Towards Sustainable Mining: GHG Considerate Open Pit Long-Term Planning Using Adaptive Large Neighborhood Search Algorithm[1]

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ABSTRACT

Mine planning involves the systematic design and coordination of mineral extraction, integrating exploration, production, and engineering considerations. The mining industry is under increasing pressure to incorporate environmental responsibility into these processes. This paper addresses the precedence-constrained production scheduling problem (PCPSP) within the context of green long-term mining planning, aiming to optimize extraction processes while restricting carbon emission. Given the NP-hard nature of the PCPSP, this study introduces an adaptive large neighborhood search (ALNS) algorithm tailored specifically for long- term mine planning. A range of computational experiments have been carried out, including parameter tuning for the ALNS algorithm, comparisons against an exact solver, and analysis of our destroy- repair operators to determine their key elements. The efficacy of developed ALNS, evaluated using various benchmarks, reveals optimality gaps around 0.08. These results highlight the effectiveness of the proposed approach in addressing the PCPSP within mine planning and production scheduling, providing insights into improving mining operations while considering environmental concerns.

1. Introduction

Mine planning is the strategic process of designing and coordinating the extraction of minerals from the earth's crust, encompassing stages from exploration to production. This involves meticulous analysis of geological data, resource estimation, and engineering considerations to optimize extraction while minimizing environmental impact and ensuring safety [20]. Effective mine planning maximizes the recovery of valuable minerals, reduces operational costs, significantly contributing to national economies and global resource supply chains. Moreover, it ensures the responsible utilization of finite natural resources, aligning with sustainability objectives and environmental regulations.

The mining industry is experiencing a significant effect from growing environmental concerns and the drive toward achieving net-zero carbon emissions, given its vast scale of processing and

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operations. Thus, the pursuit of sustainable mining practices has become imperative, which necessitates a delicate balance between economic viability, environmental stewardship, and societal benefits [28]. Addressing ecological issues through reclamation plans and environmental impact assessments (EIAs), both of which need to be submitted to regulatory agencies. The mining plan, EIA, and reclamation plan are revised and progressively become more detailed as mining proceeds [7].

The tactical and operational aspects of mine planning are subject to periodic updates, presenting opportunities to integrate environmental considerations. Strategic planning, which spans the entire lifespan of a mine, often struggles with the precedence-constrained production scheduling problem (PCPSP), recognized for its NP-hard complexity [42]. The PCPSP is crucial for balancing operational efficiency, economic viability, and environmental sustainability within the dynamic landscape of modern mining operations.

Despite significant advancements in modeling and solution methodologies, the optimization of mineral value chains still requires the development of improved algorithms to overcome challenges related to scale, complexity, and uncertainty [24]. This challenge motivates the current study, which aims to pioneer the development of an adaptive large neighborhood search (ALNS) algorithm specifically tailored to address PCPSP within mine planning. Although the ALNS has demonstrated superior performance on various routing and scheduling problems [27], its application in production scheduling remains relatively rare [15-16].

This research addresses the PCPSP in the context of mine planning to maximize the net present value (NPV) while adhering to multiple constraints. These constraints include upper limits for environmental costs, grade blending limitations, equipment availability, and processing plant capacity. To tackle this complex optimization task, we introduce a novel solution approach based on the ALNS algorithm.

This paper is structured as follows: Section 2 provides a literature review of the most relevant studies on PCPSP in mine planning. Section 3 defines the proposed problem, presents the mathematical formulation, then Section 4 details the development of the ALNS algorithm to address the PCPSP with a focus on environmentally responsible mine planning. Section 5 presents the experimental setup and the results of testing the proposed algorithm and optimization model. Finally, Section 6 offers conclusions, discusses potential findings, highlights limitations, and proposes directions for future research.

2. Literature Review

Significant advancements have been made in the development of mathematical and computational approaches for optimizing open-pit mine planning. These strategies, whether exact or heuristic, focus on optimizing the NPV. Johnson (1968) identified the need of optimizing NPV by considering constraints such as mining and processing capacity, ore grades, and pit slopes, among other essential input considerations. Several studies written by Askari Nasab et al., Fathollahzadeh et al., Lambert and Newman, Lamghari, Newman et al., Osanloo et al., and Zeng et al. reviewed long-term optimization models for open-pit scheduling [4, 17, 22-23, 32-33, 45]. Tabesh et al. introduced a two-stage simultaneous optimization approach for long-term production planning in open-pit mines, incorporating multi-range stockpiling, which resulted in significantly improved NPV and throughout quality control [41].

Alipour et al., Busnach et al., Chicoisne et al., Cullenbine et al., and Lamghari et al. have employed heuristic strategies to discover integer viable solutions that roughly match the optimal linear programming solution [3, 9-10, 12, 25]. Ali et al. introduced an efficient Lagrangian relaxation reformulation using a neighborhood-based algorithm to solve the proposed model [2].

Furthermore, GU et al., and Moradi and Osanloo argued the importance of incorporating environmental considerations into optimizing mine design [19, 29]. Efforts have been made to integrate sustainable development concepts into mine design procedures, such as cut-off grade optimization [1, 11, 35-37]. Xu et al. developed a method for planning the production schedule of open pit mining operations, including ecological costs as part of the internal costs [44]. Building upon this, Xu et al. added an insightful layer by incorporating ecological costs, NPV, and social benefits into a multi-objective formulation confined to the pit limit [43]. However, the lack of integration with block extraction and sequencing decisions remained. Gong et al. explored integrating near-face stockpile mining methods with IPCC systems, showing demonstrating significant improvements in efficiency and output rates for open-pit operations [18].

Attari and Torkayesh developed an optimal approach using multi-objective mixed integer programming to minimize costs and CO_2 emissions associated with transportation [5]. Pell et al., presented a novel life cycle assessment (LCA) methodology to quantify the environmental costs of mining projects [34]. For sustainable long-term production planning in open-pit mines, Mirzehi and Moradi Afrapoli developed an integrated LCA-MILP framework, balancing economic and environmental performance and ensuring optimal extraction schedules that adhere to both profitability and environmental responsibility [28].

