

Studies on Selection of Controlled Variables

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Thesis outline

1. Introduction
2. Overview of control structure design and optimizing control
3. The null space method for selecting controlled variables
4. Measurement selection in the null space method
5. Disturbance discrimination in self-optimizing control
6. Effect of non-optimal nominal setpoints in self-optimizing control
7. Dynamics of controlling measurement combinations
8. Self-optimizing control structures for a Petlyuk distillation column
9. Energy savings by over-fractionation in the Petlyuk column
10. Control structure selection for oil and gas production networks
11. Control structure selection for an evaporator example
12. Appendices A-E

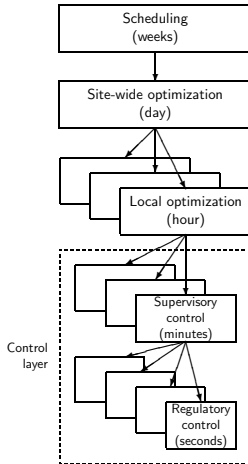


Presentation outline

- ▶ Introduction
- ▶ Part I: (Chapters 3 and 4)
 - ▶ Self-optimizing control
 - ▶ The null space method
 - ▶ Measurement selection
- ▶ Part II: (Chapters 8,10 and 11)
 - ▶ The Petlyuk Column
 - ▶ Oil & gas production networks
 - ▶ Evaporator
- ▶ Part III: (Chapters 5, 6 and 7)
 - ▶ Effect of nominal setpoint error
- ▶ Concluding remarks and further work

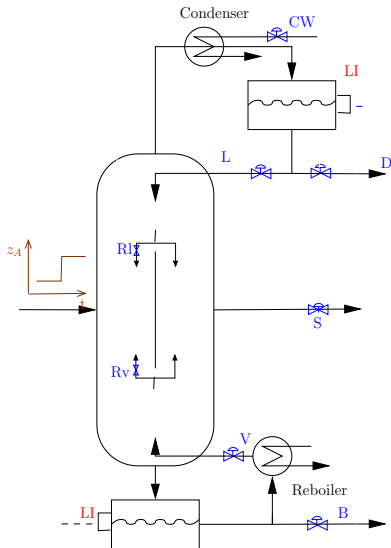


Control structure hierarchy in chemical plants

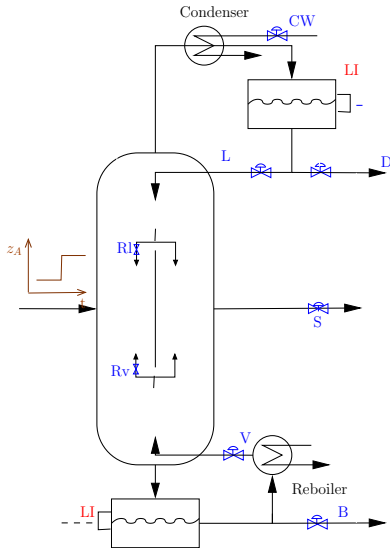


- ▶ Each layer in the control hierarchy operates at different time scales
- ▶ Layers connected through the controlled variables
- ▶ Focus on the interaction between the local optimization layer and the control layer
- ▶ Economics primarily decided by steady-state

Introduction - Selection of controlled variables: Petlyuk column

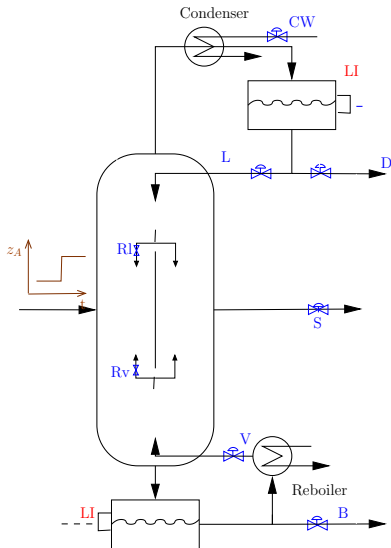


Introduction - Selection of controlled variables: Petlyuk column



► Persistent disturbance z_A .

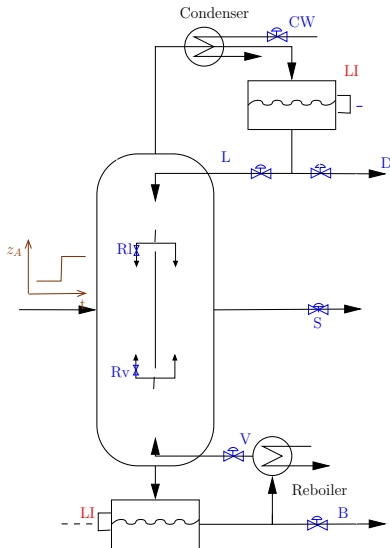
Introduction - Selection of controlled variables: Petlyuk column



