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A Dynamic Scheduling Model for Underground Metal Mines under Equipment Failure Conditions

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Abstract: Equipment failure is a common problem in mining operations, resulting in significant delays and reductions in production efficiency. To address this problem, this paper proposes a dynamic scheduling model for underground metal mines under equipment failure conditions. The model aims to minimize the impact of equipment failures on production operations while avoiding extensive equipment changes. A case study of the southeastern mining area of the Chambishi Copper Mine is presented to demonstrate the effectiveness of the proposed model. The initial plan was generated using the multi-equipment task assignment model for the horizontal stripe pre-cut mining method. After equipment breakdown, the proposed model was used to reschedule the initial plan. Then, a comparative analysis was carried out. The results show that the proposed model effectively reduces the impact of equipment failures on production operations and improves overall mining execution at a low management cost. In general, the proposed model can assist schedulers in allocating equipment, coping with the disturbing effects of equipment failure, and improving mine production efficiency.

Keywords: dynamic scheduling; equipment failure; rescheduling plan; multi-equipment task assignment; underground metal mine

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1. Introduction

Underground mine scheduling is complex and challenging, and it involves coordinating different equipment and tasks to achieve optimal production outcomes [1]. To maximize production, mine operators must develop a scheduling plan that minimizes operation time and increases the utilization of available equipment. The scheduling of underground mining activities is influenced by a range of factors, including the availability of equipment, geological conditions, and safety considerations. The efficient scheduling of mining requires the use of advanced optimization techniques to develop optimal schedules that minimize operational costs while maximizing productivity [2,3].

The scheduling optimization of intelligent mining equipment in underground metal mines is a flexible production problem that involves generating different scheduling plans by integrating various combinations of multiple stopes, processes, and equipment under complex temporal and spatial constraints. The solution to this problem requires an intelligent optimization algorithm to identify the optimal initial scheduling plan [4–6]. Research on intelligent mining equipment scheduling optimization in underground metal mines is critical to achieving high-efficiency, real-time operation, reliability, stability, and flexibility in mine production scheduling. This problem exhibits several characteristics, such as complexity, dispersion, parallelism, multiple constraints, multiple resources, and multi-target coordination, making it a strong NP-hard (nondeterministic polynomial) problem [7,8].

In the actual production processes of the mine, the production environment is challenging, and the working procedures are complex and discrete. The working equipment is difficult to coordinate, and the workplaces are scattered, which often results in a long production cycle. Furthermore, dynamic events such as equipment failures, rock collapses, and ore pass blockages occur frequently [9–12]. Due to the highly dynamic and complex production environment, the actual production process tends to deviate from the initial scheduling plan gradually, reducing the feasibility of the initial scheduling plan. Therefore, it is crucial to adjust the initial scheduling plan to prevent production interruptions or delays and to quickly respond to dynamic events to minimize their impacts [13].

The dynamic scheduling of underground mining equipment aims to reduce the deviation from actual progress by adjusting the initial scheduling plan, ensuring scheduling stability, responding promptly to dynamic events, and optimizing equipment operation. Consequently, research on the dynamic scheduling of underground mining equipment under dynamic events has become a hot topic in production scheduling research field.

Several researchers have made significant contributions to the field of the dynamic scheduling of underground mining equipment. Song et al. [14] developed a decision support tool for underground mining equipment that assists miners in quickly reassigning equipment to cope with dynamic events such as roadway blockages and equipment failures. Hou et al. [15] built a dynamic scheduling optimization model for underground mining equipment that considers the uncertain operation time of mining equipment, which facilitates the rapid readjustment of scheduling plans. Hammami et al. [16] studied the dynamic scheduling of mining equipment in underground mines, considering dynamic events such as equipment failure, production interruption, and equipment movement. Åstrand et al. [17] proposed an underground mining equipment scheduling model based on constraint programming, considering dynamic events such as production interruptions and delays. They also considered equipment movement time and proposed a simple neighborhood search strategy with a fixed neighborhood size based on constraint programming to study the scheduling problem of mining equipment in underground mines [18]. In addition, they also put forward a large neighborhood search strategy, based on constraint programming, that dynamically adjusts the size of the neighborhood to study the scheduling problem of mining equipment in underground mines, enabling the quick adjustment of the scheduling plan [19]. Feng et al. [20] proposed a rescheduling optimization model of underground mine transportation equipment, considering equipment failure and adopting the wolf colony algorithm to optimize the solution.

In summary, few research studies have been conducted on the dynamic scheduling problem of mining equipment in underground mines. Most studies have focused on how to generate new rescheduling plans after various dynamic events occur, but they lack a specific analysis of dynamic events. Each type of dynamic event has its own dynamic characteristics, such as the duration, severity and frequency. The dynamic scheduling characteristics determine the dynamic scheduling mechanism and method, and they generate different scheduling plans. In addition, previous studies have seldom considered deviations between rescheduling plans and initial scheduling plans in combination with equipment changes, and they have not been able to effectively evaluate the stability, real-time adaptiveness, and robustness of dynamic scheduling.

At present, workshop dynamic scheduling has matured. Li et al. [21] considered five types of workshop dynamic events, studying the dynamic scheduling problem of flow shops, with the minimization of the maximum completion time and instability as the optimization goals, using the DTLBO algorithm to optimize the solution, which greatly improves the robustness, stability, and real-time performance of scheduling. Peng et al. [22] considered three kinds of dynamic events simultaneously, studying the dynamic scheduling problem of hybrid flow shops and using the MSVND algorithm to optimize the solution with the goals of minimizing the maximum completion time and system instability. Ma et al. [23] proposed a dynamic scheduling optimization method for multiple production-line workshops. The optimization goal was to minimize the deviation between the rescheduling plan and the initial scheduling plan, and the genetic algorithm was used as the solution generator. The results show that the method effectively solves the dynamic scheduling problem of multiple production-line workshops.

For underground mining, we must urgently analyze the characteristics of dynamic events, study the dynamic scheduling mechanism and dynamic scheduling method, consider the deviation between the rescheduling plan and the initial scheduling plan, consider the change cost of mining equipment, and improve the stability, real-time robustness, and adaptability of dynamic scheduling.

In the present research study, the dynamic characteristics of dynamic events (mining equipment failures) were considered. The direct application of the available methods to underground mines has certain limitations [24]. However, through the analysis of the dynamic scheduling driving mechanism and method, we found it possible to solve this problem via the reconfiguration of dynamic scheduling mechanisms and methods. Therefore, we constructed a dynamic scheduling model to verify the dynamic scheduling process. Consequently, we reconstructed a dynamic scheduling process for underground mining, and then we constructed a dynamic scheduling model to verify it. The optimization objective of the model considers the deviation between the rescheduled plan and the initial plan, as well as the frequency of equipment changes. The optimization results are objective, avoiding the subjective errors of traditional manual decision making. The original contribution of this paper is to propose a dynamic scheduling process and to construct a rescheduling optimization model for underground mines under equipment failure conditions, and the optimization results can provide decision support for schedulers, which provides a new perspective on mine scheduling in intelligent mines.

2. Dynamic Scheduling Process

2.1. Dynamic Scheduling Characteristics

The operating environment of underground mining equipment is dynamic, featuring discrete operating locations, complex and harsh environments, and various operating processes. Equipment failures can disrupt production and cause delays. Dynamic scheduling characteristics mainly involve the type of the equipment failure, the failure frequency, a severity assessment, the reasons for failure, the repair location, and the repair time.

The type of equipment failure can be classified as either an internal reason or an external reason. Internal reasons for failures mainly include damage caused by fatigue due to long operation times. External reasons for failures mainly include abnormal damage caused by harsh operating environments. A detailed analysis of reasons for failure is shown in Table 1.

Table 1. Reasons for failures of underground mining equipment.

