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Adaptive Intelligent Control of Nonlinear dynamic system Using Immune Fuzzy Fusion

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

Nonlinear dynamic 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 control approaches by immune fuzzy for the nonlinear control system inverted pendulum, through computer simulation. This paper defines relationship state variables $x, \dot{x}, \theta, \dot{\theta}$ using immune fuzzy and applied its results to stability.

Key words : Immune Algorithm, Multiobjective, Neural network, Boiler control, Power plant control, PI controller.

I. 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 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.

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].

This paper suggests control scheme to control effectively non-linear system using immune algorithm based fuzzy. The variation of affinity decided between initial value and present value of position in the pendulum with cart is applied to improve control performance.

II. Dynamic model of immune system

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

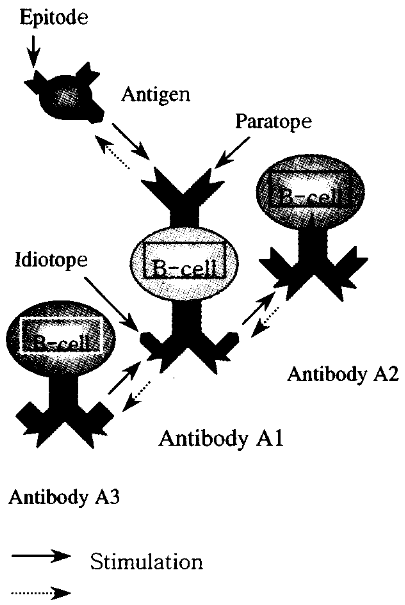

Fig. 1. Relationship between antibody and antigen on immune network.

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 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]:

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

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

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]:

$$\Omega_j(N) = \sum_{i=1}^{S} -x_{ij}\log x_{ij}, \tag{2}$$

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]:

$$\begin{aligned} \Omega_{ave}(N) &= \frac{1}{M}\sum_{j=1}^{M}\Omega_j(N) \\ &= \frac{1}{M}\sum_{j=1}^{M}\left\{ \sum_{i=1}^{S} -x_{ij}\log x_{ij} \right\} \end{aligned}, \tag{3}$$

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:

$$m_{\alpha\beta} = \frac{1}{\{1+\Omega(\alpha\beta)\}}, \tag{4}$$

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

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.

III. Controller design of non-linear system using immune fuzzy fusion

A. Sugeno Fuzzy Logic

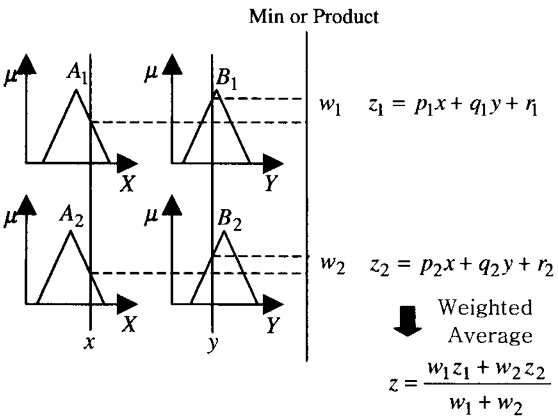

Fig. 2. Sugeno fuzzy model.

Takagi, Sugeno, and Kang proposed the Sugeno fuzzy model [10] in an effort to develop a systematic approach to generating fuzzy rules from a given input-output data set. A typical fuzzy rule in that fuzzy model has the form

$$\textit{If } x \textit{ is } A \textit{ and } y \textit{ is } B \textit{ then } z=f(x, y), \tag{5}$$

where A and B are fuzzy sets in the antecedent, while z=f(x, y) is a crisp function in the consequent.

f(x, y) is a polynomial in the input variables x and y. When $f(x, y)$ is a first order polynomial, the resulting fuzzy inference system is called a first-order Sugeno fuzzy model. Fig. 2 represents the fuzzy reasoning procedure for a first-order Sugeno fuzzy model. Since each rule has a crisp output, the overall output is obtained by weighted average as Fig. 2.

