



Article Micro-Factors-Aware Scheduling of Multiple Autonomous Trucks in Open-Pit Mining via Enhanced Metaheuristics

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Abstract: Traditional open-pit mineral transportation systems are typically subject to manual command, frequently leading to vehicular delays and traffic congestion. With the advancement of automation and electrification technologies, this study proposes a highly accurate scheduling method for multiple autonomous trucks in an open-pit mine. This model considers micro-level temporal and spatial factors to tackle the task of scheduling autonomous trucks within open-pit mines. The cost function of the concerned scheduling problem is a comprehensive evaluation of energy consumption, time, and output. Beyond the loading and unloading activities, the model also factors in the charging requirements of autonomous trucks in mining regions. The scheduling model integrates a Voronoi diagram search and optimal spatial path time matching, aiming to provide superior mission planning and decision-making solutions for autonomous trucks in mining regions. For an efficient solution to the scheduling problem, we propose an improved-evolution artificial bee colony (IE-ABC) algorithm. This algorithm improves the global search and re-initialization processes and conducts algorithm ablation experiments to closely examine their impact on optimization. Simulation results across various algorithms, cost function definition strategy, and encoding strategy show that our method can improve scheduling performance in energy consumption and time. Experimental results demonstrate that the proposed model and algorithm can effectively solve the scheduling decision-making problem in an unmanned open-pit mine.

Keywords: open-pit mine; autonomous truck; scheduling; artificial bee colony algorithm

1. Introduction

Open-pit mining presents benefits such as large-scale production, high resource recovery rates, and minimal environmental impact [1]. The complexity of the working environment within the open-pit mining area and the low efficiency of manual mining necessitate the introduction of autonomous mining systems [2].

In light of the rapid advancement of robotics, big data, artificial intelligence, and 5G technology, we are now observing the emergence of intelligent unmanned dump truck systems [3,4]. Given that around 50% of the gross operating costs in an open-pit mine would be spent on material transport [5], it has been an obvious trend to deploy unmanned transport tools to replace human labor [6]. Figure 1 illustrates that typical unmanned transportation tools in an open-pit mine include unmanned dump trucks, excavators, crushing stations, and charging piles. The excavator is used for mining ore, while the unmanned dump truck is designated for ore transportation. The truck moves to the location of the excavator for ore loading and then delivers it to the crushing station for unloading. Positioned within the mining area, the crushing station primarily serves to crush and pulverize the raw ore to meet the demands of further processing and utilization. When the unmanned dump truck needs recharging, it navigates to the charging pile to undergo the necessary charging process.



Citation: Fang, Y.; Peng, X. Micro-Factors-Aware Scheduling of Multiple Autonomous Trucks in Open-Pit Mining via Enhanced Metaheuristics. *Electronics* 2023, 12, 3793. https://doi.org/10.3390/ electronics12183793

Academic Editor: Mahmut Reyhanoglu

Received: 12 August 2023 Revised: 4 September 2023 Accepted: 5 September 2023 Published: 7 September 2023



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Figure 1. Schematic on an unmanned transport system in an open-pit mine.

Operating all of the aforementioned devices automatically is difficult because it requires simultaneously considering the features, principles, and capabilities of all devices when generating control commands, otherwise the automated control performance would be worse than that of human laborers [7]. In this sense, dividing the entire control scheme into multiple layers is a practical and feasible solution [8,9]. As shown in Figure 2, a scheduling module first assigns a traverse order for each of the devices; a decision-making module decides how two or more devices interact locally when their nominal trajectories are conflicting [10,11]; a planning module generates a spatio-temporal curve for each device to track [12,13]. This solution is inherently holding a decoupled strategy, i.e., the features, principles, and capabilities of all devices are no longer considered in a simultaneous way. Adopting such a decoupled strategy easily renders the loss of solution optimality, although it reduces the computational burden. Herein, the scheduling module is particularly important because a suboptimal decision made in the scheduling module would largely influence the downstream modules so that there is no chance to achieve optimality in mining operations. This analysis indicates that the scheduling module is important to guarantee the solution quality of an autonomous operating system in an open-pit mine [14]. The goal of this study is to propose a high-precision scheduling methodology with microscopic factors of each device considered, especially temporal factors. Through this, the scheduling method promises to coarsely find an ideal dispatch solution for the downstream modules efficiently without loss of optimality.



Figure 2. Overall flowchart of an unmanned transport system.

1.1. Related Work and Motivations

This subsection reviews the prevalent scheduling methods for dispatching multiple devices (especially transport vehicles) in an open-pit mine or similar scenarios.

