# Control of pH Processes Based on the Genetic Algorithm

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**Abstract−**In this work, we propose a PID control strategy based on the genetic algorithm coupled with cubic spline interpolation method for the control of pH processes. The control scheme proposed in the present work consists of closed-loop identification based on the genetic algorithm and cubic spline method. First, we compute the parameters ($K_C$, $\tau_I$, $\tau_D$) of the PID controller using relay feedback and apply these parameters to control the pH Process. Then approximate linear models corresponding to each pH range are obtained by the closed-loop identification based on closed-loop operation data. The optimal parameters of the PID controller at each pH region are then computed by using the genetic algorithm. From numerical simulations and control experiments we could achieve better control performance compared to the conventional fixed gain PID control method.

Key words: pH Process, Closed-loop Identification, Genetic Algorithm, Cubic Spline Method, PID Controller

## INTRODUCTION

PID (Proportional-Integral-Derivative) controllers are most widely used in various operational fields. But it is well known that they are not efficient in the control of nonlinear processes. In this work, we propose a new gain scheduling PID control strategy based on closed-loop identification and genetic tuning method coupled with cubic spline interpolation method for the control of pH processes. The pH process is a typical nonlinear chemical process and the control of the process has attracted concerns of many researchers.

Klatt and Engell [1996] proved experimentally that gain scheduling trajectory control is more efficient control strategy compared to the PI control. In their experiments the pH region tested was 6-10 which can be approximated linearly. It was shown that gain scheduling based on fuzzy theory exhibits improved control performance than conventional PID controllers and that the performance of a well tuned PID controller is as good as that of a model predictive control scheme especially in thermal control problems [Blanchett et al., 2000]. Application of the artificial neural network to control pH processes has been reported [Loh et al., 1995]. They divided the system into static and dynamic parts and proved that the controller shows good control performance for various external noise variables. The authors designed a PID controller based on the artificial neural network and showed experimentally that the controller gives good performance both for load change and set point change to pH processes [Kwon and Yeo, 1999]. The pH control problem based on the adaptive bilinear model predictive control has been investigated both theoretically and experimentally [Kim et al., 2000]. Zhang [2001] constructed a nonlinear type controller that was coupled with some local nonlinear controllers by using neural networks and fuzzy schemes. Control commands are obtained from the union of local controllers based on the membership function of the local linear models.

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 operations. The closed-loop identification has attracted much attention [Van den Hof, 1997; Hjalmarsson et al., 1996]. The reason may be that the plant is unstable, or that it has to be controlled for production, economic, or safety reasons. Moreover, the operation data can be directly used to identify the plant model without additional treatment. Ljung and McKelvey [1996] investigated the subspace identification method which calculates the state-space model from the closed-loop data. They proposed a new closed-loop identification method that showed better performance than existing N4SID.

In the gain scheduling control scheme proposed in this work the PID controller parameters ($K_C$, $\tau_I$, $\tau_D$) are first obtained from the relay feedback. These preliminary controller parameters are employed in the control of a pH process, and closed-loop operation data is collected. From the closed-loop identification we get approximate linear models for each range of pH values. These linear models are used in the computation of optimum tuning parameters based on the genetic algorithm. These optimal tuning parameters are interpolated by the cubic spline method to be applied to the gain scheduler.

## pH NEUTRALIZATION PROCESS

The pH process is widely used in various areas such as the neutralization of industrial waste water, the treatment of boiler feed water and cooling water in the cooling tower, and the maintenance of the desired pH level at various chemical reactions, coagulation and precipitation processes. The pH process shows high nonlinearity during the titration of strong acids by strong bases. In the control of pH processes, very small values of controller gains are required in the neutralization of strong acid by strong base. On the other hand,

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[‡] This paper is dedicated to Professor Hyun-Ku Rhee on the occasion of his retirement from Seoul National University.

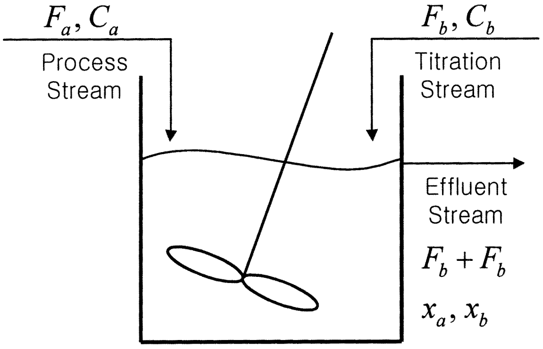

**Fig. 1. pH neutralization process.**

the change in the compositions and concentrations of fluids flowing into the reactor causes large changes in the process gain. For this reason the use of conventional PID controllers requires very small operational range to achieve acceptable control performance.

The model of the pH neutralization process used in this study follows that proposed by McAvoy et al. [1972] as shown in Fig. 1. Assumption of perfect mixing is general in the modeling of pH processes. Material balances in the reactor can be given by

$$V\frac{dx_a}{dt}=F_aC_a+(F_a+F_b)x_a$$

$$V\frac{dx_b}{dt}=F_bC_b+(F_a+F_b)x_b \tag{1}$$

where $C_a$ represents the concentration of the acid inlet stream, $C_b$ represents the concentration of base used in the neutralization, $x_a$ and $x_b$ are the concentration of acid ion and base ion in the reactor, respectively. $F_a$ denotes the flow rate of acid inlet stream, $F_b$ represents the flow rate of base used in the neutralization and V is the volume of the reactor.

