

Article

Research on Multi-Objective Ore Blending Optimization Based on Non-Equilibrium Grade Polymetallic Mine of Shizhuyuan

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Abstract: The ore blending of non-equilibrium grade polymetallic ore is affected by various factors such as mineral resources, production technology, and economic efficiency. Aiming at the problems of Shizhuyuan Polymetallic Mine being diverse in nature, uneven in size, having many mining points, with large grade fluctuation, this paper proposes an optimization method for ore blending based on an artificial bee colony (ABC) algorithm. A multi-metal and multi-objective ore-blending optimization model is established with the minimum fluctuation of ore grade, mining transportation cost, and production capacity as the objective function. The ore mining plan was prepared according to the actual production situation of the mine and the optimization results. While ensuring that the average grade of the output ore reaches the minimum selected grade of the beneficiation plant, the recovery rates of tungsten, molybdenum, and bismuth in the beneficiation plant are significantly increased by 8.95%, 12.20%, and 8.33%, respectively. This study has discovered the first refined and high-efficiency blending of polymetallic ore such as tungsten, molybdenum, and bismuth in China, with simultaneous mining of low-and high-grade ore, cost control, balanced selection of grades, and coordinated production tasks.



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Keywords: multi-metal and multi-objective ore blending; artificial bee colony algorithm; multi-objective optimization; non-equilibrium ore grade

1. Introduction

Shizhuyuan Mine is rich in mineral resources and has a wide variety of ores. It is an important non-ferrous metal resource base in China and a world-famous polymetallic deposit, known as the “World Non-ferrous Metals Museum”. The reserves of ore resources in the region are about 360 million tons, and there are about 143 kinds of ores, including about 747,000 tons of tungsten, accounting for 20.7% of the world’s proven reserves; about 305,000 tons of bismuth, accounting for 42% of the world’s proven reserves; molybdenum, of about 132,000 tons [1]. At present, the general mining system and mining method of Shizhuyuan Polymetallic Mine have been determined, the scale and layout of the beneficiation plant have also been finalized, and the basic production conditions and production processes of the entire mining, transportation, and beneficiation system have become mature. However, in the actual production process, there are problems such as large fluctuations of ore grade, low average grade selected, and many mining points, which make it very difficult to formulate production plans. The most important thing now is to optimize the management of the system, especially to strengthen the overall quality management of the ore blending. A multi-metal and multi-objective high-efficiency ore blending system for Shizhuyuan Mine urgently needs to be established, to promote the smooth production of the mining enterprise with low cost and high efficiency.

Ore blending optimization should consider the influence of ore grade fluctuation, mining and transportation cost, recovery rate, and other factors; and the ore type is not single, making the multi-metal multi-objective allotment optimization research one of the

hot spots of general interest in the industry [2–6]. At present, scholars have carried out a lot of research on the optimization of ore blending. Early research mostly involved linear programming, 0–1 integer programming, the unascertained model, etc. Wilke et al. [7] proposed the application of linear programming to formulate production plans, and established a linear optimization solution model by assigning weights to stopes or working faces. Wang et al. [8] established a 0–1 integer programming model for ore blending and introduced a computer program. Li et al. [9] established an operation plan optimization model based on 0–1 integer programming, aiming at the minimum grade deviation, and completed the preparation of mining plans. Lin [10] established an unascertained model for quality control and verified that the method is applicable. However, the above studies are all single-objective studies, which often cannot meet their production needs in actual blending production, especially in polymetallic mines. Wang et al. [11] proposed an optimization method for automatic ore blending in open-pit mines based on objective planning, aiming at the problems of a long time and rough result of ore blending caused by multi-metal and multi-unloading-point ore blending in open-pit mines. Souza et al. [12] studied the open-pit mining operation planning problem based on dynamic truck allocation and proposed an optimization model to minimize the number of trucks under the premise of ensuring production and grade. Huang et al. [13] proposed a circular geometric constraint model to solve the ore blending optimization problem in open-pit mines based on the mining sequence of each ore nugget and the mining geometric constraints in the blasting process. For the multi-metal multi-objective problem with complex ore blending conditions, the conventional solution method cannot be solved. Therefore, the research on ore blending optimization is not only developed in the direction of the multi-objective aspect, but the solution method also combines intelligent optimization algorithms with computers. Huang et al. [14] used the particle swarm algorithm to solve the dynamic ore allocation problem of mining enterprises. Yao et al. [15] established a multi-objective ore blending model for underground mines based on the immune clone selection algorithm. Xu et al. [16] proposed a fuzzy optimization algorithm to solve the multi-objective ore blending problem. Gu et al. [17] used the improved gray wolf algorithm to optimize the multi-objective production planning model of open-pit mines. Moosavi et al. [18] proposed a method combining the genetic algorithm and Lagrangian relaxation to optimally determine the production schedule of open pit mines. Sattarvand et al. [19] applied the ant colony algorithm to mine planning. Shishvan et al. [20] applied the ant colony algorithm to mining planning, considering various objective functions, nonlinear constraints, and practical technical limitations.

Currently, there are many calculation methods for allotment optimization. Xu et al. [21] proposed a fuzzy multi-objective blending optimization algorithm that requires information on linguistic preferences and the satisfaction of the decision maker. Mustafa [22] proposed multi-objective simulated annealing-based chance-constrained programming for ore blending optimization, where each process of the method is simulated to reproduce the characteristics or behavior of the phenomenon observed in the available data. Ye et al. [23] used a genetic particle swarm hybrid intelligence algorithm to optimize the ore blending with good optimization results, but its calculation speed is slower. The algorithms proposed in References [16–20] are well-used in the study of ore blending optimization, but they also have problems such as complex algorithms and slow convergence. The ABC algorithm proposed in this paper is more convenient, easy to learn, and fast to converge compared with these algorithms. However, these previous algorithms are based on different projects to verify the superiority of the algorithm. We also looked for online field data about polymetallic mines for calculation. Huang et al. [1] used a genetic algorithm to optimize ore blending and obtained a tungsten recovery of 8 percentage points when the tungsten ore grade fluctuated within 10%, while this paper used an ABC algorithm to optimize the ore blending and obtained a tungsten recovery of 8.95 percentage points when the tungsten ore grade fluctuated within 3%. Therefore, the ABC algorithm has good applicability in

multi-metal and multi-objective ore blending optimization, and the optimization results are good.

