Sustainable Open Pit Mining through GHG-Conscious Short-Term Production Scheduling[1]

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ABSTRACT

The mining industry is a notable contributor to global greenhouse gas (GHG) emissions, posing challenges to achieving the Paris Agreement's goal of capping emissions at 30 Gt CO_2-equivalent annually by 2030. This paper introduces a novel Mixed Integer Linear Programming (MILP) model tailored for short-term open-pit mine planning that integrates environmental considerations, particularly GHG emissions, alongside economic objectives. The model manages complex operational challenges including block sequencing, multiple transport destinations, and stockpile management. Additionally, it provides the opportunity to examine the adoption of In-Pit Crushing and Conveying (IPCC) systems as the main transport method, an innovative approach aimed at reducing emissions from haulage—which accounts for over 35% of GHG emissions in open-pit mining. Applied to a case study in an iron ore mine, the model not only considers the environmental benefits of IPCC systems compared to traditional truck and shovel (TS) operations but also highlights significant reductions in haulage costs and carbon tax liabilities. The findings demonstrate that fixed IPCC (FIPCC) systems, in particular, offer substantial decreases in GHG emissions, presenting a compelling case for their broader adoption in the industry.

1. Introduction

The mining sector is pivotal in the global transition to a low-carbon future. However, as a significant contributor to global GHG emissions, the industry faces the urgent need to reduce its environmental impact to effectively combat climate change. Industrial activities, being complex and integrated processes, require holistic approaches when introducing new methods and technologies. Identifying emission hotspots during operations is the first step towards devising actionable and sustainable practices, considering that about 35% of the scope 1 GHG emissions in open-pit mining are due to fuel consumed in hauling [1]. But this alone is not sufficient. It is

[1] This paper is submitted to International Journal of Mining, Reclamation and Environment on April 24, 2024.

ISBN: 978-1-55195-520-9

equally essential to consider the economic impacts and the inherent trade-offs of the green solutions to facilitate informed decision-making through considerate strategic and operational planning. Furthermore, it is vital to determine the stages of planning where environmentally friendly solutions can be most effectively implemented. While environmentally considerate planning is gaining traction in the mining field, with some studies addressing long-term [2] and operational planning [3] aspects that incorporate sustainability, a notable gap remains in short-term planning. This paper seeks to address this gap by presenting an environmentally considerate approach specifically designed for short-term production scheduling, thereby contributing a novel perspective to the sustainable transformation of the industry. This paper's primary contribution lies in utilizing a developed mathematical model to assess the environmental and economic performance of novel solutions against traditional methods. Specifically, it evaluates short-term production plans that employ IPCC as the principal mode of material transportation versus TS.

As a response to the pressing demand for sustainable mining practices, mathematical models offer a framework for viewing the entire process in a comprehensive and efficient manner. The advent of mathematical programming has marked a significant milestone in mining, particularly with the application of integer programming and MILP models, enhancing the intricacies of mine production scheduling. The seminal work by Smith et al., which introduced integer programming to mining optimization, the field has seen significant advancements, leveraging both traditional and novel computational techniques to enhance operational efficiency and decision-making [4]. Kumral and Dowd's exploration of simulated annealing and Caccetta's discussion on the broad applications of optimization in mining indicate the versatility and critical importance of these techniques in tackling the sector's complexities, from ore-body modeling to equipment selection [5-6]. Rehman and Asad, and Li and Knights further contribute by introducing MILP models and integrating real options into mine planning, respectively, showcasing the potential of mathematical programming to navigate economic uncertainties and optimize production schedules [7-8]. Bley et al. fortified the formulations for mine production scheduling and Newman et al. providing a comprehensive review of operations research in mine planning, highlighting the sector's growing reliance on sophisticated analytical models to drive efficiency and profitability [9-10]. The innovation extends to methodologies for block aggregation by Tabesh and Askari-Nasab, and multi-destination routing optimization by Eivazy and Askari-Nasab, each contributing to the refinement of production scheduling and operational logistics within mining [11-12].

Despite these advancements, L'Heureux et al. point out the computational challenges inherent in large-scale applications, a sentiment echoed by others in the field seeking more scalable and efficient solutions [13]. Responding to this need, Kozan et al. and Lambert et al. introduce innovative scheduling methodologies and block-sequencing tutorials, respectively, pushing the envelope in mining optimization and planning [14-15]. Recent contributions by Mousavi et al., Blom et al., and Matamoros and Dimitrakopoulos showcase the diversification of optimization techniques in mining, from metaheuristic approaches for block sequencing to multi-objective algorithms for short-term scheduling, each aiming to maximize operational value while navigating the sector's uncertainties and constraints [16-18]. The adoption of portfolio optimization models and dynamic shovel allocation approaches by Osanloo and Rahmanpour, and Upadhyay and Askari-Nasab further illustrate the sector's movement towards integrating advanced optimization tools with detailed operational models to achieve strategic alignment and enhance mine productivity [19-22]. The culmination of these efforts is evident in the works of Otto and Lindeque, and Pathak and Samanta, who demonstrate the practical application and benefits of these advanced mathematical programming techniques in real-world mining operations, underscoring the critical role of integrated planning and optimization in driving the future of mining efficiency and sustainability [23-24]. In reviewing the emerging trajectory of mathematical modeling in mining as outlined by Blom et al., it is apparent that the emphasis has been on the economic aspects of the industry [17]. There has been less focus on utilizing it as a potent tool for investigating sustainable practices. This study bridges this gap by introducing a novel Mixed Integer Linear Programming (MILP) model for GHG considerate short-term open-pit mine planning. The developed model transcends mere economic optimization by explicitly incorporating environmental considerations. This includes the impact of carbon taxes and the potential of In-Pit Crushing and Conveying (IPCC) systems on emissions reduction.

To showcase the effectiveness of the proposed mathematical model in identifying sustainable strategies, we validated the proposed model using a real mining case study that reflects an actual iron ore mining operation. Given that the model considers both the tonnage and distances for block extraction and transportation, the case study develops yearly plans for an open-pit mine to evaluate the effectiveness of both SMIPCC and FIPCC systems in comparison to conventional TS material handling systems, with an emphasis on economic feasibility and reduction of GHG emissions. This practice is supported by early studies such as the one by Mohammadi et al., which highlight the cost-effectiveness of IPCC systems, which can account for up to 50% of mining expenses [25]. These systems are praised for their energy efficiency and reduced operational costs, making them particularly beneficial for large-scale operations dealing with high fuel and labor costs. Environmental considerations, specifically GHG emissions, play a crucial role in the adoption of IPCC. Norgate and Haque's life cycle assessment indicates that IPCC systems can significantly lower GHG emissions compared to conventional TS systems [26]. This reduction is even more pronounced when electricity from cleaner sources replaces diesel fuel [26]. Nehring et al. further emphasize the environmental benefits of IPCC, including notable decreases in CO_2 emissions and dust and noise pollution, contributing to a more sustainable mining environment: operational efficiency is another critical aspect of IPCC systems [27]. Dzakpata et al. demonstrate that conveyors, a key component of IPCC, outperform TS in terms of efficiency, particularly in valuable operating time [28]. This efficiency translates into significant improvements in loading equipment productivity [28].

The strategic integration of IPCC systems into mining operations requires careful planning and consideration of several factors. Nehring et al. detail crucial prerequisites for the effective integration of IPCC systems, which encompass: (1) A desirable material movement exceeding 4 Mtpa to validate the initial CAPEX, with a preference for amounts exceeding 10 Mtpa. (2) A mine lifespan extending beyond 10 years to ensure the lower OPEX compensates for the elevated initial CAPEX. (3) Electricity expenses ($/kWh) that are less than a quarter of the diesel cost ($/L) [27]. These elements are instrumental in evaluating the feasibility of replacing traditional TS systems with IPCC systems. Recent studies have further explored the economic and operational implications of IPCC systems. Hay et al. provide a methodology for determining the ultimate pit limit when considering semi-mobile IPCC (SMIPCC) systems, showing that these systems can achieve higher net present value (NPV) despite smaller pit sizes due to reduced mining costs [29]. De Werk et al. conduct a cost analysis showing that despite higher initial investments, IPCC systems offer substantial operational cost savings in the long run, particularly as mine depths and haul distances increase [30]. The choice of an appropriate IPCC system—whether fixed, semi-mobile, or fully mobile—is critical and must be based on the unique operational and economic challenges of each mining project. Nasirinezhad et al. emphasize the need for a meticulous selection process to ensure that the chosen IPCC system aligns with the project's specific requirements and maximizes operational efficiency and sustainability [31]. In terms of energy consumption, Purhamadani et al. emphasize the significant energy savings achievable with IPCC systems, projecting considerable reductions in energy consumption and associated costs, thereby enhancing the overall mining economy [32]. Advancements in short-term mine planning have also been influenced by IPCC. The review by Al Habib et al. highlights significant advancements in integrating IPCC systems into short-term mine planning, emphasizing their potential for reducing operational costs and GHG emissions.

