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RESEARCH ARTICLE

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Deep Reinforcement Learning for automated scheduling of mining earthwork equipment with spatio-temporal safety constraints

Abstract Large-scale machinery operated in a coordinated manner in earthworks for mining constitutes high safety risks. Efficient scheduling of such machinery, factoring in safety constraints, could save time and significantly improve the overall safety. This paper develops a model of automated equipment scheduling in mining earthworks and presents a scheduling algorithm based on deep reinforcement learning with spatio-temporal safety constraints. The algorithm not only performed well on safety parameters, but also outperformed randomized instances of various sizes set against real mining applications. Further, the study reveals that responsiveness to spatio-temporal safety constraints noticeably increases as the scheduling size increases. This method provides important noticeable improvements to safe automated scheduling in mining.

Keywords deep reinforcement learning, mining earthwork, automated scheduling, spatio-temporal safety constraints

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1 Introduction

Mining projects are often characterized by complex and hazardous terrain conditions, involving a significant number of construction machines, frequently of considerable size. These operations may sometimes neglect established safety regulations. For instance, between 2008 and 2021, there were a total of 528 mining-related fatalities reported in the United States, with 83 deaths specifically attributed to safety rule violations. This makes such violations the leading contributing factor to accidents (Quintero 2023). Mine earthwork represents a critical aspect of mining engineering and requires the coordination of numerous bulldozers and trucks. However, challenges such as blind spots (Gauthier et al., 2022; Imam et al., 2023) and driver fatigue (Inayah et al., 2023) make it unreliable to depend on operators to consistently adhere to safety regulations over extended durations. Consequently, scheduling mining earthmoving machinery with a focus on safety regulations presents a viable solution.

Existing research in mining engineering has primarily concentrated on long-term strategic planning (Flores-Fonseca et al., 2022; Guo et al., 2021; Liu et al., 2023; Ogunmodede et al., 2022; Paithankar and Chatterjee 2019; Xu et al., 2023) and short-term mechanical management (Both et al., 2020; Joshi et al., 2022; Manríquez et al., 2023; Paithankar et al., 2020), with some consideration given to transit engineering (Huo et al., 2023; Mirzaei-Nasirabad et al., 2023; Mohtasham et al., 2022; Mu et al., 2020; Wang et al., 2023; Yan et al., 2023; Zhang et al., 2022). However, there is a noticeable lack of research specifically addressing mine earthworks, which include not only trucks but also a large number of simultaneous bulldozer operations. Therefore, effective planning and management of mine earthworks are essential.

In contrast, extensive research has been devoted to automated equipment scheduling in earthworks for construction projects. Early methods were based on databases and progress mapping (Hong et al., 2023; Lee et al., 2023; Lee et al., 2022; Li and Lu 2019; Stipanovic et al., 2021). With advancements in artificial intelligence, genetic algorithms, and deep reinforcement learning (DRL), these techniques are gradually being integrated into automated scheduling approaches (Choi and Han 2023; Deng et al., 2020; Hwang et al., 2014; Liu et al., 2022; Shehadeh et al., 2022; Woo et al., 2018). Furthermore, the focus of scheduling has shifted from single-objective to multi-objective optimization (Hwang et al., 2014; Liu et al., 2022; Shehadeh et al., 2022). Unfortunately, a critical aspect, safety, is often overlooked. This concern is especially pressing in mining engineering, where large-scale machinery introduces significant safety risks. Therefore, it is crucial to prioritize scheduling methods that effectively incorporate safety considerations.

Operations management incorporating safety considerations has been researched. A common method for safety risk prediction is to build this prediction using early information modeling (Feng et al., 2023; Liang and Liu, 2022; Zhou et al., 2024) and more advanced artificial intelligence prediction (Ayhan and Tokdemir 2020; Gondia et al., 2023; Hallowell et al., 2013; Kulikova and Balovtsev 2020; Liu et al., 2020; Lu et al., 2023; Ou et al., 2021; Sadeghi et al., 2020). Real time safety control, for instance, utilization of safety rules or real time sensing (Deepak and Mahesh 2023; Lee D et al., 2023; Saurin et al., 2008), has been of recent interest. Nevertheless, though these are management approaches at the macro level including a system of safety indicators routine assessment of safety risks and work control perception system, the perception of safety work of subordinates reduces to the passive fulfillment of the requirements of safety procedures. Furthermore, safety constraints are an appropriate method for use in project scheduling. Shop operation scheduling has been a focus of current research rather than safety scheduling in earthwork projects.

Artificial intelligence technology has been developed widely and a great number of intelligent methods and tools have been used in the engineering field for industrial automation (Lu et al., 2024; Qin et al., 2024; You et al., 2023; Zhou et al., 2023). Consequently, the focus of this research is on mine earthworks and a method for the modeling of the automated scheduling of machinery is proposed. In addition, it presents operational constraint for mine earthworks incorporating safety. This research then proceeds to develop an automated machinery scheduling method that incorporates spatio-temporal safety constraints. This paper presents an optimization based on the DRL method which optimizes the machinery scheduling scheme in conjunction with safety constraints. This research proposes a method with high value in reducing safety accidents in mine earthworks.

2 Related work

2.1 Planning and management for mine construction

Mining engineering is a highly complex field that has attracted extensive scholarly attention, particularly in the areas of planning and management. The primary focus of mining engineering lies in mining operations, making the planning and management of these operations the most researched topic within the discipline. The principal aim is to maximize profitability, which is achieved through the optimization of mining planning, taking into account capital flow and mining costs (Guo et al., 2021; Paithankar & Chatterjee, 2019). However, profitability represents just one dimension of mining operations. Other crucial aspects of mine planning development include the socio-economic context (Liu et al., 2023) and the production lifespan of the mine (Xu et al., 2023). Furthermore, various in-mine factors, such as ventilation and cooling requirements, play a significant role in creating a safe and productive working environment for operators (Ogunmodede et al., 2022). Additionally, warehouse capacity considerations are vital (Flores-Fonseca et al., 2022). Beyond macro-level planning, substantial research exists on micro-level operations management, which centers on short-term resource allocation constraints (Joshi et al., 2022; Manríquez et al., 2023). Nonetheless, effective short-term planning often necessitates optimization across multiple objectives to achieve satisfactory mining operation planning solutions (Both et al., 2020; Paithankar et al., 2020).

In addition to mining operations, the transshipment of materials within the mine requires the coordinated efforts of various machines, which has become a prominent area of study. Trucks serve as the primary transportation machinery in mining, making the optimization of truck management a critical research focus. Successful truck management involves considerations of fleet size, fleet allocation, and other relevant factors (Mohtasham et al., 2022). Given the typically large size of mining trucks, reducing idle time (Mirzaei-Nasirabad et al., 2023) and minimizing energy consumption (Zhang et al., 2022) are essential objectives. Conveyor transportation is also a widely used method in mines, and its effective planning and management can significantly lower electricity costs (Mu et al., 2020). Moreover, the advent of intelligent technology has paved the way for the use of robotic transloading systems in mining operations (Yan et al., 2023). Intelligent methods are increasingly being employed for scheduling and managing transloading operations (Huo et al., 2023; Wang et al., 2023). Additionally, some researchers have explored the scheduling and management of resources such as water (Bo et al., 2022) and electricity (Nikolaev et al., 2023).

While significant research has focused on planning and managing mining and transshipment operations, there has been relatively less exploration of mine earthworks. However, mine earthwork operations involve a substantial number of bulldozers and trucks working in concert, necessitating careful planning and management in this domain.

2.2 Automated equipment scheduling for earthwork

Earthwork is vital to construction projects, characterized by an extensive construction cycle and the need for coordination among a large array of engineering machinery. In recent years, the advancement of automated construction has elevated the automation of earthwork equipment scheduling into a prominent area of research. Effective scheduling prioritizes resources, prompting some researchers to devise scheduling methods based on resource databases (Lee C et al., 2023) or the status of assets (Stipanovic et al., 2021) involved in earthwork. However, these methods often require considerable time and financial investment to establish the necessary databases. As a result, some researchers have investigated the automation of scheduling by directly extracting information from progress diagrams (Hong et al., 2023; Lee et al., 2022; Li and Lu, 2019). Furthermore, simulation has emerged as an effective approach for enhancing scheduling decisions by developing simulation models through the use of sensors or drones (Rachmawati et al., 2023; Zamani et al., 2023).

With the rise of artificial intelligence, intelligent algorithms, such as genetic algorithms, are becoming increasingly prominent in the automatic scheduling of earthwork equipment. For example, earthwork can be conceptualized as a path assignment problem, solvable through genetic algorithms (Deng et al., 2020). A particularly notable advantage of genetic algorithms is their capability for multi-objective optimization, which is essential for the successful execution of earthwork projects (Hwang et al., 2014; Liu et al., 2022; Shehadeh et al., 2022). Consequently, many researchers advocate for the application of genetic algorithms in the scheduling of earthworks from a multi-objective optimization standpoint. Additionally, DRL—combining deep learning capabilities with reinforcement learning—has proven to be an effective strategy for addressing scheduling challenges. Some researchers have begun implementing DRL in earthwork scheduling, yielding significant results (Choi and Han, 2023; Woo et al., 2018).

While numerous methods for scheduling automated equipment for earthworks exist, many primarily focus on cost, time, and similar considerations, often overlooking safety. In practice, safety is significant due to the diverse range of construction machinery involved in earthwork operations. This concern is heightened in mining contexts, where the number of pieces of equipment is substantially greater, underscoring the necessity of incorporating safety as a critical factor in scheduling.

2.3 Project management and scheduling considering safety

In construction projects, inherent safety risks must be continuously addressed. Consequently, an increasing number of scholars are investigating strategies to integrate safety into operations management. One practical and efficient method is to predict safety risks prior to the commencement of construction. Building information modeling (BIM) is employed not only during the design phase but also plays a crucial role in forecasting safety risks. The synergy between BIM and the Internet of Things (IoTs) presents significant potential for effectively anticipating risks throughout the construction process (Feng et al., 2023; Liang and Liu, 2022). Furthermore, researchers have begun to consolidate essential safety risk assessment principles and indicators through an analysis of existing literature standards and accident case studies (Hallowell et al., 2013; Kulikova and Balovtsev, 2020; Liu et al., 2020). With advancements in artificial intelligence, machine learning, and neural network-based methods have become mainstream for safety risk prediction, yielding promising results (Ayhan and Tokdemir, 2020; Gondia et al., 2023; Lu et al., 2023; Ou et al., 2021; Sadeghi et al., 2020).

