ROBUST PID CONTROL USING GAIN/PHASE MARGIN AND ADVANCED IMMUNE ALGORITHM

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Abstract: Up to the present time, PID Controller has been widely used to control industrial process loops because of its implementational advantages. However, it is very difficult to achieve an optimal PID gain with no experience, since the parameters of the PID controller has to be manually tuned by trial and error. This paper focuses on tuning of the PID controller using gain/phase margin and immune algorithm. After deciding optimal gain/phase margin specifications for the given process, the gains of PID controller using fitness value of immune algorithm depending on error between optimal gain/phase margin and the gain/phase margin obtained by tuning is tuned for the required response. To improve effectiveness of the suggested scheme, simulation results are compared with the FNN (Fuzzy Neural Network) based responses and illustrate more desirable performance.

Key-Words: - PID control; Disturbance control; Immune algorithm, PID tuning, Multiobjective control.

1 Introduction

A Proportional – Integral – Derivative (PID) controller has been using in the most control loops of plant despite continual advances in control theory: process control, motor drives, thermal power plant and nuclear power plant, automotive, fight control, instrumentation, etc. This is not only due to the simple structure which is conceptually easy to understand but also to the fact that the algorithm provides adequate performance in the vast majority of applications [11, 13, 17, 19-22]. Also, the advantage of a PID controller includes simplicity, robustness but it cannot effectively control such a complicated or fast running system, since the response of a plant depends on only the gain P, I, and D. Because of this, a great deal of effort has been spent to find the best choice of PID parameters for different process models [7, 9, 11, 12, 29, 30]. In the tuning problems of a PID process control, the classical tuning methods based on the ultimate gain and the period of the ultimate oscillation at stability limit [1-4], based on tuning identification methods which determine the frequency response of process [5-8], adaptive tuning [8], based on relay feedback [9, 10]. However, these approaches have some problems with tuning such as oscillatory operation's problems, difficulty of physical characteristics in real system. That is, since most of the PID tuning rules developed in the past years use the conventional method such as frequency-response methods, this method needs a highly technical experience to apply as well as they can not provide simple tuning approach to determine the PID controller parameters. For example, the Ziegler-Nichols approach often leads to a rather oscillatory response to set-point changes because the system has non-linearities such as directionally dependent actuator and plant dynamics, and various uncertainties, such as modeling error and external disturbances, are involved in the system [1-2].

Due to a result of these difficulties, the PID controllers are rarely tuned optimally. Therefore, to improve the performance of PID tuning for processes with changing dynamic properties, the complicated system, and dead time process, several tuning strategies such as, automatic tuning PID, adaptive PID, and intelligent tuning technique have been proposed [11-30].

However, the PID controller parameters are still computed using the classic tuning formulae and these can not provide good control performance in control situations. When there is the disturbance in a PID controller loop, the design of a PID controller has to take care of specifications on responses to the disturbance signals as well as robustness with respect to changes in the process [29].

Since load disturbances are often the most common problems in process control, most design methods should therefore focus on disturbance rejection and try to find a suitable compromise between demands on performance at load disturbances and robustness [29]. It will be a great advantage if this compromise can be decided using a tuning method. For instance, if we use to give a good approximation for the gain and phase margins of the system design without having to solve for the equations using numerical methods, on process model such as dead-time model [11-12], tuning approaches will be satisfaction. Therefore, in order to provide consistent, reliable, safe and optimum parameter to industrial control problems, novel tuning PID control schemes are needed.

In this paper, for robust control against disturbance, tuning method of PID controller is suggested using gain margin/phase margin and immune algorithm.

2 Gain Margin and Phase Margin For PID controller

A. Gain Margin and Phase Margin

When the PID controller is given as

$$K(s) = k_p\left(1 + \frac{1}{sT_i} + sT_d\right), \tag{1}$$

and the process is given by

$$G_p(s) = \frac{k_c}{1+s\tau}e^{-sL}, \tag{2}$$

the loop transfer function is obtained by

$$KP_p(s) = \frac{k_p k(1+sT_i)}{sT_i(1+s\tau)}e^{-sL}. \tag{3}$$

On the other hand, the basic definitions of phase margin and gain margin are given as [15]:

$$G_m = \frac{1}{\left|K(j\omega_c)G_p(j\omega_p)\right|}, \tag{4}$$

$$\Phi_m = \arg\left|K(j\omega_c)G_p(j\omega_p)\right| \tag{5}$$

Substituting equation (3) into (4)-(5) gives

$$\frac{1}{2}\pi + \arctan\omega_p T_i - \arctan\omega_p\tau - \omega_p L = 0, \tag{6}$$

$$G_m k_p k = \omega_p T_i\sqrt{\frac{\omega_p^2\tau^2+1}{\omega_p^2 T_i^2+1}}, \tag{7}$$

$$k_p k = \omega_g T_i\sqrt{\frac{\omega_g^2\tau^2+1}{\omega_g^2 T_i^2+1}}, \tag{8}$$

$$\Phi_m = \frac{1}{2}\pi + \arctan\omega_g T_i - \arctan\omega_g\tau - \omega_g L. \tag{9}$$

