Multi-Model Soft-Sensor Design for a Depropanizer Distillation Column

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Goals

This contribution presents a novel design methodology for multi-model inferential (soft) sensors (MMS). The use of MMS leverages on advantages of linear and nonlinear soft sensors and hinders their disadvantages. The case study is a high-fidelity model of a real-world depropanizer column built within gPROMS ModelBuilder. The MMS is considered due to the varying operating conditions stemming from uncertain feedstock quality. The highlights of the novel design methodology for MMS are (a) continuous switching between the sensor models and (b) optimised a priori labelling. The performance of MMS is compared with single-model soft sensors (SMS) designed by most popular approaches (e.g., PCA, PLS, LASSO, SS).

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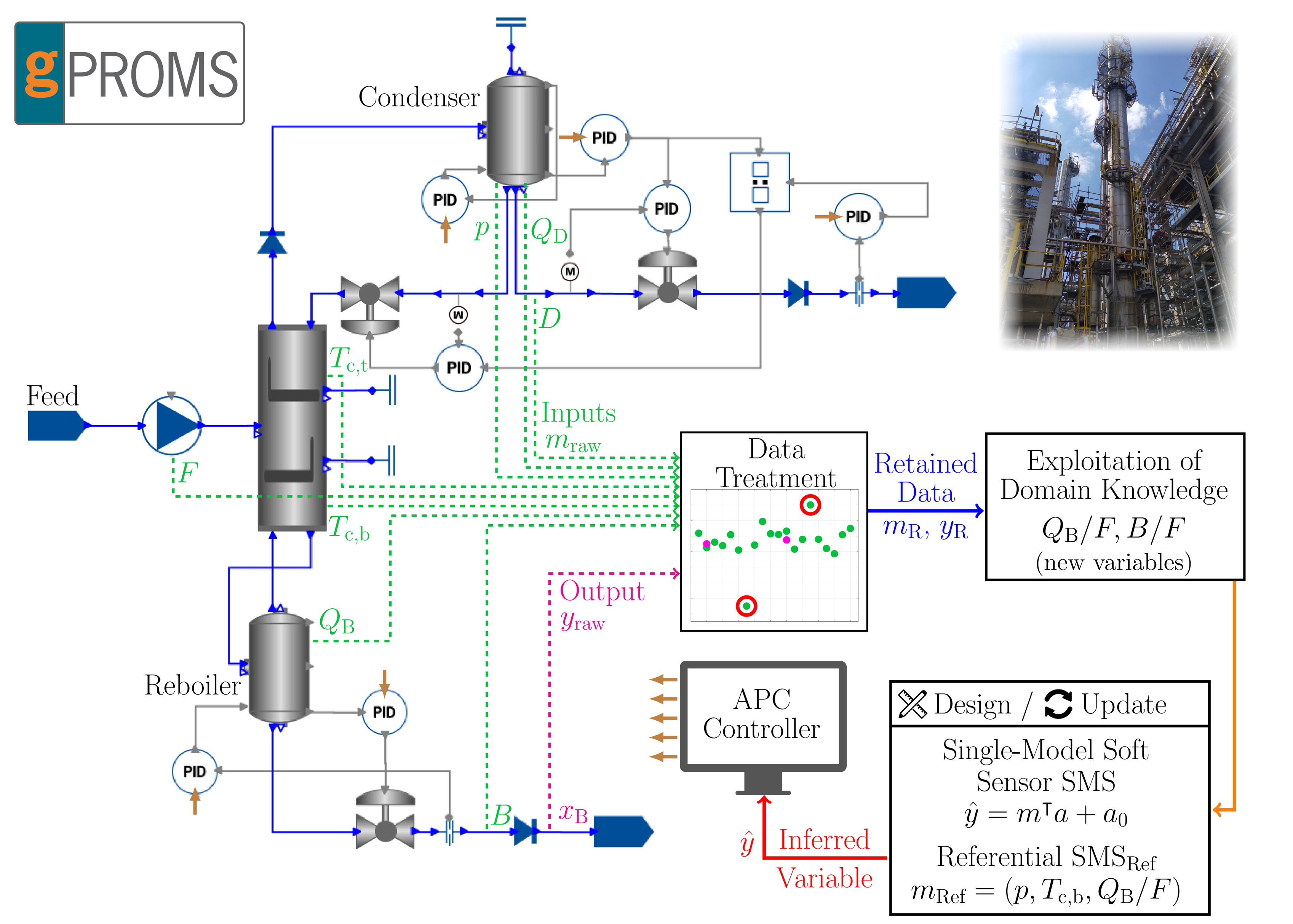
Soft-Sensor Implementation



Soft-sensor life cycle in an industrial plant.

