Fuzzy Gain Scheduling of PID Controllers

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***Abstract*—This paper describes the development of a fuzzy gain scheduling scheme of PID controllers for process control. Fuzzy rules and reasoning are utilized on-line to determine the controller parameters based on the error signal and its first difference. Simulation results demonstrate that better control performance can be achieved in comparison with Ziegler–Nichols controllers and Kitamori's PID controllers.**

I. Introduction

The best-known controllers used in industrial control processes are proportional-integral-derivative (PID) controllers because of their simple structure and robust performance in a wide range of operating conditions. The design of such a controller requires specification of three parameters: proportional gain, integral time constant, and derivative time constant. So far, great effort has been devoted to develop methods to reduce the time spent on optimizing the choice of controller parameters [8], [15]. The PID controllers in the literature can be divided into two main categories. In the first category, the controller parameters are fixed during control after they have been tuned or chosen in a certain optimal way. The Ziegler–Nichols tuning formula is perhaps the most well-known tuning method [5], [19]. Some other methods exist for the PID tuning (see e.g., [1], [6], [7]). The PID controllers of this category are simple, but cannot always effectively control systems with changing parameters, and may need frequent on-line retuning. The controllers of the second category have a structure similar to PID controllers, but their parameters are adapted on-line based on parameter estimation, which requires certain knowledge of the process, e.g., the structure of the plant model [2], [17]. Such controllers are called adaptive PID controllers in order to differentiate them from those of the first category.

The application of knowledge-based systems in process control is growing, especially in the field of fuzzy control [9], [10], [12]–[14]. In fuzzy control, linguistic descriptions of human expertise in controlling a process are represented as fuzzy rules or relations. This knowledge base is used by an inference mechanism, in conjunction with some knowledge of the states of the process (say, of measured response variables) in order to determine control actions. Although they do not have an apparent structure of PID controllers, fuzzy logic controllers may be considered nonlinear PID controllers whose parameters can be determined on-line based on the error signal and their time derivative or difference.

In this paper, a rule-based scheme for gain scheduling of PID controllers is proposed for process control. The new scheme utilizes fuzzy rules and reasoning to determine the controller parameters, and the PID controller generates the control signal. It is demonstrated in this paper that human expertise on PID gain scheduling can be represented in fuzzy rules. Furthermore, better control performance can be expected in the proposed method than that of the PID controllers with fixed parameters.

II. PID Controller

The transfer function of a PID controller has the following form:

$$G_c(s) = K_p + K_i/s + K_d s \tag{1}$$

where K_p, K_i, and K_d are the proportional, integral, and derivative gains, respectively. Another useful equivalent form of the PID controller is

$$G_c(s) = K_p(1 + 1/(T_i s) + T_d s) \tag{2}$$

where $T_i = K_p/K_i$ and $T_d = K_d/K_p$. T_i and T_d are known as the integral and derivative time constants, respectively.

The discrete-time equivalent expression for PID control used in this paper is given as

$$u(k) = K_p e(k) + K_i T_s \sum_{i=1}^{n} e(i) + \frac{K_d}{T_s} \Delta e(k).$$

Here, $u(k)$ is the control signal, $e(k)$ is the error between the reference and the process output, T_s is the sampling period for the controller, and $\Delta e(k) \triangleq e(k) - e(k-1)$.

The parameters of the PID controller K_p, K_i, and K_d or K_p, T_i, and T_d can be manipulated to produce various response curves from a given process. Finding optimum adjustments of a controller for a given process is not trivial. In the following section, an on-line gain scheduling scheme of the PID controller based on fuzzy rules is introduced.

III. Fuzzy Gain Scheduling

Fig. 1 shows the PID control system with a fuzzy gain scheduler. The approach taken here is to exploit fuzzy rules and reasoning to generate controller parameters.

It is assumed that K_p, K_d are in prescribed ranges $[K_{p,\min}, K_{p,\max}]$ and $[K_{d,\min}, K_{p,\max}]$, respectively. The ap-

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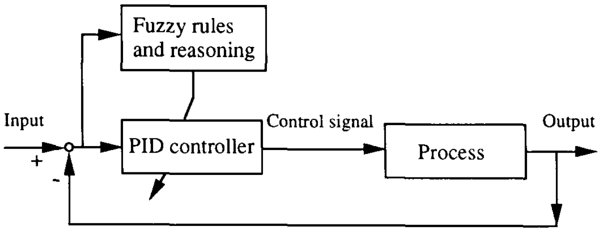

Fig. 1. PID control system with a fuzzy gain scheduler.

