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Experimental Study of a Combined Global/Local Control System Robust to Model Inaccuracy for Sensitive Nonlinear Systems

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Abstract—Chemical processes are nonlinear. Processes with extremely high nonlinearities, such as neutralization and high-purity distillation, are very important and need special consideration. The basic problem with such nonlinear processes is that the performance of model-based control is very sensitive to model inaccuracy. It seems that robust control is impossible with pure model based control algorithms. Model predictive control (MPC) has been widely implemented in the chemical industry. However, not very many successful cases of implementing nonlinear models can be found in the literature. In addition, when such a model is inaccurate, high-frequency oscillation appears across the sensitive region. On the other hand, an accurate model is expensive and frequently impossible since operating data in the sensitive region are scarce. The above factors lead to unacceptable control results. To solve the above problem, we propose a combined global/local control (GLC) in which, when disturbances occur, the global control (GC, MPC in this study), a nonlinear controller, steers the process under control into or near the sensitive region; then, the local control (PI in this study) takes over and finally settles the process at the desired set point. Both simulation and experimental results show that such a combination control is economical. In this study, unlike our previous research, a PI controller was implemented, because PI control can be easily tuned for the sensitive region and a model of moderate accuracy for other non-sensitive regions can be built with much less effort.

Key Words : Model inaccuracy, Global/local control, Model predictive control, Sensitive nonlinear system, PI controller

INTRODUCTION

Model predictive control has been mature for many years. In recent years, many simulations (e.g., Ricker and Lee, 1995; Manner *et al.*, 1996) and experimental works (e.g., Halggblom, 1993; Wright and Edgar, 1994) showed that nonlinear predictive control can be a better control mode than a linear control. In addition, MPC is important because it provides a general control mode in which material and/or energy conversion of equipment and control devices can be considered as a whole in the design of a control system. The basic idea behind MPC is to use a model to forecast the future output of controlled variables and calculate the manipulated actions, in order to minimize the difference between the predicted trajectory and forecasted output. In the case of a nonlinear system, it is intuitive to implement a nonlinear empirical model, such as an artificial neural network (ANN) model (e.g., MacMurray and Himmelblau, 1995; Hussain, 1999), to pursue better performance. However, the performance of an MPC scheme is closely related to the accuracy of the process model. Very poor performance occurs if the system is very sensitive to modeling error as pointed out by the authors (Tsai *et al.*, 2002). Since modeling

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error is inevitable, the following two steps are necessary to guarantee the performance of MPC: (1) identify the inaccuracies of the model; (2) improve the robustness of the MPC. Lin and Jang (1998) presented a systematic ANN approach based on information theory in order to cope with the above mentioned problems. However, it may be very expensive and even impossible to use such an approach because of the high expensive of on-line experiments. In this work, we present appropriative control schemes with comparatively low experimental cost to solve the above difficulties.

Krishnapura and Jutan (2000) developed a neural adaptive controller (NAC) to accommodate mode uncertainty. Their NAC is computationally fast and works as a general auto-tuning feedback controller, thus it does not require any process knowledge. For a nonlinear process with fast system responses, however it turns out to be unsatisfactory (Tsai *et al.*, 2002).

In many chemical processes, such as neutralization and distillation, severe nonlinearity and high sensitivity exist. In the past, some researchers (e.g., Astrom and Hagglund, 1988; Williams *et al.*, 1990; Chan and Yu, 1995) used classical control theory, e.g., PID (proportional-integral-derivative control) theory to control the pH system. A PID controller works well for a linear system, but for a nonlinear and sensitive system, its performance is poor. It has been reported that ANN models work well in pH control processes (Palancar *et al.*, 1996, 1998). However, in the case of a highly uncertain and sensitive model, it is quite difficult for an MPC to track set-point changes. Mahmoud and Mohammad (2000) and Ylostalo *et al.* (2001) used multiple models through controller switching to achieve better performance. Nevertheless, until now, few satisfactory results for pH processes have been reported in the literature. The reason is that a neutralization process always operates in a very sensitive region where a small change in a manipulated variable will have in a tremendous effect on the controlled variable. This phenomenon happens all the time in the region about the equivalence point. A traditional proportional-integral (PI) controller can be tuned in the sensitive region using a small gain, as reported by Chan and Yu (1995), and Ho *et al.* (1995). However, such a controller may become sluggish if the process is operated in non-sensitive regions. Some studies (e.g., Yeo and Kwon, 1999) use gain-scheduling technique to solve this problem. Nonlinear MPC with robust performance is desirable. The problem with a nonlinear MPC is that of finding an "accurate" empirical model that can cover a sufficiently large region of operation and to be extremely accurate in the sensitive area. Such models, however, are expensive and frequently impossible to employ since operating data in the sensitive region are scarce.

