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Review

Self-optimizing control – A survey

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A B S T R A C T

Self-optimizing control is a strategy for selecting controlled variables. It is distinguished by the fact that an economic objective function is adopted as a selection criterion. The aim is to systematically select the controlled variables such that by controlling them at constant setpoints, the impact of uncertain and varying disturbances on the economic optimality is minimized. If a selection leads to an acceptable economic loss compared to perfectly optimal operation then the chosen control structure is referred to as "self-optimizing". In this comprehensive survey on methods for finding self-optimizing controlled variables we summarize the progress made during the last fifteen years. In particular, we present brute-force methods, local methods based on linearization, data and regression based methods, and methods for finding nonlinear controlled variables for polynomial systems. We also discuss important related topics such as handling changing active constraints. Finally, we point out open problems and directions for future research.

1. Introduction

1.1. What is self-optimizing control?

The purpose of a process plant is to generate profit. Beside plant design choices like size and type of equipment, plant operation has a major influence on the overall economic performance. The profitability of plant operation is strongly influenced by the design of the control structure. In the control structure design phase, engineers make fundamental decisions about which variables to manipulate, to measure and to control (Skogestad, 2004a). Especially when the operating conditions vary, a judicious selection of controlled variables (CVs) can lead to large operational savings and increased competitiveness. In the context of control structure design, Skogestad (2000) was the first to formulate the concept of a self-optimizing control structure. It is characterized by the choice of self-optimizing CVs:

> A set of controlled variables is called *self-optimizing* if, when it is kept at constant setpoints, the process is operated with an acceptable loss with respect to the chosen objective function (also when disturbances occur).

It is important to note that "self-optimizing" is not a property of the controller itself, as it is in e.g. adaptive control (Åström & Wittenmark, 2008). Rather, the term *self-optimizing control* has been used for describing a strategy for desinging the control structure, where the aim is to achieve close to optimal operation by (constant) setpoint control (Alstad, Skogestad, & Hori, 2009; Skogestad, 2000; 2004a). In this paper, we will also use the term self-optimizing control in this sense.

The successful application of self-optimizing control requires tools and methods for selecting good CVs, and this is the topic of this review paper. The main difference between self-optimizing control and other methods for designing control structures, that typically consider controllability and control performance as a selection criterion, see e.g. van de Wal and de Jager (2001), is that in self-optimizing control the selection is done to systematically minimize the loss of optimality with respect to a given economic cost function. Typically, this cost function is directly linked to the economic cost of plant operation, but also other objectives, such as energy efficiency, or also indirect control type objectives are possible (Skogestad & Postlethwaite, 2005). Thus, the selection procedure is driven by a clearly defined cost function, which is minimized during plant operation by simply controlling the self-optimizing CVs at their setpoints.

Unlike in real-time optimization approaches (Grötschel, Krumke, & Rambau, 2001; Marlin & Hrymak, 1997), where a cost function is repeatedly optimized online to update the setpoints of the CVs, in self-optimizing control a model is used

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off-line to study the structure of the optimal solution. This insight is then translated into the design of a simple control structure, that keeps the process close to the optimum despite varying disturbances. Of course, this may lead to a loss due to simplification, but in many cases the benefits of a simple scheme outweigh the increased "optimality" of complex schemes, because of the high costs of implementation and maintenance.

Self-optimizing CVs have been used in industry for a long time. Well-known examples, where self-optimizing control is inherently realized, include ratio control with a constant ratio setpoint, or controlling constrained variables at their constrained values, e.g. keeping a pressure variable at the maximal allowable value. The aim of the research field of self-optimizing control is, however, to provide a mathematical framework and systematic methods for finding CVs that give good economic performance.

1.2. The purpose of this review

After more than fifteen years of research on self-optimizing control methods, we feel that it is time to summarize the main results and give a self-contained overview of the state-of-the-art and open issues in the development of methods for finding self-optimizing CVs. In large part, this survey paper is written as a tutorial, where the basic concepts are presented with examples. We hope that both experienced researchers and newcomers to the field will find it a useful resource that stimulates further applications and research.

1.3. Defining optimal operation

The goal for designing a control structure is nicely captured in the statement by Morari, Stephanopoulos, and Arkun (1980), who mentioned that "our main objective is to translate the economic objective into process control objectives". Thus, process control is not an end in itself, but is always used in the context of achieving best performance in terms of economics for a given set of operating conditions and constraints. Mathematically, this can be stated as an optimization problem.