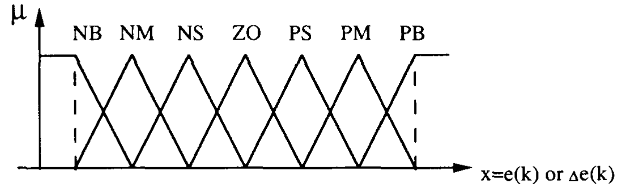

Fig. 2. Membership functions for $e(k)$ and $\Delta e(k)$.

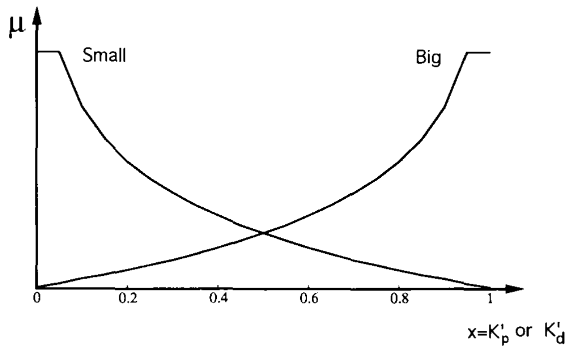

Fig. 3. Membership functions for K_p' and K_d'.

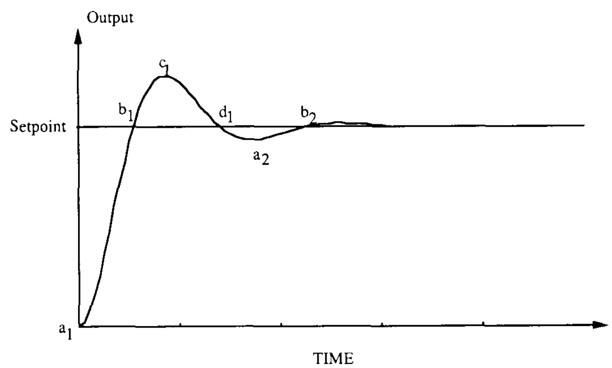

Fig. 4. Process step response.

propriate ranges are determined experimentally and will be given in equation (12). For convenience, K_p and K_d are normalized into the range between zero and one by the following linear transformation:

$$K_p' = (K_p - K_{p,\min})/(K_{p,\max} - K_{p,\min})$$
$$K_d' = (K_d - K_{d,\min})/(K_{d,\max} - K_{d,\min}). \qquad (3)$$

In the proposed scheme, PID parameters are determined based on the current error $e(k)$ and its first difference $\Delta e(k)$. The integral time constant is determined with reference to the derivative time constant, i.e.,

$$T_i = \alpha T_d \qquad (4)$$

and the integral gain is thus obtained by

$$K_i = K_p/(\alpha T_d) = K_p^2/(\alpha K_d). \qquad (5)$$

The parameters K_p', K_d', and α are determined by a set of fuzzy rules of the form

$$\text{if } e(k) \text{ is } A_i \text{ and } \Delta e(k) \text{ is } B_i, \text{ then } K_p' \text{ is } C_i,\ K_d' \text{ is } D_i, \text{ and } \alpha = \alpha_i$$
$$i = 1, 2, \cdots, m. \qquad (6)$$

Here, A_i, B_i, C_i, and D_i are fuzzy sets on the corresponding supporting sets; α_i is a constant. The membership functions (MF) of these fuzzy sets for $e(k)$ and $\Delta e(k)$ are shown in Fig. 2. In this figure, N represents negative, P positive, ZO approximately zero, S small, M medium, B big. Thus NM stands for negative-medium, PB for positive big, and so on.

