An associate Design of Fuzzy logic with Grey-Neural prediction in PID controller

Lon-Chen Hung* Yuan-Chih Liu* Hung-Yuan Chung**
Department of Electrical Engineering
National Central University
Chungli, Taiwan 320,R.O.C
TEL(03)4227151-4475
E-mail: hychung@cc.ncu.edu.tw
Key words: Fuzzy control, Neural network, Grey

ABSTRAT

Fuzzy control has been successfully applied to various industrial processes in recent years. However, its control rules and membership functions are usually obtained by trial-and-error method. In this research, we propose an associate Grey-neural model design for a compensator.

A hybrid Proportional-Integral-Derivative (PID) controller which combines the Ziegler-Nichols PID controller with the Grey-neural prediction model is presented. Different characteristics of the employed controllers have been appropriately acquired. It is easy to implement and is efficient for multivariable optimization problems. The simulation result shows that the fuzzy controller can be designed to achieve good performance merely using the Grey-neural prediction.

1. INTRODUCTION

A lot of applications of fuzzy control have already received much attention and interest since the concept of the fuzzy control was introduced [1]. The experience gained over the past few years has shown that fuzzy control may often be a preferred method of designing controllers for dynamic systems even if traditional methods can be used [2-3].

The structure of fuzzy system can be classified into many types according to a variety of applications [4-5]. One of the most popular types is the error feedback fuzzy controller, the first application in the world, which is called conventional fuzzy logic controller (FLC) in this paper. The control method of modeling human language has many advantages, such as simple calculation, as well as high robustness, without need to find the transfer function of the system, suitability for nonlinear systems, etc. The human-friendly controls are extensively implemented by people. In particular, fuzzy control compared with classical control or modern control has a better control effect in the case of the nonlinear, time-varying, uncertain system.

Most FLC's are designed based on the experience or knowledge of experts. However, it is sometimes the case that no expert is available. Therefore, the trial-and-error method is usually used to find fuzzy control rules and membership functions.

In practice, usually, if we only used the fuzzy logic as a controller[9], the system performance such as the rising time and the overshoot would not be satisfactory. Thus, we propose a new technique that can prevent the system response from exceeding the set point and can adjust the rising time using the compensator model with grey-neural prediction.

The experimental result shows that the proposed fuzzy hybrid PID controller not only drastically reduces the overshoot, but also maintains a small extent of steady-state error, and will not cause a longer settling time.

2. A BRIEF OF FUZZY CONTROLLER

In recent years, fuzzy logical controllers appear to give a new technique to obtain a good response without having good models of process to be controlled. Up to the present, fuzzy theory and its application still have been developed constantly, and have been used successfully and widely in a variety of fields.

There are three processes involved in the implementation of an FLC; fuzzification of inputs, a rule base or an inference engine, and defuzzification to obtain a "crisp output." Fuzzification involves dividing each input variables' universe of discourse into ranges called fuzzy sets. A function applied across each range determines the membership of the variable's current value to the fuzzy sets. The value at which the membership is maximum is called the peak value. Width of a fuzzy set is the distance from the peak value to the point where the membership is zero. Linguistic rules express the relationship between input variables. Fig. 1. is an example of a matrix of rules

** Corresponding author
*   Graduate student

that covers all possible combinations of fuzzy sets for two input variables. The rules describe a proportional-integral-derivative FLC (PIDFLC). The rule matrix is just a convenience and still represents all the rules in "English" of the form:

R_N : *If* error is E_i and change in error is ΔE_j then output is U_{ij}

where $1\le i \le$ (number of sets for error), $1\le j \le$ (number sets for change in error) and $1\le N \le$ (number of sets for error multiplied by the number of sets for change in error). E_i and ΔE_j are fuzzy sets for error and change in error, respectively and U_{ij} are the output fuzzy sets. In this case, each variable has seven fuzzy sets with the total of 49 rules. The notation PB means positive big; PM means positive medium; PS means positive small; ZO means zero; NS means negative small; NM means negative medium; and NB means negative big. The defuzzification process determines the "crisp output" by resolving the applicable rules into a single output value.

