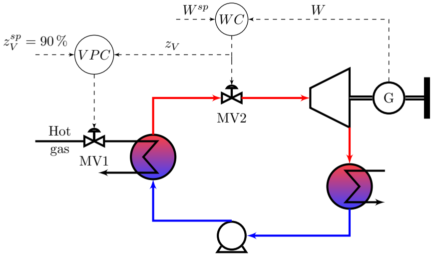
Turbine driven



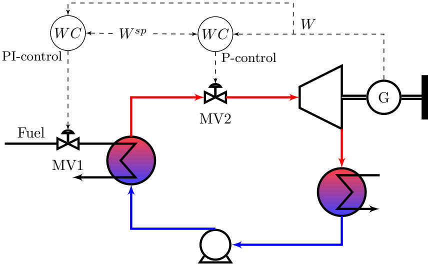
2. Optimal operation and control of steam cycles: dynamic analysis

Operation modes – parallel control

Valve position control

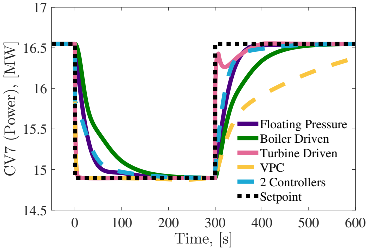


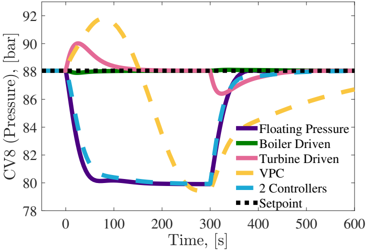
2 controllers: P and PI



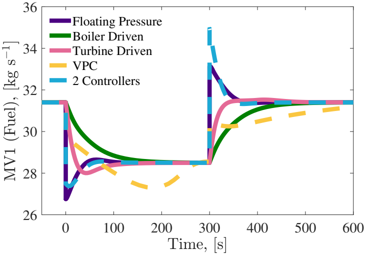
2. Optimal operation and control of steam cycles: simulation results

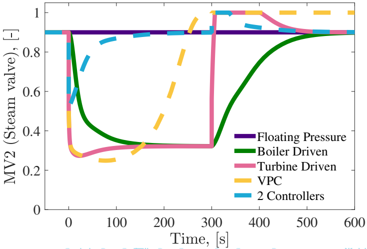
CVs

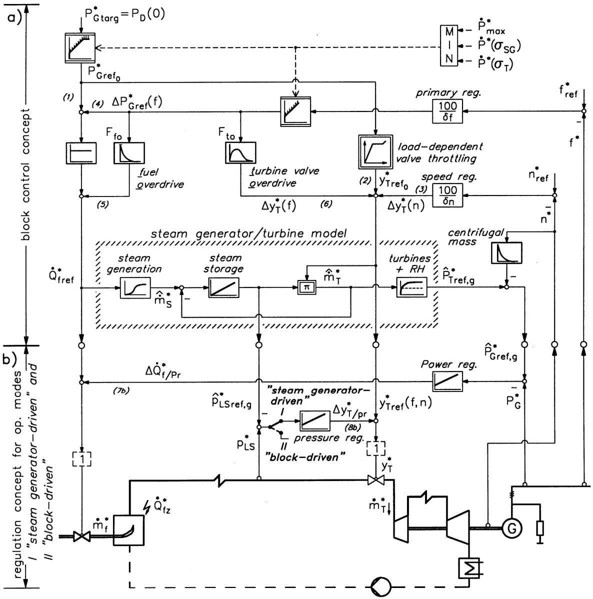




MVs

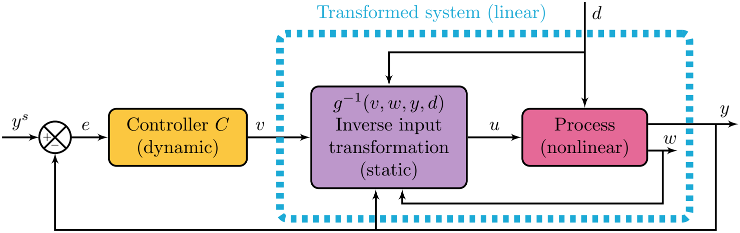





a)
block control concept
b)
regulation concept for op. modes
I "steam generator–driven" and
II "block–driven"
primary reg.
load–dependent valve throttling
speed reg.
fuel overdrive
turbine valve overdrive
steam generator/turbine model
steam generation
steam storage
turbines + RH
centrifugal mass
Power reg.
"steam generator–driven"
pressure reg.
"block–driven"
M
I
N

