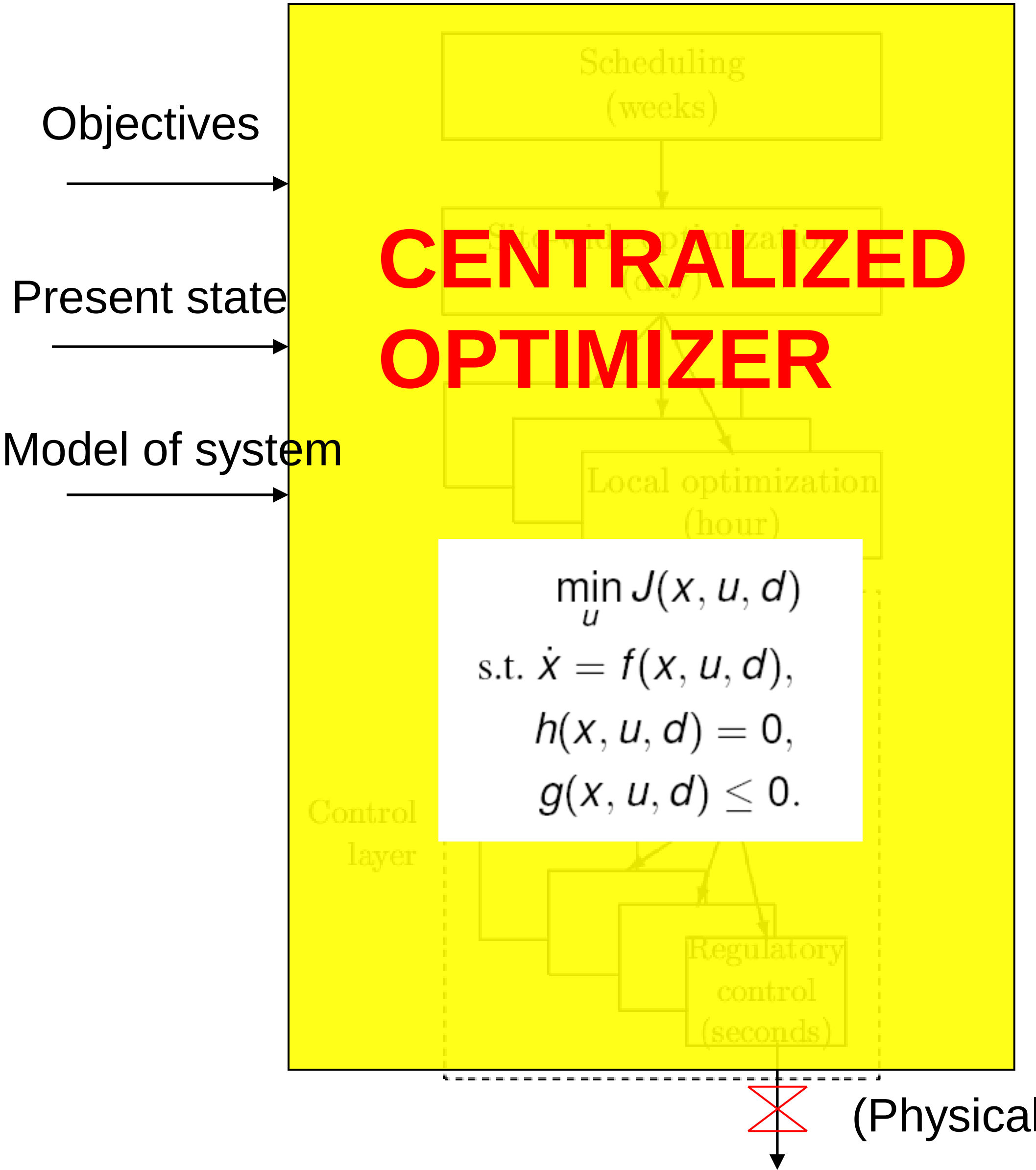
Part 2. Decomposition

- Hierarchical decomposition. Control layers.
- Design of overall control system for economic process control
- CV selection

Optimal operation and control of process

- Given process plant
- Want to Maximize profit P => Minimize economic cost $J_\$=-P$ [$/s]
  - $J_\$$ = cost feed + cost energy – value products
    - Excluding fixed costs (capital costs, personell costs, etc)
- Subject to satisfying constraints on
    - Products (quality)
    - Inputs (max, min)
    - States = Internal process variables (pressures, levels, etc)
      - Safety
      - Environment
      - Equipment degradation
- Degrees of freedom = manipulated variables (MVs) = inputs u

In theory: Centralized controller is always optimal (e.g., EMPC)



$$
\begin{aligned}
&\min_u J(x,u,d) \\
\text{s.t. } &\dot{x} = f(x,u,d), \\
&h(x,u,d) = 0, \\
&g(x,u,d) \leq 0.
\end{aligned}
$$

(Physical) Degrees of freedom, u= valve positions

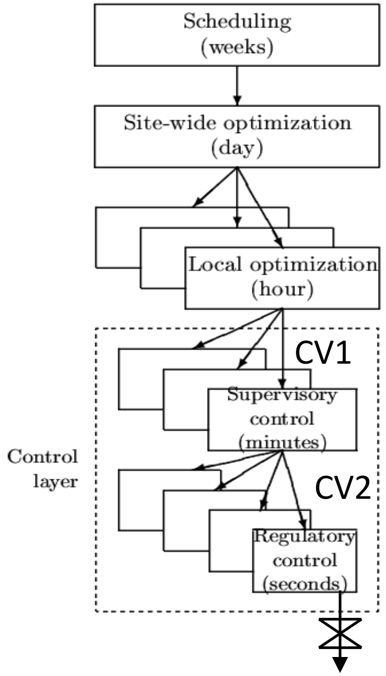
Approach:
- Model of overall system
- Estimate present state
- Optimize all degrees of freedom

Process control:
- Excellent candidate for centralized control

Problems:
- Model not available
- Objectives = ?
- Optimization complex
- Not robust (difficult to handle uncertainty)
- Slow response time

Two fundamental ways of decomposing the controller

- Vertical (hierarchical; cascade)
- Based on time scale separation
- Decision: Selection of CVs that connect layers



- Horizontal (decentralized)
- Usually based on distance
- Decision: Pairing of MVs and CVs within layers

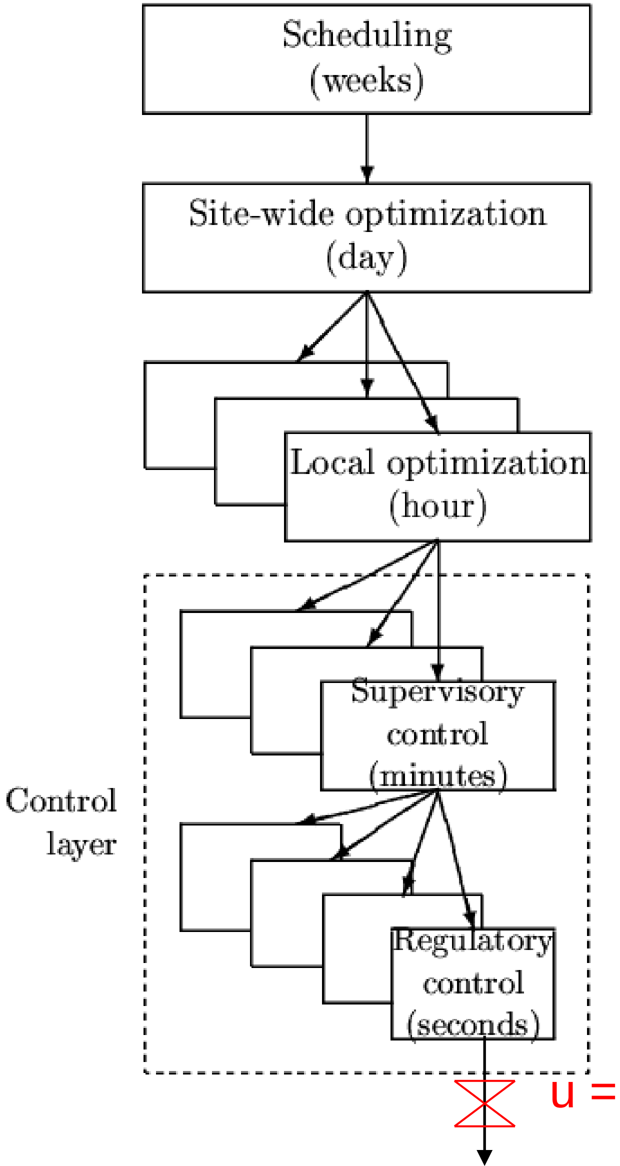
CV = controlled variable
MV = manipulated variable

Preferred Paradigm

Practical operation: Hierarchical (cascade) structure based on time scale separation

NOTE: Control system is decomposed both
- Hierarhically (in time)
- Horizontally (in space)

Status industry:
- RTO is rarely used.
- MPC is used in the petrochemical and refining industry, but in general it is much less common than was expected when MPC «took off» around 1990
- ARC is common
- Manual control still common…