B. Cart with Inverted Pendulum

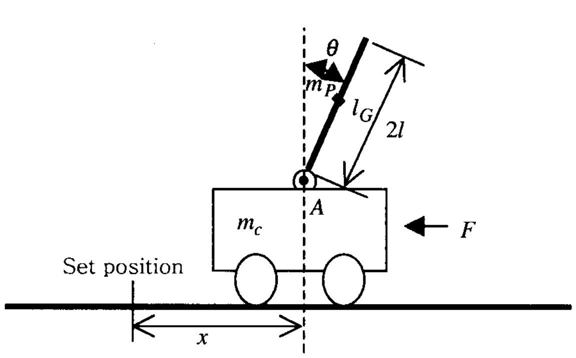

Fig. 3. The structure of cart with inverted pendulum.

To demonstrate the availability, this paper takes an inverted pendulum system for simulation. The inverted pendulum system is composed of a rigid pole and a cart on which the pole is hinged as shown in Fig. 3. The cart can move on the rail tracks to its right or left, depending on the force exerted on the cart. Therefore, it is a classical non-linear control problem that can be explained as the task of balancing a pole on a movable cart. The pole is hinged to the cart through a frictionless free joint such that it has only one degree of freedom. The control target is to balance the pole starting from nonzero conditions by supplying appropriate force to the cart. The dynamics of the inverted pendulum system are characterized by four state variables: θ (angle of the pole with respect to the vertical axis), $\dot{\theta}$ (angular velocity of the pole), x (position of the cart on the track), $\dot{x}$ (velocity of the cart). The behavior of these four state variables can be expressed by the following two second-order differential equations [51]:

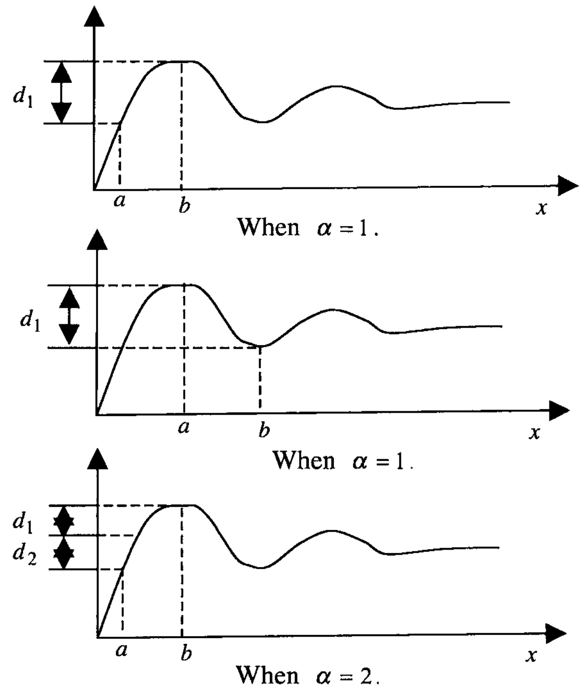

Fig. 4. Expression of resolution, depending on α .

$$\ddot{x} = \frac{F + m_p l\left[\dot{\theta}^2 \sin\theta - \ddot{\theta}\cos\theta\right]}{m_c + m_p}, \tag{6}$$

$$\ddot{\theta} = \frac{g\sin\theta + \cos\theta\left[\dfrac{-F - m_p l\dot{\theta}^2 \sin\theta}{m_c + m_p}\right]}{l\left[\dfrac{4}{3} - \dfrac{m_p\cos^2\theta}{m_c + m_p}\right]}, \tag{7}$$

where, l_G is the half length of the pole(=0.5m), m is the mass of the pole (=0.1 kg), M is the mass of the cart (=1.0kg).