Equipment	Failure Reason	Failure Type
Drilling rig	The components of the drilling rig have not been maintained or replaced for a long time.	Internal failure
	Drill pipe damage caused by drilling hard rock or the abnormal operation of a drilling rig caused by a high-temperature and high-humidity environment.	External failure
Charging rig	The charging quality of the charging rig is not up to the standard due to an unstable and insufficient charging quantity that cannot meet the requirements of subsequent blasting operations.	Internal failure
	The charging rig cannot work normally due to the deformation of the borehole, or the charging operation is abnormal due to the high-temperature and high-humidity environment.	External failure
Scaling rig	The components of the scaling rig have not been maintained or replaced for a long time.	Internal failure
	The falling pumice caused damage to the mechanical arm of the scaling rig.	External failure

Table 1. *Cont.*

Equipment	Failure Reason	Failure Type
LHD	The components of the LHD have not been maintained or replaced for a long time.	Internal failure
	The high-temperature and high-humidity environment led to the abnormal loading operation of the LHD.	External failure
Bolter	The components have not been maintained or replaced for a long time, the anchor rod is broken, the air leg is jammed, and the positioning is inaccurate, resulting in abnormal support operation.	Internal failure
	The high-temperature and high-humidity environment led to abnormal support operation.	External failure

Equipment failures can be divided into low-frequency, medium-frequency, and high-frequency failures, based the frequency of occurrence. When the frequency of equipment failure is in (A, B), we call it a low-frequency failure. When the frequency is in (B, C), we call it an intermediate-frequency failure. Otherwise, we call it a high-frequency failure. Here, the values of A, B, and C need to be determined according to the experience portrayed in the actual mining data.

In terms of severity, equipment failures can be classified as Class I, Class II, Class III, or Class IV. If the equipment failure causes a particularly significant delay and a particularly significant economic loss, it is considered a Class I failure. If the equipment failure causes a major delay and a major economic loss, it is considered a Class II failure. If the equipment failure, causes a large delay and a large economic loss, it is considered a Class III failure. If the equipment failure causes a small delay and a small economic loss, it is considered a Class IV failure.

The severity of the failure can affect the equipment repair time. When a Class III or IV failure occurs, the repair time is usually short. However, when a Class I or II failure occurs, the repair time is usually long, and this can cause significant production delays. Based on repair time, equipment failure can be categorized as either short-term or long-term failure. The maintenance location for the equipment is influenced by the above factors, and it can be classified as on-site maintenance or off-site maintenance. The various types of failures have been classified based on the five dimensions, and we analyzed the coupling relationships between them, as shown in Figure 1. The higher the severity of the failure, the lower the frequency of the failure, and the longer the repair time. Therefore, the repair time is negatively correlated with the failure frequency, and it is positively correlated with the failure severity. It is necessary to send equipment with long repair times to the maintenance point for long-term maintenance. For equipment with short repair times, short-term, on-site maintenance can be carried out directly.

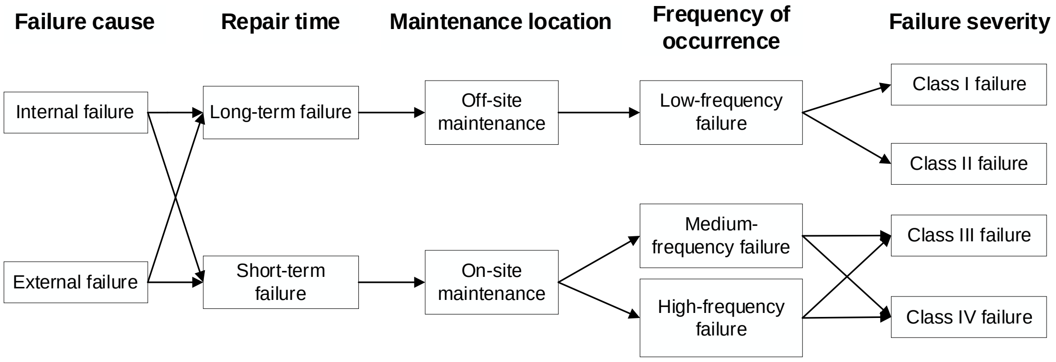

Figure 1. The coupling relationship between dynamic scheduling characteristic.

2.2. Dynamic Scheduling Mechanisms

The dynamic scheduling mechanisms are primarily aimed at determining when to initiate adjustments to the initial scheduling plan. These mechanisms are categorized into three types: event-driven, interval-driven, and hybrid-driven mechanisms [25,26].

For low-frequency, long-term, complex failures, an event-driven mechanism is employed. These failures have a significant impact on the production schedule, and the immediate readjustment of the initial scheduling plan is required. To avoid production interruptions or major delays, the operating site uses other available equipment, as shown in Figure 2. The event-driven mechanism can respond to equipment failure events in real-time, and it has high real-time performance, but it has poor stability.

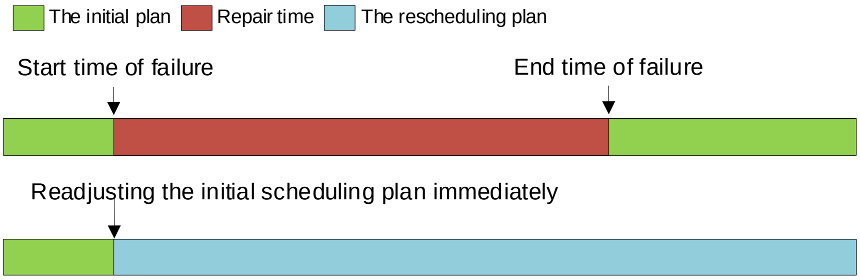

Figure 2. Event-driven mechanism.

For high-frequency, short-term, simple failures, a cycled, interval-driven mechanism is employed. These types of failures occur more frequently, but they usually have less of an impact. Frequent rescheduling would not be conducive to effective management. Therefore, the scheduling plan is readjusted at regular intervals, as shown in Figure 3. The cycled, interval-driven mechanism cannot respond to equipment failure events in real-time, but it has high stability.

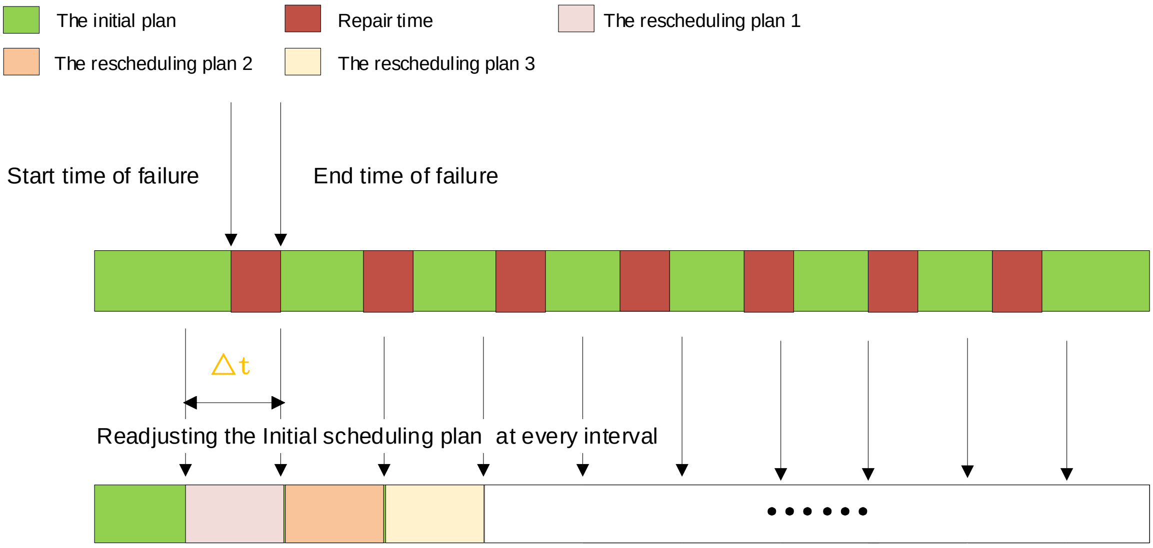

Figure 3. Cycled interval-driven mechanism.

