Decentralized Closed-loop Identification and Controller Design for a Kind of Cascade Systems[1)]

CHEN Qing LI Shao-Yuan XI Yu-Geng

(*Institute of Automation, Shanghai Jiaotong University, Shanghai* 200030)

(E-mail: syli@sjtu.edu.cn)

Abstract Decentralized closed-loop identification and controller design for a kind of cascade processes composed of several sub-processes are studied. There are only input couplings between adjacent sub-processes. First, the cascade process is divided into several two-input two-output systems and coupling models of adjacent sub-processes are obtained via decentralized identification. TITO system is decoupled equivalently into four independent single open-loop processes with the same input signal. Then, a distributed model predictive control algorithm is proposed based on the coupling models of adjacent sub-processes.

Key words Plant-wide control, model identification, cascade system, predictive control

1 Introduction

In some industrial processes, the final product quality is influenced by the overall process, which is made up of several sub-processes. Many researchers are interested in plant-wide control for large-scale processes[1]. Decentralized structure is often used in plant-wide control. There are input couplings between each sub-process. It is necessary to obtain the coupling models in order to design the decentralized controller.

In this paper, decentralized identification and distributed predictive control method for a kind of cascade process is studied. Sub-processes of this kind of cascade processes are interconnected serially, and there are only input couplings in adjacent sub-processes. There are a lot of such systems in chemical industry engineering. A considerable number of identification methods and their application have been reported[2]. The identification method is based on step test, which has the advantage of simple and easy operation and is dominant in process control applications[3∼4]. Many researchers have done work on predictive control and distributed predictive control in recent years[5∼7].

In this paper paper the cascade system is divided into several two-input two-output (TITO) sub-processes. Decentralized close-loop identification method based on step test is proposed. Through sequential step change of set points of each sub-process, the error signals are obtained and the overall process is decoupled equivalently into several individual single open-loop processes and the parameters of transfer function can be obtained. Then, distributed predictive controller is designed for each sub-process considering the coupling models. Simulation study is given for a cascade system composed of four sub-processes.

2 Description and structure analysis of the kind of cascade processes

The process under study is composed of several sub-processes which are serially interconnected. Only the input couplings between adjacent sub-processes are considered and other couplings are weak which are not considered. This kind of cascade system is shown in Fig. 1.

The output of sub-process i is:

$$y_{ii}(s) = G_{i,i-1}(s)u_{i-1}(s) + G_{ii}(s)u_i(s) + G_{i,i+1}(s)u_{i+1}(s), \quad i = 1, \cdots, n \tag{1}$$

It is influenced by the input of the two adjacent sub-processes except for the input of sub-process i. While designing distributed controller for each sub-process, the coupling between sub-processes should be considered. So we need to obtain the coupling models between sub-processes. Because there are only input couplings between adjacent sub-processes, the cascade system can be divided into several TITO

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systems for identification. The cascade process is divided into $n-1$ two-input two-output (TITO) sub-systems as shown in Fig. 1. The i-th TITO sub-system is made up of sub-process i and sub-process $i+1$, which can be shown as:

$$\text{TITO process } i: \ \{subprocess\ i,\ subprocess\ i+1\},\ i=1,\cdots n-1 \tag{2}$$

We can identify the transfer function parameters for each TITO local system sequentially. In detail, the coupling model between sub-process 1 and sub-process 2 will be obtained when the TITO process 1 is identified, and the coupling model between sub-process 2 and sub-process 3 will be obtained by identifying the TITO process 2. Thus, all the coupling models will sequentially be obtained.

