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Comparison of PID Controller Tuning of Power Plant Using Immune and Genetic Algorithms

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Abstract **– Optimal tuning plays an important role in operations or tuning of the complex process such as the main steam temperature of the thermal power plant. However, it is very difficult to maintain the steam temperature of power plant using conventional optimization methods, since these processes have the time delay and the change of the dynamic characteristics in the reheater.**
Up to the present time, the PID controller has been used. 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. This paper suggests immune algorithm based tuning technique for PID Controller on steam temperature process with long dead time and its results are compared with genetic algorithm based tuning technique.

Keywords: **PID control; Steam temperature control; Immune algorithm; genetic algorithm; Auto-tuning.**

1. INTRODUCTION

The operational strategy of electric power plants was traditionally based upon the concept of generating electric power with a reliability and little regard for fuel economy, since fuel was cheap and abundant. However, since the sixties, due to the world economic crisis which gave rise to the oil crisis of the seventies, the utility industry began to show more interest for a deeper understanding of their own power plants with the objective of improving their economic behavior [1]. In the fossil-fired power plant, high-pressure and high temperature boilers are used for generation of electric power large capacity. Also, steam temperature deviation must be kept within $\pm 5°C$ in order to maintain boiler operating efficiency and equipment life time as well as to ensure safety. This control performance is depended on air flow and fuel flow.
Start-up and shutdown procedures of the steam temperature control loop including air flow control in the electric power generation boilers are the most challenging problems when developing new control algorithms. The sequence of operations must be successfully performed to maintain steam temperature at the outlet of the superheater and the reheater regardless of the changes in the plant load, properties of the fuel, the conditions of the furnace through a sequence of safe states. At the same time, many variables must be monitored and controlled to ensure operational safety [1, 2]. Moreover, minimal time and energy losses during start up and run-up procedures would be desirable.

Up to now, a Proportional – Integral – Derivative (PID) controller has been used in the steam temperature control of boiler. However, it cannot effectively control such a complicated or fast running system, since the response of a plant depends on only the gain P, I, D, and steam temperature process has a long dead time. This paper addresses comparison of immune algorithms based tuning and genetic algorithm based tuning for power plant.

II. CONTROL CHARACTERISTICS FOR CONTROLLER DESIGN

A. Control Characteristic In The Thermal Power Plant

In the coal-fired thermal power plant, there are six manipulated variables: main steam flow, feedwater flow, fuel flow, air flow, spray flow, and gas recirculation flow. In addition, there are five controlled variables; generator output, main steam pressure, main steam temperature, exhaust gas O_2 density, and reheater steam temperature [2, 8]. Therefore, the coal-fired power plant is a multi-input and multi-output system, which must alter the generator output in response to changes in the load demand dictated by the DCS in a central load dispatching office.

Fig. 1 shows a functional diagram of the control system of power plant. In the thermal power plant, strict control of the steam temperature is critical to maintain safety and avoid thermal stress, which leads to premature failure of the steam turbines [1, 2].
1) The heating value of coal, which cannot be measured on-line, varies according to the coal source. The coal source changes within a period ranging from a week to a month and the heating value of the coal can vary from approximately 90% to 110% of a typical value during the course of a day. Furthermore, process characteristics change slowly during a long operation. These factors make it difficult to provide accurate control of the heat input to the boiler.
(2) Since the coal pulverizing process proceeds slowly and the heat capacity of coal-fired plants is larger than that of oil or gas burning plants, the time delay of changes in main steam temperature versus the changes in fuel flow rate greatly exceeds the delay experienced in oil or gas burning plants. That is, accurate steam temperature control is very difficult to attain during

