Simultaneous Optimization of In-pit Crusher Locations and Long-Term Planning of Open Pit Mines

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ABSTRACT

In-pit crushing and conveying system (IPCC) is a solution to decrease the haulage costs in open-pit mining. These costs could be due to the progressive depth of a pit leading to lengthy roads and creating a huge truck maintenance cost. They also could be because of moving towards reducing carbon footprints by using battery electric vehicles (BEVs). Having a shorter route is likely more practical for the BEVs where there are multiple problems if they are to be implemented on a longer road. Some of the challenges are recharging times, variable electrical load tradeoffs, and hauling on steep ramps. In this study, the goal is to propose a generalized optimization model which uses the road network to find the best in-pit locations of the crusher and generates a mine schedule that maximizes the Net Present Value (NPV). Applying this model will enable us to decrease the haulage distance per tonnage of transferable material and optimize the mine plan simultaneously. The model has been verified by applying it to an iron mine case study with two pushbacks. The result shows a significant NPV improvement compared to an out-pit crusher scenario.

1. Introduction

Material handling plays a crucial role in open pit mining operations, encompassing truck haulage and/or conveyor transport. One innovative approach to optimize this process is the use of In-Pit Crushing and Conveying systems (IPCC). This system consists of placing the crusher inside the pit, while the conveyor is positioned in a safe area alongside the benches and outside the pit. The main objective of the IPCC system is to efficiently transfer materials from the mining faces to the processing plant, reducing the reliance on truck haulage and thereby increasing overall efficiency. The success of an open-pit mining operation heavily relies on the reliability of the IPCC system. Factors such as equipment reliability, maintenance, and design play a crucial role in ensuring the practicality and effectiveness of the system. For instance, the location and capacities of the crusher and conveyor are critical design factors that should be integrated into the overall mine planning and design. Ignoring these factors could lead to disruptions in the extraction sequence of the blocks and even impact the ultimate pit limit design (UPL), which determines the final shape and size of the pit. To better understand the concept, refer to Figure 1, which illustrates a schematic view of the mine with two pushbacks, demonstrating the relative locations of different haulage equipment in the presence of the IPCC system.

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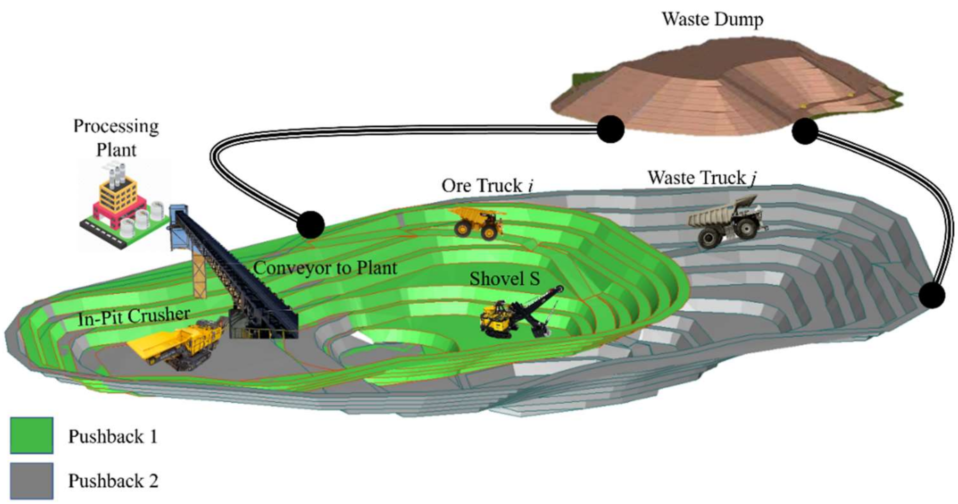

Figure 1. Schematic view of two open pit mine pushbacks with the relative locations of different equipment including semi-mobile IPCC.

This paper proposes a long-term planning methodology to optimize the NPV while minimizing the haulage costs of transporting material to the best locations of the IPCC and conveying them outside of the mining area to the processing plant. While some of the related constraints of this model is similar to the general open pit long-term planning models, there are specific objective function and necessary constraints to make it applicable for finding the best locations and relocation times of the IPCC which in this case is assigned to crush only the ore material inside of the pit. The model takes into account the road network and utilizes the shortest path function to find the minimum travel distance between the loading and dumping spots. Road network is a series of haul roads which connects loading points and dumping points within the mining cuts to inside or outside of the pit (Moradi-Afrapoli & Askari-Nasab, 2022). The important issues in the IPCC location finding in accordance with maximizing the NPV are the contradictory nature and non-linearity of the objective function. Therefore, finding a way to linearize the objective function was one of the biggest challenges of this research.

Mining is an endeavor that demands substantial capital investment, and its success hinges on meticulous production planning to prevent any suboptimal outcomes, particularly regarding equipment utilization. The fundamental goal of any mining project is to maximize the net present value (NPV) while minimizing costs. To achieve this, mine planning is divided into two key phases: long-term planning and short-term planning. Each phase is designed to optimize specific objectives and is based on the planning time horizon. Long-term planning takes place at the strategic level and revolves around maximizing NPV over the entire lifespan of the mine. This comprehensive plan considers various factors such as ore reserves, mineral grades, and economic conditions to devise a sustainable and profitable mining strategy. Conversely, short-term planning focuses on operational optimization within specific timeframes. It aims to enhance day-to-day efficiency by streamlining processes, ensuring optimal equipment utilization, and adapting to changing market conditions.

Throughout history, there has been a consistent endeavor to find ways to incorporate In-Pit Crushing and Conveying systems (IPCC) into open pit mining operations, considering various technical, environmental, design, and planning factors. The 20th century witnessed numerous attempts to explore the feasibility of utilizing IPCC, with particular focus on addressing its technical aspects. These efforts involved studying the installation processes and identifying necessary adjustments to the pit geometry. One significant area of attention in the implementation of IPCC was the modification of pit slopes to accommodate the conveyor ramp design. This adjustment aimed at reducing the overall costs associated with slope reduction, thereby optimizing the conveyor system's efficiency. The exploration of using high slope conveyors was also part of these trials, as it presented another potential solution to improve the functionality and practicality of the IPCC system. (Dos Santos & Stanisic, 1986; Lonergan & Barua, 1985; Sturgul, 1987).

Based on Al Habib et al. (2023) post 2010 there are around 32 papers investigating IPCC option only four of which are about the incorporation of long-term planning and IPCC. Al Habib et al. (2023) says this number reduces to zero when it comes to the short-term planning and IPCC reconciliation. In recent times, the emphasis of researchers has shifted towards conducting investigations aimed at identifying optimal, near optimal or even best placements for in-pit crushers within mining operations. These studies delve into the intricate task of pinpointing strategic locations where the in-pit crusher can be situated. These identified locations present an array of benefits, ranging from technical advantages to economic gains (Konak et al. 2007; Rahmanpour et al., 2014; Roumpos et al., 2014). In 2023, Gong et al. proposed a MILP model for solving a near face stockpile where there is a crusher next to the stockpile to crush the blended material. Based on them, this new way of mining will increase the tolerance on production uncertainty and equipment utilization. They further developed their work to integrate simulation and optimization to propose a new model of near-face stockpile for short-term planning. Their model is then validated by an oil-sand mine data (Gong, Moradi Afrapoli, et al., 2023).

