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MEMBERSHIP FUNCTION TUNING OF FUZZY NEURAL NETWORKS BY IMMUNE ALGORITHM

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Abstract

This paper represents that auto tunings of membership functions and weights in the fuzzy neural networks are effectively performed by immune algorithm. A number of hybrid methods in fuzzy-neural networks are considered in the context of tuning of learning method, a general view is provided that they are the special cases of either the membership functions or the gain modification in the neural networks by genetic algorithms. On the other hand, since the immune network system possesses a self organizing and distributed memory, it is thus adaptive to its external environment and allows a PDP (parallel distributed processing) network to complete patterns against the environmental situation. Also, it can provide optimal solution. Simulation results reveal that immune algorithms are effective approaches to search for optimal or near optimal fuzzy rules and weights.

Key Word : Immune networks, Fuzzy neural network, Auto-tuning, Membership function.

1. Introduction

In recent years, there has been growing interest in using intelligent approaches such as neural network, evolutionary method, and their combined technologies for control systems. [1-4] Since there a design approach for the intelligent control system is often subjected to changes due to various sources of uncertainty, fuzzy sets, neural network, and evolutionary techniques have been considered as effective information tools to deal with uncertainties in terms of vagueness, ignorance, and imprecision. One of the key advantages of the fuzzy sets in control system is useful for representing linguistic terms numerically and making reliable decisions with ambiguous and imprecise dynamic or nonlinear parts. A design approach with a fuzzy set can also provide a variety of linguistic representation as grades of membership. Fuzzy controllers are most suitable for systems that cannot be precisely described by mathematical formulations. That is, the benefit of the simple design procedure of a fuzzy controller leads to the successful applications of a variety of engineering systems [2]. However, a control designer captures operator"s experience and knowledge, and converts it into a set of fuzzy control rules, and tuning of membership function often has problems with a trial and error in design for some requirements of system.

Automatic rule generation or automatic rule calibration is required to overcome difficulty in generation of the membership function for controller. Therefore, some papers suggest that learning capability of neural networks and optimization techniques such as genetic algorithms play the important role for fuzzy neural network. [9-11]

In spite of their individual philosophies and structural difference, all of these approaches share the same difficulty of fuzzy rule generation. Since fuzzy rules and weights in a mixed learning structure, e.g. fuzzy neural networks must be different according to the plant and the conditions in which they are operated, fuzzy rule generation and weight are difficult and time consuming procedure. That is, it is required to have a systematic method for constructing appropriate auto-tuning method and rules.

On the other hand, 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).

This paper is to represent that immune network algorithm (IMA) is an efficient tool for generating weight and auto-tuning membership function in fuzzy neural network.

To resolve the problem of the optimized fuzzy rule, this paper has introduced a cost function (affinity in

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antigen) and has constructed the optimized fuzzy rule by immune algorithm for the improved control performance of fuzzy-neural hybrid.

2. Structure of Fuzzy Neural Networks

There are has been great interest in researching of fuzzy neural networks [2-3] and there three different types of fuzzy neural networks depending on the type of inputs fuzzy neural network and weight coefficients as the following description:

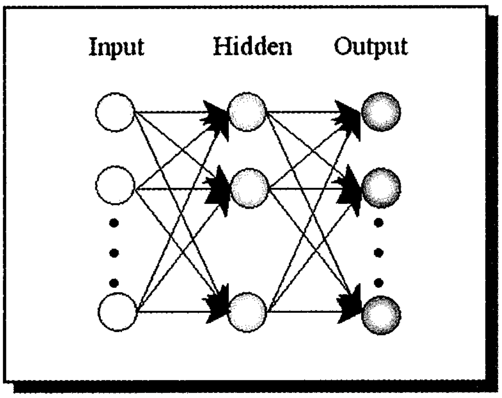

Fig. 1. A three layered fuzzy neural network.

- Type1: fuzzy weights and fuzzy inputs;
- Type2: fuzzy weights and crisp inputs;
- Type3: crisp weights and fuzzy inputs.

