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LPV model development and control of a solution copolymerization reactor ☆

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ABSTRACT

In this paper, *linear parameter-varying* (LPV) control is considered for a solution copolymerization reactor, which takes into account the time-varying nature of the parameters of the process. The nonlinear model of the process is first converted to an exact LPV model representation in the state-space form that has a large number of scheduling variables and hence is not appropriate for control design purposes due to the complexity of the LPV control synthesis problem. To reduce such complexity, two approaches are proposed in this paper. First, an approximate LPV representation with only one scheduling variable is obtained by means of a *parameter set mapping* (PSM). The second approach is based on reformulating the nonlinear model so that it provides an LPV model with a fewer number of scheduling parameters but preserves the same input–output behavior. Moreover, in the implementation of the LPV controllers synthesized with the derived models, the unmeasurable scheduling variables are estimated by an extended Kalman filter. Simulation results using the nonlinear model of the copolymerization reactor are provided in order to illustrate the performance of the proposed controllers in reducing the convergence time and the control effort.

1. Introduction

Controlling the operation of polymer reactors is a highly important task that aims at maximizing the production rate and the product quality and also minimizing the transition losses due to the high consumer demands, as well as the tight market competition for producing different grades of polymers (Embirucu, Lima, & Pinto, 1996). However, the control design task is nontrivial due to the nonlinear behavior of polymer reactor systems which exhibit strong dependence on multiple operating regimes (Özkan, Kothare, & Georgakis, 2003; Richards & Congalidis, 2006; Soroush & Kravaris, 1993). Furthermore, polymer reactors exhibit unstable modes at some operating points (Congalidis & Richards, 1998), as well as time-varying parameters that need to be measured since a polymerization reactor switches through different operating points depending on the needed polymer grades (Richards & Congalidis, 2006). Due to the existence of unmeasured disturbances influencing these systems, the development of a robust control strategy is highly desired. Several control approaches have been investigated in the literature (Özkan et al., 2003; Richards & Congalidis, 2006). For example, a classical PID controller is developed in Congalidis, Richarards, and Ray (1989) without the need of an accurate dynamical model. However, PID controllers are not adequate to cope with such complex systems, in which strong interactions exist between the controlled variables. Hence, model predictive control (MPC) based on simple process models has been proposed in Özkan et al. (2003) and Maner and Doyle (1997), where a rapid transition between two typical operating points is ensured. A nonlinear controller has been designed and validated experimentally in Soroush and Kravaris (1993), which depends on online measurements of time-varying model parameters of a nonlinear model of the process.

Generally speaking, optimal control techniques are preferred if a good process model is available (Embirucu et al., 1996). Moreover, adaptive control strategies can be applied in order to take the

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time-varying nature of the process into account, provided that online measurements/estimations are available. In this paper, linear parameter-varying (LPV) control techniques (see Apkarian, Gahinet, & Becker, 1995) are considered to control a free radical solution copolymerization reactor described in Congalidis et al. (1989). LPV systems describe a class of nonlinear/time-varying systems that can be represented in terms of parametrized linear dynamics in which the model coefficients depend on a number of measurable variables called *scheduling variables* (Rugh & Shamma, 2000; Tóth, chap. 3). The LPV methods provide powerful tools for designing controllers for nonlinear/time-varying plants (Mohammadpour & Scherer, 2012). The LPV controller synthesis tools extend the well-known methods of controlling linear time-invariant (LTI) systems to control nonlinear systems with guaranteed stability and high performance over a wide range of operation (Abbas, Ali, Hashemi, & Werner, 2014; Bachnas, Tóth, Ludlage, & Mesbah, 2014; Tóth, Van de Wal, Heuberger, & Van den Hof, 2011).

The design of LPV controllers often involves two major problems: the presence of several scheduling variables in the LPV model, as is the case in the copolymerization reactor, and the conservatism arising from the overbounding of the range of variation of the scheduling variables (Kwiatkowski & Werner, 2005). For the standard LPV-$\mathcal{H}_\infty$ design approach with polytopic models (Apkarian et al., 1995), the number of linear matrix inequalities (LMIs) to be solved increases exponentially with the number of scheduling variables so the control synthesis problem becomes computationally intractable (Hoffmann & Werner, 2014). On the other hand, overbounding the range of the scheduling variables often renders the LPV model to include some behaviors that are not exhibited by the original plant due to the dependence of the scheduling variables on the physical variables, which results in conservatism.

