MINIMUM DEVIATION ADAPTIVE CONTROL OF A BINARY DISTILLATION COLUMN

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Introduction

Ever since computers were introduced in chemical process control, a wide variety of advanced control techniques have been developed. Among others, one of fixed model-based control techniques, dynamic matrix control (DMC)[5], is most widely employed in the chemical industry because of its robustness and stable application. However, it lacks adaptability in process variation, and it is not suitable for nonlinear systems since the model is fixed and linear. One of the strategies to improve control performance for the nonlinear systems is to use an adaptive model which can be adjusted for process variation[10]. Even if an adaptive model is linear, linearization for a relatively short time does not produce a large error from the true model except in fast-changing processes. Therefore, the adaptive technique can be implemented in processes with variable parameters or nonlinearity.

In this study, a multivariable adaptive control technique minimizing the sum of absolute predictive errors is proposed and its performance is examined through simulation and experimental application to a binary distillation column. A multi-input/multi-output adaptive model is employed in the prediction of one-step future output and the sum of absolute errors between the predicted output and set point is minimized in order to improve small error rejection[11], which is useful to chemical processes. For the enhancement of control performance, two tuning parameters are introduced and their properties are investigated through simulation. Also, the performance of the proposed control scheme is surveyed in experimental application for set-point tracking and disturbance rejection. The results of the performance evaluation are compared with those of DMC.

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1. Control Scheme

1.1 Control objective

An adaptive multi-input/multi-output model is used as process model and the instrumental variable method[12] is employed in parameter estimation. Details of the model and the parameter estimation are given in Kim *et al.*[7]

When the sum of absolute error between set point and predicted output is minimized, the objective function is written as

$$\text{Min. } J = \sum_{i=1}^{m} w_i \left| y_{is}(k+1) - y_i(k+1) \right| \tag{1}$$

and process limitation on input variable is expressed as

$$\boldsymbol{u}_{min} \leq \boldsymbol{u}(k) \leq \boldsymbol{u}_{max} \tag{2}$$

The w_i in Eq. (1) is weight on output i. The weight adjusts not only magnitudes of each output error but also numerical value of objective function to be comparable to constraint. The value of w_1 is 100 and w_2 is 130. The same values were used in simulation and experiment.

The predicted outputs in Eq. (1) are replaced with the new outputs in the adaptive model where inputs of the present sampling step are unknown variables and are found from the minimization of control objective.

1.2 Implementation

Introducing artificial variables to the previous min-

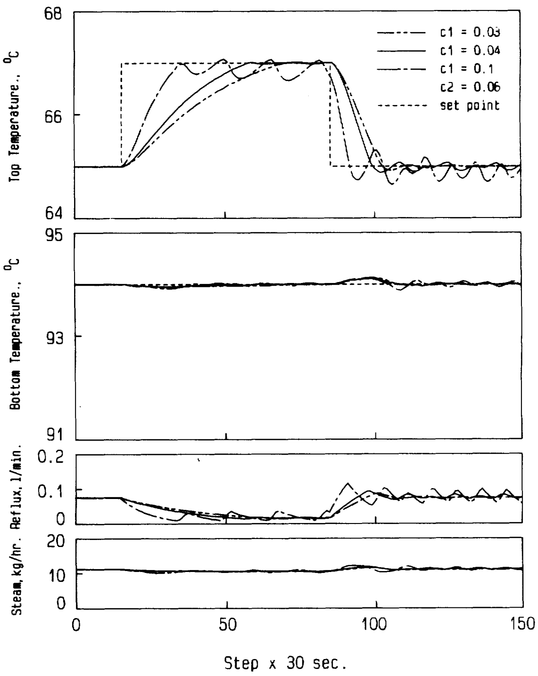

Fig. 1 Simulation result for top set-point change with different values of tuning parameter

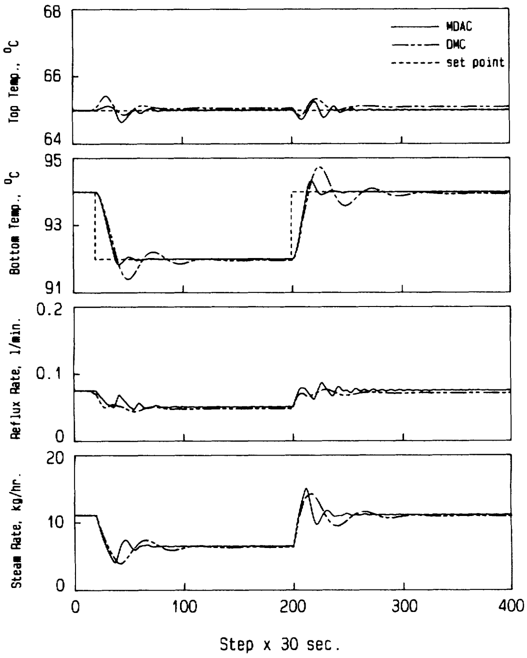

Fig. 2 Comparison of minimum deviation adaptive control with dynamic matrix control for bottom set-point change

imization problem makes linear programming applicable to the process of problem solving[2, 3]. Linear programming is simple to implement and gives fast solutions. Moreover, its convergence is assured in a wide variety of conditions not like the case for nonlinear procedures.

