2009 American Control Conference
Hyatt Regency Riverfront, St. Louis, MO, USA
June 10-12, 2009

System Identification of an Interacting Series Process for Real-Time Model Predictive Control

Tri Chandra S.Wibowo, Nordin Saad, and Mohd Noh Karsiti
Department of Electrical and Electronics Engineering, Universiti Teknologi PETRONAS,
Bandar Seri Iskandar, Tronoh, 31750 Perak, Malaysia
Email: tri_chandra@yahoo.com, nordiss@petronas.com.my, nohka@petronas.com.my

Abstract—**This paper presents the empirical modeling of the gaseous pilot plant which is a kind of interacting series process with presence of nonlinearities. In this study, the discrete-time identification approach based on subspace method with N4SID algorithm is applied to construct the state space model around a given operating point, by probing the system in open-loop with variation of input signals. Three practical approaches are used and their performances are compared to obtain the most suitable approach for modeling of such a system. The models are also tested in the real-time implementation of a linear model predictive control. The selected model is able to well reproduce the main dynamic characteristics of gaseous pilot 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 MIMO state space model are discussed.**

Index Terms—**Gaseous pilot plant, Serial interacting process, Empirical modeling, Model predictive control (MPC)**

I. Introduction

A structure involving a series of systems occurs often in process plants. This structure commonly occurs in processing sequences such as feed heat exchanger, chemical reactor, product cooling, and product separation. For optimal operation of such a plant, a model that can be used to describe the overall behavior, upstream as well as downstream variables, can be very useful for advanced control design.

A discussion on the open loop response of the systems with series structures is given by Marlin [1] which divides them into two categories: noninteracting and interacting series. The main difference between these categories is about how the downstream properties influence the upstream properties. For noninteracting series systems the states in one process unit influence the states in the downstream unit, but not the other way round. In contrast with the noninteracting systems, the downstream properties in the interacting series processes influence the upstream properties. As Marlin points out, the procedure for deriving overall transfer function of an interacting series system is somewhat more complex than for a noninteracting system.

The use of system identification to develop the empirical linear model of processes with series structures has attracted considerable attention in the control research community. Gatzke *et al.* [2] perform the parametric identification process of a quadruple tank using subspace system identification method. Such a system has series structure with recycles. As the input signals, the pseudo-random binary sequence (PRBS) is used. The identification process is carried out without taking into account the prior knowledge of process, and no assumption are made about the state relationships or number of process states. Weyer [3] presents the empirical modeling of water level in an irrigation channel using system identification technique with taking into account the prior physical information of the system. The identified process is a kind of interacting series process, however, the model only has a single output variable. Sotomayor *et al.* [4] present the multivariable identification of an activated sludge process benchmark, which can be categorized as a system that has series structure with recycle. The system is probed in open-loop with multi-level random signals as the inputs. One of the major challenges is to select either the input or output variables of the process. To improve the model accuracy, the properties of several internal states are involved in the identification process and assumed as measurable disturbances.

This paper aims at identifying a linear time-invariant (LTI) with lumped parameters state space model of the gaseous pilot plant which has a typical structure of interacting series process where the strong influences between upstream and downstream variables occur in both ways. The process is also showing some nonlinearities either in the overall response, such as the shiftiness of output variables, or in the response of individual units from the respective inputs. The limited available measurements presence another challenge since the internal states of the system such as inlet, outlet, and internal flowrates are unmeasured. In a previous paper [5] the authors pointed out that the subspace identification method using Numerical algorithm for Subspace State Space System IDentification (N4SID) algorithm was a more suitable method for constructing a state space model of an interacting series process rather than prediction error method (PEM), indicated by smaller identification and validation errors. In this work, as an extension of the previous work [5], the focus has been on the practical approaches for constructing a multiple-input multiple-output (MIMO) state space model from input-output data using a linear system identification technique that is robust against the nonlinearities in such a plant, which would then be used in the real-time model-based control implementations. Detail evaluation of three approaches to construct a linear MIMO state space model of such a system is presented. It is shown in this paper that the selected approach can deal with such difficulties in the modeling of an interacting series process, in this case the gaseous pilot plant, from input-output data using a linear system identification technique, and produces zero steady-state errors during the real-time implementation of a linear model predictive control (MPC).

