Modeling and Optimal for Vacuum Annealing Furnace Based on Wavelet Neural Networks with Adaptive Immune Genetic Algorithm

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Abstract. The accurate control of the work pieces temperature is a nonlinear, large time-delay, and cross-coupling complicated control problem in vacuum annealing furnace. In order to control the temperature of work pieces accurately. The optimization model for accurate work pieces temperature control has been proposed by the data gathered from the scene. The model was set up with Wavelet Neural Networks (WNN). Adaptive Immune Genetic Algorithm (AIGA) optimized the WNN structure and parameters (weights, dilation and translation). Simulation and experiment results show that the model in this paper is better than the model established with NN and optimizing the weights of NN by GA. And, it improves the training rate of Networks and obtains a system with good steady state precision, real timeliness and robustness.

1 Introduction

The high vacuum annealing furnace is primarily used to process the vacuum annealing of metal pieces that desire higher precision for the characteristics of pieces in aerospace and national defense. In the aspect of common metallurgy heat treatment, people have done much work on modeling and optimizing of metallurgy annealing that takes temperature of heat zones as the control target[1][2][3][4], and there are also some paper on the modeling and optimizing of ordinary heating furnace that takes the heat state of work pieces temperature as the target have been reported[5][6]. But these methods can’t satisfy the requirement of high accuracy annealing at all.

This paper will use Wavelet Neural Networks with many data of heat zones and work pieces which were gathered from the production to set up a model. The model will adopt the compound coding adaptive immune genetic algorithm in which has strong ability to search for optimum construction to optimize the weights, dilation and translation parameters of WNN. It has overcome many weak points of BP algorithm which difficult to search for the best, and the early maturity of GA which easy to fall into local optimization and slow-rate convergence[7]. An optimization model for accurate control work pieces temperature is acquired. Through comparing with the model was based on NN and optimizing the weights and bias of NN that based on

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genetic algorithm in simulation and experiment. The model based on the method in this paper improves the training rate of Networks and steady state precision of system. It makes system obtain much better characteristics in real-time and robustness.

2 Determination of Model

According to wavelet transform theory and document[8]. We have known to assume $\psi(x)$ is a mother function, and $\psi(x) \in L^2(R)$. Then a group of wavelet functions can be expressed as formula (1) by dilation and translation:

$$\psi_{a,b}(x) = |a|^{-\frac{1}{2}} \psi\left(\frac{x-b}{a}\right) \tag{1}$$

where a, b are respectively dilation and translation parameters.

The satisfactory condition of $\psi(x)$ is:

$$\int_{-\infty}^{+\infty} \psi(x) dx = 0 \tag{2}$$

i.e. : $$\int_{-\infty}^{+\infty} |\psi(x)| dx < \infty \tag{3}$$

The compatible condition satisfied is:

$$2\pi \int_{-\infty}^{+\infty} \frac{|\psi(\omega)|^2}{|\omega|} d\omega < +\infty \tag{4}$$

where $\psi(\omega)$ is the Fourier transform of $\psi(x)$.

From this, an unknown function $f(x)$ may be approximated as by a group of

$\psi(x)$: $$\hat{f}(x) = \sum_{k=1}^{M} W_k \Psi_k \left(\frac{x-b_k}{a_k}\right) \tag{5}$$

where $\hat{f}(x)$ is the synthesized function of $f(x)$. Weights are W_k . Dilation parameters are a_k . Translation parameters are b_k . M is the wavelet number.

The least average square error energy function is expressed as :

$$E = \frac{1}{2} \sum_{j=1}^{P} \left[\hat{f}(x) - f(x)\right]^2 \tag{6}$$

where p is sample number .

For MIMO system formula (5) can be expressed as :

$$\hat{f}_j(x) = \sum_{k=1}^{M} W_{jk} \Psi_k \left(\frac{\sum_{i=1}^{N} W_{ki} x_i - b_k}{a_k} \right) \tag{7}$$

where $\hat{f}_j(x)$ is the Number j output of system. M is wavelet number.

