Optimal operation strategies for dynamic processes under uncertainty

Public PhD Defence

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Main goal

Find implementation strategies for the optimal operation of processes during transients

✓ Focus on cases where *dynamic behavior* is important in terms of economic performance

We are not only interested in finding (numerical) optimal solutions

→ but specially in the practical implementation strategies using feedback control

→ Challenge: disturbances and uncertainties!!

Main question

How to achieve acceptable performance in the face of unknown disturbances and uncertainties?

By *acceptable* we mean:

- Near-optimal economic cost
- stable operation
- minimum constraint violations

Our focus is to find **simple** policies to achieve this goal

Presentation outline

Introduction

Near-optimal operation of uncertain batch systems

- ✓ Chapters 7 and 8

Optimal operation of energy storage systems

- ✓ Chapters 2, 3 and 4

Optimal operation of dynamic systems at their stability limit: anti-slug control system for oil production optimization

- ✓ Chapters 5 and 6

Concluding remarks

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Optimal operation of dynamic systems at their stability limit: Application to anti-slug control

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Null-space method for optimal operation of transient processes (Ch. 8)

We consider a dynamic optimization problem in the form

$$\min_u J(x(t_f), d)$$

subject to:

$$\dot{x} = f(x, u, d)$$
$$y = g(x)$$
$$p(x, u) \leq 0$$

$x \in \mathcal{R}^{n_x}$:=differential states
$u \in \mathcal{R}^{n_u}$:=control inputs
$y \in \mathcal{R}^{n_y}$:=measurements
$d \in \mathcal{R}^{n_d}$:=uncertain parameters

Nominal solution:
- d_0, u_0, x_0, y_0

Main goal

Achieve near-optimal economic performance despite uncertainty/disturbances without the need for re-optimization*

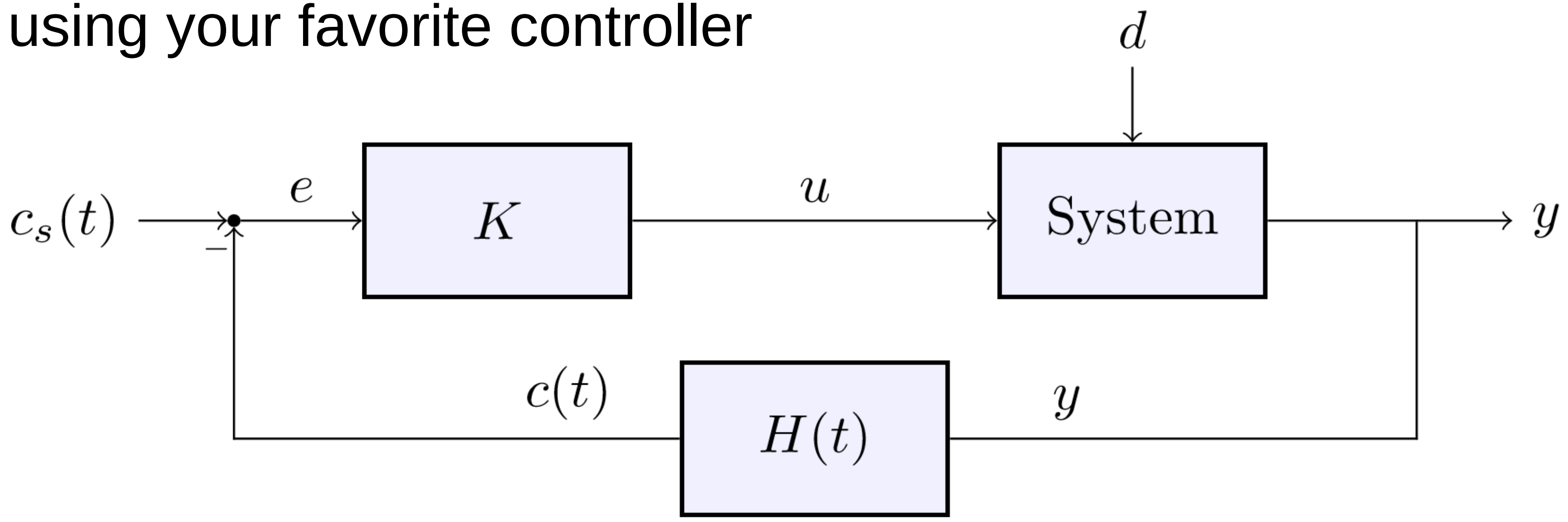
(*) Solving dynamic optimization problems can be veeery time-consuming

Self-optimizing control

Step 1) Find a function of measurements $c \coloneqq h(y)$ whose optimal is invariant to changes in d

$$c_{opt}(t, d_0) = c_{opt}(t, d_1) = \cdots$$

Step 2) Control c(t) to its reference $c_s = c_{opt}(t, d_0)$ using your favorite controller



Step 3) Be optimal without re-optimizing despite uncertainties in d

Proposed method

Optimal sensitivities

$$F(t) = \frac{\partial y_{opt}(t,d)}{\partial d}$$

Control a linear combination

$$c(t) = H(t)y(t), \qquad (H \text{ is a } n_u \times n_y \text{ matrix })$$

This is the (local) optimal choice if

$$H(t)F(t) = 0$$

$H(t)$ must lie in the left nullspace of $F(t)^*$ → Thus the name, 'Nullspace method'

(*) Nullspace method for steady-state problems originally published in Alstad (2007).

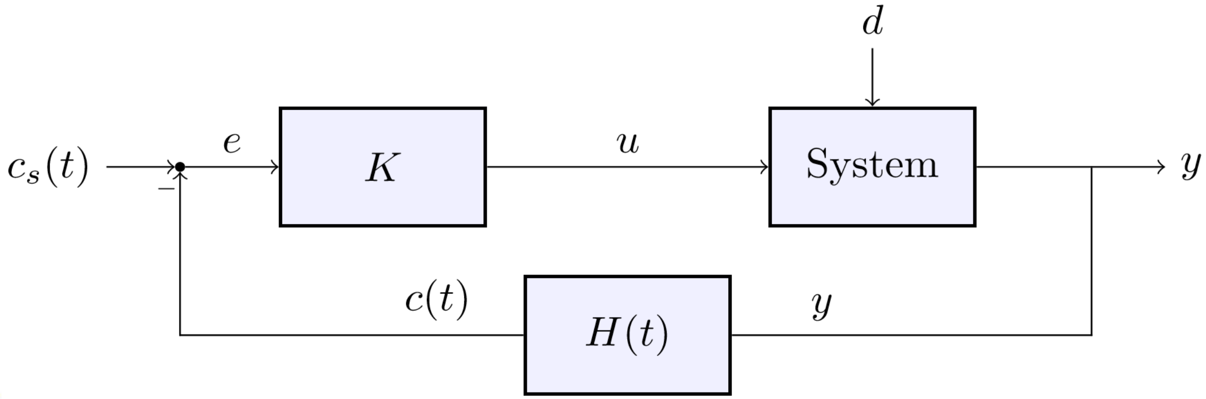
Outline of the procedure

Offline steps

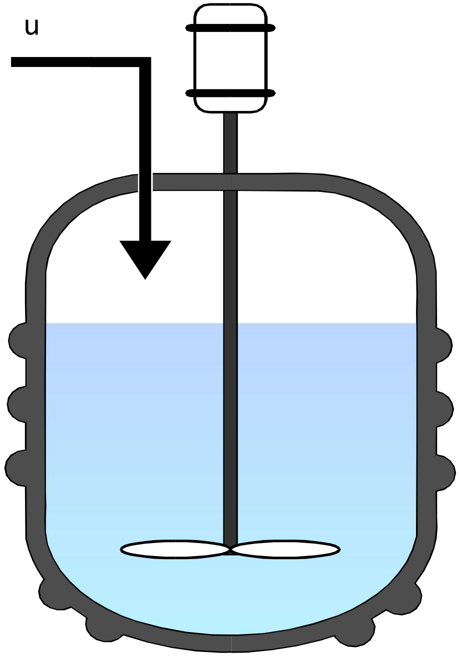
- Define main uncertainties d
- Compute nominal solution d_0, u_0, x_0, y_0
- Compute sensitivities $F(t)$ and the matrix $H(t)$
- Compute the reference trajectory $c_s(t) = H(t)y_0(t)$

Online step

- Track references c_s using feedback control
- By doing so, we are near-optimal without the need for re-optimization, despite *d*



Simulation example: fed-batch reactor



We have two chemical reactions happening

$$A + B \rightarrow C \quad \text{and} \quad B \rightarrow D$$

Subject to the following dynamics

$$\dot{c}_A = -k_1 c_A c_B - \frac{c_A u}{V}$$

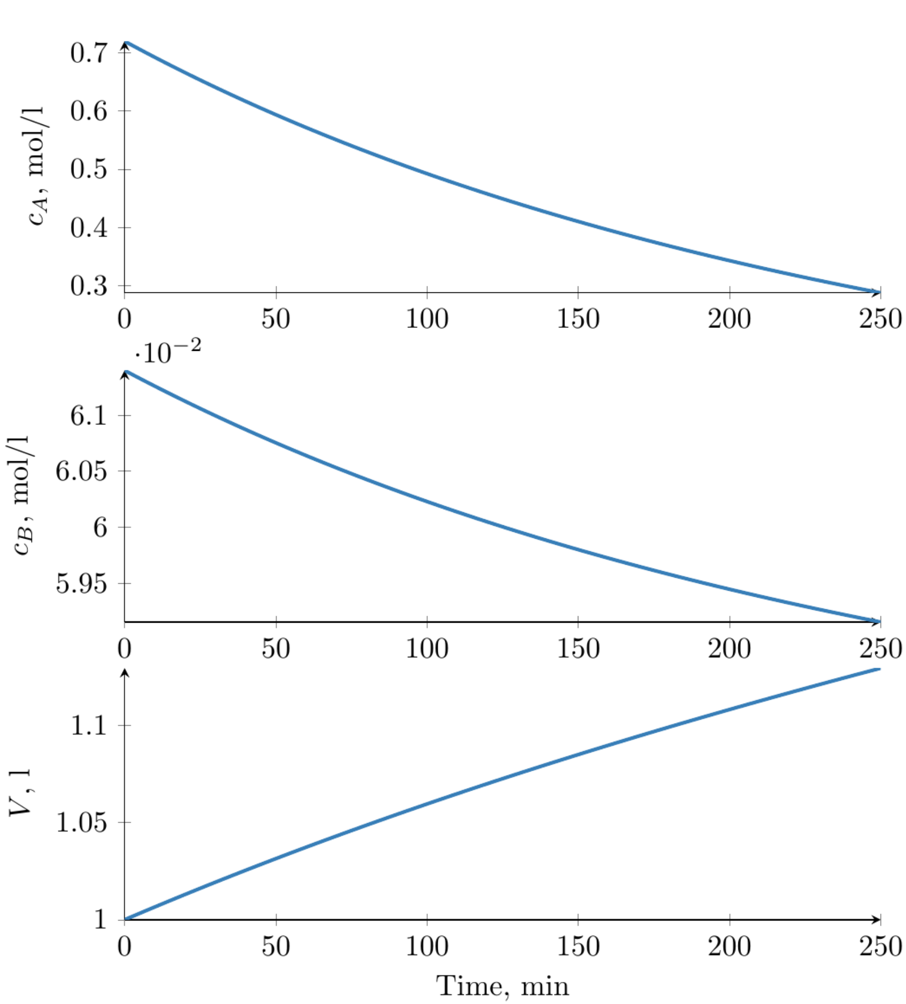
$$\dot{c}_B = -k_1 c_A c_B - 2k_2 c_B - \frac{(c_B - c_{B,in})u}{V}$$

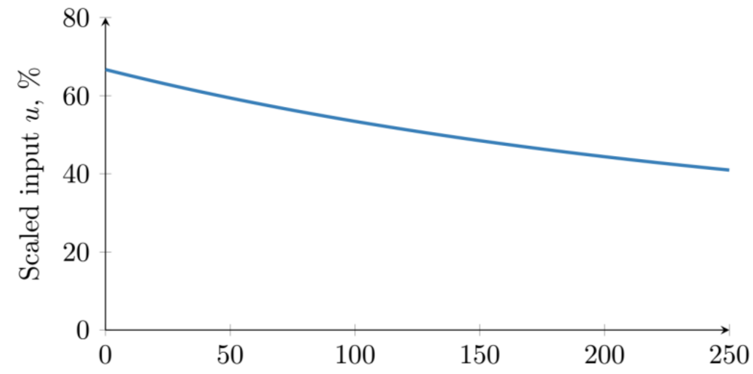
$$\dot{V} = u$$

We want to compute to maximize $C - D$

Main uncertainties (k_1 and k_2)

Nominal solution

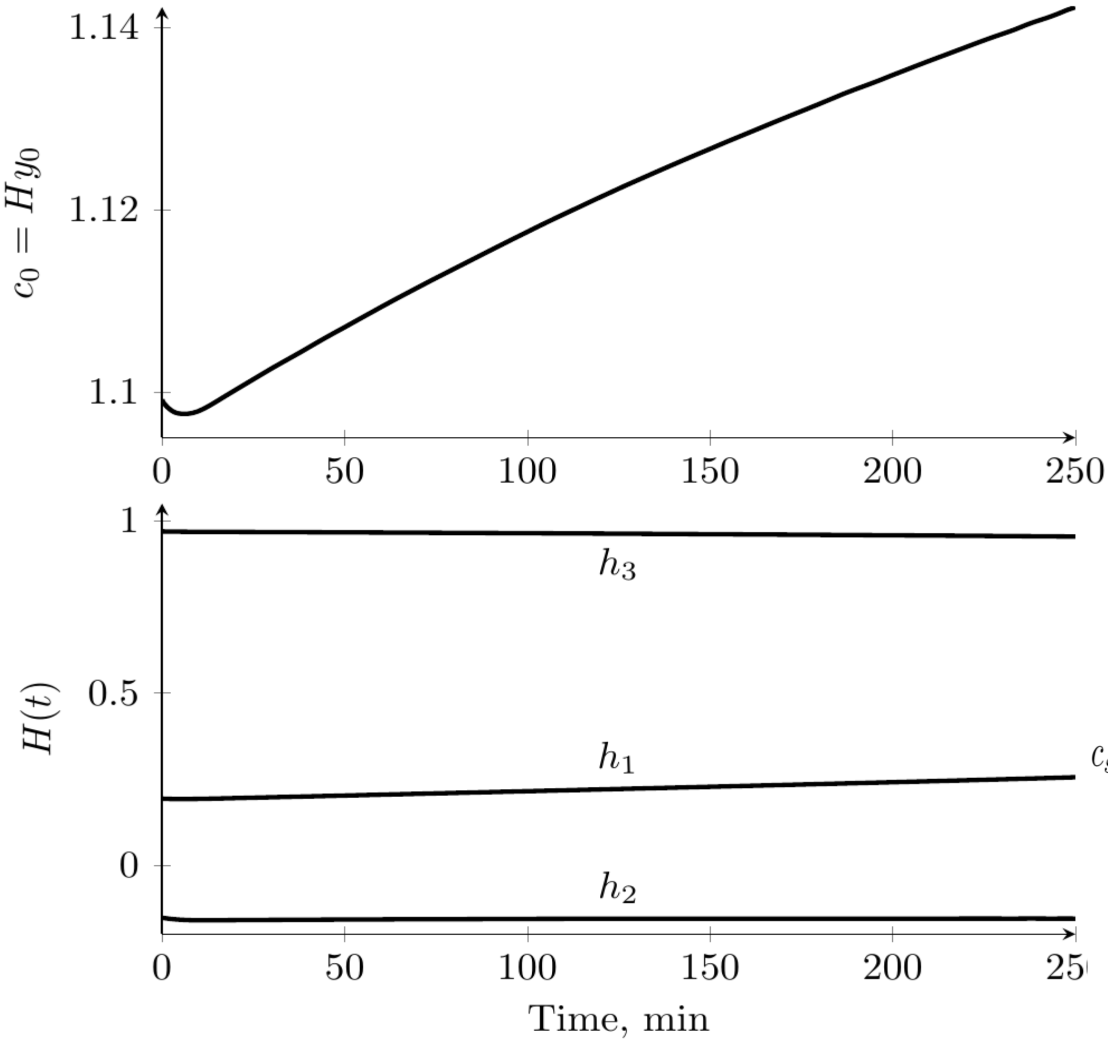




Next steps

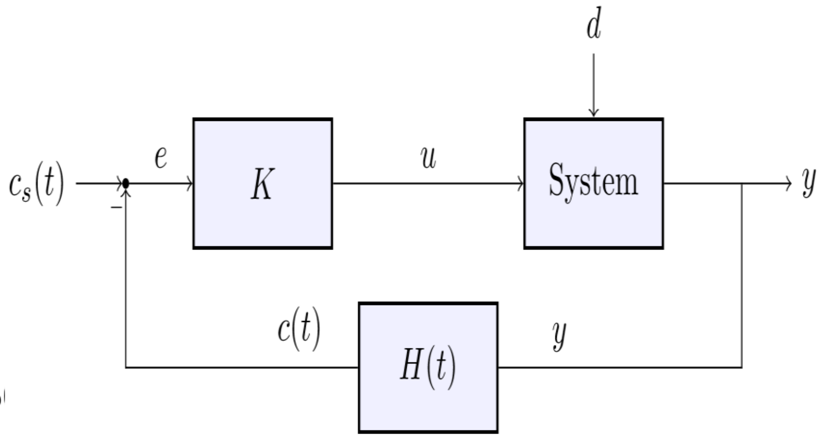
- Compute sensitivity matrix $F(t)$ and combination $H(t)$
- Obtain $c_s(t) = H(t)y_0(t)$

