Autoprofit

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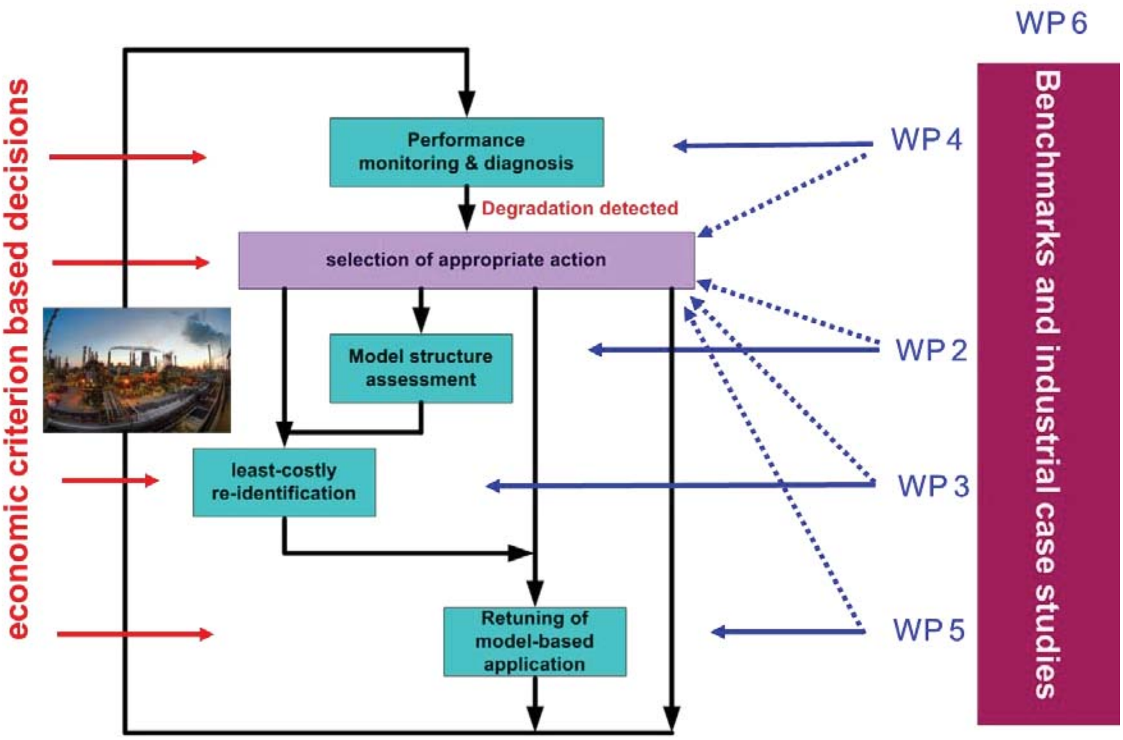
Advanced Autonomous Model-Based Operation of Industrial Process Systems

BACKGROUND OF THE PROJECT

The goal of AUTOPROFIT is to significantly improve life-time performance of model-based systems, like Model Predictive Control (MPC), Real Time Optimization (RTO), Model Based Sensors (MBS). Performance of the model based systems is known to degrade over time due to changes in the units and the operational conditions which require regular maintenance. Maintenance however is very labor intensive and highly specialized work. It is a serious cost factor, which may and does result in a limited life-time performance of the system.

An answer on how to seriously reduce maintenance costs and at the same time significantly improve the life time performance of the system is given in the AUTOPROFIT project.

THE BASIC IDEA OF AUTOPROFIT



The ultimate goal of the project is to autonomously and continuously maintain real-time model based systems based on a business relevant cost function:

- Continuously evaluate the performance of the process and automatically detect relevant performance degradation.
- Autonomously diagnose the cause of the degradation and determine the best action.
- Execute the selected maintenance action

What action to take depends on the diagnosis and the outcome of the economic evaluation:

- o No further activity required
- o Retune the model based system
- o Remodel the plant and retune the controller

The procedure is given in more detail in the decision tree.

PARTNERS INVOLVED IN AUTOPROFIT:

