Design Research of an Adaptive-Fuzzy-Neural Controller

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***Abstract*—The regular fuzzy system can not change the expert's experience into inference rule storage and is short of effective method to improve the membership function. Adaptive neural fuzzy inference system combines fuzzy logic and neural unit and tunes the precondition parameter and conclusion parameter with backpropagation algorithm and least-square method and can produce fuzzy rules automatically. This paper gives an adaptive-fuzzy-neural controller based on this and applies it to superheated temperature control of boiler. In the simulation, we compare it with fuzzy controller and neural network controller. The result shows that: this method improves dynamic property, steady precision and anti-jamming characteristic.**

***Index Terms*—adaptive-fuzzy-neural, superheated temperature, fuzzy controller; neural network controller**

I. INTRODUCTION

In modern control area, there are many systems with strong interference, nonlinear, time-varying characteristics, and the traditional PID control is not satisfactory. In addition, the control quality of its parameters will decline when the object or operating condition changes [1].

Currently, intelligent control has become a central issue in control field, especially neural network control and fuzzy control. Artificial neural networks (ANNs) have been used as computational tools for data quality identification because of the belief that they have greater predictive power than signal analysis techniques [2]. Fuzzy logic and pruning rules are used to enhance system capabilities for the evidential reasoning over attribute data. Fuzzy set theory plays an important role in dealing with uncertainty when making decisions in data fusion [3]. However, neural network control is easy to fall into local minimum; fuzzy rules are unable to be selected and adjusted automatically, and they can only be selected by experienced designers. Later, some researchers combines neural network with fuzzy and forms into fuzzy neural network control. Neuro-fuzzy systems are fuzzy systems which use ANNs theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems harness the power of the two paradigams: fuzzy logic and ANNs in tuning rule-based fuzzy systems that approximate the complex unknown information [4-6]. A specific approach in neuro-fuzzy development is the adaptive neural fuzzy inference system (ANFIS), which has shown significant results in modeling nonlinear functions. In ANFIS, the membership function parameters are extracted from a data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion. Successful implementations of ANFIS in electrical engineering have been reported, for signal classification and data analysis [7, 8].

On the basis of adaptive neural fuzzy inference system, this paper proposes an adaptive fuzzy neural network controller which maintains the characteristic of traditional cascade control. The deputy controller is still a proportional one, and the main controller is made of a fuzzy-neural- network one and an intelligent proportional integral one by parallel. The designed controller in this paper is simulated, and simulation results show that the controller does not have good control performance but also enhances adaptive capacity.

II. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Adaptive neural fuzzy inference system uses neural network to realize fuzzy reasoning, it can improve the traditional fuzzy control design which relies on people's thinking adjusting the membership function to reduce the error, and can also establish a set of IF -THEN rules based on compound-learning process, so that adjusts the required relationship between input and output of fuzzy inference. The structure is shown in figure 1:

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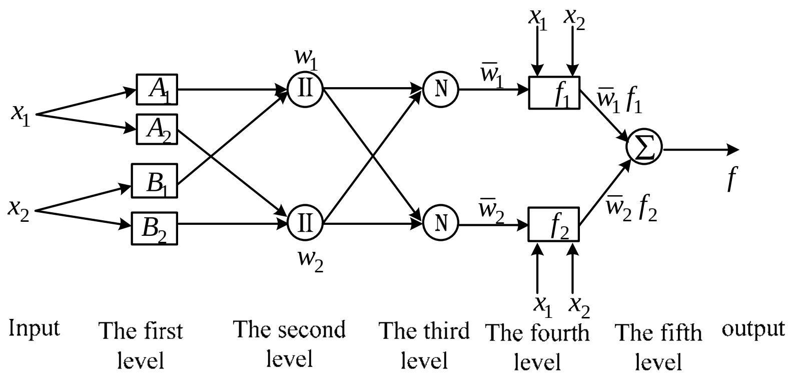

Figure 1. Adaptive neural fuzzy intelligent structure

Where, x_1, x_2 are inputs of system, f is output of the inference system, $O_{1,i}$ is output of the i^{th} node of the first level [9].

The first level：Fuzzification layer, it is used to calculate membership of input, and the output functions of every node in this level are:

$$O_{1,i} = \mu_{A_i}\left(x_i\right), i = 1,2 \tag{1}$$

$$O_{1,j} = \mu_{B_j}\left(x_2\right), j = 1,2 \tag{2}$$

Where, A_i and B_j are fuzzy sets, $\mu_{A_i}\left(x_1\right), \mu_{B_j}\left(x_2\right)$ are the corresponding membership functions of the fuzzy sets.