To sum up, the research trend of the non-equilibrium grade ore blending optimization model has developed from single-objective to multi-objective, and the solution method has also developed from the original conventional linear programming to modern intelligent evolutionary algorithms, such as the genetic algorithm and particle swarm algorithm. Among them, the ABC algorithm does not need to understand the special information of the problem, but only needs to compare the advantages and disadvantages of the problem, and through the local optimization-seeking behavior of each worker bee, the global optimum value is finally made to emerge in the colony, which has a fast convergence speed. A large number of simulation results show [24,25] that the ABC algorithm can solve multi-dimensional numerical problems better than the differential evolution algorithm, genetic algorithm, particle swarm, and other algorithms, and can be used efficiently. At present, few researchers have studied [1,26] the multi-objective ore blending optimization problem of non-equilibrium grade polymetallic ore with integrated mining and beneficiation, associated or symbiotic mineral resources, and few researchers have applied the ABC algorithm to the multi-objective ore blending optimization problem of a polymetallic mine. Therefore, this paper takes Shizhuyuan Mine as the background and establishes an ore blending optimization model in terms of minimum ore grade fluctuation, mining and transportation cost, and production capacity under the constraints of maximum ore volume limitation at the mining point, the ore grade requirement at the receiving point, and maximum production capacity. The main contribution of this paper is that the problem of uneven distribution of polymetallic ore grades in the Shizhuyuan Mine is addressed by an optimization approach of multi-metal and multi-objective blending of the polymetallic ore. Then, this optimization approach is solved by the ABC algorithm. The optimization results provide theoretical support for planning a reasonable scientific and efficient mining plan, reducing production costs and improving the recovery rate of polymetallic resources in Shizhuyuan. It perfects the foundation for the subsequent establishment of a multi-metal and multi-objective efficient ore blending system at the Shizhuyuan mine.

The rest of this paper is laid out as follows. Section 2 proposes the multi-metal and multi-objective ore blending model in Shizhuyuan Mine. The ideal-point method is used to transform the three objective functions into one function for the solution. A penalty function is used to deal with the constraints, and the constrained multi-objective optimization problem is transformed into an unconstrained minimization problem. Section 3 introduces the ABC algorithm to solve the proposed problem. Section 4 uses the multi-metal and multi-objective ore blending models and the ABC algorithm to optimize the production plan of the Shizhuyuan Polymetallic Mine. The results show the reliability and practicability of the method. Section 5 summarizes this research and proposes ideas for future research.

2. Multi-Metal and Multi-Objective Ore Blending Model in Shizhuyuan Mine

This section briefly introduces the multi-metal and multi-objective ore blending problem in Shizhuyuan Polymetallic Mine. A multi-metal and multi-objective ore blending model is built, using the ideal-point method to deal with the objective functions and the penalty function to deal with the constraints.

2.1. Problem Statement

The multi-metal and multi-objective ore blending model [27,28] mainly solves the problem of non-equilibrium distribution of polymetallic ore grades in the Shizhuyuan Mine, to ensure that the ore grade fluctuation of the beneficiation plant is relatively small to improve the ore recovery of the plant. Since ore blending is extremely complex and influenced by many factors, the following simplifications can be made to build this model. Assume that the mine has m ore exit points (mining points) and n ore receiving points (beneficiation plants), and let m ore exit points coordinate the production according to their respective grades, to ensure that the ore grades of n ore receiving points meet the

requirements. There are 47 ore exit points ($m = 47$) and 2 ore receiving points ($n = 2$) in the Shizhuyuan Mine. On the premise of meeting the mine production tasks, a scientific and economical mining plan is formulated to minimize the fluctuation of the ore grade and the lowest mining and transportation costs. According to the linear programming model in system engineering and operations research [29], the ore quantity of each mining point is reasonably allocated, so that the sum of the transportation cost and the mining cost is minimized after ore blending. Considering that the distance of each mining point from the beneficiation plant is not much different, the mining cost and transportation cost are combined, and the transportation cost is charged according to the number of transportation times. The ore grade of each metal at each mining point, the total amount of stored ores, the total amount of new ores planned to be mined, and the average minimum grade and maximum bearing capacity of each metal at each receiving point are known. The description of basic symbols can be found in Appendix A.

2.2. Model Building

Under the condition of integrated mining and beneficiation, multi-metal and multi-objective ore blending is a complex nonlinear optimization problem. Its objective function should consider the fluctuation of ore grade, the ore output capacity of the mining point, the ore receiving capacity of the beneficiation plant, the mining and transportation cost, and other factors. In this paper, the objective functions are established in terms of minimum ore grade fluctuation, mining and transportation cost, and production capacity. Ore blending also involves various constraints such as the beneficiation plant production plan, average grade requirements of selected ore, ore recovery rate, and other constraints, ignoring the constraints of time and space, the mathematical model of multi-metal and multi-objective ore blending optimization is expressed as follows:

$$f_1(x) = \min \left[\frac{\sum_{r=1}^k \sum_{j=1}^n \left| \sum_{i=1}^m (q_{ri} - q_{rj}) x_{ij} \right|}{\sum_{j=1}^n \sum_{i=1}^m x_{ij}} \right] \quad (1)$$

$$f_2(x) = \min \left| \sum_{i=1}^m (C_i \sum_{j=1}^n x_{ij}) - f_2' \right| \quad (2)$$

$$f_3(x) = \min \left| \sum_{j=1}^n \sum_{i=1}^m x_{ij} - Q \right| \quad (3)$$

$$s.t. \begin{cases} q_i^{max} - \sum_{j=1}^n x_{ij} \geq 0 (i = 1, 2, 3, \dots, m) \\ \sum_{j=1}^n x_{ij} - q_i^{min} \geq 0 (i = 1, 2, 3, \dots, m) \\ p_j^{max} - \sum_{i=1}^m x_{ij} \geq 0 (j = 1, 2, 3, \dots, n) \\ \sum_{i=1}^m x_{ij} - p_j^{min} \geq 0 (j = 1, 2, 3, \dots, n) \\ g_r^{max} - f_1(x) \geq 0 (r = 1, 2, 3) \\ f_1(x) - g_r^{min} \geq 0 (r = 1, 2, 3) \end{cases} \quad (4)$$

where the objective Function (1) represents the minimization of the grade fluctuation of the selected ore in the beneficiation plant; the objective Function (2) represents the minimization of the mining and transportation cost; the objective Function (3) represents the minimum value of the mine output requirement; constraints (4) represent the maximum ore quantity constraint of ore exit point i , the minimum ore quantity constraint of ore exit point i , the maximum ore quantity constrained by ore receiving point j , the minimum ore quantity constrained by ore receiving point j , the r th grade of metal in r kinds of ore is constrained by the maximum value, t the r th grade of metal in r kinds of ore is constrained by the minimum value.