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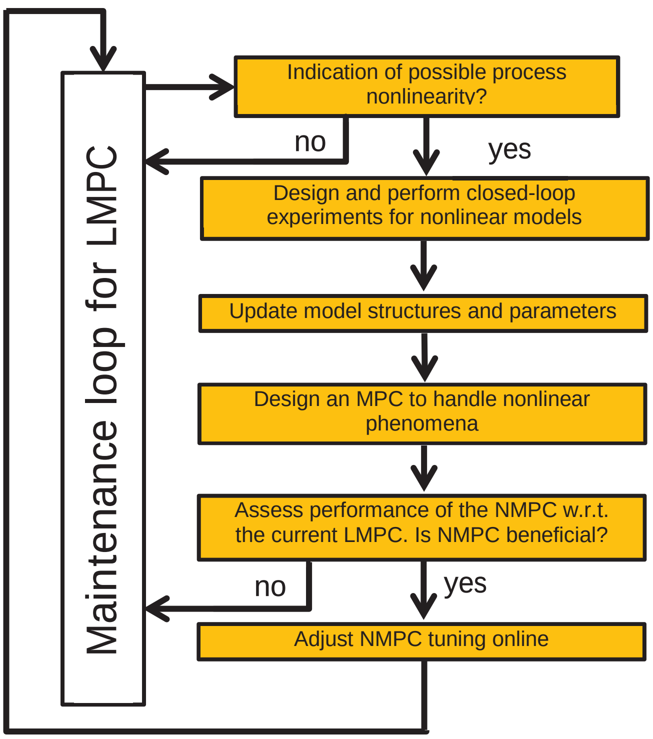
WP2 – MODELS IN MODEL-BASED SYSTEMS

WORK PACKAGE OBJECTIVES

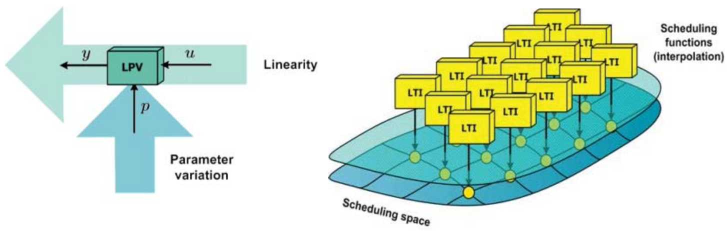
The aim of WP2 is to extend the linear maintenance loop such that situations, where an appropriate nonlinear MPC is likely to improve control performance are detected. After detection, the current linear model of the controller is gradually adapted to describe the nonlinear and time-varying process behavior. The strategy follows the least-costly philosophy of the project and allows an autonomous, smooth transition between linear and nonlinear MPC.

NONLINEAR MAINTENANCE LOOP



INCREMENTAL MODELS (BEYOND LTI)

The LPV concept



Benefits in using LPV models:

- Representing between multiple operating points and transient them in an efficient manner.
- Outer and inner approximation concept of the dynamic behavior: global vs local approaches of LPV modeling
- Preserving linearity between input and output signals (this allows to extend the stealth excitation approach).
- For frozen values of the scheduling parameters, LPV systems become LTI (this provides the possibility for an efficient gain-scheduled MPC design).

DATA-DRIVEN MODELING OF LPV SYSTEMS

The developed identification approaches are able to:

- Efficiently handle general conditions on the noise affecting the output signal observations.
- Efficiently handle the correlation (due to the closed-loop) between the noise corrupting the output measurements and the input of the system.
- Directly estimate the LPV model structure (order, dependencies) from the data.

MPC FOR LPV SYSTEMS

Gain-scheduled MPC: Underlying control strategy:

1. Measure the scheduling parameter p at time k.
2. Keep the scheduling parameter constant (and equal to $\mathrm{p}(\mathrm{k})$) during prediction (LPV → LTI)
3. Compute an LMPC for the frozen LTI model.
4. $k \leftarrow \mathrm{k}+1$. and go back to Step 1.

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WP2 – MODELS IN MODEL-BASED SYSTEMS

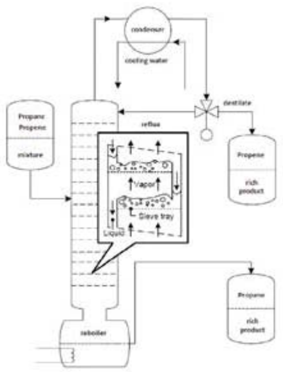
SUMMARY

The main idea of the WP2 is to detect when model/plant mismatch due to appearing nonlinearities deteriorate the MPC performance and correcting that by re-tuning the controller and/or updating (extending) the model. Simulation models are used to evaluate the developed solutions in a Matlab based benchmarking environment.

The data-driven incremental modeling methods, developed in WP2, have been applied for modeling of a high-purity distillation column and of a continuous pulp digester. The obtained models have been used in the gain-scheduled MPC design and applied on the pulp digester benchmark. Studies have been conducted to ensure data-driven detection of plant nonlinearities.