In recent years, the scheduling problem in open-pit mines has received considerable attention. Patterson et al. [15] constructed a unique mixed-integer linear programming problem for multi-truck scheduling and used a Tabu Search algorithm to solve it, aiming to minimize the energy consumption of trucks and excavators. Zhang et al. [16], Yuan et al. [17], Wang et al. [18], Bastos et al. [19], Zhang et al. [20], and Bao et al. [21] employed similar strategies to build a model. However, the optimization objectives in these formulated problems only considered fuel consumption while ignoring factors such as consumed time and output amount. Wang et al. [22] proposed a multi-objective optimization (MOO) algorithm for truck scheduling, while Zhang et al. [23] proposed a decomposition-based constrained dominance genetic principle algorithm (DBCDP-NSGA-II) to solve the multiobjective intelligent scheduling problem for trucks in open-pit mines. Ahumada et al. [24], Chang et al. [25], and Afrapoli et al. [26] also built a multi-objective scheduling model. However, a common limitation of refs. [22–26] is that the formulated problem did not consider the refueling or charging requirements of the trucks. Zhang et al. [27] proposed a meta-heuristic search algorithm to solve a mixed-integer programming problem formulated for the concerned multi-truck scheduling scheme and demonstrated by experimentation that this approach improves the energy efficiency of the transport system in open-pit mines. Smith et al. [28] proposed a time-discretized mixed integer programming (MIP) model for the truck scheduling problem in open-pit mines, and a heuristic is used to quickly generate high-quality feasible solutions. However, the proposed model ignored the path planning between loading and unloading spots. Similarly, Zeng et al. [29], de Melo [30], and Yeganejou et al. [31] did not consider the path planning between loading and unloading spots either.

Most previous scheduling models focused on single-objective optimization, particularly energy consumption, and often overlooked the need for multiple optimization objectives. Additionally, these methods focused solely on truck-carrying activities without considering the refueling or charging requirements of the trucks. Path planning between loading and unloading spots, a crucial aspect of scheduling, has also been largely ignored in previous research. As a conclusion of this subsection, the prevalent scheduling methods do not model the concrete dynamics/kinematics and other temporal constraints of the operating devices; thus, they did not account for the actual complexity of operating an open-pit mine.

1.2. Contributions

Following the motivations introduced in the preceding subsection, we summarize the contributions of this paper and are as follows.

First, we propose a high-precision scheduling model with microscopic factors of each device considered. The model incorporates the use of a Voronoi diagram for spatial path estimation and velocity assignment. The diagram is used to enhance the scheduling accuracy so that local factors are well considered.

Second, this paper proposes a novel structure to present each of the solutions, thus enhancing the interpretability of the scheduling process and facilitating the solution generation process.

Third, a novel metaheuristic optimizer is proposed to search for a high-quality scheduling solution based on the aforementioned model and solution structure. The proposed optimizer is a special variant of the artificial bee colony (ABC) algorithm, which enhanced the ability to quickly exploit feasible solution candidates.

1.3. Organization

In the remainder of this paper, Section 2 formulates the concerned scheduling problem as a combinatorial optimization problem. Section 3 introduces the proposed optimizer to

solve the formulated optimization problem together with a novel solution presentation structure. Simulation results are reported and discussed in Section 4, followed by Section 5, where conclusions are finally drawn.

2. Problem Formulation

This section formulates the concerned scheduling scheme as a combinatorial optimization problem, which is focused on how to use unmanned dump trucks and excavators to deliver mine materials efficiently in open-pit mining. The purpose of the combinatorial optimization problem is to minimize the consumed energies, maximize the mineral transport capacity, and minimize the operation time.

In this work, unmanned dump trucks and excavators are the two types of machinery operated in the concerned mining transport scheme. Given that the terrain of the open-pit mine is not even, some parts of the terrain occupied by obstacles are not drivable; thus, the uneven parts of the terrain are regarded as obstacles. Suppose that the number of deployed unmanned dump trucks is N_{truck} . This work assumes that each excavator is fixed at a loading spot, a designated location where loading operations occur. The gross number of loading spots is denoted as $N_{loading_spots}$. Similarly, we assume that the number of unloading spots is $N_{unloading_spots}$. Before its battery is completely depleted, an unmanned dump truck should visit a charging spot for battery recharging. The basic working states of an unmanned dump truck include moving to the loading spot, loading, moving to the unloading spot, unloading, and moving to the charging spot. Given that the excavators are fixed, operating the devices in this open-pit mine means manipulating the N_{truck} unmanned dump trucks. Thus, the concerned scheduling task is about deciding the working states and targets of each unmanned dump truck in a sequence for the next N_{step} steps.