Manager

Process engineer

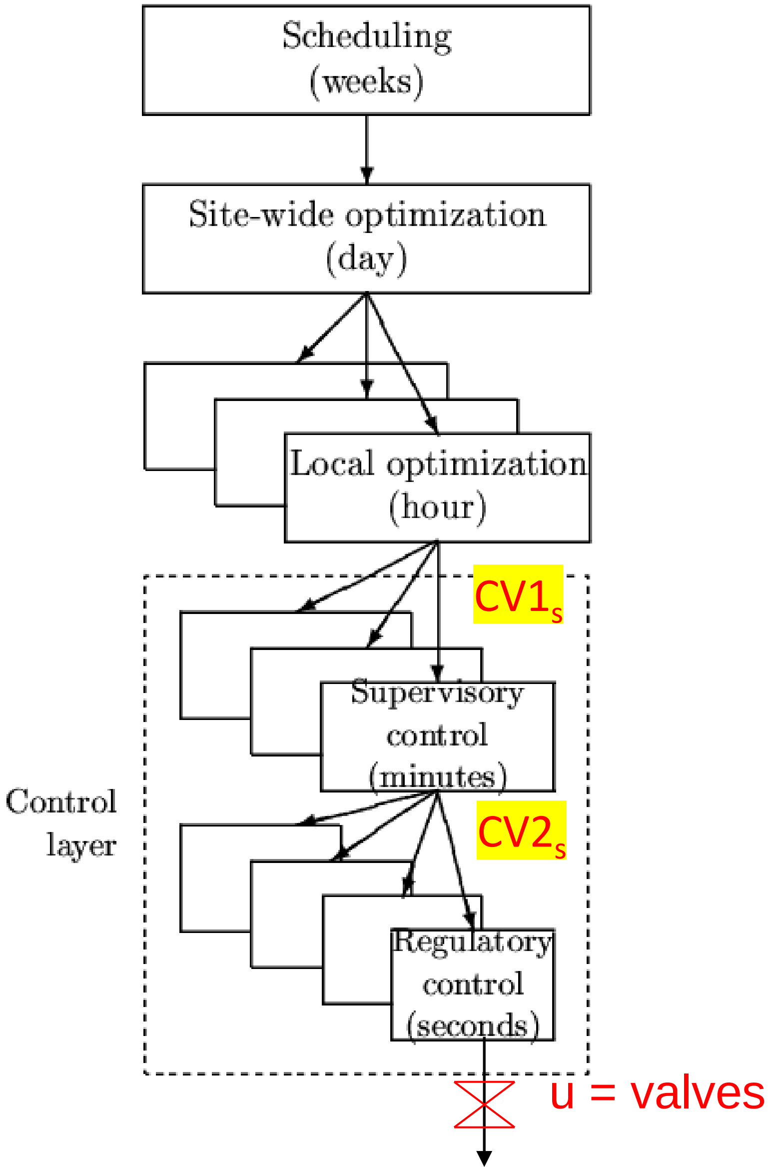
Operator/RTO

Operator/Advanced regulatory control (ARC)/MPC

PID-control
May include some ratio/feedforward and cascade control

u = valves

What is the difference between optimization and control?



My definition:

Optimization:

- Minimizes economic cost

Control:

- Follow setpoints y_s

Objectives of layers

Optimization layer:

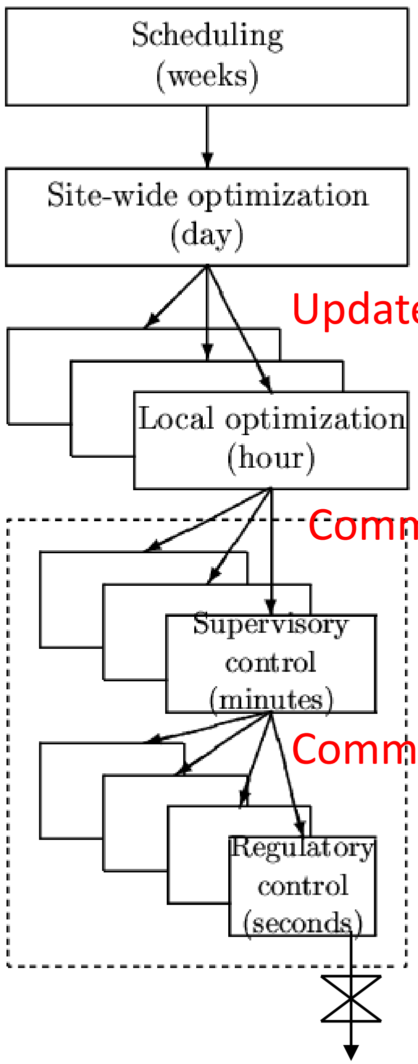
- Min. operation cost (economics. [$/s]) by changing $CV1_s$

Supervisory control layer:

- Follow set points for CV1 from economic optimization layer
- Switch between active constraints (change CV1)
- Look after regulatory layer (avoid that MVs saturate, etc.)

Regulatory control layer:

- Stabilize + avoid drift (CV2)



Manager

Process engineer

Update constraints and prices…

Operator/RTO

Command/setpoint, $CV1_s$

Advanced regulatory control/MPC

Command/setpoint, $CV2_s$

PID-control

u = valves

Cost functions in layers

RTO: Minimize economic cost

$J_\$$ = cost feed + cost energy – value products

Setpoint control

$J_{c1} = Q(y_1-y_{1s})^2 + R\Delta u_1^2$ (MPC)

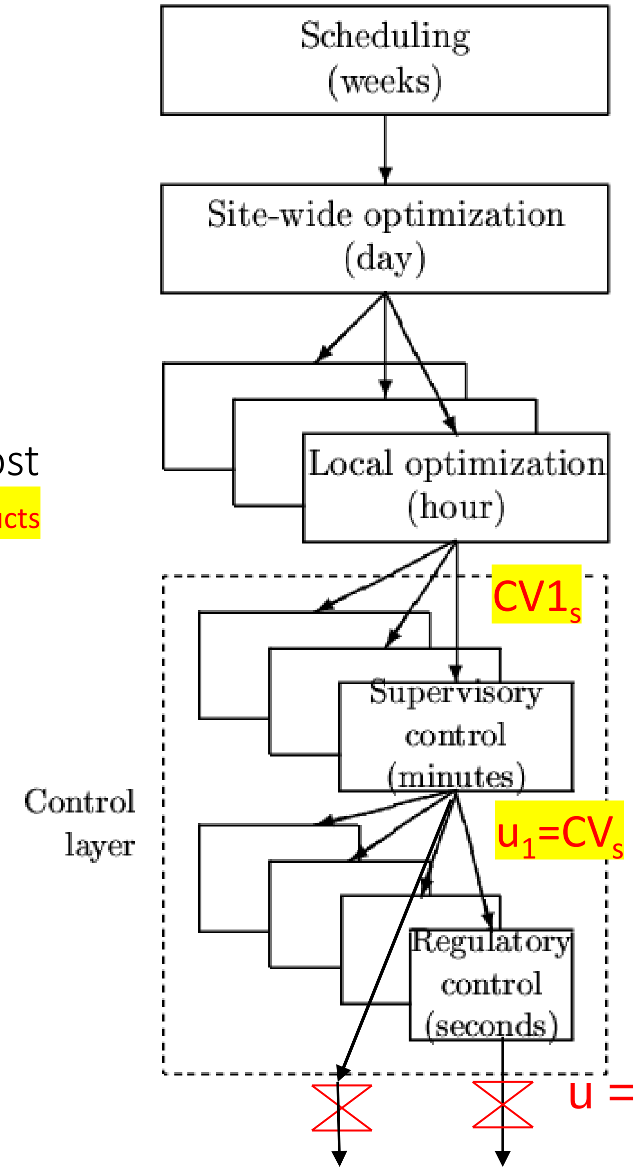
(+ look after other variables,
Avoid constraints)

PID: Stabilize + avoid drift

$J_{c2} = Q(y_2-y_{2s})^2 + R\Delta u^2$

+ look at Gain margin…

(or just use SIMC-rules!)



Manager

Process engineer

RTO (usually steady state)

”Advanced control”/MPC

PID-control

May include some
feedforward and cascade

u = valves

«Advanced» control (supervisory control layer)

