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Multiple model LPV approach to nonlinear process identification with EM algorithm☆

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ABSTRACT

This paper is concerned with the identification of a nonlinear process which operates over several working points with consideration of transition dynamics between the working points. Operating point changes due to economic considerations (e.g. grade change in polymer plants) or working environment changes (e.g. feed raw materials property change) are commonly experienced in process industry. These transitions among different operating conditions excite the inherent nonlinearity of the chemical process and pose significant challenges for process modeling. To circumvent the difficulties, we propose a probability-based identification method in which a linear parameter varying (LPV) model is built using process input–output data. Without knowing the local model dynamics *a priori*, only excitation signals around each operating point are required to identify linear models of the local dynamics, and then the local models are synthesized with transition data to construct a global LPV model. Simulated numerical examples as well as an experiment performed on a pilot-scale heated tank are employed to demonstrate the effectiveness of the proposed method.

1. Introduction

During the last few decades, process plants have seen an astonishing increase in their complexity which poises great challenges for process modeling and control. Although linear modeling technologies have been quite sophisticated after decades of development [10], however, due to the inborn nonlinearity of chemical production processes, the performance of single linear model-based controllers or optimizers may be compromised or even unsatisfactory. To overcome the limitations imposed by the nonlinearity of the process, researchers have developed various strategies for nonlinear process modeling. Black box modeling approaches characterized by the usage of theoretically sound nonlinear functions such as Nonlinear Autoregressive eXogenous (NARX) models [4,15], artificial neural network models [14] and block-oriented models such as Wiener or Hammerstein models [13] have been proposed. No specific process knowledge is required and the model parameters are chosen to optimize certain optimization criteria. However, since the model is developed purely based on process data, to ensure the validity of the model within a large operating range, global identification tests throughout the whole process operation region have to be conducted which, may greatly interfere the plant operation. In addition, the search of the nonlinear model structure is also of great challenge. On the other hand, fundamental modeling methods based on first principles of the process (such as heat/mass conversation law) [4] have also gained popularity in nonlinear process modeling research community. It normally provides a more meaningful model structure with less model parameters compared with the ones identified from black box methods. However, given the complexity of the industrial-scale process nowadays, it may become overly costly to build a model that meets the accuracy requirement due to the lack of the understanding of the process.

A linear parameter varying (LPV) model, as being indicated from its name, is featured by its linear model structure and varying model parameters. In the past few years, a considerable number of publications on the LPV model identification have already appeared thanks to its capability in approximating complex nonlinear systems [9,2,1,21,12]. Bamieh and Giarr [1] put forward a LPV identification method in which the input–output data and the scheduling variable(s) are assumed to be measured. The LPV model identification problem is formulated in such a way that the least squares method (off-line estimation) or recursive least squares method (on-line estimation) can be directly applied to estimate the coefficients of the polynomial dependence functions between the LPV model parameters and the scheduling variable(s) values. The method requires the input signal to be manipulated sufficiently throughout the whole operating range so that persistent excita-

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