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Research on Multi-Decision Sinter Composition Optimization Based on OLS Algorithm

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Abstract: The adjustment of sintering raw materials has a decisive influence on the composition of blast furnace slag and the properties of sinter. In order to smelt high-quality molten iron in the blast furnace, the composition of the sinter must be properly adjusted so that the composition of the blast furnace slag and the metallurgical properties of the sinter are optimal for the quality of the iron and are conducive to the smooth operation of the blast furnace. In view of the huge difference in the quality and price of sintering raw materials, this paper proposes an automatic sintering ore blending model to quickly configure sintering raw materials according to the requirements of the production line. This method is based on the calculation process of blast furnace charge, combined with the constraints of process composition and cost performance, to establish a multi-decision sintering ore blending model based on the OLS(Ordinary least squares) algorithm to automatically screen from available raw materials and give the sinter that meets the requirements of the furnace. The plan finally makes TFe, CaO, MgO, SiO_2, TiO_2, Al_2O_3, P, Mn, Na_2O, K_2O, Zn, and other components meet the requirements of the production line, and meet the cost performance requirements of the enterprise for sinter. The model can complete the screening and proportioning of 43 kinds of raw materials within 10 s, and its performance can meet the requirements of the production of variable materials. Combined with an example, a comparative analysis experiment is carried out on the accuracy and practicability of the designed sintering and ore blending model. The experimental results show that the accuracy and efficiency of the method proposed in this paper are higher than those of the current ore blending scheme designed by enterprise engineers. This method can provide an effective reference for the stable operation of the sintering production line.

Keywords: sintering decision; sinter; sintering change material

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1. Introduction

Sinter is an important raw material for smelting molten iron, accounting for about 70–80% of the blast furnace charge, and its physical and chemical properties play a decisive role in the smooth operation of the blast furnace and the quality of molten iron. The iron and steel industry, with its high energy consumption and heavy pollution, has become the focus of national energy conservation. Enterprises have higher and higher requirements for the precision and efficiency of sinter raw material optimization, so that the existing ore blending methods are difficult to meet the needs of enterprise production. Sintering is a very complex process requiring the control and optimization of about 500 parameters to ensure high sintering quality. Reasonably adjusting the amount of raw materials such as iron, coke, and anthracite can reduce costs and pollution emissions [1–3]. At present, the enterprise ore blending requires that the error of the main elements be within 0.01, and the error of the rare elements be within 0.001, so as to ensure that the slag can meet the production requirements. The sinter automatic ore blending mode can improve the stability of the operation, which is conducive to the production of sinter with stable chemical composition, uniform particle size, and good strength, reducing costs and improving productivity [4–6]. Iron and steel enterprises rationally adjust the raw material composition and particle size of sinter by combining mathematical methods and establishing a reliable ore blending system, which can effectively solve the problems of serious burning loss and production decline in the production of high-basic sinter [7–9]. Especially for an enterprise with a daily output of 20,000 tons of molten iron, any fluctuations in harmful elements and small cost differences will be magnified many times, eventually leading to serious consequences [10,11]. At present, iron and steel enterprises mainly use manual methods for sintering ore blending. Although this method is direct and effective, its effect on ore blending largely depends on the experience and judgment of professional technicians, lacks real-time performance, and cannot meet actual production requirements. When the production needs to change the material, the engineer needs to specify the plan based on the data of the silo, mixing material, and sintering machine and submit it to the leader for feasibility discussion. This process takes at least one hour. The calculation and decision-making of sinter composition are two of the most important links in production [12,13]. The analysis and optimization of sinter composition based on data mining needs to consider all the incoming charges and establish a complete measurement model for blast furnace charge composition [14]. Therefore, the analysis and optimization of sinter composition need to establish a complete calculation model for blast furnace batch composition [15].

Sintering ore blending is a predictable material change based on the conditions of each production line. The purpose is to find a more suitable raw material ratio for the next stage of production. Compared with real-time, whole-process prediction models, the sintering ore blending method is easier to build. Modeling, development, and application costs are lower [16,17]. To a certain extent, this method is also suitable for short-term sinter production forecasting. Not only that, the process of sintering ore and blending can also take into account the storage capacity of raw materials and other factors other than the production line. The method of sintering ore blending has been used in iron and steel enterprises for decades and has been unanimously recognized by engineers [18]. With the development of artificial intelligence (AI), various sinter quality prediction models from the perspective of sinter blending have emerged. The newly developed artificial intelligence method for sinter quality prediction includes a deep learning algorithm, an artificial neural network, an adaptive neuro-fuzzy reasoning system, fuzzy logic, a support vector machine, an evolutionary optimization algorithm, and a neuro-fuzzy network. With the wide application of artificial intelligence technology in the metallurgical industry, the continuous adoption of new algorithms and optimization control theory for the sintering process can further improve sintering control accuracy and product quality and finally achieve the goal of large-scale industrial promotion [19].

The sintering process includes many non-linear and high-delay steps, especially since there is no way to monitor the quality of sintered ore in real time by changing the raw material ratio scheme. Therefore, it is necessary to build a model to predict the composition of sinter [20]. In order to reduce the fluctuation of alkalinity and its impact on sinter, real-time and accurate detection of alkalinity is the key to improving the sintering process and sinter quality [21]. Studying the principles in the process of sintering batching and choosing an appropriate algorithm to model the raw material composition can well improve the quality of sinter and contribute to the stable operation of the blast furnace. Compared with the traditional mineral blending technology, better prediction results can be achieved by learning a large amount of tag data, and the prediction results based on prediction algorithms and mathematical modeling methods are highly instructive. However, the above-mentioned modeling and calculation methods require professional and technical personnel to operate and are still difficult to apply in traditional iron and steel enterprises, and it is difficult to ensure the accuracy and timeliness of diagnosis.

