Feedback:

The simple and best solution.

Applications to self-optimizing control and stabilization of new operating regimes

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Abstract

- Feedback: The simple and best solution
- Applications to self-optimizing control and stabilization of new operating regimes
- Sigurd Skogestad, NTNU, Trondheim, Norway
- Most chemical engineers are (indirectly) trained to be “feedforward thinkers" and they immediately think of “model inversion" when it comes doing control. Thus, they prefer to rely on models instead of data, although simple feedback solutions in many cases are much simpler and certainly more robust.

  The seminar starts with a simple comparison of feedback and feedforward control and their sensitivity to uncertainty. Then two nice applications of feedback are considered:

  1. Implementation of optimal operation by "self-optimizing control". The idea is to turn optimization into a setpoint control problem, and the trick is to find the right variable to control. Applications include process control, pizza baking, marathon running, biology and the central bank of a country.

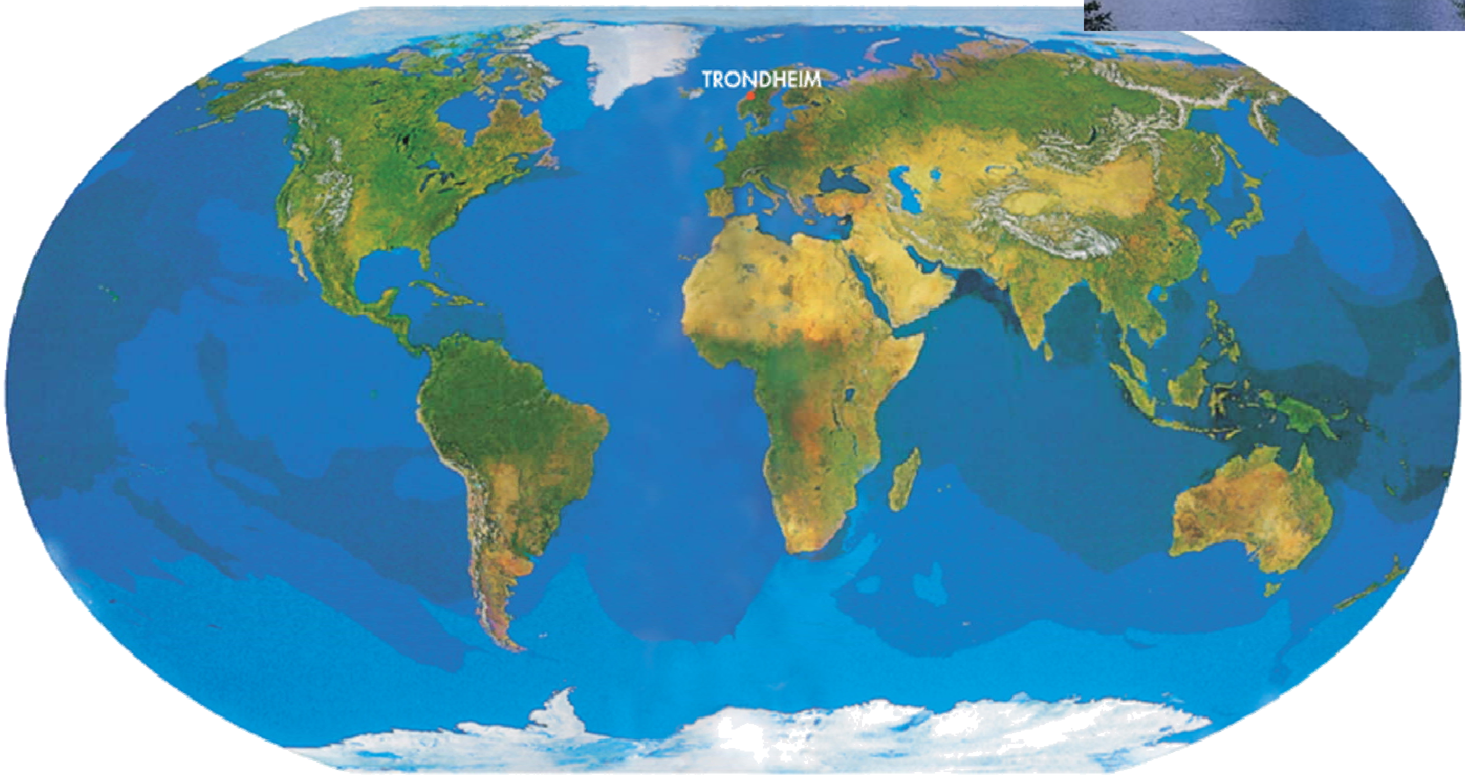
  2. Stabilization of desired operating regimes. Here feedback control can lead to completely new and simple solutions. One example would be stabilization of laminar flow at conditions where we normally have turbulent flow. I the seminar a nice application to anti-slug control in multiphase pipeline flow is discussed.

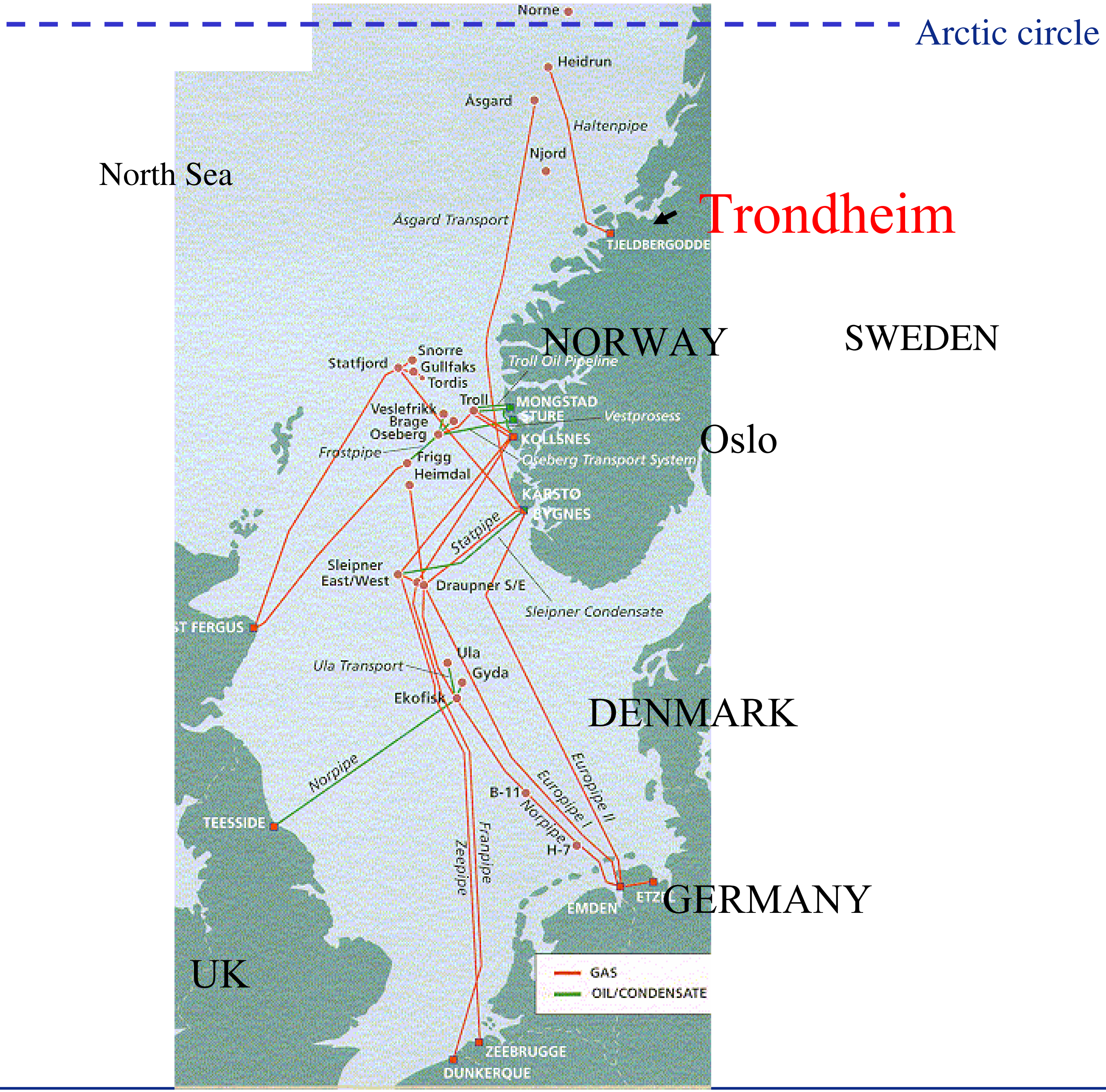
Outline

- About Trondheim
- I. Why feedback (and not feedforward) ?
- II. Self-optimizing feedback control: What should we control?
- III. Stabilizing feedback control: Anti-slug control
- Conclusion

- More information:

Trondheim, Norway




Arctic circle
Norne
Heidrun
Åsgard
Haltenpipe
Njord
North Sea
Åsgard Transport
Trondheim
TJELDBERGODDE
NORWAY
SWEDEN
Troll Oil Pipeline
Snorre
Statfjord
Gullfaks
Tordis
Troll
MONGSTAD
STURE
Vestprosess
Veslefrikk
Brage
Oseberg
KOLLSNES
Oslo
Frostpipe
Frigg
Heimdal
Oseberg Transport System
KÅRSTØ
BYGNES
Statpipe
Sleipner
East/West
Draupner S/E
Sleipner Condensate
T FERGUS
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Ula Transport
Gyda
Ekofisk
DENMARK
Norpipe
Europipe II
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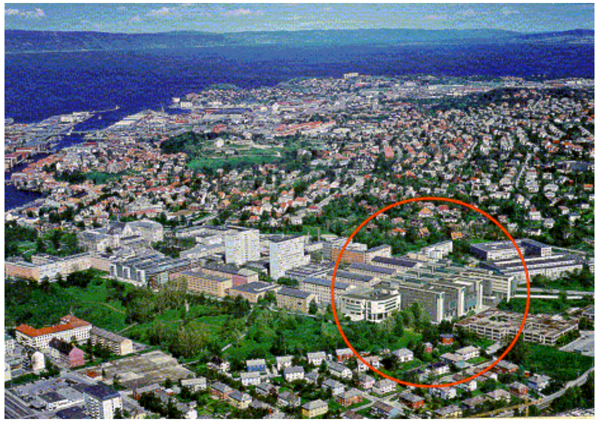

NTNU, Trondheim

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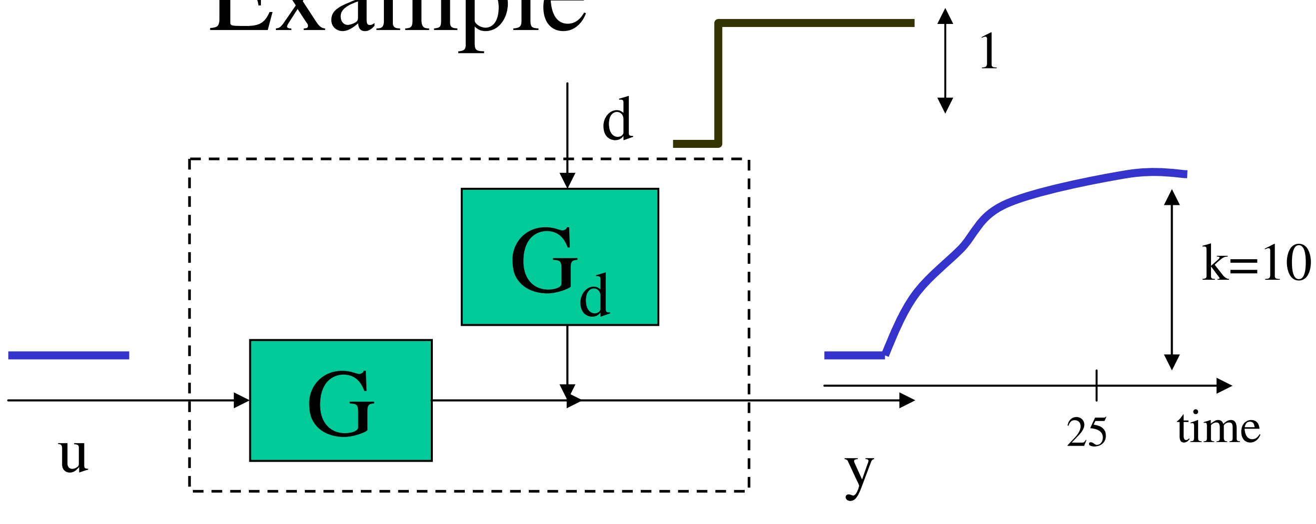
Example



Plant (uncontrolled system)

State space:

- $\frac{dx_1}{dt} = -\frac{1}{\tau}x_1(t) + k \cdot u(t-\theta), \quad \frac{dx_2}{dt} = -0.1x_2(t) + 10 \cdot d(t)$
- $y(t) = x_1(t) + x_2(t)$

Laplace:

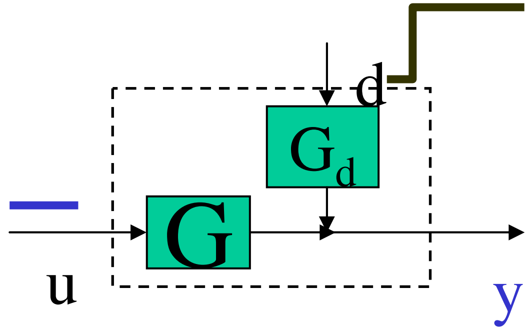
- $G(s) = \frac{k}{\tau s+1}e^{-\theta s}, \quad G_d(s) = \frac{10}{10s+1}$

Nominal parameters ($G = G_d$):

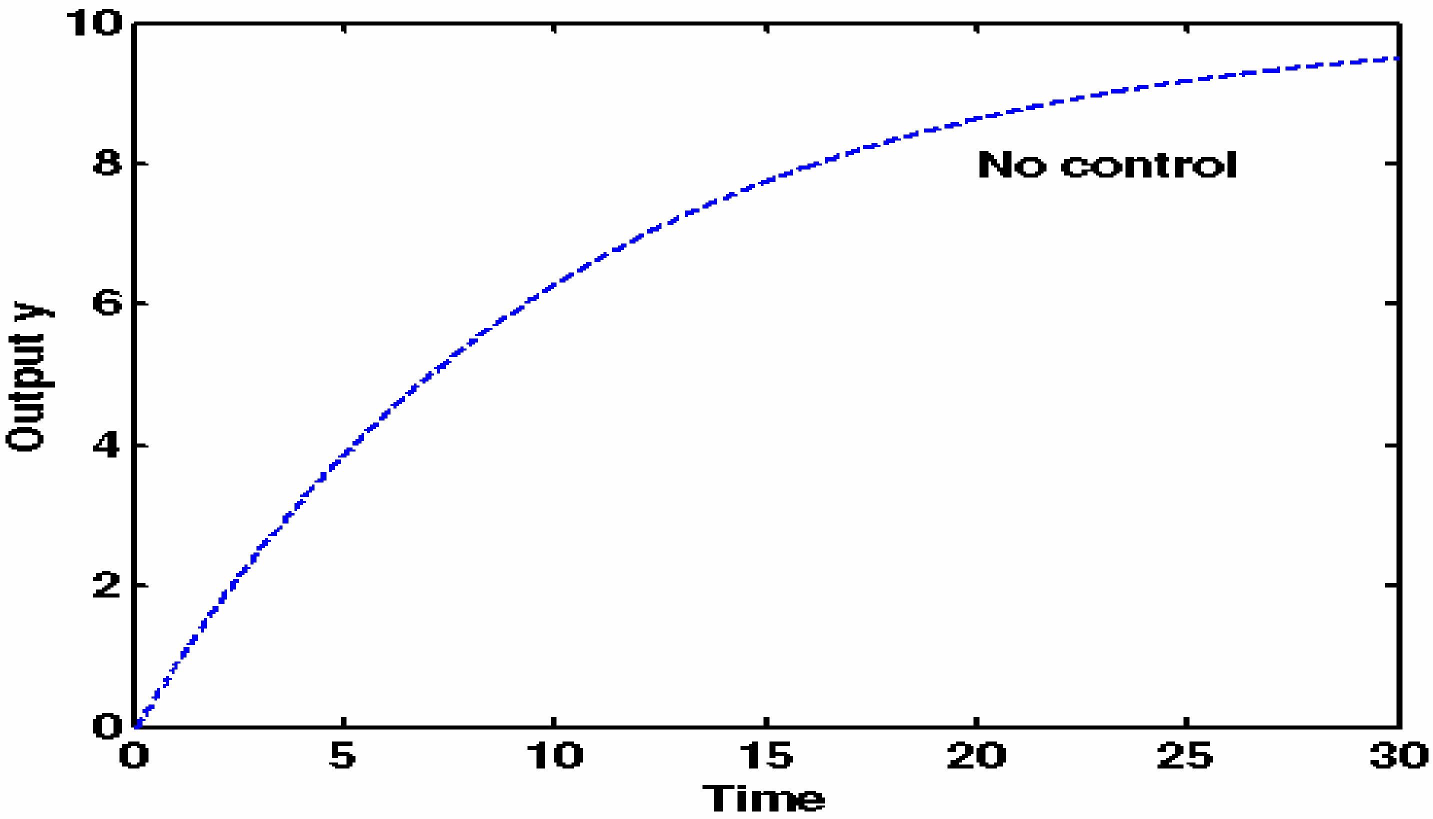
- $k = 10; \quad \tau = 10[s]; \quad \theta = 0$

Consider feedforward and feedback control:

- with changes in G: gain (k), time constant (τ) and input delay (θ)

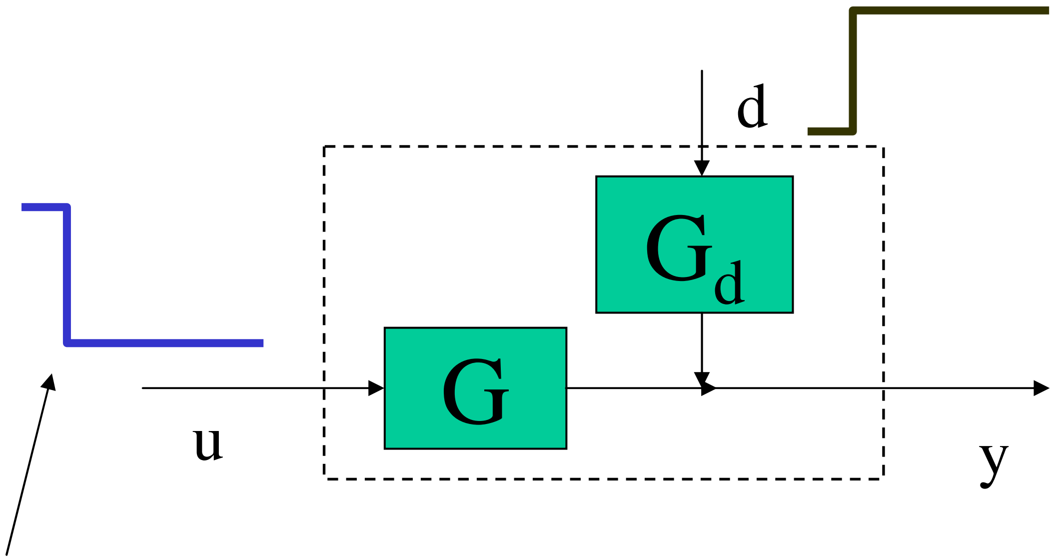


d
G_d
G
u
y



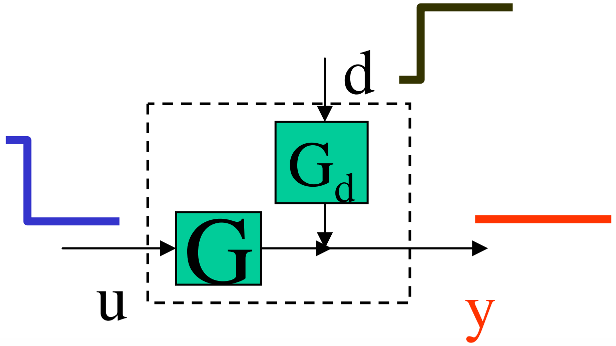
No control
Output y
Time
0
2
4
6
8
10
0
5
10
15
20
25
30

