Semi-Mobile In-Pit Crushing and Conveying vs. Truck-Shovel Systems: Long-Term Scheduling with Road and Conveyor Networks Integration

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ABSTRACT

In-pit crushing and conveying systems (IPCC) integrate crushing and conveying directly from the pit, minimizing the need for extensive truck fleets and haulage infrastructure that is typical in Truck Shovel systems (TS). This approach reduces truck-related costs and environmental impacts while enhancing operational efficiency. The current study optimizes long-term scheduling in open-pit mining operations by comparing IPCC and traditional TS systems. Our methodology employs a two-step mathematical optimization model to determine optimal crusher locations or crusher panels and establish a practical long-term extraction sequence. Through a comprehensive case study involving pushbacks with roads and conveyor ramps and analyzing different road and conveyor network configurations, we examine the capital and operational costs across four scenarios for the in-pit crusher: without a crusher, with an ore crusher, with a waste crusher, and with both ore and waste crushers. Results include comparisons of Net Present Value (NPV), tonne-kilometers traveled, total kilometers traveled, and the number of trucks required. Significant improvements in NPV are observed in scenarios with both ore and waste crushers, reflecting reduced hauling distances and operational costs. The waste crusher scenario also demonstrates substantial savings, while the ore crusher scenario shows moderate improvements compared to the base case without a crusher.

Keywords: *IPCC, Long-term planning, MILP, Crusher Panel, Road Network, Conveyor Network*

1. Introduction

Open-pit mining operations are constantly evolving to meet the demands of efficiency and cost-effectiveness in material handling. Traditional truck shovel systems (TS), although prevalent, face challenges such as high operating costs, operational efficiency, economic viability and environmental impacts. A promising solution to these challenges is the In-Pit Crushing and Conveying system (IPCC), which integrates the crusher within the mining pit and employs conveyor belts for material transport. This approach not only minimizes truck dependency but also enhances operational safety and efficiency and it could bring about a huge financial advantage through reduced operating costs, lower energy consumption, lower emissions and improved productivity. Nevertheless, the implementation of IPCC systems is complex, requiring meticulous planning regarding the crusher's location, capacity, and integration within the mine's overall design. Failing to properly plan for the IPCC's locations can disrupt the mining sequence and adversely affect the ultimate pit limit (UPL) design. This paper aims to address these challenges by proposing

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a comprehensive long-term planning methodology that optimizes the open-pit mine extraction sequence under four scenarios: full IPCC implementation, partial IPCC implementation for either of ore or waste material, and without IPCC.

In-pit crusher is an expensive option in the capital-intensive field of open pit mining making meticulous planning inevitable. The objectives of a precise production planning study are to optimize net present value (NPV) while minimizing net present cost (NPC). Mine planning is typically divided into two primary phases: long-term and short-term, with additional subphases such as medium-term and operational planning. Therefore, the adoption of IPCC technology demands comprehensive evaluation across both long-term and short-term planning horizons to ensure its effective implementation.

According to Al Habib et al., there are five types of IPCC studies published, including: 1) finding the optimal location for the IPCC, 2) industry-related research and viewpoints, 3) economic and environmental comparative studies, 4) mine planning optimization in the presence of the IPCC and TS systems, and 5) other related studies [5-6]. These categories encompass a broad range of research efforts aimed at enhancing the efficiency and sustainability of mining operations. For instance, studies focusing on the optimal location for IPCC systems delve into spatial analysis, pit alteration layout, pit slope adjustments, and the strategic placement of crushers to maximize operational efficiency. This topic has received considerable attention over time, ranging from early studies in the 20th century to more recent publications [2, 4, 20, 34, 54, 61].

Industry-related viewpoints studies from professionals and stakeholders, can be investigated through various aspects such as productivity issues, failure stories and detailed risks and challenges followed by implementation examples presented by in addition to the deep open pit mine application of IPCC system [19, 39, 41-42]. These perspectives provide an understanding of the practical implications and operational challenges associated with the IPCC system.

The studies explore the environmental impacts of mining haulage systems using Life Cycle Assessment (LCA) including comparative studies between TS and IPCC or conveyor systems. Awuah-Offei et al. developed a methodology to evaluate the environmental impacts of belt conveyors and truck haulage systems in a hypothetical hard rock gold mine in Alberta, Canada [10]. The study considered a 20-year mine lifespan, productivity of 4,000 tonnes per hour, and haul distances of 4 km to the waste dump and 15 km to the run-of-mine (ROM) pad. They used ISO 14040 standards for LCA and Monte Carlo simulations for uncertainty analysis, finding that truck haulage had lower global warming potential (GWP) and acidification potential (AP) compared to belt conveyors. Norgate and Haque conducted an LCA to estimate the greenhouse gas (GHG) emissions reduction potential of IPCC and ore sorting technologies in a hypothetical copper mining operation [45]. The study, focused on processing one tonne of copper ore, showed that IPCC could reduce GHG emissions by 4% to 22%, depending on the electricity source, while ore sorting offered greater GHG reductions with coal-based electricity but was less effective with natural gas. Erkayao and Demirel evaluated the environmental impacts of off-highway mining trucks and belt conveyors in a coal mining operation with a daily production of 20,000 tonnes transported over a 5 km distance [23]. Using SIMAPRO 7.3 software and data from equipment manufacturers, they found that trucks had higher acidification impacts due to diesel combustion, while conveyors had higher climate change impacts from coal-fired electricity. These LCA studies showed that trucks have lower acidification impacts than conveyors due to fuel combustion, but the environmental benefits of conveyors depend on cleaner electricity sources, with IPCC showing significant greenhouse gas reduction potential compared to trucks when natural gas is used instead of coal for electricity production.

Klanfar and Vrkljan compared stationary and mobile processing models for quarrying crushed dolomite for concrete aggregates, finding that mobile processing offers distinct advantages in reducing transport costs, environmental impact, and energy consumption [29]. Mobile plants process material directly on-site, reducing infrastructure needs and costs, especially effective in protected or spatially constrained fields. A case study at surface pits in Hercegovac and Oršulica Kosa demonstrates mobile plants' lower costs (€7.23/m³) compared to stationary ones (€8.03/m³) due to reduced transport distances. Similarly, Londoño et al. explore alternative In-Pit Crushing and Conveying (IPCC) configurations in an open cut coal mine in Central Queensland, Australia, highlighting the benefits of parallel conveyor lines with spreaders, which, despite higher Equivalent Unit Costs (EUCs), increase productivity by up to 12.6%, leading to an additional AUD 376 million over ten years [33]. Rahmanpour et al. applied a hub location model to minimize haulage costs in the Sarcheshmeh Copper Mine in Iran, suggesting the optimal location for an IPCC system at level 2450 [53-54]. The study emphasizes cost efficiency and environmental benefits, noting reduced truck requirements and overall lower operating costs. Roumpos et al. optimized the location of the belt conveyor distribution point (BCDP) in a lignite surface mine to minimize transportation costs [55]. Using a Matlab-based optimization algorithm, the study determines the BCDP location considering mine geometry and excavation sequences, showing significant cost savings influenced by optimal BCDP placement. All studies show the importance of IPCC placement to enhance operational efficiency, reduce costs, and mitigate environmental impact.

Paricheh and Osanloo employed a facility location model to address uncertainties in production and operating costs by focusing on scenario investigation for determining the optimal location of in-pit crushers at the Sungun Copper Mine in Iran [48]. The study aimed to minimize haulage costs and maximize NPV, using a semi-mobile crusher with a 2000 tons/hour capacity. This research simplifies the candidate location of the crusher to the gravity center of each extracting level. Additionally, the uncertainty handled through searching some known scenarios which can not be generalized. Paricheh et al. further investigated optimal placement and relocation of crushers at Sungun, utilizing a dynamic location-relocation problem model, and estimated a $150 million saving from the 6th year of operation by optimizing crusher locations and reducing haulage distances [50]. Paricheh et al. extended this research by addressing the optimal time and location problem for implementing IPCC systems in large open-pit mines [51]. Their heuristic approach divided the problem into determining the optimal location for the crusher and the optimal time for its application, resulting in a $150 million improvement in NPV by implementing the IPCC system in the 17th year of mine life. The case study at Sungun Copper Mine demonstrated a 1% NPV improvement by transitioning to IPCC at the optimal time and location. The focus of these two mentioned study by Paricheh et al. is to find the best locations and relocation time and maximizing NPV by minimizing haulage cost. As a result, the mine plan remained the same even by incorporating the in-pit crusher. Yarmuch et al. concentrated on Chuquicamata mine in Chile, using Markov chain models to determine optimal locations for a third crusher, considering equipment failure probabilities [72]. They concluded that an in-pit crusher configuration, although more expensive, was more reliable and cost-effective, influencing haulage distances and truck requirements over four years.

Abbaspour et al. explored safety and social impacts of different transportation systems in open-pit mining, comparing TS and various IPCC systems through system dynamics modeling [1, 3]. The study revealed that Fully Mobile IPCC (FMIPCC) had the highest safety index due to zero traffic density, while TS ranked highest in social indices because of higher employment and training rates. Abbaspour et al. formulated a transportation problem to determine optimal locations and relocation plans for Semi-Mobile IPCC (SMIPCC) systems in open-pit mines, demonstrating cost efficiency through minimized operating and relocation costs [2, 4]. The SMIPCC system is used exclusively for ore and the relocation of the SMIPCC is analyzed at various intervals (every 12.5m to 75m). de Werk et al. conducted a comprehensive cost analysis comparing TS with IPCC in an iron ore prefeasibility study, finding that despite a 41% higher investment cost, IPCC reduced unit operating costs by 13.6%, making it more cost-effective long-term [18]. Nehring et al. investigated strategic mine planning approaches for IPCC versus TS systems in a conceptual simplified Australian copper orebody, finding significant economic benefits and improved resource recovery when using IPCC [43]. Nunes et al. evaluated the feasibility of SMIPCC in a Brazilian copper-gold mine, showing that despite higher initial CAPEX, SMIPCC had significantly lower OPEX, reducing life-of-mine costs by 28% and offering environmental benefits [47]. This substantial cost reduction and lower environmental impact highlighted the advantages of adopting SMIPCC over conventional truck haulage.

Table 1 presents an ample overview of post-2010 studies on the IPCC system. The table systematically categorizes each paper based on their case study and their critical parameters such as crusher types, crusher capacity, the presence of a road or conveyor ramp design, investment and operating costs of crushers and conveyors, and the type of material handled (ore, waste, or both). By consolidating this information, we highlight the key aspects that have been explored in recent research, providing a foundation for what we will present in this current research about the IPCC system implementations.

According to Table 1, a prominent effort in size reduction is evident in the case studies of the investigated research, particularly where mine planning and IPCC are modeled using mathematical methods due to the complexity of managing large open pits with numerous sophisticated constraints. There are constant indications of either haul truck roads, conveyor ramps, or both being ignored, leading the models to adhere to undesigned block models for optimization purposes, resulting in impractical outcomes. Additionally, there is a significant lack of knowledge regarding the capital and operating costs of IPCC systems, causing any trade-off studies between TS and IPCC to suffer from a lack of precision. Furthermore, some studies either did not provide or did not consider the capacity of the assumed operation and/or crusher, resulting in oversimplification of their cases.

When examining the studies that focus on mine planning in the context of applying IPCC systems, the following works can be mentioned. Paricheh and Osanloo, who developed a new mixed-integer linear programming (MILP) model to optimize the concurrent planning of open-pit mine production, truck fleet sizing, and IPCC systems [49]. Their objective was to enhance the net present value (NPV) and overall cash flow by integrating these aspects into a single optimization framework. Their case study, focusing on a copper deposit, employed hypothetical instances geometrically similar to real mines using semi-mobile IPCC systems. Shamsi et al. proposed a mathematical integer programming model to optimize open-pit mine production scheduling by selecting the optimal transportation system and SMIPCC [60]. Their case study on a copper reserve demonstrated that despite higher capital costs, the SMIPCC system significantly improved NPV to the traditional TS system. In these two instances, their models, though similar to real mines, were hypothetical. There is no indication of having roads or ramps in the model, so the distances were calculated based on the minimum distance rather than the shortest road or path, making it difficult to resemble a realistic scenario.

Table 1. IPCC research case studies comparison

		Case Study	Production Capacity (Million Tonnes per Year)	Crusher Type & Capacity	Road Design	Conveyor ramp	Investment Costs Crusher/ Conveyor	Operating Costs Crusher/ Conveyor	Ore/ Waste/ Both
1	Awuah-Offei et al. [10]	A hypothetical hard rock gold mine located in Alberta, Canada.	21 (Ore & Waste)	Not specified 4,000 tph	-	-	-	-	Both
2	Klanfar and Vrkljan [29]	The surface pits of dolomite for concrete aggregates named Hercegovac and Oršulica kosa near Orahovica.	-	Mobile impact crusher 110 - 300 m3/h	-	-	Stationary Crusher: €400,315 or €8.03/m³ crushing and screening operations and 1.8 km of conveying	Mobile Crusher: €361,487 or €7.23/m³ crushing and screening operations	Both
3	Londoño et al. [33]	Multiseam open-cut coal in Queensland, Australia	20-24 (Overburden)	Fully mobiled 10,000 tph	✓	✓	-	1.22 - 1.39 $/t (Equivalent Unit Cost)	Waste
4	Norgate and Haque [45]	A hypothetical copper mining and mineral processing operation	3.6	- -	-	-		Reduction by 0.18 - 0.82 $/t compared with TS option	Ore

5	Rahmanpour et al. [53-54]	Sarcheshmeh Copper Mine, Iran	40 (Waste)	Mineral Sizer (semi-mobile)	-	-	-	-	Waste
6	Roumpos et al. [55]	A Simplified lignite surface mine with 4 benches	8 - 10 (Different in different benches)	- -	✓	✓	€3520 per meter of conveyor length	-	Both
7	Dean et al. [19]	deep open pit metalliferous mine from various cases including a Brazilian iron ore mine and the Yimin He Mine in China	-	Fully mobiled 4,000 to 10,000 tph	-	✓	U$180-250 Million Fully mobile unit with conveyor components	-	Both
8	Erkayao & Demirel [23]	A conceptual production capacity of 20,000 tons/day of coal transported for 5 km. The comparison includes 23 off-highway trucks and 8 belt conveyors.	20,000 tonne per day	- -	✓	-	-	-	Ore
9	Paricheh and Osanloo [48]	The 10th year of the mine life, based on the Sungun Copper Mine	7 - 14	Semi-Mobile 2000 tph	-	-	-	-	Both

10	de Werk et al. [18]	An iron ore deposit. The mine model assumes a 500-meter diameter conical-shaped pit with constant bench heights of 20 meters.	8,000 tonne per day (ore) 12,000 tonne per day (waste)	Semi-Mobile 907 tph	✓		\$1.6 to \$3.3 Million - with additional costs of \$1,300 to per meter based on in-pit or overland conveyors. \$23.9 Million in Total for conveyors.[1]	\$47.91 to \$97.88 per hour, with labor costs of \$67.43 to \$137.71 per hour based on in-pit or overland conveyors	Ore
11	Paricheh et al. [50]	Sungun copper mine in Iran.	7 - 14	Semi-Mobile 4,000 tph	✓	Uses the haul road ramp for conveyors	\$3000 per meter for conveyor	-	Ore
12	Yarmuch et al. [72]	The Chuquicamata copper mine examining the addition of a third crusher to improve the reliability	-	gyratory type 5,600 tph	-	Conveyor is installed in the tunnel	Crusher: approximately U\$15 million, with an additional U\$35 million for installation. Conveyor belts: approximately U\$2500 per meter.	-	Ore

[1] Not Specified (-) in the road design and conveyor design might be assigned even for a case study that considered a road or conveyor ramp but not mentioned anything in the study or not provided any details about the design.

