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Endpoint Prediction of BOF Steelmaking based on BP Neural Network Combined with Improved PSO

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This paper concerns the endpoint estimation of the basic oxygen furnace (BOF) steel making process. More specifically, a back propagation (BP) neural network is employed to estimate the endpoint carbon content and the endpoint temperature of BOF, and an improved particle swarm optimization (PSO) algorithm is proposed to optimize the prediction model for improving the accuracy of the endpoint prediction. Simulation examples demonstrate the effectiveness of the proposed method.

1. Introduction

The iron and steel industry plays an important role in the process of economic development as essential raw and processed materials needed in the industry support the country's economy. BOF is a widely preferred and effective steelmaking method due to its high productivity and considerably low production cost in all steelmaking methods. BOF steelmaking is a very complex multi-variate and multi-phase physicochemical process. Its most notable characteristics are fast response, more influence factors, complex reaction and forward manual operation. It is aslo difficult with the BOF method to obtain timely detection information accurately. The endpoint carbon content and temperature of the BOF are the key parameters to raise steel quality and reduce costs. So, the BOF steelmaking endpoint control and prediction are very important and have been a major research issue.

A neural network is capability of self-learning, approaching any nonlinear function, and processing data quickly. For the purpose of modelling and predicting the endpoint carbon content and temperature of the BOF, a considerable group of authors have used different methodologies. At present, the mechanism model, statistical model, and artificial neural network model are common static models for BOF steelmaking endpoint control and prediction (Wang et al. 2005). With the development of artificial intelligence technology the intelligent model is widely used in BOF steelmaking endpoint control and prediction. Geng (2011) utilizes the echo state network to establish a prediction model of the first turning down carbon content and temperature, and uses the converter's furnace data from a domestic steel mill to test and analyze the model effect. Taking full advantage of the artificial neural network, the prediction model of the endpoint based on a neural network was established (Zheng & Feng 2007; Feng et al. 2008). Xie et al. (2006) set up an RBF network model of endpoint temperature and the carbon content using the nearest neighboring algorithm and the recursive least square method. Han et al. (2010) combined particle swarm optimization algorithm, independent component analysis, support vector machine algorithm and involved membrane algorithm with a radial basis function neural network. The results show an effective improvement in the precision of prediction models (Han et al. 2010; Wang et al. 2010; Liu et al. 2014).

However, due to the sophisticated thermal and chemical reaction processes of BOF, the distribution of the measurement data is dispersed and irregular. In addition, the performance of machine learning algorithms above depends on the parameters. If a specific parameter of the machine learning algorithm's setting is different, the result will be different. So, it is difficult for the methods above to accurately predict the endpoint temperature and the carbon content in BOF. In this paper, an improved PSO algorithm of reducing inertia weight and adding the constriction factor combined with BP neural network is presented for endpoint prediction in BOF.

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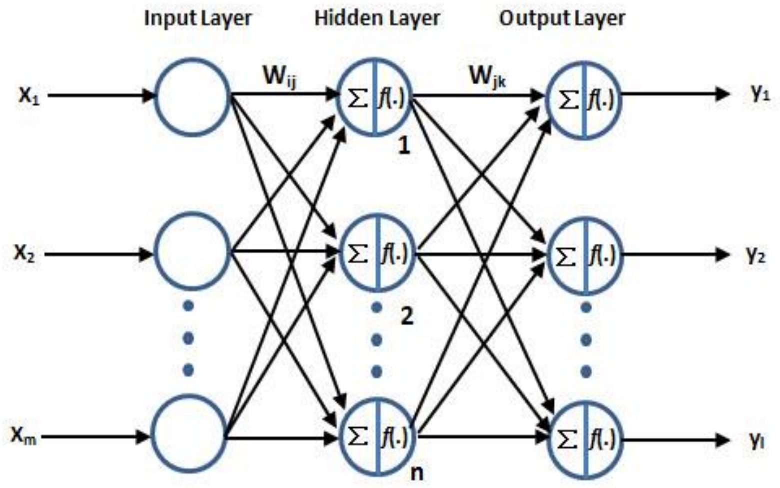

Figure 1: BP neural network structure

2. Basic oxygen steelmaking process

Then basic oxygen furnace steel making process is one of the key processes in the steel industry. The basic oxygen furnace is a widely preferred and effective steel making method due to its high productivity and low production cost. The BOF comprises a vertical solid-bottom crucible with a vertical water-cooled oxygen lance entering the vessel from above. After putting molten pig iron and scrap into the converter, which is able to tilt for charging and tapping, it is rotated with blowing oxygen. In the process， various types of slag material, burnt-lime, dolomite, iron, etc., are added into the converter in two or three batches during the blowing time. The BOF process aims to remove impurities and improve the temperature of the molten pool for the purpose of refining the molten steel. When the carbon level and temperature arrive a specific target, the liquid steel is tapped and slag is left in the converter. In general, the process includes charge material, blowing, endpoint control, tapping, splash protection, deslagging, and so on.