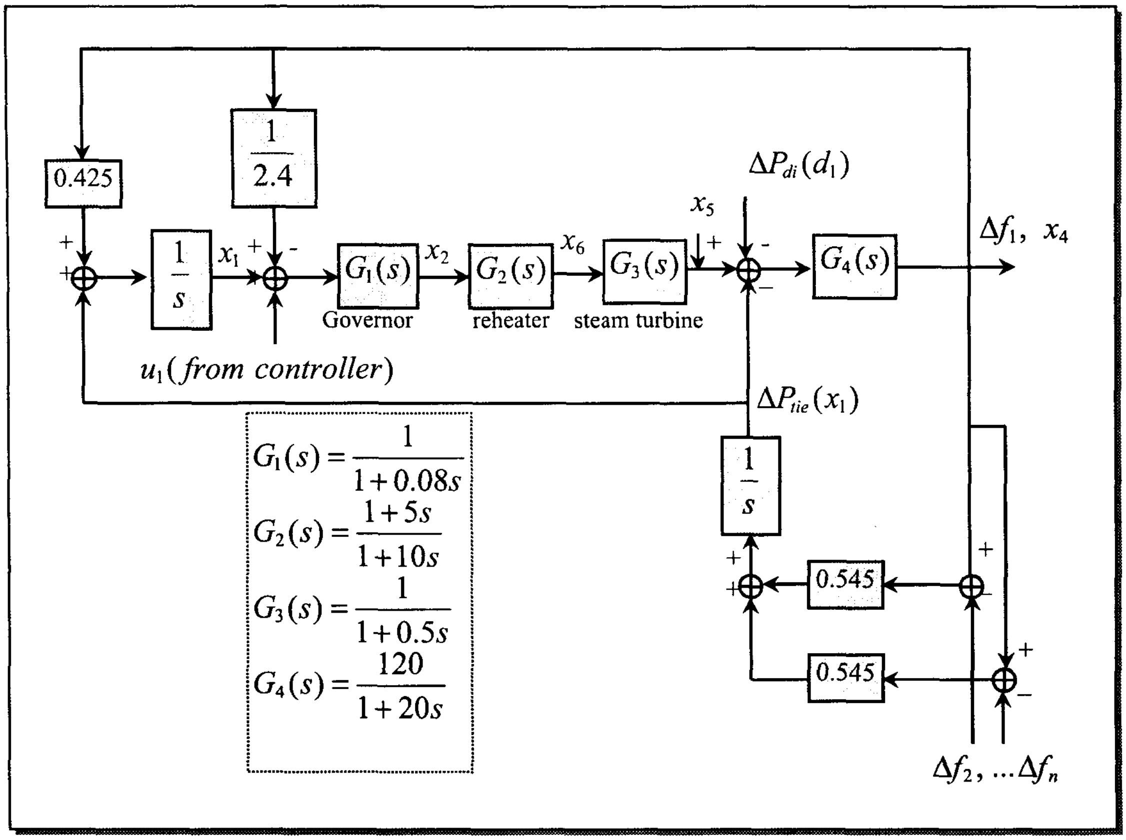

Fig. 1. Power plant block diagram.

rapid load changes. If the load changes rapidly, the conventional PID controller adjusts the input variables to values corresponding to the boiler load, causing steam temperatures deviation from its set point (more than $\pm 5°C$).

(3) The main steam temperature control system and the reheater steam temperature control system may interfere with each other. This means that overall temperature control comprises a multi-input and output interference system. Hence, it is difficult to control well both the main steam temperature and the reheater steam temperature.

(4) Flow rates in water and steam fluctuate widely during load-following operation. For example, both the time constant and the gain vary by more than a factor of two during a load-following operation.

B. Air Flow Control System For Steam Temperature Control

For the most efficient operation on the power plant, since the signal that dictates the quantity of air must be related to the amount of air theoretically needed to burn the fuel flowing to the burners, controlling the air to maintain a defined steam-flow/air-flow ratio must be well established. However, owing to the multiplicity of burners in large boilers, difficulties arise in distributing the air flow to individual burners, further problems arise when a mixture of fuels is being burned. A general control method is to regulate the air pressure with respect to the steam flow, because the optimum pressure at that location for a given coal flow will be related to the boiler load. However, for the best control, the parameters defined by the boiler designer may need to be adapted in the light of practical operating experience with the actual plant.

III. PID CONTROLLER DESIGN FOR THE POWER PLANT CONTROL

The combustion air flow demand resulting from the boiler steam load is satisfied by positioning the controlled device. The controlled device determines a close approximation of the flow rate at constant fan speed. However, this is true only if a high percentage of total system pressure drop occurs across the controlled device. That is, if this not true and the upstream or downstream pressure varies, the flow rate will vary. The closed loop feedback control is used in order that the flow rate and control signal remain equal to compensate for such changes. On the other hand, the PID controller has been widely used due to its simplicity and robustness in chemical process, power plant, and electrical systems and many sophisticated tuning algorithms have been tried an attempt to improve the PID controller performance under such difficult conditions. However, using 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. Since the PID controller is usually poorly tuned, a higher of degree of experience and technology is required for tuning in the actual plant [5].

