Detection of Significant Model-Plant Mismatch from Routine Operation Data of Model Predictive Control System

Manabu Kano * **Yohei Shigi** * **Shinji Hasebe** *
Satoshi Ooyama **

* *Kyoto University, Nishikyo-ku, Kyoto 615-8510, Japan*
(e-mail: manabu@cheme.kyoto-u.ac.jp)
** *Mitsubishi Chemical Corporation, Ibaraki 314-0102, Japan*

Abstract: The maintenance of model predictive control (MPC) systems is one of the major problems identified by industrial process control engineers. Since performance deterioration is usually caused by changes in process characteristics, effective re-modeling is the key to success. Obviously, not all sub-models have to be reconstructed; thus, it is crucial to identify sub-models that have significant model-plant mismatch. In the present work, a novel method is proposed for significant model-plant mismatch detection from routine closed-loop operation data on the basis of the statistical test concept. The effectiveness of the proposed method is demonstrated through case studies. The results clearly show not only that the proposed method can detect sub-models that have significant mismatch but it is superior to the other methods based on multivariate analysis.

Keywords: Model-based control, Model predictive control, System identification, Statistical test, Control system maintenance.

1. INTRODUCTION

Model predictive control (MPC) has been widely and successfully applied to various processes in various industries. The benefit of MPC is not only the improvement of the control performance by using model-based control, but also the realization of stable operation close to the optimal point under disturbances through optimization. In addition, MPC makes it possible to maximize the production rate by making the most use of the capability of the process and to minimize cost through energy conservation by moving the operating condition toward the control limit. Both the energy conservation and the productive capacity were improved by an average of 3 to 5% as the result of advanced process control (APC) projects centered on MPC, as reported by Kano and Ogawa (2009). The control performance of MPC depends on the accuracy of the process model and the appropriateness of tuning, although MPC has outstanding robustness.

A recent questionnaire survey on chemical process control clarifies that MPC has been widely and successfully implemented in the chemical and petroleum refining industries, but problems still remain to be solved (Kano and Ogawa (2009)). One of major problems identified is the maintenance of MPC. To keep sufficient control performance and to prevent, or at least cope with, performance deterioration, control engineers need to know the cause of performance deterioration and take effective countermeasures. Since performance deterioration is usually caused by changes in process characteristics, effective re-modeling is the key to success in the maintenance. Obviously, not all sub-models have to be reconstructed. For reducing engineers' burden of re-modeling, it is crucial to identify sub-models that have significant model-plant mismatch and that need to be corrected. In general, MPC systems have tens of manipulated variables and controlled variables, which makes detection of significant model-plant mismatch very important in practice.

Regarding the maintenance of MPC, very recently, Badwe et al. (2008) proposed a model-plant mismatch detection method by using partial correlation analysis, and Huang (2008) proposed the use of Bayesian methods.

In the present work, another novel method is proposed for significant model-plant mismatch detection from routine closed-loop operation data on the basis of the statistical variable selection method. The proposed method is very simple. It should detect significant model-plant mismatch without plant tests so as not to impose a burden on operators and engineers. The effectiveness of the proposed method is demonstrated through case studies.

2. BACKGROUND: SURVEY OF MPC

In Japan, a task force was launched in 2007 to sift through problems regarding process control and investigate solutions. The task force, named "Workshop No.27 Process Control Technology," consists of 32 engineers from industry and 12 researchers from universities. It is supported by the 143rd committee on process systems engineering, the Japan Society for the Promotion of Science (JSPS).

The task force sent a questionnaire to member companies of the JSPS 143rd committee on their process control applications including MPC. Since the results are extremely

Table 1. Statistics of MPC applications (from the survey JSPS143 WS27 2009)

targeted process			
distillation			40 %
reaction			30 %
others			30 %
number of variables	number of applications		
	MV	DV	CV
0	0	28	0
1	40	45	24
2	57	50	33
3-5	83	103	58
6-9	47	40	59
10-19	59	27	48
20-29	12	5	25
30-39	1	3	29
40-49	1	3	16
50 or more	5	1	13

MV: manipulated variable
CV: controlled variable
DV: disturbance variable

Table 2. Key-to-success of MPC applications (from the survey JSPS143 WS27 2009)

major key to success	
careful modeling	37 %
suitability for objective	33 %
education of operators and engineers	15 %
suitability for process characteristics	11 %
hardware/software environment	4 %

useful for grasping the state of the art in MPC, a part of the questionnaire survey results is introduced in this section. More detailed results have been reported by Kano and Ogawa (2009).

