Mining Optimization Laboratory

Report Ten –2021/2022

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Executive Summary

This year, we have prepared a report including 16 papers. We continue to update all the research results on the MOL webpage www.ualberta.ca/mol on the members section. Sponsors have access to current and past research results, publications, prototype software, and source code. Let's review the contributions in the MOL Report Ten (2021/2022) by considering some of the main contributors.

In **paper 101**, ***Ali*** presents a two-stage clustering-MILP algorithm for long-term production planning in open-pit mines incorporating multi range stockpiles in the decision-making process, that leads to determining the optimum number of stockpiles required to maximize the discounted value of the mine as well as balancing the quality and quantity of throughput. They evaluate the developed model in a real open pit mine case study, and show that with a four-bin stockpile they can maximize the discounted value of the mine by minimizing head-grade deviation and maximizing the reclaimed material delivered to the plant. In **paper 208**, he presented a bi-objective mathematical model that aims to minimize the transportation costs and carbon released to the environment concurrently. This paper also considers different aspects related to material handling systems like the speed of trucks, different age bins, etc. The results show that a short improvement can significantly improve the efficiency of the mine and decrease its operational costs and carbon emission. Ali also developed a multiple objective mathematical programming model for blend optimization in oil sands mines. As presented in **paper 209**, the model takes the processing targets as inputs and minimizes deviations from each desired target by considering material properties at mining faces, the capacity of trucks, and shovels' production rate.

Alireza has focused on incorporating the in-pit Crushing and Conveying (IPCC) system in long-term open pit mine planning. He first reviews the literature on the long-term mine planning and the IPCC locations and relocations in **paper 102**, and investigates the integration of IPCC within the long-term mine planning optimization. In this paper, the goal is to understand the proposed academic solutions that could be hired to optimize the integrated model over the mine life and identify any gaps in the literature. He documents the limitations of current algorithms for separately-optimization of long-term planning and IPCC decision, in terms of mining practicality and optimality of the solution. The results of this literature review enables us to find the best solution for both questions simultaneously. Following this paper, in **paper 103** he has developed a Mixed-Integer Linear Programming (MILP) model to optimize the strategic mine planning in presence of an IPCC system. He finds the optimal in-pit crusher locations and relocation times over the mine life, and establishes a new truck fleet sizing as a result of the decrements in haulage distances. To achieve the research objectives, he has developed a two-step mathematical programming model 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 Truck-Shovel (TS) system to investigate 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.

Roberto has investigated the implementation of Artificial Intelligence (AI) and data-driven methods in solving the mine planning optimization problem. In **paper 104**, he presents a systematic literature review to identify research trends in this field, both in the specific area of application and the AI technique used. Papers from popular scientific databases were compiled and categorized into three main identified research areas, as: production planning and scheduling, equipment management and grade control, and individual AI techniques. The results indicate an exponential growth in the general number of publications, where the most consolidated techniques across all applications were Genetic Algorithms and Discrete Simulation. Afterwards, in **paper 206** he proposes a Deep Reinforcement Learning (DRL) approach based on the Deep Q-Learning algorithm to obtain a robust shovel allocation plan for open-pit short-term planning. He has developed a discrete-event simulation model of the mining production system incorporating trucks, shovels, crushers, dumps and the road network. Each component of the equipment operating cycles is subject to uncertainties modeled based on historical activity records to serve as the environment to train the DRL agent. His goal is to learn a robust shovel allocation strategy for the next 3-months to meet the tonnes per hour (TPH) production target. As a result, the agent successfully learns a shovel allocation plan that achieves the goal considering all the operating uncertainties for the case study.

Hongshuo has been carrying out research on implementation of Near Face Stockpiles (NFS) that could decouple the whole mining flow into two weakly related subsystems of mining and processing, to enhance the Net Present Value (NPV) and the plant throughput. Incorporating the NFS has many theoretical advantages in comparison to the traditional open-pit mining method, including higher tolerance on uncertainties without compromising production, higher equipment utilization, less operating cost, and better blending results. The introduction of NFS, however, requires reconsideration of production planning in open pit mines. In **paper 105**, he has developed an MILP model to solve long-term production scheduling problem in open pit mines, considering the NFS. To quantitatively measure the performance of the NFS mining method, he implemented the model in a real mining case study and compared the results with the traditional open pit mining method with an out-of-pit crusher. The results revealed an improvement in both the NPV and the plant head grade by implementing the NFS method.

Shadrach has been conducting research on implementation of Evolutionary algorithms to solve the mine planning optimization models, as they are capable of generating good solutions at shorter computational time. In **paper 106** he presents an evolutionary algorithm framework based on Genetic Algorithm (GA) to solve the stochastic open pit production scheduling problem in the presence of grade uncertainty. For implementation, he has used a set of equally probable simulated orebodies generated through Sequential Gaussian Simulation as input to the stochastic optimization model. Two case studies are presented that compare results from a stochastic GA against the results from a stochastic MILP model.

Nasib has reviewed the state-of-the-art in short-term open pit mine planning with IPCC in **paper 201**. The IPCC has gained momentum to replace the TS system, partially or fully because of increasing fuel and labor cost and low operating cost of conveyors. He has reviewed the work done on short-term mine planning and IPCC in open pit mines to find research gaps and future research opportunities in implementation of IPCC as the prime means of material handling. The most recent literature since 2010 on different formulations of short-term mine planning and IPCC are reviewed, with the primary objectives such as optimum crusher location. The review reveals a gap in generating mine extraction sequences with IPCC integration. He proposes a theoretical problem formulation to explore this research gap. He followed his research direction in **paper 202** with implementation of Semi-mobile in-pit crusher, currently the most popular IPCC system, in the short-term mine planning. In his research work, he proposes a mixed integer programming model to generate short-term production plan within a time horizon of 12 months. The objective of the model is to optimally allocate shovels to minimize the material handling cost and maximize the revenue, subject to plant requirement, maximum allowable tonnage variation and the IPCC location constraints. The proposed model has been implemented in a hypothetical case study and is solved using MATLAB. The comparison of results between scenarios with and without IPCC justifies the use of IPCC in large open pit mines from a short to medium term perspective.

Mohammad has been carrying out research on understanding the efficiency of truck and shovel loading practices, evaluating them and developing a framework that can be implemented in short-term plans. In **paper 203**, he has proposed a simulation model using Haulsim software. Multiple scenarios on the number of trucks, number of shovel passes and the rolling resistance of the road are simulated. Based on the simulation results, the operation manager insights into the material handling system opportunities, deciding to switch between a higher pass and a lower pass based on the operation plan, match factor and production targets. Further outcomes are operation Key Performance Indicators (KPIs) such as queuing time, number of trucks, trucks queue at the shovel, cycle time, and the production cost per ton. He checked the Short-term production analysis and deep comparison between two loading strategies, and the elements that induce this dynamic change are studied and analyzed using suitable machine learning. Finally, he highlights all associated mining operation parameters that determine the potential sweet spot of the loading strategy.

Pedro has been working towards developing an intelligent autonomous supervisor to manage a continuous mining environment in real-time to achieve the required key performance indicators. He designed the performance objectives for each process and monitored accordingly during continuous mining. In **paper 204** he focuses on the application of deep reinforcement learning with Deep Q Networks algorithm for short-term mine planning. This approach uses a discrete event simulation model of the mining operation and an agent-based model to simulate equipment's behavior. His developed simulation model interacts with an autonomous intelligent agent to manage the continuous mining environment by addressing random and dynamic processes during the mining operation. The intelligent supervisor identifies trends and shortfalls by observing huge amounts of mine planning and mine operations data and makes changes to improve the KPIs. The intelligent agent autonomously selects mining zones and allocates shovels and trucks to minimize real-time deviations from the set ore grade and ore tonnage targets for the processing plant.

Pouya has presented the machine learning method as a novel and profitable idea to optimize fleet management and achieve a sufficient output to reduce operational costs through diminishing trucks' queuing time and excavators' idle time. In **paper 205**, he has studied the performance of this method at the Zenouz kaolin mine to optimize the type of loader and the number of trucks used to supply the processing plant's ore demands. He has collected and processed the five years' data of weather conditions, number of trucks, routes, loader types, and daily hauled ore, to train five practical algorithms of linear regression, decision tree, K-nearest neighbor, random forest, and gradient boosting algorithm. He has compared the results of the algorithms and identified the gradient boosting algorithm as the best fit to predict test data values with 75% accuracy. He selected the data with the minimum variation of the required scheduled value and indicated the related data containing loader type and the number of required trucks for each day of the working year. In **paper 402**, he studied another application of AI in detection of ore type in drilling cores using deep learning (DL). Pouya developed a novel DL algorithm to recognize the types of kaolin samples. He collected a dataset of drilled cores' images and their relative types, which is examined using chemical and physical analyses, and presented two eight-layer convolutional neural network (CNN) topologies based on individual features. The results showed more efficiency of Model A with 91% accuracy than Model B with 84% accuracy. Furthermore, the exactness of recognizing the model according to four criteria, including accuracy, precision, recall, and F1-score, is equal to 90%, 92%, 92%, and 90%, respectively, which are acceptable accuracies to identify the type of samples when using this approach on six different types of kaolin.

Milad presented a framework to integrate carbon emissions into short-term planning of surface mines. The mining industry is under pressure from regulators, investors, and society to limit global warming to at or below 1.5 ˚C – 2 ˚C. In response to climate change and sustainability, most mining companies are taking major steps to minimize their greenhouse gas emissions (GHG). In **paper 207** he tried to explore how the contradicting goals of sustainable mining and the increase in the demand for raw materials will impact the short-term production planning in surface mines. We aim to investigate the possibility of translating the CO2 emissions into a quantifiable factor being imposed to the process of short-term planning in surface mines.

Soroush presents a literature review in **paper 301** that focuses on sublevel caving production scheduling using mathematical programming methods. The sublevel caving (SLC) method is a common method with moderate development requirements, high production rate, and high degree of mechanization and flexibility. The mixed-integer programming models have been applied to provide an operationally feasible multi-time period's schedule. However, confined blasting conditions, chaotic material flow, and frequent mixing of ore and waste while loading broken ore at the drawpoint make sublevel caving method unique to produce a holistic plan. He reviewed all mathematical programming models presented in sublevel caving production scheduling optimization, highlighted the inherent characteristics of the sublevel caving that affect production, and put forward some promising ideas for future works. Soroush continued his research in **paper 302** by developing an integrated MILP model for long-term production scheduling optimization of sublevel caving mines. The model determines the optimal machine placements in each period over the horizon to maximize the NPV. Furthermore, the model satisfies constraints like development activities, mining, and processing capacities, continuous mining of machine placements, restrictions on the allowable number of active machine placements, grade blending, and vertical and horizontal sequencing. The formulations are coded and developed in Jupyter Notebook, and the Python interface of IBM ILOG CPLEX Optimization Studio 20.1.0 is used to solve the model.

Magreth conducted her research about assessment of blast-induced damage in hard rock blasting. In **paper 401**, she presented an approach to analyze the effects of rock mass properties on explosive energy. It is divided into steps to estimate total blast energy produced, characterize the rock mass, assess failure mechanisms, and the blast-induced damage. Through a case study in an open pit gold mine, she investigated five production shots of variable sizes with over 1300 charged holes to analyze the explosive energy/rock mass interaction. She calculated the ratio of in-situ block size to the average fragmentation size to evaluate the effect of rock mass on energy distribution and fragmentation in variable rock masses.

Arman carried out his research with attempts to conduct a retrospective overview on the applications of simulation, optimization and machine learning in the surface mining concept to elicit their merits and demerits. In **paper 403**, he presented a retrospective overview of conventional solutions in surface mines and assessment of Digital Twin (DT) incorporation. He developed a six-layer Digital-Twin-based architecture to be applied as a roadmap in the mineral industry.

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Annual Research Report Ten
Mining Optimization Laboratory (MOL) 2021-2022

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Mining Optimization Laboratory (MOL) Researchers / Graduate Students

Following are researchers and students affiliated with Mining Optimization Laboratory in September 2022.

1.	**Hooman Askari-Nasab**	Professor - Director of MOL
2.	**Yashar Pourrahimian**	Associate Professor, University of Alberta
3.	**Eugene Ben-Awuah**	Associate Professor, Laurentian University
4.	**Ali Moradi Afrapoli**	Assistant Professor, Université Laval

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5.	**M. Mahdi Badiozamani**	PhD, Research Assistant - 2018/03
6.	**Rozan Chahardoli**	MSc, Research Assistant - 2019/09
7.	**Emmanuel Appianing**	PhD Student – 2017/05
8.	**Hongshuo Gong**	PhD Student – 2018/09
9.	**Nasib Al-Habib**	PhD Student – 2018/09
10.	**Alireza Kamrani**	PhD Student – 2018/09
11.	**Magreth Dotto**	PhD Student – 2018/09
12.	**Mohammadreza Kazemi**	PhD Student – 2019/01
13.	**Roberto Noriega**	PhD Student – 2019/09
14.	**Soroush Khazaei**	PhD Student – 2019/09
15.	**Pedro P. Vasquez Coronado**	PhD Student – 2019/09
16.	**Milad Rahnema**	PhD Student – 2022/05
17.	**Arman Hazrathosseini**	PhD Student – 2022/09
18.	**Mohammad Lashgari**	PhD Student – 2022/09
19.	**Sandra Fahl**	PhD Student – 2022/09
20.	**Samaneh Moradi Pirbalouti**	PhD Student – 2022/09
21.	**Solomon Acheampong**	MSc Student – 2020/09
22.	**William Junkin**	MSc Student – 2018/01

23.	**Agar Bulgan**	MSc Student – 2019/09
24.	**Shadrach Amponsah**	MSc Student – 2020/01
25.	**Mohammad Al-Masri**	MSc Student – 2020/09
26.	**Bahar Amirmoeini**	MSc Student – 2022/09
27.	**Yaa Karikari**	MSc Student – 2022/09
28.	**Tebasto Mothupi**	MEng student - 2020/09
29.	**Mohammadreza Moghaddam**	Visiting Student - 2021/12

A Two-Stage Simultaneous Optimization of NPV and Throughput in Production Planning of Open Pit Mines by Introducing Multi Range Stockpiles[1]

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ABSTRACT

Open-pit mines are complex businesses with lifelong profits of millions and in large mines billions of dollars. These mines consist of a minimum of one discrete (mining) and one continuous (processing) subsystem working subsequently to deliver input raw material to several downstream industries. The inherent difference between these two subsystems causes operational challenges in the production process leading to nonoptimal NPV and quality and quantity of throughput from discrete to continuous subsystem. In this paper, we present a two-stage clustering-MILP algorithm for long-term production planning in open-pit mines incorporating multi range stockpiles in the decision-making process that leads to determining the optimum number of stockpiles required to maximize the discounted value of the mine as well as balancing the quality and quantity of throughput. We evaluated our developed model in a real open pit mine case study. Results show that with a four-bin stockpile we can maximize the discounted value of the mine by minimizing head-grade deviation to 5.1% and maximizing the reclaimed material up to 10.7% of the total ore delivered to the plant.

1. Introduction

Among all mechanical and non-mechanical mining methods, open-pit mining method is the most common ore extraction method being applied for exploitation of more than 80% of raw material delivered to the market [1]. As multi-million/-billion-dollar expenditures with the same profit scale, open-pit mines usually integrate a discrete system (mining operation) with a continuous system (processing) to mine and deliver raw material to the market. Having the discrete and the continuous systems synchronized and at the same time decoupled, so that the material flows through the production chain with consistent quantity and quality is one of the major challenges of mining operations. This challenge is delt with by the introduction of stockpiles to the open pit mining operations.

Adding stockpiles to the open pit mining operations, subsequently leads to requirement of including them in the open pit mine production scheduling (OPMPS). Two approaches are common in the integration of stockpiles into OPMPS: making stockpiling decisions during the long-term OPMPS stage or postponing stockpiling decisions to the short-term OPMPS stage. The long-term OPMPS models must make decisions on the combination of millions of mining blocks and several

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time spams to maximize net present value (NPV) which already is a challenging and time-consuming task [2]. Thus, adding stockpiling decisions to the long-term OPMPS will make it even more challenging. Herein, we developed a two-stage aggregation-stockpiling decision-making framework that solves the long-term OPMPS in presence of stockpiles in a few seconds while creating a higher NPV compared to the same operation without any stockpile.

OPMPS problems have attracted several researchers since Johnson's introduction of mathematical programming to the field of mine planning [3] over 50 years ago. The literature of OPMPS until 2010 have been reviewed critically by Osanloo and Newman and are presented in [4] and [5], respectively. Since then, three streams of research can be tracked in OPMPS. The first is the direction where researchers have tried to reduce the solution time. Moreno et al. and Samavati et al. developed a multi-step algorithm that deals with the OPMPS as a multi-period precedence-constrained knapsack problem [6], [7]. Implementation of their multi-step algorithm on Marvin and other datasets showed approximately five times improvement in the solution time with a confidence interval of 94%. Most of the other works in this stream focus on the implementation of different relaxation approaches to cut the solution time for the OPMPS problems [8]–[11]. None of these proposed solution methodologies include stockpiling in their procedure.

In the second trackable stream of OPMPS literature, researchers integrated in-pit crushing and conveying (IPCC) systems location optimization problems with OPMPS and tried to solve both problems at the same time. As IPCC material handling systems have been practically proven to be economically premier to the regular truck and shovel system [12] especially over the recent two decades, researchers have proposed different algorithms to incorporate IPCC into OPMPS solution procedure [13]–[16]. Same as the first stream, none of the solution methodologies that integrate IPCC with OPMPS explicitly incorporate stockpiling in their procedure.

In the third traceable stream in the literature, researchers of introduced the stockpiling option into the OPMPS problem and tried to propose solution methodologies for that. The main challenge of adding the stockpiling option to the OPMPS problem is nonconvexity and nonlinearity of the produced optimization models [17]. Bley et al. relaxed the nonlinear constraints and received a linear outer approximation and introduced a branching method and a primal heuristic that generates feasible solutions [17]. The model proposed by Bley et al. [17] has the capability to track the material flow from aggregates to stockpile and plant. In another attempt, Gholamnejad and Kasmaee defined a block model over one low grade and one high grade stockpile in [18] and developed a goal programming model for selective rehandling of material from each of the two stockpiles to provide optimum blend for the plant. Although they targeted optimality of the blend, their model ignores material from the mine.

Grade or quality of material delivered to and rehandled from stockpile have been addressed by Dimitrakopoulos works with Asad in [19] and his work with Ramazan in [20]. In the former, researchers model the stockpile by dividing grade ranges on the grade-tonnage curve and determining material from each grade range. In the later, however, the model has a constant grade for the stockpile that is determined prior to scheduling which is used for the reclamation of material from the stockpile. Predetermined grade for stockpiles has also been considered by Mousavi [21] and Kumar [22] in their proposed models for OPMPS. The researchers in [21] implemented non-exact solution methodology to solve their model. Despite the novelty of their work, they have not evaluated its performance in a large-scale case study and neither they evaluated the possible errors caused by fixed stockpile reclamation grade. The researchers in [22] apply the same logic in an open pit coal mine. In another grade-based attempt, Smith and Wicks proposed an OPMPS model for a copper mine where low grade material was stored in a stockpile for future use in case needed [23]. Finally, in a series of studies, Moreno, Rezakhah, and Newmann classify the production scheduling and stockpiling models in the literature and propose new modeling approaches in [2], [24].

Lack of OPMPS models that consider more than one of the abovementioned streams (speed, IPCC, and stockpiles) convinced us to develop a multi-step algorithm to tackle the first stream (speed) and the third stream (stockpiling) by clustering mining blocks and introducing a mixed-integer linear model that incorporates stockpiling in the OPMPS solution procedure. Thus, in the following sections, we first explain how we developed the algorithm. Then, we discuss its implementation in a series of scenarios in a case study. Finally, we present the results of our evaluation on improvement of the run time and the net present value of the project.

2. Materials and Methods

2.1. Two-step algorithm

As mentioned earlier, we integrated a clustering algorithm with a mixed-integer linear model to schedule open pit production in presence of stockpiles. Our two-step algorithm helped us to incorporate the stockpiling decisions with the OPMPS decisions without sacrificing the solution time. In the first step of this two-step algorithm, we implemented the agglomerative hierarchical clustering method to aggregate blocks of the same bench (bench-phase) into larger units called mining-cuts. This clustering method merges the closest pairs of inputs respecting satisfaction of pre-defined similarity indices [25]. We defined distance, grade, rock type, destination, and under-cluster which tracks the ore beneath each cluster for developing a better schedule by accessing the higher-grade ore faster.

From the five defined indices, grade and distance have numeric values. Thus, we implemented Minkowski distance method [26], [27] to calculate similarity of those indices in our blocks and clusters as presented in equation (1).

$$d\,(j,k) = \left(\sum_{i=1}^{n} \left|x_{ji} - x_{ki}\right|^{r}\right)^{\frac{1}{r}} \tag{1}$$

Where r is always greater or equal to one. If $r=1$ then it turns into Manhattan distance and if $r=2$ the equation turns into Euclidean distance. For each dimension (i) in n possible dimensions, $d(j,k)$ is dissimilarity index value of index d between variables (in our case blocks) x_{ji} and x_{ki}.

Among our indices, we have rock type, under-cluster, and destinations which are categorical indices and do not take numerical values. So, implementing Minkowski distance method in these cases are not possible. Thus, to evaluate similarity of our clusters in terms of these categorical indices, we implemented the method proposed by Dosea and his colleagues [28] based on integration of simple matching method offered by Huang [29], [30] and calibrated penalties for extent of dissimilarity between values. As the similarity indices are not of the same measurement units, we implemented linear scaling technique to normalize the numeric indices with the maximum value to be able combine them with the categorical indices for which we have chosen zero for not being similar and one for being similar to one another. The process has been explained in the Algorithm 1.

We designed the clustering algorithm to only cluster best matches blocks in a single bench since each shovel mining face will only be consisted of one bench of material. The clustering procedure is presented in Algorithm 1.

Algorithm 1: generating bench-phase mining cuts from the block model

Inputs

Block model; maximum number of possible clusters; maximum length of possible clusters;

Begin

NC ← Total number of blocks

NC_{max} ← Maximum number of possible clusters

LC_{max} ← Maximum length of possible clusters

A ← zeros [N]

S ← zeros [N]

$D_{max} \leftarrow \left(\sum_{d=1}^{2} \left|x_{id} - x_{jd}\right|^2\right)^{\frac{1}{2}} \ \forall\, i \,\&\, j \in \{1, \ldots, N\}$

$G_{max} \leftarrow g_i \ \forall\, i \in \{1, \ldots, N\}$

for i = 1 to N **do**

  for j = 1 to N **do**

    if i = j **then**

      $S_{ij} \leftarrow 0$

      $A_{ij} \leftarrow 0$

    else

      $R_{ij} \leftarrow \{1\ if\ i \,\&\, j\ same\ rock\ type\ r\ otherwise$

      $C_{ij} \leftarrow \{1\ if\ i \,\&\, j\ above\ same\ cluster\ c\ otherwise$

      $D_{ij} \leftarrow \{1\ if\ i \,\&\, j\ same\ destination\ d\ otherwise$

      $L_{ij} \leftarrow \frac{\left(\sum_{d=1}^{2} \left|x_{id} - x_{jd}\right|^2\right)^{\frac{1}{2}}}{D_{max}}$

      $G_{ij} \leftarrow \{\frac{\left(\left|x_{id} - x_{jd}\right|^2\right)^{\frac{1}{2}}}{G_{max}}\ if\ \left|x_{id} - x_{jd}\right|^2 \neq 0\ \varepsilon\ otherwise$

      $S_{ij} \leftarrow \frac{R_{ij} \times C_{ij} \times D_{ij}}{L_{ij} \times G_{ij}}$

      if i & j are adjacent **then**

        $A_{ij} \leftarrow 1$

      else

        $A_{ij} \leftarrow 0$

      endif

while NC > NC_{max}

(i,j) $\leftarrow \{\{A_{ij}\}\}$

if $(LC_i + LC_j) \le LC_{max}$ **then**

$S_{i:} \leftarrow \{(S_{it} | \, t \in \{1, ..., N\})\&(S_{jt} | \, t \in \{1, ..., N\})\}$

$S_{j:} \leftarrow 0$

$A_{i:} \leftarrow \{(A_{it} | \, t \in \{1, ..., N\})\&(A_{jt} | \, t \in \{1, ..., N\})\}$

$A_{j:} \leftarrow 0$

$C_i \leftarrow C_i + C_j$

$NC \leftarrow NC - 1$

else

$A_{ij} \leftarrow 0$

endif

endwhile

After the clustering process following Algorithm 1, two post-processing steps are performed to deal with the geometrical constraints such as shape of the cluster and mining precedence. Then, the mathematical model explained in the next subsection is implemented on the practical representation of the deposit with a reduced number of variables and constraints.

2.2. Open pit mine production scheduling model

Introducing stockpiles imposes nonlinearity to the OPMPS models. To practically deal with this nonlinearity, we introduced operationally approved stockpiling method. With this stocking method, ore is stored in a divided area with a range of acceptable grades to be able to assign fixed reclamation grades to each stockpile. The storing grades and the reclaiming grades of this multi bin stockpiling method are determined based on the grade-tonnage graph prior to any OPMPS model implementation. After this step, we implement the mathematical formulation presented here to develop production schedule for the mine. Following we present the our developed OPMPS model.

- Sets

S^m	For each bench-phase m, there is a set of bench-phases (S^m) that have to be extracted prior to extracting bench-phase m to respect slope and precedence constraints
U^m	Each bench-phase m is divided into a set of clusters. U^m is the set of clusters that are contained in bench-phase m

- Indices

$d \in \{1,...,D\}$	Index for material destinations
$m \in \{1,...,M\}$	Index for bench-phases

$p \in \{1,...,P\}$	Index for clusters
$c \in \{1,...,C\}$	Index for processing plants
$e \in \{1,...,E\}$	Index for elements
$t \in \{1,...,T\}$	Index for scheduling periods

- Parameters

D	Number of material destinations (including processing plants and waste dumps)
M	Total number of bench-phases
P	Total number of clusters
E	Number of elements in the block model
T	Number of scheduling periods
$\overline{MC}^t$	Upper bound on the mining capacity in period t
$\underline{MC}^t$	Lower bound on the mining capacity in period t
$\overline{PC}_c^t$	Maximum tonnage allowed to be sent to plant c in period t
$\underline{PC}_c^t$	Minimum tonnage allowed to be sent to plant c in period t
$\overline{G}_c^{t,e}$	Upper limit on the allowable average grade of element e at processing plant c in period t
$\underline{G}_c^{t,e}$	Lower limit on the allowable average grade of element e at processing plant c in period t
s_m	Number of predecessors of bench-phase m (members of S^m)
o_m	Total ore tonnage in bench-phase m
w_m	Total waste tonnage in bench-phase m
o_p	Total waste tonnage in cluster p
w_p	Total waste tonnage in cluster p

c_m^t	Unit discounted cost of mining material from bench-phase m in period t
$r_{p,c}^t$	Unit discounted revenue of sending material from processing unit p to processing destination c in period t minus the processing costs
$r_c^{t,e}$	Unit discounted revenue of processing one unit of element e from stockpile in processing destination c in period t minus the processing and rehandling costs
g_p^e	Average grade of element e in cluster p

- Decision Variables

$y_m^t \in [0,1]$	Continuous decision variable representing the portion of bench-phase m extracted in period t
$x_{p,c}^t \in [0,1]$	Continuous decision variable representing the portion of ore tonnage in cluster p extracted in period t and sent to processing plant c
$b_m^t \in \{0,1\}$	Binary decision variable indicating if all the predecessors of bench-phase m are completely extracted by or in period t
f_c^t	Continuous decision variable representing the tonnage reclaimed from the stockpile and sent to processing plant c in period t
$G^{t,e}$	Continuous decision variable representing the reclamation grade of element e in period t

With the abovementioned parameters and variables, now we define our multi destination objective function. To do so and for the purpose of enhancing the solution procedure we defined $y_m^t \in [0, 1]$ as a set of variables to monitor the portion of the bench that is mined in each period *t* and $b_m^t \in \{0, 1\}$ to control the mining precedence in each period *t.* This will help the solver to solve the model faster as the variables are reduced compared to the number of blocks. To avoid non-linearity in the model, as we discussed earlier, we define operationally approved S number of stockpiles within acceptable grade range. This will lead to adding S destinations to the list of ore destinations in the model. Then, we determine average reclamation grade of element *e*, $G_s^{e,t}$, for each stockpile *s* to be delivered to the processing plant in period *t*. We also need to incorporate revenue and cost of stockpiling and rehandling from each stockpile in the OPMPS model. Thus, we define $r_{s,c}^t$ as the discounted profit from processing the reclaimed material of the stockpile *s* in the plant *c* during the period *t*. For each destination of mined material in the range of stockpiles ($d = C + s$), we define $\underline{G}_d^{e,t}$ as the upper bound and $\bar{G}_d^{e,t}$ as the lower bound of acceptable *e* grade range for material being delivered to stockpile *s*. Finally, we define a set of variables, $f_{s,c}^t \geq 0$, representing tonnage of material reclaimed from *s* and processed in *c* during the period *t*. That being elaborated, the OPMPS model we formulated is as followed.

- Objective Function

$$\sum_{t=1}^{T}\left(\sum_{p=1}^{P}\sum_{c=1}^{C}\left(r_{p,c}^{t}\times o_{p}\times x_{p,c}^{t}\right)-\sum_{m=1}^{M}\left(c_{m}^{t}\times\left(o_{m}+w_{m}\right)\times y_{m}^{t}\right)+\sum_{s=1}^{S}\sum_{c=1}^{C}\left(f_{s,c}^{t}\times r_{s,c}^{t}\right)\right) \tag{2}$$

- Constraints

$$\underline{MC}^{t}\leq\sum_{m=1}^{M}\left(\left(o_{m}+w_{m}\right)\times y_{m}^{t}\right)\leq\overline{MC}^{t}\qquad\forall t\in\{1,...,T\} \tag{3}$$

$$\sum_{p\in U^{m}}\sum_{d=1}^{D}\left(o_{p}\times x_{p,d}^{t}\right)\leq\left(o_{m}+w_{m}\right)\times y_{m}^{t}\qquad\forall t\in\{1,...,T\}\,,\forall m\in\{1,...,M\} \tag{4}$$

$$\underline{PC}_{c}^{t}\leq\sum_{p=1}^{P}\left(o_{p}\times x_{p,c}^{t}\right)+\sum_{s=1}^{S}f_{s,c}^{t}\leq\overline{PC}_{c}^{t}\qquad\forall t\in\{1,...,T\}\,,\forall c\in\{1,...,C\} \tag{5}$$

$$\underline{G}_{c}^{t,e}\leq\frac{\sum_{p=1}^{P}\left(o_{p}\times g_{p}^{e}\times x_{p,c}^{t}\right)+\sum_{s=1}^{S}\left(f_{s,c}^{t}\times G_{s}^{t,e}\right)}{\sum_{p=1}^{P}\left(o_{p}\times x_{p,c}^{t}\right)+\sum_{s=1}^{S}f_{s,c}^{t}}\leq\overline{G}_{c}^{t,e}\ \forall t\in\{1,...,T\},\forall c\in\{1,...,C\},\forall e\in\{1,...,E\} \tag{6}$$

$$\underline{G}_{d}^{t,e}\leq\frac{\sum_{p=1}^{P}\left(o_{p}\times g_{p}^{e}\times x_{p,d}^{t}\right)}{\sum_{p=1}^{P}\left(o_{p}\times x_{p,d}^{t}\right)}\leq\overline{G}_{d}^{t,e}\ \forall t\in\{1,...,T\}\,,\forall e\in\{1,...,E\},\forall d\in SC|d=C+s \tag{7}$$

$$\sum_{i=1}^{t}\sum_{c=1}^{C}f_{s,c}^{i}\leq\sum_{i=1}^{t-1}\sum_{p=1}^{P}\left(o_{p}\times x_{p,d}^{i}\right)\ \forall s\in\{1,...,S\},\forall t\in\{2,...,T\},\forall d\in SC|d=C+s \tag{8}$$

$$\sum_{i=1}^{t}\sum_{c=1}^{C}G_{s}^{t,e}\times f_{s,c}^{i}\leq\sum_{i=1}^{t-1}\sum_{p=1}^{P}\left(o_{p}\times g_{p}^{e}\times x_{p,d}^{i}\right) \tag{9}$$
$$\forall s\in\{1,...,S\},\forall t\in\{2,...,T\},\forall e\in\{1,...,E\},\forall d\in SC|d=C+s$$

$$\sum_{t=1}^{T}y_{m}^{t}=1\qquad\forall m\in\{1,...,M\} \tag{10}$$

$$\sum_{i=1}^{t}y_{m}^{i}\leq b_{m}^{t}\qquad\forall m\in\{1,...,M\},\forall t\in\{1,...,T\} \tag{11}$$

$$s_{m}\times b_{m}^{t}\leq\sum_{i\in S^{m}}\sum_{j=1}^{t}y_{i}^{j}\qquad\forall m\in\{1,...,M\},\forall t\in\{1,...,T\} \tag{12}$$

$$b_m^t \leq b_m^{t+1} \qquad \forall m \in \{1,..., M\}, \forall t \in \{1,..., T-1\} \tag{13}$$

The model optimizes discounted net present value from processing ore sent to the plant either directly from the mine or by rehandling the stockpiled material in equation (2). We introduced equations (3) for controlling the extraction capacity of the mine and equation (5) for controlling the processing capacity of the plant for each period of the mine life. We cap the maximum amount of material sent to be processed from a bench to the total amount available in the same bench by equation (4). In case the total tonnage mined from the bench and processed from the same bench vary, the difference is the amount of the waste from that bench and is sent to the dumping location. The blending is controlled by equation (6) where our model calculates the weighted average of the material sent to the plant controls the average head grade of the summation material sent to processing plants from both the mine and the stockpile in each period and keeps this weighted average between the minimum and the maximum acceptable head grade. To avoid nonlinearity here, we adjust the equation prior to matrix creation. We also appended stockpiles to the blending control constraint so that the model controls its input quality and quantity using the same constraint. The reclamation grade for element e in period t, $G^{t,e}$, is determined using equation (7). By defining constraint (8) we make sure that total amount of material reclaimed from stockpile will not exceed the total amount have been stockpiled since day one of the operation. Using the equation (9) the model guarantees content adjustment in case the predetermined average grade is higher than the grade of material currently available in the stockpile. To make sure that all the material inside the optimal pit limit is mined, we implement equation (10) in the model formulation. We also ensure the geotechnical practicality of our production schedule using precedence constraints presented in equations (11) to (13).

To implement the two-stage algorithm presented here, we used the Gurobi engine of Matlab software. For the case study presented in the following section, it takes the software five seconds to perform the first stage and 15 seconds to do the second stage.

3. Case Study

The case study we implemented our two-stage algorithm is an iron ore deposit. The final pit consists of 19561 blocks with a tonnage of 430 million tonnes from three ore rock types and four waste rock types. The ore zones contain desired iron trackable through mass precent of magnetic weight (MWT). The zones also contain deleterious elements including Sulfur (S) and Phosphor (P). The final pit includes four production pushbacks with a total of 40 bench-phases where the clustering algorithm can be implemented. The mining of this pit will be done with a fleet of trucks and shovels with a maximum capacity of 32 million tonnes of material movement which will incrementally decrease to eight million tonnes by the end of the mine life. The mine will have a processing plant with a capacity of seven million tonnes of ore per year which will start its operation from year four of the mine life. The plant will accept ore with a minimum MWT grade of 78% and a maximum S grade of 1.7% and a maximum P grade of 0.14%.

The OPMPS of the case study without incorporating the two-step algorithm we developed in this paper is presented in Figure 1. As shown in Figure 1 the mine has 20 years of life to mine and process all the material located inside the optimum final pit limit.

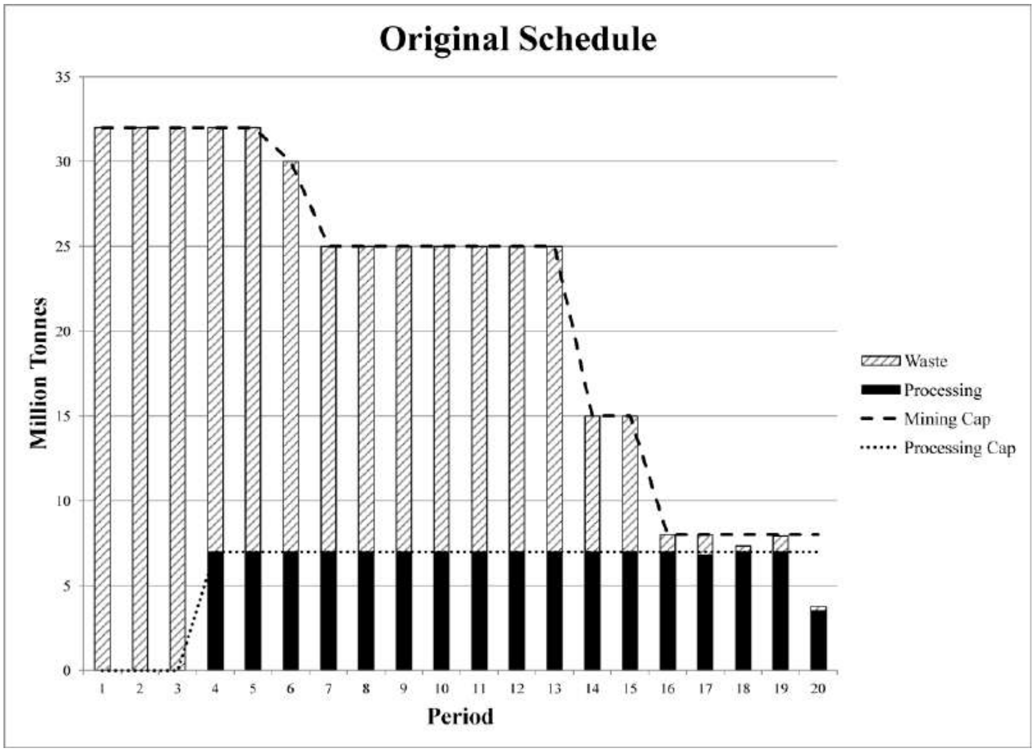

Figure 1. Life of mine production schedule of the case study prior to incorporating grade control in the production process.

Although taking a glance on the production schedule shows no issues in the production, investigating the grade control over the course of the mine life reveals issues with the quality of material delivered to the processing plant (Figure 2). As depicted in Figure 2 between the year four and eight as well as the year 12 and the year 15 if the mine life, the desired minimum MWT head grade has not been met. The same is true for the maximum P content that does not follow the plant requirement for the first four years and the year 11 of the mine life. The main reason for this problem is that the original model does not incorporates the blending constraints into the OPMPS procedure. It is worth noting that as the Sulfur content of the ore deposit is below 1.7% in all the collected samples, we do not present its impact on the schedule in Figure 2 for readability of the figure.

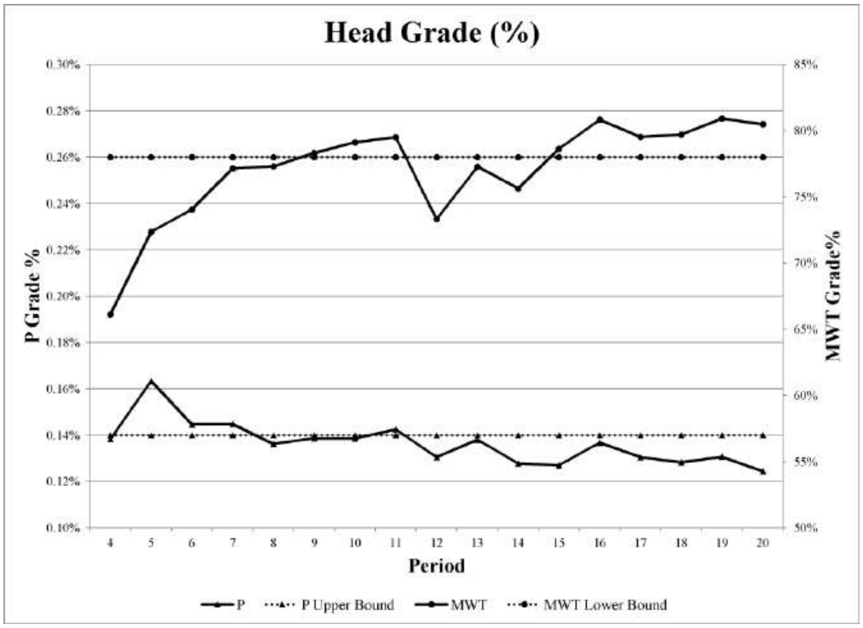

Figure 2. A comparison between desired and achieved iron and phosphor head grades without grade control.

3.1. Head grade constraints

First of all, the algorithm converted the case study to 1870 mining cuts in its first stage. Then, we ran the second stage of the algorithm (OPMPS) without introducing any stockpile option for the operation. This schedule generates 2109 million dollars of NPV. However, as presented in Figure 3, due to grade control enforcement, the plant is not fed to its maximum capacity for approximately 60% of the mine life. Moreover, despite availability of the plant in period four of the mine life, as the mining fleet could not extract material with desired processing grade, no ore has been sent to the plant.

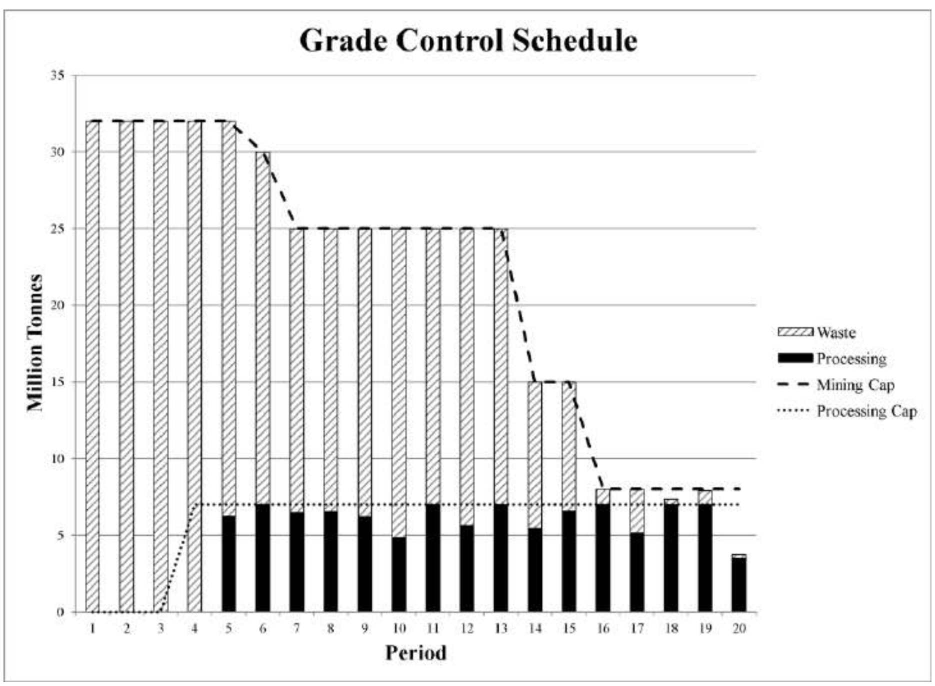

Figure 3. Life of mine production schedule after implementing grade control constraints in the optimization process.

We then add the stockpiling component to the OPMPS model. To analyze the impact of stockpiling in the production schedule of the open pit mine, we defined four different stockpiling scenarios in the operationally practical ranges of material quality as listed in Table 1. In the following subsections we will explain the effects of each scenario on the OPMPS of the case study.

Table 1. Operational scenarios defined for practical stockpiling options.

Stockpile Type	Bin Number	Element	$\underline{G}_d^{t,e}$ (%)	$\overline{G}_d^{t,e}$ (%)	$G_s^{t,e}$ (%)
Single	1	P	0.10	0.15	0.13
		S	1.00	2.00	1.59
		MWT	70.00	80.00	76.55
Double	1	P	0.10	0.13	0.12
		S	1.00	2.00	1.59
		MWT	70.00	75.00	72.42
	2	P	0.13	0.15	0.14
		S	1.00	2.00	1.59
		MWT	75.00	80.00	79.49
Triple	1	P	0.10	0.11	0.10
		S	1.00	2.00	1.59
		MWT	70.00	74.00	71.83
	2	P	0.11	0.13	0.12
		S	1.00	2.00	1.59
		MWT	74.00	78.00	76.47
	3	P	0.13	0.15	0.14
		S	1.00	2.00	1.59
		MWT	78.00	82.00	80.34
Quadruple	1	P	0.10	0.13	0.12
		S	1.00	2.00	1.59
		MWT	75.00	80.00	77.75
	2	P	0.13	0.15	0.14
		S	1.00	2.00	1.59
		MWT	75.00	80.00	77.75
	3	P	0.10	0.13	0.12
		S	1.00	2.00	1.59
		MWT	70.00	75.00	72.24
	4	P	0.13	0.15	0.14
		S	1.00	2.00	1.59
		MWT	70.00	75.00	72.24

3.2. Scenario I single bin stockpile

Now we will add a stockpile to help the operation balance the head grade. In the single bin stockpile type, as shown in Table 1 only one specific range of grades can be piled in the stockpile. Based on information presented on Table 1, we plotted the acceptable range of MWT and P grades on Figure 4. Based on this acceptable range, the model calculates the reclamation grade by taking weighted average over the material. Using the rehandling cost of $0.5/tonne and the calculated average reclamation grade, revenue added to the project from the stockpiling is calculated. Figure 5 shows that, using Scenario I, we are able to feed the plant at its maximum input capacity for all the ore producing years except for year four when the ore was stored in the stockpile due to not meeting the desired plant quality and for further reclamation in the later periods. This resulted in a

9% increase in the NPV of the project (2,291 million dollars) compared to the no stockpile scenario. Keeping track of material delivered to the stockpile in this scenario, Figure 6 compares the grade of material stored in the stockpile with the predetermined reclamation grade for each period and plots the deviation. As shown in this figure, the model tried to store loads with lower MWT and higher P content in stockpile and reclaim with higher grade in the same period to increase the NPV. Over the mine life, the model reclaims 12 million tonnes of material with an average grade difference of 11.6% between stored and reclaimed grades in each period.

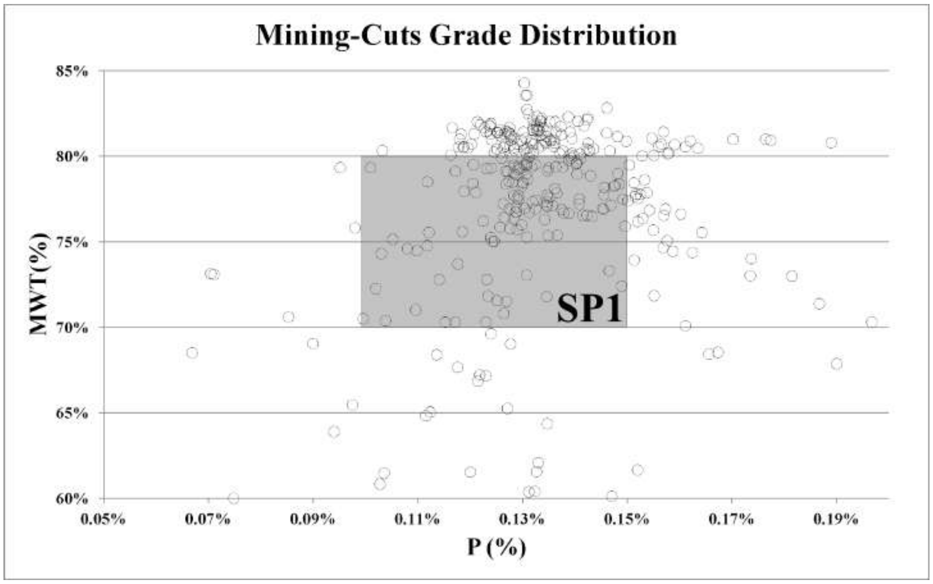

Figure 4. Grade range for MWT and P to be delivered to the stockpile in Scenario I.

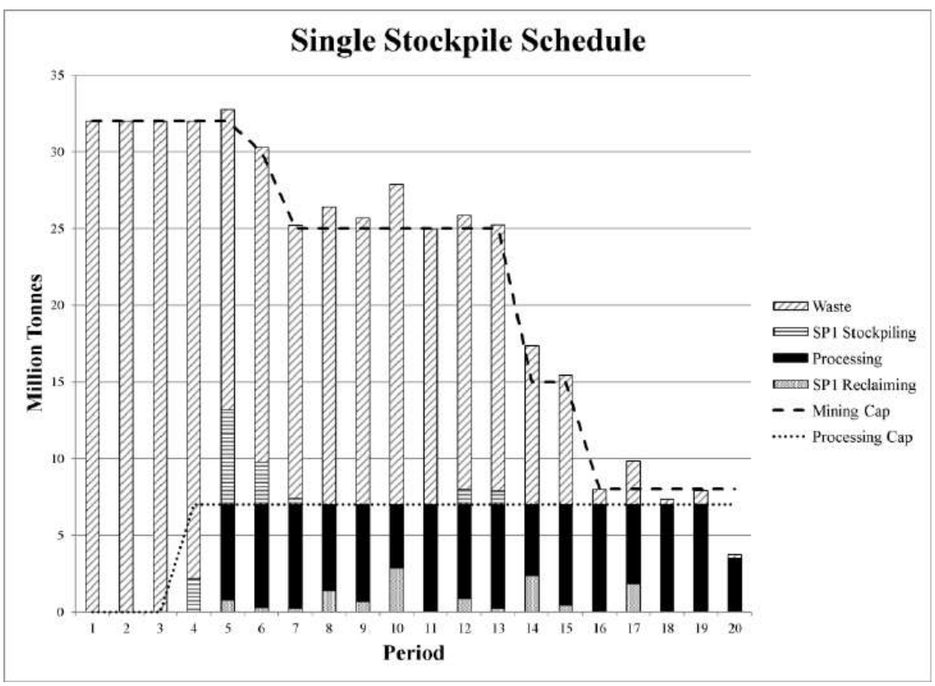

Figure 5. Life of mine production schedule of the deposit in Scenario I.

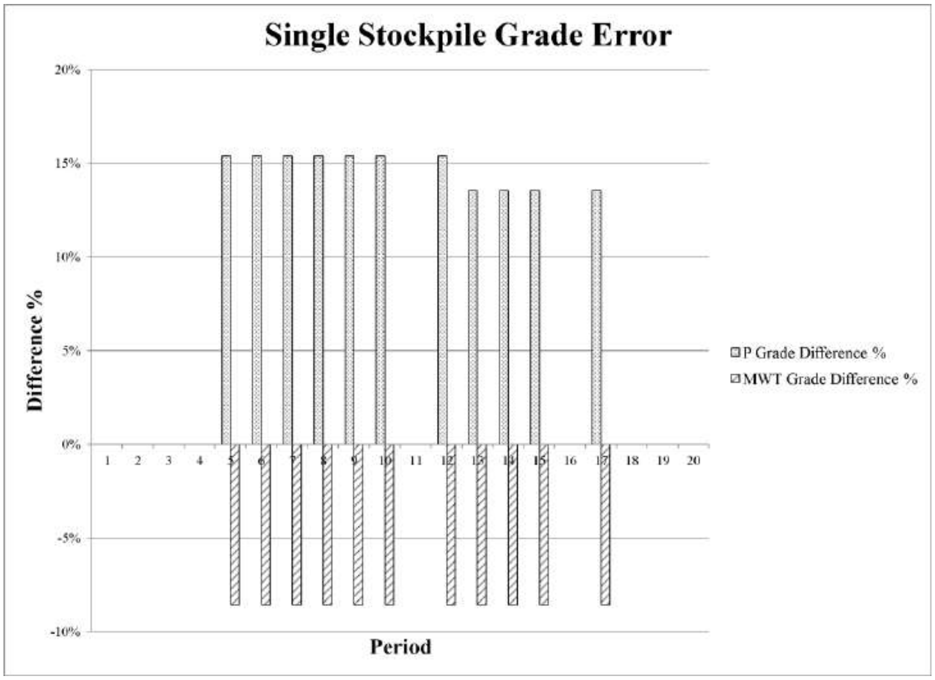

Figure 6. Stockpiling and reclamation grade difference in Scenario I.

3.3. Scenario II double bins stockpile

Now we want to increase selectivity of stockpiling by adding another bin with more strict boundaries for storing and reclaiming grades as listed under double stockpiling type in Table 1. Figure 7 shows the range grades in the deposit that Scenario II will try to store in bin 1 and 2. It worth noting that adding a new bin to the stockpile will not have any cost associated with it. With a comparison between Figure 4 and Figure 7 we can navigate impact of double bin stockpiling on the mining units. Running the OPMPS model under Scenario II conditions generates production schedule, Figure 8, with 2234 million dollars NPV. Adding a new bin cuts the NPV by 2.6% as it increases the selectivity of the stockpiling and reclamation process with an actual to predetermined reclamation grade difference of 5% in each period, Figure 9.

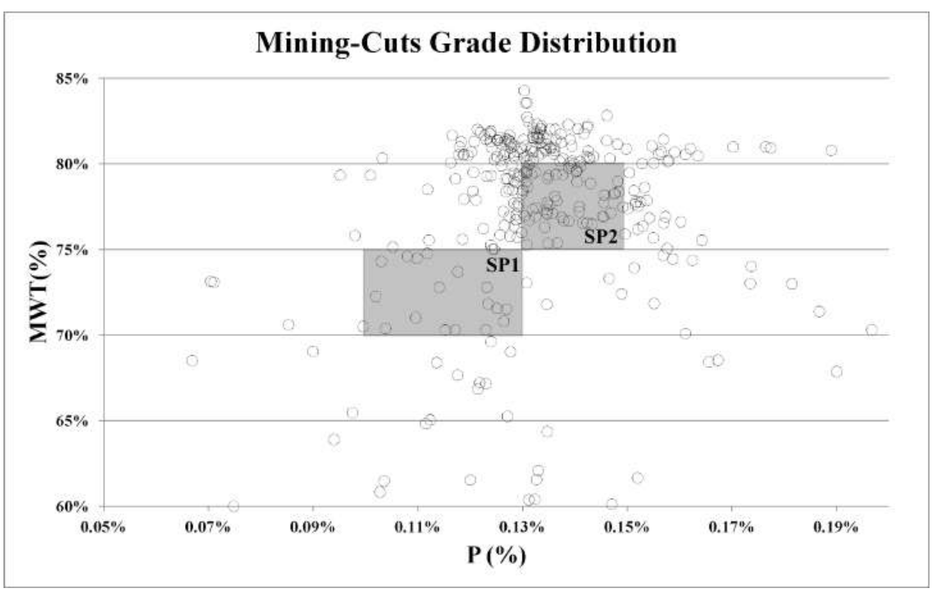

Figure 7. Grade range for MWT and P to be delivered to the stockpile in Scenario II.

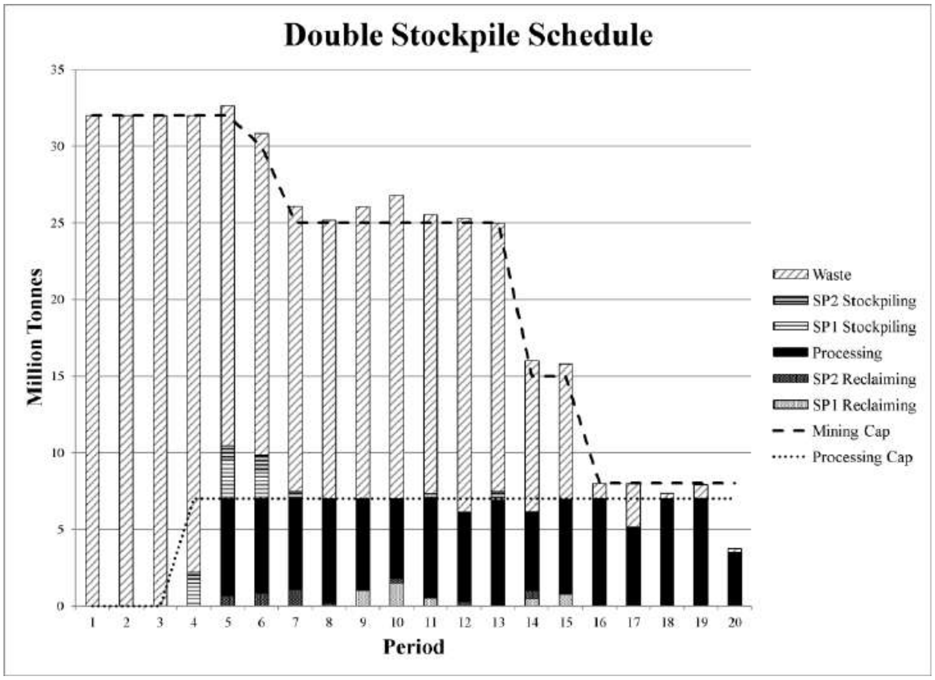

Figure 8. Life of mine production schedule of the deposit in Scenario II.

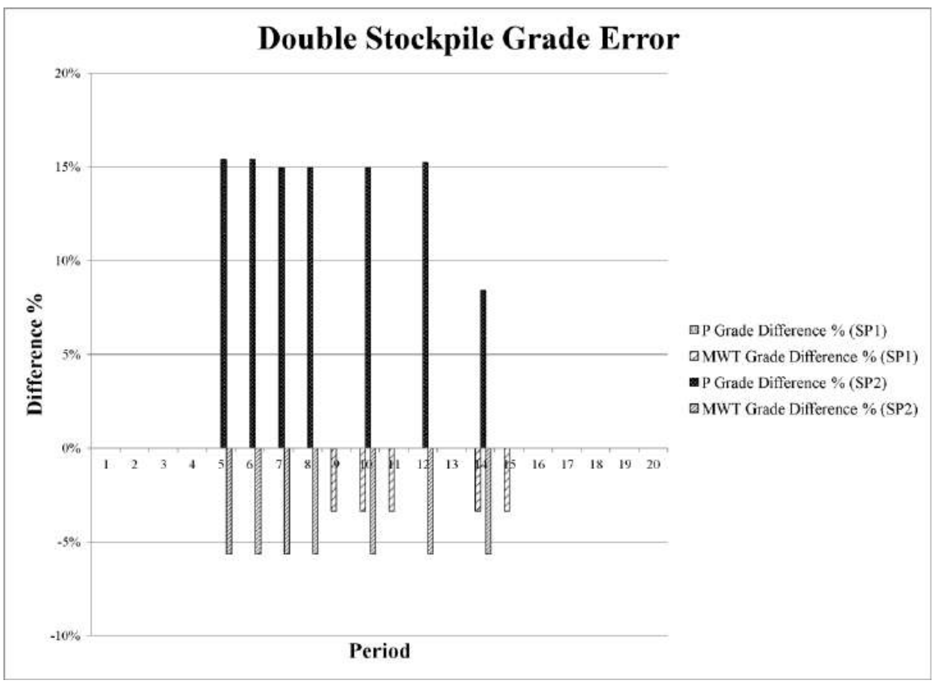

Figure 9. Stockpiling and reclamation grade difference in Scenario II.

3.4. Scenario III triple bins stockpile

In Scenario III we want to tighten the grade range for stockpile bins to investigate its effects on the production. Thus, we ran the OPMPS model with the parameters and grade ranges as shown in triple stockpile section of Table 1 and Figure 10. dividing the stockpile into three different grading bins drops the NPV for 3.4% to 2,155 million dollars compared to the Scenario II double bin stockpile. However, it helps in reducing the actual to planned grade deviation for each period to around 3% (Figure 12) with a total reclamation of 6 million tonnes of stockpiled ore by the end of the mine life. The resulted life of mine schedule is presented in Figure 11.

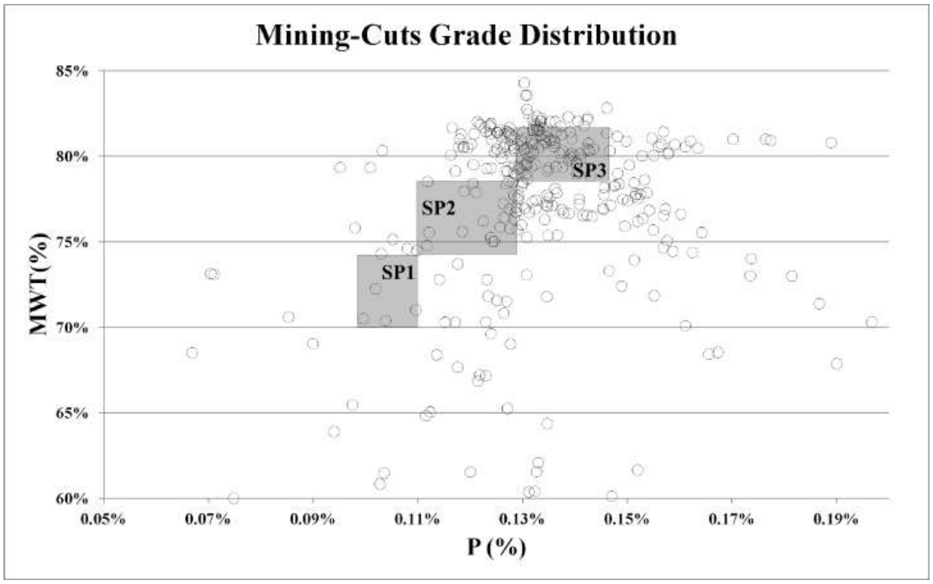

Figure 10. Grade range for MWT and P to be delivered to the stockpile in Scenario III.

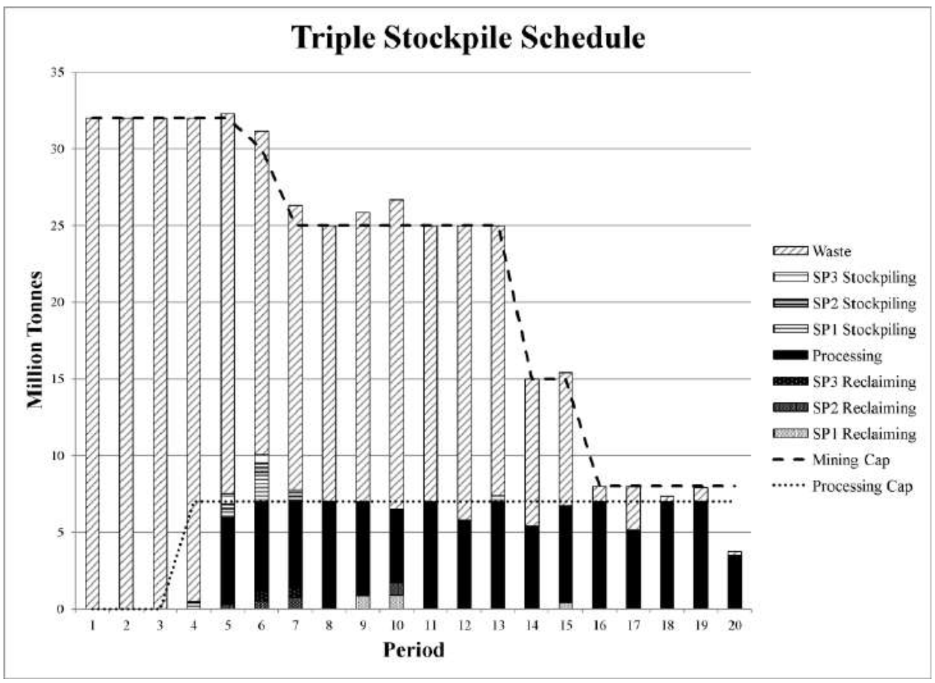

Figure 11. Life of mine production schedule of the deposit in Scenario III.

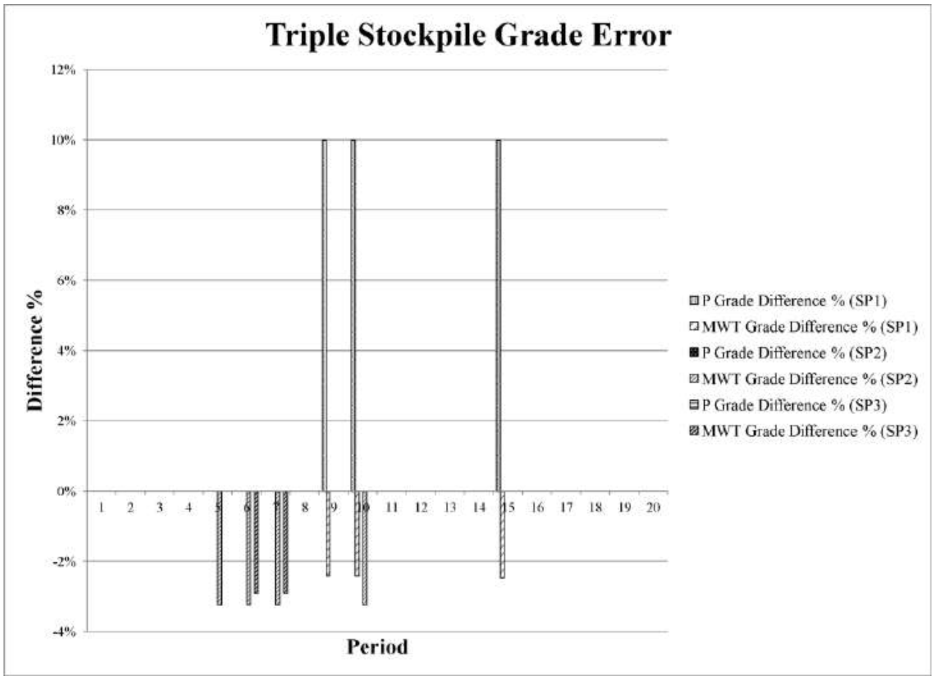

Figure 12. Stockpiling and reclamation grade difference in Scenario III.

3.5. Scenario IV quadruple bin stockpile

In this scenario we divide the grade range of Scenario I into four distinctive grade bins as presented in quadruple scenario type section of Table 1 and Figure 13. AS we need to divide two grades (MWT and P) we divide the bin range in Scenario I into four bins. Running the OPMPS model with the new grade ranges we can generate 2,331 million dollars NPV from the deposit, with the schedule presented in Figure 14, which is 40 million dollars higher than Scenario I and 10.6% higher than when we did not define any stockpiling option. This scenario also reduces the actual to predetermined reclamation grade difference from 11.6% in Scenario I to 5.1% (Figure 15).

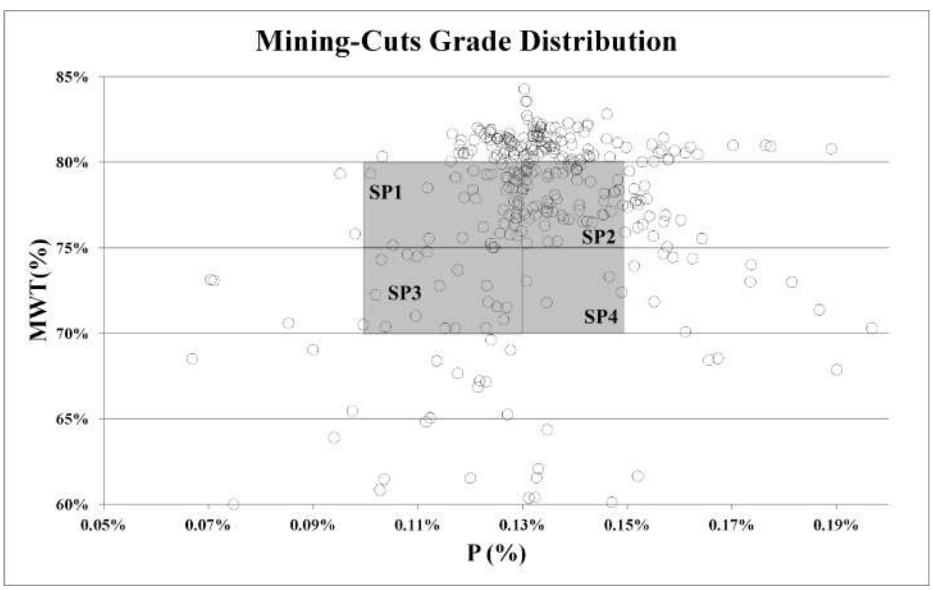

Figure 13. Grade range for MWT and P to be delivered to the stockpile in Scenario IV.

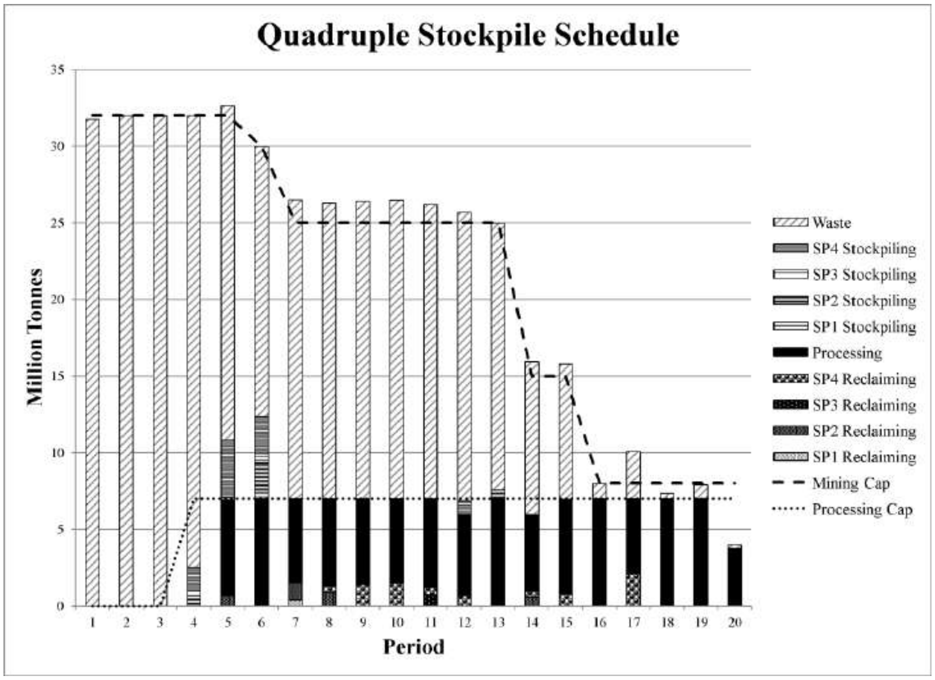

Figure 14. Life of mine production schedule of the deposit in Scenario IV.

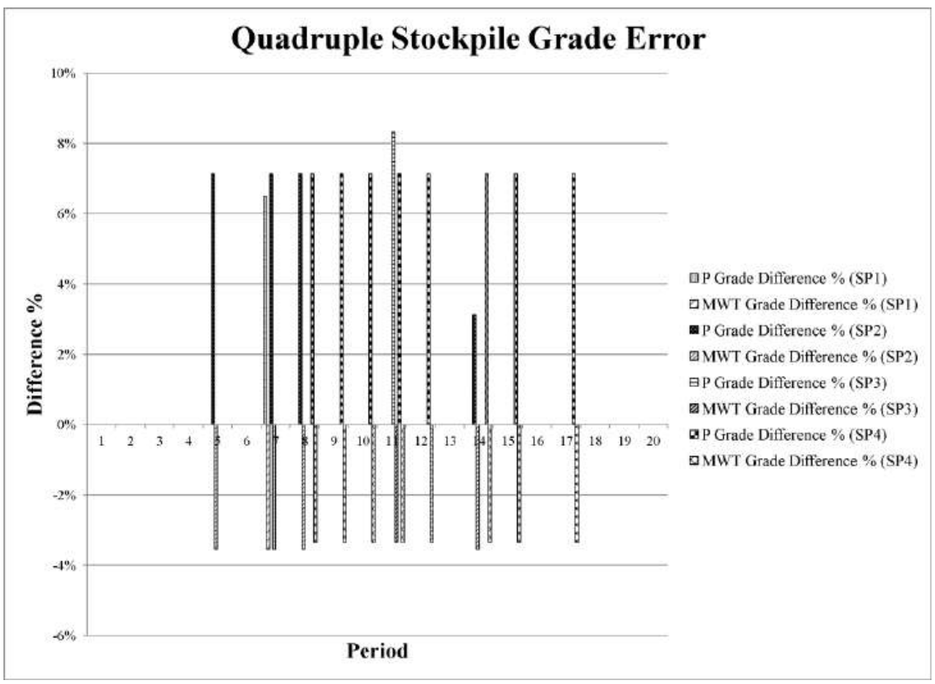

Figure 15. Stockpiling and reclamation grade difference in Scenario IV.

3.6. Summary of the results

We summarized the main Key Performance Indicators (KPIs) resulted from the five investigated scenarios in Table 2. The results show that the base scenario with no stockpile definition generates the least possible NPV as directly delivers all the mined ore to the processing plant without any consideration of the best possible timing. We added stockpiles to increase the NPV and balance the plant feed rate. Referring to the life of mine production schedule (Figure 3, Figure 5, Figure 8, Figure 11, and Figure 14) delivery to the plant was balanced for all stockpiling scenarios except for year four and in some cases year 14 of the mine life. Moreover, the NPV generated from the project was improved by a minimum of 2.2% and a maximum of 10.6%. Based on the results listed in Table 2, choosing Scenario IV with four bins will generate the highest NPV, 223 million dollars higher than the base case, and lowest grade difference of %5.1 in the mining of the deposit in hand.

Table 2. Comparison on the key performance indicators over the five scenarios.

Scenario	NPV ($M)	NPV Improvement (%)	Reclaimed Tonnage (MT)	Average Grade Difference (%)	CPU Time (s)
Base Case: No Stockpile	2108	-	-	-	2.17
Scenario I: Single Bin	2291	8.6%	12.0	11.6	4.17
Scenario II: Double Bins	2234	5.9%	8.2	6.5	8.43
Scenario III: Triple Bins	2155	2.2%	5.7	3.0	8.82
Scenario IV: Quadruple Bins	2331	10.6%	12.0	5.1	15.86

4. Conclusions

This paper presents a two-stage algorithm for open pit mine production scheduling (OPMPS) problem. The algorithm generates mining units by clustering blocks on the same bench to reduce the run time. Then in its second stage it implements a new mixed integer linear programming model to maximize net present value (NPV) of the project while controlling the quality and quantity of the throughput of the processing plant. It controls the quantity (tonnage) by utilizing stockpile option in the production scheduling process and quality (head grade) by defining different bins in the stockpile. Implementation of our developed algorithm on an iron ore case study shows that it needs less than five seconds to reduce the size of the problem from more than 19000 blocks to 1870 mining units in its first stage and less than 16 seconds to generate a production schedule for the same deposit. Examining different scenarios with different number of piling bins based on predetermined grade ranges show that the best possible stockpiling option for a deposit with two important material, iron and phosphor in this case, is a stockpile with four bins. This will lead to the highest NPV and the best quality and quantity control in the plant feed.

Data Availability

The data that support the findings of this study are available from the corresponding author, HA, upon reasonable request.

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In-Pit Crushing and Conveying Systems in Long-term Open Pit Mine Planning – Literature Review

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ABSTRACT

One of the transportation options in surface mining to reduce operating costs, especially in the deep open pit mines, is In-Pit Crushing and Conveying (IPCC). In this paper, broad research has been done over the literature on the long-term mine planning and the IPCC locations and relocations. Also, the possibility of integrated modeling of IPCC and long-term mine planning is investigated. The goal is to review and document the main optimization models considering IPCC's best locations and relocation times. The purpose is to understand the proposed academic solutions that could be hired to optimize the mining schedules and IPCC locations during a mine life and identify any gaps in the current literature so that one can define the opportunities to establish research questions for better optimization modeling of the IPCC and long-term open pit mine planning. It is evident that by locating the crusher inside the pit, lots of blocks are required to replaced. Elaboration on how to model these blocks in the constraints of a mathematical model is another aim of this review. Finally, the obstacles of current algorithms for general long-term planning or IPCC best locations problems, when explored separately, are documented in terms of mining practicality and optimality of the solution. The results of this literature review enable us to evaluate the logical links between significant components of an integrated optimization problem which could provide the best solution for both questions simultaneously.

1. Introduction

Surface mining is one of the most common methods compared to underground ones, and usually receives more attention from researchers. For example, we can take an orebody reserve with the equal score for selecting a mining method between underground and open pit options. Based on the Nicholas and UBC mining selection methods, an open pit extraction method is preferable to underground (Kuchta, M., Martin, R.K., & Hustrulid, 2013). It is mainly because an open pit mine is safer, more accessible in ore extraction, and has a higher production rate, bringing the money back much sooner. These factors make surface mining methods more desirable. In addition, original equipment manufacturers (OEMs) are providing equipment that tends to ease using surface mining methods. One effort to achieve this aim is providing the trucks with more capacities or equipping trucks with automated haulage system (AHS). These opportunities usually allow the mine designers to tackle the reservoir with a considerably low grade. As a result, the average and cut-off grade will decrease, and the stripping ratio will increase drastically. Increasing the stripping ratio means that a massive amount of waste must be extracted to reach one tonnage of ore. Mines will sustain longer, and their life and depth will increase more. However, by increasing the depth of

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the open pit, the distance between material destinations becomes more extended, which is not a desirable phenomenon, especially when the truck-shovel system (TS) is the most common and convenient way of transportation in the open pit mining. An extra cost of transportation accompanies the distance increment for trucks. Additional tire depreciation, fuel, and truck demand are some of the extra costs. These costs are divided into 1) capital costs, such as buying more trucks, and 2) operating costs, such as fuel and tires. One solution for overcoming these costs is designing In-Pit Crushing and Conveying (IPCC).

1.1. Motivation

The motivation for this paper is to review the latest knowledge in designing and scheduling the open pit extraction with IPCC. Usually, the mine designers do not consider the IPCC and its associated costs in the first steps of mine designs. By increasing the open pit's depth, trucks' operating cost suddenly turns into the mine's major problem. On the other hand, the whole mine scheduling must be changed since IPCC will change the mining and operating costs, and it needs a significant amount of capital investment. Planning is an impartible part of every open pit mining because mining operations must be optimized. Not considering this critical parameter, i.e., IPCC could jeopardize the mining operation's optimality and the mine's financial and operational targets' achievability. Investigating the reasons for this unwillingness is appealing and could reveal the advantages and disadvantages of such a decision.

1.2. Factors Contributing to Open Pit Mine Planning and Design

Many technical, geological, environmental, and economic factors must be addressed in open pit mine planning. IPCC can be mentioned mainly as a technical and financial factor. Nowadays, the size of mining operations is immense, so it is impossible to decide when exactly a specific block of ore or waste should be extracted and where it should be sent to be treated properly. The cost or profit is always involved in strategic and technical mine planning studies. The objective sometimes is to minimize the cost or maximize the profit within the specified time horizon. Mine planners are almost consensus that in the short-term, the cost must be minimized, and in the long-term, profit or Net Present Value (NPV) should be maximized (Mahdi & Morteza, 2014; Matamoros & Dimitrakopoulos, 2016; Osanloo & Rahmanpour, 2017; Blom, Pearce, & Stuckey, 2018). However, some improvised ideas are presented to minimize the capacity deviation by penalizing the extra costs while optimizing the long-term planning and keeping the NPV to a fixed constant level (Kumral, 2013). It is also known that the level of data uncertainty is higher in long-term planning compared to medium-term or short-term planning (Rahmanpour & Osanloo, 2014). In the short-term planning, however, most of the data are touchable and more reliable. Production targets set by long-term planning should be considered a goal of every short-term planning, which could be interpreted as the collaboration of long-term and short-term planning (Matamoros & Dimitrakopoulos, 2016). One of the main costs of every open pit mining is haulage, regardless of capital or operating cost. Tutton & Streck (2009) state that haulage costs in an open pit mine form 45% of the total operating costs and 40-50% of the total capital costs. Thus, IPCC is a crucial factor playing an essential role in mine planning despite the tendency of decision makers to evaluate and consider IPCC in the first step of the mine design or not.

1.3. Outline of the Paper

The rest of this paper is organized into the following five sections; in the first upcoming section, some of the features that a proper mine should have for implementing IPCC will be discussed in the background information. The necessity of using IPCC will be explained, and some past research will be presented in the second part. In the third section, the progress of the IPCC method will be covered. It mainly includes the issues solved using such a system and what makes this system attractive. Discussion about the main technological and commercial is covered in the fourth section of this paper. Also, the alternatives that the mining industry can hire in similar cases where IPCC has limitations will be investigated briefly. Three types of in-pit crushers are widely used in mining operations as the fixed, semi mobile and mobile in-pit crushers. The fifth section reviews the studies in which the three types of IPCCs are applied in long-term planning. Finally, the last section introduces two research directions as the leading subjects in optimizing the long-term scheduling in presence of IPCC.