IV. PID CONTROLLER TUNING BY IMMUNE ALGORITHMS

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 in the primary response.

B. Antibodies In 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.

C. Interaction Between Antibodies

The interaction among antibodies is important to understand dynamic characteristics of immune system. Consider the two antibodies that respond to the antigens. 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

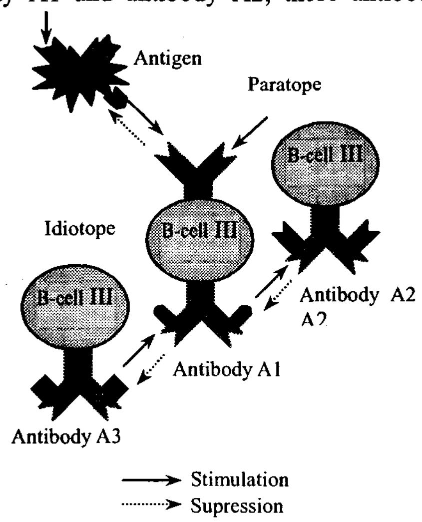

Fig. 2. Structure of idiotypic on Jerne network.

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.

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 [3]:

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

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

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 [10]:

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

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:

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

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

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

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

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

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. Adaptive Multiobjective Optimization By Immune Algorithm

Conventional optimization techniques, such as gradient-based and simplex-based methods, were not designed to cope with multiple-objectives search problems, which have to be transformed into single objective problems prior to optimization. On the other hand, evolutionary algorithms are considered to be better tailored to multiple-objectives optimization problems. This is mainly due to the fact that multiple individuals are sampled in parallel, and the search for multiple solutions can be more effective.

Chromosome representation: there are three control parameters to be determined for an adaptive optimal control.

Objective functions: for the general control problem, it is desirable to optimize a number of different system performances. Consider a step input R(t) and the output response Y(t). The following objectives are stated for design.

- Minimizing the maximum overshoot of the output

$$f_1 = OV = \max_t Y(t) \tag{7}$$

- Minimizing the settling time of the output

$$f_2 = ST = t_s \tag{8}$$

such that $0.98R \le Y(t) \le 1.02R,\ \forall t \ge t_s$.

- Minimizing the rise time of the output

$$f_3 = RT = t_1 - t_2 \tag{9}$$

such that $Y(t_1) = 0.1R$ and $Y(t_2) = 0.9R$.

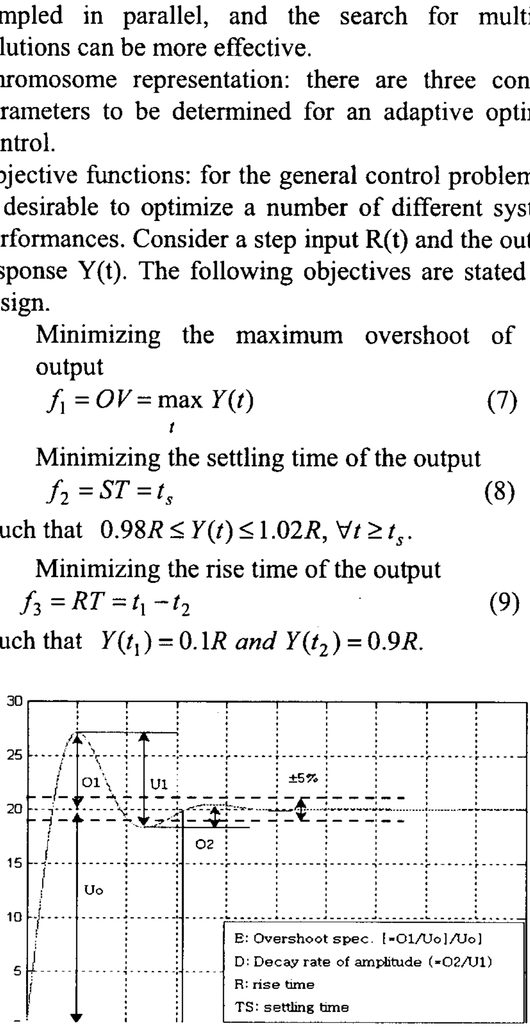

Fig. 3. Responsc spccification.

