Advanced Process Control of an Industrial Depropanizer Column using Data-based Inferential Sensors

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Goals

We design inferential (soft) sensors for advanced process control (APC) of an industrial depropanizer column of the Slovnaft refinery situated in Bratislava, Slovakia to improve the inferential sensors present at the plant. Linear inferential sensors of top and bottom product compositions are designed using various statistical methods, which are compared among each other.

Plant and Data Description

Industrial Data

Time period

- 13.12.2016 – 21.2.2019

Online sensors

- 9 measured variables:
  - flow rates: R, F
  - reboiler duty Q_B
  - temperatures: $T_{10,37,\mathrm{D},\mathrm{B}}$
  - pressures: p_D, p_B

  (38,360 measurements)

Lab analysis

- distillate composition x_D (28 measurements)
- bottom composition x_B (176 measurements)

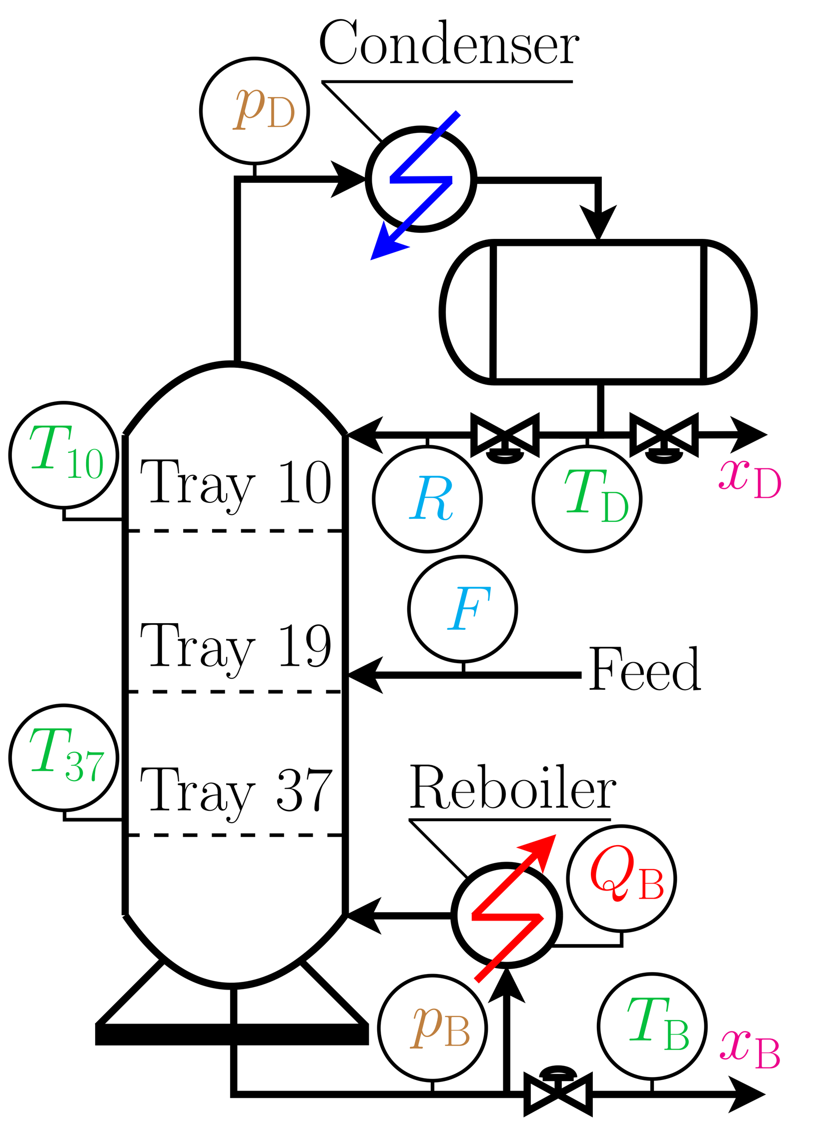

Fig. 1: The depropanizer scheme.