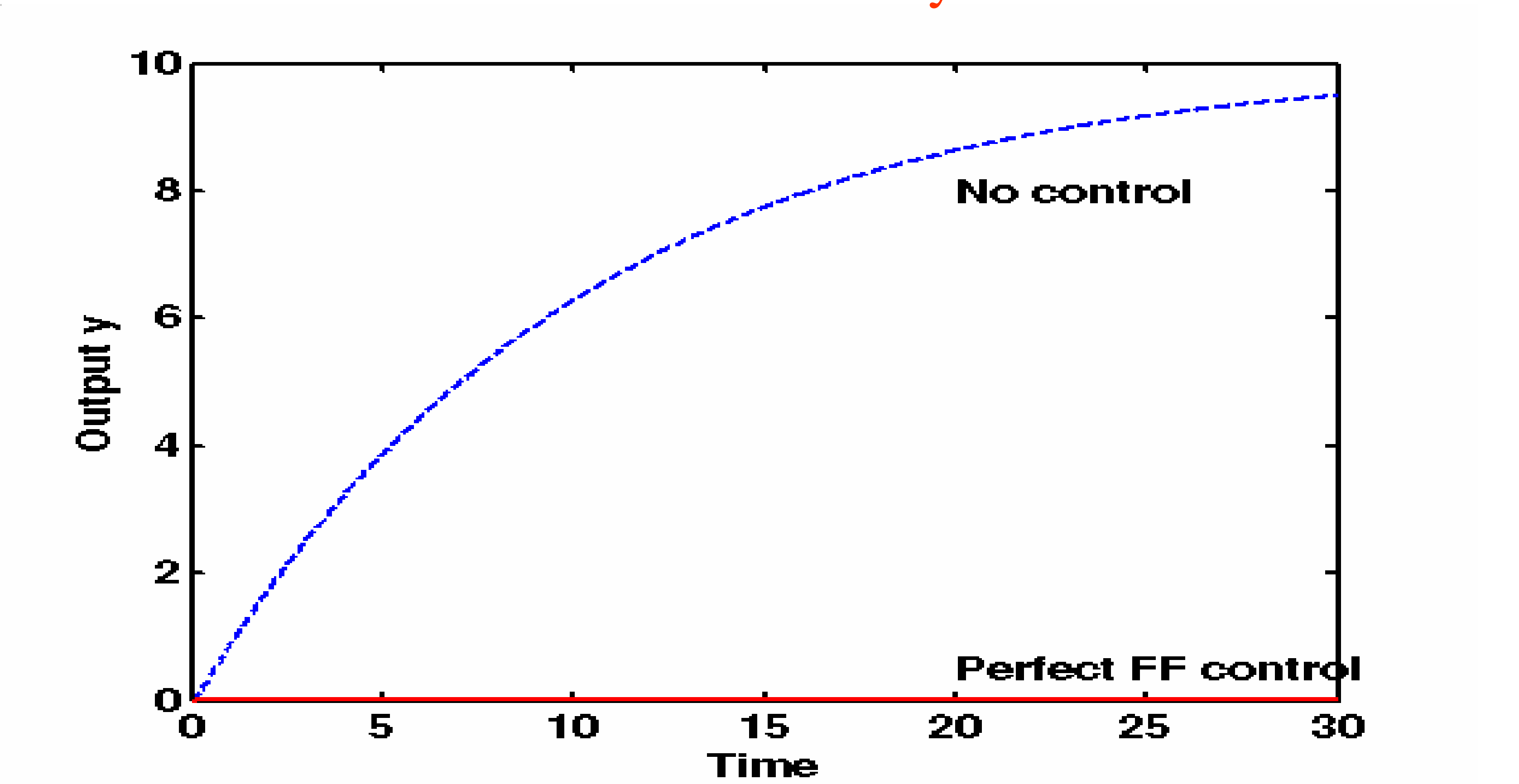
Model-based control = Feedforward (FF) control



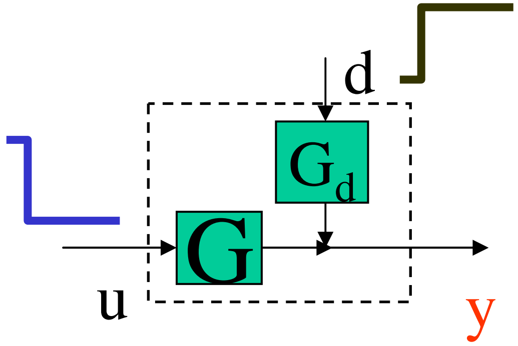
"Perfect" feedforward control: $u = - G^{-1} G_d d$

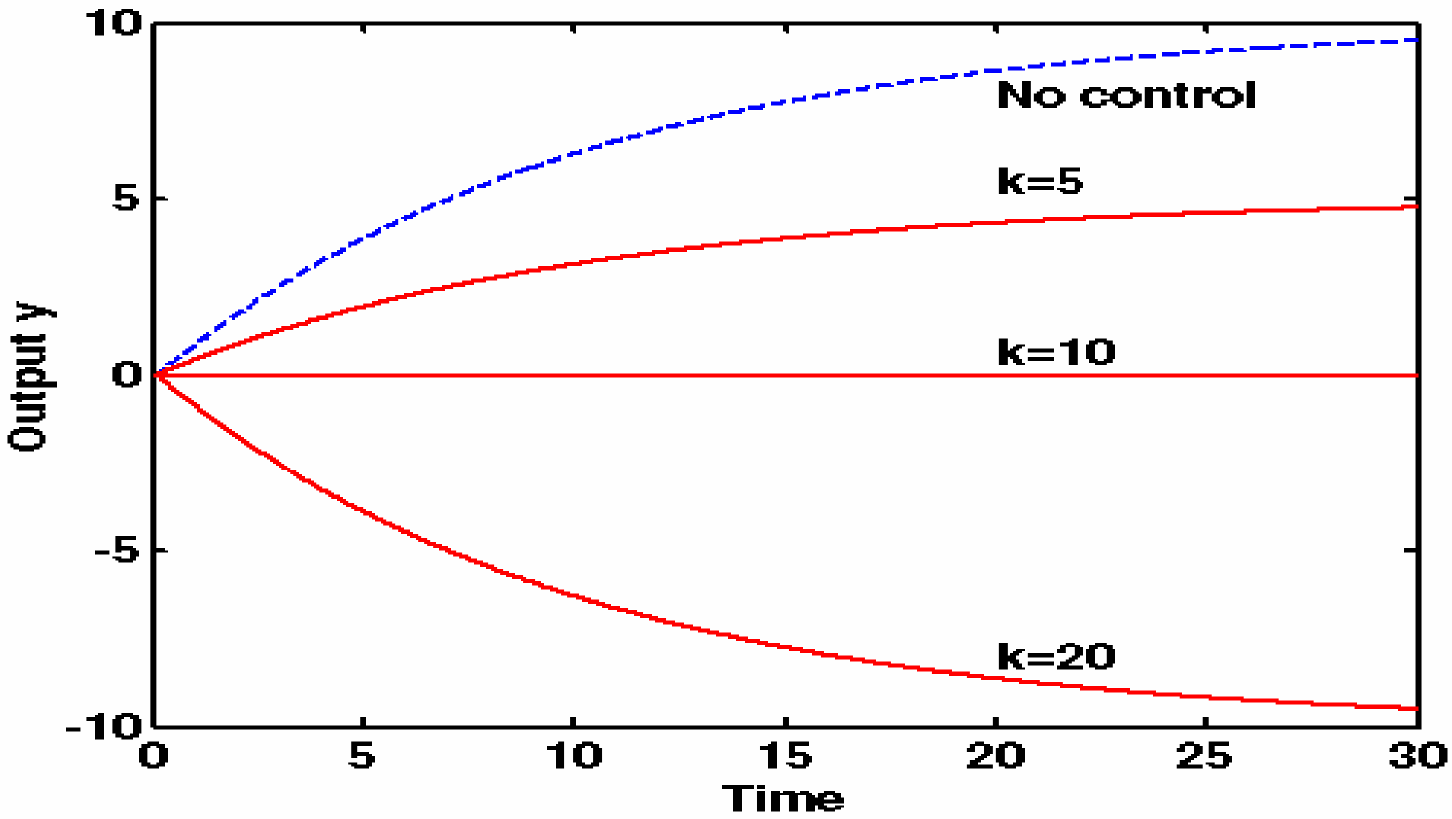
Our case: $G=G_d \rightarrow$ Use $u = -d$



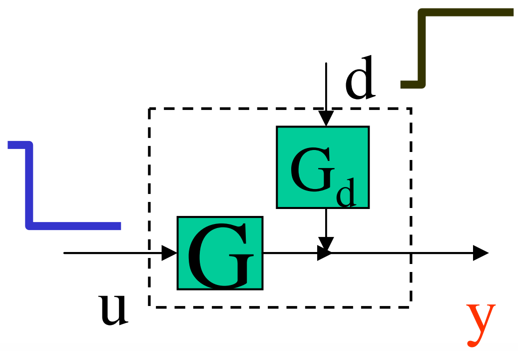


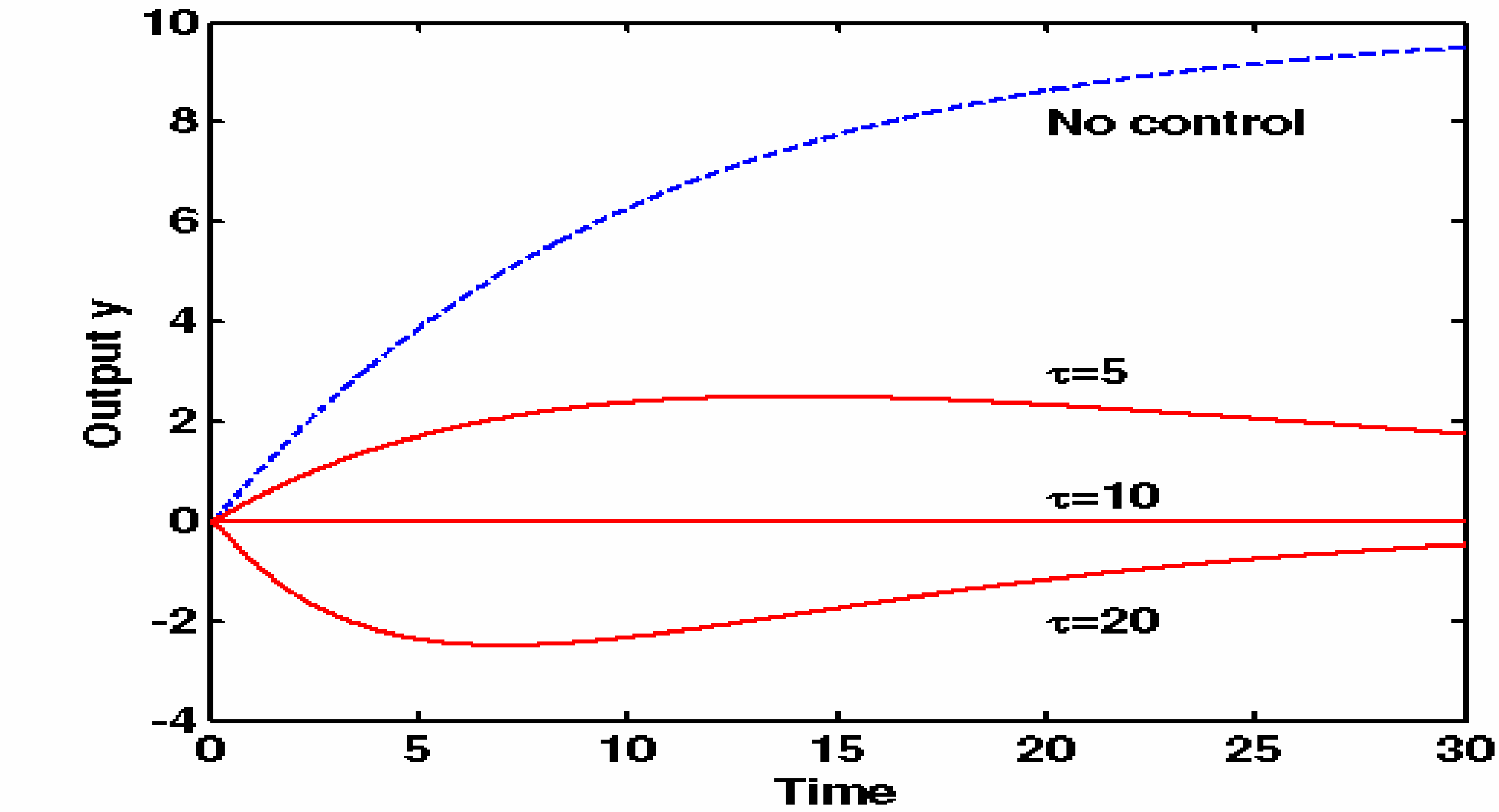
Feedforward control: Nominal (perfect model)



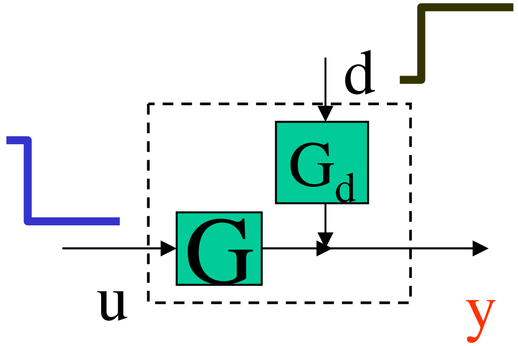


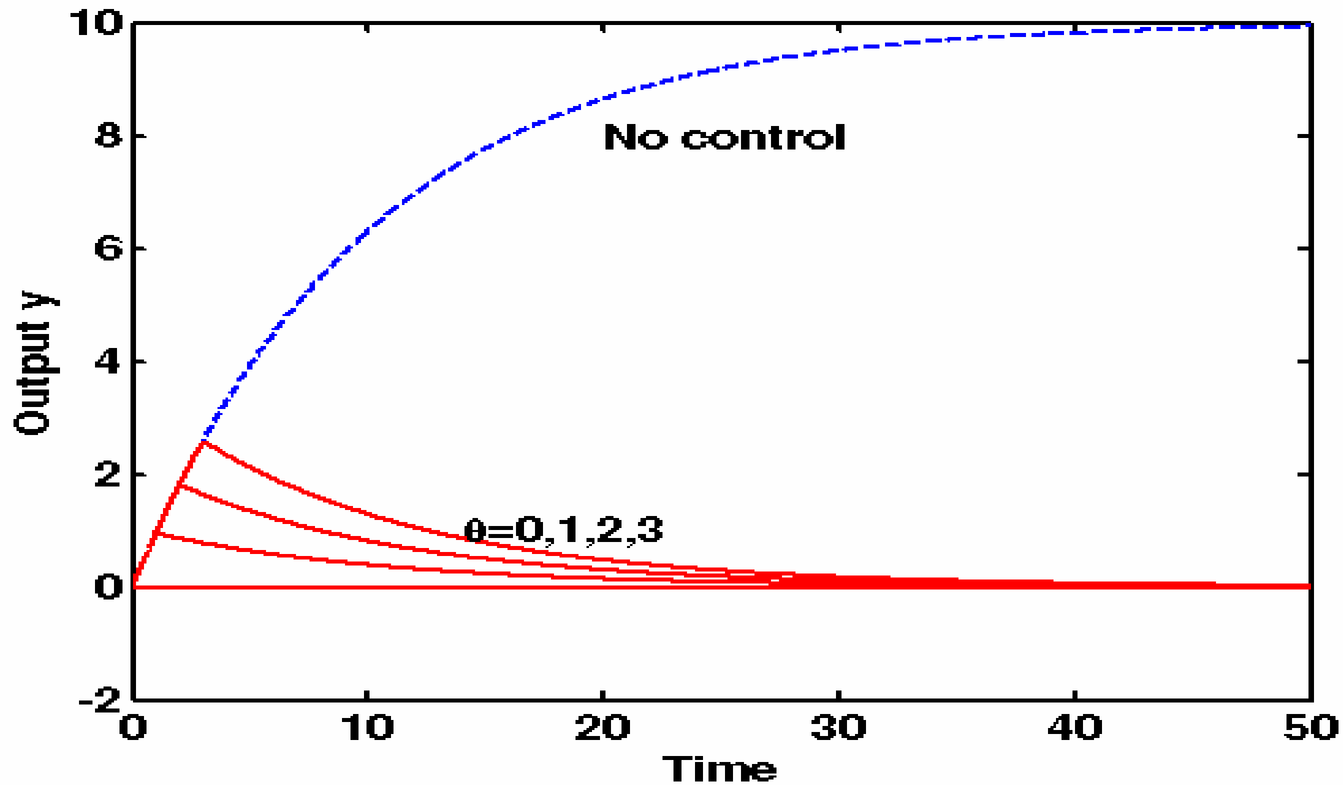
Feedforward: sensitive to gain error





Feedforward: sensitive to time constant error

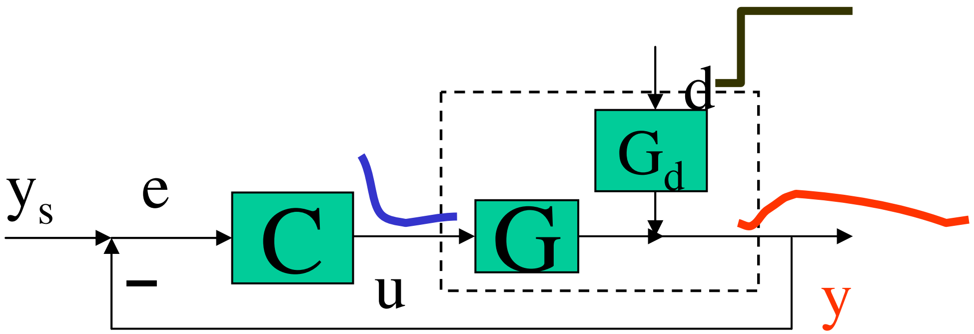




Feedforward: Moderate sensitive to delay

(in G or G_d)