Recent research has investigated sophisticated optimization methods for complex optimization contexts, such as long-term open-pit mining planning using large neighborhood search (LNS), mineral value chain optimization through ALNS [8, 24], and product disassembly algorithms employing a tailored ALNS approach [15-16].

While significant advancements have been made in the development of mathematical and computational approaches for optimizing open-pit mine planning, the incorporation of sustainability factors has not been thoroughly investigated. In 2022, Azhar et al. advanced the PCPSP by incorporating carbon emission costs as a constraint [6]. Subsequently, in 2023, they developed a multi-objective framework to balance profit maximization with environmental costs [7]. Despite a growing interest in sustainable mining planning, quantitative studies utilizing operations research, artificial intelligence, and machine learning are still scarce compared to qualitative techniques [7]. Additionally, the application of advanced optimization methods like ALNS within open-pit mine planning has been limited, despite their development for various other purposes.

This research addresses PCPSP to maximize NPV while adhering to constraints such as environmental costs, grade blending, equipment availability, and processing plant capacity. To address these complexities and achieve optimal results, we introduce an ALNS algorithm tailored for open-pit mine planning.

3. Methodological Framework

Methodology In the following, we begin by delineating the optimization problem in Section 3.1, followed by introducing the carbon cost formulation aimed at enhancing the environmental sustainability of mine planning in Section 3.2. We then establish the notations pertinent to the optimization problem and present the mathematical optimization model in Section 3.3. After that we present the data by the benchmark’s definition in Section 3.4.

3.1. PCPSP Problem

The PCPSP is a pivotal challenge within the mining industry, shaping critical decisions in both the extraction and processing phases of valuable mineral ores. Beyond its operational significance, the PCPSP is crucial for providing investors with a detailed comprehension of a mine’s potential value. A typical mining operation includes key elements like the pit, dump, stockpiles, processing plants, and a fleet of heavy machinery. The mineral ore deposits within the pit are divided into uniform blocks for modeling, each having its own value and adhering to specific precedence constraints linked to geological features. These constraints determine the sequence of block extraction over time, influencing the entire ore processing workflow.

Once extracted, the blocks are transported to processing facilities for treatments, including crushing, grinding, and screening to meet stringent quality specifications. The material then undergoes further refinement to enhance its quality and transform it into desired end products. However, the intricate value chain of mining operations is not without its challenges. Mining activities are resource-intensive, consuming significant amounts of energy, water, and gases. Additionally, the mining process generates harmful by-products, ranging from water and air pollution to chemical waste, which present significant environmental and social challenges that necessitate careful management and mitigation strategies.

In essence, the PCPSP is crucial for balancing operational efficiency, economic viability, and environmental sustainability in modern mining operations.

3.2. Environmental Costs of Open Pit Mining

Our primary goal is to enrich the formulation of the PCPSP by integrating carbon costing within predefined constraints. To quantify carbon emissions, we use the following formula proposed by Xu et al. [43]:

$$C_{i,e} = \frac{(Q_{i,o} + Q_{i,w})e_m + Q_{i,o}e_p}{1000} f_c f_a C_c \tag{1}$$

In this formulation, the quantity of excavated and processed ore is denoted by $Q_{(i,o)}$, while $Q(_{i,w})$ represents the volume of waste material handled. The energy required to extract a single ton of material, regardless of whether it's ore or waste, from the pit is symbolized by e_m. Processing energy consumption per ton of ore is indicated by e_p. The coefficient f_c represents the carbon content of coal, f_a indicated the conversion coefficient from carbon-to-carbon dioxide, and C_c denotes the expense linked to carbon dioxide absorption.

3.3. Problem Formulation

Based on the problem definition, our notations, encompassing sets, parameters, and decision variables, are defined as follows:

- Sets
  - $m \in M$ Set of machines,
  - $b \in B$ Set of blocks,
  - $t \in T$ Set of periods,
  - $l \in L_b$ Set of blocks that must be extracted prior to block $b \in B$
- Parameters
  - s_{bt} NPV from mining block $b \in B$ in the period $t \in T$
  - α Discount factor
  - n_t Number of available machines for mining in each period $t \in T$
  - c_m Capacity of mining from machine $m \in M$
  - f_b Cost of mining block $b \in B$
  - G Total budget for carbon cost of mining
  - f_{mb} Carbon emission generated by machine $m \in M$ from mining each unit of block $b \in B$
  - r_b Amount of effortneeded for mining block $b \in B$

g_b The average grade of block $b \in B$
Max The maximum grade value for blocks mining
Min The minimum grade value for blocks mining

- Variables

x_{mbt} 1, If machine $m \in M$ is used on mining on block $b \in B$ during period $t \in T$, otherwise, 0.

Using above notations, we build the following integer programming model:

- Objective function

$$Z = \max\left(\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}}\sum_{t\in\mathcal{T}}\frac{s_{bt}}{(1+\propto)^t}\times x_{mbt}\right) \tag{2}$$

$$s.t.$$

$$x_{mlt'} \geq x_{mbt} \qquad \forall m \in \mathcal{M}, l \in \mathcal{L}_b, b \in \mathcal{B}, t, t' \in \mathcal{T}, t' < t \tag{3}$$

$$\sum_{b\in\mathcal{B}} r_b \times x_{mbt} \leq c_m \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{4}$$

$$\sum_{t\in\mathcal{T}}\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}} f_{mb} \times x_{mbt} \leq G \tag{5}$$

$$\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}} x_{mbt} \leq n_t \qquad \forall\, t \in \mathcal{T} \tag{6}$$

$$\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}} (g_b - Max)x_{mbt} \leq 0 \qquad \forall\, t \in \mathcal{T} \tag{7}$$

$$\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}} (g_b - Min)x_{mbt} \geq 0 \qquad \forall\, t \in \mathcal{T} \tag{8}$$

