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Multiobjective Optimization of Carbon Emission Reduction Responsibility Allocation in the Open-Pit Mine Production Process against the Background of Peak Carbon Dioxide Emissions

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Abstract: In the context of the "carbon peaking" policy for mining companies, this study was conducted to clarify the amount of carbon emission reduction required for each production process to achieve the carbon peaking target for mining companies. In this paper, after determining the fair interval of the carbon emission distribution, the fair deviation index was constructed, and a multiobjective carbon emission distribution model of the mine production process was established by combining the objectives of maximum stability and maximum efficiency with the constraint of output growth. The study found: (1) More carbon emission quotas should be allocated to the beneficiation link, while fewer carbon emission quotas should be allocated to the crushing link; (2) beneficiation, mining and transportation are all responsible for emission reduction, but crushing and blasting produced a carbon emission surplus and (3) after optimization, the carbon emission intensity in the beneficiation, mining and transportation processes was reduced. This paper argues that mining companies should increase their efforts to reduce emissions in beneficiation, mining and transportation. The study's findings have important implications for achieving carbon emission reduction targets and refining carbon emission management in open pit mines in the context of carbon peaking.

Keywords: peak carbon dioxide emissions; open-pit mine production; carbon emission reduction responsibility; multiobjective optimization

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1. Introduction

Sustainability is a multidimensional concept that affects the environment, economy, and society [1]. Thus the achievement of sustainability includes multiple aspects such as carbon capture and storage, material recycling, water management, and clean energy use [2]. Especially in the climate context of global warming, carbon emission control and responsibility for emission reduction have become mandatory considerations in the sustainability process of countries [3]. Especially after China proposed the double-carbon goal [4] of achieving peak carbon dioxide emissions in 2030 and carbon neutrality in 2060, all regions and industries in China have introduced measures to reduce carbon emissions. As the basic industry of the national economy, the carbon emissions in the mineral industry account for a large proportion of the total carbon emissions. Globally, the mining industry currently accounts for approximately 2.7% of the global energy use, resulting in a large amount of greenhouse gas (GHG) emissions (IPCC, 2007). The GHG emissions related to the production of primary minerals and metals were equivalent to approximately 10% of the total global energy-related GHG emissions in 2018 [5]. It has been estimated that in 2020, China's nonferrous metal industry emitted 660 million tons of carbon dioxide, accounting for 4.7% of the total national emissions [6]. It can be found that mineral enterprises, as the main body of carbon emissions, shoulder an important responsibility for emission reduction. As national policies are driven, more and more companies are moving towards low-carbon and sustainable business models [7]. Sustainable mining practices are critical to the industry's long-term health [8]. Achieving overall corporate emission reduction targets by controlling carbon emissions from production processes is an essential means of achieving the sustainable development of mining companies. As a key area of emission reduction, mining enterprises should greatly contribute to achieving the carbon emission reduction goal.

The diesel, electricity, natural gas, coal and gasoline amounts consumed in mining operations account for 34%, 32%, 22%, 10% and 2%, respectively, of the total energy consumption [9]. An unreasonable energy structure and massive energy demand result in the production characteristics of high input and high energy consumption levels by mining enterprises. In addition, electricity, explosives, coalbed methane and spontaneous coal combustion are considered the main carbon sources in the production process of mining enterprises [10]. The carbon emissions attributed to mine production are affected by ore production, mining methods, geological conditions and mine layout [11]. The usage of various carbon sources in blasting, loading, lifting, roof construction, ventilation, transportation, crushing, screening, washing, dewatering, backfilling and other links also vary, so there are obvious differences in carbon emissions along each link. The relationship between carbon emissions and emission reduction responsibility in the production process of mining enterprises is shown in Figure 1. The realization of the overall national emission reduction target is based on the achievement of the emission reduction targets of each production enterprise. However, the emission reduction targets set by mining enterprises represent an overall number for specific enterprises, but specific planning efforts targeting emission reduction along certain links are still lacking. Moreover, the production capacity, process and carbon emissions of each link of mining enterprises vary. Therefore, reasonable decomposition of the overall emission reduction task into various processes is of great significance to implementing fine carbon emission management in mining enterprises at the micro level and overall national carbon emission control at the macro level. At present, little attention has been given to carbon emission control in the production links of enterprises, and the depth of carbon emission reduction management mostly only reveals superficial goals of the entire enterprise, while there exists no suitable answer regarding the emission reduction responsibility that should be assigned to each process. In contrast to previous studies, we believe that the most significant innovation of this paper is the use of a multiobjective optimization approach and the combination of relevant allocation principles to answer the question of how much carbon emission reduction is required for each production process to achieve the carbon peak target of the mining enterprise. Among them, we think the possible contributions of this paper are as follows: (1) Under the idea of target management and carbon emission control, the concept of carbon allowance in carbon emission trading is borrowed and extended to the value of allowable emission for each process when the mining enterprise achieves the carbon peak. (2) Combined with the relevant allocation principles, the multiobjective optimization method is innovatively used to establish the carbon emission reduction responsibility sharing model for the production process of the mining enterprise under the carbon peak time requirement. (3) The responsibility value of carbon reduction for each production process of the target company is proposed with the actual case.

The rest of this paper is organized as follows: the second part summarizes the existing relevant research, the third part establishes a responsibility-sharing model for carbon emission reduction in the production process of mining enterprises, the fourth part describes a specific case application, and the fifth part provides the conclusions and suggestions.

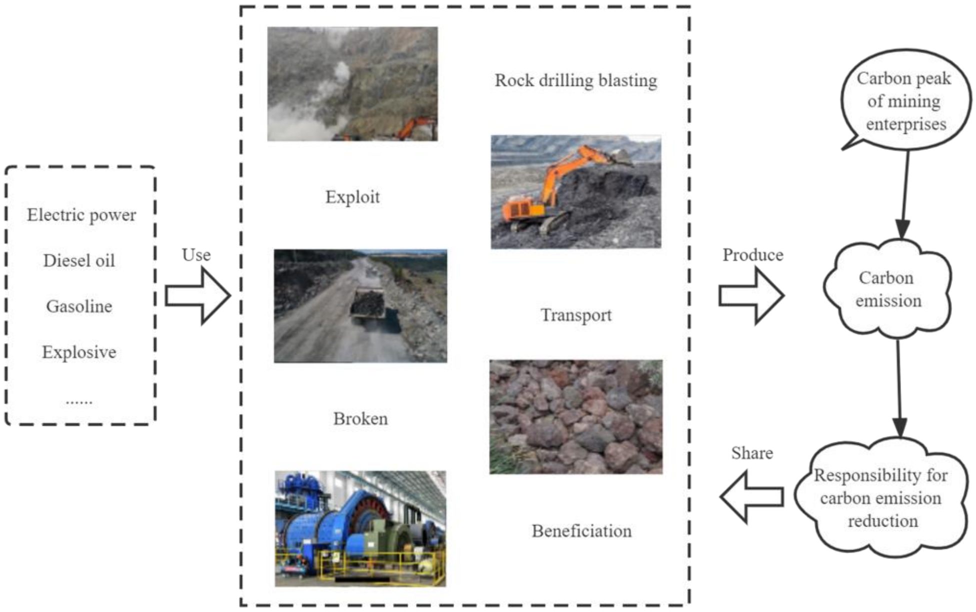


Figure 1. The process of sharing responsibility for carbon emissions and carbon reduction among mining companies.

2. Literature Review

2.1. Carbon Tax versus Carbon Quota

Regarding carbon emission reduction, carbon tax and carbon trading based on carbon allowances are two critical measures to control carbon emissions [12]. Among them, the carbon tax is an economic instrument that sets a price tag on greenhouse gas emissions and can guide producers to use other alternative clean energy sources and gradually improve energy use efficiency. Carbon trading systems are often referred to as cap-and-trade mechanisms, which require society to set carbon allowances (the maximum amount of carbon emissions allowed) by an initial allocation of property rights rather than raising prices and reducing demand through taxation. There are some differences between the two in terms of theoretical basis, emission reduction mechanisms, implementation costs, emission reduction effects and policy weaknesses [13,14]. The former is based on the "polluter pays principle" advocated by environmental economics theory [15]. The latter is logically based on Coase's "Coase theorem" [16]. The former is price control and government-led redistributive "indirect" abatement mechanism, while the latter is a market-dependent positive incentive abatement policy with quantity control [17]. Regarding implementation cost, the carbon tax is a tax in the national taxation system, and the implementation cost is lower than the cost of establishing a carbon trading platform and carbon trading settlement mechanism. In terms of the effect of emission reduction, scholars differ significantly. Some scholars believe the carbon tax policy is more effective [18]. The first dividend is the "green dividend" of curbing pollution and improving environmental quality; The second dividend is the "blue dividend" of using carbon tax revenues to reduce the tax burden of distortionary taxes such as income and corporate taxes, thereby improving the labor market and creating more job [19]. Other scholars argue that carbon emissions trading is more advantageous [20,21]. They argue that carbon trading can achieve a specific number of emission reduction targets for more stringent emission reduction scenarios. Regarding policy weaknesses, carbon tax policies are related to the elasticity of demand for a product and do not lead to fully effective results. In contrast, carbon allowance mechanisms provide little incentive to bring carbon emissions down below carbon allowances.

