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An Energy Effective PID Tuning Method for the Control of Polybutadiene Latex Reactor Based on Closed-loop Identification

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Abstract−The PBL (Polybutadiene Latex) production process is a typical batch process. Changes of the reactor characteristics due to the accumulated scaling with the increase of batch cycles require adaptive tuning of the PID controller being used. In this work we propose a tuning method for PID controllers based on the closed-loop identification and the genetic algorithm (GA) and apply it to control the PBL process. An approximated process transfer function for the PBL reactor is obtained from the closed-loop data by using a suitable closed-loop identification method. Tuning is performed by GA optimization in which the objective function is given by ITAE for the setpoint change. The proposed tuning method showed good control performance in actual operations.

Key words: PBL Process, PID Controller, GA Optimization, Closed-loop Identification

INTRODUCTION

Although many advanced control strategies have been developed including model-based control techniques [Chin et al., 2002; Arpornwichanop et al., 2002], the structurally simple proportional-integral-derivative (PID) controller is still widely used in industrial control systems [Astrom and Hagglund, 1995]. The use of PID control algorithms in various application fields stems from the fact that the PI or PID controller structure is simple and its principle is easy to understand; the performance of the PID control is robust and acceptable in a wide range of applications. Tuning of PID controllers has attracted the concern of many researchers. If the target process approximates to the first or second order model, the tuning parameters can be obtained by the Ziegler-Nichols (Z-N), Cohen-Coon, ITAE (Integral of the Time-weighted Absolute Error) and IMC (Internal Model Control) methods [Seborg et al., 1989]. An analytical derivative formula that enables one to compute optimal tuning parameters for the anti-derivative-kick PID controller was derived based on the well-known Levenberg-Marquardt optimization method [Sung et al., 2002]. A design method for PID controllers was proposed based on the direct synthesis approach and specification of the desired closed-loop transfer function for disturbances [Chen and Seborg, 2002].

So far, tuning of PID controllers has relied mainly on open-loop analysis. But usually the open-loop test is prohibited in operating plants, and disturbances and noises may cause unexpected control errors during closed-loop operation. For these reasons closed-loop identification has attracted much attention [Hof, 1997; Hjalmarsson et al., 1996]. The transfer function using the closed-loop identification was calculated for the bioreactor controlled by a PID controller [Pramod and Chidambaram, 2000]. In this calculation it was assumed that the target process was the FOPTD (First-Order Plus Time-Delay) model and noises in the closed-loop identification were not considered.

The PBL (Polybutadiene Latex) process considered in the present study is a typical nonlinear batch process and is controlled by PID controllers in cascade control structure. As operation batches proceed, dynamics of the process change and the control performance gets worse. But PID controllers with fixed tuning parameters are used during the whole operation cycle. For this reason, consistent product quality could not be achieved and the number of batches in one operation cycle was limited only to 44-47. Increase of the number of batches in one operation cycle while maintaining the product quality as desired is imperative to enhance the economics of the plant.

In the present study, we propose a tuning method for PID controllers and apply the method to control the PBL process in LG chemicals Co. located in Yeochun. In the tuning method proposed in the

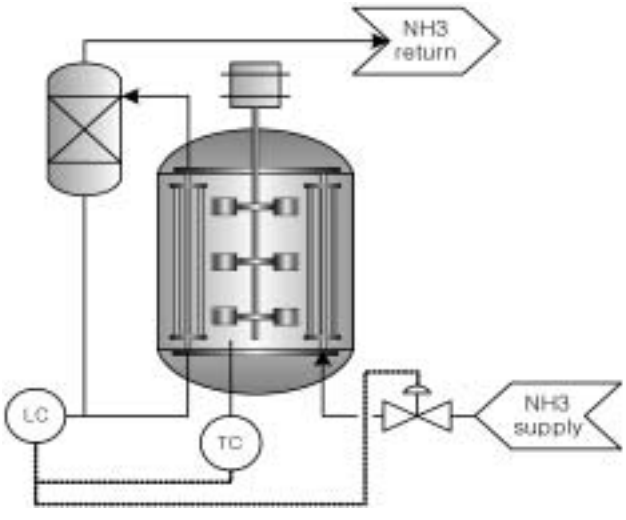

Fig. 1. Schematics of the PBL batch reactor.

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present work, we first find the approximated process model after each batch by a closed-loop identification method using operating data and then compute optimum tuning parameters of PID controllers based on the GA (Genetic Algorithm) method.