$$x_{mbt} \in \{0, 1\} \tag{9}$$

The proposed integer programming model addresses the PCPSP for challenge of green mine planning. The objective function is given in Eq. (2) and its associated constraints are outlined in Eq. (3) to Eq. (8). The goal, as represented by Eq. (2), is to maximize the NPV. The value of each block is estimated by geologists based on its ore composition and grade. Summing up the NPV over the entire duration of the mine highlights the significance of prioritizing the extraction of higher-value blocks at earlier stages. Constraint set Eq. (3) specifies that a block can only be extracted after the extraction of other linked blocks, establishing the sequence that must be followed within a given time frame. Eq. (4) defines the machinery capacity for mining blocks in each time period, highlighting the limits of mineral processing capacity. Meanwhile, Eq. (5) introduces financial restrictions, including carbon expenses incurred during mining operations. The constraint set Eq. (6) represents the availability of machinery in each time period, which restricts the mining capacity accordingly. Also, the grade blending constraint sets, Eq. (7) and Eq. (8), enforce a specific grade threshold when material is dispatched to a mill in each period. Finally, Equation Eq. (9) defines the allowable range for the variables, establishing feasibility criteria.

3.4. Benchmark Cases for Model

To evaluate the efficacy of our mine planning model, we conducted rigorous assessments using three diverse real-world benchmarks. Firstly, we leveraged a modified version of the Wilma1 dataset, extracted from an active copper and gold mine, meticulously tailored to align with our overarching optimization framework. This dataset, originally studied by Azhar et al. offers a nuanced representation of operational intricacies [6]. Expanding our evaluation, we enriched our dataset with benchmark cases drawn from MineLib [13], a renowned repository of mining case studies. Among these, Newman1 and Kd emerged as pivotal benchmarks for their distinct characteristics. Newman1 encapsulates a compact dataset, serving as an ideal yardstick for evaluating algorithmic efficiency in smaller-scale scenarios. Conversely, Kd embodies a medium-scale dataset sourced from a copper mine in North America, reflecting the complexities inherent in larger operational settings. These benchmark instances, originally cataloged by Muñoz et al. provide a comprehensive spectrum of challenges for robust algorithmic evaluation [30].

Finally, Table 1 provides details regarding the number of blocks ($|B|$), precedence ($|L_b|$), time periods ($|T|$), and machines or resources ($|M|$). All the parameters linked with the traditional PCPSP are taken from MineLib. The remaining parameters specific to our green mine planning optimization model are the total budget for our carbon cost of mining (G) is 100, 000, 000, the average grade value of each block (g_b), the maximum grade value of each block (Max) is 1, and the minimum grade value of each block (Min) is 0.

Table 1. Size of our test instances.

Name of instances	$\|\boldsymbol{B}\|$	$\sum_{b\in\mathcal{B}} \|\mathcal{L}_b\|$	$\|\boldsymbol{T}\|$	$\|\boldsymbol{M}\|$
Newman1	1060	3922	6	2
Wilma1	1960	7112	4	3
Kd	14153	219778	12	2

4. ALNS Framework

The adaptive large neighborhood search (ALNS) is a heuristic approach derived from Shaw's large neighborhood search (LNS), introduced by Røpke and Pisinger [38, 40]. The underlying principle of this method is to iteratively deconstruct and rebuild solutions to enhance variety and escape local optima [39]. This method is distinguished by considering a set of destroy and repair operators, while its predecessor uses only a single destroy and repair operator [27].

The ALNS search space is a set of feasible solutions, which include diverse options regarding the assignment of machines to blocks across different time periods [15-16]. The algorithm effectively explores the search space by applying decision rules within the destroy and repair operators, aiming to identify high-quality solutions.

This paper adopts the ALNS strategy with a combination of three destroy operators, three repair operators, alongside a local search-based algorithm, and the Simulated Annealing (SA) metaheuristic algorithm to solve the optimization problem. The ALNS algorithm is adapted from Fathollahi-Fard et al. [15-16]. The process begins with the construction of an initial solution set up using repair operators.

The algorithm explores new solutions in each iteration by using operators for destroying and repairing the current best-known solution. Each new solution is evaluated, and if it improves, it replaces the existing best solution. Otherwise, the SA decision rule is applied to determine its retention. Subsequently, a local search method is employed to refine the solution. Then, the algorithm updates its parameters to guide the following iterations. The algorithm presents the optimal solution identified after completing a predetermined number of iterations.

4.1. Algorithm Components

4.1.1. Operator Selection

Operator selection is one of the activities that ALNS requires. The primary reason for this is that different operators are more useful at different stages of the search process than others. The selection among the destroy and repair operators is based on the roulette wheel selection principle, prioritizing those who have historically proven to be more effective. The probability of selecting each destroy operator, denoted as P_r^-, and each repair operator, denoted as P_c^+, is calculated as follows:

$$P_d^- = \frac{w_d^-}{\sum_{r \in R} w_d^-}, \qquad \forall r \in R \tag{10}$$

$$P_r^+ = \frac{w_r^+}{\sum_{c \in C} w_r^+}, \qquad \forall c \in C \tag{11}$$

where w_r^- and w_c^+, reflect the historical performance of the respective destroy and repair operators. Initially, these weights are assigned a value of one and then modified in each iteration as shown in Eq. (12) and Eq. (13).

$$w_d^- = \vartheta \times w_d^- + (1 - \vartheta)\Omega \qquad \forall r \in R \tag{12}$$

$$w_r^+ = \vartheta \times w_r^+ + (1 - \vartheta)\Omega \qquad \forall c \in C \tag{13}$$

A forgetting factor, denoted by $\theta \in [0, 1]$, and a performance score, **Ω**, are assigned to each operator based on its effectiveness in identifying superior solutions during the most recent iteration, determined as follows:

$$\Omega = \begin{cases} \omega_1 & \text{If the new solution is the new global best.} \\ \omega_2 & \text{If the new solution is accepted.} \\ \omega_3 & \text{If the new solution is rejected.} \end{cases} \tag{14}$$

A method is considered effective when it has a high value of **Ω**, with the parameters arranged as $\omega_1 \geq \omega_2 \geq \omega_3$.

