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## Temperature Control of Water Bath by using Neuro- Fuzzy Controller



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### Abstract

In this paper a neuro- fuzzy controller (NFC) for temperature control of a water bath system is proposed. A five layer neural network is used to adjust input and output parameters of membership function in a fuzzy logic controller. The hybrid learning algorithm is used for training this network. The simulation results shows that the proposed controller has good set point tracking and disturbance rejection properties. Also it is robust against changes in the system parameters. It is also superior to the conventional PID controller.

**Key words:** Neuro- Fuzzy Controller, temperature control, hybrid learning

### Introduction

The concept of fuzzy logic and artificial neural network for control problem has been grown into a popular research topic in recent years(Kuo-Ho Su , Yih-Young Chen and Shun-Feng Su, 2010). The reason is that the classical control theory usually requires a mathematical model for designing the controller. The inaccuracy of mathematical modeling of the plants usually degrades the performance of the controller, especially for nonlinear and complex control problems. The advent of the fuzzy logic controllers (FLC) and the neural controllers based on multilayered neural networks has inspired new resources for the possible realization of better and more efficient control. In recent years, the integration between fuzzy logic and neural network namely fuzzy neural network (FNN) has been proposed and developed (Guo Zhi-rong, Gao Wei Xie Shun-yi 2009; Kuo-Ho Su, Yih-Young Chen and Shun-Feng Su, 2010).FNN has been applied to many engineering fields, for examples, system identification (Abiyev.R.H, Kaynak.O, Alshanaheh.T, Mamedov.F 2011), system uncertainty estimation (Jassar.S, Lian.Zhao, Zaiyi

Liao, Ng, K.L.R 2009), and neuro-fuzzy controller (NFC) (Peymanfar.A, Khoei.A, Hadidi.Kh 2010).

Zhenjun. D, Lide. F, Zhanbiao. S and Yameng. Z (2010) uses Fuzzy Controller for control of Water Temperature of Heat Exchanger. In their article, The system parameters charged with is exporting water temperature of the heat exchanger. System mainly includes three parts: normalized fuzzy quantization module, intelligent integration module, and the control algorithm module. They shows that in the case of the same response time, the performances of the fuzzy controller with intelligent integration in a stable time, overshoot, robustness and several areas are better than conventional PID controller.

Wei Peng and Da-fa Zhang (2010) uses Fuzzy Controller for control of Steam Generator Water Level. This article has been shown, as regards, the steam generator's is time delay system with model uncertainty, The conventional PID controller has a poor control performance to the steam generator. Therefor Fuzzy controller gives satisfactory results.

Johan M.A, Md Kamal.M and Hanum Yahaya. F (2009) uses Fuzzy Controller to Water Temperature control. In this case, fuzzy logic is going to be applied to the waterbath system. The result of the fuzzy design can be check using debug mode that are available, The system is turning two heaters during the condition when the water level is high and the temperature is below normal.

Mangar.L.O and Rathee.V (2009) compared fuzzy logic controller and neuro fuzzy controller for water bath system. They showed the advantages of ANFIS system over the traditional estimation methods are simple complementing of the model by new input parameters without modifying the existing model structure, automatic searching for the non-linear connection between the inputs and outputs. They showed that the ANFIS produces a stable control signal  $u(k)$  than fuzzy logic controller and has a perfect temperature-tracking capability.

Cheng-J L, Chi-Y Lee and Cheng-C Chin (2006) uses Compensatory Wavelet Neuro-Fuzzy System (CWNFS) for temperature control. An on-line learning algorithm, which consists of structure learning and parameter learning, is presented. The structure learning is based on the degree measure to determine the number of fuzzy rules and wavelet functions. The parameter learning is based on the gradient descent method to adjust the shape of membership function, compensatory operations and the connection weights of WNN. Simulation results shows that For the fuzzy and PID controllers, therefore, they usually require a long time in design for achieving good performance. In the CWNFS controller, however, no controller parameters have to be decided in advance. We only need to choose propose training patterns of the CWNFS controller. Although the structure of CWNFS controller is more complicated than the fuzzy and PID controllers, in general, the CWNFS controller usually spends a relatively short time in design for achieving good performance.