The transformed problem with the artificial variables is

$$\begin{aligned} \text{Min. } F &= \sum_{i=1}^{m} (p_i + q_i) \\ \text{s. t. } p_i - q_i &= w_i [y_{is}(k+1) - y_i(k+1)] \\ \boldsymbol{u}_{min} &\le \boldsymbol{u}(k) \le \boldsymbol{u}_{max} \end{aligned} \tag{3}$$

The second constraint is modified by replacing $\boldsymbol{u}$ with $\boldsymbol{u} - \boldsymbol{u}_{min}$ and it becomes a single inequality constraint. Even if the number of constraints is increased, computational time is very small compared with the 30-second sampling time of this study.

Since not all the model parameters are accurately estimated during closed-loop operation, leading to unstability of the system[1], some modification is necessary before the computed input is applied. A constant scale factor was used in the control experiments[6, 9] with a binary distillation column using a minimum variance regulator with adaptive model. In a similar manner, two modified constant scale factors are employed as tuning parameters and the applied input is obtained as

$$\boldsymbol{u}'(k) = \boldsymbol{c}_i [\boldsymbol{u}(k) - \boldsymbol{u}'(k-1)] + \boldsymbol{u}'(k-1) \tag{4}$$

More detail of the implementation is found in Kim and Sohn[8].

2. Results and Discussion

The performance of proposed minimum deviation adaptive control (MDAC) was investigated through simulation and experiment and its several features were discussed.

2.1 Simulation result

From the trial simulation, two marginal values were found: $c_1 = 0.04$ and $c_2 = 0.1$. To show the property of the parameters, three different values were applied in simulation and the result is shown in **Fig. 1**. A high value of the tuning parameter gives an oscillatory response as demonstrated in top temperature variation (single-dashed line). Since the constraint in control input computation limits input variation, runaway of top temperature is not observed, but persistent output alteration indicates that the control is unstable. Meanwhile, a smaller parameter than the marginal value gives very stable performance (double-dashed line).

From the simulation study the best performance was obtained at $c_1 = 0.03$ and $c_2 = 0.06$, and the performance of the proposed control with those parameters was compared with the result of DMC (**Fig. 2**). As indicated by the solid line, MDAC shows better performance than DMC (double dashed line). MDAC gives less overshoot and faster settlement to the new steady state than DMC. For numerical comparison of MDAC and DMC control performances, the sums of absolute errors between set point and measured output were computed for top and bottom set-point changes and feed flow rate change and are summarized in **Table 1**.

2.2 Experimental results

A six-inch distillation column with 10 bubble-cap

Table 1. Integral of absolute errors

case		simulation DMC step	simulation DMC IAE	simulation MDAC step	simulation MDAC IAE	experiment MDAC step	experiment MDAC IAE
set-point change							
top	y_1	200	59.0	200	71.0	352	175.7
	y_2	200	16.8	200	3.3	352	75.2
bottom	y_1	400	38.0	400	12.3	400	48.0
	y_2	400	85.3	400	44.6	400	144.3
feed flow change							
	y_1	200	17.3	200	6.3	320	68.1
	y_2	200	12.0	200	3.8	320	63.6

trays was used in experimental implementation of the proposed control scheme for top and bottom set point changes and feed flow rate change. The description of the column and the experimental procedure are given in Kim and Sohn[8].

Practical performance was investigated through experimental operation of a pilot-scale distillation column. Best-performance tuning parameters were obtained from simulation.

When the set point of top temperature varies, the set point tracking performance for both top and bottom temperatures is shown in **Fig. 3**. At the increased set point, oscillatory fluctuation is observed in both top and bottom temperatures, but its deviation is reduced as control proceeds and reaches a new set point. For the reduced set point much more stable performance was achieved compared with the raised set point. Slow tracking in the top set-point change due to the slow response of the column is shown, even though adjustment of the main manipulated variable, reflux flow rate, is followed right after the set point is altered. Similar delay is also shown in simulation (Fig. 1).

For the change of the set point of bottom temperature, the set point tracking performance is shown in **Fig. 4**. The outcome is better than in the case of top set-point change in both top and bottom temperatures. However, oscillatory input variation persists even after output settles at the new set point. It is not seen in top set-point change. Since the tuning parameter in the bottom loop, c_2, is twice that in the top loop, it is easy for the steam flow rate to oscillate when the bottom loop is disturbed. Though the steam flow rate oscillates, its amplitude diminishes slowly and slow settlement is expected.

An altered feed flow rate was applied in order to examine the regulatory performance of the proposed control scheme, and the results are included in Table 1. Disturbance was effectively rejected and no significant variation was observed in top an bottom temperatures.

