

3.3 Data Reconciliation: What's the Real Operating Condition?

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Digitalization Tools for the Chemical and Process Industries

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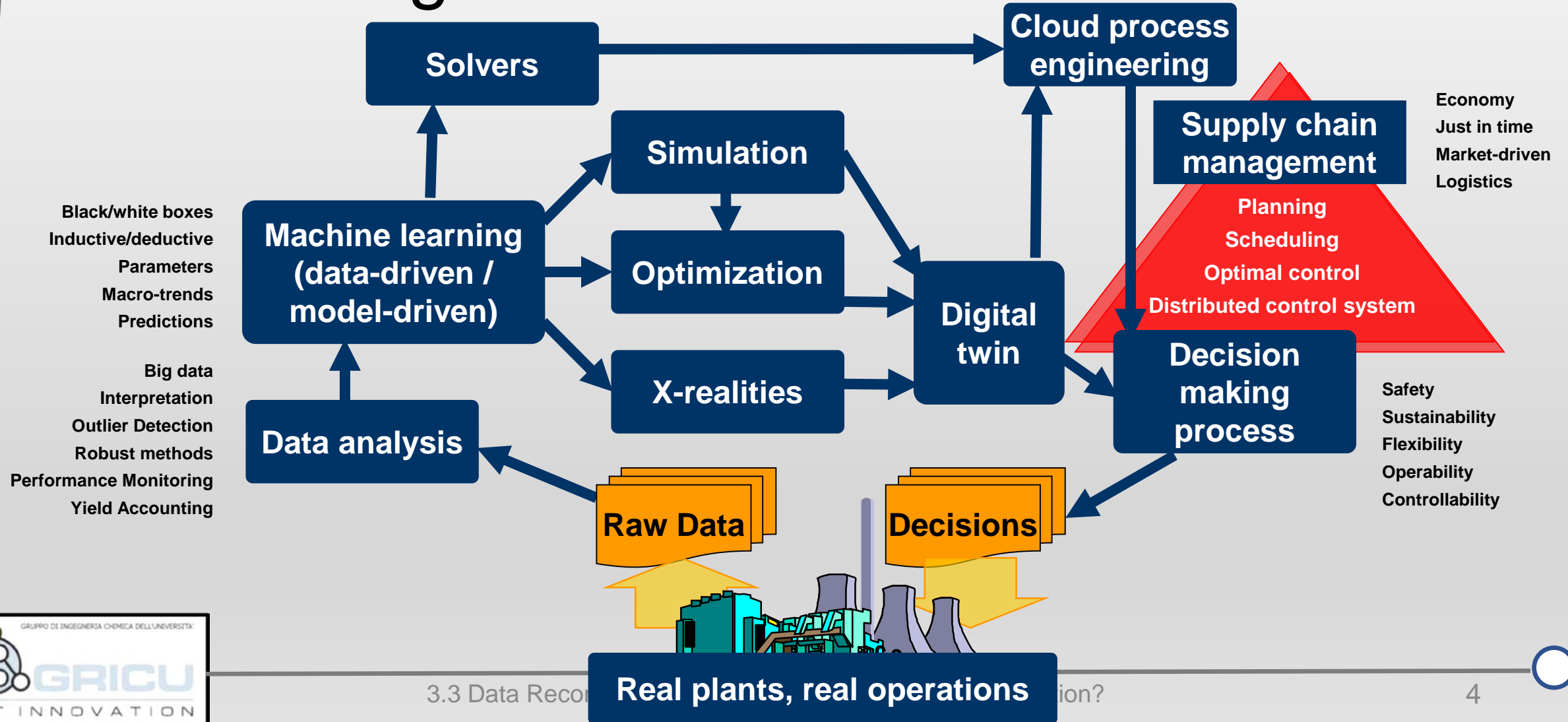
Outline

- A process engineering (personal) vision of digitalization
- Fundamentals of data reconciliation
- Mathematical formulation
- Exercise
- Gross errors
- Industrial case studies
 - Itelyum regeneration
 - Lukoil ltd

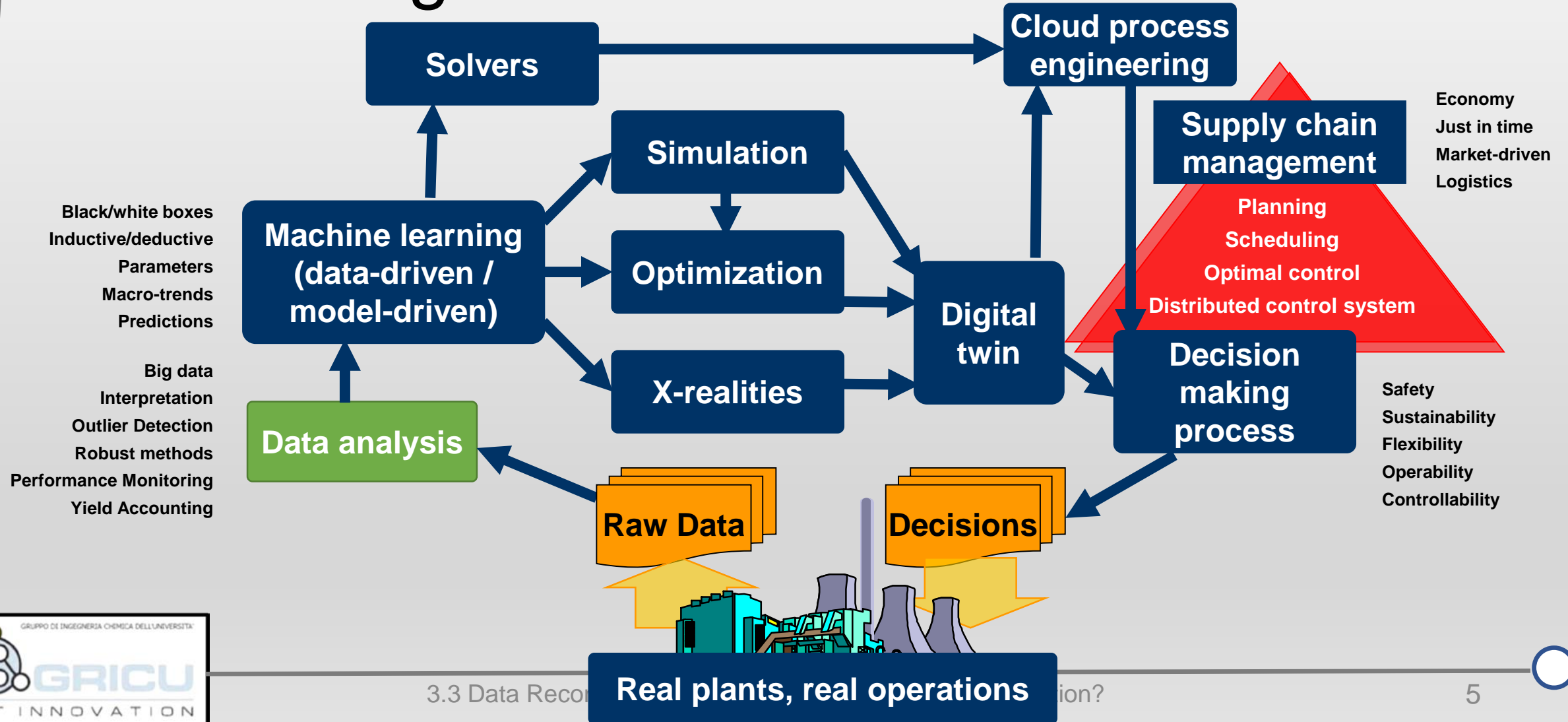
Digitalization

Which topics?

A process engineering (personal) vision of digitalization



A process engineering (personal) vision of digitalization



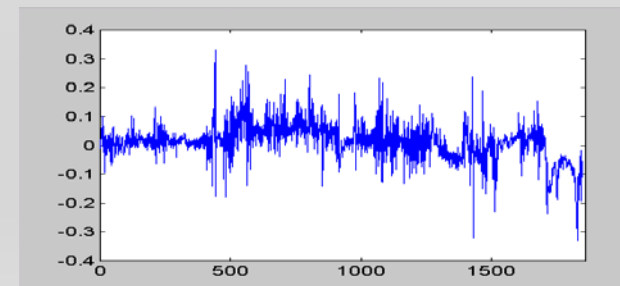
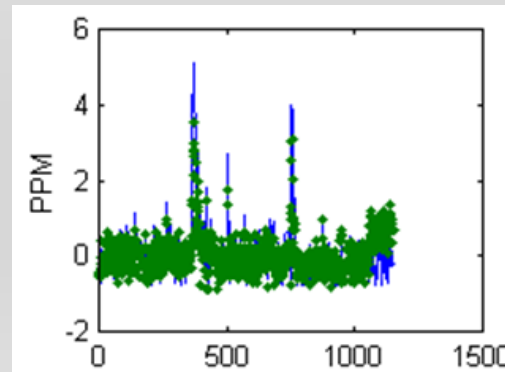
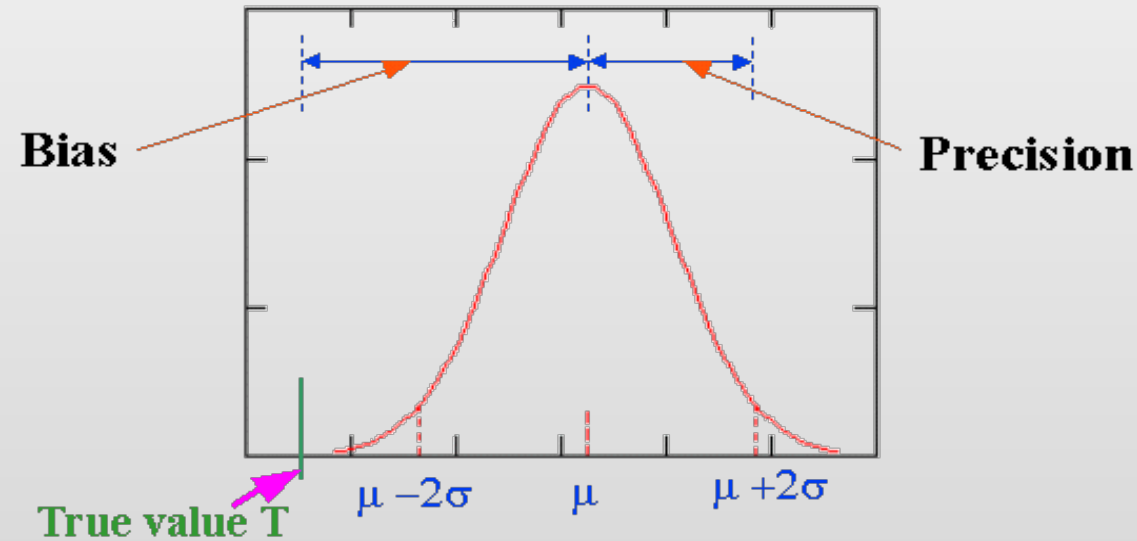
Data reconciliation

Fundamentals

Plant measurements

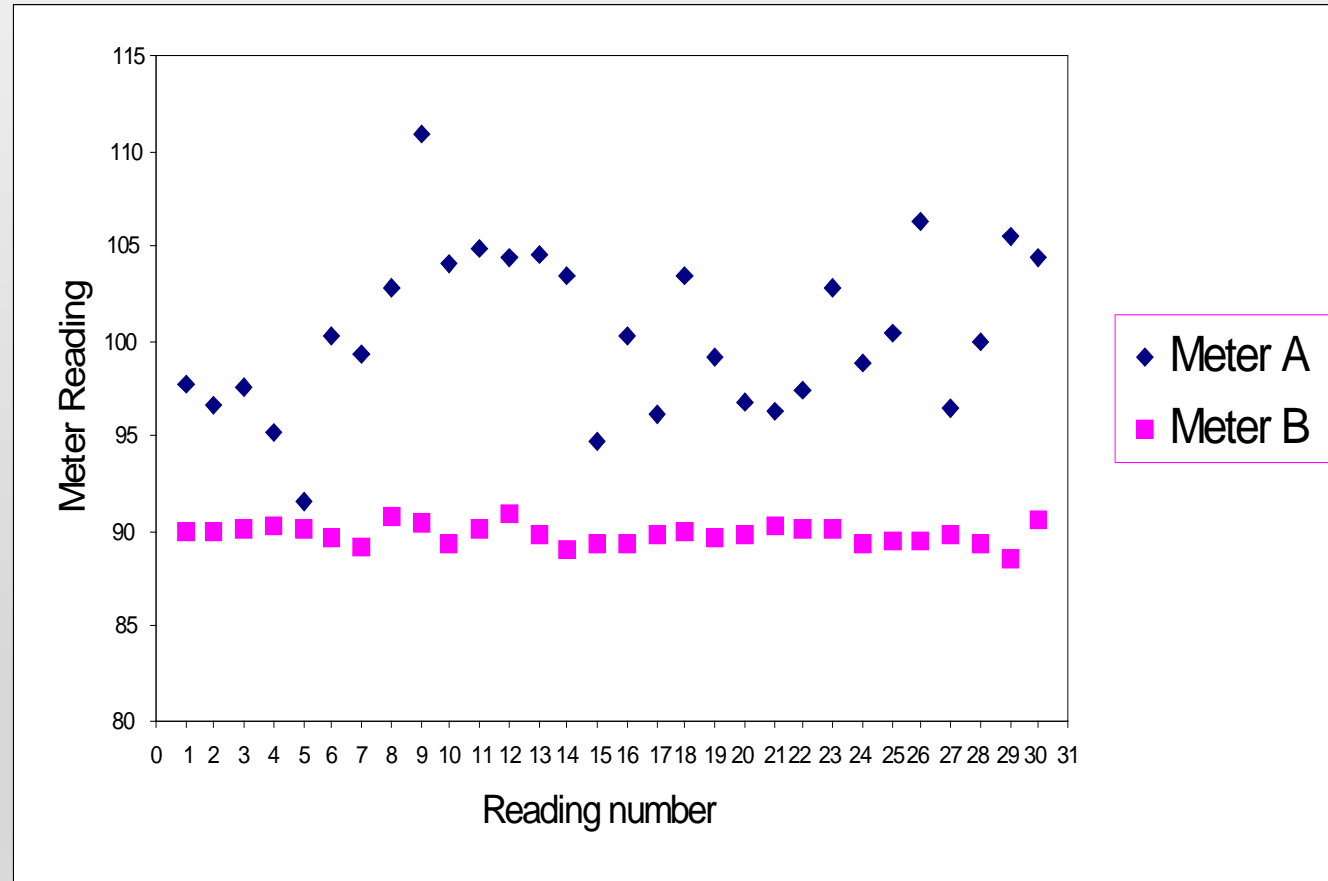
- All measurements are subject to **uncertainty**
- **Random Errors** (unavoidable and hopefully small)
- **Gross Errors** (conceptually avoidable) and **outliers**

