

Part 2. Decomposition and optimal operation

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

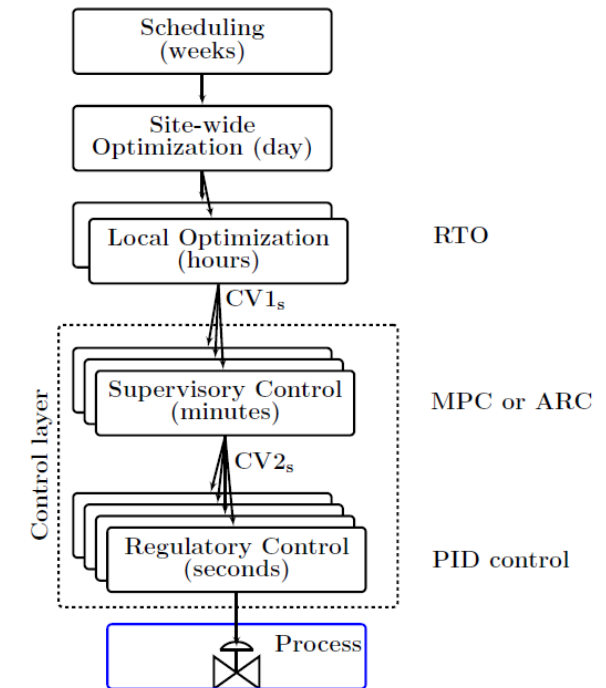


Figure 4: Decomposition of “overall control system” for optimal operation in typical process plant. This involves a vertical (hierarchical) decomposition [\[Richalet et al. \(1978\)\]](#) into decision layers based on time scale separation, and a horizontal decomposition into decentralized blocks/controllers, often based on physical distance. There is also feedback of measurements (y , w , $CV1$, $CV2$) (possibly estimates) from the process to the various layers and blocks but this is not shown in the figure. This paper considers the three lowest layers, with focus on the supervisory control layer.

$CV1$ = Economic controlled variables

$CV2$ = Regulatory/stabilizing controlled variables

RTO = Real-time optimization

MPC = Model predictive control

ARC = Advanced regulatory control

PID = Proportional-Integral-Derivative

Optimal operation and control of process

- Given process plant
- Want to Maximize profit $P \Rightarrow$ Minimize economic cost $J_{\xi} = -P$ [\$/s]
 - $J_{\xi} = p_F F + p_Q Q - P_p P = \text{cost feed} + \text{cost energy} - \text{value products}$
 - 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