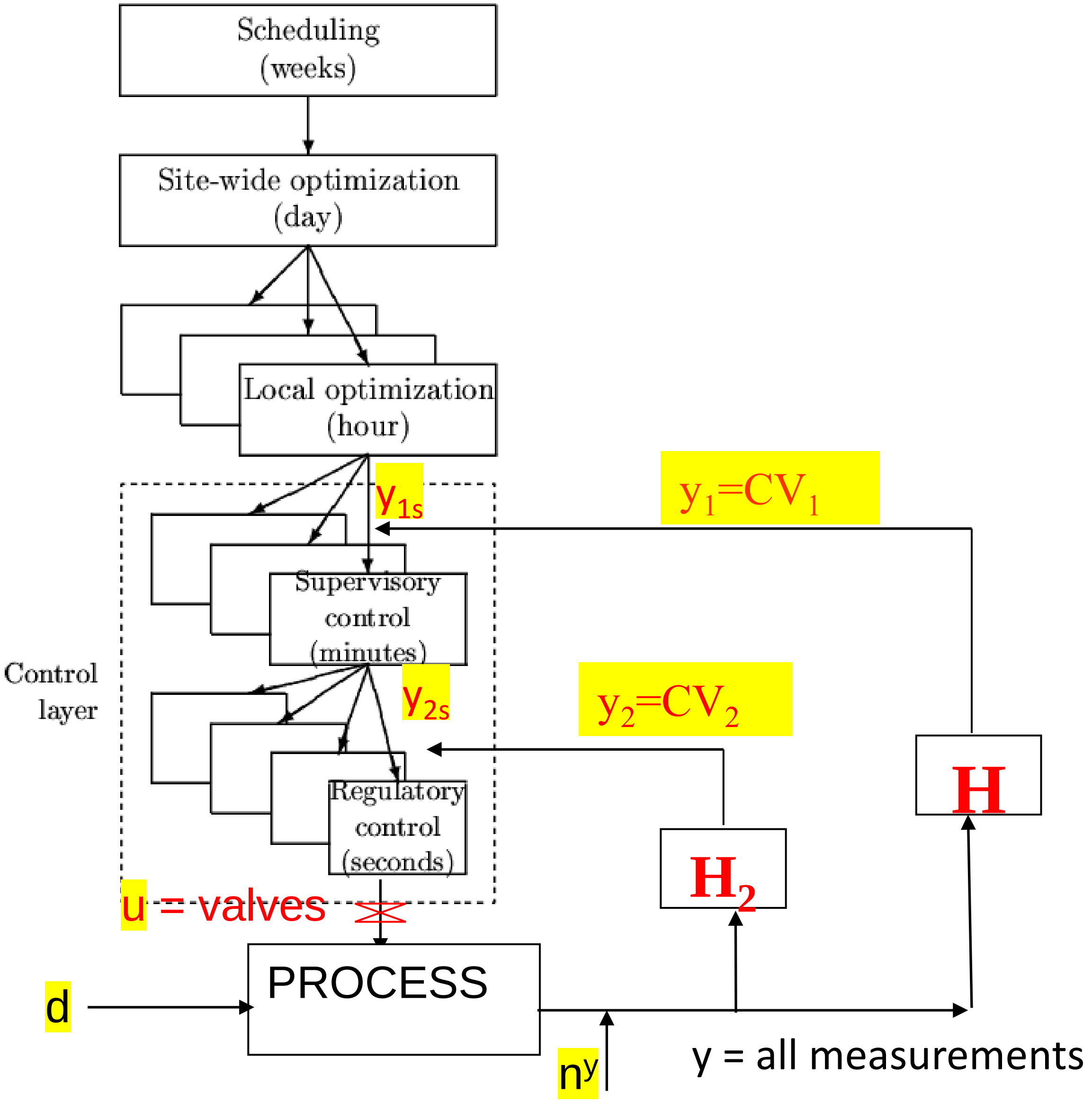
- This is a relative term
- Usually used for anything than comes in addition to (or in top of) basic PID loops
- Main options
  - Advanced regulatort control (ARC) using standard «advanced control elements»
    - Cascade, feedforward, selectors, etc.
    - This option is preferred if it gives acceptable performance and it’s not too complicated
  - Model predictive control (MPC)
    - Requires more effort to implement

Use of data (feedback) in Hierarchical structure

- Use of measurements y

Use of data (feedback)

Engineer: Must choose what to control (H and H_2)



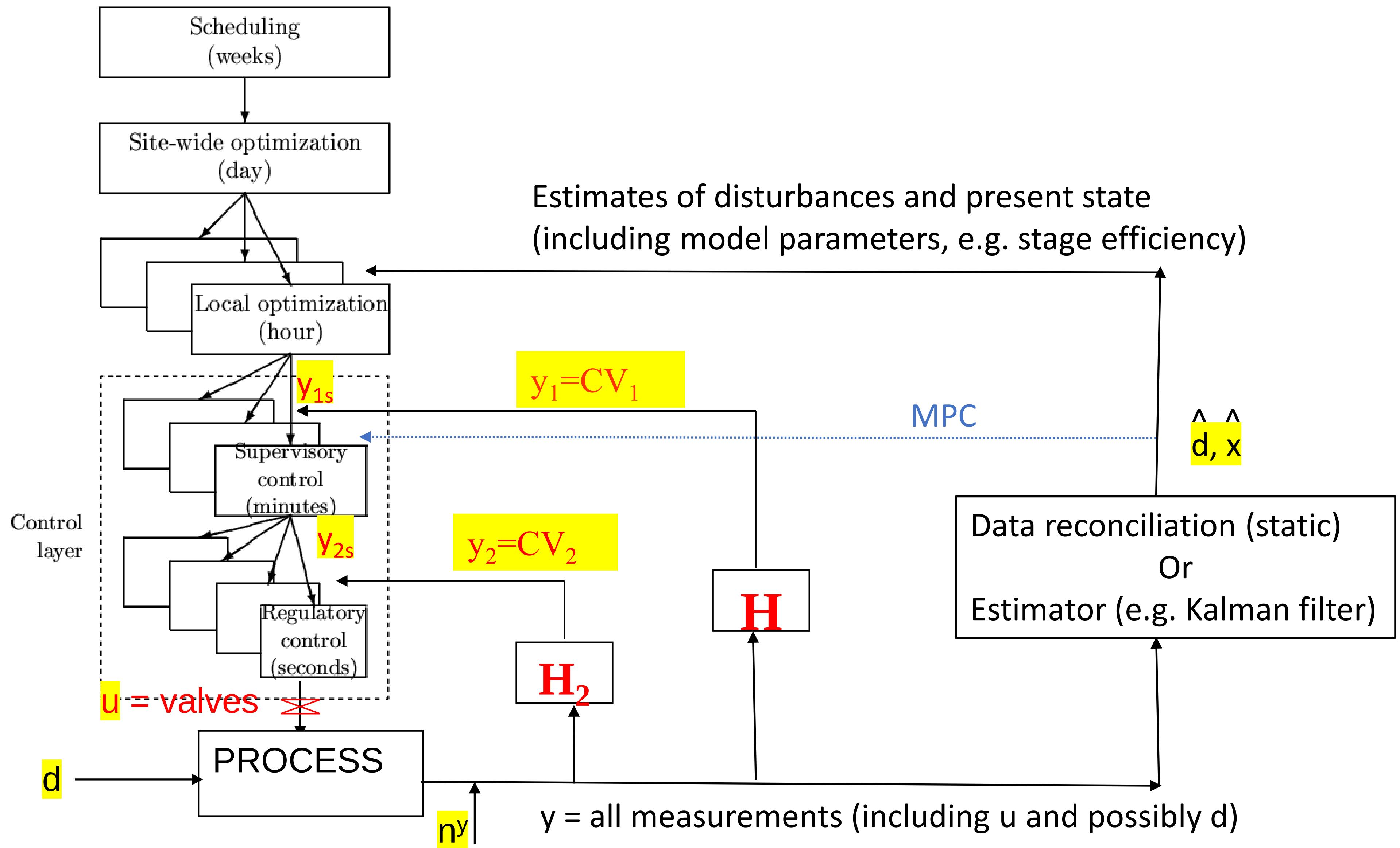
- H and H_2 are usually selection matrices

Typically:

- y_1=Hy = active constraints + «self-optimizing» variables
- y_2=H_2y = drifting variables (levels, pressures, temperatures)

Use of data

Optimization layer: Needs model parameters and disturbances

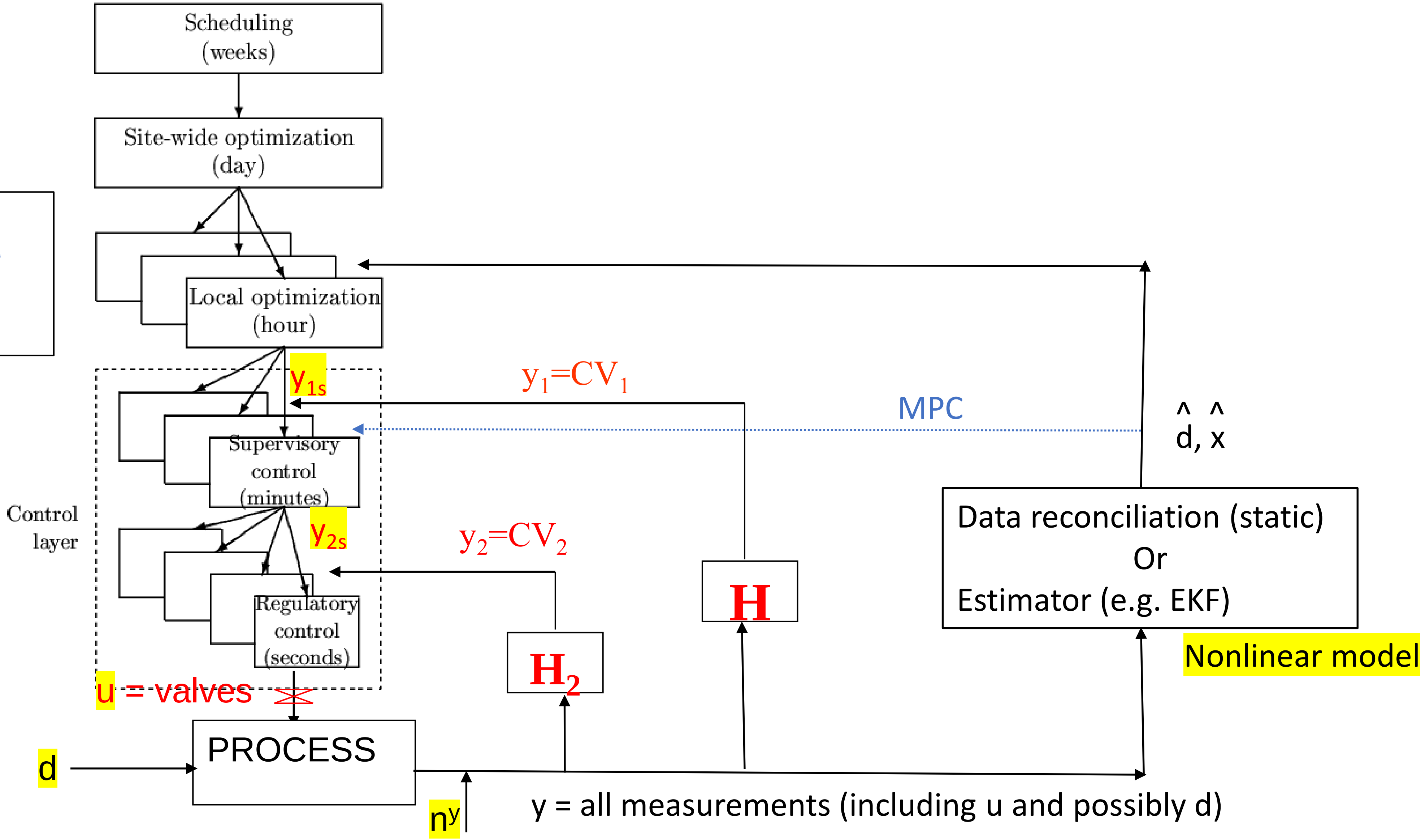


Use of models

RTO layer:
- Nonlinear model of whole process
- usually physical and static

MPC layer:
- Multivariable dynamic linear model for each unit
- usually from data

