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Auto-Tuning of Reference Model Based PID Controller Using Immune Algorithm

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Abstract

In this paper auto-tuning scheme of PID controller based on the reference model has been studied for a process control system by immune algorithm. Up to this time, many sophisticated tuning algorithms have been tried in order to improve the PID controller performance under such difficult conditions. Also, a number of approaches have been proposed to implement mixed control structures that combine a PID controller with fuzzy logic. However, in the actual plant, they are manually tuned through a trial and error procedure, and the derivative action is switched off. Therefore, it is difficult to tune. Since the immune system possesses a self organizing and distributed memory, it is thus adaptive to its external environment and allows a PDP (Parallel Distributed Processing) network to complete patterns against the environmental situation. Simulation results reveal that reference model based tuning by immune network suggested in this paper is an effective approach to search for optimal or near optimal process control.

Key Words :

1. INTRODUCTION

The Proportional-Integral-Derivative (PID) controller has been widely used owing to its simplicity and robustness in chemical process, power plant, and electrical systems. Its popularity is also due to easy implementation in hardware and software. However, with only the P, I, D parameters, it is very difficult to control a plant with complex dynamics, such as large dead time, inverse response, and highly nonlinear characteristics. That is, since the PID controller is usually poorly tuned, a higher of degree of experience and technology is required for the tuning in the actual plant [5].

Up to the present time, a PID controller has been studied for process control system. However, it cannot effectively provide requirements of both the set-point-following and disturbance rejection as well as industrial experience is required for a higher automatic tuning since the PID controller is usually poorly tuned in practice [5]. Especially, since its tuning method and performance in control system depend on the system used, it is necessary to study the tuning in each system.

In recent years, there has been growing interest in using intelligent approaches such as fuzzy, neural network, evolutionary method, and their combined technologies for the PID controller [1]-[3]. Also, a number of approaches have been proposed to implement mixed control structures that combine a PID controller with fuzzy logic.

Since the immune system possesses a self organizing and distributed memory, it is thus adaptive to its external environment and allows a PDP (Parallel Distributed Processing) network to complete patterns against the environmental situation. That is, it can play an important role to maintain own system dynamically changing environments. Therefore, immune system would be expected to provide a new paradigm suitable for dynamic problem including control problem dealing with unknown environments their rather than static system [7, 8].

In this paper auto-tuning scheme of auto-tuning of PID controller using reference model and immune network is suggested and simulated in process control. Both methods of binary representation and arithmetic representation is used for calculation of affinity to difference between reference model and plant response.

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2. STRUCTURE OF IMMUNE NETWORK ALGORITHMS

2.1 Previous Works

Jerne first point out the idea that there are some remarkable similarities between the nervous system and the immune system [6] and he also proposed that the immune response is regulated by a network of autoimmune interactions. That idea has been elaborated by Cohn, Edelman & Mountcastle, and Edelamn &

Reeke.

John E. Hunt & Denise E. Cooke described an artificial immune system which is based upon models of the natural immune system and Geoffrey W. Hoffman suggested a neural network model based on the analogy with the immune system.

Brooks, a pioneer of the approaches, has presented subsumption architecture for behavior arbitration of autonomous robots. He has argued that intelligence should emerge from mutual interactions among competence modules (i.e. simple behavior/action), and interactions between a robot and its environment. However, the behavior based artificial intelligence still has the following open questions: how do we construct an appropriate arbitration mechanism among multiple competence modules, how do we prepare appropriate competence modules. The above mentioned problems is a biologically-inspired approach for AIS (Artificial Intelligence System).

In engineering field, robot, decentralized automation, data mining, memory, automatic control have been studied [4]-[10]. To understand for model exactly, we need to figure out how they are constructed among the structures in immune system.

2.2 Characteristics of Immune Networks

The artificial immune system (AIS) implements a learning technique inspired by the human immune system which is a remarkable natural defense mechanism that learns about foreign substances, However, the immune system has not attracted the same kind of interest from the computing field as the neural operation of the brain or the evolutionary forces used in learning classifier systems [6].