Economic motivation for better control: Squeeze and shift rule

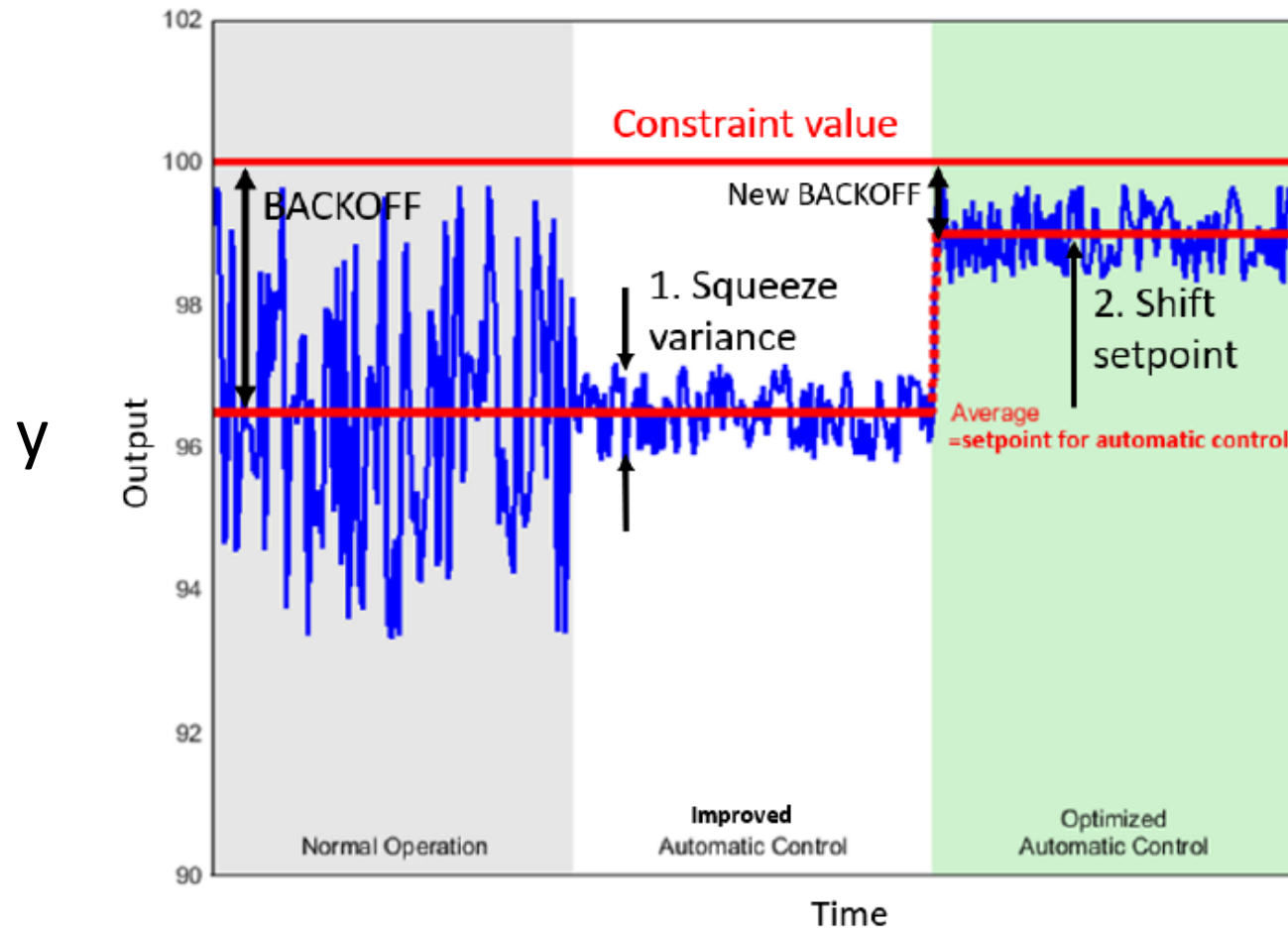


Figure 8: Squeeze and shift rule: Squeeze the variance by improving control and shift the setpoint closer to the constraint (i.e., reduce the backoff) to optimize the economics (Richalet et al., 1978).

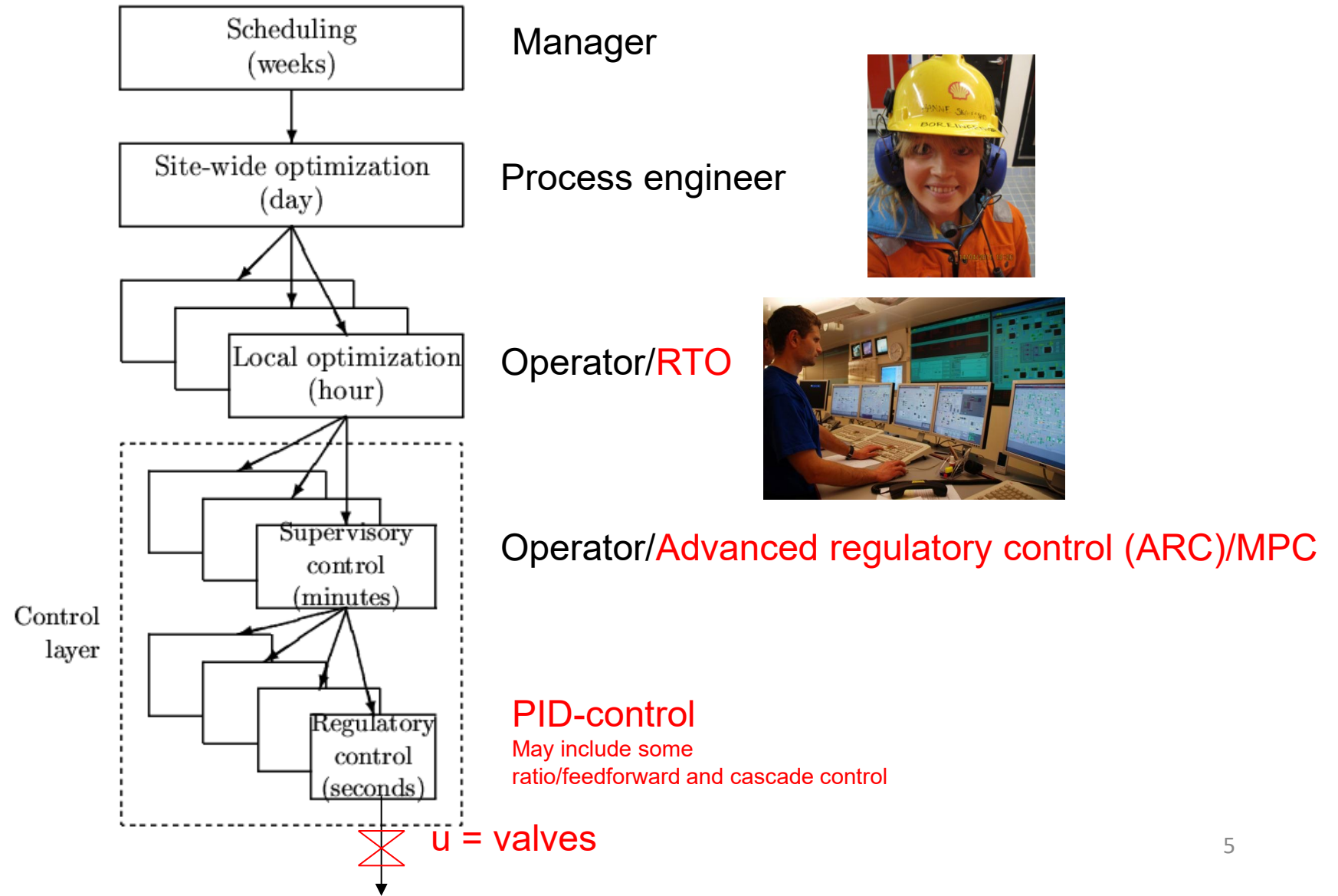
Practical operation: Hierarchical (cascade) structure based on time scale separation

NOTE: Control system is decomposed both

- Hierarchically (in time)
- Horizontally (in space)

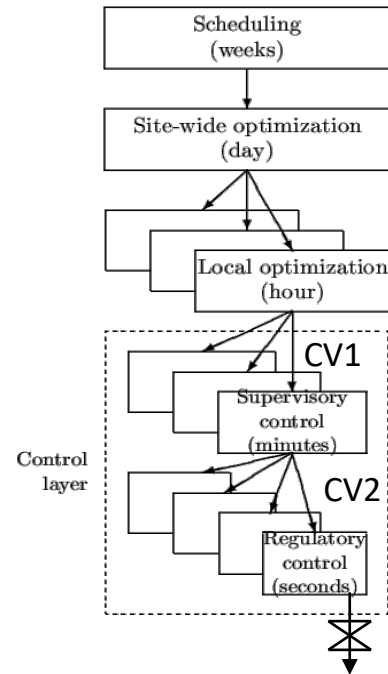
Status industry:

- **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...



