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Collaborative Production Planning Based on an Intelligent Unmanned Mining System for Open-Pit Mines in the Industry 4.0 Era

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Abstract: Open-pit mining is a cornerstone of industrial raw material extraction, yet it is fraught with safety concerns due to rough operating conditions. The advent of Industry 4.0 has introduced advanced technologies such as AI, the IoT, and autonomous systems, setting the stage for a paradigm shift towards unmanned mining operations. With this study, we addressed the urgent need for safe and efficient production based on intelligent unmanned mining systems in open-pit mines. A collaborative production planning model was developed for an intelligent unmanned system comprising multiple excavators and mining trucks. The model is formulated to optimize multiple objectives, such as total output, equipment idle time, and transportation cost. A multi-objective optimization approach based on the genetic algorithm was employed to solve the model, ensuring a balance among conflicting objectives and identifying the best possible solutions. The computational experiments revealed that the collaborative production planning method significantly reduces equipment idle time and enhances output. Moreover, with the proposed method, by optimizing the configuration to include 6 unmanned excavators, 50 unmanned mining trucks, and 4 unloading points, a 92% reduction in excavator idle time and a 44% increase in total output were achieved. These results show the model's potential to transform open-pit mining operations by using intelligent planning.

Keywords: open-pit mine; unmanned excavator; unmanned mining truck; collaborative production planning; Industry 4.0

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1. Introduction

Primary energy, industrial raw materials, and agricultural means of production mainly come from mineral resources [1]. Mines are divided into open-pit mines and underground mines. In open-pit mines, the top earth layer should be removed to mine the ores underneath [2]. The mining process includes bursting, loading, transportation, and unloading. In the bursting step, holes are drilled to place explosives, and the earth and ores are loosened after the blasts. In the loading step, excavators at loading points load the earth or ores onto mining trucks. In the transportation step, the mining trucks transport the earth to dump sites and transport the ores to crushing stations. In the unloading step, the mining trucks unload the earth or the ores; then, they travel back to the loading points. The mining of open-pit mines is characterized by rough conditions, and safety accidents happen frequently. For instance, on 22 February 2023, a devastating landslide took place in an open-pit coal mine in Inner Mongolia, resulting in the tragic loss of 53 lives and leaving 6 individuals injured. There is an urgent need for unmanned mining methods for open-pit mines to improve production safety. In the Industry 4.0 era, many advanced technologies have been developed, such as artificial intelligence (AI) [3], the Internet of Things (IoT) [4], sensors, Digital Twin (DT) [5], etc. On this basis, unmanned systems have been successfully developed and applied in the fields of automatic driving, unmanned aerial vehicles (UAVs), service robots, and intelligent factories. Industry 4.0 technologies have also facilitated the advancement of the mining industry [6]. For instance, UAVs can perform 3D mapping to build a static digital mine model [7]. Furthermore, the application of sensor technology provides the foundations for building a real-time digital mine model, allowing for sustainability and safety monitoring [8]. Finally, AI technology has showed the ability to predict disasters and explosions in the process of mining, reducing the risks of accidents caused by human factors [9].

Currently, as shown in Figure 1, mining is mainly carried out through the manual operation of excavators and mining trucks. Operators are responsible for environmental perception, task decision, control and execution, and collaborative planning during operations. In order to replace operators, unmanned excavators and mining trucks need to be equipped with a certain level of single-machine intelligence; that is, they need to become machines capable of perception [10], decision-making [11], planning [12], motion control [13], and trajectory control [14]. In recent years, researchers have focused on the development of intelligent unmanned systems [15] due to their significant advantages and potential in various fields, including industry, military, and services. Some representative examples include autonomous driving, drones, marine robots, space robots, service robots, unmanned factories, etc. The development of intelligent unmanned systems provides valuable insights for unmanned mining by engineering machinery. For example, in the fields of perception, decision-making, and control technology, autonomous driving serves as a good reference for engineering machinery. However, significant differences exist between construction and road scenarios, such as uneven ground, dynamic change in operating environments, and demands of coupling degrees of freedom for both mobility and operation. These differences result in challenges when attempting to directly apply existing technology to engineering machines. Therefore, the adaptive development of unmanned excavators and mining trucks becomes necessary.

Figure 1. Xinjiang Southern open-pit coal mine in China.

On the basis of electromechanical hydraulic servo control technology, Li et al. [16] conducted a study on machine vision, fault diagnosis, and remote communication technology in intelligent excavators. The integration of remote operation, environmental perception, and intelligent diagnosis was studied, aiming at implementation in practical applications such as earthquake relief, space operation, and underwater scenarios. Baidu systematically investigated perception, decision-making, and control technology to develop an autonomous excavator system [17]. The multimodal sensor fusion algorithm and the target detection algorithm were applied for perception. The data-driven learning algorithm and an optimization-based method were combined to build hierarchical task- and motion-planning algorithms. The closed-loop motion control algorithm was utilized to realize high-precision operation. Experiments, including loading materials onto dump trucks, positioning and moving stones, clearing heaps of soil, and excavating trenches, were conducted to validate the function of the autonomous excavator system. Autonomous operation was achieved in the scenario of automatically processing industrial waste.

Based on autonomous driving technology, research has been conducted on remote control function realization [18], environmental perception [19], and planning control [20] in unmanned mining trucks in mining scenarios. Liu et al. proposed a multi-target detection and tracking method based on the fusion of lidar and millimeter-wave radar [19]. By establishing a segmentation algorithm suitable for the open-pit mine scenario, the detection distance and accuracy for irregular obstacles on an unstructured road were enhanced. Further, an adaptive heterogeneous multi-source fusion strategy for filtering dust was proposed; by adaptively adjusting the confidence degree of the output target, the detection and tracking ability for various targets can be improved in a dusty environment. Teng et al. [21] proposed a multi-task motion-planning method which utilizes multi-sensor fusion techniques to adapt to the lateral and longitudinal control tasks. In our previous work, an intelligent unmanned system was proposed for open-pit mines, and an unmanned excavator and an unmanned mining truck were designed [22].

On the basis of single-machine intelligence, it is necessary to complete the mining of an open-pit mine through multi-machine cooperation. At present, relevant research is mainly focused on truck transportation planning and scheduling [23]. As shown in Figure 2, a mining truck delivers ore from different loading points to different unloading points [24]. In mining truck production planning, it is generally necessary to reduce the transportation cost and increase the total output of ore production [25]. In unmanned driving production planning, the total transportation cost mainly includes the driving cost of the trucks, without the labor cost for drivers. An unmanned system can carry out operations continuously without considering drivers' break times [26].

