FUZZY NEURAL NETWORK'S APPLICATION IN FURNACE TEMPERATURE COMPENSATION BASED ON ROLLING INFORMATION FEEDBACK

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Abstract: In hot rolling process, reheating furnace and roughing mill are controlled separately in general, and the transfer of production information between the two facilities is very limited, so rolling information of roughing mill can not be fed back to reheating furnace to adjust slab's heating process dynamically, which leads to exceeding energy consumption. In this paper, fuzzy neural network (FNN) is used to deal with the feedback of rolling information, and then real-time compensation of furnace temperature setting can be obtained. Simulation results show that by using this method slab's heating process can be optimized dynamically, and energy consumption of hot rolling process can be reduced greatly, and rolling security of roughing mill can be guaranteed at the same time.

Keywords: reheating furnace; optimizing setting; temperature compensation; rolling information feedback; energy consumption; FNN

1. INTRODUCTION

Slab's heating and rolling process are two of the most important production processes in hot rolling process. Heating process should provide qualified slabs to roughing mill, and roughing mill should roll these slabs into desired dimensions. The research on the control of slab's heating and rolling process has made great progress in resent years ((Nicklaus *et al.*, 1995);(Wang *et al.*, 1999*a*);(Wang *et al.*, 2001);(Wang *et al.*, 1999*b*)). However, because of the separate control of reheating furnace and roughing mill, the information transfer between the two facilities is very limited and always delayed. So this situation often occurs: in order to reduce energy consumption of heating process, the operators often diminish furnace temperature setting, whereas energy consumption of rolling process and rolling load will increase in result, which sometimes will lead to the shutting down of roughing mill. Aiming at this problem, according to the characteristics of hot rolling process, this paper uses fuzzy control and artificial neural network ((Roger and Sun, 1995);(Tang *et al.*, 2002);(Xu, 1999)) to feed useful rolling information back to heating process to compensate furnace temperature setting dynamically. By using this method, not only the energy consumption of slab's heating and rolling process can be reduced, but also the good running of rolling production can be guaranteed.

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2. COMPENSATE FURNACE TEMPERATURE SETTING BY FUZZY CONTROL RULES

For a certain piece of slab, its roll force, roll torque, rolling rhythm and temperature decline in rolling process can contribute to furnace temperature setting compensation, but in this paper only roll force error and its change rate will be considered. Because the two parameters are the most important factors which will take effect, and if necessary, the other parameters can be disposed with the same method as the two parameters mentioned above. A simplified diagram of these parameters is showed in figure 1.

2.1 The construction of fuzzy control system based on rolling information feedback

2.1.1. The determination of input and output spaces There are two input spaces, roll force error P and change rate of roll force error PE. Output space is furnace temperature setting compensation ΔT_f, which has three components, preheat zone compensation, heating zone compensation and holding zone compensations. The variation ranges of P, PE and ΔT_f are:

$$\begin{aligned} P &= [P_{min},\ P_{max}] \\ PE &= [PE_{min},\ PE_{max}] \\ \Delta T_f &= [\Delta T_{fmin},\ \Delta T_{fmax}]. \end{aligned} \tag{1}$$

2.1.2. The establishment of fuzzy relation Generally, there are two methods to establish fuzzy relation: expertise of skilled operators and mathematical function representation. As far as hot rolling process is concerned, using the expertise of skilled operators of each production process to establish membership function is preferred. In this paper, the membership function of roll force error (see table 1) and the membership function of change rate of roll force error (see table 2) as well as the membership function of furnace temperature setting compensation (see table 3) are established by using expertise of skill operators. By these membership functions, the expertise can be stored in the fuzzy control system, which is the basis of computer control with on-line dynamical amendment. In table 1, 2 and 3, $n1$, $n2$ and $n3$ are respectively the domain amount of fuzzy variables, namely, the quantity space amount of fuzzy variables; P_0, PE_0 and ΔT_{f0} are quantized values of roll force error, change rate of roll force error and furnace temperature setting compensation.

