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Handling sensor malfunctions in control of particulate processes

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Abstract

This work focuses on feedback control of particulate processes in the presence of sensor data losses. Two typical particulate process examples, a continuous crystallizer and a batch protein crystallizer, modeled by population balance models (PBMs), are considered. In the case of the continuous crystallizer, a Lyapunov-based nonlinear output feedback controller is first designed on the basis of an approximate moment model and is shown to stabilize an open-loop unstable steady-state of the PBM in the presence of input constraints. Then, the problem of modeling sensor data losses is investigated and the robustness of the nonlinear controller with respect to data losses is extensively investigated through simulations. In the case of the batch crystallizer, a predictive controller is first designed to obtain a desired crystal size distribution at the end of the batch while satisfying state and input constraints. Subsequently, we point out how the constraints in the predictive controller can be modified as a means of achieving constraint satisfaction in the closed-loop system in the presence of sensor data losses.

Keywords: Population balance model; Model reduction; Lyapunov-based control; Predictive control; Input constraints; Sensor malfunctions; Crystallization processes

1. Introduction

Particulate processes play a key role in a broad range of process industries ranging from chemical, materials and minerals to agricultural, food and pharmaceutical. These areas of manufacturing have a current value exceeding, according to some estimates, two trillion dollars and a growth factor of 5 to 10 over the next decade. Examples include the crystallization of proteins for pharmaceutical applications, the emulsion polymerization for the production of latex, the fluidized bed production of solar-grade silicon particles through thermal decomposition of silane gas and the aerosol synthesis of titania powder used in the production of white pigments. Particulate processes are widely recognized as presenting a number of processing challenges which are not encountered in gas or liquid processes. One of these challenges is to operate the particulate process in a way that it consistently makes products with a desired particle size distribution (PSD). For example, in crystallization processes, the shape of the crystal size distribution is an important quality index which strongly affects crystal function and downstream processing such as filtration, centrifugation and milling (Rawlings et al., 1993).

Population balances have provided a natural framework for the mathematical modeling of PSDs (see, for example, the tutorial article (Hulburt and Katz, 1964) and the review article (Ramkrishna, 1985)), and have been successfully used to describe PSDs in many particulate processes. Population balance modeling of particulate processes typically leads to systems of nonlinear partial integro-differential equations that describe the rate of change of the PSD. The population balance models (PBMs) are also coupled with the material, momentum and energy balances that describe the rate of change of the state variables of the continuous phase, leading to complete particulate process models. In the context of PBM-based control of particulate processes, the main difficulty in synthesizing practically implementable nonlinear feedback controllers is the distributed parameter nature of the PBMs which does not allow their direct use for the synthesis of low-order (and therefore, practically implementable) nonlinear output feedback controllers. To overcome this problem, we took advantage of the property that the dominant dynamic behavior of many particulate process models

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is low-dimensional and proposed (Chiu and Christofides, 1999) a model reduction procedure, based on a combination of the method of weighted residuals and the concept of approximate inertial manifold, which leads to the construction of low-order ordinary differential equation (ODE) systems that accurately reproduce the dominant dynamics of broad classes of particulate process models. These ODE systems were subsequently used for the synthesis of nonlinear (Chiu and Christofides, 1999; Kalani and Christofides, 1999; Christofides, 2002), robust (Chiu and Christofides, 2000; El-Farra et al., 2001), and predictive (Shi et al., 2005, 2006) controllers that enforce desired stability, performance, robustness and constraint handling properties in the closed-loop system. Owing to the low-dimensional structure of the controllers, the computation of the control action involves the solution of a small set of ODEs, and thus, the developed controllers can be readily implemented in real-time with reasonable computing power. In addition to these results, an online optimal control methodology including various performance objectives was developed for a seeded batch cooling crystallizer in Xie et al. (2001) and Zhang and Rohani (2003). The reader may refer to Daoutidis and Henson (2002), Doyle et al. (2002), Braatz and Hasebe (2002) and Christofides et al. (2007) for reviews of results on simulation and control of particulate processes.