Despite these benefits, challenges such as high initial capital costs, the need for skilled labor, and reduced operational flexibility remain significant barriers. The imposition of carbon taxes enhances the economic attractiveness of IPCC systems due to their lower emissions. The review identifies a gap in short-term planning methodologies that integrate IPCC systems and proposes a theoretical framework to address this. The authors recommend expanding research on short-term IPCC planning models and developing strategies to overcome implementation challenges [33]. Al Habib et al. introduces a methodology focusing on shovel allocation that highlights the economic benefits of IPCC, particularly in terms of haulage cost savings. This approach highlights the operational cost advantages of IPCC over traditional TS systems [34]. The paper by Al Habib et al. proposes a mixed-integer programming model for short-term planning in open-pit mines using SMIPCC, demonstrating higher profits and lower operational costs compared to traditional truck-shovel systems through a case study [35]. Nehring et al. explore strategic planning approaches for both IPCC and traditional systems [36]. They demonstrate the environmental advantages of IPCC, including lower CO2 emissions, reduced dust, and noise pollution [36]. Their comparative analysis shows that IPCC systems can achieve higher net present value (NPV) despite smaller pit sizes due to reduced mining costs [36]. Shamsi and Nehring corroborate these findings, emphasizing the cost-effectiveness and energy efficiency of IPCC systems, especially for large-scale operations with high fuel and labor costs [37]. Wachira et al. investigate the productivity of SMIPCC systems using the mine productivity index (MPi), finding that scenarios with more loading equipment have higher productivity compared to traditional truck-shovel systems [38]. Their study suggests that SMIPCC systems can significantly reduce operational costs by minimizing the use of trucks [38]. Nunes et al. provide a decision-making method to assess the benefits of SMIPCC early in mining projects [39]. They highlight that while the initial capital expenditure (CAPEX) for IPCC is higher, the operational expenditure (OPEX) is lower, resulting in overall cost savings and environmental benefits over the life of the mine [39]. Hay et al. focus on the ultimate pit limit determination for SMIPCC systems, demonstrating that these systems can optimize pit designs by reducing haul distances and lowering overall costs [40]. Similarly, Liu et al. introduce a framework for production scheduling in open-pit mines using SMIPCC, emphasizing the need for models that integrate economic, technical, and environmental factors to optimize short-term planning [41]. Further comparison by Bernardi et al. between fixed and mobile IPCC systems with truck-shovel systems reveals that IPCC systems offer greater operational savings due to more efficient energy use and lower labor requirements [42]. Osanloo and Paricheh discusses the application and benefits of IPCC technology in open-pit mining operations, noting significant improvements in cost efficiency and environmental impact [43]. Collectively, these studies highlight the substantial economic and environmental benefits of IPCC systems, while also highlighting the need for further research to develop robust short-term planning models that effectively integrate these systems. Addressing challenges such as high initial costs, operational flexibility, and the need for skilled labor will be crucial for the broader adoption of IPCC in the mining industry.

It is important to highlight that the study of GHG emissions in mining operations is dependent on thorough data gathering and examination. Carvalho et al. highlight the significance of precise CO_2 measurements from mining trucks de [44]. This is further supported by the frameworks developed by Jiskani et al. and Katta et al. for GHG emission calculation and quantification, integrating factors like fuel consumption, energy use, and material handling, and assessing reduction potentials and costs across sectors [45-46]. Additionally, Kecojevic and Komljenovic provide a model for determining fuel consumption and CO_2 emissions under varying conditions, offering insights into the economic impacts of CO_2 legislation [47]. This case study thus presents a comparative analysis based on this scholarly research and expert insights, underscoring the essential need for accurate data when investigating complex issues within the mining industry.

This study introduces a holistic approach to short-term strategic production planning in open-pit mines, prioritizing both economic efficiency and environmental preservation. We enhance an economic-focused Mixed Integer Linear Programming (MILP) model by integrating the impacts of carbon taxes on mining operations, reflecting the global trend towards eco-friendly mining practices. Utilizing a case study that mirrors a real-world operation, this paper demonstrates the efficacy of the proposed MILP model in formulating production plans that not only ensure economic profitability but also significantly reduce emissions. This dual achievement emphasizes the model's potential as a pivotal tool in the sustainable transformation of the mining industry.

This paper is organized into four sections. Section 2 elaborates on the MILP formulation employed in the study. Section 3 provides a description of the case study, encompassing the basis of the data and context, the approach to the solution, the main findings, and the discussion of the results. Section 4 concludes by summarizing the key findings, contributions, and recommendations for future research.

2. Methodological Framework

The primary challenge addressed in this study is to develop and apply a MILP model for optimizing short-term production scheduling in open-pit mines. Therefore, a comprehensive MILP model was formulated. Employing binary and continuous decision variables, the formulation precisely determines block sequencing, material flows, and resource allocation across processes and destinations. Rigorous constraints enforce precedence relationships, capacities, grade requirements, and stockpile balancing. This robust mathematical framework enables optimized scheduling for operational efficiency and profitability.

In the block sequencing approach, the utilization of side-cut and drop-cut methods during the extraction process from blocks has been considered. For the side-cut method, each block within a bench can be extracted if its adjacent side includes three adjacent blocks in the same direction that have been completely mined beforehand. The drop-cut extraction method is authorized once all nine blocks directly above the target block have been fully extracted. In this overall mining strategy, the drop-cut scenario has been activated along with just two perpendicular side-cut methods (north and east directions). To improve the efficiency of optimization, the mathematical framework of block sequencing that has been proposed to date has been fine-tuned.

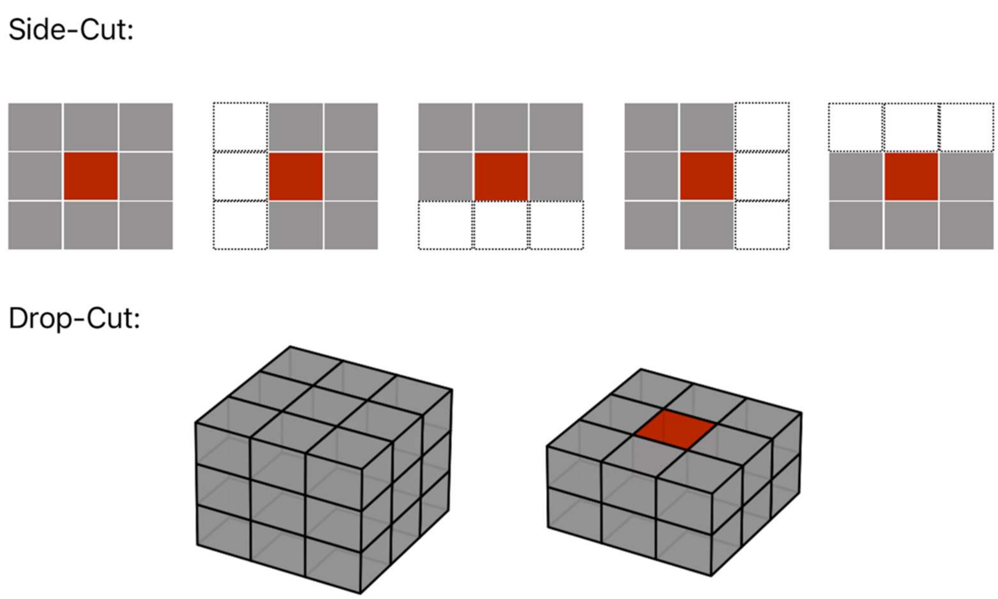

Figure 1. Side-Cut and Drop-Cut Mining Techniques.