The fuzzy sets C_i and D_i may be either Big or Small and are characterized by the membership functions shown in Fig. 3, where the grade of the membership functions μ and the variable x (= K_p' or K_d') have the following relation:

$$\mu_{\text{SMALL}}(x) = -\tfrac{1}{4}\ln x \quad \text{or} \quad x_{\text{SMALL}}(\mu) = e^{-4\mu}$$
$$\text{for Small,}$$
$$\mu_{\text{BIG}}(x) = -\tfrac{1}{4}\ln(1 - x) \quad \text{or} \quad x_{\text{BIG}}(\mu) = 1 - e^{-4\mu} \quad \text{for Big.} \qquad (7)$$

The fuzzy rules in (6) may be extracted from operator's expertise. Here we drive the rules experimentally based on the step response of the process. Fig. 4 shows an example of a desired time response. At the beginning, i.e., around a_1, we need a big control signal in order to achieve a fast rise time. To produce a big control signal, the PID controller should have a large proportional gain, a large integral gain, and a small derivative gain. Thus the proportional gain (K_p') can be represented by a fuzzy set Big, and the derivative gain K_d' by a fuzzy set Small. The integral action is determined with reference to the derivative action as in (4). For the PID controller, taking a small α or a small integral time constant T_i will result in a strong integral action. Whether the integral action should be strong or weak is determined in the scheme by comparison with the well-known Ziegler–Nichols PID tuning rule. In the Ziegler–Nichols rule, the integral time constant T_i is always taken four times as large as the derivative time constant. That is, α is equal to 4. In the proposed scheme, α takes a value less than 4 (say 2) to generate a "stronger" integral action. Therefore, the rule around a_1 reads

> if $e(k)$ is PB and $\Delta e(k)$ is ZO, then K_p' is Big, K_d' is Small, and $\alpha = 2$.

Note that α may also be considered as a fuzzy number which has a singleton membership function as shown in Fig. 5. For example, α becomes 2 when α is Small.

Around point b_1 in Fig. 4, we expect a small control signal to avoid a large overshoot. That is, the PID controller should have a small proportional gain, a large derivative gain, and a small integral gain. Thus the following fuzzy rule is taken:

> if $e(k)$ is ZO and $\Delta e(k)$ is NB, then K_p' is Small, K_d' is Big, and $\alpha = 5$.

Thus a set of rules, as shown in Table I, may be used to adapt the proportional gain (K_p'). The tuning rules for K_d' and α are given in Tables II and III, respectively. In the tables, B stands for Big, and S for Small.

The truth value of the ith rule in (6) μ_i is obtained by the product of the MF values in the antecedent part of the rule:

$$\mu_i = \mu_{A_i}[e(k)] \cdot \mu_{B_i}[\Delta e(k)] \tag{8}$$

where μ_{A_i} is the MF value of the fuzzy set A_i given a value of $e(k)$, and μ_{B_i} the MF value of the fuzzy set B_i given a value of $\Delta e(k)$.

Based on μ_i, the values of K_p' and K_d' for each rule are determined from their corresponding membership functions. The implication process of a fuzzy rule is shown in Fig. 6.

By using the membership functions in Fig. 2, we have the following condition [18]:

$$\sum_{i=1}^{m} \mu_i = 1. \tag{9}$$

Then, the defuzzification yields the following:

$$K_p' = \sum_{i=1}^{m} \mu_i K_{p,i}' \tag{10a}$$

$$K_d' = \sum_{i=1}^{m} \mu_i K_{d,i}' \tag{10b}$$

$$\alpha = \sum_{i=1}^{m} \mu_i \alpha_i. \tag{10c}$$

Here $K_{p,i}'$ is the value of K_p' corresponding to the grade μ_i for the ith rule (see Fig. 6). $K_{d,i}'$ is obtained in the same way.

Once K_p', K_d', and α are obtained, the PID controller parameters are calculated from the following equations that are due to (3) and (5):

$$K_p = (K_{p,\max} - K_{p,\min}) K_p' + K_{p,\min} \tag{11a}$$

$$K_d = (K_{d,\max} - K_{d,\min}) K_d' + K_{d,\min} \tag{11b}$$

$$K_i = K_p^2/(\alpha K_d). \tag{11c}$$

Based on an extensive simulation study on various processes, a rule of thumb for determining the range of K_p and the range of K_d is given as

$$K_{p,\min} = 0.32K_u, \quad K_{p,\max} = 0.6K_u$$
$$K_{d,\min} = 0.08K_u T_u, \quad K_{d,\max} = 0.15K_u T_u \tag{12}$$

where K_u and T_u are, respectively, the gain and the period of oscillation at the stability limit under P-control [19].

