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Intelligent temperature control system of quench furnace①

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Abstract: A fuzzy-neural networks intelligent temperature control system of quench furnace was presented. Combined genetic algorithm with back-propagation algorithm, the weight values of neural networks, parameters of fuzzy membership functions and inference rules can be adjusted automatically, which realizes the optimal control of temperature. The results show that this control system can run effectively with satisfied temperature precision: in temperature uprising stage, overshot of temperature is under 4 ℃; in stable stage, the scope of temperature change is controlled within ±2 ℃, which meets the need of control veracity of temperature.

Key words: fuzzy-neural networks; MIMO system; genetic algorithm
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1 INTRODUCTION

Quench furnace is a kind of key equipment used to heat treat large complex components of aircrafts or rockets, with height of 24 m, containing two heating rooms and a workroom, with steel boards set between the rooms. Both heating rooms are separated into six sections, each of which contains a heating resistance controlled by a power adjuster. Workpieces are put in workroom. A centrifugal electromotor is used to blow hot air into workroom from heating room. The demand of alloy in temperature-rising rate and stable veracity at fixed temperature point is high, rising time needs to be short, overshoot temperature should keep under 6 ℃, at the stable stage, the scope of temperature change is not more than ±3 ℃. These two factors affect the structure and quality of workpieces, especially the latter. The structure of the quench furnace is shown in Fig. 1.

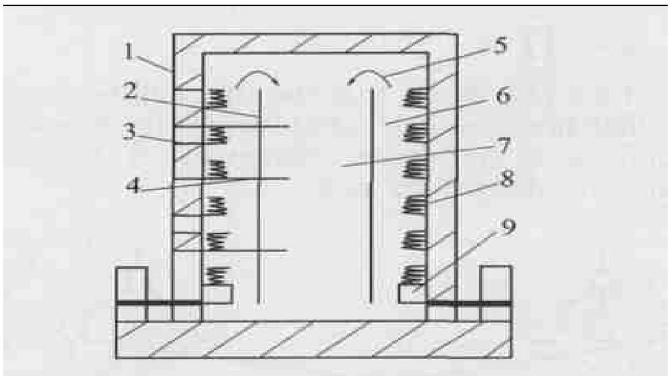

Fig. 1 Structure of quench furnace
1—Shell; 2—Steel board; 3—Thermocouple in heating room; 4—Thermocouple in work room; 5—Direction of wind; 6—Heating room; 7—Work room; 8—Heating resistance; 9—Electromotor

Temperature control system of quench furnaceis nonlinear, strong-coupling, time-varying, long-time delay, which makes construction of accuracy system model impossible. Mathematical model was discussed in Ref. [1], temperature prediction was given by the acquired mathematic model in Ref. [2], because the existence of undeterminable factors, the veracity of model and prediction were constrained. Multi-section temperature control was discussed in Ref. [3], which was also based on mechanic mathematical model.

When the system model is complicated or hard to construct, engineers often describe the plant by expert knowledge and control it by intelligent methods, such as fuzzy or expert method. If fuzzy control is chosen, the knowledge base, rule base, type of membership functions, defuzzification methods and so on, will all affect the control effect.

2 FUZZY-NEURO STRUCTURE OF CONTROL SYSTEM

Many research results have been acquired in generating fuzzy rules and adjusting fuzzy member functions by neural networks or genetic algorithms[4-8], the combination of neural networks and fuzzy inference has the advantages of self-learning and inference. It has been widely applied in solving engineering problems[9-11].

Among these researches, most of them are simple input and simple output system (SISO)[5-7], or multi-input and simple output system [4, 8, 9, 12, 13],

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then regarding the multi-input and multi-output system (MIMO) as the combination of MISO system, in the meantime, number of the membership functions of input and output is regarded to be similar. Research on abstracting rules by GA can be found in Refs. [6, 14], but only MISO system was discussed. In this paper, MIMO fuzzy-neuro system with different semantic term is discussed, GA optimal method is also employed to attain general MIMO method, eventually, this method is used in temperature control of quench furnace.