4.1.2. Acceptance Criteria

As previously described, each iteration involves applying a pair of destroy and repair operators to the current solution to generate a new one (S^n). If the new solution, New_S^n, does not improve upon the best-known solution (S^*), the SA algorithm determines whether to accept it for the next iteration. This decision is made by comparing a randomly generated value in the range [0, 1] (*rand₁*) with a probability of $e^{-|Z(New\_S^n) - Z(S^*)|/Tem}$, where Tem is the temperature parameter. It steadily decreases by being multiplied by a cooling rate of α during each iteration, leading to a lower acceptance rate for worse solutions over time. (15)

4.1.3. Solution Refinement

In the proposed ALNS algorithm, the best solution obtained thus far is refined by conducting a local search at each iteration, using a combination of destroy-repair operators. It begins by randomly choosing one or two blocks from the current best solution, which were initially assigned to specific time periods. Initially, one of three repair operators is chosen at random to rebuild the partially feasible solutions. Additionally, a new solution is generated by randomly assigning blocks to time periods. Among these new solutions, the best one is compared with S^*. Thus, the local search algorithm follows these steps:

Step 0: Initiate the local search algorithm with the current best solution (S^*).

Step 1: Randomly select one or two blocks from S^* and remove the associated machines and time periods.

Step 2: Utilize one of the repair operators to repair the partial feasible solution obtained in Step 1.

Step 3: In addition to the repaired solution, generate a random solution from the search space and select the best solution among the two alternatives.

Step 4: If the newly identified best solution (S^n) surpasses the S^*, update S^* accordingly.

Step 5: If the maximum number of sub-iterations (*Sub_n*) has not been reached, return to **Step 1**. Otherwise, display the current best solution (S^*).

4.2. Destroy and Repair Operators

This study focuses primarily on three repair operators, extending those introduced by Naderi and Ruiz (2010), but also introduces and applies novel destroy operators, enriching the landscape of research in this domain.

In crafting the initial solution (S^0), we have utilized the power of three distinct repair operators, each contributing to the formation of an optimal starting point for the optimization process. This initial solution serves as our baseline representation of the best-known solution (S^*), setting the stage for subsequent iterations to refine and improve upon it.

R1: This operator prioritizes assigning blocks from first to the last block to time periods based on the highest available NPV before the assignment. By selecting the most economically beneficial blocks first, we aim to maximize the overall profitability of the solution. When multiple blocks have the maximum NPV, the operator selects the first encountered block for assignment. Following block allocation, an idle machine is chosen for processing to ensure efficient resource utilization. To prevent the re-selection of blocks in subsequent assignments, the NPV of each assigned block is set to negative infinity, effectively removing it from consideration. The details of this repair operator are given in Figure 1.

Algorithm 1 R1 greedy repair

Data: Destroyed assignment variables: x_{mbt}, NPV: s_{bt}
Result: Repaired assignment variables: x_{mbt}
while b less than B **do**
    $m \leftarrow$ randomly if this machine is not busy $x_{mbt} = 0$
    $x_{mbt} = 1 \leftarrow$ Select a period t with maximum s_{bt} if only if $x_{mbt} = 0$
    $s_{bt} = 0 \leftarrow$ The selected period for is equal to zero.
    $b \leftarrow b + 1$
end while

Figure 1. R1 greedy repair.

R2: In contrast to R1, this operator allocates blocks to time periods based on the highest available NPV after the assignment. By prioritizing immediate gains, we aim to maximize the potential profitability of recently allocated blocks. Similar to R1, if multiple blocks have the maximum NPV, the first encountered block is prioritized for assignment. Following block allocation, an available machine not currently engaged in processing is selected to perform the assigned task.

As with R1, the NPV of each assigned block is set to negative infinity to prevent its re-selection in subsequent assignments, maintaining solution integrity. The pseudo-code provided in Figure 3 demonstrates this greedy repair.

Algorithm 2 R2 greedy repair

Data: Destroyed assignment variables: x_{mbt}, NPV: s_{bt}
Result: Repaired assignment variables: x_{mbt}
while p less than B **do**
  $m \leftarrow$ randomly if this machine is not busy $x_{mbt} = 0$
  $b \leftarrow$ randomly if this block is not extracted before $x_{mbt} = 0$
  $x_{mbt} = 1 \leftarrow$ Select a period t with maximum s_{bt} if only if $x_{mbt} = 0$
  $s_{bt} = 0 \leftarrow$ The selected period for is equal to zero.
  $p \leftarrow p + 1$
end while

Figure 3. R2 greedy repair.

R3: This operator introduces randomness into the allocation process by randomly assigning blocks to time periods based on the availability of machines. While less deterministic than R1 and R2, this approach offers flexibility and exploration potential within the solution space. Unlike R1 and R2, the allocation of blocks in this operator is not influenced by NPV concerns. Instead, blocks are assigned purely based on machine availability, providing a different perspective on solution generation. Similar to the other operators, an infinite negative value is assigned to infeasible allocations that violate capacity or grade constraints. This ensures compliance with the problem constraints and solution feasibility. This random repair is shown in Figure 2.

Algorithm 3 R3 random repair

Data: Destroyed assignment variables: x_{mbt}
Result: Repaired assignment variables: x_{mbt}
while p less than B **do**
  $m \leftarrow$ randomly if this machine is not busy $x_{mbt} = 0$
  $b \leftarrow$ randomly if this block is not extracted before $x_{mbt} = 0$
  $x_{mbt} = 1 \leftarrow$ Select a period t randomly if only if $x_{mbt} = 0$
  $s_{bt} = 0 \leftarrow$ The selected period for is equal to zero.
  $p \leftarrow p + 1$
end while

Figure 2 R3. random repair.