13	Abbaspour et al. [1, 3]	A hypothetical copper open pit mine with a total ore reserve of 700 million tonnes.	21.52	All crusher types	-	-	-	-	-
14	Nehring et al. [43]	A two-dimensional vertical cross-section, 25 blocks wide and 8 blocks deep. Each block contains 5 million tonnes of material.	15 for processing and 20 for mining	Semi - Mobile & fully - Mobile	-	-	$200 Million	$2.5 to $2 per tonne with 10% to 5% increasing rate for each lower level	Both
15	Paricheh et al. [51]	Sungun copper mine in Iran.	7 - 14	Semi - Mobile 4,000 tph	✓	Uses the haul road ramp for conveyors	the crusher relocation estimated at $1.5 million	-	Both
16	Rahimdel and Bagherpour [52]	Kahnuj titanium mine in Iran	4	fixed, semi-mobile, and fully mobile crushing systems 1333 tph	✓	-	-	-	Both Ore Crusher & Waste sizer

17	Abbaspour et al. [2, 4]	A hypothetical copper mine where the ore is extracted over five years across seven levels.	17.4	Semi - Mobile 3,000 tph	-	-		$0.2 to $0.42 per tonne	Ore
18	Nunes et al. [47]	A Brazilian copper-gold mine with a life of mine set at 20 years.	16	Semi - Mobile 3,805 tph to 2,718 tph	✓	-	SMIPCC CAPEX = $46.97M	-	Ore
19	Paricheh and Osanloo [49]	The constructed hypothetical instances geometrically similar to real open-pit mines	-	Semi - Mobile	-	-	-	-	Ore
20	Samavati et al. [57]	A hypothetical open pit mine with an East-West oriented main 'trunk' conveyor and includes details on the setup and operation of main, transfer, and bench conveyors.	15,000 tonne per day ore 30,000 tonne per day waste	Mobile crusher 3,000 tph	-	✓	$25 M	$5 per tonne for Crusher $1 per tonne for Conveyor	Both

21	Bernardi et al. [16]	A copper porphyry deposit, characterized by high tonnage and massive lateral and vertical extents, making it one of the largest types of open-pit mines in the world	-	Fixed Crusher Semi Mobile	✓	-	-	-	Ore
22	Shamsi and Nehring [59]	A conceptual cylinder-shaped copper deposit with an average radius and depth of 345 m and 670 m, respectively, and 20 m of overburden.	20	Semi Mobile 2690 tph	✓	✓	Crusher: $20 M Conveyor: $10.7	-	Both

23	Shamsi et al. [60]	A copper reserve with an outcrop at the surface and a uniform slope of 45 degrees. The final pit limit of this reserve is 1,000 meters deep, containing 137.5 Mt of ore, 127.5 Mt of waste, and an average Cu grade of 0.68%	20	Semi Mobile	-	-	$74 M more CAPEX for SMIPCC than the TS scenario	Average 0.0015 $/t . m	Both
24	Liu and Pourrahimian [32]	A small-scale copper mine dataset with 2006 blocks and six levels	30-25	Semi Mobile	-	-	$1million for crusher relocation	$0.3 per level·t for conveyors	Both
25	Wachira et al. [71]	A limestone quarry in Kenya	2.7	Semi Mobile	-	-	-	-	Ore
26	Gong et al. [26]	An iron mine with a block model comprising 19,561 blocks and a total of 430 million tons of material in its final pit	32	Mobile	-	-	-	$0.35 per tonne per km	Ore

27	Gong, et al. [25]	An oil sands mine case study with two working shovels and sixteen trucks was used to verify the proposed simulation and optimization model.	93.09	Semi Mobile	✓	-	-	-	Ore
28	Al Habib et al. [6]	An iron mine case study involving 16 million tonnes of ore and 35 million tonnes of waste over four benches	16 (ore) 35 (waste)	Semi Mobile 2700 tph	✓	-	-	-	Ore
29	Kamrani et al. (2024)[28]	Two pushbacks of an iron ore mine and ten benches including 9952 blocks	3.2 (ore) 7.1 (waste)	Semi Mobile -	✓	-	-	-	Ore + Ore & Waste scenario s

Samavati et al. introduced a new integer programming model to address the complexities introduced by IPCC systems in open-pit mining [57]. They aimed to maximize the NPV by optimizing block extraction schedules, conveyor placements, and integration of mining and processing capacities. They used a heuristic solution to manage the large-scale nature of the problem and the non-linear relationships between variables. Their case study featured a fully mobile IPCC system by considering the different compartments of the conveyor. The mathematical model in this study contains 16 constraints to honor block precedence based on the conveyor locations meaning that the model could grow exponentially in the real mine instances with the large number of blocks. Liu and Pourrahimian presented a methodology to optimize production scheduling and crusher location under SMIPCC systems, aiming to maximize NPV by simultaneously solving these problems [32]. They used hierarchical agglomerative clustering and an integer linear programming model to integrate material handling and crusher relocation costs into the NPV maximization process. Their case study on a small-scale copper mine indicated the importance of careful design and optimization of IPCC system layout, with substantial variations in NPV based on conveyor location.

Al Habib et al. proposed a methodology to generate monthly production schedules by optimally allocating shovels to maximize revenue while minimizing haulage costs [6]. Their case study in an iron mine demonstrated significant cost savings and increased efficiency with IPCC, reducing truck requirements by 35% and generating a higher objective function value. Gong et al. developed a MILP model to solve the long-term production scheduling problem in open-pit mines, comparing the performance of the Near Face Stockpile (NFS) mining method with traditional methods [26]. Their case study in an iron mine showed an improvement in NPV and in head grade deviation with the NFS method. Additionally, another study by Gong et al. introduced the NFS method, integrating IPCC systems with a pre-crusher stockpile to enhance stability and efficiency [25]. Their oil sands mine case study showed significant operational improvements and increased equipment utilization.

Kamrani et al. introduced a two-step methodology for optimizing in-pit crusher locations, focusing on minimizing haulage costs and maximizing the NPV [28]. Their model employs a k-medoids clustering algorithm to designate crusher panels as candidate locations for the in-pit crusher and a hierarchical clustering algorithm to create extraction units or blast polygons. The case study, involving an iron ore mine with two designed pushbacks and a road network, used the shortest path algorithm to calculate truck travel distances. Conversely, conveyor distances were calculated using the minimum distance method due to the absence of a conveyor ramp or conveyor network in the case study. The first mathematical model determines the optimal crusher panels and the best material tonnages to be processed while the crusher is in place. The second step schedules the extraction while respecting the physical precedence of the optimal crusher panels. This methodology demonstrated substantial reductions in haulage distances and a 15% improvement in cumulative discounted cash flow compared to scenarios without an in-pit crusher.

After a systematic review of artificial intelligence applications in strategic open pit min planning. Noriega and Pourrahimian stated that due to the scale of the life-of-mine plans, research solutions tend to metaheuristic algorithms which are case specific and cannot be generalized [46]. In long-term open-pit mine planning with an IPCC system, developing a practical and solvable model is essential. This model must account for additional constraints beyond those previously existing, creating a large-scale problem, and ensuring comprehensive and effective planning. According to Mariz et al. one of the dominant methods of scale reduction in the mine planning problems is block aggregation [36]. Askari-Nasab et al. proposed employing fuzzy logic clustering to generate mining cuts on a bench-by-bench basis [7, 9]. This method aims to improve the model size by aggregating blocks into meaningful clusters. Eivazy and Askari-Nasab further developed the fuzzy logic clustering algorithm into a fuzzy c-means approach for a short-term MILP model [22].

Koushavand et al. also utilized the enhanced fuzzy c-means to create mining cuts as extraction units for their stochastic strategic mine planning model [31]. Despite the limitation of not considering the spatial arrangement of mining pushbacks, fuzzy logic clustering for efficiency improvement was subsequently applied in various instances, including iron ore and oil sand mining [8, 13-14] .

To address the challenge of a mining cut encompassing blocks from adjacent pushbacks, which could result in suboptimal outcomes, Tabesh and Askari-Nasab developed a hierarchical clustering method based on an unsupervised machine learning technique [63]. This method uses a similarity index equation to group the mining blocks within each individual pushback. After its initial development, the approach was refined to enhance its functionality. Significant improvements included the automatic generation of mining polygons, a post-processing phase, and validation using a gold deposit, as detailed by Tabesh and Askari-Nasab [64]. Later, Tabesh and Askari-Nasab introduced an algorithm designed to manage geological uncertainty [65]. In this model, hierarchical clustering is applied separately to each ore-body realization, and the individual clustering are then combined to finalize the solution. These advancements highlight the methodology's robustness and adaptability in optimizing mining operations under complex geological conditions. The flexibility and reliability of this method have enabled numerous studies to apply the clustering approach, utilizing hierarchical clustering and Tabu Search, to aggregate mining blocks. This methodology has been employed in both strategic and operational mine planning contexts, transcending specific scenarios and significantly contributing to a broader understanding of optimizing mining operations efficiently [9, 11-12, 15 21, 35, 44, 58, 66-67, 68-70]. In the current study, we used the same similarity index function along with the hierarchical clustering method to create mining cuts that match the size of the blast polygons. The detailed calculations will be presented in the methodology section. This approach ensures that the mining cuts are not only consistent in size and shape with the blast polygons but also optimized for operational efficiency and resource management. We also aim to achieve a more systematic and coherent arrangement of mining cuts, which can lead to improved overall productivity and reduced operational costs.

In the latest application of mining block aggregation, Mariz et al. proposed a MILP-based mathematical model to achieve better control over the shapes of mining cuts [37]. They employed the similarity index function proposed by Tabesh and Askari-Nasab as their objective function, with the goal of maximizing it [63-63]. Also, they utilized a geometric propagation heuristic for refining the shapes of mining cut clusters. This method can modify the boundaries of the mining cuts to account for the constraints and capabilities of the mining equipment. This approach enhances the precision and efficiency of mining operations by ensuring that the cut shapes are optimized not only for geological and economic factors but also for the practical aspects of mining equipment operation.

Selecting optimal locations for crushers is crucial for the efficiency of IPCC systems, impacting both operational costs and productivity. The literature presents two categories of methods often used to select the candidate locations for the crushers which we can interpret as automated and manual. Automated methods typically follow a general principle for identifying candidate spots. Examples include dividing the deposit into slides [30], assuming a specific height or segmenting the pit circumference into different regions [2, 4, 32]. In contrast, manual selection focuses on the practicality of the location, with detailed considerations specific to each spot [48, 50-51]. For a detailed comparison of candidate locations in research studies, readers are referred to Kamrani et al. [26]. Assessments of these studies revealed that manual approaches often cannot be generalized due to their specificity. On the other hand, while less detailed, automated methods often seem impractical for many IPCC placements as they frequently overlook or excessively account for the spatial requirements necessary for effectively accommodating both in-pit crushers and conveyors.

Additionally, both approaches often ignore the distribution of nominated locations throughout the pit, making distance-based location optimization less effective.

we propose an automated method using the k-medoid clustering algorithm to select candidate locations, which we refer to as crusher panels. Each crusher panel's dimension is considered greater than or equal to the minimum mining width, providing sufficient space for the crusher and other necessary equipment, even in the narrower bottom benches of the pit. The implementation of a semi-mobile IPCC system requires establishing appropriate locations for various components, including dump points for trucks, the crusher feeder, and the conveyor belts up to the crusher discharge point. Each individual crusher panel should provide the required space for these components.

In this paper, building on the work of Kamrani et al., the optimization of IPCC systems is advanced by including a conveyor network in a real mine case study with the NPV calculation [26]. The methodology employs a two-step mathematical optimization model, modified to accommodate the new conditions and scenarios, to determine the optimal crusher panels and establish a practical long-term extraction sequence. This study includes detailed designs of the mining cuts as blast polygons or extraction units and the design of conveyor ramps and conveyor networks in a real mine-sized operation case study through which the model is verified. Additionally, a detailed cost analysis of in-pit crushing and conveying implementations is provided. The study encompasses a comprehensive case analysis involving five pushbacks, various road and conveyor ramp configurations, and multiple network scenarios. The capital and operational costs across four scenarios are evaluated: without a crusher, with an ore crusher, with a waste crusher, and with both ore and waste crushers. Because of the road distances and the possibility of calculating traveled distances, some key metrics such as total kilometers traveled, and the number of trucks required are compared. Figure 1 depicts a schematic view of five open pit mine pushbacks with road and conveyor networks, relative locations of different equipment, and crusher panels including two semi-mobile IPCC for different material types.

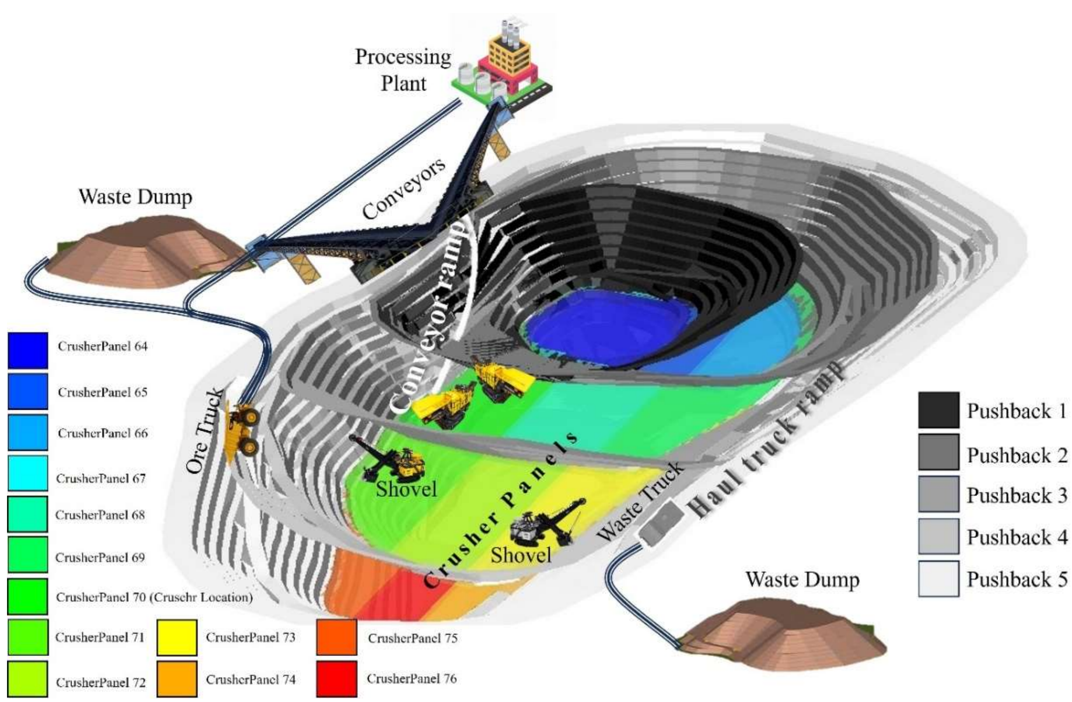

Figure 1. A schematic view of five open pit mine pushbacks with road and conveyor networks, relative locations of different equipment and crusher panels including two semi-mobile IPCC for different material types.

The significance of the current work can be summarized as proposing a comprehensive method that encompasses all four categories of previously mentioned published studies: 1) finding the optimal location, 2) addressing important industry viewpoints, 3) evaluating the IPCC option through comparative scenarios, and 4) optimizing long-term mine planning in the presence of IPCC and TS systems. This method involves designing size-managed mining cuts to represent more practical extraction units as blast polygons, ensuring these cuts are relatively rectangular in shape and contain enough blocks to feed the production until the next blasting time. It also includes proposing crusher panels as candidate locations for the crusher, which are created automatically using k-medoid clustering and provide sufficient space for the crusher placement, trucks to queue and discharge material, and conveyors to be front-fed by the crushers. In addition, the method entails designing conveyor ramps to specify material flow location and direction, thereby guiding the process of finding the optimum crusher panel(s) and designing the road network to calculate truck travel distances and determine the required number of trucks. Furthermore, the work evaluates the capital costs of the IPCC using information acquired from real manufacturers of crushers and sizers, enabling an exact trade-off cost analysis between TS and IPCC through practical scenarios. Finally, it presents a near-optimal long-term schedule that honors the precedence of the optimum crusher panels, as well as slope precedence and extraction sequence. The study assumes deterministic input parameters, serving as a strategic decision support tool without addressing variability, conveyor belt design specifics, or installation requirements for in-pit crushers, and focuses on planning for a mine with a semi-mobile IPCC system, adaptable to fixed IPCC systems with minor modifications.

2. Methodology

The methodology involves a series of preparatory steps, along with explanatory data analysis. It begins with block model optimizations and designs and concludes with the block schedule. The starting point is optimizing the blocks to find the ultimate pit boundaries and pushbacks, accompanied by a long-term schedule. This process can be executed using any mine planning software, such as GEOVIA Whittle or any related proposed mathematical model [24]. However, to the best of our knowledge, no existing mine planning software can provide a mine schedule while accounting for the in-pit crusher and conveyor system. Consequently, the output from the mine planning software must be sent to the clustering stage. Here, a two-stage clustering method is applied as part of the explanatory data analysis to identify potential crusher locations, known as crusher panels, and block aggregations called mining cuts, which create a larger extraction unit. These identified crusher panels and mining cuts form the basis for solving the first and second mathematical models, which are MILP-based models capable of handling the required constraints. Figure 2 shows the detailed breakdown of the methodology stages highlighting the process flow from start to end.