In summary, it can be found that both the carbon tax and carbon trading based on carbon allowances are aimed at the whole enterprise. This paper aims to control the carbon emission of each production process of mining enterprises and thus achieve the enterprise's overall carbon emission reduction goal. If the carbon tax is used to regulate the carbon emissions of each production process, the research content may be more similar to the optimization of the carbon source use structure of each production process based on the idea that the carbon tax provides incentives for clean energy use. Since this paper aims to determine how much carbon emissions need to be reduced in each production process to achieve the carbon peak target for mining companies, we believe that the idea of carbon quotas is closer to the research content of this paper. Therefore, we borrowed the concept of carbon quotas and extended the conventional regional or industry-oriented carbon quota concept to the enterprise production process level.

2.2. Current Status of Research on Carbon Quota Allocation

Regarding implementing carbon emission reduction targets, the key issue involves the allocation of emission reduction targets to various economic entities [22]. Fair and effective allocation of carbon emission reduction quotas constitutes the basis for any organization or country to achieve its carbon emission reduction targets. Carbon emission reduction responsibility allocation aims to assign carbon emission reduction targets to different carbon emission subjects and strives to achieve the goal of carbon dioxide emission reduction through joint efforts of the different carbon emission subjects. This process comprises the basis of defining carbon emission rights and provides important support for formulating a reasonable carbon emission reduction policy. At present, domestic and foreign research on the allocation of carbon emission reduction responsibilities mainly focuses on the definition, allocation principles and methods.

In relevant research, studies on the definition of responsibility have mainly focused on measuring the carbon emissions embodied in trade [23] and producer, consumer and joint responsibilities [24]. The responsibility share for carbon reduction is mostly measured based on the amount of future CO_2 emissions. The allocation method can affect the burden and cost-sharing process of emission reduction [25]. Therefore, the premise of carbon emission reduction responsibility allocation is carbon emission quota determination, and fairness and efficiency are the most important allocation criteria when determining carbon emission quota. The principle of fairness holds that people have equal rights to the atmospheric environment [26]. The carbon rights management department distributes carbon rights to different regions according to equal, reasonable and unbiased standards, considering the carbon emission reduction capacity, emission reduction potential and carbon emission status of the different regions. Related content includes allocation methods based on per capita emissions whereby everyone has equal emission rights [27], methods based on the unit gross domestic product (GDP) [28] and methods based on the carbon emission intensity [26]. Fairness can be divided into different categories, such as egalitarianism, historical responsibility, ability to pay and the polluter pays fairness concept [29]. However, the principle of efficiency states that lowering the cost of emission reduction should represent the goal of greatest concern [30,31]. It is essential to achieve fair distribution while improving the overall efficiency [32]. Therefore, many scholars have combined these two concepts [33,34]. In addition, the principle of feasibility and sustainability has recently received attention. The distribution principle of combining multiple criteria has been increasingly applied.

Carbon emission reduction responsibility allocation methods mainly focus on the following aspects: first, various data envelopment analysis (DEA) models are represented by the zero-sum gains (ZSG)-DEA approach [35], multiregional environmental input-output models, fixed-cost allocation models and game models [29]. Second, via index system construction and comprehensive use of factor, econometric and cluster analysis methods [36] or directional (nonradial) distance functions [37], the carbon emission reduction potential can be analyzed. Moreover, based on the conditions in different regions, carbon emission rights quotas can finally be adjusted to divide carbon emission reduction responsibilities among the different regions. The multiobjective optimization method has been increasingly applied, such as Xu et al. [38], who used a three-level multiobjective approach to optimize carbon emission allowances in the power supply sector from three aspects, namely, government, power plants and grid companies, and an interactive genetic algorithm based on Karush–Kuhn–Tucker (KKT) conditions was employed to determine the equilibrium point. Yang et al. [39] used the carbon Gini coefficient and abatement cost function to measure fairness and efficiency, respectively. A multiobjective nonlinear programming model was then introduced to realize optimal emission allowance allocation. After solving the allocation problem among sectoral groups, Zhao and Yang [40] constructed a biobjective DEA model and applied genetic algorithms to allocate carbon emission allowances to various sectors in China. Huang et al. [41] developed a two-tier multiobjective carbon emission allowance allocation model based on an equilibrium strategy, which fully considered the government and conventional power plants. This model fully accounted for the conflict between the government and conventional power plants and the contradiction between benefits and carbon emissions. Li et al. [42] adopted the abatement cost and carbon assets as objective functions to allocate carbon emission allowances in the Pearl River Delta region of China using a biobjective planning model (BPM). At the research level, the research objects of different scholars vary, mostly concentrated on countries [43], domestic provinces [44], different industries [45] or various enterprises within the same industry [46]. However, the allocation of carbon emission allowances within enterprises has not been considered.

The above literature indicates that most research on carbon emission reduction responsibility allocation is based on determining carbon emission allocation quotas. However, the scale of the research objects is very large. Most studies considered the issues of carbon emission reduction responsibility and emission quotas among countries, provinces or industries but rarely focused on the level of process management. In addition, previous allocation models mainly focused on DEA and other methods. Although studies nominally adopted various principles, such as fairness, efficiency and sustainability, they did not highlight the essence of multiobjective allocation. It can be observed that there exists no article on the multiobjective allocation of carbon emission quotas and emission reduction responsibilities to production processes from the perspective of fine carbon management within enterprises. However, the realization of national overall carbon emission reduction targets is the result of the achievement of the emission reduction targets of various economic entities, i.e., enterprises and production processes. Therefore, only by control at the microlevel can macrolevel targets be realized. In this paper, considering mining enterprises with clear carbon emissions in their production process as an example, the peak carbon dioxide emissions targets set by mining enterprises were adopted as the background. Via the integration of the principles of fairness and efficiency, considering mineral development and environmental protection, a multiobjective optimization model for carbon emission reduction responsibility allocation in the production process of mining enterprises given the peak carbon dioxide emissions target was constructed. This study provided detailed objectives and targeted emission reduction measures for enterprises to achieve carbon emission reduction and peak carbon dioxide emissions.

3. Models and Methods

3.1. Objectives

As shown in the literature review, there are several principles of carbon emission allocation, and fairness and efficiency are the most important allocation criteria. In this paper, carbon emission allocation smoothness is considered based on balancing the principles of fairness and efficiency, i.e., to ensure that the allocation of carbon allowances does not show excessive ups and downs compared with previous data in order to prevent affecting enterprise production. We follow the existing studies in setting the objective function, in which the smoothness and efficiency functions are mainly referred from Zhang and Wang [47], and the fairness function is mainly referred to Wang et al. 2019 [46]. The three functions of carbon emission allocation are combined, and the multiobjective gray wolf algorithm is used to solve the multiobjective problem of carbon emission allocation, which we believe is the first of its kind in existing research. This is also the most critical innovation in the application of the method in this paper.

3.1.1. Maximum Stability

In the process of carbon emission allocation, past emission data and related information of mining enterprises should be considered important reference standards for quota distribution; in particular, quotas must be allocated by respecting historical rights. The principle of carbon emission quota stationarity fully considers current and historical performance data. Maximum stability indicates that there are no excessive fluctuations and deviations from reality in the process of carbon emission distribution. This paper referred to the practice of Zhang and Wang [47]: under the stationarity principle, if only the absolute decrease in the carbon emission amount is considered, then the distance of carbon emission deviation can be given, and the maximum objective function of stationarity can be obtained via standardization as follows:

$$\min(F1) = \frac{\sqrt{\sum_{i=1}^{N}(X_i - C_i)^2}}{2\sum_{i=1}^{N}C_i} \quad (1)$$

where F1 is the stationarity index, and the smaller F1 is, the higher the stationarity. The minimum value of F1 represents the maximum stationarity. X_i is the carbon emission allowance of each process over the next three years, and C_i denotes the historical carbon emissions of each process over the past three years.

3.1.2. Maximum Efficiency

Regarding economic efficiency, quotas can be regarded as a scarce resource. To maximize efficiency, quotas should be allocated to production links with a high utilization rate to maximize the output per unit input and finally realize optimal resource allocation. Based on the method of Zhang and Wang [47], this paper set the maximum target of carbon emission allocation efficiency as follows:

$$\min F2 = \frac{\sum_{i=1}^{N}\left(\xi_i - \xi\right)\left(1 + \frac{|\xi_i - \xi|}{\xi_i - \xi}\right)}{2M} \quad (2)$$

where ξ_i is the carbon emission efficiency of the process, expressed as X_i/G_i', G_i' denotes the ore processing capacity of each process over the next three years, ξ is the overall carbon emission efficiency of the mine, expressed as X/G', X denotes the total carbon emission quota over the next three years, and G' denotes the ore processing capacity of the mine over the next three years. Because the efficiency of each process eventually approaches the overall emission efficiency coefficient of the mining enterprise, m processes not reaching the average emission coefficient of the mining enterprise should be promoted. The M value can be calculated with the following equation:

$$M = \frac{\sum_{i=1}^{N}\left(1 + \frac{|\xi_i - \xi|}{\xi_i - \xi}\right)}{2} \quad (3)$$

where F2 is the efficiency index, and the smaller the value is, the higher the efficiency. This objective function is generally obtained iteratively in other models, but in this paper, the production link not reaching the average emission efficiency factor was directly provided, and the value of the overall emission efficiency factor matching the average value of the mining enterprise was defined as the highest efficiency. In the above equation, $1 + \frac{|\xi_i - \xi|}{\xi_i - \xi}$ can only take a value of 0 or 2, which suggests that the ith process can or cannot reach the average emission coefficient of the mining enterprise, respectively. The value of

$\left(\xi_i - \xi\right)\left(1 + \frac{|\xi_i - \xi|}{\xi_i - \xi}\right)$ in the above equation indicates the deviation of the ith process from the overall emission efficiency coefficient of the mining enterprise, and F2 is the sum of the deviations of all processes not matching the average emission efficiency coefficient of the mining enterprise, and the smaller the F2 value, the more efficient the mining enterprise. F2 = 0 is the extreme ideal value, indicating that the emission efficiency is consistent across provinces.