The phosphoric acid ($H_3PO_4$) and the sodium hydroxide (NaOH) are used in the experiments. The phosphoric acid in water decomposes into a phosphoric ion and three hydrogen ions. At 298 K, dissociation constants for each ion are given by

$$H_3PO_4 \leftrightarrow H^+ + H_2PO_4^-,\ K_{a1}$$
$$=[H^+][H_2PO_4^-]/[H_3PO_4]=7.11\times10^{-3} \tag{2}$$

$$H_2PO_4^- \leftrightarrow H^+ + HPO_4^{2-},\ K_{a2}$$
$$=[H^+][HPO_4^{2-}]/[H_2PO_4^-]=6.34\times10^{-8} \tag{3}$$

$$HPO_4^{-2} \leftrightarrow H^+ + PO_4^{3-},\ K_{a3}=[H^+][PO_4^{3-}]/[HPO_4^{2-}]=4.2\times10^{-13} \tag{4}$$

The equilibrium constant of water at the same temperature is $K_w=10^{-14}$. Reaction invariants can be written as

$$x_a=[H_3PO_4]+[H_2PO_4^-]+[HPO_4^{2-}]+[PO_4^{3-}] \tag{5}$$

$$x_b=[Na^+] \tag{6}$$

The equilibrium equation for ions from which pH is calculated is given by

$$\begin{aligned}&10^{-5pH}+(K_{a1}+x_b)\times10^{-4pH}+(K_{a1}x_b+K_{a1}K_{a2}-K_w-K_{a1}x_a)\times10^{-3pH}\\&+(K_{a1}K_{a2}x_b+K_{a1}K_{a2}K_{a3}-K_{a1}K_w-2K_{a1}K_{a2}x_a)\times10^{-4pH}\\&+(K_{a1}K_{a2}K_{a3}x_b-K_{a1}K_{a2}K_w-3K_{a1}K_{a2}K_{a3}x_a)\times10^{-4pH}-K_{a1}K_{a2}K_{a3}K_w=0\end{aligned} \tag{7}$$

Fig. 2 shows the titration curve obtained from the above model at several pH regions.

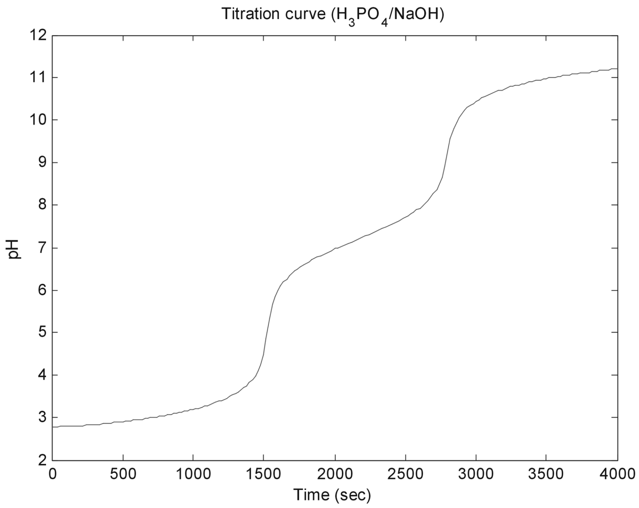

**Fig. 2. Titration curve ($H_3PO_4$/NaOH).**

## CLOSED-LOOP IDENTIFICATION METHOD

In the use of the ultimate gain method the increase of the gain to reach the critical point might drive the system to the unstable region. The relay feedback method is introduced as a substitute for the ultimate gain method. This method is also called auto-tuning method. This method is widely used in most commercially available PID controllers.

First, a relay feedback signal generator replaces the controller. The output of the relay feedback signal generator is represented as

$$m(t)=\begin{cases} d & \text{for } e(t)=-c(t)>0\\ -d & \text{for } e(t)=-c(t)<0\end{cases} \tag{8}$$

where d is the output of the controller multiplied by 0.5, e is the error and c is the output of the process. The ultimate gain $K_{cu}$ is then given by

$$K_{cu}=\frac{4d}{\pi A} \tag{9}$$

where A is the amplitude of the process output. PID parameters can be easily determined by conventional tuning methods such as the Ziegler-Nichols method:

$$K_c=K_{cu}/1.7,\ \tau_I=P_u/2.0,\ \tau_D=P_u/8.0 \tag{10}$$

where $P_u$ is the ultimate period.

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 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 the correlation between process inputs (i.e., controller outputs) and unmeasured disturbances. Based on Prediction Error Method (PEM), several closed-loop identification methods have been presented [Forssell and Ljung, 1999]: direct,

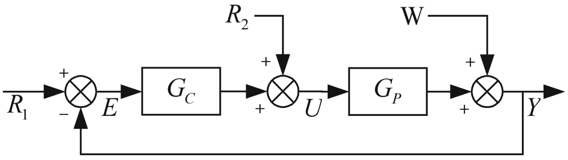

**Fig. 3. Block diagram of a closed-loop system.**

indirect, joint input-output, and two-step methods.

1. Direct method: Data from the closed-loop test are treated as if they were from open-loop operations. PEM is applied to the data set ignoring the presence of the feedback. Only input U and output Y are needed to perform the identification.