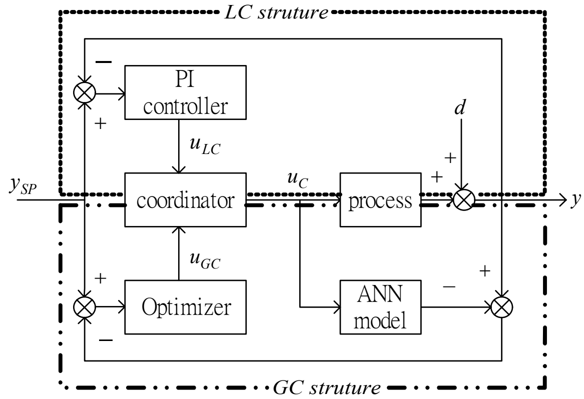

Fig. 1. Diagram of the global/local control system.

To solve the above problem, Tsai *et al.* (2002) developed a robust model predictive control scheme through regional knowledge analysis of ANN. They proposed a coordinate controller that harmonizes each other to make the final control decision. The coordinator is composed of an MPC and an NAC. The concepts behind the controller are novel and simulation results obtained have been positive, but experimental results have not been encouraging because NAC is very sensitive to measurement noise. Since PI controllers have been successfully used in industrial, we replace the NAC with the PI controller to construct a combined global/local control system to handle the pH control system. In the combined controller, the MPC is viewed as a global control, and the PI controller is regarded as a local control. When a disturbance occurs, the global control is used to steer the process under control into or near the sensitive region; then the local control takes over the task of finally settling the process at the desired set point. Both simulation and experimental results showed that such a combination is more economical, because PI control can be easily tuned for a sensitive region and a model of moderate accuracy for other non-sensitive regions can be built with much less effort. Furthermore, it should be noted that this is the first study, in which experimental results were obtained using a global/local controller.

THEORY

The global/local combined controller

A combined global/local control system comprises an MPC and a PI control as depicted in Fig.1. Despite the complexity and nonlinearity of the system, the design of an ANN model only requires the input/output data. In order to investigate the dynamic behaviors of a pH control system, firstly, an ANN model can be implemented instead of first principal model. Next, an optimizer based on the ANN model can be used to generate the controller actions of the global control model. That is to say, we can adopt an MPC (Tasi *et al.*, 2002) containing an ANN model and an optimizer as the global controller. The objective function J of the optimizer is as follows:

$$\underset{\Delta u_{GC}(k),\Delta u_{GC}(k+1),\ldots,\Delta u_{GC}(k+c)}{\mathrm{Min}}\left[\sum_{t=k}^{k+p-1}(y_{SP}(t+1) - y(t+1)+h_{GC}(t))^2+\sum_{t=k}^{k+c}w(\Delta u_{GC}(t))^2\right] \quad (1a)$$

subject to

$$\begin{cases} u_{GC,min} \le u_{GC} \le u_{GC,max} \\ \Delta u_{GC,min} \le \Delta u_{GC} \le \Delta u_{GC,max} \end{cases}, \quad (1b)$$

where y_{SP} is the set point value, y is the controlled variable, u_{GC} is the manipulated variable of the global controller, $u_{GC,min}$ and $u_{GC,max}$ are the lower ad upper limits, respectively, of u_{GC}, w is the penalty factor used to suppress excessive control actions, p is the prediction horizon, c is the control horizon, and $h_{GC}(t)$ is the deviation value between $y(t)$ and $y_{\mathrm{MPC}}(t)$, *i.e.*,

$$h_{GC}(t)=y(t)-y_{\mathrm{MPC}}(t) \quad (2)$$

As indicated in our previous work (Tasi *et al.*, 2002), an MPC is nearly perfect if the model/plant mismatch is negligible. However, the results is usually in a longer settling time if the plant/model mismatch becomes larger, *i.e.* the robust problem becomes important. According to the analysis of many authors (e.g., Ricker and Lee, 1995; MacMurray and Himmelblau, 1995), the robust control issue exists on a case-by-case, and hence there exists no general rule exists. It is necessary to provide an extra assistance to support the MPC control to solve this problem.

It is intuitive to seek an easily tuned controller as a partner for the MPC controller. Of course, a classical control, for example, a PI controller is the primary candidate rather than an NAC controller. The major reasons are: (1) it is the most widely used controller in most industries, and (2) the tuning rule of a PI controller is better known than that of NAC. In the study, we implemented a PI controller as the local controller in our combined control approach as follows:

$$u_{LC}(t)=K_C\left(1+\frac{T_S}{\tau_I(1-z^{-1})}\right)\times (y_{SP}(t+1)-y(t+1)), \quad (3)$$

where K_C is the proportional gain, τ_I is the integral constant, and T_S is the sampling period. The disadvantages of an NAC controller will be shown in our experimental results discussed later (Fig. 12).

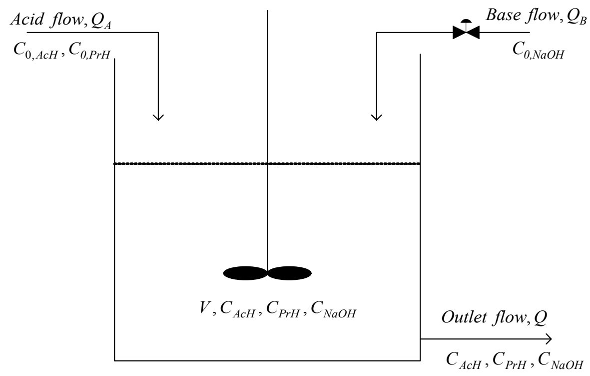

Fig. 2. Diagram of the simulated neutralization CSTR.

