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MULTI-SOURCE AND MULTI-TARGET IRON ORE BLENDING METHOD IN OPEN PIT MINE

Iron ore blending in an open-pit mine is an important means to ensure ore grade balance and resource recycling in iron mine industrial production. With the comprehensive recovery and utilisation of resource mining, the multi-source and multi-target ore blending method has become one of the focuses of the mining industry. Scientific and reasonable ore blending can effectively reduce the transportation cost of the enterprise. It can also ensure that the ore grade, washability index and iron carbonate content meet the requirements of the concentrator and significantly improve the comprehensive utilisation rate and economic benefits of the ore. An ore blending method for open-pit iron ore is proposed in this paper. The blending method is realised by establishing the ore blending model. This model aims to achieve maximum ore output and the shortest transportation distance, ore washability index, total iron grade, ferrous iron grade and iron carbonate content after the ore blending meets the requirements. This method can meet the situation of a single mine to a single concentrator and that of a single mine to multiple concentrators. According to the results of ore blending, we can know the bottleneck of current production. Through targeted optimisation management, we can tap the production potential of an open-pit mine.

Keywords: Iron Ore blending; Multi-source and Multi-target; Open Pit Mine

1. Introduction

China is the largest iron and steel country in the world, accounting for more than 55% of the world's output, and also the largest consumer of steel, reaching more than 1.2 billion tons. However, Chinese iron ore mainly depends on imports, with an iron ore output (OO)

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of 866.72 million tons in 2020 and an iron ore import of 1170.1 million tons, accounting for more than 57%. Chinese iron ore reserves are ranked fifth in the world, with 63.6 billion tons. However, Chinese domestic iron ore grade is poor, accounting for more than 80%. The ore grade is low, there are many multi-element composite ores, the ore body is complex, hematite and magnetite are associated with it, making it difficult to beneficiate. Iron ore blending in open-pit mines is an essential means to ensure ore grade balance and resource recycling in iron mine industrial production. With the comprehensive recovery and utilisation of resource mining, the multi-source and multi-target (MSMT) ore blending method has become one of the focuses of the mining industry. Scientific and reasonable MSMT ore blending can effectively reduce the transportation cost of the enterprise. It ensures that the ore grade (OG) and washability index (WI) meet the requirements of the concentrator, and significantly improves the comprehensive utilisation rate and economic benefits of the ore.

At present, the research on ore blending optimisation is predominantly divided into three categories: the first is the application of mathematical programming method in ore blending optimisation, which is mainly used in the modelling of the ore blending plan of an open-pit mine; The second is the research of intelligent optimisation algorithm in ore blending, including genetic algorithm, particle swarm optimisation, immune clonal selection algorithm, etc.; The third is the application of computer and intelligent ore blending systems, which is more common in open-pit mine ore blending management systems.

The mathematical programming method is mainly used for the modelling of ore blending optimisation in an open-pit mine. The objective function of the model is to achieve maximum profit and mining quantity, minimum grade deviation and minimum total cost, and the constraints generally consider the equipment production capacity, ore quality, task quantity, etc. Linear programming is one of the earliest mathematical programming methods used in the optimisation modelling of open-pit mine blending. In the early stage of research, many scholars actively applied it to the optimisation modelling of production planning and solved many problems in mine blending. Some scholars have applied the SIP (Stochastic Integer Programming) model to the ore blending [1-6]. Liu et al. [7] established an ore matching model by linear programming, which solved the problem of ore matching for simultaneous mining of multiple coal seams. Some scholars use integer dynamic programming to calculate ore blending schemes [8,9]. Moreno et al. [10] considered the impact of ore storage on production and constructed multiple linear programming models to optimise production planning. Compared with the nonlinear model, the effect is significant. Some studies use metaheuristics to solve the problem of ore blending [11-16].

