Long-term Mine Planning Optimization for IPCC-Based Open-Pit Mining Operations

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ABSTRACT

The costs of the truck-shovel system in open-pit mining operation increases when the distances between mining faces and the dumping locations increase. In-pit crushing and conveying (IPCC) system is an option to decrease the enormous operating costs that a truck-shovel (TS) system can introduce in an open-pit mine. In-pit crusher, if installed in an optimum spot, would reduce the haulage distance and subsequently decrease the haulage operating costs. Finding the best locations for the IPCC over the mine life will impose a new set of requirements for the mine planning problem. Furthermore, it can lead to a new set of calculations for the mine's extraction sequence and estimating the number of trucks. This research finds the optimal in-pit crusher locations over the mine life and calculates the relocation time. A new truck fleet sizing is also established following in the decrements in haulage distances. To achieve the research objectives a two-step mathematical programming model is developed that determines the optimal long-term scheduling of the mine at the first stage, and then determines the optimal locations and relocation times for IPCC alongside the mine road network. The proposed model is implemented in a real mine case with a conventional TS system to decide whether it could be improved by IPCC. The results show that the truck number could be reduced by five times for the two benches of a real mine while achieving mine schedules with the proper targets.

1. Introduction

In a typical open pit mine operation, the trucks carry the material extracted by shovel to their final destinations, which could vary based on material types, rock types, grades, etc. There has always been a triumph in reducing truck use due to notable reasons such as substantial maintenance costs, fuel costs, costs of roads and ramps construction and maintenance, safety issues regarding the truck's incidents, and so on. The related costs of the TS system would become more intense as the depth of mines increases. Among different efforts and various options for cost reduction such as automated or ultra-class trucks, bringing the crusher inside the pit and taking the material out via a conveyor network has attained more attention by mine designers over the recent years.

A noticeable cost is associated with purchasing, preparing, and installing the In-Pit Crushing and Conveying System. Additionally, the extraction sequence cannot remain the same where the crusher will be installed and kept in the spot for some time. On the other hand, as soon as an IPCC is installed and ready for utilization, it adds another destination to the list of potential destinations, meaning that some of the trucks will be commuting to this spot to discharge their loads. Therefore, finding the proper spot for the in-pit crusher is vital. Figure 1 shows the schematic view of a mining operation with IPCC for ore where the waste is moved out of the pit with the conventional truck-shovel system via pit road and ramps.

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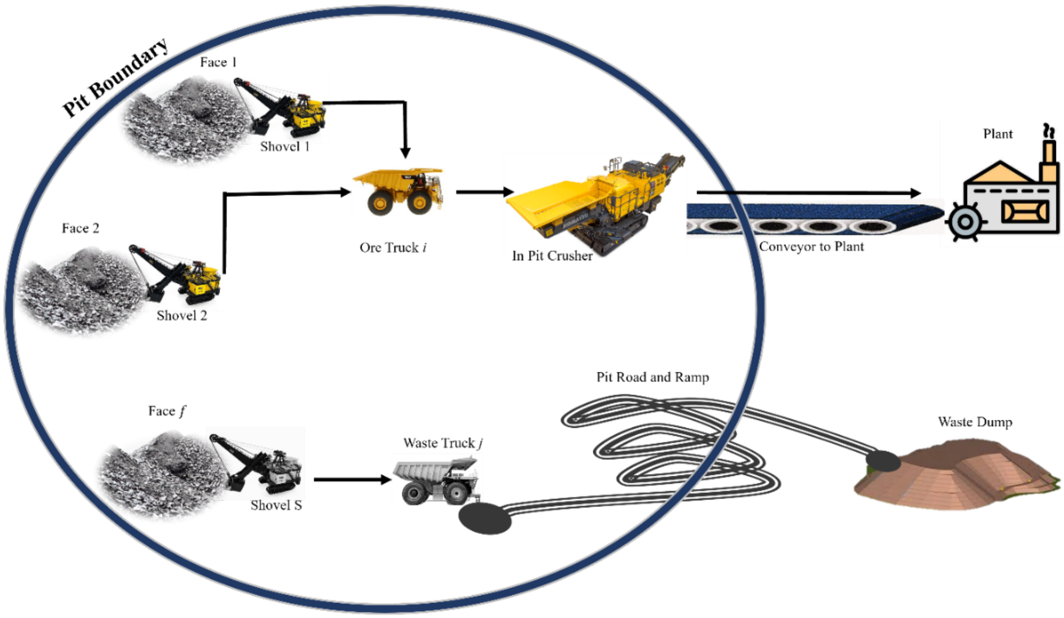

Figure 1. A schematic view of IPCC in a mining operation.

Many researchers tried to address the efficient use of IPCC; Lonergan & Barua (1985) investigated slope reduction costs to minimize the haulage cost by minimizing the conveyor slope. Dos Santos & Stanisic (1986) reintroduced and explored the option of hiring high slope conveyors. Sturgul (1987), Rahmanpour et al. (2014), and Konak et al. (2007) tried to find the best location for an in-pit crusher. Another solution Roumpos et al. (2014) mentioned is finding the best place of distribution points for belt conveyors.

In an effort to unite the long-term planning and crusher optimization, Londoño et al., (2013) modeled the alternatives of IPCC engaging with the dragline and hopper for coal digging in a coal mine. The authors use simulation with "3D-Dig" package software to analyze three options for the IPCC location, and the in-pit option is identified as the most cost-effective one. Roumpos et al., (2014) provide an optimal location among the various nominated points for the belt conveyor system in a continuous surface mining operation. The study is more of a search algorithm with a heuristic approach within the limited number of nominees for a belt conveyor. Paricheh & Osanloo, (2016) introduced a robust (scenario-based) approach that can use three methods for incorporating scenarios into the model: 1- expected performance optimization within all scenarios. 2- worst case performance optimization and 3- expected loss or regret minimization within all scenarios. They also created a cost equation that gives the haulage cost in different periods of the mine life. The facility location problem, solved in their paper, is designed for two or more facilities; otherwise, the model's scope will turn into a deterministic problem, not an uncertain one.