Measurement-based correction = Feedback (FB) control

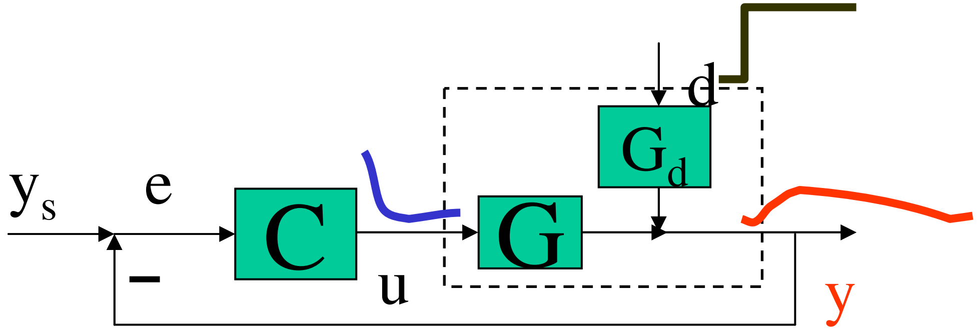


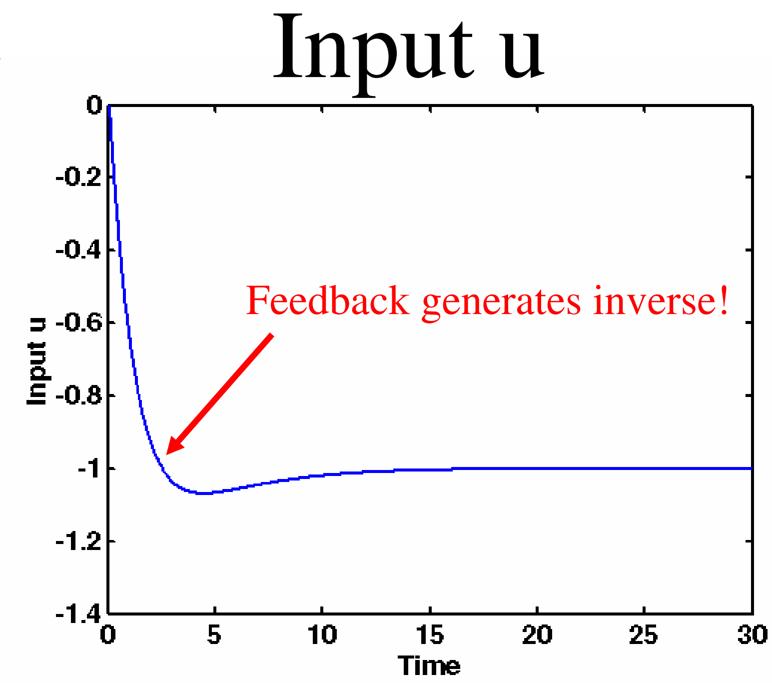
- Most common in industry: C = PID controller.
  Two adjustable tuning parameters: K_c and τ_I

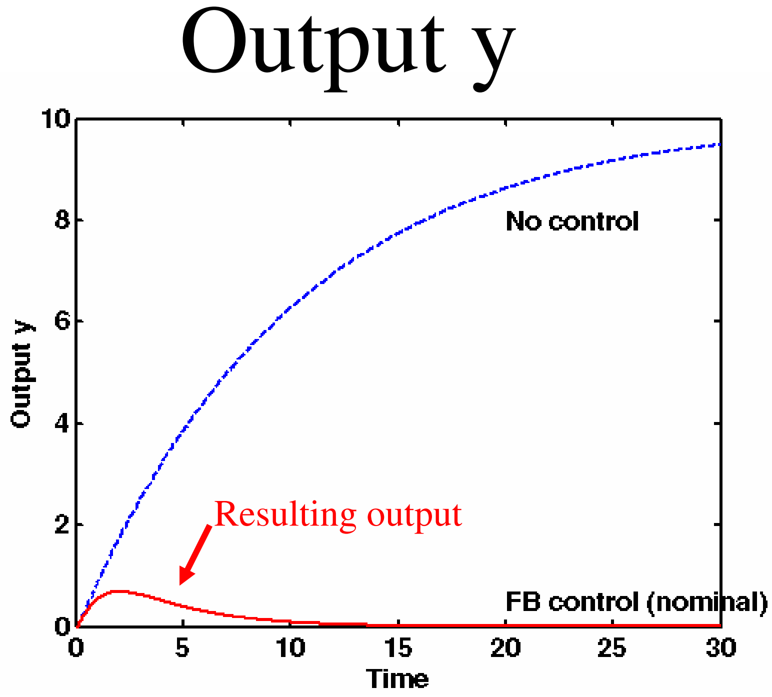
- Exists many tuning rules including Skogestad's (SIMC) tuning rules
  $K_c = \frac{1}{k} \cdot \frac{\tau}{\tau_c+\theta}; \quad \tau_I = \min\{\tau, 4(\tau_c+\theta)\}$

  "Probably the best simple PID tuning rules in the world"

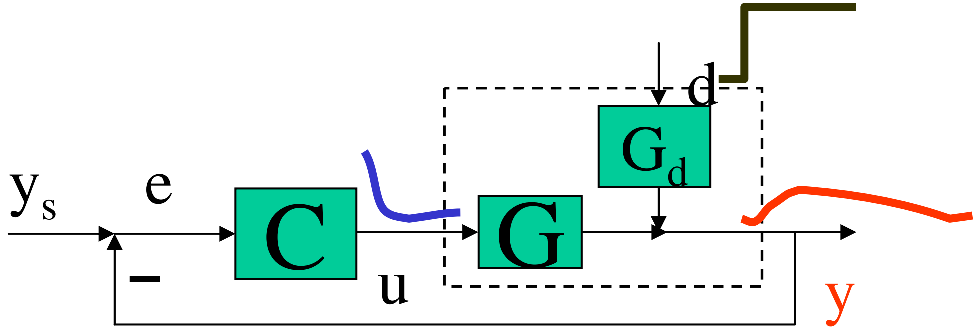
- Example ($k = 10, \tau = 10, \theta = 0$ and $\tau_c = 1$):
  $K_c = \frac{1}{10} \cdot \frac{10}{1} = 1 \quad \tau_I = \min\{10, 4 \cdot 1\} = 4\ [s]$

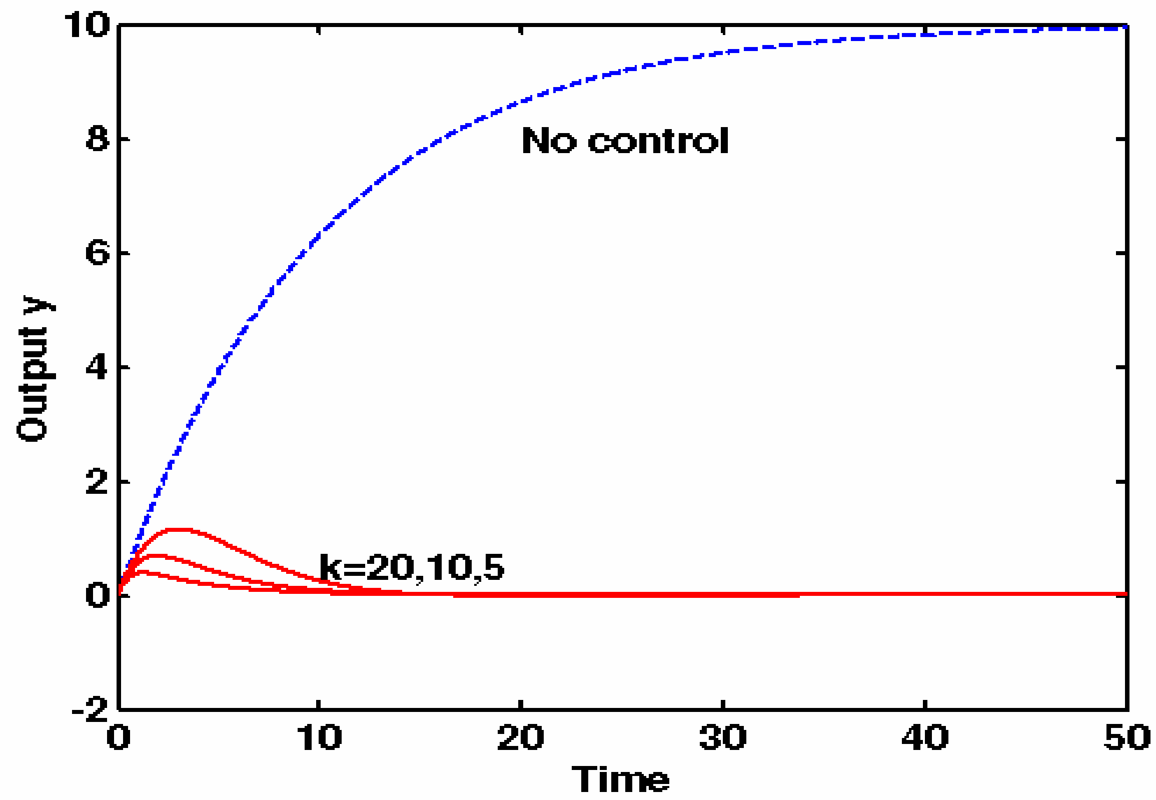




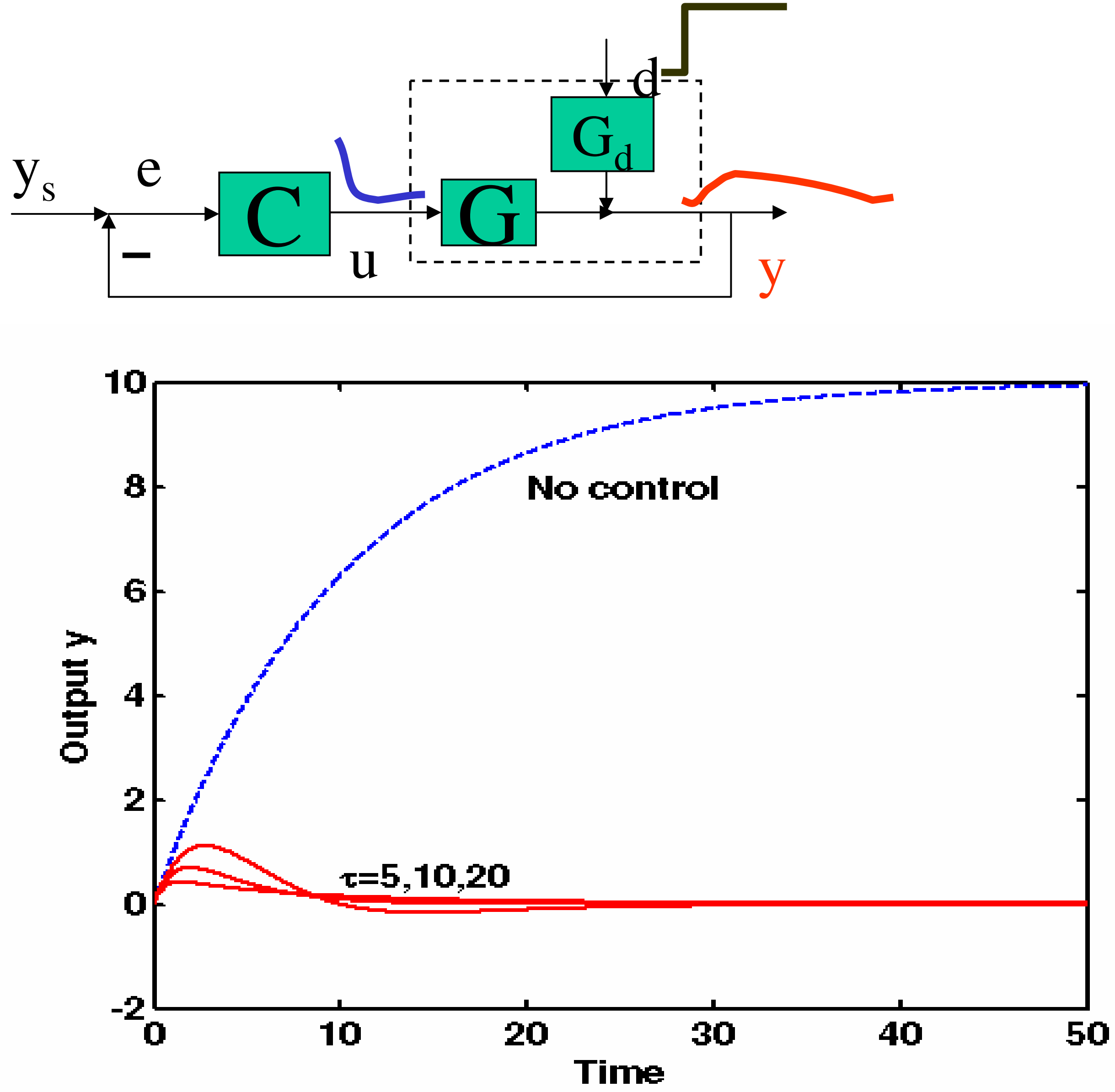


Feedback PI-control: Nominal case

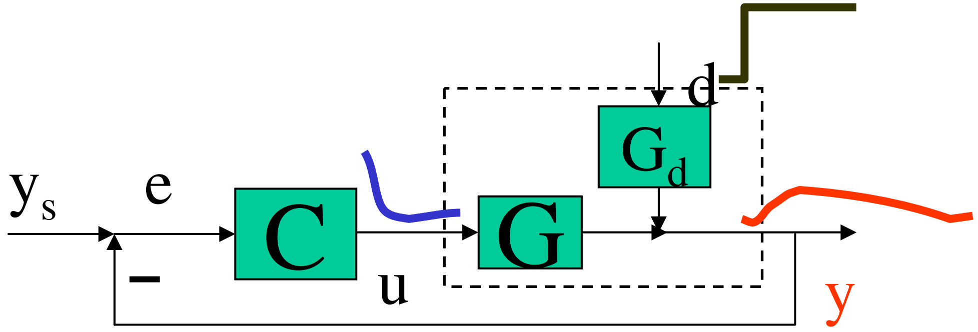


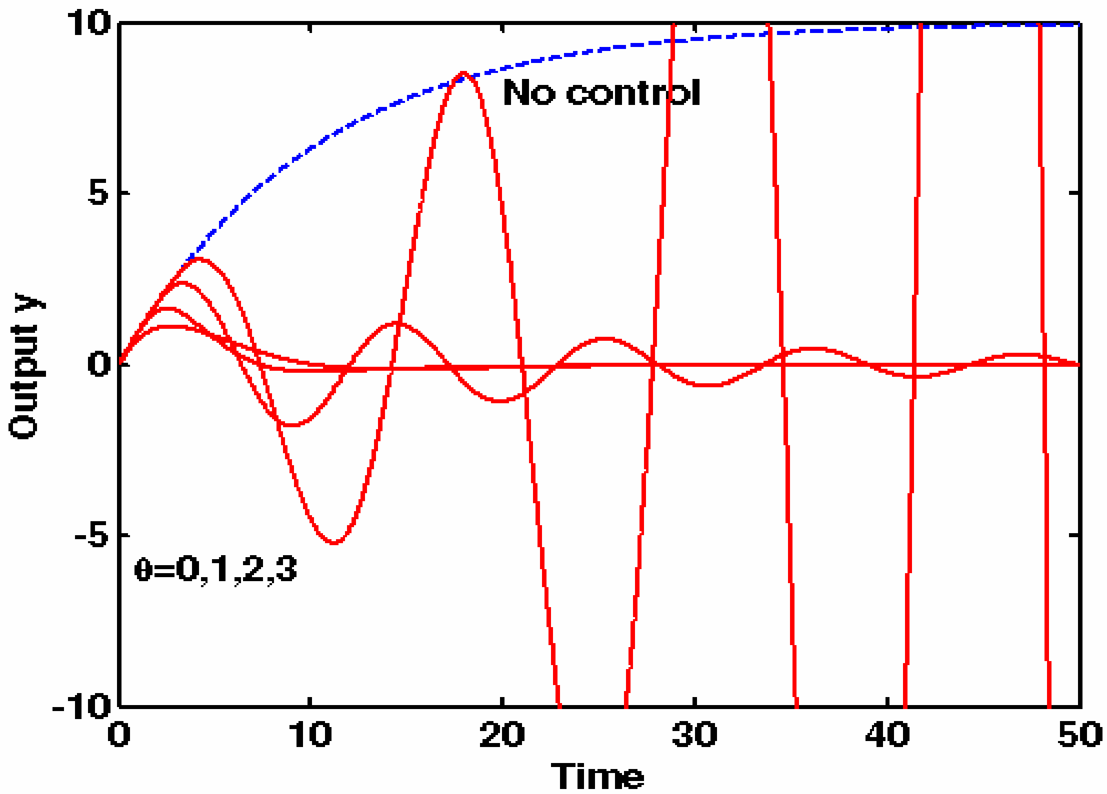


Feedback PI control: insensitive to gain error



Feedback: insenstive to time constant error





Feedback control: sensitive to time delay

Comment

- Time delay error in disturbance model (G_d): No effect (!) with feedback (except time shift)
- Feedforward: Similar effect as time delay error in G

Conclusion: Why feedback? (and not feedforward control)

- Simple: High gain feedback!
- Counteract unmeasured disturbances
- Reduce effect of changes / uncertainty (robustness)
- Change system dynamics (including stabilization)
- Linearize the behavior
- No explicit model required

- MAIN PROBLEM
- Potential instability (may occur “suddenly”) with time delay/RHP-zero

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Optimal operation (economics)

- Define scalar cost function $J(u_0,d)$
  - u_0: degrees of freedom
  - d: disturbances

- Optimal operation for given d:

$$\min_{u0} \; J(u_0,x,d)$$

subject to:

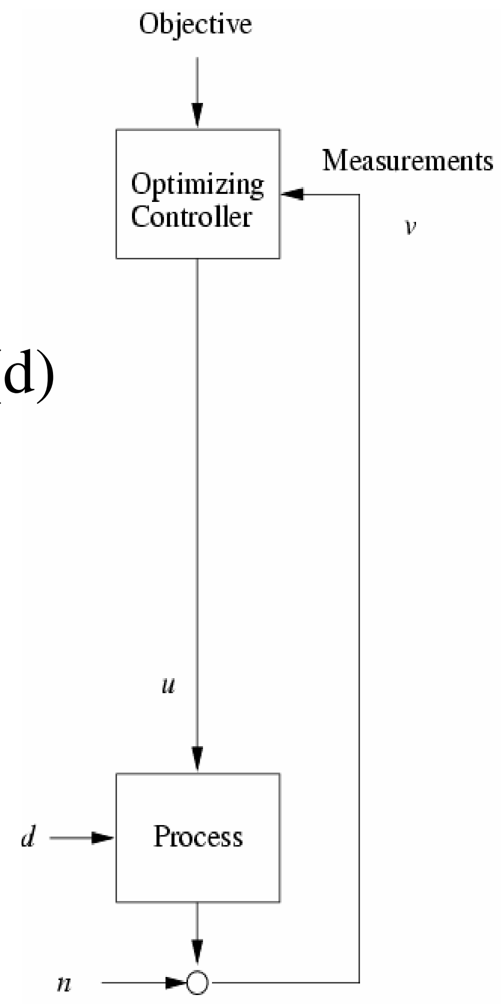
$$f(u_0,x,d) = 0$$

$$g(u_0,x,d) < 0$$

”Obvious” solution: Optimizing control = ”Feedforward”