II. Subspace Method of System Identification

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

$$x(k+1) = Ax(k) + Bu(k) + Ke(k)$$
$$y(k) = Cx(k) + Du(k) + e(k) \quad (1)$$

where $y \in \Re^p$ is the output vector, $u \in \Re^m$ the input vector, $x \in \Re^n$ the state vector, $e \in \Re^p$ the innovation vector with zero mean and covariance matrix $R > 0$, and A, B, C, D, and K are the coefficient matrices of appropriate dimensions. The unknown parameters in the state space model are contained in these system matrices and covariance matrix R of the innovation process.

The subspace identification methods are based on the following idea. Suppose that an estimate of a sequence of state vectors of the state space model of (1) are somehow constructed from the input-output data. Then for $\varepsilon(k),\ k = 0,1,\cdots,N-1$, its relation can written as

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

where $\bar{x} \in \Re^n$ is the estimate of state vector, $u \in \Re^m$ the input vector, $y \in \Re^p$ the output vector, while η and υ are residuals. Since all the variables are given, (2) is a regression model for system parameters $\Theta = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \in \Re^{(n+p)\times(n+m)}$.

Thus the least-squares estimate of Θ is given by

$$\Theta = \left(\sum_{k=0}^{N-1} \begin{bmatrix} \bar{x}(k+1) \\ y(k) \end{bmatrix} \begin{bmatrix} \bar{x}^T(k) \\ u^T(k) \end{bmatrix}^T \right) \left(\sum_{k=0}^{N-1} \begin{bmatrix} \bar{x}(k) \\ u(k) \end{bmatrix} \begin{bmatrix} \bar{x}^T(k) \\ u^T(k) \end{bmatrix}^T \right)^{-1} . \quad (3)$$

This class of approaches are called the direct N4SID methods. This estimate uniquely exist if the rank condition

$$\text{rank} \begin{bmatrix} \bar{x}(0) & \bar{x}(1) & \cdots & \bar{x}(N-1) \\ u(0) & u(1) & \cdots & u(N-1) \end{bmatrix} = n + m \quad (4)$$

is satisfied. The covariance matrices of residuals are given by

$$\begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} = \frac{1}{N} \sum_{k=0}^{N-1} \begin{bmatrix} \eta(k) \\ \upsilon(k) \end{bmatrix} \begin{bmatrix} \eta^T(k) & \upsilon^T(k) \end{bmatrix} . \quad (5)$$

Related to (1), it is assumed that the system is asymptotically stable, the pair (A,C) is observable and the pair of (A,B) is controllable [4, 6, 7].

As De Moor pointed out, the general algorithm of the subspace methods involves three major steps [8, 9]:

1. The N4SID technique relies on subspace fitting strategies for the approximation of the extended observability matrix, Γ_i, and/or the state sequence, X_i, which are defined by

$$\Gamma_i = \begin{pmatrix} C & CA & CA^2 & \cdots & CA^{i-1} \end{pmatrix}^T , \quad (6)$$

$$X_i = \begin{pmatrix} x_i & x_{i+1} & x_{i+2} & \cdots & x_{i+j-1} \end{pmatrix} . \quad (7)$$

2. Secondly, a singular value decomposition of the previously estimated matrix is computed to estimate the order n of the state space model.
3. The final step is computing the matrices $\hat{A}$, $\hat{B}$, $\hat{C}$, and $\hat{D}$ by solving over-determined sets of linear equations owing to least-squares or total least-squares computation techniques.

