The application of improved back propagation neural network model

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Abstract

During the granulation process of Iron ore sinter mixture, there are many factors affecting the granulation result such as chemical composition, size distribution, surface feature of particle, and so on. Some researchers use traditional fitting calculation methods like least square method and regression analysis method to predict granulation result, where exists big error. In order to provide better performance in prediction, we use improved BP (Back propagation) neural network model to do data analysis and processing. Granulating effect neural network model with a shooting rate of 92%, has a good prediction accuracy, robust, and the high ability of recognition to new sample, which can give a good guidance to granulation process. It obtains better effect than traditional fitting calculation methods.

Keywords: iron ore sinter mixture, size distribution, granulation result, BP, neural network

1 Introduction

The granulation process has recently emerged as one of promising research areas in iron ore sintering process for that the granulating efficiency directly determines the mixture of particle size distribution and permeability. Based on the granulation mechanism of sinter mixture, there are many factors influence granulation result.

In certain conditions of granulation equipment, the main factor is due to the sinter mixture's own nature, including the chemical composition of the material, size distribution, moisture capacity, microscopic structure and other factors.

The main chemical composition of sinter mixture is TFe, Feo, SiO_2, CaO, Al_2O_3, MgO, MnO, TiO_2, K_2O, Na_2O, S, P, in which CaO, Al_2O_3, MgO are conducive to granulation, while SiO_2 has an adverse effect to granulation.

From the ore chemistry and initial moisture content, the blend of 15 kg (total dry weight) was created based on 5.0% SiO2 in the sinter product, 4.0% coke breeze (total dry mass basis), 1.8 basicity (the CaO: SiO2 ratio in the sinter product) and 30% returns (ore basis). Moisture was varied from dry to wet conditions to assess the granulability of the ores. The content of these chemical constituents should be used as the input parameters of the model. While the rest of the chemical ingredients, such as MnO,TiO_2,K_2O,Na_2O,S,P, which has low content, will not be considered for the purpose of reducing the complexity of the model. Similarly, we select <0.2mm, 0.2-0.7mm and 0.7-3mm as size distribution input, and other two parameter like moisture capacity, moisture content are considered [1].

So there are nine parameters as granulating effect prediction model's input, that is CaO, Al_2O_3, MgO, SiO_2, <0.2mm, 0.2-0.7mm and 0.7-3mm, moisture capacity, moisture content.

The performance quality of iron ore sinter mixture granulation is determined by permeability, however it is not measured in actual production but in experimental conditions. We use content of 3-8mm in the granulation to evaluate the permeability in actual production. There are two output parameters in granulating effect prediction model, permeability and 3-8mm granularity content.

Research into granulation has been progressing over several decades. Initial work by Newitt et al. on damp sand advanced the fundamental understanding of the granulating process [2]. This has been assisted by significant improvements in the fundamental knowledge of granulation summarized by Peter Knight [3].

Work by Matsumura et al. provides a model to predict the optimal granulating moisture of an ore or ore blend from the saturation moisture (water retention value) and particle void age (open void volume) of the blend components [4]. Work by Wildeboer et al. provides a model to predict granulation permeability by knowing a number of raw material characteristics and operating factors [5]. These include densities of the components and blend, particle sizes and amount of absorbed water [6].

By the way, it is well know that the structure and strength of quasi-particle formed by granulation of fine and coarse iron ores are influenced greatly by the water absorptivity of iron ore, wettability between iron and water, adding moisture and characteristic of surface of iron ore.

As the fundamental study for determining the optimal adding moisture for granulation of fine and coarse iron ore

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particles, the contact angle between iron oxide and water was measured by the sessile drop method using reagent grade hematite samples which have different porosity and five kinds of iron ores. In addition, the granulation experiment was conducted using five kinds of iron ores and the effects of adding moisture and wettability on the granulation property were investigated [7].

A study was conducted into the effects of ore type and size distribution on granulation for seven ores covering abroad range of ore types. The aim of this paper is to present granulation models that are based on an ore's composition and size distribution and simulate the addition of an ore to a sinter blend containing coke, flux and returns [8].

Increased demand and diminishing high grade resources have resulted in a large diversity of iron ore sources used in the modern steel mill. Using research on the effect of ore type and size on granulation for ore blends containning coke, flux and returns, a paper presents a study to model the optimum granulating moisture and related green bed permeability of an iron ore from the size distribution and composition of the ore [9].

In this paper, we mainly introduce the concept and application of moisture capacity, establish the optimum moisture prediction model, and based on BP neural network established granulating effect, prediction model predict the fraction of mixture 3-8 mm and the permeability of the particle bed.