Other areas of the characteristic relating to the immune system for engineering field are summarized below:

- The learning rule of the immune system is a distributed system with no central controller, since the immune system is distributed and consists of an enormous number and diversity of cells throughout our bodies.
- The immune system has a naturally occurring event-response system which can quickly adapt to changing situations and shares the property with the central nervous system that a definite recognition can made be made with a fuzzy stimulus.
- The immune system possesses a self organizing and distributed memory Therefore, it is thus adaptive to its external environment and allows a PDP (parallel distributed processing) network to complete patterns against the environmental situation.
- The correct functioning of the immune system is to be insensitive to the fine details of the network connections, since a significant part of the immune system repertoire is generate by somatic mutation processes.

In particular, immune system can play an important role to maintain own system dynamically changing environments. Therefore, immune system would be expected to provide a new paradigm suitable for dynamic problem dealing with unknown environments their rather than static system.

Among AIS, this paper particularly focuses on the immune system, since it has various interesting features such as immunological memory, immunological tolerance, pattern recognition, and so on viewed from an engineering standpoint. Furthermore, recent studies on immunology have clarified that the immune system does not just detect and eliminate non-self substances called antigen such as virus, cancer cells and so on; rather it plays important roles to maintain its own system against dynamically changing environments through the interaction among lymphocytes and/or antibodies.

Therefore, the immune system would be expected to provide a new methodology suitable for dynamic problems dealing with unknown hostile environments rather than static problems.

From the above facts, some researchers particularly focused on the similarities between the behavior arbitration system and the immune system, and have proposed a new decentralized consensus-making system inspired by the biological immune system in [7]-[10], since both systems deal with various sensory inputs (antigens) through interactions among competence modules (lymphocytes and/or antibodies).

From this study, they have expected that there would be an interesting AI technique suitable for dynamically changing environments by imitating the immune system in living organisms. However, the determination of the appropriate repertoire of competence modules (antibodies) or arbitrary affinity still remains an open question. They also try to incorporate an off-line meta-dynamics function into the previously proposed artificial immune network in order to autonomously construct appropriate immune networks [6]. However, the resulting stimulation signal is not delicate since they used the crisp mathematical approach.

Therefore, immune algorithm can be robust optimization and search mechanisms that mimic natural selection. They have been successfully applied to diverse areas such as design of aircraft, VLSI technology, robot path planning, schedule optimization, and machine learning. Evolution is a process that operates on chromosomes. Chromosomes are organic devices that encode the structure of living beings. Natural selection to antibody links chromosomes with the performance of their decoded structure. The process of natural selection makes such chromosomes that encode successful structures to reproduce more often than others.

Immune network incorporates these features of

natural evolution in computer algorithms. In contrast that traditional optimization techniques deal with a single candidate. The size of a population depends on the problem under consideration. This makes it possible for immune network to search several areas of a solution space.

3. DYNAMIC OF IMMUNE ALGORITHM FOR AUTO-TUNING WEIGHT FUNCTION OF NEURAL NETWORKS

3.1 The Response of Immune System

The immune system has two types of response: primary and secondary. The primary response is reaction when the immune system encounters the antigen for the first time. At this point the immune system learns about the antigen, thus preparing the body for any further invasion from that antigen. This learning mechanism creates the immune system's memory.

The secondary response occurs when the same antigen encountered again. This has response characterized by a more rapid and more abundant production of antibody resulting from the priming of the B-cells in the primary response.

3.2 Antibodies in Immune System

In the AIS the antibodies blind to infectious agents and then either destroy these antigens themselves attract help from other components of the immune system. Antibody is actually three-dimensional Y shaped molecules which consist of two types of protein chain: light and heavy. It also possesses two paratopes which represents the pattern it will use to match the antigen. The regions on the molecules that the paratopes can attach are so-called epitopes.

3.3 Interaction Between Antibodies

Describing the interaction among antibodies is important to understand dynamic characteristics of immune system. For the ease of understanding, Consider the two antibodies that respond to the antigens A1 and A2, respectively. These antigens stimulate the antibodies, consequently the concentration of antibody A1 and A2 increases. However, if there is no interaction between antibody A1 and antibody A2, these antibodies will have the same concentrations. Suppose that the idiotope of antibody A1 and the paratope of antibody A2 are the same. This means that antibody A2 is stimulated by antibody A1, and oppositely antibody A1 is suppressed by antibody A2 as Fig. 2. In this case, unlike the previous case, antibody A2 will have higher concentration than antibody A1. As a result, antibody A2 is more likely to be selected.