In this paper, an LPV representation of the copolymerization reactor is obtained through a transformation capturing the system nonlinearities in the scheduling variables. However, due to the existence of different nonlinear terms in the copolymerization reactor model, the obtained LPV model turns out to have 15 scheduling variables. Two approaches are then introduced for coping with the high number of scheduling variables. In the first approach, the number of scheduling variables is reduced via the *parameter set mapping* (PSM) procedure based on *principal component analysis* (PCA) (Kwiatkowski & Werner, 2005). The parameter set mapping is an effective way to reduce the conservatism in LPV modeling by *resizing* the scheduling range such that the reduced model matches the original system behavior as closely as possible (Azuma, Watanabe, Uchida, & Fujita, 2000; Kwiatkowski, 2008). The second method is a specific model reduction approach aiming at reducing the complexity, as well as the number of scheduling variables of the model while the input–output behavior of the original system is preserved. This method is based on an alternative conversion of the nonlinear model to an LPV form by truncating the state variables that have no significant role in the state evolution.

Once the operating region and the resulting LPV models are determined, a control design methodology is applied on each produced model. For the LPV-PSM approach, LPV $\mathcal{H}_\infty$ control synthesis, introduced in Apkarian et al. (1995), is used to synthesize a controller for the reduced LPV model of the reactor. For the model based on the second approach, a linear fractional transformation (LFT) based LPV controller synthesis approach is used to synthesize a controller (Scherer, 2001). However, the implementation of the designed LPV controllers requires the availability of all the scheduling variables, some of which are not measurable in the copolymerization reactor model. Therefore, an extended Kalman filter (EKF) (Sorenson, 1985) is designed for the nonlinear model of the copolymerization reactor in order to estimate its state vector. The aim of this paper is to emphasize the capability of the LPV controllers, designed on the basis of a reduced model, to provide high performance control of the polymerization reactor by enhancing the settling time of the output and reducing the control effort. A comparative study on the designed LPV controllers highlights the compromise between the design complexity and performance of the LPV controller on one hand, and the stability guarantee of the closed-loop with the nonlinear process on the other hand.

The paper is organized as follows. In Section 2, the nonlinear copolymerization reactor model is introduced. Then, an LPV representation of the copolymerization reactor model is derived in Section 3. First, a parameter set mapping-based method for reducing the scheduling variables is applied. Then, an LPV representation of a specific model reduction approach for the process is developed. In Section 4, an LPV controller is synthesized for each approach produced model. Next, the estimation of state variables through the use of the extended Kalman filter is detailed. In Section 5, the performance of the synthesized EKF-based controllers is examined and discussions addressing different aspects of both approaches are presented. Finally, Section 6 concludes the paper.

Notation: The symmetric completion of a matrix is denoted by $*$, $\mathbf{ker}[\boldsymbol{X}]$ denotes the null-space of a matrix $\boldsymbol{X}$ and $\mathbf{diag}(\boldsymbol{X}, \boldsymbol{Y})$ represents a block diagonal matrix with diagonal blocks $\boldsymbol{X}$, $\boldsymbol{Y}$.

2. Copolymerization reactor model

Copolymerization is the process of uniting two or more different monomers together to produce a copolymer. In this study, two monomers are considered, monomer A is methyl methacrylate (MMA) and monomer B is vinyl acetate (VA). In addition, it is assumed that the solvent is benzene, the initiator is azobisisobutyronitrile (AIBN), the chain transfer agent is acetaldehyde and the inhibitor is *m*-dinitrobenzene (*m*-DNB). These ingredients are continuously added into a well-mixed tank (Fig. 1) where an inhibitor is considered as an impurity and a coolant flows through the reactor jacket to remove the liberated heat via polymerization. The polymer, solvent, unreacted monomers, initiator and chain transfer agent compose the outflow of the reactor.

The model of the solution copolymerization reactor is based on a free radical mechanism (Congalidis et al., 1989) described with the differential equations given as follows (Özkan et al., 2003):

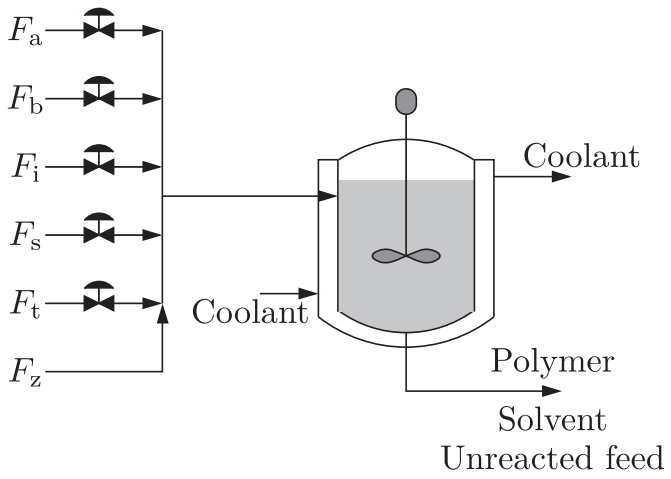

Fig. 1. Copolymerization reactor.