- Bias :- $\mu - T$ (True value)
- Precision:- 2σ (95% confidence)



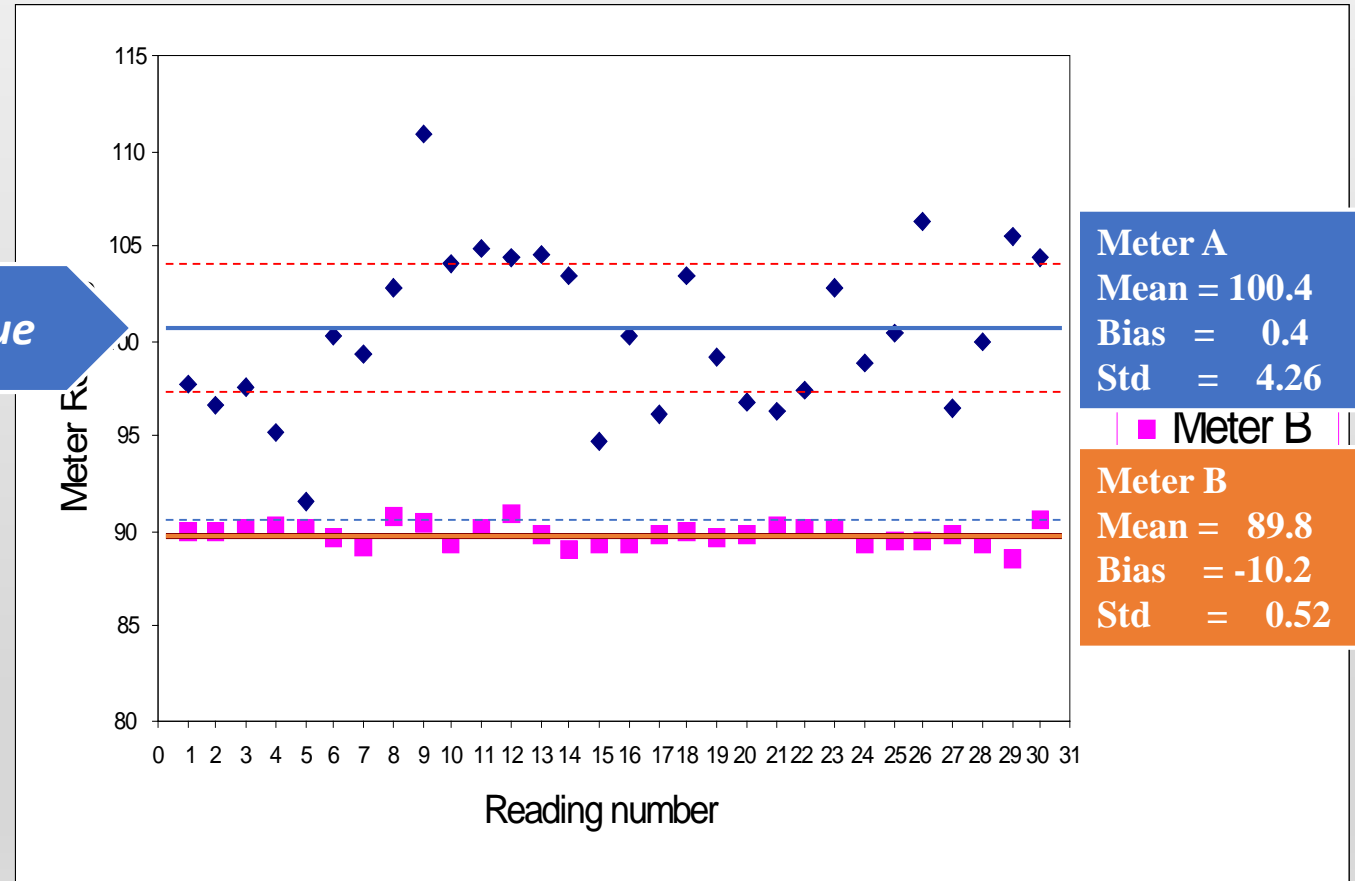
Plant measurements

What's the good one?



Plant measurements

True value

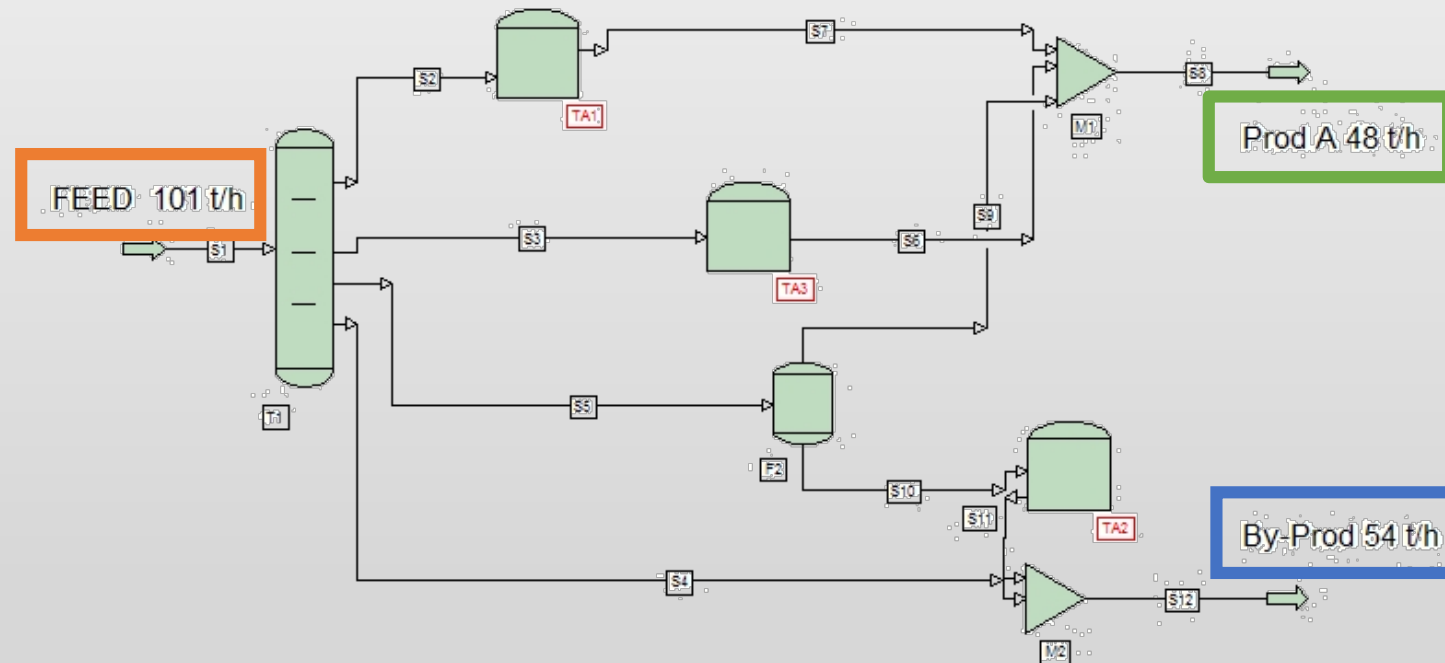


Process data reconciliation

What and why

Error effects on process operations management

Because of errors, measures do not conserve mass and energy



Feed = 101 t/h



Prod = 48 t/h



By-pProd = 54 t/h

Process data reconciliation

Process data reconciliation is **NOT averaging**, but **NLP**:

$$\min_{\mathbf{x}} \Phi = \sum_{i=1}^{NM} \omega_i (m_i - x_i)^2$$

$$s.t.: \quad g(\mathbf{x}) = 0$$

$$h(\mathbf{x}) \leq 0$$

i = *ith measurement device*

NM = *total number of measurement devices*

M = *measured values*

x = *reconciled and it points out the degrees of freedom of the optimization problem*
elements of omega are the weights, usually: $\omega_i = 1 / \sigma_i^2$

$s.t.$ = *subject to*

g and h = *constraints of the optimization problem*

$g(x)$ = *equality constraints*

$h(x)$ = *inequality constraints*

Mass reconciliation

When the measured information is only mass flowrate (no composition measures):

$$\begin{aligned} \min_{\mathbf{w}^{rec}} \Phi &= \sum_{i=1}^{NM} \omega_i \left(w_i - w_i^{rec} \right)^2 \\ s.t.: \quad &g(x) = 0 \\ &h(x) \leq 0 \end{aligned}$$

*Assumption
of no outliers*

where \mathbf{w} are the measured and reconciled mass flowrates, respectively

Feasible? It depends...

Degree of redundancy: data reconciliation is possible only if measures are **enough** and **well distributed**:

$$DoR = Measures + Balances - Reconciled$$

DoR < 0

*Unsolvable,
too many
unknowns*

DoR = 0

*Coaptation
(unsolvable
data rec.)*

DoR = 0

*Inference (if
the rest is
reconciled)*

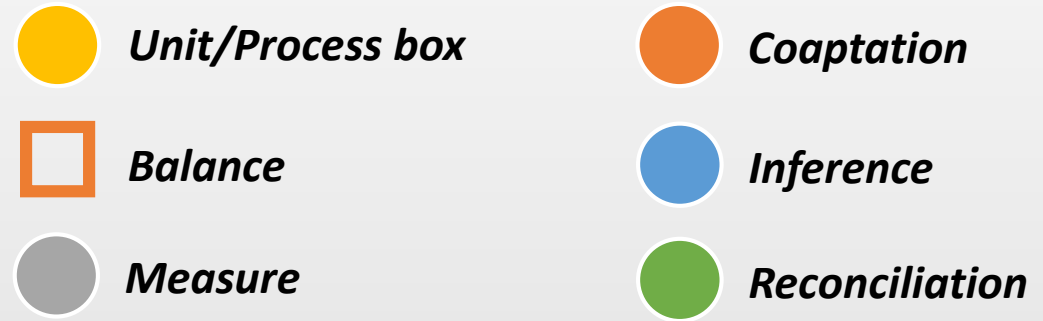
DoR > 0

*Solvable,
reconciliation
(usually) possible*

DoR

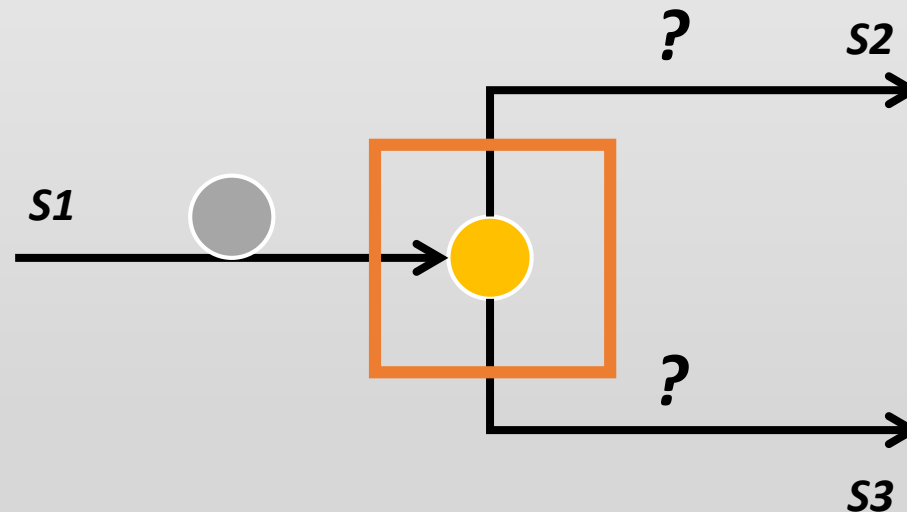
The larger, the better for the data reconciliation
The smaller, the better for instrumentation/CapEx