However, implementing a safety risk prediction approach in operations management is not a one-time solution. In practical engineering scenarios, it is often crucial to actively manage safety risks in real-time during construction. For instance, a systems engineering approach can be employed to analyze the construction process and identify critical safety management principles (Saurin et al., 2008). Establishing a comprehensive safety framework based on safety indicators is another effective strategy (Deepak and Mahesh, 2023). Additionally, the integration of safety regulations with sensor technologies, such as cameras, can significantly enhance real-time monitoring and safety control, thereby facilitating intelligent safety management (Lee D et al., 2023).

For project scheduling challenges, incorporating constraints to ensure safety is an effective strategy. In the context of shop scheduling, it is crucial to consider ergonomic risks while optimizing energy consumption, thereby safeguarding the well-being of shop workers through adherence to safety goals (Destouet et al., 2024). Worker fatigue is also a significant safety concern (Aribi et al., 2023). Beyond physical collisions, environmental factors such as dust and noise pose additional threats to worker safety, and these issues have been the subject of various research studies (Fu et al., 2020). Furthermore, the reliability of safety can be quantitatively represented as safety time (Yang and Xu, 2021) and safety distance (Zhou and Liao, 2020). However, current scheduling methodologies that account for safety primarily focus on the scheduling of shop jobs within factories, with limited research dedicated to the safe scheduling of earthwork operations at construction sites. Earthwork tasks entail the coordinated operation of numerous large machinery units; therefore, incorporating safety considerations into scheduling constraints is both important and valuable.

3 Methodology

As illustrated in Fig. 1, this research proposes an automated equipment scheduling method tailored specifically for mine earthworks. Initially, the study models the scheduling issues associated with mine earthworks and introduces operational constraints that emphasize safety considerations. Subsequently, spatio-temporal safety constraints are formulated and integrated into a DRL algorithm. This approach allows for a more scientific methodology in scheduling machinery for mine earthworks, taking potential risks into account to enhance overall construction safety.

3.1 Modeling of scheduling for automated mining earthwork equipment

3.1.1 Problem description

Mining earthwork is a vital component of mining engineering, particularly in coal mines and other mineral resource sites. These operations produce significant amounts of waste soil that must be transported to designated discharge locations for dumping, followed by subsequent earthwork activities performed by bulldozers. It is important to note that mining earthwork differs from conventional earthwork practices. The detailed process is illustrated in Fig. 2 and consists of four key steps: a) trucks enter the site to transport large quantities of soil to the discharge point for unloading; b) trucks adjust their positions accordingly for this unloading; c) upon completion of the unloading, trucks exit the site while bulldozers enter the area to carry out bulldozing operations at the unloading point; d) after finishing their tasks, bulldozers leave the discharge yard in preparation for the next work cycle. Specifically, as shown in Fig. 3, each machine operates along roughly parallel paths known as discharge lines. The end of these lines is where machinery pushes and fills soil—this location is referred to as the soil discharge point. In actual mine earthwork scenarios, continuous filling leads to an ongoing extension of the discharge line as it gradually advances toward new areas needing attention.

Given the collaboration of multiple large-scale machines in mine earthmoving operations, it is essential to implement a scientifically designed automated scheduling system. Such a system not only enhances standardization and efficiency within the workflow but also improves overall productivity. The machinery involved in mine earthmoving operations consists of various bulldozers and trucks. The primary work area is the soil discharge field, which contains multiple soil discharge points where machinery unloads and performs soil pushing operations in a specific sequence. The

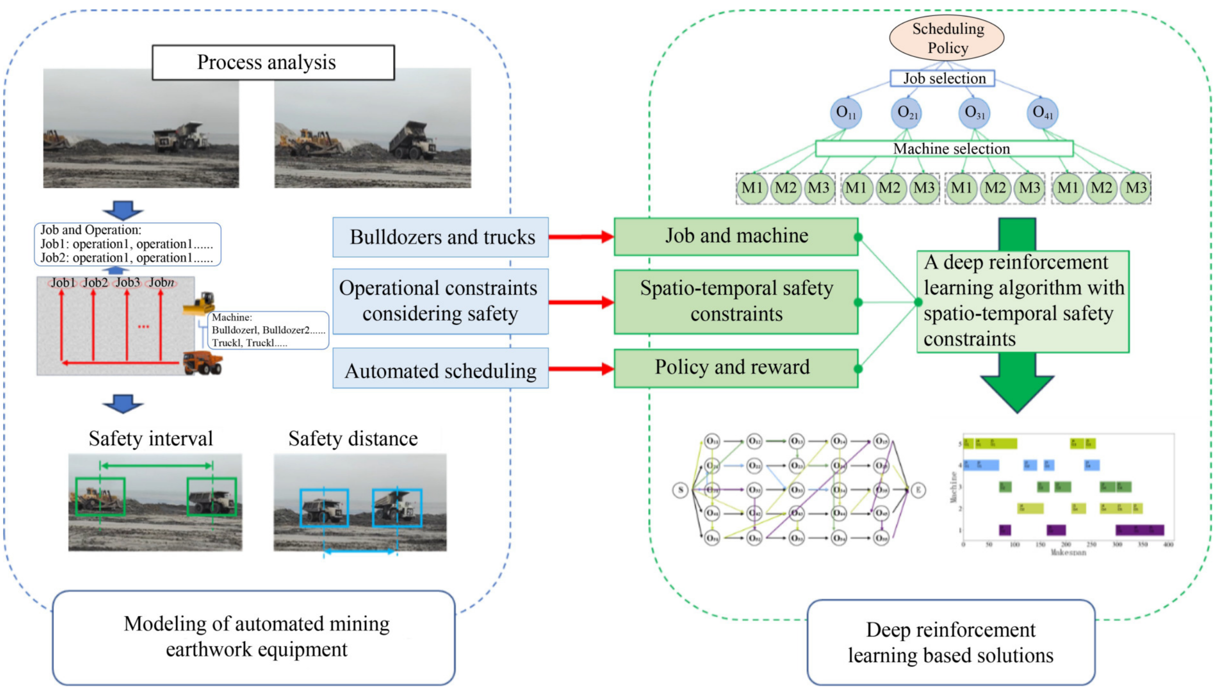

Fig. 1 Abstract diagram of the proposed method.

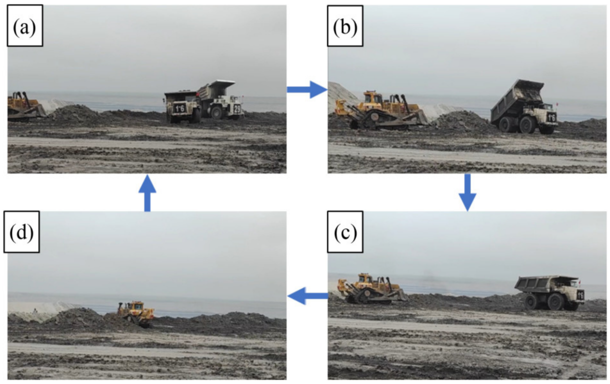

Fig. 2 Flow of mining earthwork: (a) Truck coming in; (b) Truck unloading; (c) Truck leaving and bulldozer moving in for bulldozing operations; (d) Bulldozer leaving.

scheduling of all jobs and machines adheres to the following rules:

Rule 1: A machine can work only on one line at one time step.

Rule 2: No more than one machine can work on a single line at the same time

Rule 3: Once a machine starts a job, it cannot be interrupted.

Rule 4: Operations within the same job have a sequential order.

Thus, the scheduling of machinery for mine earth removal operations can be regarded as a problem analogous to the Flexible Job Shop Scheduling Problem (FJSP).

As illustrated in Fig. 4, this paper proposes a model for scheduling earthmoving operations in mining within the framework of FJSP. In this model, the discharge field is segmented into parallel discharge lines, through which the bulldozers and trucks involved in the operations access the earth displacement area. Each line culminates at a discharge point, which serves as the principal site for the machinery's tasks. At each discharge point, the machinery is required to complete a series of operations. Consequently, the FJSP model for mine earthmoving operations emphasizes the scientific scheduling of multiple bulldozers and trucks at each discharge point.

3.1.2 Operational constraints considering safety

The engineering machinery utilized in mine earthmoving operations is often large, leading to numerous blind spots for operators. This increases the risk of accidents, as well as potential casualties and property damage. Therefore, while optimizing the scheduling of machinery in earthwork operations, it is essential to ensure that adequate safety

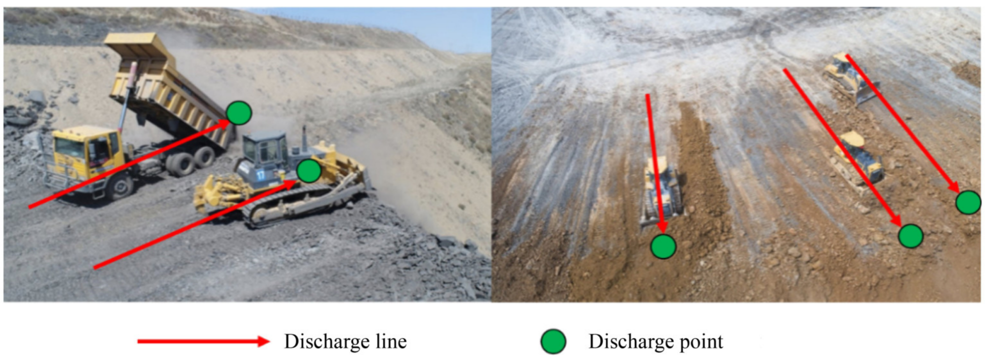

Fig. 3 Schematic illustration of soil discharge line and point.

