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Integrated dispatching and coordination of electrical drill rigs in open-pit mines: A constraint programming approach

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Abstract : This paper addresses the Integrated Electrical Drill Rig Dispatching and Drilling Coordination Problem (IDRDCP) in open-pit mining operations, combining machine assignment across multiple patterns with drilling scheduling within each pattern. We propose a constraint programming formulation incorporating spatial and temporal complexities, aiming to minimize total lateness across all blast holes and patterns. Computational experiments were conducted on diverse instances with varying numbers of patterns, drill rigs, and blast holes to evaluate the model's performance. Results demonstrate the effectiveness of our approach in terms of solution quality and resource utilization across different problem configurations. The model shows promising capabilities in handling both simple and complex priority relationships while maintaining computational tractability. This work contributes a comprehensive approach to drill rig management at a detailed operational level, capable of handling challenging scenarios and optimizing drilling operations under tight constraints.

Keywords: Open-pit mining, drill rig scheduling, constraint programming, operational optimization, resource allocation

Résumé : Cet article traite du problème intégré d'affectation et de coordination des foreuses électriques dans les mines à ciel ouvert, combinant l'attribution des machines à travers plusieurs schémas de foration avec l'ordonnancement des opérations au sein de chaque schéma. Nous proposons une formulation par programmation par contraintes qui intègre les complexités spatiales et temporelles, visant à minimiser le retard total sur l'ensemble des trous de tir et des schémas. Des expérimentations numériques ont été menées sur différentes instances, en faisant varier le nombre de schémas, de foreuses et de trous de tir pour évaluer les performances du modèle. Les résultats démontrent l'efficacité de notre approche tant en termes de qualité des solutions que d'utilisation des ressources pour différentes configurations du problème. Le modèle démontre des capacités prometteuses dans la gestion des relations de priorité, des plus simples aux plus complexes, tout en maintenant un temps de calcul raisonnable. Ce travail propose une approche globale de la gestion des foreuses au niveau opérationnel détaillé, capable de traiter des scénarios complexes et d'optimiser les opérations de forage sous contraintes strictes.

Mots clés : exploitation minière à ciel ouvert, ordonnancement des foreuses, programmation par contraintes, optimisation opérationnelle, allocation de ressources

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1 Introduction

Open-pit mining is a dominant method for extracting valuable minerals from near-surface deposits, contributing significantly to global mineral production (Hustrulid et al., 2013). As the mining industry continually strives to enhance operational efficiency and sustainability (Carvalho, 2017), optimizing various stages of the mining process has become increasingly important (Moors and Mulder, 2002). Among these stages, drilling operations play a crucial role as the initial step in the extraction process, significantly influencing the efficiency of subsequent blasting, loading, and hauling operations (Hayashida et al., 2023). This interconnected nature of mining operations, often referred to as "mine-to-mill" optimization, emphasizes the importance of considering the entire production chain when seeking to improve overall mine performance.

This paper introduces the Integrated Drill Rig Dispatching and Drilling Coordination Problem (IDRDCP), a novel approach to optimizing drilling operations in open-pit mines. The IDRDCP addresses a significant gap in current research by focusing on two main components: the assignment of drilling machines to multiple drilling patterns across the mine, and the detailed coordination of drilling operations within each pattern, all within a short-term operational timeframe. This integrated approach aims to enhance overall drilling efficiency and resource utilization in open-pit mining operations by addressing immediate operational challenges.

The complexity of the IDRDCP arises from several factors inherent in open-pit mining operations:

- Multiple drilling patterns within a single bench, necessitated by varying rock characteristics, geometric considerations, and production requirements;
- Simultaneous drilling across multiple benches;
- Pattern movement relationships dictated by the mine's extraction sequence;
- Inter-pattern travel times for drill rigs, considering bench accessibility and haul road conditions;
- Safety distances between operating drill rigs;
- Directional drilling constraints within patterns;
- Dynamic changes in blast hole accessibility as drilling progresses.

To address these challenges, we propose a constraint programming model that efficiently captures the complexities of the IDRDCP. Our approach aims to minimize the total lateness across all blast holes and drilling patterns in relation to their planned completion times, ensuring timely completion of the drill and blast cycle while optimizing resource utilization.

The main contributions of this paper are:

1. A formal definition of the IDRDCP, integrating drill rig dispatching across multiple patterns with detailed drilling coordination within each pattern;
2. A constraint programming model that efficiently captures both the spatial and temporal constraints of the problem;
3. An analysis of the model's performance on simulated problem instances designed to reflect realistic open-pit mining scenarios.

This research has the potential to significantly impact open-pit mining operations by:

- Optimizing resource utilization through efficient drill rig dispatching;
- Improving drilling efficiency by considering both inter-pattern and intra-pattern constraints;
- Enhancing safety by incorporating operational constraints into the scheduling process;
- Increasing overall mining productivity by ensuring timely completion of drilling operations.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature in the field of drilling optimization and open-pit mine planning. Section 3 provides a detailed description of the

IDRDCP, including its constraints and operational considerations. Section 4 presents our constraint programming formulation for the problem. Section 5 discusses the results of computational experiments conducted to evaluate the model's performance. Finally, Section 6 concludes the paper and suggests directions for future research in this area.

2 Literature review

The Integrated Drill Rig Dispatching and Drilling Coordination Problem (IDRDCP) in open-pit mining intersects several key areas of research in mining operations and optimization. This literature review examines the state of the art in relevant fields to provide context for our work and highlight the gaps that our research aims to address. We focus on three main areas: the application of Constraint Programming (CP) in open-pit mine planning and optimization, specific research on drilling operations in open-pit mining, and equipment dispatching in open-pit mining.

By examining these interconnected areas, we aim to demonstrate the potential of CP for addressing complex mining problems, identify the current limitations in drill rig management research, and highlight the gap in existing equipment dispatching literature regarding drill rig operations. This review will emphasize the lack of comprehensive models that consider both the assignment of drilling machines to multiple patterns and the detailed coordination of drilling operations within each pattern in the short-term, operational timeframe. Through this analysis, we establish the foundation for our CP-based approach to the IDRDCP and highlight its potential contributions to the field of mining operations optimization.

2.1 Application of constraint programming in open-pit mining

Constraint Programming (CP) has emerged as a powerful and flexible approach for addressing complex optimization problems in mining. Unlike traditional mathematical programming methods, CP allows for more intuitive modeling of intricate operational constraints and has shown promise in handling large-scale problems with high levels of discretization. This section explores key developments in the application of CP to open-pit mining problems, highlighting its advantages and potential for addressing challenges in areas such as production scheduling, block sequencing, and resource allocation.