For process given as k, τ, L and specifications defined by G_m, Φ_m. Equations (8)-(11) can be solved for the PID controller parameters, k_p, T_i, T_d and crossover frequencies ω_g, ω_p numerically but analytically because of the presence of the arctan function. Through reference [15], final gain margin and phase margin can be given by

$$G_m = \frac{\pi\tau}{4kL}\left(1 + \sqrt{1 - \frac{4L}{\pi T_i} + \frac{4L}{\pi\tau}}\right), \tag{10}$$

$$\Phi_m = \frac{1}{2}\pi - \frac{kk_pL}{\tau} + \frac{\pi}{4k_pk}\left(1 - \frac{\tau}{T_i}\right). \tag{11}$$

Whatever the design approach, tuning technique based on gain margin and phase margin can has robustness and stability without plant operation condition.

3 Immune Algorithms for Tuning of PID controller Based on Gain Margin and Phase Margin

3.1 Immune Algorithm

In Fig. 1, when an antibody on the surface of a B cell binds an antigen, that B cell becomes stimulated. The level of stimulation depends not only on how well the B cell's antibody matches the antigen, but also how it matches other B cells in the immune network [23-26]. The stimulation level of the B cell also depends on its affinity with other B cells in the immune network. This network is formed by B cells possessing an affinity to other B cells in the system. If the stimulation level rises above a given threshold, the B cell becomes enlarged and if the stimulation level falls below a given threshold, the B cell die off. The more neighbours a B cell has an affinity with, the more

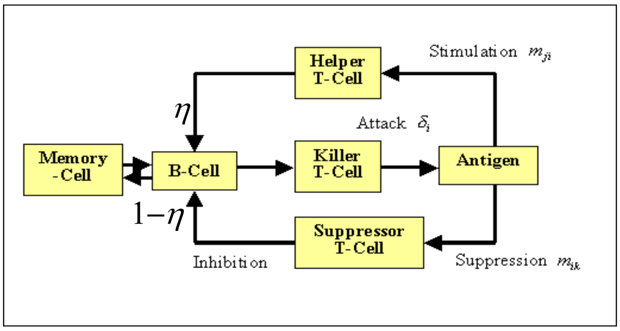

Fig. 1. Dynamic relationship between cells, antigen.

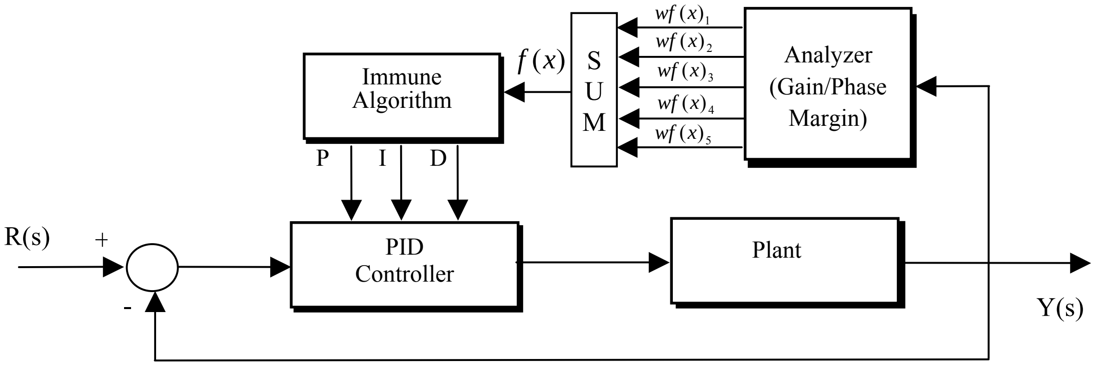

Fig. 2. Structure of immune based PID controller tuning.

stimulation it will receive from the network, and vice versa. Against the antigen, the level to which a B cell is stimulated relates partly to how well its antibody binds the antigen. We take into account both the strength of the match between the antibody and the antigen and the B cell object's affinity to the other B cells as well as its enmity.

Therefore, generally the concentration of i-th antibody, which is denoted by δ_i, is calculated as follows [23, 25]:

$$\frac{dS_i(t)}{dt} = \left(\begin{array}{l} \alpha \sum_{j=1}^{N} m_{ji}\delta_j(t) \\ -\alpha \sum_{k=1}^{N} m_{ik}\delta_k(t) + \beta m_i - \gamma_i \end{array} \right) \delta_i(t), \quad (12a)$$

$$\frac{d\delta_i(t)}{dt} = \frac{1}{1+\exp\left(0.5 - \frac{dS_i(t)}{dt}\right)}, \quad (12b)$$

where in Eq. (12), N is the number of antibodies, and α and β are positive constants. m_{ji} denotes affinities between antibody j and antibody i (i.e. the degree of interaction), m_i represents affinities between the detected antigens and antibody i, respectively.