This paper is dealing with the type 1 of fuzzy feed-forward neural networks. In this type, the neurons are organized into a number of layers and the signals flow in one direction. That is, from neurons of one layer to the neurons of the consequent layer. There are no interactions among the neurons of the same layer, and no feedback loops. Fig. 1 shows this type fuzzy neural network. Input neurons receive a vector of fuzzy input signals from system and simply transfer them to all fuzzy neurons of the hidden layer. The connections between the layers may be illustrated as a matrix of fuzzy weights W_{ji}, which provides a fuzzy weight of a connection between ith neuron of the input layer, and jth neuron of the hidden layer. The total fuzzy input of jth neuron in the second layer is defined as

$$O_j = \sum_{i=1}^{n} W_{ji} x_i + \delta_i \tag{1}$$

Where, O_j is the total fuzzy input of the jth neuron of hidden layer, x_i is the ith fuzzy input of that neuron, and δ_i is fuzzy bias of the jth neuron. The operations on fuzzy numbers in Equation (1) are defined by the rules of fuzzy arithmetic.

The fuzzy output of the jth neuron is defined by the transfer function. The fuzzy output of the jth neuron is defined by the transfer function

$$O_f = f(O_i) \tag{2}$$

The output is computed using Equation (2). The following sigmoidal function is used:

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

These outputs are then passed to the neurons of the consequent layer, which perform similar operations. In three-layered neural nets the consequent layer will be the output layer which produces vector $\overline{Y}$. Multi-layer fuzzy neural networks, fuzzy signals propagate layer until they reach the output layer.

The key purpose of training fuzzy neural networks is in designing such a fuzzy neural network that exhibits the desired behavior. The following Equation is used for the objective:

$$d = \sum_{i=1}^{m} | Y_i^d - Y_i | \tag{4}$$

In equation (4), Y_i^d is the desired output for ith training pair, and Y_i is the actual output of fuzzy neural networks.

3. Characteristic of Immune Network Algorithm

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 [6].

Other areas of the characteristic relating to the immune system for engineering field are summarized below:

- 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 can play an important role to maintain own system dynamically changing environments. Therefore, some papers insist that immune system would be expected to provide a new paradigm suitable for dynamic problem dealing with unknown environments their rather than static system.

4. Dynamic of Immune Algorithm For Tuning of Fuzzy Neural Networks

4.1 Immune Dynamic Equation for learning

Here, the objective function of IMA used in this paper for parameter tuning in fuzzy system or neural network can be written as the followings:

$$\begin{aligned} \delta_i &= \sum_{n=1}^{z}\{(L_n - L_n^{object})\}^2 + \zeta f_n \\ L_n &= \sum_{i=1}^{p}(R_i I_{in}) \\ f_n &= \begin{cases} 0: L_n \le L_n^{limit} \\ 1: Otherwise \end{cases} \end{aligned} \tag{5}$$

δ_i: objective function

z: the number of process for obtaining an optimal gain, respectively

L_n: optimal level in process for selection of an optimal gain

L_n^{object}: target optimal value in process in process for selection of an optimal gain

ζ: penalty constant

f_n: penalty function

P: the number of route for selection of an optimal gain

R_i: gain level in route I

$I_{i,n}$: subsidiary function

$L_n^{\lim}$: limit speed in gain

This algorithm is implemented by the following procedures.

[step 1] Initionalization and recognition of antigen: The immune system recognizes the invasion of an antigen, which corresponds to input data or disturbances in the optimization problem.

[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.

[step 3] Calculation of affinity between antibodies: The affinities η_k obtained by Eq. (6) and the affinity σ_k using Eq. (7) is calculated for searching the optimal solution.

[step 4] Differentiation of lymphocyte: The B-lymphocyte cell, the antibody which matched the antigen, is dispersed to the memory cells in order to respond to the next invasion quickly. This dispersed corresponds to strong the solution in a database.