III. Gaseous Pilot Plant

To investigate the empirical modeling of an interacting series process, a lab-scale pilot plant that able to demonstrate the dynamics of gas inside the vessel and pipeline is used. This plant has a continuous air as feed, which is generated from a centralized compressor, and the pressure is maintained at 7 barg. There will be some pressure drop when the gas passes the inlet control valve (PCV202) and when enters the buffer tank (VL-202). The pressure will drop slightly further when the gas passes through the middle control valve (FCV211) and when it enters the primary tank (VL-212). These pressure balances are also affected by the opening of outlet control valve (PCV212). The pressure inside the buffer tank, which is also called the upstream pressure, is indicated by pressure transmitter PT202, while the pressure inside the primary tank, which is also called the downstream pressure, is indicated by pressure transmitter PT212. The schematic diagram of the gaseous pilot plant is shown in Fig. 1.

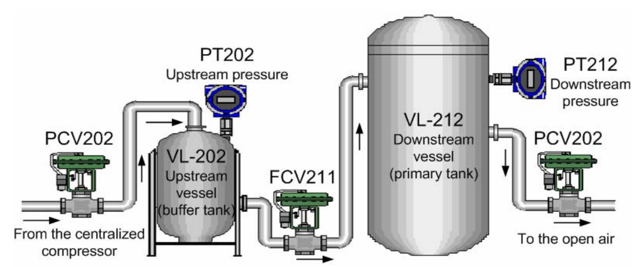

Fig. 1. The gaseous pilot plant.

The control objective is to maintain pressure balance inside the primary tank as well as the buffer tank by manipulating the control valves. This requires the construction of a suitable mathematical model that able to describe its dynamics. The state space model is chosen, since the control system that will be used is a class of model-based control that much involves the state space system and matrices manipulations.

During normal operating conditions, the operating range of pressure inside the buffer tank is from 4 to 6.5 barg while the pressure inside the primary tank will varies from 3.5 to 6 barg.

From the analyses of plant dynamics, the responses of the changes on each control valve, and considering the interaction from one to another output variable, the dynamics of gaseous pilot plant is then considered as in Fig. 2, with G_{ij} represents the transfer function of i^{th}-input to j^{th}-

output while $G_{y\text{-}ij}$ represents the transfer function of i^{th}-output to j^{th}-output.

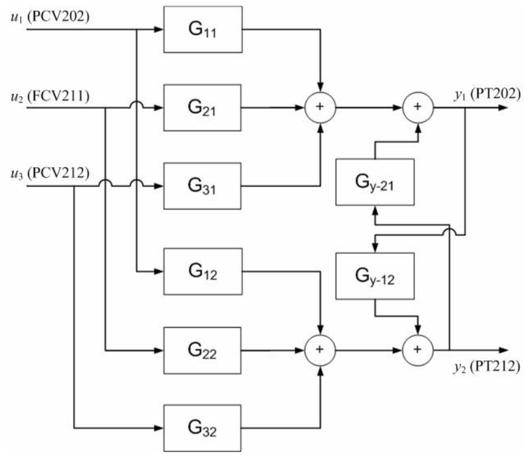

Fig. 2. The dynamics of gaseous pilot plant.

There are two ways to develop the model from input-output data which have the relation as given above. The first is by using the MIMO model structure which three inputs and two outputs as shown below:

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} (1-G_{y-12}G_{y-21})^{-1}\left(\begin{bmatrix} G_{11} \\ G_{21} \\ G_{31} \end{bmatrix}^T + G_{y-12}\begin{bmatrix} G_{12} \\ G_{22} \\ G_{32} \end{bmatrix}^T\right) \\ (1-G_{y-12}G_{y-21})^{-1}\left(\begin{bmatrix} G_{12} \\ G_{22} \\ G_{32} \end{bmatrix}^T + G_{y-21}\begin{bmatrix} G_{11} \\ G_{21} \\ G_{31} \end{bmatrix}^T\right) \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}. \quad (8)$$

Suppose the responses from the control valves are not linear, or the operating ranges are somehow exceeding the plant linearities, the model structure in (8) may not able to capture this phenomenon since the estimated plant outputs are only obtained from the linear combination of the opening of control valves. Another way is by taking into account of the measurement of another plant output as the true input. Here, the relation of y_1 in Fig. 2 can also be written as

$$y_1 = \begin{bmatrix} G_{11} & G_{21} & G_{31} & G_{y-12} \end{bmatrix}\begin{bmatrix} u_1 & u_2 & u_3 & y_2 \end{bmatrix}^T, \quad (9)$$

and for y_2 as

$$y_2 = \begin{bmatrix} G_{12} & G_{22} & G_{32} & G_{y-21} \end{bmatrix}\begin{bmatrix} u_1 & u_2 & u_3 & y_1 \end{bmatrix}^T. \quad (10)$$