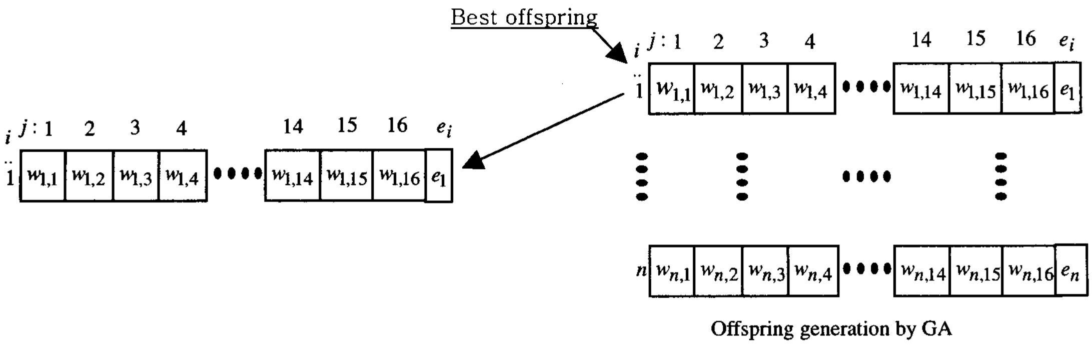

Fig. 5. Feedback of optimal solution to memory cell.

C. Non-linear Controller Design Using Immune-Fuzzy Fusion

This paper expresses the distance between the target position (B) and the initial position (A) as α , and a resolution is regulated by:

$$\left|\min(A,B)+\left(\frac{\max(A,B)-\min(A,B)}{\alpha}\right)\times(i-1)\right|<|d_i|$$

$$|d_i|\le\left|\min(A,B)+\left(\frac{\max(A,B)-\min(A,B)}{\alpha}\right)\times i\right|, \tag{8}$$

$i=\alpha,\alpha-1,\alpha-2,\cdots,1.$

Where, d_i is the present position of the given cart. The antibody in immune network is produced as much as the number of the resolution, α .

The performance definition for error is given by

$$e_i=\int_{t=1}^{n} t\left(xc^2+\theta^2\right)dt,\ i=\alpha,\alpha-1,\cdots,1. \tag{9}$$

Where, n is time from present position to target position, xc is given as $xc=a-b$.

Fuzzy output for each partition is depicted as:

$$f'_{i,j}=w_{i,j}\times f_j,\ i=\alpha,\alpha-1,\cdots,1.\ j=a\ number\ of\ fuzzy\ rule. \tag{10}$$

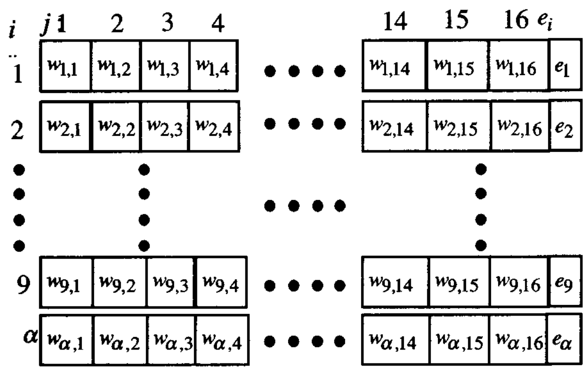

Fig. 6. The structure of antibody for memory cell.

Where $w_{i,j}$ is fuzzy output gain,

$$f_j(j=a\ number\ of\ fuzzy\ rule.)$$
$$\text{on partition } i(i=\alpha,\alpha-1,\alpha-2,\cdots,1.) \tag{11}$$

If it has 16 rules, j is $j=1,2,3,\cdots,16.$

The structure of the antibody for learning is given as Fig. 6.

The affinity between antibody and antigen is decided by $e_{i=1,2,3,\cdots,\alpha}$, and the affinity between antibodies is decided by e_i and size of neighbor antibody defined as Equation (11):

$$\eta_i=\frac{\alpha}{\alpha+f(x)}, \tag{12}$$

$$f(x)=\sum_{i=1}^{\alpha}x_i,\ x_i=\begin{cases}-1, & if\ e_i<e_{i+1},\\ 0, & if\ e_i=e_{i+1},\\ 1, & if\ e_i>e_{i+1}.\end{cases} \tag{13}$$

Where, the concentration of the total antibody is given by:

$$\Phi=\sum_{i=1}^{\alpha}\eta_i\Big/\alpha. \tag{14}$$

This paper used a simple crossover and mutation as genetic algorithm.

