BAS Intelligent Recommendation Model for Optimum Proportion of Pellets

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Abstract. Combined with the advantages of GRNN in non-linear fitting and flexible network structure, the prediction model of pellet compressive strength is established, the ratio of raw materials (Ca, Si, Mg) is determined, and the important parameters (aged particles) that characterize the particle quality in the particle production process are also determined. Based on the prediction model of compressive strength and the search algorithm of beetle antenna, the intelligent recommendation model of pellet loading proportion optimization is established. The results show that in the range of pellet loading variation not more than 20%, the best charging scheme recommended by intelligent can increase the compressive strength of cooked ball by more than 16% on average, the system runs stably, and the simulation results are effective. Bas intelligent recommendation model significantly improved the average daily compressive strength of cooked balls in the same period of last year.

1. Introduction
The scale of infrastructure construction is expanding year by year, and the limited natural rich lump ore resources cannot meet the needs of larger-scale ironmaking raw materials [1]. Pelletite is one of the man-made rich ores, which has excellent characteristics of high temperature reduction and softening, and high iron content [2]. An important indicator to characterize the mechanical strength of pellets is the compressive strength of cooked balls [3]. Looking at the current situation, it can be seen that the batching scheme, roasting system, parameter setting and other operations in the production process of pellets mostly use linear proportional adjustment methods, and there are problems such as low ball formation rate and poor compressive strength [4-6]. This paper combines the advantages of General Regression Neural Network (GRNN) in nonlinear fitting and flexible network structure to build a prediction model of compressive strength of cooked ball. The implementation of the longhorn search (BAS) algorithm program is simple, the algorithm has few artificial operating parameters, and is not easy to fall into the local optimal and fast convergence speed [7-13]. Therefore, this paper introduces
the BAS algorithm into the recommendation of the raw material ratio of pellets, and develops an intelligent recommendation model of the optimal ratio of pellet raw materials that effectively improves the compressive strength of the cooked balls to provide indirect support for the blast furnace going forward.

2. Prediction Model of Compressive Strength

2.1. Construction of the Sample Set

Sample input: Pellet production ingredients use 3 kinds of mineral powder as the main raw materials, and Yanshan bentonite is used as the main additive. Four kinds of raw material chemical components: \(x_1-[\text{SiO}_2]\ \%\), \(x_2-[\text{CaO}]\ %\), \(x_3-[\text{MgO}]\ \%\), \(x_4-[\text{Al}_2\text{O}_3]\ \%\) are used as four input indicators. In order to comprehensively consider the production process of pellets, the roasting time \(x_5-[t]\ \text{min}\) and the roasting temperature \(x_6-[T]\ ^\circ\text{C}\) were used as sample input indicators.

Sample output: Compressed strength of cooked balls is an important indicator to characterize the quality of pellets. This index is the maximum crushing load value (N) of compressive strength of pellets. This research base examined the compressive strength of cooked balls of 65 batches (Take the average value of 10 samples for each batch). The load is applied at a fixed speed of 12 mm / min throughout the test. When the load is reduced to 50% or less than the maximum load or the gap between the platen and the initial average test diameter is 50%, the compressive strength is the maximum load obtained in the experiment. The compressive strength \((Y)\) of the tested cooked ball is output as a sample.

2.2. GRNN Model for Prediction of Compressive Strength of Pellets

General Regression Neural Network (GRNN) was proposed by American scholar Donald F. Specht in 1991 [10]. It is a neural network similar to RBFNN, but GRNN has certain advantages in nonlinear fitting and flexible network structure, etc. It has stronger generalization performance than RBFNN neural network. GRNN consists of input layer, pattern layer and summation layer. The specific implementation steps are:

**Step1:** Transfer 60 sets of 6-dimensional sample data to the 6 units of the input layer, each unit is a simple independent distribution unit, without affecting each other, so that the data of the input vector can be passed to the downstream mode layer.

