International Journal of Fuzzy Logic and Intelligent Systems, vol. 3, no. 1, June 2003 pp. 78-86

Multiobjective PI Controller Tuning of Multivariable Boiler Control System Using Immune Algorithm

Dong Hwa Kim, Jin ILL Park

Dept. of Instrumentation and Control Eng., Hanbat National University,

16-1 San Duckmyong-Dong Yusong-Gu, Taejon City Seoul, Korea, 305-719.

E-mail : kimdh@hanbat.ac.kr

Tel: +82-42-821-1170, Fax: +82-821-1164

Abstract

Abstract-Multivariable control system exist widely in many types of systems such as chemical processes, biomedical processes, and the main steam temperature control system of the thermal power plant. Up to the present time, PID Controllers have been used to operate these systems. However, it is very difficult to achieve an optimal PID gain with no experience, because of the interaction between loops and gain of the PID controller has to be manually tuned by trial and error. This paper suggests a tuning method of the PID Controller for the multivariable power plant using an immune algorithm, through computer simulation. Tuning results by immune algorithms based neural network are compared with the results of genetic algorithm.

Key Words : PID tuning, Power plant control, Immune algorithm, Multiobjective control, Auto-tuning, Neural network.

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 [1]-[7]. Its popularity is also due to easy implementation in hardware and software. However, with only the P, I, D parameters, it can not effectively control a plant with complex dynamics, such as large dead time, inverse response, and highly nonlinear characteristics in power plants [4]-[5]. When using a PID controller in these plants, the plant is generally controlled without consideration of disturbance rejection. Therefore, an industrial experience is required for higher automatic tuning; the PID controller is usually poorly tuned in practice [4]. Traditionally, PID controllers applied to these plants are tuned with a reduction of gain so that overall stability can be obtained. This results in poor performance of control. That is, the process with large dead time such as steam temperature process of a power plant is usually difficult to be controlled without a highly experience tuning [3][7].

Failure to tune in control will cause an inevitable plant shutdown, and a loss of production and considerable damage to the plant may result. An effective tuning is required to maintain the system reliability and stability following a system disturbance [3][7]. However, any new theory should be proven on the physical plant or equipment before being used on the real plant to ensure safety and reliability.

It is a challenge in controller tuning technologies to explore novel control strategies and philosophies for complex industrial processes [5][7]. The application of intelligent system technologies in industrial control has been developing into an emerging technology, so-called 'Industrial intelligent control'[9]-[16]. This technology is highly multi-disciplinary and rooted in systems control, operations research, artificial intelligence, information and signal processing, computer software and production background [14].

Chronologically, fuzzy logic was the first technique of intelligent systems. Neural, neuro-fuzzy and evolutionary system and their derivatives followed later [10]. Each technique is offering new possibilities and making intelligent system even more versatile and applicable in an ever-increasing range of industrial applications [16]-[17].

On the other hand, biological information processing systems such as human beings have many interesting functions and are expected to provide various feasible ideas to engineering fields, especially intelligent control or robotics [21], [39]. Biological information in living organisms can be mainly classified into the following four systems: brain nervous, genetic system, endocrine system, and immune system [26]-[32]. Among these systems, brain nervous and genetic systems have already been applied to engineering fields by modeling as neural network and genetic algorithms [37]. However, only a little attention has been paid to application of the other system such as immune algorithm in engineering, not to mention their important characteristics and model.

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 [34]-[38].

The immune system is a rich source of theories and as such can act as an inspiration for computer-based solutions. Other areas of the interest relating to the characteristics of the immune system are listed below [17]-[41]:

- 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 has various interesting features such as immunological memory, immunological tolerance, so on viewed from engineering. That is, it can play an important role to maintains 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.

Brooks, a pioneer of the approaches, has presented subsumption architecture for behavior arbitration of autonomous robots [21], [39]. 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 AI 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.

Among AIS, we particularly focus 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 [38], [43], [49]. Therefore, it can play important roles to maintain its own system against dynamically changing environments and would be expected to provide a new methodology suitable for dynamic problems dealing with unknown hostile environments rather than static problems through the interaction among lymphocytes and/or antibodies.

From the above facts, some researchers [39], [46] 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 engineering [26], [43].

In this paper auto-tuning scheme of the PID controller using reference model and immune network is suggested and simulated for an effective control in dead time process.

2. PROBLEMS OF THE PID ONTROLLER ON THE MULTIVARIABLE BOILER SYSTEM

There are many well known PI and PID tuning formulas for stable processes. However, PID tuning formulas for unstable processes, complex plants, and dead time process are less common.

Up to this time, many sophisticated tuning algorithms have been tried an attempt to improve the PID controller performance under such difficult conditions since the control performance of the system depends on the P, I, D parameter gains.

In the PID tuning methods, the method proposed by Ziegler Nichols (1942) needs the ultimate gain and the period of the ultimate oscillation at stability limit. But it is difficult to determine their exact values experimentally in real processes, since the oscillatory operation must be avoided.