- ▶ Persistent disturbance z_A .
- ▶ 7 degrees of freedom:

$$\mathbf{u}^T = [S, D, B, L, V, R_L, R_V]$$

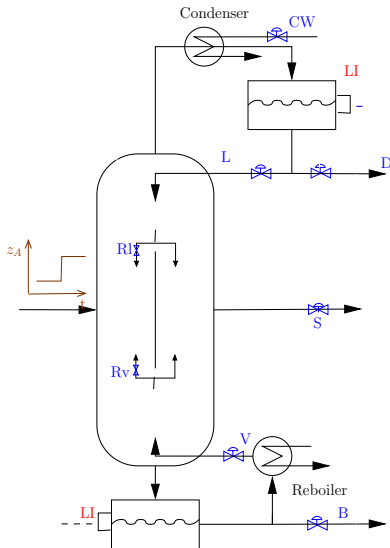
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- ▶ Persistent disturbance z_A .
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- ▶ -2 levels need to be stabilized

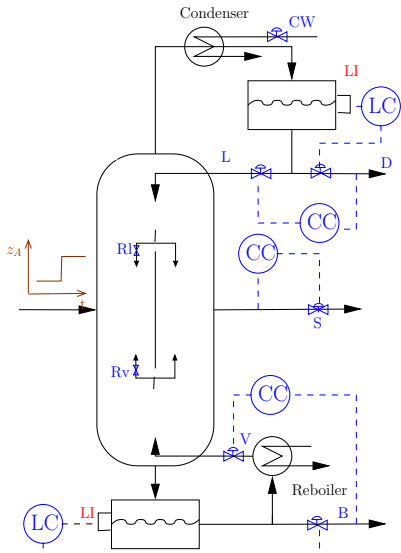
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- ▶ $= 5$ steady-state DOF

Introduction - Selection of controlled variables: Petlyuk column

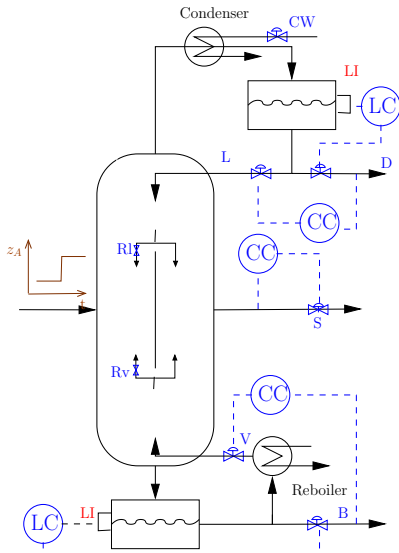


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- ▶ = 5 steady-state DOF
- ▶ -3 product specifications



Introduction - Selection of controlled variables: Petlyuk column

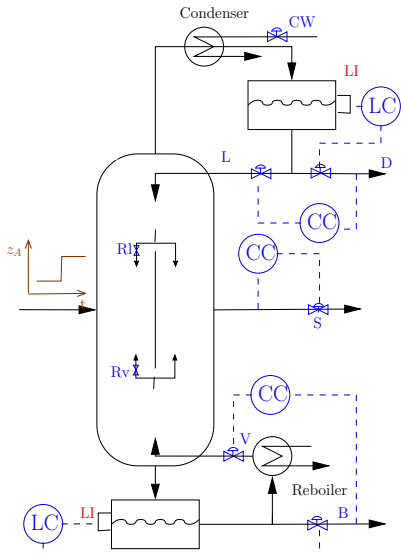


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- ▶ = 2 DOF left. What to control?



Introduction - Selection of controlled variables: Petlyuk column



- ▶ Persistent disturbance z_A .
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 $\mathbf{u}^T = [S, D, B, L, V, R_L, R_V]$
- ▶ -2 levels need to be stabilized
- ▶ = 5 steady-state DOF
- ▶ -3 product specifications
- ▶ = 2 DOF left. What to control?
- ▶ **Optimize the operation!**

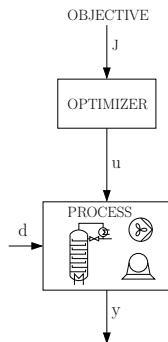
$$\min_{R_L, R_V} J(R_L, R_V, z_A, \dots)$$



Introduction - Strategies for ensuring optimal operation

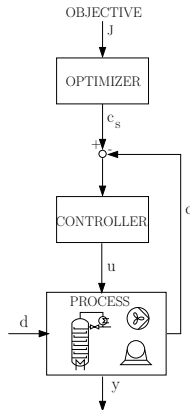
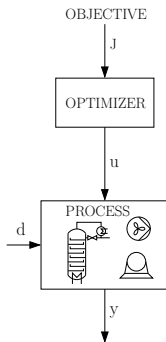
Introduction - Strategies for ensuring optimal operation

Open loop implementation



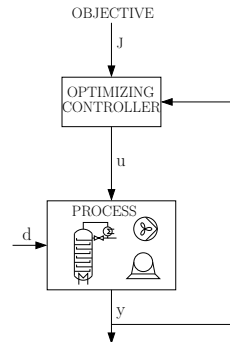
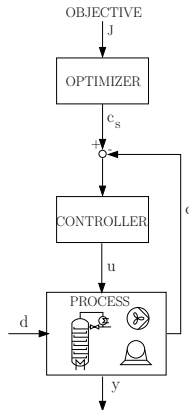
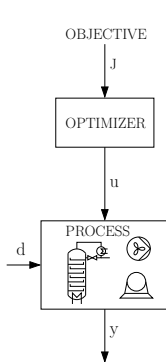
Introduction - Strategies for ensuring optimal operation