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

Main objectives operation

1. Economics: Implementation of acceptable (near-optimal) operation

2. Regulation: Stable operation around given setpoint

ARE THESE OBJECTIVES CONFLICTING?

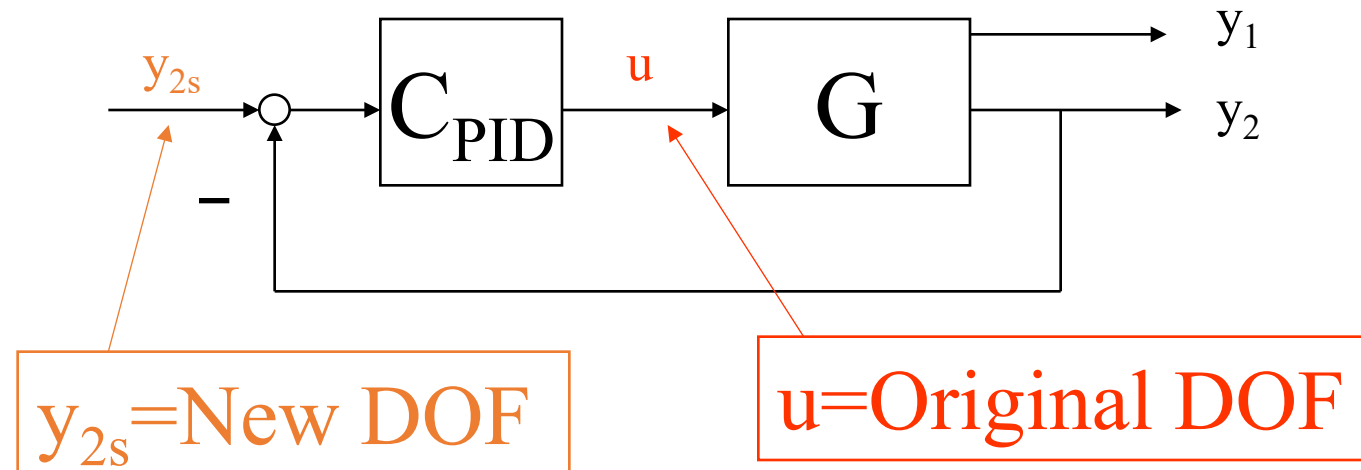
IS THERE ANY LOSS IN ECONOMICS?

- **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):

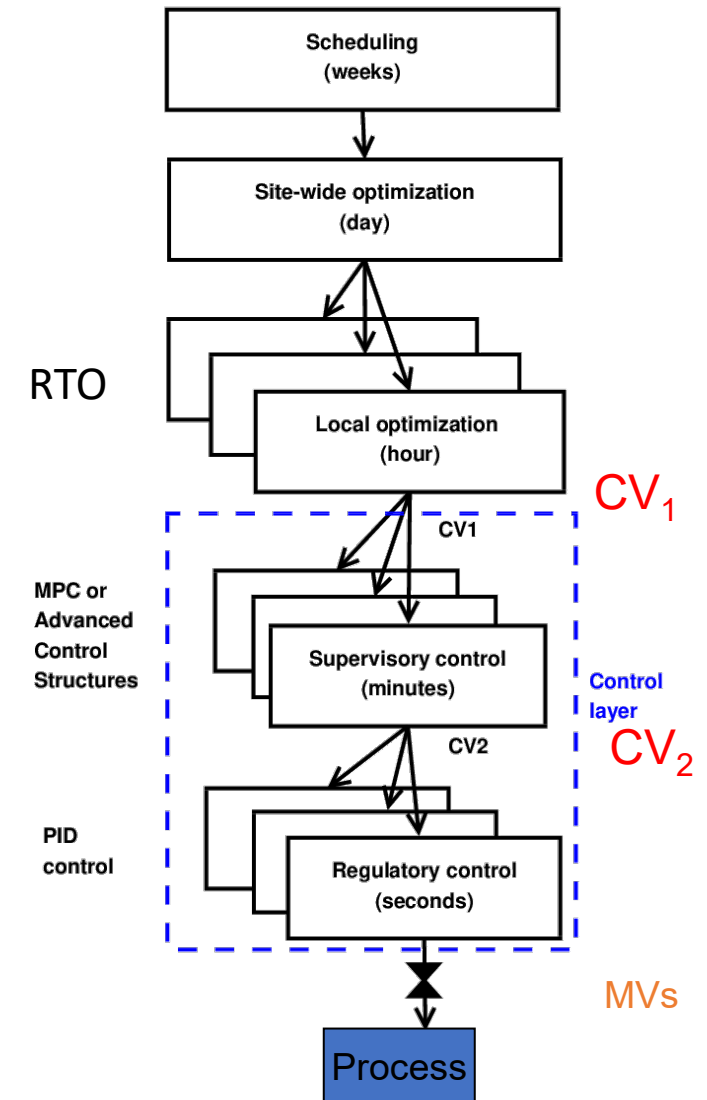
- Step 1: Define operational objectives (J) and constraints
- Step 2: Optimize steady-state operation
- Step 3: Decide what to control (CVs)
 - Step 3A: Identify active constraints = primary CV1.
 - Step 3B: Remaining unconstrained DOFs: Self-optimizing CV1 (find H)
- Step 4: Where do we set the throughput?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



Step 1. Define optimal operation (economics)