Unlike (8), the two model structures in (9) and (10) can not be simply put in a single matrix notation. Since having a variable as the input and at the same time as the output is not allowed in system identification procedures, then the model parameters in (9) and (10) have to be estimated separately.

IV. System Identification Processes

In this section, three different approaches are used to perform the linear state space system identification for the gaseous pilot plant using subspace method which can be briefly described as follows:

1. The first approach is using (8) as the model structure. The input signals are step signals, which will be applied to the three control valves sequentially. The resulted model is called model 1.
2. The second approach also using (8) as the model structure, with PRBS signals as the input signals. The design of three PRBS signals is carried out independently and will be applied to the three control valves simultaneously. This model is called model 2.
3. The third approach is using (9) and (10) as the models structure. The step signals are chosen as the input signals, and the identification processes are performed as two separate MISO identifications. The MISO models are combined to a single MIMO state space model. The model is called model 3.

A. Model 1

Plant testing

Considering the operating conditions of the plant, the step input signal is designed to have the amplitude range for 30% until 70% of valve opening. The sampling time used in the experiment is one second, and the total of recorded data is 4500. The identification process was carried out off-line in batch form by using the first half of the data set (2250), whereas the remaining data were applied for model validation. The open loop identification procedure is used and the purely deterministic case is considered.

Order estimation

There is an extensive literature for order estimation algorithms for linear, dynamical, state space systems [10-12]. Nevertheless, there exist only few references dealing with the estimation of the order in the context of subspace identification methods [4]. In this experiment, two approaches are used for estimating the order of state space model.

The first approach is by examining the singular values plot given by N4SID algorithm. From the singular value decomposition, the suggested order is $n = 4$.

The second approach is by choosing the order n that minimize the simulation errors. According to Bastogne *et al.* [8] and Sotomayor *et al.* [4], this approach is referred as the more practical procedure to determine the system order using system identification techniques. Among the 20 variations of the model order, it is found that the 4^{th}-order system gives the minimum of simulation errors.

Considering the singular values inspections and the relative estimation errors indexes, the state space model of gaseous pilot plant for model 1 is chosen to be of 4^{th}-order.

B. Model 2

Brosilow and Joseph [13] point out the key parameters that are needed to design a PRBS signal. This design employs the prior knowledge of process behavior in form of first-order plus delay-time (FOPDT) transfer function. These design parameters are: the frequency range of PRBS signal, $\omega_{\min}$ and $\omega_{\max}$, the clock tick time, T_c, the number of shift registers used to generate the PRBS signal, n_r, the number of clock ticks in every period, T, the sampling time, T_s, and the amplitude of PRBS signal, a.

Since there are nonlinearities in the plant responses, it is not plausible to obtain the true FOPDT transfer functions of the plant. In this work, the prior information of plant are chosen as the FOPDT transfer functions that best fit to the step responses data used in the development of model 1. Considering that there are two outputs with different plant dynamics for the respective input, then the transfer function that has the longest time constant will be selected for designing the PRBS input signal. In the preliminary test, the 20 % of input signal amplitude produce a very big signal to noise ratio. Examining the gain of plant and noise statistics, then 10 % of input signal amplitude is still considered to produce adequate signal to noise ratio. Since the lowest clock tick time is 86 second, then the recommended time sampling is 8.6 second or less. In this research, the sampling time is chosen as one second. Table I shows the parameters used in the design of PBRS input signals.

During the experimental tests, the three different PRBS signals are transmitted to the respective control valve simultaneously, and the pressure changes in upstream and downstream are recorded as plant outputs.

The model order is also determined by considering the singular values inspections and the relative estimation errors indexes, which suggest that the most suitable state space model is of the 4th-order.

