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Intelligent Control of Power Plant Using Immune Algorithm Based Multiobjective Fuzzy Optimization

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***Abstract-* This paper focuses on design of nonlinear power plant controller using immune based multiobjective fuzzy approach. The thermal power plant is typically regulated by the fuel flow rate, the spray flow rate, and the gas recirculation flow rate. However, Strictly maintaining the steam temperature can be difficult due to heating value variation to the fuel source, time delay changes in the main steam temperature, the change of the dynamic characteristics in the steam-turbine system.**
Up to the present time, PID Controller has been used to operate this system. However, it is very difficult 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. These parameters tuned by multiobjective based on immune network algorithms could be used for the tuning of nonlinear power plant.

***Keywords:* Fuzzy control; Power plant control; Immune algorithm, Multiobjective control.**

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, 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. In the area of steam power plant control, most of the research has been done by manufactures and is protected under proprietary rights. In particular, any procedure to be implemented in a power plant should be tested in some kind of model before actual implementation. In the fossil-fired thermal power plant, a control system to keep the steam temperature deviations within specified ranges around their rated values is required in order to maintain the nominal efficiency and ensure the safety and equipment life of the plant. 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.
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, and D. This paper addresses whether an intelligent tuning method by multiobjective fuzzy based on a immune network algorithms can be used effectively in tuning for nonlinear power plant system.

2. CONTROL CHARACTERISTICS OF THERMAL POWER PLANT FOR CONTROLLER DESIGN

A. Control Characteristics 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 [6]. 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.
Temperature system for the Boryong power plant and is composed of three subsystems such as S/H (Super Heater) tube control subsystem, Platon S/H tube control subsystem, ECO tube control system. The each subsystem has a feedforward loop and a feedback-control system. 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. The main steam temperature typically is regulated by the fuel flow rate and the spray flow rate, and the reheater steam temperature is regulated by the gas recirculation flow rate. However, the following problems have been identified in steam temperature control [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. These factors make it difficult to provide accurate control of the heat input to the boiler.

