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A Novel Intelligent Control System Design for Water BathTemperature Control

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Abstract: In this paper a neuro- fuzzy controller (NFC) for temperaturecontrol 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 show that the proposedcontroller has good set point tracking and disturbance rejectionproperties. Also it is robust against changes in the systemparameters. 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 hasbeen grown into a popular research topic in recent years (Kuo-Ho Su, Yih-Young Chen and Shun-Feng Su, 2010). The reason isthat the classical control theory usually requires a mathematical model for designingthe controller. The inaccuracy of mathematical modeling of the plantsusually degrades the performance of the controller, especially for nonlinearand complex control problems. The advent of the fuzzy logic controllers (FLC) and the neural controllers based on multilayeredneural networks has inspired new resources for the possible realization of better and more efficientcontrol.In recent years, the integration between fuzzy logic andneural network namely fuzzy neural network (FNN) hasbeen proposed and developed (GuoZhi-rong, Gao, WeiXie Shun-yi 2009; Kuo-Ho Su, Yih-Young Chen and Shun-Feng Su, 2010). FNN has been applied to many engineering fields, forexamples, system identification (Abiyev. R.H, Kaynak, O., Alshanableh, 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 HeatExchanger. In their article, The system parameters charged with is exporting watertemperature of the heat exchanger. System mainly includesthree parts: normalized fuzzy quantization module,intelligent integration module, and the control algorithmmodule. They shows that in the case of the sameresponse time, the performances of the fuzzy controller withintelligent integration in a stable time, overshoot, robustnessand 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 controlperformance to the steam generator. Therefor Fuzzy controller gives satisfactory results.

Johan M.A, MdKamal, M., and HanumYahaya, 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 debugmode 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 thetraditional estimation methods are simplecomplementing of the model by new inputparameters without modifying the existing modelstructure, automatic searching for the non-linearconnection between the inputs and outputs. They showed that the ANFISproduces a stable control signal u (k) thanfuzzy logic controller and has a perfecttemperature-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, ispresented. 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, compensatoryoperations 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 forachieving good performance. In the CWNFS controller, however, no controller parameters have to be

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decidedin advance. We only need to choose propose training patterns of the CWNFS controller. Although the structureof CWNFS controller is more complicated than the fuzzy and PID controllers, in general, the CWNFS controllerusually 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, Finallysimulation for a bath water system with neuro- fuzzy controlleris given.

Adaptive Neuro- Fuzzy Inference Systems (ANFIS):

Takagi and Sugeno proposed the T-S fuzzy model in1985. Students called it as Sugeno fuzzy model after. TheSugeno fuzzy model is a nonlinear model. It can aptlyexpress the dynamic characteristic of complex systems.Further more, it is the fuzzy inference model that is in themost common use. A typical fuzzy rule in a Sugeno fuzzymodel has the format:

Ifx 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-orderpolynomial, we have the first-order Sugeno fuzzy model.Consider a first-order Sugeno fuzzy inference system,which contains two rules.

Rule 1: Ifx isA_1andy is B_1Then $f_1 = p_1x + q_1y + r_1$

Rule 2: Ifx is $A_2$and y is B_2Then$f_2 = p_2x + q_2y + r_2$

Fig.1. show the first-order Sugeno fuzzyinference system. ANFIS is created through the concepts of fuzzy sets andthe Sugeno fuzzy inference system which imitates thehuman decision making. The advantage of ANFIS is toimmediately calculate output. It is not necessary to create thecomplex mathematical model. ANFIS can learn from thesample data such as the input output

sets from the system andcan adapt parameters inside its network.In this paper the output of ithnode in layer l is denoted as $O_{l,i}$.

