Research and Application on Two-stage Fuzzy Neural Network Temperature Control System for Industrial Heating Furnace

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***Abstract*—Industrial heating furnace has a great deal of special characteristics such as big capacity, long lag and non-linear trait, etc. In order to control it better, we present a sort of fuzzy neural network temperature control model. It can transform the rulers of fuzzy logic control to a pair of input-output samples of multilayer forward neural network.The knowledge is not expressed by a serial of rules but distributed into the whole network. Based on this model, we have designed a two-stage fuzzy neural network temperature control system for industrial heating furnace. The first-stage controller is responsible for determining the control variable according to deviation information of controlled variable. The second-stage controller takes charges of adjusting the control variable coming from the first-stage controller through other process parameters. The system takes full account of the impact of many process parameters on controlled variable. It uses two-stage fuzzy neural network controller to decentralize process of control parameters, which makes it easy to extract fuzzy rules, greatly reduces the number of fuzzy rules and produces reasonable control outputs. Engineering applications show that the system has a lot of advantages such as high accuracy, strong robustness, etc. Its quality is superior to conventional control and it is suitable for long lag, non-linear system in particular.**

***Index Terms*—fuzzy control, heating furnace, temperature control, fuzzy neural network**

I. INTRODUCTION

Heating furnace takes an important part in industrial production. There are many features such as long tag, large inertia and nonlinear characteristics existed in control system for industrial heating furnace, which leads to a lot of factors to disturb the system. Traditional PID control is a type of control with fixed parameters, thus it is difficult to achieve a good stability and good control quality simultaneity. Fuzzy control is a new control technology which is coming from the combination of control theory and fuzzy set theory. It can make use of the operating experience of skilled operators and the experts' knowledge in the field. Through the selection of appropriate fuzzy control rules, it can ensure control system stably to work and to maintain a good control performance [1, 2]. Thus, fuzzy control has immediately aroused wide interests in the control community since its beginning and has acquired a rapid development.

Wu Suixin, Liu Xiangjie, Rong Li[3，4，5] used fuzzy control technology in boiler combustion system and got satisfactory results. Nie Yunfeng, Dai Luping[6, 7] adopted fuzzy predictive method to control heating furnace and obtained a good control performance. Chen Bofang, Li Qingru and their colleagues [8, 9]got a higher accuracy to heater though combination of both fuzzy control and neural network control.

However, among these studies above, control systems were designed only based on a single fuzzy controller to replace traditional PID control. In general, fuzzy control rules consist of the three linguistic variables: deviation of controlled variable, change of error and control variable. The principle of fuzzy control based on the rule structure is the same as PID control. The controlled variable is determined according to the deviation of controlled variable measured at present. This control method is generally applicable to the control object with small lag, but it is not suitable for the control target with large lag. The reason is that the deviation of controlled variable can not reflect changes of control variable in time. So, the control effect is poor [10].

Fuzzy logic has a strong power for structural intellectual expression. It can better express experience

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knowledge and qualitative knowledge, but it doesn't usually have ability to learn. Neural network has strong learning ability and data direct processing ability, but mode of knowledge expression in its interior is not clear. Its learning begins from arbitrary initial conditions, and its learning result is totally dependent on training sample. Fuzzy neural network control combines the advantages of both fuzzy control and neural network, not only taking use of expert's experience knowledge, but also possessing gradually optimized learning function.

Therefore, in this paper, we present a two-stage fuzzy neural network control model. The first-stage controller is responsible for determining the control variable according to deviation information of controlled variable. The second-stage controller takes charge of adjusting the control variable, which is coming from the first-stage controller, through other process parameters. The algorithm takes full account of the impact of many process parameters on controlled amount. It uses two-stage fuzzy neural network controller to decentralize process of control parameters, which makes it easy to extract fuzzy rules, greatly reduces the number of fuzzy rules and produces reasonable control outputs.