An intelligent optimisation algorithm has considerable advantages in solving the optimisation model. With the continuous in-depth study of open-pit ore blending optimisation, the model is more and more complex. Jélvez et al. [17] proposed a new aggregation and decomposition heuristic algorithm for plan optimisation. The algorithm can obtain a feasible approximate optimal solution with low time complexity, which provides a solution for solving large-scale problems. Sattarvand et al. [18,19] proposed a heuristic approximation algorithm based on the ant colony algorithm, which was applied to the planning of open pit mine, and considered the influence of ore grade uncertainty in the planning process. Dervis Karaboga [20] proposed a relatively new evolutionary algorithm, the artificial bee swarm (ABC) algorithm. The colony of artificial bees contains three groups of bees: employed bees, onlookers, and scouts in the ABC algorithm [21]. Li [22] used a new ABC algorithm and a wavelet neural network (WNN) to predict the gold price. Bahram and Nader [23] combined ABC with radial basis function (RBF) and backpropagation

(BP) neural network to predict phosphate ore grade. Chen et al. [24] introduced the differential evolution (DE) algorithm and ABC algorithm into the new ABC search equation in order to improve the convergence speed of the algorithm. Anuar [25] combines the artificial neural network with ABC to apply the proposed algorithm to the classification of criminal data while avoiding the problems that neural networks can easily fall into the local optima. Ghanem [26] combined ABC with particle swarm optimisation (PSO) and tested the classification accuracy of the method on multiple datasets. Cui et al. [27] proposed an ABC algorithm based on distance fitness and verified it with a standard data set. Tosun et al. [28] established a relationship to determine the optimal number of trucks.

The research object of computer and intelligent ore blending systems is the system problems with large scale, complex structures and a large amount of information. Its control and planning process involves a lot of calculation and information processing, which is beyond the reach of human beings. With the development trend of digitalisation and intellectualisation in mines, the application of computers has been accelerated, and the role of ore blending systems in mine production has become increasingly prominent. Therefore, various types of mine production software and ore blending systems began to appear. Some studies proposed an expert decision support system for ore blending, which considered the balance of macro and micro ore quality. Gema et al. [29] aimed at determining an exploitability index with geographical information systems tools. Because of the limitation of the development level of computers at that time, it was not widely used, but it marked the arrival of intelligent ore blending. Other studies proposed a large-scale integrated hardware and software ore blending system for mining and beneficiation combined production. This improved the control level of ore quality and set a precedent for Chinese mining and beneficiation combined ore blending.

The following sums up the deficiencies of existing research:

(1) Large-scale open-pit iron ore production may need to provide ore to many concentrators. Each concentrator for the ore requirements may be different, which increases the difficulty of ore blending. This results in the actual production of ore blending, and the existing ore blending method cannot solve the actual demand for open-pit iron ore for MSMT ore blending.
(2) Most of the research on ore blending optimisation of open-pit mines mainly focuses on a single mineral resource, but most of the mineral resources do not exist independently. For example, iron exists in nature as a variety of compounds, and different forms of existence also have different treatment methods for the follow-up beneficiation process.
(3) The current computer and intelligent ore blending system is still a relatively single-function system, which cannot be combined with a mine digital geological system or open-pit truck dispatching system. These systems cannot complete a more accurate and faster intelligent ore blending.

To solve the above technical problems, meet the actual demand for MSMT ore blending in the current open-pit iron mine, and solve the existing problems, an ore blending method is proposed in this paper. By establishing an ore blending model with the maximum OO and the shortest transportation distance as the goal, and with the constraints of WI, total iron grade (TFeG), ferrous iron grade (FFeG) and iron carbonate content ($FeCO_3G$) after ore blending. The MSMT ore blending optimization of open-pit iron ore is realised. The purpose is to make the mixed ore properties more convenient for production, thus improving production efficiency and reducing production costs.

In view of the situation that the open-pit iron ore supplies ore to many concentrators, the ore blending model is designed so that the method can meet the situation of a single mine to a single concentrator and that of a single mine to multiple concentrators. Van Tonder et al. [30] proved that well-mixed ore properties significantly impact flotation production. The ore blending conditions are restricted by specifying whether the electric shovel draws ore, the range of production capacity of the electric shovel in the ore blending period, the range of OO at each ore unloading point (OUP), the range of mining WI, the range of TFeG, the range of FFeG and the range of $FeCO_3G$, so as to make the ore blending closer to the actual production. Ore blending results are generated according to the selected ore blending time period, which makes the software more flexible and meets the ore blending requirements of different time dimensions. According to the results of ore blending, we can know the bottleneck of current production. Through targeted optimisation management, we can tap the production potential of an open-pit mine.

