

# Design of a Hybrid Fuzzy Controller with the Optimal Auto-tuning Method

## 최적 자동동조 방법에 의한 하이브리드 퍼지제어기의 설계

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**요약** : 퍼지논리제어기는 산업응用に 광범위하게 연구되고 있으며, 계속적으로 사용되고 있다. 그러나 퍼지집합의 조정을 통해 최적규칙을 구축하기 위하여, 시행착오에 의한 매우 능숙한 기술이 요구된다. 이 논문에서는 첫째로, 퍼지논리제어기와 기존의 PID제어기로 구성된 하이브리드 퍼지제어기를 제안한다. 즉 시스템의 제어입력은 퍼지변수로서, 과도상태에서의 FLC출력과 정상상태에서의 PID출력의 컨벡스(convex) 결합이다. 둘째로, 간략추론법과 개선된 콤플렉스방법을 이용한 강력한 자동동조알고리즘이 퍼지논리제어기의 성능을 자동적으로 개선하기 위해 사용된다. 이 방법은 오차변화율 및 제어출력의 제한조건에 의하여, 언어제어규칙, 퍼지계수(Scaling factor), PID계수, 하이브리드 퍼지논리제어기의 하중계수의 최적값을 자동적으로 추정한다. 시물레이션은 시간지연 플랜트 및 하수처리시스템의 활성오니공정과 같은 비선형 플랜트에서 실행되고, 시스템의 성능은 평가지수 ITAE로 평가된다.

**Keywords**: hybrid fuzzy controller, auto-tuning algorithm, optimal tuning parameters, linear and nonlinear plants

### I. Introduction

The aim of designing controllers is to compensate the dynamic characteristics of the plant under control. Because of simplicity of the parameter tuning and the controller design, the PID controller has been well established and widely employed. However, the conventional PID controller with linear relation to plants becomes so sensitive to the control environment and the change of parameters that the efficiency of its utility for the complex and nonlinear plants has been questioned in transient state [1,4,9,16].

The fuzzy logic controller (FLC) may be able to utilize a large number of the linguistic control rules based on the human experience and knowledge, and it has been proved that the fuzzy logic controller is suitable for controlling the linear plants as well as the nonlinear plants [1]. The FLC's output can be biased because the linguistic control rules are difficult to express precisely the human experience and knowledge [3,5,11-13]. The hybrid fuzzy logic controller that uses the PID in steady state and the fuzzy logic in transient state should be required.

One of the difficulties to control a complex system is in the selection of optimum parameters, such as the linguistic control rules, scaling factors, membership functions, PID coefficients and weighting coefficients of a (hybrid) fuzzy logic controller. These parameters are very important elements of a (hybrid) fuzzy logic controller in order to improve control performances [6-10,14]. The novel algorithm for auto-tuning of parameters by means of the analysis of plant responses

should be developed.

In this paper, first, a hybrid fuzzy logic controller (HFCL) is proposed. The control input of the system in the HFCL is a convex combination by a fuzzy variable of the FLC's output in transient state and the PID's output in steady state. Second, a powerful auto-tuning algorithm is presented to automatically improve the performance of hybrid fuzzy logic controller, utilizing the simplified reasoning method and the improved complex method. The algorithm estimates automatically the optimal values of the linguistic control rules, scaling factors, PID coefficients and weighting coefficient of fuzzy logic controller, according to the rate of change and limitation condition of control output. The algorithm is developed for the (hybrid) fuzzy logic controllers, such as fuzzy PID including fuzzy PI, hybrid fuzzy (fuzzy PID + PID) and hybrid fuzzy with Smith-predictor[17]. They are applied to the plants with time-delay and nonlinearity, such as the activated sludge process of sewage treatment system. Computer simulations are conducted at the step input and the system performances are evaluated in the ITAE (Integral of the Time multiplied by the Absolute value of Error).

### II. Hybrid Fuzzy Logic Controller

The hybrid fuzzy logic controller (HFCL) consists of a fuzzy PID controller (FLC) and a PID controller. In other words, the control input of the system is a convex combination of the output of the FLC and the PID. The principal elements are scaling factors, linguistic control rules, weighting coefficient and PID coefficients. The block diagram of the hybrid fuzzy logic controller is shown in Figure 1.

The fuzzy controller with linguistic control variables consists of the N control rules which are implemented by the fuzzy logic implications as (1) [13].

접수일자 : 1995. 5. 15.

1차 수정 : 1995. 8. 20., 2차수정 : 1995. 9. 1.