C. Tuning Of The PID Controller By Adaptive Multiobjective Based On Immune Algorithms

In this paper, for the immune algorithm based control reference model is used to computer fitness function as shown in Fig. 3. On the other hand, multiobjective functions are defined as the following equation.

$$f_1(E;a_1,b_1,c_1) = \begin{cases} 1-0, & E \le a_1 \\ 1-\dfrac{E-a_1}{b_1-a_1}, & a_1 \le E \le b_1 \\ 1-\dfrac{c_1-E}{c_1-b_1}, & b_1 \le E \le c_1 \\ 1-0, & c_1 \le E \end{cases} \tag{10}$$

$$f_2(R;a_2,c_2) = \frac{1}{1+e^{-a_2(R-c_2)}},$$

$$f_3(TS;a_3,c_3) = \frac{1}{1+e^{-a_3(TS-c_3)}},$$

Function $f_1(E;a_1,b_1,c_1)$: $[f_1(x_1)]$ is inverse-triangular membership function, $f_2(R;a_2,c_2)\,[f_2(x_2)]$ and $f_3(TS;a_3,c_3)\,[f_3(x_3)]$ are sigmoid curve membership function as shown in Fig. 4.

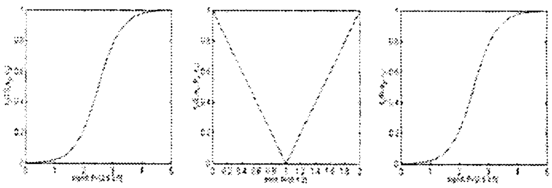
Fig. 4. Membership function for multiobjective.

Using immune algorithm, controller function is defined as

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

$I,\ D = samevalue,$

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

$$f_{su}(P_n^i): \text{sup}\,pression \begin{cases} 1, & if\ P_n^i\ is\ \text{sup}\,pression \\ 0, & Others \end{cases} \quad i = 1,..I,\ exception\ n \tag{11}$$

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

α, β: $integer\ constant\ (0 \sim 1)$.

Fitness between antibody and antigen is defined by objective function, $f(x)$. When $H(s)$ is close to zero, fitness is good and is given as:

$$f(x) = w_1 f_1(x_1) + w_2 f_2(x_2) + w_3 f_3(x_3). \tag{12}$$

where,

$x = [E,R,TS], x_1 = E;a_1,b_1,c_1, x_2 = R;a_2,c_2, x_3 = TS;a_3,c_3.,$

$w_{i=1,2,3} = Weight$

and w_i is weight function.

$$H(s) = 1 - \frac{n}{n+f(x)},\quad n = \max(f(x)) \tag{13}$$

V. SIMULATIONS AND DISCUSSIONS

A. Genetic Algorithm Based Tuning Characteristic Of The PID Controller

The transfer function with dead time is used as the following equation.

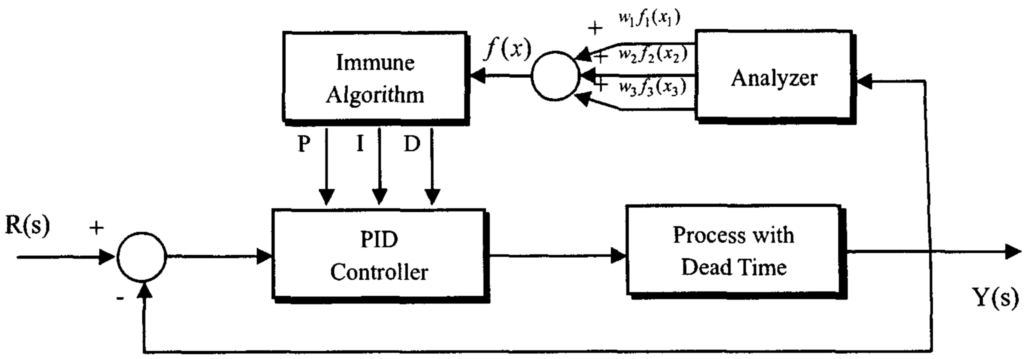

Fig. 5. Immune based PID controller tuning.