Despite this progress on the design of advanced feedback control systems for particulate processes, the problem of investigating controller stability, performance and robustness in the presence of sensor data losses has received no attention. Sensor data losses may arise due to a host of reasons including measurement sample loss, intermittent failures associated with measurement techniques, as well as those induced via data packet losses over transmission lines. Previous work on control subject to actuator/sensor faults has exclusively focused on lumped parameter systems. Specifically, in El-Farra et al. (2005), communication losses were modeled as delays in implementing the control action and in Mhaskar et al. (2006) the problem of unavailability of some of the states for measurement was considered and reconfiguration-based strategies were devised to achieve fault-tolerance subject to faults in the control actuators. Furthermore, in Mhaskar et al. (2007), a theoretical framework was developed for the modeling, analysis and reconfiguration-based fault-tolerant control of nonlinear processes subject to asynchronous sensor data losses (intermittent unavailability of measurements). Specifically, for each control configuration, the stability region (i.e., the set of initial conditions starting from where closed-loop stabilization under continuous availability of measurements is guaranteed) as well as the maximum allowable data loss rate which preserves closed-loop stability was computed and this characterization was utilized in taking preventive action, i.e., to trigger reconfiguration, as well as in making the decision as to which backup configuration should be employed in the closed-loop system to maintain stability. The method was applied to a lumped polyethylene reactor model.

This work focuses on the problem of feedback control of particulate processes in the presence of sensor data losses. Two typical particulate process examples, a continuous crystallizer and a batch protein crystallizer, are considered and are modeled by PBMs. In the case of the continuous crystallizer, a Lyapunov-based nonlinear output feedback controller is first designed on the basis of an approximate moment model and is shown to stabilize an open-loop unstable steady-state of the PBM in the presence of input constraints. Then, the robustness of the nonlinear controller with respect to data losses is extensively investigated through simulations. In the case of the batch crystallizer, a predictive controller is first designed to obtain a crystal size distribution at the end of the batch that has desired shape while satisfying state and input constraints. Subsequently, we point out how the constraints in the predictive controller can be modified as a means of achieving constraint satisfaction in the closed-loop system in the presence of sensor data losses. Extensive simulations are presented to demonstrate the effect of sensor data losses on closed-loop stability and performance in both examples.

2. Handling sensor malfunctions: continuous crystallizer

In the present section, we consider a standard model of a continuous crystallizer and address the problem of stabilization of its open-loop unstable steady-state using both state feedback and output feedback control in the presence of sensor data losses. We begin with the presentation of the crystallizer model, continue with the controller design and modeling of sensor data losses and conclude with extensive simulation results and discussion.

2.1. PBM of a continuous crystallizer

We consider a continuous crystallizer which is fed by a stream of solute at concentration c_0. Under the assumptions of isothermal operation, constant volume, mixed suspension, nucleation of crystals of infinitesimal size and mixed product removal, a dynamic model for a continuous crystallizer can be derived from a population balance for the particle phase and a mass balance for the solute concentration of the following form (Lei et al., 1971; Jerauld et al., 1983):

$$\frac{\partial n}{\partial \bar{t}} = -\frac{\partial(R(\bar{t})n)}{\partial r} - \frac{n}{\tau} + \delta(r-0)Q(\bar{t}),$$
$$\frac{\mathrm{d}c}{\mathrm{d}\bar{t}} = \frac{(c_0-\rho)}{\bar{\varepsilon}\tau} + \frac{(\rho-c)}{\tau} + \frac{(\rho-c)}{\bar{\varepsilon}}\frac{\mathrm{d}\bar{\varepsilon}}{\mathrm{d}\bar{t}}, \tag{1}$$

where $n(r,\bar{t})$ is the density of crystals of radius $r \in [0,\infty)$ at time $\bar{t}$ in the suspension, τ is the residence time, c is the solute concentration in the crystallizer, c_0 is the solute concentration in the feed and $\bar{\varepsilon}=1-\int_0^\infty n(r,\bar{t})\frac{4}{3}\pi r^3\,\mathrm{d}r$ is the volume of liquid per unit volume of suspension. $R(\bar{t})$ is the growth rate, $\delta(r-0)$ is the standard Dirac function, and $Q(\bar{t})$ is the nucleation rate. The term $\delta(r-0)Q(\bar{t})$ accounts for the production of crystals of infinitesimal (zero) size via nucleation. $R(\bar{t})$ and $Q(\bar{t})$ are assumed to follow McCabe's law and Volmer's nucleation law,