II. CONTROL MODEL AND ALGORITHM

We take a heat-conducting oil furnace in a chemical plant as a controlled object and design a two-stage fuzzy temperature control system for industrial heating furnace. The first-stage is a fuel flux fuzzy neural network controller with responsibility to control fuel flux. Its input variables are temperature deviation of out-furnace heat-conducting oil and the difference between the temperature of in-furnace heat-conducting oil and the temperature of out-furnace heat-conducting oil to be set, while its output variable is increment of fuel flux. The second–stage is air flux Fuzzy Neural Network controller with responsibility to track real-time changes of fuel flux and to regulate air flux. Its input variables are temperature increment of out-furnace heat-conducting oil and increment of fuel flux, while its output variable is increment of air flux. The structure of control system is shown in Fig. 1.

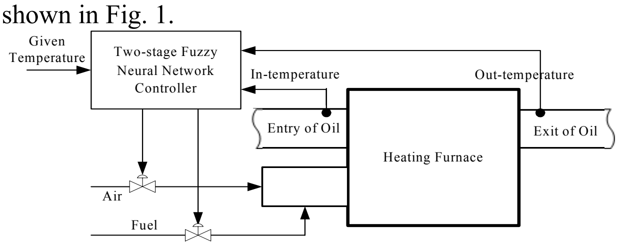

Figure 1. Structure of Fuzzy Control System

According to the operating experience of on-spot operators, the temperature control algorithm can be described as:

Step 1 First of all, set temperature of out-furnace heat-conducting oil Q. Calculation the best fuel flux U as its initial value.

Step 2 Measure the temperature of in-furnace heat-conducting oil B and the temperature of out-furnace heat-conducting oil C_i in unit time. Calculate temperature difference of out-furnace heat-conducting oil ΔA ($\Delta A = C_i - Q$), temperature difference of in-furnace heat-conducting oil ΔB ($\Delta B = B - Q$), temperature increment of out-furnace heat-conducting oil (namely, the temperature difference of out-furnace heat-conducting oil between the temperature measured this time and the previous) ΔT ($\Delta T = C_i - C_{i-1}$)

Step 3 According to ΔA and ΔB, through the fuzzy inference made by the first-stage fuel flux fuzzy neural network controller, obtain increment of fuel flux to be ΔU.

Step 4 Calculate the current fuel flux $U = U + \Delta U$. Calculate the best air flux as its initial value P.

Step 5 According to ΔA and ΔU, through the fuzzy inference made by the second-stage air flow fuzzy neural network controller, obtain increment of air flow to be ΔP. Goto step 2.

III. DESIGN OF FUZZY NEURAL NETWORK CONTROLLER

A. Fuel Flux Controller

1) Controller structure: Here we use a five-layer neural network to construct fuzzy controller, as shown in Fig. 2.

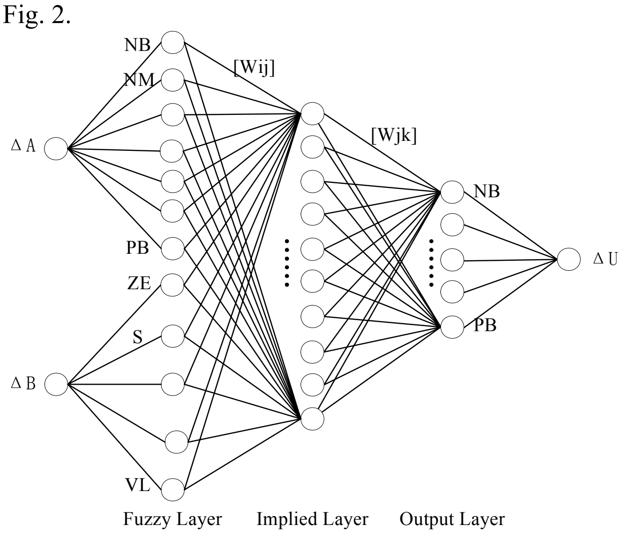

Figure 2. Fuel flux neural network topology structure

The first layer is input one with two nodes. Each node directly connects with each component of input vectors, Its input variables are temperature difference of out-furnace heat-conducting oil ΔA and temperature difference of in-furnace heat-conducting oil ΔB. Inspirit function of the nodes is

