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END POINT PREDICTION OF BASIC OXYGEN FURNACE (BOF) STEELMAKING BASED ON IMPROVED BAT-NEURAL NETWORK

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A mixed bat optimization algorithm based on chaos and differential evolution (CDEBA) is proposed for the end-blow process of basic oxygen furnance (BOF) after sub-lance detection, and a prediction model based on BP neural network optimized by chaotic differential bat algorithm (CDEBA-NN) is presented. The simulation results show that the prediction model of carbon content achieves a hit rate of 94 % with the error range of 0,005 %, and 90 % for temperature with the error range of 15 °C, the accuracy is higher than the traditional neural network model, and then it verifies the effectiveness of the proposed model.

Key words: steelmaking, BOF, end point prediction, back propagation (BP) neural network, bat algorithm

INTRODUCTION

In order to improve the accuracy of dynamic model calculation, many scholars have introduced intelligent technology into the terminal prediction of steelmaking [1,2]. For example, Ai xiaoli et al. established a BP neural network based model for prediction of oxygen consumption in basic oxygen furnace (BOF) steelmaking, thus the prediction error of oxygen consumption was reduced [3]. Tao ziyu et al. used the improved artificial neural network algorithm to develop the prediction model of the end temperature of molten steel in the refining process of 40t ladle furnace, which improved the prediction speed and accuracy of neural network [4]. Therefore, the prediction model established after the improvement of BP neural network can effectively improve the prediction effect of the model.

In this paper, aiming at the disadvantages of slow convergence speed of BP neural network, a prediction modeling method based on bat algorithm [5,6] was proposed to optimize BP neural network, which effectively improved the prediction ability of the network. However, the bat algorithm has the defect of premature convergence and easy to fall into local optimum, therefore, the chaos algorithm and differential evolution algorithm were used to improve the bat algorithm [7-9], then the quality of the initial solution and species diversity are improved.

Currently, BOF steelmaking is a top priority in steel production and occupies an important position in production. The steelmaking model has gone through three development stages of static control, dynamic control and full automatic. The whole steelmaking process is a periodic temperature-rising and carbon-reducing process, which contains very complex multi-phase high-temperature reaction. The main purpose is to achieve the carbon content and temperature of target molten steel as much as possible at the end point of blowing. Therefore, it is very important to establish an accurate carbon content and temperature prediction model.

Hence, an chaotic difference bat algorithm based BP neural network (CDEBA-NN) prediction model is proposed to improve the global search ability and the prediction accuracy.

ESTABLISHMENT OF CDEBA-NN PREDICTION MODEL

Back Propagation (BP) neural network is an artificial intelligence algorithm, which can be used to predict the end-point information of BOF by learning and mastering the dependence of data. Compared with the traditional methods, this method has great advantages and avoids the influence of many human factors. Therefore, it has its unique advantages in the rationality and adaptability of the carbon content and temperature prediction model.

Bat Algorithm (BA) is a new intelligent Algorithm, which can avoid the Algorithm falling into local optimization and has better convergence. It can achieve good results in prediction.

Chaotic differential bat algorithm (CDEBA)

In view of the shortcoming of the bat algorithm, it is easy to fall into the local optimum. In the later optimization process, the precocious judgment mechanism of particles is adopted. If the fitness function value of the bat algorithm is less than the given threshold value, the cha-

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otic bat algorithm is considered to fall into the local optimum. The diversity of population is enhanced by the main operation of the differential evolution algorithm, which makes the algorithm jump out of local optimum.

For the optimization problem with the objective function of min $f(X)$ and the objective variable of $X = (X_1, X_2, ..., X_d)^T$, the relevant definition of bat algorithm is as follows:

Definition 1: The pulse frequency, speed and position of bats in the process of searching for prey are divided into:

$$f_i = f_{min} + (f_{max} - f_{min})\,\beta \tag{1}$$

$$v_i(t+1) = v_i(t) + (X_i(t) - X^*)\,f_i \tag{2}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{3}$$

where f_i represents the pulse frequency in the search for prey by the i, $[f_{min}, f_{max}]$ is the pulse frequency range, and β is a random variable uniformly distributed on [0,1]. $v_i(t+1)$ and $v_i(t)$ represent the velocity of i bat at two moments in $t+1$ and t, $X_i(t)$ is the location of i bat t moment in space, and X^* is the best location of all bats in the current search process.