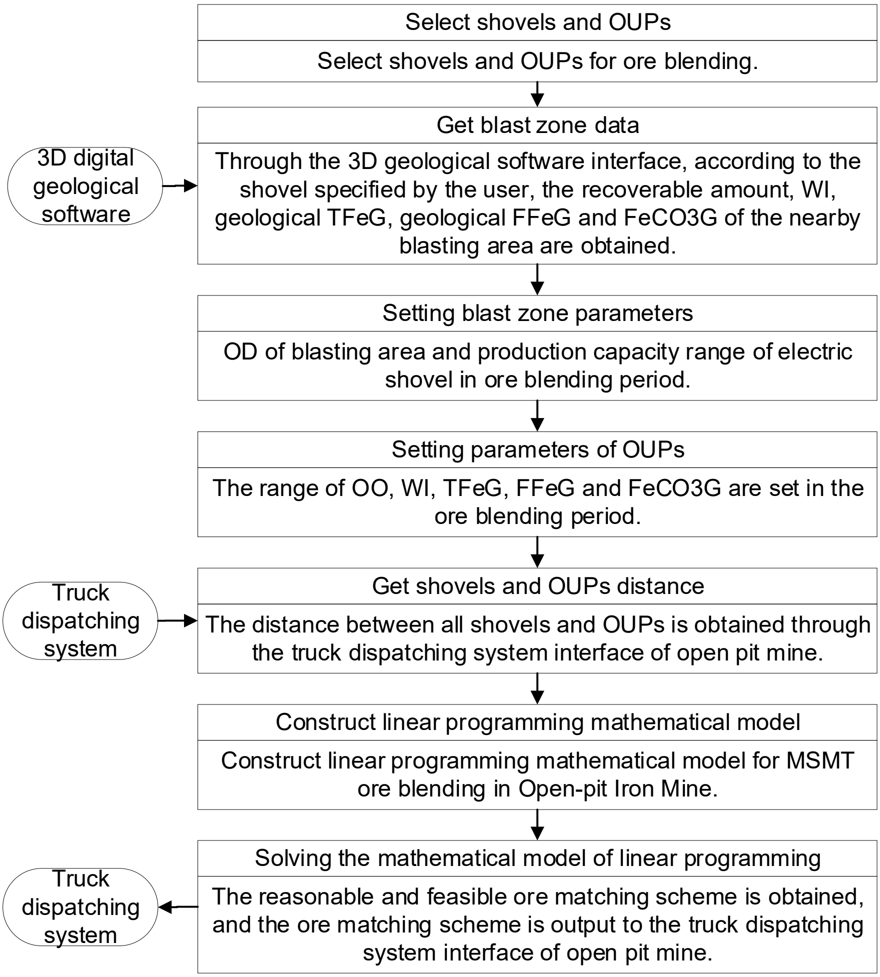

Fig. 1. Schematic diagram of ore blending process

2. Ore blending method and processing

As shown in Fig. 1, The ore blending method and process mainly include the following steps. Step 1: Selection shovels and OUPs; Step 2: Get blast zone data; Step 3: Setting blast zone parameters; Step 4: Setting parameters of OUPs; Step 5: Get shovels and OUPs distance; Step 6: Construction of linear programming mathematical model for ore blending; Step 7: Solving the mathematical model of linear programming for ore blending.

2.1. Select shovels and OUPs

Select shovels and OUPs for ore blending. Suppose there are n electric shovels, $i = 1, 2, 3, ..., n$; There are m OUPs, $j = 1, 2, 3, ..., m$.

2.2. Get blast zone data

Through the 3D geological software interface, according to the shovel specified by the user, the recoverable amount, geological WI, TFeG, FFeG and $FeCO_3G$ of the nearby blasting area are obtained. Among them, Q_i is the recoverable amount of the explosive area where the number i shovel is located, GP_i is the geological WI, GT_i is the geological TFeG, GF_i is the geological FFeG, and GC_i is the geological $FeCO_3G$.

