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PREDICTION AND ANALYSIS OF SLAB QUALITY BASED ON NEURAL NETWORK COMBINED WITH PARTICLE SWARM OPTIMIZATION (PSO)

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Based on the study of the mechanism of bloom crack, the main factors affecting the quality of bloom are determined. The intelligent optimization algorithm combining PSO and Back Propagation(BP) neural network is introduced to establish the prediction model based on typical defects. Collect on-site sample data, normalize it, and PSO is used to recalculate the weights and thresholds to accelerate the convergence and improve the accuracy and stability of the results. The experimental results show that the prediction accuracy of the optimized neural network model is high, and it is closer to the actual production of continuous casting.

Keywords: continuous casting, steel slab quality, neural network, particle swarm optimization, prediction model

INTRODUCTION

Hot delivery, hot charging and direct rolling have become the established standards of continuous casting production, and the primary premise is to ensure the quality of casting slabs [1]. Due to the complexity of field conditions and the diversity of slab quality problems, the traditional cold chain billet quality detection method can no longer adapt to the current production situation, while the hot billet detection equipment is expensive [2]. Therefore, artificial intelligence dynamic modeling can be used to implement dynamic monitoring of slab.

In view of the complexity of slab quality judgment, a neural network model combined with particle swarm optimization is proposed to simulate [3,4]. Among them, the samples are processed by neural network, the related processing function is established by metallurgical parameters, and the weights of neural network are optimized by intelligent algorithm. The experiment shows that the prediction model has high accuracy and strong feasibility.

THE PRINCIPLE OF SLAB QUALITY ANALYSIS AND PREDICTION

In this paper, the quality of bloom is investigated, which is mainly reflected in the internal cracks, including corner cracks, intermediate cracks and central cracks [5]. The factors affecting the internal crack include steel grade, process and equipment. Crystal growth and nucleation are necessary conditions for solidification of metals, and the gradient of superheat and temperature will directly affect the speed of crystal growth. In addition, the melting degree of mold fluxes or the reason of humidity will affect the thickness of shell. With the increase of superheat, the crystal growth is too fast, which is easy to cause the billet shell to be too thin, the center segregation and center looseness will be higher. If the superheat reaches a certain level, even intermediate cracks will occur, and even steel leakage will be dangerous. Under the premise of production efficiency, the casting speed is particularly important, but the high drawing speed will make the center segregation and central porosity grade continue to improve. If it is not well-matched with the specific water, it will cause the risk of leakage when it is serious [6].

PREDICTION MODEL OF SLAB QUALITY BASED ON BP NEURAL NETWORK

Data collection

In the data modeling, the dependence on the specific steel grade, process and equipment is abandoned, and the continuous casting equipment is assumed to be in normal operating state, the generation of internal cracks is completely determined by the process and chemical composition. The real-time data come from steel grade, chemical composition, casting speed, superheat, cooling water temperature, water volume, shell surface temperature, shell thickness and other process conditions and information.

In order to improve the performance of the neural network, the data obtained by manual verification is taken as the standard data in learning, and the expected value is compared with the measured data in production. When the deviation is large, the value is deleted;

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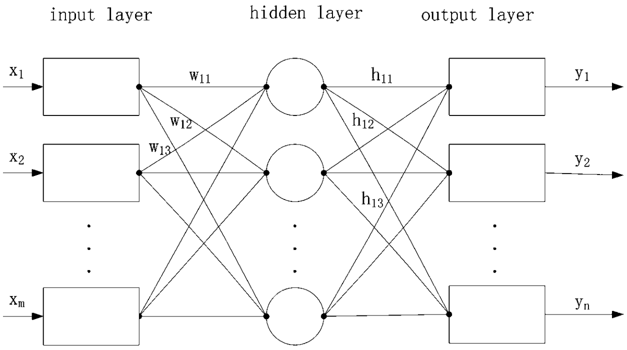

Figure 1 Topological structure of neural network

while the value with smaller deviation is retained and combined with the previous data to adjust the weight of the neural network; if the actual measured value is the same as the manual verification value, then there is no need to deal with it.

In data collection, the dimensions of the original data are different. Some data values are very large, while others are very small. Starting to learn directly may easily cause huge deviations in the output results. Therefore, it is necessary to normalize the samples and limit the values between [0,1]. In this paper, the maximum and minimum normalization function is used as follows:

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

In the formula, $x=\{x_1,x_2,\cdots,x_n\}$ is the original sample data, n is the dimension, x_{max}, x_{min} are the maximum and minimum values of the sample respectively.

Network structure

BP (back propagation) neural network is a kind of multilayer feedforward neural network trained by error back propagation algorithm. It can solve nonlinear problems and is widely used in engineering. However, it is essentially a descending gradient algorithm. It has some unavoidable defects, such as slow convergence speed, strong dependence on initial weight and threshold value, and unable to guarantee global optimum. This paper introduces particle swarm optimization (PSO), which is a global random search algorithm, which can optimize the weight and threshold, and improve the convergence speed. When the particle swarm is initialized, the weight is mapped to each particle, and the particle represents the weight in the dimension space. The fitness function of PSO algorithm is set as the mean square error of neural network training, and the minimum fitness value obtained is the optimal connection of neural network. The corresponding network topology is as follows:

Parameter design

In this paper, a three-layer network structure is established. The output vector is $y=[y_1,y_2\cdots y_n]$, which is used to identify the defect grade of the slab, and the input vector is $x=[x_1,x_2\cdots x_m]$ to identify the associated process parameters.