In view of the limitations of the above-mentioned artificial neural network fault diagnosis model, the neural network model optimized based on an intelligent optimization algorithm is widely used in the production of the metallurgical industry to improve the accuracy of the results. BP (back propagation) is a multi-layer feed-forward neural network trained according to the error back propagation algorithm and is one of the most widely used neural network models. The BP neural network obtains the solution with the minimum variance from the expected output value through gradient descent. Alkalinity prediction models established using algorithms such as the BP neural network have strong adaptive and self-learning capabilities and perform well in predicting total iron content and alkalinity [22]. At present, in iron and steel, data such as feeding conditions, the operation status of primary and secondary mixing, and real-time parameters of sintering machines are mainly used for real-time forecasting of sintering production. In production, the sensors on each production line report and count data every 30 s, but this needs to be calculated on a high-performance server.

The purpose of combining the OLS algorithm and decision-making algorithm is to take advantage of data processing and high adaptability to obtain globally optimal forecasting performance [23]. Due to the limited information contained in individual prediction methods, the combined method can maximize the use of available sintering raw material information, integrate individual model information, and fully utilize the advantages of multiple methods, thereby improving prediction accuracy. The hybrid method combines different methods, such as mixed data algorithms and statistical methods, or uses big data for forecasting. Not only is the accuracy higher than a single algorithm, but the operating efficiency is far better than a single algorithm. The literature shows that hybrid methods generally yield better forecast results in industrial production than models using a single algorithm.

2. Least Square Method (OLS)

2.1. OLS Algorithm

When a variety of raw materials are combined, an exponential explosion phenomenon will occur, which makes the ore blending process very difficult. Therefore, there is an urgent need for a method to reduce the difficulty of ore blending. As a discrete parameter estimation algorithm, the OLS algorithm is very suitable for discrete data collected in the metallurgical and other industrial industries. It has the advantages that other algorithms find difficult to achieve, and it is an important algorithm in this system. The OLS algorithm can integrate model information and make full use of the advantages of various mathematical methods, thereby improving prediction accuracy and its effect in practical applications. [24] Calculate the sintering composition under different proportions by changing the calculation formula; finally, judge whether the scheme can be applied to actual production through a series of decisions. In view of the above problems, this paper proposes a multi-decision sintering ore blending model combined with the OLS algorithm for sintering ore blending decision-making in order to solve the disadvantages of many current algorithms that require a large number of samples for learning and cannot meet the actual production needs. This method has the following features and advantages:

(1) The raw material composition analysis method based on the OLS algorithm can analyze the characteristics and differences of different raw materials. This method takes into account the analysis of raw material composition by traditional ore blending and the dimensionless machine learning algorithm, and can improve the sintering process while complying with the sintering process.

(2) The raw material ratio adjustment method based on multiple decisions can accurately adjust the ratio according to the weight of various constraints and can adapt to a variety of production environments.

(3) The calculation time complexity of the sintering ore blending model is low, and the calculation performance is significantly better than other sintering ore blending algorithms, which can meet the real-time requirements of online material change.

2.2. Fitting to the Analysis

In order to explore the relationship between raw material adjustment and sinter composition, the OLS algorithm was used to fit the change in sinter composition when each raw material was changed. A model with coefficients is fitted to the influence of a raw material ratio change on the sinter composition in the material change scheme so that the residual sum of squares between the actual observed data and the predicted data (estimated value) of the data set is minimized; see Formula (1). For this unary linear regression model, an array of observations is obtained from the population, and for the n points in the plane, a curve is used for fitting, and the fitted curve is used to adjust the relationship between a raw material and sinter composition between changes (see Formula (2)). Taking the total fitting error (that is, the total residual error) as the standard for the smallest best fitting curve, it can be seen that all sets of data are fitted with a more reasonable curve. Its sample regression model is Formula (3):

$$w = (w_1 \ldots\ldots w_p) \tag{1}$$

$$(X_1, Y_1), (X_2, Y_2), \ldots\ldots (X_n, Y_n) \tag{2}$$

$$e_i = Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i \tag{3}$$

where $e_i(X_1, Y_1)$ is the error in the sample.

Quadratic loss function:

$$Q = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 = \sum_{i=1}^{n}\left(Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i\right)^2 \tag{4}$$

This curve can be determined by $Q_{\min}$, i.e., $\hat{\beta}_0, \hat{\beta}_1$ can be determined. Treating them as functions of Q, this formula becomes a problem of finding the extremum, and can be obtained by taking derivatives. Find the partial derivative of Q with respect to the two parameters to be estimated, setting the partial derivative to zero:

$$\begin{cases} \dfrac{\partial Q}{\partial \hat{\beta}_0} = -2\sum\limits_{i=1}^{n}\left(Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i\right)^2 = 0 \\ \dfrac{\partial Q}{\partial \hat{\beta}_1} = -2X_i\sum\limits_{i=1}^{n}\left(Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i\right)^2 = 0 \end{cases} \tag{5}$$

