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Economic plant-wide control design with backoff estimations using internal model control

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ABSTRACT

Economic optimal operation typically involves operating as close as possible to the active constraints. However, in the presence of disturbances it is necessary to back-off from the constraints in order to avoid violating them. The backoff approach aims at selecting the control structure that minimizes the economic loss associated with the required constraint backoffs. This paper revisits the backoff approach and proposes a framework for estimating the constraint backoffs based on well-known elements of internal model control (IMC) theory, such as an automatic procedure for tuning the IMC low-pass filters, a stability condition, and an uncertainty representation based on diagonal input multiplicative uncertainty. Since the constraint backoffs are estimated using a linear dynamic model, the inclusion of input multiplicative uncertainty allows introducing conservatism in the estimation of the backoffs, which is required in order to avoid constraint violations. A forced-circulation evaporator benchmark problem is used to illustrate the approach.

1. Introduction

In the process industries, an important design decision concerns the selection of an appropriate control structure (CS). Plantwide control (PWC) is a well-known research topic that addresses the decisions involved in control structure design [1–3]. Typical decisions involve the appropriate selection of the following elements: the controlled variables (CVs); the manipulated variables (MVs); the input–output pairing between these sets; and various characteristics associated with the controller itself, such as the interaction degree (diagonal, sparse, full); the control policy (decentralized or centralized); the controller technology (classical or advanced); and controller tuning. There are several approaches in the literature addressing the PWC problem in many different contexts and by using many different tools. Common procedures involve heuristic tools, model-based optimization, controllability assessments, steady-state indexes, etc. A good review of these techniques can be found in Skogestad and Postlethwaite [1] and Rangaiah and Kariwala [2].

The attempts to integrate control structure selection, process design, and optimal process operation have demonstrated the need to parameterize the controller structure in some suitable manner. Some of the approaches that have been proposed for this purpose are the following ones: decentralized proportional-integral (PI) control [4], internal model control (IMC) [5], Q-parameterization [6], and model predictive control (MPC) [7,8]. The last three strategies have strong structural resemblances between them, in particular when the unconstrained case is considered. The classical IMC theory is a useful and well-known tool for controller design. Moreover, there are several developments in this area that serve to analyze tuning, performance, stability, and robustness [9]. The IMC design procedure allows to represent single-input single-output (SISO), as well as multiple-input multiple-output (MIMO) controllers easily by mean of the respective process model selected. In the MIMO case, the controller interaction (decentralized, full or sparse) can be investigated by defining a particular structural plant-model mismatch [10]. Due to all these interesting characteristics, the IMC approach becomes an excellent option for making control structure design decisions.

Among model-based optimization approaches, the use of dynamic optimization has been proposed in order to determine the most economic design that satisfies all the operability

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constraints in the presence of bounded disturbances [11–13]. The optimum operating point is often located at the intersection of the active constraints. However, in the presence of disturbances it is necessary to include safety margins or backoffs in order to avoid constraint violations. The size of the backoffs depends on the variability of the constrained variables in the neighbourhood of the constraint boundaries for the closed-loop controlled system. The backoff approach for process control structure selection is based on the idea of selecting the control structure that minimizes the economic loss associated with the required constraint backoffs [4,14–16]. In these works, controller design is avoided by assuming perfect control. Heath et al. [4] also propose a more realistic approach wherein the constraint backoffs are estimated using decentralized PI controllers.

In this paper, we propose an alternative procedure for process control structure selection based on the backoff methodology, wherein the dynamic constraint backoffs are computed using IMC theory for parameterizing the controller. In this context, the tuning rules, the potential controller interaction, and the stability/robustness at closed-loop, can be evaluated in an unified framework. Although this article presents an analysis for decentralized and full controller interaction, the IMC structure allows to extend the methodology to sparse controllers [10]. The uncertainty representation based on diagonal input multiplicative uncertainty is proposed in order to introduce robustness in the estimation of the constraint backoffs. The overall problem can be formulated as a mixed-integer nonlinear program (MINLP). In this paper, a stochastic sequential global search approach based on genetic algorithms (GA) is proposed as solution strategy. In addition, a deterministic approach based on classical optimization tools is also tested in the Appendix. The performance of the proposed strategy is illustrated by means of a forced-circulation evaporator process.