Definition 2: The formula of pulse transmission frequency and sound intensity in the search for prey is as follows:

$$r_i(t+1) = r_0[1 - \exp(-\gamma t)] \tag{4}$$

$$A_i(t+1) = \alpha A_i(t)] \tag{5}$$

where $r_i(t+1)$ represents the pulse frequency of bat at the moment of $t+1$, r_0 represents the maximum pulse frequency of bat, γ represents the coefficient of pulse frequency increase, which is a constant greater than zero, α represents the attenuation coefficient of pulse intensity, which is a constant on [0, 1], $A_i(t)$ and $A_i(t+1)$ represent the sound intensity of bat at the moment of t and $t+1$.

Set the value range of the j ($j \in D$) dimensional space variable of the population as $[a_j, b_j]$. For a randomly initialized vector $y_0 = [(y_{0,1}, y_{0,2}, ..., y_{0,j}, \cdots, y_{0,D})^T]$, $y_0 \in (0, 1)$, and $y_{0,j} \neq 0{,}25, 0, 5, 0, 75)$, y_0 is regarded as the initial value, and the sequence $y_{n+1,j}$ is obtained according to the operation of Logistic chaotic map:

$$y_{n+1,j} = \mu y_{n,j}\,(1 - y_{n,j}) \tag{6}$$

where $n = 0,1,2,...$, $j = 1,2, ..., D$, μ is the control parameter.

According to the following formula, the chaotic sequence $y_{n+1,j}$ is mapped to the position vector $x_{n+1,j}$:

$$x_{n+1,j} = a_j + (b_j - a_j)\cdot x_{n+1,j}, \tag{7}$$

In the case of $j = 1, 2, ..., D$, there are D variables in the search space mapped from the chaotic sequence, forming the vector D in the dimension of $X_i = [(x_{i,1}, x_{0,2}, ..., x_{0,D})$. The constructed vector X_i is the position of a bat in the search space, which is a feasible solution in the optimization problem. Because of $i = 1, 2, ..., p$, the initial position of each bat with a number of p in space can be obtained. In the same way, the pulse rate and flight speed of the bat can be calculated according to the above chaos algorithm, and the parameters of the bat algorithm can be initialized.

In this paper, the reciprocal of the error is used as the fitness function. The larger the fitness value indicates that the selected solution is closer to the optimal one, and the fitness function is as follows:

$$f = \frac{1}{E}, \tag{8}$$

where f represents the fitness value of the individual and E represents the error of predicted results and actual expectations.

In the later stage of the algorithm iteration, the bat position after evolution does not directly enter the next iteration, but carries out differential evolution operation on individuals in the population with the following operation steps:

(1)Mutation operation: three different individuals, X_a, X_b, X_c, and $i \neq a \neq b \neq c$, $a, b, c \in \{1, 2, ..., p\}$ are randomly selected from the population

$$V_{ij}(t) = X_a(t) + F\,(X_b(t) - X_c(t)), \tag{9}$$

where, $X_{b,j}(t) - X_{c,j}(t)$ represents the differentiation vector, and F is the scaling factor and $F \in [0,2]$.

(2) Crossover operation: the crossover

Operation between individuals is performed according to formula (8) for generation t and intermediate populations:

$$U_{ij}(t+1) = \begin{cases} X_{ij}(t), & rand > CR \ or \ j \neq i \\ V_{ij}(t), & rand \leq CR \ or \ j = i \end{cases}, \tag{10}$$

where: *rand* is a random number, uniformly distributed on [0, 1], and $CR \in [0,1]$ represents the crossover probability. Using the above crossover strategy, it can ensure that at least one variable in $U_{ij}(t+1)$ is generated by $X_i(t)$.

