*Mathematical & Computational Applications*, Vol. 8, No. 2, pp. 245-252, 2003


# FUZZY INFERENCE SYSTEM BASED ON NEURAL NETWORK FOR TECHNOLOGICAL PROCESS CONTROL

Rahib Abiyev

Near East University, Department of Computer Engineering, P.O. Box 670, Lefkosha, TRNC, Mersin-10, Turkey
rahib@neu.edu.tr

**Abstract-** The implementation of a fuzzy system for technological process control based on parallel architecture and learning capabilities of neural networks is considered. The algorithms of fuzzy inference system on neural network (neuro-fuzzy system) are described. To train unknown coefficients of the system, the supervised learning algorithm is used. As a result of learning, the rules of neuro-fuzzy system are generated. The neuro-fuzzy system is applied to control a dynamic plant. Using desired time response characteristics of the system the synthesis of neuro-fuzzy controller for technological process control is carried out. The simulation result of the neuro-fuzzy control system is compared with the simulation results of control systems based on PID- and neural controller. It is found that the neuro-fuzzy control system has better control performance than the others.
**Keywords-** Fuzzy logic, neural network, neuro-fuzzy system, control system

## 1. INTRODUCTION

Taking into account all possible factors, which influence the object's activity and create a model of given object on the base of traditional methods, is very difficult and impossible for its practical use. Simplification of these processes leads to their non-adequate description. Such as in the deterministic models the consideration of all factors is impossible, the use of these models leads to ineffective determination of control parameters. In such case for operative control of technological processes, man-operator makes decision using his long-term experiences. Taking into consideration all these and the importance of the described above, it is important to develop an intelligent control system on the base of knowledge of the experienced specialists and experts. During the development of such system it is necessary to take into account specific characters of technological processes. For such cases one of effective means for information processing is the use of fuzzy logic introduced by Zadeh [1]. Fuzzy system, which is thoroughly dealing with ill-defined, uncertain systems, can model the qualitive aspects of human knowledge and reasoning process without employing precise quantitative analyses. By using fuzzy concepts for estimation of situations and creation of logic rules in control models, the decision-making problems and information processing are simplified.

Fuzzy systems have found a number of practical applications in identification, control, prediction and diagnosing [2-4]. Traditionally, to develop a fuzzy system, human experts often carry out the generation of IF-THEN rules by expressing their knowledge. In case of complicated processes it is difficult for human experts to test all the input-output data, to find necessary rules for fuzzy controller. To solve this problem and simplify the generating of IF-THEN rules, several approaches have been proposed

[4-8]. In this paper the development of neuro-fuzzy inference system for technological processes control is considered, regarding the problems stated above.

## 2. NEURO-FUZZY INFERENCE SYSTEM

Neuro-fuzzy system combines the learning capabilities of neural networks with the linguistic rule interpretation of fuzzy inference systems. The synthesis of neuro-fuzzy inference system for controller includes the generation of knowledge base rules that have IF-THEN form. Here, the problem consists of optimal definition of the premise and consequent part of fuzzy IF-THEN rules for controller through the training capability of neural networks, evaluating the error response of the system. There are following types of IF-THEN rules;

$$\text{IF } x_1 \text{ is } A_{i1} \text{ and } x_2 \text{ is } A_{i2} \text{ and} \ldots \text{and } x_n \text{ is } A_{in} \text{ THEN } y_i \text{ is } C_j \tag{1}$$

Here $x_i$ and $y_i$ are input and output variables of system, respectively. $A_{ij}$ and $C_j$ are fuzzy sets.

For the second type fuzzy system the rule base has the following form

$$\text{IF } x_1 \text{ is } A_{i1} \text{ and } x_2 \text{ is } A_{i2} \text{ and} \ldots \text{and } x_n \text{ is } A_{in} \text{ THEN } y_i \text{ is } B_i \tag{2}$$

$B_i$ is crisp value of output signal. (2) is Takagi-Sugeno-Kanag (TSK) type fuzzy IF-THEN rules. The second type of fuzzy system can employ the other types of fuzzy reasoning mechanism [4].

In figure 1 the architecture of neuro-fuzzy inference system is given.

To make decision on the base of IF-THEN rules the fuzzy system includes fuzzification, inference engine and defuzification functional blocks.