In terms of network convergence speed, learning speed is the key factor. If the setting is too small, it will slow down the convergence speed. If the setting is too large, the optimal value can not be obtained and convergence can not be achieved. In this paper, considering the complexity of the actual environment, the main consideration is the non-convergence, so some unnecessary parameters need to be eliminated.

The three nodes of the output layer correspond to the corner crack grade, the intermediate crack grade and the central crack grade respectively, and the interval is set as 0.5 units. The design of input parameters should reflect the practicability as much as possible, including chemical parameters, equipment parameters, such as C content, P content, s content, superheat, casting speed, shell thickness, surface temperature of each casting section, etc. The selection of the number of nodes in the hidden layer is more complex, and there is no theoretical basis at present. Too few nodes are easy to cause poor training effect and affect the overall performance of the algorithm; too many nodes make the training time longer and affect the fault tolerance. According to the komlogorov theorem, the relationship between the number of nodes in the input layer and the number of nodes in the hidden layer is as follows:

$$m \le 2n + 1 \quad (2)$$

In the formula, m is the number of hidden layer nodes, n is the number of input layer nodes.

According to the grade of slab defects, the number of nodes in output layer is 3, that of input layer is 14, and that of hidden layer is 16.

Optimization of BP neural network

In this paper, PSO algorithm is used to optimize the training of neural network to redesign the velocity and position of particles. Set A^1, A^2 as the weight matrix between input layer and hidden layer, hidden layer and output layer respectively, then the i-th particle can be defined as $\{A_i^1, A_i^2\}$, in this way, the formula of particle velocity and position can be redefined as:

$$\begin{aligned} v_{i,j}(t+1) &= \alpha v_{i,j}(t) + \beta^0(t)(x_{lb}(t) - A_i^1(t)) \\ &+ \beta^1(t)(x_{gb}(t) - A_i^2(t)) \end{aligned} \quad (3)$$

$$X_{i,j}(t+1) = X_{i,j}(t) + cv_{i,j}(t+1) \quad (4)$$

In the formula, α is a constant in (0,1], β is a random number of normal distribution N[0,1], $x_{lb}(t)$ is local optimal, $x_{gb}(t)$ is global optimal, c is the velocity factor, $\in$[0,1]; $i\in[1,n]$, $j\in[1,m]$, n is the number of particles, m is the spatial dimension.

According to the characteristics of slab quality judgment, the structure of neural network is determined, the corresponding weights of neurons are coded, and the algorithm is iterated according to PSO algorithm. The mean square error of fitness function is selected, and the weight is restored by continuous iteration to finally meet the accuracy. The specific steps are as follows:

Step 1: Samples are collected and preprocessed to initialize the threshold of BP neural network, and the weights and thresholds are coded to obtain the initial population;

Step 2: The velocity and position of particles are initialized, and the fitness value is calculated;

Step 3: Update the extreme value, and update the speed and position again to determine whether the conditions are met;

Step 4: Get the weight and threshold, calculate the mean square error of BP neural network, determine whether the conditions are met, if not, turn to step 3, otherwise end.

EXPERIMENTAL ANALYSIS

Combined with the field data of a steel plant, BP neural network: introduce 14 equipment and process parameters, namely 14 dimensional vector, extract 3 000 groups of samples, the number of output vectors is 3, the reference formula of normalization algorithm is the formula (1); the maximum iteration limit is 600, the training target is 10^{-5} ; PSO: set the population size is 40, the speed factor is c=0,6, and the maximum iteration is 400. The selected samples are used to analyze BP algorithm and PSO-BP algorithm, as shown in Figure 2.

It can be seen from the above figure that PSO-BP algorithm has completed convergence after 350 iterations and reached the training accuracy. The speed of PSO-BP algorithm is much higher than that of traditional BP neural network, and its stability is stronger.

It can be seen from Figure 3 that the predicted value obtained by PSO-BP algorithm after training is close to the actual measured value, and the neural network model has high accuracy.