Finally, the solution:

$$\begin{aligned} \hat{\beta}_2 &= \tfrac{n\sum X_i Y_i - \sum X_i - \sum Y_i}{n\sum X_i^2 - (\sum X_i)^2} \\ \hat{\beta}_1 &= \tfrac{\sum X_i^2 \sum Y_i - \sum X_i \sum X_i Y_i}{n\sum X_i^2 - (\sum X_i)^2} \end{aligned} \tag{6}$$

When one raw material is adjusted, the rest of the raw materials are weighted according to the ratio to follow the adjustment ratio, so we can use the OLS algorithm to fit the composition change curve of the sintered ore when each raw material is adjusted. Use the API (Application Programming Interface) interface in the statsmodels library in Python to call the OLS algorithm model and encapsulate the data in a two-dimensional table of pandas. DataFrame, where each set of data includes the ratio of each raw material and the composition of sinter, and the ratio of raw materials between different sets of data is different, so the composition of sinter is also different. By calling the OLS algorithm model, we obtained the impact of a certain raw material on various sinter components when changing.

3. Multiple Decision Ore Allocation Algorithm Based on OLS Analysis

3.1. Overall Algorithm Framework

For practical applications, mineral blending must not only have high enough precision but also require real-time response to production material changes. For this reason, this paper proposes a multiple decision-making algorithm based on OLS analysis. By analyzing and fitting the characteristics of various raw materials, multiple decision-making algorithms are used to establish multiple decision-making algorithms with different weights in the sintering process to achieve sintering batching decisions. The framework of the multiple decision-making ore-allocation algorithm based on OLS analysis is shown in Figure 1.

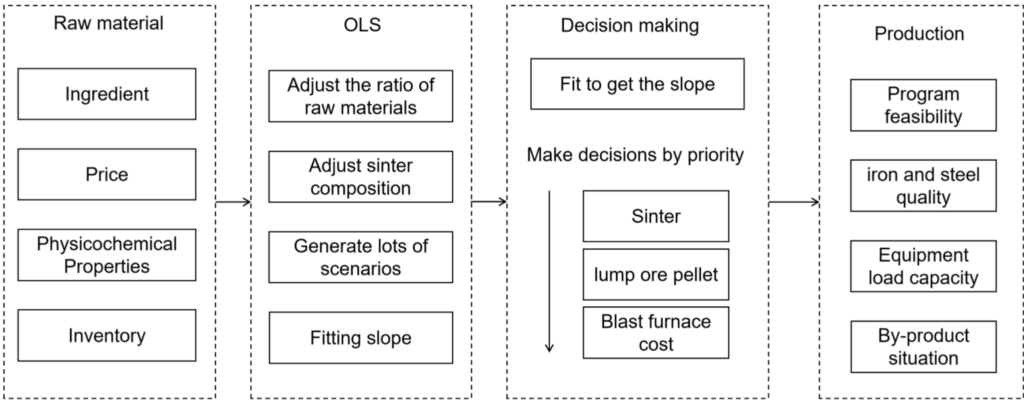

Figure 1. Framework of multiple decision ore allocation algorithm based on OLS analysis.

3.2. Multiple-Decision Ore Allocation Algorithm Based on OLS Analysis

The calculation of the furnace charge needs to analyze the composition of feed materials such as sinter and lump ore, which is an important part of production. Therefore, the analysis and optimization of sinter composition based on data mining requires a complete calculation model of blast furnace charge composition. Sintering production has a decisive impact on blast furnace ironmaking production from the perspectives of raw materials, smelting costs, slag discharge, and environmental protection. Calculation of the incoming charge requires analysis of the composition of the incoming materials, such as sinter and lump ore.

The calculation model for blast furnace charge is mainly composed of two parts: sinter calculation and lump ore calculation. The sinter calculation is based on the available iron ore and its quantity, the slag agent and its quantity, and fuel and its quantity to calculate the composition of sinter and prepare the data for lump ore calculation. The lump ore calculation is to calculate the composition of the blast furnace charge based on the sinter and its amount, the available high-grade lump ore and pellets, and the comprehensive blast furnace fuel, and finally obtain the composition of the blast furnace charge.

In order to calculate the composition of iron in sinter, the formula is as follows.

$$I_{Fe} = \left(\sum \frac{M_{Fe} \times D_{raw}}{D}\right) \times \sum D_{raw}(1 - R_{raw} \times 100\%) \tag{7}$$

Among them, I_{Fe} is the Fe mineral composition of sinter, M_{Fe} is the Fe content of each raw material, D_{raw} is the dry ratio obtained by subtracting the moisture ratio of each raw material from the wet ratio, D is the total dry ratio, and R_{raw} is the burning loss of each raw material. Among them, R_{raw} is represented by a number from 0–100 in the company, which is converted into a percentage and added to the calculation when used. According to this formula, replace the elements represented by I_{Fe} and M_{Fe} with CaO, MgO, SiO_2, TiO_2, Al_2O_3, P, Mn, Na_2O, K_2O, and Zn one by one to get the content of the corresponding elements in the sinter. For example, replacing it with I_{CaO} and M_{CaO} can calculate the content of CaO in the sinter. The final composition ratio is obtained by combining the amounts of iron, coal, and coke in the feed. It will be used to calculate information such as iron grade, basicity of blast furnace slag, and magnesium to aluminum ratio of the feed. The comprehensive measurement model of sinter and blast furnace charge composition has a better effect than the traditional artificial ore blending method.