When considering long-term planning for mining operations involving In-Pit Crushing and Conveying (IPCC) systems, the selection and development of a suitable mine scheduling model becomes pivotal. This model must possess both technical prowess and practical applicability to effectively accommodate the complexities of the operation. According to Noriega & Pourrahimian (2022) using the metaheuristic has become a prevalent approach to tackle the complex large-scale feature of the long-term and short-term production planning with emphasis on genetic algorithm and simulated annealing methods. The important concern of these metaheuristic approaches is creating a model relying too much on the case study and making the model hard to be generalized. To address this complexity, the concept of creating mining cut implications emerges as a prominent solution, offering a practical approach to streamline the mathematical model's complexity. Notably, this idea was first introduced by (Askari-Nasab et al., 2010). In their research, they proposed the utilization of fuzzy logic clustering as a means to generate mining cuts for individual benches. This approach aimed to enhance efficiency by partitioning the mining blocks into coherent groups. However, a limitation arose in their initial implementation, as the technique did not account for the spatial arrangement of mining pushbacks. Consequently, instances occurred where a single mining cut encompassed blocks from adjacent pushbacks, potentially leading to suboptimal results. To overcome this challenge, an evolution took place in the method for generating mining cuts. This transformation occurred when Tabesh & Askari-Nasab (2011) introduced an innovative approach, replacing fuzzy logic clustering with an unsupervised machine learning technique known as hierarchical clustering. This advancement enabled the creation of mining cuts not only within each individual pushback but also by leveraging similarity indices for crucial parameters such as ore grade, rock type, and more. As a result, the revised method fostered more accurate and coherent mining cut delineations, enhancing the precision of long-term mine scheduling. Then this notion of mining cut creation resonates widely across diverse mine planning endeavors. Whether the focus is on scheduling for operations involving oil sands extraction or addressing environmental considerations such as tailing storage facility management or using it to schedule an underground mine, the approach has found successful implementation. The adaptability and robustness of this approach have enabled it to transcend specific contexts, contributing to a broader understanding of how to optimize mining operations efficiently (Badiozamani et al., 2019; Eivazy & Askari-Nasab, 2012; Koushavand et al., 2014; Maremi et al., 2021; M Tabesh et al., 2015; Mohammad Tabesh et al., 2014; Farshad Nezhadshahmohammad & Yashar Pourrahimian, 2019; Seyed Hosseini et al., 2020). Subsequent to its initial development, this approach underwent further refinement to enhance its capabilities. Notably, the method was subjected to iterative enhancements that encompassed the automatic generation of mining polygons, as pioneered by (Tabesh & Askari-Nasab, 2013). Additionally, in a subsequent advancement, the method was fortified to confront the complexities arising from geological uncertainty (Tabesh & Askari-Nasab, 2019).

Since the location of the IPCC will impact the extraction sequence of the successor blocks or mining cuts due to the relocation time span and the fact that a specific location/s must be kept unextracted during the mine life, the mine schedule needs to be reassessed for making it compatible with the new condition. The critical point in this subject is to find the best locations which minimizes the haulage costs while obtaining the optimum extraction sequence and maximizing the NPV. This type of optimization is what we call it the simultaneous optimization in this research. Regarding the simultaneous optimization literature, there are only a few studies that are solved either for hypothetical case studies or with heuristic approaches. For example, in a study prepared by Paricheh & Osanloo (2020) the Mixed Integer Linear Programming (MILP) is proposed for a simultaneous optimization scenario for a semi-mobile IPCC where both the mine scheduling and IPCC location and relocation times are considered at the same time. However, they used two hypothetical copper deposits to verify their model with either a very limited number of blocks or very large block sizes which does not represent a practical mine open pit mining operation. Another example is a model proposed by Samavati et al. (2020) to optimize the mine schedule and a mobile IPCC which accounts for the locations of the conveyor. They attempted to schedule the blocks looking at the different compartments of the conveyor for a fully mobile IPCC system suggesting 16 equations to honor the block precedence considering different locations of the conveyors which will simply multiply by the number of blocks meaning that the model could grow up exponentially . Liu & Pourrahimian (2021) proposed a method to identify the conveyor line by exploring the pit limit from different perspectives. In their approach, the shape of mining cuts, or aggregated mining blocks is determined based on the conveyor location which the extraction should follow. They evaluated eight different conveyor locations and compared the scenarios to identify the best mine schedules that maximize the net present value (NPV). Once the optimal scenarios are identified, the location of the crusher and the relocation time (an input parameter) can be determined. The methodology's optimization is at the mining cut level, but since the extraction decision variable is binary, the model may not satisfy capacity constraints. Additionally, their model will not result in an optimal solution since it investigates scenarios to find the best answer among specified scenarios rather than calculating the global optimal solution Shamsi et al. (2022). addressed a mathematical model comparing the truck-shovel and IPCC system as the transportation means aiming to select the highest NPV. According to their model, each haulage method, truck shovel or IPCC for each type of material being ore or waste is one binary decision variable creating four different decision variables. The results show that the IPCC system could improve the NPV by 69%. However, to verify their model, they solved it in a 2D section of a deposit case study with few blocks.Top of Form

The existing literature in both Long-term planning optimization and IPCC optimization models reveals significant gaps that hinder the practical integration of long-term models with IPCC considerations. Three main obstacles emerge: Firstly, cost estimation predominantly relies on a simplistic $/t metric. Secondly, the models overlook critical equipment demands, such as truck requirements over the mine's operational lifespan. Thirdly, the excessive simplification assumption within the models renders them infeasible for real-world case applications. In the realm of IPCC optimization, two distinct modeling approaches are evident: one focusing solely on optimizing in-pit crusher locations without considering the mine extraction sequence, and another that simultaneously optimizes both mine scheduling and crusher placements. Additionally, the process of identifying potential locations for crushers entails either algorithm-based automated results or parametric-based dispersed outcomes.

The study reveals a conspicuous absence of the use of road network alongside the optimization of IPCC locations in the mine planning literature. Although previous research attempted to estimate costs based on direct distances, such an approach fails to account for the actual travel distance, which could be accurately represented by incorporating the road network. To address the identified research gaps, a novel approach is proposed, centered around integrating the road network into the optimization framework. This integration would transform the unit cost from the traditional $/tonne to $/tonne.Km, offering a more realistic cost estimation. Furthermore, leveraging the road network enables a straightforward calculation of equipment demand by considering both material tonnage transferred and the total distance to be covered. To mitigate the complexity imposed by numerous constraints and to enhance practicality, this study introduces the concept of creating practical extraction units or blast polygons through techniques like block aggregation or mining cut creation.

Furthermore, the study recognizes the need for meticulous preparations when implementing a semi-mobile IPCC system. This entails a series of assembly arrangements spanning from truck dump locations to crusher feeders or bridges, culminating in the crusher discharge point at the conveyor. The study introduces the concept of "crusher panels" to denote these key installation spots. Notably, the selection of crusher panel placement significantly influences the extraction sequence and precedence constraints. As such, the study emphasizes the importance of choosing appropriately scaled crusher panels that align with practical mining widths and the average differences between pushback sizes. Figure 2 visually illustrates the interplay between in-pit crusher placement, the road network, conveyors, and crusher panels, underscoring their interconnectedness.