2. Background Information

In-Pit Crushing and Conveying is a system in which the first step of crushing material is done in a specific location and elevation of the pit. The conveyor carries material from the crusher spot to the second crusher or mill plant located far outside the pit. This is one of the notable solutions for the distance problem that the TS system recently encountered. There are still some other solutions for the distance problem of the TS system, such as the ultra-class haul trucks, which need larger blasting size and loader capacity and lead to higher altitudes of benches. Applying a new technology like automated trucks or transferring from open pit to underground mining are two other solutions for distance problems.

2.1. Features of the Mine for Using IPCC

There are some features one mine should have to be proper for implementing the IPCC. Additionally, IPCC has different models, each of which is appropriate for specific surface mining methods. However, uncertainty is a prevailing phenomenon governing the whole mining operation. Due to the lack of data, particularly in the first stages of mine design, the mine reserve might be estimated with errors. Despite being large or small, which is a key factor in deciding whether IPCC is suitable or not, the uncertainty within the parameters needs to be measured. Three types of uncertain sources in the mining industry are economic, technical, and geological uncertainties (Meagher et al., 2014). However, there is not any trace of investigating the IPCC option under these uncertainties in any research on this subject.

There are three types of IPCC, according to Utley (2011), which have their specifications and usage limitations: fully mobile crusher, semi-mobile/ semi-fixed crusher, and fixed crusher. Fully mobile crushers are usually used in horizontally advanced surface mining like surface coal or open cast mining. Using fully mobile crushers could significantly reduce or even eliminate the truck requirement that reduces the operating costs drastically. Semi-mobile/ semi-fixed are two types of crushers with many similarities, so they have been taken together. The only difference is the time of relocation, which occurs by deepening the pit. They need to be inside the pit within the benches, and trucks to be available beside the loader or shovel for carrying the material from working faces to the crusher. The relocation time for this type of crusher varies between 1 to 10 years. Fixed crushers usually stay inside the pit in a specific location for at least 15 years (Osanloo & Paricheh, 2019a). This type of crusher is like the semi-mobile/semi-fixed crusher, but its cost of relocation is considerably lower.

Koehler (2003) mentioned three specifications that a mine needs to be capable of for IPCCs to be practicable as: 1) long project life, 2) lengthy transportation system, and 3) high production rate. When the mines become more extensive, a series of problems start, and the consequence is an increment in operating costs. In a deep pit, the truck cycle time may increase, resulting in requests for ore trucks. Dispatching could become a big issue with a large fleet of trucks, so more labor and supervision should control the haulage process. Maintenance and repairs are other irritating factors that would increase the number of trucks. Diesel fuel is used as an energy resource for trucks, which is the main reason for operating costs and environmental pollution. Using IPCC will reduce fuel consumption by up to 60 million liters per annum (MLA) as happened in a Brazilian iron ore mine with two fully-mobile IPCC and a combined capacity of 800 t/h (Raaz & Mentges, 2011).

Based on McCarthy (2011) and Turnbull (2011), the fundamental keys for the IPCC nominated mines are as follows.

1- For IPCC to be cost-effective from the capital cost point of view, the production rate of the mine must be greater than 4 Mtpa, but 10 Mtpa is more desirable.

2- Making the operating costs lower so that the payback period of IPCC becomes shorter. It usually happens when the mine life is more than ten years. Since most of the IPCC's installed in the middle or last years of mine life, it is recommended that the remaining mine life will not be less than ten years.

3- Electricity costs ($/kWh) should be less than diesel fuel costs ($/t) for IPCC to be favorable. This range should be greater than or equal to 25%.

2.2. Necessity of Using IPCC

There are several research studies about the possibility of installing IPCC as an option for cost reduction (Koehler, 2003; Szalanski, 2010; Ribeiro, Sousa, & Luz, 2016; Dzakpata, Knights, Kizil, Nehring, & Aminossadati, 2016; Abbaspour, Drebenstedt, & Dindarloo, 2018). These all show that the cost, which is increased by the depth increment, grade decrement, and commodity price variability is a serious concern among mine managers. Implementing the IPPC has been reported even among those mines which already passed the depth of 1000 meters and might even have switched to the underground at this time (Osanloo & Paricheh, 2019a). Some examples of these mines are Bingham Canyon, Morenzi, and Chuquicamata, where semi-mobile/ semi-fixed systems were used in the 1980s. Chuquicamata has used this system for ore and waste transportation, and Bingham Canyon used this system just for ore transportation (Kammerer, 1988; Tutton & Streck, 2009). Investigating the options of hauling waste with IPCC has always been a subject of serious discussion because of its disadvantages.

Based on the data gathered from IPCC manufacturers by Ritter (2016), From 1956 onward, 447 IPCC system have been installed throughout the world, with Europe having the maximum number of installations (147) and the Middle East having the minimum installation (16). Since then, the application of in-pit crushing and conveying systems has been increasing in the mining industry. Additionally, the capacity of IPCCs is increasing from 100 - 500 (t/h) in the early use of this technology to 10,000 - 14,000 (t/h) recently. The three most common uses of such a technology are limestone, coal, and iron ore. There is also a significant number of installations of this system for waste material transportation rather than ore. This could be because of the single destination of waste material has, and there is no need to separate it for different destinations. Historical data shows that most European IPCCs have fully mobile capacities of less than 2000 (t/h).

2.3. Past Research

In 1956, the first IPCC system was introduced in Werk Hover mine, Germany (R. Ritter, A. Herzog, 2014). Many researchers tried to address the efficient use of IPCC from that time onwards. 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) and Rahmanpour et al. (2014) tried to find the best location for an in-pit crusher. Another solution that Roumpos et al. (2014) mentioned is finding the best place of distribution point for belt conveyors.

Nowadays, mine designers are more concerned about the semi-mobile/ semi-fixed model of IPCC because it has more flexibility to work with TS systems. Therefore, most of the studies are related to the subject of installing and relocating the semi-mobile/ semi-fixed crusher in a proper time and transferring it to the most appropriate location. This problem is solved through mathematical modeling concerning optimizing the crusher's location and time of relocation. A simplifying assumption is an integral part of any optimization problem, mainly because of the complexity of most technical problems. For instance, in this optimization problem, the relocation places are some fixed points in the centroid of the working faces, but they can vary in height. On the other hand, the optimum time problem is limited to the end of each production year, but assembling and disassembling time are not considered.

Abbaspour et al. (2018) provided a Simple transportation model to solve an optimum location and time problem. They claimed that this model enables them to search for the optimum time and location simultaneously. Using this model, they solved a 2D hypothetical mining section. Paricheh et al. (2017) modeled the IPCC location problem with the linear programming method as a dynamic problem. The authors calculated the haulage cost with two functions, one for truck systems and the other one for conveyor systems. These two functions evaluated the haulage cost based on the annual mining elevation. Therefore, the location and time of relocation can be provided. With those two cost functions and mathematical models which can determine the optimal location, Paricheh et al. (2018) presented a heuristic approach to find the optimum time and location. In the proposed heuristic, the data model has two objective functions: the first one to minimize costs and the second one to maximize the NPV. Because the variables for these two models were not the same,the maximization of NPV needs a nonlinear function and hence the model is solved with a heuristic approach. Based on this model, when the haulage system is changed, the cost of the transportation method will be updated and the block value must be recalculated with a new cost. Using IPCC will reduce the costs, which should enlarge the pit size. This model has to run for several iterations to access each defined step, like finding the transportation costs for each period, determining the best location and the best time, and then reaching the new ultimate pit limit. Nehring et al. (2018) offered a strategic mine planning comparison between IPCC and TS systems. According to the authors, *"A completely different approach to planning and design must be followed. This is principally due to the unique shape and sequencing constraints associated with introducing conveyors into the pit for haulage purposes."* Relying on this thought, they came up with a number of hypothetical 2D sections of the block model. Searching among the various options through the possible sequence of extraction may result in catching a higher NPV and cash flow. The most beneficial point about investigating the possibilities for finding the optimum sequence of extraction is that once the operation is set, it cannot be changed easily in the IPCC system. Therefore, doing so helps to measure the feasible consequences of every option.

The only research which claimed that it considered uncertainty in parameters for the optimum in-pit crusher's location is an article by Paricheh & Osanloo (2016). Different production scenarios were added to the mathematical modeling to minimize transportation costs. For this purpose, three equal possible states with a 10% increase or decrease for each parameter are assumed, in which every one of the three possible productions has a costs scenario. These scenarios can remain either fixed, decreased, or increased. Taking the haulage cost into consideration may yield the optimum solution.

3. The Progress of the IPCC System

This section discusses some of the progress since this system's early application. Now, the installed location for this system is constrained to limestone mines, coal mines, and some of the large mining operations with iron ore or copper. This system seems to have a long way to progress and adapt to the mining industry since it is in the middle of this path. We can still talk about the TS system for at least tens of years as the most dominant transportation system in open pit mining.

3.1. What types of IPCC problem have been solved?

One of the most common problems for the IPCC application is the optimum location and time of IPCC installation. Almost all of the literature that applied mathematical modeling for this optimization problem has been reviewed in the previous section. Still, several key factors have to be taken care of. Regarding facility location problems, there are two types: static and dynamic. When the parameters are fixed within the scheduling time, such a problem is "static facility location". In contrast, "dynamic facility location" is when the parameters change through the time of the mine planning.

The main factors which may affect optimum location and relocation are as follows.

1. Haulage distance and truck operating costs
2. Mine schedule and block sequences
3. Rate of increase in haulage costs with increasing in haulage distance and time
4. Conveyor operating costs
5. Additional haulage costs, which may divide into vertically depth increment and energy loss
6. Cost of relocating the system, which may categorize as: engineering, disassembling, installation, labourer, transportation, overhead costs and cost of purchasing an additional conveyor (Paricheh et al., 2017).

Some of the factors mentioned above are not considered, or are considered but solved for the hypothetical sections in the research studies, like the mine scheduling and sequencing of the blocks, which is mentioned by Nehring et al. (2018) but for a hypothetical section without modeling it mathematically. Some others are calculated for a specified case which cannot be extended for the other cases, like rate of increase in haulage costs with increasing in haulage distance, time, and additional haulage costs in the works of Paricheh & Osanloo, (2016), Paricheh et al., (2017) and

Paricheh et al., (2018). Another flaw in the rough cost estimation exists in Paricheh et al. (2017), which is worth noting.

Capital cost requirements, and the laborers and engineers' unfamiliarity with the new system will be discussed as two of the main limitations of the IPCC system later in the next section. Flexibility and selectivity problems are addressed mainly by Paricheh & Osanloo (2016) and Nehring et al. (2018). Both of these papers try to solve the flexibility before installing the system. However, the problem with the idea of studying various options is that it often ignores most of the other occurrences that might be the case, so it cannot be generalized. For example, if the commodity price increases suddenly, we will try to utilize this opportunity by increasing the production rate. Although such a circumstance is predictable, it can not be well-treated through the option investigation methods. The capacity of IPCC is fixed, so using IPCC with excessive capacity imposes financial loads on the mining managers, which will be rejected undoubtedly. Another example of a bizarre event is slope failure which could cause an unprecedented problem according to the size of the incident.

3.2. What makes this system more attractive?

As mentioned earlier, except for the IPCC system, there are three other alternatives proposed by the researchers that are tested or used by the mining industries throughout the world to overcome the increasing stream of operating costs. These three alternatives are ultra-class trucks, automated driverless trucks, and underground transition.

The ultra-class trucks need more space for the haulage road, which increases the incident possibility. The blasting operation must be extensive enough to feed these types of trucks properly so that mining recovery will decrease, and dilution will increase. This will result in higher costs in the processing plant and less recovery. They also create a dispatching problem since the fleet size becomes much disparate. The transition from open pit to underground also needs considerable capital investment and preparation in tunneling and well-drilling, which takes time and money. Automated driverless off-highway trucks are another option used in Western Australia (the Nammuldi and Yandicoogina iron ore mines. They can only compensate for the driver costs, which is 20-30% of the haulage cost. These trucks require a high investment and proper hardware and software with a price of up to 20 M$ (Bellamy & Pravica, 2011).

Flexibility and selectivity, plus mine engineers' and laborers' tendency, are among the most important factors hindering the widespread usage of the IPCC system (Morrison, 2017). The target of each mine for each year determines by the expected revenue. However, the price sometimes falls in a way that special planning may be needed. In addition, the TS system has been used for decades in open pit mining. The technicians cannot easily incorporate in-pit crushing and conveying into the mine planning. Almost none of the mine planning software have an IPCC option, so this is where researchers must interfere to facilitate the application of such a system for the industry.

4. Main Limitations of the IPCC

Although, the IPCC system has been designed in a way to settle into most of the TS systems, still big limitations remain. Some of these limitations are capital investment mine designer's unfamiliarity and labor intensiveness. In addition to those fundamental limitations, there is a shortage in the related research topics to make the subject clearer for the mine planners and designers. Here in this section, the financial and technical limitations will be mentioned and then the existing mathematical models will be criticized.

4.1. Financial limitations

The amount of money that a mine requires to install an in-pit crushing and conveying system is 180 – 250 million dollars (Foley, 2012). This cost will be desirably decreased to almost 5 million dollars for buying a 360-ton truck (Czaplicki, 2008). The story starts with the huge capital costs of the IPCC, but it has some remarks. Increasing the haulage distance will necessitate more tier, fuel, road maintenance, parking lot, water wagon, dozers, front-end loaders, and cranes. These factors, plus having 3 to 4 times more trucking per kilometer than the conveyor's cost, lead to more operating costs for the TS system. However, the TS system has more flexibility in the case of multiple destinations (Osanloo & Paricheh, 2019a). Moreover, by using a semi-fixed/ semi-mobile crusher, the need for a TS system will not be completely eliminated. Every mine has at least two destinations: one for the mill plant and one for the waste dump, apart from the fact that most mines have more than two destinations. A separate installation of the IPCC system can be considered for each destination. Likewise, crushing the waste sometimes, as in waste stripping, would not be necessary most of the time, and implementing IPCC would be a waste of time and energy. Hence, by using the IPCC system, some trucks must still go down deep and return to the surface.

A good number of papers evaluate the IPCC option for ore or waste. The IPCC implementation could be approved using a feasibility study for the mines that are big enough (i.e., more than ten years of operation or having a long haulage road). Although Dilhuydy et al. (2017) and Dixon (2015) proved that for a big mine like Highland Valley Copper, the IPCC installation option for the waste material is still worth the price, such a decision is controversial mainly because sizing the waste through crushing would not be rational.
Using mobile crushers will eliminate the haul truck usage, at least for the ore part. On the other hand, using fixed crushers or semi-mobile/semi-fixed crushers will not entirely eliminate haul trucks in the open pit mines, but it will drastically decrease the required truck number. For example, in an iron ore deposit investigated by Marco de Werk et al. (2017), conducting semi-mobile/semi-fixed IPCC for the ore will decrease the number of haul trucks with 144 capacities to 2, where it was required 6 of them without conducting the IPCC.

4.2. Technical Limitations

Due to the lack of flexibility in the in-pit crushers, there is a strong disinclination toward this system. Applying IPCC in the middle of the mine life must be done after the first payback period (Paricheh et al., 2017). After the first payback period, there are two options on the desk: going for the new truck fleet (if needed) or installing the IPCC. However, the easiest option is to use the existing truck fleet and do the required modifications. That is why most mines will not use IPCC after the first payback period. When a mine gets deep adequately, the necessity of using this system will make more sense. This is when most of the laborers and truck operators should either change their workspace or be fired from the company. It is a case of major conflict that directly influences mine's productivity.
There are a few but major problems, which is accompanied by conducting an IPCC in the open pit mines. For example, for moving the movable IPCCs from one bench to a lower bench, the road width must be wide enough since the crusher's dimensions and the crawler carrying it is different from the regular haul truck's dimension (Konak et al., 2007). As a result, the geometry of the pit

and the appropriate required access must be further created. Another problem is the labor's unfamiliarity with the system and unprecedented incidents such as conveyor damages by blasting operation, which make this system cause a considerable loss of time. Due to this unfamiliarity and unprecedented incidents, the maintenance time will take longer than predicted, or the conveyor moving or repairing time might need more labor than calculated. The loss of time could be why most IPCCs cannot provide the return on the investment in the promised period (Morrison, 2016).

4.3. Mathematical models limitations

There are a few studies about the optimum location and optimum time of relocation. The simplest one which models this problem within the transportation problem is presented by Abbaspour et al. (2018). The general idea of this model is to find the amount of material that must be sent to a specific level ($x_{i,j}$), resulting in a minimum amount of total operating and relocating cost ($c_{i,j}$). The mathematical formulation of the problem is as shown in Equations (1-5).

$$minimize\ Z = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}x_{ij} \quad (1)$$

$$x_{i1} + x_{i2} + x_{i3} + \ldots + x_{in} = a_i \ (i = 1, 2, 3, \ldots, m) \quad (2)$$

$$x_{1j} + x_{2j} + x_{3j} + \ldots + x_{mj} = b_i \ (j = 1, 2, 3, \ldots, n) \quad (3)$$

$$\sum_{i=1}^{m} a_i = \sum_{j=1}^{n} b_j \quad (4)$$

$$x_{ij} \geq 0 \quad (5)$$

Equation (1) is the model's objective function and minimizes the total haulage cost. Equation (2) indicates that all sources' total availability is equal to *ai*. Similarly, Equation (3) indicates that the total demand at all destinations equals *bj*. Additionally, Equation (4) guarantees that total availability and demand must be equal. Finally, Equation 5 sets the non-negativity condition of the variables.

As it was mentioned earlier, since IPCC changes the total costs of transportation, the value of each block model should be updated, which may cause changes in the ultimate pit limit and the whole mine planning. So, any mathematical modeling for optimization of IPCC must keep the mine planning optimum. Otherwise, the idea of adding a new system into the optimum system to reduce the costs of keeping the system optimum would not be rational. This model's first drawback is its inability to check the mine planning optimality. The second impediment of this model is that there is a possibility of sending the entire production in one year to only one level or a different level other than the destination level. Finally, this model has been tested for the hypothetical 2D section of a copper deposit, which might have a bad result since the case sensitivity of the problem has not been investigated.

The second mathematical modeling effort is a series of the dependent models presented by Paricheh (2016), (2017), and (2018). These models are developed one after another to the point that they can return the optimum pit while optimizing the IPCC's location and time of relocation. They require two functions for cost calculation estimated for the case study and cannot be used as a general formula. In the first step, they simply optimize the location of the crusher by integer programming and assuming some predefined locations in which the transportation cost of each location for both IPCC and TS systems is known. Since the depth of mine is the function of time and production rate, searching different times enables them to find the best relocation time (Paricheh et al., 2017). This search can also be done using different production rates (Paricheh & Osanloo, 2016). The third study starts with the integer programming for optimization of the crusher location, and in the next step, it estimates the NPV. This model is processed through the heuristic approach using a particular procedure and series of iterations (Paricheh et al., 2018). The mathematical form of the problem is as shown in Equations (6-17).

Objective Function:

$$z = \sum_{k=1}^{r}\sum_{j=1}^{p}\sum_{i=1}^{m_k+1} F_{kij}x_{kij} + \sum_{k=2}^{r} C_k y_k \tag{6}$$

Subject to:

$$y_k = 0.5\sum_{j=1}^{P} w_{kj} \forall k \tag{7}$$

$$w_{kj} \geq z_{kj} - z_{(k-1)j} \ \forall j, k \tag{8}$$

$$w_{kj} \geq z_{(k-1)j} - z_{kj} \ \forall j, k \tag{9}$$

$$\sum_{j=1}^{P} z_{kj} = P \ \forall k \tag{10}$$

$$\sum_{j=1}^{P} x_{kij} = 1 \ \forall i, k \tag{11}$$

$$x_{kij} - z_{kj} \leq 0 \ \forall \ i, j, k \tag{12}$$

$$z_{kj} = \{1, 0\} \ \forall j, k \tag{13}$$

$$x_{kij} = \{1, 0\} \ \forall \ i, j, k \tag{14}$$

$$y_k = \{1, 0\} \ \forall \ k \tag{15}$$

$$Z = \sum_{k=1}^{t} \frac{CF_{truck}}{(1+d)^k} + \sum_{k=t}^{r} \frac{CF_{IPCC}}{(1+d)^k} \tag{16}$$

$$b \leq t \leq r \tag{17}$$

Where r is the number of periods, p is the number of candidate locations, m_k is the number of faces in period k, and F_{kij} is the total haulage cost from face i to candidate point j in period k. In order to consider the operating and capital costs of the conveyor from candidate point j to the mill in period k, the value one is added to m_k on the third summation. C_k is the relocation cost, including engineering, disassembling, installation, labor, transportation, and overhead costs. x_{kij}, z_{kj} and y_k are binary decision variables. CF_{truck} and CF_{IPCC} represent the cash flow of pure truck and IPCC systems, respectively. The variable t is the upper bound of the first summation, meaning that the pure truck system will be used up to the year t. Also, it is the lower bound of the second summation because the IPCC system will be used from the year t to the end of the mine life. d is the discounted rate and k is the periods' index, $k = 1, 2, \ldots, r$.

This model improves NPV by 1% and cash flow by 150 million dollars based on the results being extracted from the case study. The author states that the solution will improve closer to the optimum point by performing the procedure for more than one iteration. However, the reason why it is not being run for more than one iteration for the case study is not explained. This model is non-linear, and the procedure is heuristic which does not guarantee the optimal answer. Since the NPV changes the transportation system, it is not appropriate to calculate the time of starting IPCC beyond the scope of mathematical modeling. The reason is that there is a possibility that increasing the production rate and reaching the specific depth will accelerate the installation of the crusher, which improves the NPV more as a consequenc.

5. Long-term production planning and IPCC

IPCC is a complex transformer that needs a good number of blocks extracted before and after installation. That is why the mines with IPCC must have a long-term production plan considering IPCC in the planning. Additionally, IPCC requires relocation to reduce the transportation time and facility so that the extraction sequence will be disturbed from the usual long-term planning.

It has been discussed earlier that the IPCCs are being divided into three categories, each having its particular characterization and application. Undoubtedly, providing an optimized mine plan for each category will differ mainly by the necessary constraints and the required precedence. The TS-related cost must be replaced by the operating cost of applying, relocating, and maintaining IPCC in the mining cost calculation section of the block economic value estimation.

The first step towards any planning for the mine with the IPCC is to decide where to install such a system in the mine and what would be the possible places for the IPCC. Paricheh & Osanloo (2019) provided a new search algorithm aiming to do so. The authors divided the whole pit into some areas which have the same pushback among some benches, and then based on the azimuth of these areas, the location of the IPCC will be confined within the several hundreds of points as the candidate locations named as a Phase-Bench-Slice (PBS)

Afterward, some of the candidate areas removed with the below-mentioned specifications.:

I. Depth: Minimum depth with the maximum haulage distance – they assumed that the IPCC would not be installed above this altitude.

II. Pushback: for a mine to be applicable for IPCC installation, it is necessary to pass the first payback period so the IPCC location cannot be within the first pushback.

III. Required space for installation: some of the PBSs are not big enough for an IPCC to be installed.

IV. Radius of influence: IPCC will stay in each candidate location for a while after installation and will not relocate before one year. On the other hand, the progress of the mine could be more than one or two benches within a year. So those locations will be eliminated.

V. Value restriction: best candidates have the zero-value underneath them or at least the minimum value.

5.1. Long-term planning with fixed crushers

The time of installing a crusher inside the mine, its capacity, and its location are among the decisions that must be made for fixed crushers. Londoño et al. (2013) has modeled the alternatives of In-Pit Crusher and Conveyor. In this paper, a coal mine is modeled to engage the IPCC with a dragline and hopper for coal digging. The authors use simulation with “3D-Dig” package software to analyze three options for the IPCC location, and the inside of the pit option is determined as the most cost-effective one. Additionally, they searched through the application of a parallel conveyor and spreader through simulating it for one hundred replications and comparing it with a single conveyor and spreader. It is concluded that the parallel conveyor and spreader can increase the availability by more than 9 percent, although the cost of a single conveyor is indeed lower than the parallel one.

Roumpos et al. (2014) provides an optimal location among the various nominated points for the belt conveyor system in a continuous surface mining operation. This paper is mostly about finding the location of the conveyor belt in an actual lignite deposit that is expanded horizontally in four benches. The authors proposed a method to find the conveyor belt location by searching through the perimeter of the pit level by level and giving the location with the minimum cost. The cost formulation is presented based on the distance of the conveyor and its energy consumption. The study is more of a search algorithm with a heuristic approach within the limited number of nominees for a conveyor belt.

5.2. Long-term planning with semi mobile/semi fixed crusher

For these crushers, all of the previously mentioned parameters for the fixed IPCC plus two other parameters must be estimated. Thus, the decisions are to be made about the time of installation, capacity and location, plus the time and the new location. The subsidiary parameters are the conveyor's location, the pit's geometry, and the conveyor's angle. Knowing the mentioned considerations, determining the location of the IPCC is categorized as a long-term planning parameter. Finding the best locations for the IPCC is searched through a simplified method by Konak et al. (2007) for crashing gravels in a limestone mine in Turkey. In their research, the best location for the crusher is decided based on the number of nominated locations, selected mainly by dividing the mine area into various segments. The idea behind this research is to find a location with the minimum haulage cost, which starts from the stationary crusher and goes all the way to change the location of the crusher for the first, second, and finally a third time. However, this study does not consider the cost of relocation, nor it provides the appropriate optimization process in which the structure dictates a confined objective function. Thus, the haulage cost minimization process between thousands of nominees is to be done for three relocations. It is proven that the haulage cost is decreased by increasing the number of relocations. The most important result of this study is that the number of relocations must be well calculated and strongly determined before the operation, which cannot be decided in the middle of the mining operations. The reason is that the optimum locations of the crusher for two relocations are simply different from the same situation with three or more relocations. Therefore, haulage cost will not remain minimum if one decides to add or deduct another relocation in the middle of the mining operations without preplanning, resulting in a robust model.

Yarmuch et al. (2017) is another study that tried to find the best location for adding one crusher in the Chuquicamata mine. This mine is one of the deepest mines in the world, which already has two crushers; one is located inside the pit, and the other one outside the pit. The authors try to search for the best possible location for adding another crusher so that this newly added one could compensate for the possible operational failures that two other crushers might have. The candidate locations are beside two existing crushers. The authors formulated these two options based on the probability of operational failures of the crushers and their conveyor belt. The Markov chain is used to simulate their problem with the probability and costs of the failure and the installation costs. This problem is solved for four years with an 8 percent discount rate in the cost calculations.

One of the related studies about finding the IPCC location, which was done using short-term planning parameters such as operating costs, is done by Paricheh and Osanloo (2016). The authors first introduced two common approaches for facility location’s uncertainty as the probabilistic and robust (scenario-based). In the latter approach, three models can be hired or 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.

The developed model is based on the third concept for the 10th year of mine life if the mine needs two IPCCs, and they optimized the location of these two IPCCs for the year 10 with GAMS. The authors also proposed 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.

In another study, Paricheh and Osanloo (2017) tried to minimize the costs throughout the proposed model and at the same time, they optimized the model for 22 years (from year 6 to 27 of the mine life). Two cost estimations formulations are created by them in which there is no relocation cost, so they provided an estimate solution for that.

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. In another work Paricheh and Osanloo (2020) tried to optimize the production schedule in presence of the IPCC through a MILP model concurrently. There are a few assumptions that authors have considered for their MILP model.

a) The UPL is pre-calculated based on the known average haulage costs.

b) The costs and prices are all constant during the mine life.

c) The truck fleet has the same size as all the fleet.

d) In-pit and ex-pit crushers have the same costs.

e) There is a separate conveyor for each crusher

The objective is to optimize the schedule by maximizing the NPV and, simultaneously, find the location and time of relocation of the ex/in-pit crushers and optimize their capacities.

The author compared the original proposed MILP model with two simple benchmark MILP models, one of which is scheduling while optimizing the fleet size and the other one just scheduling the blocks assuming the predefined fleet size. The authors solved these three models for two hypothetical copper block models over 15 years. All the three models are solved in CPLEX. The run time for the first model was around two hours, and around a few seconds for the other model. This model, however, is solved for a limited number of blocks and does not represent a complete mine, so it cannot be considered as a practical model.

5.3. Long-term planning with mobile crusher

The capacity is still vital for this type of crusher; however, the crusher's location is no longer a field of discussion as it moves alongside the loader. On the contrary, the conveyors' location is important, so a series of precedence must be defined.

One of the most recent works towards mine planning and production scheduling for the mobile crusher is the study of Samavati et al. (2020). That divided the conveyors into three types, as the main conveyor, the transfer conveyor, and bench conveyor. Between these three, the transfer conveyor is fixed within the level, and the bench conveyor moves alongside it. The main conveyor that transfers all the material from each bench to the outside of the pit is usually inclined, and its longitude increases towards the pit's depth. They have developed a MILP model for the problem, with a set of constraints controlling the precedence among the blocks to make sure that the conveyor's location will not be extracted.

The authors solved the model for the hypothetical block model through three different heuristic approaches plus the MILP, and then compared the answers, showing that the M3 heuristic approach is faster and more precise. The biggest block model they could solve 40,000 blocks which could barely account for a medium mine, meaning that the proposed model cannot be used in real mines. Additionally, the number of precedences they considered makes a significant number of constraints roughly equal to the number of blocks multiplied by 16, making the problem so complicated to solve using exact solution methods.

6. Future Research Direction

The future direction of the long-term mine planning with the in-pit crusher can be introduced into three following topics; The first proposes a cyclic procedure to start from the pit and end with the crusher-related optimization. Since the process of optimizing a mine schedule is a cyclic process, a small change might burden starting the process from scratch. Bringing the crusher inside the pit, installing the conveyor, changing the slopes for conveyor placement, and preparing the related ramps and roads to the crusher are some significant changes that make the workload of starting over more appealing. As for the second direction, the necessity of optimizing in-pit crusher and mine scheduling is overexplained here in this paper and other related papers (Osanloo & Paricheh, 2019b; Morteza Paricheh & Osanloo, 2020a; Samavati et al., 2020). The third research direction refers to the uncertainty of the IPCC models, which is generally rare in ideas and applications due to the lack of information on the technical and operational aspects of the area.

6.1. An effort to optimize a pit to crusher operation

Liu & Kozan (2012) provided an interactive planning and scheduling framework for optimising pits-to-crushers operations. This study, after reviewing mine design papers, mine production sequencing papers and mine transportation scheduling papers, provides a model based on the job sequencing for the minimization of the costs throughout the mine life. This model takes the ultimate pit limit from a MILP method and tries to make a block sequencing using an assigned timeline for each job. In this model, the so-called jobs are transporting material from multiple sources to multiple destinations. The timelines consist of ready times, starting times, completion times, flow times and tardiness times which, according to the authors, there has not been any research about the influence of a time in a job sequencing. However, the authors did not implement their proposed model in any real case study.

6.2. Simultaneous optimization

The process of optimizing the crusher locations and relocation times is often taken separately from the mine planning; however, it affects the extraction sequence so as the block destinations and requires a new set of precedences. As yet, two papers propose models for optimizing the crusher and mine planning simultaneously (Paricheh & Osanloo, 2020b; Samavati et al., 2020). The first one is for the semi-mobile crusher, which is solved for a hypothetical 2D block model with a heuristic approach. The second one is for the fully-mobile crusher, which provides a solution for a relatively medium mine size. Both proposed methods are within the block level, making them inefficient to take the real mine operation. Additionally, both methodologies are robust with many precedences and ignore the road network of the mine, so a new type of methodology is required.

6.3. Uncertainty based models

The uncertainty-based models usually give a better perception to the researchers of the areas which should move cautiously. Generally, a sensitivity analysis is required to find the delicate parameters and change them appropriately. Nevertheless, in the area of in-pit crushing and conveying, the ambiguity of the parameters' effectiveness has not been studied yet. Although in the literature, one study takes different options for production and operating cost by creating varios production deviations from the production target to determine the optimum locations (M Paricheh & Osanloo, 2016). The missing portions are the stochastic programming models, which could give a better horizon of the technical or financial parameters in the IPCC and mine planning optimization.

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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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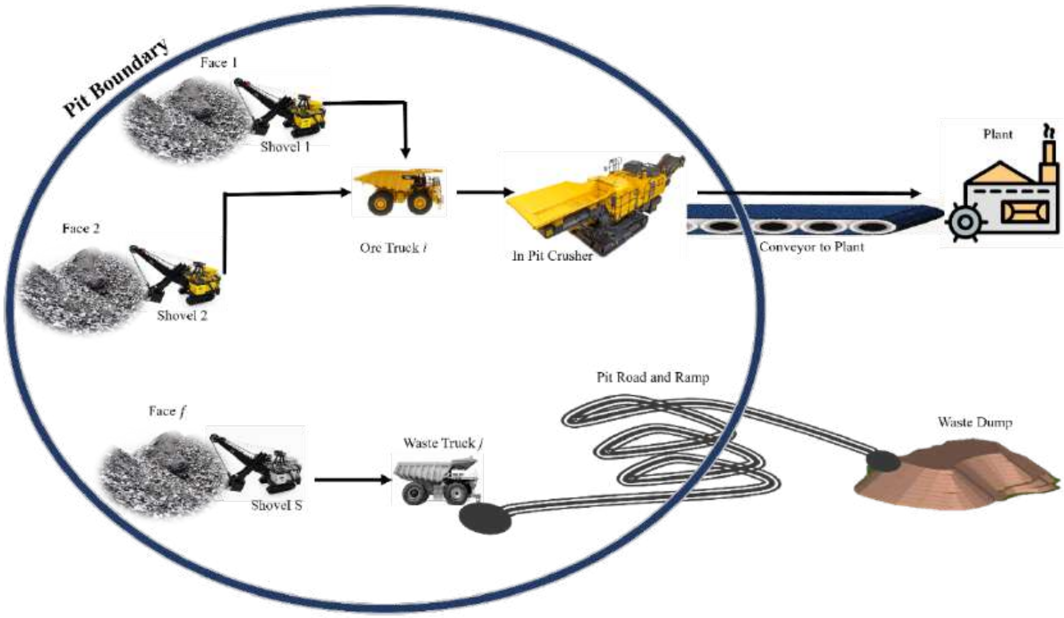

Figure 1. A schematic view of IPCC in a mining operation.

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.

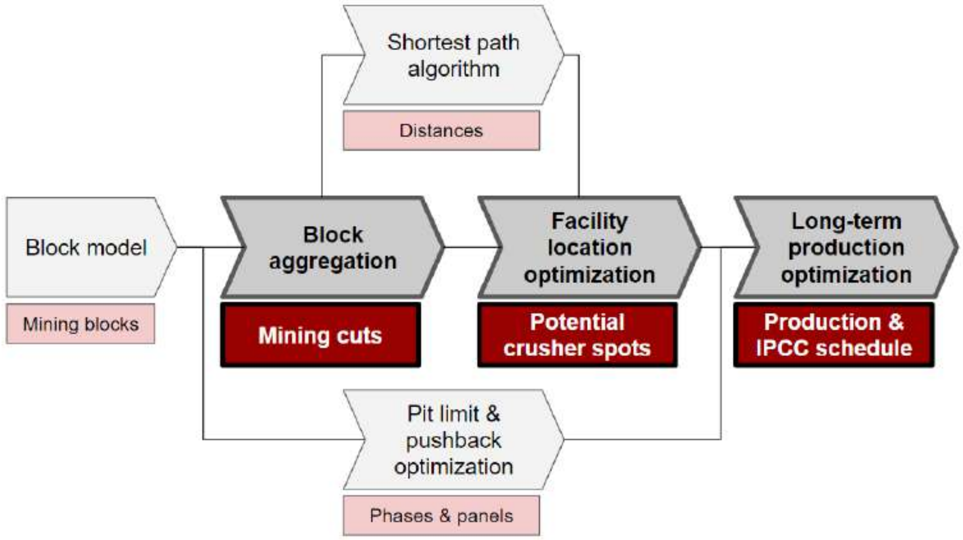

Figure 2. The methodology flow diagram.

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.

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

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, $\tilde{D}_{ij}$ represents the normalized distance value between blocks i and j, $\tilde{G}_{ij}$ 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.

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

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

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

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

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

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

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

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

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

$$b_p^t - b_p^{t+1} \leq 0 \forall \; p \in \{1, ..., P\}, \; t \in \{1, ..., T - 1\} \tag{16}$$

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

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

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

- $x_k^t \in [0, 1]$ 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, ..., $S_n = PT$, 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.

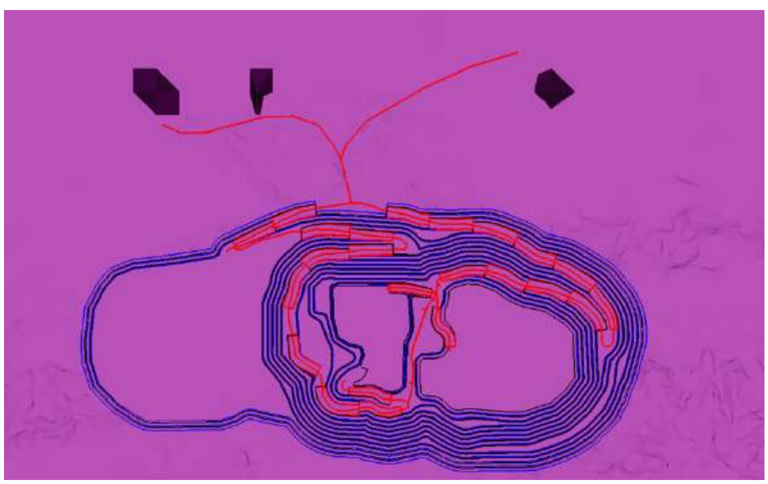

Figure 3. Plan view of the iron ore mine.

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.

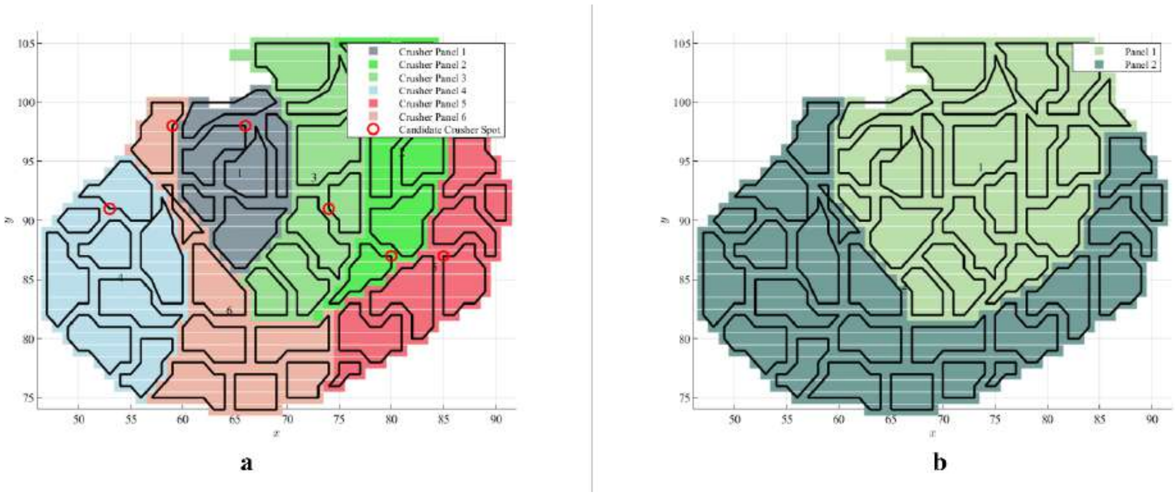

Figure 4. Plan view of the first bench a) clustering blocks to create the crusher panels, b) mining panels or phases.

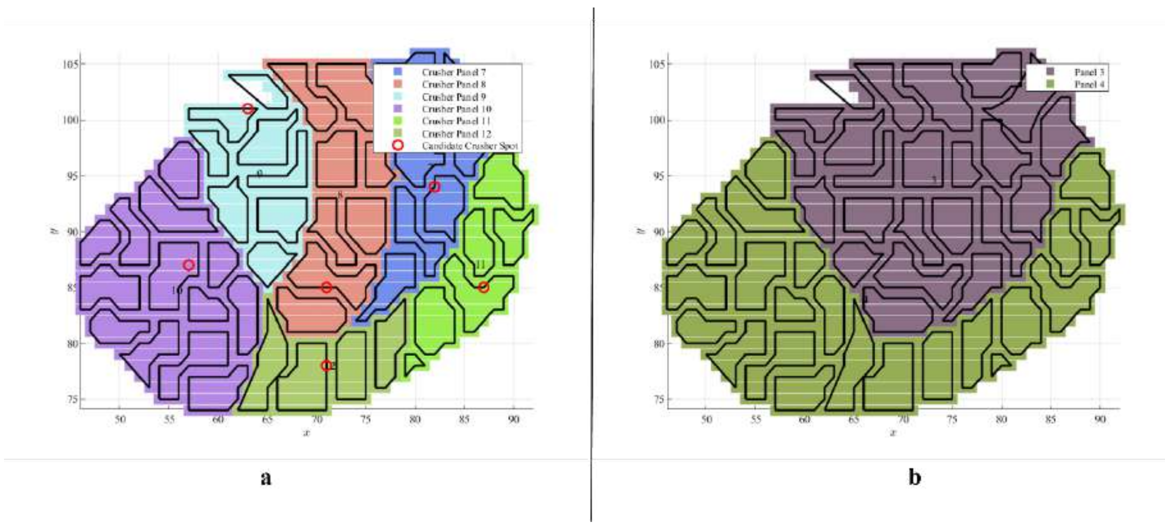

Figure 5. Plan view of the second bench a) clustering blocks to create the crusher panels, b) mining panels or phases.

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.

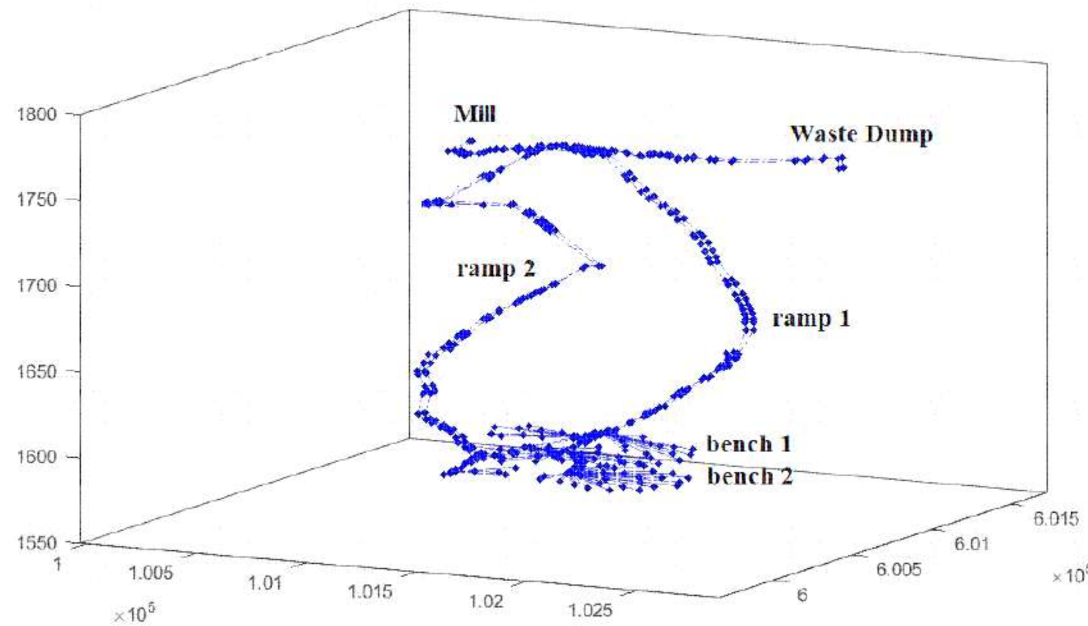

Figure 6. Schematic view of the road network of the case study.

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.

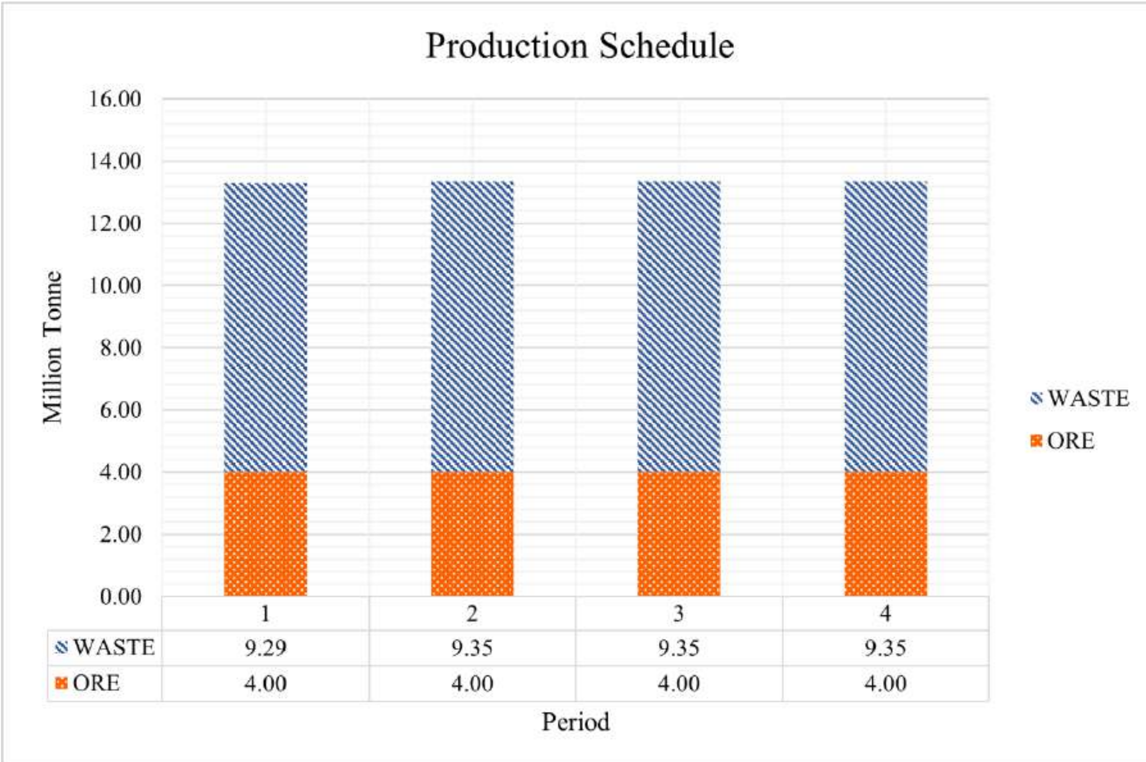

Figure 7. Mine production schedule during four periods.

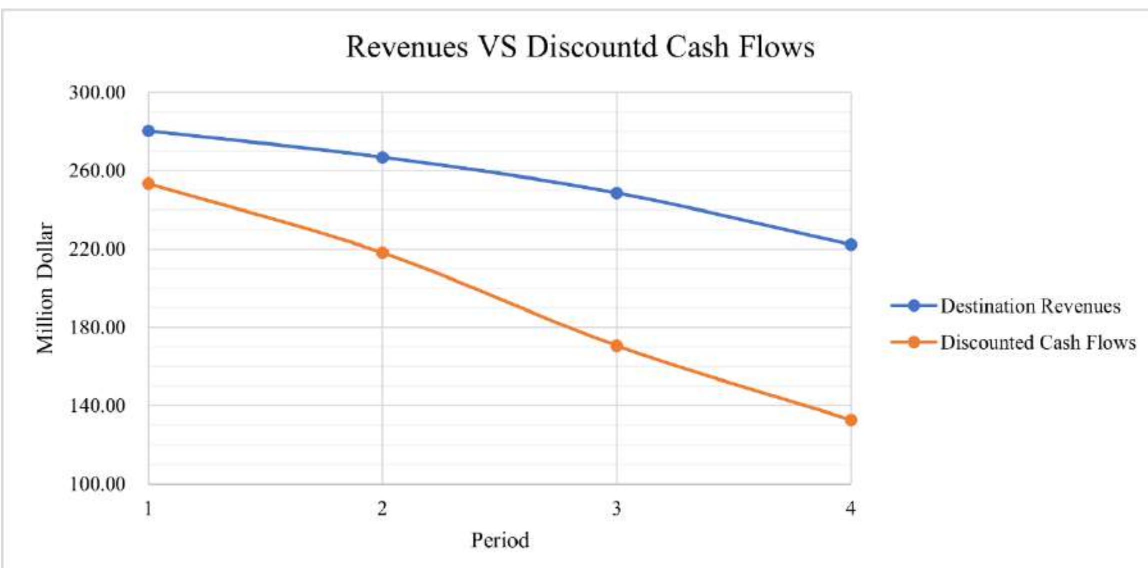

Figure 8. Revenues and discounted cashflows over four periods.

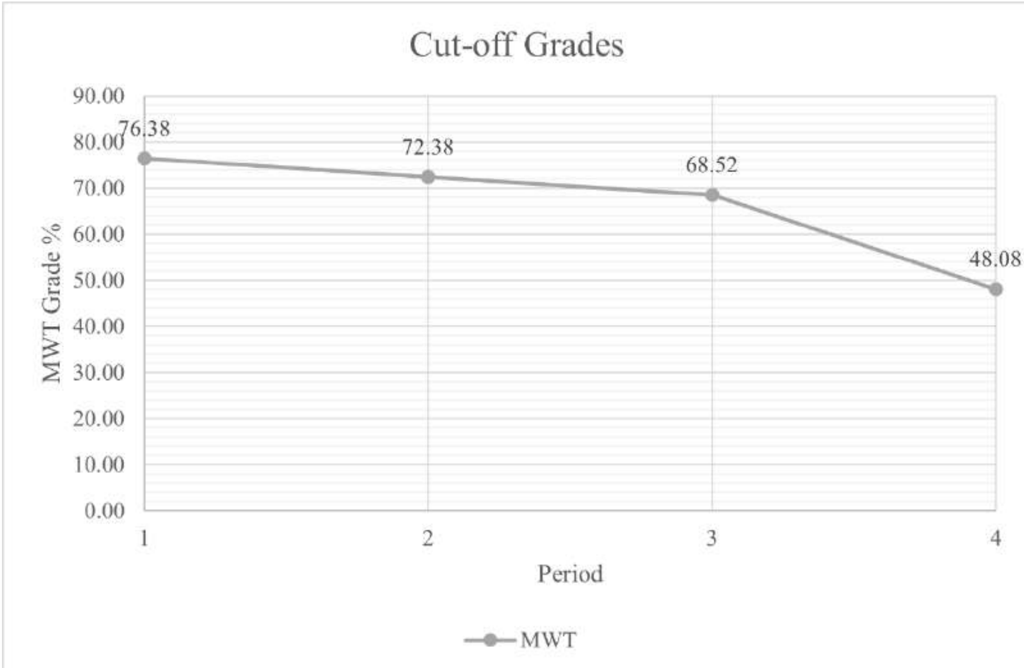

Figure 9. Cut-off grade variations during four periods.

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.

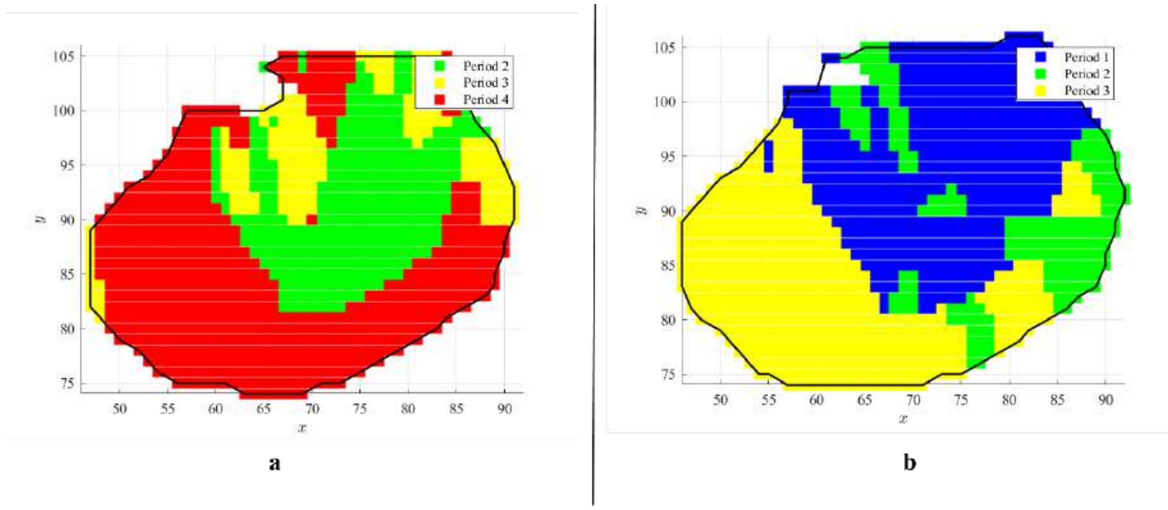

Figure 10. The extraction sequence for the usual MILP model without in-pit crusher and with mining panels. a) plan view of the first bench, and b) plan view of the second bench.

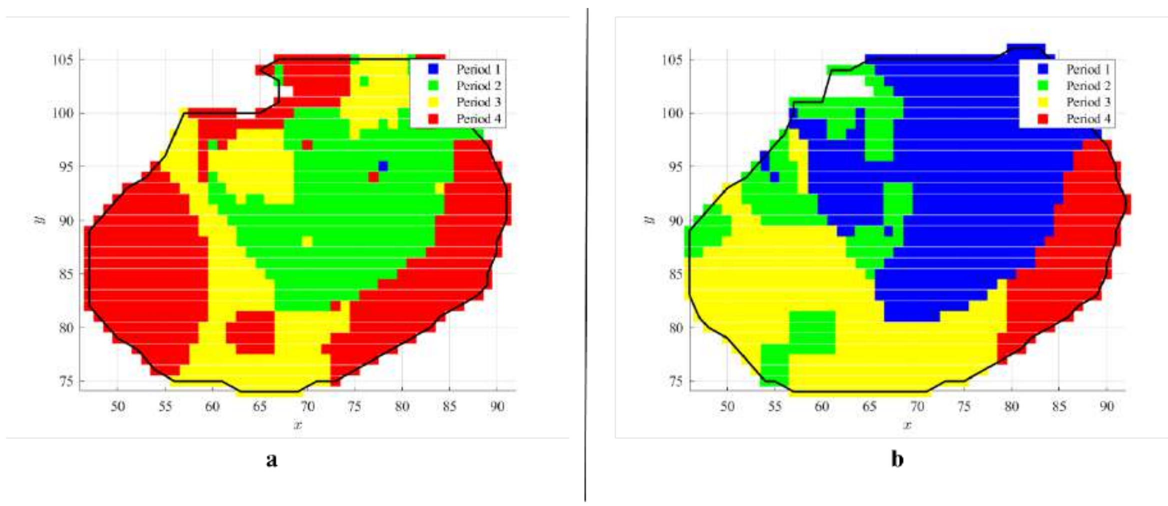

Figure 11. The extraction sequence for the MILP model with in-pit crusher and with crusher panels. a) plan view of the first bench, and b) plan view of the second bench.

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.

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Literature Review of Artificial Intelligence Applications in Open-Pit Strategic Mine Planning[1]

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ABSTRACT

The significant increase in data availability and high-computing power and innovations in real-time monitoring systems enable the technological transformation of the mining industry. Artificial Intelligence (AI) and data-driven methods are becoming appealing solutions to tackle different challenges in mining operations where an increasingly larger body of research is being published. Strategic mine planning is one of the areas that can be greatly enhanced with the adaptation of AI techniques to make intelligent data-driven decisions. This paper presents a systematic literature review to identify research trends in this field both in the specific area of application and the AI technique used. Papers from popular scientific databases were compiled and categorized into three main identified research areas in this field: Production Planning and Scheduling, Equipment Management and Grade Control, and individual AI techniques were cataloged. The results indicated an exponential growth in the general number of publications, where the most consolidated techniques across all applications were Genetic Algorithms and Discrete Simulation.

1. Introduction

Artificial Intelligence (AI) has seen a dramatic surge in interest from researchers and practitioners across all industries in the past few years, with successful real-world applications in consumer products, like digital assistants or content recommendation, and industrial settings, such as autonomous equipment and robotics. There is no clear-cut definition of AI, as it is a mixture of different research fields, each with its own goal and methods. A good definition can be found in Russell and Norvig [1] as the designing of intelligent agents that operate within an environment, take actions that affect it and receive feedback signals from it to achieve some goal. It can be seen as a general-purpose technology with sophisticated learning capabilities that can take large amounts of data for a wide range of applications like advanced analytics, process optimization, and automation that promise significant business improvements and new opportunities [2].

Machine learning (ML) is one area of AI that has received the most attention and hype in the past few years, with successful real-world AI applications based on this group of techniques. ML methods can be defined as a set of algorithms that can uncover complex patterns in data and use them to predict future outcomes. ML methods are commonly divided into three areas: supervised learning (SL), unsupervised learning (USL), and reinforcement learning (RL) [3]. SL aims to learn a good function approximation from an input vector, representing the problem of interest, to an output vector or target for future prediction. SL requires labelled data to learn the relation between

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attributes and targets explicitly. USL, on the other hand, is concerned with unlabeled datasets, where the outcome of the target for each data entry is not recorded. Therefore, its main goal is not a prediction but discovering patterns in data. USL's main applications are data clustering, density estimation, and dimensionality reduction [3]. RL proposes a framework in which a computational agent learns by interacting with an environment, real or virtual. In RL, the goal is to learn a mapping between situations (description of the environment) to optimal actions [4].

Moreover, AI also comprises other methods besides ML, such as metaheuristics (MTHs) and evolutionary algorithms, which have played a key role in engineering systems optimization [5]. MTH algorithms are concerned with searching for optimal solutions in challenging mathematical problems drawing inspiration from nature and evolution, and have seen significant applications in mining engineering [6]. Other data-driven approaches have also emerged in recent years, such as Discrete Event Simulation (DES) and Digital Twins (DT), which comprise the development of the detailed simulation of systems and processes for anticipating behaviour and supporting decision-making [7].

The mining industry is poised to reap the rewards of AI and data-driven approaches as it deals with a complex integrated value chain of exploration, extraction, and refining that has a history of integrating high-technology systems for increased productivity [8]. However, it remains one of the industrial sectors with lower levels of adoption of AI and digital technologies [9,10], where some of the major challenges that the mining industry faces for digital transformation are the availability of high-quality data, connectivity of operations and human resources skilled in these new areas [10].

The backbone for the digital transformation of any industry relies on three main pillars: data, connectivity and decision-making [10]. These three components are deeply intertwined, each providing necessary resources for the others to succeed. Connectivity plays an important role where the Internet-of-Things (IoT), a mixture of integrated technologies which can communicate via a network, provide the required infrastructure to enable automatic data collection and workflow control from which the mineral industry can significantly benefit [11]. The mineral extraction industry has already seen important innovations for real-time data acquisition and storage across the entire mineral value chain [12], that have enabled applications such as improved production decision-making with real-time updating and reconciliation of mineral quality models by integrating sensor data [13,14], or accurate estimation of ore production from the truck haulage system with ML and IoT [15].

Jung and Choi [16] present a systematic review of ML applications for mineral exploration, exploitation and reclamation, where a significant growth in the number of studies was observed starting from 2018, with the main applications receiving attention by researchers being mineral exploration and drilling and blasting. On the other hand, McCoy and Auret [17] present a review of ML applications in mineral processing exclusively, identifying equipment fault-detection and diagnosis and machine vision for quality control. The applications of ML and AI within the mining industry as a whole are very broad.

Surface mining methods dominate the mining industry, accounting for more than 95% production of non-metallic minerals and more than 90% production of metallic ones [18]. Surface mining method involves selectively extracting shallow mineral resources by excavation or cut made from the surface using one or multiple benches. One of the key stages in the life cycle of surface mines is strategic planning, which involves decisions taken for the long-term vision of the operation and short-term execution.

Therefore, this paper presents a systematic review focused on the use of AI and data-driven methodologies in strategic surface mine planning to analyze trends in the adoption of different techniques and get insight into what applications in this area are being tackled by researchers and the industry. This paper is organized as follows. In the remainder of this section, a brief overview of surface mining methods and the role of strategic planning and its operations within the mine project life cycle are presented. Section 2 describes the research methodology followed in this paper stating the research questions that will be answered and the literature search strategy and inclusion criteria. Section 3 presents a systematic review, including the classification and detailed review of selected publications and analysis of the research trends in the area. Section 4 discusses the results obtained from the literature review and proposes some directions for future work. Finally, Section 5 presents the conclusions of this research.

1.1. Overview of strategic planning in surface mining

The life cycle of a mining project consists of six main stages or phases: (1) exploration and feasibility, (2) design and planning, (3) construction and development, (4) exploitation, (5) mine closure and (6) post-mining reclamation [19]. The first stage comprises activities such as geological exploration and drilling and determining mineral resource quantity and quality. The second stage of design and planning involves the engineering studies to plan the extraction of the mineral resource from the ground and the design of the integrated system to sell it on the market. The decisions taken at this stage play a key role in the mining project's long-term economic and technical performance. In the third stage, once the extraction plan was determined, the construction of facilities and preparation of the land for the extraction phase takes place. The fourth phase of exploitation also involves key decision-making processes to execute the long-term vision for the mining project at shorter time intervals. During the exploitation phase, revisions to the long-term plan are also conducted periodically to adapt to new circumstances such as different market prices or unexpected behaviour or quality of the mineral rock mass. The final stages of the mining life cycle include all the activities involved to guarantee a safe and sustainable closure to the mining project and restoration of the land for its post-mining use.

The general geometry of an open-pit mine consisting of multiple benches and a haul road network is shown in Figure 1. Strategic mine planning is concerned with the goal of maximizing the value of a mining project from the feasibility stage to the mining production environment, optimizing the utilization of resources such as equipment, labour, and technology, and plays a crucial role in the success of a mining operation. For this purpose, our goal is to understand how AI and data-driven methodologies are starting to disrupt this area and what the potential is for the future. Strategic planning involves two stages in the mine life cycle previously discussed, design and exploitation, under which long-term and short-term planning tasks are carried out [20].

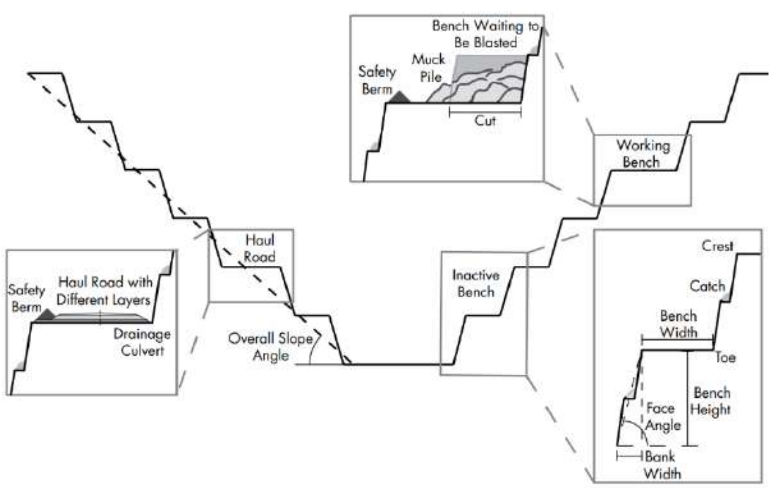

Figure 1. General geometry of an open-pit mine. After [21].

1.1.1. Long-term planning

Long-term planning deals with determining the final pit limits and the life-of-mine production schedule of the operation, where mining extraction sequences and destination policies for the mined areas (i.e. processing plant, waste dump) are decided at long time horizons to maximize the project's economic value. The mineral resource is discretized into a set of blocks, where for each block, different properties are estimated like rock type and metal grade using information gathered from the exploration campaigns. The long-term planning process uses the mineral resource block model, along with an economic scenario, to define the ultimate pit limits (UPL) and the open-pit production schedule (OPS) for the life-of-mine at long-term periods of time usually expressed in years [22].

The problem of defining the UPL can be described as finding the optimal final boundaries for the open-pit operation that maximize the total profit for the extraction of the mineral ore contained within, considering the costs of mining overlying rock waste material. The final pit boundaries must comply with operational and geotechnical constraints such as bench widths and overall slopes. Sophisticated computational methods have been proposed and are used in the industry to solve this problem, for a review of such please refer to Mwangi et. al. [23].

The open-pit production scheduling (OPS) problem can be defined as finding the sequence of extraction and destination of the blocks or benches within the ultimate pit limits under production, metal grade quality, geotechnical and other operational constraints. The long-term production scheduling solves this problem on a time horizon comprising the life-of-mine with decisions expressed in years or larger time periods. Fathollahzadeh et. al. [24] present a comprehensive review of current mathematical solution strategies for this problem.

Due to the large scale of surface mining projects and the complex sequencing constraints and ore quality requirements, it is often computationally intractable to obtain a true optimal mine plan, for which metaheuristics and intelligent computing methods seem particularly promising and have been widely adopted to approximate good solutions under a reasonable amount of time for the open pit scheduling (OPS) problem. A review of metaheuristic approaches for the specific problem of long-term open-pit planning problem is presented by Franco-Sepulveda et. al. [6].

1.1.2. Short-term planning

Short-term planning differs from long-term applications by emphasizing operational level decisions dealing with equipment and resources allocation over a shorter time scale on a monthly, weekly or shift-by-shift basis, usually under the guidance of the long-term plan. At these shorter time scales, mine operations are modelled with greater detail, considering the available equipment and different tasks required to execute the long-term strategic vision of the mine.

Model formulations for the open-pit mine operational planning (OPMOP) vary amongst researchers but commonly seek to minimize deviations from production targets, minimize operating costs or maximize NPV, and include a more detailed mathematical representation of equipment interaction. Common formulations aim to obtain decisions on shovel allocations to mining areas and production scheduling of development and extraction activities such as drilling and blasting and preparation of the working area. For an overview of short-term planning methods for open-pit mining, the users are referred to Blom et. al. [25].

Truck fleet management also represents a key aspect of the short-term and operational planning of open-pit mining, which comprises the allocation of truck fleets to shovels and mine production areas, and the definition of a truck dispatching strategy. For a review of current methods in truck fleet management, the readers are referred to Moradi Afrapoli and Askari-Nasab [26].

2. Research Methodology

This research aims to identify current research trends in applying AI and data-driven approaches for the strategic planning of surface mining operations to understand better the current state of adoption, future potential, and potential flaws of these new technologies in this field.

To fulfill the objectives of this study, a systematic literature review was carried out following the guidelines given by Tranfield et al. [27], who transfers systematic review methods from the medical field to the management sciences, and Xiao and Watson [28], who propose a rigorous methodology for literature reviews in the planning sciences. The main steps for the systematic literature review presented in this study include the formulation of the problem as research questions, the development of the search protocol including the search query and selection of databases, the definition of screening criteria for inclusion and rejection of documents and the synthesis and analysis of the information retrieved.

The review focuses on the following research questions:

1. How and within which main research areas have AI and data-driven technologies been adopted for the strategic planning of surface mining operations?
2. Which are the most common AI and data-driven approaches for strategic planning in surface mining operations?
3. How have AI and data-driven approaches been applied in the strategic planning of surface mining operations over time?

Research question 1 deals with uncovering the main application areas in which AI and data-driven methods have been applied within the strategic planning of surface mines to understand better where most of the research effort is put on. Research question 2 is more specific to the AI and data-driven approaches to understand which methodologies have been more successful when applied to this field. Finally, research question 3 is concerned with synthesizing the evolution of AI and data-driven specific techniques (e.g., neural networks, genetic algorithms) in the literature relating to strategic planning of surface mining operations to point out potentially favourable and possibly obsolete techniques.

The search included papers from the year 2000 up to June 31st of 2021 in the following scientific databases: Science Direct, Springer Link, Scopus, IEEE Xplore, and Taylor and Francis. These databases include most scientific peer-reviewed work in engineering applications, with some containing relevant mining engineering journals.

The general structure of the search query is presented below, which was adapted to match the format for each of the different scientific databases.

(OR[keywords for surface mining]) AND (OR[keywords for AI and Data-driven approach]) AND (OR[keywords for strategic planning])

The [ ] indicates the following set of relevant keywords for the search:

- Keywords for surface mining: Surface mining, open pit mining.
- Keywords for AI and Data-driven approach: Artificial intelligence, machine learning, deep learning, reinforcement learning, data analysis, intelligent system, metaheuristic, simulation.
- Keywords for strategic planning: strategic planning, production scheduling, production monitoring, equipment management, equipment monitoring, grade control.

The OR[ ] notation indicates that the query targets at least one of the keywords from that particular set. Therefore, the query targets papers containing at least one keyword from each set corresponding to surface mining, AI and data-driven approaches, and strategic planning.

Afterwards, the literature records obtained were screened based on the following inclusion criteria:

- Only peer-reviewed journal papers or conference proceedings.
- Only publications from the year 2000 onwards.
- Unique studies with duplicates or similar studies by the same authors on different journals or conferences were removed.

Moreover, to stay in the scope of strategic planning and operations management, the following topics related to surface mining that partially appears as part of the search query were not considered in this review: geological exploration, mining rock mechanics, mining equipment reliability, blasting and mineral processing. These topics can be considered a whole field on their own, and although critical for the success of mining projects, they are out of the scope of this specific research, and to be able to cover them a different search strategy would be needed systematically. For interested readers, an overview of research trends in rock mechanics is presented in Lawal and Kwon [29] and mineral processing in McCoy and Auret [17]. To the best of the authors' knowledge, there is no systematic literature review work in geological exploration, mine safety, or rock blasting; however, there is a significant body of specific applied research in those areas.

By applying the search-query and inclusion conditions, 87 papers were retrieved for a detailed analysis of the research areas and trends. Figure 2 illustrates the general overview of the literature search and compilation.

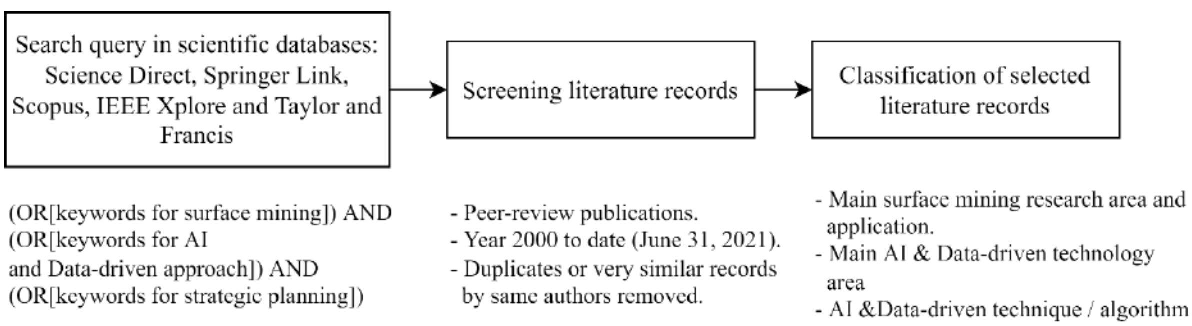

Figure 2. Methodology for literature database compilation.

3. Systematic Review

The literature database obtained from the systematic search was categorized based on main research area, application and AI and data-driven technique used. Then the results were analyzed to answer the research questions posed. This introduced different abbreviations to deal with the variety of applications and methods found in the literature. To facilitate the reader's comprehension, a list of all the abbreviations introduced in this section is presented in Table 1.

Table 1. List of abbreviations

Research Areas (RA)		**AI & Data-Driven Approach (AIA)**	
EM	Equipment Management	*DES*	Discrete Event Simulation
GC	Grade Control	*MT H*	Metaheuristic
PPS	Production Planning and Scheduling	*RL*	Reinforcement Learning
		SL	Supervised Learning

USL Unsupervised Learning

AI & Data-Driven techniques

ACO Ant Colony Optimization
BA Bat Algorithm
CLS Clustering
CNN Convolutional Neural Network
FA Firefly Algorithm
GA Genetic Algorithm
HOG Histogram of Oriented Gradients
ICA Imperialist Competitive Algorithm
KNN K-Nearest Neighbors
NN Neural Network
PSO Particle Swarm Optimization
PH Progressive Hedging
RL Reinforcement Learning
RL Reinforcement Learning
S-B Search-based Algorithms
SA Simulated Annealing
SVM Support Vector Machine
T-B Tree-based algorithms

3.1. Classification of literature

All 87 selected papers were reviewed in detail. Then, to answer the research questions, they were classified based on the research area they targeted and the specific mining application and based on the AI and data-driven approach used and technique applied.

- Research area (RA): General area of interest targeted in the publication.
- AI and data-driven approach (AIA): General AI approach from which the techniques used in the publication belong.

The RA observed from the corpus acquired are the following: Production Planning and Scheduling (PPS), Grade Control (GC), and Equipment Management (EM). All papers target a particular application within these broad fields of interest for the strategic planning of surface mining operations. The AIA considers SL, USL, agent-based approaches and RL, MTH, and DES.

Moreover, within each RA, the mining application the research targeted was identified and tabulated. Table 2 shows a summary of the number of research papers by RA and application and by AIA.

Figure 3 illustrates a visual representation of the number of papers by category. PPS is the RA that dominates research efforts, including long-term and short-term or operational production planning and scheduling, and forecasting production capacities and capital costs. The principal AIA taken has been the development of MTH algorithms to tackle the large-scale and complex problems of real-sized mines, with SL impacting cost forecasting applications. RL approaches were tested initially in 2009 by Askari-Nasab and Awuah-Offei [30] for long-term planning and resurfaced again by 2017 over multiple research efforts. Discrete simulation is used extensively for planning and scheduling at an operational level where the interactions between equipment considerably impact production Key Performance Indicators (KPIs).

Table 2. Number of research papers by RA and application (in parenthesis) and AIA.

Research Areas and Applications	**AI & Data-Driven Approach (AIA)**				
	SL	**USL**	**RL**	**MTH**	**DES**
Production Planning and Scheduling (67)	8	1	6	41	11
Long-term planning (41)	1	1	2	35	2
Short-term planning (22)	4	0	4	5	9
Production capacity forecasting (11)	1	0	1	0	9
Cost forecasting (4)	3	0	0	1	0
Grade Control (14)	3	3	1	7	0
Cut-off grade strategy (5)	0	0	0	5	0
Grade Control and Ore delineation (14)	3	3	1	7	0
Equipment Management (21)	6	0	5	2	8
Equipment tracking (10)	6	0	2	0	2
Equipment dispatch & sizing (13)	0	0	3	2	8

The EM area includes research publications that deal explicitly with mining equipment where tracking, consumption control, and equipment dispatching are the main applications. Multiple types of AIA have been tested in which DES methods are the most favoured approach by researchers. It can potentially exploit large datasets that are more commonly available with the development of sensors and monitoring technologies for mining equipment. Agent-based approaches and RL appear with research focused on the dispatching and optimal routing of trucks and shovels. SL techniques also play a key role here, where large mine records can be used to predict equipment behaviour and consumption.

Research on applications for grade control in open-pit mining operations appeared significantly in the database. Papers under this category cover applications in which the goal is to find techniques to discriminate ore from waste better and delineate ore zones for improved mine planning and determining cut-off grade strategies for the operation. MTHs appear to be favoured algorithms in this area to solve the complex problems of delineating ore boundaries and determining cut-off strategies.

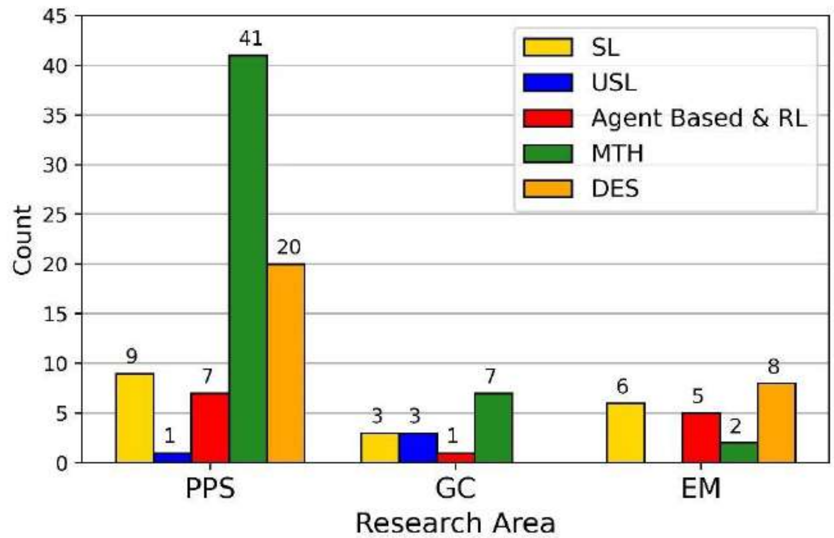

Figure 3. Number of papers by RA and AIA.

Following the research questions, Figure 4 shows the number of papers by specific mining applications and AIA to get some insights into which AI and data-driven approaches have had a broader adoption for mining applications. MTHs, such as genetic algorithms (GA), significantly impact long-term planning and grade control research. These applications solve large and complex computational models for surface mines' scheduling and decision-making process. On the other hand, DES is commonly used for more operational and short-term planning where equipment cycles are more concerned. SL approaches have seen some adoption across multiple applications, RL and agent-based approaches which have been tried for long- and short-term planning, and equipment dispatching.

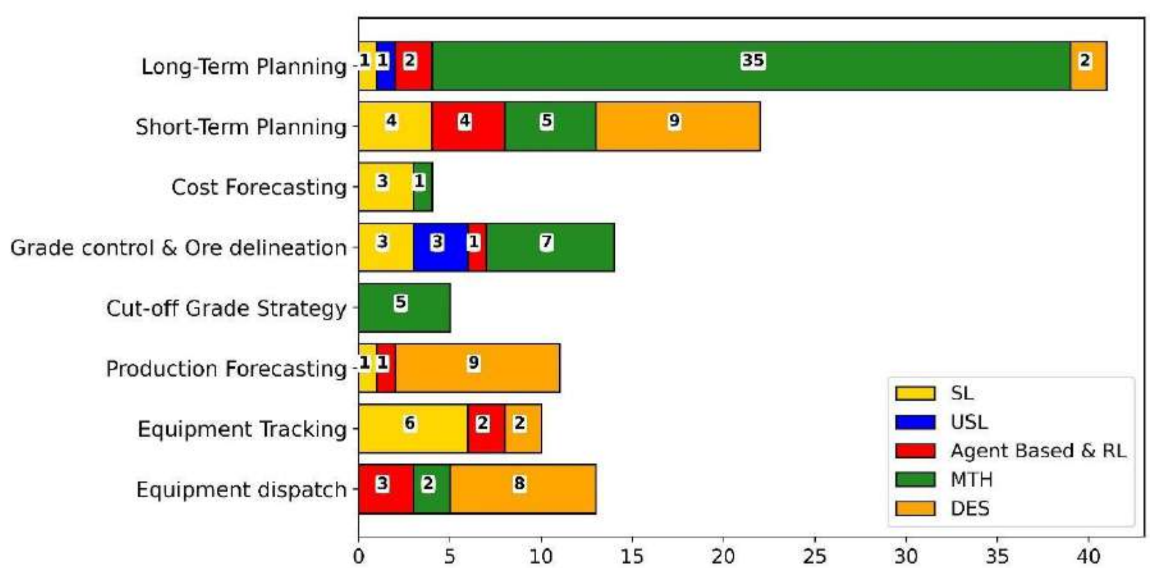

Figure 4. Number of papers by specific mining application and AIA.

3.2. Trend Analysis

Topic modelling and trend analysis techniques provide an important tool for researchers to navigate the large corpus of publications and studies within an area and get an overview of the evolution of topics and techniques explored by the research community [31]. To answer research question 3 and get an idea of the evolution of the adoption of different AIA within surface mining strategic planning, Figure 5 shows the number of publications by AIA throughout the period in question, 2000-2021. The publications were grouped in bins of 3 years to allow for better visualization, including the last year, 2021, in the last group.