The endpoint control plays an essential role in the whole process of BOF steelmaking which is mainly completed in the last stage. The goal of BOF steelmaking production is to make the carbon content and temperature of the molten metal be in the target range.

3. Principle

3.1 Back propagation (BP) neural network

Artificial neural networks (ANN) are the abstraction, simplification and simulation of biological neural networks which have the capability of self-study, self-adaptation, self-organizing, etc. (Haykin 1994). The most widely used BP neural network, first presented in 1986 by Rumelhant and McClelland, is a multi-layer feedforward neural network including input layer, hidden layer and output layer as shown in Figure 1. The process of the BP learning algorithm can be divided into two stages: the forward propagation process and the backward propagation process. In the former, the input signal is transferred from the input layer to the output layer through a hidden layer, and if the output cannot attain the satisfactory values, then it will turn to the latter. In the backward propagation process, the error signal will return to the original connection and the weights and thresholds will be adjusted by constantly training until the network error is reduced to the satisfactory error level to attain the required accuracy.

Where m, n, l, respectively is the input layer nodes, the hidden layer nodes and output layer nodes, w_{ij} is called input-hidden layer link weights, w_{jk} is called hidden-output layer link weights.

So, the output value of the hidden layer is:

$$H_j = f\left(\sum_{i=1}^{m}\left(w_{ij}\ x_i - \theta_j\right)\right) \quad \mathrm{j} = 1,2,\ldots \mathrm{n}. \tag{1}$$

Where, θ_j is the threshold of the hidden layer nodes, $\mathrm{f}(.)$ is a nonlinear transfer function which generally uses the Sigmoid function:

$$\mathrm{f(x)} = \frac{1}{1+\mathrm{e}^{-\mathrm{x}}} \tag{2}$$

So, the output value of the output layer is:

$$Y_k = \sum_{j=1}^{n} H_j w_{jk} - a_k \quad \kappa = 1,2,\ldots,\mathrm{l}. \tag{3}$$

Where, a_k is the threshold of the output layer nodes.
The total errors of the output of the network can be defined as follows:

$$\mathrm{E} = \frac{1}{2\mathrm{N}} \sum_{\mathrm{p}=1}^{\mathrm{N}} \left(\mathrm{T_p} - \mathrm{Y_p}\right)^2 \quad \mathrm{p} = 1,2,\ldots,\mathrm{N}. \tag{4}$$

Where p is the number of the total training samples, $\mathrm{Y_p}$ is the the actual outputs of the network and $\mathrm{T_p}$ is the target outputs when the total training sample is used for training (Laha et al. 2015). During the learning process, the weight of the network is modified by calculating the errors of each layer according to the total errors. By training, the relationships of the inputs and outputs is generalized so that it can make reliable estimates for data to which it has not been exposed. The BP algorithm is effective and has great nonlinear mapping capability (Liu et al. 2015; Ge et al. 2015; Ma et al. 2012). But the weights and thresholds of the BP neural network is easily run into the local minimum. To overcome this disadvantage, the paper applies PSO to improve effectively the short-coming. A considerable group of authors have used BP-PSO methodologies in a wide variety of fields in (Liu & Yang 2015; Li et al. 2014; Yu et al. 2011).

3.2 Particle swarm optimization

The PSO algorithm proposed by James Kennedy and Russell Eberhart is an evolutionary computation technique based on the swarm intelligence theory, which graphically simulate the foraging behavior of a flock of birds. In the PSO algorithm the space of the solution to the optimization problem is viewed as the foraging area of the bird. The flock is referred to as a swarm, the foraging area is referred to as the searching space, and the bird is referred to as a particle to represent a candidate solution to the problem. The performance of each particle is evaluated using a predetermined fitness, which encapsulates the characteristics of the optimization problem. In the process, the location and velocity of the particle will be dynamically updated according to its own flying experience and that of neighboring particles. The best position obtained is the optimal solution to the problem through the cooperation among particles in group.
It is assumed that there is a D-dimensional searching space and the number in the swarm is n. Suppose that the current best previous position of the ith particle is referred to as the individual extreme point and the current best global position of the whole group is the global extreme point. The basic parameters of PSO algorithm are as follows:
The swarm composed of n particles:

$$\mathrm{X} = (\mathrm{X_1}, \mathrm{X_2}, \mathrm{X_3}, \ldots \mathrm{X_n}) \tag{5}$$