Example of invariant trajectory

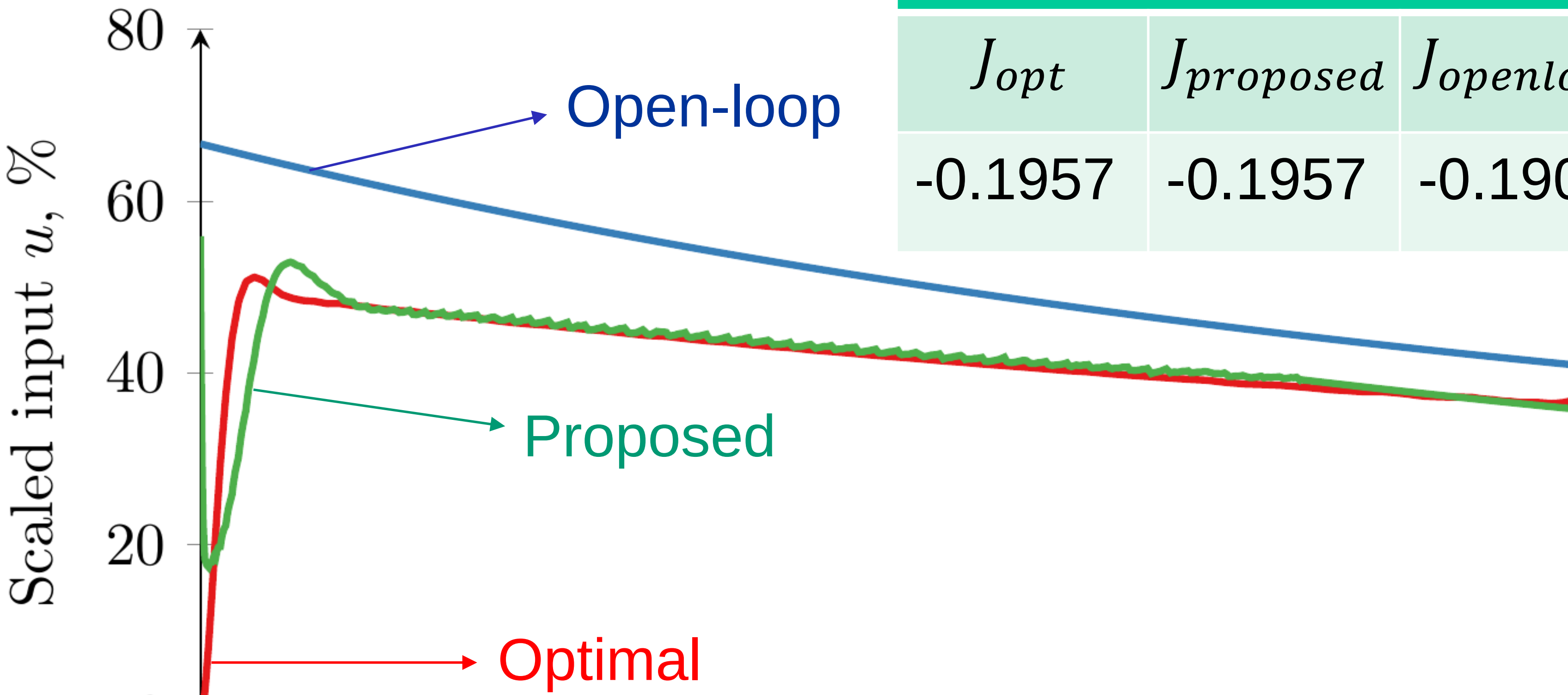


$$c = [h_1\ h_2\ h_3] \begin{bmatrix} c_A \\ c_B \\ V \end{bmatrix}$$

Control c using a PI controller



Results with 20% error in k_1 and k_2



Cost comparison

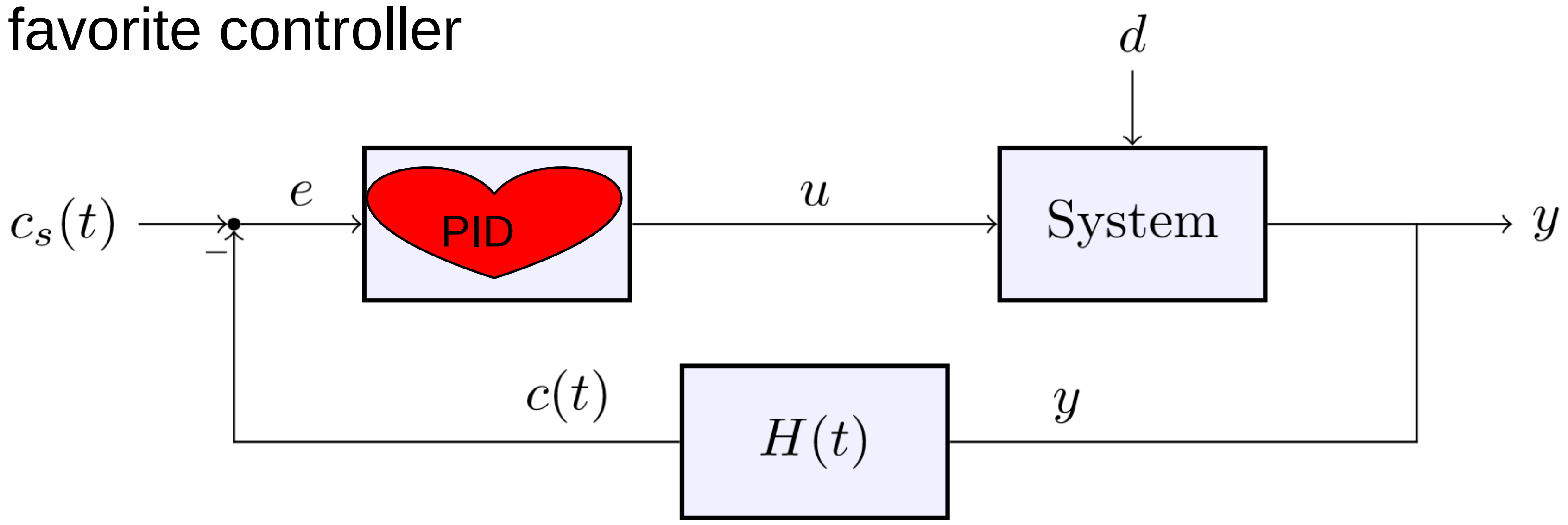
J_{opt}	$J_{proposed}$	$J_{openloop}$
-0.1957	-0.1957	-0.1904

Near-optimal operation without re-optimization despite disturbances

What you should remember

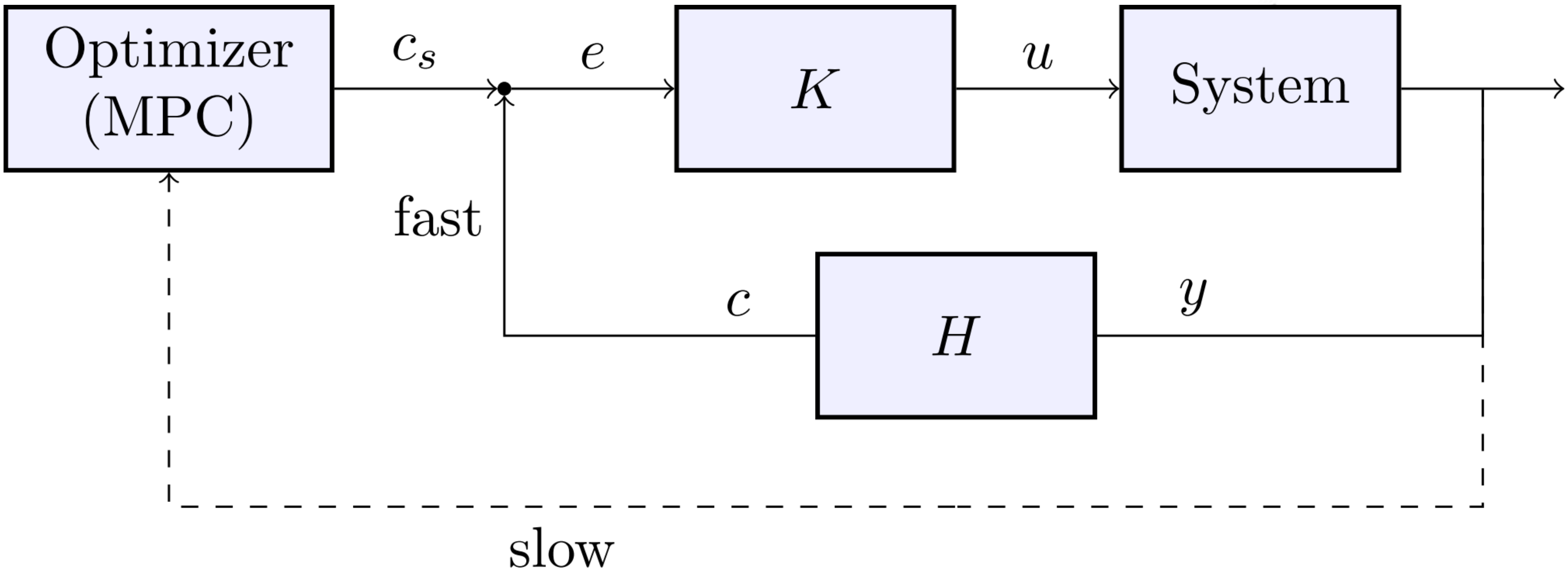
Step 1) Compute reference $c_s(t) := H(t)y_0(t)$ whose optimal is invariant due to disturbances. We showed how to compute $H(t)$.

Step 2) Control $c(t)$ to its reference $c_s = c_{opt}(t, d_0)$ using your favorite controller



Step 3) Be (almost) optimal without re-optimizing despite uncertainties in d

How could you best use the approach? Combine with EMPC



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Motivation

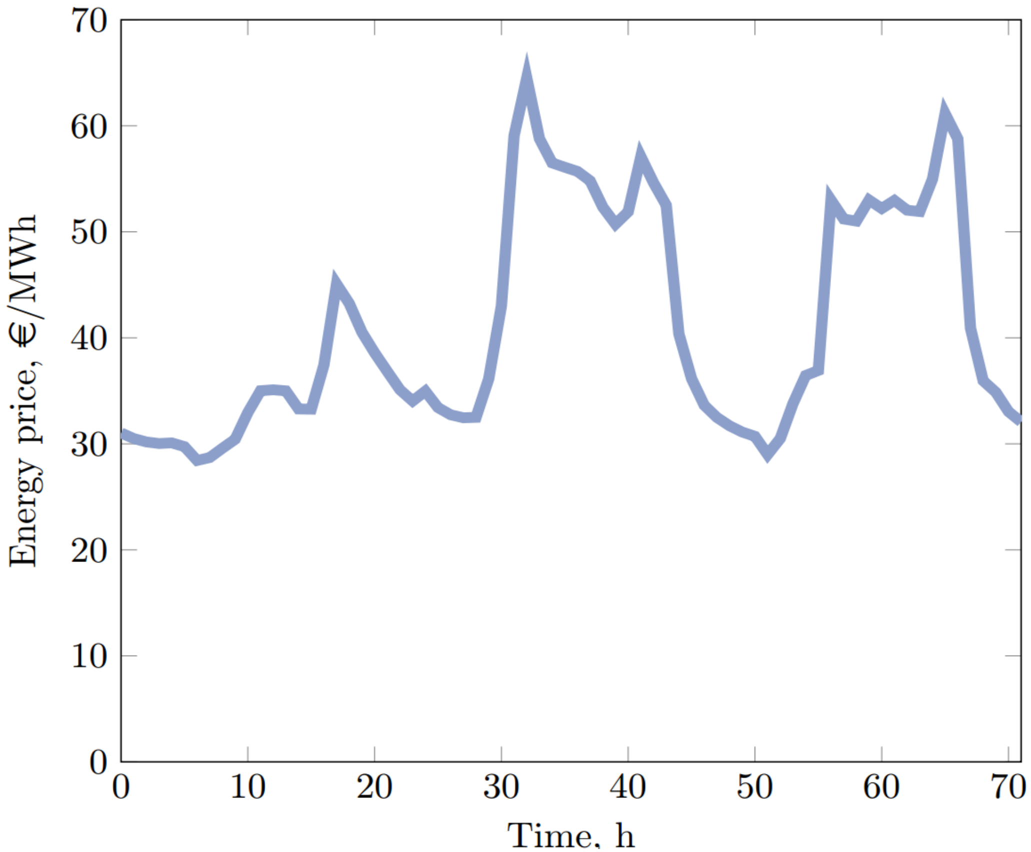
Increase of use of renewable energy

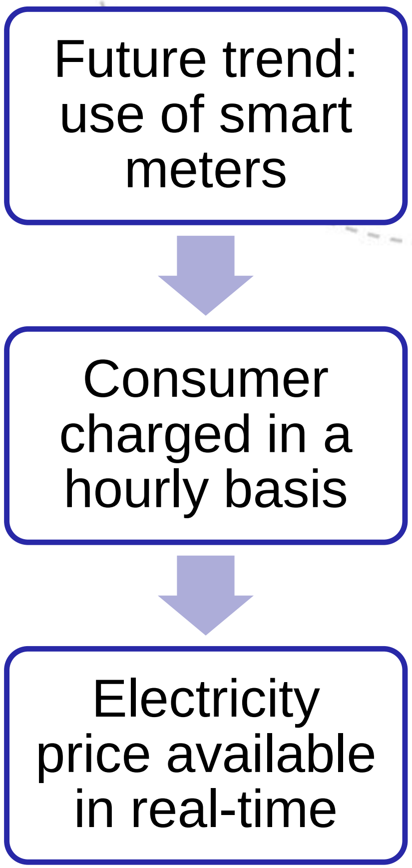
Strong dependence on weather conditions

Energy production must cover demand at all times

Influence demand by real-time pricing

Example of electricity price in Norway*





(*) http://www.nordpoolspot.com/

How can end-user take advantage of this scenario?

Key requirement: energy storage

- Allows us to move the consumption to more favorable periods → *flexible consumption*

Storage capacity is not enough

Users are unlikely to change their behavior → Need automatic control and optimization

Main requirements:

- Near-optimal results→ good savings without sacrifices
- Low (computational) cost for widespread use

Some examples of energy storage

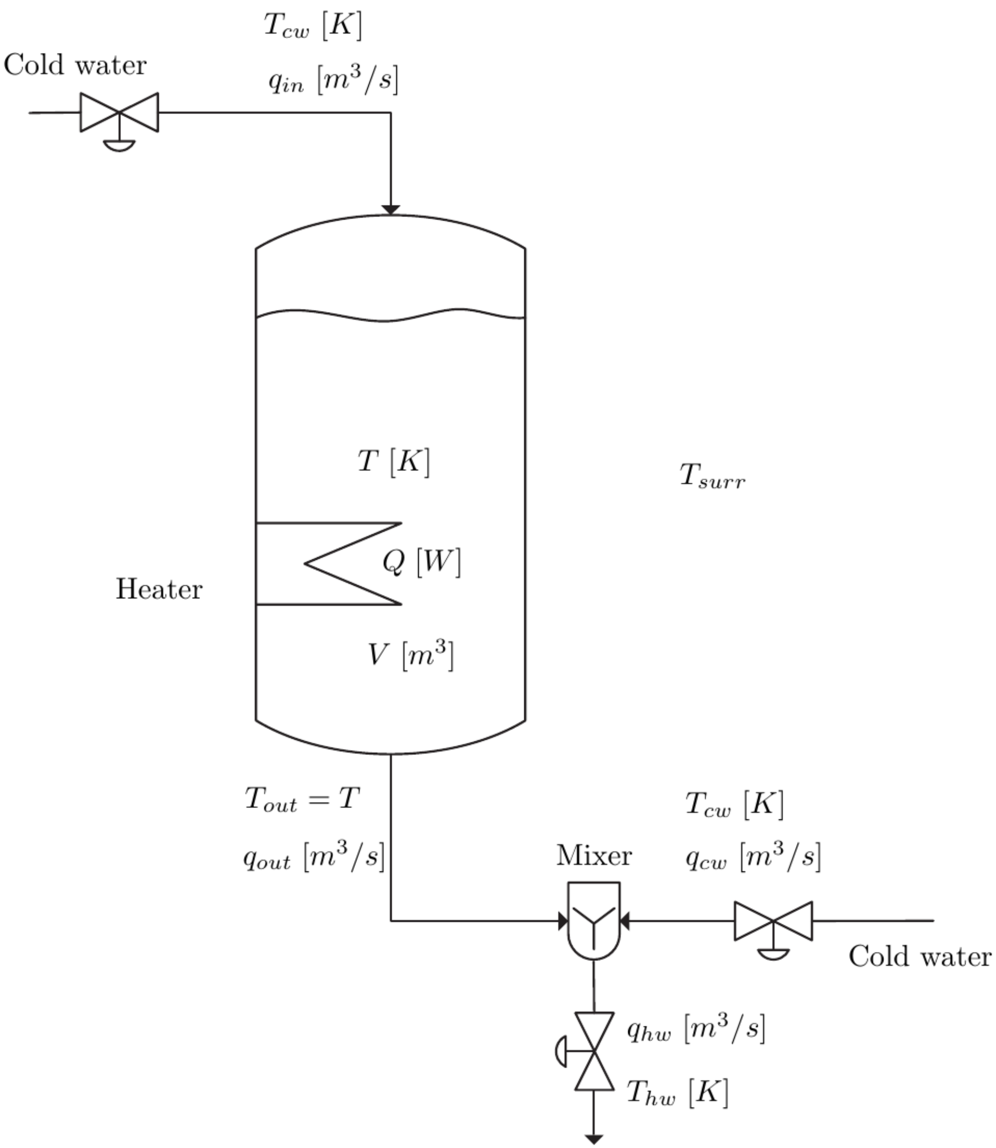
- Batteries

- Ice banks

- Building's mass (Topic of Ch. 4)

- Compressed air storage
- **Hot-water tanks** (Topic of Ch. 2 and 3)

Process model



Control degrees of freedom (u)

- Electric power: Q
- Inflows: q_{cw}, and q_{in}

Differential variables (x)

- Liquid temperature: T
- Liquid volume: V

Algebraic variables (y)