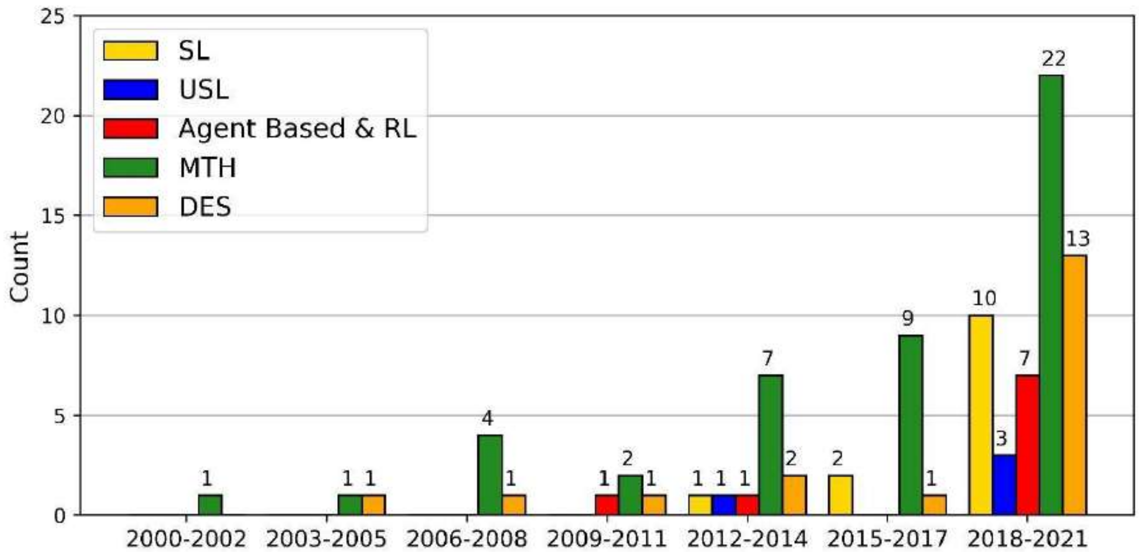

Figure 5. Trend of publications by AIA.

Figure 5 shows that the past few years have seen considerable efforts directed in applying AIA in the mining industry, along with trends in other sectors. MTH approaches have seen the largest positive trend, showing an exponential growth pattern in the number of publications. This type of intelligent computation approach has benefitted immensely from the general increase in computational power and seem to be a reliable option to solve large scale mine production planning and scheduling problems, both at a long-term and operational scale, which require the evaluation of many possible combinations of resource allocation and mining extraction patterns decisions. DES approaches have seen extensive adoption, especially in the past four years. These methods require large databases to reproduce equipment production cycles and interactions accurately and have benefited from the large-scale adoption and focus on data-driven applications within the mining industry.

From the ML approaches, SL has the largest adoption, increasing within the past four years. SL requires large, labeled datasets to work efficiently, which have become more readily available recently with advances in monitoring technology. On the other hand, USL seems to be the least adopted approach, appearing just after the 2012-2014 period. USL tries to discover insights from unlabeled data and is particularly challenging to bring into practical applications since the lack of a ground truth label (e.g., machine failure, ore grade) makes its interpretation challenging. This is a complication in the adoption of USL in other industries as well. Finally, RL approaches appeared as early as 2009-2011 but then faded away from the literature, making a significant comeback just in the past four years. RL is benefited from very recent key breakthroughs that promise to make their application feasible in real-world settings. RL high complexity remains a hurdle for industry adoption; however, it shows great potential as it explicitly combines data-driven learning capacity with decision-making processes.

To get further insight into the specific techniques tried by researchers, a trend evolution map was created for the techniques identified in each paper, shown in Figure 6. Analyzing the research trends of particular AI and data-driven techniques and their evolution through time can provide researchers with a better understanding of what techniques have been already tried and are starting to fade away, what techniques have seen consistent success in their applications and what are some of the new hot topics in the literature, which greatly supports the directions for future research and work as it has been applied in other industries [32]. An example was applied by Bertolini et al. [33] to model the topic trend evolution of ML adoption in industrial processes and understand which techniques have seen a more successful adoption in the field interest and which are becoming obsolete. Bertolini et al. [33] identified five main clusters of techniques based on their position in the trend evolution map denominated: Question Marks, Hot Topics, Consolidated, Stars, and Obsolete. The AI and data-driven methods identified in the compiled literature database are classified in similar clusters based on their trend evolution throughout time as detailed below. This trend score captures both number of appearances in publications and how consistent they appear throughout time, to differentiate methods that appeared in short bursts in past years but then faded away, and methods that are consistently applied by researchers throughout time to tackle a variety of challenges in the strategic planning of surface mining operations.

The SL techniques include convolutional neural network (CNN), tree-based classification and regression (T-B), support vector machine (SVM), neural networks (NN), k nearest neighbours (KNN), and histogram of oriented gradients (HOG). USL techniques include clustering (CLS), and RL techniques account for a single group of RL and agent-based algorithms. MTH techniques include ant colony optimization (ACO), particle swarm optimization (PSO), genetic algorithm (GA), simulated annealing (SA), search-based algorithms (S-B), bat algorithm (BA), imperialist competitive algorithm (ICA), firefly algorithm (FA) and progressive hedging (PH). DES techniques account for a single group.

Each topic is represented as a bubble whose size is proportional to the number of publications that use that technique. In Figure 6, the x-axis (Age) indicates the number of years since its first appearance in the literature. The y-axis (Trend) shows a percentage deviation from the technique publication life's 'center of gravity'. A stable topic that has appeared consistently in the literature since its first publication without a recent surge in a short amount of time would have a trend value near zero. A positive trend indicates that a topic is appearing more frequently in recent years or has had a significant comeback after initially fading away. A negative trend indicates a topic that is disappearing from the recent literature. From these definitions, six topic clusters can be identified.

- Stars (High age and positive trend):

  Techniques that have appeared consistently since early on the research time period and experiencing a surge in applications include GA and DES. These techniques seem to have the most success and are reliable to solve problems within surface mining strategic planning.

- Consolidated (Medium-to-high age and positive trend):

  Techniques applied for a long time in the literature with still significant research interest include SA, S-B, ACO, and PSO. These techniques have proven to be successful in research efforts for a long time and are a solid choice to tackle complex problems within this field.

- Emerging trends (Low-to-medium age and positive trend):

  Techniques that have been recently adopted and seem to have had some success with increasing research interest include RL, NN, and CLS. Given due time, these techniques could either move to become consolidated choices in the field or fade away.

- Hot topics (Very low age and positive trend):

Very recent techniques that have seen a large interest. Only includes CNN, a very recent deep learning technique that has also seen a surge in applications across multiple fields. These techniques are new promises that are yet to stand the test of time to become solid choices within this field.

- Question marks (Very low age and zero to negative trend):

  Very recent techniques that have seen limited introduction and could potentially see a follow-up in the coming years include FA, KNN, SVM, and T-B.

- Exiting/Obsolete (Medium to high age and negative trend):

  Techniques that have been tried in research for some time now but that have faded away include ICA, BA, PH, and HOG. These techniques do not seem to give good results within surface mining strategic planning or have been displaced by newer developments. For example, HOG is an approach to computer vision problems that have been replaced by the appearance of CNN in general use.

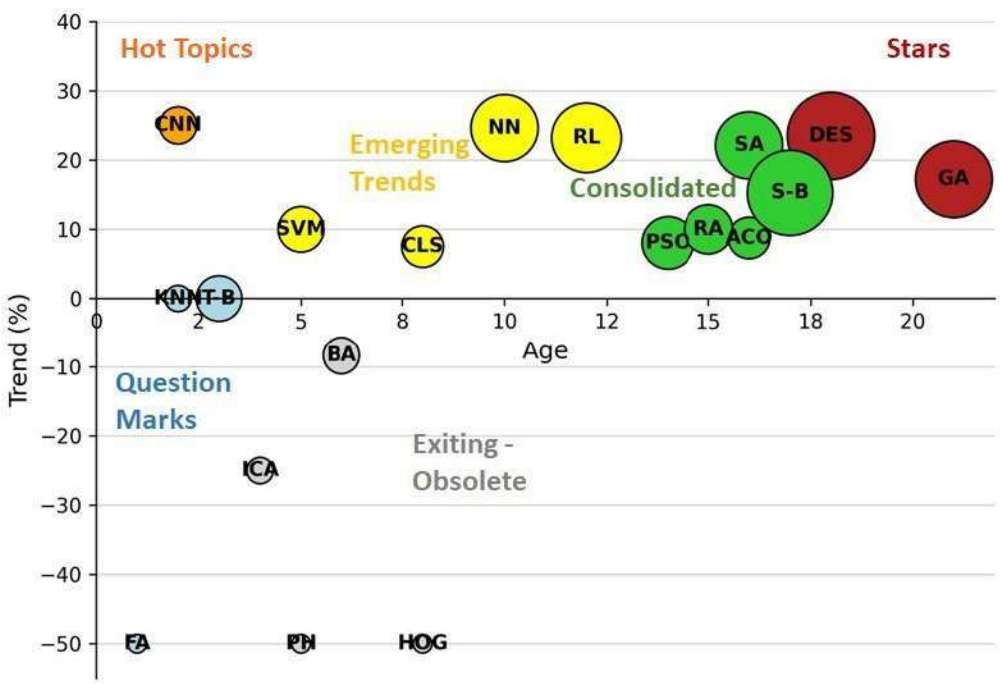

Figure 6. Trend evolution of specific AIA techniques during the research period 2000-2021.

3.3. Detailed Review by Research Area

3.3.1. Production Planning and Scheduling

The production planning and scheduling area concerns applications in which AI and data-driven techniques support tactical decision-making for the mining operation strategy, both long-term and short-term, including decisions on resource allocation and ore extraction to achieve economic and production targets. Research classified into this area includes specific long-term planning, short-term planning, production and cost forecasting applications.

One of the earliest efforts is presented by Pendharkar and Rodger [34]. They developed a Genetic Algorithm (GA) to determine the production, transportation, ore blending schedules, and selection of markets for multiple coal mines, highlighting the potential of GA for complex decision-making processes within the mining industry. GA has become a reliable technique to solve open-pit long-term production scheduling (OPS) problems. Moosavi et al. [35] developed a hybrid model using a GA and augmented Lagrange multipliers to solve OPS for two pushbacks of an iron mine containing 6770 blocks. Alipour et al. [36] compared a GA approach with the commercial software SimSched DBS for OPS, where they reported the GA achieves a 4% increase in the net present value (NPV) for the Marvin mineral resource dataset. In this research, the authors state that the commercial solver IBM CPLEX [37], a state-of-the-art optimization engine, could not solve the OPS after 25 days, whereas the GA reached a competitive solution within 20 to 30 minutes.

GA has also been extensively used to introduce uncertainty and extend stochastic optimization models to the OPS problem. For example, Samantha et al. [38] formulated a multi-objective GA for OPS with mineral grade uncertainty, represented via orebody conditional simulations, for an iron deposit. The objectives of the GA were defined to obtain a schedule that minimizes deviations from targeted grades of iron, silica, and alumina elements. Moreover, Franco-Sepulveda et al. [39] incorporated market uncertainty as well in the future prices of the minerals of interest, with a GA formulated to maximize NPV and minimize its standard deviation. Additional GA-based methods to solve the OPS problem under uncertain inputs are presented by Alipour et al. [40] and Paithankar and Chatterjee [41], highlighting GA's flexibility as a technique for robust decision making.

Other successful evolutionary computing approaches for long-term planning include Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). ACO methods are based on the ability of ants to find the shortest paths to food and are efficient algorithms to search for shortest paths over-weighted graphs. The earliest ACO application found was by Riff et al. [42], who named their approach Miner Ants Colony. They tested their model on 50 artificial mine block models, which were similar to a confidential real mine. They reported positive results in obtaining close to optimal solutions for some of the largest and more complex datasets in about one hour. Shishvan and Sattarvand [27] presented a similar but more detailed presentation of an ACO algorithm for OPS. Their model provides some insights into the calibration of the different parameters of the algorithm and obtains good results within reasonable computing times for a large-scale problem. Gilani and Sattarvand [43] developed an ACO-clssed framework to integrate geological uncertainty via multiple conditional simulations of the ore deposit. The framework was tested on a large-scale dataset (about 2.5 million blocks), obtaining an NPV improvement of about 8% from a commercial software solution.

PSO algorithms follow a similar approach where solutions to a problem dubbed ‘particles’ are moved around searching for an optimal solution; it was inspired by the movement of collective organisms in nature. Ferland et al. [44] presented an early attempt to adapt a PSO solution for OPS, where the only constraints considered were slope and mining capacity. Furthermore, Khan and Niemann-Delius [45] designed a PSO that could handle processing capacity as well, testing on a 7,836 blocks orebody. Results were benchmarked against an exact solution using CPLEX, which after 22 hours, reported a solution with a 4.5% optimality gap. In contrast, the PSO achieved a better optimality gap in under 12 minutes for different parameter settings. A stochastic approach was developed by Gilani et al. [46], for mining sequence decisions under mineral grade uncertainty. Under different PSO strategies, improvements around 9% to 12% in NPV were achieved with a required time of about 15 hours. An application by Gu et al. [47] described a PSO method for an in-pit crushing and conveying system to determine the optimal crusher location that minimizes transportation costs.

Simulated Annealing (SA) is another successful metaheuristic applied in the long-term planning and production scheduling of surface mines, which is a method inspired by the annealing technique in metallurgy that deals with the heating and controlled cooling of materials. The earliest application found by the search query was done by Kumral and Dowd [48]. They detailed a SA algorithm for OPS considering three objectives: minimizing deviation from required tonnage, penalty and opportunity cost, and mineral content variability. The authors report a case study on a

Western Australia iron ore body containing 2,773 and considering iron, silica, and alumina variables, obtaining a result in approximately 25-30 minutes, although no benchmark was presented. Danish et al. [49] considered the single OPS to integrate stockpiling management with material mixing. They presented three test cases with the largest comprising 12,822 blocks, where the CPLEX was unable to generate a solution, whereas the SA framework proposed achieved a solution with a 7.78% optimality gap within 2 hours.

SA techniques have been especially successful for the OPS problem under uncertainty. Leite and Dimitrakopoulos [50], integrated geological uncertainty by multiple orebody simulations and a SA detailed that seeks to find a production schedule that minimizes deviation from production targets, reporting a 20% increased NPV and better risk management than deterministic counterparts on a copper deposit test case. Albor Consuegra and Dimitrakopoulos [51] analyzed the same stochastic SA algorithm's sensitivity, reporting no significant improvement after 10 orebody simulations and an increase of 17% of mineral reserves due to an increased final pit limit. Montiel and Dimitrakopoulos [52] presented a similar SA to handle multiple process destinations depending on material types (e.g., acid leaching, bio-leaching) and tested on the Escondida Norte mine in Chile, a massive copper deposit. Thy benchmarked against a schedule generated by commercial software and reported a 4% increase in NPV and average deviations in the mill and waste production smaller than 5%, whereas the commercial software schedule yielded average mill production deviations of 20% and 12% for waste. On the same problem, Montiel and Dimitrakopoulos [53] integrated multiple material transportation options. Kumral [54] used a SA to jointly solve the block sequencing problem with the ore-waste classification problem, considering metal uncertainty. The SA approach uses multiple orebody simulations to determine whether a block should be considered ore or waste rather than relying on a previous cut-off.

Goodfellow and Dimitrakopoulos [55] proposed a stochastic SA to optimize the whole mineral value chain, including multiple pits, processing streams, transportation options, and markets under geological uncertainty. Two test cases were reported for nickel laterite and copper-gold mineral value chains obtaining an increased NPV and a better production risk profile in both cases. Multiple extensions to this algorithmic framework appear in the literature. Saliba and Dimitrakopoulos [56] incorporated market uncertainty, Kumar and Dimitrakopoulos [57] integrated geo-metallurgical variables, Levinson and Dimitrakopoulos [58] added waste management decisions and Saliba and Dimitrakopoulos [59] tailings management of acid generating material, including the capital and operating costs involved.

Local search-based MTHs have seen some success in the literature as an alternative to solve the OPS problem, particularly tabu search and variable neighbourhood search algorithms. Both are local search methods that explore immediate neighbours of a potential solution to discover an improved one. These methods have been particularly appealing to the stochastic version of OPS to obtain a near-optimal mining schedule robust to mineral grade uncertainty. The particular implementation of these search-based strategies are discussed by Lamghari and Dimitrakopoulos [60], Senécal and Dimitrakopoulos [61], Lamghari et al. [62], and Lamghari et al. [63].

Although other MTHs have been tested to solve the OPS problem for strategic planning, researchers have not seen similar levels of attention suggesting that they may not be efficient in tackling the structure of OPS. These are bat algorithm (BA) by Moosavi [64], imperialist competitive algorithm (ICA) by Mohammadi et al. [65], and progressive hedging (PH) by Lamghari and Dimitrakopoulos [66]. Tolouei et al. [64] presented a comparison between BA and firefly metaheuristic algorithm (FA) to solve OPS under metal uncertainty, reporting that the FA achieved better results.

RL approaches to solve the OPS problem were initially proposed by Askari-Nasab and Awuah-Offei [30] in 2009, under the name of intelligent agent-based open pit mine planning (IOPS), to determine the optimal combination of pushbacks that maximized the expected return over the pit life-of-mine. The authors developed a discrete simulation engine to model pit pushback expansions and how it impacted the project's economics to train the scheduling agent, as detailed in [67]. Although they highlighted the potential of RL techniques to address complex decision-making in long-term OPS, there were no follow-up revised methods or attention from other researchers. Lamghari and Dimitrakopoulos [68] reintroduced some RL concepts for long-term OPS within a hyper-heuristic framework. The hyper-heuristic approach is described as a heuristic selection framework, in which given multiple heuristic choices for solving the OPS problem, the framework learns which is better at each iteration to produce an optimal solution.

Souza et al. [69] presented different search-based MTHs for short-term mine scheduling and truck and shovel allocation plans to minimize deviations from production goals and number of trucks used, which were benchmarked against an exact solution obtained using the CPLEX solver and found to be competitive but requiring significantly lower time. Alexandre et al. [70], on the other hand, reported a GA that obtained better short-term schedules than the search-based MTH for the same problem. Mousavi et al. [71] introduced shovel allocation decisions and proposed a tabu search, and simulated annealing hybrid metaheuristic to solve the problem. Both and Dimitrakopoulos [72] integrated uncertainty in fleet production capacity by simulating production capacity scenarios based on the mining block location and truck cycle uncertainty, along with metal uncertainty, by orebody simulations, in the OPMOP. The authors develop a SA approach to solve the problem, remarking it is impractical to solve via an exact solver like CPLEX.

More recent research efforts aim to combine discrete simulation with optimization engines to obtain operational schedules that explicitly account for equipment interaction within mine layout. Integration of DES could potentially allow more robust and data-driven based schedules. Upadhyay and Askari-Nasab [73] presented a detailed discrete simulation of mining operations that uses CPLEX engine to obtain optimal shovel allocations to mining faces. They extend their approach in [74] to optimize mining faces extraction sequences, truck and shovel allocations using a multi-objective optimization approach within the simulation engine. Shishvan and Benndorf [75] proposed a similar framework for simulation-optimization of operational decisions for a coal continuous mining system in Germany. The simulation captures the details of the excavation and dumping practices of the mining site. The optimization model seeks to minimize downtimes of excavators and spreaders to minimize cost and maximize production.

RL for mining operational decision-making was introduced by Paduraru and Dimitrakopoulos [76,77], in which an RL agent is trained to learn optimal destination decisions for each mining block for a given production schedule. Although it does not capture the full dynamics of truck-shovel operations and focuses more on the global supply chain, a DES serves as an environment. Furthermore, Kumar et al. [78] and Kumar et al. [79] extend this same research to account for real-time new information obtained through sensors or other monitoring technologies, focusing on a mechanism to incorporate new information on mineral grades and characteristics. They highlighted the potential of RL for adaptive and self-learning mining systems.

Another major application of AI approaches in the literature for PPS is for production forecasting. This includes research directed towards predicting the productivity of a mine given its layout and equipment. It is a problem where uncertainties due to the movement of trucks and operation of shovels within a shared mine layout (roads, mining faces, crushers) can have a significant impact and lead to overestimated production capacities or unfeasible production schedules. The favoured approach to tackle this problem seen in the literature is using data-driven DES to reproduce the equipment interaction within the mine layout and evaluate multiple scenarios for strategic decision-making.

Awuah-Offei et al. [80] presents an early practical application to estimate truck and shovel requirements for a production period of 4 years in an African mine. A DES model was built using historical records of the operation in the SIMAN programming language. More recent applications have transitioned to using the Rockwell ARENA software to build discrete simulation models. Multiple variations in data sourcing and KPI targets have been proposed to build and use the DES of truck-shovel production cycles for operational decision-making. For instance, Tan et al. [81] proposed using GPS data from mining truck control systems along with a DES to evaluate dispatching strategies. Soofastaei et al. [82] proposed a DES of truck-shovel cycles to evaluate the effect of truck payload variance on cycle times and productivity for a mine in Arizona, USA. Other similar DES research applications are presented in Upadhyay et al. [83] for an accurate estimation of Tonne per Gross Operating Hour (TPGOH), a critical productivity KPI in open-pit mines, and by Ozdemir and Kumral [84] to evaluate the productivity improvement of a proposed dispatching model benchmarking against historical mine records. Ozdemir and Kumral [85] proposed integrating the capability of evaluating dynamic variables along with discrete events under a framework known as agent-based Petri net simulations. They highlighted the possibility of tracking dynamic variables such as equipment fuel consumption more accurately under this approach. Different applications for data-based DES models are presented by Ugurlu et al. [86] for surface drilling operations productivity and Yaghini et al. [87] to evaluate the impact of shovel operator performance on different mine productivity key performance indicators.

A different approach to production forecasting was proposed by Choi et al. [15]. A large dataset collected by Internet-of-Things (IoT) devices installed in an open-pit was analyzed using supervised learning techniques to predict ore production. The authors reported that SVM achieved the best performance amongst the techniques tested. This recent effort highlights the possibilities of fully utilizing data generated by mine monitoring systems.

Estimating capital costs for mining projects is another recurring application where AIA appears as a promising method in the literature. Nourali and Osanloo [88] tested tree-based regression methods on a dataset comprising 28 copper porphyry mines reporting annual waste and ore production and capital cost. They reported encouraging results in predicting capital costs based on rock production; however, the dataset used was of small size, and conclusions from it may not be entirely accurate for new mining projects. The authors extended their research in [89] to a dataset comprising 52 copper porphyry mines, recording annual mine and mill production, reserve tonnages, and stripping ratio. A support vector regression (SVR) algorithm was tested to predict mining capital cost from these parameters. Guo et al. [90] tested multiple techniques to predict mining capital costs based on annual mine and mill production, reserves average grade and mine life for a dataset of 74 open-pit copper projects, and found a NN predictor to yield the best results with an average error of 7.77%. Zhang et al. [91] explored the NN method in more detail, combining it with an ACO MTH for the NN training and reported improved results on the same dataset. The main drawback of AI approaches for cost estimation is the availability of datasets, which hinders the performance of more complex AI methods like NN that require tuning a large number of hyperparameters.

3.3.2. Grade Control

Grade control and ore delineation is another major area of research interest. Under this category, we found applications dealing with finding the optimal cut-off grade strategy, ore classification, and dig limits delineation. The cut-off strategy for an open-pit mine refers to determining values over which mineral resource units are considered ore throughout the lifespan of the mine. An early application by Ataei and Osanloo [92] formulated the cut-off strategy problem as a nonlinear optimization problem. They proposed the use of GA to obtain the cut-off strategy for multi-metal mines. GA based approaches are further proposed by Azimi et al. [93], to incorporate variable commodity prices and in Ahmadi and Bazzari [94]. Other MTH to solve the cut-off grade strategy problem have appeared in recent literature, such as the Imperialist Competitive Algorithms (ICA) and Particle Swarm Optimization (PSO) algorithms described by Ahmadi and Bazzazi [95].

Beretta et al. [96] proposed a framework for automatic lithology classification of a mining face. They used unmanned aerial vehicles to obtain imagery of a mining bench and then compared k-nearest neighbors (KNN), SVM, and tree-based methods (T-B) to classify the bench imagery into waste, ore, vegetation, and soil areas. Although they reported promising results, they recommend further investigation of more complex image classifiers like CNN. CNN were studied by Pu et al. [97] to classify coal images as ore or gangue reporting accuracy of 82.5% and remarking the potential of CNN methods for ore/waste image-based discrimination.

Aggregation of mineral resource blocks into selective mining units groups blocks of adequate size for the mining method and equipment to be employed. Tabesh and Askari-Nasab [98] presented a hierarchical clustering algorithm to group mineral blocks into larger units based on grade and rock type similarities, applying a shape control method afterward to adjust for feasible mineable shapes. The approach is extended in Tabesh and Askari-Nasab [99] to account for geological uncertainty and create mineable units that are less sensitive to metal variability. In Li et al. [100] the impact of block aggregation in the downstream mineral processing process was considered, testing different clustering techniques. The authors reported a k-means based clustering algorithm as the top performer that maximized the profits from the mining-mineral processing integrated system. Another application by Williams et al. [101] focused on developing a CNN to evaluate the quality of mining dig limit clusters generated by a GA. Although they reported multiple hurdles to overcome before a real-world deployment initial results were encouraging for short-term planning where fast computations are required. One of the main drawbacks of block clustering is the loss in ore-waste discrimination and potential dilution. Lotfian et al. [102] proposed a GA for the clustering process. They reported long-term planning using their clustering framework achieved at least an 82% of the NPV obtained from scheduling original blocks in some test cases.

RL approaches also see an application in Dirkx and Dimitrakopoulos [103]. A multi-armed bandit framework was applied to select the best infill drilling pattern amongst a set of patterns within a budget, accounting for multiple geological elements' uncertainty. They remarked on the applicability of the method for general infill drilling campaigns.

3.3.3. Equipment Management

Mining operations depend on efficient control and allocation of equipment to meet both production and financial targets. In the equipment management research area (RA) we detail research found in the application of AI and data-driven approaches directed towards mining equipment consumption control and equipment allocation and dispatching.

The allocation and sizing of truck fleets to shovels, and shovels to available mining faces are key decisions in the operational planning of mining activities, where data-driven approaches such as Discrete Event Simulations (DES) have been widely used to evaluate different strategies, and metaheuristics like Genetic Algorithms (GA) have been popular to generate equipment allocation and routing plans. In the strategic planning section, we detailed some applications that overlap with this category but that emphasize short-term production planning; here, the remaining research is described.

Mena et al. [104] described a simulation-optimization approach for allocating trucks' mine routes, to maximize the expected productivity of each truck on each route. They proposed a detailed DES simulation based on historic mine data to interact with the optimization engine and remark the need for accounting of equipment productivity and reliability in operational planning. Moradi Afrapoli et al. [105] combined an optimization model for truck dispatching with a rich data-driven DES of an operating mine and processing plant. They applied the framework in a test case to determine an optimal truck fleet configuration, reporting meeting production targets with 13% fewer trucks than the configuration estimated without using a DES to account for uncertainties. Moradi Afrapoli et al. [106] detailed a DES built to benchmark a proposed dispatch optimization model against commercial alternatives applied to a mine test case, which remarks the potential use of DES as a powerful tool for accurate data-driven scenario and mine strategy evaluation.

Agent-based approaches have also been explored for the truck-dispatching problem in which, rather than posing a global optimization problem, trucks are considered individual agents that receive information from the mining system and seek to optimize a goal. The first record of this application retrieved by the query is by Bastos et al. [107], in which an agent-based optimization algorithm is proposed to find the optimal routing of loaded trucks between shovels and dumping stations, using a DES of the upcoming mining shift as the training environment. On the other hand, Icarte et al. [108] proposed a novel approach in which truck dispatching problem as a multi-agent system in which trucks, shovels, and unloading points (e.g., crushers, dumps) are represented by independent intelligent agents, and these collection of agents interact with each other in the shared mine environment. The truck-shovel interaction was modelled using a Contract Net Protocol (CNP). In CNP a shovel sends a call for proposals to the truck agents, which check their current state and the condition of the unloading agents and send a proposal to the shovel. The shovel then selects the best proposal amongst trucks for the assignment. They benchmarked their approach against a heuristic rule and mathematical optimization model using a DES of a real copper mine in Chile and reported achieving production targets with an 18% decrease in operating costs. Furthermore, the researchers extended their work in Icarte et al. [109], to add a mechanism to handle machine failures by rescheduling trucks optimally.

Researchers have also used AI and data-driven approaches to accurately predict mining truck fuel and energy consumption. Siami-Irdemoosa and Dindarloo [110] reported good results when testing a NN to predict fuel consumption per operating cycle of mining trucks based on truck payload, loading times, idled while loaded, and idle while empty times. Soofastaei et al. [111] developed a NN to predict truck fuel consumption (liters/h) based on gross vehicle weight, truck velocity, and total road resistance using data from a coal mine in Australia.

Some applications were found that proposed a practical implementation of AI systems for equipment tracking and visual sensing. Rezazadeh and McCabe [112] described a framework for identifying and tracking mining trucks throughout the production cycle in real-time video recordings. The authors proposed a Histogram of Oriented Gradients (HoG) computer vision technique and presented an application to recognize and count hauling trips. Yao et al. [113] proposed a CNN – NN framework to estimate the piled-up status and payload distribution (PSPD) of bulk materials in a dump truck from camera images. The PSPD describes the alignment and amount of bulk material in a dump truck's body and helps determine dumping positions to improve stress state and equipment service life. The authors presented some successful pilot tests.

Ali and Frimpong [114] proposed a framework to improve autonomous truck steering capabilities named DeepHaul. An object recognition module was proposed to detect mining equipment, humans, and animals using a CNN from images and video recordings in the haul truck's path. Afterwards, a RL framework was used to optimize the truck steering decision capabilities based on the visual sensing detection by putting the truck in multiple scenarios involving different objects in its path throughout a haul road.

4. Discussion and Future Work

The vast majority of research is directed into the open-pit production planning and scheduling problem, where a big focus has been on developing metaheuristics and intelligent computation techniques to solve complex large-scale production scheduling for the life-of-mine strategic plan. The specific problem of long-term and short-term planning has received the most attention with a large variety of solution methods, mostly metaheuristics. The challenge with metaheuristic methods is that their implementation tends to be very problem-specific, and their performance could vary wildly between problem instances. However, Genetic Algorithms (GA) and Simulated Annealing

(SA) have proven to be the most consistent techniques used throughout the period analyzed. Although metaheuristics are a promising approach to tackle these complex problems, the presentation of new metaheuristic techniques should follow some good practices such as those proposed by Osaba et. al. [115] for a clear statement of assumptions, implementation details and results reporting to encourage transparency and reproducibility of methods.

Discrete Event Simulation (DES) has also been widely adapted as an approach to support data-driven decision-making for mine planning and operation. Researchers have used DES to improve mine plans by providing an environment that simulates the interaction between the different processes and equipment during the mine operation and build algorithms that incorporate this dynamic to improve on decision-making to achieve the desired goals. DES also plays a key role for truck fleet management, especially for research applied for the truck dispatching problem, which requires near real-time decisions that have a significant impact on mining production.

To successfully implement a DES model, a large amount of historical data on equipment behaviour is required. Data compilation and cleaning from raw databases is one of the main hurdles for the adoption of AI and machine learning techniques for any industrial case [33]. So it also represents an important challenge here. Future work should also focus on guidelines and good practices for how to best handle mining operation databases to build a DES or digital twin model to support decision-making.

From the more traditional Machine Learning (ML) domain, the Supervised Learning (SL) techniques are the most widely used across applications such as short-term planning, cost forecasting, grade control and equipment tracking. SL techniques rely on the availability of large amounts of labelled data to implement algorithms that learn patterns on it to make accurate predictions. For this purpose, equipment tracking and control applications seem particularly fitting for SL techniques, where problems such as forecasting truck fuel consumption and payload, and estimating hauling cycles appear in the literature. These problems use large equipment databases that have been available for a long time and improve internet network connectivity in surface mining operations.

Grade control applications also reap the rewards of recent advances in SL techniques for image processing, which have enabled researchers to present automated rock type and ore classification algorithms using drones and digital camera images, as well as determining optimal ore dig limits. Future work in the direction towards a real-time ore and waste discrimination system based on digital images could positively impact the mining production environment to tackle issues such as unplanned dilution.

Cost forecasting applications also appear in the literature, however, in all cases, the authors report use cases with very few data points, usually less than 100, which present a major hurdle for its potential application. This specific use case reflects one of the major challenges in developing AI and data-driven approaches, which is the availability of data.

More recent applications involve Reinforcement Learning and agent-based (RL) techniques used for production planning and scheduling, and equipment management. Although the idea of RL has been around for a long time, it has not seen much real-world application and is just starting to show some successful use cases [116]. More work in this area is needed to showcase its potential on different applications within surface mining systems, as it has seen large volumes of research for production planning and control in dynamic systems [117], vehicle routing [118], problems very similar in structure short-term production planning, and truck dispatching.

5. Conclusions

This research systematically reviewed applications of AI and data-driven approaches for open-pit strategic planning. The research goals were to uncover trends in AIA adoption in the period

2000-2021, understand which applications in this field are being solved using these approaches, and which specific AIA techniques have been more successful as measured by the number of appearances in peer-reviewed research publications. A comprehensive search query was designed, and 86 publications were reviewed in detail.

The goal achieved by this paper was to establish the current state of use of AI and data-driven technologies for the strategic planning of surface mines, identifying the algorithms and workflows that have been implemented for specific application cases in this domain. Overall, the adoption of AIA within open-pit strategic planning has seen exponential growth within the period considered, with successful applications across different areas of interest. The large adoption of metaheuristic and intelligent algorithmic techniques indicates the attractiveness of fast and reliable computation methods for large and complex problems. The increased attention in discrete simulation points to an interest in using large historical mining databases to recreate operations for decision-making support as a sort of digital twin. The surge in supervised learning and reinforcement learning techniques shows the potential of ML adoption operational management tasks. Finally, researchers have shown willingness to adapt state-of-the-art AI and data-driven techniques to solve open-pit strategic planning problems, showing these technologies' potential to unlock value within the mining industry.

6. References

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Near-Face Stockpile Open Pit Mining: a Method to Enhance NPV and Quality of the Plant Throughput[1]

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ABSTRACT

Nowadays, stockpiles are of great importance in open pit mine production scheduling and are widely used for different reasons while being placed in different locations. Near face stockpile (NFS) mining method is a new mining concept which could decouple the whole mining flow into two weakly related subsystems, which are the mining subsystem and processing subsystem. There are many theoretical advantages in comparison to the traditional open-pit mining method, such as higher tolerance on uncertainties without compromising production, higher equipment utilization, less operating cost, better blending results, etc. The introduction of NFS, however, requires reconsideration of production planning in open pit mines. In this paper, we developed a mixed integer linear programming model to solve long-term production scheduling problem in open pit mines. To quantitatively measure the performance of the NFS mining method, we implemented the model in a real mining case study and compared the results with the traditional open pit mining method with an out-of-pit crusher. The results reveal that we can improve the net present value by 9.3% and the plant head grade by above 58% by implementing the NFS method.

1. Introduction

More than 90% of the minerals are extracted using surface mining methods including open pits (Osanloo & Paricheh, 2020). Open pits are usually multi-million/billion-dollar long-term projects with two main subsystems: mining (mostly discrete processes) and processing (mostly continuous processes). As the transportation of material throughout these two weakly coupled systems vary in nature, their integration is a challenging problem that pushes the whole project away from optimality. Stockpiling (Koushavand et al., 2014) and in-pit crushing and conveying (IPCC) (Paricheh & Osanloo, 2020) have been introduced to improve the interaction of these two subsystems. When IPCC system is implemented in an open pit mine, the ore stockpiling option is removed as materials are being fed to the in-pit crusher directly from shovels. In this paper, we introduce a new concept by integrating IPCC and stockpiles called the *near-face stockpile (NFS) open pit mining method* that facilitates the integration of the two abovementioned subsystems while keeping the advantages of both IPCC and stockpiles, implementing this new mining method results in an improvement in the quality of material delivered to the processing plant and an increase in the net present value (NPV) of the whole project.

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The concept of stockpiling in the open pit mines can be used for any type of material piled for usage later on in the mine life (Darling, 2011). Although not recommended due to the economic and environmental challenges, waste materials are delivered to waste stockpiles (Adrien Rimélé et al., 2018) for the mines that have in-pit tailings disposal areas to be built later in the mine life. Oil sands mines in Canada are explicit examples of such an operation. However, the main role of stockpiles in open pit mines is as a buffer in the blend control process (Rezakhah & Newman, 2020). The location of the ore stockpiles, for the purpose of minimizing the rehandling costs, is usually outside of the pit rim and as close to the main crusher as possible.

With the introduction of IPCC systems, the crusher which is the connecting point between mining and processing operation is moved inside the pit and closer to the operating mining faces. Finding the optimal location of the crusher inside the pit is a challenging task and is either treated as a stand-alone optimization problem (Paricheh et al., 2017) or a subproblem which is a part of the long-term production scheduling task (Paricheh & Osanloo, 2020). The location optimization varies based on the type of the IPCC system. The IPCCs are categorized into three main classes: fixed, semi-mobile, and fully mobile systems (Utley, 2011). In the NFS method, the mobile crusher with the medium to long-term relocation strategy is the desired class as the in-pit crusher and the stockpile could be relocated when needed. This means that the equipment could be placed and reassembled in different benches with the development of the pit while the mine expands year by year. Figure 1 shows the basic layout of the NFS mining method.

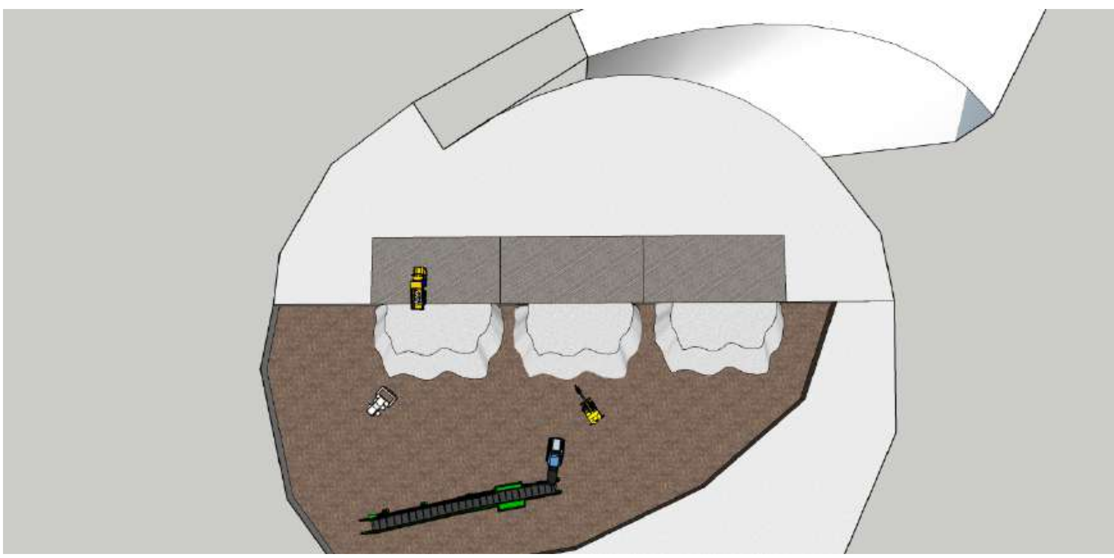

Figure 1. The layout of the near-face stockpile open pit mining method.

In an NFS mine, the material handling cycle for the waste material is the same as in conventional open pit mining. However, the ore transportation cycle is modified in a way that instead of truck dumping ore directly into the crusher, as in either conventional truck and shovel open pit or IPCC open pit, it dumps its ore loads on the designated grade bin in the in-pit stockpile. Then the reclaiming shovel loads the ore from different grade bins into a mobile crusher. The crushed materials are then transported to the secondary crusher outside of the pit rim by the conveyor belt. Therefore, the essential difference between the NFS mining method and traditional open-pit mining methods is that the discrete and continuous subsystems are connected through the shovel-crusher interaction instead of the truck-crusher interaction. As the discrete shovel cycle time is far less than the discrete truck cycle time, the coupling of the two systems will be stronger in comparison.

According to Jupp et al. (2013), a near crusher stockpile plays four roles at the same time, which are storing, buffering, blending and grade separation. Obviously, the NFS mining method inherits all advantages from the near crusher stockpile. The benefit of two weakly coupled subsystems is that the whole system is more likely to have higher production and generate more profits since the stockpile could act as a buffer and avoid unnecessary production loss due to equipment failure or maintenance. Meanwhile, the existence of a near-face stockpile will lead to a more stable grade feed to the crusher since, in traditional mining methods, the materials are truck-by-truck blended while the NFS method allows batch blending. Nevertheless, another apparent benefit of the near face stockpile is that it could shorten the hauling time significantly and reduce the costs from three aspects. Firstly, it requires a smaller number of trucks in the fleet. Currently, most of the mines in the world hire more trucks to avoid the idle of the mining shovels, while with NFS, the truck cycle time will be reduced dramatically. Therefore, some investment on equipment, especially on trucks, could be saved. Secondly, as mentioned in (Alarie & Gamache, 2002; Moradi Afrapoli & Askari-Nasab, 2019) truck and shovel operating cost make up to 50 percent or even more in overall operation cost in open-pit mines, which means even a small increase of utilizations of those equipment will yield significant benefits for mining enterprises. Thirdly, shortening the haulage distance could lower the possibility of traffic jams, and make the autonomous haulage system more practical.

Given that NFS mining method has so many theoretical advantages against normal open-pit mining method, how to quantitatively measure and verify the performance of the NFS method is a scientific question worth studying. Thus, in this paper, we develop a long-term production planning model for the NFS mining method to investigate its performance on the plant throughput quality and the net present value of the whole project.

2. Literature Review

Undoubtedly, with no solid mining plan, no matter how good the mining method is, it may lead to poor decisions with possible serious losses (Badiozamani et al., 2019; Ben-Awuah & Askari-Nasab, 2013). Therefore, to better understand the performance of the NFS mining method, an efficient strategic plan is needed. Usually, an optimized strategic plan consists of two main parts. The first part is the pit limit optimization, which defines the final shape of the open pit and it is the basis for the following part and affects the value of a mine to the most. Although different mathematical methods and models are published in past years, Lerchs-Grossman (LG) algorithm is still the dominant method that has been adopted by most researchers (Askari-Nasab et al., 2007; Dimitrakopoulos et al., 2007; Lerchs & Grossmann, 1965). In the second part of the strategic plan, a production schedule optimization model makes decisions on the sequence of blocks to be mined annually and addresses two main problems – when the blocks should be mined and where the materials from those blocks should be sent to. One of the most important objectives of this part is to maximize the NPV while meeting mining requirements like grade blending, plant capacity and other constraints (Askari-Nasab et al., 2008, 2011; Askari-Nasab & Awuah-Offei, 2009; Ben-Awuah et al., 2015; Lamghari, 2017). Due to the inherent complexity of the entire mining planning, time horizons are divided into three different phases: short-term, medium-term, and long-term (Tabesh et al., 2014). Then, the mine planning process aim at optimizing each time horizon separately to obtain a near-optimal results in a reasonable computer run-time (Badiozamani & Askari-Nasab, 2013; Dagdelen, 2001; Hustrulid et al., 2013). Since we want to investigate the NFS method performance on NPV and the grade blend and these two are directly involved in the strategic long-term production planning, herein we briefly survey the associated literature.

The long-term production plans of open pit mines are generated by implementing operations research techniques. Among those techniques, linear programming, and its mutant mixed integer linear programming (MILP) and mixed integer linear goal programming (MILGP) are the most popular and widely applied algorithm (Maremi et al., 2021; Upadhyay & Askari-Nasab, 2016).

The long-term planning algorithms take block models of the deposit as an input and as the number of blocks in the deposit increases the computing time for generating the plan increases. One way to reduce this processing time is to decrease the number of blocks in the block model. Tabesh and Askari-Nasab (Tabesh & Askari-Nasab, 2013) developed a two-stage clustering approach for block aggregation which has a significant impact on CPU time and the long-term production plan (LTPP) optimization and leads to a 10% higher NPV. The ore grade, block distance, and rock types are included in their clustering model but only one element was considered and many of explicit parameters have to be defined to get reasonable results. Shishvan and Sattarvand (Shishvan & Sattarvand, 2015) applied one metaheuristic algorithm - ant colony optimization (ACO) model to solve LTPP problem and tested the model in a real size copper -gold deposit. However, there is no guarantee that a global optimum schedule is generated, and the model is very sensitive to ACO parameters. Ramazan and Dimitrakopoulos (Ramazan & Dimitrakopoulos, 2018) proposed a stochastic integer programming (SIP) model for LTPP optimization while capturing the uncertainty of orebody. However, only hypothetical data are tested, and the results showed no significant difference with traditional model results. Although stockpiles are indispensable parts of mining operations these days as they can be helpful in achieving mine operation's economic goals such as minimizing the deviation of the tonnage and grade feed to the crusher compared against the target production, the abovementioned models do not incorporate stockpile into the modelling process.

In another stream of the literature of LTPP for open pit mines, Gholamnejad and Kasmaee(Gholamnejad & Kasmaee, 2012) proposed a linear goal programming model for open pit mining where they incorporated the role of stockpiles in the formulation. In their proposed model, the focus is dedicated to the reclamation of the material from the stockpile and ore delivery to it is totally ignored. Later on, a mixed integer linear programming (MILP) model for LTPP problems that considers grade uncertainty and a stockpile was proposed by Koushavand et al. (Koushavand et al., 2014). The objective function of their model is to maximize profit while including the cost of uncertainty. Mousavi et al. (Mousavi et al., 2016) and Kumar and Chatterjee (Kumar & Chatterjee, 2017) proposed similar formulations for LTPP in open pit mines. These two models have predetermined stockpile grades that force their models to perform far from reality. Instead of using classical linear programming, a goal programming model that aiming at reducing stockpile fluctuation was purposed in Souza et al. (Souza et al., 2018). In their model, Souza et al. minimized operating costs and deviation from head grade. The model has limitations in test dataset. For those models listed above, although stockpile is incorporated, an automatic perfect blending assumption is adopted. The main drawback of perfect blending is that the stockpile in traditional open-pit mining will not be fully reclaimed, so there will be a difference between real reclaimed material grade and hypothesized reclaimed grade, which would definitely introduce errors into the result and make it not credible.

There are also non-linear models proposed for LTPP optimization which incorporate stockpiles. Bley et al. (Bley et al., 2012) added a non-convex quadratic constraint for stockpile in each period and used s primal heuristic method to find feasible solutions for a specific problem. Ramazan and Dimitrakopoulos (Ramazan & Dimitrakopoulos, 2013) proposed a non-linear SIP model and applied it in a gold mine in Australia. That model is based on conditionally simulated deposit which captures more uncertainty compared to normal predetermined deposit. Tabesh et al. (Tabesh et al., 2015) suggested to model stockpiles nonlinearly. Then they linearized the nonlinear model by defining fixed tight grade intervals for different stockpiling bins. Paithankar and Chatterjee (Paithankar & Chatterjee, 2019) proposed a mathematical model based on genetic algorithm to simultaneously optimize production sequence and dynamic cut-off grades. The final goal is set to generate the highest NPV. The model assumes that stockpile has infinite capacity and no fluctuation on yearly mining capacity, which is not realistic in real operation. However, although most of the proposed non-linear models claimed a higher NPV under a specific case study, these types of models require more variables than linear models, especially for stockpiles which causes inefficiency issues. Besides, overall optimal results or near optimal results are not guaranteed and the time consumption is much higher than linear models.

3. Material and Methods

As the first step of our study, we implemented clustering algorithm developed by (Tabesh & Askari-Nasab, 2019) to aggregate mining blocks into mining-cuts and panels in an iron ore open pit mine. Then we used the LTPP model developed by Tabesh and Askari-Nasab (Tabesh et al., 2015) as our benchmark LTPP model and generated long-term production plan for the case study considering traditional open pit mining method with stockpile located outside of the pit rim. Then, we improved their model to develop our new LTPP model that can generate long-term production plan for the mine considering the NFS open pit mining method. In this section we are presenting the formulation of our LTPP model for the NFS open pit mining method. Various optimization mathematical models for long-term mining schedule that contain stockpiles were developed in the past decades and the typical ones are reviewed in literature review section of this paper. In order to have a feasible near-optimal solution within reasonable time periods, we selected a mixed integer linear programming approach for our LTPP model. Following, we first define indices, sets, parameters, and variables we used in the model. Then, we present the objective function and the constraints.

Indices

k	index for mining cuts ($k \in \{1, 2, \ldots K\}$)
p	index for panels ($p \in \{1, 2, \ldots P\}$)
t	index for scheduled periods ($t \in \{1, 2, \ldots T\}$)
d	index for destinations (stockpile or waste dump)
s	index for stockpiles zones ($s \in \{1, 2, \ldots S\}$)

Sets

C_p	set of the panels that must be extracted prior to mine panel p
K_p	set of the mining-cuts within panel p

Parameters

r_s^t	discounted revenue generated by sending 1 unit of material from stockpile zone s in period t to crusher minus the dozing, reclaiming cost and processing cost
q_p^t	discounted cost of mining all the material in panel p as waste in period t
o_k	ore tonnage in mining-cut k
o_p	ore tonnage in panel p
w_p	waste tonnage in panel p
o_r	ore tonnage in reserve

w_r	waste tonnage in reserve
c_{sp}	total capacity of stockpile
c_s	capacity of stockpile zone s
g_k^e	average grade of element e in ore portion of mining-cut k in percent
g_s^e	average grade of element e reclaimed from stockpile zone s in percent
gsu_e^t	upper bound of stockpiled head grade of element e in period t in percent
gsl_e^t	lower bound of stockpiled head grade of element e in period t in percent
gcu_e^t	upper bound of crusher acceptable grade of element e in period t in percent
gcl_e^t	lower bound of crusher acceptable grade of element e in period t in percent
pu^t	upper bound on ore processing capacity in period t in tonnes
pl^t	lower bound on ore processing capacity in period t in tonnes
mu^t	upper bound on mining capacity in period t in tonnes
ml^t	lower bound on mining capacity in period t in tonnes

Decision variables

$x_k^t \in [0,1]$	continuous variable, representing the portion of mining-cut k to be extracted as ore and send to stockpile in period t
$y_p^t \in [0,1]$	continuous variable, representing the portion of panel p to be mined in period t, fraction of y characterizes both ore and waste included in the panel
$b_p^t \in \{0,1\}$	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
$f_s^t \geq 0$	continuous variable, representing the tonnage of material sent from stockpile zone s to crusher in period t

Objective function and constraints

$$\max \sum_{t=1}^{T} \left\{ \underbrace{\sum_{s=1}^{S} (r_s^t \times f_s^t)}_{Discounted\ revenue} - \underbrace{\sum_{p=1}^{P} (q_p^t \times y_p^t)}_{Discounted\ cost} \right\} \tag{1}$$

$$ml^t \leq \sum_{p=1}^{P} (o_p + w_p) \times y_p^t \leq mu^t \qquad \forall t \in \{1,...,T\} \tag{2}$$

$$\sum_{t=1}^{T} \sum_{p=1}^{P} o_p \times y_p^t \leq o_r \qquad \forall p \in \{1,...,P\}, \quad t \in \{1,...,T\} \tag{3}$$

$$\sum_{t=1}^{T} \sum_{p=1}^{P} w_p \times y_p^t \leq w_r \qquad \forall p \in \{1,...,P\}, \quad t \in \{1,...,T\} \tag{4}$$

$$pl^t \leq \sum_{s=1}^{S} f_s^t \leq pu^t \qquad \forall t \in \{1,...,T\} \tag{5}$$

$$\sum_{k=1}^{K} o_k \times x_k^t - c_{sp} \leq \sum_{s=1}^{S} f_s^t \leq \sum_{k=1}^{K} o_k \times x_k^t + c_{sp} \qquad \forall t \in \{1,...,T\} \tag{6}$$

$$\sum_{s=1}^{S} \left(g_s^e - gcl_e^t \right) \times f_s^t \geq 0 \qquad \forall t \in \{1,...,T\}, \quad e \in \{1,...,E\} \tag{7}$$

$$\sum_{s=1}^{S} \left(g_s^e - gcu_e^t \right) \times f_s^t \leq 0 \qquad \forall t \in \{1,...,T\}, \quad e \in \{1,...,E\} \tag{8}$$

$$gsl_e^t \leq (\sum_{k=1}^{K} g_k^e \times o_k \times x_k^t) / (\sum_{k=1}^{K} o_k \times x_k^t) \leq gsu_e^t \qquad \forall t \in \{1,...,T\}, \quad e \in \{1,...,E\} \tag{9}$$

$$\sum_{t=1}^{T} y_p^t = 1 \qquad \forall p \in \{1,...,P\} \tag{10}$$

$$b_p^t - \sum_{i=1}^{t} y_b^i \leq 0 \qquad \forall p \in \{1,...,P\}, \quad t \in \{1,...,T\}, \quad b \in C_p \tag{11}$$

$$\sum_{i=1}^{t} y_p^i - b_p^t \leq 0 \qquad \forall p \in \{1,...,P\}, \quad t \in \{1,...,T\} \tag{12}$$

Equation (1) is the objective function that aims at generating the highest discounted net present value of the project. Equation (2) ensures that the tonnage of total material mined in each period does not exit the mining capacity. Equation and Equation enforce the mining of ore and waste to not exit the available reserve. Equation (3) ensures that the total tonnage of material reclaimed from different stockpile zones matches the required processing capacity. Equation (4) limits reclaiming the material from different stockpile zones in each period. The reclaimed tonnage should not be less than ore material mined in that period minus stockpile capacity and more than ore material mined in that period plus stockpile capacity. We defined equations (5) and (6) for stockpile grade control. Constraint (7) ensures that the average grade of material being reclaimed from the stockpile in each period does not fall below the lowest acceptable head grade for the processing. Moreover, the constraint (8) ensures that the average grade reclaimed from stockpile does not exceed the upper bound of required processing head grade. Equation (9) limits the average ore grade mined from mining-cuts. Equation (10) puts a limit on all panels to be fully extracted within the mine life. Equation (11) ensures that all predecessor panels of the current active panel are fully extracted before mining the current panel. Constraint (12) limits mining of each panel to its maximum available reserve.

4. Results

To verify the performance of the NFS open pit mining method, we implemented it in an iron mine case study with 19,561 blocks in the deposit's block model and a total of 430 million tons of material in its final pit after performing pit optimization process. The dimension of each block in the block model is 25m (length)×25m (width)×15m (height) and the main element of interest is iron which is tracked by magnetic weight recovery (MWT) and the accompanying impurity contents (sulfur and phosphor) are tracked by percent mass units (%). The target processing head grade for MWT is 78% and maximum acceptable content for sulfur and phosphor are 1.7% and 0.14%, respectively.

The pit optimization resulted in four pushbacks and 40 panels in its optimal case. Meanwhile, the mining capacity is 32 million ton in early years which decreases to 9 million ton in the last year while processing capacity is 7.5 million ton from year five to the end of the mine life. We then implemented an adopted version of hierarchical clustering method proposed by (Tabesh & Askari-Nasab, 2013) to create mining polygons, resulting in 1883 mining-cuts. The clustering algorithm takes approximately 75 seconds to finish the block aggregation process in an Intel Core i7-7700HQ CPU at 2.80GHz, and 16 GB of RAM computer.

After the block aggregation stage, we generated LTPP for the conventional open pit mining and LTPP for the NFS open pit mining for the case study. We formulated both LTPP models in MATLAB (The MathWorks Inc., 2018) and solved them using the CPLEX (CPLEX, 2014). The following we first present results of implementing the NFS open pit mining method and then present a comparison against conventional open pit mining. It worth noting that the near face stockpile is considered during mine life consists of three zones representing low-grade, medium-grade and high-grade ore.

By the implementation of the NFS method in the case study, the project will generate a net present value of $2355 million dollars in the 20 years of mine life following the life of mine production schedule/plan presented in Figure 2. Meanwhile, the amount of materials processed each year is fairly stable with the average deviation of 2.7% from the capacity of the plant (Table 1).

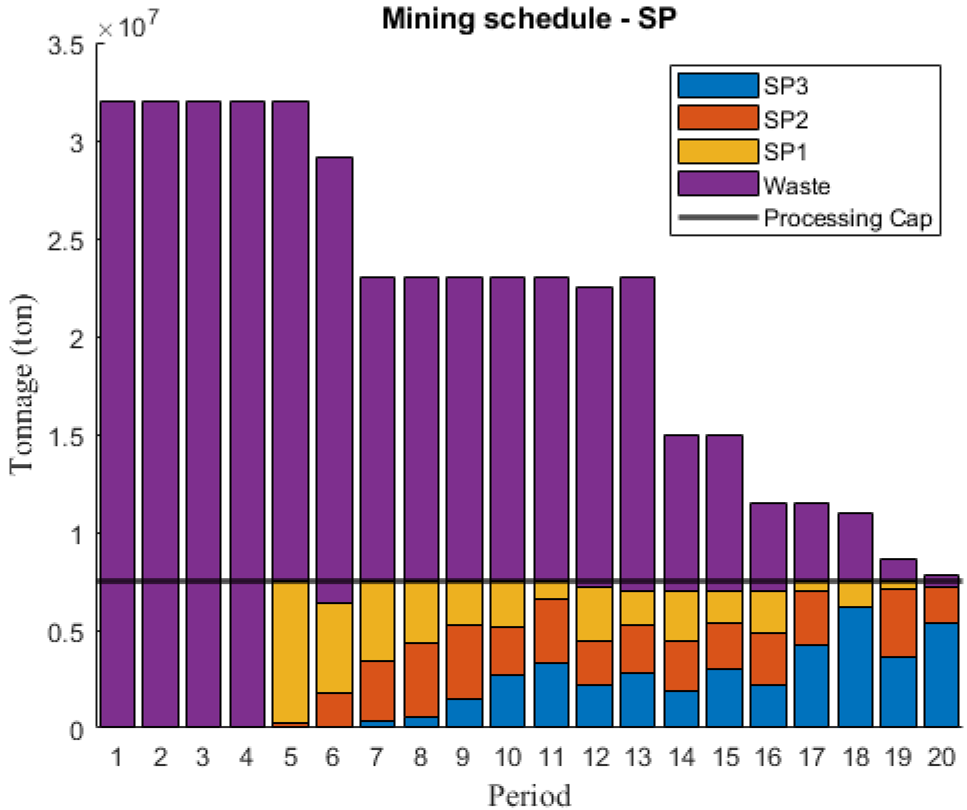

Figure 2. Long-term production schedule of the case study extracted using the NFS open pit mining method.

Table 1. Yearly tonnage of ore delivered to the processing plant using the NFS open pit mining method.

Year	5	6	7	8	9	10	11	12
Processed (Mt)	7.5	6.4	7.5	7.5	7.5	7.5	7.5	7.2
Difference (%)	0.0	-14.5	0.0	0.0	0.0	0.0	0.0	-3.9
Year	13	14	15	16	17	18	19	20
Processed (Mt)	7.0	7.0	7.0	7.0	7.5	7.5	7.5	7.2
Difference (%)	-6.7	-6.7	-6.7	-6.7	0.0	0.0	0.0	-4.3

Due to the particularity of the NFS mining method, all target minerals excavated from mining faces will be sent to the stockpile prior to be reclaimed by a shovel and delivered to the plant through the mobile IPCC system. The associated cost of reclaiming one ton of blended ore from the NFS in the case study is $0.5/ton. As mentioned before, the NFS has three zones in its stockpile. In order to equally utilize these zones as much as possible, we calculated the material tonnage and grade in each block, and selected two interim MWT grade values of 76.65% as the transition point from low-grade to medium-grade and 80.23% as the transition point from medium-grade to high-grade. The grade of iron in the deposit varies between the minimum MWT grade of 41.22% and the maximum MWT grade of 84.52% (Table 2). Figure 3 shows the yearly average MWT grade of each zone in stockpile and the MWT grade of the final blend reclaimed and processed each year, and Figure 4 and Figure 5 show the yearly average grade of phosphor and sulfur in each stockpile zone and the overall phosphor and sulfur grade of the blended material processed in each year of the mine life.

Table 2. Stockpile zoning parameters for the NFS method.

	Lower MWT (%)	Upper MWT (%)	Avg MWT (%)	Avg P (%)	Avg S (%)	Tonnage (Mt)
Zone1	41.22	76.65	70.02	0.14	1.31	37.56
Zone2	76.65	80.23	78.68	0.13	1.69	38.72
Zone3	80.23	84.52	81.26	0.14	1.60	40.01

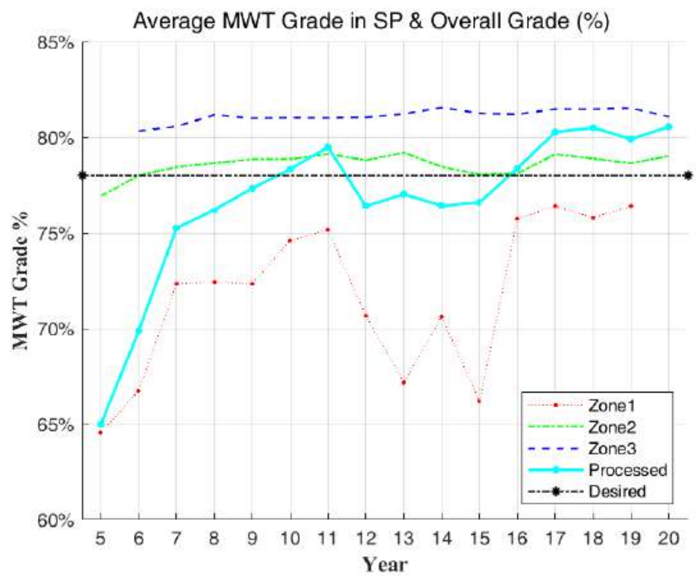

Figure 3. MWT grade delivered to each zone of the stockpile and the MWT grade of final blend reclaimed from the stockpile by year of the mine life.

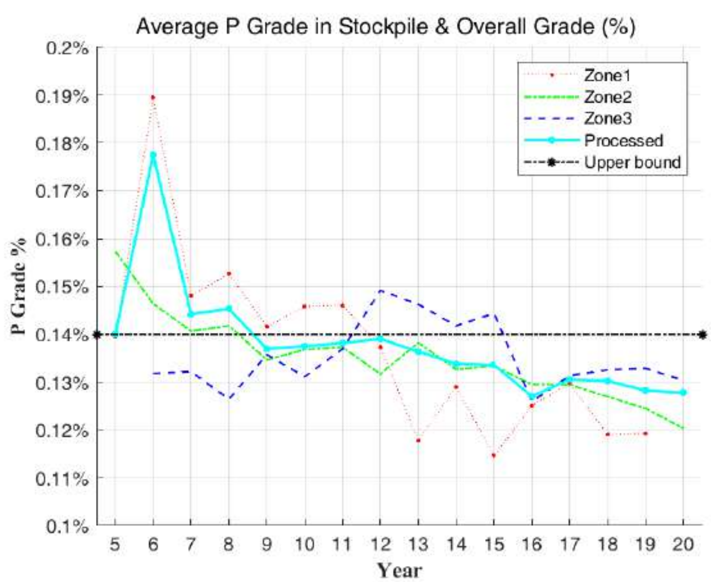

Figure 4. Phosphor grade delivered to each zone of the stockpile and the phosphor grade of final blend reclaimed from the stockpile by year of the mine life.

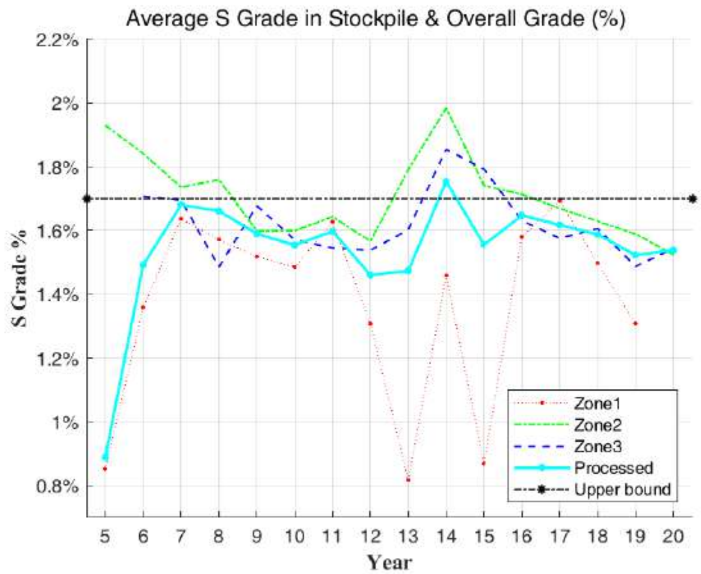

Figure 5. Sulfur grade delivered to each zone of the stockpile and the sulfur grade of final blend reclaimed from the stockpile by year of the mine life.

In Table 3, we present the average yearly deviation of blended grade processed from the target head grade.

Table 3. Deviation of the blended material grade from the desired head grade.

Year	5	6	7	8	9	10	11	12
S grade	0.89	1.49	1.68	1.66	1.59	1.55	1.60	1.46
Difference (%)	-	-	-	-	-	-	-	-
P grade	0.14	0.18	0.14	0.15	0.14	0.14	0.14	0.14
Difference (%)	0.05	26.8	2.99	3.8	-	-	-	-
MWT grade	65.0	69.9	75.3	76.2	77.3	78.3	79.5	76.4
Difference (%)	-17	-10	-4	-2	-1	0	2	-2
Year	13	14	15	16	17	18	19	20
S grade	1.47	1.75	1.56	1.65	1.62	1.59	1.52	1.54
Difference (%)	-	3.2	-	-	-	-	-	-
P grade	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Difference (%)	-	-	-	-	-	-	-	-
MWT grade	77.0	76.4	76.6	78.4	80.3	80.5	79.9	80.6
Difference (%)	-1	-2	-2	0	3	3	2	3

Table 2 and Table 3 show that inside the near face stockpile, zone 1 has widest grade range for both MWT and phosphor and is the dominant zone to be reclaimed and processed in the first two years after processing starts, leading to a higher grade deviation in early years. However, with the development of pit limit, more material are sent to the zone 3 of the NFS improving the reclamation grade in the later years of the mine life.

To evaluate the performance of the NFS open pit mining method, we compared results of our proposed LTPP with the results of the benchmark LTPP that was developed for mining the same case study using conventional mining method in two important KPIs (the NPV and the head grade deviation). In the benchmark model, the case study generates $2155 million dollar of NPV with an average grade deviation of 3% for MWT. This means that by switching from conventional open pit mining to the NFS open pit mining method the NPV generated by the case study will increase for 9.3% and the average head grade deviation will reduce for 58.3%. This is mainly due to the higher turnover rate of near face stockpile since material in different zones are fully reclaimed in a predetermined time range while in traditional mining method, stockpile is only reclaimed when material mined in that period is not enough and rarely does stockpile realize a fully turnover in life of mine. To be more specific, high stockpile turnover rate has a strong positive effect on the blending results since with higher turnover rate, the tolerance for ore grade fluctuations will increase, and some relatively extreme high-grade and low-grade ore material will become acceptable. This is particularly beneficial to those mining companies whose material of interest comes with associated impurities – just as the iron mine used in the case study. Moreover, with more materials becoming acceptable for processing, a higher production is expected which will eventually bring higher revenues and profits to the company.

5. Conclusions

To scientifically understand the performance of the near face stockpile open pit mining method under life of mine schedule, especially the blending process, this article proposed a mixed integer linear programming model to generate a near-optimal long-term production schedule. The proposed mathematical model was implemented in a real mining case study and the results were presented in this paper. Then, the impact of the near face stockpiling open pit mining method on the NPV and the head grade has been compared with the conventional open pit mining method. The results of this comparison show that the near face stockpile open pit mining method outperforms the conventional open pit mining method in the NPV with 9.3% improvement and the head grade deviation with 58.3% improvement in the quality of blended material delivered to the plant.

However, there are many theoretical advantages of the near face stockpile open pit mining method and only two aspects were verified in this paper. Some unnecessary losses due to uncertainties like equipment failure and saved cost for shorter haul which may lead to higher NPV are not included in our investigations. The authors will investigate the operational performance of the near face stockpile open pit mining method by simulating the daily operation of the case study in the next step of the research.

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Genetic Algorithm Framework for Stochastic Open Pit Production Scheduling in the Presence of Grade Uncertainty

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ABSTRACT

In the optimization of open pit production scheduling, the major challenge found in literature is finding the balance between optimality and computational time. Mathematical programming models such as Mixed Integer Linear Programming (MILP) are capable of attaining optimal solutions. However, this comes at the expense of computational time for tractable optimization problems. Evolutionary algorithms such as Genetic Algorithm (GA) are able to generate good solutions at shorter computational time. In this research, we present an evolutionary algorithm framework based on GA to solve the stochastic open pit production scheduling problem in the presence of grade uncertainty. For implementation, a set of equally probable simulated orebodies generated through Sequential Gaussian Simulation are used as input to the stochastic optimization model. Two case studies are presented which compares results from a stochastic GA with a stochastic MILP model. For Case study 2, while the SMILP model was at a gap of 101% after 28 days, the SGA model generated NPV of $10,045M at 10.6% gap after 1.5 hours

1. Introduction

Genetic algorithm is a metaheuristic evolutionary algorithm that has widely been studied and applied in combinatorial optimization problems in the areas of Finance, Supply Chain Management, and Information Technology. Some researchers have investigated its application to mining-related optimization spanning across different aspects of mine planning optimization. Denby and Schofield [26]; Myburgh and Deb [77]; Alipour et al. [4]; Paithankar and Chatterjee [81]; Alipour et al. [5] used genetic algorithm for open pit production scheduling optimization. Ahmadi and Shahabi [2] also used genetic algorithm for cut-off grade optimization while Ruiseco et al. [83] used genetic algorithm in ore-waste pit limit optimization. Similarly, Franco-Sepúlveda et al. [37] used genetic algorithm for the optimization of open-pit mining operations with geological and market uncertainty.

Mine planning optimization is a complex yet necessary combinatorial optimization problem. Combinatorial optimization problems are problems whose optimal solution must be obtained from a finite number of possibilities [7]. Mine planning optimization specifies the source, destination, time, and extraction sequence of mineral resources that maximizes the net present value (NPV) of a mining operation. A resultant activity of mine planning is the production scheduling of the mineral resource from the mine. Production scheduling can be carried out on either an open pit or an underground mine with various physical and technical constraints. Production scheduling can also be classified into short term, medium term or long term. Caccetta and Hill [18] described the time and sequence of extracting blocks from an open pit mine in order to maximize the NPV of the

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mining project as open pit production scheduling (OPPS) optimization. Alipour et al. [4] referred to the OPPS problem as a combinatorial optimization problem in the class of Non-deterministic polynomial-time (NP) hardness. An optimization problem is said to be NP-hard if the algorithm for solving it can be converted to one for solving any NP problem. NP-hard therefore means "at least as hard as any NP-problem," although it might, in fact, be harder [97]. As the OPPS optimization problem gets larger and the number of integer variables increase, finding an optimal solution to the problem in some instances becomes intractable or uses too much computing resources when an exact solution methodology is implemented. An optimization problem is tractable if a solution is obtained in polynomial time. This solution may or may not be optimal. Setting an optimality gap for the optimization problem can ensure tractability for exact algorithms. An optimality gap, therefore, refers to the difference between the best known solution (best integer) and the value that bounds the best possible solution [55]. An optimal solution in the case of exact algorithms is a solution with a 0% optimality gap. This demonstrates that the solution is the best that exists because the difference between the best integer and the best bound is 0%.

This research focuses on using a metaheuristic optimization approach in the field of evolutionary algorithms to tackle the NP-hard large scale OPPS problem. Bianchi et al. [16] define metaheuristics as algorithms that incorporate or develop heuristics (heuristics are simple approximate algorithms that look for good solutions in a solution space) to solve an optimization problem in a generic framework. Metaheuristics are thus higher level than heuristics, as the term "meta" in metaheuristics implies. The concept of metaheuristics is mostly inspired by natural biology.

The conventional approach to orebody modelling based on Ordinary Kriging [62] generates a single interpolated block model for pit limit and production scheduling optimization. In using this single interpolated block model for production scheduling, geological uncertainties which are inevitable in a typical mining project are not taken into consideration. This may result in schedules that either 1) overestimate or 2) underestimate the true representation of the optimal solution. Researchers such as Dimitrakopoulos and Ramazan [30]; Sabour and Dimitrakopoulos [84] and more recently Mbadozie [70] have investigated the incorporation of grade uncertainty in the OPPS problem formulation using simulation and mathematical programming. Multiple realizations of the block model are generated with Sequential Gaussian Simulation (SGS) and used as input to the mathematical programming model. The primary limitation of their implementation relate to generating tractable solutions for large scale optimization problems in a reasonable run time. The optimization solution run time is directly related to the problem size which is also a function of the size of the deposit, the number of simulation realizations, and the life-of-mine.

In this research, a metaheuristic optimization framework based on genetic algorithm has been designed and implemented for a large scale OPPS problem. A real number chromosome encoding technique is used in the genetic algorithm initial population to make possible partial block processing. Two variations of the GA framework referred to as Deterministic Genetic Algorithm (DGA) and Stochastic Genetic Algorithm (SGA) were implemented. DGA basically refers to the application of the GA framework in a conventional approach to production scheduling using an OK block model, while SGA refers to the application of the GA framework in a stochastic approach to production scheduling using SGS block model realizations. The conventional approach to the OPPS problem which does not consider grade uncertainty is investigated with a Mixed Integer Linear Programming (MILP) model with CPLEX and the DGA framework. The stochastic formulation of the OPPS problem that incorporates grade uncertainty is also considered and the resulting problem is optimized with a Stochastic Mixed Integer Linear Programming (SMILP) model with CPLEX and the SGA framework. The NPV and solution time for the conventional and stochastic frameworks are compared.

2. Summary of Literature Review

Open pit production scheduling (OPPS) problems can be defined as specifying the time and sequence in which blocks should be extracted from the mine in order to maximize the NPV subject to a variety of physical, environmental, operational and economic constraints [18]. Production scheduling of an open pit mine is a major concern in mine planning and a complex optimization problem. Usually, the planning of an open pit mine starts with finding the ultimate digging or pit limit. This pit limit provides the list of blocks to be considered for production scheduling. The main algorithm used in the literature to find the ultimate pit limit is the Lerch Grossman (LG) algorithm [66]. Once the final pit is determined, the production scheduling process can commence. Researchers in their bid to solve the OPPS problem have formulated mathematical models with different optimization techniques [9; 18; 61]. These models take the form of an objective function for maximizing the NPV subject to the set constraints. There are two major research areas in the development of production scheduling algorithms: (1) Deterministic algorithms and (2) Heuristics and Metaheuristic optimization algorithms.

Johnson [57] introduced Linear Programming (LP) for OPPS problems. The author did not obtain an optimal schedule for the problem due to the computational intractability. LP however proved to be a capable option for modelling the OPPS problem. Gershon [43]; Dagdelen [21] presented a MILP model which was an improvement of the LP model by Johnson. Formulating the model with MILP allowed for some of the decision variables to be presented as continuous variables to prevent infeasibility and allow for partial block processing. The model however could not obtain an optimum schedule for a real-size large scale OPPS problem. Caccetta and Hill [18] proposed a MILP model solved with branch and cut algorithm for the OPPS problem. The authors used a cutting plane algorithm and a search strategy involving best first and depth first search to achieve a ‘‘good spread’’ of possible pit schedules. Their approach was capable of solving the OPPS problem on a small and medium scale optimization problem with 6,720 to 209,664 blocks. However, the optimization was computationally expensive. Due to commercialization and confidentiality agreements, the authors did not provide detailed information about their work. Dimitrakopoulos and Ramazan [29] also proposed a MILP model for solving the OPPS problem. In their approach, they presented waste blocks as continuous variables in order to reduce the number of integer variables and improve the solution time.

Integer programming has also been studied and applied to the OPPS problem. Dagdelen and Johnson [22] formulated the OPPS problem with integer programming and solved it using the Lagrangian relaxation method. Lagrangian relaxation is a method used to reduce the complexity of the optimization problem by relaxing one or more constraints. A penalty term and a multiplier known as a Lagrangian multiplier used in the relaxed constraint is then added to the objective function. This is done to avoid violations of the relaxed constraint [11]. In Dagdelen and Johnson [22] formulation, the mining and processing constraints were relaxed and adjusted with Lagrangian multipliers to find the optimal solution. The authors decomposed the problem into smaller problems to allow for tractability of the solution. Ben-Awuah et al. [15] implemented a MILP model that incorporates goal programming; a reward and penalty based approach to maximize the NPV. The authors used the clustering algorithm developed by Tabesh and Askari-Nasab [92] to reduce the size of the optimization problem to ensure computational tractability. Their case study involved 16,985 blocks, and their model was able to find the optimal solution at 0% optimality gap.

Heuristics are basic approximation algorithms that search the solution space to find a good solution and metaheuristics are algorithms that combine heuristics (that are usually very problem-specific) in a more general framework [16]. Metaheuristics are able to solve large optimization problems at a reasonable computational time. The difficulties associated with NP-hard class of problems and the general large instances of the problems make exact approaches that often generate optimal solution not ideal to solve such problems; taking into account, the resources and computational time required. Researchers have investigated the trade-off between finding a good solution at smaller computational time and finding an optimal solution, which at times is intractable or resource intensive. The uncertainties associated with stochastic OPPS optimization problems make the application of metaheuristics more ideal in applying it to large problem instances, since it is capable of finding a good solution in a much smaller computation time. Popular metaheuristic algorithms for large scale optimization includes: tabu search, genetic algorithm, simulated annealing, ant colony optimization, and particle swarm optimization.

Tabu search (TS) is a metaheuristic algorithm used to solve large combinatorial optimization problems. The process of TS was designed by Glover [44]. It optimizes or improves a solution by searching through a neighbourhood of solutions and selecting the best ones. TS classifies certain solutions as forbidden (taboo; where the name 'tabu' is derived from) to prevent the algorithm from selecting those solutions which is a strategy to avoid cycling of the algorithm. There are three TS specific concepts that improves it solution approach over other combinatorial optimization algorithms according to Bianchi et al.[16]. These concepts are: best improvement, tabu lists, and aspiration criteria. Best improvement is an approach in TS algorithm in which each existing solution is replaced with its best neighbouring solution. This is a method for avoiding local optima, however it may result in cycling when each current solution is replaced. TS counteracts this problem by creating a tabu list. Tabu list is a list that stores attributes of recently visited solutions. The type of attribute saved is the 'move' made by the algorithm in arriving at a result. The algorithm is then restricted from selecting from this set of solutions with attributes on the tabu list. The aspiration criterion is a criterion check in the TS algorithm that, if met, permits a 'move' to a banned solution to be chosen. Such criterion, according to Glover [45], can be set as follows: if the existing solution is worse than the newer one, then the tabu can be overridden. TS has been explored by researchers to solve the OPPS problem. Lamghari and Dimitrakopoulos [65] used TS and Variable Neighborhood Descent (VND) algorithms for solving the OPPS problem. In their implementation, a definite number of neighborhood was set and the algorithm was made to search the neighborhood until the optimal solution was found. The authors implemented their model on a copper and gold dataset to validate the effectiveness of the proposed model. In their conclusion, the authors stated that a near optimal solution was found at a reasonable computational time. Senécal and Dimitrakopoulos [86] presented a TS that uses multi-neighborhood to solve the long term OPPS problem. In their approach, the authors considered multiple processing streams under mineral uncertainty. The objective function from their model maximizes the discounted cash flow and penalizes deviations from production targets.

Alipour et al. [4] presented a Genetic Algorithm (GA) approach for the OPPS problem. The researchers used an initial population of 20 with each population consisting of a 10 x 20 matrix in the GA model which represents the total blocks in the copper orebody. The initial population was then normalized to cater for the various constraints associated with the OPPS problem, namely; the mining capacity, processing capacity and block precedence constraints. A fitness function to evaluate the population was also formulated. The OPPS problem was solved with the GA and the results were compared to solution from IBM CPLEX solver. The authors indicated that, the computation time needed to solve the optimization problem with GA was significantly lower than that of the IBM CPLEX solver. However, the optimal solution from the GA was 5% lesser than that from the IBM CPLEX solver. The researchers further emphasized GA as computationally efficient but does not always give the optimal solution compared to LP and MILP with IBM CPLEX solver.