(3) Selection operation: the fitness

Function value of $U_{ij}(t+1)$ and $X_i(t)$ individual vectors is compared to determine whether $X_i(t)$ is better to generate the next generation individual $X_i(t+1)$.

$$X_i(t+1) = \begin{cases} U_{ij}(t+1), & if\left(f\left(U_{ij}(t+1)\right) > f\left(X_i(t)\right)\right) \\ X_i(t), & else \end{cases}. \tag{11}$$

CDEBA-NN prediction model

Firstly, the BP neural network model is established and the initial position of individual bat in the bat algorithm is determined according to the Logistic chaotic map sequence formula. Secondly, the individual position, speed and frequency of bat are updated, and the mutation and crossover mechanism of differential evolution algorithm is introduced in the later optimization stage. Finally, the global optimal solution of bat algorithm is corresponded to the weight and threshold of BP neural network, and the result is output when the condition is met. The implementation steps are listed below:

Step 1: initialize the relevant parameters of BP neural network, set the number of input layer nodes as M, the number of hidden layer nodes as I, the number of output layer neurons as J, the input vector of network is $X(n)$, the actual output vector is $Y(n)$, and the expected output vector is $d(n)$.

Step 2: initialize bat population: suppose that bat number is p, population space is D dimension, and $D = M \cdot I + I \cdot J + I + J$, bat pulse frequency belongs to $[f_{min}, f_{max}]$, maximum pulse frequency and maximum sound intensity are r_0 and A_0, respectively. The attenuation coefficient and frequency increase coefficient of pulse intensity are α and γ, maximum iteration number is $MaxT$, search accuracy is ε. Parameters of differential evolution algorithm: F is a scaling factor and $F \in [0,2]$, and $CR \in [0,1]$ represents crossover probability.

Step 3: According to the Logistic chaotic mapping formula (6), (7) randomly initialize the position, velocity and frequency of the bat, discover the best position of bats X^*.

Step 4: update the pulse rate f_i, velocity V_i and position X_i of the bat according to formula (1) - (3).

Step 5: generate random number *rand* 1; if *rand* 1 > r_i, adopt disturbance operation for individual bat in the optimal position, and replace the current position with the new position of bat after disturbance.

Step 6: generate random numbers *rand* 2. If *rand* 2 < A_i, and the bat position is optimized, the new solution obtained by Step 5 is accepted and updated according to formula (4) - (5).

Step 7: cross, mutate and select the bat according to formula (9) - (11) to obtain the new population location.

Step 8: according to the sequencing comparison of the fitness value of bat population in formula (8), the optimal position of bat individuals after optimization is determined.

Step 9: if the maximum number of searches or the search accuracy is met on one hand, go to Step11; otherwise, go to Step 3 and continue the new round of search.

Step 10: output the global optimal individual value, output the global optimal solution of bat algorithm, corresponding to the weight and threshold of BP neural network.

Step 11: if the maximum number of iterations or the minimum error value given by BP neural network is reached, the optimal value is output and the operation is completed; Otherwise, go to Step 3.

SIMULATION AND ANALYSIS

Based on the historical production data in a steel plant, we conducted the prediction analysis, respectively using BP neural network, BA-NN, and CDEBA-NN to carry out the precision simulation comparison analysis of carbon content and temperature prediction.

Data sources

After preprocessing the historical data, 300 groups of qualified data are obtained. The first 250 sets of data are used as input samples, and the last 50 sets of data are used as test samples. The reblowing oxygen volume, the carbon content measured and the temperature measured by the sub-lance are taken as input variables, and the end-point carbon content and temperature measured are respectively taken as output variables.

Parameter setting

BP neural network parameter settings: input layer, hidden layer and output layer neuron number can be divided into: $M = 3$, $I = 6$, $J = 1$, activation function for Tan-Sigmoid function, learning step size $\eta = 0,2$, learning $l > 2\ 000$, carbon content prediction model of the error range is set to 0,005 %, the temperature prediction model of the error range is set to 15 °C.

Parameter settings of bat algorithm: the population size is $p = 40$, the population space is D dimension, and $D = M \cdot I + I \cdot J + I + J$, the bat pulse frequency range is $[f_{min}, f_{max}] = [-1,]$, the maximum pulse frequency and maximum sound intensity are $r_0 = 0,75$ and $A_0 = 0,25$, the attenuation coefficient and frequency increase coefficient of impulse intensity are $\alpha = 0,5$ and $\gamma = 0,05$, and the maximum iteration number is $MaxT = 300$.