2.1 MIMO fuzzy-neuro system

Suppose control system has m inputs and n outputs, each input has $S_i (i = 1, 2, \cdots, m)$ membership functions, each output has T_j membership function $(j = 1, 2, \cdots, n)$, then the total rule is

$$q = \prod_{i=1}^{m} S_i \qquad (1)$$

Eqn. (1) shows that the rule number increases in index law with the variables and the membership functions of variables. Structure of fuzzy-neuro system is shown in Fig. 2.

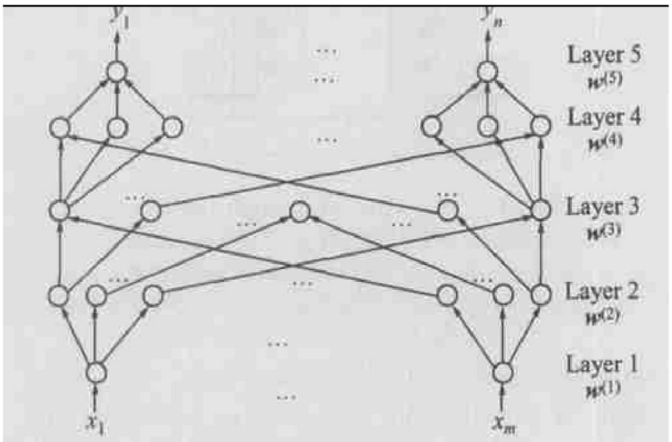

Fig. 2　Structure of fuzzy-neuro system

The first layer is input layer which is crisp, the node functions perform the transfer of input to the next layer, equations between the inputs and the outputs can be written as

$$O_{ji}^{(1)} = w_{ji}^{(1)} x_i^{(1)} = \boldsymbol{w}^{(1)} x_i^{(1)}$$

The second layer performs fuzzification of the input variables, the neuron node functions transfer the crisp input into semantic term, if the Gauss activation function is employed, we have the following equation:

$$O_j^{(2)} = \mu_{ji} = \exp[-(\frac{x_{ji}^{(2)} - c_{ji}}{a_{ji}})^2] \quad x_{ji}^{(2)} = O_{ji}^{(1)} \qquad (2)$$

where the weights and biases of neural networks represent the widths (a_{ji}) and the means (c_{ji}) of input membership functions respectively. Number of neurons at this layer is $n^2 = \sum_{i=1}^{m} S_i$. Weights matrix is represented by $\boldsymbol{w}^{(2)}$, number of row and line is identical, so it is a diagonal matrix.

$$\boldsymbol{w}^{(2)} = \begin{bmatrix} \frac{1}{a_{11}} & 0 & \cdots & 0 \\ 0 & \frac{1}{a_{12}} & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{a_{ms_m}} \end{bmatrix}$$

$$\boldsymbol{w}^{(3)} = \begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & \ddots & 0 \\ 0 & \cdots & 0 & 1 \end{bmatrix}$$

The third layer describes the antecedent part of rules. At the beginning, neuron node number is the maximum rules, the weights matrix of neural networks $\boldsymbol{w}^{(3)}$ is used to describe the antecedent part, each row of the matrix represents the antecedent of a rule, the elements of matrix consist of 1 and 0, where '1' denotes that the correspondent antecedent exists, '0' is on the versus, the total number of 1 is less than m. The node function calculates the firing strength, multiplier method is adopted, so the jth output node has the following form:

$$O_j^{(3)} = \min(\mu_{ji}) = I_j^{(4)} \qquad j = 1, 2, \cdots, \prod_{i=1}^{m} S_i \qquad (3)$$

The row and line of weight matrix $\boldsymbol{w}^{(3)}$ is $\prod_{i=1}^{m} S_i$ and $\sum_{i=1}^{m} S_i$, respectively, the elements 1 in the first row and the second column, the first row and the last column represent the following antecedent:

rule^i: IF x_1 IS μ_{12} AND $\cdots$ AND x_m IS μ_{mM} THEN $\cdots$

The others represent the antecedent of rules in the similar manner.