De / e \ u	NB	NM	NS	ZO	PS	PM	PB
NB	NB	ZO	NM	NM	ZO	ZO	ZO
NM	NM	NM	NS	NM	ZO	ZO	ZO
NS	NM	ZO	ZO	ZO	ZO	ZO	PB
ZO	ZO	NS	ZO	ZO	ZO	PB	ZO
PS	NS	ZO	ZO	PS	ZO	PS	PM
PM	ZO	ZO	ZO	PM	PS	PM	PM
PB	ZO	ZO	ZO	PM	PM	PM	PB

Fig. 1. Rule Matrix for PIDFLC

3. GREY THEORY

Grey system is a novel scientific theory and is first proposed by Professor Deng_Julong in the 1982[1-2]. It, mainly, works on a system analysis with poor, incomplete, or uncertain messages[8-9]. Particularly the single-variable first-order differential equation is used to model the GM(1,1) that only uses a few data for modeling process. The GM(1,1) model is defined as

$$\frac{dx^{(1)}(k)}{dk} + ax^{(1)}(k) = b \qquad (1)$$

In the modeling procedure of GM, the original data are preprocessed by using the Accumulated Generating Operation (AGO) for getting the information of the modeling and decreasing the random behavior of system, and then take the generated data to construct the grey model. The modeling procedure is given below.

Step1. Let the original data be $x^{(0)}$

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)) \qquad (2)$$

Step2. Let $x^{(1)}$ be the one time AGO (1-AGO) of the $x^{(0)}$

$$x^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)) \qquad (3)$$

$$\text{where} \quad x^{(1)}(k) = \sum_{m=1}^{k} x^{(0)}(m) \quad k = 1,2,\ldots,n \qquad (4)$$

Step3. Using the least square method to calculate the model parameters $\hat{a}$

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} y_n \qquad (5)$$

which can be expressed in the following matrix form:

$$y_n = B\hat{\theta} \qquad (6)$$

$$\text{where} \quad y_n = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdot \\ \cdot \\ x^{(0)}(n) \end{bmatrix}, \quad B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \cdot & \\ \cdot & \\ -z^{(1)}(n) & 1 \end{bmatrix}, \quad \hat{\theta} = \begin{bmatrix} a \\ b \end{bmatrix}$$

$$z^{(1)}(k) = \alpha_k x^{(0)}(k) + (1-\alpha_k) x^{(1)}(k-1)$$

Using the least square method, the solution is derived as

$$\hat{\theta} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y_N \qquad (7)$$

Step4. The predictive function is obtained

$$x^{(l)}(k+1) = [x^{(1)}(1) - \frac{b}{a}] \cdot e^{-a(n+p-1)} + \frac{b}{a}, \ n \ge 4 \qquad (8)$$

where the parameter "p" is the forecasting step-size. Taking the inverse AGO (IAGO) on $x^{(1)}$, we can obtain the forecasting value of $y^{(0)}(n+p)$ given as follows:

$$x^{(l)}(k+1) = [x^{(1)}(1) - \frac{b}{a}] \cdot e^{-a(n+p-1)} \cdot (1-e^{a}), \ n \ge 4$$

Based on the above description, the grey predictor composed of AGO, IAGO and GM(1,1) can be constructed by

$$\hat{x}^{(0)} = IAGO \circ GM(1,1) \circ AGO \circ x^{(0)} \qquad (10)$$

Since the GM(1,1) model owns nonlinear predictive character under a few data samples (at least 4 points) as well as neural network has memory function, we present a grey-neural model compensator approach in this study.

The past data $x(t-k), \ldots x(t-1), x(t)$ are used to establish the GM(1,1) model and a threshold value is used to decide whether the signal $[x(t-k),....x(t-1),x(t);x(t+\gamma)]$ is a kind of anomalous condition or not. Namely, if the forecasting error is larger than the threshold value, then the $[x(t-k),....x(t-1),x(t);x(t+\gamma)$ are transferred to neural network .The GM(1,1) is primary predictor, while the neural tuner analyzes the data. If there is an improper condition, the neural network residual error will appropriately modify the predictive data [10-13].