[step 5] Stimulation and suppression of antibody: The expected value η_k of the stimulation of the antibody is given by:

$$\eta_k = \frac{m_{\phi k}}{\sigma_k} \tag{6}$$

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:

$$\sigma_k = \frac{\textit{sum of antibodies with same affinity as } m_{\phi k}}{\textit{sum of antibodies}} \tag{7}$$

Using by equation (7), the immune system can control the concentration and the variety of antibodies in the lymphocyte population. If antibody obtains a higher affinity against an antigen, the antibody stimulates. However, an excessive higher concentration of an antibody is suppressed. Through this function, an immune system can maintain the diversity of searching directions and a local minimum.

[step 6] 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. This procedure can generate a diversity of antibodies by a genetic reproduction operator such as mutation or crossover. These genetic operators are expected to be more efficient than generation of antibodies.

4.2 Tuning of Fuzzy System in Fuzzy Neural Networks by IMA

Fuzzy neural networks have been used as an important tool for acquiring and adjusting learning in engineering field.

1	O1	S1	S2	• • •	Sk-1	K1
2	O2	S2-1	S2-2	• • •	Sk-2	k2
			• • •			
N	1	2	1		1.5	knN

Fig. 2. The coding for fuzzy parameter

Fig. 3. Allocated structure of gain scheduling of fuzzy function in locus in antibody.

Recently, there has been great interest in developing and training of fuzzy neural networks [2], since there are some different types of fuzzy neural networks. The coding of an antibody in an immune network is very important because a well designed coding of antibody can give an increase of the efficiency of the controller.

To incorporate immune network into our scheme, immune network is coded with the weight parameters. The coding is illustrated in the following Figs. 2 and 3:

Antibody type 1 which is encoded to represent only substring 1; Antibody type 2 which is encoded to represent substring 2; Final antibody which is encoded to represent substring 3 shown in Fig. 3.

The value of the k-th locus of antibody type 1 shows substring 1 allocated to the optimal fuzzy rule route.

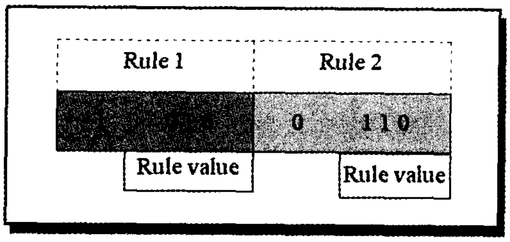

Fig. 4. The coding for fuzzy fule

Therefore, there are many fuzzy rules in the cell.On the other hand, the k-th locus of antibody type 2 represents a substring 2 for many kinds of scaling factor to membership functions and antibody 3 has a cell allocated for membership function. There are three types antibody for fuzzy system and on antibody for neural network in this paper:

1) Substring one: Rule string

There are four bits to represent one rule. The first bit is used to indicate whether the rule is used or not. A rule is selected by the immune network search if the bit is set to 1. Otherwise, it will not be used in the testing of the fuzzy controller. The next three bits represent the rule value which takes in the interval 0 (0 0 0) to 7 (1 1 1). While o means NB, 1 means NM, …,7 means PB.

2) Substring two: Scaling factors

IA_e : 101000010

IA_{de} : 10000100001

IA_{out}: 00010101010

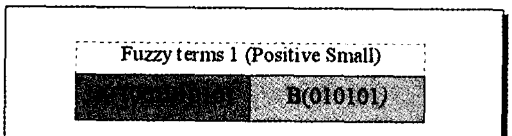

Fig. 5. The coding for fuzzy terms

w_{ji} : 01100 11101 01000

w_{sr} : 11100 101 11 11100

•
•
•

w_{ml} : 10010 11101 01100

Fig. 6(a). choromsomes before crossover.

w_{ji} : 01100 11101 01000

w_{sr} : 11100 101 11 11100

•
•
•

w_{ml} : 10010 11101 01100

Fig. 6(b). choromsomes after crossover.

Parameters IA_e, IA_{de}, IA_{out} are shown in Fig. 3.

3) Substring three: Membership functions

Where and are parameters of the symmetrical Gaussian membership functions given by:

$$h_{ij}(x_j; a, b, c) = \begin{cases} o & x < a \\ (x-a)/(b-a) & \le x \le b \\ 0 & xc \end{cases} \tag{8}$$

The Gaussian form is chosen on the basis of formal considerations; membership functions of any other form, for example, triangular or trapezoidal, can be considered as well.