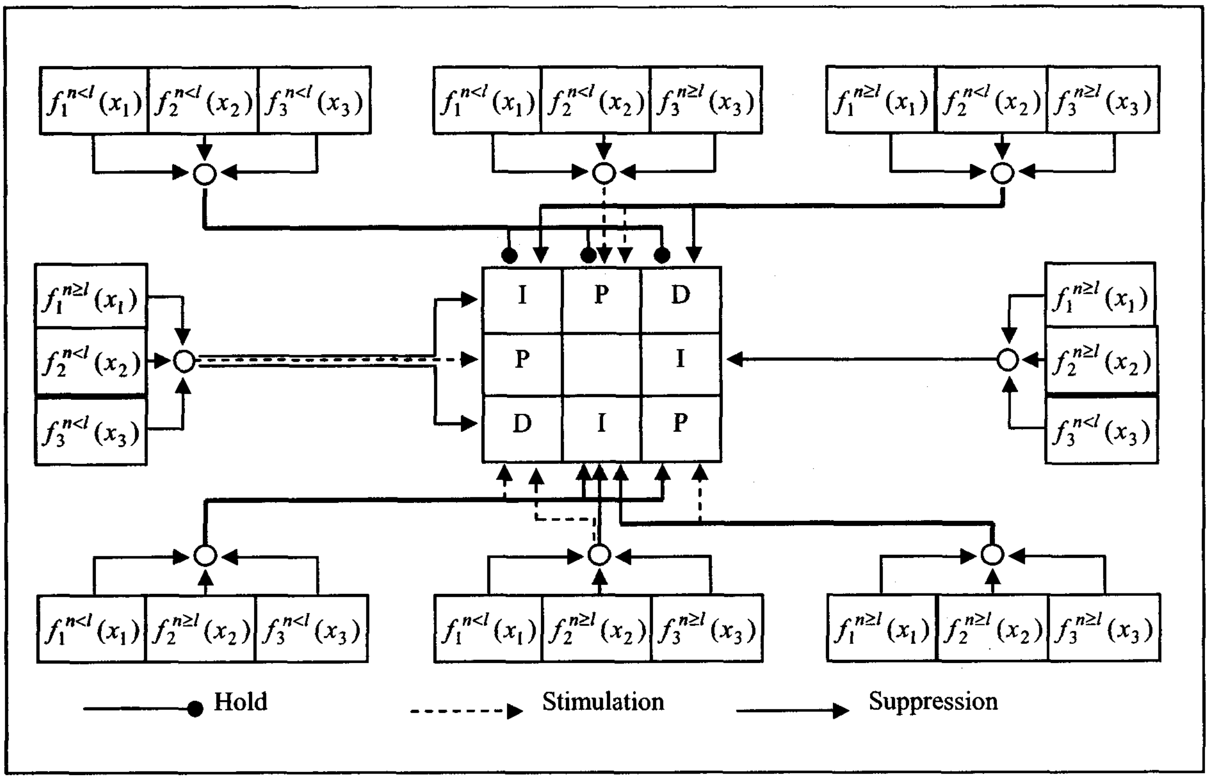

Fig. 5. Immune based PID controller.

$$G(s) = \frac{2(0.5s+1)e^{-0.1s}}{(s+1)(4s+1)} \quad (14)$$

$$PID(s) = P + \frac{I}{s} + Ds \quad (15)$$

Real coded genetic algorithm is applied to tuning of PID controller.

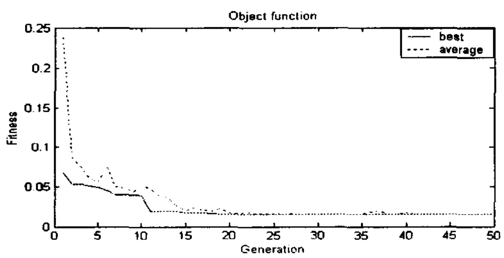

Fig. 7. Fitness function by genetic algorithm.

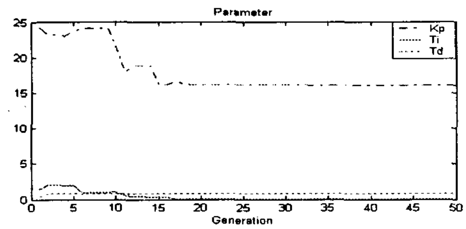

Fig. 8. Tuning result by genetic algorithm.