Theoretically, in order to achieve the best ratio of raw materials in the blast furnace charge, the calculation model can be used in reverse. However, the company's calculation model is one-way, and it cannot complete the reverse calculation from the result to the raw material ratio. As shown in Figure 2 below, the forward calculation is from the raw material wet ratio to the raw material dry ratio, and the sinter composition is calculated according to the formula. After the composition of the sinter is calculated, the composition of the furnace charge is calculated, and finally the basicity and magnesium-aluminum ratio of the blast furnace slag are obtained. However, in order to calculate the ore composition from the raw material composition, it is necessary to calculate the burning loss during the sintering process by means of unit consumption. The purpose of back-projection is to calculate the ratio, and the process of calculating the back-projection ratio is still used, so back-projection is not established. Figure 2 below is a flow chart of the steps for calculating the composition of raw materials and the steps for inferring the ratio in reverse.

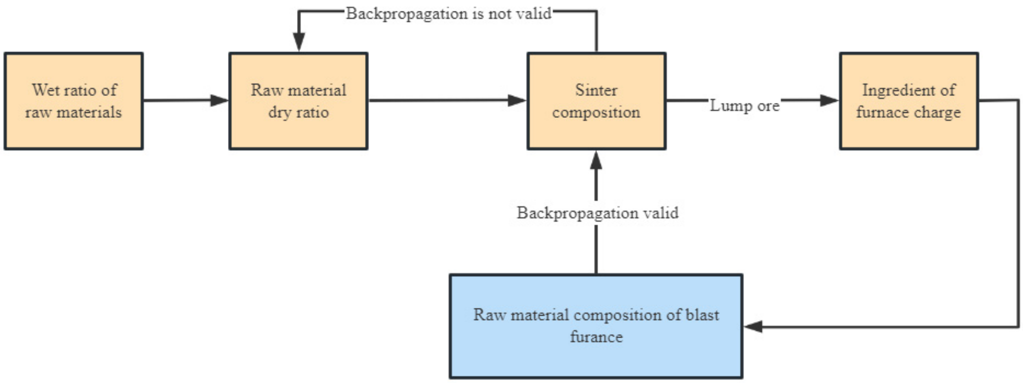

Figure 2. Flowchart of reverse push raw material ratio.

Taking Ca_1 as an example, the formula for calculating the mineral composition in Section 2.1.

$$Ca_1 = M_{Ca} \times \frac{D_1^2(1 - R_1 \times 100\%)}{D} \tag{8}$$

Among them, the constant M_{Ca} is the known calcium content of iron ore fines, R_1 is the known residual amount of iron ore fines, D_1 is the dry ratio of iron ore fines, and d is the total amount. The total amount only needs to be calculated when the dry ratio of each raw material is known, but the purpose of this equation is to find the dry ratio of iron ore powder. Therefore, the above equation has no solution, and the equation system for inverting the dry mix ratio is not established.

Before performing OLS fitting, we need to determine the method of changing materials. Situation 1: In actual production, after the laboratory detects that a certain element index of the sinter product does not meet the requirements for entering the blast furnace, the iron ore blending personnel need to adjust the raw materials to bring the composition of the sinter back to the ideal range. In the second case, when a raw material is insufficient, other raw materials need to be used instead, so the raw materials that have not been replaced must be adjusted to finally keep the composition of the sintered ore reasonable. So we can increase the ratio of one ingredient and adjust the ratio of other ingredients by weight. We use the np.linspace algorithm to generate the arithmetic sequence of the adjusted raw material ratio and the np.random.normal normal noise algorithm to generate a wide range of raw material ratios. We use the above Formula (1) to calculate the composition of the blast furnace charge, and we finally encapsulate the raw material ratio and sinter composition in a set of data in a DataFrame. When n is determined as the adjustment step size of the main mineral powder, the weighted adjustment formula of the remaining mineral powder is as follows:

$$M_2 + \frac{nM_2}{(100 - M_1)} \tag{9}$$

Among them, M_1 is the proportion of mineral powders that are actively adjusted, and M_2 is the proportion of other mineral powders after weighting. As shown in the table below, mineral powder 1 was adjusted by -0.3%, and then the remaining mineral powders were increased accordingly according to their weights. Combined with the trend of change in sinter raw materials obtained by OLS algorithm fitting analysis, the above formula is used to calculate the composition of a blast furnace charge and is applied to multiple decision-making processes. The algorithm of the OLS least squares method is:

(1) We need to use the OLS algorithm to fit the ratio and each component of the sintered ore one by one. Among them, x is the ore powder to be mainly adjusted, and y is the composition of sintered ore.
(2) Import the DataFrame data source in Python, specify x and y for fitting, and establish the mapping relationship between x and y in the program through the fit() method.
(3) Obtain the OLS fitting report through the summary() method, and count the slopes in all OLS reports. Sintering ore blending should not only consider the influence of composition but also factors such as price and equipment operation. In the company's sintering ore blending process, the items that need to be considered in weight are listed in Table 1 below:

Table 1. Items for multiple decisions.