2.3. Processing Objective Function

The ideal-point method [30] is a sorting method for solving multi-attribute decision-making. In this paper, the ideal-point method is used to deal with the objective function, and the value of each objective function is as close as possible to its ideal value to solve the multi-objective optimization problem. First, according to the importance of each objective, the three objective functions are assigned weights, namely ω_1 , ω_2 , and ω_3 , the optimal solution is selected by comparing the degree of proximity to the objective, and then the multi-objective solution problem is transformed into a single-objective solution to solve the multi-objective function solution problem. Finally, the objective function can be expressed as Equation (5).

$$f(x) = \min(\omega_1 f_1(x) + \omega_2 f_2(x) + \omega_3 f_3(x)) \quad (5)$$

2.4. Processing Constraints

The penalty function [31] is a common way to deal with constraints. Add a penalty function, convert the multi-objective optimization problem with constraints into solving an unconstrained minimization problem, construct an obstacle function, introduce a penalty factor σ , obtain an augmented objective function, and finally perform an intelligent algorithm on the augmented objective function solve. In the actual calculation, it is very important to choose a reasonable penalty factor; if it is too large, it will increase the computational difficulty for the minimization of the penalty function, if it is too small, the minimum point of the penalty function will be far away from the optimal solution of the constraint problem, and computational efficiency is poor. The obstacle function Equation (6) and the augmented objective function Equation (7):

$$P(x) = \sum_{i=1}^l h_i^2(x) + \sum_{i=1}^u [\min\{0, g_i(x)\}]^2 \quad (6)$$

$$F(x, \sigma) = f(x) + \sigma P(x) \quad (7)$$

where $h_i(x)$ represents an equality constraint; $g_i(x)$ represents an inequality constraint. l represents the number of equation constraints. u represents the number of inequality constraints.

3. Solving Ore Blending Model Based on ABC Algorithm

ABC is an emerging swarm intelligence algorithm inspired by bee colony behavior and proposed for the optimization of algebraic problems. The ABC algorithm was first proposed by Karaboga in 2005, and the first journal paper [32] describing the ABC algorithm and evaluating its performance was published by Karaboga and Basturk in 2007. We used the ABC algorithm to solve the ore blending model. The ABC algorithm consists of three parts: food source, employed bees, and unemployed bees (onlooker bees and scout bees). The specific process is briefly described as follows [33–36]. Firstly, employed bees search for new food sources near known food sources and compare them, save the higher-quality food source information, return to the hive, and dance the “8” dance to share the food source information. Secondly, onlooker bees select the higher-quality food source information after receiving the information, and look for better food sources around these food sources; if the quality of some food source cannot be improved for a long time, these food sources will be discarded, and bees that collect these food sources will turn into scout bees and search for new food sources. Finally, the scout bees will transform into employed bees, and enter the search again. Onlooker bees, similar to employed bees, retain only higher-quality food source information. Among them, the number of employed bees is equal to the number of food sources, and the number of onlooker bees is equal to the number of employed bees. The flowchart of the ABC algorithm is shown in Figure 1.

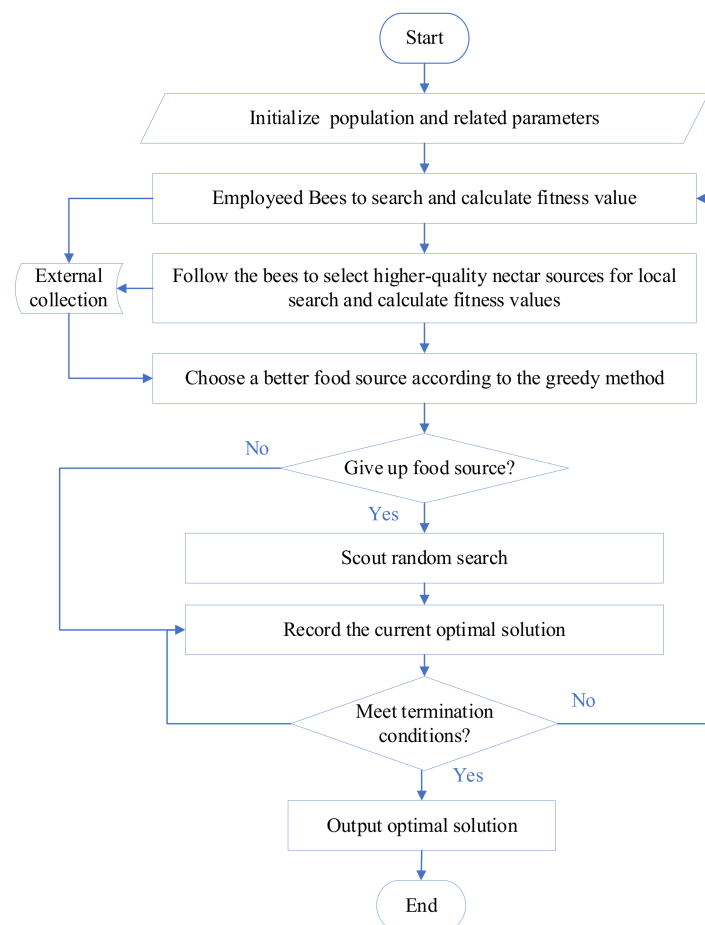


Figure 1. Flow chart of the ABC algorithm.

3.1. Food Source

ABC is an algorithm of combinatorial optimization based on populations; the position of a food source represents a possible solution to the optimization problem. In the Shizhuyuan multi-metal and multi-objective ore blending model, the food source is ore quantity at each mining point. The location of the initial food source can be decided according to Equation (8). At this step, the ABC algorithm generates a randomly distributed initial population of $nPop$ solutions (food source positions), where $nPop$ represents the size of the population. Each solution (food source) x_{id} ($i = 1, 2, \dots, nPop$) is a d -dimensional vector. Both optimizations in this paper are defined with 1000 food sources, i.e., $nPop = 1000$. The maximum value of the traversal is 500,000, and the minimum value is 0.

$$x_{id} = L_d + rand(0, 1)(U_d - L_d) \quad (8)$$

where L_d represents the maximum value of the traversal; U_d represents the minimum value of the traversal.

3.2. Employed Bees

The employed bees carry the food source information and share the information with their other companions with a certain probability. At this stage, Equation (9) can be used to locally search for the location of the food source near the initial food source and judge the quality of the food source. If the new food source is better than the initial food source, keep the new food source, otherwise, keep the original food source, and use the greedy rule to select the food source. That is, the updated ore output of each ore point makes the value of

the objective function smaller compared with the initial ore output, then the new ore output is saved. The calculation equation of the greedy algorithm is shown in Equation (10).

$$x_{id}^{new} = x_{id} + a \times \phi(x_{id} - x_{ed}) \quad e \neq i \quad (9)$$

where x_{id} represents the initial food source; x_{ed} represents the adjacent food source; ϕ represents the rate of change of the food source, which is a random number uniformly distributed in $[-1, 1]$, which determines the degree of disturbance to a certain extent; a is the acceleration coefficient, usually taking 1.

$$P = \{T_S(x_{id}, x_{id}^{new}) = x_{id}^{new}\} = \begin{cases} 1, f(x_{id}^{new}) \geq f(x_{id}) \\ 0, f(x_{id}^{new}) < f(x_{id}) \end{cases} \quad (10)$$

where T_S represents a random mapping in the decision space. This method can maximize the retention of higher-quality food sources and avoid the occurrence of degradation.