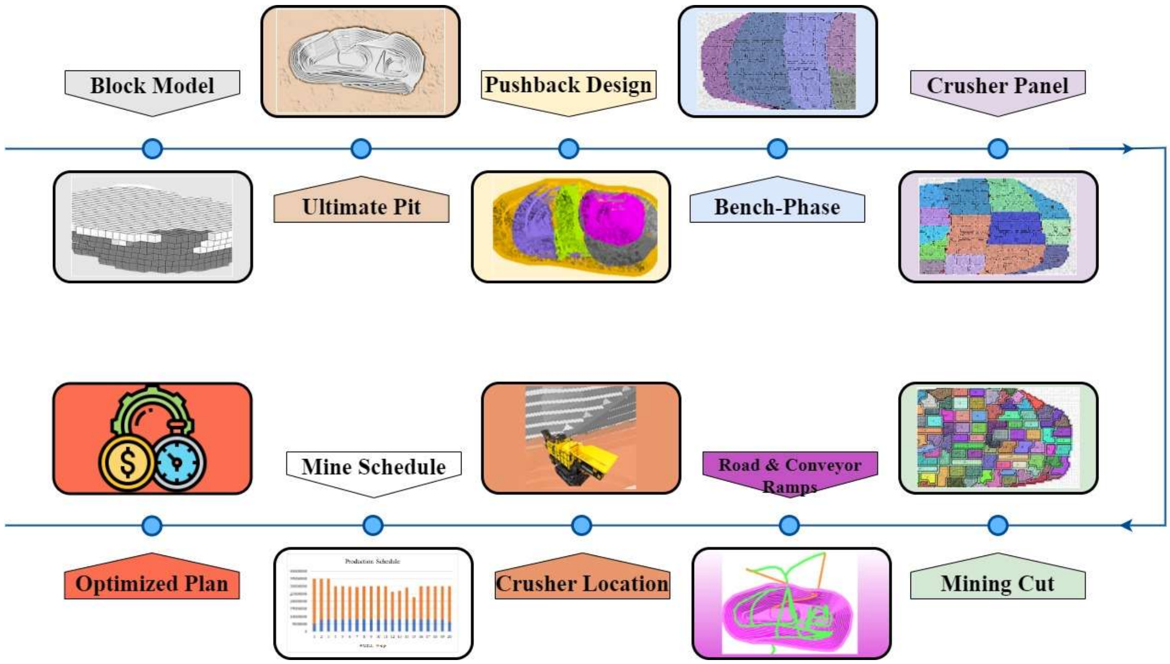

Figure 2. Detailed breakdown of the methodology stages, showcasing the process flow from start to finish.

2.1. Block Model & Design

The methodology starts with the block model optimization and design, a critical phase that lays the groundwork for all subsequent planning and scheduling. This begins with the use of advanced mine planning software, such as GEOVIA Whittle, or any appropriate mathematical modeling such as the one proposed by Tabesh et al. to optimize the block model [24, 67]. The optimization process involves identifying the ultimate pit boundaries and designing the necessary pushbacks to ensure a comprehensive long-term schedule. The optimized block model provides crucial insights into the most efficient and economical ways to extract the ore, considering various geological and operational constraints that have been suggested so far.

Once the pushbacks are designed, the block model is constrained by the pushback surfaces to create a detailed bench-by-bench model featuring the pushback boundaries, referred to as bench-phases. These bench-phases are essential for breaking down the mining process into manageable units, allowing for precise control over the extraction sequence. Each bench-phase is further partitioned into smaller extraction units, ensuring a structured mining process. This detailed block model not only aids in planning but also in visualizing the extraction process, making it easier to identify and address potential issues early on. The meticulously designed block model serves as the foundation for the subsequent clustering and scheduling stages, ensuring that the overall methodology can handle the complexities of modern mining operations.

The constrained blocks defined by the pushbacks' surfaces are categorized based on coordinates, pushback number, grade, metal content, recovery, block value, and block tonnage. Each subsequent clustering stage, whether creating crusher panels or mining cuts, maintains a record of the included ore and waste blocks. This allows for the calculation of the value, ore and waste tonnage, and metal content of the mining cuts or crusher panels. The grade and metal recovery of the mining cuts or crusher panels are averaged from the included blocks, although optimization focuses on the total value. Askari-Nasab et al. provided a detailed guidance on the parameters stored within the mining cuts [7, 9]. This same approach is used for crusher panels to record the history of the mining cuts, ensuring compliance with precedence rules defined as constraints in the mathematical model to manage the extraction process.

2.2. Crusher Panels

As discussed earlier, this study involves two separate clustering processes, each using a distinct methodology. The first stage aims to identify crusher panels for each bench-phase. Kamrani et al. proposed the concept of a “crusher panel” as a suitable location for an in-pit crusher, factoring in spatial needs for various components, and the k-medoids clustering algorithm is used to define these panels, effectively partitioning pushbacks and controlling their dimensions and orientation [28].

The k-medoids algorithm is a partitioning clustering method similar to k-means, but with a key difference: k-medoids selects medoids from the actual data points being clustered, unlike k-means, which uses the average as the cluster center. This makes k-medoids more suitable for our specific scenario involving mining cuts. The k-medoids clustering approach begins with k arbitrary clusters, each represented by a medoid (S1, S2, ..., Sk). Using these initial medoids, each cluster is updated by minimizing the distance to the performance function, resulting in new clusters (ck'). Within each cluster, the medoid is updated and the process checks for a stopping condition. If the new cluster configuration (ck') matches the previous one (ck), the process terminates. If not, the steps are repeated.

In the k-medoids clustering approach for defining crusher panels, the process begins by setting the number of clusters equal to the number of mining pushbacks in each bench-phases. Initially, *k* arbitrary clusters are selected, each with a representative point. For each cluster, the algorithm iteratively updates the cluster assignments, the representative point and the number of clusters until the distance between the representative becomes greater or equal to the minimum mining width, ensuring the clusters fit the spatial requirements. The algorithm continues by refining the clusters and their representatives, adjusting the cluster memberships to accurately reflect the constraints of the mining operation. Once this iterative process converges, the resulting crusher panels are determined, providing a practical configuration for the in-pit crusher that meets the spatial needs within the specified minimum mining width. Therefore, the first stage of this framework applies the k-medoids algorithm and categorizes each bench within its pushback to divide the pushbacks into crusher panels, followed by aggregating blocks within these panels while maintaining precedence relationships to create mining cuts, with the medoids optimizing the crusher's location by calculating distances and costs effectively.

2.3. Mining Cuts

As mentioned, dividing the deposit into individual blocks is a common practice. Blocks are usually rectangular in shape and uniform throughout the deposit. For decades, blocks were the extraction units of any open pit mine planning, but it was soon realized that optimizing an operation with such a large number of extraction units was impractical. To address this issue, aggregation techniques were developed to create continuous, minable plans that are practical and reduce the complexity of the problem. One approach involves using clustering algorithms to group blocks based on similarities such as rock type, ore grade, and distance or dissimilarities such as mineral composition, destination and environmental impact. In long-term open pit mine planning, block aggregation has been a common practice to reduce problem size and computational demands, and at the same time generating a practical plan in accordance with practical selective mining units. This aggregation can be simplified based on the technical attributes of the blocks, or it can be more sophisticated, using clustering methods that involve solving linear programming optimization problems. This paper discusses creating mining cuts using hierarchical clustering within crusher panels, which have already been clustered using the k-medoids algorithm.

In hierarchical block aggregation clustering for mining cut creation, the process starts with evaluating each crusher panel within the bench-phase. Initially, the number of clusters is set equal to the number of individual blocks, and both the similarity and adjacency matrices are initialized to zero. The similarity matrix can be calculated using Equation 1 where sim_{ij} represents the similarity index between block i and j. RT_{ij} denotes the penalty assigned for different rock types between blocks i and j, with integer values starting from 1 indicating no penalty. $\widetilde{Dist_{ij}}$ and $\widetilde{Grade_{ij}}$ correspond to the normalized distance and grade difference between blocks i and j, respectively.

$$Sim_{ij} = \frac{1}{\widetilde{Dist_{ij}}} \times \frac{RT_{ij}}{\widetilde{Grade_{ij}}} \tag{1}$$

The adjacency matric estimates block distances that are smaller than the adjacency threshold and it can be calculated by Equation 2 where Adj_{ij} is the adjacency index and $Dist_{ij}$ is the Euclidean distance between centres of blocks i and j.

$$Adj_{ij} = (Dist_{ij} < Threshold) \tag{2}$$

The algorithm enters a loop that runs until the number of clusters is reduced to a specified maximum. During each iteration, the similarity and adjacency values for each block are calculated. If the combined size of two clusters is within the allowed maximum cluster size, the similarity and adjacency matrices are updated to reflect the merging of these clusters. A new cluster is then formed, and the total number of clusters is adjusted accordingly. This process of calculating values, updating matrices, and merging clusters continues iteratively until the number of clusters meets the desired maximum. The final output of this hierarchical aggregation is the creation of mining cuts, defined by the clusters formed throughout the process.

2.4. Shortes Path Algorithm

The 'shortestpath' function in Matlab relies on established algorithms from graph theory to determine the shortest path between two nodes in a graph [38]. Graphs consist of vertices (nodes) and edges (connections between nodes), where edges may have weights representing distances. The most common algorithms used are different variations of Dijkstra algorithm for graphs with non-negative weights. Dijkstra algorithm efficiently finds the shortest path by repeatedly selecting the node with the smallest known distance from the source, updating the distances to its neighboring nodes, and ensuring that once a node's shortest path is found, it does not need to be revisited.

To use Dijkstra algorithm in the 'shortestpath' function, we need to calculate the distance matrix between all the mining cuts and crusher panels with the road network, and then from the crusher panel to the processing plant or waste dump with the conveyor network, under the following conditions. This is done after reading DXF files for both networks for each pushback and creating their appropriate graphs. For horizontal moves, i.e., from the mining cut to the road ramp entrance point and from the road ramp exit point to the crusher panel, the shortest distance will be used. For vertical moves, the shortest path will be determined by specifying the entrance point and exit point of the related elevation. Since the crusher panel assignment is automatic, any panel assigned without direct access to the conveyor ramp should be excluded from the distance matrix and the first step of the mathematical model. This condition, which occurred in our case study, led to the exclusion of nearly 43 crusher panels out of the total 215. However, to calculate the cost matrix required for both the first step and the second step of the mathematical model, as well as to handle all four scenarios of in-pit crushing, we need to find the shortest path from all mining cuts and crusher panels to the processing plant and waste dump using each of the road networks and conveyor networks, plus their horizontal shortest distance to the entrance point of road ramps and conveyor ramps at each elevation. Having these distances will also help us find important outputs needed for further analysis, such as tonne-kilometers, kilometers traveled, and the required number of trucks. Figure 3 provides the pseudocode illustration of the process of distance matrix calculations.

```
** Initialize graphs and distance matrices
FOR EACH Pushbacks
  READ DXF file for RoadNetwork
  RoadGraph{i} = create_graph_from_DXF(DXFFile)

  READ DXF file for ConveyorNetwork
  ConveyorGraph{i} = create_graph_from_DXF(DXFFile)

 ** Initialize distance matrices for road and conveyor networks
 DistanceMatrixRoad = initialize(numMiningCuts, numCrusherPanels)
 DistanceMatrixConveyor = initialize(numCrusherPanels, numProcessingPlant/s + numWasteDump/s)

 ** Function to calculate shortest path
 FUNCTION shortestpath(graph, source)
   FOR EACH vertex IN graph
     SET distance[vertex] = infinity
     SET previous[vertex] = undefined
   NEXT
   SET distance[source] = 0
   CREATE PriorityQueue
   ADD source TO PriorityQueue

   WHILE PriorityQueue is NOT empty
     CurrentVertex = vertex IN PriorityQueue WITH smallest distance
     REMOVE CurrentVertex FROM PriorityQueue

     IF distance[CurrentVertex] == infinity THEN
       BREAK
     ENDIF
     FOR EACH neighbor of CurrentVertex
       AlternativePath = distance[CurrentVertex] + EdgeWeight(CurrentVertex, neighbor)
       IF AlternativePath < distance[neighbor] THEN
         SET distance[neighbor] = AlternativePath
         SET previous[neighbor] = CurrentVertex
         ADD neighbor TO PriorityQueue
       ENDIF
     NEXT
   ENDWHILE

   RETURN distance, previous

 ** Calculate shortest path/distances for all required moves
 FOR EACH MiningCut
   FOR EACH CrusherPanel
     RoadDistance_vertical = shortestpath(RoadGraph{i}, MiningCut,CrusherPanel)
     RoadDistance_horizontal = MinimumDistance (MiningCut/CrusherPanel,RoadEntrance/RoadExit)
     RoadDistance[MiningCut][CrusherPanel] = RoadDistance_vertical + RoadDistance_horizontal

     ConveyorDistance = shortestpath(ConveyorGraph{i}, CrusherPanel,ProcessingPlant/WasteDump)
     DistanceMatrixConveyor[CrusherPanel][ProcessingPlant/s] = conveyorDistance[ProcessingPlant]
     DistanceMatrixConveyor[CrusherPanel][WasteDump/s] = ConveyorDistance[WasteDump]
   END
 END

RETURN DistanceMatrixRoad and DistanceMatrixConveyor
```

Figure 3. Pseudocode of the process of distance matrix calculations.

2.5. Crusher Locations

To determine the optimal locations for the crusher throughout the mine's life, the cost of transporting materials between different locations must be calculated. This cost is derived by multiplying each distance matrix by the cost factor according to their respective scenarios. For the first scenario, which involves only truck and shovel operations, there is no need to implement the initial step of the model. However, for the other scenarios, the formulation of the initial step varies.

The next quantitative involves creating an adapted version of the capacitated facility location model to identify the best locations for crushers. Although the model can accommodate flexible scenarios, the technical considerations for each material type and scenario, including conveyor components such as belts, rollers, frames, drives, pulleys, etc., must be carefully studied. To adapt the model to our scenarios, it is necessary to modify the equations, as each scenario requires a specific type of objective function and sets of constraints that are slightly different. The scenarios can be categorized as follows: 1) Ore IPCC scenario, where only one in-pit crusher handles ore materials, with conveyors installed on the conveyor ramp, while waste material is hauled out by trucks, 2) Waste IPCC scenario, where only a waste in-pit crusher transports waste materials with conveyors installed on the conveyor ramp on the same side of the pit, and ore materials are hauled out by trucks, 3) Ore & Waste IPCC scenario, where two in-pit crushers are placed on the same crusher panel using two different conveyors installed on an adequately spaced conveyor ramp, hauling both ore and waste materials out of the pit.