Estimate d and compute new $u_{opt}(d)$

Probem: Complicated and sensitive to uncertainty



Engineering systems

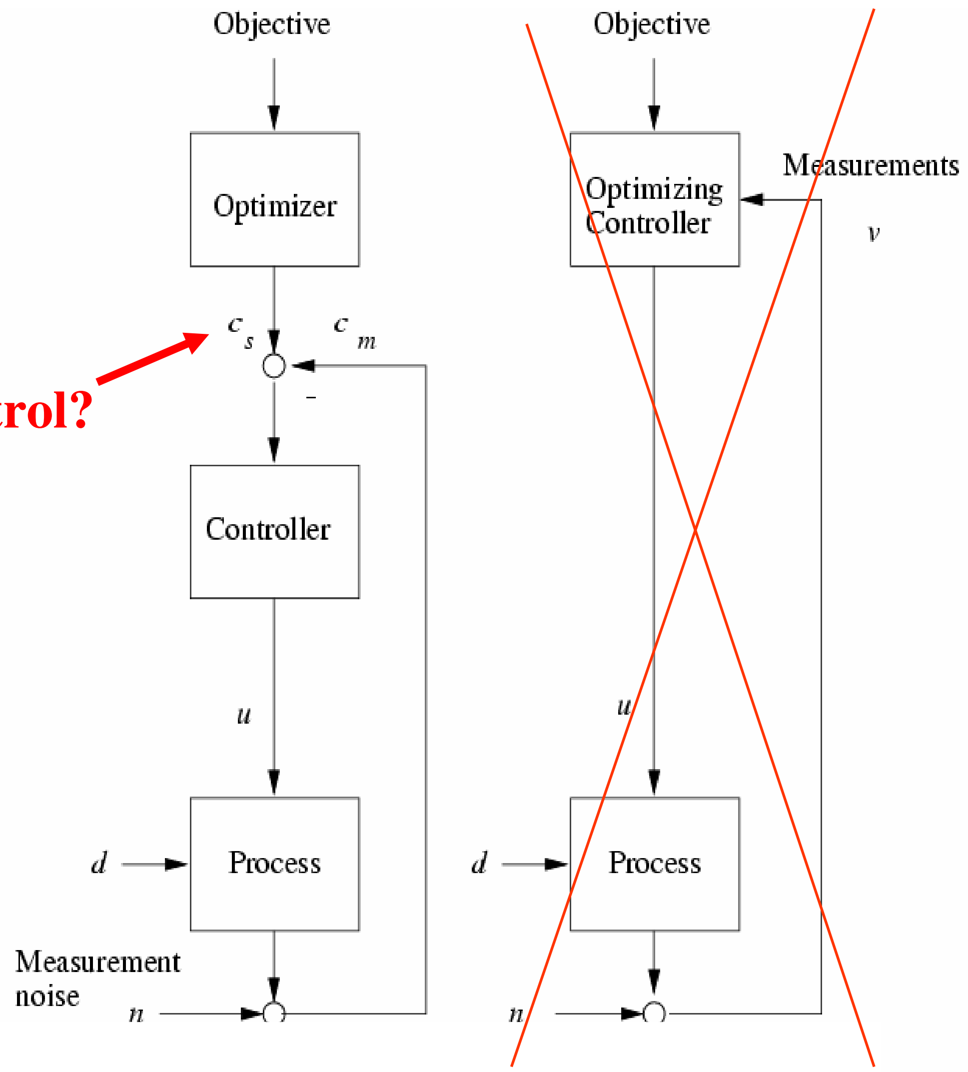
- Most (all?) large-scale engineering systems are controlled using hierarchies of quite simple single-loop controllers
  - Commercial aircraft
  - Large-scale chemical plant (refinery)
- 1000's of loops
- Simple components:

  on-off + P-control + PI-control + nonlinear fixes + some feedforward

Same in biological systems

In Practice: Feedback implementation

Issue:
What should we control?

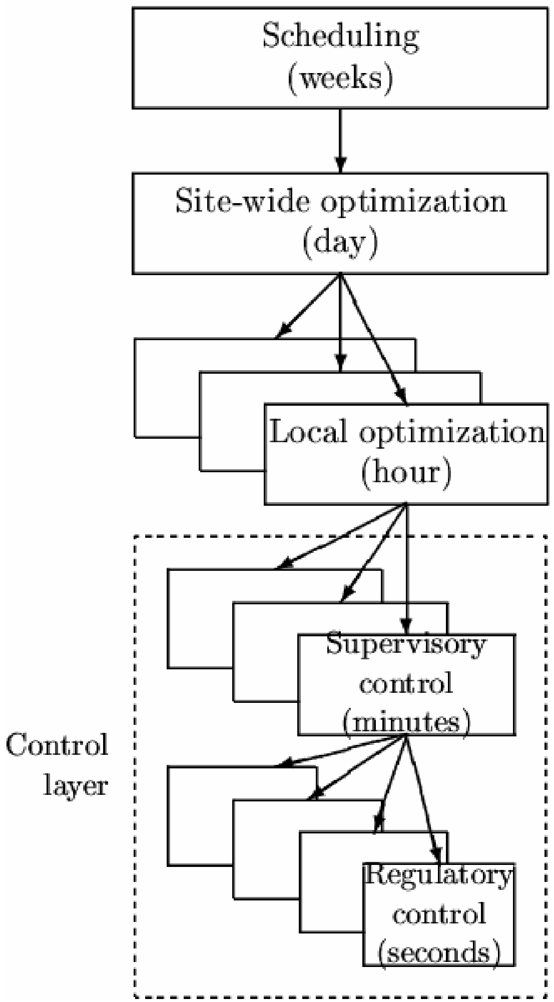


Further layers: Process control hierarchy

RTO

MPC

PID



$y_1 = c$? (economics)

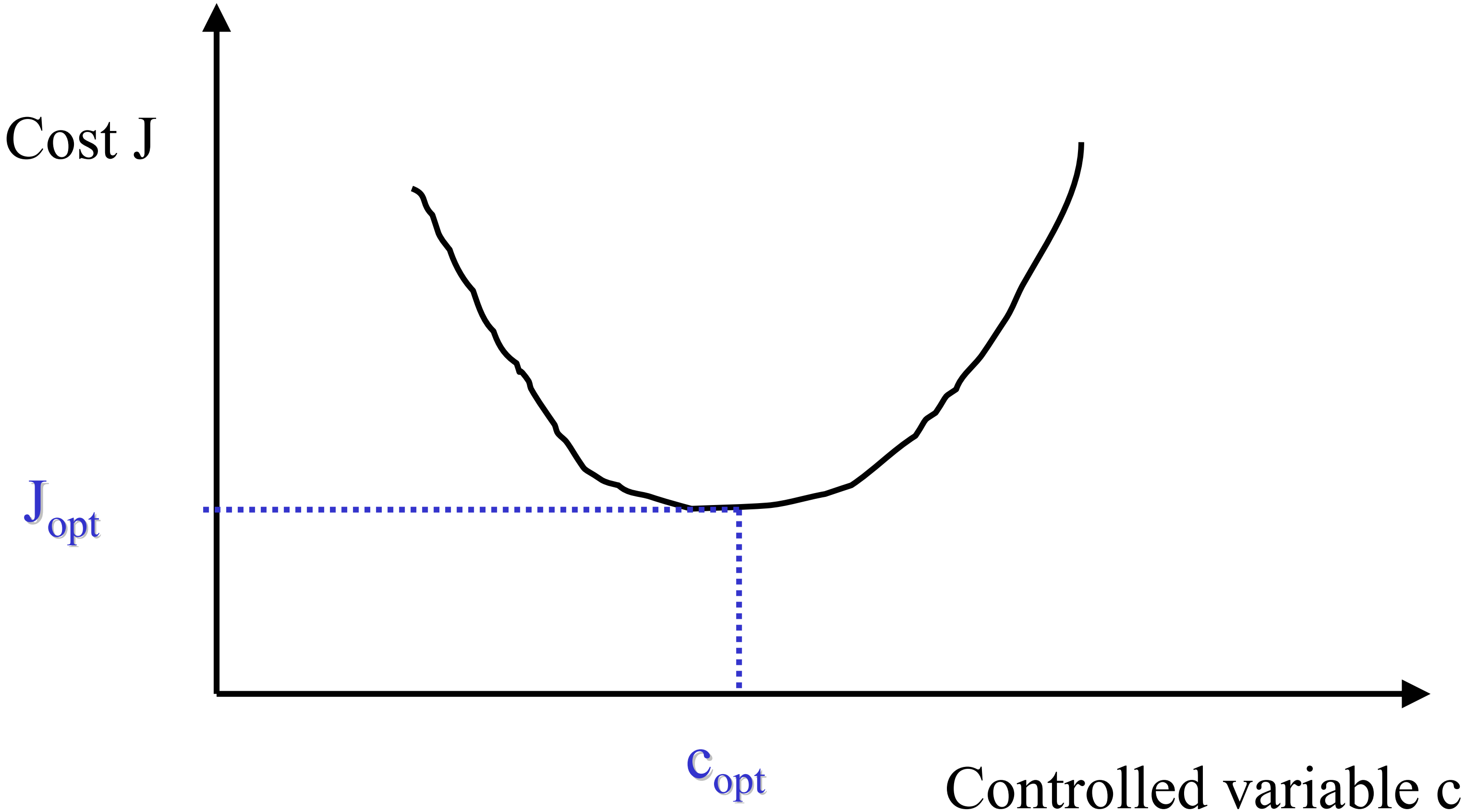
Implementation of optimal operation

- Optimal solution is usually at constraints, that is, most of the degrees of freedom are used to satisfy "active constraints", $g(u_0,d) = 0$

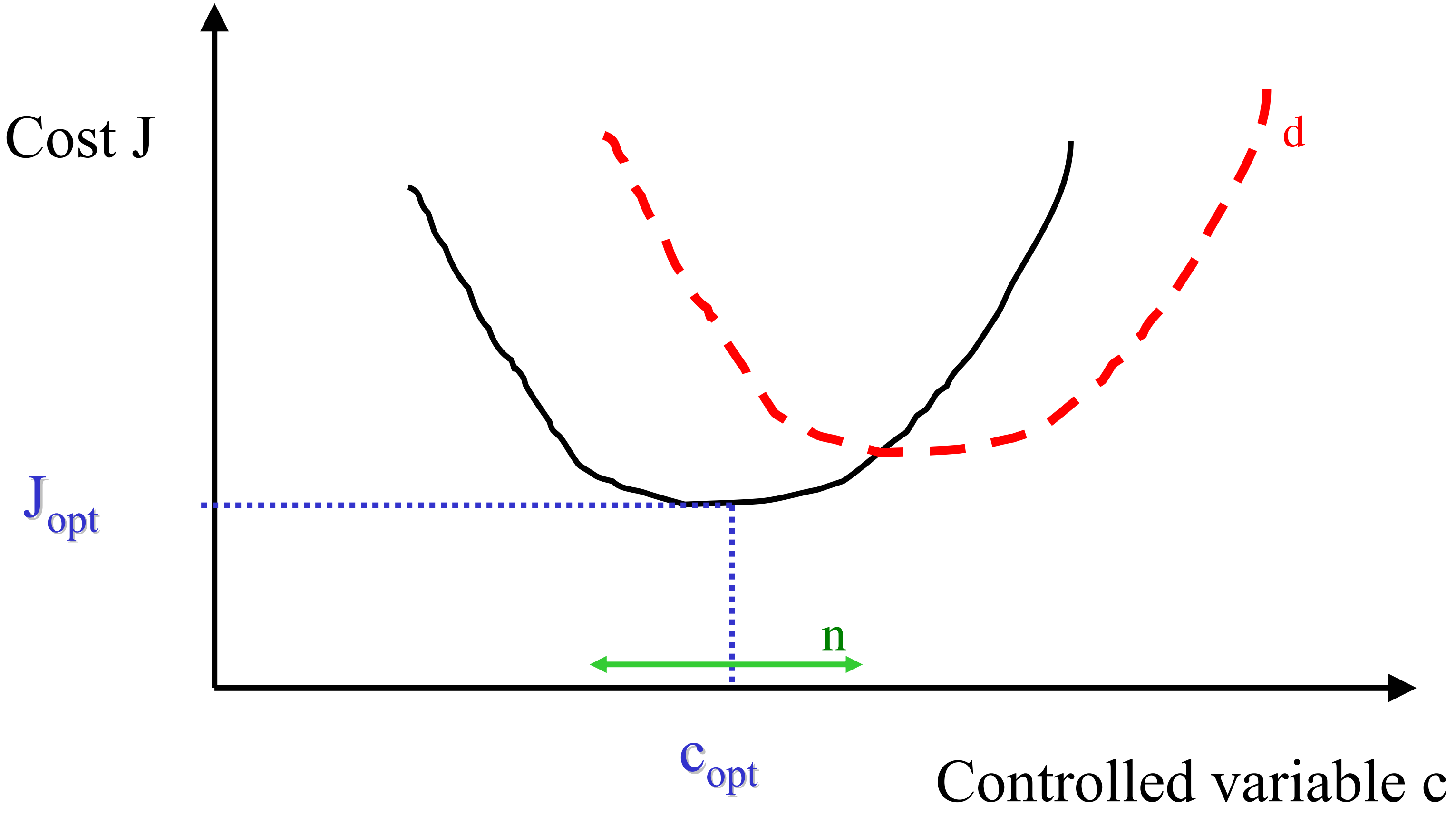
- CONTROL ACTIVE CONSTRAINTS!
  - Implementation of active constraints is usually simple.

- WHAT MORE SHOULD WE CONTROL?
  - We here concentrate on the **remaining unconstrained degrees of freedom.**

Optimal operation



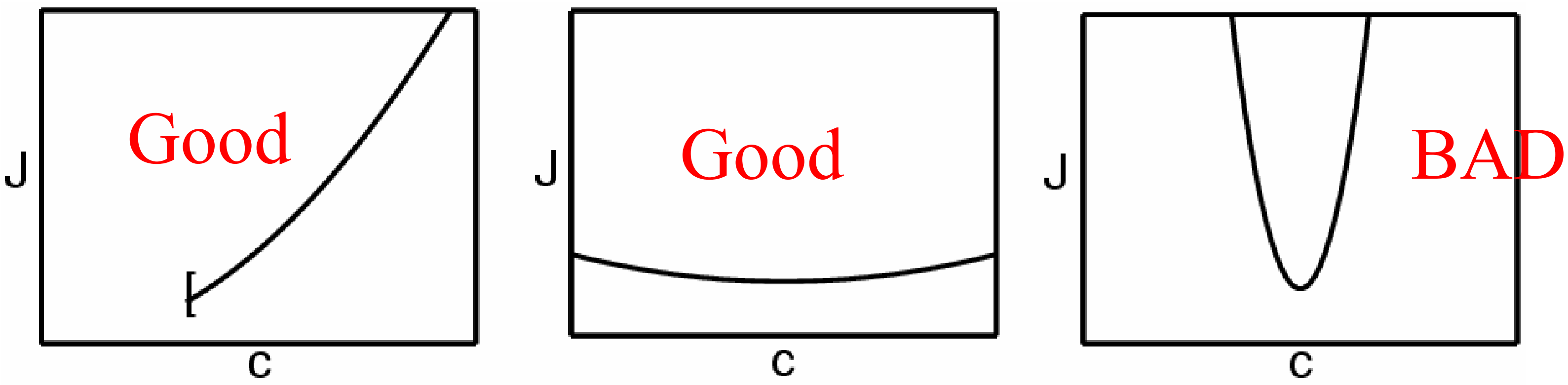
Optimal operation



Two problems:

- 1. Optimum moves because of disturbances d: $c_{opt}(d)$
- 2. Implementation error, $c = c_{opt} + n$

Effect of implementation error



(a) Active constraint control: Implememtation easy

(b) Flat optimum: Implementation easy

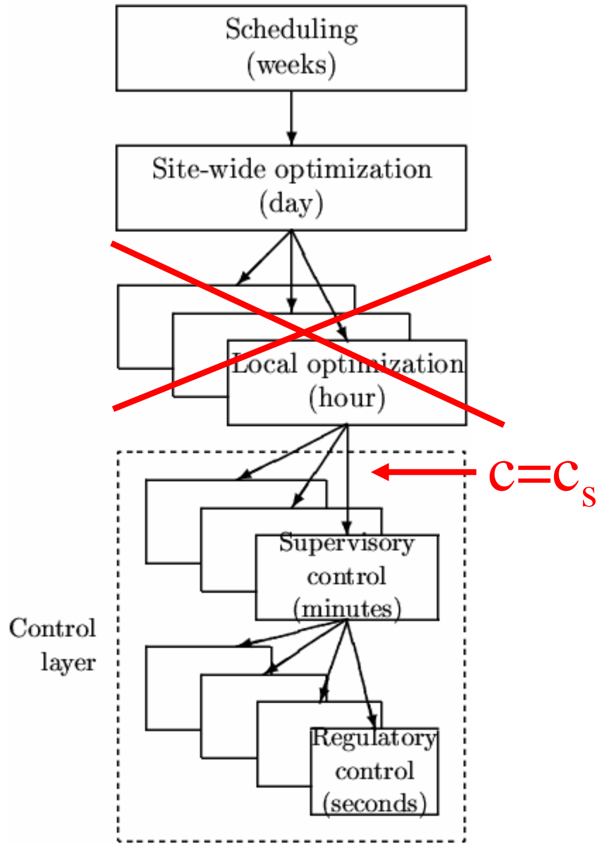
(c) Sharp optimum: Sensitive to implementation erros

Self-optimizing Control

- Define loss:

$$L(u,d) = J(c_s + n, d) - J_{opt}(d)$$

- Self-optimizing Control
  - *Self-optimizing control is when acceptable operation (=acceptable loss) can be achieved using constant set points (c_s) for the controlled variables c (without the need for re-optimizing when disturbances occur).*



Self-optimizing Control – Marathon

- Optimal operation of Marathon runner, J=T
  - Any self-optimizing variable c (to control at constant setpoint)?