2.3. Setting blast zone parameters

Ore dilution (OD) of blasting area and production capacity range of electric shovel in ore blending period. Among them, R_i is the OD of the blasting area where the number i shovel is located, $SMIN_i$ and $SMAX_i$ is the minimum and maximum production capacity of the shovel in the ore blending time period.

2.4. Setting parameters of ore OUPs

The range of OO, WI, TFeG, FFeG and $FeCO_3G$ is set in the ore blending period. Among them, $UMIN_j$ and $UMAX_j$ are the lower limits (LL) and upper limit (UL) of ore production in the ore blending time period of the j OUP, $PPMIN_j$ and $PPMAX_j$ are LL and UL of mining WI, $PTMIN_j$ and $PTMAX_j$ are LL and UL of mining TFeG, $PFMIN_j$ and $PFMAX_j$ are LL and UL of mining FFeG, $PCMIN_j$ and $PCMAX_j$ are LL and UL of the mining $FeCO_3G$.

2.5. Get shovels and OUPs distance

The distance between all shovels and OUPs is obtained through the truck dispatching system interface of the open-pit mine. Where Dij is the distance from the number i shovel to the number j OUP.

2.6. Construct linear programming mathematical model for ore blending

Assuming that x_{ij} is the amount of ore transported from the number i blasting area to the number j OUP, the objectives and constraints of the MSMT ore blending linear programming mathematical model of open-pit iron ore include:

- Target of maximum OO and shortest haul distance:

$$\max f_1(x) = \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{x_{ij}}{D_{ij}} \tag{1}$$

- Mineable quantity constraint of blasting area:

$$\sum_{j=1}^{m} x_{ij} \le Q_i \tag{2}$$

- Shovel capacity constraint:

$$SMIN_i \le \sum_{j=1}^{m} x_{ij} \le SMAX_i \tag{3}$$

- OO requirements of OUP:

$$UMIN_j \le \sum_{i=1}^{m} x_{ij} \le UMAX_j \tag{4}$$

- WI constraint of mining at OUP:

$$PPMIN_j \le \frac{\sum_{i=1}^{n} x_{ij} \cdot GP_i}{\sum_{i=1}^{n} x_{ij}} \le PPMAX_j \tag{5}$$

- TFeG constraint produced at OUP:

$$PTMIN_j \le \frac{\sum_{i=1}^{n} x_{ij} \cdot GT_i \cdot \left(1 - \frac{R_i}{100}\right)}{\sum_{i=1}^{n} x_{ij}} \le PTMAX_j \tag{6}$$

- FFeG constraint produced at OUP:

$$PFMIN_j \le \frac{\sum_{i=1}^{n} x_{ij} \cdot GF_i \cdot \left(1 - \frac{R_i}{100}\right)}{\sum_{i=1}^{n} x_{ij}} \le PFMAX_j \tag{7}$$

- $FeCO_3G$ constraint produced at OUP:

$$PCMIN_j \le \frac{\sum_{i=1}^{n} x_{ij} \cdot GC_i \cdot \left(1 - \frac{R_i}{100}\right)}{\sum_{i=1}^{n} x_{ij}} \le PCMAX_j \tag{8}$$

2.7. Solving the mathematical model of linear programming for ore blending

The reasonable and feasible ore matching scheme is obtained, and the ore matching scheme is the output to the truck dispatching system interface of the open-pit mine.

3. Results and Discussion

Qidashan Iron Mine (QDSIM) is a metallurgical mine that integrates mining and beneficiation. It supplies iron ore to both Qidashan and Diaojuntai concentrators, with an annual design production capacity of 51 million tons of mining and stripping, 14.4 million tons of raw ore processing, 4.8 million tons of iron concentrate and a concentrate grade of more than 67.5%. The current ore blending method of QDSIM is completed manually by ore blending personnel using Excel. The operation is complex, requires high experience of ore blending personnel, has too many human factors, and has certain blindness, which leads to the inaccuracy of the ore blending scheme.