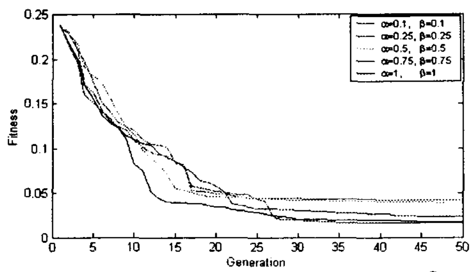

Fig. 9. Fitness variation depending on α, β.

Range for P, I, and D is given by 1-50, 0-10, 0-2, respectively. Weight function is $w_i = [1\ 1\ 1]$. PID=[16.119 0.00010546 0.87083] is obtained in generation 47 through simulation. The value of function is

$$f_1(x_1) = 0.0071108,\ f_2(x_2) = 0.0042675,$$

$$f_3(x_3) = 0.036165,\ f(x) = 0.047543,\ H(s) = 0.0156.$$

Fig. 7 shows fitness function obtained by genetic algorithm and Fig. 8 represents is tuning result by genetic algorithm. From Fig. 7, optimum fitness function is achieved on about the 15th generation.

B. Immune Algorithm Based The PID Controller Tuning

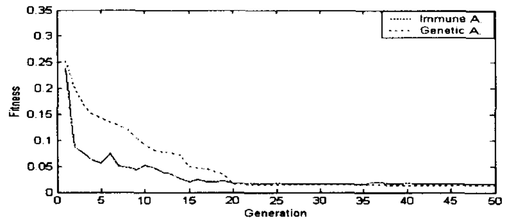

Fig. 10. Comparison of fitness variation between genetic algorithm and immune algorithm.

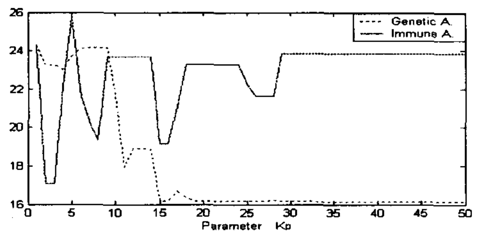

Fig. 11. Kp variation on genetic algorithm and immune algorithm.

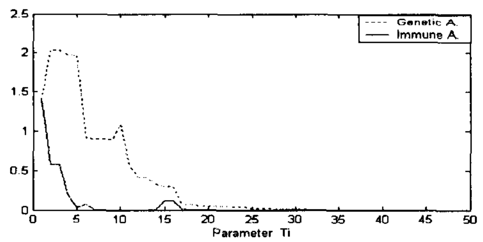

Fig. 12. Ti variation on genetic algorithm and immune algorithm.

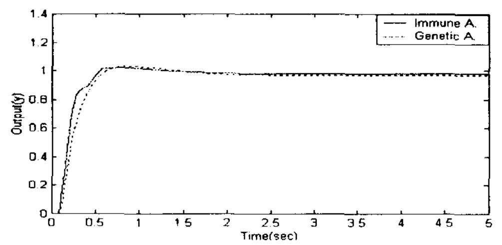

Fig. 13. Response characteristics of PID controller tuned by on immune algorithm and genetic algorithm.

Table 1. Comparison of immune and genetic.

Item	Weight fun.	Fitness				
		Gen	Fit	Kp	Ti	Td
Ge	[1 1 1]	47	0.0156	16.119	0.000106	0.8708
Im	[1 1 1]	29	0.0111	23.852	0.000067	1.7733

Fig. 9 shows fitness variation depend on α, β in immune algorithm. Fig. 10 shows variation of fitness function between genetic algorithm and immune algorithm. Figs. 11 and 12 represent variations of Proportional gain (Kp) and Integral gain (Ti) and Fig. 13 is response characteristics of PID controller tuned by on immune algorithm and genetic algorithm.

VI. CONCLUSION

To design an optimal controller that can actually be operated on the air flow of generating system, this paper focuses on comparing the characteristics of the PID controller tuned by genetic algorithm and the result of PID controller based on immune algorithms for developing tuning technology on the power plant control.

For this purpose, we suggest an immune algorithm based multiobjective tuning method for the PID controller. Parameters P, I and D encoded in antibody are randomly allocated during selection processes to obtain an optimal gain for plant. The object function can be minimized by gain selection for control, and the variety gain is obtained. The suggested controller is compared with genetic algorithm based results in the power plant.

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