The application of CP to open-pit mining problems has gained significant traction in recent years. Soto et al. (2014) conducted one of the first comprehensive evaluations of CP solvers for the open pit mining long-term scheduling problem, considering constraints such as processing capacity, slope requirements, and grade blending. This study opened new avenues for optimization in the field and provided valuable benchmarks for future research.

Building on this foundation, Crawford et al. (2014) demonstrated how CP can model open pit mining problems in a declarative and intuitive manner, making it more accessible to mining practitioners without extensive optimization backgrounds. This work highlighted the versatility of CP in solving mining problems traditionally addressed by classic mathematical programming or metaheuristics.

Recent advancements have further showcased CP's potential in mine planning. Oleynik and Zuenko (2022) introduced a new global constraint for open pit mine production scheduling, enabling efficient handling of block extraction sequences. Their approach significantly reduced RAM consumption through implicit constraint representation, allowing for higher levels of discretization in pit models that were previously challenging with integer linear programming methods.

Kumar et al. (2023) applied CP to the open pit mine production scheduling problem with stockpiling, achieving results that outperformed existing solutions in terms of net present value. Their CP-based model, tested on the Newman1 dataset from the Minelib library, obtained a production schedule with approximately 2.69% higher NPV than previously recorded solutions, demonstrating CP's competitive advantage in handling complex mining scenarios.

Expanding the application of CP, Valenca Mariz et al. (2024) proposed a novel multi-stage approach to solve clustering problems in open-pit mine planning. Their method optimizes the assignment of blocks to clusters and refines cluster boundaries considering mining equipment size, addressing the NP-hard problem of open-pit mine sequencing with block precedence. Applied to a real gold-ore dataset, their method achieved feasible solutions in acceptable computation times, with more clusters increasing the objective function and profit by up to 60%.

These studies collectively highlight CP's potential to address complex mining constraints, adapt to changing requirements, and improve upon existing optimization approaches in terms of both solution quality and accessibility to practitioners. The flexibility of CP in handling diverse constraints makes it particularly promising for integrating aspects of mining operations that have traditionally been difficult to model, such as detailed drilling operations. As research in this area continues to evolve, CP stands out as a powerful tool for developing more comprehensive and realistic planning models in the mining industry.

2.2 Drilling operations in open-pit mining

Recent research in open-pit mining has increasingly focused on optimizing various technical aspects of drilling operations. These studies aim to improve efficiency, reduce costs, and enhance overall mine productivity by addressing challenges in drill rig management, parameter optimization, and integration with other mining processes. The following literature review highlights key contributions in this field, demonstrating the diverse approaches researchers have taken to improve drilling operations.

Abbaspour et al. (2018) proposed a system dynamic model for drilling and blasting operations that considers technical and economic uncertainties such as rock density, uniaxial compressive strength, bit life, and operating costs. Their work emphasizes the importance of integrated optimization under uncertain conditions. Ugurlu and Kumral (2020b) used reliability analysis and discrete event simulation to determine the number of bits required in a given period and compute the number of holes to be drilled under uncertainty. This approach focuses on optimizing drill bit management and inventory strategies. Rais et al. (2017) conducted an experimental study to determine optimal drilling parameters using the design of experiments method. Their work highlights the importance of considering geological formations and drilling technologies in optimizing drilling operations. Uurlu (2021) addressed the problem of drill bit monitoring and replacement optimization in open-pit mines, formulating it as a cost minimization problem solved by a genetic algorithm. This research contributes to the efficient management of drilling equipment. Ugurlu and Kumral (2020a) focused on cost optimization of drilling operations through parameter tuning, using face-centered central composite design and genetic algorithms to find the best configuration of controllable drilling parameters. Ahsan et al. (2015) applied adaptive sampling to geology modeling in surface mining, aiming to minimize the number of blast holes drilled and accidental penetrations of geological boundaries. Their approach demonstrates the potential for reducing drilling costs while maintaining accuracy. Qu et al. (2021) optimized single-layer drilling parameters based on pressure arch theory in auger drilling, focusing on determining the effective width of coal pillars between adjacent drilling holes. Munagala et al. (2024) provided a comprehensive survey on machine learning applications for drilling and blasting in surface mining, focusing on optimizing blast designs, improving safety, and addressing site-specific uncertainties. Their work demonstrates how ML approaches can significantly reduce blasting costs and explosive usage compared to traditional methods while accounting for operational challenges such as data quality and model selection.

While these studies have made significant contributions to various technical aspects of drilling operations, they primarily focus on optimizing individual drill rigs, specific operational parameters, or integrating drilling with blasting operations. In contrast, our research on the Integrated Drill Rig Dispatching and Drilling Coordination Problem (IDRDCP) complements these efforts by focusing on the coordination and scheduling of drilling activities across multiple patterns and drill rigs.

Some researchers have addressed the scheduling aspect of mining operations, integrating multiple phases including drilling. L'Heureux et al. (2013) proposed a comprehensive mixed integer programming model for short-term planning in open-pit mines. Their model integrates the scheduling of multiple drilling operations with shovel movements, blasting, and extraction activities over periods ranging from days to several months. This work represents an important step in addressing the co-ordination of multiple drills within the broader context of mine operations. However, the authors found that instances larger than 10-12 periods became computationally intractable, underscoring the challenges in developing comprehensive models that can be solved efficiently for realistic problem sizes.

Building on this approach, Kozan and Liu (2016), Kozan and Liu (2017), and Kozan and Liu (2018) developed comprehensive multi-stage mine production timetabling models that optimize open-pit mine production operations across drilling, blasting, and excavating stages. These models consider equipment capacity constraints and various mining attributes, aiming to maximize throughput and minimize total idle times of equipment at each stage. Given their broad scope, these models necessarily operate at a higher level of abstraction, typically considering mining jobs as aggregate sets of block units. This approach is well-suited for mid-term planning and coordination across different mining phases.

Our IDRDCP model, while focusing specifically on the drilling phase, complements these broader planning approaches by examining operations at a finer level of detail. By considering individual blast holes rather than aggregated blocks, our model allows for more granular scheduling of drilling operations. This fine-grained approach is particularly suited for very short-term operational planning, potentially allowing for further optimization within the framework of broader mid-term plans. Together, these different levels of planning contribute to a more comprehensive and flexible approach to mine scheduling and optimization.

In a related field of study, Mansouri et al. (2016) and Mansouri et al. (2017) have explored the application of robotics and motion planning techniques to drill planning in open-pit mines. Their work, while considering individual blast holes like our approach, stems from a fundamentally different perspective rooted in robotics and multi-vehicle routing. Mansouri et al. (2016) propose a hybrid reasoning approach for multi-robot drill planning, addressing task allocation, motion planning, and coordination for individual blast holes within a pattern. They extend this work in Mansouri et al. (2017) by introducing a variant of the multi-vehicle routing problem (MVRP-DDO) that accounts for nonholonomic constraints and dense, dynamic obstacles.

