

Multiobjective Nonlinear Model Predictive Control of a Class of Chemical Reactors

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ABSTRACT: Many problems in science and engineering can be posed as multiobjective optimization problems where several objectives must be met simultaneously. Commonly such multiobjective optimization problems are reduced to a single optimization problem by merging all the involved objective functions by using rather subjective weighting functions. This solution procedure can produce suboptimal solutions, and it is not a systematic method since the choice of the weighting functions is up to the designer. Process control is one of the engineering fields where multiobjective optimization control problems frequently emerge because such problems normally involve conflicting objective functions such as economical profit and environmental concerns. Because the optimal value of the conflicting objective functions cannot be simultaneously achieved one has to compute a trade-off solution that best suits, in a given sense, all the objective functions. Moreover, additional requirements, beyond upset rejection and set-point tracking, such as the determination of optimal operating conditions should also be handled by dynamic real time optimal control approaches. In this work we propose a novel multiobjective optimization and control approach able to get target points while simultaneously computing optimal operating conditions. The proposed approach can be applied to nonlinear dynamic systems and does not require the specification of arbitrary weighting functions to handle conflicting multiobjective optimization problems. Several case studies using chemical reactors of varying nonlinear behavior are deployed to illustrate the practical application of the proposed dynamic real time optimization approach.

INTRODUCTION

Traditionally the aim of chemical process control has been the regulation of a given processing system even in presence of disturbances and set-point changes. In this context regulation means the achievement of desired operating goals. Because early industry was not faced with tight production and environmental constraints, process control problems were not so complicated to handle, and the use of proportional-integral-derivatives (PID) controllers and clever arrangements of them proved to be enough for acceptable regulation purposes. However, in the past decades the world globalization of economy and the awareness about environmental issues led to a situation where to raise process profit and to reduce environmental impacts demanded to solve harder process control problems. Moreover, there is a strong feeling that disturbance rejection and set-point tracking should not be the only two main objectives of process control.¹ In fact, the determination and attainment of optimal operating conditions should also be considered as an additional control objective. This aim has been partially achieved with the deployment of real time optimization (RTO) systems.² Here the objective consists in computing online steady-state processing conditions that are passed as set-points to a control system. Moreover, RTO systems can react to process changes and reject slow upsets. However, RTO systems neglect process dynamics, and therefore they are unable to exploit directly the process dynamic degrees of freedom through the manipulation of the input or manipulated variables and cannot reject short-term upsets. Traditionally, the optimal set-points computed by RTO layers were passed to a control system mostly composed up to the 1970s of PID controllers. In this setting, the aim of the control layer consists in rejecting short-term upsets keeping the process around steady-state

processing conditions. However, since the 1980s the PID control layer in RTO systems shifted to model predictive control (MPC) systems. MPC systems have taken over PID controllers mainly because they were well equipped to handle process interactions and to meet explicit process constraints. Initially MPC models embedded in MPC systems were mainly linear dynamic models obtained from running input/output experiments and fitting model parameters.³ Moreover, the integration of RTO and MPC systems have presented some issues. In fact, the optimal set-points computed by the RTO layer deploying steady-state models can be infeasible (i.e., nonreachable) for the MPC layer, or even worse they may feature different signs of the steady-state gains.⁴ The problem of model consistency between RTO and MPC approaches stems from the fact that both operating layers actually deploy models with different aims and level of sophistication. Hence, it is not hard to realize that better optimization and control results can be obtained by gathering both RTO and MPC approaches in a single processing approach: the so-called dynamic real time optimization (DRTO) layer.⁵ Since DRTO systems will be based upon different operating objectives (i.e., maximum profit, minimum transition times, etc.) an approach for handling several and possibly conflicting operating objectives will be needed. In this work we propose an algorithm for the efficient solution of multiobjective optimization problems embedded in DRTO systems.

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