Usually steady state

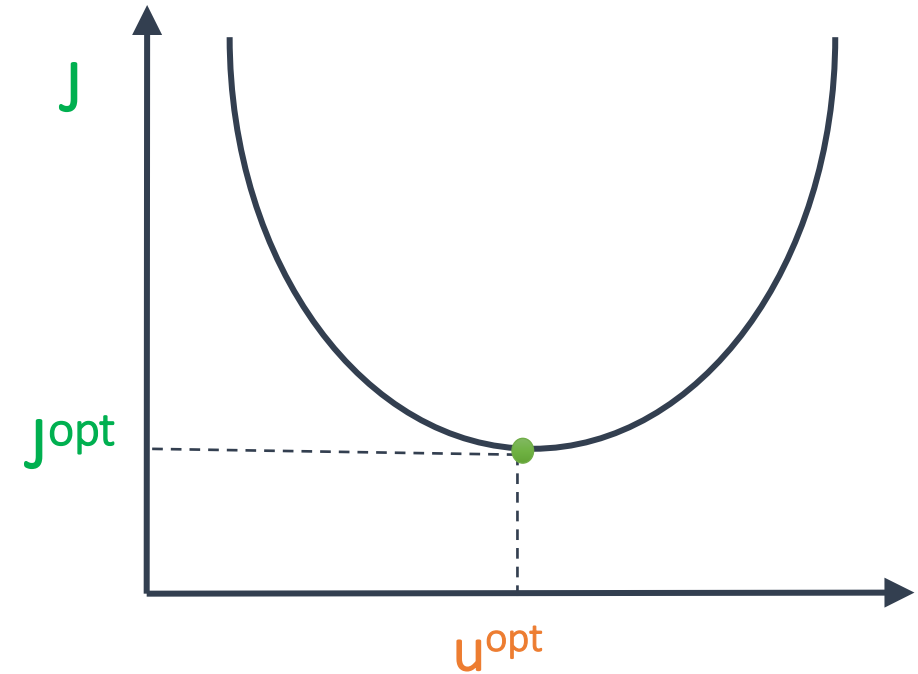
Minimize cost $J = J(\mathbf{u}, \mathbf{x}, \mathbf{d})$

subject to:

Model equations: $f(\mathbf{u}, \mathbf{x}, \mathbf{d}) = 0$

Operational constraints: $g(\mathbf{u}, \mathbf{x}, \mathbf{d}) < 0$

- $\mathbf{u}$ = degrees of freedom
- $\mathbf{x}$ = states (internal variables)
- $\mathbf{d}$ = disturbances



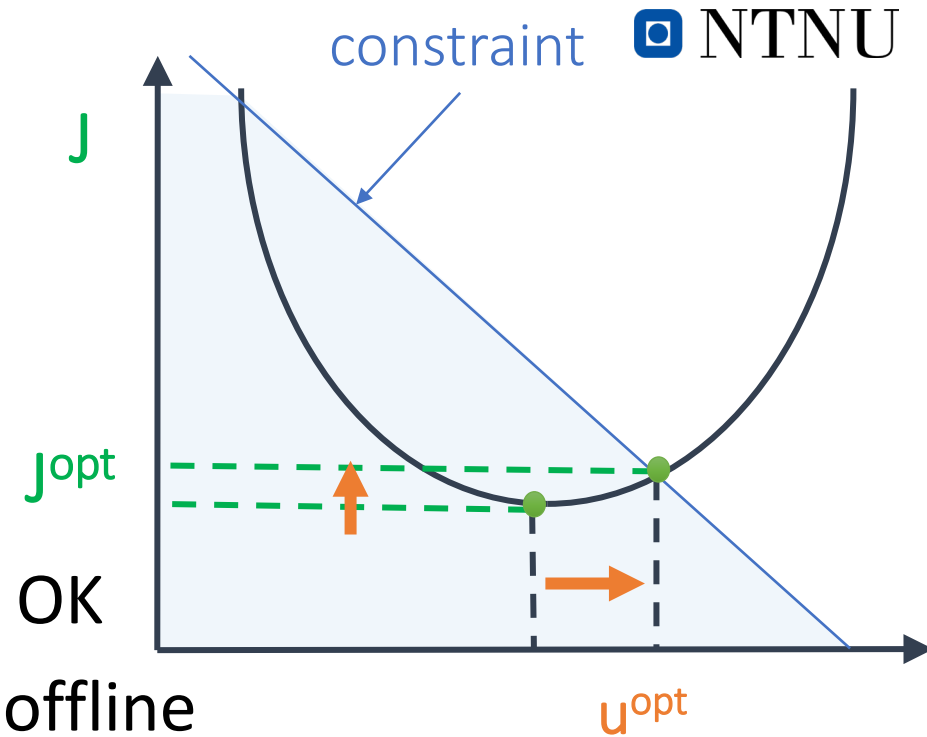
Typical cost function in process control:

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

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



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

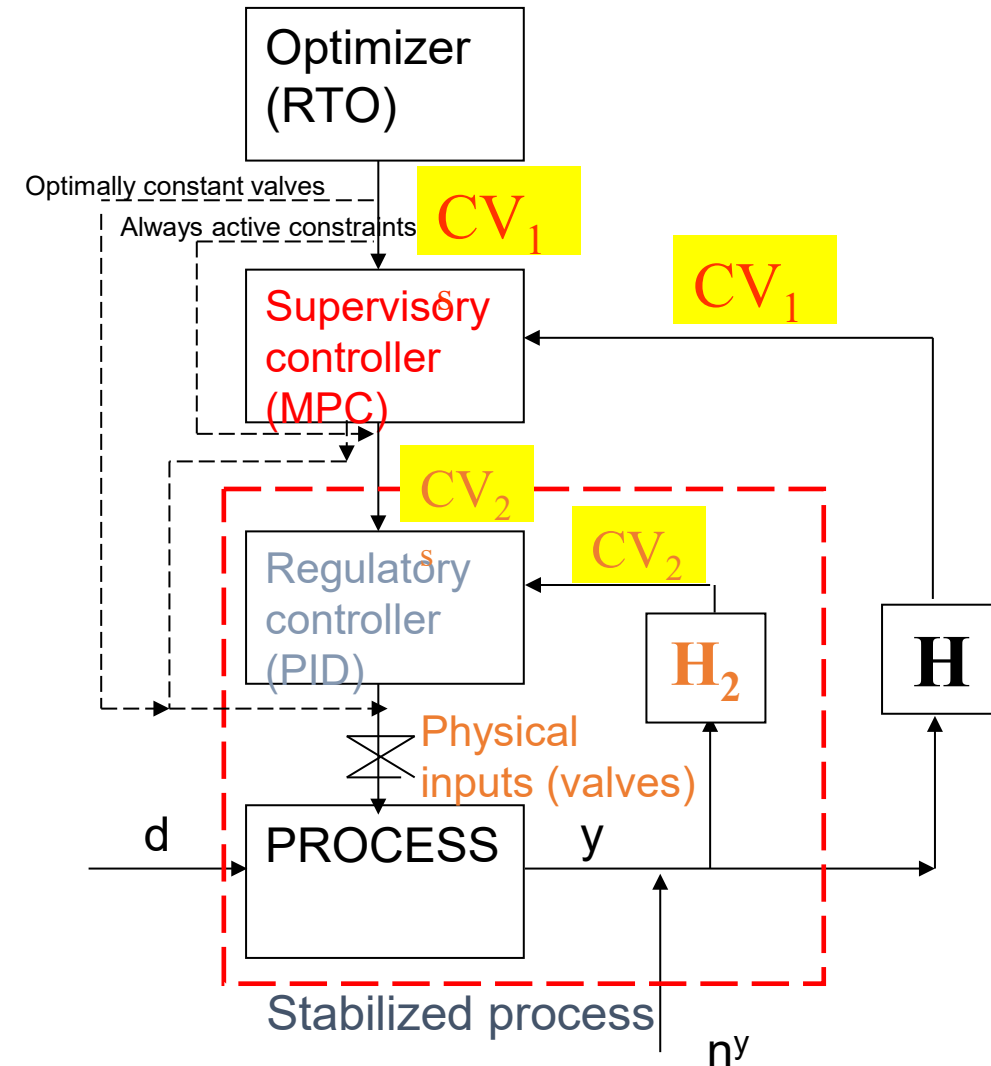
“Move optimization into the control layer by selecting the right CV1”

(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

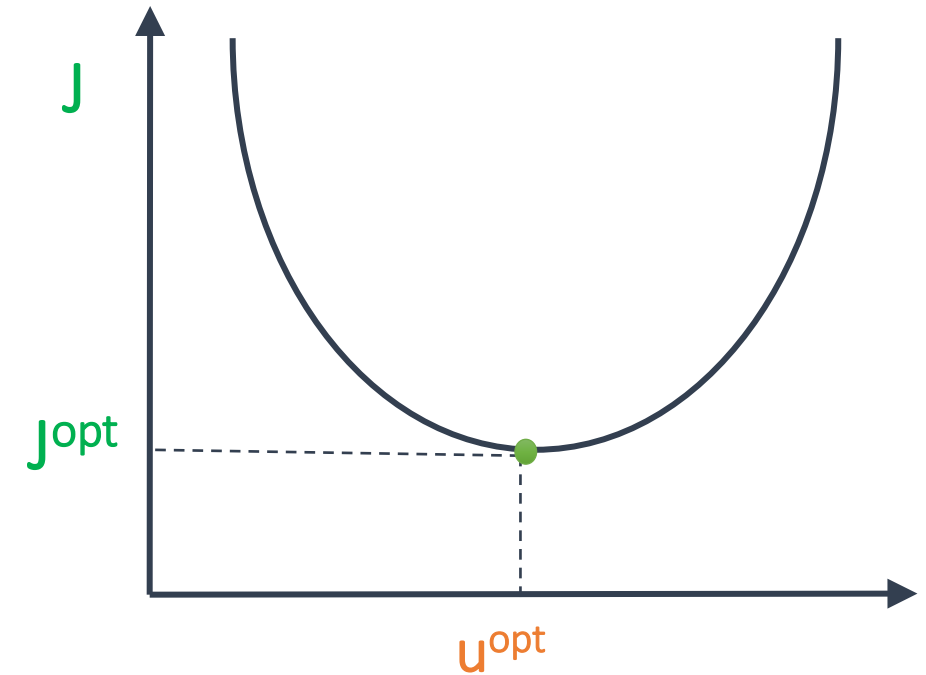
1. Always control active constraints! (almost always)
2. Purity constraint on expensive product always active (no overpurification):
 - (a) "Avoid product give away" (e.g., sell water as expensive product)
 - (b) Save energy (costs energy to overpurify)

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., $J = V = \text{energy}$) - and we make the stupid choice of selecting $CV = V = J$
 - Then setting $J < J_{\min}$: Gives infeasible operation (cannot meet constraints)
 - and setting $J > J_{\min}$: Forces us to be nonoptimal (which may require strange operation)

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 ($u=\text{power}$)
- What should we control?