Another application of GA to the OPPS problem was presented by Alipour et al. [5]. In this application, the authors built on their earlier research in 2017. A 3D orebody model consisting of 10,529 blocks was used for a case study. The authors compared the GA solution to the solution from SimSched DBS software [80] developed based on surface constrained stochastic life-of-mine production scheduling by Marinho de Almeida [68]. From the analysis by the authors, GA proved capable of solving not just a 2D OPPS problem but also a 3D OPPS problem. SimSched DBS obtained its solution in a shorter computation time than the GA. This was because SimSched DBS software mined blocks accumulated as surfaces which reduces the number of decision variables and level of selectivity for processing. The optimal solution from the GA was 4% better than that from the SimSched DBS software. The authors concluded at the time that, due to the size of the problem, any comparison to an exact optimization methodology was not possible. This further emphasizes the use of metaheuristics in attempting the OPPS problem. Grade uncertainties were not considered in their research. The researchers through the case study demonstrated the viability of using a GA model to solve OPPS optimization problems.

Amponsah et al. [6] also presented a GA model to solve a small-scale 3D OPPS problem. The researchers used a literal permutation encoding scheme from Gen et al. [41] for chromosomes encoding. They compared their results to a MILP solution from CPLEX. In the authors' findings, the GA model's solution was within 10% of the MILP solution with CPLEX. This was partly because the MILP allowed for fractional block processing across multiple periods, which the GA did not. In extending Amponsah et al. [6] research, a GA framework that allows for fractional block processing across multiple periods is presented in this research. The extended GA model, also considers grade uncertainties in its formulation and optimization.

Kirkpatrick et al. [60] proposed simulated annealing (SA) as a combinatorial optimization algorithm. SA optimization algorithm in principle is based on local search heuristics, and uses a pre-defined neighborhood structure on the search space. In the OPPS problem, Kumral and Dowd [63] proposed a SA algorithm approach to solve the problem. The authors simulated the mineral deposit with Sequential Gaussian Simulation and created the block model. The ultimate pit limit was then determined from the block model by pit-blend using LP and the LG algorithm. Their model contained a total of 2,773 blocks, SA was able to provide a suitable and uniform mine schedule in a relatively short computational time. The authors however; used lagrangian parameterization to incorporate the constraints of the optimization into the objective function which created sub-pits within the ultimate pit to allow for the satisfaction of the tonnage capacity constraints. Goodfellow and Dimitrakopoulos [50] also presented a SA optimization approach to the OPPS problem. Their model used a stochastic push-back design to adjust and minimize the deviation of materials sent to the waste and processing destinations. A copper deposit was used as the case study by the researchers and found that SA to be capable of handling real world application since the algorithm efficiently handled the multiple metals, slope zones and the multiple destinations.

Ant colony optimization (ACO) is a population based metaheuristic algorithm. The concept that inspired ACO is based on the behavior ants display when plying a route in search of food [32]. Ants on their quest for food scan their nest in a random manner, and when a food source is found, the ant releases a chemical called pheromone on its way to the nest. This chemical serves as a way of communicating to other ants to ply the same route in search of food [27]. The route with the highest pheromone concentration tends to be the preferred route or the shortest. Subsequently, the pheromone evaporates as time goes on. In combinatorial optimization problems, Dorigo et al. [32] presented the ACO as an optimization algorithm for the Travelling Salesman Problem (TSP). An application of the ACO algorithm was proposed by Shishvan and Sattarvand [88] for the OPPS problem. In their implementation, the authors used the Max-Min ant colony system and tested the model on a copper-gold deposit. The deposit consisted of 350,000 blocks. The ACO algorithm generated a 12% improvement in the initial mining schedule. The authors carried out a sensitivity analysis on the ACO parameters consisting of initial pheromone values, pheromone evaporation rate, and perturbation distance. In the author's findings, they stated that a higher initial pheromone value reduced the algorithms chances of exploring better solutions thereby generating poor results. In the analysis of the evaporation rate, the authors concluded that lower evaporation rate increases the time spent by the algorithm on poor solutions.

Particle swam optimization (PSO) is a nature inspired metaheuristic optimization which was first proposed by Kennedy and Eberhart [58]. PSO is based on the social interaction of individuals living together in groups. PSO algorithm performs the search process by using a population of individuals living in groups [59]. Khan and Niemann-Delius [59] implemented the PSO on a OPPS problem, the authors used a continuous version of the PSO and a guaranteed convergence PSO algorithm. The authors' inspiration for this approach was the number of blocks available in the ultimate pit limit of an open pit mine which may contain hundreds of thousands of blocks therefore according to the authors using a continuous PSO reduced the computational time. The precedence constraints in the OPPS problem was handled by normalization in the model, the model checks and repair each solution to ensure solution feasibility at all times. The other constraints were handled by the application of a penalty method. The proposed model was implemented on two copper orebodies with 10,120 and 7,863 blocks respectively. The model was successful in solving the OPPS problem with an optimality gap of 12.61% for the first case study and 4.80% for the second case study.

2.1. Stochastic open pit optimization in the presence of grade uncertainty

The conventional OPPS problem is optimized with a single interpolated orebody block model which does not account for grade uncertainties. As the conventional OPPS approach does not consider grade uncertainties, a true representation of the optimal NPV is rarely achieved. As reported by Sabour and Dimitrakopoulos [84], due to uncertainties associated with mining projects, the mining industry in Canada lost in excess of 1.4 billion dollars in 1991. In the incorporation of uncertainties in the OPPS problem, the stochastic model takes several simulated orebody realizations as input with each orebody model having varying grades. The stochastic model then seeks to optimize for the maximum NPV and minimum waste management cost, while providing risk-based solution that tends to minimize deviations from operational targets.

Dimitrakopoulos and Ramazan [30] introduced a stochastic integer programming (SIP) formulation that considered grade uncertainty. The authors elaborated that the SIP model considers multiple scenarios and generate a desirable outcome for a set of specified objectives which made its application to the OPPS problem preferable. The authors implemented their SIP model on two case studies: a gold deposit and a copper deposit. The case study with the gold deposit had 22,296 blocks. In the analysis of the results by the authors, the gold deposit case study was optimized in two stages with both optimizations totaling 42 hours in computational time with 14 simulated orebody realizations. The authors indicated that the SIP model with the simulated orebody realizations had a 9.7% increase in NPV over the traditional (conventional) mixed integer programming (MIP) model with a single interpolated orebody block model. There was a similar outcome from the copper case study. The number of simulated orebody realizations for this case study was 20 and the authors recorded an increase in NPV of ~ 25% over the traditional MIP model's NPV. Mbadozie et al. [71] {Mbadozie, 2020 #214}also presented a stochastic mixed integer linear programming (SMILP) formulation for oil sands production scheduling and waste management that considers grade uncertainty. The author used 20 orebody realizations to represent grade variability in the deposit. The results from the oil sands case study demonstrated that the SMILP schedule generated 16.85% improvements in NPV over the conventional schedule. These promising gains in NPV from stochastic production schedules form the basis of this research.

3. Genetic Algorithm

Genetic algorithm (GA) is an evolutionary algorithm that follows biological processes as proposed by Darwin [48; 52]. GA, therefore, generates its solution to the optimization problem by strictly following the biological evolution process; such as inheritance, crossover, mutation, and selection. The inherent theory in this process is the survival of the fittest where organisms with good or fitter genes survive and transfer their genes to the next generation. Consequently, only organisms with the best gene will exist over time. GA follows the same approach when formulating problems. In summary, the GA workflow includes the following: 1) An initial population of individuals is created; the fitness functions of the created individuals are evaluated. 2) A set of genes and chromosomes are selected based on the fittest individuals; the selected genes will then crossover and mutate. 3) Elitism is then applied on the best individuals in the population to keep them for the next generation. 4) This process is repeated until a population of the best genes are obtained or a set of maximum generations are reached. Fig. 1 shows a flow chart of the genetic algorithm process.

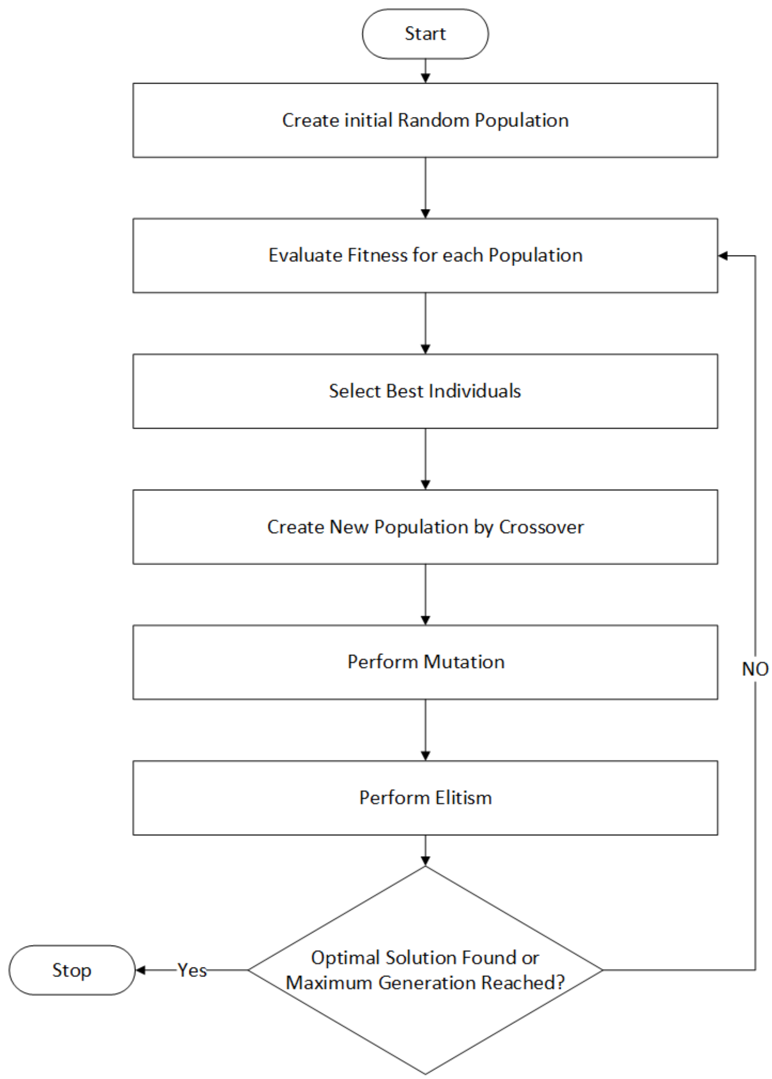


Figure 1. Flow chart of genetic algorithm process.

3.1. Initial population

This is the starting point of the GA where the population is initialized. According to Gen et al. [40], there are two methods for generating initial population; the heuristic method and the random number generation method. In the random number generation method, GA randomly generates a solution space based on the problem size and this is referred to as the initial population. This initial population can be generated from a Gaussian distribution to increase diversity. The population includes multiple solutions, which represents chromosomes and genes of individuals. Each chromosome has a set of variables which simulates the genes [75]. In the heuristic approach, a problem specific encoding algorithm is used to generate the initial population. Gen et al. [40] however illustrated that this approach sometimes explore only a smaller portion of the solution space in a large scale combinatorial optimization problem. This then leads to a local optimum in the GA. In this research, the random number generation method was used. Fig. 2 shows a sample initial population (Chromosomes 1, 2 and 3) obtained by the random number generation method. This figure shows the flexibility in setting up GA optimization problems as the initial population can be represented in different ways and with different characters.

Chromosome ***1***	0	0	1	0	1	0	1	0	0	1	1
Chromosome ***2***	3	5	7	4	8	1	8	12	56	4	7
Chromosome ***3***	0.3	0.2	0.6	0.05	0.6	0.52	0.41	0.3	0.3	0.54	0.8
~											
Chromosome ***n***	A	B	H	J	I	L	K	M	G	H	V

Chromosome / Solution

Genes

Figure 2. Sample initial population showing genes and chromosomes.

3.2. Chromosome encoding

Chromosome encoding is an essential process in GA. It specifies the nature of the genotype in a population. The encoding scheme is mostly problem dependent and thus relies on the structure of the problem being optimized. Binary encoding, real number encoding, literal permutation encoding (LPE), and general data structure encoding are the various classifications of chromosome encoding according to Gen et al. [40]. In binary encoding, the genes in the population are represented by either 0 or 1. The encoded genes are then decoded to decimals when evaluating for their fitness. This process is done for every gene in the chromosome and may pose performance issues for large number of genes. This encoding forms the genotype of a feasible solution to the problem. An example of a problem that benefits from the binary encoding scheme is the general knapsack problem. In the knapsack problem, the objective is to find the sum of weights producing the maximum profit or minimum cost to a problem while respecting the stipulated capacity of the knapsack. Given a set of *n* $\forall_n \in \{1,...n\}$ items each having a weight of w_i and a value of v_i with a maximum capacity of *C,* the knapsack problem can be modelled as in Eqs. and [36].

$$Max\sum_{i=1}^{n} v_i x_i$$

Subject to

$$\sum_{i=1}^{n} w_i x_i \leq C$$

Where x_i is the decision variable to this problem which can be encoded as 1 (if selected) or 0 (otherwise). When binary encoding is employed, it indicates that the problem assumes only discrete values, which is not always the case for many optimization problems.

Real number encoding or continuous variable encoding is the representation of the decision variables in the genotype with real numbers as opposed to binary encoding. In this process, there is no binary to decimal decoding and this improves the efficiency of the approach. According to Gen et al. [40], real number encoding is suitable for functional and constrained optimization problems. The genotypic representation in real number encoding is close to the phenotypic space of the problem since there is no conversion between both spaces. To represent genes with this encoding scheme, genes have to be between a lower and upper bound of the decision variable. This is represented in Eq. .

$$x_n = (x_{ub} - x_{lb}) \times r + x_{lb}$$

Where x_n is the *n-th* gene; x_{ub} is the upper bound; x_{lb} is the lower bound; and *r* is a random number between [0, 1].

LPE or order encoding is the representation of the gene by the permutation of the decision variables. Since LPE is represented as the permutation of the decision variables, it is mostly suitable for optimization problems that involve permutation. An example is the travelling salesman problem. In the travelling salesman problem, a salesman has to visit *n* number of cities and every city can be visited only once. In such a problem, the genotype can be encoded as the order or sequence in which the cities are visited which is the permutation of the *n* cities. Fig. 3 shows a sample LPE. Chromosome A and B in Fig. 3 shows the sequence in which the cities can be visited by the travelling salesman as represented by the GA.

Chromosome A	1	4	2	3	6	7	8	10	12	14	15	17	9	11	13	16	5

Chromosome B	2	4	3	5	7	6	8	10	15	14	16	12	11	13	17	1	9

Figure 3. Literal permutation encoding representation.

Every combinatorial optimization problem that is optimized with GA requires its own chromosome encoding technique that represents the problem in great detail. There are no one size fits all chromosome encoding although certain type of combinatorial optimization problems do benefit from specific encoding schemes. Once a suitable encoding scheme is modeled for the problem, the various genetic operators can then be formulated around the specific chromosome encoded. The phenotype of the population is then derived from the genotype representation in the encoded chromosomes. In this research, multiple chromosome encoding was used to represent the genes in the population. A real number encoding or continuous encoding technique was used to represent the genotype of each block in the population. This allowed for fractions of blocks in the population to be processed. In addition, the LPE technique was also used as part of the encoding scheme to provide the order or sequence in which blocks could be mined. More on the problem specific chromosome encoding techniques used in this research are discussed in Section 4.

3.3. Fitness function

In GA, the fitness function is the function used to determine the viability of a gene in a population. The objective function in an optimization problem in GA is referred to as the fitness function. This function tests the population at every generation and becomes the means of determining fitter genes that survives to the next generation. The fitness function also aides in the selection of parents from the population as selection algorithms in GA ranks population based on their fitness value. When evaluating the fitness function, the genotype from the population is converted or decoded into phenotype. This phenotype is evaluated and assigned a value which becomes the fitness of that solution. The decoding of the gene is dependent on the chromosome encoding scheme used during the initialization of the problem. At the end of every generation, the fitness value of each member of the population is assessed and ranked based on the objective of the optimization problem. If the objective of the optimization is to minimize cost, then the member solution with the least minimum fitness value is chosen as the best solution from that generation. If the objective of the optimization is to maximize profit, then the member solution with the maximum fitness value is selected. The fitness function and its evaluation ensures that the GA does not violate the general objective of the problem.

3.4. Selection

GA uses different selection algorithms with the inspiration of attaining the fittest individual from the initial population. Sharma and Gargi [87]; Sivanandam and Deepa [88] defined selection in GA as a method that randomly picks chromosomes out of the population according to their fitness function value. The higher the fitness function value, the better chance that an individual will be selected. There are several popular selection algorithms but there is no one preferred selection algorithm for GA. Each selection algorithm may have advantage over the other based on the specific problem being optimized. Various selection algorithms found in the literature are: Boltzmann selection [46], Roulette wheel selection also known as the Fitness proportionate selection algorithm [19; 47], Tournament selection [17; 47], Random selection, Rank selection, and Stochastic universal sampling [89]. Roulette wheel selection and Tournament selection are explored for this research as they are the two well studied selection algorithms in GA [64].

3.5. Crossover

Crossover is the method of selecting two parents at random and recombining their chromosomes at a point with the intent of making offspring with better genes [90]. Single point crossover and double point crossover are the two main approaches to crossover. Fig. 4 shows a single and Fig. 5 shows a double point crossover. However there are several other crossover approaches used in the literature: uniform crossover [85], three parents' crossover [94], half uniform crossover [54], partially matched crossover [49], position-based crossover [91], order crossover [24], cycle crossover [79], multi-point crossover [34], masked crossover [67], and heuristic crossover [51]. In this research, the double point crossover was implemented. Double point crossover was used since it has a high capacity to transmit useful genetic information from parent to offspring based on the study by [35].

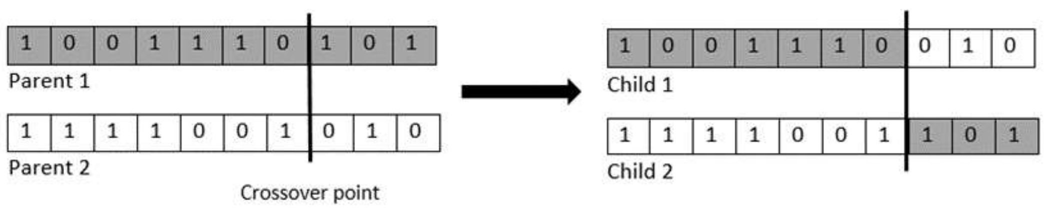


Figure 4. Single point crossover.

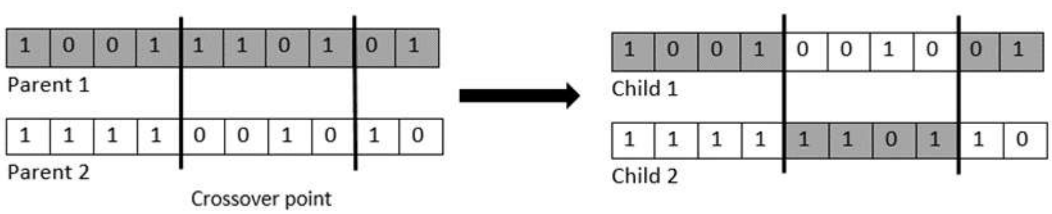


Figure . Double point crossover.

3.6. Mutation

Mutation is the next stage after crossover in the GA algorithm process. When offspring from two parents are generated through crossover, it may occur that these offspring do not possess good enough genes to generate a good solution. Therefore, the GA process introduces mutation to alter or change the genes. Mutation is the other way to get new genomes. Mutation results in changing the value of genes [90]. These changes occur randomly with a probability of mutation parameter set between [0, 1]. A random number in the same interval is generated for each gene in the new child.

If this random number is less than the probability of mutation, the gene is assigned with a random number within the lower and upper bounds of the decision variable [76]. In Fig. 6 is an illustration of before and after a mutation process where a new gene is introduced.

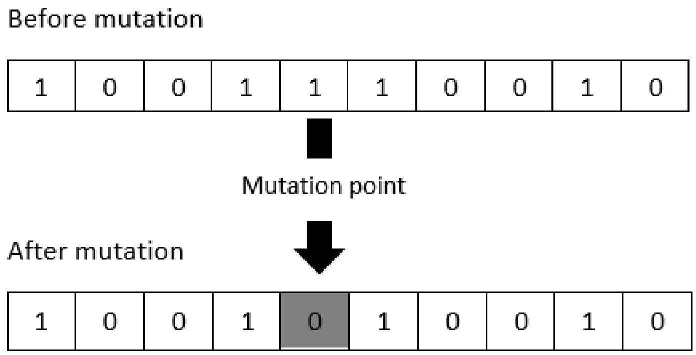


Figure 6. Sample mutation.

3.7. Elitism

Elitism is a genetic operator applied to the chromosomes obtained after selection, crossover and mutation in some cases to preserve or copy the traits of the best chromosomes to the next generation [3; 33]. This helps to keep a fit chromosome in each generation at all times by ensuring that these fit chromosomes are not lost during the iteration process. Elitism as a genetic operator was not part of the initial operators during the theoretical formulation of GA but has through the years proven to be efficient when applied as a genetic operator [76; 3].

3.8. Constraint handling

Evolution algorithms have different methods for handling constraints. These methods are generally problem dependent although some may be applied across different optimization problems. In the literature, the methods for handling constraints can be grouped into four different categories; the repair method, rejection method, penalty method and modification of genetic parameters [40; 72]. Each method has merits that may suit a particular combinatorial optimization problem over the other.

In the repair method, population with infeasible chromosome is neither discarded nor penalized but rather a deterministic method for normalizing the infeasible chromosome is applied. This converts the infeasible chromosome to a feasible one [73]. The method for normalizing or repairing the chromosome must consider the bounds of the constraints and create a chromosome that lies in the feasible region. This method is problem dependent and cannot be applied to any problem without first re-writing the repairing algorithm to suit the said problem. Two approaches of this method exists: (1) Always replacing the infeasible chromosome in the population with the repaired chromosome, and (2) using the repaired chromosome only for evaluation purposes without feeding it into the evolution. Both approaches are used in the literature. Nakano and Yamada [78] used the always replacing approach and termed it as "forcing" where a feasible chromosome *g'* repaired from an infeasible chromosome *g* is forced to replace the chromosome *g* in the population.

The rejection method also termed as "death penalty" by Michalewicz [73] works by completely removing any infeasible chromosome from the population. In this approach, any infeasible chromosome in the population is discarded as opposed to being repaired. This approach has limitations. The initial population generated for a problem may have several infeasible solutions and per this method all these infeasible solutions need to be discarded which may lead the GA into premature convergence. Michalewicz [72] tested this method on five different cases and stated that it performed worse than the other constraints handling approaches. Outright rejection of infeasible solutions go against the nature of evolution algorithms [82].

The penalty method is widely used and by far the easiest to implement. Constrained optimization problems are converted to unconstrained problems by applying a penalty function to the objective function of the problem. According to Dasgupta and Michalewicz [23], the basic approach is to extend the objective function which in GA is represented as the fitness function of a Chromosome *i* in the following Equation;

$$fitness\ function = f(i) \pm Q(i)$$

Where $Q(i)$ represents the penalty for an infeasible Chromosome *i*, and $f(i)$ represents the objective function of the problem. For a maximization problem, the penalty function is expressed as $Q(i) < 0$ where *i* is infeasible and $Q(i) = 0$ where *i* is feasible; whereas $Q(i) > 0$ where *i* is infeasible and $Q(i) = 0$ where *i* is feasible for a minimization problem. The general challenge with penalty functions as stated by Michalewicz [72]; Richardson et al. [82] is knowing exactly what degree of penalty to apply to an infeasible chromosome or solution since all infeasible solutions are not alike. Fig. 7 illustrates feasible and infeasible solution regions in a solution space. Assuming Solution *x* is the optimal solution without any prior knowledge, Solution *c* is closer to the optimal solution than Solution *b* and Solution *a,* although these solutions are in the infeasible region. Solution *c* may contain certain genes that may be relevant to attaining the optimal solution as opposed to Solution *b* and Solution *a*. Therefore, applying the same penalty value in this instance may not be ideal. Secondly, Solution *y* is farther than Solution *c* relative to the optimal Solution *x* although Solution *y* is in the feasible region. These complexities make finding the appropriate penalty value challenging.

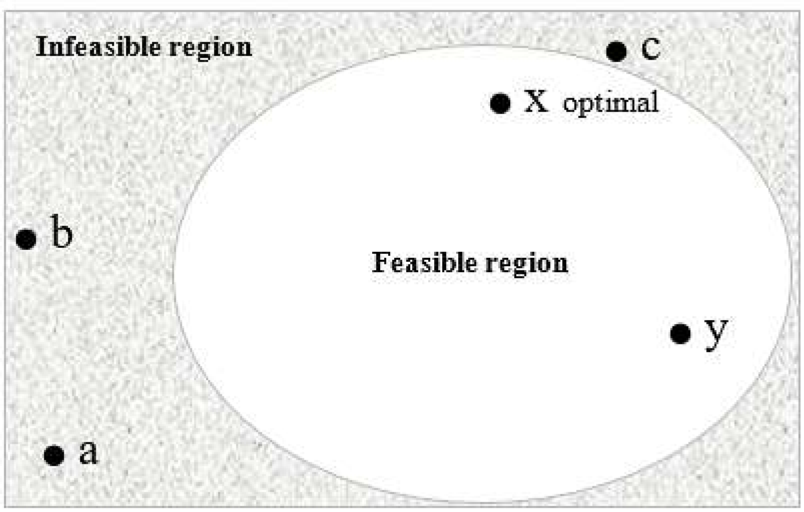


Figure 7. Feasible and infeasible solution space modified after Michalewicz [73].

The modification of genetic parameters approach works by creating problem specific methods that (1) represent the problem, and (2) modifies the conventional GA parameters such as crossover and mutation to keep the optimization problem in the feasible domain [40]. The approach always ensure the GA is kept only in the feasible search space at all times. Although this is desirable, it also limits the search space for the GA. In this research, both the repair and penalty methods were implemented in handling constraints.

3.9. Termination

Generally, GA terminates when the maximum number of generations are reached. GA can also be terminated when a desired fitness value is met or when subsequent iterations does not improve the solution quality.

4. Open Pit Production Scheduling (OPPS) Optimization Framework

4.1. Model formulation for open pit production scheduling

The NPV of OPPS is based on the economic block value (EBV) of individual blocks in the orebody block model. The EBV of a block depends on its value and the costs incurred in mining and processing the block. The cost of mining a block is a function of the block's location in relation to how deep the block is from the surface and how far it is to its final destination. To calculate the NPV, the EBV is discounted since OPPS is undertaken over multiple periods. The discounted profit from block *n* is therefore given as the discounted revenue generated from mining block *n* minus the discounted cost for extracting and processing block *n*. This is presented in Eq..

$$discounted\ profit_n^t = discounted\ revenue_n^t - discounted\ cost_n^t \quad \forall_n \in \{1,...N\};\forall_t \in \{1,...T\};$$

4.1.1. Indices and set

$s \in \{1,....,S\}$	index for realizations
$n \in \{1,....,N\}$	index for blocks
$t \in \{1,....,T\}$	index for scheduling periods
$N = \{1,...,N\}$	set of all blocks in the model
$S = \{1,...,S\}$	set of all equally probable orebody realizations
$H_n(D)$	For each block, there is a set $H_n(D)$ defining the immediate predecessor blocks that must be extracted prior to extracting block *n* with safe slopes; where *D* is the total number of blocks in $H_n(D)$

4.1.2. Parameters

r	discount rate
o_n	ore tonnage in block *n*
$o_{n,s}$	ore tonnage in block *n* of realization *s*
w_n	waste tonnage in block *n*

$w_{n,s}$	waste tonnage in block *n* of realization *s*
dr	geological discount rate
v_n^t	revenue obtained by selling the final product within block *n* in period *t*, minus the extra discounted cost of mining all the material in block *n* as ore
$v_{n,s}^t$	revenue obtained by selling the final product within block *n* of realization *s* in period *t*, minus the extra discounted cost of mining all the material in block *n* as ore
q_n^t	cost of mining all the materials in block *n* in period *t* as waste
$q_{n,s}^t$	cost of mining all the materials in block *n* of realization *s* in period *t* as waste
Cl^t	lower bound of the mining capacity in period *t*
Cu^t	upper bound of the mining capacity in period *t*
Ql^t	lower bound of the processing capacity in period *t*
Qu^t	upper bound of the processing capacity in period *t*
g_n	average grade in ore portion of block *n*
$g_{n,s}$	average grade in ore portion of block *n* for realization *s*
$\underline{g}^t$	lower bound of the required average head grade in period *t*
$\overline{g}^t$	upper bound of the required average head grade in period *t*
pc_{o-}^t	penalty cost for lower ore tonnage target deviation in period *t*
pc_{o+}^t	penalty cost for upper ore tonnage target deviation in period *t*
pc_{g-}^t	penalty cost for lower grade target deviation in period *t*

pc_{g+}^{t} penalty cost for upper grade target deviation in period t

4.1.3. Decision variables

$x_n^t \in [0,1]$ continuous variable representing the portion of block n to be extracted as ore and processed in period t

$y_n^t \in [0,1]$ continuous variable representing the portion of the block n to be mined in period t; fraction of y characterizes both ore and waste in the block

$b_n^t \in \{0,1\}$ b_n^t binary integer variable controlling the precedence of extraction of mining block n; b_n^t equal to one if extraction has started in period t, otherwise it is zero

$od_{s,+}^t \in [0,1]$ continuous variable representing the excess from the ore tonnage upper bound in period t for realization s

$od_{s,-}^t \in [0,1]$ continuous variable representing the shortage to the ore tonnage lower bound in period t for realization s

$gd_{s,+}^t \in [0,1]$ continuous variable representing the excess from the grade upper bound in period t for realization s

$gd_{s,-}^t \in [0,1]$ continuous variable representing the shortage to the grade lower bound in period t for realization s

4.2. Deterministic MILP formulation

In the conventional formulation of the OPPS, grade uncertainties are not considered and the main objective is to maximize the NPV of the mining operation subject to a set of constraints. The objective function and constraints are outlined in Eqs. to . This MILP formulation is consistent with the research undertaken by Askari-Nasab et al. [10].

4.2.1. Objective function

The objective function of the MILP model (Eq.) is formulated to maximize the NPV of the mining operation. The objective function consists of two continuous decision variables for block n. The first decision variable x_n^t represents the portion of block n to be processed in period t if it is ore. The decision variable y_n^t represents the portion of block n to be extracted in period t; fraction of y characterizes both ore and waste in the block. Using continuous decision variables allows for the fractional extraction of blocks in different periods.

$$Max \sum_{t=1}^{T} \sum_{n=1}^{N} \left(\frac{v_n^t \times x_n^t - q_n^t \times y_n^t}{(1+r)^t} \right)$$

Subject to:

4.2.2. Mining capacity constraints

Eqs. and define the mining capacity constraints for each period. Eq. defines maximum capacity for mining. This ensures that the total amount of material mined is less or equal to the stipulated capacity of mining equipment while Eq. defines the minimum capacity and controls the minimum amount of materials mined. These constraints are controlled by the continuous decision variable y_n^t and allows the mine planner to use different mining capacities in each period throughout the life-of-mine.

$$\sum_{n=1}^{N}(o_n + w_n)\times y_n^t \le Cu^t \qquad \forall_t \in \{1,...T\};$$

$$\sum_{n=1}^{N}(o_n + w_n)\times y_n^t \ge Cl^t \qquad \forall_t \in \{1,...T\};$$

4.2.3. Processing capacity constraints

The processing capacity constraints aids the mine planner in ensuring a consistent feed throughout the mine life, resulting in a mine-to-mill operation that is well integrated. This is a soft constraint and depends on the availability of ore blocks. The processing objective may not be met in some periods depending on the orebody's ore grade distribution. In such circumstances, pre-stripping might be considered to ensure a consistent mill feed. This effectively forces the optimizer to mine waste in the early stages so that when ore production begins, the plant feed supply will be consistent and uniform. Eqs. and define the processing capacity of the mining operation. Eq. sets the upper bound and Eq. sets the lower bound for the amount of ore processed. These constraints are controlled by the continuous decision variable x_n^t and allows the mine planner to provide a uniform mill feed throughout the life-of-mine. In practice, the processing targets must be set with minimal periodic deviations to ensure maximum utilization of the mill.

$$\sum_{n=1}^{N}(o_n \times x_n^t) \le Qu^t \qquad \forall_t \in \{1,...T\};$$

$$\sum_{n=1}^{N}(o_n \times x_n^t) \ge Ql^t \qquad \forall_t \in \{1,...T\};$$

4.2.4. Grade blending constraints

The goal of blending in production scheduling is to mine in such a way that the ore materials fulfil the processing plant's quality and quantity specifications. The grade blending constraints are essential constraints during production scheduling. These constraints ensure that an acceptable range of ore is sent to the mill at all times. Therefore, this grade range should be set between a lower and upper limit to facilitate blending of mill feed material. Eq. defines the upper limit of the ore grade and Eq. defines the lower limit of the ore grade to be sent to the mill. These constraints are controlled by the continuous decision variable x_n^t .

$$\sum_{n=1}^{N}(g_n - \overline{g}^t)\times(o_n \times x_n^t) \le 0 \qquad \forall_t \in \{1,...T\};$$

$$\sum_{n=1}^{N}(g_n - \underline{g}^t)\times(o_n \times x_n^t) \geq 0 \qquad \forall_t \in \{1,...T\};$$

4.2.5. Block precedence constraints

Eqs. to enforce the block extraction precedence constraints. Binary integer decision variable, b_n^t, is used to control the precedence of block extraction. b_n^t is equal to one if the extraction of mining blocks has started by or in period *t*; otherwise, it is zero. For each mining block *n,* Eq. checks the set of immediate predecessor blocks in $H_n(D)$ that must be mined prior to mining block *n.* Eq. checks that extraction of mining block *n* can start only when the mining block has not been previously extracted. Eq. ensures that once extraction of block *n* starts, this block is available for extraction in subsequent periods.

$$b_n^t - \sum_{i=1}^{t} y_d^i \leq 0 \quad d \in H_n(D) \qquad \forall_n \in \{1,...N\};\ \forall_t \in \{1,...T\};$$

$$\sum_{i=1}^{t} y_n^i - b_n^t \leq 0 \qquad \forall_n \in \{1,...N\};\ \forall_t \in \{1,...T\};$$

$$b_n^t - b_n^{t+1} \leq 0 \qquad \forall_n \in \{1,...N\};\ \forall_t \in \{1,...T-1\};$$

4.2.6. Variable control constraints

Eq. ensures that the total ore material mined in any given scheduling period is less or equal to the sum of the ore, and waste materials mined in that period. Eqs. and ensures that the sum of the partials of block *n* extracted is at most one over all periods at the end of the mine life.

$$\sum_{n=1}^{N}(o_n \times x_n^t) \leq \sum_{n=1}^{N}((o_n + w_n)y_n^t) \qquad \forall_t \in \{1,...T\};$$

$$\sum_{t=1}^{T} y_n^t \leq 1 \qquad \forall_n \in \{1,...N\};$$

$$\sum_{t=1}^{T} x_n^t \leq 1 \qquad \forall_n \in \{1,...N\};$$

4.2.7. Non-negativity constraints

Non-negativity constraints monitor the decision variables to ensure they do not take negative values. Eq. defines the non-negativity of decision variables.

$$x_n^t, y_n^t, b_n^t \geq 0 \qquad \forall_n \in \{1,...N\};\ \forall_t \in \{1,...T\};$$

4.3. Stochastic MILP formulation in the presence of grade uncertainty

The stochastic formulation for the OPPS problem considered in this research is modified after the formulation by Vallejo and Dimitrakopoulos [96]; Mbadozie [71]. The approach for including grade uncertainty in the mining project stems from having multiple simulated orebody realizations generated through SGS which are equally probable and serve as input to the stochastic model. Equally probable orebody realizations mean each simulated realization can be a valid representation of the actual orebody. The simulated orebody realizations capture the varying grade distribution that would not have been realized with a single interpolated block model based on a method like Kriging. Previous research from Albor and Dimitrakopoulos [1]; Vallejo and Dimitrakopoulos [96] have identified that, 20 simulated orebody realizations are adequate to capture the uncertainty in grade distributions.

4.3.1. Multi-objective function

The objective function for the stochastic model is derived from the average of all the simulated orebody realizations. Since these realizations are equally probable, each realization depicts varying grades for the orebody model. This can be assumed as having *S* number of schedules at the end of the optimization with each *s* schedule representing a probable solution. To simultaneously optimize with all the equally probable orebody realizations, an average of the revenue and cost from the realizations are taken into account in the objective function (Eq.).

The multi-objective function has two components: 1) Maximize the NPV of the mining operation (Eq.); and 2) Minimize the cost of uncertainty associated with deviating from the operating targets, including ore tonnage and ore grade (Eq.). This is achieved by applying penalty costs and a geological risk discount rate to the ore tonnage and ore grade targets. Continuous deviation decision variables $od_{s,+}^{t}$, $od_{s,-}^{t}$, $gd_{s,+}^{t}$ and $gd_{s,-}^{t}$ as well as their respective penalty parameters pc_{o+}^{t}, pc_{o-}^{t}, pc_{g+}^{t} and pc_{g-}^{t} are used for minimizing deviations from ore tonnage and ore grade production targets defined by Eqs. to . These are introduced in the second component of the objective function (Eq. to enable the optimizer to select realization blocks with ore tonnage and ore grade that minimizes deviations from the corresponding production targets simultaneously through a balancing act. For example, if the optimizer selects realization blocks with high grade, it will lead to a large ore tonnage deviation resulting from reduced ore reserve which is undesirable and vice versa.

Additionally, a geological risk discount rate (*dr*) is applied to the cost of deviation to defer the risk of not meeting production targets to later periods. From Eq. , by applying the *dr* parameter as a denominator tied to periods, early periods have larger impact on the minimization objective function value than later periods. This means the overall penalty value is higher in the earlier periods than in latter periods ensuring that early-year deviations from stated targets are lower than later-year deviations. Conceptually, the higher penalty in earlier periods drive the optimizer to limit deviations from the ore tonnage and ore grade targets early in the mine life and postpone extraction of areas with larger deviations until later periods when more geological understanding of the deposit becomes available.

$$Max \frac{1}{s} \sum_{s=1}^{S} \sum_{t=1}^{T} \sum_{n=1}^{N} \left(\frac{v_{n,s}^{t} \times x_{n}^{t} - q_{n,s}^{t} \times y_{n}^{t}}{(1+r)^{t}} \right)$$

Where *S* is set of all equally probable realizations.

$$Min\frac{1}{S}\sum_{s=1}^{S}\sum_{t=1}^{T}\left(\frac{pc_{o+}^{t}\times od_{s,+}^{t}+pc_{o-}^{t}\times od_{s,-}^{t}}{(1+dr)^{t}}\right)+Min\frac{1}{S}\sum_{s=1}^{S}\sum_{t=1}^{T}\left(\frac{pc_{g+}^{t}\times gd_{s,+}^{t}+pc_{g-}^{t}\times gd_{s,-}^{t}}{(1+dr)^{t}}\right)$$

Eqs. and can be combined together as a single objective function as shown in Eq. .

$$Max\frac{1}{s}\sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{n=1}^{N}\left(\begin{array}{l}\left(\frac{v_{n,s}^{t}\times x_{n}^{t}-q_{n,s}^{t}\times y_{n}^{t}}{(1+r)^{t}}\right)-\\ \frac{1}{N}\left(\frac{pc_{o+}^{t}\times od_{s,+}^{t}+pc_{o-}^{t}\times od_{s,-}^{t}}{(1+dr)^{t}}\right)-\\ \frac{1}{N}\left(\frac{pc_{g+}^{t}\times gd_{s,+}^{t}+pc_{g-}^{t}\times gd_{s,-}^{t}}{(1+dr)^{t}}\right)\end{array}\right)$$

Subject to:

4.3.2. Mining capacity constraints

Eqs. and defines the mining capacity constraint for each period. Eq. ensures that the total blocks tonnage mined is equal to or less than the stipulated capacity of mining equipment while Eq. controls the minimum amount of materials mined. The tonnage of materials mined is the sum of the ore tonnage and waste tonnage represented as $o_{n,s}$ and $w_{n,s}$ respectively. The continuous decision variable y_{n}^{t} controls this extraction process in each period.

$$\sum_{n=1}^{N}(o_{n,s}+w_{n,s})y_{n}^{t}\leq Cu^{t} \qquad \forall_{t}\in\{1,...T\};\ \forall_{s}\in\{1,...S\};$$

$$\sum_{n=1}^{N}(o_{n,s}+w_{n,s})y_{n}^{t}\geq Cl^{t} \qquad \forall_{t}\in\{1,...T\};\ \forall_{s}\in\{1,...S\};$$

4.3.3. Processing capacity constraints

Eqs. and define the processing capacity of the mining operation for each period. Eq. sets the upper bound and Eq. sets the lower bound for the amount of ore processed. The deviation decision variables $od_{s,+}^{t}$ and $od_{s,-}^{t}$ are introduced to serve as buffers to the ore tonnage targets. These decision variables are penalized in the objective function (Eq.) to ensure that the ore tonnage targets are achieved with minimum deviation. These constraints are controlled by the continuous decision variables x_{n}^{t}, $od_{s,+}^{t}$ and $od_{s,-}^{t}$ in each period.

$$\sum_{n=1}^{N}(o_{n,s}\times x_{n}^{t})-od_{s,+}^{t}\leq Qu^{t} \qquad \forall_{t}\in\{1,...T\};\ \forall_{s}\in\{1,...S\};$$

$$\sum_{n=1}^{N}(o_{n,s}\times x_{n}^{t})+od_{s,-}^{t}\geq Ql^{t} \qquad \forall_{t}\in\{1,...T\};\ \forall_{s}\in\{1,...S\};$$

4.3.4. Grade blending constraints

Eq. defines the upper limit of the ore grade and Eq. defines the lower limit of the ore grade to be sent to the mill in each period. The deviation decision variables $gd^{t}_{s,+}$ and $gd^{t}_{s,-}$ are introduced to serve as buffers to the ore grade targets. These decision variables are penalized in the objective function (Eq.) to ensure that the ore grade targets are achieved with minimum deviation. These constraints are controlled by the continuous decision variables x^{t}_{n}, $gd^{t}_{s,+}$ and $gd^{t}_{s,-}$ in each period.

$$\sum_{n=1}^{N} g_{n,s} \times (o_{n,s} \times x^{t}_{n}) - \sum_{n=1}^{N} \overline{g}^{t} \times (o_{n,s} \times x^{t}_{n}) - gd^{t}_{s,+} \leq 0 \quad \forall_{t} \in \{1,...T\};\ \forall_{s} \in \{1,...S\};$$

$$\sum_{n=1}^{N} g_{n,s} \times (o_{n,s} \times x^{t}_{n}) - \sum_{n=1}^{N} \underline{g}^{t} \times (o_{n,s} \times x^{t}_{n}) + gd^{t}_{s,-} \geq 0 \quad \forall_{t} \in \{1,...T\};\ \forall_{s} \in \{1,...S\};$$

4.3.5. Block precedence constraints

Eqs. to enforce the block extraction precedence constraints. Binary integer decision variable, b^{t}_{n}, is used to control the precedence of block extraction. b^{t}_{n} is equal to one if the extraction of mining blocks has started by or in period *t*; otherwise, it is zero. For each mining block *n,* Eq. check the set of immediate predecessor blocks in $H_{n}(D)$ that must be mined prior to mining block *n.* Eq. checks that extraction of mining block *n* can start only when the mining block has not been previously extracted. Eq. ensures that once extraction of block *n* starts, this block is available for extraction in subsequent periods.

$$b^{t}_{n} - \sum_{i=1}^{t} y^{i}_{d} \leq 0 \quad d \in H_{n}(D) \quad \forall_{n} \in \{1,...N\};\ \forall_{t} \in \{1,...T\};$$

$$\sum_{i=1}^{t} y^{i}_{n} - b^{t}_{n} \leq 0 \quad \forall_{n} \in \{1,...N\};\ \forall_{t} \in \{1,...T\};$$

$$b^{t}_{n} - b^{t+1}_{n} \leq 0 \quad \forall_{n} \in \{1,...N\};\ \forall_{t} \in \{1,...T-1\};$$

4.3.6. Variable control constraints

Eq. ensures that the total ore material mined in any given scheduling period is less or equal to the sum of the ore, and waste materials mined for all realizations in that period. Eqs. and ensure that the sum of the partials of block *n* extracted is at most one over all periods at the end of the mine life.

$$\sum_{n=1}^{N} (o_{n,s} \times x^{t}_{n}) \leq \sum_{n=1}^{N} ((o_{n,s} + w_{n,s}) y^{t}_{n}) \quad \forall_{t} \in \{1,...T\};\ \forall_{s} \in \{1,...S\};$$

$$\sum_{t=1}^{T} y^{t}_{n} \leq 1 \quad \forall_{n} \in \{1,...N\};$$

$$\sum_{t=1}^{T} x_n^t \leq 1 \qquad \forall_n \in \{1,\ldots N\};$$

4.3.7. Non-negativity constraints

Eq. defines the non-negativity constraints for the decision variables for mining, processing, extraction precedence, and ore tonnage and ore grade target deviations. These constraints enforce that none of these variables can take on negative values during the optimization process.

$$x_n^t,\ y_n^t,\ b_n^t,\ od_{s+}^t,\ od_{s-}^t,\ gd_{s+}^t,\ gd_{s-}^t \geq 0 \qquad \forall_n \in \{1,\ldots N\};\ \forall_t \in \{1,\ldots T\};\ \forall_s \in \{1,\ldots S\};$$

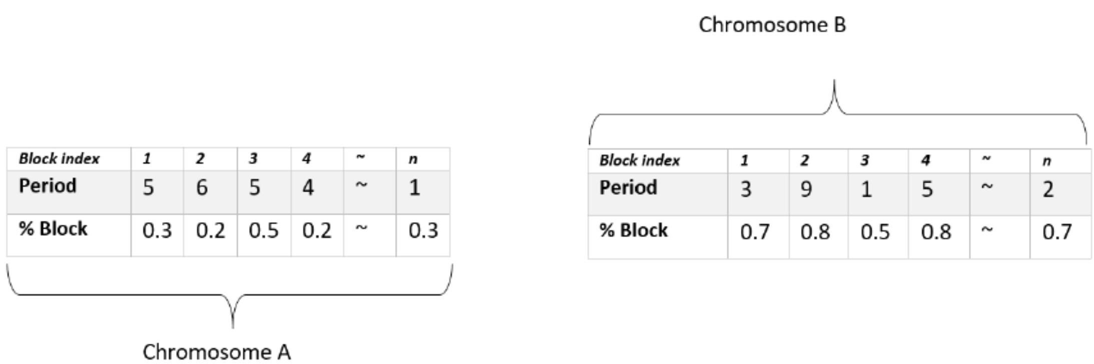
4.4. Genetic algorithm problem representation

The starting point of the optimization problem in GA is the problem initialization which consists of the chromosome encoding phase. A multi-layer chromosome encoding technique was used in this research: (1) a literal permutation encoding scheme, and (2) a real number or continuous variable encoding scheme. Fig. 8 shows a sample of the chromosome encoding represented in the GA. The literal permutation encoding was employed for the genes representing the period and realization where real number encoding was used for the genes representing the fractions blocks extracted.

Block index	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*~*	*n*
Period	5	6	5	4	3	1	1	2	2	6	7	8	7	8	8	~	8
% Block	0.3	0.2	0.5	0.2	0.1	0.3	0.6	0.9	0.4	0.22	0.23	0.41	0.74	0.25	0.33	~	0.2

Figure 8. Sample chromosome encoding.

In this research, every block is assumed to be mined over at most two periods. Therefore, the chromosomes were encoded in two halves as shown in Fig. 9. The first and second halves represent the fractions of each block mined at different periods respectively. The constraints in Eqs. and are therefore satisfied in the chromosome encoding when these two halves are reconciled at the end of the optimization. Every block in the model is mined at most once during the mine life.



Block index	*1*	*2*	*3*	*4*	*~*	*n*
Period	5	6	5	4	~	1
% Block	0.3	0.2	0.5	0.2	~	0.3

Block index	*1*	*2*	*3*	*4*	*~*	*n*
Period	3	9	1	5	~	2
% Block	0.7	0.8	0.5	0.8	~	0.7

Figure 9. Sample chromosome encoded in two halves.

Eq. was used in generating the genes in the chromosome representing the block fractions since this requires a continuous variable encoding. The other genes were generated using a Gaussian random distribution. The GA was implemented to optimize either a deterministic or stochastic production schedule based on input from the user. The objective function of the optimization was represented as a fitness function to test each solution in the population. The fitter population survives the current generation and proceeds in the iteration process.

4.4.1. Constraints handling and representation

The major constraint in the OPPS problem that presents great levels of complexities is the precedence constraint. The precedence constraint determines the sequence of block extraction and ensures that blocks on the surface are extracted in the same or an earlier period to blocks directly beneath them. As shown in Fig. 10, Blocks 1, 2 and 3 must be extracted prior to extraction of Block 10 or in the same period as Block 10. In three-dimensional (3D) block representation, every block has at least nine different blocks forming its precedence.

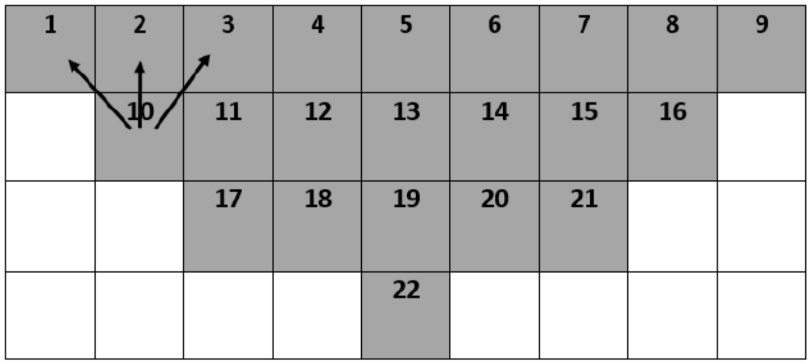


Figure 10. Block extraction precedence modified after Ben-Awuah and Askari-Nasab [12].

In order to ensure that the precedence constraints are enforced as defined, a check-and-repair method is implemented in the GA. In each population, if a block cannot be mined in period *t* due to precedence constraints, it is moved to the next period or a period where the requirements of immediate predecessor blocks in $H_n(D)$ are not in violation. The entire population is then normalized to accept the current gene as a feasible solution for evaluation. For every violation of the normalized precedence constraints, the fitness function is penalized to ensure that the optimizer finds a feasible solution in each generation.

Capacity constraints are treated as knapsack problems. Knapsack problems are primarily resource allocation problems. The maximum allowable capacity is derived from the optimization problem since the scheduling is performed annually (periods). All the extracted blocks for that period should be less or equal to the maximum capacity for that period. Using sliding window technique [8; 20], an array containing the tonnage of every block scheduled in each period is created. The total tonnage of every period is checked against the maximum capacity from the optimization problem. When the maximum capacity for a period is reached, all subsequent blocks or block fractions that were originally in that period are moved to the next period. The population is then normalized afterwards so that the current population contains the right blocks that satisfy the capacity constraint for that period. The window is then slid to the next period and the steps above are repeated until the last period is reached.

4.4.2. Normalization

Due to the randomness associated with GA at every stage of the optimization process, the genes in each population tend to violate constraints when mutation or crossover occurs. There is therefore the need to normalize the population after each mutation and crossover to ensure that the constraints are satisfied [26]. This process is termed as normalization or regularization. Fig. 11 shows an example of a double point crossover that violates the precedence constraints. As illustrated in Fig. 11(A), before crossover occurs, both Parents 1 and 2 are feasible solutions satisfying the precedence constraints. That is, all blocks on the lower level are extracted in periods later than or equal to extraction periods of blocks above them. During crossover, the genes in Parents 1 and 2 representing Blocks 10, 11, 12 and 13 within the crossover point are swapped. Child 1 receives genes from Parent 2 whiles Child 2 receives genes from Parent 1. As highlighted in Fig. 11(B), after the crossover, both Child 1 and Child 2 violate the precedence constraint because Block 10 in Child 1 and Block 18 in Child 2 are extracted in periods earlier than the blocks above them and therefore require normalization. This process ensures that a population with a feasible solution is kept at all times throughout the GA optimization process.

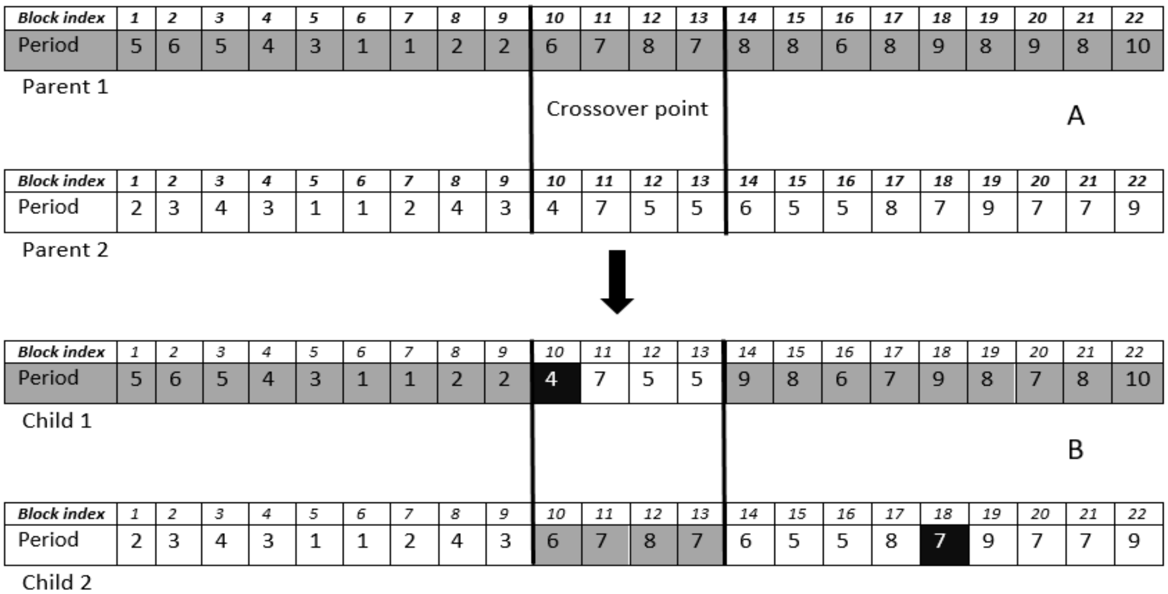


Figure 11. Sample crossover showing precedence constraint violation. (A) Illustrates a feasible solution before crossover. (B) Demonstrates a solution that violates the precedence constraint after crossover.

4.4.3. Mutation and crossover strategy

Genetic operators such as crossover and mutation are key to the success of any genetic algorithm optimization process and as such finding the best strategy for them is always paramount. In this research, a 'smart' mutation was implemented to curtail the complexities in handling the partial extraction of blocks in the population. Fig. 12 shows a sample chromosome with twenty genes. To represent a chromosome with *n* number of blocks or genes; the corresponding length of that chromosome is 2*n.* This method is used to implement the assumption that each block can be extracted in at most two periods. The first part of the chromosome represented as Chromosome A in Fig. 12 shows portions of the blocks and corresponding periods the extraction occurs in; same for Chromosome B.

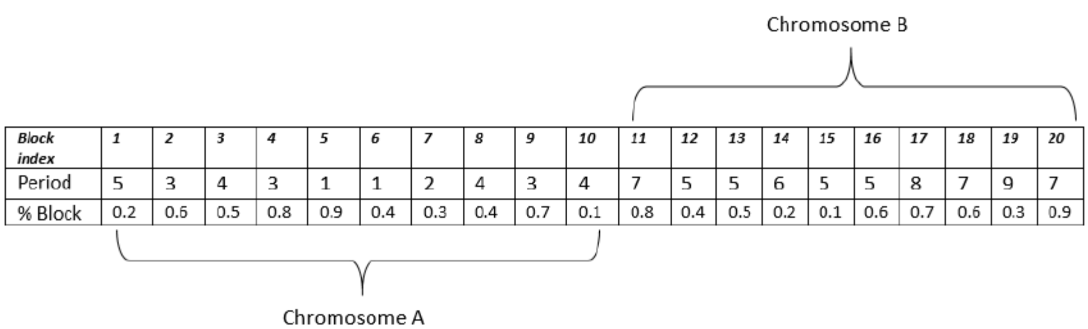


Figure 12. Sample chromosome representing the multi-part chromosome encoding.

During the mutation process, a probability of mutation is applied to determine the gene that must mutate. In Fig. 13, genes at block index 6, 7, 8 and 9 of Chromosome A will mutate per the probability of mutation applied. This however needs to occur in tandem with the corresponding genes in Chromosome B. The mutation algorithm keeps the index of the genes in Chromosome A and determines the corresponding position of the other genes in Chromosome B. When the mutation occurs in Chromosome A, a subsequent mutation and normalization takes place in Chromosome B. The genes representing the periods are mutated at random from a feasible set of periods that the block can be extracted in. Based on the precedence constraints. Given a feasible set of period (3, 2, and 4) for Block 6, a period is chosen at random and assigned to the block during the mutation for the period of that block. The mutation for the fractions of blocks that should be extracted is determined by Eq. . The mutation algorithm again keeps the index of the gene representing the fraction of the block to be extracted in Chromosome A and determines the corresponding position of the other gene in Chromosome B. The double point crossover used in this research also employs the same chromosome representation and index retention approach. Fig. 14 shows a sample chromosome after mutation showing the result of mutation for Chromosome A and Chromosome B. Table 1 shows the pseudo code for the proposed mutation strategy used to handle the block extraction by the GA.

Fig. 15 shows the flow chart for the GA optimization process and sub processes. A two-step GA framework was implemented; where based on the data provided and the input from the user, the framework will decide whether the problem is stochastic or conventional before proceeding to evaluate the fitness function for each population.

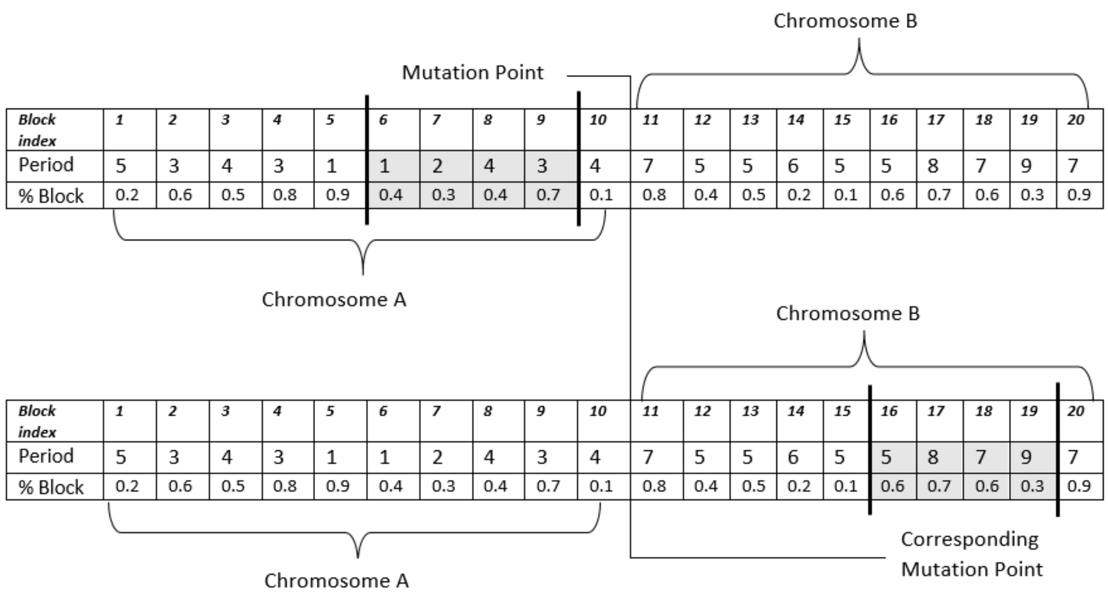


Figure 13. Sample chromosome before mutation showing the mutation point of Chromosome A and Chromosome B.

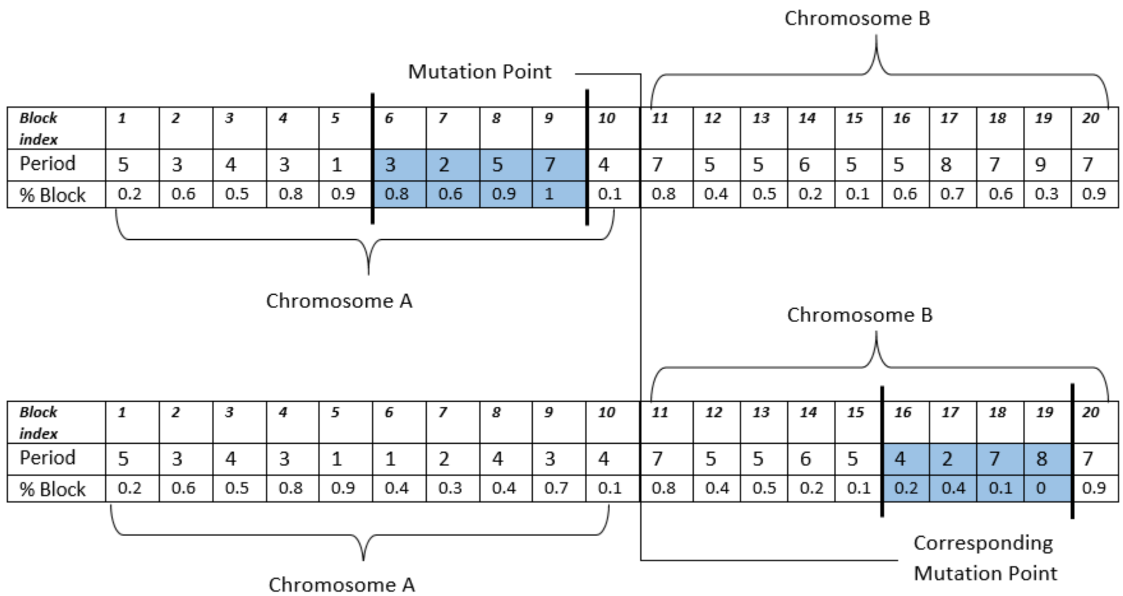


Figure 14. Sample chromosome after mutation showing the result of mutation for Chromosome A and Chromosome B.

Table 1. Pseudo code for the proposed mutation strategy.

Pseudo Code for proposed mutation strategy

Start
get *chromosomeLength;*
get *popabilityOfMutation;*
get *numberOfBlocks*
Select number of individual to be mutated based on the propablilityOfMutation.
split the chromosome into two halves A and B based on numberOfBlocks
While *n = Number of individuals to be mutated*
Get the index a of the individual in chromosome A and corresponding index b in chromosome B
Perform mutation on gene n at a in chromosome A and gene n at b in chromosome B
EndWhile

Combine chromosome A and B after mutation and return to the main generation

End

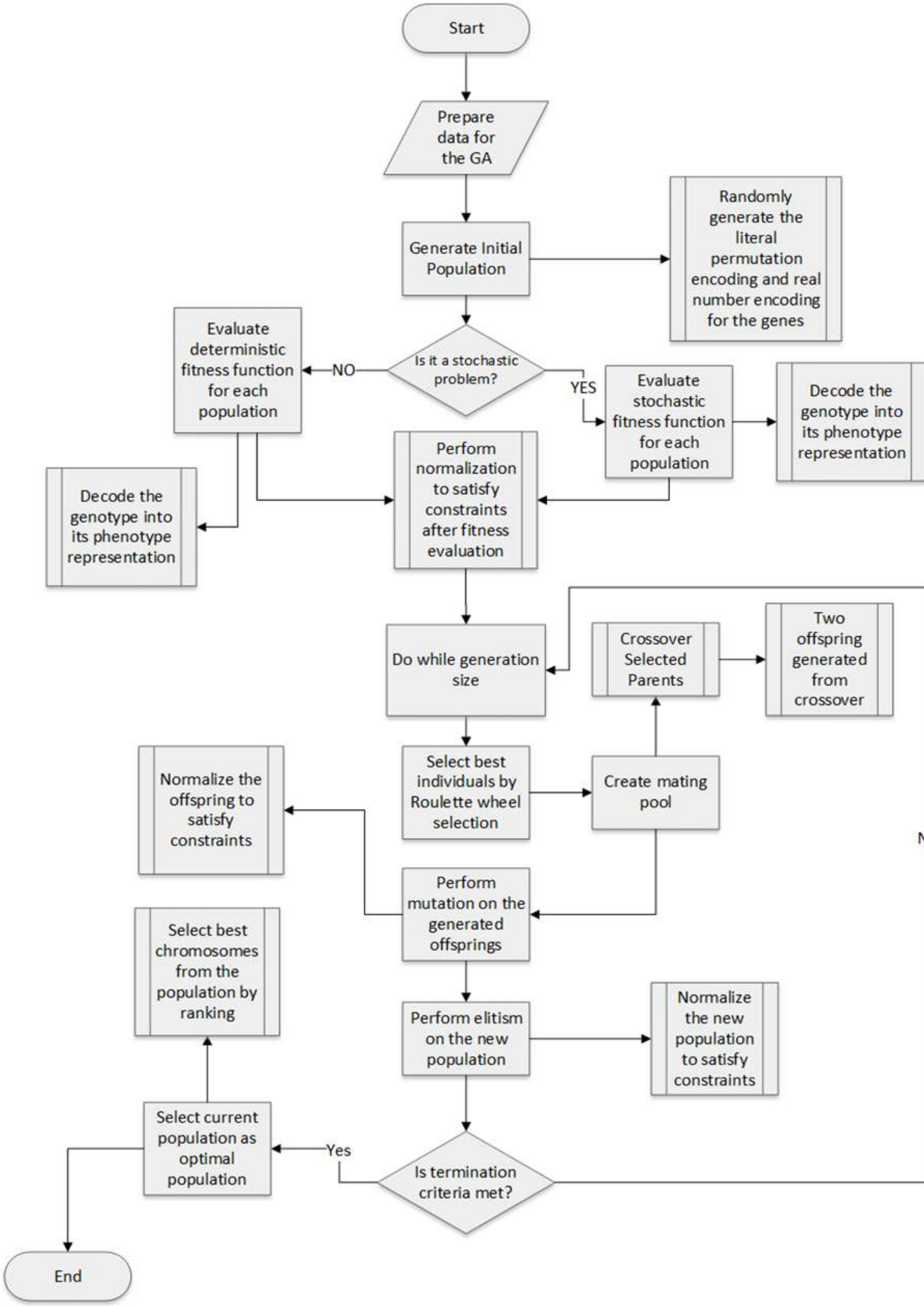


Figure 15. Proposed GA optimizations and sub process.

5. Computational Experiments

The GA model was implemented for two different oil sands datasets obtained from Ben-Awuah and Askari-Nasab [12] and Mbadozie [70]; the first case study with 4476 blocks and the second with 1569 blocks. Two scenarios were implemented for the first case study as proof of concept: (1) A deterministic model with GA (DGA); and (2) A stochastic model with GA (SGA). Subsequently, the SGA model was implemented for the second case study. The orebody model for the DGA was based on Ordinary Kriging which did not consider grade uncertainty. The SGA scenario considered grade uncertainty through equally probable orebody realizations generated using sequential Gaussian simulation. Table 2 shows the block model data and Table 3 outlines the economic parameters for both case studies. Table 4 highlights the mining and processing requirements for both case studies. In Table 5, the risk parameters for the stochastic scenario are outlined. The DGA results were compared with a similar implementation using MILP model with CPLEX formulated by Mbadozie (2022). The SGA results were also compared with a similar implementation using a Stochastic MILP (SMILP) model with CPLEX formulated by Mbadozie (2022). These comparisons were done to assess the practicality of the generated schedules as well as the NPV and computational efficiency. The production schedule for Case study 1 was optimized over ten periods whereas Case study 2 was scheduled over twenty periods. The primary focus for the GA framework was to generate a uniform and practical schedule while respecting the constraints for all periods in the schedule. The DGA and SGA were implemented in a MATLAB environment (MathWorks Inc., 2020) on a Lenovo ThinkPad computer with Intel(R) Core(TM) i7-8565U CPU @ 1.80GHz and 16 GB of RAM. Table 6 outlines the GA parameters used in both case studies.

Table 2. Oil sands block model data for case studies.

Block model data (Units)	Case study 1	Case study 2
Total block tonnage (Mt)	318	3539
Total ore tonnages (Mt)	145	1141
Block dimensions (m x m x m)	50 x 50 x 15	300 x 300 x 15
Mine life (Years)	10	20
Number of blocks	4476	1569

Table 3. Economic parameters for case studies.

Parameter (Units)	Value
Mining cost ($/tonne)	4.60
Processing cost ($/tonne)	5.03
Selling price ($/bitumen %mass)	4.50
Economic discount rate (%)	10

Table 4. Mining and processing requirements for case studies.

	Case study 1		Case study 2	
Parameters (Units)	**Min value**	**Max value**	**Min value**	**Max value**
Mining capacity (Mt/year)	25	32	100	150

Processing capacity (Mt/year)	10	14	25	50
Ore bitumen grade (%m)	7	16	7	16

Table 5. Risk parameters for stochastic scenario.

Parameters (Units)	value
Number of realizations	20
Cost of shortage in ore production ($/tonne)	5
Cost of excess in ore production ($/tonne)	10
Cost of shortage in ore bitumen grade ($/%m)	2.5
Cost of excess in ore bitumen grade ($/%m)	1.5

Table 6. GA parameters used for both case studies.

GA parameter	**Description**
Population size	**20**
Selection type	**Roulette wheel**
Crossover type	**Double point**
Probability of mutation	**0.2**
Probability of crossover	**0.85**
Probability of elitism	**0.2**
Maximum generations	**1000**

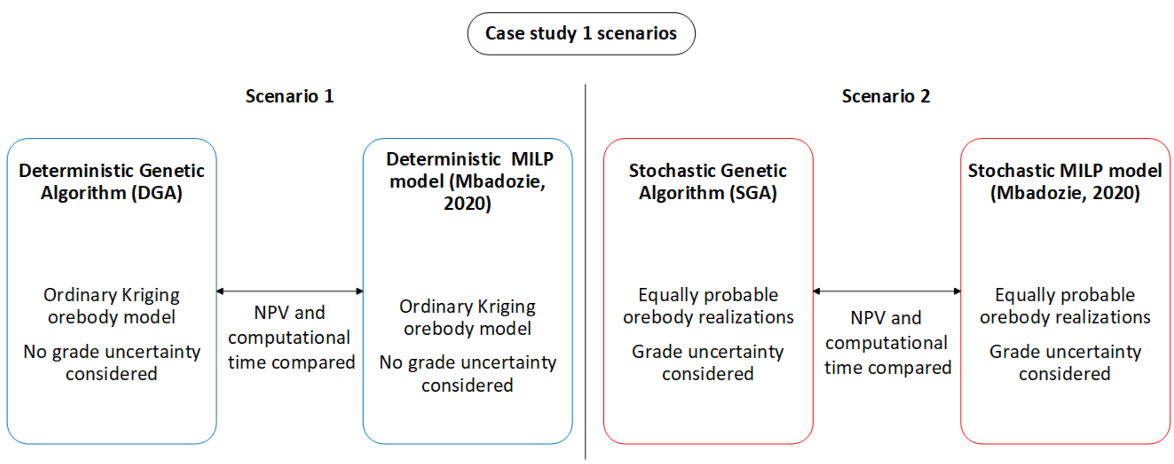


Figure 16. Case study 1 scenario comparisons.

Fig. 16 presents a summary of the experimental methodology and comparisons made between the DGA and MILP model, and SGA and SMILP model for Case study 1. For Case study 2, the SMILP integer solution was terminated after 28 days. Therefore, CPLEX was used to solve the relaxed LP problem to estimate the optimality gap for the GA results. Eq. by IBM ILOG CPLEX Inc [55] was used to ascertain the optimal difference between the GA solution and the relaxed LP solution by CPLEX.

$$\frac{|\,bestbound - bestinteger\,|}{(1e-10+|\,bestinteger\,|)}$$

The *bestbound* in Eq. for an optimization problem refers to the objective function value at which a feasible optimal solution could potentially exist [55]. In the case of an intractable integer problem, the *bestbound* is the only solution. This is the case because the relaxed problem does not have a *bestinteger* solution. Therefore, in determining the gap for the GA solution using Eq. , the relaxed objective function value is represented as the *bestbound* and the solution for the GA as the *bestinteger* to compute the optimality gap.

5.1. Results and discussion

5.1.1. Case study 1 comparative analysis: MILP model with CPLEX and DGA results

The results from the DGA for Scenario 1 was compared with a similar implementation from the MILP model with CPLEX at 0% optimality gap. The NPV generated from the proposed DGA and MILP model with CPLEX were $1,830 M and $1,929 M respectively. The total time taken for the MILP to generate its results was 4.1 hours whereas the DGA generated its results in 1.9 hours. The NPV of the DGA solution was 5.1% less than that of the MILP solution. The DGA was able to generate a uniform schedule over the mine life. The production schedule results generated by the DGA are shown in Table 7. Fig. 17 and Fig. 18 shows the cross-sectional view and the plan view of the extraction sequence generated by the DGA for the production schedule respectively. It can be seen from Fig. 17 that, the DGA model enforced the precedence constraints set in the optimization problem; blocks were mined according to their precedence and scheduled appropriately. Blocks on the lower levels were mined in later periods as opposed to blocks on the surface The total tonnage and ore tonnage generated by the DGA are shown in Table 8. Table 8 also shows the duration and NPV comparison of the MILP with the DGA results. It can be seen from Fig. 19A that the DGA respected the maximum annual mining capacity constraint which was set at 32 Mt across all the scheduling periods. Although less material was extracted in the first period, the extraction gradually ramped up and was uniform for the subsequent periods until declining in the last period. The maximum annual processing capacity of 14 Mt was respected by the DGA as seen in Fig. 19A. Fig. 20 shows the graph of the average ore bitumen grade for the DGA and the MILP with CPLEX production schedules. It can be seen from Fig. 20 that there is a gradual decline of the ore bitumen grade as the mine life progresses, which ultimately influences the NPV.

Table 7. Scheduling results for the DGA.

Period	Total tonnage (Mt)	Ore tonnage (Mt)	Average ore bitumen grade (%m)
1	24.41	8.51	12.87
2	31.93	13.32	12.32
3	31.94	13.54	12.00
4	31.90	13.96	11.31
5	31.93	13.91	11.33
6	30.91	13.91	10.54
7	31.93	13.90	10.81
8	31.90	13.94	9.92
9	31.27	13.93	8.76
10	9.13	6.70	7.92

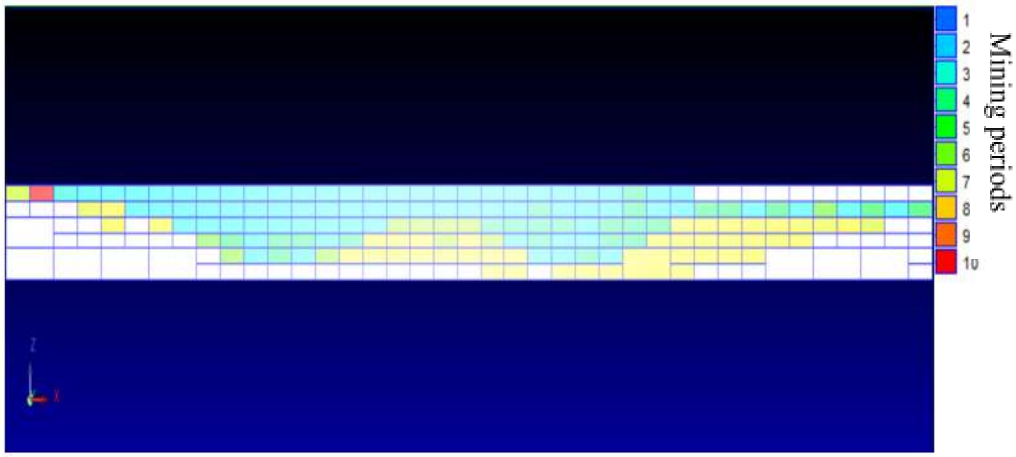


Figure 17. Cross sectional view of the block extraction sequence by the DGA.

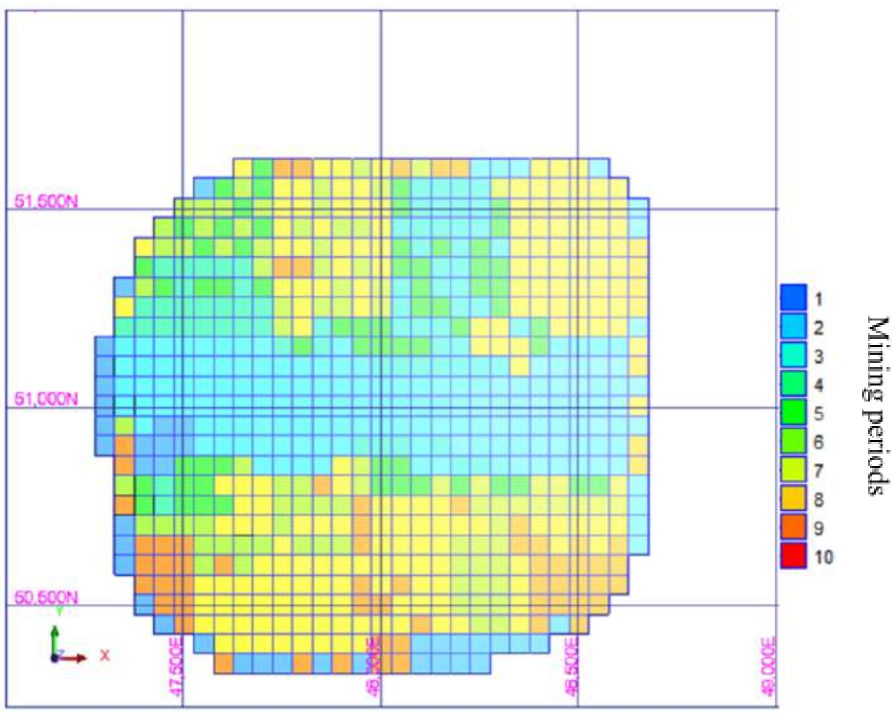


Figure 18. Plan view of the block extraction sequence by the DGA on Bench 3.

Table 8. Solution comparison between the MILP model with CPLEX and the DGA.

Parameter (Units)	MILP model with CPLEX	DGA
Number of blocks	4476	4476
Tonnage mined (Mt)	287	285
Ore processed (Mt)	121	124
NPV ($M)	1929	1830
Time (hours)	4.1	1.9
Optimality gap (%)	0	-

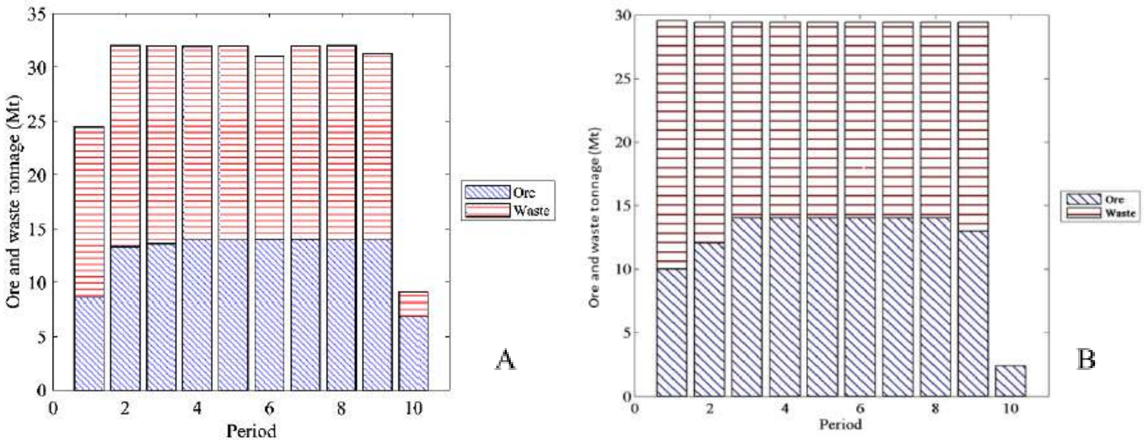


Figure 19. Total tonnages mined. (A) Illustrates the total tonnage mined by the DGA and (B) illustrates the total tonnage mined from the MILP with CPLEX [71].