4) Substring four: Weighing factors

The value of the k-th locus of antibody type 4 shows substring 4 allocated to the optimal weight gain in the neural networks shown in Figs. 6 and 7.

w_{ji} : 01100 11101 01000

w_{sr} : 11100 1 0 111 11100

•
•
•

w_{ml} : 10010

Fig. 7(a). choromsomes before mutation.

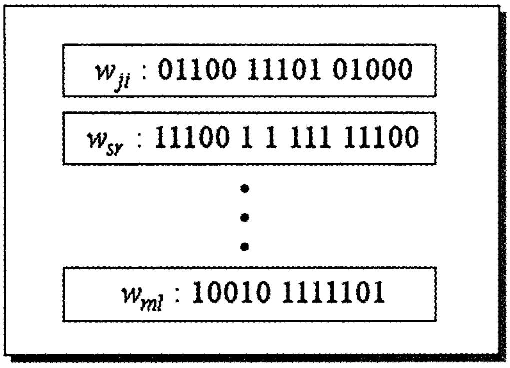

Fig. 7(b). choromsomes after mutation.

4.3 Tuning of Weighing Function of Neural Network in Fuzzy Neural Networks by IMA

Immune network algorithms (IMA) are optimization techniques based on the principles of natural evolution. IMA operates on the population of potential solutions to a problem. A notion of fitness is used in IMA like GA to measure the goodness of a candidate solution (chromosome). IMA operators of selection, crossover, and mutation are repeatedly applied to the population to increase the fitness of chromosomes. The success of employing IMA to solve a given optimization problem greatly depends on correctly choosing the fitness function. Fitness function must positive values and must be maximized. In training fuzzy neural network the following distance equation is used for a measure of distance:

The larger the distance between the actual output of fuzzy neural networks and the desired outputs, the smaller is the fitness value, and versa.

$$F=\frac{1}{1+d} \tag{9}$$

IMA use binary encoding to build chromosomes. An adequate mapping of problem variables to binary strings and vice versa is required. A single chromosome carries the values of all fuzzy weights of fuzzy neural networks in a binary format. A fuzzy weight is represented by n binary strings of a specified length. Each of the n binary strings corresponds to a particular parameter of a fuzzy weight. For the case of Gaussian representation of weights. The following chromosome can be illustrated.

Where, W_{ji} is a fuzzy weight between jth hidden and ith input neurons, W_{ml} is a fuzzy weight between mth output and lth hidden neurons. Also, W^{p}_{ji}, W^{l}_{ji}, W^{r}_{ji} are the peak, and the left and right spreads of a fuzzy weight. The strings are translated into the real-valued numbers for parameters using the pre-specified ranges for the weights. The learning algorithm of fuzzy neural network can be summarized as follows:

1) Mapping solution space into immune search space, binary strings. Constructing fuzzy fitness function F using fuzzy measure of distance d, objective function given by Eq. (4).
2) Creating initial population(set of chromosomes) randomly, i.e. a population of fuzzy weights of fuzzy neural networks which are randomly specified.
3) Evaluating each chromosomes in the population in terms of fitness value using Eq. (9).
4) If termination conditions are met go to step 7.
5) Generating new population using selection operator. This operator randomly selects chromosomes from the current population with the probabilities proportional to the values of fitness of the chromosomes.
6) Creating new chromosomes by mating randomly selected (with some specified probability called probability of crossover, chromosomes. The resulting offspring replaces the original parent chromosomes in the population.
7) Mutating some randomly selected (with some specified probability called probability of mutation, chromosomes. Return to step 3.

We used fuzzy neural network learned by IMA for quality assessment on the base of fuzzy regression and for estimation of fuzzy profit in an oligopolistic environment.