4. SIMULATION AND DISCUSSION

To test the proposed method, we use the fuzzy proportional-integral-derivative (PID) controller structure [14-16], as shown in Fig. 2. The PID control is the master controller and the fuzzy control is the slave control to enhance the master one. The antecedent variables of the fuzzy control rule are the error (e) and the error rate (er) of the system's step response. The e and the er are defined as follows[16]:

$$\begin{aligned} e(k) &= y(k) - y_r(k) \\ er(k) &= (e(k) - e(k-1))/T \end{aligned} \tag{11}$$

where y_r is the reference output of the system, and T is the sampling period. The consequent variable is the error variation (Δe) in the FLC system. The FLC uses the variation to tune the errors of the system, thus, it can ameliorate the performance of system's step response. The structure of the Grey-neural network model compensator fuzzy PID control is shown in Fig. 3. The transfer function of the simulated plant is[17]:

$$\frac{1}{(s+1)(s+2)(s+3)} \tag{12}$$

The PID control parameters are chosen initially according to Ziegler-Nichols' rule. The resulting values of k_p, k_i *and* k_d are 9.126, 4.67,and 2.35, respectively. The analog PID control plant system is simulated by using MATLAB. The response of the system has a short rising time of 0.0012s, and zero overshoot, and small steady-state error less than 0.011%.

A comparison of the step response between the fuzzy PID controller with Grey-neural network model system and the PID control system is shown in Fig 3. The simulation result shows that the Grey-neural is efficient and effective for obtaining a hybrid FLC.

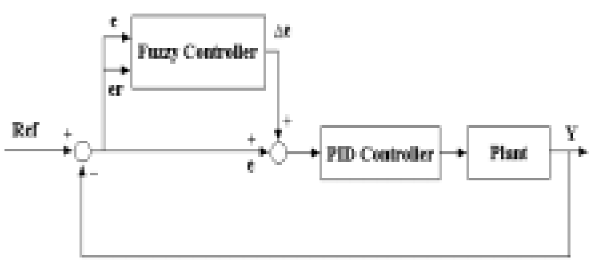

Fig. 2. Fuzzy PID controller structure

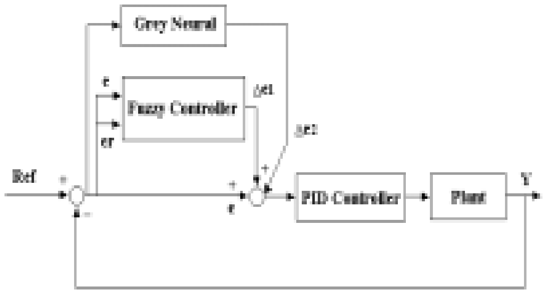

Fig. 3. A hybrid fuzzy PID controller system

	PID controller	Fuzzy controller with PID	Grey Neural with Fuzzy controller with PID
Max	1.1624	1.0442	0.9999
overshoot	16.2358%	4.4180%	0%
Rising time	0.0010sec	0.0011sec	0.0012sec
Settling time (0.02%)	4.4855sec	4.0759sec	2.7269sec
Steady-state error	less than 0.01%	less than 0.01%	less than 0.01%

Fig 4. The response of the various controllers

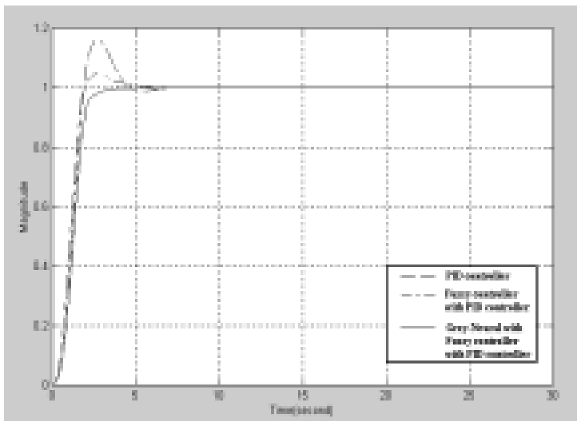

Fig 5. Step responses of the PID controller, the fuzzy PID controller systems and the hybrid fuzzy PID controller systems

5. CONCLUSION

In this paper, an associate Grey-neural model design for a compensator. The simulation result shows that the proposed method is efficient. We propose a hybrid model which can integrate the advantages of fuzzy controller and grey-neural predictor to reduce the overshoot, and adjust rising time. The simulation results have demonstrated the availability of this new model which combines Grey-neural predictor and fuzzy controller.