Problem Definition

Simulated (production) window: 2 years

Problem: two different feed mixtures (varying each two months)

	Propane	Propylene	n-Butane	1-Butene	n-Pentane
Feed 1	0.060	0.317	0.273	0.341	0.009
Feed 2	0.065	0.377	0.249	0.302	0.007

Possible Solutions →	Linear Single-Model Soft Sensor	Nonlinear Single-Model Soft Sensor	Linear Multi-Model Soft Sensor
Different Operating Points Coverage	✗	✓	✓
Transparency and Ease of Maintenance	✓	✗	✓
Computational Efficacy	✓	?	✓
Online Evaluation (Estimation)	✓	?	✓

Methodology: Soft-Sensor Design Approaches

Single-Model Soft Sensor (SMS)

$$\hat{y} = m^{\intercal} a + a_0$$

Data-based approaches:

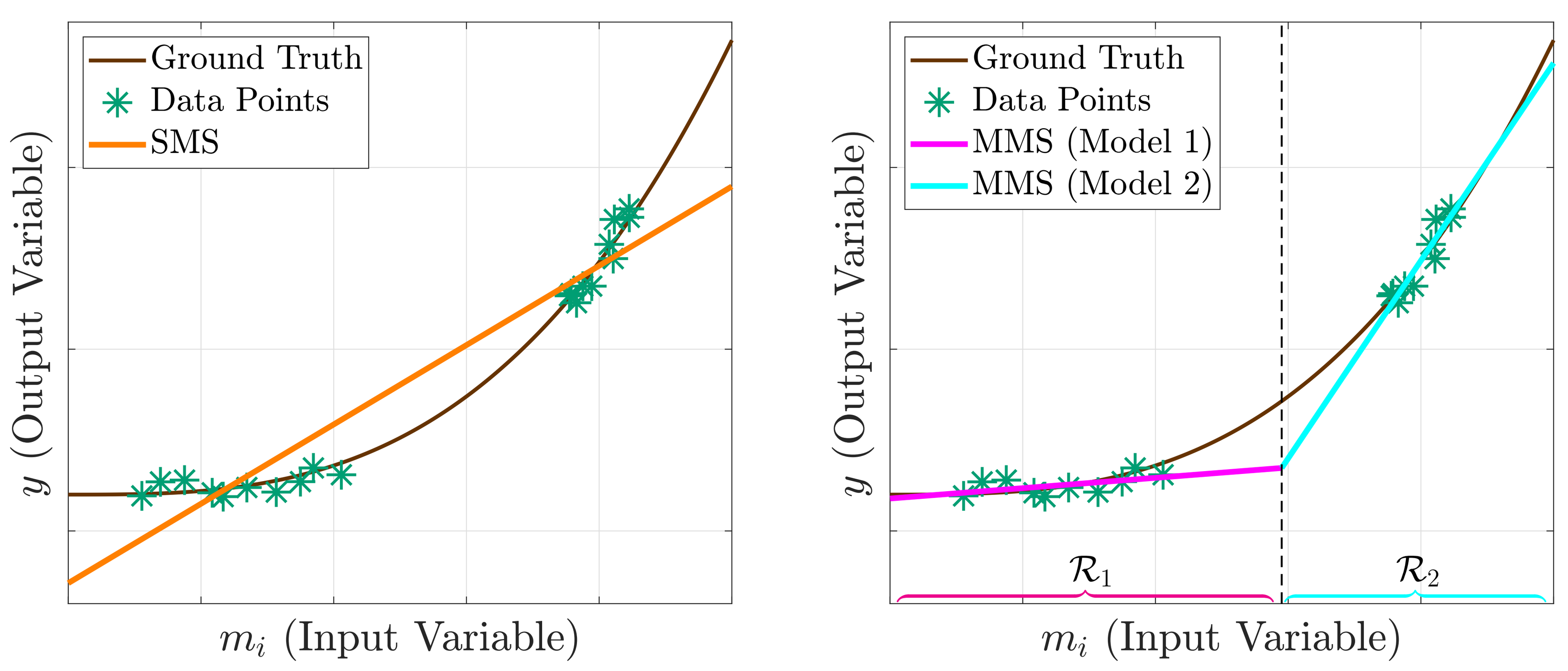
- Principal Component Analysis (PCA)
- Partial Least Square (PLS)
- LASSO, SS, etc.

Multi-Model Soft Sensor (MMS)

$$\hat{y}_i = \begin{cases} m_i^{\intercal} a_1 + a_{0,1}, & \text{if} \quad m_i \in \mathcal{R}_1, \\ m_i^{\intercal} a_2 + a_{0,2}, & \text{if} \quad m_i \in \mathcal{R}_2, \end{cases}$$

Algorithm structure:

- A priori labeling of the available dataset.
- Classifier design.
- Individual sensor training.



The visualization of SMS and MMS performances.

Results: Performance Criteria

Soft-Sensor Performance Criteria

Accuracy: $\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$

Complexity: number of selected input variables n_p^*

	SMS_{Ref}	SMS_{LASSO}	MMS	
RMSE (TR)	0.036	0.019	0.028	0.018
RMSE (TS)	0.039	0.020	0.028	0.019
n_p^*	3	8	3	4

Results: Profitability Analysis

The impacts of the various features on the profitability of designed soft sensors:

+ Positive
− Negative

	SMS_{Ref}	SMS_{LASSO}	MMS
Structural Complexity	+	−	+
Accuracy of the Estimates	−	+	+
Appropriateness for APC	−	+	++

Conclusions

According to the achieved results, multi-model inferential sensors (MMS) hold a significant potential to achieve better plant performance while not giving up any advantages of linear sensors in the inferential sensor life cycle as is the case for fully nonlinear models. The studied illustrative industrial use case documents this. We design an MMS with a simple structure (three or four input variables) and similar complexity as the sensor currently used in the plant. The designed sensor proves to be effective and robust. Its prediction accuracy is comparable to a more involved sensors designed using advanced state-of-the-art techniques.

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