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\* This paper was supported in part by SPECIAL FUND for UNIVERSITY RESEARCH INSTITUTE(1994), Korea Research Foundation.

$$R^i : \text{ If } E_k \text{ is } A_i, \Delta E_k \text{ is } B_i, \text{ and } \Delta^2 E_k \text{ is } C_i, \text{ then } \Delta U_k \text{ is } D_i \quad (1)$$

where

$R^i$  :  $i$ -th control rule, ( $i = 1, 2, \dots, N$ )

$N$  : the number of control rules

$E_k$  : error

$\Delta E_k$  : change of error

$\Delta^2 E_k$  : change of variation input

$\Delta U_k$  : change of plant control input

$A_i, B_i, C_i$  and  $D_i$  : linguistic values

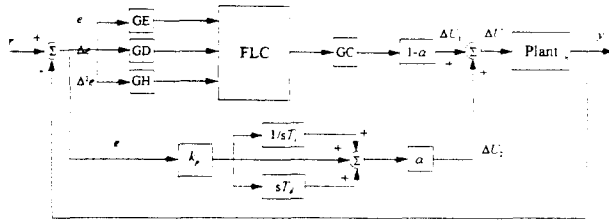


Fig. 1. The scheme of a hybrid fuzzy logic controller.

If the non-fuzzy values,  $E_k$ ,  $\Delta E_k$ , and  $\Delta^2 E_k$ , are substituted for the fuzzy rules in (1), these are fuzzified by membership functions. The inferred value of antecedent part in each rule is calculated as (2).

$$W_i = \min \{ \mu_{A_i}(E_k), \mu_{B_i}(\Delta E_k), \mu_{C_i}(\Delta^2 E_k) \} \quad (2)$$

If the linguistic value,  $D_i$ , of consequent part in (1) is not fuzzy set but singleton, the non-fuzzy value of the fuzzy PID controller is derived from (3), using the simplified reasoning method.

$$\Delta U = \frac{\sum_{i=0}^n W_i D_i}{\sum_{i=0}^n W_i} \quad (3)$$

The PID controller is composed of a conventional one with  $k_p$ ,  $k_i$  and  $k_d$ . PID coefficients are tuned with the other parameters of fuzzy controller. The output of hybrid fuzzy controller is presented as (4). The weighting coefficient  $\alpha$ , between fuzzy and PID controller, is assumed as a fuzzy variable, defined by  $ZR(E)$ .  $\alpha$  is tuned with parameters in fuzzy logic controller simultaneously. In this paper, all the parameters are automatically estimated and optimized by improved complex method. Optimal parameters are applied to hybrid fuzzy logic controller.

$$\Delta U = \Delta U_1 + \Delta U_2 \quad (4)$$

### III. Autotuning by Improved Complex Method

Consider the optimal control to minimize the output error, using ISE (Integral of Square Error) or ITAE (Integral of the Time multiplied by the Absolute value of Error) that shows an error characteristic of the control response to the step input and is a cost function to evaluate the optimal tuning state.

Hybrid fuzzy logic controller also has an objective to minimize ISE or ITAE as cost function. As we regulate the scaling factors, linguistic control rules, weighting coefficient and PID coefficients in order to minimize ISE

or ITAE, the cost function of hybrid fuzzy logic controller has the nonlinear dynamic characteristics that can not be formulated. Also hybrid fuzzy logic controller has a serious problem to apply general optimal techniques, because it is difficult to obtain the cost function and differential of ISE or ITAE.

In order to solve the problems, the autotuning algorithm adapts the improved complex method that extracts the scaling factors, linguistic control rules, weighting coefficient and PID coefficients for the minimum error.

The variables of a cost function are given by scaling factors, linguistic control rules, weighting coefficient and PID coefficients. After we select ITAE as a cost function, we try to minimize the cost function with the step input. Since ISE is also a single optimal value, it can be chosen as the cost function. Even if ISE satisfies the minimum value, the parameters of ISE are somewhat different from ITAE. Hence, the overshoot and reaching time etc. are a little different. When the difference is small, low-order plant can use ISE or ITAE as a cost function. However, as the difference is relatively big in the high-order plant, ISE or ITAE is chosen according to the object of control.

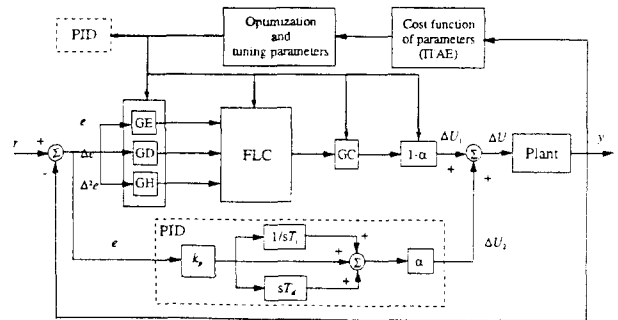


Fig. 2. The auto-tuning scheme of a hybrid fuzzy logic controller.

The scheme of the hybrid fuzzy logic controller as shown in Figure 2 will autotune all the parameters at the same time. After the control output is calculated in off-line, ITAE is obtained. Such a series of values are repeatedly calculated by the improved complex method until the standard deviation of ITAE is smaller than some prescribed small quantity. The parameters of optimal ITAE are stored as the new parameters of the scaling factors, linguistic control rules, weighting coefficient and PID coefficients.