PBL REACTOR

Fig. 1 shows the schematics of the PBL reactor considered in the present study. Reaction begins with the injection of the reactant (Acrylonitrile butadiene styrene). The heat generated during the reaction is removed by the refrigerant (NH_3) flowing inside the internal tube. The reactor temperature is controlled by adjusting the level of the internal tube. As the operation batch is repeated, the polymer fouling is accumulated on the surface of the internal tube, causing decrease of cooling efficiency and poor control performance.

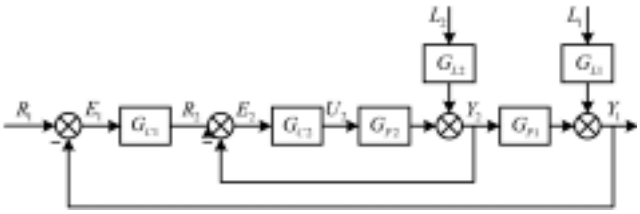

Fig. 2. Block diagram of the PBL reactor control system.

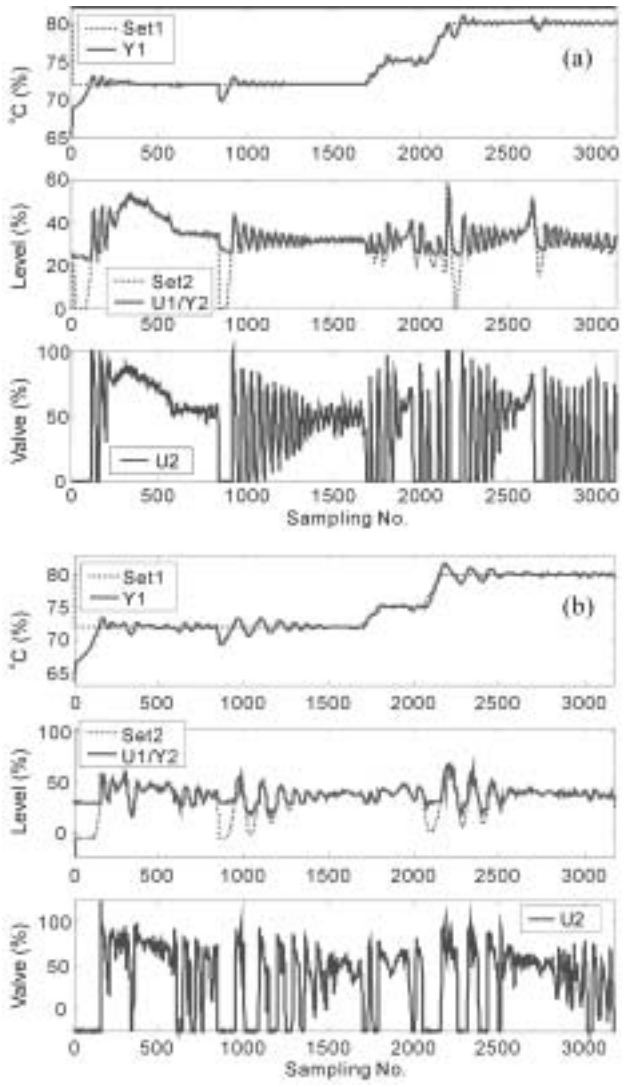

Fig. 3. Operation data of (a) 1st and (b) 35th batch.

The control structure of the PBL reactor is a typical cascade control system as shown in Fig. 2. The master controller (G_{C1}) determines the setpoint for the slave controller by comparing the present reactor temperature with the setpoint, and the slave controller (G_{C2}) regulates the refrigerant level of the internal tube to control the reactor temperature. In Fig. 2, G_{P2} represents the dynamic characteristics of the level of refrigerant (NH_3) and G_{P1} represents the dynamic characteristics of the reactor temperature due to the change of refrigerant level. In the actual operation, the same tuning parameters are used from the first batch to the last batch resulting in the poor control performance due to the change of reactor dynamics. Fig. 3 shows the typical operation data obtained at the 1st and 35th batch operation. It is obvious from the figure that the control performance is getting worse as the operation batch proceeds.

CLOSED-LOOP IDENTIFICATION

The identification of plant models has traditionally been done in the open-loop mode. The desire to minimize the production of the off-spec product during an open-loop identification test and to avoid the unstable open-loop dynamics of certain systems has increased the need to develop methodologies suitable for the system identification.

Open-loop identification techniques are not directly applicable to closed-loop data due to correlation between process input (i.e., controller output) and unmeasured disturbances. Based on Prediction Error Method (PEM), several closed-loop identification methods have been presented [Forssell and Ljung, 1999]: Direct, Indirect, Joint Input-Output, and Two-Step Methods.

