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Mathematics and Computers in Simulation 57 (2001) 367–385

MATHEMATICS AND COMPUTERS IN SIMULATION

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Robust iterative learning control of an exothermic semi-batch chemical reactor

M. Mezghani [a,b,*], G. Roux [b], M. Cabassud [a], B. Dahhou [b], M.V. Le Lann [b], G. Casamatta [a]

[a] *Laboratoire de Génie Chimique — UMR CNRS 5503 Ecole Nationale Supérieure, d'Ingénieurs de Génie Chimique — INPT 18, Chemin de la Loge, 31078 Toulouse Cedex 4, France*

[b] *Laboratoire d'Analyse et d'Architecture des Systèmes, 7 Avenue du Colonel Roche, 31077 Toulouse Cedex 4, France*

Received 1 May 2000; accepted 27 February 2001

Abstract

This work focuses on the temperature control of a semi-batch chemical reactor used for flue chemicals production. Such reactor is equipped with a heating/cooling system composed of different thermal fluids. In order to ensure the tracking performance of the desired temperature profile, an iterative learning control (ILC) named batch model predictive control (BMPC) has been adopted. The synthesis of the considered strategy is illustrated and improvements of the algorithm scheme are proposed. Firstly, a guaranteed convergence of the algorithm is illustrated. Secondly, in presence of high frequency disturbance effects, an off-line filtering is adopted for enhancing the achieved performances. Third, a robust supervisory control procedure is employed to choose the right fluid and to reduce the superfluous fluid changeovers, mainly where fluids are of different nature. Finally, the incidence of repetitive disturbances, on line low frequency disturbances and model mismatch are investigated through simulation runs. © 2001 IMACS. Published by Elsevier Science B.V. All rights reserved.

Keywords: Model predictive control; Iterative learning control; Chemical reactor; Batch control; Simulation

1. Introduction

The competitive edge of chemical processes industry, in the actual economic climate, is to cope with the constantly increasing market conditions changes. This trend motivates the shift from continuous to batch processes which has been remarkable, particularly since the early eighties. Batch processes are considered as an important segment of the chemical processes industry and present some unique process control challenge. Monitoring batch processes involves a thermal control problem, which is essentially conditioned by the thermal heating/cooling system equipment (non-fluid or multi-fluid). Accurate output

* Corresponding author. Tel.: +33-34423-4953; fax: +33-34423-4477.
E-mail address: mezghani@hds.utc.fr (M. Mezghani).

PII: S0378-4754(01)00317-2

following by a dynamical system is a frequent problem that arises in many applications such as the unit batch chemical operations, mainly when using a linear concept design. Besides, essential features of batch processes are underlined by the absence of a steady state behaviour whilst the batch, behind the non-linear variations that can be induced.

While most of chemical batch operations are characterised by their repetitive behaviour, a related technique has been suggested to overcome the conventional design techniques limitations [1–3], in order to improve the achieved performances. Such technique developed as an alternative approach under the generic name “iterative learning contro1” (ILC), where learning can be intuitively considered as a bridge between knowledge and experience: that is to say the lack of knowledge is compensated by experience. When only partial knowledge about the plant is available, learning can then be described as a process where the desired objectives are achieved by experience. The concept of ILC was originally introduced in 1984 by Arimoto et al. [4–6], who presented an algorithm that generates the new trial control input by adding a “correction” term to the control input of the previous trial. This is the key feature that distinguishes the ILC from the conventional feedback control. The field of iterative learning control (ILC) has a relatively small, but steadily growing literature: some surveys can be found in [7–9]. In order to improve the tracking control of batch processes, namely coping with on line disturbance removal and constraints handling, an elaborated learning control algorithm was developed by Lee et al. [10,11]. Such algorithm combines the predictive control enhancements with the ILC ones under the name of batch model predictive control (BMPC).

Based on this advanced learning control technique (BMPC), an effective control synthesis for batch process industries will be investigated in our studies. The methodology is based on a set of repetitive simulation runs, the first run will be controlled by a conventional predictive feed-back controller (in our case the generalised predictive controller (GPC)). Then, the acquired input/output data, will be considered as the initial training data for the BMPC algorithm. Somewhere, between GPC and BMPC controllers, joint efforts will lead to improve unit batch operations.

This paper will be organised as follows: Section 2 provides a brief description of the semi-batch chemical reactor, its environment and the associated thermal control strategy. Based on, the derived input/output model of the temperature mixture, the model of the whole repetitive operation is presented. In the Section 3, we define the predictor which incorporates two indexes: the batch number (k) and the time evolution (t) during the batch. In Section 4, we briefly describe the objective function and the control synthesis. Then, the proposed improvements of the BMPC strategy are presented, through a reinitialisation of the output error sequence, an off-line filtering and a robust supervisory control. In Section 5, series of simulation sets are presented to show features of the BMPC algorithm face to: noise on the simulated process input/output, repetitive disturbances, on line disturbances and model mismatch. Finally, conclusions are given.

2. Scheme and modelling

2.1. Thermal control strategy

The main thermal control strategy is based on the thermal flux exchanged between the utility fluid and the mixture as the manipulated variable. The control strategy is composed of a model based on the iterative linear learning controller (BMPC) cascaded with two blocks. The first one is a supervision block enabling the choice of the adequate thermal fluid based on thermal flux limits analysis. The maximal