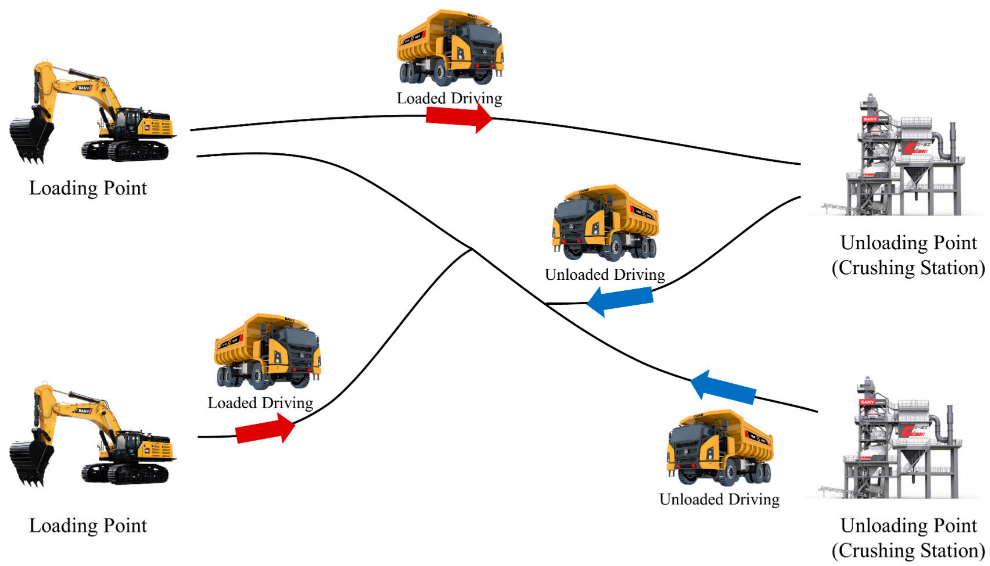

Figure 2. Schematic diagram of excavators and mining trucks in open-pit mines.

The truck production planning issue in open-pit mines belongs to the optimization category. Under the given objectives and constraints, the optimal solution of truck production planning is searched for with an optimization algorithm [27]. The objectives include total output, equipment idle time, transportation cost, etc. [28]. In terms of the traffic flow planning model, Bastos et al. introduced an uncertainty factor linked to the truck driver's decision-making in the production planning model, which was established so that it could consider the delay time factor [29]. In view of the energy consumption caused by idle equipment during loading, unloading, and transportation, Patterson et al. established a traffic flow planning transportation model with the goal of minimizing energy consumption [30]. Taking the fuel consumption of excavators and trucks as the cost function, Bajany et al. built truck teams with different loads for a traffic flow scheduling model [31]. For electric mining trucks in open-pit mines, Wang et al. [32] comprehensively considered the constraints of energy recovery and electricity and proposed a scheduling model with power consumption, ore grade deviation, and the total idle time of the excavators to maximize the use of electric energy, reduce the transportation cost, and improve mining efficiency. Sun et al. [33] established a method for predicting the real-time driving period of open-pit trucks and established a production planning model by employing machine learning technology and Big Data technology.

The optimization algorithms for solving the mining truck production planning problem include the integer programming method [34], the dynamic programming algorithm [35], the genetic algorithm [36], the simulated annealing algorithm [37], the improved ant colony algorithm [38], the agent-assisted evolution algorithm [39], etc. Among them, the first two can obtain high-speed solutions and are suitable for simple models, while the genetic algorithm, the simulated annealing algorithm, the improved tabu search algorithm, the improved ant colony algorithm, and the agent-assisted evolution algorithm are suitable for complex models.

Previous studies on mining truck production planning provide the basis for developing collaborative mining technology for unmanned systems in open-pit mines. Currently, the excavators cooperating with mining trucks are generally manually operated. In order to simplify the model, the position of the excavator at the loading point is assumed to remain unchanged. For collaborative mining based on an intelligent unmanned mining system in an open-pit mine, an unmanned excavator replaces the manned one in carrying out the excavation and loading tasks [14]. Consequently, the mining planning of unmanned excavators needs to be considered. Thus, the operations of the unmanned excavators and mining trucks should be scheduled collaboratively.

The aim of this study was to explore effective strategies for collaborative production planning based on an intelligent unmanned mining system in open-pit mines. Specifically, a collaborative production planning model was established for a mining system that includes multiple unmanned excavators and mining trucks. The multi-objective optimization approach based on the genetic algorithm was implemented to solve the model to minimize equipment idle time while improving output. Moreover, the method can be utilized to determine the optimal configuration of mining equipment. This paper is organized as follows: Section 2 presents the production planning model including unmanned excavators and mining trucks, as well as the assumptions, objective functions, constraints, and production planning strategy. Section 3 introduces the multi-objective optimization algorithm for solving the production planning model. Section 4 presents the collaborative production planning computational experiments conducted, for which the parameters were set according to an actual mine scenario, and following which, the production planning optimization results were obtained and compared, and the optimized configuration scheme was established. In Section 5, we present the conclusions.

2. Methodology

2.1. Multi-Machine Collaborative Production Planning Model

2.1.1. Description

There are multiple loading and unloading points in an open-pit mine. Unmanned excavators dig and load material in different subareas at a loading point, and unmanned mining trucks transport the material between loading and unloading points. Production planning based on an intelligent unmanned mining system should increase the output as much as possible and reduce the idle time of unmanned excavators and mining trucks.

Multi-machine collaborative production planning in open-pit mines needs some assumptions to be set: The time period of a shift is 8 h. The unmanned excavators and mining trucks have no break time. Within one shift cycle, the unmanned excavators and mining trucks operate without faults, and the energy is sufficient. The unmanned mining trucks only drive between loading points and unloading points, where their speed tends to have a fixed value during transportation. Unloading and loading speeds have different values. The loading time is determined by the bucket capacity of the unmanned excavators and the container capacity of the unmanned mining trucks. Loading areas can only accommodate one unmanned mining truck for loading; thus, other unmanned mining trucks that arrive during the loading process need to stop and wait until the previous one completes loading and leaves before entering a loading area. Similarly, unloading points initially have one unloading position which can only accommodate one unmanned mining truck for unloading.

2.1.2. Objective Functions

The collaborative production planning model for multiple unmanned excavators and mining trucks in open-pit mines includes four goals, i.e., large total output, less idle time for unmanned excavators, less idle time for unmanned mining trucks, and low transportation cost. The objective function of the multi-machine collaborative production planning model is expressed as

$$F(S) = \{f_1(S),\ f_2(S),\ f_3(S),\ f_4(S)\} \tag{1}$$

where $f_1(S)$ is the total output, $f_2(S)$ represents the total idle time of the unmanned excavators, $f_3(S)$ refers to the total idle time of the unmanned mining trucks, and $f_4(S)$ is the total transportation cost.

The total output is the total amount of ore transported by the unmanned mining trucks to the unloading points in a shift, expressed as

$$f_1(S) = \sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{j=1}^{J} x_{rij} w_r \tag{2}$$

where S represents the production planning scheme of the unmanned excavators and mining trucks; x_{rij} is the number of trips for the r-th unmanned mining truck from the i-th loading point to the j-th unloading point in a shift of production planning scheme S; w_r refers to the load weight of the r-th unmanned mining truck; R is the number of unmanned mining trucks; I is the number of loading points; and J is the number of unloading points.

