Interpretable, Online Soft Sensors for Process Control

Mark Eastwood, Petr Kadlec
11.12.2011
Introduction – problem description

Technique for development of adaptive transparent models for process control

Conclusions and further steps
Motivation: Why explanatory modeling?

Benefits of **data-driven explanatory** models:

- Improvement of understanding of the process
- Possibility for comparison with expert knowledge
- Aid in overcoming barriers to uptake a soft sensor – soft sensor acceptance

Above points needs to be fulfilled when the soft sensor has to be used for **process control** (inferential control)
Case study: Analysis of states in reactive distillation column

In this plant the occurrence of sub-optimal states should be analysed and the cause identified.

A lot of data is available - 2 years of data were analysed.

Process is heavily instrumented with high number of sensors - 85 used in this study.
Introduction – problem description

Technique for development of adaptive transparent models for process control

Conclusions and further steps
Explanatory model structure: Soft sensor framework using ensemble methods and local learning
Explanatory model structure: Local experts

Can be any predictive model

Constraints on the models in this work:
  • Have to be transparent
  • Have to be adaptive

Suitable techniques:
  • Recursive Partial Least Squares
  • Adaptive decision trees
Explanatory model structure: Adaptive decision trees

- Using variance reduction as splitting rule
- Incremental updates in each node as new data arrives possible
- Requires only the sum of observations falling to left of each potential split for the updates
- Rebuilding the tree only below the node where optimal split significantly changes

Contribution plots indicating the significance of the variables can be extracted

\[ R = \frac{1}{|\nu_p|} V(\nu_p) - \frac{1}{|\nu_L|} V(\nu_L) - \frac{1}{|\nu_R|} V(\nu_R) \]

\[ = \left( \sum_p y^2 - \sum_L y^2 - \sum_R y^2 \right) + \frac{1}{|\nu_p|} \left( \sum y \right)^2 - \frac{1}{|\nu_L|} \left( \sum_L y \right)^2 - \frac{1}{|\nu_R|} \left( \sum_R y \right)^2 \]
Adaptive soft sensing algorithm – Local Expert Descriptors
Results of the study

Contribution plots extracted from the decision trees

Due to the adaptive nature of the model, the changes during the time can be observed.
Introduction – problem description

Technique for development of adaptive transparent models for process control

Conclusions and further steps
Conclusions

Previously available framework used for development of adaptive explanatory models

Tested using two techniques – one standard (PLS), one novel (adaptive regressive decision trees)

Gained information:
  • Influence of the input data on the target variable
  • Dynamic changes of the influence
Further steps

Development of recommendation engine for avoiding the sub-optimal states:
www.infer.eu

- Computational INtelligence Platform For Evolving and Robust Predictive Systems
- EU-FP7 Marie Curie IAPP
- Members: Bournemouth University (GB), Research and Engineering Center (Poland), Evonik Industries (Germany)