Yarmuch et al., (2017) is another study that tries to find the best location for adding one crusher in the Chuquicamata mine by simulating the probability and failure costs possibilities and installation costs with the Markov chain algorithm. Paricheh et al. (2017) modeled the IPCC location problem with the linear programming method as a dynamic problem using the haulage cost for truck and conveyor systems functions. Paricheh et al. (2018) hire the mentioned two cost functions one more time to present a heuristic approach for finding the optimum time and location. The heuristic approach solves the model iteratively based on which, when the haulage system is changed, the cost of the transportation method will change so as the block value. Thus, the IPCC will reduce the costs causing the pit size to expand through the proposed iterative process. Abbaspour et al. (2018) provided a Simple transportation model to solve an optimum location and time problem. Using this model, they solved a 2D hypothetical mining section. Nehring et al. (2018) offered a strategic mine planning comparison between IPCC and TS systems with several hypothetical 2D sections of the block model searching the possible extraction sequence, hoping to catch the higher NPV and cash flow.

So far, there is not any mathematical optimization introduced or proposed so that it could optimize the IPCC location and relocation time while optimizing the long-term planning of the mine. However, Paricheh & Osanloo (2020) tried to optimize the production schedule with the presence of the IPCC through a MILP model concurrently with the NPV maximization as the objective function. The mentioned model is solved in CPLEX, assuming two hypothetical copper deposits for 15 years of the mining operation. Nevertheless, this model is solved for the limited number of blocks, which do not represent a complete mine operation without designing the road network and ramps, so it cannot be considered a practical model. (Samavati et al., 2020) proposed a model to schedule the blocks based on the position of different parts of the conveyor for a fully mobile IPCC system. The proposed MILP model uses 18 equations plus one objective function in which 16 of those equations define the block precedence honoring the conveyors' spots for each bench. The largest solvable block model with such a formulation has 40,000 blocks, suggesting that the amount of decision variables is limited due to the considerable number of precedence constrain.

The literature shows that among the few mathematical models incorporating the IPCC optimization and long-term planning, the decision variable of optimization is at the block level. That is why the case studies for Paricheh & Osanloo (2020)and Samavati et al. (2020)are either hypothetical or small mining operations. Keeping the model's decision variable at the block level creates an optimization model with many decision variables and constraints. Therefore, the practicality of the model for the actual mine operation will be questionable. On the other hand, none of the studies considered the road network resulting in an IPCC optimization model which cannot be compared with the TS system because the roads and ramp distances are unknown. In this proposed method, the decision variables are assumed the mining cuts and the actual road network of the mine with specific roads and ramps will be used to not only does optimize the IPCC location and mine schedule but makes it practical for a real mine size to be calculated and compared.

2. Methodology

Finding the optimal location and relocation time for the crusher could be considered as part of an iterative process. For instance, when it is set to relocate the crusher every two periods, the different optimum locations in each timespan are the decision variables. Now, suppose the goal was to optimize the timespan. In that case, the required truck number for various relocation timespans or a comparison of NPVs for the scheduled blocks after finding the optimum locations for various relocation timespans can satisfy this goal. The essential assumption is that the relocation times should be taken as equal timespans. In this study, we propose a two-step formulation in which the first step accounts for finding the best locations of the crusher using the road network and then scheduling blocks one step after another.

First, this section explains the two-step clustering method hired to determine the nominated crusher spots and will be used in the next tread to solve the modified facility location mathematical formulation. Next, the MILP formulation proposed by (Mohammad Tabesh et al. (2014) will be presented and modified to be applicable in solving the block scheduling in the presence of the in-crusher. Figure 2 shows a diagram elaborating on the main steps to solve the problem. The input of this model is the block model, whose pit limit and pushbacks being decided prior in addition to the road network requires a design over the pit limit with the roads, ramps, and access points. In the first step of the following three steps, the crusher panel will be generated then the blocks will be aggregated using a two-step clustering method. Following the clustering, the facility location optimization will optimize the crusher spot among the crusher panels, which are the crusher candidate locations. Finally, the mining cuts will be scheduled to be extracted sequentially, ensuring the crusher panel will be extracted at the latest stage.

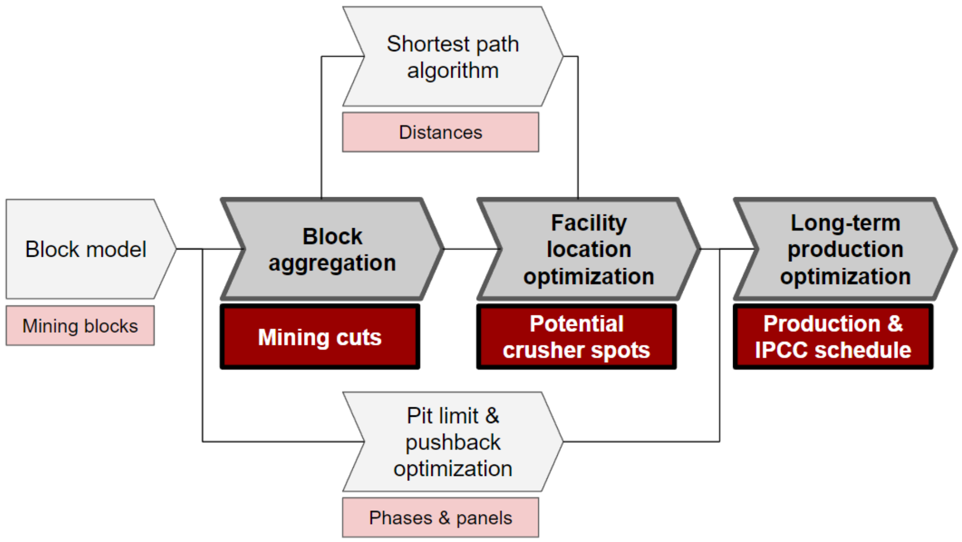

Figure 2. The methodology flow diagram.