$$f(x)=x \tag{1}$$

The second layer is fuzzy one including 12 nodes. Each node represents a language variable value {NB, NM, NS, ZO,PS, PM, PB, ZE, S, M, L,VL}. They represent the all fuzzy set of input language variables and carry out the map from accurate input to fuzzy values.

The third layer is implied one of the neural network including 10 neurons. Implied layer takes charges of operating membership values from fuzzy layer to implement the process of fuzzy reasoning by means of the relation of input data and types.

The fourth layer is output one. The output is a membership function of input samples relative to increment of fuel flux ΔU, including 5 neurons. Connection weight [Wij] and [Wjk] are trained to indicate the control rules. S curve is used as prompting functions for the third and fourth layers:

$$f(x)=1/(1+\exp(-x)) \quad (2)$$

The fifth layer is defuzzification one. The final identification results are determined by the rule of largest membership.

2) Foundation of fuzzy relation: The fuzzy relation of fuzzy system, namely the library of fuzzy rules, may be stored by parallel through the study of neural network [12]. There are two inputs (ΔA and ΔB) and an output (ΔU).

The universes of discourse of ΔA are {-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5}. Its fuzzy language values are {NB, NM, NS, ZO, PS, PM, PB}. Its membership function assignment table is as shown in TABLE I.

TABLE I. ΔA MEMBERSHIP FUNCTION ASSIGNMENT TABLE

ΔA	-5	-4	-3	-2	-1	0	1	2	3	4	5
NB	1.0	0.9	0.6	0.2							
NM	0.2	0.7	1.0	0.7	0.2						
NS		0.2	0.8	1.0	0.8	0.2					
ZO			0.1	0.4	0.6	1.0	0.6	0.4	0.1		
PS						0.2	0.8	1.0	0.8	0.2	
PM							0.2	0.7	1.0	0.7	0.2
PB								0.2	0.6	0.9	1.0

The universes of discourse of ΔB are {0, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20}. Its fuzzy language values are {ZE, S, M, L, VL}. Its membership function assignment table is as shown in TABLE II.

TABLE II. ΔB MEMBERSHIP FUNCTION ASSIGNMENT TABLE

ΔB	0	2	4	6	8	10	12	14	16	18	20
ZE	0.2	0.7	1.0	0.7	0.2						
S		0.2	0.8	1.0	0.8	0.2					
M				0.1	0.6	1.0	0.6	0.1			
L						0.2	0.8	1.0	0.8	0.2	
VL							0.2	0.7	1.0	0.7	0.2

The universes of discourse of ΔU are {-3, -2, -1, 0, 1, 2, 3}. Its fuzzy language values are {NB, NS, ZO, PS, PB}. Its membership function assignment table is as shown in TABLE III

TABLE III. ΔU MEMBERSHIP FUNCTION ASSIGNMENT TABLE

ΔU	-3	-2	-1	0	1	2	3
NB	0.7	1.0	0.7				
NS	0.2	0.8	1.0	0.8	0.2		
ZO		0.1	0.6	1.0	0.6	0.1	
PS			0.2	0.8	1.0	0.8	0.2
PB					0.7	1.0	0.7

For a temperature control system, when the temperature error is larger, the primary task of controller is to quickly eliminate the error. Therefore, a larger control signal is needed to speed up raising or falling the temperature in order to increase the rapid response of the system. In contrast, when the temperature error is smaller, the primary task of controller is to stabilize the system as soon as possible. Therefore, a small control signal is needed to avoid a large overshoot. Combining operating experience of on-spot workers, we obtain fuel flux fuzzy control rules as shown in TABLE IV