2.1.3. The construction of fuzzy control rule base From table 1 to table 3 we can see that the input space of roll force error has three fuzzy language

Table 1. Membership function of roll force error

Domain	Membership function		
	PS	PM	PB
$P^*_{min} \le P_0 < P^1_0$	1.0	0	0
$P^1_0 \le P_0 < P^2_0$	0.8	0.2	0
...	...	...	...
$P^{n1}_0 \le P_0 \le P^*_{max}$	0	0	1.0

Table 2. Membership function of change rate of roll force error

Domain	Membership function				
	NB	NS	ZE	PS	PB
$PE^*_{min} \le PE_0 < PE^1_0$	1.0	0	0	0	0
$PE^1_0 \le PE_0 < PE^2_0$	0.8	0.2	0	0	0
...	...	...	...	...	...
$PE^{n2}_0 \le PE_0 \le PE^*_{max}$	0	0	0	0	1.0

Table 3. Membership function of furnace temperature setting compensation

Domain	Membership function		
	PS	PM	PB
$\Delta T^*_{fmin} \le \Delta T_{f0} < \Delta T^1_{f0}$	1.0	0	0
$\Delta T^1_{f0} \le \Delta T_{f0} < \Delta T^2_{f0}$	0.8	0.2	0
...	...	...	...
$\Delta T^{n3}_{f0} \le \Delta T_{f0} \le \Delta T^*_{fmax}$	0	0	1.0

sets and change rate of roll force error has five fuzzy language sets, thus fifteen pieces of fuzzy control rules can be established. By using these fuzzy control rules, a fuzzy controller can be constructed. That controller can compensate furnace temperature setting according to the feedback of roll force. And the fuzzy control rules may be simplified if there are too many complicated rules, but the integrality of fuzzy control rules should be maintained. In this paper we just consider the compensation of a certain zone of reheating furnace, and the other zones can be compensated by making some amendments to the fuzzy control rules.

3. THE FUZZY CONTROL STRATEGY COMBINING WITH NEURAL NETWORK'S LEARNING FUNCTION

Fuzzy control can give furnace temperature setting a reasonable compensation based on the expertise of skilled operators, however because fuzzy control does not have the ability of self-learning, it can not correct fuzzy control rules according to the change of production conditions. So fuzzy control should be used combining with neural network which has the ability of self-learning, and

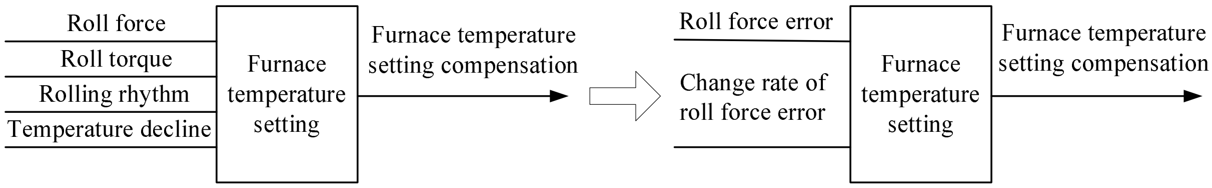


Fig. 1. Parameters affecting furnace temperature setting compensation and their simplification

then the constructed fuzzy neural network controller can work better than fuzzy controller.

3.1 The model structure and function of fuzzy neural network

Four 3-layer BP neural networks are used to realize the fuzzification of inputs, the construction of fuzzy control rules, the fuzzy reasoning and decision and the defuzzification of the output. The structure diagram of fuzzy neural network is showed in figure 2.

Network I disposes the fuzzification of roll force error, and network II disposes the fuzzification of change rate of roll force error. The input and output of the zeroth layer nodes are described as follows:

$$Net_i^{(0)} = x_i, \quad Out_i^{(0)} = x_i \quad i = 1,2 \tag{2}$$

where $x_1 = P$, $x_2 = PE$, and the connection weights are equal to 1. The second layer nodes represent the language values of language variables x_1 and x_2. Here, x_1 has three language values PS, PM and PB, and x_2 has five language values NB, NS, ZE, PS and PB, so the second layer has 8 nodes in all, whose inputs are the outputs of the first layer, and whose outputs are the membership function values of language values. We can set the connection weights between the first layer and the second layer as a function of the membership function of language value, so that the membership function of language value can be optimized on line when the connection weights are being corrected.

Neural network III can establish fuzzy control rules and realize fuzzy reasoning and decision. The third layer has 15 nodes, each of which represents a piece of fuzzy control rule, and the amount of nodes is equal to the amount of fuzzy control rules. The inputs of these nodes are described as follows:

$$Net_i^{(3)} = \min[Out_j^{(2)},\ Out_k^{(2)}] \tag{3}$$

where $i = 1, 2, \cdots, 15;\ j = 1, 2, 3;\ k = 4, 5, \cdots, 8.$ The outputs are described as follows:

$$Out_l^{(3)} = Net_l^{(3)},\ l = 1, 2, \cdots, 15, \tag{4}$$

and the outputs represent the excitation intensities of fuzzy control rules. The connection weights between the second layer and the third layer are all equal to 1.