2.1. Clustering

A Block model with its rectangular shape represents an orebody that is divided into sets of uniformed-sized shapes called blocks (Espinoza et al., 2013). While the block model is a way to facilitate both the mine planning and mine extraction, it could increase the size of the problem and makes it intractable for large deposits with millions of blocks, especially when a planner wants to optimize the extraction schedule over a large number of time periods. Aggregation techniques are used here to reduce the problem size. For that purpose, block aggregation using a clustering algorithm is suggested by Tabesh & Askari-Nasab (2011). Using their method, blocks aggregate to mining cuts based on their similarity in rock type, ore grade, and distance.

Clustering is an unsupervised machine learning algorithm meant to discriminate between data based on similarities or dissimilarities. From a broad perspective, hierarchical and partitioning are two ways of dealing with data clustering. The clustering algorithms will be used, in this study, 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 the 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 (Busnach et al., 1985; Gershon, 1983; Gershon & Murphy, 1989; Klingman & Phillips, 1988). However, more complicated clustering methods have been developed to comply with mine planning requirements which requires solving a linear programming mathematical optimization (Ramazan, 2007; Ramazan et al., 2005). However, the most common procedure is applying either hierarchical or partitioning clustering (Ben-Awuah & Askari-Nasab, 2012; Goodfellow & Dimitrakopoulos, 2016; Koushavand et al., 2014; Lotfian et al., 2021; Tabesh & Askari-Nasab, 2011).

The clustering algorithm proposed in this paper is developed to create crusher panels using the k-medoid algorithm and then the hierarchical clustering is used within the crusher panels, similar to what proposed by (Tabesh & Askari-Nasab, 2011) in that they applied the idea of distance hierarchy to calculate the similarities between the categorical variables. For calibrating the function in the distance hierarchy method, they developed a function called penalty function. The similarity value between blocks *i* and *j* is estimated in Equation 1.

$$S_{ij} = \frac{R_{ij}C_{ij}}{\widetilde{D}_{ij}^{w_D}\widetilde{G}_{ij}^{w_G}} \quad (1)$$

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

- Start by assuming K arbitrary clusters where there are S_1, S_2,…S_k representatives as medoids for each cluster c_1 to c_k.
- 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'.
- Given cluster c_k, update the medoid S_k and check the stop condition.
- Stop if the new c_k'= c_k, then make S_k = S'; otherwise, repeat steps 2 and 3.

Using the k-medoid 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 and generate the precedence within each cluster. The crusher location optimization process uses the medoids of each panel as one scenario to calculate the facility location problem formula modified for the crusher location problem.

2.2. Facility location problem

The facility location problem is a well-known formulation that can be applied to many optimization problems, including transportation costs minimization or geometry computation. The objective function could be minimizing the cost, optimizing the location of one or multiple facilities with different costs, or including the capacity optimization problem in the capacitated version of the problem. Geometry-wise, it can be a solution to different discrete or continuous space distance problems, which is referred to as a single facility location problem. The general formulation for this problem is reviewed and modified as follows (Goemans & Skutella, 2004).

$$minimize \sum_{i\in F} f_i y_i + \sum_{i\in F\, j\in N} c_{ij} x_{ij} \quad (2)$$

$$Subject\ to \sum_{i\in F} x_{ij} = 1\ for\ all\ j\in N \quad (3)$$

$$\sum_{j\in N} y_j = 1 \quad (4)$$

$$y_i - x_{ij} \geq 0\ for\ all\ i\in F,\ j\in N \quad (5)$$

$$x_{ij},\ y_i \in \{0, 1\}\ for\ all\ i\in F,\ j\in N \quad (6)$$

Where

- $i\in F$ is the crusher nominated location or crusher panel.

- $j \in N$ is the mining cuts which eventually goes to crusher panel i in N.
- F is the crusher panels within the assumed bench/period interval.
- N is the mining cuts within the assumed bench/period interval.
- f_i is the cost associated with installing the crusher in the i^{th} crusher panel. It could be different for the crusher panels if they were not chosen within the same phase. Additionally, the cost of conveying material to the specific mill differs in each crusher panel i.
- y_i is a binary decision variable meaning to install the crusher in the i^{th} crusher panel or not.
- c_{ij} is the transportation cost from the j^{th} mining cut to the i^{th} crusher panel.
- x_{ij} is a binary decision variable deciding if mining cut j is connected to crusher i or not.

In the mentioned revised facility location formulation, Equation 2 minimizes the crusher installation and material transportation cost. Equation 3 ensures that every mining cut is connected to precisely one optimized crusher panel. Equation 4 constraining the number of facility locations to one among all the crusher panels for every bench/period interval. Equation 5 makes sure that the mining cuts can only be sent to the selected crusher locations. Equation 6 defines x and y decision variables.

