A Study on Prediction of Phosphorus Content for AOD Furnace Based on PSO-RBF Neural Network

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***Abstract* — AOD (Argon Oxygen Decarburization) smelting low carbon ferrochrome is extremely complex and multiphase, which is carried out under high temperature chemical process of nonlinear physical. The discretion of the phosphorus' impurity content is an important factor to affect the quality of ferrochrome products. In order to predict the quality of the product control, it is an optimization method taking the grey incidence degree between the network's output and input as an objective. The RBF neural network predictive control theory is taken as the foundation and then used as an identification prediction model of AOD furnace system. At the same time, the modified particle swarm optimization (PSO) is used as an optimization algorithm of the network predictive controller to get the online prediction phosphorus content control. The simulation results show that the accuracy of optimization control model is 95.4% with error rate of ±0.003%, which realizes the effective and optimal control of phosphorus content. The established prediction model is an optimal process control model, which provides an important theoretical support for improving the quality of low carbon ferrochromium.**

Keywords - RBF neural network; Particle swarm optimization (PSO); Predictive control; AOD furnace

I. INTRODUCTION

AOD smelting is a complex high temperature multiphase reaction process, which involves a variety of interface reaction and includes a series of complex reactions. In the actual production, due to the low carbon ferrochrome smelting process by means of testing and production conditions of the restrictions, it is difficult to establish an accurate model of the control process. With the development of detection and control technology, the control model of AOD furnace has been improved. However, there are a lot of process parameters which can not be clearly expressed in the process of smelting, so it is difficult to realize accurate model. With the gradual maturation of the neural network theory application, the theory of predictive control algorithm is introduced into the static control. On line prediction of AOD furnace is not only in the identification and prediction, but also can achieve the further optimization. Therefore, this paper makes a deep research on the control method of the static model combined with the neural network predictive model. This paper further research for control method, with the guidance of predictive control, established the optimal control based on neural network prediction model. The method, which is a combination of static models and prediction model of neural network identification, improves the finish control of phosphorus content hits. The predictive model based on RBF neural network is used as the controlled system. Meanwhile, the PSO algorithm is used to achieve the input optimization and to improve the optimization accuracy [1,2,3].

According to the production data of a Ferro Alloys Co., the RBF network is established as a system identification model in the controller, and the particle swarm optimization algorithm is adopted [4]. In order to avoid the local optimum, the grey correlation degree between the network output value and the true value of the test sample is used as the fitness function to realize the predictive control of the phosphorus content in the AOD furnace.

II. NETWORK PREDICTION SYSTEM

Neural network prediction is a control prediction model based on neural network, which is commensurate with the expectation of stability for nonlinear systems performance [5]. The control is divided into two phases: 1) system identification stage, to establish the online prediction of phosphorus content based on neural network identification; 2) optimum control stage, to achieve the optimal performance of the system control input selection [6]. Neural network predictive controller is established for the prediction model of the nonlinear controlled object, which predicts the output value in the future.

In Figure 1, y_r is system expected value, $y_p(k)$ is the actual output value of the system under optimal control, $y_m(k)$ is real time response value.

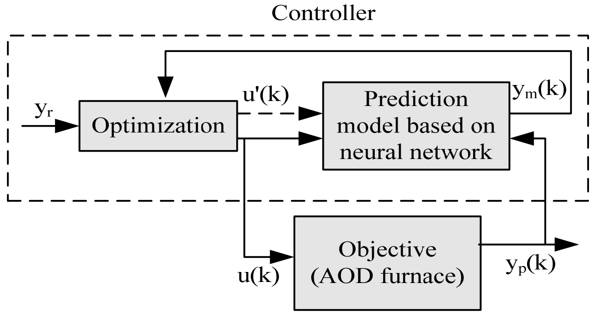

Figure1. Neural Network Prediction Structure

III. PREDICTION MODEL OF PSO-RBF NEURAL NETWORK IDENTIFCATION

RBF neural network belongs to the feed-forward network type, which has been proved to be a universal function approximation. It is widely used in complex system modeling because of its local approximation to any nonlinear function. In this paper, the PSO optimization neural network is used to improve the local optimum of RBF neural network. A neural network prediction model is established, which is shown in Figure 1.