Open loop implementation Closed loop implementation with
separate control layer

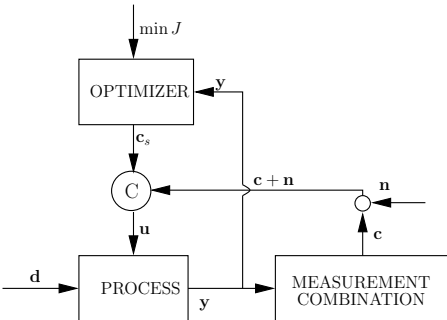


Introduction - Strategies for ensuring optimal operation

Open loop implementation Closed loop implementation with separate control layer Optimizing controller



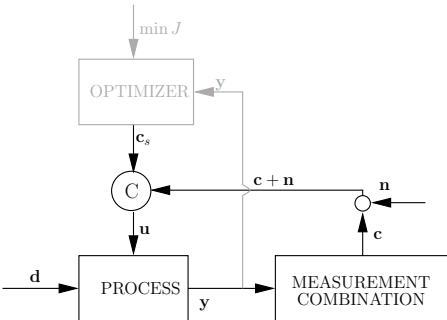
Part I: Self-optimizing control



- ▶ Which variables to measure? y
- ▶ Which variables to control? c
- ▶ What setpoints to use? c_s



Part I: Self-optimizing control



- ▶ Which variables to measure? y
- ▶ Which variables to control? c
- ▶ What setpoints to use? c_s
- ▶ Can we achieve acceptable steady-state economic performance with constant setpoints?

▶ \Rightarrow Self-optimizing control

Example: How to keep your wife happy!

- ▶ Objective: $J = \text{"wife happiness"}$



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Example: How to keep your wife happy!



- ▶ Objective: $J = \text{"wife happiness"}$
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Example: How to keep your wife happy!



- ▶ Objective: $J = \text{"wife happiness"}$
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 - ▶ time used by husband domestic work \leq free time **active**



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- ▶ Disturbances: $d = \begin{bmatrix} \text{"Bad day"} \\ \text{"Husband"} \\ \text{"Anniversary"} \end{bmatrix}$



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 - ▶ $c = \text{"smiles (by wife)"}$



Mathematical formulation

- How to find the best set of controlled variables c ?

$$\{c(x, u_0, d)\} = \arg \min_c \int_{\substack{d \in \mathcal{D} \\ n_c \in \mathcal{N}_c}} J(c, d, n)$$

$$\mathbf{f}(\mathbf{x}, \mathbf{u}_0, \mathbf{d}) = 0$$

Model equations

$$\mathbf{g}(\mathbf{x}, \mathbf{u}_0, \mathbf{d}) \leq 0$$

Inequality constraints

$$\mathbf{c}(\mathbf{x}, \mathbf{u}_0, \mathbf{d}) = \mathbf{c}_s + \mathbf{n}$$

Controlled variables



Mathematical formulation

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Controlled variables

- Simplify

$$\min_{\mathbf{u}_0} J(\mathbf{x}, \mathbf{u}_0, \mathbf{d})$$

$$\mathbf{g}' = 0 \quad \forall \quad \mathbf{d}$$

$$\min_{\mathbf{u}} J(\mathbf{x}, \mathbf{u}, \mathbf{d})$$

$$\mathbf{f}(\mathbf{x}, \mathbf{u}_0, \mathbf{d}) = 0$$

Active for all
disturbances

$$\begin{bmatrix} \mathbf{f}(\mathbf{x}, \mathbf{u}, \mathbf{d}) \\ \mathbf{g}'(\mathbf{x}, \mathbf{u}, \mathbf{d}) \end{bmatrix} = 0$$

$$\mathbf{g}(\mathbf{x}, \mathbf{u}_0, \mathbf{d}) \leq 0$$

$$\mathbf{y}_0 = \mathbf{f}_{y_0}(\mathbf{x}, \mathbf{u}_0, \mathbf{d})$$

\implies

\mathbf{u} DOF left

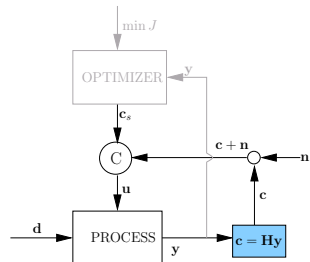
$$\mathbf{y}_0 = \mathbf{f}_{y_0}(\mathbf{x}, \mathbf{u}, \mathbf{d})$$