TABLE I
PARAMETERS DESIGN FOR PRBS INPUT SIGNALS

PRBS parameters	Input 1 (PCV202)	Input 2 (FCV211)	Input 3 (PCV212)
$\omega_{\min}$ (rad/sec)	0.0065	0.0024	0.0033
$\omega_{\max}$ (rad/sec)	0.0328	0.0143	0.0196
T_c (sec)	86	196	143
n_r	4	4	4
T	15	15	15
T_s (sec)	1	1	1
a (% of opening)	10	10	10

C. Model 3

As (9) and (10) are used as the model structures, the empirical modeling is then first to construct two MISO models, which each of them has four inputs. These models are then combined into a single MIMO model, which would later be used in the real-time implementation of multivariable model-based control.

The input signals are step signals, which have 30% until 70% of amplitude. These signals are applied to the three control valves sequentially.

MISO identification process

The total recorded data is then divided into two: the first half is used for identification purpose, and the rest is used for model validation.

The singular values inspections and the relative estimation errors indexes are also used to estimate the system order. From these analyses, both of MISO models are selected to be of a 2nd-order system.

Combination of MISO models

Let the two MISO models be named model 3a, which is used to estimate the upstream pressure, and model 3b, which is used to estimate the downstream pressure, respectively. The method to combine model 3a and model 3b into a single MIMO model can be explained in these three following steps:

1. The new input, state, and output vectors.

In the matrix notation, the common inputs used by model 3a and model 3b can be written as

$$u_c = \left[\text{PCV202} \quad \text{FCV211} \quad \text{PCV212}\right]^T . \tag{11}$$

The input which is used only by one model is called the individual input. The individual input for model 3a, u_{ind-1}, and the individual input for model 3b, u_{ind-2}, are

$$u_{ind-1} = [\text{PT212}]\,;\; u_{ind-2} = [\text{PT202}] . \tag{12}$$

The new input vector is then defined as

$$u = \left[u_c^T \quad u_{ind-1} \quad u_{ind-2}\right]^T . \tag{13}$$

The new state vector is obtained by combining the state vector of model 3a, x_1, and the state vector of model 3b, x_2, as follow:

$$x = \left[x_1^{\,T} \quad x_2^{\,T}\right]^T . \tag{14}$$

And the new output vector consist of the output of both models, which are arranged in the matrix notation as

$$y = \left[y_1 \quad y_2\right]^T . \tag{15}$$

2. Splitting the input and feedthrough coefficients matrices.

Each of the input and feedthrough coefficient matrices of model 3a and model 3b is necessary to be divided into two new matrices. The first new matrix contains the elements which are coupled with the common inputs, and the second contains the elements which are coupled with the individual input.

Let B_1 and D_1 be the input and feedthrough coefficient matrix of model 3a, and B_2 and D_2 be the input and feedthrough coefficient matrix of model 3b respectively, then these matrices can be reformulate as:

$$B_1 = \left[B_{11} \quad B_{12}\right];\; D_1 = \left[D_{11} \quad D_{12}\right];$$
$$B_2 = \left[B_{21} \quad B_{22}\right];\; D_2 = \left[D_{21} \quad D_{22}\right], \tag{16}$$

where B_{11}, D_{11}, B_{21}, and D_{21} contain the elements which are coupled with the common inputs, and B_{12}, D_{12}, B_{22}, and D_{22} contain the elements which are coupled with the individual inputs.

3. The new coefficient matrices.

The new state coefficient matrix, A, is obtained by locating the state coefficient matrices of model 3a, A_1, and model 3b, A_2, in the pseudo-diagonal formation as

$$A = \begin{bmatrix} A_1 & 0 \\ 0 & A_2 \end{bmatrix}. \tag{17}$$

In the same way, the new output coefficient matrix, C, is obtained:

$$C = \begin{bmatrix} C_1 & 0 \\ 0 & C_2 \end{bmatrix}, \tag{18}$$

with C_1 and C_2 be the output coefficient matrix for model 3a and model 3b respectively.