2. Indirect method: First, the closed-loop transfer function is obtained by using the signal $R_1$ and Y or $R_2$ and Y since the external injected signal will be uncorrelated with the noise in the output. Then, the controller transfer function is used to extract the process transfer function from the closed-loop transfer function (Fig. 3).

3. Joint input-output method: Closed-loop system is considered as a black box with fictitious white noise signal. The external input signal is considered as the input and the process input U and output Y as the output. Since the newly defined input and output will not be correlated, the joint model can be identified accurately.

4. Two-step method: The so-called sensitivity function is obtained from the external signal R and the process input U. The noise free process input is reconstructed from this sensitivity function and then used with the process output to identify the process model.

However, the methods described above require a priori knowledge on the plant order and time delay. The identifiability can be guaranteed under mild conditions. The newly developed, so-called the 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 the powerful tools such as Singular Value Decomposition (SVD) and QR factorization. No nonlinear search is performed nor is a canonical parameterization used. The advantages of the subspace identification method can be summarized as follows:

1. No prior model set assumption: In subspace identification algorithms, we use full state space models and the only "parameter" is the order of the system, which can be obtained by inspection of certain singular values. When using the traditional PEM method, a model set is needed and what one gets from the identification is, in fact, only the best model in this particular model set.

2. Numerical Efficiency: This method is not iterative and so there are no convergence problems. By using the always numerically reliable SVD, numerical robustness of the identification procedure can be guaranteed. By using QR factorization, the efficiency can be greatly improved.

3. Model reduction: Complex models can describe a system more accurately, but, at the same time, they are more difficult to apply. What we try to find is the simplest model that can describe the system fairly well. In the subspace identification, the reduced model can be obtained directly, without having to be constructed from the high order model.

There are many different algorithms in the subspace identification field, such as N4SID [Van Overschee and Moor, 1994], MOESP [Verhaegen and Dewilde, 1992] and CVA [Larimore, 1990].

Recently, Ljung and McKelvey [1996] investigated the subspace identification method which calculates the state-space model [Eq. (11)] from the closed-loop data.

$$x(t+1)=Ax(t)+Bu(t)+Ke(t) \tag{11}$$

$$y(t)=Cx(t)+Du(t)+e(t) \tag{12}$$

We can summarize the basic steps of 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 using one of the following methods:

Method 1:

i) Using LS (Least Squares) method, estimate C and D from Eq. (12). The residual is e(k), k=0, 1, 2, …, j−2.

ii) Using LS method, estimate A, B and K for the Eq. (11) (note that we know the residual e(k) from the previous step).

Method 2:

i) Using LS method, estimate A, B, C and D and residuals $\rho_1$=K [e(0) e(1) … e(j−2)] and by $\rho_2$=K[e(0) e(1) … e(j−2)]

$$\begin{bmatrix} x(k+1) \\ y(k) \end{bmatrix} = \begin{bmatrix} A\ B \\ C\ D \end{bmatrix} \begin{bmatrix} x(k) \\ u(k) \end{bmatrix} + \begin{bmatrix} Ke(k) \\ e(k) \end{bmatrix} \tag{13}$$

ii) From the residuals, estimate K by

$$K=\rho_1\rho_2^T[\rho_2\rho_2^T]^{-1} \tag{14}$$

In the above steps, we decide the state by SVD. The future outputs are given by the following equation with future inputs and noises being set to zero:

$$\begin{aligned} y(k+i) &= \sum_{m=1}^{na} CA^i H_m^y y(k-m) + \sum_{m=1}^{nb} CA^i H_m^u u(k-m) \\ &+ \sum_{m=1}^{i} CA^{i-m} Bu(k+m-1) + Du(k+i) \\ &+ \sum_{m=1}^{i} CA^{i-m} Ke(k+m-1) + e(k+i)\ ,\ i=0, 1, 2, \ldots, i-1 \end{aligned} \tag{15}$$

If the test data sets are gathered from open-loop tests, we apply the LS method to Eq. (15). 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. Therefore, subspace identification methods for the open-loop test give biased estimation results regardless of the accuracy of each step. This is the main problem in the subspace identification method for the closed-loop system.

We can assume D=0 for usual processes since almost all processes have at least one delay between the process output and the process input. Then, Eq. (15) becomes

$$\begin{aligned} y(k+i) &= \sum_{m=1}^{na} CA^i H_m^y y(k-m) + \sum_{m=1}^{nb} CA^i H_m^u u(k-m) \\ &+ \sum_{m=1}^{i} CA^{i-m} Bu(k+m-1) \\ &+ \sum_{m=1}^{i} CA^{i-m} Ke(k+m-1) + e(k+i)\text{ , i=0, 1, 2, …, i}-1 \quad (16) \end{aligned}$$

If i=0, Eq. (16) becomes a high order ARX (Auto-Regressive with exogenous) input model as

$$y(k) = \sum_{m=1}^{na} CH_m^y y(k-m) + \sum_{m=1}^{nb} CH_m^u u(k-m) + e(k) \quad (17)$$

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 LS method to the ARX model given by Eq. (17), we obtain unbiased estimates of $P_y$, $P_u$ for and $CH_m^y$.

$$\hat{y}(k) = \sum_{m=1}^{na} P_y y(k-m) + \sum_{m=1}^{nb} P_u u(k-m) \quad (18)$$

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

$$= [U_1 \ \ U_2] \begin{bmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix} = U_1 \Sigma_1 V_1^T \quad (19)$$

The elements of the first column in Eq. (19) can easily be obtained from Eq. (18). Subsequent steps for the state estimation and the system matrix estimation are exactly the same with those of previous subspace identification methods for open-loop test. Those methods do not require knowledge on the order and the time delay of the process.