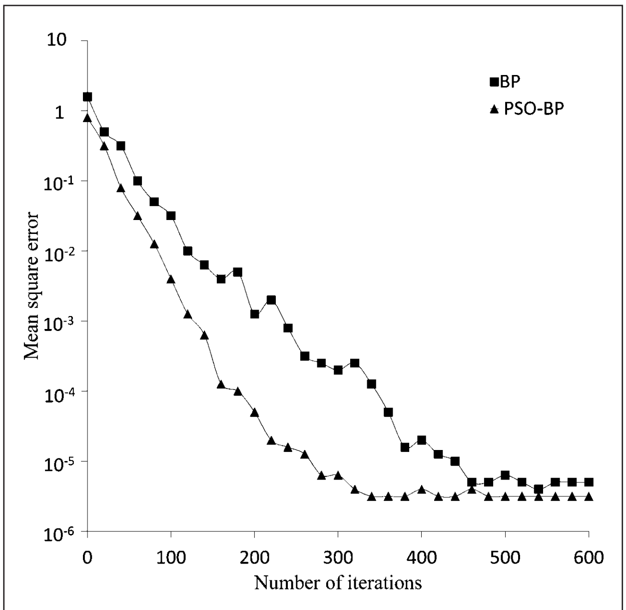

Figure 2 Analysis of neural network training process

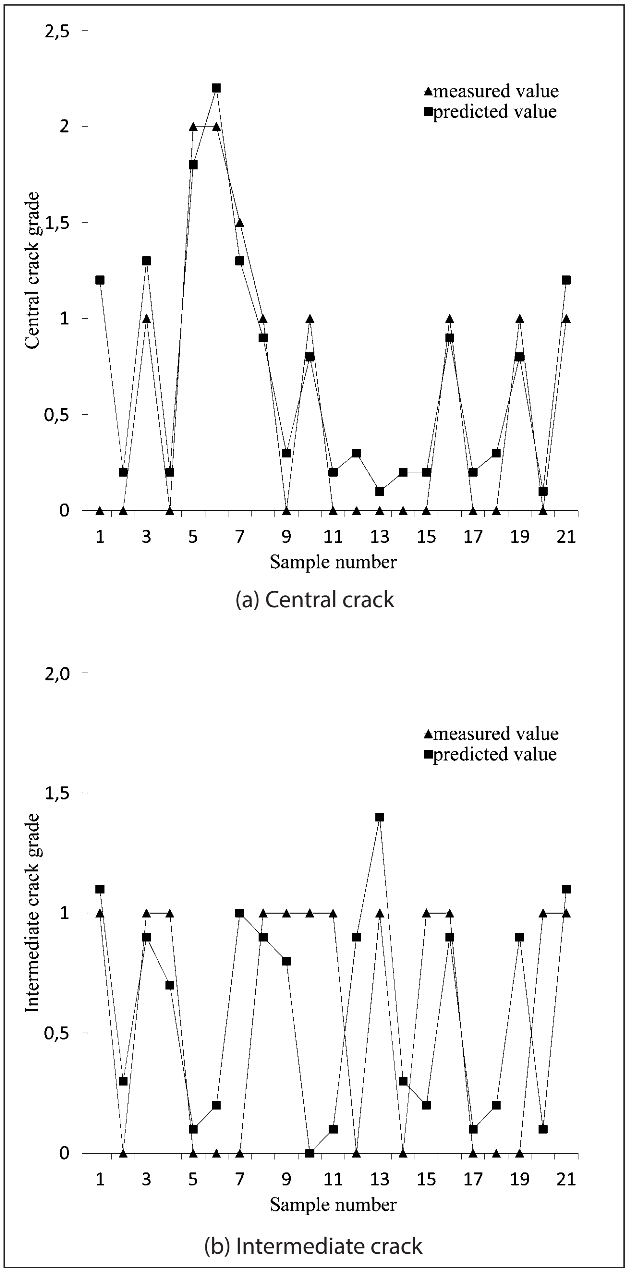

Figure 3 Comparison of predicted value and measured value

CONCLUSION

In this paper, PSO algorithm with strong global search ability is combined with BP neural network training, which overcomes the shortcomings of traditional BP neural network training, such as slow convergence speed and easy to fall into local optimum. The weight and threshold value are optimized in training to accelerate the overall convergence speed of the algorithm. The experimental results show that the convergence speed is significantly faster than expected. At the same time, the prediction accuracy of common defects of bloom is improved significantly.

Acknowledgments

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REFERENCE

[1] Stulov V.V., Aldunin A.V.. Production of hot-rolled sheet of specified quality by a new slab-casting technology[J]. Steel in Translation 47(2017), 645-649.

[2] Simonov M.Yu., Simonov Yu.N., Shaimanov G.S.. Structure, Dynamic Cracking Resistance, and Crack Growth Micromechanism in Pipe Billets after Thermomechanical Treatment[J]. Physics of Metals and Metallography 119(2018), 52-59.

[3] Adam S. P., Likas A. C., Vrahatis M.N.. Evaluating generalization through interval-based neural network inversion[J]. Neural Computing and Applications 31(2019), 9241-9260.

[4] Yasrab R.. SRNET: A Shallow Skip Connection Based Convolutional Neural Network Design for Resolving Singularities[J]. Journal of Computer Science and Technology 34(2019), 924-938.

[5] Fedosov A. V., Skrebtsov A. M., Pashchuk D.V.. Formation of Transverse Surface Cracks During Peritectic Steel Continuous Casting[J]. Metallurgist 62(2018), 39-48.

[6] Varfolomeev I. A., Ershov E. V., Vinogradova L. N.. Statistical Control of Defects in a Continuously Cast Billet Based on Machine Learning and Data Analysis Methods[J]. Automation and Remote Control 79(2019), 1450-1457.

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