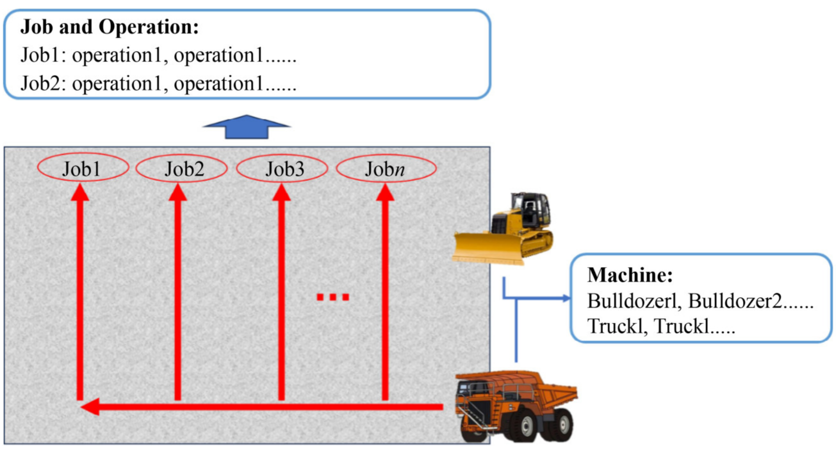

Fig. 4 FJSP-like modeling of mining earthwork

distances and durations are maintained between large machines. Figure 5 illustrates the proposed operational constraints derived from the modeling of mine earthmoving operations, with an emphasis on safety considerations.

The safety constraints proposed in this paper include two aspects. The first aspect pertains to the *X*-axis constraint, which governs the independent functioning of parallel row lines. Although machinery may operate concurrently in adjacent row lines, their close proximity significantly elevates the risk of accidents. Consequently, the *X*-axis safety constraint highlights the importance of maintaining a safe distance between machinery in parallel rows, thereby prohibiting simultaneous work in neighboring rows.

The second aspect involves the *Y*-axis constraint, which focuses on the sequence of operations within a row. Multiple pieces of equipment enter and exit a row of lines, and failing to maintain a safe time interval between them may result in safety incidents. As such, the *Y*-axis safety constraint is designed to ensure a safe exit time for successive operations performed by machines in the same row of soil lines. This requires maintaining a safe time interval between the start time of the latter machine's work and the end time of the former machine's work.

3.2 A deep reinforcement learning algorithm with spatio-temporal safety constraints

3.2.1 Markov decision modeling

For the solution to the scheduling problem in mine earthwork, we utilize a Markov decision process. The agent selects an action at each moment based on the current state and transitions to the next state while receiving an instantaneous reward. This instantaneous reward accumulates progressively as the scheduling process continues. The primary objective of scheduling is to identify a sequence of actions that maximizes the cumulative reward.

In the context of earthwork within a mine, the agent includes the overall scheduling solution, making choices about scheduling actions based on the current state S_t at each time step. As illustrated in Fig. 6, the scheduling actions involve two key considerations. First, the agent must decide which job J_i to perform, determining which operation O_{ij} at which discharge point will be executed. Second, the agent needs to select which machine M_k will be employed to carry out the job. Depending on the selected action, the agent receives a reward value R and updates the state to S_{t+1} (Table 1).

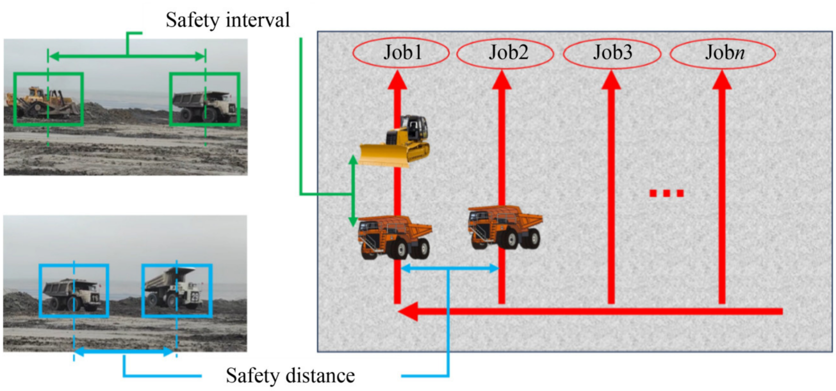

Fig. 5 Safety constraints on machine

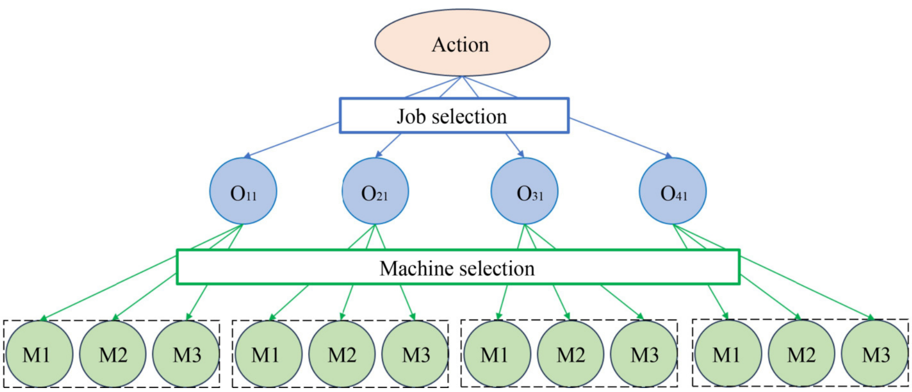

Fig. 6 Action selection in scheduling solutions for mine earthwork.

Table 1 Parametric representation of solution

Parameter	Definition and detailed description
J_i	The job at No.i soil discharge location. When the number of soil discharge locations is n.
O_{ij}	The operation #j of the No.i soil discharge location.
M_k	Machine No. k. When the number of machines is m.
Action	Action selection of each time step
R	Reward value for each action implementation
S_t	The scheduling solution at moment t. It is a three-dimensional matrix that represents the current scheduling status. State = [J_i, O_{ij}, M_k]

3.2.2 Model architecture

To address the Markov decision problem related to mine earthworks, this paper employs a DRL algorithm. DRL represents an advanced methodology that integrates deep learning with reinforcement learning, making it particularly effective for resolving complex scheduling challenges.

The algorithm employed in this research is grounded in the multi-action DRL framework (Lei et al., 2022), which serves as an end-to-end solution for efficiently and swiftly addressing scheduling problems. This framework adeptly integrates graph neural networks with multi-Proximal Policy Optimization (multi-PPO), yielding outstanding performance across various scheduling scenarios. The structure of the algorithm is illustrated in Fig. 7. Each job contains specific structural information, such as priority constraints and the set of compatible machines for each operation. This structural information can be extracted and leveraged effectively. The Graph Isomorphism Network (GIN), a variant of Graph Neural Networks (GNNs), demonstrates even greater efficacy (Wang and Zhang, 2022). The GIN encodes the state nodes guiding the job selection strategy, which are then processed through a multilayer perceptron (MLP). There is no inherent structural information between the machine's state data; therefore, it can be directly encoded using a fully connected layer. Subsequently, both the job selection and machine selection outputs are linked in series with MLP-based decoders, utilizing an identical network structure while maintaining separate parameters. During the decoding stage, each decoder computes the probability distribution for the job operation space or the machine operation space, respectively, producing both the job operation score and the machine operation score.

3.2.3 Spatio-temporal safety constraints

To integrate safety considerations into job constraints, spatio-temporal safety constraints are implemented within the context of DRL. As illustrated in Fig. 8, this research employs spatio-temporal safety constraints to refine certain parameters of the Markov decision process. In this process, the state matrix defined in this study incorporates StartTime and Dur as correction parameters,

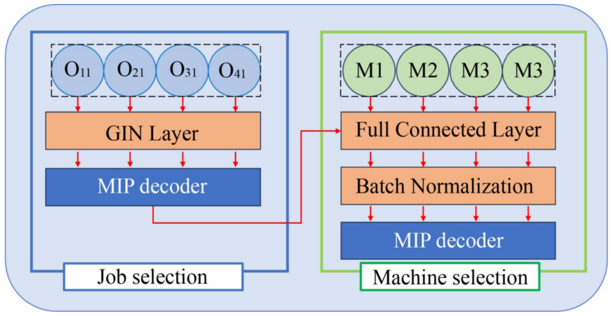

Fig. 7 Structure of the algorithm

in addition to the three standard values of J_i, O_{ij}, and M_k. Specifically, at time step t, the StartTime and Dur of state S_t are transferred to two matrices, Safety_jz[] and Dur_jz[], for safety assessments. The new state S_{t+1}', generated after action selection, does not immediately enter the next decision-making phase but must first undergo the safety assessment dictated by the spatio-temporal safety constraints. Only upon passing this assessment can it be deemed the new state S_{t+1}. If it fails, the StartTime is adjusted to ensure compliance with the safety criteria.

Pseudo-code for spatio-temporal safety constraints is presented in **Algorithm 1**. Initially, this research establishes two matrices, Safety_jz[] and Dur_jz[] to log the StartTime and duration information throughout the scheduling process. The index value i in both matrices signifies the number of epochs, while the dimensions of the matrices are defined by the number of jobs and operations, represented by the row and column indices, respectively. It is crucial to note that these matrices are updated with a delay; focusing solely on historical states when making decisions aligns with the principles of a Markov decision process. These two matrices serve primarily for comparing safety decisions in subsequent analyses.

Specifically, the code includes five conditional statements, each addressing different safety constraints. The first if statement pertains to Y-axis constraints, stipulating that, within the same row of soil lines, the time interval between the start time of the subsequent machine and the end time of the preceding machine must exceed the operational duration of the latter. This requirement ensures that the former machine can safely exit after completing

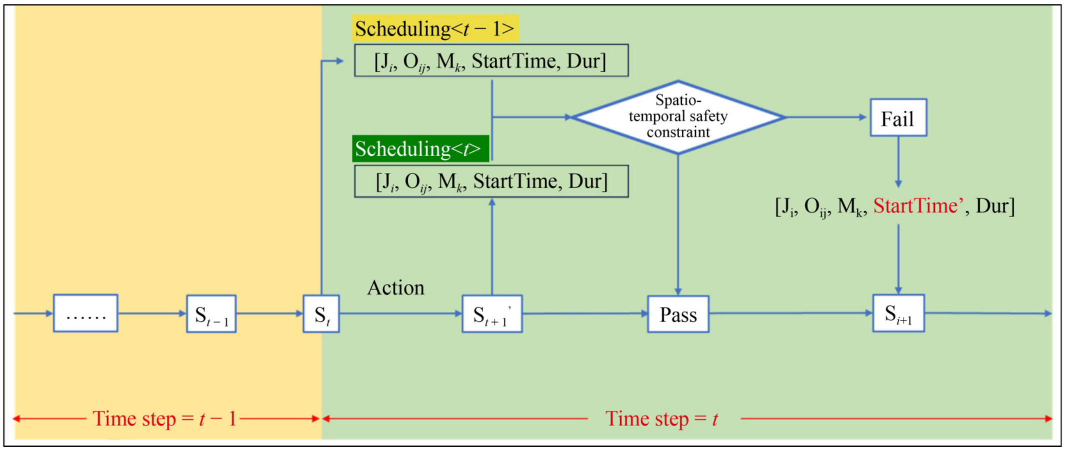

Fig. 8 The effect of spatio-temporal safety constraints on Markov decision processes.