2.1. Cost Function Formulation

The concerned scheduling scheme is inherently a combinational optimization problem, aiming to minimize overall energy consumption, maximize transport capability, and reduce vehicle idle times, for N_{step} tasks assigned to each of the N_{truck} unmanned dump trucks. The cost function of the combinational optimization problem, as described in Equation (1), is a weighted sum of three terms: each truck's transport capability, energy consumption, and the total time spent when the last truck among all the N_{truck} ones finishes its N_{step}-th task. The three terms are summed up after being multiplied by weighting coefficients w_1 , w_2 , and w_3 :

$$\sum_{i=1}^{\text{truck}} \left(\frac{\mathbf{w}_1}{Q_i} + \mathbf{w}_2 \times E_i \right) + \mathbf{w}_3 \times T, \tag{1}$$

where Q_i denotes the gross transport capability of unmanned dump truck *i* after finishing all of its N_{step} tasks, E_i denotes the consumed energies of unmanned dump truck *i* after it finishes all of its N_{step} tasks, and *T* denotes the earliest moment that all of the N_{truck} trucks finish their N_{step} tasks. Details behind these variables are defined as follows.

2.2. Transport Capability Composition

In Equation (2), Q_i is defined as the product of the basic loading capability of the truck *i* (i.e., C_i) and $N_{\text{unloading}}$, the steps among all of the N_{step} ones that involve unloading actions. Notably, $N_{\text{unloading}}$ is determined according to a specific solution.

$$Q_i = C_i \times N_{\text{unloading}}.$$
 (2)

2.3. Energy Consumption Composition

Equation (3) shows that the energy consumption of each unmanned dump truck is composed of the energy consumption during the on-road cruising process, the en-

ergy consumption during the loading actions, and the energy consumption during the unloading actions:

$$E_i = E_{\text{cruising}} + E_{\text{loading}} + E_{\text{unloading}}.$$
 (3)

Herein, E_{cruising} sums up the energy consumption of unmanned dump truck *i* during its cruising process. E_{loading} sums up the energy consumption of unmanned dump truck *i* during all of its loading actions. $E_{\text{unloading}}$ sums up the energy consumption of unmanned dump truck *i* dump truck *i* during its unloading actions.

 E_{cruising} consists of two components: energy consumed by the drive system and that of the accessory system [32]. According to the classical vehicle dynamics principle [33], the energy consumption of an unmanned dump truck is defined as

$$E_{\rm cruising} = w_4 \times v_i^3 \times T_{\rm cruising} + w_5 \times v_i \times T_{\rm cruising},\tag{4}$$

where T_{cruising} is the driving time of unmanned dump truck *i* to complete N_{step} tasks, which is determined as per a specific solution candidate. v_i denotes the average speed of unmanned dump truck *i* during cruising process. w₄ and w₅ are weighting parameters.

Equations (5) and (6) define the energy consumption during loading and unloading actions, respectively:

$$E_{\text{loading}} = w_6 \times T_{\text{loading}},\tag{5}$$

$$E_{\text{unloading}} = w_6 \times T_{\text{unloading}}.$$
 (6)

Herein, T_{loading} is the loading time of unmanned dump truck *i* during loading tasks; $T_{\text{unloading}}$ is the unloading time of unmanned dump truck *i* during its unloading tasks. w₆ is the coefficient that converts loading/unloading time to energy consumption.

2.4. Time Composition

In the process of completing N_{step} assigned tasks, each unmanned dump truck encounters several stages, including a driving stage, a waiting stage, a loading stage, an unloading stage, and a charging stage. Equation (7) defines the time for each truck to complete the corresponding N_{step} established tasks.

$$T_i = T_{\text{cruising}} + T_{\text{loading}} + T_{\text{unloading}} + T_{\text{waiting}} + T_{\text{charging}}$$
(7)

where T_i is the total time of unmanned dump truck *i* to complete N_{step} tasks; $T_{unloading}$ is the waiting time of unmanned dump truck *i* to complete N_{step} tasks; and $T_{charging}$ is the charging time of unmanned dump truck *i* to complete the scheduled N_{step} tasks.

Equation (8) presents the total time taken by N_{truck} unmanned dump trucks to complete N_{step} given tasks.

$$T \equiv \max\{T_1, T_2, T_3 \dots T_{N_{\text{truck}}}\}.$$
(8)

Equation (9) indicates that the driving time of unmanned dump truck *i* is related to the task spots that need to be visited:

$$T_{\text{cruising}} = \sum_{j=1}^{N_{\text{step}}} TravelTime(taskspot_j, taskspot_{j+1}).$$
(9)

Herein, TravelTime(a, b) is a function that estimates the driving time from task spot *a* to *b*. $taskspot_j$ denotes the task spot that the jth task of unmanned dump truck *i* is required to visit.

Equation (10) defines the loading time of unmanned dump truck *i* during loading tasks:

$$T_{\text{loading}} = N_{\text{step}_\text{load}} \times T_{\text{load}_p}, \tag{10}$$

where T_{load_p} is the loading time for unmanned dump truck *i* loading at each loading spot. N_{step_load} is the number of loading tasks.