For the proposed combined control system, a coordinator is inserted into the scheme to conjugate the two controllers. In the following section, a coordinator will be introduced.

The coordinating rule

The concept behind the Parzen-Rosenblatt (Haykin, 1999) probability density function is used to estimate the reliability of the model. For simplicity, the probability decision factor Ψ is defined as

$$\Psi=\Psi(f_{\{x\}}(x_{new}))=\frac{1}{b-a}f_{\{x\}}(x_{new})-\frac{a}{b-a}, \quad a<f_{\{x\}}(x_{new})\le b, \quad (4)$$

where x_{new} represents the input variables of the ANN model, and a and b are constants. From Haykin's work (Haykin, 1999), $f_{\{x\}}(x_{new})$ is defined as the probability density estimator from the new event x_{new} based on the training data set. Then a coordinating rule is defined and used to make the final decisions regarding the combined controllers system:

$$u_C=\Psi\times u_{GC}+(1-\Psi)\times u_{LC}, \quad (5)$$

where u_C is the control action of the combined global/local control system.

The neutralization system

Neutralization reactions are widely used in chemical industries. The pH control system has been widely studied because the model benefits from highly sensitive and nonlinear operating conditions. Many researchers have tried to solve the pH control problem, but their results have not always been accepted by chemical industries. In this paper, we will use an example which was researched by Palancar *et al.* (1996, 1998) and is depicted in Fig. 2. The simulated pH control system is composed of two inlet streams and one outlet stream in a continuous stirred tank reactor (CSTR). There are two inlet streams: one is the acid flow, Q_A, an aqueous solution consisting of acetic acid and propionic acid; the other is the base flow, Q_B, an aqueous solution consisting of sodium hydroxide. The outlet stream is Q. The neutralization reactions are as follows:

$$AcH \rightleftharpoons Ac^{-}+H^{+}, \tag{6}$$

$$PrH \rightleftharpoons Pr^{-}+H^{+}, \tag{7}$$

$$NaOH \rightleftharpoons Na^{+}+OH^{-}, \tag{8}$$

$$H_2O \rightleftharpoons H^{+}+ OH^{-} . \tag{9}$$

For the CSTR, the material balance equations can be derived as

$$Q_A C_{0,\mathrm{PrH}} = QC_{\mathrm{PrH}} + V\frac{\mathrm{d}C_{\mathrm{PrH}}}{\mathrm{d}t} \tag{10}$$

$$Q_A C_{0,\mathrm{AcH}} = QC_{\mathrm{AcH}} + V\frac{\mathrm{d}C_{\mathrm{AcH}}}{\mathrm{d}t} \tag{11}$$

$$Q_B C_{0,\mathrm{NaOH}} = QC_{\mathrm{NaOH}} + V\frac{\mathrm{d}C_{\mathrm{NaOH}}}{\mathrm{d}t} \tag{12}$$

where, C_{AcH}, C_{PrH}, and C_{NaOH} are the concentrations of the components AcH, PrH, and NaOH, V is the volume of the reactor. Then the pH value can be derived from the dissociation equilibrium:

$$\frac{C_{\mathrm{AcH}}}{1+\dfrac{10^{-\mathrm{pH}}}{K_{\mathrm{AcH}}}} + \frac{C_{\mathrm{PrH}}}{1+\dfrac{10^{-\mathrm{pH}}}{K_{\mathrm{PrH}}}} + 10^{(\mathrm{pH}-14)} = C_{\mathrm{NaOH}} + 10^{-\mathrm{pH}} \tag{13}$$

where the ionization constants $K_{\mathrm{AcH}} = 10^{-4.75}$ and $K_{\mathrm{PrH}} = 10^{-4.87}$ at 25°C. At this temperature, the system has an equivalence point around pH = 8.9.

EXPERIMENTAL SETUP

The experimental instruments used in the neutralization system include: (1) a pH sensor, (2) a pH transmitter, (3) an agitator, and (4) metering pumps, as depicted in Fig. 3. An aqueous solution consisting of acetic acid, propionic acid, and sodium hydroxide were prepared for the experiment. Table 1 shows detailed information about the above instruments and chemicals. The initial states of the pH control system are given in Table 2. Figure 4 shows the real titration behaviors observed in the neutralization experiment and demonstrates the sparseness and sensitivity around the regions of the equivalence points. The aim of the experiment was to effectively control a nonlinear, sensitive system. Therefore, we chose the pH control system shown in Fig. 2 as our experimental model. For simplicity, we let the pH value be the controlled variable, we regarded the base flow rate Q_B as the manipulated variable, and we viewed the mixed acid flow rate Q_A as the disturbance variable. The pH control was a single input and single output (SISO) system. In order to maintain the liquid level fixed in the CSTR, the output stream was implemented as the overflow of the reactor.