In order to adapt the method to a nonlinear pH control process, we first perform control of the pH process at broad range of pH using a conventional PID controller to get closed-loop data. In this case large control errors might result due to the nonlinearity of the process. The overall pH region is inherently nonlinear, but the narrow region can be approximated as linear. We can divide the data according to pertinent pH regions and calculate parameters of the linear state space model through closed-loop identification.

## GENETIC TUNING METHOD

The genetic algorithm has been investigated and employed especially in optimization studies for more than 30 years. The main advantage of the use of the genetic algorithm in optimizations lies in improved possibility of finding the global optimum [Goldberg, 1989; Kim et al., 2001]. As the objective function in the optimization, both ITAE (Integral of Time-Averaged Error) and ISE (Integral of Squared Error) are widely used. The ITAE criterion can be effectively used when the errors persist for long time periods. In the pH control process, frequent change of the magnitude of errors with respect to time, rather than persistence of errors, make the control problem very complicated. In the optimization of the present study, the ISE was chosen as the objective function to achieve minimal control errors:

$$\min \text{ ISE} = \int_0^\infty e(t)^2 dt \quad (20)$$

$$\begin{aligned} \text{subject to } & K_{C,\,low} < K_C < K_{C,\,upper} \\ & \tau_{I,\,low} < \tau_I < \tau_{I,\,upper} \\ & \tau_{D,\,low} < \tau_D < \tau_{D,\,upper} \end{aligned}$$

Tuning parameters ($K_C$, $\tau_I$, $\tau_D$) 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 to local minimum depending on the choice of initial values. For this reason GA is our choice for the optimization. In the solution of an optimization problem by using the GA 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).

First, a population of individuals is created. In its simplest form each individual in the population consists of a string of binary digits which may also be referred to as bits. Chromosomes are bit strings - lists of 0’s and 1’s. There are a variety of techniques for mapping bit strings to different problem domains. The initial population of individuals is generated randomly within certain boundaries. Each individual is run in the current environment to determine its effectiveness which is assigned a numerical evaluation of its merit by a fitness function. The fitness function determines how each gene (bit) of an individual will be interpreted.

There are many properties of the evaluation function that enhance and hinder GA performance. Therefore, each structure is evaluated according to specific domain criteria and assigned a measure of rating or “utility”. All the individuals in the population have been evaluated and their fitnesses are used as the basis for selection, which is determined by the standard deviation. Selection probabilities are then computed for each structure based on its utility, with proportionally higher probabilities assigned to higher utility structure. As a result, selection is implemented by eliminating low-fitness individuals from the population and inheritance is implemented by making multiple copies of high-fitness individuals.

Genetic operations such as mutation, crossover and inversion are applied probabilistically to the selected individuals to produce a new population (or generation) of individuals. Crossover takes two selected current generation structures, splits the string at the same randomly determined point and then creates the new generation structures by swapping the tail portion of the string. Mutation, on the other hand, randomly changes a bit in a structure thereby introducing a new individual. This operation is assigned a very low percentage of action, causing it to function as a background operation. By transforming the previous set of good individuals to a new one, the operator generates a new set of individuals that have a better than average chance of also being good. Each combination of genetic operators, representation, and problem has it own characteristics. Tuning of PID parameters by GA can be summarized as follows:

Step 1. Create the initial population for tuning parameters ($K_C$, $\tau_I$, $\tau_D$).

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

Step 3. If the criteria are satisfied, stop computation. If not, go to the next step.

Step 4. Select superior chromosomes that have low ISE value.

Step 5. Create the new population ($K_C$, $\tau_I$, $\tau_D$) using crossover/mutation.

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

The schematic diagram showing the GA tuning for the PID controller is given in Fig. 4.

In the computation of parameters for the PID controller ($K_C$, $\tau_I$, $\tau_D$) to be used in the state space model, GA is used to minimize the ISE (Integral of Squared Error), i.e., to minimize the discrepancy between the process output and the set point. The reason we use GA in this work lies in the fact that the optimization methods based on the information of gradients such as SQP (Successive Quadratic Programming) can fail in the identification of the optimum values.