PID-layer:
- Dynamic linear model for each loop
- usually from data.
- May use physical model for linearization, decoupling and feedforward
  - see: input transformation



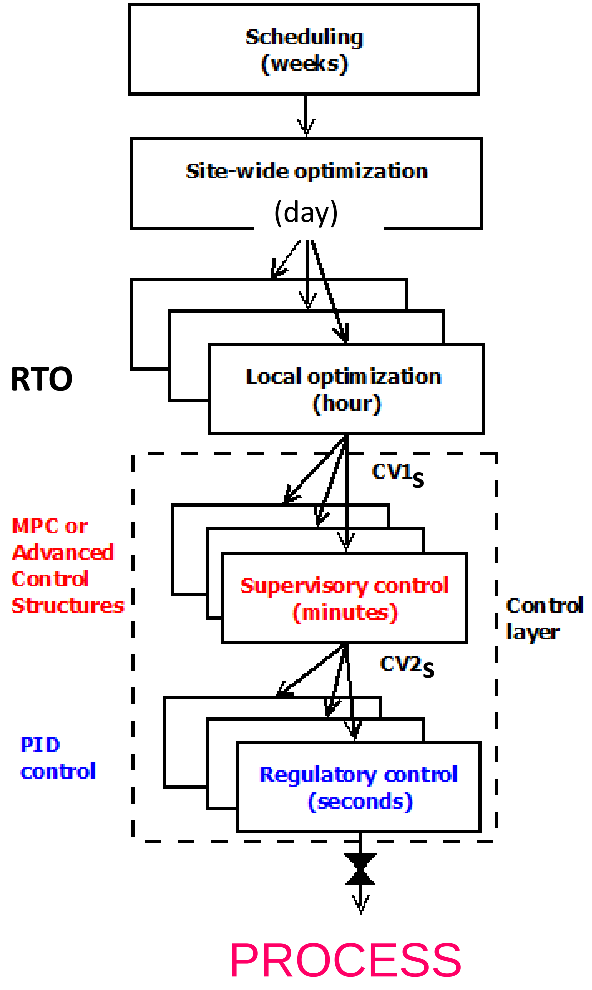
Is there a problem with model consistency between layers?

Quote from a recent paper I reviewed

- "One of the difficulties in practical implementations of classic Real-Time Optimization (RTO) strategy is the integration between optimization (RTO) and control layers (MPC), mainly due to the differences between the models used in each layer, which may result in unreachable setpoints coming from optimization to the control layer. In this context, Economic Model Predictive Control (EMPC) is a strategy where optimization and control problems are solved simultaneously."

- Is this likely to happen?

- **No, This is a myth** and no reason for choosing EMPC
- Truth: With integral action in the control layer (MPC), the process will go to the setpoints (y_{1s}=$CV1_s$) desired by the RTO layer, irrespective of any model error in the MPC layer
  - $J_{MPC} = Q(y_1-y_{1s})^2 + R\Delta u_1^2$
- Of course, the setpoints from the RTO layer must correspond to a feasible steady state, but the model in the MPC layer does not affect this
- Of course, there may be economic losses dynamically, for example, dynamic constraints may mean it takes some time to reach the setpoints



Main objectives operation

1. **Economics**: Implementation of acceptable (near-optimal) operation
2. **Regulation:** Stable operation around given setpoint

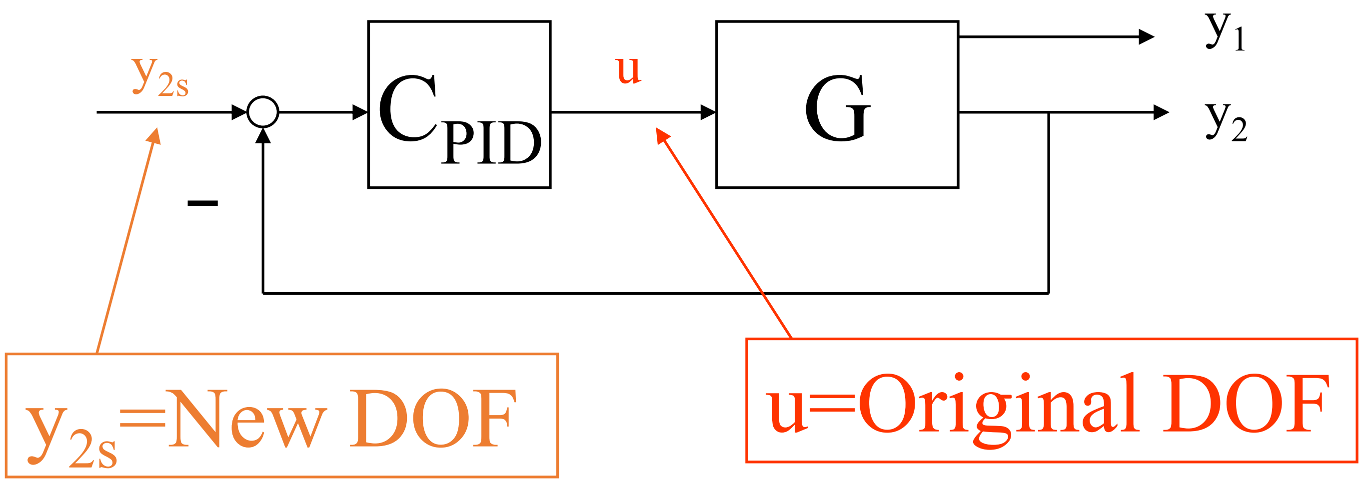
ARE THESE OBJECTIVES CONFLICTING?
IS THERE ANY LOSS IN ECONOMICS?

- Usually NOT
  - Different time scales
    - Stabilization fast time scale
  - Stabilization doesn't "use up" any degrees of freedom
    - Reference value (setpoint) available for layer above
    - But it "uses up" part of the time window

Hierarchical structure: Degrees of freedom unchanged

- No degrees of freedom lost as setpoints y_{2s} replace inputs u as new degrees of freedom for control of y_1

Cascade control:



Systematic procedure for economic process control

Start "top-down" with economics (steady state):

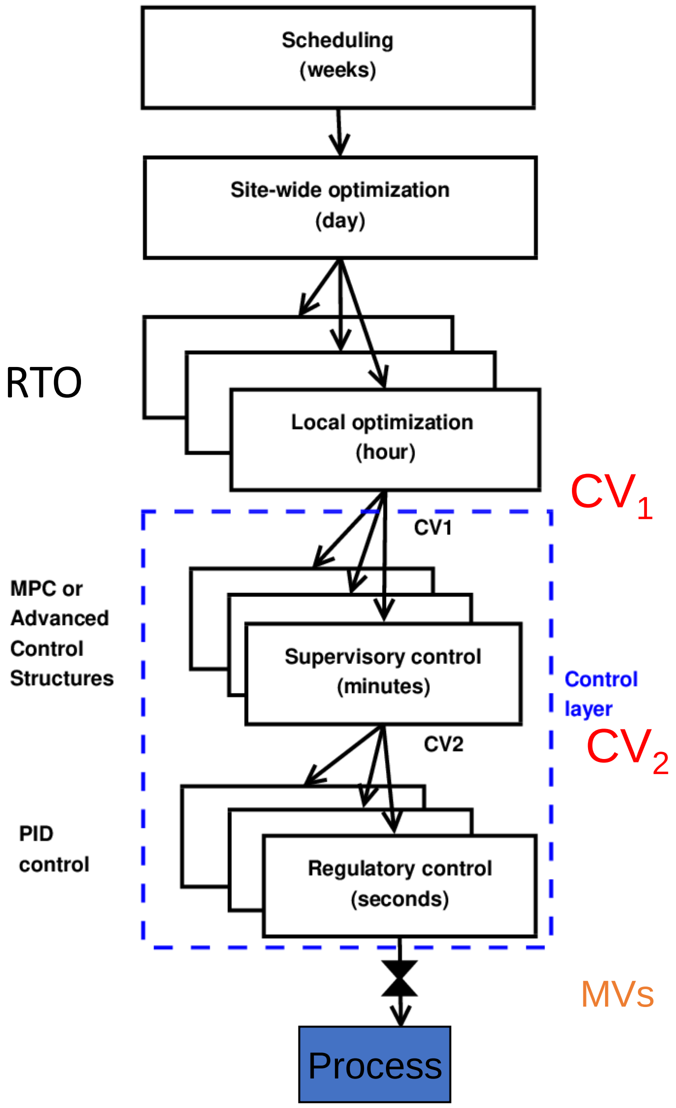
- Step 1: Define operational objectives (J) and constraints
- Step 2: Optimize steady-state operation
- Step 3: Decide what to control (CVs)
  - Step 3A: Identify active constraints = primary CV1.
  - Step 3B: Remaining unconstrained DOFs: Self-optimizing CV1 (find H)
- Step 4: Where do we set the throughput? TPM location

Then bottom-up design of control system (dynamics):

- Step 5: Regulatory control
  - Control variables to stop "drift" (sensitive temperatures, pressures, ...)
  - Inventory control radiating around TPM

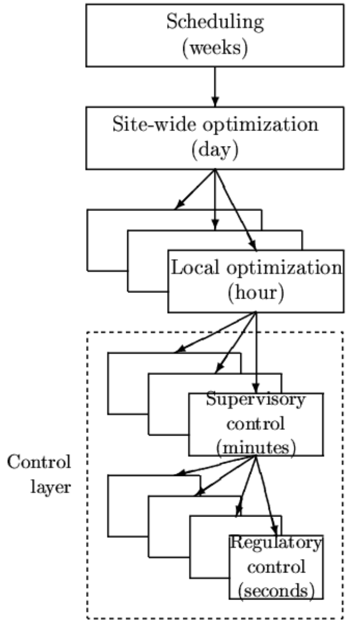
Finally: Make link between "top-down" and "bottom up"

- Step 6: "Advanced/supervisory control"
  - Control economic CVs: Active constraints and self-optimizing variables
  - Look after variables in regulatory layer below (e.g., avoid saturation)
- **Step 7: Real-time optimization** (Do we need it?)