The idle time of each unmanned excavator is obtained by subtracting the loading time from the duration of the shift. Then, the total idle time of all unmanned excavators is calculated by summing them up:

$$f_2(S) = \sum_{i=1}^{I}\left(T_l - \sum_{r=1}^{R}\sum_{j=1}^{J} x_{rij} t_i\right) \tag{3}$$

where T_l indicates the time of a shift and t_i indicates the average time spent by an unmanned excavator at the i-th loading point to fill the container of a mining truck.

The idle time of each unmanned mining truck is obtained from the time of the shift minus the time of transportation on the route, including the loaded driving time from the loading point to the unloading point and the unloaded driving time from the unloading point to the loading point. The idle time of the unmanned mining trucks is the total idle time of each unmanned mining truck:

$$f_3(S) = \sum_{r=1}^{R}\left(T_l - \sum_{i=1}^{I}\sum_{j=1}^{J} \frac{d_{ij}^n}{v_f} x_{rij} - \sum_{j=1}^{J}\sum_{i=1}^{I} \frac{d_{ij}^n}{v_e} x_{rji}\right) \tag{4}$$

where v_f and v_e are the average loaded and unloaded driving speeds of the unmanned mining trucks, respectively; d_{ij}^n is the distance from the i-th loading point to the j-th unloading point when an unmanned excavator operates in the n-th subarea of the i-th loading point; and x_{rji} is the driving time of the r-th unmanned mining truck from the j-th unloading point to the i-th loading point in production planning scheme S.

The transportation cost of an unmanned mining truck includes the cost of loaded driving from the loading point to the unloading point and that of unloaded driving from the unloading point to the loading point:

$$f_4(S) = \sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{j=1}^{J}\left(d_{ij}^{n}C_{rf}x_{rij} + d_{ij}^{n}C_{re}x_{rji}\right) \tag{5}$$

where C_{rf} and C_{re} represent the loaded and unloaded driving costs of the unit distance of the r-th unmanned mining truck, respectively.

2.1.3. Constraints

In the multi-machine collaborative production planning model for open-pit mines, according to the actual operation situation, factors such as production demand, production capacity, and continuity constraints need to be considered. Correspondingly, there are loading point production constraints, unloading capacity constraints, unmanned mining truck flow continuity constraints, and constraints on the number of transportation trips. In the process of finding an optimization solution, it is crucial to ensure compliance with these constraint conditions.

The production capacity constraint of a loading point can be expressed as

$$\sum_{r=1}^{R}\sum_{j=1}^{J}x_{rij}w_r \le g_i \tag{6}$$

where g_i represents the maximum production capacity of the i-th loading point during a shift.

The capacity constraint of an unloading point can be expressed as

$$\sum_{r=1}^{R}\sum_{i=1}^{I}x_{rij}w_r \le q_j \tag{7}$$

where q_j represents the maximum capacity of the j-th unloading point within a shift.

The quantity constraint of an unloading point is expressed as

$$\sum_{r=1}^{R}\sum_{i=1}^{I}x_{rij}w_r \ge h_j \tag{8}$$

where h_j represents the production demand of the j-th unloading point within a shift.

According to the unmanned mining truck flow continuity constraint, the number of unmanned mining trucks entering each loading point or unloading point is the same as the number of unmanned mining trucks leaving each loading point or unloading point, respectively, which can be expressed as

$$\sum_{r=1}^{R}\sum_{j=1}^{J} x_{rij} = \sum_{r=1}^{R}\sum_{j=1}^{J} x_{rji} \tag{9}$$

$$\sum_{r=1}^{R}\sum_{i=1}^{I} x_{rij} = \sum_{r=1}^{R}\sum_{i=1}^{I} x_{rji} \tag{10}$$

The constraint on the number of trips of unmanned mining trucks refers to the number of trips from the loading point to the unloading point or from the unloading point to the loading point, expressed as a positive integer:

$$x_{rij} \in \{1, 2, 3, \ldots\} \tag{11}$$

$$x_{rji} \in \{1, 2, 3, \ldots\} \tag{12}$$

2.1.4. Collaborative Production Planning Strategy

The multi-machine collaborative production planning scheme for open-pit mines is a method that involves optimizing the initial production plan under the given constraints and assumptions through the use of optimization algorithms. Thereafter, an improved production plan is obtained, aiming to achieve better objectives. The initial production planning scheme can be obtained by randomly generating the loading and unloading sequence of each unmanned mining truck. The loading points are represented by {A, B, C, ...} and the unloading points by {a, b, c, ...}. An example of the loading and unloading sequence is

$$\mathrm{S}_{cr} = \{\mathrm{AaBbCcDaEbFc}\ldots\ldots\}, r = 1, 2, 3, \ldots, R \tag{13}$$

which means that the unmanned mining truck drives from loading point A to unloading point a and then to loading point B, unloading point b, loading point C, unloading point c, loading point D, unloading point a, loading point E, unloading point b, loading point F, unloading point c, etc.

A construction sequence for an unmanned excavator is

$$\mathrm{S}_{ei} = \{A_2 A_3 A_1 \ldots\}, i = 1, 2, 3, \ldots, I \tag{14}$$

which means that at loading point A, construction work starts in subarea A_2, followed by subareas A_3 and A_1, etc. When the loading point has n subareas, according to the mathematical formula of permutation and combination, there are $n!$ kinds of construction sequences.

The loading and unloading sequence of all unmanned mining trucks and the subarea construction sequence of the unmanned excavators constitutes a multi-machine collaborative production planning scheme.

$$\mathrm{S} = \{\mathrm{S}_{c1}, \mathrm{S}_{c2} \ldots, \mathrm{S}_{e1}, \mathrm{S}_{e2} \ldots\} \tag{15}$$

To transform the production planning model into an optimization problem format, production planning scheme S is mapped into an integer vector:

$$\boldsymbol{x} = [\boldsymbol{x}_1,\ \boldsymbol{x}_2,\ \boldsymbol{x}_3] \tag{16}$$

where $\boldsymbol{x}_1$ represents the vector composed of the loading point in the loading sequence of an unmanned mining truck, and the integer {1, 2, 3 ...} refers to the loading point {A, B, C, ...}; $\boldsymbol{x}_2$ represents the vector composed of unloading points in the unmanned mining truck unloading sequence, where the integer {1, 2, 3 ...} refers to the loading point {a, b, c, ...}; and $\boldsymbol{x}_3$ represents a vector composed of the loading point subarea arrangement, where the integer {1, 2, 3 ...} represents the serial number among $n!$ kinds of arrangement for n subareas. By mapping the production planning scheme into an integer vector, a possible production planning scheme can correspond to the vector satisfying the following equation:

$$\boldsymbol{l} \leq \boldsymbol{x} \leq \boldsymbol{b} \tag{17}$$

where $\boldsymbol{l}$ is a vector composed of 1, representing that the element of $\boldsymbol{x}$ is at least 1; $\boldsymbol{b} = [\boldsymbol{b}_1,\ \boldsymbol{b}_2,\ \boldsymbol{b}_3]$; $\boldsymbol{b}_1 = [I,\ I,\ I, \ldots]$ means that the serial number of the loading point cannot exceed the number of loading points, I; $\boldsymbol{b}_2 = [J,\ J,\ J, \ldots]$ indicates that the serial number of the unloading point cannot exceed the number of loading points, J; and $\boldsymbol{b}_3 = [n!, n!, n!, \ldots]$ indicates that the serial number of the subarea construction sequence does not exceed the number of permutations. Therefore, based on the model assumptions, by satisfying the model constraint conditions and the inequality equations of vector $\boldsymbol{x}$, an optimal production plan and the corresponding objective results can be obtained by using the multi-objective algorithm.