We realize the algorithm to expand and unite the simplex concept to the complex method [2] - constrained optimization technique. The flowchart of the proposed optimal autotuning algorithm is described in Figure 3. The algorithm called the improved complex method, is the constrained complex method that minimizes a cost function, as follows:

Minimize  $f(x)$

Subject to  $g_j(x) \leq 0, j = 1, 2, \dots, m$

$X_i^{(l)} \leq X_i \leq X_i^{(u)} i = 1, 2, \dots, n$

where  $l$  denote the lower bound and  $u$ , the upper bound.

<step 1>

The set of the initial values for the parameters is prepared more than the number of variables, arbitrarily. The parameters mean the scaling factors, linguistic control rules, weighting coefficient and PID coefficients. They are defined as  $X_k = (x_1^k, x_2^k, \dots, x_m^k; k=1, 2, \dots, n, n+1, \dots, m)$  in  $n$  dimensional space. In general,  $m$  is selected as  $2n$  ( $n$  is the number of initial vertices).

<step 2>

The initial values of  $\alpha$ ,  $\gamma$  and  $\beta$  is specified using the Reflection, Expansion and Contraction of simplex concept as follows:

i) Reflection :  $X_r = X_o + \alpha(X_o - X_h)$  (5)

ii) Expansion :  $X_e = X_o + \gamma(X_r - X_o)$  (6)

iii) Contraction :  $X_c = X_o + \beta(X_h - X_o)$  (7)

<step 3>

$X_h$  and  $X_l$  are the vertices corresponding to the maximum function value  $f(X_h)$  and the minimum function value  $f(X_l)$ .  $X_o$  is the centroid of all the points  $X_i$  except  $i=h$ . Reflected point  $X_r$  is given by (5), with  $X_h = \max f(X_i), (i=1, \dots, k)$ ,  $X_o = (1/(m-1))((\sum_{i=1}^n X_i) - X_h)$  and  $\alpha = \|X_r - X_o\| / \|X_h - X_o\|$ .

If  $X_r$  may not satisfy the constraints, a new point  $X_r$  is generated by  $X_r = (X_o + X_r)/2$ . This process is conducted repeatedly until  $X_r$  satisfies the constraints. A new simplex is started.

<step 4>

If a reflection process gives a point  $X_r$  for which  $f(X_r) < f(X_l)$ , i.e. if the reflection produces a new minimum, we expand  $X_r$  to  $X_e$  by (6), with  $\gamma = \|X_e - X_o\| / \|X_r - X_o\| > 1$ .

If  $X_e$  may not satisfy the constraints, a new point  $X_e$  is generated by  $X_e = (X_o + X_e)/2$ . This process is conducted repeatedly until  $X_e$  satisfies the constraints. If  $f(X_e) < f(X_l)$ , we replace the point  $X_h$  by  $X_e$  and restart the process of reflection. On the other hand, if  $f(X_e) > f(X_l)$ , we replace the point  $X_h$  by  $X_r$ , and start the reflection process again.

<step 5>

If the reflection process gives a point  $X_r$  for which  $f(X_r) > f(X_l)$ , for all  $i$  except  $i=h$ . and  $f(X_r) < f(X_h)$ , then we replace the point  $X_h$  by  $X_r$ . In this case, we contract the simplex as in (7), with  $\beta = \|X_c - X_o\| / \|X_h - X_o\|$ .

If  $f(X_r) > f(X_h)$ , we will use  $X_c$  without changing the previous point  $X_h$ . If  $X_c$  may not satisfy the constraints, a new point  $X_c$  is generated by  $X_c = (X_o + X_c)/2$ . This process is conducted repeatedly until  $X_c$  satisfies the constraints. If the contraction process produces a point  $X_c$  for which  $f(X_c) < \min[f(X_h), f(X_r)]$ , we replace the point  $X_h$  by  $X_c$ . and proceed with the reflection again. On the other hand, if  $f(X_c) \geq$

$\min[f(X_h), f(X_r)]$ , we replace all  $X_i$  by  $(X_r + X_i)/2$ , and start the reflection process again.

<step 6>

The method is assumed to have converged whenever the standard deviation of the function at the vertices of the current simplex is smaller than some prescribed small quantity  $\epsilon$  as follows:

$$Q = \left( \frac{\sum_{i=1}^{n+1} [f(X_i) - f(X_o)]^2}{n+1} \right)^{1/2} \leq \epsilon \quad (8)$$

If  $Q$  may not satisfy (8), we go to step 3.