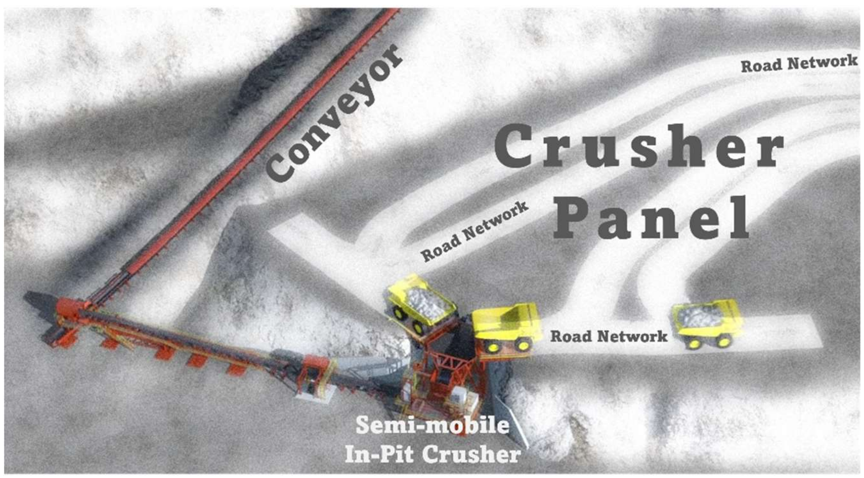

Figure 2. IPCC system position with the crusher panel and road network.

This paper introduces a pioneering simultaneous Mixed Integer Linear Programming optimization model designed to optimize the placement of in-pit crushers within a mine concurrently with the long-term mine schedule. The decision variables of this innovative approach operate at the mining-cut level, encompassing mine polygons or blast patterns formed through a hierarchical clustering algorithm. The methodology harnesses the mine's actual road network, inclusive of distinct roads and ramps, to optimize the positioning of the In-Pit Crushing and Conveying (IPCC) system. This optimization aims to minimize haulage costs through a nonlinear objective function, which is subsequently linearized by introducing an auxiliary variable. The primary objective of this model is to maximize the mine's Net Present Value (NPV) while simultaneously minimizing haulage costs. In essence, this proposed method presents a pragmatic avenue for enhancing in-pit crusher placement by factoring in the tangible road network within the mine, thereby enriching the decision-making process. The method further takes into meticulous consideration the precise geometry of mining cuts, a factor with considerable influence on extraction process efficiency and efficacy.

2. Methodology

In this research, we present a comprehensive methodology for optimizing the strategic placement and relocation timing of in-pit crushers within a mining operation. The primary goal is to maximize the Net Present Value (NPV) of the mining project while minimizing haulage costs. This approach combines economic, operational, and geological considerations to facilitate well-informed decision-making in mining operations. The optimization problem is framed as a dual objective: maximizing NPV and minimizing haulage costs within one objective function, with a focus on haulage optimization influencing in-pit crusher placement and movement. This entails the compound task of determining the optimal locations for in-pit crushers, strategically forming crusher panels, delineating mining cuts, and establishing efficiently adopting the road networks. Moreover, factors such as the minimum mining width and pushback dimensions are taken into account to ensure the feasibility and practicality of the proposed solution. The following steps are mandatory for the proposed model application.

1. Pushback and Road Network Design:

The initial step involves delineating pushbacks, which serve as distinct mining areas. Within each pushback, the road network and ramps are extracted to establish a basis for subsequent analysis and optimization.

2. Crusher Panel Nomination via K-Medoid Clustering:

To identify potential in-pit crusher sites, we employ the k-medoid clustering algorithm. This technique allows us to cluster nominated crusher locations, referred to as "crusher panels," based on their alignment with the minimum mining width. These panels represent potential sites for in-pit crushers.

3. Crusher Panel Formation:

Building upon the nominated locations, we establish crusher panels within each pushback. The number of panels is influenced by both the dimensions of the pushback and the minimum mining width. These panels serve as fundamental units for subsequent stages of optimization.

4. Mining Cut Aggregation using Hierarchical Clustering:

Practical blasting polygons, or mining cuts, are formed within each crusher panel to streamline the mining process. Hierarchical clustering is employed to aggregate identified blocks into coherent mining cuts based on the similarity index of each of the blocks, enhancing operational efficiency.

5. Haulage Cost Calculation:

Calculating haulage costs is pivotal in optimizing the crusher locations and relocation times. By assessing transportation expenses from each mining cut to the respective crusher panel center, as well as from the panels to the processing plant, we obtain a comprehensive understanding of operational costs.

6. Simultaneous Optimization Model:

At the heart of our methodology lies the development of a simultaneous optimization model. The nonlinear formulation is transformed into a linear representation, which is then solved using the CPLEX solver connected to MATLAB. This model seeks to strike a balance between maximizing NPV and minimizing haulage costs, thereby guiding decision-making.

The results of the optimization process yield the optimal crusher panels that offer the lowest haulage costs. These panels, along with the most favorable relocation times, contribute to defining an optimized mine schedule that simultaneously maximizes NPV and minimizes operational expenses.

3. Clustering

The shape of a block model is rectangular and represents an orebody that is divided into uniform-sized shapes called blocks. Although the block model facilitates mine planning and extraction, it can make the problem size intractable for large deposits with millions of blocks, especially when optimizing the extraction schedule over many time periods. Aggregation techniques are used to generate minable continuous mine plans that are achievable in practice and to reduce the problem size. To this end, block aggregation using a clustering algorithm is suggested. Blocks aggregate to mining cuts based on their similarity in rock type, ore grade, and distance.

Clustering is an unsupervised machine learning algorithm that distinguishes between data based on similarities or dissimilarities. Hierarchical and partitioning are two ways to cluster data. In this study, clustering algorithms are used to propose a new way of choosing candidate locations for the crusher and creating crusher panels inside each mining phase on every bench. Block aggregation has a long history in long-term open pit mine planning to reduce the problem size and computational time of such an optimization problem. The methods of block aggregation in their early use were based on the technical features of the blocks. However, more complicated clustering methods have been developed to comply with mine planning requirements, which require solving a linear programming mathematical optimization. The most common procedure is applying either hierarchical or partitioning clustering.

The clustering algorithm proposed in this paper creates crusher panels using the k-medoids algorithm, and then hierarchical clustering is used within the crusher panels. Similar to what was proposed by (M Tabesh & Askari-Nasab, 2011), the idea of distance hierarchy is applied to calculate the similarities between categorical variables. A penalty function is developed to calibrate the function in the distance hierarchy method. The similarity value between blocks i and j is estimated using Equation 1.

$$S_{ij} = \frac{R_{ij} C_{ij}}{\tilde{D}_{ij}^{w_D} \tilde{G}_{ij}^{w_G}} \tag{1}$$

where R_{ij} is the penalty assigned if blocks are from different rock types, C_{ij} is the penalty assigned to blocks not located above the same cluster, $\widetilde{D_{ij}}$ represents the normalized distance value between blocks i and j, $\widetilde{G_{ij}}$ represents the normalized grade difference between blocks i and j, and D_{ij} is the Euclidean distance between centers of blocks i and j.