Network IV will determine and defuzzificate the fuzzy control output. In the fourth layer, the three nodes represent language values PS, PM and PB of the fuzzy control output. The inputs and outputs of the nodes in the fourth layer are expressed as follows:

$$Net_i^{(4)} = \sum_{j=1}^{15} W_{ji} Out_j^{(3)} \quad i = 1,2,3 \tag{5}$$

$$Out_i^{(4)} = \min(1,\ Net_i^{(4)}) \quad i = 1,2,3 \tag{6}$$

where W_{ji} represents the connection weight between fuzzy control rule j and ΔT_f's language value i, which can only be 0 or 1.

For the node in the sixth layer, it represents the final control output ΔT_f that has been defuzzificated.

3.2 The learning algorithm of neural network

The correction of connection weights between nodes is determined by the learning algorithm of gradient descent, which is described as follows:

$$\Delta W_{ji}(p+1) = \eta \delta_{pj} O_{pj} + \alpha \Delta W_{ji}(p) \tag{7}$$

where, η is learning steplength; O_{pj} is the output of node j which has been trained p times; α is momentum factor which can diminish the oscillation occurring in the learning process, usually $\alpha = 0.9$; the definition of δ_{pj} is showed in reference ((Xu, 1999)). In order to guarantee the astringency of BP algorithm and overcome the influence to training speed caused by the shape of error camber, the learning steplength should be corrected in the form as follows:

$$\eta(p+1) = \begin{cases} (1+\beta)\eta(p), & E_p > E_{p+1} \\ (1-\beta)\eta(p), & E_p \le E_{p+1} \end{cases} \tag{8}$$

where β is a small positive number, usually $\beta \in [0.01,\ 0.03]$; E_p is the performance error function of neural network which has been trained p times.

4. SIMULATION RESEARCH

A 6-stage walking beam reheating furnace proceeding to a two-roller reversing roughing mill group is considered in this paper. The furnace length is 30m; the slab's residence time in the reheating furnace is 4-5 hours; rough rolling process

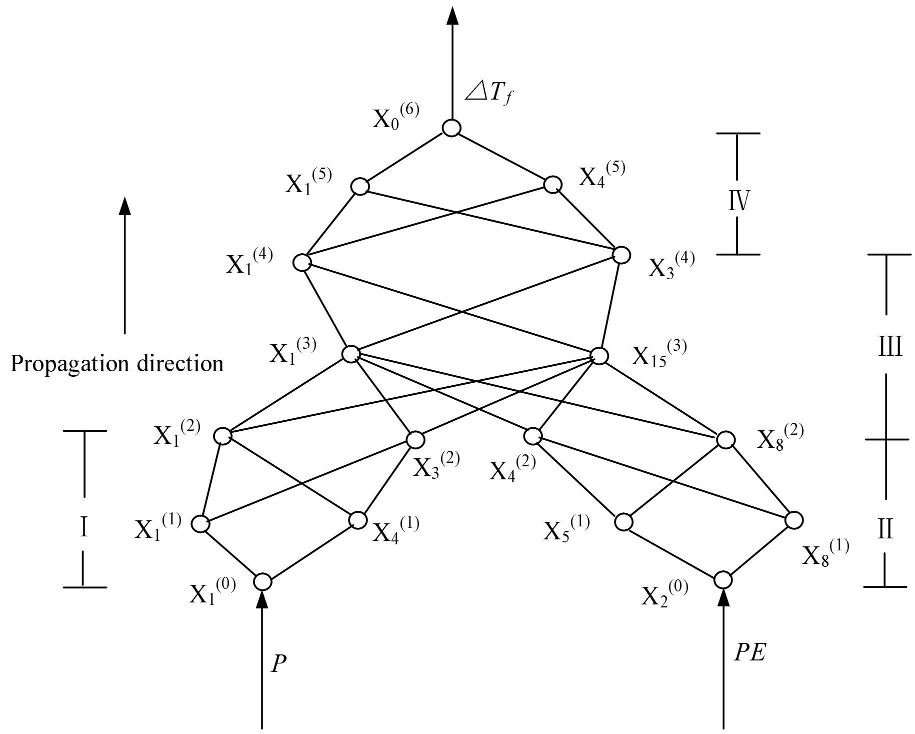
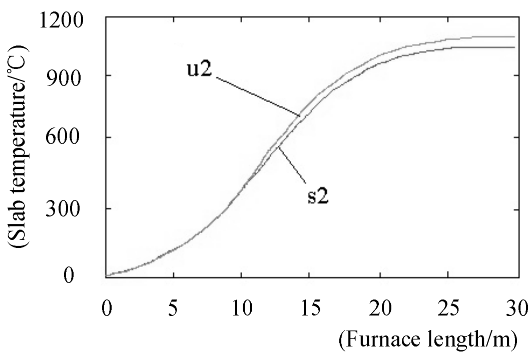