2.1. Indices

t	Time period (t = 1, 2, . . ., K)
e	Element e (e = 1, 2, . . ., E)
p	Process p (p = 1, 2, . . ., P)
s	Stockpile s (s = 1, 2, . . ., S)
w	Waste dump w (w = 1, 2, . . ., W)
r	Ramps r (r = 1, 2, . . ., R)

2.2. Parameters

J(n)	Set of blocks that must be extracted during the short-term time horizon (set in long-term planning)
N	Number of blocks in J(n)
ME^t	Minimum fraction of each block that could be extracted in period t
O_n	Tonnage of mineralized zone in block n
R_n	Rock tonnage of block n
g_e^n	Grade of element e in block n
WPB(n)	Set of blocks that are directly above and adjacent to the west side of block n
SPB(n)	Set of blocks that are directly above and adjacent to the south side of block n
VPB(n)	Set of vertical precedent blocks for block n
$N_{WPB}(n)$	Number of blocks in the set W P B(n)
$N_{SPB}(n)$	Number of blocks in the set SP B(n)
$N_{VPB}(n)$	Number of blocks in the set V P B(n)
R(n)	Set of corresponding ramps to haul extracted materials of block n
P(n)	Set of processes that can receive ore from block n
SP(n)	Set of stockpiles that can receive ore from block n
W(n)	Set of waste dumps that can receive waste material from block n
MC^t	Unit mining cost in period t
WC_w^t	Unit waste rehabilitation cost in period t for waste dump w
PR_p^t	Unit processing revenue in period t for process p
PC_p^t	Unit processing cost in period t for process p (includes both the unit cost of processing by process p and the unit cost of transport of ore to process p)
$RH_s^{t,p}$	Unit re-handling cost for stockpile s sending ore to process p in period t (includes the unit cost of transporting ore from stockpile s to process p)
H^t	Unit haulage cost in period t (includes the unit cost of haulage of material inside the pit to the pit exit)

MU^t	Maximum acceptable tonnage that could be mined based on maximum available mining capacity in period t
ML^t	Minimum acceptable tonnage that could be mined based on minimum available mining capacity in period t
PU_p^t	Maximum acceptable ore tonnage that process p can process based on maximum process p capacity in period t
PL_p^t	Process p minimum ore acceptable tonnage in period t
$gu_p^{t,e}$	Upper bound on acceptable grade of element e for process p in period t
$gl_p^{t,e}$	Lower bound on acceptable grade of element e for process p in period t
$OGSP_s^e$	Grade of element e in the ore which is sent from the stockpile s to processes
$UGSP_s^e$	Upper bound of grade of element e in the stockpile s
$LGSP_s^e$	Lower bound of grade of element e in the stockpile s
CSPs	Maximum storage capacity of stockpile s
IMC_s^e	Initial metal content of element e in stockpile s
dE_n^r	Distance of block n to the exit of the pit
P[SP(s)]	Set of processes that can receive ore from stockpile s (destination of stockpile s)
SP[P(p)]	Set of stockpiles that can send ore to process P (source of process p)

2.3. Variables

u_n^t	Fraction of block n extracted in period t (where n ∈ J(n))
$uw_n^{t,w}$	Fraction of block n extracted in period t and sent to waste dump w (where w ∈ W (n))
$us_n^{t,s}$	Fraction of block n extracted in period t and sent to stockpile s (where s ∈ SP (n))
$up_n^{t,p}$	Fraction of block n extracted in period t and sent to process p (where p ∈ P (n))
x_n^t	Binary variable, if block n is extracted in period t it gets a value of one, otherwise zero
$b_n^{t,r}$	Binary variable, if ramp r is selected for haulage of extracted material from block n in period t, it gets value of one, otherwise zero
$y_s^{t,p}$	Ore tonnage sent from stockpile s to process p in period t (where s ∈ SP |P (p) is the set of stockpiles that send ore to process p)
I_s^t	Inventory of stockpiles at the end of period t

2.4. Objective function

Maximizing Profit in Ore Processing Operations To maximize profit in ore processing operations, the objective function calculates the total revenue generated from processing ore minus the total costs incurred over the planning horizon. The profit maximization problem can be defined as follows:

$$\text{Maximize Profit} = \text{Total Revenue} - \text{Total Costs}$$

where:

- **Total Revenue** is calculated based on the price per tonne of the product processed and the total tonnes processed.
- **Total Costs** include all operational costs associated with mining, processing, waste management, rehandling, and haulage.

The components of Total Revenue and Total Costs are detailed below:

Total Revenue from processed ore is given by the equation (1):

$$\text{Total Revenue} = \underbrace{\sum_{t=1}^{K} \sum_{n=1}^{N} \sum_{p \in P(n)} u_n^{t,p} \times R_n \times PR_p^t + \sum_{t=1}^{K} \sum_{s=1}^{S} \sum_{p \in P(SP(s))} y_s^{t,p} \times PR_p^t}_{\text{Total Revenue from processed ore}} \quad (1)$$

Total Costs encompass various operational expenses and are defined by equation (2):

$$\begin{aligned} \text{Total Costs} = {} & \underbrace{\sum_{t=1}^{K} \sum_{n=1}^{N} R_n \times u_n^t \times MC^t}_{\text{total mining cost}} + \underbrace{\sum_{t=1}^{K} \sum_{n=1}^{N} \sum_{p \in P(n)} u_n^{t,p} \times R_n \times PC_p^t}_{\text{total processing cost}} + \\ & \underbrace{\sum_{t=1}^{K} \sum_{n=1}^{N} \sum_{w \in W(n)} u_n^{t,w} \times R_n \times WC_w^t}_{\text{total waste cost}} + \underbrace{\sum_{t=1}^{K} \sum_{s=1}^{S} \sum_{p \in P(SP(s))} y_s^{t,p} \times RH_{s,p}^t}_{\text{total haulage cost}} + \\ & \underbrace{\sum_{t=1}^{K} \sum_{n=1}^{N} \sum_{r \in R(n)} b_n^{t,r} \times dE_n^r \times H^t}_{total\ haulage\ cost} \end{aligned} \quad (2)$$

When considering the implementation of IPCC instead of the traditional TS system, we use the cost factors detailed in Table 4. This table provides a comparison of the unit costs for various stages of mining operations under both IPCC and TS systems, highlighting the potential cost savings and efficiency improvements with IPCC.

2.5. Constraints

Constraint (3) ensures that all blocks within the mine are mined exactly once during the planning horizon, preserving the unique mining event for each block:

$$\sum_{t=1}^{K} u_n^t = 1, \forall n = 1, \dots, N \quad (3)$$

Constraint (4) guarantees that each block n is allocated to only one destination per time period t, whether it is for processing, stockpiling, or waste:

$$\sum_{p \in P(n)} u_n^{t,p} + \sum_{s \in SP(n)} u_n^{t,s} + \sum_{w \in W(n)} u_n^{t,w} = u_n^t, \forall n = 1, \dots, N, \forall t = 1, \dots, K \quad (4)$$

Constraint (5) asserts that the total amount of ore directed from block n over all periods should equal the ore content available in block n, ensuring full extraction:

$$R_n \times \sum_{t=1}^{K} \left(\sum_{p\in P(n)} u_n^{t,p} + \sum_{s\in SP(n)} u_n^{t,s}\right) = O_n, \forall n = 1, \dots, N \quad (5)$$

Constraint (6) connects the act of mining to the decision process, requiring that a block can only be mined if the decision to mine it has been made:

$$u_n^t \leq b_n^t, \forall n = 1, \dots, N, \forall t = 1, \dots, K \quad (6)$$

Constraint (7) establishes that mining can only take place if the amount extracted meets or exceeds a predefined minimum threshold, promoting efficient use of resources:

$$ME_t \times b_n^t \leq u_n^t, \forall n = 1, \dots, N, \forall t = 1, \dots, K \quad (7)$$

Constraint (8) controls the total amount of ore mined in each period, ensuring it stays within the operational limits set for the mining project:

$$ML^t \leq \sum_{n=1}^{N} R_n \times u_n^t \leq MU^t, \forall t = 1, \dots, K \quad (8)$$

Constraint (9) stipulates that the tonnage targets for all processing plants are met each period, adhering to the upper and lower bounds of their requirements:

$$PL_p^t \leq \sum_{n\in P(n)} R_n \times u_n^{t,p} + \sum_{s\in SP|P(p)} y_s^{t,p} \leq PU_p^t, \forall t = 1, \dots, K, \forall p = 1, \dots, P \quad (9)$$

Constraints (10) to (13) enforce the precedence relationships between blocks, ensuring that mining operations adhere to a logical and safe sequence. This includes the conditions under which mining can proceed based on the status of adjacent blocks and encompasses several specific cases:

Constraint (10) ensures that a block can only be mined if all blocks that are above and adjacent to its west side have been mined, reflecting the activated drop-cut scenario:

$$N_{WPB(n)} \times b_n^t - (1 - y_1^t) \leq \sum_{\tau=1}^{t} \sum_{i\in WPB(n)} u_i^\tau, \forall n = 1, \dots, N, \forall t = 1, \dots, K \quad (10)$$

Constraint (11) dictates that a block can only be mined if all blocks that are above and adjacent to its south side have been mined, representing one of the perpendicular side-cut methods:

$$N_{SPB(n)} \times b_n^t - (1 - y_2^t) \leq \sum_{\tau=1}^{t} \sum_{i\in SPB(n)} u_i^\tau, \forall n = 1, \dots, N, \forall t = 1, \dots, K \quad (11)$$

Constraint (12) states that a block can only be mined if all blocks that are directly above it have been mined, ensuring vertical precedence is maintained:

$$N_{VPB(n)} \times b_n^t - (1 - y_3^t) \leq \sum_{\tau=1}^{t} \sum_{\mathrm{i\in VPB(n)}} u_i^\tau, \forall n = 1, \dots, N, \forall t = 1, \dots, K \quad (12)$$