Samples were immediately taken to assess the actual moisture and permeability of the granules and the granule size distribution.

The BP neural network is a forward multi-layer network, which based on BP algorithm, while the topological structure is a layered feed-forward network, composed of the input layer, hidden layer and output layer. In essence, the BPNN algorithm makes the input and output of a set of samples into a nonlinear optimization problem with using the gradient descent algorithm optimization technique, which uses the iterative solution to get the right value [10].

Comparing our model with others, it is not necessarily to consider whether the variables are independent, as well as whether meet the conditions of normal distribution, and so on. Our model can reflect the relationship among the variables accurately.

2 Model building

2.1 GRANULATING NERUAL MODEL

BP neural network has hierarchical feed forward network architecture. While there can be many layers, but the processing can be done with a minimum of three layers: one layer that receives and distributes the input pattern, one middle or hidden layer that captures the nonlinearities of the input/output relationship, and one layer that produces the output pattern[11]. BP neural network also may contains a bias neuron in the input or hidden layers that produce a constant output of 1.0 and is fully connected to the layer above but receives no input. Based on the theory of Kolmogorov [12], the arbitrary non-linear function can be achieved with a three layers Network, which is made of input layer, hidden layer and output layer.

In this paper, we build a three layers BP neural network model as Figure 1. In it the three layers are denoted as Input layer, Hide layer, Output layer.

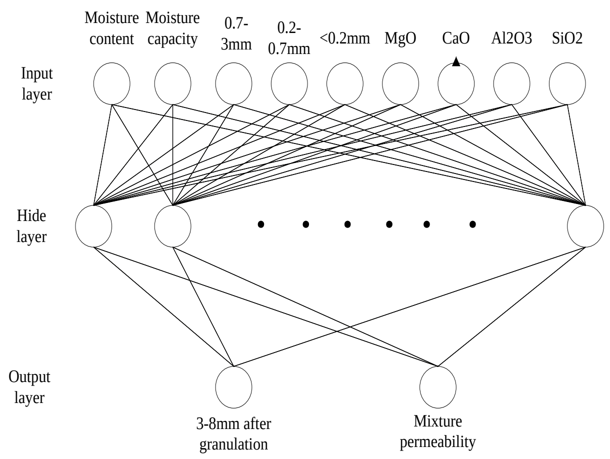

FIGURE 1 Granulating neural model

From Figure 1, we can see there are nine input nodes in the network, which are moisture capacity, moisture content, CaO, Al2O3, MgO, SiO2,<0.2mm, 0.2-0.7mm and 0.7-3mm.

There are also two output nodes in the network, which are permeability and 3-8mm granularity content. We make those two parameters as granulating effect prediction output.

2.2 BP PROCESS

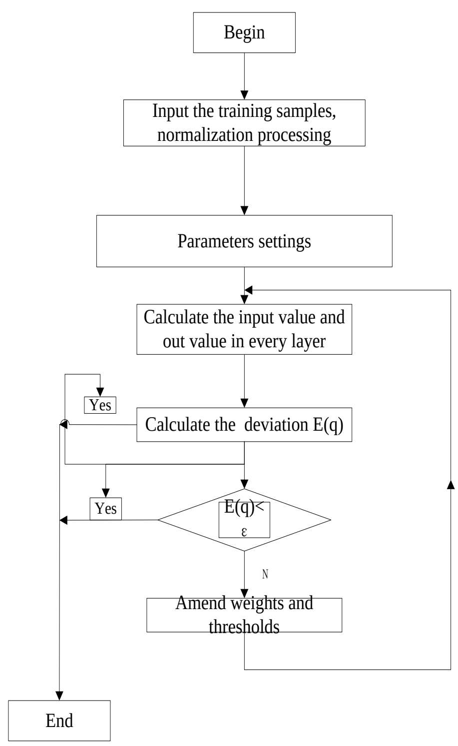

FIGURE 2 Process of network

From Figure 2, we can clearly see the process of this article, and follow this process to build the model, at last obtain the prediction of granulating effect.

There are two phases of positive transmitting processsing and error reverse transmitting processing in the study processing of BP neural network [13].The signal inputted from outside spreads to the output layer, then gives the result through processing layer for layer of neurons which is in input layer and hidden layer. If the expected output can't be obtained in output layer, it shifts to the conversed spreading processing, the true value and the error outputted by network will return along the coupled access formerly. The error is reduced by modifying contacted weight value of neurons in every layer and then it shifts to the positive spreading processing and revolves iteration until the error is smaller than the given value [14].