The tuning method by Chien, Hrones and Reswick (1952) requires an exact form of the process expressed by a transfer function, but many of real processes fail to reveal their transfer functions.

For the automatic tuning based on process parameters estimation tuning based on process parameters estimation, Astrom and Wittenmark (1973) proposed the self-tuning controller and Isermann (1978) has been developing the self-adaptive controller. These controllers rely upon the modern control theory, and contain many control parameters.

Therefore field engineers and plant operators are often

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} \dfrac{(-0.16s^2+0.052s+0.0014)\times10^{-3}}{s^2+0.0168s} & \dfrac{(3.1s-0.032)\times10^{-3}}{s^2+0.0215s} & 0 \\ \dfrac{-0.0395\times10^{-3}}{s+0.018} & \dfrac{2.51\times10^{-3}}{s+0.0157} & \dfrac{(0.588s^2+0.2015s+0.0009)\times10^{-3}}{s^2+0.0352s+0.000142} \\ \dfrac{-0.00118s+0.000139}{s^2+0.01852s+0.000091} & \dfrac{0.448s+0.0011}{s^2+0.0127s+0.000095} & \dfrac{0.582s-0.0243}{s^2+0.1076s+0.00104} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}$$

embarrassed in attempting to understand the conceptual structure of the control theory and the relationships between parameter settings and control system actions.

To consider that, in practical designs and operations, the continuity of understanding of the object system among design engineers, field engineers, plant operators, automatic tuning method must be developed for improving the PID control technique which is still dominant in practical use. Hence, a new idea for automatic tuning of the PID control parameters, auto-tuning, is required.

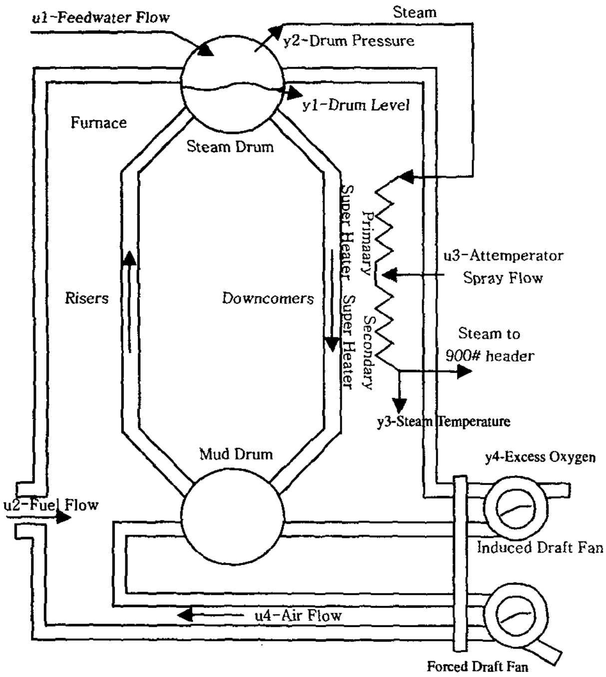


Fig. 1. Boiler control system.

3. Boiler Model

This paper used dynamic model given in reference [50] and its structure is as in Fig. 1. In Fig. 1,

u_1 *feedwater flow rate* (kg/s),

u_2 *fuel flow rate* (kg/s),

u_3 *attemperator spray flow rate* (kg/s),

y_1 *drum level* (m),

y_2 *drum pressure* (MPa),

y_3 *drum temperature* (^{O}C).

The control input u_1, u_2, u_3 is constrained by

$$\begin{aligned} &0 \le u_1 \le 120, 0 \le u_2 \le 7, 0 \le u_3 \le 10, \\ &-0.017 \le \dot{u}_2 \le 0.017. \end{aligned} \tag{2}$$

4. MULTIOBJECTIVE CONTROLLER DESIGN OF BOILER-TURBINE SYSTEM USING IMMUNE ALGORITHM BASED NEURAL STRUCTURE

A. 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 (B-lymphocytes) in the primary response. When a naïve B-cell encounters an antigen molecule through its receptor, the cell gets activated and begins to divide rapidly; the progeny derived from these B-cells differentiate into memory B-cells and effector B-cells or plasma cells. The memory B-cells have a long life span and they continue to express membrane bound antibody with the same specificity as the origin parent B-cell [18]-[31].

B. Antibodies In Immune System

The antibody molecule acts as a bridge between cytotoxic cell and the target cell, subsequently causing the target cell due to activation of cytotoxic cell through receptor. 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. These same molecules with antigenic peptide bound to them will be responsible for interaction with T-cell receptor. The site on an antigenic peptide that interacts with a T-cell receptor is called epitode [18], [33].