3.Input transformations for linearization, decoupling and feedforward disturbance rejection

The main idea



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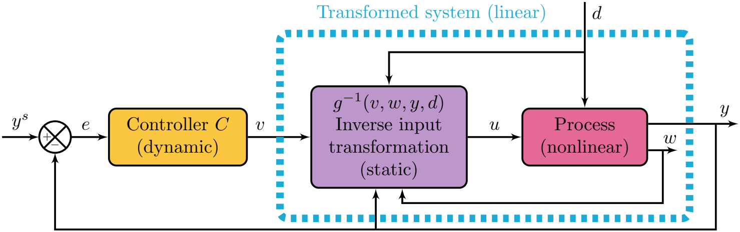


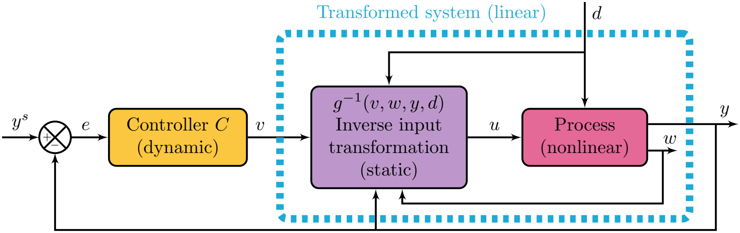
What?

Why?

How?

3.Input transformations for linearization, decoupling and feedforward disturbance rejection

The main idea



What? Powerful and simple approach for control of nonlinear systems to achieve decoupling, linear response and disturbance rejection.

Why?

How?

3.Input transformations for linearization, decoupling and feedforward disturbance rejection

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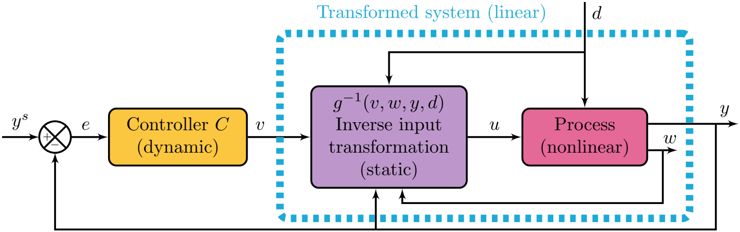


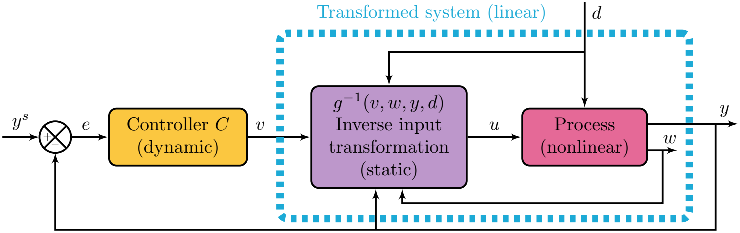
What? Powerful and simple approach for control of nonlinear systems to achieve decoupling, linear response and disturbance rejection.

Why? Existing theories (e.g. feedback linearization) are (seemingly) very complex and not widely used in industrial settings.

How?

3.Input transformations for linearization, decoupling and feedforward disturbance rejection

The main idea



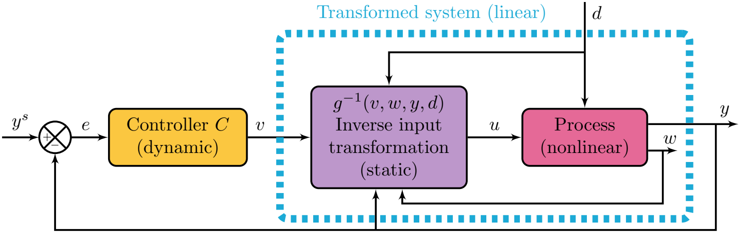
What? Powerful and simple approach for control of nonlinear systems to achieve decoupling, linear response and disturbance rejection.

Why? Existing theories (e.g. feedback linearization) are (seemingly) very complex and not widely used in industrial settings.