Table 1. Instruments and chemicals.

Instruments	pH sensor: HI1090T, HANNA Instruments pH transmitter: HI18711E, HANNA Instruments agitator: HI190M/U, HANNA Instruments metering pump: version 30E/32E,LANG APPARATEBAU GmbH
Chemicals	acetic acid propionic acid sodium hydroxide pH standard solution

Table 2. Initial states of the pH control system.

pH value	6.5
$C_{0,\mathrm{ArH}}$	1.0 mol/L
$C_{0,\mathrm{PrH}}$	1.0 mol/L
$C_{0,\mathrm{NaOH}}$	2.0 mol/L
Q_A	14.2 mL/min
Q_B	14.0 mL/min
Q	28.2 mL/min
V	1.0 L

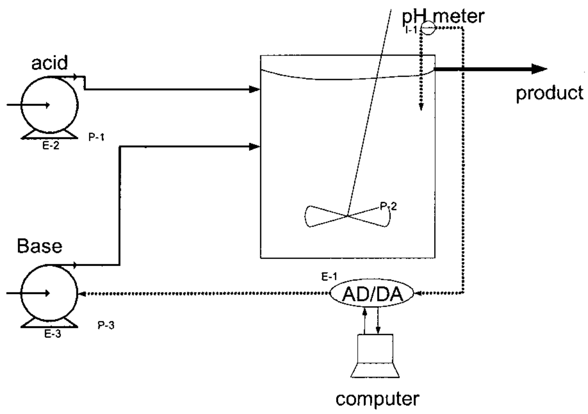

Fig. 3. Diagram of the neutralization pilot plant.

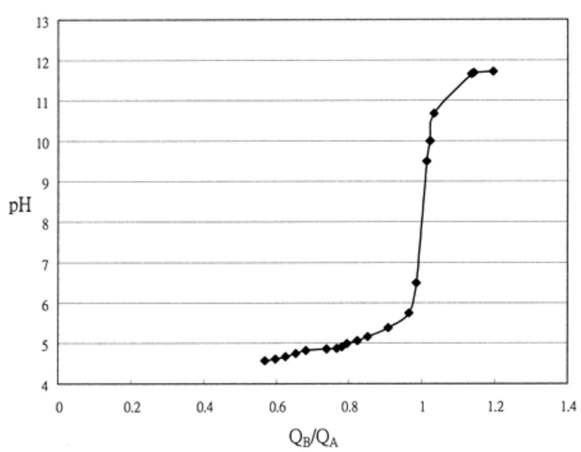

Fig. 4. Titration curve of the neutralization pilot plant.

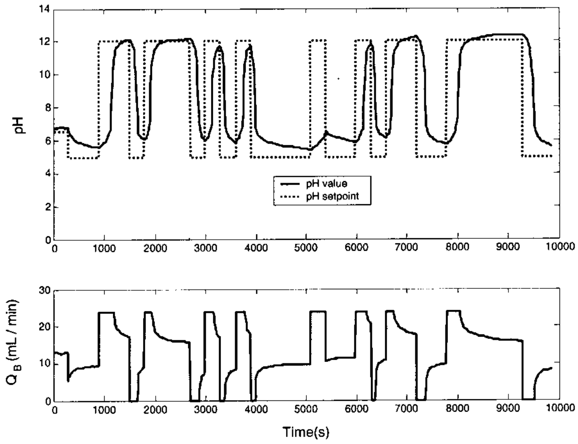

Fig. 5. The training data from a PRBS generator.

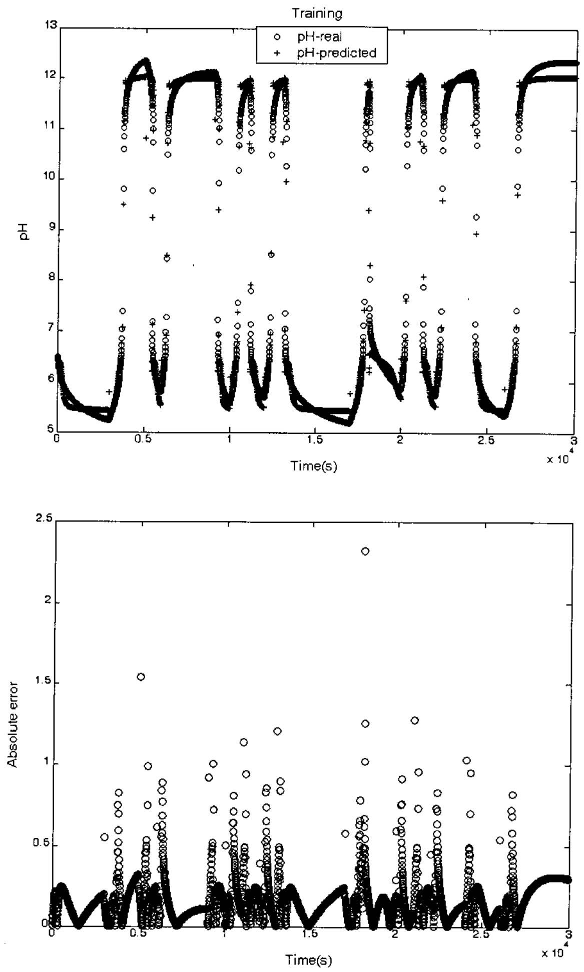

Fig. 6. The training results for the ANN model.