Equation (11) shows the unloading time of unmanned dump truck *i* during unloading tasks:

$$T_{\text{unloading}} = N_{\text{step_unload}} \times T_{\text{unload_p}}, \tag{11}$$

where T_{unload_p} denotes the unloading time for unmanned dump truck *i* unloading at each unloading spot. N_{step_unload} is the number of unloading tasks.

Equation (12) indicates that waiting time includes the time waiting for loading, waiting for unloading, and waiting for charging.

$$T_{\text{waiting}} = T_{\text{waiting}_\text{load}} + T_{\text{waiting}_\text{unload}} + T_{\text{waiting}_\text{charge}},$$
(12)

where $T_{\text{waiting_load}}$ denotes the time that unmanned dump truck *i* spends on waiting for loading during the completion of N_{step} tasks; $T_{\text{waiting_unload}}$ denotes the time that unmanned dump truck *i* spends on waiting for unloading during the completion of N_{step} tasks; and $T_{\text{waiting_charge}}$ denotes the time that unmanned dump truck *i* spends on waiting for charging during the completion of N_{step} tasks.

Equation (13) shows that the charging time depends on the residual capacity when the unmanned dump truck reaches the charging spot for charging:

$$T_{\text{charging}} \equiv \frac{\mathrm{E}_{\text{full}} - \mathrm{E}_{\text{remain}}}{\mathrm{q}}.$$
 (13)

Herein, E_{full} is the full electric quantity of unmanned dump truck *i*; E_{remain} is the residual capacity when the unmanned dump truck *i* reaches the charging spot; and q represents the charging efficiency.

The residual capacity of the unmanned dump truck depends on how many tasks are completed and which loading and unloading spots are visited.

3. Methodology

In the scheduling problem formulated in the previous section, the solution candidates differ from one another in their task scheduling sequences, thereby resulting in different cost function values. This section introduces how to solve the formulated problem. To that end, the first thing is to define an encoding principle so that all of the solution candidates can be presented uniformly in such a solution space. Thereafter, an efficient solver should be proposed to search for the optimal or near-optimal solution in the defined solution space. The technical details are introduced in the next few subsections.

3.1. Principle of Solution Vector Encoding

The encoding strategy for the scheduling sequence is determined by the number of loading and unloading spots in the environment. Concretely, if there are two loading spots and three unloading spots, the serial numbers for the loading spots are designated as {1, 2}. Meanwhile, the serial numbers for the unloading spots are set to {3, 4, 5}, and the serial number for the charging spot is represented as {6}. As shown in Figure 3, suppose that there are eight tasks to be scheduled for each unmanned dump truck. The scheduling sequence for the unmanned dump truck #1 might be {1, 3, 2, 4, 2, 1, 2, 5}. In such a sequence, the red part of the figure should be penalized for repeated selections of the loading spot while the green part should not be penalized for repeated selections of the unloading spot while the green part should not be penalized.



Figure 3. Schematic of solution vector encoding.

3.2. Scheduling Problem Re-Formulation

Ν

In the previous section, Equation (1) defines the cost function. However, the cost function does not adequately consider the establishment of the hard constraint. Therefore, we redefine the cost function here to ensure that the feasibility of the solution vector is not determined solely by the constraint, but also by the penalty function. This redefinition is beneficial for the subsequent utilization of the optimization algorithm, which will be discussed in detail later.

When allocating tasks to multiple unmanned dump trucks, it is vital to ensure that the optimal task scheduling sequence prevents excessive idle time for any truck. Thus, the variance of time taken by each unmanned dump truck to finish its tasks is incorporated into the cost function as a penalty term. This inclusion promotes quicker identification of the optimal task scheduling sequence, averting significant disparities in the completion times among trucks. As a result, the revised cost function is defined as follows:

$$\sum_{i=1}^{\mathcal{N}_{\text{truck}}} \left(\frac{\mathbf{w}_1}{Q_i} + \mathbf{w}_2 \times E_i \right) + \mathbf{w}_3 \times T + \mathbf{w}_7 \times N_{\text{punish}} + \mathbf{w}_8 \times T_{\text{var}},\tag{14}$$

where N_{punish} is the number of repeated loading and unloading spots in the task scheduling sequence. w_7 is the weight coefficient of the penalty term for repeated spots. T_{var} represents the variance of the time taken by all unmanned dump trucks to complete the given task according to the current task scheduling sequence. w_8 is the weight coefficient of the penalty term for variance.

3.3. Improved-Evolution Artificial Bee Colony Search Procedure

The artificial bee colony (ABC) algorithm is a heuristic optimization algorithm based on bee behavior. It is used to solve complex optimization problems by simulating the foraging behavior and information exchange of bees. The local search accuracy of the conventional ABC algorithm is not satisfactory. The improved-evolution artificial bee colony (IE-ABC) algorithm used in this paper is an improved artificial bee colony algorithm. The search intensity is manipulated by adding an adaptive change multiplier to the global search equation, and the traditional re-initialization process is improved by the overall degradation strategy to obtain a better optimal solution.