First-Level Decision Items	Second-Level Decision-Making
Raw material comprehensive composition and cost	Original main material accessory material
Fuel and power costs	solid fuel Energy media
cost of production	Fixed equipment damage and environmental protection costs Controlled consumables and maintenance costs Employee compensation affected by production volume
Powder rate influence	Price and performance
The alkali metal, and the negative effects	Price and product performance Equipment carrying capacity

In the decision-making process, there will also be situations where certain raw materials account for an excessively large proportion, which is obviously unreasonable. For example, Brazil card powder is high quality and suitable for adding in large quantities, but its price is about 30% more expensive than other raw materials. Apparently, the addition of too much Brazil card powder will lead to a substantial increase in the cost of ore blending and ultimately reduce the cost performance of sintered ore. However, it is reasonable to use more high-quality ore powder under the condition of ensuring cost performance. We use the single product price of sinter ore, that is, the price per 1% of TFe, to measure the cost performance of sinter ore. Therefore, when the cost performance of sintered ore is reduced by 5%, no more high ore powder will be added.

Taking SiO_2 as an example, in fact, because the SiO_2 content of dolomite powder and limestone powder is too different, in order to quickly adjust SiO_2 to the target value, it is necessary to set a large step size adjustment to make the plan quickly approach the target value and set the standard step size to cover the mineral blending plan close to the target value, then set a small step size to fine-tune the ore blending plan to meet the accuracy requirements.

In order to make the ore blending plan quickly reach the final adjustment accuracy of sinter composition required by the enterprise within 0.005, the gradient descent method is adopted, and the adjustment step size of the raw material amount that can reach the target the fastest is obtained after many experiments and adjustments: the step size is 0.3% The adjustment ratio for large step size adapts to the change in SiO_2 content of different iron ore powders and optimizes the scheme with 0.18% as the standard step adjustment ratio. Accompanied by a 0.07% step adjustment ratio for precise adjustment. The model will adjust the large, medium, and small adjustment steps according to the distance between the currently judged sinter composition and the target value and use various raw materials flexibly to quickly make the sinter composition reach the target value together.

In actual production, the sintering ore blending scheme often cannot reach the theoretical value required by the production line. Therefore, when the composition of the mineral blending plan tends to be stable, the system should stop continuing the mineral blending.

In order to express more intuitively the 1.2 OLS analysis-based multiple decision-making ore allocation algorithm, the main solution steps are as follows:

(1) Maintain the raw material warehouse and update information such as available raw materials, storage volume, raw material composition, and price.
(2) Set the ratio of raw materials used in the current production line and the ratio of blast furnace charge as a benchmark for the ore blending plan.
(3) Set the target element target value of the blast furnace charge.
(4) Start by solving the decision and getting the result.

4. Case of Multiple Decision Ore Blending Algorithm Based on OLS Analysis

4.1. Evaluation Criteria for Experimental Data Sets and Protocol Feasibility

A company has 1634 records of external ore composition and cost data from 2019 to 2022, including the characteristics of iron ore powder and other auxiliary materials in metallurgy; 129 evaluations of the amount of ore powder used in production; and a material change plan. On the basis of data fitting, multiple decision-making is used to plan the sintering scheme, and the final scheme will be compared with the actual production line implementation scheme. Considering the allowable error of the equipment on the production line, when judging whether the sintering scheme is feasible, we believe that an error within 1% is acceptable.

4.2. Performance Test

All simulation experiments are carried out on a computer with a Windows operating system, an Intel(R) Xeon(SkyLake) CPU, and 16 GB of memory, and the software environment is Python 3.9. The OLS algorithm is based on the statsmodels library of the Python language and has good execution efficiency. It takes about 0.8–0.9 s to complete the fitting of each mineral powder in the sintering scheme using 12 raw materials, and the calculation performance meets the actual production requirements. The experimental simulation on the machine shows that when the number of training samples is large and the set step size threshold is small (such as less than 0.01), the OLS and decision-making algorithm run very slowly and do not run at the expected speed, and "oscillation" occurs Phenomenon." However, using the step size provided above, you can get relatively satisfactory results quickly. Although the ore blending scheme obtained by using the algorithm model does not significantly improve the accuracy, the running time is significantly reduced, and the effect is better than the traditional ore blending method.

In order to further verify the operating efficiency of the model algorithm, this paper screens out samples whose repeated decision-making times are multiples of 5 from all data samples and counts their running time. It can be seen that when the number of times is 20 or less, as the number of decisions increases, the time required also increases synchronously, while outside of 20 times, as the number of decisions increases, the time required gradually tends to stabilize.

4.3. Model Application

In order to further verify the effectiveness of the multiple decision-making ore blending algorithm based on OLS analysis, 30 ore blending and material change records were randomly selected from the material change adjustment records from 2019 to 2022 to verify the feasibility of the model. Figure 3 below shows the company's sintering raw material mixing equipment. Engineers adjust the hopper feeding speed and belt speed through the remote-control system to achieve batching control.