3.1.3. Maximum Fairness

Regarding the fair measurement of carbon emission allocation, this paper draws on the approach of Wang et al. 2019 [46]. First, the carbon allowances under the principle of historical responsibility and production equality are calculated. Second, the range included in these two values is considered the fairness interval of carbon allowance allocation. Third, the satisfaction of carbon allowance allocation is established based on this interval. Fourth, the absolute difference in the allocation satisfaction between the two processes is used as the allocation fairness deviation index to measure the fairness of carbon allowance allocation. The specific process is:

Step 1: Calculate carbon allowances under the principle of historical responsibility and the principle of equality of production

According to the principle of historical responsibility, the emission allowance should be allocated according to the historical carbon emissions of each process, with the formula:

$$C_{ih} = C_{if} - \frac{DC_w \times HC_i}{\sum_{i=1}^{N} HC_i} \tag{4}$$

where C_{ih} denotes the carbon dioxide emissions available for allocation to process i under the historical responsibility principle, C_{if} is the total carbon emission forecast for process i over three years, DC_w is the total carbon emission reduction to be achieved by each process, and HC_i denotes the historical carbon emissions of process i. N is the total number of processes participating in allocation, so $\frac{DC_w \times HC_i}{\sum_{i=1}^{N} HC_i}$ denotes the carbon emission reduction allocated to process i under the historical responsibility principle.

Based on the principle of equal production, carbon emission allowances should be allocated according to the projected ore processing capacity of each process, with the formula:

$$C_{ip} = \frac{C_w \times G_i^{'}}{\sum_{i=1}^{N} G_i^{'}} \tag{5}$$

where C_{ip} is the carbon emission allowance allocated to process i under the equal production principle, $G_i^{'}$ is the average ore processing capacity of process i over the calculation period, and C_w is the total amount of carbon emission rights to be allocated.

Step 2: Use the range contained in the two values calculated above to determine the upper and lower bounds of the fairness interval for the carbon emission quota of process i. The formula is as follows:

$$X_{ia} = \mathrm{Max}\left(C_{ih}, C_{ip}\right) \tag{6}$$

$$X_{ib} = \mathrm{Min}\left(C_{ih}, C_{ip}\right) \tag{7}$$

Step 3: Satisfaction with carbon credits allocation based on a fair interval.

Regard $\frac{X_i - X_{ib}}{X_{ia} - X_{ib}}$ as the satisfaction of carbon emission right allocation.

Step 4: The absolute difference of distribution satisfaction between two processes is used as the distribution fairness deviation index, and the minimization of the distribution fairness deviation index is used as the objective function 3.

$$\mathrm{minF3} = \sum_{1 \le i \le j \le N} \left| \frac{X_i - X_{ib}}{X_{ia} - X_{ib}} - \frac{X_j - X_{jb}}{X_{ja} - X_{jb}} \right| \tag{8}$$

3.2. Constraints

3.2.1. Total Carbon Emission Quota Constraint

The sum of carbon emission allowances obtained from each production process is controlled in this paper as follows:

$$\theta C_w \leq \sum_{i=1}^{N} X_i \leq C_w \tag{9}$$

where C_w denotes the carbon emissions to be allocated. This constraint requires that the sum of carbon emission allowances for each process after optimization should be between θ times the carbon peak and the carbon peak.

3.2.2. Quota Interval Constraint

This paper controls the carbon emission allowances obtained from each production process within the following limits:

$$X_{ia} \leq X_i \leq X_{ib} \tag{10}$$

where X_{ia} is the lower limit of the carbon emission quota of each process and X_{ib} is the upper limit of the carbon emission quota of each process. The carbon emissions of each optimized process should remain within this range.

3.2.3. Ore Output Constraints

To consider the contradiction between environmental protection and production development, ensure that the mine can still meet the demand of supply under low-carbon requirements, and achieve a stable output while reducing carbon emissions, this paper defined an ore output growth constraint.

$$\sum_{i=1}^{N} \frac{\left((1+t_i)^M - 1\right) \times G'_{i0}}{E_i} \geqslant G'_{goal} \tag{11}$$

where G'_{i0} is the ore processing capacity of process i at the beginning of the calculation period, G'_{goal} is the annual output growth target value set by the enterprise considering future date m, M is the calculation period, and t_i is the annual growth rate of carbon emissions of process i over the calculation period. The calculation equation can be expressed as follows:

$$\sum_{k=1}^{M} X_{i0}(1+t_i)^K = X_i \tag{12}$$

where E_i is the elasticity coefficient of the current low-carbon development stage of process i, which can be calculated as follows:

$$E_i = \frac{\Delta C/C}{\Delta G/G} \tag{13}$$

3.2.4. Non-Negative Constraint

The decision variable should not be less than 0. Therefore, the non-negative constraint is set as follows:

$$0 \leq X_i \tag{14}$$

In summary, the multiobjective optimization model proposed in this paper is shown below:

$$\left\{\begin{array}{l}\left\{\begin{array}{l}\min F1=\frac{\sqrt{\sum_{i=1}^{N}(X_i-C_i)^2}}{2\sum_{i=1}^{N}C_i}\\ \min F2=\frac{\sum_{i=1}^{N}\left(\xi_i-\xi\right)\left(1+\frac{\left|\xi_i-\xi\right|}{i-\xi}\right)}{2M}\\ \min F3=\sum_{1\le i\le j\le N}\left|\frac{X_i-X_{ib}}{X_{ia}-X_{ib}}-\frac{X_j-X_{jb}}{X_{ja}-X_{jb}}\right|\end{array}\right.\\ s.t.\left\{\begin{array}{l}\theta C_w\sum_{i=1}^{N}\le X_i\le C_w\\ \sum_{i=1}^{N}\frac{\left((1+t_i)^M-1\right)\times G'_{i0}}{E_i}\geqslant G'_{goal}\\ X_{ia}\le X_i\le X_{ib}0\le X_i\end{array}\right.\end{array}\right. \tag{15}$$

3.3. Multiobjective Gray Wolf Algorithm

The multiobjective gray wolf (MOGWO) algorithm is an optimization algorithm to solve multiobjective problems based on the gray wolf (GWO) algorithm proposed by Sm et al. [48]. Its ideological source is the GWO algorithm, which combines external archiving and leader selection strategies. The GWO algorithm is inspired by the hunting behavior of wolves, which simulates the hunting behavior and social leadership aspects of gray wolves. There exists a strict social hierarchy within the wolf pack, in which a pyramid of rights naturally occurs. The first level of the pyramid is the leader, responsible for various decision-making matters. The second layer of the pyramid encompasses the think tank team of the first layer, which is responsible for assisting in decision-making processes. The third level of the pyramid obeys the orders of the first and second levels and is mainly responsible for investigation, sentry duty, care and other affairs. The lowest-level wolves obey the above three levels of gray wolves and are largely the executors of hunting plans. The GWO algorithm abstracts this process into the following algorithm-based optimization model: each individual in the population is regarded as a solution, and wolves representing the current optimal solution, optimal solution and suboptimal solution are selected (labeled as α, β and δ wolves, respectively, while the remaining individuals are labeled ω wolves). In the hunting process, the wolves approach the food position (global optimal solution) under the guidance of the above α, β and δ wolves, and the guiding equation can be written as follows:

$$D_p = C \cdot X_p(t) - X(t) \tag{16}$$

$$X(t+1) = \frac{1}{3}\sum_{p=a,\beta,\gamma}\left(X_p(t) - A \cdot D_p\right) \tag{17}$$

where X denotes the position of the gray wolf, X_p denotes the guiding position of the prey (i.e., the position of the α, β and δ wolves), T is the number of iterations, and C and A are guiding coefficients, which can be determined as follows:

$$A = 2 \cdot a \cdot r_1 - a \tag{18}$$

$$C = 2 \cdot r_2 \tag{19}$$

where r_1 and r_2 are random numbers within the range of [0, 1], A is a control parameter, and its value occurs in the range of [0, 2] and linearly decreases with the number of algorithm iterations.

Compared to the GWO algorithm, the MOGWO algorithm differs in two aspects: (1) an external population archive is used to store the current nondominated solution; (2) a new wolf selection strategy (including α, β and δ wolves) suitable for multiobjective optimization is proposed. The MOGWO algorithm inherits the characteristics of the GWO algorithm but achieves a higher convergence speed than most similar algorithms.

Therefore, this paper used the MOGWO algorithm to solve the proposed multiobjective optimization model.

