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The Application of Fuzzy Neural Network to Boiler Steam Pressure Control

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Abstract

The control effect of steam pressure is one of the most important factors influencing stability in chain type boiler. Aimed at the problem that the control of steam pressure is restricted by many factors, a kind of fuzzy neural network (FNN) is presented in this paper. The controller has the advantage of self-adapting, self-learning and tuning on-line. In simulation, this system exerts stably, with a less effect of uncertain factors, so it has a perfect control effect to main steam pressure systems of boiler.

Keywords: *Chain Furnace, Fuzzy Neural Network, Steam Pressure Controller.*

1. Introduction

During the normal working of the boiler in thermal power plant, steam pressure is one of the main operating parameters that needs close watching and controlling. Too high steam pressure will affect the life span of pressure containing components, cause explosion fault, bring serious harm to the equipment; steam pressure dropping will consume more steam and coal, influencing the efficiency of electricity generation and heat supply; too fast pressure change will make the boiler water circulation worse. Therefore, in the operation of the boiler, steam pressure should be controlled at a given value. The traditional PID control is computationally simple, intuitive in nature and strong robustness etc, but it needs to gain control of the mathematics model. While boiler is a nonlinear, strong coupled, multi-variable and complex system with large delay, it is hard to set an accurate mathematical model. And there are many internal and external factors influencing the boiler steam pressure, making it hard for the traditional PID control to achieve ideal controlling effects.

Fuzzy control and neural network control are controlling methods that develop very fast in recent years, the two methods do not depend on mathematical model of the controlled objects, and has good control effect and anti-jamming. But the fuzzy control rules and membership functions of the fuzzy design parameter can only rely on experience to choose, it is very difficult for it to design and adjust automatically, thus it lacks self-learning and self-adaptability. Although the neural network control has strong self-learning and self-adaptability, it has no the function of accessing uncertain information. The fuzzy neural network control combines the advantages of fuzzy control and neural network control, building a fuzzy controlling system with neural network. That is, with the learning method of neural network, it fulfills the automatic update of fuzzy rules' online modification and membership functions, bringing self-study and self-adaptive ability to fuzzy control. [1].

2. Fuzzy Neural Network Steam Pressure Control System

According to the structure and characteristics of boiler combustion in thermal power plant, a kind of fuzzy neural network controller is presented and it may control the system on line. Its structure is shown in Figure 1.

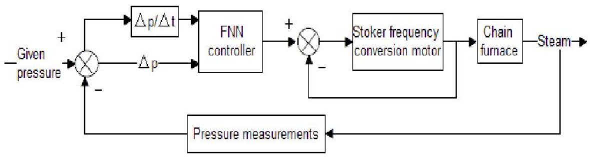

Fig. 1 Boiler steam pressure control loop.

Boiler steam pressure can be controlled by adjustment of coal supply, and the quantity of coal given is in proportion with stoker speed, so we control steam pressure through controlling the stoker speed. If there is a great positive deviation between the actual steam pressure and the given value, the steam pressure value would be high, then it needs reducing stoker speed to control combustion in order to reduce steam pressure. If there is a great negative deviation between the actual steam pressure and the given value, the steam pressure would be low, then it needs increasing stoker speed to help combustion in order to increase steam pressure.[2]

The fuzzy neural network controller fulfills fuzzy control algorithm through neural network structure. Theoretically speaking, the higher the dimension of neural network, the more accurate the control. But if the dimension is too large, fuzzy control rules becomes overly complicated, it is quite difficult to realize the control algorithm. In order to achieve the purpose of preciseness and simplicity, neural network use a five-layer network of two inputs and one output. We take the bias of steam pressure's real duration, given value and error rate as the input of fuzzy neutral network, and the output is the incremental of the stoker frequency conversion motor frequency. Its structure is shown in Figure 2.

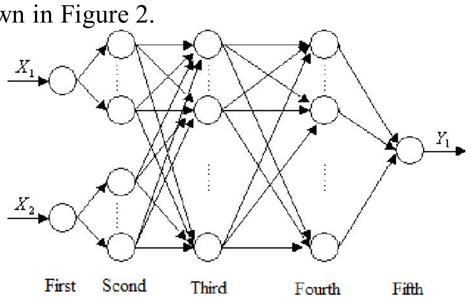

Fig. 2 Fuzzy neural networks controller structure.