S. Skogestad, ``Control structure design for complete chemical plants'', *Computers and Chemical Engineering*, **28** (1-2), 219-234 (2004).

Example: Bicycle riding
Design of control system



Note: design starts from the bottom

- *Regulatory control (step 5)*:
  - First need to learn to stabilize the bicycle
    - CV = y_2 = tilt of bike
    - MV = body position

- *Supervisory control (step 6)*:
  - Then need to follow the road.
    - CV = y_1 = distance from right hand side
    - MV=y_{2s}
  - Usually a constant setpoint policy is OK, e.g. y_{1s}=0.5 m

- *Optimization (step 7)*:
  - Which road should you follow?
  - Temporary (discrete) changes in y_{1s}

Step 1. Define optimal operation (economics)

Usually steady state

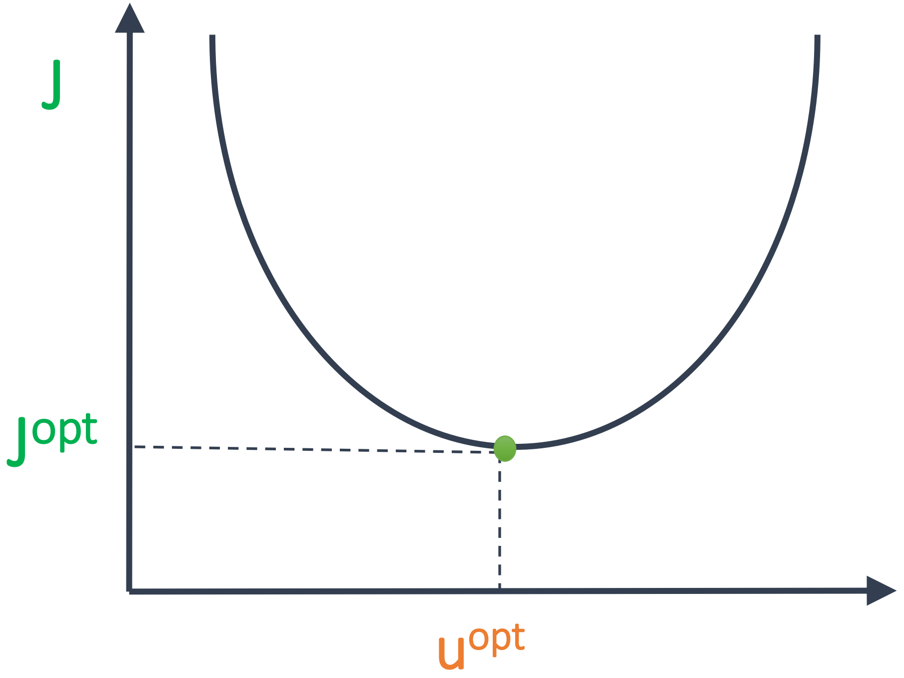
Minimize cost $J = J(u,x,d)$

subject to:

Model equations: $f(u,x,d) = 0$

Operational constraints: $g(u,x,d) < 0$

- u = degrees of freedom
- x = states (internal variables)
- d = disturbances



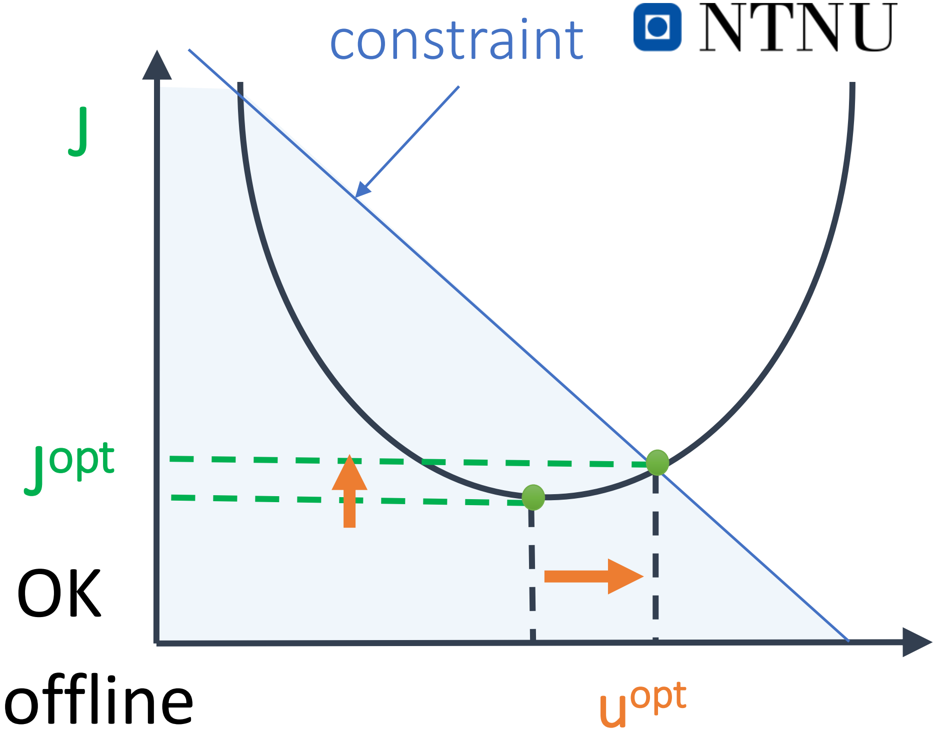
Typical cost function in process control:

$$\boxed{J = \text{cost feed} + \text{cost energy} - \text{value of products}}$$

Step 2. Optimize

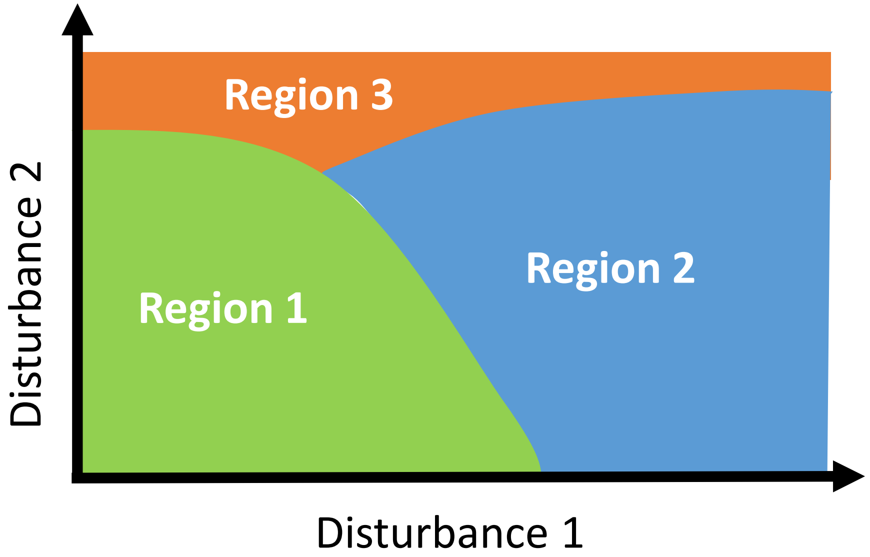
(a) Identify degrees of freedom
(b) Optimize for expected disturbances

- Need good model, usually steady-state is OK
- Optimization is time consuming! But it is offline
- Main goal: Identify **ACTIVE CONSTRAINTS**
- A good engineer can often guess the active constraints



Active constraints

- **Active constraints:**
  - variables that should optimally be kept at their limiting value.
- **Active constraint region:**
  - region in the disturbance space defined by which constraints are active within it.



Optimal operation:
Need to switch between regions
using control system

How many active constraints regions?

