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MIMO model of an interacting series process for Robust MPC via System Identification

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ABSTRACT

This paper discusses the empirical modeling using system identification technique with a focus on an interacting series process. The study is carried out experimentally using a gaseous pilot plant as the process, in which the dynamic of such a plant exhibits the typical dynamic of an interacting series process. Three practical approaches are investigated and their performances are evaluated. The models developed are also examined in real-time implementation of a linear model predictive control. The selected model is able to reproduce the main dynamic characteristics of the plant in open-loop and produces zero steady-state errors in closed-loop control system. Several issues concerning the identification process and the construction of a MIMO state space model for a series interacting process are deliberated.

1. Introduction

Model predictive control (MPC) strategy offers an effective way to tackle the problems in multivariable control system by including the process model in the computation of control actions. Without any doubt, MPC has attracted notable attention in process industries and has been the most popular advanced process control (APC) strategy over the past few years [1–3]. From the control engineering viewpoint, MPC promises a great benefit to maintain the optimal economic operation of the plant and preserves the lifetime of the equipment. One of the main drawbacks of MPC is the difficulty to incorporate model uncertainties of plant explicitly, and for this reason, increasing attention has been placed on robust MPC problems [3,4].

In practice, the implementation procedure of MPC can be divided into two stages. The first is on developing the plant model, and the second is on developing the controller. In general, the system identification technique is preferred to perform the plant modeling. Moreover, for a plant which consisting of interconnected structures the problem of developing the plant model based only on the physical laws for control purposes using the system identification techniques have rarely been attempted in practice. In particular, a number of issues arise such as the type of model structure that should be considered, [5–7]. In some cases, multiple-input single-output (MISO) structure is used, in which a separately parameterized model is fitted for each output. According to Jørgensen and Lee [5], this practice is inefficient compared to the use of multiple-input multiple-output (MIMO) structure, in view of the fact that most industrial process outputs exhibit significant levels of cross-correlation. However, several researches [7,8] highlighted that, for certain cases, MISO identification remains relevant.

One type of interconnection that commonly found in a process plant is the series process. In a noninteracting series system, the states in one process unit influence the states in the downstream unit, but not the other way round. One example of such a system is pH neutralization performed in several tanks in series [9]. Morud and Skogestad [10] pointed out that the poles and zeros of the transfer function of a noninteracting series process are the poles and zeros of the transfer functions of the individual units. Thus, the overall responses may be predicted directly from the individual units. This also implies that if each system is stable, the series system is stable. In contrast with the noninteracting system, the downstream properties in an interacting series system influence its upstream properties. Interestingly, the poles of the interacting system are different from the poles of the individual systems. Hence, the dynamic behavior of the interacting process has to be determined from the analysis of the overall transfer function, not the individual unit.

The use of system identification to develop the empirical linear model of a process with series structure have been reported by several researches. In their paper, Gatzke et al. [11] performed the

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parametric identification process of a quadruple tank that has series structure with recycles using subspace system identification method and used the pseudo-random binary sequence (PRBS) as the input signals. The identification process is carried out to determine the number of the states used in the resulting process model without taking into account the prior knowledge of the process, and no assumption is made about the state relationships and the number of the process states. Weyer [12] presented the empirical modeling of water level in an irrigation channel using system identification technique taking into account the prior physical information of the system, employing nonlinear equations. The identified process is a kind of interacting series process with MISO structure. Sotomayor et al. [13] presented the multivariable identification of an activated sludge process benchmark, which can be categorized as a system that has series structure with recycles, using subspace-based algorithms. A discrete-time identification approach based on subspace methods is applied to estimate a nominal MIMO state-space model, and interestingly, the selected state-space model is a very low-order which can well describe the complex dynamics of the process.

This paper's contributions are as follows: an investigation of identifying a linear time-invariant (LTI) with lumped parameters state-space model of a pilot plant which has a typical structure of an interacting series process, with some nonlinearities. The limited available measurements presents another challenge, since some internal states are unmeasured. The parameters estimations were carried out using numerical algorithm for subspace state-space system identification (N4SID) algorithm [14], which have been commended by many researches as an excellent technique to perform a multivariable identification, see [8,14–16]. The focus is to address the problem of developing a proper procedure for constructing an empirical model of an interacting series process from input–output data using system identification technique, and to further validated it in a real-time implementation of a linear MPC on controlling a nonlinear process plant.

2. Methodology

The flow chart representation of the methodology used in the model development that has been evolved during this investigation is given in Fig. 1. For the purpose of the study, a lab scaled gaseous pilot plant that has the typical characteristics of an interacting series process is used.

The investigation is begun with an examination of the plant behaviors and the analysis of the plant dynamics. This includes the study of the plant responses from the external available inputs. From the analysis of the plant dynamics, two kinds of model structure is proposed. The first model structure is treated with two different kinds of input signals, while another model structure is perturbed with one kind of input, i.e., step signal, resulted in three different state space models. The open-loop validations is then performed using a fresh data set which has not been used in the identification procedures. The model which gives the best performance in an open-loop validation is expected to be robust against the plant nonlinearities when it goes to the real-time implementation of model predictive control.