Illustrative case

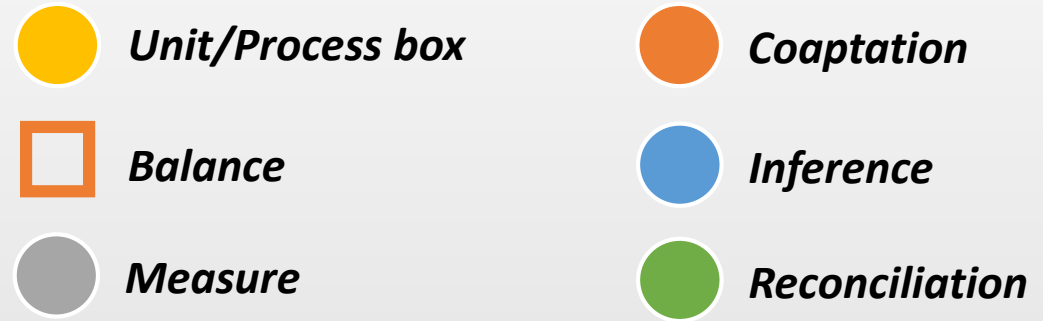


$DoR < 0$

*Unsolvable,
too many
unknowns*

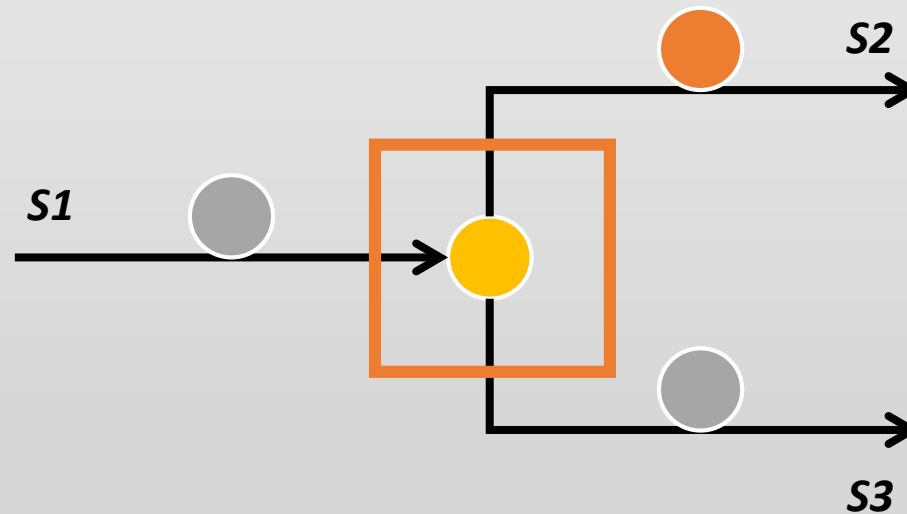


Illustrative case

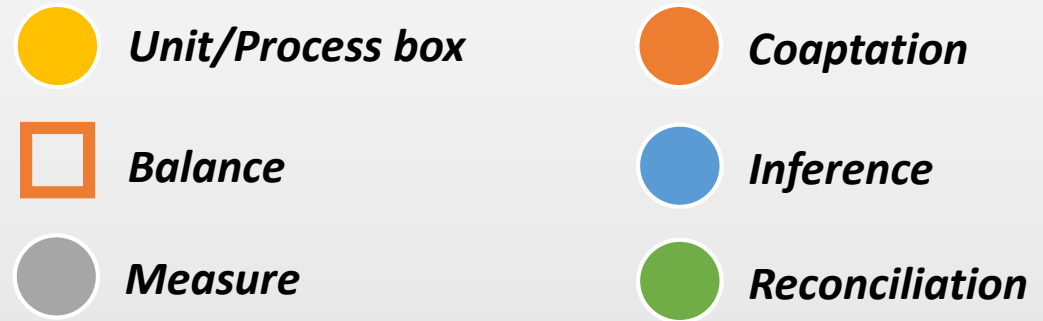


DoR = 0

*Coaptation
(unsolvable
data rec.)*

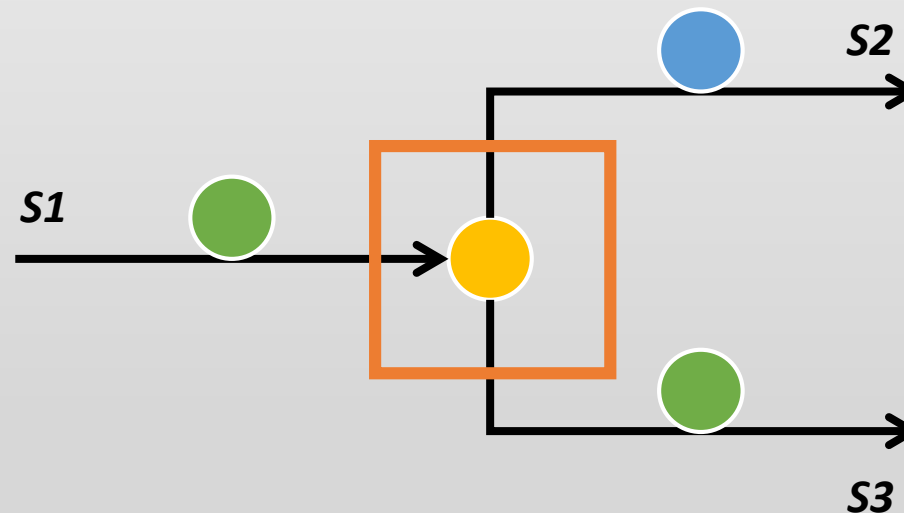


Illustrative case



$DoR = 0$

Inference (if
the rest is
reconciled)

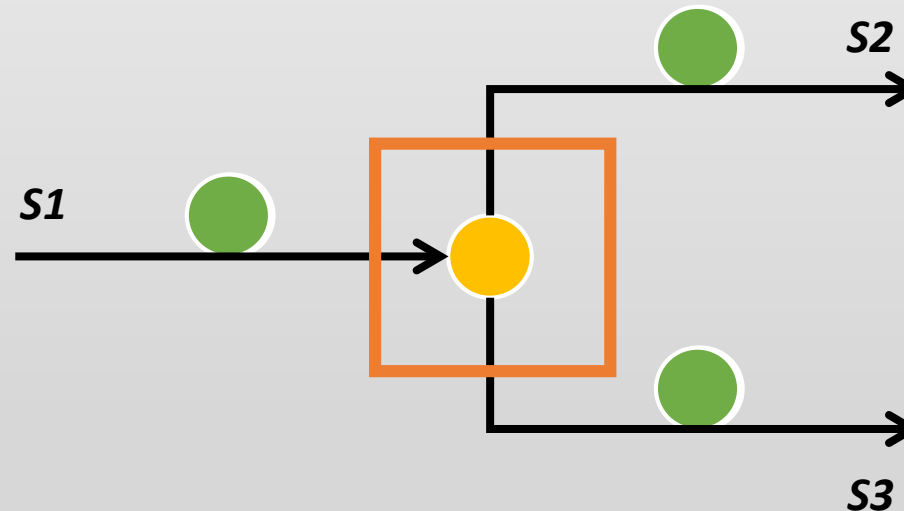


Illustrative case



$DoR > 0$

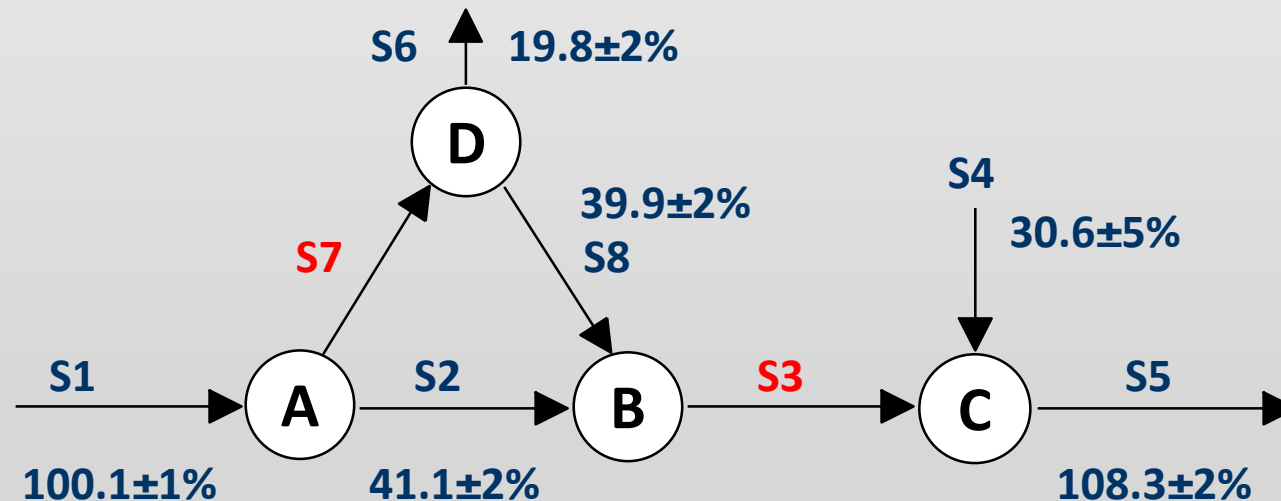
Solvable,
reconciliation
(usually) possible