DISTILLATION COLUMN

Process description



Manipulated variables:
- Vapor and liquid flows

Measured variables:
- Top & Bottom purity

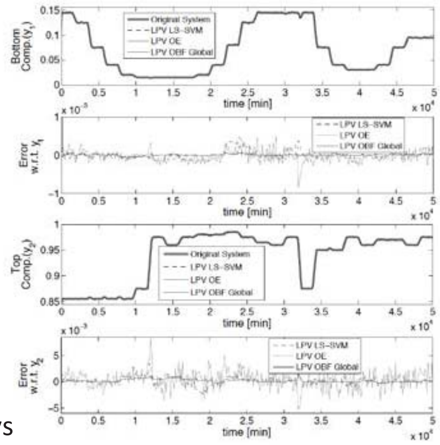
Scheduling variables:
- Top & Bottom purity

Sampling time: 2.5 min

Feautures:
- Directionality
- Locally changing order
- Large OP region
  Top: 99.5% - 85%
  Bottom: 1% - 15%

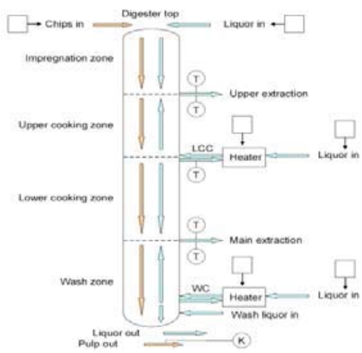
Data-driven Modeling:

- Comparing several LPV methods
- Fully data driven selection of the model structure
- SNR: 25 dB
- Data: 26 days



PULP DIGESTER

Process description



Manipulated variables:
- 3 liquor flows
- 2 temperature set points

Process variables:
- 5 temperatures

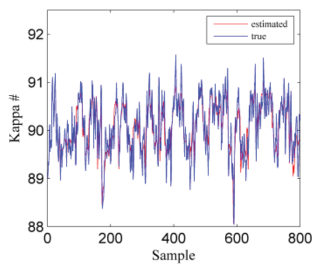
Controlled variable:
- Kappa number

Scheduling variable:
- Chip feed rate

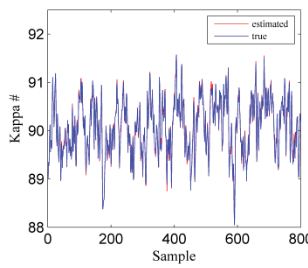
Generating data

- Closed-loop simulation (LMPC designed based on a linearized model of the pulp digester)
- Sampling time: 10 minutes
- Measurements of the Kappa number corrupted by noise (SNR=15 dB)
- Number of measurements used for estimation: N=1200

Data-driven modeling

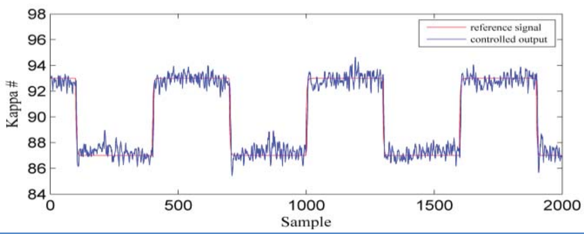


LTI model



LPV model

Gain-scheduled MPC



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WP 3 – LEAST COSTLY CLOSED-LOOP TESTING

WORK PACKAGE OBJECTIVES

- Develop methodology and tools for autonomous and low cost closed loop testing.
- Methods adapted to constrained control, such as MPC, and MIMO system requirements.
- Link experimental costs to actual economic costs.

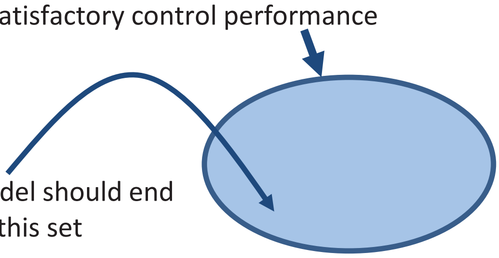
WORKPACKAGE OUTCOMES

- Experiment design methods for MPC:
  - Constrained open loop signal generation
  - MPC-X - MPC with eXperiment design
  - Stealthy MPC – MPC with open loop excitation
- MOOSE – A toolbox for optimal input design in MATLAB

APPLICATIONS ORIENTED EXPERIMENT DESIGN

- Identification experiments with precisely the information necessary for models giving satisfactory performance.
- Least costly experiment design.
- Information matrix requirements.

Set of models that when used in the MPC give satisfactory control performance



Identified model should end up in this set

PROBLEMS WITH EXPERIMENT DESIGN UNDER MPC

- Current closed loop experiment design methods based on designing the signal spectra.
- Methods developed for linear controllers.
- MPC is nonlinear. The map from reference to input is non-linear.

SOLUTIONS FOR EXPERIMENT DESIGN UNDER MPC

- **Stealthy MPC** – by hiding the excitation from the controller the identification becomes an open loop problem.
- **MPC-X –** including constraint on experiment design in the MPC so that the excitation is generated by the controller.

CONSTRAINED SIGNAL GENERATION

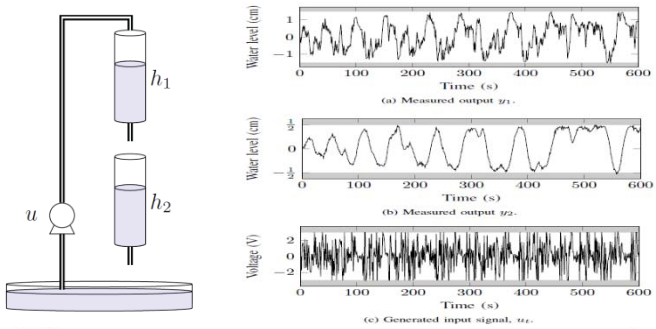
- Generation of signal with prescribed autocorrelation while satisfying input and output constraints.