Algorithm 1 Spatio-temporal safety constraints

Input: Number of jobs: n_j; Number of machines: n_m;

1: Initialize Safety_jz = [[[0 for _ in range(n_m)] for _ in range(n_j)] for _ in range(epochs)]

1: Initialize Dur_jz = [[[0 for _ in range(n_m)] for _ in range(n_j)] for _ in range(epochs)]

2: **while** in Markov decision processes

3: select Action

4: $S_t \rightarrow S_{t+1}$'

5: $\boldsymbol{S_{t+1}}'$ = [J_i, O_{ij}, M_k, StartTime, Dur_a]

6: if StartTime < (Safety_jz[i][row][col-1] + Dur_jz[i][row][col-1] + Dur_jz[i][row][col-1]):

7: StartTime = (Safety_jz[i][row][col-1] + Dur_jz[i][row][col-1] + Dur_jz[i][row][col-1])

6: if StartTime < (Safety_jz[i][row-1][col-1] + Dur_jz[i][row][col-1]):

7: StartTime = (Safety_jz[i][row-1][col-1] + Dur_jz[i][row][col-1])

8: if StartTime < (Safety_jz[i][row-1][col] + Dur_jz[i][row][col]):

9: StartTime = (Safety_jz[i][row-1][col] + Dur_jz[i][row][col])

10: if StartTime < (Safety_jz[i][row + 1][col-1] + Dur_jz[i][row + 1][col-1]):

11: StartTime = (Safety_jz[i][row + 1][col-1] + Dur_jz[i][row + 1][col-1])

12: if StartTime < (Safety_jz[i][row + 1][col] + Dur_jz[i][row + 1][col]):

13: StartTime = (Safety_jz[i][row + 1][col] + Dur_jz[i][row + 1][col])

14: Safety_jz[i][row][col] = StartTime

15: Dur_jz [i][row][col] = Dur_a

its task. Regarding X-axis constraints, this research mandates that machinery operating in adjacent rows of soil lines cannot function simultaneously, as indicated by the second through fifth if statements. In instances where these regulations are breached, the StartTime will be reverted to a point that complies with the specified safety constraints.

3.3 Optimization strategies for deep reinforcement learning

3.3.1 Instances generation

Publicly available data sets are insufficient in providing scheduling examples for mining earthwork operations. To affirm the scientific validity of the proposed method, this paper outlines a data pipeline for automatic instance generation rooted in engineering practices. The generation of instances adheres to the following three principles:

Rule 1: The total number of machines available for dispatch is contingent upon the size of the schedule; however, there is variability in the number of bulldozers and trucks assigned to each schedule.

Rule 2: Variability in machinery efficiency arises from factors such as the machinery's performance and the operator's proficiency.

Rule 3: The first operation in any row must be a truck unloading dirt, while the final operation must be a bulldozer pushing dirt.

Algorithm 2 illustrates the process in detail. Initially, the method employs two random arrays to generate the foundational data for the examples. The 'time0' array is a three-dimensional array with values predominantly ranging between 30 and 60, signifying that the majority of equipment operates within this time frame. Conversely, the 'time1' array is similar to 'time0', but consists of a single column with values ranging between 20 and 30. This indicates that a small number of devices are permitted to perform exceptionally, operating between 20 and 30. These two arrays are subsequently concatenated and reshaped to form an array named "times," with dimensions n_j * n_m * n_m.

Building upon the time array and the established construction rules, various factors must be considered and evaluated. First, it is essential to determine the respective number of bulldozers and trucks using a random number generation method described in this paper. A random value, denoted as num_kk and falling between the maximum and minimum number of bulldozers, is selected to represent the number of bulldozers for this example, while the number of trucks is calculated as n_m - num_kk. Following this, specific construction rules must be established. It is evident that unloading of trucks should be the first operation in any job, while bulldozer operations should occur last. Therefore, in the generation of arithmetic examples, this research designates the bulldozer working time for the first operation and the truck working time for the final operation of each job as −999, indicating that these operations are unavailable. Moreover, to illustrate a defined construction rhythm, a random interpolation method is utilized to render certain operations unavailable. Consequently, an example representing mine earthmoving operations is generated.

3.3.2 Optimization strategies

Leveraging the instance generation method discussed in Section 3.3.1, the training and optimization of the DRL algorithm can proceed efficiently. Since the instance generation module operates independently, it can be invoked multiple times within each epoch to produce varying instances for model learning. Specifically, an epoch comprises several batches, with each batch generating and inputting a fixed number of instances for computation. The results are then aggregated by epoch to produce reward and loss values for model iteration and optimization.

In this study, the model aims to allocate an appropriate workload to the machinery while optimizing the solution. The primary optimization objective is to minimize the total scheduling time. The following formula represents the total makespan:

$$C_{\max} = \max\{C_{\mathrm{in}_i}\},\ i \in \{1, \ldots, n\}, \tag{1}$$

where $C_{\max}$ is the value of makespan; where C_{in_i} denotes

Algorithm 2 Reward computation rules with spatio-temporal safety constraints

Input: Number of jobs: n_j, Number of machines: n_m. Minimum number of bulldozers: b_m, Maximum number of bulldozers: b_l.

```
Initialize data_set = []
random.seed(seed)
time0 = random(low = 30, high = 60, size = (n_j, n_m, n_m - 1))
time1 = random(low = 20, high = 30, size = (n_j, n_m, 1))
times = concatenate((time0, time1), −1)
times[j][m][n] = permute_rows(times)
num_kk = random.randint(b_m, b_l)
while j in range(n_j):
for kk in range(0,num_kk):
times[j][0][kk] = −999
for ee in range(num_kk,5):
times[j][n_m][ee] = −999
for m in n_m
for i in range(n_m/5):
col_idx = np.random.randint(1, n_m)
times[i][m][col_idx] = −999
data_set = array(times)
```

Output: A three-dimensional array for the problem representing the time spent by each machine on each operation of each job.

the completion time of job i; and $n \times m$ denotes the size of the FJSP instance.

The scheduling problem addressed in this research focuses on strategies for both job selection and machine selection. To resolve this issue, a multi-PPO algorithm is employed, which utilizes a multi-subject-critic architecture to learn two sub-policies, using Proximal Policy Optimization (PPO) as the policy optimization method (Wu et al., 2022). The multi-PPO architecture consists of two component networks, with each network responsible for a singular policy. Within this architecture, a single critic network with parameters is utilized, serving as an estimator to learn the approximate value state function. The specific computation is depicted below:

$$A_{\mathrm{t}} = \sum\nolimits_{\mathrm{t0=t}}^{\mathrm{t0}=T} \gamma^{\mathrm{t0}} \mathrm{r}_{\mathrm{t}} - \mathrm{V}_{\phi}(\mathrm{s}_{\mathrm{t}}), \tag{2}$$

where A_{t} is the empirical tuple; $\mathrm{V}_{\phi}(\mathrm{s}_{\mathrm{t}})$is the estimator used to compute the variance-approximate minus dominance function; and γ is the discount factor.

4 Model evaluation and implementation

4.1 Training setup

4.1.1 Environment setting

This research utilized a computing platform featuring an 11th Gen Intel(R) Core(TM) i7-11800 CPU and an RTX 3090 (24GB) GPU. The algorithms were implemented using Python 3.8 and configured with essential libraries, including PyTorch 1.8.1 and CUDA 11.1.

4.1.2 Input conditions

To comprehensively evaluate the performance of the proposed methodology, three scales with varying instance sizes were designed. The instance sizes are determined by the number of available machines. The small-sized instances comprise five available machines, featuring a minimum of 2 bulldozers and a maximum of 3. The specific sizes include ($J \times M$): 5 × 5, 5 × 10, and 5 × 20. The medium-sized instances consist of 10 available machines, with a minimum of 4 bulldozers and a maximum of 6. The designated sizes include ($J \times M$): 10 × 10 and 10 × 20. The large-sized instances feature 20 available machines, with a minimum of 10 bulldozers and a maximum of 15, represented by the specific scale of ($J \times M$): 20 × 20.

4.2 Scheduling results of generated instances

4.2.1 Analysis of scheduling results

This section analyzes the training and scheduling results at different scales, as presented in Table 2 and Fig. 8. The model demonstrates faster convergence during small-scale mechanical training, achieving convergence around the 1,000th batch. Due to the smaller scheduling scale, model training initiates with a lower loss. In medium-scale training, although convergence is still satisfactory, it is slightly slower compared to small-scale training. In large-scale training, the model initially experiences a higher loss due to the increased scheduling size. However, as training progresses, the loss curve for large-scale scheduling displays good convergence trends.

As shown in Table 2, the incremental increase in scheduling size results in only a modest rise in total scheduling time. The implementation of the surface security rule has a minimal effect on the overall scheduling time, contributing only a negligible increase. This indicates that our proposed method can effectively adapt and converge in the presence of spatio-temporal safety constraints while preserving strong learning capabilities.

Moreover, as illustrated in Fig. 9, although scaling up the scheduling leads to a proportional increase in the loss associated with the training start time, this does not significantly affect the model’s training process. In fact, the DRL model demonstrates rapid and consistent learning and convergence, even when applied at varying scheduling scales.

4.2.2 Analysis of spatio-temporal analytic map

To demonstrate the performance of the proposed method in this study, spatio-temporal analysis plots at various scales are presented in this section to visualize the specific effects of scheduling. It is important to note that the algorithms employed in this research, including those that generate the spatio-temporal analysis graphs, are automatically produced without any human intervention.