This means that antibody A2 has higher priority over antibody A1 in this situation. As we know from this description, the interaction among the antibodies acts based on the principle of a priority adjustment mechanism.

3.4 Dynamics of Immune System

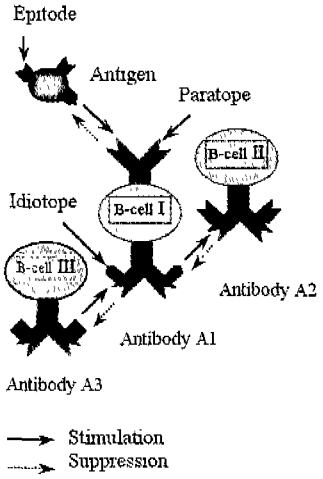

Fig. 2. Structure of idiotypic on Jerne network.

In the immune system, 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 [3] :

$$\frac{ds_i(t)}{dt} = \left(\begin{array}{l} \alpha \sum_{j=1}^{N} m_{ji}\delta_j(t) \\ -\alpha \sum_{k=1}^{N_1} m_{jk}\delta_k(t) + \beta m_i - \gamma_i \end{array} \right) \delta_i(t) \qquad (6a)$$

$$\frac{d\delta_i(t)}{dt} = \frac{1}{1+\exp\left(0.5 - \frac{dS_i(t)}{dt}\right)} \qquad (6b)$$

where in Eq. (6), 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), represents affinities between the detected antigens and antibody i, respectively.

4. AUTO-TUNING OF REFERENCE MODEL BASED PID CONTROLLER USING IMMUNE ALGORITHM

4.1 Selection Mechanism For Auto-tuning of PID Controller

If an antigen is presented to the B cell object, an

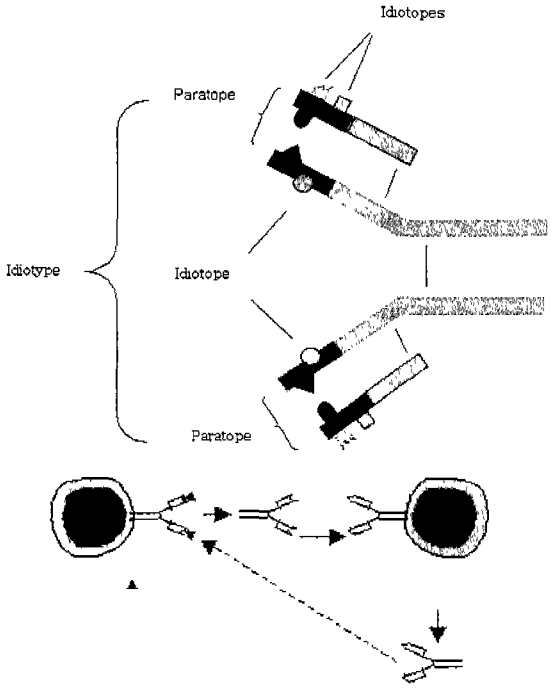

Fig.3. Structure of paratope and idiotpoe in antibody.

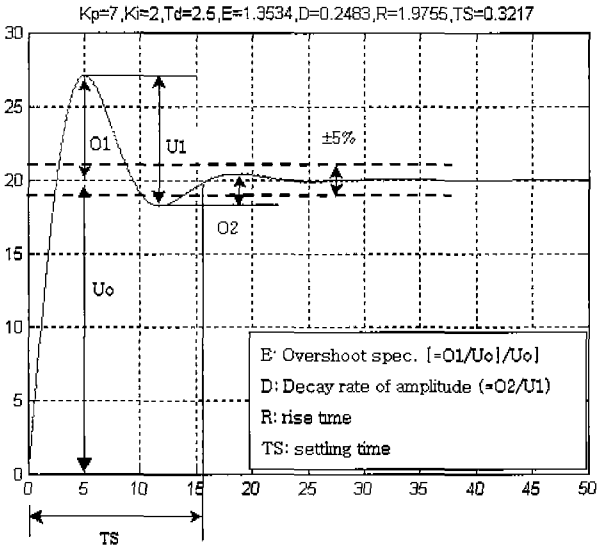

Fig. 4. Response specification of reference model.

