Sensors & Transducers, Vol. 153, Issue 6, June 2013, pp. 100-104

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Sensors & Transducers

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Application and Simulation of Fuzzy Neural Network PID Controller in the Aircraft Cabin Temperature

Ding Fang, Feng Na
Department of Aeronautic Automation, Civil Aviation University of China,
Tianjin, 300300, China
Tel.: (086)18602615819
E-mail: dingfang_60@163.com, fengna6868@126.com

Received: 3 May 2013 /Accepted: 14 June 2013 /Published: 25 June 2013

Abstract: Considering complex factors of affecting ambient temperature in Aircraft cabin, and some shortages of traditional PID control like the parameters difficult to be tuned and control ineffective, this paper puts forward the intelligent PID algorithm that makes fuzzy logic method and neural network together, scheming out the fuzzy neural net PID controller. After the correction of the fuzzy inference and dynamic learning of neural network, PID parameters of the controller get the optimal parameters. MATLAB simulation results of the cabin temperature control model show that the performance of the fuzzy neural network PID controller has been greatly improved, with faster response, smaller overshoot and better adaptability. *Copyright © 2013 IFSA.*

Keywords: PID, Fuzzy control, Neural net, Cabin temperature.

1. Introduction

The function of the aircraft cabin temperature control system is to adjust the temperature of the air inside the cabin, then to meet the comfortable requirements of human. The precise control of cabin temperature is a key to guarantee comfort of passenger in cabin and normal operation of election equipment. Many research results and experimental data tell us that, factors affecting the internal temperature of the cabin are quite complex; the aircraft cabin is bulky; there is a large inertia link. The most traditional PID control method is deviation proportional, integral, derivative control, so how to choose the three parameters would be the key issues of designing PID controller. Because of the difficult tuning parameters, poor robustness and convergence, preventing overshoot phenomenon, the traditional PID controller is very difficult to meet precise control of cabin temperature. Fuzzy control algorithm is based on the actual situation of the system, and doesn't need to establish precise actual mathematical model, for it uses expert knowledge, experience, or operating data to control the complex controlled object by fuzzy arithmetic and fuzzy inference [1,2]. But fuzzy rules' making is one-sided, and adaptability is poor, so control effects will be affected. The neural network has strong fault tolerance and adaptive learning ability, and it can make up for the deficiencies of fuzzy control algorithm.

Therefore, this article combines PID neuron adaptive control with fuzzy logic inference control together, and make full use of the advantages of both to tune the three PID parameters. Dynamic and static performance of the entire system is adjusted by fuzzy reasoning, and then learning ability of the neural network and adaptive adjustment are used for achieving optimal control.

Article number P_1225

The basic working principle of fuzzy controller is that the input signal is fuzzified into fuzzy variables, then entering into fuzzy reasoning module. After fuzzy rule reasoning to get fuzzy sets, it converts to clear amount through defuzzification module. To adjust the controlled object, he satisfying control results can be output [3].

In order to get the fuzzy inference control strategy of better system control effect, this paper uses two-dimensional fuzzy PID controller [4], the controller structure shows in Fig. 1. In this figure, r(t) refers to setting temperature value of cabin temperature; u (t) serves as the output value of system, the difference between these two errors is e, with the error rate of change ec as the fuzzy controller input together. The output is correction factor for PID control parameters K_P, K_I, K_D, and neurons in the hidden layer of PID neural network model to be dynamically adjusted.

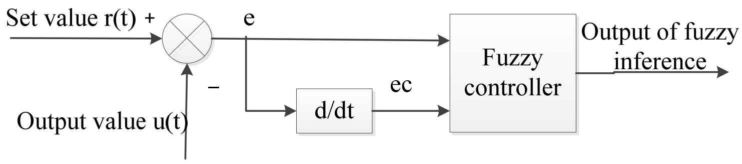

Fig. 1. Fuzzy PID controller structure diagram.

In the fuzzy inference process, fuzzy subset are e, ec, K_P, K_I, K_D ={NB, NM, NS, ZO, PS, PM, PB}, the elements of subset are in turn expressed as: Negative Big, Negative Middle, Negative Small, Zero, Positive Small, Positive Middle, Positive Big. Membership function combines the triangle with S-function, and the input and output of five linguistic variables membership function relationship is established. Then 7×7 fuzzy inference rules are got, each rule corresponds to a different operator control logic result. The linguistic description of 49 fuzzy control rules shows in Table 1-3.