- Hot water temp. T_{hw}
- Tank outlet: q_{out}

Disturbances (d)

- Hot water flow rate: q_{hw}
- Hot water temp. setpoint: $T_{hw,sp}$
- Electricity price: p

Problem formulation

Minimize: $J = \int_{t_0}^{\infty} p(t)Q(t)\,dt$ $(energy\ cost)$

subject to:

$$\begin{cases} V_{min} \leq V \leq V_{max} \\ T_{min} \leq T \leq T_{max} \\ 0 \leq Q \leq Q_{max} \\ \dot{x} = f(x, d, u) \end{cases}$$

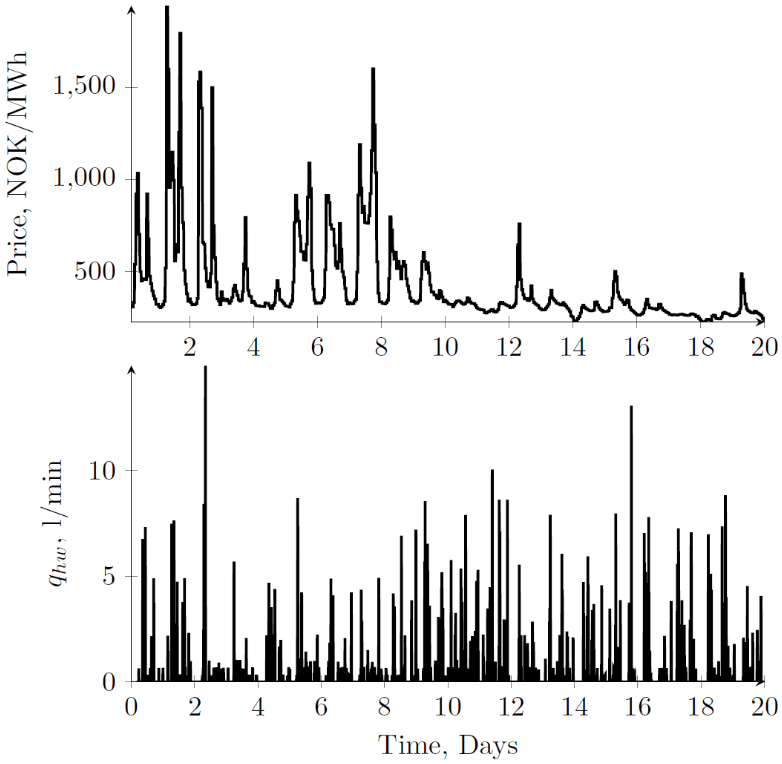
Satisfy demand at all times

Most important constraint for optimization

$$T \geq T_{min} = T_{hw,sp}$$

Main complications:

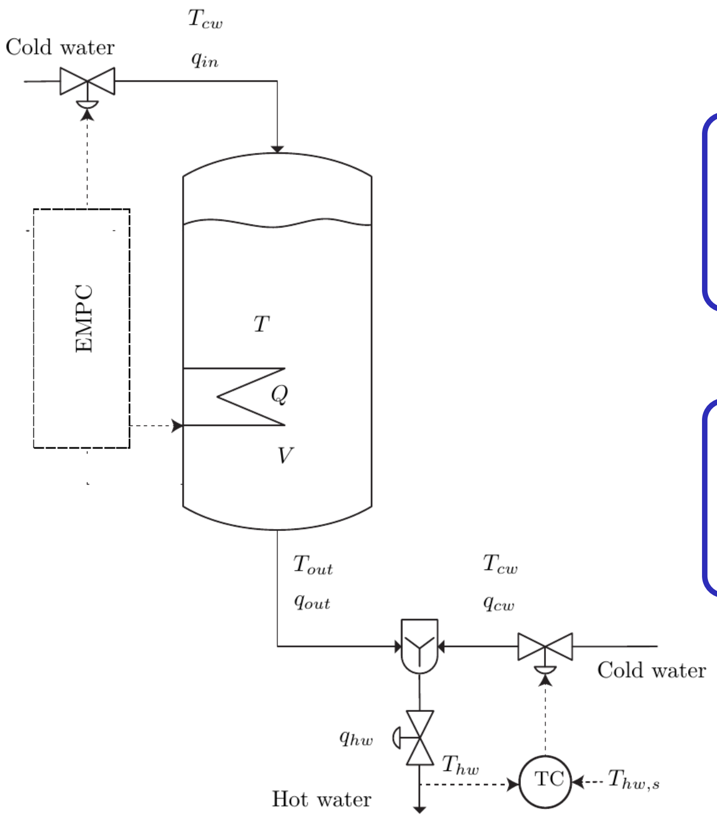
- Time-varying electricity price $p(t)$
- Time-varying and highly uncertain hot water demand q_{hw}
- Nonlinear dynamics



Demand varies in a fast time-scale (s-min) → need fast sampling time

Economics evolve in a slower pace (hours-days)→ need long horizon

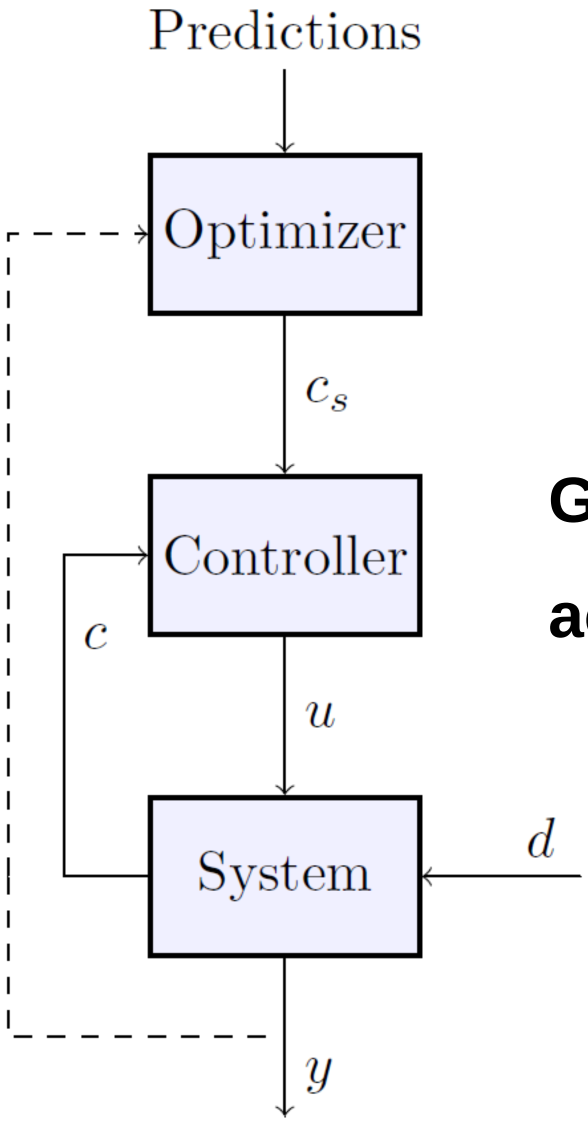
Popular at the moment: Economic Model Predictive Control (EMPC)



Combine optimization and control in one big layer

Computational cost very high!

Proposed hierarchical control structure



Great simplification of the problem is achieved with this structure

Great simplification of the problem by

Right choice of DoF for the optimization.

Use of time-scale separation

Make use of periodic behavior of problem

Optimization layer problem formulation

Right choice of decision variables

We use the concept of energy storage

$$E = \rho c_p V (T - T_{cw})$$

Because of the choice of reference temp ($T_0 = T_{cw}$), q_{in} does not affect E → Reduction of # of degrees of freedom

Using $E(t)$ as our decision variable → problem becomes linear

Optimization layer problem formulation

time-scale separation

Disturbances can be split into two frequency components

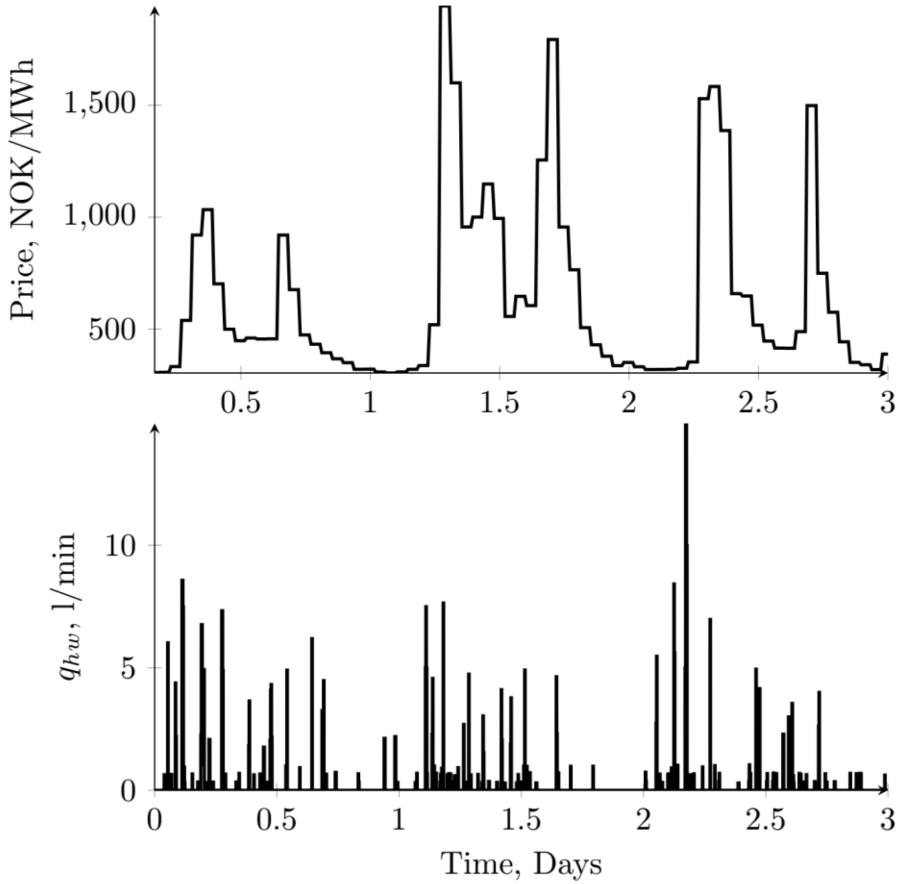
$$d = d_{slow} + \Delta d_{fast}$$

Assume d_{slow} is more important for the economics → e.g. electricity price (hours)

- Optimize E according to d_{slow} time-scale
- Use feedback control to reject fast variations Δd_{fast}

Optimization layer problem formulation

Take advantage of the periodicity of the problem



Add a final constraint

$$E(t_f) = E_{max}$$

This constraint the optimization problem of two consecutive days

Proposed formulation (in terms of energy storage)

$$\min_{E} J_N = \sum_{k=0}^{N-1} p_k [E_{k+1} - E_k + \Delta t_o Q_{k,\text{demand}}] + \sum_{k=1}^{N} \mu [\varepsilon_k]^-$$

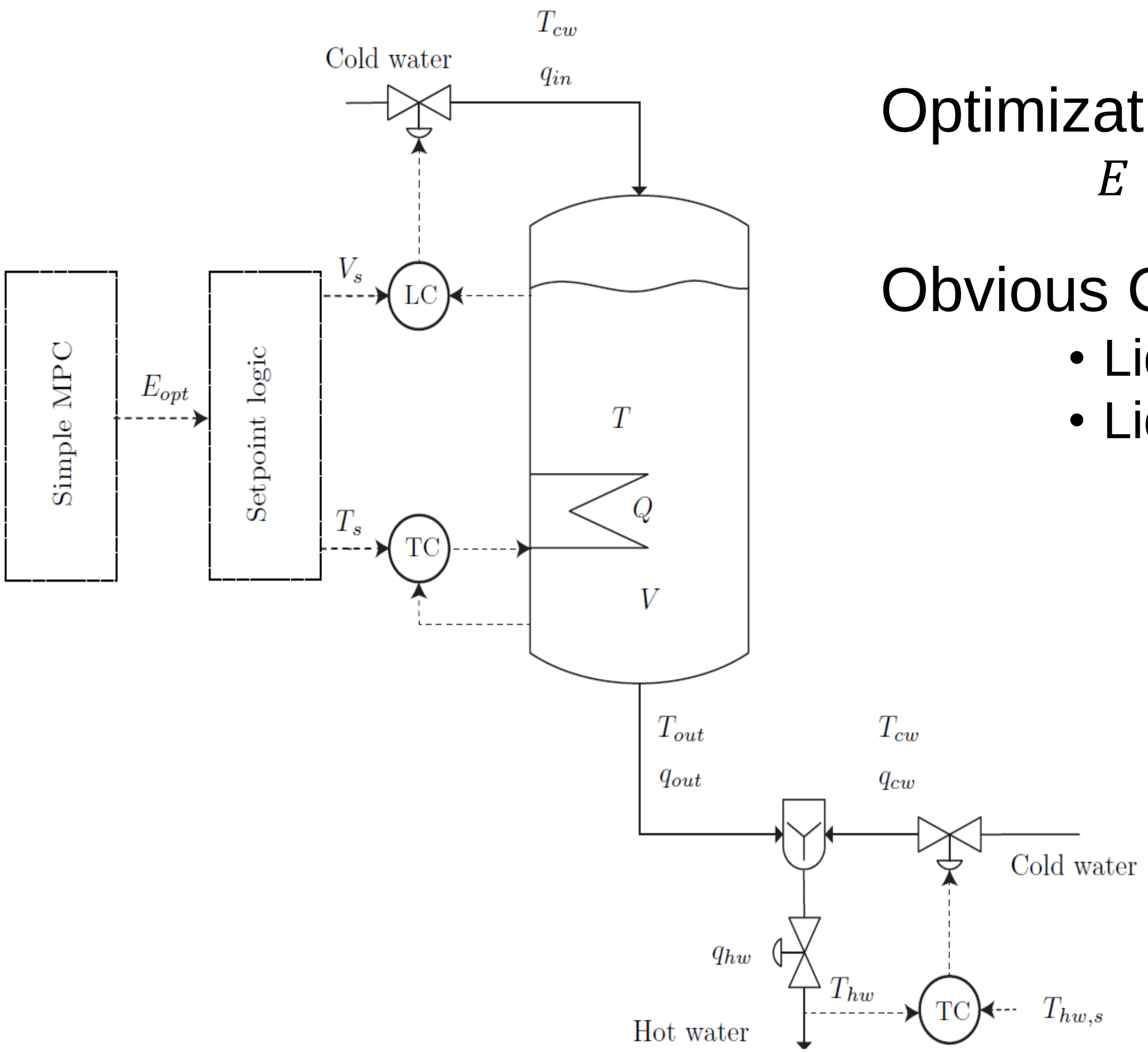
subject to:

$$E_{min} - \varepsilon_k \leq E_k \leq E_{max}$$
$$0 \leq (E_{k+1} - E_k)/\Delta t_o + Q_{k,\text{demand}} \leq Q_{max}$$
$$E_N = E_{max}$$

Linear program (LP) + Small number of decision variables

Very low computational cost

Controlled variable selection



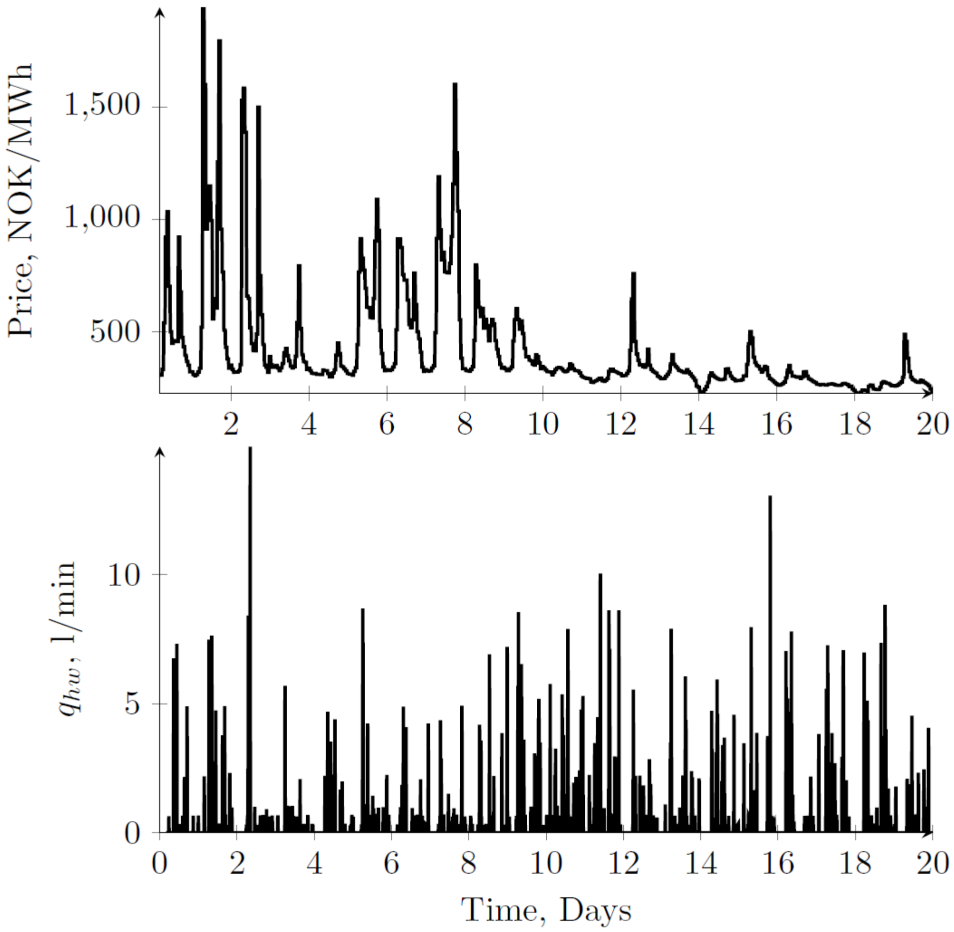
Optimization DoF:

$$E = \rho c_p V (T - T_{cw})$$

Obvious CV candidates:

- Liquid volume V
- Liquid temperature T

Case study



Compare our approach with:

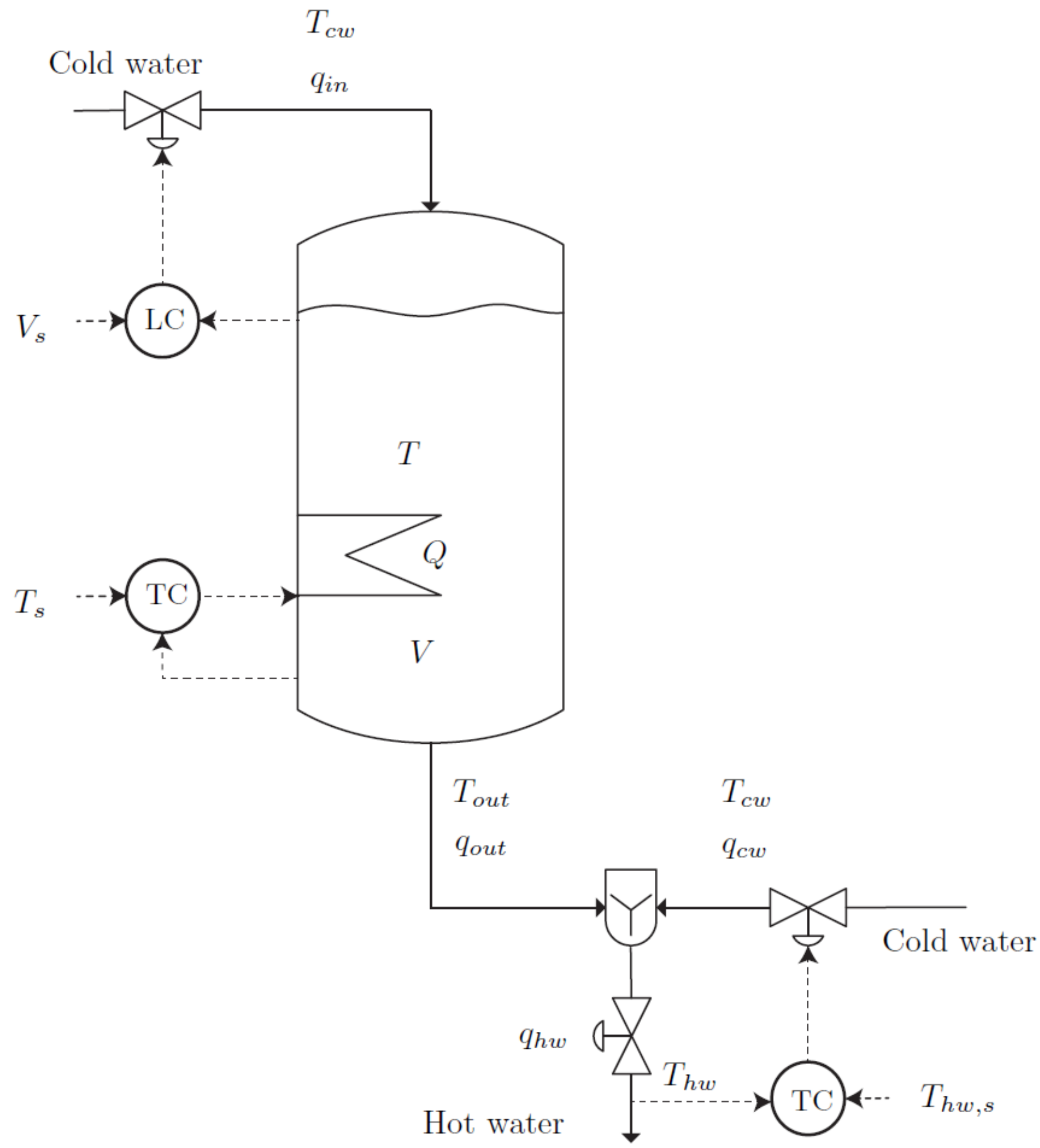
- Maximum storage policy (full tank all the time)
- Ideal case (assume perfect knowledge of the future)

Alternative strategy:

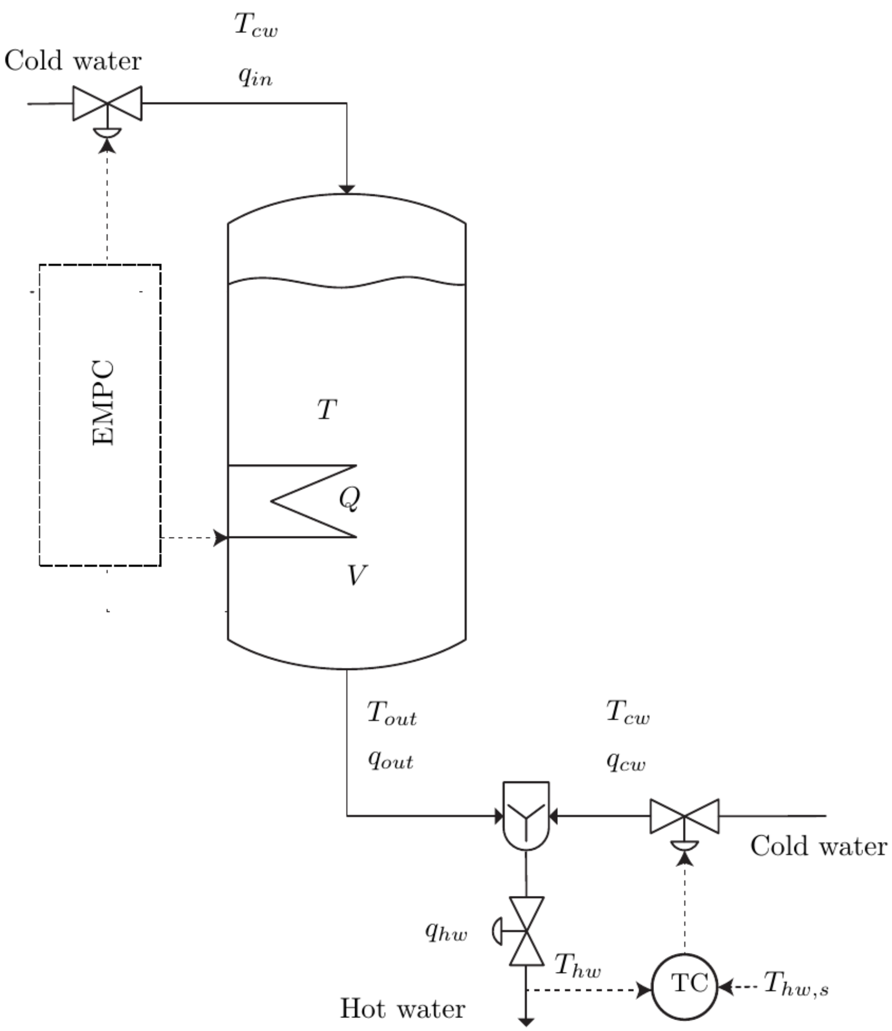
Maximum storage policy:

- $T_s = T_{max}$
- $V_s = V_{max}$

Safest policy in terms of constraint violations



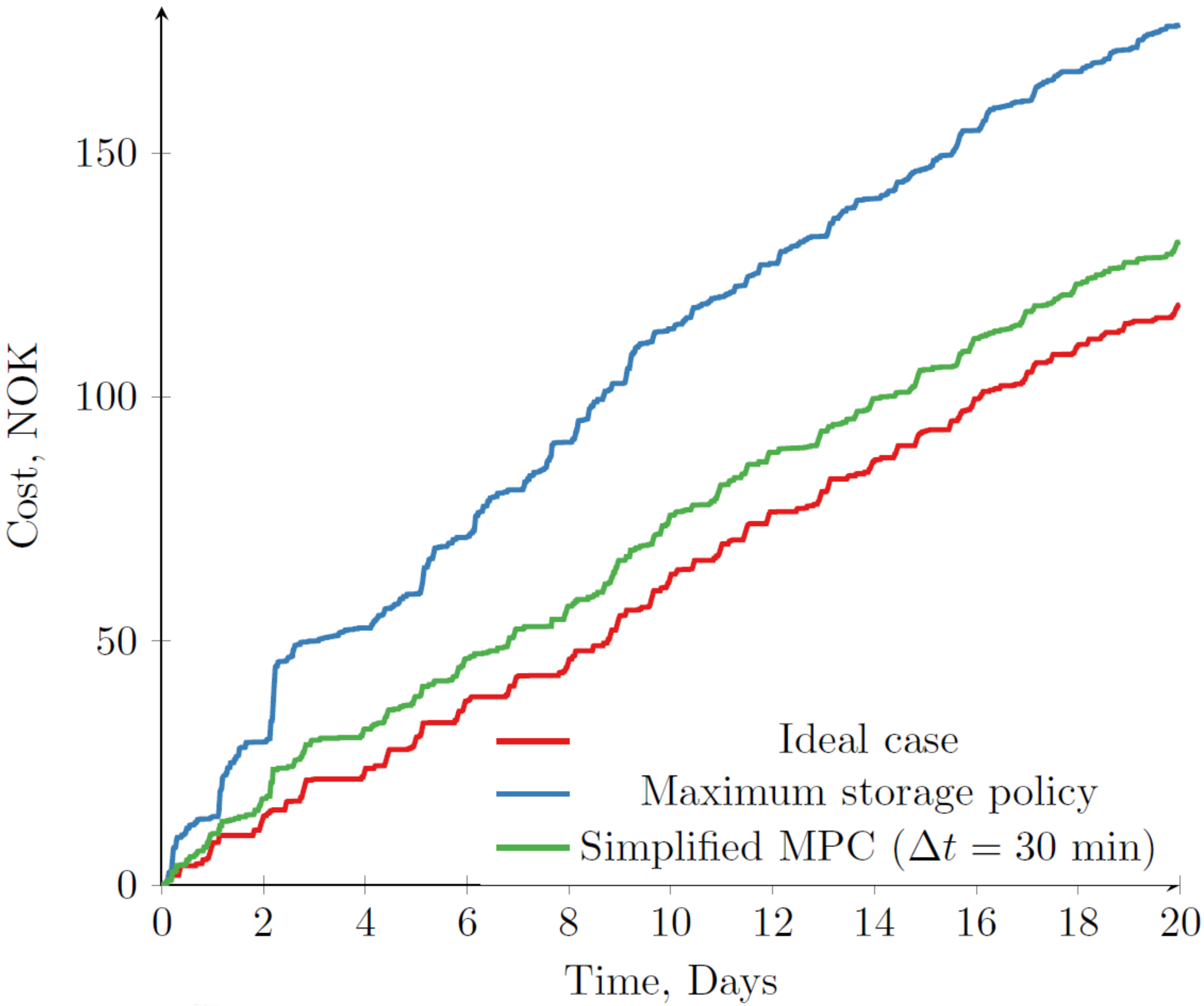
Ideal case



EMPC with perfect knowledge about the future

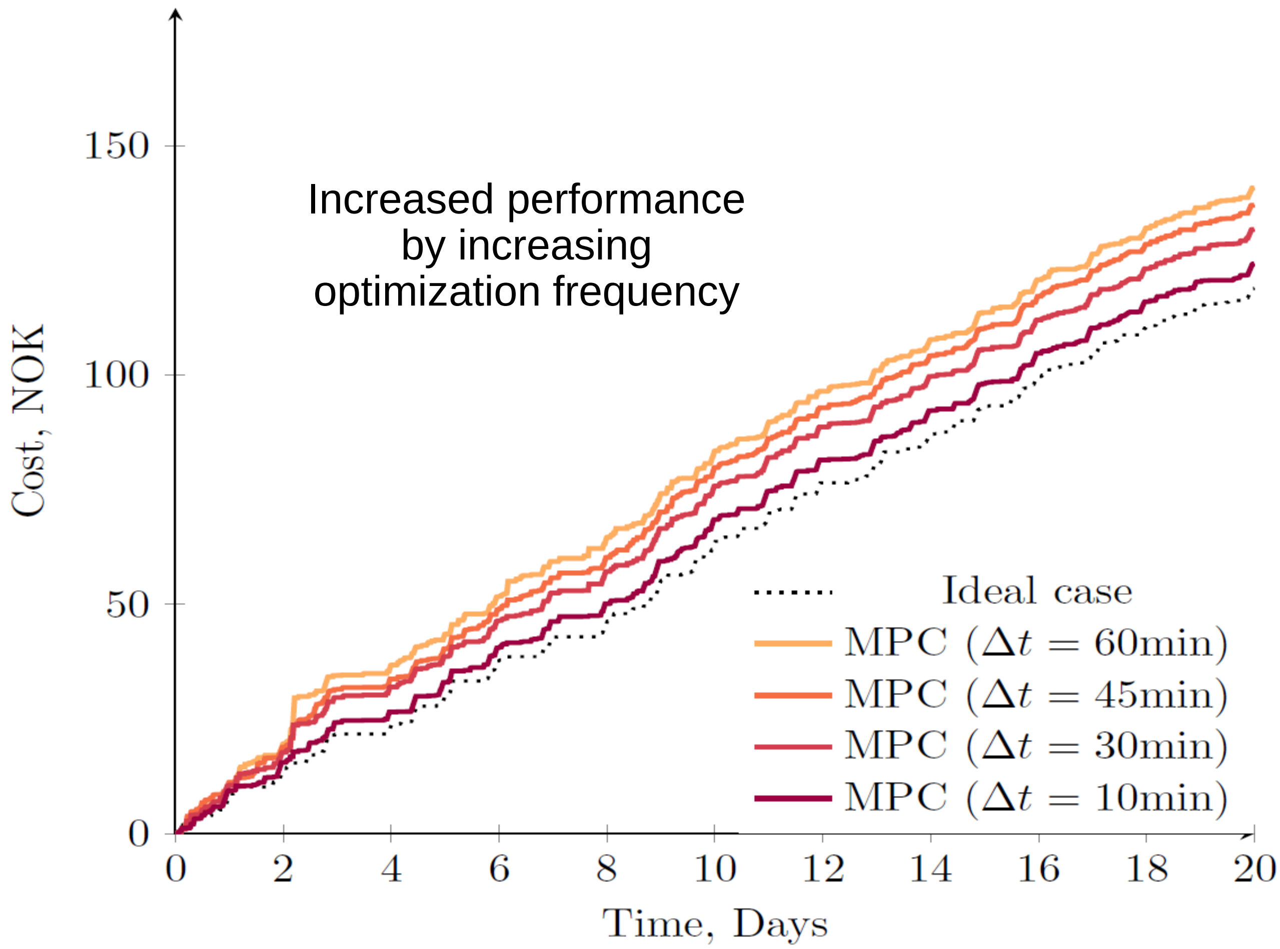
Not achievable in practice

Results



Considerable savings at low computational cost

Results



Considerable savings at low computational cost

Great simplification of the problem by

Right choice of DoF for the optimization. Use process insight.

- Introduction of energy storage E allows a linear formulation
- Fewer decision variables since water refilling q_{in} has no effect in E

Use of time-scale separation

- Energy storage E varies in a slower time-scale compared to heat input Q
- Control layer takes of fast varying disturbances and handle constraints

Make use of periodic behavior of problem

- We add a constraint $E = E_{max}$ late in the night.
- Decouples the optimization problem of two consecutive days

Main benefits

- Optimal operation
- Minimum modeling efforts
- Very low computational cost →suitable for embedded hardware

Low-cost solutions → Enable widespread usage of energy storage → Ease integration of renewable energy sources into the grid