However, these methods require a priori knowledge of the plant order and time delay. And, theoretically, the identifiability can be guaranteed under mild conditions. The newly developed so-called open-loop subspace identification method has been proven to be a better alternative to the traditional parametric methods. This is especially true for high-order multivariable systems, for which it is very difficult to find a useful parameterization among all possible candidates.

The subspace identification method has its origin in classical state-space realization theory developed in the 60's. It uses powerful tools such as Singular Value Decomposition (SVD) and QR factorization. No nonlinear search is performed, nor is a canonical parameterization used. There are many different algorithms in the subspace identification field, such as N4SID [Overschee and Moor, 1994], MOESP [Verhaegen and Dewilde, 1992; Verhaegen, 1994] and CVA [Larimore, 1990]. Recently, some researchers investigated the subspace identification method which calculates the state-space model (Eq. (1)) from the closed-loop data [Ljung and McKelvey, 1996].

$$x(t+1)=Ax(t)+Bu(t)+Ke(t) \quad (1)$$

$$y(t)=Cx(t)+Du(t)+e(t) \quad (2)$$

We can summarize the basic steps of the subspace identification

as follows:

1. Estimate states x(k), k=0, 1, 2, …, j−1 from measured process inputs and outputs.
2. Estimate the system matrices (A, B, C, D, K) from the estimated states by the following procedure:

i) Using LS method, estimate A, B, C and D and residual ρ_1=K [e(0) e(1) … e(j−2) and ρ_2=[e(0) e(1) … e(j−2) by

$$\begin{bmatrix} x(k+1) \\ y(k) \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} x(k) \\ u(k) \end{bmatrix} + \begin{bmatrix} Ke(k) \\ e(k) \end{bmatrix} \tag{3}$$

ii) From the residual, estimate K by

$$K = \rho_1 \rho_2^T [\rho_2 \rho_2^T]^{-1} \tag{4}$$

In the above steps, the state can be determined by using SVD. The future outputs are given by Eq. (5) with future inputs and noises being set to zero.

$$\begin{aligned} y(k+i) = &\sum_{m=1}^{na} CA^i H_m^y y(k-m) + \sum_{m=1}^{nb} CA^i H_m^u y(k-m) \\ &+ \sum_{m=1}^{i} CA^{i-m} Bu(k+m-1) + Du(k+i) \\ &+ \sum_{m=1}^{i} CA^{i-m} Ke(k+m-1) + e(k+i),\ i=0, 1, 2, \ldots, i-1 \end{aligned} \tag{5}$$

If the test data sets are gathered from open-loop tests, we can apply the LS method to Eq. (5). The solutions are unbiased since the process inputs are uncorrelated with process noise terms. But, if the process input is a function of the process noise as in the closed-loop test, the solution for $CA^iH_m^y$, $CA^iH_m^u$, $CA^{i-m}B$ and D would be biased. For this reason, application of subspace identification methods for the closed-loop test gives biased estimation results regardless of the accuracy of the next steps. This is the main problem in the application of the subspace identification method for the closed-loop system.

We can assume D=0 since most processes have at least one delay between the process output and the process input. Then, Eq. (5) becomes

$$\begin{aligned} y(k+i) = &\sum_{m=1}^{na} CA^i H_m^y y(k-m) + \sum_{m=1}^{nb} CA^i H_m^u u(k-m) \\ &+ \sum_{m=1}^{i} CA^{i-m} Bu(k+m-1) \\ &+ \sum_{m=1}^{i} CA^{i-m} Ke(k+m-1) + e(k+i),\ i=0, 1, 2, \ldots, i-1 \end{aligned} \tag{6}$$

If i=0, Eq. (6) becomes a high order ARX (Auto-Regressice with eXogeneous) input model as

$$y(k) = \sum_{m=1}^{na} CH_m^y y(k-m) + \sum_{m=1}^{nb} CH_m^u u(k-m) + e(k) \tag{7}$$

It should be noted that the process input u(k−1) is a function of the past process outputs y(k−m), m=1, 2, …, na for usual feedback controllers and that the process inputs u(k−m), m=1, 2, …, nb are uncorrelated with e(k). Therefore, if we apply the LS method to the ARX model given by Eq. (7), we can obtain unbiased estimates of P_y, P_u for CH_m^y and CH_m^u.