- Fuzzification unit determines the membership degree of the crisp inputs for each linguistic value.
- Inference engine makes decision on the base of rules.
- Defuzzification unit transforms the fuzzy results of the inference engine into a crisp output.

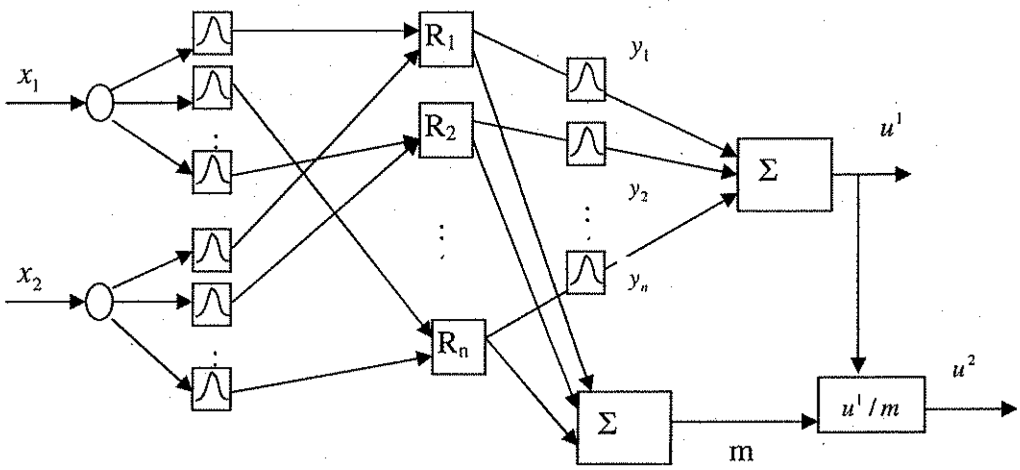


Figure 1. Structure of neuro-fuzzy inference system

The realization of these blocks on neuro-fuzzy structure is considered. In first layer each node corresponds to one linguistic term. The number of linguistic terms is determined by the expert of problem domain. For each input signal entering the system the membership degree to which input value belongs to a fuzzy set is calculated. To describe linguistic terms the Gaussian membership function is used.

$$\mu_{ij}(x_i) = e^{\frac{(x_{ij}-c_{ij})^2}{\sigma_{ij}^2}} \tag{3}$$

Here $c_{ij}$ and $\sigma_{ij}$ are the center and width of the Gaussian membership function of the j-th term of i-th input variable, respectively.

In the next layer the number of nodes corresponds to the number of rules. Each node represents one fuzzy logic rule. Here to calculate the values of output signals of the layer AND (min) operation is used.

$$\mu_j(x_i) = \prod_i \mu_{ij}(x_i) \tag{4}$$

These signals are input signal for the next last layer. This layer is a consequent layer. In this layer the output signals of previous layer are multiplied to the weight coefficients of network and sum of these products is calculated. Weight coefficients of neuro-fuzzy system are represented by fuzzy set of output variables. They are described by Gaussian function. If as a defuzzification operation we use "local mean of maximum" or "center of average" then only the center of Gaussian function is used in the next layer for defuzzification. In this case during development of control system the width of Gaussian function is not used. In formula 5 the parameters $y_j$ will represent the center of fuzzy coefficients. Output of third layer is calculated as

$$u^1 = \sum_{j=1}^{n} \mu_j(x_i) * y_j \tag{5}$$

After the sum of output signals of second layer $m = \sum_{j=1}^{n} \mu_j(x_i)$ is determined. Using the values of calculated variables and m the output of the fuzzy system is determined.

$$u^2 = \frac{\sum_{j=1}^{n} \mu_j(x_i) * y_j}{\sum_{j=1}^{n} \mu_j(x_i)} \tag{6}$$

*Learning:* The unknown parameters of the system are $y_j$ parameters of last layer and membership functions of first layer of neuro-fuzzy system. To define the accurate values of unknown parameters supervised learning algorithm is used.

$$y_j(t+1) = y_j(t) + \eta \frac{\partial E}{\partial y_j} \tag{7}$$

here $\gamma$ is learning rate.

$$E = \frac{1}{2}\sum_{l=1}^{m}(u_l(t) - u_l^d(t))^2 \tag{8}$$

where $u_l(t)$ and $u_l^d$ are current and desired outputs of the system, m is number of outputs. For given case m=1.