3.3. Onlooker Bees

The onlooker bees do not have any memory of the food source, so the onlooker bees select the employed bees to follow in a specific way. We use the roulette wheel selection. The selection probability equation is shown in Equation (11). The better information the employed bees carry about the ore quantity from each mining point, the higher the probability of being selected by the onlooker bees.

$$p_i = \frac{fit_i}{\sum_{i=1}^{nPop} fit_i} \quad (11)$$

where fit_i is the fitness value of the solution i evaluated by its employed bee, which is proportional to the nectar amount of the food source in position i and $nPop$ is the number of food sources, which is equal to the number of employed bees. In this way, the employed bees exchange their information with the onlookers. The fitness is calculated to normalize the food sources, evaluate the quality of the food sources and select the food sources with high quality for searching. The fitness calculation equation is shown in Equation (12).

$$fit_i = \begin{cases} 1/(1 + f_i), f_i \geq 0 \\ 1 + abs(f_i), f_i < 0 \end{cases} \quad (12)$$

where f_i represents the objective function value of the i th food source.

3.4. Scout Bees

During the search process, if the food source has not been updated to a better food source after it reaches the threshold S after $trial$ iterations, the food source will be discarded. A scout takes charge of searching in the environment that surrounds the beehive's new sources of food. The food source position is calculated as Equation (13). To a certain extent, this process can effectively avoid the ABC algorithm from falling into the local optimum prematurely and allows it to continue to search for the optimal solution in the global scope.

$$x_i = \begin{cases} L_d + rand(0, 1)(U_d - L_d), trial \geq S \\ x_i, trial < S \end{cases} \quad (13)$$

4. Applications

In this section, the multi-metal and multi-objective ore blending model and the ABC algorithm are applied to optimize the production plan of the Shizhuyuan Polymetallic Mine in 2022. A detailed analysis of the optimization results is presented.

4.1. Production Plan of Shizhuyuan Polymetallic Mine

Taking the mining plan of Shizhuyuan Polymetallic Mine in 2022 as an example, it is known that the mine has 47 mining points and two beneficiation plants. The ore grade of each metal at each mining point (stope), the cost of mining and transportation, the amount of ore stored in 2021, and the amount of new ore planned to be mined in 2022, are shown in detail in Table 1. According to the mining plan for 2022, the annual planned mine output is 2,266,325 tons, the monthly planned mine output is 188,860 tons, and the daily planned mine output is 7159 tons. The selected target grades of tungsten, molybdenum, and bismuth from the two beneficiation plants are also different, as shown in Table 2.

Table 1. Ore grade and comprehensive production index of each mining point.

Mining Point	Stope Number	Stope Grade/%			Mining and Transportation Cost/Yuan·t – 1	Ore Stored in 2021/t	Ore Mined in 2022/t	The Total Amount of Ore/t
		Tungsten	Molybdenum	Bismuth				
1	K1-1	0.258	0.036	0.117	52	3546	0	3546
2	K1-2	0.27	0.043	0.145	52	2913	0	2913
3	K1-5	0.303	0.048	0.16	51	4929	0	4929
4	K1-7	0.54	0.073	0.143	50	4419	0	4419
5	K2-2	0.342	0.057	0.091	45	21,008	0	21,008
6	K2-3	0.201	0.033	0.089	45	11,036	0	11,036
7	K2-5	0.304	0.040	0.105	47	8209	0	8209
8	K2-6	0.334	0.040	0.102	47	5070	0	5070
9	K2-7	0.666	0.05	0.106	49	48,994	0	48,994
10	K2-8	0.49	0.05	0.104	49	12,747	30,000	42,747
11	K3-0	0.378	0.085	0.136	51	6537	0	6537
12	K3-3	0.248	0.036	0.099	51	3532	0	3532
13	K3-6	0.351	0.053	0.164	52	14,190	0	14,190
14	K3-8	0.486	0.063	0.116	52	16,624	0	16,624
15	K4-1	0.283	0.056	0.124	55	12,311	0	12,311
16	K4-2	0.3	0.056	0.137	55	7161	0	7161
17	K4-4	0.314	0.049	0.151	55	30,719	0	30,719
18	K4-6	0.347	0.064	0.168	57	12,780	0	12,780
19	K4-7	0.336	0.053	0.103	57	39,871	0	39,871
20	514-536K5-0-1	0.343	0.03	0.12	58	1266	0	1266
21	445-490K4-6	0.474	0.048	0.105	55	533	30,000	30,533
22	445-470K4-7	0.446	0.102	0.108	55	5000	30,000	35,000
23	470-490K4-7	0.336	0.053	0.103	52	12,676	10,000	22,676
24	K2-3	0.57	0.42	0.191	52	5000	25,000	30,000
25	K3-3	0.53	0.261	0.073	51	0	25,000	25,000
26	N6, N7	0.255	0.027	0.087	55	56,806	100,000	156,806
27	N1	0.35	0.17	0.094	68	92,794	0	92,794
28	N3	0.35	0.05	0.108	65	921	10,000	10,921
29	N5	0.31	0.067	0.103	57	70,179	0	70,179
30	E1	0.442	0.04	0.06	57	96,000	40,000	136,000
31	E3	0.354	0.047	0.101	57	49,000	160,000	209,000
32	E5	0.347	0.036	0.103	56	40,007	279,742	319,749
33	E7	0.326	0.045	0.119	56	0	50,000	50,000
34	N8	0.234	0.032	0.06	55	0	40,000	40,000
35	N9	0.26	0.036	0.07	52	0	20,000	20,000
36	N10	0.14	0.069	0.109	52	0	10,000	10,000
37	C5(P2-P3)	0.598	0.056	0.154	55	0	25,000	250
38	25P3(C6-C7)	0.56	0.060	0.103	53	0	25,000	25,000
39	514p3(C4-C5)	0.66	0.064	0.111	51	0	25,000	25,000
40	514C7(P3-P4)	0.6	0.069	0.103	51	0	20,000	20,000
41	536-603	0.42	0.046	0.101	71	44,184	380,000	424,184
42	zero panel surface by-products	0.18	0.01	0.104	55	556,913	200,000	756,913
43	514-610K6-2	0.345	0.082	0.114	58	74,629	350,000	424,629
44	514-610K5-2	0.32	0.032	0.11	58	0	60,000	60,000
45	514-570K4-0	0.36	0.063	0.107	57	0	60,000	60,000
46	514-558K6-0/1	0.282	0.068	0.104	57	0	40,000	40,000
47	excavation by-products	0.2	0.04	0.075	60	0	100,000	100,000
Total						1,378,165	2,169,742	3,547,907

Table 2. Selected target grades of metals in the two beneficiation plants.