- Maximum: $$2^{n_c}$$

  n_c = number of constraints

Distillation
$n_c = 5$
$2^5 = 32$

BUT there are usually fewer in practice

- Certain constraints are always active (reduces effective n_c)
- Only n_u can be active at a given time
  n_u = number of MVs (degrees of freedom)
- Certain constraints combinations are not possible
  - For example, max and min on the same variable (e.g. flow)
- Certain regions are not reached by the assumed disturbance set

x_B always active
2^4 = 16

-1 = 15

In practice = 8

Step 3. Decide what to control (Economic CV1=Hy)

"Move optimization into the control layer by selecting the right CVs"

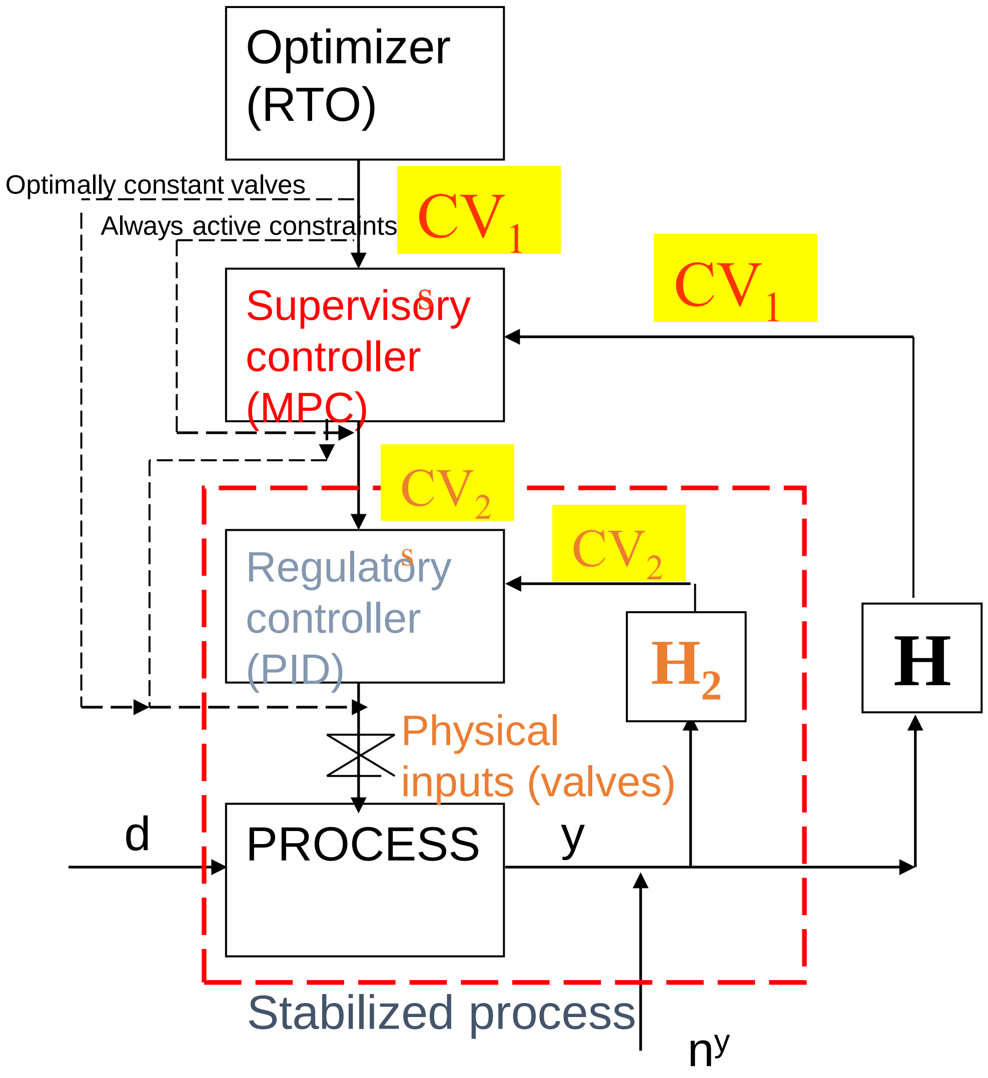
(Morari *et al.*, 1980): *"We want to find a function c of the process variables which when held constant, leads automatically to the optimal adjustments of the manipulated variables, and with it, the optimal operating conditions."*

Economic CV1:

1. Control active constraints

2. Control Self-optimizing variables

- Look for a variable c that can be kept constant



Sigurd’s rules for CV selection

1. Always control active constraints! (almost always)
2. Purity constraint on expensive product always active (no overpurification):
   (a) "Avoid product give away" (e.g., sell water as expensive product)
   (b) Save energy (costs energy to overpurify)

Unconstrained optimum:

3. Look for “self-optimizing” variables. They should
   - Be sensitive to the MV
   - have close-to-constant optimal value
4. **NEVER try to control a variable that reaches max or min at the optimum**
   - In particular, never try to control directly the cost J
   - Assume we want to minimize J (e.g., J = V = energy) - and we make the stupid choice os selecting CV = V = J
     - Then setting J < Jmin: Gives infeasible operation (cannot meet constraints)
     - and setting J > Jmin: Forces us to be nonoptimal (which may require strange operation)

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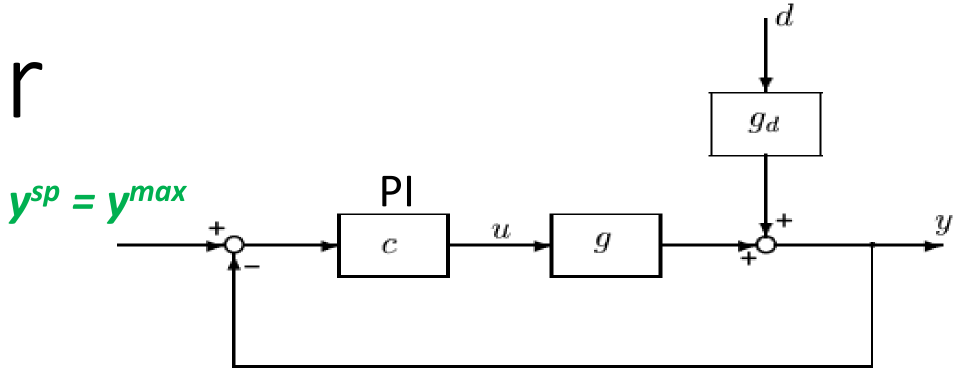
Optimization with PI-controller

$\max y$

s.t. $y \leq y^{max}$

$u \leq u^{max}$



Example: Drive as fast as possible to airport (u=power, y=speed, y^{max} = 110 km/h)

- **Optimal solution has two active constraint regions:**
  1. $y = y^{max}$ → **speed limit**
  2. $u = u^{max}$ → **max power**
- Note: Positive gain from MV (u) to CV (y)
- **Solved with PI-controller**
  - $y^{sp} = y^{max}$
  - Anti-windup: I-action is off when $u=u^{max}$

s.t. = subject to

y = CV = controlled variable

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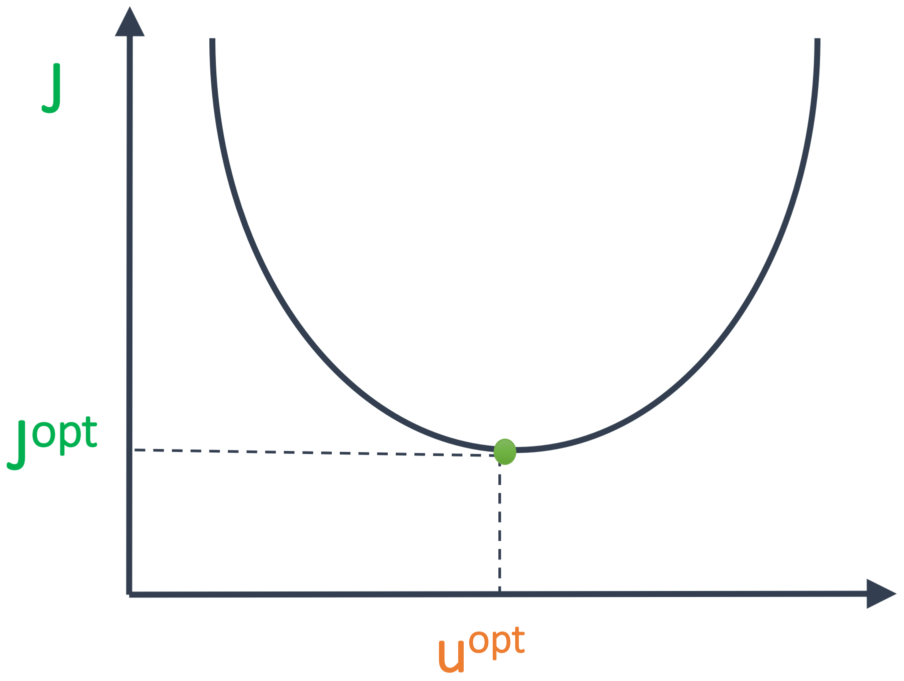
The less obvious case: Unconstrained optimum

- u = unconstrained MV
- What to control? y=CV=?



Example: Optimal operation of runner

- Cost to be minimized, J=T
- One degree of freedom (u=power)
- What should we control?

1. Optimal operation of Sprinter

- 100m. J=T
- Active constraint control:
  - Maximum speed (”no thinking required”)
  - CV = power (at max)

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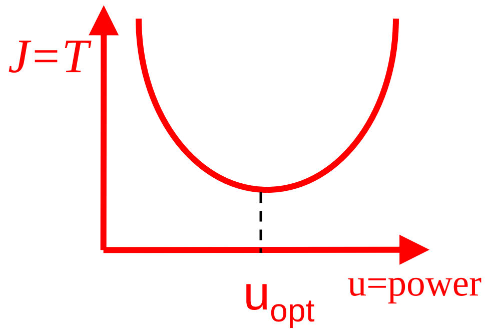
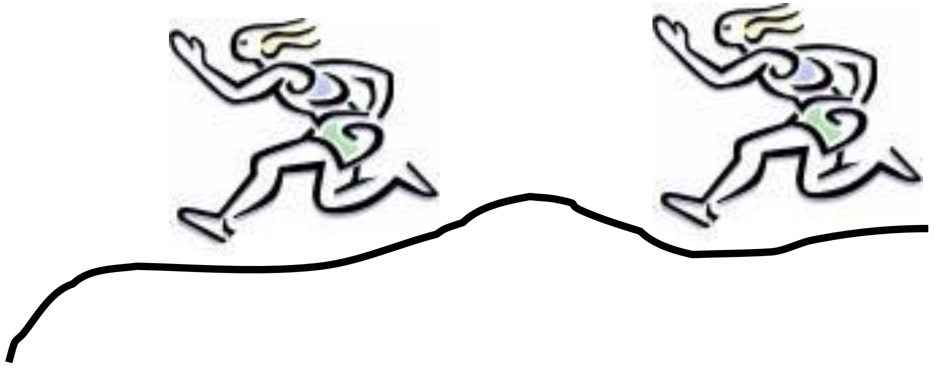
2. Optimal operation of Marathon runner