The fourth layer consists of outputs. Neuron output in this layer is the sum of firing strength of rules with similar consequence, the number of neuron is $n^4 = \sum_{j=1}^{n} T_j$, and T_j is the number of membership function of jth output. Weight matrix can be adjusted in the training process, every element in which consists of 0 or 1, each row represents the output membership function term in the consequence part of a rule which is defined by column number. Since there are n outputs, n separate block matrix exists representing every output. Row of each block matrix is T_j, column is $\prod_{i=1}^{m} S_i$, the form of which is similar to the $\boldsymbol{w}^{(2)}$, only the number of row and column and the number of 1 in them is different. For example, position of 1 in the first row and the second column of ith block matrix row show that the second rule has the ith membership function term in the consequence part, as in the following:

R^2: IF … THEN … y_i IS T^1_{yi}

Several '1' may exist in each row of $\boldsymbol{w}^{(4)}$ because consequence of several rules may have similar output semantic term, however, a rule can have only one output term, number of 1 in a column is not more than one, then $\boldsymbol{w}^{(4)}$ is as

$$\boldsymbol{w}^{(4)} = [\, w_1 \mid w_2 \mid \cdots \mid w_i \mid \cdots \mid w_n \,]^{\mathrm{T}}$$

$$\boldsymbol{w}_i = \begin{bmatrix} 0 & 1 & \cdots & 1 \\ 0 & 0 & 0 & 0 \\ \vdots & 0 & \ddots & 0 \\ 0 & \cdots & 0 & 0 \end{bmatrix} \quad i = 1, 2, \cdots, n$$

The fifth layer is output layer, defuzzification is performed in this layer, if center of gravity method is employed, output can be written as

$$y_i = \sum_{j=1}^{T_j} m^j_{yi}\delta^j_{yi} \Big/ \sum_{j=1}^{T_j} \delta^j_{yi} \qquad (4)$$

where m^j_{yi} and δ^j_{yi} are mean and width of the jth output membership function for the ith system output. Weight matrix is similar to the second layer, row and column are equal, it consists of a diagonal matrix.

2.2 Fuzzy-neuro structure of quench furnace

Because the two heating rooms have the same structure, here only one is discussed, the quench furnace can be treated as a 6 inputs and 3 outputs control system. The inputs control the on and off time of the resistance, output is the temperature of workroom. In the heating room, hot air rises, so the bottom resistance needs to produce more heat to maintain the uniformity of the temperature in the working room. In the working room, the hot air is from top to bottom, loading workpieces is through bottom, which causes the lower part with low temperature. In order to simplify the problem, temperature value measured in up and middle part is averaged, treated as one output.

The difference of temperature (e) and the change of difference (Δe) are treated as fuzzy-neuro inputs, the difference is described by 5 semantic terms, the change of difference is described by 3 semantic terms. So the fuzzy-neuro networks has 4 nodes in the first layer, 16 and 225 nodes in the second and third layer, respectively. Like the output of temperature, the bottom heating room is described by 5, the others used 3 to present, so the fourth layer and the fifth layer has 20 and 6 nodes, respectively, and thus the fuzzy-neuro networks is determined, the weight matrix is adjusted by GA and BP, optical realization of the system are acquired by the optical parameters.

3 GA AND BP TRAINING ALGORITHMS

In oder to acquire an optimal fuzzy-neuro structure of the system, training is performed by experiment data, by adjusting the parameters and rules. Before training process, the initial parameters and rules are chosen at random or by expert experience. The structure frame is shown in Fig. 3.

