Study on PIDNN Control of Circulating Fluidized Bed Boiler based on T-S Model

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***Abstract*—Temperature and pressure are two main parameters of CFBB in the control system. Because of the CFBB possess the characteristics of time-varying, large lag and strong coupling, it is difficult to set up the arithmetical model and achieve better control effects. According to above difficulties, this paper adopts T-S fuzzy modeling method to description the input-output relationship for the control system based on collected data of system. On this basis, it adopts the PIDNN controller algorithm which has very strong adaptability and the whole system simulation is carried out by using MATLAB. The results of simulation experiment show that the designed model is effective and the control system achieves satisfied control effect.**

***Index Terms*—T-S model; Fuzzy Modeling: circulating fluidized bed; PIDNN**

I. INTRODUCTION

CFBB(Circulating fluidized bed boiler) has been developed rapidly in recent decades, which has the advantage of high-efficient and low-pollution. So it is widely used in industry and heating system. In recent years, the capacity and control requirements of CFBB continue to increase. There are many control parameters and the couple between them are serious, it is difficult to establish a precise mathematical model based on traditional method and achieve good control effect. Currently, there are still many imperfections, especially in automatic control and optimization whether in theory or in practice for Circulating fluidized bed boiler system. The majority of circulating fluidized bed boiler automation level is not very high, and some individual still using manual operation so far [1].

According to the control status, this paper adopts T-S fuzzy modeling method to descript the input-output relationship for the control system based on the collected input-output data of system. Compared with the traditional method, the physical meaning of the nonlinear fuzzy model is clear and easy to understand[2-4].

For T-S fuzzy model, the system is difficult to control by traditional PID controller, because of the model parameter is varied in different running process, so it is hard to achieve satisfied control result. To improve its performance, this paper adopts PIDNN (PID Neural network) to improve the performance of the controller. PIDNN algorithm is not tuning PID parameters by neural network, but defining proportional, integral, derivative characteristics neurons. So PIDNN algorithm integrate PID into neural network, which overcomes the shortcomings of slow convergence rate, easy to fall into local minimum point and difficult to determine the initial values of weights in ordinary neural network. The input signal doesn't need differential and integral action from external network. Meanwhile it has the arbitrary function approximation ability and can acquire better control effect[5].

II. FUZZY MODELLING

A. The Description of T-S Model

T-S model realizes the global nonlinear by the local linearation method for nonlinear system. The whole input space is divided into several small fuzzy spaces. It has different local linear equation model for each fuzzy subspace. So it becomes simply to analyze control system and design controller with this representation. The total output of the model is the sum of each local linear model output weight [6].

doi:10.4304/jcp.8.8.2069-2076

MIMO system can be expressed by many MISO systems. Propose a system with k-input single-output, its T-S fuzzy rule can be described as follows:

$$\begin{aligned} &R^i \ \ If \ \ x_1 \ is \ A_1^i \ and \ x_2 \ is \ A_2^i \ ...... \ and \ x_k \ is \ A_k^i \\ &Then \ \ y_i = b_{i0} + b_{i1}x_1 + b_{i2}x_2 + ...b_{ik}x_k \qquad i=1,2,3...m \end{aligned} \tag{1}$$

Where m is the number of rules and x_1 ...... x_k are input variables, A_k^i is the membership function. $b_{i0}...b_{ik}$ are constants. y_i is the output of i the rule.

The overall fuzzy system output can be obtained with the equation (2):

$$y = \frac{\sum_{i=1}^{m} \omega^i y_i}{\sum_{i=1}^{m} \omega^i} \tag{2}$$

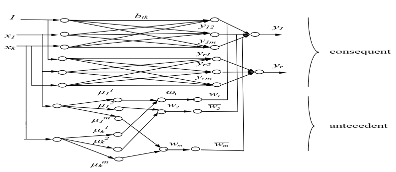
Where ω^i are the weights. Compared with traditional mathematical modeling method, the ability of mathematical reasoning of T-S fuzz modeling is stronger [7,8].

B. Structure Identification of T-S Fuzzy Modeling

Fuzzy modeling includes two tasks: structure identification and parameters estimation. Structure identification divided input space into some subspaces. Fuzzy rules can be detected from input and output datum of each subspace. Up to now, many methods have been proposed for this task including heuristics, clustering-based method, neural networks, kernel-based method [8]. The method of clustering is the best way to identify object model structure. This paper uses subtractive clustering method to solve the problem of structure identification.

In this paper it uses subtractive clustering method to solve the problem of structure identification. The main processes are provided in the following paragraphs:

(1) Calculate the density of each input data x_i with the below equation:



(3)

Where, α is the neighborhood selected, x_i *and* x_k are defferent data, P_i is the density value of the x_i .