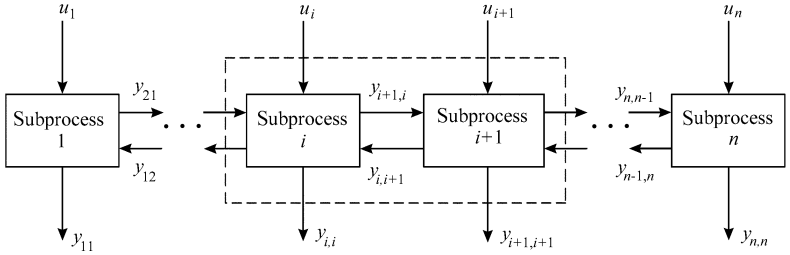

Fig. 1 Structure of cascade process

3 Identification of cascade processes

For each TITO local system of the cascade process, a novel decentralized close-loop identification method based on step test is adopted. The coupled close-loop TITO system is decoupled equivalently into four individual single open-loop processes with the same input signal acting on the four transfer functions through sequential step change of set points. The transfer function of first-order or second-order plus dead time is used to describe the model of each single open-loop system and the parameters can be identified using existing identification methods such as least squares method.

3.1 Signal testing procedure

Consider the piece-TITO sub-system under decentralized control, which is made up of sub-process i and sub-process $i+1$ as shown in Fig. 2, where r_i, e_i, y_i, K_i, and G_{ij} are set points, errors, process outputs, controllers, and process transfer functions, respectively. Without loss of generality, it is further assumed that the controller K_i is proportional type and the stability of the whole system should be guaranteed. To simplify our derivation, the notations r_i, e_i, y_i are used in both s and t domain. The fundamental relationship between error signals and transfer function outputs for the sub-process are described by

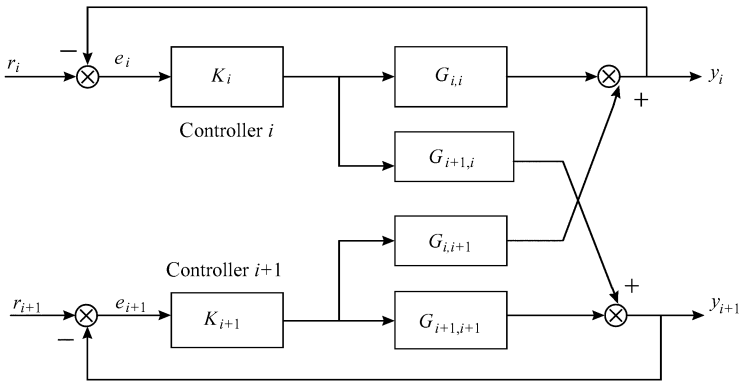

Fig. 2 Closed-loop TITO control system

$$\begin{cases} y_i = G_{ii}K_ie_i + G_{i,i+1}K_{i+1}e_{i+1} \\ y_{i+1} = G_{i+1,i}K_ie_i + G_{i+1,i+1}K_{i+1}e_{i+1} \\ e_i = r_i - y_i \\ e_{i+1} = r_{i+1} - y_{i+1} \end{cases} \tag{3}$$

Assume that the process initially rests at a steady state with initial set point, error and output variables as $r_i^0, r_{i+1}^0, y_i^0, y_{i+1}^0, e_i^0$ and e_{i+1}^0, respectively, with

$$e_i^0 = r_i^0 - y_i^0, \quad e_{i+1}^0 = r_{i+1}^0 - y_{i+1}^0 \tag{4}$$

To identify the process parameters, the test involves the following steps:

1) Make a step change to r_i, from r_i^0 to r_i^1, with r_{i+1} being kept unchanged, and record the error signals e_i^1, e_{i+1}^1 for the two loops until the new steady state is reached at $t \triangleq t_1 = T$. The incremental equation from state (4) to the new state becomes

$$\triangle y_i^1 = G_{i,i}K_ie_i^1 + G_{i,i+1}K_{i+1}e_{i+1}^1 \tag{5}$$

$$\triangle y_{i+1}^1 = G_{i+1,i}K_ie_{i+1}^1 + G_{i+1,i+1}K_{i+1}e_{i+1}^1 \tag{6}$$

where

$$e_i^1 = (r_i^1 - r_i^0) - (y_i^1 - y_i^0) \triangleq \triangle r_i - \triangle y_i^1 \tag{7}$$