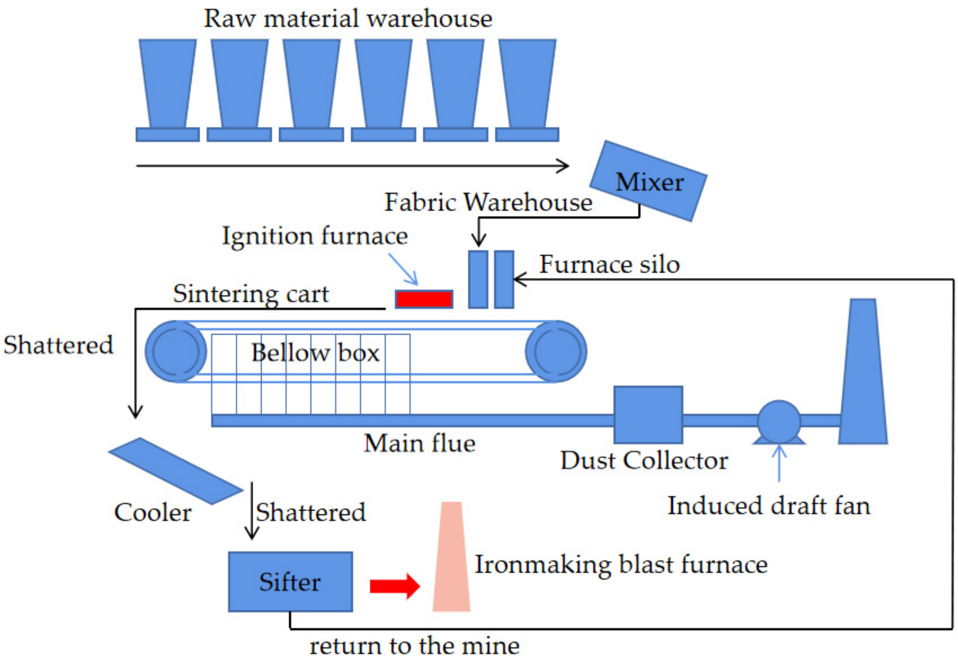

Figure 3. The sintering process of the company.

The company's sintering process aims to fix the composition of sinter ore. While keeping it unchanged, it replaces and adjusts the proportion of iron ore powder, supplemented by adjusting the proportion of flux, so that the sinter ore can reach the specified composition. Therefore, the process of ore blending needs to adjust the ratio of at least multiple raw materials at the same time. Since the amount of raw materials is always 100%, the total amount of the three raw materials after adjustment must remain the same as before the adjustment, while the amounts of other unadjusted raw materials remain unchanged. In fact, the operation of adjusting the ratio of multiple raw materials at the same time is very complicated, and it is also very difficult to implement the simultaneous adjustment of the ratio of multiple raw materials. At present, enterprises rely entirely on experienced ore blending engineers to operate. In this paper, the automatic ore blending model follows the above principles for raw material blending. First, analyze each raw material in the ore blending plan, and use the OLS algorithm to fit the raw materials one by one. Taking Mineral Powder 1 as an example, take the interval between plus and minus 2 and use the random normal noise method to generate 30 random ratios close to the current ratio, and then adjust the other raw materials according to the proportion weight. In the end, the final total ratio after adjustment is still 100%, thus creating 30 corresponding mineral blending schemes. Table 2 below shows the proportioning situation of each main raw material before and after the batching adjustment.

Table 2. Proportioning of main raw materials before and after ingredient adjustment.

Scheme	Mineral Powder 1	Mineral Powder 2	Mineral Powder 3	Mineral Powder 4	Mining Powder 5	Mining Powder 6	Mineral Powder 7	Mineral Powder 8	Mine Powder 9	Mineral Powder 10	The Others
Before the dressing	22.48	3.88	20.15	4.65	6.98	6.98	9.30	1.80	3.20	3.10	17.50
After the dressing	22.18	3.89	20.23	4.67	7.00	7.00	9.34	1.81	3.21	3.11	17.57

When the weight of the ratio that needs to change increases, using the above calculation model, the corresponding sinter composition also changes. Table 3 below shows the changes in the sinter composition (the main elements in the table retain 2 decimal places, and the rare elements retain 4 decimal places).

Table 3. Changes of sinter composition.

Scheme	TFe	CaO	MgO	SiO_2	TiO_2	Al_2O_3	P	Mn	Na_2O	K_2O	Zn	S	V_2O_5
Before the dressing	53.25	11.43	2.92	6.29	0.41	2.75	0.0649	0.4879	0.0820	0.0775	0.0092	0.060	0.090
After the dressing	53.10	11.46	2.93	6.29	0.41	2.74	0.0650	0.4852	0.0821	0.0775	0.0092	0.060	0.101

We obtained the slope of the single composition of each powder. Table 4 below shows the slope of the change of various elements in sinter after the proportion of various powders used increases. The unit of each value is the change in the proportion of elements in the sinter whenever the raw material rises by 1%.

Table 4. The change of sinter composition caused by the adjustment of different mineral powder.