3.2 Evaluation Method for Tuning of PID Controller Based on Gain Margin/Phase Margin and Immune Algorithm

In this paper, for the constrained optimization tuning for gain margin and phase margin, immune algorithms are considered, i.e., memory cell of immune algorithm to minimize fitness function for gain margin G_m and phase margin Φ_m, as depicted in Fig. 3. Initially, memory cell is started with the controller parameters within the search domain as specified by the designer. These parameters are transferred then to network, which is initialized with the variable gain margin and phase margin [23].

Immune algorithm minimizes fitness function for P, I, D gain and gain/phase margin during a fixed number of generations for each individual of memory cell in immune network. Next, if the minimum value will be associated to the corresponding individual of memory cell. Individuals of memory cell that satisfy the tuning requirement will not be penalized. In the evaluation of

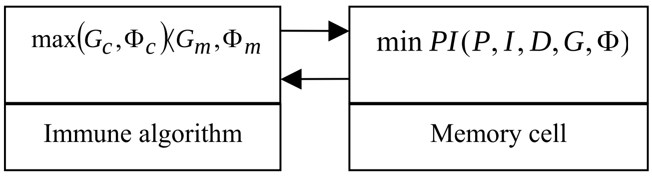

Fig. 3. Immune algorithm based computational structure for optimal parameter selection.

the fitness function of memory, individuals with higher fitness values are selected automatically and those penalized will not survive the evolutionary process. For the implementation of the immune algorithm, this paper used tournament selection, arithmetic crossover, and mutation [2-28].

- Representation

In the immune based representation, the parameters of the controller were coded in floating – point and concatenated in an individual of immune network. For memory cell of immune network, an individual consists of only one gene (gain margin and phase margin to frequency ω).

- Fitness Function

The value of the fitness of each individual of immune network $\Gamma_i(c_i(i=1,\ldots,n))$ is determined by the evaluation function, denoted by $\Gamma(c_i)$ as

$$\Gamma_i(c_i) = -\left(PI_n(G_m^i, P_m^i) + \Phi(P_i, I_i, D_i)\right), \qquad (13)$$

where n denotes the population size of immune network and $\Gamma_i(c_i)$ is total fitness function, $PI_n(G_m^i, P_m^i)$ is fitness function for calculation of gain/phase margin, $\Phi(P_i, I_i, D_i)$ is fitness function for computing P, I, and D gain. For robust tuning of PID controller, this paper uses five kinds of objective function such as gain margin, phase margin, P (proportional gain), I (Integral gain), and D (Derivative gain). In each objective function, fitness value is obtained as the followings; For example, when value of overshoot on reference model is over the given value 1.2, fitness value is 0 but if overshoot value is within the given value 1.2, fitness value is calculate by level of membership function defined in Fig. 6(a). Fitness value for rise time, settling time, gain margin, and phase margin is computed using each membership function in Fig. 6. In Fig. 6, $f_1(\bullet)$, $f_2(\bullet)$ $f_3(\bullet)$, $f_4(\bullet)$, and $f_5(\bullet)$ show membership function for settling time, rise time, overshoot, gain margin, and phase margin, respectively.

3.3 Computational Procedure for Optimal Selection of Parameter

The coding of an antibody in an immune network is very important because a well designed antibody coding can increase the efficiency of the controller. As shown in Fig. 4, there are three type antibodies for tuning of PID controller gain: 1) antibody type 1 is encoded to represent only P (c1) gain in the PID controller; 2) antibody type 2 is encoded to represent I (c2) gain; 3) antibody is encoded to represent D (c3) gains. For calculation of gain/phase margin, the similar antibody is given.

C1	2	1	0.5	• • •	0.2	0.1
C2	2	1	0.5	• • •	0.2	0.12
C3	2	1	0.5	• • •	0.2	0.1

Fig. 4. Allocation structure of P, I, and D gains in locus of antibody of immune algorithm.

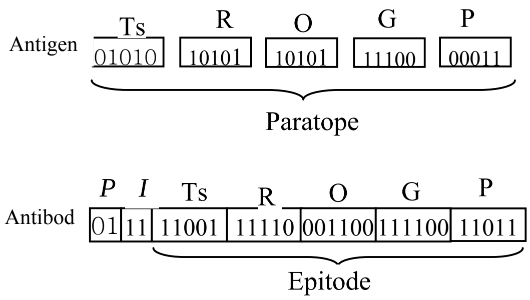

Fig. 5. Antigen and antibody structure for reference model, gain margin and phase margin based tuning.

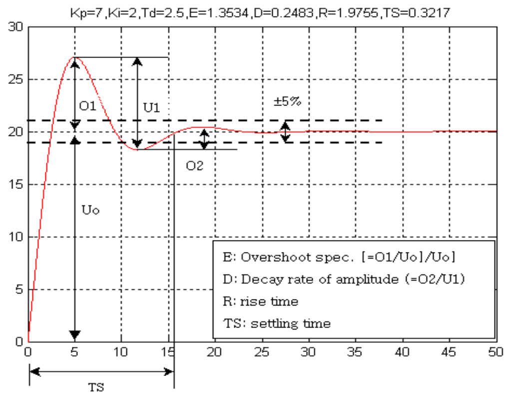

Fig. 6. Specification of reference model.