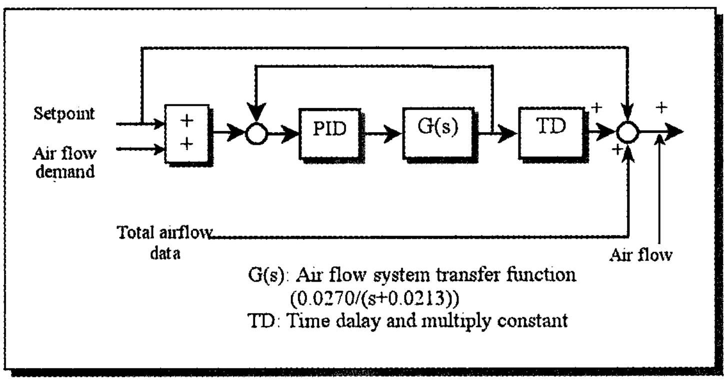

Fig. 8. Block diagram of air flow control system for steam temperature control of the S/H

4.4 Performance Criteria For Tuning

In this paper, air flow for steam temperature of S/H in power plant is used to prove tuning algorithms suggested in this paper. Therefore, the performance of tuning is measured using the following criteria:

1) Minimum time-weighted integral of squared errors.

$$TWIS=\int_0^t t^k e^2 dt,\ k=0,1,2,\cdots,m \tag{10}$$

2) Combined performance index using overshoot (OV) and rise time (T_r).

$$PF=k_1 OV+k_2 T_r \tag{11}$$

where in Equation (10) and (11), k, k_1, k_2 are experimental parameters in order to emphasize our requirement about OV or T_r.

5. Simulation and Discussions

In this paper the following plant transfer function is used for simulation:

$$G(s)=\frac{0.0270}{s+0.0323}\times e^{-13.5s} \tag{12}$$

Eq. (12) is the transfer function of air flow control loop in boiler of the thermal power plant as shown in Fig. 8. Tables 1-2 represent variation of each parameter in immune cells and Table 3 represents fuzzy rule with N (Negative), Z (Zero), and P (Positive). Figs. 9-11 represent the shapes of membership function for output, error, and delta error trained by immune algorithms with generation 100, respectively. Fig. 12 shows the controlled result using membership function of Figs 9-11 on plant given by Eq. 12. Result has some unstable response.

Figs. 13-14 show shape of membership function trained by final generation 300 and Fig. 15 is response of air flow control system of the thermal power plant controlled by these membership functions. Fig. 15 illustrates more stable response than that shown in Fig. 12.

Table 1
Variation of parameter range in immune cell.

	1	2	3	4	5	6	7	8	9
1	1	9.9924	0.0477	0.2742	0.0614	0.1451	1.9927	36.7678	0
2	2	9.9814	0.1440	1.2715	0.0484	0.3056	1.9992	50.3795	0
3	3	9.9987	0.2760	9.8956	0.0005	0.4876	1.9926	53.3106	0
4	4	9.8954	0.0737	0.3311	0.0027	0.4938	1.9929	44.2300	0
5	5	9.9639	0.1504	1.4831	0.0200	0.1645	2.0000	51.3173	0
6	6	9.7525	0.0538	0.3207	0.0160	0.4497	1.9867	44.2624	0
7	7	9.9987	0.1558	1.0949	0.0065	0.2115	1.9927	50.6656	0
8	8	9.9512	0.1425	1.6210	0.0277	0.2439	1.9928	52.4954	0
9	9	9.8927	0.1527	1.2761	0.0005	0.2227	1.9997	52.4823	0
10	10	9.9985	0.1537	1.0670	0.0091	0.4407	1.9917	50.5203	0

Table 2
Variation of parameter range in immune cell.