Comparative analysis

Evaluation analysis is conducted from the five aspects of root mean square error (RMSE), average absolute percentage error (MAPE), ratio of squares (SSE/SST, SSR/SST), hit rate (CHR,%, THR,%). The smaller the RMSE and MAPE, the smaller the prediction error and the better the result. SSE/SST indicates the fitting degree of the model and data, and the smaller the ratio, the higher the fitting degree. SSR/SST indicates that the predicted fluctuation and actual value are consistent, and the closer the ratio is to 1, the higher the anastomosis. CHR, %, THR, % respectively represent the carbon content and temperature hit rate. The comparison results are shown in Table 1:

Table 1 **Comparisons of three prediction methods**

Model	Criteria	BP	BA-NN	CDEBA-NN
C_model (±0,005 %)	RMSE	0,0067	0,0065	0,0055
	MAPE	0,1310	0,1280	0,1111
	SSE/SST	0,0235	0,0220	0,0160
	SSR/SST	1,2321	1,2366	1,2041
	CHR, %	84	88	94
T_model (±15 oC)	RMSE	16,0873	15,5718	15,1513
	MAPE	0,0079	0,0066	0,0070
	SSE/SST	0,8355	0,7828	0,7411
	SSR/SST	0,5013	0,5038	0,7027
	THR, %	78	84	90

It can be seen from table 1 that in the prediction of carbon content, RMSE of BP, BA-NN and CDEBA-NN prediction models is 0,0067, 0,0065 and 0,0055 respectively, and MAPE is 0,1310, 0,1280 and 0,1111 respectively. It can be concluded that the CDEBA-NN prediction model has the smallest prediction error and the optimal effect. The SSE/SST of BP, BA-NN and CDEBA-NN prediction models are 0,0235, 0,0220 and 0,0160, respectively. The ratio of CDEBA-NN is the smallest, and the fitting degree of the model and data is the highest. The SSR/SST of BP, BA-NN and CDEBA-NN prediction models are 1,2321, 1,2366 and 1,2041, respectively. The carbon content percentages of BP, BA-NN and CDEBA-NN prediction models are 84 %, 88 % and 94 %, respectively. It can be seen that the CDEBA-NN prediction model has the highest carbon content percentages. According to the above analysis, the CDEBA-NN prediction model has the highest accuracy, and the prediction effect is better than that of BP and BA-NN prediction models.

In the prediction of temperature, RMSE of BP, BA-NN and CDEBA-NN prediction models are respectively 16,0873, 15,5718 and 15,1513. The CDEBA-NN prediction model has the smallest root mean square error and the best effect. MAPE of BP, BA-NN and CDEBA-NN prediction models are 0,0079, 0,0066 and 0,0070, respectively. MAPE of CDEBA-NN prediction model is larger than that of BA-NN prediction model and smaller than that of BP prediction model. The SSE/SST of BP, BA-NN and CDEBA-NN prediction models are 0,8355, 0,7828 and 0,7411, respectively. The ratio of CDEBA-NN was the smallest and the fitting degree of model and data is the highest. The SSR/SST of BP, BA-NN and CDEBA-NN prediction models are 0,5013, 0,5038 and 0,7027, respectively. The SSR/SST ratio of the CDEBA-NN prediction model is closest to 1, and the predicted value and the actual value had the highest consistency degree of fluctuation. The temperature percentages of BP, BA-NN and CDEBA-NN prediction models are 78 %, 84 % and 90 %, respectively. It can be seen that the CDEBA-NN prediction model has the highest temperature percentages. Although the MAPE of the CDEBA-NN prediction model is not the best effect, the CDEBA-NN prediction model has the highest accuracy, and the prediction effect is better than that of BP and BA-NN prediction models

In summary, the effectiveness of the improved CDEBA-NN prediction model for carbon content and temperature prediction is demonstrated.

CONCLUSIONS

In this paper, an algorithm based on chaos differential evolution algorithm with the combination of BA and hybrid algorithm CDEBA algorithm has been proposed to established the BOF prediction model. The simulation results show that CDEBA-NN model achieve the satisfactory prediction results, the carbon content has achieved a hit rate of 94 %, and 90 % for temperature. For the further work, it can be used to estbalish the BOF dynamic control model and guide the real productin in steel plant.

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