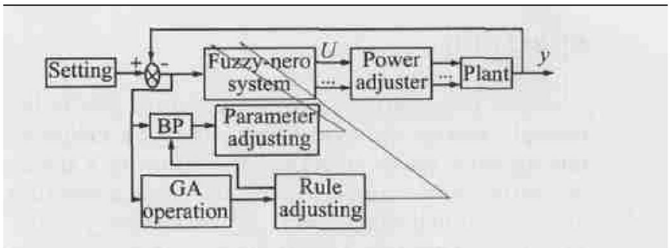

Fig. 3 Structure of control system

From the above analysis, we know that the fuzzy rules are defined in layers 3 and 4. The weight matrix is coded as the chromosomes of GA, which has the structure as follows: each chromosome has n parts, each part is called a sub-chromosome, the number of genes in each sub-chromosome is the sum of rules Q, the antecedent and conclusion matrix is encoded by an integer, which belong to a set $C_j \in [0, 1, \cdots, T_j]$ ($j = 1, 2, \cdots, Q$). In the initial phase, the length of each part is equal to the number of membership function, the value of C_j denotes the row position of 1 in each column of the ith conclusion block matrix: if there is no membership function of certain output, C_j is zero, the structure of chromosome can be depicted in Fig. 4.

Fig. 4 Form of chromosome

GA acts on each sub-chromosome to find the optimal fuzzy rules. Calculating the sum of square error of difference for each individual in the population, subtracting it from the largest error value of that generation makes the fitness function of each individual, if there are enough input/output experiment data, GA can be applied to find the optimal set of fuzzy rules. Initialization contents contain the following: number of population, times of iteration, permitted errors, selection probability, cross probability, mutation probability and so on, the chromosomes are chosen randomly at the beginning, denoting the weight matrix of layers 3 and 4.

Because the initial parameters of Gauss function is chosen at random or by expert experience, BP algorithm is employed to optimize the weight matrix parameters of layers 2 and 5. The object function is the minimum of square error sum.

$$E = \frac{1}{2}\sum_{k=1}^{n}(y_k - y_{kd})^2 \qquad (5)$$

The optimal weights and thresholds are attained by BP algorithm, which are the optimal membership function parameters of inputs and outputs. Two inputs MF have the similar parameters, and the upper 5 outputs have the similar MF parameters.

4 RESULTS

The temperature is measured every 400 millisecond, average value of every 5 measure values as one measure value, average value of every 4 measure value as one sample value. The set temperature value of up and middle part in work room is 470, 468 ℃ at bottom part, respectively. Sample internal is 8s, the sample data is also the feedback value of control system. In GA, initial population is 50, iterative times is 200, permitted error is 0.3 ℃, selection probability is 0.5, cross probability is 0.3, mutation probability is 0.05, after the GA and BP, the data in Tables 1 and 2 are acquired. Experiment shows that better control effect is attained by these parameters, the biggest relative error is 0.89%.

Table 1 MF Parameter of 3 inputs

Class	e		Class	Δe	
	a	c		a	c
NB	90	182	N	34	38
NS	85	262	Z	38	68
Z	71	338	P	42	98
PS	58	396			
PB	52	445			

Table 2 MF Parameters of 6 outputs

Class	δ	m	Class	δ	m
S	0.24	0.32	VS	0.20	0.25
M	0.16	0.68	S	0.13	0.43
B	0.22	0.87	M	0.14	0.56
			B	0.23	0.71
			VB	0.30	0.86

5 CONCLUSIONS

1) The MIMO system model of quench furnace is constructed according to the demand of temperature. Combining genetic algorithm with back-propagation algorithm, the weight values of neural networks, parameters of fuzzy membership functions and inference rules are adjusted automatically to realize the optimal control of temperature.

2) This control system can run effectively with satisfactory temperature precision: in uprising stage, overshot of temperature is 3 ℃, in stable stage, the scope of temperature change is controlled within ±2 ℃. It has been used in a factory successfully.

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