The three objective functions presented in Equations 3 to 5 correspond to the Ore IPCC, Waste IPCC, and Ore & Waste IPCC scenarios, respectively. The first component, which is shared among all three equations, accounts for the cost of installing the crusher on a specific crusher panel. This cost could be the same for all crusher panels or vary based on factors such as location, accessibility, and the physical properties of the bedrock, but it cannot be zero. In the Ore IPCC scenario, the second component calculates the cost of transporting ore tonnage from each mining cut to each crusher panel and sending the crushed material to the mill via the conveyor belt. The same applies to the second component of the Waste IPCC scenario, with the difference being that waste is crushed and hauled by the conveyor belt. In the Ore & Waste IPCC scenario, the components from the previous two scenarios are summed up. The following equations show the objective functions and constraints of the first-step model:

$$\min \sum_{p=1}^{P}(f_p \times y_p) + \sum_{k=1}^{K}\sum_{p=1}^{P}(co_{k,p} \times z_{k,p}) \rightarrow Ore\ IPCC\ Obejective\ Function \tag{3}$$

$$\min \sum_{p=1}^{P}(f_p \times y_p) + \sum_{k=1}^{K}\sum_{p=1}^{P}(cw_{k,p} \times s_{k,p}) \rightarrow Waste\ IPCC\ Objective\ Function \tag{4}$$

$$\min \sum_{p=1}^{P}(f_p \times y_p) + \sum_{k=1}^{K}\sum_{p=1}^{P}(co_{k,p} \times z_{k,p}) + \sum_{k=1}^{K}\sum_{p=1}^{P}(cw_{k,p} \times s_{k,p}) \rightarrow Ore\ \&\ Waste\ IPCC\ Objective\ Function \tag{5}$$

Subject to

$$\sum_{p=1}^{P} z_{k,p} = do_k \quad \forall\ k \in \{1,\ldots,K\} \tag{6}$$

$$\sum_{p=1}^{P} s_{k,p} = dw_k \quad \forall\ k \in \{1,\ldots,K\} \tag{7}$$

$$lMo_p \times y_p \le \sum_{k=1}^{K} z_{k,p} \le uMo_p \times y_p \quad \forall\, p \in \{1,...,P\} \tag{8}$$

$$lMw_p \times y_p \le \sum_{k=1}^{K} s_{k,p} \le uMw_p \times y_p \quad \forall\, p \in \{1,...,P\} \tag{9}$$

$$\overline{pu} \times \sum_{k=1}^{K} s_{k,p} - \overline{mu} \times \sum_{k=1}^{K} z_{k,p} \le 0 \;\; \forall\, p \in \{1,...,P\} \tag{10}$$

$$z_{k,p} \le do_k \times y_p \quad \forall\; k \in \{1,...,K\},\; p \in \{1,...,P\} \tag{11}$$

$$s_{k,p} \le dw_k \times y_p \quad \forall\; k \in \{1,...,K\},\; p \in \{1,...,P\} \tag{12}$$

$$z_{k,p}\,,\; s_{k,p} \ge 0 \;\; \forall\; k \in \{1,...,K\},\; p \in \{1,...,P\} \tag{13}$$

$$y_p \in \{0,1\} \;\; \forall\;\; p \in \{1,...,P\} \tag{14}$$

Where:

- $p \in P$ is the index for crusher panels.
- $k \in K$ is the index for the mining cuts.
- f_p is the cost of installing crusher in the crusher panel p. It could be different for the crusher panels if they were not chosen within the same bench phase. Otherwise, it has the same value for all the crusher panels.
- y_p is a binary decision variable that is equal to one if the crusher is located in crusher panel p, otherwise zero.
- $co_{k,p}$ is the cost of transporting each tonne of the ore from mining cut k to crusher panel p and sending the crushed material to the mill via the conveyor.
- $cw_{k,p}$ is the cost of transporting each tonne of the waste in mining cut k to crusher panel p and sending the crushed material to the waste dump via the conveyor.
- $z_{k,p}$ is a continuous decision variable representing the tonnage of ore from mining cut k sent to crusher panel p.
- $s_{k,p}$ is a continuous decision variable representing the tonnage of waste from mining cut k sent to crusher panel p.
- do_k is the ore tonnage of mining cut k.
- dw_k is the waste tonnage of mining cut k.
- $\overline{pu}$ is the average of the upper bounds on the tonnage of ore processing capacity in all the periods.
- $\overline{mu}$ is the average of the upper bounds on the tonnage of mining capacity in all the periods.
- uMo_p is the upper bound on the total ore tonnage milled during the time that the ore crusher is located on the crusher panel *p*.
- uMw_p is the upper bound on the total waste tonnage dumped during the time that the waste crusher panel is located on the crusher panel *p*.

- lMo_p is the lower bound on the total ore tonnage milled during the time that the ore crusher is located on the crusher panel p.
- lMw_p is the lower bound on the total waste tonnage dumped during the time that the waste crusher is located on the crusher panel *p.*

As mentioned, Equation 3 to 5 serve as the objective functions of various scenarios which in the given formulations aimed at minimizing the cost of installing the crusher and transporting ore and waste materials. Equations 6 and 7 ensure that all ore and waste tonnages from each mining cut are extracted and assigned to a crusher panel. For the Ore IPCC scenario, only Equation 6 is implemented, and for the Waste IPCC scenario, only Equation 7 is implemented. However, for the Ore & Waste IPCC scenario, both Equations 6 and 7 are necessary. Equations 8 is for the Ore IPCC and Equation 9 is for the waste IPCC and both are required for the Ore & Waste IPCC. These Equations establish lower and upper limits for ore and waste, on the total ore tonnage milled or the total waste tonnage dumped during the time that the crusher is located on crusher panel p. Equation 10 is specific to the Ore & Waste scenario, ensuring that both crushers in the selected optimal crusher panel are fed with an equal amount of material relative to the average upper bound of mining and processing capacities across all periods. Equations 11 and 12 set an upper bound for variables z and s to ensure the feasibility of the solution. Finally, Equations 13 and 14 represent the decision variables' boundaries for z, s, and y, respectively. To sum up, for the Ore IPCC scenario, we use Equation 3 for the objective function and Equations 6, 8, 11, 13, and 14 as constraints. For the Waste IPCC scenario, we use Equation 4 for the objective function and Equations 7, 9, 12, 13, and 14 as constraints. For the Ore & Waste IPCC scenario, we use Equation 5 for the objective function and all remaining Equations from 6 to 14 as constraints.

2.6. Production & IPCC Schedule

The production schedule and the relocation times of the crusher(s) will be determined through a MILP formulation designed to control the optimal crusher panels from being extracted until the assumed total ore tonnage is milled or the presumed total waste tonnage is dumped. This period corresponds to the time that the crusher(s) are located on crusher panel p., as determined by the first step of the model. Equation 15 describes the objective function to maximize NPV, recognizing the extraction times (*T*) for both the mining cut ($x_{k,t}$) and the crusher panels ($d_{p,t}$). The decision variables identifying the extraction time and extraction portion of mining cuts and crusher panels ($x_{k,t}$ and $d_{p,t}$) are continuous variables ranging from 0 to 1. Moreover, $v_{k,t}$ and $q_{p,t}$ represent the discounted revenue minus the extra cost of mining ore in the mining cut and the discounted cost of mining, respectively. These parameters will be further analyzed to include the road and conveyor networks in the calculation. The definitions of indexes, parameters, and decision variables are as follows:

Indexes:

$t \in T$ *mining periods (year).*

$k \in K$ *mining cut.*

$p \in P$ *crusher panel or the in-pit crusher candidate location.*

$ocp \subset P$ *optimum crusher panels.*

$l \in L \subset P$ *counter for optimum crusher panels or ocp (L=Length (ocp)).*

$t' \subset t$ *starts from 1 to whatever the value of t or period is in that certain loop in the formulation.*

pl *processing plant(s)*

du *waste dump(s)*

Parameters:

$v_{k,t}$ represents the discounted revenue minus the extra cost of mining ore in the mining cut $x_{k,t}$.

$q_{p,t}$ denotes the discounted cost of mining.

o_k is the ore tonnage in the mining cut *k.*

o_p is the ore tonnage in the crusher panel *p.*

w_k is the waste tonnage in the mining cut *k.*

w_p is the waste tonnage in the crusher panel *p.*

ml_t & mu_t are the lower and the upper bounds on the tonnage of mining capacity in period *t*, respectively.

pl_t & pu_t are the lower and upper bounds on the tonnage of ore processing capacity in period *t*, respectively.

$g_{k,e}$ is the average grade of element *e* in ore portion of mining-cut *k*.

$gl_{t,e}$ & $gu_{t,e}$ are the lower and upper bounds on the percentage of the acceptable average head grade of element *e* in period *t*, respectively.

C_p is the set of the precedence panels that must be extracted prior to panel *p*.

s_p is the number of the precedence panels that must be extracted prior to panel *p*.

$Rev_{k,t}$ is the revenue because of extracting mining cut *k* in period *t*, sending it to the processing plant, smelter and refinery and selling the product considering all the recoveries and grades minus the processing, smelting and refining costs.

$TMC_{k,t}$ is the total mining cost of extracting mining cut *k* in period *t*.

$TMC_{p,t}$ is the total mining cost of extracting crusher panel *p* in period *t*.

$mc_{k,t}$ is the mining cost of extracting mining cut k minus the haulage cost of mining cut k to its destinations (*pl* or *du*) in period *t*.

$mc_{p,t}$ is the mining cost of extracting crusher panel p minus the haulage cost of crusher panel p to the waste dump *du* in period *t*.

$RNdist$ is the shortest path calculated from the road networks. It can be the shortest path distance between either mining cut k or crusher panel p to the optimum crusher panel *ocp*, the processing plant *pl* or the waste dump *du*.

$CNdist$ is the shortest path calculated from the conveyor networks. It can be the shortest path distance between the optimum crusher panel *ocp*, the processing plant *pl* or the waste dump *du*.

r is the discount rate.

c is the dollar cost of hauling one tonne of ore or waste per one kilometre in period t with haul truck to its destination which is either the optimum crusher panel *ocp*, the processing plant *pl* or the waste dump *du* in period t (\$/ton.km).

cn is the dollar cost of transferring one tonnage of ore or waste per one kilometre using the conveyor from the optimum crusher panel *ocp* to its destination which is either the processing plant *pl* or the waste dump *du* in period t.

pt_{ocp} is the maximum tonnage of ore milled or waste dumped while the crusher is in the optimum crusher panel *ocp*.

Decision Variables:

$x_{k,t} \in [0,1]$ is a continuous variable, representing the portion of mining-cut k to be extracted as ore and processed in period t.

$d_{p,t} \in [0,1]$ is a continuous variable, representing the portion of the crusher panel p to be mined in period t, as either ore or waste included in the panel.

$b_{p,t} \in \{0,1\}$ is a binary integer variable controlling the precedence of extraction of panels. $b_{p,t}$ is equal to one if extraction of panel p has started by or in period t, otherwise it is zero.

$y' \in \{0,1\}$ is a binary integer auxiliary variable to make the if-else possible for the MILP model. It is used to activate Equation 22 when the extraction condition of Equation 21 satisfies.

Parameters:

$$\max \sum_{t=1}^{T} \left(\sum_{k=1}^{K} (v_{k,t} \times x_{k,t}) - \sum_{p=1}^{P} (q_{p,t} \times d_{p,t}) \right) \tag{15}$$

Subject to

$$ml_t \le \sum_{p=1}^{p} (o_p + w_p) \times d_{p,t} \le mu_t \quad \forall t \in \{1,...,T\} \tag{16}$$

$$pl_t \le \sum_{k=1}^{K} o_k \times x_{k,t} \le pu_t \quad \forall t \in \{1,...,T\} \tag{17}$$

$$\sum_{k=1}^{K} o_k \times x_{k,t} \le \sum_{p=1}^{p} (o_p + w_p) \times d_{p,t} \; \forall t \in \{1,...,T\} \tag{18}$$

$$0 \le \sum_{k=1}^{K} (g_{k,e} - gl_{t,e}) \times o_k \times x_{k,t} \; \forall t \in \{1,...,T\}, e \in \{1,...,E\} \tag{19}$$

$$\sum_{k=1}^{K} (g_{k,e} - gu_{t,e}) \times o_k \times x_{k,t} \le 0 \; \forall t \in \{1,...,T\}, e \in \{1,...,E\} \tag{20}$$

$$\sum_{t=1}^{T} d_{p,t} = 1 \; \forall p \in \{1,...,P\} \tag{21}$$

$$s_p \times b_{p,t} - \sum_{s \in C_p} \sum_{i=1}^{t} d_s^i \le 0 \; \forall t \in \{1,...,T\}, p \in \{1,...,P\}, p \notin \{1,...,L\}, s \in C_p \tag{22}$$

$$\sum_{i=1}^{t} d_p^i - b_{p,t} \le 0 \; \forall t \in \{1,...,T\}, p \in \{1,...,P\}, p \notin \{1,...,L\} \tag{23}$$

$$b_{p,t} - b_{p,t+1} \le 0 \; \forall t \in \{1,...,T-1\}, p \in \{1,...,P\}, p \notin \{1,...,L\} \tag{24}$$

$$s_m \times b_{p,t+[\frac{pt_{opc}}{mu} \; or \; \frac{pt_{opc}}{pu}]} - \sum_{s \in C_p} \sum_{i=1}^{t} d_s^i \le 0 \; \forall t \in \{1,...,T\}, p \in \{1,...,L\}, s \in C_p \tag{25}$$

$$b_{p,t+[\frac{pt_{opc}}{mu} \; or \; \frac{pt_{opc}}{pu}]} - b_{p,t+1+[\frac{pt_{opc}}{mu} \; or \; \frac{pt_{opc}}{pu}]} \le 0 \; \forall t \in \{1,...,T-1\}, p \in \{1,...,L\} \tag{26}$$

$$\sum_{t'=1}^{t} \sum_{ocp} \left[\sum_{k=1}^{K} (o_k \times x_{k,t}) \; or \; \sum_{p=1}^{P} (w_p \times d_{p,t}) \right] + M \, y'_{t,l} \le pt_{ocp} \forall t \in \{1,...,T\}, l \in \{1,...,L\} \tag{27}$$

$$\sum_{t'=1}^{t} \sum_{ocp} -b_{ocp} - M \, y'_{t,l} \le -t \;\; \forall t \in \{1,...,T\}, l \in \{1,...,L\} \tag{28}$$

$$\sum_{t'=1}^{t} \left(y'_{t,l} + \sum_{i=t'+1}^{t} \left(\frac{y'_{i,l}}{t'-t} \right) \right) \le 1 \; \forall t' \in \{1,...,T\}, l \in \{1,...,L\} \tag{29}$$

$$x_{k,t}, d_{p,t} \in [0,1] \; \forall t \in \{1,...,T\}, p \in \{1,...,P\}, k \in \{1,...,K\} \tag{30}$$

$$b_{p,t}, y'_{t,l} \in \{0,1\} \; \forall t \in \{1,...,T\}, p \in \{1,...,P\}, l \in \{1,...,L\} \tag{31}$$

In the proposed model, Equation 15 serves as the objective function to maximize the NPV. Equations 16 and 17 impose constraints on mining and processing capacities. Equation 18 adjusts the relationship between the tonnage of ore extracted and the total tonnage extracted from the corresponding cuts and panels. Equations 19 and 20 regulate the maximum and minimum grade of the material sent to either the mill or the waste dump, with these limits being freely determined within this specific model. Equation 21 ensures that all crusher panels are extracted over the mine's lifespan. Equations 22-24 establish the extraction precedence for crusher panels that are not selected as the optimal panels in the model's initial step. These equations are formed within the mine phases and include mining cuts. Equation 22 sets a precedence constraint, preventing the extraction of crusher panel p until all its predecessor panels are extracted. Equation 23 ensures that extraction of crusher panel p does not begin until its predecessors are fully mined (i.e., its binary variable is set to one). Equation 24 sets all precedence binary variables for a crusher panel to one for all subsequent periods once its extraction begins. Equations 25 and 26 create a time delay for extracting the optimal crusher panels nearly equal to the years that the crusher(s) must be placed on these panels.