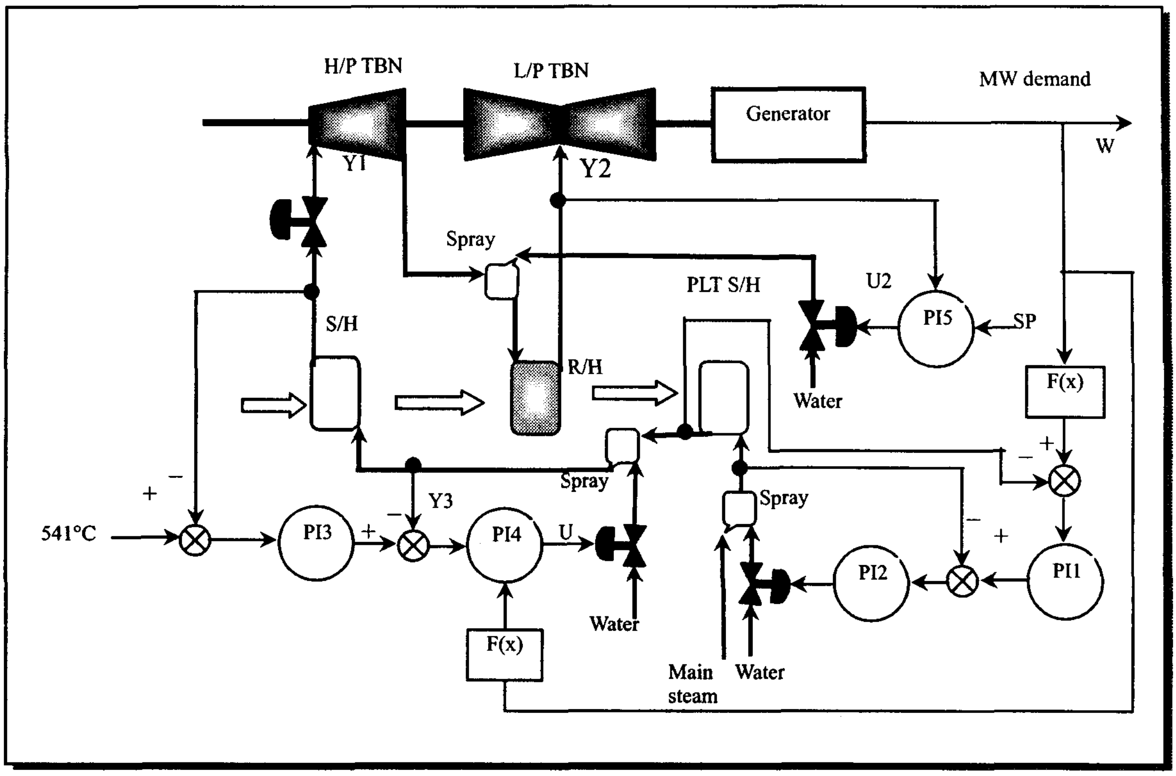

Fig. 1. Block diagram of nonlinear power plant system.

(2) Since the coal pulverizing process proceeds slowly and since 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. 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.

(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. Steam Temperature Control Approaches In Power Plant Boiler

In the power plant, the strategy used for the control of steam temperature for power plant boilers is normally recommended by the boiler manufacturer. The normal steam temperature control requirement has to sustain the temperature within $\pm 5°C$. Fig. 1 shows two methods of controlling the superheater temperature using a water spray in the power plant.

C. Superheated Steam Temperature Control

Fundamentally, the temperature of the final superheated steam is a function of the boilers firing rate and the steam flow, and of the design of the heating surfaces and the plant generally.

The control systems for the final superheated steam temperature in boilers rely almost exclusively on attemperators-usually of the spray type. A cascade control system is used to overcome the long time constants of the secondary superheater in steam temperature control.

D. Multistage Superheaters For Steam Temperature Control

In boilers with several stages of superheating and employing cascade systems for each section as shown in Fig. 1, spray attemperators are normally provided between the major superheating banks. The first key condition in this system is to generate the desired value for the secondary superheater outlet temperature controller from the outlet of the final steam temperature controller. The second point is the maximum selector block interposed between the first-stage main controller, PID and its slave, PID.

3. NONLINEAR POWER PLANT MODEL

For this study the following nonlinear model is used [11];

$$\frac{dp}{dt} = -A_1 s p^{1/8} + A_2 u_1 - A_3 u_3 + A_4 L_{water}^{level} + A_5 T_{feedwater}^{temp}$$

$$\frac{ds}{dt} = 10 u_2 p^{1/2} - A_6 F_{steam}^{flow}$$

$$\frac{dl}{dt} = A_7 u_3 + A_8 u_1 + A_9 u_2 - A_{10} p^2 - A_{11} L_{water}^{level} - A_{12} \left(L_{water}^{level}\right)^2 - A_{13} F_{steam}^{flow} \qquad (1)$$

where

p = *drum pressure,*

F^{flow}_{steam} = *steam flow to a HP turbine,*

L^{level}_{water} = *drum water level,*

u_1 = *fuel (pulverized coal) input,*

u_2 = *control valve displacement,*

u_3 = *feed water input,*

$T^{temp}_{feedwater}$ = *feed water input temperature*

The system parameters are

$$A_1 = 0.0193\ A_2 = 0.014524\ A_3 = 0.000739$$
$$A_4 = 0.00121\ A_5 = 0.000176\ A_6 = 0.78576$$
$$A_7 = 0.00863\ A_8 = 0.002\ A_9 = 0.463$$
$$A_{10} = 0.000006\ A_{11} = 0.00914\ A_{12} = 0.000082$$
$$A_{13} = 0.007328\ T^{temp}_{feedwater} = 0.288^o\ C$$

$$\begin{aligned}
\frac{dp}{dt} &= -0.014524u_1 - 0u_2 + 0.000736u_3 - 0.00193sp^{1/8} \\
&+ 0.00121L^{level}_{water} + 0.000176T^{temp}_{feedwater} \\
\frac{ds}{dt} &= 0u_1 + 10u_2p^{1/2} - 785F^{flow}_{steam} \\
\frac{dl}{dt} &= 0.002u_1 + 0.463u_2 + 0.00863u_3 - 0.000006p^2 \\
&- 0.00914L^{level}_{water} - 0.000082\left(L^{level}_{water}\right)^2 - 0.00732F^{flow}_{steam}
\end{aligned} \quad (2)$$