Synthetic Data

gPROMS

- High-fidelity gPROMS model
- 49 possible measured variables (200 different operating points)

Reference Inferential Sensors

Distillate inferential sensor

$$x_\mathrm{D} = a_1 T_{10} + a_2 p_\mathrm{D} + a_3 \frac{R}{F} = \underbrace{(a_1\ a_2\ a_3)}_{\boldsymbol{a}_\mathrm{ref}^\intercal} \underbrace{\left(T_{10}\ p_\mathrm{D}\ \tfrac{R}{F}\right)^\intercal}_{\boldsymbol{m}_\mathrm{D}}$$

Bottom inferential sensor

$$x_\mathrm{B} = a_1 T_{37} + a_2 p_\mathrm{B} + a_3 \frac{Q_\mathrm{B}}{F} = \underbrace{(a_1\ a_2\ a_3)}_{\boldsymbol{a}_\mathrm{ref}^\intercal} \underbrace{\left(T_{37}\ p_\mathrm{B}\ \tfrac{Q_\mathrm{B}}{F}\right)^\intercal}_{\boldsymbol{m}_\mathrm{B}}$$

Design of Inferential Sensors

1. Design of the sensor structure.

$$x = \boldsymbol{a}^\intercal \underbrace{(R, F, Q_\mathrm{B}, T_{10}, T_{37}, T_\mathrm{D}, T_\mathrm{B}, p_\mathrm{D}, p_\mathrm{B}, R/F, Q_\mathrm{B}/F)^\intercal}_{\boldsymbol{m}}$$

2. Calculation of the sensors parameters.

$$\min_{\boldsymbol{a}} \mathrm{SSE} := \min_{\boldsymbol{a}} \sum (x_i - \boldsymbol{a}^\intercal \boldsymbol{m}_i)^2$$

Method	Structure (**1.**)	Parameters (**2.**)
ref	✗	$\min_{\boldsymbol{a}_\mathrm{ref}} \mathrm{SSE}$
OLS	?	$\min_{\boldsymbol{a}} \mathrm{SSE}$
PCA	✓	$\min_{\tilde{\boldsymbol{a}}} \mathrm{SSE}$
PLS	✓	$\min_{\tilde{\boldsymbol{a}}} \mathrm{SSE}$
LASSO	✓	$\min_{\boldsymbol{a}} \mathrm{SSE} + \lambda \lVert \boldsymbol{a} \rVert_1$

OLS: Ordinary Least Squares, PCA: Principal Component Analysis, PLS: Partial Least Squares, LASSO: Least Absolute Shrinkage and Selection Operator.

