Quantifying the effects of process design on controllability and operability

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Extended Abstract

The plant design and control tasks are usually carried out sequentially. Initially the plant is designed and then the control structure is determined as a function of the design. Such a formulation neglects the coupling between design and control. This may lead to processes where a suitable control scheme cannot be synthesized for a given design. Even if a control scheme can be generated, it has been shown that it is, in general, sub-optimal [1]. This has further implications since with increasing competition and rising costs, plants are expected to operate at different operating conditions to make different grades of product. These factors motivate the study of the coupling between design and control for chemical plants.

Comprehensive studies on the coupling of design and control has been minimally addressed. Generally, some controllability measures such as the relative gain array, minimum singular value, etc. have been used to include control analysis in the design exercise [2]. Some research has focused on solving a design and control optimization problem simultaneously [3, 4, 5] but issues such as feasibility of a solution and computing burden have not been treated rigorously. Other work includes the decision-based methodology of Vasbinder et al. [6] for plantwide control synthesis, wherein a particular decomposition of the design flowsheet is done that prioritizes among the competing objectives of the controlled variables and design constraints.

In this work, a novel bi-level optimization strategy first proposed by [1] that takes into consideration the coupling between design and control is investigated. The bi-level strategy is compared with the usual sequential and sequential iterative strategy. The effect of tighter operational constraints and uncertainty on the coupling term derived by [1] is discussed.

The optimization strategy may be mathematically represented as follows [1]:

$$
\begin{aligned}
& \min_{\mathbf{d}} \ \mathbf{w}_p \, \mathbf{e}(\mathbf{d}) + \mathbf{w}_c \left(\mathbf{\Phi}(\mathbf{x}(T), T) + \int_{t_0}^{T} \mathbf{L}(\mathbf{x}(t), \mathbf{u}(t)) \, dt \right) \\
\text{subject to:} \quad & \mathbf{h}(\mathbf{d}) = 0, \quad \mathbf{g}(\mathbf{d}) \leq 0 \\
& \min_{\mathbf{u}(t), \mathbf{x}(t), t_0} \ \mathbf{\Phi}(\mathbf{x}(T), T) + \int_{t_0}^{T} \mathbf{L}(\mathbf{x}(t), \mathbf{u}(t)) \, dt \\
\text{subject to:} \quad & \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), t) \\
& \eta(\mathbf{u}(t), t), \quad \mathbf{\Psi}(\mathbf{x}(T), T) = \mathbf{0} \quad \mathbf{x}(t_0) = \mathbf{x}_0
\end{aligned}
\tag{1}
$$

Here, $\mathbf{d}$ are design variables, $\mathbf{e}(\mathbf{d})$ is the design objective function, and $\mathbf{h}(\mathbf{d})$ and $\mathbf{g}(\mathbf{d})$ represent the equality and inequality constraints for the design problem. Similarly, for the control sub-problem, $\mathbf{u}(t)$ are the manipulated variables; $\mathbf{x}(\mathbf{t})$ are state variables; and $\eta(\mathbf{u}(t), t)$ and $\mathbf{\Psi}(\mathbf{x}(T), T)$ are constraints; $\mathbf{\Phi}(\mathbf{x}(T), T)$ is the terminal cost function; $\mathbf{L}(\mathbf{x}(t), \mathbf{u}(t))$ is the running cost, $\mathbf{x}_0$ is the initial state of the process; and T represents time horizon for the process to meet the endpoint constraints. For continuous processes, T is selected to be a multiple of the largest open-loop time constant, while for batch

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processes, T is usually the final batch time [2]. The vectors, $\mathbf{w}_p$ and $\mathbf{w}_c$ represent weights selected to specify the relative importance of the process design to the controller design. For example, the case where process design is much more important than controller design corresponds to $\mathbf{w}_p/\mathbf{w}_c \rightarrow \infty$. In this case, the nested optimization becomes equivalent to the sequential optimization.

This work compares the sequential optimization and nested optimization strategies by applying these to the optimal design and control of a spray dryer to manufacture hollow micro-particles [7]. The process consists of injecting a spray of a polymeric solution (droplets) into a spray drying chamber co-currently with circulating hot air. Rapid heat and mass transfer occurs, which causes the sprayed droplets to form a skin [8] leading to the formation of hollow particles. The product requirements include the *tap density* (a packing density) and the amount of residual solvent in the final product.

The design variables are the dimensions of the spray dryer, the amount of air to be supplied and the amount of heat supplied; the objective function is the profit minus the operating costs. The Lagrangian framework used in [7] is used as the model for the design problem while the constraints are obtained from the requirements on product quality. For example, the maximum allowable residual moisture content is to be less than 10%.

In the control problem, the objective is to maintain the quality (size distribution) of the particles during operation. The control variables are the air feed rate and the inlet droplet size.

The objective function is maximized subject to the model developed in [7] and the constraints of a maximum residual moisture in the product and a desired mean particle size. To develop the optimal control strategy, the distributed model is transformed to a lumped model. Results demonstrating the optimal design and control are presented and discussed.

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