2.3. MILP formulation

This part of the proposed algorithm uses the MILP formulation developed by Tabesh et al. (2014) to schedule the extraction of blocks while the crusher occupies multiple blocks hindering that specific crusher panel from being extracted for some determined periods. However, some modifications in the formulation are required for the crusher problem. According to Equation 7, the objective function maximizes the NPV by taking different extraction periods (T) for the extraction of the portion of the mining cut (x_k^t) to send it to the mill, and the extraction of the portion of the panel y_p^t to send it to the waste dump. In this equation, x_k^t is a continuous variable between 0 to1 same as the y_p^t. v_k^t is the discounted revenue minus the extra cost of mining ore in the mining cut x_k^t, whereas q_p^t is the discounted cost of mining.

$$\sum_{t=1}^{T}\left(\sum_{k=1}^{K}\left(v_k^t \times x_k^t\right) - \sum_{p=1}^{P}(q_p^t \times d_p^t)\right) \tag{7}$$

$$subject\ to \qquad ml^t \leq \sum_{p=1}^{P}\left(o_p + w_p\right) \times d_p^t \leq mu^t \ \ \forall\ t \in \{1, ..., T\} \tag{8}$$

$$pl^t \leq \sum_{k=1}^{K} o_k \times x_k^t \leq pu^t \ \ \forall\ t \in \{1, ..., T\} \tag{9}$$

$$\sum_{k \in K_p} o_k \times x_k^t \leq \left(o_p + w_p\right) \times d_p^t \ \forall\ p \in \{1, ..., P\},\ t \in \{1, ..., T\} \tag{10}$$

$$0 \leq \sum_{k=1}^{K}\left(g_k^e - gl^{t,e}\right) \times O_k \times x_k^t \ \forall\ \ t \in \{1, ..., T\},\ e \in \{1, ..., E\} \tag{11}$$

$$\sum_{k=1}^{K}\left(g_k^e - gu^{t,e}\right)\times O_k \times x_k^t \le 0 \ \forall \ t\in\{1,\ldots,T\},\ e\in\{1,\ldots,E\} \tag{12}$$

$$\sum_{t=1}^{T} d_p^t = 1 \ \forall\ p\in\{1,\ldots,P\} \tag{13}$$

$$b_p^t - \sum_{t=1}^{T} d_s^t \le 0 \ \forall\ p\in\{1,\ldots,P\},\ t\in\{1,\ldots,T\},\ s\in C_p \tag{14}$$

$$\sum_{t=1}^{T} d_s^t - b_p^t \le 0 \ \forall\ p\in\{1,\ldots,P\},\ t\in\{1,\ldots,T\} \tag{15}$$

$$b_p^t - b_p^{t+1} \le 0 \forall\ p\in\{1,\ldots,P\},\ t\in\{1,\ldots,T-1\} \tag{16}$$

$$x_k^t = 0 \ \ \forall\ t\in\{S_1,\ S_2,\ \ldots,\ S_n\} \tag{17}$$

$$d_p^t \le \sum_{k=1}^{K_p} x_k^t \ \forall\ t\in\left\{S_1,\ S_2,\ \ldots,\ S_n\right\},\ K_p\subseteq p\in\{1,\ldots,P\} \tag{18}$$

$$\sum_{t=1}^{T} x_k^t = 1 \ \forall\ K_p\subseteq p\in\{1,\ldots,P\} \tag{19}$$

- $x_k^t \in [0, 1]$ 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*, fraction of *y* characterizes both ore and 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.
- C_p is the set of the panels that have to be extracted prior to panel *p*.
- K_p is the set of the mining-cuts within panel *p*.
- o_k is the ore tonnage in mining-cut *k*.
- w_p is the waste tonnage in the crusher 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, Equations 8 and 9 are the mining and processing capacity constraints. Equation 10 modifies the relation between the extracted ore tonnage and the total extracted tonnage from the corresponding cuts and panels respectively. Equation 11 and 12 control the maximum and minimum grade of the material sent to the mill or waste dump. Equation 13 ensures that all the panels will be extracted during the mine life. Equation 14-16 are constraining the extraction with the determined slope. we need to constrain the mining cut chosen for the crusher placement for that specific period. The crusher replacement time follows a predetermined equal timing, i.e. in every PT period, the crusher will move down to the current extracting bench. Depending on the number of mining periods T, the variable n that is the number of crusher movements, is: $n = \frac{T}{PT}$. Knowing that there are $S_1, S_2, \ldots, S_n = PT$, we need to add n series of constraints to the MILP model to avoid the optimum mining cut for crusher spot from being extracted in the S_n timespan (Equation 17). Because of the nature of this MILP model, not only that specific mining cut but part of the panel in that bench must be kept unextracted (Equation 18). Additionally, after the crusher moves to a new location, the model ensures that the mining cut that was hosting the crusher, and its successor mining cuts will be extracted (Equation 19).

Adding three Equations 7,8 and 9 to the MILP model presented by Tabesh et al. (2014) will result in optimizing the extraction plan in the presence of an in-pit crusher with the explained method.

3. Case Study

For the purpose of evaluating the proposed method, a dataset from a real iron ore mine is selected. The case study includes two consecutive benches from a mine with 21 benches in total, with which the primary mineral is magnetite but has phosphorus (P) and sulfur (S). The selected part has 2184 blocks of 25m×25m×15m in total. The mill and the waste dump are two destinations fed by seven 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. Figure 3 shows a plan view of the selected part of the mine, which is supposed to accommodate a crusher inside.

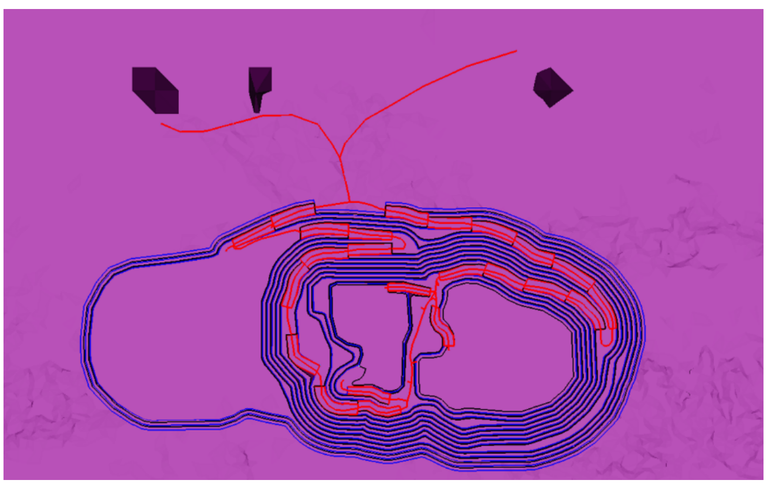

Figure 3. Plan view of the iron ore mine.