The k-medoids algorithm is a type of partitioning clustering and is similar to the k-means algorithm in terms of performance function and iterative process. The general procedure of k-medoids clustering is summarized as follows (Kaufman & Rousseeuw, 2009):

1. Assume k arbitrary clusters where there are $S_1, S_2, \ldots, S_k$ representatives as medoids for each cluster c_1 to c_k.
2. Given S_1 to S_k medoids, update cluster c_k with the minimum distance rule applied to the performance function and call it c_k'.
3. Given cluster c_k, update the medoid S_k and check the stop condition.
4. Stop if the new $c_k' = c_k$, then make $S_k = S'$; otherwise, repeat steps 2 and 3.

Using the k-medoids and categorizing each bench within its pushback would be the first step of this framework in which the blocks are clustered as crusher panels. The next step is to implement the blocks' cluster within the boundary of the crusher panel while preserving the precedence. The crusher location optimization process uses the medoids to calculate the related distance and cost for the crusher location problem.

4. Mine scheduling in presence of IPCC

In this section, the MILP formulation will be presented which will take care of the optimization for the IPCCs locations, relocation times and mine schedules while a crusher occupies multiple blocks, thereby obstructing a specific crusher panel from being extracted for a predetermined period. However, the general MILP formulation in the long-term open pit mine planning premise can not handle the IPCC arrangement therefore needs to be reformulated to address all the objectives of this research. The objective function, as described in Equation 2, aims to maximize NPV by identifying the optimal extraction periods (T) for both the portion of the mining cut ($x_{k,p,t}$) sent to the mill and the portion of the panel ($d_{p,t}$)sent to the waste dump. In this equation, $v_{k,p,t}$ represents the discounted revenue minus the extra cost of mining ore in the mining cut $x_{k,p,t}$, whereas $q_{p,t}$ denotes the discounted cost of mining.

This model has six decision variables, three of which are continues from zero to one and the other three are binary. The first three continuous starts with the variable accounting for the amounts of ore must be sent to the mill (x) from each mining cut k in which period t and to which crusher panel p. The second one is the amounts of waste must be extracted (d) in which period t from each panel p, and the third one is an auxiliary variable w which is added to linearize the non-linear equation of $x \times l$. The other three binary decision variables are b which is to hold the precedence corresponding to the crusher panels extracted in period t and onwards equals to one and zero otherwise. The second binary variable is y', an auxiliary variable to guarantee that the crusher panel will remain unextracted for the assigned period/s. The last binary variable is l to decide the best locations of the IPCC by finding the best crusher panels p over time t and assigning mining cut k for transferring to them. The goal here is to minimize the haulage costs.

$$\max \sum_{t=1}^{T}\sum_{p=1}^{P}\left(\sum_{k=1}^{K}(v_{k,p,t}\times x_{k,p,t})-(q_{p,t}\times d_{p,t})\right) \tag{2}$$

subject to

$$ml^{t} \le \sum_{p=1}^{p}(o_{p}+w_{p})\times d_{p,t} \le mu^{t} \quad \forall t\in\{1,...,T\} \tag{3}$$

$$pl^{t} \le \sum_{p=1}^{P}\sum_{k=1}^{K} o_{k}\times x_{k,p,t} \le pu^{t} \quad \forall t\in\{1,...,T\} \tag{4}$$

$$\sum_{k=1}^{K} o_{k}\times x_{k,p,t} \le (o_{p}+w_{p})\times d_{p,t} \quad \forall t\in\{1,...,T\}, p\in\{1,...,P\} \tag{5}$$

$$0 \le \sum_{k=1}^{K}(g_{k}^{e}-gl^{t,e})\times o_{k}\times x_{k,p,t} \quad \forall t\in\{1,...,T\}, e\in\{1,...,E\} \tag{6}$$

$$\sum_{k=1}^{K}(g_{k}^{e}-gu^{t,e})\times o_{k}\times x_{k,p,t} \le 0 \quad \forall t\in\{1,...,T\}, e\in\{1,...,E\} \tag{7}$$

$$\sum_{t=1}^{T} d_{p,t} = 1 \quad \forall p\in\{1,...,P\} \tag{8}$$

$$b_{p}^{t}-\sum_{i=1}^{T} d_{s}^{i} \le 0 \quad \forall t\in\{1,...,T\}, p\in\{1,...,P\}, s\in C_{p} \tag{9}$$

$$\sum_{i=1}^{T} d_{p}^{i}-b_{p}^{t} \le 0 \quad \forall t\in\{1,...,T\}, p\in\{1,...,P\} \tag{10}$$

$$b_{p}^{t}-b_{p}^{t+1} \le 0 \quad \forall t\in\{1,...,T-1\}, p\in\{1,...,P\} \tag{11}$$

$$FORLOOP \quad d_{v} = the\ No.\ of\ Optimum\ Crusher\ Panels$$

$$\sum_{h\in d_{v}}\sum_{t=1}^{tloop} d_{h}^{t} + M\, y_{t}^{'} \ge length(d_{v}) \quad \forall tloop\in\{1,...,T\} \tag{12}$$

$$\sum_{ny\in No.of\ Yrs} -b_{ny} - M\, y_{tloop}^{'} \le -ny \quad \forall tloop\in\{1,...,T\} \tag{13}$$

$$\sum_{t=1}^{tloop}\left(y_{t}^{'}+\sum_{i=t+1}^{tloop}\frac{y_{i}^{'}}{tloop-t}\right)\le 1 \qquad \forall tloop\in\{1,...,T\} \tag{14}$$

$$END\ of\ FOR\ LOOP$$

$$x_{k,p,t}, d_{p,t}, w_{k,p,t} \in [0,1] \ \forall t\in\{1,...,T\}, p\in\{1,...,P\}, k\in\{1,...,K\} \tag{15}$$

$$b_{k,t}, y_{t}', l_{k,p,t} \in \{0,1\} \ \forall t\in\{1,...,T\}, k\in\{1,...,K\}, p\in\{1,...,P\} \tag{16}$$

Knowing that $x_{k,p,t}$ and $d_{p,t}$ are the decision variables, $v_{k,p,t}$ and $q_{p,t}$ can be broken down to Equations 17 & 20 from which we can obtain the revenue of selling mining cut *k* being extracted in period *t* and sent to the crusher panel *p* as $Rev_{k,p,t}$. Similarly, the Total Mining Cost (TMC) of extracting mining cut *k* in period *t* and sending it to the crusher panel *p* is called $TMC_{k,p,t}$. From there, $TMC_{k,p,t}$ is equal to general cost of mining cut *k* extraction ($mc_{k,p,t}$) plus the haulage cost which constitutes the Equation 18 if there is an ore crusher in the pit and Equation 19 if the material is transferred to outside of the pit using truck shovel. It is worth noting that since there is no need to optimize the crusher location when the material handling method is truck shovel, in Equation 19 we do not need to have subset *p* referring to the crusher panels.

$$v_{k,p,t} = \frac{\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T} \mathrm{Re}\, v_{k,p,t} - TMC_{k,p,t}}{(1+r)^t} \tag{17}$$