Fig. 2. The model structure diagram of fuzzy neural network controller

has five passes; the allowable roll force of roughing mill is 40000KN; it is water cooling between passes. The slab sort is Q235; the slab's furnace loading temperature is 25°C; the desired slab temperature at the exit of reheating furnace is 1100-1200°C; the slab's cross section temperature difference should be smaller than 40°C.

In order to reduce production cost, the roughing mill adopts low temperature rolling technology, which often makes the roughing mill overload, not only shortens the service life of the rollers but also increases the energy consumption of rolling process. So in order to reduce the energy consumption of rolling process, and guarantee the security of roughing mill, the method presented in this paper is used to solve this problem and simulation results are showed in figure 3 and 4.

From figure 3 we can see that after using the method presented in this paper, slab temperature at the exit of reheating furnace is increased to 1123°C, which meets the requirement of roughing mill, whereas before using this method the slab temperature of 1043.4°C can not meet the requirement of roughing mill. The slab's cross section temperature difference before optimization is 28.5°C, and after optimization it is 35.4°C, both of which are in the allowable range of rolling technology. Though the slab's cross section temperature difference has a little increase after optimization, while because the slab's temperature distribution is increased as a whole after optimization, the slab is more suitable for the roughing mill to roll than before optimization. The slab's temperature distribution is increased to a higher value, so the energy consumption of roughing mill is reduced accordingly, and the rolling load is also reduced, which guarantees the production security of roughing mill.

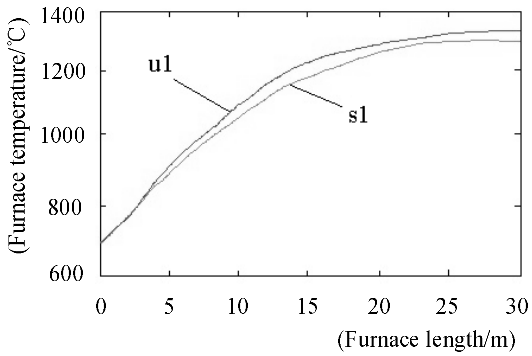


s2-slab temperature rise curve before optimization
u2-slab temperature rise curve after optimization

Fig. 3. Comparison of slab temperature rise curve before and after optimization

From figure 4 we can see that the furnace temperature distribution is increased after optimization, which improves the heating quality of the slab and provides a guarantee for the slab's normal rolling on the roughing mill.

In addition, for the condition that the slab's temperature distribution is higher than the requirement of rolling technology, in order to avoid unnecessary energy waste of heating process, by using the same method presented in this pa-



s1-furnace temperature distribution before optimization
u1-furnace temperature distribution after optimization

Fig. 4. Comparison of furnace temperature distribution before and after optimization

per, a furnace temperature compensation can be achieved, and then the furnace temperature setting can be decreased. In this way the energy consumption of heating process can be reduced consequently.

5. CONCLUSION

In hot rolling process, the control of reheating furnace and roughing mill is considered separately, so the two facilities can not have good production information transfer between each other, and the production process is not optimal. In this paper, fuzzy control rules are established to compensate furnace temperature setting by using expertise of skilled operators, and then the learning ability of neural network is used to correct fuzzy control rules dynamically. Through the training of a great deal of on-site data, the applicability and adaptation ability of the fuzzy control rules can be improved greatly. The running results show that by using the method presented in this paper, the energy consumption of heating process and rolling process can be reduced, and the production security of roughing mill can be guaranteed as well.

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