$$e_{i+1}^1 = -(y_{i+1}^1 - y_{i+1}^0) \triangleq -\triangle y_{i+1}^1 \tag{8}$$

2) Make a step change to r_{i+1}^0, from r_{i+1} to r_{i+1}^1, while keeping $r_i = r_i^1$, and record the error signals until the new state is reached. Again, the incremental equation from state (5)∼(8) to the new state can be written as

$$\triangle y_i^2 = G_{i,i}K_ie_i^2 + G_{i,i+1}K_{i+1}e_{i+1}^2 \tag{9}$$

$$\triangle y_{i+1}^2 = G_{i+1,i}K_ie_i^2 + G_{i+1,i+1}K_{i+1}e_{i+1}^2 \tag{10}$$

where

$$e_i^2 = -(y_i^2 - y_i^1) \triangleq -\triangle y_i^2 \tag{11}$$

$$e_{i+1}^2 = (r_{i+1}^2 - r_{i+1}^0) - (y_{i+1}^2 - y_{i+1}^0) \triangleq \triangle r_{i+1} - \triangle y_{i+1}^2 \tag{12}$$

From (5) and (12), we obtain

$$G_{i,i}(s) = \frac{\mathcal{L}[K_{i+1}\triangle r_i \odot e_{i+1}^2 - K_{i+1}(e_i^1 \odot e_{i+1}^2 - e_i^2 \odot e_{i+1}^1)]}{\mathcal{L}[K_iK_{i+1}(e_i^1 \odot e_{i+1}^2 - e_i^2 \odot e_{i+1}^1)]} \triangleq \frac{\mathcal{L}[y_{i,i}]}{\mathcal{L}[u]} \tag{13}$$

$$G_{i,i+1}(s) = \frac{\mathcal{L}[-K_i\triangle r_i \odot e_i^2]}{\mathcal{L}[K_iK_{i+1}(e_i^1 \odot e_{i+1}^2 - e_i^2 \odot e_{i+1}^1)]} \triangleq \frac{\mathcal{L}[y_{i,i+1}]}{\mathcal{L}[u]} \tag{14}$$

$$G_{i+1,i}(s) = \frac{\mathcal{L}[-K_{i+1}\triangle r_{i+1} \odot e_{i+1}^1]}{\mathcal{L}[K_iK_{i+1}(e_i^1 \odot e_{i+1}^2 - e_i^2 \odot e_{i+1}^1)]} \triangleq \frac{\mathcal{L}[y_{i+1,i}]}{\mathcal{L}[u]} \tag{15}$$

$$G_{i+1,i+1}(s) = \frac{\mathcal{L}[K_i\triangle r_{i+1} \odot e_i^1 - K_i(e_i^1 \odot e_{i+1}^2 - e_i^2 \odot e_{i+1}^1)]}{\mathcal{L}[K_iK_{i+1}(e_i^1 \odot e_{i+1}^2 - e_i^2 \odot e_{i+1}^1)]} \triangleq \frac{\mathcal{L}[y_{i+1,i+1}]}{\mathcal{L}[u]} \tag{16}$$

where $\mathcal{L}[\cdot]$ is Laplace transform and $\odot$ is dot product of vectors. In terms of parameter identification, the coupled closed-loop TITO system has been decoupled into four individual single open-loop systems with the same input signal acting on the four transfer functions. The relation between the original system input/output and the decentralized identification system are given as below. The system input for all of the four loops is

$$u = K_iK_{i+1}(e_i^1 \odot e_{i+1}^2 - e_i^2 \odot e_{i+1}^1) \tag{17}$$

For the transfer function input given in (17), the output signals for the equivalent identification systems are

$$y_{i,i} = K_{i+1}\triangle r \odot e_{i+1}^2 - K_{i+1}(e_i^1 \odot e_{i+1}^2 - e_i^2 \odot e_{i+1}^1) \tag{18}$$

$$y_{i,i+1} = -K_i \triangle r_i \odot e_i^2 \tag{19}$$

$$y_{i+1,i} = -K_{i+1} \triangle r_{i+1} \odot e_{i+1}^1 \tag{20}$$

$$y_{i+1,i+1} = K_i \triangle r_{i+1} \odot e_i^1 - K_i(e_i^1 \odot e_{i+1}^2 - e_i^2 \odot e_{i+1}^1) \tag{21}$$

During the testing, step change for each set point is performed sequentially.