Algorithm 1 uses the IE-ABC search framework to search for the optimal scheduling scheme, which includes the initialization phase (lines 1–2), the employed bee phase (lines 4–12), the calculation of the probability index to prepare for the roulette selection strategy (lines 13–20), the onlooker bee phase (lines 21–38), and the scout bee phase (lines 39–44). *trial(i)* records the number of times an inefficient search is performed by the ith employed bee or any onlooker bee that searches around the ith employed bee. $\frac{trial(item)}{trial(item)+trial(k)}$ in the fifth line is utilized as an adaptive change multiplier to regulate the search intensity. The solution vector *X* represents the scheduling sequence, and Equation (14) represents the objective function GetCostFun(). *P* represents the probability index. During the scout bee stage, if the number of searches exceeds the limit, the position of the scout bee is reinitialized.

The pseudo-code of the IE-ABC algorithm is given as follows.

Algorithm 1. IE-ABC.

- 1. Set the population size PN, and maximum cycle number MCN; Set the inefficient trial time counter $trial(i) \leftarrow 1$ (i = 1, 2, ..., PN/2);
- 2. Randomly initialize locations of PN/2 scout bees;
- 3. for *iter* = 1 to MCN do
- 4. for *item* = 1 to PN/2 do
- 5. Generate X^{*}_{item} for the *item*-th employed bee to search according to

$$X_{item}^* \leftarrow X_{item} + rand(-1,1) \times (X_k - X_{item}) \times \frac{trial(item)}{trial(item) + trial(k)};$$

- 6.
- $\begin{array}{l} X'_{item} \leftarrow \text{ChargeConstruct}(X^*_{item});\\ \text{if GetCostFun}(X'_{item}) < \text{GetCostFun}(X_{item}) \text{ then} \end{array}$ 7.
- 8. $X_{item} \leftarrow X^*_{item}$, and set $trial(item) \leftarrow 1$;
- 9. else
- 10. $trial(item) \leftarrow trial(item) + 1;$
- 11. end if
- 12. end for
- 13. for i = 1 to PN/2 do
- 14. if GetCostFun(X_i) ≥ 0 then
- 15. $fitness(i) \leftarrow \frac{1}{1 + \text{GetCostFun}(X_i)};$
- 16. else
- 17. $fitness(i) \leftarrow 1 + |\text{GetCostFun}(X_i)|;$
- 18. end if

19.
$$P(i) \leftarrow \frac{\sum_{j=1}^{i} fitness(j)}{\sum_{j=1}^{PN/2} fitness(j)};$$

- 20. end for
- 21. Set *item* = 0;
- 22. Set j = 1;
- 23. while *item* < PN/2 do
- 24. **if** P(i) > rand(0, 1) **then**
- 25. *item* \leftarrow *item* +1;
- Choose the jth employed bee to follow, and then generate, 26. trial(i)

$$Y_{item} \leftarrow X_j + rand(-1,1) \times (X_k - X_j) \times \frac{irrat(j)}{trial(j) + trial(k)};$$

- 27. $Y'_{item} \leftarrow \text{ChargeConstruct}(Y_{item});$
- if GetCostFun $(Y'_{item}) < \text{GetCostFun}(X_j)$ then 28.
- 29. $X_j \leftarrow Y_{item}$, and set $trial(j) \leftarrow 1$;
- 30. else
- 31. $trial(j) \leftarrow trial(j) + 1;$
- 32. end if
- 33. end if
- $i \leftarrow j + 1;$ 34.
- 35. **if** j > PN/2 **then**
- Set $j \leftarrow 1$; 36.
- 37. end if
- end while 38.
- 39. for *item* = 1 to PN/2 do;
- 40. if *trial*(*item*) > Limit then
- Re-initialize the location of the *item*-th employed bee; 41.
- 42. Set *trial*(*item*) \leftarrow 1;
- end if 43.
- 44. end for
- 45. Memorize the best solution;
- 46. end for
- 47. Output the best solution;

During the initialization phase, the sequence for scheduling is arranged based on the loading and unloading order to streamline the search for the best solution. After establishing this sequence, the energy consumption required for the unmanned dump truck to complete its tasks is assessed. This assessment subsequently informs when the truck needs recharging.

Algorithm 2 identifies the best recharging moments, relying on the loading and unloading order of the unmanned dump truck. The algorithm starts by accepting the sequence of loading and unloading tasks as its input. In its third line, it estimates the driving time between successive task spots, as dictated by the task sequence. The next line, i.e., line 4, computes the truck's residual energy, based on the calculated driving time. Then, from lines 5 to 10, the algorithm discerns if there exists a need for recharging by considering the leftover energy. If charging is deemed necessary, it then updates the task sequence to accommodate this.

