ABSTRACT

This paper suggests that the immune network algorithm based on fuzzy set can effectively be used in tuning of a PID controller for multivariable process or nonlinear process. The artificial immune network always has a new parallel decentralized processing mechanism for various situations, since antibodies communicate to each other among different species of antibodies/B-cells through the stimulation and suppression chains among antibodies that form a large-scaled network. In addition to that, the structure of the network is not fixed, but varies continuously. That is, the artificial immune network flexibly self-organizes according to dynamic changes of external environment (meta-dynamics function). However, up to the present time, models based on the conventional crisp approach have been used to describe dynamic model relationship between antibody and antigen. Therefore, there are some problems with a less flexible result to the external behavior.

On the other hand, a number of tuning technologies have been considered for the tuning of a PID controller. As a less common method, the fuzzy and neural network or its combined techniques are applied. However, in the case of the latter, yet, it is not applied in the practical field, in the former, a higher experience and technology is required during tuning procedure. In addition to that, tuning performance cannot be guaranteed with regards to a plant with non-linear characteristics or many kinds of disturbances.

Along with these, this paper used the fuzzy set in order that the stimulation and suppression relationship between antibody and antigen can be more adaptable controlled against the external condition, including noise or disturbance of plant. The immune network based on fuzzy set suggested here is applied for the PID controller tuning of multivariable process with two inputs and one output and is simulated.

The result of study shows the artificial immune based on fuzzy set can effectively be used to tune the nonlinear process or the multivariable process, since it can more fit modes or parameters of the PID controller than that of the conventional tuning methods, against the noise or disturbance, various inputs, and coupling action between loops.

1. INTRODUCTION

In recent years, a combined learning-based artificial intelligence (AI) such as neural network, immune network structure have been interested in studying much attention for their robustness and flexibility against a dynamically changing system or complex system, since conventional artificial intelligent systems based on a functional decomposition, leading to a so-called “sense-model-plan-action” cycle have been criticized on many grounds over the last decade [1-3]. It is a challenge in control and computer communities to explore novel control strategies and philosophies for complex industrial processes. Each technique such as fuzzy, neural, and neuro-fuzzy is offering new possibilities and making intelligent system even more versatile and applicable in an ever-increasing range of industrial applications. Over the past decade or so, significant advances have been made in two distinct technological area: fuzzy logic (FL) and neural networks (NNs) [5].

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.

The immune system is a rich source of theories and as such can act as an inspiration for computer-based solutions. 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. 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 have 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. From the above facts, some researchers 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 [3, 4]. From this study, they have expected that there would be an interesting AI technique suitable for dynamically changing environments by imitating the immune system in living organisms. However, the determination of the appropriate repertoire of competence modules (antibodies) or arbitrary affinity still remains an open question. They also try to incorporate an off-line meta-dynamics function into the previously proposed artificial immune network in order to autonomously construct appropriate immune networks [3-4]. In this paper, we suggest a new fuzzy set-based AIS technique that can cope with a dynamic and complicated environment from the immunological standpoint inspired by dynamic equations.

2. OVERVIEW OF THE ARTIFICIAL IMMUNE SYSTEM

The immune system protects our bodies from attack of foreign matters (antigens) which enter the bloodstream. The basic components of the biological immune system are macrophages, antibodies, and B-cell. B-cell is the cells maturing in bone marrow, which collectively form what is known as the immune network. Roughly $10^7$ distinct types of B-cell are contained in a human body, each of which has a distinct molecular structure and produces “Y” shaped antibodies from its surfaces [4]. When a B cell encounters an antigen, an artificial immune response is elicited, which causes the antibody matches the antigen sufficiently well, its B cell becomes stimulated and can produce mutated clones which are incorporated into the immune network. That is, the antibody recognizes specific antigens which are the foreign substances that invade living creatures, and this reaction is often likened to a key and keyhole relationship. This network hypothesis is the concept that antibodies/B-cells are not just isolated, that is they are communicating to each other among different species of antibodies/B-cells. As illustrated in Fig.1, the stimulation and suppression chains among antibodies form a large-scaled network and works as a self and not-self recognizer. Therefore, the immune system is expected to provide new parallel decentralized processing for various situations. Furthermore, the structure of the network is not fixed, but varies continuously. It means that the artificial network flexibly self-organizes according to dynamic changes of external environment. This remarkable behavior, called metadynamics function, is mainly realized by incorporating newly-generated cells/antibodies and/or removing useless ones. The new cells are generated by both gene recombination in bone marrow and mutation in the proliferation process of activated cells. Although many new cells are generated every day, most of them have no effect on the existing network and soon die away without any stimulation [4-5].