Plantwide applications and exceptions

$$\text{DOR} = 6 + 4 - 8 = 2 > 0:$$

8 flowrates, 4 mass balances, 6 flow measurements

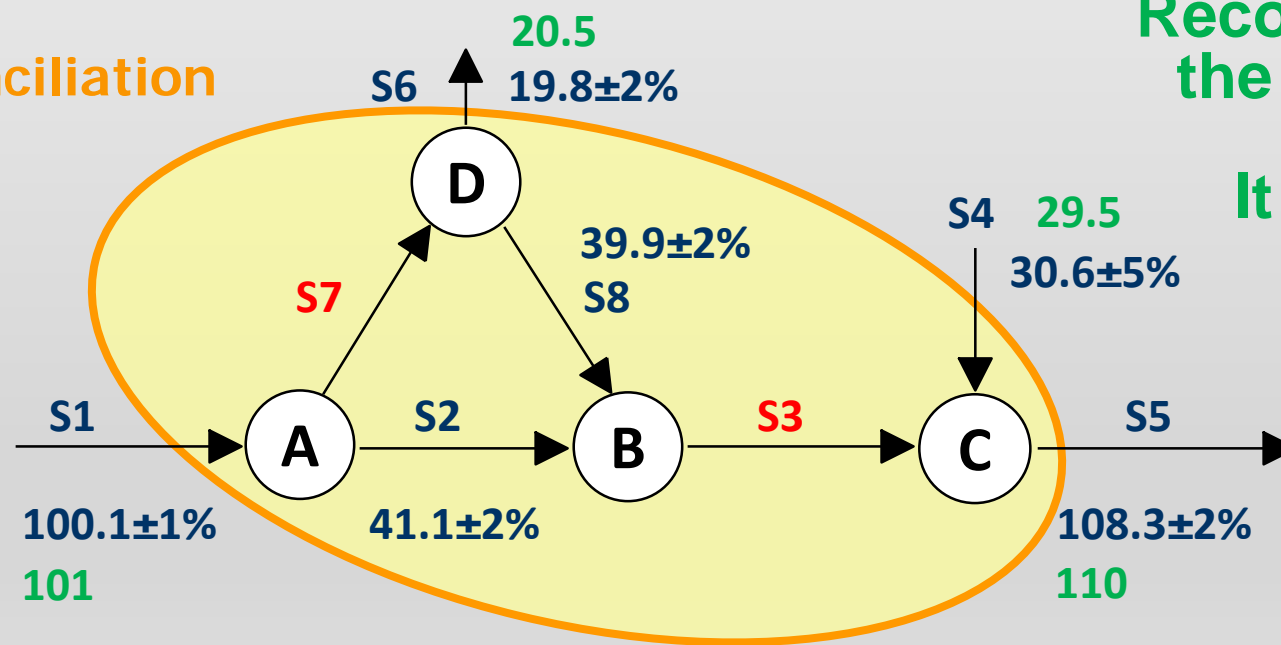


Plantwide applications and exceptions

$$\text{DOR} = 6 + 4 - 8 = 2 > 0:$$

8 flowrates, 4 mass balances, 6 flow measurements

Reconciliation
space



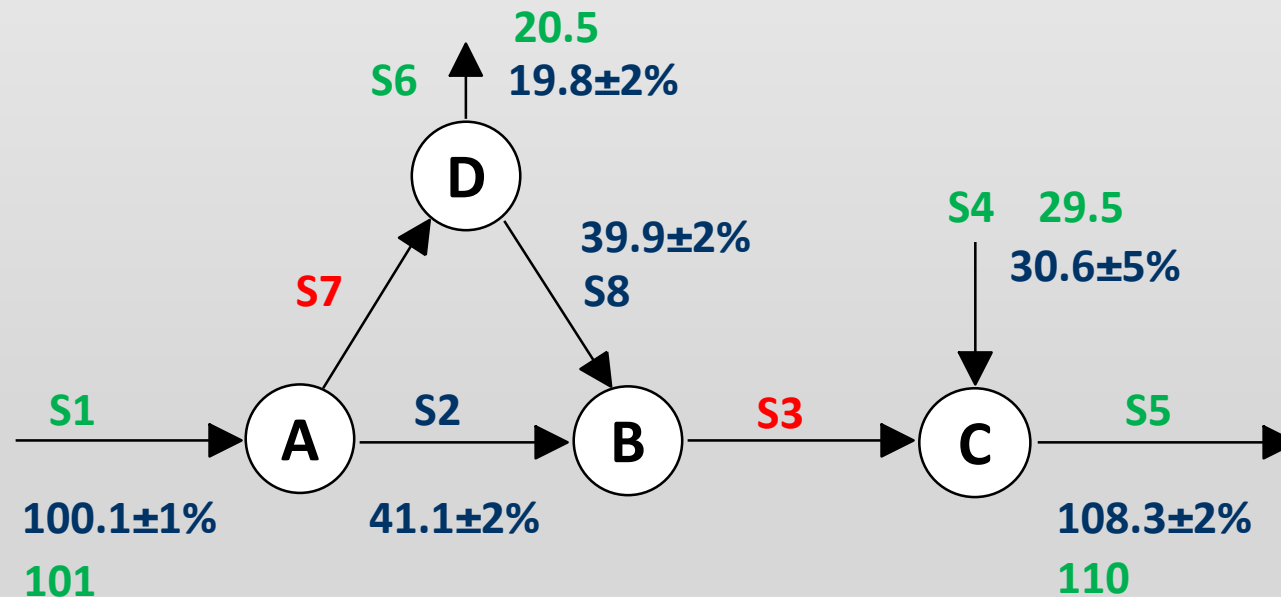
Reconciled data is
the correct data

It fits the balances

Plantwide applications and exceptions

$$\text{DOR} = 6 + 4 - 8 = 2 > 0:$$

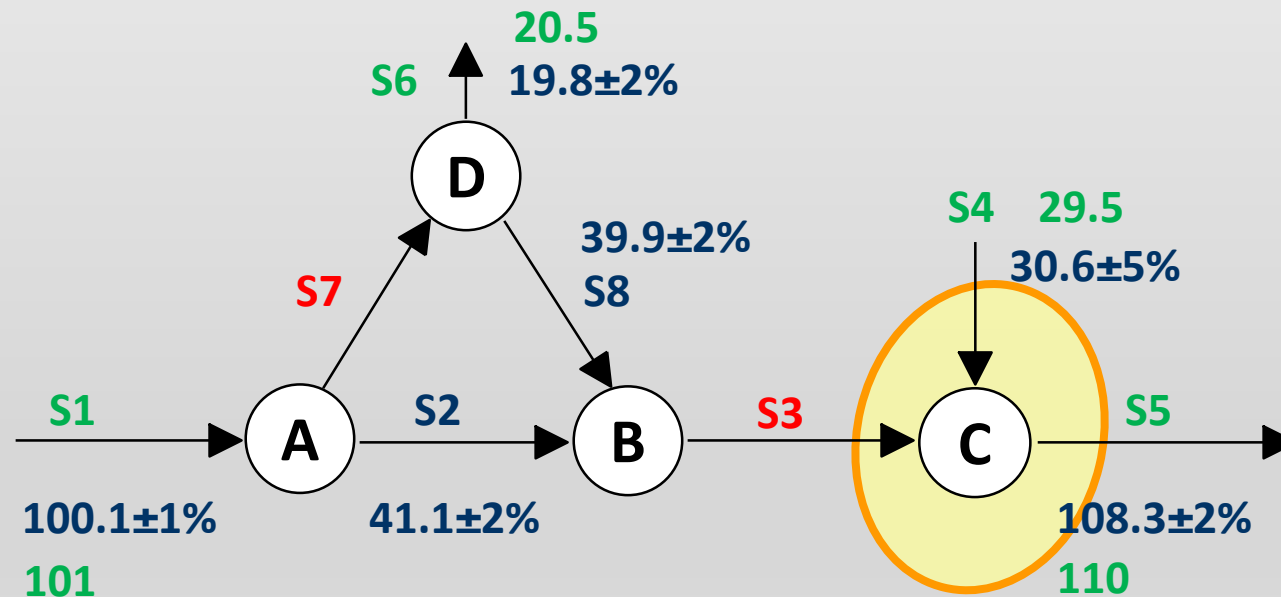
8 flowrates, 4 mass balances, 6 flow measurements



Plantwide applications and exceptions

$$\text{DOR} = 6 + 4 - 8 = 2 > 0:$$

8 flowrates, 4 mass balances, 6 flow measurements



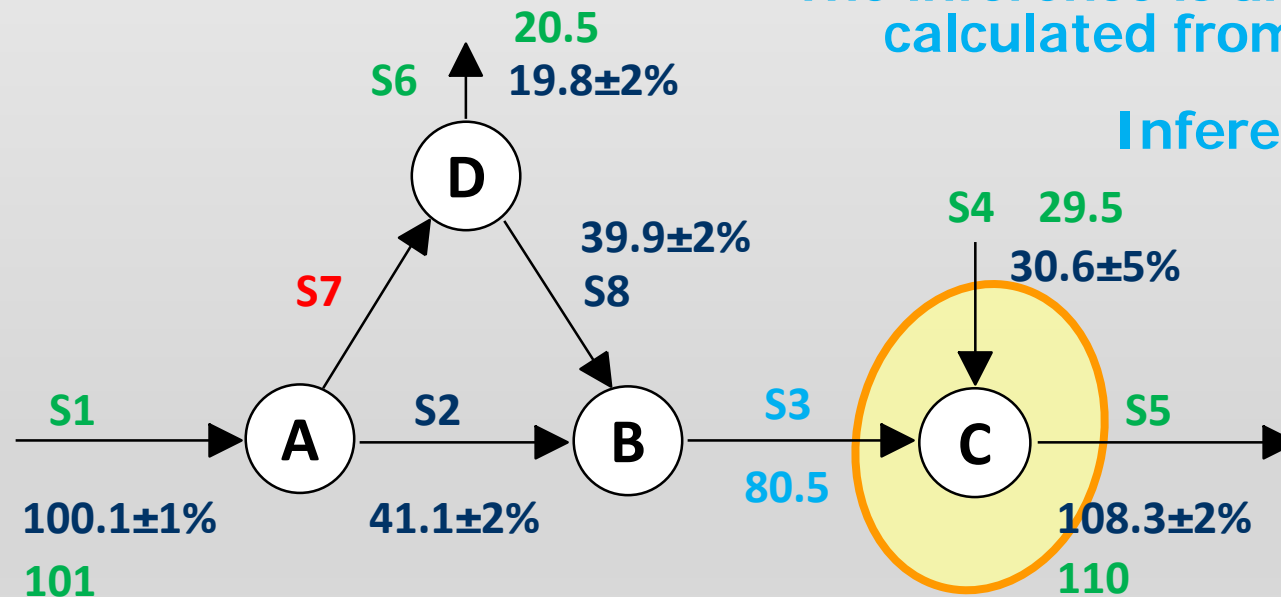
Plantwide applications and exceptions

$$\text{DOR} = 6 + 4 - 8 = 2 > 0:$$

8 flowrates, 4 mass balances, 6 flow measurements

The inference is an unmeasured entity
calculated from reconciled data

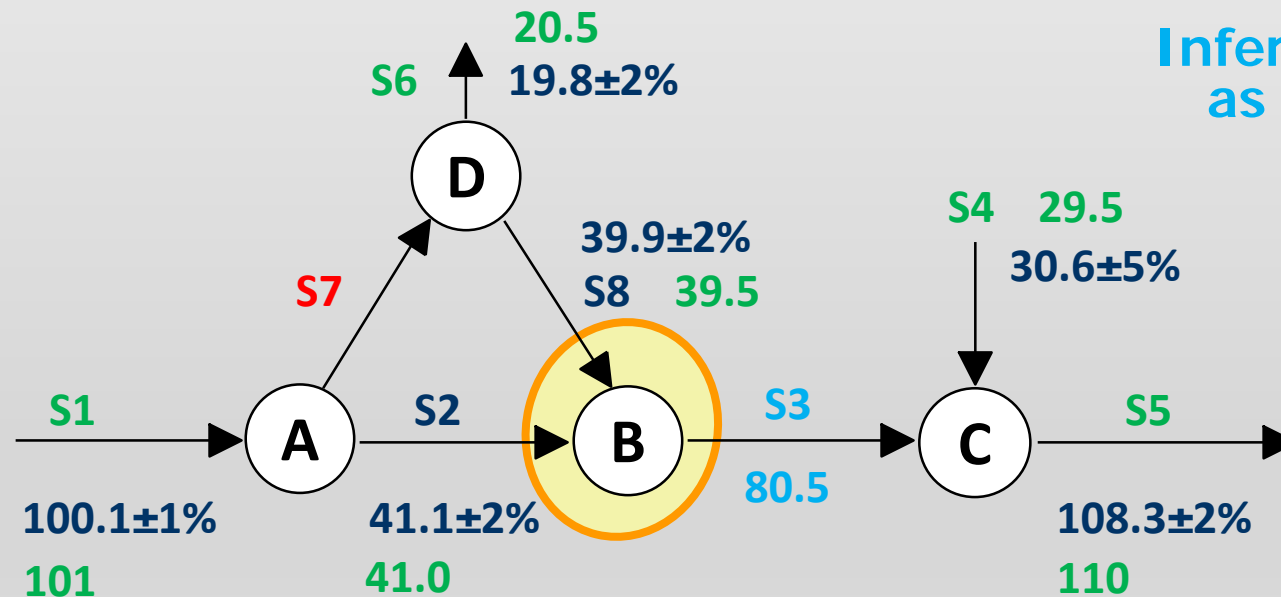
Inference is a safe number



Plantwide applications and exceptions

$$\text{DOR} = 6 + 4 - 8 = 2 > 0:$$

8 flowrates, 4 mass balances, 6 flow measurements

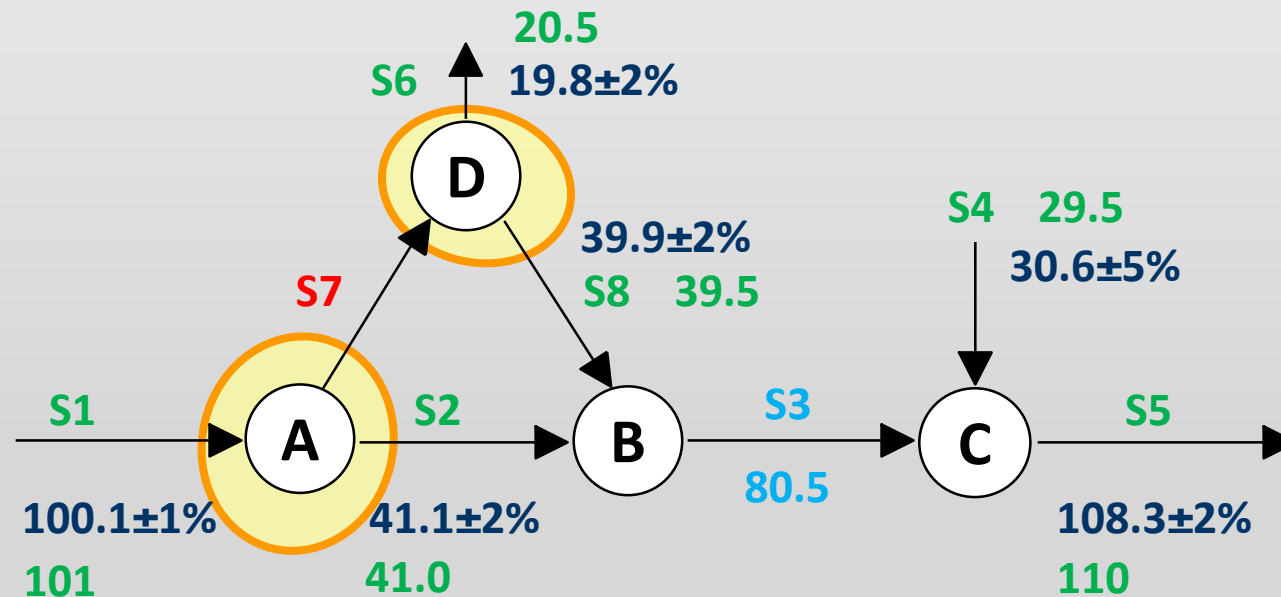


Inference can be used
as reconciled data

Plantwide applications and exceptions

$$\text{DOR} = 6 + 4 - 8 = 2 > 0:$$

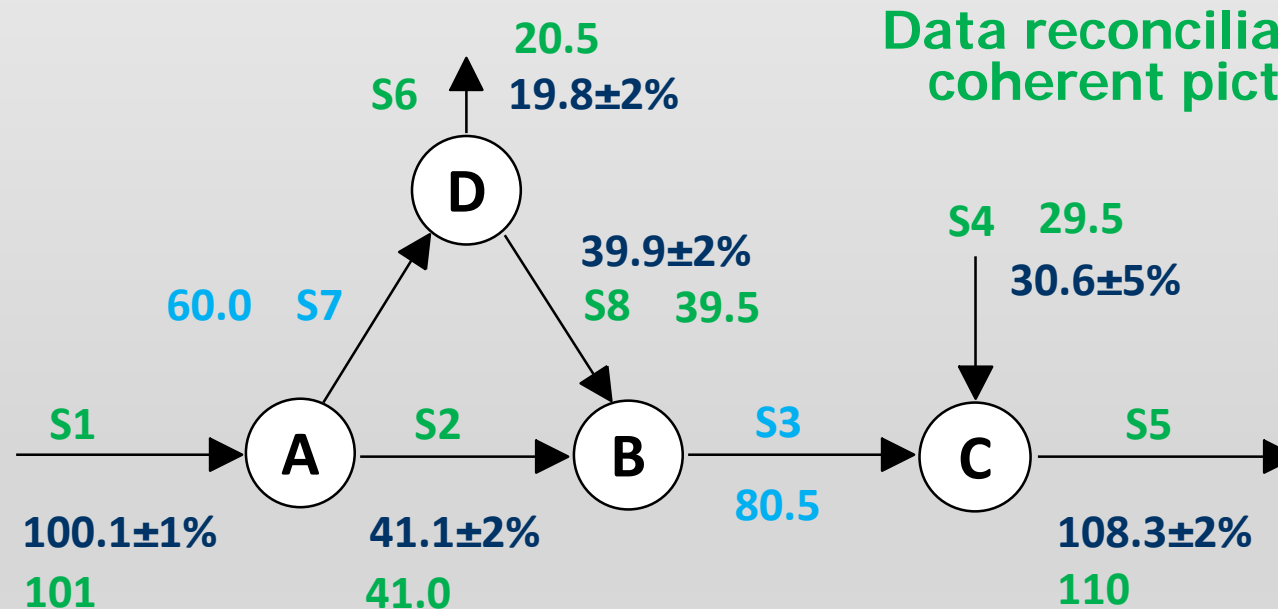
8 flowrates, 4 mass balances, 6 flow measurements



Plantwide applications and exceptions

$$\text{DOR} = 6 + 4 - 8 = 2 > 0:$$

8 flowrates, 4 mass balances, 6 flow measurements





Main remarks

With data reconciliation:

**The overall plant behavior is known
Operations are properly monitored**

Decisions are therefore safe...