$$\hat{y}(k) = \sum_{m=1}^{na} P_y y(k-m) + \sum_{m=1}^{nb} P_u u(k-m) \tag{8}$$

$$\begin{bmatrix} y(k|k) & y(k+1|k+1) \ldots & \hat{y}(k+j-1|k+j-1) \\ y(k+1|k) & y(k+2|k+1) \ldots & \hat{y}(k+j|k+j-1) \\ y(k+2|k) & y(k+3|k+1) \ldots & \hat{y}(k+j+1|k+j-1) \\ \vdots & \vdots \quad \ddots & \vdots \\ y(k+j-1|k) & y(k+1|k+1) \ldots & \hat{y}(k+i+j-2|k+j-1) \end{bmatrix}$$

$$= \begin{bmatrix} U_1 & U_2 \end{bmatrix} \begin{bmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix} = U_1 \Sigma_1 V_1^T \tag{9}$$

The elements of the first column in Eq. (9) can easily be obtained from Eq. (8). Subsequent steps for state estimation and the system matrix estimation are exactly the same as those of subspace identification methods. These methods do not require knowledge on the order and the time delay of the process.

The PBL reactor considered in the present study is a typical batch process and the open-loop test is inadequate to identify the process. We employed a closed-loop subspace identification method which is similar to that proposed by Ljung and McKelvey [1996]. This method identifies the linear state-space model using high order ARX model.

To apply the linear system identification method to the PBL reactor, we first divide a single batch into several sections according to the injection time of initiators, changes of the reactant temperature and changes of the setpoint profile, etc. Each section is assumed to be linear. The region divided by the arrows in Fig. 4 represents each section to be modeled. The initial state values for each section should be computed in advance. The linear state models obtained for each section were evaluated through numerical simulations.

The PID controllers being used in the PBL plant can be represented by

$$E(k) = Y(k) - R(k)$$

$$\begin{aligned} MV(k) = \frac{1}{P}\Big[&E(k) - E(k-1) + \frac{dT}{1} E(k) \\ &+ \frac{D}{dT}\{Y(k) + Y(k-2) - 2Y(k-1)\} \Big] \end{aligned} \tag{10}$$

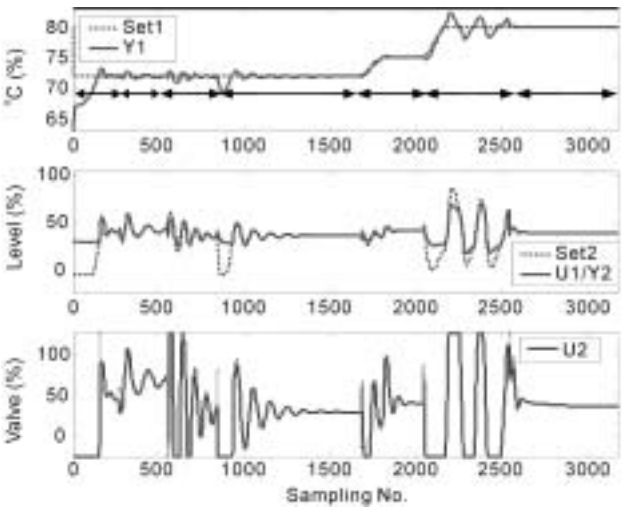

Fig. 4. Simulation results of closed-loop response (35th batch).

Results of closed-loop simulations are shown in Fig. 4. As for tuning parameters, values used in actual operations were used (the master controller: P=5%, I=1,300 sec, D=0.2 sec, for the slave controller: P=200%, I=3 sec, D=0.6 sec). Compared with plant operation data shown in Fig. 3, we can see the effectiveness of the model obtained by the closed-loop identification method.

GENETIC TUNING OF PID CONTROLLERS

The genetic algorithm has attracted the attention of many researchers and found its application especially in optimization studies. The main advantage of the use of the genetic algorithm in optimizations lies in improved possibility of finding the global optimum [Goldber, 1989]. In the present study, the ITAE was chosen as the objective function to achieve minimal control errors. The optimization problem to determine optimal tuning parameters can be represented as

$$\underset{P,I,D}{\text{Min}}\ \text{ITAE} = \int_0^\infty t|e(t)|dt \tag{11}$$

subject to $P_{low}<P<P_{upper}$

$I_{low}<I<I_{upper}$

$D_{low}<D<D_{upper}$

Tuning parameters (P, I, D) for the PID controller are obtained by the genetic optimization consisting of selection, mutation and crossover operations.