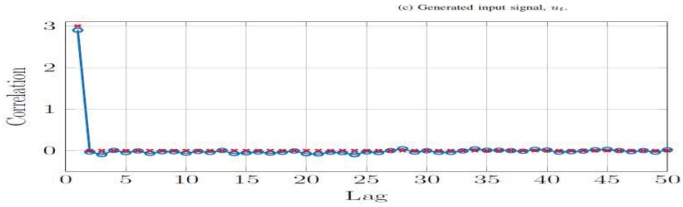
$$\begin{aligned} \underset{u(1),\dots,u(N)}{\text{minimize}} \quad & \left\| \boldsymbol{r}_N - \boldsymbol{r}^d \right\|_2^2 \\ \text{subject to} \quad & x_{t+1} = F x_t + G u_t \\ & y_t = H x_t \\ & u_{min} \le u_t \le u_{max} \\ & y_{min} \le y_t \le y_{max} \end{aligned}$$

- Difficult optimization can be simplified using receding horizon control ideas.
- Extended to robust MPC to satisfy constraints under model uncertainties

EXAMPLE – DOUBLE TANK SYSTEM

- Parameters re-identified online





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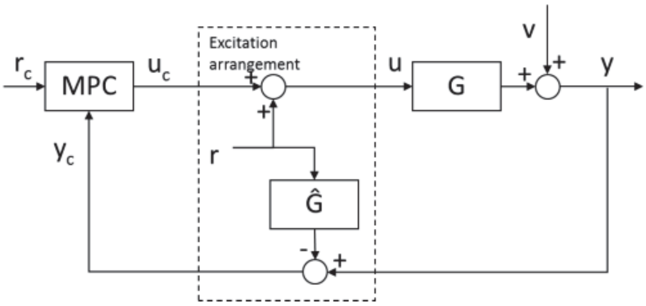
WP 3 – LEAST COSTLY CLOSED-LOOP TESTING

STEALTHY MPC

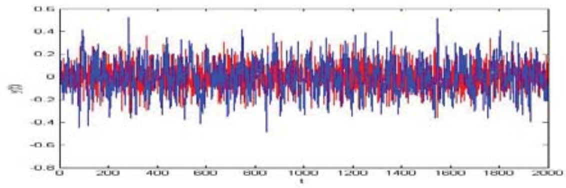
- **Idea –** Hide excitation from MPC – open loop identification!

- Patent pending.



EXAMPLE

- **Experiments**
  - Least costly experiment design
  - White noise signal with same power
- **Results**
  - Output with (blue) and without (red) excitation.



  - White noise does not give satisfactory model.
- **Conclusion –** Stealthy MPC works even if $\hat{G}$ is not exactly G.

MPC-X – MPC with eXperiment design

- Challenges:
  - Which constraint should be added?
  - Computational tractability.

$$
\begin{aligned}
\underset{\{u(k)\}_{k=1}^{N_u}}{\text{minimize}} \quad & \underbrace{\sum_{k=1}^{N_y} \|\hat{y}(k) - r(k)\|_Q^2 + \sum_{k=1}^{N_u} \|\Delta u(k)\|_{Q_u}^2}_{} \\
& x(k+1) = Ax(k) + Bu(k) \\
& y(k) = Cx(k),\ k = 1, \dots, N_y \\
& x(1) = \hat{x}(t) \\
\text{subject to} \quad & u_{min} \le u(k) \le u_{max},\ k = 1, \dots, N_u \\
& y_{min} \le y(k) \le y_{max},\ k = 1, \dots, N_y
\end{aligned}
$$

Standard MPC

$$\boxed{\mathcal{I}_1^t + \mathcal{I}_{t+1}^{t+N_y} \succcurlyeq \kappa(t) \frac{\gamma \chi_\alpha^2(n_\theta)}{2} V_{app}''(\theta_0)}$$

Past Information matrix | Predicted Information matrix | Performance specification

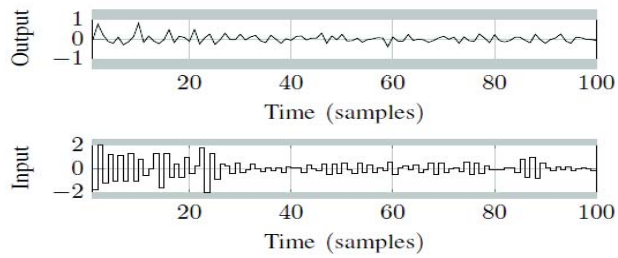
Different methods to achieve same closed loop performance