Note that there are other forms for the fuzzy tuning rules in (6). Some examples are as follows:

1) if $e(k)$ is A_i and $\Delta e(k)$ is B_i, then K_p' is C_i, K_d' is D_i, and K_i' is E_i

2) if $e(k)$ is A_i and $\Delta e(k)$ is B_i, then K_p' is C_i, T_d' is D_i, and T_i' is E_i

3) if $e(k)$ is A_i and $\Delta e(k)$ is B_i, then $u(k) = K_{p0}^i\, e(k) + (K_{i0}^i T_s)\, \Sigma_j\, e(j) + (K_{d0}^i/T_s)\, \Delta e(k)$

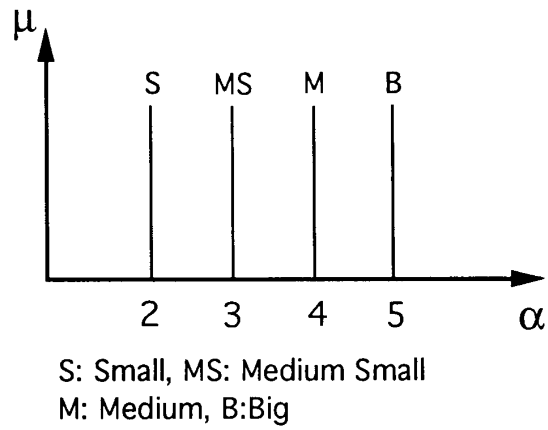

Fig. 5. Singleton membership functions for α.

TABLE I
FUZZY TUNING RULES FOR K_p'

		$\Delta e(k)$						
		NB	NM	NS	ZO	PS	PM	PB
	NB	B	B	B	B	B	B	B
	NM	S	B	B	B	B	B	S
	NS	S	S	B	B	B	S	S
$e(k)$	ZO	S	S	S	B	S	S	S
	PS	S	S	B	B	B	S	S
	PM	S	B	B	B	B	B	S
	PB	B	B	B	B	B	B	B

TABLE II
FUZZY TUNING RULES FOR K'_d

		$\Delta e(k)$						
		NB	NM	NS	ZO	PS	PM	PB
	NB	S	S	S	S	S	S	S
	NM	B	B	S	S	S	B	B
	NS	B	B	B	S	B	B	B
$e(k)$	ZO	B	B	B	B	B	B	B
	PS	B	B	B	S	B	B	B
	PM	B	B	S	S	S	B	B
	PB	S	S	S	S	S	S	S

TABLE III
FUZZY TUNING RULES FOR α

		$\Delta e(k)$						
		NB	NM	NS	ZO	PS	PM	PB
	NB	2	2	2	2	2	2	2
	NM	3	3	2	2	2	3	3
	NS	4	3	3	2	3	3	4
$e(k)$	ZO	5	4	3	3	3	4	5
	PS	4	3	3	2	3	3	4
	PM	3	3	2	2	2	3	3
	PB	2	2	2	2	2	2	2

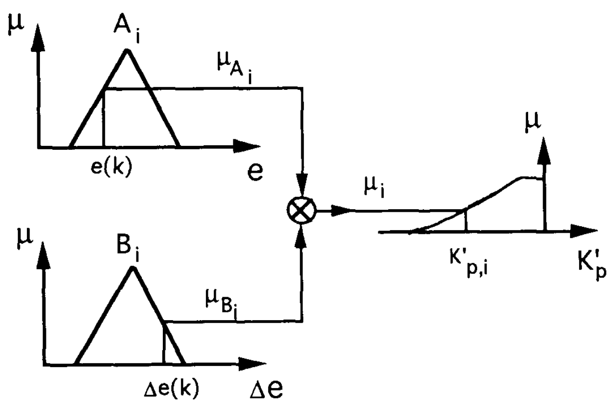

Fig. 6. Implication process of a fuzzy rule.

where K^i_{p0}, K^i_{i0}, K^i_{d0} are constant. Although these rules have different forms, they are equivalent to each other under certain conditions. It seems relatively easier to set the fuzzy tuning rules by (6).

IV. Stability

Since the parameters of the present PID controller are functions of time, it is very difficult to analyze the stability of the closed-loop control system. Even if the asymptotic stability is assured, wild start-up transients may be intolerable in many applications. Therefore, a hierarchical entity like a supervisor is desired to monitor the performance of the control system. Instability is detected preferably in an early stage if the system is unstable. Once stability is identified during process monitoring, certain corrective action is taken. For example, the controller parameters are switched to a set of known stabilizing parameters that guarantees that the control system will remain stable; or the system is shut down by setting K_p to zero if necessary.