4. Case Study

This paper selected the X iron mine in northern China as the research object. This mine involves a large-scale integrated and selective mining enterprise. Open-pit mining is adopted, and the production process can be divided into five major segments: rock drilling and blasting, mining, transportation, crushing, and washing. The peak planning period of this mining enterprise is 2024, so this paper, based on relevant production data for this mining enterprise from 2017 to 2021, calculated the carbon emissions of each production process in different years and used the multiobjective optimization model to assess the allocation of carbon emission quotas and emission reduction responsibilities in each link from 2022 to 2024.

4.1. Carbon Emission Accounting

4.1.1. Carbon Source Identification and Carbon Emission Coefficient Setting

In this paper, the main sources of GHG emissions originating from open-pit mines were divided into the following categories:

(1) Explosives. In the preparation of ore and rock in large-scale open-pit mines in China, the blasting method is widely used, and the GHG emissions resulting from the use of explosives comprise an emission source of open-pit mines. Open-pit mines usually use explosives for blasting, producing large amounts of GHGs. The GHG emissions resulting from the use of explosives in an open-pit coal mine with a capacity of 10 million tons per year can reach more than 10,000 tons. In this paper, the carbon emission coefficients for ammonium nitrate explosives and ammonium nitrate and fuel oil (ANFO) explosives commonly applied in mines were 0.2629 and 0.1768 t CO_2/t, respectively, based on the method of Zhang [49].

(2) Fuel oil. Diesel oil and gasoline are the two most important fuel oils in open-pit mines, and these fuel oils are mainly used as an equipment power source. Generally, diesel oil is more widely used in open-pit coal mines than is gasoline, and the combustion process of fuel oil is accompanied by the generation of a large amount of GHG emissions, mainly CO_2. In this paper, using the calculation method of the Intergovernmental Panel on Climate Change (IPCC), the carbon emission factors for diesel oil and gasoline were determined as 3.2 and 3.08 t CO_2/t, respectively [50].

(3) Electricity. The most important indirect emission source in the production process of open-pit mines entails the use of electric power. Electric power is mainly used to drive all types of large equipment in open-pit mines. Since most electric power in open-pit mines originates from thermal power, notable power consumption and high CO_2 emissions are the main characteristics of open-pit mine production. Electric power emission factors should be determined based on the region containing the considered mining enterprises. The carbon emission factor for North China is 1.0069 t CO_2/(MWh) [51].

(4) Personnel. Operator breathing health is also an important factor influencing the carbon emissions in mine production. According to the breathing minutes and short-term breathing minutes of Chinese residents involved in different activities [52], the breathing minute volume of personnel under physical labor is 36.6 L/minute. Based on the calculation equation of the carbon emission coefficient for personnel [53], the carbon emission coefficient for personnel under manual labor was calculated as 0.53×10^{-7} t CO_2/s.

(5) Water used in the mining process. The carbon emission coefficient for freshwater is 2.12×10^{-7} t CO_2/kg [54].

4.1.2. Accounting Model of Carbon Emissions in Production Links

In this paper, the production process of an open pit mine is divided into two major parts: mining and beneficiation, where mining includes rock drilling and blasting, mining and loading, transportation, and crushing.

1. Rock drilling and blasting

The carbon emission accounting equation for rock drilling and blasting is as follows:

$$E_{RD} = M_{RD\_die} \times C_{die} + C_{die} M_{RD\_ele} \times C_{ele} + M_{RD\_sta} \times T_{RD\_sta} \times C_{sta} + M_{RD\_exp} \times C_{exp} \quad (20)$$

where E_{RD} denotes the carbon emissions originating from the drilling and blasting session, M_{RD_die} is the consumption of diesel fuel during the drilling and blasting session, C_{die} is the carbon emission factor for diesel fuel, M_{RD_ele} is the consumption of electricity during the drilling and blasting session, C_{ele} is the carbon emission factor for electricity, M_{RD_sta} is the number of laborers needed during the drilling and blasting session, T_{RD_sta} is the average working time of laborers during the drilling and blasting session, C_{sta} is the carbon emission factor for laborer work, M_{RD_exp} is the consumption of explosives during the drilling and blasting session, and C_{exp} is the carbon emission factor for explosives.

2. Mining

The carbon emission accounting equation for the mining link can be expressed as follows:

$$E_{ML} = M_{ML\_ele} \times C_{ele} + M_{ML\_dis} \times C_{dis} + M_{ML\_sta} \times T_{ML\_sta} \times C_{sta} \quad (21)$$

where E_{ML} denotes the carbon emissions originating from the mining session, M_{ML_die} is the consumption of diesel during the mining session, C_{die} is the carbon emission factor for diesel, M_{ML_ele} is the consumption of electricity during the mining session, and C_{ele} is the carbon emission factor for electricity. M_{ML_sta} is the number of laborers needed during the mining session, T_{ML_sta} is the average working time of laborers during the mining session, and C_{sta} is the carbon emission factor for laborer work.

3. Transport

The carbon emission accounting equation for the transportation link is as follows:

$$E_{TR} = M_{TR\_ele} \times C_{ele} + M_{TR\_dis} \times C_{dis} + M_{TR\_sta} \times T_{TR\_sta} \times C_{sta} \quad (22)$$

where E_{TR} is the carbon emission of the transportation link, M_{TR_die} is the consumption of diesel fuel in the transportation link, C_{die} is the carbon emission factor of diesel fuel, M_{TR_ele} is the consumption of electricity in the transportation link, and C_{ele} is the carbon emission factor of electricity. M_{TR_sta} is the number of laborers in the transportation link, T_{TR_sta} is the average working time of laborers in the transportation link, and C_{sta} is the carbon emission factor of the laborer's work.

4. Crushing

The carbon emission accounting equation for the crushing link can be written as follows:

$$E_{FR} = M_{FR\_ele} \times C_{ele} + M_{FR\_sta} \times T_{FR\_sta} \times C_{sta} \quad (23)$$

where E_{FR} denotes the carbon emissions of the crushing link, M_{FR_ele} is the power consumption of the crushing link, and C_{ele} is the carbon emission coefficient for power. Moreover, M_{FR_sta} is the number of laborers needed in the crushing link, T_{FR_sta} is the average working time of the labor force in the crushing link, and C_{sta} is the carbon emission coefficient for the labor force.

5. Mineral Beneficiation Processing

The carbon emission accounting equation for mineral processing is as follows:

$$E_{BE} = M_{BE\_ele} \times C_{ele} + M_{BE\_wat} \times C_{wat} + M_{BE\_sta} \times T_{BE\_sta} \times C_{sta} \quad (24)$$

where E_{BE} denotes the carbon emissions of the beneficiation link, M_{BE_ele} is the electricity consumption of the beneficiation link, and C_{ele} is the carbon emission factor for electricity.

In addition, M_{BE_wat} is the water consumption of the beneficiation link, C_{wat} is the carbon emission factor for water, M_{BE_sta} is the number of laborers needed in the beneficiation link, T_{BE_sta} is the average working time of laborers in the beneficiation link, and C_{sta} is the carbon emission factor for laborer work.

4.2. Data and Parameters

(1) Total amount of carbon emission reduction to be achieved by each process (DC_w): The research background of this paper encompasses the allocation of emission reduction responsibilities to various processes given the peak carbon dioxide emissions target. Therefore, the total emission reduction responsibility of mining enterprises should include the carbon emissions of mining enterprises exceeding the peak carbon dioxide emissions target.

(2) Total amount of carbon emission rights to be distributed (C_w). This paper proposes that the peak carbon dioxide emissions formulated by a given enterprise can be defined as the total amount of carbon emissions limiting the future production process of the enterprise. Therefore, the overall carbon emission rights to be distributed within the mining enterprise are equivalent to the peak carbon dioxide emission plan value determined by the mining enterprise.

(3) Low-carbon production coefficient (E): This coefficient can be obtained according to the carbon emission and output data pertaining to each link from 2017 to 2021.

(4) Ore processing capacity of each process over the next three years ($G_i{\prime}$): The ore processing capacity of each link from 2022 to 2024 can be calculated according to the output growth plan of each link of the mining enterprise.

(5) Target value of future M-year production growth set by the company (G'_{goal}). This value can be obtained as the difference in each link's predicted ore processing capacity between 2022 and 2024.

(6) Forecast value of carbon emissions over the next three years (C_{if}). According to the production coefficient and output growth of low-carbon development of each link from 2017 to 2021, the carbon emissions in each production link from 2022 to 2024 can be predicted.

(7) Calculation period (M): The calculation period in this paper is the 2022–2024 period, totaling 3 years, so M = 3.

4.3. Results and Discussion

4.3.1. Scheme Selection

Figure 2 shows the three-dimensional Pareto front surface generated using MATLAB software, which consists of each objective function forming a three-dimensional coordinate system, with the F1 axis being the stationarity function, F2 axis being the efficiency function, and F3 being the fair deviation function. In this study, the multiobjective gray wolf algorithm generates a set of optimal solutions that are uniformly distributed on the Pareto front surface. According to the definition of the Pareto optimum, each solution on the Pareto front is not dominated by each other, and they represent allocation schemes with different carbon emissions.

Theoretically, the set of solutions obtained can be used by the decision maker in the production process because they are all solutions that satisfy the model, except that each solution may behave differently on a single objective because of the multiple objectives. Scholars mostly perform scenario setting according to goal preferences to solve this problem. Therefore, when selecting the optimal solution from the Pareto optimal solution set, we select the decision values with preferences by setting the weights of the objective values to be used as the optimal solution in different scenarios. In order to study the impact of different allocation targets on the allocation results of carbon emission reduction responsibilities, we obtained four optimization schemes concerning the method of Yu, Zheng and Li [55].