The value of the k locus of antibody type 1 shows P gain allocated to route 1. That is, the value of the first locus of antibody type 1 means that P gain allocated to route 1 is obtained by route 2 [26-28]. Structures of antibody for I-gain, D-gain, gain margin and phase margin are allocated like antibody of P-gain.

When it is coding for controller tuning, the lower and upper bounds of the controller parameters are specified and immune network and memory cell parameters should be set up: crossover probability, mutation provability, population size, and maximum number of generations.

For calculation of gain/phase margin and controller gain, the following procedure is used.

[Step 1] Initialization and recognition of antigen: The immune system recognizes the invasion of an antigen, which corresponds to reference model such as settling time (Ts), rise time (R), overshoot (O), gain margin (Gm), and phase margin (Pm) in the optimization problem as shown in Fig. 3.

[Step 2] Product of antibody from memory cell: The immune system produces the antibodies that were effective to kill the antigen in the past. This is implemented by recalling a past successful solution from memory cell.

For each individual c_i of the network population, calculate the fitness function using memory cell. In this paper, we calculates gain margin and phase margin the given plant, When error of the calculated gain and phase margin in memory cell to optimal gain and phase margin is smaller, fitness function is larger. The fitness level is decided by membership function as Eqs. 16-20 and Fig. 6.

$$f_1(x_1;a_1,b_1) = \frac{1}{1+e^{-a_1(x_1-b_1)}}, \tag{16}$$

$$f_2(x_2;a_2,b_2) = \frac{1}{1+e^{-a_2(x_2-b_2)}}, \tag{17}$$

$$f_3(x_3;a_3,b_3) = \begin{cases} 0, & x_3 \le a_3 \\ \frac{x_3-a_3}{b_3-a_3}, & a_3 \le x_3 \le b_3 \\ \frac{c_3-x_3}{c_3-b_3}, & a_3 \le x_3 \le b_3 \\ 0, & c_3 \le x_3 \end{cases} \tag{18}$$

$$f_4(x_4;a_4,b_4) = \begin{cases} 0, & x_4 \le a_4 \\ \frac{x_4-a_4}{b_4-a_4}, & a_4 \le x_4 \le b_4 \\ \frac{c_4-x_4}{c_4-b_4}, & a_4 \le x_4 \le b_4 \\ 0, & c_4 \le x_4 \end{cases} \tag{19}$$

$$f_5(x_5;a_5,b_5) = \begin{cases} 0, & x_5 \le a_5 \\ \frac{x_5-a_5}{b_5-a_5}, & a_5 \le x_5 \le b_5 \\ \frac{c_5-x_5}{c_5-b_5}, & a_5 \le x_5 \le b_5 \\ 0, & c_5 \le x_5 \end{cases} \tag{20}$$

[Step 3] Antibody with the best fitness value obtained by calculation for searching an optimal solution is stored in memory cell.

[Step 4] Differentiation of lymphocyte: The B - lymphocyte cell, the antibody that matched the antigen, is dispersed to the memory cells in order to respond to the next invasion quickly. That is, select individuals using tournament selection and apply genetic operators (crossover and

Fig. 6. Shape of membership functions for decision of fitness level.

mutation) to the individuals of network.

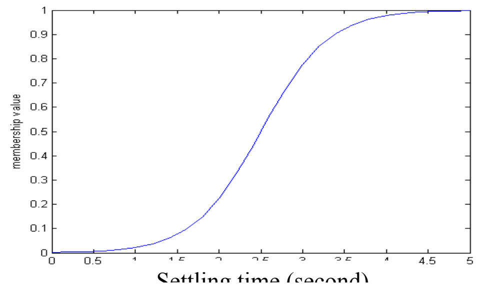

Fig. 6 (a) Membership function for settling time.

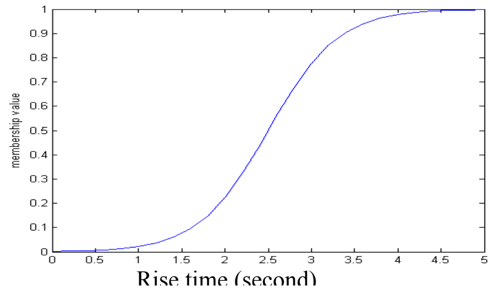

Fig. 6 (b) Membership function for rise time

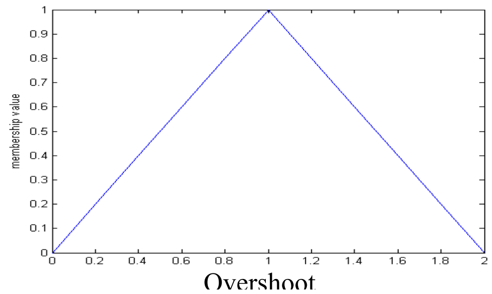

Fig. 6 (c) Membership function for overshoot.