The first layer: input layer. Contains two input nodes, they are directly under the signals to the next layer.

$$Net_i^{(1)} = X_i \tag{1}$$

$$O_i^{(1)} = X_i, (i = 1,2) \tag{2}$$

In the equation: $Net_i^{(1)}$—net input of the i-th neurons of the first layer; $O_i^{(1)}$—output of the i-th neurons of the first layer; X_1 is pressure deviation, $X_1 = \Delta P = P_{Real} - P_{Given}$; X_2 is the rate of pressure deviation, $X_2 = \Delta P / \Delta t$. The connecting weight of the first layer is 1.

The second layer: fuzzification layer. The first fuzzy set of the input includes seven linguistic variables. The second fuzzy set of the input also includes seven linguistic variables, and both fuzzy divisions of two input are seven, node is used to realize the value of language input variables of the membership function.

$$Net_i^{(2)} = O_j^{(1)}, i = 1,2,\cdots\cdots,14 \tag{3}$$

Including: $j=1$， $1 \le i \le 7$； $j=2$， $8 \le i \le 14$

$$O_i^2 = \exp\{-(\frac{Net_i^{(2)} - m_i^{(2)}}{\sigma_i^{(2)}})^2\}, (i = 1,2,\cdots\cdots,14) \tag{4}$$

m_i and σ_i represent the center and width of the Gaussian membership function of the j-th linguistic value of the i-th input linguistic variable respectively. They are adjustable parameters. The connecting weight of the second layer is 1.

The third layer: Contains 49 nodes, and each node represents a fuzzy rule. Control rules which are shown in table 1. The connection between the third layer and the second layer which is used to match the fuzzy rules. Its output determines each rules of excitation intensity. Function:

$$Net_i^{(3)} = (O_j^{(2)} \times O_k^{(2)}), i = 7(j-1) + (k-7) \tag{5}$$

Including: $j = 1,2,\cdots\cdots 7$; $k = 8,9,\cdots\cdots 14$

$$O_i^{(3)} = Net_i^{(3)}, \quad i = 1,2,\cdots\cdots,49 \tag{6}$$

The connecting weight of the third layer is 1.

The fourth layer: Contains 49 nodes. Each node of this layer executes fuzzy "or" operation so as to form the rules in line with the requirement. Function

$$Net_i^{(4)} = \sum_{j=1}^{49} \omega_{ij} O_j^{(3)} \tag{7}$$

$$O_i^{(4)} = \min(1, Net_i^{(4)}), i = 1,2,\cdots\cdots,49 \tag{8}$$

ω_{ij} represents the i-th output lingual variables and the j-th rule connection strength, which only equals 0 or 1.

The fifth layer: solving fuzzification layer. m_j and σ_j represent the center and width of membership functions of the fuzzification layer, respectively. Now,solving fuzzification layer.

$$Net_1^{(5)} = \sum_{j=1}^{49} (m_j^{(4)} \sigma_j^{(4)}) O_j^{(4)} \tag{9}$$

$$O_1^{(5)} = \frac{Net_1^{(5)}}{\sum_{j=1}^{49} \sigma_j^{(4)} O_j^{(4)}} \tag{10}$$

The connecting weight of the first layer is $m_j^{(4)} \sigma_j^{(4)}$.

3. Simulation of the Control System

The fis structure is generated automatically by using anfisedit in Matlab toolbox and Sugeno system, each of the two inputs is the pressure deviation e and the deviation variance ratio ec, measures are defined at 7.The primary function is Gaussian Function, the error is limited to take default 0. Based on the gradient descent method, the neural network was established and trained by the real experiment data.

The membership function which needs input variables is acquired after training of adaptive learning. The membership functions with input variables before and after learning are shown in Figure.3 and Figure.4.