Equations 27 to 29 are executed in a loop for the number of optimal crusher panels identified in the first step, equivalent to the number of crusher relocations over the mine's life. This decision is made based on parameters uMo_p, lMo_p and uMw_p , lMw_p which define the upper and lower bounds for the total tonnage milled or dumped while the crusher is located on the panel. In these equations, *"y'_{tloop}"* is an auxiliary binary variable required for each loop and *"M"* is a big number exceeding the maximum upper bound of ore or waste milled or dumped. The material type tonnage decision hinges on the four considered scenarios. For the Ore & Waste IPCC scenario, since the optimal crusher panels for both crushers are identical, the relative tonnage to capacity is equalized to synchronize the relocations of both crushers. The decision variable boundaries are specified in Equations 30 and 31. As distance and transportation cost calculations differ between trucks and conveyors, adjustments to parameters $v_{k,t}$ and $q_{p,t}$ are necessary. Equations 32 to 39 detail the modified versions of these components. It is critical to note that "shortest path" references the use of a road network or conveyor network, denoted by either "*RNdist*" or "*CNdist*" parameters in the formulation.

$$v_{k,t} = \frac{\sum_{k=1}^{K}\sum_{t=1}^{T} \mathrm{Re}\, v_{k,t} - TMC_{k,t}}{(1+r)^t} \tag{32}$$

If there is an Ore Crusher in the pit (Ore IPCC):

$$TMC_{k,t} = mc_{k,t} + \Big((RNdist_{k,ocp} \times o_k \times c_{k,ocp,t}) + (CNdist_{ocp,pl} \times o_k \times cn_{ocp,pl,t}) - (RNdist_{k,du} \times w_k \times c_{k,du,t})\Big) \tag{33}$$

Else, if there is a Waste crusher in the pit (Waste IPCC):

$$TMC_{k,t} = mc_{k,t} + \Big((RNdist_{k,pl} \times o_k \times c_{k,pl,t}) - (RNdist_{k,ocp} \times w_k \times c_{k,ocp,t}) - (CNdist_{ocp,du} \times w_k \times cn_{ocp,du,t})\Big) \tag{34}$$

Else, if there is an Ore and Waste IPCC (Ore & Waste IPCC):

$$TMC_{k,t} = mc_{k,t} + \begin{pmatrix} (RNdist_{k,ocp} \times o_k \times c_{k,ocp,t}) + (CNdist_{ocp,pl} \times o_k \times cn_{ocp,pl,t}) \\ -(RNdist_{k,ocp} \times w_k \times c_{k,ocp,t}) - (CNdist_{ocp,du} \times w_k \times cn_{ocp,du,t}) \end{pmatrix} \tag{35}$$

Else, the ore material will be handled by trucks (No IPCC):

$$TMC_{k,t} = mc_{k,t} + \Big((RNdist_{k,pl} \times o_k \times c_{k,pl,t}) - (RNdist_{k,du} \times w_k \times c_{k,du,t})\Big) \tag{36}$$

$$q_{p,t} = \frac{\sum_{p=1}^{P}\sum_{t=1}^{T} TMC_{p,t}}{(1+r)^t} \tag{37}$$

If there is a Waste Crusher in the pit (Waste IPCC + Ore & Waste IPCC):

$$TMC_{p,t} = mc_{p,t} + \left((RNdist_{p,ocp} \times w_p \times c_{p,ocp,t}) + (CNdist_{ocp,du} \times w_p \times cn_{ocp,du,t}) \right) \quad (38)$$

Else, the waste material will be handled by trucks (No IPCC):

$$TMC_{p,t} = mc_{p,t} + (RNdist_{p,du} \times w_p \times c_{p,du,t}) \quad (39)$$

Equation 32 defines the components of the $v_{k,t}$ as the Revenue minus the Total Mining Costs (TMC) of mining cuts, discounted by the rate *r*. Equation 33 shows the Ore IPCC scenario haulage cost calculation Total Mining Costs (TMC) each mining cut in each period which is mining cost of each cut in each period ($mc_{k,t}$) plus the cost of hauling o_k tonnages of ore to the optimum crusher panel (*ocp*) by truck with the road network plus cost of conveying it to the processing plant (*pl*) taking the conveyor network minus hauling the waste portion of the mining cut if any to the waste dump (*du*) by truck with the road network. Similarly, Equation 34 shows the Waste IPCC scenario haulage cost calculation in which the waste portion of the mining cut will be carried away using the conveyor belts requiring the use of conveyor network, while the ore is hauled by trucks all the way to the processing plant. Equation 35 presents the haulage calculation for the Ore & Waste IPCC scenario, where there are two crushers. In this scenario, both the ore and waste portions of a mining cut are conveyed by their respective conveyors. However, initially, both materials need to be transported to the optimum crusher panel by trucks in period *t*. In Equation 36, the haulage system of the mine is dominated by the conventional TS method, with distances calculated using road networks, as there is no IPCC.

Equation 37 represents the components of the discounted Total Mining Costs (*TMC*) of crusher panels shown by $q_{p,t}$. Equation 38 can calculate the mining cost for the Waste IPCC and Ore & Waste IPCC scenarios at the same time. It takes the waste material from a crusher panel, hauling it to the optimum crusher panel at time *t* using trucks, and then conveying it to the waste dump (*du*). The distances are estimated using both the road network and the conveyor network. Equation 39 is for the truck and shovel haulage option when there is no IPCC. It calculates the Total Mining Costs (*TMC*) solely based on the road network distances to handle waste material. Since there is not any ore component in Equation 37, the Ore IPCC scenario will not be affected by it.

3. Case Study

To verify the mathematical model, an iron ore deposit case study is selected, which is designed for five pushbacks. The case study includes 19 benches with the primary element of magnetite, containing approximately 440 million tonnes of waste and 160 million tonnes of ore, 85,856 blocks, 20 years of operation with a scheduled mining capacity of 30 million tonnes (MT) and a processing capacity of 8 MT per year. It was decided to hire a contractor for the first three years of mining to increase the capacity from 30 MT to 35 MT to compensate for the plant shortage due to the pre-stripping stage. The first to fifth pushbacks contain 13,541, 13,064, 20,362, 11,328, and 14,561 blocks measuring 20m × 10m × 15m in X, Y, and Z dimensions, respectively. The total tonnages for each of the pushbacks from the first to the last one are approximately 90 MT, 73 MT, 147 MT, 214 MT, and 74 MT. These blocks are fed to one mill and dumped into two waste dumps located on the northern and southern sides of the pit. The waste dump selection happens based on the shorter distance, meaning each waste dump that has a shorter distance from a working panel will be chosen as the waste dump destination of that panel.

Both mathematical models ran on a machine equipped with an Intel® CPU featuring seven cores operating at 2.10 GHz speed and 64 GB of RAM, and both mathematical models were solved using the CPLEX solver (IBM ILOG CPLEX Optimization Studio., 2011). The runtime of the first step of the proposed model, when applied to the described case study, ranged from 25 to 30 minutes, while the runtime for the second step to get to the 5% gap tolerance is around 3 to 4 hours, depending on the scenario. Figure 4 provides an illustration of the layout of the last pushback of the iron ore mine, with two waste dumps on both sides of the pit, and crusher panels of the 9th bench accompanied by the road and conveyor network.

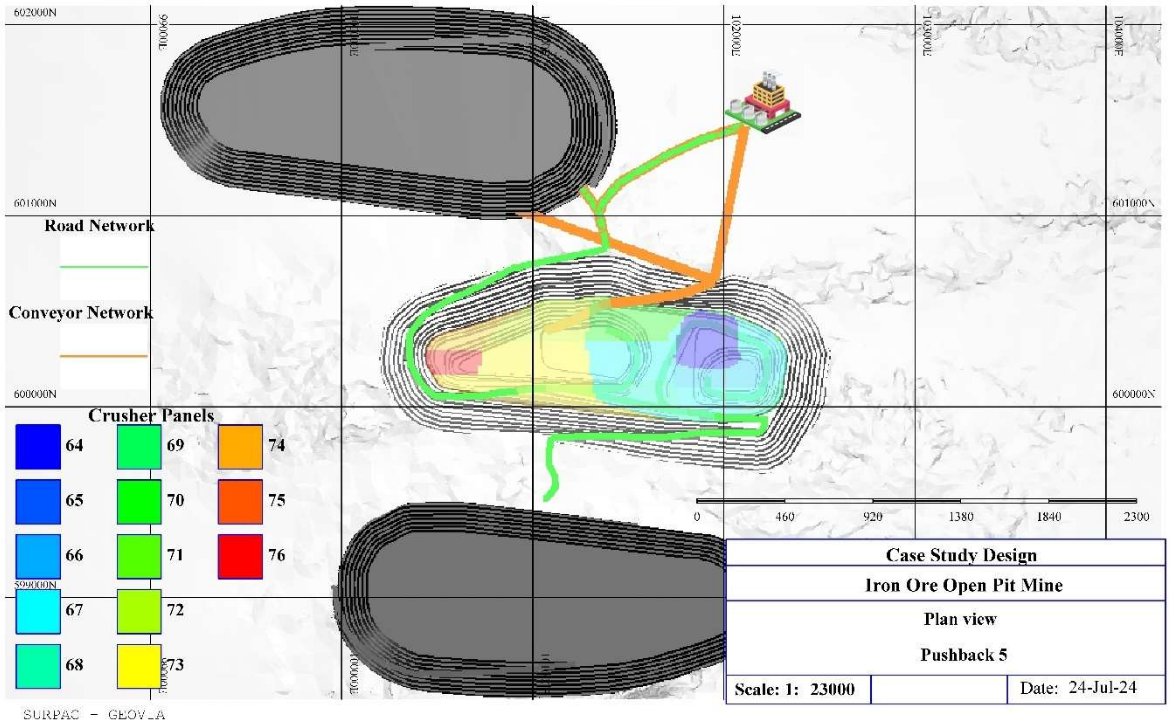

Figure 4. Last pushback and waste dumps layout and crusher panels of the 9th bench with their relative road and conveyor networks.

The coordinate extension of each pushback from the first to the fifth in the X direction is 860 m, 1100 m, 1460 m, 2040 m, and 2360 m, and in the Y direction is 710 m, 980 m, 1140 m, 1150 m, and 1150 m, respectively. Pushbacks one to three contain 12 benches each, pushback four has 18 benches, and pushback five has 19 benches. This arrangement results in crusher panels with a diagonal distance of 400m to 450m, based on the minimum mining width considered for the creation of the crusher panels. The algorithm chosen to find medoids is “partitioning around medoids,” and the method for distance minimization in cluster creation is “Euclidean”.

Considering 52 weeks of operation in this iron ore open pit case study, and knowing that the yearly production is 30 MT, we require around 580,000 tonnes of blasted material every week if it is decided one blast per week. With an average density of 4.31 tonnes/m³ (for both ore and waste) and the volume of each block being 10×20×15, totaling 3,000 m³, we can assume a total of 45 blocks for each blast polygon or mining cut. Therefore, setting the blocks per cluster range equal to 45 will create a base for the second stage of our clustering, which is aggregating blocks into mining cuts. The rest of the parameters in the hierarchical clustering method, according to Equations 1 and 2, are 0.1 for distance weight, 1 for rock type difference penalty, and close to zero (e.g. 0.01) for grade difference penalty. Figure 5 illustrates the schematic view of the crusher panels and the mining cuts’ boundaries within each crusher panel on the 9th bench-phase.

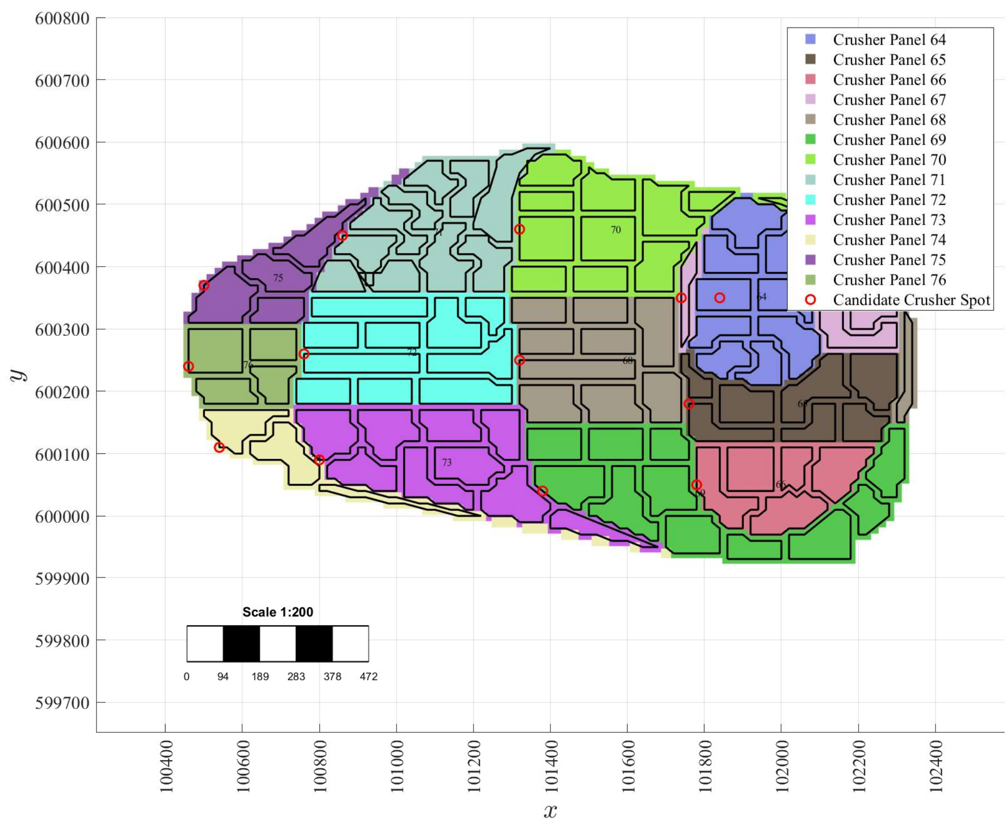

Figure 5. The schematic view of the 9th bench-phase crusher panels and mining cuts.

For the case study, the selected fleet comprises two types of shovels and three types of trucks, each chosen for their specific capacities and roles. The shovels include the Hitachi EX2500 for ore, with a bucket capacity of 12 m³, and the Hitachi EX5500 for waste, with a bucket capacity of 22 m³. Correspondingly, the primary trucks in use are the Caterpillar 785C, which has a 140-tonne nominal capacity and an overall width of 6.64 meters for ore, and the Caterpillar 793C, with a 178-tonne nominal capacity and an overall width of 7.44 meters for waste. Additionally, the Caterpillar 797B with a substantial 350-tonne capacity and an overall width of 9.15 meters, was included as a potential upgrade to the fleet to ensure meeting the operations' targets. Therefore, the main ramp width was designed based on the dimensions of the largest truck, ensuring a two-way traffic capacity of 32 meters. For smaller, right-side bottom benches, a narrower ramp was calculated at 16 meters. All ramps feature a consistent gradient of 10%, ensuring safe and efficient ascent and descent. The curvature for the switchbacks is designed with a radius of 40 meters, accommodating the turning radius of the largest trucks and ensuring smooth navigation through the pit.

4. Results and Discussion

In this study, we explore the semi-mobile IPCC option through four distinct scenarios: 1) No IPCC, 2) Ore IPCC, 3) Waste IPCC, and 4) Ore & Waste IPCC. The initial step of the model, designed to identify optimal crusher locations, is not applied to the first scenario, as traditional truck and shovel (TS) methods are used for material hauling. Nonetheless, crusher panels remain the primary extraction units for determining the waste material. For the other scenarios, the ore crusher's upper and lower limits (*uMo* & *lMo*) are set at 28 MT and 16 MT, respectively, while the waste crusher's upper and lower limits (*uMw* & *lMw*) are set at 105 MT and 60 MT. Adjusting these limits would yield varying relocation counts, though determining the optimal number of relocations lies beyond this study's scope. Table 2 presents the results from both steps of the model, showcasing the optimum crusher panels and their relative tonnages from the first step, as well as the relocation year or extraction sequence of the optimum crusher panels from the second step for scenarios 2-4. This indicates the extraction of 159.5 MT of ore and 439.9 MT of waste material.

Table 2. The results of the first and second steps for the optimum crusher panels.

Bench No.	Crusher Panel No. (CP)	Ore Crusher (MT)	Ore Crusher Relocation Year	Waste Crusher (MT)	Waste Crusher Relocation Year	Ore Crusher (MT)	Ore & Waste Crusher Relocation Year	Waste Crusher (MT)
Bench 4	**CP 154**	-	-	60	1	24	2	60
Bench 5	**CP 139**	27.7	2	60	2	-	-	-
Bench 6	**CP 124**	16	4	61.6	5	24	5	60
Bench 7	**CP 114**	16	7	-	-	-	-	-
Bench 8	**CP 99**	16	9	68.8	9	24	9	60
Bench 10	**CP 70**	19.8	12	-	-	24	12	60
Bench 11	**CP 57**	16	14	60	12	24	15	60
Bench 12	**CP 47**	16	16	-	-	-	-	-
Bench 13	**CP 31**	16	18	60	18	23.5	19	79.9
Bench 17 (Pit bottom)	**CP 4**	16	20	69.5	20	16	20	60
Total Tonnage		159.5		439.9		159.5	-	439.9

As illustrated in Table 1, the number of relocations varies across the scenarios. Notably, scenario 2 experiences two more relocations than scenarios 3 and 4. The model identifies the pit bottom as the final location for the crusher(s) across all scenarios, underscoring the efficiency of the conveyor networks. The crusher panel numbers, shown in the second column of the table, will be utilized as input parameters for the second step of the mathematical model within the *ocp* subset. Additionally, the tonnages in each scenario will be used to ensure that the *ocp* crusher panels remain unextracted.