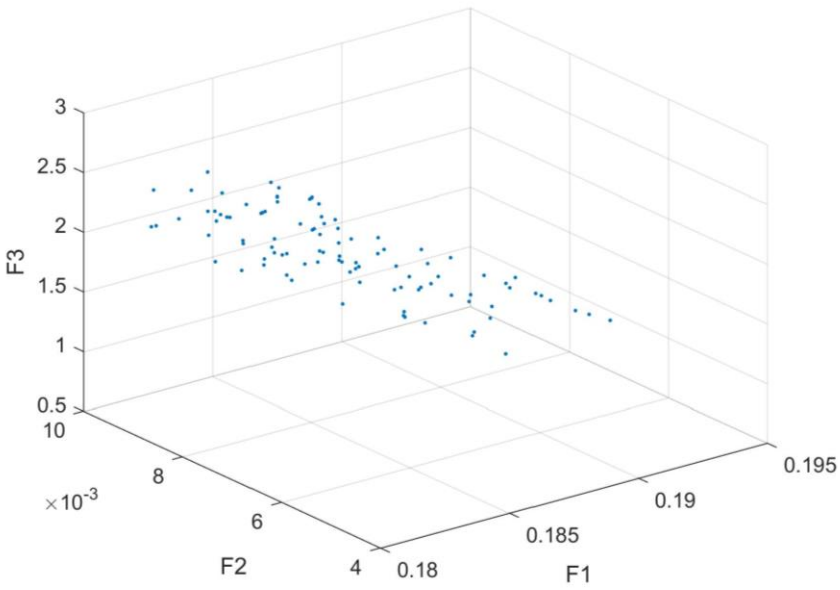


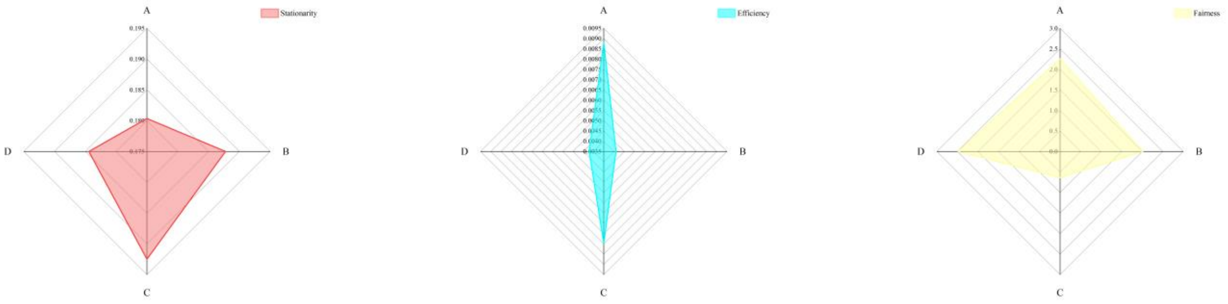
Figure 2. Three−dimensional Pareto frontier.

Table 1 summarizes the smoothness, efficiency and fair deviation index values under the different decision preferences. Under the stationarity preference, the deviation between the carbon emission quota of each production process of the mining enterprise and the previous carbon emission quota was the lowest, with a value of 0.1804. Under the efficiency preference, the carbon emission efficiency of each production process of the mining enterprise tended to remain consistent with the overall carbon emission efficiency of the mining enterprise, with a value of 0.0041. Under the fairness preference, the allocation of carbon emission allowances to each production process of the mining enterprise could satisfy each link to the greatest extent, with a value of 0.6367. Under the equal preference, the allocation scheme could equally consider the stationarity, efficiency and fair satisfaction preferences during the carbon emission quota allocation for each production process of the mining enterprise, and each target value reached the intermediate level.

Table 1. Weights and target values of four decision preferences.

Preference	Criteria	Weight	F1	F2	F3
Stationarity preference (A)	f1 f2 f3	(0.60, 0.20, 0.20)	0.1804	0.0088	2.2518
Efficiency preference (B)	f1 f2 f3	(0.20, 0.60, 0.20)	0.1878	0.0041	2.0160
Fairness preference (C)	f1 f2 f3	(0.20, 0.20, 0.60)	0.1925	0.0080	0.6367
Equal preference (D)	f1 f2 f3	(0.33, 0.33, 0.33)	0.1844	0.0042	2.4835

The values of the three objective functions under the four scenarios are shown in Figure 3. It can be observed that the smoothness objective was the best reflected under scenario A. The performance was similar between scenarios B and D. The smoothness of carbon emission allocation was the worst under scenario C. The efficiency objective indicated the highest efficiency of carbon emission allocation under scenario B and the lowest efficiency under scenario A. Scenario C best reflected fairness, and the fairness deviation was similar between scenarios A and B. Still, the performance of scenario D was lower in terms of fairness.



(**a**) (**b**) (**c**)

Figure 3. Radar chart of four schemes. (**a**) Comparison of stability of four schemes; (**b**) comparison of the efficiency of the four schemes; (**c**) comparison of the fairness of the four schemes.

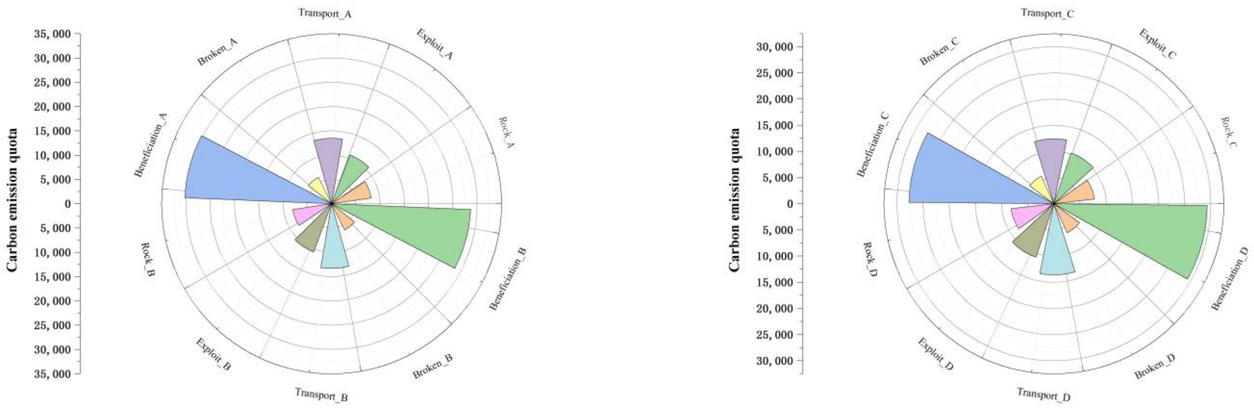
4.3.2. Analysis of the Optimized Target Values

Figure 4 shows a heatmap of each process's smoothness, efficiency and satisfaction values. The figure reveals that the four scenarios were approximately similar, and the magnitude of the efficiency and smoothness values was the smallest among these three indicators. The carbon emission allowance in the whole mining process remained relatively consistent, probably because the mining amount of the mining enterprise remained very stable, and the values assigned to carbon emissions were therefore consistent. Regarding the efficiency value, the efficiency of carbon emission allocation for each process remained approximately the same. Regarding the satisfaction of carbon emission allowance allocation for each process, the satisfaction of the broken link was the highest, whereas the satisfaction of the exploit link was the lowest. This may occur because the exploit link contained the largest proportion of carbon emissions before optimization. Still, after optimization, the carbon emission allowance of the exploit link was reduced, leading to a decrease in the satisfaction of this link.

Figure 4. Comparison of the stability, efficiency, and fairness of obtaining carbon emission allowances for each production process.

4.3.3. Carbon Allowances under the Four Options

Figure 5 shows the allocation of carbon emissions under the four preference options. As shown in Figure 5, in the whole mining process, the transportation link obtained the largest number of allowances, while the crushing link obtained the smallest number of allowances. This may be because the crushing process itself produces less CO_2. The need for crushing in the mine production process is determined by the process used and the lithological characteristics. In crushing and sorting lines, the power consumption of crushing equipment such as jaw crushers is the main source of carbon emissions. The amount of energy consumed in the crushing process is determined by the degree of ore crushing, the size of the crushed particles, etc. [56]. At the same time, the crushing process does not process all the ore in the actual mining process, so the workload is smaller, resulting in fewer carbon emissions and less carbon quota amount. However, the carbon emissions from the transportation stage are larger. The main factors affecting the carbon emissions from the transportation stage are the transportation distance, followed by transportation volume and energy efficiency. In the actual mine production, the spatial location of the ore is transferred mainly by trucks and belts. The X mine is mainly transported by lorries, using trucks to transport the ore to the processing plant or gangue mountain [57]. The process consumes a large amount of fossil energy and thus becomes the link of the whole production chain with more carbon dioxide emissions. The transportation segment generates a large base of carbon emissions. Therefore, the value of this phase is the largest in the allocation of carbon emission allowances regardless of the scenario. This is similar to many studies on carbon emissions from the transport phase of mines [58].