Optimization methods based on the gradient information such as QP (Quadratic Programming) and SQP (Sequential Quadratic Programming) etc. often reach a local minimum depending on the choice of initial values [Choi and Manousiouthakis, 2002]. The possibility of reaching a local minimum increases if we confine the output of the PID controller within a certain range (for example, 0 : 100%) or if we use a modified PID controller based on the integral anti-windup or anti-derivative-kick technique. For this reason the GA (Genetic Algorithm) is our choice for the optimization. In the solution of an optimization problem by using the GA's, the key steps to be followed can be summarized as:

1. A chromosomal representation of solution to the problem.
2. Creation of an initial population of solutions.
3. Evaluation of a function that plays the role of the environment, rating solution in terms of their "fitness".
4. Choice of a set of operators used to manipulate the genetic composition of the population.
5. Determination of parameter values used in GA (population size, probabilities of applying genetic operators).

Details on the GA can be found elsewhere [Goldber, 1989]. Determination of PID tuning parameters by GA can be summarized as follows:

Step 1. Create the initial population for tuning parameters (P, I, D).

Step 2. Calculate ITAE for step response using closed-loop control system about the approximated process model ($\hat{G}_P$).

Step 3. If the criterion is satisfied, stop computation. If not, go to the next step.

Step 4. Select the superior chromosomes that have low ITAE value.

Step 5. Create the new population (P, I, D) using crossover/mutation.

Step 6. Compute the ITAE value for the closed-loop control system based on the results of step 5 and go to step 3.

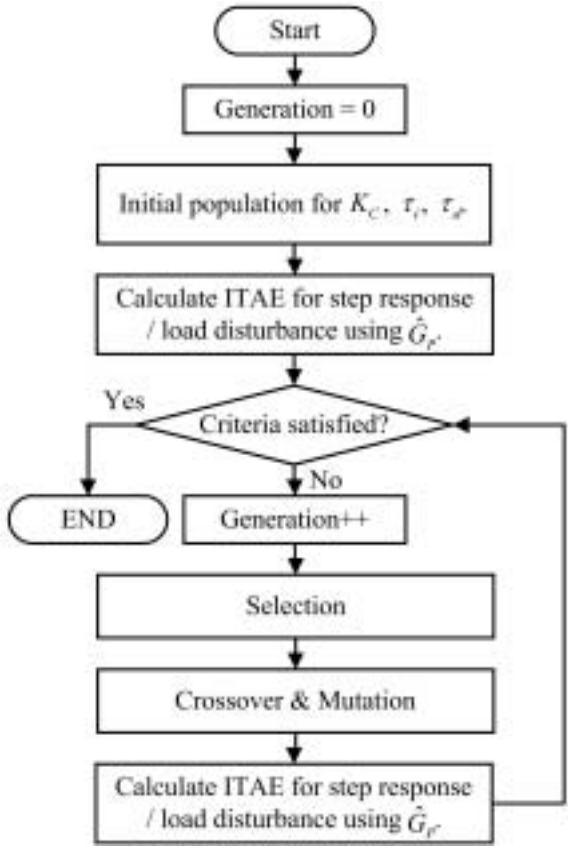

Fig. 5. Flow diagram of GA tuning of the PID controller.

The schematic diagram showing the GA tuning for the PID controller is given in Fig. 5.

RESULTS AND DISCUSSIONS

In the present work only the tuning of the parameters of the master controller is considered. The process model is identified based on the operation data of 35th batch for illustration. The operation data of any other batch can be used and identification and tuning after each batch would be most desirable. The computation time is 2 minutes on a platform based on the Pentium 5, which is quite acceptable for on-line application considering the cleaning and charging time of 20 minutes. On-line identification and tuning after each batch is planned in the plant. Fig. 6 shows the results of closed-loop simulations with the PID parameters of the master controller being tuned by GA tuning method described above. We can see the improved control performance compared with the results shown in Fig. 4. Remember that the control parameters used in Fig. 4 are those being used in actual operations without GA tuning.

There are 11 reactors in the PBL plant considered in the present study, and only two reactors among them (they are denoted as reactor A and reactor B hereafter) were selected for the test application. Table 1 shows the tuning parameters of the master controller. The

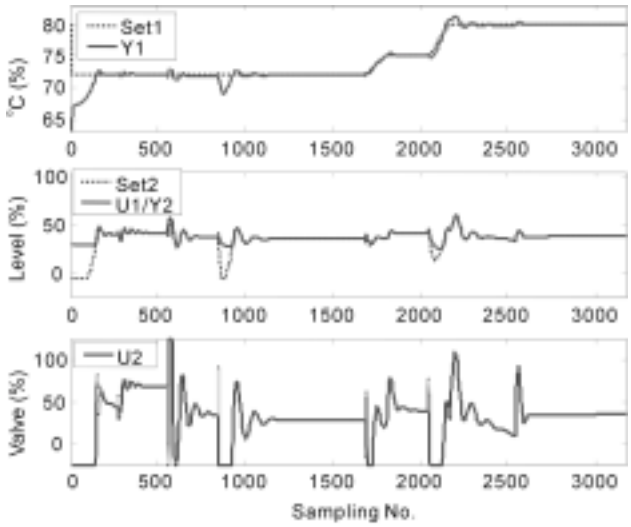

Fig. 6. Simulation result of GA tuning.

