

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.

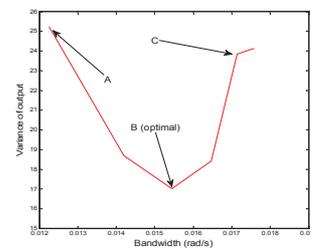


Figure 1. Relation between closed-loop bandwidth and variance of key output(s).

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.

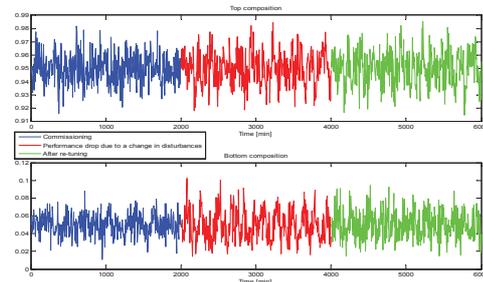


Figure 2. Top and bottom compositions of the column.

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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.

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.

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

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.

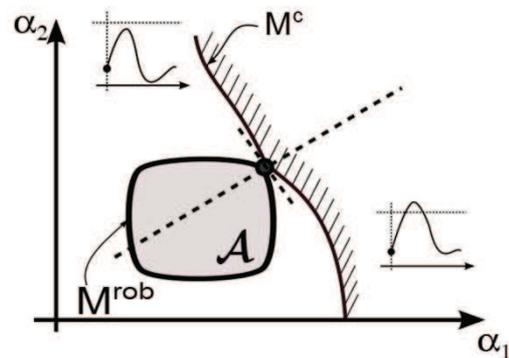


Fig. 1: Critical manifold M^c and its normal vector provides a local representation for the local reduced approach, and separates regions in the parameter space with qualitatively different system behaviour

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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