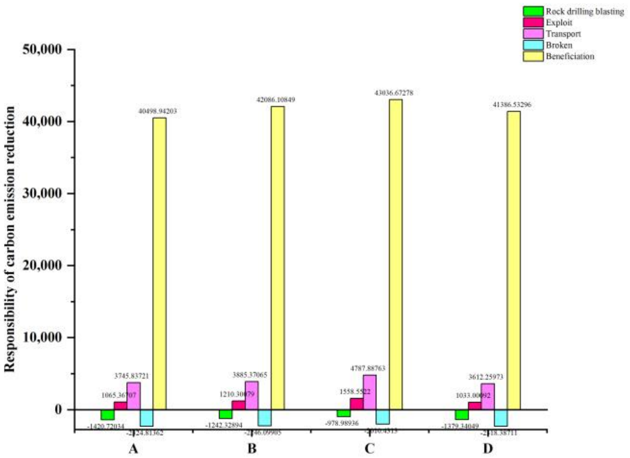
(**a**) (**b**)

Figure 5. Carbon emission quotas of four schemes (Unit: tons). (**a**) Carbon emission allocation of scheme A and scheme B; (**b**) Carbon emission allocation of scheme C and scheme D.

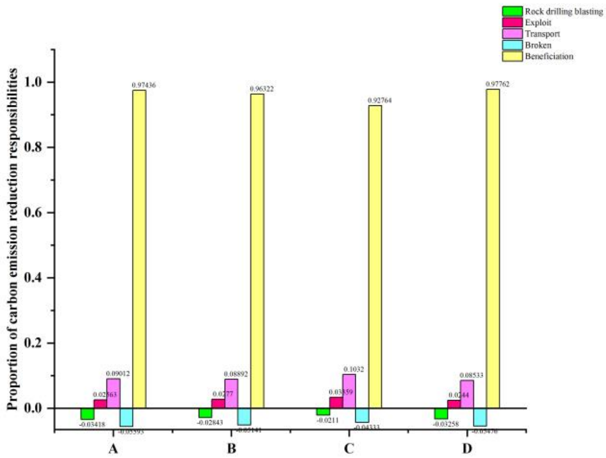
The beneficiation process gets much more carbon emission allowances than the mining process. Because in mining enterprises, mining consumes 1/3 of the energy, and beneficiation consumes 2/3, while in beneficiation plants, grinding energy accounts for 50% of the whole plant, i.e., 1/3 of the mining [59]. Therefore, the energy consumed in the beneficiation process is much more considerable than in the mining process. In mining operations, the ore product to be processed is generally 400–600 mm. The ore product processed in the beneficiation plant is below 0.3 mm, and the ore state is nearly powdery. The energy consumption factors of the beneficiation process are mainly the nature of the ore, the beneficiation process, the scale of the beneficiation plant and the beneficiation method. Electrical energy consumption accounts for roughly 90% to 93% [60]. Therefore, compared to the whole mining process, the energy consumption of the beneficiation process is large, and the carbon emissions are also more, so more carbon emission allowances are obtained.

4.3.4. Carbon Emission Reduction Responsibility of the Production Process

Figure 6 shows the carbon emission reduction responsibility amount to be shared by the various links in the production process of the mining enterprise and the share of the overall emission reduction responsibility of the mining enterprise. From the production process perspective, the carbon emission reduction pressure of ore dressing is the largest, with an emission reduction ratio of more than 90%, followed by transportation, mining, and blasting processes, and the carbon emission reduction pressure of the crushing process is the smallest. At the same time, the beneficiation, mining, and transportation processes are responsible for emission reduction under either preference. The crushing and blasting operations generate carbon emission surpluses, indicating that these two segments have less carbon emission reduction pressure. From the perspective of different preferences, the carbon emission reduction pressure of the mining process under equal preference is the smallest, at 1033 tons; the carbon emission reduction pressure under fair preference is the largest, at 1558 tons. The transportation process has the highest carbon emission reduction pressure under fair preference, 4787 tons; the smallest carbon emission reduction pressure under equal preference, 3612 tons. The beneficiation process has the highest carbon emission reduction pressure under fair preference with 43,036 tons; the lowest carbon emission reduction pressure under smooth preference with 40,498 tons.



(**a**)



(**b**)

Figure 6. Carbon emission reduction responsibilities of each production process. (**a**) Carbon emision reduction responsibilities (Unit: tons); (**b**) proportion of carbon emission reduction responsibilities (Unit: %).

The higher carbon emission reduction pressure in transportation, mining and beneficiation processes may be because the carbon sources in these segments are less fungible. For example, most of the equipment in the transportation process is powered by diesel, and the beneficiation equipment consumes mostly electricity. However, there is room for emission reduction in the tight carbon quota segment. For example, in the mining stage, the scheduling process of production equipment can be optimized to reduce energy consumption on the one hand, and new mining equipment can be used to improve labor productivity on the other. In the transportation stage, new energy vehicles can be used to replace traditional trucks, or biodiesel can be used.

4.3.5. Analysis of the Carbon Emission Intensity Decline

Figure 7 shows that before carbon emission quota optimization, the carbon emission intensity at the beneficiation stage was the highest and that at the crushing stage was the lowest. After optimal allocation of carbon emissions to each link, the changes in the carbon emission intensity in the four cases were similar, exhibiting the characteristics of the largest at the beneficiation stage and the smallest at the crushing stage. After carbon emission allocation, the carbon emission intensity in the mining, transportation and beneficiation processes decreased. Among them, the carbon emission intensity of the beneficiation process decreases the most, and the carbon emission intensity of the beneficiation stage after optimization is about 40% of that before optimization. The carbon emission intensity of the transport stage after optimization is about 77% before optimization, while the carbon emission intensity of the mining process before the optimization is about 90%.

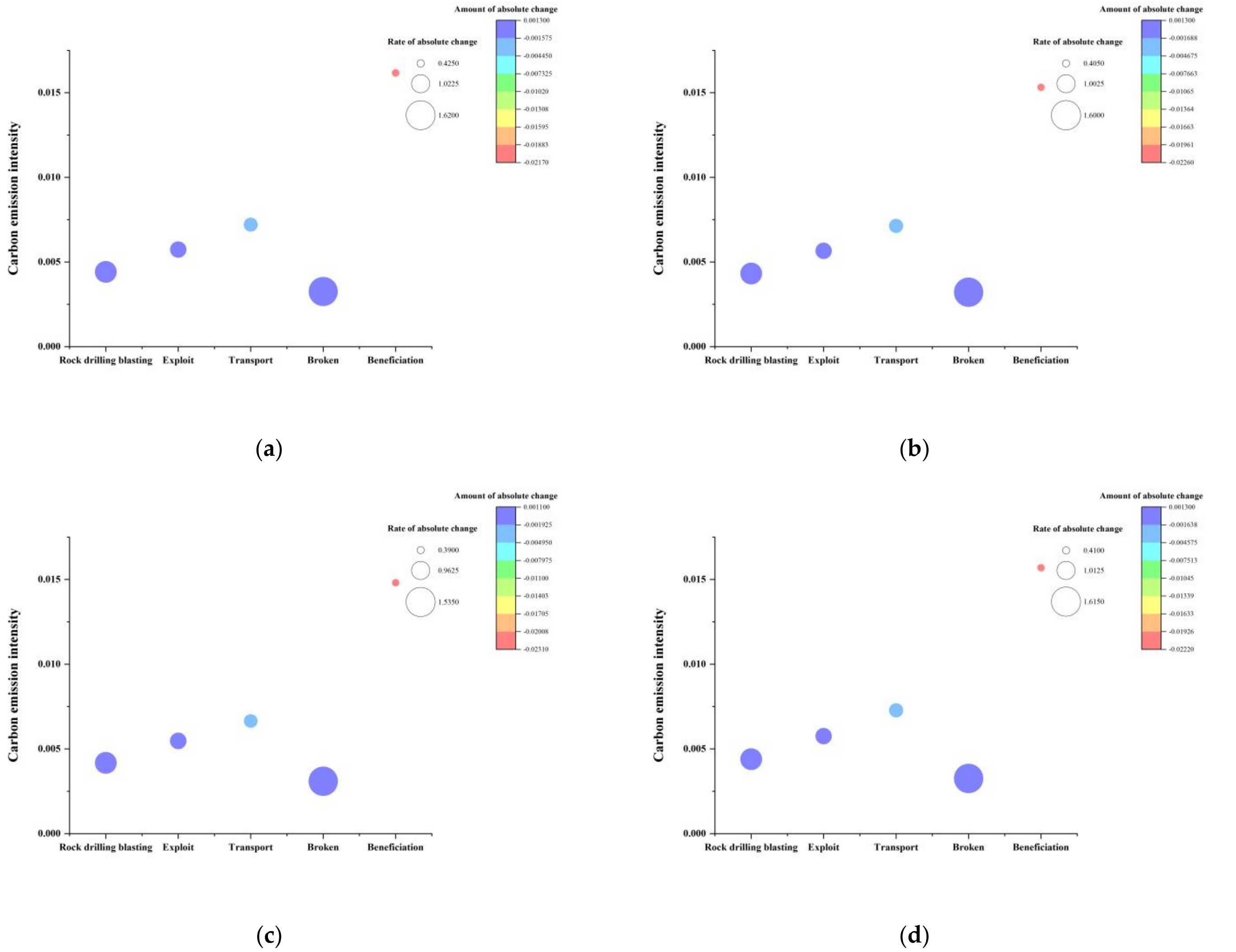


Figure 7. Changes in carbon emission intensity. (**a**) Carbon emission intensity of Scenario A, ratio and difference between Scenario A and carbon emission intensity before optimization; (**b**) carbon emission intensity of Scenario B, ratio and difference between Scenario A and carbon emission intensity before optimization; (**c**) carbon emission intensity of Scenario C, ratio and difference between Scenario A and carbon emission intensity before optimization; (**d**) carbon emission intensity of Scenario D, ratio and difference values.

