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Calculation of PID controller parameters by using a fuzzy neural network

Ching-Hung Lee,[a,*] Ching-Cheng Teng[b,†]

[a]Department of Electrical Engineering, Yuan Ze University, 135 Yuan Tung Rd., Chung-Li, Taoyuan 320, Taiwan, Republic of China
[b]Department of Electrical and Control Engineering, National Chiao Tung University, Hsinchu 300, Taiwan, Republic of China

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Abstract

In this paper, we use the fuzzy neural network (FNN) to develop a formula for designing the proportional-integral-derivative (PID) controller. This PID controller satisfies the criteria of minimum integrated absolute error (IAE) and maximum of sensitivity (M_s). The FNN system is used to identify the relationship between plant model and controller parameters based on IAE and M_s. To derive the tuning rule, the dominant pole assignment method is applied to simplify our optimization processes. Therefore, the FNN system is used to automatically tune the PID controller for different system parameters so that neither theoretical methods nor numerical methods need be used. Moreover, the FNN-based formula can modify the controller to meet our specification when the system model changes. A simulation result for applying to the motor position control problem is given to demonstrate the effectiveness of our approach. © 2003 ISA—The Instrumentation, Systems, and Automation Society.

Keywords: PID controller; Dominant pole assignment; Fuzzy neural network

1. Introduction

The proportional-integral-derivative (PID) controllers are still widely used in process industries even though control theory has been developed significantly since they were first used decades ago. There are many well-known PI and PID tuning formulas for stable processes that are suitable for autotuning and adaptive control [1–9]. Astrom and Hagglund, in 1984, first proposed a tuning method for PID controllers based on phase and amplitude specifications [3]. Then, Ho *et al.* presented a tuning method for stable and unstable processes [5–9]. In Refs. [10,11], the author proposed a tuning method based on the integrated error (IE) and maximum of sensitivity (M_s) for special model. However, this method cannot be applied to high-order process. In this paper, we modify the ideas of [10,11] and use the fuzzy neural network system (FNN) to develop an FNN-based tuning formula of PID controller for general processes.

To accomplish the specified performance, fuzzy controllers were proposed including a nonlinear fuzzy PI controller with proportional gain [12] and nonlinear fuzzy PID controller [13,14]. These nonlinear controllers are not easy to implement because of the nonlinearity. In our previous papers [4,15], we presented a tuning method that uses fuzzy neural network (FNN) systems to tune the PID controller parameters efficiently. This approach enjoys the advantage of functionally mapping the FNN, and gives better performance than

*Corresponding author. Tel.: +886-3-4638800, ext. 427; fax: +886-3-4639355. *E-mail address*: chlee@saturn.yzu.edu.tw

†Tel.: +886-3-5712121, ext. 54345; fax: +886-3-5715998. *E-mail address*: ccteng@cn.nctu.edu.tw

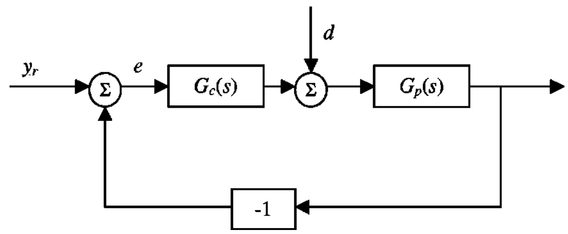

Fig. 1. Block diagram of a simple feedback loop.

the result of [5–9]. Indeed, the proposed method is valid for the general system and guaranteed the stability of the closed-loop system [15]. As the previous results, The FNN is capable of universal approximation with high mapping accuracy [15–19] and offers the following benefits: (1) the ability to learn from experience and adaptability, (2) a simple learning algorithm, and (3) a high degree of robustness and fault tolerance. Here, we will use the FNN to automatically tune the PID controller parameters for a different model.

In this paper, we use the FNN to develop a formula for designing the PID controller. This PID controller satisfies the criterions IAE and M_s. The FNN system will be used to identify the relationship between the plant model and controller parameters. To derive the tuning rule, the dominant pole assignment method is applied to simplify our optimization processes. Therefore, the FNN system is used to automatically tune the PID controller for different system parameters. The FNN-based formula can modify the controller to meet our specification when the system model changes (parameters or plant order varies). Simulation results are given to demonstrate the effectiveness of our approach.

The arrangement of this paper is as follows. In Section 2, we briefly introduce problem formulation, dominant pole assignment method, and the FNN structure. Section 3 presents the proposed tuning formula using the FNN. Section 4 gives the simulation result. Finally, conclusions are summarized in Section 5.