(2)Choose the first center which has the highest density as x_1^* and P_i^* is its density value.

(3)For the second cluster center, to reduce the effect of the first cluster center, (4) is used to calculate the rest data density .

$$P_i \Leftarrow P_i - P_1^* \exp\left(- \frac{\left\| x_i - x_1^* \right\|^2}{(\frac{\beta}{2})^2} \right) \qquad \beta > 0 \tag{4}$$

Where β is the neighborhood. Usually $\beta = 1.5\alpha$ to avoid the too close distance between two cluisterng centers.

(4)After determining the m*th* cluster center, the density is revised as (5):

$$P_i \Leftarrow P_i - P_m^* \exp\left(- \frac{\left\| x_i - x_m^* \right\|^2}{(\frac{\beta}{2})^2} \right) \qquad \beta > 0 \tag{5}$$

(5)Cluster centers are selected iteratively until the stopping criteria are satisfied .

C. Parameter Estimation of T-S Fuzzy Model

Parameter estimation is based on a certain criteria to determine the model parameter. In recent years, neural networks have been widely used for its strong ability of learning. According to the characteristics of the T-S fuzzy reasoning, it makes the mathematical model into a network structure, and creates an adaptive neural-fuzzy system [9,10].

Self adaptive fuzzy neural network is a multilayer feedforward network based on T-S model. It is composed by antecedent network and consequent network. The former parts of the network used to match the antecedent of the fuzzy rules and the latter part generate the consequent of fuzzy rules. The antecedent network consists of five layers and the latter part of the network consists of r parallel sub-networks , which is shown in fugure 1.

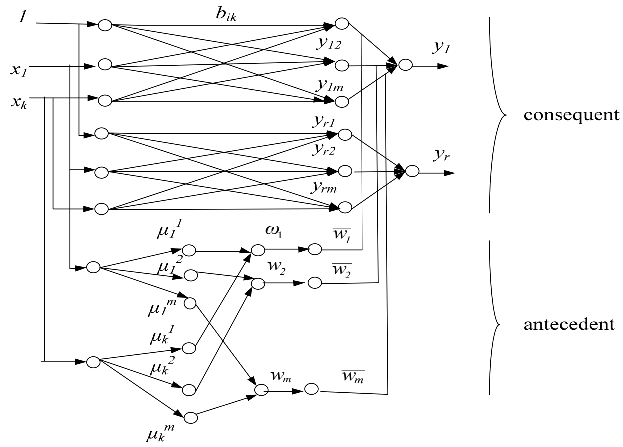


Figure 1 Fuzzy neural system based T-S model structure

Layer 1: Each neuron corresponds to an input variable. It receives an input value and delivers it to the next layer of neurons which are related to the input variable. The first input node provide constant to the consequent of fuzzy rules.

Layer 2: Each neuron corresponds to a linguistic term and contains the membership function of the corresponding linguistic term in itself. In this paper, Gaussian function has been used to calculate its membership.

Layer 3: Each neuron corresponds to rule and is connected with layer 2 neurons. Each output represents its matching degree of the rule.

$$\omega_i = \mu_{i1}(x_1) \wedge \mu_{i2}(x_2) \wedge \ldots \mu_{ik}(x_k) \tag{6}$$

Layer 4 : The nodes of this layer calculates the ratio of the i th rule's firing strength to the sum of all rules' firing strengths.

$$\overline{\omega}_i = \omega_i \Big/ \sum_{i=1}^{m} \omega_i \tag{7}$$

Layer 5: The nodes of this layer calculate the output of models

$$y = \sum_{i=1}^{m} \overline{\omega}_i y_i \tag{8}$$

D. *T-S Model of Bed Temperature of CFBB*

Basing on the existing boiler data of primary air (F), flow amount of coal (M), bed temperature (T) and main steam pressure (P), 251 sets data are selected to establish the model. The clustering radius is 0.4, training times is fifty steps. In the experiments process, the T-S model has high accuracy when the input vector number is four. And [M(t-2),M(t-1),F(t-2),F(t-1)] is chose as the input vector of the T-S model of bed temperature. The membership function curves of these parameters are shown in figure 2 to figure 5.