The data for training the ANN model were generated by changing the set-point values for the PI controller (K_C = 5, τ_I = 150), based on a pseudo random binary sequence (PRBS). Note that the PI settings were obtained using a simple Ziegler-Nichols reaction curve approach. The sampling and control actions were performed every 10 s. The set-point values y_{SP} of the pH control system had to fully cover the range around the equivalence point pH = 8.9, so y_{SP} was calculated as

$$y_{SP} = 8.5 + 3.5k\,, \tag{14}$$

where $|k| \le 1$ and the value of k is obtained from the PRBS generator. Equation (14) produces y_{SP} values between pH = 5 and pH = 12. Figure 5 shows the training data. Figures 6 and 7 show the training and testing results obtained with the ANN model. From these two figures, it is observed that the prediction accuracy in the equivalence region is worse than that in the non-equivalence regions. This is because fewer experimental data exist around the equivalence region. We solved this difficulty with the help of a PI controller rather than by improving the model accuracy.

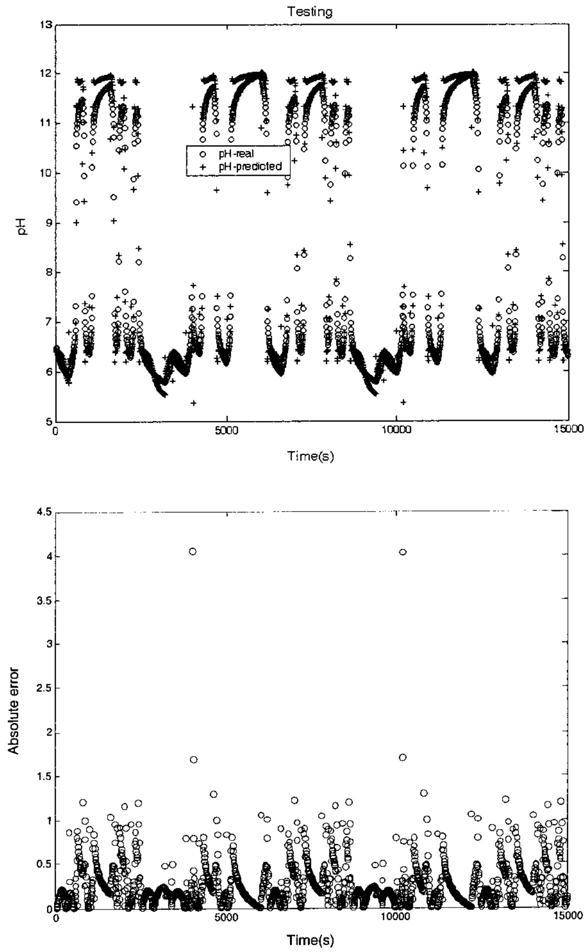

Fig. 7. The testing results for the ANN model.

RESULTS

In this section, we will use the results obtained simulation and experimental results demonstrate the superiority of the combined global/local controller.

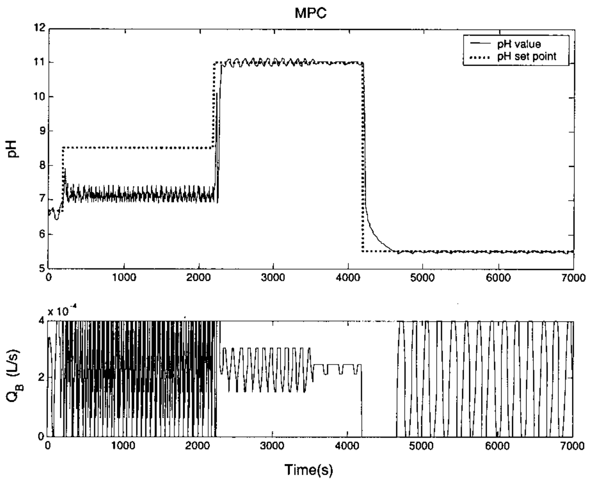

Fig. 8. Dynamics of the simulated pH system under MPC while a series of step changes in the pH set point occur.

Simulation results

Before discussing the experimental study, we will examine the results obtained with the simulated pH system. Figure 8 displays the performance of the MPC, which employed an ANN model trained with data from the simulated plant. Note that the parameters of the MPC were implemented based on our previous analyses (Tsai *et al.*, 2002). The simulation results show that the simulated plant could not be controlled well around the equivalence point. In Fig. 9, we show that the PI controller could be tuned to control the simulated pH plant under set point changes. Note that the PI controller was tuned so as to be stable around the equivalence point; hence, the PI controller could not perform well beyond that range. Also note that the PI controller was very conservative since the system behaved in a very sensitive manner around that point; and hence, the closed loop system behaved sluggishly other around set point values. In Fig. 9, we also compare the servo behaviors of the pH system obtained by implementing the PI, nonlinear MPC, and combined approach derived in this paper. As expected, the combined approach achieved faster response than the PI controller and was much more stable than the nonlinear MPC. Figure 10 compares the regulatory behaviors of these three controllers based on a step changes in the acid input. Once again, the combined approach is shown to be superior to the PI and nonlinear-MPC.