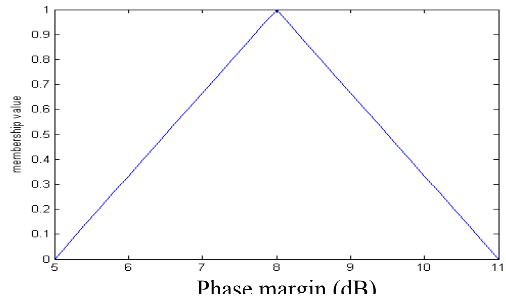

Fig. (d) Membership function for gain margin.

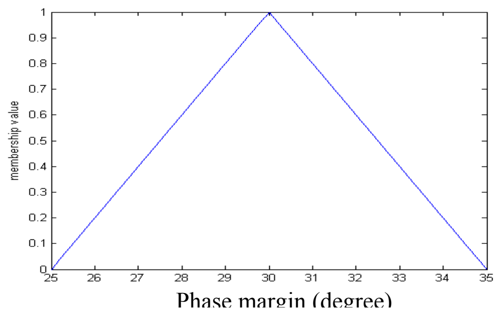

Fig. 6 (e) Membership function for phase margin.

[Step 5] Stimulation and suppression of antibody: The expected value η_k of the stimulation of the antibody is given by

$$\eta_k = \frac{m_{ji}}{\sigma_k} \tag{21}$$

where σ_k is the concentration of the antibodies. The concentration is calculated by affinity. So, σ_k is represented by

$$\sigma_k = \frac{\text{sum of antibodies with same the affinity as } m_{ji}}{\text{sum of antibodies}} \quad .(22)$$

Using equation (22), an immune system can control the concentration and the variety of antibodies in the lymphocyte population. If antibody obtains a higher affinity against an antigen, the antibody stimulates. However, an excessive higher concentration of an antibody is suppressed. Through this function, an immune system can maintain the diversity of searching directions and a local minimum. That is, for each individual loop of the network, calculate reproduction of antibody by:

$$P_n^{'} = \left[\alpha \sum_{i=1}^{l} f_{st}(P_n^i)/L - \beta \sum_{i=1}^{l} f_{su}(P_n^i)/L \right] \times P_n + P_{n-1}, \tag{23}$$

$$T_{in}^{'} = \left[\alpha \sum_{i=1}^{l} f_{st}(T_{in}^i)/L - \beta \sum_{i=1}^{l} f_{su}(T_{in}^i)/L \right] \times T_{in} + T_{in-1}, \tag{24}$$

where, $f_{st}(P_n^i)$, $f_{su}(P_n^i)$ is defined by

$$f_{st}(P_n^i): stimulation \begin{cases} 1, & if \ P_n^i \ is \ stimulation \\ 0, & Others \end{cases} \quad i = 1,...l, \ exception \ n,$$

$$f_{su}(P_n^i): suppression \begin{cases} 1, & if \ P_n^i \ is \ supression, \ i = 1,...,l \\ 0, & Others \end{cases}$$

$$f_{st}(P_n^i) = f_{su}(P_n^i) = 0, \ if \ P_n^i \ is \ Hold,$$

L = the number of pcell.

[Step 6] Calculate fitness value between antibody and antigen. This procedure can generate a diversity of antibodies by a genetic reproduction operator such as mutation or crossover. These genetic operators are expected to be more efficient than the generation of antibodies.

[Step 7] If the maximum number of generations of memory cell is reached, stop and return the fitness of the best individual fitness value to network; otherwise, go to step 3.

5 Simulation Results and Discussions

In order to prove robust control scheme based on the gain margin and phase margin and immune algorithm suggested in this paper, we used the plant models as the following equations [30]:

$$G_p = \frac{[18:15]}{[0.0032:0.005]s^3 + [0.072:0.1]s^2 + [1.28:1.305]s} \tag{25}.$$

For this model, when gain margin $G_m = 8dB$, phase margin $\Phi = 30^\circ$ is given as the design requirement, tuning results tuned by gain margin-phase margin and immune algorithm are obtained as shown in Figs. 8-28. Fig. 7 shows gain margin and phase margin for robust controller design.

Fig. 28 shows that bigger stimulation factor than α =0.25 has no an impact to control response and immune based control response more stable.

Table 1. Parameters designed by FNN.

	Kp	Ti	Gm	Pm
FNN	0.29	1.11	8.17	29.21

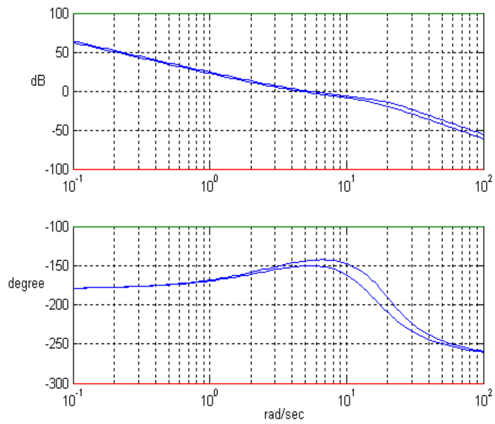

Fig. 7. Bode plot for reference gain margin and phase margin.