2.2. Multi-Objective Optimization Algorithm

The objectives in the multi-machine collaborative production planning model are coupled and conflicting with each other, making it difficult to achieve comprehensive and synchronized improvement. A set of optimized production planning schemes can be obtained by adopting a multi-objective optimization algorithm called the Pareto Front. For each scheme in this set of production planning results, if a target function needs to further improve, then at least one other target will be worse. The Pareto Front is a comprehensive set of possible optimal solutions considering multiple objective functions that realize a balance among multiple targets.

The Non-dominated Sorting Genetic Algorithm (NSGA) is a typical multi-objective optimization algorithm [40]. The NSGA divides each individual in the population into a non-dominant layer. The child population is generated by combining the selection and variation of the genetic algorithm. The Pareto Front of the multi-objective optimization problem is solved. To improve the efficiency of the NSGA, Deb proposed a fast non-dominant ranking method and introduced the elite strategy and crowding distance in the NSGA to establish NSGA-II [41]. Further, based on NSGA-II, the spread value index is introduced to evaluate the search effect of the solution process as one of the evaluation conditions for stopping the calculation [42]. The multi-objective optimization algorithm for solving the multi-machine collaborative production planning model is shown in Figure 3, and the overall process of the algorithm is as follows: First, the initialization of the population is generated randomly, and the fitness and crowding distance are calculated. Genetic operations such as selection, crossover, and mutation are performed to generate the child population. Next, the parent and child populations are merged, and the resulting population undergoes fast non-dominated sorting and crowding distance calculation, giving a spread value indicator. The population is trimmed based on sorting and crowding distance. Then, the termination condition is determined based on the number of iterations and the spread value indicator. If the condition is satisfied, the computation is terminated. Otherwise, the iteration and population optimization continue.

In the algorithm, the individual dominance relationship, the rank value, the crowding distance, and the index of the spread value of the population are calculated. Regarding the first two terms, the value of each objective function is solved for the individual. Individual p dominates individual q if p has at least one target better than q, and all targets of p are no worse than q. In the sorting process, the NSGA starts from the order value of 1. Taking the *k*-th round ranking as an example, the individuals in the set that are not sorted are analyzed. If there is an individual $\mathrm{p_k}$ that is not dominated by other individuals, the rank value of $\mathrm{p_k}$ is k. After the *k*-th round of sorting, before the $(k + 1)$th round, individuals with a rank value of k are removed, and the remaining unsorted individuals in the population are calculated and sorted. To improve efficiency, the fast non-dominant ranking algorithm of NSGA-II is utilized. For all individuals, $\mathrm{n_p}$ and $\mathrm{S_p}$ are calculated, where $\mathrm{n_p}$ is the number of individuals that dominate individual p and $\mathrm{S_p}$ is the set of individuals dominated by p. Then, the sorted set $\mathrm{F_i}$ is calculated. The individuals with $\mathrm{n_p} = 0$ are for $\mathrm{F_1}$. Then, $\mathrm{n_p}$ of $\mathrm{S_p}$ of the individual in $\mathrm{F_1}$ is decreased by 1. For the individual in $\mathrm{F_k}$, the corresponding set, $\mathrm{S_p}$, is extracted. The individuals with $\mathrm{n_p} = 0$ are chosen in $\mathrm{F_k}$. Then, the $\mathrm{n_p}$ values of the individuals in $\mathrm{F_k}$ are decreased by 1. After completing all sorting in turn, the rank values for all individuals can be obtained. The set of individuals with a rank value of 1 represents the current population's Pareto Front with respect to the objective function.

The crowding distance reflects the diversity of individuals. For each individual, the objective function values are computed. The crowding distance for the individuals at the ends of the Pareto Front is defined as positive infinity. For other individuals, it is the projection of the difference in objective function values onto the range (0, 1). The crowding distance is calculated by summing up the results for all objective functions. The larger the crowding distance, the better the diversity. In the same rank, the individual with a larger crowding distance is preferred. The spread value indicator reflects the convergence of the algorithm's search process.

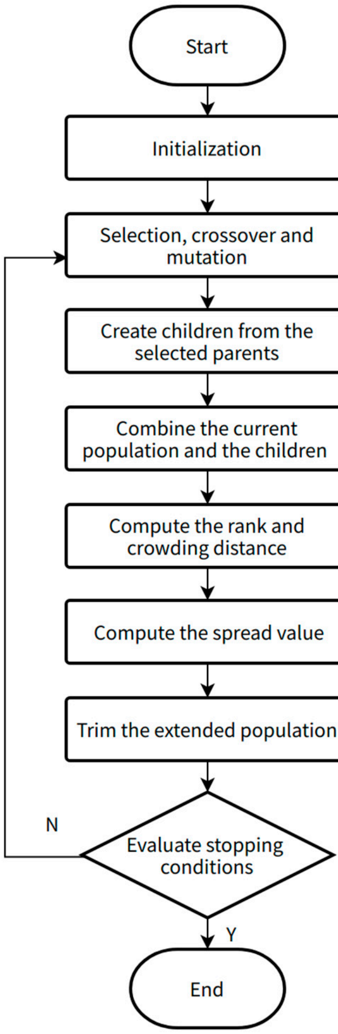

Figure 3. The multi-objective optimization algorithm process.

$$s_{pd} = \frac{\mu + \sigma}{\mu + Qd} \tag{18}$$

where σ is the standard deviation of the crowding distance of the individuals that are extracted from the Pareto Front with finite crowding distance, except for the individual with infinite crowding distance; Q is the number of these individuals; d is the average of the individual crowding distance; and μ is the sum of the norm of differences between the two iterations obtained by calculating the objective function. A small spread value index means that the objective function is almost unchanged during the iteration and the individuals are evenly distributed on the Pareto Front. Moreover, it signifies that the algorithm has successfully converged, and further iterative calculations can be ceased.

