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An MPC-based control structure selection approach for simultaneous process and control design

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ABSTRACT

An optimization framework that addresses the simultaneous process and control design of chemical systems including the selection of the control structure is presented. Different control structures composed of centralized and fully decentralized predictive controllers are considered in the analysis. The system's dynamic performance is quantified using a variability cost function that assigns a cost to the worst-case closed-loop variability, which is calculated using analytical bounds derived from tests used for robust control design. The selection of the controller structure is based on a communication cost term that penalizes pairings between the manipulated and the controlled variables based on the tuning parameters of the MPC controller and the process gains. Both NLP and MINLP formulations are proposed. The NLP formulation is shown to be faster and converges to a similar solution to that obtained with the MINLP formulation. The proposed methods were applied to a wastewater treatment industrial plant.

1. Introduction

Incorporating control decisions during the design phase of a process is recognized as an effective way to improve process profitability (Kookos & Perkins, 2001; Luyben, 2004; Mohideen, Perkins, & Pistikopoulos, 1996; Sakizlis, Perkins, & Pistikopoulos, 2004; Munoz, Gerhard & Marquardt, 2012; Ricardez Sandoval, Budman and Douglas, 2008). This integrated approach involves the minimization of plant costs related to process design, e.g., capital and operating costs, and to process control, e.g., variability costs, dynamic feasibility, and controller implementation. Control decisions related to the design of a new plant, or retrofit of an existing plant, involves different aspects such as the selection of a suitable control structure, the specification of the control algorithms to be included in that control scheme and the calculation of the controllers' tuning parameters. This paper presents an approach for the integration of design and control that combines process design-related costs with these different aspects of control decisions, and its associated costs, into a single optimization problem.

While the idea of adding control decisions at the design stage is relatively straightforward, the development of a mathematical framework that can simultaneously consider steady state and plant dynamics in a closed loop is a challenging task. Earlier approaches used for integrating design and control differed in the way that the closed loop performance was accounted for in the analysis. A first group of studies involved formulations where the capital and operating costs are minimized while considering a controllability index such as the RGA, Resiliency index (Lenhoff & Morari, 1982; Luyben & Floudas, 1994), condition number (Palazoglu & Arkun, 1986, 1987; Skogestad & Postlethwaite, 1996) and minimum square deviation (Molina, Zumoffen, & Basualdo, 2011; Zumoffen & Basualdo, 2013; Zumoffen, Molina, Nieto, & Basualdo, 2011). While the use of these indexes is computationally attractive, they may be inaccurate since they rely on steady state and/or dynamic linear process models, which may not capture the true process (nonlinear) dynamics. In a second group of approaches that consider the true process (nonlinear) dynamic model, a formal mixed-integer dynamic optimization problem (MIDO) is formulated to assess the optimal process design under uncertainty (Bahri, Bandoni, & Romagnoli, 1997; Bansal, Perkins, & Pistikopoulos, 2002; Kookos & Perkins, 2001; Mohideen et al., 1996; Sakizlis et al., 2004). In those dynamic, optimization-based methods the closed loop variability is estimated using the mechanistic process model and a user-defined, time-dependent disturbance function with uncertain (critical) model parameters, e.g., a sinusoidal function with uncertain amplitude and frequency. Therefore, the designs obtained by these dynamic approaches may not be valid when the actual disturbance affecting the process deviates significantly from the disturbance function model assumed in the analysis. Systematic approaches based on process heuristics and dynamic simulations (Gani, Hytoft, Jaksland, & Jensen, 1997) and probabilistic-based disturbances (Ricardez-Sandoval, 2012) have also been proposed in the literature. A review on