The statistics of 305 MPC applications are summarized in Table 1. Distillation and reaction processes cover about 70% of the applications. In addition, there are a variety of sizes of MPC systems.

Table 2 clarifies key-to-success of MPC. Process control engineers have identified the following major keys to success: 1) a process model should be developed with care, 2) MPC should be suitable for objectives, 3) operators and engineers should be adequately educated, and 4) MPC should be suitable for process characteristics.

Although MPC has been widely and successfully applied in the chemical and petroleum refining industries, problems still remain to be solved as summarized in Table 3. The major problem can be described as follows. To achieve desirable performance, it is necessary to build an accurate model and to tune control parameters appropriately. However, both of them are difficult in practice due to process nonlinearity and changes in process characteristics. To keep sufficient control performance and to prevent or at least cope with performance deterioration, the maintenance of MPC is crucial. Control engineers need to know the reason for performance deterioration and the effective countermeasure. In addition, they would like to know the relationship between model accuracy and achievable control performance. Modeling of a multivariable process is an exceedingly laborious engineering task; thus it needs to be clarified how accurate a model should be to achieve

Table 3. Problems of MPC applications (from the survey JSPS143 WS27 2009)

problem: general	
low robustness against model error	26 %
difficulty in tuning	23 %
inability to cope with specific objective	15 %
difficulty in modeling	12 %
others	24 %
problem: maintenance	
transfer of engineering technology	44 %
response to performance deterioration	33 %
education of operators	7 %
difficulty in tuning	7 %
others	9 %
need for improvement: general	
to improve modeling technology	28 %
to clarify method of estimating effect	25 %
to simplify implementation	22 %
to increase process control engineers	14 %
others	11 %
need for improvement: theory	
to cope with changes in process characteristics	26 %
to clarify relations between model accuracy and control performance	24 %
to cope with unsteady operation (SU/SD)	16 %
to incorporate know-how in control system	16 %
to cope with nonlinearity	13 %
others	5 %

the goal. As a matter of course, not only clarifying the relationship but also improving modeling and tuning methods is necessary. Moreover, the implementation of MPC should be easier. Another problem is how to transfer engineering technology from skilled engineers to others. Unfortunately, a shortage of process control engineers aggravates the situation. It is also crucial in practice to answer the question: how can we estimate the economical benefit of installing MPC to justify the project? Most APC suppliers and users are required to report the benefit to management. Bauer and Craig (2008) reported that benefit estimation methods based on variance reduction are still carried out, but they are sometimes rudimentary and based on experience.

3. MISMATCH DETECTION METHOD

As shown in Table 1, there are tens of controlled variables (CV), manipulated variables (MV), and disturbance variables (DV) in an ordinary MPC system. To reduce control engineers' burden of re-modeling or system identification, it is crucial to identify sub-models that have significant model-plant mismatch. If such sub-models can be detected from routine operation data without plant tests, the maintenance of MPC will be accomplished very effectively. In this section, our proposed method is explained.

In a model-based control system shown in Fig. 1, model residuals are given by

$$\boldsymbol{e} = \boldsymbol{y} - \boldsymbol{y}_m \tag{1}$$

where $\boldsymbol{y}$ and $\boldsymbol{y}_m$ are the plant and model outputs, respectively. The outputs can be written as

$$\boldsymbol{y} = \boldsymbol{P}\boldsymbol{u} + \boldsymbol{d} \tag{2}$$

$$\boldsymbol{y}_m = \boldsymbol{P}_m\boldsymbol{u} \tag{3}$$

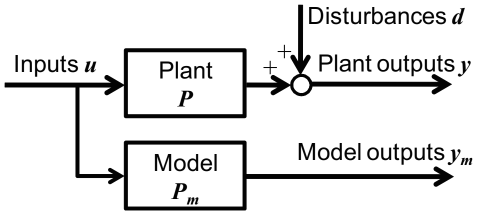

Fig. 1. A part of model-based control system

where $\boldsymbol{P}$ and $\boldsymbol{P}_m$ are the plant and the model, respectively, and $\boldsymbol{u}$ and $\boldsymbol{d}$ denote the plant inputs and disturbances, respectively. Here, model-plant mismatch is defined as

$$\boldsymbol{M} = \boldsymbol{P} - \boldsymbol{P}_m \tag{4}$$

The mismatch $\boldsymbol{M}_{ij}$ from the jth input to the ith output can be generally written as an impulse response model of the form:

$$\boldsymbol{M}_{ij} = \sum_{k=1}^{\infty} a_{ij,k} q^{-k} \tag{5}$$

where $a_{ij,k}$ is an impulse response coefficient and q^{-1} is a backward shift operator. Model residuals can then be expressed as linear combinations of past plant inputs and disturbances.

