# Adaptive Intelligent Control of Inverted Pendulum Using Immune Fuzzy Fusion

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**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.

## 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].

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 [4].

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 [2].

● 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 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.

## 2. DYNAMIC MODEL OF IMMUNE SYSTEM

### 2.1 The Response Of Immune System

The immune system has two types of response: primary and secondary. The primary response is reaction when the immune system encounters the antigen for the first time. At this point the immune system learns about the antigen, thus preparing the body for any further invasion from that antigen. This learning mechanism creates the immune system's memory. The secondary response occurs when the same antigen encountered again. This has response characterized by a more rapid and more abundant production of antibody resulting from the priming of the B-cells (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 [5].

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

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

where in Eq. (1), N is the number of antibodies, and $\alpha$ and $\beta$ 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]:

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

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 [2]:

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

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

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

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

## 3. CONTROLLER DESIGN NON-LINEAR SYSTEM USING IMMUNE FUZZY FUSION

### 3.1 Sugeno Fuzzy Logic

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

*If x is A and y is B then z=f(x, y),* (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.

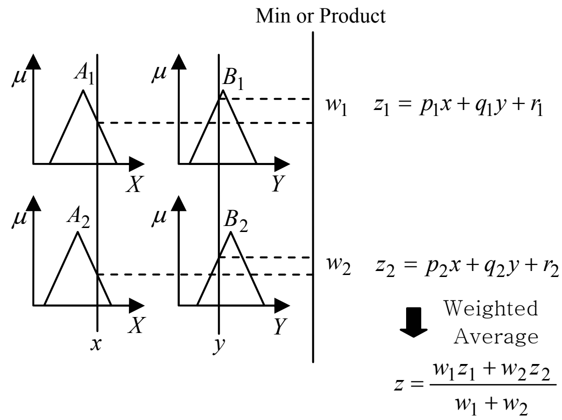


Fig. 1. Sugeno fuzzy model.

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. 1.

*B. Cart with Interted Pendulum*

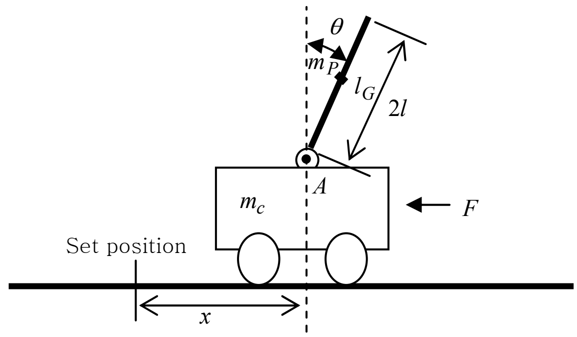


Fig. 2. The structure of cart with inverted pendulum.

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. 2. 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: $\theta$ (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]:

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

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

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).

*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 $\alpha$, 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, $\alpha$.

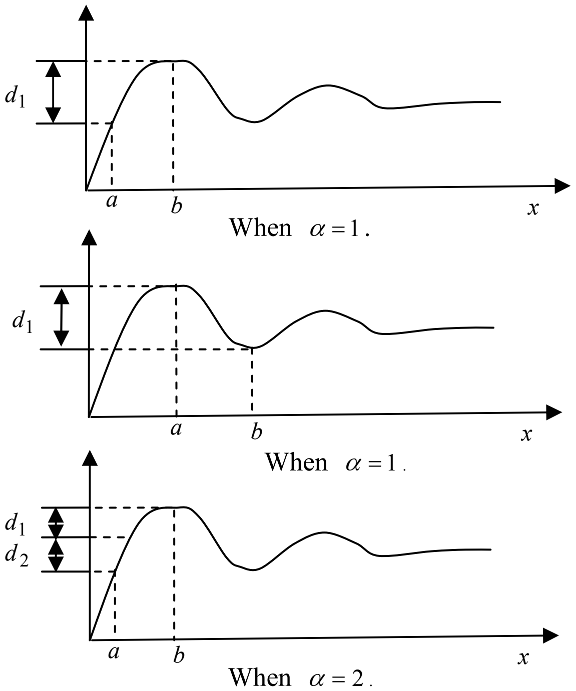


Fig. 3. Expression of resolution, depending on $\alpha$.

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:

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

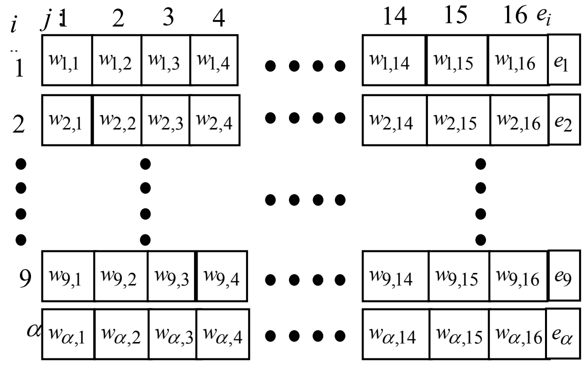


Fig. 4. The structure of antibody for memory cell.