In the first step, eight different crusher panels are selected for each of the benches using the k-medoid clustering method. 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 designed pushbacks and the benches and will be used as mining units in the MILP mine planning formulation. Table 1 shows the clustering parameters for both methods used to create the crusher panels and mining cuts.

Figure 4 and Figure 5 shows a plan view of the first and second benches with two features of a) clustering blocks to create the crusher panels, and b) mining panels or phases, respectively.

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
Number of Crusher Panels per Bench	8

The next stage is calculating the distance from each selected block or medoid to all the mining cuts and estimating the cost of transporting materials there. The distances are based on the shortest paths between two nodes along the road network, meaning that the existing mine roads will be employed to commute to different spots. The conveyor length, however, has the most expenses where it could be determined from the Euclidean distance between each medoid and the mill. The wastes will be carried out of the mine using the trucks and the designed ramps. It is assumed that the conveyor costs \$0.3 for transferring one tonne to the next level, and the cost of hauling by truck is \$0.2 for hauling one tonne in one kilometer. The model is solved using the CPLEX solver, and the solution indicates the seventh crusher panel of the lower bench as the optimum spot to place the crusher. The average travel distance between the ore mining cuts to the crusher spot is around 0.8 km. In contrast, the average travel distances for waste transportation to the waste dump or carrying ore to the mill is more than 4 km, assuming no in-pit crusher in place. Figure 6 shows the road network used for this case study.

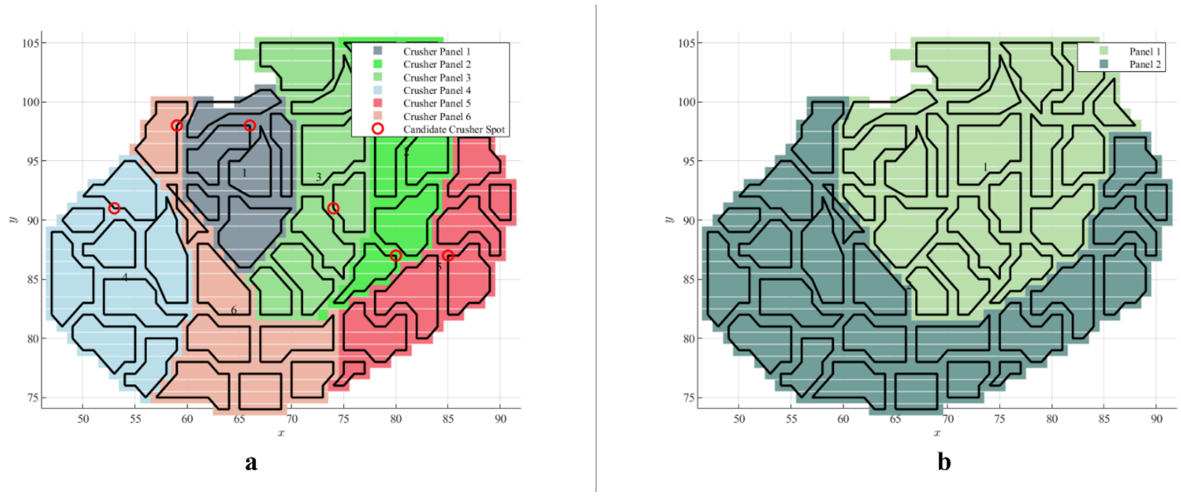

Figure 4. Plan view of the first bench a) clustering blocks to create the crusher panels, b) mining panels or phases.

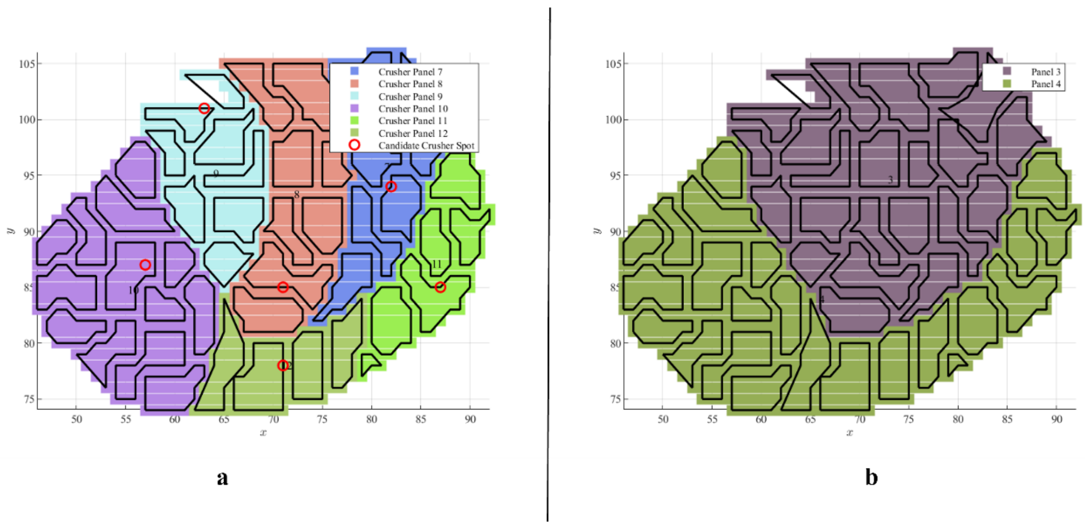

Figure 5. Plan view of the second bench a) clustering blocks to create the crusher panels, b) mining panels or phases.

After applying the clustering algorithms and finding the optimum spot for the crusher, mine scheduling with the proposed MILP formulation is the final step in the proposed method. Table 2 shows the input parameters of the mine scheduling. The MILP was formulated in MATLAB and solved with the CPLEX IBM 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.