The new input and feedthrough coefficient matrices, B and D, are obtained by locating the matrices in (16) into these following formations:

$$B = \begin{bmatrix} B_{11} & B_{12} & 0 \\ B_{21} & 0 & B_{22} \end{bmatrix};\ D = \begin{bmatrix} D_{11} & D_{12} & 0 \\ D_{21} & 0 & D_{22} \end{bmatrix}. \quad (19)$$

The new MIMO state space model obtained returns exactly the same equations with model 3a and model 3b that resulted from subspace system identification. Hence, although each MISO models, model 3a and model 3b, may be estimated in the different state bases, this technique remains relevant.

D. Models validation

To examine the goodness of fit of the model, the percentage of the output that the model reproduces, called as the best fit criterion, is used. The best fit of the model is calculated as [14]

$$\text{Best Fit} = \left(1 - \frac{\sum_{i=1}^{n} | y_i - \hat{y}_i |}{\sum_{i=1}^{n} | y_i - \bar{y} |} \right) \times 100\% , \quad (20)$$

with $\bar{y}$ is the mean of measured output.

To make a fair comparison of how good the models can reproduce the system behaviors and to examine the robustness against the nonlinearities, another kind of input signal which is not used earlier in the models development should be considered. In this work, the authors prefer to use APRBS (Amplitude modulation Pseudo Random Binary Sequence) signals as the plant inputs, where three different APRBS signals are transmitted to the three control valve simultaneously. The upstream and downstream pressure is then recorded with one second sampling time with total recorded data of 1200.

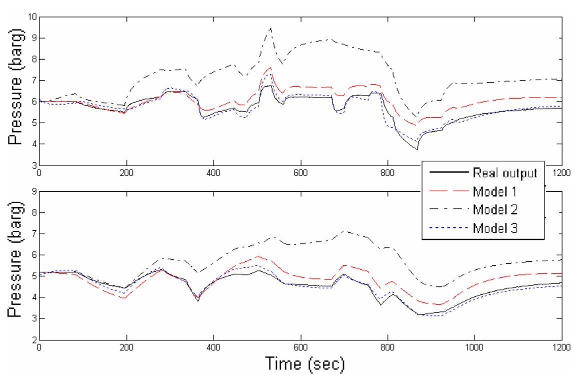

Fig. 3. The comparison of real measured and simulated outputs generated by model 1, model 2, and model 3 using APRBS inputs for upstream (top) and downstream (bottom) pressures.

The comparison of simulated outputs generated by the three models versus real measured outputs of APRBS response data are shown in Fig. 3. An estimated initial state of the respective model is assigned at the beginning of the simulation.

Table II shows the best fit criterions of model 1, model 2, and model 3 for APRBS response data. The definition of the best fit criterion in (20) allows this value to be negative. One of the reasons is that the validation data set was not preprocessed in the same way as the estimation data set [14], which in this case the input signals of the identification data are different from the input signals of validation data.

As it can be seen in Fig. 3 and Table II, the best simulation data is given by model 3. This model is able to correctly reproduce the main dynamic characteristics of the plant for a given operating points and time horizons. By taking into account another measurement of plant output, model 3 shows the robustness against the nonlinearities in the plant.

TABLE II
PERFORMANCE COMPARISON OF MODEL 1, MODEL 2, AND MODEL 3

Simulated Output	Best Fit Criterion (%)		
	Model 1	Model 2	Model 3
PT202 (upstream pressure)	9.15	-241.38	68.48
PT212 (downstream pressure)	8.30	-171.47	75.07

Model 2 give the worse result compares to model 1. The bigger prediction errors are produced. Inappropriately, the shiftiness of simulated outputs generated by model 2 goes to the opposite directions with real measured output. Comparing the performance of model 1 and model 2, the open loop identification using PRBS input signal with simultaneous excitation for MIMO system is not a guaranteed to obtain the better model. The rapid frequency may deteriorate some significant information of the plant dynamics.