2.3 BP ALGORITHM

Back Propagation neural network is one kind of neural networks with most wide application. It is based on gradient descent method which minimizes the sum of the squared errors between the actual and the desired output values.

Suppose *p* is the input of network, *a* is the output of neurons in hidden layer, *o* is the output of neurons in output layer, *r* is the number of input nodes, *s* is the number of neurons in hidden layer, *t* is the number of neurons in output layer, *w*1 is the connection weight of hidden layer, *w*2 is the connection weight of output layer [15,16].

The output of *i* neurons in hidden layer:

$$a_i = f_1(\sum_{j=1}^{r} w1_{ij} p_j + b1_i) . \quad (1)$$

The output of *i* neurons in output layer:

$$o_k = f_2(\sum_{i=1}^{s} w2_{ki} a_i + b2_k) . \quad (2)$$

In Equation (1) and Equation (2), f_1, f_2 are the excitation function in hidden layer and output layer respecttively, *b*1, *b*2 are the threshold value in hidden layer and output layer, respectively. In which, i=1,2,…,s; k==1,2,…,t.

The training of BP network is realized by updating the connection weight according to error between real data and respect value.

Now we define the error function:

$$E_p(k) = \frac{1}{2}\sum_{k=1}^{t}(t_k - o_k)^2 . \quad (3)$$

In Equation (3), t_k and o_k is the real output and respect value respectively.

The total error function:

$$E(k) = \sum_{p=1}^{r} E_p(k) . \quad (4)$$

Then compute the fluctuating value of connection weight:

$$\Delta w2(k+1) = -\mu \frac{\partial E(k)}{\partial w2(k)} = u\sum_{p=1}^{r}[\delta_2(k) o_k] , \quad (5)$$

$$\Delta w1(k+1) = -\mu \frac{\partial E(k)}{\partial w1(k)} = u\sum_{p=1}^{r}[\delta 1(k) a_k] , \quad (6)$$

in which,

$$\partial_2(k) = [t_k - a_k].a_k.[1 - a_k] , \quad (7)$$

$$\partial_1(k) = p_j[1 - p_j].\sum_{t=1}^{t}[\partial_2(k).w2(k)] . \quad (8)$$

We can adjust the connection weight:

$$w1(k+1) = w1(k) + \Delta w1(k+1) , \quad (9)$$

$$w2(k+1) = w2(k) + \Delta w2(k+1) . \quad (10)$$

2.4 THE IMPROVED MODEL

The BP algorithm is simple, easy, small amount of calculation, and has the parallel advantages, so it is one of the largest and most mature training algorithms for network training at present. The essence of the algorithm is to solve the minimum value of the error Equation (6). Because it uses the method of steepest descent in nonlinear programming, there exists following problems [17]:

1) Slow convergence, low learning efficiency.
2) Easily falling into local minima.

In order to make the model more accurate, we use momentum adaptive learning rate adjustment algorithm. The weights and threshold adjustment formula with additional momentum factor [18]:

$$\Delta w_{ij}(k+1) = (1\text{-}mc)u\delta_i p_j + mc\Delta w_{jj}(k) , \quad (15)$$

$$\Delta b_i(k+1) = (1\text{-}mc)u\delta_i + mc\Delta b_i(k) , \quad (16)$$

in which, *k* is the training times, we take 10000, *mc* is the momentum factor, we take 0.9. w_{ij} is the weight between *i* node in hidden layer and *j* node in input layer; Δw_{ij} is the adjustment weight for hidden layer and Δb_i is the adjustment threshold for hidden layer. At the same time it is not an easy thing to select appropriate learning rate for a particular problem. To solve the problem, it is natural to adjust the learning rate automatically in training process. The adaptive learning rate adjustment formula [19,20].

$$u(k+1) = \begin{cases} 1.05u(k) & E(k+1) < E(k) \\ 0.7u(k) & E(k+1) > 1.04E(k) \\ u(k) & other \end{cases} . \quad (17)$$

$E(k)$ is sum of squared errors for the k step. The selection of the initial learning rate can be optional, we take 1.0 [16,17].

This method can ensure that the network train the samples by a learning rate which is always acceptable to the network. The system setting is showed in Table 1, including accuracy, rate, time, momentum factor.

TABLE 1 System setting

System settings	Data settings
System accuracy	0.001
Learning rate	1.0
Training time	10000
Momentum factor	0.9

3 Model solution

In order to get the relation between moisture capacity and moisture content, we collect and measure different ores from different factory.

It was found that the contact angle of sample becomes small with progress of time regardless of the polishing method. This tendency was observed in all reagent hematite samples and iron ore samples.