The pseudo-code for the ChargeConstruct algorithm is presented below.

Algorithm 2. ChargeConstruct				
Input: X;				
Output: X';				
1. Set $i = 1$;				
2. while $i < N_{\text{step}} \mathbf{do}$				
3. $T_{\text{cruising}} \leftarrow \text{TravelTime}(X_i, X_{i+1});$				
4. $E_{\text{remain}} \leftarrow \text{Energycost}(T_{\text{cruising}});$				
5. if $E_{\text{remain}} < 0$ then				
6. $X_i \leftarrow \text{chargespot};$				
7. $X \leftarrow \text{new}X$;				
8. $N_{\text{step}} \leftarrow \text{new } N_{\text{step}}$;				
9. $i \leftarrow 1$;				
10. end if				
11. end while				
12. $X' \leftarrow X$;				
13. return.				

The energy consumption of the unmanned dump truck is related to the working time. The driving time of the unmanned dump truck between the loading spots, unloading spots, and charging piles is proportional to the path length. The planning space is modeled by using the Voronoi diagram, and the optimal path is obtained by combining the A* search algorithm [34], so as to estimate the optimal path length.

The Voronoi diagram is a fundamental geometric concept used to divide a plane based on a discrete set of spots. The diagram ensures that the distance from any spot in a given region to its corresponding spot in the discrete set is smaller than the distance to any other spot in the set.

Assuming that the set of discrete spots $D = \{d_1, d_2, d_3 \dots d_n\}$, the mathematical expression of the Voronoi diagram is as follows:

$$\sqrt{(x-x_i)^2 + (y-y_i)^2} < \sqrt{(x-x_j)^2 + (y-y_j)^2}, \ i \neq j$$
(15)

where (x_i, y_i) and (x_j, y_j) represent the coordinates of any two discrete spots d_i and d_j in the set D, respectively. (x, y) represents the coordinates of any spot on the plane.

By satisfying Equation (15), the set of spots (x, y) forms the Voronoi region for the discrete spot d_i . Consequently, the plane can be divided into *n* polygons, where each polygon contains only one discrete spot d_i .

Furthermore, the spots lying on the edges of the Voronoi polygon satisfy specific constraints.

$$\begin{cases} \sqrt{(x-x_i)^2 + (y-y_i)^2} = \sqrt{(x-x_j)^2 + (y-y_j)^2} \\ \sqrt{(x-x_i)^2 + (y-y_i)^2} < \sqrt{(x-x_k)^2 + (y-y_k)^2} \end{cases}, \ i \neq j \neq k \tag{16}$$

where (x_i, y_i) and (x_j, y_j) represent the coordinates of adjacent discrete spots d_i and d_j , respectively. (x_k, y_k) represents the coordinates of any other discrete spot d_k .

The planning space is segmented into multiple Voronoi regions based on the placement of obstacles within the environment. Recognizing that obstacles can vary in size and shape, their boundaries are discretized using a method that employs numerous discrete spots to encapsulate these boundaries. The Delaunay triangulation algorithm constructs the Voronoi diagram from this. To enhance this representation, virtual nodes are placed near pivotal areas, including loading spots, unloading spots, and charging spots. These nodes are then integrated with the original Voronoi diagram, yielding the final representation.

The A* algorithm operates on a traversal search principle, leveraging a heuristic function. This function gauges the cost of moving from any location to the destination, steering the search towards the most viable routes. By adopting the Voronoi diagram as the model for the planning space, the A* algorithm's search is limited to traversing only the nodes within the diagram, substantially enhancing its efficiency. After identifying the best path, the algorithm can then estimate its length.

4. Simulation Results and Discussion

This section reports the simulation results, together with our in-depth discussions. Concretely, the simulation experiments will be conducted in three aspects. First, comparative experiments will be performed using various optimization algorithms. Second, comparative experiments will be carried out with different cost function definition strategies. Third, comparative experiments will be performed using different encoding strategies for the solution vector.

4.1. Simulation Setup

Simulations are implemented in a MATLAB platform and executed on an Intel(R) Core(TM) i7-7700 CPU with 16 GB RAM that runs at 8×3.6 GHz.

Critical parameters are listed in Table 1. In order to increase the diversity of unmanned dump trucks, two kinds of unmanned dump trucks are set up, which have different load capacities and loading and unloading times, respectively. Each unmanned dump truck has two average speeds during cruising.