The null space method

- ▶ Method for selecting self-optimizing controlled variables
- ▶ Assume as many c 's as u 's given disturbances d
- ▶ Select a subset of measurements y
- ▶ Proposal: Controlled variables as linear combination of measurements

$$\begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_{n_c} \end{bmatrix} = \begin{bmatrix} h_{1,1}y_1 + h_{1,2}y_2 + \dots + h_{1,n_y}y_{n_y} \\ h_{2,1}y_1 + h_{2,2}y_2 + \dots + h_{2,n_y}y_{n_y} \\ \vdots \\ h_{n_c,1}y_1 + h_{n_c,2}y_2 + \dots + h_{n_c,n_y}y_{n_y} \end{bmatrix}$$



$$\mathbf{c} = \mathbf{H}\mathbf{y}$$



The null space method - Continued

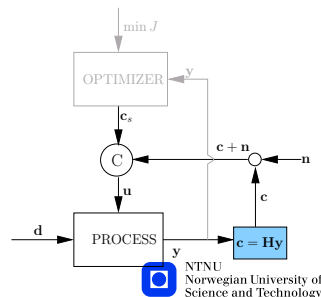
How to find \mathbf{H} ?

- Simple insight: $\Delta \mathbf{c}^{opt}(\mathbf{d})$ should be small

Reduced space optimization problem

$$\min_{\mathbf{u}} J(\mathbf{u}, \mathbf{d})$$

$$\mathbf{y}_0 = \mathbf{f}_{y_0}(\mathbf{u}, \mathbf{d})$$



The null space method - Continued

How to find \mathbf{H} ?

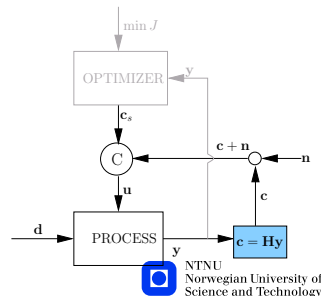
- ▶ Simple insight: $\Delta \mathbf{c}^{opt}(\mathbf{d})$ should be small
- ▶ Find optimal sensitivity matrix:

$$\Delta \mathbf{y}^{opt} = \left(\frac{d\mathbf{f}_y}{d\mathbf{d}} \right)_{|\mathbf{u}^{opt}} \Delta \mathbf{d} = \mathbf{F} \Delta \mathbf{d}$$

Reduced space optimization problem

$$\min_{\mathbf{u}} J(\mathbf{u}, \mathbf{d})$$

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The null space method - Continued

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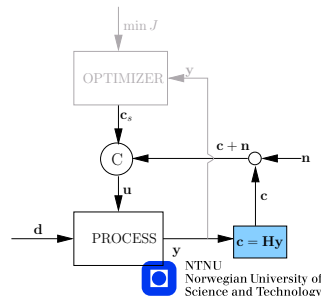
- ▶ Select \mathbf{c} such that

$$\Delta \mathbf{c}^{opt} = \mathbf{H} \Delta \mathbf{y}^{opt} = \mathbf{H} \mathbf{F} \Delta \mathbf{d} = 0$$

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The null space method - Continued

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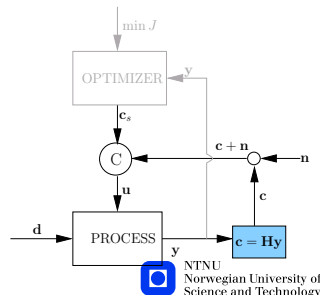
- ▶ Achieved if

$$\mathbf{H} \mathbf{F} = 0$$

Reduced space optimization problem

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The null space method - Continued

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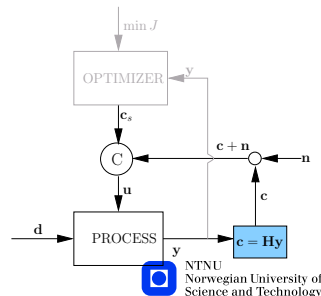
$$\mathbf{H} \mathbf{F} = 0$$

- ▶ Select \mathbf{H} in the left null space of \mathbf{F}

Reduced space optimization problem

$$\min_{\mathbf{u}} J(\mathbf{u}, \mathbf{d})$$

$$\mathbf{y}_0 = \mathbf{f}_{y_0}(\mathbf{u}, \mathbf{d})$$



The null space method - Continued

How to find \mathbf{H} ?

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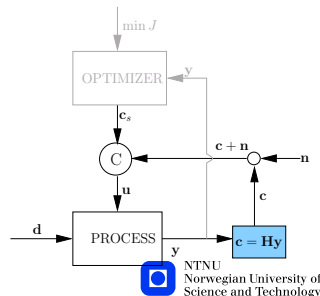
- ▶ Select \mathbf{H} in the left null space of \mathbf{F}
- ▶ Need

$$\#y \geq \#u + \#d$$

Reduced space optimization problem

$$\min_{\mathbf{u}} J(\mathbf{u}, \mathbf{d})$$

$$\mathbf{y}_0 = \mathbf{f}_{y_0}(\mathbf{u}, \mathbf{d})$$



Self-optimizing control - Simple example

- ▶ Objective: $\min_u J = (u - d)^2 \quad d^* = 0$
- ▶ Measurements:

$$y_1 = 0.9u + 0.1d$$

$$y_2 = 0.5u - d$$

- ▶ Optimal input:

$$\frac{\partial J}{\partial u} = 2(u^{opt} - d) = 0$$

$$\Rightarrow u^{opt} = d$$



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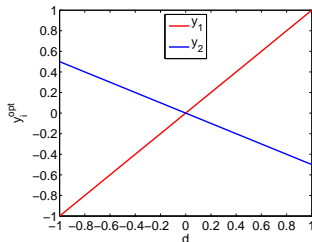
- ▶ Optimal input:

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$$y_1^{opt} = d \quad y_2^{opt} = -0.5d$$



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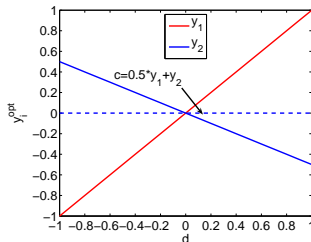
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- ▶ Select $c = 0.5y_1 + y_2$



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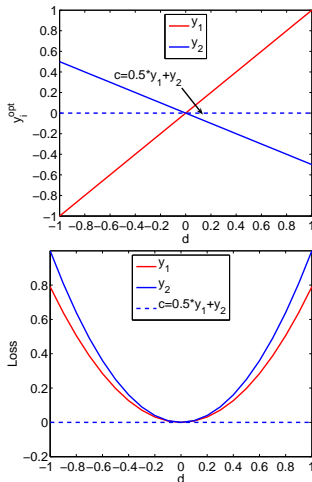
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- ▶ Optimal change:

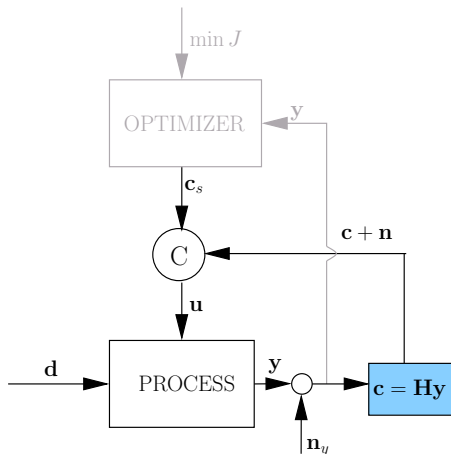
$$y_1^{opt} = d \quad y_2^{opt} = -0.5d$$

- ▶ Select $c = 0.5y_1 + y_2$
- ▶ Loss: $L = J(u, d) - J^{opt}(d)$



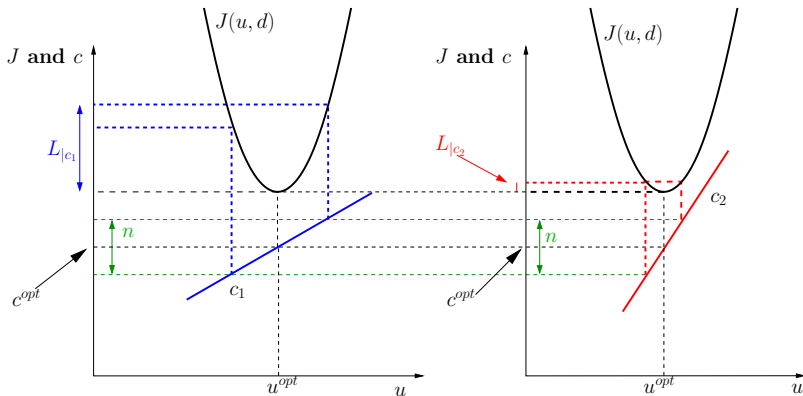
Self-optimizing control - How to select measurements?

- ▶ Dealt with disturbances d
- ▶ How about measurement errors n_y ?



Self-optimizing control - How to select measurements?

► Implementation error



Self-optimizing control - How to select measurements?

- ▶ Optimal selection criteria

$$y_{j|j=\{1,\dots,n_y\}} = \arg \min_{y_{0_i}} \bar{\sigma}(\tilde{\mathbf{J}}[\tilde{\mathbf{G}}^y]^{-1})$$

- ▶ Suboptimal

$$y_{j|j=\{1,\dots,n_y\}} = \arg \max_{y_{0_i}} \underline{\sigma}(\tilde{\mathbf{G}}^y)$$

- ▶ Methods for handling too few and using all measurements

Models

- ▶ All measurements y_0 :

$$\Delta y_0 = \mathbf{G}^{y_0} \Delta \mathbf{u} + \mathbf{G}_d^{y_0} \Delta \mathbf{d}$$

- ▶ Selected measurements y :

$$\Delta y = \mathbf{G}^y \Delta \mathbf{u} + \mathbf{G}_d^y \Delta \mathbf{d}$$

- ▶ $\tilde{\mathbf{J}} = \begin{bmatrix} \mathbf{J}_{uu}^{1/2} & \mathbf{J}_{uu}^{1/2} \mathbf{J}_{uu}^{-1} \mathbf{J}_{ud} \end{bmatrix}$
where $\mathbf{J}_{uu} = \frac{\partial^2 J}{\partial \mathbf{u}^2}$ and $\mathbf{J}_{ud} = \frac{\partial^2 J}{\partial \mathbf{u} \partial \mathbf{d}^T}$