The spatio-temporal analysis plot is a three-dimensional representation, where the x and y axes correspond to jobs and their respective scheduling times, while the chosen machinery is depicted as distinct colored orbs. Notably, the z-axis in this context illustrates the trend of the total safety response value (SafetySum) in the scheduling results, representing the delays incurred due to the influence of spatio-temporal safety constraints at each time step.

Table 2 Scheduling results of different scales

M_num	J_num	Makespan
M = 5	J = 5	403.76 ± 25.35
	J = 10	530.674 ± 31.98
	J = 20	1399.31 ± 88.24
M = 10	J = 10	838.884 ± 50.55
	J = 20	1498.87 ± 90.67
M = 20	J = 20	1786.963 ± 108.99

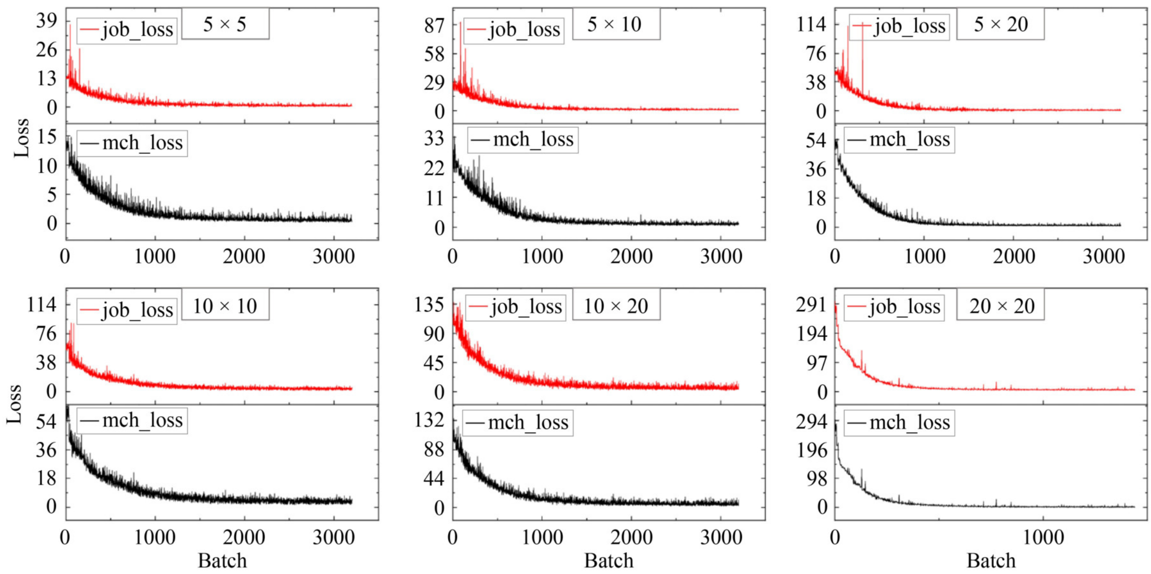

Fig. 9 Loss curves for training.

In Fig. 10, the spatio-temporal analysis diagram is presented at a scale of 5 × 10. Due to the smaller-scale scheduling, the spatio-temporal relationships are distinctly visible, with all five machines being relatively evenly engaged in the work. Furthermore, as time progresses, it is clear that the SafetySum value gradually increases, indicating that the spatio-temporal safety constraints consistently affect work progress, with later scheduling times experiencing a higher effect from these constraints.

Transitioning to Fig. 11, which displays the spatio-temporal analysis graph at a scale of 10 × 10, the overall trend becomes more evident as the scheduling scale increases. The graph exhibits a consistent upward trend from the bottom left to the top right, reinforcing the notion that spatio-temporal safety constraints exert a more pronounced effect as time progresses.

Figure 12 presents the spatio-temporal analysis graph at a scale of 20 × 20. The graph reveals a nearly uniform plate-like pattern and shows a discernible upward trend from the bottom left to the top right. This indicates that the influence of spatio-temporal safety constraints gradually intensifies over time, following a linear and uniform trajectory. Consequently, it is evident that as scheduling progresses, the interactions between machinery become more complex, leading to an increased occurrence of safety rule violations. This highlights the importance of implementing spatio-temporal safety constraints.

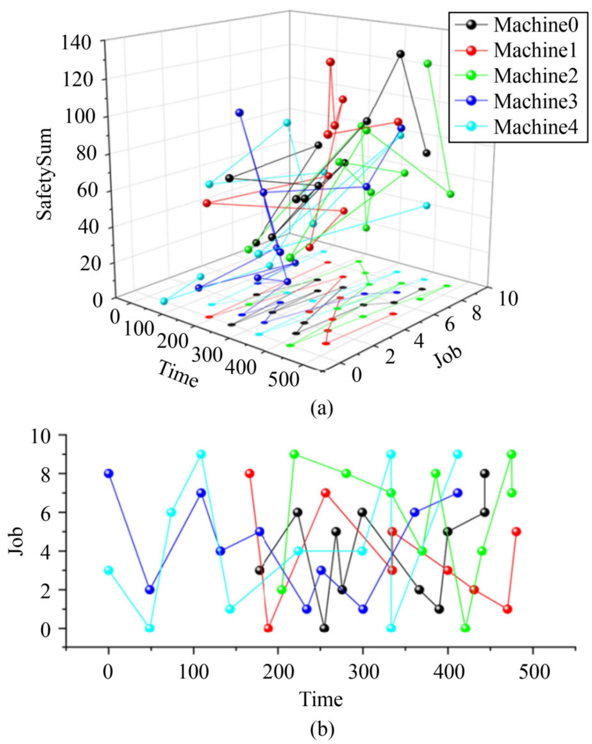

Fig. 10 Spatio-temporal analytic map and scheduling diagram for 5 × 10: (a) 3D spatio-temporal analysis map; (b) XY projection of 3D spatio-temporal analysis map.

4.2.3 Analysis of response to spatio-temporal safety constraints

To further evaluate the significance of spatio-temporal safety constraints, this study conducts a statistical analysis of their responses at various scales, based on the scheduling results. It is crucial to note that the response values in this context do not represent instantaneous reactions at individual time steps; rather, they reflect cumulative responses over time.

As illustrated in Table 3 and Fig. 13, in small-scale scheduling, both safetyXsum and safetyYsum show an

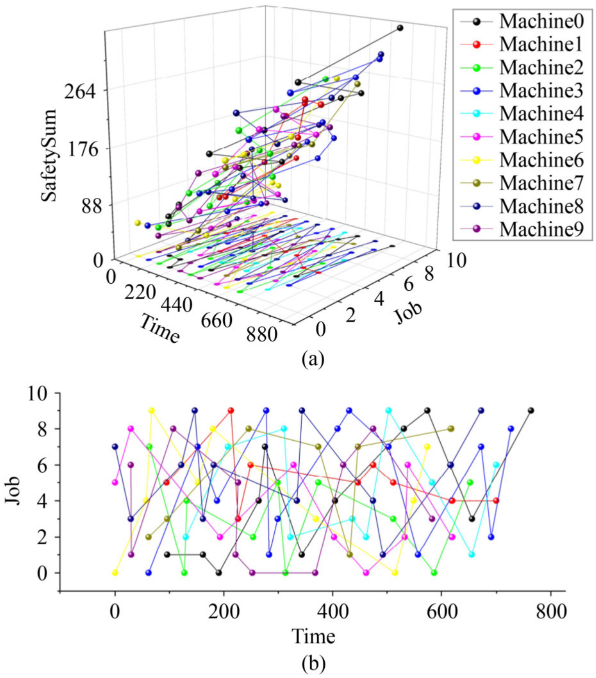

Fig. 11 Spatio-temporal analytic map and scheduling diagram for 10 × 10: (a) 3D spatio-temporal analysis map; (b) XY projection of 3D spatio-temporal analysis map.

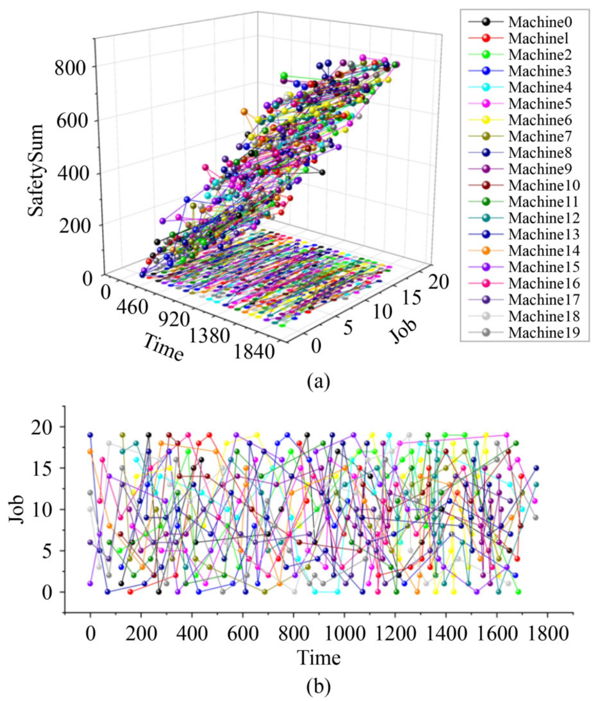

Fig. 12 Spatio-temporal analytic map and scheduling diagram for 20 × 20: (a) 3D spatio-temporal analysis map; (b) XY projection of 3D spatio-temporal analysis map.

upward trend, albeit with certain irregularities. Furthermore, as time advances, the slopes of safetyYsum exhibit an increasing trajectory, while the slope of safetyXsum gradually diminishes, potentially indicating a shift in the

Table 3 Response to spatio-temporal safety constraints

M_num	J_num	safetyXsum	safetYsum
M = 5	J = 5	419.18	1973.66
	J = 10	744.06	2255.54
	J = 20	9618.84	4149.94
M = 10	J = 10	1478.97	13076.81
	J = 20	11263.17	55671.71
M = 20	J = 20	10144.24	163470.65

prioritization of X and Y responses. Figures 14 and 15 present scheduling results at medium and large scales, respectively, and their fundamental trends correspond with those observed in small-scale scheduling. However, it becomes apparent that with the increasing scale of scheduling, the curves of both safetyXsum and safetyYsum tend to exhibit smoother changes. SafetyYsum demonstrates an increasing slope, whereas safetyXsum exhibits a decreasing slope.