In the process of running, according to the principle of fuzzy control and fuzzy inference rules, constantly testing e and ec, eventually finding fuzzy relationship among the PID control parameters K_P, K_I, K_D and e, ec. Online correction of these three parameters can meet the control requirements, making controlled object owing a good dynamic and static characteristics.

3. PID Neuron Network Structure

Proportional-Integral-Derivative Neural Network (PIDNN) [1, 5] applies the neural network into PID parameter tuning, then it uses neural network to control PID parameters and form the PID neurons structure controller. In this paper, the 2-3-1 neural network structure is used, and network structure is shown in Fig. 2.

In the PID neurons net structure, first is input layer, the input of two neurons were error e, and PID control parameters correction factor after fuzzy inference controller operating and analyzing. By calculating of proportional threshold function, the output value of input layer is x_i(i=1, 2). Three neural units of hidden layer are the proportional unit, the integral unit and the derivative unit, and their input value is the weighted value of input layer to hidden layer:

Table 1. Fuzzy rule table of K_P.

e \ ec	NB	NM	NS	ZO	PS	PM	PB
NB	PB	PB	PM	PM	PS	ZO	ZO
NM	PB	PB	PM	PS	PS	ZO	NS
NS	PM	PM	PM	PS	ZO	NS	NS
ZO	PM	PM	PS	ZO	NS	NM	NM
PS	PS	PS	ZO	NS	NS	NM	NM
PM	PS	ZO	NS	NM	NM	NM	NB
PB	ZO	ZO	NM	NM	NM	NB	NB

Table 2. Fuzzy rule table of K_I.

e \ ec	NB	NM	NS	ZO	PS	PM	PB
NB	NB	NB	NM	NM	NS	ZO	ZO
NM	NB	NB	NM	NS	NS	ZO	ZO
NS	NB	NM	NS	NS	ZO	PS	PS
ZO	NM	NM	NS	ZO	PS	PM	PM
PS	NM	NS	ZO	PS	PS	PM	PB
PM	ZO	ZO	PS	PS	PM	PB	PB
PB	ZO	ZO	PS	PM	PM	PB	PB

Table 3. Fuzzy rule table of K_D.

e \ ec	NB	NM	NS	ZO	PS	PM	PB
NB	PS	NS	NB	NB	NB	NM	PS
NM	PS	NS	NB	NM	NM	NS	ZO
NS	ZO	NS	NM	NM	NS	NS	ZO
ZO	ZO	NS	NS	NS	NS	NS	ZO
PS	ZO	ZO	ZO	ZO	ZO	ZO	ZO
PM	PB	NS	PS	PS	PS	PS	PB
PB	PB	PM	PM	PM	PS	PS	PB

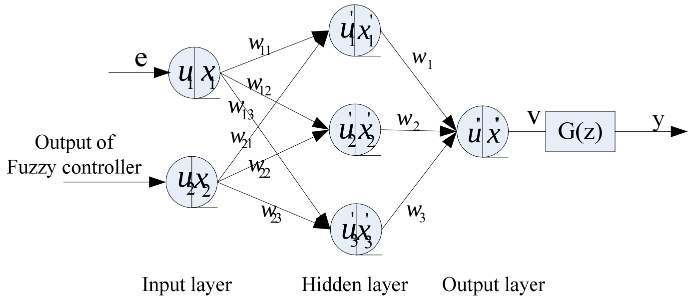

Fig. 2. PID neural network structure.

$$net'_j(k) = \sum_{i=1}^{2} w_{ij} x_i(k) \tag{1}$$

The state of proportional unit, integral unit, derivative unit:

$$u'_1(k) = net'_1(k) \tag{2}$$

$$u'_2(k) = u'_2(k-1) + net'_2(k) \tag{3}$$

$$u'_3(k) = net'_3(k) - net'_3(k-1) \tag{4}$$

Each neuron input value through bipolar threshold function learning and training obtain the output value of hidden layer:

$$x'_j(k) = f\left(u'_j(k)\right) = \begin{cases} 1 & u'_j(k) > 1 \\ u'_j(k), -1 \le u'_j(k) \le 1 \\ -1 & u'_j(k) < -1 \end{cases} \tag{5}$$

There is only one neural unit in the output layer to achieve the whole output function of network, the input value:

$$u''(k) = \sum_{j=1}^{3} w_j x'_j(k) \tag{6}$$

Then use the same function to get the output value. The system compare output with setting value, if the error doesn't satisfy the requirements, then the back-propagation procedure will be performed. Ultimately make the mean squared error of the actual output and the desired output being least.