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

$$f_j (j = a \text{ number of fuzzy rule.})$$

$$\text{on partition } i (i = \alpha, \alpha-1, \alpha-2, \cdots, 1.) \tag{11}$$

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.

## 4. SIMULATION AND DISCUSSIONS

*A. The characteristics for the fixed initial value $\alpha$*

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

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

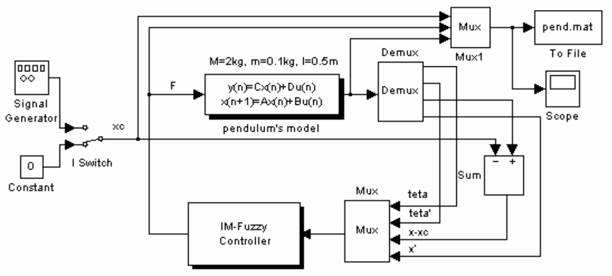


Fig. 5. Simulation structure for the immune algorithm-fuzzy model.

Fig. 7 shows learning algorithm by immune algorithm and fuzzy logic. Fig. 7(a) is leaning method when the value of $\alpha$ is constant and Fig. 7(b) is flowchart when the value of $\alpha$ 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]

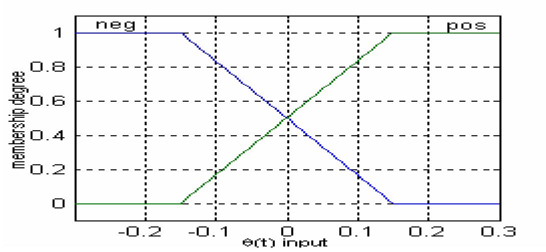


Fig. 7. $\theta(t)$ input membership functions.

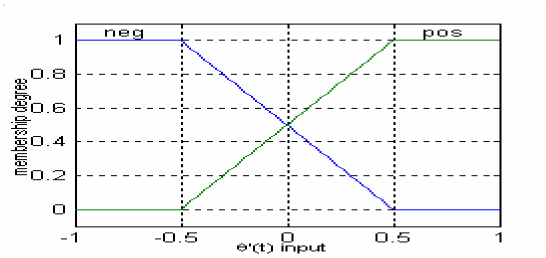


Fig. 8. $\dot{\theta}(t)$ input membership functions.

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.