Assuming that there are 7 electric shovels in a certain shift of QDSIM one day, the ore is planned to be discharged to 2 OUPs. In order to obtain the ore blending scheme, do the following steps:

(1) Select 7 electric shovels, namely 1#, 10#, 11#, 15#, 17#, 21# and 22# respectively, and 2 OUPs for ore blending, namely North Crushing Station (NCS) and Ore Crushing Station (OCS). NCS's ore is transported to Qidashan concentrator and OCS's ore is transported to Diaojuntai concentrator.

(2) Obtain the geological data of the blasting area where the electric shovel is located. Through the three-dimensional geological software interface, according to the electric shovel specified by the user, the recoverable quantities of the blasting area are all 20000t, the WI are 59.71, 47.66, 63.50, 58.50, 57.60, 67.90 and 63.56 respectively, and the geological TFeG are 30.35%, 30.66%, 30.60%, 31.67%, 29.12%, 31.21% and 30.85% respectively, the geological FFeG is 11.39%, 13.15%, 12.74%, 12.56%, 10.76%, 12.36% and 10.54% respectively, the $FeCO_3G$ of 15# shovel is 4%, and the others are 0%. Detailed data are shown in Table 1.

(3) The OD of the specified blasting area is input by the user, as shown in Table 1, which are 2%, 2%, 0%, 1%, 0%, 1% and 1%, respectively. The recoverable quantity of the shovel is all 20000t. The LL and UL of OO are 500t ~ 2500t, 500t ~ 3000t, 500t ~ 3000t, 500t ~ 3000t, 500t ~ 3000t, 500t ~ 2000t, and 500t ~ 2000t, respectively.

(4) The user inputs the OO range within the ore blending time period of each OUP, as shown in Table 2, which are 1t ~ 18000t and 1t ~ 7000t, respectively. The mining WI range is all 28 ~ 70, the TFeG range is all 28.00 ~ 34.00, the FFeG range is all 6.00 ~ 13.00, and the $FeCO_3G$ range is all 0.00 ~ 6.00.

(5) The distance between all electric shovels and the OUPs is obtained through the interface of the truck dispatching system of the open-pit mine. As shown in Table 3, the distances between the seven selected shovels and OCS are 2000m, 1500m, 1800m, 2500m, 500m, 900m and 800m, respectively. The distances between the seven selected shovels and NCS are 400m, 200m, 300m, 1000m, 1500m, 1300m and 1600m, respectively.

TABLE 1

Data and parameter setting of explosion area

Shovel No.	Recoverable quantity (t)	Geological WI	Geological TFeG (%)	Geological FFeG (%)	Geological $FeCO_3G$ (%)	OD (%)	OO LL (t)	OO UL (t)
1#	20000	59.71	30.35	11.39	0.00	2	500	2500
10#	20000	47.66	30.66	13.15	0.00	2	500	3000
11#	20000	63.50	30.60	12.74	0.00	0	500	3000
15#	20000	58.50	31.67	12.56	4.00	1	500	3000
17#	20000	57.60	29.12	10.76	0.00	0	500	3000
21#	20000	67.90	31.21	12.36	0.00	1	500	2000
22#	20000	63.56	30.85	10.54	0.00	1	500	2000

TABLE 2

OUP parameter setting

No.	OUP	OO (t)		WI		TFeG (%)		FFeG (%)		$FeCO_3G$ (%)	
		LL	UL	LL	UL	LL	UL	LL	UL	LL	UL
1	OCS	1	18000	28.00	70.00	28.00	34.00	6.00	13.00	0.00	6.00
2	NCS	1	7000	28.00	70.00	28.00	34.00	6.00	13.00	0.00	6.00

TABLE 3

Distance between shovel and OUP

Shovel No.	Distance from OCS (m)	Distance from NCS (m)
1#	2000	400
10#	1500	200
11#	1800	300
15#	2500	1000
17#	500	1500
21#	900	1300
22#	800	1600