By employing these diverse operators, our goal is to generate initial solutions that are both feasible and strategically advantageous, establishing a solid foundation for subsequent optimization iterations. Each operator brings its unique perspective and methodology to the solution generation process, enriching the exploration of the solution space and contributing to the overall effectiveness of the optimization algorithm.

Destroy operators differ from repair operators in that they prioritize exploration of the search space by discovering unexplored areas, rather than just focusing on exploitation [27]. Let n represent the iteration index of the ALNS algorithm, ranging from 1 to *Max_N*. At the first iteration (n = 1), the algorithm uses the solution produced by the repair operators as its initial optimal solution, denoted as S^*, which is equal to S^0. As the algorithm progresses through iterations, it systematically applies various destroy operators to eliminate elements from the existing solution structure. This process involves modifying certain values of the decision variables x^{n}_{mbt} to yield a provisional solution for the next iteration, represented as x^{n+1}_{mbt}. The destroy operators involve a parameter Q that defines the proportion of components to be removed from the solution in each iteration n, represented as S^n. The value of Q ranges from 0 to 1. Each destroy operator employs a distinct approach to obtaining partial feasible solutions:

1. Random-block-based destroy operator (D1): Randomly selects a maximum percentage Q of blocks from the set B. Removes the time periods assigned to the selected blocks, resulting in a modification of the solution. This destroy operator is shown in Figure 4.

Algorithm 4 Random-block-based destroy operator (D1)

Data: Percentage of removal: Q, Assignment variables: x_{mbt}
Result: Destroyed assignment variables: x_{mbt}
$p \leftarrow 0$
while p less than $Q \times |B|$ **do**
    $x_{mbt} = 0 \leftarrow$ Select a random block p if only if x_{mbt}=1
    $p \leftarrow p + 1$
end while

Figure 4. Random-block-based destroy heuristic (D1).

2. Random-machine-based destroy operator (D2): Randomly selects a maximum percentage Q of machines from the set M. Removes the blocks assigned to these selected machines, facilitating solution modification. This destroy operator is coded in Figure 5.

Algorithm 5 Random-machine-based destroy operator (D2)

Data: Percentage of removal: Q, Assignment variables: x_{mbt}
Result: Destroyed assignment variables: x_{mbt}
$p \leftarrow 0$
$t \leftarrow 0$
while t less than $Q \times |T|$ **do**
    while p less than $Q \times |M|$ **do**
        $x_{mbt} = 0 \leftarrow$ Select a random machine p if only if x_{mbt}=1
        $p \leftarrow p + 1$
    end while
    $p \leftarrow 0$
    $t \leftarrow t + 1$
end while

Figure 5. Random-machine-based destroy heuristic (D2).

3. Random-time-period-based destroy operator (D3): Randomly selects a percentage Q of time periods from set T. Removes these time periods from the sequence of blocks assigned to machines, affecting solution adjustment. This destroy operator is coded in Figure 6.

Algorithm 6 Random-time-period-based destroy operator (D3)

Data: Percentage of removal: Q, Assignment variables: x_{mbt}
Result: Destroyed assignment variables: x_{mbt}
$p \leftarrow 0$
$b \leftarrow 0$
while b less than $Q \times |B|$ **do**
    while p less than $Q \times |T|$ **do**
        $x_{mbt} = 0 \leftarrow$ Select a random time period p if only if x_{mbt}=1
        $p \leftarrow p + 1$
    end while
    $p \leftarrow 0$
    $b \leftarrow b + 1$
end while

Figure 6. Random-time-period-based destroy heuristic (D3).

By employing these diverse destroy operators, our ALNS algorithm navigates through the solution space. It strategically modifies solutions to explore new possibilities while maintaining feasibility and meeting optimization objectives.

5. Result and Discussion

5.1. Calibration of Our ALNS

The algorithm consists of several key parameters, as defined in Table 2 and discussed earlier. Given their significance in determining the algorithm's performance, it is imperative to fine-tune them before proceeding with experiments and comparisons. Various methods exist for parameter calibration, including the Response Surface Method, the Taguchi Method, and the Design of Experiments (DoE) approach [15-16]. For this study, we opt for the widely recognized DoE approach. The DoE approach initiates by providing a comprehensive factorial set encompassing all potential parameter configurations, which are then evaluated on test instances. Following this assessment, the configuration striking a balance between solution quality and computational time is selected [14].

Key parameters within the proposed ALNS, including those of the ALNS and SA, were identified through preliminary experiments. Notably, four parameters significantly influence both algorithmic speed and efficiency. During calibration, we set forth three candidate values for each parameter, resulting in a total of 81 parameter combinations ($3^4 = 81$). Moreover, the values of other parameters, such as those governing the destroy procedure and adaptive mechanism, are derived from insights gleaned from the classical ALNS algorithm [38]. Finally, Table 2 illustrates the candidate values and tuning configurations for the ALNS parameters, facilitating a systematic approach to parameter optimization.

Table 2. The tuning results for the ALNS.

Symbol and explanation	Range of parameter's value	Selected value
q: The percentage of removals	{[0.1, 0.15], [0.15,0.25], [0.25,0.35]}	[0.15, 0.25]
T_0: Initial temperature	[5, 10, 20] $\times$|B|	|B| $\times$10
T_l: Terminal temperature	[0.01, 0.05, 0.1] $\times$|B|	|B| $\times$0.01
β: Cooling rate	[0.99, 0.995, 0.999]	0.999

|B| represents the number of blocks in the corresponding instance.

5.2. Comparisons and Evaluations of Our ALNS

Once the input parameters of proposed ALNS algorithm have been fine-tuned, we proceed to execute the ALNS for a designated time frame of one hour per test instance. Recognizing the stochastic nature of our ALNS approach, we iterate the algorithm 10 times for each test instance to capture variability. The choice of 10 iterations is based on established practices in similar studies, which often use a comparable number of iterations to balance computational effort and result reliability [15-16, 26]. Subsequently, we aggregated the results, comprising the best, worst and average solutions derived from these 10 runs, along with their corresponding standard deviations.