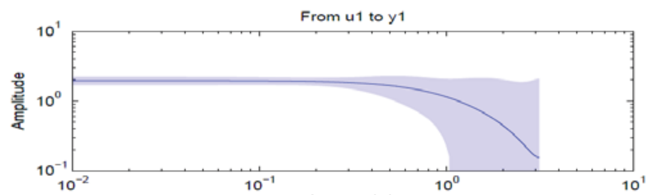
Method	Simulation time	Output variance
MPC-X	100	0.12
White ref.	100	0.20
White ref.	520	0.12

EXAMPLE – DOUBLE TANK SYSTEM

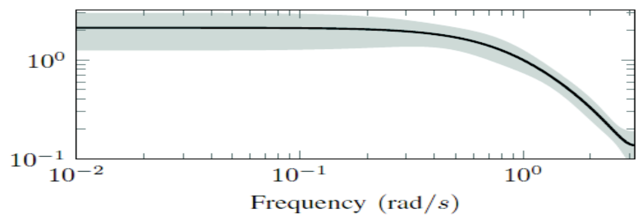
- N = 100 samples
- Umax = 2, Ymax = 1

MPC-X: Input variance 0.36 (0.28 minimum possible)





Qu=100



Qu=0.001

WORK PACKAGE PARTICIPANTS

KTH, TU Delft, ABB and TU Eindhoven

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WP 4 – PERFORMANCE MONITORING AND DIAGNOSIS

WORK PACKAGE OBJECTIVES

The objective of this workpackage is twofold and applies to MPC-controlled processes.

One objective is the development of a performance monitoring algorithm. This algorithm triggers a diagnostic tool when performance is deemed insufficient.

The diagnostic tool is the second objective, i.e., the development of a detection algorithm that is able to - using least-costly experiments on the process - detect the cause of the observed performance drop.

EXPECTED OUTCOME

- A generic performance measure which is applicable to many large-scale industrial processes.
- A diagnosis algorithm that can distinguish between two types of performance drops: changes in plant dynamics and in disturbance characteristics. We exclude base-layer problems from our diagnosis.

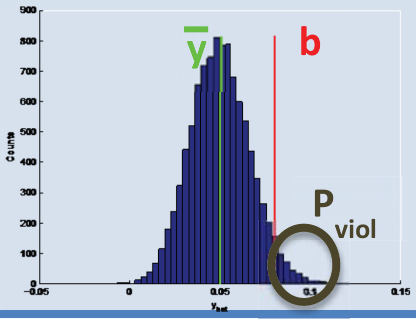
PROGRESS AND PLANS

The proposed performance measure computes the cost of the process, using data from a moving time window, and consists of two components. One part is associated with the distance between the mean of the money-making variable ($\bar{y}$) and its respective constraint (b). The second part is a cost involved due to constraint violations. The cost at time t is given by

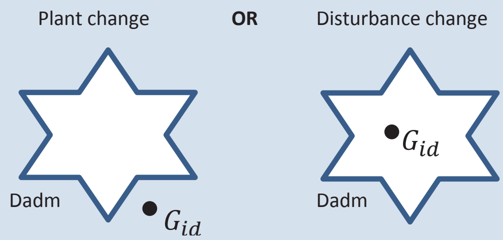
$$J(t) = c_1 P_{viol}(t) + c_2 |\bar{y} - b|$$

where c_1, c_2 are user-defined constants and $P_{viol}(t)$ is the probability of violating constraint b. A performance drop occurs when $J(t) > \beta$. This measure accommodates typical MPC behaviour in where a money-making variable is pushed towards its constraint.

The figure shows a histogram of a money-making variable (blue) at a particular point in time, from which the cost is computed.



The above mentioned types of performance drops are diagnosed by checking whether an identified model (G_{id}) of the true system lies in a set (D_{adm}) containing all models that exhibit satisfactory closed-loop performance under the original disturbances. See visualisation below.



We also consider optimal design of the diagnosis experiment, in where the excitation signal has minimal power whilst ensuring a particular accuracy on the identified model. Furthermore, a joint framework has been developed for optimal design of both the diagnosis experiment and the (eventual) re-identification experiment (WP3).
It allows us to minimize the overall excitation cost incurred for detection and re-identification through optimal design of the excitation signals.

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WP 5 – TUNING OF MODEL-BASED SYSTEMS

WORK PACKAGE OBJECTIVES

The quality of MPC, like any other model-based operation support systems (such as Real-Time Optimization), is mainly determined by the accuracy and the maintained calibration of the model. If proper supervision is not performed, the performance of MPC degrades over time due to the model-plant mismatch. Hence, the influence of the modeling uncertainty on the performance of MPC is of great importance.