How? Simple manipulated variable (MV) transformations derived from nonlinear model equations

3.Input transformations for linearization, decoupling and feedforward disturbance rejection

The main idea



Example: static process

Model: $y = u - d$

Transformed input: $v = u - d$

$\Rightarrow$ Transformed system: $y = v$

Find u: $u = v + d$, given v and d.

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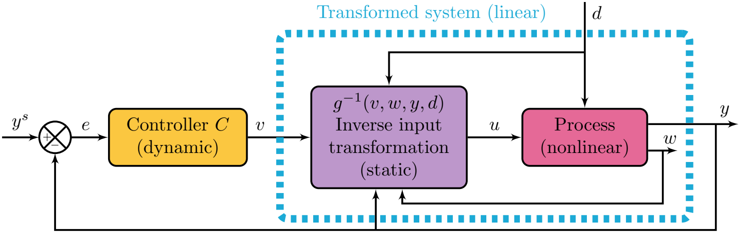
The main idea



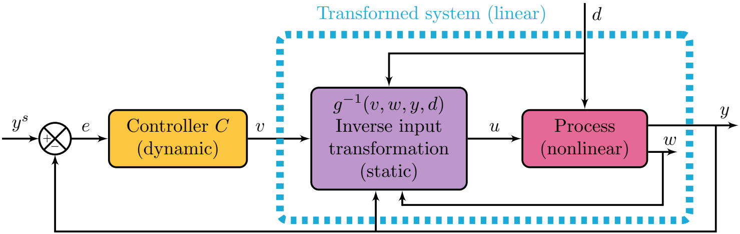
Other examples:

$$v = u + d \qquad v = \frac{u}{d} \qquad v = \frac{u_1}{u_2}$$

$$v = u_1 - u_2$$

$$v = w$$

3. Input transformation



$y \in \mathbb{R}^{n_y}$ outputs

$w \in \mathbb{R}^{n_w}$ additional measurements

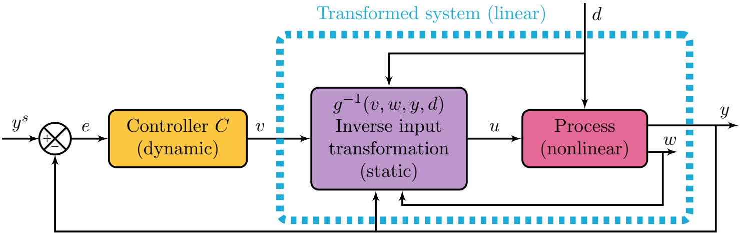
$u \in \mathbb{R}^{n_u}$ original inputs

$y^s \in \mathbb{R}^{n_y}$ setpoint

$d \in \mathbb{R}^{n_d}$ disturbances

$v \in \mathbb{R}^{n_u}$ transformed inputs

3. Input transformation



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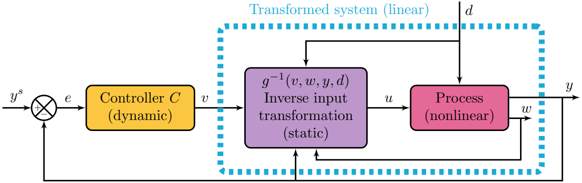
Assumptions

- *as many* outputs as inputs ($n_y = n_u$)
- disturbances (d) can be measured
- some variables (w) can be measured (e.g. flows, or additional states)

3. Derivation of transformed inputs



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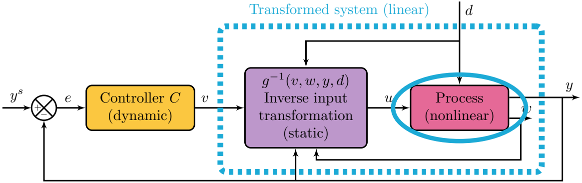


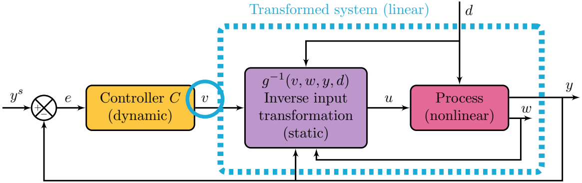
Dynamic

Static

Model: $\frac{dy}{dt} = f(y, u, d)$

$y = f_0(u, d)$

3. Derivation of transformed inputs



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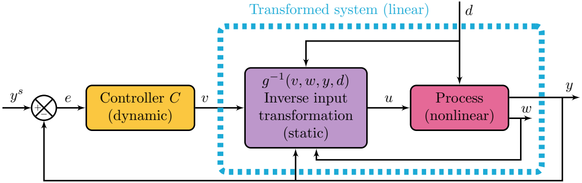

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A, B and B_0 are tuning parameters.