A. *RBF Netural Network Model*

Radial Basis Function neural network is a nonlinear multilayer network proposed by J. Moody and C. Darken at the end of 1980s. It is a kind of neural network structure which is simulated in the human brain and covered each other receiving domains. With local approximation characterize, it can approximate arbitrary continuous function with arbitrary precision.

Three compact type neural networks are used to predict the contents of P value end of the argon oxygen decarburization alloy by all connections.

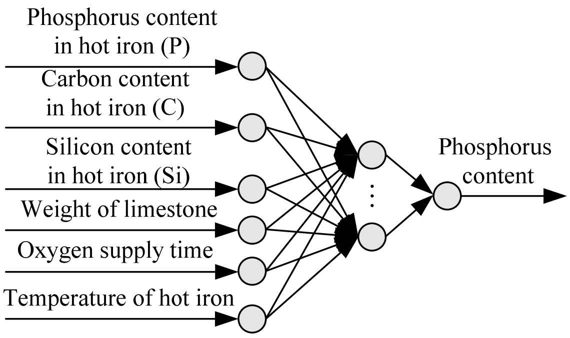

Figure 2. Prediction Model of Phosphorus Content Based on RBF Neural Network

The first layer is the input layer, which is only the transmission signal:

$$Q_i^{(1)} = I_i^{(1)} = x_i, i = 1,2,3,4,5,6 \tag{1}$$

The second layer is the hidden layer, the number of hidden units is determined by the description of the problem, the implicit unit of the transformation function is the central point of the radial symmetry and attenuation of nonnegative nonlinear function:

$$h_j = \exp(-\frac{\left\| X - C_j \right\|^2}{2b_j^2}), j = 1,2,\cdots,l \tag{2}$$

Where, h_j is the output of the first *j* hidden layer node; *X* is an n-dimensional input vector; C_j is the center vector; b_j is the width of Gaussian function; *l* is the number of neurons. In addition the center distance between the input sample and the Gaussian function is smaller, the output is larger.

Output of the network is got by the third layer:

$$f(x) = WH = \sum_{j=1}^{n} \omega_j h_j \tag{3}$$

This study is to a ferroalloy company's actual production data as the test sample, using five-number summary method to remove unreasonable data. According to the actual smelting process of AOD furnace, the multi dimensional mutual information theory is used to determine the input factors of the single output prediction model [7], which are phosphorus content in hot iron (%), carbon content in hot iron (%), silicon content in hot iron (%), the weight of limestone (Kg), oxygen supply time (min), temperature of hot iron (°C), and so on.

B. *Modified PSO Algorithm*

PSO algorithm is proposed in 1995, which emulates the behavior of birds flying in the cluster, and the collective cooperation among birds enables the group to achieve the optimal goal. PSO algorithm is widely used in industrial process control and optimization, and has achieved the ideal result, which is simple and easy to implement and fast convergence.

The basic particle swarm optimization also has some shortcomings, such as poor local search ability, search accuracy is not high, easy to fall into the local optimal solution, and so on [8]. Therefore, the contraction factor and genetic algorithm are introduced to improve the variance of these issues.

In a D dimension search space, assuming that there are M particles to form a group, the position of the first i particle is represented as a vector $x_i = [x_{i1}, x_{i2}, \cdots, x_{iD}], i = 1,2,\cdots, M$, and velocity vector $v_i = [v_{i1}, v_{i2}, \cdots, v_{iD}]$. The current position of the particle is evaluated by the objective function of the particle swarm. The best position of the i particle is p_{best}, which is the individual extremum of the particle. g_{best} can be found the best place all the particles is global extremum of a group. For the first k iteration, the speed and position of each particle in the PSO will be updated according to the following formula:

$$v_{id}^{k+1} = wv_{id}^k + c_1 r_1 (p_{id} - x_{id}^k) + c_2 r_2 (p_{gd} - x_{id}^k) \tag{4}$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \tag{5}$$

$$w = w_{\max} - k \times \frac{w_{\max} - w_{\min}}{iter_{\max}} \tag{6}$$

After adding the contraction factor, the formula 4 will become the formula 7:

$$v_{id}^{k+1} = \phi[wv_{id}^k + c_1 r_1 (p_{id} - x_{id}^k) + c_2 r_2 (p_{gd} - x_{id}^k)] \tag{7}$$