To mitigate the influence of response priority, this study aggregates safetyXsum and safetyYsum to further analyze the combined response, referred to as safetySum. As illustrated in Fig. 16, safetySum consistently increases with an upward trend as time progresses, aligning with the findings presented in Section 4.2.2. Notably, safetySum experiences a significant surge at higher multiples as the scheduling scale expands. This indicates that instances of safety rule violations become more frequent as scheduling scales increase, emphasizing the importance of employing scheduling methods that account for spatio-temporal safety constraints on a larger scale.

To gain a deeper understanding of the effect of spatio-temporal safety constraints on scheduling results, this study examined the changes in results during model training iterations. As shown in Fig. 17, without these constraints, scheduling results exhibit minimal variation throughout the iterations. Additionally, the makespan of scheduling results without spatio-temporal safety constraints for epochs 20 and 100 reveals a difference of just under 100. In contrast, when spatio-temporal safety constraints are incorporated, the model demonstrates significant fluctuations during the iterations. For instance, at epoch 20, Machine 1 has yet to be utilized, but this situation improves markedly by epoch 60. This suggests that the presence of spatio-temporal safety constraints has a substantial effect on the scheduling of a significant portion of machinery. However, as the iterations progress, improved convergence is observed by epoch 100, indicating that the spatio-temporal safety constraints among the machines are being satisfactorily met. Ultimately, the makespan difference between epochs 20 and 100 for scheduling results with spatio-temporal safety constraints exceeds 300, highlighting the robust iterative capabilities of the model proposed in this research.

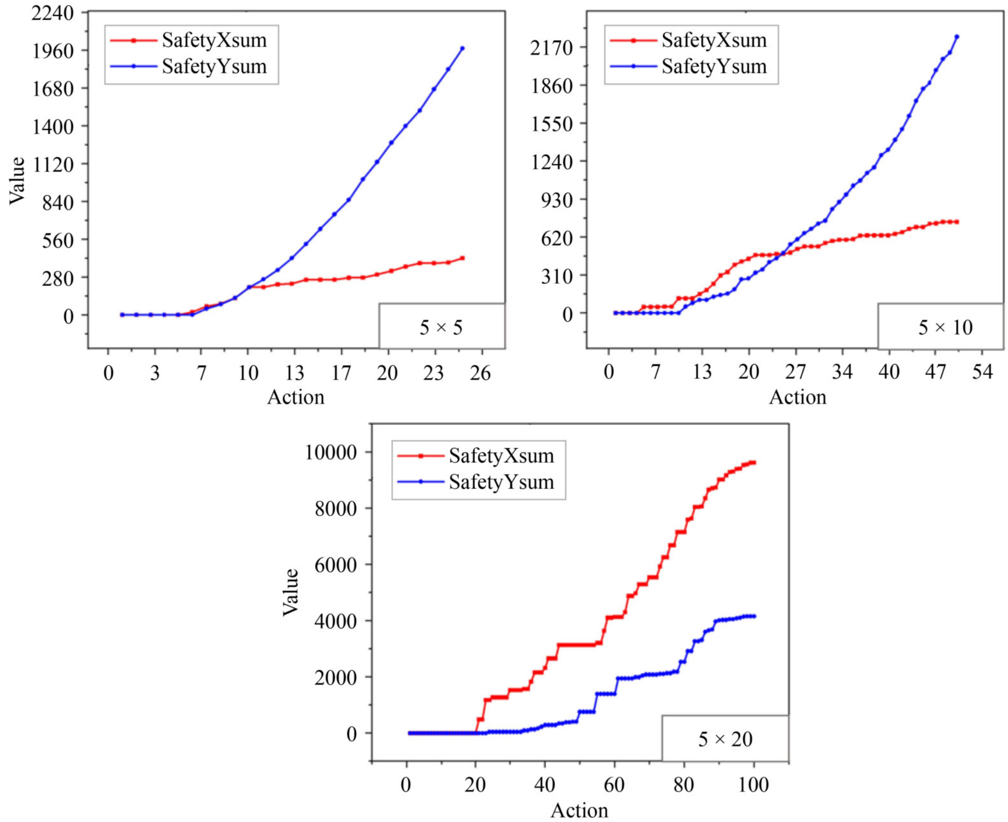

Fig. 13 Response to spatio-temporal safety constraints for small-scale.

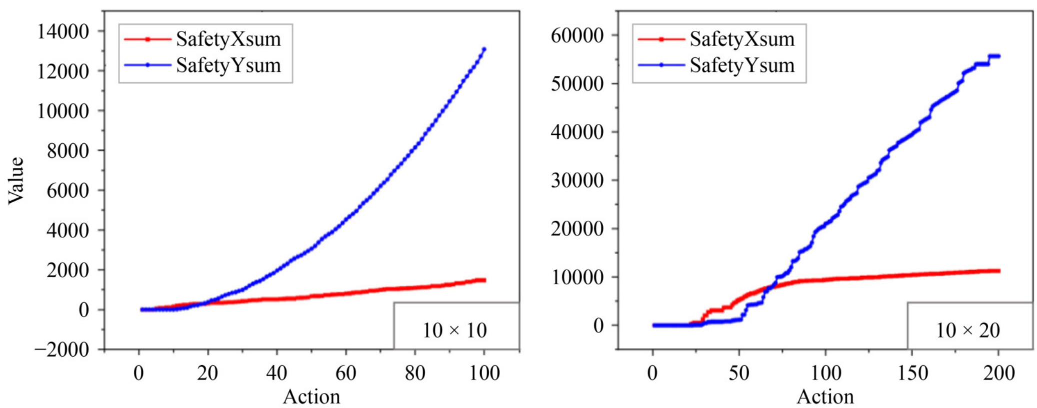

Fig. 14 Response to spatio-temporal safety constraints for medium-scale.

4.3 Scheduling results for multiple earthwork sites

In practical engineering contexts, there are scenarios in which multiple earthmoving yards are dispatched uniformly. This research provides further investigation into this operational scenario. The working conditions for multiple rows of earthmoving yards are largely similar to those for single rows, with the primary difference being that the *X*-axis safety constraints do not need to be considered when machinery is situated in different rows of earthmoving yards.

In this research, model training and testing were conducted with various numbers of earth discharge fields. It is important to note that the number of discharge yards functions as an intrinsic variable in the model training, which facilitates the direct application of scheduling across different numbers of discharge yards using a single training process. The training loss curves are illustrated in Fig. 18. A scale of 10 × 20 was employed for training, and the model exhibited good convergence, showing minimal variations in the loss curves when compared to a single row of soil fields.

Following the training, scheduling tests were conducted using the obtained weights to evaluate instances with

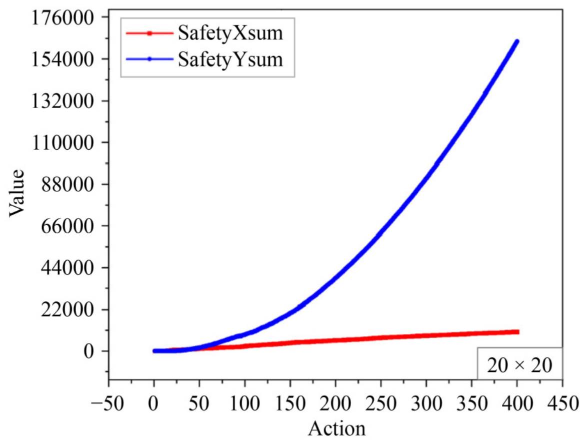

Fig. 15 Response to spatio-temporal safety constraints for large-scale.

varying numbers of earth displacement fields, as presented in Table 4. It is significant to emphasize that, in the instances illustrated in Table 4, the machinery's working time for each job remains constant; the only variation lies in the division of the earth displacement yard. It is clear that the total scheduling time shows a decreasing trend as the number of discharge yards increases. This trend can be attributed to the fact that a greater number of earthmoving fields allows for more rows to operate without needing to comply with X-axis safety constraints. Consequently, the time delays arising from these constraints are diminished, resulting in a reduction in total scheduling time. Additionally, Fig. 19 displays the scheduling results for different numbers of earth rows, which are consistent with the findings in Table 4. While the overall structure of the four scheduling result graphs remains similar, slight variations at certain node locations arise due to differing safety constraints.

5 Discussion

5.1 Performance comparison with different parameters

The model's performance can be influenced by its parameters. This section presents comparative results of the model's performance utilizing different parameter combinations. Two key parameters of interest are the learning rate and the size of the experience pool. An excessively large learning rate may hinder model convergence, while a rate that is too small can extend the convergence time. The second parameter, the experience pool size, must also be carefully considered; a pool that is too small may result in poor model performance, whereas an overly large pool can lead to an excess of experience, potentially causing early termination of model training.

As indicated in Table 5, this study conducted performance comparisons across three different learning rates and three different empirical pool sizes. At a learning rate of 0.01, the higher learning rate resulted in model makespan values exceeding 900, suggesting that the model did not converge as effectively as it could have. Furthermore, the increased learning rate led to the premature convergence of the experience pools at both 3200 and 6400, indicating an underutilization of these pools. Conversely, at a learning rate of 0.0001, the 6400

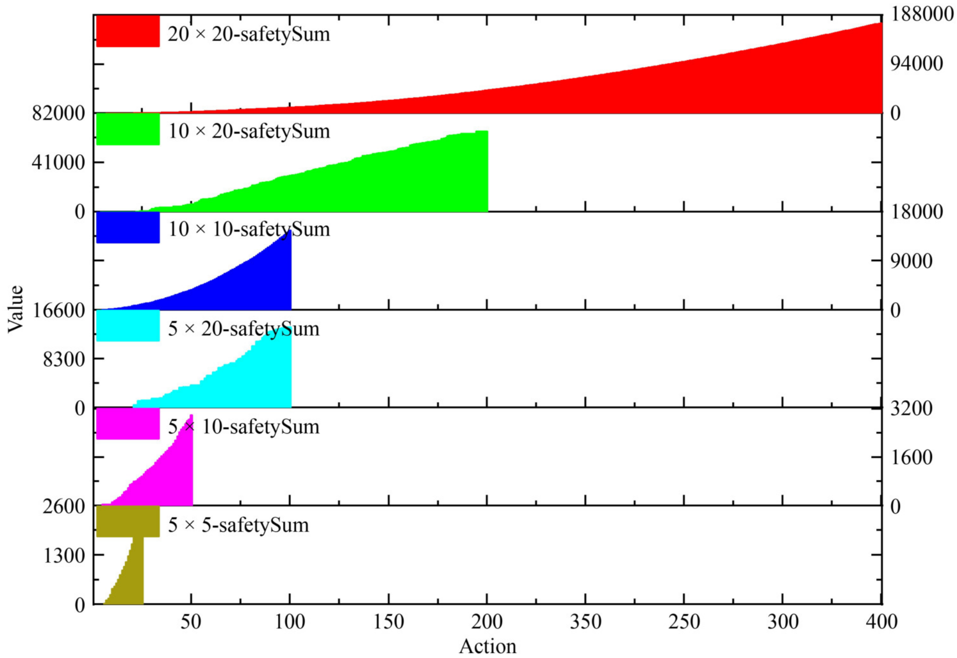

Fig. 16 Plot of variation in total response.