The mean:

$$E = \frac{1}{2}\left(r(k) - y(k)\right)^2 = \frac{1}{2} e^2(k) \tag{7}$$

According to the error gradient descent method adjusting weights value [1], the iterative equation:

$$W(k+1) = W(k) - \alpha \frac{\partial E}{\partial W}, \tag{8}$$

where α is the learning rate. Layers corresponding to the weight adjustment formula are as follows:

The hidden layer to output layer:

$$w_j(k+1) = w_j + \alpha_j \sum_{k=1}^{N} \delta'(k) x'_j(k) \tag{9}$$

and

$$\delta'(k) = [r(k) - y(k)] \operatorname{sgn} \frac{y(k+1) - y(k)}{v(k) - v(k-1)}$$

The input layer to hidden layer:

$$w_{ij}(k+1) = w_{ij}(k) + \alpha_{ij} \delta_j(k) x_i(k) \tag{10}$$

and

$$\delta_j(k) = \delta'(k) w_j \operatorname{sgn} \frac{u'_j(k) - u'_j(k-1)}{net'_j(k) - net'_j(k-1)}$$

4. Design and Simulation of Fuzzy Neural Network PID Controller

Based on the above analysis and design, the structure of the fuzzy neural network PID controller schematic is shown in Fig. 3.

This controller mainly consists of fuzzy controller and PID neural network controller, and compares setting value r(t) with output value y(t) to obtain error e(t) and error rate of change ec(t). In the fuzzy controller, according to the fuzzy inference rules, the corresponding control strategy is formed and correction parameters are got. Then entering the correction parameters into PID neural network controller, after dynamically learning and correcting, the new parameters K_P, K_I, K_D are obtained, the operating flow chart of system is shown in Fig. 4.

The working principle of aircraft cabin temperature control system: real-time monitor the temperature inside and outside the cabin through temperature sensor; according to error and error change rate between the setting and monitoring temperature, fuzzy neural network PID controller deals with algorithm to get adjusting parameters factor; then converting to the output signal and sending to stepper motor, thus adjusting the size of the hot air valve or cold valve opening degree, to achieve the adjustment of the cabin temperature.

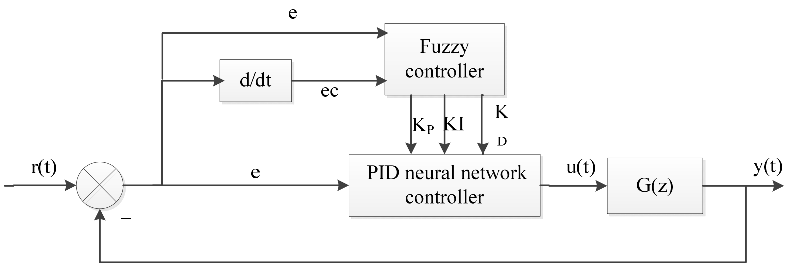

Fig. 3. Fuzzy Neural Network PID Controller schematic structure.

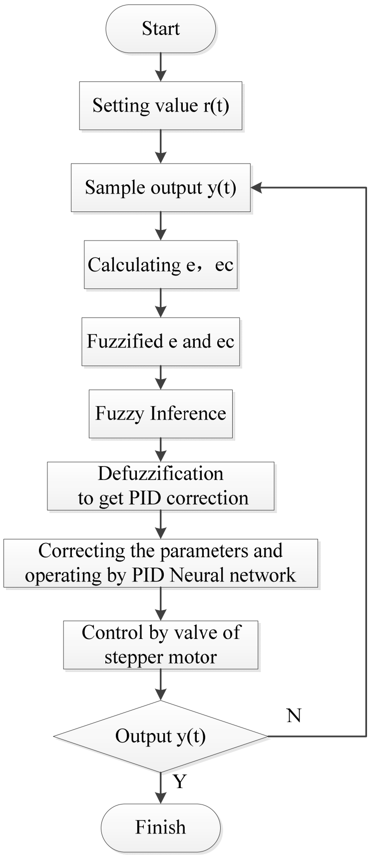

Fig. 4. Operating flow chart.

