Journal of Process Control 34 (2015) 1–12

Contents lists available at ScienceDirect

Journal of Process Control

journal homepage: www.elsevier.com/locate/jprocont

System identification and distributed control for multi-rate sampled systems

Quan Min Shao [a,b], Ali Cinar [a,*]

[a] Department of Chemical and Biological Engineering, Illinois Institute of Technology, Chicago, IL 60616, USA
[b] Air Products and Chemicals, Allentown, PA 18195, USA

ARTICLE INFO

Article history:
Received 2 November 2014
Received in revised form 19 May 2015
Accepted 29 June 2015
Available online 31 July 2015

Keywords:
Multi-rate sampling
Subspace identification
Multi-rate distributed model predictive control
Agent-based systems
Tennessee Eastman challenge problem

ABSTRACT

System outputs with different sampling times may challenge traditional subspace identification methods to generate accurate process models and consequently provide model-based control systems that may not be very effective. The multi-rate identification problem is addressed by dividing the multi-rate sampled system into different subsystems, and a multi-rate distributed model predictive control technique is proposed to control such systems. The performance of the proposed method is evaluated and illustrated by modeling and controlling the Tennessee Eastman challenge problem.

1. Introduction

Chemical processes may have controlled variables with different sampling rates. Classical subspace identification to model a multi-rate sampled system at basic rate (the greatest common factor of different sampling rates) may yield poor prediction results for the variables with large sampling times. A better approach for identification of multi-rate systems is based on a lifted model, in which the system inputs and outputs with slower sampling rates are lifted to a basic (fastest) rate, which will generate larger dimensions of inputs and outputs for system models. There are two alternatives for using the lifted model in control system design. The lifted model can be used directly in subspace predictive control [1], or the lifted model can be converted to the basic-rate model which is then used in regular model predictive control (MPC) [2]. The limitation of the first approach is the increase in dimensionality of the model due to lifting, and the worst situation happens when some of the variables have much slower sampling rates compared to the fast rate. For the second approach, the inaccuracy of the lifted model may cause noticeable errors in the basic-rate model when extracting the basic-rate model from the lifted model.

We propose a new approach to solve the control problem of multi-rate sampled systems that utilizes the lifted model, and leverages the advantages of distributed control techniques. The key is to let the local controllers communicate with each other and generate the optimized inputs sequences, which guarantee global stability and (sub)optimality, similar to the concepts of distributed MPC (DMPC) and feasible cooperative MPC (FC-MPC) [3–6]. Extension of DMPC to nonlinear systems is also an active research area, such as an effective nonlinear DMPC based on Lyapunov-based MPC, which follows similar information exchange mechanism as FC-MPC [7]. Interest in distributed MPC has increased in recent years and various novel techniques and implementations have been reported [8–20]. In literature, centralized MPC was utilized to deal with multi-rate sampling process in [21], as well as distributed MPC in [22,23]. Compared to the distributed control in [22,23] which are based on Nash equilibrium, the proposed method in this paper focuses on global objective therefore it is approaching Pareto optimality.

In the proposed method for a multi-rate sampled systems, system outputs will be assigned to different subsystems based on their sampling times (in each subsystem, all the controlled variables have the same sampling time, but it is not necessary to have all the variables that have the same sampling time in a single subsystem). Then, only input lifting (to basic rate) is required when identifying the lifted model of one subsystem, with the outputs unchanged, which further reduces the dimensions of the subsystem

* Corresponding author. Tel.: +1 312 567 3042; fax: +1 312 567 8874.
E-mail address: cinar@iit.edu (A. Cinar).

http://dx.doi.org/10.1016/j.jprocont.2015.06.010
0959-1524/

models. For the model of a subsystem, the influences from neighbor subsystems also need to be considered in order to develop distributed control. Thus, system identification (SI) should also include the related inputs of neighbor subsystems as inputs to this subsystem. Subspace identification will be utilized to obtain the state space model for each subsystem. After the distributed models under different sampling times are available, DMPC is proposed to design the control system for the process with multi-rate sampling.

The Tennessee Eastman (TE) challenge problem is used to illustrate the proposed method [24]. In the TE process, concentration measurements are sampled every 6 or 15 min, while other measurements are sampled at higher frequency and could be assumed to be continuous variables. Several groups proposed various control methods for the TE process. Ricker and his coworkers reported control systems ranging from PI base control and decentralized control, to first-principles modeling and state estimation, optimization of operating conditions, to nonlinear model predictive control [25–28]. Srinivas and Arkun reported an identification-control scheme that achieved very good results with a DMC-based MPC technique that uses the identified linear model [29]. Most researchers focused on MPC with state space models. One drawback is the use of too many PI controllers that sometimes reduces the MPC to play a coordinator/assistant role in control. Juricek and Larimore used subspace identification based on canonical variate analysis (CVA) for SI of the TE process [30]. However, their base control for stabilizing the process is not desirable for a control problem; the E feed is used to control the reactor level and thus eliminates one important MV for regulating the product concentration. They also state that the composition measurements in the TE process were omitted to avoid a multi-rate sampling problem, which subspace methods do not readily handle. Consequently, their SI approach would not be useful for concentration control of the TE process.