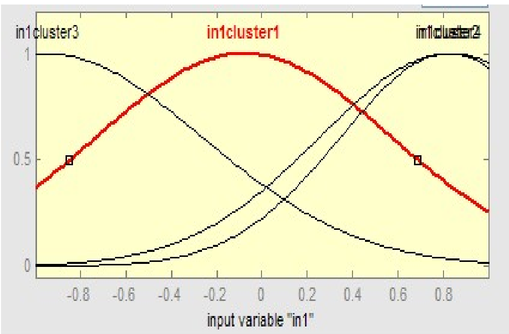


Figure 2. Membership function of M(t-2)

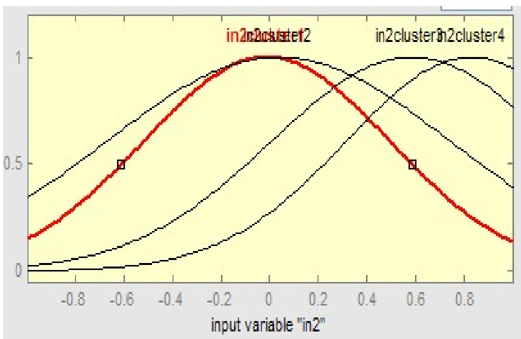


Figure 3 Membership function of M(t-1)

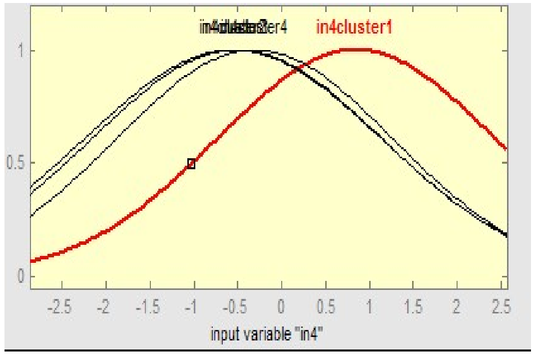


Figure 4 Membership function of F(t-2)

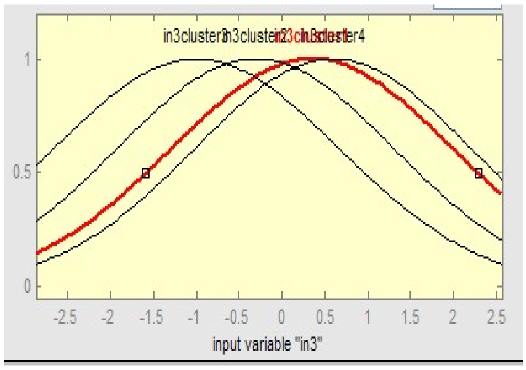


Figure 5 Membership function of F(t-1)

The training error curve is shown in figure 6.

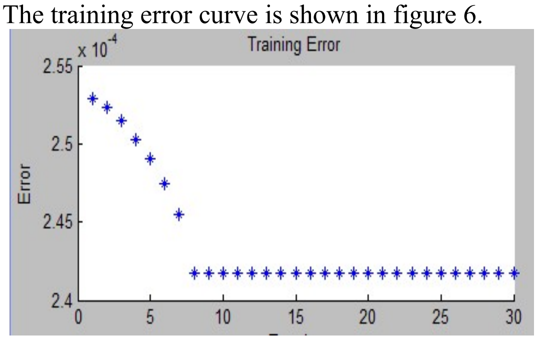


Figure 6 Taining error curve

T-S model of bed temperature receives 4 groups if-then rules as follows:

$$1: \ \text{If} \quad M(t-2) \ \text{is} \ in1mf1 \ \text{and} \ M(t-1) \ \text{is} \ in2mf1$$
$$\text{and} \quad F(t-2) \ \text{is} \ in3mf1 \ \text{and} \ F(t-1) \ \text{is} \ in4mf1$$
$$\text{Then} \quad T_1 = 4.784e^{-2} - 3.97e^{-2}M(t-2) - 0.01156e^{-2}M(t-1)$$
$$3.625e^{-2}F(t-2) + 0.1098F(t-1)$$

$$2: \ \text{If} \quad M(t-2) \ \text{is} \ in1mf2 \ \text{and} \ M(t-1) \ \text{is} \ in2mf2$$
$$\text{and} \quad F(t-2) \ \text{is} \ in3mf2 \ \text{and} \ F(t-1) \ \text{is} \ in4mf2$$
$$\text{Then} \quad T_2 = 0.1465 - 8.121e^{-2}M(t-2) + 5.243e^{-2}M(t-1)$$
$$- 2.78e^{-2}F(t-2) - 0.2974F(t-1)$$

$$3: \ \text{If} \quad M(t-2) \ \text{is} \ in1mf3 \ \text{and} \ M(t-1) \ \text{is} \ in2mf3$$
$$\text{and} \quad F(t-2) \ \text{is} \ in3mf3 \ \text{and} \ F(t-1) \ \text{is} \ in4mf3$$
$$\text{Then} \quad T_3 = 5.277e^{-2} + 4.912e^{-2}M(t-2) + 2.164e^{-2}M(t-1)$$
$$7.058e^{-2}F(t-2) - 1.845e^{-2}F(t-1)$$

$$4:\ \text{If}\quad M(t-2)\ \text{is}\ in1mf4\ \text{and}\ M(t-1)\ \text{is}\ in2mf4$$
$$\text{and}\quad F(t-2)\ \text{is}\ in3mf4\ \text{and}\ F(t-1)\ \text{is}\ in4mf4$$
$$\text{Then}\quad P_4 = 9.186e^{-2} - 8.523e^{-2}M(t-2) - 1.015e^{-2}M(t-1)$$
$$5.788e^{-2}F(t-2) + 3.017F(t-1)$$

Similarly, [M(t-2),M(t-1),F(t-2),F(t-1)] is also chose as the input vector of the T-S model for main steam pressure. The membership function curves of these parameters are shown in figure 7 to figure 10.