In this paper the Adaptive Neuro- Fuzzy Inference Systems (ANFIS) be used to controller for control of water temperature in the bath system. First, the used neuro- fuzzy controller is introduced, then the structure of bath system is introduced, Finally simulation for a bath water system with neuro- fuzzy controller is given.

### **Adaptive Neuro- Fuzzy Inference Systems (ANFIS)**

Takagi and Sugeno proposed the T-S fuzzy model in 1985. Students called it as Sugeno fuzzy model after. The Sugeno fuzzy model is a nonlinear model. It can aptly express the dynamic

characteristic of complex systems. Further more, it is the fuzzy inference model that is in the most common use. A typical fuzzy rule in a Sugeno fuzzy model has the format:

If x is A and y is B, Then  $z = f(x, y)$

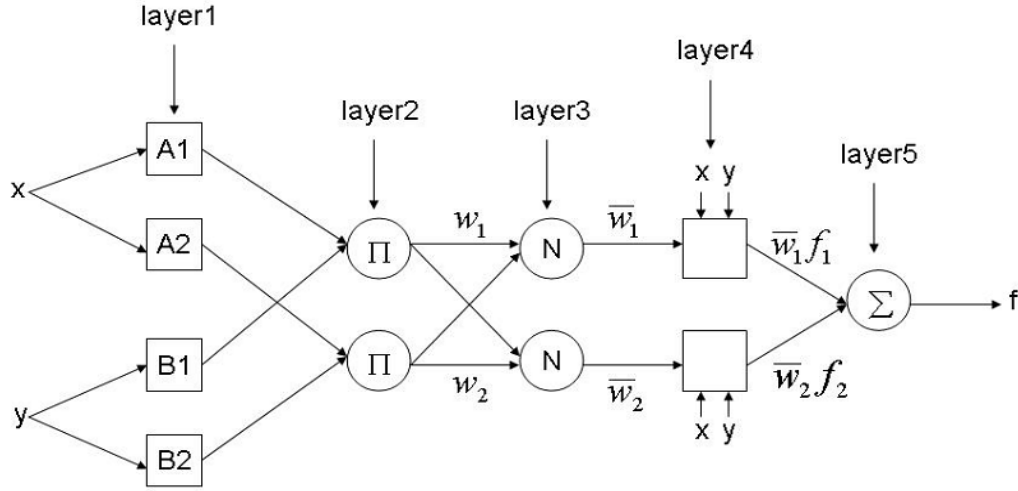
Where A and B are fuzzy sets in the antecedent;  $z = f(x, y)$  is a crisp function in the consequent.

When  $f(x, y)$  is a first-order polynomial, we have the first-order Sugeno fuzzy model. Consider a first-order Sugeno fuzzy inference system, which contains two rules.

Rule 1: If x is  $A_1$  and y is  $B_1$  Then  $f_1 = p_1x + q_1y + r_1$

Rule 2: If x is  $A_2$  and y is  $B_2$  Then  $f_2 = p_2x + q_2y + r_2$

Fig.1. show the first-order Sugeno fuzzy inference system. ANFIS is created through the concepts of fuzzy sets and the Sugeno fuzzy inference system which imitates the human decision making. The advantage of ANFIS is to immediately calculate output. It is not necessary to create the complex mathematical model. ANFIS can learn from the sample data such as the input output sets from the system and can adapt parameters inside its network. In this paper the output of *ith* node in layer 1 is denoted as  $O_{1,i}$ .



**Fig.1.** Corresponding ANFIS architecture

Layer 1: Every node *i* in this layer is an adaptive node with a node function

$$O_{1,i} = \mu_{A_i}(x) = \exp \left[ - \left( \frac{x - m_i}{\sigma_i} \right)^2 \right] \quad \text{for } i = 1,2 \text{ or} \quad (1)$$

$$O_{1,i} = \mu_{B_{i-2}}(y) = \exp \left[ - \left( \frac{y - m_i}{\sigma_i} \right)^2 \right] \quad \text{for } i = 3,4 \quad (2)$$

where  $\{m_i, \sigma_i\}$  is the parameter set. These are called premise parameters.