This overarching constraint (13) combines the conditions for all three scenarios, affirming that a block's mining is contingent on the completion of mining in all relevant preceding blocks:

$$b_n^t \leq y_1^t + y_2^t + y_3^t \tag{13}$$

Constraint (14) dynamically calculates the grade of stockpiles after changes in their composition, ensuring the material quality stays within specified bounds:

$$gl_{t,p}^e \leq \frac{\sum_{s\in SP|P(p)} y_s^{t,p} \times OGSP_s^e + \sum_{n\in P(n)} u_n^{t,p} \times R_n \times g_n^e}{\sum_{s\in SP|P(p)} y_s^{t,p} + \sum_{n\in P(n)} u_n^{t,p} \times R_n} \leq gu_{t,p}^e, \quad \forall t = 1, \dots, K, \forall p = 1, \dots, P, \forall e = 1, \dots, E \tag{14}$$

Constraint (15) balances the flow of materials, ensuring that the amount reclaimed from a stockpile during a period does not exceed the stockpile's inventory at the end of the previous period:

$$\sum_{n\in SE(SP(n))} R_n \times u_n^{t,s} - \sum_{p\in SP|S(s)} y_s^{t,p} + I_s^{t-1} = I_s^t, \forall t = 1, \dots, K, \forall s = 1, \dots, S \tag{15}$$

Constraint (16) ensures that the reclaimed material from a stockpile does not exceed the accumulated inventory up to that point, effectively managing the stockpile levels:

$$\sum_{p\in SP|S(s)} y_s^{t,p} \leq I_s^{t-1}, \forall t = 1, \dots, K, \forall s = 1, \dots, S \tag{16}$$

Constraint (17) controls the average grade of elements in the material sent to stockpiles, keeping it within acceptable limits to ensure quality control:

$$LGSP_s^e \leq \frac{\sum_{n\in SE(SP(n))} u_n^{t,s} \times R_n \times g_n^e}{\sum_{n\in SE(SP(n))} u_n^{t,s} \times R_n} \leq UGSP_s^e, \forall t = 1, \dots, K, \forall s = 1, \dots, S, \forall e = 1, \dots, E \tag{17}$$

Constraints (18) and (19) manage the flow of materials from stockpiles, ensuring the reclaimed material maintains the required grade for processing.

$$\sum_{p\in SP|S(s)} y_s^{t,p} \leq \frac{N_{e,s}^{t-1} - LGSP_s^e \times I_s^{t-1}}{OGSP_s^e - LGSP_s^e}, \forall t = 1, \dots, K, \forall s = 1, \dots, S, \forall e = 1, \dots, E \tag{18}$$

$$\sum_{\mathrm{p}\in \mathrm{P[SP(s)]}} y_{\mathrm{s}}^{\mathrm{t,p}} \leq \frac{-N_{\mathrm{s}}^{\mathrm{e,t-1}} + UGSP_s^e \times I_s^{\mathrm{t-1}}}{-OGSP_s^e + UGSP_s^e}, \forall t = 1, \dots, K, \forall s = 1, \dots, S, \forall e = 1, \dots, E \tag{19}$$

N_s^e represents the metal content of element e in stockpile s at the end of period t − 1, which is calculated by the equation (20):

$$N_{\mathrm{s}}^{\mathrm{e,t-1}} = \sum_{\tau=1}^{t-1} \sum_{\forall \mathrm{n:s \in SP(n)}} un_{\mathrm{n}}^{\tau,\mathrm{s}} \times R_{\mathrm{n}} \times g_{\mathrm{n}}^{\mathrm{e}} + IMC_{\mathrm{s}}^{\mathrm{e}} - \sum_{\tau=1}^{t-1} \sum_{\mathrm{p \in P[SP(s)]}} y_{\mathrm{s}}^{\tau,\mathrm{p}} \times OGSP_{\mathrm{s}}^{\mathrm{e}}, \quad \forall e = 1, \dots, E, \forall t = 1, \dots, K, \forall s = 1, \dots, S \tag{20}$$

Constraint (21) determines that each block can only be assigned to one of the available ramps for hauling per period, ensuring exclusive routing for the material:

$$\sum_{r \in R(n)} x_n^{t,r} = R_n \times u_n^t, \forall n = 1, \dots, N, \forall t = 1, \dots, K \tag{21}$$

Constraint (22) ensures that the total material hauled for a block in any given period must match the total material that has been extracted from that block:

$$x_n^{t,r} \leq M \times b_n^{t,r}, \forall n = 1, \dots, N, \forall t = 1, \dots, K, \forall r = 1, \dots, R(n) \text{ (} M \text{ is a large number)} \tag{22}$$

Constraint (23) asserts that the binary decision for hauling material from each block is consistent across the periods and ramps:

$$\sum_{r \in R(n)} b_n^{t,r} = b_n^t, \forall n = 1, \dots, N, \forall t = 1, \dots, K \tag{23}$$

Constraints (24) to (29) are domain constraints that set feasible operational ranges for the utilization of blocks, stockpiles, and ramps, ensuring that all variables stay within bounds that reflect realistic mining operations:

$$0 \leq u_n^t \leq 1, \forall n = 1, \dots, N, \forall t = 1, \dots, K \tag{24}$$

$$0 \leq u_n^{t,w} \leq 1, \forall n = 1, \dots, N, \forall t = 1, \dots, K, \forall w \in W(n) \tag{25}$$

$$0 \leq u_n^{t,p} \leq 1, \forall n = 1, \dots, N, \forall t = 1, \dots, K, \forall p \in P(n) \tag{26}$$

$$0 \leq u_n^{t,s} \leq 1, \forall n = 1, \dots, N, \forall t = 1, \dots, K, \forall s \in SP(n) \tag{27}$$

$$0 \leq x_n^{t,r} \leq 1, \forall n = 1, \dots, N, \forall t = 1, \dots, K, \forall r \in R(n) \tag{28}$$

$$0 \leq y_s^{t,p} \leq 1, \forall t = 1, \dots, K, \forall s = 1, \dots, S, \forall p \in SP \mid S(s) \tag{29}$$

Constraint (30) maintains that the inventory of any stockpile cannot exceed its maximum capacity, avoiding overstocking and potential operational inefficiencies:

$$I_s^t \leq CSP_s, \forall t = 1, \dots, K, \forall s = 1, \dots, S \tag{30}$$

Constraint (31) imposes binary conditions on decision variables for block mining and ramp selection, restricting them to be either 0 or 1. This binary nature enforces clear decisions on whether a block is mined or a ramp is used in each period:

$$b_n^t, b_n^{t,r} \in \{0,1\}, \forall n = 1, \dots, N, \forall t = 1, \dots, K, \forall r \in R(n) \tag{31}$$

This MILP model optimizes short-term open pit production schedules through a comprehensive set of decision variables and constraints. Binary variables determine block extraction sequencing and ramp allocations, while continuous variables track material flows to processing plants, stockpiles, and waste dumps. Key constraints ensure precedence relationships are respected, mining and processing capacities are met, stockpile inventories are balanced, and transportation distances are minimized.

3. Case Study

The open-pit mine under consideration comprises 200 mining cuts with varying tonnages, iron grades, and rock types, which need to be extracted and allocated to various destinations. These destinations include two mineral processing plants with capacity limits and grade requirements, two stockpiles for temporary storage and blending, and two waste dumps. The model accounts for routing distances connecting blocks to destinations and incorporates a carbon tax imposed at a fixed rate per tonne of CO_2 emitted based on estimated GHG emissions from mining equipment and activities.

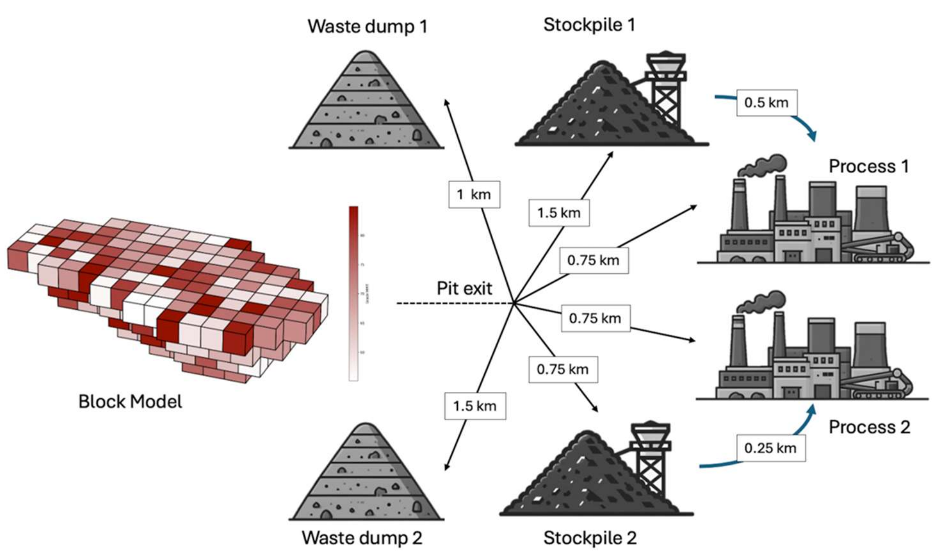

Figure 2. Open Pit Mine Schematic.