	CaO	MgO	SiO_2	TiO_2	Al_2O_3	P	Mn	Na_2O	K_2O	Zn	S	V_2O_5
Mineral powder 1	−0.97066	−0.89448	−0.95274	−0.27248	−0.89135	3.61644	−0.38733	2.65449	2.86947	0.00001	0.011	0.011
Mineral powder 2	−0.97121	−0.89494	−0.95444	−0.27235	−0.89041	3.62297	−0.38502	2.65344	2.86396	0.00001	0.006	0.008
Mineral powder 3	−0.97066	−0.89444	−0.95174	−0.27229	−0.89173	3.63016	−0.38410	2.65397	2.86303	0.00001	0.008	0.012
Mineral powder 4	−0.97116	−0.89493	−0.95347	−0.27246	−0.89074	3.61664	−0.38696	2.65616	2.86936	0.00001	0.006	0.014
Mining powder 5	−0.97098	−0.89521	−0.95142	−0.27479	−0.88956	3.60947	−0.38392	2.66428	2.88015	0.00001	0.007	0.007
Mining powder 6	−0.97466	−0.89761	−0.95258	−0.27330	−0.89081	3.62086	−0.38469	2.66288	2.87497	0.00001	0.004	0.010
Mineral powder 7	−0.99654	−0.89364	−0.95040	−0.27203	−0.88708	3.60594	−0.38412	2.64744	2.85967	0.00001	0.006	0.012
Mineral powder 8	−0.96999	−0.94617	−0.95161	−0.27280	−0.88879	3.61330	−0.38440	2.65255	2.86519	0.00001	0.009	0.008
Mine powder 9	−0.97904	−0.91616	−0.95155	−0.27275	−0.89069	3.61259	−0.38432	2.65205	2.86463	0.00001	0.010	0.009
Mineral powder 10	−0.98394	−0.89454	−0.95165	−0.27254	−0.88873	3.61269	−0.38438	2.65233	2.86501	0.00001	0.005	0.013

According to the slope, for example, we need to change the content of SiO_2, and we expect to determine the plan of raw material adjustment. We can adjust the raw material with the largest absolute value of SiO_2 in the table and continue to use this method to balance the changes of other elements, finally getting a mineral blending plan that meets the requirements.

Another situation is when a certain raw material is assumed to be insufficient in stock and needs to be replaced with other raw materials. We can set a desired ratio of new raw materials, specify the composition of sintered ore, and finally use this method to fine-tune the raw materials so that the composition of sintered ore meets the production requirements.

After obtaining several sinter ratios that conform to the sinter composition, the ratio of the blast furnace charge is calculated in the order of TFe, CaO, MgO, SiO_2, TiO_2, Al_2O_3, P, Mn, Na_2O, K_2O, and Zn. After obtaining the proportion of the blast furnace charge, the decision on the availability of the charge in the blast furnace is made in the order of Table 1, and finally the ore blending plan according to the set demand is obtained.

4.4. Accuracy of Decision-Making

In order to verify the accuracy of the multiple decision-making ore blending algorithm analyzed by OLS in this paper and to further compare it with the situation of historical material change schemes, we analyzed the feasibility of 100 schemes in the test set.

We randomly take a certain sinter material change plan in October 2022 as an example and simulate the model accuracy rate according to the raw material ratio, sinter composition, and lump ore pellet ratio and composition during this period. The engineer noted the requirements and reasons for this material change as follows:

① According to the recent iron powder purchase situation, the ore powder 8 in the warehouse is about to be used up. It is expected that the cost of molten iron will increase after the material change, and the subsequent adjustment of the blast furnace charge structure and the increase in the proportion of pellets will reduce the cost of molten iron;

② It is estimated that after reducing the proportion of ore powder 8, the alkali load of the sintering blast furnace will decrease;

③ In addition, due to the influence of limestone powder procurement, the lime ratio is increased, the daily consumption of limestone powder is controlled to be about 700 t/day, the daily consumption of limestone is controlled to be 1650 t/t, and the coke powder is calculated based on 55.8 Kg/t of sintered ore;

④ MgO in sinter is controlled according to the 2.6–2.7 midline, and it is estimated that the pre-mixing will start to change at 6 o'clock after 8 days;

Therefore, we replace the mineral powder 8 in the raw material with the new raw material mineral powder 5 and set the ratio of lime to only increase. The reduction of K and Na elements in the final sinter composition is taken as the target; the MgO is controlled within the range of 2.6–2.7; and the sinter basicity (CaO/SiO_2) and magnesium-aluminum ratio (MgO/Al_2O_3) are kept stable. After setting the target for ore blending adjustment, input the sinter raw material data into the model, in which the initial test ratio of mineral powder 5 is the same as that of mineral powder 8, and perform OLS fitting and analysis on the new mineral powder 5. After 48 rounds of adjustment and decision-making and after consuming 41.7 s, the multiple decision-making ore blending algorithm of OLS analysis obtained the raw material ratio in Table 5 below (the main elements in the table retain 2 decimal places, and the rare elements retain 4 decimal places). Wherein the slag powder 8 is replaced by the new raw material slag powder 5, with the increase of lime, the proportion of limestone decreases.

Table 5. Change of sinter raw materials ratio.

Scheme	Mineral Powder 1	Mineral Powder 2	Mineral Powder 3	Mineral Powder 4	Mining Powder 5	Mining Powder 6	Mineral Powder 7	Mineral Powder 8	Mine Powder 9	Mineral Powder 10	Mineral Powder 11	Mineral Powder 12	The Others
Before the dressing	3.94	11.81	14.17	22.82	0	3.94	5.51	3.94	8.66	5.00	3.70	6.80	9.71
After the dressing	4.01	12.02	14.42	23.23	5.61	4.01	4.01	0	8.81	7.30	3.70	3.20	9.68

Due to the change in raw material ratio, the composition of sinter is shown in Table 6 below. The K and Na elements in the final sinter composition decreased significantly, with MgO within the range of 2.6–2.7. The alkalinity of sinter decreased from 1.8325 to 1.8199, and the ratio of magnesium to aluminum decreased from 1.0715 to 1.0723, which met the requirements for sinter quality.

Table 6. Changes of sinter composition.