Beneficiation Plant	Selected Target Grade (%)		
	Tungsten	Molybdenum	Bismuth
Dongbo	0.311	0.039	0.101
Shizhuyuan	0.340	0.045	0.103

According to the actual production situation of the mine, the mining points 26–29, 34–36, 38–47, a total of 17 mining points, are transported to the Dongbo beneficiation plant, and the mining points 1–27, 30–33, 37–38, 40, 42, and 47, a total of 36 mining points, are transported to the Shizhuyuan beneficiation plant, of which six mining points 26, 27, 38, 40, 42, and 47 can supply ore to Dongbo beneficiation plant and the Shizhuyuan as well. According to the original ore extraction plan, the grades of tungsten, molybdenum, and bismuth supplied to the Dongbo beneficiation plant are 0.312%, 0.042%, and 0.099%, respectively, and the grades of tungsten, molybdenum, and bismuth supplied to Shizhuyuan Beneficiation plant are 0.341%, 0.045%, and 0.101%, respectively, of which the bismuth supply grade does not reach the selected grade of beneficiation plants, and the production requirements of the beneficiation plants have not been met and the full utilization of resources has not been realized. Therefore, the multi-metal and multi-objective ore blending model based on the ABC algorithm can be used to optimize the ore production plan to solve the actual ore blending problem faced by the Shizhuyuan Polymetallic Mine.

4.2. Experimental Setting

The algorithm is programmed using Matlab. The computer characteristics to execute the algorithm are shown in Table 3. We define the number of variables as $nVar$, and the variable matrix as $varSize$. The main parameters of the ABC algorithm are shown in Table 4.

Table 3. Computer Characteristics.

Name	Characteristics
CPU	11th Gen Intel® Core™ i5-11400F @ 2.60 GHz 2.59 GHz
RAM	8.00 GB
System Type	64-bit operating systems, x64-based processors
Operation System	Windows 11

Table 4. The main parameters of the ABC algorithm.

Parameter	Meanings	Parameter Value	
		Shizhuyuan	Dongbo
$nVar$	The number of variables	36	17
$varSize$	Variable Matrix	[1 36]	[1 17]
L_d	The maximum value of the traversal	500,000	500,000
U_d	The minimum value of the traversal	0	0
$nPop$	The number of food source	1000	1000
$MaxIt$	Maximum iterations	300	300
a	The upper limit of the acceleration factor	1	1
Q	Threshold	$F = \text{round}(0.6 \times nVar \times nPop)$	
$\omega_1, \omega_2, \omega_3$	Weights	$\omega_1 = 0.4, \omega_2 = 0.3, \omega_3 = 0.3$	

4.3. Results

Substitute the above raw data into the ore blending optimization model, take the selected target grade of each metal required by the two beneficiation plants as the goal, and use the ABC algorithm to solve the model. The maximum iterations are 300. The fitness values of the objective functions are finally close to 0. It verifies the effectiveness and feasibility of the ABC algorithm in solving the multi-metal multi-objective ore blending optimization problem. The convergence curve of the Dongbo beneficiation plant is

shown in Figure 2, and the convergence curve of the Shizhuyuan beneficiation plant is shown in Figure 3.

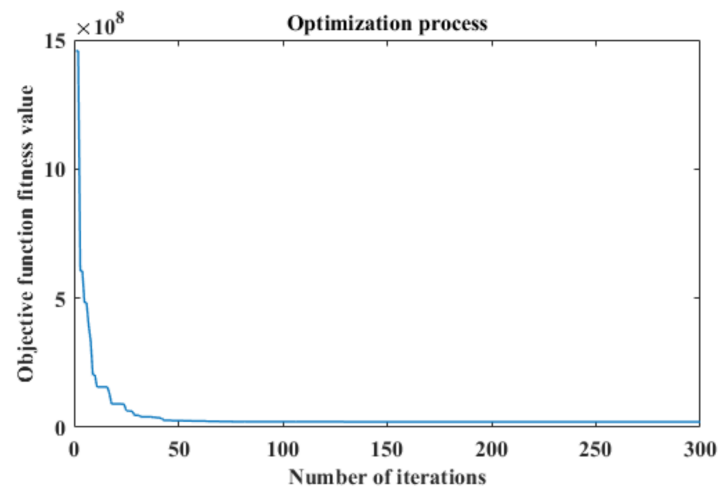


Figure 2. Convergence curve of Dongbo.

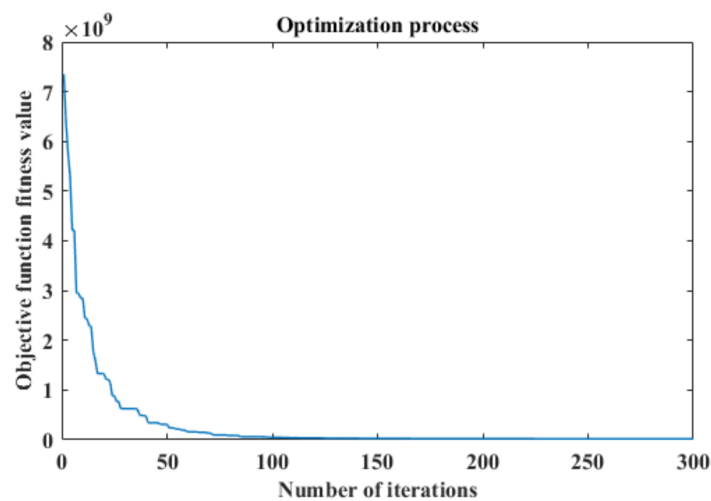


Figure 3. Convergence curve of Shizhuyuan.

The optimization results of the Dongbo beneficiation plant are shown in Table 5, and the optimization results of the Shizhuyuan beneficiation plant are shown in Table 6.

Table 5. The optimization results of the Dongbo beneficiation plant.

Mining Point	Ore Output/t	Tungsten/t	Molybdenum/t	Bismuth/t
26	104,376.155	266.159	28.182	90.807
27	35,991.914	125.282	59.287	33.828
28	8079.468	28.278	4.040	8.726
29	58,321.112	180.795	39.075	60.071
34	21,379.885	50.029	6.842	12.828
35	11,469.290	29.820	4.129	8.029
36	8474.469	11.864	5.847	9.237
38	3446.682	19.301	2.068	3.550
39	8491.348	56.043	5.434	9.425
40	3500.704	21.004	2.415	3.606
41	397,898.088	1671.172	183.033	401.877
42	288,386.885	519.096	28.839	299.922
43	152,284.824	525.383	124.874	173.605

Table 5. *Cont.*

Mining Point	Ore Output/t	Tungsten/t	Molybdenum/t	Bismuth/t
44	38,287.093	122.519	12.252	42.116
45	18,321.052	65.956	11.542	19.604
46	18,319.494	51.661	12.457	19.052
47	28,230.315	56.461	11.292	21.173
Total	1,205,258.777	3800.824	541.608	1217.455
Average ore grade per year/%		0.315	0.045	0.101

Table 6. The optimization results of the Shizhuyuan beneficiation plant.