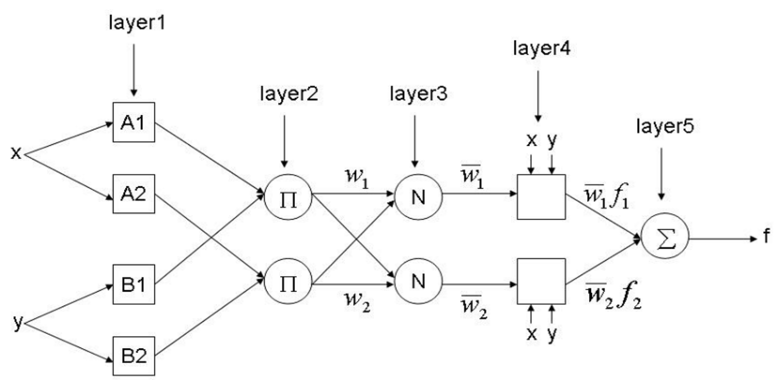

Fig. 1: Corresponding ANFIS architecture.

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

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

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

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

Layer 2*:* Every node in this layer is a fixed nodelabeled Π, whose output is the product of all the incomingsignals.

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

Layer 3: Here, the ithnode calculates the ratio of the ithrule's firing strength to the sum of all rule's firing strengths.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \; for \; i = 1,2 \tag{4}$$

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

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

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 parametersare referred to as consequent parameters.
Layer 5: The single node in this layer is a fixed nodelabeled $\sum$, which computes the overall output as thesummation of all incoming signals:

$$O_5 = f = \sum_i \bar{w}_i f_{\text{i}} \tag{6}$$

Hybrid Learning Algorithm:

The Hybrid Learning Algorithm is a combination ofleast square and backpropagation methods. In the least squaremethod, the output of a model y is given by the parameterizedexpression.

$$y = \theta_1 f_1(U) + \theta_2 f_2(U) + \cdots\cdots + \theta_n f_n(U) \tag{7}$$

where$U = [u_1, \cdots, u_n]$ is the models input vector,$f_1, \cdots, f_{\text{n}}$are known functions of u, and $\theta_1, \cdots, \theta_n$areunknown parameters to be optimized. To identify theseunknown parametersθ_i, usually a training data set of datapairs $\{(\text{u}_i, \text{y}_i), i = 1, \cdots, m\}$ is taken; substituting each datapair in (7) a set of linear equations is obtained, which can be

$$A\theta = Y \tag{8}$$

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

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

θisn $\times$ 1 unknown parameter vector

$$\theta = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_n \end{bmatrix} \tag{10}$$

y is an $m \times 1$output vector

$$Y = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix} \tag{11}$$

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

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

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

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

In case of backpropagation learning rule the central partconcerns how to recursively obtain a gradient vector in whicheach element is defined as the derivative of an error measurewith respect to a parameter. Assuming that a givenfeedforward adaptive network has L layers and layer l has $N(l)$nodes, then the output function of node i in layer l can berepresented as $x_{l.i}$and $f_{l,i}$respectively. For the node function $f_{l,i}$we can write:

$$x_{l,i} = f_{l,i}\left(x_{l-1,1}, \cdots x_{l-1,N(l-1)}, \alpha, \beta, \gamma, \cdots\right) \tag{14}$$

where α, β, γ,etc. are the parameters of this node.Assuming that the given training data set has P entries, anerror measure can be defined for the $pth(1 \leq p \leq P)$ entry ofthe training data set as the sum of squared errors:

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

whered_k is the kthcomponent of the pthdesired outputvector and $x_{L,k}$is the kthcomponent of the actual output vectorproduced by presenting the pthinput vector to the network. Thetask here is to minimize an overall error measure, which isdefined as $E = \sum_{p=1}^{P} E_p$. The basic concept in calculating thegradient vector is to pass a form of derivative informationstarting from the output layer and going backward layer bylayer until the input layer is reached. The derivative of the overall error measure E with respect to α is

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

Accordingly, for simplest steepest descent without lineminimization, the update formula for generic parameterα is

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \tag{17}$$

In which h is the learning rate. So, for parameter a it maybe written that,

$$\alpha_{new} = \alpha_{old} + \Delta\alpha \tag{18}$$

In this type of learning, the update action occurs only afterthe whole set of training data pair is presented. This process ofpresentation 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

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

wherey(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 bordersand surroundings.