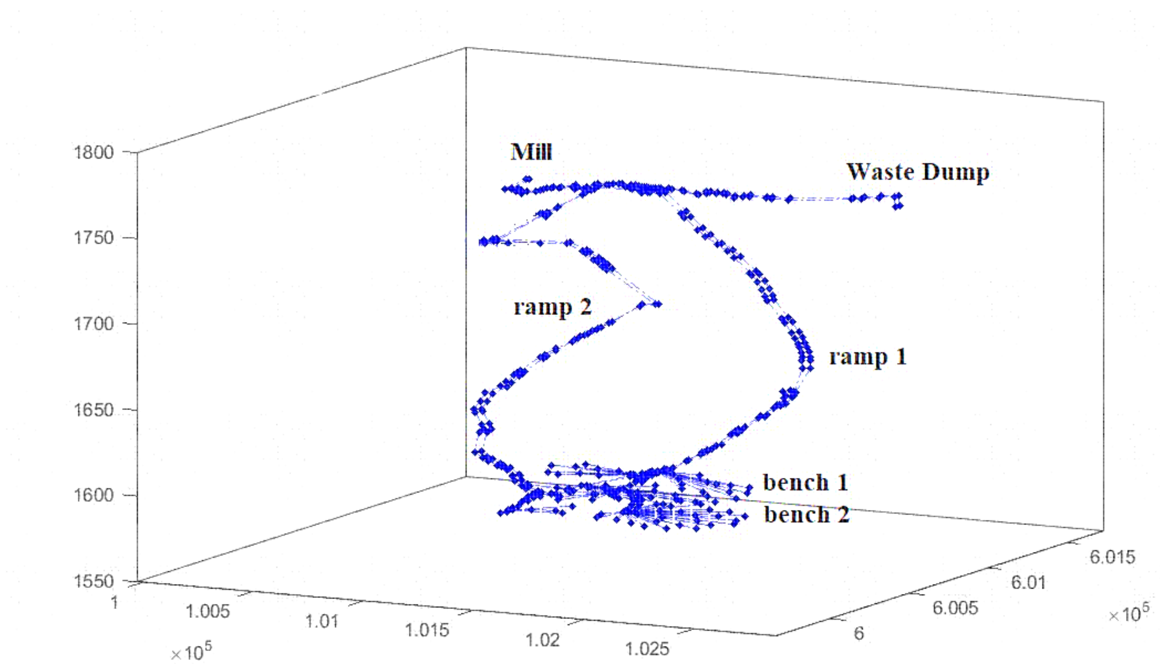

Figure 6. Schematic view of the road network of the case study.

Table 2. Mine scheduling inputs.

Total Ore Tonnage (MT)	Total Waste Tonnage (MT)	Total Minable Material (MT)	Yearly Mining Production (MT)	Yearly Processing Capacity (MT)
16.1	37.34	53.33	13.35	4
Num. of Mining Cuts per Bench	Num. of Mining Panels per Bench	Num. of Blocks	Num. of Periods	
48	2	2,184	4	

Figure 7, Figure 8, and Figure 9 show that the model solved the mine scheduling with the defined capacities, and the mine has a positive cash flow from extracting the mining cuts. During these four years of mining, where the crusher will be on the second bench and the seventh crusher panel, the cut-off grades change 28%, the destination revenues change 21%, and the discounted cashflows change 47%. The crusher spot remains untouched until the end of the 3rd period and will be extracted after that, implying that moving the crusher to the lower benches must be started in the 4th year.

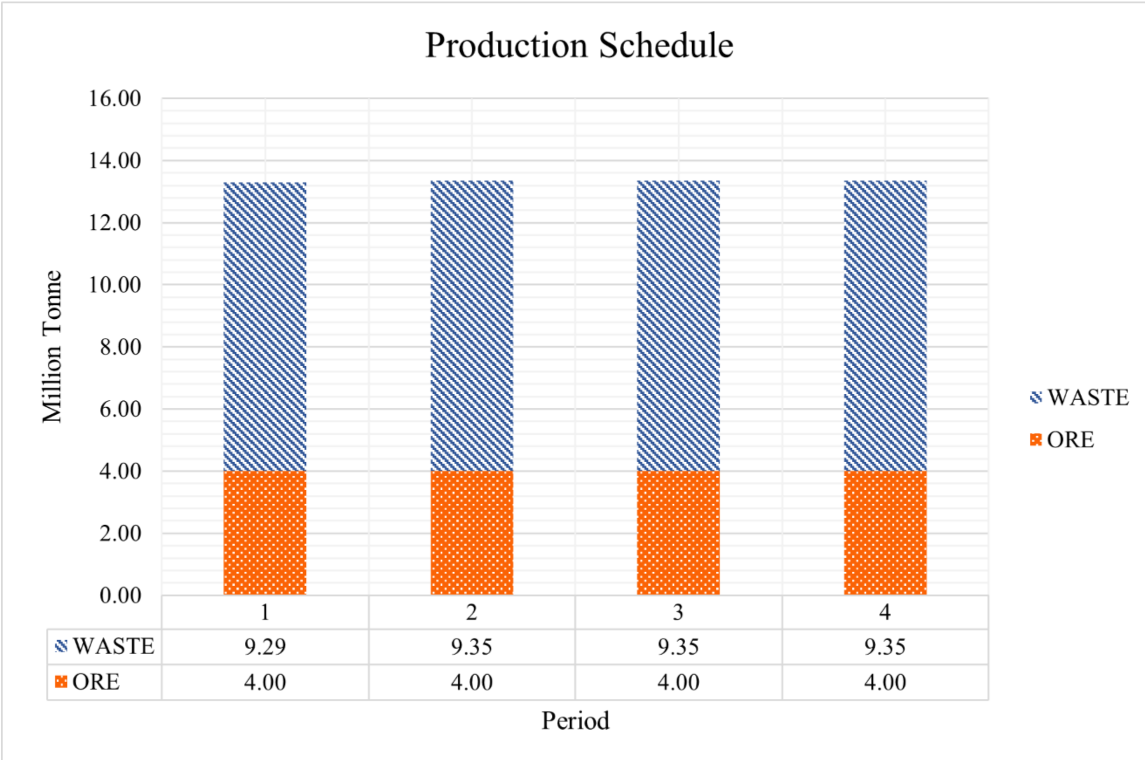

Figure 7. Mine production schedule during four periods.