2. Preliminaries

2.1. Problem formulation

Consider the feedback control system, shown in Fig. 1, that composes a process and a controller, where d denotes the external disturbance. Assume that the process is modeled by an nth-order process with time delay

$$G_p(s)=\frac{b_m s^m+b_{m-1}s^{m-1}+\cdots+b_1 s+b_0}{s^n+a_{n-1}s^{n-1}+\cdots+a_1 s+a_0}e^{-Ls}. \tag{1}$$

Here, we assume $n>m$. Here we assume process (1) is stable, i.e., all poles of Eq. (1) have a negative real part. For the PID controller, the transfer function is given by

$$G_C(s)=k+\frac{k_i}{s}+k_d s, \tag{2}$$

and the implementation is

$$u(t)=ke(t)+k_i\int e(t)dt+k_d\frac{de(t)}{dt},$$

where $e=y_r-y$, u, y_r, and y are the control signal, the set point, and plant output, respectively.

Thus,

$$1+G_c(s)G_p(s)$$
$$=1+\frac{(k_i+sk+k_d s^2)(b_m s^m+b_{m-1}s^{m-1}+\cdots+b_0)}{s(s^n+a_{n-1}s^{n-1}+\cdots+a_0)}e^{-Ls}. \tag{3}$$

Herein, we adapt the second-order Padé approximation to replace the time-delay element, i.e.,

$$e^{-Ls}=\frac{a(s)}{b(s)}=\frac{1-\frac{Ls}{2}+\frac{(Ls)^2}{12}}{1+\frac{Ls}{2}+\frac{(Ls)^2}{12}}. \tag{4}$$

Therefore, the characteristic polynomial is obtained as follows:

$$\begin{aligned}\Delta(s)=&(b_m s^m+\cdots+b_1 s+b_0)(k_i+sk+k_d s^2)\\&\times\left(1-\frac{Ls}{2}+\frac{(Ls)^2}{12}\right)\\&+s(s^n+\cdots+a_1 s+a_0)\\&\times\left(1+\frac{Ls}{2}+\frac{(Ls)^2}{12}\right).\end{aligned} \tag{5}$$

It is clear that there are $n+3$ poles in Eq. (5). For system to be stable, we should properly design the controller parameters (k,k_i,k_d) such that all roots

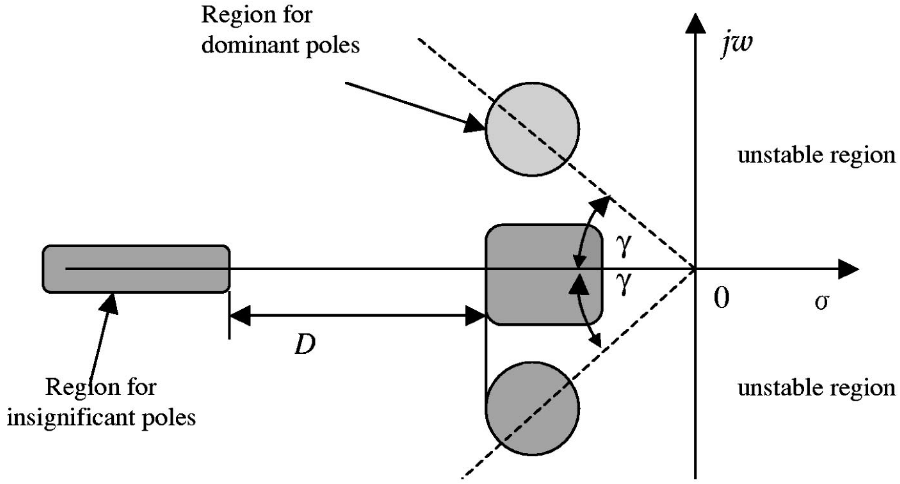

Fig. 2. Regions of dominant and insignificant poles in the complex plane.

of Eq. (5) lie on the left half of the complex plane. The purpose of this paper is to propose a method that designs the PID controller satisfying stabilization and performance index for different models. That is, when the plant model is changed, then the PID controller varies to be a proper one by the FNN system at the same time.

For system performance and robustness requirement, let us introduce the integrated absolute error (IAE) and maximum sensitivity M_s [2]. The IAE is defined as

$$\mathrm{IAE}=\int_0^\infty |e(t)|dt. \tag{6}$$

The criterion IAE is in many cases a natural choice, at least for control of quality variables. The robust specifications usually include gain margin, phase margin, and sensitivity. Herein, a robustness measure for stability, the maximum sensitivity M_s, is adopted. Let M_s be defined as

$$M_s=\max_{0\leqslant w<\infty}\left|\frac{1}{1+G_p(jw)G_C(jw)}\right|. \tag{7}$$

The typical values for the maximum value of the sensitivity function are in the range of 1.3 to 2 [2]. These two specifications are adopted to select the proper parameters that results robustness and good static-state response.