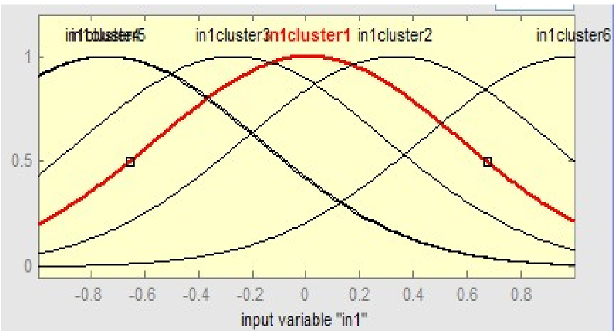


Figure 7. Membership function of M(t-1)

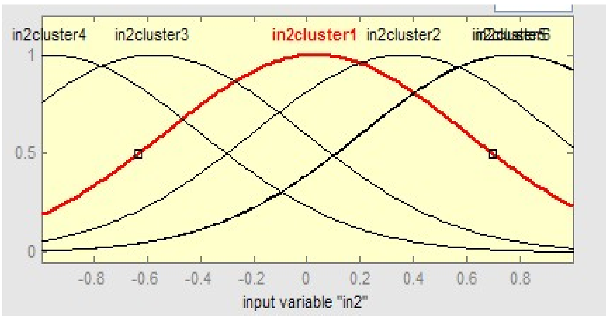


Figure8. Membership function of M(t-2)

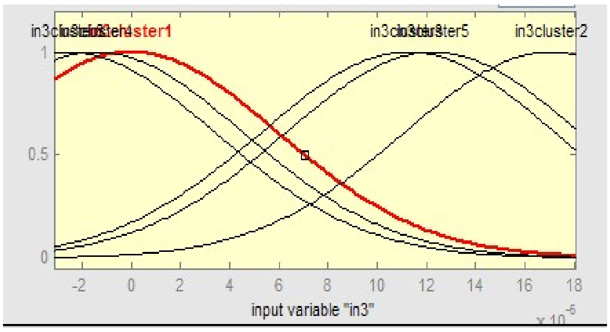


Figure9. Membership function of F(t-1)

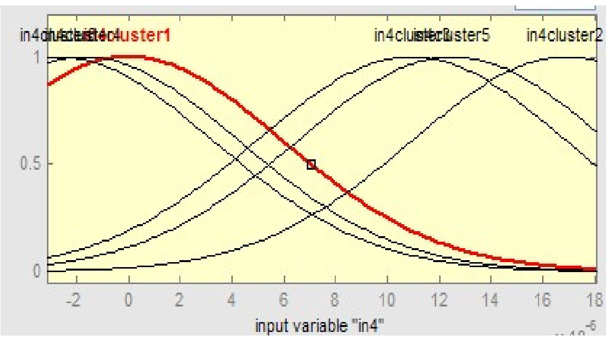


Figure 10. Membership function of F(t-2)

T-S model of main steam pressure receives 5 if-then rules as follows:

$$1:\ \text{If}\quad M(t-1)\ \text{is}\ in1mf1\ \text{and}\ M(t-2)\ \text{is}\ in2mf1$$
$$\text{and}\quad F(t-1)\ \text{is}\ in3mf1\ \text{and}\ F(t-2)\ \text{is}\ in4mf1$$
$$\text{Then}\quad P_1 = 1.255e^{-3} + 7.64e^{-3}M(t-1) - 0.8926M(t-2)$$
$$1.905F(t-1) - 4.087e^{-3}F(t-2)$$

$$2:\ \text{If}\quad M(t-1)\ \text{is}\ in1mf2\ \text{and}\ M(t-2)\ \text{is}\ in2mf2$$
$$\text{and}\quad F(t-1)\ \text{is}\ in3mf2\ \text{and}\ F(t-2)\ \text{is}\ in4mf2$$
$$\text{Then}\quad P_2 = -1.978e^{-3} - 1.184e^{-3}M(t-1) - 0.9507M(t-2)$$
$$1.947F(t-1) - 6.955e^{-3}F(t-2)$$