V. REAL-TIME LINEAR MODEL PREDICTIVE CONTROL

All the three models are then implemented as the internal model of a real-time linear model predictive control, with the same setting of controller parameters. Fig. 4 shows the closed-loop responses of upstream pressure (PT202) and downstream pressure (PT212) controlled by MPC. In the upstream control system, it seems that the MPC controller using model 1 and model 2 give better results in the transient conditions. However, in the steady-state conditions, the plant responses controlled by MPC using model 1 and model 2 tend to have large steady-state errors (offsets). The steady-state errors occur either in the initial condition or in the final steady-state condition. In the downstream control system, the offsets also persist in both conditions, initial and final steady-state condition, when model 1 and model 2 are used as the internal model of the MPC controllers.

For MPC controller using model 3 as the internal model, the transient response of controller are showing some overshoots. However, the steady-state errors either in upstream or downstream responses are no more appearing.

In the practical process control, zero steady-state error commonly is one of the necessary conditions for control system design. In the real-time implementation of a linear model predictive control, the steady-state errors indicate the presence of nonlinearities or disturbances which are not a kind of white noise signals. Since the 'true' measurement of plant outputs are taken to estimate the plant states, and the control actions are based on the predicted outputs, then the 'wrong' prediction of plant outputs can produce the steady-state errors.

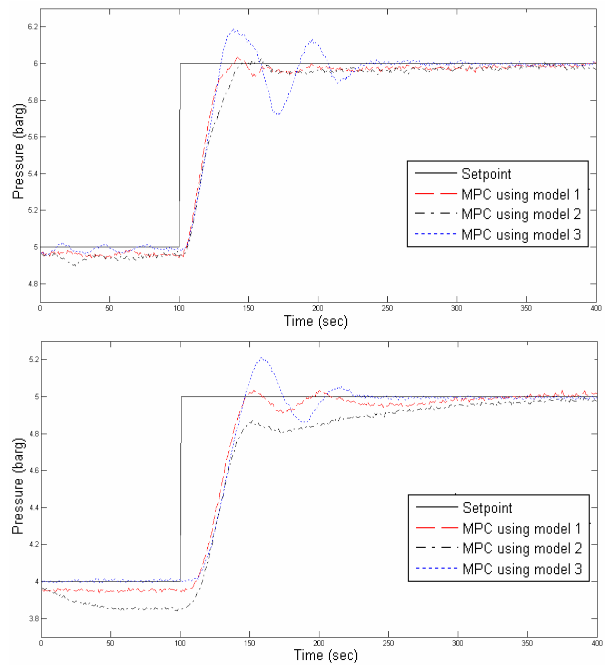

Fig. 4. Closed-loop responses of upstream (top) and downstream (bottom) control system using MPC controller with model 1, model 2, and model 3 as the internal model.

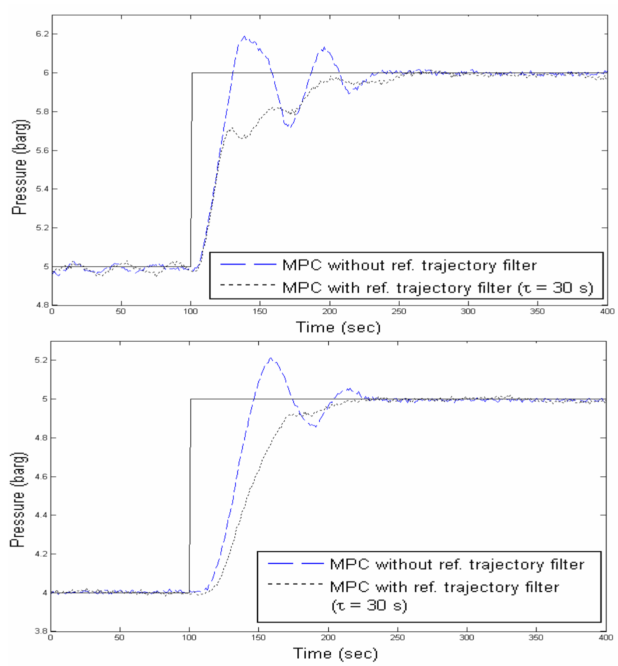

Fig. 5. The closed-loop responses of upstream (top) and downstream (bottom) control system before and after tuning the controller.