Scheme	TFe	CaO	MgO	SiO_2	TiO_2	Al_2O_3	P	Mn	Na_2O	K_2O	Zn	S	V_2O_5
Before the dressing	53.61	11.23	2.66	6.15	0.3536	2.48	0.0625	0.4054	0.0671	0.0931	0.0115	0.078	0.100
After the dressing	53.60	11.23	2.61	6.17	0.2948	2.50	0.0668	0.4083	0.0592	0.0844	0.0101	0.071	0.093

Compared with the company's traditional ore blending process, when the ore blending model is not used, it is necessary to refer to the reports of the silo, batching production line, sintering machine, and other links, and it will take 10–20 min for experienced engineers to formulate the plan. It is also necessary to hand the plan over to the leadership and discuss the feasibility of the plan. The whole process is very tedious and takes at least 1 h. However, after adopting the multiple decision-making ore blending algorithm of OLS analysis, the time of the ore blending process is shortened. Since the decision is made by the algorithm, there are fewer links in the feasibility discussion process. In summary, the multiple decision-making ore blending algorithm analyzed by OLS greatly improves the efficiency while ensuring the accuracy of sintering ingredients and can meet the requirements of real-time material change.

Figure 4 shows the feasibility of the final results obtained by the model, in which the resulting solutions are divided into three categories, namely: feasible solutions, feasible proportioning but infeasible production decisions, and infeasible solutions. It can be seen from Figure 4 that there is a certain degree of error in the judgment of the actual production availability by the multiple decision-making ore blending algorithm based on OLS analysis, especially when the cost rises and the warning threshold is reached. The graph also shows situations where blending is not available, where mistakes are made in forming feasible blends, and where iron grades are often reduced too low. The model mainly considers the actual production availability when it goes through multiple decision-making steps. Therefore, it can be seen from the results in Figure 4 that 96% of the ore blending schemes can meet the production demand of sinter ore, but 4% cannot meet the actual production demand. In fact, the success rate of formulating the ore blending plan in the production environment is very high, and this method can show better performance advantages, but when the predictive ore blending plan is formulated, the sinter ratio itself does not fully consider the actual application scenarios, so there will be varying degrees of situations that do not meet production requirements. The figure shows the results of the multiple decision-making ore blending algorithm proposed by the OLS analysis proposed in this paper. Among them, the feasible schemes account for 96% of the total, but 2% of the schemes are not feasible in production. The final ore blending results are better than the traditional ones. The speed and precision of manual ore blending.

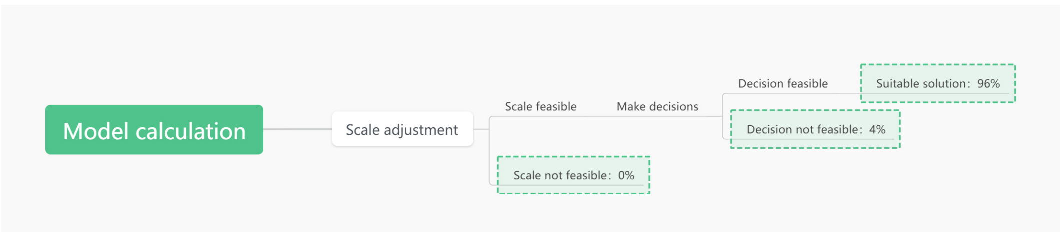

Figure 4. Model results feasibility.

It can be seen from the above comparison results that the model proposed in this paper shows good ore blending performance and high accuracy. In the case of limited production conditions, the feasible ore blending scheme can be generated quickly online, resulting in fast and accurate sintering ore blending materials.

4.5. Model Improvement and Practical Application

We hope to reduce the number of OLS operations through conditional restrictions. It is necessary to set restrictive conditions to screen out a series of raw materials that are not conducive to sinter production. When the composition of a certain ore powder is obviously harmful to sintering, it will no longer be counted. On the other hand, according to the actual production situation, it is also necessary to revise the conditions required for decision-making, which will help select the appropriate scheme. Engineers still use the traditional method, where the work is done using the model for calculations, which are then validated and revised. That is to say, the engineer needs to carry out two kinds of blending work to adjust the model to be consistent with the actual situation. In the near future, model accuracy will improve to a reliable level and be able to replace traditional methods.

5. Conclusions

According to the calculation process of the blast furnace charge, combined with the composition of process components and cost-effective constraints, a multi-decision sinter ore blending model based on the OLS algorithm was established. The model realizes the automatic ore blending of available raw materials and finally enables the sinter composition to meet the requirements of the production line and the cost performance requirements of the enterprise.

According to the calculation process of blast furnace charging, combined with the composition of process components and economic constraints, a multi-decision sintering blending model based on the OLS algorithm was established. The model realizes the automatic blending of available raw materials and finally makes the sinter composition meet the requirements of the production line and the cost performance requirements of the enterprise.

This model can achieve the following effects:

(1) The model realizes the calculation of the composition of sinter and blast furnace charge. On this basis, there are 15 decision-making items to evaluate the sintering scheme to get the optimal scheme.
(2) By simulating the real production situation for ore blending, a solution that meets the requirements can be calculated within 0.9s.
(3) According to the experimental results, 96% of the final schemes are feasible, 4% are not suitable for practical application, and the comprehensive effect is better.
(4) Engineers continuously revise the model according to the production situation, and the model will become more accurate until it can replace the traditional method.

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