The next step is to perform the closed-loop validation of the developed models by using them as the internal model of the real-time model predictive controller for a given operating condition. The necessary condition is that the selected model has to be able to produce zero steady-state error, which implies that such a model is robust against the plant nonlinearities in a closed-loop control system. When the proper model is obtained, the work is continued to 'tune' the controller, so that the plant responses can be shaped to what is desired. The performance of three developed models in open-loop and closed-loop conditions is analyzed and it is intended that the finding will provide an insight for further investigation in the empirical modeling of the interacting series processes using system identification technique.

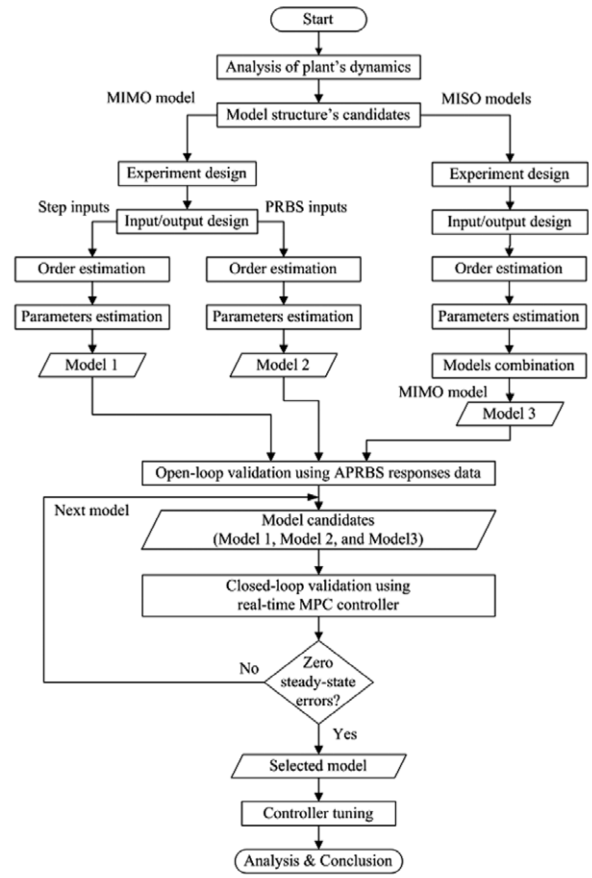

Fig. 1. The flow chart representation of the modeling and validation steps.

3. Subspace method of system identification

As the main tool to estimate models parameters, subspace system identification using N4SID algorithm is used. A brief introduction regarding such an algorithm is presented in this section. The main notation to be used is as shown in Table 1. Additional notation will be introduced as the need arises.

In discrete-time domain, a linear time-invariant system can be formed as

$$\begin{aligned}\mathbf{x}(k+1) &= \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \boldsymbol{\Lambda}\mathbf{w}(k)\\ \mathbf{y}(k) &= \mathbf{C}\mathbf{x}(k) + \mathbf{D}\mathbf{u}(k) + \mathbf{v}(k);\end{aligned} \tag{1}$$

where $\mathbf{y}$ is the output vector, $\mathbf{u}$ the input vector, $\mathbf{x}$ the state vector, $\mathbf{w}$ and $\mathbf{v}$ are the innovation vectors, commonly refer to the plant noise and the measurement noise respectively, with zero mean and covariance matrix $\mathbf{R} > 0$, and $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, $\mathbf{D}$, and $\boldsymbol{\Lambda}$ are the coefficient matrices of appropriate dimensions. The unknown parameters in the state-space model are contained in these system matrices and covariance matrix $\mathbf{R}$.

Suppose that estimates of a sequence of state vectors of the state-space model of (1) are somehow constructed from the input–output data. Then for the prediction error $\boldsymbol{\varepsilon}(k)$, $k = 0, 1, \ldots, N-1$, with N is the number of data, its relation can be written as

$$\begin{bmatrix}\hat{\mathbf{x}}(k+1)\\ \mathbf{y}(k)\end{bmatrix} = \begin{bmatrix}\mathbf{A} & \mathbf{B}\\ \mathbf{C} & \mathbf{D}\end{bmatrix}\begin{bmatrix}\hat{\mathbf{x}}(k)\\ \mathbf{u}(k)\end{bmatrix} + \begin{bmatrix}\boldsymbol{\eta}(k)\\ \boldsymbol{\upsilon}(k)\end{bmatrix} \tag{2}$$

where $\hat{\mathbf{x}} \in \Re^{n_x}$ is the estimate of state vector, $\mathbf{u} \in \Re^{n_u}$ the input vector, $\mathbf{y} \in \Re^{n_y}$ the output vector, while $\boldsymbol{\eta}$ and $\boldsymbol{\upsilon}$ are residuals. Since all the variables are given, (2) is a regression model for system