The adjusting of the membership functions of input layer is carried out by correction unknown coefficients $c_{ij}$ and $\sigma_{ij}$. The following formulas can be used for learning these coefficients.

$$c_{ij}(t) = c_{ij}(t) + \gamma\frac{\partial E}{\partial c_{ij}}, \quad \text{where} \quad \frac{\partial E}{\partial c_{ij}} = \sum_j \frac{\partial \mathrm{E}}{\partial \mathrm{u}}\frac{\partial u}{\partial \mu_j(x_i)}\frac{\partial \mu_j(x_i)}{\partial c_{ij}} \tag{9}$$

$$\sigma_{ij}(t) = \sigma_{ij}(t) + \gamma\frac{\partial E}{\partial \sigma_{ij}}, \quad \text{where} \quad \frac{\partial E}{\partial \sigma_{ij}} = \sum_j \frac{\partial \mathrm{E}}{\partial \mathrm{u}}\frac{\partial u}{\partial \mu_j(x_i)}\frac{\partial \mu_j(x_i)}{\partial \sigma_{ij}} \tag{10}$$

It is needed to note that if we use the signal $u^1$ as output signal of system then at the result of learning we can get the same result as we get by using the output signal $u^2$ (as known $u^2 = u^1/m$). Because of learning processes the values of each parameter of $y_j$ can combine themselves the value of 1/m.

## 3. NEURO-FUZZY CONTROL SYSTEM

The approach and neuro-fuzzy structure described above is used for development of controller to control parameters of technological processes. In figure 2 the structure of neuro-fuzzy control system is given. The inputs for neuro-fuzzy controller are error and change of error. The coefficients $k_e$, $k_{e'}$ and $k_u$ are used for scaling input and output signals of controller. Using values of error and change of error it is needed to determine such values of control signal that by using them in control system the target characteristic of the system would be provided.

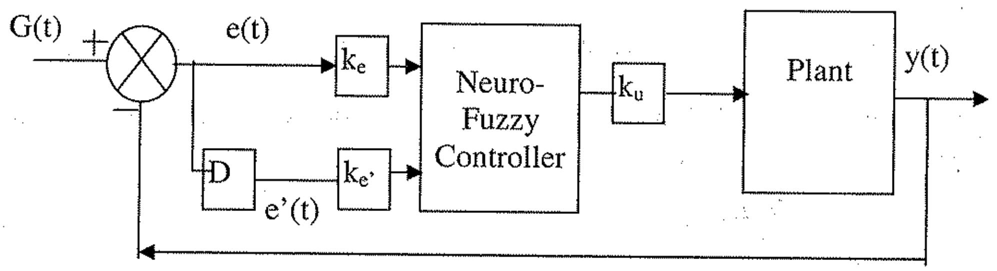


Figure 2. Structure of Neuro-Fuzzy control system.

At first stage for these input variables we define linguistic terms. As an example the seven linguistic values was taken. In figure 3 (a, b) the membership functions of linguistic values for the error and change of error are described. Here NL- negative large, NM- negative medium, NS- negative small, Z- zero, PS- positive small, PM- positive medium, PL- positive large. In neuro-fuzzy structure, in the first layer, to represent linguistic values the 14 nodes are used (for each input variable 7 linguistic term). Then in the second layer the maximum number of rules will be 49. Using linguistic values of input variables error and change of error and neuro-fuzzy structure the generation of IF-THEN rules for controller in closed loop control system is performed. The consequent part of rules includes control signal given to the object. To find association between input and output variables of the controller u=f(e,e'), the learning of unknown parameters of neuro-fuzzy controller in closed loop control system is performed. For learning of the unknown coefficients of neuro-fuzzy controller the error between target characteristic of control system and current output value of implemented system (output of control object) $\Delta = k_e(g(t) - y(t))$ is used. For learning controller coefficients the above described supervised learning algorithm is used. Using learning algorithm the values of weight coefficients of neuro-fuzzy controller are determined.