C. Interaction Between Antibodies

The antigen antibody interaction is similar to that of enzyme substrate interaction except that this interaction does not lead to irreversible alteraction either in antibody or antigen and therefore reversible. The reaction between an antigen antibody is of noncovalent type, where the antigenic determinants or epitodes interact with domain of the antibody molecule. The noncovalent interaction between antigen and antibody is brought about by hydrogen bonds, vander Waals interactions, ionic bonds and hydrophobic interactions. Therefore, a strong affinity interaction should occur between antigen and antibody to form a stable complex [12]. In Fig. 2, Describing the interaction among antibodies is important to understand dynamic characteristics of immune system. These antigens stimulate the antibodies, consequently the concentration of antibody A1 and A2 increases. However, if there is

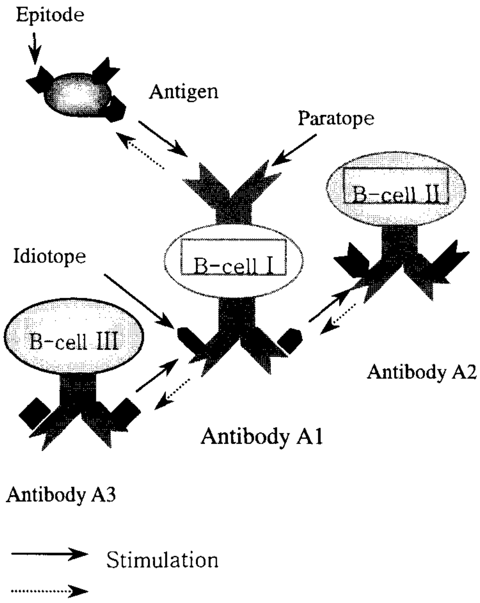


Fig. 2. Relationship between antibody and antigen on immune network.

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 [18], [25], [37].

D. Dynamics Of Immune System

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 [21], [24], [31]:

$$\frac{dS_i(t)}{dt} = \left(\begin{array}{c} \alpha \sum_{j=1}^{N} m_{ji}\delta_j(t) \\ -\alpha \sum_{k=1}^{N} m_{ik}\delta_k(t) + \beta m_i - \gamma_i \end{array} \right) \delta_i(t) \qquad (3a)$$

$$\frac{d\delta_i(t)}{dt} = \frac{1}{1+\exp\left(0.5 - \frac{dS_i(t)}{dt}\right)} \qquad (3b)$$

where in Eq. (3), 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.

On the other hand, information obtained in lymphocyte population can be represented by [17]:

$$\Omega_j(N) = \sum_{i=1}^{S} -x_{ij} \log x_{ij} \,, \qquad (4),$$

where N is the size of the antibodies in a lymphocyte population, S is the variety of allele and x_{ij} has the probability that locus j is allele i. Therefore, the means of information $\Omega_{ave}(N)$ in a lymphocyte population is obtained as the following equation [17], [39]:

$$\begin{aligned} \Omega_{ave}(N) &= \frac{1}{M}\sum_{j=1}^{M}\Omega_j(N) \\ &= \frac{1}{M}\sum_{j=1}^{M}\left\{ \sum_{i=1}^{S} -x_{ij}\log x_{ij} \right\}, \end{aligned} \qquad (5)$$

where M is the size of the gene in an antibody.

The affinity $m_{\alpha\beta}$ between antibody α and antibody β is given as follows:

$$m_{\alpha\beta} = \frac{1}{\{1+\Omega(\alpha\beta)\}}, \qquad (6)$$

$$\Omega(\alpha\beta) = H_s(x) = [f_1(x) + f_2(x) + f_3(x)]$$

where $\Omega(\alpha\beta)$ is an information which obtained by antibody α and antibody β . If $\Omega(\alpha\beta)$ =0, the antibody α and antibody β match completely. Generally $m_{\alpha\beta}$ is given by range of 0-1.

E. Controller Design

In Fig. 4, $r_{=1,2,3}$: reference input over 0, $y_{i=1,2,3}$: plant output.

Immune algorithm typed neural network has the following function in each layer;

Layer1: As function comparing the reference input with the output of the given plant, comparing result, $r_{=1,2,3}$ is selected for affinity in sub-function and it is defined by the followings.

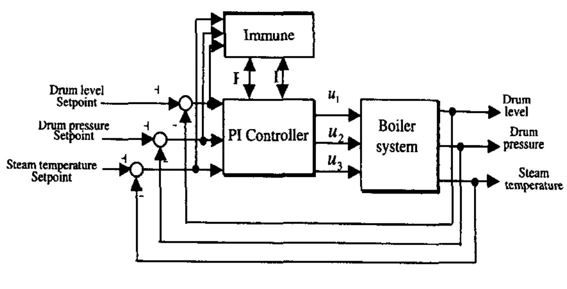


Fig. 3. Block diagram of boiler control system

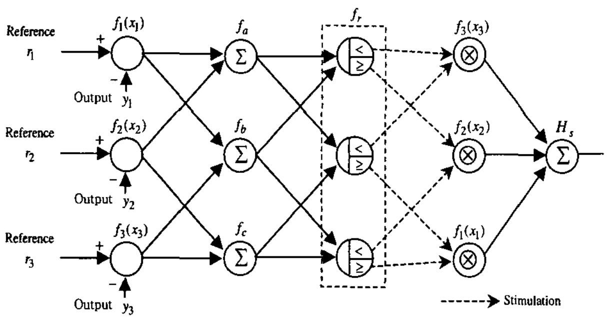


Fig. 4. Flow diagram of controller.