Self-optimizing Control – Marathon

- Optimal operation of Marathon runner, J=T
  - Any self-optimizing variable c (to control at constant setpoint)?
    - c_1 = distance to leader of race
    - c_2 = speed
    - c_3 = heart rate
    - c_4 = level of lactate in muscles

Self-optimizing Control – Marathon

- Optimal operation of Marathon runner, J=T
  - Any self-optimizing variable c (to control at constant setpoint)?
    - c_1 = distance to leader of race (Problem: Feasibility for d)
    - c_2 = speed (Problem: Feasibility for d)
    - c_3 = heart rate (Problem: Impl. Error n)
    - c_4 = level of lactate in muscles (Problem: Impl.error n)

Self-optimizing Control – Sprinter

- Optimal operation of Sprinter (100 m), J=T
  - Active constraint control:
    - Maximum speed (”no thinking required”)

Further examples

- Central bank. J = welfare. u = interest rate. c=inflation rate (2.5%)
- Cake baking. J = nice taste, u = heat input. c = Temperature (200C)
- Business, J = profit. c = ”Key performance indicator (KPI), e.g.
  - Response time to order
  - Energy consumption pr. kg or unit
  - Number of employees
  - Research spending

  Optimal values obtained by ”benchmarking”
- Investment (portofolio management). J = profit. c = Fraction of investment in shares (50%)
- Biological systems:
  - ”Self-optimizing” controlled variables c have been found by natural selection
  - Need to do ”reverse engineering” :
    - Find the controlled variables used in nature
    - From this possibly identify what overall objective J the biological system has been attempting to optimize

Candidate controlled variables c for self-optimizing control

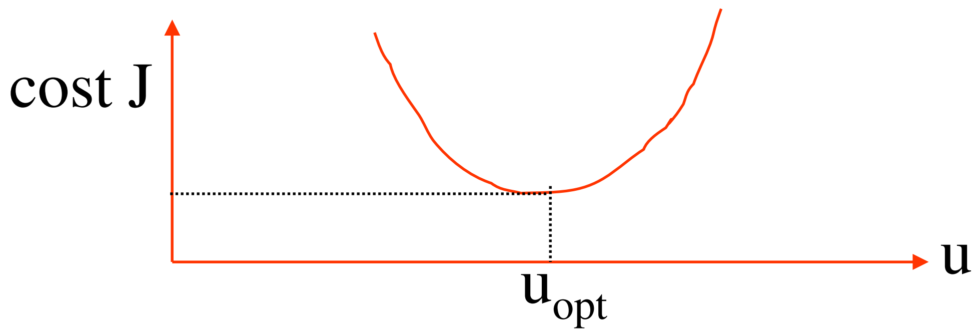
Intuitive

1. The *optimal value* of c should be *insensitive* to disturbances (avoid problem 1)

2. Optimum should be flat (avoid problem 2 – implementation error).
   Equivalently: *Value* of c should be *sensitive* to degrees of freedom u.
   "Want large gain"

   Charlie Moore (1980's): Maximize minimum singular value when selecting temperature locations for distillation

Mathematical: Local analysis



c = G u

$$\text{Loss} = J(u,d) - J_{\text{opt}}(d) = \underbrace{\left(\frac{\partial J}{\partial u}\right)^T_{\text{opt}}}_{=0} (u - u_{\text{opt}}(d))$$

$$. \quad + \frac{1}{2}(u - u_{\text{opt}}(d))^T \underbrace{\left(\frac{\partial^2 J}{\partial u^2}\right)_{\text{opt}}}_{=J_{uu}} (u - u_{\text{opt(d)}}) + \cdots$$

$$. \quad \approx \frac{1}{2}\left(c - c_{\text{opt}}(d)\right)^T G^{-T} J_{uu} G^{-1} (c - c_{\text{opt}}(d))$$

$$. \quad \approx \frac{1}{2}\; G_s^{-T} J_{uu} G_s^{-1} \text{ where } G_s\text{=scaled gain}$$

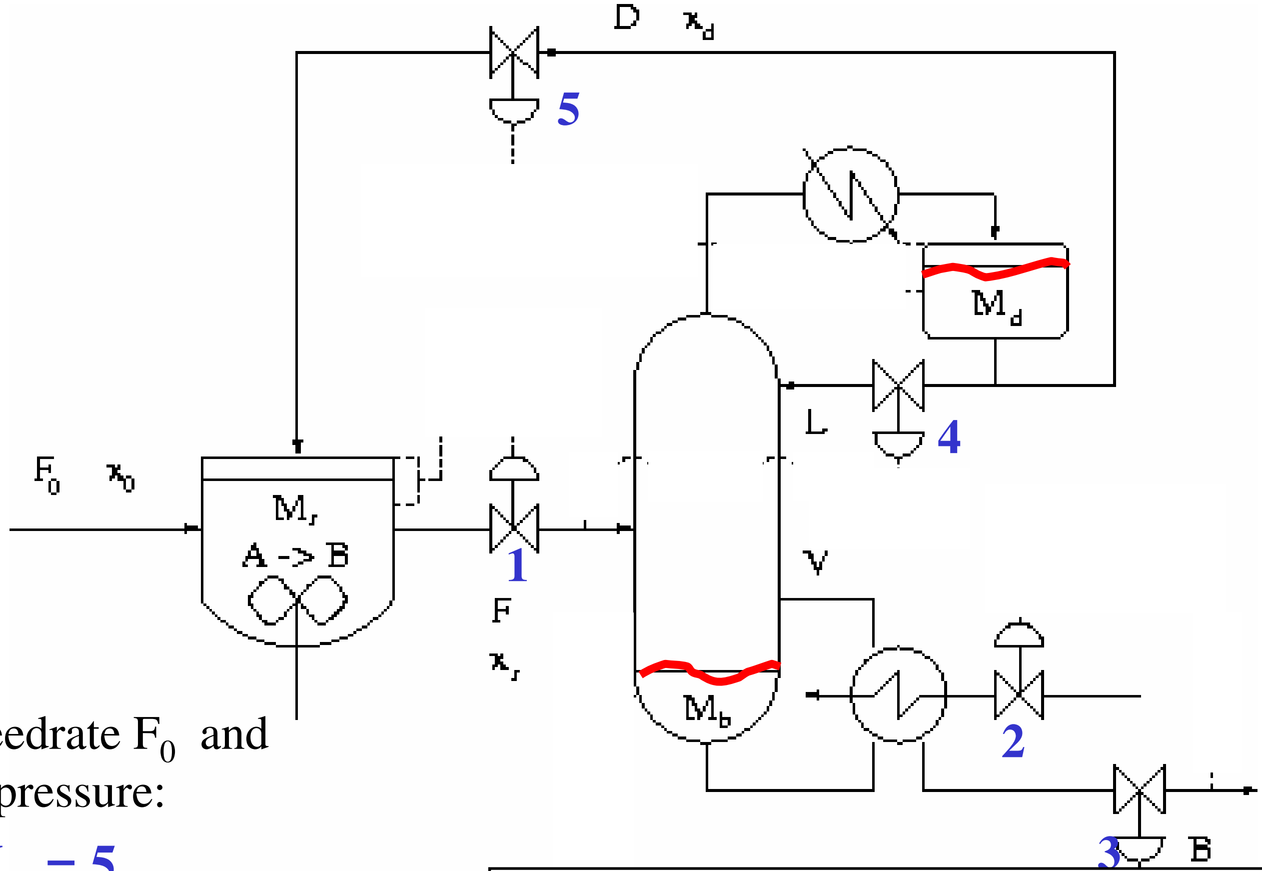
Minimum singular value of scaled gain

Maximum gain rule *(Skogestad and Postlethwaite, 1996): Look for variables that maximize the scaled gain _(G_s) (minimum singular value of the appropriately scaled steady-state gain matrix* G_s *from u to c)*

$$\text{Loss} \approx \frac{\bar{\sigma}(J_{uu})}{2} \cdot \frac{1}{\underline{\sigma}(G)^2}$$

Self-optimizing control: Recycle process

J = V (minimize energy)



Given feedrate F_0 and column pressure:

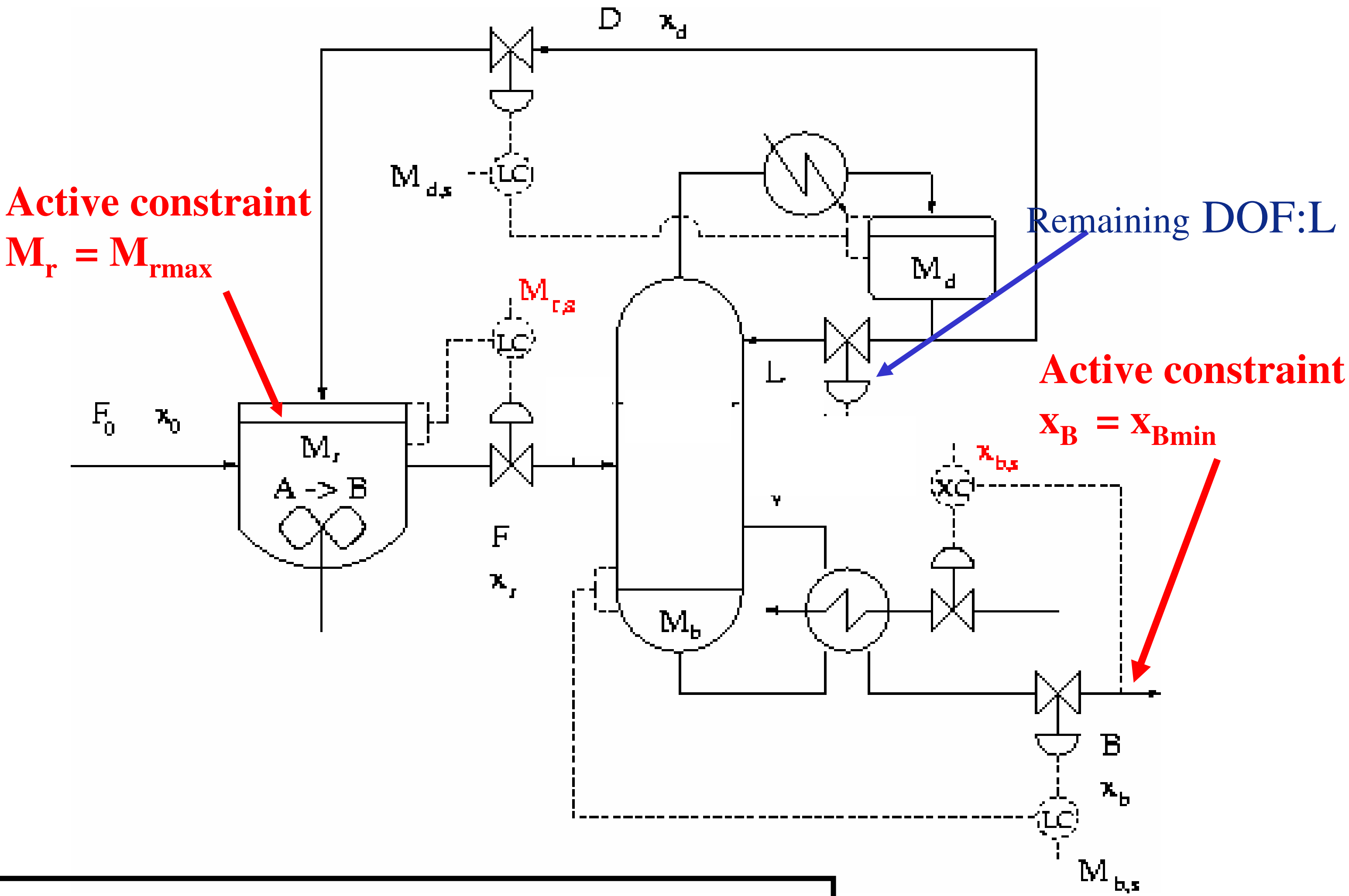
$N_m = 5$

3 economic (steady-state) DOFs

Constraints: Mr < Mrmax, xB > xBmin = 0.98

DOF = degree of freedom

Recycle process: Control active constraints



One unconstrained DOF left for optimization:
What more should we control?

Maximum gain rule: Steady-state gain

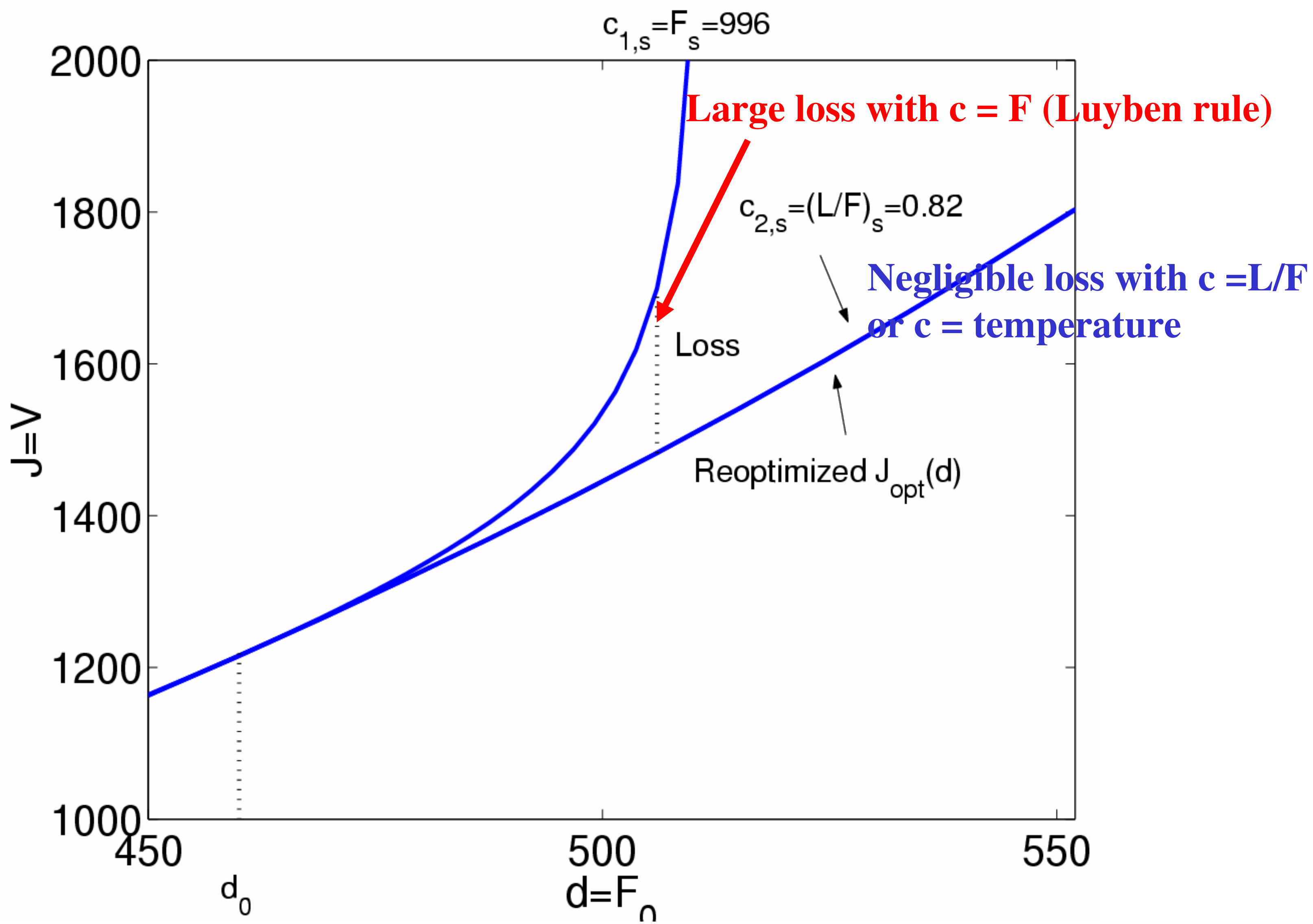
Rank	c	$\|G(0)\| \cdot 10^3$
1	x_D	13.1
2	L/F	8.9
3	D/L	7.7
4	D/V	5.8
5	V/L	4.5
6	B/L	4.1
7	V/F	4.0
8	B/D	3.3
9	L	3.0
10	B/F	2.6
11	D	2.6
12	F/F_0	2.5
13	D/F	2.5
14	F	1.9
15	B/V	0
15	V	0
15	x_r	0
15	B	0

Conventional: Looks good

Luyben snow-ball rule: Not promising economically

Gain from $u = L$ to c with active constraints (M_r and x_B) constant.
Scaling: $\Delta c_i = \max_d |c_{opt,i}(d) - c_{opt,i}(d^*)|) +$ implementation error.
$d = F_0, z_F$.

Recycle process: Loss with constant setpoint, c_s

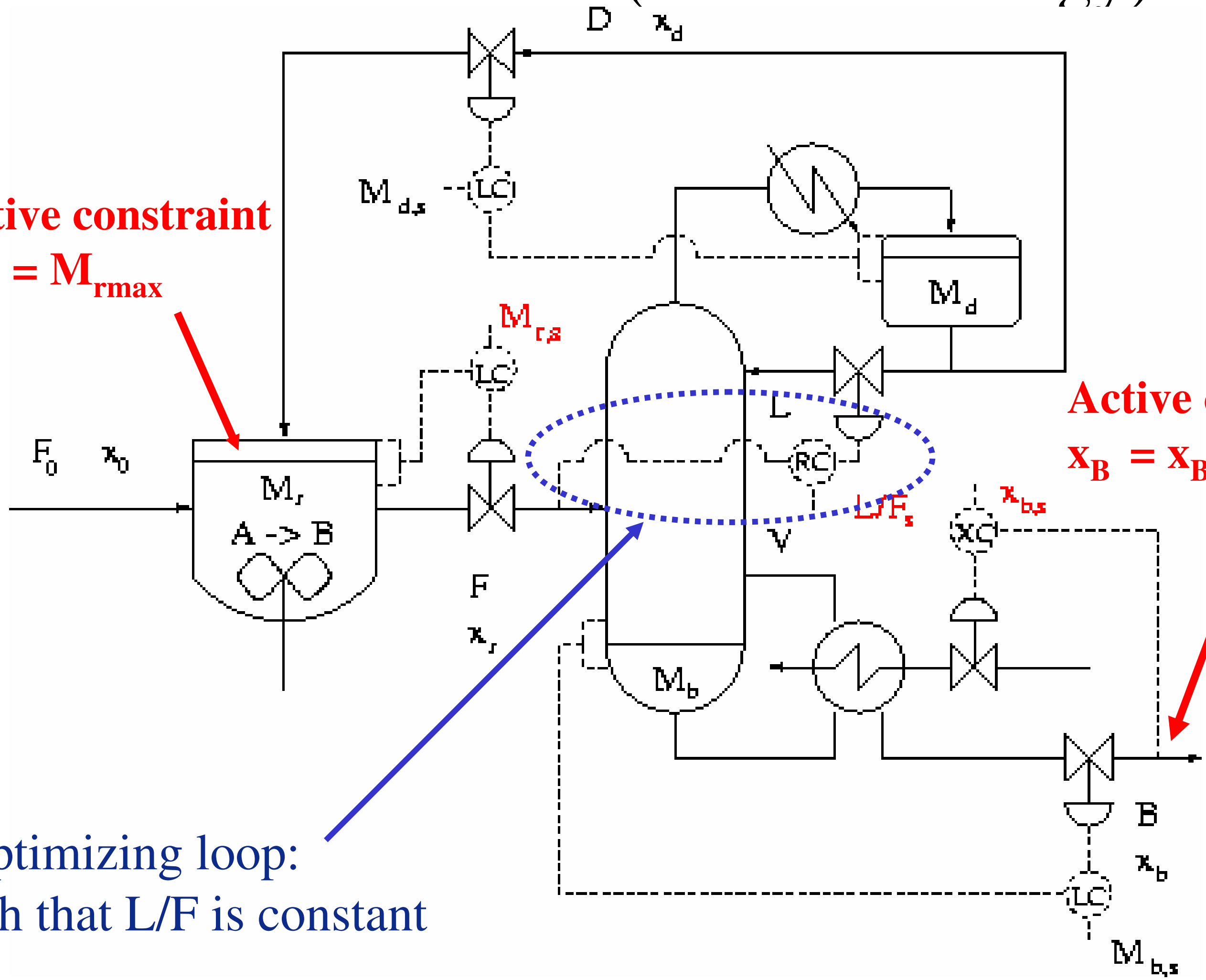


Recycle process: Proposed control structure

for case with J = V (minimize energy)