2.2. Dominant pole assignment method

Herein, the dominant pole assignment method [2] is introduced by choosing controller parameters (k,k_i,k_d) based on the above specifications for the poles placement. In practical use, these systems are usually approximated by lower-order systems based on transient response [20]. Therefore, in design, we can use the dominant poles to control the dynamic performance of the system. As in Ref. [20], for design purposes, such as in the pole-placement design, the dominant poles and the insignificant poles, as selected by the designer, should most likely be located in the shaded regions in Fig. 2. According to this method, for different models, the time responses of the closed-loop systems with the same dominant poles will have similar results. The remaining question is to choose proper dominant poles. In this paper, the dominant poles are set based on the IAE and M_s criteria.

In the following, we briefly introduce the relation of dominant poles and PID controller parameters. Note that there are three tuning parameters (k,k_i,k_d) and $n+3$ roots in Eq. (5). Therefore, we can assign three poles of the closed-loop system. Thus, the other poles are obtained relatively. Assume the desired poles are

$$\begin{gathered} P_{1,2}=w_0(-\zeta_0\pm j\sqrt{1-\zeta_0^2})=w_0e^{j(\pi-\gamma)},\\ P_3=-\alpha_0 w_0, \end{gathered} \tag{8}$$

where $\cos\gamma=\zeta_0$. For simplicity, we introduce the quantities $a(w_0)$, $b(w_0)$, and $\phi(w_0)$ defined by

$$\begin{gathered} G_P(w_0e^{j(\pi-r)})=a(w_0)e^{j\phi(w_0)},\\ G_P(-\alpha_0 w_0)=-b(w_0). \end{gathered} \tag{9}$$

The condition that P_1, P_2, and P_3 are roots of Eq. (5) is given as follows [2]:

$$\begin{bmatrix} b & \dfrac{-b}{\alpha_0 w_0} & -\alpha_0 w_0 b \\ -a\cos\phi & \dfrac{a\cos(\phi+\gamma)}{w_0} & w_0 a\cos(\phi-\gamma) \\ -a\sin\phi & \dfrac{a\sin(\phi+\gamma)}{w_0} & w_0 a\sin(\phi-\gamma) \end{bmatrix} \times \begin{bmatrix} k \\ k_i \\ k_d \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}. \tag{10}$$

Thus,

$$k = -\frac{\alpha_0^2 b\sin(\gamma+\phi) + b\sin(\gamma-\phi) + \alpha_0 a\sin 2\gamma}{ab(\alpha_0^2 - 2\alpha_0\cos\gamma + 1)\sin\gamma}, \tag{11a}$$

$$k_i = -\alpha_0 w_0 \frac{a\sin\gamma + b[\sin(\gamma-\phi) + \alpha_0\sin\phi]}{ab(\alpha_0^2 - 2\alpha_0\cos\gamma + 1)\sin\gamma}, \tag{11b}$$

$$k_d = -\frac{\alpha_0 a\sin\gamma + b[\alpha_0\sin(\gamma+\phi) - \sin\phi]}{w_0 ab(\alpha_0^2 - 2\alpha_0\cos\gamma + 1)\sin\gamma}. \tag{11c}$$

By the definition of the dominant poles, we have to check the system's stability and the other poles are far from the dominant pole. Therefore, we use the superposition principle to select (ζ_0, w_0, α_0) and then design the PID controller by IAE and M_s.

Remark 1. *As in the above discussion, the process is of order n with time delay L such that the closed-loop system has n+3 poles. If the considered plant is of lower order without time delay, for example, first order or second order, the domain-pole properties is not obvious. Therefore, in this case, we set the dominant poles to be P_1 and P_2. In Section 4, a motor position control is used as an example to explain this case.*

2.3. Fuzzy neural network

The FNN is one kind of fuzzy inference system [15–19]. Herein, the FNN system is a static case of the recurrent fuzzy neural network (RFNN) [18]. A schematic diagram of the four-layered FNN is shown in Fig. 3. The simplified fuzzy reasoning is briefly described as follows.