$$3:\ \text{If}\quad M(t-1)\ \text{is}\ in1mf3\ \text{and}\ M(t-2)\ \text{is}\ in2mf3$$
$$\text{and}\quad F(t-1)\ \text{is}\ in3mf3\ \text{and}\ F(t-2)\ \text{is}\ in4mf3$$
$$\text{Then}\quad P_3 = 5.11e^{-3} - 2.512e^{-3}M(t-1) - 0.986M(t-2)$$
$$1.976F(t-1) - 6.908e^{-2}F(t-2)$$

$$4:\ \text{If}\quad M(t-1)\ \text{is}\ in1mf4\ \text{and}\ M(t-2)\ \text{is}\ in2mf4$$
$$\text{and}\quad F(t-1)\ \text{is}\ in3mf4\ \text{and}\ F(t-2)\ \text{is}\ in4mf4$$
$$\text{Then}\quad P_4 = 3.831e^{-3} + 4.297e^{-3}M(t-1) - 1.079M(t-2)$$
$$2.05F(t-1) - 5.796e^{-2}F(t-2)$$

$$5:\ \text{If}\quad M(t-1)\ \text{is}\ in1mf5\ \text{and}\ M(t-2)\ \text{is}\ in2mf5$$
$$\text{and}\quad F(t-1)\ \text{is}\ in3mf5\ \text{and}\ F(t-2)\ \text{is}\ in4mf5$$
$$\text{Then}\quad P_5 = -3.72e^{-3} - 2.256e^{-3}M(t-1) - 0.9889M(t-2)$$
$$1.984F(t-1) - 4.144e^{-2}F(t-2)$$

III. Decoupling Control Algorithm of PIDNN

When we control the bed temperature by the fuel rate, the main steam pressure also produce fluctuation in the CFBB bed temperature and main steam pressure control system, but the safe operation of the units are not allowed the fluctuation of the main steam pressure. Therefore, it must solve the coupling problems between the bed temperature and the main steam pressure. Considering the fuzzy model of the system, traditional decoupling method can not meet the control requirements. So, the paper adopts the control method of PIDNN.

A. Structure of PIDNN

The PIDNN is a multi-layered neural network. It is combinations of neural network and the control law of PID. The hidden layer of the network has respectively characteristics, including proportion, integral and differential. It uses the paralleled structure of subnet. The PIDNN has better self-learning ability and adaptive decoupling ability in the multi-variable control system. And the system has good dynamic and static characteristics by decoupling and control[11].

This paper selects two-variables control system as research object, which is verified the method of PIDNN efficiency, as in figure 11.

In this system, the control goal are r_1 and r_2, the actual output are y_1 and y_2, the controlling parameters are u_1 and u_2. The network weight from input layer to hidden layer and from hidden layer to output layer are ω_{ij} and ω_{jh} separately.

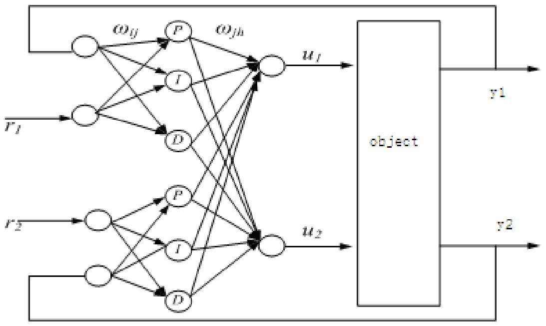


Figure 11 Structure of PIDNN

B. Decoupling Control Algorithm of PIDNN

Reference [7] gives the calculation method of PIDNN. PIDNN is similar to forward neural network, including forward algorithm and backward algorithm.

(1) The forward algorithm

The forward algorithm includes the input-output relationship in input layer, hidden layer and output layer.

1) The input-output relationship in input layer

The input and output functions of input neurons:

$$x_i(k) = u_{si}(k) \tag{9}$$

The input values of input neurons are u_{si} ,the output values of input neurons are x_i ,the serial number of sub-network is s , the serial number of input layer neurons is i.

2) The input-output relationship in hidden layer

In the neurons of input layer, the design formulas of input total value are the same.

$$u'_{si}(k) = \sum_{i=1}^{2} \omega_{sij} x_{si}(k) \tag{10}$$

The input and output functions of proportion neurons:

$$x'_{s1}(k) = \begin{cases} 1 & u'_{s1} > 1 \\ u'_{s1}\ (k) & -1 \le u'_{s1} \le 1 \\ -1 & u'_{s1} < -1 \end{cases}$$

The input and output functions of integration neurons:

$$x'_{s2}(k) = \begin{cases} 1 & u'_{s2} > 1 \\ x'_{s2}(k-1) + u'_{s2}\ (k) & -1 \le u'_{s2} \le 1 \\ -1 & u'_{s2} < -1 \end{cases}$$

The input and output functions of differential neurons:

$$x'_{s3} = \begin{cases} 1 & u'_{s3} > 1 \\ u'_{s3}(k-1) + u'_{s3}\ (k) & -1 \le u'_{s3} \le 1 \\ -1 & u'_{s3} < -1 \end{cases}$$

The input values of hidden layer neurons are u'_{sj}, the output values of hidden layer are x'_{ij} ,the network weight from input layer to hidden layer are ω_{ij}, the serial number of sub-network is s, the serial number of input layer neurons is i, the serial number of hidden layer neurons is j .