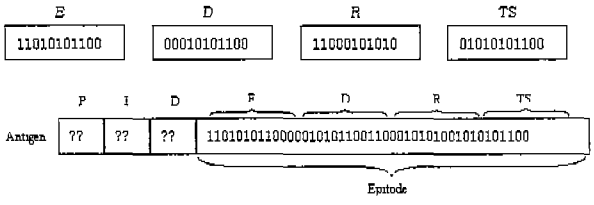

Fig. 5. Coding structure for antigen.

immune response, that is, the learning is initiated. The level on B cell stimulation depends not only on how well it matches the antigen, but also how it matches other B cell objects in the immune network. The B cell object produces copies of itself, which turn on a mutation mechanism that generates mutations in the genes that code specially for the antibody molecule. That mirrors the mechanism called somatic hypermutation which occurs in the human immune system. Alternatively, if the stimulation level falls below a given threshold, the B-cell object will die off and does not replicate. The stimulation of B cell object also depends on its affinity with other B cell objects in the immune system. The network is formed by B cell objects recognizing other B cell objects in the system. Survival of the new B cell objects depends on their affinity to the antigen and to the other B cell objects in the network. The new B-cell objects may have an improved match for the antigen and thus proliferate, and then it can survive longer than existing B cell objects. The immune network reinforces the B cell objects which are useful and have proliferated. By repeating this process of mutation and selection a number of imes, the immune system "learns" to produce better matches for the antigen [7-8].

This algorithm is implemented by the following procedures for reference model based PID controller tuning.

[step 1] Initionalization and Recognize pattern of reference as antigen: The immune system recognizes the invasion of an antigen, which corresponds to input data or disturbances in the optimization problem.

Code the selected E, D, R, and TS with binary and string for response specification of reference model as the following Fig. 5.

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

Coding of antibody consists of P, I, D and E, D, R, and TS as the following Fig. 6.

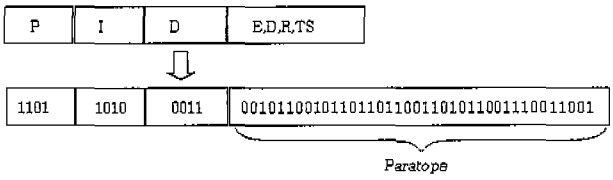

Fig. 6. Structure of antibody group

- I_j^P : the P value of affinity in antibody j
- I_j^I: the I value of affinity in antibody j
- I_j^D : the D value of affinity in antibody j
- P_j : the value of paratope in antibody j
- A : the value of epitope in antigen
- $\otimes$: exclusive or operator
- $\oplus$: mutation and crossover
- j : the length of antibody from 1

A_c : Positive constant

$$-I_{P,I,D}^{new\_k} = F^{*w}(\oplus(F(m_j - m_{j+1})\alpha I_k)) \quad (7)$$

$$F^{*w}(x) = \begin{cases} Present\ value: \text{ if } x \geq A_c \\ Previous\ value: \text{ if } x \pi A_c \end{cases}$$

$$\alpha = \begin{cases} 1 \text{ if } |I_j - I_{j+1}| \geq A_{delta} \\ 0 \text{ if } |I_j - I_{j+1}| \geq A_{delta} \end{cases}$$

$$\oplus(x) = \begin{cases} \oplus(x) & \text{if } x = 1 \\ I_j & \text{if } x = 0 \end{cases}$$

$$F(x,k) = \begin{cases} 1, \ j \text{ if } x \geq 0 : Stimulation \\ 0, \ j+1 \ x \pi 0 : Suppression \end{cases}$$

$$m_j = P_j \otimes A$$

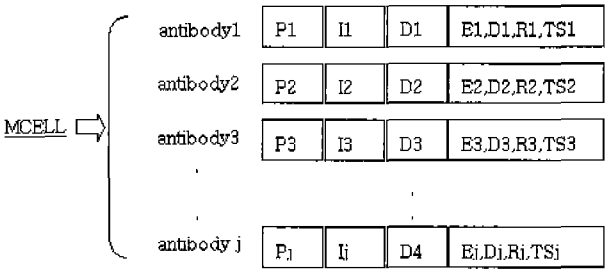

Fig. 7. Structure of antibody group.