There are several practical methods available to identify instability. Anderson et al. [1] suggest monitoring the magnitude of peaks and the system is determined to be unstable when peaks are growing in magnitude for three peaks in row. Nesler [11] uses the ratio of short-term average of the error to that of the absolute value of the error to detect instability. Gertler and Chang [3] propose an instability indicator by observing the output. It is also possible to combine the above quantitative indexes with rule-based logic to make more accurate and reliable decisions.

In some situations, a hybrid controller may be more useful and reliable. For example, if a large set point change is made, the fuzzy gain scheduling scheme is first employed to yield a fast transient response. When the error $e(k)$ is small, i.e., the output is settling to the set point, the scheme is then switched to a fixed gain PID controller. The stability of the closed-loop control system can be guaranteed while maintaining some level of control. Sometimes a set of PID parameters are good for set point responses but may be inappropriate for load disturbance rejection [4], [16]. Hang [4] finds that the heuristic Ziegler–Nichols design rule gives a set of PID parameters that are good at load disturbance rejection. Therefore, a PID controller with a set of fixed parameters that are obtained by the Ziegler–Nichols rule can be used after the transient stage of the process response.

V. Simulation Results and Discussions

The fuzzy gain scheduling scheme has been tested on a variety of processes. Table IV shows the representative simulation results of the following second-, third-, and

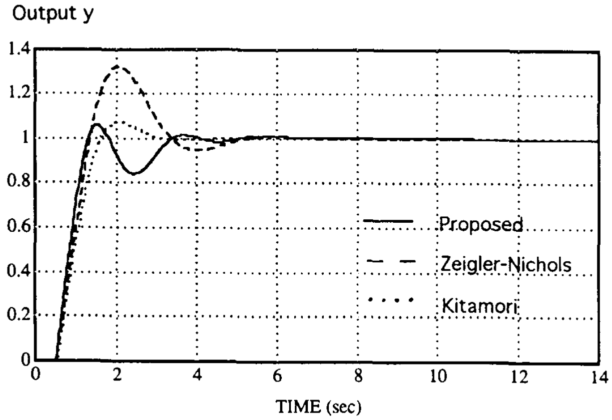

Fig. 7. Comparison of step responses of the controlled second-order process.

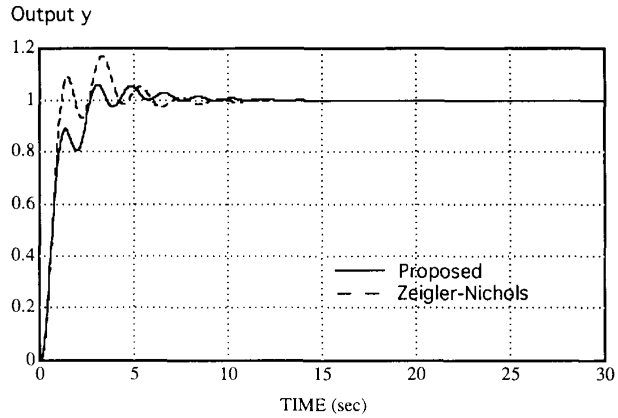

Fig. 8. Comparison of step responses of the controlled third-order process.

fourth-order processes:

$$G_1(s) = \frac{e^{-0.5s}}{(s+1)^2} \tag{13a}$$

$$G_2(s) = \frac{4.228}{(s+0.5)(s^2+1.64s+8.456)} \tag{13b}$$

$$G_3(s) = \frac{27}{(s+1)(s+3)^3}. \tag{13c}$$

In the table, Y_{os} represents the percent maximum overshoot, T_5 stands for the 5 percent settling time, and IAE, ISE are the integral of the absolute error and the integral of the squared error, respectively [8]. The time responses are plotted in Fig. 7, Fig. 8, and Fig. 9, respectively. The results obtained by using Ziegler–Nichols PID controllers and Kitamori's PID controllers are also presented for comparison. The parameters of Ziegler–Nichols PID controllers are determined as $K_p = 0.6K_u$, $T_i = 0.5T_u$, and $T_d = 0.125T_u$; while those of Kitamori's controllers are obtained by partial model matching method [7]. A brief description of the method is given in the Appendix. Fig. 10 shows the PID parameters determined by the fuzzy gain scheduling scheme for controlling the second-order process (13a). The determination process is as follows. First the error and its first difference are calculated from the sampled process output. Then the values of K_p' and K_d' for each rule are determined by the fuzzy reasoning process, as shown in Fig. 6. Finally, the PID parameters are obtained by using (10) and (11).