While their research shares some similarities with our work in terms of granularity, there are key differences:

1. Vehicle type: They focus on diesel-powered drill rigs, which have different movement constraints compared to the electrical drill rigs we consider.
2. Scope: Their approach emphasizes motion planning within a single pattern and later extends to multiple patterns, whereas our IDRDCP model addresses scheduling and coordination across multiple patterns from the outset.
3. Methodology: Mansouri et al. employ a combination of local search, motion planning, and scheduling techniques, while we use constraint programming techniques.
4. Perspective: Their approach is rooted in robotics and multi-vehicle routing, whereas ours tackles the problem from an operations research perspective.
5. Objectives: Their focus is on minimizing makespan and computation time, while our approach aims to minimize total lateness across all blast holes with respect to their drilling pattern horizons, incorporating constraints specific to electrical drill rigs.

These fundamental differences in methodology and focus allow us to address the unique challenges of scheduling and coordinating electrical drill rigs across multiple patterns, providing a complementary approach to the robotics-based solutions proposed by Mansouri et al.

Our Integrated Drill Rig Dispatching and Drilling Coordination Problem (IDRDCP) model bridges several gaps in the existing literature. It explicitly accounts for drilling operations in mine planning, provides a middle ground between aggregate block-level scheduling and single-pattern robotics-based motion planning, and applies constraint programming techniques to a problem previously approached from either a high-level planning or a robotics standpoint.

By focusing on the operational level and considering the unique constraints of electrical drill rigs, our constraint programming approach has the potential to enhance the efficiency and productivity of open-pit mining operations. It offers a complementary perspective to existing strategic and tactical planning methods, as well as to robotics-based solutions for diesel-powered rigs, providing mining companies with more comprehensive and realistic planning tools for optimizing the drilling phase in open-pit mining.

2.3 Equipment dispatching in open-pit mining

Equipment dispatching, particularly for trucks and shovels, has been a significant area of research in open-pit mining operations over the past decade. The focus has primarily been on optimizing the allocation and routing of mining equipment to improve efficiency, reduce costs, and enhance overall productivity.

Recent research trends in equipment dispatching for open-pit mines include:

Real-time optimization: Researchers have developed sophisticated models for real-time truck dispatching, considering both loaded and empty truck movements. Wang et al. (2023) proposed a comprehensive real-time dispatching model that addresses both full and empty truck dispatching for heterogeneous fleets. Similarly, Chaowasakoo et al. (2017) explored real-time truck dispatching decisions using GPS technology and stochastic simulation. Moradi Afrapoli et al. (2019) developed a multiple objective transportation model for real-time truck dispatching that simultaneously minimizes shovel idle times, truck wait times, and deviations from production requirements.

Multi-objective optimization: Many studies have focused on balancing multiple objectives in equipment dispatching. Mirzaei-Nasirabad et al. (2023) presented a multi-objective mathematical model for dynamic truck allocation. Wang et al. (2023), in addition to their real-time focus, incorporated multiple objectives including minimizing waiting time, deviation from planned path flow rate, and transportation cost. Moradi Afrapoli et al. (2019), as mentioned in the real-time optimization category, also addressed multiple objectives in their model.

Integration with production planning: There is a growing trend towards integrating fleet management with short-term production planning. de Carvalho and Dimitrakopoulos (2023) developed an actor-critic reinforcement learning method for making mining equipment allocation and production scheduling decisions simultaneously. Both and Dimitrakopoulos (2020) presented a stochastic optimization model that integrates short-term extraction sequencing with fleet management.

Environmental considerations: Recent research has begun to incorporate environmental factors into dispatching decisions. Anaraki and Afrapoli (2023) introduced a bi-objective mathematical model that incorporates carbon emission minimization into the truck allocation optimization process. Huo et al. (2023) proposed a reinforcement learning-based fleet dispatching system aimed at reducing greenhouse gas emissions in open-pit mining operations, also demonstrating the application of advanced AI techniques.

Advanced technologies and autonomous systems: The application of artificial intelligence, machine learning, Internet of Things (IoT) technologies, and autonomous systems in fleet management has gained traction. Bnouachir et al. (2020) proposed an intelligent distributed fleet management system architecture incorporating AI algorithms and IoT technologies. Aguirre-Jofre et al. (2021) explored the use of low-cost IoT for monitoring and optimizing mining trucks and surface mining shovels. Gamache et al. (2023) proposed a real-time multi-agent fleet management strategy for autonomous underground mine vehicles, demonstrating the potential for advanced coordination in complex mining environments. Additionally, Chiarot Villegas et al. (2024) developed a deep reinforcement learning model for effective material supply and equipment management, further illustrating the application of advanced AI techniques in mining operations. de Carvalho and Dimitrakopoulos (2023) and Huo et al. (2023), mentioned earlier, also exemplify the use of advanced AI techniques in real-time optimization and environmental considerations respectively.

Simulation-based approaches: Many researchers have utilized discrete event simulation and more advanced simulation techniques to evaluate and optimize dispatching strategies, primarily focusing on truck and shovel operations. Jaoua et al. (2009) introduced a realistic microscopic simulator for surface mining transportation systems called Surface Mining Transportation Simulator (SuMiTSim), which allows for more accurate traffic analysis and control in mining environments. Building on this work, Jaoua et al. (2012a) proposed an intelligent simulation-based real-time control system for industrial applications, demonstrating its effectiveness in real-time truck dispatching for surface mining operations. Their approach, which uses a trajectory tracking strategy inspired by model-based predictive control, showed improvements in productivity under both steady and transient state conditions. Further advancing this line of research, Jaoua et al. (2012b) presented a simulation framework that incorporates a traffic simulator with a classical discrete event simulation model, allowing for more accurate representation of traffic behavior in internal transport systems, including surface mines. This approach enables better real-time fleet management and traffic control for trucks. More recently, Moradi-Afrapoli and Askari-Nasab (2020) developed an integrated simulation and optimization framework for solving truck dispatching problems in surface mines. Mohtasham et al. (2022) presented a simulation-based optimization method to evaluate the optimal number of trucks and develop heuristic algorithms for operational decisions.

It is worth noting that many of these studies overlap multiple categories, reflecting the integrated nature of modern approaches to equipment dispatching in open-pit mining. Researchers are increasingly combining real-time optimization, multi-objective approaches, environmental considerations, and advanced technologies to develop comprehensive solutions for mining operations.

While these studies have significantly advanced the field of equipment dispatching in open-pit mining, they have primarily focused on truck and shovel operations. The unique challenges associated with drill rig dispatching, such as pattern movement relationships and inter-pattern travel considerations, have not been adequately addressed in existing research. This gap in the literature highlights the need for integrated approaches that consider the specific requirements of drill rig management within the broader context of mine equipment dispatching.