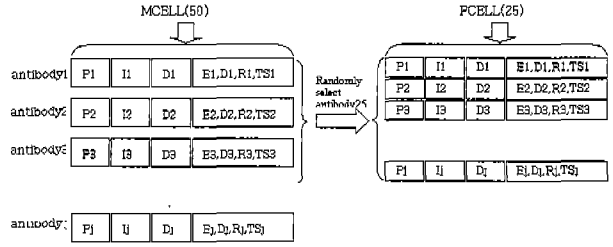

Fig. 8. Structure of the selected antibody group.

[step 3] Initialize antibody group (MCELL) for parameter P=0-1, I=1-10, D=0-10 of the given condition to the desired response of plant.

[step 4] Calculation of affinity between antibodies: The affinities obtained by Eq. (7) and $m_j = P_j \otimes A$ for searching the optimal solution. Arrange with the number of order of affinity value. Select randomly the number of antibody, 25 among the number of MCELL, 100 and calculate affinity, α between both antibodies.

[step 5] Stimulation of antibody: To capture to the unknown antigen, new lymphocytes are produced in the bone marrow in place of the antibody eliminated in step 5. 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 generation of antibodies.

5. SIMULATIONS AND DISCUSSIONS

5.1 Simulation Results Using Binary Code For Affinity

To confirm some effect of affinity between antibodies for reference model, this paper used binary code for calculation of affinity. Figs. 9-12 show plant response and affinity variation curve to variation of affinity. The big affinity more close response to reference model is showed. In Fig. 9 (b), the value of final affinity is represented on around 200 generations.

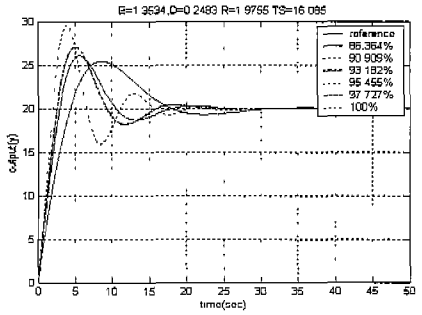

Fig. 9 (a). Affinity variation to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=86.364%)

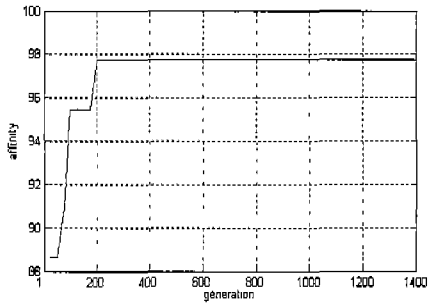

Fig. 9 (b). Response to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=86.364%)

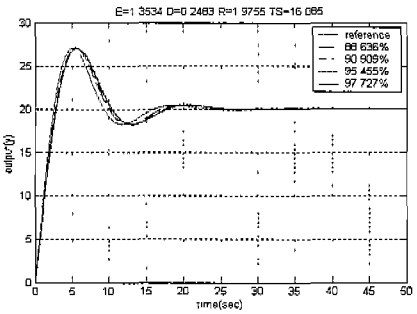

Fig. 10 (a). Response to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=88.636%)

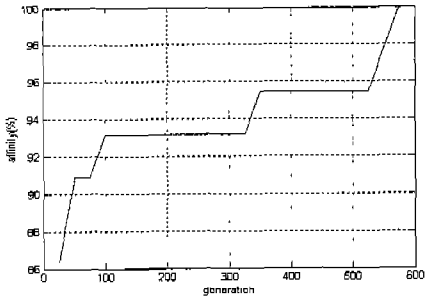

Fig. 10 (b). Affinity variation to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=88.636%)

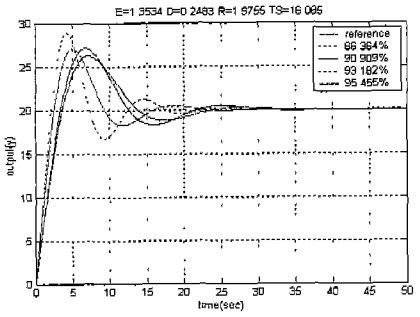

Fig. 11 (a). Response to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=90.906%)