Mining Point	Ore Output/t	Tungsten/t	Molybdenum/t	Bismuth/t
1	1345.915	3.472	0.485	1.575
2	946.480	2.555	0.407	1.372
3	3875.622	11.743	1.860	6.201
4	4419.000	23.863	3.226	6.319
5	18,390.348	62.895	10.482	16.735
6	9063.617	18.218	2.991	8.067
7	5658.228	17.201	2.263	5.941
8	2779.094	9.282	1.112	2.835
9	28,971.065	192.947	14.486	30.709
10	20,170.024	98.833	10.085	20.977
11	6537.000	24.710	5.556	8.890
12	1578.710	3.915	0.568	1.563
13	14,190.000	49.807	7.521	23.272
14	12,101.176	58.812	7.624	14.037
15	10,494.773	29.700	5.877	13.014
16	4317.766	12.953	2.418	5.915
17	30,791.000	96.684	15.088	46.494
18	12,000.000	41.640	7.680	20.160
19	12,676.000	42.591	6.718	13.056
20	1266.000	4.342	0.380	1.519
21	10,114.396	47.942	4.855	10.620
22	9247.631	41.244	9.433	9.987
23	20,000.112	67.200	10.600	20.600
24	24,486.000	139.570	102.841	46.768
25	5643.437	29.910	14.729	4.120
26	51,624.000	131.641	13.938	44.913
27	17,185.083	59.818	28.308	16.152
30	100,800.000	445.536	40.320	60.480
31	156,241.867	553.096	73.434	157.804
32	310,000.000	1075.700	111.600	319.300
33	50,000.000	163.000	22.500	59.500
37	10,000.000	59.800	5.600	15.400
38	3494.913	19.572	2.097	3.600
40	3569.336	21.416	2.463	3.676
42	148,164.880	266.697	14.816	154.091
47	70,746.265	141.493	28.299	53.060
Total	1,192,889.737	4069.801	592.659	1228.724
Average ore grade per year/%		0.341	0.050	0.103

Tables 5 and 6, respectively, show the ore supply and the ore volume of the three metals at each ore outlet of the two beneficiation plants. It can be seen from the table that the ore output of the Dongbo beneficiation plant is 1,205,258.777 tons, at Shizhuyuan beneficiation plant the ore output is 1,192,889.737 tons, with a total of 2,398,148.514 tons, while the planned ore output is 2,266,325 tons, meeting the production requirements. In the process of optimization with the algorithm, the optimized ore output is always larger than the planned ore output, which is due to the possible overfitting in the optimization process. In this paper, the penalty function is used to process the constraints to reduce the

complexity of the model, to avoid overfitting as much as possible. In the actual production process, the low-grade ore should also be retrieved to achieve simultaneous mining of low-and high-grade ore to increase the utilization rate of resources and better meet the requirements of actual mining production. This also verifies the superiority of the model and improves the economic benefits of the mine.

The proportion of tungsten, bismuth, and molybdenum at each mining point is shown in Figure 4, among which the ore mining volume of tungsten is the largest, and the ore mining volume of bismuth is the smallest. The proportion of tungsten ore output exceeds 50% except for No. 24 and No. 36 ore mining points, which is greater than the sum of the bismuth and molybdenum ore output proportion. This is because, in the optimization calculation, the ore grade fluctuation affects the optimization result, compared with the other mining points, the bismuth and molybdenum grades are higher in mining point 24, and the tungsten grade is lower in mining point 36. This optimization result is in line with the actual situation and directly verifies the reliability of the model. The proportion of metal at each ore point in the figure also implies the level of its grade; it can be seen intuitively that the metal grade of the ore point is high and low, which lays the foundation for mining engineers to conduct ore blending in real-time in the actual production process and improves mine production efficiency.