$$\boldsymbol{e} = \boldsymbol{M}\boldsymbol{u} + \boldsymbol{d} \tag{6}$$

The relationship between the ith model residual and the jth input variable is described by

$$e_i(t) = \boldsymbol{M}_{ij} u_j(t) + d_i(t) \tag{7}$$

$$= \sum_{k=1}^{\infty} a_{ij,k} u_j(t-k) + d_i(t) \tag{8}$$

If a sub-model has significant mismatch, that is, if it is significantly different from the corresponding sub-plant, past inputs of such a sub-model contribute greatly to model residuals. In other words, past inputs and model residuals have a significant cause-and-effect relationship when the corresponding sub-model has significant mismatch. It seems possible to find significant mismatch by checking impulse response coefficients from past inputs $u_j(t-k)$ to model residuals $e_i(t)$. In general, however, both autocorrelation and cross-correlation exist among input variables due to multivariable feedback control; the collinearity problem occurs. Thus, it is impossible to identify impulse response models and detect significant mismatch correctly from routine operation data. In other words, routine operation data do not satisfy the persistently exciting condition.

In the present work, a novel approach is proposed. Instead of building impulse response models, important explanatory variables, i.e., past inputs which contribute greatly to each model residual, are selected by using the stepwise method, which is a well-known variable selection method based on the statistical test. If a large number of past inputs are selected, it can be concluded that the corresponding sub-model has significant model-plant mismatch. This is the basic concept of the proposed method for model-plant mismatch detection.

A problem of using the stepwise method is that it selects variables regardless of their importance. That is, the method might select input variables that have very small mismatch and make judgment difficult, because the stepwise method checks the statistical significance instead of the importance. To avoid this problem, white noise is artificially added to model residuals before the stepwise method is executed. This operation is very effective for mismatch detection as shown in the next section.

The detection procedure is as follows:

[Step 1] Get the routine operation data of plant inputs, plant outputs, and model outputs. Then calculate model residuals by (1).
[Step 2] Normalize the model residuals by the standard deviation of plant output variables.
[Step 3] Add white noise to the model residuals. This operation is effective to avoid the selection of unimportant input variables.
[Step 4] For every model residual $e_i(t)$, select explanatory variables by using the stepwise method, in which explanatory variables are the past input variables $u_j(t-k)$. Then, notate the number of selected variables.
[Step 5] Repeat steps 3 and 4 with changing the variance of white noise added at step 3.
[Step 6] Find combinations of plant inputs and plant outputs, at which one or more explanatory variables are selected even when large white noise is added to model residuals. The method concludes that significant mismatch exists at such combinations, i.e., sub-models.

It is useful to introduce a measure of significance of mismatch so as to make the judgment easy. In the present work, the following "mismatch score" is introduced.

$$\text{score} = \sum_{k=1}^{K} v(k)(n(k) - n(k+1)) \tag{9}$$

where K is the number of levels of the variance of white noise v, n is the number of selected variables, and $v(0) = 0$. The variance of white noise v is changed at regular intervals. The score becomes larger when more variables are selected in spite of large white noise. On the other hand, the score cannot be large even though many variables are selected at $v(0) = 0$.

4. CASE STUDIES

The proposed mismatch detection method is validated through case studies, where a distillation process and a continuous-stirred-tank-reactor (CSTR) are controlled by multivariable MPC.