A schematic layout of an open-pit mining operation (as depicted in Figure 2) showcases the various components critical to mining logistics and planning. In the center is the block model that represents the mine itself, with pathways leading to different operational sites. On either side, there are two waste dumps where overburden and waste material are stored. Near the mine there are two stockpiles that serve as temporary storage for ore. The two processing plants, labeled Process 1 and Process 2, are where the ore is treated and processed.

3.1. Assumptions and Limitations

The study makes several key assumptions regarding the input data and estimation of GHG emissions. The input data, such as mining cuts and production targets, are derived from long-term planning models. It assumes consistent operational practices and conditions across all mining activities. Additionally, the accuracy of GHG emission estimates relies on available data related to fuel consumption, energy use, and material handling, as well as insights from industry experts. However, there are limitations to consider. The synthetic data was created to resemble the real case to verify the model's functionality. However, without access to actual data, scalability remains a limitation of this research. Actual GHG emissions can vary significantly based on operational practices, site-specific conditions, and equipment efficiency, which may not be fully captured by the assumptions used. The findings are constrained by the availability and accuracy of data on fuel consumption, energy use, and emissions. Inaccuracies or gaps in this data can affect the reliability of the emission estimates. The study focuses on open-pit mining activities and may not be directly applicable to other types of mining operations, such as underground mining, which have different emission profiles and operational characteristics. Economic factors such as fluctuations in energy prices, changes in carbon tax policies, or variations in operational costs are not accounted for, which could impact the economic feasibility of the proposed strategies over time. Additionally, advances in mining technology and equipment efficiency could alter the emission factors used in the study, potentially affecting the relevance of the findings in future scenarios. Furthermore, GHG emissions related to mining activities can be influenced by factors like equipment maintenance, operational downtime, and changes in mining intensity, which may not be fully considered. These assumptions and limitations highlight the need for careful consideration of operational practices, data accuracy, and the specific context of each mining operation when applying the study's findings to real-world scenarios.

3.2. Data Foundation and Context

To enable an exhaustive juxtaposition between IPCC systems and conventional TS systems, a synthetic data set was meticulously assembled. This data set serves as a robust and credible foundation for the rigorous analytical examination.

Figure 2 shows the possible destinations for extracted material, detailing distances and pathways involved. By visually representing these elements, the figure helps understand the scale of distances and different destinations when using IPCC instead of TS systems. The heart of this data set is a theoretical geological block model, made up of 200 blocks cuts. This carefully crafted model outlines the spatial arrangement of these blocks, offering detailed insights into different rock types, grades (like phosphor, sulfur, and iron), and the dimensions and capacity of every single block. Through the synthesis of this data set, the goal is to accurately simulate operational situations, thereby facilitating a thorough investigation of the relative strengths and weaknesses of each transportation approach.

Table 1 presents an overview of the general characteristics of the block model, while Figure 1 offers a visual perspective of the block model as described in the study.

Table 2 presents the specifications of two processes, including the lower and upper grade percentages of the input, as well as the range of capacity for each process, which is measured in millions of tons.

Table 1. General information about the problem.

	Bench No.			
	0	1	2	3
Number of Cuts	93	61	34	12
Ramps no.	1, 2	3, 4	5, 6	7, 8
Number of periods/months	12			
Total number of Cuts	200			
Total rock tonnage/ x 106 t	94.7			

Table 2. Processes' main features.

Process	Grade %		Capacity / x 106 t
	Lower	Upper	Min. – Max.
Process 1	70	85	1 - 2
Process 2	70	85	1 – 1.75

Table 3 provides an overview of the key characteristics of two stocks. It presents information on the acceptable input percentages for lower and upper grades, as well as the output grade percentage.

Table 3. Stockpiles' main features.

Stockpile	Lower grade/%			Upper grade/%			Output grade/%		
	MWT	S	P	MWT	S	P	MWT	S	P
Stockpile 1	55	0	0	65	8	7	60	4	3.5
Stockpile 2	65	0	0	78	8	7		4	3.5

Table 4 presents the unit cost breakdown by mining operation stage and revenue per processed ore for three mining methods - TS, FIPCC, and SMIPCC. The cost components include processing (PC), stockpile to plant haulage (RHI), waste rock handling (WR), mining (MC), haulage per tonne-meter (H), crusher costs (CR) and the revenue per processed ore (PR)

Table 4. Unit Cost Breakdown by Mining Operation Stage and Revenue from Processed Ore [12, 39].

Method	PC ($/t)		RHI ($/t)		WR ($/t)		MC ($/t)	H ($/t-m)	CR ($/t)	PR ($/t)
	P1	P2	SP1 to P1	SP2 to P2	W1	W2				
TS	4	5	0.5	0.25	1.75	1.5	1	1.00×10^{-3}		130
FIPCC								6.50×10^{-4}	2.80×10^{-2}	
SMIPCC								6.90×10^{-4}	4.03×10^{-2}	

Mining operations require a significant amount of energy to power the equipment used in mining. The primary sources of energy for mining operations are typically diesel fuel, electricity, and natural gas, all of which produce GHG emissions. The amount of GHG emissions associated with energy consumption in mining operations can vary widely depending on the type of energy source used and the efficiency of the equipment.

Within the scope of this study on open-pit mining activities, we have made specific assumptions about the machinery used to estimate GHG emission factors. These assumptions include the use of the Caterpillar 793 E truck (rated payload capacity: 218 tonnes) for haulage (with average speed of 40 kph), the 6090 FS Hydraulic Shovel (bucket capacity: 42.6 cubic meters) for mining operations, the MD6290 Rotary Drill for drilling, and standard industrial explosives for blasting. These specific models are chosen to provide a standardized basis for emission estimation, although we acknowledge that actual emissions can vary based on operational practices and site-specific conditions.

Following these assumptions, in Table 5, we present the GHG Emission Factors for each aspect of open-pit mining. This includes emissions from mining, haulage, ancillary and processing which are significant sources in mining operations.

Table 5. GHG Emission Factors for Open Pit Mining Activities [47, 48].

Activity	CO_2-eq (kg)	Unit
Mining	5.37×10^{-1}	per tonne
Processing	6.90×10^{-1}	per tonne
Ancillary Operations	6.86×10^{-2}	per tonne
TS	2.23×10^{-1}	per tonne-m
Crusher	1.61×10^{2}	per hour
Conveyor	1.61×10^{-1}	per hour-m

It must be noted that the calculation of the GHG emissions is assumed as a post-process and is done with the help of the data provided in Table 5 and the results of the model after optimization. As a result, by having the total amount of GHG emissions produced and the carbon tax penalty ($ per tonne of CO_2-equivalent), the carbon tax penalty can be calculated.

3.3. Solution approach

In the field of optimization, particularly in complex domains like mining, the choice of a solver—a software or algorithm designed to find solutions to mathematical problems—is critical. Solvers are valuable for their ability to navigate large solution spaces and avoid entrapment in local optima. They vary in approach and complexity, ranging from exact algorithms for Linear Programming (LP) to heuristic and metaheuristic methods for more intricate problems.

In this research, we utilized the Gurobi Optimizer (version 10.0.1), renowned for its efficiency in handling large-scale MILP problems. Gurobi was selected due to its robustness and advanced capabilities in dealing with the multifaceted requirements of the proposed mining model. The developed model, executed on a system with an Apple M2 CPU (eight physical cores and eight logical processors), with 24GB of RAM, took nine hours to achieve the optimized results.

3.4. Results and Discussion

3.4.1. Model Validation

Figure 3 showcases a range of extraction and dispatch trends. The cumulative extraction tonnage, illustrated by the dotted line, displays a consistently upward trend indicative of a progressive increase in material extraction over time. This trend validates the model's capability to simulate continuous mining operations over the project's lifespan. The total block tonnage, represented by a solid horizontal line, serves as a reference for the total available material, demonstrating the model's static resource estimation component. The steadiness of the total waste and mineral tonnage lines suggests that the model appropriately accounts for the conservation of mass in the system.

Figure 4 presents the results of the model's optimization. This stacked bar chart conveys the monthly planned output for various materials, categorized as products P1 and P2, stockpiles SP1 and SP2, and waste W1 and W2. The color-coded segmentation indicates the model's ability to differentiate and allocate tonnage to various operational categories. The pattern across the months reflects the model's scheduling functionality, highlighting the balance between ore extraction and waste management. The clear distinction between different material types over time indicates the model's sophisticated handling of multiple product streams and its ability to forecast the temporal distribution of mining outputs.