IV. Simulation and discussions

A. The characteristics for the fixed initial value α

In this paper, we used the pendulum with cart ($m_c=2kg,\ l=0.5m,\ m_p=0.1kg$) and the initial values for simulation are $\theta=0.1\,rd$, $x=0.5m$. The final position is $x=0$ and partition for deciding affinity is selected by

$$-0.3<\theta<0.3,$$
$$-1<\dot{\theta}<1,$$
$$-3<x<3,$$
$$-6<\dot{x}<6.$$

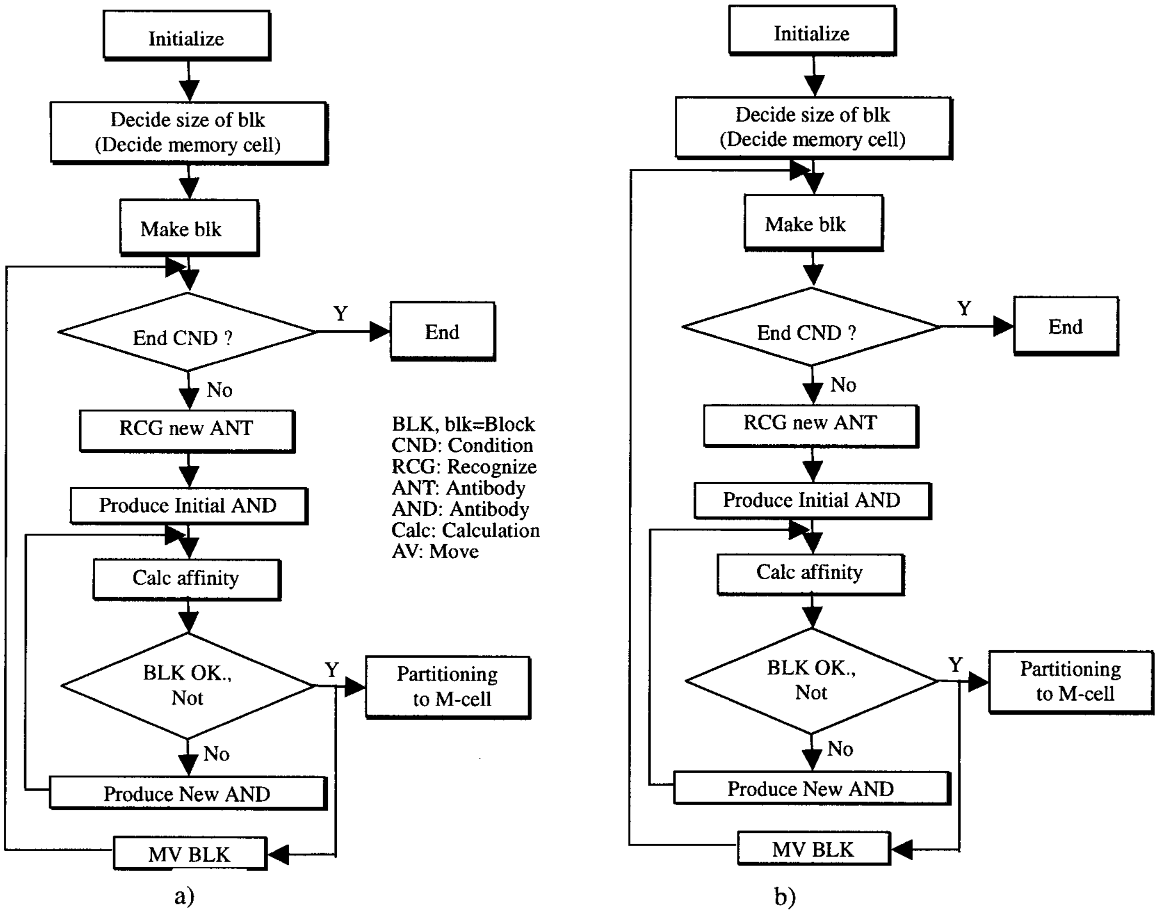

Fig. 7. Learning Algorithm by immune and fuzzy logic.

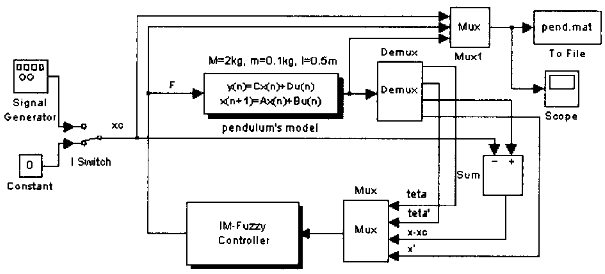

Fig. 8. Simulation structure for the immune algorithm-fuzzy model.