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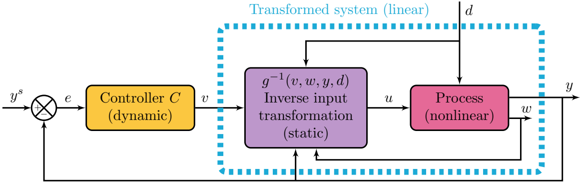

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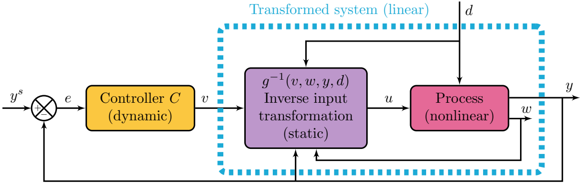

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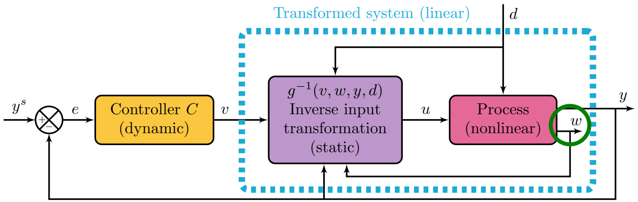
First-order (dynamic case), linear, decoupled system and with no effect from disturbances.

Use of extra measurements



Model: $\frac{dy}{dt} = f(y, u, w, d)$

Transformed input (v): $v_A = B_0^{-1}(f(y, u, w, d) - Ay$

Extra variables w that depend on u

- may replace measurements of disturbances
- may be used for unmodelled dynamics or uncertainties
- should be stable (i.e. no RHP-zeros).

Tuning parameters A and B

Transformed input (v): $v_A = B^{-1}\left(f(y,u,w,d) - Ay\right)$

How to select A? $\Rightarrow$ Design decision

1. $A = \mathrm{diag}\left(\frac{\partial f(y,u,w,d)}{\partial y}\Big|^{*}\right)$, i.e. diagonal elements of the Jacobian
   $\Rightarrow$ small positive feedback from y to v nominally

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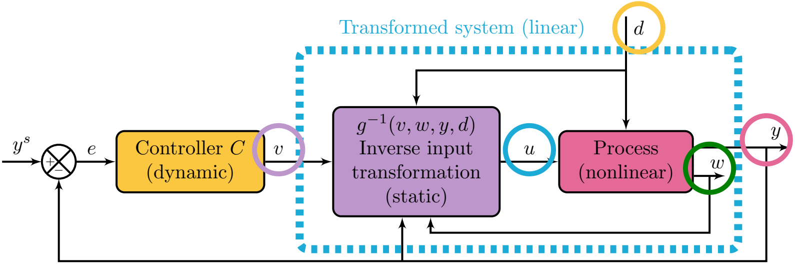
How to select B? $\Rightarrow$ Design decision

- $B = I$
- keep $k_{vy} = k_{uy} \Rightarrow B = \text{diag}(\tilde{B}) = \text{diag}(\frac{\partial f(y,u,w,d)}{\partial u})_{*}$
- $B = -A$

Implementation of transformed inputs

Solves $v = f(y, u, w, d) - Ay$ w.r.t u, given v, y, d, and in some cases w.
Nonlinear feedforward controller



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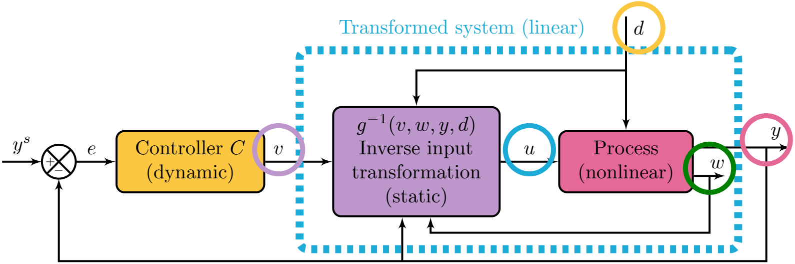
Nonlinear feedforward controller