Experimental results

The simulation results show the superiority of the proposed combined controller. The verifying experiments performed on the pilot plant will be discussed in this section. In the experiments, particular

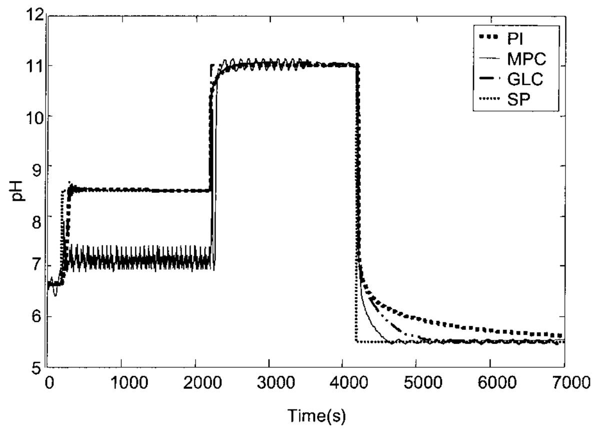

Fig. 9. Dynamics of the simulated pH system controlled by means of PI, MPC, and GLC, respectively, while a series of step changes in the pH set point occur.

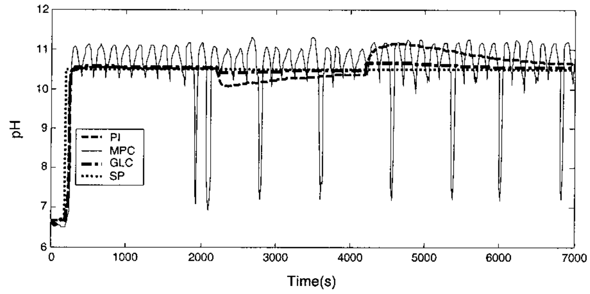

Fig.10. Dynamics of the simulated pH system controlled by means of PI, MPC, and GLC, respectively, while a series of disturbances (acid flow) are introduced.

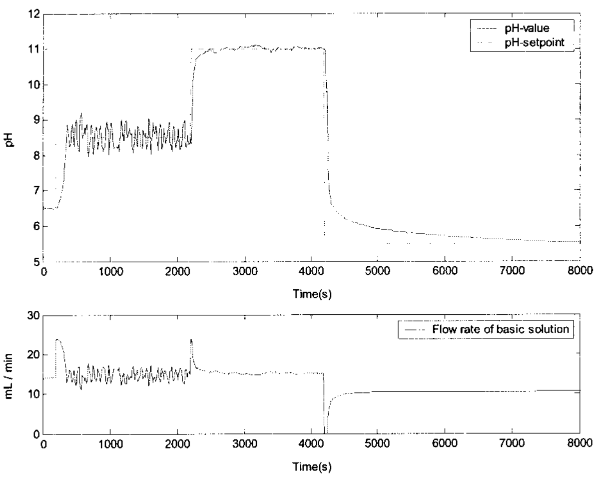

Fig. 11. Dynamics of the pilot plant under PI control ($K_C = 3$, $\tau_I = 150$) while a series of step changes in the pH set point occur.

attention was paid to the following two different domains: one was the highly sensitive, nonlinear region located around pH values ranging from 6.5 to 10.5; the other was the less sensitive region around pH < 6.5 or pH > 10.5. The initial experimental states are given in Table 1, and the period for sampling and

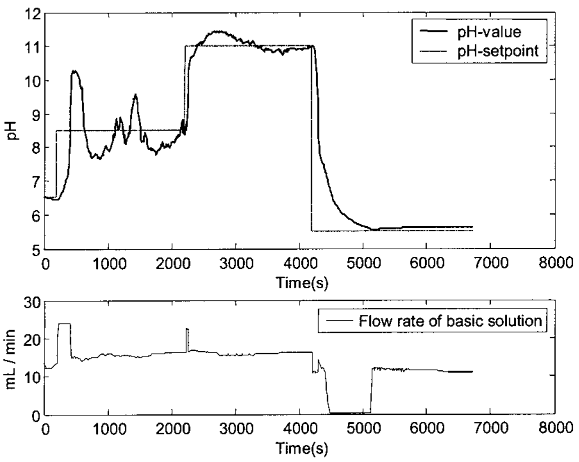

Fig. 12. Dynamics of the pilot plant under NAC for set point change.