2.4 Conclusion

This literature review has highlighted several key themes and gaps in the current research landscape relevant to the Integrated Drill Rig Dispatching and Drilling Coordination Problem (IDRDCP). While significant progress has been made in open-pit mine planning, drilling operations optimization, and equipment dispatching, there remains a notable lack of integrated approaches that comprehensively address the complexities of drill rig management across multiple drilling patterns.

The review of Constraint Programming (CP) applications in mining demonstrated its potential for addressing complex constraints and improving upon existing optimization approaches. However, CP has not yet been extensively applied to drilling operations or drill rig dispatching.

Research on drilling operations in open-pit mining has primarily focused on optimizing parameters for individual drill rigs or specific drilling patterns, often overlooking the broader context of managing multiple drill rigs across various patterns within a mine. Some exceptions from the field of robotics consider individual blast holes within a single pattern but focus on motion planning for diesel-powered drill rigs.

The literature on equipment dispatching in mining shows significant advancements in areas such as real-time optimization, multi-objective optimization, and the application of advanced technologies. However, these studies have primarily focused on truck and shovel operations, leaving the unique challenges associated with drill rig dispatching largely unaddressed.

Our proposed IDRDCP model aims to bridge these gaps by providing an integrated approach to drill rig management. By leveraging CP techniques, our model captures the complexities of drill rig dispatching and coordination in a more comprehensive and detailed manner than previous approaches, focusing on the immediate operational needs of open-pit mining.

This review underscores the need for further research in integrated drill rig management and highlights the potential of our IDRDCP model to contribute significantly to the field of open-pit mining optimization. Future work in this area should continue to explore integrated approaches that consider the full scope of drilling operations within the broader context of mine planning and production scheduling, while maintaining the level of detail necessary for operational decision-making. There is also potential for cross-pollination between CP techniques, block-level optimization methods, robotics-based approaches, and advanced dispatching strategies. Such integration could lead to more comprehensive solutions for open-pit mining optimization that span strategic, tactical, and operational levels of decision-making.

3 Problem description

The Integrated Drill Rig Dispatching and Drilling Coordination Problem (IDRDCP) in open-pit mines is an extension of the previously studied Drilling Coordination Problem (DCP) (Maftah et al., 2024a). This integrated problem encompasses two main aspects:

1. Drill Rig Dispatching: Assigning and moving drilling machines between multiple drilling patterns within the open-pit mine.
2. Drilling Scheduling: Coordinating the drilling operations for each blast pattern.

The IDRDCP significantly expands the scope of the original DCP by incorporating multiple drilling patterns and inter-pattern machine movements, thus presenting a more comprehensive approach to open-pit mine planning and operations.

3.1 Drilling Coordination Problem (DCP) background

The DCP, which forms the foundation of the IDRDCP, is a complex scheduling problem involving a fleet of electrical drilling machines in an open-pit mine. Key aspects of the DCP include:

Resources: A set of electrical drilling machines ($\mathcal{M}$) that must complete a series of drilling tasks ($\mathcal{J}$) at specified locations (blast holes).

Spatial layout: Blast holes are uniquely numbered and positioned within a grid-like arrangement forming the blast pattern, requiring precise drilling by any available machine.

Directional constraints: Machines must traverse the pattern in one direction across columns (conventionally left-to-right) due to their tethered power cables. For the same reason, within columns, drilling must proceed in one direction only. They start from the power source side, move to the far side, then drill their way back. By convention, we label the side with the power source as "bottom" and the other side as "top".

Non-preemptive operations: Once drilling at a blast hole begins, it must be completed without interruption to maintain hole integrity.

Machine coordination: Machines must maintain consistent relative positioning due to their tethered connection to power sources, requiring careful coordination to avoid collisions and cable entanglement on the bench.

Safety protocols: A minimum column-based separation (d_s) between machines must be maintained on the bench, temporarily rendering adjacent blast holes inaccessible during a machine's operation.

Dynamic environment: Completed tasks reshape the bench's operational landscape in real-time, requiring adaptive scheduling strategies.

3.2 Integrated Drill Rig Dispatching and Drilling Coordination Problem (IDRDCP) Extension

The IDRDCP extends the DCP by incorporating multiple drilling patterns and flexible drill rig dispatching. Key components of the IDRDCP include:

Multiple drilling patterns: The problem considers several drilling patterns ($\mathcal{S}$) within the open-pit mine, each with its own set of blast holes arranged in columns ($\mathcal{C}_s$).

Flexible machine dispatching: Drilling machines can be assigned to different drilling patterns and can move between any patterns as needed, considering bench accessibility and haul road conditions.

Priority relationships: There are priority relationships between drilling patterns ($\mathcal{P}$), which guide the overall sequence of operations based on the mine's extraction sequence and logistical considerations.

Time constraints: Each drilling pattern has its own time horizon (H_s) based on production schedules, priority relationships, and estimated workload. Machines have initial availability times (a_m) and pattern-specific setup times (ts_{ms}).

Inter-pattern travel: Machines have travel times ($tm_{ss'}$) between drilling patterns, accounting for bench-to-bench movement and pit geometry.

Pattern-specific drilling: Each drilling pattern has its own set of blast holes ($\mathcal{J}_s$) that need to be drilled, following the same rules as in the original DCP (e.g., column-based drilling, precedence constraints, safety distances).

Task processing: Each blast hole has an associated processing time (p_{jms}) that represents the duration required for machine m to drill hole j at pattern s, which can vary based on characteristics such as rock hardness, hole depth, and machine capabilities.

Safety considerations: The model maintains safety distances between machines (d_s) on the bench, ensuring that drill rigs maintain a minimum separation during operations to prevent interference and enhance workplace safety.

3.3 Flexible machine movement and operation sequencing

The IDRDCP adopts a flexible approach to machine movement and operation sequencing:

Flexible movement: Drill rigs can move freely between any drilling patterns, not just adjacent ones. This flexibility allows for more efficient resource allocation and potentially shorter overall completion times.

Priority relationships: The set $\mathcal{P}$ represents pairs of drilling patterns with a priority relationship. These relationships guide the overall sequence of operations based on the mine's extraction plan, but do not strictly enforce a complete-before-start constraint between patterns.

Deadline-based prioritization: The time horizons (H_s) for each drilling pattern are calculated based on the relationships in set $\mathcal{P}$, the estimated workload, and available resources. These deadlines serve to prioritize work across the mine without imposing rigid constraints on the sequence of operations.

Objective function-driven movement: The objective function, which minimizes total lateness across all blast holes and patterns, guides the movement of machines. This approach allows the model to naturally find efficient paths for machines based on where they are most needed, rather than being constrained by predefined movement patterns.

Travel time considerations: The model accounts for realistic travel times between patterns through the $tm_{ss'}$ parameter. This ensures that solutions remain practically feasible while allowing for more optimal resource allocation.