3.2 Model identification method

The first- or second-order plus dead-time models are often used to described most practical industrial processes. Least squares method is employed here to identify the multiple single equivalent identification systems and the parameters in $G_{ii}(s), G_{i+1,i}$, $G_{i,i+1}$ and $G_{i+1,i+1}$ can be obtained. The data employed in the identification algorithm is the equivalent input and output signals in (17)∼(21). In the identification for TITO $i-1$ local system, the parameters of coupling models $G_{i,i-1}(s)$ and $G_{i-1,i}(s)$ are obtained. So we obtain all the transfer function models in (1) for sub-process i. Repeat the procedure for $n-1$ TITO sub-system sequentially and model of the whole cascade system can be obtained. The main advantages of the proposed identification method is that the testing procedure is straightforward, the computation is simple and can be easily implemented. The parameters of first- or second-order plus dead-time models for each transfer function can be directly obtained.

4 Predictive control algorithm for cascade processes

Distributed predictive algorithm is designed for each sub-process of the cascade system shown in Fig. 1. For sub-process i, the predictive equation over a finite time horizon in the future is

$$\boldsymbol{y}_{i,PM}(k) = f_i[\boldsymbol{y}_{i,p0}(k), \triangle \boldsymbol{u}_{i-1,M}(k), \triangle \boldsymbol{u}_{i,M}(k), \triangle \boldsymbol{u}_{i+1,M}(k)], \quad (i = 1, \cdots, n) \tag{22}$$

where

$$\begin{aligned} \triangle \boldsymbol{u}_{i,M}(k) &= [\triangle u_i(k|k) \ \cdots \ \triangle u_i(k+M-1|k)]^{\mathrm{T}} \\ \boldsymbol{y}_{i,PM}(k) &= [y_i(k+1|k) \ \cdots \ y_i(k+P|k)]^{\mathrm{T}}, \qquad (i = 1, \cdots, n) \\ \boldsymbol{Y}_{i,p0}(k) &= [y_{i,0}(k+1|k) \ \cdots \ y_{i,0}(k+P|k)]^{\mathrm{T}} \end{aligned} \tag{23}$$

P is predictive horizon; $\boldsymbol{y}_{i,PM}(k)$ and $\boldsymbol{y}_{i,p0}(k)$ are the predictive output of sub-process i and the initial values of the predictive output; $\triangle \boldsymbol{u}_{i,M}(k)$ is control increments for sub-process i over M control period in the future; $\triangle \boldsymbol{u}_{i-1,M}$ and $\triangle \boldsymbol{u}_{i+1,M}(k)$ are the control increments of the two adjacent sub-processes of sub-process i. The optimization objective for sub-process i is

$$J_i = \sum_{j=1}^{P} L_i[y_i(k+1|k), \triangle u_{i,M}(k)], \quad i = 1, \cdots, n \tag{24}$$

At instant k, when solving the optimization problem of predictive control algorithm for sub-process i, the control increments $\triangle \boldsymbol{u}_{i-1,M}(k)$ and $\triangle \boldsymbol{u}_{i+1,M}(k)$ at instant k of sub-process $i-1$ and sub-process $i+1$ should be known. The coupling models between each sub-process have been obtained via TITO identification method. They can be considered in solving the optimal control actions for sub-process i. So we design the distributed predictive control structure as shown in Fig. 3.