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

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

is obtained, where $\alpha$and $\beta$are some constant values describing R and C. The system parameters used in thisexample are α = 1.0015e–4, β = 8.67973e–3 and Y0 = 25.0 (◦C), which were obtained from a real water bathplant in (Tanomaru.J and Omatu.S. 1992)The sampling period is Ts = 30.The used of ANFIS in control system is to learnthe inverse of the plant, so that, this can be usedas a controller after training phase. In this,Sugeno-type inference system is used. ANFISuses a hybrid-learning algorithm to identifyparameters of Sugeno-type inference system. Itapplies a combination of the least square methodand the back propagation method for trainingfuzzy inference system membership functionparameters to emulate a given training data set.We first obtain the training data by imposingrandom input voltages to the water bath systemand recording the corresponding temperature.a sequence of random input signals u(k) limited to 0 and5 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.

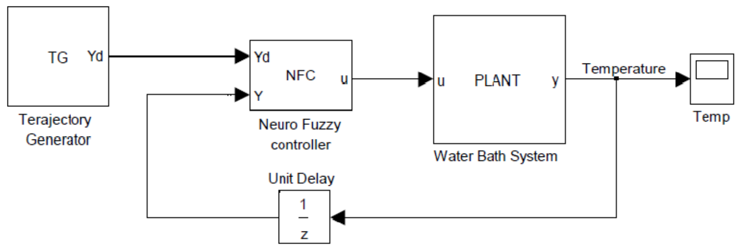

Fig. 2: Schematic diagram of the water bath temperature control system..

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 fromthe input-outputs characteristic in order to cover the entire reference output. The initial temperature of the water is35◦C, and the temperature rises progressively when random input signals are injectedNotethat the good control system for water bath temperaturecontrol should produce no overshoot in its outputresponse.

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

The goal is to design aNeuro- Fuzzy Controllerwhat will control the water temperature to followa reference profile as closely as possible. Thisreference profile is 40 ℃ for $0 \le t \le 40$ minutes,60 ℃ for $40 \le t \le 80$ minutes, 80 ℃ for$80 \le t \le 120$ minutes and 90 ℃ for $120 \le t \le 150$minutes. There are total twenty five rules usedfor this system.This controllerhas five membership function andgaussian type membership function are used in theirfuzzification process. The regulation performance of the Neuro- Fuzzy Controller model is shown in Fig. 3.

For the aforementioned simulation results, Figure 4 has shown that the proposed Neuro- Fuzzy Controller has betterperformance 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 forachieving good performance.In the Neuro- Fuzzy controller, however, no controller parameters have to be decidedin advance. We only need to choose propose training patterns of the Neuro- Fuzzy controller. Although the structureof Neuro- Fuzzy controller is more complicated than the PID controller, in general, the Neuro- Fuzzy controllerusually spends a relatively short time in design for achieving good performance.