**Step2:** The number of neurons in the model layer is 60, and each neuron corresponds to an independent sample. The first neuron in the pattern layer follows the transfer function:

\[
P_i = \exp \left[ -\frac{(x-x_i)^2}{2\sigma^2} \right], i = 1,2,...,60
\]

In the formula, \(x\) is the input variable of the neural network, and \(x_i\) represents the learning sample data corresponding to the \(i\) th neuron, and \(\sigma\) is the smoothing factor parameter.

**Step3:** The two types of neurons in the summation layer respectively process the output of the mode layer: the first type is to sum the output of all neurons in the mode layer. The weight of each neuron in the mode layer is 1, and the transfer function can be expressed as:

\[
S_P = \sum_{i=1}^{n} P_i
\]

The second type assigns different weights to the output of the pattern layer. The connection weight between the \(i\) th neuron in the pattern layer and the \(j\) th neuron in the summation layer is the \(i\) th in the \(y_i\) th output sample \(j\) Element \(y_{ij}\), the transfer function of the neuron \(j\) in the summing layer is:
\[ S_j = \sum_{i=1}^{d} y_i P_i, \quad j = 1, 2, \ldots, l \] (3)

Since the input indicators have not equal effects on the output indicators, the second category is chosen to give different weights to the output of the model layer. For the selection of initial comprehensive weights and initial normalized weights, see Figure 1.

**Step 4:** The number of neurons in the output layer is equal to the dimension of the output vector in the learning sample. Each indicator of the output layer divides the output data of the two types of summation layers, namely:

\[ y_j = S_j / S_D, \quad j = 1, 2, \ldots, l \] (4)

By inputting the filtered index into the generalized regression neural network for solving, the mapping relationship between the input index and the output index can be obtained.

The RBFNN network and the GRNN network are used to model the sample set to construct a compressive strength prediction model for pellets of pellets. The comparison between the two types of prediction algorithms and actual values is shown in Figure 1.

**Fig. 1** Selection of initial weights of indexes

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**Fig. 2** Comparison chart of compression prediction results

**Fig. 3** Prediction error of anti-compression

In-depth analysis of Figure 2 and Figure 3 shows that the GRNN forecast results basically coincide with the actual value, and the forecast error is between ±5N. This error can be well applied to the guidance of production practice; and there is a certain amount of difference between the RBFNN forecast result and the actual value. Deviations, part of the forecast results exceed the actual value by ±12N. When the forecast error exceeds ±10N, the guiding significance for actual production is weakened, and even misleading. Therefore, the GRNN forecasting model applied in this paper has higher forecasting accuracy, and is more suitable for forecasting the compressive strength of mature pellets of pellets, so as to accurately guide the decision-making of pellet manufacturing process control.
3. Intelligent Recommendation Model of Raw Material Ratio

3.1. Architecture of Recommendation Engine

The recommendation system is a medium that connects users and items. The user refers to the automatic batching system for pellet production. The items refer to raw materials such as ore powder 1, ore powder 2, ore powder 3, and Yanshan bentonite. The recommended system architecture of the raw material ratio of pellets is shown in Figure 5:

![Figure 4: Recommendation system structure of pellet raw material proportion](image)

Fig.4 Recommendation system structure of pellet raw material proportion

The key part of the recommendation system for pellet raw material proportioning is the recommendation engine. The recommendation engine uses the GRNN model for predicting the compressive strength of pellets. Within the feasible space of raw material proportioning, the compressive strength of cooked balls is maximized and a type Recommendation results for items. The specific recommendation engine architecture includes the following three parts:

![Figure 5: Recommended engine structure chart for pellet proportion of raw materials](image)

Fig.5 Recommended engine structure chart for pellet proportion of raw materials

**Part 1:** Responsible to get the behavior data of automatic production of pellets from the database or cache, and analyze the different behaviors to generate the current user's feature vector \( \{x_1, x_2, x_3, x_4, x_5, x_6\} \).
Part 2: Responsible for converting the user's feature vector into a list of recommended items through the feature-item correlation matrix. After obtaining the user's feature vector, the initial item recommendation list can be obtained according to the offline correlation table (according to the relationship between the pellet automatic batching system and the feature vector), the offline correlation table can be stored in MySQL, The storage format is shown in Table 1:

Table 1: Storage format of offline related tables in MySQL

| src_id | dst_id | weight |
|--------|--------|--------|
| Characteristic ID | Item ID | The weight of linear inversion for the prediction model of compressive strength |

Part 3: Responsible for filtering and ranking the initial recommendation list to generate the final recommendation result.