The paper is arranged in the following order. Section 2 formulates the economic optimization problem, and introduces the different elements that are required for the approach proposed in this paper. Section 3 describes the methodology proposed in this paper, which consists in implementing the constraint backoff approach using IMC theory for parameterizing the controller. The overall control structure selection algorithm is presented. In Section 4 the evaporator process is presented and the suggested procedure is applied. Several optimization results and dynamic simulations are presented in order to illustrate the overall methodology. Finally, Section 5 concludes the paper.

2. Preliminaries

2.1. Economic optimization problem

The open-loop behavior of the plant is represented by the following system of differential-algebraic equations:

$$\mathbf{f}_D(\dot{\mathbf{x}}, \mathbf{x}, \mathbf{w}, \mathbf{u}, \mathbf{d}) = \mathbf{0}, \quad (1a)$$

$$\mathbf{f}_A(\mathbf{x}, \mathbf{w}, \mathbf{u}, \mathbf{d}) = \mathbf{0}, \quad (1b)$$

$$\mathbf{y} = \mathcal{F}(\mathbf{x}, \mathbf{w}, \mathbf{u}, \mathbf{d}), \quad (1c)$$

where $\mathbf{x} \in IR^{n_x}$ is the vector of state variables, $\mathbf{w} \in IR^{n_w}$ is the vector of algebraic variables, $\mathbf{u} \in IR^{n_u}$ is the vector of input variables, $\mathbf{d} \in IR^{n_d}$ is the vector of uncertain parameters and disturbances, and $\mathbf{y} \in IR^{n_y}$ is the vector of measured output variables.

Continuously operating plants are typically designed to operate at steady-state conditions. The optimum steady-state operating point is given by the solution of the following nonlinear program (NLP):

$$\mathbf{u}^\star(\boldsymbol{\mu}, \mathbf{d}) = \operatorname*{argmin}_{\mathbf{u}} \quad J(\mathbf{x}, \mathbf{w}, \mathbf{u}, \mathbf{d}) \quad (2a)$$

$$\text{s.t.} \quad \mathbf{f}_D(\mathbf{0}, \mathbf{x}, \mathbf{w}, \mathbf{u}, \mathbf{d}) = \mathbf{0}, \quad (2b)$$

$$\mathbf{f}_A(\mathbf{x}, \mathbf{w}, \mathbf{u}, \mathbf{d}) = \mathbf{0}, \quad (2c)$$

$$\mathbf{y}^{\mathrm{L}} + \boldsymbol{\mu}_y \le \mathbf{y} = \mathcal{F}(\mathbf{x}, \mathbf{w}, \mathbf{u}, \mathbf{d}) \le \mathbf{y}^{\mathrm{U}} - \boldsymbol{\mu}_y, \quad (2d)$$

$$\mathbf{u}^{\mathrm{L}} + \boldsymbol{\mu}_u \le \mathbf{u} \le \mathbf{u}^{\mathrm{U}} - \boldsymbol{\mu}_u, \quad (2e)$$

where J is the economic objective function (or cost) to be minimized, $\mathbf{y}^{\mathrm{L}}$ and $\mathbf{y}^{\mathrm{U}}$ are the lower and upper bounds on the output variables, and $\mathbf{u}^{\mathrm{L}}$ and $\mathbf{u}^{\mathrm{U}}$ are the lower and upper bounds on the input variables. The vectors $\boldsymbol{\mu}_y \in IR^{n_y}$ and $\boldsymbol{\mu}_u \in IR^{n_u}$, with $\boldsymbol{\mu}_y$, $\boldsymbol{\mu}_u \ge \mathbf{0}$, denote the output and input constraint backoffs, respectively. These constraint backoffs are typically included in order to avoid dynamic constraints violations due to perturbations. Alternatively, the output and input constraints (2d) and (2e) can be written collectively as the constraints

$$\mathbf{g}(\mathbf{x}, \mathbf{w}, \mathbf{u}, \mathbf{d}) + \boldsymbol{\mu} \le \mathbf{0}, \quad (3)$$

with the constraint backoffs $\boldsymbol{\mu} \ge \mathbf{0}$. Note that $\mathbf{g}$ may also include constraints for unmeasured predicted variables.