TABLE IV. FUEL FLUX FUZZY CONTROL RULE TABLE

ΔB	ΔA						
	NB	NM	NS	ZO	PS	PM	PB
ZE	PB	PB	PS	PS	PS	ZO	ZO
S	PB	PB	PS	PS	ZO	NS	NS
M	PB	PB	PS	ZO	NS	NB	NB
L	PS	PS	ZO	NS	NS	NB	NB
VL	ZO	ZO	NS	NS	NS	NB	NB

Then, the input of second layer corresponding to the membership function of input fuzzy set can be expressed as following:[NB, NM, NS, ZO,PS,PM, PB, ZE, S, M, L,VL].

The output of the fourth layer is the membership function of output fuzzy set, which can be shown as following:[NB,NS,ZO,PS,PB].

It can be expressed by corresponding training samples.

For example, for control rule R1: "ΔA is NB and ΔB is ZE,then ΔU is PB".

Input sample is [1 0 0 0 0 0 0 1 0 0 0 0 0 0]

Output sample is [1 0 0 0 0]

For other rules, their train samples are similar to the above ones. After learning, all the control rules can be expressed by a series of input and output signals. Thus, the trained network is equivalent to storage of fuzzy relationships where all the fuzzy rulers can be stored by weights of the network.[11].

B. Air Flux Controller

Through analysis and on-spot observation to combustion process of heat-conducting oil furnace, we have found that in addition to fuel flux, the air flux is also an important parameter affecting temperature. So the air/fuel ratio will directly affect heating effect for furnace. If the ratio is too large, although the fuel can be fully burned, but excess air will take part of heat in the heating furnace away, which will arouse a waste of energy. If the ratio is too small, the fuel will not fully burned, which will reduce the thermal efficiency and also arouse a waste of energy. At the same time, a lot of smoke is emitted to pollute the environment. In addition, there are a lot of technological devices as users who will get heat from heat-conducting oil and different users have different temperature control, which leads to greater temperature fluctuations of heat-conducting oil which is cycling back to furnace.

The key to control combustion efficiency of heating furnace is to set the air/fuel ratio, namely, the ratio between the air flux and the fuel flux sent to the furnace. When the fuel flux is certain, to control air/fuel ratio actually becomes to regulate air flux. Its input variables are temperature increment of out-furnace heat-conducting oil ΔT and increment of fuel flux ΔU. Its output variable is increment of air flux ΔP.

1) Fuzzy Process of Input and Output Variables: The universes of discourse of ΔT are {-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5}. Its fuzzy language values are {NB, NM, NS, ZO, PS, PM, PB}. Its membership function assignment table is as shown in TABLE V.

TABLE V. ΔT MEMBERSHIP FUNCTION ASSIGNMENT TABLE

ΔT	-5	-4	-3	-2	-1	0	1	2	3	4	5
NB	1.0	0.9	0.6	0.2							
NM	0.2	0.7	1.0	0.7	0.2						
NS		0.2	0.8	1.0	0.8	0.2					
ZO			0.1	0.4	0.6	1.0	0.6	0.4	0.1		
PS						0.2	0.8	1.0	0.8	0.2	
PM							0.2	0.7	1.0	0.7	0.2
PB								0.2	0.6	0.9	1.0

The universes of discourse of ΔU and ΔP are {-3, -2, -1, 0, 1, 2, 3}. Fuzzy language values of ΔU are {NB, NS, ZE, PS, PB}. Fuzzy language values of ΔP are {NB, NS, ZO, PS, PB}.ΔU and ΔP membership function assignment table is as shown in TABLE VI and TABLE VII.