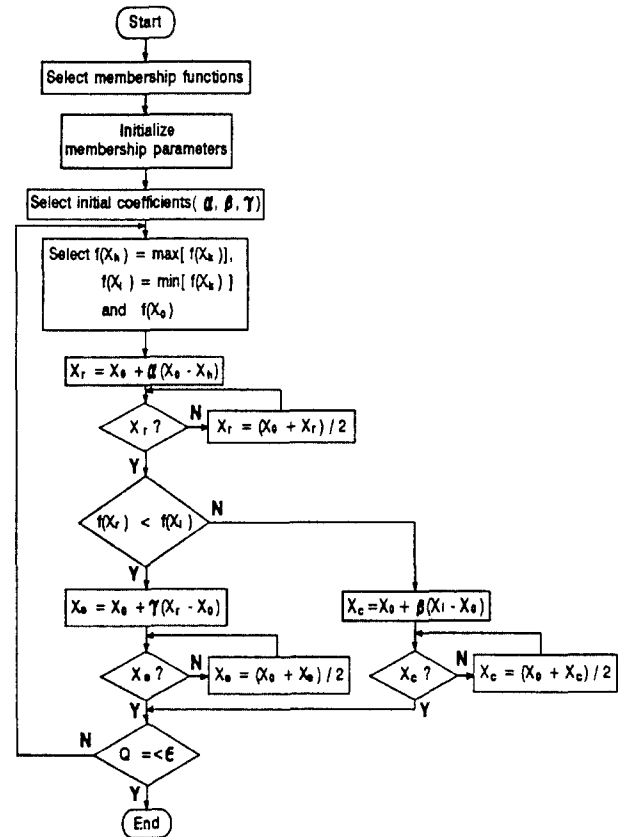


Fig. 3. The flowchart of proposed auto-tuning algorithm.

**IV. Computer Simulation and Results**

To evaluate the performances and characteristics of (hybrid) fuzzy logic controllers with optimal auto-tuning algorithm, the linear and nonlinear plants with time-delay are given in (9)-(11) [16,18]. Computer simulations are performed with the step input of sampling time 0.5[sec]. We analyze the various cases of the fuzzy PID and hybrid fuzzy logic (with Smith-predictor) controllers with 3-fuzzy variables or 5 fuzzy variables in examples. Especially, Plant 1 is mainly explained for 3-fuzzy variables. Table 1 and Figure 4 are initial linguistic control rules and membership functions used in examples.

Plant 1 :  $Y(s)/U(s) = e^{-0.8s} / ((s+1)(s+2))$  (9)

Plant 2 :  $y(k+1) = 0.7 \sin(2u(k)) + y(k)$  (10)

Plant 3 :  $y(k) = u(k-1) + 0.2 u(k-2) + 0.7 y(k-1) + 0.3 y(k-2) - 0.1 y(k-3) - 0.1 y(k-1)^2$  (11)

There are several types of parameterized membership functions commonly used such as triangular and bell

shape membership functions. This paper uses the triangular type, because that is more convenient than the bell type.

Table 1. Linguistic control rules for 3-fuzzy variables.

(a)  $\Delta^2 E = N$       (b)  $\Delta^2 E = Z$       (c)  $\Delta^2 E = P$

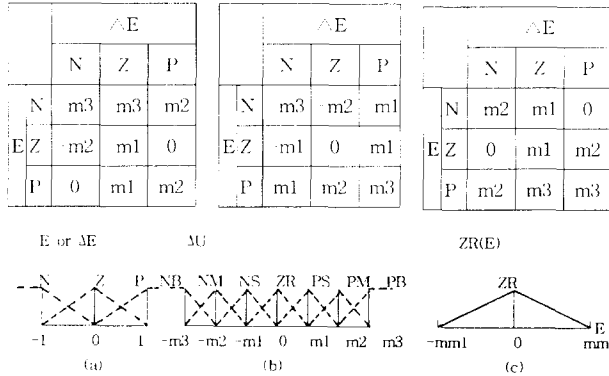


Fig. 4. (a),(b) : Membership functions of linguistic control rules (c) : Membership function of weighting coefficient.

Tables 2-6 represent the initial and tuned parameters for the scaling factors, linguistic control rules, weighting coefficient and PID coefficients, and the performance indices of ITAE, for hybrid fuzzy logic controllers. Figures 5-9 also show the characteristics of process outputs and the convergence procedures to optimal values of scaling factors under the hybrid fuzzy logic controllers. Similarly, Plants 1, 2 and 3 are analyzed.

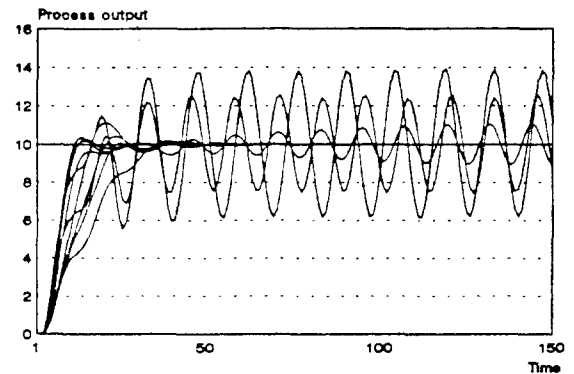
Figure 5 represents the fuzzy PID (FPID) controller for Plant 1 smoothly carries out the tuning under ill conditioned initial values of the parameters. Figure 5 (a) shows the process outputs oscillate under initial conditions but gradually reduce the rising time, the settling time and the overshoot, finally reach the reference values with the decreased steady-state error after tuning process. Simultaneously, Figure 5 (b) shows that the scaling factors change abruptly under initial condition, but converge the optimal values after several iterations of the tuning process. Table 2 shows the initial parameters, and tuned parameters and performance indices for fuzzy PID controller in Plant 1.