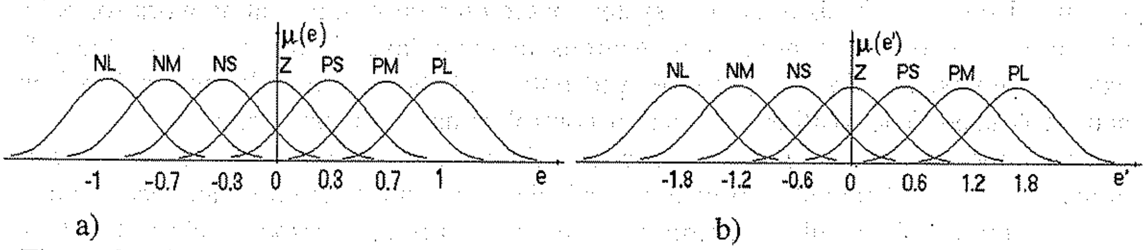

Figure 3. Membership functions of linguistic variables a) error and b) change of error.

The development of neuro-fuzzy control system is carried out for controlling temperature of rectifier K-2 column. During simulation the model of plant is described by the following differential equation.

$$a_0 y^{(2)}(t) + a_1 y^{(1)}(t) + a_2 y(t) = b_0 u(t) \tag{11}$$

where $a_0 = 0.042\text{min}^2$, $a_1 = 0.072\text{min}, a_2 = 1,\ b_0 = 60°\text{C/(kgf/cm}^2)$; here y(t) is regulation parameter of plant, u(t) is controller's output. Sampling time for the plant is 15 sec.

## 4. SIMULATION

Computer simulation of neuro-fuzzy control system for plant (11) is carried out. During learning of the parameters of neuro-fuzzy system the weight coefficients of output layer are adjusted. The initial values of the parameters of membership functions of input layer are chosen such that the interval of changing of input variables error and change of error in control system is covered. In figure 4 the curve that describes the learning processes of neuro-fuzzy control system for different values of set-point signals is given.

As a result of learning corresponding values of coefficients neuro-fuzzy system are determined.

Simulation result of neuro-fuzzy control system is compared with the simulation results of two other type of control system: a) Control system with PID controller and b) Control system with neural controller.

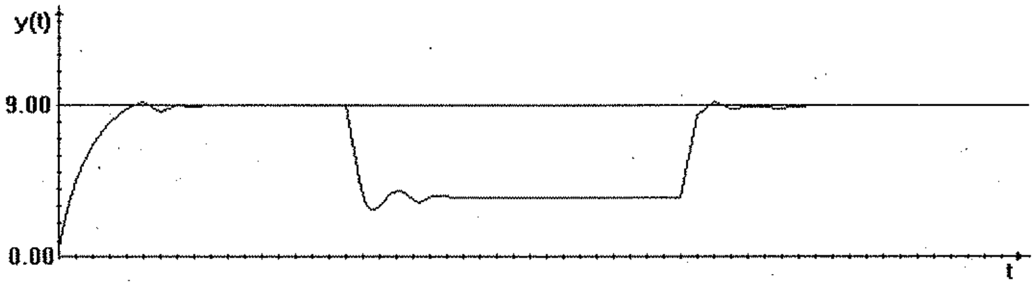


Figure 4. Learning curve of time response characteristic of Nero-Fuzzy control system for different values of set-point signal.

The optimal values of proportional, differential and integral coefficients of PID controller to control object (11) is determined by trial-and-error method. These parameters are corresponded to the best time response characteristic of PID control ystem. Also the synthesis of control system based on recurrent neural network for object (11) is carried out. The number of neurons in input layer is three- two of them for external inputs, one for one step delayed output of the network. In output layer one neuron is used. The synthesis of neural controller has been performed for two cases, when number of neurons in hidden layer is eight and sixteen. For both case in the result of learning the optimal value of weight coefficients of neural network have been found.

In figure 5 the results of comparative estimation of time response characteristic of control systems based on neuro-fuzzy (a) neural (b) and PID (c) controllers are given. Here learned weights of neuro-fuzzy and neural controllers are used to control plant.