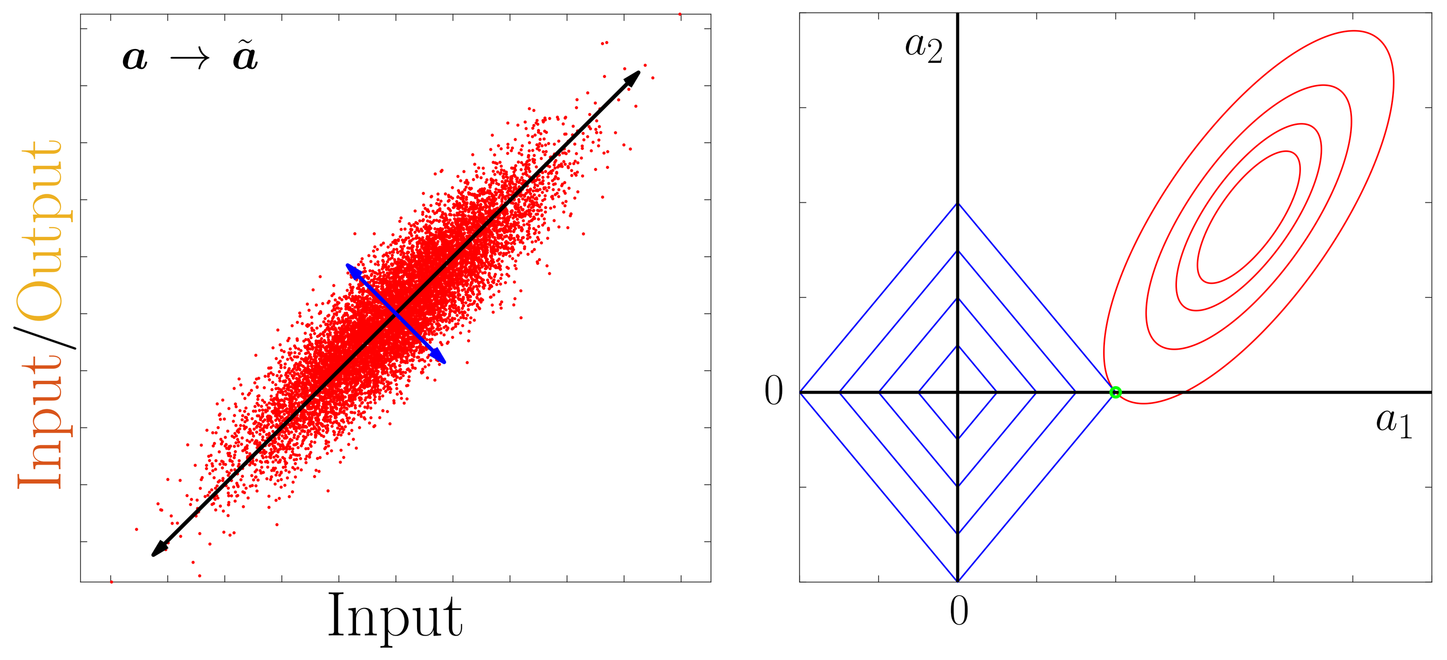

Fig. 2: Principle of PCA/PLS (left) and LASSO (right).

Results

Accuracy of Estimation

- The improvement of the bottom sensor is around 20 %.
- The distillate soft sensor requires more complex model.

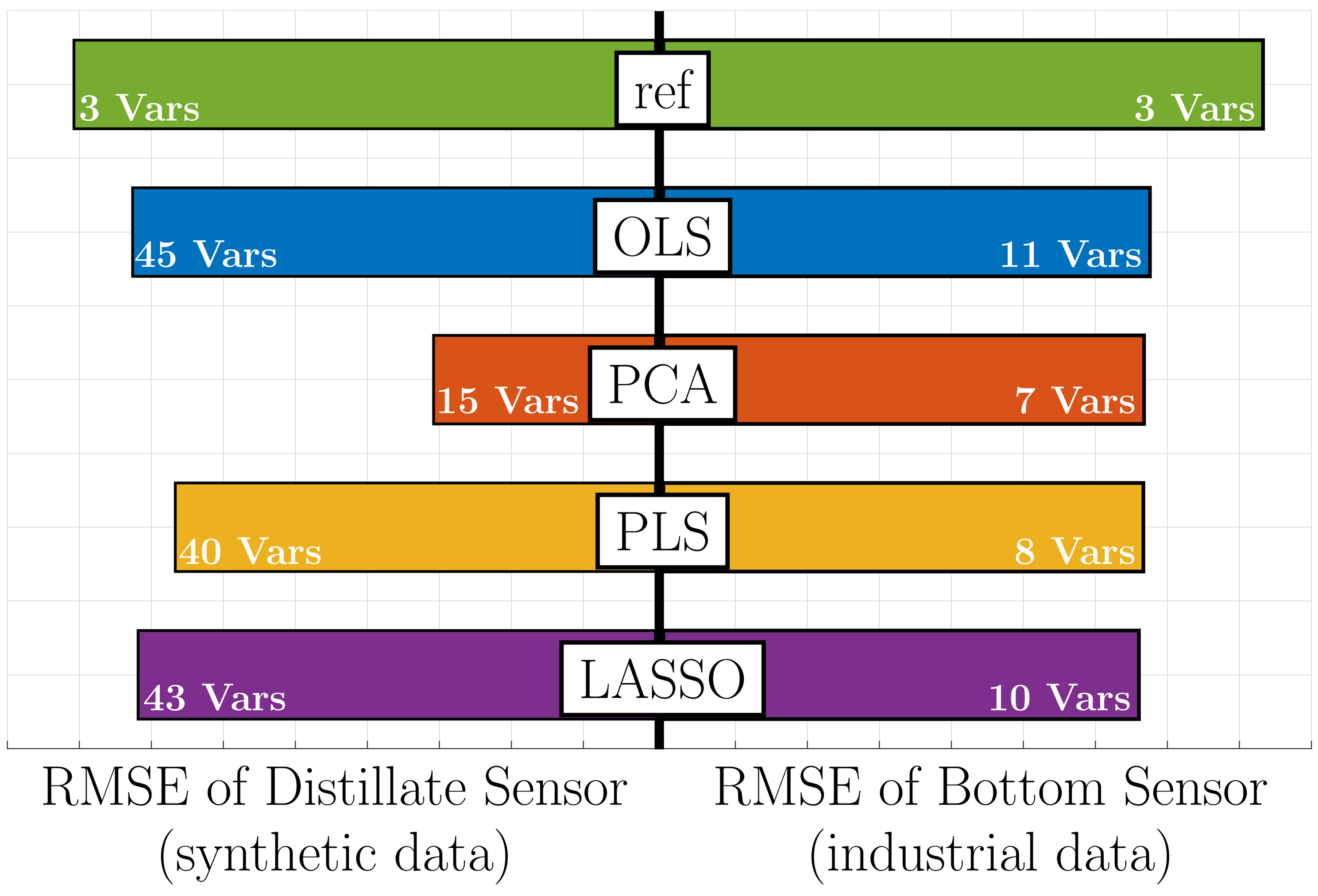

Fig. 3: The accuracy of designed inferential sensors.