For medium-frequency, short-term failures, a hybrid-driven mechanism is employed. This mechanism integrates event-driven and interval-driven mechanisms. The initial scheduling plan is first adjusted at intervals using the interval-driven mechanism. If a failure with serious consequences occurs during the interval, the event-driven mechanism is immediately applied, as shown in Figure 4. The hybrid-driven mechanism not only retains the real-time performance of the event-driven mechanism, but it also ensures the stability of the cycled, interval-driven mechanism.

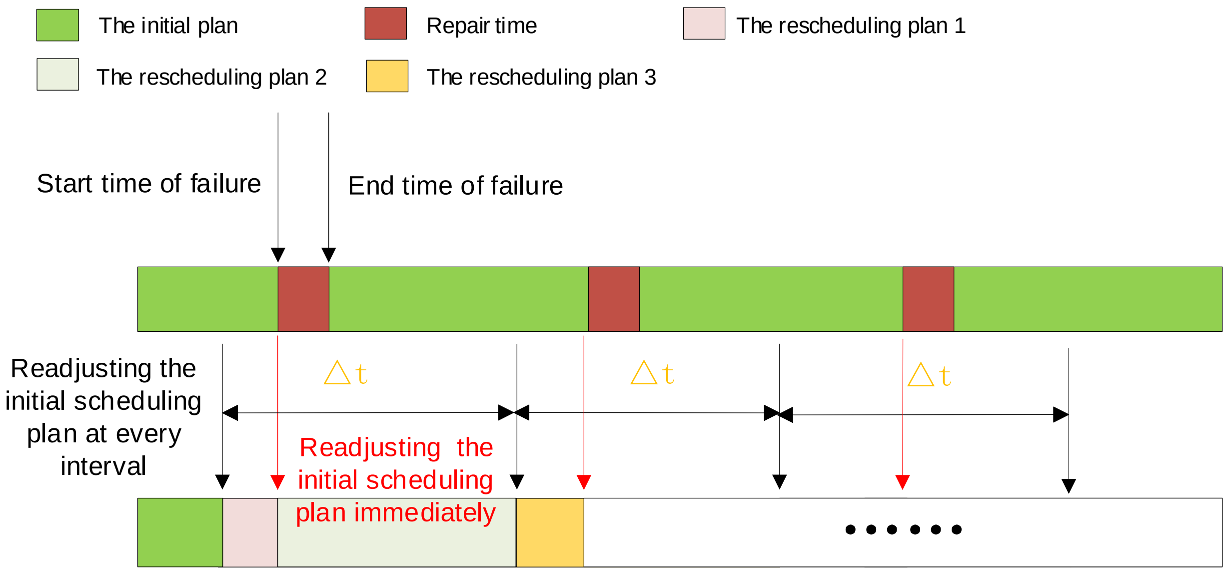

Figure 4. Hybrid-driven mechanism.

2.3. Dynamic Scheduling Methods

Dynamic scheduling methods play a critical role in adjusting initial scheduling plans, with complete adjustment, partial adjustment, and backward adjustment being the primary approaches [27]. Figure 5 depicts an initial scheduling plan that includes the stope process, equipment type, specific individuals, and process intervals.

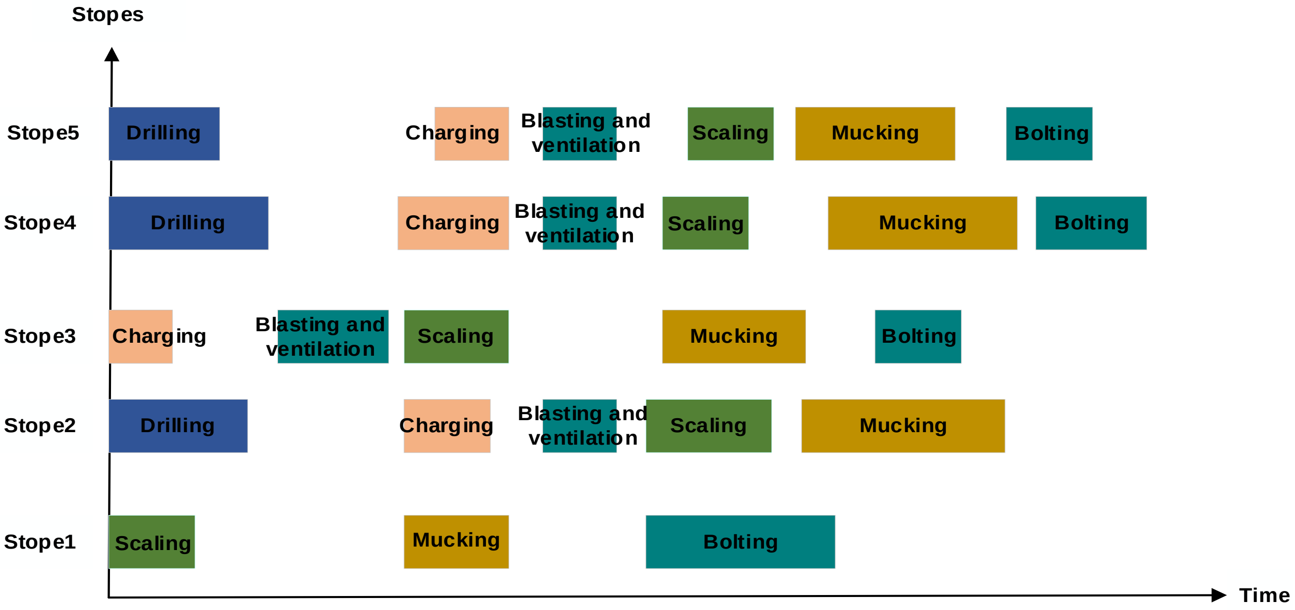

Figure 5. The initial scheduling plan.

The complete adjustment method involves re-adjusting all unexecuted tasks at all locations when equipment failure occurs. It identifies the interrupted tasks due to the equipment failure and unstarted tasks, optimally adjusts the equipment involved, and forms a rescheduling plan. This method is effective in reducing the impacts of interruptions or significant delays and in quickly responding to equipment failures, but it requires extensive schedule adjustments and multiple changes. As shown in Figure 6, a scaling rig broke down at a certain time in Stope 3, and the dotted line indicates the initial scheduling plan, which was adjusted to fit the task deadlines.

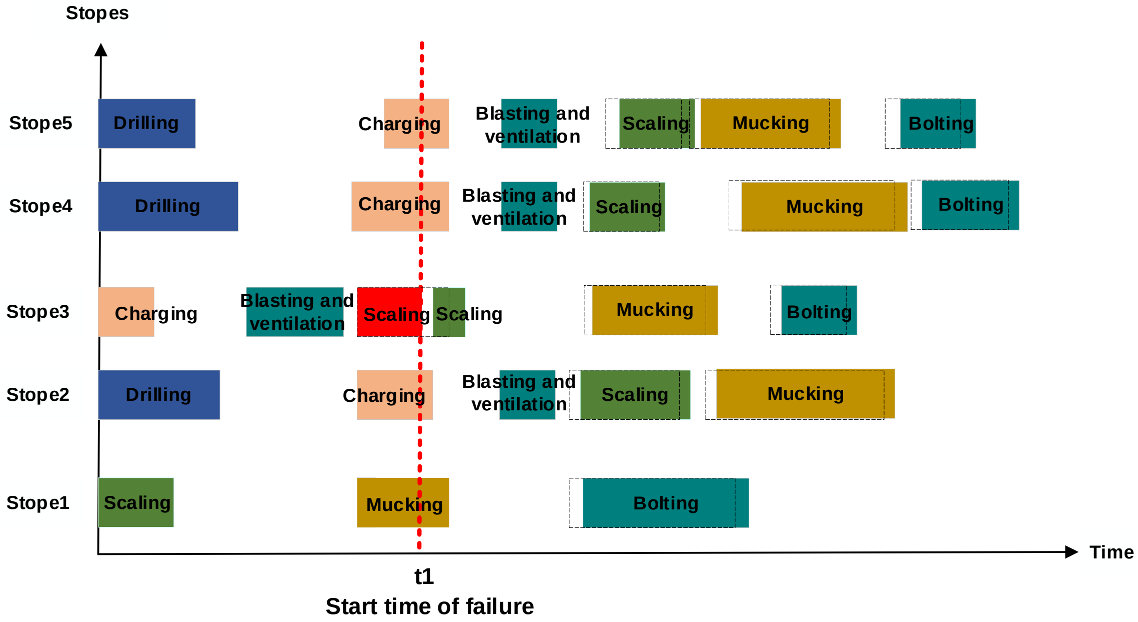

Figure 6. The complete adjustment method.