3.2. Recommended Model of The Optimal Ratio of Raw Materials Based on BAS Algorithm

The position of the time of Taurus t is represented by vector x(t), f(x) is the odor concentration of x position, that is, the fitness function is f(x), where the maximum value of f(x) corresponds to the odor source point. When the Taurus is in random search in unknown environment, there are two kinds of behaviors to inspire the Taurus to modify the walking route: search behavior and detection behavior. In order to simulate the search behavior of longicorn, formula (5) is used to describe the random direction of longicorn search, and formula (6) is used to describe the left and right activities of tentacles of longicorn.

\[
\mathbf{b}_t = \frac{\text{rand}(k,1)}{\|\text{rand}(k,1)\|} \quad (5)
\]

\[
\begin{cases}
  x_r = x' + d'\mathbf{b}_t \\
  x_l = x' - d'\mathbf{b}_t
\end{cases} \quad (6)
\]

Rnd (.) in equation (5) represents random function, and K represents dimension of position. In formula (6), XR represents the right position of the search area, xl represents the left position of the search area, and d represents the detection distance of the Taurus whisker (this distance is large enough to cover the appropriate search area, which can ensure convergence to the global maximum point, and then gradually reduce with the extension of time).

In order to simulate the odor detection behavior of the nearby area, equation (7) is used to describe the iterative pattern of the next walking strategy associated with odor detection.

\[
x'(t) = x'(t-1) + \delta' \text{sign}(f(x_r) - f(x_l)) \quad (7)
\]

In equation (7), \(\delta\) represents the step size of search, and its convergence rate does not increase with the decrease of t. the initial \(\delta\) size can cover the whole search area, and sign(.) represents the sign function.

In the selection of the search parameter step \(\delta\) and the length d of the antenna whisker, the design can be carried out according to formula (8). It is worth noting that the two parameters can be set as constants if necessary.

\[
\begin{cases}
  d'(t) = 0.95d'(t-1) + 0.01 \\
  \delta'(t) = 0.95\delta'(t-1)
\end{cases} \quad (8)
\]
4. System Simulation and Experimental Verification
Randomly select 10 groups of sample sets for compressive strength prediction. In order not to change the baking system (baking time $x_5$ and baking temperature $x_6$) and make the experiment repeatable, PSO [14] algorithm and target algorithm bas are applied to intelligently recommend the best batching decision of pelletizing raw materials in variable solution space.

$$
\begin{align*}
&x_1 \in [0.8x_1, 1.2x_1] \quad x_2 \in [0.8x_2, 1.2x_2] \quad x_3 \in [0.8x_3, 1.2x_3] \\
&x_4 \in [0.8x_4, 1.2x_4] \quad x_5 = x_5 \quad x_6 = x_6
\end{align*}
$$

Based on the prediction model of compressive strength, in the variable space, PSO algorithm is used as the comparison algorithm, and PSO and bas algorithm are used to find the pellet raw material ratio when the compressive strength is the maximum, and the iteration times, time consumption and optimization effect of the two algorithms are compared. The method to determine the effect of optimization is to bring the pellet proportioning decision obtained by PSO algorithm and bas algorithm into the compressive strength prediction model for simulation, and compare the simulation results, the greater the compressive strength, the better the optimization effect, and vice versa.