The methodology is designed to be adaptable to various mining scenarios with different numbers of loading and unloading points, types of machinery, and operational constraints. By incorporating advanced technologies such as AI and the IoT, the methodology leverages the potential of Industry 4.0, paving the way for more automated and intelligent mining operations. The optimized planning of unmanned excavators and mining trucks is expected to minimize equipment idle time and maximize productivity. However, the sophisticated nature of the model and algorithms may pose challenges in terms of implementation and required computational resources. The system's performance is heavily reliant on the reliability of the unmanned equipment technology, including sensors, communication systems, and control algorithms. As mining conditions and equipment change, the planning model and algorithms will need regular updates and maintenance to remain effective. If the unmanned excavators or mining trucks break down in the mining process and there is no alternative equipment, real-time scheduling is needed to modify the production plan. Moreover, the blend types of different crushing stations are here assumed to be the same. If there are different blend types of ores, the requirements of the crushing stations should be defined as constraints of the planning model. The above issues will be addressed in our future studies.

3. Results: Computational Experiments

3.1. Parameters

According to an open-pit mine scenario in China [17], a production planning computational experiment was carried out, with six loading points and three unloading points. The distances between loading and unloading points are shown in Table 1. There was an unmanned excavator at each loading point. Twenty unmanned mining trucks were equipped, whose unloading and loading speeds were 20 km/h and 15 km/h, respectively. The loading time for the unmanned mining trucks was 5 min, and their unloading time was 3 min. The bucket capacity of the unmanned excavators was 5 m^3, and the load of the unmanned mining trucks was 75 t. The maximum production capacity of the loading points during a shift was 7200 t. The maximum capacity of the unloading points was 2000 t/h. The minimum production demand of the unloading points within a shift was set to 5000 t.

Table 1. Distances between loading and unloading points (unit: km).

	Unloading Point a	Unloading Point b	Unloading Point c
Loading point A	1.77	2.36	1.91
Loading point B	1.26	2.01	1.94
Loading point C	0.78	1.53	1.48
Loading point D	1.28	1.87	1.42
Loading point E	1.50	1.83	2.20
Loading point F	0.96	1.39	1.66

3.2. Results

The production planning computational test was conducted for three cases separately. In the first case, the unmanned excavators randomly selected the construction sequence of the subareas at each loading point, and the unmanned mining trucks randomly selected the loading and unloading points. In the second case, the unmanned mining trucks adopted the production planning optimization algorithm to generate the traffic flow planning scheme, while the unmanned excavators randomly selected the construction sequence of the subareas. In the third case, collaborative production planning optimization was conducted for the unmanned excavators and mining trucks. The computational experiments were conducted by using the MATLAB R2022a software with the processor 11th Gen Intel(R) Core(TM) i5-1135G7 @ 2.40 GHz. The running time of the collaborative production planning was 69.03 s. This running time is insufficient for real-time scheduling but sufficient for production planning.

The Pareto Front of the collaborative production planning optimization results is shown in Figure 4. As the idle time of the unmanned excavators decreased and the effective working time increased, the total output increased accordingly. The results of the objective functions, including transportation cost, idle time of the unmanned excavators, and idle time of the unmanned mining trucks, are shown in Figure 4. Due to the high cost of the unmanned excavators and the objective of increasing the total production, the idle time of these machines should be minimized in mining. The result of the minimal idle time of the unmanned excavators in the Pareto Front should be taken as the optimization result of collaborative production planning and compared with other production planning schemes.

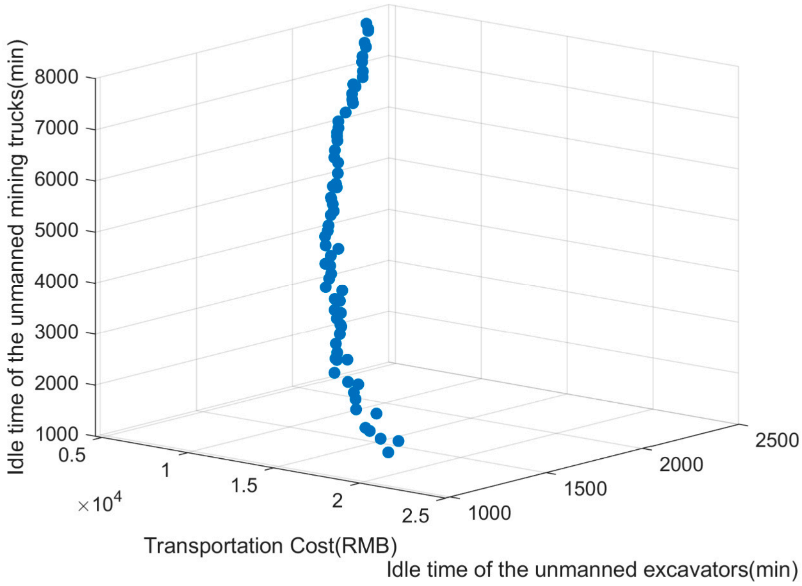

Figure 4. Pareto Front of collaborative production planning optimization results.

For the three cases, Gantt charts for the mining process of 6 unmanned excavators and 20 unmanned mining trucks were obtained through calculation. Figures 5–7 show the Gantt charts for the three cases for the first two hours of the mining process of autonomous excavators. In these graphs, red represents the mining time, and blue represents the idle time. As shown in Figure 5, it is evident that the excavators experienced extended idle time in several instances, indicating inefficiency in operation.

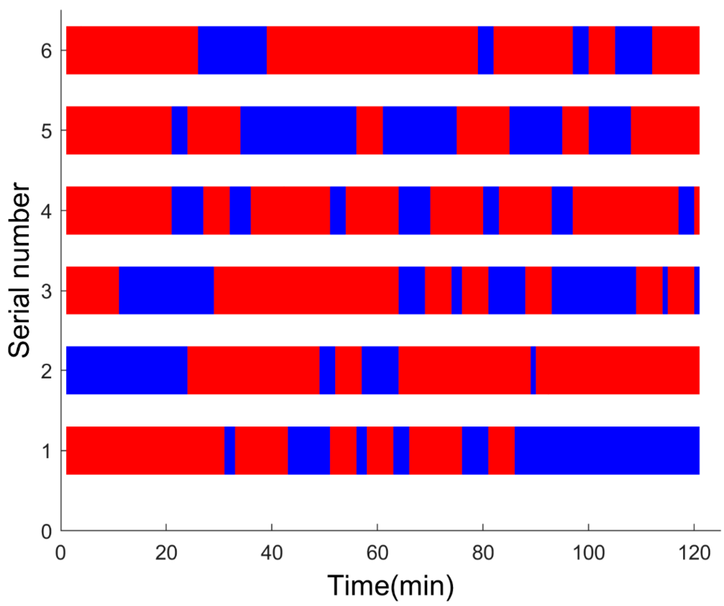

Figure 5. Gantt chart of unmanned excavators without production planning.