Part II: Petlyuk column

- ▶ Manipulated variables:

$$\mathbf{u}^T = [S, D, B, L, V, R_L, R_V]$$

- ▶ Steady-state degrees of freedom: 5
- ▶ Minimize cost: $\min_{\mathbf{u}} V$
- ▶ Constraints:

$$x_{A,D} \geq 0.97 \quad \text{active}$$

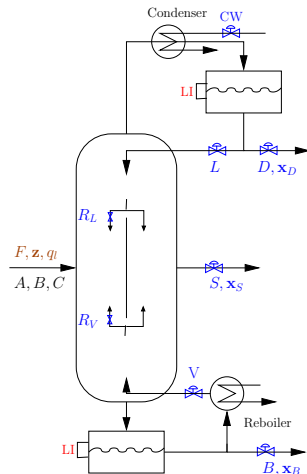
$$x_{B,S} \geq 0.97 \quad \text{active}$$

$$x_{C,B} \geq 0.97 \quad \text{active}$$

$$\text{Flows} \geq 0 \text{ kmol/h}$$

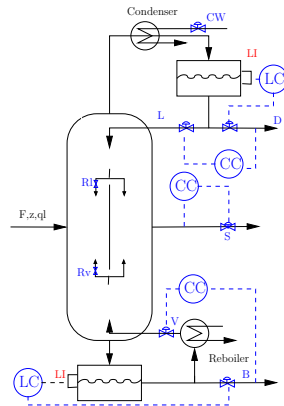
$$0 \leq R_L, R_V \leq 1$$

- ▶ Disturbances: $[F \ z_A \ z_B \ q_l] = [1 \pm 0.1 \text{ kmol/h} \ 1/3 \pm 0.1 \ 1/3 \pm 0.1 \ 0.477 \pm 0.1]$



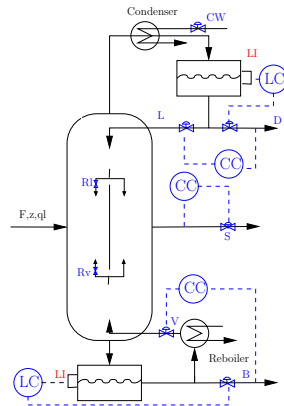
Petlyuk column

- Goal with case study two-fold:
 1. Compare NSM with previously proposed method for selecting self-optimizing controlled variables
 2. Compare with previously proposed structures (DT_S)



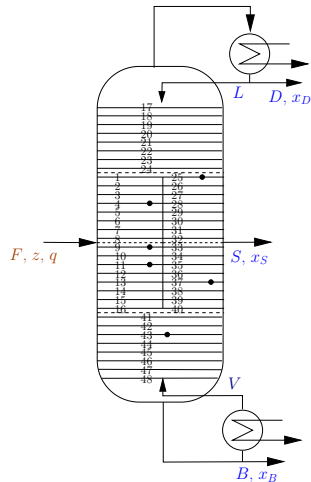
Petlyuk column

- ▶ Goal with case study two-fold:
 1. Compare NSM with previously proposed method for selecting self-optimizing controlled variables
 2. Compare with previously proposed structures (DT_S)
- ▶ Two new proposed structures
 - ▶ NSM using both R_V and $R_L \Rightarrow$ using 7 temperatures
 - ▶ NSM using only $R_L \Rightarrow$ using 7 temperatures



Petlyuk column - Continued - Loss

CS #			Disturbances		Noise	
	c_4	c_5	L_a [%]	L_w [%]	L_a^n [%]	L_w^n [%]
1	c_{idf}^1	c_{idf}^2	0.0252	0.2082	0.0117	0.0213
2	R_V	c_{odf}	0.0607	0.2247	0.0206	0.0847
3	R_V	DT_S	1.4916	11.88	0.0475	0.2108
4	R_V	R_L	12.9508	95.16	3.6254	9.3142
7	R_V	T_{34}	0.4063	2.8982	0.1034	0.1215
11	R_V	T_4	4.1310	42.029	0.0589	0.1046