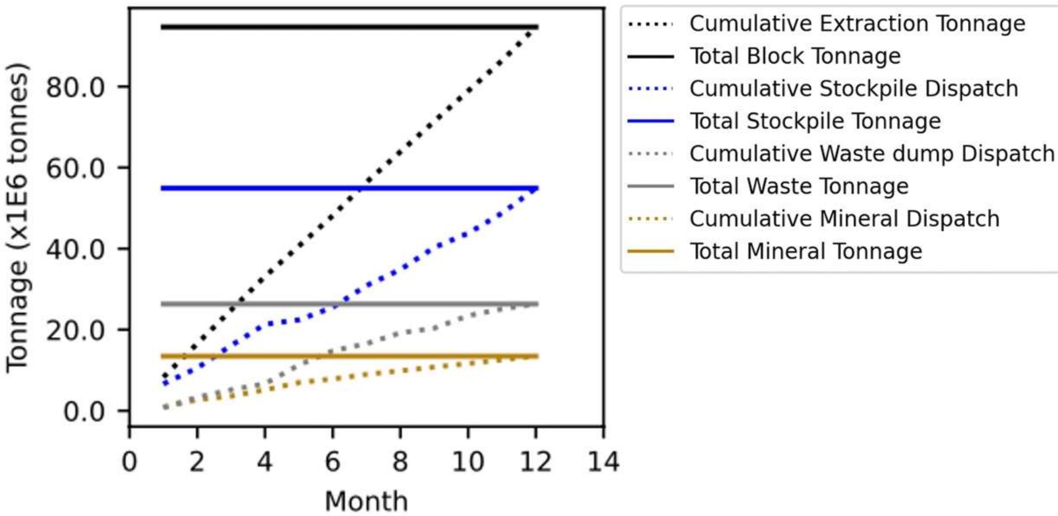

Figure 3. Extraction Trends from Block Model.

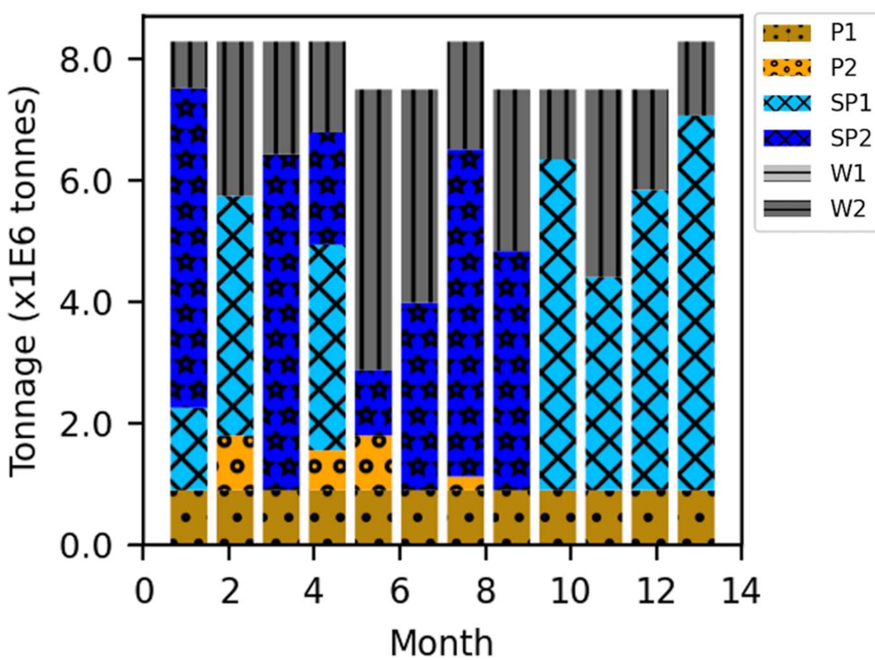

Figure 4. Optimal Production Schedule.

Figure 5 presents the inventory levels of two different stockpiles over the same one-year period. In Figure 5(a), the consistent increase in the inventory tonnage of SP1 suggests a model that predicts a steady inflow of material to the stockpile, indicative of a phased extraction plan or a certain processing capacity. The absence of fluctuations implies that there are no significant disruptions in the mining or processing throughput as modeled. The dotted line in each bar chart represents the cumulative tonnage of material sent to the respective stockpile over time, offering a visual representation of the material flow and inventory accumulation in accordance with the operational model's predictions. For Stockpile 1, as seen in Figure 5(a), the steady rise without significant fluctuations indicates a consistent flow of materials to the stockpile, affirming the model's forecast of a regular and uninterrupted inflow of material. Figure 5(b) not only shows the inventory tonnage of SP2 increasing over time but also introduces a pattern of rehandled tonnage. This reflects the model's ability to account for operational scenarios where material is moved between stockpiles or returned to the process stream, potentially to manage grade quality or respond to other processing requirements. The inclusion of re-handled material in this sub-figure validates the model's comprehensive nature, capable of simulating complex logistical operations within a mining context. Figure 5(b)'s dotted line for Stockpile 2 not only traces the growth in inventory levels but also shows intermittent increases that correspond to the model's rehandling events. These peaks represent the additional tonnage moved to Stockpile 2, either from mining or from other stockpiles, reflecting the model's dynamic capability to simulate operational adjustments, such as grade blending. Both sub-figures together validate the model's inventory management predictions, showcasing the system's capability to handle both straightforward accumulation scenarios as well as more complex operations involving material rehandling. This demonstrates the model's utility in not just forecasting stockpile levels but also in planning for the downstream logistics that are crucial in real-world mining operations.

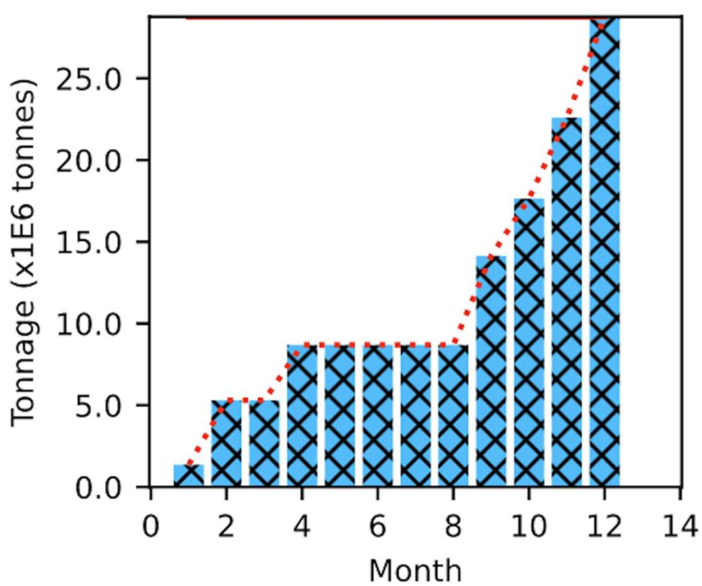

Figure 5(a). Inventory of Stockpile 1.

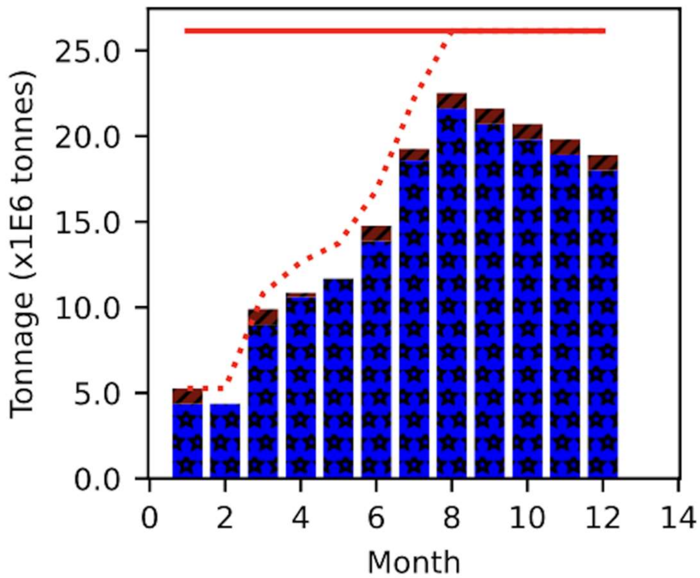

Figure 5(b). Inventory of Stockpile 2.

Figure 6(a) shows a consistent tonnage dispatched to Process Plant 1 each month, indicated by the uniform height of the bars throughout the year. This suggests that the model assumes a steady operational capacity or demand from Process Plant 1, which does not vary with time. Figure 6(b) illustrates the monthly dispatch to Process Plant 2, with a noticeable pattern of increasing tonnage towards the latter months. Additionally, there are portions of the bars filled with a pattern, which represents rehandled tonnage. This increment in total tonnage, including rehandled material, indicates that the model predicts a growing output requirement for Process Plant 2, due to scaling up of production or processing of stockpiled material as the year progresses. The uniformity in figure 6(a) and the increasing trend in figure 6(b), along with the appearance of rehandled material, validate the model's ability to simulate different operational scenarios for each processing plant. It reflects the adaptability of the model to account for variations in production scheduling and material handling requirements, which is crucial for validating the model's application in real-world mining operations.