If there is an Ore Crusher in the pit :

$$TMC_{k,p,t} = mc_{k,p,t} + \left[\left((SPath_{k,p} \times o_k \times c_{k,p,t}) + (Pdist_p^{pl} \times o_k \times cn_p^{pl,t})\right) \times l_{k,p,t} - (SPath_k^{du} \times w_k \times c_k^{du,t})\right] \tag{18}$$

else, will be handled by Truck Shovel (Shortest Path):

$$TMC_{k,t} = mc_{k,t} + \left((SPath_k^{pl} \times o_k \times c_k^{pl,t}) - (SPath_k^{du} \times w_k \times c_k^{du,t})\right) \tag{19}$$

$$q_{p,t} = \frac{\sum_{p=1}^{P}\sum_{t=1}^{T} TMC_{p,t}}{(1+r)^t} \tag{20}$$

The Waste will be handled by Truck Shovel (Shortest Path) :

$$TMC_{p,t} = mc_{p,t} + (SPath_p^{du} \times w_p \times c_p^{du,t}) \tag{21}$$

Let's look further at the Equation 18 where we have general mining cost + haulage costs making it look like the following:

$$TMC_{k,p,t} = mc_{k,p,t} + \left\{ \begin{matrix} \begin{bmatrix} \text{To Ore InPit Crusher } (\text{By Truck \& ShortestPath}) + \\ \text{To Plant } (\text{By Conveyor \& MinimumDistance}) \end{bmatrix} \times l_{k,p,t} \; - \\ \text{To Waste Dump } (\text{By Truck \& ShortestPath}) \end{matrix} \right\} \tag{22}$$

We can summarize Equation 22 into the following:

$$TMC_{k,p,t} = mc_{k,p,t} + (HC_{k,p,t} \times \; l_{k,p,t}) - Ext_{k,p,t} \tag{23}$$

Now we can change the objective function and make it compatible with the new condition of in-pit crusher location determination. Equation 24 is the new non-linear objective function having the $x_{k,p,t}$ and $l_{k,p,t}$ multiplied both are decision variables aiming for maximizing NPV. We will then linearize this objective function by introducing a new auxiliary variable *w* and a set of constraints relating *w* to *x* and *l*.

$$\max \sum_{t=1}^{T}\sum_{p=1}^{P}\left(\sum_{k=1}^{K}\left((Rev_{k,p,t} - mc_{k,p,t} + Ext_{k,p,t}) \times x_{k,p,t} - HC_{k,p,t} \times x_{k,p,t} \times l_{k,p,t}\right) - (q_{p,t} \times d_{p,t})\right) \tag{24}$$

Assuming that $x_{k,p,t} \times l_{k,p,t} = w_{k,p,t}$ $0 \le w \le 1$ we can rewrite the Equation 24 and add the relative constraints to linearize the objective function as follows.

$$\max \sum_{t=1}^{T}\sum_{p=1}^{P}\left(\sum_{k=1}^{K}\left((Rev_{k,p,t} - mc_{k,p,t} + Ext_{k,p,t})\times x_{k,p,t} - HC_{k,p,t}\times w_{k,p,t}\right) - (q_{p,t}\times d_{p,t})\right) \quad (25)$$

$$x_{k,p,t} - N(1-l_{k,p,t}) \le w_{k,p,t} \quad \forall N>1,\ k\in\{1,...,K\},\ p\in\{1,...,P\},\ t\in\{1,...,T\} \quad (26)$$

$$w_{k,p,t} \le l_{k,p,t} \quad \forall k\in\{1,...,K\},\ p\in\{1,...,P\},\ t\in\{1,...,T\} \quad (27)$$

$$w_{k,p,t} \le x_{k,p,t} \quad \forall k\in\{1,...,K\},\ p\in\{1,...,P\},\ t\in\{1,...,T\} \quad (28)$$

The rest of the constraints are for controlling the l and controlling how it should behave.

$$\sum_{t=1}^{T}\sum_{p=1}^{P} o_k \times x_{k,p,t} = do_k \quad \forall\ k\in\{1,...,K\} \quad (29)$$

$$lM^{p}\times\sum_{t=1}^{T}\sum_{k=1}^{K} l_{k,p,t} \le \sum_{t=1}^{T}\sum_{k=1}^{K} o_k\times x_{k,p,t} \le uM^{p}\times\sum_{t=1}^{T}\sum_{k=1}^{K} l_{k,p,t} \quad \forall\ p\in\{1,...,P\} \quad (30)$$

$$\sum_{t=1}^{T} o_k\times x_{k,p,t} \le do_k\times\sum_{t=1}^{T} l_{k,p,t} \quad \forall\ k\in\{1,...,K\},\ p\in\{1,...,P\} \quad (31)$$

$$\sum_{p=1}^{P}\sum_{k=1}^{K} l_{k,p,t} = 1 \quad \forall\ t\in\{1,...,T\} \quad (32)$$

$$\sum_{t=1}^{T}\sum_{p=1}^{P} l_{k,p,t} = 1 \quad \forall\ k\in\{1,...,K\} \quad (33)$$

Indexes:

t: mining periods based on year. $t \in T$

k: mining cut. $k \in K$

p: crusher panel which are the candidate locations for the crusher. $p \in P$

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

pl: processing plant/s

du: waste dump/s

Variables:

Rev_k^t: revenue as a result 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 and smelting and refining costs.

TMC_k^t: Total Mining Costs of extracting mining cut *k* in period *t*.

TMC_p^t: Total Mining Costs of extracting crusher panel *p* in period *t*.

mc_k^t: 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: mining cost of extracting crusher panel *p* minus the haulage cost of crusher panel *p* to the waste dump *du* in period *t.*

SPath: The shortest path in the road network which could be between either mining cut *k* or crusher panel *p* to the optimum crusher panel *ocp* or waste dump *du.*

$Pdist_{pl}^{ocp}$: The minimum distance between the processing plant *pl* and the optimum crusher panel *ocp.*

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

w : is the waste tonnage in the mining cut k or crusher panel p.

r: is the discount factor.

c^t: is the dollar cost of hauling one tonnage of ore or waste per one kilometre with haul truck to their destination either the optimum crusher panel *ocp* or waste dump *du* or directly to the processing plant *pl* in period *t* ($/ton.km).

$cn_{pl}^{ocp,t}$: is the dollar cost of transferring one tonnage of ore per one kilometre using the conveyor from the optimum crusher panel *ocp* to the processing plant *pl* in period *t*.

v_k^t: represents the discounted revenue minus the extra cost of mining ore in the mining cut x_k^t based on the Eq. 13 and 14.

q_p^t: denotes the discounted cost of mining based on the Eq. 15 and 16.

$x_k^t \in [0,1]$ is a continuous decision 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 decision variable, representing the portion of the crusher panel p to be mined in period t, fraction of y characterizes both ore and waste included in the panel.

$l_k^{p,t} \in \{0,1\}$ is a binary decision variable deciding which crusher panel should be the location of the in-pit crusher.

$b_p^t \in \{0,1\}$ is a binary integer decison 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.

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

K_p is the set of mining-cuts within panel *p*.

g_k^e is the average grade of element e in ore portion of mining-cut *k*.

$gl^{t,e}$ and $gu^{t,e}$ are the upper bound and lower bound on acceptable average head grade of element e in period t in percent.

pl^t and pu^t are the upper and lower bounds on ore processing capacity in period t in tonnes.

ml^t and mu^t are the upper and the lower bounds on mining capacity in period t in tonnes.