... but not necessarily wise!

Additional remark

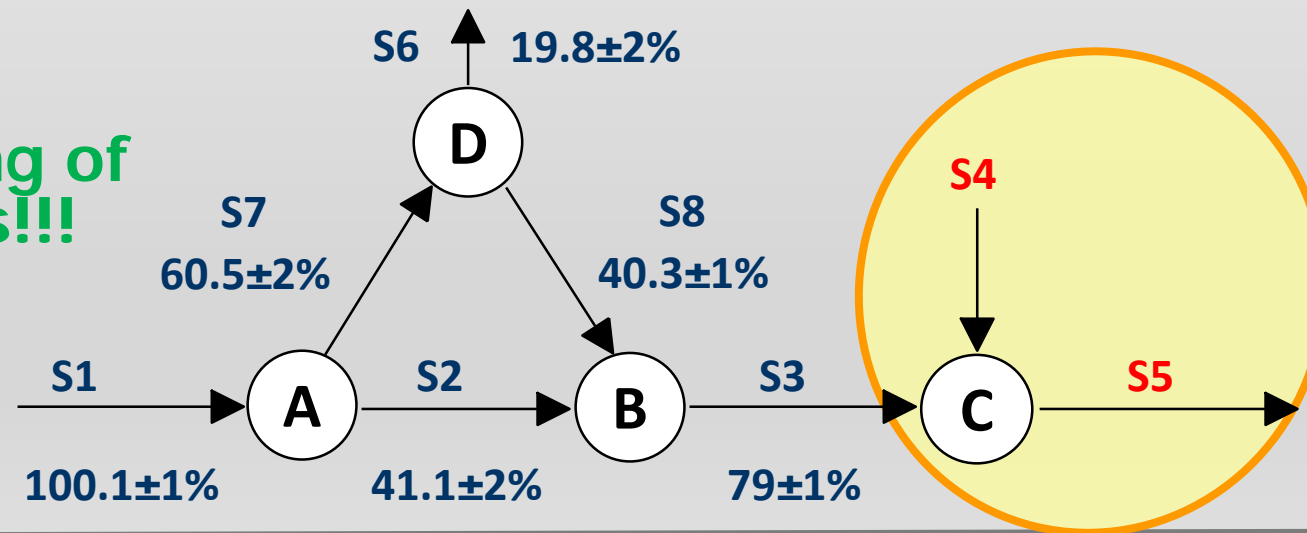
$$\text{DOR} = 6 + 4 - 8 = 2 > 0:$$

8 flowrates, 4 mass balances, 6 flow measurements

Pay attention: measurements must be cleverly positioned!

DOR > 0 is the necessary but not sufficient condition

Clever positioning of
plant measures!!!

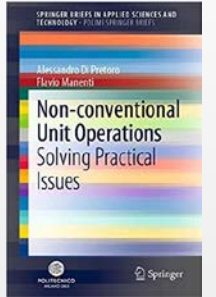
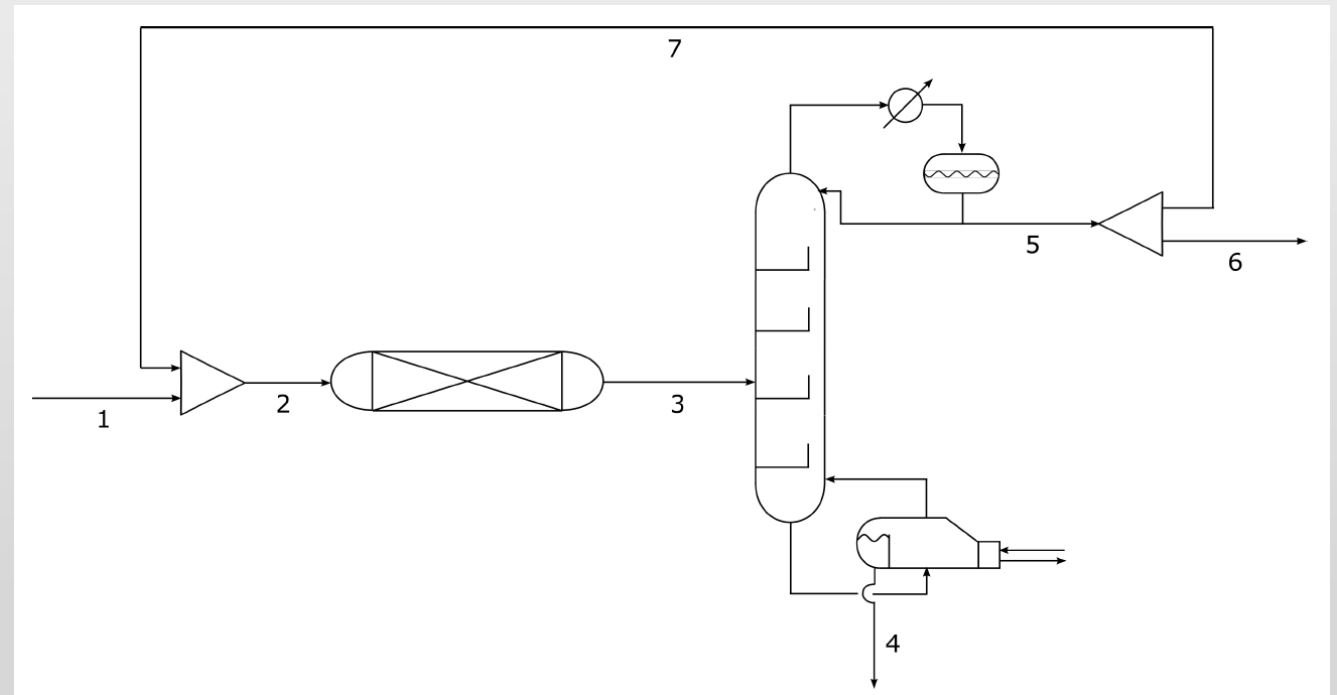


Local DOR
negativity!

Exercise

Consider the following isomerization process. It consists of synthesis and purification/recycle sections. All the relevant mass flowrates are measured, but balances are not fulfilled.

(I) Reconcile the process data.



Process data

Stream #	Flowrate [kg/h]
1	95.00
2	170.00
3	175.00
4	75.00
5	103.00
6	15.00
7	82.00




Solution

Supplementary material (to be uploaded tomorrow)

Correction at 01:45 PM, March 12th, 2021





Outliers and gross errors

Reconciliation is nothing without robustness...



Definition

Gross error



*A gross error
is **CLEARLY** a
bad point...*



Definition Outlier

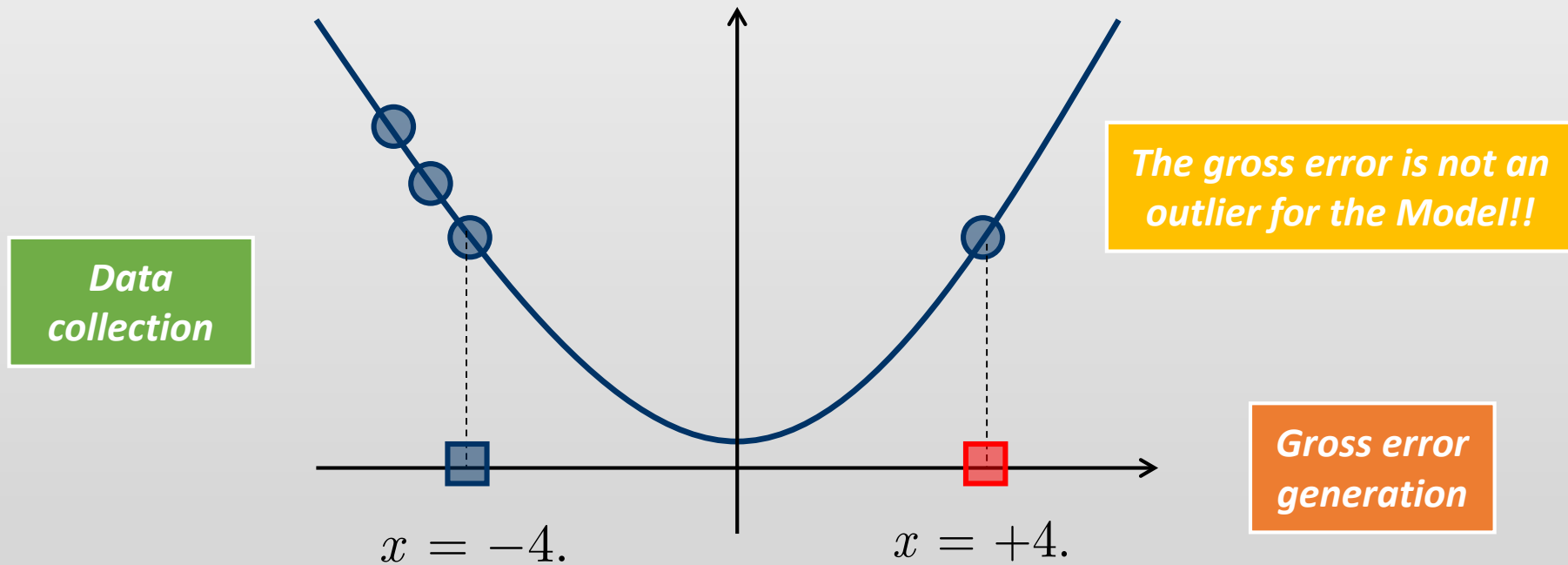
Whatever data unsuitable for a model is called outlier for that model

*Whatever outlier is always
joined to a specific model*

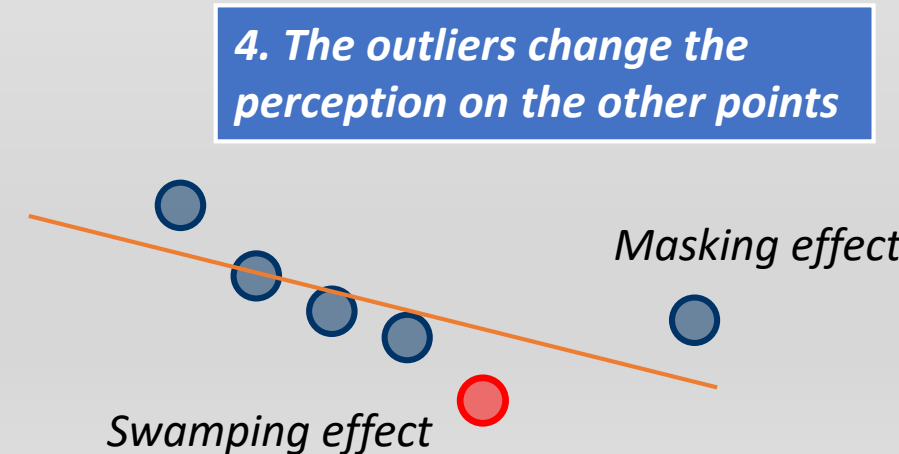
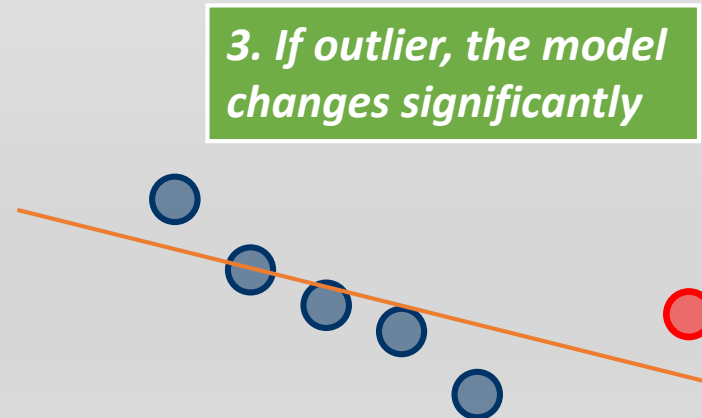
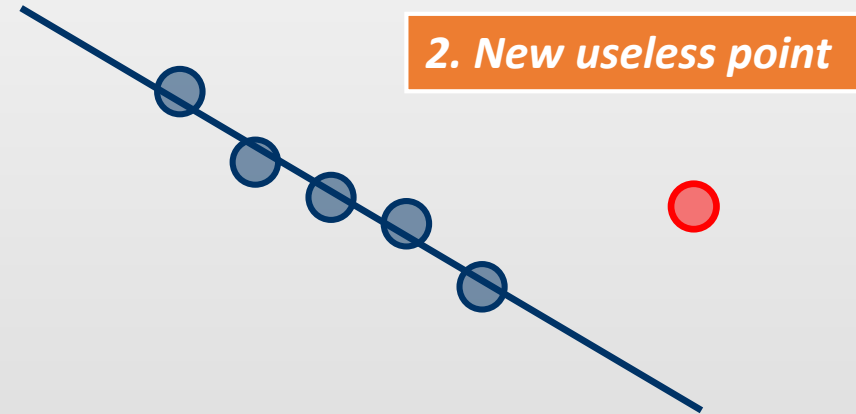
Their (outlier and gross error) presence generates a significant increase for the mean square error (measure – true value).