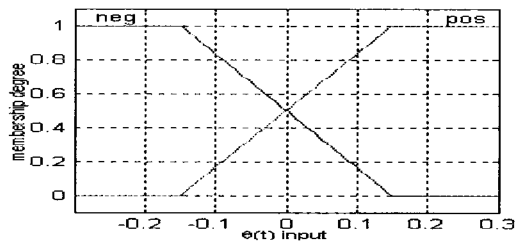

Fig. 9. $\theta(t)$ input membership functions.

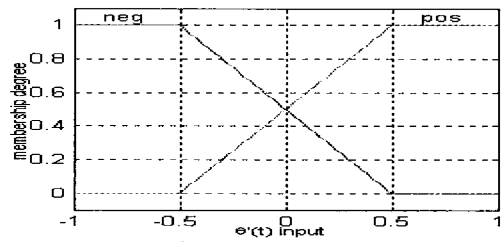

Fig. 10. $\dot{\theta}(t)$ input membership functions.

Fig. 7 shows learning algorithm by immune algorithm and fuzzy logic. Fig. 7(a) is leaning method when the value of α is constant and Fig. 7(b) is flowchart when the value of α is variable. Fig. 8. is simulation block diagram for the immune algorithm-fuzzy model by Simulink. The membership function for parameters of the pendulum is given as Figs 9-12.

Fuzzy rule for Sugeno fuggy logic is defined by 8-rules as the Table 1.[1]

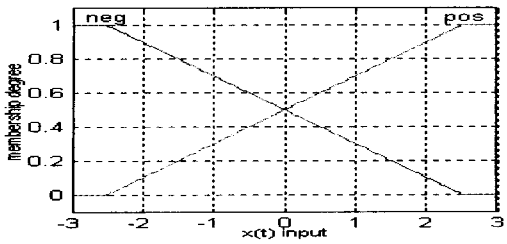

Fig. 11. $x(t)$ membership functions.

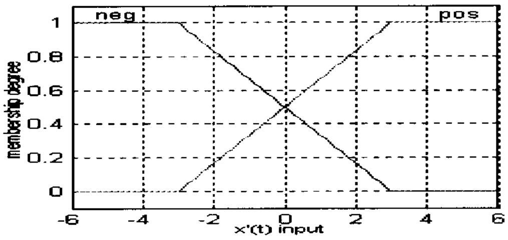

Fig. 12. $\dot{x}(t)$ input membership functions.

Fig. 13 is the response of $x(t)$, $x'(t)$ of fuzzy controller on initial value $\theta = 0.1$, $x=0.5$ when set-point is moving from $x=0$ to 0 and Fig. 14 represents the response of $\theta(t), \theta' x(t)$ of fuzzy controller on the same initial value ($\theta = 0.1$, $x=0.5$) and the same set-point ($x=0$ to 0.5).
Tables 2- 4 are data for Figs. 13-14.

Table 1. Fuzzy rules.

	x	pos	pos
θ	$\dot{\theta}$ \ $\dot{x}$	neg	pos
neg	neg	f_1	f_2
neg	pos	f_3	f_4
pos	neg	f_5	f_6
pos	pos	f_7	f_8

Table 2. Data on $\alpha = 5$.

	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	e_i
1	1.7092	1.1366	1.8172	1.8651	0.9971	0.3958	0.4252	0.1375	2747.3
2	1.6256	1.3709	1.864	1.8614	1.1668	1.67	1.7432	0.2961	22.206
3	0.2030	0.6786	0.0061	0.7707	0.0365	0.3096	1.9885	0.4221	4.2395
4	0.9361	0.4963	1.2069	0.4873	0.7342	1.9955	1.7916	0.7562	0.6114
5	1.2857	1.2261	1.9534	1.9603	0.9868	1.7432	1.8806	0.5040	78.815

Φ : 5.0299

Table 3. The data on $\alpha = 10$.