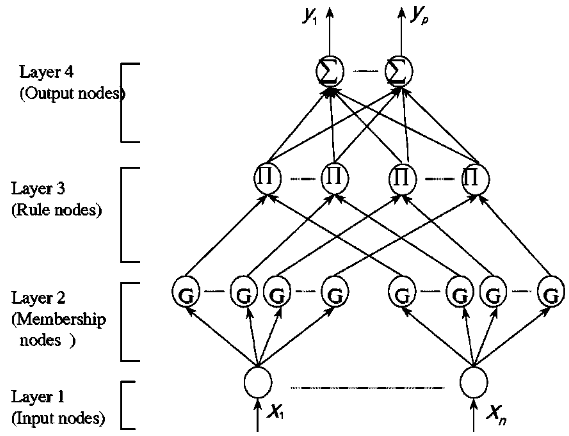

Fig. 3. Schematic diagram of fuzzy neural networks.

Given the training input data x_k, $k=1,2,\ldots,n$ and the desired output y_p, $p=1,2,\ldots,m$, the ith control rule has the following form:

$$R^i:\ If\ \ x_1 \text{ is } A_1^i \text{ and } \cdots x_n \text{ is } A_n^i$$

$$\text{then } y_1 \text{ is } w_1^i \text{ and } \cdots y_m \text{ is } w_m^i,$$

where i is a rule number, the A_q^i's are membership functions of the antecedent part, and w_p^i's are real numbers of the consequent part. When the inputs are given, the truth value μ_i of the premise of the ith rule is calculated by

$$\mu_i = A_1^i(x_1)A_2^i(x_2)\cdots A_n^i(x_n). \tag{12}$$

Among the commonly used defuzzification strategies, the simplified fuzzy reasoning yields a superior result. The output where y_p of the fuzzy reasoning can be derived from the following equation:

$$y_p = \sum_i w_p^i \mu_i, \quad p=1,2,\ldots,m, \tag{13}$$

where μ_i is the truth value of the premise of the ith rule. The FNN system has total four layers.

Nodes in the first layer are input nodes representing input linguistic variables. Layer two has membership nodes. Here, the Gaussian function is used as the membership function. Each membership node is responsible for mapping an input linguistic variable into a possibility distribution for that variable. The rule nodes reside in layer three. The last layer contains the output variable nodes.

More details about FNNs, convergent theorems, and the learning algorithm can be found in Refs. [15–19]. Also, the FNN used here has been shown to be a universal approximator. That is, for any given real function h: $\Re^n \to \Re^p$, continuous on a compact set $K \subset \Re^n$, and arbitrary $\varepsilon > 0$, there exists a FNN system $F(\mathbf{x}, W)$, such that $\|F(\mathbf{x}, W) - h(\mathbf{x})\| < \varepsilon$ for every x in K.

As in the previous discussion, the FNN system is used to find the mapping of the plant model and controller parameters. Therefore, the FNN system used is with $n+m+2$ inputs and three outputs, i.e., input variables $(a_{n-1}, \ldots, a_0, b_m, \ldots, b_0, L)$ and output variables (k, k_i, k_d). Details will be described in the following section.

3. Tuning method for PID controller

Our proposed method can be described in two stages. The design goal of the first stage is to select (k, k_i, k_d) for a process such that IAE is minimized under the constraint that M_s is between 1.3 and 2.0. The second stage is to get training pattern and train the FNN system for developing the parameter tuning formulas.

3.1. Controller design method

Here, our purpose is to design the PID controller to satisfy the IAE and M_s criteria. As previously discussed, it is clear that the PID controller parameter (k, k_i, k_d) is obtained by using Eq. (11) if the dominant poles of Eq. (5), P_{1-3}, are chosen. From the discussion of Ref. [21], the transient response properties are guaranteed by dominant pole assignment. Also, the characteristics of the closed-loop systems having the dominant poles P_{1-3} are similar. Therefore, we can predesign for a plant with three poles P_{1-3} satisfying our specifications. Then, ranges as shown in Fig. 2 are chosen for the considered plant to find the optimal results.

In practice, the industrial processes are usually modeled as a first-order plus time delay plant, e.g., $G(s) = [K_p/(1+as)]e^{-sL}$. Therefore, for clarity, we here choose this system to predesign the dominant pole locations $(\zeta_0^*, w_0^*, \alpha_0^*)$ that satisfy our requirement, i.e., IAE and M_s criteria.

For convenience, the design procedure is described as follows:

Procedure 1.

Step 1. Consider the open-loop response of plant

$$G_b(s) = \frac{k}{s^3 + a_2 s^2 + a_1 s + a_0} e^{-sL},$$

and set the poles of $G_b(s)$ as the dominant poles $(\zeta_0^*, w_0^*, \alpha_0^*)$.