4. IMMUNE ALGORITHMS BASED MULTIOBJECTIVE FUZZY OPTIMIZATION

A. Multiobjective Fuzzy Optimization

The multiobjective fuzzy optimization problem and fuzzy convex decision-making principles is stated. The general multiobjective fuzzy optimization can be defined as finding x which minimizes $f(x)$ such that $g_j \in b$.

$$f(x) = [\, f_1(x), f_2(x), \ldots, f_k(x)\,] \quad (3)$$

Eq. (3) is a vector objective function and $g_j(x)$ are constraints, with the symbol indicating that the constraints mean fuzzy information [12].

The first stage of the multiobjective fuzzy optimization is to fuzzify the objective functions and the fuzzy constrains. The membership function for the fuzzy objective function is given by

$$\eta_{f_i}(x) = \begin{Bmatrix} 0 & if\ f_i(x) > f_i^{\max} \\ \dfrac{-f_i(x) + f_i^{\max}(x)}{f_i^{\max} - f_i^{\min}} & \\ & if\ f_i^{\min} < f_i(x) \le f_i^{\max} \\ 1 & if\ f_i(x) \le f_i^{\min} \end{Bmatrix}, \quad (4)$$

where $\eta_{f_i}(x): R^n \to [0,1]$ and $\eta_{f_i}(x)$ is a mapping from real number set R^n to the closed interval [0, 1], which is a measure of the degree of satisfaction for any $x \in R^n$ in the ith fuzzy objective function. $f_i^{\min}$ and $f_i^{\max}$ represent the minimum and maximum values for the objective function, respectively and they are defined as

$$f_i^{\min} = \min_i f_i(x^*) \text{ and } f_i^{\max} = \max_i f_i(x^*) \quad (5)$$

where x^* is the solution for each of the objective functions in the crisp domain.

The fuzzy constraints membership function is defined as

$$\eta_{gi}(x) = \begin{Bmatrix} 0 & if\ g_j(x) > b_j + d_j \\ 1 - \left(\dfrac{g_j(x) - b_j}{d_j}\right) & \\ & if\ b_j \le g_j(x) \le b_j + d_j \\ 1 & if\ g_j(x) \le b_j \end{Bmatrix}, \quad (6)$$

where $\eta_{gi}(x): R^n \to [0,1]$ and $\eta_{gi}(x)$ is the mapping from the real number set R^n to the closed interval [0,1], which is an indication of the degree of satisfaction for any $x \in R^n$ in the jth fuzzy constraint. $\eta_{gj}(x)=1$ means complete satisfaction, $\eta_{gj}(x)=0$ is not satisfied and values between 0 and 1 show the degree of satisfaction of the jth constraint. The allowable tolerances for each fuzzy constraint are defined by d_j

B. Fuzzy Decision-Making

The objective functions and constraints have been defined as fuzzy subsets in the space of alternatives using linear membership functions $\eta_{fi}(x)$ and $\eta_{gi}(x)$, respectively. The optimal decision is made by selecting the best alternative from the fuzzy decision space D characterized by the membership function η_D. That is, find the optimum x^* which maximizes η_D defined mathematically as

$$\eta_D(x^*) = \max \eta_D(x),\ \eta_D \in [0, 1]. \quad (7)$$

The fuzzy decision can be made by employing one of the three generalized fuzzy decisions: intersection decision, convex decision, and product decision.