Table 2. Tuning parameters and performance index for FPID controller(Plant 1).

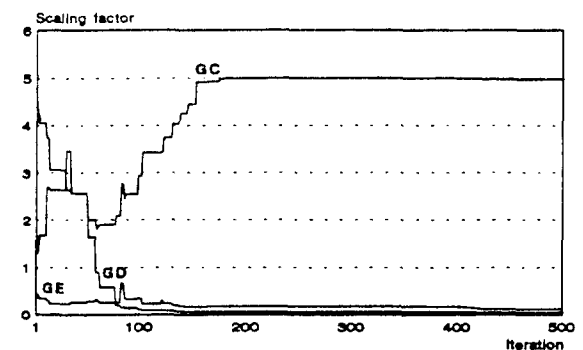
Controller type	FPI - scaling factor tuning - control rule tuning - 3 fuzzy variables					
Initial ITAE	203.050			Tuned ITAE : 40.000		
Initial scaling factor	GE	0.500	GD	1.500	GH	GC 4.570
Tuned scaling factor	GE	0.045	GD	0.118	GH	GC 4.977
Initial control rule	m1	0.333	m2	0.667	m3	1.000
Tuned control rule	m1	0.460	m2	0.947	m3	1.300

Figure 6 represents the tuning procedure of process output and the convergence procedure of optimal parameters by hybrid fuzzy PID (HFPIID) controller for Plant 1. In Figure 6 (a), though the initial overshoot is

big, but after tuning, the overshoot is decreased to optimal output with the fast rising time. In Figure 6 (b)



(a) Tuning procedure of process output.



(b) Convergence procedure to optimal values of scaling factors.

Fig. 5. Process output of FPID controller and convergence procedure to optimal values of control parameters (Plant 1).

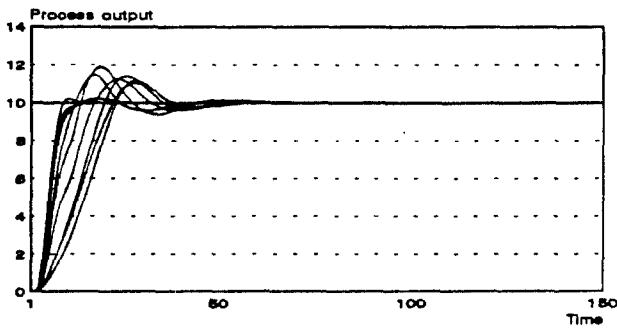
Table 3. Tuning parameters and performance index for HFPIID controller (Plant 1).

Controller type	PID - FPID - scaling factor tuning - control rule tuning - 3-fuzzy variables					
Initial ITAE	90.862			Tuned ITAE : 31.960		
Initial scaling factor	GE	0.410	GD	0.450	GH	GC 1.600
Initial PID parameters	KP	0.100	KI	0.145	KD	1.150
Tuned scaling factor	GE	2.713	GD	5.464	GH	GC 12.841
Tuned PID parameters	KP	1.104	KI	0.015	KD	0.019
Initial control rules	m1	0.330	m2	0.667	m3	1.000
Tuned control rules	m1	0.086	m2	0.607	m3	1.064

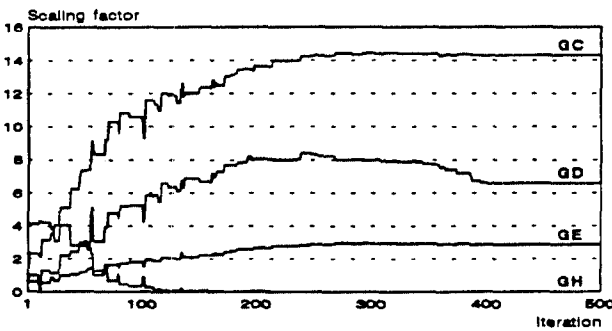
and (c), we observe the scaling factors and PID coefficients approach to the optimal values. Table 3 shows the initial, tuned parameters and performance indices for hybrid fuzzy PID controller in Plant 1.

Figure 7 represents the tuning procedure of process output and the convergence procedure of optimal parameters by the hybrid fuzzy PID controller with Smith-predictor (SPHFPIID) for Plant 1. The controller, consisted of the hybrid fuzzy controller and Smith-predictor radically reduces the performance index, ITAE, that evaluates the control accuracy. It has the fast rising time but has a little overshoot. Therefore, when the overshoot is less than the bounded values, the controller extracts the optimal parameters from the proper process output through the tuning procedure. Table 4 shows the initial and tuned parameters and

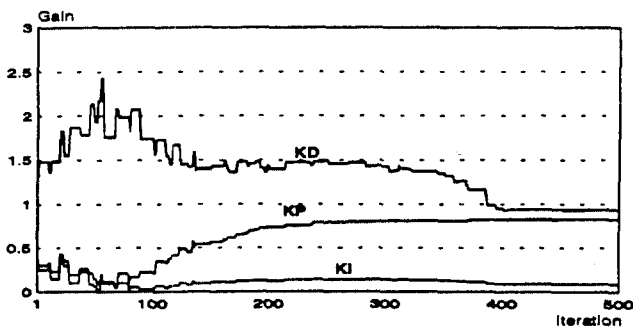
performance indices for hybrid fuzzy PID controller with Smith-predictor in Plant 1.