The ith particle of D dimension vector:

$$\mathrm{X_i} = (\mathrm{X_{i1}}, \mathrm{X_{i2}}, \mathrm{X_{i3}}, \ldots \mathrm{X_{iD}})^{\mathrm{T}}; \tag{6}$$

The velocity of the ith particle:

$$\mathrm{V_i} = (\mathrm{V_{i1}}, \mathrm{V_{i2}}, \mathrm{V_{i3}}, \ldots \mathrm{V_{iD}})^{\mathrm{T}}; \tag{7}$$

The individual extreme point:

$$\mathrm{P_i} = (\mathrm{P_{i1}}, \mathrm{P_{i2}}, \mathrm{P_{i3}}, \ldots \mathrm{P_{iD}})^{\mathrm{T}}; \tag{8}$$

The global extreme point:

$$\mathrm{P_g} = \left(\mathrm{P_{g1}}, \mathrm{P_{g2}}, \mathrm{P_{g3}}, \ldots \mathrm{P_{gD}}\right)^{\mathrm{T}}; \tag{9}$$

The states of the particles are updated according to the following equations:

$$V_{i.j}(t+1) = V_{i.j}(t) + c_1 r_1 [p_{i.j} - x_{i.j}(t)] + c_2 r_2 [p_{g.j} - x_{i.j}(t)] \quad j = 1, \dots, D. \tag{10}$$

$$x_{i.j}(t+1) = x_{i.j}(t) + x_{i.j}(t+1) \quad j = 1, \dots, D. \tag{11}$$

Where i=1,2,3,…,n, j=1,2,3,…,D. t represents iteration times. r_1 and r_2 are uniformly distributed stochastic numbers in the interval [0,1]. c_1 and c_2 are learning factors, also named accelerated coefficients. When c_1 is larger it is beneficial for the global search, and when c_2 is larger it is beneficial for the local search. To improve the convergence performance and balance the ability of the PSO in both global and local searches, the contraction factor φ is introduced to the basic PSO as defined as follows:

$$V_{i.j} = \varphi v_{i.j}(t) + c_1 r_1 [p_{i.j} - x_{i.j}(t)] + c_2 r_2 [p_{g.j} - x_{i.j}(t)] \tag{12}$$

$$\varphi = \frac{2}{|2 - C - \sqrt{C^2 - 4C}|}, \ C = c_1 + c_2, \text{ and } C > 4 \tag{13}$$

3.3 Improved PSO-BP optimization algorithm

The above analysis yields the following conclusion. While the BPNN is a well-established and effecitve algorithm, there are some disadvantages associated with it; namely being slow in convergence speed and easily being trapped in the local minimum. PSO can be a solution to this problem which is a population optimization algorithm and has strong capability for global searching. Moreover, the calculated strength of PSO is relatively small. The PSO-BP, a new computational intelligence method, is proposed by combining the improved PSO and BP. PSO-BP applies the improved PSO to optimize the initial weights and thresholds of BP neural networks. The detailed description of the improved PSO-BP algorithm is described as follows:

Step 1: Establish the BP neural network. According to practical problems determine the number of nodes of the input layer, hidden layer, and output layer as m,n,l respectively.

Step 2: Set the number of particle swarm as N, the dimension of the particle swarm:

$$D = m \times n + n \times L + n + l \tag{14}$$

The maximum iteration times t_{max}, learning factors c_1 and c_2

Step 3: Set the initialization position and velocity of particle.

Step 4: Set the fitness function of particle swarm as Eq (3).

Step 5: Select training sample, calculate the fitness value of each particle.

Step 6: Compare and then update the velocity and position in accordance with Eq (5, 6).

Step 7: Determine whether the conditions are met to stop the algorithm. If the fitness of each particle does not meet the error requirement or maximum number of iteration, then go to Step 5; otherwise go to Step 8.

Step 8: End the algorithm and output the optimized weights and thresholds.

Step 9: Traning samples with the optimized weights and thresholds obtained in the BP network, the optimal solution can be obtained.