Here, we assume that the controller of sub-process i can obtain the optimal control sequences of its adjacent sub-processes and send its control sequences to other sub-processes by distributed communication. The distributed information is used to compensate the couplings. This control structure maintains the advantage of decentralized control in which each sub-process has its sub-controller and the control parameters can be designed independently. At the same time, the coupling models are considered which will improve the control performance of the whole cascade system. Here we consider a local communication mode, which will be described as below. At time k, the controller of sub-process i can obtain the optimal control sequences of its adjacent sub-processes at time $k-1$.

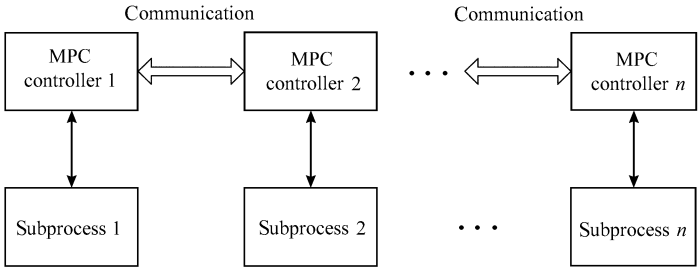

Fig. 3 Control structure of the cascade process

At instant k, when solving the optimization problem of predictive control algorithm for sub-process i, $\triangle \boldsymbol{u}_{i-1,M}(k)$ and $\triangle \boldsymbol{u}_{i+1,M}(k)$ in (22), which are the optimal control sequences of sub-process $i-1$ and sub-process $i+1$ should be known:

$$\triangle \boldsymbol{u}_{j,M}(k) = [\triangle u_j(k|k) \ \cdots \ \triangle u_j(k+M-1|k)]^{\mathrm{T}}, \quad j = i-1, i+1 \tag{25}$$

The following optimal control sequences at time $k-1$ of sub-process and $i-1$ sub-process $i+1$ can be obtained via distributed communication:

$$\triangle \boldsymbol{u}^*_{j,M}(k-1) = [\triangle u^*_j(k-1|k-1) \ \cdots \ \triangle u^*_j(k+M-2|k-1)]^{\mathrm{T}}, \quad j = i-1, i+1 \tag{26}$$

Adopt the moving-window approach[7], let

$$\triangle \boldsymbol{u}_{j,M}(k) = s \triangle \boldsymbol{u}^*_{j,M}(k-1), \quad j = i-1, i+1 \tag{27}$$

where

$$s = \begin{bmatrix} 0 & 1 & 0 & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & 1 \\ 0 & 0 & \cdots & 1 \end{bmatrix} \tag{28}$$

Then the predictive equation of sub-process i can be written as

$$\boldsymbol{y}_{i,PM}(k) = f_i[\boldsymbol{y}_{i,p0}(k), s \triangle \boldsymbol{u}^*_{i-1,M}(k-1), \triangle \boldsymbol{u}_{i,M}(k), s \triangle \boldsymbol{u}^*_{i+1,M}(k-1)], \quad (i = 1, \cdots, n) \tag{29}$$

The predictive control law for sub-process i can be described as (30), in which (29) is the predictive equation and (24) is the performance index.

$$\begin{aligned} &\min \ J_i|_{\triangle \boldsymbol{u}^*_{i-1,M}(k-1),\, \triangle \boldsymbol{u}^*_{i+1,M}(k-1)} \\ &\text{s.t. } \boldsymbol{y}_{i,PM}(k) = f_i[y_{i,p0}(k), s \triangle u^*_{i-1,M}(k-1), \triangle \boldsymbol{u}_{i,M}(k), s \triangle \boldsymbol{u}^*_{i+1,M}(k-1)] \end{aligned} \tag{30}$$

The predictive control algorithm based on distributed communication for cascade processes can be described as follows:

Step 1. At sampling instant k, sub-process i sends out its optimal control sequence at time $k-1$ $\triangle \boldsymbol{u}^*_{i,M}(k-1)$ to its two adjacent sub-processes and also receives, $\triangle \boldsymbol{u}^*_{j,M}(k-1), j = i-1, i+1$ from the two adjacent sub-processes. Set $\triangle \boldsymbol{u}_{j,M}(k) = s \triangle \boldsymbol{u}^*_{j,M}(k-1), j = i-1, i+1$.