Implementations

- exact model based inversion $\Rightarrow$ explicit solution $u = g^{-1} y, v, w, d$



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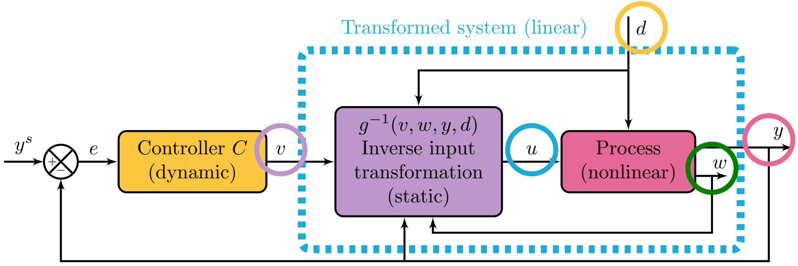
Implementations

- exact model based inversion $\Rightarrow$ explicit solution $u = g^{-1}y, v, w, d$
- feedback based using an I-controller (cascade).



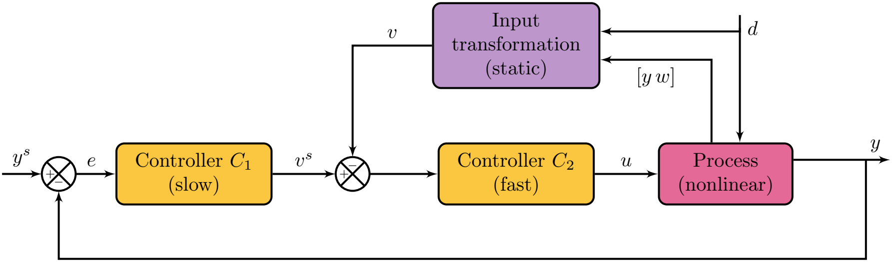
Feedback based implementation

Advantages

- safer implementation ⇒ does not invert the input transformation eq. to solve for u
- handles ⇒ RHP-zeros, measurement delays, plant-model mismatch
- more robust

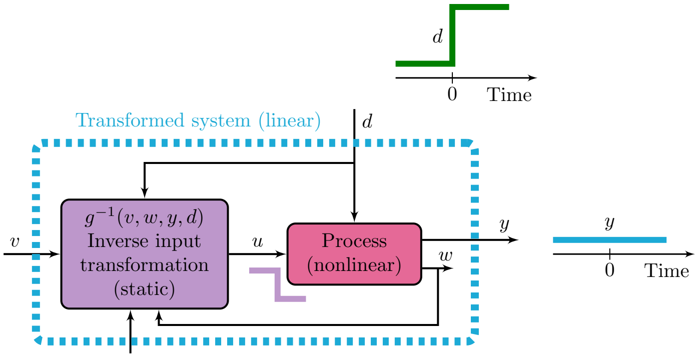
Drawback

- does not give perfect disturbance rejection



Linear controller

- perfect model and measurements ⇒ do not need the outer feedback loop because the transformation ⇒ nonlinear feedforward controller



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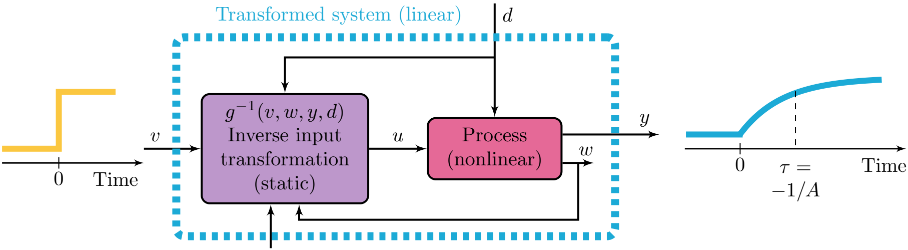
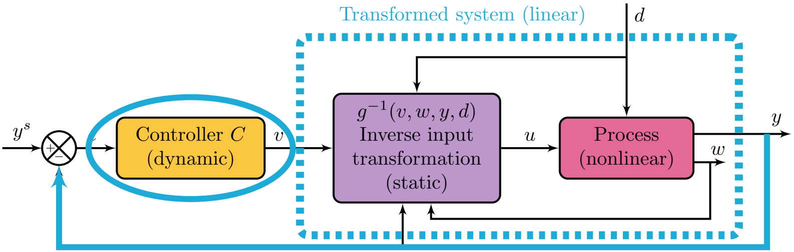
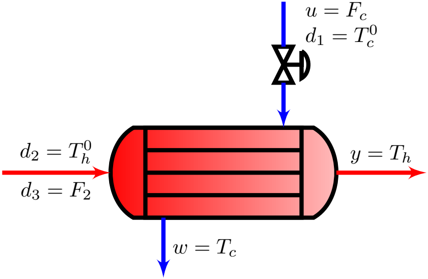