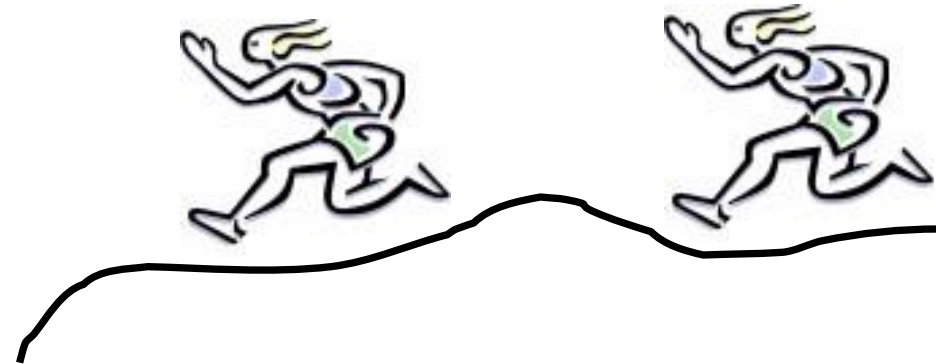
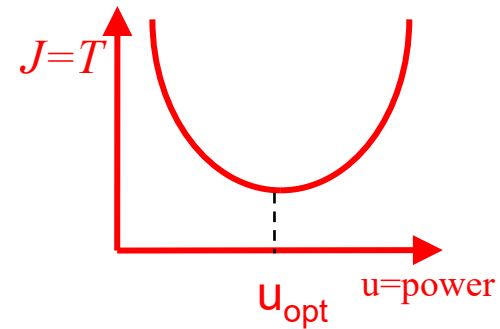
1. Optimal operation of Sprinter

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



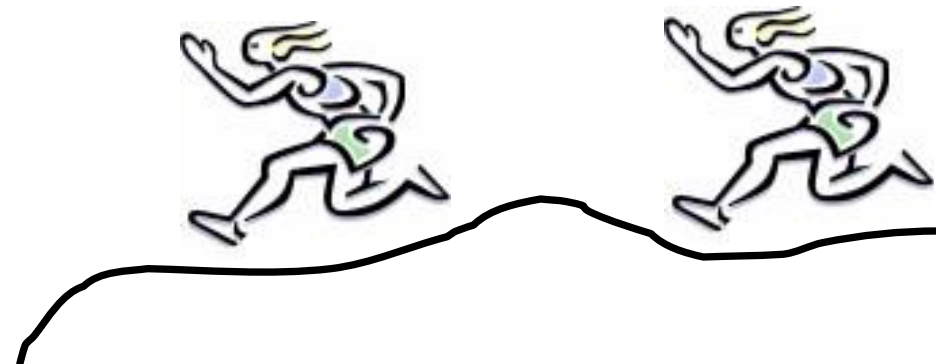
2. Optimal operation of Marathon runner

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



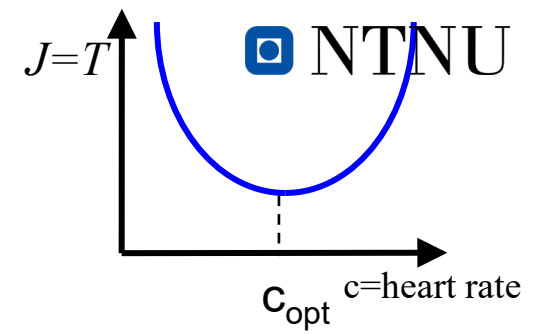
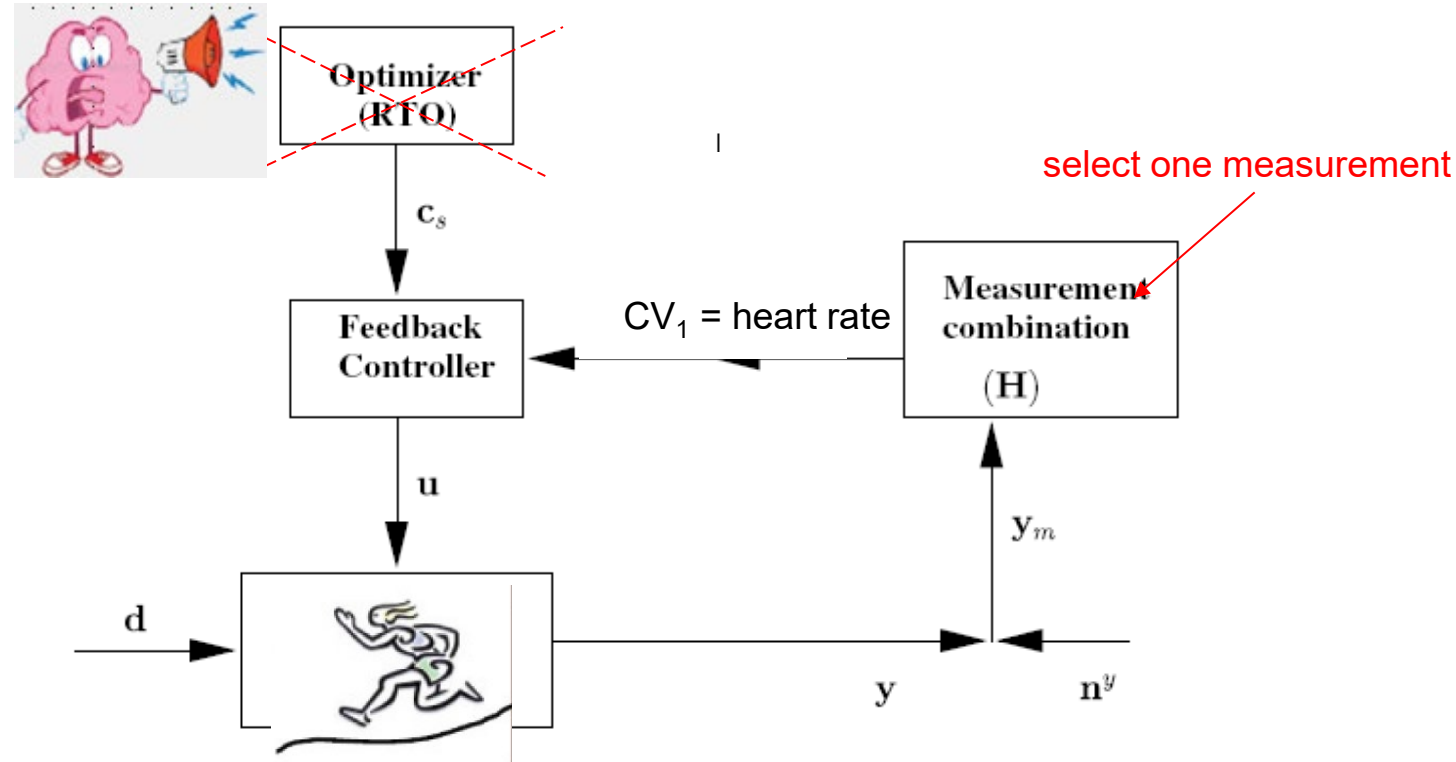
Marathon runner (40 km)