3. ARTIFICIAL IMMUNE SYSTEM BASED MODEL

3.1 Immune Network Model

Jerne first point out the idea that there are some remarkable similarities between the nervous system and the immune system [10] and he also proposed that the immune response is regulated by a network of autoimmune interactions. That idea has been elaborated by Cohn, Edelman & Mountcastle, and Edelmann & Reek.

John E. Hunt & Denise E. Cooke described an artificial immune system which is based upon models of the natural immune system and Geoffrey W. Hoffman suggested a neural network model based on the analogy with the immune system.

In engineering field, robot, decentralized automation, data mining, memory, automatic control have been studied. To understand for model exactly, we
need to figure out how they are constructed among the structures in immune system.

3.2 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.

3.3 Antibodies in Immune System
In the AIS the antibodies blind to infectious agents and then either destroy these antigens themselves attract help from other components of the 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. The regions on the molecules that the paratopes can attach are so-called epitopes.

3.4 Interaction Between Antibodies
Describing the interaction among antibodies is important to understand dynamic characteristics of immune system. For the ease of understanding, Consider the two antibodies that respond to the antigens A1 and A2, respectively. 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. As we know from this description, the interaction among the antibodies acts based on the principle of a priority adjustment mechanism.

3.5 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 $\delta_i$, is calculated as follows [3]:

$$\frac{d\delta_i(t)}{dt} = \left( \alpha \sum_{j=1}^{N} m_{ij} \delta_j(t) - \alpha \sum_{k=1}^{N} m_{ik} \delta_k(t) + \beta n - \gamma_i \right) \delta_i(t) \quad (1a)$$

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

where in equation (1), N is the number of antibodies, and $\alpha$ and $\beta$ are positive constants. $m_{ij}$ 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.

4. BASIC CONCEPT OF SELECTION MECHANISM

4.1 Basic Conception
If an antigen is presented to the B cell object, an immune response, that is, the learning is initiated. The level on B cell stimulation depends not only on how well it matches the antigen, but also how it matches other B cell objects in the immune network. The B cell object produces copies of itself, which turn on a mutation mechanism that generates mutations in the genes that code specially for the antibody molecule. That mirrors the mechanism called somatic hypermutation which occurs in the human immune system. Alternatively, if the stimulation level falls below a given threshold, the B-cell object will die off and does not replicate. The stimulation of B cell object also depends on its affinity with other B cell objects in the immune system. The network is formed by B cell objects recognizing other B cell objects in the system. Survival of the new B cell objects depends on their affinity to the antigen and to the other B cell objects in the network. The new B-cell objects may have an improved match for the antigen and thus proliferate, and then it can survive longer than existing B cell objects. The immune network reinforces the B cell objects which are useful and have proliferated. By repeating this process of mutation and selection a number of cells, the immune system “learns” to produce better matches for the antigen [7-8]. In this paper, we suggest antibody’s dynamic mechanism for tuning of PID controller’s parameter.
5.3 Immune Algorithm Using Fuzzy Set

The general structure of a TSK fuzzy model with \( r \) inputs \( X_1, X_2, \ldots, X_r \) and output \( Y \) is represented. Generally, a TS fuzzy model with \( L \) fuzzy rules \( R_i \) \((i=1, 2, \ldots, N)\) is expressed in the following equation:

\[
R_i: \text{If } (X_i \text{ is } A_{i1} \text{ and } X_2 \text{ is } A_{i2} \text{ and } X_3 \text{ is } A_{i3}) \text{ then } Y_i = P_{0i} + P_{11}X_1 + P_{12}X_2 + P_{13}X_3, \quad (4)
\]

where \( A_{i1}, A_{i2}, A_{i3}, A_{i4} \) are fuzzy sets defining the antecedent (left) part of the \( i \)th fuzzy rule \( R_i \). All fuzzy sets are characterized by their membership functions: \( A_{ij}(X_j) \), for \( i=1, 2, \ldots, 4 \) and \( j=1, 2, \ldots, 4 \). In eq (4), the consequent (right) part of each fuzzy rule has an algebraic form where \( P_{0i}, P_{11}, P_{12}, P_{13} \) are coefficients.