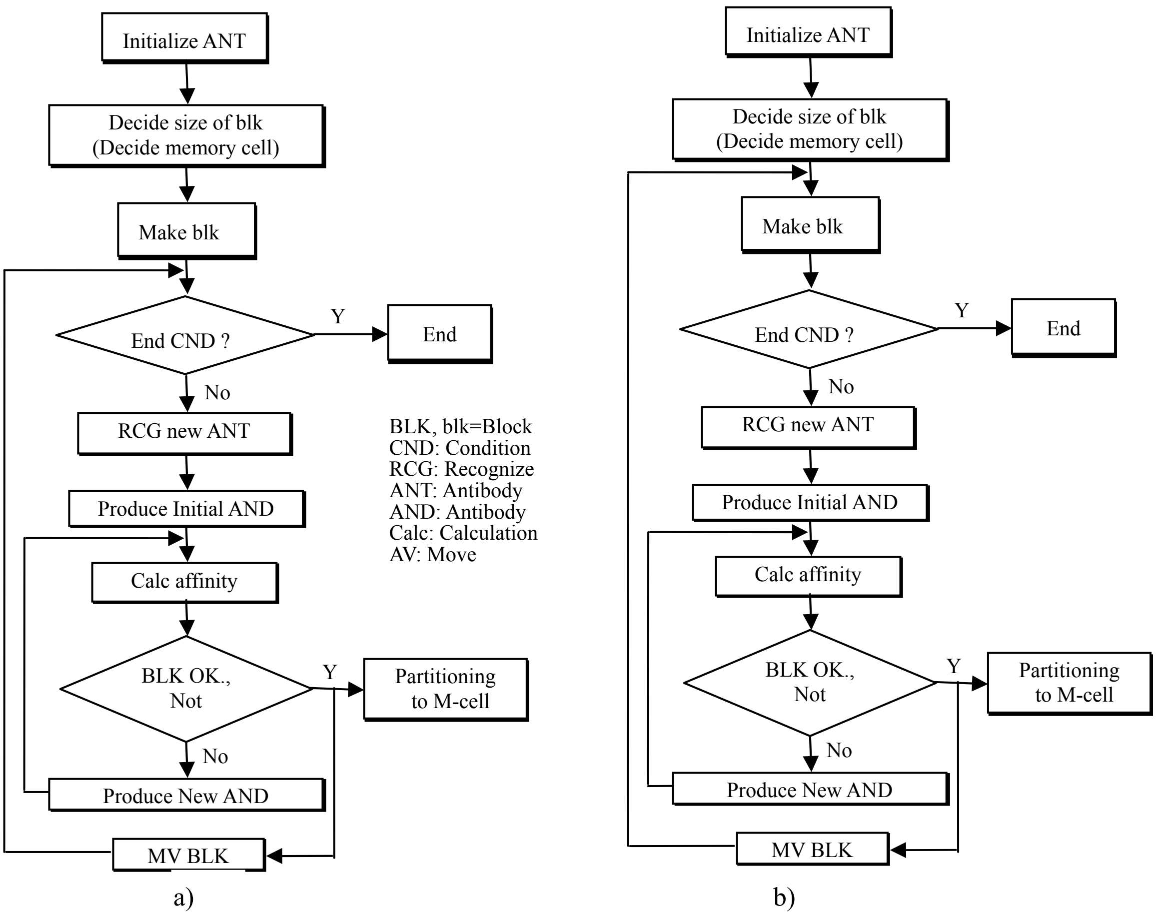


Fig. 6. Learning Algorithm by immune and fuzzy logic.

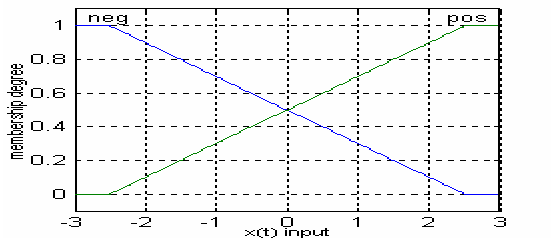


Fig. 9. $x(t)$ membership functions.

Table 1. Fuzzy rules.

| | $x$ | pos | pos |
|---|---|---|---|
| $\theta$ | $\dot{x}$ / $\dot{\theta}$ | 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 |

$\Phi$ : 5.0299

Table 3. 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 |

$\Phi$ : 2.4797

*A. The characteristics for the variable initial value* $\alpha$

Fig. 10 $x(t)$, $x'(t)$ response of fuzzy controller on initial value $\theta = 0.1$, $x=0.5$ when set-point is moving from $x=0$ to $0.5$.

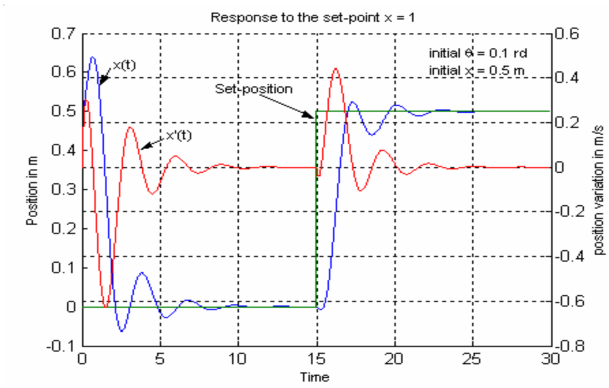


Fig. 10. $x(t), x'(t)$ response of fuzzy controller on initial value $\theta = 0.1$, $x=0.5$ when set-point is moving from $x=0$ to $0.5$.

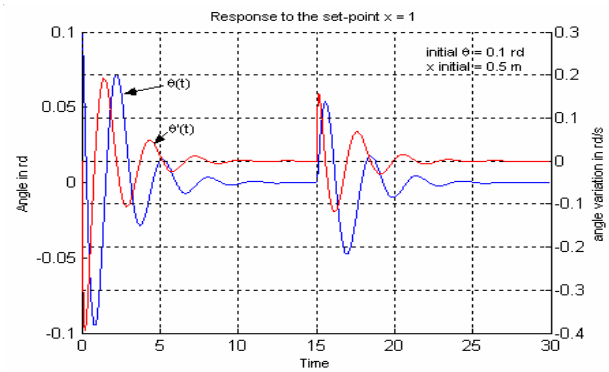


Fig. 11. $\theta(t)$, $\theta'$ $x(t)$ response of fuzzy controller on initial value $\theta = 0.1$, $x=0.5$ when set-point is moving from $x=0$ to $0.5$.