Distributed control and multi-rate sampling paradigm fits well in the framework of MADCABS (Monitoring, Analysis, Diagnosis, and Control with Agent-Based Systems), a software platform developed at IIT to provide a real-time supervision and control system for distributed and networked processes [31–35]. MADCABS is a multi-agent system to implement adaptive, decentralized, hierarchical supervision of process operations (Fig. 1). The proposed DMPC and a coordinator agent [36] implemented in MADCABS enable multi-rate sampling and enhance the closed-loop control functionality of MADCABS.

The remainder of the paper is organized as follows. In Section 2, the motivation for the multi-rate system identification problem is illustrated by using the TE process. The distributed system identification method for multi-rate sampled systems is presented in Section 3, and multi-rate distributed model predictive control based on the identified model is proposed in Section 4. In Section 5, the results of multi-rate distributed control of the TE problem are given to illustrate the performance of the methods proposed. Conclusions are provided in Section 6.

2. Motivation for use of the multi-rate identification

Modeling of the TE challenge problem illustrates the limitations of using typical identification techniques for modeling multi-rate systems. When we used standard subspace identification [37,38] to obtain the system model for MPC control of the TE challenge problem, the identified model yielded poor predictions for the controlled variables with larger sampling times and caused poor control. The main objective in the TE challenge problem is to maintain the product flowrate and composition at desired levels [24]. The process contains three main operation units: a reactor, a separator, and a stripper. It has total 41 measured variables and 12 manipulated variables (MV), four reactants labeled as A, C, D, and E,

Table 1
Notations of CVs for TE process.

Notation	CV
y_1	Product flowrate
y_2	Product G concentration
y_3	Reactor pressure

Table 2
Notations of MVs for TE process, and the amplitudes of PRTS and step changes for system identification and validation respectively.

Notation	MV	δu(SI)	δu(Val)
u_1	D feed	200 kg/s	80 kg/h
u_2	E feed	200 kg/h	120 kg/h
u_3	Reactor temp.	0.5 °C	2 °C
u_4	Purge flowrate	0.05 kscmh	0.1 kscmh

two products labeled as G and H. Because of the process is unstable, base control consisting of several PI controllers is applied similar to [27]. First, the controlled variables (CV) and MVs are analyzed for defining the control problem. The MVs and CVs are the inputs and outputs for system identification, respectively. Since product concentration is directly related to the control objective, G concentration in product and the product flowrate are chosen as the CV. Also, the reactor pressure is very sensitive to changes in process operations, and it may cause safety issues. Hence, it is selected as another CV. Several factors that affect the concentration of G in the product are considered as MVs. The feed D forms product G, and E forms product H and thus will also influence the ratio of G. Therefore, D and E feed are chosen as two MVs. Moreover, reactor pressure control is challenging because it is too sensitive to several variables, including D feed and E feed. When concentration control is sought, and D and E feeds change, the reactor pressure will be affected significantly. Initially, purge flowrate was picked as MV for the reactor pressure. This caused two problems and limited the ability to regulate reactor pressure. One problem is the dynamics between purge flowrate and reactor pressure that is not fast enough to cover dramatic changes in reactor pressure. The second problem is caused by the maximum purge flowrate which cannot compensate very large changes in reactor pressure. Thus, another MV (reactor temperature) is added to help reactor pressure control. The response of reactor pressure to changes in reactor temperature is fast, but large temperature changes could cause instability and this drawback must be dealt with carefully during control. The selected CVs and MVs are listed in Tables 1 and 2.

Pseudo random ternary sequence (PRTS) signals are sent to MVs to stimulate the system to generate data rich in dynamic variations for open-loop system identification. The amplitudes of the PRTS are listed in Table 2. The sampling time for TE process is 1 min (for variables with sampling time longer than 1 min, the zero-order hold (ZOH) is used, which means the measurement value is unchanged until the next update), and the switch time of PRTS is set to be 30 min. In addition to the pure PRTS, some small white noise is also added to the PRTS to reduce the singularity of the intermediate matrices when performing system identification. The amplitude of white noise is set to be 10% of the amplitude of PRTS. The total sampling period is 96 h [30].

For validation, the responses of CVs to step changes in each MV are considered, and the amplitudes of the MVs are shown in the last column of Table 2. Three prediction horizons are considered and compared to assess the accuracy of the identified model in high, intermediate, and low frequencies in order to evaluate model performances for each data set:

- 1-Step ahead prediction. The states are estimated by Kalman filter.