3.4 Time discretization and planning horizon

Time is discretized into 10-minute intervals for practical implementation and computational efficiency. The planning horizon for each drilling pattern (H_s) is determined based on the total workload of the pattern, the number of available machines, and the priority relationships between patterns.

3.5 Objective and challenges

The primary goal of the IDRDCP is to minimize the total lateness across all blast holes and drilling patterns within their respective time horizons, ensuring timely completion of the drill and blast cycle.

The integration of multiple drilling patterns and flexible machine dispatching introduces several challenges:

- Coordinating machine movements between drilling patterns while respecting travel time constraints, considering pit geometry and access ramps.
- Managing pattern-specific drilling operations that account for varying geological conditions and operational characteristics across the pit.
- Balancing workload distribution across multiple drilling patterns with different time horizons, aligning with the overall mine production schedule.
- Ensuring efficient resource utilization while adhering to safety constraints and operational requirements within and across patterns.

The IDRDCP thus presents a unique blend of scheduling, spatial coordination, and logistical challenges in the context of open-pit mining. It requires modeling and solution approaches to optimize the overall drilling process while managing the complexities introduced by the multi-pattern, integrated nature of the problem within the dynamic open-pit environment.

4 Constraint programming formulation

We present a constraint programming (CP) model using IBM's CP Optimizer for scheduling to formulate the Integrated Drill Rig Dispatching and Drilling Coordination Problem (IDRDCP) in open-pit mines.

Regarding notation, we use ordered sets throughout the model to simplify the expression of certain constraints. Machines are indexed from left to right, with the leftmost machine having the lowest index 1. Tasks (blast holes) are numbered sequentially from 1 to $|J|$, starting with the first task in the first row of the first column and ending with the last task in the last row of the rightmost column. Within each column, task indices increment as we move downward, reflecting the top-to-bottom drilling sequence. This systematic numbering scheme facilitates the formulation of various constraints, particularly for collision avoidance and precedence relationships both within and across columns.

With these considerations in mind, we now present the formal definition of our model, beginning with the sets, parameters, and variables that form its foundation.

Sets	
$\mathcal{M}$	Set of drill rigs, indexed by $m \in \{1,\ 2,\ \ldots,\ \lvert\mathcal{M}\rvert\}$.
$\mathcal{S}$	Set of drilling patterns, indexed by s.
$\mathcal{P}$	Set of pairs of drilling patterns with priority relationships guiding the overall operation sequence.
$\mathcal{J}_s$	Set of blast holes at drilling pattern s, indexed by i and $j \in \{1,\ 2,\ \ldots,\ \lvert\mathcal{J}_s\rvert\}$.
$\mathcal{C}_s$	Set of columns at drilling pattern s, indexed by c.
$\mathcal{J}_{cs}$	Set of blast holes that belong to column c at drilling pattern s, indexed by j.
$\mathcal{J}_{cs}^-$	Set $\mathcal{J}_{cs}$ without its highest-indexed element.
Parameters	
a_m	Initial availability time of drill rig m.
ts_{ms}	Time required for drill rig m to move from its initial location to drilling pattern s.
$tm_{ss'}$	Time required for a drill rig to move from drilling pattern s to s'.
col_{js}	Column to which blast hole j at drilling pattern s belongs.
p_{jms}	Drilling time of blast hole j at drilling pattern s when drilled by machine m.
d_s	Number of columns that have to be kept empty between pairs of drill rigs at drilling pattern s.
H_s	Time horizon for drilling pattern s.
Decision Variables	
u_{ms}	Optional interval variable representing the assignment and stay duration of drill rig m to drilling pattern s.
x_{jms}	Optional interval variable that determines if blast hole j at drilling pattern s is drilled by drill rig m,
y_{js}	Interval variable that represents the task of drilling a blast hole j at drilling pattern s, with start $\geq a_m + ts_{ms}$, end $\leq \max_{k\in\mathcal{S}} H_k$, and size determined by the selected machine.
z_{ms}	Sequence of interval variables x_{jms} on drill rig m at drilling pattern s.
l_{ms}	State variable that represents the location of drill rig m at drilling pattern s.
f_s	Cumulative function representing the number of active drill rigs at drilling pattern s at any given time.

The problem is formulated as follows:

$$\text{Minimize} \quad Z = \sum_{s\in\mathcal{S}} \sum_{m\in\mathcal{M}} \sum_{j\in\mathcal{J}_s} \max(0, \texttt{EndOf}(x_{jms}) - H_s) \tag{1.1}$$

$$\text{s.t.} \quad \texttt{EndBeforeStart}(u_{ms},\ u_{ms'}, tm_{ss'}), \quad \forall s,\ s' \in \mathcal{S},\ \forall m \in \mathcal{M}, \tag{1.2}$$

$$\texttt{PresenceOf}(x_{jms}) \implies \texttt{PresenceOf}(u_{ms}), \quad \forall s \in \mathcal{S},\ \forall m \in \mathcal{M},\ \forall j \in \mathcal{J}_s, \tag{1.3}$$

$$\texttt{Span}(u_{ms},\ \{x_{jms} \mid j \in \mathcal{J}\}), \quad \forall s \in \mathcal{S},\ \forall m \in \mathcal{M}, \tag{1.4}$$

$$\texttt{Alternative}(y_{js},\ \{x_{jms} \mid m \in \mathcal{M}\}), \quad \forall s \in \mathcal{S},\ \forall j \in \mathcal{J}_s, \tag{1.5}$$

$$\texttt{NoOverlap}(z_{ms}), \quad \forall s \in \mathcal{S},\ \forall m \in \mathcal{M}, \tag{1.6}$$

$$\texttt{EndBeforeStart}(y_{js},\ y_{j+1,s}), \quad \forall s \in \mathcal{S},\ \forall c \in \mathcal{C}_s,\ \forall j \in \mathcal{J}_{cs}^-, \tag{1.7}$$

$$\texttt{AlwaysEqual}(l_{ms},\ x_{jms},\ col_{js}), \quad \forall s \in \mathcal{S},\ \forall m \in \mathcal{M},\ \forall j \in \mathcal{J}, \tag{1.8}$$

$$\texttt{AlwaysIn}(l_{ms},\ x_{j,m-1,s}, col_{js} + d_s + 1, \lvert\mathcal{C}_s\rvert + d_s + 1), \quad \forall s \in \mathcal{S},\ \forall m \in \mathcal{M} \setminus \{1\},\ \forall j \in \mathcal{J}, \tag{1.9}$$

$$f_s = \sum_{m\in\mathcal{M}} \sum_{j\in\mathcal{J}_s} \texttt{Pulse}(x_{jms}, 1), \quad \forall s \in \mathcal{S}, \tag{1.10}$$

$$\texttt{CumulRange}(f_s, 0, \lfloor \frac{\lvert\mathcal{C}_s\rvert + d_s}{d_s + 1} \rfloor), \quad \forall s \in \mathcal{S}. \tag{1.11}$$

Objective function explanation:

The objective function (1.1) minimizes the total lateness across all blast holes, drilling patterns, and drill rigs. This objective function addresses several key aspects of the scheduling problem:

- It prioritizes completing blast holes within their respective drilling pattern horizons, ensuring timely completion of the drill and blast cycle.
- It penalizes late completions proportionally to their degree of lateness, encouraging the model to find solutions where unavoidable delays are kept as small as possible, minimizing disruptions to the overall mining schedule.
- It allows for a balanced approach where slight delays might be accepted if they lead to a better overall schedule, optimizing the utilization of drill rigs across the open-pit mine.