In the proposed model, the objective function, as described in Equation 2, aims to maximize NPV by identifying the optimal extraction periods (T) for both the portion of the mining cut ($x_{k,p,t}$) sent to the mill and the portion of the panel ($d_{p,t}$) sent to the waste dump. Equations 3 and 4 are the mining and processing capacity constraints. Equation 5 modifies the relation between the extracted ore tonnage and the total extracted tonnage from the corresponding cuts and panels respectively. Equation 6 and 7 control the maximum and minimum grade of the material sent to the mill or waste dump. Equation 8 ensures that all the panels will be extracted during the mine life. Equations 9-11 provide the extraction precedence of the crusher panels, which are created within the mine phases and contain the mining cuts. Equation 9 is a precedence constraint which forces b_p to be 0 until all the predecessors crusher panels ($\sum d_s$) are extracted. Equation 10 is to ensure that the crusher panel *p* does not extract unless the subsequent $b_p^t$for that crusher panel in a period *t* becomes 1. Equation 11 makes all the *b* variables 1 for *t+1* after it becomes 1 in period *t*. For instance, if crusher panel one should be extracted prior to crusher panel two, all the mining cuts within crusher panel one is the dependent clusters for the mining cuts within the crusher panel two.

Equations 12-14 are within a loop which they repeat based on the number of optimum crusher panels coming from the decision of how many crusher relocations should occur during the mine life. This decision has been made *l* variable where it constrains to consider the lower bound and upper bound of the total tonnage milled during the time that 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 which should be bigger than the maximum number of dependent panels on top of the optimized panel or the crusher panel. For instance, if we only have two crusher panels introduced by *l*, and if there are three crusher panels on top of the first optimized panel, and four panels on top of the second optimized panel, then the value of *"M"* must be greater or equal to 5. The variable *"d^t_h"* is responsible to keep track of the extraction percentage of the dependent panels of an optimized panel and eventually the Equation 12 will determine when all the top panels are extracted. Only then the Equation 13 will bring to an action preventing the optimized panel from extraction for as long as the next *l* in the next crusher panel becomes one. Therefore, *"b_{ny}"*, which is a binary variable controlling the precedence of panels' extractions, is now being forced to become zero only for those certain years. Equation 14 is to control the *"y'_t"* by making sure that it does not change value from zero to one haphazardly.

The decision variable boundaries are Equation 15 and 16 which will make the whole formulation result in optimizing the extraction plan in the presence of an in-pit crusher with the explained method. Equation 17 shows the components of $v_{k,p,t}$ which the total mining cost component will be the result of Equation 18 for the case where there is a crusher in the pit and Equation 19 for the case where there is not any crusher in the pit. Similarly, Equation 20 shows the components of $q_{p,t}$ which the total mining cost component will be the result of equation 21. Equation 22 and 23 is the written form and another form of the Equation 18 respectively. Equation 24 is the objective function in its new form considering the changes occurred in Equation 18. Equation 25 is the final form of the objective function with the auxiliary variable *w* used for linearization and Equations 26-28 are the necessary constrains to build the dependency between *w* and *x*×*l*. Equation 29 ensures that every mining cut, along with its corresponding ore tonnage, is assigned to a crusher panel. Equation 30 establishes a lower and an upper limit on the total tonnage milled during the time that the crusher is located on panel *p*. To ensure the problem's solvability, Equation 31 sets an upper bound for variable *z*. Finally, Equations 32 and 33 certify that in each period *t* there is only one optimum crusher panel available, and each mining cut *k* is sent to one optimum crusher panel, respectively.

5. Case Study

For verifying the method, a data set from real iron ore is selected which contains two pushbacks and 10 benches. The primary element is magnetite, but the deposit has a small amount of phosphorus (P) and sulfur (S). In these two pushbacks, we have 9952 blocks with the following dimension 20m × 10 m × 15m in X, Y, and Z respectively. The mill and the waste dump are two destinations fed by five different rock types, only three of which would be processed. The case study is tested on a machine with Intel® CPU with seven cores with 1.8 GHz speed and 16 GB of RAM. It is worth mentioning that the run time for the proposed model with the explained case study was between 30 to 50 seconds implying that this model is capable of tackling much larger deposits. Figure 3 shows the layout of the iron ore mine which is planned to accommodate a crusher inside.

In the first step, the number of crusher panels is selected automatically based on the minimum mining width in a way that each pushback is divided based on its area to a different number of crusher panels which results in having not more than three crusher panels in each pushback. The k-medoid clustering algorithm is used to create the crusher panels. Through the medoids, one block represents the whole panel forming the candidate locations for the crusher in each selected panel. Then, the blocks are aggregated within the crusher panels by applying the hierarchical clustering algorithm developed by (Tabesh & Askari-Nasab, 2011) to obey the mining phase boundaries. It is important to note that since the mining extraction follows the phases in each bench, the extraction of the next bench starts just after the current phase is fully extracted. However, the next phase might start within the current bench but will be left for the next stage. Therefore, the mining phases must cover the mining cuts.

The mining phases will create the panels that intersect between the designed pushbacks and the benches and will be used as mining units in the proposed mine planning formulation.

Table 1 shows the clustering parameters for both methods used to create the crusher panels and mining cuts.

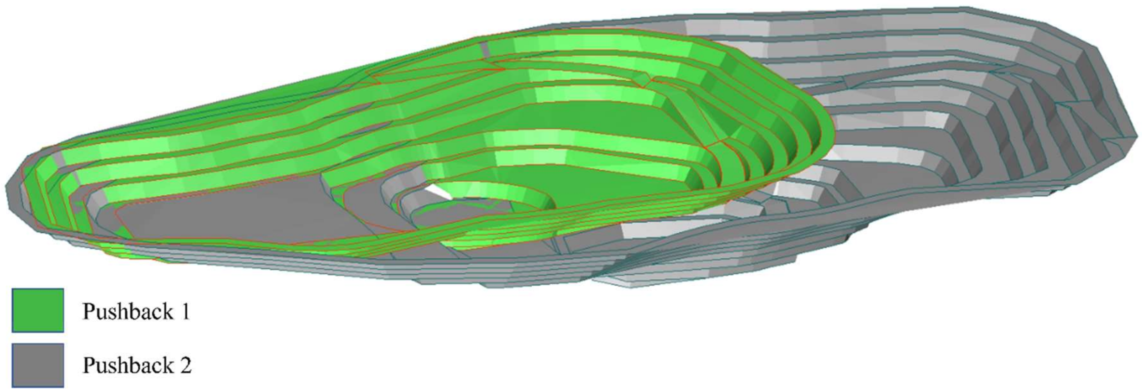

Figure 3. The iron mine layout with ramps and road network.

Table 1. Clustering Parameters.