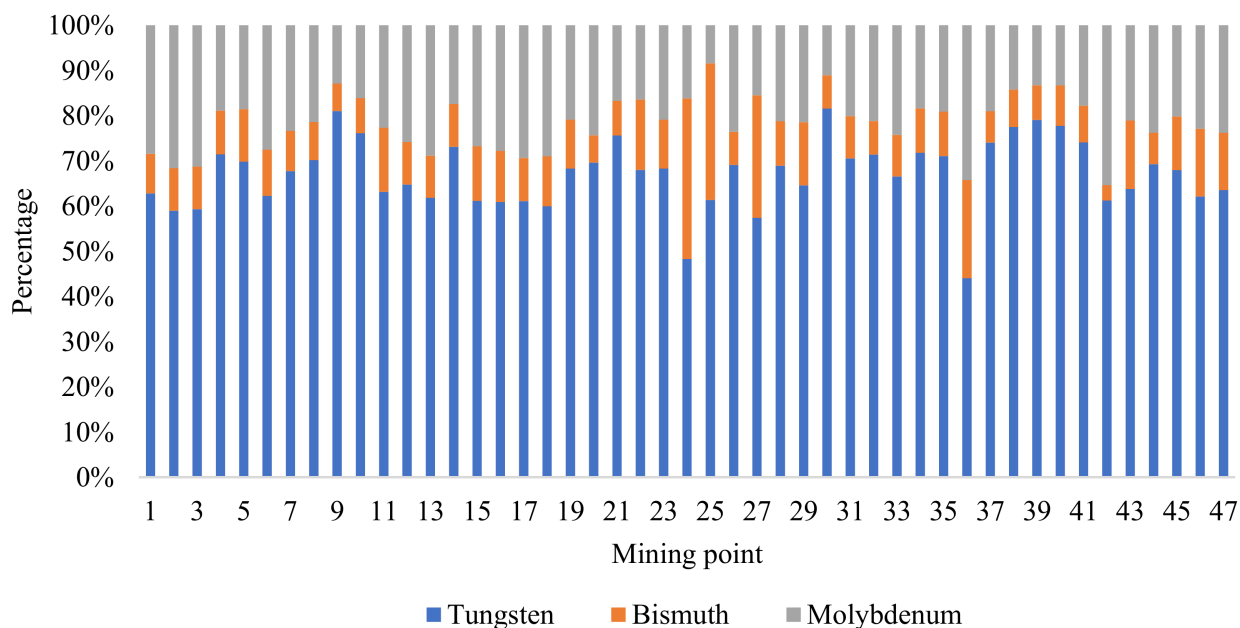


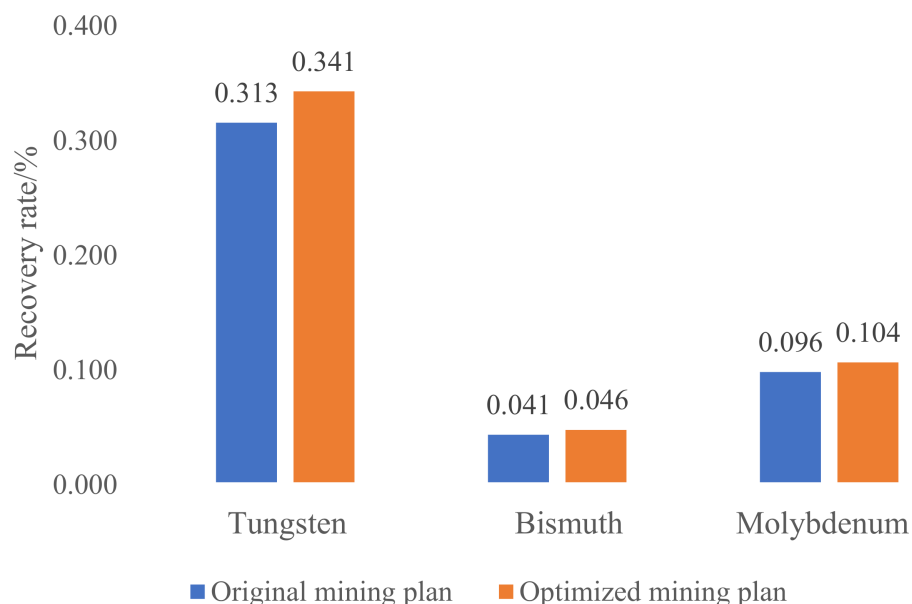
Figure 4. The proportion of tungsten, bismuth, and molybdenum at each mining point.

Table 7 shows the comparison of the grades of the three kinds of ores before and after optimization. In the table, you can intuitively see the changes in the grades of the three metals in the two beneficiation plants after the ore blending, all of which have reached the target grade, which improves the stability of the ore quality and meets the mine production target. This also shows that the proposed multi-metal multi-objective ore blending model based on the ABC algorithm is in line with the actual production of the mine and improves the quality stability of the ore.

Table 7. The comparison of the grades of the three kinds of ores before and after optimization.

Beneficiation Plant	Metal Type	Target Grade/%	Originally Planned Grade/%	Optimized Grade/%
Dongbo	Tungsten	0.311	0.312	0.315
	Molybdenum	0.039	0.042	0.045
	Bismuth	0.101	0.099	0.101
Shizhuyuan	Tungsten	0.340	0.341	0.341
	Molybdenum	0.045	0.045	0.050
	Bismuth	0.103	0.101	0.103

The ore recovery rate of mining is a measure of the utilization of ore resources and determines the service life of the mine. Properly increasing the recovery rate can effectively increase the mineral resources and prolong the service life of the mine. The ore recovery rate of the original mining plan was 0.45%, and it was 0.491% after optimization, which was 9.11% higher than that before optimization, which improved the resource utilization rate. Figure 5 shows the comparison of the recovery rates of the three metals before and after optimization. The recovery rates of tungsten, bismuth, and molybdenum ores are greatly improved, rising by 8.95%, 12.20%, and 8.33%, respectively.

**Figure 5.** Comparison of recovery rates of three metals.

5. Conclusions

Aiming at the optimization problem of multi-metal and multi-objective ore blending in Shizhuyuan, a multi-metal and multi-objective ore blending optimization model based on the ABC algorithm was established, and a scientific and efficient mining plan was formulated. It effectively solves the problem of multi-objective blending of polymetallic ore in Shizhuyuan and has important guiding significance for the optimization of ore blending of similar polymetallic ore.

The multi-metal and multi-objective ore blending based on the ABC algorithm can help enterprises to achieve economical and efficient ore blending with both simultaneous mining of low-and high-grade ore, cost control, and a balanced selection of grades. The optimization results are relatively reliable. The average grades of tungsten, molybdenum, and bismuth in the Dongbo beneficiation plant's ore supply increased by 0.96%, 7.14%, and 2.02%, respectively, and the average grade of molybdenum and bismuth in Shizhuyuan beneficiation plant's ore supply increased by 11.11% and 1.98%, respectively, and the average grade of tungsten supply ore remained unchanged. Under the condition that

the ore grade meets the requirements of the beneficiation plant, the grade fluctuation of tungsten and bismuth is controlled by 3%, and the grade fluctuation of molybdenum is basically controlled by around 10%, and the recovery rates of tungsten, molybdenum, and bismuth of the beneficiation plant are increased by 8.95%, 8.33%, and 12.20%, respectively.

Future research can be carried out in the following aspects: (1) Introduce influencing factors such as comprehensive utilization rate of mineral resources and transportation work to reduce the differences with actual production. Because although a better mining solution than the original one was obtained in this paper, there may still be differences with the actual production. (2) Future research can also focus on improving the algorithm and increasing the convergence speed of the algorithm. (3) Based on the existing work, we can study the establishment of the ore blending algorithm software to optimize multi-metal and multi-objective ore blending and lay the foundation for intelligent ore blending.

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Appendix A

Table A1. Description of basic symbols.

Basic Symbols		Description
Decision variable	x_{ij}	The number of ore from ore exit point i to ore receiving point j
	Q	Target output of ore blending plan
Parameter	n	The number of ore receiving points
	k	The number of metal types
	m	The number of ore exit points
	q_{ri}	The grade of metal r in the ore at ore exit point i
	q_{rj}	The grade of metal r in the ore at the ore receiving point j
	C_i	The cost of mining and transportation per ton of ore at ore exit point i
	f_2'	Mining and transportation expectation cost
	q_i^{max}	Maximum output of ore exit point i
	q_i^{min}	Minimum output of ore exit point i
	p_j^{max}	Maximum receiving number of ore receiving point j
	p_j^{min}	Minimum receiving number of ore receiving point j
	g_r^{max}	The maximum value of the r^{th} grade of metal in r kinds of ore
	g_r^{min}	The minimum value of the r^{th} grade of the metal in r kinds of ore

References

- He, B.Q. Study on the Continuous Mining Scheme of the Shizhuyuan Polymetallic Deposit. Master's Thesis, Central South University, Changsha, China, 2014.
- Huang, L.Q.; He, B.Q.; Wu, Y.C.; Shen, H.M.; Lan, X.P.; Shang, X.Y.; Li, S.; Lin, W.X. Optimization of multi-objective blending of polymetallic mine with non-equilibrium grades in Shizhuyuan Mine. *Min. Res. Dev.* **2021**, *41*, 193–198.
- Gu, Q.H.; Meng, Q.Q.; Lu, C.W.; Ma, L. Research on multi-objective ore blending model and optimization algorithm for open-pit mine. *Min. Res. Dev.* **2019**, *39*, 16–21.
- Li, Z.G.; Cui, Z.Q. Multi-objective optimization of mineral blending based on genetic algorithm. *J. Guangxi Univ. Nat. Sci. Ed.* **2013**, *38*, 1230–1238.
- Wang, X.T.; Lu, C.W.; Zhang, Y.C.; Jing, S.G. Dynamic management information system for multi-mineral comprehensive mixing in Sandaozhuang Open-pit Mine. *Met. Mines* **2012**, *8*, 98–102.
- Ke, L.H.; He, X.Z.; Ye, Y.C.; He, Y.Y. Research status and development trend of ore blending optimization technology. *China Min. Mag.* **2017**, *26*, 77–82.
- Wilke, F.L.; Reimer, T.H. Optimizing the Short Term Production Schedule for an Open Pit Iron Mining Operation. In Proceedings of the 15 Application of Computers and Operations Research in the Mineral Industry, Brisbane, Australia, 4–8 July 1977.
- Wang, K.; Lu, H.H.; Du, Y.J. Using 0-1 integer programming method for raw ore blending. *Light Met.* **1997**, *12*, 13–15.