- It guides the movement of machines by naturally directing them to where they are most needed to minimize overall lateness.

Constraint explanations:

(1.2): This constraint enforces that when a drill rig moves from drilling pattern s to s', there must be a minimum time gap of $tm_{ss'}$ between the end of its presence at drilling pattern s and the start of its presence at drilling pattern s'. This ensures that travel times between drilling patterns are respected in the schedule, accounting for factors such as bench-to-bench movement and haul road conditions.

(1.3): This constraint links the blast hole assignments to drilling pattern assignments, ensuring that a blast hole can only be drilled by a drill rig if that drill rig is assigned to the drilling pattern. It maintains consistency between blast hole and drilling pattern assignments.

(1.4): The Span constraint ensures that the time a drill rig spends at a drilling pattern covers all the blast holes it drills at that pattern. This constraint defines the duration of a drill rig's presence at each drilling pattern, crucial for efficient utilization of equipment.

(1.5): This constraint ensures that each blast hole is assigned to exactly one drill rig, preventing duplicate assignments and ensuring all blast holes are covered in the drilling plan.

(1.6): This constraint prevents overlap of blast holes assigned to the same drill rig at a drilling pattern, considering travel time between blast holes. It ensures the sequential execution of drilling by each drill rig at a pattern, reflecting the physical limitations of the equipment.

(1.7): This enforces the precedence constraints between blast holes within the same column at a drilling pattern, ensuring that blast holes are drilled in the correct order within each column.

(1.8): This constraint fixes the position of a drill rig to the column of the blast hole it is drilling, reflecting the physical positioning of the equipment on the bench.

(1.9): This constraint ensures that drill rig $m-1$ always stays to the left of drill rig m by maintaining the order of rigs based on column positions (using Constraint 1.8, which sets the column location via an `AlwaysEqual` constraint). Additionally, by offsetting with d_s, it enforces a minimum safety distance between rigs, preventing equipment collisions and ensuring safe operations on the bench.

(1.10): This constraint defines a cumulative function f_s for each drilling pattern, representing the number of active drill rigs at any given time.

(1.11): This constraint uses the cumulative function to set an upper bound on the number of simultaneously operating drill rigs at each pattern. As a redundant constraint, it helps reduce the search space, potentially improving solving efficiency.

This formulation allows for flexible movement of drill rigs between any drilling patterns while respecting travel times and maintaining the essential constraints of the drilling process. The model captures the key aspects of the IDRDCP, balancing the need for efficient resource allocation with the practical constraints of open-pit mining operations.

5 Computational experiments

To assess the performance and scalability of the proposed model for the IDRDCP, we conducted a series of computational experiments using randomly generated test instances. These experiments aim to evaluate the algorithm's ability to solve instances of varying sizes and characteristics, providing insights into its effectiveness for real-world applications in open-pit mining operations.

5.1 Configuration of test instances

To thoroughly test our model, we generated a diverse set of problem instances that extend from realistic scenarios in open-pit mining operations. The instances vary in size and complexity, considering the following parameters:

Number of drilling patterns ($|\mathcal{S}|$): ranging from 3 to 7.

Number of blast holes per pattern ($|\mathcal{J}_s|$): ranging from 50 to 200.

Priority relationships between patterns ($|\mathcal{P}|$): Priority relationships between patterns represent the preferred order of operations based on the mine's extraction plan and logistical considerations. We generated two types of relationship structures:

- Simple: A straightforward linear sequence of patterns, as illustrated in Figure 1.
- Complex: A more intricate structure where patterns are organized into 2-4 layers, with relationships established between patterns in adjacent layers. This allows for more flexible operational sequences while ensuring all patterns are connected. Figure 2 demonstrates an example of such a complex structure.

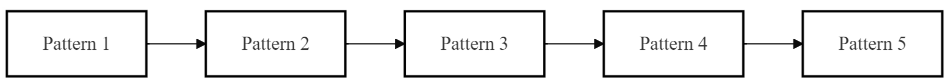

Figure 1: Example of a simple (linear) priority relationship structure

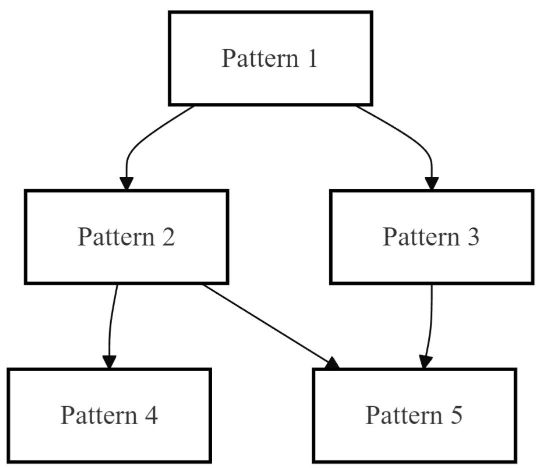

Figure 2: Example of a complex priority relationship structure with patterns organized into layers

Pattern deadlines (H_s): Pattern deadlines represent the target completion times for each drilling pattern. These deadlines are calculated based on the pattern's workload, available resources, and its priority relationships with other patterns. They help prioritize work across the mine without imposing overly rigid (i.e., strict precedence) constraints on the sequence of operations.

Number of drill rigs ($|\mathcal{M}|$): ranging from 3 to 9. While the reference data came from an operation with only 3 drill rigs, we expanded this to test the model's performance with larger fleets.

Machine separation (d_s): 2 columns. This value was chosen based on consultation with our industrial partner and aligns with common safety practices in open-pit mining. Given that the distance between two columns (burden or spacing) is typically 25 meters in our data, a separation of 2 columns results in a safety distance of approximately 75 meters between operating drill rigs. While specific safety distances may vary depending on equipment size and local regulations, this separation ensures a reasonable buffer zone for safe operations.