The convex decision [11] is given mathematically as follows

$$D = \alpha f(x) + \beta g(x) \quad (8)$$

where α and β are weighting factors, which satisfy

$$\alpha + \beta = 1 \quad \alpha \ge 0\ \beta \ge 0. \quad (9)$$

For any fuzzy optimum set points, the weights α_j and β_j are given so that a linear weighted sum can be achieved. That is, the membership function of the convex decision is defined as

$$\eta_D(x) = \sum_{i=1}^{k} \alpha_i \eta f_i + \sum_{j=1}^{m} \beta_j \eta_{gj}, \quad (10)$$

$$\sum_{i=1}^{k}\alpha_i + \sum_{j=1}^{m}\beta_j = 1,$$
$$\alpha_i \geq 0 \quad i = 1,2,\ldots,k$$
$$\beta_j \geq 0 \quad j = 1,2,\ldots,m \tag{11}$$

From Eq. 11, the multiobjective fuzzy optimization problem can be transformed into the following single-objective nonfuzzy optimization problem:

$$\max \eta_D(x) = \sum_{i=1}^{k}\alpha_i \eta f_i(x) + \sum_{j=1}^{m}\beta_j \eta_{gj}(x) \tag{12}$$

$$g_i(x) \leq b_j + d_j \quad j = 1,2,\ldots,m\,. \tag{13}$$

C. Membership Weighting

A membership weighting strategy is defined for a convex-decision multiobjective fuzzy optimization problem. The membership weighting factor is formulated as follows:

$$\psi_{fi} = 1 - \eta_{fi}(x) \quad \text{and} \quad \psi_{gi} = 1 - \eta_{gi}(x)$$

$$\alpha_i = \frac{\psi_{fi}}{\sum_{i=1}^{k}\psi_{fi}} \quad \text{and} \quad \beta_i = \frac{\psi_{gi}}{\sum_{j=1}^{m}\psi_{gi}} \tag{14}$$

$$\sum_{i=1}^{k}\alpha_i + \sum_{j=1}^{m}\beta_j = 1$$
$$\alpha_i \geq 0 \quad i = 1,2,\ldots,k$$
$$\beta_j \geq 0 \quad j = 1,2,\ldots,m \tag{15}$$

These equations represent the problem in which the designer is not certain how to quantify the relative importance of each objective. It can be easily extended to cases where a particular objective or subset of objectives are more important, although the designer has no means of quantifying their relative importance. Using convex decision, the multiobjective fuzzy optimization problem for selecting the control laws $u_1, u_2,$ *and* u_3 for Eq. 2 can be formulated in the following manner.

From the above specifications, rise time and settling time are defined as fuzzy objectives and peak overshoot, phase margin, and gain margin as constraints.

All the constraints are nonfuzzy and the membership functions corresponding to the fuzzy objective functions are defined as

$$\eta_{t_s}(x) = \begin{cases} 0 & \text{if } t_s \geq 45 \\ 1 - \dfrac{t_s - 25}{20} & \text{if } 25 < t_s < 45 \\ 1 & \text{if } t_s \leq 25 \end{cases} \tag{16}$$

and

$$\eta_{t_r}(x) = \begin{cases} 0 & \text{if } t_r \geq 25 \\ 1 - \dfrac{t_r - 17}{8} & \text{if } 17 < t_r < 25 \\ 1 & \text{if } t_r \leq 17 \end{cases}. \tag{17}$$

The convex decision for multiobjective fuzzy optimization of Eq. 12 is used, since there are no fuzzy constraints ($\beta_i = 0$). To achieve the highest degree of membership to th fuzzy convex decision set, the multiobjective fuzzy optimization is formulated as; find u_1, u_2, u_3 which maximize $\eta_D = \alpha_1\eta_{ts} + \alpha_2\eta_{tr}$, where α_i are defined Eqs. 14, 15.

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]:

$$\frac{dS_i(t)}{dt} = \left(\begin{array}{l} \alpha \sum_{j=1}^{N} m_{ji}\delta_j(t) \\ -\alpha \sum_{k=1}^{N} m_{ik}\delta_k(t) + \beta m_i - \gamma_i \end{array} \right) \delta_i(t) \tag{18a}$$

$$\frac{d\delta_i(t)}{dt} = \frac{1}{1 + \exp\left(0.5 - \dfrac{dS_i(t)}{dt}\right)} \tag{18b}$$

where in Eq. (18), 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.