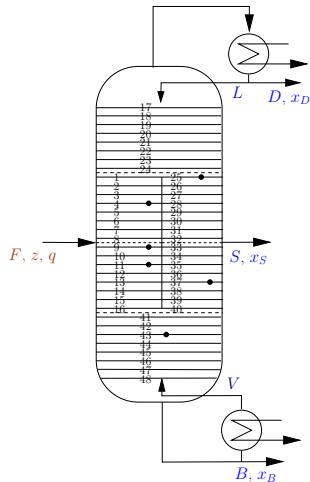


Petlyuk column - Continued - Loss

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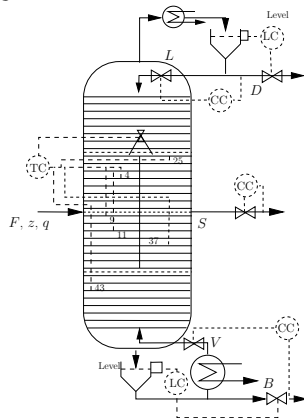
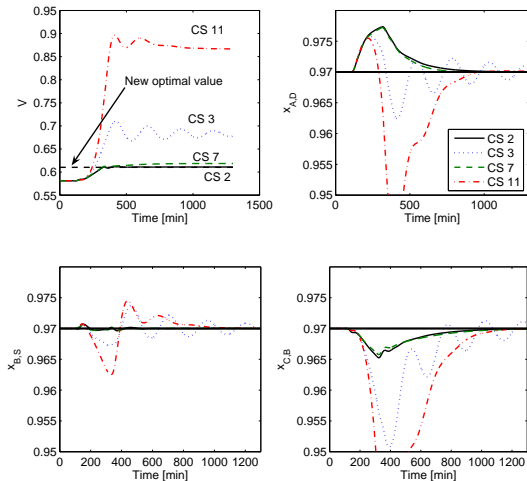
► Dynamic simulation

- Decentralized control structure using PI(D) controllers
- All PI(D) controllers tuned using Skogestad's IMC tuning rules



Petlyuk column - Dynamic simulations

- Step in feed composition $z_A : 0.33 \rightarrow 0.43$



Other case studies

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Chapter 9:

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Part III: Topics in self-optimizing control

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Effect of non-optimal nominal point

- ▶ Nominal optimal point: $(\mathbf{u}^*, \mathbf{d}^*) = (\mathbf{u}^{opt}(\mathbf{d}^*), \mathbf{d}^*)$
- ▶ Actual nominal point: $(\mathbf{u}^0, \mathbf{d}^*) \neq (\mathbf{u}^*, \mathbf{d}^*)$



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Example: Nominal optimum

$$(u^*, d^*) = (0, 0)$$

- ▶ Objective:

$$\min_u (u - d)^2$$

- ▶ Candidate controlled variables:

$$y_1 = 0.1(u - d)$$

$$y_2 = 2u - d$$

$$y_3 = 2u - 0.5d$$

$$y_4 = u - 3d$$



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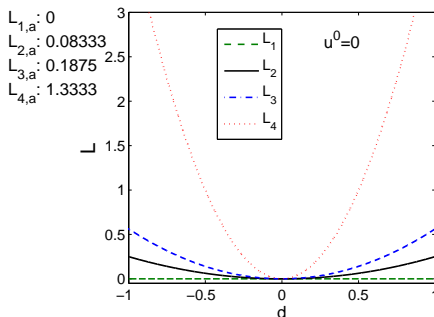
- ▶ Candidate controlled variables:

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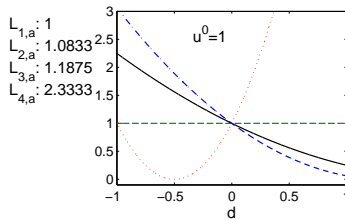
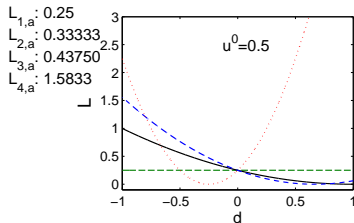
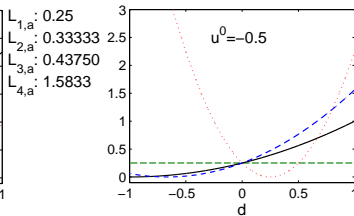
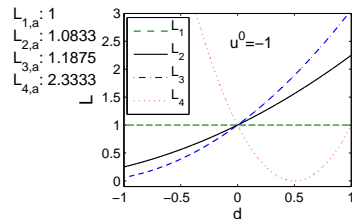
$$y_2 = 2u - d$$

$$y_3 = 2u - 0.5d$$

$$y_4 = u - 3d$$



Effect of non-optimal nominal point: Example cont.



Effect of non-optimal nominal point cont.

- ▶ Average increase in loss independent of what we control
- ▶ Non-nominal point no effect on candidate rank
- ▶ True for linear plant and quadratic objective

Part III: Topics in self-optimizing control

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- ▶ Appendix C: Perfect steady-state indirect control:
E. Hori, S. Skogestad, V. Alstad



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- ▶ Acknowledgments: ABB, Norsk Hydro and The Research Council of Norway



Petlyuk column: Energy savings by over-fractionation

- ▶ Energetically optimal to over-fractionate one product stream

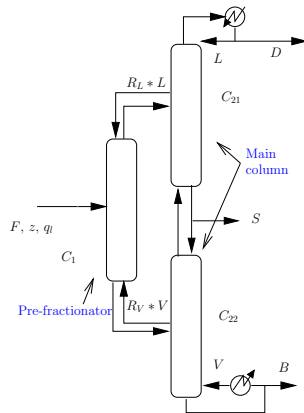
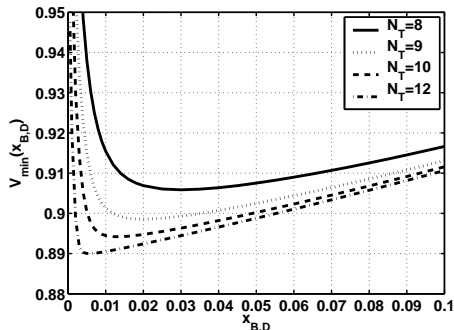
Problem formulation

$$\begin{aligned} \min_{\mathbf{u}} V \\ x_{A,D} &\geq x_{A,D}^0 \\ x_{B,S} &\geq x_{B,S}^0 \\ x_{C,B} &\geq x_{C,B}^0 \end{aligned}$$