We denote by $\mathbf{u}^\star(\boldsymbol{\mu}, \mathbf{d})$ the optimal input as a function of the constraint backoffs and the disturbances. The constraint backoff vector $\boldsymbol{\mu}$ is said to be *implementable* if for that $\boldsymbol{\mu}$ there exists a feasible solution to Problem (2) for any $\mathbf{d} \in \mathcal{D}$, where the disturbance set $\mathcal{D}$ is considered to be a box set of the form $\mathcal{D} = \{\mathbf{d} \in IR^{n_d} : \mathbf{d}_{\min} \le \mathbf{d} \le \mathbf{d}_{\max}\}$.

2.2. Plantwide control problem

Let us consider a stable (or stabilized) linear process model with n_u inputs, n_y outputs, and n_d disturbance variables, represented as

$$\mathbf{y}(s) = \mathbf{G}(s)\mathbf{u}(s) + \mathbf{D}(s)\mathbf{d}(s), \quad (4)$$

where $\mathbf{y}(s)$, $\mathbf{u}(s)$, and $\mathbf{d}(s)$ are the vectors of output, input, and disturbance variables, respectively, and $\mathbf{G}(s)$ and $\mathbf{D}(s)$ are transfer functions matrices (TFM) of dimensions $(n_y \times n_u)$ and $(n_y \times n_d)$. We assume that the linear model (4) is obtained at the nominal optimum operating point $\mathbf{u}^\star(\mathbf{0}, \mathbf{d}_{\mathrm{n}})$, i.e., the solution to Problem (2) with zero offset ($\boldsymbol{\mu} = \mathbf{0}$) and nominal disturbances $\mathbf{d}_{\mathrm{n}}$. Let us consider the following partitioning of the variables

$$\mathbf{y}(s) = \begin{bmatrix} \mathbf{y}_s(s) \\ \mathbf{y}_r(s) \end{bmatrix} = \begin{bmatrix} \mathbf{G}_s(s) & \mathbf{G}_s^*(s) \\ \mathbf{G}_r(s) & \mathbf{G}_r^*(s) \end{bmatrix} \begin{bmatrix} \mathbf{u}_s(s) \\ \mathbf{u}_r(s) \end{bmatrix} + \begin{bmatrix} \mathbf{D}_s(s) \\ \mathbf{D}_r(s) \end{bmatrix} \mathbf{d}(s) \quad (5)$$

where $\mathbf{G}_s(s)$ is the square $(n_q \times n_q)$ subprocess to be controlled, $\mathbf{u}_s(s) \in IR^{n_q}$ is the selected subset of MVs used for controlling the selected CVs $\mathbf{y}_s(s) \in IR^{n_q}$, $\mathbf{u}_r(s) \in IR^{n_u - n_q}$ are the remaining input variables, which are not used for control purposes, $\mathbf{y}_r(s) \in IR^{n_y - n_q}$ are uncontrolled output variables (UVs), and $\mathbf{G}_s^*(s), \mathbf{G}_r(s), \mathbf{G}_r^*(s), \mathbf{D}_s(s)$, $\mathbf{D}_r(s)$ are transfer function matrices of appropriate dimensions.

Note that the partitioning in Eq. (5) depends on $n_q \le \min(n_u, n_y)$, which represents the number of controlled variables. Let us consider the parametrization vector $\mathcal{Z} = [\mathbf{c}_O, \mathbf{c}_I, n_q]$, where $\mathbf{c}_O = [c_1^O, \ldots, c_{n_y}^O]$ and $\mathbf{c}_I = [c_1^I, \ldots, c_{n_u}^I]$ are two vectors for which each component c_i^O (or c_j^I) is a binary decision variable, and $0 < n_q \le \min(n_y, n_u)$ represents an integer variable. The subprocess $\mathbf{G}_s(s)$ to be controlled can then be selected as

$$\mathbf{G}_s^{\mathcal{Z}}(s) = \mathbf{T}_O \mathbf{G}(s) \mathbf{T}_I \quad (6)$$

with

$$\|\mathbf{c}_O\|_1 = \|\mathbf{c}_I\|_1 = n_q, \quad \mathbf{T}_O = \mathrm{nre}[\mathrm{diag}(\mathbf{c}_O)], \quad \mathbf{T}_I = \mathrm{nce}[\mathrm{diag}(\mathbf{c}_I)]. \quad (7)$$

The first equation in (7) is the condition to guarantee a square control problem. Note that $\|\cdot\|_1$ is the 1-norm for vectors, i.e., the sum of the absolute values of the elements of the vector. The matrices $\mathbf{T}_O$ and $\mathbf{T}_I$ are selection matrices. The operator $\mathrm{diag}(\mathbf{c})$ returns