E. Immune Based Multiobjective Fuzzy Optimization

[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. 2 [9, 10].

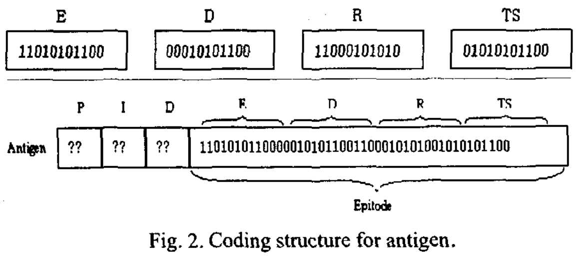

Fig. 2. Coding structure for antigen.

[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(α), I(β), D(η) and E, D, R, and TS as the following Figs. 3 and 4. E, D, R and TS is fitness function defined by between reference model and response.

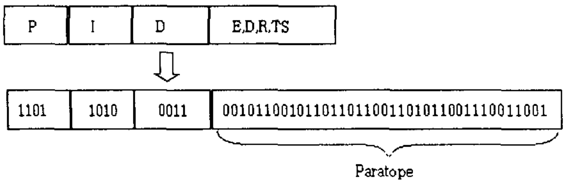

Fig. 3. Structure of antibody group.

- 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

cut_delta : Positive constant

$$- \; I_{P,I,D}^{new\_k} = F^{new}(\oplus(F(m_j - m_{j+1})\alpha I_k)) \qquad (19)$$

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

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

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

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

$$m_j = P_j \otimes A$$

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

[step 4] Calculation of affinity between antibodies: The affinities obtained by Eq. (19) 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.

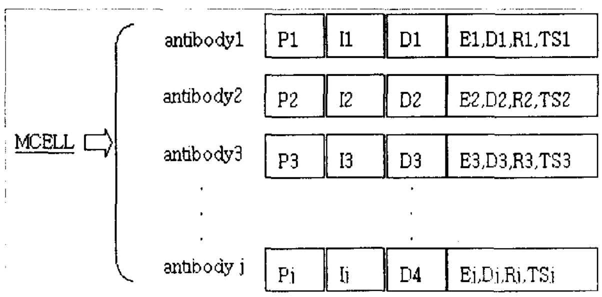

Fig. 4. Structure of antibody group.

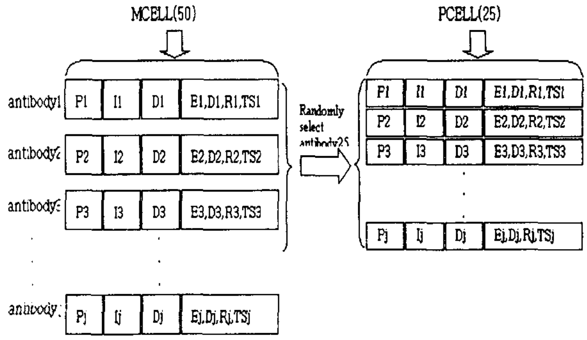

Fig. 5. Structure of the selected antibody group.

[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. The expected value η_k of the stimulation of the antibody is given by

$$\eta_k = \frac{m_{\varphi k}}{\sigma_k} \qquad (20)$$

where σ_k is the concentration of the antibodies. The concentration is calculated by affinity based on phenotype but not genotype because of the reduction of computing time. So, σ_k is represented by

$$\sigma_k = \frac{sum\ of\ antibodies\ with\ same\ affinity\ as\ m_{\varphi k}}{sum\ of\ antibodies}. \qquad (21)$$

[step 6] Stimulation of Antibody: To capture the unknown antigen, new lymphocytes are produced in the bone marrow in place of the antibody eliminated in step 5.