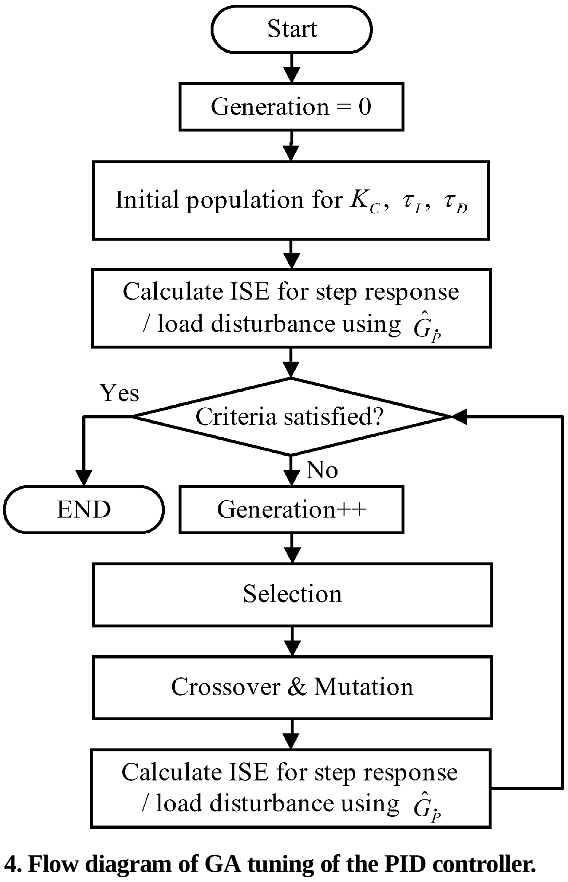
Start
Generation = 0
Initial population for $K_C$, $\tau_I$, $\tau_D$
Calculate ISE for step response / load disturbance using $\hat{G}_P$
Yes
Criteria satisfied?
No
END
Generation++
Selection
Crossover & Mutation
Calculate ISE for step response / load disturbance using $\hat{G}_P$

**Fig. 4. Flow diagram of GA tuning of the PID controller.**

Cubic spline is one interpolation method that connects each data point in soft curved line. The optimum values of control parameters ($K_C$, $\tau_I$, $\tau_D$) for each interval pH region are obtained by using the cubic spline method to apply to the gain scheduler.

## NUMERICAL SIMULATIONS

In the simulations MATLAB and SIMULINK were employed for the pH control process. The sampling time was set to 5 sec and the time delay of sensor to 5 sec. Random noises of ±0.1% to pH were assumed.

First, we applied the relay feedback signal in the range of pH 7-8, and then we obtained the ultimate gain and ultimate period from which control parameters ($K_C$, $\tau_I$, $\tau_D$) were calculated by Ziegler-Nichols method. Next, we changed the set point by making use of the same control parameters as before. As can be seen in Fig. 5, we have poor control performance because of the use of inappropriate control parameters. The good control performance for the set point of pH 7-8 is compared to the poor control results when the set point lies in the region of 5 or 10.

The control data shown in Fig. 5 were classified according to the pH regions. The linear process models for each region were obtained by using the closed-loop identification method. For each linear model we set up the PID controller and calculated the control pa-

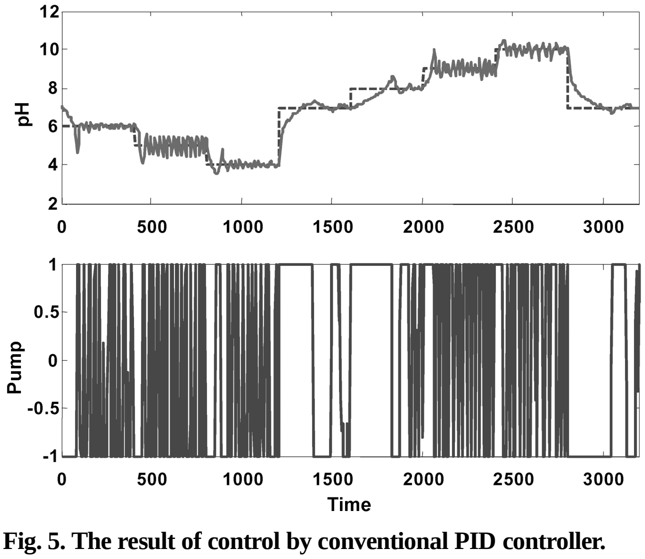

**Fig. 5. The result of control by conventional PID controller.**

**Table 1. Optimal parameters of the PID controller at each pH region**

| | | | |
|---|---|---|---|
| pH≅4.0 | $K_C$=6.13 | $\tau_I$=48.90 | $\tau_D$=0.39 |
| pH≅5.0 | $K_C$=4.85 | $\tau_I$=24.02 | $\tau_D$=1.01 |
| pH≅6.0 | $K_C$=8.70 | $\tau_I$=105.67 | $\tau_D$=1.84 |
| pH≅7.0 | $K_C$=8.71 | $\tau_I$=199.94 | $\tau_D$=2.23 |
| pH≅8.0 | $K_C$=8.22 | $\tau_I$=200.21 | $\tau_D$=0.52 |
| pH≅9.0 | $K_C$=6.57 | $\tau_I$=73.80 | $\tau_D$=1.63 |
| pH≅10.0 | $K_C$=4.02 | $\tau_I$=198.32 | $\tau_D$=1.05 |