(6) The linear programming mathematical model of MSMT ore blending in open-pit iron mine can be expressed in the following forms:

$$\max\left(\begin{array}{l}\dfrac{x_{11}}{2000}+\dfrac{x_{12}}{400}+\dfrac{x_{21}}{1500}+\dfrac{x_{22}}{200}+\dfrac{x_{31}}{1800}+\dfrac{x_{32}}{300}+\dfrac{x_{41}}{2500}+\\ +\dfrac{x_{42}}{1000}+\dfrac{x_{51}}{500}+\dfrac{x_{52}}{1500}+\dfrac{x_{61}}{900}+\dfrac{x_{62}}{1300}+\dfrac{x_{71}}{800}+\dfrac{x_{72}}{1600}\end{array}\right) \tag{9}$$

$$\begin{cases} x_{11}+x_{12}\le 20000 \\ x_{21}+x_{22}\le 20000 \\ x_{31}+x_{32}\le 20000 \\ x_{41}+x_{42}\le 20000 \end{cases} \tag{10}$$

$$
S.T.\begin{cases}
x_{51}+x_{52}\le 20000\\
x_{61}+x_{62}\le 20000\\
x_{71}+x_{72}\le 20000\\
500\le x_{11}+x_{12}\le 2500\\
500\le x_{21}+x_{22}\le 3000\\
500\le x_{31}+x_{32}\le 3000\\
500\le x_{41}+x_{42}\le 3000\\
500\le x_{51}+x_{52}\le 3000\\
500\le x_{61}+x_{62}\le 2000\\
500\le x_{71}+x_{72}\le 2000\\
1\le \sum\limits_{i=1}^{7} x_{i1}\le 18000\\
1\le \sum\limits_{i=1}^{7} x_{i2}\le 7000\\
28\le \dfrac{\sum_{i=1}^{7} x_{i1}\cdot GP_i}{\sum_{i=1}^{7} x_{i1}}\le 70\\
28\le \dfrac{\sum_{i=1}^{7} x_{i2}\cdot GP_i}{\sum_{i=1}^{7} x_{i2}}\le 70\\
28\le \dfrac{\sum_{i=1}^{7} x_{i1}\cdot GT_i\cdot\left(1-\dfrac{R_i}{100}\right)}{\sum_{i=1}^{7} x_{i1}}\le 34\\
28\le \dfrac{\sum_{i=1}^{7} x_{i2}\cdot GT_i\cdot\left(1-\dfrac{R_i}{100}\right)}{\sum_{i=1}^{7} x_{i2}}\le 34\\
6\le \dfrac{\sum_{i=1}^{7} x_{i1}\cdot GF_i\cdot\left(1-\dfrac{R_i}{100}\right)}{\sum_{i=1}^{7} x_{i1}}\le 13\\
6\le \dfrac{\sum_{i=1}^{7} x_{i2}\cdot GF_i\cdot\left(1-\dfrac{R_i}{100}\right)}{\sum_{i=1}^{7} x_{i2}}\le 13\\
0\le \dfrac{\sum_{i=1}^{7} x_{i1}\cdot GC_i\cdot\left(1-\dfrac{R_i}{100}\right)}{\sum_{i=1}^{7} x_{i1}}\le 6\\
0\le \dfrac{\sum_{i=1}^{7} x_{i2}\cdot GC_i\cdot\left(1-\dfrac{R_i}{100}\right)}{\sum_{i=1}^{7} x_{i2}}\le 6
\end{cases}
\qquad \text{(10 continued)}
$$

Where

$$\sum_{i=1}^{7} x_{i1} = x_{11} + x_{21} + x_{31} + x_{41} + x_{51} + x_{61} + x_{71} \tag{11}$$

$$\sum_{i=1}^{7} x_{i2} = x_{12} + x_{22} + x_{32} + x_{42} + x_{52} + x_{62} + x_{72} \tag{12}$$

$$\begin{aligned}\sum_{i=1}^{7} x_{i1} \cdot GP_i &= x_{11} \times 59.71 + x_{21} \times 47.66 + x_{31} \times 63.5 + \\ &+ x_{41} \times 58.5 + x_{51} \times 57.6 + x_{61} \times 67.9 + x_{71} \times 63.56\end{aligned} \tag{13}$$

$$\begin{aligned}\sum_{i=1}^{7} x_{i2} \cdot GP_i &= x_{12} \times 59.71 + x_{22} \times 47.66 + x_{32} \times 63.5 + \\ &+ x_{42} \times 58.5 + x_{52} \times 57.6 + x_{62} \times 67.9 + x_{72} \times 63.56\end{aligned} \tag{14}$$