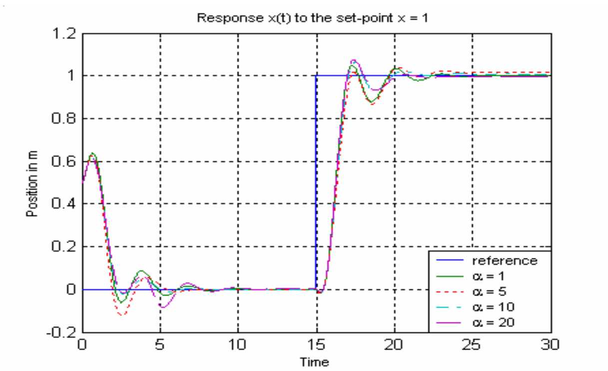


Fig. 12. Response of pendulum position $x(t)$ on set-point $x=1$ and variation of $\alpha$ by algorithm of Fig. 6(a).

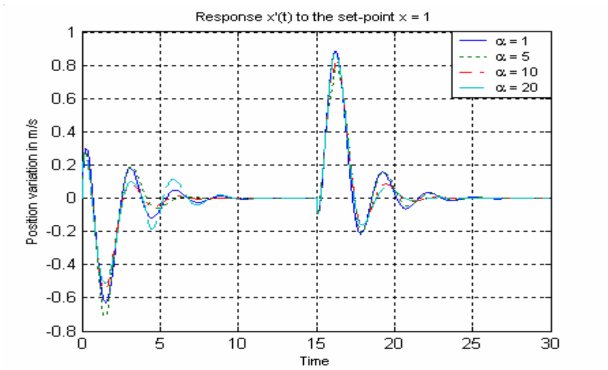


Fig. 13. Response of pendulum position $x'(t)$ on set-point $x=1$ and variation of $\alpha$ by algorithm of Fig. 6(a).

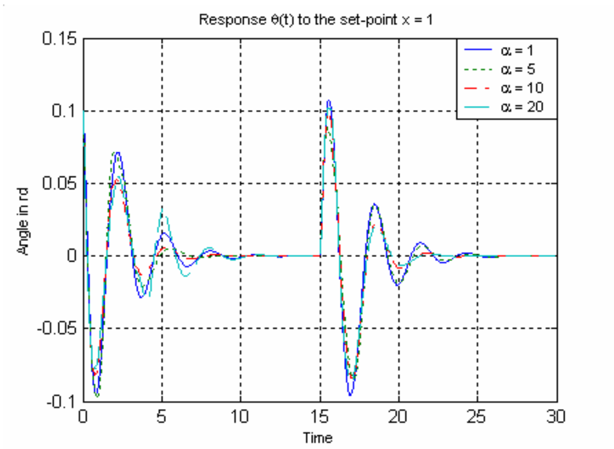


Fig. 14. Response of pendulum angular $\theta(t)$ on set-point $x=1$ and variation of $\alpha$ by algorithm of Fig. 6(a).

Fig. 11. $\theta(t)$, $\theta'$ $x(t)$ 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. 12-14 illustrate the response of pendulum position $x(t)$ and $x'(t)$ on set-point $x=1$ and variation of $\alpha$ by algorithm of Fig. 6(a). Figs. 15 is the response of pendulum position $x(t)$, $\dot{x}\ (t)$ and pendulum angular $\theta$, $\dot{\theta}$ by algorithm of Fig. 6(b) when set-point $x=1$ and variation of $\alpha$ are 1-20. Comparisons of curves of position $x(t)$ in Fig. 13, Fig. 14, and Fig. 15 give are 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 $\alpha$, the lower overshoot.

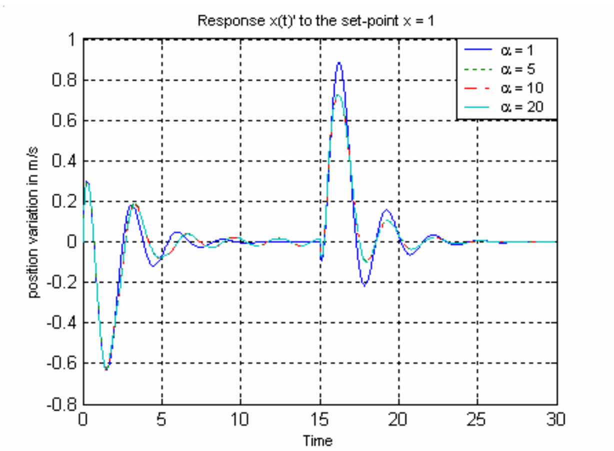


Fig. 15. Response of pendulum position $\dot{x}\ (t)$ on set-point $x=1$ and variation of $\alpha$ by algorithm of Fig. 6(b).

## 5. CONCLUSIONS

This paper proposes 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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