Layer 2: Every node in this layer is a fixed node labeled  $\Pi$ , whose output is the product of all the incoming signals.

$$O_{2,i} = w_i = \mu_{A_i} * \mu_{B_i} \quad \text{for } i = 1,2 \quad (3)$$

Layer 3: Here, the *ith* node calculates the ratio of the *ith* rule's firing strength to the sum of all rule's firing strengths.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad \text{for } i = 1, 2 \quad (4)$$

Layer 4: Every node  $i$  in this layer is an adaptive node with a node function

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad (5)$$

where  $\bar{w}_i$  is a normalized firing strength from layer 3 and  $\{p_i, q_i, r_i\}$  is the parameter set of the node. These parameters are referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node labeled  $\Sigma$ , which computes the overall output as the summation of all incoming signals:

$$O_5 = f = \sum_i \bar{w}_i f_i \quad (6)$$

## HYBRID LEARNING ALGORITHM

The Hybrid Learning Algorithm is a combination of least square and backpropagation methods. In the least square method, the output of a model  $y$  is given by the parameterized expression

$$y = \theta_1 f_1(U) + \theta_2 f_2(U) + \dots + \theta_n f_n(U) \quad (7)$$

where  $U = [u_1, \dots, u_n]$  is the models input vector,  $f_1, \dots, f_n$  are known functions of  $u$ , and  $\theta_1, \dots, \theta_n$  are unknown parameters to be optimized. To identify these unknown parameters  $\theta_i$ , usually a training data set of data pairs  $\{(u_i, y_i), i = 1, \dots, m\}$  is taken; substituting each data pair in (7) a set of linear equations is obtained, which can be

$$A\theta = Y \quad (8)$$

in matrix form. Where  $A$  is a  $m \times n$  matrix

$$A = \begin{bmatrix} f_1(u_1) & \dots & f_n(u_1) \\ \vdots & \ddots & \vdots \\ f_1(u_m) & \dots & f_n(u_m) \end{bmatrix} \quad (9)$$

$\theta$  is  $n \times 1$  unknown parameter vector

$$\theta = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_n \end{bmatrix} \quad (10)$$

$y$  is an  $m \times 1$  output vector

$$Y = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix} \quad (11)$$

In this paper Recursive least square method for adjust linear output parameters is proposed. The equation of Recursive least square method as follows

$$P_{k+1} = P_k - \frac{P_k a_{k+1} a_{k+1}^T P_k}{1 + a_{k+1}^T P_k a_{k+1}} \quad (12)$$

$$\theta_{k+1} = \theta_k + P_{k+1} a_{k+1} (y_{k+1} - a_{k+1}^T \theta_k) \quad (13)$$

where  $a_k$  is  $k$ th row vector of  $A$  and  $P_k$  is covariance matrix at time  $k$ .

In case of backpropagation learning rule the central part concerns how to recursively obtain a gradient vector in which each element is defined as the derivative of an error measure with respect to a parameter. Assuming that a given feedforward adaptive network has  $L$  layers and

layer  $l$  has  $N(l)$  nodes, then the output function of node  $i$  in layer  $l$  can be represented as  $x_{l,i}$  and  $f_{l,i}$  respectively. For the node function  $f_{l,i}$  we can write:

$$x_{l,i} = f_{l,i}(x_{l-1,1}, \dots, x_{l-1,N(l-1)}, \alpha, \beta, \gamma, \dots) \quad (14)$$

where  $\alpha, \beta, \gamma$ , etc. are the parameters of this node. Assuming that the given training data set has  $P$  entries, an error measure can be defined for the  $p$ th ( $1 \leq p \leq P$ ) entry of the training data set as the sum of squared errors:

$$E_p = \sum_{k=1}^{N(L)} (d_k - x_{L,k})^2 \quad (15)$$

where  $d_k$  is the  $k$ th component of the  $p$ th desired output vector and  $x_{L,k}$  is the  $k$ th component of the actual output vector produced by presenting the  $p$ th input vector to the network. The task here is to minimize an overall error measure, which is defined as  $E = \sum_{p=1}^P E_p$ . The basic concept in calculating the gradient vector is to pass a form of derivative information starting from the output layer and going backward layer by layer until the input layer is reached. The derivative of the overall error measure  $E$  with respect to  $\alpha$  is