The second level: its function is to calculate w_i which is the fitness of every rule and to multiply the memberships of every input signal, the product result is taken as fitness of the rule in the end.

$$O_{2,i} = w_i = \mu_{A_i}\left(x_1\right)\mu_{B_i}\left(x_2\right), i = 1,2 \tag{3}$$

The third level: normalize the fitness of every rule:

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

The fourth level: the transfer function of every node is linear function which expresses local linear model and calculates the output of every rule:

$$O_{3,i} = \bar{w}_i f_i = \bar{w}_i\left(p_i x_1 + q_i x_2 + r_i\right),\ i = 1,2 \tag{5}$$

Where, f_i is output function of Sugeno-type fuzzy conclusion.

The fifth level: the defuzzification layer, it is used to calculate the sum of all rule outputs:

$$O_{5,i} = \sum \bar{w}_i f_i = \frac{\sum_i \bar{w}_i f_i}{\sum w_i}, i = 1,2 \tag{6}$$

Given condition parameters, ANFIS output can be expressed as a linear combination of conclusion parameters：

$$\begin{aligned} f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_1}{w_1 + w_2} f_2 = \bar{w}_1 f_1 + \bar{w}_2 f_2 \\ &= \left(\bar{w}_1 x_1\right) p_1 + \left(\bar{w}_1 x_1\right) q_1 + \bar{w}_1 r_1 + \left(\bar{w}_2 x_2\right) p_2 \\ &\quad + \left(\bar{w}_2 x_2\right) q_2 + \bar{w}_2 r_2 \end{aligned} \tag{7}$$

It is easy to fall into local minimum for the method of gradient descent during parameter learning, so we use a mixed algorithm that combines the gradient descent method and least square learning algorithm [10], and it can be divided into two steps:

(1) Determine the initial value of the conditional parameters, then calculate the conclusion parameters by the least square method , from (7) we can know:

$$f = A \cdot X \tag{8}$$

Where, the factors in vector X constitute $\left\{p_1, q_1, r_1, p_2, q_2, r_2\right\}$ which is a set of conclusion parameters, if there are p groups of input-output data and conditional parameters, then the dimensions of matrixes A, X, f are $p \times 6, 6 \times 1, p \times 1$.The number of the general sample data is much larger than that of position parameters, finally we can get the best valuation of conclusion vector X^* under $\min\left\|AX - f\right\|$ by least square learning algorithm, that:

$$X^* = \left(A^T A\right)^{-1} A^T f \tag{9}$$

(2) According to the conclusion parameters obtained in step 1, the error can be calculated. We can use BP algorithm in forward-feedback neural network to send the error from output to input in reverse, and then apply the gradient descent algorithm to update the conditional parameters, thereby change the shape of membership function.

Before simulation, through input and output data, train the ANFIS whose rule number and membership functions shape are defaulted, and then form a fuzzy inference module which is suited for existing data model. The module’s working principle and process are similar to the typical fuzzy inference, including input fuzzification, fuzzy inference, defuzzification, output control.

III. DESIGN OF ADAPTIVE FUZZY NEURAL CONTROLLER

Figure 2 shows adaptive fuzzy neural network controller that maintains the conventional cascade control [11], the main controller is replaced by a fuzzy controller on basis of ANFIS and an intelligent proportional integral controller, while the deputy controller is still a P controller.

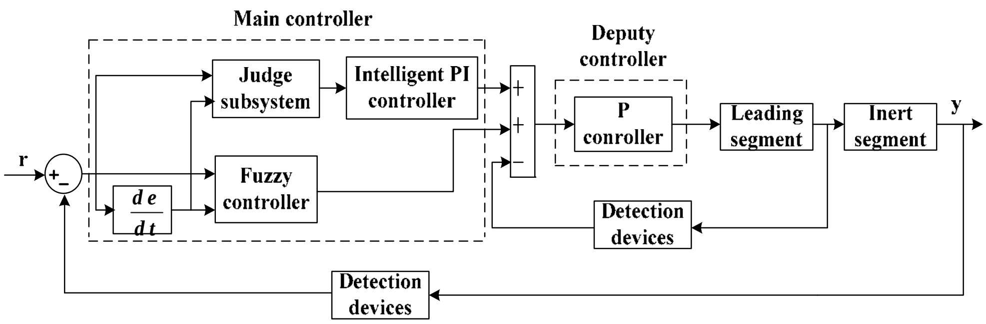

Figure 2. Adaptive neural fuzzy intelligent structure

A. Adaptive fuzzy neural network controller

The fuzzy rule of adaptive fuzzy neural system applies a linear combination of input variables, that:

$$R_j: \text{if } x_1 \text{ is } A_1^j \text{ and } x_2 \text{ is } A_2^j, \cdots, x_i \text{ is } A_i^j \cdots,$$

$$\text{then } y_j = p_{j0} + p_{j1}x_1 + \cdots p_{ji}x_i + \cdots \quad (10)$$

Where, $(i = 0,1,\cdots,n; j = 1,2,\cdots,m)$, R_j is fuzzy implication relationship of the j^{th} fuzzy rule, A_j^i is the j^{th} linguistic variable value of x_i ,and p_{ji} is the connection weight of back network. For the given input x, if the input uses single fuzzification, we can calculate the fitness of every rule:

$$\alpha_j = \mu_{A_1^j}(x_1) \wedge \mu_{A_2^j}(x_2) \cdots \wedge \mu_{A_n^j}(x_n) \quad (11)$$

Where, $\mu_{A_i^j}(x_i)$ is the membership function of fuzzy set A whose i^{th} input component is attached to the j^{th} linguistic variable. The output of fuzzy system is the weighted average of every rule output, that:

$$y = \frac{\sum_{j=1}^{m} \alpha_j y_j}{\sum_{j=1}^{m} \alpha_j} \quad (12)$$

Where, α_j is the fitness of every rule for the given input x [12].

The error e of superheater outlet temperature and the error ratio ec are two input variables of adaptive fuzzy neural network controller. The corresponding fuzzy variables of e and ec are E and EC, and the basic domain of E and EC are both selected as [-6, +6]. According to the training sample data query table of conventional temperature fuzzy control [13], load the training sample data into training data set by neural fuzzy inference editor [14], and then define the number and the style of input variable's membership function as seven and "gaussmf", at the same time the style of output variable's is defined as "constant".

Set the initial step of the training 0.01, goals error 0, after a 400-step training, it can generate the initial fuzzy inference system automatically which is a 2-14-49-49-1 five-level fuzzy neural network, as shown in figure 3. Figures 4, 5 respectively show the membership function curves of E and EC that are obtained through training.