Input variable number of system is N . Formula (6) can be expressed as:

$$E = \frac{1}{2} \sum_{j=1}^{P} \left[\hat{f}_j(x) - f_j(x) \right]^2 \tag{8}$$

In this paper we select radical wavelet function as:

$$\Psi(x) = \cos(1.75x) \exp(-\frac{x^2}{2}) \tag{9}$$

2.1 The Construction of Wavelet Neural Networks

An internal heating type of vacuum annealing furnace is discussed in this paper. In order to heat work pieces evenly. The heating wires and thermocouples are installed at the top, side and bottom of the furnace. Thermocouple of work pieces is installed at the middle of work pieces. During the annealing process, vacuum degree is maintained between 10^{-4}–10^{-3}Pa. According to thermodynamics theory. The primary transmission form is heat release in which the electric heating wires generate energy is transmitted to work pieces. Simultaneously another transmission form is heat conduction in which the remnant part of energy is transmitted to the external. The heat release is a typical nonlinear process. There is time delay in the heating device. It exists cross-coincidence between heating devices. Because of it exists the difference characteristics for the devices and space distribution. So vacuum annealing furnace is a typical nonlinear time delay inertia cross coincidence complicated control object.

Three layers NN construction is adopted in this paper. The first is input layer. The second is hidden layer. The third is output layer. Input neural unit number and output layers are 4 and 1 respectively. Neural number of hidden layer M can be obtained by optimization using AIGA. WNN construction is shown as Fig.1 :

The relationship between input and output of the first layer neural units (input layer) is expressed as:

$$v_i = x_i \quad (i = 1, 2, 3, 4) \tag{10}$$

where: v_i is neural unit output of number i . x_i is neural unit input of number i .

The relationship between input and output of the second layer neural units is expressed as:

$$s_k = \sum_{i=1}^{N} W_{ki} v_i \tag{11}$$

($N = 4$ is the neural unit number of the first layer neural Networks)

$$h_k = \Psi\left(\frac{s_k - b_k}{a_k}\right) \tag{12}$$

where: v_i is the number i neural unit input. h_k is the number k neural unit output. W_{ki} are the weights between input layer and output layer which are optimized by AIGA. $\Psi(\bullet)$ is transform function. Where is radical wavelet function. a_k are the dilation parameters of radical wavelet function. b_k are the translation parameters of radical wavelet function.

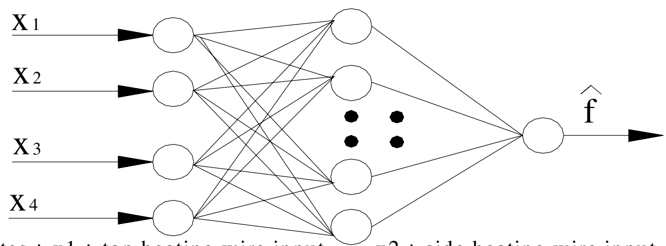

Fig. 1. The component frame chart of Neural Networks

The relationship between input and output of the third (output layer) is expressed as:

$$\hat{f} = \sum_{k=1}^{M} W_k h_k \quad \text{(M is the hidden neural unit number)} \tag{13}$$

where $\hat{f}$ is the output Neural Networks. W_k are the weights between hidden layer and output layer. h_k is the Number k output of hidden layer.

2.2 Optimization of the Weights of NN and Dilation Parameters Translation Parameters and the Number of Wavelet Function

The AIGA is an improving algorithm in order to avoid the immature convergence and to improve the population diversity. It is used to optimize the weights of NN and dilation parameters translation parameters and the number of radical wavelet function. This algorithm includes such three kinds of basic operations. They are selection extension and mutation[7]. The concrete optimization procedures are described in the following:

(1) Process initialization: in this operation. The main work is determined the range of each parameter in searching for optimization. Accordingly, the parameter range should be appropriate medium. Therefore, too small range is bound not to obtain the optimal solution. But too large range is bound to prolong the process of searching for optimization and to affect real timeliness. It is here that we should be first on the site

to select the relative optimal parameters of several groups. Then fix the range of searching for optimization in the vicinity of these parameters. It is just here that we will fix the weights w. Dilation parameters a_k. Translation parameters b_k of the wavelet Networks range as $[-2, 2]$ and the number of the wavelet function maximal number as 15.

(2) Population initialization: the parameters and structure of the wavelet Networks are coded firstly when optimizing the wavelet Networks based on the AIGA. The compound coding system combines the advantages of decimal system and binary system that usually is used to code the initial population. It is selected to code the initial population. An individual is composed of 4 parts. The part 1 to 3 coded by decimal system denote the weights, dilation and translation parameters of wavelet Networks. The part 4 coded by binary system denotes the structure of the wavelet Networks (here 0 denotes invalid and 1 denotes valid). The larger number of the population is the wider. It is representation that the larger possibility of obtaining optimal solution. But it is inevitable to cause an increase in calculation time. In general, the number p of the population is to select 20 to 100. It is here that the number of population is fixed as $p = 26$.