Step 2. Solve the optimal control problem for each sub-process to obtain the optimal control sequence $\triangle \boldsymbol{u}^*_{i,M}(k)$ at instant k.

Step 3. $\triangle \boldsymbol{u}_i(k) = [1 \quad 0 \quad \cdots \quad 0] \triangle \boldsymbol{u}^*_{i,M}(k)$, The first control in that sequence is applied to the physical sub-process.

Step 4. Set $k = k+1$, and return to Step 1 at the next sample time. Repeat the procedure.

In section 3, the transfer function model in (1) has been obtained for each sub-process. The step response coefficients a_{ij} for each output y_i to the input u_j, $j = i-1, i, i+1$ have been got by identification. Considering the dynamic matrix control (DMC) algorithm, for sub-process i, the predictive equation is

$$\boldsymbol{y}_{i,PM}(k) = \boldsymbol{y}_{i,P0}(k) + \boldsymbol{A}_{ii} \triangle u_{i,M}(k) + \boldsymbol{A}_{i,i-1} s \triangle u^*_{i-1,M}(k) + \boldsymbol{A}_{i,i+1} s \triangle \boldsymbol{u}^*_{i+1,M}(k-1) \tag{31}$$

The optimization objective is

$$\min J_i = \|\boldsymbol{w}_i(k) - \boldsymbol{y}_{i,P0}(k)\|^2_{Q_i} + \|\triangle \boldsymbol{u}_{i,M}(k)\|^2_{R_i} \tag{32}$$

The unconstrained predictive control law for sub-process i is

$$\triangle \boldsymbol{u}_{i,M}(k) = (\boldsymbol{A}_{ii}^{\mathrm{T}}\boldsymbol{Q}_i\boldsymbol{A}_{ii} + \boldsymbol{R}_i)^{-1}\boldsymbol{A}_{ii}^{\mathrm{T}}\boldsymbol{Q}_i[\boldsymbol{w}_i^*(k) - \boldsymbol{y}_{i,p0}(k)] \tag{33}$$

where

$$\boldsymbol{w}_i^*(k) = \boldsymbol{w}_i(k) - \boldsymbol{A}_{i,i-1}s\triangle \boldsymbol{u}^*_{i-1,M}(k-1) - A_{i,i+1}s\triangle \boldsymbol{u}^*_{i+1,M}(k-1) \tag{34}$$

The second and the third items in the right side of (34) are the feed-forward compensation for the coupling between sub-process i and its two adjacent sub-processes. The control sequences of the two adjacent sub-processes at time $k-1$ are obtained via distributed communication. The control algorithm proposed in this paper will improve the control performance of the whole system greatly because the couplings between sub-processes have been considered.

5 Simulation

We consider a cascade system, which consists of four sub-processes. The structure of the cascade system is shown in Fig. 1. There are only input couplings in adjacent sub-processes. Simulation work has been done based on the decentralized closed-loop identification method and the distributed predictive control algorithm proposed in this paper. Assume the transfer function matrix of the cascade system is

$$G(s) = \begin{bmatrix} \frac{5e^{-2s}}{50s+1} & \frac{3e^{-4s}}{100s+1} & 0 & 0 \\ \frac{3e^{-4s}}{100s+1} & \frac{6e^{-2s}}{50s+1} & \frac{2e^{-4s}}{200s+1} & 0 \\ 0 & \frac{2e^{-4s}}{100s+1} & \frac{4e^{-2s}}{50s+1} & \frac{2e^{-4s}}{100s+1} \\ 0 & 0 & \frac{1.5e^{-4s}}{100s+1} & \frac{4e^{-2s}}{50s+1} \end{bmatrix} \tag{35}$$

The whole cascade system is divided into three TITO local systems to be identified. In practice, the real measurement of the process output under closed-loop test are inevitably corrupted by measurement noise, which leads to the corruption of the constructed test signals. In our simulation, we assume the output signals are measured under measurement noise and the noise-to-signal ratio (NSR) of the noise is 20%[3~4]. In order to show the accuracy of the identification results, we adopt the frequency domain identification error index, *i.e.*,

$$E = \max_{\omega}\left\{\left|\frac{\hat{G}(j\omega) - G(j\omega)}{G(j\omega)}\right| \times 100\%\right\} \tag{36}$$

where $G(s)$ and $\hat{G}(s)$ are the actual and estimated process frequency responses, respectively.