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$$\phi = \frac{2}{\left|2 - C - \sqrt{C^2 - 4C}\right|}, C = c_1 + c_2 > 4 \tag{8}$$

Where, v_{id}^k is particle velocity; x_{id}^k is particle position; p_{id} is the D dimension component for particle i individual extremum of p_{best} ; p_{gd} is component of the D dimension; c_1 and c_2 are accelerating factors; r_1 and r_2 are randomly distributed between [0,1]; w is inertia weight; k is the current number of iterations; $iter_{\max}$ is maximum number of iterations; φ is compression factor.

C. Hybrid Optimization Strategy of Modified PSO-RBF Network

1) Particle dimension of modified PSO algorithm

It is important to establish the mapping between the dimension search space of PSO particles and the network structure to be optimized [9].If the network structure is m-n-q, then the dimension of the particle is: $m \times n + n \times q + n + q$.

2) Structure of fitness function

Grey correlation is a measure reflecting the degree of association between the size of each factor. It will produce the results of each test and the true value of the grey relation degree as the objective function. In the smelting process, if the change trends of the two factors are consistent, they will be relatively high degree of correlation. In this paper, the grey relational degree function is used as the fitness function of the algorithm:

$$\begin{aligned} \rho_{0j}(k) &= \frac{A_1 + 0.5A_2}{\left|y_0(k) - y_j(k)\right| + 0.5A_2} \\ A_1 &= \min_{j'} \min_{k'} \left|y_0(k') - y_{j'}(k')\right|, \\ A_2 &= \max_{j'} \max_{k'} \left|y_0(k') - y_{j'}(k')\right| \end{aligned} \tag{9}$$

$$r(Y_0, Y_j) = \frac{1}{n}\sum_{k=1}^{n} \rho_{0j}(k) \tag{10}$$

$$fitness = \frac{1}{\sum_{i=1}^{k} r(f_{0i}, f_i)} \tag{11}$$

Where, $Y_0 = \{y_0(k) \mid k = 1, 2, \cdots, n\}$, $Y_j = \{y_j(k) \mid k = 1, 2, \cdots, n, j = 1, 2, \cdots, m\}$, f_i is test result of *i* test samples, f_{0i} is actual value.

3) The steps of hybrid optimization algorithm

Step 1. To give N samples of input and output for training network.
Step 2. To carry out the modified PSO coding, and to initialize the particle swarm.
Step 3. By decoding each particle string, the corresponding RBF network parameters are obtained for each particle. The corresponding output is calculated, and the input and output is brought into the performance index function of the RBF network approximation to get the p_{best} of the particle.
Step 4. To evaluate the function of each particle is evaluated, and the g_{best}t of the particle swarm is obtained.
Step 5. To judge whether the g_{best} will meet the end of the modified PSO conditions, if it meets the conditions to exit the modified PSO optimization method, it jumps into the RBF local optimization, which is the step 7.
Step 6. To update the speed and position of each particle and then return to Step 3.
Step 7. To decode the g_{best} corresponding to the individual string of particles, as the initial value of the RBF network to optimize the value of the network.
Step 8. To code the parameters of the local optimization, and then RBF network training, to judge whether to meet the end of the condition, if not satisfied, it returns to step 6, otherwise it will output the simulation results [10].

IV. THE SIMULATION ANALYSIS

A. Determination of Neural Network Prediction Model

The simulation model of RBF neural network, based on the production process of low carbon ferrochromium and field data in AOD smelting, includes one input layer, one hidden layer and one output layer. Input layer includes 6 nodes which correspond to the different control variables that effect on the content of element P; output layer includes one point that corresponds to the phosphorus content. The number of neurons in the hidden layer automatically adds the number of hidden neurons from zero in the course of training, and stop training when prediction error less than 0.02.