The transient behaviors of closed-loop control system are commonly affected by tuning of the controller. To avoid overshoots, the reference trajectory formulation can be used [15]. Wojsznis *et al.* [16] point out that modifying reference trajectory is the primary and intuitive method of on-line MPC tuning. Fig. 5 shows the plant responses of MPC controller using model 3 with the reference trajectories filter in the controller, for time constants equal to 30 seconds.

VI. Conclusion

An investigation into the development of the practical approaches to construct a linear MIMO state space model of an interacting series process using system identification technique was presented. The APRBS response data were used to perform the open-loop comparison among the models, where the model constructed from two MISO models shown to give the best performance. Following the development and validation of the models, a linear MPC was implemented using the developed state space models to examine their performances in a real-time closed-loop control system. Taking into account of the measurement of the upstream output as one of the inputs to predict the downstream output, and vice versa, proven to give the effective prediction and control over an interacting series process. It may be worthwhile if the approach described here can be further examined and experimentally tested on the larger systems.

References

[1] T. E. Marlin, "Process control: Designing processes and control systems for dynamic performance," Singapore: McGraw-Hill Companies Inc., 2000, pp. 143-166, 239-350, 583-757.

[2] E. P. Gatzke, E. S. Meadows, C. Wang, and F. J. Doyle, "Model based control of a four-tank system," *Computer and Chemical Engineering,* vol. 24, pp. 1503-1509, 2000.

[3] E. Weyer, "System identification of an open water channel," *Control Engineering Practice,* vol. 9, pp. 1289-1299, 2001.

[4] O. A. Z. Sotomayor, S. W. Parka, and C. Garcia, "Multivariable identification of an activated sludge process with subspace-based algorithms," *Control Engineering Practice,* vol. 11, pp. 961-969, 2003.

[5] T. C. S. Wibowo, N. Saad, and M. N. Karsiti, "Multivariable system identification of gaseous pilot plant," in *National Postgraduate Conference on Engineering, Science, and Technology*, Tronoh, Perak, Malaysia, 2008.

[6] P. V. Overschee and B. D. Moor, "Subspace identification for linear systems," London: Kluwer Academic Publishers, 1996, pp. 1-12.

[7] T. Katayama, "Subspace methods for system identification," London: Springer, 2005, pp. 1-13.

[8] T. Bastogne, H. Noura, P. Sibille, and A. Richard, "Multivariable identification of a winding process by subspace methods for tension control," *Control Engineering Practice,* vol. 6, pp. 1077-1088, 1998.

[9] W. Favoreel, B. D. Moor, and P. V. Overschee, "Subspace state space system identification for industrial processes," *Journal of Process Control,* vol. 10, pp. 149-155, 2000.

[10] D. Bauer, "Order estimation for subspace methods," *Automatica,* vol. 37, pp. 1561-1573, 2001.

[11] Y. Zhang, Z. Zhang, X. Xu, and H. Hua, "Modal parameter identification using response data only," *Journal of Sound and Vibration,* vol. 282, pp. 367-380, 2005.

[12] L. Mevel, A. Benveniste, M. Basseville, and M. Goursat, "Blind subspace-based eigenstructure identification under nonstationary excitation using moving sensors," *IEEE Transactions on Signal Precoessing,* vol. 50, January 2002.

[13] C. Brosilow and B. Joseph, "Techniques of model-based control," Upper Saddle River, New Jersey: Prentice Hall PTR, 2002, pp. 387-393.

[14] L. Ljung, "System Identification Toolbox™ 7 user's guide," The MathWorks, Inc., 2008.

[15] S. J. Qin and T. A. Badgwell, "An overview of industrial model predictive control technology," in *Fifth International Conference on Chemical Process Control*, 1997, pp. 232-256.

[16] W. Wojsznis, J. Gudaz, T. Blevins, and A. Mehta, "Practical approach to tuning MPC," *ISA Transactions,* vol. 42, pp. 149-162, 2003.