To assess the effectiveness of our approach, we compute the optimality gap by comparing the best solution attained through ALNS with an exact solution benchmark. Detailed results are presented in Table 3, providing insight into the performance characteristics of the proposed algorithm in diverse test instances.

Table 3. The results of our ALNS.

Name of instances	**Exact solution from benchmarks**	**ALNS**				
		Best	Worst	Average	Standard deviation	Optimality gap
Newman1	23658230	21765572	20241982	21037105	482454	0.08
Wilma1	67826631	59687435	56106189	57975152	1134024	0.12
Kd	406871207	313290829	297626289	305801221	4960277	0.23

The results presented in Table 3 underscore the efficacy of our ALNS approach, particularly evident in the Newman1 and Wilma1 test instances, characterized as smaller-scale scenarios. Here, the optimality gaps of 0.08 and 0.12, respectively, signify the remarkable proximity of our ALNS solutions to optimality. Even in the more complex operational setting represented by the Kd instance, classified as a large-scale scenario, the optimality gap of 0.23 showcases the ability of our ALNS to produce solutions of substantial quality.

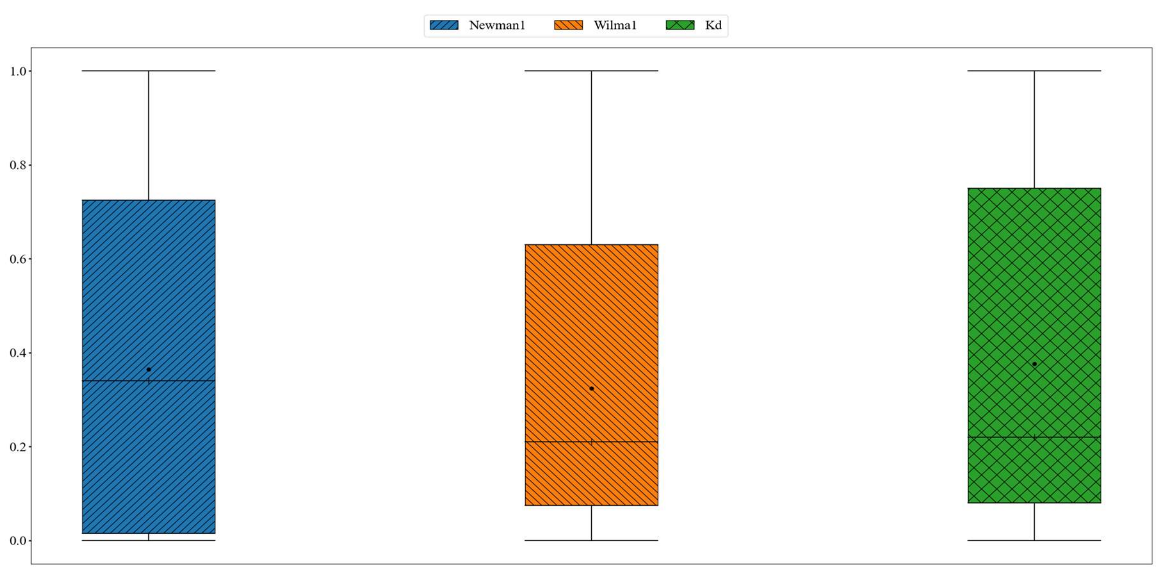

Figure 7. Box plot for solving test instances by the ALNS.

Figure 7 provides valuable insights into the performance characteristics of our ALNS algorithm across the various test instances. Through normalization of 10 algorithm runs for each instance, the box plot offers a comprehensive view of the distribution and consistency of the solutions obtained. The analysis reveals a consistent performance of the ALNS across all test instances, indicating the algorithm’s reliability and stability in diverse operational settings. However, noteworthy distinctions emerge, particularly in the case of the Wilma1 instance. This heightened accuracy and robustness in the Wilma1 test instance suggests that our ALNS approach is exceptionally well-suited to addressing the specific challenges and intricacies inherent in this operational context. Such findings underscore the adaptability and effectiveness of our algorithm in achieving superior performance, particularly in scenarios resembling the Wilma1 dataset.

To get a more comprehensive understanding of the performance dynamics of the ALNS algorithm, we performed a thorough analysis of the destroy-repair pairs. Our objective is to determine which combination yields optimal outcomes compared to others within the context of a specific test instance, namely Wilma1. To identify the optimal combination of operators for the Wilma1 test instance, we systematically evaluate the average performance of each destroy-repair operator pair by conducting multiple runs of our ALNS algorithm. These findings are presented in Table 4, which shows the percentage of changes observed relative to the original scenario where all destroy-repair operator pairs are available.

Table 4. Analyzing the destroy-repair operators.

Destroy operators	Repair operators	Percentage of average changes on the solution quality
D1	R1	37.28%
	R2	24.55%
	R3	35.26%
D2	R1	14.25%
	R2	19.47%
	R3	18.84%
D3	R1	13.47%
	R2	15.13%
	R3	16.64%

The analysis presented in Table 4 underscores the pivotal role of the destroy-repair operator pair comprising the D1 and R1 repair in augmenting solution quality within the context of our ALNS algorithm.

Figure 8 provides a visual representation of the average changes in solution quality attributed to each destruction and repair operator.

Notably, D1 emerges as the standout performer among the destroy operators, exerting a pronounced influence on enhancing solution quality. Conversely, among the repair operators, R3 demonstrates the highest average performance, consistently contributing to superior solutions.