2.3 Discussion

As mentioned earlier, a control objective to minimize absolute error instead of squared error helps to eliminate small errors fast. This is seen in the comparison with DMC through simulation as illustrated in Fig. 2. In the variation of top temperature with bottom set-

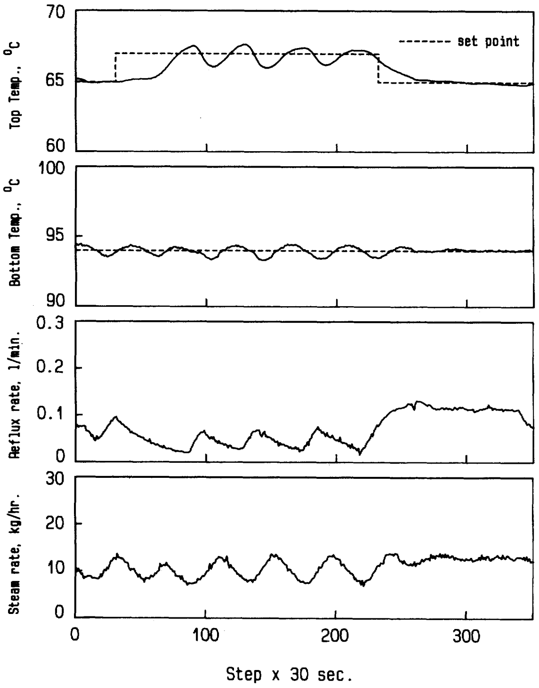

Fig. 3 Experimental result of minimum deviation adaptive control for top set-point change

point change, DMC does not eliminate small deviation. With MDAC, however, the small error diminishes in a short time.

One other advantage of minimum deviation control is that the simple linear programming technique is applicable. In simulation and experiment the technique was successfully implemented and carried out the control computation very quickly. Also, it does not have the convergence problem which is often encountered in nonlinear control procedures.

Tuning of the proposed control technique is simple because it has only two tuning parameters, which are determined from preliminary experimental data and simulation. One problem is that there is no criterion to adjust the parameters except that smaller values give stable performance and slow response, as shown in Fig. 1.

A graphical demonstration of performance comparison between MDAC and DMC is given in Fig. 2, but it is hard to see how much improved is the new technique. Accordingly, sums of absolute errors between set point and measured temperature for both techniques in top and bottom temperature variations and feed flow rate change were calculated and are summarized in Table 1 along with number of sampling steps. Overall, the total error of MDAC is 38 % less than with DMC. Also, sums of absolute errors in control experiment are given in the table. Average absolute error per step is 0.28°C for all cases. In the same distillation column, DMC was applied[4] and its average absolute error per step was 0.50°C. The numbers of total experimental steps in the two controls are different, so direct comparison of the two average errors does not give a definite answer. But it is evident that the proposed MDAC improved the con-

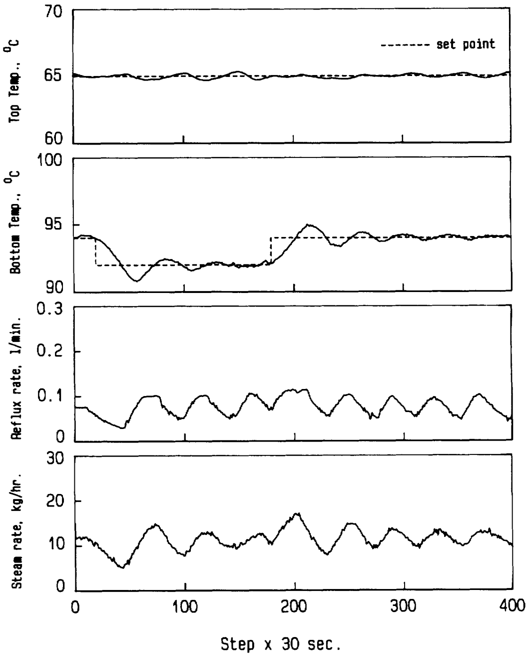

Fig. 4 Experimental result of minimum deviation adaptive control for bottom set-point change

trol performance in the experimental application as wall.

From the experimental application, on-line applicability of the proposed MDAC was also proved. That is very important for industrial implementation. In a word, the experimental result shows that the proposed control strategy gives good performance and its stable implementation shows that the new technique can be used for industrial processes.

Conclusion

An adaptive control technique to minimize the sum of absolute errors between set point and predicted process output was proposed and its performance was compared with the existing DMC procedure. Also, two tuning parameters for stable implementation of the proposed control scheme were introduced and their characteristic was investigated through simulation.

In simulation and control experiment, the proposed control scheme was successfully implemented. In addition, it was proved that a simple linear programming procedure is applicable and no convergence problem is involved in the implementation of the scheme. A stable on-line application of the technique to a real process was also exhibited through experimental application.

Acknowledgement

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Nomenclature

c	=	tuning parameter	[-]
F	=	modified control objective function	[-]
J	=	control objective function	[-]
k	=	time step	[-]
m	=	total number of output	[-]
p	=	artificial variable	[-]
q	=	time shift operator, artificial variable	[-]
$\mathbf{u}$	=	input vector	[-]
w	=	output error weight	[-]
$\mathbf{y}$	=	output vector	[-]
y_1	=	top tray temperature	[°C]
y_2	=	bottom temperature, reboiler temperature	[°C]

<Superscript>

$'$	=	adjusted value

<Subscripts>

i	=	output number
s	=	set point

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