	1	2	3	4	5	6	7	8	9
1	1	9.9924	0.0477	0.2742	0.0614	0.1451	1.9927	36.7678	0
2	2	9.9814	0.1440	1.2715	0.0484	0.3056	1.9992	50.3795	0
3	3	9.9987	0.2760	9.8956	0.0005	0.4876	1.9926	53.3106	0
4	4	9.8954	0.0737	0.3311	0.0027	0.4938	1.9929	44.2300	0
5	5	9.9639	0.1504	1.4831	0.0200	0.1645	2.0000	51.3173	0
6	6	9.7525	0.0538	0.3207	0.0160	0.4497	1.9867	44.2624	0
7	7	9.9987	0.1558	1.0949	0.0065	0.2115	1.9927	50.6656	0
8	8	9.9512	0.1425	1.6210	0.0277	0.2439	1.9928	52.4954	0
9	9	9.8927	0.1527	1.2761	0.0005	0.2227	1.9997	52.4823	0
10	10	9.9985	0.1537	1.0670	0.0091	0.4407	1.9917	50.5203	0

Table 3. Fuzzy rule.

Δe \ e	N	Z	P
N	N	N	P
Z	N	Z	P
P	N	P	P

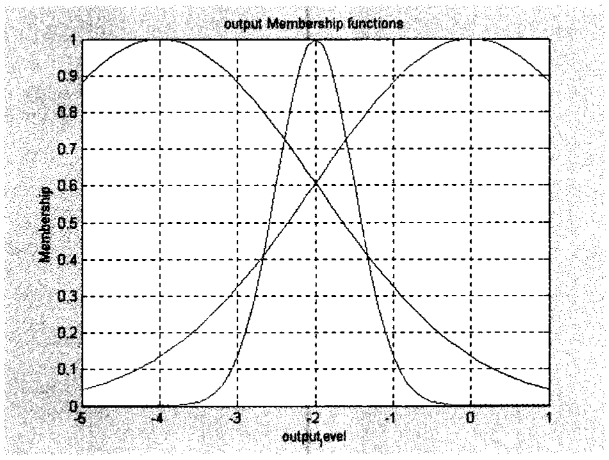

Fig. 9. Memversship function for output before final train.

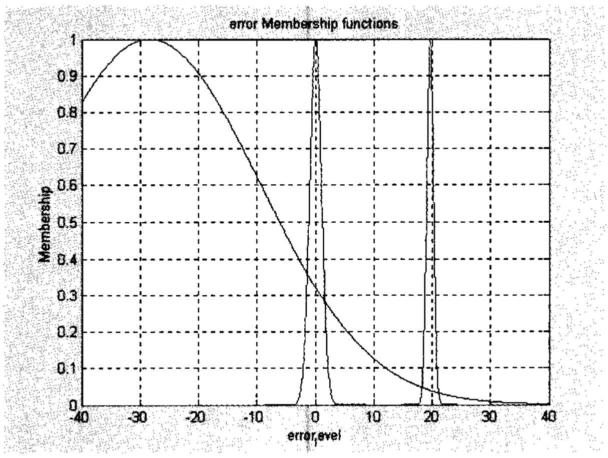

Fig. 10. Membership funcion for error after trained by immune algorithms(Generation: 100)

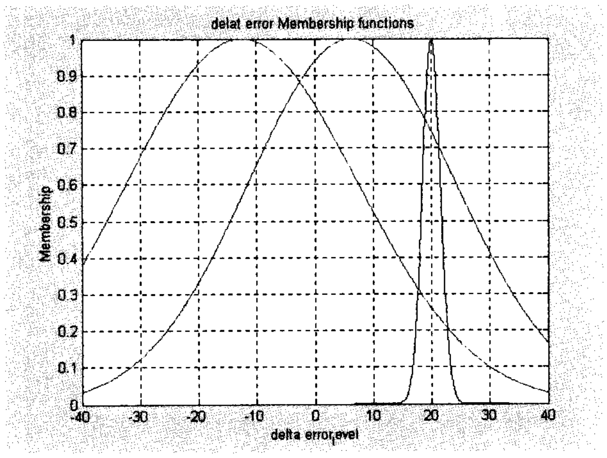

Fig. 11. Membership function for delta error trained by immune algorithms(Generation: 100)