The current tuning practice of these controllers is heuristic and there has been no standard way of tuning MPC that takes into account model-plant mismatch. Despite the research efforts in tuning methods for MPC in literature, MPC tuning strategies that consider robustness in process industries often lead to a conservative tuning, which might be too far from the optimal trade-off between robustness and nominal performance. With this observation in mind, work package 5 focuses on finding the optimal tuning which achieves this balance.

APPROACH

A good tuning is reflected in the low variance of key output variable(s) without any constraint violation. The relation between the variance of the key output(s) and the bandwidth of the closed-loop system is given in Figure 1. Point A of the curve reflects an overly conservative tuning, point C is an overly-high-bandwidth tuning and point B corresponds to the optimal bandwidth. To find the optimal closed-loop bandwidth, a two-layer tuning method is proposed:

- Upper layer: Solve an online-optimization problem to find the optimum (e.g. by extremum-seeking or online monitoring the output variance).
- Lower layer: Find the weighting matrices such that the bandwidth of the closed-loop system matches the bandwidth in the upper layer.

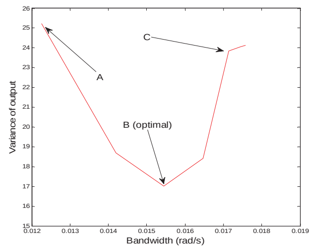

Figure 1. Relation between closed-loop bandwidth and variance of key output(s).

Methods to calculate weighting matrices

- Controller matching by inverse optimality.
- Controller matching by optimization.
- Studying the asymptotic behavior of the Toeplitz matrix, which reflects the relation between future inputs and future outputs.

EXAMPLE: BINARY DISTILLATION COLUMN

The controller matching by optimization is applied to a model of a binary distillation column. The optimal tuning is obtained by manually changing the bandwidth. The performance deteriorates due to a change in the disturbance and restored by re-tuning the MPC.

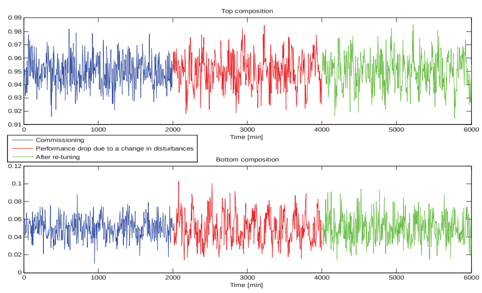

Figure 2. Top and bottom compositions of the column.

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WP 5 – Optimization-based MPC tuning

"The research leading to these results has received funding from the European Union's Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 257059, The 'Autoprofit' project (www.fp7-autoprofit.eu)"

Diego A. Muñoz and Wolfgang Marquardt

MOTIVATION

Optimization-based tuning methods are proposed to satisfy a performance specification and at the same time to guarantee state constraints in the presence of unknown disturbances represented uncertain parameters.

However, this idea results in a semi-infinite problem where an additional inner optimization problem must be solved for the closed-loop behaviour because at every sampling time, the control calculation involves the solution of an optimization problem.

APPROACH

One of the strategies to solve the optimization-based MPC design and tuning problem requires two reformulation steps. First, the bi-level optimization problem is converted to a single-level dynamic optimization problem replacing the inner optimization problem, i.e., the MPC, by its Karush-Kuhn-Tucker (KKT) conditions.

$$\min_{Q_l, R_l, \nu, \lambda, z^*, \zeta} \mathcal{P}(x^p(t_r), Q_l, R_l)$$

$$\begin{aligned}
\text{s.t.}\quad & \dot{x}^p(t) = Ax^p(t) + Bu^*(r|r) \qquad r = 0,1,2,\ldots \\
& \qquad\qquad + Wd(\alpha, t), \\
& x^p(t_0) = x_0^p, \\
& 0 \leq \hat{g} - Jx^p(t), \\
& \forall \alpha \in \mathcal{A}, \\
& u^*(r|r) = [I \quad 0 \quad \cdots \quad 0] z^*, \\
& 0 = c + Qz + E^T\zeta + H^T\lambda, \\
& 0 = e + Ez, \\
& 0 = h - Hz - \nu, \\
& 0 = \nu^T\lambda, \;\; \nu \geq 0, \;\; \lambda \geq 0.
\end{aligned}$$

The resulting single-level optimization problem constitutes a semi-infinite program (SIP) [1], for which finitely many degrees of freedom Q_l, R_l are optimized on a feasible set described by infinitely many constraints. Thus, the second reformulation reduces the infinite number of constraints to a finite number using the so-called local reduction approach.

This approach requires a local representation of the so-called lower level problems associated with the SIP for which normal vectors of critical manifolds were employed to provide such kind of representation.

The so-called normal vector approach [2] reduces the infinite number of constraints to a finite number of restrictions based on detecting and backing-off critical boundaries. These boundaries are defined by a set of points at which a property of interest changes qualitatively. In this case, the normal vector approach will be applied to guarantee that the state constraints are satisfied in the presence of unknown disturbances represented by uncertain parameters.