Step 2. Randomly choose poles $[\text{Data}_l = (\zeta_0^l, w_0^l, \alpha_0^l),\ l = 1,\ldots,N]$ from the desired ranges as shown in the shaded region of Fig. 2, i.e.,

$$\begin{aligned}\Omega = \{(\zeta_0, w_0, \alpha_0) | w_0^* e^{j(\pi-\gamma^*)} + R_{p_{1,2}} e^{j\theta} \\ \leqslant w_0 e^{j(\pi-\gamma)} \leqslant w_0^* e^{j(\pi-\gamma^*)} + R_{p_{1,2}} e^{j\theta}, \\ \alpha_0^* w_0^* - R_{p_3} \leqslant \alpha_0 w_0 \leqslant \alpha_0^* w_0^* + R_{p_3}, \\ R_{p_{1,2}} > 0,\ R_{p_3} > 0,\ 0 \leqslant \theta < 2\pi\}. \end{aligned} \tag{14}$$

Step 3. Using Eq. (11), we have the corresponding PID controller parameters $C_l = (k^l, k_i^l, k_d^l)$.

Step 4. Choose the proper parameters $C_l = (k^l, k_i^l, k_d^l)$ that satisfy the dominant pole property and system stability for each control $C_l = (k^l, k_i^l, k_d^l)$.

Step 5. Calculate the corresponding IAE and M_s.

Step 6. If $l < N$, go to Step 1.

Step 7. Choose the pair satisfying $C_l^* = \min_l \text{IAE}(k^l, k_i^l, k_d^l),\ 1.3 \leqslant M_s(k^l, k_i^l, k_d^l) \leqslant 2.0$.

Remark 2. *In Step 2, we select three poles (the dominant poles), and the other n poles $(P_4, \ldots, P_{n+3})$ are set simultaneously. Therefore, for system stability, we must prove these poles lie on the left-half plane. Besides, in Step 4, we should also guarantee the dominant pole properties. That is, these insignificant poles $(P_4,\ldots,P_{n+3})$ should be far from the dominant poles $(P_1,\ldots,P_3)$. In this paper, the distance D is set to be $5w_0 \max(\alpha_0, \zeta_0)$; see Fig. 2.*

3.2. FNN-based PID tuning formulas

Herein, our goal is to develop a tuning formula for general plant, $(k, k_i, k_d) = f(\mathbf{a}, \mathbf{b}, L)$, where $\mathbf{a} = (a_{n-1}, \ldots, a_0), \mathbf{b} = (b_m, \ldots, b_0)$. That is, this formula can automatically tune the PID controller so that neither theoretical methods nor numerical methods need to be used. In this paper, we first obtain the PID controller for given processes using

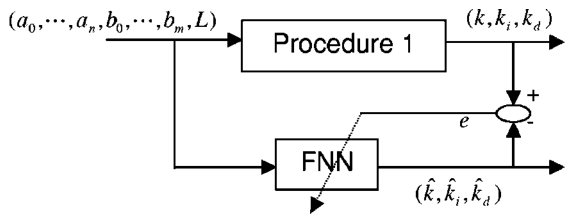

Fig. 4. Training architecture of the FNN-based PID tuning formulas.

Procedure 1. These processes are randomly chosen from a known range, i.e., $a_i=(\underline{a}_i,\overline{a_i})$, $b_i=(\underline{b}_i,\overline{b_i})$, and $L=(\underline{L},\overline{L})$. This is called the variation of plant parameters. We then train the FNN system to identify the mapping of process model and controllers. Fig. 4 summarizes our approach. Because our objective is controller parameters and FNN's inputs are plant parameters, we must create the training data to train the FNN. For the controlled plant, using Procedure 1, we have the corresponding PID controller. Subsequently, train the FNN to develop the PID controller tuning formula.

Remark 3. *In practice, the typical industrial processes are usually modeled as follows (see [2,21]):*

Two-parameter model: $G_1(s)=\dfrac{K}{1+sT}$.

Three-parameter model:

$$G_2(s)=\frac{K}{1+sT}e^{-sL}.$$

Four-parameter model:

$$G_3(s)=\frac{K}{(1+sT_1)(1+sT_2)}e^{-sL}.$$

For generalizing and applying our approach to these test plants, we presented our approach for general systems in this manuscript. Consequently, the number of FNN input is less or equal to 4. From the previous literature [15–19], it is known that the FNN system is capable of universal approximation with high mapping accuracy and offers the ability to learn from experience, adaptability, and a high degree of robustness and fault tolerance. Moreover, our approach is applicable for high-order system by previous discussion.