Active constraint
$M_r = M_{rmax}$

Active constraint
$x_B = x_{Bmin}$



Self-optimizing loop:
Adjust L such that L/F is constant

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Application stabilizing feedback control:

Anti-slug control

Petronics

ABB

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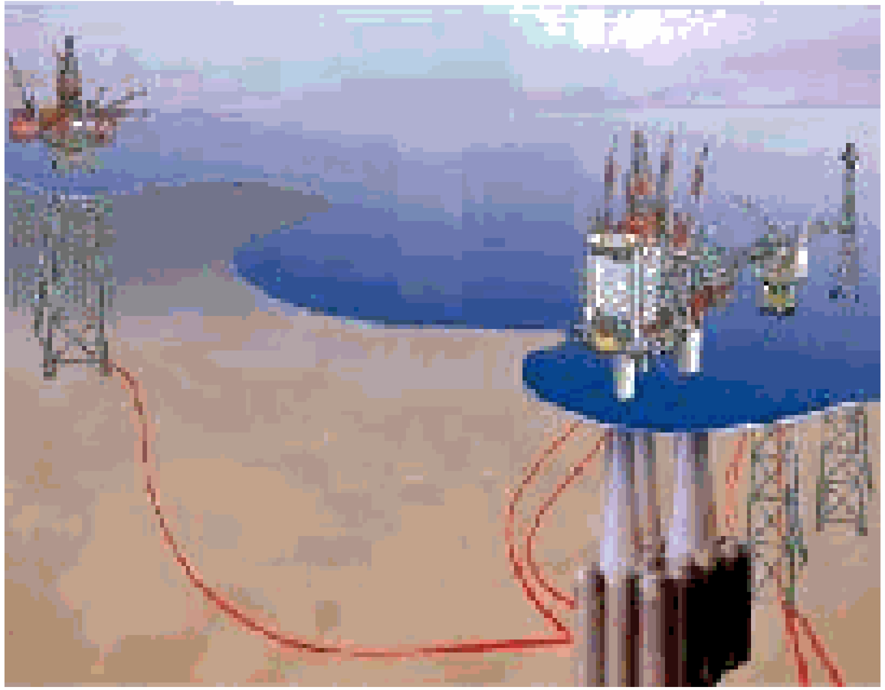
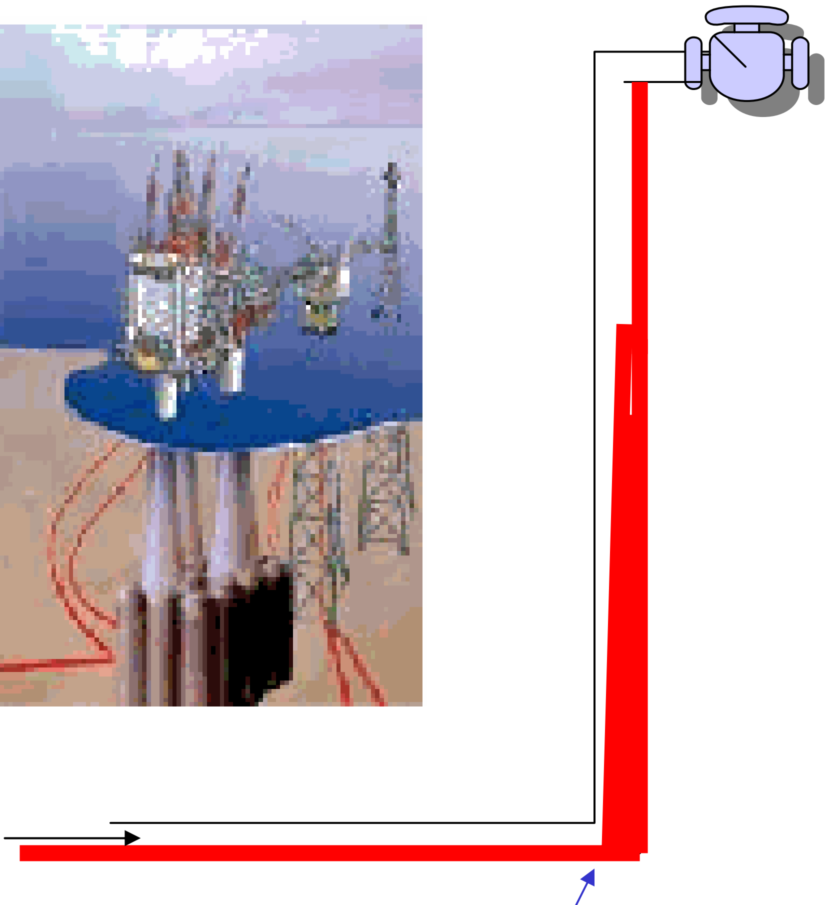
HYDRO



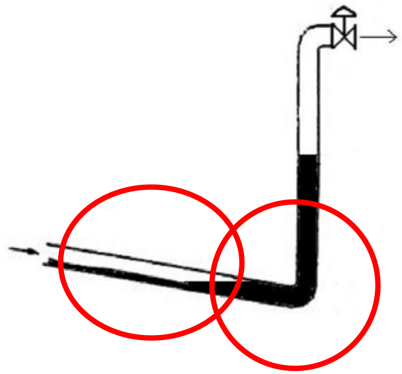


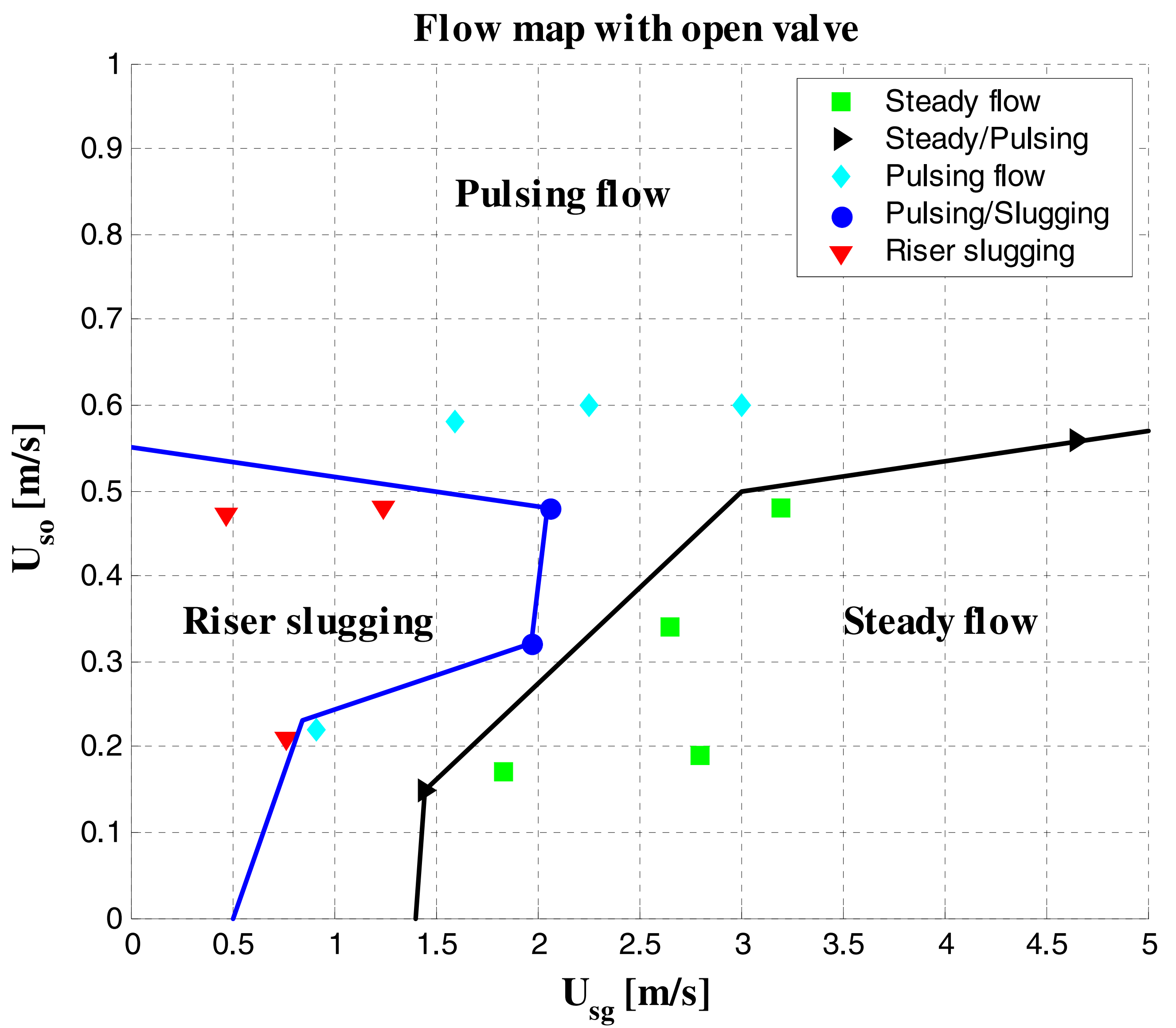
Two-phase pipe flow
(liquid and vapor)

Slug (liquid) buildup

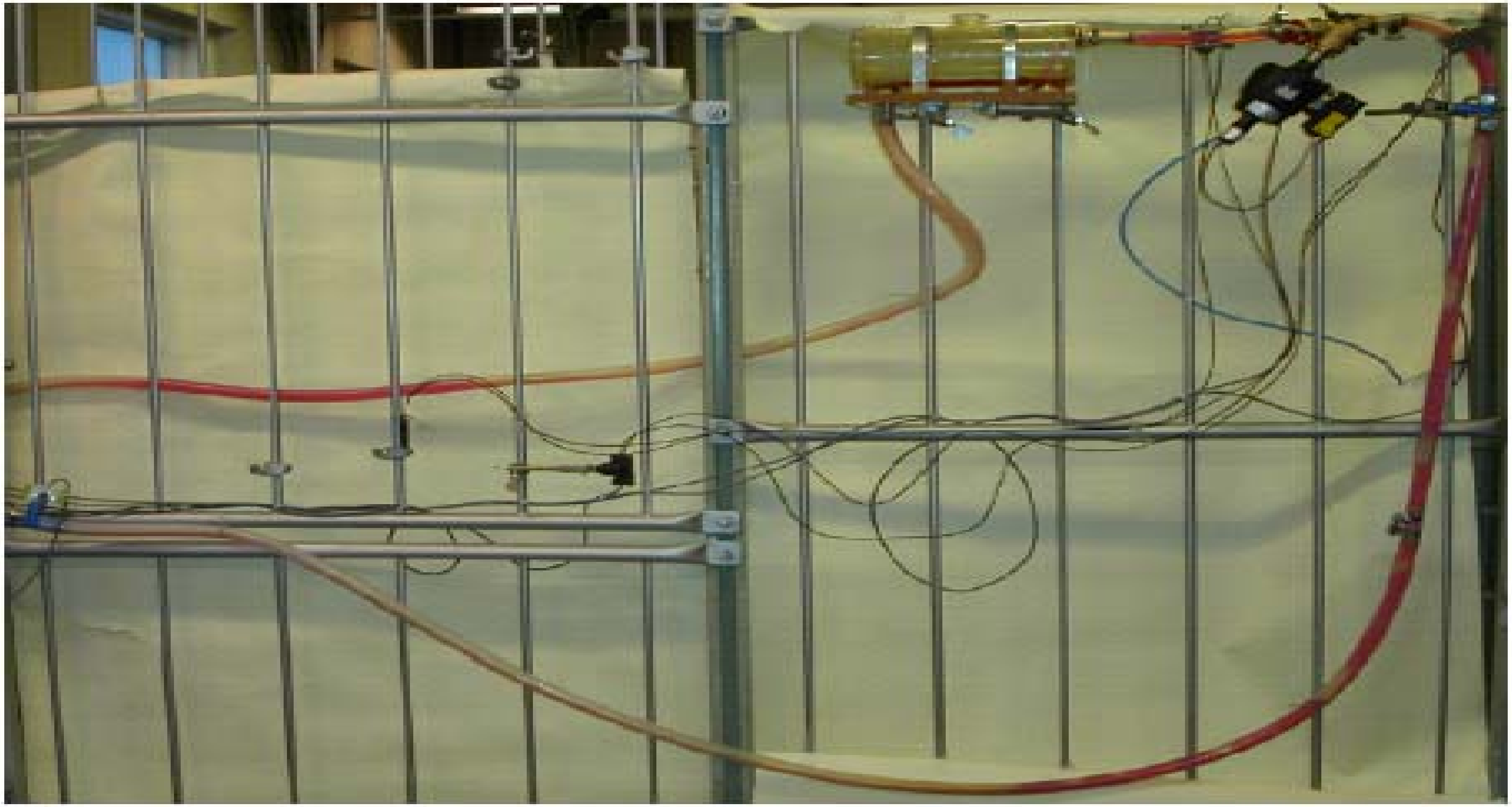
Slug cycle (stable limit cycle)

Experiments performed by the Multiphase Laboratory, NTNU

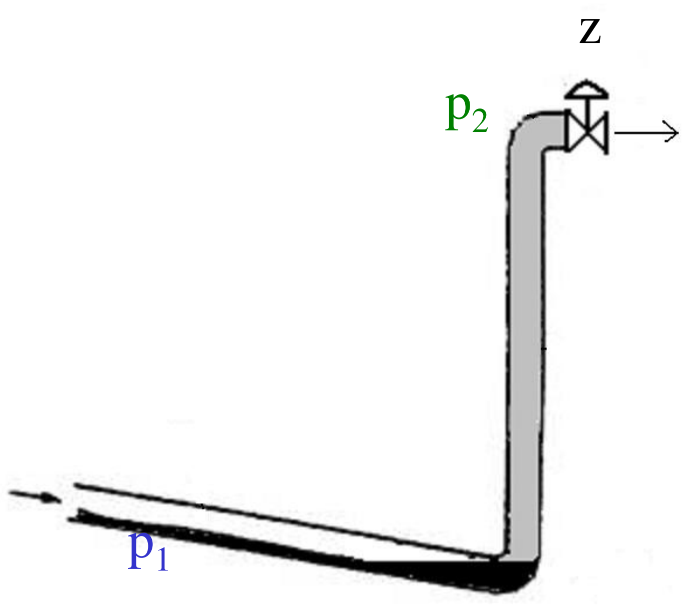


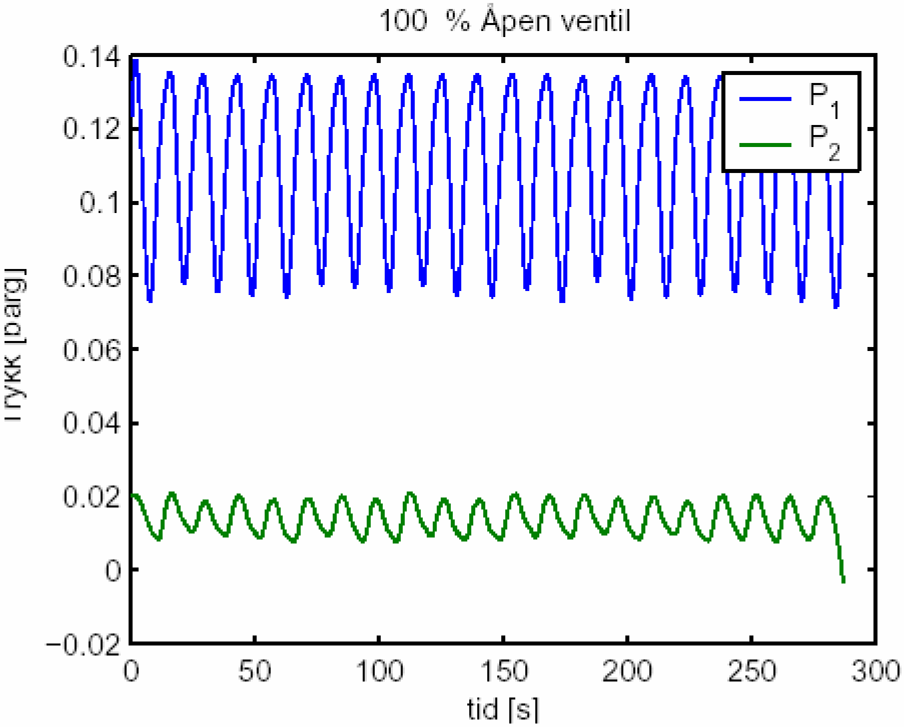

Flow map with open valve
Pulsing flow
Riser slugging
Steady flow
Steady flow
Steady/Pulsing
Pulsing flow
Pulsing/Slugging
Riser slugging
U_{so} [m/s]
U_{sg} [m/s]
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5

Experimental mini-loop

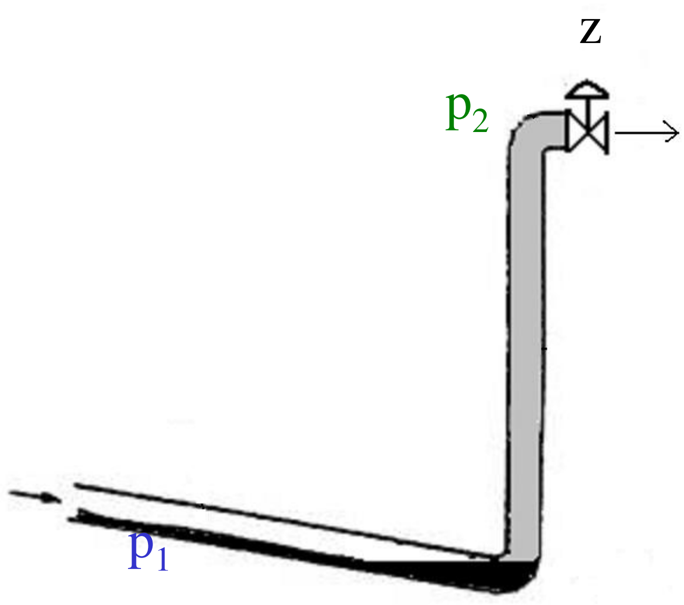


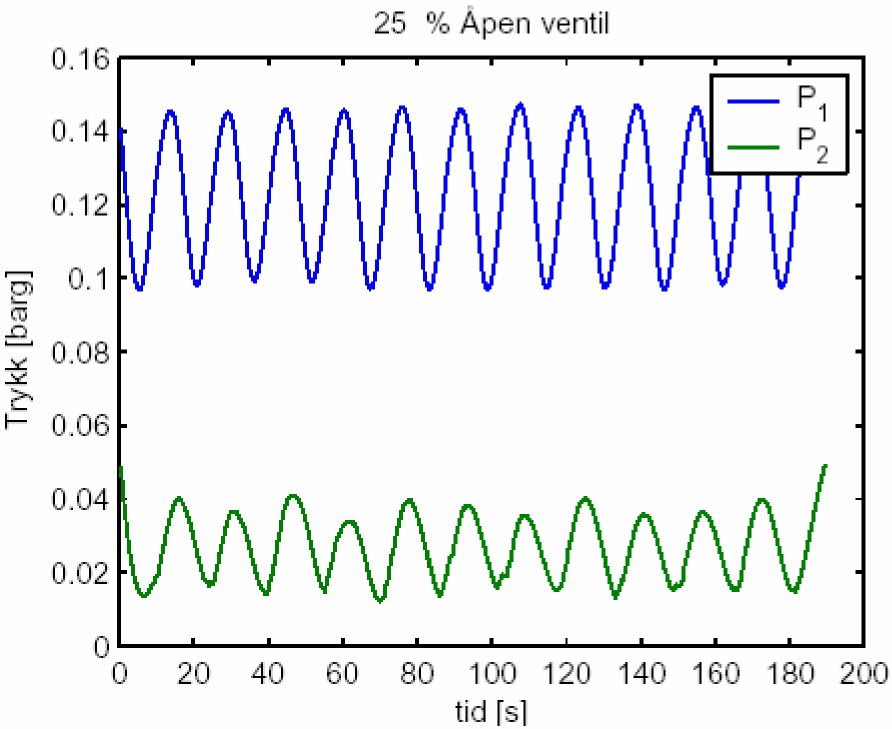
Experimental mini-loop
Valve opening (z) = 100%