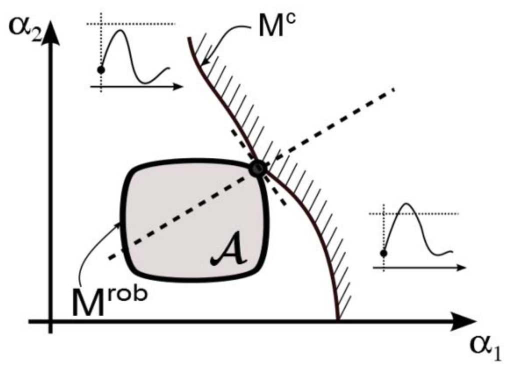

Fig. 1: Critical manifold M^c and its normal vector provides a local representation for the local reduced approach, and separates regions in the parameter space with qualitatively different system behaviour

References

[1] Stein, O.: 2012, How to solve a semi-infinite optimization problem, European Journal of Operational Research 223(2), 312 – 320.

[2] Muñoz, Gerhard & Marquardt, "A normal vector approach for integrated process and control design with uncertain model parameters and disturbances," *Computers and Chemical Engineering*, vol. 40, 2012

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WP 6 – BENCHMARKING AND INDUSTRIAL APPLICATION

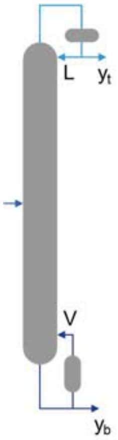
WORK PACKAGE OBJECTIVES

Autoprofit's main idea is to detect when model/plant mismatch destroys MPC performance, and then correct that by updating the model and/or tuning. Simulation models are used to evaluate the tools and functions developed in a Matlab based benchmarking environment. This is a first step of validation.

As further validation the resulting prototype tools are applied to two industrial cases. By this it is expected to learn:

- How well do they work in practice
- If they don't work, find out why
- What needs to be added to improve usability

SIMULATION MODELS



Distillation column

Control and optimization objectives

Top composition above constraint – But not too far
Bottom composition less important

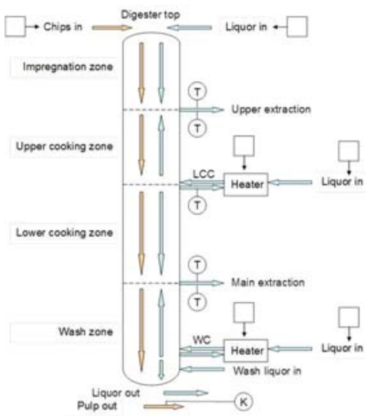
Control solution: MPC with …

Controlled variables (CV):	Top composition, yt
	Bottom composition yb
Manipulated variables (MV):	Liquid flow, L
	Vapor flow, V

Main scenarios to study

Change of plant gain directionality by use of a rotation matrix
Increased disturbance level in feed composition and flow rate

Pulp digester



Control objectives

- Kappa number (remaining lignin) at setpoint or below constraint
- Temperatures within constraints

Control solution: MPC with …

Controlled variable (CV):
- Kappa number

Manipulated variables (MV):
- 3 liquor flows,
- 2 temperature setpoints

Feedforward variable (FF):
- Chip feed rate

Process variables for state estimation (PV):
- 5 temperatures

Main scenarios to study

Hardwood or softwood pulp
Operating at different Kappa

INDUSTRIAL CASES

FT Depropanizer in synthetic fuel catalytic cracker plant

A 56 tray distillation column that separates C3 and lighter components (side draw) from C4 and heavier components (bottom)

SCC plant

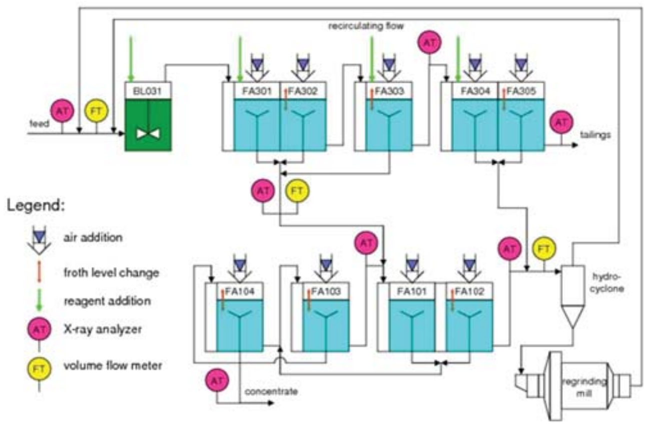
MPC with …

11 CV: C4 content in side draw; Feed drum level and rate-of-change; Column pressure; Bottom temperature; Reboil flow; 5 control valve positions
4 MV: Feed; Ratio between side draw and feed; Delta pressure; Feed to C3 header sharing the same feed drum
3 FF: Feed drum pressure and its control valve position; Another feed sharing the same feed drum

Objectives:

Maximize C3 production (side draw flow) while maintaining its C4 impurity within specification. Prevent flooding and flaring. Use buffer capacities in feed drum and bottom to reduce feed variations.