$$MSE = \sum_{i=1}^{NM} \frac{(y_i - y_i^{rec})^2}{NM} \quad NM > 30$$

But... Exceptions

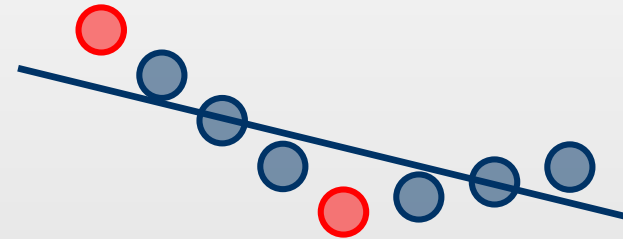


Sources of outliers in big data sets

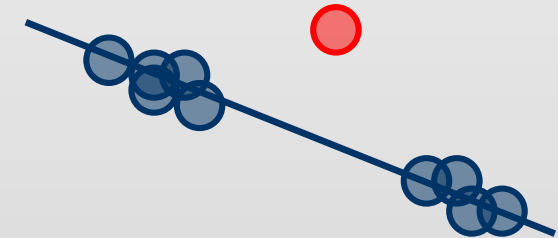


Sources of outliers in big data sets

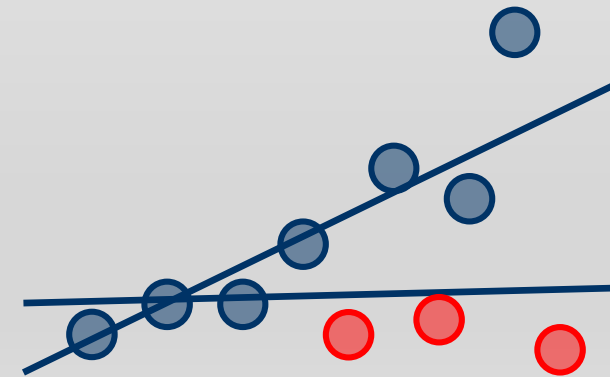
Inadequate models



Inadequate DoE or measures

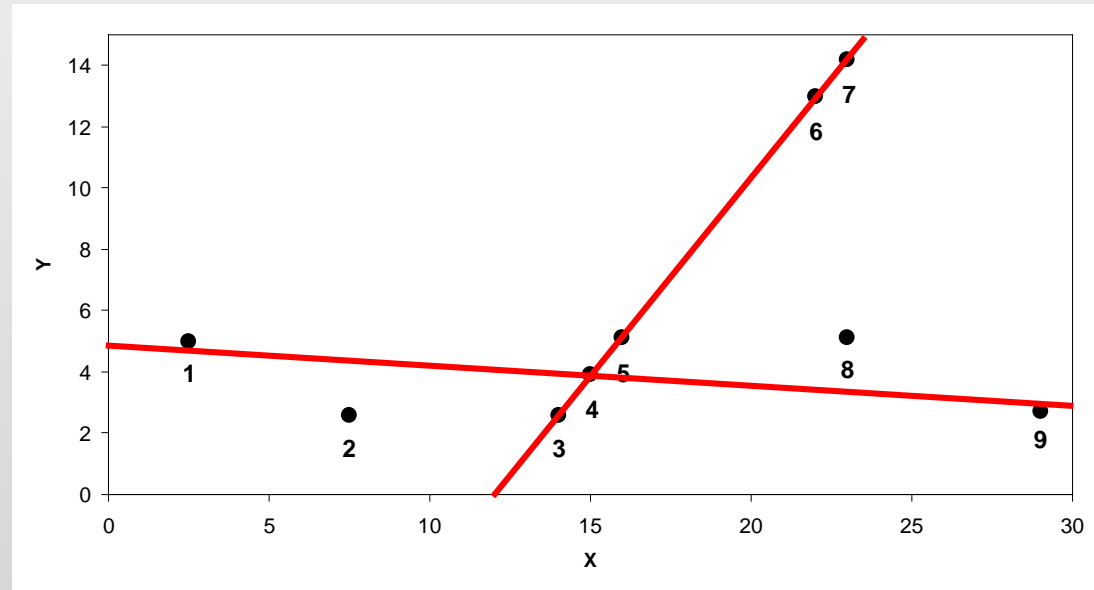


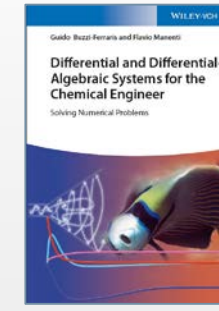
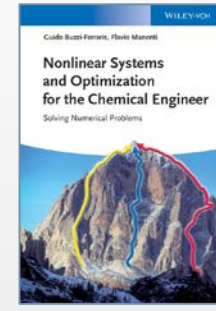
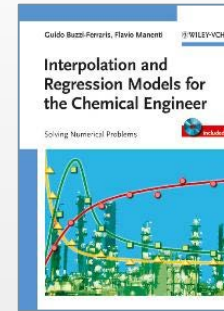
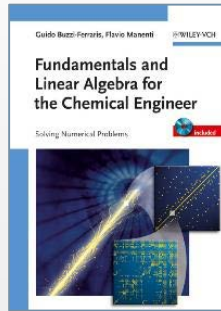
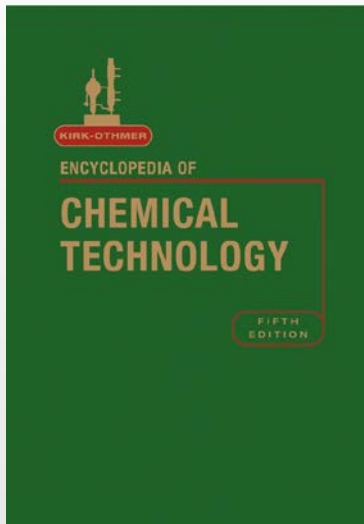
Violated homoscedasticity



Literature example

*Ryan, T. P., Modern
Regression Methods.
2nd Ed., Wiley, NJ, 2009*





Kirk-Othmer Encyclopedia of Chemical Technology

Guido Buzzi-Ferraris, Flavio Manenti

Data Interpretation and Correlation, John Wiley & Sons, New York, USA

Identification of outliers

Robustness? Yes, but not too much

Computers and Chemical Engineering 35 (2011) 388–390

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

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Note

Outlier detection in large data sets

Guido Buzzi-Ferraris*, Flavio Manenti

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**Recommended
3-pages reading**

Clever mean and clever variance

n points $y_i (i = 1, \dots, n)$ with very large n

Symmetrical distribution with $\mu \sigma^2$ and data reading/ordering on the DCS w.r.t. the error

Zeroth-order clever mean: $cm_0 = \frac{\sum_{i=1}^n y_i}{n} = \bar{y}$

Zeroth-order clever variance: $cv_0 = \frac{\sum_{i=1}^n (y_i - cm_0)^2}{n-1} = s^2$

Outliers at the boundaries

Assuming y_1^* as the first possible outlier, first-order clever mean and clever variance are:

$$cm_1 = \frac{\sum_{i=1}^n y_i - y_1^*}{n-1} \quad cv_1 = \frac{\sum_{i=1}^n (y_i - cm_1)^2 - (y_1^* - cm_1)^2}{n-2}$$

Identification condition: $|cm_1 - y_1^*| > \delta \cdot \sqrt{cv_1}$

If confirmed as outlier, the procedure is iterated until

$$|cm_k - y_k^*| > \delta \cdot \sqrt{cv_k}$$

$$|cm_{k+1} - y_{k+1}^*| < \delta \cdot \sqrt{cv_{k+1}}$$



POLITECNICO
MILANO 1863

ITELYUM 

Industrial application

Big data analytics in process industry

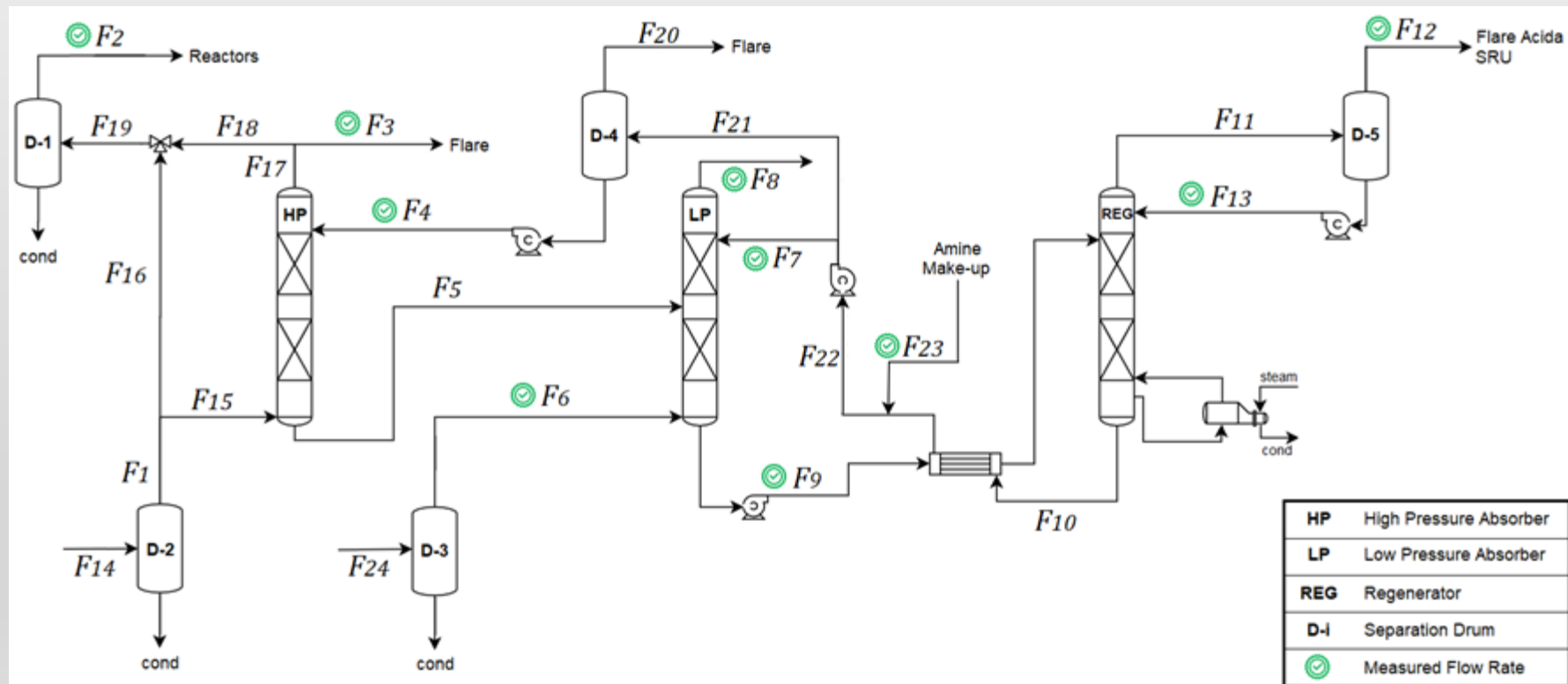
CO₂ capture industrial plant

Courtesy of
Ing. Gallo



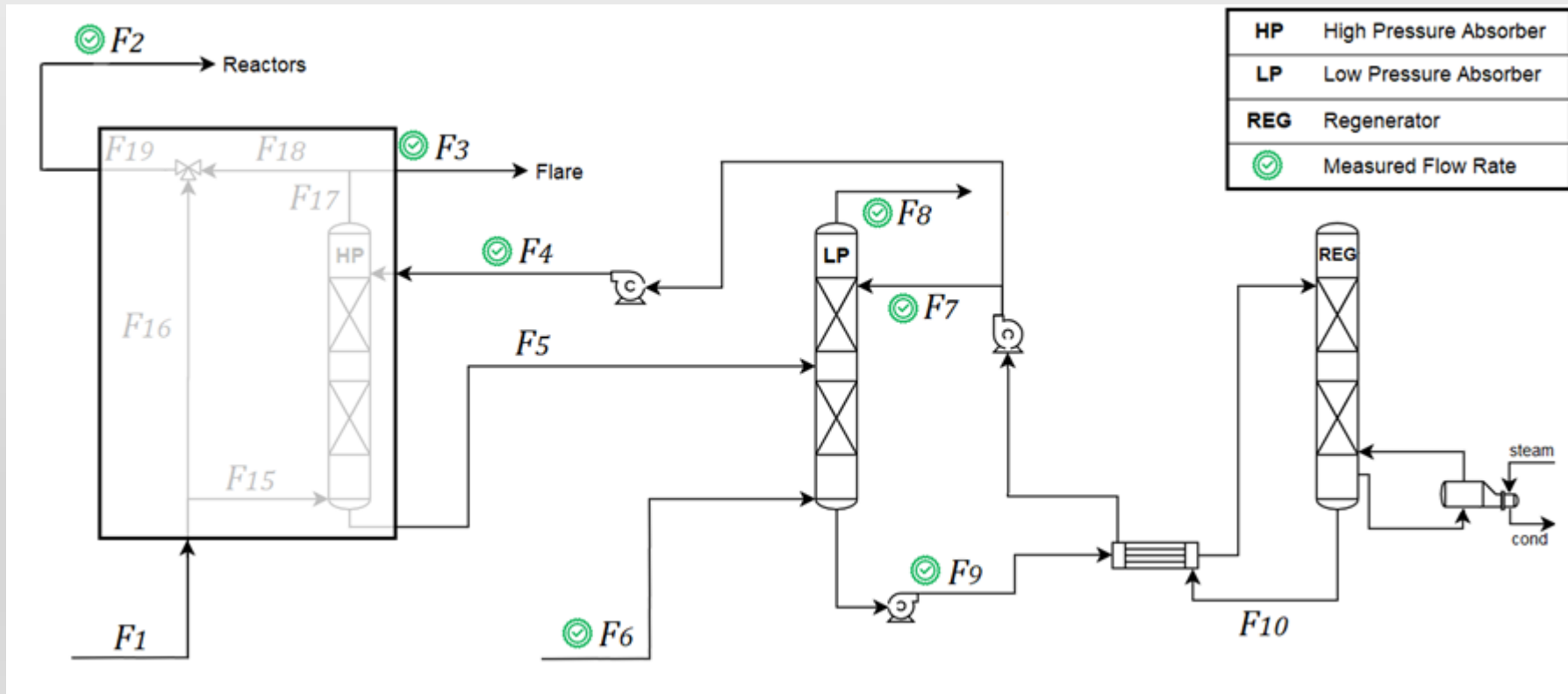
Process scheme and measures

Redund... WHAT??? Ok... it's infeasible...