3) The input-output relationship in output layer

The input of output layer neurons is the adding weigh-sum of the output values from all neurons.

$$u''_h(k) = \sum_{s=1}^{n} \sum_{j=1}^{3} \omega_{sjh} x'_{sj}(k) \tag{11}$$

The input and output functions of output neurons:

$$x''_h(k) = \begin{cases} 1 & u''_h > 1 \\ u''_h(k) & -1 \le u''_h \le 1 \\ -1 & u''_h < -1 \end{cases} \tag{12}$$

In this formula, the input values of output layer neurons are u''_h , the output values of output layer neurons are $x''_h(k)$, the network weight from hidden layer to output layer areω_{sjh}.

(2) The backward algorithm

The controller of PIDNN is a self-learning control without teachers. The backward algorithm regards PIDNN and multi-variable plant as Multi-Layer Network. The multi-variable plant is the last layer or a few layers. This network adopts error back-propagation algorithm and the target function is as follows:

$$\begin{aligned} J &= \sum_{p=1}^{n} E_p = \frac{1}{m} \sum_{p=1}^{n} \sum_{k=1}^{m} [r_p(k) - y_p(k)]^2 \\ &= \frac{1}{m} \sum_{p=1}^{n} \sum_{k=1}^{m} e^2{}_p(k) \end{aligned} \tag{13}$$

In this formula, the sampling number is m, the numbers of controlled variable are n, the expect output are rp, the actual output is yn.

This network adjusts the weights of PIDNN by the gradient descent method. We can obtain weights by training and studying.

1) The iterative formulas from the hidden layer to output layer:

$$\omega_{sjh}(n_0+1) = \omega_{sjh}(n_0) - \eta_{sjh} \frac{\partial J}{\partial \omega_{sjh}} \tag{14}$$

Because of coupling function between input and output:

$$\frac{\partial J}{\partial w_{sjh}} = -\frac{2}{m} \sum_{p=1}^{n} \sum_{k=1}^{m} [r_p(k) - y_p(k)] \bullet \mathrm{sign} \frac{y_p(k+1) - y_p(k)}{\upsilon_p(k) - \upsilon_p(k-1)} x'_{sj}(k) \tag{15}$$

2) The iterative formulas from the input layer to hidden layer:

$$\omega_{sij}(n_0+1)=\omega_{sij}(n_0)-\eta_{sij}\frac{\partial J}{\partial\omega_{sij}} \tag{16}$$

Where

$$\frac{\partial J}{\partial\omega_{sij}}=\sum_{p=1}^{n}[\frac{\partial J}{\partial E_p}\frac{\partial E_p}{y_p}(\sum_{h=1}^{n}\frac{\partial y_p}{\partial\upsilon_h}\frac{\partial\upsilon_h}{\partial\omega_{sij}})] \tag{17}$$

The weights of PIDNN concem the convergent speed and convergent direction, but we can not know how to decides the neural network's evaluation.This paper adopts the method of random.

The ability of PIDNN decoupling control comes from the characteristic of nonlinear mapping. When PIDNN conducts to training and studying, it can not know decoupling or control. The PIDNN completes the mapping from input to output based on the target function. Therefore, if the training samples contain the request of decoupling control, PIDNN can achieve better effect of decoupling control by adjusting weights.

IV. Analysis of System Simulation

We can realize the control of the system by PIDNN controller with four inputs and two outputs based on T-S model. The input value and output value are the four units of input layer. The two units of output are linked to the input terminal of the object.