- 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

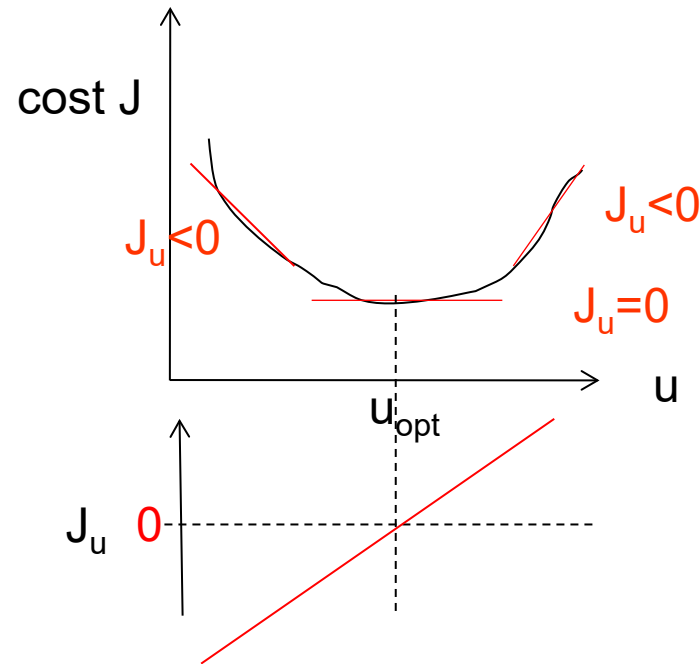


- CV = heart rate is good “self-optimizing” variable
- Simple and robust implementation
- Disturbances are indirectly handled by keeping a constant heart rate
- May have infrequent adjustment of setpoint (c_s)

The ideal “self-optimizing” variable is the gradient, J_u

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

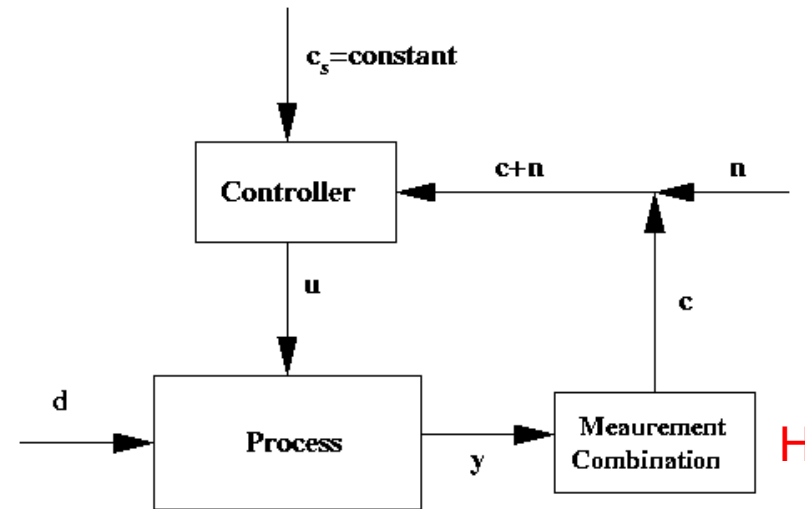
- Keep gradient at zero for all disturbances ($c = J_u = 0$)



Problem: Usually no measurement of gradient

Ideal: $c = J_u$

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



- Single measurements:

$$c = Hy \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

- Combinations of measurements:

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

- Combinations of measurements, $c = Hy$

Nullspace method for H (Alstad):

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

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

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

- 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)

Example. Nullspace Method for Marathon runner

u = power, d = slope [degrees]

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

$c = Hy$, $H = [h_1 \ h_2]$

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

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

Choose $h_1 = 1$ $\rightarrow h_2 = 0.25/0.2 = 1.25$

Conclusion: **$c = \text{hr} + 1.25 v$**

Control **$c = \text{constant}$** $\rightarrow$ hr increases when v decreases (OK uphill!)

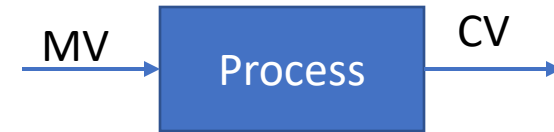
Step 4: Inventory control and TPM
(later!)