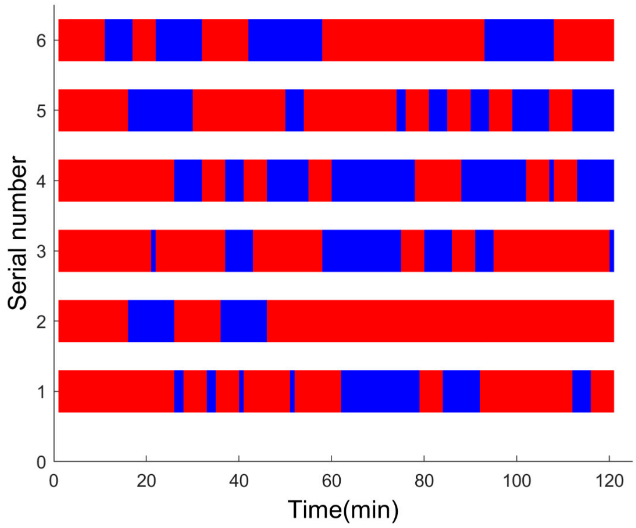

Figure 6. Gantt chart of unmanned excavators under the condition of only planning unmanned mining truck operation.

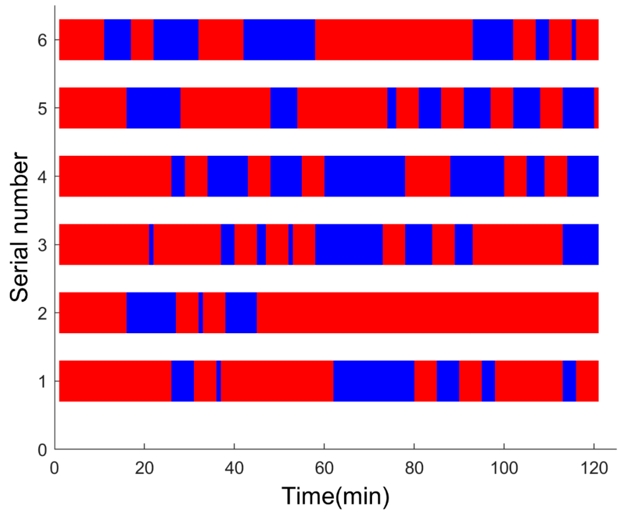

Figure 7. Gantt chart of unmanned excavators under collaborative production planning.

The Gantt chart in Figure 6 shows the excavators' schedule when the mining truck operation was planned but the excavator operation was not. There was a noticeable improvement in the balance between operational and idle time compared with Figure 5, suggesting that the operation planning of the trucks alone optimizes the system to a certain extent.

Based on collaborative production planning, the chart in Figure 7 demonstrates a further enhancement in excavator utilization. The red blocks, indicating mining time, are longer, and the blue idle blocks are significantly reduced, highlighting the benefits of a coordinated approach to planning.

Figures 8–10 show the Gantt charts of three cases for the first two hours of the mining process of unmanned mining trucks. Compared with the first case without production planning, the operation scheme obtained by only planning the unmanned mining truck operation is more balanced, with fewer instances of extended idle time. Collaborative production planning further improves the problem of equipment idleness and enhances the time utilization effect. Figure 8 presents the activity of the unmanned mining trucks over the first two hours without any production planning. The disjointed pattern of the red and blue blocks indicates irregular operation and substantial idle time, reflecting a lack of coordination.

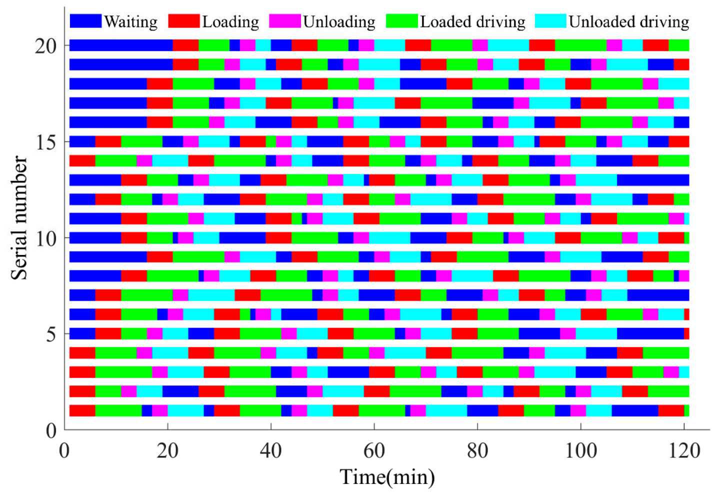

Figure 8. Gantt chart of unmanned mining truck driving without production planning.

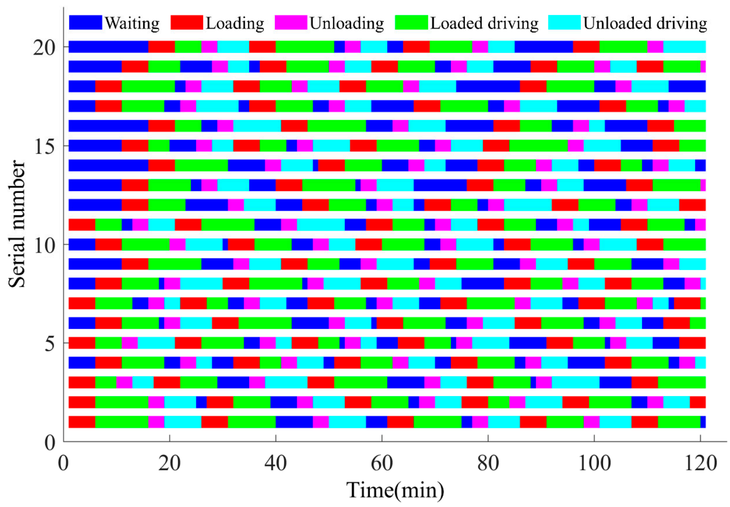

Figure 9. Gantt chart of unmanned mining trucks under production planning.

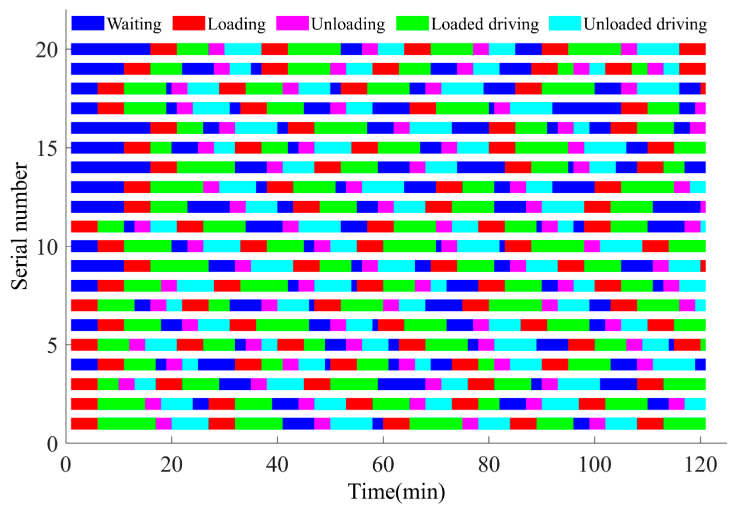

Figure 10. Gantt chart of unmanned mining trucks under collaborative production planning.