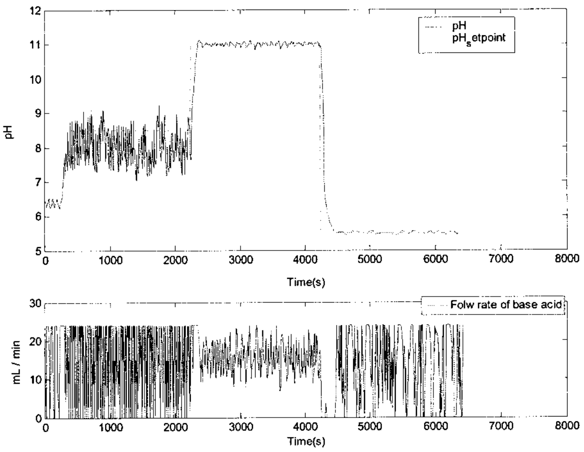

Fig. 13. Dynamics of the pilot plant under MPC while a series of step changes in the pH set point occur.

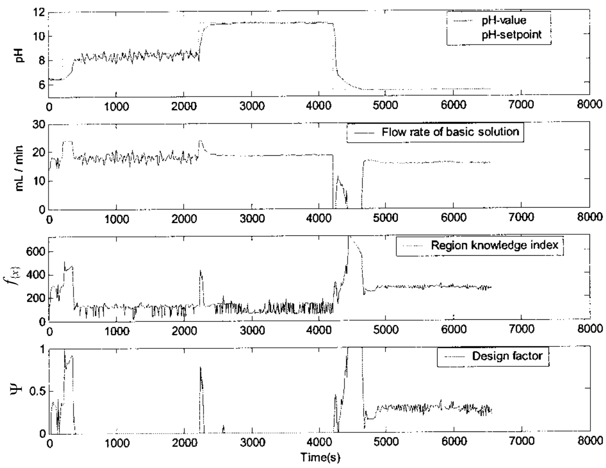

Fig. 14. Dynamics of the pilot plant under the combined controller while a series of step changes in the pH set point occur.

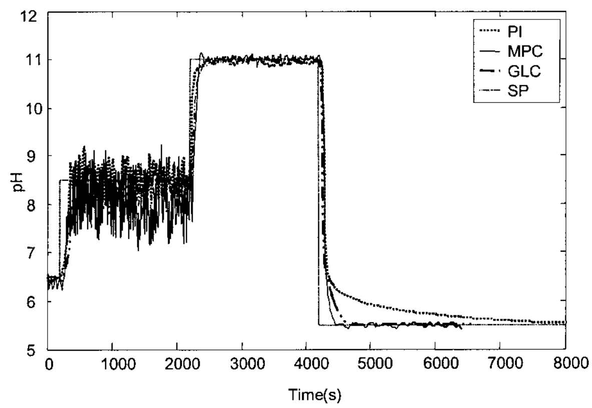

Fig. 15. Dynamics of the pilot plant under PI, MPC, and GLC, respectively, while a series of step changes in the pH set point occur.

controlling actions was 10 s. Firstly, we will compare the experimental results achieved with the above three control strategies for a series of step changes in the set points of pH values. With the single PI controller, Fig. 11 shows that satisfactory performance was achieved even though there was a bit of oscillation around the nonlinear region, but there was a longer settling time when the set point was far away from the equivalence point. Figure 12 shows the experimental servo behavior of this pH system with an NAC controller. Unlike the simulation obtained in our previous study (Tasi *et al.*, 2002), the experimental results obtained here show that the NAC is very sensitive, and that much effort is needed to tune it. This also explains why we implemented the PI controller, as shown in Fig. 11, a local controller. Through the training and testing of an ANN model as depicted in Figs. 6 and 7, we built the MPC for the pH control system. As shown in Fig. 13, the MPC quickly tracked the change of the set point in the less nonlinear region, but this led to poor performances around the sensitive regions. However, as shown in Fig. 14, much better performance was achieved with the combined controller, whether the set point was in the nonlinear region or not. Note that the region knowledge index and design factor were derived in Eq. (4). In Fig. 15, the experimental obtained with the above three control schemes are compared. In all the regions, including the sensitive region, the controlled variable was closely tracked by the combined controller. Comparing Fig. 15 and Fig. 9, reveals that the responses obtained in the experiments were much noisier than those obtained in the simulation, and with our experimental results shown in Fig. 12 reveal that the NAC is not suitable for real applications.

Finally, the rate of acid flow was changed to evaluate the regulatory properties of these three controllers, and the experimental results, as shown in Fig. 16, clearly confirm the superiority of the combined controller. Figure 17 displays the results of a 36-hour reliability test performed with the combined control algorithm in a pilot neutralization plant.

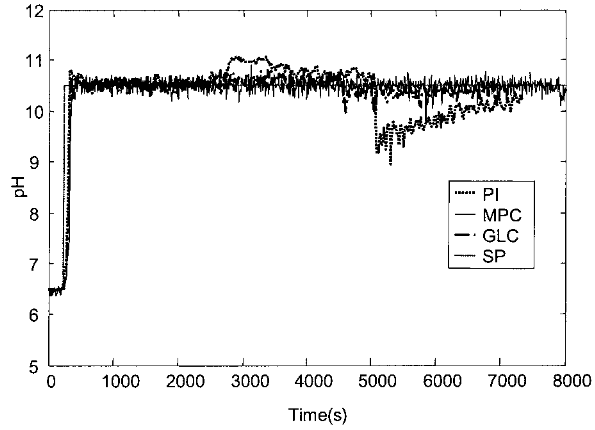

Fig. 16. Dynamics of the pilot plant under PI, MPC, and GLC, respectively, while step changes in the disturbance variable (acid flow rate) are introduced.