Linear controller

- perfect model and measurements ⇒ do not need the outer feedback loop because the transformation ⇒ nonlinear feedforward controller
- setpoint changes can be handled by directly changing v^s
- real plant ⇒ unmeasured disturbances and unmodelled dynamics ⇒ use decentralized SISO controllers for controlling y using v as inputs.



Example: control of heat exchanger hot outlet temperature



MVs (original inputs):

$$u = F_c \text{ [kg/s]}$$

CVs (outputs):

$$y = T_h \text{ [°C]}$$

DVs (disturbances):

$$d_1 = T_c^0 \text{ [°C]}$$
$$d_2 = T_h^0 \text{ [°C]}$$
$$d_3 = F_h \text{ [kg/s]}$$
$$d_4 = UA \text{ (unmeasured)}$$

w -variables:

$$w = T_c \text{ [°C]}$$

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Objective: find transformed input (v_0) $\Rightarrow$ disturbance rejection.

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$$y = T_h = \underbrace{(1 - \epsilon_h) T_h^{in} + \epsilon_h T_c^{in}}_{v_0}$$

with $\epsilon_h = \epsilon_h(u, d_1, d_2, d_3)$

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Static energy balance using $w-$ measurements (T_c)

$$y = T_h = \underbrace{T_h^0 + \frac{F_c c_{p_c}}{F_h c_{p_h}}(T_c^0 - T_c)}_{v_{0,w}}$$

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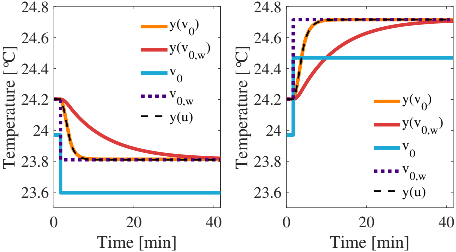
Transformed system: $y = v_0$ or $y = v_{0,w}$ Tuning parameter: $B_0 = I$
Actual process is dynamic, but we use an input transformation derived from a static model