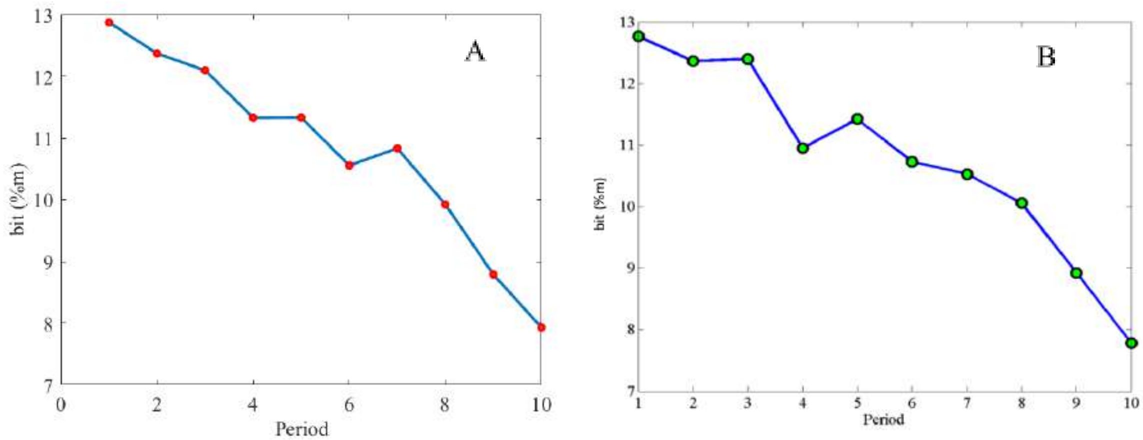


Figure 20. Average ore bitumen grade from the DGA illustrated in (A) and average ore bitumen grade from the MILP model with CPLEX illustrated in (B).

For Scenario 2, the motivation for the SGA was to ascertain the impact of grade uncertainty on the production schedule. To achieve this, multiple simulated orebody realizations generated through SGS were used as input to the optimization problem. The NPV generated from the SGA and SMILP model with CPLEX were $2,128 M and $2,248 M respectively. The NPV for the SGA was 5.3% less than that for the SMILP model with CPLEX. The optimality gap for the SMILP model with CPLEX was set at 5%. The total time taken for the SMILP to generate its results was 11.70 hours whereas the SGA generated its results in 2.9 hours. Table 9 shows the scheduling results. Fig. 21 and Fig. 22 show the extraction sequence of the SGA. Table 10 shows the solution comparison between the SMILP model with CPLEX and the SGA. The impact of grade uncertainty is evident in the NPV generated by the stochastic schedule. The NPV generated by the SGA schedule was 16.3% better than the NPV from the DGA schedule. In Fig. 23, a comparison between the SGA and the SMILP model with CPLEX is shown. The capacity constraints were respected by the SGA as seen in Fig. 23A. Fig. 24 shows the average ore bitumen grade comparison between the SGA and SMILP model as well as comparison with individual orebody realizations. From Fig. 25, it can be observed that, the stochastic model maintained a balanced average grade throughout the mine life, which accounted for the improvement in NPV compared to the DGA's average grade, which declined gradually as the mine life progressed.

Table 9. Scheduling results for the SGA.

Period	Total tonnage (Mt)	Ore tonnage (Mt)	Average ore bitumen grade (%m)
1	24.44	9.71	11.67
2	31.92	13.30	11.80
3	31.91	13.51	11.61
4	31.93	13.53	11.72
5	31.91	13.84	11.67
6	30.90	13.90	11.70
7	31.93	13.93	11.52
8	31.94	13.98	11.65
9	31.22	12.9	11.41
10	9.10	5.70	11.73

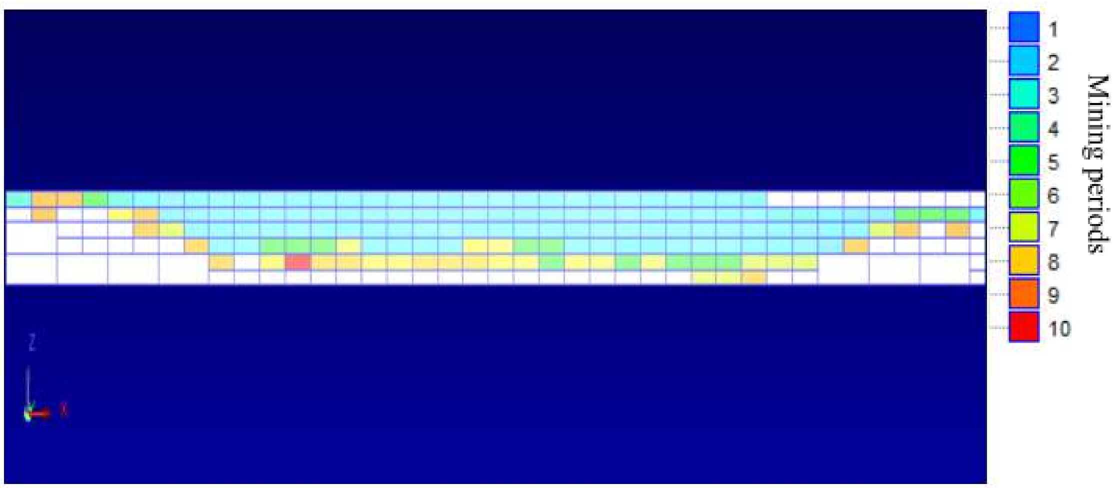


Figure 21. Cross sectional view of the block extraction sequence by the SGA.

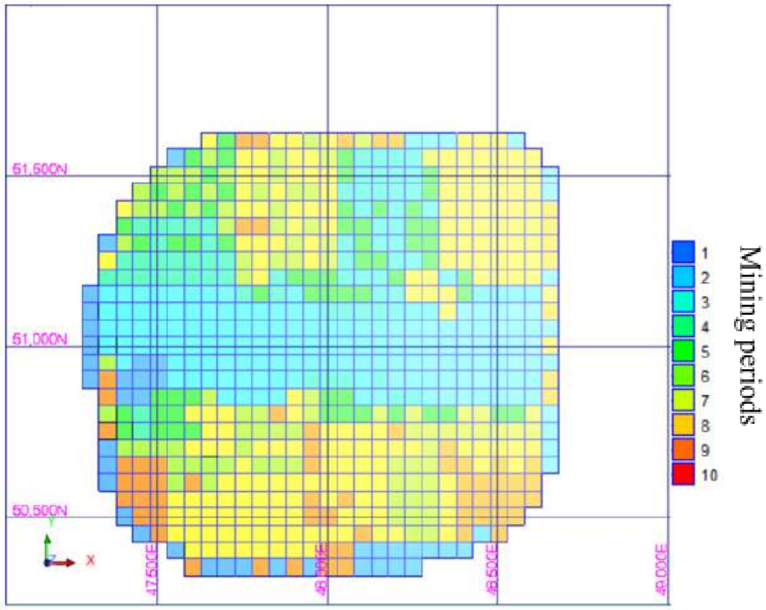


Figure 22. Plan view of the block extraction sequence by the SGA on Bench 3.

Table 10. Solution comparison between the SMILP model with CPLEX and the SGA.

Parameter (Units)	SMILP model with CPLEX	SGA
Number of blocks	4476	4476
Tonnage mined (Mt)	290	287
Ore processed (Mt)	124	125
NPV ($M)	2248	2128
Time (hours)	11.70	2.9
Optimality gap (%)	5	-

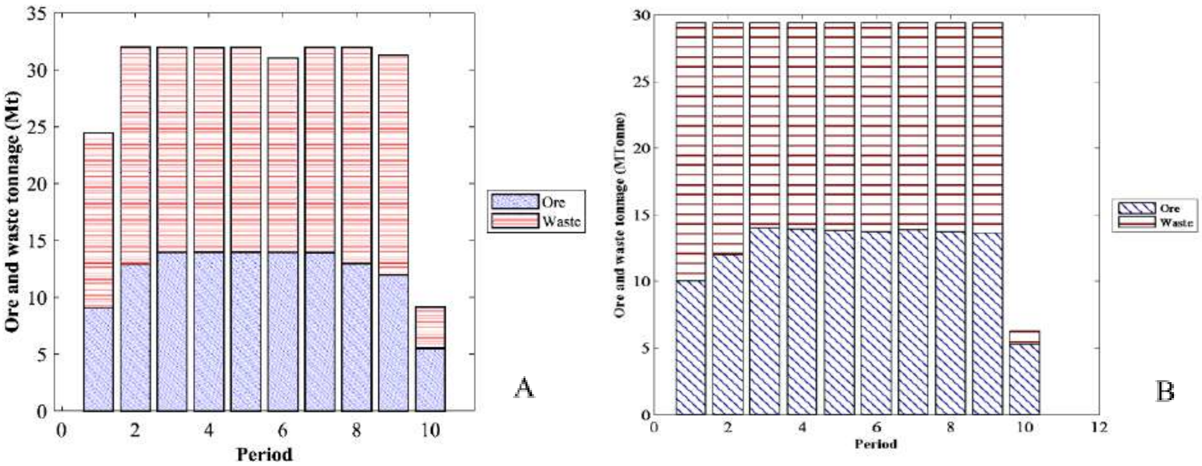


Figure 23. Total tonnages mined. (A) Illustrates the total tonnage mined by the SGA and (B) illustrates the total tonnage mined from the SMILP with CPLEX [71].

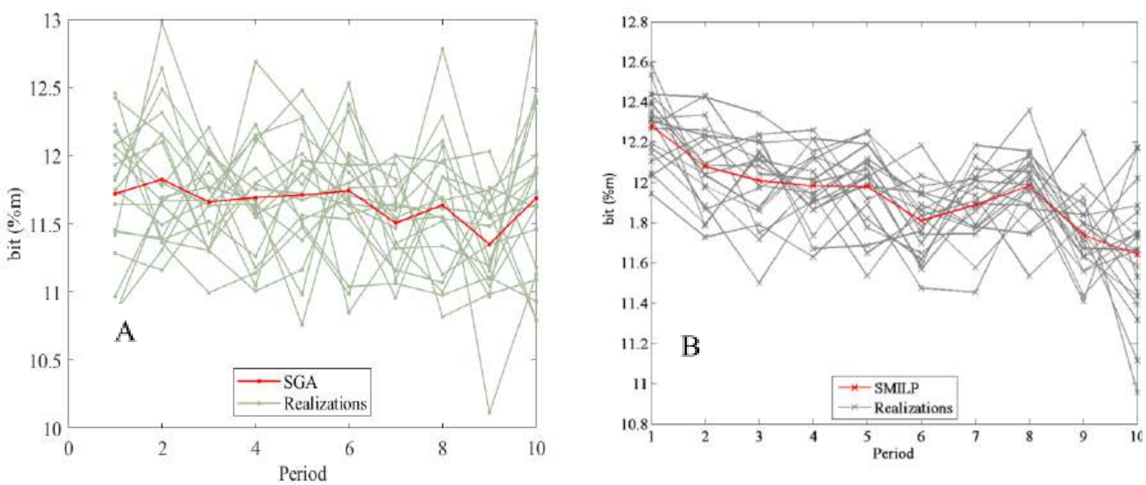


Figure 24. Average ore bitumen grade from the SGA illustrated in (A) with 20 realizations and the average ore bitumen grade from the SMILP model with CPLEX illustrated in (B) with 20 realizations.

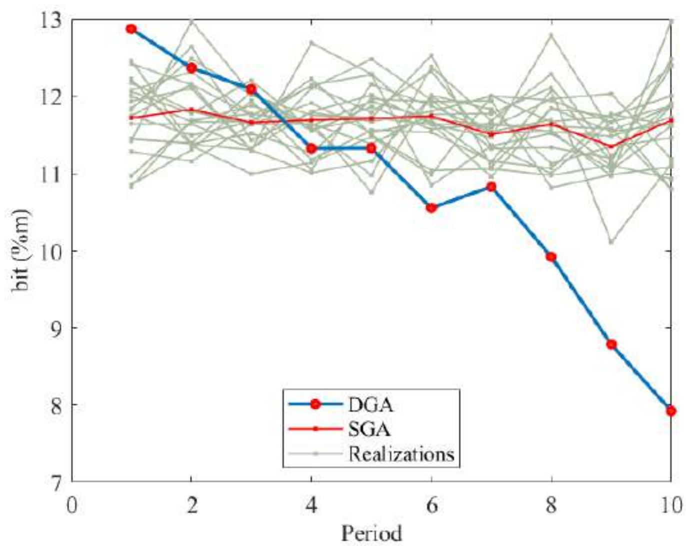


Figure 25. Average ore bitumen grade comparison for the DGA, SGA and 20 realizations.

5.1.2. Case study 2 comparative analysis: SMILP model with CPLEX and SGA results

The solution for Case study 2 while the SMILP model was at a gap of 101% after 28 days, the SGA generated a solution in 1.5 hours. This further emphasizes the application of metaheuristics to NP-hard combinatorial optimization problems. In the bid to verify and compare the results generated by the SGA, a relaxed LP form of the problem was solved and Eq. was used to compute the optimality gap. Based on Eq. , the objective function value generated by the relaxed LP was 12,810 and that for the SGA was 11,629. Using Eq. gives us a gap of 10.16%. This therefore means the SGA solution is in the worst case scenario at 10.16% of the optimal solution to the SMILP model if it exists since the relaxed LP solution is the upper bound to it. The NPV generated from the SGA was $10,045 M. Table 11 shows the total tonnage, ore tonnage and average ore bitumen grade for the GA scheduling results. The solution comparison for NPV, runtime, and optimality gap are summarized in Table 12. The SGA results respected the maximum annual mining capacity constraint set at 150 Mt and maximum annual processing capacity constraint set at 50 Mt as seen in Fig. 26. Fig. 27 shows the average ore bitumen grade per period for the SGA schedule.

Table 11. Scheduling results for the SGA.

Period	Total tonnage (Mt)	Ore tonnage (Mt)	Average ore bitumen grade (%m)
1	149.91	29.98	9.80
2	149.84	33.96	10.14
3	149.94	37.92	9.79
4	149.62	39.98	9.53
5	149.72	49.95	9.94
6	149.87	49.93	10.04
7	149.82	49.82	9.56
8	149.11	49.91	10.16
9	149.32	49.92	9.93
10	149.33	49.90	9.82

11	149.28	49.96	9.79
12	149.33	49.89	9.39
13	149.36	49.90	9.81
14	149.41	49.93	10.22
15	149.28	47.92	10.05
16	149.46	44.86	9.78
17	149.64	44.94	10.30
18	149.25	44.86	9.84
19	149.55	44.92	9.62
20	149.30	28.64	9.17

Table 12. Solution comparison between the SMILP model with CPLEX and the SGA.

Parameter	SMILP model with CPLEX	SGA
Number of blocks	1569	1569
Tonnage mined (Mt)	-	2990
Ore processed (Mt)	-	897
NPV ($M)	-	10054
Runtime (hours)	*Terminated after 28 days	1.5
Optimality gap from relaxed LP (%)	101	10.6

* Job scheduling policies - Compute Canada Cedar Cluster

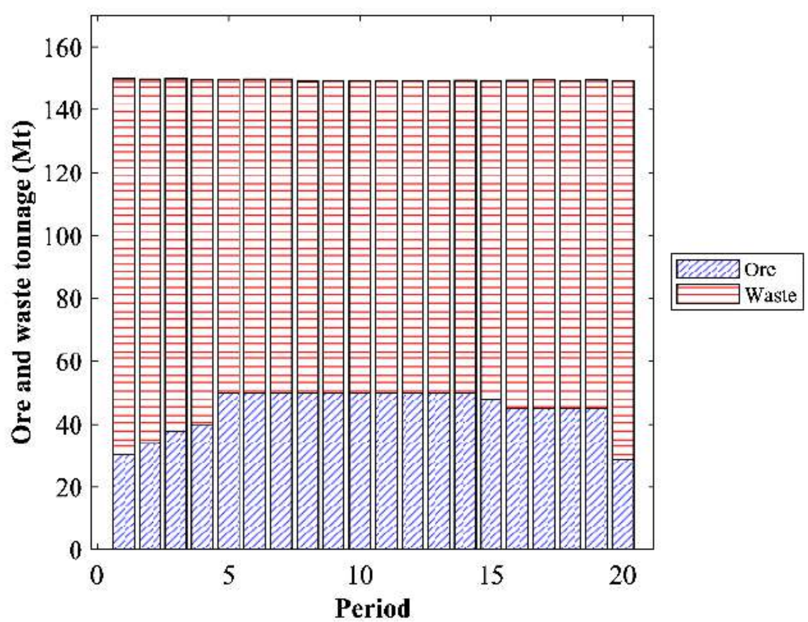


Figure 26. Total tonnage mined for the SGA.

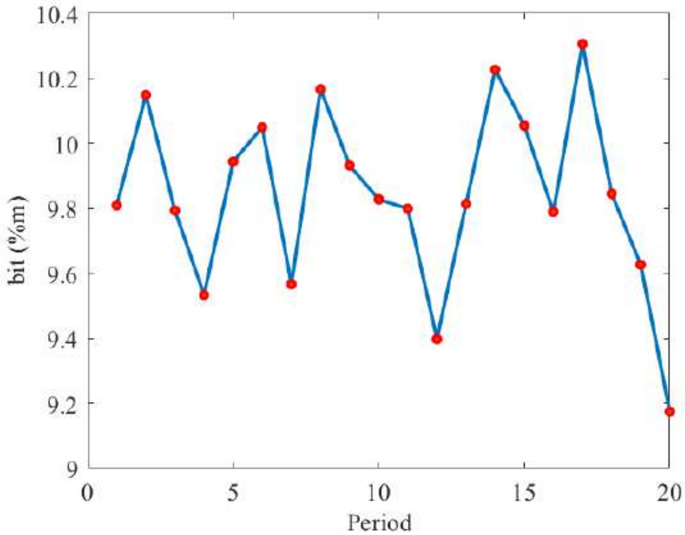


Figure 27. Average ore bitumen grade for the SGA.

6. Conclusions and Future Work

In this research, the authors presented a GA framework for solving the OPPS problem and evaluated it with two case studies. A multiple chromosome-encoding scheme was proposed and implemented to represent the blocks and periods of extractions. Deterministic and stochastic production scheduling scenarios were investigated in this research; the deterministic production schedule with a block model based on ordinary kriging, and the stochastic production schedule based on SGS orebody realizations. The equally probable simulated orebody realizations capture the varying grade distribution in the mineralization of the deposit to allow for consideration of grade uncertainty. Due to the multiple chromosome encoding scheme, the GA was capable of fractional block processing. In the implementation of the GA, the relaxed LP solution was used as the upper bound to estimate the optimality gap for the GA solution. The solutions from the GA were compared with that from mathematical programming models with CPLEX solver to assess the practicality of the generated schedules as well as the NPV and computational efficiency.

For deterministic production scheduling in Case study 1 Scenario 1, the NPV of the DGA schedule was 5.1% less than that of the MILP model with CPLEX schedule while there was a 53.7% improvement in computational time comparing the DGA solution runtime to that of the MILP model with CPLEX solution runtime. For the second scenario based on stochastic production scheduling, while the NPV of the SGA schedule was 5.3% less than that of the SMILP model with CPLEX schedule, there was 75.2% improvement in computational efficiency comparing the SGA solution runtime to that of the SMILP model with CPLEX solution runtime. It is also important to note that the NPV generated by the SGA schedule was 16.3% better than the NPV from the DGA schedule. For Case Study 2, the solution from the SMILP model with CPLEX was terminated after 28 days at 101% gap while the SGA generated solution in 1.5 hours at 10.6% optimality gap. In both case studies, the GA models produced uniform schedules over the life of mine, although the NPVs were lower than that from the MILP and SMILP models with CPLEX solver.

In summary, the results generated by the GA were encouraging in the area of computational efficiency. In cases where the mathematical programming model solution runtime is lengthy or intractable, GA proves to be capable of generating a 'good' solution at a reasonable runtime. The authors' ongoing research aims at extending the GA model to include stockpiling and investigating the best combination of genetic parameters to improve the GA computational time and solution quality.

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Review of Recent Developments in Short-Term Mine Planning and IPCC

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ABSTRACT

Equipment allocation is an integral part of short-term planning. In the past few decades, In Pit Crushing and Conveying (IPCC) has gained much momentum to replace trucks partially or fully in large open pit mines because of increasing fuel cost, labor cost and low operating cost of conveyors. This article aims at reviewing the work done on short-term mine planning and IPCC in open pit mines to find research gaps and future research opportunities in short-term planning with IPCC as the prime means of material handling. The most recent literature since 2010 on short-term planning, based on different formulation and solution approaches, and IPCC, based on primary objectives such as optimum crusher location, economic/environmental comparison etc., have been reviewed. The review reveals that there is hardly any short-term planning model that can generate mine extraction sequences with IPCC integration. The authors propose a theoretical problem formulation to explore this research gap as a future research direction. One of the key contributions of this article is to point out the fact that developing a short-term planning methodology considering the IPCC system would be a pioneering step in mine planning literature.

1. Introduction

Open pit or surface mining is a highly capital-intensive operation. Studies have shown that about 50% of operating costs in surface mining are allocated to truck-shovel operation and the number can go up to as much as 60% in large open-pit mines (Moradi Afrapoli and Askari-Nasab 2017). Therefore, hauling has the highest operating cost among all the material handling operations in open-pit mines. Short-term planning is concerned with operational activities such as, maximizing the production rate, equipment availability, utilization, minimizing equipment movement and cost of ore extraction, etc. In pit crushing and conveying (IPCC) has gained much momentum in the past few decades because of high fuel cost, labor cost and low operating cost of conveyors (McCarthy 2011). Many mines have been employing IPCC in recent years with a comparatively smaller fleet of trucks. S11D, the largest iron ore mine in Brazil valued at $14.3 billion, started its operation in 2017 with a truckless IPCC operation. The total length of the conveyor belts operating in the mine and the plant is an astounding 68 km (Topf 2017). A list of all mines from 1956 to 2014 with in-pit crushing and conveying has been summarized by (Ritter 2016). Researchers are now looking to integrate IPCC systems in mine planning and scheduling. Mine planning can be divided into long-term and short-term planning based on the planning time-horizon and the objectives being optimized.

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1.1. Short-term vs Long-term Planning

Short and long-term planning are different from several aspects. These include but are not limited to the type of block model used as input to the planning process; the time horizon (weekly or shorter time periods vs. longer time periods i.e., quarterly to yearly); the objectives being optimized; the constraints that must be considered during optimization and the level of detail to which mine operations are modelled. In the long-term context, a block model generally consists of millions of equally sized blocks. Precedence exists between the blocks in this model, defining constraints on sequences of blocks to be extracted.

The primary objective of any mining project is to maximize the profit by keeping the cost minimum. While the long-term plan is created at the management level to maximize the net present value (NPV) throughout the life of mine, the short-term planning aims at optimizing the operational activities like shovel allocation, grade blending, truck requirement etc. to help achieve the ultimate long-term schedule. The time horizon of short-term planning can be monthly, weekly or even daily. Short-term planning can be branched into production planning in upper level and dispatching in lower-level stages. The several stages of mine planning are delineated in Figure 1.

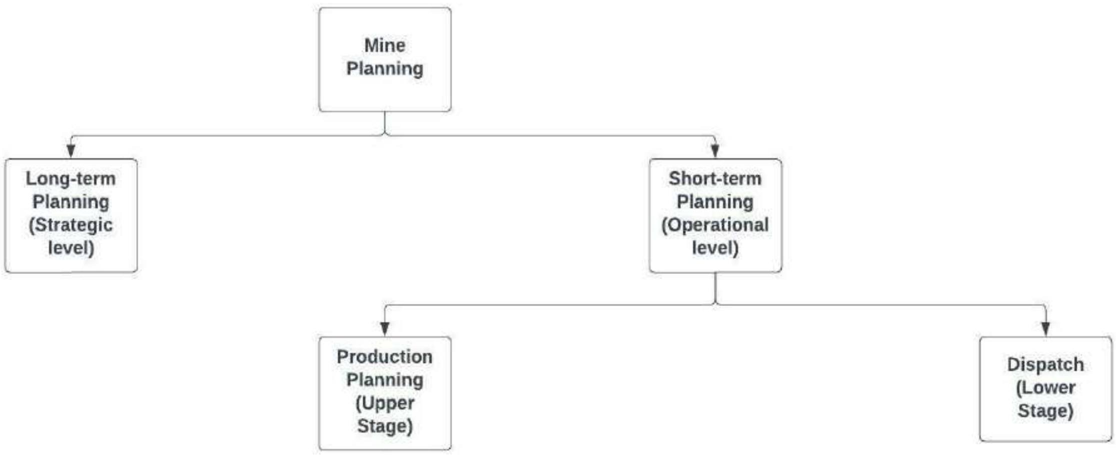

Figure 1. Mine planning stages.

1.2. In-Pit Crushing and Conveying (IPCC)

In-pit crushing and conveying is not a new concept in mining. It has been in use since 1956 (Osanloo and Paricheh 2020) in mines to partially or fully replace trucks in mining operation. However, it has thrived in the past two decades for several reasons discussed in the next section of this article. IPCC can be divided into three categories: fully mobile, semi-mobile and fixed. Fully mobile IPCC can be loaded directly from shovels, which completely eradicates the need for off-highway trucks. However, it is the least flexible and not quite suitable for deep metalliferous mines (Dean, et al. 2015). Semi-mobile IPCC (SMIPCC) systems are the most flexible. They retain a small haulage fleet for transferring material from the shovel to the crusher, which makes them the most suitable option for mines that have been being actively extracted for years (McCarthy 2011). These crushers are relocated once every one to ten years and have the highest potential for being the most popular IPCC system in large mines in coming years because of its increasing capacity and flexibility (Osanloo and Paricheh 2020). Fixed-type in-pit crushers are placed inside the pit and are not relocated at least for a period of 15 years or more. They are also typically installed in a concrete structure and fed by trucks. Up until 2014, 209 fully-mobile, 213 semi-mobile and 25 fixed in-pit crushers were in use around the world (Osanloo and Paricheh 2020).

1.2.1. Why IPCC is Thriving in Open Pit Mines

(McCarthy 2011) explained the advantages, disadvantages and the reasons of using IPCC in open pit mines. We will review some of these reasons for the readers' ease and to shed light on IPCC integration to existing and new mines:

- ✔ Mines are getting deeper resulting in increasing haulage distance and grade of existing reserves getting lower.
- ✔ Increasing diesel price; 10% increase from 2005 to 2018 (2018) and 67% increase from 2019 to 2022 (2022).
- ✔ Availability of equipment, i.e., long lead time for purchasing trucks.
- ✔ Tire shortages and high tire costs resulting in inability to adequately utilize truck fleet.
- ✔ Personnel shortages for trucking operations. IPCC systems require fewer operating personnel.
- ✔ Environmental considerations: IPCC offers 60 million liters per year reduction in diesel consumption which is equivalent to 130,000 tonnes per year reduction in CO_2 emissions and lesser noise pollution (Nehring, et al. 2018).
- ✔ Less operational risk due to fewer mobile vehicles and simpler maintenance.
- ✔ Lower operating cost in most applications because of lower personnel requirement and higher energy efficiency; 81% of the consumed energy is used to transport material compared to 39% by trucks (Nehring, et al. 2018).

1.2.2. When to Use IPCC

- ✔ Large mine life of at least 10 years because IPCC is capital intensive and short mine life cannot make up for the capital investment by lower operating cost. The initial investment for an IPCC system is about $220M compared to $5M for a 360-ton truck (Osanloo and Paricheh 2020).
- ✔ Large quantity of material movement is required to justify the use of IPCC; 4 to 10 Million ton per year (McCarthy 2011).
- ✔ The difference bw. diesel and electricity cost should be over 25% (Nehring, et al. 2018).

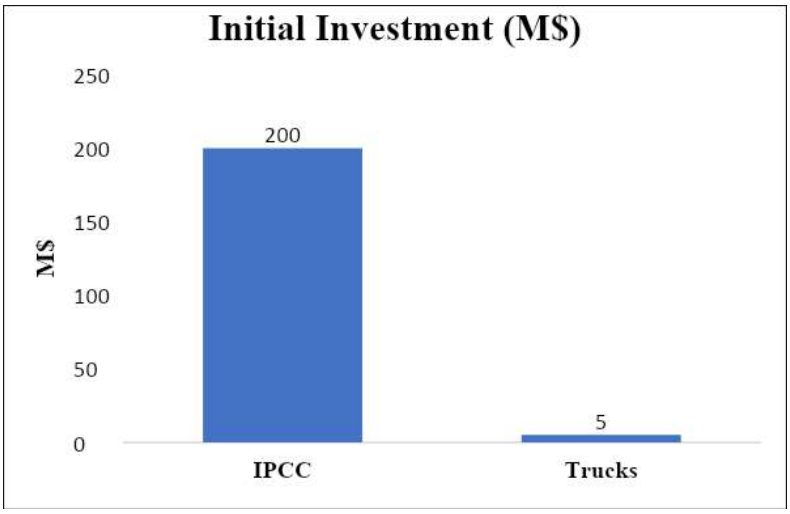

Figure 2. Initial investment for truck vs IPCC.

1.2.3. Risks Associated with IPCC

- ✔ IPCC installation results in higher stripping ratio to accommodate the crusher and conveyor belts.
- ✔ Skilled labor is required to operate IPCC systems (especially fully mobile), which might be a challenge as people are habitually avert to new technologies (McCarthy 2011).
- ✔ IPCC system reduces overall flexibility of mining operation because they cannot be scaled to increase or decrease production as required (Osanloo and Paricheh 2020).
- ✔ Failure of one part might shun the complete production because of the interdependency of the conveyor parts.

1.3. Motivation

As discussed before, equipment operations comprise more than 50% of the operational cost in mining. Various algorithms have been proposed to optimize mine plan and schedule over the past few decades to deal with this cost. (Blom, et al. 2018) summarized the range of techniques developed and used for generating short-term plans, capturing both mathematical programming-based methods and heuristic approaches. (Moradi Afrapoli and Askari-Nasab 2017) reviewed mining fleet management algorithms used in both academic and industrial purposes. (Osanloo and Paricheh 2020) reviewed the development in IPCC literature. The primary motivation of this article is to explore short-term planning of open pit mines with in-pit crushing and conveying to find research gaps and propose a future research direction. IPCC is assumed to be the future of open pit mines, but mine planning with IPCC is an area of research that has not been explored extensively yet. A comprehensive review of short-term planning and IPCC literature after 2010 is done to find the shortcomings of existing methodologies. The findings of the review pave the way to provide logical and scientific suggestions to IPCC integration in short-term mine planning.

2. Short-Term Mine Planning

Researchers have used several methodologies, such as, linear programming, mixed integer programming, simulation, stochastic programming etc. to optimize short-term schedules. The most recent short-term planning articles are reviewed in this section based on the methodologies used.

2.1. Mixed Integer Programming (MIP) Based Models

Most of the modern short-term planning models are MIP based with explicit precedence constraints applied. (Smith 1998), was the first to use the precedence constraints in mine planning and scheduling. The authors used an MIP for constructing short-term schedules with explicit accessibility constraints, requiring the nine blocks above a block to be mined before that block can be accessed. The objective of this MIP is to minimize deviation between expected and produced grade. (Smith 1998) model is preferred by most researchers while modeling precedence among blocks.

(Gholamnejad 2008) proposed a binary integer programming model to solve the short-term mine scheduling problem to decide which blocks of ore and waste to be mined in which period (shift, days, weeks or months) by satisfying several operational and geometrical constraints simultaneously. This model ensures that all the blocks have been opened and the material can be loaded and transported by shovels and trucks respectively.

(Askari-Nasab, et al. 2011) proposed two deterministic MILP models to optimize long-term open pit mining schedule with an objective to maximize NPV by meeting grade blending, mining and processing capacities, and block precedence constraints. The study introduced mining-cuts by combining blocks, to reduce binary variables in the formulation, problem size and solution time. While the first model controls mining in cut level and processing at block level, the second model controls both at mining-cut level. The authors verified the second model with an iron ore mine case study to illustrate that the model is capable of handling large size life-of-mine scheduling problems. Use of mining-cuts or clustering helps reduce the computational expense of MIP models by reducing the number of variables involved.

(Eivazy and Askari-Nasab 2012) solved a short-term planning MIP model under several different scenarios, in which the direction of mining varies with different mining precedence constraints. The objective is to minimize the overall cost of mining operations including mining, processing, haulage, re-handling and rehabilitation costs. One major drawback of this model is the use of aggregation of mining blocks prior to optimizing that might lead to suboptimal solutions because aggregation of the blocks ignores the practical selectivity of preferred ore types and cannot deal with the actual hauling process during optimization. This model generates schedules based on cost savings only and does not take the revenue earned into account. Even from a short-term planning perspective, it is important to generate mining sequences the earned revenue.

(L'Heureux, et al. 2013) proposed a detailed mathematical optimization model for short term planning for a period of up to three months by incorporating operations in detail. The objective is to minimize operational costs caused by trucks, shovels, drilling and blasting. They solved the problem for up to 5 shovels, 90 periods and 132 faces. (Kozan, et al. 2013) modelled drilling, blasting and mining of blocks, and allocation of equipment to these activities with an objective of minimizing the make-span that is the elapsed time between the start and end of a schedule. The model takes mine scheduling as a multi-resource multi-stage scheduling problem. An initial schedule is generated using hybrid shifting bottleneck approach (Liu and Kozan 2012) in the form of a disjunctive graph which is re-optimized using neighborhood and tabu search. The process is reiterated until there is no improvement in makespan. A comparison of the proposed approach to CPLEX optimizer in an iron ire mine showed that the solution time is significantly lower with a negligible optimality gap (<5%) for up to 10 jobs.

Later (Kozan and Liu 2016) formulated another short-term planning model to maximize the throughput and minimize the total idle times of equipment at each stage of drilling, blasting and excavation. The optimization was subject to equipment capacity, speed, read times and activity precedence constraints. The MIP model determine how and when the mining equipment will be allocated to the selected block units to perform the mining tasks at various operational stages. Variables in the MIP model assign pieces of equipment to each job, with binary sequencing variables indicating whether job ‘i’ just precedes job ‘j’ on a particular equipment. The resulting timetable generated for an Australian iron ore mine is confusing because the time units have not been clarified and the optimality gap of the model's results has not been disclosed.

The latest contribution of (Liu and Kozan 2017) is an innovative mine management system by integrating a series of mathematical models for long-term ultimate pit limit determination, medium-term block sequencing over quarterly, half-yearly or yearly time periods, and operational level planning of equipment with a job-shop scheduling model to achieve an overall mining efficiency improvement. While the long- and medium-term MIP models maximize the net present value of the blocks to be mined throughout the life of mine and for a specific period respectively, the operational-level MIP minimizes the makespan and tardiness in job completion times. The integrated model combines block sequencing and the scheduling of equipment while minimizing total weighted tardiness in job completion times. This model can act as an efficient tool to synchronize medium-term and operational level planning with long-term planning using a mathematical approach rather than traditional manual ways.

(Thomas, et al. 2013) formulated an integrated planning and scheduling problem for a coal supply chain with multiple independent mines where they have to share the limited transportation capacity available. The objectives are to minimize the total earliness, tardiness and operation cost constrained by due dates and transportation capacity. The proposed Lagrangian Relaxation-based solution approach performs better than traditional MILP models in terms of upper and lower bounds generation and the lower CPU time. Later, (Thomas, et al. 2014) presented a column generation based solution approach for a similar case study.

(Mousavi, et al. 2016b) proposed an MIP model to minimize the stockpile rehandling cost constrained by upper and lower bounds of ore grade. The objective is attained by maximizing mine-to-processing, minimizing mine-to-stockpile and stockpile-to-processing material flows in each period. The MIP is solved using three metaheuristics: simulated annealing, Tabu search and a hybrid of these two methods. Each method uses a time move to mine a block in a period and a destination move to decide the destination of the mined material. The Tabu search algorithm yields the best results when a pre-defined lower bound is used as a termination criterion. The hybrid approach performs better for large instances with an optimality gap of less than 4%. The major contribution of this model is to introduce the application of the three metaheuristics in short-term block sequencing problem. A similar study by (Mousavi, et al. 2016a) presents a comprehensive mathematical formulation model for a short-term block sequencing problem constrained by precedence relationship, machine capacity, grade requirements and processing demands, which aims to minimize the total cost including rehandling, holding, misclassification and drop-cut costs. The authors presented a hybrid solution approach of branch and bound and simulated annealing which is able to yield solutions with less than 1% optimality gap compared to CPLEX solution, when large neighborhood search is applied.

(Blom, et al. 2014) and (Blom, et al. 2016) present a breakdown and MIP-based algorithm for the short-term planning of a supply chain consisting of multiple open-pit iron ore mines and multiple ports. The problem is divided into two parts: mine optimization and port blending. The mine optimization model solves MIPs to generate a set of candidate blocks to be extracted in a short-term planning horizon. The production grade is assumed to be normally distributed about the target given as input. The port-side optimizer solves an MIP to select a single schedule for each time period, assigns trainloads of ore from mine to port and at the same time, minimizes deviation of the average compositions of ore arriving at each port from desired targets. Based on the solution of the port-side problem, new grade targets are generated as input to each mine-side optimizer. The overall objective is to maximize profit by maximizing production of blended products.

Later, (Blom, et al. 2017) presented a rolling planning horizon-based MIP model to generate multiple short-term production schedules to optimize equipment use and shovel movement, constrained by precedence relationships, blending requirements, equipment availability and trucking hours considering multiple processing paths. Multiple schedules are generated using a split-and-branch approach where the optimizer makes several different choices on activities performed in period ‘t’ and a new schedule is generated for each of these sets of choices. The model produces weekly extraction schedules for a three-month planning horizon.

(Manriquez, et al. 2019) developed a short-term planning methodology to optimize multiple hierarchical objectives. The objectives of this model are minimizing the maximum deviation between ore tonnage sent to plant and the plant capacity, between metal fines and the expected metal fines in processing plant and minimizing the overall shovel fleet movement cost. The authors used weighted sum and hierarchical method (Grodzevich, et al. 2006), two goal programing techniques to optimize the defined objectives. The case study in a Copper mine showed that both methods can produce short-term plans with the same optimum objective function values. This model is strictly deterministic and does not take geological uncertainties into account.

2.1.1. Drawbacks of MILP Models

While MILP models guarantee convergence to optimality, it has several shortcomings.

One general shortcoming of the MIP models is that they are generally strictly deterministic except for the two-stage stochastic programming, which requires a higher level of mathematical understanding. The Mining operations have inherent uncertainties that cannot be captured by deterministic models.

Non-linearity is beyond the limits of MIP formulations (Urbanucci 2018).

Big MIP models are computationally very expensive if the planning horizon or solution space is large.

Some strategies that researchers use to overcome these difficulties are clustering, rolling planning horizon etc., that reduce the number of variables involved (Urbanucci 2018). Another approach that researchers frequently use is a combination of simulation with MIP models that enables the models to consider operational uncertainties (Michael 2015). The next section of this article reviews the simulation optimization approaches used in short-term mine planning. A summary of the short-term planning models showing the key aspects, objectives and constraints, time horizon, tools used etc., has been presented in Table 3 in the appendix.

2.2. Simulation Optimization Models

Many researchers have focused on simulation optimization of equipment selection and efficiency in mine planning because simulation can handle uncertainty involved in operations. (Fioroni, et al. 2008) used simulation in conjunction with a MIP model to reduce mining costs by optimal production planning. The objective is to demonstrate how simulation and optimization models can be combined, with simultaneous execution, in order to achieve a feasible, reliable and accurate solution.

(Ben-Awuah, et al. 2010) developed a discrete event simulation model to minimize discrepancies between long and short-term planning in the context of a life-of-mine planning problem considering uncertainties associated with mining and processing capacities, crusher availability, stockpiling strategy and blending requirements. The simulation model could bridge the gap between the deterministic long-term plan and the dynamic short-term plan. Comparison of the simulated schedule and the expected behavior allows the planner to analyze the short-term feasibility or robustness of a long-term schedule.

(Bodon, et al. 2011) and (Sandeman, et al. 2011) proposed simulation optimization models to maximize tonnes mined and shipped, minimize the deviation of the quality of all mine and port stockpiles from their assigned targets and meet blending requirements. The model was constrained by equipment capacity, port capacity and precedence constraints for a supply chain consisting of pit, port and ships. A linear program (LP) is defined to determine the tons of ore to be extracted from each mining face and its destination. The model shows how integrating optimization with simulation allows a more accurate representation of a system, provides a better solution, although with a longer run time. It also demonstrates that simulation optimization models have the ability to examine trade-offs between different options for capital expenditure and assess alternative operating practices, including maintenance options.

(Soleymani Shishvan and Benndorf 2014) and (Soleymani Shishvan and Benndorf 2016) presented a stochastic simulation approach to predict performance and reliability of complex continuous mining operations for optimal decision making in short-term production planning. The authors considered geological uncertainty in the model. The objective function value is the weighted sum of the two key performance indicators (KPIs) defined: penalty due to deviation in production and equipment utilization. The framework can be used as a valuable tool to foresee critical situations affecting supply of material and system performance through the two-fold uncertainty management: geological uncertainty by geostatistical simulation of 20 realizations of the block model, and the operational uncertainty by discrete event simulation. However, the details of the simulation framework are not provided in the article. The developed simulation model was applied in some industrial case studies later by (Soleymani Shishvan and Benndorf 2017).

(Torkamani and Askari-Nasab 2015) developed and verified a stochastic discrete event simulation model to analyze the behavior of truck-shovel material handling and haulage system in open pit mining. The authors developed an MIP model to deal with the optimum allocation of trucks and shovels in mining faces, and then linked the solutions to the simulation model.

Linear programming only focuses on a single linear objective function with linear constraints. Goal programming is an extension of linear programming that is capable of handling multiple and conflicting objectives. The objective function of the model, therefore, is usually a combination of multiple objectives. combination of multiple objectives. It does not get a single optimal solution, but it generates the so-called pareto optimal solutions, meaning that there is no other solution that is better at all of the objectives. (Upadhyay and Askari-Nasab 2016) and (Upadhyay and Askari-Nasab 2017) used goal-programming for a simulation optimization based short-term planning model, to illustrate how proactive decisions can be made in dynamic environment of mining and operational plans and how they can be synced with long-term planning to reduce opportunity cost, maximize production and equipment utilization.

(Manríquez, et al. 2020) proposed a simulation optimization framework to increase the adherence of short-term mining schedules to execution. The model generates an initial schedule based on an MILP model embedded in UDESS and then simulated in any data encryption standard (DES) software to replicate the schedule and estimate equipment utilization. The utilization of each iteration is fed as input to the next iteration. The user runs the iterations until a termination criterion is satisfied, which in this case, is a material adherence index less than 5%. A case study in an underground bench and fill mine, with a monthly schedule and horizon of 1.5 years, shows that the adherence of the schedule to execution increases with each iteration without any significant compromise (less than 1%) in the overall NPV of the mine. The integration of simulation accounts for the uncertainty of equipment in this strictly deterministic model. It is a generic framework, therefore, applicable to open pit mines too. One shortcoming of the model is that the optimization model generates the schedules with just a single objective of increasing the value of each extraction without considering any costs associated with operations.

2.2.1. Limitations of Simulation-optimization

While simulation is a powerful tool to mimic operations and capture uncertainties, simulation-based optimizations have their limitations.

A true representative simulation model is hard and time consuming to develop (Dellino, et al. 2014).

A simulation model is just as good as the data fed to it.

Most simulation models provide less user flexibility towards various stochastic parameters of the system, such as shovel bucket cycle time, truck spotting, hauling on various gradients, payload, dumping, and queuing etc. Truck haulage is a major part of the total production time, which needs more attention.
All situations can not be evaluated using simulation. Without randomness in a candidate of interest, all simulated scenarios would produce the same result (Wang, et al. 2021).

The runtime for simulation optimization models is generally greater than mathematical optimization models.

Despite the limitations involved in simulation-based optimization, it is a preferred method in mine scheduling to get the best of both worlds: dealing with uncertainties involved in equipment operation and haulage by simulation and the guarantee of convergence of mathematical models (Michael 2015).

2.3. Stochastic Optimization Models

Stochastic programming models solve optimization problems under uncertain environment. Variables that would be constant in a deterministic approach, follows a probability distribution in stochastic programming models. A stochastic program may be formulated with probabilistic constraints (constraints that must hold with a specified probability) or alternative realizations. In a stochastic program with recourse, possible alternative realizations of the stochastic parameters in the problem are defined with first and second stage variables. In the context of scheduling, while the first-stage decision variables define the plan, the second-stage variables define the alternative scenarios that could arise, and adjustments required for each of these alternative scenarios. Several algorithms have been used to solve stochastic minimization or maximization problems.

(Dimitrakopoulos and Jewbali 2013) and (Jewbali and Dimitrakopoulos 2018) proposed a multi-stage planning process that incorporates potential short-term variability in the long-term planning process. Short-term schedules usually deviate from the long-term plans due to the unavailability of grade control data at the time of long-term planning. This simulation based stochastic integer programming model maximizes NPV and minimizes deviation in planned production, where a set of possible realizations of future grade control data is generated based on the grade of material in mined out areas of the mine site. These sets of potential future observations are integrated into a set of conditionally simulated realizations of the mine's orebody, with each orebody forming a different scenario. The compliance of short-to long term production schedules and performance is expected to augment the probability of meeting production targets and increased productivity. Application of this approach at a large gold mine generated substantially higher amount of ore and NPV.

(Matamoros and Dimitrakopoulos 2016) formulated a stochastic integer programming model that simultaneously optimizes fleet and production schedules by taking uncertainty in orebody metal quantity and quality, fleet parameters and equipment availability. They divided the objective function into eight components to minimize the cost of extraction, haulage time under uncertainty of trucks' availability, loss of shovel production and geological risks. The authors claim that this model improves the overall production performance and minimizes the production scheduling changes required during operation, compared to the deterministic models because of their simultaneous optimization approach by considering the uncertainties of the input parameters.

(Quigley and Dimitrakopoulos 2019) proposed an improvement of (Matamoros and Dimitrakopoulos 2016) model to generate short-term schedule to minimize cost of shovel movement and production deviation, deviation of tonnage and grade sent to plants and maximize truck hours of the allocated fleet, constrained by processing capacity, equipment availability, shovel performance and truck cycle time. The model considers uncertainty of geology by geostatistical simulation.

Paduraru and Dimitrakopoulos (2018) showed how new information, such as updated estimates on the grades of extracted material, can be integrated into the short-term planning process. This integration is achieved via the use of adaptive short-term policies for assigning destinations to mined blocks. These policies are state dependent. A state, in this context, is a numerical vector describing the attributes of the block. A policy selects a destination for the block that yields the largest immediate improvement in revenue or cost for each destination. As new estimates become available for the contents of a block, a new state is formed and the short-term policy reassigns a destination to the block. New data typically results in a reduction of local uncertainty. The use of state-dependent destination policies led to better cash flows and more reliable mill usage. The approach is expected to help mill operators decide in advance when the best time to close the mill for maintenance would be.

(Both and Dimitrakopoulos 2020) developed an optimization model for simultaneous optimization of short-term extraction sequence and fleet management, in contrast to the traditional approach of optimizing production schedule first and then allocating the fleet. The objectives are to maximize total profit/revenue and production by minimizing risk of underproduction by shovels and trucks. The model is constrained by precedence relationships, production targets and number of trucks available over a 12-month planning horizon under geological and equipment performance uncertainty. Table 3 in appendix contains a summary comparison of short-term planning models.

2.3.1. Drawbacks of Stochastic Optimization Models

Stochastic programming is a powerful methodology to deal with dynamic and uncertain environment of open pit mining. However, there are several problems associated with it, including:

- Dealing with non-linearity is computationally expensive and mathematically convoluted (Can and Grossmann 2021).
- Handling non-convexity is still a major challenge for stochastic optimization of scheduling.
- Generating a scenario tree that has a low error in practice requires high fidelity and accurate historical data, which is very difficult to attain and use in capital sensitive mining industry (Can and Grossmann 2021).

The above-mentioned shortcomings and difficulties are reasons why stochastic scheduling optimization is still not very common in mine planning. Most of the available models are tested on hypothetical data sets under simplified assumptions that might not hold true in real mining operations.

3. IPCC Review

In-pit crushing and conveying related research has increased in recent times as mines are looking into IPCC as a feasible alternative to traditional truck-shovel operations. The IPCC articles have been divided into the following categories depicted in Figure 3.

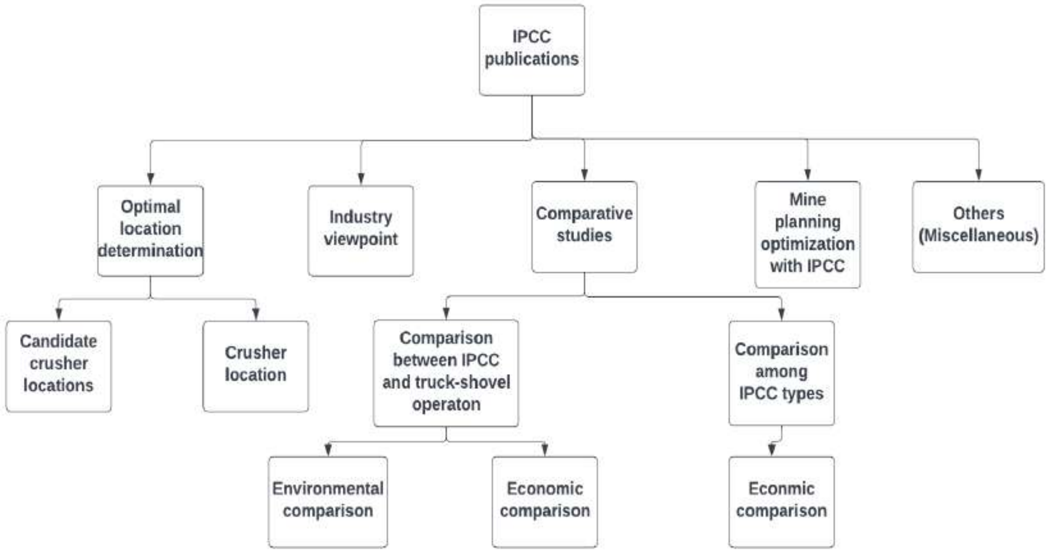

Figure 3. Categories of IPCC research.

The most recent publications will be discussed under the above-mentioned categories to find the progress and research opportunities in the field of IPCC. A summary of the IPCC models has been presented in Table 1 and Table 2 of the Appendix section.

3.1. Crusher Location Optimization

(Konak, et al. 2007) worked on selecting an optimum crusher location based on minimum haulage distance for an aggregate production plant in Turkey. The authors considered both stationary and semi-mobile crusher cases to find the optimum in pit location. The developed algorithm calculates the average haulage distance to crusher from mine for all the possible crusher locations, for up to three relocations of the crusher during the life-of-mine. The problem with this model is that it oversimplified the calculation by taking haulage distance as the only decision variable. The significant cost savings shown by the model might be offset by the capital or relocation cost of the in-pit crusher.

A similar but comparatively simpler approach was used by (Taheri, et al. 2009) to determine optimum crusher location in deep open pit mines. This approach is simpler than (Konak, et al. 2007) because it only considers the case of a stationary in-pit crusher, which would remain in the same location throughout the life of the mine and thus substantially reduces the possible alternative routes. Three alternatives were considered as the crusher location in a hypothetical mine with a life of 18 years. The net present value of the haulage and installation costs were calculated for each of these candidate locations throughout the life of the mine. The one with the minimum cost was selected as the optimum location. The assumptions of this model are too facile because no uncertain costs that might occur due to crusher breakdown or shovel downtime were deliberated. The model also includes systematic approach towards selecting the candidate crusher locations. Unlike (Konak, et al. 2007), this model added IPCC installation costs along with haulage costs to find the total cost associated with the in-pit crusher.

(Rahmanpour, et al. 2013) came up with a more systematic approach to find an optimum in pit crusher location with an objective of minimizing haulage cost by formulating it as a single hub location problem. The crusher location is the hub which will be connected to all the destinations and source locations. Using hubs in a transportation network increases haulage capacity by not increasing the number of trucks proportionally that offers more control over traffic. Although the decision variables are haulage and installation cost like (Taheri, et al. 2009) model, the candidate locations are selected using analytical hierarchical process (AHP) by considering 6 economic factors, such as, haulage distance, reinstallation cost etc. and 11 technical factors including mine plan, geography and safety. The candidate locations are the ones that best satisfy these factors in consideration, which implicitly makes the model consider variables beyond the decision variables used in the objective function. AHP gives quantitative estimates for qualitative factors, which makes it a good tool to select the candidate locations for crushers. One potential disadvantage of using hub-spoke network is the delay and queueing during transshipment at the hubs, which is not considered in the proposed model.

(Roumpos, et al. 2014) developed an iterative method to find the optimal location of the belt conveyor distribution point in the mine perimeter with the objective of minimizing the total transportation cost throughout the life-of-mine. They used simulation to verify the model in a mine with simplified geometric assumptions and showed that the location of external waste dump and belt conveyor distribution point directly affect transportation cost. This model has advantages over (Taheri, et al. 2009) and (Konak, et al. 2007) from the context that it does not need to specify a few initial candidate locations among which the best one is to be selected. It keeps calculating the total transportation cost for all the points on the mine perimeter until the minimum cost value is attained. The authors claim that the model can be used for mines with irregular geometry. However, no case study is illustrated without the simplified geometric assumptions. The only decision variables used in the model are the operating and capital investment cost without considering any operational uncertainties, which can be viewed as a flaw of this model, because conveyor downtime by unplanned and scheduled maintenance affects the operating cost of the conveyor system.

(Paricheh, et al. 2016) proposed a heuristic model to find the optimum locations and movement time of in-pit crusher in open pit mines hierarchically. The crusher location is optimized by a linear dynamic facility location model with an objective of minimizing cost of haulage. Transferring time of crusher is optimized by maximizing the discounted cash flow throughout the life of the mine. This is an iterative model that keeps repeating the steps until the solution keeps getting better. Later (Paricheh, et al. 2017) developed another model with the objective of finding out the optimum in-pit crusher location to minimize the haulage cost by modeling it as a dynamic location problem based on the prime factors, such as haulage distance, that affect IPCC location. The results of the model in a case study of a hypothetical mine show that the application of IPCC will reduce cost by 6% from 6th year of mining, saving a total of $150 million throughout the mine life.

The models discussed so far are all strictly deterministic. (Paricheh and Osanloo 2016) proposed a stochastic approach to determine the optimal crusher location for open pit mines under production and haulage cost uncertainty using stochastic facility location model. The formulated the model as a P-median problem with an objective of minimizing the expected loss across all scenarios. The expected loss is the difference between the optimum haulage cost and the p-median haulage cost from each candidate location to the destinations. A case study using the model in Sungun Mine, Iran, to find 2 crusher locations across 9 different equally likely scenarios for fixed, increasing and decreasing production and cost showed that the model is capable of minimizing deviation between optimal and p-median haulage cost. However, the model does not work well if the value of p is less than 2.

There has not been many research works on finding the best candidate locations from which the optimum in-pit crusher location can be chosen. (Paricheh and Osanloo 2019b) explored this opportunity to propose a new search algorithm to find the best candidates for in-pit crusher locations, in terms of practicality and less opportunity cost. Apart from the general rules that are used conventionally to find candidate locations, such as topography prohibition or intersection with ramps etc., the authors proposed a block aggregation policy and six specific rules to bring down the number of candidate locations significantly. The proposed model aggregates blocks located within the same phase, bench and azimuth domain to account for mining direction. The depth, pushback, required space, radius of influence and frozen economic values constraints are used to reduce the number of feasible candidate locations. The depth restriction makes sure that the minimum depth of a candidate location is the maximum distance that can be economically hauled by trucks. The first pushback is eliminated from consideration by pushback limitation because IPCC investment is not recommended before payback which is usually returned once the first pushback is mined. Blocks that cannot provide enough space for the facility are eliminated by the required space rule. The number of candidates is further reduced by only keeping the blocks having the lowest economic value underneath a block. Validation of the algorithm in Sungun mine, with 79000 blocks and 2063 pushback-bench-slices yielded only 23 candidate locations, while applying the general rule showed 283 candidates. The results also indicated that the number of pushbacks and origin selection affect the number of candidate locations notably. This algorithm does not consider geotechnical (adjacency of blocks) and shape restrictions which are important factors to define a candidate location.

3.1.1. Drawbacks of Crusher location Optimization Models

The major problem of the crusher location optimization models is that the mine plan is not considered for location optimization. Hence, it cannot guarantee NPV maximization in the long run.

The case study results are not reliable because most of them have been applied in hypothetical mines with simplified geometrical assumptions.

There is not enough research work on finding the candidate crusher locations systematically. While Paricheh and Osanloo (2020) proposed a hierarchical approach to finding feasible candidate locations, most of the other models choose candidate locations randomly or based on shortest path without considering a real road network.

IPCC design aspects need to be considered for optimal location determination (Dean, et al. 2015).

3.2. Industry Perspective

(Morris 2008) explained a few industry practices on several productivity issues of semi-mobile (SMIPCC) and full-mobile IPCC (FMIPCC) and the effect of IPCC's interaction on the availability and utilization of trucks and shovels. While this article does not involve any rigorous mathematical modeling, it gives readers a general idea on how large mining companies are dealing with in-pit crushers in real mining operations. The author also explained that semi mobile IPCC tends to have a better overall utilization than fully mobile IPCC because of its lesser dependence on shovel feed. The article highlighted that the service meter unit, defined as the ratio of engine run time and effective working time, is high in IPCC systems. The reason is that they are hardly shut down when idling, unlike trucks or shovels, to avoid queuing at dump pocket. Because of the high service meter unit, prediction of fuel consumption from historic data might lead to distorted results while planning if there is substantial idle time during operation. A comparison of instantaneous and average throughput between SMIPCC and FMIPCC demonstrated that FMIPCC gains slightly better throughput than SMIPCC. This is a good article for beginners to get along with some IPCC concerns and understand the industry perspective.

Another non-academician (McCarthy 2011) highlighted the risks and scopes of replacing truck shovel haulage system by IPCC and the ways to deal with the difficulties that exist in introducing IPCC. As an industry member, the author explained how employees might be avert to new technologies such as IPCC despite the financial gains it provides and the importance of proper management planning and training to overcome this aversion. This article is a commendable effort that edifies beginners on the type of IPCC, the difference between them, the advantages of IPCC and the numerous risks associated with it. While increasing oil price and labor cost favor the introduction of IPCC, the loss of slope stability and mobility makes the use of IPCC in large deep mines dicey. The author recommended probabilistic risk assessment for the areas of uncertainty associated with IPCC, such as supply prices and availability, differences between oil and electricity price etc., during the planning stage by using Monte Carlo simulation, and presented two examples of decision making based on risk assessment used in Sandvik mine by Snowden Mining Company. This article helps readers to get an initial understanding about IPCC and its industry perspectives. (Utley 2011) published a similar article that focused mostly on general ideas and challenges associated with implementing IPCC in large mines.

(Dean, et al. 2015) addressed the pros, such as, cost savings, less emission etc., and challenges, i.e., large investment, loss of flexibility etc., of employing FMIPCC in deep mines and proposed a theoretical design approach to implement FMIPCC in such mines using hydraulic excavators. The model proposes mine sinking by truck-shovel and pit widening by conveyor system. The use of hydraulic shovel allows narrow bench width to facilitate high ramp angles which is necessary for deep mines to keep the stripping ratio in check. The model proposes radial and parallel belt conveyor moves to minimize the frequency of belt extensions. The authors definitely explored an aspect of IPCC through implementing it in deep mines, which has not been in practice before. However, the problem with this model is that it is still a theory and there has not been any practical execution of the idea in any deep mines yet to examine its usefulness and feasibility.

The efforts of the members of industry to address existing issues with introducing IPCC in new and existing mines can prove handy because it will help the companies to switch to IPCC with more confidence and assurance.

3.3. Comparative Studies

3.3.1. Environmental Comparison

(Norgate and Haque 2013) looked at the advantages of using IPCC over Truck-shovel system in open pit mining from a different perspective. They presented a life cycle assessment for IPCC and ore sorting to highlight the potential of reduced greenhouse gas emission these technologies offer. Environmental regulations have made it imperative for large mining companies to ponder about CO2 emission reduction in mining and mineral processing stage. The study showed that IPCC offers 5% and 22% reduction in CO2 emission compared to tradition truck-shovel system for black coal based and natural gas-based electricity respectively. The problem with such studies is that they are highly subjective and the assumptions used might change the outcome of the result.

(Awuah-Offei and Askari Nasab 2009) presented a similar life cycle assessment (LCA) study which gleaned results that were contradictory to (Norgate and Haque 2013).

(Erkayaoğlu and Demirel 2016) investigated the environmental impact of trucks and conveyors, used in mining during utilization stage, in terms of climate change and acidification by life cycle assessment in a Turkish mine. The authors selected these two categories because they have the maximum impact on human health and environment compared to the other categories, such as, land use, eco toxicity etc. Another reason to use these factors for this comparative study is that the data required for LCA study is not readily available because of the confidentiality of mining companies and the uncertainty in data for these two categories is usually minimum. The study revealed that trucks are more environmentally burdensome than conveyors in acidification category because of its dependence on diesel fuel during operation, which produces nitrogen and Sulphur oxides, major components causing acidification, upon burning. On the contrary, conveyors are more detrimental than trucks from climate change perspective because the electricity used to run the conveyors is produced primarily from lignite coal, which produces greenhouse gas like carbon dioxide when burns. Studies like this show the importance of LCA as a powerful tool for equipment selection in mining. However, this study is case specific, and the assumptions used apply in Turkish mines only. Therefore, using the results of the study without appropriate modifications in assumptions for equipment selection of other countries' mines might be inappropriate and erroneous.

A similar life cycle assessment study was presented by (Fuming, et al. 2015) that concluded IPCC system to be more energy efficient and environment friendly compared to traditional truck-shovel system.

3.3.2. Economic Comparison

The economical comparative studies mainly focus on the advantages and disadvantages of truck-shovel and IPCC systems in terms of the cost associated with them. Some studies present a financial comparison between fixed, semi-mobile and mobile IPCC systems. (Koehler 2003), (Schroder 2003) highlighted the technical and economic aspects of IPCC system to demonstrate the advantages it offers over the traditional truck-shovel system.

(Klanfar and Vrkljan 2012) compared stationary and mobile crushers and plants in quarrying stone in terms of cost of processing, loading and transportation by a case study in Sungun mine, Iran. The results showed that mobile crusher offers about 11% cost saving compared to stationary crusher mostly because of its significant cost saving in transportation of material. This article assumes that all the costs are known with certainty which hardly happens in real operations. The results might vary substantially based on the size of the mine.

(Londoño, et al. 2013) investigated alternative IPCC configurations for pre-stripping application in an open pit coal mine to demonstrate that introducing parallel conveyor lines with spreaders can improve IPCC productivity by 9.4–12.6% and provide more profit compared to single conveyor line despite having a higher equivalent unit cost. Simulation of five different IPCC configurations with and without parallel conveyor lines assuming 25% loss due to unavoidable delays and a weibull failure model for conveyor and spreader showed that an IPCC system comprised of 3 conveyors with 4 parallel conveyor lines generated 20% higher annual production which makes up for the 15% higher operating cost compared to its single conveyor line counterpart. The assumed constant process delay and weibull failure distribution are subject to the type of operation and any changes to these assumptions might affect the results substantially.

(Dzakpata, et al. 2016) presented a numerical comparative study among shovel, trucks and IPCC based on utilized time, operating time and valuable operating time. The results showed that shovels lose about 40% of its operating time spotting trucks, which demonstrate that introduction of IPCC system can significantly improve the performance of shovel by improving the productivity by 20 to 25%. The study also showed that while trucks attain higher utilization and operating time than conveyors, the conveyors offer 25% higher valuable operating time than trucks because trucks travel empty about 38% of their operating time. The use of multiple performance metrics makes this study a reasonable tool for equipment selection decision. However, the authors did not reveal the data and mining data is highly case specific and context dependent (mine condition, haul routes etc.). Therefore, using the results of this study for any mine without further appropriate assumptions and modifications might not help taking the best decision.

(de Werk, et al. 2017) presented the Comparison of two material handling systems, Semi-mobile IPCC(SMIPCC) and traditional truck-shovel (TS) system in terms of haulage cost in a hypothetical iron ore mine. Results indicate that although the capital cost of IPCC is higher than that of TS, the total cost of IPCC is lower due to its lower operational cost. Sensitivity analysis showed that while both methods were sensitive to production rate, TS is more sensitive to fuel prices than IPCC because of the smaller number of trucks needed with IPCC. As electricity prices are more stable than fuel prices historically, IPCC has less risk compared TS in terms of operational cost. Risk analysis via Monte Carlo Simulation in terms of electric and fuel prices, TS and IPCC availability and truck fill factor shows that the range of minimum and maximum unit operating costs of IPCC is 10% narrower than TS. While this article verifies most of the cost advantage assumptions of IPCC over TS, the case study was run in a perfectly cone shaped hypothetical mine. The outcome of the comparison might vary substantially in real mines.

Another decision making method to choose between TS and SMIPCC was proposed by (Nunes, et al. 2019). The aim of this study is to develop a methodology to compare transportation alternatives (TS and SMIPCC) and select the best one in terms of cost saving and environmental sustainability. The results from a Copper mine show that while the CAPEX of SMIPCC is 60% higher than TS, the OPEX is 43% lower because of low maintenance and labor cost, which results in a 34% saving in net present cost over a LOM of 20 years.

(Bernardi, et al. 2020) developed an ARENA simulation model to compare semi-mobile and fixed IPCC systems for open pit mines in terms of NPV and proximity to target production rate. They ran the simulation model for a simplified cone shaped hypothetical mine with 1500m depth and 15 benches with an initial number of trucks, maintenance, operating and capital costs on an hourly basis. The simulated cost results are used to calculate NPV and the number of trucks is adjusted based on the difference between target production and actual production. The simulation was run for five iterations and the results improved significantly with semi-mobile IPCC generating 10% higher NPV and more proximity to production targets. The model yields quick results which is helpful to decide on the fleet and type of IPCC system requirement in open pit mines. However, the cost model and mine geometry used here are too simple and the input parameters are too inaccurate to represent any typical mine project complexity.

3.3.3. Shortcomings of the Comparative Studies

- ✔ Environmental comparison via life cycle assessment is highly case sensitive and qualitative. The results of one case study is not applicable for another mine.
- ✔ Data required for life cycle assessment studies is difficult to get. If data collection is poor, the study will not lead to solid conclusions (Curran 2014).
- ✔ Contradictory outcomes to similar studies on environmental sustainability of IPCC and truck-shovel operations (Ben-Awuah, et al. (2010); (Norgate and Haque 2013).

- ✔ Economic comparison between IPCC and TS systems is also case specific. The cost of labor and haulage vary substantially based on the geological location of a mine.

Despite the limitations of the life cycle assessment and economic comparison studies, they provide valuable insight on the environmental sustainability and economic viability of IPCC system compared to traditional haulage.

3.4. Simultaneous Optimization of IPCC and Mine Plan

The most recent addition to IPCC literature is the simultaneous optimization of mine planning, IPCC location and relocation. This integration is very important from the aspect of mine planning. The inclusion of IPCC affects the number of required haulage equipment, mining direction, availability of mineable faces or cuts which need to be considered while formulating the strategic or even operational plan. Otherwise, the NPV calculation and generated mining sequence could end up being sub-optimal.

(Samavati, et al. 2018) explored the fact that there is almost no study for optimizing the operations with IPCC in open pit mines and estimating the costs of IPCC systems, which makes large mining companies avert to using IPCC system despite the advantages, such as, the low operating cost it offers over traditional trucks and shovels. This article points out the fact that while researchers mostly focus on finding an optimal in-pit crusher location for IPCC, there is not much concern about the integration of IPCC with mine planning and scheduling, without which it is very hard to estimate the costs and savings that might be generated by IPCC throughout the mine life. The authors proposed research in finding out the optimal location of the conveyors and how open pit mine planning would be affected by the modified precedence constraints due to the location of the conveyors and crushers inside the pit. This is a descriptive article that raised concerns about a few research agenda that need to be explored to make IPCC integration more lucrative and risk free for large mining companies.

The research gap pointed out by (Samavati, et al. 2018) has been explored by (Paricheh and Osanloo 2019a), who proposed an MILP model to simultaneously optimize crusher location inside the pit to minimize total haulage cost. The model also optimizes fleet requirement and eventually maximize the NPV of the mine by considering the dynamic changes in block sequencing by the location and relocation of the IPCC. One main feature of the proposed model is that it determines the block destination in or external pit crusher/waste dump along with the extraction sequences. A comparison of the proposed model with two existing long term planning models without IPCC was presented. The model showed substantial increase in NPV, decrease in fleet requirement and changes in extraction sequence compared to the two benchmark models M2 and M3, that optimize scheduling and fleet simultaneously and separately, respectively. The proposed model increased NPV by 2.3% and 3.4% compared to M2 and M3, respectively. The required fleet size was 75% less than the required fleet size of M3. The improvements shown in the model surely proves the value of IPCC in open pit mines. However, this model is strictly deterministic because all the parameter values related to costs in consideration, grade and tonnage of each block etc., are known with certainty, which is hardly the case in real life mines. The reliability of this model can be enhanced by incorporating uncertainties associated with some of the vital parameters such as grade, price and cost.

A more comprehensive approach to integrate long-term plan with fully-mobile IPCC (FMIPCC) conveyor locations was proposed by (Samavati, et al. 2020). Their research proposes a mathematical model that simultaneously generates long time mine planning with optimum crusher and conveyor locations for IPCC with an objective of maximizing net profit over the life of mine. They solved the model with three different relaxation techniques using the proposed heuristic and direct MILP solver, where the heuristics required only 10% time of exact solver to find near optimal solution. While the model has not been applied to a real mine yet, the case study was run in a hypothetical mine that is geologically similar to copper porphyry deposits in Australia.

A framework for simultaneous optimization of long-term mine scheduling with semi-mobile IPCC was developed by (Liu and Pourrahimian 2021). The authors proposed an integer linear programming model that maximizes NPV by maximizing block values and minimizing haulage and crusher relocation cost. They solve the model for several candidate conveyor and crusher locations and the one that generates the maximum NPV is considered as the optimum conveyor/crusher location. The candidate crusher locations are determined using a pit rotation approach developed by (Hay, et al. 2020). Assuming the conveyor locations to be fixed in one side of the pit throughout the mine life, this model shows that the conveyor location can significantly impact the NPV of a mine.

The latest attempt to integrate long-term plan with IPCC location and relocation time has been proposed by (Shamsi, et al. 2022). The objective of this study is to maximize the NPV of an open pit mine, considering SMIPCC, TS capital and operating cost, and find the optimum locations and relocation time of crushers constrained by mining and processing capacity, blending requirements etc. Unlike (Samavati, et al. 2020), this model does not consider the location and relocation of the conveyors. The case study in a copper mine shows that while the capital is $74M higher for SMIPCC than the traditional truck-shovel system, it generates 70% higher NPV over the life of mine. This model can be used as decision making tool to choose between TS and SMIPCC systems in large open pit mines.

3.4.1. Areas to Improve

The simultaneous optimization of mine planning with IPCC is very new and requires a lot of work to be put in to make them suitable to be applied in a real mining project. The major limitations to be overcome are summarized below.

The simultaneous optimization of mine planning with IPCC is very new and requires a lot of work to be put in to make them suitable to be applied in a real mining project. The major limitations to be overcome are summarized below.

The existing models are all still in theoretical level. They have not been applied to a real mine yet.

The models developed so far are all deterministic and cannot consider uncertainties associated with geology or IPCC operations.

We are yet to find out the effect of IPCC on short-term or operational level planning. Most of the simultaneous optimization models are concerned with strategic mine planning.

IPCC integration to mine planning is difficult because of the complex design of conveyor, belt distribution points and dynamic crusher locations (Samavati, et al. 2018).

Following the footsteps of the limited research work exist will lead to more comprehensive simultaneous optimization model in future.

3.5. Others

Some of the recent research work related to IPCC fall outside the five categories discussed above. For example, a significant contribution to IPCC literature was made by (Ritter 2016), who proposed a method for calculating the annual capacity of SMIPCC system considering the random delays that occur due to system performance and inter connection between several parts. The system induced delays have been determined by a discrete event simulation model. The case study shows that the SMIPCC capacity is substantially affected by system delays and the capacity has an inversely proportional relationship with mean repair time. An economic comparison between TS and IPCC system proved SMIPCC to be cheaper than TS for the same annual capacity. This method of determining SMIPCC annual capacity is the first numerical method that considers random system behavior. Another significant contribution of this thesis is the list of all the IPCC systems employed across the world by different companies in different mines.

A comparative study was published by (Abbaspour, et al. 2018), where the different types of transportation systems (truck-shovel and IPCC) are evaluated based on safety (such as accidental death) and social indexes (higher number of employees). FMIPCC presented the highest safety index in contrast with SMIPCC, which showed the lowest. In addition, Truck-Shovel and SMIPCC systems demonstrated the highest social index because of benefiting from higher number of employees and hours of training. In contrast, FMIPCC ranked the last in social index. Such system dynamic models are highly dependent on the variables, which depend on the judgement of the modeler. Hence, the results are not always reliable. The model has not been applied to any real mine yet.

(Abbaspour and Drebenstedt 2020) used system dynamics modeling to determine the optimum transition time from Truck-shovel to IPCC. The model shows that whereas TS system is preferable at the first five years of a mining project, FMIPCC system shows a better economic performance in the rest of the mine’s life.

Shamsi and Nehring (2021) determined the optimum depth at which it is the most convenient to switch to SMIPCC from truck-shovel by scenario analysis. The economic analysis in a cone shaped hypothetical mine with 4 pushbacks showed that switching to IPCC from truck-shovel from the second phase at a depth of 335m generates the maximum discounted cost savings. This model is based on a lot of simplified assumptions on mine geometry and the results will vary depending on the depth and phases of mine.

(Wachira, et al. 2021) developed a methodology to determine SMIPCC performance based on mine productivity index. The study found that a reduction in loading equipment (shovel) reduces the truck requirement by 33%. The mine productivity is higher with multiple loading equipment than a single shovel. The case study in a hypothetical mine shows mine productivity index is higher for SMIPCC system than traditional TS system.

4. Non-departmental Analogies Suitable for Mine Planning

Vehicle routing problem, more specifically capacitated vehicle routing problem (CVRP), which is a commonly used idea in industrial engineering, can be useful for mine planners because the analogy of vehicle routing can be brought into the haulage management to minimize cost of material handling. The basic idea of vehicle routing problem is to meet the demand of customers with limited resources. The objective in general is to choose the best or shortest possible route to minimize the cost of movement. We will review a few vehicle routing problem literatures here to put light on the fact that these ideas can be useful in mining engineering too.

(Xiao, et al. 2012) proposed a CVRP model to minimize fuel consumption by considering Fuel Consumption Rate (FCR) as a load dependent function using simulated annealing algorithm with a hybrid exchange rule. Experimental results show that the proposed model can reduce fuel consumption by 5% on average compared to the classical CVRP model. This model can be used to manage the tradeoff between the total distance and the priorities of serving customers with larger demands. The model in its current state of art cannot assume factors such as road condition, driver behavior etc. on fuel consumption.

A similar model was proposed by (Feng, et al. 2017) with normally distributed vehicle speed and fixed vehicle cost to minimize the total fixed cost and fuel consumption. The non-linear objective function is linearized which can be solved quickly using solvers like CPLEX when the number of customers (destinations) is small. An improved simulated annealing algorithm has been proposed to achieve optimal or near optimal solutions which outperforms CPLEX and simulated annealing approach when the number of destinations is high (n>=50). The maximum optimality gap is always reasonable (<5%) and the CPU time is remarkably short when n is large. Model shows that the fuel consumption is always larger for stochastic vehicle speed than that with fixed speed model which indicates that assuming fixed speed would result in underestimation of cost of fuel consumption is always larger than that with fixed speed model. Model does not account for randomness of demand and Vehicle speed is not necessarily normally distributed.

(Feld, et al. 2019) proposed a hybrid solution approach to CVRP to minimize total distance travelled using quantum annealer device. The challenge is to translate the CVRP into a quadratic unconstrained binary optimization problem so that it can be mapped to D-wave quantum annealer. Comparison of the hybrid solution approach to classical 2-phase heuristics method shows that it does not offer any patent advantage in terms of solution quality or computation time in its current state. However, the approach shows how to split complex combined problems and solve them in a hybrid way using a quantum annealer. Future research should investigate the effect of the of the hardware on efficiency of the problem mapping, the necessity of using additional tools like QBSolv etc.

(Sarasola, et al. 2016), (Errico, et al. 2016), (Marinaki and Marinakis 2016) and many other researchers have worked on capacitated vehicle routing problem formulation. The whole point of introducing IPCC in big mines is to reduce the number of trucks to minimize haulage cost. The fleet management in mine planning might be optimized by applying the CVRP approach because the basic idea of meeting production target (mill demand) by limited resource (fleet) with minimum cost is the same in both cases.

The emission minimization vehicle routing problem (EVRP) formulation methodologies similar to (Bektaş and Laporte 2011), (Figliozzi 2010), (Franceschetti, et al. 2013), (Jabali, et al. 2012) etc., might be applicable to life cycle assessment studies for IPCC and TS system in mines because the general objective of EVRP is to reduce the greenhouse gas emission while solving the CVRP.

Another arena of operations research that needs to be explored more is facility location problem. While (Paricheh, et al. 2016), (Rahmanpour, et al. 2013) used facility location models to find optimum in-pit crusher locations, there is still a lot of opportunities to formulate more efficient models to optimize IPCC location and relocation using this particular field of study.

5. Future Research Direction

As discussed in the previous sections, mines are getting deeper and the average ore grade is depleting ((McCarthy 2011; Osanloo and Paricheh 2020), which leaves mines with only two options going ahead: switching to underground mining which is not feasible in most cases because the total setup needs to be changed or introducing IPCC to exploit the benefits of a lower operating cost and longer life span than truck-shovel system. This detailed review of the short-term planning and IPCC literature shows that, while most of the articles concerning IPCC are focusing typically on conveyor design or finding an optimal crusher location inside mines based on the cost of traveling from crusher to destinations assuming a predefined and fixed strategic mine plan, some articles are comparing the pros and cons of IPCC with traditional truck-shovel system to promote IPCC system to the mining industry. The comparisons among most recent short-term planning and IPCC literature show that while very few models can generate a strategic plan with IPCC in place ((Paricheh and Osanloo 2019a), (Samavati, et al. 2020), (Shamsi, et al. 2022), (Liu and Pourrahimian 2021)) etc., there is hardly any short-term planning model with IPCC integration. To make things worse, there is no study that can help mine planners estimate the cost of IPCC systems in a systematic manner considering all the variables and uncertainties associated with it (Samavati, et al. 2018), forcing mine planners to use intuition and experience to come up with a cost estimate that are mostly error-prone and affect the planned NPV in a negative manner.

Commercial tools like Geovia Whittle, Minesched, XPAC, Leapfrog etc., can generate long and short-term production schedule for traditional truck-shovel systems but to the best of our knowledge, there is no such commercial tool that can do the same for IPCC system in place. Therefore, it is evident that IPCC which is considered to the future of open pit mines but production sequencing (both long and short-term) considering in-pit crusher is still under-developed and neglected. While strategic planning with IPCC needs to find out the optimal locations of IPCC as a function of time to maximize the NPV, short-term sequencing needs to consider the effects of IPCC location and relocation over time, such as, change in production capacity, haulage distance etc. to come up with a practical production schedule that will sync with the long-term plan.

Operations research tools, such as, transportation problem, vehicle routing, facility location etc. need to be used more rigorously in mining literature so that the existing gaps can be filled in and mathematical models and commercial tools capable of generating strategic and short-term planning with IPCC can be developed. The following sub-section will propose a brief research proposal for short-term planning optimization with Semi-Mobile IPCC.

5.1. A Brief Research Proposal

The authors would like to develop a mixed integer linear programming model with the objective of generating monthly production schedules that minimize the haulage cost with IPCC system in place. The assumptions are:

1. The IPCC system is semi-mobile.
2. The optimum locations and relocation time of the crusher is known throughout the life of mine from strategic planning.
3. There is no waste crusher. Waste material goes directly to external waste dumps.
4. The ore and waste faces are labelled. Hence, ore shovels will be assigned to ore faces and waste shovels will go to waste faces only.
5. The time horizon is 12 to 36 months.