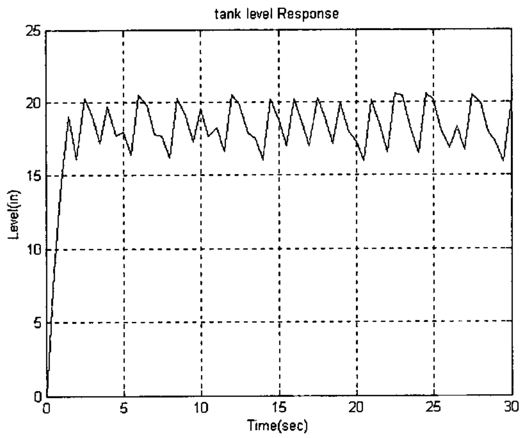

Fig. 12. Response using membership function of Figs. 9-11

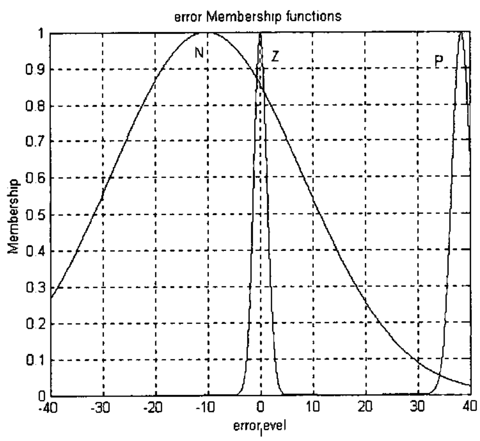

Fig. 13. Response using membership function for error after trained by immune algorithms(Generation: 300)

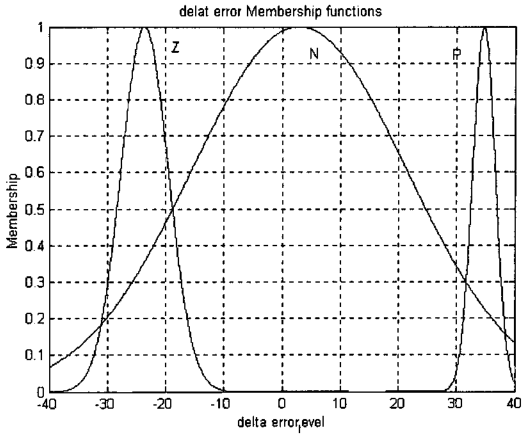

Fig. 14. Membership function for delta error after trained by immune algorithms(Generation: 300).

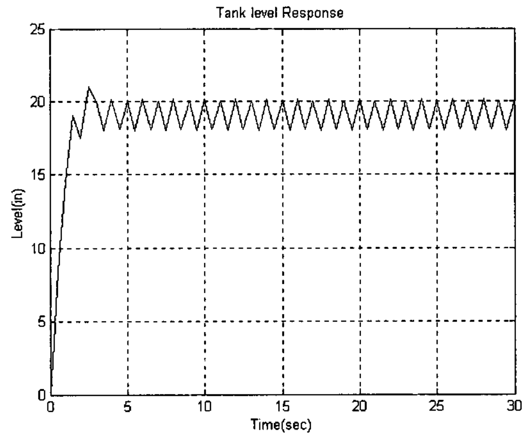

Fig. 15. Response using membership function of Figs. 13-14

6. Conclusions

In this paper, method to generate fuzzy rules using immune network algorithm (IMA) for fuzzy neural networks control structures has been described. A number of the combined intelligent techniques have been studying in the viewpoint of tuning of control systems. However, there are still many problems must be improved in parameter tuning for learning. The simulation studies have been performed using the immune based parameter tuning for fuzzy neural networks control structure and have revealed that the fuzzy rules searched by immune algorithms effectively regulate a plant with a time delay. In the simulation, it has been observed that the fuzzy rules can be optimized by immune algorithm. To resolve this problem, this paper has introduced a cost function (affinity in antigen) and has constructed the optimized fuzzy rule by immune algorithm for the improved control performance of fuzzy-neural hybrid. It is believed that the same method can be also applied successfully to other type of fuzzy-based hybrid control structures.

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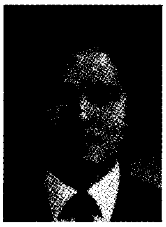

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