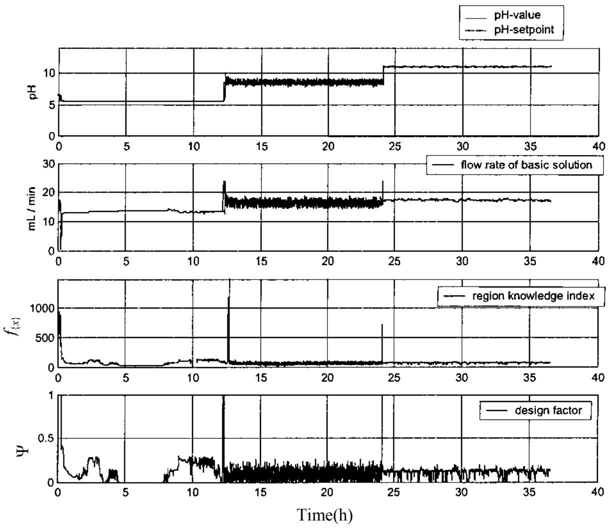

Fig. 17. Record of a 36-hour reliability test for the combined global/local algorithm as used in the pilot neutralization plant.

CONCLUSION

This study solved the problem that occurs when the operation point is located in a highly sensitive region surrounded by non-sensitive regions. This problem is typically occurs in pH processes and high-purity distillation columns. The proposed control system consists of a local controller that works in the sensitive region and a global controller that works in regions with normal sensitivity. The central idea is that when a disturbance kicks the operation out of the sensitive region, the global controller is employed to bring the operation back to the boundary of the sensitive region, where control is handed over to the local controller, which is implemented by combining the outputs from both the local and global controllers. In the framework of combined global/local control (GLC), the global controller can be built with much less effort since its task is only to push the operation from surrounding non-sensitive regions to the boundary of the sensitive region. The concept of GLC has been demonstrated using both a simulated pH control process and a pilot neutralization plant. Results obtained from both simulations and experiments reveal the excellent dynamical behavirs of the GLC schemes.

ACKNOWLEDGEMENT

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NOMENCLATURE

a,b	constant in the probability density function
C_{AcH}	concentration of acetic acid, mol/L
C_{NaOH}	concentration of sodium hydroxide, mol/L
C_{PrH}	concentration of propionic acid, mol/L
$C_{0,\mathrm{AcH}}$	initial concentration of acetic acid, mol/L,
$C_{0,\mathrm{NaOH}}$	initial concentration of sodium hydroxide, mol/L,
$C_{0,\mathrm{PrH}}$	initial concentration of propionic acid , mol/L,
$f_{\{x\}}$	probability density estimator
h_{GC}	value of deviation between $y(t)$ and $y_{\mathrm{MPC}}(t)$
K_{AcH}	ionization constant of acetic acid
K_C	proportional gain
K_{PrH}	ionization constant of propionic acid
Q	outlet flow, mL/min
Q_A	acid flow, mL/min
Q_B	base flow, mL/min
T_S	sampling period, s
t	time, s
u_C	control action of the GLC controller
u_{GC}	manipulated variable of the global controller
u_{LC}	manipulated variable of the local controller
V	tank volume, L
w	penalty factor
x_{new}	new event
y	controlled variable
y_{MPC}	controlled variable of the MPC controller
y_{SP}	set point
z^{-1}	backward shift operator

Greek symbols

Δ	operator of $(1–z^{-1})$
Ψ	probability decision factor
τ_I	integral constant, s

Abbreviation

ANN	artificial neural network
GLC	global/local control
MPC	model predictive control
NAC	neural adaptive control
PID	proportional integral derivative control
PRBS	pseudo random binary sequence

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全域—局域組合控制策略對一靈敏之非線性系統在模式不確定性下之實驗探討

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摘　要

一般傳統的的比例—積分自適控制器，在解決非線性系統之制器問題時，通常採用調諧比例—積分控制器參數的方式；而本文，則以模式預測控制作爲一個全域的控制器，而比例—積分控制器僅擔任局域控制的角色，發展出一全域—局域組合控制策略，來解決既靈敏又兼具不確定性的非線系統之控制問題。另外，在控制模式不準確的系統時，若以人工智慧類神經網路建模時，常使用模式預測控制，但是因爲訓練資料不完全或其它的因素，使得模式有誤差存在，而無法達到有效的控制；而應用此諧合控制策略，則可用比例—積分來修正輔助模式預測控制的控制效果。最後，爲了證明此控制理論的強健性，特別以酸鹼中和反應爲驗證實驗，因爲中和反應在滴定當量點附近之區域是相當敏感又非線性化的；經由多次的模擬與實驗的結果顯示，此全域—局域組合控制策略，確實能夠在高度非線性的系統有非常好的控制表現。