Step 5: Design of regulatory control layer

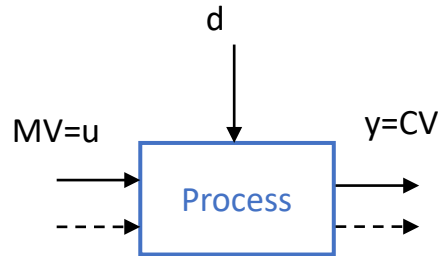
Usually single-loop PID controllers

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



Single-loop PID control



MV-CV Pairing. Two main pairing rules:

1. ***“Pair-close rule”***

- *The MV should have a large, fast, and direct effect on the CV.*

2. ***“Input saturation rule”***

- *Pair a MV that may saturate with a CV that can be given up (when the MV saturates)*

Additional rule for interactive systems:

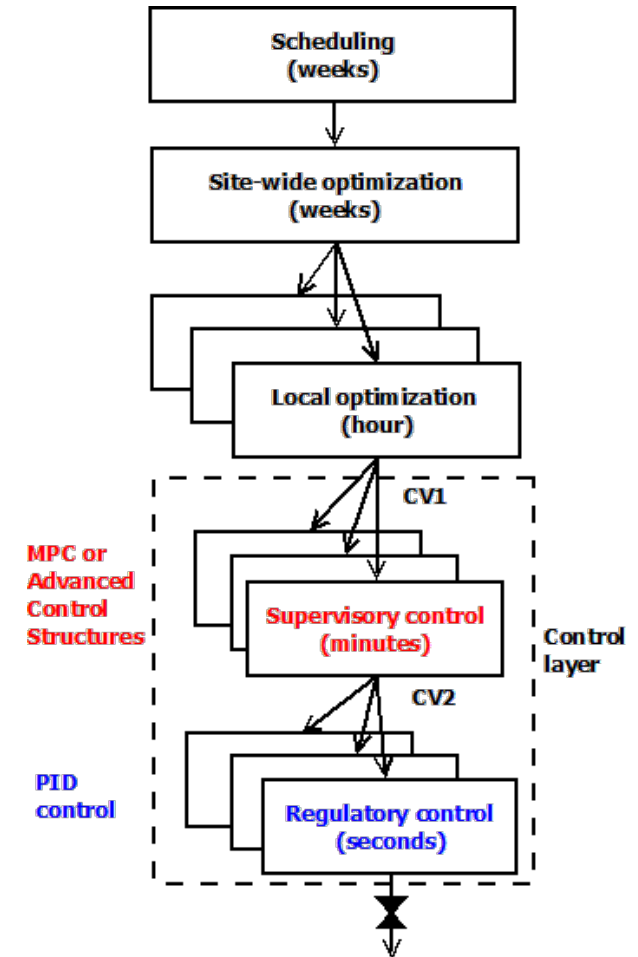
3. ***“RGA-rule”***

- *Avoid pairing on negative steady-state RGA-element. Otherwise, the loop gain may change sign (for example, if the input saturates) and we get instability with integral action in the controller.*

Step 6: Design of Supervisory layer

Alternative implementations:

1. Model predictive control (MPC)
2. Advanced regulatory 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 control

- Industrial literature (e.g., Shinskey).
Many nice ideas. But not systematic. Difficult to understand reasoning
- Academia: Little work

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

Summary: Systematic procedure for economic process control

Start “top-down” with economics (steady state):

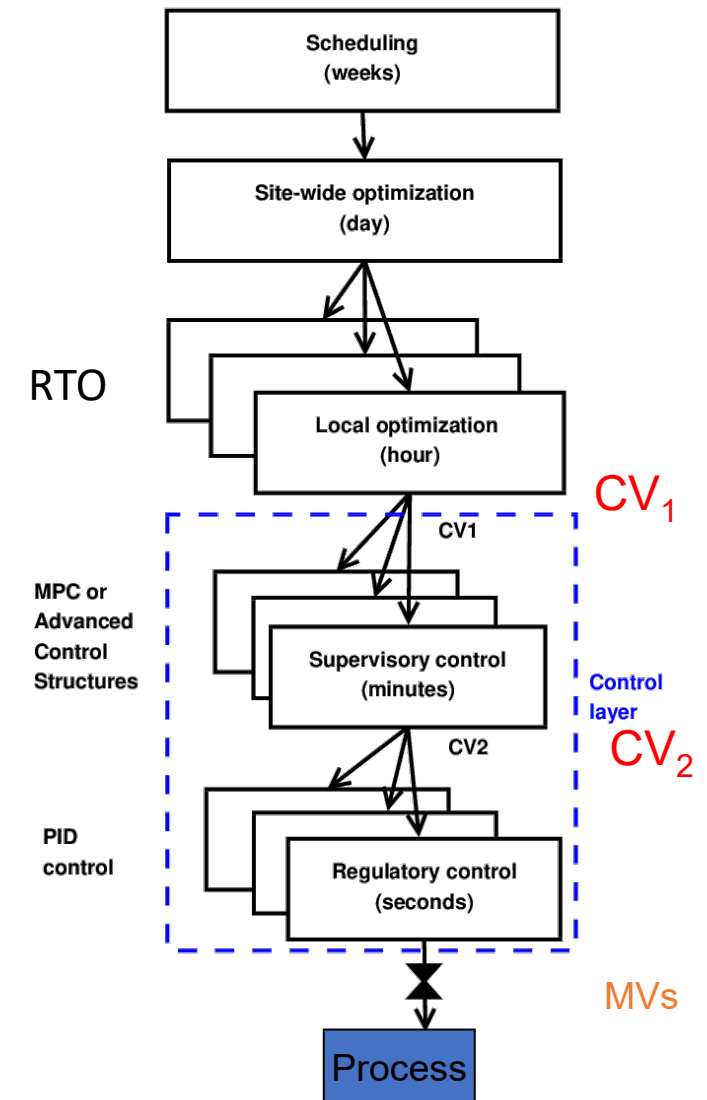
- Step 1: Define operational objectives (J) and constraints
- Step 2: Optimize steady-state operation
- Step 3: Decide what to control (CVs)
 - Step 3A: Identify active constraints = primary CV1.
 - Step 3B: Remaining unconstrained DOFs: Self-optimizing CV1 (find H)
- Step 4: Where do we set the throughput?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



Conclusion

- Move optimization into the control layer by selecting good CVs
- CV = Active constraints

Unconstrained degrees of freedom:

- CV = Self-optimizing variables
- CV = Gradients