3rd column shows the controller parameters being used in actual operations. The 4th, 5th and 6th column show the values of tuning parameters obtained from the closed-loop identification and GA optimization based on the operation data of 1st, 26th and 35th batch, respectively. Values in the 7th column are the average values of the previous three columns and are used in the 10th batch of the reactor A and 16th batch of the reactor B. Inconsistent values of P, I and D indicate that the master controller should be tuned after each batch.

Fig. 7 shows results of operations of the reactor A. Fig. 7(a) shows the results of operation at the 9th batch with the parameters without tuning, i.e., the parameters used in the 1st batch are still being used. Fig. 7(b) shows the results of operation at 10th batch with the parameters tuned by the closed-loop identification and GA optimization method (see Table 1). As can be seen, oscillations are suppressed and the movement of the valve is more stabilized. For comparison, the parameters used in the 9th batch were used again in the 11th batch (Fig. 7(c)). From Fig. 7, we can see clear improvement of the control performance with the use of GA tuning method.

Fig. 8 shows results of operations of the reactor B. Fig. 8(a) and (c) show the results of operation at 15th and 17th batches, respectively, without tuning, i.e., the parameters used in the 1st batch are still being used. By tuning the parameters based on the closed-loop identification and GA method as before, we could achieve better control performance (Fig. 8(b)).

CONCLUSIONS

Closed-loop identification and GA optimization were used to tune the parameters of the PID controller used in the PBL (Polybutadiene Latex) reactor. The one cycle of operation consists of 44-47 batches. We first identify the model of the PBL reactor by the closed-loop identification followed by the determination of PID parameters using the GA optimization method. The process model is identified based on the single batch operation data for illustration. The operation data of any batch can be used and identification and tuning after each batch would be most desirable. The computation time is 2 minutes on the platform based on the Pentium 5, which is quite acceptable for on-line application considering the cleaning and charging time of 20 minutes. On-line identification and tuning after each batch is planned in the plant. The proposed tuning method showed good control performance in actual operations.

ACKNOWLEDGMENT

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NOMENCLATURE

A, B, C, D : n-dimensional system matrixs
CVA : canonical variate analysis
e : white noise
GA : genetic algorithm
G_C : transfer function of the controller
G_P : transfer function of the process
$\hat{G}_P$: transfer function of the approximated process
ITAE : integral of the time-weighted absolute error
K : matrix of kalman gain
K_C : controller gain
K_{cu} : ultimate gain
MOESP : multivariable output-error state space identification
N4SID : numerical algorithms for subspace state space system identification
PID : proportional-integral-derivative controller
R : reference signal

Table 1. Tuning parameters for the master controller

Section		Values used in operations	Optimum values			Parameters applied
RE_A			1st batch	26th batch	35th batch	10th batch*
	P (%)	5.0	6.5	5.5	5.9	6.0
	I (sec)	1300	3219	3197	3048	3200
	D (sec)	0.2	1.7	0.7	1.1	1.2
RE_B			1st batch	20th batch	43th batch	16th batch*
	P (%)	5.0	8.9	4.7	3.6	6.8
	I (sec)	1300	2105	2980	2010	2550
	D (sec)	0.2	0.8	1.5	1.0	1.2

*: reactor to which corresponding parameters were applied.