Parameter	Description	Setting
N _{truck}	Number of unmanned dump trucks	4
N _{step}	Number of tasks to be completed per unmanned dump truck	20
N _{loading_spots}	Number of loading spot	2
N _{unloading_spots}	Number of unloading spot	3
w ₁ , w ₂ , w ₃	Weight coefficient in Equation (1)	$100, 2.7 imes 10^{-7}, 0.01$
	Weight coefficient in Equation (4)	0.925, 430
w ₆	Weight coefficient in Equation (5)	4000
Ci	The load capacity of unmanned dump truck <i>i</i>	1 t, 2 t
vi	The average speed of unmanned dump truck <i>i</i> during cruising	10 m/s, 15 m/s
T _{load_p}	Loading time of unmanned dump truck i at loading spot	10 s, 20 s
T _{unload_p}	Unloading time of unmanned dump truck <i>i</i> at unloading spot	10 s, 20 s
E _{full}	Full electric quantity of unmanned dump truck <i>i</i>	0.25 kWh
q	Charging efficiency	$3 imes 10^4 { m J/s}$
	Weight coefficient in Equation (14)	1,0.0001

Table 1. Parametric settings for simulations.

4.2. Simulation Results

The conventional ABC and the proposed IE-ABC are used to solve the proposed scheduling problem. The results are shown in Table 2. The cost function value obtained by IE-ABC is 10.31, while the cost function value obtained by ABC is 10.43. The cost function value obtained by IE-ABC is 0.67% lower than that of ABC. Additionally, the energy consumption and time required for the solution obtained by IE-ABC to complete the task are 8.93×10^6 J and 620.0 s, respectively. On the other hand, the energy consumption and time required for the solution obtained by IE-ABC reduces the energy consumption and time required to complete the task by 0.23% and 0.93%, respectively, compared to ABC. The improved algorithm has achieved steady advantages in terms of both energy consumption and time. The scheduling Gantt chart of the solution obtained by IE-ABC is shown in Figure 4.



Table 2. Simulation result of different optimization algorithms.

Figure 4. Vehicle scheduling results presented in a Gantt chart.

It can be seen from Figure 4 that the effectiveness of the scheduling scheme is guaranteed. The obtained scheduling sequence can arrange the loading and unloading tasks of the unmanned dump truck in an orderly manner, and the charging tasks are interspersed among them to ensure the coordination and sustainability of the tasks. As shown in Figure 4, the Gantt chart of the scheduling scheme for 20 tasks is arranged for the four unmanned dump trucks, respectively. Different colors represent the unmanned dump trucks working at different task spots, among which No. 1 and No. 2 represent the loading spots, No. 3, No. 4, and No. 5 represent the unloading spots, No. 6 represent the charging spot, red represents the unmanned dump truck driving stage, and purple represents the unmanned dump truck waiting stage.

It can be seen from the figure that the unmanned dump truck #1 first travels to the No. 2 loading spot to complete the loading task, and then travels to the No. 4 unloading spot to perform the unloading task. The unmanned dump truck #2 reaches the No. 2 loading spot later than the unmanned dump truck #1, so the unmanned dump truck #2 waits for the unmanned dump truck #1 to complete the loading task at the No. 2 loading spot, and then performs the loading task at the No. 2 loading spot.

In order to explore the influence of different factors on ABC optimization, ablation experiments are carried out. The ablation experiment results are shown in Figure 5. Compared with the conventional ABC, IE-ABC mainly changes two factors. One is to add an adaptive multiplier to the global search equation to manipulate the search intensity, and the other is to implement the traditional re-initialization process through the overall degradation strategy. In Figure 5, AE-1 only changes the first factor compared with the conventional ABC, and AE-2 only changes the second factor. It can be seen from the results in the figure that changing these two items has promoted the optimization search, and changing the second factor has a greater impact on the early optimization.



Figure 5. Ablation experimental results.

In order to explore the impact of different cost function definition strategies on solving the scheduling problem, a cost function considering energy consumption, time, and output is established. This function is compared against a cost function that disregards time and only considers energy consumption and output. The experimental results are presented in Table 3. The cost function value of the optimal solution obtained using the cost function considering energy consumption, time, and output is 10.31. In comparison, the cost function value of the optimal solution obtained ignoring time and only considering energy consumption, the former is 3.1% lower than the latter. With the time-incorporated cost function, the energy consumption and time for the optimal solution to complete the task are 8.93×10^6 J and 620.0 s, respectively. Using the cost function without time, the energy consumption and time required for the optimal solution to complete the task are 9.00×10^6 J and 652.9 s, respectively. Compared to the latter, the former reduces energy consumption and task time by 0.78% and 5.04%, respectively.

Table 3. Simulation result of different cost function definition strategies.

Cost Function Definition Strategy	Cost	Consumed Energy (10 ⁶ J)	Time (s)
Regarded-time Strategy	10.31	8.93	620.0
Disregarded-time Strategy	10.63	9.00	652.9

As shown in Figure 6, the Gantt chart illustrates the optimal scheduling scheme obtained using the cost function that disregarded time and only considered energy consumption and output. The meaning of different colors and numbers in Figure 6 is the same as that in Figure 4. Compared to the optimal scheduling scheme in Figure 4 found by comprehensively accounting for energy consumption, time, and output in the cost function, the time for each unmanned dump truck to complete its corresponding 20 tasks is increased. This indicates that incorporating time into the cost function along with energy consumption and output enabled optimization to find an improved solution.