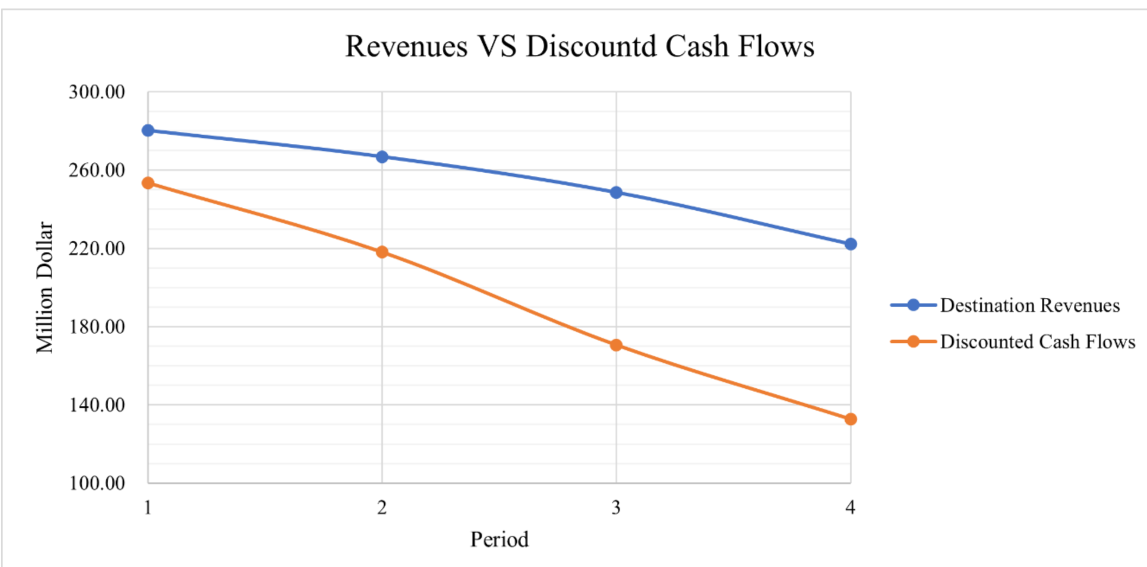

Figure 8. Revenues and discounted cashflows over four periods.

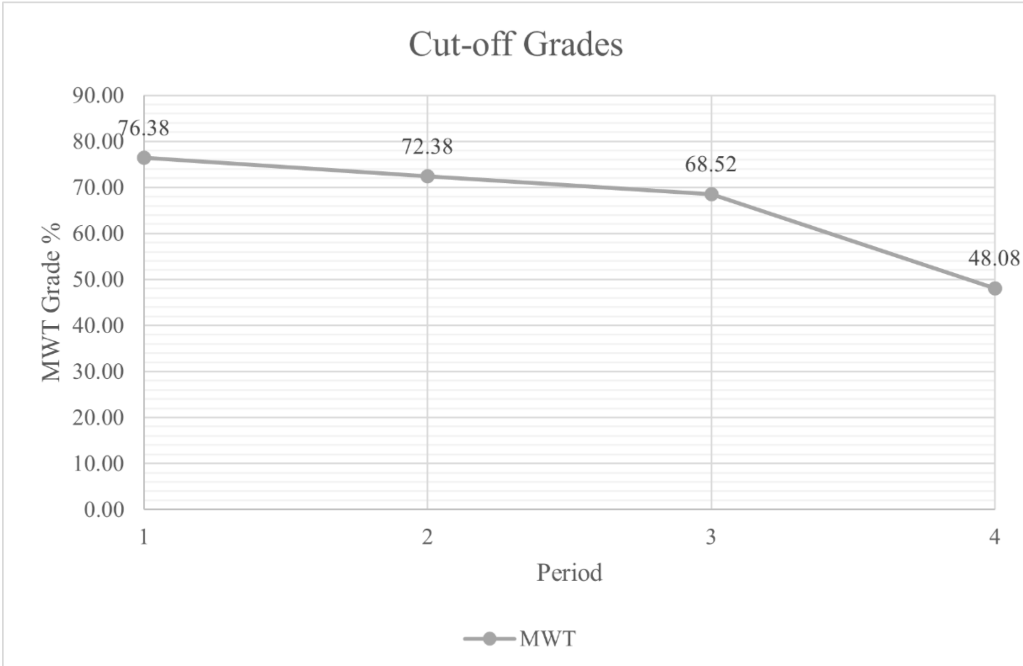

Figure 9. Cut-off grade variations during four periods.

4. Discussion of Results

In order to verify that the MILP model with crusher panel acts differently from the MILP with the mining panel, a schematic view of the extraction sequence for both of the benches employed in this study is shown in Figure 10 and Figure 11. Figure 10 shows the extraction sequence for the usual MILP model and four different periods with mining panels or phases where there is no crusher constraints or assumption for the in-pit crusher, while Figure 11 shows the exact same model with all the capacity and grade assumption for when there is a crusher inside. In Figure 11 model, the crusher panels were used to be save the spot till period 4, for the crusher. As it can be seen from these two figures, the scheduling follows either the mining panels or crusher panels to some extent. The order of the benches are from bottom to top meaning that in order to reach to the first bench, some precedence in the block level, cut level and mining/crusher panel level of the second bench must be honored.