The working principle of aircraft cabin temperature control system: real-time monitor the temperature inside and outside the cabin through temperature sensor; according to error and error change rate between the setting and monitoring temperature, fuzzy neural network PID controller deals with algorithm to get adjusting parameters factor; then converting to the output signal and sending to stepper motor, thus adjusting the size of the hot air valve or cold valve opening degree, to achieve the adjustment of the cabin temperature.

Cabin temperature control system is a second-order control system, and contains the inertia link [6], the transfer function of control model can be written as:

$$G(s)=\frac{400}{(s+50)(2s+1)}$$

In fuzzy reasoning control module, the domain range of three output variables are: e, ec=[-3,3], K_P=[-0.3,0.3], K_I=[-0.06,0.06], K_D=[-3,3], sampling time is 0.001s, learning rate of the neural network algorithm is 0.35. The results of simulation for traditional PID control, fuzzy PID control and fuzzy neural network as follows (Figs. 5-7).

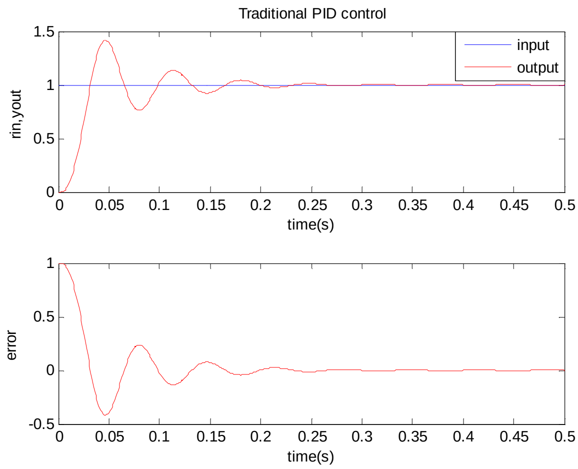

Fig. 5. Traditional PID control.

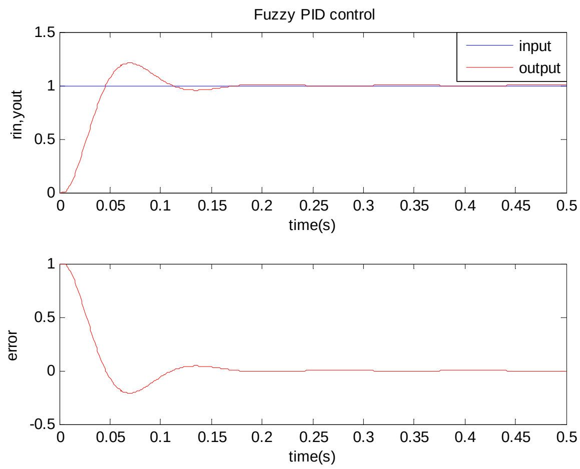

Fig. 6. Fuzzy PID control.

From the simulation graph we can see that, in the adjustment process of cabin temperature, traditional PID control has a large overshoot in the case of a short rise time, curve has excessive wave and is instability; only using fuzzy PID control still has overshoot, control performance is not stable; after tuning of fuzzy neural network PID parameter, there is neither an over shoot, nor fluctuations, approximating the input curve fast and steady, finally achieving good control effect.

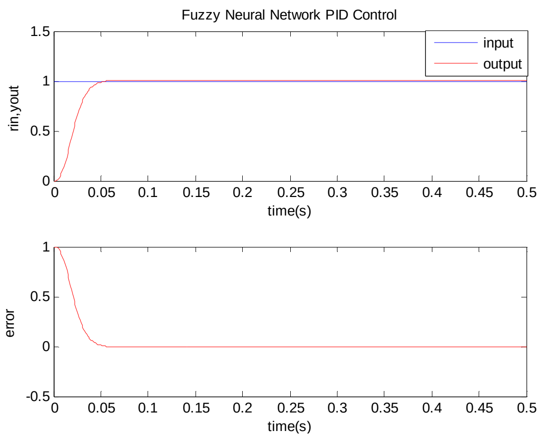

Fig. 7. Fuzzy Neural Network PID control.

5. Conclusion

The problem of tuning and optimizing PID control parameters has always been focus in the control research. This article combines fuzzy inference control with neural network control algorithm, and makes full use of the advantages of both to make up for their shortcomings. From the simulation consequence of the aircraft cabin temperature system, we can see that fuzzy neural network PID controller has good dynamic performance and steady-state performance, better self-learning ability and robustness, there will be a good prospect in industrial applications.

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