Most continuous processes are operated at a steady-state (or close to it) for most of the time, which means that the disturbances stay constant long enough to make the economic effect of the transients negligible.[1] Therefore, we formulate the problem of optimal operation as a steady state optimization problem:

$$\begin{aligned}&\min_{\bar{u}} \bar{J}(\bar{u}, x, d)\\&\quad \text{s.t.}\\&f(\bar{u}, x, d) = 0\\&g(\bar{u}, x, d) \leq 0. \end{aligned} \tag{1}$$

Here $x \in \mathbb{R}^{n_x}$ denotes the state variables, $d \in \mathbb{R}^{n_d}$ denotes the disturbances, and $\bar{u} \in \mathbb{R}^{n_{\bar{u}}}$ the steady state degrees of freedom[2] that affect the steady state operational cost $\bar{J}: \mathbb{R}^{n_{\bar{u}}} \times \mathbb{R}^{n_x} \times \mathbb{R}^{n_d} \mapsto \mathbb{R}$. Further, the function $f: \mathbb{R}^{n_{\bar{u}}} \times \mathbb{R}^{n_x} \times \mathbb{R}^{n_d} \mapsto \mathbb{R}^{n_f}$ denotes the model equations, and $g: \mathbb{R}^{n_{\bar{u}}} \times \mathbb{R}^{n_x} \times \mathbb{R}^{n_d} \mapsto \mathbb{R}^{n_g}$ the operational constraints. We denote the optimal objective value of Problem (1) as $\bar{J}^*(d)$. In this paper we assume that the optimization problems are sufficiently smooth, and have a unique (local) minimum. This assumption generally excludes problems with logic and integer decision variables, such as the schedule for shutting a pump on and off at given times.

[1] In the case where transient behavior significantly contributes to the operating cost, optimal operation is formulated as a dynamic optimization problem, see Section 8.

[2] For example, degrees of freedom that do not affect the steady-state are the levels in the condenser and reboiler of a distillation column.

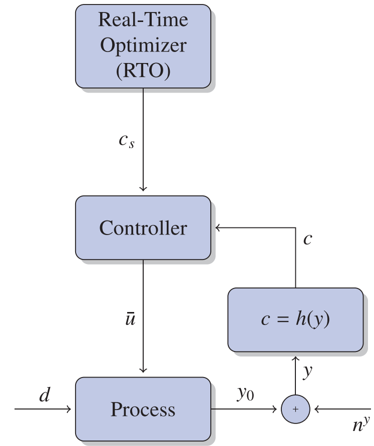

Fig. 1. Hierarchical control structure. The setpoint c_s is calculated in the RTO, and passed down to a controller. The controller adjusts the inputs $\bar{u}$ such that the CV $c = h(y)$ tracks the value of the setpoint c_s closely.

Under operation, the cost $\bar{J}(\bar{u}, x, d)$ should be minimized while satisfying the plant constraints. If all the states x, disturbances d, were perfectly known, one could attempt to solve Problem (1) and apply the optimal inputs $\bar{u}^*$ to the plant. Under ideal conditions this would result in optimal operation with the associated cost $\bar{J}^*(d)$. However, in practice such a strategy is not implementable because the plant is never truly at steady state, and because perfect knowledge of the model states and disturbances is not available. Instead, the knowledge about the plant conditions is typically available from measurements, and we assume to have a model for the plant measurements

$$y_0 = m(\bar{u}, x, d), \tag{2}$$

where the function $m: \mathbb{R}^{n_{\bar{u}}} \times \mathbb{R}^{n_x} \times \mathbb{R}^{n_d} \to \mathbb{R}^{n_y}$ describes the relationship between the variables $\bar{u}, x, d$ and the model outputs $y_0 \in \mathbb{R}^{n_y}$. However, the signals y that are measured in the real plant are corrupted by measurement noise $n^y \in \mathbb{R}^{n_y}$, such that

$$y = y_0 + n^y. \tag{3}$$

1.4. Implementation of optimal operation

Using the measurements y, the task of the control structure and the controllers is to implement the optimal solution of Problem (1) into the real plant. A good control structure will ensure that the plant runs close to the economically optimal point, also when the operating conditions and disturbances change.

The control system of a chemical plant is typically decomposed and organized in a hierarchical manner, where different control layers operate on different time-scales (Skogestad, 2000). An example for such a hierarchical control structure is given in Fig. 1. On top of the hierarchy is the real-time optimizer (RTO), which usually operates on a time scale of several hours and computes the setpoints c_s for the controller below which operates on a time scale of seconds and minutes. In many cases, the real-time "optimization" is done by plant operators, who adjust the setpoints of the controllers according to their experience and best practices. However, with availability of cheap computing power, the optimization of the setpoints is increasingly performed by a computer.

The controller then adapts the inputs dynamically to keep the CVs, which are functions of the measurements,

$$c = h(y), \tag{4}$$

at the setpoints c_s that are given by the RTO. The choice of the control structure is manifested in the choice of the variable c.