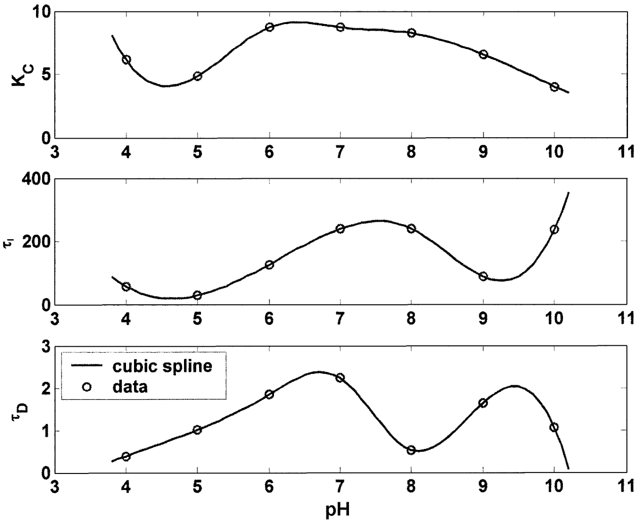

**Fig. 6. Changes of controller parameters ($K_C$, $\tau_I$, $\tau_D$).**

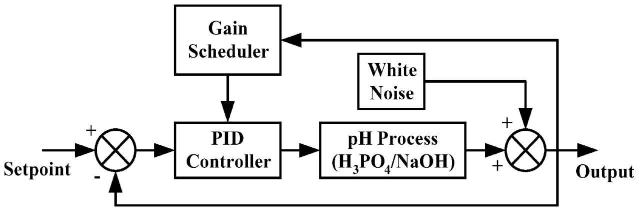

**Fig. 7. Schematic of the PID control based on gain scheduling.**

rameters from the minimization of ISE by GA. The numerical results are shown in Table 1.

The next step is the proper interpolation by the cubic spline to obtain optimum control parameters for each pH region listed in Table 1. Fig. 6 shows the change of each parameter ($K_C$, $\tau_I$, $\tau_D$) in the region of pH 4-10 and Fig. 7 shows the structure of the feedback control loop using a cubic spline interpolation for the gain scheduler. The gain scheduler receives the current pH value as an input and gives the optimum control parameters as outputs. These parameters are then plugged into the PID controller. Fig. 8 depicts the results of PID controls by using gain scheduling and shows better control performance compared to the conventional PID controller (Fig. 5). We can see that the PID control parameters at each pH region are properly changed.

## EXPERIMENTS

Fig. 9 shows the experimental equipment used in the present study. In the experiment we used phosphoric acid and sodium hydroxide as acid and base, respectively. Phosphoric acid was fed to the reactor with constant flow rate and NaOH was introduced to the reactor through the pump being controlled by the gain scheduling controller. Concentrations of phosphoric acid and NaOH were $C_a$=0.02 mol/L and $C_b$=0.05 mol/L respectively. The flow rate of phosphoric acid was kept constant as $F_a$=0.1188 L/min while the range of the flow rate of NaOH was $F_b$=0.0-0.2532 L/min.

In the experiment a PC with Pentium III processor (650 MHz) was used and the control algorithm developed in the present work