	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	e_i
1	1.5573	1.3378	1.8236	1.9768	1.2524	0.4730	0.7890	0.5098	2565.1
2	1.4217	1.4463	1.9638	1.9708	1.0641	1.741	1.8501	0.3886	22.515
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
9	1.9562	1.6739	0.4960	0.6976	0.6808	1.652	0.7104	0.1879	2.8855
10	0.6437	1.2815	1.5168	1.5599	0.8642	1.6509	0.9751	0.5104	7.0122

Φ : 3.2245

Table 4. The data on $\alpha = 20$.

	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	e_i
1	1.3637	1.3506	1.9641	1.9977	0.5965	1.1083	0.5674	1.3617	2404.2
2	1.4226	1.4286	1.9488	1.9476	1.0436	1.7317	1.8966	0.3320	10.519
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	1.5253	0.9494	1.1296	0.8922	0.5828	1.1661	1.2184	0.9951	6.5374 e-005
20	1.5253	0.9494	1.1296	0.8922	0.5828	1.1661	1.2184	0.9951	5.1733 e-005

Φ : 2.4797

A. The characteristics for the variable initial value α

Fig. 13. $x(t)$, $x'(t)$ response of fuzzy controller on initial value $\theta = 0.1$, $x=0.5$ when set-point is moving from $x=0$ to 0.5.

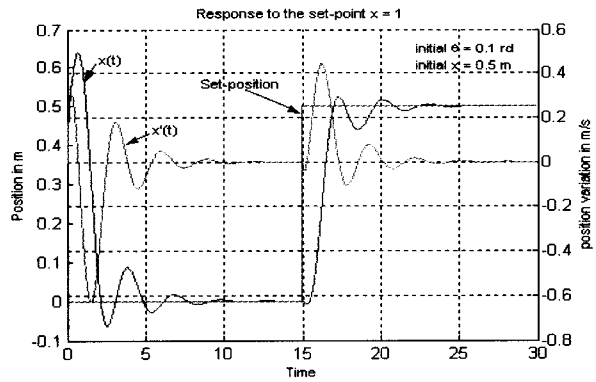

Fig. 13. $x(t), x'(t)$ response of fuzzy controller on initial value $\theta = 0.1$, $x=0.5$ when set-point is moving from $x=0$ to 0.5.

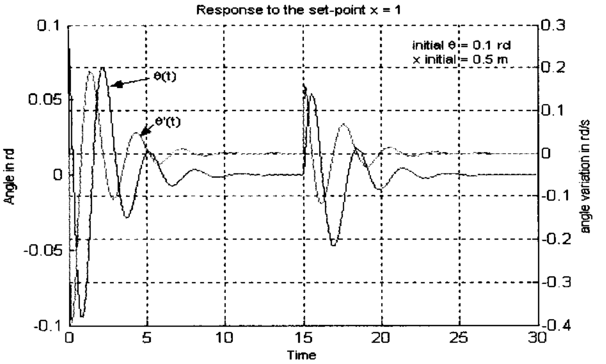

Fig. 14. $\theta(t)$, θ' *x(t)* response of fuzzy controller on initial value $\theta = 0.1$, *x=0.5* when set-point is moving from *x=0* to *0.5*.

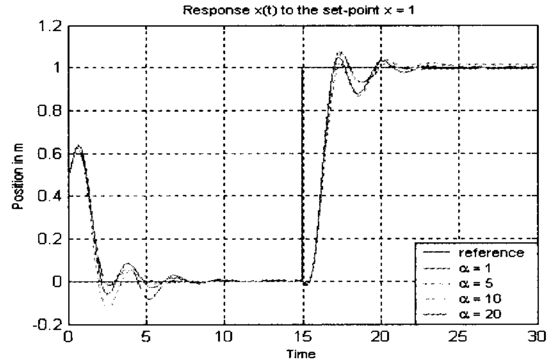

Fig. 15. Response of pendulum position *x(t)* on set-point *x=1* and variation of α by algorithm of Fig. 7(a).