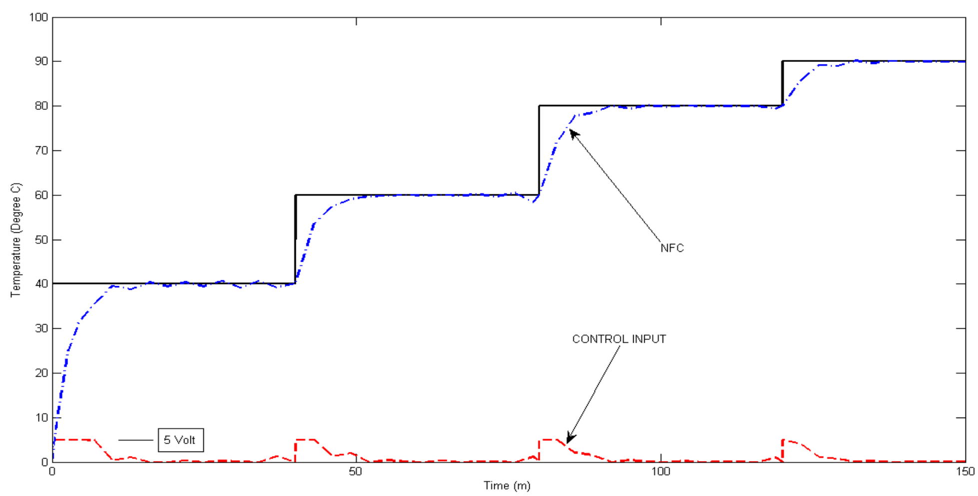

Fig. 3: Final regulation performance of the NFC for water bath system.

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

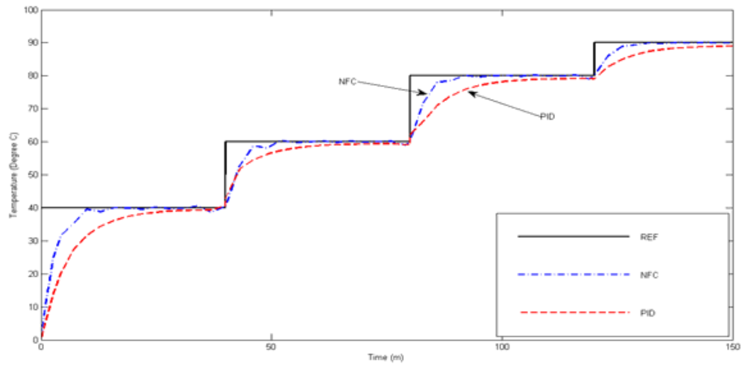

Fig. 4: Performance of the NFC and PID Controller.

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

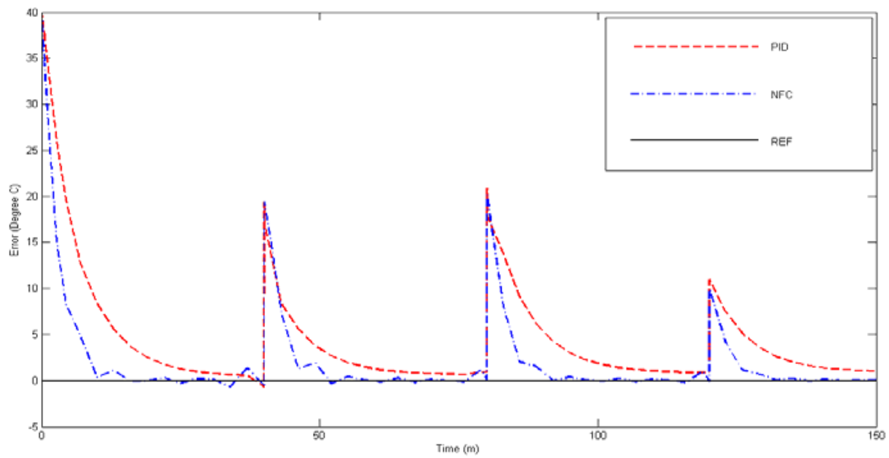

Fig. 5: The error curves of NFC and PID controller.

Conclusions:

In this paper a neuro- fuzzy controller (NFC) for temperaturecontrol of a water bath system is proposed. ANFIS based NFC is suitablefor 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 learningability.In contrast to the general Adaptive Neuro- Fuzzy Inference Systems, where the rules should be decided in advance beforeparameter learning is performed, there are no rules initially in the ANFIS. Simulation results show that the ANFISproduces a stable control signal u(k) thanPID controller and has a perfecttemperature-tracking capability.

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