The overall output \( Y \) of the fuzzy model is calculated as a weighted average of the outputs of all fuzzy rules as follows:

\[
S = \sum_{i=1}^{N} \delta_i \sum_{i=1}^{N} \delta_i \left( C_{10} + C_{11}x_1 + C_{22}x_2 + C_{33}x_3 + C_{44}x_4 \right)
\]

where \( \delta_i \) is the activation degree (firing function) of the \( i \)th fuzzy rule \( L_i \). It is computed by the following T-norm calculation methods:

\[
\delta_i = \min \{ A_{i1}, A_{i2}, A_{i3}, A_{i4} \}
\]

Then the overall output of the fuzzy model is rewritten as

\[
S = \sum_{i=1}^{N} \delta_i \left( C_{10} + C_{11}x_1 + C_{22}x_2 + C_{33}x_3 + C_{44}x_4 \right)
\]

We choose the triangular shape membership function as equation (5).

\[
h_a : \Omega \rightarrow [0, 1], \ h_a(x) = \begin{cases} 
  x - a & \text{if } x \in [a, b], \\
  c - x & \text{if } x \in [b, c], \\
  0 & \text{otherwise}
\end{cases} \quad (5)
\]

5.2 RGA Design Method

A 2\( \times \)2 system with two input-two output variables in Fig. 5 has an interaction characteristics through the coupling transfer functions \( G_{11} \) and \( G_{22} \). Therefore, one use RGA, INA, CL described in the above for the design of controller with a good performance.

If both loops are open, \( m_1, m_2 \) can be manipulated independently and effect of each of these inputs on each of the outputs is represented by the following transfer function model:

\[
y_1(s) = G_{11}(s)m_1(s) + G_{12}(s)m_2(s) \quad (2)
\]

\[
y_2(s) = G_{21}(s)m_1(s) + G_{22}(s)m_2(s) \quad (3)
\]

From the above equation, we can have the RGA.
coefficient by using the numerator partial derivative and straightforward differentiation, respectively:

$$\left( \frac{\partial y_1}{\partial m} \right)_{\text{all loops open}} = k_{11} \cdot \left( \frac{\partial y_2}{\partial m} \right)_{\text{all loops open}} = k_{21}$$

The relative gain $\mu_{ij}$ between output variable $y_i$ and input variable $m_j$ in defined as the ratio of two steady state gain:

$$\mu_{ij} = \left( \frac{\partial y_i}{\partial m_j} \right)_{\text{all loops open}}$$

$$= \frac{k_{ij} k_{21}}{1 - \xi} = k_{11} k_{22}$$

This the RGA for the 2×2 system is obtained by:

$$\Psi = \begin{bmatrix} \mu_{11} & 1 - \mu_{11} \\ 1 - \mu & \mu_{22} \end{bmatrix}, \quad \mu_{ij} = \mu_{ij} = \frac{1}{1 - \xi}$$

If the given system is decoupled by the above method, controller is designed with a single loop design approach.

6. SIMULATION AND DISCUSSION

6.1 Decoupling by RGA method

The model for a distillation column used in separating method and water is given with two output, two input variables, and one disturbance variable as the follows:

$$y_1 = \text{overhead mole fraction methanol}$$

$$y_2 = \text{bottoms mole fraction methanol}$$

$$m_1 = \text{overhead reflux flowrate}$$

$$m_2 = \text{bottoms feed flowrate}$$

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \left[ G(s) \right] \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

6.2 Response of PID Controller by Immune Network Tuning

This paper suggests tuning method of PID controller by immune network. The results of simulation represent a satisfactory response than the Ziegler-Nichols tuning method.

7. Conclusions and Further Work

This paper suggests the tuning method of PID controller by immune network. The results of simulation illustrate more satisfactory response than the Ziegler-Nichols method. In the future study, experiments should be showed in the actual plant by this method.
Fig. 3. Response to the range of PID controller’s parameter $P=0-10$, $I=0-10$, $D=0-10$ on parameter learning of immune network.

Fig. 4. Response to the range of PID controller’s parameter $P=0-20$, $I=0-20$, $D=0-20$ on parameter learning of immune network.

Fig. 5. Response to the PID controller’s average parameter value on parameter learning of immune network.

Fig. 6. Response to the PID controller’s maximum parameter value on parameter learning of immune network.

REFERENCES