Based on the production planning of the mining trucks, the Gantt chart shown in Figure 9 demonstrates more structured and efficient operation. The unmanned mining trucks' idle time is reduced, and their active transportation time is better distributed, leading to a more streamlined workflow.

Figure 10 represents the optimized operation of the unmanned mining trucks under the collaborative planning model. The chart shows a well-organized schedule with minimized idle time and maximized transportation activity, reflecting efficient and synchronized mining operation.

The specific results are shown in Table 2. Without production planning, the total idle time of the unmanned mining trucks was 2028 min, that of the unmanned excavators was 1055 min, and the total output was 26,400 t. With the production planning of the unmanned mining trucks, the total output was increased to 27,150 t, the total idle time of the unmanned mining trucks was reduced to 1983 min, and that of the unmanned excavators was reduced to 1011 min. With the collaborative production planning of the unmanned mining trucks and excavators, the total output was further increased to 27,750 t, the total idle time of the unmanned mining trucks was 1700 min, and that of the unmanned excavators was 973 min. Collaborative production planning effectively increased the total output and reduced the idle time of the unmanned excavators and mining trucks. Due to the decreased idle time and increased operation time, the transportation cost increased.

Table 2. Results of production planning calculations.

	Full Production Capacity (t)	Unmanned Excavator Idle Time (min)	Unmanned Mining Truck Idle Time (min)	Transportation Cost (RMB)
No planning	26,400	1055	2028	20,978
Planning of unmanned mining trucks only	27,150	1011	1983	20,624
Collaborative production planning	27,750	973	1700	21,672

3.3. Optimization

Based on the results of the production planning calculation tests mentioned above, even with multi-machine collaborative production planning, the idle time of the unmanned excavators was as long as 973 min. This can be attributed to the mismatch among the numbers of unmanned excavators, unmanned mining trucks, and unloading points. Considering the high cost of unmanned excavators, such long idle time prevents us from fully utilizing their capacity and negatively impacts the total output. Therefore, the multi-machine collaborative production planning algorithm was utilized to determine the optimal number of unmanned mining trucks and unloading points that can maximize the efficiency of the unmanned excavators.

In the case of 6 unmanned excavators, the target results were obtained through multi-machine collaborative production planning for the cases where the numbers of unmanned mining trucks were 20, 30, 40, 50, and 60. As shown in Figure 11, the idle time of the unmanned excavators improved from 973 min to 611 min when the number of trucks increased from 20 to 30. Further increasing the number of unmanned mining trucks to 40 led to an additional reduction of 160 min in idle time. However, once the number of unmanned mining trucks reached 50, the improvement in idle time began to slow down significantly. Increasing the number of unmanned mining trucks beyond this point did not significantly improve the idle time of the unmanned excavators. Considering the cost implications, it was determined that the matching effect of 50 unmanned mining trucks and 6 unmanned excavators was satisfactory, while the original scheme using 20 unmanned mining trucks resulted in extended idle time for the unmanned excavators.

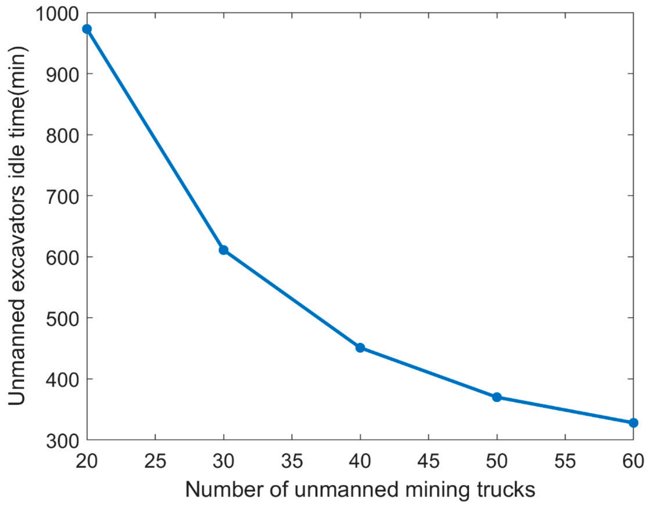

Figure 11. Relationship between idle time of unmanned excavators and number of unmanned mining trucks with 3 unloading positions.

Although increasing the number of unmanned mining trucks effectively reduced the idle time of the unmanned excavators, the remaining idle time of 370 min was still considered substantial. The limiting factor in further reducing this idle time was the number of unloading points. To address this, an additional unloading position was created at a point capable of accommodating two unmanned mining trucks simultaneously. In the case of six unmanned excavators, it was determined that by increasing the number of unloading positions from three to four, the idle time of the unmanned excavators was reduced by 297 min, decreasing it to 73 min, as shown in Figure 12. However, as the number of unloading positions continued to increase, the improvement effect became limited. Ultimately, with 6 unmanned excavators, 4 unloading positions, and 50 unmanned mining trucks, the total idle time of the unmanned excavators within an 8 h shift was reduced to 73 min, averaging 12.17 min per unit. This would allow for the full utilization of unmanned excavators.

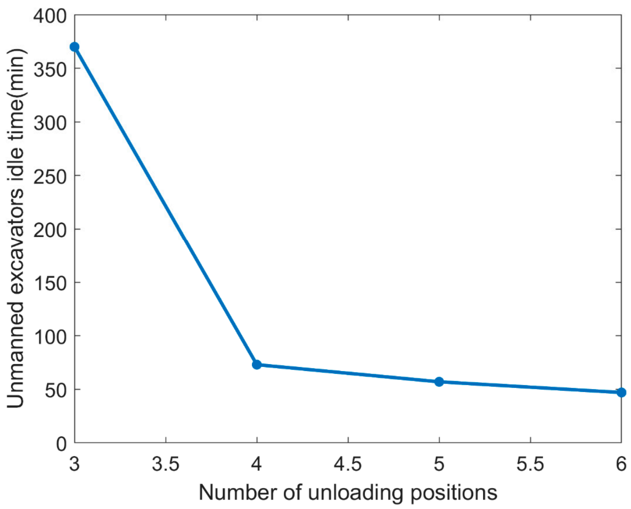

Figure 12. Number of unloading positions vs. idle time of unmanned excavators with 50 unmanned mining trucks.

Compared with the original configuration scheme with only 6 unmanned excavators, 20 unmanned mining trucks, and 3 unloading points, the optimized scheme included 6 unmanned excavators, 50 unmanned mining trucks, and 4 unloading points. This optimized scheme significantly improved the utilization rate of the unmanned excavators.