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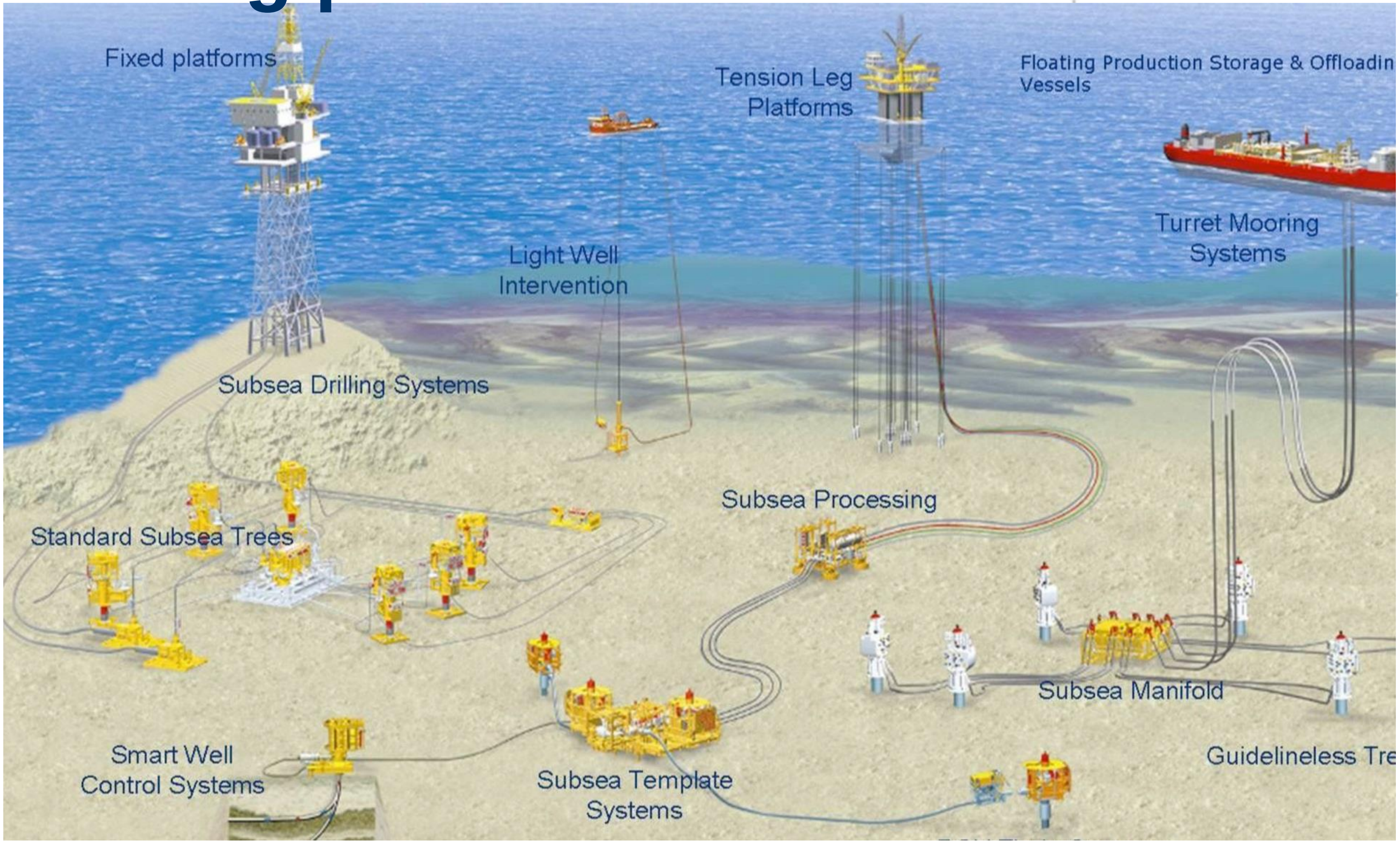
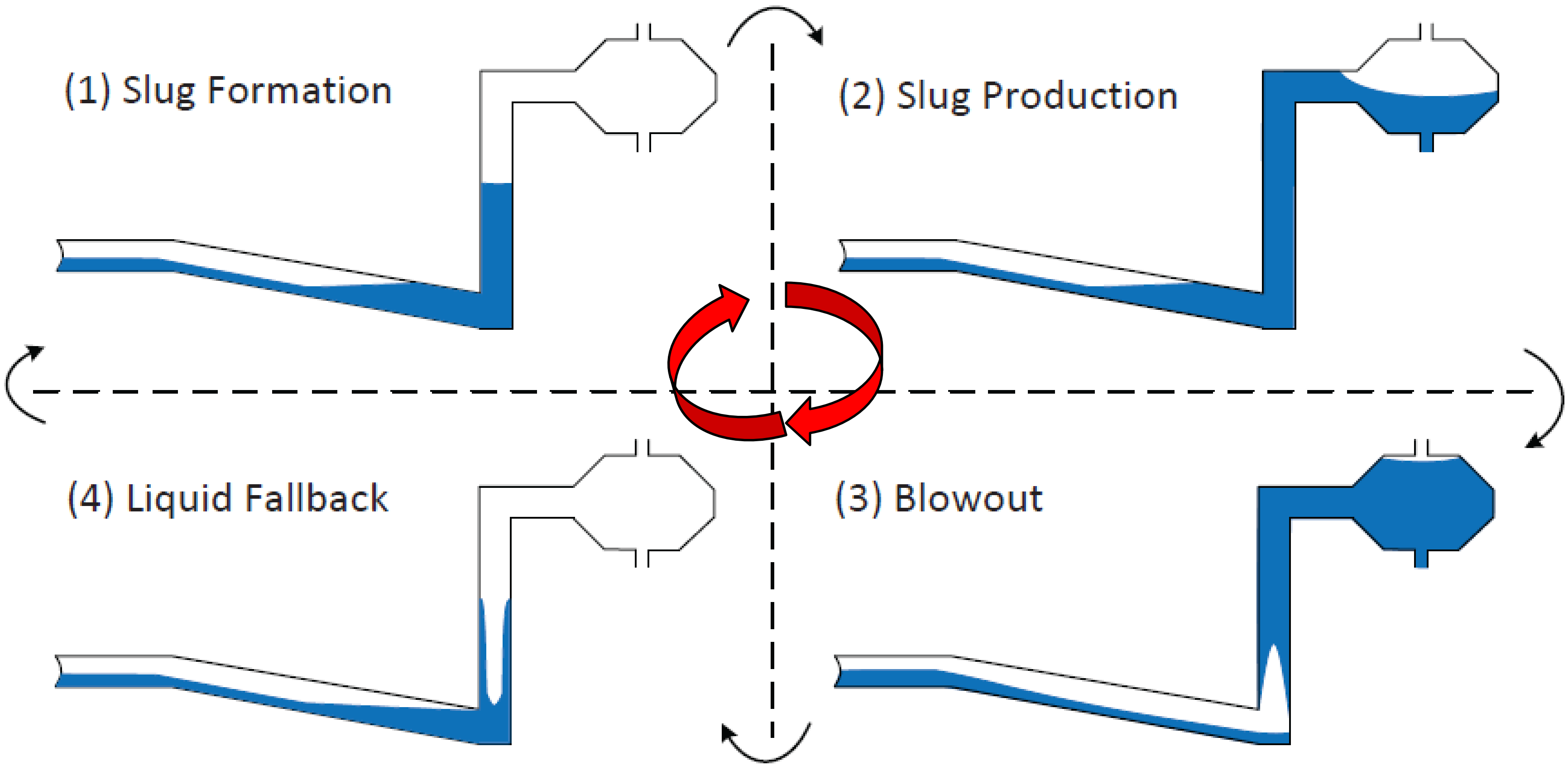
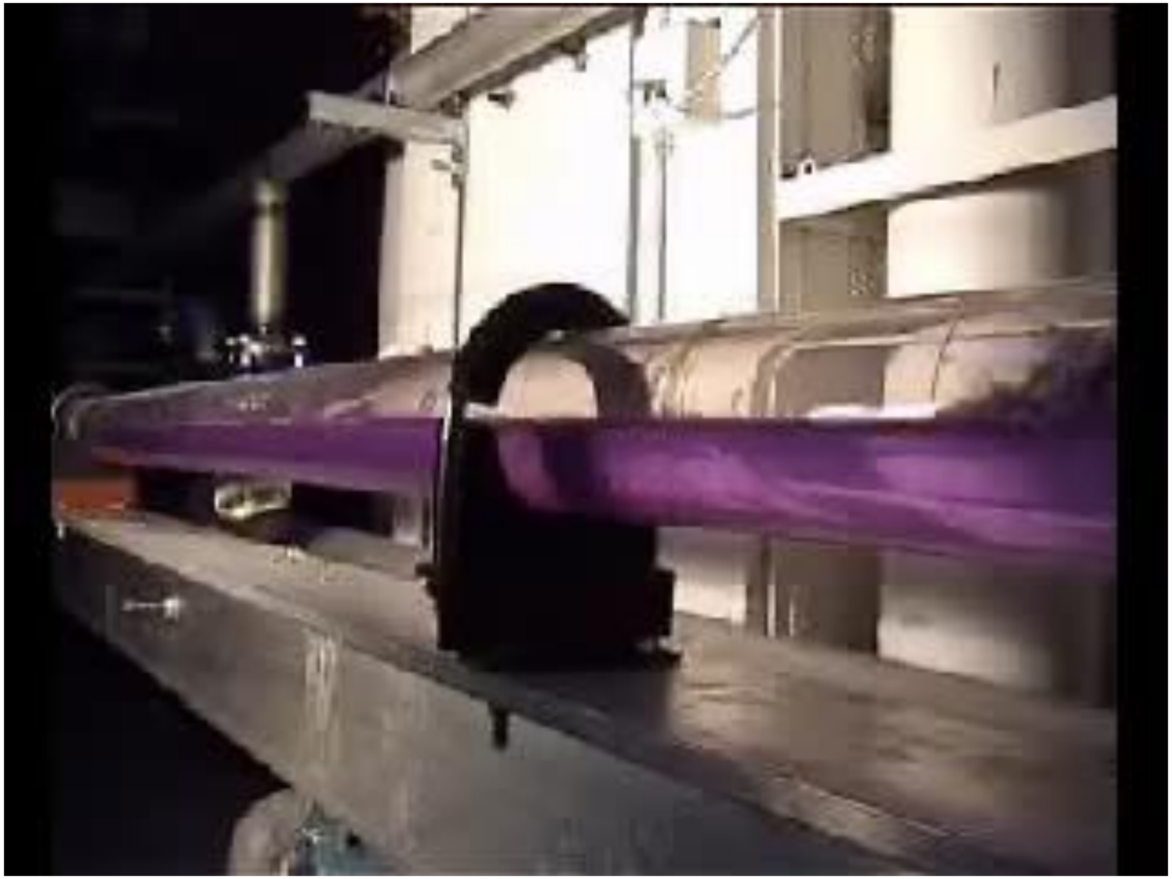
The big picture



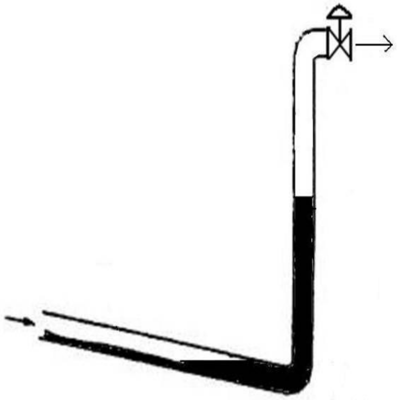
The slug cycle



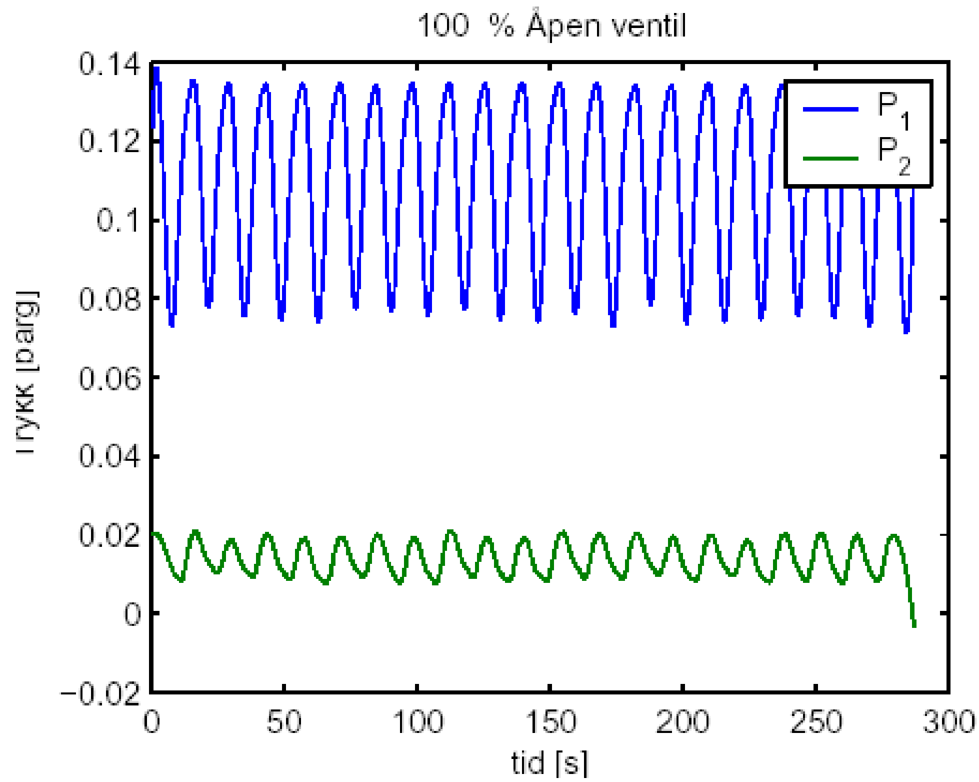
The slug cycle (video)

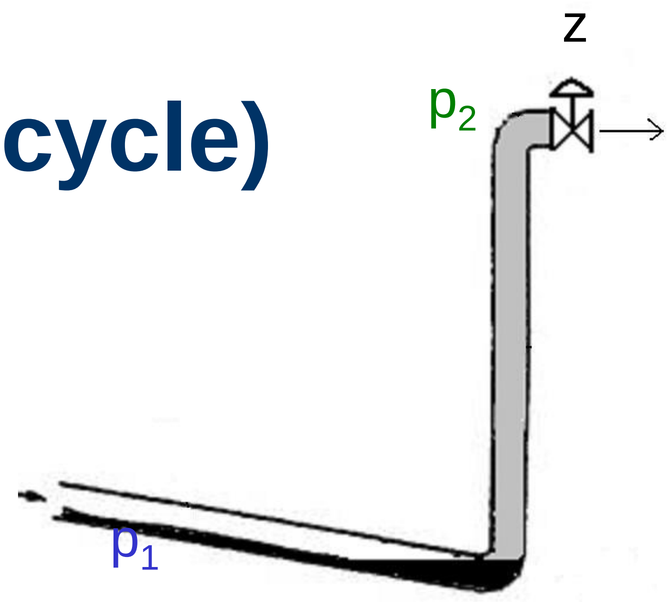


Experiments performed by the Multiphase Laboratory,

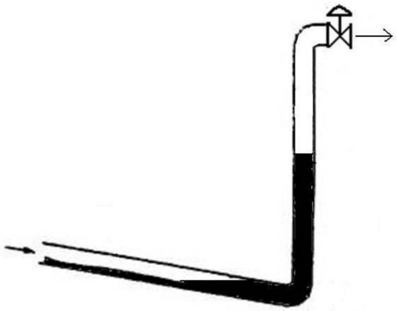


Slug cycle (stable limit cycle)



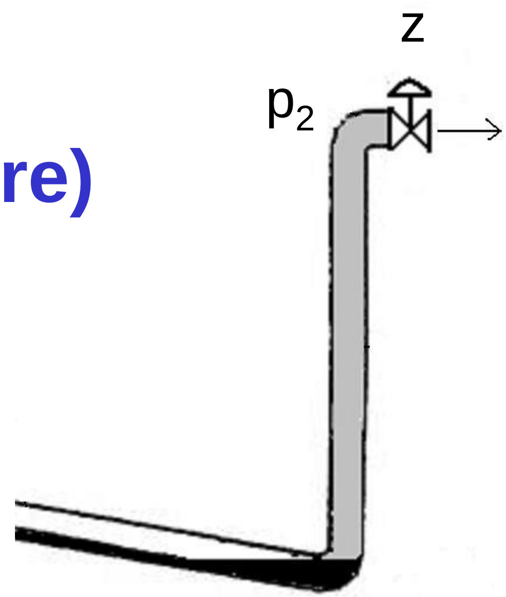


Problems caused by severe slugging

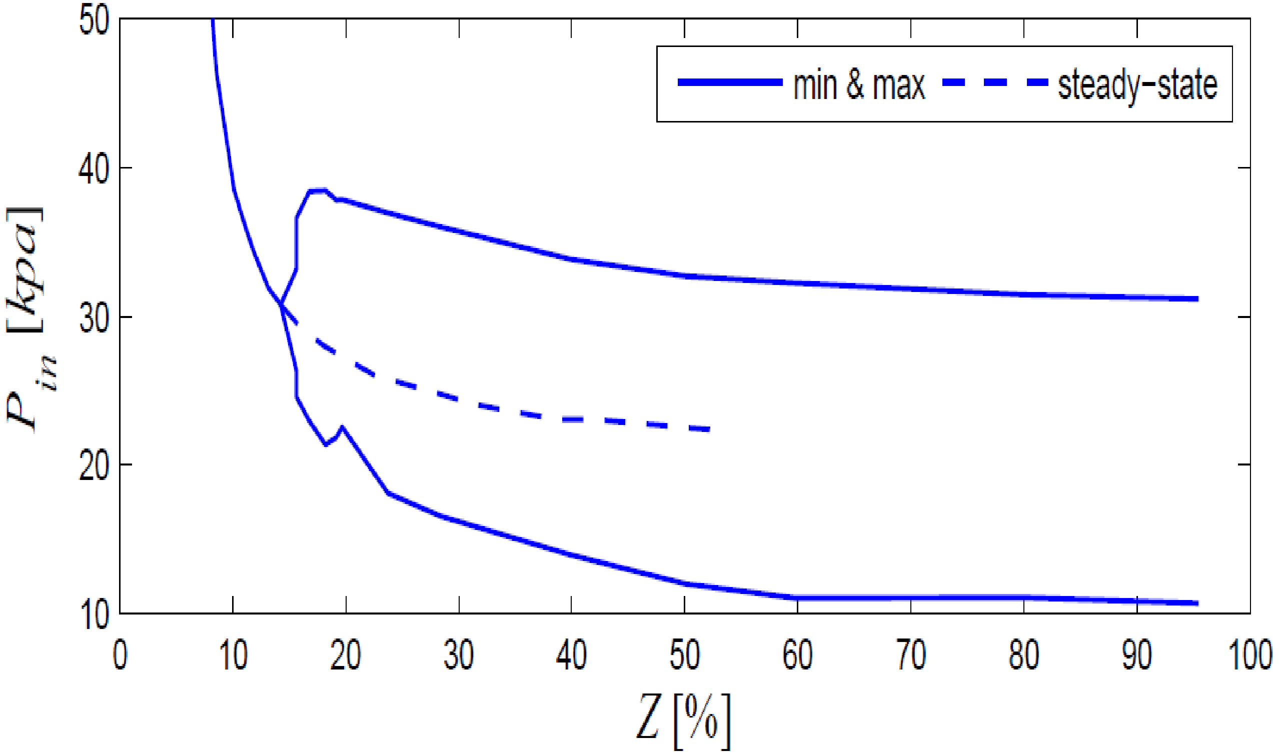


- Large disturbances in the separators
  - Causing poor separation performance
  - Can cause total plant shutdown → production losses!
  - Increase flaring.
- Large and rapid variation in compressor load
- Limits production capacity (increase pressure in pipeline)

Avoid slugging: Close valve (but increases pressure)