5. SIMULATIONS AND DISCUSSIONS

A. The Response Characteristics By The Immune Algorithms Based Multiobjective On Off-line Of The Thermal Power Plant

Fig. 6 and Fig. 7 shows the learning generation of immune network response to obtain optimization and control results on off line by the proposed control method. Figs. 8, 9 are results of learning and response using another parameter

Fig. 10 shows steam temperature response to disturbance (air flow, fuel flow) to setpoint steam temperature, 250[◦ C] using the proposed controller.

Fig. 11 represents steam temperature response to disturbance (feedwater flow) to setpoint steam temperature, 423[◦ C] using the proposed controller.

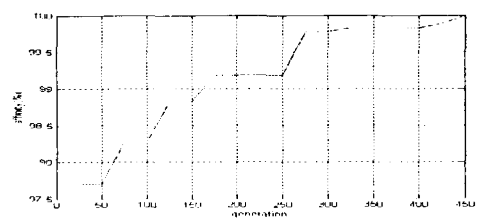

Fig. 6. Relationship between affinity and generation to learning on Immune algorithm.

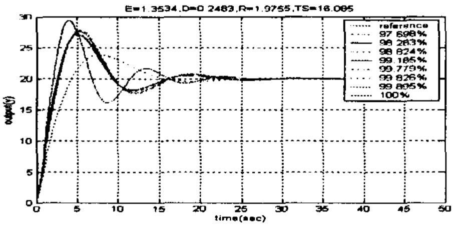

Fig. 7. Response to average values on parameter learning of immune network (off line).

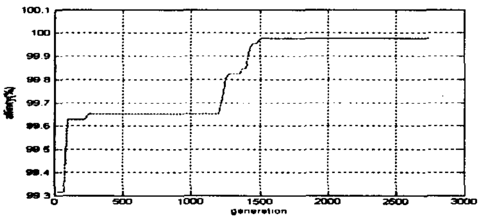

Fig. 8. Relationship between affinity and generation to learning on Immune algorithm.

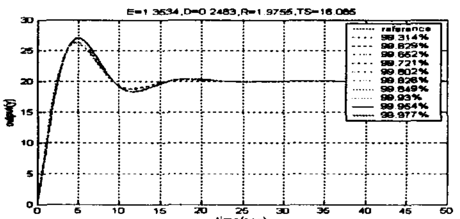

Fig. 9. Response to average values on parameter learning of immune network (off line).

C. The Response Characteristics Using Operating Data Of The Thermal Power Plant

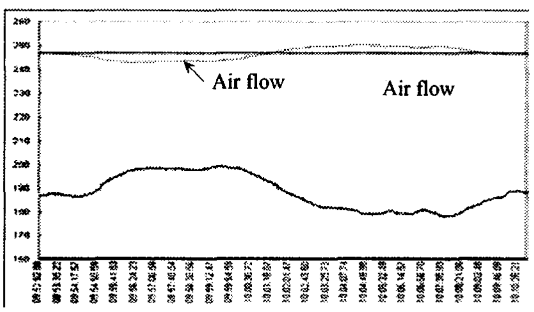

Fig. 10. Steam temperature response to disturbance using the proposed controller (disturbance: air flow, fuel flow).

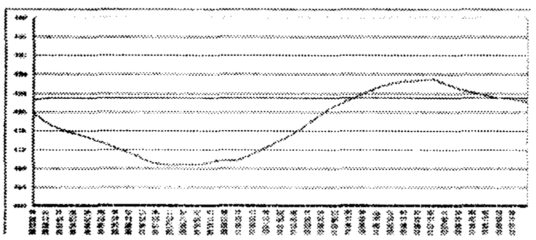

Fig. 11. Steam temperature response to disturbance using the proposed controller (disturbance: feedwater flow).

6. CONSULIONS

Up to now, the PID controller has been used to operate the power plants. However, achieving an optimal PID gain is very difficult for the steam temperature control loop with disturbances since the gain of the PID controller has to be tuned manually by trial and error. To design an optimal controller that can actually be operated on a generating system, we suggest an immune algorithm based multiobjective fuzzy control method. The suggested controller can be used effectively in the power plant, also the controller needs no feedforward or cascade loop.

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