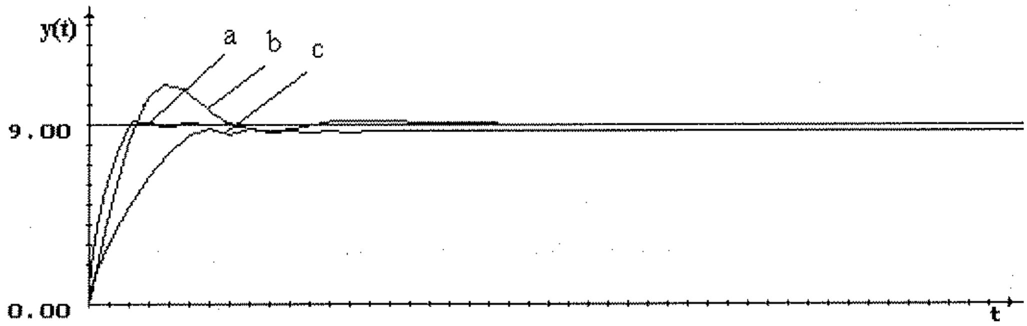


Figure 5. Time response characteristics of control systems with a) Neuro-Fuzzy, b) Neural and c) PID- controller.

Using formula (12) for all controllers the values of sum of square error are calculated.

$$J = \sum_{l=1}^{M} e^2(k) \tag{12}$$

Here M is number of samples. In table 1 the values of sum of square error for all three types control system are given.

Table 1. Results of comparison among three controllers

| Criteria | Neuro-Fuzzy | Neural | | PID |
|---|---|---|---|---|
| | | With 8 hidden neuron | With 15 hidden neuron | |
| $\sum_{l=1}^{M} e^2(k)$ | 105.98 | 131.81 | 129.93 | 176.47 |

The results of simulation of neuro-fuzzy control system show that the value of sum of square error less than other types of control system. Static error of time response characteristics of neuro-fuzzy system is absent (zero), transient overshoot is also absent. The settling time of system with neuro-fuzzy controller is less than other ones. The results of simulation and experimental analysis of the automatic control system with neuro-fuzzy controller show its efficiency.

## 5. CONCLUSION

In this paper the neuro-fuzzy system for control of parameters of technological processes is presented. The learning capability of neuro-fuzzy inference system allows it to deal with non-stationary plants, which can not efficiently controlled by conventional controllers. Also presented approach allows describing processes characterizing with uncertainty of environment, fuzziness of information.

The simulation of neuro-fuzzy system for control of dynamic plant is carried out. The result of simulation of neuro-fuzzy system is compared with the results of simulations of control systems based on PID- and Neural controller. Result of comparative estimation demonstrates the efficiency of presented approach.

## REFERENCES

[1] Zadeh L.A. Fuzzy Sets, Information and Control, vol.8, 338-353, 1965.

[2] Aliev R.A., Tserkovni A.E., Mamedova G.A. Production management at fuzzy initial information. Moscow, Energiatomizdat, 1991. (Russian)

[3] Kosko B. Neural networks and fuzzy systems. A dynamical system approach to machine intelligence. Prentice- Hall International Inc., 1993.

[4] Yager R.R., Zadeh L.A.(Eds). Fuzzy sets, neural networks and soft computing, Van Nostrand Reinhold, New York, 1994.

[5] Jyh-Shing Roger Jang. ANFIS: Adaptive-Network-Based Fuzzy Inference System. IEEE Transactions on Systems, Man and Cybernetics, Vol.23, No.3, 665-683, May/June,1993.

[6] M.Onder Efe, Okyay Kaynak, "On stabilization of Gradient-Based Training Strategies for Computationally Intelligent Systems". IEEE Transactions on Fuzzy Systems, Vol.8, No.5, 564-575, October, 2000.

[7] R.A.Aliev, R.H.Abiyev, R.R.Aliev. Automatic control system synthesis with the learned neural network based fuzzy controller. Texnicheskaya kibernetika, Moscow, N2, 192-197, 1994, (Russian)

8. R.H.Abiyev, K.W.Bonfig, F.T.Aliev. Controller based on fuzzy neural network for control of technological process.//ICAFS-96, Siegen, Germany, 295-298, June 25-27, 1996.

9. Rahib Abiyev. Controllers based on Soft computing elements// Electrical, Electronics and Computer Engineering Symposium NEU-CEE2001 & Exhibition. Nicosia, TRNC, Turkey, 182-188, May 23-25, 2001.