In Figure 13, it can be seen that the numbers of unmanned excavators, unmanned mining trucks, and unloading positions are well matched, allowing the unmanned excavators to operate continuously almost without shutting down under collaborative production planning. However, due to the nearly doubled number of unmanned mining trucks, there were significant changes in the operation of these trucks. Figure 14 shows that the idle time of the unmanned mining trucks increased significantly compared with the original scheme. Under the optimized scheme, the target functions were calculated as follows: The total production was 39,975 t, the transportation cost was RMB 28,380, the idle time of the unmanned excavators was 73 min, and that of the unmanned mining trucks was 13,065 min. Increasing the number of unmanned mining trucks and unloading points would further reduce the idle time of the unmanned excavators. However, this would also result in an increase in equipment quantity, mining cost, and idle time for the unmanned mining trucks. Therefore, the appropriate configuration scheme should be selected based on the actual demand and budget of the open-pit mine.

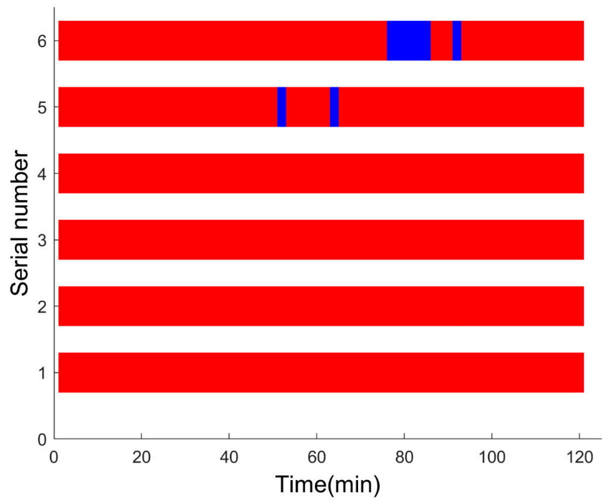

Figure 13. Gantt chart of unmanned excavator operation under optimized configuration scheme.

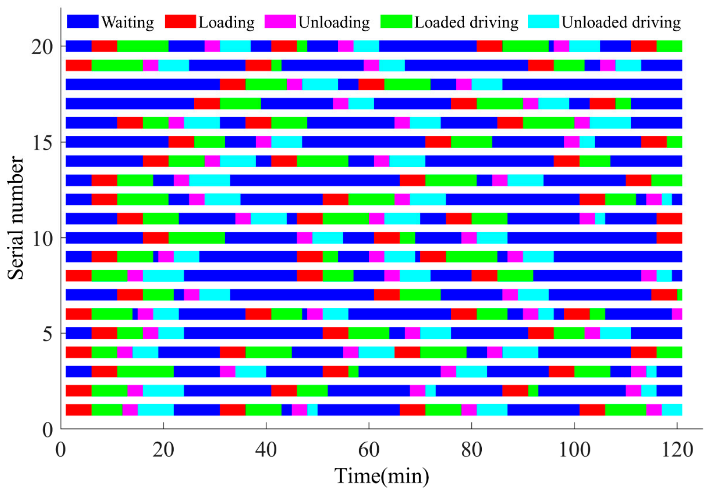

Figure 14. Gantt chart of unmanned mining truck operation under optimized configuration scheme.

4. Discussion

The results of this study indicate that the proposed collaborative production planning model outperforms traditional planning approaches in the context of unmanned mining operations. These findings underscore the potential of intelligent systems to improve the mining industry by enhancing both safety and efficiency. The findings are corroborated by similar studies in the field. For instance, Zhironkina et al. [6] highlighted the transformative impact of Industry 4.0 technologies on mining, aligning with the results that showcase the benefits of AI, the IoT, and advanced optimization algorithms. Liu et al. [19] employed multi-sensor fusion for the detection of unmanned mining trucks, showing the application of unmanned equipment in open-pit mines. Additionally, the work by Alexandre et al. [25] on maximizing ore production by using truck scheduling complements our focus on improving total output and efficiency.

Moreover, it is important to note that the results of this study advance the field by presenting an approach to collaborative production planning that considers both unmanned excavators and mining trucks simultaneously. Unlike previous research, which has often only focused on the individual components of the mining process [24–27], this model addresses the system as a whole, leading to more synergistic improvements. Compared with only considering unmanned mining trucks, with the model proposed in this study, we increased the total output by 600 t, reduced the idle time of the unmanned excavators by 38 min, and reduced the idle time of the unmanned mining trucks by 283 min in a shift. In previous studies [43,44], the configuration scheme of mining equipment was fixed in the planning. With the proposed method, the equipment configuration could be further improved. The optimized configuration, which integrates 6 unmanned excavators, 50 unmanned mining trucks, and 4 unloading points, leads to a 92% reduction in the idle time of the unmanned excavators and a 44% increase in total output.

The computational experiments provide empirical evidence that the proposed model can achieve the desired outcomes. The use of a multi-objective optimization approach allows for the balancing of competing objectives, obtaining a solution that optimizes multiple aspects of mining operation simultaneously. In this research study, we effectively addressed the main questions posed at the outset. The feasibility and advantages of implementing a collaborative production planning model in open-pit mines are demonstrated, particularly in the context of Industry 4.0. The model's ability to reduce idle time and increase output is a direct response to the urgent need for safer and more efficient mining practices. The results of this study are well supported by the evidence and arguments presented.

5. Conclusions

In this study, we established a collaborative production planning method for unmanned mining in open-pit mines with Industry 4.0 technologies. A collaborative production planning model was developed for unmanned excavators and mining trucks and solved by using a multi-objective optimization approach based on the genetic algorithm. To validate the effectiveness of this method, computational experiments were conducted for three different scenarios, including no production planning, the planning of the unmanned mining trucks only, and collaborative production planning. The results demonstrate that the proposed multi-machine collaborative production planning method can further reduce the idle time of equipment and improve the overall output compared with the planning of the unmanned mining trucks only. Moreover, in this study, we optimized mining equipment configuration schemes by using the multi-machine collaborative production planning method. The initial scheme, consisting of 6 unmanned excavators, 20 unmanned mining trucks, and 3 unloading positions, was optimized to a scheme of 6 unmanned excavators, 50 unmanned mining trucks, and 4 unloading positions. After optimization, the idle time of the unmanned excavators was reduced by 92%, and the total output was increased by 44%. The collaborative production planning method effectively enhances equipment utilization and output, providing technical support for safe and efficient production and unmanned mining in open-pit mines in the Industry 4.0 era.

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Conflicts of Interest: Kui Liu, Bin Mei, Shuai Sun, Qingping Zhang were employed by the company Sany Group, Changsha, China. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

AI	Artificial Intelligence
IoT	Internet of Things
DT	Digital Twin
NSGA	Non-dominated Sorting Genetic Algorithm
NSGA-II	Non-dominated Sorting Genetic Algorithm with elitist strategy
RMB	RenMinBi
min	Minute
3D	Three Dimensional
etc.	et cetera
t	ton
lidar	Light Detection and Ranging

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