The above simulations show that a variety of processes can be satisfactorily controlled by the fuzzy gain scheduling PID controller. It yields better control performance than the Ziegler-Nichols controller does, which is confirmed by comparing performance indexes such as the percent maximum overshoot, the settling time, IAE, and ISE. It seems that the derivative time constant T_d for the

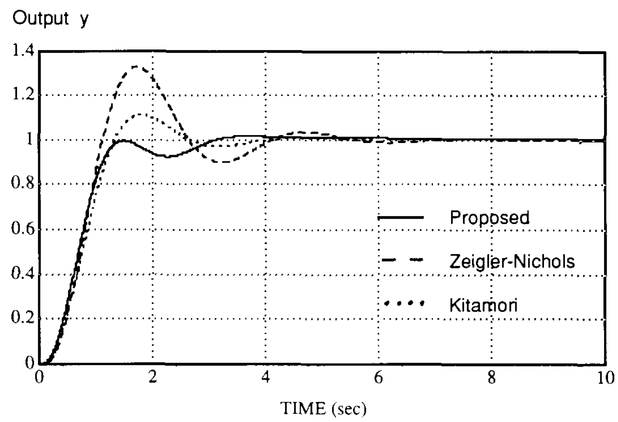

Fig. 9. Comparison of step responses of the controlled fourth-order process.

Ziegler–Nichols controller could be chosen slightly larger in order to obtain a smaller maximum overshoot. It is also found that the proposed controller is as good as or better than the delicately tuned PID controller of Kitamori's, which needs much more information on the plant.

VI. Conclusions

The proposed gain scheduling scheme uses fuzzy rules and reasoning to determine the PID controller parameters. Human knowledge and experience in control system design is exploited in the tuning of a PID controller. The scheme has been tested on various processes in simulation, and satisfactory results are obtained. A supervisory level may also be included to monitor the stability of the controlled system, and a hybrid controller, i.e., rule based, plus fixed gain is possible. Although a rule of thumb for choosing the ranges for K_p and K_d was obtained experimentally in (12), it is still possible to make further

TABLE IV
SUMMARY OF SIMULATION RESULTS

Process	Zeigler–Nichols PID Controller		Kitamori's PID Controller[a]		Proposed PID Controller
$G_1(s)$	$K_p = 2.808$ $T_i = 1.64$ $T_d = 0.41$	$Y_{os} = 32\%$ $T_S = 4.16$ IAE = 1.37 ISE = 0.871	$K_p = 2.212$ $T_i = 2.039$ $T_d = 0.519$	$Y_{os} = 6.8\%$ $T_S = 2.37$ IAE = 1.04 ISE = 0.805	$Y_{os} = 6.0\%$ $T_S = 3.09$ IAE = 1.18 ISE = 0.772
$G_2(s)$	$K_p = 2.19$ $T_i = 1.03$ $T_d = 0.258$	$Y_{os} = 17\%$ $T_S = 5.45$ IAE = 0.99 ISE = 0.526	— — —		$Y_{os} = 6.1\%$ $T_S = 5.01$ IAE = 1.01 ISE = 0.533
$G_3(s)$	$K_p = 3.072$ $T_i = 1.352$ $T_d = 0.338$	$Y_{os} = 32.8\%$ $T_S = 3.722$ IAE = 1.13 ISE = 0.628	$K_p = 2.357$ $T_i = 1.649$ $T_d = 0.414$	$Y_{os} = 10.9\%$ $T_S = 2.3$ IAE = 0.833 ISE = 0.596	$Y_{os} = 1.9\%$ $T_S = 2.632$ IAE = 0.811 ISE = 0.537

[a]The PID parameters of the Kitamori's controller are not available for the process $G_2(s)$ because it has a small damping ratio, 0.282. Y_{os} is the percent maximum overshoot, T_S is the 5 percent settling time, and IAE, ISE are the integral of the absolute error and the integral of the squared error, respectively.