Layer1: As layer for detecting error between reference input and plant output, the following equation is defined as

$$f_1(x_1)=\sum_{t=0}^{n}\left(\left|r_1-y_1\right|_t\right)/n,$$
$$if\ \left|r_1-y_1\right|_t \geq r_1\ then\ f_1(x_1)_t=1,\ else\ f_1(x_1)_t=\left|r_1-y_1\right|$$
$$f_2(x_2)=\sum_{t=0}^{n}\left(\left|r_2-y_2\right|_t\right)/n,$$
$$if\ \left|r_2-y_2\right|_t \geq r_2\ then\ f_2(x_2)_t=1,\ else\ f_2(x_2)=\left|r_2-y_2\right|$$
$$f_3(x_3)=\sum_{t=0}^{n}\left(\left|r_3-y_3\right|_t\right)/n,$$
$$if\ \left|r_3-y_3\right|_t \geq r_3\ then\ f_3(x_3)_t=1,\ else\ f_3(x_3)_t=\left|r_3-y_3\right|$$

n : the number of sample. (7)

Layer2: as layer for computing coupling degree between inputs of multivariable system as Fig. 3, the sub-function defined as f_a, f_b, f_c is used for coupling degree. The sub-function f_a, f_b, f_c calculates interaction between loops by exclusive computing method as;

$$\begin{aligned} f_a &= f_1(x_1)+f_2(x_2) \\ f_b &= f_1(x_1)+f_3(x_3) \\ f_c &= f_2(x_2)+f_3(x_3) \end{aligned} \tag{8}$$

Layer 3, 4: they provide stimulation action by algorithms defined as

$$\begin{aligned} &f_{r1}: if\ f_a<f_b\ then\ stimulation\ f_3(x_3) \\ &\quad else\ stimulation\ f_2(x_3). \\ &f_{r2}: if\ f_a<f_c\ then\ stimulation\ f_3(x_3) \\ &\quad else\ stimulation\ f_1(x_1). \\ &f_{r3}: if\ f_b<f_c\ then\ stimulation\ f_2(x_2) \\ &\quad else\ stimulation\ f_1(x_1). \end{aligned} \tag{9}$$

Layer 5: affinity is calculated with

$$H_s=f_1(x_1)+f_2(x_2)+f_3(x_3)\,. \tag{10}$$

When the value of H_s is smaller, more satisfactory results is obtained.

V. Simulation and Discussion

Fig. 5 is simulation block diagram by the simulink and Fig. 6 represents for PI controller block diagram.

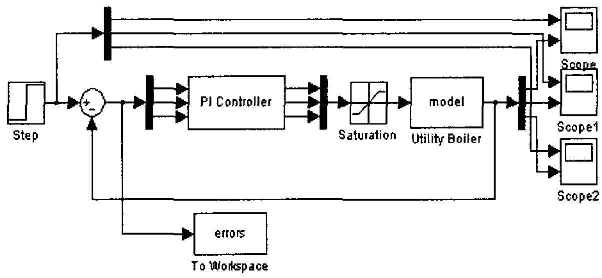


Fig. 5. Simulation block diagram using the Simulink.

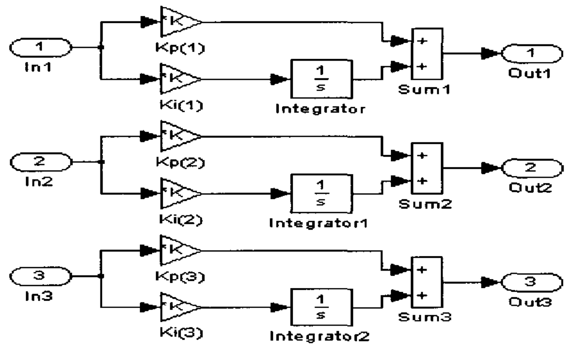


Fig. 6. PI Controller block diagram.

Fig. 7, 8 are showing the variation of objective function obtained by genetic algorithm and immune algorithm. The objective function of immune algorithm is smaller and is obtained in the shorter generation.

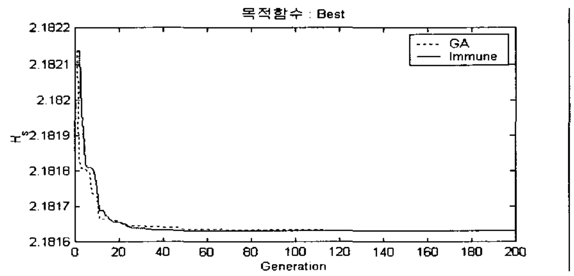


Fig. 7. Object function graph (Best).