Given the existing ore and waste amounting to approximately 600 MT of mineable material, the optimal operational setup to sustain mill throughput over the mine's lifespan includes a mill with an 8 MT annual capacity and a mining capacity of 30 MT annually. During the initial three-year pre-strip period, a contractor will be engaged to boost the mining capacity by an additional 5 MT per year, resulting in a total mining operation span of 20 years. The long-term production rates, determined by the model's second step, produce four distinct outcomes for each scenario. Figure 6 Figure 7, Figure 8, and Figure 9 display the yearly production charts over the long term, as derived from the model's second step for scenario 1 to 4, respectively.

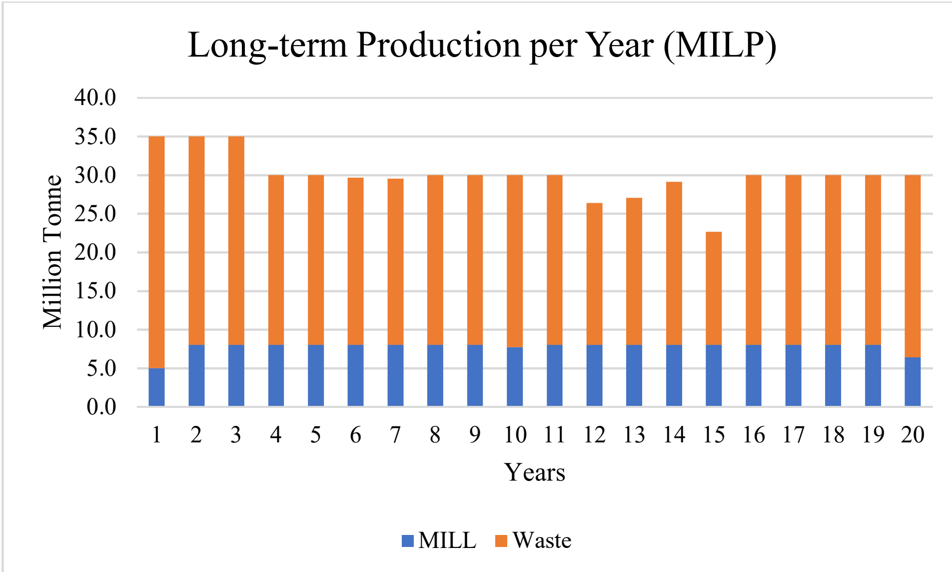

Figure 6. Long-term schedule for No IPCC scenario.

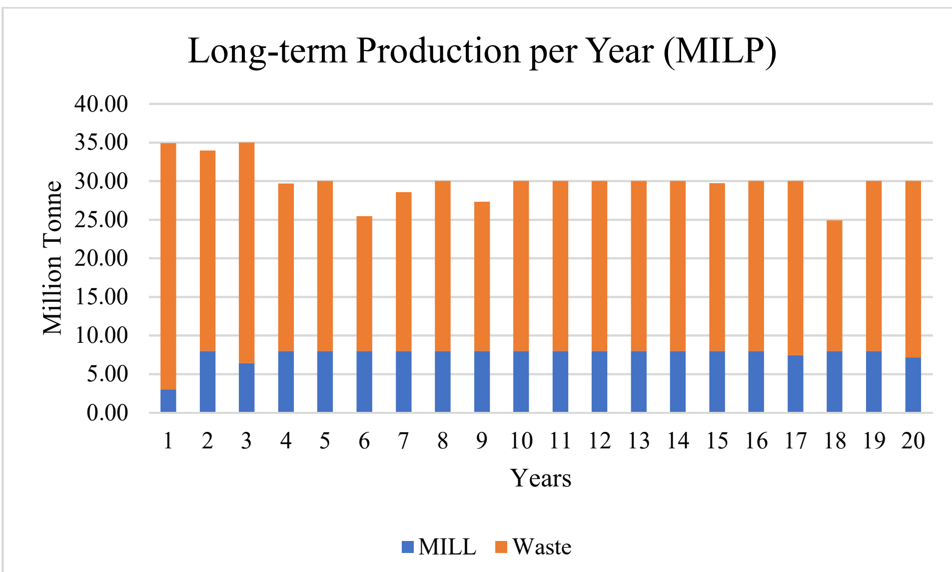

Figure 7. Long-term schedule for Ore IPCC scenario.

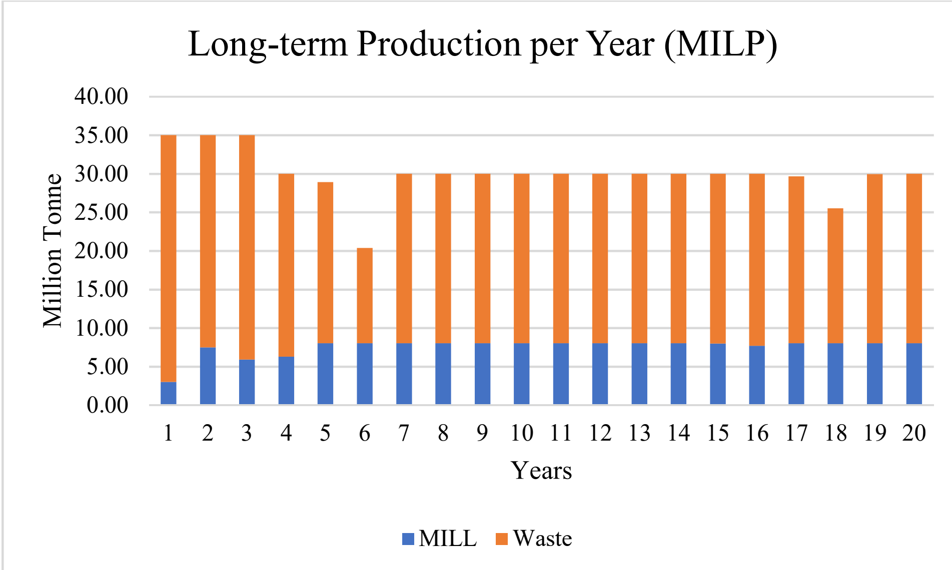

Figure 8. Long-term schedule for Waste IPCC scenario.

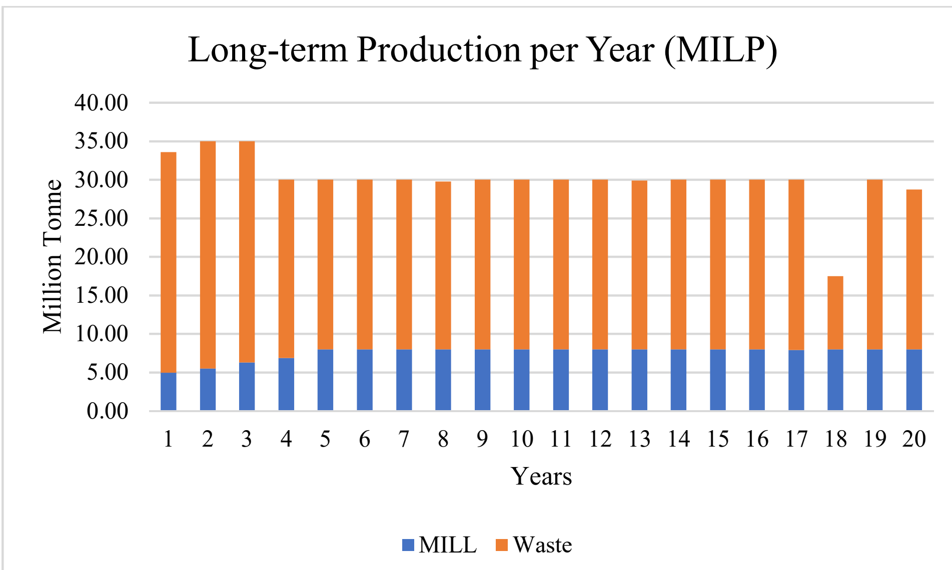

Figure 9. Long-term schedule for Ore & Waste IPCC scenario.

The operation is constrained by the capacity of the mill, meaning the primary objective of the model is to consistently reach the target for feeding the mill. This goal is achieved in scenarios 1 and 4. In scenarios 2 and 3, however, there are noticeable, albeit acceptable, fluctuations in feeding the mill to its maximum capacity due to delays in extraction from the optimum crusher panels. Despite these variations, all scenarios remain profitable, as the discounted cash flow values for the scenario 1 to 4 are $2042M, $2130M, $2119M, and $2350M showing 4.22% improvement by only implementing ore crusher, 3.70% improvement by only implementing waste crusher and 14.02% improvement by implementing both ore and waste crusher.

The subsequent figures demonstrate the sequence of extraction of the crusher panels in the cross-sectional view of northing direction with the plan view strip on the top of the plot. The Y coordinates for the cross-sectional view remains 600400 the same for all the plots. Figure 10 shows the schedule for all the crusher panels in the mentioned section for the No IPCC scenario. However, Figure 11, Figure 12, and Figure 13 show the schedule of the optimum crusher panels demonstrating the capability of the model to account for not extracting the crusher panels for as long as the crusher must be placed on them for Ore IPCC, Waste IPCC and Ore & Waste IPCC scenarios, respectively. The scale, the schedule coloring legend and the Y coordinate kept similar to make the plots comparable. For the sake of better visualization of the pit and the crusher panels, the "to" and "away" distance of 150 m is selected which makes the strips of the cross-section thicker than they should be.

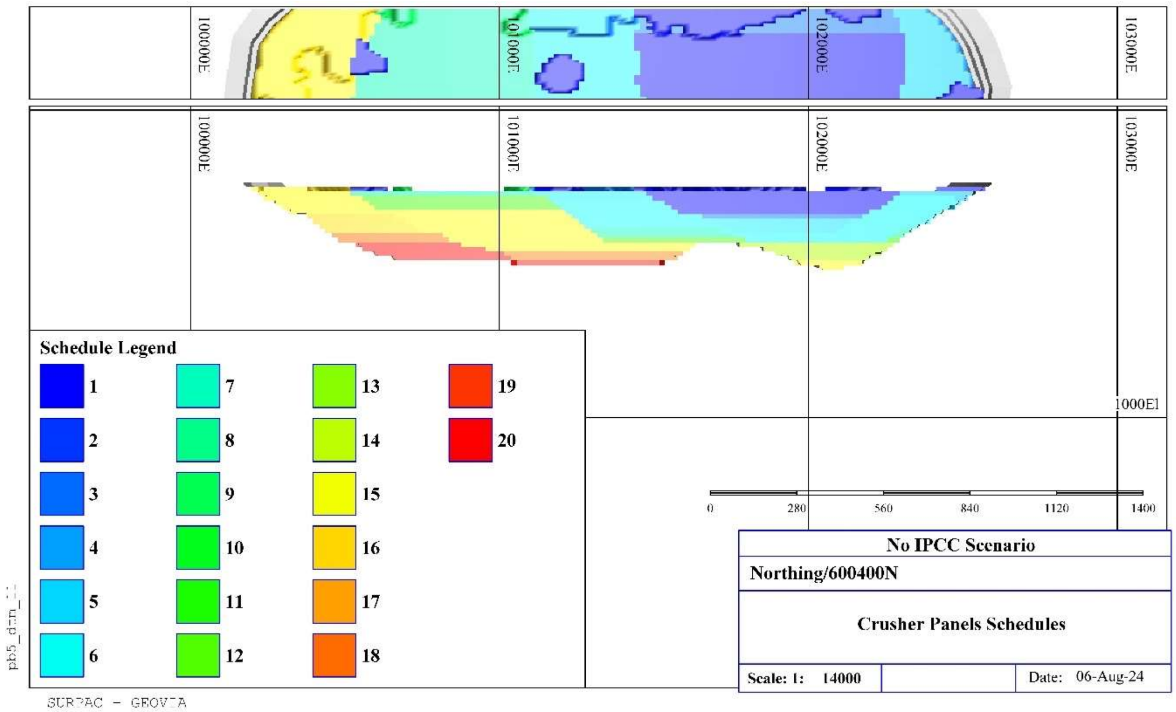

Figure 10. Crusher panels sequence of extraction, No IPCC Scenario.

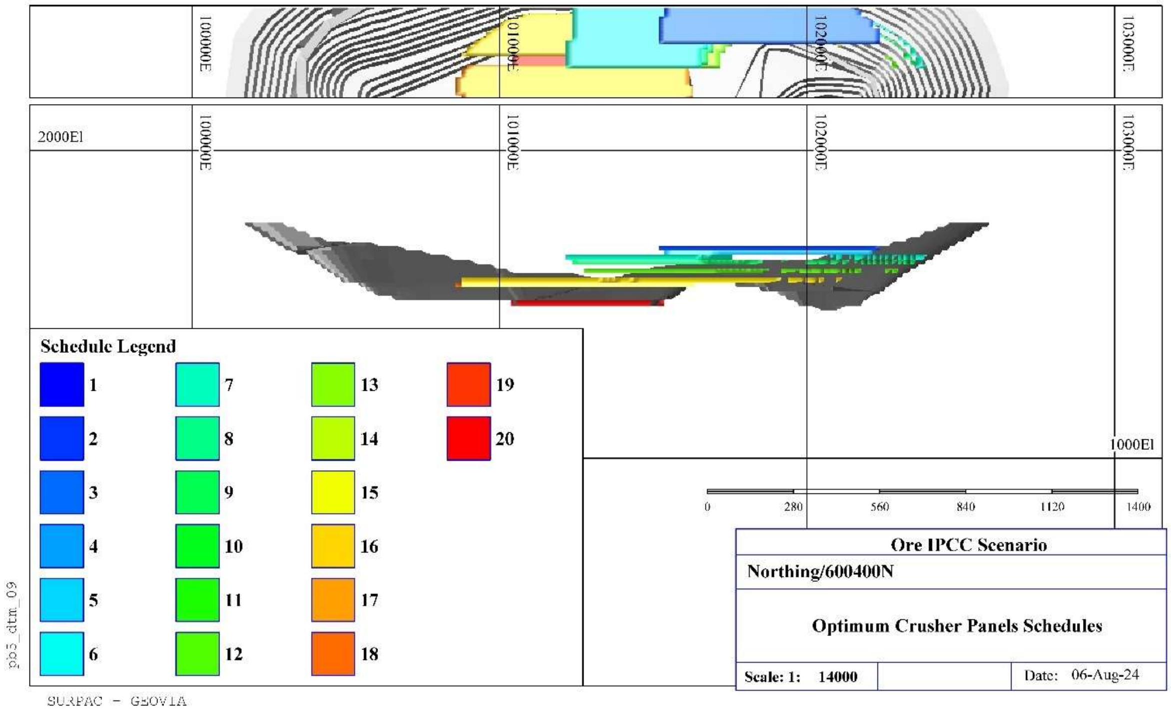

Figure 11. Optimum Crusher Panels sequence of extractions, Ore IPCC Scenario.

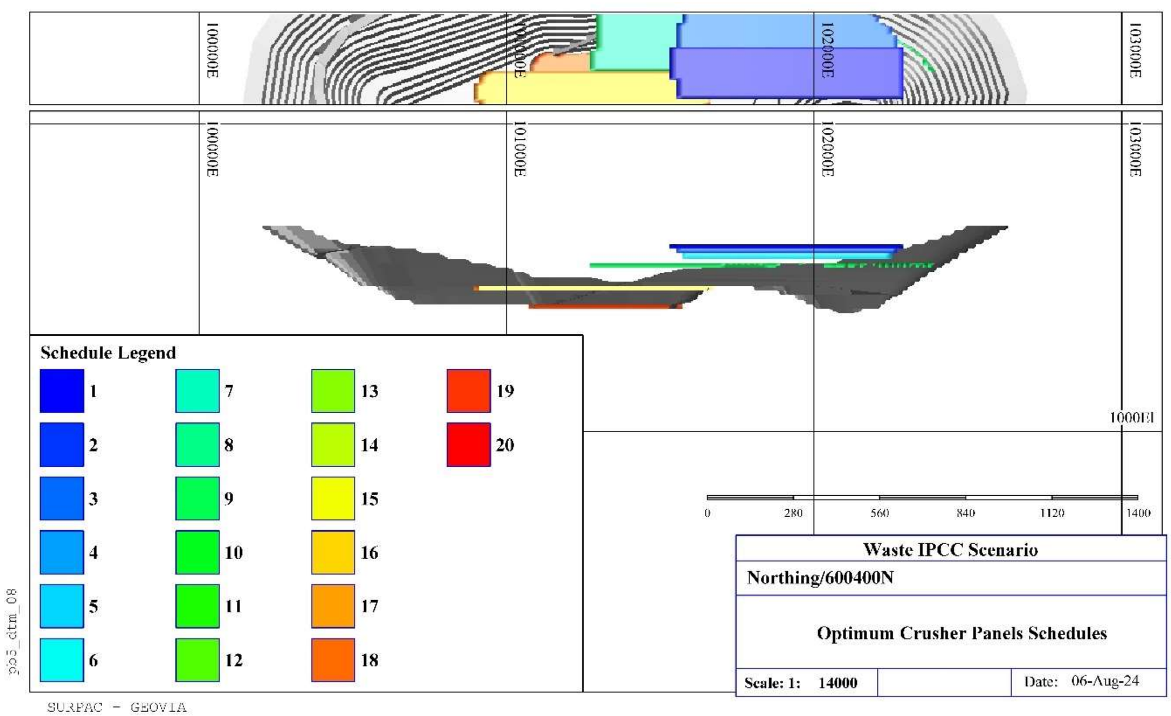

Figure 12. Optimum Crusher Panels sequence of extractions, Waste IPCC Scenario.