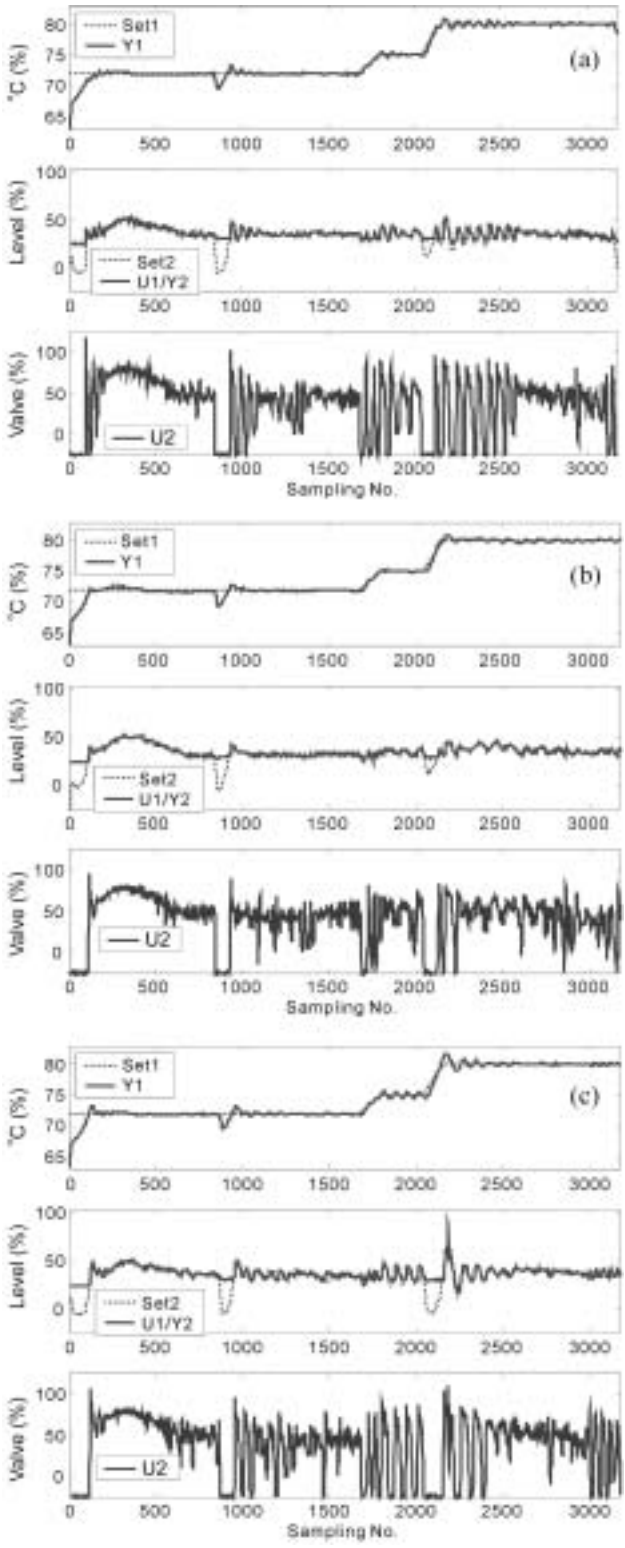

Fig. 7. Results of closed-loop operations (reactor A).
(a) 9th batch: without tuning, (b) 10th batch: GA tuning, (c) 11th batch: without tuning