B. Parameter Settings

Select the Gaussian function as hidden layer excitation function in RBF neural network, chosen network parameters by the following methods:

$$c_j = \frac{1}{N_j}\sum_{x \in \theta_j} x \tag{12}$$

$$\sigma_j^2 = \frac{1}{2N_j}\sum_{x \in \theta_j} (x - c_j)^T (x - c_j) \tag{13}$$

Where, θ_j is representative of all samples in group j , x is input sample, c_j is the center vector of Gaussian radial basis function, σ_j is the width of Gaussian radial basis function, N_j is number of sample in j group.

Using the vector that integrated by the initial value of σ_j, c_j and w which need to optimize, adopting floating point code, as an improvement of the PSO requirements of the optimal position vector [11]. The encoding format of particle searching in D dimension space is |Particle position| |Particle velocity| |Objective function|. In the process of POS improving, setting $w_{\max} = 0.9$, $w_{\min} = 0.4$, $c_1 = 2.8$, $c_2 = 1.3$. The progress can reach the optimal state when the size of particle is 20~40.

C. The Analysis Result of Simulation Comparison

Randomly choose 80 furnace production data which include the main component content of low carbon ferrochromium in hot iron and the working parameters in the process, according to the experiment data of AOD low carbon ferrochrome smelting that has removed the abnormal data, to carry out RBF network learning. Using 60 heats actual production data are appropriated for modeling as training samples. And using 20 heats actual production data as test sample, as shown in Table 1. Using Matlab to program and simulate.

TABLE 1. THE PRODUCTION DATA

n	C (%)	Si (%)	P (%)	T (°C)	Limestone (kg)	t (min)
1	7.8210	0.2902	0.0263	1716.7	309.5975	133.7043
2	6.9667	0.2512	0.0245	1789.5	275.6503	132.2467
3	7.6168	0.4957	0.0254	1742.9	206.9014	117.5673
4	6.9338	1.0921	0.0268	1750.4	333.0125	128.4867
5	7.4102	0.3687	0.0265	1786.8	88.5198	126.8466
6	6.8910	1.0211	0.0252	1747.9	379.8675	147.5400
7	7.5088	0.3546	0.0274	1746.8	382.3652	122.9846
8	7.9789	1.4251	0.0266	1747.1	370.4206	124.2767
9	7.0452	0.7813	0.0258	1742.3	264.6758	120.2186
10	6.9545	1.5421	0.0278	1795.5	147.2016	124.6794
11	7.8657	0.2540	0.0270	1698.9	356.9732	128.6101
12	7.9890	0.5121	0.0260	1710.8	234.5541	115.0780
13	7.2312	1.1021	0.0294	1786.4	182.5057	128.0966
14	8.1423	0.3022	0.0286	1743.7	146.4925	124.5899
15	7.9013	1.5415	0.0271	1794.5	263.0124	126.9314
16	7.1055	1.0861	0.0278	1777.0	76.7971	133.2716
17	7.3221	0.6804	0.0273	1771.2	256.7544	110.0506
18	7.8676	0.7811	0.0247	1736.4	298.1596	120.5141
19	7.9041	1.4865	0.0243	1714.8	387.2901	133.1604
20	7.4866	0.6975	0.0246	1714.3	315.1764	114.5259

Compare with the prediction of general RBF neural network (without the PSO optimization) and the above mentioned method to verify the validity of this study method, the comparison results are as shown in Figure 3.