In contrast, the partial adjustment method only re-adjusts unexecuted tasks at limited locations. By identifying the interrupted tasks due to equipment failure and all other unstarted tasks, it delineates the minimum number of stopes to be adjusted, and it makes optimal adjustments within that area to obtain the rescheduled plan, as shown in Figure 7. When the failure occurred, Block 3 and the adjacent Block 4 were adjusted, and the other locations remained unchanged. While this method requires fewer equipment changes than the fully adjusted method, it sacrifices some operating time.

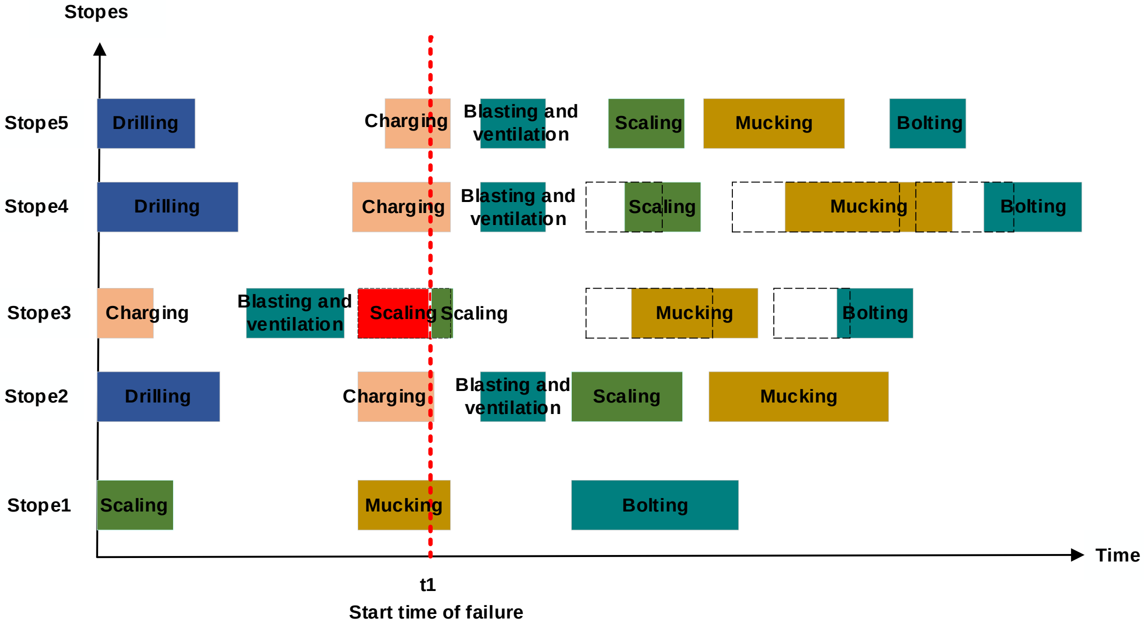

Figure 7. The partial adjustment method.

The backward adjustment method defers equipment repair time for global tasks without changing the order of tasks or executors. The task execution equipment remains unchanged, and all processes that have not started are moved backward without changing the equipment arrangement, as shown in Figure 8. All tasks in each stope are delayed for a certain amount of time to maintain the initial order when equipment failure occurs.

However, since blasting in mines usually occurs at a fixed time, the backward adjustment method requires a delay in the blast and ventilation process, and it is not applicable to mine scheduling.

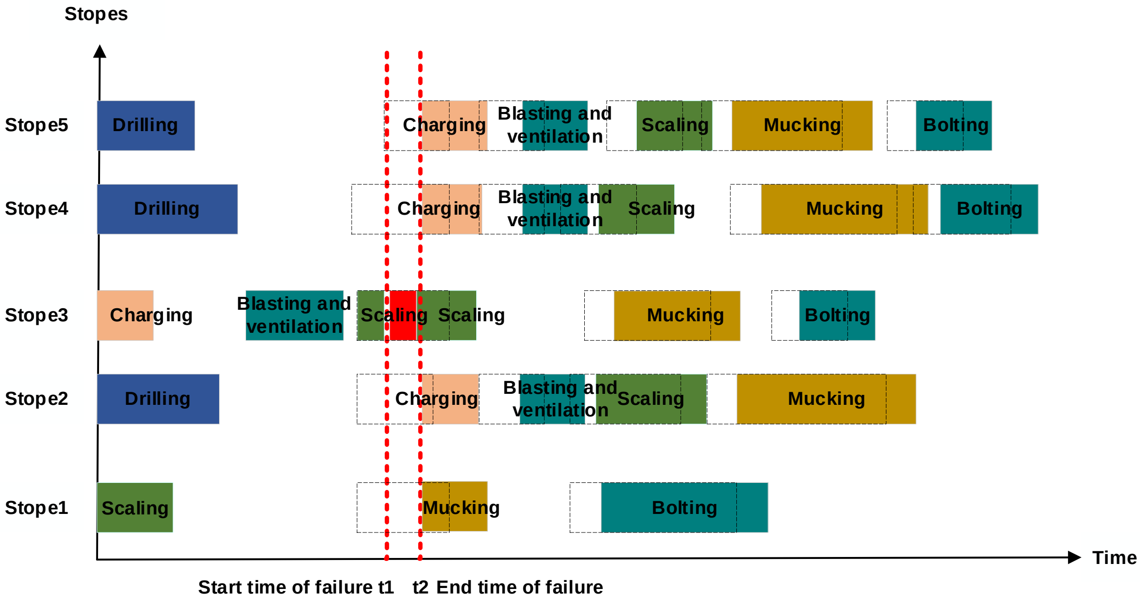

Figure 8. The backward adjustment method.

2.4. Process Reconfiguration

The advantages and disadvantages of dynamic scheduling mechanisms and methods are summarized in Tables 2 and 3. The hybrid-driven mechanism has been found to have high real-time performance and scheduling stability. The comprehensive, complete adjustment method and the partial adjustment method have been shown to maintain equipment stability while ensuring the robustness, flexibility, and time stability of scheduling. However, the backward adjustment method is not applicable to mine scheduling as it requires a delay in the blasting and ventilation process, which occurs at a fixed time.

Table 2. Advantages and disadvantages of the dynamic scheduling mechanism.

Dynamic Scheduling Mechanism	Advantages	Disadvantages
Event-driven	Responds to events quickly; High real-time performance.	Poor in scheduling stability.
Cycled, interval-driven	High stability.	Poor in real-time scheduling.
Hybrid-driven	Responds to events quickly; High stability.	Complex in management

Table 3. Advantages and disadvantages of dynamic scheduling methods.

Dynamic Scheduling Methods	Advantages	Disadvantages
Complete adjustment	High robustness; High flexibility; High completion time stability.	High equipment change cost.
Partial adjustment	Low equipment change cost; High equipment stability.	Low robustness.
Backward adjustment	High equipment stability.	Low robustness; Low flexibility; Low time stability.