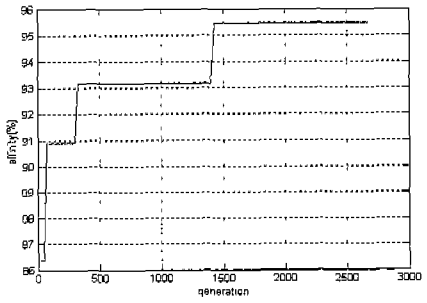

Fig. 11 (b). Affinity variation to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity= 90.906%)

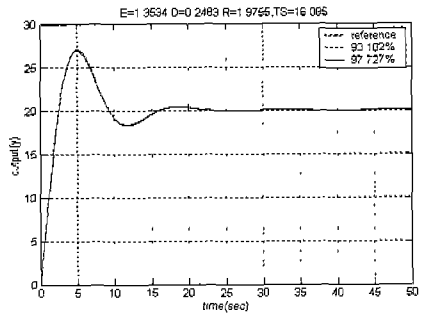

Fig. 12 (a). Response to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=93.182%)

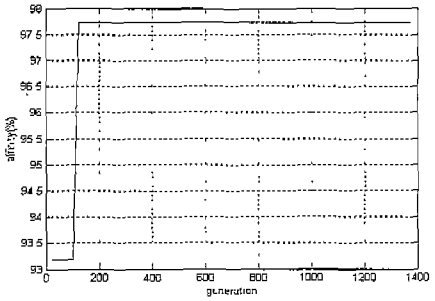

Fig. 12 (b). Affinity variation to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=93.182%)

On the other hand, in Figs. 10-11, optimal affinities are showed on about 520 and 1300 generations, respectively. Its optimal values is achieved through multi-step procedures.

However, Fig. 12 illustrates result of the closer response to reference model and final affinity value is acquired on around 10 generations.

Figs. 13-16 shows the result of simulation using arithmetic affinity instead of binary representation. An arithmetic affinity method represents more satisfactory response on the lower generations against the binary code methods.

Table 1 Relationships between binary code and affinity.

						affinity
0	0000	xor	0101	=	0101	0.5
1	0001	xor	0101	=	0100	0.75
2	0010	xor	0101	=	0111	0.25
3	0011	xor	0101	=	0110	0.5
4	0100	xor	0101	=	0001	0.75
5	0101	xor	0101	=	0000	1
6	0110	xor	0101	=	0011	0.5
7	0111	xor	0101	=	0010	0.75
8	1000	xor	0101	=	1101	0.25
9	1001	xor	0101	=	1100	0.5
10	1010	xor	0101	=	1111	0

5.2 Simulation Results Using Arithmetic Code For Affinity

In Fig. 13, the required affinity shows at 25 generations of immune cells and it is acquired through multi-step. However, in Fig. 14 (b) the final affinity for the

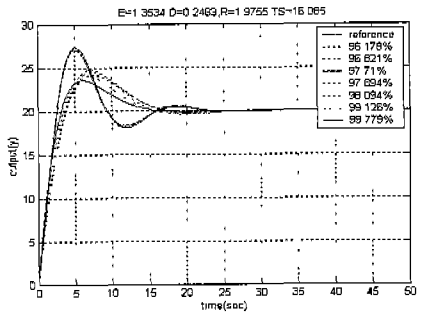

Fig. 13 (a). Response to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=96.178%)

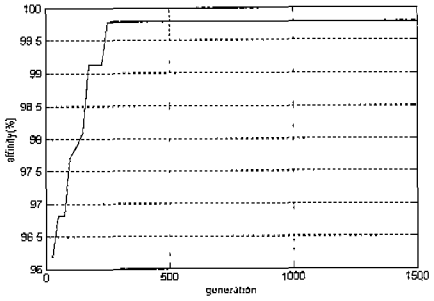

Fig. 13 (b). Affinity variation to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=96.178%)