TABLE VI. ΔU MEMBERSHIP FUNCTION ASSIGNMENT TABLE

ΔU	-3	-2	-1	0	1	2	3
NB	0.7	1.0	0.7				
NS	0.2	0.8	1.0	0.8	0.2		
ZE		0.1	0.6	1.0	0.6	0.1	
PS			0.2	0.8	1.0	0.8	0.2
PB					0.7	1.0	0.7

TABLE VII. ΔP MEMBERSHIP FUNCTION ASSIGNMENT TABLE

ΔP	-3	-2	-1	0	1	2	3
NB	0.7	1.0	0.7				
NS	0.2	0.8	1.0	0.8	0.2		
ZO		0.1	0.6	1.0	0.6	0.1	
PS			0.2	0.8	1.0	0.8	0.2
PB					0.7	1.0	0.7

2) Fuzzy Rule Table: Its control principle is: Add an increment to air flux, detect the temperature of out-furnace heat-conducting oil. If the temperature of out-furnace heat-conducting oil is raising or increment of fuel flux is increasing, then continue to increase air flux. If the temperature of out-furnace heat-conducting oil is falling or increment of fuel flux is reducing, then reduce air flux. Fuzzy control rules are as shown in TABLE VIII.

TABLE VIII. AIR FLUX FUZZY CONTROL RULE TABLE

ΔU	ΔT						
	NB	NM	NS	ZO	PS	PM	PB
NB	NB	NB	NB	NB	NB	NS	NS
NS	NB	NB	NB	NB	NS	NS	NS
ZE	PS	PS	ZO	ZO	ZO	PS	PS
PS	PS	PS	PS	PS	PB	PB	PB
PB	PS	PS	PB	PB	PB	PB	PB

Neural network model of air flux controller has the same structure with fuel flux controller, namely, taking five-layer neuron network, as shown in Fig. 3. Input of the network is temperature increment of out-furnace heat-conducting oil ΔT and increment of fuel flux ΔU. Its output is increment of air flux ΔP. While similar train method can be used, all the fuzzy rulers can be stored by weights of the network.

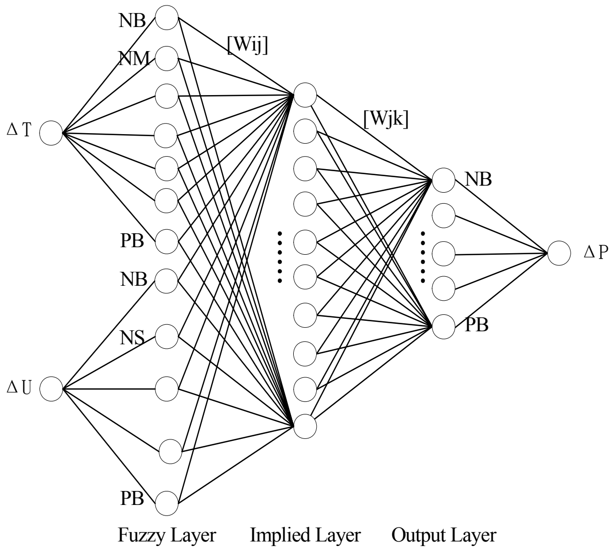

Figure 3. Air flux neural network topology structure

IV. SYSTEM SIMULATIONS

In the system experiment, we use a furnace with power of 3.2MM BUT / HOUR. It can be heated up to 500 □. Setting of temperature is 275 □. The main controller is S7-300PLC among SIMENS series. When it is heating, show circuit on hardware system real time can show the temperature setting value and the current out-furnace temperature value. At the same time, the temperature values collected by the hardware circuit can be transmitted to the host computer through the RS 232 serial port. Using C + + to develop a temperature monitoring program to show temperature control curve of out-furnace heat-conducting oil, and making a comparison with fuzzy control method[12], we achieve two different temperature control curves of out-furnace heat-conducting oil which are coming from two different temperature control algorithms. The result of system simulations is shown in Fig. 4.