The identified models and parameters under measurement noise are given in Table 1. It shows that the frequency-domain characteristic of estimated model is close to that of actual process. The simulation results show that the identification method is practical and accurate.

Table 1 Identification results (under 20% noise level)

$\hat{G}(s)$	$E(\%)$
$g_{11}(s) = \frac{4.798e^{-1.98s}}{48.74s+1}$	5.0511
$g_{12}(s) = \frac{2.97e^{-3.79s}}{99.825s+1}$	10.347
$g_{21}(s) = \frac{2.829e^{-3.83s}}{94.25s+1}$	8.6268
$g_{22}(s) = \frac{5.757e^{-1.8s}}{50.7s+1}$	9.4779
$g_{23}(s) = \frac{2.036e^{-3.82s}}{205s+1}$	9.1627
$g_{32}(s) = \frac{2.044e^{-3.75s}}{103.6s+1}$	12.2991
$g_{33}(s) = \frac{3.961e^{-1.92s}}{50.34s+1}$	3.3935
$g_{34}(s) = \frac{2.012e^{-3.81s}}{101.3s+1}$	9.4214
$g_{43}(s) = \frac{1.512e^{-3.8s}}{101.6s+1}$	9.8725
$g_{44}(s) = \frac{3.941e^{-1.99s}}{49.53s+1}$	1.4715

Then, the distributed predictive controller is designed for the cascade process. The optimization objective for each sub-process is

$$J_i = \|\boldsymbol{r}_i(k) - \boldsymbol{y}_{i,PM}(k)\|^2_{Q_i} + \|\triangle \boldsymbol{u}_{i,M}(k)\|^2_{R_i} \quad (i = 1, \cdots, 4) \tag{37}$$

In the simulation case, the sampling time is 100 seconds and total simulation time is 400 seconds. The expected output values for the four sub-processes are (0.5,1,2,3). At time $t = 200$, change the expected output value for the forth sub-process from 3 to 1 while keeping other expected output values un-changed. The simulation result is shown in Fig. 4, which shows that all the outputs of four sub-processes track their expected values well. Then we compared the complete decentralized predictive control algorithm in which the couplings models between sub-processes are not considered with our distributed predictive control algorithm proposed in this paper. Fig. 5 shows the simulation result. (Solid line: the output and control input of the third sub-process for the completed decentralized predictive control algorithm, not considering the coupling models; Dashed line: the output and control input of the third sub-process for the algorithm proposed in this paper). It shows that our control algorithm in which the couplings between sub-processes have been compensated has improved the control result greatly.