4.1 Distillation Process

In the first case study, the proposed mismatch detection method is applied to operation data obtained from a linearized distillation process model, expressed by

$$\begin{bmatrix} x_D \\ x_B \end{bmatrix} = \begin{bmatrix} \dfrac{12.8e^{-s}}{16.7s+1} & \dfrac{-18.9e^{-3s}}{21.0s+1} \\ \dfrac{6.6e^{-7s}}{10.9s+1} & \dfrac{-19.4e^{-3s}}{14.4s+1} \end{bmatrix} \begin{bmatrix} R \\ S \end{bmatrix} + \begin{bmatrix} \dfrac{3.8e^{-8.1s}}{14.9s+1} \\ \dfrac{4.9e^{-3.4s}}{13.2s+1} \end{bmatrix} F \tag{10}$$

This model was developed by Wood and Berry (1973) to investigate control system design for a pilot-scale binary

Table 4. Basic steady state of pilot-scale distillation process

	symbol	variable	steady-state value
x_D	distillate composition	CV	96.0 wt%
x_B	bottoms composition	CV	0.500 wt%
R	reflux flow rate	MV	1.95 lb/min
S	steam flow rate	MV	1.71 lb/min
F	feed flow rate	DV	2.45 lb/min

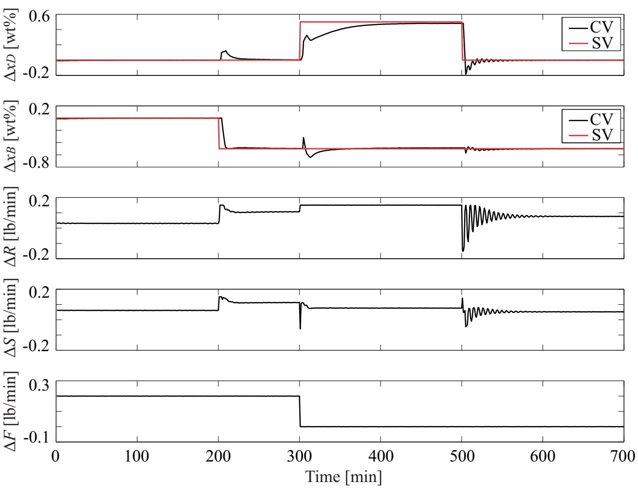

Fig. 2. Control responses in the gain mismatch case

distillation column. Later, this model was used to illustrate the effects of the MPC design parameters by Seborg et al. (2004). In this case study, (10) is used as a process.

The basic steady-state operating condition is summarized in Table 4. This distillation process is controlled by using MPC. For each simulation, the sampling and control period is 1 min, the prediction horizon is 10 min, and the control horizon is 5 min. In addition, the disturbance F and the set-points are changed step-wise at times separately, and measurement noise is added to all measured variables.

The effectiveness of the proposed method is tested in two types of mismatch: gain mismatch, and time constant and time delay mismatch. In the case of gain mismatch, it is assumed that the model from R to x_D has -50% of gain mismatch, the model from F to x_B has -20% of gain mismatch, and all other models have ±5% of gain mismatch. That is, the model is expressed as:

$$\begin{bmatrix} x_D \\ x_B \end{bmatrix} = \begin{bmatrix} \dfrac{6.4e^{-s}}{16.7s+1} & \dfrac{-18.7e^{-3s}}{21.0s+1} \\ \dfrac{6.5e^{-7s}}{10.9s+1} & \dfrac{-19.3e^{-3s}}{14.4s+1} \end{bmatrix} \begin{bmatrix} R \\ S \end{bmatrix} + \begin{bmatrix} \dfrac{3.9e^{-8.1s}}{14.9s+1} \\ \dfrac{3.92e^{-3.4s}}{13.2s+1} \end{bmatrix} F \tag{11}$$

The control responses are shown in Fig. 2. The operation data of 700 sampling points are used for mismatch detection in the gain mismatch case. In this control result, R is wildly oscillating because the sub-model from R to x_D has -50% of gain mismatch.

The orders of impulse response models are set at 40; input variables measured at 1–40 minutes before are used for mismatch detection. The significance levels for adding and removing input variables in the stepwise method are set at 0.5% and 1%, respectively. The results of mismatch detection are shown in Table 5. To detect model-plant mismatch, the variance of white noise is changed from zero to one at intervals of 0.01; only a part of the results are summarized in this table. Two sub-models that had significant mismatch, i.e., $R \to x_D$ and $F \to x_B$, were correctly detected by the proposed method. In fact, the numbers of selected variables for $R \to x_D$ and $F \to x_B$ are significantly larger than the others regardless of the variance of white noise. In addition, scores for $R \to x_D$ and $F \to x_B$ are significantly larger than the others.