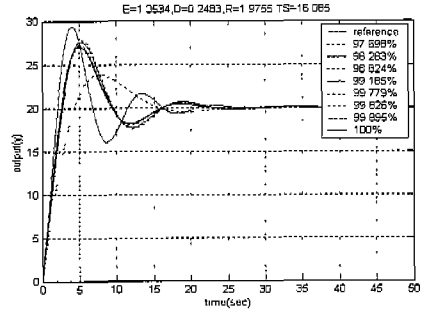

Fig. 14 (a). Response to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=97.698%)

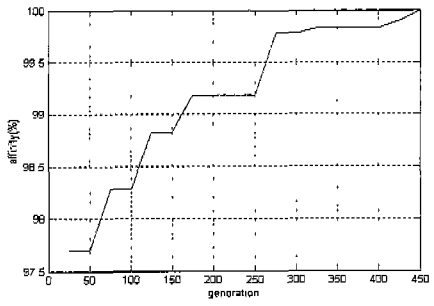

Fig. 14 (b). Affinity variation to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=97.698%)

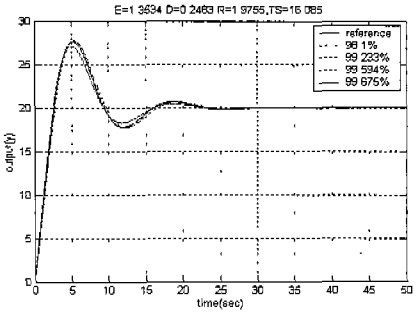

Fig. 15 (a). Response to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=98.1%)

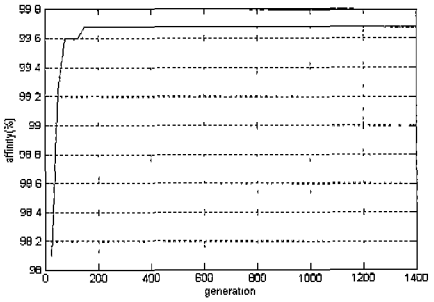

Fig. 15 (b). Affinity variation to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=98.1%)

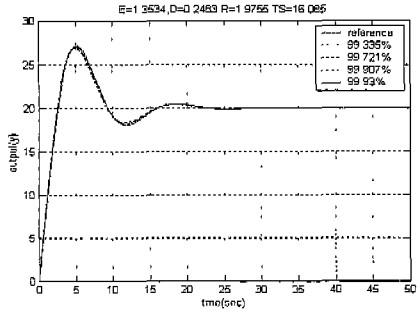

Fig. 16 (a). Response to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=99.335%)

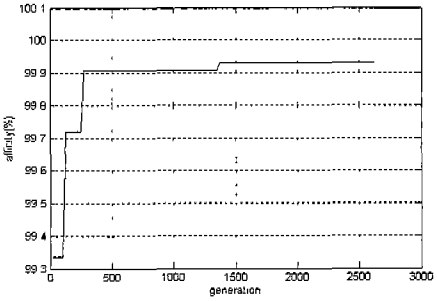

Fig. 16 (b). Affinity variation to reference of Fig. 4. (MCELL=50, PCELL=25, A_c=40, A_{delta}=0.001, P=0-10, I=0-10, D=0-10, affinity=99.335%)

required response is achieved at 450 generation through some complicated curve. In Fig. 15(b), optimal affinity is acquired at 150 generations but it is acquired at 1400 generations in Fig. 16(b). Therefore, These both results show that longer generation is needed for more delicate affinity.

6. CONCLUSIONS

This paper focuses on tuning of the PID controller based on the required reference model using immune algorithms. A number of intelligent approaches have been investigated in the viewpoint of tuning of PID controller for process control. However, in the actual plant, they are manually tuned through a trial and error procedure, and the derivative action is switched off. Therefore, it is difficult to tune. On the other hand, immune network is thus adaptive to its external environment and allows a PDP (Parallel Distributed Processing) network to complete patterns against the environmental situation because it possesses a self organizing and distributed memory. In this paper both methods of binary representation and arithmetic representation is used for calculation of affinity to difference between reference model and plant response. The simulation results have revealed that the PID parameters tuned by immune algorithms effectively control a plant for optimal or near optimal process control.

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