- 40 km. J=T
- What should we control? CV=?
- Unconstrained optimum





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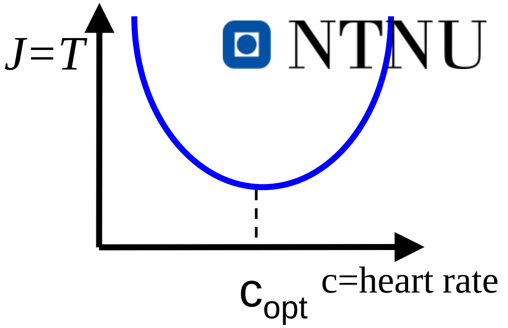
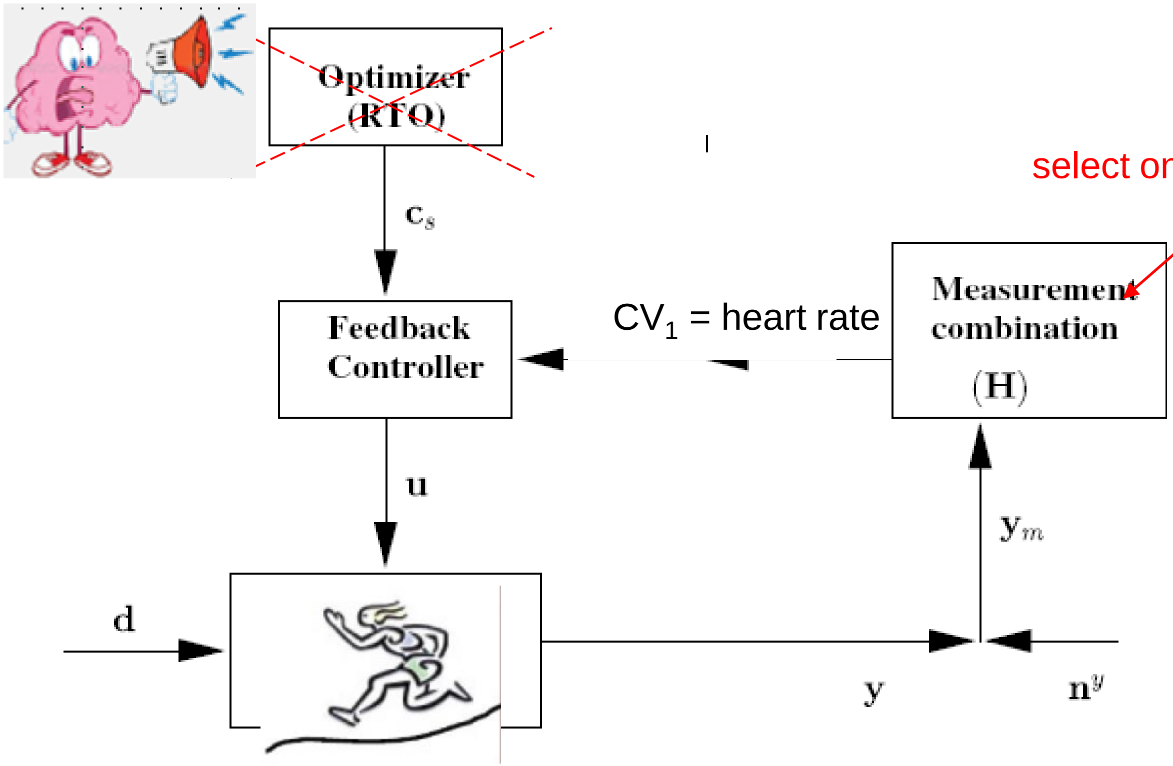
Marathon runner (40 km)

- Any self-optimizing variable (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

2. Control self-optimizing variables

Conclusion Marathon runner

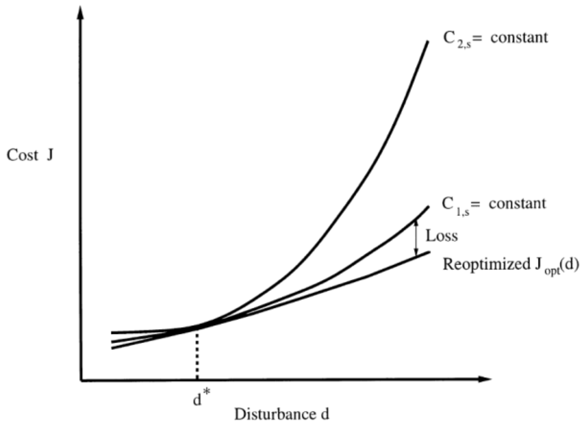


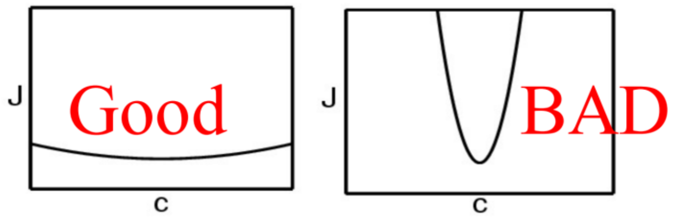


- CV = heart rate is good “self-optimizing” variable
- Simple and robust implementation
- Disturbances are indirectly handled by keeping a constant heart rate
- May have infrequent adjustment of setpoint (c_s)

Self-optimizing control

Self-optimizing control is when we can achieve an acceptable loss (between re-optimizations) with constant setpoint values for the controlled variables





(b) Flat optimum: Implementation easy

(c) Sharp optimum: Sensitive to implementation erros

c = controlled variable

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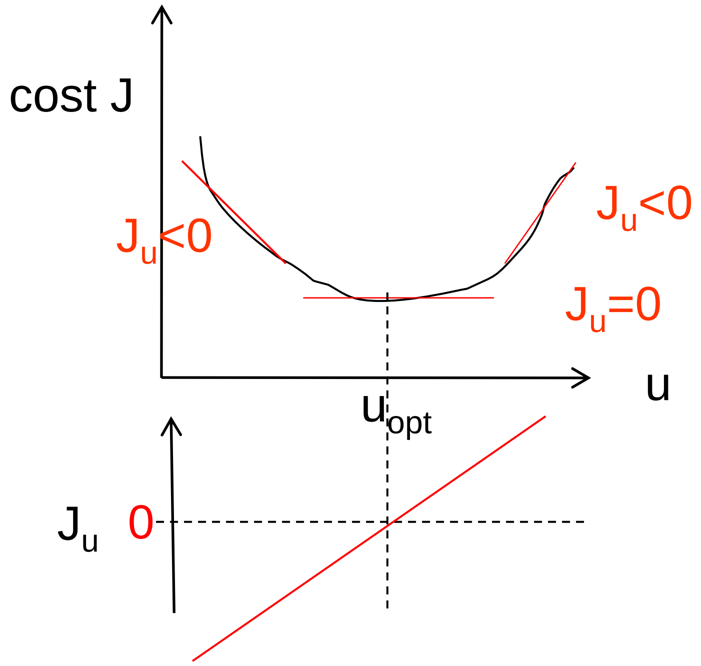
The ideal "self-optimizing" variable is the gradient, J_u

$$c = \partial J/\partial u = J_u$$

- Keep gradient at zero for all disturbances ($c = J_u = 0$)



Problem: Usually no measurement of gradient

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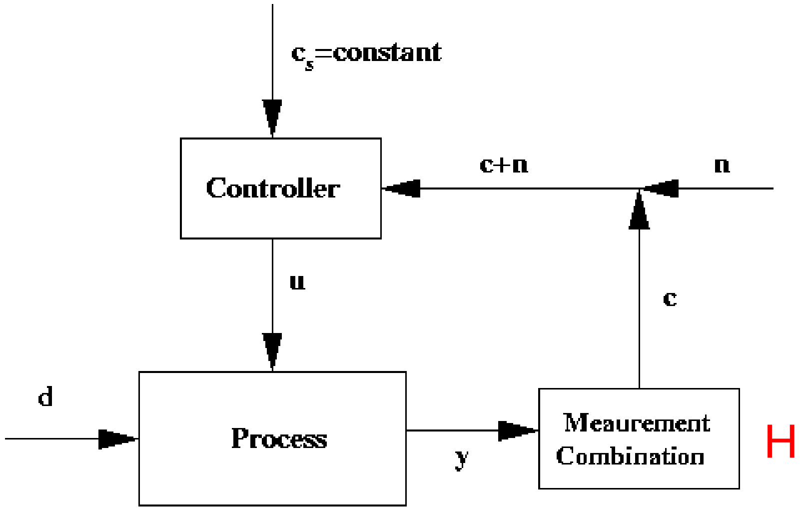
Ideal: $c = J_u$

In practise, use available measurements: $c = H y$. Task: Select H!