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^P \frac{\partial E_p}{\partial \alpha} \quad (16)$$

Accordingly, for simplest steepest descent without line minimization, the update formula for generic parameter  $\alpha$  is

$$\Delta \alpha = -\eta \frac{\partial E}{\partial \alpha} \quad (17)$$

In which  $\eta$  is the learning rate. So, for parameter  $\alpha$  it may be written that,

$$\alpha_{new} = \alpha_{old} + \Delta \alpha \quad (18)$$

In this type of learning, the update action occurs only after the whole set of training data pair is presented. This process of presentation of whole set of training data pair is called epoch.

### Control of water bath temperature system

The goal of this section is to control the temperature of a water bath system given by

$$\frac{dy(t)}{dt} = \frac{u(t)}{C} + \frac{Y_0 - y(t)}{RC} \quad (19)$$

where  $y(t)$  is system output temperature in °C;  $u(t)$  is heating flowing inward the system;  $Y_0$  is room temperature;  $C$  is the equivalent system thermal capacity; and  $R$  is the equivalent thermal resistance between the system borders and surroundings.

Assuming that  $R$  and  $C$  are essentially constant, we rewrite the system in Eq. (19) into discrete-time form with some reasonable approximation. The system

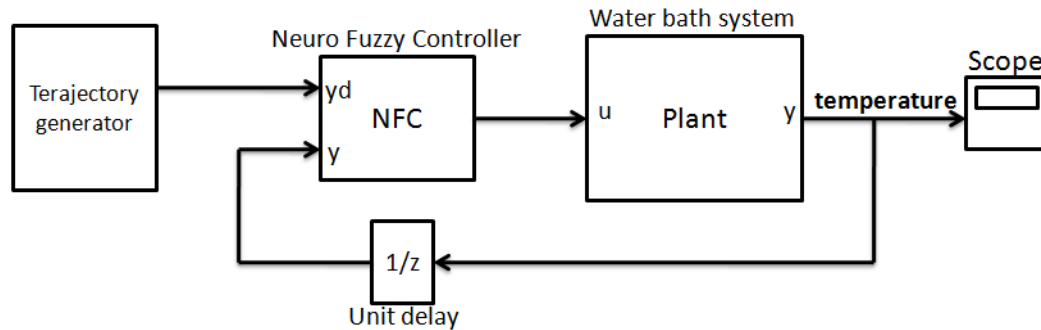
$$y(k+1) = \exp(-\alpha Ts) \cdot y(k) + \frac{\beta}{1 + \exp(0.5y(k) - 40)} u(k) + (1 - \exp(-\alpha Ts)) y_0 \quad (20)$$

is obtained, where  $\alpha$  and  $\beta$  are some constant values describing  $R$  and  $C$ . The system parameters used in this example are  $\alpha = 1.0015e-4$ ,  $\beta = 8.67973e-3$  and  $Y_0 = 25.0$  (°C), which were obtained from a real water bath plant in (Tanomaru.J and Omatu.S. 1992) The sampling period is  $T_s = 30$ . The used of ANFIS in control system is to learn the inverse of the plant, so that, this can be used as a controller after training phase. In this, Sugeno-type inference system is used. ANFIS

uses a hybrid-learning algorithm to identify parameters of Sugeno-type inference system. It applies a combination of the least square method and the back propagation method for training fuzzy inference system membership function parameters to emulate a given training data set. We first obtain the training data by imposing random input voltages to the water bath system and recording the corresponding temperature. a sequence of random input signals  $u(k)$  limited to 0 and 5 V is injected directly into the simulated system described in Eq. (20).

## SIMULATION

The block diagram of Neuro- Fuzzy Controller and water bath system is shown in Figure. 2.