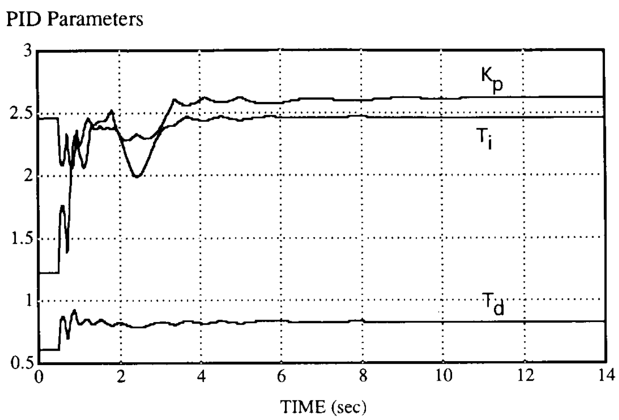

Fig. 10. PID parameters of the fuzzy gain scheduler for the control of the second-order process.

performance improvements by fine tuning the ranges as well as by modifying the tuning rules in Table I through Table III. These points require further research and development.

APPENDIX
KITAMORI'S PID CONTROLLER

Assume that the plant is described by the following transfer function:

$$P(s) = \frac{b_0 + b_1 s + \cdots}{a_0 + a_1 s + \cdots} = \frac{1}{a_0' + a_1' s + a_2' s^2 + \cdots}$$

and the PID controller is

$$C(s) = K_p\left(1 + \frac{1}{T_i s} + T_d s\right) = \frac{c_0 + c_1 s + c_2 s^2}{s}.$$

Choose a reference model as

$$G_M(s) = \frac{1}{\bar{\alpha}} = \frac{1}{\alpha_0 + \alpha_1 \sigma s + \alpha_2 \sigma^2 s^2 + \cdots}$$

$$(\alpha_0 = \alpha_1 = 1)$$

where σ is a time-scaling factor, which is chosen as small as possible. A set of α's standard values is given

$$\{\alpha_i\} = \{1, 1, 0.5, 0.15, 0.03, \cdots\}$$

that would result in a time response with adequate damping characteristics and a short rise-time. The closed-loop transfer function of the PID controlled system is then given

$$W(s) = \frac{1}{1 + 1/(P(s)C(s))} = \frac{1}{1 + s(\boldsymbol{a}'/\boldsymbol{c})}$$

where

$$\boldsymbol{a}' = a_0' + a_1' + a_2' s^2 + \cdots$$

$$\boldsymbol{c} = c_0 + c_1 s + c_2 s^2.$$

Equating $G_M(s)$ to $W(s)$ gives

$$\boldsymbol{c} = s\boldsymbol{a}'/(\bar{\alpha} - 1).$$

Expanding the right side of the above equation in s yields

$$\boldsymbol{c} = \frac{a_0'}{\sigma}\left[1 + \left(\frac{a_1'}{a_0'} - \sigma\alpha_2\right)s + \left\{\frac{a_2'}{a_0'} - \sigma\alpha_2\frac{a_1'}{a_0'} + \sigma^2(\alpha_2^2 - \alpha_3)\right\}s^2 + \left\{\frac{a_3'}{a_0'} - \sigma\alpha_2\frac{a_2'}{a_0'} + \sigma^2(\alpha_2^2 - \alpha_3)\frac{a_1'}{a_0'} + \sigma^3(2\alpha_2\alpha_3 - \alpha_2^2 - \alpha_4)\right\}s^3 + \cdots\right]$$

where $\alpha_0 = \alpha_1 = 1$. By matching the coefficient in s from low order to high order, we obtain

$$c_0 = a_0'/\sigma$$

$$c_1 = a_0'(a_1'/a_0' - \sigma\alpha_2)/\sigma$$

$$c_2 = a_0'\{a_2'/a_0' - \sigma\alpha_2 a_1'/a_0' + \sigma^2(\alpha_2^2 - \alpha_3)\}/\sigma$$

where σ is obtained by choosing the smallest positive root of the following equation:

$$a_3'/a_0' - \sigma\alpha_2 a_2'/a_0' + \sigma^2(\alpha_2^2 - \alpha_3)a_1'/a_0' + \sigma^3(2\alpha_2\alpha_3 - \alpha_2^3 - \alpha_4) = 0.$$

Thus, the PID parameters are obtained as follows:

$$K_p = c_1, \quad T_i = c_1/c_0, \quad T_d = c_2/c_1.$$

Note that the PID parameters are not available by this method when there is no positive root for σ.

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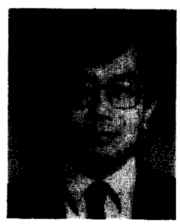

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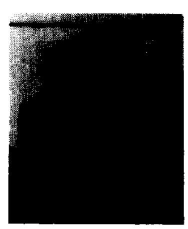

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