(a) Tuning procedure of process output.



(b) Convergence procedure to optimal values of scaling factors.



(c) Convergence procedure to optimal values of gains.

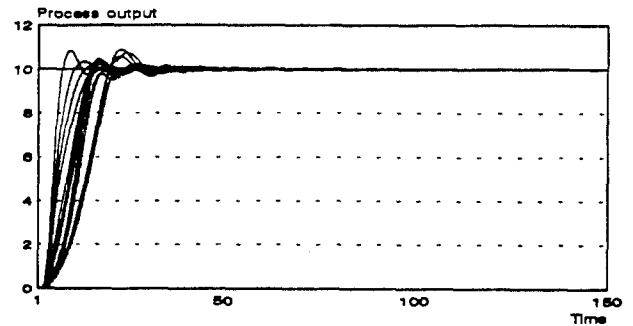
Fig. 6. Process output of HFPID controller and convergence procedure to optimal values of control parameters (Plant 1).

Table 4. Tuning parameters and performance index for SPHFPID controller (Plant 1).

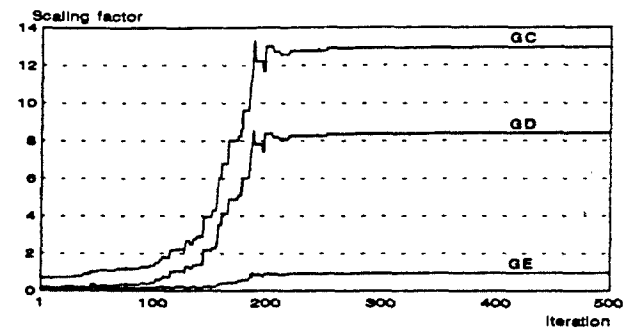
Controller type	PI + FPI + scaling factor tuning + Smith-predictor + 3-fuzzy variables						
Initial ITAE	107.340			Tuned ITAE			20.256
Initial scaling factor	GE	0.192	GD	0.115	GH	GC	0.700
Initial PID parameters	KP	0.500	KI	0.650	KD		
Tuned scaling factor	GE	0.960	GD	8.410	GH	GC	12.942
Tuned PID parameters	KP	0.806	KI	1.e-6	KD		
Initial control rules	m1	0.333	m2	0.667	m3	1.000	mm1 10.00

Figures 8-9 represent the tuning procedures of process outputs and the coverage procedures of optimal parameters by hybrid fuzzy PID (HFPID) controller for nonlinear systems like Plants 2 and 3. This controller can also supply optimal outputs after auto-tuning the

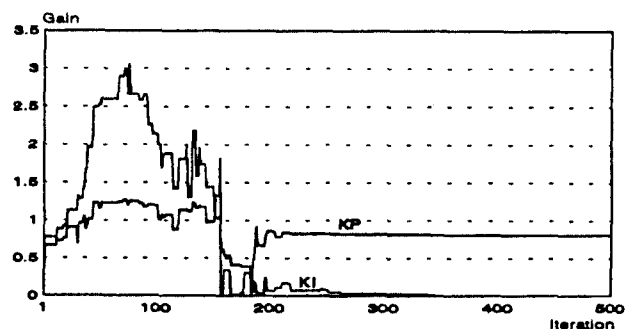
scaling factors, linguistic control rules, PID coefficients and weighting coefficient in the nonlinear system. Tables 5-6 show the initial, tuned parameters and performance indice for hybrid fuzzy PID controller in Plants 2 and 3.



(a) Tuning procedure of process output.



(b) Convergence procedure to optimal values of scaling factors.

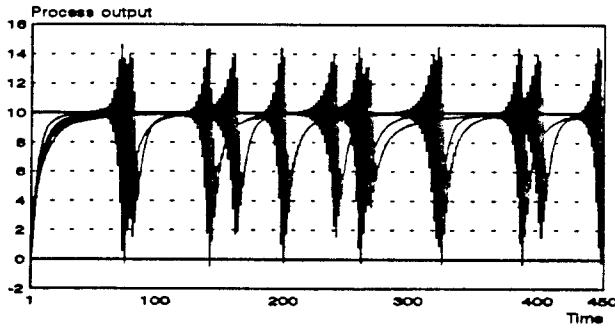


(c) Convergence procedure to optimal values of gains.