Example: control of heat exchanger hot outlet temperature. Open loop responses

Feedback-based implementation without the outer controller

Step response from v to y



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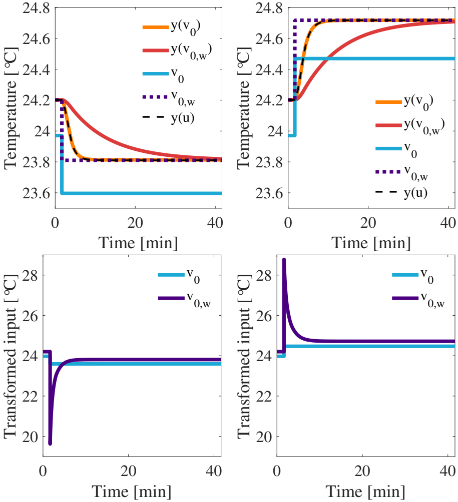
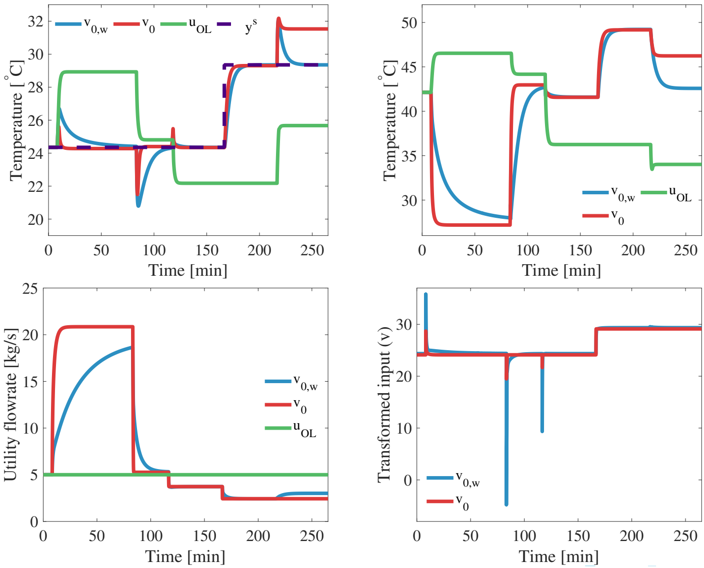
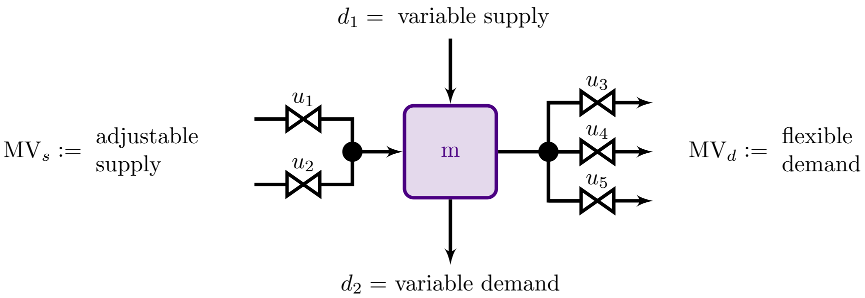
Step response from u to v



Example: control of heat exchanger hot outlet temperature. Closed loop responses



Handling constraints on manipulated variables (MVs) used to balance supply and demand



Inventory *m*: measure of demand-supply balance

Control objective: design decentralized control structure that sets the values of MV_s and MV_d to control *m*

Use MV_s when $d_2 > d_1$ Use MV_d when $d_1 > d_2$

Handling constraints on (MVs) used to balance supply and demand

How to handle MV saturation?

$MV_s = MV_s^{max} \Rightarrow$ use MV_d

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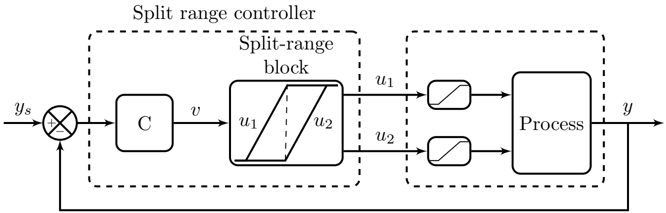
- split-range control



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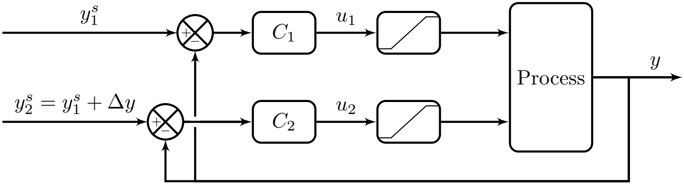
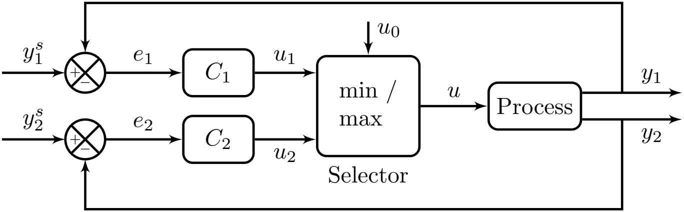


Handling constraints on (MVs) used to balance supply and demand

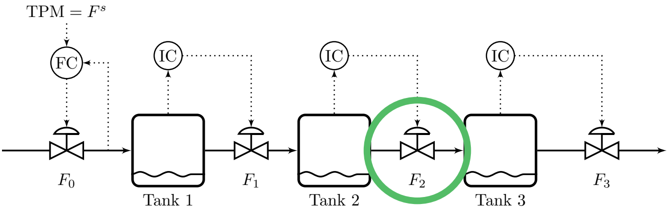
How to handle MV saturation?