Mine scheduling is a shift-cycle process, which requires the cycled, interval-driven mechanism. However, major events can disrupt the initial plan, and the scheduling department must respond in a timely manner; thus, only the event-driven mechanism can satisfy this condition. The appropriate mechanism for mine scheduling was determined to be a hybrid-driven mechanism.

Mine scheduling adjustments are complex, and making limited adjustments of a partial scope will not likely achieve the desired results. However, since the adjustment of large equipment is costly, we also do not want to make too many equipment changes, which is a contradiction. In addition, blasting and ventilation in mines need to be time-fixed, so backward adjustment cannot be used. For this reason, it is necessary to construct a new method for minimizing equipment changes while maximizing scheduling, which we call the hybrid adjustment method for underground mines.

Figure 9 illustrates that, when the initial scheduling plan is established, its dynamic scheduling characteristics are evaluated, and the appropriate dynamic scheduling mechanism is selected. The dynamic scheduling method is then applied to adjust the plan, and the algorithm is utilized to optimize the solution and create an optimal rescheduling plan.

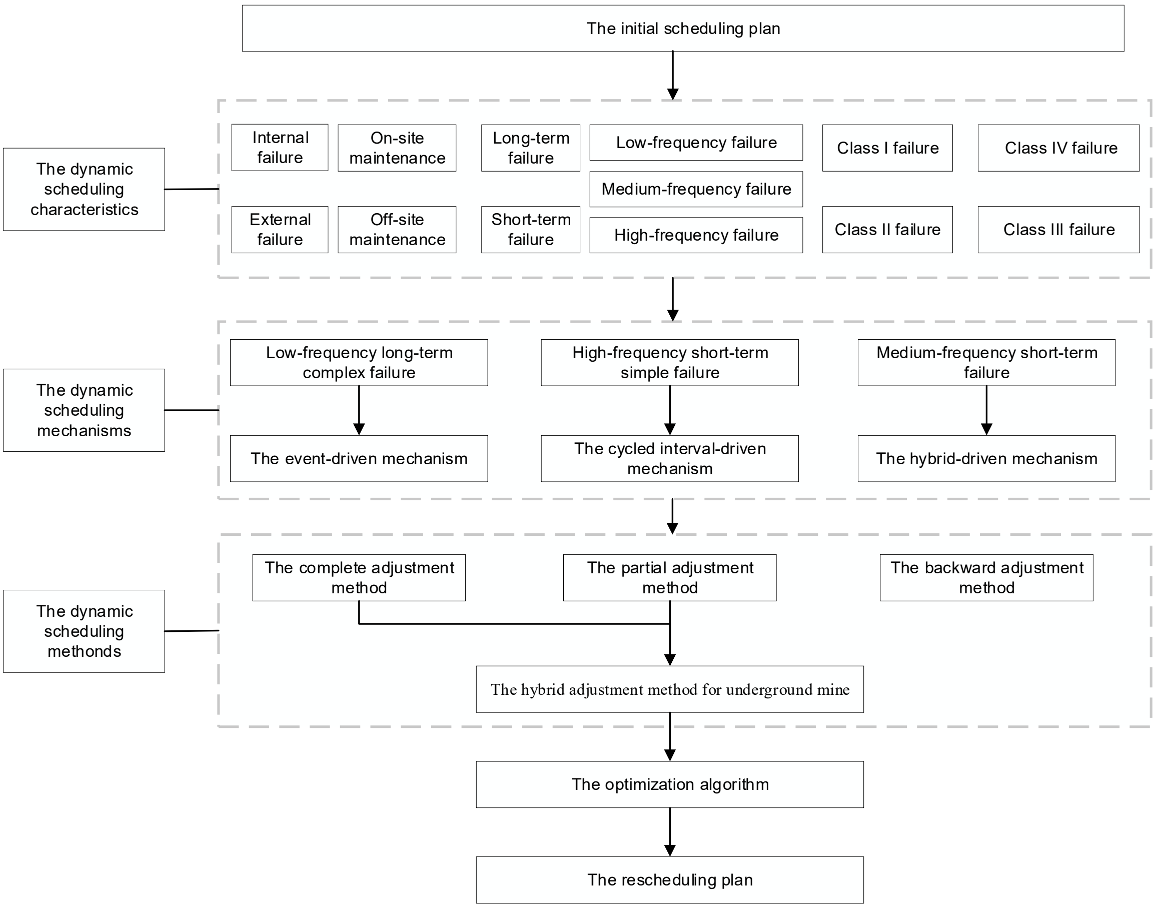

Figure 9. The dynamic scheduling process.

To meet multiple requirements at the same time and to improve the stability, real-time robustness, and agility of scheduling, it is necessary to reconfigure the existing rescheduling mechanisms and methods in combination with the mine characteristics. This process is based on the hybrid-driven scheduling mechanism, partial adjustment method, and complete adjustment method, and it aims to reduce the deviation of the new scheduling plan from the initial one and to reduce the number of equipment changes. In summary, we propose a dynamic scheduling process based on the characteristics, mechanisms, and methods of dynamic scheduling.

3. Dynamic Scheduling Modeling

3.1. Description of the Problem

The dynamic scheduling problem for intelligent mining equipment in underground metal mines is an extension of the flexible production scheduling problem. Underground metal mines are categorized into areas, strips, and blocks based on spatial fineness and mine design, with the block being the smallest operational recovery unit. Each block requires multiple processes, and each process can require multiple mining equipment types with specific quantities and work efficiencies. The processes and corresponding equipment of multiple blocks are arranged in a rational manner to form the initial plan. However, equipment failures can occur, requiring the dynamic scheduling mechanism to activate, rescheduling the process and the corresponding equipment to reduce negative impacts and avoid serious lags, large production fluctuations, and efficiency reductions.

Based on the idea of a dynamic scheduling process as described in Section 2.4, we constructed the corresponding dynamic scheduling model. Due to the problem's complexity, the following assumptions were made to simplify the model and reduce computation:

(1) The available equipment was limited, and no backup was set. When a single piece of equipment failed, other available equipment was selected for the current task.

(2) Equipment reverted to the repair state immediately after a failure and could not function during the process, but it could be reselected after repair.

(3) Only one piece of equipment failed at a given moment. The rescheduling interval began at the failure moment, and the repair time was known.

(4) After equipment failure, ongoing tasks were interrupted. The completed part was excluded from optimization as a given fact, and the unfinished part was considered a new task.

3.2. Mathematical Model

3.2.1. Symbol Definition

The indices and set definitions are shown in Table 4.

Table 4. Indices and sets.

Name	Meaning
A	Set of areas, $A = \{A_1, A_2 \ldots, A_i\}$, $i \in [1, I]$
B_i	Set of stripes, $B_\mathrm{i} = \{B_{i1}, B_{i2}, \ldots, B_{ik}\}$, $i \in [1, I], k \in [1, K], k \neq f$
C_{ik}	Set of all blocks, $C_{ik} = \{C_{ik1}, C_{ik2}, \ldots, C_{ikn}\}$, $i \in [1, I], k \in [1, K], n \in [1, N], n \neq x$
M	Set of equipment, $M = \{M_1, M_2, \ldots, M_h\}$, $h \in [1, H]$, $h \neq u$
J	Set of processes, $J = \{J_1, J_2, \ldots, J_m\}$, $m \in [1, 6]$, $J_1 = 1$ (Drilling), $J_2 = 2$ (Charging), $J_3 = 3$ (Blasting and ventilation), $J_4 = 4$ (Scaling), $J_5 = 5$ (Mucking), $J_6 = 6$ (Bolting)

The decision variables are defined as shown in Table 5.

Table 5. Decision variables.