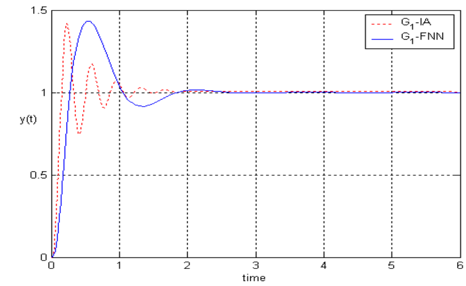

Fig. 8. Step response by IA and FNN (α =0.05, β =0.95)

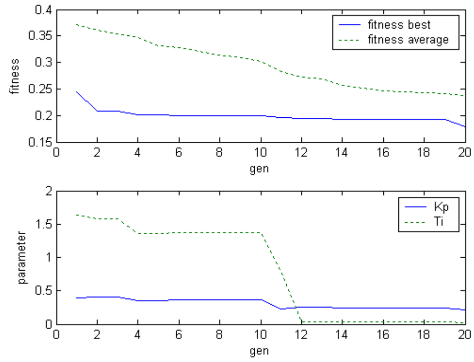

Fig. 9. Fitness value and parameters. (α =0.05, β =0.95)

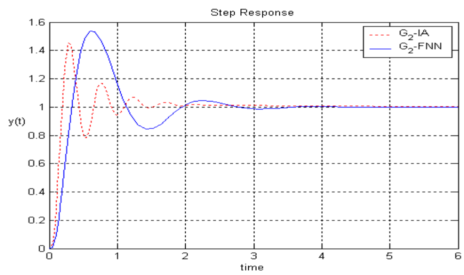

Fig. 10. Step Response by IA and FNN. (α =0.1, β =0.9)

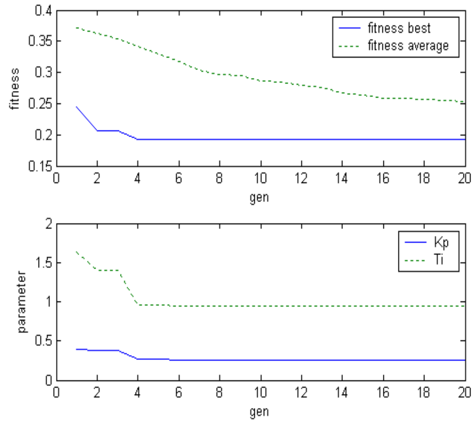

Fig. 11. Fitness value and parameters. (α =0.15, β =0.85)

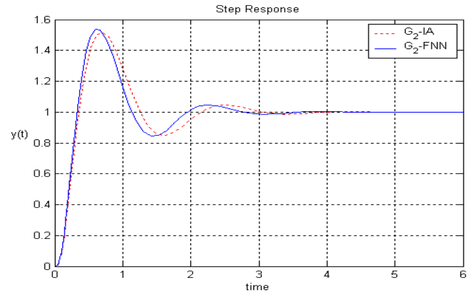

Fig. 12. Step Response by IA and FNN. (α =0.15, β =0.85)

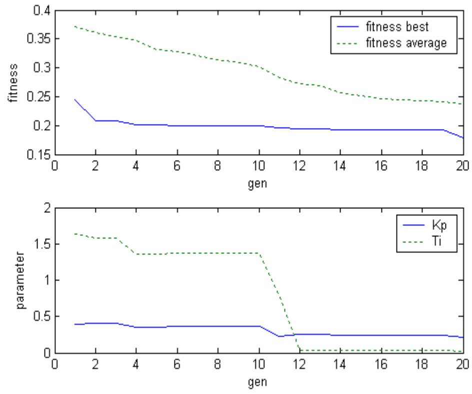

Fig . 13. Fitness value and parameters. (α =0.15, β =0.85)

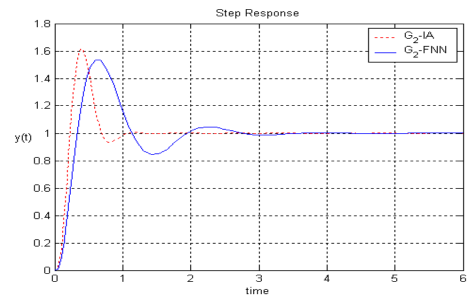

Fig. 14. Step Response by IA and FNN. (α =0.2, β =0.8)

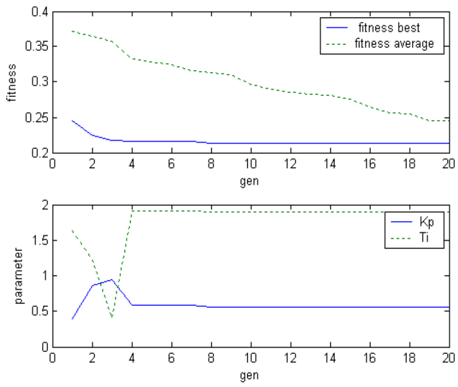

Fig . 15. Fitness value and parameters. (α =0.2, β =0.8)