Remark 4. *From the previous discussion, after developing and training the FNN system, we can conclude that the FNN system automatically designs the PID controller for system model so that neither theoretical methods nor numerical methods need be used. Moreover, the FNN-based formula is able to modify the PID controller according to the system model variation.*

3.3. Training of the FNN system

Considering the single-output case for clarity, our goal is to minimize the error function

$$E(k)=\frac{1}{2}[y_P(k)-\hat{y}(k)]^2=\frac{1}{2}e^2(k), \quad (15)$$

where y_P and $\hat{y}$ denote the desired output (k,k_i,k_d) and estimated output $(\hat{k},\hat{k}_i,\hat{k}_d)$, respectively. Then, the gradient of the above error function is

$$\frac{\partial E}{\partial \Theta}=e(k)\frac{\partial e(k)}{\partial \Theta}=-e(k)\frac{\partial \hat{y}(k)}{\partial \Theta}, \quad (16)$$

where $\Theta=[m,\sigma,w]$ represents the weighting vector of the FNN, m is the mean (center of membership function), σ is the standard deviation (width of the membership function), and w is the linking weight between layers 3 and 4. By using the general backpropagation algorithm, we can describe the update law for the linear system as

$$\begin{aligned}\Theta(k+1)&=\Theta(k)+\Delta\Theta(k)\\&=\Theta(k)+\eta_\Theta\left(-\frac{\partial E(k)}{\partial \Theta}\right)\\&=\Theta(k)+\eta_\Theta e(k)\left(-\frac{\partial \hat{y}(k)}{\partial \Theta}\right).\end{aligned} \quad (17)$$

Therefore, we have the update laws for the FNN:

$$m_{ij}(k+1)=m_{ij}(k)+\eta_m e(k)\frac{\partial \hat{y}(k)}{\partial m}, \quad (18a)$$

$$\sigma_{ij}(k+1)=\sigma_{ij}(k)+\eta_\sigma e(k)\frac{\partial \hat{y}(k)}{\partial \sigma}, \quad (18b)$$

$$w_{ij}(k+1)=w_{ij}(k)+\eta_w e(k)\frac{\partial \hat{y}(k)}{\partial w}, \quad (18c)$$

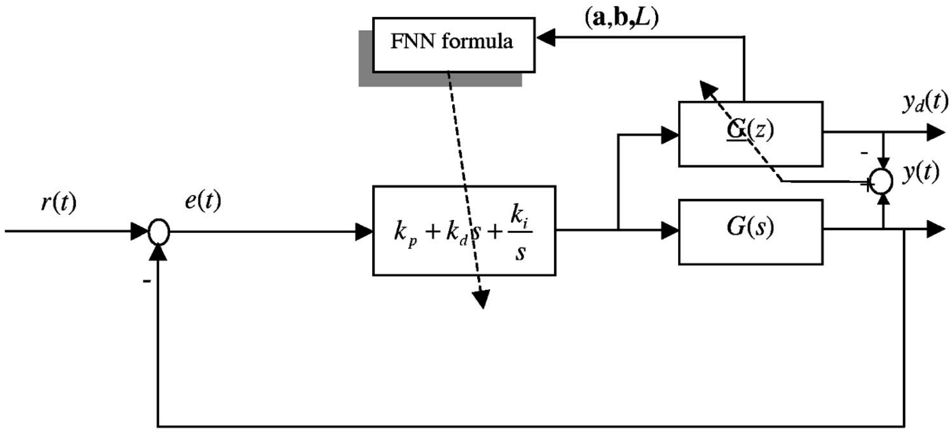

Fig. 5. Control architecture for on-line tuning.

where η_m, η_σ, and η_w are the learning rates for m (mean), σ (STD), and w (weight), respectively. The convergence of the FNN system's parameters is guaranteed by Refs. [15–19]. Details can be found in Refs. [15–17].

3.4. On-line tuning of the FNN formula

After training the FNN system, the FNN-based PID formula is available for system control problem. The control architecture is shown in Fig. 5, where the identification block is to obtain the system's parameter variation. For system identification, we first digitize the continuous-time system to a discrete-time system by a small sampling time T_s. Details for system identification can be found in Ref. [22]. Consequently, the least squares algorithm is used to identify the system parameters. In Section 4, a simulation for applying to a motor position control system is shown to illustrate the effectiveness of this scheme.