Accuracy of APC

- The tolerance is ± 10 % of the composition setpoint.
- The distillate product exceeds the expected purity.

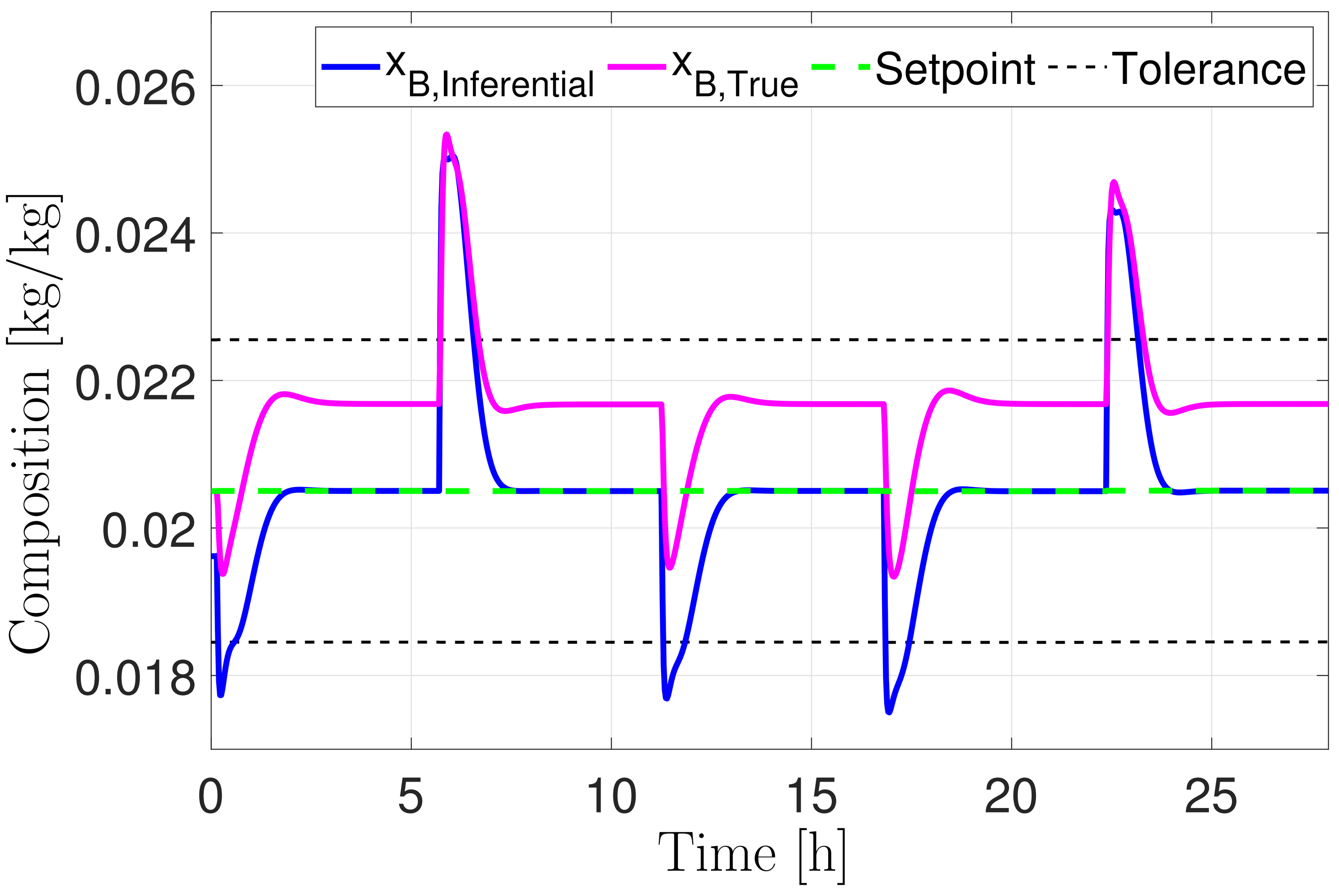

Fig. 4: Bottom composition (plant vs. inferential sensor).

Conclusions

The current inferential sensors were improved for estimating the bottom composition (just a change of the sensor model is required) as well as the top composition (inclusion of nine new measuring devices is required at the plant). The best methods to design the inferential sensors are PCA regression (requires large datasets) and LASSO (can work well with small datasets).

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