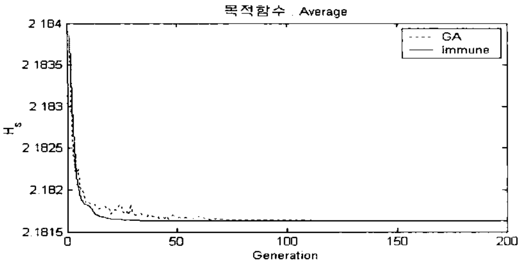


Fig. 8. Object function graph (Average).

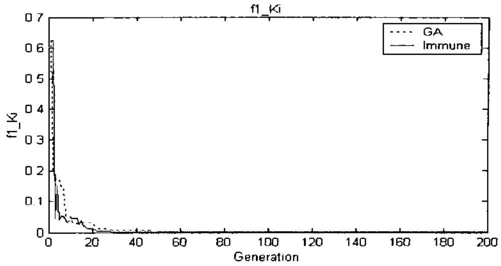


Fig. 13 . Graph of sub-function f_1, K_i.

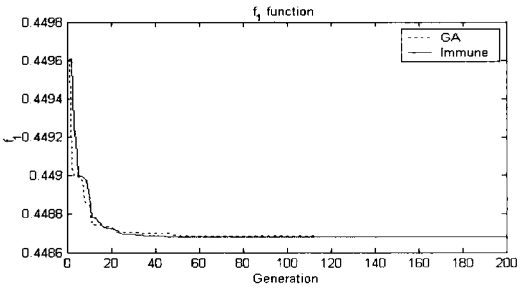


Fig. 9. Graph of sub-function f_1.

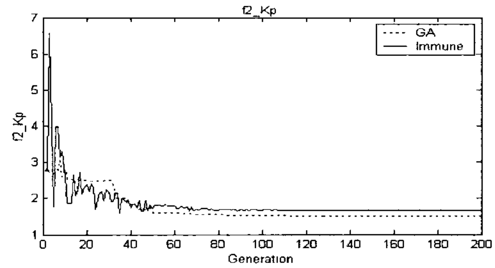


Fig. 14 . Graph of sub-function f_2, K_p.

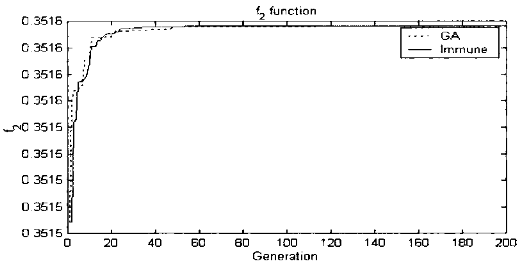


Fig. 10. Graph of sub-function f_2.

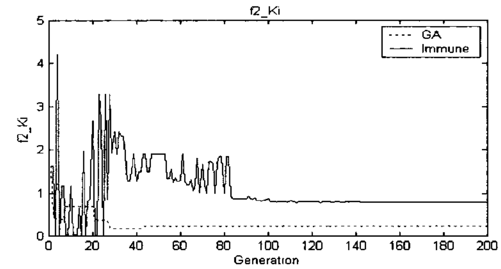


Fig. 15 . Graph of sub-function f_2, K_i.

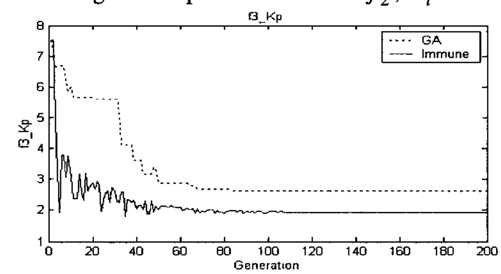


Fig. 16 . Graph of sub-function f_3, K_p.

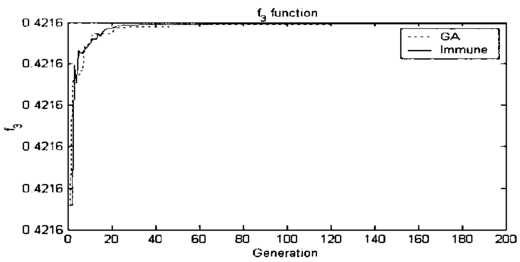


Fig. 11. Graph of sub-function f_3.

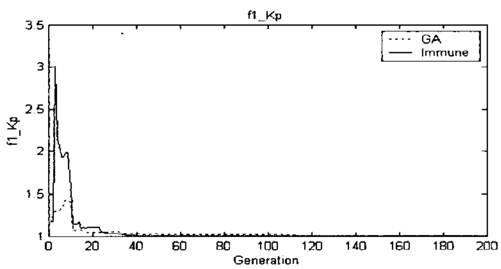


Fig. 12. Graph of sub-function f_1, K_p.