Name	Meaning
TF_{iknmh}	In the initial plan, the starting time of M_h failure of J_m in C_{ikn}, h, $m \neq 3$
TE_{iknmh}	In the initial plan, the ending time of M_h of J_m in C_{ikn}, h, $m \neq 3$
TE_{ifxmu}	In the initial plan, the ending time of M_u of J_m in C_{ifx}, h, $m \neq 3$
TS_{iknmu}	In the rescheduled plan, the starting time of M_u of J_m in C_{ikn}, h, $m \neq 3$
TW_{iknmu}	In the rescheduled plan, the operation time of M_u of J_m in C_{ikn}, h, $m \neq 3$
TE_{iknmu}	In the rescheduled plan, the ending time of M_u of J_m in C_{ikn}, h, $m \neq 3$
Ml_{iknm}	If the equipment selection of J_m in C_{ikn} changes, the value is *1*; otherwise, it is *0*, $m \neq 3$
$T_{ven,ikn}$	Blasting and ventilation time in C_{ikn}
TM_{iknu}^{ifxu}	Time of movement between C_{ifx} and C_{ikn} with M_u, h
Bl_{siknm}	Number of blasting and ventilation process for J_m in C_{ikn}, $m \neq 3$

3.2.2. Objective Function

The objective function aims to:

(1) Minimize the deviation between the ending time of the rescheduled plan and the ending time of the initial plan.

$$min\left(\sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{n=1}^{N}\sum_{m=1}^{6}\left|TE_{\mathrm{iknmu}}-TE_{\mathrm{iknmh}}\right|\right) \tag{1}$$

(2) Minimize the frequency of equipment changes.

$$\min\left(\sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{n=1}^{N}\sum_{m=1}^{6}Ml_{iknm}\right), m \neq 3 \tag{2}$$

3.2.3. Equivalence Relations

The rescheduled plan uses replacement equipment when the process starting time is related to the failure starting time, the process ending time of the replacement equipment in another block operation, and the movement time between blocks.

$$TS_{iknmu} = \mathrm{TF}_{\mathrm{iknmh}} + TE_{ifxmu} + TM_{iknu}^{ifxu} \tag{3}$$

The process ending time for the rescheduled plan is related to the process starting time, equipment movement time, and blast and ventilation time.

$$TE_{\mathrm{iknmu}} = TS_{\mathrm{iknmu}} + TW_{\mathrm{iknmu}} \tag{4}$$

3.2.4. Constraints

Constraint 1: The rescheduled plan should strictly follow the blasting and ventilation constraint. Operations in violation of regulations cannot be allowed, even if progress needs to be made up. When blasting and ventilation occurs, all processes must be suspended, and the operation must be started after the blasting and ventilation are complete.

$$TE_{\mathrm{iknmu}} \geq TS_{\mathrm{iknmu}} + Bl_{siknm} \times T_{ven,ikn} + TW_{iknmu}, m \neq 3 \tag{5}$$

Constraint 2: The rescheduled plan should follow the process sequence of the initial plan. That is, the starting time of the next process should lag behind the ending time of the previous process.

$$TS_{iknm+1} \geq TE_{\mathrm{iknm}} \tag{6}$$

Constraint 3: The rescheduled plan should follow the mining sequence of the initial plan. That is, the starting time of the next ore block should lag behind the ending time of the previous ore block.

$$TS_{ikn+1} \geq TE_{ikn} \tag{7}$$

3.3. Model Solving

In this study, we used a genetic algorithm to solve the dynamic scheduling problem of intelligent mining equipment for underground metal mines. The main process is shown in Figure 10.

(1) Encoding and Decoding

For chromosome encoding, we adopted a two-layer coding method [28]. The first layer, Part A, includes block mining information, while the second layer, Part B, includes available equipment information. The scheduling plan consists of both Part A and Part B, as shown in Figure 11.

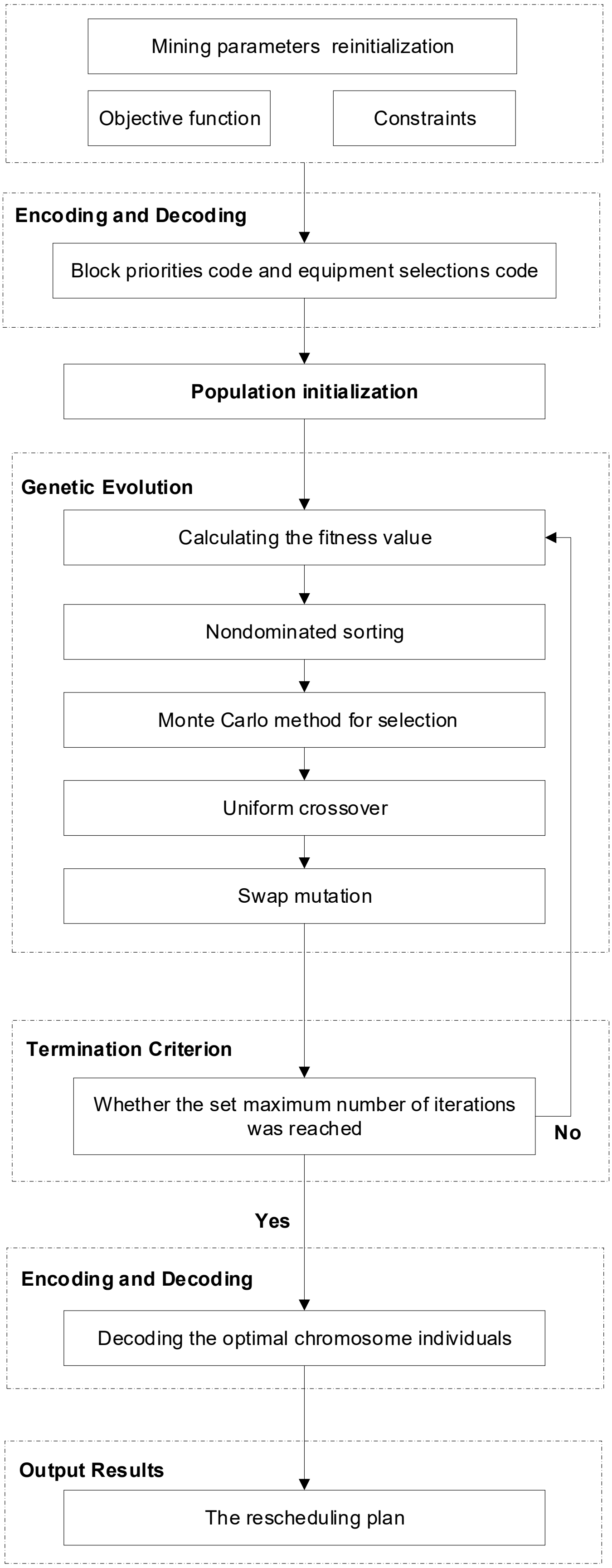

Figure 10. The main process of model solving.

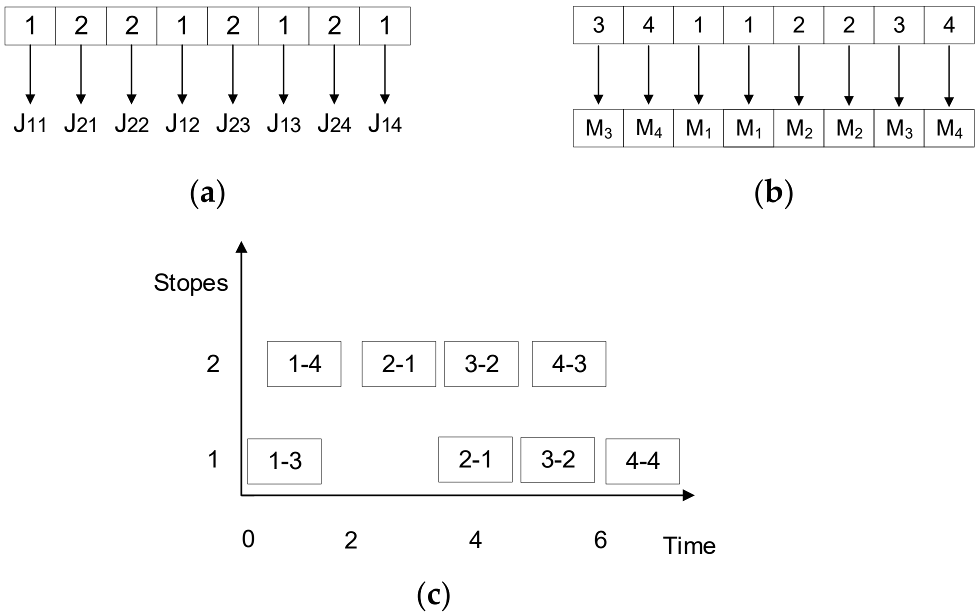

Figure 11. Two-layer coding method: (**a**) Part A: block priorities code; (**b**) Part B: equipment selections code; (**c**) Encoding and decoding of chromosome.