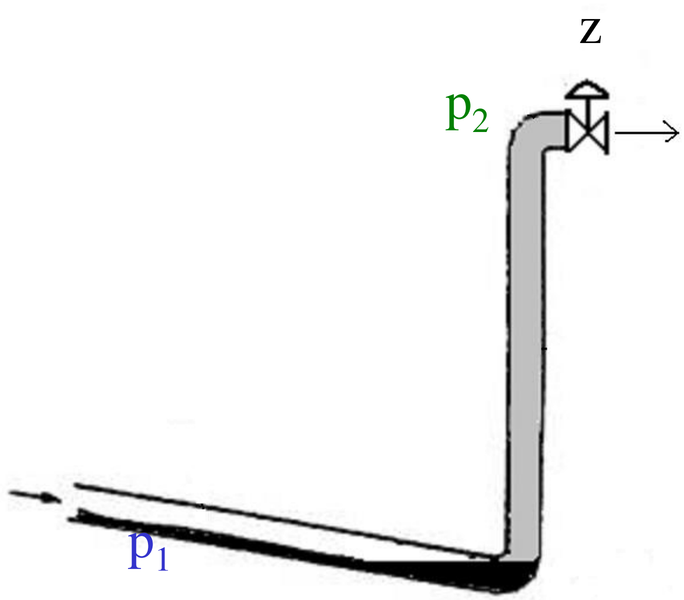


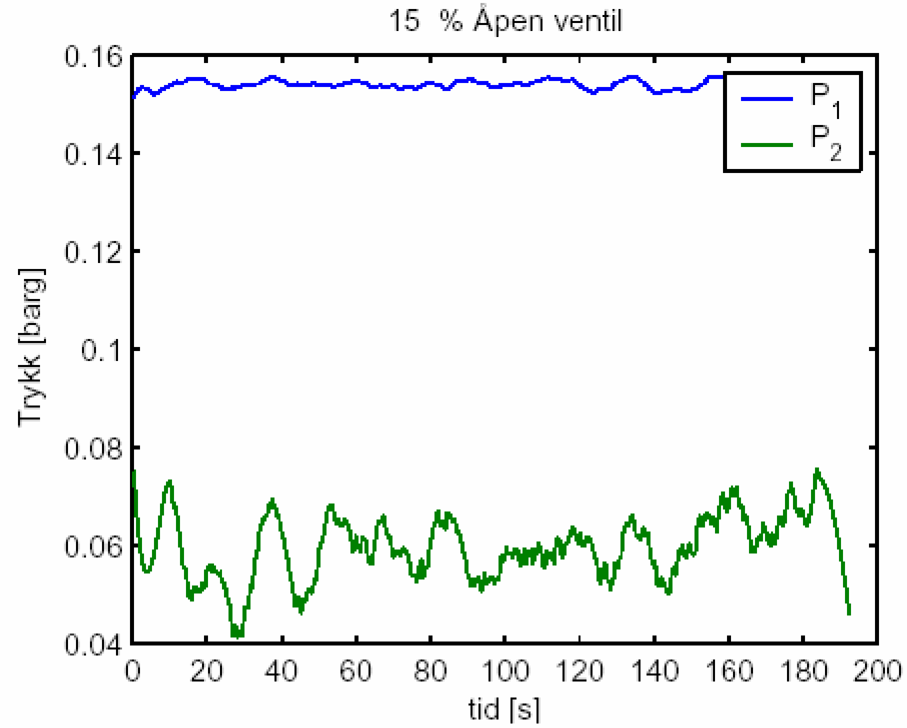
Experimental mini-loop
Valve opening (z) = 25%



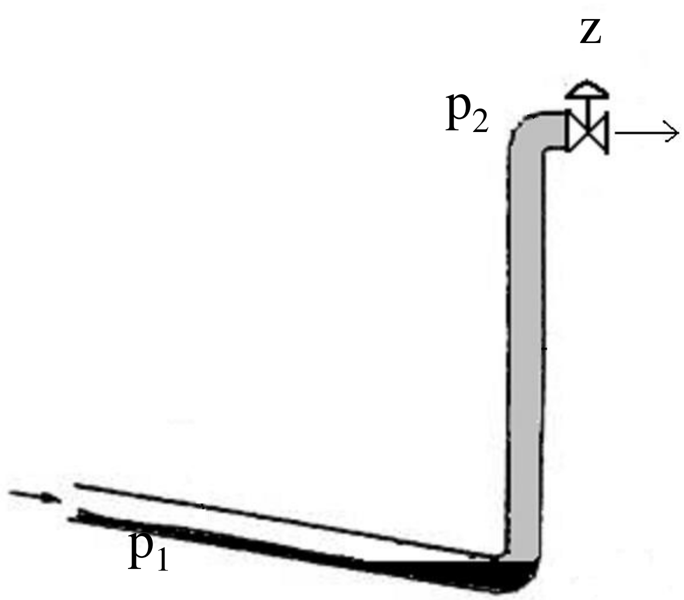


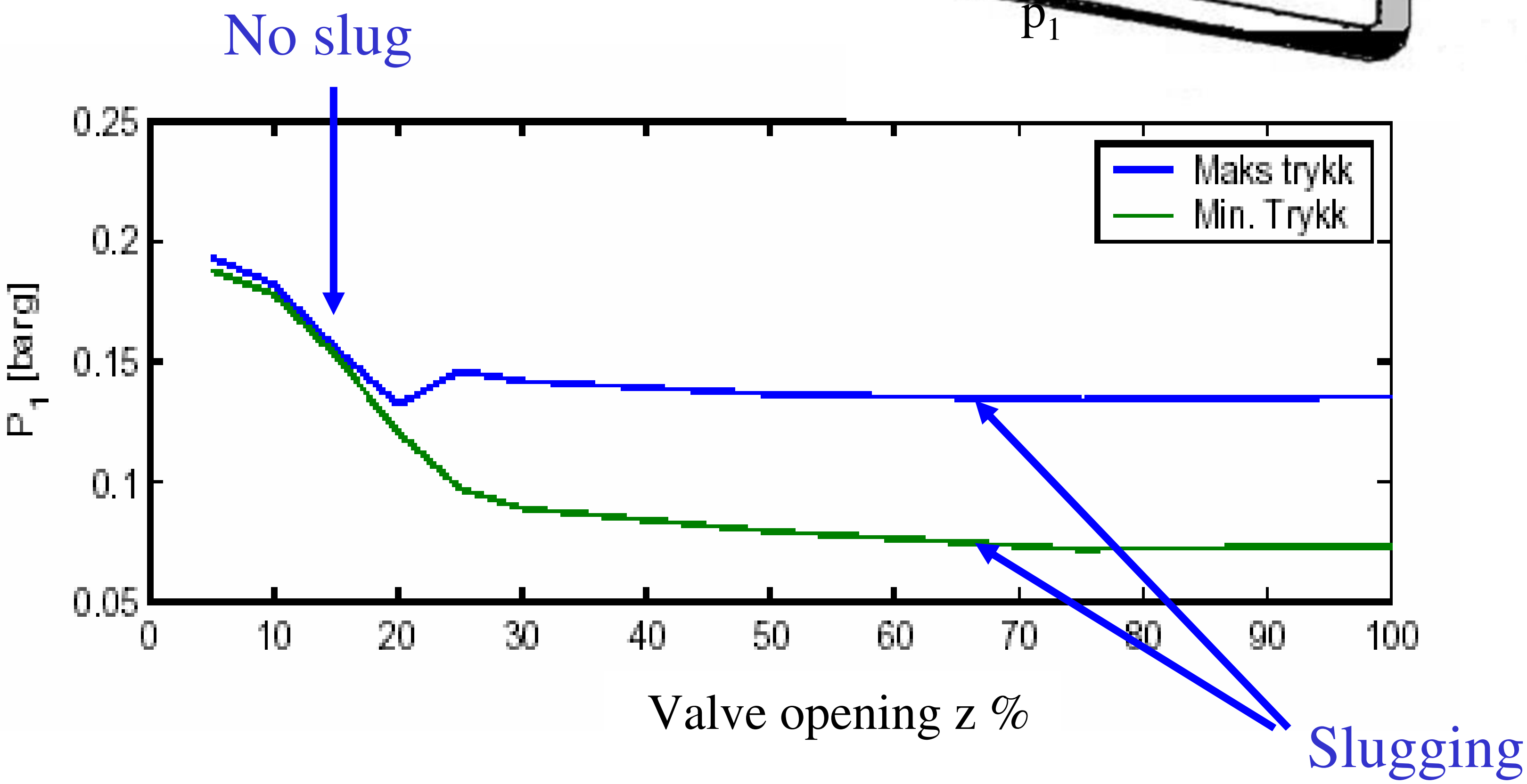
Experimental mini-loop
Valve opening (z) = 15%





Experimental mini-loop: Bifurcation diagram



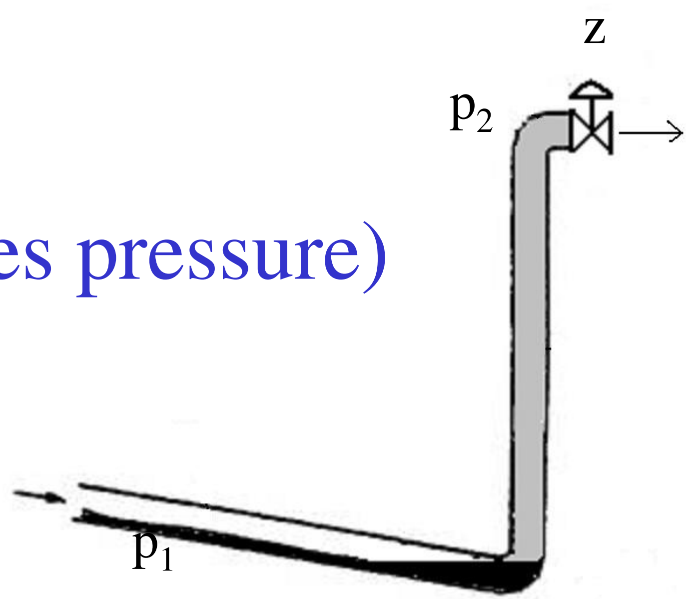


Avoid slugging?

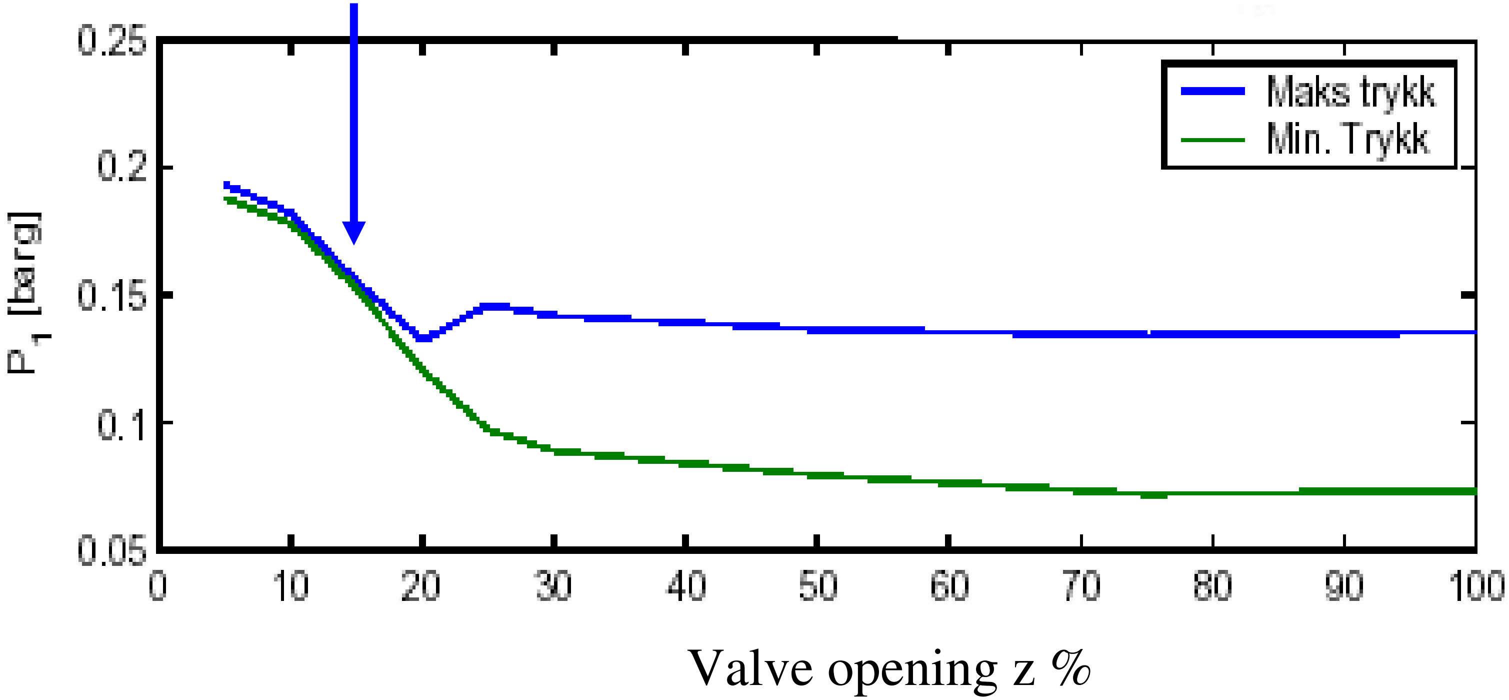
- Design changes
- Feedforward control?
- Feedback control?

Design change

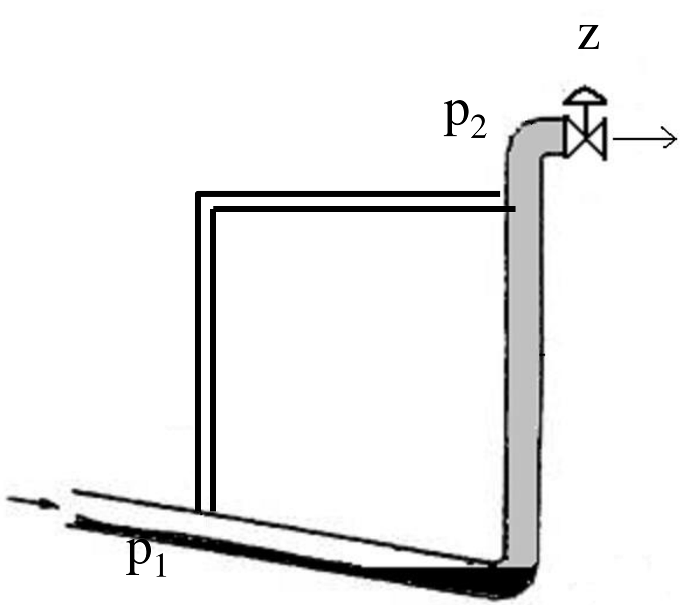
Avoid slugging:
1. Close valve (but increases pressure)