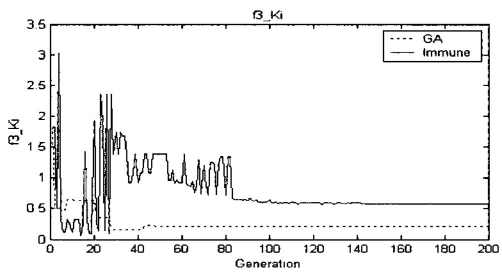


Fig. 17 . Graph of sub-function f_3, K_i.

Figs 9, 10, and 11 represent the variation results of sub-function, f_1, f_2, f_3 compared by immune algorithm and genetic algorithm. The sub-function f_1, f_2 on immune algorithm is smaller than those on genetic algorithm. However, incase of f_3 is showing opposite results. Figs. 12-18 are the results that relationship between sub-function f_1, f_2, f_3 and the PI controller parameters, K_p, K_i is compared on immune algorithm and genetic algorithm.

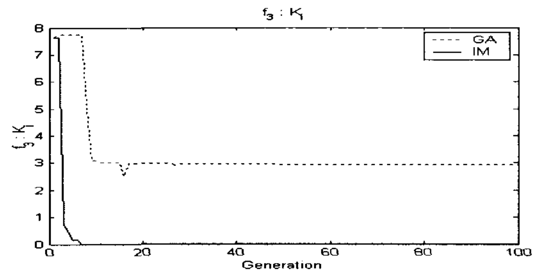


Fig. 18 . Graph of sub-function f_3, K_i.

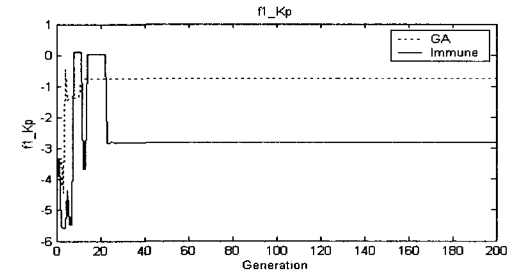


Fig. 19. Graph of sub-function f_1, K_p
(Initial value P:-10-10, I=-5-5).

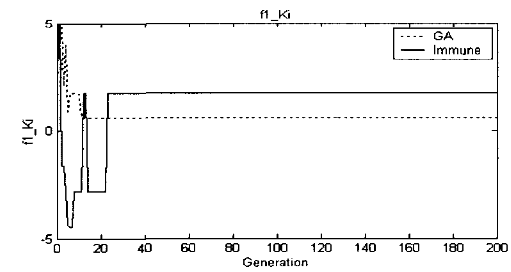


Fig. 20. Graph of sub-function f_1, K_i.
(Initial value P:-10-10, I=-5-5).

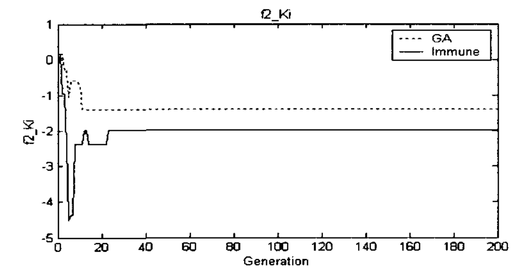


Fig. 21. Graph of sub-function f_2, K_i.
(Initial value P:-10-10, I=-5-5).

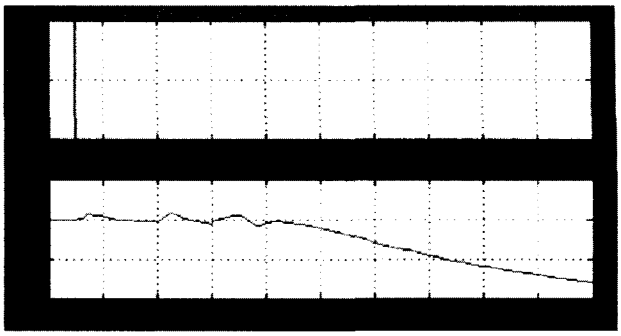


Fig. 22. Temperature response using immune algorithm.

Figs. 19-21 illustrate the results that relationship between sub-function f_1, f_2, f_3 and the PI controller parameters, K_p, K_i is compared on immune algorithm and genetic algorithm when initial value for search is p=-10-10, I=-5-5.

Fig. 22 represents temperature response using immune algorithm based PI tuning. As Fig. 21 is showing temperature response by immune based tuning controller, its response is smoothly deviation.

4. CONCLUSION

Optimal tuning for nonlinear and long dead time processes such as chemical processes, biomedical processes, and the main steam temperature control system of the thermal power plant need a highly experience. However, it is not easy to achieve an optimal PID gain with no experience, since the gain of the PID controller has to be manually tuned by trial and error.

On the other hand, 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. That is, it can play an important role to maintain own system dynamically changing environments and it is known as more useful than the learning method of neural network.