4. Modeling and simulation

4.1 Model structure

A three BP neural network is established as in Figure 1. m, n, l are assigned the values of 16, 32, 1 respectively. By analyzing the factors affecting endpoint temperature and carbon content, the input of the model are selected as the quantity of molten iron x_1, the temperature of molten iron x_2, the quantity of auxiliary material (C, Si, Mn, P, S, scrap steel, etc.) x_3 to x_{14} the quantity of oxygen x_{15}, the time of oxygen supplying x_{16}. The output of the model is endpoint temperature or the carbon content respectively. In this paper the improved PSO-BP optimization algorithm detailed in 3.3 is used, where the number of the particle swarm is 200, c_1 and c_2 both are 2.05, and t_{max} is 500.

4.2 Simulation

Since the different parameters have different units, the data are to be normalized to avoid numerical overflow and underflow. In this study, the normalization is processed according to the following equations:

$$x' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{15}$$

In this research, 90 data points are extracted from the BOF process and the data set is divided into two groups: the training set with the first 62 data points and the testing set with later 28 data points. Then the PSO-BP neural network is training by the set of input-output data to predict the endpoint carbon content and the endpoint temperature in the BOF process.

After the PSO-BP neural network training stage, the model is verified by 28 testing data points. The results are shown in Figures 2 and 3. Figure 2 shows that when the carbon content prediction error is within ±0.02, the prediction accuracy rate of carbon content is 92.85%.

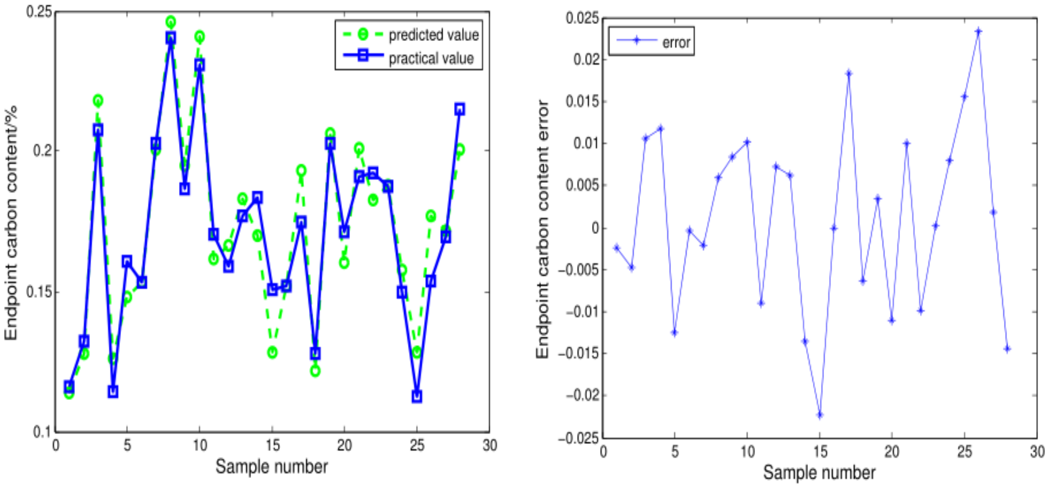

Figure 2: Prediction of endpoint carbon content

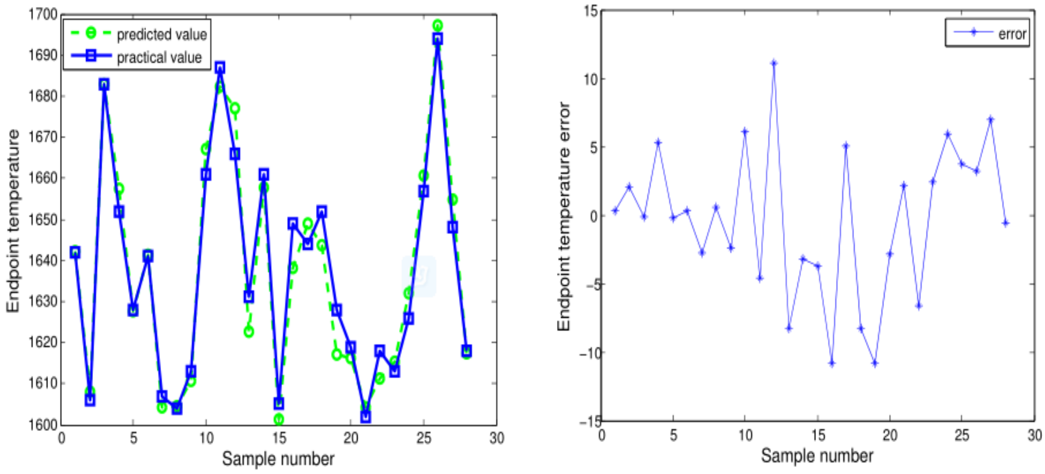

Figure 3: Prediction of endpoint temperature

Figure 3 Shows that when the endpoint temperature prediction error is within±10℃, the prediction accuracy rate of the endpoint temperature is 89.28%.