To investigate the impact of different vector encoding strategies on the solution of the scheduling problem, we compared the solution vector encoding strategy proposed in Section 3.1 with the binary encoding strategy. In the binary encoding strategy, the allocation of tasks is represented by a binary string. For example, if there are two loading spots and three unloading spots, the scheduling sequence {01001} represents that the unmanned dump truck travels to No. 2 loading spot to load and then proceeds to No. 5 unloading spot to unload.



Figure 6. Scheduled Gantt chart with cost function that disregards time.

The comparative experimental results of the two encoding strategies are presented in Table 4. The cost function value of the optimal solution obtained using the proposed encoding strategy is 10.31, compared to 10.61 for the binary encoding strategy. The proposed encoding strategy's cost function value is 2.83% lower than that of the binary encoding strategy. The energy consumption and time for the proposed encoding strategy's optimal solution are 8.93×10^6 J and 620.0 s, respectively. In comparison, energy consumption and time for the binary encoding optimal solution are 9.07×10^6 J and 636.2 s, respectively. Compared to the binary encoding solution, the proposed encoding strategy's solution reduces energy consumption and task time by 1.54% and 2.55%, respectively.

Table 4. Simulation result of different encoding strategies.

Encoding Strategy	Cost	Consumed Energy (10 ⁶ J)	Time (s)
Proposed Encoding	10.31	8.93	620.0
Binary Encoding	10.61	9.07	636.2

Figure 7 shows the Gantt chart for the optimal scheduling scheme obtained through binary encoding. The meaning of different colors and numbers in Figure 7 is the same as that in Figure 4. Compared to the Gantt chart in Figure 4 using the proposed encoding strategy, a larger time gap existed between the earliest finishing unmanned dump truck #3 and the latest finishing unmanned dump truck #2 for their respective 20 assigned tasks. Additionally, the total time is longer with the binary encoding strategy. This indicates that the encoding strategy used in this study enabled obtaining an improved scheduling scheme.



Figure 7. The scheduling Gantt chart with binary encoding strategy.

4.3. Discussion

The developed scheduling algorithm is suitable for the unmanned dump truck scheduling problem in a complex open-pit mine environment. First, for the complex terrain and road network in the open-pit mine area, the algorithm can select the best path according to the location and target of the unmanned dump truck to minimize energy consumption and time cost. Second, the algorithm can intelligently allocate the driving route for the unmanned dump truck according to the energy situation of the unmanned dump truck, so as to avoid the occurrence of energy exhaustion. In addition, the algorithm can reasonably arrange the driving sequence and work allocation of unmanned dump trucks, so as to maximize the location and task requirements between unmanned dump trucks, so as to maximize the overall production efficiency. However, it is important to note that the algorithm may face certain technical limitations in the open-pit mine environment. Factors such as terrain changes and weather conditions can impact the algorithm's performance.

5. Conclusions

This article has proposed a high-precision multi-vehicle collaborative scheduling proposition model considering micro-space-time factors to solve the unmanned dump truck scheduling problem in open-pit mines.

The optimization objective comprehensively considers energy consumption, time, and output. In addition to the loading and unloading activities, the unmanned dump truck also considers charging demand in the scheduling model. The model incorporates Voronoi graph search and optimal time matching of spatial paths. It aims to provide a better task decision planning solution for unmanned dump trucks in mining areas. To effectively solve the scheduling problem, an improved artificial bee colony algorithm is proposed. The original algorithm is enhanced in the global search process and the re-initialization process. An ablation experiment is conducted to explore the impact of these improvements on the optimization process. The ablation experiment result shows that changing these two items has promoted the optimization search. In addition, comparative simulation experiments are conducted using different algorithms, cost function definition strategies, and encoding strategies. Comparative simulations indicate the proposal can reduce energy consumption and time. Compared to the models utilizing ABC algorithms, cost function strategy definition without considering time, and binary encoding strategy, the proposed model and method achieved reductions of 0.67%, 3.1%, and 2.83% in the comprehensive cost functions of energy consumption, time, and output, respectively. Moreover, simulation

results demonstrate that the proposed model and method offer an effective solution for scheduling decisions in mining areas.

There are numerous factors that impact the overall cost of the unmanned dump truck scheduling problem. In the future, it is worth exploring the optimization of speed and scheduling arrangements in the event of unmanned dump truck failures. These areas present promising avenues for further research.

Author Contributions: Conceptualization, Y.F. and X.P.; methodology, X.P.; validation, Y.F. and X.P. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Natural Science Foundation of China under Grant 52275105.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The simulation data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflict of interest.

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