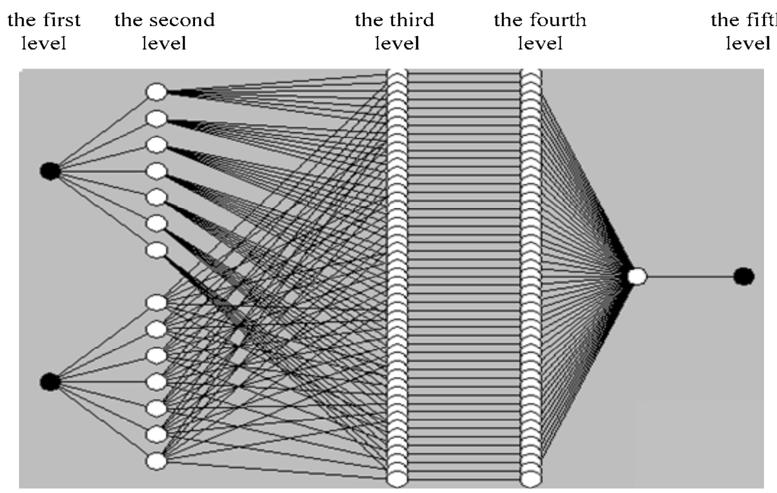

Figure 3. Fuzzy neural network structure

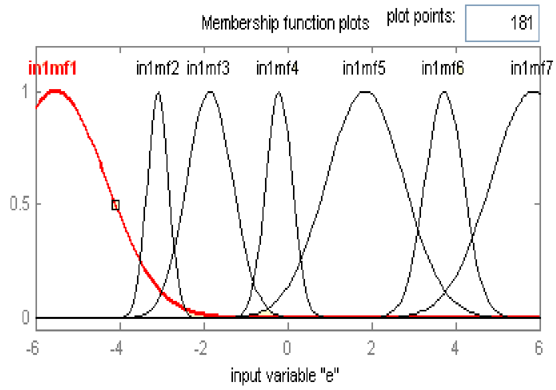

Fig. 4. The membership function of E

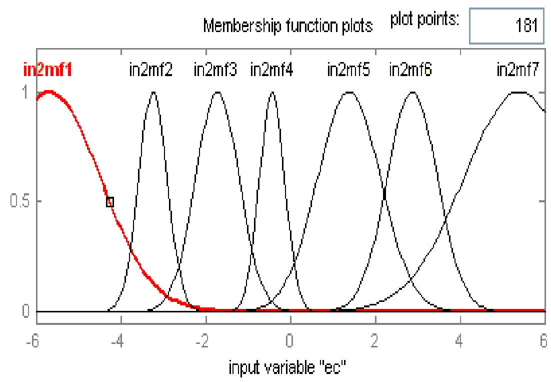

Fig. 5. The membership function of EC

B. Intelligent proportional integral controller

Intelligent PI controller is made of a logical judge subsystem with enabled port and a proportional integral part, as shown in figure 6. According to the signs of e and ec, the logical judge subsystem determines the state of system in order to control effectiveness of the PI part. Define error $e = r - y$, ec is error ratio, if $e \cdot ec > 0$ *or* $e = 0$ *and* $ec \neq 0$, then the main controller is constituted with fuzzy neural network controller and proportional integral controller, and if $e \cdot ec < 0$ *or* $ec = 0$, then the PI part is invalid, the main controller contains only fuzzy neural network controller.

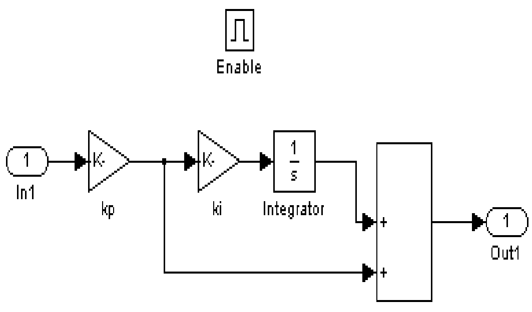

Fig. 6. Intelligent PI controller structure

C. Simulation analysis

This paper uses superheated steam temperature model of 600MW boiler in a power plant as controlled object, Table 1 shows the transfer functions of superheated steam temperature under different loads [15]. Simulate the adaptive fuzzy neural network controller (AFNNC) by Matlab/Simulink, then compare with fuzzy control (FC) and neural network control (NNC).

In the case of no outside interference, the three controllers are simulated separately. The given input is an adopted unit step signal, and the controlled objects are superheated steam temperature models under 100% load, 75% load and 50% load.

In the superheated steam temperature cascade control system, we set the parameter of deputy controller which is a single proportional one as 25, that, $k_{p2} = 25$. Meanwhile, we also set the parameters of the main controller, that, quantization factor $k_e = 65$, $k_{ec} = 350$, scale factor $k_u = 0.02$. The parameters of intelligent proportional integral controller are: $k_{p1} = 1.2$, $k_{i1} = 100$ .The simulation results are shown in Figure 7, 8, 9. Data in table 2, 3, 4 describes system's response curves performance indicators under different loads.

Table 1. Models of superheated temperature plant

Load	Anterior zone	Inert zone
100% load	$\frac{0.815}{(1+18s)^2}$	$\frac{1.276}{(1+18.4s)^6}$
75% load	$\frac{1.657}{(1+20s)^2}$	$\frac{1.202}{(1+27.1s)^7}$
50% load	$\frac{3.067}{(1+25s)^2}$	$\frac{1.119}{(1+42.1s)^7}$

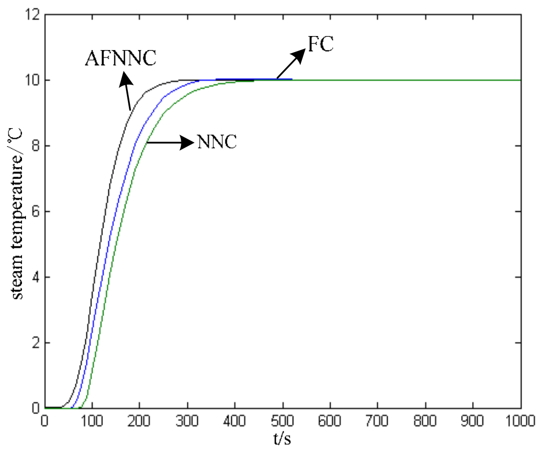

Fig. 7. The step response curves under 100% load

From the data of the tables, we can see adaptive fuzzy neural network control is significantly better than any other control method. This control system has shorter adjusting time. When the object changes load, it shows good dynamic and static characteristics and it has better adaptability

We still use the above steam temperature model under 100% load as controlled object. At 100s, join a disturbance signal which is a unit step one. The simulation results are shown in figure 10. Table 5 describes its response curves performance indicators.