Flotation process in a zinc ore concentration plant



Flotation tanks

MPC with …

2 CV: Zn concentration in product and tailings
3 MV: Two air flows, reagent addition
1 FF: Ore feed Zn concentration (varies 3-11%)
3 PV: Two Zn concentrations, recirculating flow

Objective: Maintain the CVs at their setpoints, and adjust the setpoints for optimal operation

WORK PACKAGE PARTICIPANTS

All Autoprofit partners are taking active part in this work package

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WP 6 –APPLICATION TO AN INDUSTRIAL FT-DEPROPANISER

INTRODUCTION

The Experimental Validation Campaign at SASOL

The purpose of the industrial validation campaign was to determine whether the AUTOPROFIT work package developments may be successfully implemented on industrial scale processing units.

The SASOL FT-Depropaniser

The FT-depropanizer is a total reflux 56-tray tower with a side draw section above tray 38. The purpose of the unit is to separate C_3s and lighter from heavier components.

The variables used to control the fractionation are primarily the feed-to-side draw ratio and the column pressure differential.

Control and optimization objectives

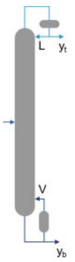
Maximize the side-draw product (C_3s) while maintaining the quality (no impurities such as C_4s)

Avoid flaring and column flooding from column pressure and delta-pressure high limits violations.

MPC-X Control Solution

Primary MVs	Primary CVs
Feed-to-Side draw ratio	Side draw composition
Delta-pressure	Column bottom's temperature

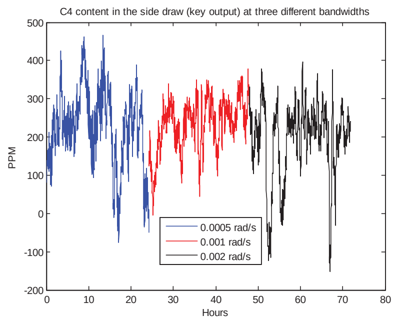
VALIDATION EXPERIMENTS

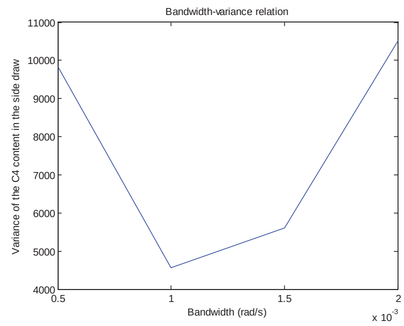


- **Establish initial conditions\benchmarks:** Open-loop binary step tests were executed and models were successfully identified. Initial tuning and performance benchmarks were established for MPC-X.
- **Manually force a plant-model mismatch:** Changes to the MPC-X model poles and gains were made.
- **Performance improvements via tuning:** After the plant-model mismatch was forced and the consequent performance drop established; MPC-X tuning changes were made.
- **Performance improvement via closed-loop step tests and re-identification:** Minimally disturbing excitation signals were executed under closed-loop conditions for model re-identification

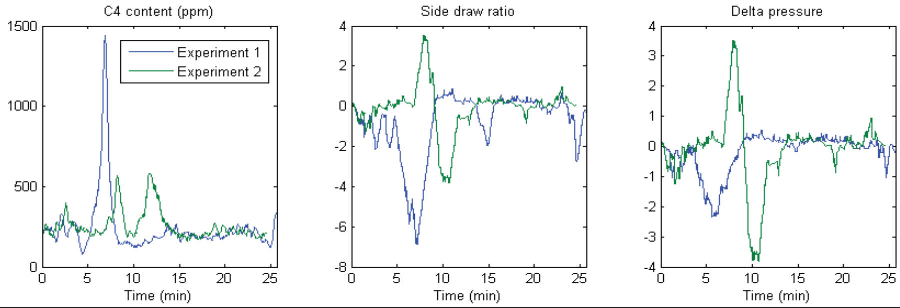
RESULTS

Tuning

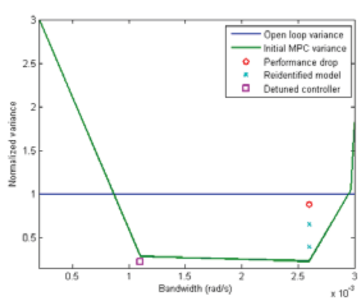


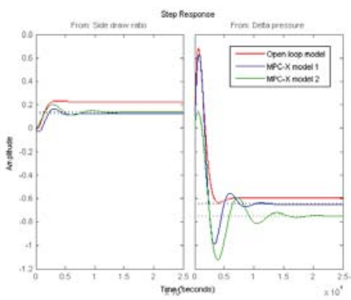


Closed loop excitation



Performance





Model Identification and Validation

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