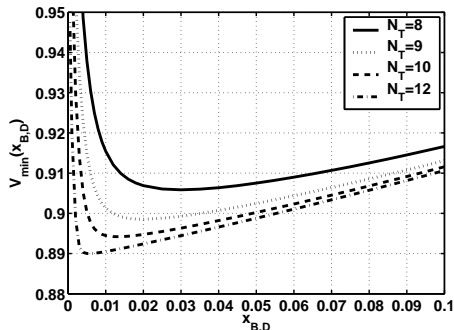
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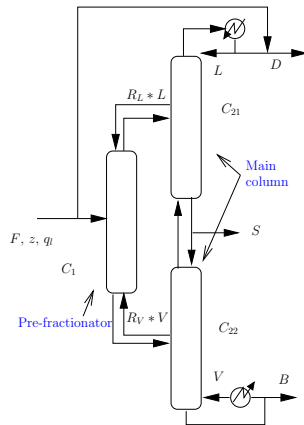


Petlyuk column: Energy savings by over-fractionation

- ▶ Energetically optimal to over-fractionate one product stream
- ▶ Same vapor flow in main column



- ▶ Increased savings bypassing a portion of the feed



Petlyuk column - Loss

<i>CS #</i>			Loss [%]					
	F_-	F_+	z_{A-}	z_{A+}	z_{B-}	z_{B+}	q_l-	q_l+
1	0.0	0.0	0.0171	0.0207	0.0166	0.0111	0.0001	0.0000
2	0.0	0.0	0.0037	0.1340	0.2247	0.1666	0.1876	0.1084
3	0.0	0.0	5.0840	11.8810	0.3469	0.8295	1.0441	1.1740
4	0.0	0.0	46.7037	6.3019	95.1660	9.8256	32.4629	6.0578
5	0.0	0.0	0.22826	2.6973	0.30078	0.40385	0.18903	0.12882
6	0.0	0.0	0.43234	inf	0.56891	1.7347	0.20494	0.17341
7	0.0	0.0	0.12667	1.3807	0.22211	0.18703	0.18794	0.11290
8	0.0	0.0	0.82264	inf	1.1556	inf	0.25233	0.31315
9	0.0	0.0	0.11772	1.7075	0.31570	0.16848	0.21236	0.10722
10	0.0	0.0	1.6053	inf	2.3873	inf	0.38058	1.0685
11	0.0	0.0	9.3786	42.029	0.22507	0.28417	0.66607	1.0851
12	0.0	0.0	inf	33.300	0.52408	0.28762	0.77086	1.0070



Petlyuk column - Loss

CS #			Loss [%]					
	F_-	F_+	z_{A-}	z_{A+}	z_{B-}	z_{B+}	q_{l-}	q_{l+}
1	0.0	0.0	0.0171	0.0207	0.0166	0.0111	0.0001	0.0000
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CS #	Loss [%]						L_n^{max}	L_n^{avg}
	$n_{x_{A,D+}}^0$	$n_{x_{A,D-}}^0$	$n_{x_{C,B+}}^0$	$n_{x_{C,B-}}^0$	$n_{x_{B,S+}}^0$	$n_{x_{B,S-}}^0$		
1	0.0025	0.0095	0.0639	0.2082	0.0002	0.0007	0.0213	0.0117
2	0.0040	0.0110	0.0060	0.0174	0.0004	0.0004	0.0847	0.0206
3	0.0074	0.0207	0.0033	0.0034	0.0025	0.0075	0.2108	0.0475
4	0.0262	0.0253	0.0245	0.0311	0.2579	1.0198	9.3142	3.6254
5	0.0040	0.0110	0.0029	0.0035	0.3334	2.5693	0.0861	0.0673
6	0.0040	0.0110	0.0041	0.0063	0.3088	2.7112	0.0857	0.0587
7	0.0040	0.0112	0.0028	0.0026	0.4040	2.8982	0.1215	0.1034
8	0.0040	0.0110	0.0069	0.0126	0.3037	3.6569	0.0864	0.0586
9	0.0044	0.0128	0.0055	0.0042	0.7108	4.9155	0.7517	0.3805
10	0.0040	0.0110	0.0132	0.0289	0.3148	inf	0.0881	0.0667
11	0.0036	0.0108	0.0072	0.0106	0.3439	1.9349	0.1046	0.0589
12	0.0034	0.0131	0.0087	0.0130	0.3318	1.7321	0.1097	0.0963