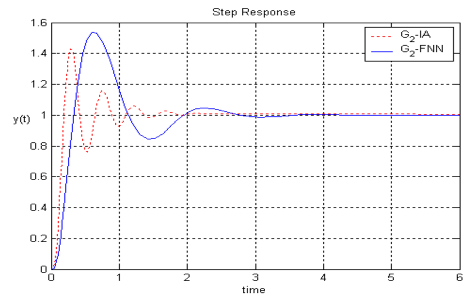

Fig. 16. Step Response by IA and FNN. (α =0.25, β =0.75)

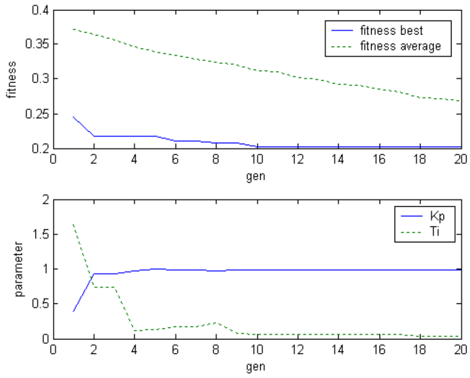

Fig .17. Fitness value and parameters. (α =0.25, β =0.75)

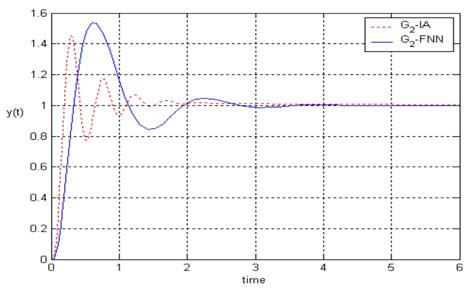

Fig. 18. Step Response by IA and FNN. (α =0.3, β =0.7)

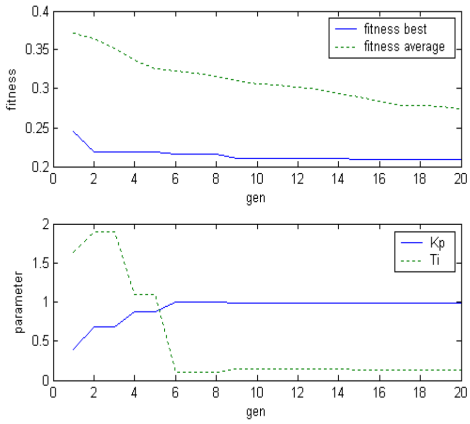

Fig. 19. Fitness value and parameters. (α =0.3, β =0.7)

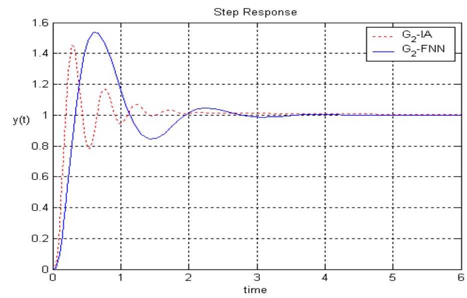

Fig. 20. Step Response by IA and FNN. (α =0.35, β =0.65)

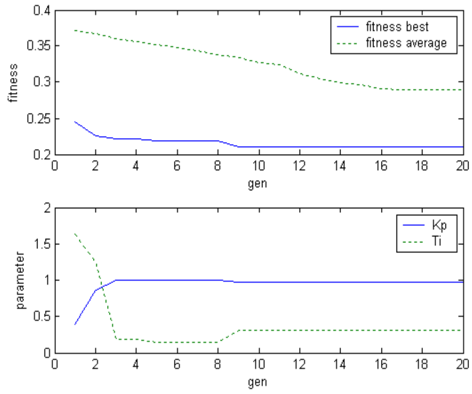

Fig. 21. Fitness value and parameters. (α =0.35, β =0.65)

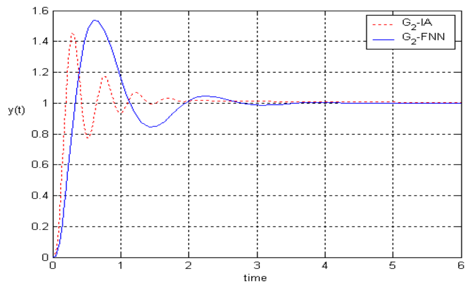

Fig. 22. Step Response by IA and FNN. (α =0.4, β =0.6)

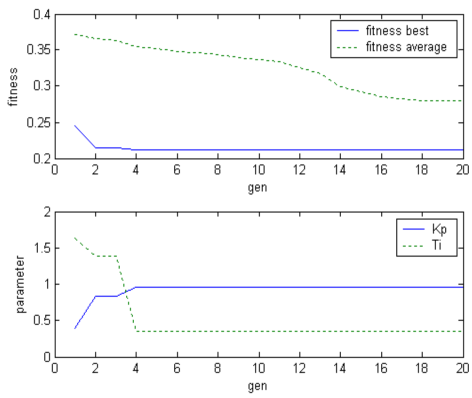

Fig. 23. Fitness value and parameters. (α =0.4, β =0.6)