(2) Population initialization

After equipment failure, the state of the mining system changes, and mining parameters require re-initialization. This includes removing completed processes, blocks, and failed equipment. Multiple chromosomes are then randomly generated according to the coding rules to form the initial population.

(3) Genetic Evolution

Genetic evolution includes selection, crossover, and mutation.

Selection generates the next generation of populations by calculating the objective value based on the chromosome and generating the fitness value. Then, better individuals are selected based on their fitness value to generate the offspring population. Nondominated sorting helps to select individuals closer to the optimal value of the target in the case of multiple objectives, but it will reduce the diversity of the population and fall into the local optimal solution. Adding the Monte Carlo method is an effective way to mitigate this shortcoming. In this study, we used nondominated sorting and the Monte Carlo method for selection.

Crossover recombines parental genes to create offspring with inherited traits. Uniform crossover can better search the solution space, maintain good information exchange, and make progeny generations more diverse. With long chromosomes, such as those here, uniform crossover can ensure the adequacy of evolution. In this study, we used the uniform crossover method to create a large variety of individuals.

Mutation introduces population diversity through genetic mutations to avoid entrapment in local optimal solutions. Because the total number of processes was fixed, insertion mutation was not applicable here. Therefore, we used swap mutation to swap gene positions in the block priority coding and to change the block priorities, or to swap gene positions in the equipment selection coding and change the equipment selection, so as to improve the sample diversity.

(4) Termination Criterion

We determined whether the set maximum number of iterations was reached. If not, we continued the selection, crossover, and mutation operations until it was reached.

(5) Output Results

Finally, we decoded the optimal chromosome individuals into a rescheduling plan.

4. Case Study

This paper presents a case study of the southeastern mining area of the Chambishi Copper Mine. The multi-equipment task assignment model and GA algorithm [29–32] were used to generate an initial plan, which was then rescheduled based on the proposed model to analyze the interference and countermeasures of equipment failure.

4.1. Initial Plan and Basic Data

The zone consisted of eight stopes, and the initial plan, shown in Figure 12, was part of the optimal plan created by a multi-equipment task assignment model for the horizontal stripe pre-cut mining method [24].

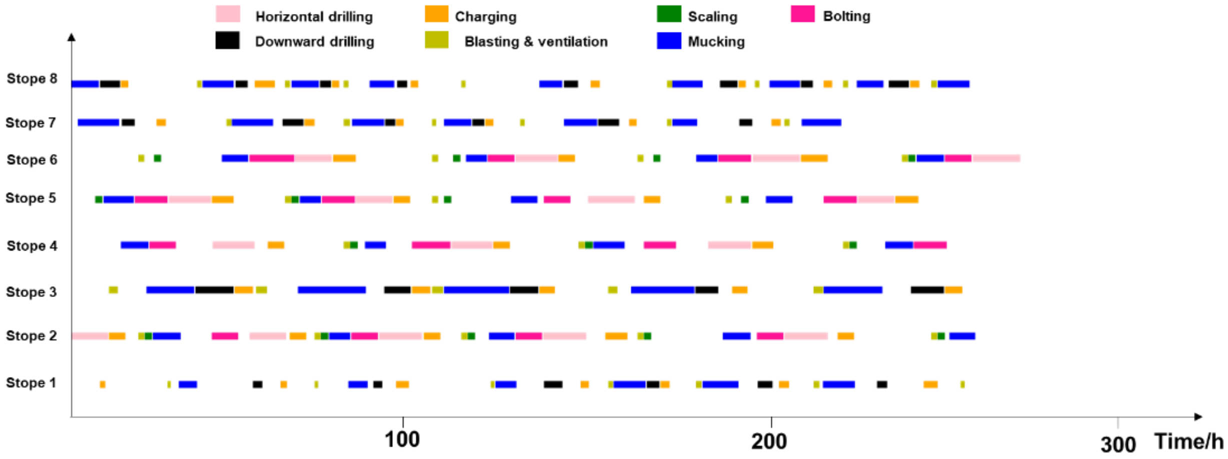

Figure 12. The initial scheduling plan.

The main technical parameters of the mining equipment, including the horizontal hole drilling rig, medium–deep hole drilling rig, charging rig, scaling rig, LHD, and bolter, are listed in Table 6.

Table 6. Main technical parameters of mining equipment.

Equipment	Task	Operational Efficiency	Number
Horizontal drilling rig	Drilling horizontal holes	40 m/h	4
Downward drilling rig	Drilling vertical holes	30 m/h	2
Charging rig	Drilling holes for charging with explosives	90 m/h	3
Scaling rig	Exposed roof area scaling for removing loosely attached rock	10 m^2/h	1
LHD	Ore mucking	1500 t·m/h	4
Bolter	Anchor support for reinforcing surrounding rock mass	10 anchors/h	3

4.2. The Rescheduled Plan

The initial plan was invalidated due to equipment failure and had to be rescheduled. Specifically, a horizontal hole drilling rig in a stope broke down at 5:00, and the repair time was 12.25 h. The algorithm parameters used were as follows: population size: 800; number of iterations: 400; crossover probability: 0.2; and variance probability: 0.1. The simulation was run on an Intel(R) Core(TM) i7-8550U CPU, 16 GB RAM, Python 3.7 @ Anaconda 3. After the iteration of the genetic algorithm, the optimal solution was obtained with 79 h and 11 equipment changes as objectives, as shown in Figure 13. The rescheduled Gantt chart is shown in Figure 14, and a comparison between the initial and rescheduled plans is presented in Figure 15. Delays occurred at five stopes in the rescheduled plan, with delays generally ranging from 10 to 20 h.

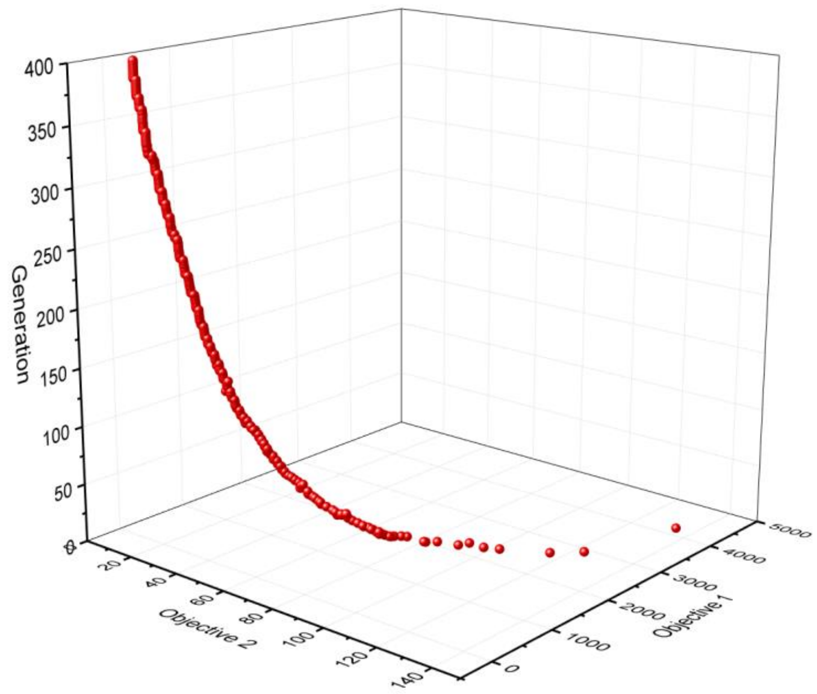

Figure 13. The iteration process of the genetic algorithm.