(3) Calculation of evaluation value of individuals: the E value of optimal objective functions should be worked out. E is used to obtain the evaluation function value *fit*. $fit = \frac{1}{E+1}$. In here, the denominator of the evaluation function formula. We can be expressed as $E+1$. It is to prevent the occurrence of calculation overflow when the optimal objective function value tends to become zero. The optimal objective function E is calculated from formula (8).

(4) It is necessary to judge whether the evaluation function value reaches the requirement of optimization or not. If the requirements are met with the most optimal values of structure and parameters of WNN can be obtained so that the process of searching for the optimization should be exited. Otherwise continue operations as following.

(5) Selective operation: It is here that the q pieces of individuals with the highest evaluation values can form the population *pop1*. Here *p=integer* $(\beta \times p)$ The selective probability β can be obtained by the calculation with formula (16). The β value taking range here is (0,1).

(6) Extension operation: Each individual in new population *pop1* formed through selective operation should have the extension probability calculated through formula (14)

$$pr_l = \frac{fit_l}{\sum_{s=1}^{q} fit_s} \tag{14}$$

And then, the roulette wheel method is used to determine the number of new individual extended from each individual. And then, the corresponding number of new individuals is selected at random in the adjacent field to obtain new population *pop2*. The adjacent field is selected with the l pieces of individual as the center. The section space with $\boldsymbol{r_1}$ as the radius, and r_1 selection is obtained through the calculation with formula (17). The r_1 value taking section space can be *(-d, d)*, and d is the minimum value of the two ends distance from the l pieces of individuals to the tracking zone of searching for the optimization.

(7) Mutation operation: The mutation operation is conducted for the poorest $p-q$ pieces of individuals in population *pop2*. Whose mutation can be any individual in the adjacent field. The adjacent field selection is the same as the method used in the (6) step. The radius r_2 here can be obtained through the calculation with formula (18).

In the process of optimizing parameters the adaptive adjustment of the immune genetic algorithm is realized mainly via such three parameters as β , r_1 and r_2 . Once the searching for the optimization starts. It is expected to have a larger selective probability and a smaller extension and mutation radius. When searching for the optimization is carried out to a certain extent, and particularly nearing convergence. The diversity of the population becomes small so that it is just at this time. It is expected to have a smaller selective probability and a larger extension and mutation radius. In order to judge the population diversity and be able to have the adaptive adjustment of such three parameters as β , r_1 and r_2 . The method set in literature[7]can be borrowed to introduce the function of determining population diversity in the following:

$$V=\frac{1}{p}\sum_{s=1}^{p-1}\left\|gen(s)-gen(s+1)\right\| \tag{15}$$

where, V is the judgment function. p is the number of the population. gen(s) is the s pieces of individual. If β 、 r_1 and r_2 variable range can be (c_0,d_0) , (c_1,d_1) , (c_2,d_2) respectively. The adaptive adjustment of algorithm parameters should be as follows:

$$\beta = c_0 + \frac{(c_0 - d_0)V}{1+V} \tag{16}$$

$$r_1 = c_1 + \frac{c_1 - d_1}{1+V} \tag{17}$$

$$r_2 = c_2 + \frac{c_2 - d_2}{1+V} \tag{18}$$

3 The Simulation and Test Results

3.1 Simulation Test

It is here that takes a Φ2100×2100 high vacuum annealing furnaces as a research object. The simulation model is carried out through the method in this article. It is based on the amount of data gathered from the production scene. It takes the temperature of annealing work pieces as a target temperature parameter. In order to proved the availability of the model set up with the method in this article. One of group data is recorded in table1:

Table 1. The data gathered from scene

Time(M)	0	15	30	45	60	75	90	105
Top heating current(A)	0	120	420	280	300	400	400	400
Side heating current (A)	0	100	300	420	420	420	420	420
Bottom heating current (A)	0	100	700	300	400	640	700	760
Workpieces temperature （℃）	0	24	70	139	220	287	375	461

Time(M)	120	135	150	165	180	195	210
Top heating current(A)	400	400	400	380	320	320	300
Side heating current (A)	420	420	420	400	380	240	260
Bottom heating current (A)	680	700	700	700	700	700	700
Workpieces temperature （℃）	529	576	600	609	615	616	616

Test: A simulation is carried out through the MATLAB program language with the data in table1, and the compare between the simulate result and the real output is shown in Fig.2 and Fig.3