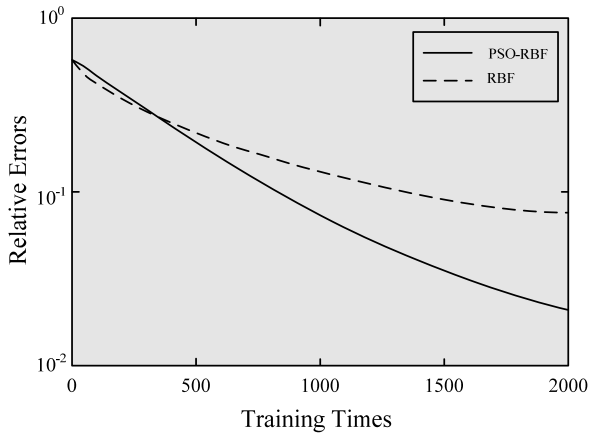

Figure.3. Relationship between Relative Errors and Training Times under Different Algorithms.

RBF neural network in Matlab toolbox is used to build the prediction model. The error is the minimum when the distribution density spread is set to 2, and the error becomes large when the spread is set to 2.5 or 3. In the simulation, the number of hidden neurons reaches maximum when RBF algorithm training 50 times. The modified PSO algorithm proposed in this paper has a better identification accuracy, on the meanwhile, it reduces the chances of a local optimum. In addition, because of taking full advantage of the variety of sample, the improved PSO-RBF has a better forecast effect. Using the improved PSO-RBF network predictive control algorithm and RBF neural network predictive control algorithm for Matlab simulation, the predicted results are as shown in Figure 4, 5 and Table 2.

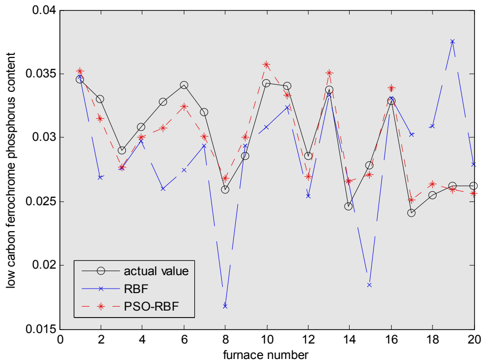

Figure4. Comparison of Forecasting Results of RBF and Modified PSO-RBF Algorithms

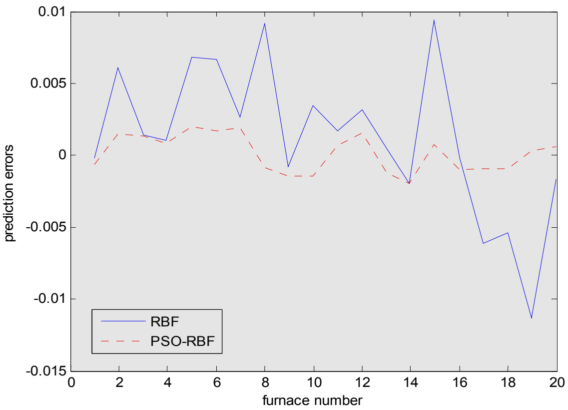

Figure5. Comparison of Prediction Error of RBF and Modified PSO-RBF Algorithms.

TABLE 2. PREDICTION ACCURACY COMPARISON OF RBF NETWORK MODEL

Model types	The prediction of P content	
	(error±0.001%)	(error±0.003%)
Before optimization	40.4%	85.7%
After optimization	46.1%	95.4%

From Table 2, it can be seen that the control effect is improved 5.7% when the prediction control error of phosphorus content in modified PSO-RBF network is set as ±0.001%. The control effect is improved 9.7% when the error is set as ±0.003%.

V. CONCLUSIONS

In this research, the modified particle swarm optimization algorithm is integrated into the neural network predictive control. And the paper raises predictive model, based on modified PSO-RBF mixed optimization, which can improve the predictive control of phosphorus content in AOD smelting for low carbon ferrochromium, reduces the inverted furnace times in temperature measuring progress, and increases economic benefits for enterprises. When the prediction control error of phosphorus content is set as ±0.003%, the prediction accuracy is improved to 95.4%, and the control effect is satisfied. The optimal control model, based on improved RBF neural network predictive control, is easy to be implemented once the parameters are selected. If the static control model is applied in actual production of the AOD low carbon ferrochromium smelting, the product quality can be improved, and the smelting production costs can be reduced.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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