After unified carbon emission quota allocation, production in the beneficiation, mining and transportation processes became more efficient. However, due to the carbon emission quota surplus at the two stages of crushing and blasting, the carbon emission intensity at these two production stages was higher after optimization than before optimization. Therefore, in the actual production process, the carbon emissions of these two production processes should not be forcibly linked to the allocated carbon emission quota, but a state of cleaner production should be maintained.

5. Discussion

5.1. Universality of the Model

Theoretically, the model proposed in this paper can be applied to most production enterprises. However, the following aspects need to be noted. On the one hand, the framework of this model is based on the division of production processes, which is the allocation of carbon emission responsibility for production processes. Therefore, when applied to other enterprises, it is necessary to clarify the production process of the target industry. On the other hand, the model considers both production and environmental protection, requiring production data and carbon emission data of relevant production processes to support the application to enterprises.

5.2. Suggestions for Emission Reduction of Mine Production Process

(1) Mining process emission reduction measures

Mining enterprises in the mining process to reduce carbon dioxide emissions first need to optimize the mining process, such as the intermittent mining process change into semi-continuous, continuous mining and non-blasting continuous mining process or take steep gang mining and other energy-saving mining technology, the use of the final slope angle to reduce the amount of waste rock stripping to achieve the purpose of energy saving. Secondly, the existing equipment can be gradually replaced, using new energy drilling rigs, new energy excavators and other low carbon emission equipment

(2) Emission reduction measures for transportation

Mining companies can achieve fuel savings through refinement management on the one hand in the transportation link, such as strengthening tire pressure management in car transportation and reducing the occurrence of oil exposure and other situations. On the other hand, it is necessary to strengthen equipment management, use the truck scheduling system in digital mines, optimize the matching of digging trucks, reduce the waiting time of mining trucks and excavators and eliminate unnecessary consumption. In addition, mines with conditions can be equipped with new energy mining trucks to reduce fossil energy consumption.

(3) Emission reduction measures for the beneficiation process

First is the use of clean energy to replace fossil energy. For example, using the roofs of production plants and open spaces to build new distributed photovoltaic power generation systems and the surrounding hillside uplands to build new wind power systems. The second is to adopt energy-saving production technology such as multi-crushing and less grinding, ore pre-selection technology, ore dressing wastewater recycling, and automated ore dressing technology.

6. Conclusions

Reasonable decomposition of an enterprise's carbon emission reduction target is a necessary guarantee to realize overall carbon emission reduction. This is also the key step to achieving the main objective of carbon emission reduction in each production link. In this paper, from the microperspective of carbon emission management, carbon emission quota allocation and carbon emission reduction responsibility distribution in the production process of mining enterprises were studied. First, based on establishing a carbon emission accounting model, a multiobjective carbon emission allocation model for mine production links was established under a certain output growth constraint, considering stability, efficiency and fairness. Choosing the X mine as a research example, a carbon emission reduction responsibility allocation scheme for each production link of the mining enterprise was obtained in conjunction with the above-established model. The main conclusions were as follows:

(1) More carbon emission quotas should be allocated to the beneficiation link, while fewer carbon emission quotas should be allocated to the crushing link.

(2) Beneficiation, mining and transportation are all responsible for emission reduction, but crushing and blasting produce a carbon emission surplus. The carbon emission reduction pressure in beneficiation was the highest, followed by transportation, mining and blasting, and the carbon emission reduction pressure in crushing processing was the lowest.

(3) After the optimization of carbon emission quota allocation for each process, the emission intensity in the beneficiation, mining and transportation processes was reduced.

Based on the above conclusions, mining enterprises should focus on beneficiation, mining and transportation in future production activities. Energy conservation and emission reduction should be increased in these links, and more capital and technology should be invested to transform the production process. This paper provides a reliable method and data to facilitate carbon emission reduction responsibility allocation in the production process of mining enterprises and a reference idea for microenterprises to realize refined carbon emission management.

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References

1. Ruggerio, C.A. Sustainability and sustainable development: A review of principles and definitions. *Sci. Total Environ.* **2021**, *786*, 147481. [CrossRef] [PubMed]
2. Arastoopour, H. The critical contribution of chemical engineering to a pathway to sustainability. *Chem. Eng. Sci.* **2019**, *203*, 247–258. [CrossRef]
3. Dincer, H.; Yüksel, S.; Karakuş, H.; Kalkavan, H. The Importance of Carbon Emission of Manufacturing Companies on Sustainable Economic Development. In *Globalization, Income Distribution and Sustainable Development*; Emerald Publishing Limited: Bingley, UK, 2022; pp. 81–93.
4. Shi, X.; Zheng, Y.; Lei, Y.; Xue, W.; Yan, G.; Liu, X.; Cai, B.; Tong, D.; Wang, J. Air quality benefits of achieving carbon neutrality in China. *Sci. Total Environ.* **2021**, *795*, 148784. [CrossRef] [PubMed]
5. Azadi, M.; Northey, S.A.; Ali, S.H.; Edraki, M. Transparency on greenhouse gas emissions from mining to enable climate change mitigation. *Nat. Geosci.* **2020**, *13*, 100–104. [CrossRef]
6. Xu, C.; Chen, Q. The driving factors and future changes of CO_2 emission in China's nonferrous metal industry. *Environ. Sci. Pollut. Res.* **2022**, *29*, 45730–45750. [CrossRef] [PubMed]
7. Chang, C.-H.; Lo, S.-F. Impact Analysis of a National and Corporate Carbon Emission Reduction Target on Renewable Electricity Use: A Review. *Energies* **2022**, *15*, 1794. [CrossRef]
8. Rakhmangulov, A.; Burmistrov, K.; Osintsev, N. Selection of Open-Pit Mining and Technical System's Sustainable Development Strategies Based on MCDM. *Sustainability* **2022**, *14*, 8003. [CrossRef]
9. Purhamadani, E.; Bagherpour, R.; Tudeshki, H. Energy consumption in open-pit mining operations relying on reduced energy consumption for haulage using in-pit crusher systems. *J. Clean. Prod.* **2021**, *291*, 125228. [CrossRef]
10. Pandey, B.; Gautam, M.; Agrawal, M. Greenhouse Gas Emissions from Coal Mining Activities and Their Possible Mitigation Strategies. In *Environmental Carbon Footprints*; Elsevier: Amsterdam, The Netherlands, 2018; pp. 259–294.
11. Wang, B.; Cui, C.-Q.; Zhao, Y.-X.; Yang, B.; Yang, Q.-Z. Carbon emissions accounting for China's coal mining sector: Invisible sources of climate change. *Nat. Hazards* **2019**, *99*, 1345–1364. [CrossRef]
12. Lin, B.; Jia, Z. Can carbon tax complement emission trading scheme? The impact of carbon tax on economy, energy and environment in China. *Clim. Chang. Econ.* **2020**, *11*, 2041002. [CrossRef]
13. Stavins, R.N. Policy, The Relative Merits of Carbon Pricing Instruments: Taxes versus Trading. *Rev. Environ. Econ. Policy* **2022**, *16*, 62–82. [CrossRef]
14. Zhang, Y.; Qi, L.; Lin, X.; Pan, H.; Sharp, B. Synergistic effect of carbon ETS and carbon tax under China's peak emission target: A dynamic CGE analysis. *Sci. Total Environ.* **2022**, *825*, 154076. [CrossRef] [PubMed]
15. Khan, M.R. Polluter-Pays-principle: The cardinal instrument for addressing climate change. *Laws* **2015**, *4*, 638–653. [CrossRef]
16. Yu, D.; Liu, L.; Gao, S.; Yuan, S.; Haipeng, C.; Qianling, S. Impact of carbon trading on agricultural green total factor productivity in China. *J. Clean. Prod.* **2022**, *367*, 132789. [CrossRef]
17. Jia, Z.; Lin, B. Rethinking the choice of carbon tax and carbon trading in China. *Technol. Forecast. Soc. Chang.* **2020**, *159*, 120187. [CrossRef]
18. Metcalf, G.E. Designing a carbon tax to reduce US greenhouse gas emissions. *J Rev. Environ. Econ. Policy.* **2009**, *3*, 63–83. [CrossRef]
19. Pearce, D. The role of carbon taxes in adjusting to global warming. *Econ. J.* **1991**, *101*, 938–948. [CrossRef]