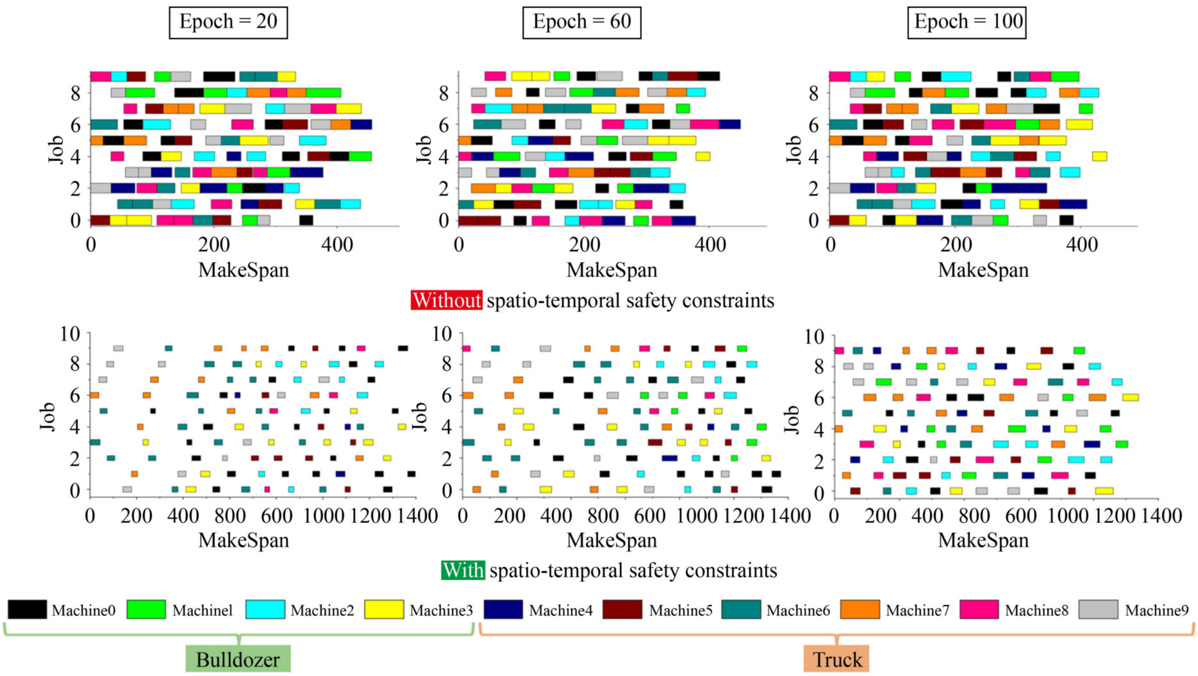

Fig. 17 Comparison of scheduling results with and without spatio-temporal safety constraints.

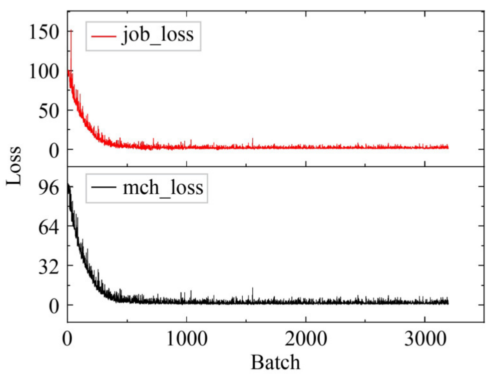

Fig. 18 Loss curves for multiple earthwork sites.

experience pool achieved a makespan of 875.87, while the other experience pools performed inadequately, implying that a lower learning rate resulted in less efficient learning. Lastly, under a learning rate of 0.001, the 3200 experience pool demonstrated optimal performance and fulfilled training requirements effectively, indicating that it fully utilized the experience pool.

5.2 Comparison with other models

To further validate the superiority of the proposed method in this study, classical scheduling algorithms were selected for comparison. The First-In-First-Out (FIFO) scheduling algorithm organizes tasks according to their arrival order, queuing them on a first-come-first-served basis. The Longest Waiting Time with Known Release (LWKR) algorithm is typically employed for real-time tasks and aims to minimize task waiting time. The

Table 4 Scheduling results for multiple earthwork sites 10 × 20

Number of earthwork sites	Quantitative distribution	Makespan
1	–	1260
2	[8,12]	1243
3	[8,4,8]	1141
4	[4,6,5,5]	1126

Most Operations Remaining Next (MOPNR) algorithm selects the job with the most remaining operations, intending to balance system load and reduce job waiting time.

As demonstrated in Table 6 and Fig. 20, the method proposed in this paper significantly outperforms the aforementioned classical scheduling algorithms regarding makespan. It is essential to note that a 10x10 arithmetic case at a medium scale was chosen to evaluate the performance of the different methods in this study. The makespan for the scheduling using DRL was 939, whereas the other scheduling algorithms exceeded 1000, with MOPNR reaching 1745. As illustrated in Fig. 18, classical scheduling algorithms exhibit varying degrees of concentration in scheduling due to their lack of advantages in learning and iteration. Consequently, certain high-performing machines are assigned a disproportionate amount of work. Specifically, Fig. 20 shows that LWKR and MOPNR demonstrate significant scheduling breaks attributable to waiting times. In contrast, DRL capitalizes on continuous learning and iteration to allocate work in a scientifically and rational manner within complex machinery, resulting in enhanced scheduling results.

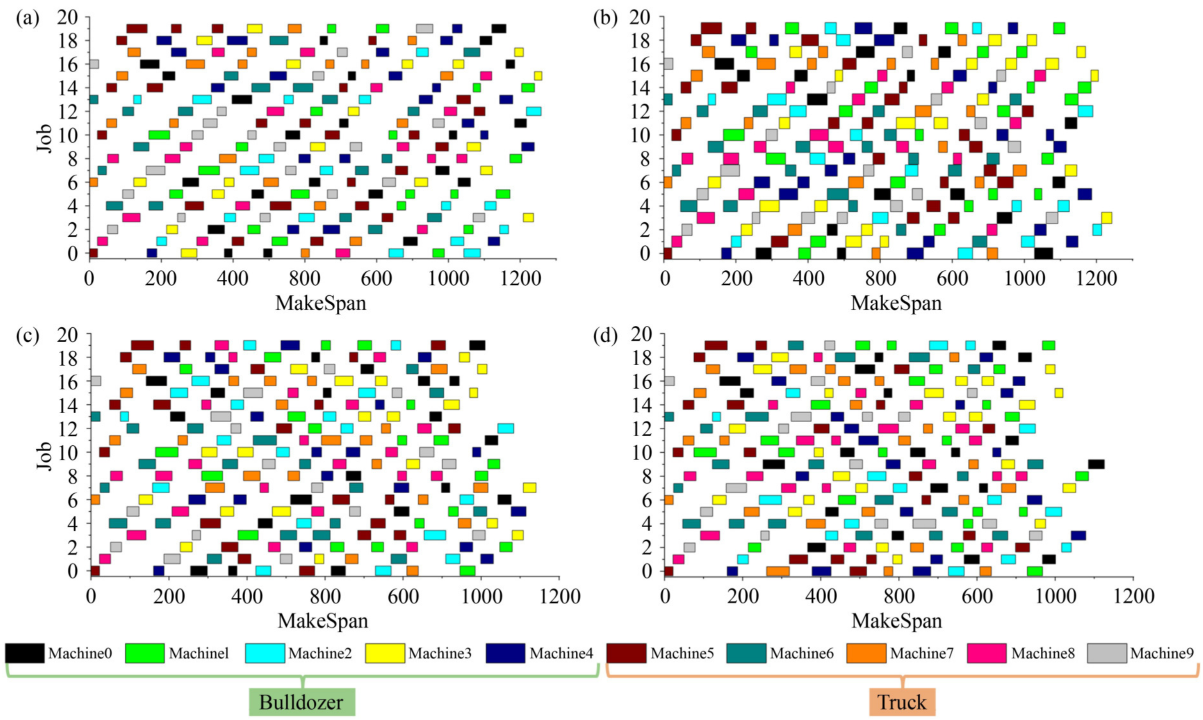

Fig. 19 Scheduling diagram for multiple earthwork sites: (a) Number = 1; (b) Number = 2; (c) Number = 3; (d) Number = 4.

Table 5 Performance comparison with different parameters

	Experience pool	Makespan	Convergence time
0.01	1600	1001.23	–
	3200	954.25	Prematurely
	6400	923.92	Prematurely
0.001	1600	899.12	–
	3200	838.88	–
	6400	846.32	Prematurely
0.0001	1600	1023.33	–
	3200	907.45	–
	6400	875.87	–

Note: Prematurely indicates that the Experience Pool is not saturated and ends training early

Table 6 Comparison with other models 10 × 10

Method	Makespan
DRL	939
FIFO	1139
LWKR	1314
MOPNR	1745

5.3 Testing and evaluation in a real mine earthworks project

The method described in this research has been implemented in the earthworks of an active mine located in Hulun Buir, Inner Mongolia, China, where lignite is the primary mineral output. As illustrated in Fig. 21, the mine spans a vast area with proven reserves of 4.166 billion tons, and it has the capacity to produce up to 35 million tons of coal annually. Currently, the mine features a large centralized earth removal site, employing two bulldozers and four trucks for its earth removal operations. This research conducts field tests using the proposed method within the operational context of this earth removal site.