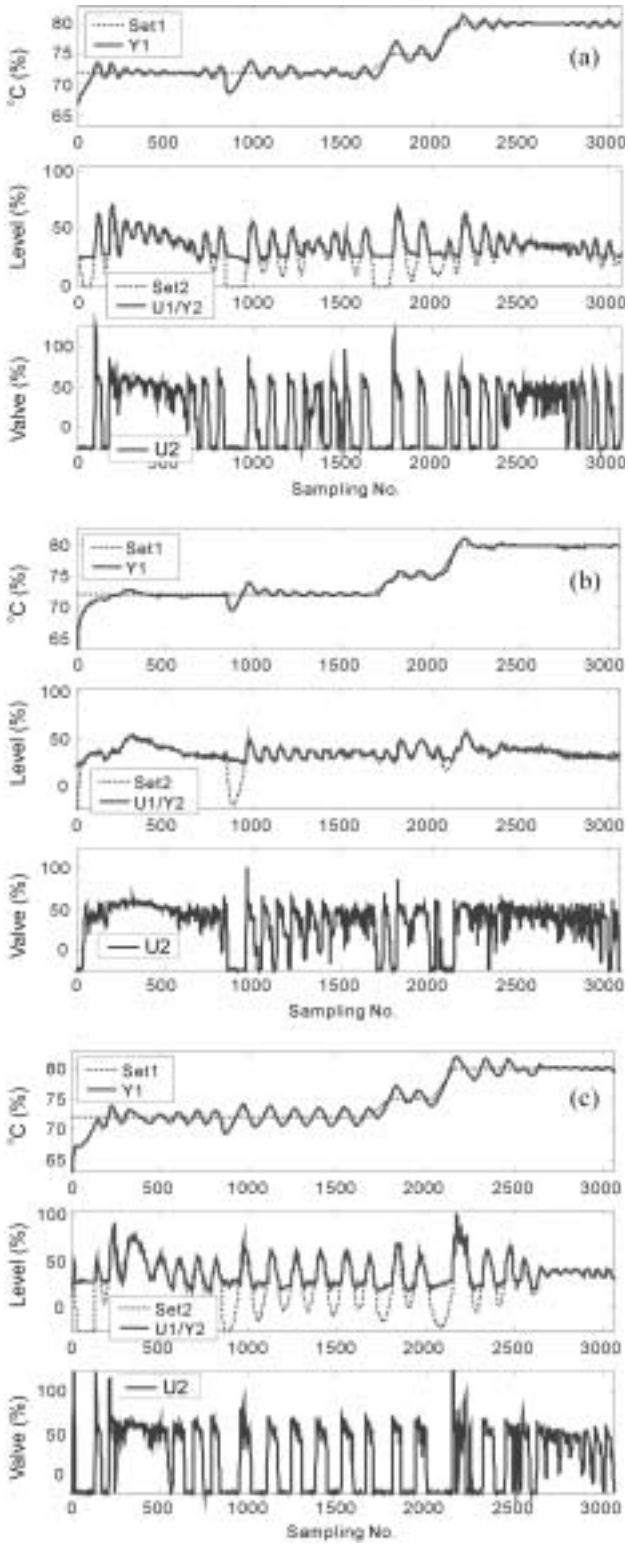

Fig. 8. Results of closed-loop operations (reactor B).
(a) 15th batch: without tuning, (b) 16th batch: GA tuning, (c) 17th batch: without tuning

t : time [sec]
u, U : process input or controller output
x : n-dimensional state vector
y, Y : process output

Greek Letters

ρ : residual
τ_i : integral time of the controller
τ_d : derivative time of the controller

REFERENCES

Arpornwichanop, A., Kittisupakorn, P. and Hussain, M. A., "Model-based Control Strategies for a Chemical Batch Reactor with Exothermic Reactions," *Korean J. Chem. Eng.*, **19**, 221 (2002).

Astrom, K. J. and Hagglund, T., "PID Controllers: Theory, Design & Tuning," 2nd Ed., IAS Research Triangle Park, NC (1995).

Chen, D. and Seborg, D. E., "PI/PID Controller Design Based on Direct Synthesis and Disturbance Rejection," *Ind. Eng. Chem. Res.*, **41**(19), 4807 (2002).

Chin, I. S., Chung, J. W. and Lee, K. S., "Model Predictive Control of a Fixed-bed Reactor with Nonlinear Quality Inference," *Korean J. Chem. Eng.*, **19**, 213 (2002).

Choi, S. H. and Manousiouthakis, V., "Global Optimization Methods for Chemical Process Design: Deterministic and Stochastic Approaches," *Korean J. Chem. Eng.*, **19**, 227 (2002).

Forssell, U. and Ljung, L., "Closed-loop Identification Revisited," *Automatica*, **35**, 1215 (1999).

Goldber, D. E., "Genetic Algorithms in Search, Optimization and Machine Learning," Addison-Wesley (1989).

Hjalmarsson, H., Gevers, M. and de Bruyne, F., "For model-based Control Design, Closed-loop Identification Gives Better Performance," *Automatica*, **32**(12), 1659 (1996).

Larimore, W. E., "Canonical Variate Analysis in Identification, Filtering and Adaptive Control," Proc. of the 29th Conference on Decision and Control, CDC 90, HI, 596 (1990).

Ljung, L. and McKelvey, T., "Subspace Identification from Closed Loop Data," *Signal Processing*, **52**, 209 (1996).

Pramod, S. and Chidambaram, M., "Closed Loop Identification of Transfer Function Model for Unstable Bioreactors for Tuning PID Controllers," *Bioprocess Eng.*, **22**, 185 (2000).

Seborg, D. E., Edgar, T. F. and Mellichamp, D. A., "Process Dynamics and Control," John Wiley & Sons, New York, 272-309 (1989).

Sung, S. W., Lee, T. and Park, S., "Optimal PID Tuning Method for Single-Input/Single-Output Processes," *AIChE J.*, **48**(6), 1358 (2002).

van den Hof, P. M. J., "Closed-loop Issues in System Identification," Proceedings of the 11th IFAC Symposium on System Identification, Fukuoka, Japan, **4**, 1651 (1997).

Van Overschee, P. and De Moor, B., "N4SID: Subspace Algorithms for the Identification of Combined Deterministic and Stochastic Systems," *Automatica*, **30**, 75 (1994).

Verhaegen, M., "Identification of the Deterministic Part of MIMO State Space Models," *Automatica*, **30**, 61 (1994).

Verhaegen, M. and Dewilde, P., "Subspace Identification, Part I: The Output-error State Space Model Identification Class of Algorithms," *Int. J. Control*, **56**, 1187 (1992).