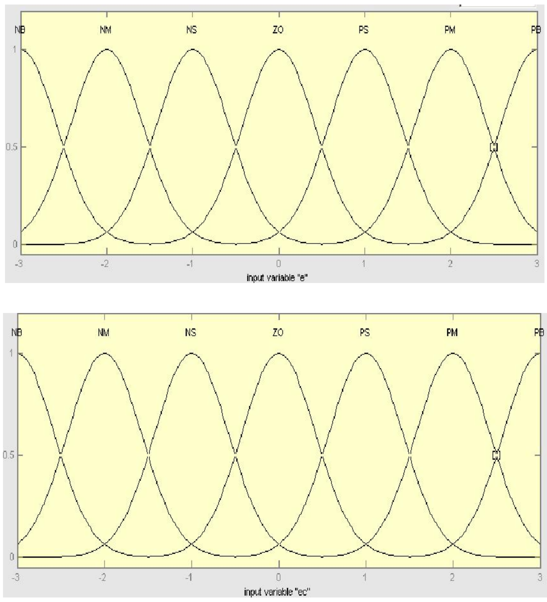

Fig. 3 Formerly membership function diagram of e and ec .

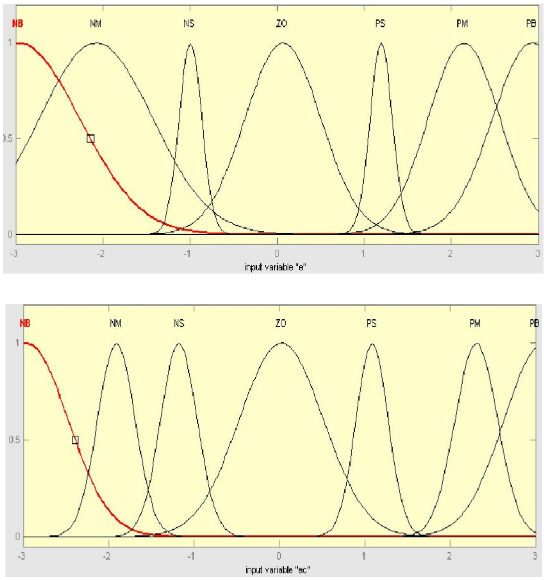

Fig. 4 Membership function diagram of e and ec after learning by fuzzy-neural network.

Through the comparison of the above two diagrams, the correcting changes of membership functions after learning can be observed, the membership functions after calibration can reflect the distribution characteristics of sample data more accurately. Apply the new fuzzy neural network controller after training to the system, the simulation as shown in Figure 5.

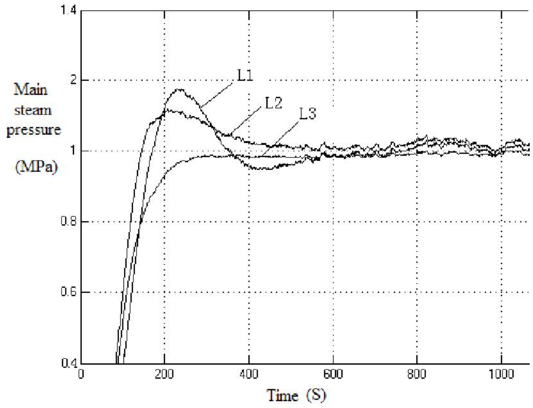

Fig. 5 Proposed beam former.

Including: L1 are traditional PID control, L2 is the fuzzy control, L3 using fuzzy neural network control. Simulations show that the system reached steady-state value at about 220s and the time decreased significantly by using the fuzzy neural network controller. Rising time and overshoot has obvious improvement compared with traditional PID method, steady-state error is less than 2%.The control effect of various control methods are shown in Table 1.

Table 1: Effect compare of three control methods

	Rise time(s)	Overshoot%	Response time s)
PID	180	18	580
Fuzzy control	170	5	400
FNN control	200	2	220

4. Conclusions

This paper focuses on the fuzzy neural network steam pressure controller which has many virtues. For example, the system responds very quickly, it can adjust the control parameters online, the steam pressure fluctuation is relatively small. This controller has not only the neural network self-learning ability and self-adapting ability, but also the advantage of accessing fuzzy information in fuzzy logic way, thus having good anti-disturbance ability and adaptive self-adapting ability. And this controller has simple structure which is easy to fulfill, with high precision in result, so it has wide application fields and great application value.

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