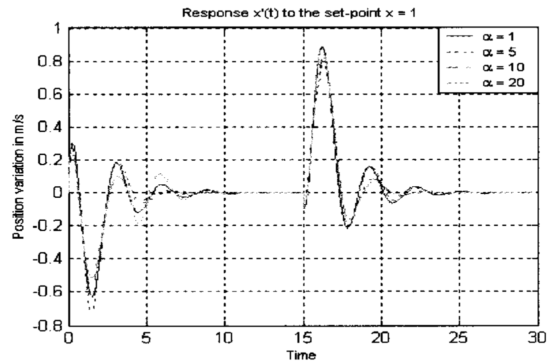

Fig. 16. Response of pendulum position *x'(t)* on set-point *x=1* and variation of α by algorithm of Fig. 7(a).

Fig. 14. $\theta(t)$, θ' *x(t)* response of fuzzy controller on initial value $\theta = 0.1$, *x=0.5* when set-point is moving from *x=0* to *0.5*.

Also, Figs. 15-16 illustrate the response of pendulum position *x(t)* and *x'(t)* on set-point *x=1* and variation of α by algorithm of Fig. 7(a). Figs. 17-18 are the response of pendulum angular $\theta(t)$ and $\theta'(t)$ by algorithm of Fig. 7(a) when set-point is *x=1* and the value of α varies.

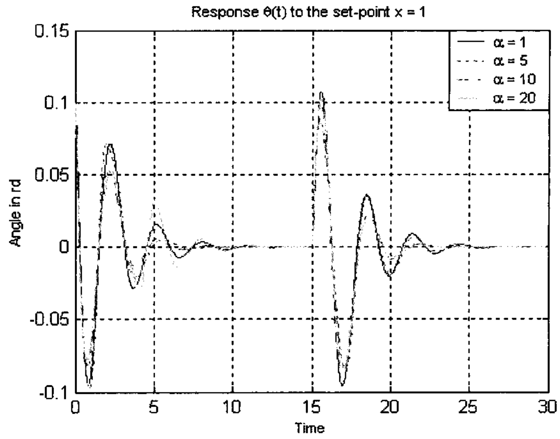

Fig. 17. Response of pendulum angular $\theta(t)$ on set-point *x=1* and variation of α by algorithm of Fig. 7(a)

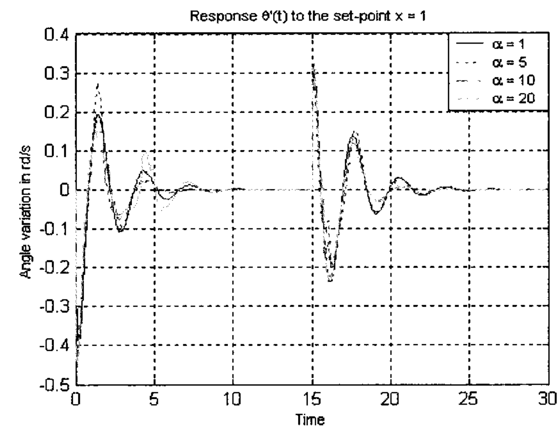

Fig. 18. Response of pendulum angular $\theta'(t)$ on set-point *x=1* and variation of α by algorithm of Fig. 7(a)

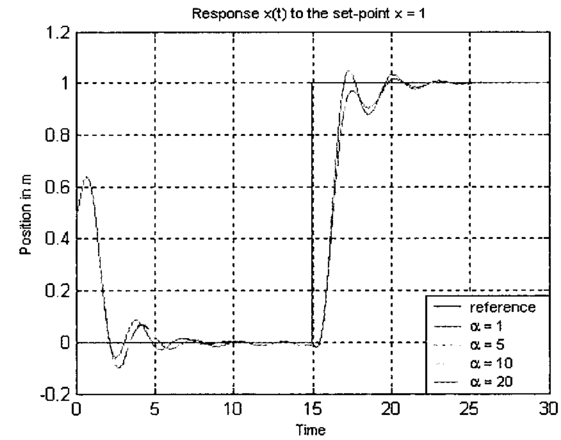

Fig. 19. Response of pendulum position *x(t)* on set-point *x=1* and variation of α by algorithm of Fig. 7(b).