20. Yang, H.; Gan, T.; Liang, W.; Liao, X. Development; Sustainability, can policies aimed at reducing carbon dioxide emissions help mitigate haze pollution? An empirical analysis of the emissions trading system. *Environ. Dev. Sustain.* **2022**, *24*, 1959–1980. [CrossRef]
21. Huang, W.; Wang, Q.; Li, H.; Fan, H.; Qian, Y.; Klemeš, J.J. Review of recent progress of emission trading policy in China. *J. Clean. Prod.* **2022**, *349*, 131480. [CrossRef]
22. Wang, K.; Zhang, X.; Wei, Y.-M.; Yu, S. Regional allocation of CO2 emissions allowance over provinces in China by 2020. *Energy Policy* **2013**, *54*, 214–229. [CrossRef]
23. Xu, L.; Wang, Y. Empirical estimation and analysis of total carbon emission quota based on carbon transfer–embedded import and export trade. *Environ. Sci. Pollut. Res.* **2022**, *29*, 42692–42708. [CrossRef] [PubMed]
24. Zhu, Y.; Shi, Y.; Wu, J.; Wu, L.; Xiong, W. Exploring the characteristics of CO2 emissions embodied in international trade and the fair share of responsibility. *Ecol. Econ.* **2018**, *146*, 574–587. [CrossRef]
25. Zhao, R.; Min, N.; Geng, Y.; He, Y. Allocation of carbon emissions among industries/sectors: An emissions intensity reduction constrained approach. *J. Clean. Prod.* **2017**, *142*, 3083–3094. [CrossRef]
26. Yi, W.-J.; Zou, L.-L.; Guo, J.; Wang, K.; Wei, Y.-M. How can China reach its CO_2 intensity reduction targets by 2020? A regional allocation based on equity and development. *Energy Policy* **2011**, *39*, 2407–2415. [CrossRef]
27. Grubb, M. The greenhouse effect: Negotiating targets. *Int. Aff.* **1990**, *66*, 67–89. [CrossRef]
28. Phylipsen, G.; Bode, J.W.; Blok, K.; Merkus, H.; Metz, B. A Triptych sectoral approach to burden differentiation; GHG emissions in the European bubble. *Energy Policy* **1998**, *26*, 929–943. [CrossRef]
29. Zhou, P.; Wang, M. Carbon dioxide emissions allocation: A review. *Ecol. Econ.* **2016**, *125*, 47–59. [CrossRef]
30. Zhang, Z.; Cao, L.; Dong, H.; Cai, B.; Geng, Y.; Pang, L.; Tang, Y. Allocating China's 2025 CO_2 emission burden shares to 340 prefecture cities: Methods and findings. *Environ. Sci. Pollut. Res.* **2022**, 1–15. [CrossRef] [PubMed]
31. Zhou, P.; Zhang, L.; Zhou, D.Q.; Xia, W.J. Modeling economic performance of interprovincial CO_2 emission reduction quota trading in China. *Appl. Energy* **2013**, *112*, 1518–1528. [CrossRef]
32. Marklund, P.-O.; Samakovlis, E. What is driving the EU burden-sharing agreement: Efficiency or equity? *J. Environ. Manag.* **2007**, *85*, 317–329. [CrossRef]
33. Dong, F.; Long, R.; Yu, B.; Wang, Y.; Li, J.; Wang, Y.; Dai, Y.; Yang, Q.; Chen, H. How can China allocate CO_2 reduction targets at the provincial level considering both equity and efficiency? Evidence from its Copenhagen Accord pledge. *Resour. Conserv. Recycl.* **2018**, *130*, 31–43. [CrossRef]
34. Wang, S.F.; Yang, S.L. Carbon Permits Allocation Based on Two-Stage Optimization for Equity and Efficiency: A Case Study within China. *Adv. Mater. Res.* **2012**, *518*, 1117–1122. [CrossRef]
35. Lins, M.P.E.; Gomes, E.G.; de Mello, J.C.C.S.; de Mello, A.J.R.S. Olympic ranking based on a zero sum gains DEA model. *Eur. J. Oper. Res.* **2003**, *148*, 312–322. [CrossRef]
36. Yu, S.; Wei, Y.-M.; Wang, K. Provincial allocation of carbon emission reduction targets in China: An approach based on improved fuzzy cluster and Shapley value decomposition. *Energy Policy* **2014**, *66*, 630–644. [CrossRef]
37. Liu, H.; Lin, B. Cost-based modelling of optimal emission quota allocation. *J. Clean. Prod.* **2017**, *149*, 472–484. [CrossRef]
38. Xu, J.; Yang, X.; Tao, Z. A tripartite equilibrium for carbon emission allowance allocation in the power-supply industry. *Energy Policy* **2015**, *82*, 62–80. [CrossRef]
39. Yang, B.; Li, X.; Su, Y.; Liu, C.; Xue, F. Carbon quota allocation at the provincial level in China under principles of equity and efficiency. *Carbon Manag.* **2019**, *11*, 11–23. [CrossRef]
40. Zhao, B.; Yang, W. Allocation of carbon emission allowance based on DLA-GA model: A case study in China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 15743–15762. [CrossRef] [PubMed]
41. Huang, Q.; Feng, Q.; Tian, Y.; Lu, L. Equilibrium Strategy-Based Optimization Method for Carbon Emission Quota Allocation in Conventional Power Plants. *Sustainability* **2018**, *10*, 3195. [CrossRef]
42. Li, L.; Ye, F.; Li, Y.; Tan, K.H. A bi-objective programming model for carbon emission quota allocation: Evidence from the Pearl River Delta region. *J. Clean. Prod.* **2018**, *205*, 163–178. [CrossRef]
43. Rose, A.; Stevens, B.; Edmonds, J.; Wise, M. International equity and differentiation in global warming policy. *Environ. Resour. Econ.* **1998**, *12*, 25–51. [CrossRef]
44. Fang, K.; Zhang, Q.; Long, Y.; Yoshida, Y.; Sun, L.; Zhang, H.; Dou, Y.; Li, S. How can China achieve its Intended Nationally Determined Contributions by 2030? A multi-criteria allocation of China's carbon emission allowance. *Appl. Energy* **2019**, *241*, 380–389. [CrossRef]
45. Cui, X.; Zhao, T.; Wang, J. Allocation of carbon emission quotas in China's provincial power sector based on entropy method and ZSG-DEA. *J. Clean. Prod.* **2021**, *284*, 124683. [CrossRef]
46. Wang, B.J.; Zhao, J.L.; Wei, Y.X. Carbon emission quota allocating on coal and electric power enterprises under carbon trading pilot in China: Mathematical formulation and solution technique. *J. Clean. Prod.* **2019**, *239*, 118104. [CrossRef]
47. Zhang, F.; Wang, C. Allocation model of carbon quota from the perspective of multi-objective optimization. *Contemp. Econ.* **2021**, *3*, 82–85.
48. Sm, A.; Smm, B.; Al, A. Grey Wolf Optimizer. *Adv. Eng. Softw.* **2014**, *69*, 46–61.
49. Zhang, Z. Study on Carbon Emissions Accounting and Carbon Emission Reduction Approach of Surface Coal Mine. Ph.D. Thesis, China University of Mining and Technology, Xuzhou, China, 2013.

50. Eggleston, H.; Buendia, L.; Miwa, K.; Ngara, T.; Tanabe, K. *2006 IPCC Guidelines for National Greenhouse Gas Inventories*; Institute for Global Environmental Strategies (IGES): Hayama, Japan, 2006.
51. Li, Z.; Zhang, H.; Meng, J.; Long, Y.; Yan, Y.; Li, M.; Huang, Z.; Liang, Y. Reducing carbon footprint of deep-sea oil and gas field exploitation by optimization for Floating Production Storage and Offloading. *Appl. Energy* **2020**, *261*, 114398. [CrossRef]
52. Ping, L.; Beibei, W.; Xiuge, Z.; Xiaoli, D.; Nan, H.; Yiting, C.; Limin, W. Study on adult respiratory volume in China. *J. Environ. Health* **2014**, *31*, 953–956.
53. Zhang, X.; Wang, L.; Chen, Y. Carbon Emission Reduction of Apparel Material Distribution Based on Multi-Objective Genetic Algorithm (NSGA-II). *Sustainability* **2019**, *11*, 2571. [CrossRef]
54. Jing-jing, L.; Chuan-sheng, W. Carbon Emission Calculation and Evaluation of Coal Enterprise. *Coal Min. Technol.* **2013**, *18*, 99–102+98.
55. Yu, S.; Zheng, S.; Li, X. The achievement of the carbon emissions peak in China: The role of energy consumption structure optimization. *Energy Econ.* **2018**, *74*, 693–707. [CrossRef]
56. Grujić, M.M. Technology improvements of crushing process in Majdanpek Copper Mine. *Int. J. Miner. Processing* **1996**, *44*, 471–483. [CrossRef]
57. Jeswiet, J.; Archibald, J.; Thorley, U.; Souza, E.D. Energy Use in Premanufacture (Mining). *Procedia CIRP* **2015**, *29*, 816–821. [CrossRef]
58. Liu, F.; Cai, Q.; Chen, S.; Zhou, W. A comparison of the energy consumption and carbon emissions for different modes of transportation in open-cut coal mines. *Min. Sci. Technol.* **2015**, *000*, 255–260. [CrossRef]
59. Chunmei, L. Research on Mechanism and Application of New Ways of Energy Saving and Consumption Reduction of Ball Mill. Master's Thesis, Kunming University of Science and Technology, Kunming, China, 2009.
60. Cuixue, X. Research on Energy Saving of Iron Ore Grinding Based on Neural Network Algorithm. Master's Thesis, Hebei Union University, Tangshan, China, 2013.