**Table.2** Key Information Table for Intelligent Recommendation Decision Making of Pellet Raw Material Proportion

| Number | $x_1$ | $x_2$ | $x_3$ | $x_4$ |
|--------|-------|-------|-------|-------|
|       | bst   | add   | range | bst   | add   | range | bst   | add   | range | bst   | add   | range |
| 1      | 15.2  | 1.0   | 6.86% | 9.5   | -1.45%| 13.3  | 1.9   | 12.60%| 6.2   | -1.61%| 1.0   | -1.61%|
| 2      | 10.8  | -     | -     | 8.3   | -6.63%| 14.0  | 2.1   | 17.40%| 12.3  | 1.0   | 9.28% |
| 3      | 16.1  | 2.4   | 13.04%| 7.3   | 14.64%| 11.1  | 3.5   | 23.82%| 11.9  | 2.7   | 18.35%|
| 4      | 11.5  | 0.9   | 8.40% | 9.6   | -9.41%| 16.1  | 2.4   | 17.45%| 16.2  | 0.4   | 2.67% |
| 5      | 9.5   | 2.3   | 19.38%| 10.6  | 14.11%| 9.9   | 0.3   | 2.82% | 15.0  | 2.4   | 18.67%|
| 6      | 15.1  | 0.1   | -0.35%| 18.3  | 5.21% | 20.2  | 2.0   | 11.05%| 12.7  | 2.3   | 22.17%|
| 7      | 19.9  | 2.5   | 14.14%| 7.0   | 1.4   | 16.21%| 9.7   | 1.1   | 12.91%| 9.3   | 2.1   | 18.85%|
| 8      | 18.8  | 2.0   | 11.94%| 6.1   | 1.4   | 18.91%| 6.4   | 1.0   | 13.17%| 14.5  | 1.0   | 7.53% |
| 9      | 11.2  | 0.3   | 2.69% | 3.1   | 0.0   | -0.50%| 10.8  | -     | -4.41%| 11.2  | 1.3   | 12.83%|
| 10     | 15.2  | 0.3   | 2.24% | 6.1   | 0.6   | -8.97%| 11.8  | 0.8   | -6.52%| 8.3   | 2.5   | 23.40%|


Fig. 6 Intuitive expression of system simulation effect

The simulation results show that under the best ratio of raw materials, the compressive strength of cooked ball has been significantly improved on the original basis, and its intuitive expression is shown in Figure 6. According to the depth analysis figure 7, the maximum increase is 30.04%, the minimum increase is 8.24%, and the average increase is 16.60%. However, all of them are based on the prediction model of compressive strength, and need to be further verified by experiments.

It can be seen from Fig. 7 and Fig. 8 that the prediction accuracy of the pellet compressive strength prediction model is very high. Combined with the high-precision prediction results of the compressive strength and the experimental verification results, the effectiveness of the intelligent recommendation model for the best ratio of pellet raw materials based on BAS algorithm can be proved.
Fig. 7 Comparison of simulation results of optimized system Fig. 8 Comparison of test results before and after optimization

![Graph showing comparison of compressive strength]  
**Fig. 8** Comparison of practical application effect before and after introducing pellet burden recommendation model

It can be seen from Fig. 9 that the daily average value of the compressive strength of the mature ball after the introduction of the recommended model of pellet Proportioning on December 1, 2019 is significantly higher than the same period before the introduction of the model.

5. Conclusion
The GRNN prediction model based on the pellet raw material ratio and roasting system shows excellent prediction effect in the static sample data, and then on the basis of the prediction model, the intelligent recommendation model of the best ratio of raw materials for pellet production is constructed with the help of BAS algorithm. The intelligent prediction of the pellet compressive strength is verified by the analysis of system simulation results and repeated experiments. The generalization of the model and the robustness of the intelligent recommendation model for the best ratio of raw materials. In addition, the algorithm model has some advantages after being introduced into the actual production process of pellet. Therefore, the intelligent recommendation model with the best ratio of pelletizing raw materials constructed in this paper has a certain practical value, and is worth promoting in related enterprises.

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