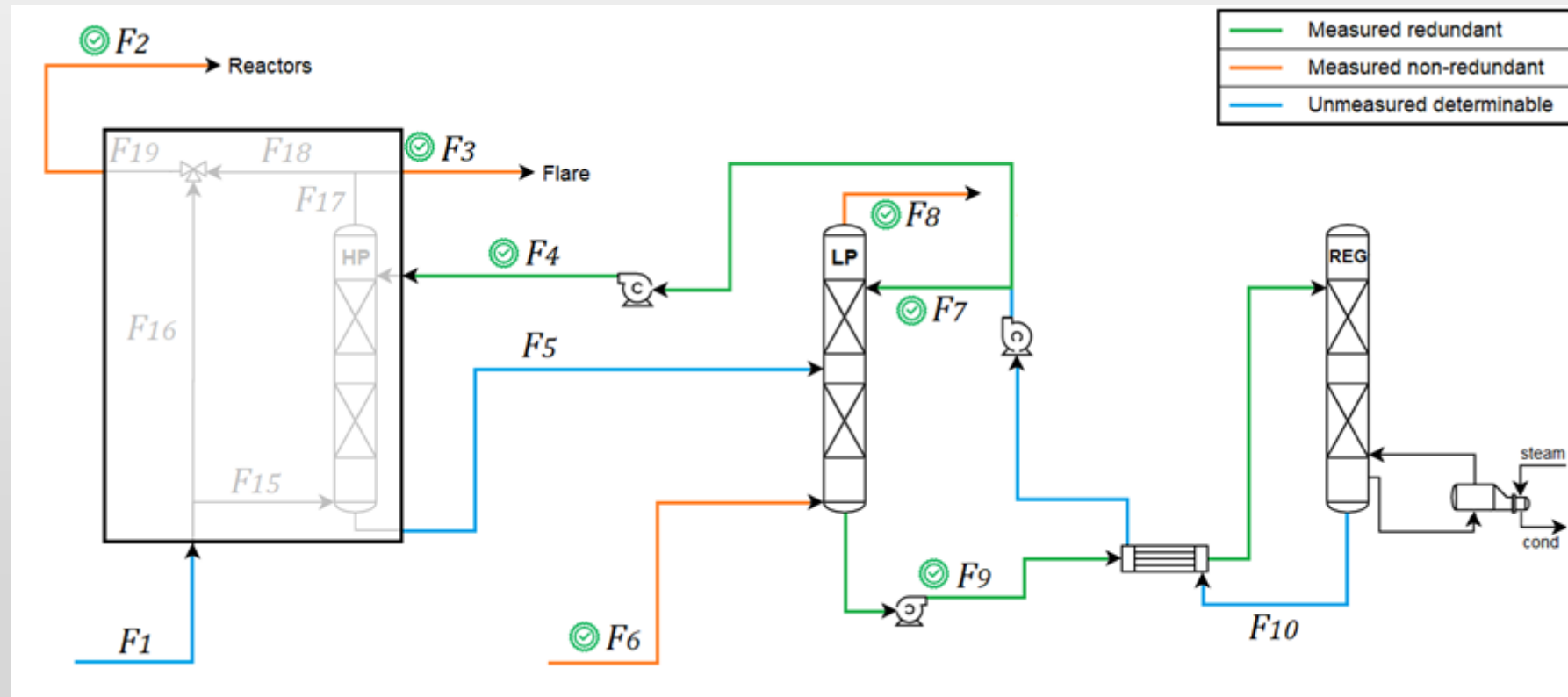


Are you sure? Simplify...

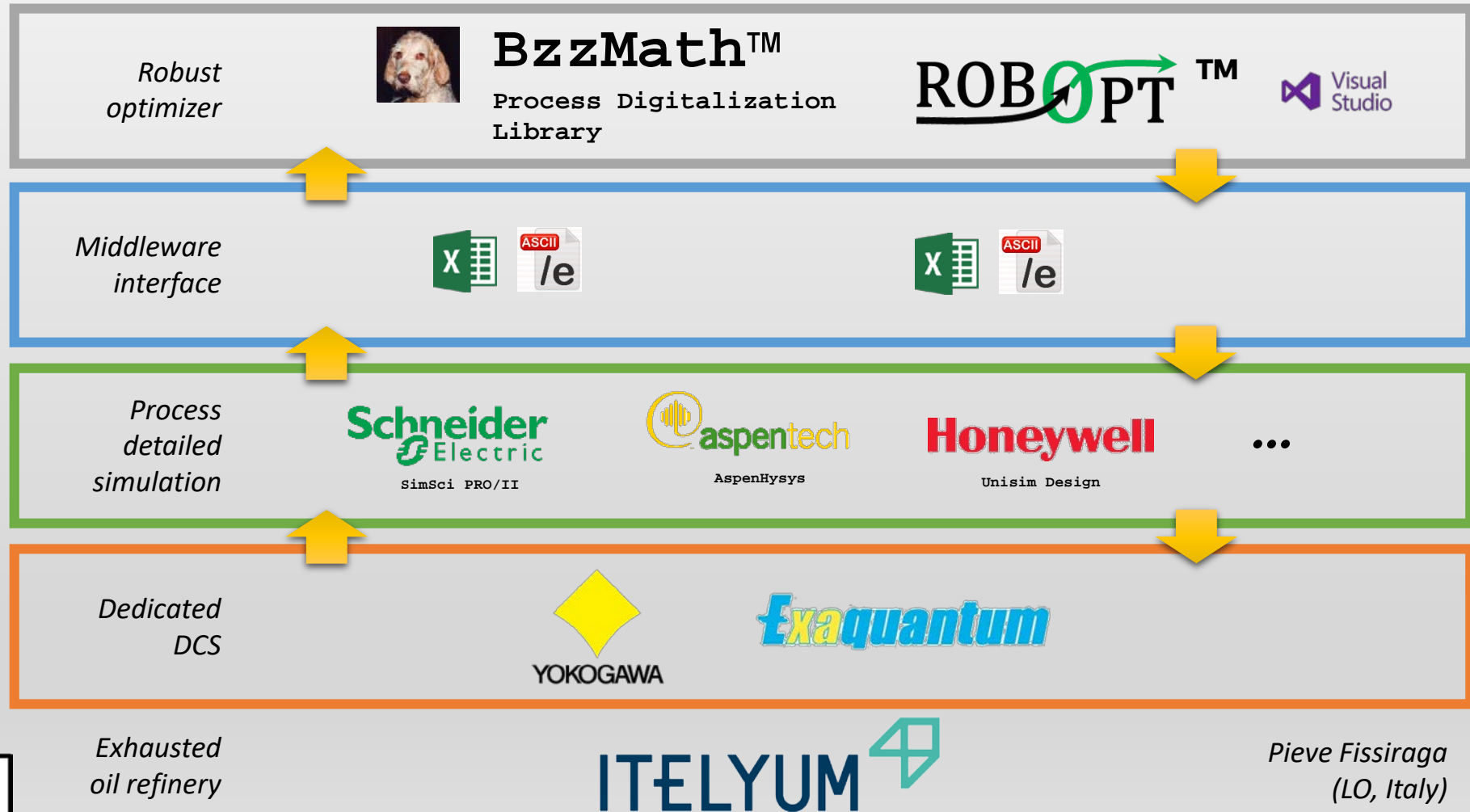
Remove NNF and introduce white boxes...



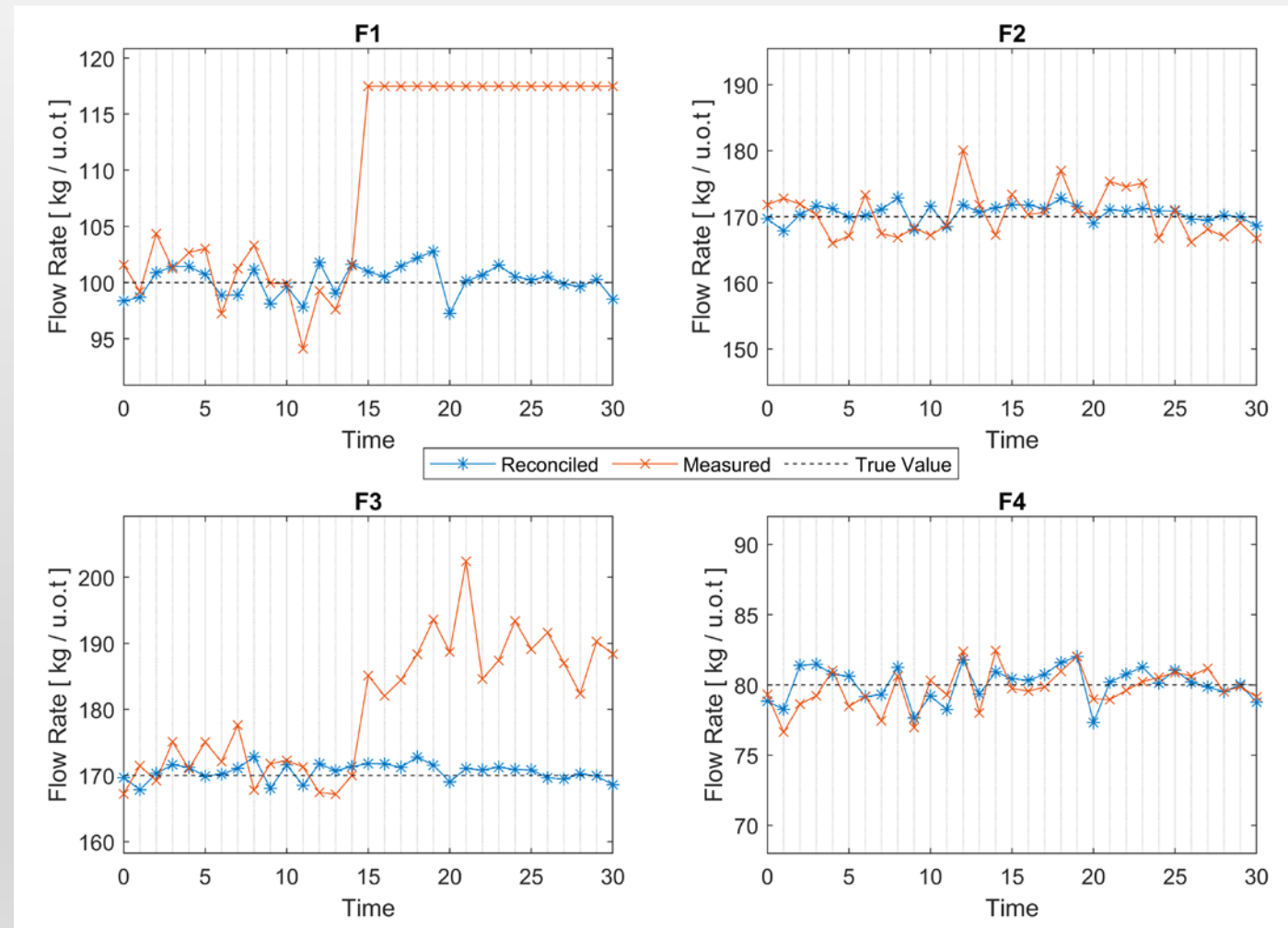
Now is feasible!