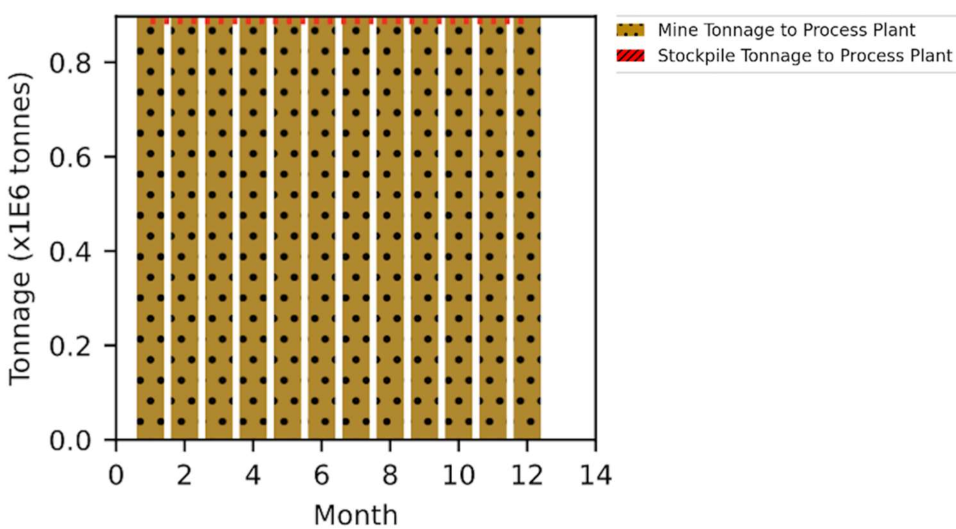

Figure 6a. Tonnage Dispatch to Process Plant 1.

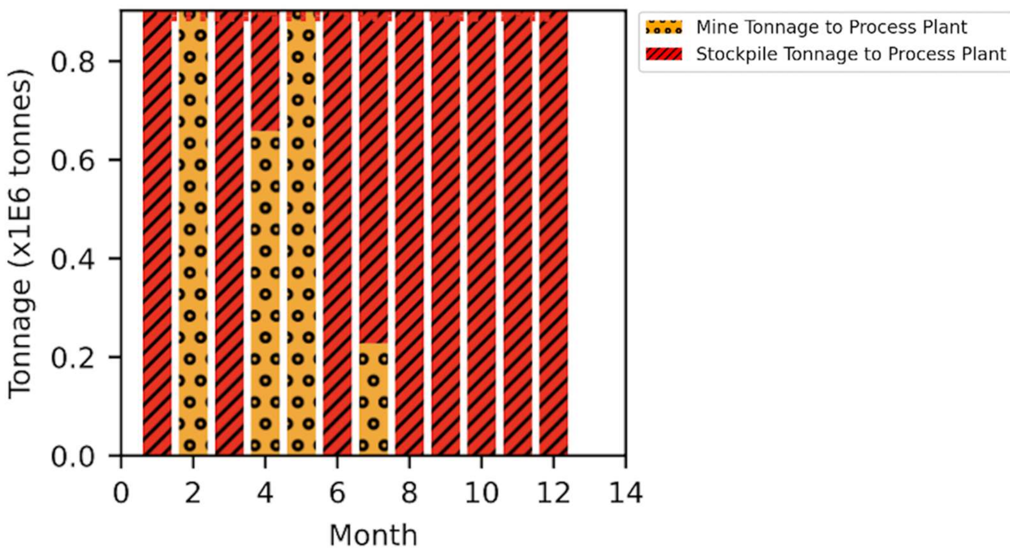

Fig. 6(b). Tonnage Dispatch to Process Plant 2.

3.4.2. Comparative Analysis and Synthesis

This section presents a comparative analysis of conventional TS systems and IPCC systems within the case study framework. The analysis focuses on economic viability and environmental impact, aiming to identify the system that best promotes sustainable mining practices.

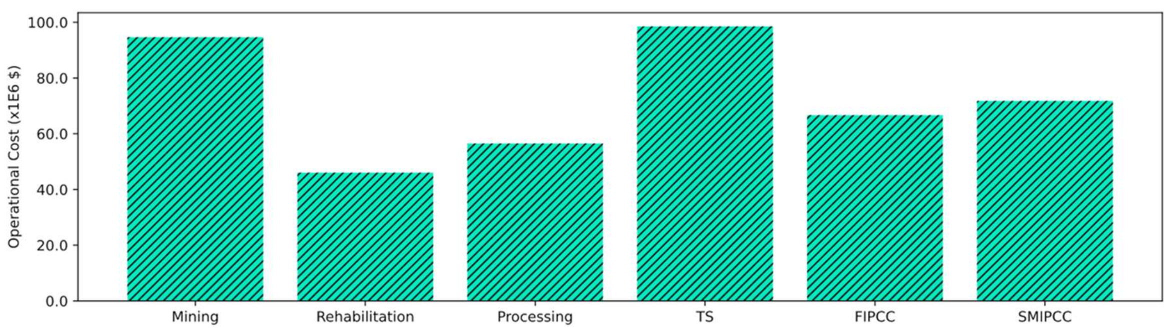

Figure. 7. Operational Cost Distribution by Mining Stages.

The bar graph in Figure 7 illustrates the distribution of operational costs in various stages within mining operations. Extraction, which is resource intensive, accounts for the highest expenses, totaling approximately $94.7 million. Following closely, rehabilitation efforts require a significant investment of around $46.1 million, highlighting their importance in environmental management and post-mining restoration. Processing costs also comprise a substantial portion of the operational budget, totaling around $56.5 million. Material haulage, particularly with traditional TS systems, generates costs that exceed $98.5 million. This high cost is likely due to factors such as fuel, equipment maintenance, labor, and other operational overheads associated with hauling materials over long distances using trucks. The introduction of IPCC systems revolutionizes the economic landscape, providing a statistically significant 33% reduction in haulage costs compared to TS methods. This translates into cost savings of $32 million. SMIPCC configurations also demonstrate significant economic benefits, demonstrating a reduction of approximately 28% in costs compared to TS, with total haulage expenses reaching approximately $72 million. The reasoning behind this cost reduction is multifaceted. IPCC systems involve crushing the material on site and then transporting it via conveyor belts, which is more energy efficient and requires less labor compared to hauling the material using a fleet of trucks over long distances. In addition, conveyor systems have lower maintenance costs and generate fewer emissions, contributing to both economic and environmental sustainability.

The bar graph in Figure 8 delineates a comparative view of the Carbon Tax (CAT) costs incurred in various stages of the mining operation under a presumed CAT rate of $65 per tonne of CO_2-equivalent. It showcases the significant cost reductions that IPCC systems may offer over traditional TS systems in terms of CAT liability. The CAT costs for traditional TS systems are substantial, amounting to approximately $2.08 million. However, adopting FIPCC systems reduces CAT costs to around $586,490, a clear testament to their lower carbon emissions footprint. This highlights the possible environmental advantages of employing stationary IPCC systems. More strikingly, SMIPCC systems further accentuate these benefits, with CAT costs around $1.46 million. Although this figure represents notable savings compared to TS operations, it is higher than that of FIPCC systems, which may be attributed to the semi-mobile nature of the operation and associated variable factors affecting emissions. To contextualize these reductions, the CO_2 emissions mitigated by employing FIPCC systems, calculated at 153.84 tonnes of CO_2, could be analogous to the carbon sequestration of 2,540 tree seedlings grown over a decade.

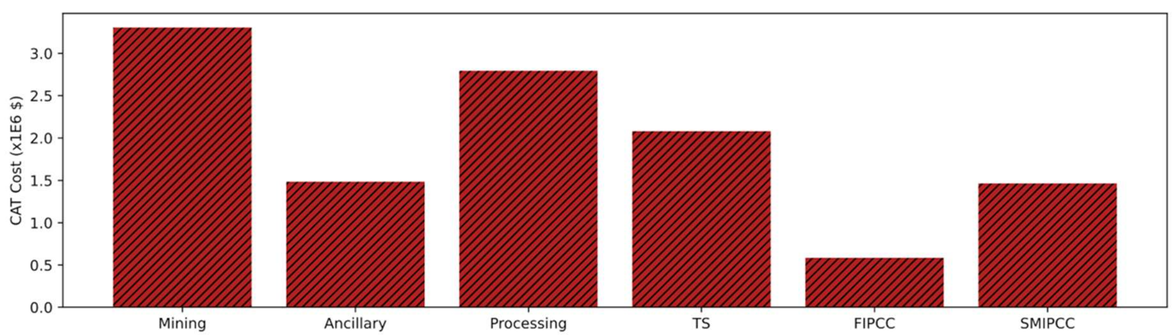

Figure 8. CAT Cost Distribution Across Mining Stages.

In contrast, SMIPCC systems, responsible for 215.38 tonnes of CO_2 emissions savings, are similar to the beneficial impact of nearly 3,550 tree seedlings over the same period.