$$\begin{aligned}\sum_{i=1}^{7} x_{i1} \cdot GT_i \cdot \left(1 - \frac{R_i}{100}\right) &= x_{11} \times 30.35 \times \left(1 - \frac{2}{100}\right) + x_{21} \times 30.66 \times \left(1 - \frac{2}{100}\right) + \\ &+ x_{31} \times 30.6 + x_{41} \times 31.67 \times \left(1 - \frac{1}{100}\right) + x_{51} \times 29.12 + \\ &+ x_{61} \times 31.21 \times \left(1 - \frac{1}{100}\right) + x_{71} \times 30.85 \times \left(1 - \frac{1}{100}\right)\end{aligned} \tag{15}$$

$$\begin{aligned}\sum_{i=1}^{7} x_{i2} \cdot GT_i \cdot \left(1 - \frac{R_i}{100}\right) &= x_{12} \times 30.35 \times \left(1 - \frac{2}{100}\right) + x_{22} \times 30.66 \times \left(1 - \frac{2}{100}\right) + \\ &+ x_{32} \times 30.6 + x_{42} \times 31.67 \times \left(1 - \frac{1}{100}\right) + x_{52} \times 29.12 + \\ &+ x_{62} \times 31.21 \times \left(1 - \frac{1}{100}\right) + x_{72} \times 30.85 \times \left(1 - \frac{1}{100}\right)\end{aligned} \tag{16}$$

$$\begin{aligned}\sum_{i=1}^{7} x_{i1} \cdot GF_i \cdot \left(1 - \frac{R_i}{100}\right) &= x_{11} \times 11.39 \times \left(1 - \frac{2}{100}\right) + x_{21} \times 13.15 \times \left(1 - \frac{2}{100}\right) + \\ &+ x_{31} \times 12.74 + x_{41} \times 12.56 \times \left(1 - \frac{1}{100}\right) + x_{51} \times 10.76 + \\ &+ x_{61} \times 12.36 \times \left(1 - \frac{1}{100}\right) + x_{71} \times 10.54 \times \left(1 - \frac{1}{100}\right)\end{aligned} \tag{17}$$

$$\sum_{i=1}^{7} x_{i2} \cdot GF_i \cdot \left(1-\frac{R_i}{100}\right) = x_{12} \times 11.39 \times \left(1-\frac{2}{100}\right) + x_{22} \times 13.15 \times \left(1-\frac{2}{100}\right) + \\ + x_{32} \times 12.74 + x_{42} \times 12.56 \times \left(1-\frac{1}{100}\right) + x_{52} \times 10.76 + \\ + x_{62} \times 12.36 \times \left(1-\frac{1}{100}\right) + x_{72} \times 10.54 \times \left(1-\frac{1}{100}\right) \tag{18}$$

$$\sum_{i=1}^{7} x_{i1} \cdot GC_i \cdot \left(1-\frac{R_i}{100}\right) = x_{41} \times 4 \times \left(1-\frac{1}{100}\right) \tag{19}$$

$$\sum_{i=1}^{7} x_{i2} \cdot GC_i \cdot \left(1-\frac{R_i}{100}\right) = x_{42} \times 4 \times \left(1-\frac{1}{100}\right) \tag{20}$$

TABLE 4

Shovel ore blending results

Shovel No.	OCS ore blending ratio (%)	NCS ore blending ratio (%)
1#	21.74	14.29
10#	26.09	42.86
11#	0.00	42.86
15#	17.39	0.00
17#	0.00	0.00
21#	17.39	0.00
22#	17.39	0.00