Digital architecture



Powerful of robust data reconciliation





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MILANO 1863

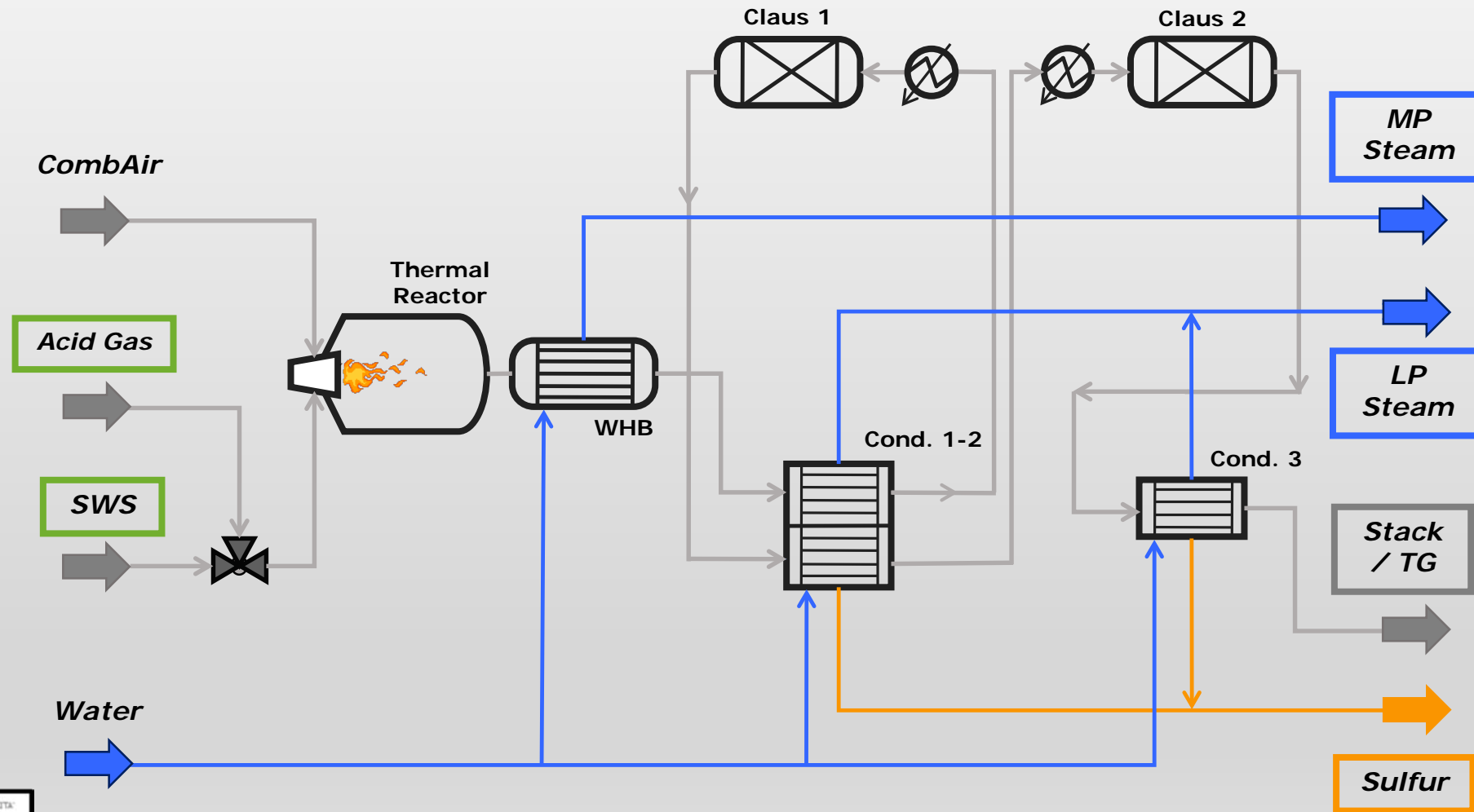


Industrial application

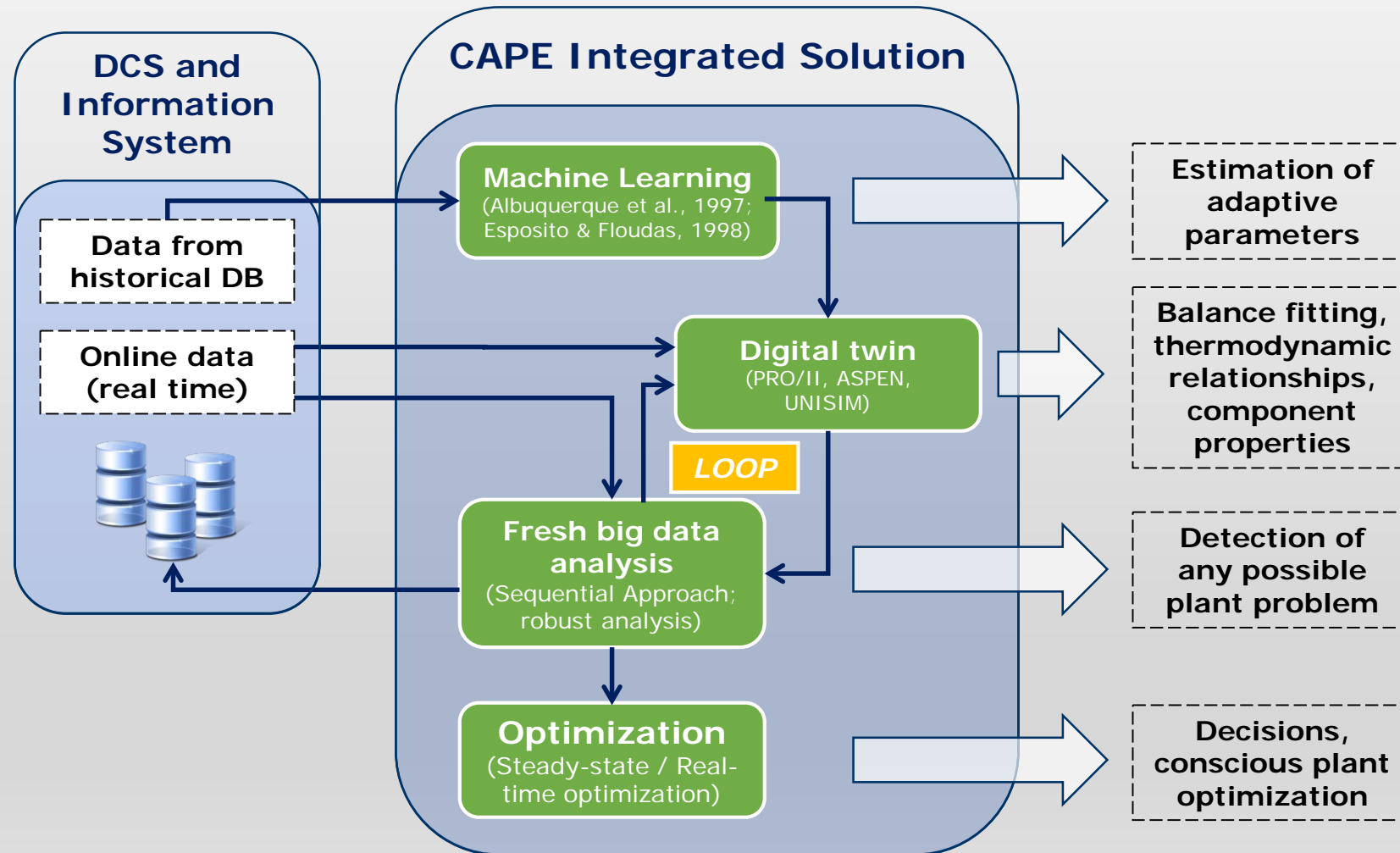
Robust data reconciliation in Lukoil



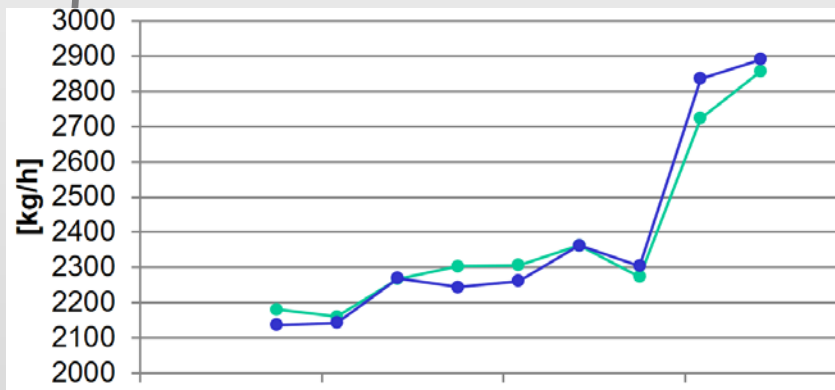
Sulfur recovery unit



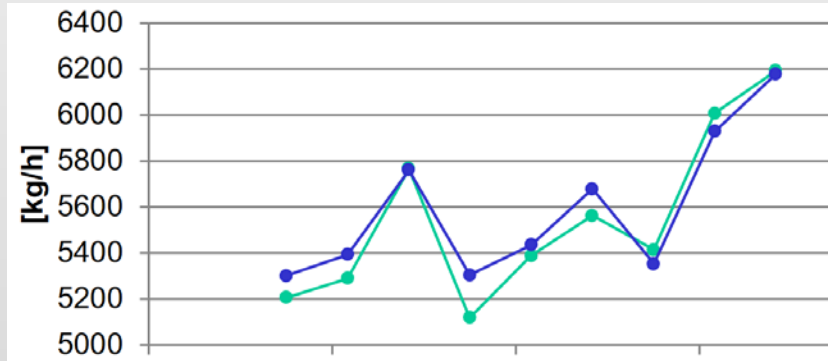
Digital architecture



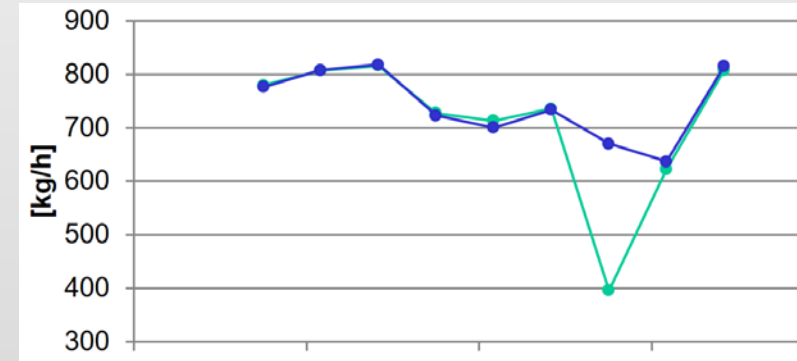
Gross error identification



*Acid gas
flowrate*



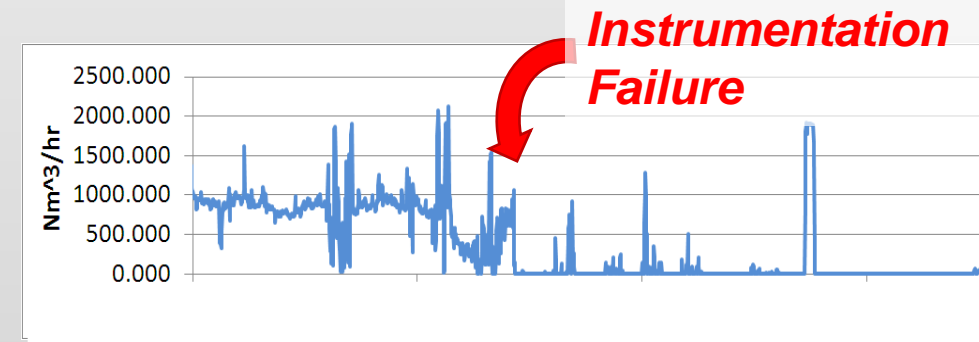
*Combustion
air*



*SWS
flowrate*

Effects of a misidentified gross error? Catastrophic ones...

Measures	Scenario #3				
	Measured	Nonrobust Rec	Res. [%]	Our CAPE Sol.	Res. [%]
AAG Flow Rate	2704.03 kg/hr	3435.84 kg/hr	27.06	2702.40 kg/hr	-0.06
Acid Gas Temp	52.66 °C	53.72 °C	2.01	50.48 °C	-4.14
Sour Water Flow Rate	0.00 kg/hr	- kg/hr	-	1179.36 kg/hr	-
Sour Water Temp	84.99 °C	- °C	-	84.29 °C	-0.82
Combustion Air Flow Rate	7352.21 kg/hr	5721.63 kg/hr	-22.18	7466.47 kg/hr	1.55
Combustion Air Temp	175.92 °C	178.97 °C	1.73	187.47 °C	6.57
Furnace Temp	1380.26 °C	1264.32 °C	-8.40	1374.59 °C	-0.41
WHB Temp	319.10 °C	305.78 °C	-4.17	310.03 °C	-2.84
First Condenser Temp	167.87 °C	168.25 °C	0.23	165.15 °C	-1.62
First Claus Inlet Temp	227.35 °C	240.84 °C	5.93	228.13 °C	0.34
First Claus Outlet Temp	290.26 °C	280.87 °C	-3.24	290.30 °C	0.01
Second Condenser Temp	163.65 °C	164.67 °C	0.62	157.04 °C	-4.04
Second Claus Inlet Temp	210.05 °C	231.74 °C	10.33	221.26 °C	5.34
Second Claus Outlet Temp	216.62 °C	234.16 °C	8.10	228.36 °C	5.42
Steam Generated at WHB	7152.15 kg/hr	5473.00 kg/hr	-23.48	7198.00 kg/hr	0.64
H ₂ S at Tail Gas	6330 ppmv	4720.27 ppmv	-25.43	6148 ppmv	-2.88
SO ₂ at Tail Gas	2631 ppmv	3029.00 ppmv	15.13	2621 ppmv	-0.38
H ₂ S/SO ₂ at Tail Gas	2.41 -	1.56 -	-35.23	2.35 -	-2.50
Recovered Sulfur	- [t/day]	65.14 t/day		62.14 t/day	
Final Value of Obj Func		0.296		0.0941	



References

1. Crowe, C. M. (1996). Data reconciliation - Progress and challenges. *Journal of Process Control*, 6(2-3 SPEC. ISS.), 89–98. [https://doi.org/10.1016/0959-1524\(96\)00012-1](https://doi.org/10.1016/0959-1524(96)00012-1)
2. Sánchez, M., Romagnoli, J., Jiang, Q., & Bagajewicz, M. (1999). Simultaneous estimation of biases and leaks in process plants. *Computers and Chemical Engineering*, 23(7), 841–857.
3. Narasimhan, S., & Jordache, C. (2000). Data reconciliation and gross error detection : an intelligent use of process data. In *Annals of the New York Academy of Sciences* (Vol. 195).
4. Buzzi-Ferraris, G., & Manenti, F. (2011). Outlier detection in large data sets. *Computers and Chemical Engineering*, 35(2), 388–390.
5. Llanos, C. E., Sánchez, M. C., & Maronna, R. A. (2015). Robust Estimators for Data Reconciliation. *Industrial and Engineering Chemistry Research*, 54(18), 5096–5105. <https://doi.org/10.1021/ie504735a>
6. Loyola-Fuentes, J., & Smith, R. (2019). Data reconciliation and gross error detection in crude oil pre-heat trains undergoing shell-side and tube-side fouling deposition. *Energy*, 183, 368–384.
7. **Romagnoli, A. J.; Sanchez, M. C. (2000). Data Processing and Reconciliation for Chemical Process Operations, Volume 2. Academic Press.** **BOOK**
8. Buzzi-Ferraris, G., & Manenti, F. (2010). *Interpolation and Regression Models for the Chemical Engineer: Solving Numerical Problems, Volume 2.* Wiley-VCH, Weinheim, Germany **BOOK**
9. **PROCESS DIGITALIZATION LIBRARY:** download section at <https://super.chem.polimi.it> **TOOL**