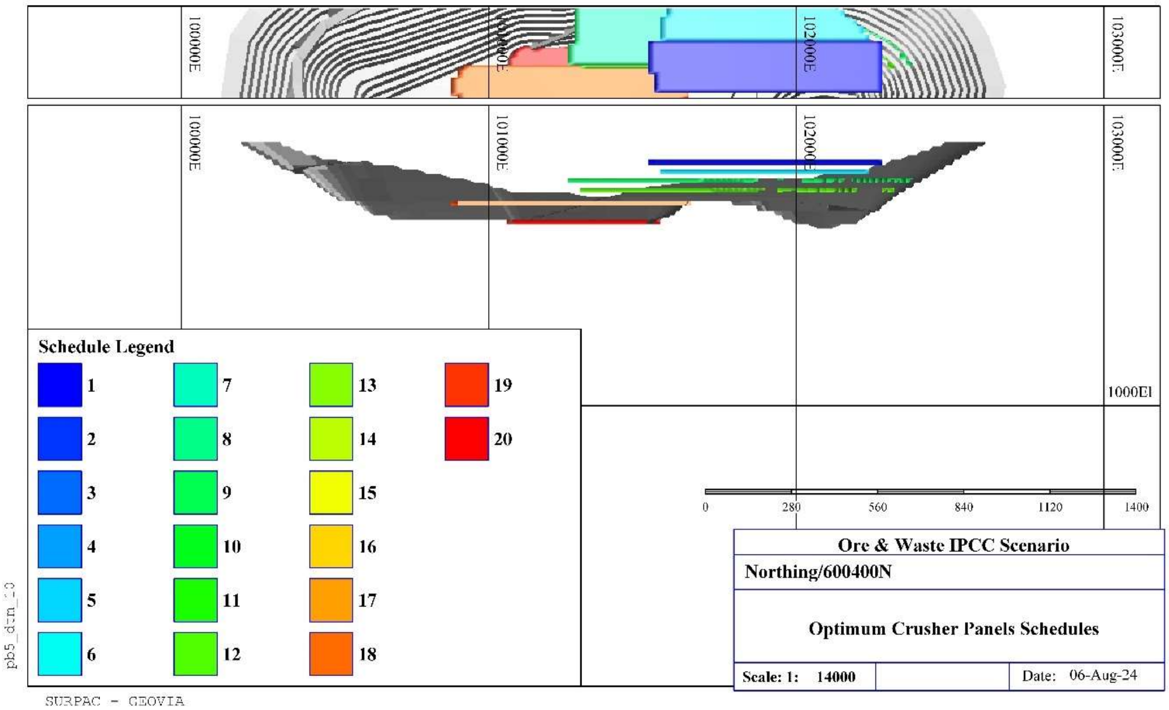

Figure 13. Optimum Crusher Panels sequence of extractions, Ore & Waste IPCC Scenario.

The tonne × kilometre (TKM) is a vital metric used to quantify the transportation of material specifically measures the movement of one tonne of material over one kilometre. TKM is also essential for assessing the efficiency and effectiveness of material handling systems when comparing different configurations, such as IPCC systems versus traditional truck-based methods. By analyzing TKM data, operators can gain insights into the operational performance, energy consumption, and cost implications associated with moving ore and waste across a mine site. To ensure an accurate comparison between scenarios with and without IPCC, it is necessary to focus on the truck-related TKM and truck kilometers traveled, excluding the distances covered by conveyors in IPCC scenarios. This adjustment allows for a direct comparison of the transportation efficiency of trucks in each scenario. Figure 14 shows the TKM cumulative and values for ore, categorized by year, across the four evaluated scenarios: No IPCC, Ore IPCC, Waste IPCC, and Ore & Waste IPCC. Figure 15 presents the TKM values for waste under the same four scenarios, illustrating the annual transportation demands for waste management.

For ore, in the No IPCC scenario, the TKM is 512 million with a total distance of 2,271 km. In the Ore IPCC scenario, after deducting the conveyor contribution, the TKM reduces to 175 million, with trucks covering 801 km. In the Waste IPCC scenario, the TKM is 497 million with a distance of 2,240 km, showing the continued reliance on trucks despite the presence of waste IPCC. In the Ore & Waste IPCC scenario, the TKM for trucks is 174 million with 855 km traveled, indicating the most efficient truck usage when both ore and waste are managed through IPCC.

For waste, the No IPCC scenario shows a TKM of 1,339 million and a distance of 9,283 km, reflecting the extensive truck usage required without IPCC. In the Ore IPCC scenario, the TKM remains high at 1,346 million, with trucks covering 9,300 km, as the waste is still primarily handled by trucks. In the Waste IPCC scenario, after accounting for conveyor contributions, the TKM decreases to 709 million with a travel distance of 5,162 km, illustrating a significant reduction in truck usage. Finally, in the Ore & Waste IPCC scenario, the TKM for trucks further drops to 619 million, with 4,663 km traveled, highlighting the efficiency gains when both ore and waste are managed by conveyors, reducing the reliance on trucks.

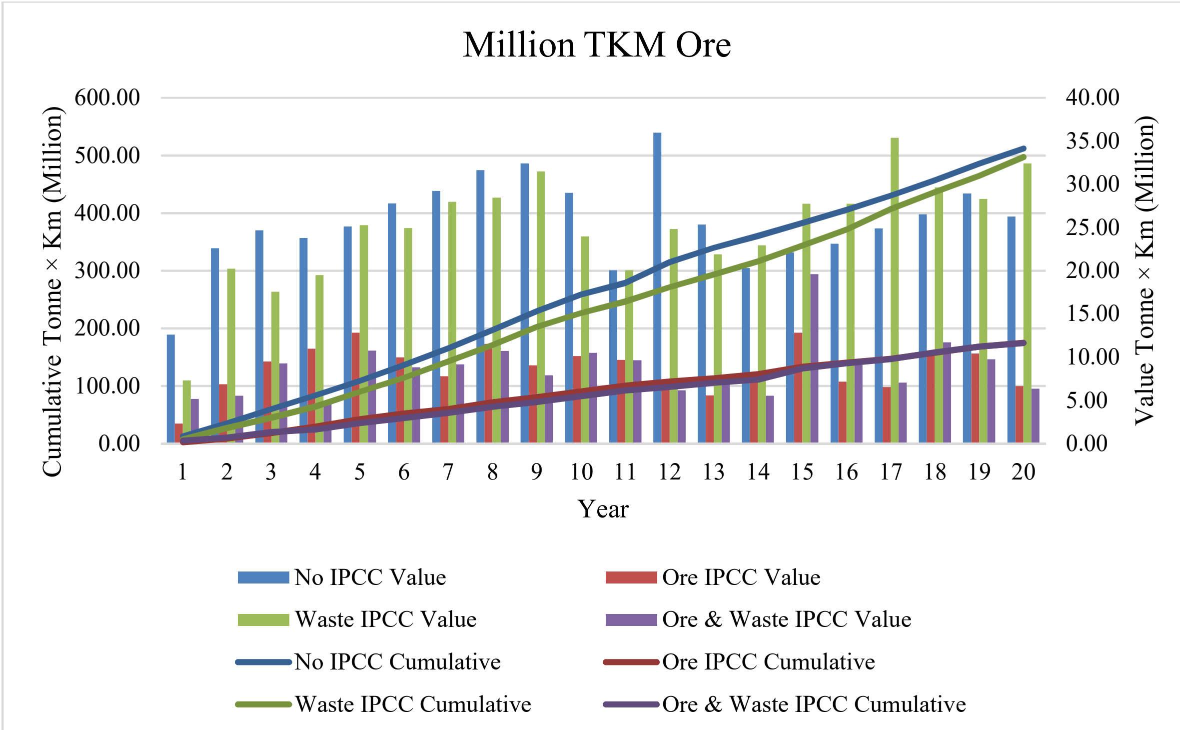

Figure 14. Yearly ore TKM cumulative and values.

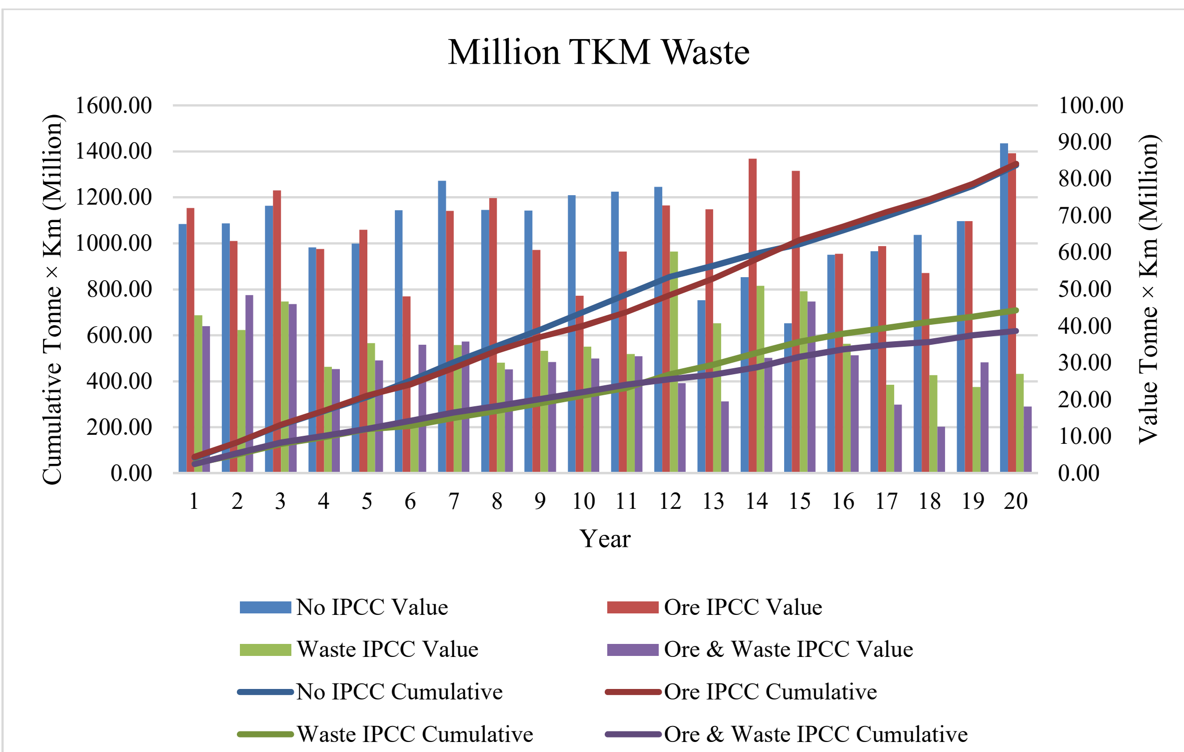

Figure 15. Yearly waste TKM cumulative and values.

To calculate the present value for each year and finally the NPV for better evaluation, we need to determine the number of trucks required for each scenario annually. Additionally, the length of the conveyor system, including the conveyor ramp, must be calculated. This length comprises the distance from the crusher in the crusher panel to the conveyor ramp, conveyer ramp, and from the ramp's exit on the topographic surface to the processing plant and waste dump. For shovel calculations, we have already established a fixed number of ore and waste shovels along with their associated costs. Regarding the conveyor system, we assume that the full length of the ore and waste conveyor costs will be incurred in the first year. This is based on the premise that the addition of a few hundred meters each year will not significantly alter the overall cost. The number of trucks required will be determined based on the total travel distance and the ore and waste tonnage of each mining cut. This calculation, in conjunction with the extraction time for each cut, will establish the necessary number of trucks for ore and waste transport annually. However, this number will vary from year to year due to the differing distances of the mining cuts from the optimal crusher panel, the processing plant, and the waste dump. Hence, it is assumed that once the number of trucks is increased for a specific year, it cannot be decreased in subsequent years. Figures 17 and 18 illustrate the required number of trucks for ore and waste in each scenario, respectively. Figure 19 shows the total kilometers of conveyor required for the ore conveyor in the Ore IPCC and Ore & Waste IPCC scenarios. Similarly, Figure 20 depicts the total kilometers needed for the waste conveyor in the Waste IPCC and Ore & Waste IPCC scenarios.

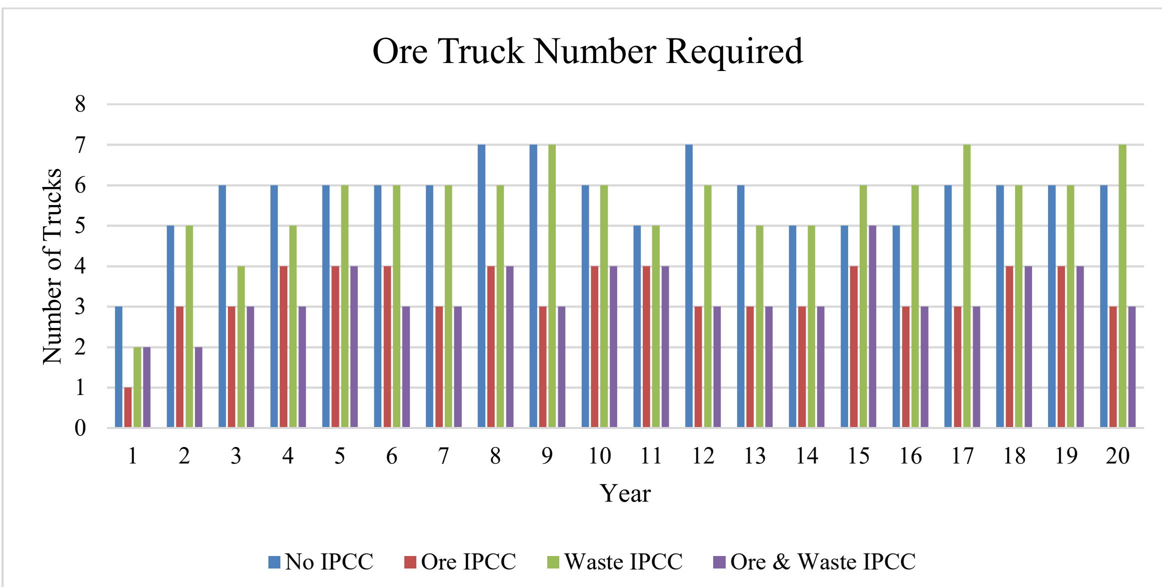

Figure 16. The required numbers of trucks for Ore in each scenario.