Assuming that the waiting times in loading and dumping for two cases of with and without in-pit crusher are proportionate based on the fact that some components such as queuing are close to zero when the required number of trucks is less, we can calculate the average number of trucks based on the average travel time. In this case study, the average travel distance for the in-pit crusher option is 837 m, while it is almost 4039m when trucks travel directly to the mill. Knowing that the safe travel speed for the loaded and empty truck is 30 km/h and 60 km/h respectively, we have around 2.5 minutes of travel time for traveling to in-pit crusher versus 12.1 minutes travel time for traveling to the mill. Therefore, installing a crusher in an optimum spot reduces the travel time 4.8 times. As a real example, implementing IPCC in a case with a complete mining operation that includes ten ore trucks, and ten waste trucks could decrease the fleet to three ore trucks and ten waste trucks. Having fewer trucks not only benefits financially but could also improve safety by reducing incidents and traffic and easing the dispatching operation.

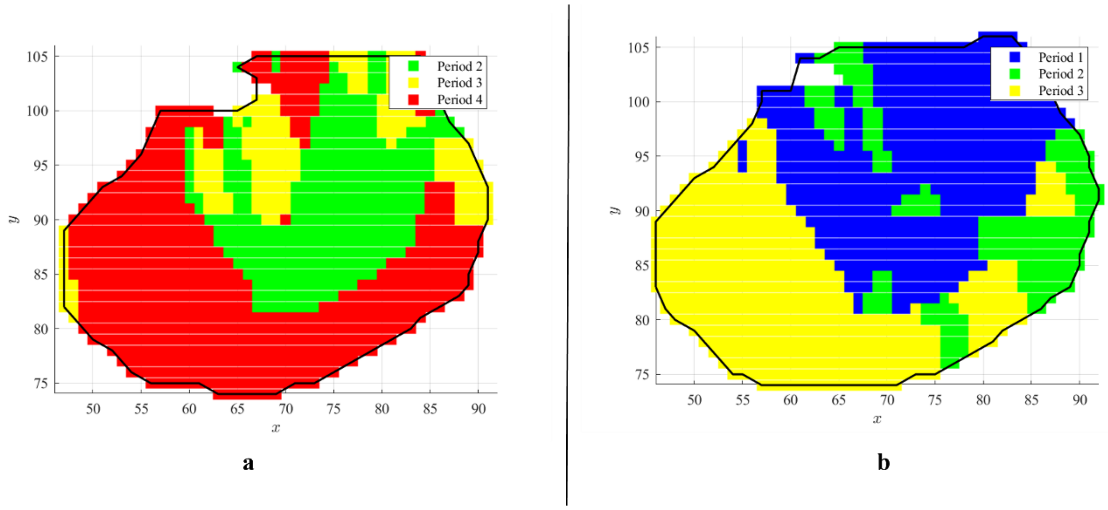

Figure 10. The extraction sequence for the usual MILP model without in-pit crusher and with mining panels. a) plan view of the first bench, and b) plan view of the second bench.

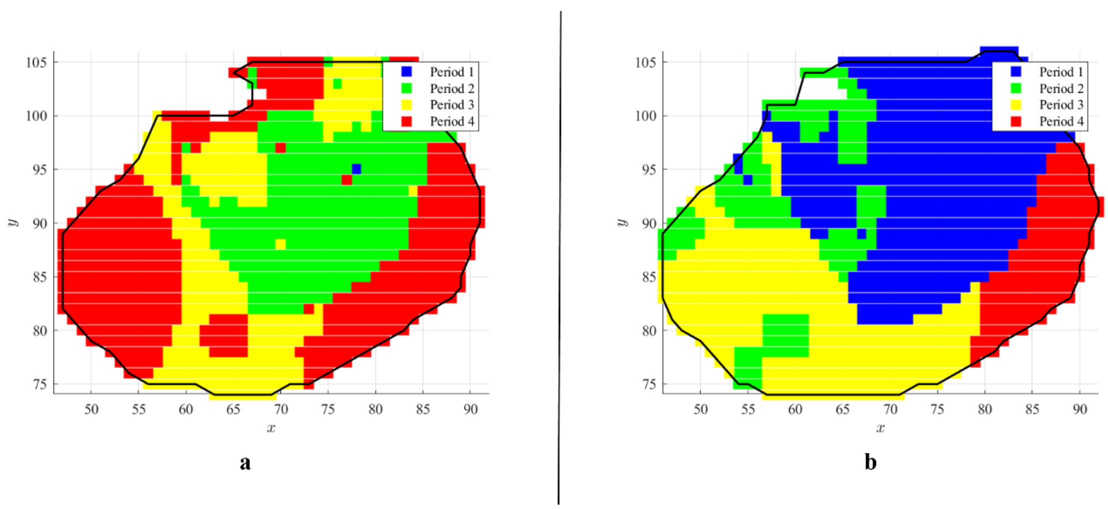

Figure 11. The extraction sequence for the MILP model with in-pit crusher and with crusher panels. a) plan view of the first bench, and b) plan view of the second bench.

5. Conclusions

In this study, we tried to optimize the location of the crusher and then model the mine schedule considering the crusher spots. For that, we used the idea of using crusher panels instead of mining panels to model the crusher spots practically. Additionally, the shortest path method with the mine road network is hired to find the best crusher spots among the crusher panels. In the proposed two-step model, the relocation time is an assumption that is presumed every two benches or four periods for the case study. The proposed model uses two-step clustering to create the crusher panels and then make the mining cuts inside the crusher panels. It is also important to create the crusher panels to honor the mining phases and the precedence. The model is implemented in two benches of an iron ore mine to test and validate the results. The model results show that using the crusher panels, the mine schedule follows the production target while extracting in the mining phases and crusher panels direction to keep the crusher spot untouched from being extracted till the last period.

It also shows a considerable deduction in the truck requirement, which eventually accounts for the mine operating cost reduction.

6. References

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