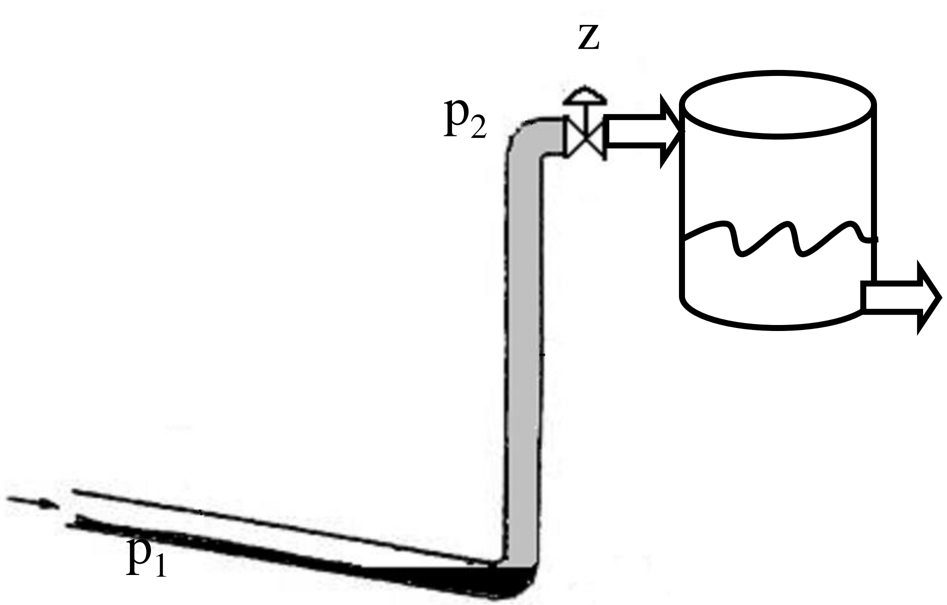
No slugging when valve is closed



Avoid slugging:
2. Other design changes to avoid slugging



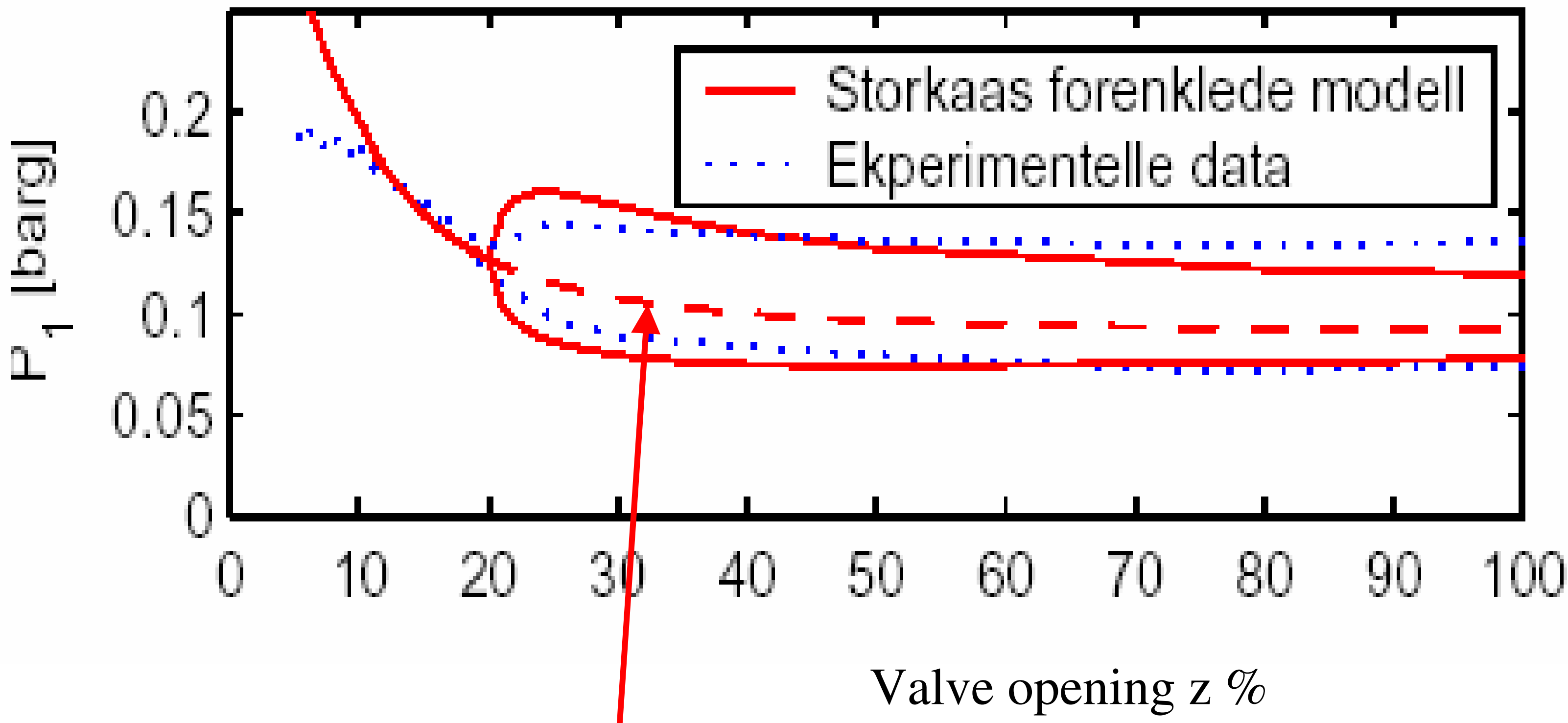
Minimize effect of slugging:
3. Build large slug-catcher



- Most common strategy in practice

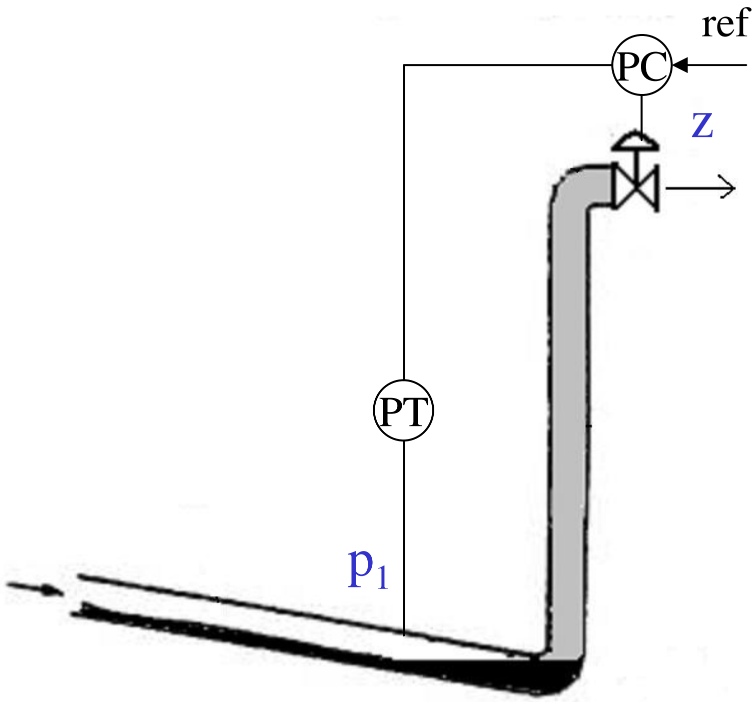
Avoid slugging: 4. Feedback control?

Comparison with simple 3-state model:



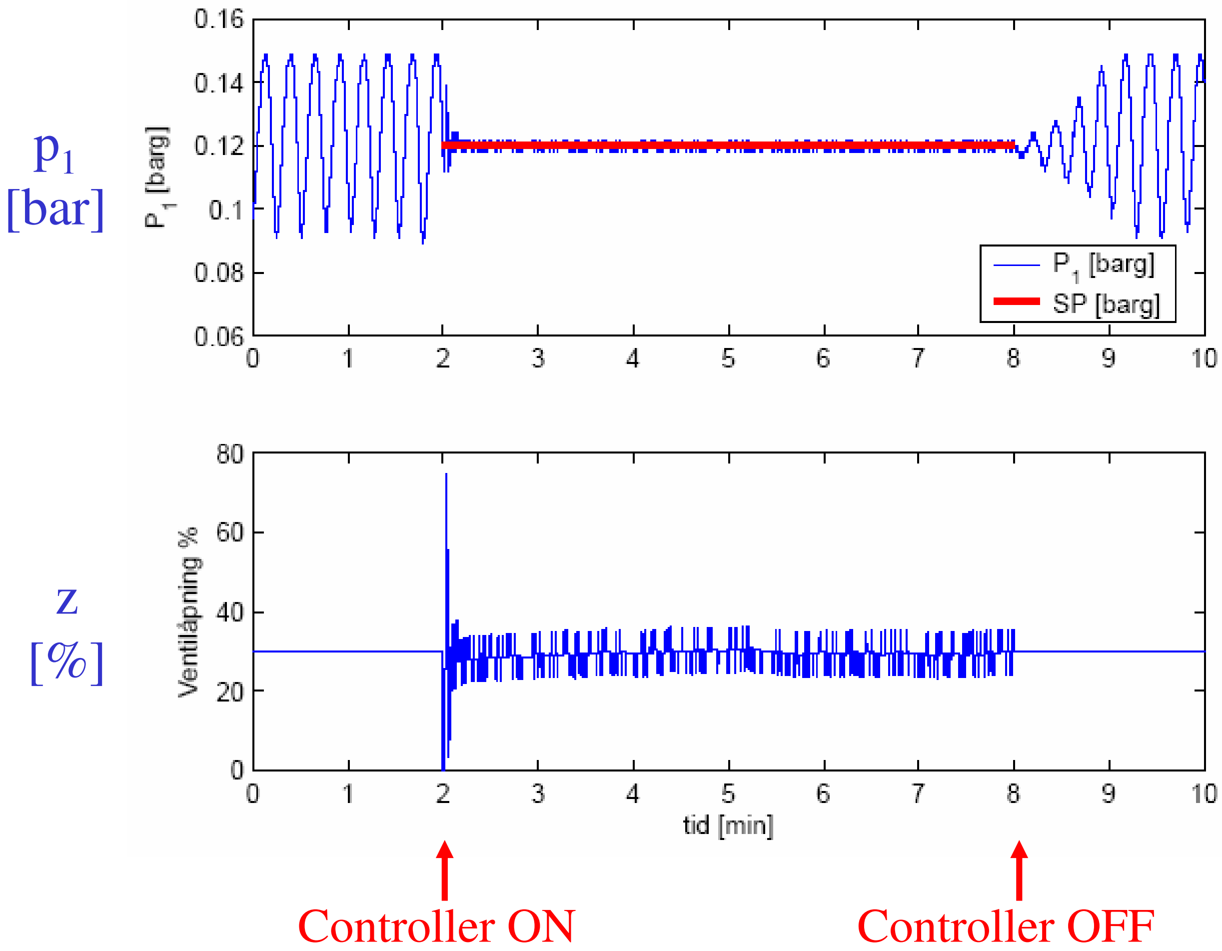
Predicted smooth flow: Desirable but open-loop unstable

Avoid slugging:
4. ”Active” feedback control

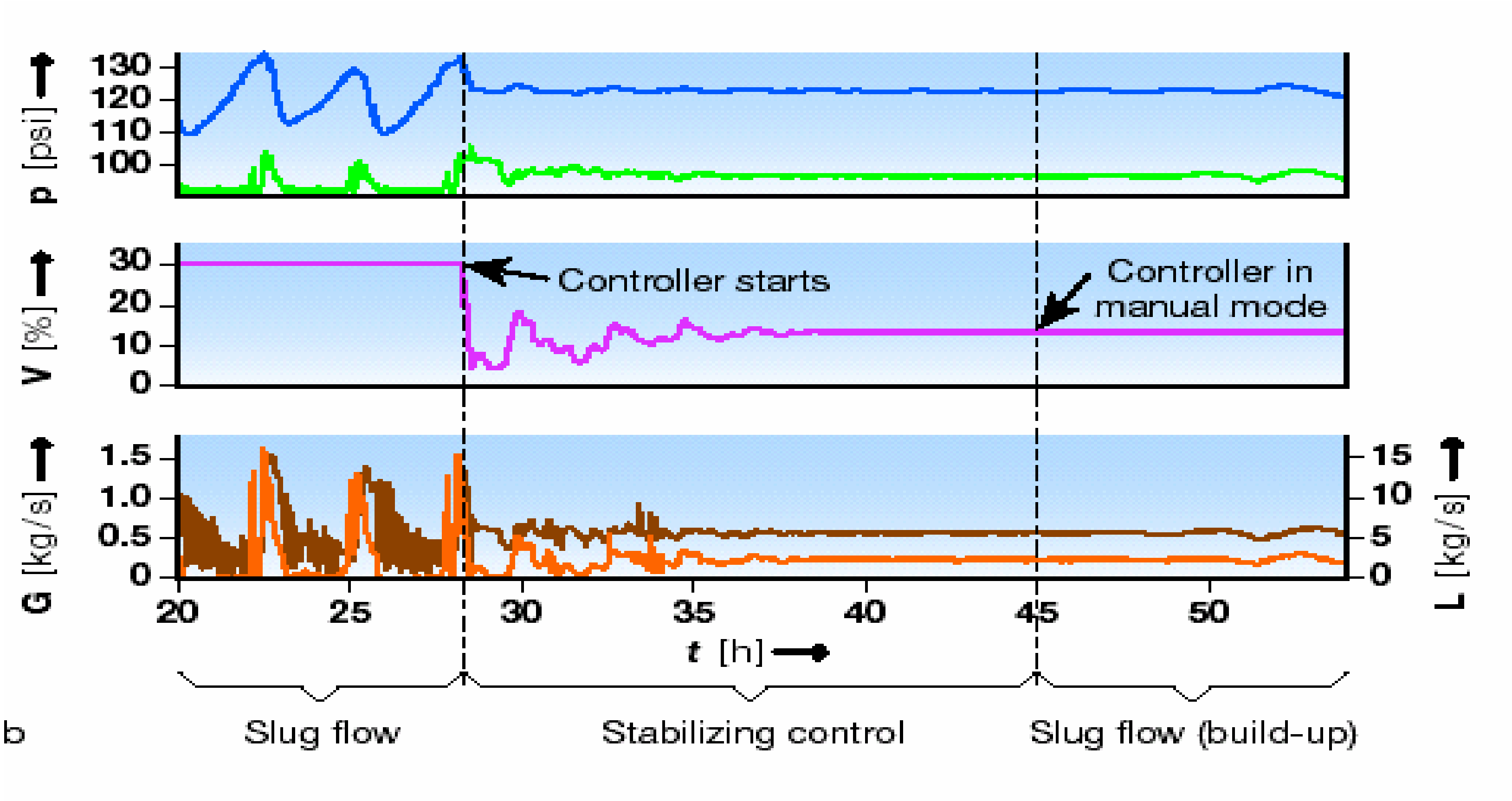


Simple PI-controller

Anti slug control: Mini-loop experiments



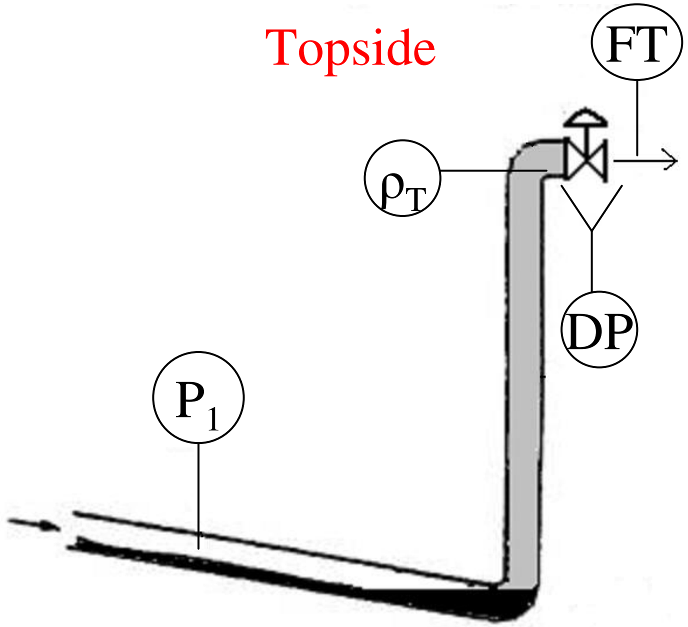
Anti slug control: Full-scale offshore experiments at Hod-Vallhall field (Havre,1999)



Analysis: Poles and zeros

Operation points:

z	P_1	DP	Poles
0.175	70.05	1.94	-6.11 0.0008±0.0067i
0.25	69	0.96	-6.21 0.0027±0.0092i

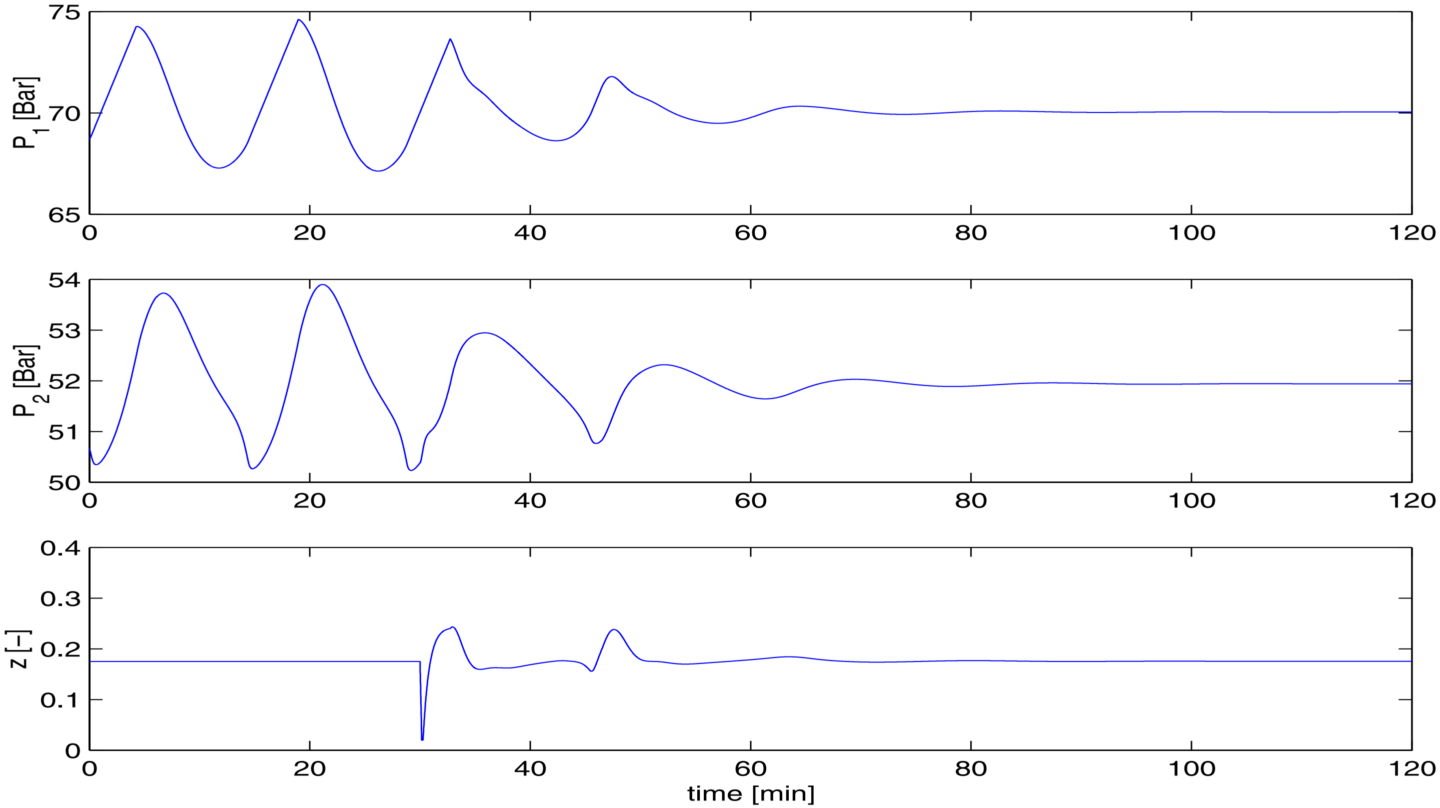


Zeros:

z \ y	P_1 [Bar]	DP[Bar]	ρ_T [kg/m^3]	F_Q [m^3/s]	F_W [kg/s]
0.175	-0.0034	3.2473 0.0142	-0.0004 0.0048	-4.5722 -0.0032 -0.0004	-7.6315 -0.0004 0
0.25	-0.0034	3.4828 0.0131	-0.0004 0.0048	-4.6276 -0.0032 -0.0004	-7.7528 -0.0004 0

Topside measurements: Ooops.... RHP-zeros or zeros close to origin

Stabilization with topside measurements: Avoid “RHP-zeros by using 2 measurements



- Model based control (LQG) with 2 top measurements: DP and density ρ_T

Summary anti slug control

- Stabilization of smooth flow regime = $$$$!
- Stabilization using downhole pressure simple
- Stabilization using topside measurements possible
- Control can make a difference!

Thanks to: Espen Storkaas + Heidi Sivertsen and Ingvald Bårdsen

Conclusions

- Feedback is an extremely powerful tool
- Complex systems can be controlled by hierarchies (cascades) of single-input-single-output (SISO) control loops
- Control the right variables (primary outputs) to achieve ”self-optimizing control”
- Feedback can make new things possible (anti-slug)