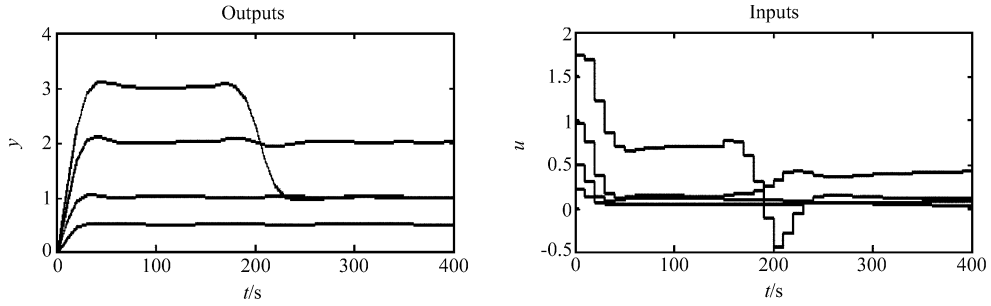

Fig. 4 Output and input of each sub-process

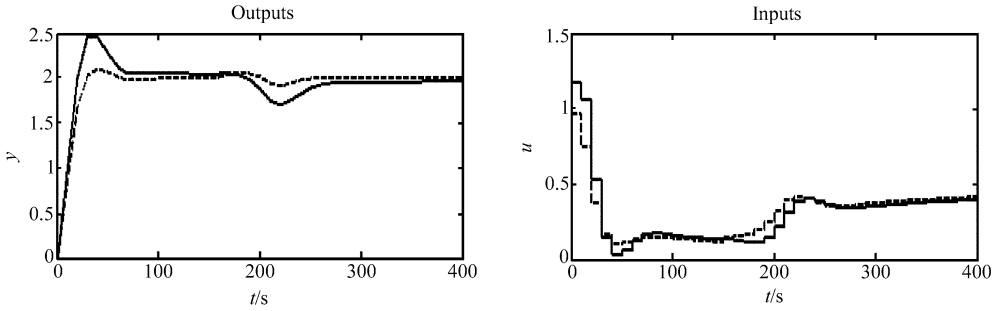

Fig. 5 Output and input of the third sub-process

6 Conclusion

Decentralized close-loop identification method and distributed predictive control for a kind of cascade processes, which has only input couplings between adjacent sub-processes, are studied in this paper. First, the cascade process is divided into several two-input two-output (TITO) systems sequentially. Each TITO system is decoupled equivalently into four independent single open-loop processes with the same input signal by transformation. Then, a distributed model predictive control algorithm is proposed based on the coupling models of adjacent sub-processes. Controller of each sub-process can obtain the optimal control sequences at the previous time instant from its adjacent sub-processes *via* communication to feed-forward compensate the coupling effects. Simulation results show the effectiveness of the identification and control algorithm.

References

1 Stephanopoulos G, Christine Ng. Perspectives on the synthesis of plant-wide control structures, *Journal of Process Control*, 2000, **10**(2∼3): 97∼111
2 Zhu Y C, Butoyi F. Case studies on closed-loop identification for MPC. *Control Engineering Practice*, 2002, **10**(4): 403∼417
3 Bi Q, Cai W J, Lee E L, Wang Q G, Hang C C, Zhang Y. Robust identification for first-order plus dead-time model from step response. *Control Engineering Practice*, 1999, **7**(1): 71∼77
4 Choi J Y, Lee J, Jung J H, Lee M, Han C. Sequential loop closing identification of multivariable process models. *Computers and Chemical Engineering*, 2000, **24**(2∼7): 809∼814
5 Richalet J. Industrial applications of model based predictive control, *Automatica*, 1993, **29**(5): 1251∼1274
6 Jeremy G, Van Antwerp, Richard D. Braatz, Model predictive control of large scale processes, *Journal of Process Control*, 2000, **10**(1): 1∼8
7 DU Xiao-Ning, XI Yu-Geng, LI Shao-Yuan. Distributed optimization algorithm for predictive control. *Control Theory and Applications*, 2002, **19**(5): 793∼796

CHEN Qing Received his master degree from Jilin University in 2001. Now he is a Ph. D. candidate at the Institute of Automation, Shanghai Jiaotong University. His research interests include modeling, control and optimization for complex processes.

LI Shao-Yuan Received his Ph. D. degree from Nankai University in 1997. Now he is a professor at the Institute of Automation, Shanghai Jiaotong University. His research interests include fuzzy systems and nonlinear system control.

XI Yu-Geng Received his Ph. D. degree from Technical University of Munich in Germany in 1984. Now he is a professor of the Institute of Automation, Shanghai Jiaotong University. His research interests include theory and application of predictive control, generalization of predictive control principles to planning, scheduling, decision problems, multi-robot coordinative system and robot intelligent technology, and new optimization algorithm.