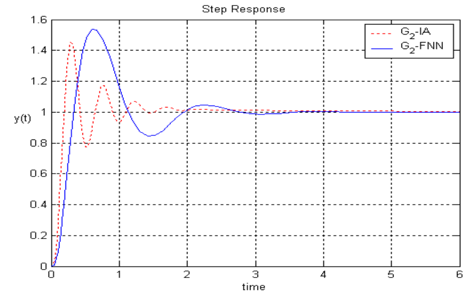

Fig. 24. Step Response by IA and FNN. (α =0.45, β =0.55)

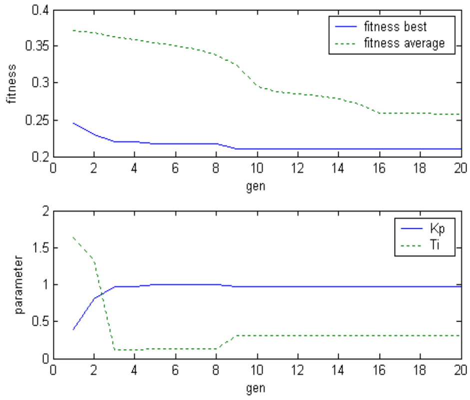

Fig. 25. Fitness value and parameters. (α =0.45, β =0.55)

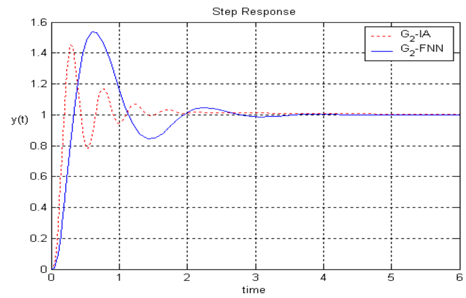

Fig. 26. Step Response by IA and FNN. (α =0.5, β =0.5)

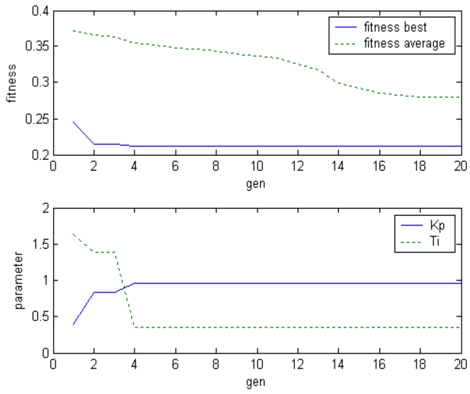

Fig. 27. Fitness value and parameters. (α =0.45, β =0.55)

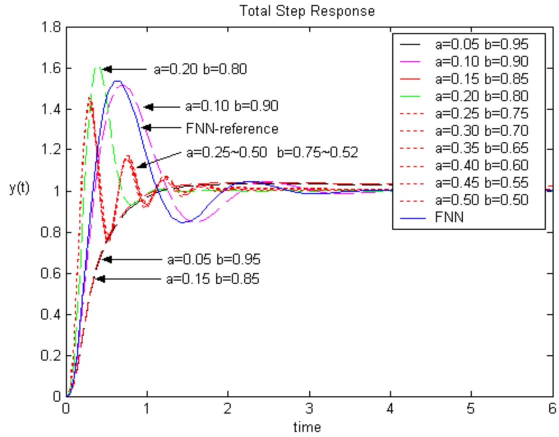

Fig. 28. Comparison of step response by FNN, value of α and β .

Fig. 28 is also illustrating that immune based controller tuning scheme can have more diversity and variety response than FNN based control response.

Table 2. Parameters designed by Immune Algorithm.

alpha	beta	Kp	Ti	Gm	Pm
0.05	0.95	0.21	0.02	8.22	76.97
0.1	0.90	0.26	0.94	4.84	29.94
0.15	0.85	0.22	0.04	7.28	75.61
0.20	0.80	0.56	1.9	2.29	29.97
0.25	0.75	0.99	0.04	1.75	30.23
0.30	0.70	0.98	0.13	1.76	30.35
0.35	0.65	0.97	0.22	1.76	30.45
0.40	0.60	0.97	0.31	1.74	29.96
0.45	0.55	0.97	0.31	1.74	29.96
0.50	0.50	0.96	0.35	1.76	30.31

6 Conclusions

The PID controller has been used to operate the industrial process including nuclear power plant since it has many advantages such as easy implementation and control algorithm to understand. However, achieving an optimal PID gain is very difficult for the feedback control loop with disturbances. Since the gain of the PID controller has to be tuned manually by trial and error, tuning of the PID controller may not cover a plant with complex dynamics, such as large dead time, inverse response, and a highly nonlinear characteristic without any control experience.

This paper focuses on tuning of PID controller using gain/phase margin and immune algorithm for tuning an optimal controller that can actually be operated on a robust control. Parameters P, I, and D encoded in antibody are randomly allocated during selection processes to obtain an optimal gain for robustness based on gain margin and phase margin. The object function can be minimized by gain selection for control, and the variety gain is obtained as shown in Table 2. The suggested controller can also be used effectively in the motor control system as seen from Figs. 28.

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