In Fig. 4, curve □ shows fuzzy control and curve □ mains the fuzzy neural network control, while test temperature is set for 275 □. From the temperature control curves of out-furnace heating-conducting oil, we can see that the two-stage fuzzy neural network temperature control algorithm is much better than fuzzy control algorithm, especially in the following aspects: short adjustment time, entering steady-state quickly, no shock, high precise control and strong robustness.

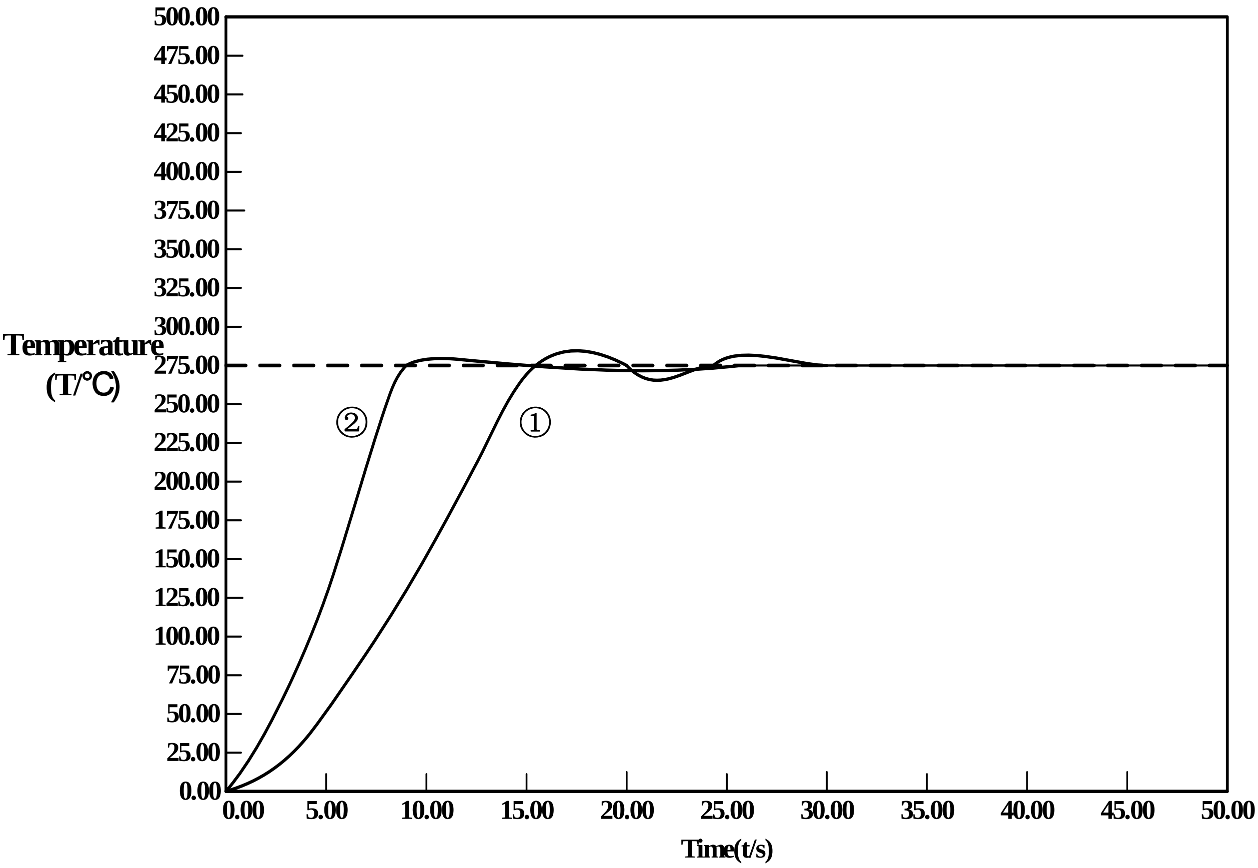

Figure 4. Temperature Control Curve

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