4. Simulation results

Our approach is applied to an example to illustrate the effectiveness and robustness. As the description in [2,21], in practice, the typical industrial processes are usually modeled as a first- or second-order with time-delay system. Consequently, a third-order with time-delay plant is adopted in the following examples. The plant is

$$G(s)=\frac{K_p e^{-sL}}{a_3 s^3 + a_2 s^2 + a_1 s + a_0}. \qquad (19)$$

Herein, plant (19) can be reduced to a second or first order if $a_3=0$, $a_2\neq 0$, or $a_3=0$, $a_2=0$, $a_1 \neq 0$. We choose the range $(\underline{a}_3,\overline{a}_3),(\underline{a}_2,\overline{a}_2)$ of parameters (a_3,a_2) that contains the zeros. Then the FNN-PID formulas can be used for the system with order less or equal to three. In the following the range is chosen as

$$a_3\in[0,1], \quad a_2\in(-1,10), \quad a_1\in(0,100),$$

$$a_0\in(0.01,100), \quad K_P\in(0.01,100), \text{ and}$$

$$L\in[0,2].$$

After eliminating the dissatisfying data, there are 2188 training data left finally. The training error is 2.1×10^{-4}.

Example 1. *For the plant*

$$G(s)=\frac{20e^{-2s}}{(s^2+2.4s+4)(s+5)},$$

We assume the plant parameters are exactly known. The developed formula is then tested for the above plant. The step point and load disturbance response in Fig. 6 demonstrates the effectiveness of our approach. The disturbance with magnitude 1 is given at time 20 to 20.1 s. The example shows that the FNN has provided a good mapping result for the system parameter and PID controller.

Example 2. *Consider the DC motor position control system in Fig. 7, where the motor is assumed to have the transfer function*

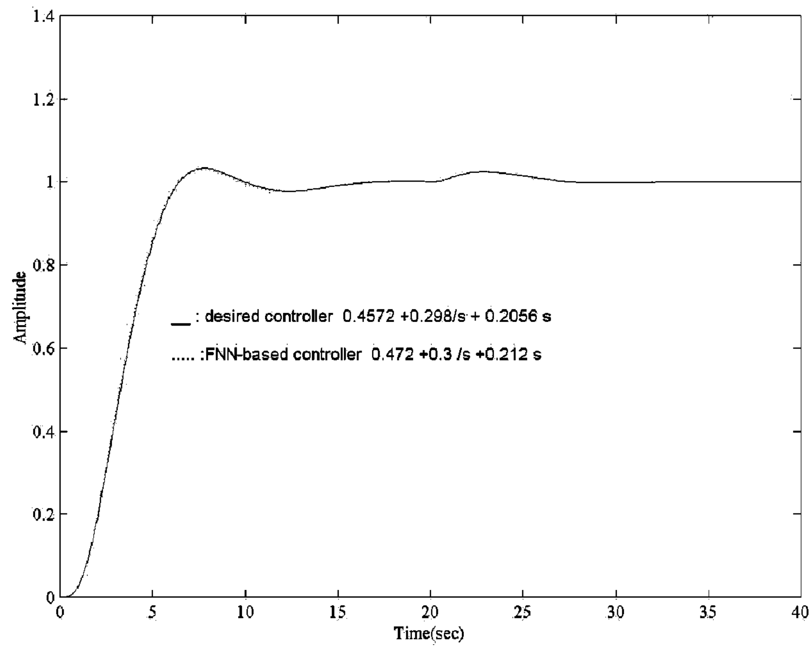

Fig. 6. Simulation result of the test plant $G(s)=20e^{-2s}/(s^2+2.4s+4)(s+5)$.

$$G_m(s)=\frac{K}{s(Js+b)(Ls+R)}=\frac{K}{LJs^3+(bL+JR)s^2+bRs}.$$

Here the parameters of the dc motor will vary when the system load changes. Therefore, the on-line control scheme is applied to solve the position control problem. Obviously, the system is without a time-delay term, and the closed-loop system has four poles. Therefore, we choose two dominant poles with a complex conjugate pair. Here, to simplify our computation, the PI controller was chosen.