This paper suggests a tuning method of the PI Controller for a steam temperature process with long dead time using an immune algorithm typed neural network, through computer simulation. Tuning results by immune algorithms based neural network are compared with the results of genetic algorithm.

REFERENCES

[1] D avid Lindsley, Boiler Control Systems, McGrawill, 1991.

[2] S. Matsummura, Adaptive control for the steam

temperature of thermal power plants," Proceedings the 1993 IEEE on Control applications," PP. 1105 - 1109, Sept. 1998.
[3] Teng Fong-Chwee, "Self-tuning PID controllers dor dead time process,"IEEE Trans., Vol. 35, No. 1, pp. 119-125, 1988.
[4] Ya-Gang Wang, "PI tuning for processes with dead time,"AACC2000, Chicago, Illinois, June, 2000.
[5] B. Stuart, "Development of PID controller," IEEE control systems, vol. pp. 58-62, Dec.1993.
[6] Y. Stephen, "A laboratory course on fuzzy control," IEEE Trans. on Education, vol. 42, no. 1, pp. 15-21, May 1999.
[7] W. K. Ho, "PID tuning for unstable process based on gain and phase-margin specifications," IEE Proc. Control Theory Appl. vol. 45, no. 5, pp. 392-396, Sept. 1998.
[8] Assilian and E.H. Mamdani, An experiment in linguistic synthesis with fuzzy logic controllers, Int. J. Man-Machine Studies 7 (1974) 1-13.
[9] A. Homaifar and E. Mccormick, Simultaneous design of membership functions and rule sets for fuzzy controllers using genetic algorithms, IEEE Trans. Fuzzy Systems 3 (1995) 129-139.
[10] B. Alfred, "Neural network-based feedforward control of two-stage heat exchange process," IEEE conference, pp. 25-29, 1997.
[11] R. Ketata, D. De Geest and A. Titli, Fuzzy controller: design, evaluation, parallel and hierarchical combination with a PID controller, Fuzzy Sets and Systems 71 (1995) 113-129.
[12] D. H. Kim, "A application of intelligent control algorithms," Conference of ICASE, pp. 15-17, 1997. Seoul.
[13] D. H. Kim, "Application of a multivariable PID controller with a neural network tuning method to the heat exchange," FUZZ-IEEE, pp. 23-25, Aug.1998, Seoul.
[14] Yong Zai Lu, Industrial intelligent control, John Wiley $Sons,1996.
[15] K. J. Astrom, Bjorn Wittenmark, Adaptive control, Addison-Wesley Publishing Com., 1995
[16] J. D. Farmer, N. H. Packard and A. S. Perelson, "The immune system, adaptation, and machine learning, Vol. Physica. D, No. 22, pp. 187 - 204, 1986.
[17] Kazuyuki Mori and Makoto Tsukiyama, "Immune algorithm with searching diversity and its application to resource allocation problem," Trans. JIEE, Vol. 113 C, No. 10, '93.
[18] C. V. Rao, An introduction to immunology, 2002, Alpha Science International Ltd.
[19] R. Brooks, "A robust layered control system for a mobile Robot," IEEE Jounal R&A, vol.2, no.& pp.14-23, 1986.
[20] R. Brooks, "Intelligence without reason," Proc. of the IJCAI-91, pp.569-595, 1991.
[21] A. Ishiguro, T. Kondo, Y. Watanabe and Y. Uchikawa, "Dynamic behavior arbitration of autonomous mobile robots using immune networks," In Proc. of ICEC' 95, vol.2, pp.722-727, 1995.
[22] N. K. Jerne, "The immune system," Scientific American, vol.229, no.1, pp.52-60, 1973.
[23] N. K. Jerne, "Idiotypic networks and other preconceived ideas", Immunological Rev., vol.79, pp.5-24, 1984.
[24] J. D. Farmer, N. H. Packard and A. S. Perelson, "The immune system, adaptation, and machine learning," Physica. D 22, pp.187-204, 1986.
[25] F. J. Valera, A. Coutinho, B. Dupire and N. N. Vaz., "Cognitive networks: Immune, neural, and Otherwise," Theoretical Immunology, vol.2, pp.359-375, 1988.
[26] J. Stewart, "The immune system: Emergent self-assertion in an autonomous network," In Proceedings of ECAL-93, pp.1012-1018, 1993.
[27] J. D. Farmer, S. A. Kauffman, N. H. Packard and A. S. Perelson, "Adaptive dynamic networks as models for the immune system and autocatalytic sets," Technical Report LA-UR-86-3287, Los Alamos National Laboratory, Los Alamos, NM, 1986.
[28] K. Nakano, H. Hiraki and S. Ikeda, "A learning machine that evolves," Proc. Of ICEC-95, pp.808-813, 1995.
[29] Various Authors, "Life, death and the immune system," Scientific American, 269(3), 20–102, 1993.
[30] S. Forrest, S. A. Hofmeyr, and A. Somayaji, "Computer immunology," Communications of the ACM, 40(10):88–96, 1997.
[31] D. Gray, "The dynamics of immunological memory," Semin. Immunology, 4:29–34, 1992.
[32] W. D. Hamilton, R. Axelrod, and R. Tanese, "Sexual reproduction as an adaptation to resist parasites," Proceedings of the National Academy of Sciences of the USA, 87:3566–3573, 1990.
[33] J. K. Inman, "The antibody combining region: Speculations on the hypothesis of general multispecificity," Theoretical Immunology, 1978.
[34] C. A. Janeway and P. Travers, "The Immune System in health and disease," immunobiology, 2nd Edition. Current Biology Ltd., London, 1996.
[35] C. A. Janeway and P. Travers, "The immune system in health and disease," immunobiology, 3rd Edition. Current Biology Ltd., London, 1996.
[36] C. R. MacKay, "Immunological memory," Advanced Immunology, 53:217–265, 1993.
[37] S. Forrest, B. Javornik, R. E. Smith and A. S. Perelson, "Using genetic algorithms to explore pattern recognition in the immune system," Evolutionary computation, vol. 1, pp. 191-211, 1993.
[38] F. D'Alche-Buc, V. Andres and J-P. Nadal, "Rule extraction with fuzzy neural network," International J. Neural systems, vol. 5, pp. 1-11, 1994.