6. The tonnage and grades of each mining cut location is known with certainty.

The objective function will have two components. The first component will calculate the cost of hauling waste material to waste dumps and ore material to crusher using regular diesel trucks. The second part calculates the cost of conveying ore material from crusher to processing plant. The following Figure 5 shows the transportation of waste and ore with and without in-pit crusher in place.

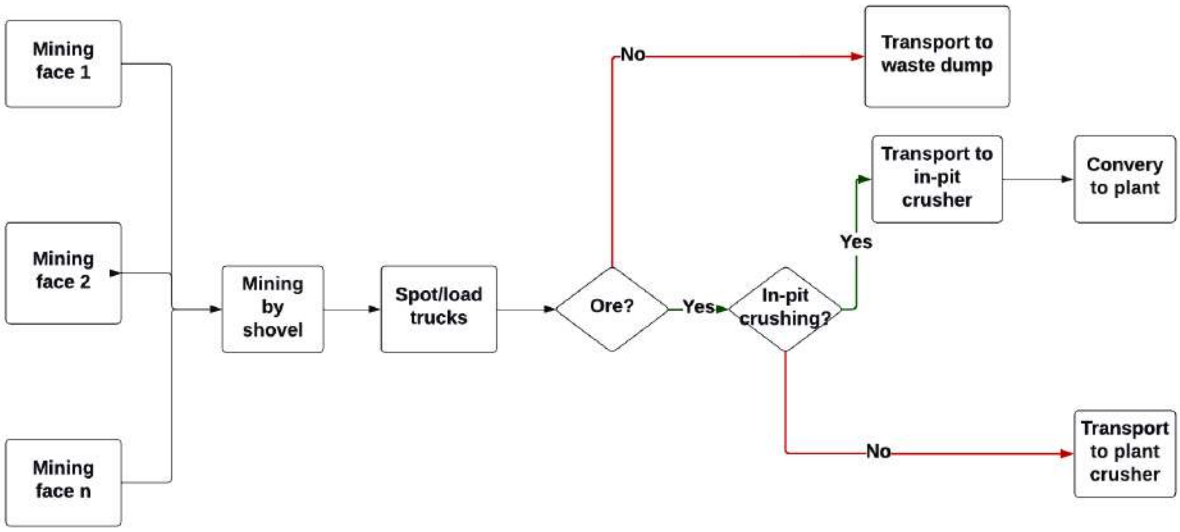

Figure 4. Flow of material from mine to crusher, plant and waste dump.

Obj function, f = cost of transporting material to crusher or waste dump from mine by trucks + cost of conveying ore material from crusher to processing plant

The distance of each face from the crusher and waste dump will be fed to the model as a road network graph. The objective function will be optimized subject to shovel allocation, grade blending, minimum plant requirement, maximum allowable grade variation and IPCC location constraints to achieve required production and grade targets set by strategic plan through accommodating crusher within ultimate pit limit. Optimum allocation of shovels to mining faces will extract required tonnage of material to feed the plant. The case study will be run for two cases: one with IPCC system with reduced number of trucks and the other with traditional truck-shovel haulage system without IPCC. The comparison of these two scenarios will verify whether the SMIPCC offers cost benefits by meeting long-term production targets within short-term planning horizon of 1 to 3 years. A mathematical formulation with case study will follow.

6. Conclusions

IPCC is the future of open pit mining. For the industry to have a smooth transition from traditional truck-shovel system to IPCC, a lot of work is required to be done in both academic and commercial sectors of mining engineering. Mathematical models and commercial tools that can produce long-term, short-term and operational plans need to be created so that IPCC can be more mainstream in the mining industry and bring about the revolution it can deliver.

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8. Appendix

Table 1:Comparison among key aspects of IPCC publications

Comparison of post 2007 IPCC papers	Key Aspects				
	Integration with Long-term Planning	Integration with Short-term planning	Type of IPCC	Case study	Uncertainty
Konak et al. (2007)	No	No	Fixed, Semi-mobile	√	×
Phil Morris (2008)	No	No	Fixed, Semi-mobile	×	×
Taheri et al. (2013)	No	No	Fixed	√	×
McCarthy (2011)	No	No	Fixed, semi-mobile, fully mobile	×	×

Comparison of post 2007 IPCC papers	**Key Aspects**				
	Integration with Long-term Planning	Integration with Short-term planning	Type of IPCC	Case study	Uncertainty
Utley (2011)	No	No	Fixed, semi-mobile, fully mobile	×	×
Klanfer, Vrkjln (2012)	No	No	Fixed, fully mobile	√	×
Rahmanpour et al. (2013)	No	No	Semi-Mobile	√	×
Roumpos et al. (2014)	No	No	Fixed, semi-mobile, fully mobile	√	×

Comparison of post 2007 IPCC papers	**Key Aspects**				
	Integration with Long-term Planning	Integration with Short-term planning	Type of IPCC	Case study	Uncertainty
Londono et al. (2013)	No	No	Fixed, semi-mobile, fully mobile	√	×
Norgate, Haque (2013)	No	No	Fixed, semi-mobile, fully mobile	√	×
Dean et al. (2015)	No	No	Fully Mobile	√	×
Erkayaoglu, Demirel (2016)	No	No	Fixed, semi-mobile, fully mobile	√	×
Ritter (2016)	No	No	Semi-mobile	√	√

Comparison of post 2007 IPCC papers	Key Aspects				
	Integration with Long-term Planning	Integration with Short-term planning	Type of IPCC	Case study	Uncertainty
Paricheh, Osanloo (2016)	No	No	Semi-mobile	√	√
Paricheh et al. (2016)	No	No	Semi-mobile	√	×
De Wark et al.(2017)	No	No	Semi-mobile	√	×
Paricheh et al. (2017)	No	No	Semi-mobile	√	×
Abbaspour et al. (2018)	No	No	Fixed, semi-mobile, fully mobile	√	×

Comparison of post 2007 IPCC papers	Key Aspects				
	Integration with Long-term Planning	Integration with Short-term planning	Type of IPCC	Case study	Uncertainty
Abbaspour, Carsten (2019)	No	No	Fully mobile	√	×
Nunes et al. (2019)	No	No	Semi-mobile	√	×
Paricheh, Osanloo (2019a)	Yes	No	Semi-mobile	√	×
Paricheh, Osanloo (2019b)	No	No	Fixed, Semi-mobile	√	×
Bernardi et al. (2020)	No	No	Fixed, Semi-mobile	√	×

Comparison of post 2007 IPCC papers	Key Aspects				
	Integration with Long-term Planning	Integration with Short-term planning	Type of IPCC	Case study	Uncertainty
Samavati et al (2020)	Yes	No	Fully Mobile	√	×
Shamsi, Nehring (2021)	No	No	Semi-mobile	√	×
DingBang, Yahsar (2021)	Yes	No	Semi-mobile	√	×
Wachira et al. (2021)	No	No	Semi-mobile	√	×
Shamsi et al. (2021)	Yes	No	Semi-mobile	√	×

Table 2: Comparison among objectives optimized and solution tool used in IPCC papers

Comparison of post 2007 IPCC papers	**Objectives**											**Solution tool**
	Economic Comparison with TS	Environmental comparison with TS	Comparison among IPCCs (Economic)	Optimum conveyor design/ exit location determination	Optimum Crusher Location determination	Crusher relocation time optimization	Candidate crusher location determination	Transportation cost minimization	IPCC risk assessment	NPV maximization	IPCC capacity/performance determination	
Konak et al. (2007)	×	×	×	×	√	×	×	√	×	×	×	NS
Phil Morris (2008)	×	×	√	×	×	×	×	×	×	×	×	NS
Taheri et al. (2013)	×	×	×	×	×	√	×	√	×	×	×	NS
McCarthy (2011)	×	×	√	×	×	×	×	×	×	×	×	NS
Utley (2011)	×	×	√	×	×	×	×	×	×	×	×	NS

Comparison of post 2007 IPCC papers	**Objectives**											**Solution tool**
	Economic Comparison with TS	Environmental comparison with TS	Comparison among IPCCs (Economic)	Optimum conveyor design/ exit location determination	Optimum Crusher Location determination	Crusher relocation time optimization	Candidate crusher location determination	Transportation cost minimization	IPCC risk assessment	NPV maximization	IPCC capacity/performance determination	
Klanfer, Vrkjln (2012)	×	×	√	×	×	×	×	√	×	×	×	NS
Rahmanpour et al. (2013)	×	×	×	×	√	×	√	√	×	×	×	NS
Roumpos et al. (2014)	×	×	×	√	×	×	×	√	×	×	×	MATLAB
Londono et al. (2013)	×	×	×	√	×	×	×	×	×	×	×	NS

Comparison of post 2007 IPCC papers	**Objectives**											**Solution tool**
	Economic Comparison with TS	Environmental comparison with TS	Comparison among IPCCs (Economic)	Optimum conveyor design/ exit location determination	Optimum Crusher Location determination	Crusher relocation time optimization	Candidate crusher location determination	Transportation cost minimization	IPCC risk assessment	NPV maximization	IPCC capacity/performance determination	
Norgate, Haque (2013)	×	√	×	×	×	×	×	×	×	×	×	Simapro
Dean et al. (2015)	×	×	×	√	×	×	×	√	×	×	×	NS
Erkayaoglu, Demirel (2016)	×	√	×	×	×	×	×	×	×	×	×	Simapro 7.3
Ritter (2016)	√	×	×	×	×	×	×	×	×	×	√	ARENA /VBA
Paricheh, Osanloo (2016)	×	×	×	×	√	×	×	√	×	×	×	CPLEX

Comparison of post 2007 IPCC papers	**Objectives**											**Solution tool**
	Economic Comparison with TS	Environmental comparison with TS	Comparison among IPCCs (Economic)	Optimum conveyor design/ exit location determination	Optimum Crusher Location determination	Crusher relocation on time optimization	Candidate crusher location determination	Transportation cost minimization	IPCC risk assessment	NPV maximization	IPCC capacity/performance determination	
Paricheh et al. (2016)	×	×	×	×	√	√	×	×	×	√	×	GAMS, Excel
De Wark et al.(2017)	√	×	×	×	×	×	×	×	×	×	×	NS
Paricheh et al. (2017)	×	×	×	×	√	×	×	√	×	×	×	GAMS
Abbaspour et al. (2018)	×	√	×	×	×	×	×	×	√	×	×	NS

Comparison of post 2007 IPCC papers	**Objectives**											**Solution tool**
	Economic Comparison with TS	Environmental comparison with TS	Comparison among IPCCs (Economic)	Optimum conveyor design/ exit location determination	Optimum Crusher Location determination	Crusher relocation time optimization	Candidate crusher location determination	Transportation cost minimization	IPCC risk assessment	NPV maximization	IPCC capacity/performance determination	
Abbaspour, Carsten (2019)	√	×	×	×	×	×	×	√	×	×	×	NS
Nunes et al. (2019)	√	×	×	×	×	×	×	√	×	×	×	Excel VBA
Paricheh, Osanloo (2019a)	×	×	×	×	√	×	×	√	×	√	×	CPLEX
Paricheh, Osanloo (2019b)	×	×	×	×	×	×	√	×	×	×	×	NS
Bernardi et al. (2020)	×	×	√	×	×	×	×	×	×	√	×	ARENA

Comparison of post 2007 IPCC papers	**Objectives**											**Solution tool**
	Economic Comparison with TS	Environmental comparison with TS	Comparison among IPCCs (Economic)	Optimum conveyor design/ exit location determination	Optimum Crusher Location determination	Crusher relocation time optimization	Candidate crusher location determination	Transportation cost minimization	IPCC risk assessment	NPV maximization	IPCC capacity/performance determination	
Samavati et al (2020)	×	×	×	√	√	×	×	×	×	√	×	Gurobi
Shamsi, Nehring (2021)	√	×	×	×	×	×	×	√	×	×	×	NS
DingBang, Yahsar (2021)	×	×	×	√	×	√	×	√	√	×	×	MATLAB/CPLEX 12.7
Wachira et al. (2021)	×	×	×	×	×	×	×	×	×	×	√	NS
	×	×	×	×	√	√	×	√	×	√	×	CPLEX 12.7

Comparison of post 2007 IPCC papers	**Objectives**											**Solution tool**
	Economic Comparison with TS	Environmental comparison with TS	Comparison among IPCCs (Economic)	Optimum conveyor design/ exit location determination	Optimum Crusher Location determination	Crusher relocation time optimization	Candidate crusher location determination	Transportation cost minimization	IPCC risk assessment	NPV maximization	IPCC capacity/performance determination	
Shamsi et al. (2021)												

Table 3: Comparison among most recent publication on short-term mine planning

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Multiple processing destinations	Stochastic or Deterministic	IPCC/ Regular TS haulage
Eivazy and Askari-Nasab (2012)	Block extraction sequence generation	12 to 36 months	CPLEX	Minimize cost of mining, processing, material movement and waste rehabilitation **subject to** head grade, precedence and capacity constraints	Yes	Deterministic	TS
Liu, Kozan (2012), Liu, Kozan, Wolff (2013,2016)	Block extraction with equipment scheduling; multi-stage, multi-resource scheduling	Not specified	C++	Minimize makespan of mining activities drilling, blasting and excavation **subject to** capacity of mining equipment and precedence constraints	No	Deterministic	TS
L'Heureux et al. (2013)	Block extraction, shovel allocation drilling and blasting schedule.	3 months	IBM ILOG CPLEX	Minimize cost of shovel movement, drilling and blasting cost **subject to** precedence of activities, capacity and blending constraints	No	Deterministic	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Multiple processing destinations	Stochastic or Deterministic	IPCC/ Regular TS haulage
Mousave et al. (2016b)	Block sequencing problem with equipment scheduling	Six months	CPLEX	Minimize the total mining cost which includes rehandling and holding costs, misclassification and drop-cut costs **constrained by** precedence relationship machine capacity, grade requirements and processing demands,	No	Deterministic	TS
Mousave et al. (2016a)	A comparative study of three meta heuristic approaches (tabu search, simulated annealing and a hybrid of these two) to short-term mine sequencing.	NS	NS	An MIP model to minimize the stockpile rehandling cost **constrained by** upper and lower bounds of ore grade.	Yes	Deterministic	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Multiple processing destinations	Stochastic or Deterministic	IPCC/ Regular TS haulage
Kozan, Liu (2016)	Multi-stage mine production timetabling model for drilling, blasting and excavating operations	18 weeks	IBM ILOG CPLEX	Maximise the throughput and minimise the total idle times of equipment at each stage of drilling, blasting and excavation **subject to** equipment capacity, speed, ready times subject to precedence constraints.	No	Deterministic	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Multiple processing destinations	Stochastic or Deterministic	IPCC/ Regular TS haulage
Liu, Kozan (2017)	An innovative mine management system by integrating a series of mathematical models for long-term (ultimate pit limit determination), mid-term block sequencing (over quarterly, half-yearly or yearly time periods), and operational level planning of equipment (with a job-shop scheduling model) to achieve an	18 weeks	CPLEX	The long and medium term MIP models maximize the net present value of the blocks to be mined throughout the life of mine and for a specific period respectively and the operational level MIP minimizes the makespan and tardiness in job completion times **subject to** block precedence and capacity constraints.	No	Deterministic	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Multiple processing destinations	Stochastic or Deterministic	IPCC/ Regular TS haulage
	overall mining efficiency						
Blom et al. (2014,2016)	A decomposition based heuristic model to solve a set of mine-side (extraction) optimisation problems and a port-side blending problem	13 weeks	IMB CPLEX	Meeting blending targets and maximizing equipment use in a multi-mine, multiple port network **constrained by** capacity and blending constraints	Yes	Deterministic	TS
Blom (2017)	A rolling planning horizon-based MIP model to generate multiple short-term production schedules	13 weeks	IMB CPLEX	Optimize equipment use and shovel movement **constrained by** precedence relationships, blending requirements, equipment availabilities and trucking hours considering multiple processing paths.	Yes	Deterministic	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Multiple processing destinations	Stochastic or Deterministic	IPCC/ Regular TS haulage
Upadhyay, Askari-Nasab (2016, 2017)	Simulation optimization model to generate optimum mining schedule by shovel allocation	12 months	CPLEX, ARENA	Maximizing shovel utilization, minimizing deviation in production and grade from expected/target, minimizing shovel movement **subject to** production capacity, grade blending and precedence constraints.	Yes	Operational uncertainty	TS
Manriquez et al. (2019)	A framework to optimize short-term planning of open pit mines	NS	Python	Minimizing maximum deviation between ore tonnage sent to plant and plant capacity, minimizing maximum deviation between metal fines and the expected metal fines in processing plant and minimizing overall shovel fleet movement cost minimization **subject to** grade blending and precedence constraints.	Yes	Deterministic	TS
Manriquez et al. (2020)	Simulation optimization model to generate short-term extraction sequence	18 months	UDESS	Maximize value of extraction **subject to** precedence, blending and equipment availability constraints.	Yes	Deterministic	TS

Comparison of post 2010 short-term papers	**key Aspects**	**Time horizon**	**Solution tool**	**Objectives**	**Multiple processing destinations**	**Stochastic or Deterministic**	**IPCC/ Regular TS haulage**
Matamoros, Dimitrakapoulos (2016)	Simultaneous optimization of fleet and production schedules	12 months	CPLEX, C++	Eight component objectives to minimize the cost of extraction, haulage time under uncertainty of trucks' haulage time and availability, loss of shovel production and geological risks **subject to** capacities and blending constraints.	No	Stochastic (geological and fleet uncertainty)	TS
Paduraru, Dimitrakopoulos (2018)	Shows how new information, such as updated estimates on the characteristics of extracted material, can be integrated into the short-term planning process	50 weeks	NS	Based on the characteristic vector of a block, determining the optimum destination for that block to impose the largest immediate improvement on cash flow **constrained by** block precedences and processing capacities.	Yes	Geological uncertainty	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Multiple processing destinations	Stochastic or Deterministic	IPCC/ Regular TS haulage
Matamoros, Jewbali (2013, 2018)	A multi-stage planning process that incorporates potential short-term variability in the long-term planning process.	NS	NS	Maximizes NPV and minimizes deviation in planned production, where a set of possible realizations of future grade control data is generated based on the grade of material in mined out areas of the mine site **satisfying** block precedence constraints. The compliance of short-to long term production schedules and performance is expected to augment the probability of meeting production targets and increased productivity.	Yes	Geological and operational uncertainty	TS
Bodon, Sandman (2010, 2011)	Model shows how integrating optimization within a simulation allows a more accurate representation of the system, providing a better solution although	9 days	Lingo	Maximize tonnes mined and shipped, minimize the deviation of the quality of all mine and port stockpiles and meet blending requirements **constrained by** equipment and port capacity and precedence constraints for a supply chain consisting of pit, port and ships.	Yes	Operational Uncertainty	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Multiple processing destinations	Stochastic or Deterministic	IPCC/ Regular TS haulage
	with a longer run time.						
Shishvan, Bendorf (2014, 2016, 2017)	stochastic simulation approach to predict performance and reliability of complex continuous mining operations for optimal decision making in short-term production planning	7days	Arena	Minimize production deviation and maximize equipment utilization **subject to** processing capacities and equipment availability.	No	Geological Uncertainty and equipment uncertainty	TS
Rahmanpour, Osanloo (2016)	stochastic optimization model to capture the effects of geological uncertainties on short and long	30 months	NS	minimize cost of mining **subject to** equipment capacity, ore quality and mill demand constraints	No	Geological Uncertainty	TS

Comparison of post 2010 short-term papers	**key Aspects**	**Time horizon**	**Solution tool**	**Objectives**	**Multiple processing destinations**	**Stochastic or Deterministic**	**IPCC/ Regular TS haulage**
	term mine planning						
Quigley, Dimitrakapolous (2019)	Improvement of Matamoros, Dimitrakapolous model (2016)	12 months	CPLEX	Generate short term schedule to minimize cost of shovel movement and production deviation, deviation of tonnage and grade sent to plants and maximize truck hours of the allocated fleet **constrained by** processing capacity, equipment availability considering uncertainty of geology, shovel performance and truck cycle time.	Yes	Geological and equipment uncertainty	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Multiple processing destinations	Stochastic or Deterministic	IPCC/ Regular TS haulage
Both, Dimitrakopoulos (2020)	Optimization model for simultaneous optimization of short-term extraction sequence and fleet management, in contrary to the traditional approach of optimizing production schedule first and then fleet allocation	12 months	NS	maximize total profit/revenue and production by minimizing risk of underproduction by shovel and trucks **constrained by** precedence relationships, production targets and number of trucks available	Yes	Geological and equipment performance uncertainty	TS

Abbreviations

IPCC – In-pit crushing and conveying

SMIPCC – Semi-mobile IPCC

FMIPCC – Fully-mobile IPCC

TS – truck-shovel

Short-term Planning of Open Pit Mines with Semi-Mobile In-Pit Crusher

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ABSTRACT

Open pit mines are getting deeper with time and transportation expenses are increasing because of the increasing haulage distance. In-pit crushing and conveying (IPCC) is getting popular in deeper open pit mines as a suitable alternative because it offers a lower operating cost due to shorter haulage distance and less truck requirement. Semi-mobile in-pit crusher, currently the most popular IPCC system, is relocated every two to five years and the short-term plan needs to be updated accordingly. To the best of our knowledge, short-term planning with IPCC is an area of research that has not been explored extensively yet and hardly any model can generate short-term extraction sequence considering an IPCC in place. This research work proposes a mixed integer programming model to generate short-term production plan within a time horizon of 12 months. The objective of the model is to optimally allocate shovels to minimize cost of material handling and maximize revenue subject to meeting plant requirement, maximum allowable tonnage variation and IPCC location constraints to achieve production and NPV targets set by strategic plan. The proposed model will be implemented in a hypothetical case study for validation. The model will be developed and solved using MATLAB. The comparison of results between scenarios with and without IPCC is expected to justify the use of IPCC in large open pit mines from a short to medium term perspective. The project on completion will be a pioneering work in the arena of short-term mine planning. A *semi-mobile IPCC system with one relocation will be considered in the case study.*

1. Introduction

Mining is a highly capital-intensive operation and proper production planning is required to keep the overall setup, including all the equipment, from performing sub-optimally. The primary objective of any mining project is to maximize the profit by keeping the cost at minimum. Mine planning can be divided into long-term and short-term planning based on the planning time-horizon and objectives being optimized. While the long-term plan is created at the management level to maximize the net present value (NPV) throughout the life of mine, the short-term planning aims at optimizing the operational activities like shovel allocation, grade blending, truck requirement etc. to help achieve the ultimate long-term schedule. The time horizon of short-term planning can be monthly, weekly or even daily. The several stages of mine planning are delineated in Figure 1.

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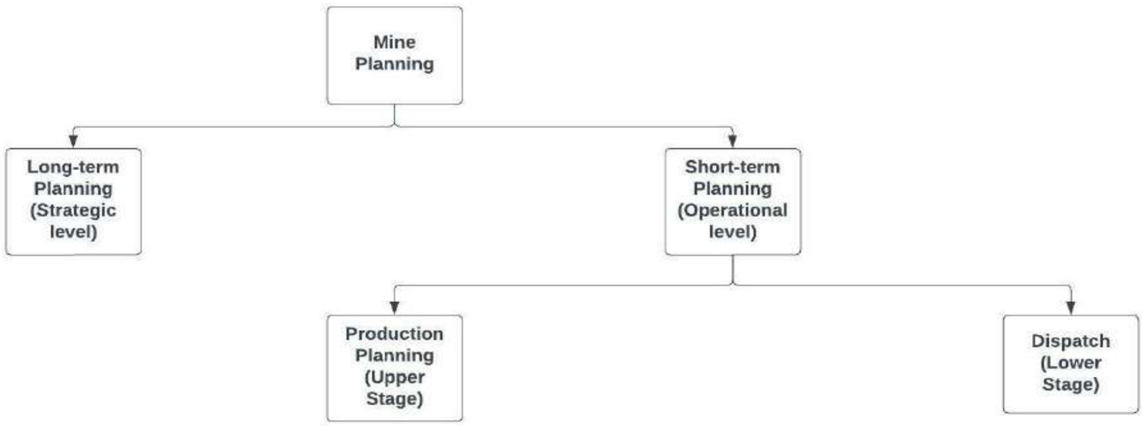

Figure 1. Mine planning stages.

Optimal utilization of the equipment used in mining is of vital importance because the truck-shovel operation may account for over 50% of the total operating cost (Moradi Afrapoli and Askari-Nasab 2017). This optimality can only be realized with efficient utilization of all the assets involved, to achieve the production targets set by the long-term production plans. Therefore, short-term scheduling by optimal allocation of assets (shovels and trucks) is of utmost importance.

Mixed integer programming (MIP) models have been used extensively to generate short-term schedules of open pit mines. Most of the modern short-term planning models are MIP based with explicit precedence constraints applied. (Smith 1998), was the first to use the precedence constraints in mine planning and scheduling. The model uses an MIP for constructing short-term schedules with explicit accessibility constraints, requiring the nine blocks above a block to be mined before that block can be accessed. (Gholamnejad 2008) proposed a binary integer programming model to solve the short-term mine scheduling problem to decide which blocks of ore and waste must be mined in which period (shift, days, weeks or months) by satisfying several operational and geometrical constraints simultaneously. (Eivazy and Askari-Nasab 2012) solved a short-term planning MIP model under several different scenarios, in which the direction of mining varies with different mining precedence constraints. The objective is to minimize the overall cost of mining operations including mining, processing, haulage, re-handling and rehabilitation costs.

(L'Heureux, et al. 2013) proposed a detailed mathematical optimization model for short-term planning, with operational details for a period of up to three months. The objective is to minimize operational costs of trucks' and shovels' activity, drilling and blasting. The authors solved the problem for up to 5 shovels, 90 periods and 132 faces. (Kozan, et al. 2013) modelled drilling, blasting and mining of blocks, and allocation of equipment to these activities with an objective of minimizing the make-span (elapsed time between the start and end of a schedule). Later (Kozan and Liu 2016) formulated another short-term planning model to maximize the throughput and minimize the total idle times of equipment at each stage of drilling, blasting and excavation subject to equipment capacity, speed, read times and activity precedence constraints. The latest contribution of (Liu and Kozan 2017) is an is an innovative mine management system. The proposed methodology integrates a series of mathematical models for ultimate pit limit determination in long-term, medium-term block sequencing over quarterly, half-yearly or yearly time periods, and operational level planning of equipment with a job-shop scheduling model to achieve an overall mining efficiency improvement.

(Blom, et al. 2017) presented a rolling planning horizon-based MIP model to generate multiple short-term production schedules to optimize equipment use and shovel movement constrained by precedence relationships, blending requirements, equipment availabilities and trucking hours considering multiple processing paths.

Integration of simulation with MIP is a tool that has been used by some researchers to account for the uncertainty that exists in mining operations such as, equipment failure, haulage etc. (Upadhyay and Askari-Nasab 2016), and (Upadhyay and Askari-Nasab 2017) integrated simulation with an MIP based short-term planning model, to illustrate how proactive decisions can be made in dynamic environment of mining and operational plans can be synced with long-term planning to reduce opportunity cost, maximize production and equipment utilization. The authors solved the MIP model to optimally allocate shovels to meet production and grade requirement and minimize shovel movement time. (Manríquez, et al. 2020) proposed a similar simulation optimization framework to increase the adherence of short-term mining schedules to execution for underground mining operation. The model generates an initial schedule based on an MILP model embedded in UDESS and then simulated in any data encryption standard (DES) software to replicate the schedule and estimate equipment utilization. The authors claim the model to be general one that is applicable to open pit mining.

The short-term planning models discussed so far are all designed to generate schedules assuming truck-shovel haulage system. While there are studies, such as, (Paricheh and Osanloo 2019), (Samavati, et al. 2020), (Shamsi, et al. 2022), (Liu and Pourrahimian 2021) etc., that justify the use of in-pit crushing in long-term, to the best of our knowledge, there is hardly any research work that do the same in operational level. Several key decisions regarding IPCC, such as, optimum location, relocation time, conveyor design and length etc., are made in the strategic level of mine planning. Therefore, short-term planning needs to investigate the changes in schedules (extraction sequence) that occur because of housing and moving a crusher inside the pit over time. It is also important to verify if the operational plans can sync with the long-term plan to deliver the desired NPV of mine with IPCC.

This research formulates a short-term planning methodology to generate monthly production schedules by optimum shovel allocation. This is a general shovel allocation model that can generate short-term schedule for both truck-shovel haulage and IPCC systems. The model will be used to compare scenarios with IPCC and traditional truck shovel haulage system to determine which one provides more cost saving and generates higher revenue from a short-term perspective with a time horizon of 1 year.

2. Problem Definition

The goal of this research study is to demonstrate the effects of IPCC installation on short-term planning by generating near optimal schedules. The proposed model is intended as a tool to compare IPCC and truck haulage system from the operational perspective of mine planning.

The proposed short-term planning methodology optimally allocates shovels to the mining faces (aggregated blocks into a single entity to reduce the number of variables) to meet production requirements, reduce the cost of haulage and maximize the revenue. The model will generate monthly schedules for a 12-month planning time horizon. The idea is to present two scenarios, one with IPCC and the other one with traditional truck haulage and compare the results to find out the overall revenue generated and cost incurred in each of the scenarios. The difference in scheduling or extraction sequence based on shovel allocation will also be highlighted to demonstrate how IPCC installation affects mine plan from an operational viewpoint. The comparison of results should enable mine planners to decide on the better haulage option for a specific year of mine life.

2.1. Objectives

The operational objectives of the study are:

1. Maximize revenue
2. Meet production requirement to feed the mill to its capacity
3. Minimize haulage cost

The paper develops, implements and verifies the model to compare schedules with semi-mobile IPCC and traditional truck-shovel haulage system.

2.2. Scope and Assumptions of the Study

The proposed model provides a tool to generate and compare short-term schedules for open pit mines.

The MILP is a general shovel allocation model. It can generate schedules for both truck-shovel haulage and IPCC systems.

The model allocates shovels considering both cost minimization and revenue maximization unlike the previous models of (Upadhyay and Askari-Nasab 2016),(Upadhyay and Askari-Nasab 2017) and (Manríquez, et al. 2020), where revenue maximization was not considered.

The model can be integrated with haulage simulation models to account for operational uncertainty.

The model can be extended to find the optimal number of trucks required in a specific period of mine life.

The model is based on the following assumptions.

1. The IPCC system is semi-mobile
2. The optimum locations and relocation time of the crusher is known throughout the life of mine from strategic planning.
3. There is no waste crusher. Waste material goes directly to external waste dumps.
4. The ore and waste faces are labeled. Hence, ore material will go to mill or crusher and waste material will go to waste dump.
5. There is no stockpiling.
6. The model does not consider ore blending in its current state.
7. The model does not consider multiple processing destinations.
8. Production loss due to shovel movement time is not considered.
9. Production loss due to equipment failure and maintenance is not considered.
10. The model is strictly deterministic.
11. The mill requirement is constant throughout the planning horizon.

3. Model Formulation

The objective function, variables, parameters and the constraints of the MILP model are described in the section below.

3.1. Objective Function

The objective function consists of three components. The first two components calculate the cost of hauling ore material to crusher or mill and waste material to waste dumps respectively, using regular diesel trucks. The third part calculates the cost of conveying ore material from crusher to processing plant. The last component calculates the revenues earned from ore production. The flow of ore and waste material from source to destination is displayed in Figure 2.

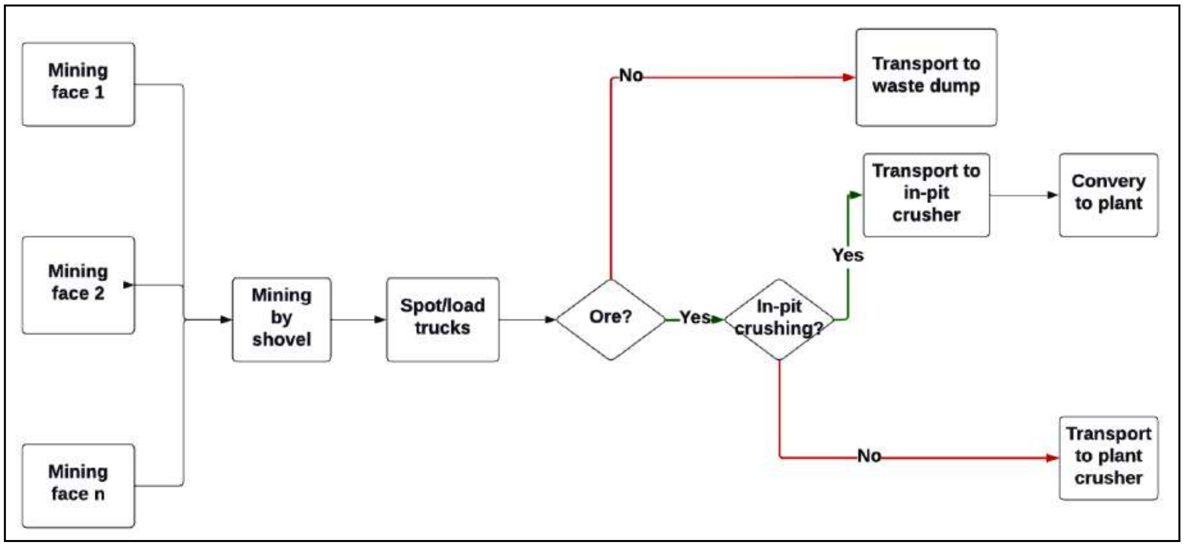

Figure 2. Flow of material from mine to crusher, plant and waste dump.

Objective function, minimize f = cost of transporting material to crusher or waste dump from mine by trucks + cost of conveying ore material from crusher to processing plant – revenue earned from selling ore.

Mathematically, the objective function can be represented as:

$$\text{Min, f} = \sum_{p\in P\in T, f\in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT \times D_{f,r} \times H_t +$$

$$\sum_{p\in P\in T, f\in F_{waste}} x_{p,f,t} \times RM_{p,f} . TT \times D_{f,w} \times H_t +$$

$$\sum_{p\in P,\in T, f\in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT \times C \times H_c -$$

$$\sum_{p\in P\in T, f\in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT \times p_k$$

3.2. Variables, Parameters and Indexes Explanations

Variable	Description
$x_{p,f,t} \in [0, 1]$	Time percentage of period $t\in T$where shovel $p\in P$ is active in face $f\in F$, 0 otherwise

$s_{p,f,t} \in \{0, 1\}$	Shovel allocation variable. Equal to 1 if shovel $p \in P$is allocated to face$f \in F$ in period$t \in T$, 0 otherwise
$m_{f,t} \in \{0, 1\}$	Equal to 1 if face $f \in F$ is mined out in period$t \in T$, 0 otherwise
$l_{f,t} \in R^{+}$	Tonnage of face f in period the beginning of period t

Parameter	Unit	Description
TT	H	Total time per period
$AV_{p,t}$	%	Availability of shovel p in period t
$RM_{p,f}$	t/h	Material throughput of shovel p in face f
TM_{f}	Tonnes	Total material in face f
$D_{f,w}$	km	Distance to waste dump from face f
TC	Tonnes	Mill capacity per period
C	Km	Conveyor length
$D_{f,r}$	Km	Distance to crusher/mill from face f
H_{t}	\$/tonneKm	Transportation cost per unit
H_{c}	\$/tonneKm	Conveying cost per unit
M		A big number
p_{k}	\$/ton	Iron ore price
N^{f}		Number of precedences for face f
$c_{f,t} \in \{0, 1\}$		Equal to 1 if crusher is located on face $f \in F$ in period $t \in T$, 0 otherwise

Indexes	Description
p	Index for shovels
f	Index for faces
t	Index for periods

3.3. Constraints

$$\sum_{p\in P} s_{p,f,t} \leq 1;\ \forall f \in F,\ \forall t \in T \tag{1}$$

$$\sum_{f\in F} s_{p,f,t} \leq 2;\ \forall p \in P,\ \forall t \in T \tag{2}$$

$$\sum_{p\in P, f\in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT <= TC;\ \forall t \in T \tag{3}$$

$$\sum_{p\in P, f\in F_{waste}} x_{p,f,t} \times RM_{p,f} \times TT >= TC;\ \forall t \in T \tag{4}$$

$$l_{f,t} = TM_f;\ \forall f \in F \,\&\, t = 1 \tag{5}$$

$$l_{f,t+1} = l_{f,t} - \sum_{p\in P} x_{p,f,t} \times\ RM_{p,f} \times TT;\ \forall f \in F \,\&\, t = 1 \ldots T - 1 \tag{6}$$

$$\mathrm{M} \times m_{f,t} <= \text{epsilon} - l_{f,t} \quad ;\forall f \in F,\ t \in T \tag{7}$$

$$\mathrm{M} \times (1 - m_{f,t}) >= -\text{epsilon} + l_{f,t}\ ;\ ;\forall f \in F,\ t \in T \tag{8}$$

$$m_{f,t+1} \geq m_{f,t}\ ;\ ;\forall f \in F,\ t \in 1 \ldots T - 1 \tag{9}$$

$$\sum_{f\in F} s_{p,f,t} \leq s_{p,f,t} + m_{f,t} + \left(1 - s_{p,f,t-1}\right) + \left(1 - s_{p,f,t}\right) \times BM;\forall f \in F, t \in T, p \in P \tag{10}$$

$$s_{p,f,t+1} \geq s_{p,f,t} - m_{f,t};\ ;\forall f \in F,\ p \in P,\ t \in 1 \ldots T - 1 \tag{11}$$

$$s_{p,f,t} \geq c_{f,t} \times BM\ ;\ ;\forall f \in F,\ p \in P,\ t \in T \tag{12}$$

$$\sum_{p\in P, t\in T} x_{p,f,t} \times RM_{p,f} \times TT \leq TM_f;\forall f \in F \tag{13}$$

$$N^f \times \sum_{p} s_{p,f,t} - \sum_{f'} m_{f',t} \leq 0;\ ;\forall f \in F,\ p \in P,\ f' \in precednece\ set \tag{14}$$

$$\sum_{f\in F} x_{p,f,t} \leq AV_{p,t};\ p\ \in\ P,\ t\ \in\ T \tag{15}$$

Where,

Equation 1: Only 1 shovel can be assigned to a face in a specific period.

Equation 2: One shovel cannot be assigned to more than 2 faces in a period. This constraint allows the shovels to move to a new face when the working face is mined out.

Equation 3: Total material extracted in a period must not exceed the destination/mill capacity.

Equation 4: Total waste material to be mined each period. The model tries to minimize waste mining as waste material increases haulage cost and does not contribute to revenue. Therefore, this constraint makes sure that the tonnage of waste mined in a period is such that the total waste material is mined out at the end of 12 periods.

Equation 5: Initial tonnage of the faces. The total tonnage of each face TM_f is assigned to the $l_{f,t}$ variable in the initial period.

Equation 6: Remaining tonnage of a face after a period of extraction. This equation keeps track of the remaining tonnage of each face at the end of a period.

Equations 7 and 8: Makes sure that when $l_{f,t}$<= epsilon (a small number), $m_{f,t}$= 1. The $m_{f,t}$ is used to keep track of faces that have been mined out.

Equation 9: If a face is mined out, it stays mined out in the next periods.

Equation 10: It strengthens equation 2. This equation controls when a shovel can be assigned to more than one faces in a period. The right-hand side of the constraint (9) looks over all the faces and takes a very large value if shovel 's' is not assigned to the face in that period. For the faces shovel is assigned to, last part of the constraint will become zero and remaining portion may take a value of 1 or 2. If the shovel was working on the face in the previous period and still hasn't finished mining it, maximum number of faces that shovel can work on can be 1, but if the face is mined out completely, $m_{f,t}$ will become 1 and thus the shovel will be allowed to be assigned to another face. For the new face as $s_{p,f,t-1}$ and $m_{f,t}$ will be zero and thus the constraint will still hold true and allow the shovel to be assigned to two faces in that period.

Equation 11: Forces a shovel to stay in the same face unless it is mined out.

Equation 12: A shovel cannot be assigned to a face in a period if the crusher is located on that face during that period. This constraint controls if in-pit crusher is present or not in the mine.

Equation 13: The total material mined by all the shovels from all the faces must not exceed the total material available in this face.

Equation 14: Face f cannot be mined before the precedence faces (f') have been mined out.

Equation 15: The fraction of time a shovel works in several faces must not exceed the shovel availability.

The model will be solved using rolling-planning horizon technic to reduce the runtime. The model will look into 3 months ahead while assigning shovels to faces. It assigns shovels to faces for the first three periods at first. Then it looks into the next three periods, assigns shovels to the available faces and so on. The periods are denoted by P in the following Figure 3 that demonstrates the rolling-planning horizon time frame used in the model.

Optimization Time frame											
P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
Decision Time Frame(T)											

Figure 3. Optimization and decision time frame of the model.

4. Case Study

The case study will present two scenarios in an iron mine with IPCC and traditional truck-shovel mining method to verify the model. The short-term schedule will be generated for the 11th year of mine life. Two benches with elevations 1595 and 1610m are available to be mined and the total available material to be mined is 16MT of ore and 16.5MT of waste. There is only one mill to process material. The crusher requirement (in-pit or plant) is 2700 tons per hour. Assuming 16 hours of operation in a day with 2 eight-hour shifts, the monthly crusher requirement is 1.33MT. The mine layout is shown in Figure 4 for year 11. Figure 5 and Figure 6 show the pit layout at the elevations of the two benches to be mined in year 11. The distances from each face to the waste dump, crusher and plant are calculated using the nodes in the road network. The grade of the designed ramps is 8%. The length of the conveyor belt for the IPCC scenario is 2550 m, which comes from the strategic plan.

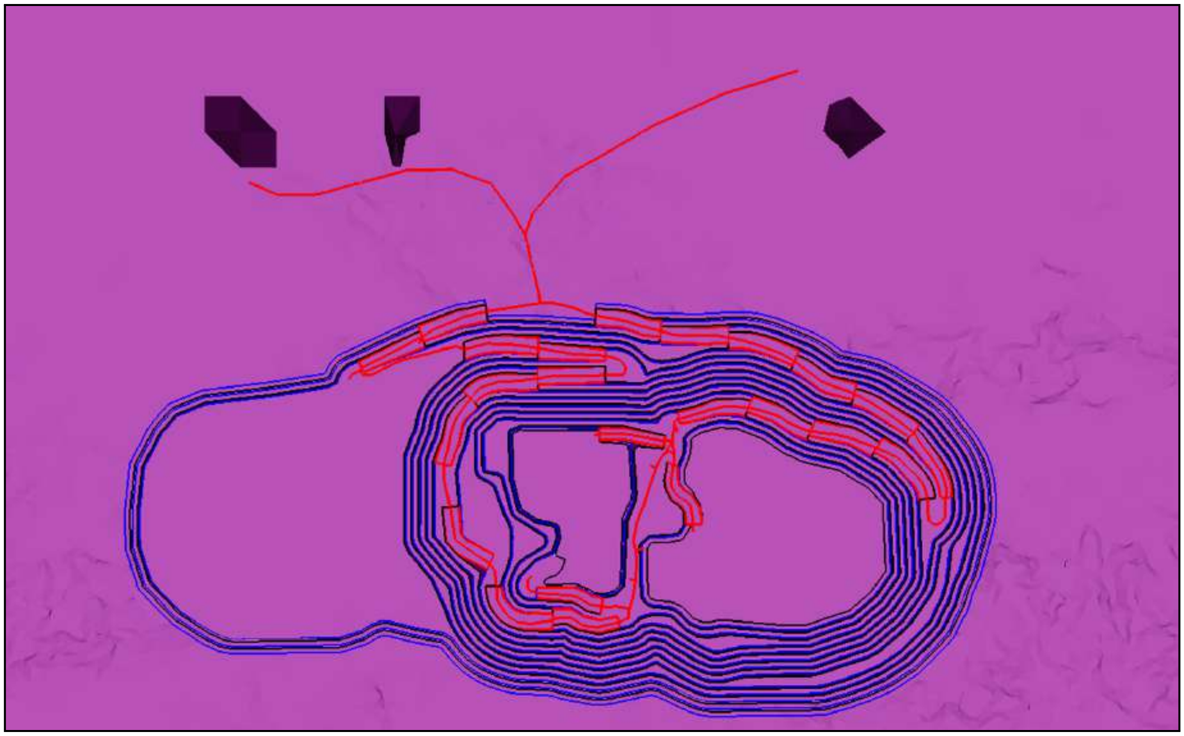

Figure 4. Pit layout with roads and ramps in year 11.

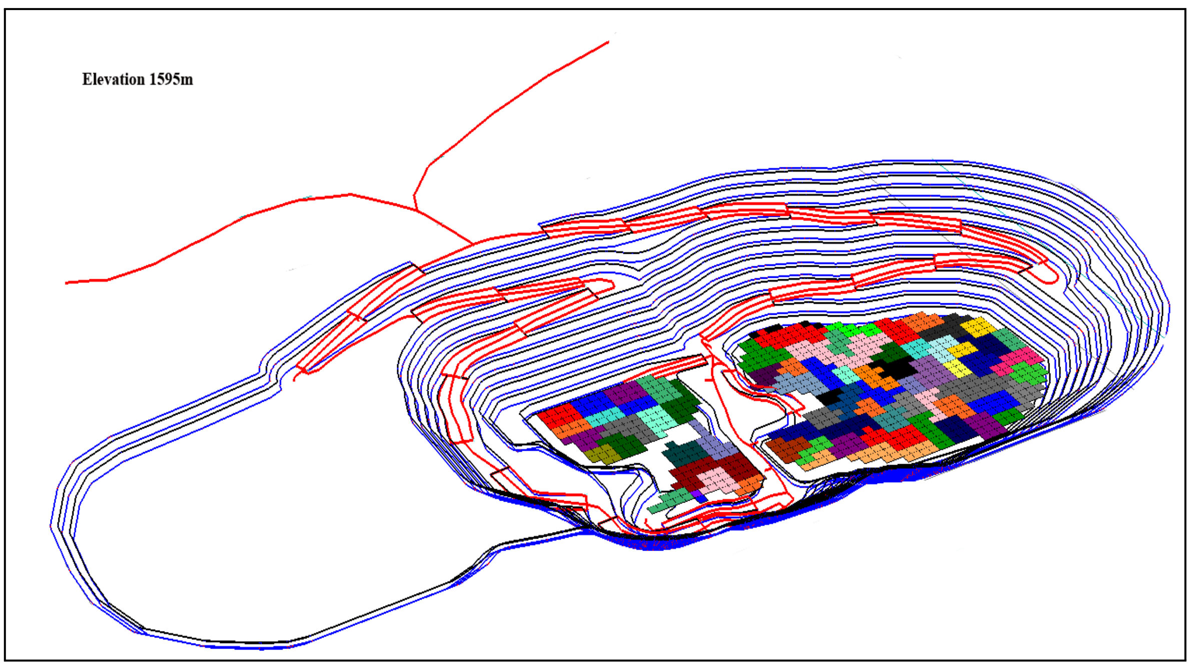

Figure 5. Layout of the pit at elevation 1595m.

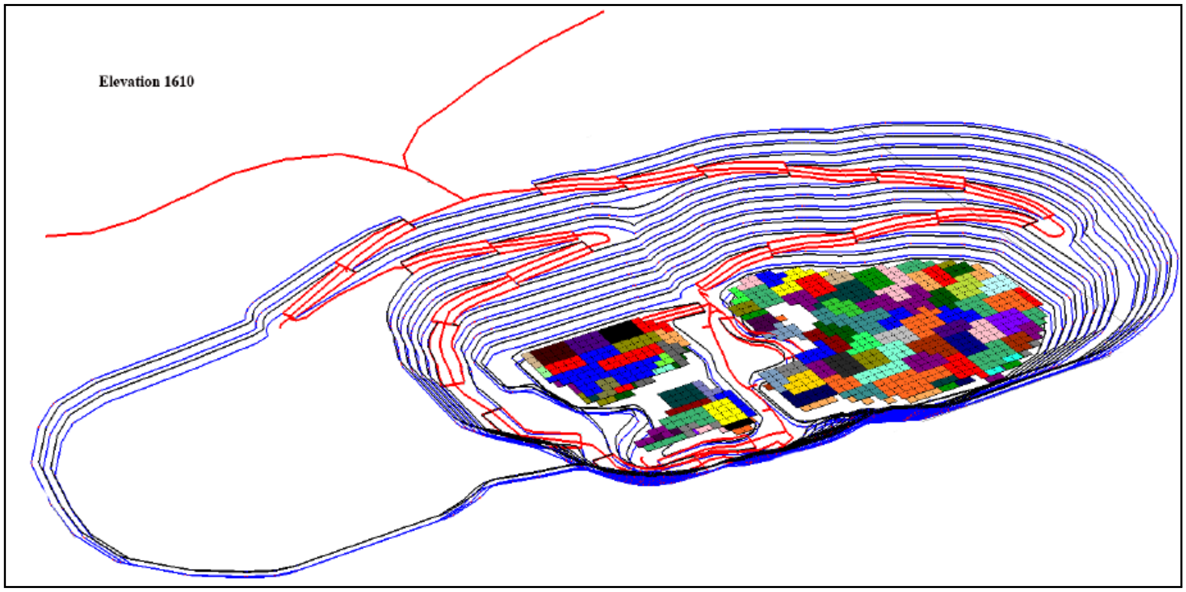

Figure 6. Layout of the pit at elevation 1610m.

The element of interest in the mine is magnetic weight recovery of iron (MWT). The grade and tonnage distribution of MWT in year 11 is presented in Figure 7.

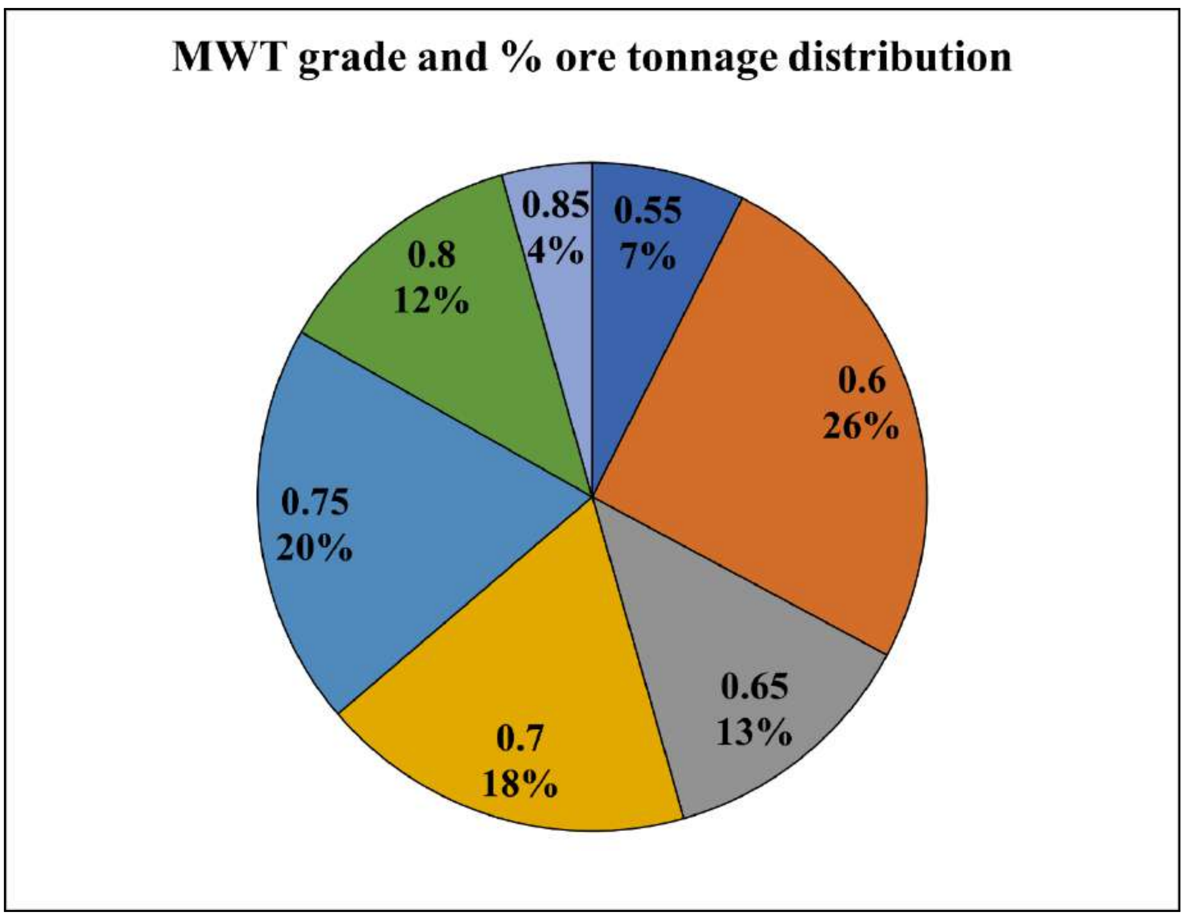

Figure 7. Grade and tonnage distribution of MWT.

A hierarchical clustering algorithm has been used (Tabesh and Askari Nasab 2013) to aggregate similar blocks together to generate 78 mining faces (polygons) out of 1900 blocks to be mined in year 11 within two benches. The face 37 on bench 1595 has a very low waste tonnage of less than 60000 tons. Hence, this face has been omitted in the data input to the model. The clustered faces in the benches are shown in the Figure 6 and Figure 7.

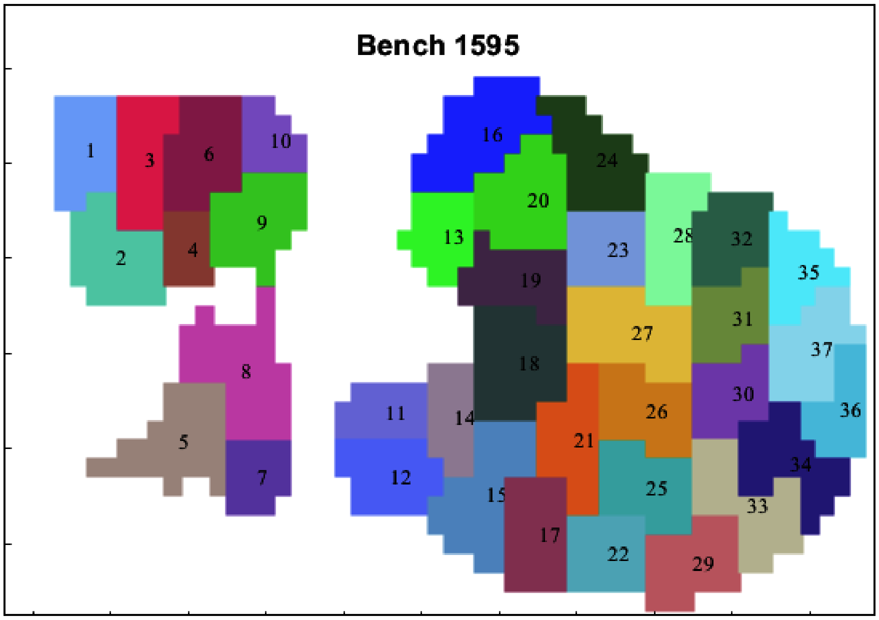

Figure 8. Clustered faces on bench 1595.

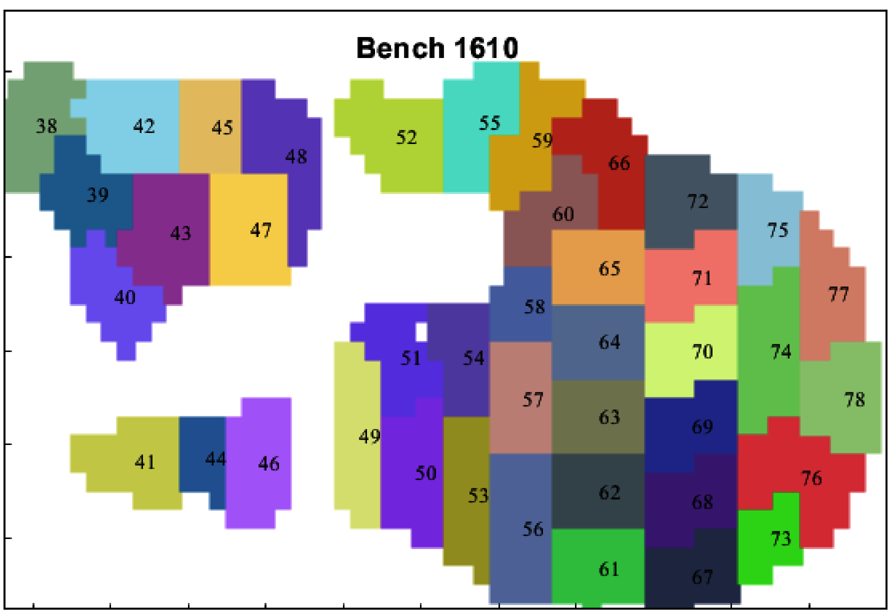

Figure 9. Clustered faces on bench 1610.

The mine employs a total of 4 shovels including 2 Hit 2500 shovels specifically for ore and 2 Hit 5500Ex shovels only for waste mining. The Hit 2500 shovels have a bucket capacity of approximately 12 ton and a bucket cycle time of about 22 seconds; whereas Hit 5500Ex shovels have a bucket capacity of approximately 22 ton and a bucket cycle time of about 23 seconds.

To haul the material from the faces mine employs Cat 785C and Cat793C trucks with nominal capacities of 140 ton and 240 tons respectively. Cat 785C trucks are locked to ore shovels and thus they may be loaded only by Hit 2500 shovels, and Cat 793C trucks can only be loaded by Hit 5500Ex shovels. The truck requirement for both the scenarios are calculated and compared based on the truck cycle time, shovel capacity and production requirement.

5. Results

The MIP model is solved for two scenarios: one with semi-mobile IPCC and one with Truck-shovel only. The two scenarios are differentiated by Equation 12, which controls whether the mine has an in-pit crusher or not. The model runs for 12 months in four steps where it allocates shovels to faces for three months, saves the results and then look for available faces for the coming three months. The model is formulated and solved in MATLAB 2021(B). The scenario without IPCC (scenario 1) took 192 seconds to run and the IPCC scenario (scenario 2) took 204 seconds. The optimality gaps in both cases are less than 0.5%. A comparison of the optimal results and generated schedules are presented in the following sections.

5.1. Scenario 1 (No IPCC):

This scenario represents a traditional truck-shovel (TS) mining operation where the mined material is hauled to the plant crusher and waste dump by trucks. Pragmatic shovel assignment to the faces is the primary goal of the model. Shovel positions and the working months are summarized to analyze the allocation decisions made by the model. The model does not take shovel movement time into account. A shovel availability of 80% is assumed to account for the lost time for movement among faces. The optimal objective function value for this scenario is **$2138M**. Figure 10 and Figure 11 show the ore and waste faces in shaded color for bench 1610 and 1595 respectively. Figure 12 and Figure 13 show the shovels in shaded color, polygon boundaries by edges and working (starting) month in numerals for bench 1610 and 1595.

1610	38	39	40	41	42	43
	44	45	46	47	48	49
	50	51	52	53	54	55
	56	57	58	59	60	61
	62	63	64	65	66	67
	68	69	70	71	72	73
	74	75	76	77	78	
			ore	waste		

Figure 10. Ore and waste faces on bench 1610.

1595	1	2	3	4	5	6
	7	8	9	10	11	12
	13	14	15	16	17	18
	19	20	21	22	23	24
	25	26	27	28	29	30
	31	32	33	34	35	36
			ore	waste		

Figure 11. Ore and waste faces on bench 1595.

1610	9	6	3	6	8	11
	7	9	5	4	6,7	1
	2	3	1	5	2	11
	11	2	7	2	4	4
	6	8	6	8	2	3
	1	1	1	5	7	8
	9	5	12	7	9	
	Sh1	Sh2	Sh3	Sh4		

Figure 12. Shovel assignment to faces and corresponding mining period in bench 1610.

1595	10	8	12	11	11	11
	10	12	10	12	4	3
	3	6	3	8	12	12
	5	9	12	7	10	9
	3	5	4	2	10	6
	12	4	7	12	11	10
	Sh1	Sh2	Sh3	Sh4		

Figure 13. Shovel assignment to faces and corresponding mining period in bench 1595.

The model assigns shovels to bench 1610 from period 1 and mining starts at bench 1595 from period 2 because of the vertical precedences that exist between the two benches. Generally, the waste faces are mined in the earlier than ore faces for both the faces because the waste faces precede the ore faces in many of the cases. The shovels do not look for the nearest faces for next assignment after a face is mined out because the model does not consider shovel movement costs. The allocations demonstrate that the model is capable of assigning shovels to faces respecting the precedence relationships and the production requirements. All the faces are mined within the 12 months optimization time frame making sure that the production requirement of the strategic plan is satisfied.

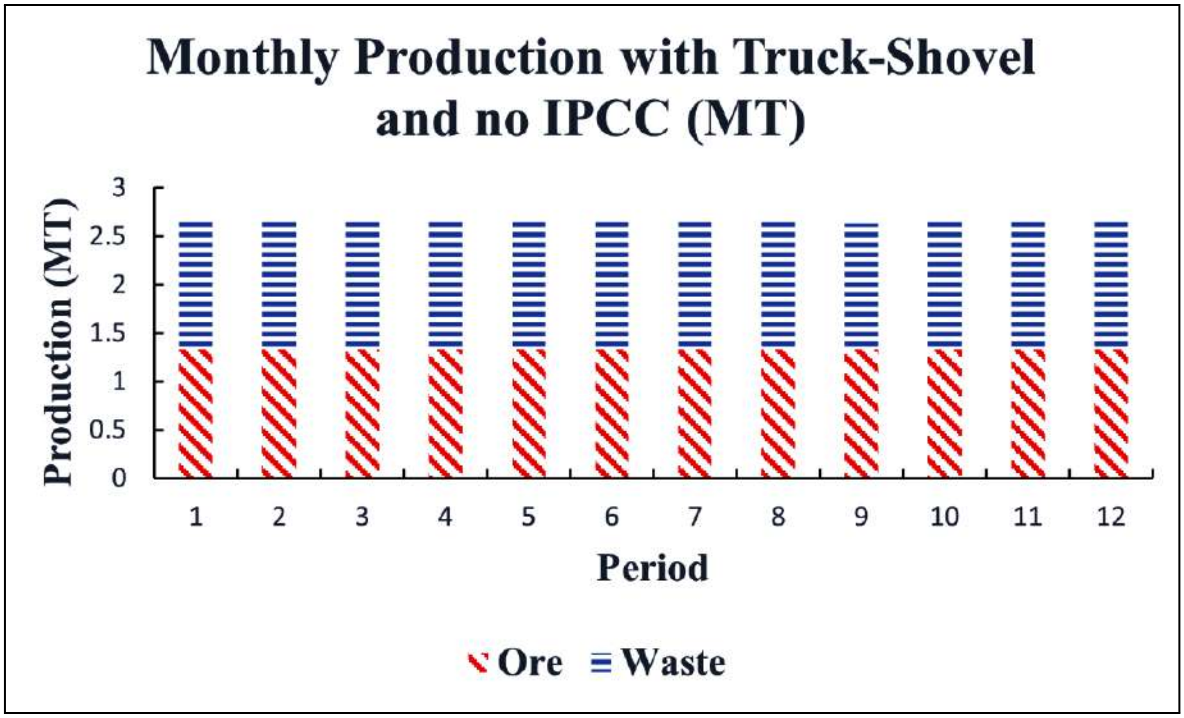

Figure 14. Monthly ore and waste production for scenario 1.

Figure 14 shows the monthly production of ore and waste. The production of ore is uniform throughout the 12 periods which ensures that the mill is fed to its capacity. The waste production is also fairly uniform too with a variation of less than 1.5% in period 9.

Figure 15 demonstrates average shovel efficiency for all four shovels over the 12 periods. The equation used to calculate shovel efficiency is displayed below.

$$Shovel\ efficiency, \vartheta \ = \ availability \times utilization \tag{16}$$

Utilization is being defined as the percent of time a shovel is busy working in a face in a period in this equation.

It is evident from Figure 15 that the ore shovels have higher efficiency compared to the waste shovels. Waste shovels have higher bucket capacity compared to the ore shovels. While the number of waste faces is significantly higher than the number of available ore faces, the tonnage of ore and waste to be mined is similar. This justifies the lower efficiency of the waste shovels. The efficiency of the waste shovels is around 50% and the ore shovels is between 70 to 75%.

The ore and waste truck requirement has been calculated based on the production requirement, truck cycle time and shovel capacity. The average one-way distance from all the faces to the plant crusher is 5km and the one-way distance to the waste dump is 3.2kms. The loaded and empty haul speed are estimated from the rimpull characteristics curve for CAT 785C and CAT 793C trucks. The equation used to calculate the truck requirement is,

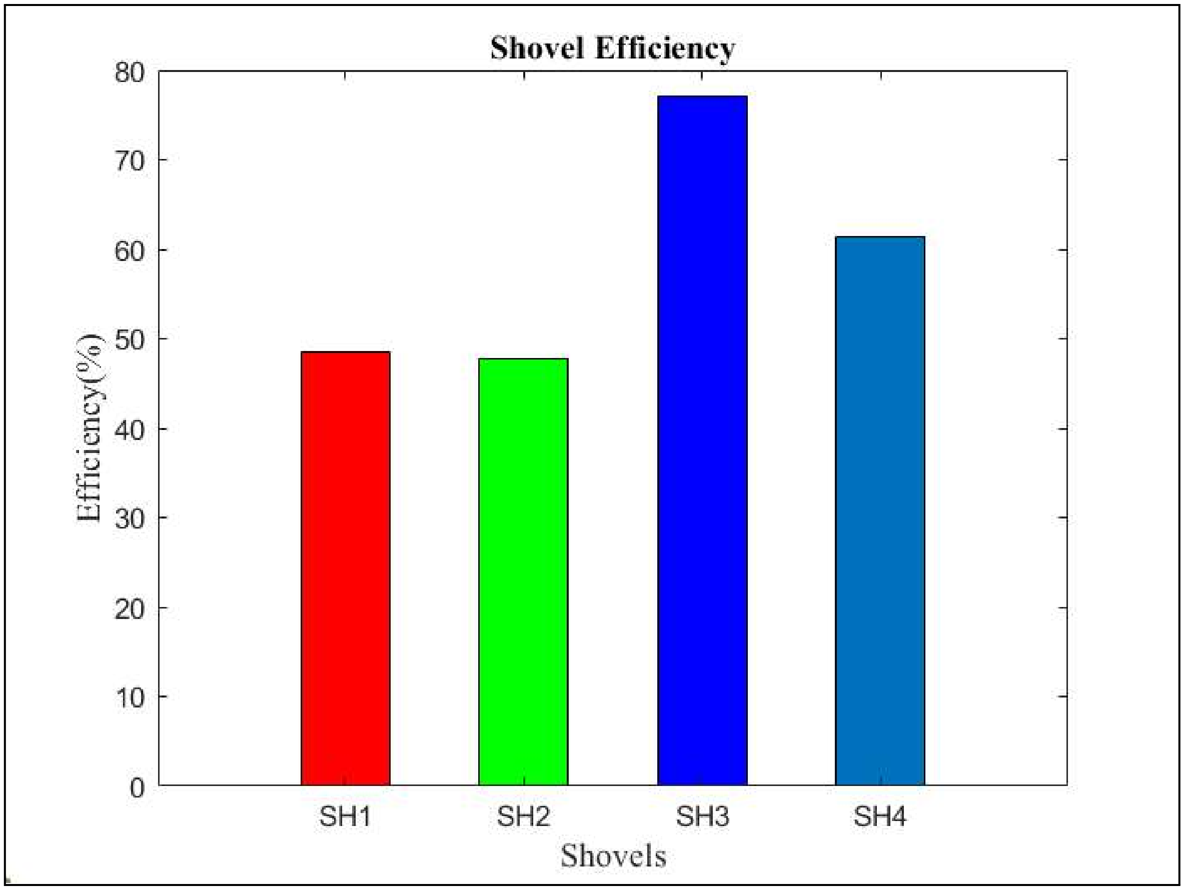

Figure 15. Average shovel efficiency.

$$N_h = \frac{P_h \times TC_{ch}}{60 \times L_h \times E} \tag{17}$$

Where, N_h = Number of trucks required

P_h = Production rate per hour

TC_{ch} = Truck cycle time

L_h = Nominal truck load

E = Operating efficiency

The required number of ore and waste trucks for this scenario is 13 and 6 respectively assuming a 65% efficiency.

5.2. Scenario 2 (IPCC):

This scenario assumes one in-pit crusher for ore crushing. The trucks haul the mined material to the crusher. The crushed material is conveyed to the processing plant by a 2.5km long conveyor belt. The location of the crusher is face 3 for the first six months and face 18 for the rest of the periods. The constraint shown in Equation 12 for IPCC prevents mining of the face that houses the crusher. The optimal objective value is **$2152M**. Figure 16 and Figure 17 display the shovel assignment and corresponding mining periods for bench 1610 and 1595 respectively.

1610	9	6	2	6	8	11
	7	9	5	4	5	1
	1	50	51	5	2	
	10	1	7	1	4	4
	6	8	6	9	1	2
	1	3	3	5	9	9,10
	7	4	12	11	8	
	Sh1	Sh2	Sh3	Sh4		

Figure 16. Shovel assignment to faces and corresponding mining period in bench 1610.

1595	10	8	12	11	11	11
	9	12	11	12	5	3
	4	6	3	8	10	
	5	9	12	12	7	7
	2	6	5	3	10	4
	12	4	8	12	11	12
	Sh1	Sh2	Sh3	Sh4		

Figure 17. Shovel assignment to faces and corresponding mining period in bench 1595.

The precedence relationships still hold for this scenario. The faces of bench 1595 starts from period 2 while mining in bench 1610 starts from the first period. The waste faces are generally mined in earlier months compared to ore faces. The crusher was located on face 3 of bench 1595 and it has been mined on period 12. Face 18 has been left unmined as the crusher has been located here from period 6 onwards. One of the waste faces (face 55) remains unmined on bench 1610.

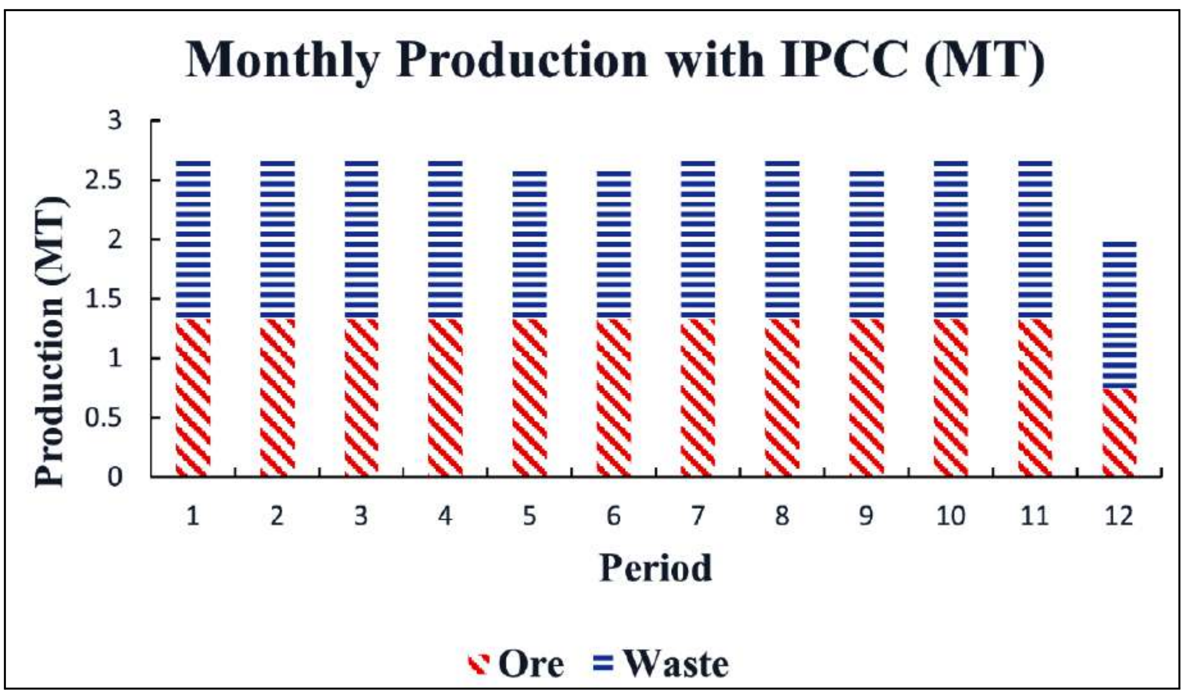

Figure 18. Monthly ore and waste production for scenario 2.

Figure 18 shows the production of ore and waste for this scenario. The ore production is low in the last period because of unavailability of faces. The overall waste production is 0.4MT less than scenario 1 because face 54 is left unmined. This face has to be mined in the next year. The tonnage of the face is negligible and does not really affect the overall production substantially.

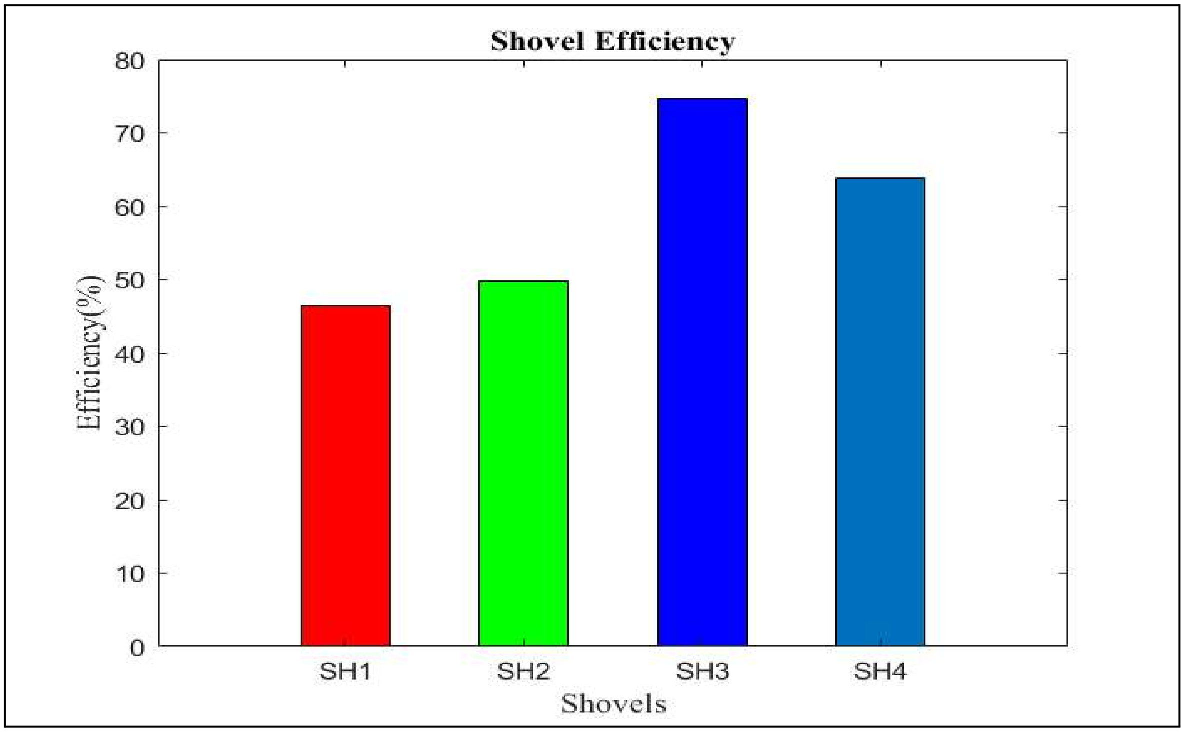

Figure 19. Average shovel efficiency across all periods.

The shovel efficiencies are displayed in Figure 19. The waste shovel efficiency is low compared to ore shovels for the same reason explained in scenario 1. A comparison of shovel efficiencies between the scenarios is shown in Figure 20. The difference in shovel efficiency between scenarios is negligible. Shovels 2 and 4 exhibit slightly higher (3%) efficiency in scenario 2. But shovels 1 and 3 display lower efficiency (2%) in scenario 2 than scenario 1.

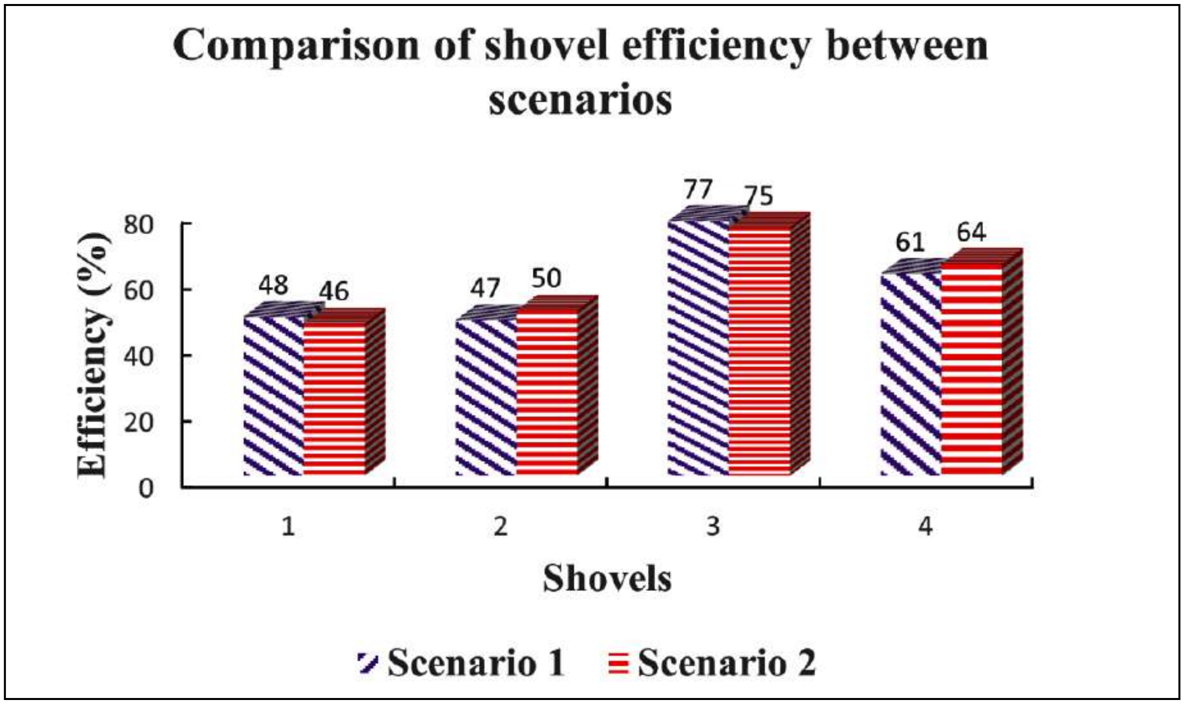

Figure 20. Shovel efficiency comparison between scenarios.

The truck requirement for ore (CAT 785C) and waste (CAT 793C) transportation for this scenario are 9 and 6 respectively for 65% efficiency. The waste truck requirement does not change as the waste transportation method does not change across the scenarios. A comparison of the required number of ore trucks between the scenarios is shown in Figure 21.

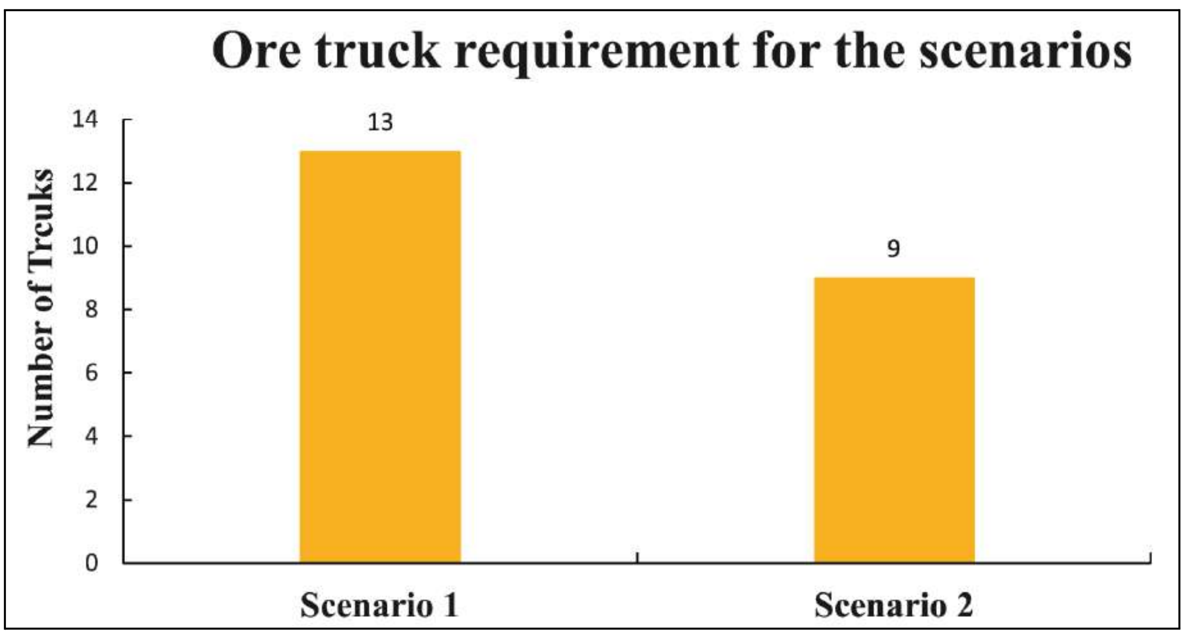

Figure 21. Ore truck requirement for scenarios without IPCC and with IPCC.