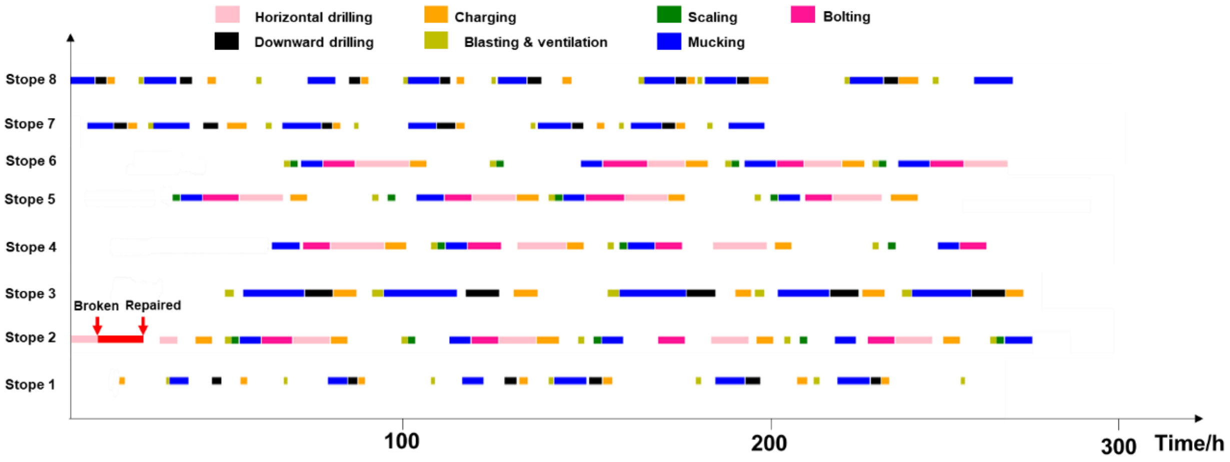

Figure 14. The rescheduled plan.

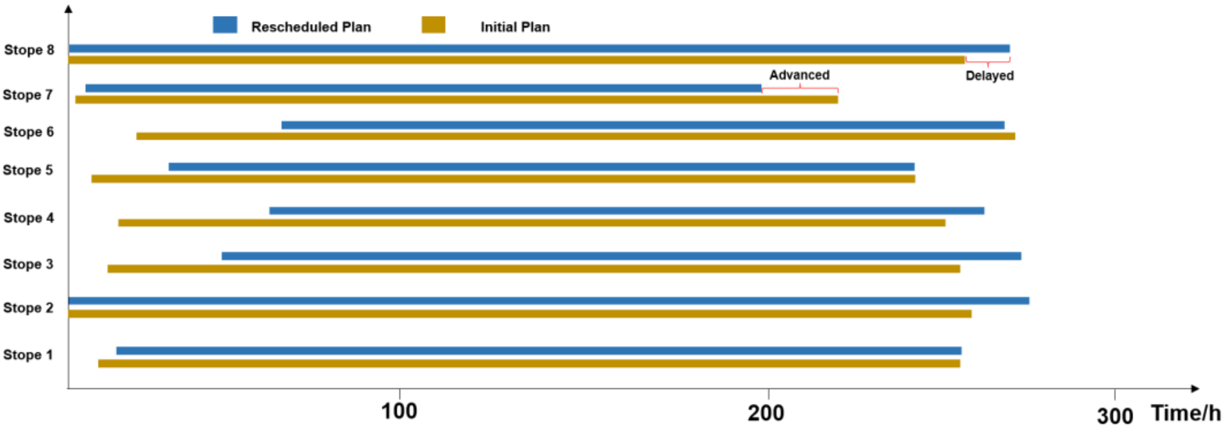

Figure 15. Comparison between the initial and rescheduled plans.

4.3. Discussion

To analyze the effectiveness of the proposed algorithm, a comparative analysis was carried out. The control group included the execution results of the initial plan under equipment failure. Specifically, after the equipment failure, it was still executed according to the initial equipment allocation and stope priority, and the execution result of the initial plan was obtained. The comparison with the initial plan, the execution result of the initial plan, and the execution result of the rescheduled plan are shown in Table 7.

Table 7. The comparison with the initial plan, the execution result of the initial plan, and the execution result of the rescheduled plan.

Name	The Initial Plan	The Execution Result of the Initial Plan	The Execution Result of the Rescheduled Plan	Improvement (%)
Completion time (h)	255	312	284	8.97
The total time deviation (h)	0	183	79	56.83
The frequency of equipment changes	0	0	11	——
Total block interval (h)	337	647	420	35.09
Total process interval (h)	638	943	691	26.72
Ore grade fluctuation	0.04	0.83	0.42	49.40

The comparison results show that the dynamic scheduling model proposed in this paper accomplished an improvement in overall mining execution at the cost of making 11 equipment changes. The execution result of the initial plan was significantly worse than the rescheduled plan. The rescheduled plan is less different from the initial plan, which avoided problems such as lags and production interruptions caused by equipment failures.

The proposed dynamic scheduling model effectively reduced the impact of equipment failure on production operations, while avoiding the disadvantages of traditional complete rescheduling with extensive equipment changes. This enabled the realization of rescheduling with low management costs by reducing the frequency of equipment adjustments. The model can reduce the adverse effects of equipment failure; ensure the stability, robustness, and agility of scheduling; effectively assist schedulers to allocate equipment; cope with the disturbing effects of equipment failure; and improve mine production efficiency.

5. Conclusions

In conclusion, this paper proposed a dynamic scheduling model to analyze the interference of equipment failure in the southeastern mining area of the Chambishi Copper Mine. The proposed model effectively reduced the impact of equipment failure on production operations while avoiding the disadvantages of traditional complete rescheduling with extensive equipment changes. The results showed that the rescheduling plan accomplished an improvement in overall mining execution at the cost of making 11 equipment changes, while the execution result of the initial plan was significantly worse than the rescheduled plan. The proposed model can reduce the adverse effects of equipment failures; ensure the stability, robustness, and agility of scheduling; and effectively assist schedulers to allocate equipment, cope with the disturbing effects of equipment failure, and improve mine production efficiency. Overall, this study provides valuable insights for mine scheduling and equipment management. After equipment failure, the initial scheduling plan is quickly adjusted, and the generated rescheduling plan is fed back to the scheduling center to assist decision makers in scheduling and reducing the interfering effect of equipment failure on production operations. This study provides a new perspective on mine production scheduling, and it can be applied to other similar mining operations.

However, we have only completed the preliminary algorithm design and simulation verification, and there is still a certain distance to implementation. It is necessary to develop a scheduling management platform to assist personnel in decision making and efficiently managing equipment. Future research will focus on the dynamic scheduling problem in the case of the simultaneous occurrence of multiple dynamic events and improve the adaptability of the model to cope with real mining environments. In addition, future research should focus on equipment operation and maintenance management, combine equipment operation and maintenance data, carry out pre-scheduling research on mining equipment, set up fault redundancy space in advance, and reduce the impact of fault interference at the source.

Author Contributions: S.T. participated in data analysis and in the design of the study, drafted the manuscript, and carried out the statistical analyses; S.F. and S.H. collected field data; L.W. and M.J. conceived of the study, designed the study, coordinated the study, and helped draft the manuscript. All authors have read and agreed to the published version of the manuscript.

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