9. Li, G.Q.; Li, B.; Hu, N.L.; Hou, J.; Xiu, G.L. Optimization model of mining operation planning in underground metal mines. *Chin. J. Eng.* **2017**, *39*, 342–348.
10. Lin, Q.T. The Application of uncertain mathematics in the study of mixed ore blending. *Syst. Eng. Theory Pract.* **2002**, *22*, 99–102, 127.
11. Wang, L.G.; Song, H.Q.; Bi, L.; Chen, X. Optimization of multi-element ore blending in open pit mines based on objective planning. *J. Northeast. Univ. Nat. Sci.* **2017**, *38*, 1031–1036.
12. Souza, M.J.F.; Coelho, I.M.; Ribas, S.; Santos, H.G.; Merschmann, L.H.C. A hybrid heuristic algorithm for the open-pit-mining operational planning problem. *Eur. J. Oper. Res.* **2010**, *207*, 1041–1051. [[CrossRef](#)]
13. Huang, J.X.; Wang, L.G.; Xiong, S.M.; Xu, S.Y.; Tan, Z.H.; Wang, H.Q. Circle geometric constraint model for open-pit mine ore-matching and its applications. *J. Cent. South Univ.* **2012**, *19*, 2598–2603. [[CrossRef](#)]
14. Huang, Q.F.; Chen, J.H. Research on dynamic ore blending optimization of mining enterprises based on PSO. *Comput. Eng.* **2011**, *37*, 175–177, 180.
15. Yao, X.L.; Hu, N.L.; Zhou, L.H.; Li, Y. Ore blending in underground mines based on immune clone selection optimization algorithm. *Chin. J.* **2011**, *33*, 526–531.
16. Xu, T.J.; Yang, P. Mine blending optimization based on the fuzzy multi-objective optimization algorithm. *Chin. J. Eng.* **2009**, *31*, 1363–1367.
17. Gu, Q.H.; Lv, Y.H.; Lu, C.W.; Ruan, S.L. Modeling and solving algorithm for multi-objective production planning optimization problem in a polymetallic open-pit mine. *Met. Mines* **2020**, *04*, 147–153.
18. Moosavi, E.; Gholamnejad, J.; Ataee, P.M.; Khorram, E. Improvement of Lagrangian relaxation performance for open pit mines constrained long-term production scheduling problem. *J. Cent. South Univ.* **2014**, *21*, 2848–2856. [[CrossRef](#)]
19. Sattarvand, J.; Niemann, D.C. A New metaheuristic algorithm for long-term open-pit production planning. *Arch. Min. Sci.* **2013**, *58*, 107–118.
20. Shishvan, M.S.; Sattarvand, J. Long-term production planning of open pit mines by ant colony optimization. *Eur. J. Oper. Res.* **2015**, *240*, 825–836. [[CrossRef](#)]
21. Xu, T.J.; Yang, P.; Liu, Z.Q. Mine ore blending planning and management based on the fuzzy multi-objective optimization algorithm. In Proceedings of the 2008 International Seminar on Business and Information Management, Wuhan, China, 19 December 2008; pp. 38–41.
22. Mustafa, K. Application of chance-constrained programming based on multi-objective simulated annealing to solve a mineral blending problem. *Eng. Optim.* **2003**, *35*, 661–673.
23. Ye, H.W.; Ou, Y.J.; Li, N.; Wang, L.G.; Lei, T.; Wang, Q.Z. Multi-objective genetic particle swarm algorithm for short-term production planning optimization in mines. *Met. Min.* **2018**, *11*, 25–30.
24. Zhang, C.R.; Ke, P.; Yin, M. Improved ABC algorithm and its application to edge computing offload. *Comput. Eng. Appl.* **2022**, *58*, 150–161.
25. Li, H.L. Improved ABC Algorithm and Related Applications. Master's Thesis, Nanjing University of Posts and Telecommunications, Nanjing, China, 2020.
26. Xie, Z.; Liu, M.S.; Wang, L.P.; Bai, L.P.; Li, L. Experimental study and production practice of rational ore blending of complex copper polymetallic ores in Jiama. *Multipurp. Util. Miner. Resour.* **2022**, *2*, 61–65.
27. Meng, Q.Q. Research on Multi-objective Production Allocation Optimization of Polymetallic Open Pit Mine. Master's Thesis, Xi'an University of Architecture and Technology, Xi'an, China, 2019.
28. Luo, L.L.; Wang, L.G.; Wu, G.H.; Ding, L.Q.; Chen, X.W. Research on refined supply and distribution management of complex deposits in open pit copper polymetallic mines. *Mod. Min.* **2019**, *35*, 123–126.
29. Dong, Z.J. *System Engineering and Operations Research*; National Defense Industry Press: Bei Jing, China, 2007; pp. 111–124.
30. Yang, W.M.; Liu, T.W. MATLAB-based ideal point method for solving multi-objective planning problems. *J. Hunan City Univ. Nat. Sci.* **2017**, *26*, 60–63.
31. Knypinski, L. Adaptation of the penalty function method to the genetic algorithm in electromagnetic device designing. *COMPEL Int. J. Comput. Math. Electr. Electron. Eng.* **2019**, *38*, 1285–1294. [[CrossRef](#)]
32. Dervis, K.; Basturk, B. A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm. *J. Glob. Optim.* **2007**, *39*, 459–471.
33. Xiao, S.Y. Research on the Improvement of ABC Algorithm and its Application in the Optimal Allocation of Water Resources. Master's Thesis, Nanchang Institute of Technology, Nanchang, China, 2020.
34. Ma, S.J. Research and Application of Multi-objective ABC Algorithm. Master's Thesis, Northeast Normal University, Changchun, China, 2019.
35. Zhao, L.L. Optimization Research of Composite Energy Heating System Based on Multi-objective ABC Algorithm. Master's Thesis, Tianjin University of Technology, Tianjin, China, 2019.
36. Cuesta, R.; Crawford, B.; Soto, R.; Paredes, F. An ABC Algorithm for the Set Covering Problem. In Proceedings of the 3rd Computer Science On-line Conference (CSOC), Electric Network, 15 May 2014.