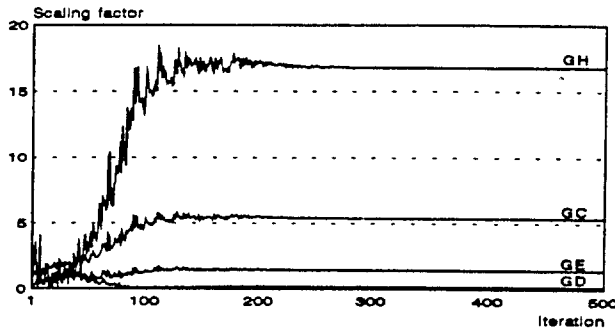
Fig. 7. Process output of SPHFPID controller and convergence procedure to optimal values of control parameters (Plant 1).

Table 5. Tuning parameters and performance index for HFPID controller (Plant 2).

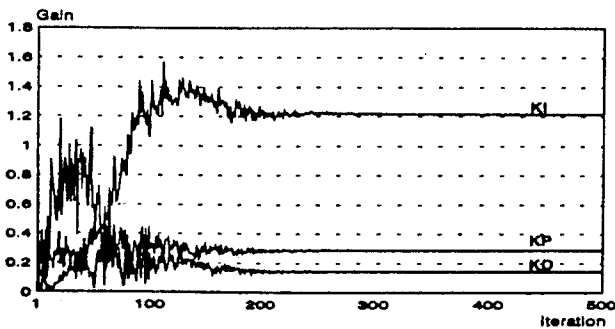
Controller type	PID + FPID + scaling factor tuning + control rule tuning + 3-fuzzy variables						
Initial ITAE	916.126			Tuned ITAE			37.875
Initial scaling factor	GE	0.140	GD	0.160	GH	1.500	GC 1.000
Initial PID parameters	KP	0.120	KI	0.115	KD	0.010	
Tuned scaling factor	GE	1.431	GD	0.167	GH	16.77	GC 5.373
Tuned PID parameters	KP	0.289	KI	1.215	KD	0.143	
Initial control rules	m1	0.333	m2	0.667	m3	1.000	mm1 10.00
Tuned contrl rules	m1	0.412	m2	0.845	m3	1.112	mm1 10.11



(a) Tuning procedure of process output.

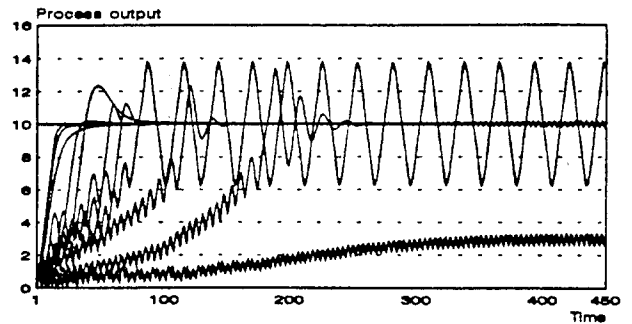


(b) Convergence procedure to optimal values of scaling factors.

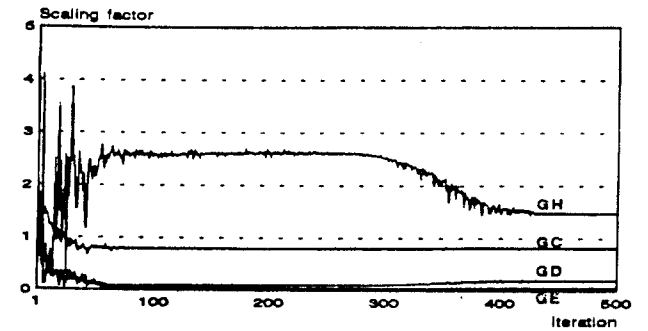


(c) Convergence procedure to optimal values of gains.

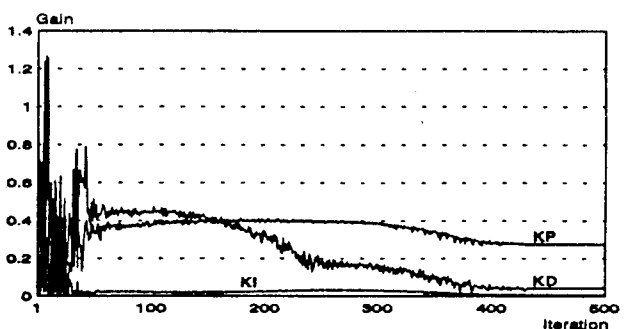
Fig. 8. Process output of HFPID controller and convergence procedure to optimal values of control parameters (Plant 2).



(a) Tuning procedure of process output.



(b) Convergence procedure to optimal values of scaling factors.



(c) Convergence procedure to optimal values of gains.

Fig. 9. Process output of HFPID controller and convergence procedure to optimal values of control parameters (Plant 3).

Table 6. Tuning parameters and performance index for HFPID controller (Plant 3).