Figs. 19-22 are the response of pendulum position *x(t)*, $\dot{x}(t)$ and pendulum angular θ, $\dot{\theta}$ by algorithm of Fig. 7(b) when set-point *x=1* and variation of α are 1-20. Comparisons of curves of position *x(t)* in Fig. 13, Fig. 15, and Fig. 19 give are

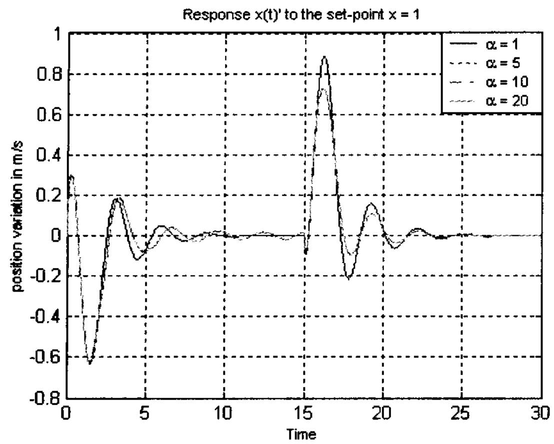

Fig. 20. Response of pendulum position $\dot{x}\ (t)$ on set-point $x=1$ and variation of α by algorithm of Fig. 7(b).

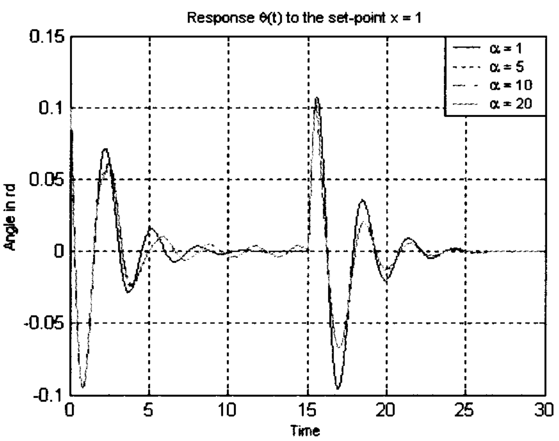

Fig. 21. Response of pendulum angular θ on set-point $x=1$ and variation of α by algorithm of Fig. 7(b).

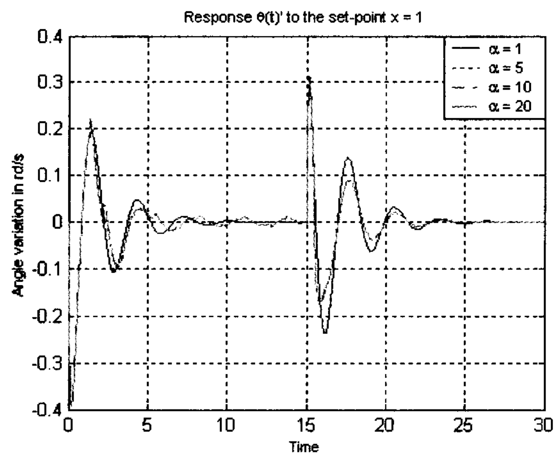

Fig. 22. Response of pendulum angular $\dot{\theta}$ on set-point $x=1$ and variation of α by algorithm of Fig. 7(b).

the same results but in Fig. 13, Fig. 16, and Fig. 20, the results of immune algorithm based control is showing the lower overshoot. When Fig. 14, Fig. 18, and Fig. 22 is comparing, the responses of the immune algorithm based control is the similar overshoot as that of the fuzzy logic controller. However, in every Figs, The bigger α , the lower overshoot.

V. Conclusions

This paper suggests control method for non-linear system such as power plant, chemical plant, inverted pendulum method using immune algorithm based fuzzy logic. PID Controllers have been used to operate these systems. However, it is very difficult to achieve an optimal PID gain with no experience, because gain of the PID controller has to be manually tuned by trial and error.

On the other hand, as 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, the learning rule is a distributed system with no central controller. Therefore, it is thus adaptive to its external environment and allows a PDP (Parallel Distributed Processing) network to complete patterns against the environmental situation.

This paper uses an inverted pendulum control problem to illustrate the efficiency of the proposed method for non-linear system and defines relationship state variables $x,\dot{x},\theta,\dot{\theta}$ using immune fuzzy, through simulation. The results represent satisfactory response.

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