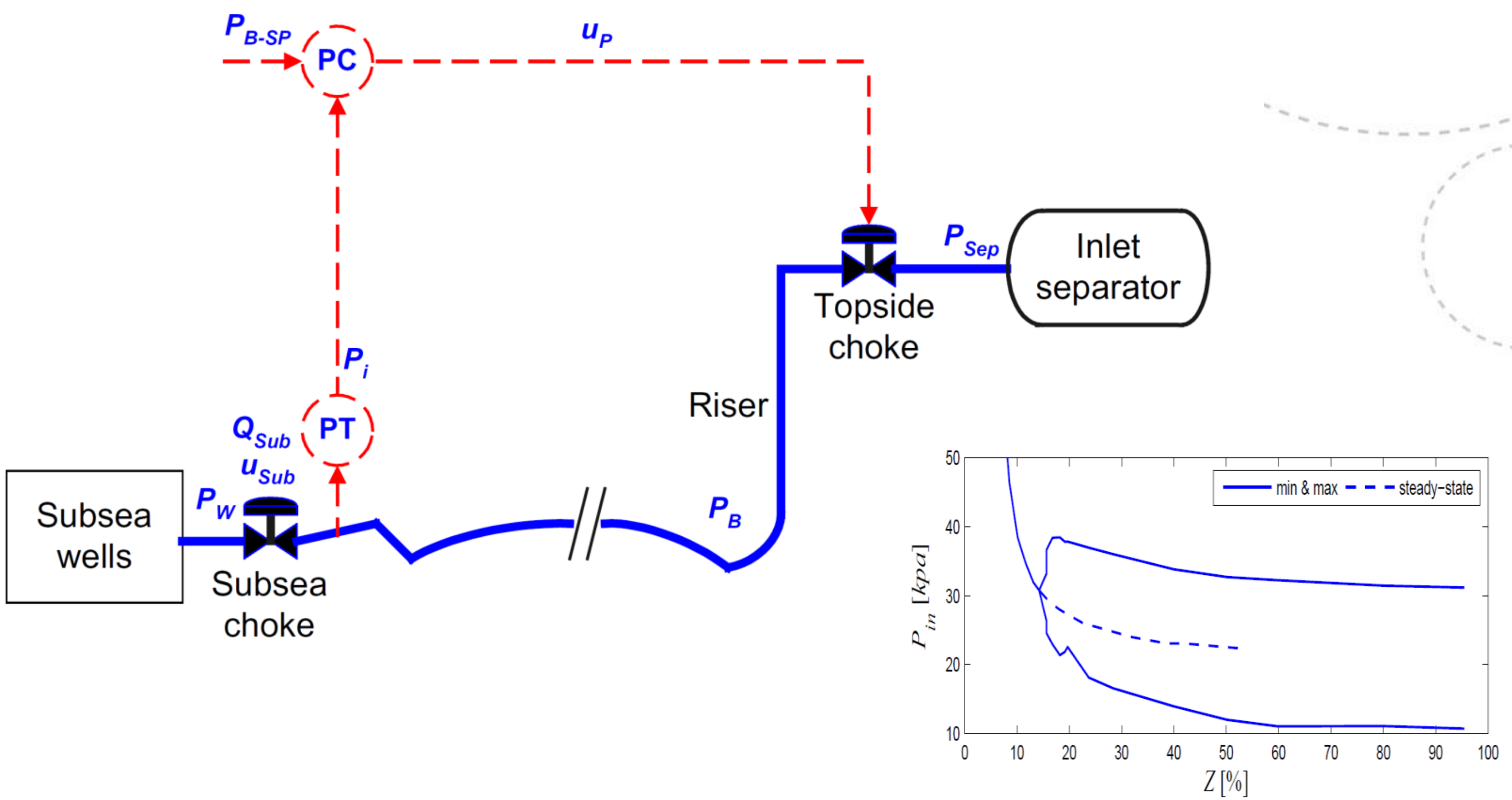


No slugging when valve is closed

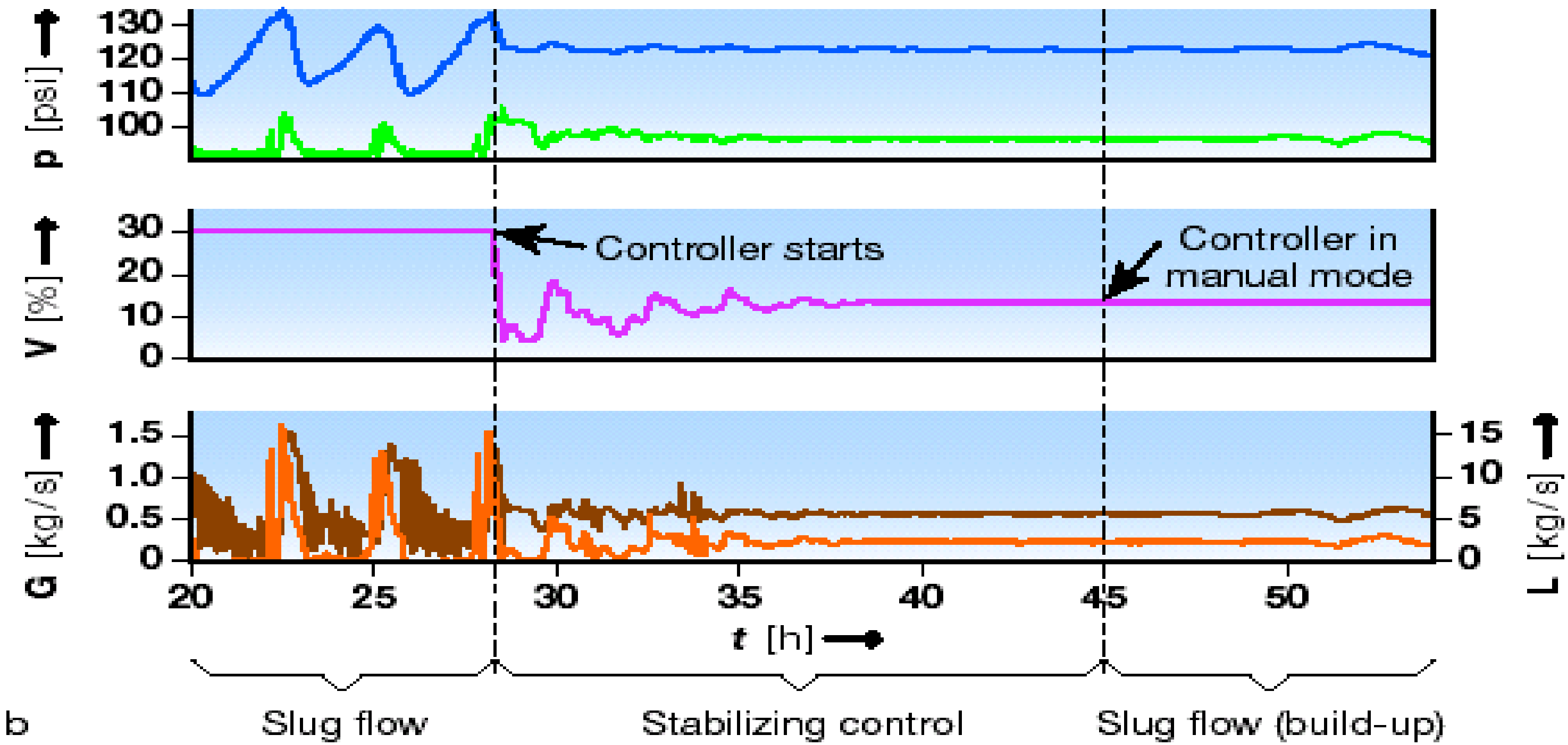


Problematic for aging fields → increased pressure limits production

Avoid slugging: "Active" feedback control



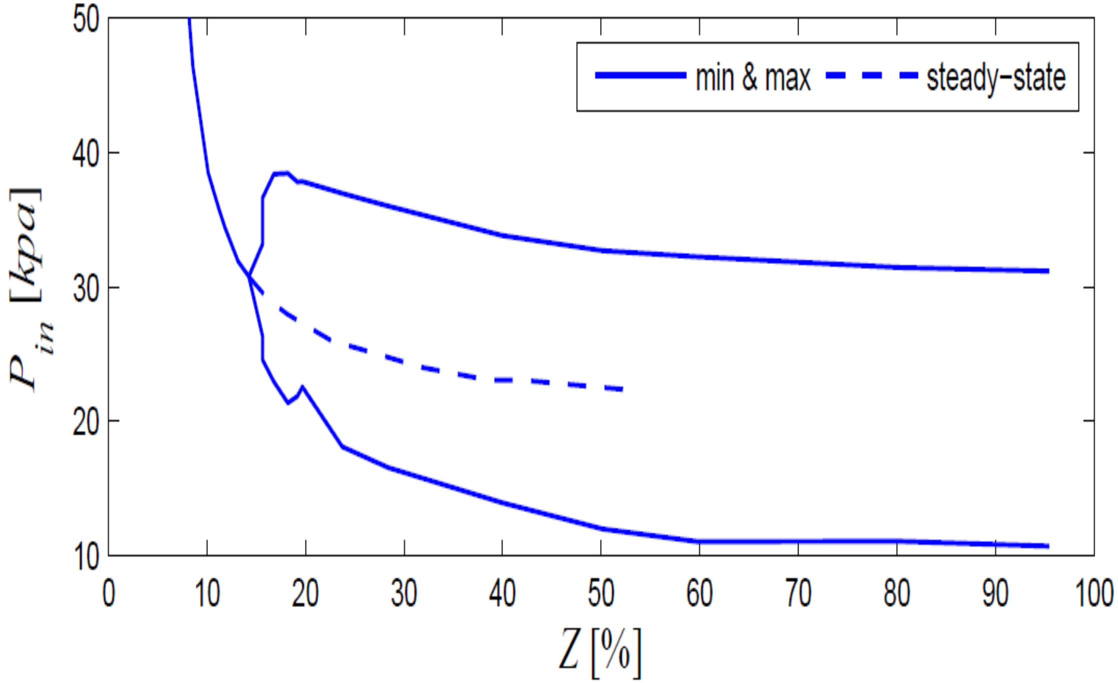
Anti slug control: Full-scale offshore experiments at Hod-Vallhall field (Havre,1999)

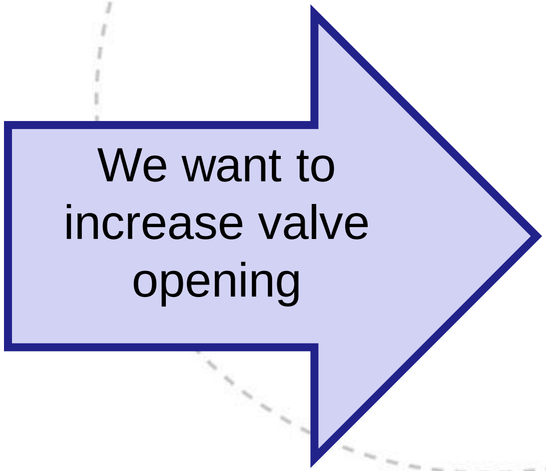


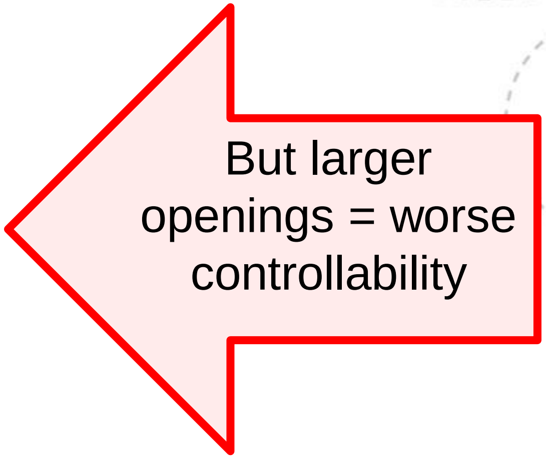
Problems with current anti-slug control systems

- Tend to become unstable (oscillating) after some time
  - *Inflow conditions change*
  - *Require frequent retuning by an expert → costly*
- Ideal operating point (pressure set-point) is **unknown**
  - *If pressure setpoint is too high → production is reduced*
  - *If pressure setpoint is too low → system may become unstable*

Motivation



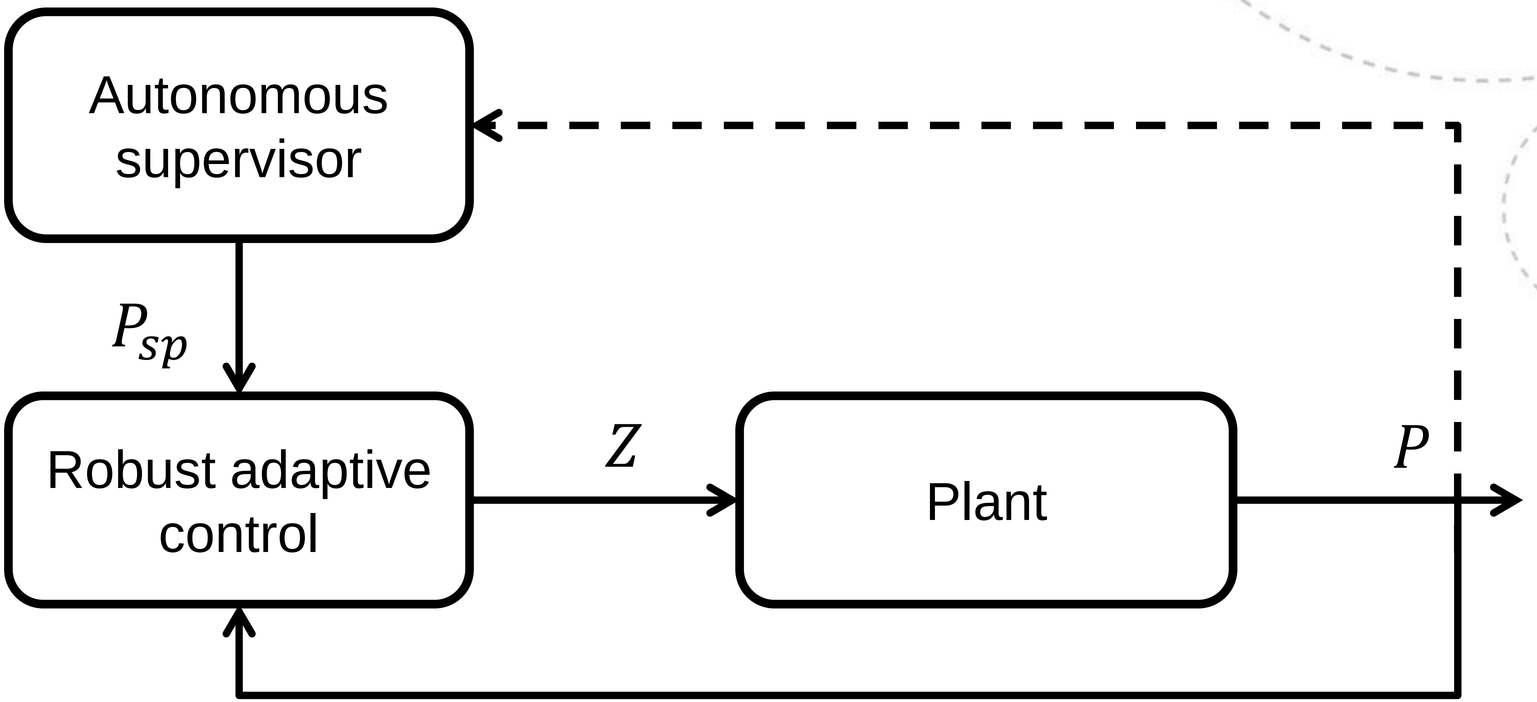




- The lager the valve opening →the more difficult it is to stabilize the system
  - – Controller gets more sensitive to uncertainties
  - – Process gain is reduced

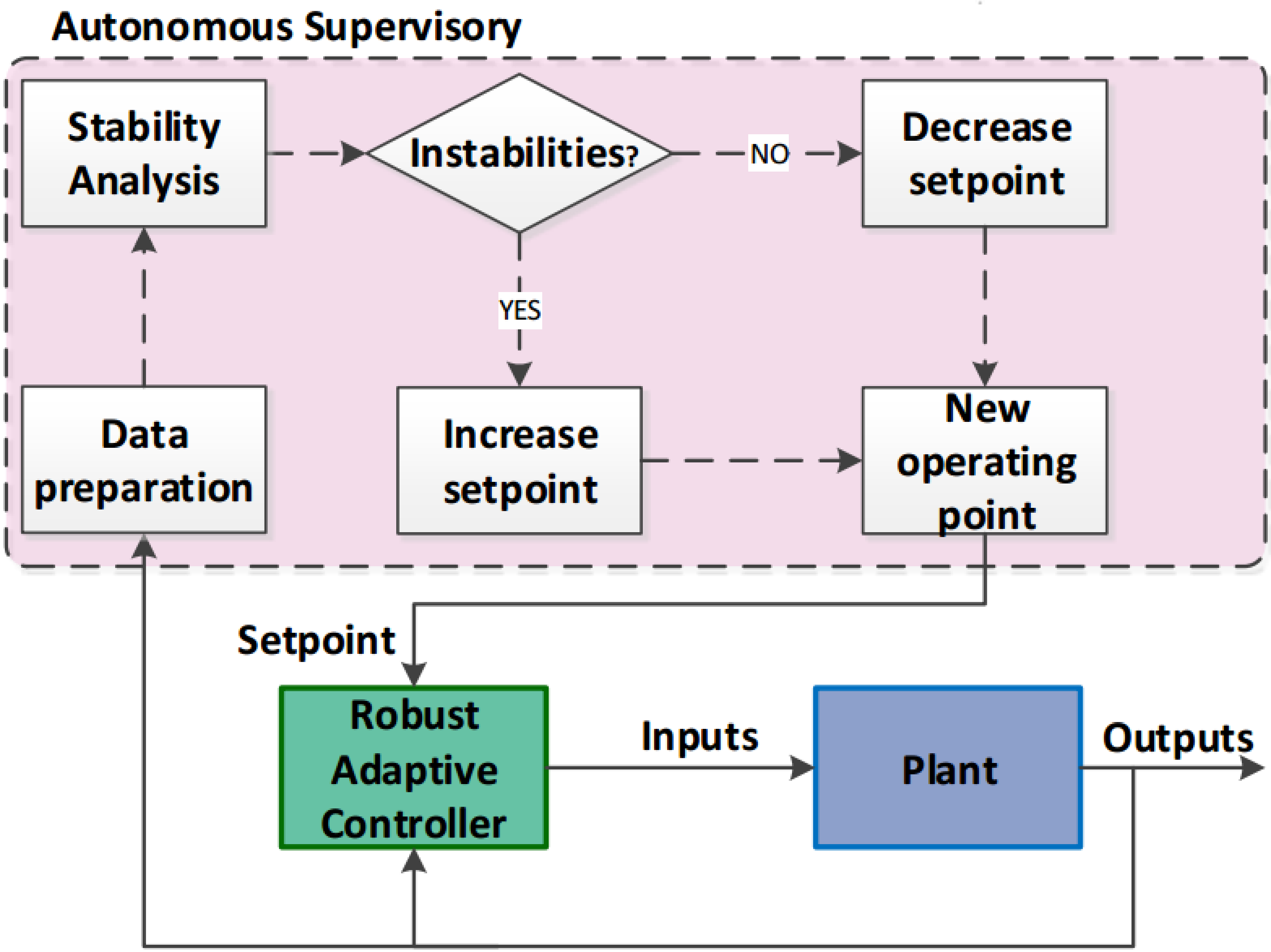
Our proposed autonomous control system

- Periodically checks the stability of the system
- Reduces setpoint if control loop is working fine