Table 5. Results of mismatch detection for MPC of distillation process: the gain mismatch case

output		x_D			x_B	
input	R	S	F	R	S	F
variance	the number of selected variables					
0	26	4	2	7	6	23
0.01	15	0	1	0	0	3
0.05	10	0	0	0	0	1
0.50	4	0	0	0	0	1
0.90	3	0	0	0	0	1
score	5.15	0.02	0.03	0.00	0.00	0.93
method	the notm of coefficients					
MRA	0.22	0.06	0.31	0.04	0.02	0.25
PLS	0.19	0.03	0.03	0.03	0.02	0.18
CA	5.45	2.28	3.87	3.28	1.99	6.18
impulse	1.10	0.03	0.02	0.02	0.02	0.19

To demonstrate the superiority of the proposed method, the results of other methods are also summarized in Table 5. MRA, PLS, and CA means multiple regression analysis, partial least squares, and correlation analysis, respectively. In MRA and PLS, the norms of regression coefficients derived by MRA and PLS are shown. The regression coefficients are estimates of impulse response coefficients from input variables to model residuals. In CA, correlation coefficients are used instead of regression coefficients to calculate the norm. The norms are defined by

$$\text{norm} \equiv \sqrt{\sum_{k=1}^{S} c_{ij,k}^2} \tag{12}$$

where c denotes regression coefficients in MRA and PLS and correlation coefficients in CA. In these methods, the mismatch is judged to be significant when the norm is large.

The result of MRA is not good; the norm for $F \to x_D$ is larger than the norms for $R \to x_D$ and $F \to x_B$. The situation can be improved by applying statistical methods that can cope with the collinearity problem. In fact, the results of PLS and CA are better than that of MRA. These two methods seem to successfully detect significant mismatches. However, the norms of PLS and CA are not identical or even proportional to the norms of true impulse response coefficients from inputs to residuals, which are labeled as "impulse" in the table. Therefore, the results of PLS and CA will be misleading and not desirable in practice. This point is investigated in more detail below.

In the case of time constant and time delay mismatch, it is assumed that the model from R to x_D has large time delay mismatch, the model from S to x_D has large time

Table 6. Results of mismatch detection for MPC of distillation process: the time constant and time delay mismatch case

output	x_D			x_B		
input	R	S	F	R	S	F
variance	the number of selected variables					
0	4	16	1	14	9	11
0.025	4	9	1	0	0	0
0.50	2	2	0	0	0	0
0.80	1	2	0	0	0	0
2.50	1	1	0	0	0	0
score	3.48	4.18	0.18	0.00	0.00	0.00
method	the norm of coefficients					
MRA	0.85	0.34	0.61	0.19	0.07	0.33
PLS	0.69	0.37	0.26	0.10	0.03	0.14
CA	2.53	2.55	2.72	2.39	1.01	6.10
impulse	1.05	1.07	0.02	0.02	0.02	0.02

constant mismatch, and all other models have $\pm 5\%$ of gain mismatch. That is, the model is expressed as:

$$\begin{bmatrix} x_D \\ x_B \end{bmatrix} = \begin{bmatrix} \frac{12.8e^{-3s}}{16.7s+1} & \frac{-18.7e^{-3s}}{40.0s+1} \\ \frac{6.5e^{-7s}}{10.9s+1} & \frac{-19.3e^{-3s}}{14.4s+1} \end{bmatrix} \begin{bmatrix} R \\ S \end{bmatrix} + \begin{bmatrix} \frac{3.9e^{-8.1s}}{14.9s+1} \\ \frac{5.0e^{-3.4s}}{13.2s+1} \end{bmatrix} F \tag{13}$$

Similarly to the gain mismatch case, the operation data of 700 sampling points are used for mismatch detection, the order of impulse response model is set at 40. The results of mismatch detection are shown in Table 6. To detect model-plant mismatch, the variance of white noise is changed from zero to 2.5 at intervals of 0.025. Two sub-models that had significant mismatch, i.e., $R \rightarrow x_D$ and $S \rightarrow x_D$, were correctly detected by the proposed method. Moreover, in this case, it has been clarified that adding white noise with various variance is effective to correctly detect significant mismatch. In fact, when the variance of white noise is zero, i.e., no white noise is added, the numbers of selected variables for $R \rightarrow x_B$, $S \rightarrow x_B$, and $F \rightarrow x_B$ are significantly larger than that for $R \rightarrow x_D$. Thus, the significant mismatch cannot be detected without adding white noise. In the proposed method, however, the significance of input variables related to minor mismatch decreases as the variance of white noise increases, and only truly important input variables can be selected. As a result, the proposed method can correctly detect the sub-models that have significant mismatch. A desirable feature of the proposed method is that only routine closed-loop operation data are necessary. The white noise is added to the model residual off-line; this operation does not affect plant operation at all.