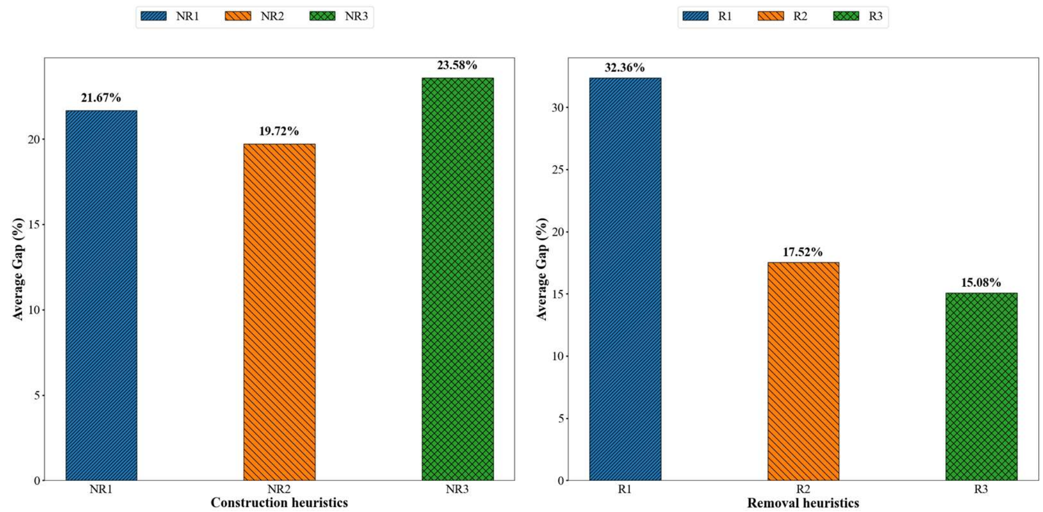

Figure 8. Evaluation of the destroy-repair operators.

5.3. Sensitivity Analysis

This sensitivity analysis aims to clarify how changes in key factors affect the overall outcomes, offering insights into the model's response to variations in carbon emissions constraints, NPV, average grade values, and carbon emissions generated in each period.

During these analyses, the ALNS algorithm is executed 10 times, and the best solution found across these runs is considered for evaluation. Regarding the initial sensitivity analysis on carbon emissions constraints, we partition our optimization model into two scenarios. In the first scenario, we maintain the carbon emissions constraint set defined by constraint set Eq. (5), while in the second scenario, we remove this constraint set.

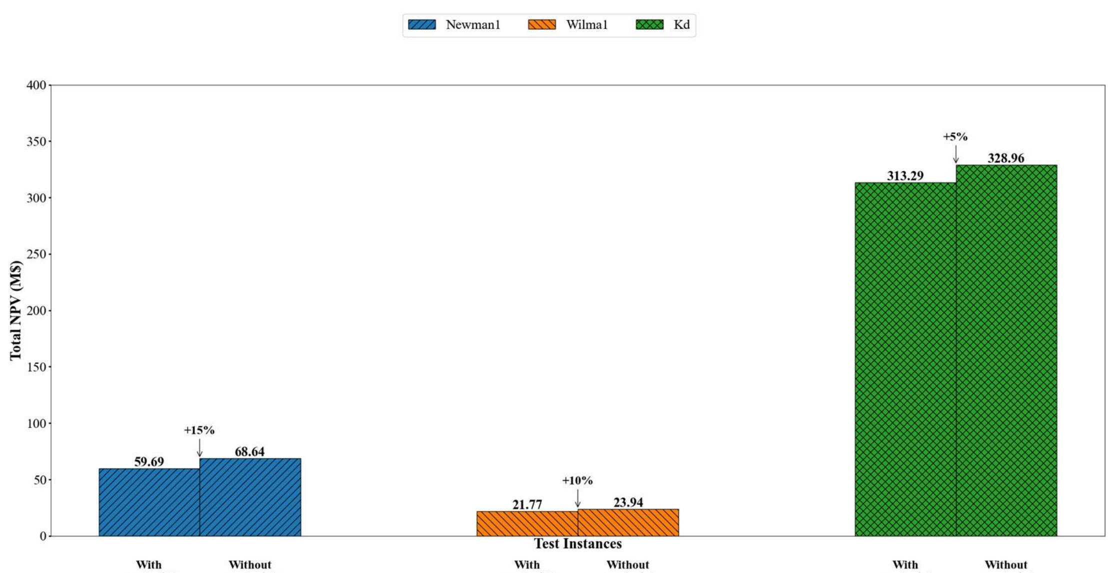

Figure 9. Sensitivity analysis on the carbon emissions constraints.

Error! Reference source not found. illustrates that relaxing the model by excluding carbon emission constraints leads to an increase in total NPV derived from our objective function. Consequently, the absence of these constraints allows an enhancement in overall profitability.

Following, we examine the NPV values obtained from the objective function per time period, as shown in Figure 10.