In recent years, many kinds of iron ores have entered the Chinese market and directly affected the performance of sintering plants. In this paper, we use 42 groups of data as samples. These data are used from the four kinds of ores, which are from Brazil, Australia and South Africa in this study, and the influence factors are analyzed. It is well known that, the ores of different types have apparently differences in bonding intensity, ores from Brazil and South Africa have high bonding intensity, while ores from Australia have low bonding intensity; The foundation of generation of effective liquid is adequate liquid phase fluidity and the lower porosity of core ore; The ratio of porosity of core ore and the index of liquid phase fluidity has negative correlation with the bonding intensity [21].

According to previous researches, good quality of sinter could be obtained when the chemical composition, the granulating properties, and the high temperature properties of blending are restricted. The appropriate range for each index can be determined by collecting and analyzing practical sintering parameters, practical ore-blending historical data, and micro-sintering experimental data. Due to the limited space, the details of determining the proper ranges for different indices will be introduced in the future [22,23].

We take 34 groups as training samples which is selected randomly from the samples.

Firstly, we process the 34 group data, as show in Table 2 can find the permeability is very bad in group 33 because of low water content. In test process, we cannot get the data from the rotermeter.

There is also obvious error in group 34 comparing with the other data, which is due to operating error in measurement process.

TABLE 2 Training samples

No.	Moisture content	3-8mm/%	Permeability/mmH2O
1	5.1	29.85	288.00
2	6.86	53.80	216.00
3	8.12	61.33	230.00
4	5.73	63.48	220.00
5	6.68	61.20	228.00
6	6.58	59.90	228.00
7	6.27	31.96	286.00
8	5.21	27.37	652.00
9	5.00	33.69	674.00
10	6.24	35.04	570.00
11	8.38	51.68	314.00
12	7.99	59.16	196.00
13	7.04	40.96	256.00
14	9.32	60.27	208.00
15	7.61	43.21	286.00
16	6.33	31.35	588.00
17	5.585	25.92	550.00
18	7.85	55.41	404.00
19	6.65	66.02	196.00
20	5.42	54.79	288.00
21	5.68	40.24	596.00
22	6.34	58.23	413.00
23	6.27	47.94	296.00
24	7.10	42.24	248.00
25	7.71	42.86	232.00
26	8.99	60.67	200.00
27	8.53	54.56	196.00
28	8.50	61.08	206.00
29	7.88	66.11	224.00
30	7.24	49.35	246.00
31	5.52	32.16	566.00
32	7.80	49.08	566.00
33	4.30	25.96	/
34	7.77	55.72	308.00

Some researchers use traditional fitting calculation methods like least square method and regression analysis method to predict granulation result, which exists big error. Jasbir Khosa [24] thinks that the key granulating parameters from the experimental work are optimal moisture, permeability and the intermediate particle.

From his research, it was apparent that there was a relationship between variation in the intermediate particle loading and the resultant granulating moisture content and permeability. Where a significant change was made to the ore by removing particles below 0.2 mm (binding particles) or removing nucleus particles above 0.2mm, this had a significant effect on the ore's granulating performance, shifting the relationship away from the expected curve for varying intermediate particle loading. Commercial iron ores fines with 0.7mm-3mm mm or <0.2 mm fraction are rare, so it was decided not to include these results in the modeling work [25,26].

To avoid the need for additional test work on an ore, a simple model is required that should be based on readily available information about an ore, the ore's composition and size distribution, to allow easy estimation of the ore's optimum granulating moisture and related green bed permeability. Additionally and most importantly, this model should be based on a simulated sinter blend, since returns, flux and fuel will all affect granulating behavior.

In order to predict it better, we build improved BP (Back propagation) neural network model to carry out data analysis and processing, and then obtain better effect than traditional fitting calculation methods.

In this paper we use nine parameters as granulating effect prediction model's input, that is CaO, Al_2O_3, MgO,

SiO_2, <0.2mm, 0.2-0.7mm and 0.7-3mm, moisture capacity, moisture content.

The performance quality of iron ore sinter mixture granulation is determined by permeability; however it is not measured in actual production but in experimental conditions [27]. We use content of 3-8mm in the granulation to evaluate the permeability in actual production. So we use two output parameters in granulating effect prediction model, which are permeability and 3-8mm granularity content.

In order to obtain better effect, we drop the two groups. Then we use c++ to write BP Algorithm, and make a small software showed in Figure 3 to train samples and get the forecast value.