- Single measurements:

$$\mathbf{c} = \mathbf{H}\mathbf{y} \qquad \mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

- Combinations of measurements:

$$\mathbf{c} = \mathbf{H}\mathbf{y} \qquad \mathbf{H} = \begin{bmatrix} h_{11} & h_{12} & h_{13} & h_{14} \\ h_{21} & h_{22} & h_{23} & h_{24} \end{bmatrix}$$

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- Combinations of measurements, c= Hy

Nullspace method for H (Alstad):

HF=0 where $F = dy_{opt}/dd$

Proof: $y_{opt} = F\,d$

$c_{opt} = H\,y_{opt} = HF\,d$

- Proof. Appendix B in: Jäschke and Skogestad, "NCO tracking and self-optimizing control in the context of real-time optimization", *Journal of Process Control*, 1407-1416 (2011)

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Example. Nullspace Method for Marathon runner

u = power, d = slope [degrees]

y_1 = hr [beat/min], y_2 = v [m/s]

c = Hy, H = [h_1 h_2]]

F = dy_{opt}/dd = [0.25 -0.2]'

HF = 0 -> $h_1 f_1 + h_2 f_2 = 0.25 h_1 - 0.2 h_2 = 0$

Choose $h_1 = 1$ -> $h_2 = 0.25/0.2 = 1.25$

Conclusion: **c = hr + 1.25 v**

Control **c = constant** -> hr increases when v decreases (OK uphill!)

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Exact local method for H

$$\min_H \left\| \underbrace{J_{uu}^{1/2}(HG^y)^{-1}}_{\text{"Minimize" in Maximum gain rule}} \underbrace{\overbrace{HF}^{\text{"=0" in nullspace method (no noise)}}\!\!\!\!\!\!\;[FW_d \quad W_{n^y}]}_{\text{"Scaling" } S_1} \right\|_2$$

"=0" in nullspace method (no noise)

"Minimize" in Maximum gain rule
(maximize S_1 G $J_{uu}^{-1/2}$, $G=HG^y$)

"Scaling" S_1

Analytical solution:

$H = G^{yT}(YY^T)^{-1}$ where $Y = [FW_d \quad W_{n^y}]$

Advantages compared to nullspace method:

- Can have any number of measurements y
- Includes measurement noise

Step 4: Inventory control and TPM (later!)

Step 5: Design of regulatory control layer

Usually single-loop PID controllers

Choice of CVs (CV2):

- CV2 = «drifting variables»
  - Levels, pressures
  - Some temperatures
- CV2 may also include economic variables (CV1) that need to be controlled on a fast time scale
  - Hard constraints

Choice of MVs and pairings (MV-CV):

- **Main rule: “Pair close**”. Want:
  - Large gain
  - Small delay
  - Small time constant
- **Avoid pairing on negative steady-state RGA-elements**
  - It’s possible, but then you must be sure that the loops are always working (no manual contriol or MV-saturation)
- **Generally: Avoid MVs that may saturate in regulatory layer**
  - Otherwise, will need logic for re-pairing (MV-CV switching)

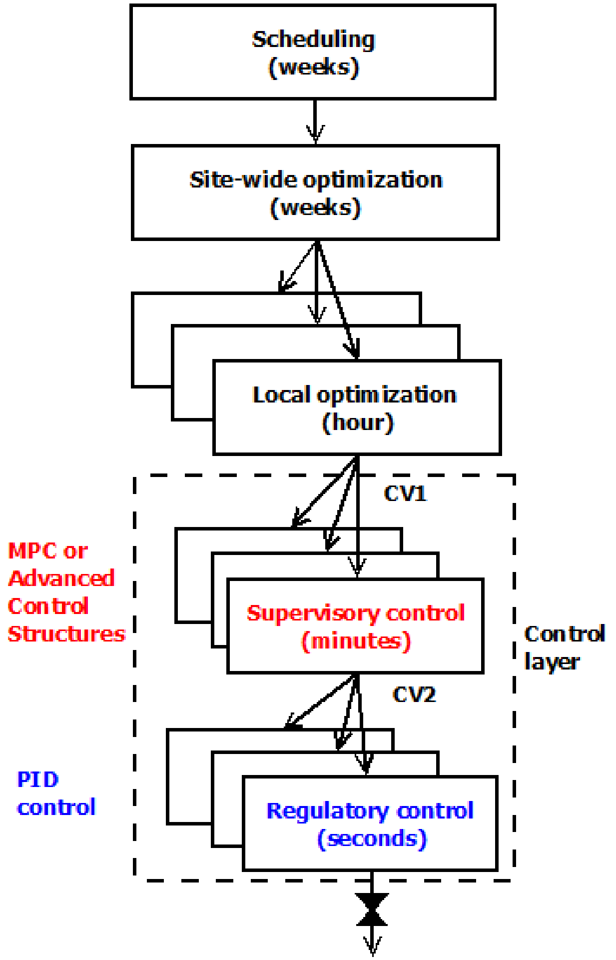
- May include cascade loops (flow control!) and some feedforward, decoupling, linearization

-

Step 6: Design of Supervisory layer

Alternative implementations:

1. Model predictive control (MPC)
2. Advanced regulatorty control (ARC)
   - PID, selectors, etc.



Academia: (E)MPC

- MPC
  - General approach, but we need a dynamic model
    - MPC is usually based on experimental model
    - and implemented after some time of operation
  - Not all problems are easily formulated using MPC

Alternative simpler solutions to MPC

- Would like: Feedback solutions that can be implemented without a detailed models

- Machine learning?
  - Requires a lot of data
  - Can only be implemented after the process has been in operation

- But we have "advanced regulatory control“ (ARC) based on simple control elements
  - Goal: Optimal operation using conventional advanced control
  - PID, feedforward, decouplers, selectors, split range control etc.
  - Extensively used by industry
  - Problem for engineers: Lack of design methods
    - Has been around since 1940’s
    - But almost completely neglected by academic researchers
  - Main fundamental limitation: Based on single-loop (need to choose pairing)

How design ARC system based on simple elements?

- Main topic of this workshop

Advanced regulatory control (ARC) = Classical APC = Advanced PID contol

- Industrial literature (e.g., Shinskey).

  Many nice ideas. But not systematic. Difficult to understand reasoning

- Academia: Very little work so far

APC = Advanced process control

Step 7: Do we really need RTO?

- Often not!
- We can usually measure the constraints
- From this we can identify the **active constraints**
  - Example: Assume it’s optimal with max. reactor temperature
  - No need for complex model with energy balance to find the optimal cooling
  - Just use a PI-controller
    - CV = reactor temperature (with setpoint=max)
    - MV = cooling
- And for the remaining unconstrained variables
  - Look for good variables to control (where optimal setpoint changes little)
  - «self-optimizing» variables

RTO = real-time optimization

Systematic procedure for economic process control

Start "top-down" with economics (steady state):

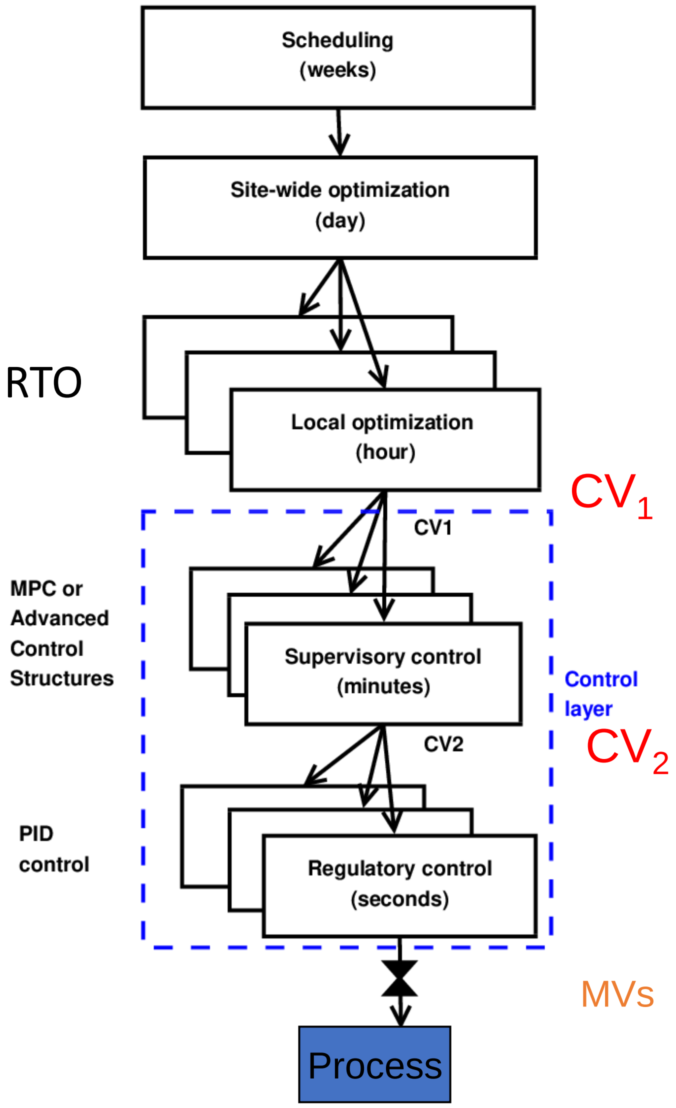
- Step 1: Define operational objectives (J) and constraints
- Step 2: Optimize steady-state operation
- Step 3: Decide what to control (CVs)
  - Step 3A: Identify active constraints = primary CV1.
  - Step 3B: Remaining unconstrained DOFs: Self-optimizing CV1 (find H)
- Step 4: Where do we set the throughput? TPM location

Then bottom-up design of control system(dynamics):

- Step 5: Regulatory control
  - Control variables to stop "drift" (sensitive temperatures, pressures, ...)
  - Inventory control radiating around TPM

Finally: Make link between "top-down" and "bottom up"

- Step 6: "Advanced/supervisory control"
  - Control economic CVs: Active constraints and self-optimizing variables
  - Look after variables in regulatory layer below (e.g., avoid saturation)
- **Step 7: Real-time optimization** (Do we need it?)



S. Skogestad, ``Control structure design for complete chemical plants'', *Computers and Chemical Engineering*, **28** (1-2), 219-234 (2004).