(7) The MSMT ore blending linear programming mathematical model ((9)~(20)) of an open-pit iron mine is solved to obtain the ore blending results of the electric shovel as shown in Table 4. The ore blending results of OUP are shown in Table 5, and the ore blending operation results as shown in Table 6. The ore blending results of electric shovels list the ore transportation proportion from each electric shovel to each OUP. The specific data is that the proportion of seven electric shovels to OCS is 21.74%, 26.09%, 0%, 17.39%, 0%, 17.39% and 17.39% respectively, and the proportion to NCS is 14.29%, 41.86%, 42.86% and others is 0% respectively. The ore blending results of OUPs list the WI, TFeG, FFeG and $FeCO_3$G predicted for each OUP if they are produced according to the ore blending results of the electric shovel. The predicted results of OCS are 58.45, 30.44, 11.89 and 0.69, respectively, and the predicted results of NCS are 60.26, 30.07, 11.85 and 0.57, respectively. According to the conclusion of Su et al. [31], when the WI is 58.45 and the comprehensive concentrate iron grade is 67.5%. It can be predicted that the comprehensive tailings iron grade is between 10.5% and 11.5%, the beneficiation ratio is between 3.26 and 3.39, and the cost per ton of concentrate is 511 yuan. When the WI is 60.26, and the comprehensive concentrate iron grade is 67.5%, it can be predicted that the comprehensive tailings iron grade is between 9.5% and 10.5%, the beneficiation ratio is between 3.14 and 3.26, and the cost per ton of concentrate is 447 yuan. Send the shovel ore blending results to the truck dispatching system of the open pit mine, and the truck dispatching system of the open pit mine will organise production.

TABLE 5

OUP ore blending results

No.	OUP	WI	TFeG (%)	FFeG (%)	$FeCO_3G$ (%)
1	OCS	58.45	30.44	11.89	0.69
2	NCS	60.26	30.07	11.85	0.57

Through the ore blending calculation results, it can be seen that the production bottleneck under the current conditions is where the limit value is reached. From this embodiment, it can be seen that the production capacity of shovels is the production bottleneck, and the output of NCS is also the production bottleneck.

TABLE 6

Ore blending operation results

Content	Setting value	Ore blending result	Status (limit value reached or not)	Difference
Shovel 1# mining volume	500-2500	2500	Reached	0
Shovel 10# mining volume	500-3000	3000	Reached	0
Shovel 11# mining volume	500-3000	3000	Reached	0
Shovel 15# mining volume	500-3000	3000	Reached	0
Shovel 17# mining volume	500-3000	3000	Reached	0
Shovel 21# mining volume	500-2000	2000	Reached	0
Shovel 22# mining volume	500-2000	2000	Reached	0
OCS output	1-18000	11500	Not reached	6500
NCS output	1-7000	7000	Reached	0

4. Conclusions

In this paper, an MSMT ore blending method for open-pit iron ore is proposed. The MSMT ore blending optimisation of open-pit iron ore is realised by establishing the ore blending model with the goal of maximum OO and shortest transportation distance, and the ore WI, TFeG, FFeG and $FeCO_3G$ after ore blending meets the requirements. Based on the above algorithm, the ore blending optimisation system was developed. It has been applied in QDSIM and achieved good application results. Through the application of the present system, the increase in ore production is achieved while the stabilisation of ore inclusion indicators in downstream concentrators is guaranteed.

In the current intelligent mine construction and even the future unmanned mine construction, the intelligent ore distribution system combines the intelligent truck dispatching system and driverless technology to lay the foundation for the realisation of the unmanned mine. In the future, the mine staff can complete the mining of the whole open-pit mine only in the remote control centre.

In the actual open-pit production, the production situation changes at any time, such as the failure of production equipment, the large fluctuation of ore grade, etc. At this point, if the production is carried out according to the previously generated ore blending plan, there will be a substantial deviation, which is contrary to the original intention of ore blending. This requires that the ore blending plan can be automatically adjusted during production, and the adjusted ore blending plan will be sent to the truck dispatching system. In this way, the deviation can be corrected in time to avoid significant errors. The next step is to carry out dynamic ore blending based on this study.

List of abbreviations

ABC	artificial bee swarm
BP	back propagation
DE	differential evolution
$FeCO_3G$	iron carbonate content
FFeG	ferrous iron grade
LL	lower limit
MSMT	multi-source and multi-target
NCS	north crushing station
OCS	ore crushing station
OD	ore dilution
OG	ore grade
OO	ore output
OUP	ore unloading point
PSO	particle swarm optimization
QDSIM	Qidashan iron mine
RBF	radial basis function
SIP	stochastic integer programming
TFeG	total iron grade
UL	upper limit
WI	washability index
WNN	wavelet neural network

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