Supposing the initial values of the proportion and differential neuron from input layer to hidden layer are as follows:

$$\omega_{s11}(0)=\omega_{s13}(0)=-\omega_{s21}(0)=-\omega_{s23}(0)=1$$

$$Where \quad s=1\ ,\ 2$$

Supposing the initial values of the integral neuron from input layer to hidden layer are as follows:

$$\omega_{s12}(0)=0.08\,,$$

$$\omega_{s22}(0)=-0.085$$

The initial values of weights form hidden layer to output layer are as follows:

$$\omega_{sjh}(0)=0.08$$

$$j=1\ ,\ 2\ ,\ 3 \qquad h=1,\ 2$$

The step of studying:

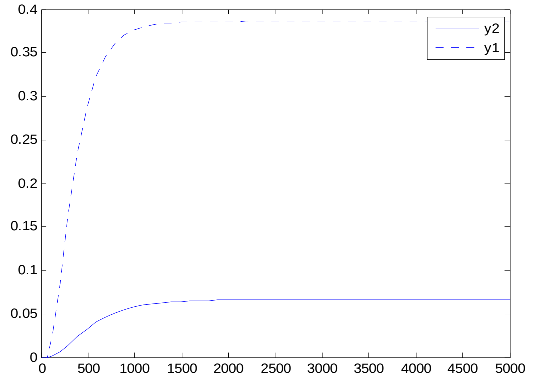
$$\eta=0.2$$

The target function:

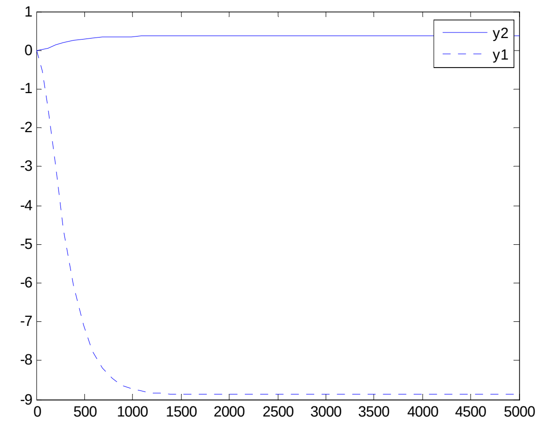
$$J=\sum_{p=1}^{n}E_p=\sum_{p=1}^{n}(r(k)-y(k))^2$$

The controlled object chooses threes kinds of situations, includes [1,0],[0,1],[1,1]. The open loop characteristic of the controlled object is shown in figure 11. The system characteristics of decoupled control are shown in figure 12. and the training objective funtion in different condition is shown in figure 13.

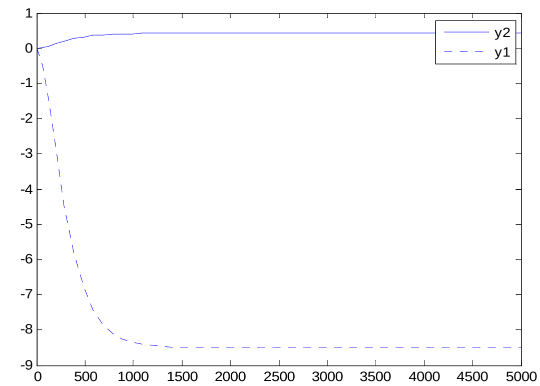
In these figures, flow amount of coal is expressed by r1, the primary air is expressed by r2, the bed temperature is expressed by y1, and the main steam pressure is expressed by y2.