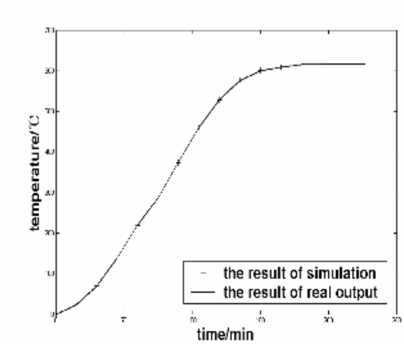

Fig. 2. Simulate result and real output compare

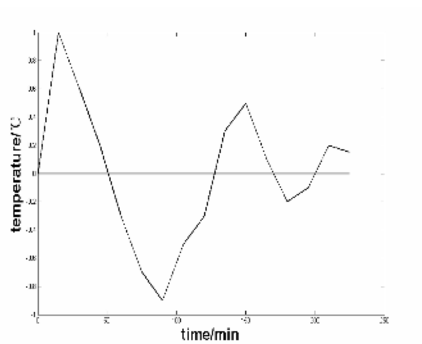

Fig. 3. Simulation error compare

It can be seen from Fig.2 and Fig.3 that the deviation between the simulate result and the real output can stabilize in ±1 ℃. So it is a satisfied precision requirement completely.

3.2 Control Test

The control component frame chart was shown in Fig. 4. It is used to test annealing system. The model as a predictive model is used to adjust on line so as to get an optimal approach between the predictive model and real vacuum annealing furnace model. Transfer unit give an input signal into heating wires and NN model as the same time that the last time vacuum annealing furnace output is put into NN model. The output of NN is used as a predictive temperature value $\hat{f}$ in which realizes the adjustment to the controller. It was optimised which the construction, weights, dilation and translation parameters of wavelet Networks. At the same time the AIGA is used to adjust the deviation of output as learning guide signal.

It is here that takes a kind of work pieces whose technology requirement is: vacuum degree as 2×10^{-3}Pa~5×10^{-4}Pa and the deviation of work pieces temperature as ≤±5℃ as an example. The results compare of control though the model set up in this article and the model set up by NN based on GA is shown in Fig. 5.

It can be seen from Fig.5.The control system based on the model in this article has a small deviation and can track the set value well in the control process. It only has ±1℃ control deviation. But that based on the model by NN has a temperature deviation as ≤±2℃. A conclusion can be obtained to prove this method is available.

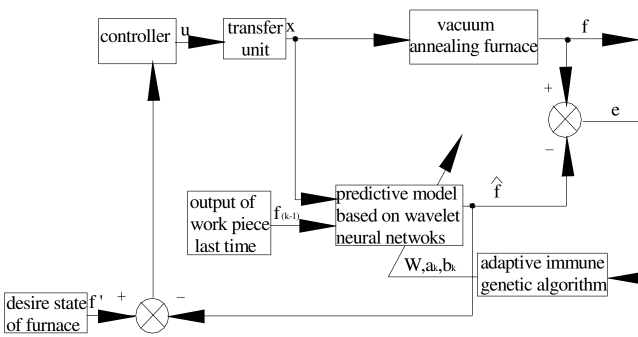

Fig. 4. The component frame chart of control

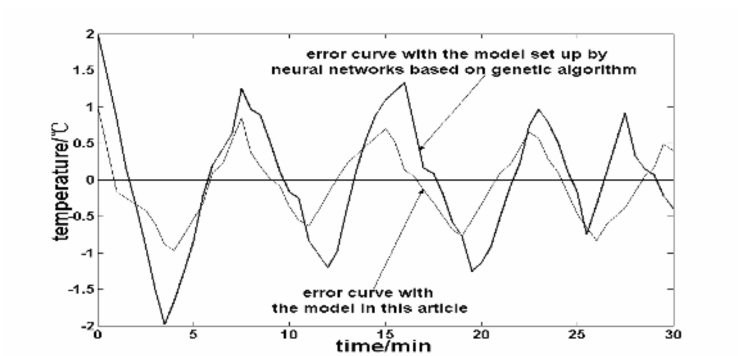

Fig. 5. Control error curve compare

4 Conclusion

As of the heating behaviors in the frontier industrial production process as well as special requirements of process control. It use of high vacuum annealing furnace used in precise machinery manufacturing, aerospace, national defense, etc. A kind of optimal model of vacuum annealing furnace is advanced in this paper. The model set up in this paper is applied to practice and realizes the combination of modeling and control, and the rolling optimization for different kinds of work pieces on line. And a good control result is realized though the model in this paper.

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Li Xiaobin (born in 1966 -) male, associate Prof. Ph.D, majors in the comprehensive automation and intelligent control system in industrial production process as the research direction.

Liu Ding (born in 1957 -) Ph..D, Prof. Ph.D tutor, has been for long engaged in researches on industrial automation, intelligent control theory and applications, and published over 300 thesis and won 4 rewards of national, provincial and ministerial sci-tech progress.

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