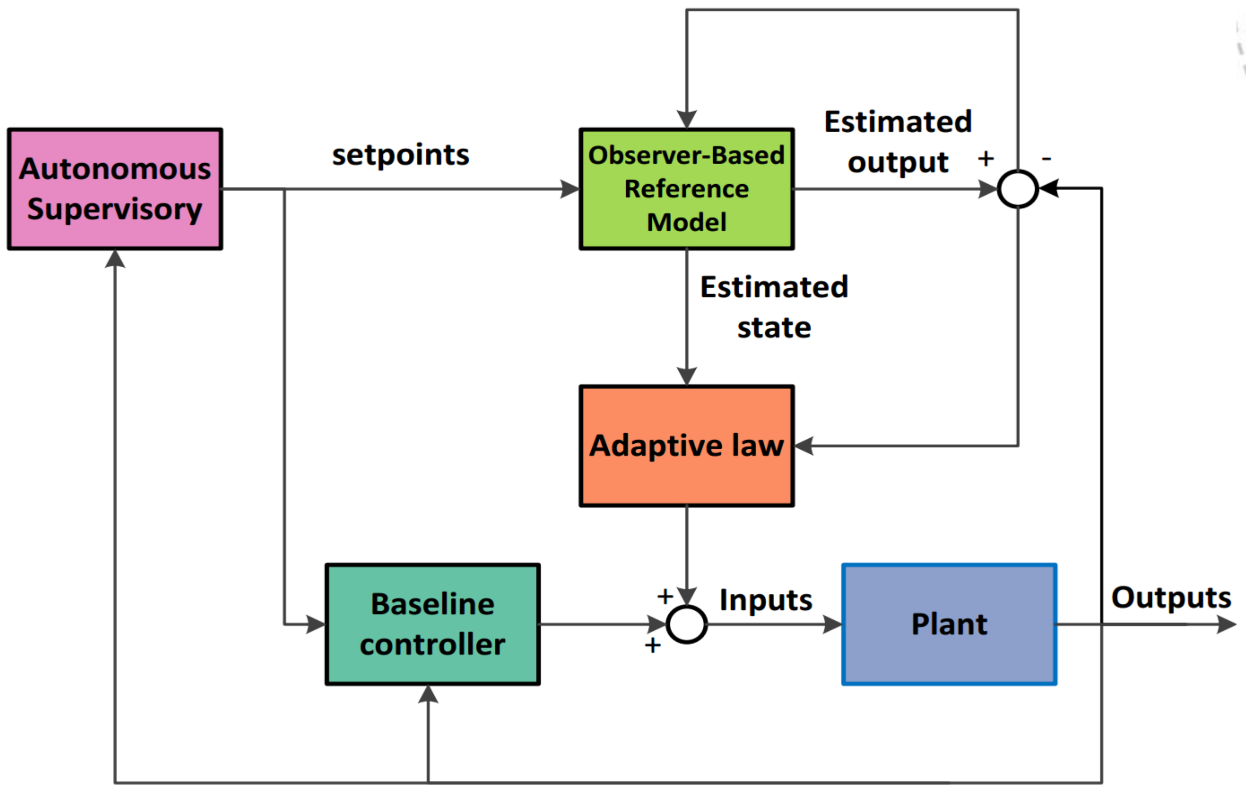


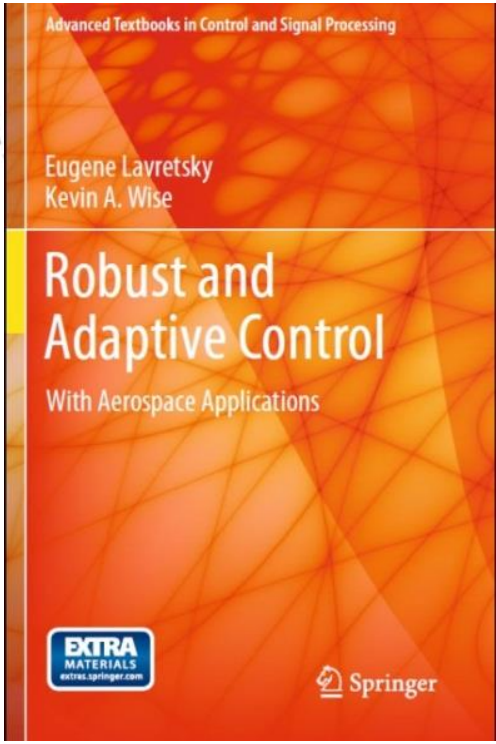
Setpoint change is key for the adaptation to work well

How does it work?



Adaptive control based on adaptive augmentation





Relies on state-of-the-art output feedback adaptive control techniques

→ Very successful in the aerospace industry

Adaptive control design

Open-loop system dynamics

$$\dot{x} = Ax + B\Lambda\left(u + \Theta^T\Phi(x)\right) \qquad y_{meas} = Cx$$

Uncertainty model

Λ → control effectiveness uncertainty. Affects the process gain

$\Theta^T\Phi(x)$ → state-dependent nonlinear uncertainty. Affects poles and zeros

Θ → matrix of unknown coefficients
$\Phi(x)$ → vector of Lipschitz basis functions

Adaptive control design

Define reference model

$$\dot{\hat{x}} = A_{ref}\hat{x} + B_{ref}r + \boldsymbol{L_v(y - \hat{y})}$$

Feedback term to improve transient dynamics

Output Feedback Adaptive Laws

- $\dot{\hat{\Theta}} = \Gamma_{\Theta}\mathrm{Proj}(\hat{\Theta}, \Phi(\hat{x}, u_{bl})(y - \hat{y})^T)$
- $\dot{\hat{K}}_u = \Gamma_{\mathrm{u}}\mathrm{Proj}(K_u, u_{bl}(y - \hat{y})^T)$
- $u_{adaptive} = -\hat{K}_u u_{baseline} - \hat{\Theta}^T\Phi(x)$

Robust baseline + adaptive output feedback

$$u = u_{baseline} + u_{adaptive}$$

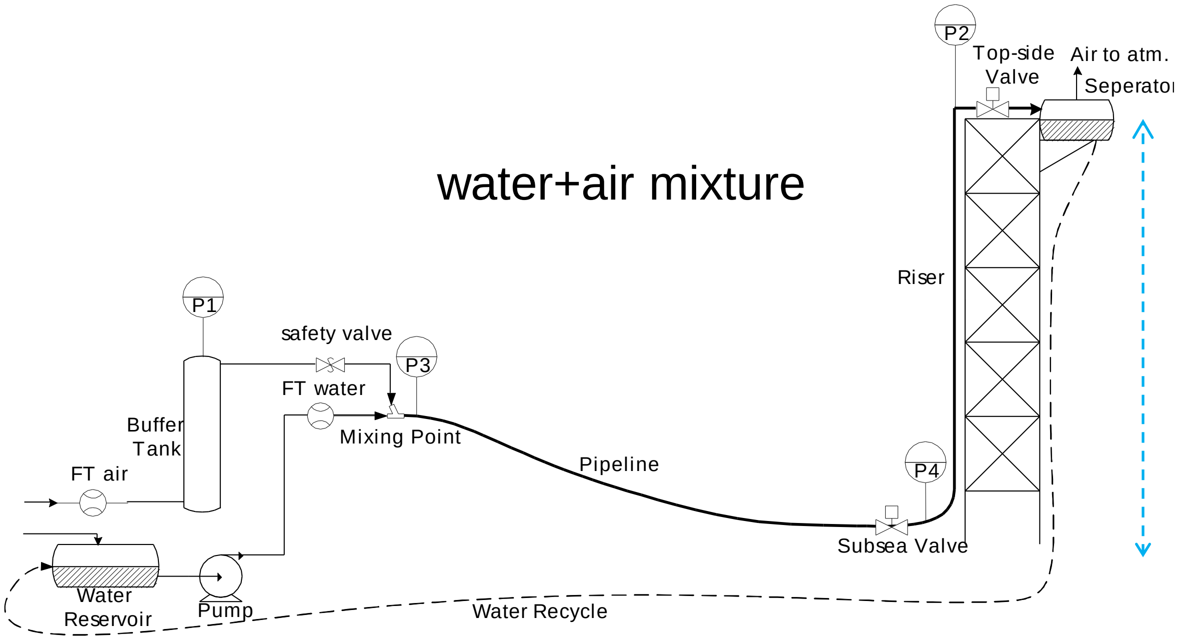
- $u_{baseline}$ → *computed using your favorite method (PID, H_∞, LQG/LTR, …)*

How does it perform in practice?

2009-2013: Esmaeil Jahanshahi, PhD-work supported by Siemens

Experimental mini-rig

water+air mixture



3m

- its dynamical behavior is quite similar to that of much larger rigs

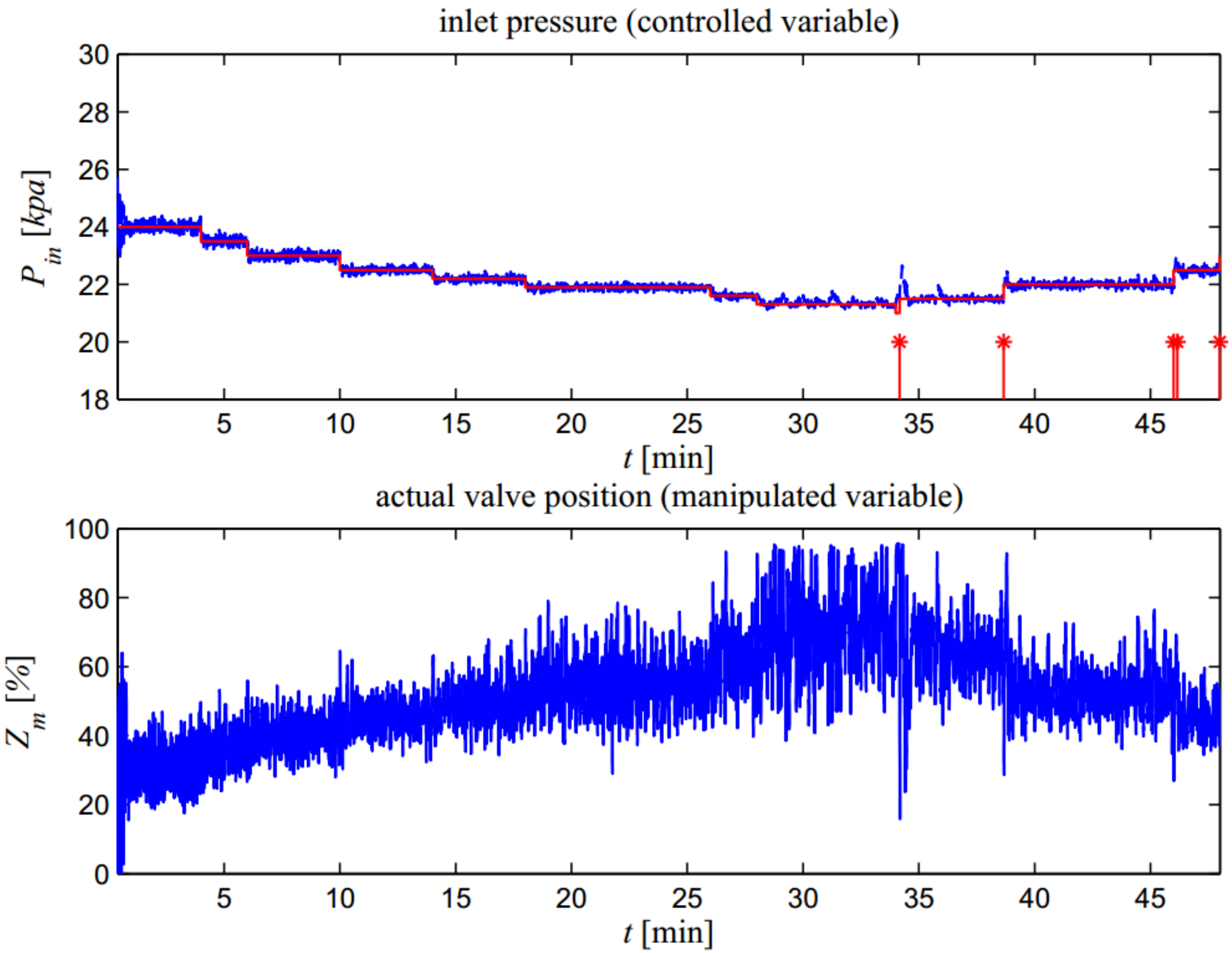
Experimental Results

- Baseline controller tuned for Z=30%

- Linearized mechanistic or simple empirical models can be used

Note: our models agree very well with experiments

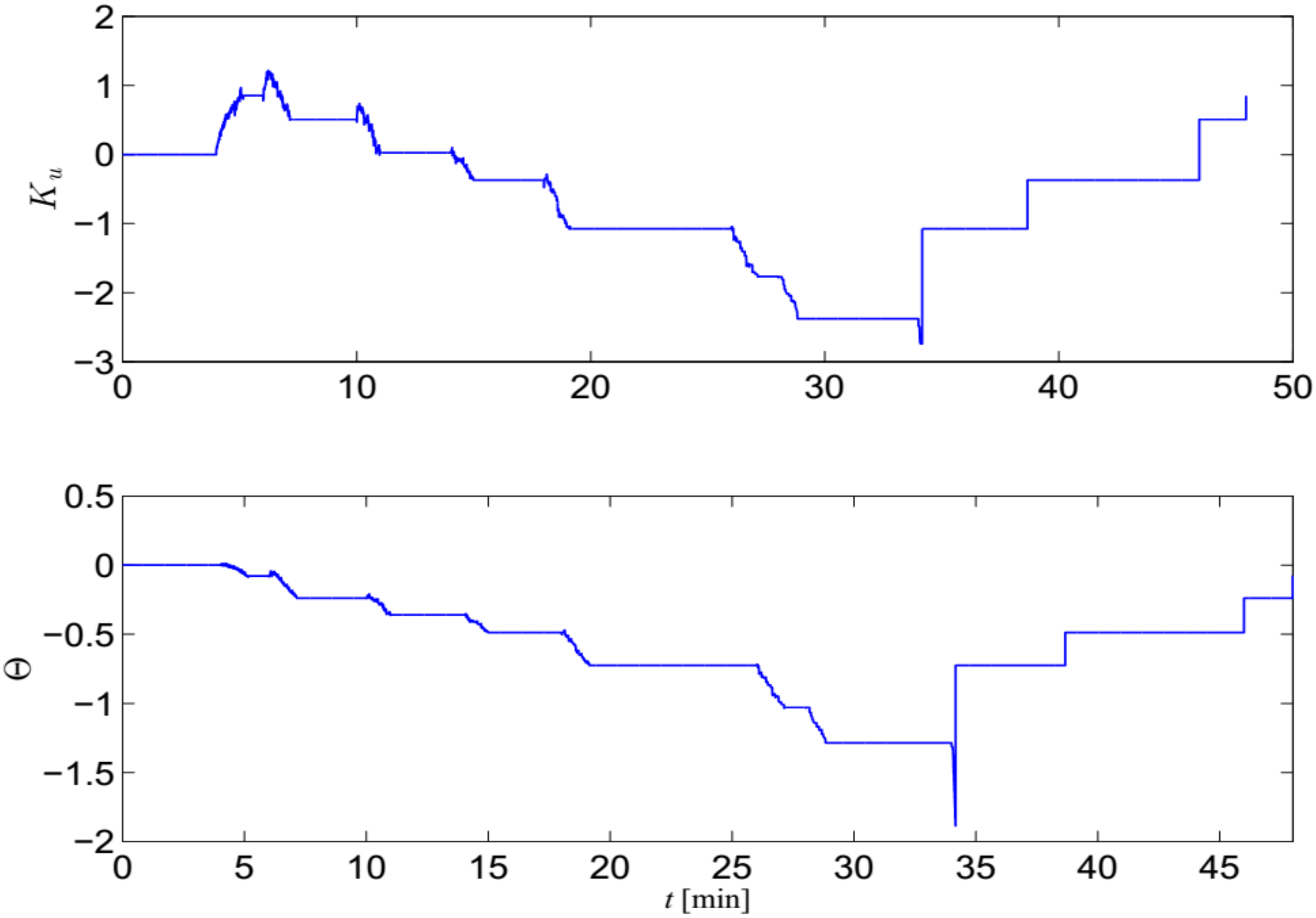
Autonomous supervisor and adaptive LTR controller