It is seen that anti-interference ability of adaptive fuzzy neural network controller can still keep a good control effect when outsides disturbance happens, and its steady-state error is almost close to 0. It is superior to conventional fuzzy controller and neural network controller.

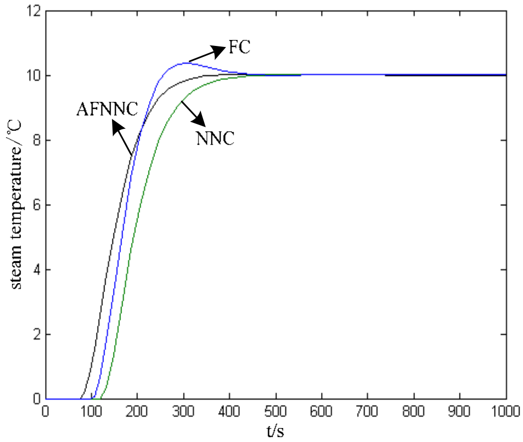

Fig. 8. The step response curves under 75% load

Table 2. Response curves performance indicators under 100% load

Control method	Delay time (s)	Overshoot σ_p (%)	Adjusting time (s)	Steady-state error (%)
NNC	60	0	420	0
FC	53	0	330	0
AFNNC	30	0	300	0

Table 3. Response curves performance indicators under 75% load

Control method	Delay time (s)	Overshoot σ_p (%)	Adjusting time (s)	Steady-state error (%)
NNC	118	0	480	0.2
FC	90	2.5	460	0.5
AFNNC	70	0	350	0

Table 4. Response curves performance indicators under 50% load

Control method	Delay time (s)	Overshoot σ_p (%)	Adjusting time (s)	Steady-state error (%)
NNC	185	0	685	0.6
FC	150	12	600	1
AFNNC	97	0	396	0

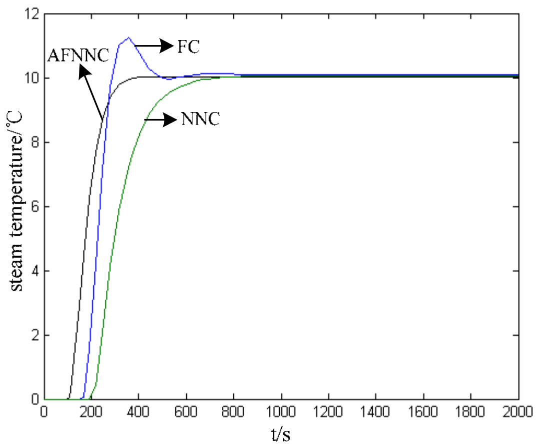

Fig. 9. The response curves under 50% load

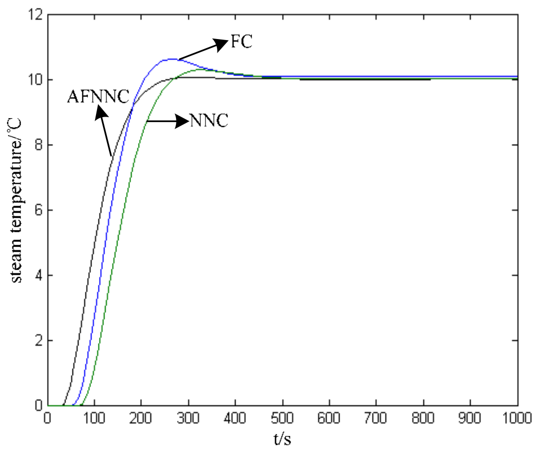

Fig. 10. The response curves with jamming under 100% load

Table 5. Response curves performance indicators under 100% load when it is disturbed

Control method	Delay time (s)	Overshoot σ_p (%)	Adjusting time (s)	Steady-state error (%)
NNC	60	1	602	0.01
FC	50	6	500	2
AFNNC	30	0.05	395	0.5

IV. CONCLUSION

For superheated steam temperature of boiler in thermal power plant has large delay and inertia, the adaptive fuzzy neural network control strategy overcomes the shortcomings of conventional fuzzy controller whose steady-state accuracy is not high and fuzzy rules are difficult to determine. In addition, it can avoid falling into local minimum during training data, which is superior to conventional neural network control.

For complex objects, this control method can achieve good control performance and show good dynamic quality, steady performance, anti-jamming characteristic, etc. It also has high engineering value.

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