Block Clustering Method	**Hierarchical**
Distance Weight	0.8
Grade Weight	0.2
Cluster Penalty	0.2
Rock Penalty	0.8
Approximate Block per Cut	30
Max Cluster Size	35
Crusher Panel Clustering Method	**k-medoids**
Algorithm to find medoids	Partitioning Around Medoids
Distance Minimization Method	Euclidean
Number of Replications	10

In this study, it assumed that the minimum diagonal distance of a crusher panel is 400m. This assumption improves the dimension of the crusher panels, especially when in the top or bottom benches, we have a small region encompassing blocks. Therefore, the current case has 16 bench-phase and 28 crusher panels in a total of 10 benches and 9 years of extraction. Figure 4 shows the plan view of the eighth bench with three features a) aggregating blocks to create mining cuts, b) clustering mining cuts to create the crusher panels, and c) mining panels or phases, respectively. In the next stage, distances are calculated from crusher panels to mining cuts, and the cost of material transportation is estimated. Existing mine roads are used for commuting. The cost of conveying materials using trucks and designed ramps is estimated to be \$0.3 for hauling one tonne in one kilometer and \$0.3 for transferring one tonne to the next level using the conveyor. The average travel distance between the ore mining cuts and the crusher is around 0.8 km, while the average travel distance for waste transportation and carrying ore to the mill is more than 4 km, assuming no in-pit crusher is in place. Figure 5 shows the road network for each of the pushbacks.

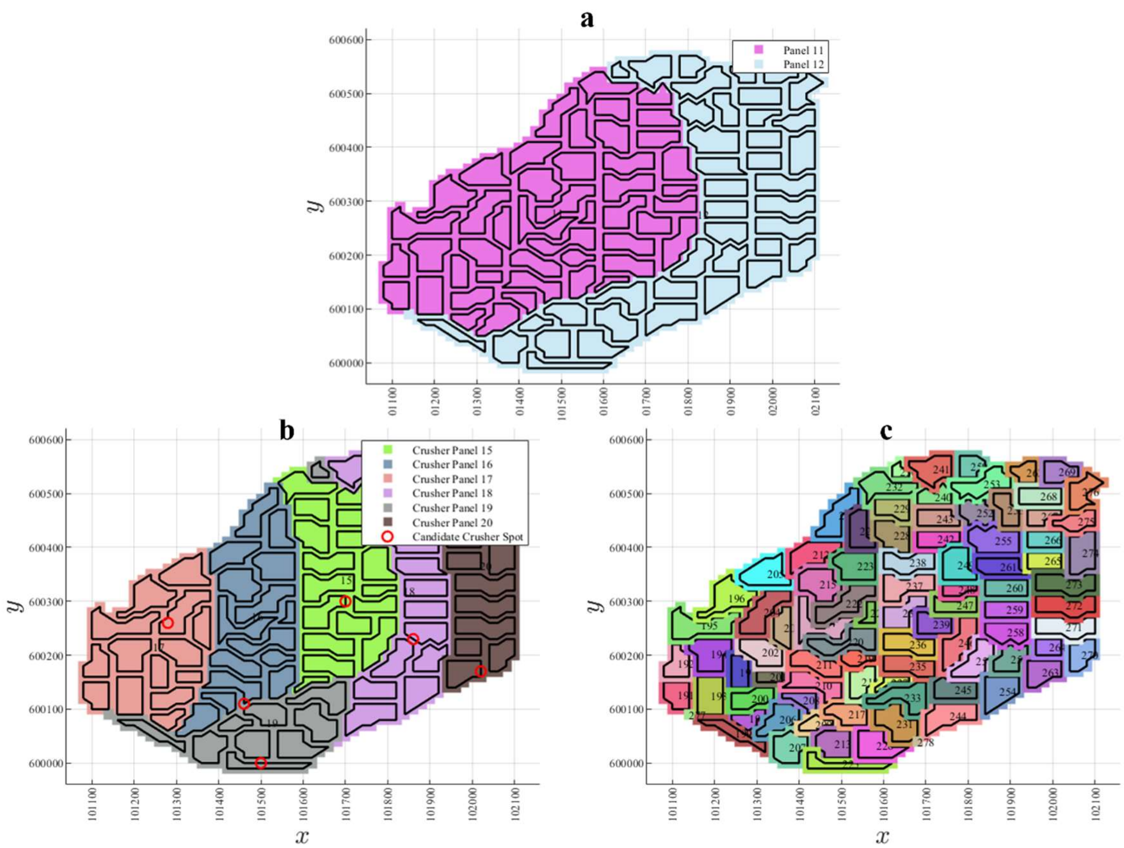

Figure 4. The plan view of bench number eight a) mining panels or phases, b) clustering blocks to create the crusher panels, and c) block aggregation to create mining cuts.

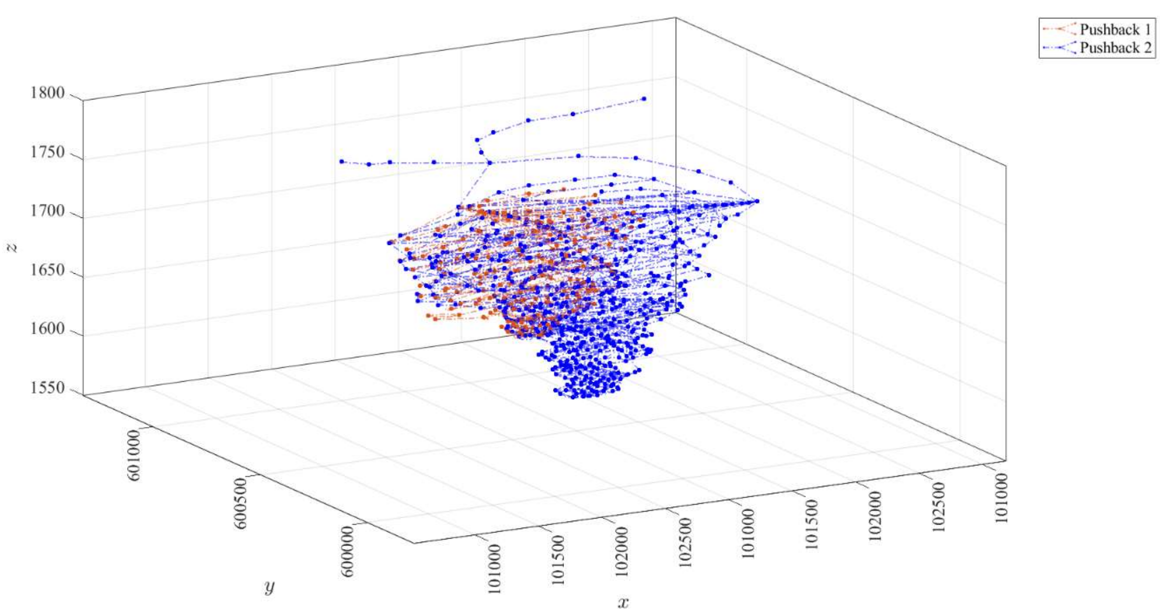

Figure 5. Schematic view of the road network.

The total minable production is around 70 million tonnes (MT) within which 30 MT is ore. The yearly mining capacity and processing capacity are further assumed to be 10.3 MT and 3.2 MT respectively. It means that the operation will continue for 9 years. The MILP was formulated in

(MATLAB, 2023) and solved with the (IBM ILOG CPLEX Optimization Studio., 2011) solver. The model has two possible destinations: the in-pit crusher and the waste dump. The mill is no longer a destination in such models, but the capacity-related variable is still referred to as the processing capacity since it is the bottleneck variable in this formulation.