The results of other methods are also summarized in Table 6. The results of CA as well as MRA are not good; they cannot detect significant mismatch correctly. Although PLS functions better than MRA and CA, it is difficult to conclude the sub-model of $S \rightarrow x_D$ has significant mismatch. As a matter of course, the norms of MRA, PLS, and CA are different from the norms of true impulse response coefficients. This case study clarifies that the proposed method is superior to the other methods.

In this case study, the maximum variance of white noise was determined beforehand and the interval was set at its 1/100. In real applications, the interval can be predetermined, e.g. 0.01, and the variance of white noise can be increased till no input variables are selected in all sub-models. In the proposed method, model residuals are normalized by the standard deviation of plant output variables. Thus, the variance of white noise will not become excessively large. If the variance need to be excessively large, it is obvious that the corresponding sub-model has significant mismatch.

Table 8. Important variables of nonisothermal CSTR process

V	holdup	CV
T_{out}	product temperature	CV
F_{out}	product flow rate	MV
F_{cin}	coolant flow rate	MV
F_{in}	feed flow rate	DV
T_{in}	feed temperature	DV
T_{cin}	coolant temperature	DV
C_{Ain}	feed concentration	-

Table 9. Linear model of CSTR for MPC

	V	T_{out}
F_{out}	$-\frac{1}{s}$	$\frac{-216.2s^2 - 6162s - 5946}{s^4 + 31.81s^3 + 104.9s^2 + 710.2s}$
F_{cin}	0	$\frac{-344.8s - 3478}{s^3 + 31.81s^2 + 104.9s + 710.2}$
F_{in}	$\frac{1}{s}$	$\frac{-50.69s^3 - 275.6s^2 + 46130s + 5946}{s^4 + 31.81s^3 + 104.9s^2 + 710.2s}$
T_{in}	0	$\frac{s^2 + 37.59s + 277.4}{s^3 + 31.81s^2 + 104.9s + 710.2}$
T_{cin}	0	$\frac{75s + 756.5}{s^3 + 31.81s^2 + 104.9s + 710.2}$

4.2 Reaction Process

In the second case study, the proposed mismatch detection method is applied to operation data obtained from a nonisothermal CSTR process.

The important variables are summarized in Table 8. The nonlinear, nonisothermal CSTR process is controlled by using MPC. The MPC controller has two controlled variables, two manipulated variables, and three disturbance variables. The feed concentration is an unmeasured disturbance. The linearized process model is shown in Table 9. For each simulation, the sampling and control period is 0.2 min, the prediction horizon is 4 min, and the control horizon is 1 min. Weight coefficients in the cost function are $F_{out} : F_{cin} = 1 : 1$ for manipulated variables and $V : T_{out} = 13 : 1$ for controlled variables. There is no constraints on the manipulated variables and the controlled variables. In addition, the disturbances and the set-points are changed independently, and measurement noise is added to all measured variables.

In this case study, the transfer function model from F_{cin} to T_{out} is modified intentionally so that it has significant mismatch; its steady-state gain is 1.2 times as large as the identified value shown in Table 9. It is obvious that all sub-models have mismatch because the process is nonlinear and linear MPC is adopted. The control responses are shown in Fig. 3. This operation data is used for mismatch detection.

The results of mismatch detection are shown in Table 7. The sub-model $F_{cin} \rightarrow T_{out}$ was correctly detected by the proposed method. Although it is not clear whether the

Table 7. Results of mismatch detection for MPC of CSTR process

output	V					T_{out}				
input	F_{out}	F_{cin}	F_{in}	T_{in}	T_{cin}	F_{out}	F_{cin}	F_{in}	T_{in}	T_{cin}
variance	the number of selected variables									
0	7	2	0	2	3	9	2	0	1	3
0.8	1	1	0	1	2	1	2	0	0	1
9.2	0	0	0	0	1	0	1	0	0	1
12.8	0	0	0	0	0	0	1	0	0	0
20.0	0	0	0	0	0	0	1	0	0	0
score	0.8	4.0	0.0	3.6	14.0	2.0	23.2	0.0	0.0	11.6
method	the norm of coefficients									
MRA	0.27	0.60	0.07	10.66	77.82	0.26	1.29	0.05	9.21	65.60
PLS	0.27	0.51	0.05	0.09	1.00	0.25	0.94	0.04	0.08	0.70
CA	0.26	1.91	0.12	1.60	1.09	0.24	3.23	0.11	0.05	2.26