(a) r1=1,r2=0



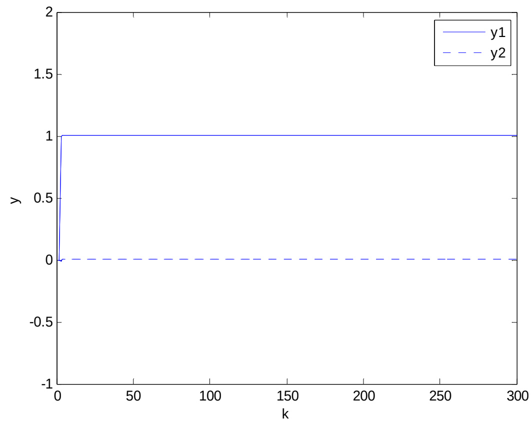
(b) r1=0,r2=1



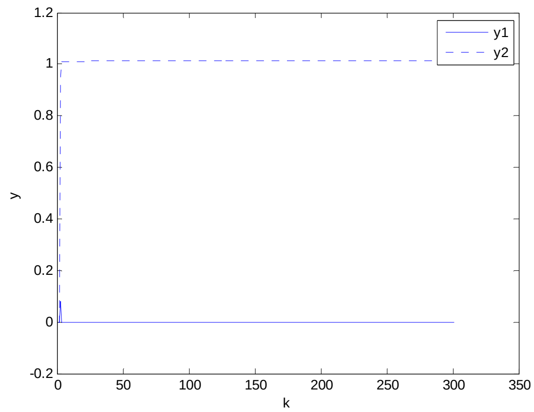
(c) r1=1,r2=1

Figure 12 Object coupling relationship with different r1 and r2

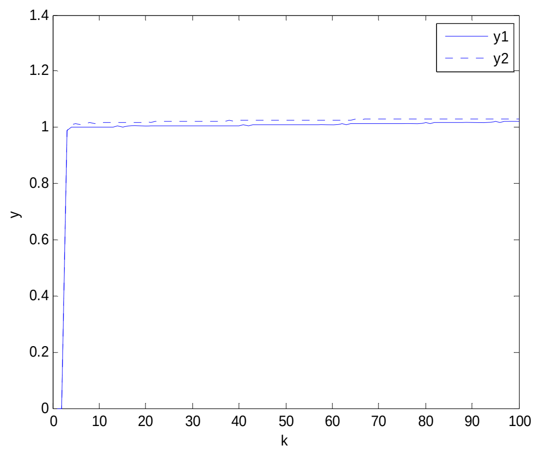
The control target of this system is to control bed temperature by flow amount of coal and control main steam pressure by the primary air. From these figures, it can be seen that there exist coupling between inputs and outputs. The flow amount of coal does not only influence bed temperature, the main steam temperature also change with it. And when we control the steam pressure by the primary air, the bed temperature also change with this parameter. To realize the satisfied control effect, it must resolve the coupling between these parameters.



(a) r1=0,r2=1



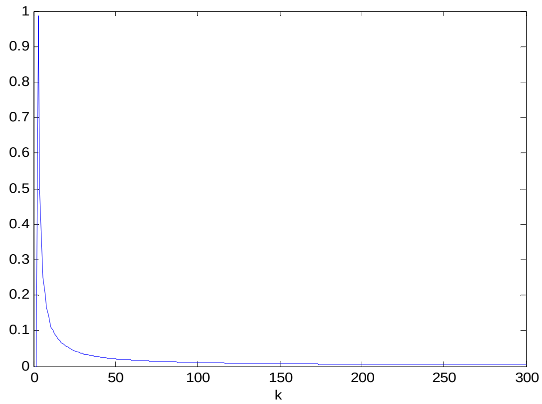
(b) r1=0,r2=1



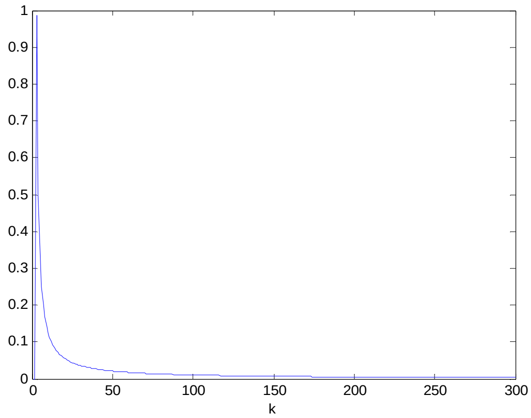
(c) r1=1,r2=1

Figure 12 System step response with different input r1 and r2

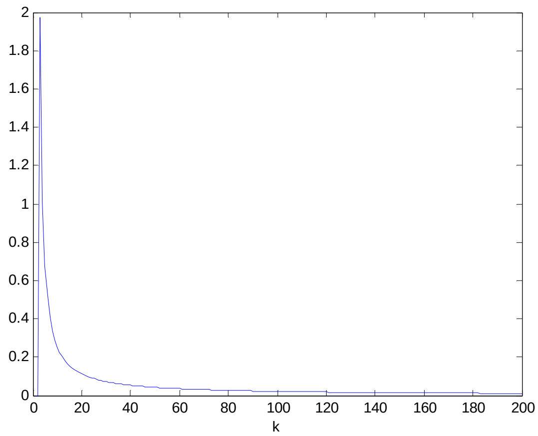
It could be found out from the simulation result that, the control scheme of PIDNN can solve the coupling problem of the system, there doesn't exist control overshoot in the control process and the adjusting time is relative short. The whole system control achieves satisfied control effect for bed temperature and main steam pressure.



(a) r1=1,r2=0



(b) r1=0,r2=1



(c) r1=1,r2=1

Figure 13 Training objective funciton curve with different input r1 and r2

The training objective function of the system is another important part in the system. In the figure 13, it shows that the convergence speed of the training objective function is very fast and it can reach its convergence aim in about eighty steps.

V. Conclusion

The bed temperature and the steam pressure are two main parameters in CFBB control system. In order to solve the difficult of model building, this paper built up non-linear model by the algorithms of T-S fuzzy. Due to the poor adaptability of traditional PID controller, this paper adopts the method of PIDNN to improve the self-learning capability, and achieves the purpose of decoupling and control and obtains better control effect. In the simulation process, we found that the performances of PIDNN controller are influenced by the initial values of weights and compensations. Therefore, future research direction is to optimize initial weight parameters of the PIDNN to get more ideal control result.

ACKNOWLEDGMENT

This paper is supported by the National Natural Science Foundation (60874003). We are pleased to acknowledgee our thankfulness.

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