Processing times (p_{js}): representing the drilling time for each blast hole. TThese were drawn from a triangular distribution with parameters (1, 2, 4), where 1 is the minimum, 2 is the mode, and 4 is the maximum, based on observed drilling times in the small-scale open-pit coal mine. For these experiments, drilling times were assumed homogeneous across machines.

Travel times between patterns ($tm_{ss'}$): representing the time required for a drill rig to move between patterns. These were generated based on the relative positions of the patterns and the direction of travel:

- For patterns in the same layer or bench: Uniform distribution between 1 and 2 hours.
- For patterns in adjacent layers or benches:
  - Traveling upwards: Uniform distribution between 3 and 5 hours;
  - Traveling downwards: Uniform distribution between 2 and 4 hours.
- For patterns separated by two or more layers or benches:
  - Traveling upwards: Uniform distribution between 5 and 7 hours;
  - Traveling downwards: Uniform distribution between 4 and 6 hours.
- A consistent "road condition factor" ranging from 1.0 to 1.5 was applied to each pair of patterns, ensuring the same road complexity for both directions of travel.
- After applying the road condition factor, travel times for downhill trips (from higher to lower layers) were reduced by 20% to reflect the ease of downhill travel.
- These travel times can also incorporate any additional operational considerations, such as:
  - Planned maintenance of the machine between patterns;
  - Installation of the power source;
  - Time for positioning the drill rig at the new pattern;
  - Any other operational activities required between drilling patterns.

This flexible definition of travel times allows for a more comprehensive representation of the time required to transition between patterns, accounting for various operational realities in open-pit mining.

Setup times (ts_{ms}): representing the time required for a drill rig m to set up at a drilling pattern s, including the initial travel time from the rig's starting position to its first assigned pattern. These were generated as follows:

- For each machine m and pattern s, a setup time was randomly generated using a uniform distribution between 24 and 36 time units (4 to 6 hours, assuming each time unit represents 10 minutes).
- This setup time encompasses various activities such as:
  - Initial travel from the machine's starting position to the pattern.
  - Positioning the drill rig at the pattern.
  - Conducting any necessary pre-drilling checks and preparations.
- The range of 24 to 36 time units was chosen to reflect the variability in initial positions of machines and the complexity of setting up at different patterns.

These setup times ensure that the model accounts for the non-trivial time investment required to begin operations at each new drilling pattern, particularly for the first pattern assigned to each machine. This contributes to a more realistic representation of the operational constraints in open-pit mining.

Initial availability times of drill rigs (a_m): representing when each drill rig becomes available for the first time. These were randomly generated between 0 and 6 hours for each drill rig. This parameter is crucial for modeling realistic operational scenarios where:

- Some machines may still be completing drilling operations from the previous planning period.
- Drill rigs might be in transit between patterns at the start of the new planning horizon.
- Machines could be undergoing maintenance or repairs carried over from the previous period.

By incorporating these varied initial availability times, the model can seamlessly integrate with ongoing operations, ensuring a smooth transition between planning periods and accurately representing the dynamic nature of continuous mining operations.

We generated a total of 20 test instances for each combination of the number of drilling patterns, number of drill rigs, and relationship structure type, resulting in a comprehensive dataset of 600 instances for evaluating the CP model. While these parameters are grounded in real-world observations from a small-scale coal mine, the overall instances are synthetic constructions designed to test our model across a range of scenarios, including larger operations than the reference mine. This approach allows us to assess the model's performance under different conditions while maintaining a connection to practical mining operations.

5.2 Performance metrics

To evaluate the performance of the CP model, we considered the following metrics:

Objective value: Total lateness across all blast holes and drilling patterns.

Computation time: The time taken to find the optimal solution.

Optimality gap: For instances not solved to optimality within the time limit, we recorded the gap between the best solution found and the best bound.

Number of optimal solutions: The count of instances solved to proven optimality within the time limit.

Machine Utilization Rate: For each machine m, we compute:

- Total Active Time (TAcT_m): Sum of durations of all drilling tasks assigned to the machine plus sum of all travel times between patterns.
- Total Available Time (TAvT_m): Time from the machine's initial availability (a_m) to the completion of its last task.
- Utilization Rate (UR_m): TAcT_m / TAvT_m

The overall machine utilization rate is then calculated as the average of all individual machine utilization rates. This metric provides a comprehensive measure of how effectively each machine's time was used, accounting for both drilling and travel times, and considering the machine's entire available period. It offers insights into the efficiency of the scheduling solution by quantifying both active and idle times for each machine.

5.3 Experimental setup

We implemented our constraint programming model using IBM ILOG CPLEX Optimization Studio 22.1.0 with the CP Optimizer as the solving engine. Default parameters were used for the solver. The experiments were executed on a computer cluster equipped with Linux machines featuring AMD EPYC microprocessors, specifically Rome 7502, Rome 7532, and Milan 7413.

5.4 Results and analysis

A total of 600 instances were generated and solved, with 20 instances for each of the 30 possible configurations. Table 1 presents a summary of the experimental results, showing averaged metrics for each configuration.

Table 1: Averaged solution metrics

Priority Relationship	Patterns	Machines	Jobs Mean	Jobs Std	Lateness Mean	Lateness Std	Solve Time Mean	Solve Time Std	Machine Utilization Mean	Machine Utilization Std
simple	3	3	379.5	78.8	55.5	91.7	126.2	63.9	0.90	0.04
simple	3	4	385.0	56.1	43.7	68.0	177.9	81.6	0.86	0.02
simple	3	5	386.0	76.7	25.7	28.6	238.3	145.1	0.83	0.04
simple	4	4	485.5	73.7	39.2	34.2	311.7	119.7	0.91	0.03
simple	4	5	480.0	73.8	116.8	219.8	472.0	465.8	0.88	0.03
simple	4	6	489.0	98.7	28.7	32.8	432.4	382.7	0.85	0.04
simple	5	5	612.5	124.2	131.1	281.2	773.1	500.5	0.91	0.02
simple	5	6	628.0	95.6	54.6	68.2	909.2	1501.4	0.89	0.02
simple	5	7	665.0	118.7	54.5	128.0	823.4	641.4	0.88	0.03
simple	6	6	721.0	118.3	84.3	112.8	1157.9	814.9	0.91	0.02
simple	6	7	740.0	94.7	56.1	72.4	1689.9	2080.0	0.90	0.03
simple	6	8	743.5	101.6	78.6	111.2	2815.0	3435.9	0.89	0.02
simple	7	7	907.0	119.3	115.5	222.5	2121.2	2097.4	0.91	0.02
simple	7	8	879.5	94.6	120.2	172.6	1841.8	1328.1	0.90	0.01
simple	7	9	898.5	110.2	32.6	39.4	2171.9	1560.2	0.90	0.02
complex	3	3	390.5	84.2	55.0	90.9	128.2	57.2	0.91	0.03
complex	3	4	387.5	81.0	22.8	36.1	148.7	54.6	0.87	0.04
complex	3	5	397.0	72.8	23.0	26.3	278.5	294.1	0.85	0.04
complex	4	4	467.0	80.8	37.3	49.3	363.5	332.2	0.90	0.02
complex	4	5	515.0	93.9	22.0	22.3	598.4	750.2	0.87	0.03
complex	4	6	496.5	102.1	22.0	48.2	570.7	579.2	0.87	0.03
complex	5	5	613.5	122.6	29.4	35.5	738.5	380.5	0.91	0.03
complex	5	6	633.5	106.0	49.1	65.0	909.5	1394.9	0.88	0.04
complex	5	7	620.0	93.6	53.1	61.0	876.6	657.2	0.87	0.03
complex	6	6	746.5	85.1	56.1	75.2	1577.1	1416.1	0.91	0.02
complex	6	7	737.0	118.1	59.2	58.9	2151.6	2746.9	0.89	0.02
complex	6	8	754.5	122.3	48.7	60.6	1692.4	1531.3	0.88	0.03
complex	7	7	832.5	90.5	45.2	87.0	2408.7	1574.3	0.91	0.02
complex	7	8	839.0	127.8	30.6	36.9	2475.2	2114.7	0.90	0.02
complex	7	9	854.0	115.7	41.1	67.1	2091.7	1831.8	0.90	0.02