In the field tests, this study examines the impact of spatio-temporal safety constraints on scheduling outcomes, as depicted in Fig. 22. The primary goal of these constraints is to ensure that machinery maintains a safe distance and time during operations. Consequently, during the initial phases of scheduling—particularly at the start of each job—the influence of safety constraints is minimal. Most operations demonstrate consistency in machinery selection; however, variations in time distribution are observed.

As the time steps progress, the effects of temporal safety constraints become increasingly apparent. In this section, we quantify both the frequency and total working duration for each type of machinery involved in scheduling, as presented in Table 7. The number of bulldozers was sufficiently low that safety restraints had negligible effects on their utilization. Conversely, trucks displayed significant changes in distribution patterns: without safety constraints, Machine 6 performed the majority of tasks; however, with the implementation of these constraints, previously underutilized machines, most notably Machine 3, were incorporated into the schedule,

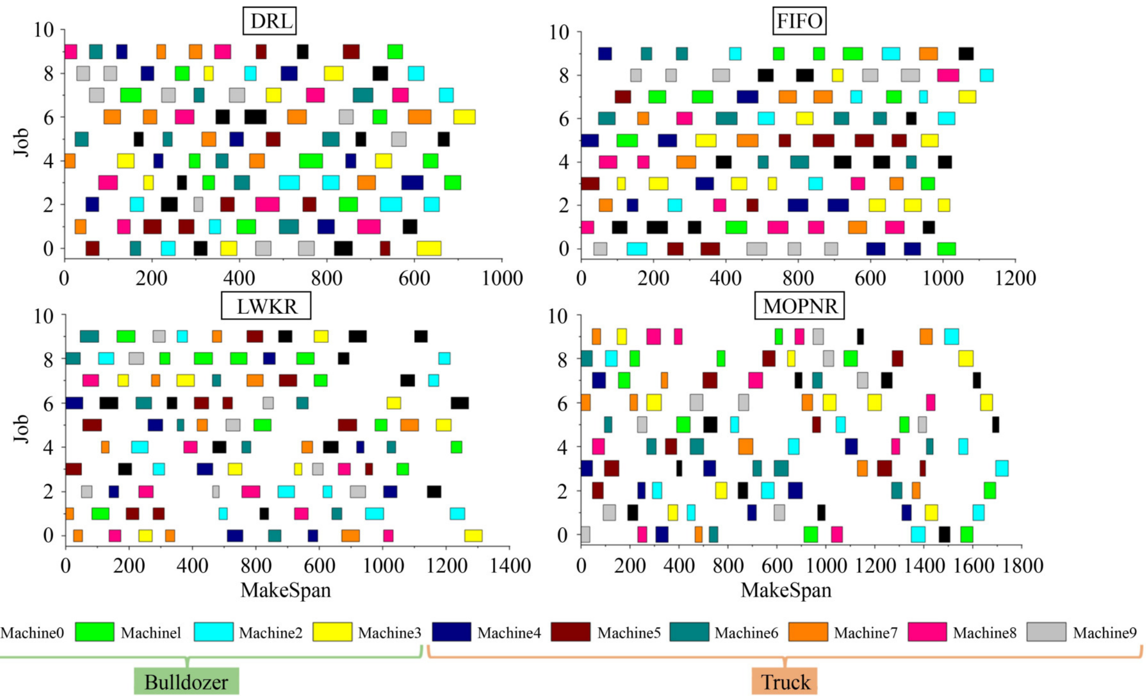

Fig. 20 Scheduling diagrams for different methods.

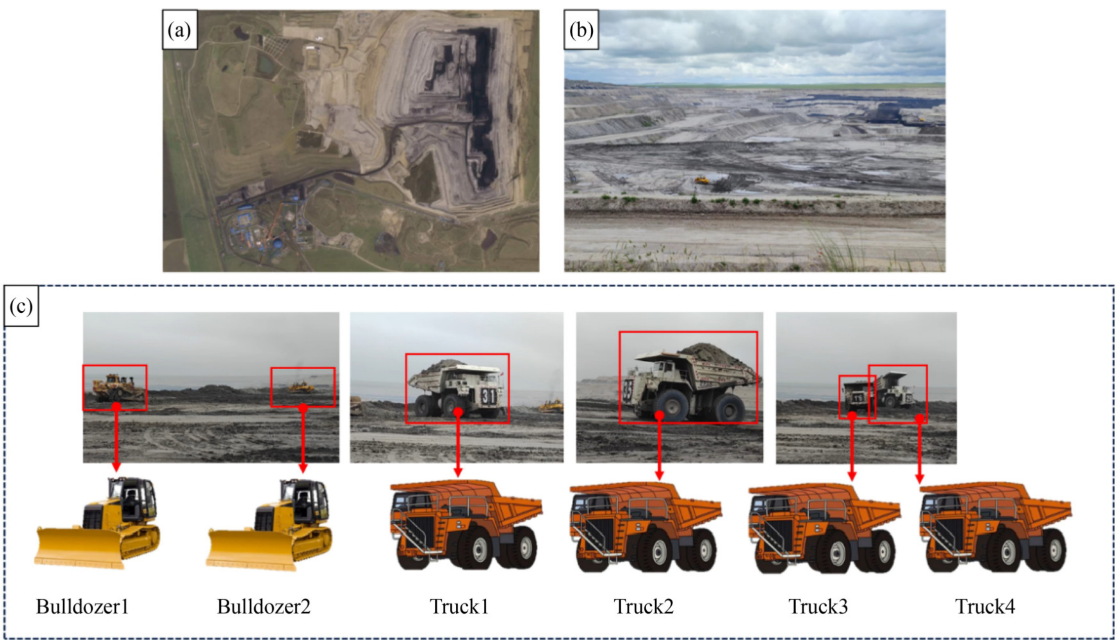

Fig. 21 A real mining scheduling case: (a) Aerial view of the mine; (b) Overview of the earthwork site; (c) The machines used.

resulting in marked increases in both usage frequency and total operational duration.

It is evident that, in the absence of safety constraints, efforts to minimize makespan can lead to an uneven allocation that favors specific machines. In contrast, the implementation of spatio-temporal safety constraints necessitates broader participation from various types of machinery to uphold operational safety standards. Thus, the spatio-temporal safety constraints proposed in this research not only enhance overall safety but also contribute to a more equitable and scientifically grounded scheduling framework.

5.4 Limitations

Although this paper provides a scientific discussion on

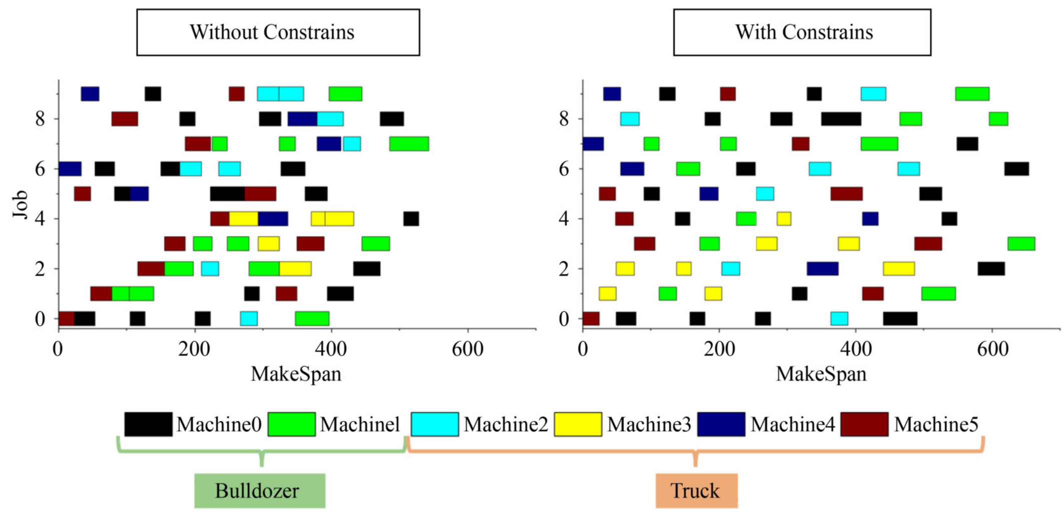

Fig. 22 Scheduling diagrams.

Table 7 Comparison of scheduling with and without spatio-temporal safety constraints

	Machine	Frequency	Total duration
Without Constrains	Machine0	17	504.11
	Machine1	12	448.51
	Machine2	8	246.38
	Machine3	5	182.78
	Machine4	6	267.48
	Machine5	12	388.87
With Constrains	Machine0	18	533.63
	Machine1	12	415.68
	Machine2	7	203.58
	Machine3	8	226.42
	Machine4	6	185.47
	Machine5	9	267.77

the safety of scheduling mine earthworks, it does have some limitations. The focus is primarily on the static scheduling problem, which considers safety during the initial conditions. The method proposed herein can mitigate the risk of accidents caused by inadequate safe distance and safe time in scheduling. However, it lacks sufficient consideration of environmental factors such as visibility and ground conditions, as well as dynamic factors like personnel interference. Future research could develop a more comprehensive dynamic scheduling technique building on the findings presented in this paper.

Additionally, this paper employs an idealized model of parallel rows of soil lines for mine earthworks. In actual construction scenarios, machinery may operate along intersecting paths. Thus, further exploration of the safe scheduling problem under complex path conditions is warranted based on the research conducted in this study.

6 Conclusions

Numerous collaborative machinery operations engaged in mine earthmoving may and obviously involve a heavy-weight portion of safety risk. This research addresses the scheduling of machinery for mine earthwork operations and provides an automated scheduling method based on DRL with spatio-temporal safety constraints. The proposed method yields promising results across various scales and has undergone real-world validation in an authentic mining environment. Thus:

1) This study proposes a model for the mine earthwork scheduling problem that prioritizes safety for the first time-a reference for safe construction practices in mining.

2) The presented spatio-temporal safety constraints are now an extension of and merged with DRL algorithms, allowing commendable performance.

Additionally, spatio-temporal safety constraints introduced in this paper enhance existing DRL algorithms by imposing restrictions on state updates during each iteration. Before long, improved structures and computational logic will be developed for such algorithms to offer fine scheduling solutions with better performance for given engineering constraints.

Competing Interests The authors declare that they have no competing interests.

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