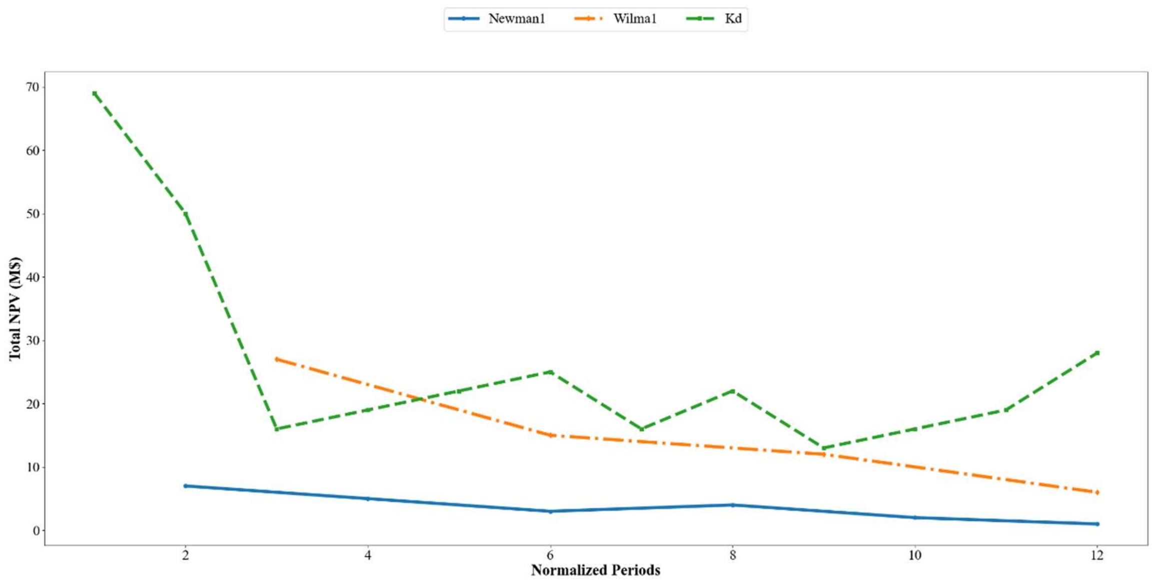

Figure 10. Sensitivity analyses on the NPV for each period.

The NPV values exhibit a downward trend across periods due to the increasing impact of precedence constraints on block extraction. This limitation results in a reduction in NPV values as each period progresses.

The grade blending constraints, Eq. (7) and Eq. (8) aim to ascertain the maximum and minimum values of grade allowed. In our scenario, we assume the minimum grade value to be zero and the maximum grade value to be one. We compute the average grade values from all extracted blocks

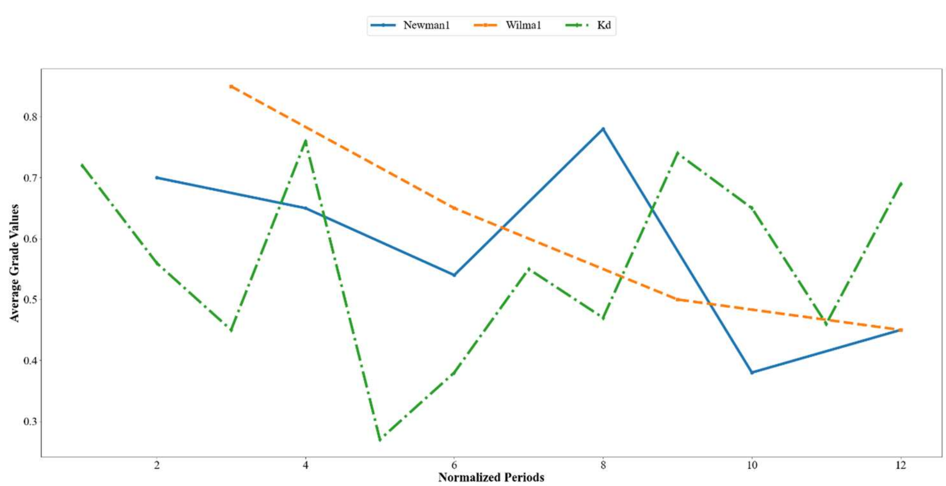

Figure 11. Sensitivity analyses on the grade values for each period.

within each period and present these analyses in Figure 11. As can be seen in, the behavior of the average grade values mirrors that of NPV per period.

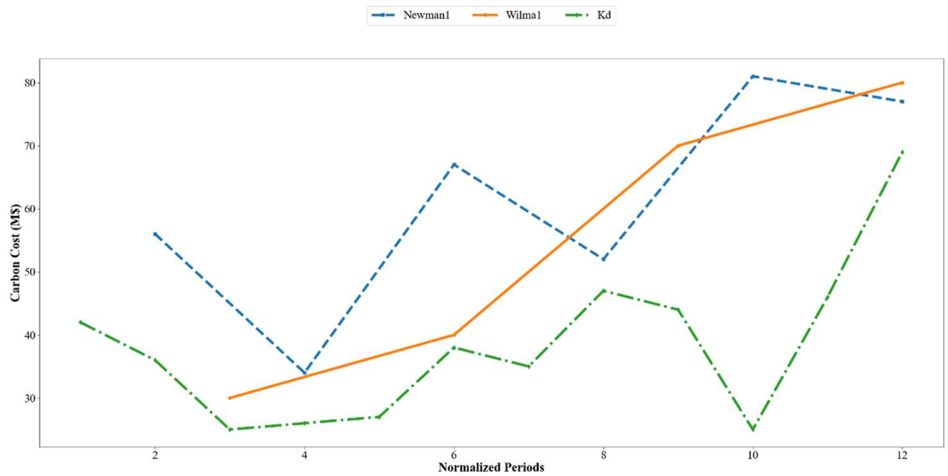

Figure 12. Sensitivity analyses on the carbon emissions generated per period.

Figure 12 illustrates the carbon emissions generated per period, with an upper bound set at 10^8. It can be observed that carbon cost increase steadily per period, contrary to the NPV trend observed earlier. As extraction progresses, blocks located in lower layers typically incur higher carbon emissions compared to those in upper layers, as described in Eq. (1). This trend underscores the importance of balancing economic objectives with environmental sustainability goals, necessitating the development of strategies that optimize both financial returns and reduce carbon emissions.

6. Conclusion

This paper introduced an efficient ALNS algorithm to tackle the PCPSP. The method was tested on three real-world mining datasets of varying complexity. We introduced carbon costing into the scheduling model and used adaptive heuristic selection strategies to improve solution quality. The results showed that the ALNS algorithm achieved near-optimal solutions with small optimality gaps, specifically 0.08 for Newman1, 0.12 for Wilma1, and 0.23 for Kd. This demonstrates its effective performance in dealing with different operating configurations. This demonstrates its effective performance in dealing with different operating configurations.

Future work will investigate how our ALNS approach performs on a stochastic version of the PCPSP. This will involve developing new heuristics to effectively handle uncertainties related to block grades, market pricing, and operational constraints. In addition, we will investigate the integration of real-time data to enable dynamic scheduling decisions. This will improve the strength and usefulness of the system in real-world mining operations.

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