In this example, we assume the plant loading changes at time 5 s, where the plant is described as follows:

Nominal plant:

$$\frac{15}{0.005s^3+0.1s^2+1.305s}.$$

Plant with loading variant:

$$\frac{18}{0.0032s^3+0.072s^2+1.28s}.$$

The identification plant:

$$\frac{18}{0.0031s^3+0.077s^2+1.25s}.$$

The FNN-based formulas for the two plants are $(0.39s+1.82)/s$ and $(0.45s+1.41)/s$, respec-

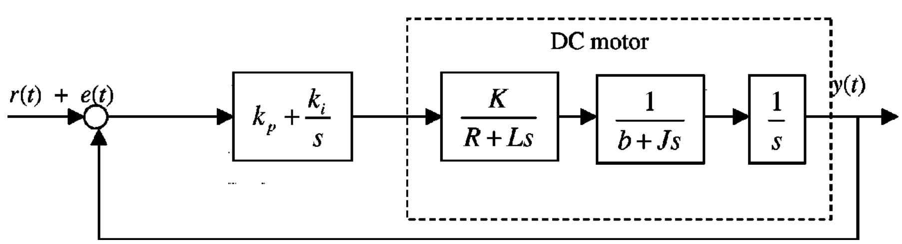

Fig. 7. DC motor position control.

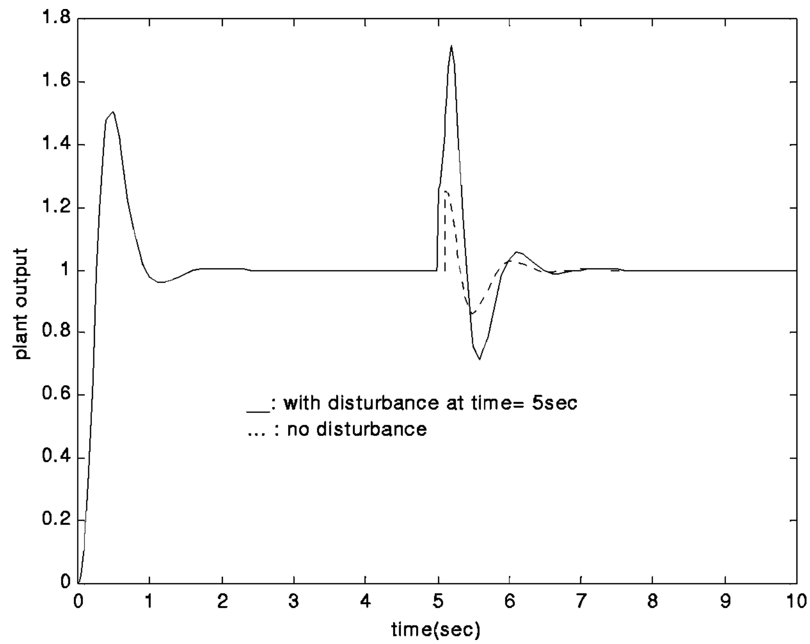

Fig. 8. Simulation result of motor position control.

tively. The parameter variation of the process is identified by the least squares method at time 5 to 5.1 s, i.e., the controller changes at time 5.1 s. Herein, in identification, 11 input-output pairs are chosen to estimate the model. To demonstrate the robustness of our approach, an impulse input disturbance with magnitude 2 is given at time 5 to 5.1 s. Fig. 8 gives the simulation result. The simulation result demonstrates the effectiveness of our approach.

According to the above example, it is indicated that the proposed FNN-based formula and architecture can estimate the parameters of the motor to adjust the self-tuning PI controller control parameters.

5. Conclusions

We have presented an efficient practical method to design the PID controller. This PID controller is based on the criteria of the minimum absolute integrated error (IAE) and maximum of sensitivity (M_s). The FNN system was used to identify the relationship between the plant model and controller parameters based on IAE and M_s. To derive the tuning rule, the dominant pole assignment method is applied to simplify our optimization processes. The FNN system automatically designs the PID controller for the system model so that neither theoretical methods nor numerical methods need be used. Moreover, the FNN-based formula is able to modify the PID controller according to the system model variation. Simulation results have demonstrated the effectiveness of our approach.

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Ching-Hung Lee was born in Taiwan, R.O.C., in 1969. He received B.S. and M.S. degrees in Control Engineering from the National Chiao Tung University, Hsinchu, Taiwan, R.O.C., in 1992 and 1994, respectively, and the Ph.D. degree in Electrical and Control Engineering from the National Chiao Tung University, in 2000. He is currently an Assistant Professor of the Department of Electrical Engineering at Yuan Ze University. His main research interests are fuzzy neural systems, fuzzy logic control, neural network, signal processing, nonlinear control systems, and robotics control.

Ching-Cheng Teng was born in Taiwan, R.O.C., in 1938. He received a B.S. degree in Electrical Engineering from the National Cheng Kung University, Taiwan, in 1961. During 1991–1998, he was the Chairman of the Department of Electrical and Control Engineering, National Chiao Tung University. He is currently a Professor of the Department of Electrical and Control Engineering at National Chiao Tung University. His research interests include H^{∞} optimal control, signal processing, and fuzzy neural systems.