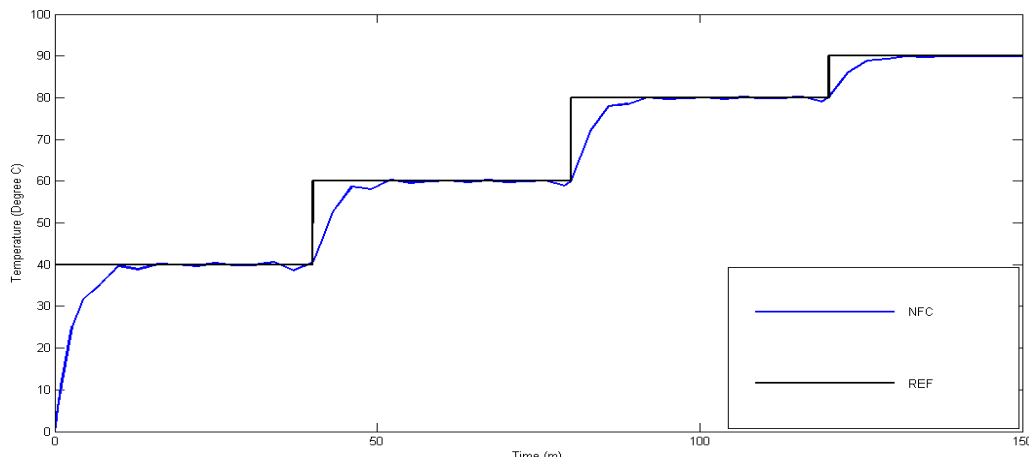


**Fig. 2.** Schematic diagram of the water bath temperature control system.

The input variables for this controller are chosen as,  $y_d(k+1)$  and  $y(k)$ , where  $y_d$  is desired output and  $y$  is actual output. Using the mathematical model of the real water bath plant our proposed approaches has been tested. The 100 training patterns are chosen from the input-outputs characteristic in order to cover the entire reference output. The initial temperature of the water is 35°C, and the temperature rises progressively when random input signals are injected. Note that the good control system for water bath temperature control should produce no overshoot in its output response.

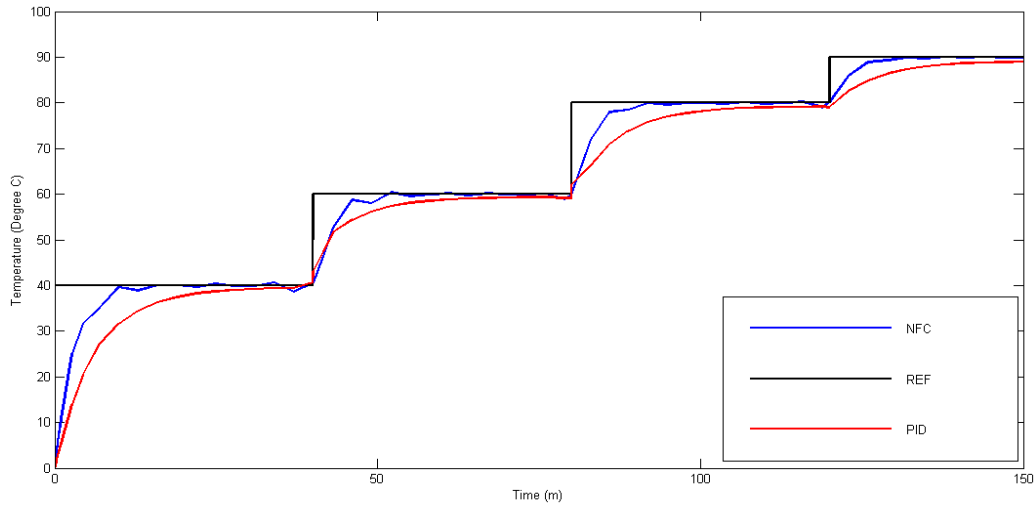
The plant input  $u(k)$  was limited between 0 and 5, and it is also assumed that the sampling period is  $T_s = 30$ . With the chosen parameters, the simulated system is equivalent to a SISO temperature control system of a water bath that exhibits linear behavior up to about 70°C and then becomes nonlinear and saturates at about 90°C.