[39] Ishiguro, Y. Watanabe and Y. Uchikawa, "An Immunological Approach to dynamic behavior control for autonomous mobile robots," In Proc. of IROS ' 95, Vol.1, pp.495-500, 1995.

[40] D. H. Kim, "A application of intelligent control algorithms," Conference of ICASE, pp. 15-17, 1997. Seoul.

[41] Dong Hwa Kim, "Tuning of a PID controller using immune network model and fuzzy Set, "June 15, ISIE2001, Pusan.

[42] Dong Hwa Kim, "Intelligent Tuning of a PID Controller for multivariable process using immune network model based on fuzzy set," FUZZ-IEEE2001, Dec. 2-9, 2001, Melbourne, Australia.

[43] Dong Hwa Kim, "A Feasibility Study on Application of Immune Network for Intelligent Controller of a Multivariable System," ICASE, Jeju, Oct, 17-18, 2001.

[44] Dong Hwa Kim, "Tuning of a PID controller using a artificial immune network model and fuzzy set, "July 28, IFSA2001, Vancouver.

[45] Dong Hwa Kim, "Parameter tuning of fuzzy neural networks by immune algorithm," May 12-16, 2002, 2002 IEEE international conference on fuzzy systems, Honolulu, Hawaii, 2002.

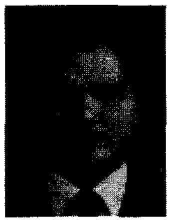
[46] Dong Hwa Kim, "Neural networks control by immune algorithm based auto-weight function tuning," May 12-16, 2002, 2002 IEEE international conference on neural networks, Honolulu, Hawaii, 2002.

[47] Dong Hwa Kim, "Auto-tuning of reference model based PID controller using immune algorithm," May 12-16, 2002, 2002 IEEE international conference on evolutionary computation, Honolulu, Hawaii, 2002.

[48] Dong Hwa Kim, "Tuning of 2-DOF PID controller by immune algorithm," May 12-16, 2002, 2002 IEEE international conference on evolutionary computation, Honolulu, Hawaii, 2002.

[49] D. H. Kim, "Intelligent tuning of the two Degrees-of-Freedom Proportional-Integral-Derivative controller on the Distributed control system for steam temperature of thermal power plant," KIEE international Transaction on SC, Vol. 2-D, No. 2, pp. 78-91, 2002.

[50] Wen Tan, Horacio J, Marquez, and Tongwen Chen, "Multivariable Robust Controller Design for a Boiler System", IEEE Trans. on control systems Technology, Vol. 10, No. 5, Sept. 2002.



Dong Hwa Kim

he was born in Nov. 15, 1949. He finished from Graduate of Ajou Univ. in Korea. (Ph. D)

He had ever studied AECL (Atomic Energy Canada Lab.) as computer aided multivariable control system from Nov. 1985 to Dec.1986.

He worked KAERI (Korea Atomic Energy Research Institute) from Nov. 1977 to March 1993. Also, He had ever worked in the University of Alberta Canada from March 2000. to March 2001 as intelligent control system. He has been worv. 1977 to March 1993. Also, He had ever worked in the University of Alberta Canada from March 2000. to March 2001 as intelligent control system. He has been working in the Hanbat National University since March 1993. He is interested in intelligent control including immune algorithm.

Jin Ill Park

he was born in Aug. 4, 1975. He finished from Graduate of the Hanbat National Univ. in Korea. (MS.)

He has been working in the Education Center for Advanced Instrumentation Technology of the Hanbat National University since March 1993. He is interested in intelligent control including immune algorithm