Controller type	PID + FPID + scaling factor tuning + control rule tuning + 3-fuzzy variables							
Initial ITAE	1023.928			Tuned ITAE 44.760				
Initial scaling factor	GE	0.052	GD	0.845	GH	2.257	GC	1.680
Initial PID parameters	KP	0.912	KI	0.125	KD	1.180		
Tuned scaling factor	GE	0.047	GD	0.200	GH	1.471	GC	0.816
Tuned PID parameters	KP	0.483	KI	0.378	KD	0.024		
Initial control rules	m1	0.333	m2	0.667	m3	1.000	mm1	10.00
Tuned control rules	m1	0.322	m2	0.659	m3	0.989	mm1	10.11

In the above-mentioned controllers, the proposed auto-tuning algorithm can also tune the weighting coefficient of membership function for control output and finds the optimal weighting coefficient. These processes show excellent characteristic of output near the reference value, 10.

Table 7 shows the comparison of ITAE in each controller of Plant 1. The ITAE is decreased to a large extent, but on the other hand the performance of controller is improved to a great extent..

Table 7. Comparison of ITAE in each controller of Plant 1.

	PID[16]	SOFPID[16]	FPID	HFPID	SPHFPID
Plant 2	46	48.68	40	31.960	20.256

SOFPID : Self-organizing fuzzy PID controller

Figure 10 shows ITAE's of HFPID are being improved along with the tuning procedure, in a case of Plant 1. The ITAE's are rapidly decreased to a large extent in the initial stage and are almost consistent in the tuned stage.

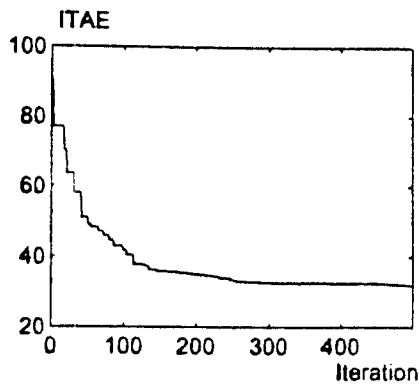
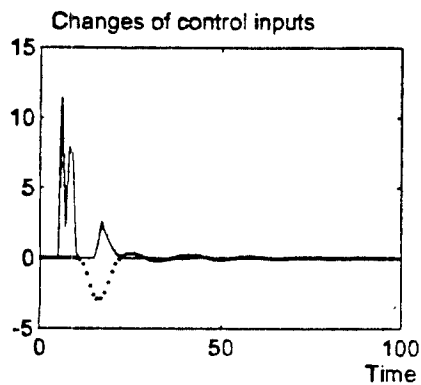


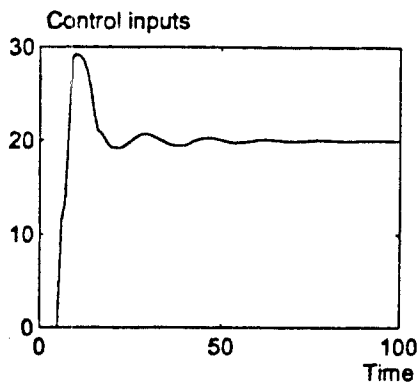
Fig. 10. The change of ITAE for HFPID in Plant 1.

Figure 11 also shows that the control input changes and control input for HFPID are being changed according to the time change, in a case of Plant 1. The control input and control input changes are oscillated in the transient state, but on the other side they are set in the steady state. Especially, the control input is obtained as the summation of the control input changes, namely,  $U_k = U_{k-1} + \Delta U$ , using (4).



-- :  $\Delta U_1$  of FPID, .. :  $\Delta U_2$  of PID

(a) The control input changes for FPID and PID.



(b) The control inputs.

Fig. 11. The control input changes and control input for HFPID in Plant 1.

## V. Conclusions

First, we propose the hybrid fuzzy controller that the control input of the system consisted of a convex combination, by a fuzzy variable, of the FLC's output in

transient state and PID's output in steady state. Second, we have a new optimal auto-tuning algorithm to optimize the scaling factors, linguistic control rules, weighting coefficient and PID coefficients using the proposed complex method. To demonstrate the improved control performance of hybrid fuzzy logic controller, the proposed method is applied to the linear and nonlinear plants with time-delay and dead time.

Some results are drawn from computer simulation as follows:

1. The scaling factors converge to the optimal values, according to automatically adjusting the scaling factors through the proposed method, iteratively.
2. It is easy to simultaneously autotune the scaling factors, linguistic control rules, weighting coefficient and PID coefficients, using the tuned parameters as the initial values, after tuning the scaling factors and weighting coefficient.
3. Because the optimal parameters are automatically tuned under the rate of change and limitation condition of control output, the proposed algorithm may be applied to the real plant, such as the activated sludge process of sewage treatment system [15].
4. The optimal parameters are obtained by not only the determination of the initial parameters (as Chien Hrones Reswrk and Cohen Coon methods), but also the choice of the initial ill-condition, using the proposed algorithm.
5. In the step responses of the linear and nonlinear plants with time delay, the hybrid fuzzy controller with Smith-predictor shows a better result than conventional fuzzy logic controllers.

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