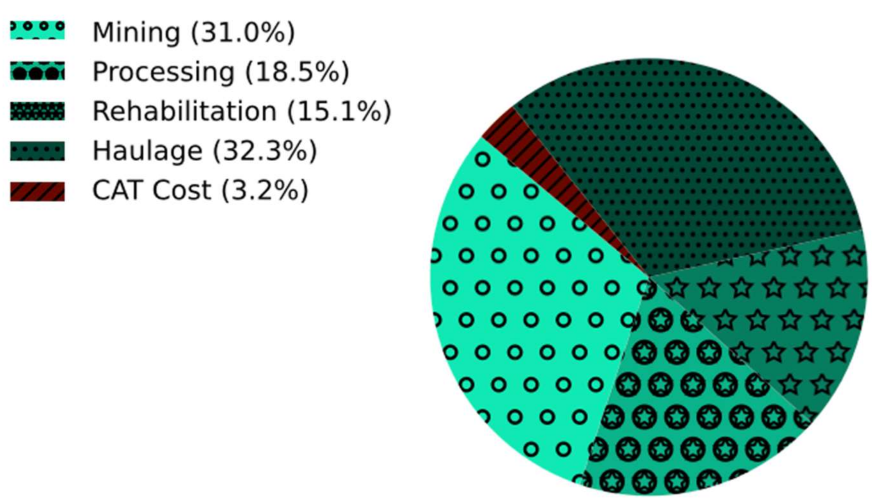

Figure 9(a). Comparative Cost Distribution for Different Mining Operations (TS in Operation).

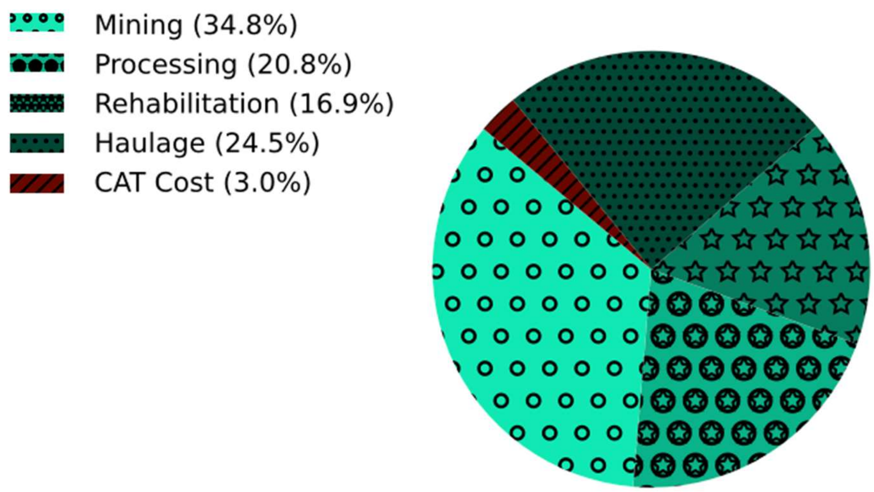

Figure 9(b). Comparative Cost Distribution for Different Mining Operations (FIPCC in Operation).

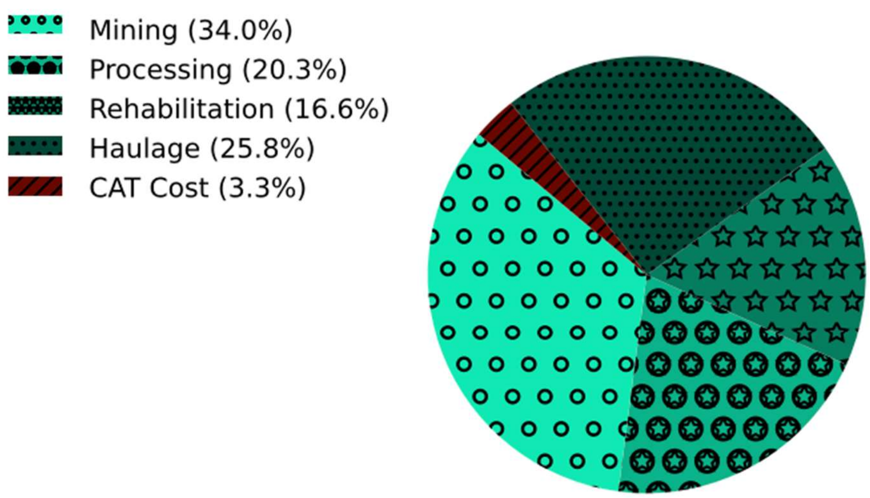

Figure 9(c). Comparative Cost Distribution for Different Mining Operations (SMIPCC in Operation).

Figure 9, composed of pie charts 9(a), 9(b) and 9(c) illustrates the cost breakdown of two mining operations, providing insights into the financial implications of employing either TS or an IPCC system. For TS systems, mining represents the most substantial cost factor, comprising 44.8% of total operational expenses, consistent with the energy-intensive nature of extraction. Rehabilitation, crucial for sustainable mining practices, accounts for a significant portion at 18.7%, highlighting the industry's commitment to environmental stewardship. Processing activities consume 26.7% of the budget, reflecting the expenses associated with ore treatment. Notably, CAT costs constitute 4.6% of the total, raising concerns regarding both the environmental impact and cost efficiency of this traditional method. The implementation of a FIPCC system results in a minor redistribution. Mining currently accounts for 34.8%, processing is at 20.8%, and the cost of rehabilitation is 16.9%. CAT costs have been reduced to 3%, indicating an increase in carbon efficiency. This decrease is noteworthy given the typically large carbon footprint associated with mining activities. The haulage costs, now at 24.5%, demonstrate the economic efficiency of the FIPCC system in contrast to the traditional approach. In the scenario where a SMIPCC system is operational, the distribution pattern remains similar, with mining accounting for 34%, processing for 20.3%, and rehabilitation for 16.6%. However, there is a slight increase in CAT costs to 3.3%. The marginal increase in CAT costs with the semi-mobile system may be attributed to additional operational complexities and variable emissions from more frequent equipment re-locations.

The trend across these charts indicates that while the shift from traditional haulage to IPCC systems does provide cost and carbon emission benefits, the SMIPCC, contrary to expectations, does not lead to the lowest CAT cost. This may reflect a trade-off between operational flexibility and environmental impact, highlighting that while SMIPCC systems offer improved mobility and adaptability, they may also carry slightly higher operational carbon costs due to the associated energy use in repositioning the system. From an environmental perspective, the reduction in CAT costs with the adoption of IPCC systems demonstrates a positive shift toward more sustainable practices. These data reinforce the environmental advantage of integrating IPCC into mining operations, with both fixed and semi-mobile systems showing reduced CAT costs compared to traditional methods.

4. Conclusion

This study has developed a comprehensive approach to optimizing short-term production scheduling in open-pit mines, prioritizing both economic efficiency and environmental sustainability. We initially developed a MILP model based on economic considerations and subsequently refined it to include environmental impacts, GHG emissions in particular. Through a comparative analysis between the traditional TS system and the IPCC system, the study has highlighted the significant potential of the IPCC systems to enhance operational efficiency and reduce greenhouse gas emissions.

The MILP model developed in this study provides a valuable tool for mine planners and decision-makers to optimize short-term production schedules while considering both economic and environmental objectives. The model's ability to generate optimal extraction sequences, allocate resources effectively, and compare different material handling systems offers significant value to the mining industry. By adopting such optimization approaches, mining companies can improve their profitability, reduce their environmental footprint, and contribute to the global effort to mitigate climate change. The detailed case study, spanning a year-long production schedule, highlights the economic and environmental benefits of adopting IPCC systems in open-pit mining operations. The results conclude that IPCC systems can lead to lower operational costs, reduced carbon tax liabilities, and reduced GHG emissions compared to conventional TS systems. These findings highlight the importance of considering alternative material handling methods to promote sustainable mining practices in an era of increasing environmental awareness and regulatory pressures. Furthermore, this study contributes to the growing body of literature on sustainable mining practices and the application of mathematical optimization techniques in the mining industry. These findings provide actionable insights for mine operators, policymakers, and environmental consultants, demonstrating the potential for IPCC systems to support the industry's transformation to more sustainable operations.

Future research could focus on extending the application of the developed MILP model to other types of mines and incorporating additional environmental impact measures, such as water consumption and land disturbance. Additionally, investigating the long-term effects of IPCC system adoption on mine profitability and sustainability could provide valuable information for strategic decision making in the mining industry.

Funding: This research received no external funding.

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

Abbreviations: The following abbreviations are used in this manuscript:

LP	Linear Programming
MILP	Mixed Integer Linear Programming
TS	Truck and Shovel
IPCC	In-Pit Crushing and Conveying
SMIPCC	Semi-Mobile In-Pit Crushing and Conveying
FIPCC	Fixed In-Pit Crushing and Conveying
GHG	Greenhouse Gas
CAT	Carbon Tax
NPV	Net Present Value
OPEX	Operating Expenditure
CAPEX	Capital Expenditure
MPI	Mine Productivity Index

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