5. Conclusion

In the complex industrial process of BOF steel making, the endpoint carbon content and endpoint temperature are key factors affecting the quality control of the BOF. Based on this analysis, the BP neural network prediction model combined with the improved PSO algorithm is proposed to predict the endpoint carbon content and endpoint temperature of the BOF. The data results from practical tests show that the model can effectively improve the forecast precision, and that the carbon content and endpoint temperature prediction accuracy rate of the model are both adequate for process control.

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Reference

Feng J.H., Zheng Y.P., Li X.J., Zhu X.H., Bi N., 2008, Prediction model of endpoint for converter smelting based on neural network, 30(3), 26-29, DOI: 10.3969/j.issn.1674-0262.2008.03.006.

Ge K., Shi B.B., Xu K.Y., Zhao J.Q., 2015, Air quality assessment based on BAPSO-PNN neural network algorithm, Environmental engineering 33, 676-681.

Geng T., Li Q.X. , 2011, Prediction for the content of carbon and temperature at the endpoint of BOF based on echo state network, Metallurgical collections 3, 4-7, DOI: 10.3969/j.issn.1671-3818.2011.03.002.

Han M., Jiang L.W., Zhao Y,, 2010, Endpoint prediction model of basic oxygen furnace steelmaking based on PSO-ICA and RBF neural network, Information and control 1, 82-87, DOI: 10.3969/j.issn.1002-0411.2010.01.015

Haykin S., 1994, Neural Networks: A Comprehensive Foundation. Macmillan College Publishing, New York.

Laha D., Ren Y., Suganthan P.N., 2015, Modeling of steelmaking process with effective machine learning techniques, Expert Systems with Applications 42, 4687-4696, DOI: 10.1016/j.eswa.2015.01.030.

Li D.J., Li J.Q., Zhang Y., Zeng Z., 2014, Gesture recognition of data glove based on PSO-Improved BP neural network, Electric machines and control 8, 87-93, DOI: 10.3969/j.issn.1007-449X.2014.08.014.

Li Q.A., Yang X., 2015, Multi-mode soft sensor modeling of naphtha dry point based on PSO-k means clustering, Computers and applied chemistry 8, 991-994, DOI: 10.11719/com.app.chem20150820.

Liu C., Han M., Wang X.Z., 2014, Endpoint prediction model for basic oxygen furnace steelmaking based on membrane algorithm evolving extreme learning machine, Journal of Dalian University of Technology 1, 124-130, DOI: 10.7511/dllgxb201401019.

Liu Z., Chen X.H., Xue L.S., Zou B., Zhang Q., 2015, Prediction of satellite clock errors based on GM-LSSVM improved by IPSO, Science of Surveying and Mapping 9, 115-119, DOI: 10.16251/j.cnki.1009-2307.2015.09.024.

Ma X.Y., Duan Y.F., Liu M., Li H.F., 2012, Prediction of pressure drop of coke water slurry flowing in pipeline by PSO-BP neural network, Proceedings of the CSEE 5, 54-60.

Wang J.H., Xu L., Fang X.K., 2005, A class of GA-RBF neural network control for the BOF steelmaking static mode,Journal of Southeast University 35(S2), 90-94.

Wang X.Z., Han M., Wang J., 2010, Applying input variables selection technique on input weighted support vector machine modeling for BOF endpoint prediction, Engineering Applications of Artificial Intelligence 23,1012-1018, DOI: 10.1016/j.engappai.2009.12.007.

Xie S.M., Sun K., Chen C., 2006, BOF endpoint prediction based on RBF neural network, Journal of shenyang university of technology 4,405-408, DOI: 10.3969/j.issn.1000-1646.2006.04.012.

Yu Y.J., Jiang W.G., Xu M.F., 2011, Prediction of chlorophyll a by BP neural network based on PSO algorithm, Research of environmental sciences 5, 526-532.

Zhen Y.P., Feng J.H., 2007, Static prediction model of Mn & P endpoint content for converter smelting based on neural network, Journal of Hebei Institute of Technology 29(2), 16-19, DOI: 10.3969/j.issn.1674-0262.2007.02.005.