Figure 22 shows the optimal objective function values for both the scenarios. The objective function value is $14M higher for scenario 2 with IPCC, which justifies the use of IPCC in the mine in year 11. Although the total production is slightly lower for scenario 2, the mill requirement is fulfilled and the difference in production compared to scenario 1 is insignificant.

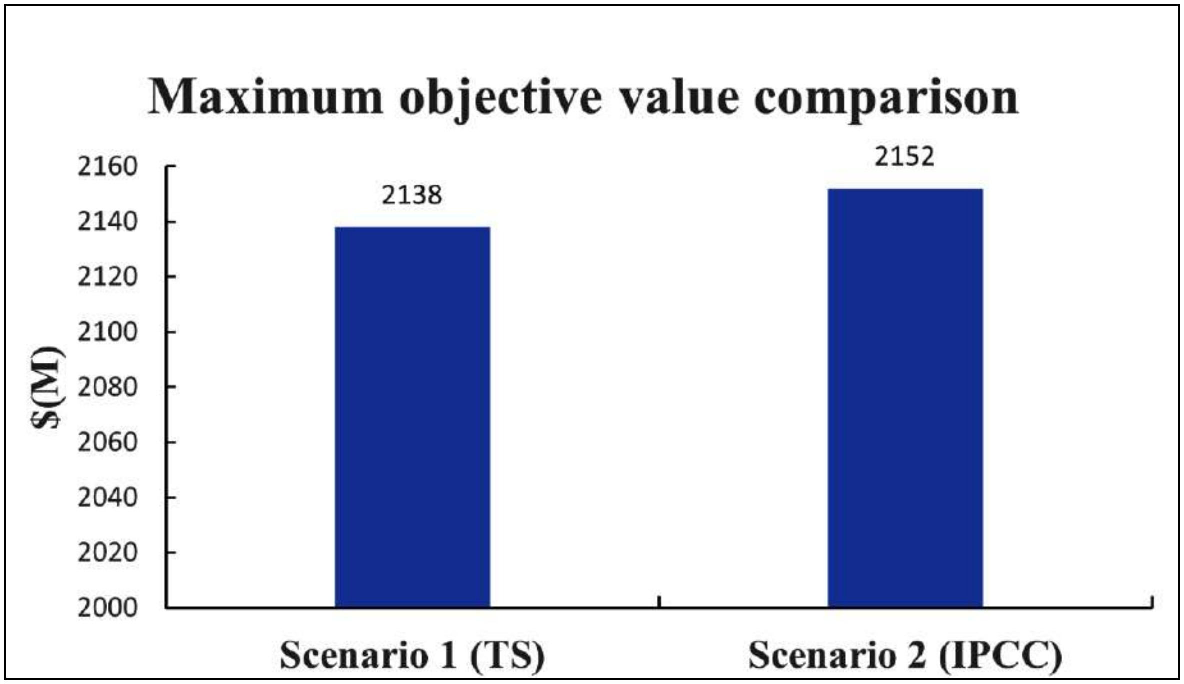

Figure 22. Comparison of (revenue - cost) between scenario 1 and scenario 2.

6. Conclusions and Future Work

The proposed shovel allocation model shows an approach to select a better haulage option for mines and a unique approach towards short-term planning with IPCC. The results show that the scenario with IPCC, scenario 2, generates 0.66% higher profit compared to the scenario with no IPCC, scenario 1. The truck requirement in scenario 2 is also 30% lower than scenario 1. Since both scenarios have been able to meet the long-term production target for year 11, introduction of IPCC in year 11 is justified in the mine in terms of haulage cost saving and revenue generation.

While the model performs well in the case study shown, the model has the following discrepancies.

- The model allocates shovels without considering ore blending requirements.
- The model does not consider shovel movement cost and constraint shovel movements between benches. This is the reason why in several periods, shovels move to a new face in a different bench after mining a face. This is acceptable in this scenario with two consecutive benches. But for cases with more than two non-consecutive benches, this issue needs to be addressed.
- The model does not consider the capital investment required for IPCC installation.
- The model cannot consider any operational uncertainty in its current state.

Constraining the model with blending requirements and shovel movement between benches by minimizing shovel movement costs will generate more realistic shovel allocations. Combining the model with a haulage simulation model will enable it to capture uncertainties associated with haulage operations. These modifications in future will make the model more pragmatic and provide a more comprehensive tool for short term production planning and analysis purposes.

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Understanding Loading Practices in Trucks and Shovels in Open-Pit Mining Under Operation Uncertainties

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ABSTRACT

Material hauling and loading account for more than 50% of open-pit mining costs. This study aims to understand the efficiency of truck and shovel loading practices, evaluate them and develop a framework that can be implemented in short-term plans. The proposed methodology is evaluated by developing a simulation model using Haulsim software. Multiple scenarios (number of trucks, number of shovel passes and road rolling resistance) are simulated by formulating the problem in the software analysis terms: full truck (FT) and full bucket (FB). Based on the simulation results, the operation manager insights into the material handling system opportunities, deciding to switch between a FT (higher passes) and a FB (lower passes) based on the operation plan, match factor and production targets. Further outcomes are operation KPIs such as queuing time, number of trucks, trucks queue at the shovel, cycle time, production cost per ton, and initial total production for both FT and FB. Short-term production analysis and deep comparison between two loading strategies are checked, and elements that induce this dynamic change are studied and analyzed using suitable machine learning. Finally, it highlights all associated mining operation parameters that determine the potential sweet spot of the loading strategy.

1. Introduction

Mining and hauling are significant components of a mining project. Whether a mining project is based on surface or underground, loading and hauling still contribute to a significant proportion of the running operation costs ranging from 50-60% Upadhyay et al. (2021). Reducing these costs is a major factor in sustaining operation time and operating costs, whether through equipment technological enhancement, operator skill efficiency, complex dispatch systems, or even modern clouding systems and various loading strategies; operation enhancement is essential and valuable for any mining project in the upcoming time.

When considering loading strategies and practices in truck shovel loading and hauling material operations, investigating opportunities for enhancing and reducing these costs and productivity losses in the running operation, especially when operations run in unpredictable, uncertain conditions that cannot be determined or planned. This will pose tremendous pressure and risk on the operation and the available optional alternatives for fleet configuration and loading strategies. For example, when truck or shovel breakdown or their availability is reduced, and they are no longer serving the trucks due to various operating reasons, a decision should be interfered to enhance the operation (whether integrated into the dispatching system or not).

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Uncertainty is not related to the equipment and fleet level alone. It expands to almost everything in the mining life; because high uncertainties with different magnitudes characterize mining. For example, commodity prices fluctuate from time to time due to various reasons that are related to supply and demand or due to unexpected events like COVID-19 and it is consequences, other factors like human factors (operators to the high management) and skills that will not be as planned to perform its role. Other significant uncertainties are related to the material in the mine (geological level), whether ore or waste and how it is extracted. This material has in place characteristics that differ when disturbed and dug up, inheriting the original characteristics with more voids (swelling) and less density per volume. In order to liberate this material from undisturbed to disturbed situations, blasting is a usual operation associated with extracting the material; uncertainties and efficiency of the conducted blasting are common things that change the final material fragment size, type, ore-waste mix, dilution, density, roundness and other factors. Consequently, when the shovel bucket encounters the material in the bench face, these uncertain parameters will affect the final material filled in the bucket; hence the final payload that is passed to the truck in a certain number of passes is also affected, especially the last pass.

Payload is another essential concept; the final payload affects and contributes to payload policy which will aid and determine whether the final truck load is good, under, over or even rejected in some cases, some systems use the conventional loading without any sensors monitoring the payload whether in shovel or truck other systems are evolving but with a marginal payload accuracy ~5%, newly systems are now emerging to monitor the dig, payload, material and send it to clouding system for further monitoring and analysis. It is also important to mention that the final payload affects the cycle time and is affected by operator skill. Moreover, the higher payload values will increase the maintenance costs of trucks and fuel consumption due to the high engine loading and mechanical fatigue frequency.

Truck shovel loading strategies have been a dilemma in loading payload and the number of passes; whether underloading or overloading the truck, each decision has its pros and cons and directly affects the efficiency. For instance, saturating a shovel to reach 100% efficiency or over will result in queuing conditions, and undersaturation of the shovel below 100% will result in higher costs.

Equipment matching is problematic as well; whether accounting for performance or production rate or operating costs or environmental impacts or operation constraints (grade, weather, accessibility, facilities matching), there will be a difference in the final results of the passes (decimal passes) and whether these passes will be rounded up or down, depending on the number of trucks and shovels, Figure 1 depicts this struggle and gives an example on the hydraulic shovel with various trucks configurations.

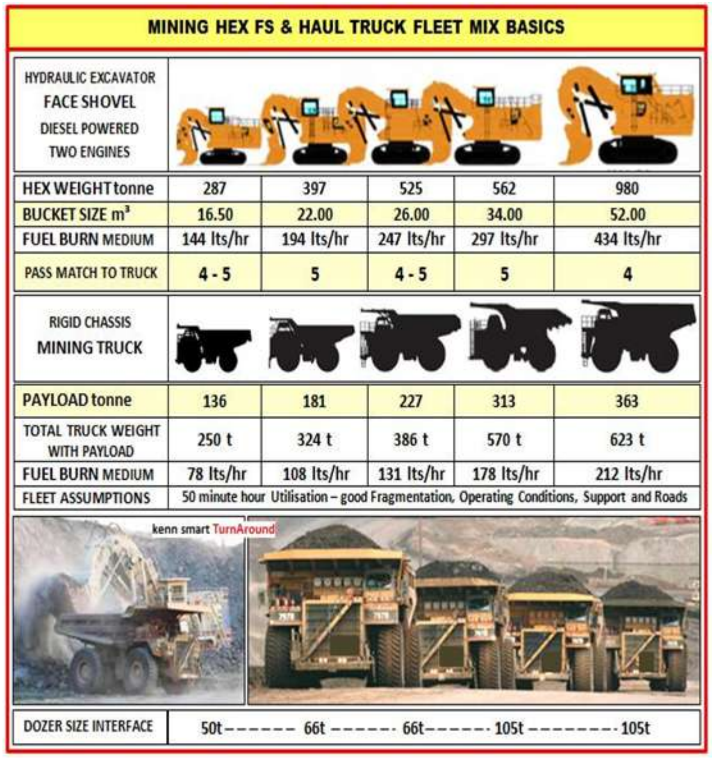

Figure 1. Equipment and pass matching in a hydraulic shovel (Kenn Smart, 2011).

2. Literature Review

The literature summary aims to gain a more comprehensive understanding of earlier work on fleet simulation. Then delving into high-level focused literature relevant to the full truck (FT) and full bucket (FB), i.e., truck-shovel loading strategies and the associated KPIs in open-pit mining. The following sections discuss other interesting literature comparable to FT and FB loading strategies: starting with theoretical simulation history and methods. Then hands on the relevant and non-traditional methods, the discussion moves on to the software that uses Discrete Event Simulation (DES) and, later, a discussion on the literature related to fleet productivity and cost. Lastly, it highlights some literature on match factor and other related strategies. Finally, a conclusion of the related literature to the FT and FB.

2.1. Simulation Types and Techniques

This section discusses the concept of simulation that different researchers defined in addition to simulation purposes and the followed methodologies related to the mining fleet operation simulation. Banks and Nelson (2014) classified simulation models into static and dynamic models. A static simulation model represents a system at a particular point in time, while a dynamic simulation model represents a system that changes over time. It is further classified to:

- *Deterministic versus stochastic models*: a deterministic simulation model contains no random variables, e.g., a linear programming model, while a stochastic simulation model has one or more random variables as inputs and outputs, e.g., a queuing model.
- *Discrete versus continuous models*: a DES model represents a system in which the state variables change only at a discrete set of points in time. For example, a truck-shovel system is a typical discrete system. On the other hand, a continuous simulation model represents a system in which the state variables change continuously over time, such as a system associated with flowing fluids.

Bauer and Calder (1973) defined simulation as a concept. They defined simulation as a modelling technique that can predict the change in the performance of a system. They divided simulation into probabilistic Monte Carlo Simulation and standard using mathematical equations. Earlier methods of simulation techniques were by Sturgul and Harrison (1987). They discussed the use of simulation models using GPSS programming language to simulate various situations, including coal mine dispatching and mine fleet for uranium mine expansion. Ataeepour and Baafi (1999) implemented Arena software in simulation models, improving mine productivity. The status of mine simulations in Canada, including software and case studies, was addressed in an earlier study of the simulation literature by Vagenas (1999).

Then moving to robust and specialized approaches using MATLAB and other platforms, Askari-Nasab et al. (2007) implemented DES to capture random field processes in open-pit and material simulations using MATLAB. Shawki et al. (2015) implemented Arena software to improve excavator performance indices. Tabesh et al. (2016) implemented a simulation approach by incorporating truck shovel operations, road networks, stockpiles and other operations. They integrated the DES model into MATLAB, Excel and VBA to understand operation scenarios and uncertainties.

Price (2017) defined DES as “a modelling technique that is widely used to model complex systems”. He also implied that comprehensive data from fleet management systems is rarely used to model fleets. The advantages include stochastic delays due to breakdowns and meal breaks, load and travel time, where some variables are random and dynamic, involving models that change with time. DES has been used extensively in different industries such as manufacturing, service providers, warehouse distribution, cashier checkout lanes market, department stores, airports, and mining. Price (2017) summarized the purposes of DES in mining as follows:

- Increase equipment utilization.
- Reduce waiting time and queuing.
- Study alternative investment ideas.
- Evaluate cost reduction ideas.
- Train operators in overall system operation.
- Support day-to-day decision-making.
- Minimize the effects of breakdowns.
- Understand the impact of mixed fleet interactions.

2.2. Fleet Different Simulation Approaches

Earthmoving operation literature is considered due to the lack of related literature in mining engineering, especially in the early stages and the similarities between construction operation trucks, off-road trucks and mining trucks. Earthmoving productivity calculation was conducted by Smith (1999), who estimated the productivity by regression analyses; his findings showed a relationship between operating conditions and productivity. However, his analysis overestimated the operation’s productivity when resources were not well known.

Several researchers have developed a system of earthmoving selection using an expert system technique (Alkass and Harris, 1988; Amirkhanian and Baker, 1992; and Kirmanli and Ercelebi, 2009). Chanda and Gardiner (2010) compared three methods of cycle time analysis productivity. These methods are simulation, artificial neural networks, and multiple regression. They benchmarked the results with a monitoring system in a mine and found that simulation underestimated and overestimated the results, and the other proposed methods showed better results. However, their data was case specific.

Smith et al. (1995) customized higher-level DES models using a programming language. They developed a DES model that was translated into a computer program written in C programming language. Morley et al. (2013) utilized DES by developing quantitative formulas; they reached that a decrease in production does not directly correlate with an increase in cost. Cheng et al. (2010) implemented optimization and simulation using Perei net for equipment allocation, considering cost and other parameters in a dynamic constraint.

Alshibani and Moselhi (2012) integrated simulation with optimization using real-time GPS. Some researchers developed a framework using genetic algorithms for simulation-optimization of earthmoving operations (Marzouk et al., 2004; Shawki et al., 2009; and Hsiao et al., 2011). Neural network systems were developed by Shi (1999) and Chao (2001) for construction practitioners to forecast truck selection as well as earthmoving operations and performance.

In the field of simulation and optimization in mining engineering, Moradi Afrapoli et al. (2019) developed a simulation-optimization framework that optimizes haul fleet size by implying heterogeneous and homogeneous fleets of various sizes and recommending that equipment failures and maintenance should be evaluated for the optimal fleet size. Moradi Afrapoli and Askari-Nasab (2019) explained in a review that connecting the strategic part of the mine plan to the operational part is difficult. However, the operation should achieve both the long-term and short-term goals. They also emphasized technical and geological uncertainty that are crucial components in fleet systems management, and the shovel relocation to new mining cut associated losses should be understood well. A multi-optimization model was created by Mohtasham et al. (2021) that determines the optimal production plan for the shovels and allocates the mine fleet in an optimal production target, head grade and fuel consumption. Upadhyay et al. (2021) developed a simulation-based algorithm that estimates the productivity under technical uncertainties, giving a solution with higher accuracy and lower dependency on haulage distance.

2.3. Simulation Software

There are several simulation software tools that one can use to model a material loading and hauling in a mining operation. Some software programs involve learning the related programming language, while others have an interactive interface with pulldowns/command line. The simulation software, programs and models for truck shovel analysis can be summarized as follows:

- Iterative models that fit discrete empirical values to cycle variables, e.g.: machine repair model.
- Regressive models modify waiting time by using correction factors such as FPC ® by Caterpillar.
- Stochastic Monte Carlo models by fitting probability distributions to cycle variables, e.g.: Talpac ® and Haulsim ® by Runge Software.
- Stochastic graphic simulation following probability distributions within Monte Carlo simulation e.g.: Arena ® by Rockwell Software.
- General purpose simulation programming languages system (GPSS/H ®) by Wolverine Software and SIMAN.
- Simulation based on programming languages, C++ (C environments), Python and Java.

2.4. Cost, Production and Loading Times

In payload analysis, the literature reveals many different claims, findings and disagreements in balancing the payload, production, cycle time and passes loaded. Smith et al. (1995) concluded that the additionally loaded bucket is an advantage provided the truck is not overloaded. Furthermore, they figured out that spotting and loading time similarly affect production; hence reducing operation cycle times is important for achieving maximum production. They also discussed the interactions of four factors in earthmoving operations: production, match factor, passes per load and load pass time. They concluded that adding trucks would not increase production. According to Schexnayder et al. (1999) payload weight affects incremental production; they emphasized matching the number of bucket loads to fill a truck as an integer number. Hardy (2007) claimed that overloading trucks would increase productivity associated with increasing unit cost. Marinelli and Lambropoulos (2012) examined cost comparisons between loading and hauling. They came to a conclusion that, depending on the hauling distance and the volume of the last pass, a loading procedure could result in a significant cost decrease. Morley et al. (2013) concluded that the four to six passes rule is not applicable when dealing with real earthmoving applications due to equipment combinations such as smaller excavators and larger trucks. They also concluded that considering trends, trucks and excavators must be analyzed separately. They also implemented that using a loader to satisfy production requirements and then selecting trucks after will result in a higher per unit cost; consequently, this may result in a high production cost to keep the loader always utilized. Soofastaei et al. (2016) developed a DES model to investigate the payload variability on trucks in order to improve productivity and energy.

Carmichael and Mustaffa (2018) examined the loading policies and environmental impacts, including loading in zero waiting time and double loading. They concluded that the former had the least impact on the environment and optimal cost advantage while the latter had the highest environmental impacts and non-favourable costs.

2.5. Match Factor

The match factor (MF) is an important indicator of a mining operation's efficiency. Burt and Caccetta (2018) defined the match factor as a measure of the fleet productivity. It is a ratio that matches truck arrival rate to loader service rate. Their definition included over-trucking (MF>1) in which the loader is 100% efficient, and trucks are queued. In contrast, when loaders are waiting for trucks the MF is less than one. There is no queueing at the loader when the match factor equals 1; this is the optimal situation but not achievable realistically due to bunching and maintenance. Krause and Musingwini (2007) named terms as over-equipped when trucks are more than required and under-equipped when there are few trucks. The consequences of an over-equipped situation will increase the capital cost substantially while the whole under-equipped situation will not achieve the planned short-/long-term production. Dabbagh and Bagherpour (2019) examined the MF in their analysis using the ant colony algorithm; however, they state that it is not correct enough. They suggest using a detailed match factor which increased the production by ten percent.

2.6. Other Approaches to Evaluate Payload

Operators' score was suggested by Yaghini (2021), who presented an approach to characterize and evaluate the payload using the operator ranking systems. The score is calculated based on the truck, shovel and mine productivity indices. He concluded that the operator with the highest score would typically load trucks to a higher capacity with less cycle time and load passes. Furthermore, he suggested a term called dynamic target loading (DTL), which modifies the conventional 10:10:20 rule by reducing term passes loading practices and giving the operator a flexible load range; consequently, the loading cycle and queue are reduced. This analogy, reducing trim passes, is comparable in concept to the FB analysis adopted in this research. Production is also covered as a project KPI that provides feedback about bucket payloads and cycle time enhancement opportunities.

2.7. Related Research

Recently, Tapia et al. (2021) investigated loading methodologies in an open-pit mine. They used FT and FB scenarios by creating simulation models using Talpac software to understand cost and production analysis and how they relate to cycle and queuing time. They further adapted Activity Based Costing (ABC) models, "which are built on the concept that resources usage is not a function of the amount of the final product, but rather, resources are consumed by the elementary tasks and processes required to produce a unit of the final product" as defined by Botín and Vergara (2015). In order to calculate production per cost, Tapia et al. (2021) concluded that a decision must be made when a situation requires a change. They argue that mining projects will favour the FT strategy over the FB till a specific transition point at which the operating cost of the FB is favoured. Mustaffa (2021) investigated the impact of alternative loading practices on production and emission using Monte Carlo Simulation to compare these practices. The results showed that double-sided loading has the lowest effect on the environment. However, it is not always doable because it is limited to specific mining conditions, and cannot be generalized. In addition, filling one bucket more than the full load can result in greater overall productivity, lower emissions, and reduced truck cycle time, which may lead to a production increase. Other similar loading terminologies in earthmoving are fractional loading as in Mustaffa (2021) known as fractional loading practice, which indicates that each truck gets loaded to a minimum of passes. However, it could be filled to higher passes if additional time is allowed, the arrival of the next truck and varies between trucks. A similar term called multiplier loading practice assumes minimum passes are used, but there could be an extra pass depending on the loader's available time. This will yield higher payloads and production rates associated with fuel consumption increases due to longer cycle time and loading time.

2.8. Summary of Literature Review

Based on findings from the previous literature, a significant part of the research is covered by earthmoving trucks in simulation. However, there are many similarities between earthmoving trucks and mining trucks; a real mining equipment evaluation and simulation will add more realistic value to the FT and FB approach. Other literature was conducted using different simulation approaches, which could be time-consuming and not flexible.

The previous work also reveals some discrepancies when dealing with the costs, utilization and production, which could be due to the adapted simulation method or operation properties. Which is still not fully understood, and there is no comprehensive framework available to understand the operation more thoroughly in open-pit mining loading practices. It is vital to note that no research used a machine learning system to understand and anticipate the data from an FT and FB analysis utilizing Haulsim software. Furthermore, no literature offered any guidance or suggestions for modifying loading techniques in developing autonomous trucks and shovels and future level 5 mining.

3. Methodology

The theoretical framework of the proposed FT and FB simulation approach in both a holistic way in mining operation and a detailed approach will be discussed with a profound explanation, as well as further analysis of the simulation results, starting from the data which was imported as a schedule data from an external software that is used in Haulsim software. Then the equipment configured in Haulsim and the final DES results are interpreted and analyzed, and more analysis of the operation parameters and the results from simulated data is analyzed using Python programming language, where exploratory data analysis is conducted. Lastly, a machine learning classification model is created to predict the loading strategies based on the provided data that more understands the operation parameters and evaluates these parameters that trigger switching between loading strategies.

Locating the FT and FB in the broad frameworks, in the beginning, allows understanding where the research topic is focused as Figure 2 illustrates the general view of FT and FB loading in mining operation. When a shovel with force applied to the working bench excavates to scoop (tuck, engage, dig, release, swing and pass); the required material that has recently been blasted with characteristics reflecting the nature of that material; loose density, fragment size and excavatability, will affect the final bucket fill factor (BFF). This stage is performed by an operator with a scalable average efficiency and equipment; shovel with a known average utilization and availability. The following sections will discuss the material characteristics.

a. Shovel-Material Interaction

Because loading and hauling are the following processes after blasting, assessing post blasting of material in the mining operation is necessary when the distribution of fragmented material controls truck and shovel production rates, resulting from blasting. As the blasting efficiency increases, the final production increases. Blasting efficiency is increased by optimizing blasting design when the objective fragmentation size is determined. Fragmentation is affected by uncontrollable parameters, including the physical and geomechanical properties of the material. Coarser material led to higher energy consumption, increase in wear rates and a decrease in the loading and hauling productivity, final crusher and mills throughputs. In addition, fragmentation size affects fill factor and payloads. Dotto and Pourrahimian (2018) mentioned that poor fragmented material results in boulder sizes that are too big to handle and affects productivity negatively. Therefore, optimal fragmentation is essential for truck and shovel productivity.

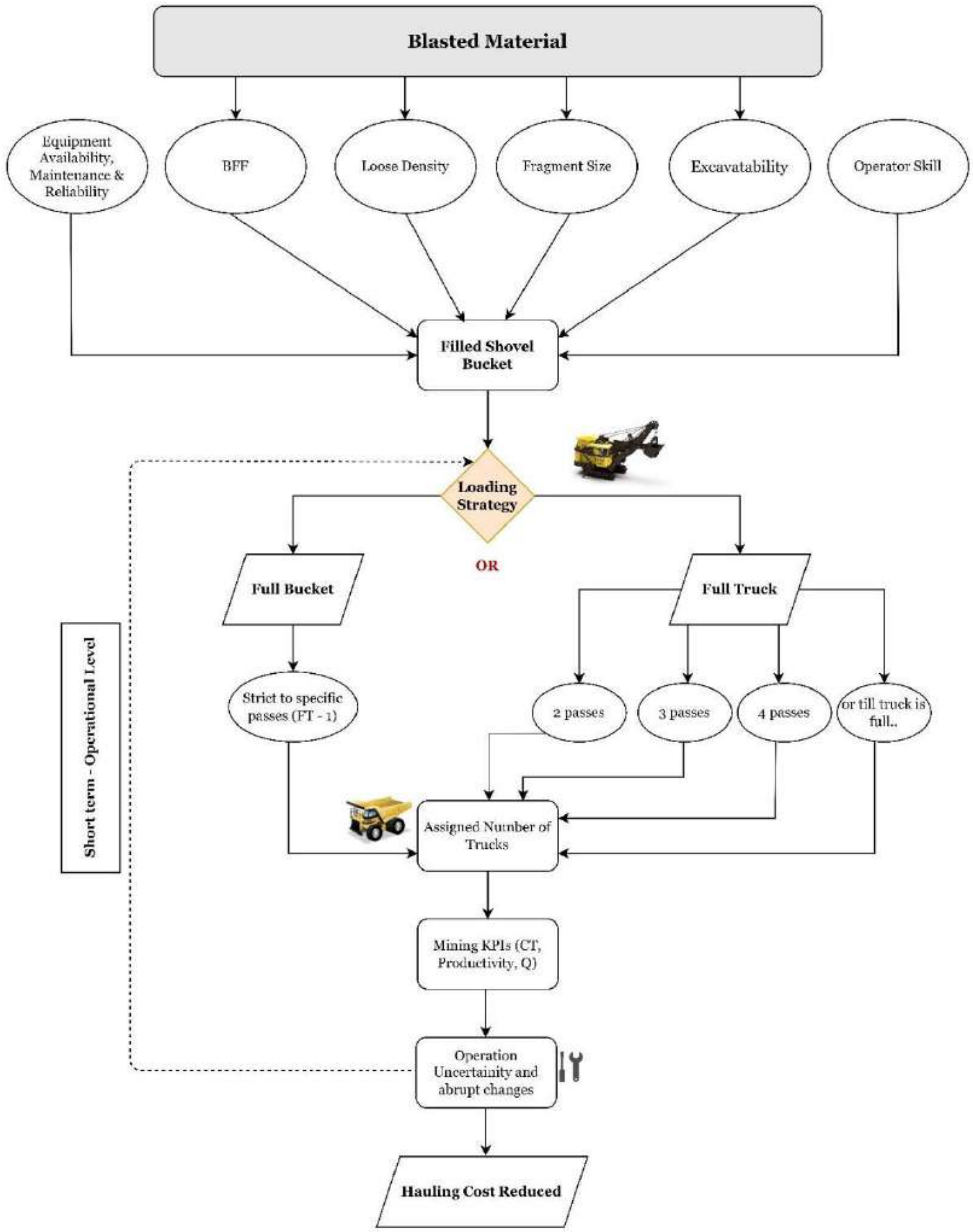

Figure 2. FT and FB flowchart in a mining operation.

Good fragmentation will result in a good heap in the bucket, while over fragmentation will make material flow more due to fines and no heaping will be formed in the bucket. Diggability which is a term used to describe how easily the material can be dug by the shovel, measured by specific dig energy. Loadsman et al. (2013) mentioned that as digging material gets harder, the payload decreases and the energy to fill increases.

Assessing the operational time in mining hauling and loading operation is important for measuring the operation's KPI. Figure 3 illustrates time usage model presented by Global Mining Guidelines Group (GMG) (2020).

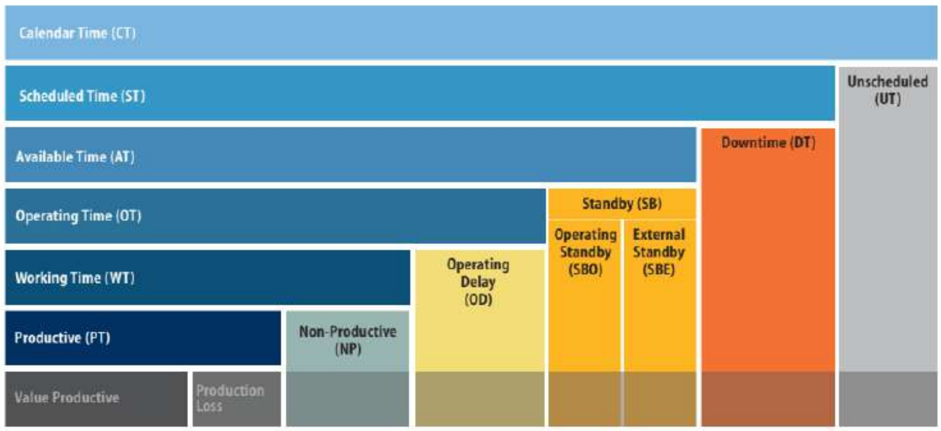

Figure 3. Time usage model (GMG - Time Usage Model, 2020).

b. Operator Skill and Efficiency

Khorzoughi and Hall (2016) studied the effect of operator skills and loading efficiency. They compared operators' KPIs in the loading and hauling operation, including passed payloads, productive cycle time, equivalent digging energy and loading rate. Yaghini (2021) emphasized that the operator role in truck shovel loading is important and greatly influences the operation's productivity and efficacy. Through operator skills and loading habits, he quantified and proposed a scoring system for evaluating the operator skills in the operation, taking into consideration the operator's payload, shovel's cycle time and other KPIs to finalize the operator rank from best to worst. All the previous performance indicators will affect the final payload in the shovel bucket, which has a specific capacity and range of filling material in the shovel bucket that will vary from struck to heaped as a filling percentage of 90 to 110% of the bucket capacity assuming average loading conditions.

c. Shovel Loading Truck (Digging and Filling)

After the bucket is filled by an operator from the shovel, the payload is passed to the truck with a set number of passes, depending on the passes required to fill the truck and the pass and equipment matching configuration. It is common in mining operations that hauling trucks are at least 100% loaded or exceeding 100% of their final load capacities depending on whether companies are strictly applying the loading policy or not and their actual compliance with these policies and skilled operators. In this step, the proposed loading strategies are involved and a proposed operational decision should be taken to proceed with the scenario of shovel's loading strategy as a FT or FB.

Before proceeding with these terms, there should be a definition for them, which could be defined as the following: shovel that loads in a fully bucket; the truck requires less than a FB load to reach its payload. Therefore truck will travel underloaded, and the additional pass time is not wasted (Haulsim, 2022). Another definition by Tapia et al. (2021) defines it as saving the additional pass of the loading equipment. While FT loading assumes the loader always tries to fill the truck, even if the last pass only requires a small portion of a bucket load. Therefore this additional pass will consume more time in shovel loading and queuing conditions will occur (Haulsim, 2022).

d. Assigned Trucks

The assigned trucks are based on MF as a reference; the usual value for MF in mining operation is 1, which means 100% efficiency. However, MF is uncertain and varies through short-term operation due to various uncertainties. Therefore, in this paper multiple trucks (1 to 30) are analyzed to determine MF values with shovel configurations. Then FB and FT loading strategies are evaluated based on the selected fleet.

e. Operation Parameters

A set of operating configurations is usually prepared before running the simulation. This includes the hauled material, mining and hauling equipment data (capital costs, operating costs, operating data), shifts configuration as scheduled and unscheduled operating and non-operating time and rolling resistance.

f. Operation Uncertainty

Generally, the mining operation is classified as considerably uncertain and unpredictable with time. In the mining equipment arena, the uncertainty and unpredictability of equipment are common, especially when equipment is getting older, this includes short and long delays, stoppages and breakdowns due to various reasons, whether related to the smallest scale mining operation or to the largest scale market situation that effect mining decision or any other reason. This research approach demonstrates shovel breakdown as an example of fleet uncertainty. Other reasons can be crusher reduced efficiency, stoppage, blasting efficiency, or variability in the material in mine. It is also known that any accident or unplanned incident will affect the operation, and a feasible option is available when adapting a modified loading strategy. Further focusing on the scheduled and unscheduled delays.

These various uncertainties in mining operation will affect the continuity of production rate and operation cost. In this research assumption, one of the shovels is stopped, or its availability is decreased for a particular time due to various reasons, as discussed previously.

g. Match Factor

In the research, the MF is calculated as a normal operation running assumption, with a set number of trucks assigned to the shovel to understand the effect of changing the number of trucks, which reflects on the final MF. However, when the shovel breaks down, MF surges to 1.5, accompanied by an increase in the number of trucks reassigned to the remaining working shovel Figure 4.

After the equipment matching for operation is done, a short-term mining operation schedule for a specific period for the operation is imported into the software. This schedule includes the sources (shovels) and destination in addition to material quantities and time steps. Next, running the operation at a MF of one, assuming two shovels are running the operation. There are assigned trucks to each shovel that are homogeneous and dependent (same trucks type and assigned to the same shovel) but with a similar destination target, the crusher.

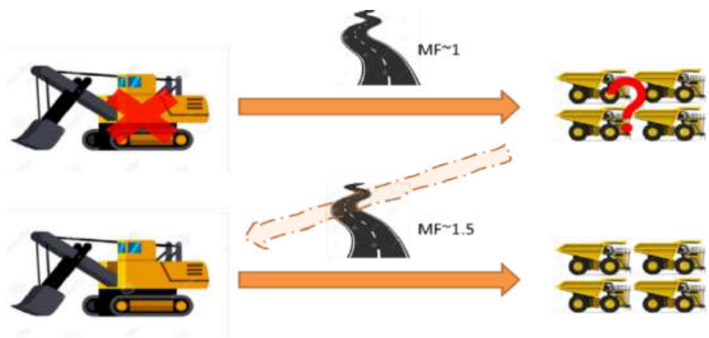

Figure 4. Reassigning trucks assumption in research methodology.

The varying number of trucks to mimic the operation uncertainty and shovel stoppage changes the MF when operation uncertainty is encountered. Here in our assumption, the second shovel is no longer operating for a specific period of time due to major mechanical failure. As discussed previously, other operation uncertainty could affect the fleet haulage. Based on the unutilized trucks, these trucks are redirected to the first shovel (the working shovel), and the match factor will increase to 1.50. In this stage, a decision should be made to switch between the loading strategy from FT to the FB; the obtained operation KPIs control this switch, mining roads cycle times and the reduced costs associated with this switch.

Figure 5 illustrates the methodology and the approach followed in comparing FT and FB.

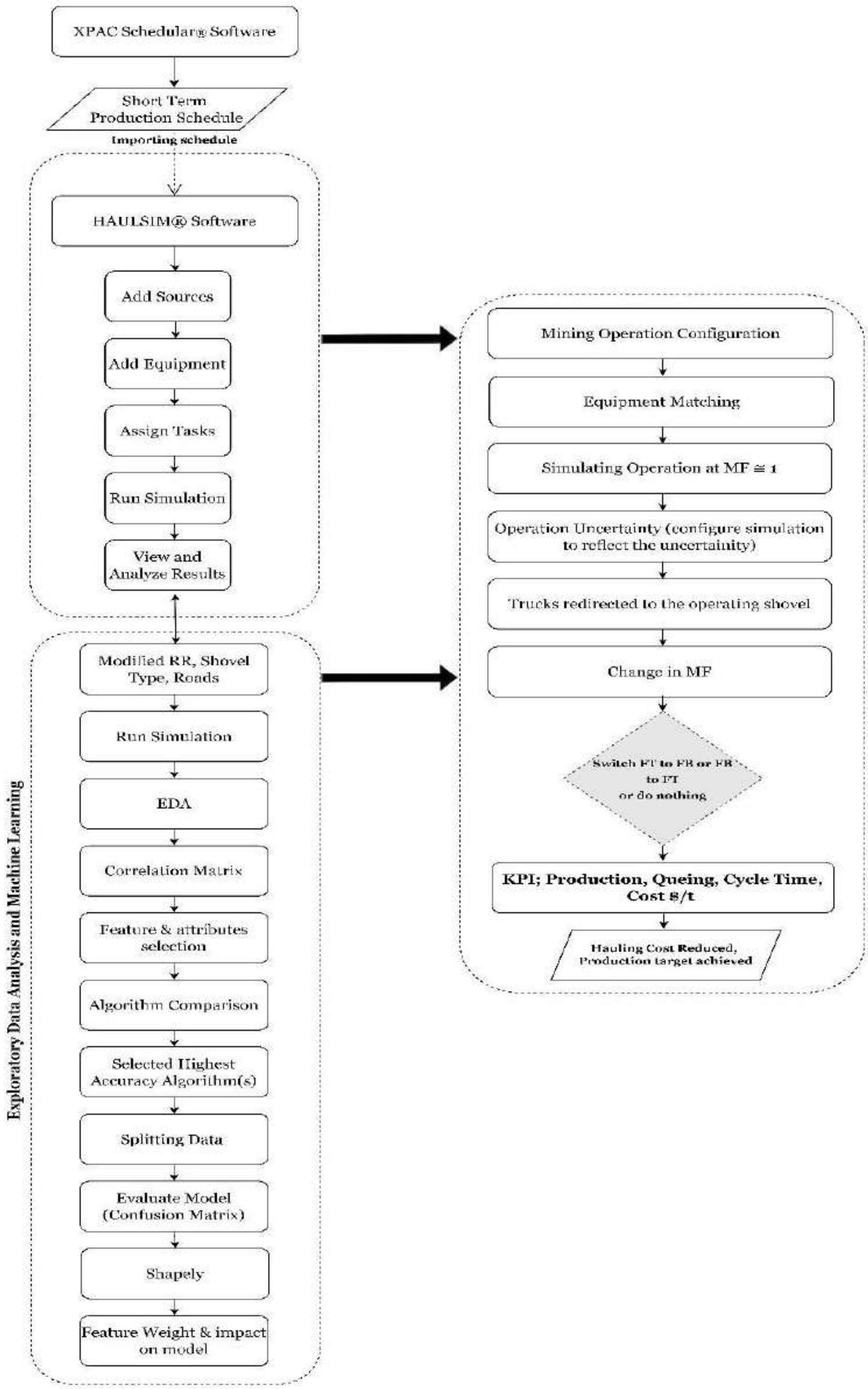

Figure 5. Detailed framework in FT and FB.

4. Case Study

Scheduling data for a gold mine was exported from a scheduling software OPMS and imported to the Haulsim.

a. Material characteristics

The selected material in simulation is high-grade sulphide (HGSx). Table 1 summarizes the material's characteristics.

Table 1. Hauled material characteristics.

Material Characteristics		Unit
In-situ Bank Density	2.4	t/m^3
Swell Factor	1.25	-
Loose Density	1.92	t/m^3
BFF-Heaped	97.5	%
BFF-Struck	97.5	%

b. Equipment Data

Operating and costing data for the mining fleet are included in the simulation for both shovels and trucks. The shovels used in the simulation are P&H 2800 XPC and the trucks are CAT 793 F. Table 2 presents shovel configuration data. Table 3 presents the configuration of the truck CAT 793 F.

Table 2. P&H 2800 XPC shovel used data in simulation.

Shovel P&H 2800 XPC			
Operating Data	Capacity	32.78	m^3
	Bucket Cycle Time	40	sec
	Filled Capacity	31.96	lcm
	Filled Payload	61.49	t
	Maximum Production Rate	5533.95	t/h
Costing Data	Purchase price	19,714,300	$
	Life	20	years
	Owning Cost	101.27	$/hour
	Operating Cost	129.95	$/hour

Figure 6 illustrates the distributions used for the shovel's loading time and bucket payload. For shovel loading time, the mean value is 40 seconds, and the distribution is skewed to the right. At the same time, the payload factor is one and skewed to the left. Figure 7 illustrates the distributions used for trucks. For truck dump time, the mean value is 30 seconds. Moreover, for the truck's load and carry time, the estimated mean of the value of which there is a 50% probability of occurrence, the mean value here is 40 seconds.

Table 3. CAT 793 truck data used in the simulation.

Truck Cat 793 F			
Operating Data	Capacity	175	m^3
	Actual Capacity	117.89	lcm
	Payload	226.8	t
	Dump Time	60	sec
	Spot Time @ Loading	24	sec
	Spot Time @ Dump	18	sec
Costing Data	Purchase price	3,568,900	$
	Life	15	years
	Owning Cost	24.44	$/hour
	Operating Cost	435.28	$/hour

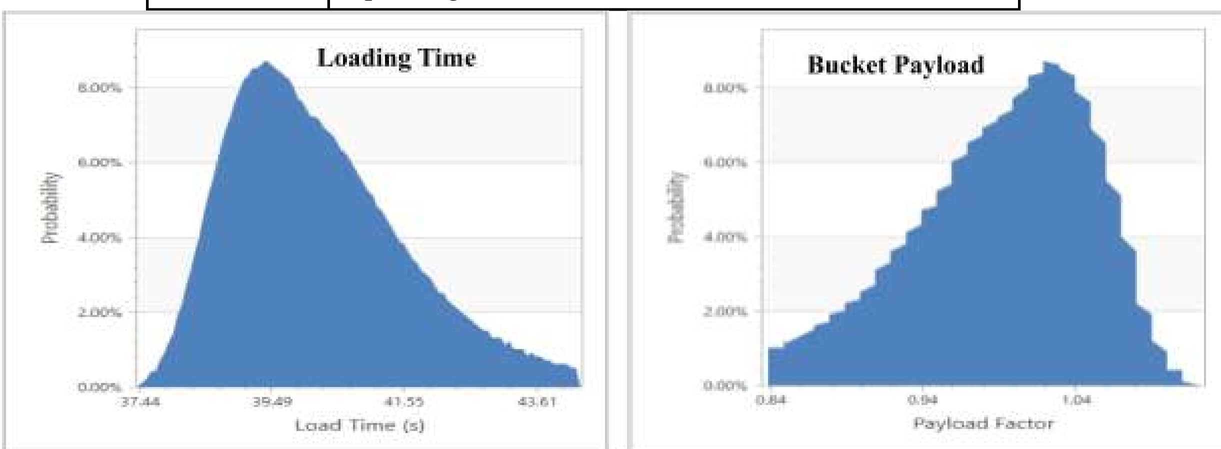

Figure 6. Distribution data for P&H 2800 XPC.

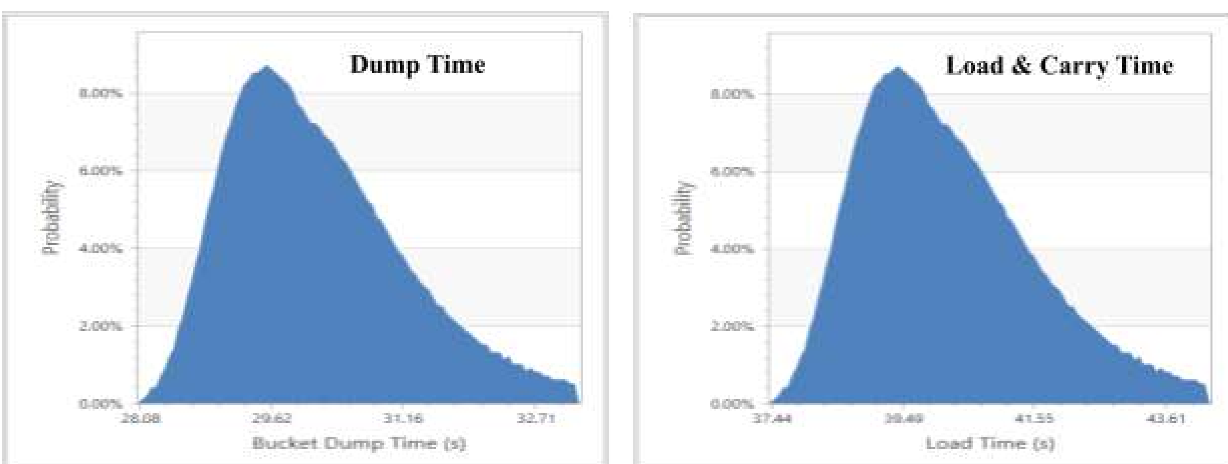

Figure 7. Distribution data for CAT 793 F.

c. Shifts and Working Times

Table 4 represents the time model used in the simulation. The non-operating shift delays are 30 min and the operating delays are 60 min in each shift; therefore, the actual working time in a shift will be 6.5 hours. Shovel and truck availability is assumed to be 85%.

Table 4. Shifts data and effective working times.

Working Time		
Mon-Fri	5	days/week
Shift Duration	8	hours
Non-Operating Shift Delays	0.5	hour
Shift Operating Time	7.5	hours
Operating Shift Delays	1	hour
Shift Working Time	6.5	hours
Shovel Availability	85	%
Truck Availability	85	%

d. Roads and Cycle Time Analysis

Two mining haul roads were implemented for simulation (denoted as R1 and R2) as in Figure 8. Each road begins in a bench face and ends in the crusher. Both working benches have high-grade sulphide (HGSx). The length of haul road 1 (R1) is 3.46 km and haul road 2 (R2) is 2.65 km. The maximum grades in R1 is 10.6 %, and in R2 8.76 %. Both road has a rolling resistance of 2%. Each haul road segment's final cycle time is different due to varying distances and the accompanied cornering speeds.

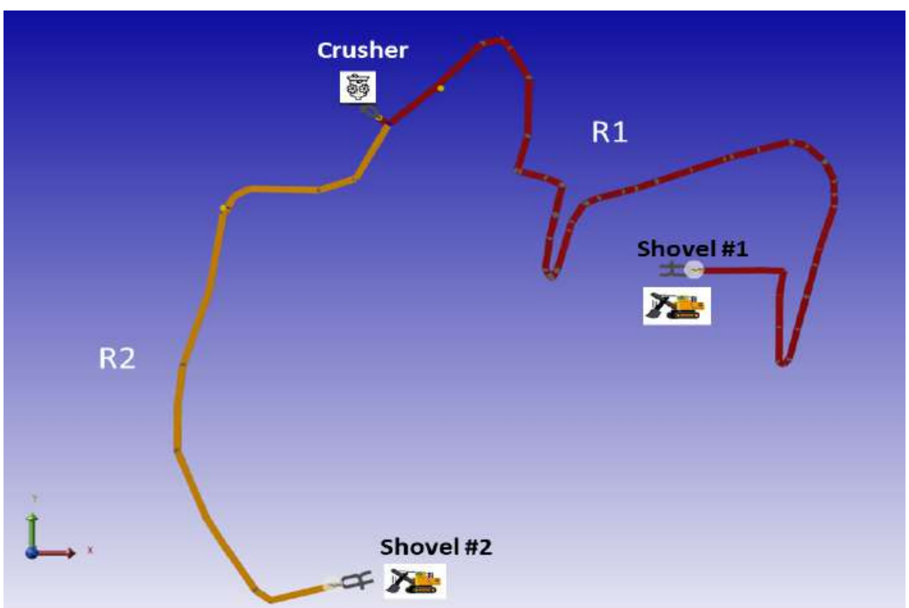

Figure 8. Haul roads layout.

The cycle time analysis was done for one truck only and one shovel to understand and analyze the differences between the haul roads. Table 5 presents the results for both the FT and FB scenarios in haul road 1 and haul road 2. Results show that cycle time with a FB loading strategy takes less cycle time (including truck travel times) than FT. This is due to the fact that the trucks have a less payload in FB scenario and consequently they travel uphill faster. In haul road 1, the cycle time in FT loading strategy is 23.42 min while in FB loading strategy is 21.68 min. There is a 7.4% difference between two loading strategies. FT travelling time also has a 8.7% difference because of the same reason explained for the cycle time. The reverse time has no differences between the loading strategies because the trucks are empty and travel on the same road in both scenarios. Analyzing haul road 2 cycle time shows FT and FB a 6.83% difference between the loading strategies. Travelling time has the same case as road 1 with a difference of 1.25%. The lesser difference can be interpreted as haul road 2 has less distance, almost 40% than haul road 1. Another reason for the difference is the rise and run and grades that are higher in road 1 over frequent segments; this affects the cycle time and travel time.

Table 5. Cycle time analysis for haul roads within loading strategies.

	Haul Road 1		**Haul Road 2**		
	Shovel	**Truck**	**Shovel**	**Truck**	**Unit**
	P&H 2800 XPC	Cat 793 F	P&H 2800 XPC	Cat 793 F	HGSx
FT Loading	Distance	3463.57	Distance	2064.89	m
	Travel Time	0:12:16	Travel Time	0:04:17	hh:mm:ss
	Reverse Travel Time	0:07:17	Reverse Travel Time	0:03:44	hh:mm:ss
	Total Distance	6927.13	Total Distance	4129.79	m
	Total Travel Time	0:19:33	Total Travel Time	0:08:01	hh:mm:ss
	Total Cycle Time	0:23:25	Total Cycle Time	0:11:53	hh:mm:ss
	Payload	226.80	Payload	226.80	tonne
FB Loading	Distance	3463.57	Distance	2064.89	m
	Travel Time	0:11:12	Travel Time	0:04:11	hh:mm:ss
	Reverse Travel Time	0:07:17	Reverse Travel Time	0:03:44	hh:mm:ss
	Total Distance	6927.13	Total Distance	4129.79	m
	Total Travel Time	0:18:29	Total Travel Time	0:07:55	hh:mm:ss
	Total Cycle Time	0:21:41	Total Cycle Time	0:11:07	hh:mm:ss
	Payload	184.17	Payload	184.17	tonne

One of the important results in cycle time analysis is the average payload for both FT and FB. Due to the higher loaded pass tendency in the FT, the calculated average payload in cycle time analysis is 226.8 tonnes. In contrast, in FB, the average payload was 184.1 tonnes. The difference in final payload between loading strategies is 18%. Considering the payloads, the productivity per truck in haul road 1 is higher in the FT at a rate of 581.15 t/h while in FB, 509.55 t/h with a difference of 12.32%. Other parameters, such as Tonne Kilometres per Hour (TKPH) (which is an essential expression of the working capacity of a tire representing the load capacity in relation to heat generation) are lower in the FT with a value of 947.35, while in the FB, the value is 978.57. Loading truck full affects the TKPH negatively and reduces the tires life and equipment reliability with time, with the general understanding that lower TKPH means lower heat resistance which is not recommended for truck hauling and higher TKPH means higher heat resistance which means better truck hauling conditions. However, the lower TKPH has a higher cut and wear resistance. Additionally, the total fuel consumed is higher by 8% in FT (36.23 litre/trip) than in FB (33.47 litre/trip). The reason is the higher payload, which requires more engine power to move the truck hence more fuel consumption.

e. Match Factor Analysis

To understand the operation correctly, match factor criteria were selected as 1 and 1.5; the latter was selected because of increasing trucks and the availability of only one shovel in operation.

The normal hauling mining operation usually runs at MF equals 1. In the case study, this resulted in 10 trucks when the loading strategy was FT. With changing the loading strategy to FB, the proper number of trucks (at MF=1) was 12. This difference in the number of trucks is due to lower passes affecting the MF formula.

f. Production-Cost-Fleet Curves

The simulation model was run for a different number of trucks to capture the effect of MF change from 1 to 1.5 in FB and FT loading strategies. Figure 9 and Figure 10 show the cost-production fleet curves for the FT and FB, respectively.

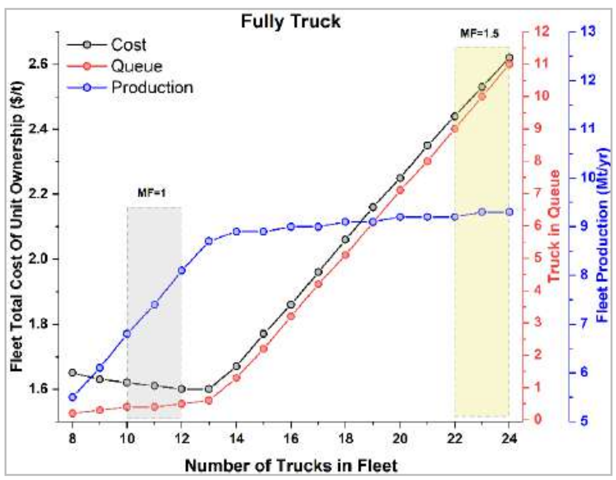

Figure 9. Cost-Production fleet curves for FT loading strategy.

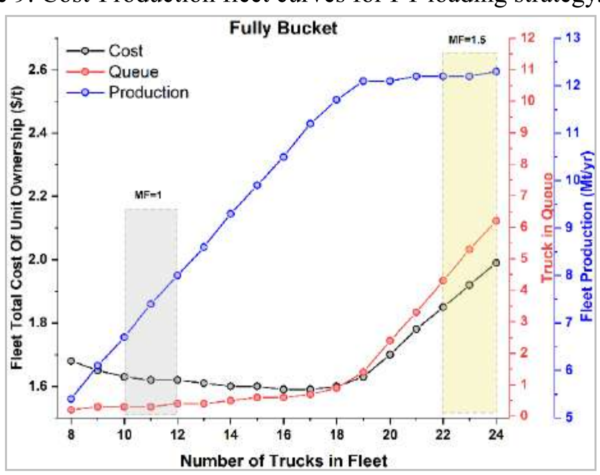

Figure 10. Cost-Production fleet curves for FB loading strategy.

In the FT loading strategy (Figure 9), with increasing the number of trucks in the fleet, the production increases until the number of the truck is equal to 13; after this point, the production slightly increases until the number of trucks in the fleet reaches to 24. In the FB loading strategy (Figure 10) the fleet production has a similar trend to the FT strategy, but the production still increases till the fleet size is equal to 19. Moving to the cost curve, in Figure 9 the cost decreases with the increased number of trucks until number 13; then it increases steadily until the last truck. The cost of the FB loading strategy decreases until the number of trucks equals 18, increasing afterwards. The increase in cost occurs earlier in the FT loading strategy. Finally, a comparison of the number of trucks in queue shows that at the beginning, there is a slight increase in both loading strategies. In the FT strategy, the number of trucks in the queue is insignificant until the fleet size is equal to 13; after this point, the number of trucks in the queue increases steadily until the fleet size is equal to 24. The FB strategy has the same behaviour, but the prominent increase in the number of trucks in the queue is stated after fleet size 18.

In Figure 9 and Figure 10, areas with MF of 1 and 1.5 has been highlighted. For MF of 1, the sufficient number of trucks is between 10 and 12. For this area, in the FT strategy, the total cost for hauling is between 1.60 and 1.62 $/t, while in the FB strategy, it is between 1.62 and 1.63 $/t, which is a small significant difference. Fleet production is the same case, 6.8 to 8.1 Mt/yr in FT and 6.7 to 8.0 Mt/yr in FB. Also, there is a negligible difference in queuing conditions between FT and FB strategies. Therefore, considering the cost, production, and number of trucks in the queue, the FT loading strategy is suitable when the MF is 1.

In contrast, when the MF increases to 1.5, the FB strategy works much better. This increase in the MF happens because of the uncertainty and unplanned equipment breakdowns or any operation stoppage or unplanned queueing that significantly affects the operation. This paper assumed that one of the shovels broke down for a time, and the trucks were sent to the other available shovel. When the MF is in 1.5, the shovel controls the operation. In this situation, the cost of FB strategy is much lesser than FT, ranging from 1.85 to 2.0 $/t, while in FT strategy, it varies between 2.45 and 2.65 $/t with a difference equal % 25. In addition, the production of FB strategy (12.25 Mt/yr) is much higher than the FT strategy. Another advantage for the FB when the MF is 1.5 is the number of trucks waiting for the shovel. The number of trucks in the queue for the FT strategy is double that for the FB strategy.

g. Machine Learning-Controlling Parameters in Loading Strategies

i. Data Preparation

In order to run machine learning properly and evaluate the model, the data should be cleaned and reflect the real situation of hauling operations in a mine. For this purpose, the raw data obtained from simulation for MF of 0.75 and greater were selected. The data for MF<1 was selected to understand the behaviour of operation parameters even with lower efficiency (MF<1) in the hauling operation.

ii. Exploratory Data Analysis (EDA)

An EDA using python programming language was conducted to understand and illustrate the resulting simulation data. Plus, the relationships between the input parameters in the hauling and loading operation and the parameters that control the switch between FT and FB strategies in the simulated loading and hauling operation. Starting from the original dataset containing 750 records with 22 attributes that resulted from Haulsim simulation and filtered out based on MF of 0.75, each entry represents the adapted loading strategy and the associated input data from simulation in the EDA.

A correlation matrix was generated to examine these relationships between operation loading strategies and selected parameters for the correlation approach Figure 11. Some input parameters are linearly correlated, such as cycle time and fleet size, the number of trucks queued, cost and fleet size. In contrast, other parameters, such as loader utilization, are reversely correlated with MF, such as loader utilization, especially when queuing condition occurs, it is reversely correlated but less strong with other operating parameters.

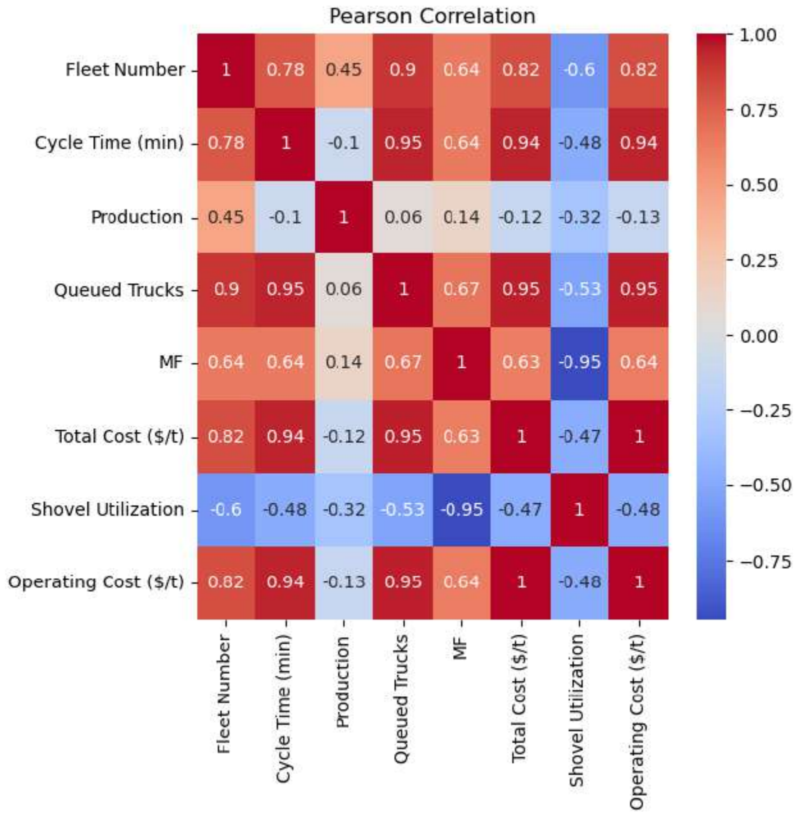

Figure 11. Correlation matrix for simulated data.

iii. Multiple Machine Learning Algorithms

In order to observe the best results of what could be simulated in operation, a set of models was prepared to examine the best recall results for various machine learning algorithms. Each model enters into train and test data. Figure 12 illustrates the comparison of the algorithms generated. These models are selected from the supervised machine learning under classification and regression models because the data set is labelled and training is possible for further prediction. The selected models are:

1) *Linear Discriminant Analysis (LDA)*

   LDA is a linear model for classification and dimensionality reduction that is used for feature extraction in pattern classification problems.

2) *K Neighbors Classifier (KNN)*

   KNN is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions of data.

3) *Decision Tree Classifier (CART)*

CART is a predictive model explains how an outcome variable's values can be predicted based on other values.

4) *Gaussian NB (NB)*

NB is a type of Naïve Bayes classifier algorithm used when the features have continuous values assuming all features have a gaussian normal distribution.

5) *Random Forest Classifier (RF)*

RF is a classification algorithm consisting of many decision trees.

6) *Support Vector Machine (SVM)*

SVM is a supervised machine learning model that uses classification algorithms for two classification problems.

Most algorithms showed a high accuracy median value except for the Gaussian NB algorithm, valued at 0.57. The LR showed the highest recall value at 0.9, followed by CART and the RF with accuracy values of 0.83 and 0.795, respectively. Therefore, machine learning implementation was done based on LR method due to its higher accuracy and the tendency of categorical values.

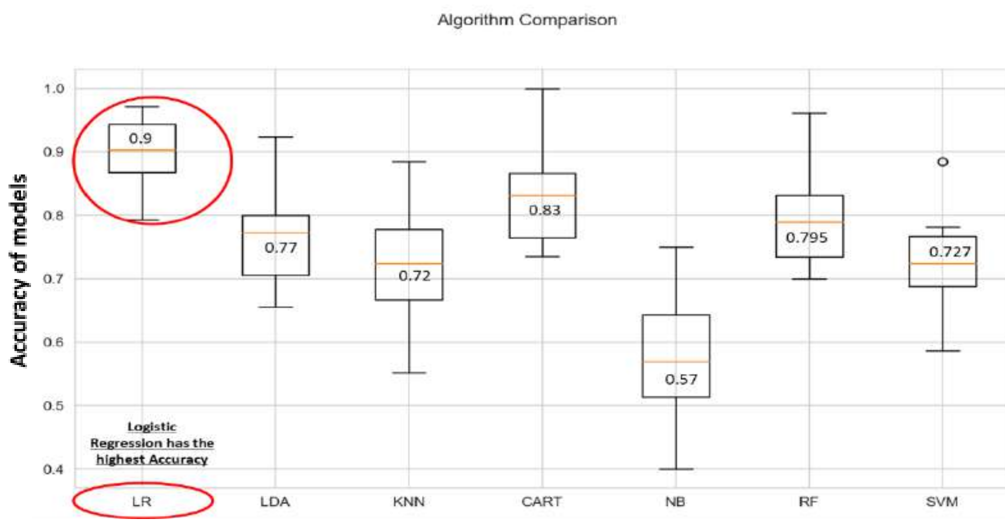

Figure 12. Analysis and comparison of multiple algorithms.

iv. Logistic Regression

The simulated data from various scenarios were implemented into the LR model to understand the effecting factors in the operation and to predict the loading strategy based on the selected data features. The training data feature included hauler fleet size, cycle time, trucks in the queue, MF and rolling resistance. The testing was based on 20% of the simulated data in 750 records, the confusion matrix illustrated in Figure 13 shows more than 90% accuracy in predicting the loading strategies.

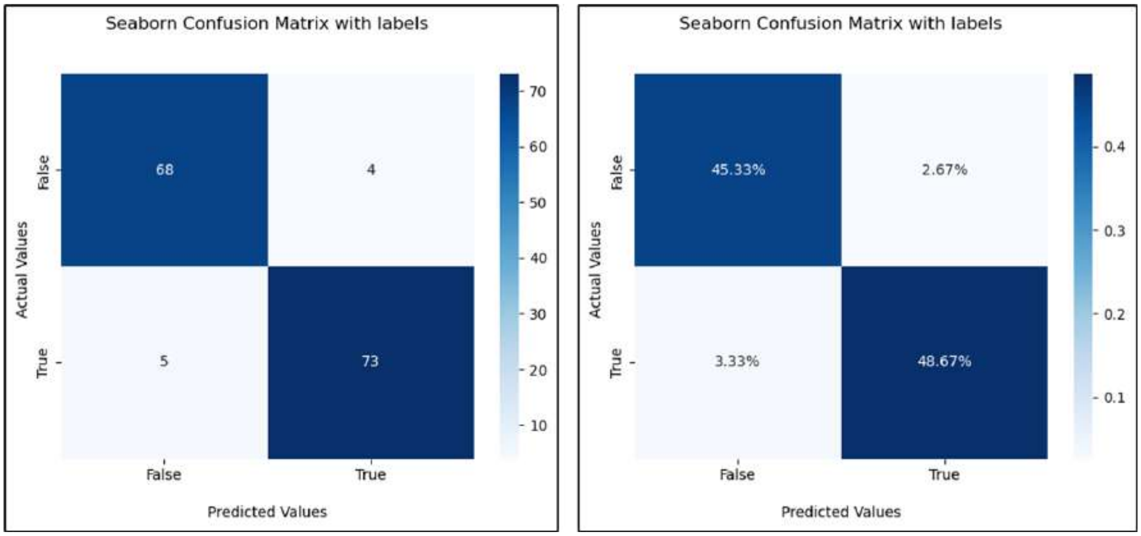

Figure 13. Confusion matrix for the logistic regression model.

v. Shap Values

Shap values (**SH**apley **A**dditive ex**P**lanations) is a cooperative game theory method used to increase the transparency and interpretability of machine learning methods. In Figure 14, the order of columns represents the amount of information accountable for in LR prediction, colour reflects the real data, and the x-axis represents the shap value impact on the model categorical decision (FT or FB). Each dot corresponds to an individual loading strategy in the simulation. The dot's position on the x-axis shows the feature's impact on the model's prediction for that strategy. When multiple dots land at the same x position, they pile up to show density.

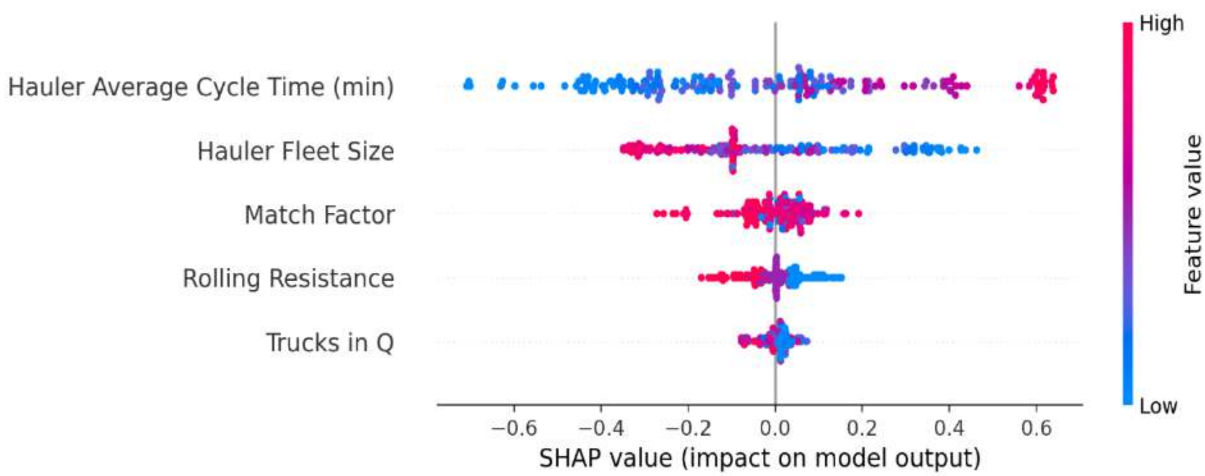

Figure 14. Set of bee swarm plots (revise) for the machine learning model.

Similarly, plotting the data in a different method, the cycle time contributes the most to the model prediction, followed by a fleet number as in Figure 15.

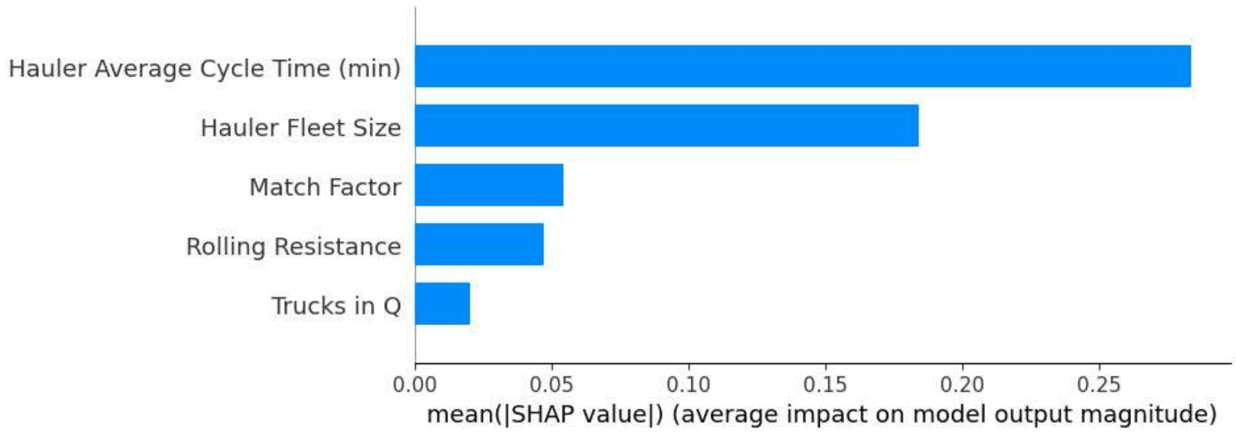

Figure 15. Bar plot Shapley feature importance in predicting model.

5. Conclusions and Discussion

The MF is equal one or averaged to one; the recommended loading strategy is FT based on balanced equipment and cycle times. When operation uncertainty is profound, there should be a consideration for changing the loading strategies in the fleet in order (i) to reduce the hauling costs (ii) to increase production and (iii) to decrease the number of trucks in the queue. In this situation, with switching from FT to FB strategy, the utilization of the shovel increases. The machine learning model showed that cycle time significantly contributes to the loading strategies in the mining operation. Autonomous trucks are promising areas in adapting this framework because they can decide more than the conventional operator. Also, linking the truck and shovel with clouding systems that evaluate the material will prioritize the loading strategy based on the current operation level conditions. These analyses showed that there is an opportunity that advantages the FB over the FT based on changing the match factor in operation, which is directly related to the shovel-truck loading time in a specific number of passes and number.

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Optimum Fleet Selection Using Machine Learning Algorithms[1]

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ABSTRACT

This paper presents the machine learning method (ML), a novel approach that could be a profitable idea to optimize fleet management and achieve a sufficient output to reduce operational costs by diminishing trucks' queuing time and excavators' idle time based on the best selection of the fleet. The performance of this method has been studied at the Zenouz kaolin mine to optimize the type of loader and the number of trucks used to supply the processing plant's ore demands. Accordingly, the five years' data, such as date, weather conditions, number of trucks, routes, loader types, and daily hauled ore, have been collected, adapted, and processed to train five practical algorithms, including linear regression, decision tree, K-nearest neighbour, random forest, and gradient boosting algorithm. By comparing the results of the algorithms, the gradient boosting algorithm was determined to be the best fit and predicts test data values with 75% accuracy. Subsequently, 11,322 data were imported into the machine as various scenarios and daily hauled minerals as output results were predicted for each working zone individually. Finally, the data with the minimum variation of the required scheduled value selected and its related data containing loader type and the number of demanded trucks have been indicated for each day of the working year.

1. Introduction

Fleet management and scheduling are the most significant components of operations in the mining cycle. So, hauling costs, including 60% of operating costs, play a crucial role in the mining economics, influencing production costs and final product price (Li, 1990). In open-pit mining, the complexity of operations, coupled with an uncertain and dynamic environment, limits the certainty of the predictions. Consequently, to achieve the production targets and decrease operational costs, the best accuracy in predictions with a minimum of opportunity lost in fleet management should be reflected by considering all the factors, although small, which are coupled to each other. Accordingly, for far years, various methods have been performed and accomplished by many scientists and industrial companies to optimize fleet management by analyzing multiple situations. Lizotte and Bonates (1987) proposed a method to minimize shovel idle time, maximizing immediate truck use and allotting trucks to shovels to meet specific production purposes. Hashemi and Sattarvand (2015) presented a dispatching simulation model in ARENA simulation software with the objective function of minimizing truck waiting times that have developed hauling cycle and a 7.8% improvement obtained by applying a flexible assignment of the trucks for the loaders compared to the fixed assignment system. Temeng and Otuonye (1998) used the

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goal-programming-based dispatching model to maximize production rate and maintain ore quality compared to linear programming. Rodrigo et al. (2013) performed a novel system productivity simulation and optimization modelling framework. In their model, equipment availability is a variable in the expected productivity function of the system. The framework is used for allocating trucks by route according to their operating performances in a truck–shovel system of an open-pit mine to maximize the overall productivity of the fleet. In 2010, Topal and Ramazan (2010) presented a mixed-integer programming model (MIP). Their model provides substantial cost savings for equipment scheduling by optimizing truck usage. Gu et al. (2010) presented a dynamic management system of ore blending in an open-pit mine based on GIS/GPS/GPRS uses technologies from space, wireless location, wireless communication, and computers to control the ore quality and ensure the stability of the ore grade. Cox et al. (2018) used a genetic algorithm to develop cyclic automata for dispatching trucks in mines. Ahangaran et al. (2012) discussed the changing trend of programming and dispatching control algorithms and automation conditions. Finally, a real-time dispatching model compatible with the requirement of trucks with different capacities was developed by using two techniques of flow-networks and integer programming (IP). Additionally, the use of innovative methods in recent years has improved the performance of the transport systems in mines. Upadhyay and Askari-Nasab (2018) presented a framework using a discrete event simulation model (DES) of mine operations, which interacts with a goal programming (GP) based mine operational optimization tool to develop an uncertainty-based short-term schedule. This framework allows the planner to make proactive decisions to achieve the mine's operational and long-term objectives. Baek and Choi (2020) proposed a deep neural network (DNN)-based method for predicting ore production by truck-haulage systems in open-pit mines, and assisted comprehension of truck-haulage-system characteristics along with discrete haulage-operation sequences and support the prediction of ore production through training of DNN-based deep learning models without the need to develop additional algorithms. Moradi-Afrapoli et al. (2021) presented a new mixed-integer linear programming model (MILP) to solve the truck dispatching problem in surface mines. This paper's results showed that fuzzy linear programming (FLP) model improved the ore production and truck wait time in the queues by more than 15%. In 2021, Mohtasham et al. (2021a) presented a multi-objective optimization model based upon a mixed-integer linear goal programming (MILGP) model, which determines the optimal production plan of the shovels and allocation plan of the trucks and shovels in order to maximize production, meet desired head grade and tonnage at the ore destinations, and minimize fuel consumption of trucks. Yeganejoo et al. (2021) performed development, implementation, and validation of an integrated simulation and optimization tool that is capable of predicting productivity of truck fleet and determining optimal fleet size based on the historical data collected from the active mine. Mohtasham et al. (2021b) proposed new strategies based on mixed-integer non-linear programming (MINLP) models for the equipment sizing (ES) problem to verify the overall efficiency of the fleet. The developed models estimate the optimal size of trucks concerning the match factor value with two different strategies; the first strategy deals with each loader type, and the second one is applied simultaneously with all types of loaders. Upadhyay et al. (2021) presented a simulation-based fleet productivity estimation and fleet size determination algorithm developed to be used in open-pit mines to estimate fleet productivity and predict the required fleet size to meet the production schedules in the presence of technical uncertainties. Results showed that the developed simulation-based algorithm could predict fleet productivity with more than 20% higher accuracy and lower dependency on haulage distances.

The mentioned studies have individual problems, including disregarding past expertise in mining operations, limited flexibility for change in the production process, and ignoring actual working situations in mines.

This paper uses machine learning methods (ML), a novel approach known as a subfield of Artificial Intelligence (AI) methods, which could be a beneficial approach to reach the best fitting with environmental conditions and work situations to optimize fleet management and attain an adequate output. While fleet management is related to several factors and procedures, ML methods consider work situations like routes, types of machinery, time, and weather conditions. Furthermore, these methods also help planners to have reliable and accurate predictions.

2. Machine Learning (ML)

ML has become one of the most critical topics within development organizations looking for innovative ideas to leverage data assets to help the business gain a new level of understanding. ML is a form of AI that enables a system to learn from data rather than through explicit programming. Resurging interest in machine learning is due to growing volumes and varieties of available data, computational processing that is cheaper and more powerful, and affordable data storage. Machines that learn can more quickly highlight or find patterns in data that human beings would have otherwise missed. Consequently, ML techniques can be used to enhance humans' abilities to solve problems and make informed inferences on a wide range of problems. ML techniques are divided into three sections: supervised learning, unsupervised learning, and reinforcement learning, each of the sections has individual performance. Figure 1 shows a division of ML techniques and their sub-fields.

ML uses various algorithms that iteratively learn from data to improve, describe data, and predict outcomes. As the algorithms ingest training data, it is possible to produce more precise models based on that data. An ML model is the output generated when a machine learns by a learning algorithm with data. Then, when the predictive model is provided with data, it will predict based on the data that trained the model (Judith Hurwitz, 2018). In this paper, five regression techniques from supervised learning are employed. Figure 2 illustrates the flowchart of the optimum model selection operation using the ML algorithms.

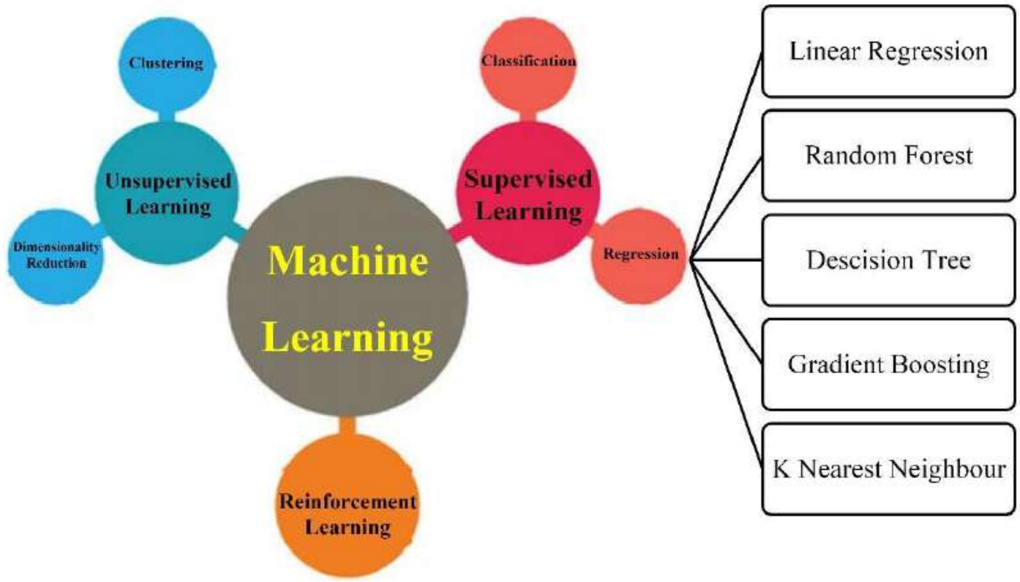

Figure 1. Types of machine learning methods and their subclasses.