Key observations from the experiments are as follows:

1. **Problem size and complexity:** The instances varied significantly in size, with the average number of jobs (blast holes) ranging from approximately 380 for the smallest instances (3 patterns) to over 900 for the largest instances (7 patterns). The standard deviation of job counts within each configuration (ranging from about 56 to 128) indicates considerable variability even among instances of the same size.
2. **Solution optimality:** The model successfully solved all instances to optimality, including the most complex scenarios with 7 patterns and 9 machines. This demonstrates the model's capability to handle a wide range of problem sizes and complexities effectively.
3. **Lateness:** The presence of lateness in the optimal solutions indicates that the instances were challenging due to tight deadlines. The lateness values vary across configurations, reflecting the difficulty of meeting all deadlines in these scenarios.
4. **Computational performance:** Solve times increased substantially with problem size:
   - For smaller instances (3-4 patterns), mean solve times ranged from about 126 to 600 seconds.
   - Medium-sized instances (5 patterns) required between 738 and 909 seconds on average.
   - The largest instances (7 patterns) took between 1841 and 2475 seconds on average.

   This trend indicates that while the model can handle all instance sizes, computational requirements grow significantly for larger problems.
5. **Machine utilization:** Machine utilization rates were consistently high across all configurations:

- Utilization rates ranged from 0.83 to 0.91, indicating efficient use of resources in most scenarios.
- There is a slight trend of increasing utilization with an increasing number of patterns, but the effect is minimal given the already high utilization rates.
- The difference in utilization rates between simple and complex priority relationships is negligible for most configurations.

6. **Impact of priority relationships:** The results show minimal differences between simple and complex priority relationships:
   - For most configurations, the performance metrics (solve time and machine utilization) are similar for both relationship types.
   - This suggests that the model is robust to different problem structures and can effectively handle both simple and complex priority relationships.

In conclusion, the computational results demonstrate that the proposed model for the Integrated Drill Rig Dispatching and Drilling Coordination Problem (IDRDCP) is capable of solving a wide range of problem sizes and complexities to optimality. The model consistently achieves high machine utilization rates, indicating efficient resource allocation. The ability to solve all instances, even with tight deadlines, highlights the model's effectiveness in handling non-trivial scenarios. However, computational time is significantly affected by problem size, with larger instances requiring substantially more time to solve. The similarity in performance between simple and complex priority relationships suggests that the model is robust to different problem structures. Future work could focus on reducing computational time for larger instances, potentially through the development of heuristic approaches or the implementation of advanced solving techniques, while maintaining the model's ability to find optimal solutions for challenging instances.

6 Conclusion

This paper introduced the IDRDCP, a novel approach to optimizing drilling operations in open-pit mines. We presented a constraint programming model that efficiently captures both the spatial and temporal complexities of drill rig management across multiple patterns and within individual patterns.

Our computational experiments, conducted on a diverse set of instances varying in complexity, with 3 to 7 patterns and 3 to 9 drill rigs, demonstrated the model's effectiveness in solving a wide range of scenarios. The results show that the proposed approach can consistently find optimal solutions for all instances, even under tight deadline constraints, with computation times varying based on problem size.

Key findings from our experiments include:

Optimal solutions: The model achieved optimal solutions for all instances, including the most complex scenarios, demonstrating its capability to handle challenging problems effectively.

Performance under tight deadlines: The presence of lateness in optimal solutions indicates the model's ability to handle instances with tight deadlines, reflecting real-world operational constraints.

Scalability: While the model solved all instance sizes, computational requirements increased significantly for larger problems, with solve times ranging from minutes for smaller instances to over an hour for the largest ones.

Efficient resource utilization: High machine utilization rates (0.83 to 0.91) across all configurations indicate effective balancing of workload and resource allocation.

Robustness: The model's performance was consistent across different problem structures (simple and complex priority relationships), demonstrating its adaptability to various operational scenarios.

The IDRDCP model addresses a significant gap in current research by focusing on the fine-grained coordination of drilling operations at the blast hole level, while also considering the broader context of drill rig dispatching across multiple patterns. This level of detail allows for more precise and efficient management of drilling resources compared to approaches that consider tasks as aggregations of block units over longer planning horizons.

However, the study also revealed challenges in computational performance for larger instances, indicating areas for potential improvement in the model's efficiency for highly complex scenarios.

Future research directions could include:

- Developing heuristic or decomposition techniques to complement the CP approach for solving larger instances more efficiently while maintaining solution quality.
- Investigating the integration of the IDRDCP with other aspects of mine planning and operations, such as blasting schedules or overall production sequencing.
- Exploring the application of advanced technologies, such as real-time data integration or machine learning, to enhance the model's adaptability to dynamic mining environments.
- Extending the IDRDCP to account for uncertain drilling durations, building upon our previous work in Maftah et al. (2024b). This could involve adapting the two-stage stochastic, probability-free, or chance-constrained approaches to create robust schedules for the integrated drill rig dispatching and drilling coordination problem, enhancing the model's applicability in real-world mining operations where uncertainty is prevalent.

In conclusion, the IDRDCP model represents a significant step forward in the optimization of drilling operations for open-pit mines. By providing a comprehensive approach to drill rig management at a high level of granularity, this research contributes to improving overall mining efficiency and productivity. The model's ability to handle complex operational constraints and find optimal solutions for challenging instances makes it a promising tool for practical implementation in the mining industry, albeit with considerations for computational requirements in large-scale applications.

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