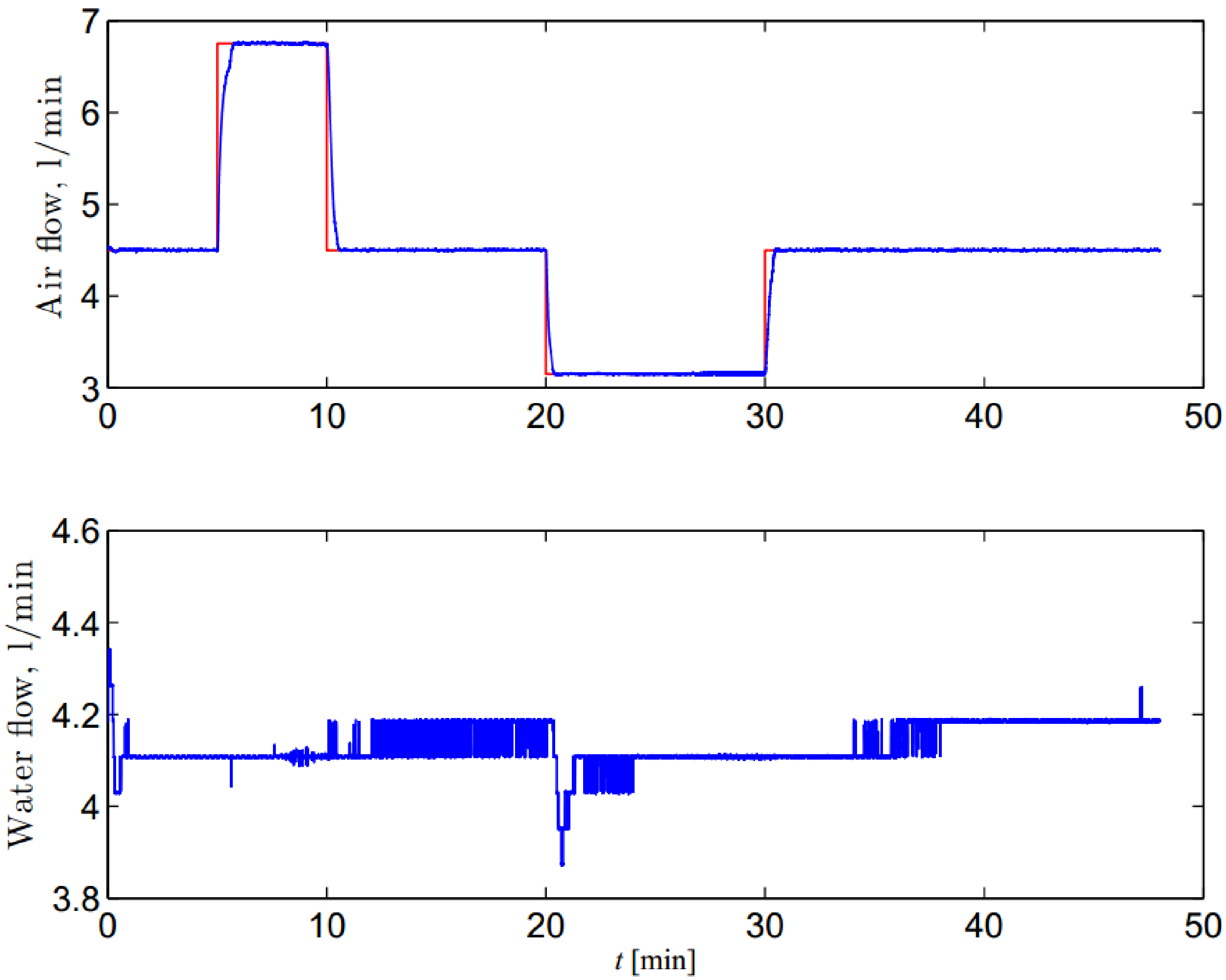
Safely operates at very large valve openings

Autonomous supervisor and adaptive LTR controller

Adaptation gains

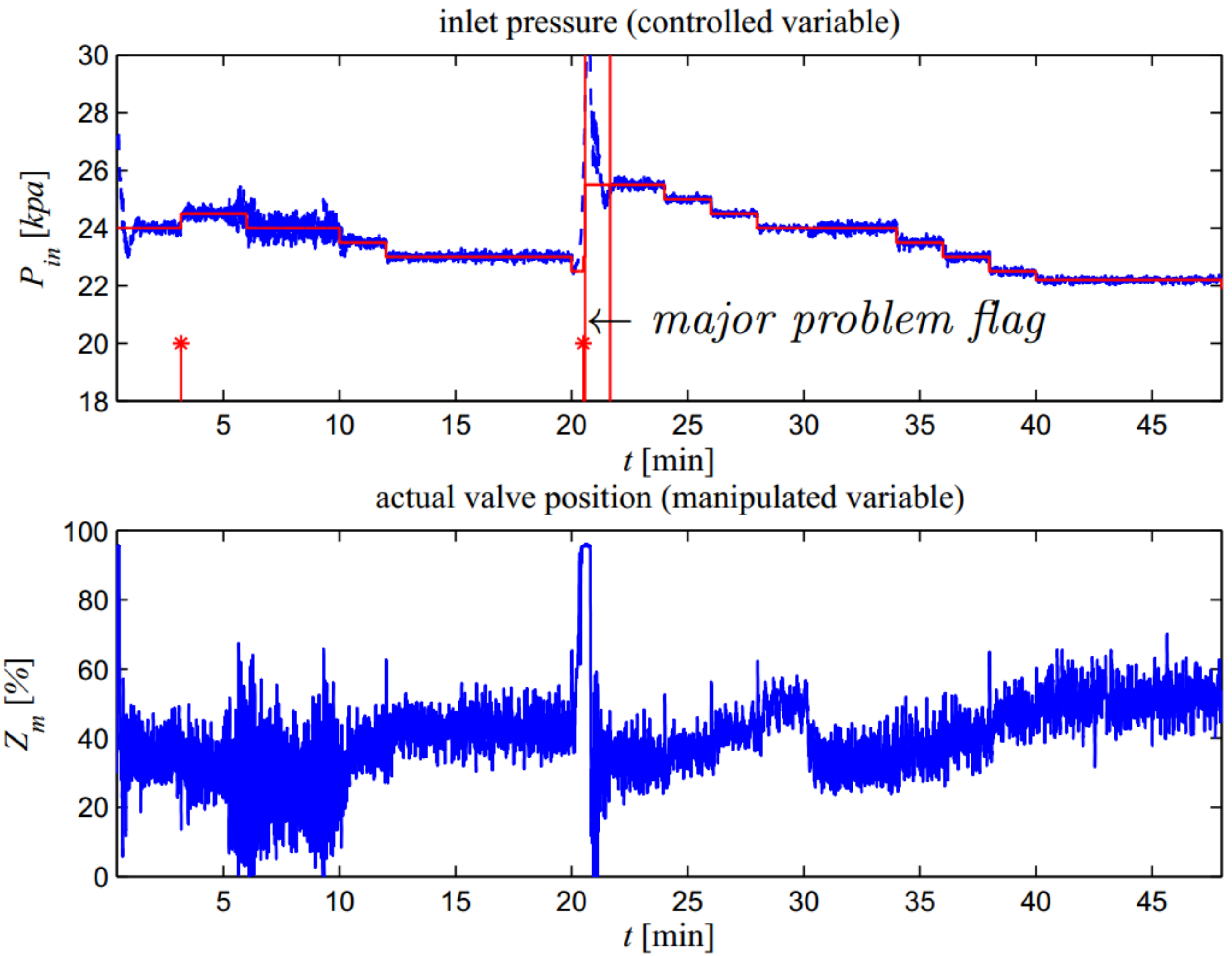


Oops, Big disturbance!



Emulates a ‘gas-to-oil’ ratio change over 60%

Large change in the operating conditions

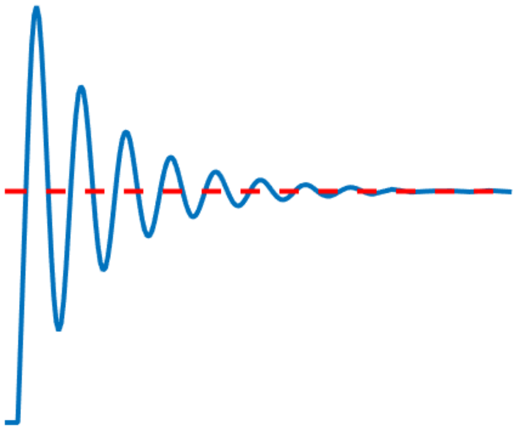


Supervisor quickly *detects* major disturbance

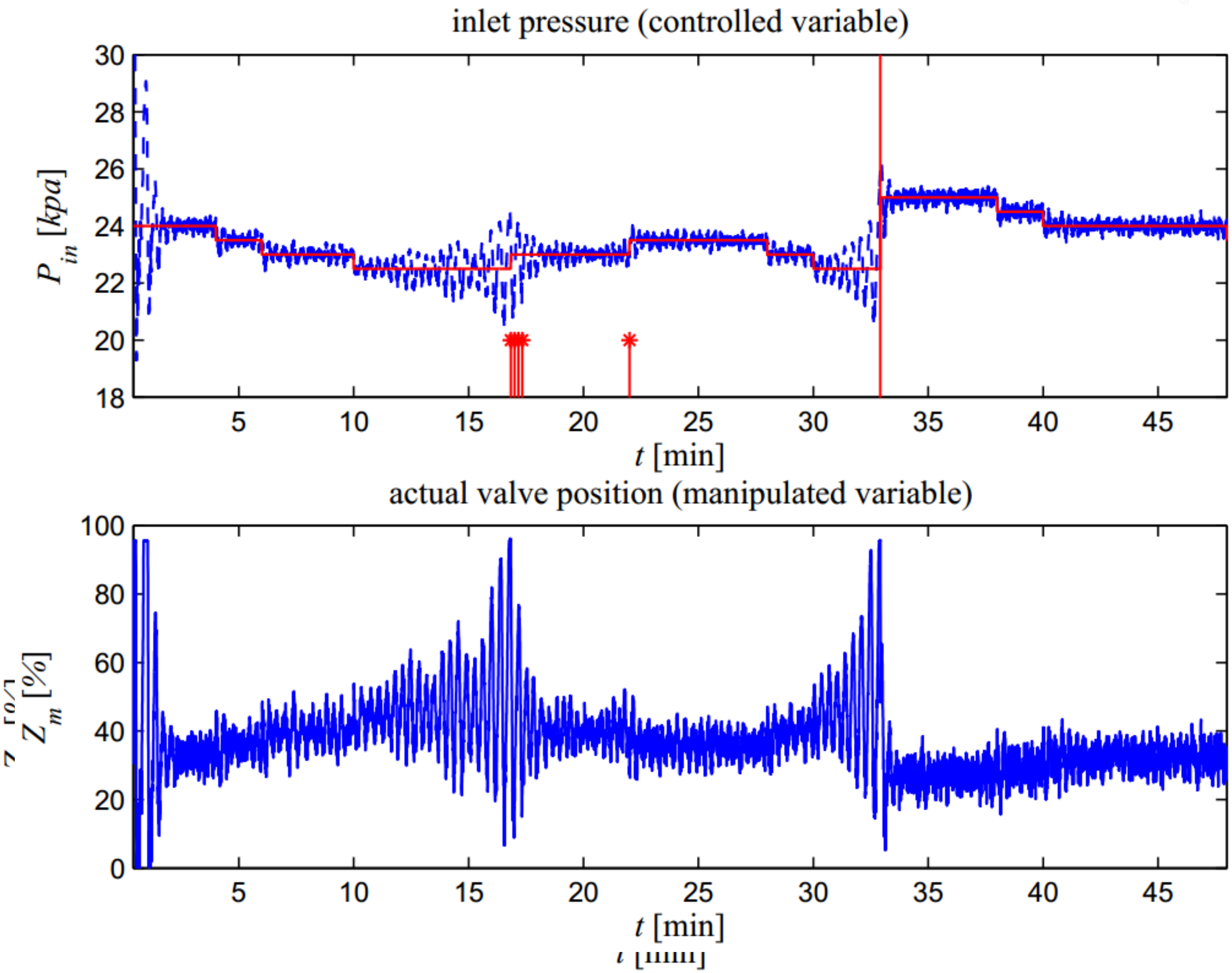
Moves to *safer* operating point

Adaptive control stabilizes under new operating conditions

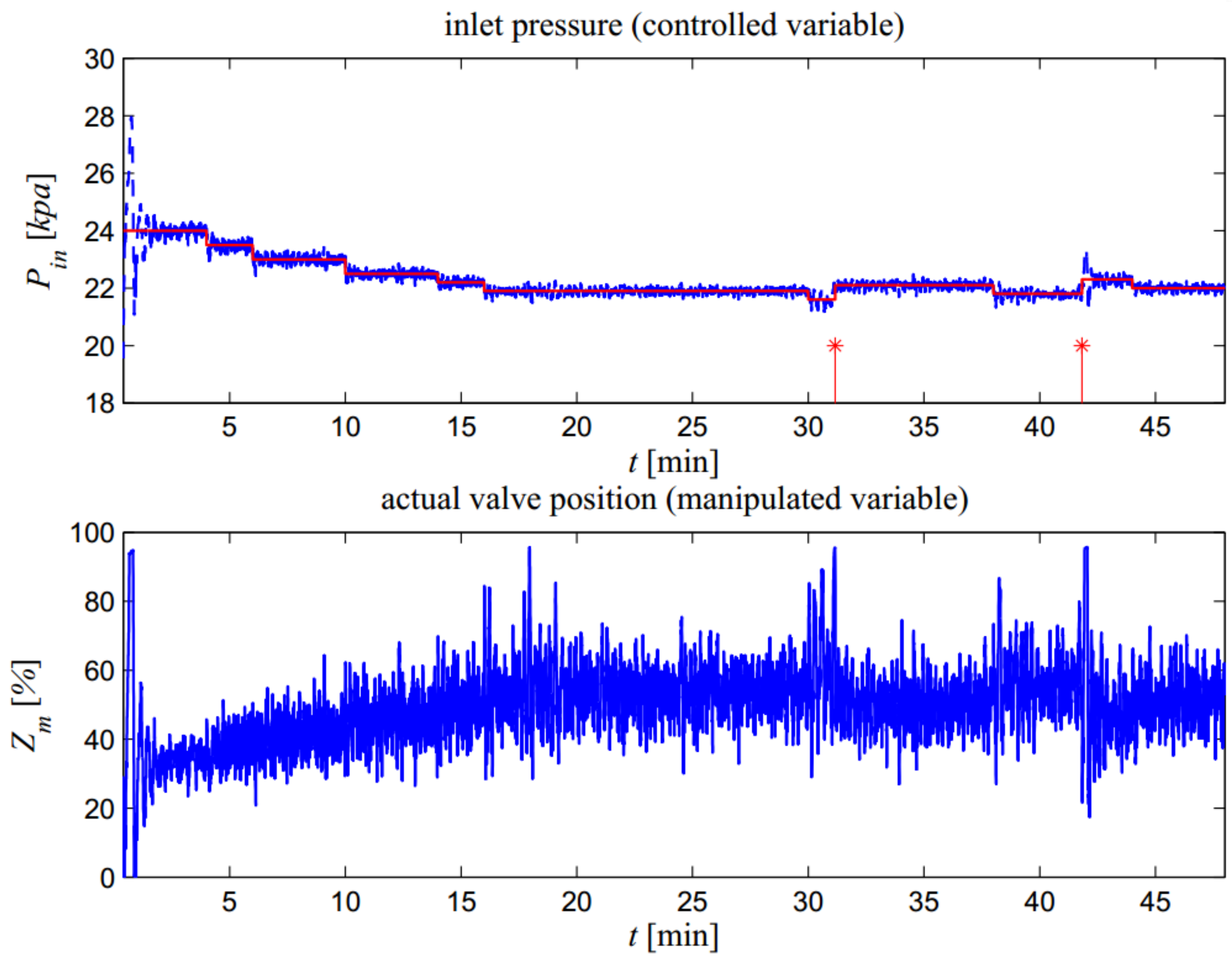
What happens if the baseline controller is poorly tuned?



Poorly tuned PI control as baseline: Adaptation is OFF



Poorly tuned PI control as baseline: Adaptation is ON



Desired closed-loop performance is recovered!

Comparison

Large is good

Case	Mean valve opening	ISE
Bad baseline + adaptation OFF	38,45 %	6,2
Bad baseline + adaptation ON	50,42%	0,76
Good baseline + adaptation ON	53,23%	0,64

Small is good

$$ISE = \int e^2 dt$$

Take home message

- Our 2-layered anti-slug control system works very well in practice

- The interaction between the two layers create a very nice synergy:

  ✓ Setpoint changes triggered by the supervisor makes the adaptation work well

  ✓ A well functioning adaptive control makes it possible to safely operate at large valve openings, thus maximizing production

Take home message

- This work resulted in a patent application
- Cooperation agreement with industrial partner on the way
- Industrial pilot project (hopefully) coming soon

Presentation outline

Introduction

Near-optimal operation of uncertain batch systems

- ✓ Chapters 7 and 8

Optimal operation of energy storage systems

- ✓ Chapters 2, 3 and 4

Optimal operation of dynamic systems at their stability limit: anti-slug control system for oil production optimization

- ✓ Chapters 5 and 6

Concluding remarks

Concluding remarks

We have seen different strategies for near-optimal operation under uncertainty:

- Null-space method for batch processes
- Simplified optimization scheme of energy storage systems based on a hierarchical control structure
- Intelligent adaptive anti-slug control system for oil production maximization

Thank you for your attention

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Not included in the presentation

Ch. 4: Dynamic online optimization of a house heating system in a fluctuating energy price scenario.

Ch. 6: A comparison between Internal Model Control, optimal PIDF and robust controllers for unstable flow in risers.

Ch. 7: Neighbouring-Extremal Control for Steady-State Optimization Using Noisy Measurements.