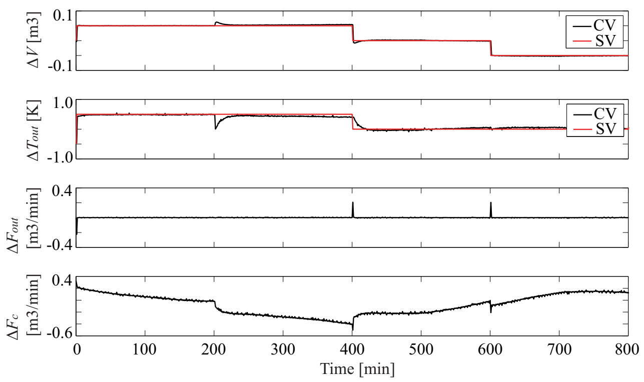

Fig. 3. Control response of CSTR process

sub-model $T_{cin} \to T_{out}$ has significant mismatch or not, the sub-model seems to be detected due to the strong correlation between F_{cin} and T_{cin}; the maximum cross-correlation coefficient is 0.97, while those of the other combinations are less than 0.11.

In addition, in this case, it has been clarified that adding white noise with various variance is effective to correctly detect significant mismatch. In fact, when the variance of white noise is zero, i.e., no white noise is added, the number of selected variables for $F_{out} \to T_{out}$ is larger than that for $F_{cin} \to T_{out}$. In the proposed method, however, the significance of input variables related to minor mismatch decreases as the variance of white noise increases.

The results of other methods are also summarized in Table 7. The results of MRA and PLS are not good. They cannot detect significant mismatch correctly; both MRA and PLS identify the sub-model $T_{cin} \to V$ instead of $F_{cin} \to T_{out}$. On the other hand, CA functions better than MRA and PLS in this case study. The largest norm is related to the sub-model $F_{cin} \to T_{out}$. These case studies results have clearly shown the superiority of the proposed mismatch detection method over the other methods.

5. CONCLUSIONS

The maintenance of model predictive control (MPC) systems is one of the major problems identified by industrial process control engineers. In the present work, a novel method was proposed for significant model-plant mismatch detection from routine closed-loop operation data. Instead of building process models, important explanatory variables, i.e., past inputs which contribute greatly to each model residual, are selected by using the stepwise method. In addition, white noise is artificially added to model residuals before the stepwise method is executed. This operation is very effective for the improvement of the mismatch detection performance. If a large number of past inputs are selected and consequently the mismatch score is large, it is concluded that the corresponding sub-model has significant model-plant mismatch. The effectiveness of the proposed method was demonstrated through case studies of the distillation process and the CSTR process. The results have clearly shown that not only can the proposed method detect sub-models that have significant mismatch but it is superior to the other methods based on multivariate analysis.

The proposed method is now being applied to several industrial MPC systems to check its practicability; encouraging results have been obtained so far.

ACKNOWLEDGEMENTS

The authors express their appreciation to the task force "Workshop No.27" members of JSPS PSE 143rd committee for their constructive comments.

REFERENCES

Badwe, A., Shah, S., Patwardhan, S., and Patwardhan, R. (2008). Model-plant mismatch detection in MPC applications using partial correlation analysis. In *IFAC World Congress*, 14926–14933. Seoul, Korea.

Bauer, M. and Craig, I. (2008). Economic assessment of advanced process control – a survey and framework. *Journal of Process Control*, 18, 2–18.

Huang, B. (2008). Bayesian methods for control loop monitoring and diagnosis. *Journal of Process Control*, 18(9), 829–838.

Kano, M. and Ogawa, M. (2009). The state of the art in advanced chemical process control in Japan. In *IFAC Symposium on Advanced Control of Chemical Processes (ADCHEM)*, CD–ROM. Istanbul, Turkey.

Seborg, D., Edgar, T., and Mellichamp, D. (2004). *Process dynamics and control - 2nd ed.* John Wiley & Sons. Inc.

Wood, R. and Berry, M. (1973). Terminal composition control of a binary distillation column. *Chemical Engineering Science*, 28(9), 1707–1717.