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Nomenclature

Indices

$i = 1,\ldots, n$ controlled variables
$j = 1,\ldots, m$ manipulated variables

Variables

$\boldsymbol{\alpha}$	vector of decision variables of problem (1)
$\mathbf{l}$	vector of design variables
$\bar{\mathbf{u}}$	vector of manipulated variables
$\bar{\mathbf{y}}$	vector of controlled variables
ϕ^d	closed-loop variability
cef_{ij}	distribution of the control effort among the different pairings controlled-manipulated variables
μ_{Δ_d}	structured singular value norm of disturbances
μ_{Δ_u}	structured singular value norm of manipulated variables
μ_{Δ_y}	structured singular value norm of controlled variables
Δu	manipulated control moves
y_p	prediction in the output variable y
λ_j	tuning predictive controller parameter: weights on the manipulated variables
γ_i	tuning predictive controller parameter: weights on the controlled variables
x	vector of system state
z_{ij}	vector of binary variables for control structure selection
t	time vector
c_o	oxygen concentration in the reactor (mg/l)
f_k	factor related with turbine speed in the reactor
b	biomass concentration in the reactor (mg/l)
b_{ir}	inlet biomass concentration (mg/l)
b_d	biomass concentration at the surface of the clarifiers, which goes out of the plant (mg/l)
b_b	biomass in the intermediate layer of the clarifier (mg/l)
b_r	biomass at the bottom of the clarifier (mg/l)
s_r	substrate concentration in the reactor (mg/l)
s_{rir}	substrate concentration in the reactor (mg/l)
v	volume of an aeration tank (m^3)
A	area of the clarifier (m^2)
vsd	settling rate of the activate sludge which depends on the biomass concentration at the surface of the clarifiers
vsb	settling rate of the activate sludge which depends on the biomass concentration at the intermediate layer of the clarifiers
f	inlet flow to the reactor (m^3/h)
q_2	flow of activate sludge at the output of the clarifier (m^3/h)
q_r	recycle flow in to the reactor (m^3/h)
q_p	purge flow (m^3/h)
q_1	outlet flow of the plant (m^3/h)
N_u	control horizon
N_y	prediction horizon

Parameters

l_d	height of the first layer (m)
l_b	height of the intermediate layer (m)
l_r	height of the third layer (m)
c_{ij}	cost assigned to the ij pairing
k	bound on the worst-case output variability
b_{in}	inlet biomass concentration (mg/l)
s_{rin}	inlet substrate concentration (mg/l)
q_i	inlet flow to the plant (m^3/h)
η	specific growth rate
τ	metabolized substrate fraction that is converted into biomass
ς_s	saturation constant
ς_d	biomass death rate
ς_s	specific cellular activity
$f_{\varsigma d}$	biomass fraction that is converted into substrate
c_s	oxygen specific saturation
k_{la}	oxygen transfer into the water constant
k_{01}	oxygen demand constant
ρ	upper bound
ξ	upper bound in problem
$\mathbf{M}$	interconnection matrix
$\mathbf{A}, \mathbf{B}, \mathbf{C}$	state space matrices of the system

Superscripts

d	disturbances
u	manipulated variable
y	process variable
lo	lower bound
up	upper bound
χ	input and output variables

previous integration of design and control methodologies can be found elsewhere, e.g., Ricardez-Sandoval, Budman, & Douglas (2009a), Sakizlis et al. (2004) and Seferlis and Georgiadis (2004).

A recent approach proposed by two of the authors in this work, Ricardez-Sandoval, Budman, & Douglas (2009b), Ricardez-Sandoval, Budman, & Douglas (2010), Ricardez-Sandoval, Douglas, & Budman (2011), involves a computationally efficient methodology that made use of uncertain process models, which are identified from numerical simulations of the mechanistic process model and used to compute closed-loop variability bounds that were used to assign variability costs to the system's dynamic performance. However, these latter methodologies were limited since the control structure considered in the simultaneous design and control analysis remained fixed during the calculations, i.e., only the controller tuning parameters were included as decision variables for optimization. Also, only PI feedback controllers were considered in those studies. The current study expands upon those previous studies of Ricardez-Sandoval et al. by considering, in addition to the choice of controller parameters, optimal controller structure selection and the use of a model-based controller, Model Predictive Control (MPC), which is widely used in the process industry (Morari & Lee, 1999). It is important to recognize the specific challenges arising from the consideration of controller structure selection and the use of MPC. First, the optimal selection of a control configuration has been generally tackled by the use of binary variables within a mixed integer problem (Flores-Tlacuahuac & Biegler, 2007, 2008; Mohideen, Perkins, & Pistikopoulos, 1997; Schweiger & Floudas, 1997) or by considering all possible combinations (Zumoffen & Basualdo, 2013), which adds numerical difficulty to an already computationally expensive and highly non-convex optimization problem. Likewise, the implementation of an MPC-based control strategy requires the identification of an internal process model. That internal model needs to be updated at each step in the optimization search since it depends on the optimization variables related to the plant's design such as the process units' dimensions and their corresponding operating conditions. Thus, using model-based controllers such as MPC is more challenging as compared to