6. Discussion of Results

The case study was first carefully tested inside of the Whittle software so that through a trial-and-error process, a near-stable schedule could be generated. Hence the stripping ratio is relatively high, the mining capacity cannot be maintained from the 6th year although the processing capacity is nearly constant. Figure 6 shows the yearly schedule generated the proposed method. The new formulation which includes IPCC was able to increase the discounted cash flow from 560 to 606 M$, especially knowing that this schedule is disturbed due to the in-pit crusher location and its requirement to postpone the extraction of the optimized crusher panel. It is also observed that the designed MILP model sends around 2MT more material to waste dump. Figure 7 shows the yearly revenues versus cash flow graph for the proposed model.
Given that some components such as queuing approach are zero when the required number of trucks is low, it is assumed that the waiting times in loading and dumping for both scenarios, with and without an in-pit crusher, are proportional. Based on the average travel time, the average number of trucks can be calculated. In this case study, the average travel distance for the in-pit crusher option is 837 m, compared to almost 4039m for trucks traveling directly to the mill. Loaded and empty trucks have a safe travel speed of 30 km/h and 60 km/h, respectively. Therefore, it takes around 2.5 minutes to travel to the in-pit crusher one way, compared to 12.1 minutes to travel to the mill one way. Installing a crusher in an optimal location reduces travel time by 4.8 times.

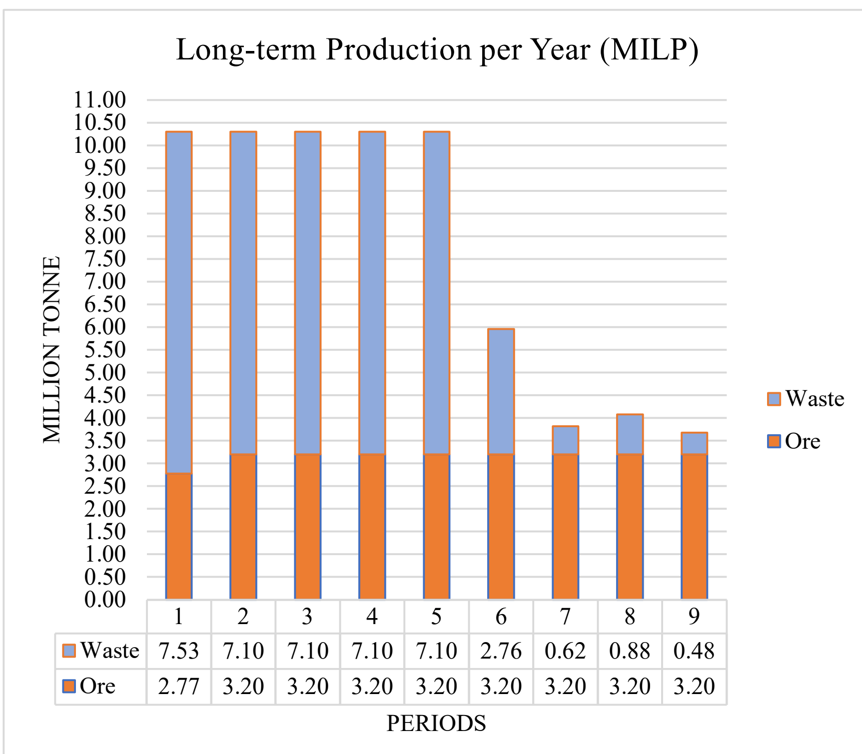

Figure 6. Long-term yearly production generated using the proposed model for the in-pit crusher.

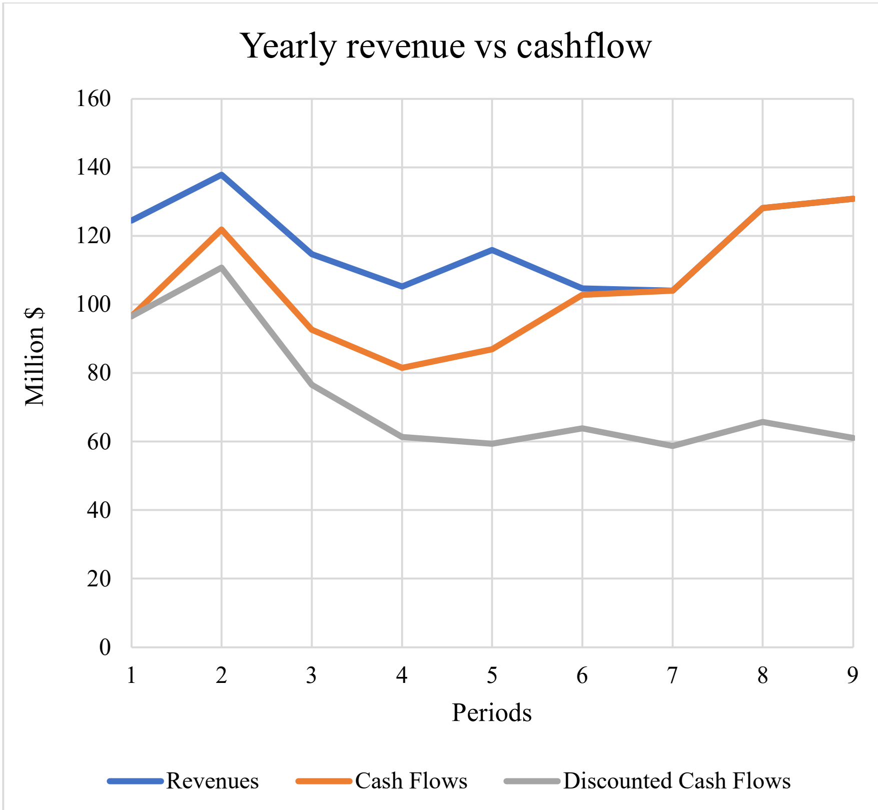

Figure 7. Revenue versus Cashflow based on each year from the proposed model for the in-pit crusher.

7. Conclusion

Due to the vast and broad use of IPCC in open pit mining operations, in this study, we tried to develop a mathematical model to not only consider the IPCC in the scheduling but provide the best locations for the crusher within the mine life at the same time. The idea was to create practical units for the crusher spots named crusher panels and employ the road network during the optimization. Additionally, the conventional MILP model should have been changed to accommodate a condition with which the optimized crusher panel remains undisturbed or unextracted when all the precedence blocks are extracted for a certain period of years. The proposed model implemented to an iron mine case study with two pushbacks, 10 benches with 9952 blocks gives 404 mining cuts, 28 crusher panels, and 2 optimized crusher panels with their associated crusher capacities of approximately 16 MT and 12 MT. We further discussed that the first optimized location was in the first bench, so it was considered an out-pit crusher location.

The simultaneous MILP model with the related IPCC constraints and the total mining capacity of 10.3 MT and processing capacity of 3.2 MT was solved using the CPLEX solver. The results show that the IPCC constraints can reinforce the in-pit crusher implementation. Furthermore, it increases the discounted cash flow by 8% compared with the best schedule without the in-pit crusher. As for one of the main reasons for the IPCC utilization which is to reduce the travel distance and truck number, the in-pit crusher could reduce truck travel time by 5 times considering the processing plant location and the optimized crusher panel.

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