The goal is to design a Neuro- Fuzzy Controller what will control the water temperature to follow a reference profile as closely as possible. This reference profile is 40 °C for  $0 \leq t \leq 40$  minutes, 60 °C for  $40 \leq t \leq 80$  minutes, 80 °C for  $80 \leq t \leq 120$  minutes and 90 °C for  $120 \leq t \leq 150$  minutes. There are total twenty five rules used for this system. This controller has five membership function and gaussian type membership function are used in their fuzzification process. The regulation performance of the Neuro- Fuzzy Controller model is shown in Fig. 3



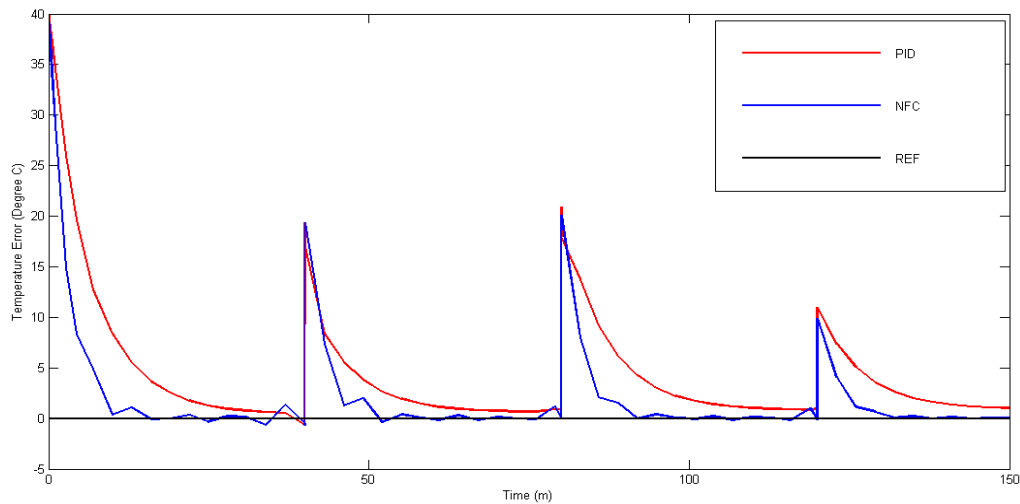
**Fig.3.** Final regulation performance of the NFC for water bath system.

Comparison between the performance of Neuro- Fuzzy Controller (NFC) and PID Controller is shown in Fig. 4.



**Fig. 4.** Performance of the NFC and PID Controller

The error curves of Neuro- Fuzzy Controller and PID controller are shown in Fig. 5



**Fig. 5.** The error curves of NFC and PID controller

For the aforementioned simulation results, Figure 4 has shown that the proposed Neuro- Fuzzy Controller has better performance than PID Controller. For the PID controller, the parameters  $K_P$

,  $K_I$  and  $K_D$  have to be decided and tuned by hand. PID Controller require a long time in design for achieving good performance. In the Neuro- Fuzzy controller, however, no controller parameters have to be decided in advance. We only need to choose propose training patterns of the Neuro- Fuzzy controller. Although the structure of Neuro- Fuzzy controller is more complicated than the PID controller, in general, the Neuro- Fuzzy controller usually spends a relatively short time in design for achieving good performance.

## CONCLUSIONS

In this paper a neuro- fuzzy controller (NFC) for temperature control of a water bath system is proposed. ANFIS based NFC is suitable for adaptive temperature control of a water bath system. The ANFIS is inherently a modified TSK (Takagi-Sugeno-Kang)-type fuzzy rule-based model possessing neural network's learning ability. In contrast to the general Adaptive Neuro- Fuzzy Inference Systems, where the rules should be decided in advance before parameter learning is performed, there are no rules initially in the ANFIS. Simulation results show that the ANFIS produces a stable control signal  $u(k)$  than PID controller and has a perfect temperature-tracking capability.

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