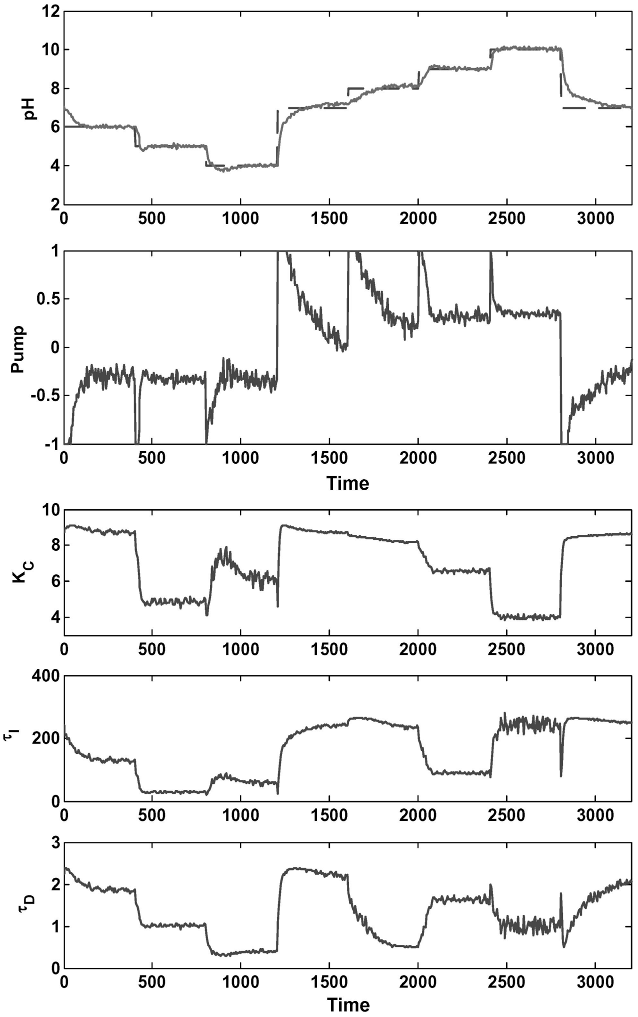

**Fig. 8. The results of PID control using gain scheduling.**

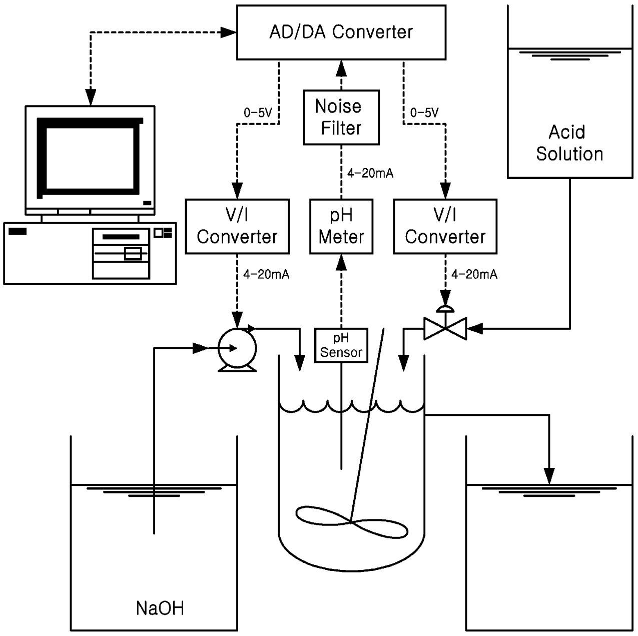

**Fig. 9. Experimental apparatus.**

was implemented by using SIMULINK of MATLAB. The volume of the reactor was 2 L and sampling time was set to 2 sec.

Fig. 10 shows the results of control experiments by the conventional PID controller. The controller parameters were obtained by using the ultimate gain method of Ziegler-Nichols based on the amplitudes and ultimate periods at pH 7. The controller parameters were obtained by using the ultimate gain method of Ziegler-Nichols

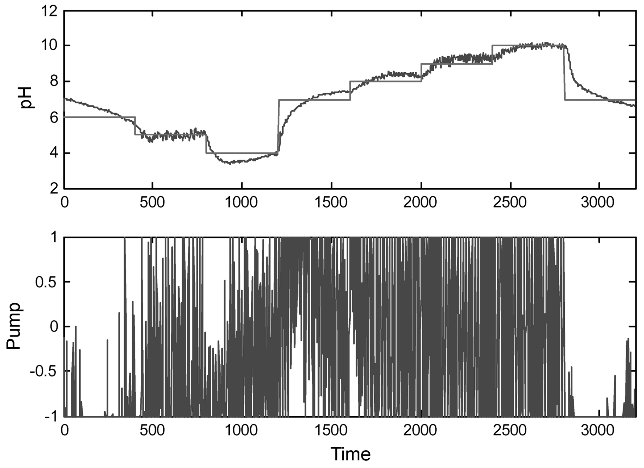

Fig. 10. Results of conventional PID control (ISE=921.52).

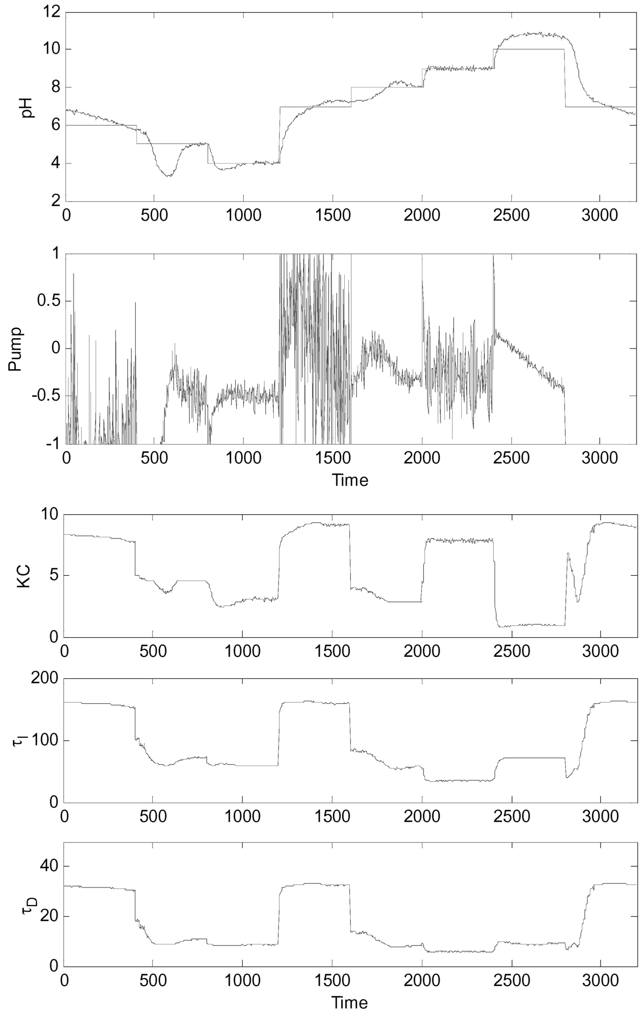

Fig. 11. Results of PID control using gain scheduling (ISE=1776.55).

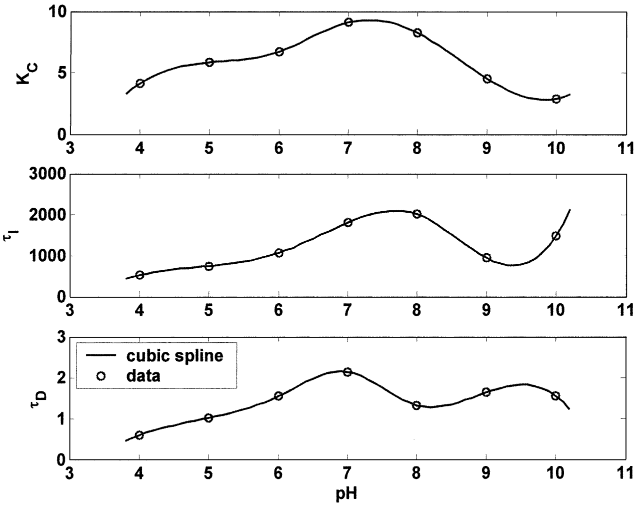

Fig. 12. Changes of controller parameters ($K_C$, $\tau_I$, $\tau_D$).