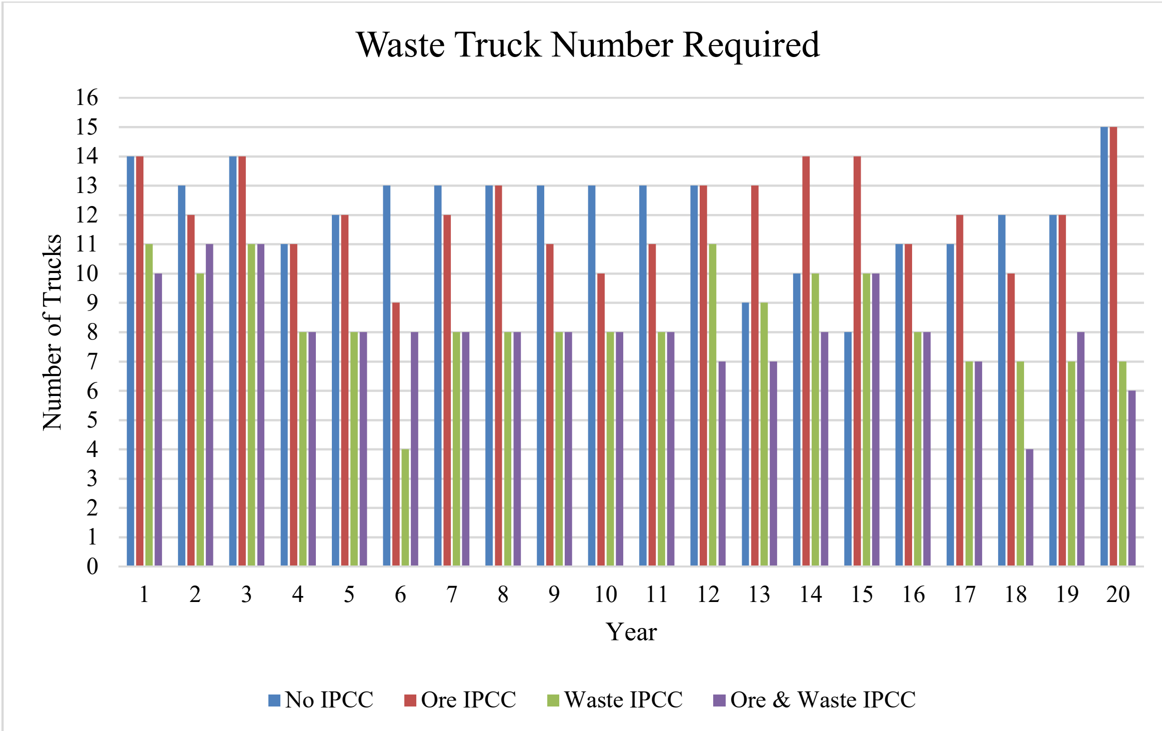

Figure 17. The required numbers of trucks for Waste in each scenario.

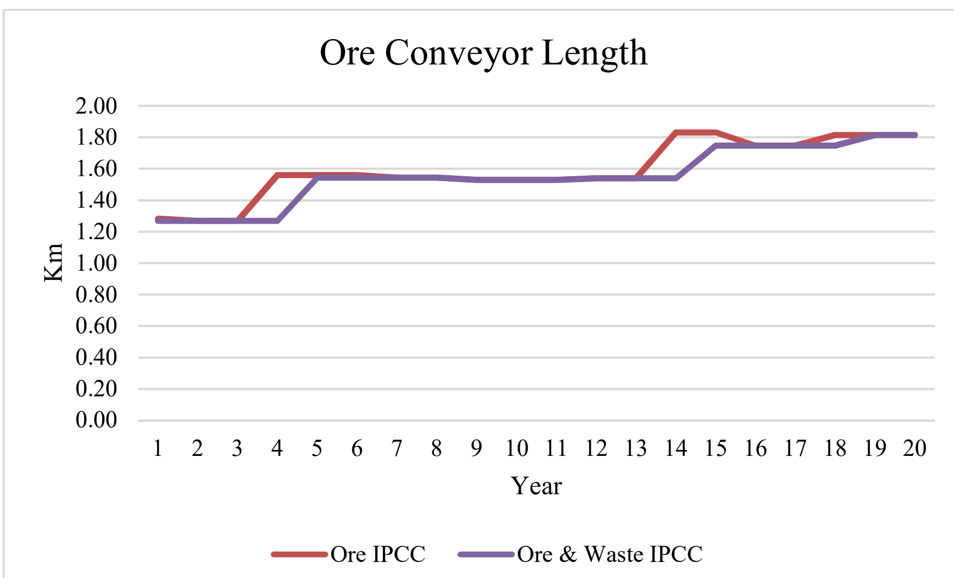

Figure 18. Ore conveyor length through the mine life.

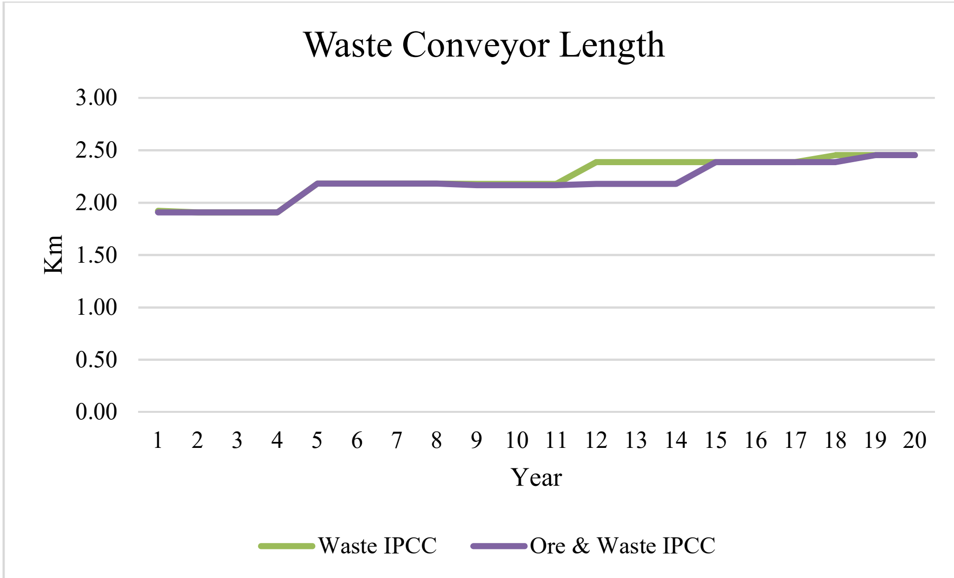

Figure 19. Waste conveyor length through the mine life.

The yearly present value graph is estimated based on the capital investments required for this case study, which includes several key components. Firstly, the investment encompasses a dry separation magnetic processing plant for iron ore with an 8 million tonne per year capacity, presumed to require U$600 million. Additionally, the capital required for drilling and blasting equipment, as well as other road, ramp, and building construction equipment such as dozers, rollers, graders, and sprinkler tankers, totals U$50 million. Furthermore, an additional U$100 million is necessary for other critical items, including an electrical substation, diesel-electric plant, surface electrical distribution system, administrative offices, maintenance shops, change houses, warehouses, and miscellaneous facilities. Altogether, these investments amount to a total capital expenditure of U$750 million.

The subsequent analysis focuses on the costs associated with trucks, shovels, crushers, and conveyors, leading to the net costs for the first scenario (No IPCC) being approximately U$865 million, for Ore IPCC U$884 million, for Waste IPCC U$881 million, and for Ore & Waste IPCC U$900 million. There is also a sizer option for waste, mentioned earlier, which is relatively cheaper compared to crushers. This will be evaluated in the Waste IPSC and Ore IPCC & Waste IPSC scenarios with the net costs of U$ 875 million and U$ 895 million, respectively. Figure 18 shows the present value yearly analysis of four scenarios to determine the economic viability of the in-pit crusher.

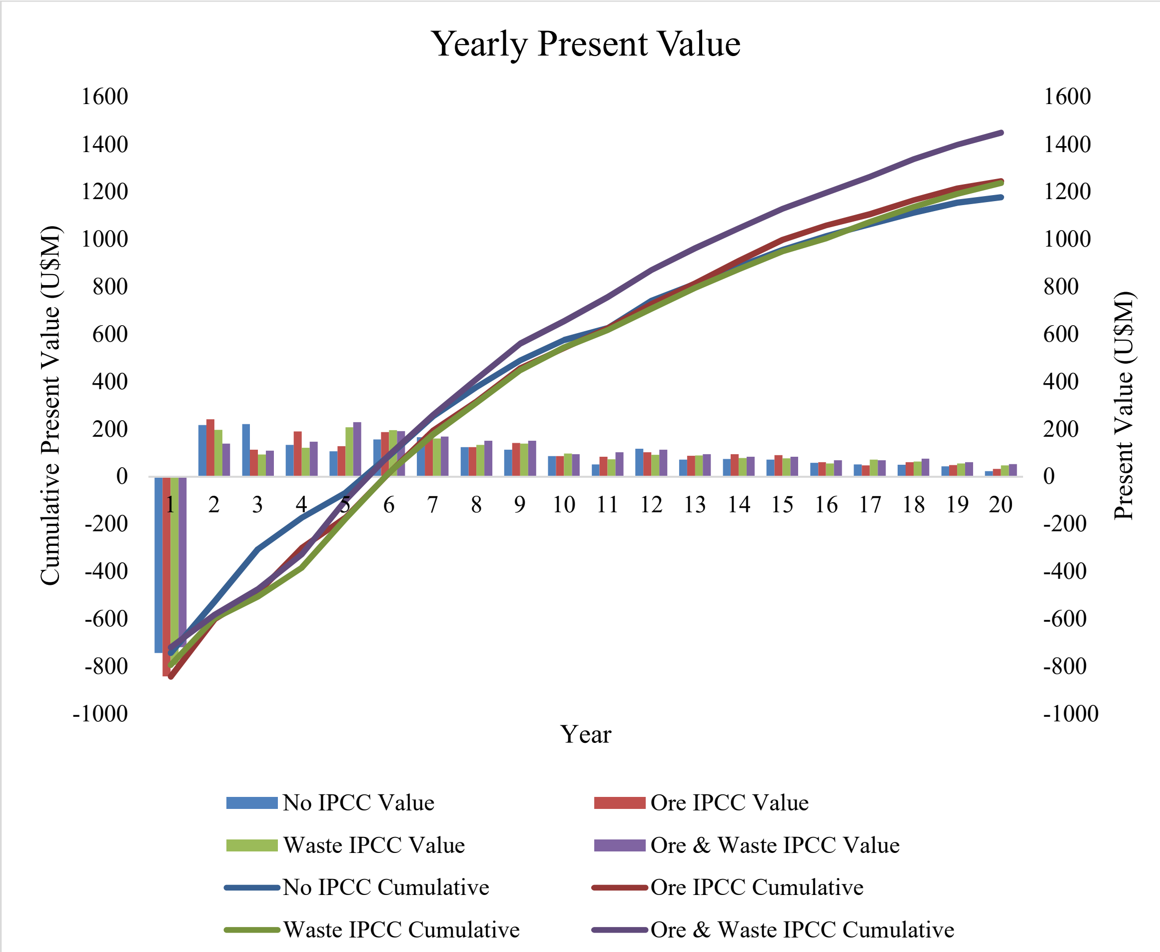

Figure 20. Present value yearly analysis of four scenarios.

The comparison of NPVs for different scenarios of IPCC and IPSC systems reveals interesting insights into their economic impacts. As it can be observed from Figure 18 the payback period is 6 years nearly for all scenarios. The "No IPCC" scenario, serving as the baseline, has the lowest NPV at U$1177 million. Introducing an IPCC system for ore increases the NPV to U$1245 million, representing a 5.76% improvement. Similarly, using an IPCC system for waste results in an NPV of U$1238 million, a 5.16% increase. Combining IPCC for both ore and waste in the Ore & Waste IPCC scenario significantly boosts the NPV to U$1450 million, a substantial 23.17% rise from the baseline. This scenario highlights the potential economic benefits of a comprehensive IPCC system in handling both ore and waste materials.

Switching to a Waste IPSC system yields an NPV of $1244 million, reflecting a 5.68% improvement over the "No IPCC" scenario. However, the most notable increase is observed when combining Ore IPCC with Waste IPSC, achieving the highest NPV of $1455 million, which is 23.66% higher than the baseline. This suggests that integrating both technologies for specific material handling tasks can optimize economic outcomes significantly. The analysis demonstrates that while each individual system (Ore IPCC or Waste IPCC/IPSC) provides moderate economic benefits, integrating IPCC and IPSC for ore and waste handling respectively delivers the most substantial improvement in NPV underscoring the value of adopting a hybrid approach to material handling in open pit mining operations to maximize economic returns.

5. Conclusion and Future Work

In this study, we conducted a comprehensive investigation into the implementation of IPCC across four distinct scenarios using a two-step mathematical model. The first step of the model determines the relocation times and the upper and lower capacities, while the second step provides the long-term schedule and the timing of relocations. This study includes key features such as two stages of clustering, the design of road and conveyor ramps and networks, and a detailed cost analysis.

Initially, the study employs a two-stage clustering approach—first using k-medoid clustering, followed by hierarchical clustering. These techniques are applied to the block model to partition the blocks into rationally sized areas for designated crusher locations, known as crusher panels, and then aggregate the blocks into practical mining units, or blast polygons, referred to as mining cuts. Both can be used as extraction units in the second step of the model. In the first step, based on the distances obtained from the road and conveyor network, we calculate the shortest path from each mining cut to each crusher panel (if all panels are practical options for crusher placement) and then from each crusher panel to either the processing plant or waste dump. The costs are calculated based on the distance for both the truck-shovel (TS) system and the IPCC system. The model then determines the optimal crusher panels based on the lower and upper capacity of material processed or dumped while the crusher operates on each panel. The optimal crusher panels and their corresponding tonnages are input into the second step of the model, which then determines the sequence of material extraction, crusher relocation times, and feeding schedule to the processing plant, aiming to maximize discounted cash flow (DCF). Considering the capital expenditure of the equipment and facilities allows for the calculation of net present value (NPV). Prior to these stages, pushbacks are designed with road and conveyor ramps, considering safety and ramp design considerations.

This proposed two-step model, incorporating two stages of clustering, has been validated with a real-sized iron ore mine, designed with five pushbacks and corresponding road and conveyor networks for IPCC implementation. Four scenarios are investigated, each requiring specific formulation or adjustment to the model: No IPCC, Ore IPCC, Waste IPCC, and Ore & Waste IPCC. These result in four different schedules and outcomes for both steps. Based on technical insights from in-pit crusher manufacturers, sizers can also be applied to waste. Consequently, two additional cost analysis scenarios are introduced: Waste IPSC and Ore IPCC & Waste IPSC. The operation size is set at 30 MT over a 20-year mine life, except for the first three years, during which a contractor increases the capacity by 5 MT. The mill is designed to process 8 MT of iron ore annually.

The results of the first step, after solving it for three scenarios involving IPCC, reveal different optimal crusher panels for each scenario, depending on the concentration of ore and waste and their distances from road and conveyor ramps. However, in all scenarios, the final crusher location is positioned at the bottom of the pit, demonstrating the model's capability to account for the conveyor ramp. After introducing the optimal crusher panels of each scenario into the second step of the model and making necessary adjustments, the results show different extraction sequences for each scenario as expected. Notably, the No IPCC scenario consistently meets mill capacity throughout the 20-year mine life, while the other scenarios exhibit slight fluctuations due to extraction disturbances caused by crushers at the optimal panels.

The Ore & Waste IPCC scenario shows significant advantages, with over a 23% increase in the NPV of the mine, despite an initial capital cost that is over US$36 million higher than the No IPCC base scenario. The impact of the sizer option is minimal (0.5% increase), so it may not be a viable option if it introduces technical complexity from using two different machines. The total kilometers traveled in the Ore & Waste IPCC scenario are reduced by more than 1,400 km for ore and over 4,600 km for waste, indicating significant savings in truck travel.

The major contributions of this study include the development of a two-step mathematical model for determining optimal crusher locations and scheduling open-pit mining in the presence of IPCC, with the goals of minimizing transportation costs in the first step and maximizing NPV within a reasonable timeframe. The model also provides the sequence of extraction while respecting both crusher and slope precedence. Additionally, the study integrates pit design with road and conveyor networks, calculates the shortest path instead of the minimum distance, creates practical blast polygons based on weekly tonnage requirements, introduces an automatic method for selecting crusher panel locations, incorporates technical insights from crusher manufacturers, and calculates NPV for a real-size mine case study under four practical scenarios. The research establishes a workflow for future in-pit crusher studies.

For future research, several areas warrant exploration, particularly those addressing the limitations of the current study. One key area is the development of a simultaneous optimization model that integrates the determination of crusher locations and the scheduling of operations into a single stage. This could enhance the efficiency and accuracy of decision-making by considering both aspects concurrently.

Additionally, future studies should incorporate the environmental impact of both IPCC and truck-shovel (TS) systems into the NPV calculation by including the costs associated with gas emissions from both electrical and diesel-powered equipment. This would provide a more comprehensive assessment of the economic and environmental trade-offs between the two systems, offering a broader perspective on their long-term viability.

Another important consideration is the inherent uncertainty in material handling systems, such as variations in equipment availability, the likelihood of failures, and fluctuations in operational efficiency. These uncertainties can significantly impact the outcomes of different scenarios. Future research should develop a dedicated model designed to handle such uncertainties, possibly through stochastic modeling or reliability analysis, to better capture the real-world variability in mining operations.

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