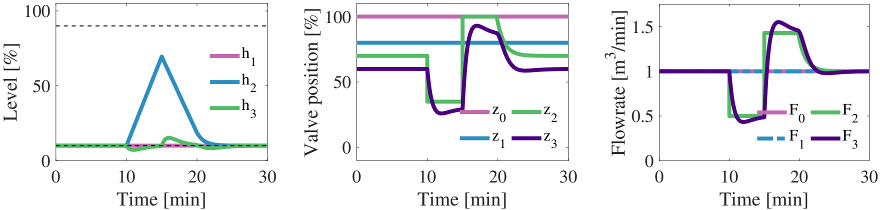
$MV_s = MV_s^{max} \Rightarrow$ use MV_d Implementation:

- split-range control
- controllers with different setpoints
- selectors



Bidirectional inventory control with optimal use of storage





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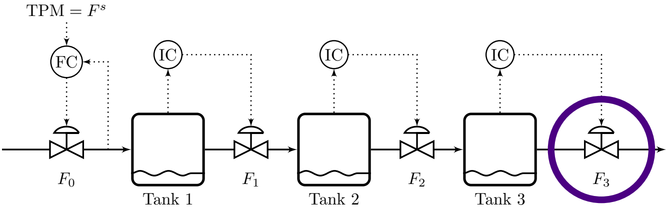

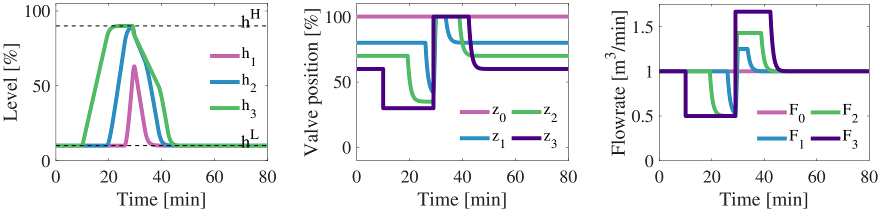

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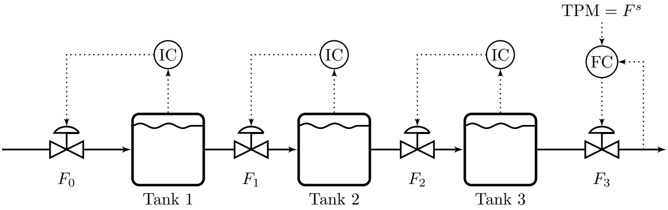

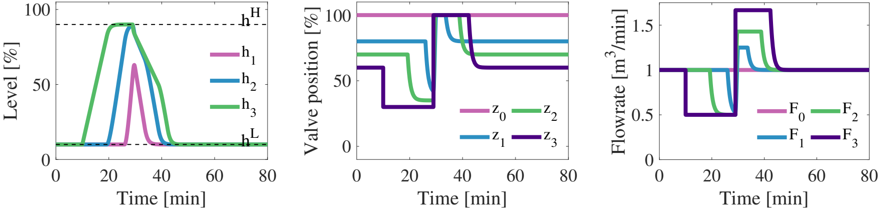

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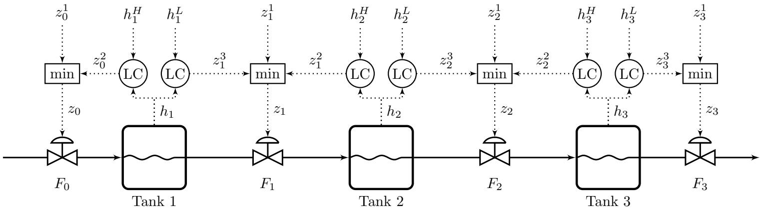

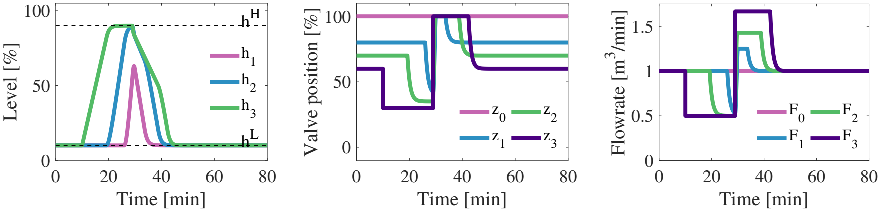

Conclusion

Optimal operation and control of heat to power cycles

- steady-state and dynamic analysis

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- CV-CV switching: selectors
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