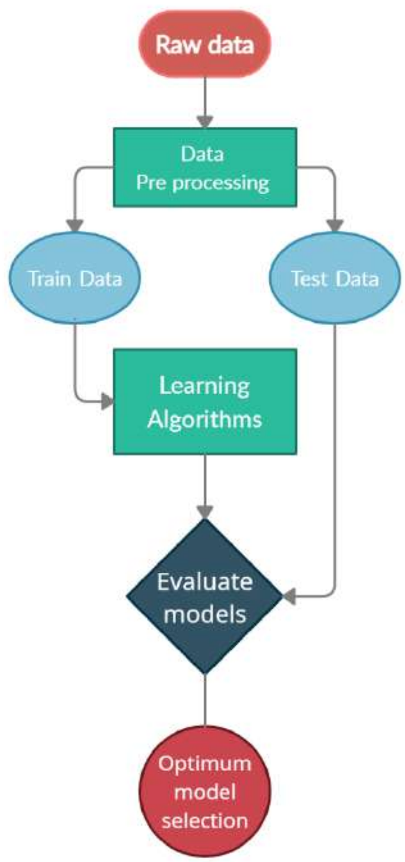

Figure 2. Optimum model selection flowchart.

3. Case Study

Zenouz kaolin mine is located near Zenouz city, approximately 15 km North of Marand city of East Azerbaijan, Iran.

Zenouz kaolin mine is the largest kaolin mine in the Middle East, producing approximately 1,700,000 tonnes of raw kaolin and supplying nearly 70% of the kaolin in the region. This mine includes five working zones. Each zone has its own characteristics and provides processing plant demands individually. The mining method in this mine is open-pit mining, and kaolin is extracted by blasting, loaded by various types of excavators, and hauled by trucks to the processing plant and low-grade stockpiles. Figure 3 shows the location of different zones and stockpile

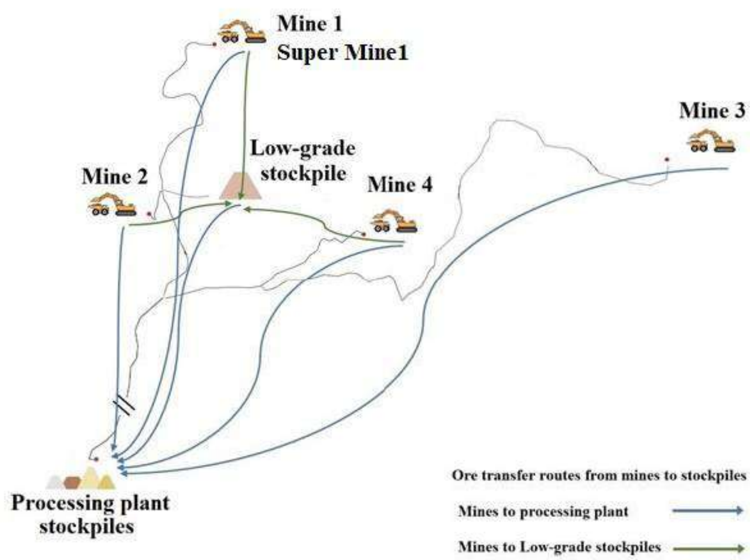

Figure 3. Working zones, low-grade stockpile and processing plant stockpiles locations.

3.1. Data Collection

By collecting the last five years' records (from May 2017 to May 2021) in eight different divisions, the 1976 data has been regarded as machine learning input data. On the other hand, they have been converted into numerical data to transform descriptive data into something understandable and agreeable to the machine. These eight categories and their related numerical forms are presented as follows:

3.1.1. Month

This information is considered because the amount of minerals hauled varies by month. Therefore, numbers 1 to 12 are allocated to the data for April to March, as shown in Table 1.

Table 1. Months and their related numerical values.

Mont h	Encoded data	Month	Encoded data	Month	Encoded data
April	1	August	5	December	9
May	2	September	6	January	10
June	3	October	7	February	11

July	4	November	8	March	12

3.1.2. Weather Condition

Weather conditions influence the operation of the hauling systems because operators and equipment perform differently in various weather conditions. Since weather conditions affect the amount of ore haulage, related data on this factor have been collected and divided into five situations, shown in Table 2.

Table 2. Weather conditions and related encoded data

Weather condition	Encoded
Cloudy	0
Foggy	1
Rainy	2
Snowy	3
Sunny	4

3.1.3. Season

According to experimental observations, the amount of mineral transportation varies in different seasons. Hence, this parameter has also been analyzed for better consideration as training data and has been presented in Table 3.

Table 3. Seasons and related encoded data

Season	Encoded
Spring	1
Summer	2
Fall	0
Winter	3

3.1.4. Weekday

Due to several spatial and temporal constraints, truck drivers' weekend driving behaviour is expected to differ considerably from their weekday driving style. Thus, the weekdays have also been considered and evaluated in Table 4.

Table 4. Weekdays and related encoded data.

Weekday	Encoded	Weekday	Encoded
Monday	1	Friday	0
Tuesday	5	Saturday	2
Wednesday	6	Sunday	3
Thursdays	4		

3.1.5. Number of Trucks

In Zenouz kaolin mine, two models of trucks, Sahand-WD615 and Mercedes-Benz-OM335, are used, and the carrying capacity of each is 26 tons on average. The number of trucks that haul minerals from different zones to stockpiles is also considered analyzable data in machine learning.

3.1.6. Routes

Zenouz mine complex includes six loading spots and two delivery points (see Figure 3). Regarding the distances of these zones from the stockpiles and considering the production plan, this parameter has also been separated into nine divisions, shown in Table 5.

Table 5. Routes and related abbreviations and encoded data.

Route	Abbreviation of routes	Encoded
LG-stockpile to plant	LGP	0
Mine 1 to plant	M1P	1
Mine 1 to LG-stockpile	M1LG	2
Mine 2 to plant	M2P	3
Mine 2 to LG-stockpile	M2LG	4
Mine 3 to plant	M3P	5
Mine 4 to plant	M4P	6
Mine 4 to LG-stockpile	M4L	7
Super Mine1 to plant	SP	8

3.1.7. Loader Types

Because different types of excavators load trucks, the efficiency of these machines has been investigated. Four types of excavators are used as loaders at the studied site, which were taken into account as part of the input data. Table 6 displays these loaders as well as the numerical data associated with them. Table 7 shows examples of the collected data, and Table 8 shows the final table after converting the data to numerical data.

Table 6. Types of excavators and their related encoded data.

Loader type	Encoded
Hyundai 250	0
Hyundai 320	1
Komatsu 200	2
Komatsu 220	3

Table 7. Sample of collected data.

Row	Month	Weather condition	Season	Weekday	No. of tucks	Routes	Loader	Hauled ore (tonne)
50	5	Sunny	Summer	Monday	6	M1 to plant	Hyundai 320	382.800
51	5	Sunny	Summer	Thursday	12	M1 to plant	Hyundai 320	1,131.310

52	5	Sunny	Summer	Friday	18	M1 to plant	Hyundai 320	2,129.650
53	5	Sunny	Summer	Saturday	18	M1 to plant	Hyundai 320	2,277.940
54	5	Sunny	Summer	Wednesday	14	M4 to plant	Hyundai 320	2,036.88

Table 8. Encoded value of the data presented in Table 7.

Row	Month	Weather condition	Season	Weekday	No. of tucks	Routes	Loader	Hauled ore (tonne)
50	5	4	2	1	6	1	1	382.800
51	5	4	2	4	12	1	1	1,131.310
52	5	4	2	0	18	1	1	2,129.650
53	5	4	2	2	18	6	1	2,277.940
54	5	4	2	6	14	1	1	2,036.88

4. Data Pre-Processing

4.1. Important Data

Since weekdays have insignificant impacts on model learning and creation basis on their low impact rates on the learning process (see Figure 4) and due to the unpredictability of the weather in the long term, their inclusion in the continuation of modelling has been omitted. Furthermore, five parameters, including season, month, number of trucks, routes, and loader types, have been used as input data. The data was processed and validated through efficient techniques to train the machine properly. Min-Max scaling and k-fold validation were used in this paper to standardize data and validate the implied prediction model, respectively.

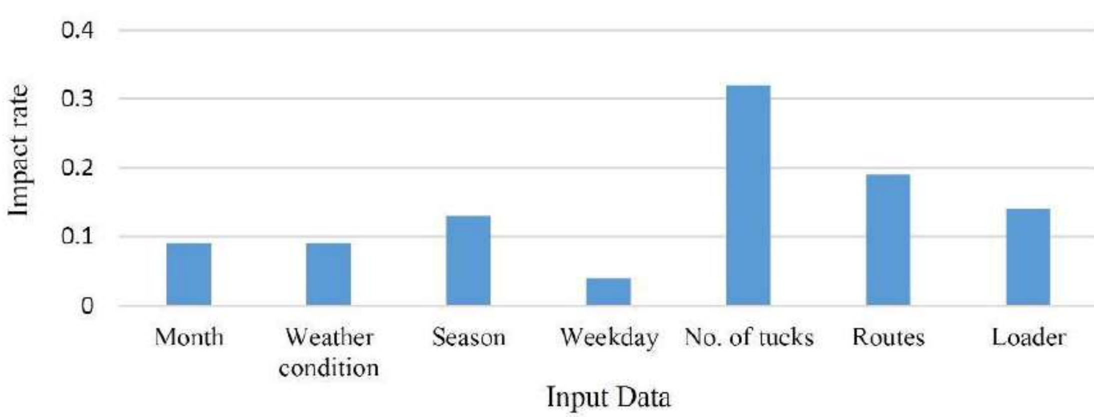

Figure 4. Impact rate of each parameter on the hauled ore.

4.2. Standardization

Considering the input data have different dimensions, to train the machine practicable, data converted to a similar scale via the min-max scaler. This method scales and translates each feature individually such that it is in the given range on the training set, between zero and one. Table 9 presents an example of data scaled by the Min-Max scaler.

Table 9. Standardized sample data presented in Table 8 by min-max scaling method

Row	Month	Season	No. of tucks	routes	Loader	Hauled ore (tonne)
50	0.363636	0.66666667	0.16666	0.125	0.33333	382.800
51	0.363636	0.66666667	0.33333	0.125	0.33333	1131.310
52	0.363636	0.66666667	0.5	0.125	0.33333	2129.650
53	0.363636	0.66666667	0.5	0.125	0.33333	2277.940
54	0.363636	0.66666667	0.38888	0.75	0.33333	2036.88

4.3. K-fold validation

K-fold cross-validation effectively partitions the data into K chunks, K-1 of which form the training set R, and the last chunk serves as the validation set V. Cross-validation iterates through all combinations of assignments of chunks to R and V. This procedure repeated for all K choices for the validation set and the performance of the model from the K runs averaged (Shalev-Shwartz and Ben-David, 2013). Figure 5 shows how this method runs. In this paper, 20% of the data is considered to be test data representing 395 values of 1975.

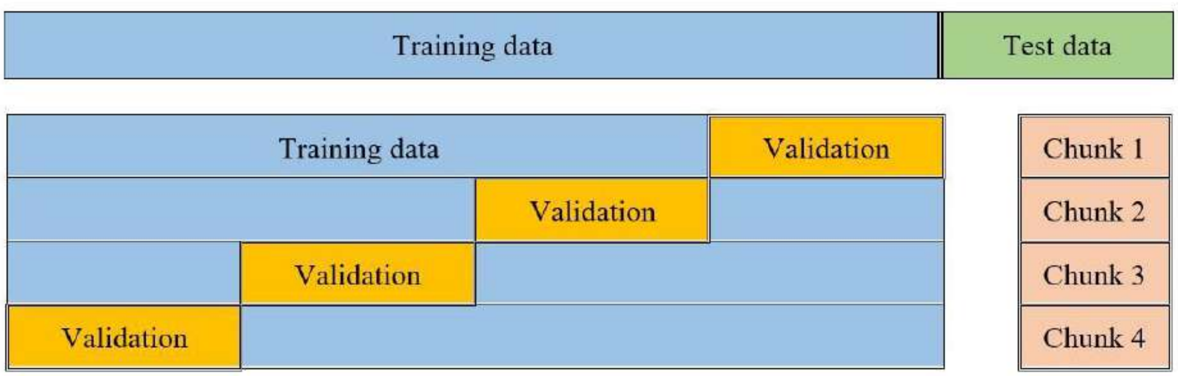

Figure 5. K-fold validation performance.

4.4. R2 score

The R^2 coefficient (Equation 1) represents the proportion of variation in the model's predicted result based on its features and real data (Raschka and Mirjalili, 2019).

$$R^2_{(ytrue,\ ypred)} = 1 - \frac{\sum(ytrue - ypred)^2}{\sum(ytrue - \bar{y})^2} = \frac{RSS}{TSS} \quad (1)$$

In which R^2 is the coefficient of determination, RSS is sum of squares of residuals, and TSS is total sum of squares.

5. Modelling

After collecting data, excluding insufficient data, and processing them, 1,580 and 395 data points were imported into the machine as training and test data, respectively. In machine learning, dozens of unique algorithms perform specialized purposes including, regression, clustering, and classification. The amount of hauled ore is continuous data; therefore, regression methods that deliver a continuous type of data was selected in this paper. The following sections describe the validation of the five algorithms.

5.1. Linear regression (LR)

The LR is a linear approach for modelling the relationship between scalar response and one or more explanatory variables. In LR, the relationships are modelled using linear predictor functions whose unknown model parameters are estimated from the data (Shalev-Shwartz and Ben-David, 2013). By running the algorithm on the processed input data, a model with 62% accuracy was achieved. Figure 6 shows the real and predicted values of the data from number 50 to 150.

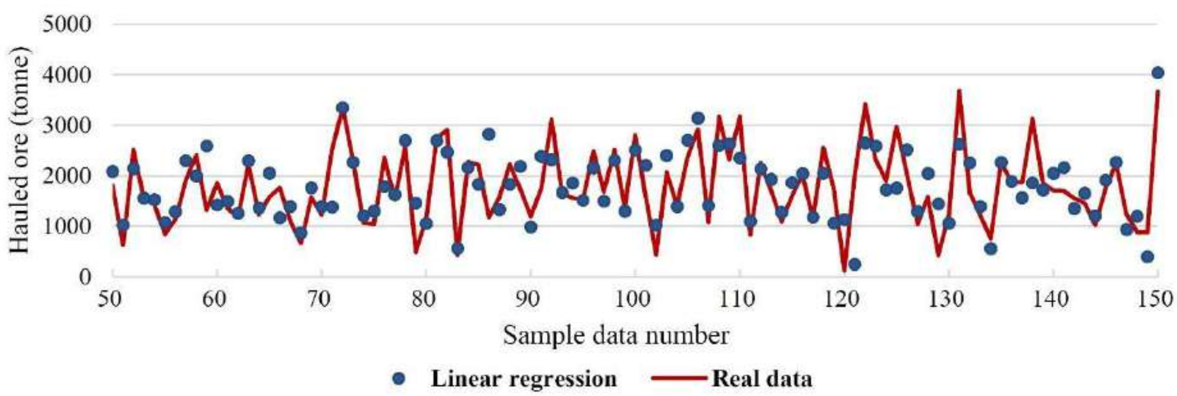

Figure 6. Comparison between real data and prediction of linear regression algorithm.

5.2. Decision Tree Regression (DTR)

The DTR algorithms are based on heuristics such as a greedy approach, where the tree is constructed gradually, and locally optimal decisions are made at the construction of each node [18]. By attempting this algorithm, predicted data have fitted to real data with 63% accuracy. Figure 7 compares real data, and DTR algorithm predicted data.

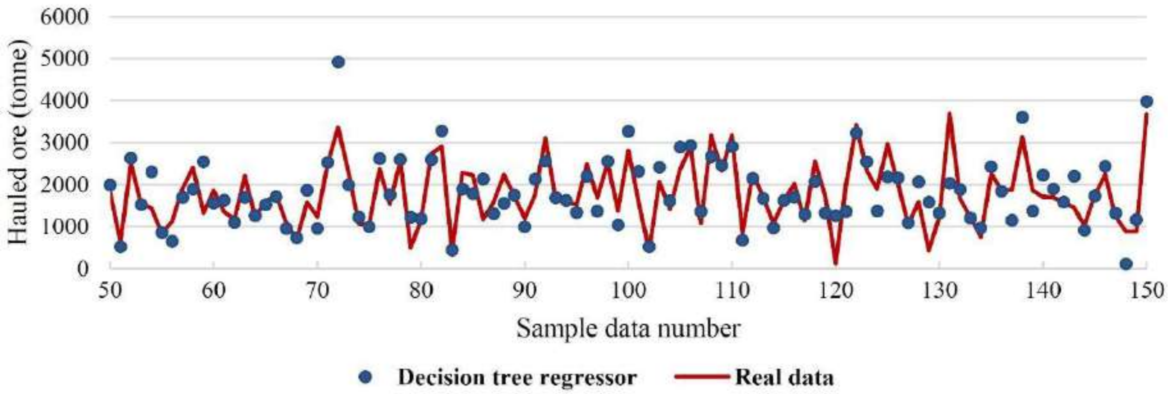

Figure 7. Comparison between real data and prediction of decision tree regression algorithm.

5.3. K-nearest Neighbors Algorithm (KNN)

The KNN algorithm is a supervised learning technique used to classify or predict new data points based on the relationship to nearby data points (Theobald, 2017). Actual and predicted values using the KNN algorithm are shown in Figure 8. The accuracy of the KNN prediction is 65%.

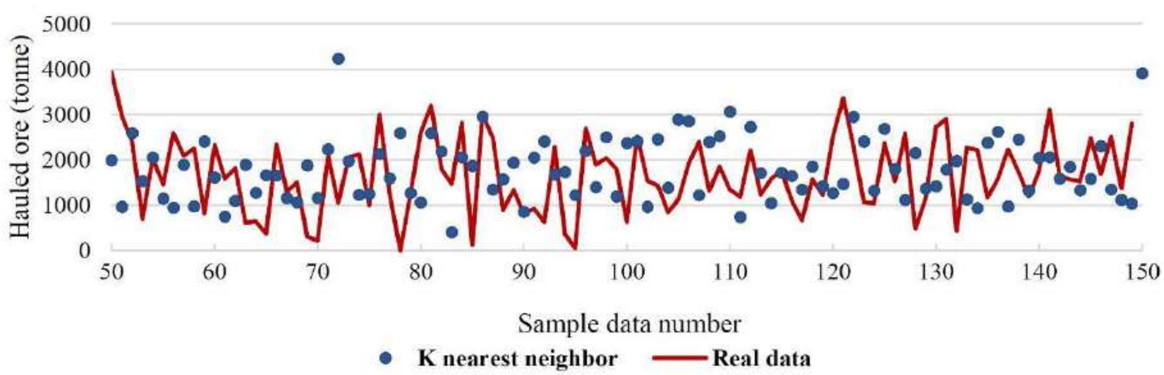

Figure 8. Comparison between real data and prediction of K nearest neighbour algorithm.

5.4. Random Forests (RF)

The RF is a regressor consisting of a collection of decision trees. The prediction of the random forest is obtained by a majority vote over the predictions of the individual trees, and also, RF generally outperform decision trees' performance (Shalev-Shwartz and Ben-David, 2013) with the implementation of this algorithm. Figure 9 shows the difference between the actual and predicted values by RF regression algorithm for the obtained accuracy of 73%.

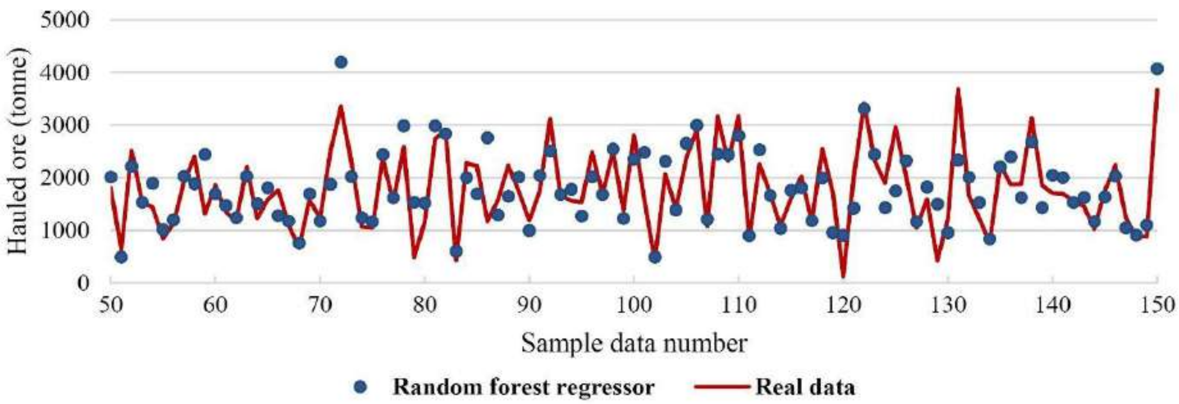

Figure 9. Comparison between real data and prediction of the random forest regression algorithm.

5.5. Gradient Boosting (GB)

Rather than selecting combinations of binary questions at random (like random forests), GB selects binary questions that improve prediction accuracy for each new tree. The way this works is that mistakes incurred with the training data are recorded and then applied to the next round of training data. At each iteration, weights are added to the training data based on the results of the previous iteration. A higher weighting is applied to instances that were incorrectly predicted from the training data, and instances that were correctly predicted receive less weighting. The training and test data are then compared, and errors are again logged in order to inform weighting at each subsequent round (Theobald, 2017). Figure 10 shows that the GB algorithm could predict the data with 75% accuracy.

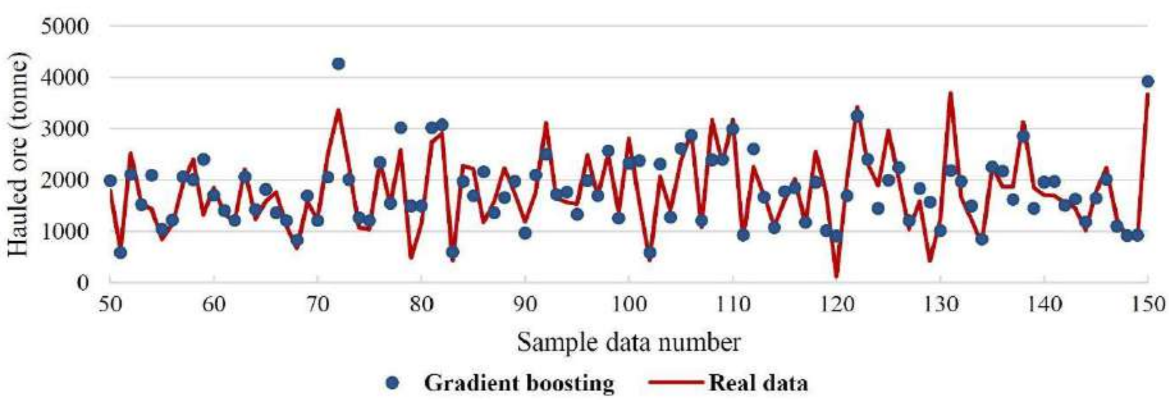

Figure 10. Comparison between real data and prediction of gradient boosting regression algorithm.

6. Model Selection

The gradient boosting algorithm was chosen as the best among the investigated algorithms. With 75% accuracy, this algorithm was used for the rest of the study after measuring the implemented algorithms to achieve an optimal model using the R^2 score formula. Each algorithm's efficiency is depicted in Figure 11.

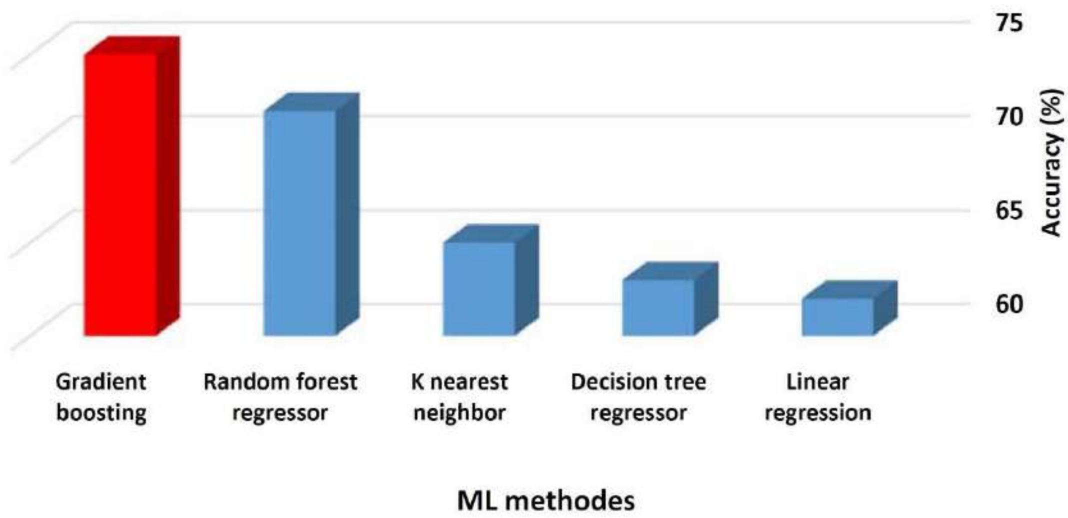

Figure 11. Implemented algorithms accuracy in percent.

7. Ore Transport Schedule

Mine Planning team calculates the required monthly ore production from each mine based on the processing plant's required monthly feed. Table 10 shows the calculated monthly amount of ore from different zones.

While there are some limitations, simultaneous loading in more than three working zones is not possible. As a result, working days for different zones have been planned according to Table 11. The Table 12 indicates an estimate of the required daily ore quantity to cover the processing plant's annual demand depending on this plan.

Table 10. Ore annual haulage scheduling (ktonne).

Month	SUP. to P	M1 to P	M2 to P	M3 to P	M4 to P	M1 to LG	M2 to LG	M4 to LG	LG to P	Total ore to the plant
1	0	60	15	0	0	15	0	0	0	75
2	12	65	17	0	0	20	0	0	0	94
3	15	65	17	14	0	20	0	0	0	111
4	15	65	17	14	25	20	10	5	0	136
5	15	65	17	0	33	30	0	5	0	130
6	15	65	17	0	33	30	0	5	0	130
7	10	65	17	0	33	30	10	5	0	125
8	8	65	17	0	33	30	0	5	0	123
9	0	65	17	0	33	25	0	5	0	115
10	0	65	17	0	33	25	8	3	0	115
11	0	65	17	0	20	25	0	3	0	102
12	0	60	15	0	0	16	0	3	10	85
Annual ore to the plant										1,341

Table 11. Working zones daily ore hauling schedule plan.

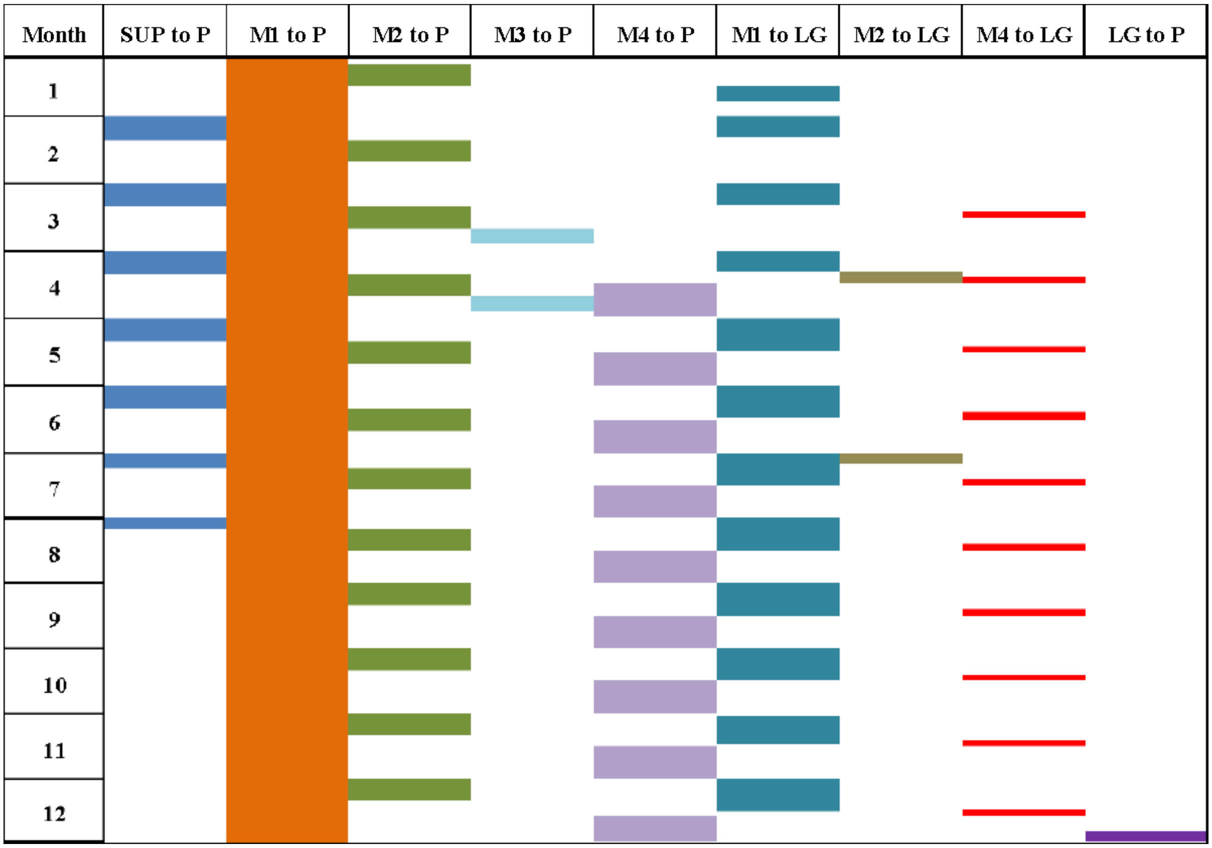

Table 12. Daily ore production schedule.

Month	SUP. to P	M1 to P	M2 to P	M3 to P	M4 to P	M1 to LG	M2 to LG	M4 to LG	LG to P
1	0	2000	1500	0	0	2143	0	0	0
2	1200	2097	1700	0	0	2000	0	0	0
3	1500	2097	1700	2000	0	2000	0	0	0
4	1500	2097	1700	2000	1667	2000	2000	1667	0
5	1500	2097	1700	0	2200	2000	0	1667	0
6	1500	2097	1700	0	2200	2000	0	1667	0
7	1429	2167	1700	0	2200	2000	2000	1667	0
8	1600	2167	1700	0	2200	2000	0	1667	0
9	0	2167	1700	0	2200	1667	0	1667	0
10	0	2167	1700	0	2200	1667	2000	1000	0
11	0	2167	1700	0	1333	1667	0	1000	0
12	0	2000	1500	0	0	1067	0	1000	2000

The algorithm used 1,258 individual scenarios after measuring the daily required ore amount. As a result, the minimum difference between the predicted and required data values were calculated, and the optimal fleet was selected based on related items to this data. According to Figure 12, for instance, the machine anticipates a Hyundai 320 excavator and 19 trucks as the ideal fleet in April to transport ore from Mine 1 to the plant's stockpiles.

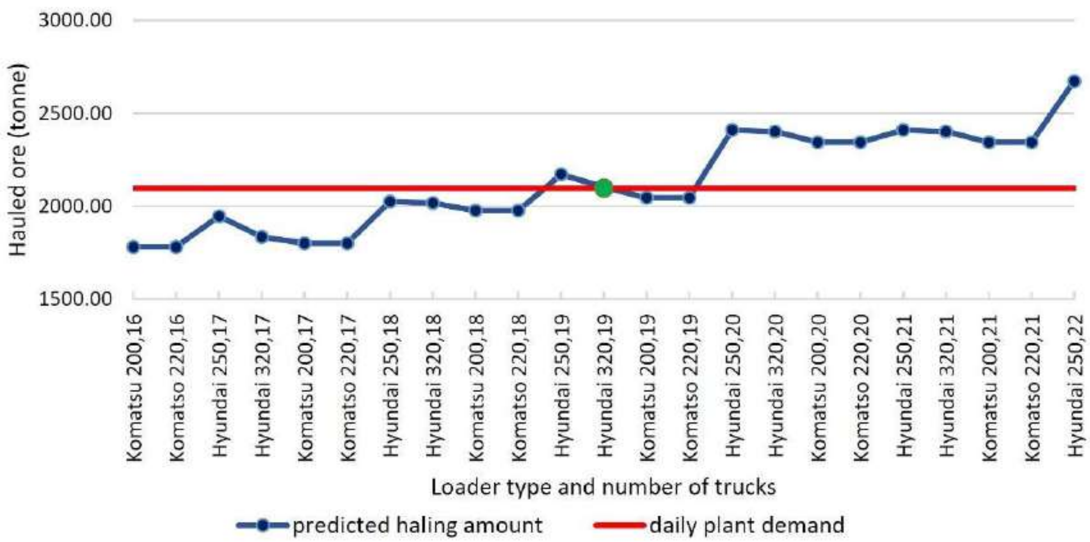

Figure 12. Optimum loader type and number of trucks selection.

Using 11,322 scenarios as input data for five loading points and two mineral discharge stockpiles, the most suitable fleet was selected. Table 13 shows the best loader and number of trucks that different zones should use in 12 months.

Table 13. Optimum fleet to supply processing plant demands.

	Sup. to plant		Mine1 to plant		Mine2 to plant		Mine3 to plant		Mine4 to plant		Mine1 to LG		Mine2 to LG		Mine4 to LG		LG to plant	
Month	Loader	# trucks	Loader	# trucks	Loader	# trucks	Loader	# trucks	Loader	# trucks	Loader	# trucks	Loader	# trucks	Loader	# trucks	Loader	# trucks
1			H250	17	H320	10					H250	11						
2	H320	9	H250	18	H320	11					H250	11						
3	H320	11	H320	19	H250	11	K200	12			K220	11						
4	K200	12	H320	19	H320	11	K200	12	K200	10	K220	11	K200	11	K200	10		
5	K200	12	H320	19	H250	11			H320	13	K220	11			H320	11		
6	K200	12	H320	19	H250	11			H320	13	K220	11			H320	11		
7	H320	11	H320	19	H250	11			K200	13	H250	11	K200	11	H320	12		
8	K220	10	H320	19	H250	11			K200	13	H250	11			H320	12		
9			K220	21	K200	12			K200	13	H250	10			H320	12		
10			H250	19	H320	11			H320	13	K220	10	K220	11	K220	9		
11			K220	18	H320	11			K200	10	H250	10			K200	8		
12			H320	16	K200	10			K200	6	H250	8			K200	8	H320	17

K200 (Komatsu 200) H250 (Hyundai 250)
K220 (Komatsu 220) H320 (Hyundai 320)

8. Conclusions

According to estimations, mineral transportation costs cover a large share of the operating costs and are becoming a challenge in mining management. So, implementing optimization in this operation can minimize the loss of capital costs, reduce the final price of the mineral, and increase profitability. In this paper, ML method was used as an innovative approach to simulate operations, which was executed in the Zenouz kaolin mine to optimize fleet selection. Consequently, the Gradient Boosting Regressor, an excellent algorithm, was chosen and taught by various operational and conditional data to fit and predict the most beneficial fleet. Finally, the best daily required fleet to supply ore transportation to stockpiles was obtained by matching the processing plant ore demands and predicted values and finding the minimum difference between these values. As a result, the suggested fleet reduces truck queuing and excavators' idle times, accounting for a considerable portion of energy consumption and capital wasting.

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Shovel Allocation and Short-Term Production Planning in Open-Pit Mines Using Deep Reinforcement Learning

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ABSTRACT

The open-pit production system is a highly dynamic and uncertain environment with complex interactions between haulage and loading equipment on a shared road network. One of the key decisions in open-pit short-term planning is the allocation sequence of shovels to mining faces to meet the production targets established by the long-term strategic plan. Deep Reinforcement Learning (DRL) techniques have been widely applied to dynamic production environments where an agent is trained on a simulation of the production system to learn the best decisions to take given the system's state at any given time. This paper proposes a DRL approach based on the Deep Q-Learning algorithm to obtain a robust shovel allocation plan for open-pit short-term planning. A discrete-event simulation of the mining production system incorporating trucks, shovels, crushers, dumps and the road network is developed, where each component of the equipment operating cycles is subject to uncertainties modelled based on historical activity records to serve as the environment to train the DRL agent. The goal is to learn a robust shovel allocation strategy for the next 3-months to meet the tonnes per hour (TPH) production target to be delivered to the crusher feeds by interacting multiple times with the production simulator. As a result, the agent successfully learns a shovel allocation plan that achieves the goal considering all the operating uncertainties for the case study.

1. Introduction and Background

The open-pit mining production system is a highly dynamic environment that comprises the operation and coordination of multiple pieces of equipment of different types and capacities to achieve a production goal, usually delivering a certain amount of ore within a certain quality range to processing facilities to comply with the long-term plan (Newman et al. (2010) [9]). A major challenge in open-pit short-term planning is the high uncertainty arising from the dynamic interaction of different machines, operating cycle times and failures, and geological uncertainties in the quality of the material being mined. This often leads to hard-to-reach plans at the operational stage due to mismatches in productivity and geological forecasts, which then require frequent efforts to update plans and resolve issues as they appear.

Commercial tools and academic research in open-pit short-term planning focus on developing mathematical programming frameworks, usually linear optimization models or similar heuristics, which require the formulation of large and complex models to capture the highly dynamic open-pit production environment (Blom et al. (2018) [1]). However, a major drawback of these approaches is the complexity in including operational uncertainties, which make an already intractable mathematical problem substantially more complex, with limited capabilities to consider a significant number of production scenarios (Both and Dimitrakopoulos (2018) [2]).

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Simulation models have been used extensively in mining to estimate the productivity of mining systems by using historical data to reproduce equipment behaviour and interactions to forecast future performance (Raj et al. (2009) [12]). In addition, simulation models provide an efficient approach to quantifying the different operational uncertainties and particularities of the day-to-day operations in open-pit mines. Therefore, researchers have proposed using simulation models to serve as a platform for an optimization engine that provides robust and optimal short-term mine planning decisions (Upadhyay and Askari Nasab (2018) [17]; Shishvan and Benndorf (2019) [14]). However, current simulation-optimization efforts still use linear optimization techniques to find the planning decisions, which struggle to efficiently model the dynamic environment of day-to-day mining operations leading to suboptimal decisions, inability to account for a wide range of production scenarios and large computation times which could render real-world use unfeasible.

This research proposes a Deep Reinforcement Learning (DRL) approach for robust and adaptive open-pit short-term planning, specifically for dynamic shovel allocation and mining sequencing decisions. Reinforcement Learning (RL) is a branch of Machine Learning (ML) that involves a computational approach to learning from interactions with an environment to maximize a goal (Sutton and Barton (2018) [16]). DRL has seen an increased application for optimizing different engineering systems, such as in the transportation, manufacturing and heavy industries, providing a highly flexible data-driven production control framework (Panzer and Bender (2021) [11]).

In an RL framework, an agent, an abstraction for the decision-maker, interacts with an environment at different time steps. At any time step t where the agent must act, it observes the current state of the system, s_t, and makes an action based on it. The environment then responds to this action by transitioning into a new state in the next time step s_{t+1}, and providing a reward R_{t+1} for the agent. This sequential decision-making behavior (Figure 3) repeats itself until the environment transitions into a final state, and the interaction ends; alternatively, the agent could interact with the environment indefinitely, depending on the application.

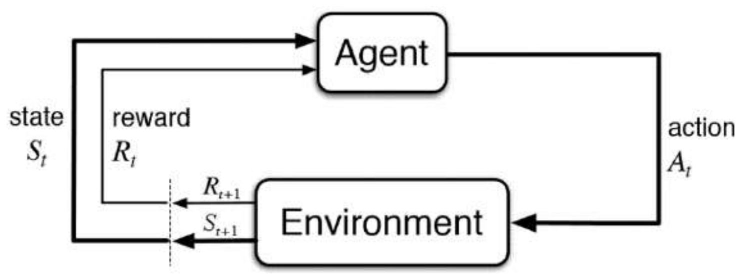


Figure 1. Reinforcement Learning conceptual framework [16].

RL aims to enable the agent to learn an optimal decision-making policy that maximizes the cumulative reward received throughout its interaction. The objective function that RL algorithms optimize is the total discounted reward accumulated by the agent by interacting with the environment. Therefore, the rewards returned by the environment are designed to reflect the desired goals achieved in each application. In the context of open-pit short-term planning, this could profit from ore deliveries to the crusher and penalties from deviations in production targets. The decision-making policy is expressed as mapping, or function, from states of the system to actions to make, and it can be implemented as a hardcoded table of state variables or a complex function approximator as an Artificial Neural Network (ANN). The development of this mapping from states to actions is achieved by a learn by doing approach, where the agent interacts with the environment, exploring it, discovering the impact of unknown actions, and exploiting well-proven high reward decisions. Due to a large number of environment interactions needed to converge to an optimal policy, the agent and environments are commonly implemented as computer simulations before moving to real-world trials and applications (Naeem et al. (2020) [8]).

A practical in the heavy industries for production planning in a chemical plant, more akin to the environment of the extractive industries, is presented by Hubbs et al. [5]. The authors proposed an actor-critic algorithm, policy-based RL, for optimal and robust chemical production scheduling under uncertain demand and equipment operating cycles. The DRL approach was built using historical records and was exhaustively benchmarked against current practices and MIP-based scheduling algorithms, reporting that the DRL scheduling led to increased profitability and better response to unforeseen situations. Another major advantage of DRL scheduling is the fast-computing times in deployment after training since it only requires a forward pass through Deep Neural Network (DNN). This was demonstrated by Wu et al. [19] where a DRL framework was developed to tackle the production planning of medical masks during the COVID-19 emergency, which caused the arrival of a large number of unexpected orders to manufacturing facilities. The DRL was trained to minimize total tardiness in order completion and was tested with data from a medical mask manufacturer, showing that the DRL system could generate production plans and efficiently handle real-time rescheduling of orders significantly better than existing heuristics during the peak of the emergency period.

The literature on DRL applications to production systems across different industries is vast. The readers are directed to Panzer and Bender [11] for a comprehensive review. The authors found that 89% of the benchmarked DRL implementations resulted in improved scheduling performance achieving lower total tardiness, higher profits, or other specific objectives, compared to current practice and other heuristics.

2. Methodology

2.1. Problem Description

Once the strategic plan for a mine is established, the operational and short-term plan requires determining an optimal and feasible sequence of mining areas to be prepared and extracted along with allocating equipment resources for these activities over shorter periods. Commonly operational plans are defined quarterly or month to month for activities such as mining sequences, mine access development and shovel allocations. At this stage, one of the critical decisions is to define a shovel allocation policy that assigns shovels to mining faces to meet ore production and quality targets. This decision is subject to high operational uncertainties in the estimated production outputs due to the stochastic nature of shovel loading and truck haulage operations, and geological and other uncertainties in estimating the rock properties.

For this purpose, many algorithms have been proposed in the literature to solve the short-term planning problem considering different decisions and constraints. Most commonly, Mixed-Integer Linear Programming (MILP) models have been developed to solve the operational short-term planning problem. However, deterministic MILP models do not allow to account for any source of uncertainty which can render their solutions unfeasible, requiring effort in the field to accommodate changes over the initial plan. Moreover, they require describing the model as a set of linear equations however the production environment of open-pit mining is a highly dynamic, uncertain environment which greatly complicates solving MILP models.

In this paper, an Artificial Intelligence (AI) agent is developed to learn a shovel-allocation policy to maintain the production targets at crusher feeds during a production quarter. The AI agent is a Neural Network that given the available mining areas to mine at any point and the shovel that requires an allocation, will suggest a matching that will meet the required production targets. For this purpose, the AI agent is trained in a simulation model of the mine production environment, that is built using historical equipment records to mimic the real mine performance, under Deep Q-Learning, a RL framework. As a result, the mine production environment reflects all the operational uncertainties, and the AI agent learns a shovel allocation policy that directly accounts for them.

2.2. Deep Q-Learning

Q-Learning is one of the most widely used RL based algorithms and has seen success in industrial production scheduling applications (Panzer and Bender (2021) [11]). Q-Learning is based on learning from a trial-and-error approach where an agent interacts with an environment over time steps $t = 1, 2, ..., T$ until a terminal time step T is reached. At every time step, the agent observes the environment state s_t and takes an action a_t, from a set of available actions at that time, after which the environment responds to this action by transitioning to a new state s_{t+1} and providing the agent a reward r_{t+1}. The goal of the agent is to find an optimal policy, action selection strategy, that maximizes the total return at any time step t, G_t, defined as the discounted cumulative reward obtained from that time step until the end of the interaction $G_t = R_{t+1} + \gamma R_{t+2} + ... + \gamma^{T-1} R_T$, where the discount factor γ determines how much the agent cares about long-term rewards relative to immediate gains.

During the training process of a Q-learning agent, it tries to build an estimate of the expected return obtained from taking action from a given state, defined as the action-value function $Q(s, a) = E[G_t | S_t = s, A_t = a]$. For this, the agent explores and exploits its current environment knowledge at every iteration. Exploration refers to selecting an action at random, and exploitation to selecting the action that maximizes the returns given the current knowledge of the environment. The most common strategy to balance the exploration versus exploitation problem is the epsilon-greedy exploration strategy, where at every time step with ε probability the agent explores, and ε is decreased over time.

Once the Q-value function is estimated, the optimal policy is that which maximizes $argmax_{a_t} Q(s_t, a_t)$ at every time step. This would require visiting every state-action pair for a given environment multiple times, which would be impossible for any real-world application. To address this issue, the action-value function is parametrized as a function with some parameters θ, $Q(s, a; \theta)$, that given a state and action vectors predicts the return from the environment. A Neural Network (NN) can be used as the function approximator and is trained to predict the action-value function $Q(s, a; \theta)$ for any state and action pair from interaction with the environment. The implementation details for the use of a NN within a Q-learning framework, Deep Q-Learning (DQL), are fully described in Mnih et. al. (2015) [7].

The training process in DQL relies on the agent interacting with the environment storing experience vectors, $e_t = (s_t, a_t, r_t, s_{t+1})$ that represent each transition observed in a memory replay buffer which serves as the training dataset for every training update of the NN. At every NN training step, a batch of experiences are drawn from the replay buffer, and the NN weights are trained to minimize the prediction loss $L_i(\theta_i)$ defined as the mean square error (MSE) between the observed return (target) and the predicted return from the network at training step i:

$$L_i\left(\theta_i\right) = (r + \gamma max_{a_{t+1}} Q\left(s_{t+1}, a_{t+1}; \theta_i^{tgt}\right) - Q(s_t, a_t; \theta_i))^2$$

Where θ_i^{tgt} refers to a NN used to evaluate target returns not trained at every step but synced with the online network defined by θ_i every C steps, which helps stabilize the training process.

The general algorithm for the original Deep Q-Learning is described below.

Algorithm General DQL framework
Initialize replay memory D to an initial capacity N. Initialize action-value function Q with weights θ and target action-value function Q^{tgt} with weights $\theta^{tgt} = \theta$. For each episode: For $t = 1, ..., T$: Observe environment state s_t With probability ε select a random action a_t otherwise $a_t = argmax_a Q(s, a)$ Execute action a_t in environment. Observe reward r and next state s_{t+1}. Store transition $(s_t, a_t, r_{t+1}, s_{t+1})$ in memory replay buffer D Sample a random batch of transitions from the replay buffer D. For every transition in the batch, calculate target $y = r$ if episode ended at this step or $y = r + \gamma max_{a_t} Q^{tgt}(s_{t+1}, a_{t+1})$ otherwise For every transition calculate loss $L = (y - Q(s_t, a_t))^2$ Update θ to minimize loss with respect to model parameters Every C steps set $Q^{tgt} = Q$

2.2.1. DQL Implementation

Since the publication of the original DQN method [7], many improvements have been proposed to enhance learning efficiency, significantly improving convergence, training stability and sample efficiency. Google DeepMind collected some of the most important improvements to the original DQN and combined them into the Rainbow DQN agent, showing a significant increase in overall performance (Hessel et al. (2018) [4]).

The DQN implementation in this paper includes the following additional components of the Rainbow DQN agent. Note that the general training framework follows the same algorithm described in Section 2.2.

- n-Step DQN

Improves convergence speed and stability by unrolling the action-value function $Q(s, a)$. The original DQN accumulates single-step rewards at each transition; however, using forward-view multi-step rewards as targets often leads to faster learning, as described by Sutton (1988) [15]. The implementation is straightforward: once an action has been taken from a given state, the return (discounted cumulative reward) observed after n steps from that action is used as the target for the action-value prediction. Values of $n = 2$ to $n = 5$ usually yield good learning behavior. In this research $n = 4$ was used.

- Double DQN

The original DQN tends to overestimate action values, leading to training instabilities and convergence problems. This is due to the maximization step in estimating the returns that serves as the target for training. Double Q-Learning was proposed by van Hasselt et al. (2016) [18] as a solution to the maximization bias, where at every time step choosing actions is done from the Q-network $Q(s,a)$, but the target network Q^{tgt} is used to evaluate the target for the updates.

- Noisy networks for exploration

The epsilon-greedy strategy for exploration can be limiting in complex environments. Fortunato et al. (2017) [3] proposed a simple but improved exploration strategy by adding noise to the weights of the NN agent rather than relying on the epsilon-greedy strategy. The noise in the NN model leads to some randomness in the agent's action selection but is adjusted automatically as an additional parameter by backpropagation during training. As training progresses, the NN can learn to ignore the noisy paths through the network at different rates in different parts of the state space, allowing for a form of state-conditional exploration.

- Prioritized experience replay buffer

The original DQN samples experiences from the replay buffer uniformly for every training step; every transition has the same probability of being used in a training step. Schaul et al. (2016) [13] argued that it would be ideal to sample transitions from which there is more to learn more frequently and proposed a prioritized replay buffer mechanism. Transitions are sampled with a probability proportional to that transition's last observed training loss. Therefore, the agent trains more often on transitions from which it had trouble predicting their outcome.

- Dueling DQN

Wang et al. (2016) developed a novel NN architecture suited for value-based RL methods that features two streams of computation, based on the observation that the action-value function $Q(s,a)$ can be decomposed as the sum between the value of the state s, $V(s)$, and the advantage of taking action a from state s, $A(s,\ a)$. The advantage of action can be interpreted as how much extra reward some particular action from a given state yields. The dueling DQN architecture takes the feature vector and processes it through two independent paths: one for predicting the state's value and another for predicting each action's advantage. After that, the values can be summed to obtain the Q-function. This architecture resulted in better training stability and faster convergence.

The integrated agent for shovel allocations to meet production targets in open-pit mining developed in this paper follows the basic DQN algorithm incorporating all the improvements discussed above. The loss function to train the NN used is the MSE, as described in Section 2.2 and the optimizer used in training is ADAM, which has become a reliable NN optimizer that typically requires little tuning [6]. This loss function and optimizer combination has shown to perform well for Rainbow-based DQN agents in small and complex environments (Obando-Ceron and Castro (2021) [10]). The entire framework is implemented in Python's Pytorch deep learning package.

2.3. The Agent

The agent is a fully connected NN with three layers and 128 neurons each. Each layer has a Rectified Linear Unit (ReLU) activation function, which helps to speed up gradient calculation times and control vanishing/exploding gradient problems. Moreover, at every step, the gradient norms are clipped to a norm within 10 to stabilize training further, a common practice described in Zhang et al. (2020) [20]; this means that rare extreme experiences will not cause extreme shifts in the NN parameters.

Since the Dueling DQN architecture is used, there will be two network paths: one for predicting state values $V(s)$ and one for predicting the advantage of taking each action from a given state

$A(s,a)$ as described in Section 2.3. The NN agent architecture is depicted in Figure 2. The agent was implemented using the Python's Pytorch package.

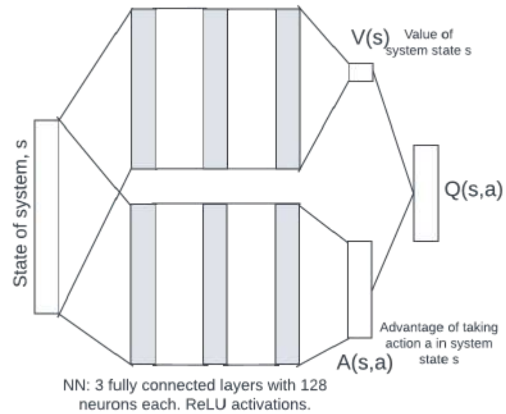


Figure 2. Shovel allocating NN agent architecture.

2.4. The Environment

A discrete-event simulation (DES) model of the operational open-pit truck and shovel environment is developed in Python using the SimPy general-purpose simulation package. The DES models the interaction between loading and hauling equipment, mining faces, crushers, and waste dumps within the mine haul road network and keeps track of different production Key Performance Indicators (KPI) of the system, such as tonnage delivered at crushers, the average grade of ore delivered to crushers amongst other commonly tracked KPIs in mining.

The DES model simulates the extraction of mining faces, aggregation of mineral blocks to be mined by a single shovel, commonly referred to as mining cuts or polygons, and the haulage of material to destination points such as crushers and waste dumps, with the potential to account for stochasticity in every component of the equipment cycles.

The DES starts with an assignment of shovels to their initial mining face and simulates the movement of trucks along the road network to get loaded by the shovels and dump their payload at the set destinations for each mining face. When a mining face is depleted, the shovel needs to be relocated to a new mining face to keep production going; at this point, the AI agent is called to decide which of the available mining faces at that time the shovel will be assigned. Then, the shovel takes some time to move to the new mining area and resumes its operation after arriving. Figure 3 illustrates the general logic.

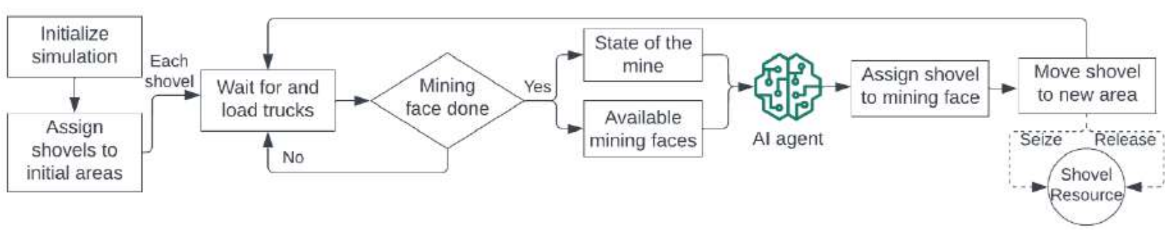


Figure 3. General logic of the open-pit DES model and interaction with the AI agent for shovel allocation decisions.

Truck haulage is modelled by calculating the travel time through the different segments in the road network that form a path between a destination and a shovel, a haul route. The velocities assigned at each individual segment depend on the rimpull curve of the truck and the rolling and grade resistance of the road segment. When a truck arrives at the shovel, it queues and waits for the shovel to be available, then seizes it and receives multiple bucket-loads of material from the mining face until full. Afterwards, it moves through the haul road network until reaching the destination set for the material coming from the mining face it received its load from, a crusher or a waste dump. If necessary, it queues, dumps its payload, and then travels back to the shovel. Each shovel can break down, which will be unavailable until it is repaired. Figure 4 illustrates the truck haulage logic.

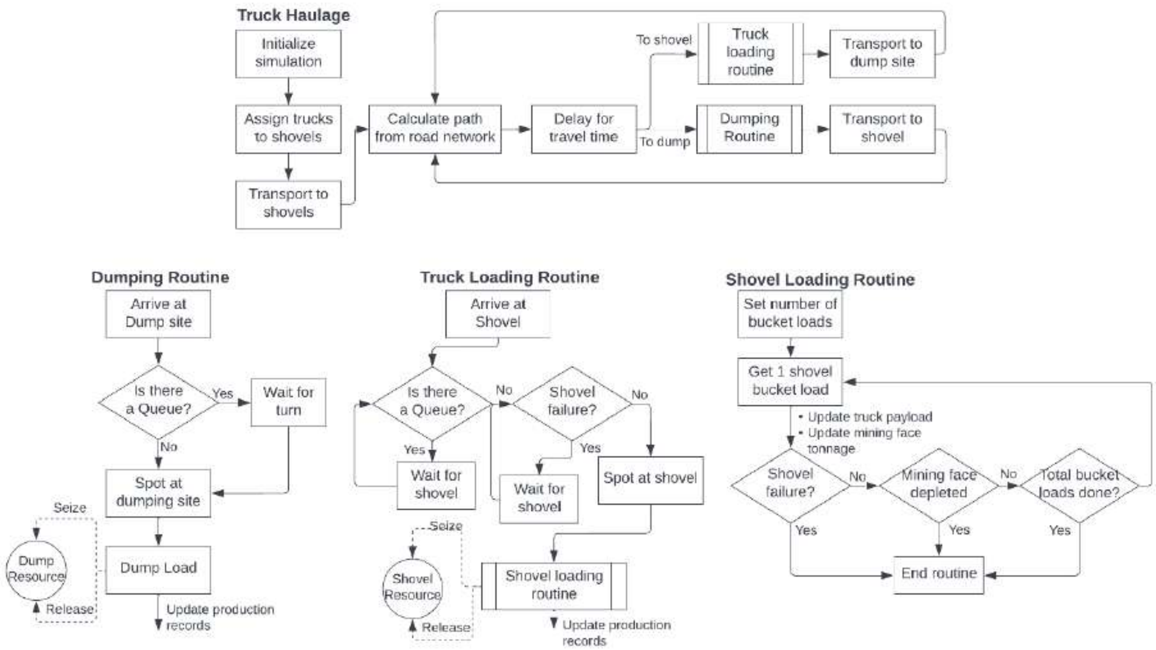


Figure 4. Truck Haulage simulation logic.

Other assumptions made in the current version of the DES model are:

- Each mining face has an average mineral grade and total tonnage. Therefore, each truck payload from a mining face will have the same average grade.
- Destinations for each face's material are fixed; each mining face has a set destination: a given crusher or a given dump. No decisions on destination policies are made at this point but will be considered in future research.
- No truck dispatching logic is considered at this point; each shovel has a fixed truck fleet assigned to it. Future research will consider truck fleet sizes and allow for incorporating a truck dispatching logic.
- No truck bunching through the haul network is considered.

2.5. State and Action Representations

During the training phase, the RL agent learns how to correlate the system state description and the actions taken with the cumulative reward obtained to identify high-value actions. The actions taken by the agent are defined as shovel allocations and happen when a mining face is depleted, and its assigned shovel requires a new mining face allocation to keep production going.

The state of the system at a given time t when an action is required must encode all features needed for the agent to learn its relationship with the desired objective to be maximized. For this purpose, the state of the system is encoded as a vector with the following components:

$$s_t = [MF_i, SH, t]$$

Where MF_i encodes information about every mining face in the system for the time period to be analyzed and is defined as:

$$MF_i = [ton_i, \ grade_i, \ dist_i, \ active_i, avlb_i]$$

Where:

ton_i:	Tonnage remaining in mining face i, expressed relative to its total tonnage
$grade_i$:	Average mineral grade in mining face i
$dist_i$:	Distance from mining face i to its given destination through the road network, normalized between [0, 1] based on the maximum distance across all mining faces
$active_i$:	Binary flag: 1 if the mining face is currently being mined by a shovel, 0 otherwise
$avlb_i$:	Binary flag: 1 if the mining face is available for mining, 0 otherwise

SH is one hot encoded vector that indicates which shovel needs to be assigned at this time, and t is the current simulation time, expressed as a fraction of the total episode length.

By interacting with the environment, selecting actions using this state representation and observing the total returns (cumulative rewards), the agent learns to predict the value of each action and, based on this prediction, to select an optimal shovel allocation with respect to the reward function.

2.6. Reward to be Optimized

The reward defines the objectives to be maximized. The objective considered here is to minimize the shortage of material delivered to the crusher feed relative to the desired production target $Prod_t$. Therefore, a penalty for production target shortages at the crushers is given to the agent for each step as:

$$Prod_t =- \sum_{h \in H} 1 - \left(\frac{actual\ tph}{target\ tph}, \ 1 \right)$$

Where tph indicates tonnes per hour delivered to the crusher feed, and H indicates the number of hours between the transition. Therefore, the agent is penalized for every hour it fails to meet the target tph between each step, by a value equal to the sum of the relative gaps between the actual tph delivered and the specified target. However, going over the tph target is not penalized, for which the minimum function is used if the actual tph is greater than the target tph.

3. Case Study

The shovel allocation AI agent proposed in this paper was tested on a case study based on an iron ore mining operation. The mining operation uses a total of 5 shovels to load material from mining faces: 2 Hitachi 2500 shovels, with a bucket payload of 12 tonnes, for ore production and 3 Hitachi 5500 Ex shovels, with a bucket payload of 22 tonnes, for waste production. A fleet of 33 trucks is employed to haul the material from the pit to their destination, either one of two crushers or a waste dump. The mine uses 15 CAT785C, with a payload of 140 tonnes, to work with the ore shovels and 18 CAT793C, with a payload of 218 tonnes, to work with the waste shovels. The mine ore production targets for the crusher feed are 1300 tonnes-per-hour (tph). The mine operates one 12-hour shift per day, seven days a week.

The agent's goal is to define a shovel allocation plan to meet the crusher feed production target for the next quarter (3 months), given the mine layout, equipment performance and available mining faces. The set of mining faces to extract is based on the long-term strategic plan of the mine, where the ones expected to be mined in the next three months are used. Each of these faces has a set of physical precedences that represent the physical space required to start extraction, which is enforced by presenting to the agent only the available faces at each step when an action is required. Figure 5 shows a plan view of the mine layout; in which, in addition to the crusher and waste dump locations, the access to the mining faces areas. From the mining faces access, it is assumed that the distance to each mining face is the linear distance between its digging coordinate and the closest access point in the road network.

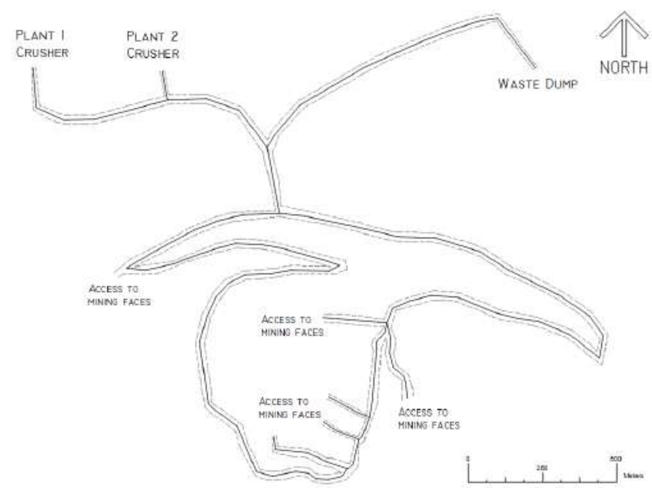


Figure 5. Mine layout for the case study.

To model the equipment production behavior, statistical distributions were fitted to recorded historical data from an available equipment dispatch database to the different activities that comprise the equipment's load and haul operating cycle in the case study. Table 1 shows the equipment distributions. Truck spotting times at the dumping sites were not retrievable, so a practical mean value was used.

Table 1. Distributions fitted to different activities in the productivity cycle of the load and haul equipment.

Activity		Distribution
Shovel bucket cycle time	Hit 2500	Triangular(15, 26, 50) [seconds]
	Hit 5500Ex	Triangular(15, 29, 50) [seconds]
Shovel up-time	Hit 2500	116 * Weibull(34) [hours]
	Hit 5500Ex	116 * Weibull(32) [hours]
Shovel down-time	Hit 2500	Gamma(1.4, 1.5) [hours]
	Hit 5500Ex	Gamma(1.4, 1.5) [hours]
Truck spot time at shovel	CAT 785C	Gamma(22.54, 1.39) [seconds]
	CAT 793C	Gamma(26.91, 1.36) [seconds]
Truck spot time at crusher	CAT 785C	30 [seconds]

	CAT 793C	30 [seconds]
Truck dump time	CAT 785C	Normal(52, 6) [seconds]
	CAT 793C	Normal(55, 8) [seconds]

The truck haulage time throughout the network was determined based on the truck's rimpull characteristics and the road's total resistance. The shortest path between the truck location and its destination is determined, and the travel time is calculated based on the road segments that compose the path by using the maximum speed the truck can achieve on each road segment based on its rimpull curve from the manufacturer specifications and the road total resistance. The mining operation was simulated as described in Section 2.4.

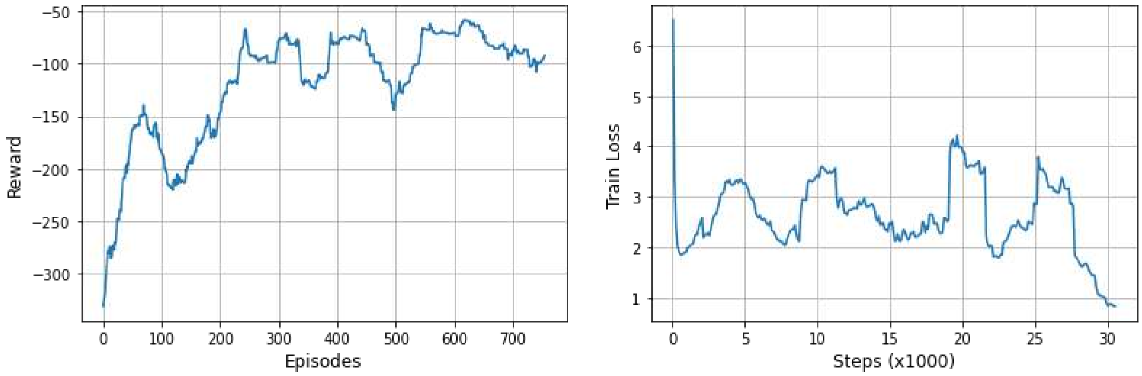
The shovel allocation agent was trained following the DQN algorithm described in Section 2.2, with the hyperparameters shown in Table 2. Future research will investigate each hyperparameter's impact on the agent's training to identify the critical ones and provide some guidelines in selection and tuning.

Table 2. Hyperparameters selected for the training of the AI shovel allocation agent.

Replay buffer size	8000
Initial samples in replay buffer	2000
Batch size for training updates	32
Discount factor	0.99
Learning rate	0.001
Iteration update frequency of target network	1000
n for multi-step returns	4

The training was performed in the Google Colab service, which provides a virtual machine with powerful GPUs to train DL models. The GPU used in the instance where the trained agent was a Tesla P100.

The agent trained for 6 hours until convergence was observed in the reward obtained on each episode, where an episode corresponds to a shovel allocation plan for 3 months (quarter). This indicates that the agent has learned a policy, a decision-making strategy, that achieves the desired goal over multiple potential outcomes based on the stochasticity of the equipment operating cycles and failures, rather than finding a solution to one potential outcome or a completely deterministic scenario based on the average performance. Figure 6 presents the training curves for both the reward achieved by the agent decision-making and the loss from the agent's NN prediction of shovel allocation action values. Both curves in Figure 6 show a moving average over 25 episodes.



(a) (b)

Figure 6. (a) Reward obtained at each episode during training. (b) Training loss of the agent NN for each training step.

Figure 6 (a) shows how at the start of training, where the agent initializes its NN with random weights, it performs poorly at each episode. The shovel allocation plans at early training stages fail to meet the production targets at the crusher feeds by a large margin, incurring a large negative cumulative reward for the production quarter. However, as training progresses and the agent becomes better at predicting the value of each shovel movement, the performance increases until converging at around -80, with some oscillations due to the stochastic nature of the system. Convergence at this reward level indicates that the agent cannot fully meet the hourly production targets at the crusher feeds due to failure in shovels, which are part of the system and can significantly halt production until repaired.

Figure 6 (b) shows the average loss for the agent's NN prediction at each step during training, where a step means a shovel allocation action and every episode is composed of multiple of these. In the early stages, the NN performs poorly but improves its performance rapidly, providing better predictions of the value of each shovel allocation. Significant oscillations are observed in the loss curve, which are common in DRL applications. Since the NN training data is generated from a decision-making policy that is also changing through the training phase as the agent improves its performance, this means that the distribution of the training examples is changing continually, and the NN is effectively chasing a moving target. The implementation of the target network for evaluation of value functions rather than using the same network that is constantly changing alleviates this issue in practice. The stagnation in the loss curve performance could suggest that the model system state representation maybe insufficient to fully predict the value of each shovel movement, giving the agent additional information such as past shovel allocations, productivity rates, or cycle times could help the agent make better predictions.

To obtain a shovel allocation plan to use in practice, the simulation can be run with a fully trained agent, and the movements can be recorded. Figure 7 shows a Gantt chart feasible shovel allocation plan obtained by the agent for the production quarter. Each horizontal bar represents the allocation of a shovel to a given mining face, based on its ID, for each day. The plan proposed by the agent is robust as after training, the agent found a shove allocation strategy to meet the desired goals over many potential productivity outcomes. Moreover, the agent can be updated with the real-world progress of the operational plan and queried at any time in production that a decision is needed to obtain a suggested shovel allocation action.

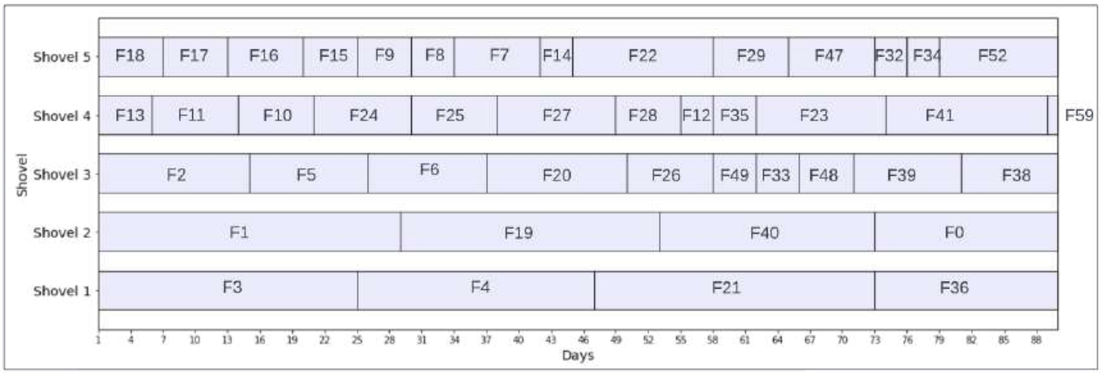
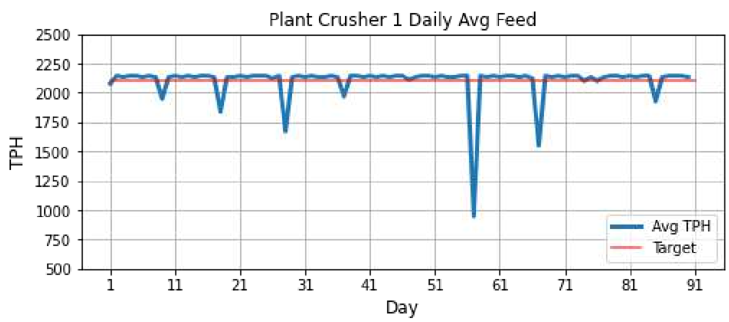
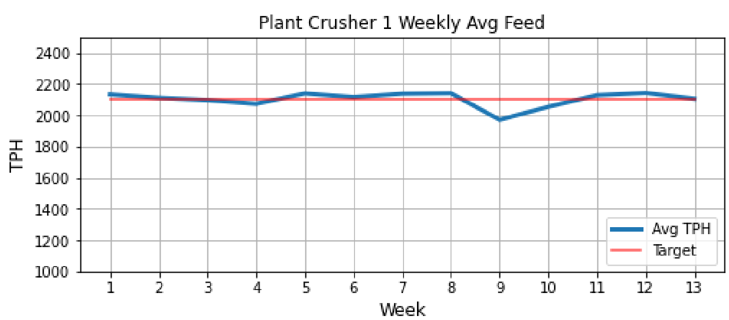


Figure 7. Shovel allocation plan for a production quarter of the case study.

The shovel allocation plan was evaluated by observing the crushers' feed to ensure it meets the desired target. Figure 8 and Figure 9 show the average daily and weekly TPH delivered at the plant crusher 1 feed and plant crusher 2 feed, respectively for the production quarter.



(a)



(b)

Figure 8. TPH delivered to plant 1 crusher feed from the shovel allocation plan. (a) Daily average and (b) weekly average

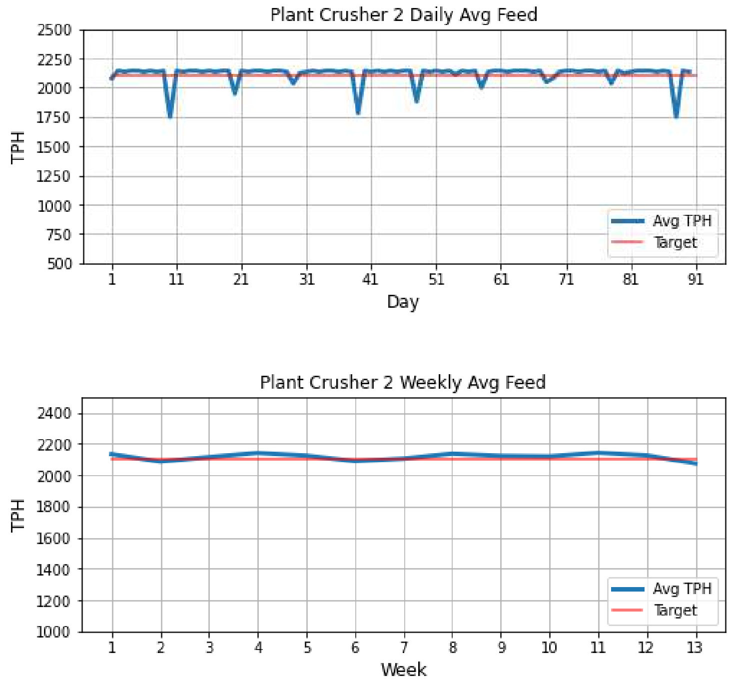


Figure 9. TPH delivered to plant 2 crusher feed from the shovel allocation plan. (a) Daily average and (b) weekly average.

Overall, the agent meets the production goals as closely as possible; the large drops in TPH are due to shovel failures since there are only two ore shovels; the agent cannot feed the crusher they were working on until repaired.

4. Conclusions and Future Research

A simulation-optimization approach for open-pit short-term planning is proposed in this research to obtain a robust shovel allocation plan that meets specified production targets under operational uncertainties of equipment performance. A RL framework is used where a NN based agent allocates shovels throughout the production simulation by observing the state of the mine and the available mining faces. The agent receives a penalty for every hour it fails to meet a specified production target, defined as tonnes per hour (TPH) delivered to crusher feeds, equal to the relative gap from the actual TPH observed in response to the shovel allocation actions. A Deep Q-learning RL framework is used to train the agent to learn an optimal allocation policy to minimize this production shortage over multiple interactions with the mine production simulator. During training, the agent's NN gets better at predicting the return of shovel allocation actions given the state of the mine and available mining faces, where the return is defined as the long-term cumulative reward obtained which gives the agent some insight into the long-term impact of each action, and it's guided towards high-value actions to define an optimal plan.

A case study is presented for an iron ore mine where a shovel allocation plan is required for the next production quarter (3 months). The agent was trained for 6 hours, and its performance converged to a shovel allocation policy that met the specified TPH target delivered at two plant crusher feeds. This plan is robust as the agent has interacted with the environment multiple times, and the strategy learned produces a similar total return over many production simulations.

Future research will be directed into different state representations and NN architectures that can enhance learning efficiency. Currently, a simple approach of representing the system's state as a long vector serving as input to a basic fully connected NN is proposed, which can be improved by investigating NN architectures more suitable for learning long-term dependencies or graph-structured problems. Moreover, additional feature engineering can also improve the learning efficiency of the agent, by improving the information used in the state representation. More complex rewards will be investigated too, including operating costs and blending to learn a minimum cost feasible short-term plan.

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A Framework for Integrating Carbon Emissions into Short-term Planning of Surface Mines

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ABSTRACT

Risks arising from climate change pose financial, environmental, and social threats to the mining industry. The mining industry consumes up to 11% of the global energy, while 70% of the mining projects from the six largest mining companies operate in water-stressed regions (Hund t al., 2020). The mining industry is under pressure from regulators, investors, and society to limit global warming to at or below 1.5 ˚C – 2 ˚C. In response to climate change and sustainability, most mining companies are taking major steps to minimize their greenhouse gas emissions (GHG). According to the Equinix Mining Technology Report (2021-22), 74% of business leaders in the industry cite sustainability as the most critical business issue. Despite its negative impact on the mining industry, the energy transition offers an excellent opportunity for the industry as it pushes the demands for raw materials higher than ever. For example, lithium demand is predicted to rise 965% by 2050 (Sovacool et al.,2020). In this study, we try to explore how the contradicting goals of sustainable mining and the increase in the demand for raw materials will impact the short-term production planning in surface mines. We aim to investigate the possibility of translating the CO2 emissions into a quantifiable factor being imposed to the process of short-term planning in surface mines.

1. Introduction:

Up to 80% of the raw materials are mined using the open pit mining method, a way of extracting near the surface minerals through an open-air pit (Osanloo et al,. 2020). Today, the mining industry is moving toward digitally integrated operations to meet the net-zero emissions targets without compromising productivity. It is necessary to handle the massive quantities of data generated by everyday mining activities to ensure the industry's efficiency. A single large open-pit copper mine can emit up to 200,000 tCO2e, annually. Mitigating carbon emissions in the mining sector requires developing intelligent strategies and planning practices to implement cutting-edge green solutions, methods, and technologies, the mine planning department is not excluded. Our work will focus on finding the best way to incorporate CO2 emission into the process of the short-term planning horizon.

2. Methodology

To consider the effect of carbon emissions in short-term planning, we first establish a life cycle assessment (LCA) framework for the surface mining value chain. LCA enables us to quantify the emission rate depending on production volume (kg CO2e/tonne), which integrates the CO2 emission and financial objectives. The short-term planning model coupled with LCA is an integrated solution to reduce direct and indirect carbon emissions while considering long-term production targets.

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3. Results and Conclusions

We integrate the LCA techniques with the optimization model in a two-step framework to introduce our integrated short-term production planning algorithm for open-pit mines (Fig. 1). Our framework uses the short-term plan to reduce machine idle times, traffic blockage, unnecessary re-handling, and machine relocation to optimize life-cycle energy use. The framework also considers the block properties and fleet allocation as two main short-term objectives with the highest impact on mining energy consumption. Unprioritized low-grade excavation increases the energy consumption of heavy machines and comminution equipment. Within the framework, the hybrid simulation-optimization algorithm selectively optimizes the short-term production sequence based on two aforementioned factors. It involves real-time optimization of mining blocks and truck-and-shovel allocation to achieve lower carbon emission objectives.

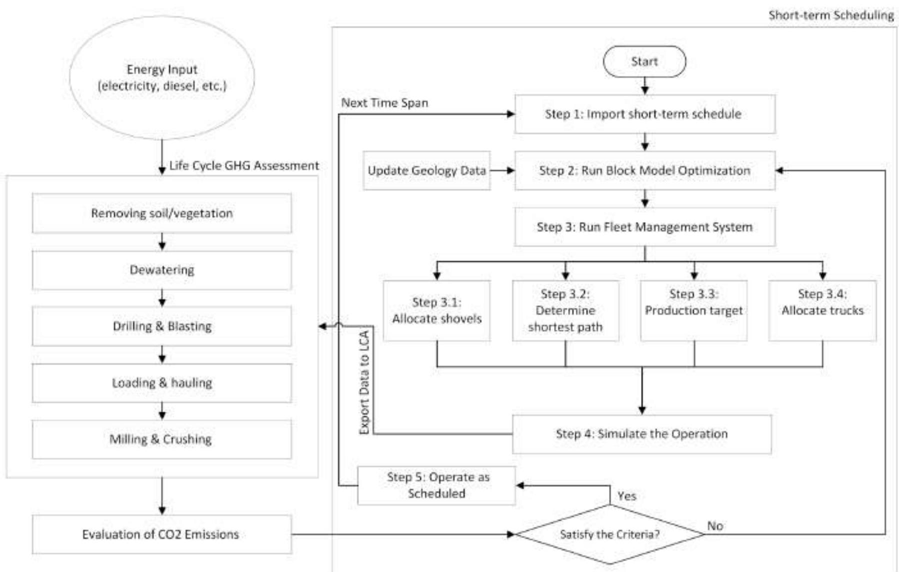

Figure 1. Schematic flow chart of integrated short-term planning with LCA.

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