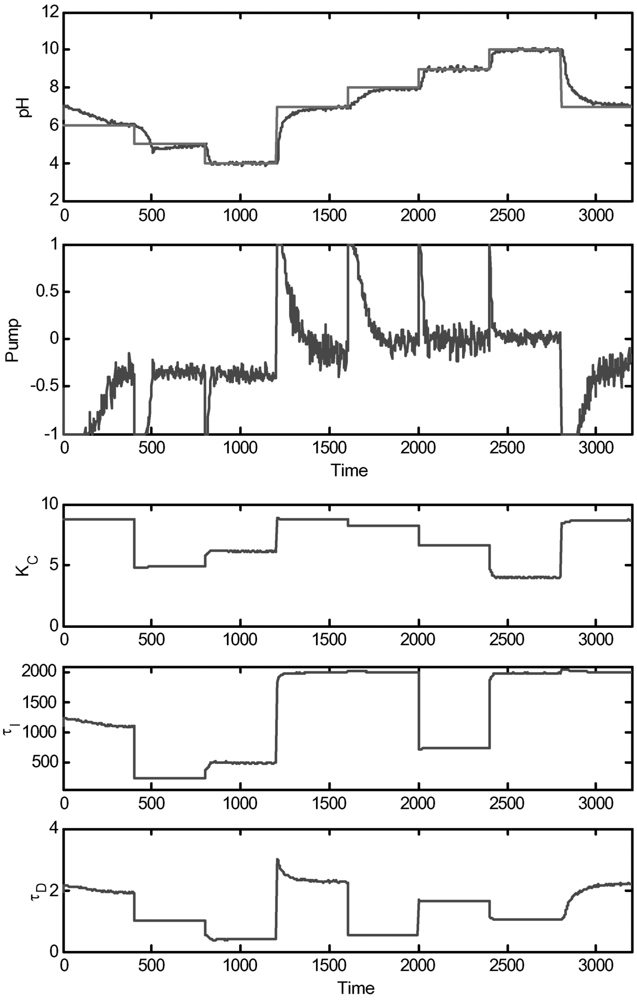

Fig. 13. Result of PID control using gain scheduling and GA (ISE=701.2).

based on the amplitudes and ultimate periods at pH 7. Control errors in experiments are indicated by ISE. The radical behavior of the pump as shown in the Fig. 10 reflects the noise of the electrical signal generated by the differential term (D) in PID parameters.

Fig. 11 represents the results of gain scheduling control experiments based on the cubic spline interpolation of the PID parameters obtained from the relay feedback. We can see the proper changes in the PID controller parameters according to the changes in pH. Even with the smooth behavior in the pump compared to the conventional PID control (Fig. 10) the control performance is not satisfactory. Fig. 12 shows the change of each parameter ($K_C$, $\tau_I$, $\tau_D$) in the region of pH 4-10 with GA tuning and Fig. 13 shows the experimental results of gain scheduling control coupled with GA. Approximate process models at each predefined pH region were obtained first by the closed-loop identification method using the experimental input-output data (Fig. 10) previously obtained. Then the optimal parameters of the PID controller to be implemented were computed by using GA. Optimal parameters were interpolated with cubic spline method. In this case, we could obtain better control performance (the ISE is 701.2) compared to previous cases. We can see that the behavior of the pump was much stabilized.

## CONCLUSIONS

A new control technique based on the genetic algorithm and the closed-loop identification was developed and applied to control the pH process experimentally. The control scheme proposed in the present work consists of relay feedback followed by closed-loop identification and gain scheduling based on the genetic algorithm and the cubic spline method. First, we compute the parameters ($K_C$, $\tau_I$, $\tau_D$) of the PID controller using relay feedback and apply these parameters in the gain scheduling control. Then approximate linear models corresponding to each pH range are obtained by the closed-loop identification based on previous input-output data. The optimal parameters of the PID controller at each pH region are computed by using the genetic algorithm based on previous models. Interpolation of the parameters by the cubic spline method is then followed. From numerical simulations and control experiments we could achieve better control performance compared to the conventional PID control method.

## ACKNOWLEDGMENT

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## NOMENCLATURE

| | |
|---|---|
| C | : concentration [mol/L] |
| $C_a$ | : concentration of input acid [mol/L] |
| $C_b$ | : concentration of base to titration [mol/L] |
| F | : influent stream flow rate [L/min] |
| $F_a$ | : influent stream flow rate of acid [L/min] |
| $F_b$ | : influent stream flow rate of base L/min] |
| GA | : genetic algorithm |
| $K_C$ | : P parameter of PID controller |
| PID | : proportional-integral-derivative controller |
| $P_u$ | : period of controller |
| t | : time [min] |
| $x_a$ | : reaction invariant of acid |
| $x_b$ | : reaction invariant of base |
| V | : volume of reactor [L] |

### Greek Letters

| | |
|---|---|
| $\tau_I$ | : I parameter of PID controller |
| $\tau_D$ | : D parameter of PID controller |

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