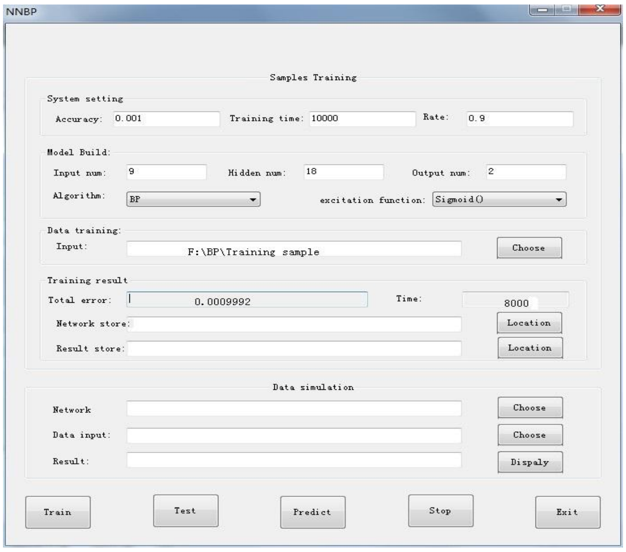

FIGURE 3 Main interface of the software

The BP software should firstly input training data as training sample, the large training time for the number of neurons and the number of input layer, hidden layer, and output layer. When the training is stopped, the forecast result will be stored [19].

From Figure 3, we can see that before training system accuracy is set to 0.001, training time is set to 10000 times, learning rate is set to 0.8. The input num represents the number of node in input layer, the hidden num represents the number of node in hidden layer, the output num represents the number of node in output layer. When the training time is up to 8000, the total error is 0.0009992(0.0009992<0.001), the training is stopped.

TABLE 3 Forecast samples

No.	Moisture content	3-8mm/%	Permeability/mmH2O
1	7.2	49.22	260.00
2	5.78	32.21	442.00
3	6.82	36.87	286.00
4	4.98	63.45	250.00
5	6.90	25.16	820.00
6	5.42	70.23	210.00
7	6.58	42.08	236.00
8	8.61	63.33	248.00

Train them to solve the weights from input layer to the hidden layer and from the hidden layer to the output layer, and then take the other samples as forecast samples, analyzing the difference between the forecast value (forecast incidence) and the actual data as follow two Figures, Figure 4 is showed as prediction results for 3-8mm granules percentage after granulation and Figure 5 is showed as prediction results for permeability after granulation.

Sequentially comparing relative errors stay between 6% ~8%, and the accuracy of the model reach 92%. So we can get this conclusion following:

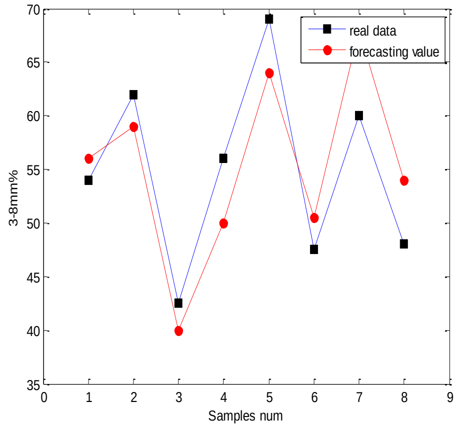

FIGURE 4 Prediction results for 3-8mm granules percentage after granulation

1) It is feasibility to predict granulating effect using BPNN model; and the model obtained very good effect.

2) The BP network has the strong misalignment to approach ability; the fitting precision is good between the output and the samples.

In this paper, neural network is applied to the modeling process of granulation which is complex, nonlinear, dynamic, multivariable, difficulty in modeling.

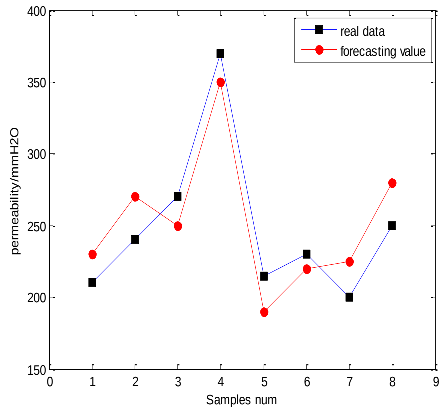

FIGURE 5 Prediction results for permeability after granulation

Granulating effect neural network model with a shooting rate of 92%, has a good prediction accuracy, robust, and the high ability of recognition to new sample, which can give a good guide to granulation process. We obtain better effect than traditional fitting calculation methods.

In future, the model will play a certain role in granulating production. According to the property of the information transferring in modern steel enterprise, the granulating effect model of sintering process is divided into three layers: the operation layer, model layer, and decision-making layer. The function is different to different users, realizing the configuration of information resources among the layered, and optimization of the sintering process for the modern enterprise.

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