ACKNOWLEDGMENT

The authors would like to thank the financial support of the National Science Council of the Republic of China under Contract NSC89-2213-E008-046.

REFERENCES

[1] Han-Xiong Li and H.B. Gatland, "Conventional fuzzy control and its enhancement," *IEEE Trans. Syst., Man, Cybern.*, Part B, vol.26 no.5, pp. 791-797, Oct. 1996.

[2] K. Hirota, Ed., *Industrial Application of Fuzzy Technology*. Berlin, Germany: Springer-Verlag, 1993.

[3] C.C. Lee, "Fuzzy logic in control systems: Fuzzy logic controller," *IEEE Trans. Syste., Man, Cybern.*, vol. 20, pp. 404-434, Mar. 1990.

[4] P. P. Wang et al., "Fuzzy dynamic systems and fuzzy linguistic controller classification," *Automatica*, vol. 30, no. 11, pp. 1769-1774,1994.

[5] Thomas Brehm and Kuldip S. Rattan, "Hybrid Fuzzy Logic PID Controller," *Proc. IEEE*, pp.1682-1687, 1994.

[6] K.J. Astrom, C. C. Hang, P. Persson and W. K. Ho, "Toward intelligent PID control" *Automatic*, Vol. 28, No.1, pp.1-9, 1992.

[7] S. Tzafestas and N.P. Papanikolopulos, "Incremental fuzzy expert PID control," *IEEE Transactions on Industrial Electronics*, Vol.37, No.5, pp.365-371, 1990.

[8] J. L. Deng, John H. Wu, "*Grey Theory and Analysis*", 1996, KaoLi publishing co., Inc.

[9] J. L. Deng, "Introduction to grey system theory", *J. Grey System* Vol. 1, pp. 1-24,1989.

[10] Yen-Tseng Hsu and Jerome Yeh, "Grey-Neural Forecasting System," *ISSPA '99, Brisbance Australia*, 22-25 August 1999.

[11] Edward S. Plumer, "Optimal Control of Terminal Processes Using Neural Networks," *IEEE Transactions on Neural networks*, Vol. 7, No.2, pp. 408-418,1996.

[12] Chyi-Tsong Chen and Wei-Der Chang, "A Feedforward Neural Network with Function Shape Autotuning," *Neural Networks*, Vol. 9, No. 4, pp. 627-641, 1996.

[13] Young-Moon Park, Myeon-Song, and Kwang Y. Lee, "An Optimal Tracking Neuro-Controller for Nonlinear Dynamic Systems," *IEEE Transactions on Neural networks*, Vol. 7, No. 5, pp. 1099-1110,1996.

[14] Shi-Zhong He, Shaohua Tan, Feng-Lan Xu and Pei-Zhung Wang, "Fuzzy self-tuning of PID controllers", *Fuzzy Sets and Systems*, Vol.56, p.p. 37-46, 1993.

[15] L.Y. Lai and M. Y. Lee, "Fuzzy tuning of integrator outputs of PID controllers for a DC motor system, " *Chung Yuan J.*, Vol. XXII, pp. 126-137, Dec. 1993.

[16] Yi-Sheng Zhou and Lin-Ying Lai, "Optimal Design for Fuzzy Controllers by Genetic Algrithms," *IEEE Transactions on Industry Applications*, Vol. 36, No.1, pp. 93-97, Jan./Feb. 2000.

[17] Charles L. Phillips and Royce D. Harbor, "*Feedback Control Systems*," 3th, 1996, Prentice-Hall co., Inc.